FINANCIAL AND SPATIAL ANALYSIS TO FACILITATE SUSTAINABLE ENERGY INVESTMENTS IN LARGE PUBLIC UNIVERSITIES: TOWARD A MORE PROPERCOUPLING BETWEEN INSTITUTIONAL, ENVIRONMENTAL, AND SOCIAL SYSTEMS

by

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DEDICATION

This dissertation is dedicated to the women in my life: My wife, sisters, mother-in-law, and my beloved mother's memory passed away before starting my higher education adventure.

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ABSTRACT

Responding to the existential threat posed by global climate change will require adaptation and evolution at multiple interacting scales. This study relates to this domain focused on sustainable energy production and consumption and ways to change significantly. Spatial context becomes a determinative factor in this perspective. Seeking civic engagement reveals the extent of preparedness for a substantial change. Leadership and decision-making in public Higher Education Institutions (HEIs) reflect (at least partially) the preferences and values of their local communities or regions as most HEIs strive to be upstanding citizens who maintain effective Town-Gown relations. This study shows discrepancies between this assumption and the results found through spatial analysis. It is instinctive to look to universities as sustainable practice models in their respective communities. This dissertation is part of the ongoing series of analyses that assess the sustainability problem's roots and the costs, benefits, and effects of different sustainable measurements. While the earlier research focused exclusively on the profitability of certain alternative energy investments at a single university, this dissertation offers a more nuanced study that analyzes renewable energy implementation or failure in four public universities through a conceptual framework lens. The proposed method will apply a root cause analysis by involving the spatial context representing the first step in creating a national-level evaluation as the main contribution. The results allow classifying every alternative energy project under investigation along four dimensions: (1) financial feasibility, (2)

community environmental preferences, (3) state energy policy arena, and (4) energy savings. In conclusion, a series of key terms and ideas are developed to show the extent of proper coupling in each institution.

1. INTRODUCTION AND RESEARCH QUESTIONS

The rising global population and growing demand for energy to support economic development led to historical fossil fuel consumption levels in recent decades. Along with that increased consumption, the world has seen an intensification and expansion of the negative environmental externalities associated with fossil fuel extraction, processing, and consumption (Baban & Parry 2000; Aydin et al., 2010; Azizi et al., 2014). Globally, climate change resulting from CO_2 and other greenhouse gas emissions poses a threat to human and planetary welfare (Climate Change Committee (CCC), 2008). At the macro-level, these changes could influence rainfall patterns, availability of drinking water, agricultural practices, and sea levels (International Energy Agency, 2013). Locally, they are projected to increase variability in weather patterns, cause extreme weather events to occur more frequently, and, as such, put countless ecosystems at risk of degradation or even collapse (Field 2014; Stocker, 2013; IPCC 2013; IPCC 2014b; Mirza, 2003; Rosenzweig et al., 2001). The adverse consequences of massive fossil fuel consumption do not include only environmental concerns. It also encompasses dependence on South West Asia and North Africa's oil, funding non-democratic regimes and representing an international threat to the security discussed in the United Nations Security Council (Shaffer, 2011).

While responding to the "existential threat" posed by global climate change (Derber, 2015) requires adaptation and change at multiple interacting scales, at least one societal domain where the action seems most urgent is energy consumption. Concerns about the environmental effects of fossil fuels have pushed several countries to invest more in alternative energy resources (Ibenholt, 2002). The constant apprehensions over rising temperatures, environmental pollution, and energy security have increased interest in achieving "environmentally friendly energy sources such as wind, solar, hydropower, geothermal, hydrogen, and biomass as the replacement for fossil fuels" (Tong, 2010 p.3). Many countries have already integrated renewable energy systems into their national energy plans. The nations of the European Union, for example, aim to provide 20% of their energy from renewable energy sources by 2020 (Atici et al., 2015). Before that, the goal was set to double the contribution to primary energy consumption from 6% to 12% by 2010 (Haralambopoulos and Polatidis, 2003). Individual countries have also adhered to this idea. For example, by 2050, the UK aims to reach an 80% reduction in CO_2 emission (Climate Change Committee (CCC), 2008). More than two decades ago, 191 countries signed the Kyoto Protocol (1997), and more recently, 174 countries and the European Union have adhered to the Paris agreement on climate change (2016), which makes them responsible for a commitment to alleviate the environmental degradation caused by traditional forms of energy production. At the micro-level, and for example, in the United States, which composes the main study area of this dissertation, States have created multiple standards to diversify their energy resources, promote domestic energy production, and encourage economic development (National Conference of State Legislatures, from here on known as NCSL).

In this dissertation, I argue that higher education institutions (HEIs) have a unique opportunity and responsibility to be the leaders on this front. HEIs are spaces where knowledge of sustainable development and sustainable energy practices come to life in research and teaching (Awuzie and Abuzeinab, 2019). At the same time, most college and university campuses function as their own spatially based communities—cities within cities—that have the potential to offer scalable solutions for creating more sustainable neighborhoods, cities, and regions (Norton et al., 2007). Putting these two observations together, it follows that HEIs can look inward and project outward to answer pressing questions about how to reduce fossil fuel consumption while still performing essential economic functions. Concerning the latter, contemporary colleges and universities face many of the same incentives and expectations as for-profit businesses (Sperling, 2017). They are pressured to grow student enrollments (as well as physical space) while offering more, higher-quality programs on tight and, in some cases, shrinking budgets (Sightlines, 2018; Fonseca et al., 2018).

One possible way to intervene in HEI energy systems—where, because of their social missions, HEIs are arguably more predisposed than for-profit businesses to want to migrate to more sustainable energy regimes—is to generate empirical evidence that new, comparably sustainable energy investments will enable HEIs to comply with sustainable goals while not causing them to sacrifice their growth-related objectives

Related emission-reduction initiatives in HEI and other governance scales seek to put global temperature change on a different, less extreme trajectory. Specifically, data released by the Copernicus Climate Change Service (C3S) tell the tale of a persistent warming climate. A recent report from C3S shows that 2018 was the fourth in a series of hot years. C3S, also reports that atmospheric CO_2 concentrations have continued to rise by 2.5 +/- 0.8 ppm/year (Figure 1). To slow the rate of warming associated with these concentrations, members of the CCC in 2008 advised that a 50% reduction of CO_2 emission is needed by 2050 on a global scale. Recognizing the need for international cooperation on this matter, the Paris Agreement entered into force in November 2016 with more than 110 cosigner countries, representing more than 75% of global emissions. However, per the International Energy Agency, even if nations fulfill the Paris Agreement goals, it is still unlikely to keep the warming climate below 1.5°C of increase on the average global temperature (World Energy Outlook, 2016).

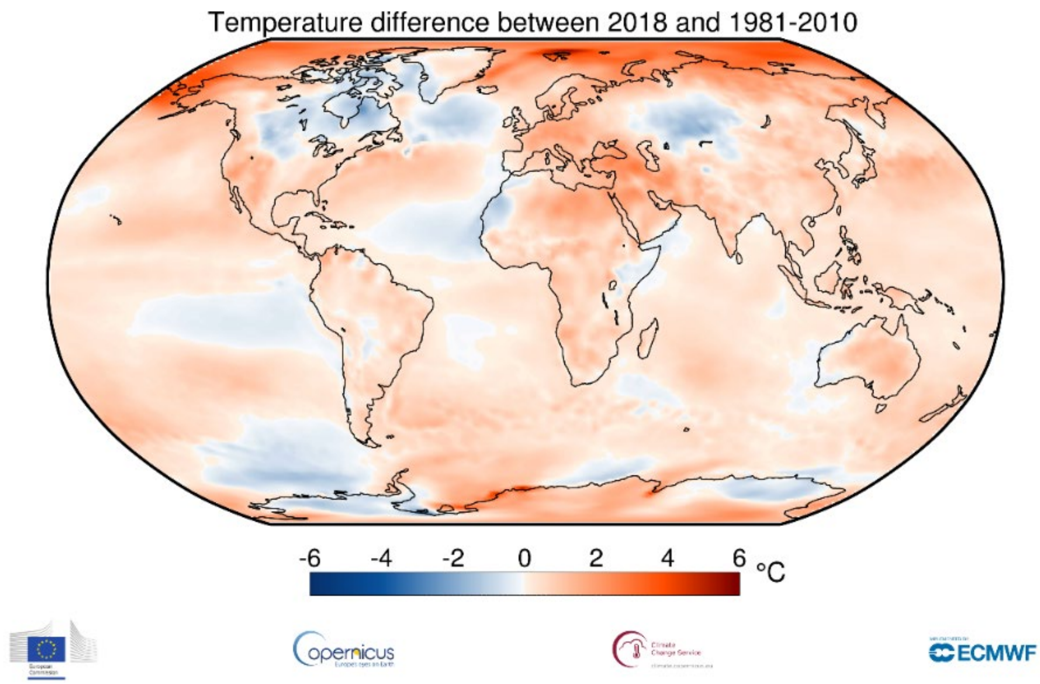

Figure 1. The temperature difference between 2018 and 1981-2010 (source: C3S)

Based on these trends and their severe and negative implications for global environmental health, the correlation between energy consumption and a warming climate has increasingly come to be a leverage point for intervention (Pérez-Lombard, 2008; de Santoli et al., 2014; Singh and Parida, 2015). To understand why energy consumption is such an intense focal point for behavioral change, consider the United States' case. In just twenty years, from 1984 to 2004, primary energy consumption in the U.S. grew by 49% and CO_2 emissions by 43%, with an average annual increase of 2% (Pérez-Lombard, 2008). This increasing trend has occurred continuously, with only a handful of exceptional years (Figures 2 and 3). The following figures produced with data provided by *Enerdata* show the amount of energy consumed in the world and the United States in million tonnes of oil equivalent (Mtoe). In the absence of energy policies explicitly designed to mitigate human contributions to global climate change, energy consumption in the United States' residential, commercial, and industrial (RCI) sectors is expected to continue to grow drastically. At least one estimate by Brown and colleagues (2010) predicts that growth to be on the order of 16% between 2010 and 2030.

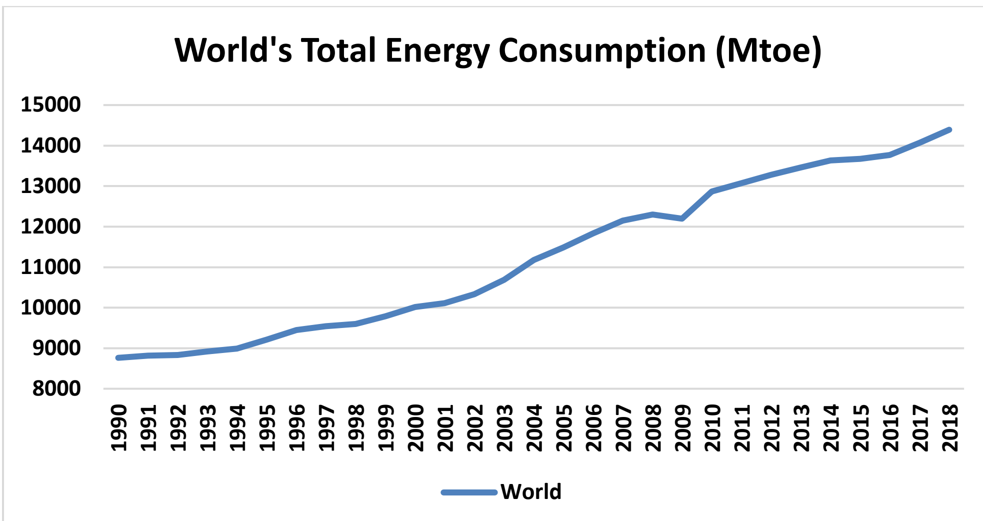

Figure 2. World's Energy Consumption Trend 1990 – 2018 (Source: Enerdata)

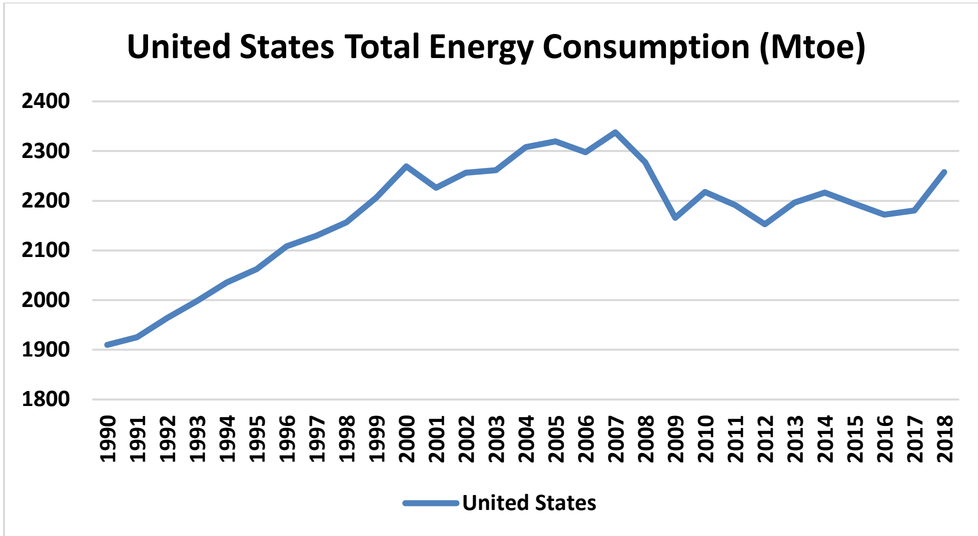

Figure 3. The U.S.A. Energy Consumption Trend 1990 – 2018 (Source: Enerdata)

Not coincidentally, given rapidly growing energy consumption levels, the world's ecological footprint exceeded the planet's sustainable capacity in 1970 and has continued to grow. It is estimated that the global ecological footprint has reached about 70% overshoot in recent years (Global Footprint Network, 2016; Harich and Rosas, 2020). At the same time, biodiversity has fallen by more than half (Howes et al., 2017), and, as illustrated above, temperatures have continued to rise. For all of these reasons and more, shrinking human society's ecological footprint is understood to be a necessary step for avoiding global environmental catastrophe (Jorgenson, A.K. 2003). Yet, while this "bottom line" might be widely accepted by the scientific community (Weinzettel et al., 2018), moving away from business-as-usual energy consumption and toward more sustainable alternatives will necessarily impact the "bottom line" profit margins of all actors—from households to goods producers, to public utilities and large-scale anchor institutions, to decision-makers at all scales of governance, and everyone in between (Borchers et al. 2018).

Put another way, one of the leading barriers to implementing a sustainable energy agenda is the short-term cost (Gallachóir, 2007). Indeed, even life cycle cost (LCC) analyses—one of the foundational methods of sustainability studies—are rarely included in large institutions' decision-making processes due to entrenched and intense foci on short-term profit maximization (Pearce and Miller, 2007). For these reasons, to reduce energy consumption, it is necessary to grapple with economic incentives (Bauner and Crago, 2015). For many institutions, organizations, and political jurisdictions, existing incentives lead decision-makers to simultaneously (1) pursue growth and (2) cut costs (Obama, 2017). To the extent that growth acts as a key indicator of *economic success* (e.g., Weaver et al. 2015). Cost minimization acts as a key indicator of *economic efficiency* (Timmons et al., 2019). In many realms of the global political economy and organizations tend to pursue these goals at the expense of competing for social goals, including ecological integrity, social equity, and livability (e.g., Godschalk, 2004). In other words, systems designed to achieve economic growth are not *properly coupled* with, for example, environmental and social systems (Harich, 2010).

To say that economic performance goals and sustainable energy use are not properly coupled is not to say that they are not *couple-able*. Consider that, in an aggregate sense, "CO_2 emissions from the [U.S.] energy sector fell by 9.5% from 2008 to 2015, while the economy grew by more than 10%" (Obama, 2017, p.1). U.S. energy-related carbon dioxide emissions decreased in 2019 by 2.8%, mainly because of a 5% decline in cooling requirements. This translates to 150 million metric tons of less CO_2 compared with 2018 (EIA, 2020). While these reductions were insufficient to meaningfully change the course of energy consumption in the U.S.—and the consequences thereof (see above)—the fact that they occurred while the nation's economy improved suggests that sustainable energy use and economic health do not have to be "either-or" phenomena. Indeed, smaller ecological footprints are likely to have positive economic outcomes. For instance, renewable energy decreases dependency on fossil fuels and can lessen the need to trade deficits with net energy-producing nations (Aydin et al., 2009; Tong, 2010).

Moreover, compared to fossil fuels, renewable energy resources are less vulnerable to price volatility (Bolinger et al., 2006). Also, electricity costs from renewable energy have fallen over the past decade due to improving technologies, better supply chains, and economies of scale (IRENA, 2020). In these and many other respects, sustainable energy investments can be more economically efficient than conventional energy sources in the long run. However, in the short run, investments into sustainable energy tend to be quite costly and can negatively affect economic performance. As such, short-term thinking and incentives often outcompete long-term goals, locking places and organizations into business-as-usual practices that fail to reverse—and in most cases exacerbate—fossil fuel consumption and its many negative externalities (Wright and Nyberg, 2017).

How might organizations and places individually, and society in the aggregate, overcome this incentive trap in ways that mobilize actors toward short-term sacrifices for the long-term benefit of local and global environmental integrity? While radical structural changes to the political economy are implicated in comprehensive answers to this question (e.g., Aronoff et al., 2019), continuing business-as-usual practices while waiting on leadership to mobilize those structural changes will only hasten the pace of global climate change. Accordingly, it is important for organizations and places to think about the changes they can make in the here-and-now, under existing pro-growth and pro-profit incentive schemes, to reduce fossil fuel consumption.

In the post-recession years of 2009-2012, HEI enrollment rose markedly across the country (Sightlines, 2018). At the same time, since 2010, there has been essentially no significant growth in the operating budgets of facilities that maintain campuses, as shown in Figure 4 (Sightlines, 2018).

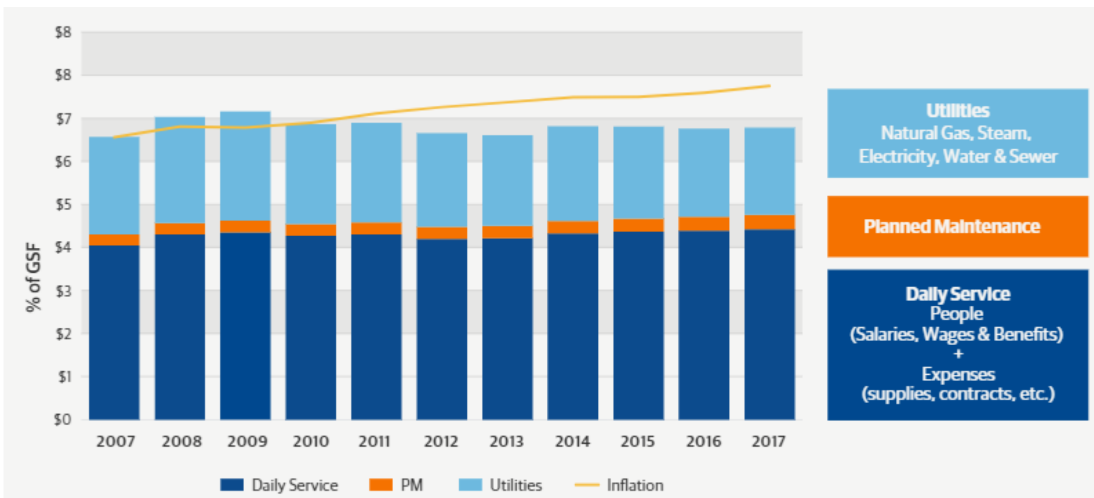

Figure 4. Facilities Operating Budget (Source: Sightlines, 2018)

According to the Sightlines report from which these data were taken, the higher education system responded to the post-recession time by:

> "adding new facilities to expand their programs and amenities. The educational landscape has become increasingly competitive in the years since, and institutions have doubled down on constructing new facilities. There is an arms race on, and institutions are building new to recruit and retain a greater share of the declining pool of potential students." (Sightlines, 2018, p.2) (Figure 5).

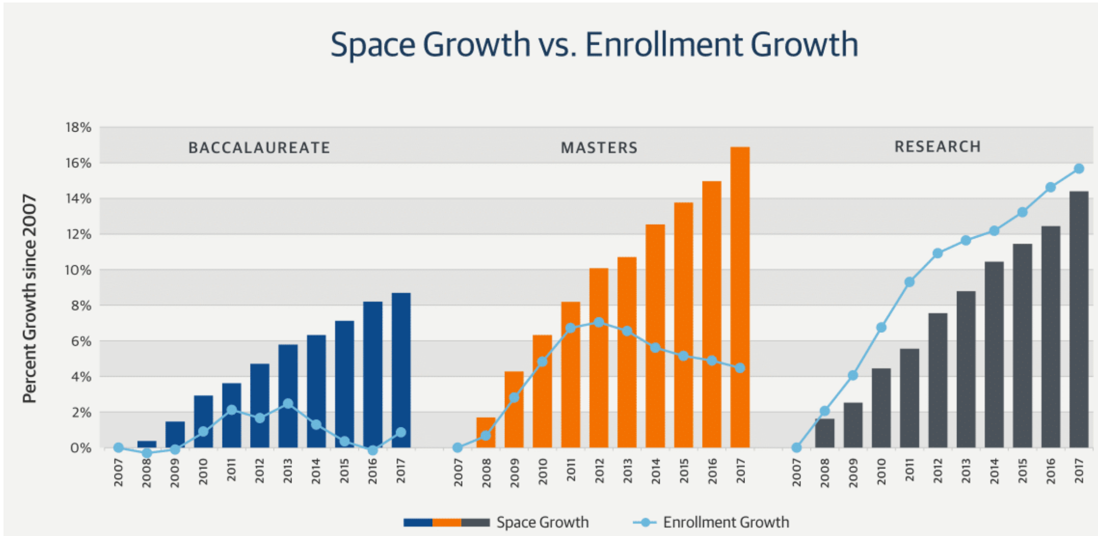

Figure 5. Space growth vs. enrollment growth in the U.A (Sightlines, 2018)

Thus, like decision-makers everywhere, HEI administrators see growth as a means for remaining competitive and economically successful. In that sense, HEIs are vulnerable to getting caught in business-as-usual traps that pursue growth (i.e., higher student enrollments bring in more tuition dollars) while striving to keep operating and capital costs down to stay under budget (Breneman, 2015).

Unlike for-profit businesses, though, HEIs play the critical social roles of 1) creating knowledge and transferring it to society and 2) preparing students for their future role in society (Stough et al., 2018). This social mission suggests that HEIs arguably have a responsibility to teach and research sustainable practices and practice sustainability in their daily operations. HEIs are increasingly being placed under the microscope to disclose how they integrate and contribute to sustainability in ways beyond formal course offerings and academic publications (Stough et al., 2018; Mohammalizadehkorde and Weaver, 2018).

Crucially, however, HEIs are not exempt from the line of reasoning articulated above, whereby places and organizations (and society at large) are playing by a set of rules that disincentivizes investments into, among other things, sustainable energy technologies. Without radical structural changes that alter those rules, then HEIs are left to fulfill their social responsibilities in an economy where money talks and short-term profit-maximization prevails. With that in mind, one possible way to intervene in HEI energy systems—where, because of their social missions, HEIs are arguably more predisposed than for-profit businesses to *want* to migrate to more sustainable energy regimes—is to generate empirical evidence that new, comparably sustainable energy investments will enable HEIs to comply with sustainable goals while not causing them to sacrifice their growth-related objectives. On the other hand, contrary evidence would seemingly provide decision-makers with a defense for the following business-as-usual practices and not investing in new energy technologies (Mohammadalizadehkorde & Weaver, 2018). Either way, however, financial analyses that document the (un)attractiveness of investments into selected sustainable energy projects arguably hold the keys to moving the current conversation forward. This study is meant to advance that discourse by focusing on selected public HEIs with large spatial footprints. The research aims to: (1) evaluate the extent to which a *proper coupling* (Harich, 2010) between the two goals of economic efficiency (in terms of money saved) and environmental protection (in terms of CO_2 and other emissions avoided) is achievable through selected alternative energy investments at the case study public HEIs; and (2) better understand reasons for (lack of) investment into alternative energy programs in the HEIs.

Financial analysis is one of the available ways to answer the critical question of whether the failure of universities to meet sustainability goals (Amaral et al., 2019) can be blamed on a lack of financial resources. To the extent that sustainable energy projects are found to be cost-effective, however, lack of implementation is likely due to other factors. According to Howes et al. (2017), these other factors fall into three main categories: (1) structural factors, (2) implementation traps, and (3) knowledge/scope issues. Structural factors are overarching economic, social, political, environmental, legal, and technical issues that stand in the way of implementation. Implementation traps relate to the network of relationships and agencies tasked with achieving results and can arise from, among other sources: incomplete specification of objectives, conflicting objectives, incentive failures, limited competence, and lack of resources. And that is why Harich and Rosas (2020) believe that superficial solutions are only effective temporarily or not efficient at all “because the superficial solution force can never exceed the root cause force (Harich and Rosas, 2020, p 6).” Knowledge/scope issues refer to inadequate knowledge of the problem at hand (Howes et al., 2017).

Insofar as the preceding three categories of implementation failure factors are wide-ranging, complex, and interconnected, a single dissertation cannot grapple with all of them at once. As such, after determining the financial feasibility of selected alternative energy interventions in four case study universities, this research focuses on the spatial context of each institution as a potential determinative factor. Spatial context spans at least two of Howes and colleagues’ (2017) three categories. With respect to structural factors, embeddedness in a neighborhood or region where residents and leaders prioritize sustainability goals might positively influence HEI sustainable energy implementation. In contrast, areas with low prioritization of sustainability goals can have negative or neutral influences on implementation. Concerning implementation traps, HEIs that are public, state-funded colleges or universities are generally subject to statewide energy policies or legislative mandates. Such legislative measures and the incentives they create (or eliminate), and the funding streams they provide (or do not provide) will undoubtedly influence HEI investments into sustainable energy programs. To account for both sources of influence, this dissertation will draw on:

- consumer survey data and municipal and regional planning documents to describe the "local" spatial context of each case study HEI;
- and statewide policies and state-level Sustainable Development Goal report cards (https://sdgindex.org/reports/sustainable-development-report-of-the-united-states-2018/), as well as descriptions of state-level politics, to describe the comparatively "global" spatial context of each case study.

Leveraging these data sources, this dissertation will address four specific research questions:

1. Are selected emissions-reducing energy investments characterized by long-run profitability in the HEIs under investigation? In other words, is there evidence that a *proper coupling* between lower energy consumption and economic profitability can be achieved at the HEIs?
2. To what extent are sustainability goals prioritized by residents and municipalities in each HEI's local spatial context?
3. What is the nature of the relationship(s) between state-level policy, state Sustainable Development Goal performance, and alternative energy investments at

the selected HEIs?

4. To what extent do (in)congruent state and local/regional spatial contexts promote (inhibit) alternative energy implementation in HEIs?

The first question from above will be analyzed via energy audits and cost-benefit analyses that can be extended and replicated for other HEIs as well as other small study areas, such as urban neighborhoods or even entire towns and villages. The second question will involve multivariate spatial analysis of consumer survey data to construct a profile for each HEI's (1) home municipality and (2) the metropolitan or micropolitan region in which it is located. Those profiles will be unpacked relative to local and regional sustainability planning documents, where available, for each HEI location. The third question will create similar profiles for each HEI's home state by engaging with the state's Sustainability Development Goal (SDG) report card and relevant energy policies. Concerning the fourth question, the dissertation will explore the ways in which barriers to implementation are minimized, where financial feasibility is embedded within the supportive state and local/regional contexts. Simultaneously, incongruent spatial contexts are likely to create "implementation traps" (Howes et al., 2017) that might contribute to maintaining the status quo, business-as-usual practices. These possibilities are explored with the help of four case studies.

2. PURPOSE

Proposed solutions to solve environmental sustainability have failed mainly because of the extreme complexity of the problem itself and the absence of root cause analysis (RCA) (Harich and Rosas, 2020). A significant portion of the problem is caused by the "broken political system" (Harich and Rosas, 2020), which acts as a barrier to solving the most critical social problems (Harich and Rosas, 2020). Several authors had determined that a new field of sustainability should rise and study the fundamental character of interactions between nature and society (Kates et al., 2001) to improve society's role in guiding those interactions (Harich and Rosas, 2020). Most scientists agree that organizations, industries, and governments must adopt more ecologically sensitive practices to prevent further degradation of the environment (Ralph and Stubbs, 2014). While much of this literature focuses on integrating sustainability into *business* practices and reconciling profitability with *corporate* social responsibility and sustainability (Wheeler et al., 2003), there is a thriving line of research on sustainability initiatives and practices at colleges and universities (Norton et al., 2007; Ralph and Stubbs, 2014). Among the reasons for this interest are that (1) academia plays a prominent role in producing knowledge about sustainability and sustainable practices (Kilmova et al., 2016; Elliott and Wright, 2013; Alshuwaikhat and Abubakar, 2008;) and, (2) college and university campuses tend to function as their own spatially based communities and might, therefore, offer scalable models for creating more sustainable neighborhoods, cities, and regions (Norton et al., 2007). Sustainability assessments study the integration of sustainability practices into HEIs (Stough et al., 2018). This study will contribute to this literature line by inventorying sustainable energy projects at four selected public HEIs. From there, financial analyses will determine the feasibility of selected alternative energy investments at each study area location. The results will provide initial answers to whether HEIs differ in their commitments to sustainable energy due to financial considerations.

This dissertation moves beyond traditional sustainability assessment in its deeper engagements with implementation successes and failures. In instances for which alternative energy investments appear to be financially profitable (i.e., where institution-scaled economic and broader-scaled environmental systems are *properly coupled*), but HEIs have not meaningfully invested in them, I argue that differences in spatial context might be contributing or decisive factors. More explicitly, while issues of HEI leadership and strategic planning are likely to be some of the more determinative factors at play in institutional energy investment decisions, those variables are difficult to observe and measure in a consistent way across study areas. However, it is reasonable to assume that leadership and decision-making in public HEIs will at least partially reflect: (1) the priorities of state government, insofar as HEIs depend on state funding and will, therefore, be accountable to state policies and directives; and (2) the preferences and values of their local communities or regions, insofar as most HEIs strive to be upstanding citizens who maintain effective Town-Gown relations (Broto & Baker, 2018; Pasqualetti, 2011; Cupples, 2011). Along those lines, where financial considerations are similar between public HEIs, differences in alternative energy commitments are likely related to differences in spatial contexts. This dissertation will investigate this possibility through four case studies. This dissertation studies sustainable energy, and specifically the electricity consumption as a spatial problem. Because much of the energy research is grounded in engineering and physical science, scholars suggest that relatively less interest has been paid to social and behavioral aspects (Hoppe & de Vries, 2018). As attention is turning more prominently to these aspects, "there has been an increasing interest in the study of energy as a spatial problem" (Broto & Baker, 2018, p.1). Spatial factors and concerns about space can influence the relationship between energy development, energy supply, and energy service, placing it at the heart of low carbon transition (Broto & Baker, 2018). For example, uneven power relations can shape renewable energy and fossil fuel developments (Pasqualetti, 2011). There is an assumption that reminds us of the fact that "spatially-engaged energy research can make step-change contributions to understand the global energy challenge," and there should be a call for thinking about the energy system and the transition to a low-carbon future as a matter of relational space (Broto & Baker, 2018, p.1-3). Within this domain, energy policy takes on particular importance, as it reflects the guidelines established by governing entities to exploit energy resources, commerce, and its relationship to population (Conde et al., 2019).

3. LITERATURE REVIEW

3.1 SUSTAINABLE ENERGY IN HEIs

Carbon emissions and fossil fuel consumption are at the epicenter of current global affairs (Conde et al., 2019). There is a consensus among researchers that principal causes of global warming, climate change, and water shortages are rooted in human practices involving the massive use of fossil fuels, conflicts of interest, and the complex global energy matrix (Mtutu and Thondhlana, 2016; Conde et al., 2019). Higher education systems are among those sectors where human behavior as an individual practice can lead to collective challenges (Altan, 2010). HEIs are significant consumers of energy in their communities (Altan, 2010). Although enrollment rates decreased in 2012, the growing space dedicated to HEIs has not stopped (Figure 5). Buildings are responsible for 30% of total energy consumption globally (International Energy Agency, 2018). Operations, maintenance, utilities, and renovations cover almost 70% of all the building-level expenditures (Amaral et al., 2019). In line with the importance of energy usage in buildings, it is possible to underline that the highest number of actions in American HEIs is dedicated to energy and buildings (Amaral et al., 2019).

To satisfy their growth imperatives, HEIs tend to increase demand for resources such as energy (Mtutu and Thondhlana, 2016). What is more, it has also been found that energy consumption (electricity and gas) can continue to rise even if the gross area of HEI buildings is reduced (Mohammadalizadehkorde and Weaver, 2020). Figure 6 and Tables 1 and 2 show the relationship between energy consumption and increasing space at Texas State University in a fiscal year starting September 1 and ending on August 31.

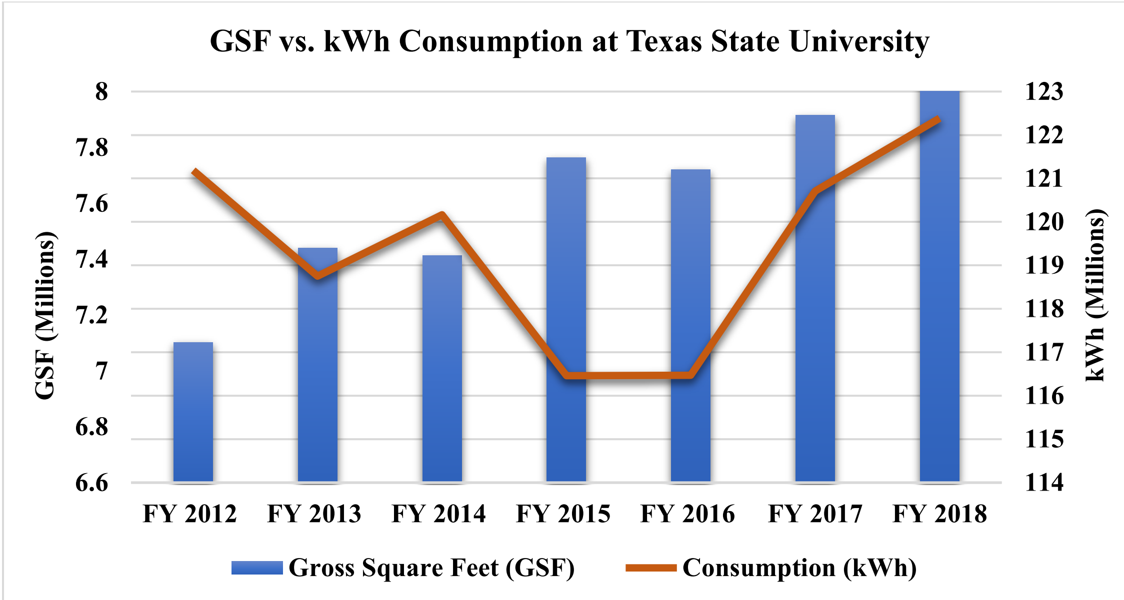

Figure 6. GSF vs. kWh consumption at Texas State University

Table 1. Electric consumption based on fiscal year and savings at TSU

Fiscal Year	GrossSquareFeet (GSF)	Consumption (kWh)	Consumption Per Sq. ft (EUI)	% Savings
FY12	7,102,422	121,184,231	17.06	Base Year
FY13	7,493,405	118,753,429	15.84	**-7.11**
FY14	7,513,016	120,167,425	15.99	**-6.25**
FY15	7,763,457	116,461,145	15.00	**-12.08**
FY16	7,719,991	116,468,027	15.08	**-11.58**
FY17	7,915,438	120,712,750	15.25	**-10.62**
FY18	8,208,942	122,386,158	14.90	**-12.66**

Percentage savings in table 1 is calculated based on the following equation:

$$Savings = \frac{EUI\ Consumption\ in\ FY - EUI\ Consumption\ in\ the\ base\ year}{EUI\ Consumption\ in\ the\ base\ year} \qquad \textit{Equation 1}$$

Table 2. Gas consumption based on fiscal year and savings at Texas State University

Fiscal Year	Square Feet	Consumption (MCF)	Consumption (BTU)	Consumption MCF/ Sq. ft	Consumption BTUs/ Sq. ft	% Saving
FY12	7,102,422	397,994	405,953,880,000	0.056	57,157	Base Year
FY13	7,493,405	355,812	362,928,240,000	0.047	48,433	**-15.263**
FY14	7,513,016	388,788	396,563,760,000	0.052	52,784	**-7.652**
FY15	7,763,457	411,137	419,360,026,519	0.053	54,017	**-5.494**
FY16	7,719,991	424,003	432,482,630,414	0.055	56,021	**-1.987**

A diverse example is given by the Electrical Engineering Department at the University of Coimbra, Portugal, where the electricity demand decreases from 2010 to 2016, reaching 510.09 MWh of demand in 2016 with an exception in 2013 due to a warmer summer (Fonseca et al., 2018). However, the latter example is based on one single building and difficult to be compared with other models unless the number of enrollments, the macroclimate, and the gross square feet are similar.

Energy efficiency as a measurement aims to reduce the amount of energy needed to provide the same level of service to the consumer. Energy efficiency can be expressed in terms of the Electricity Utilization Index (EUI), which includes all energy consumed by an area in Btu per GSF or kWh per square feet. Implemented policies often include "resource and technology standards, codes, and incentives that can advance the deployment of energy-efficient technologies and practices across all sectors of the economy (EPA, 2018)." Energy efficiency interventions can benefit society and different energy sectors in the economy (Altan, 2010). They provide an understanding of current programs' influence and encourage the systematic use of knowledge for evidence-based policy (Altan, 2010). Various measures, such as environmental audits, fines, plans, guidelines, and declarations, tried to frame unsustainable practices, but most of them limit themselves only to address the symptoms (Mtutu and Thondhlana, 2016).

What are the benefits of energy efficiency and renewable energy implementation? Multiple benefits of energy efficiency are determined by EPA (2018) as the following illustration (Figure 7):

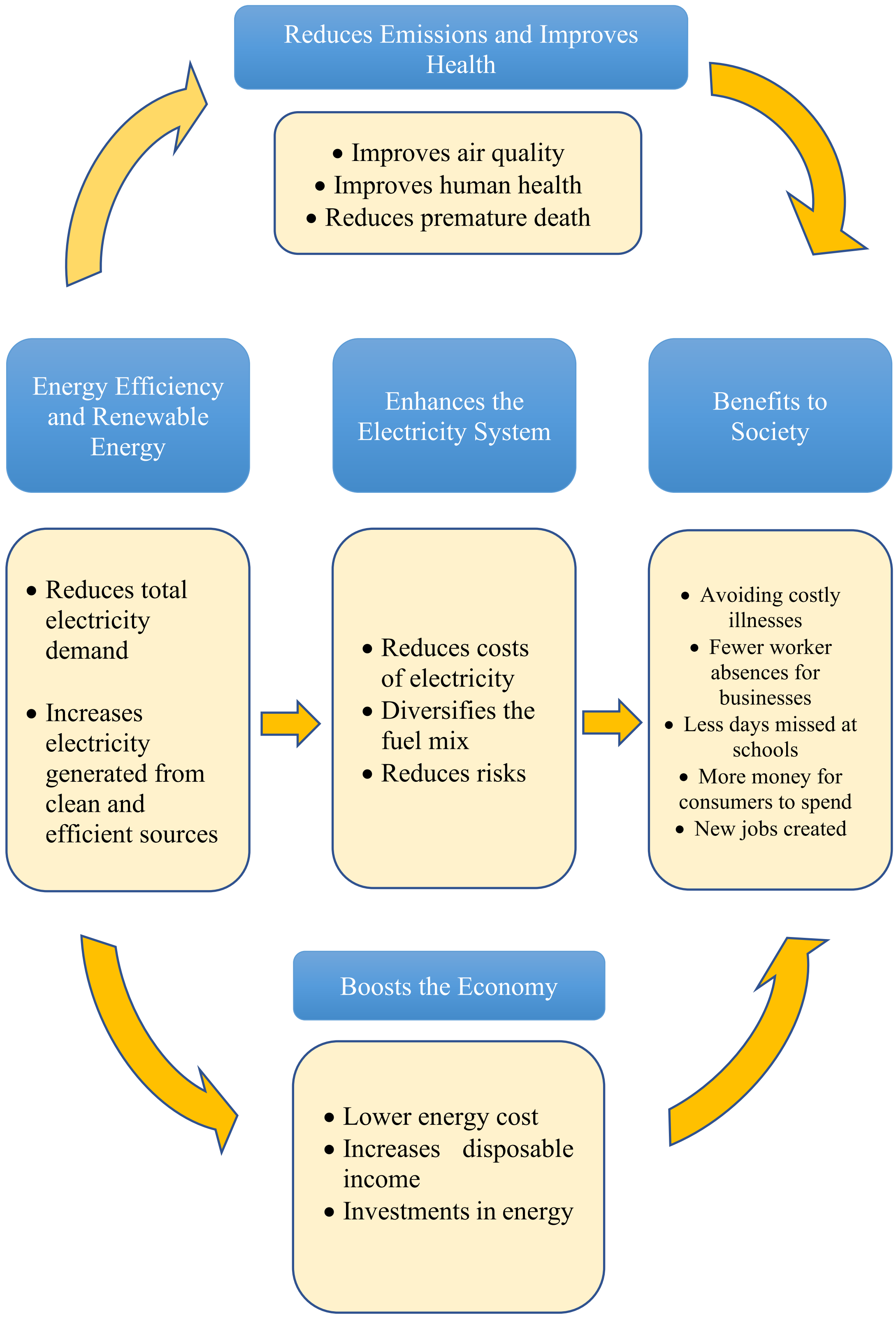

Figure 7. The benefits of energy efficiency and renewable energy. Source: EPA

How an empirical approach to reach energy efficiency should be applied? Tactics to obtain sustainable energy consumption can be based on the energy efficiency cycle provided by the Schneider Electric Organization (SEO) (Figure 8):

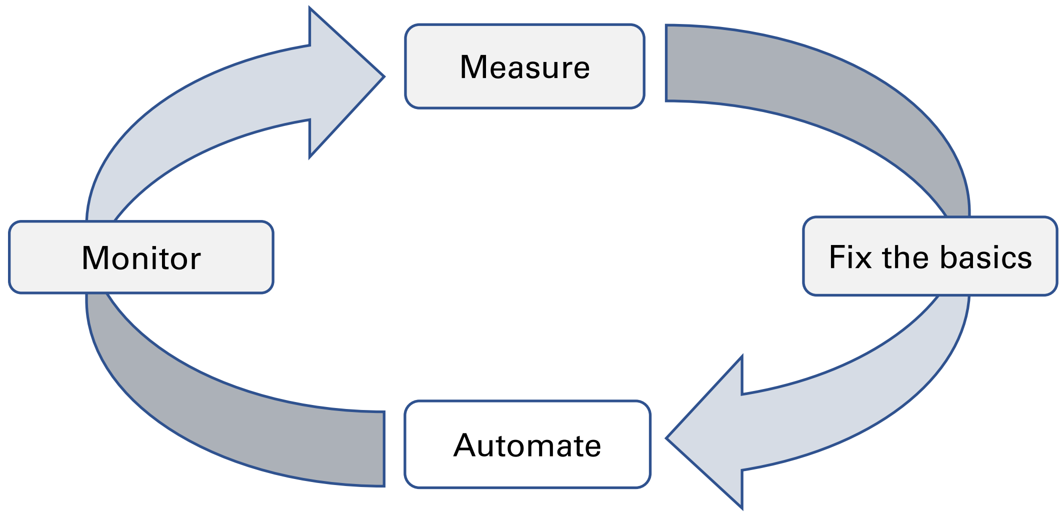

Figure 8. Energy efficiency cycle

Figure 8 shows that the *measuring* step consists of energy audits and metering to establish a benchmark and provide input for the *monitor* process. *Fixing the basics* brings low consumption devices and power reliability while *automating* consists of building a management system (Mohammadalizadehkorde & Weaver, 2018). According to SEO, low consumption devices and efficient installation can lead to energy efficiency gains of 10 to 15% of total consumption, which is in line with 17% of total energy saved in a recent study (Mohammadalizadehkorde & Weaver, 2020). This outcome is generally referred to as *passive energy efficiency*. Low consumption devices and efficient installation could be well-insulated buildings, high-efficiency motors, and more efficient lamps. Optimized usage of installation and devices will net a 5 to 15% increase in energy efficiency (SEO):

For example, up to 40% of the potential savings for a motor system are realized by the drive and automation, and up to 30% of the potential savings in a building lighting system can be discovered via the lighting control. Thirdly, a permanent monitoring and maintenance program will garner an additional 2 to 8% efficiency. This would require HEIs to implement continuous measurement and to react in case of deviations. Automation and permanent monitoring are examples of active energy efficiency (SEO). EPA has a similar approach to SEO in defining energy efficiency. The EPA approach comprises a policy, planning, and evaluation process to determine the best time to implement energy efficiency and renewable energy (Figure 9). Although the wordings are not the same, steps can be equivalent to each other once the SEO's energy efficiency cycle is compared to the EPA policy planning and evaluation process.

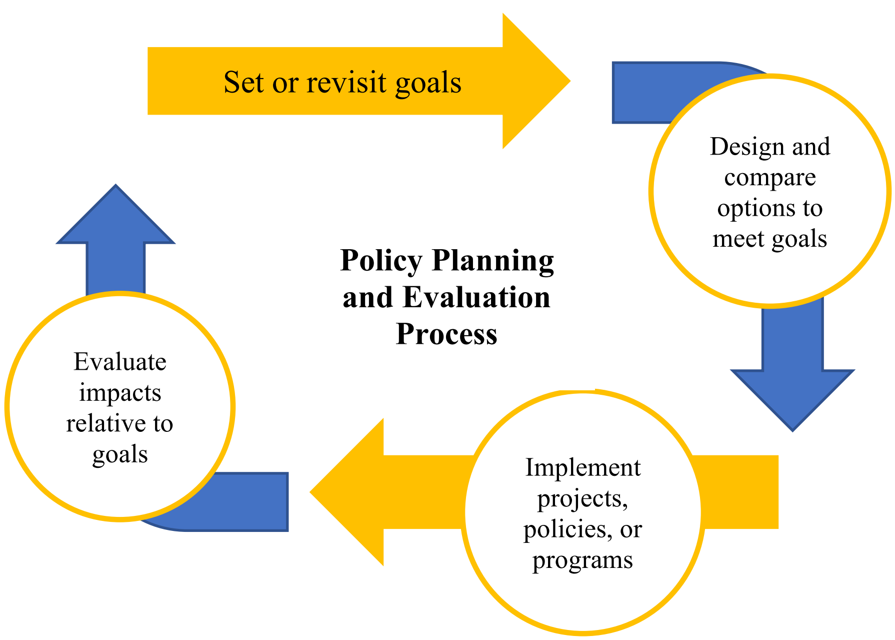

Figure 9. Energy efficiency and renewable energy policy implementation (EPA, 2018)

An Implementation example of the models above and policies can be found in Mohammadalizadehkorde & Weaver (2020). The initial audit (measure) sets the goal, and proposed options try to reach those goals. Evaluation is made possible by the results based on the amount of electricity saving. To advance in a more detailed illustration, the following Figure 10 proposes lighting system replacement extracted from a recent study and shown here for illustrative purposes (Mohammadalizadehkorde & Weaver, 2020). Capital outlay is the money invested, which will be recouped after one year (when the green line hits the x-axis on the chart). The amount of saved money is given by the green area, followed by constant energy savings for ten years. The net present value—which is discussed in detail in the Methods section—is the value of an investment in financial terms, which should be positive and distant from the capital outlay.

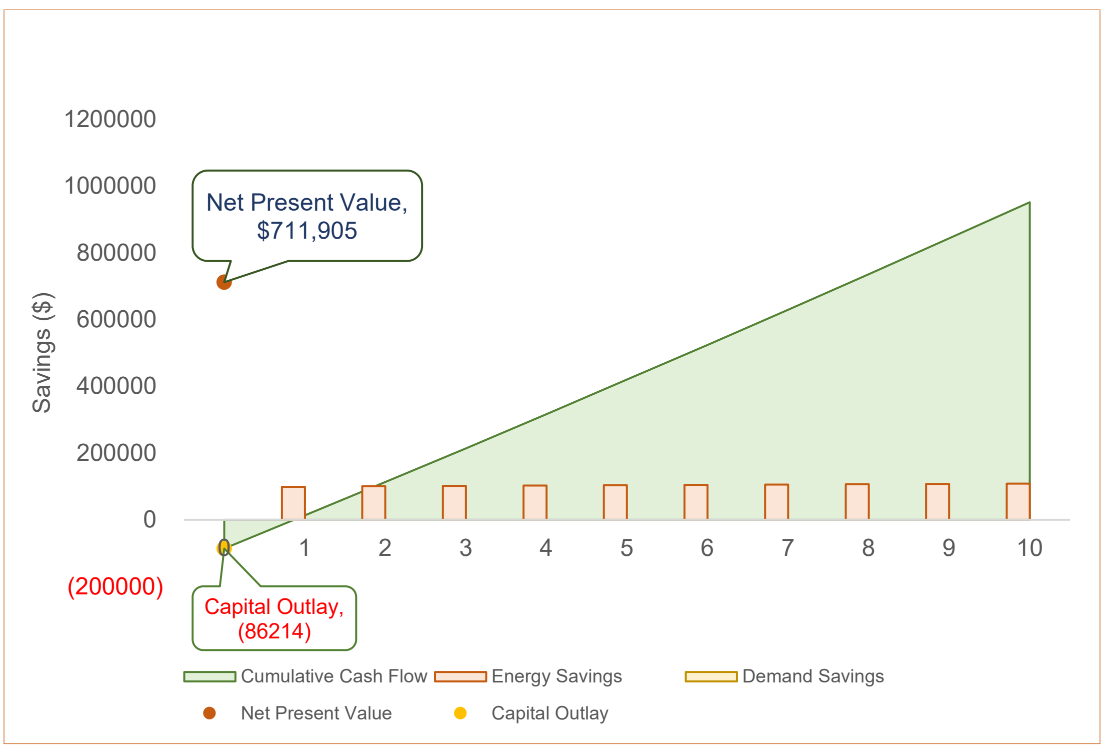

Figure 10. Lighting system replacement and NPV visualization

To assess the level of commitment, it is possible to use the GreenMetric World University Ranking, which focuses on sustainability derived from the environmental performance of HEIs (Aina et al., 2019). There are also multiple monitoring tools such as Sustainability Tracking Assessment & Rating System (STARS), Global Reporting Institute (GRI), and Leadership in Energy and Environmental Design (LEED), and the global GreenMetric World University Ranking to assess the energy consumption and policies. Table 3 and Table 4 show several ranking systems adapted from Grindsted (2011) and Tilbury (2011) to evaluate the energy consumption from an operations perspective, environmental impact, and policy aspect.

Table 3. Global Campus Sustainability Ranking (Adapted from Grindsted, 2011)

Ranking system	Coverage	Sponsors	Year	Description
GreenMetric World University Ranking	Global	Universitas Indonesia	2010	Provides profiles for universities and compare them based on campus greening and sustainability criteria, including policies
Green Rating	North America	Princeton Review	NA	Ranks top 50 colleges based on green campus criteria
University League	UK	People & Planet	2007	Ranks universities and compares environmental initiatives and plans and carbon reduction targets
SIERRA Cool Schools	USA	Sierra Magazine	2007	Benchmarks the most environmentally friendly campuses
CSRC	USA	Sustainable Endowments Institute	2007–2011	Provides sustainability profiles of institutions based on sustainability indicators
ACUPCC	USA	ACUPCC	2006	Enjoins signatory to a commitment to be climate neutral

Table 4. Declarations for Sustainable Development in Education (Tilbury, 2011)

Year	Declarations	Partners	Scope
1990	Talloires Declaration	University Leaders for a Sustainable Future	Global
1991	Halifax Declaration	Consortium of Canadian Institutions; IAU; UNU	Global
1993	Kyoto Declaration on Sustainable Development	IAU	Global
1993	Swansea Declaration	Association of Australia Government Universities	Global
1994	COPERNICUS University Charter for Sustainable Development	Association of European Universities	Regional (Europe)
2001	Luneburg Declaration	Global Higher Education for Sustainability Partnership	Global
2002	Ubuntu Declaration	UNU, UNESCO, IAU, Third World Academy of Science, African Academy of Sciences and the Science Council of Asia, Copernicus-Campus, Global Higher Education for Sustainability Partnership, and University Leaders for Sustainable Future	Global
2005	Graz Declaration on Committing Universities to Sustainable Development, Austria	COPERNICUS CAMPUS, Karl-Franzens, University Graz, Technical University Graz, Oikos International, UNESCO	-
2005	Bergen	European education ministers, the European Commission, and other consultative members	Regional (Europe)
2006	American College and University Presidents' Climate Commitment	AASHE	National (USA)
2008	Declaration of the Regional Conference on Higher Education in Latin America and the Caribbean – CRES 2008	UNESCO	Regional (the Caribbean and Latin American)
2008	Sapporo Sustainability Declaration	G8 University Network	Global
2009	World Conference on Higher Education	UNESCO	Global
2009	Turin Declaration on Education and Research for Sustainable and Responsible Development, Italy	G8 University Network	Global

The concept of sustainable development has been ambiguous and contested for several decades (Mebratu, 1998). However, researchers try to abide by the notion provided by the UN—Sponsored World Commission on Environment and Development (WCED)— such as the framework suggested by Daily & Ehrlich (1992) where they attempt to provide "a framework for estimating the population sizes and lifestyles that could be sustained without undermining the potential of the planet to support future generations" (Daily & Ehrlich, 1992; Aina et al. 2019; Amaral et al., 2019).

Although several authors recognize the Stockholm Declaration of 1972 as the first direct reference to sustainability (Mohammadalizadehkorde and Weaver, 2018) in HEIs, Amaral et al. (2019) attribute the debate of sustainable development in HEIs to Brundtland (1987). Namely, in distinguishing the inseparability of humanity and the environment, the Stockholm Declaration recommended several ways of achieving environmental sustainability (Alshuwaikhat & Abubakar, 2008), including the following statement:

> A point has been reached in history when we must shape our actions throughout the world with a more prudent care for their environmental consequences. Through ignorance or indifference, we can do massive and irreversible harm to the earthly environment on which our life and well-being depend. Conversely, through fuller knowledge and wiser action, we can achieve for ourselves and our posterity a better life in an environment more in keeping with human needs and hopes (UNESCO. Stockholm Declaration. UNESCO; 1972.)

While the concepts of *sustainability* and *sustainable development* are still subject to debate in the literature, they are sometimes merged for the sake of discussion (Stough et al., 2018). The ambiguity of sustainable development is addressed by Connelly (2007) in four different ways: 1) presenting the unproblematic concept in principle but hard to achieve in practice, 2) noting the ambiguity but selecting a preferred definition, 3) noting the ambiguity but developing praxis and 4) seeking to understand the concept of sustainable development.

Stated another way, in the aggregate, humans' aptitude for living more sustainable lives in more sustainable settlements depends on improved education. A significant portion of this expectation has relied on universities. Higher education institutions are requested to prepare the skilled workforce for sustainable challenges in the upcoming years (Kilmova et al., 2016). Accordingly, at the Stockholm Conference, education was recognized as one of the most critical factors in "fostering environmental protection and conservation" (Lozano et al., 2015). Roughly twenty years later, the Talloires Declaration, drafted in 1990 with more than 500 signatories from more than 40 countries, became the first official statement supported by university administrators of a commitment to environmental sustainability in higher education (University Leaders for a Sustainable Future, 1990). The non-binding ten points from that declaration cover the teaching, research, involvement, and collaboration on higher education environmental issues. The Talloires declaration's objectives demand a broad-scale change in universities rather than the plans' isolated execution (Bekessy et al. 2007). In the same year, the U.S. Environmental Protection Agency (EPA) funded a research group at Tufts University's Environmental Center known as Tufts Cooperation, Learning, and Environmental Awareness Now! (CLEAN!) to reduce the environmental impacts of the university's operations (Creighton, 1998). The Tufts team studied essential issues like food waste, transportation, energy efficiency, and procurement practices to develop recommendations for several departments (Creighton, S. H, 1998).

In another example, more than 680 universities signed the American College and University Presidents' Climate Commitment (AUPCC) agreement, which invites participating institutions to reduce greenhouse gas emissions (Agdas et al., 2015, p. 16).

Among more recent attempts to introduce the sustainable environment in higher education, the U.S Environmental Protection Agency, in an issue of *Enforcement Alert,* states that "colleges and universities are required to comply with all applicable environmental requirements like their counterparts in the industry to create a safe haven for human health and environment" (EPA document:300-N-00-012). *Fundamental Change to Resource Conservation and Recovery Act (RCRA) regulation in higher education,* proposed by the Campus Safety and Health Environmental Management Association (CSHEMA), suggests one possible policy for meeting the EPA regulations, which consisted of reinterpretation, exemption, or changes to existing regulations (Savely et al., 2007).

The current that underlies all the preceding examples is that sustainability in higher education is a broader concept than merely incorporating *sustainability* into classroom curricula. More specifically, while there is robust and valuable literature on *education for sustainability* (see, for example, Cortese, 1999; Junyent & Ciurana, 2008; Sterling, 2010), higher education institutions also have the power to *practice* sustainability. Practice adds a visual and authentic dimension to the ways in which universities educate students and the public on critical environmental issues. Indeed, universities can serve as models and test cases for programs and practices that could be scaled to the level of a whole human settlement, such as a neighborhood, multi-site corporation, or even a municipality (Aina et al.,2019; Grindsted, 2011; Alshuwaikhat and Abubakar, 2008; Amaral et al., 2019). As Alshuwaikhat and Abubakar (2008) observe, “universities can be compared to complex buildings and even small cities.” Peter Viebahn, the author of the *Osnabruck Environmental Management Model for Universities,* states that 334 different universities in Germany are comparable to large commercial enterprises with regard to their consumption of energy and materials (Viebahn, 2002). Creighton (1990) believes that universities’ and colleges’ use of electricity, oil, natural gas, water, and chemicals is significant and can cover the largest service in the community where they are located.

On that note, “University campuses are an excellent study set to assess the design and enforcement of sustainability and energy efficiency policies” (Agdas et al., 2015, P. 16). Furthermore, institutions like universities are examples of public sector building owners from whom is expected a commitment to the future well-being of the surrounding communities (Pullen, S., 2000) or as an example of special social responsibility (Viebahn, 2002).

The issue of campus sustainability has been subject to intensified scrutiny by governmental agencies and university stakeholders (Alshuwaikhat, & Abubakar, 2008). Brian McCall, chancellor of the Texas State University System (TSUS), during the Board of Regents of TSUS held on August 19, 2011, states the crucial impact of an articulated plan on environmental issues:

> Our administrators are not the only ones who will be aware of the environmental impact of water usage, temperature controls, insulation, and greener construction going forward. Our environmental performance will be increasingly scrutinized by the media, the public at large, and our students. And, well, it should! Therefore, I ask that each university president develop a detailed, campus-specific plan of action to improve environmental efficiencies (Sustainable Stewardship, Actions to improve campus energy efficiency, Presented by Sheri Lara, Former Director of Utilities Operations at Texas State University).

Following this statement, any university that is enthusiastic about promoting sustainability on its campus ought to have a clear vision and commitment to sustainability. According to Alshuwaikhat and Abubakar (2008), the university should establish an organizational structure providing resources to achieve the sustainability vision, which is stated in other sustainability plans such as Energy Management System or ISO 14001 as well. ISO 14001 (1996) is a standard that empowers organizations to develop policies and objectives, taking into account legislative requirements and information about significant environmental impacts. This standard has been revised in 2004 and 2015.

However, just as environmental issues are complex and multidimensional, approaches to reduce resource consumption must be multifaceted and multiscalar. Not surprisingly, such sophisticated strategies are passed over by most universities in favor of more straightforward tactics (Alshuwaikhat & Abubakar, 2008). Furthermore, building energy efficiency is a complicated process influenced by various operational and design characteristics (Agdas et al., 2015). Despite these difficulties, some researchers have tried to define sustainability in higher education. Velazquez et al. (2006) state:

> A higher educational institution, as a whole or as a part, that addresses, involves, and promotes, on a regional or a global level, the minimization of negative environmental, economic, societal, and health effects generated in the use of their resources in order to fulfill its functions of teaching, research, outreach and partnership, and stewardship in ways to help society make the transition to sustainable lifestyles (Velazquez et al., 2006, p. 812).

Alshuwaikhat and Abubakar (2008) offer their definition of sustainable campus as:

> A healthy campus environment with a prosperous economy through energy and resource conservation, waste reduction and efficient environmental management promoting equity and social justice in its affairs and export these values at the community, national and global levels (Alshuwaikhat & Abubakar, 2008, p.3).

As noted above, the concept of sustainability is subject to many different and conflicting interpretations (Weaver, 2015), which might not correspond to social and political values (Portney, 2015). Perhaps the most common definition of sustainability comes from the World Commission on Environment and Development (Brundtland, 1987), which states that "the need of present should not compromise the ability of future generation to meet their own needs" (WCED 1987:39). As noted by Portney (2015), this definition "provides a convenient point of departure for a broad understanding of this fairly abstract concept" (Portney, 2015, p.4). On the other hand, the economic aspect of sustainability has always been an inseparable part of any definition. Daly and Cobb (1989) are among those researchers who challenged the concept of economic growth based on human-built capital (Norton, 2005). In *For the Common Good* (1989), Daly and

Cobb suggest the idea of "natural capital" which should be accessible for the future generation—an interpretation in harmony with the WCED definition and used to compare the weak and robust sense of sustainability by Daly and Cobb (Norton, 2005).

Meanwhile, skeptics have questioned whether it is possible to achieve sustainability with significant positive economic growth. To Jack Harich, this question is one of system design: "how can we *properly couple* the ecological and economic systems, by finding and implementing the right policies to keep environmental impact at a sustainable level?" (Harich, 2010, p. 36; emphasis added). Kent E. Portney suggests that such a proper coupling might be achievable. In particular, Portney highlights the eight years of the Obama administration in the U.S. as an exception when policies regulated the carbon emissions under the Clean Air Act and Energy Efficiency and Conservation Block grant program (Portney, 2015). In *Science* magazine, the 44th President of the United States described this era in his administration using the following terms:

> The United States is showing that GHG mitigation need not conflict with economic growth. Rather, it can boost efficiency, productivity, and innovation. Since 2008, the United States has experienced the first sustained period of rapid GHG emissions reductions and simultaneous economic growth on record (Obama, 2017).

So, if scholarship, world leaders, and empirical evidence all argue that sustainable energy use need not undermine economic well-being, then why are most of the world's largest economic actors (e.g., corporations, governments, HEIs, etc.) so slow or resistant to replacing fossil fuel-intensive energy infrastructure with more sustainable alternatives?

Considering HEIs in particular, Table 5 summarizes findings from Amaral et al. (2019), who identified numerous drivers and barriers to sustainable technology implementation in HEIs through survey-based studies. Among other things, the findings implicate the relationship between “geographical distribution and particular drivers and barriers” (Amaral et al., 2019 p.8), which is the theme of the next subsection. This summary occurs while Harich and Rosas (2020) underline the failure of sustainability implementation and many other “difficult social problems” as a direct result of simulation-based scenarios instead of searching for the root cause.

Table 5. Drivers and barriers to sustainability implementation (Amaral et al., 2019)

Reference	Survey objectives	Drivers	Barriers	Nr. of HEIs
Wright and Horst (2013)	Faculty leaders' perception of sustainability and barriers to implementation	Funding Administration support Academia engagement	Lack of funding Lack of leadership support Governance models	32 (Canada)
Leal Filho et al. - 2013	HEI policies to SD and the relation with successful initiatives	Existence of internal SD policies increases the probability of implementing initiatives	-	35 (worldwide)
Ralph and Stubbs - 2014	Factors influencing sustainability integration in Australian and English HEIs Funding Existence of internal policies	Existence of internal policies Administration support Lack of funding Lack of resources	Lack of expertise Lack of understanding	4 (Australia) 4 (England)
Disterheft et al. -2015	Participatory approaches in sustainability initiatives	Specific skills and participatory competences	Inexistent or deficient institutional and personal engagement	15 + 36 (worldwide)
Lozano et al. -2015	The relation between commitment to declarations and sustainability implementation	Signing a declaration is a driver for sustainability implementation, but not - the sine qua non-condition	-	70 (worldwide)
Brandli et al. -2015	Preconditions and barriers to implementing sustainability in Brazil	Administration support Academia engagement Communication, training	Lack of policies Lack of interest Lack of know-how	6 (Brazil)
Maiorano and Savan (2015)	Obstacles in implementing energy efficiency measures	Revolving funds	The reluctance of HEI leaders Other priorities Lack of information	15 (Canada)
Leal Filho et al. - 2017	Obstacles in implementing sustainability	-	Lack of leadership support Lack of resources Lack of interest Lack of a committee	269 (worldwide)
Blanco-Portela et al. (2018)	Drivers and barriers to the implementation of sustainability in Latin America	Existence of internal policies Leaders' commitment Staff commitment Funding	Inexistence of internal policies Lack of leadership support Lack of staff training Lack of resources	45 (Latin America)
Aleixo et al. -2018	Challenges to sustainability	Funding	Lack of resources Lack of know-how	4 (Portugal)

	implementation in Funding Portugal	Community engagement Cultural exchange, interdisciplinary	Resistance to change Organizational structure	
Leal Filho et al. - 2018	Challenges and barriers to climate change research	-	Lack of funding Lack of expertise Lack of resources Lack of interest	82 (worldwide)
Leal Filho et al. (2019a)	Role of innovation in sustainability	Implemented innovation projects are mostly related to operations Allows raising awareness	-	73 (worldwide)
Leal Filho et al. (2019b)	Commitment level in energy efficiency and renewable measures	Administration support Funding	Lack of funding Lack of resources Lack of interest	50 (worldwide)
Leal Filho et al. (2019c)	Barriers to planning in implementing sustainability	-	Lack of funding Lack of resources Lack of leadership support	39 (worldwide)
Leal Filho et al. (2019d)	Sustainability offices and barriers to their implementation	Allows raising awareness Academia engagement Curricula improvement	Lack of funding Lack of leadership support Lack of interest Lack of resources	70 (worldwide)
Avila et al. -2019	Innovation and sustainability barriers	-	Lack of leadership support Lack of resources Lack of a committee	283 (worldwide)

3.2 THE INFLUENCE OF GEOGRAPHICAL CONTEXT

Because much energy research is grounded in engineering and physical science, scholars suggest that relatively less interest has been paid to social and behavioral aspects (Hoppe & de Vries, 2018). As attention is turning more prominently to these aspects, "there has been an increasing interest in the study of energy as a spatial problem" (Broto & Baker, 2018, p.1). Spatial factors and concerns about space can influence the relationship between energy development, energy supply, and energy service, placing it at the heart of low carbon transition (Broto & Baker, 2018). For example, uneven power relations can shape renewable energy and fossil fuel developments (Pasqualetti, 2011). There is an assumption that reminds us of the fact that "spatially-engaged energy research can make step-change contributions to understand the global energy challenge," and there should be a call for thinking about the energy system and the transition to a low-carbon future as a matter of relational space (Broto & Baker, 2018, p.1-3). Within this domain, energy policy takes on particular importance, as it reflects the guidelines established by governing entities to exploit energy resources, commerce, and its relationship to population (Conde et al., 2019).

Going back to the 1970s, Hoare (1979) first raised the issue that geographers have historically had limited engagement with energy. Since that time, however, energy geographers have pioneered new interdisciplinary approaches in energy studies, highlighting the concept of "relational space" (Bradshaw, 2013). A relational approach defines "how energy relates to and interacts with the political, social, cultural, economic, ecological and technological spheres in specific locals" (Broto & Baker, 2018 p.3). It is known that government requirements can catalyze the decision-making process related to environmental commitment (Ralph and Stubbs, 2014). In Russia, for example, the approach to energy efficiency differs from the United States and European countries, and official documents provide only recommendations without any binding conditions (Tverdokhleb et al., 2017). Cupples (2011) provides another example by underlying that the privatization of electricity in Nicaragua results from neoliberalism materialization. The relational approach challenges the concept of energy "as a neutral, technical, and physical entity" (Broto & Baker, 2018, p.3). Therefore, this might be why Harich and Rosas (2020) deviate the attention from solving the sustainability problem to the real problem, which is causing it, the broken political system.

Behavioral interventions have a significant role in this process, as well. "The transition to low carbon energy systems cannot solely rely on technological innovation," and there are social and behavioral barriers that need to be overcome to make the energy transition possible (Hoppe and de Vries, 2018). Root cause analysis can be introduced at this stage as a solution for difficult social problems. A "difficult problem" is defined by Harich and Rosas (2020) as a problem resistant to be solved at least for twenty-five years or more and are considered large-scale problems involving the behavior of many people. Sustainability and climate change have both characteristics of a difficult problem. The assumption is that the *systemic force*—meaning that the problem originates from the system and can affect most social agents' behavior— also called *force R* is the root cause of environmental sustainability problems (Harich and Rosas, 2020). Solutions to mitigate environmental sustainability and economic growth could be considered superficial solution forces (*force S*) to solve the superficial causes. The root cause analysis will allow sustainability scientists "to understand the fundamental character of interactions between nature and society," which in Harich and Rosas (2020) point of view has "the potential to change the sustainability problem from impossible-to-solve to solvable" (Harich and Rosas, 2020, p.6).

To engage with geographical context in this research, I will rely on two data sources listed here and expanded on in Chapter V: (1) the SimmonsLOCAL annual consumer survey and (2) America's Goals Report. By using these (or any other) means to engage with and better understand the spatial context, it is possible to roughly describe the interests to which university decision-makers are accountable and in which they are embedded. The assumption is that university administrators will make decisions consistent with state priorities, especially when they are state-owned and funded.

Therefore, by looking at the extent of sustainability in public/state HEIs' plans, it is possible to assess whether current priorities reflect state policy. Similarly, it is possible to draw on data obtained from local (home) populations to determine how aligned HEI energy priorities are with their neighbors' attitudes towards the environment. Mtutu and Thondhlana (2016) state that individual values such as a pro-environmental attitude do not necessarily translate to a pro-environmental behavior due to other constraining factors, but they can be a significant indicator. Once the root causes are found, the third type of force to solve the problem, fundamental solution force (*force F*), can be applied (Harich and Rosas, 2020).

How energy is used is one of the significant factors influencing the environment (Shaffer, 2011). This concept is reflected in some national legislation: Portugal aims at a 30 percent reduction in net-energy demand for public buildings, 20% of renewable energy implementation, and a low energy demand equivalent of 44kWh/m^2 per year through national legislation (Fonseca et al., 2018). Several nations and local governments have adopted or updated policies encouraging energy efficiency and renewable energy implementation (EPA, 2018). According to EPA, as of 2018, more than half of the states are implementing:

- Policies to save energy in public-sector buildings.
- Mandatory or voluntary energy efficiency resources.
- Mandatory or voluntary renewable portfolio standards (RPSs).
- Financial incentives to individuals, businesses, or utilities to encourage renewable energy or energy efficiency (DSIRE, 2020).

One of the other state priorities in the United States is given under Renewable

Portfolio Standards (RPS) (Figure 11). States have been revising their (RPS), which requires a specified percentage of the electricity that utilities provide should come from renewable resources (National Conference of State Legislatures). While different states have set other goals, some of them are distinct: California, for example, aims to reach 100% clean energy by 2045 and Maine by 2050, while Colorado aims at 100% clean energy by 2050 for utilities serving 500,000 or more customers. An analysis of renewable electricity resources application after renewable portfolio standards (RPS) enactment in 2013 shows that 98 terawatt-hours (TWh) of renewable electricity was generated in 2013, the equivalent of 2.4% of total U.S electricity generation in that year (Wiser et al., 2016). This amounts to 59 million metric tons of avoided carbon dioxide in 2013.

A quick look at the NCSL documents revealed that state policies vary on targets, entities to be included, and resources to meet requirements. Also, state legislatures might not be directly deriving their legislations based on SRP, which can be applied only to investor-owned utilities. For example, the Texas Health and Safety Code 388.005 requires a reduction of electricity consumption without any direct reference to the implementation of renewable energy, which is the continuance of Senate Bill 898 (82nd Legislature) starting in 2011. This requirement is fulfilled by Senate Bill 241 in the 86th legislature approving the state-funded institutions to follow up with the pre-set goal for another seven years:

> "Each political subdivision in a non-attainment area or an affected county to establish a goal to reduce electric consumption by at least five percent each fiscal year. In 2019, the 86th Legislature passed Senate Bill 241, extending the timeline for this requirement seven years beginning September 1, 2019."

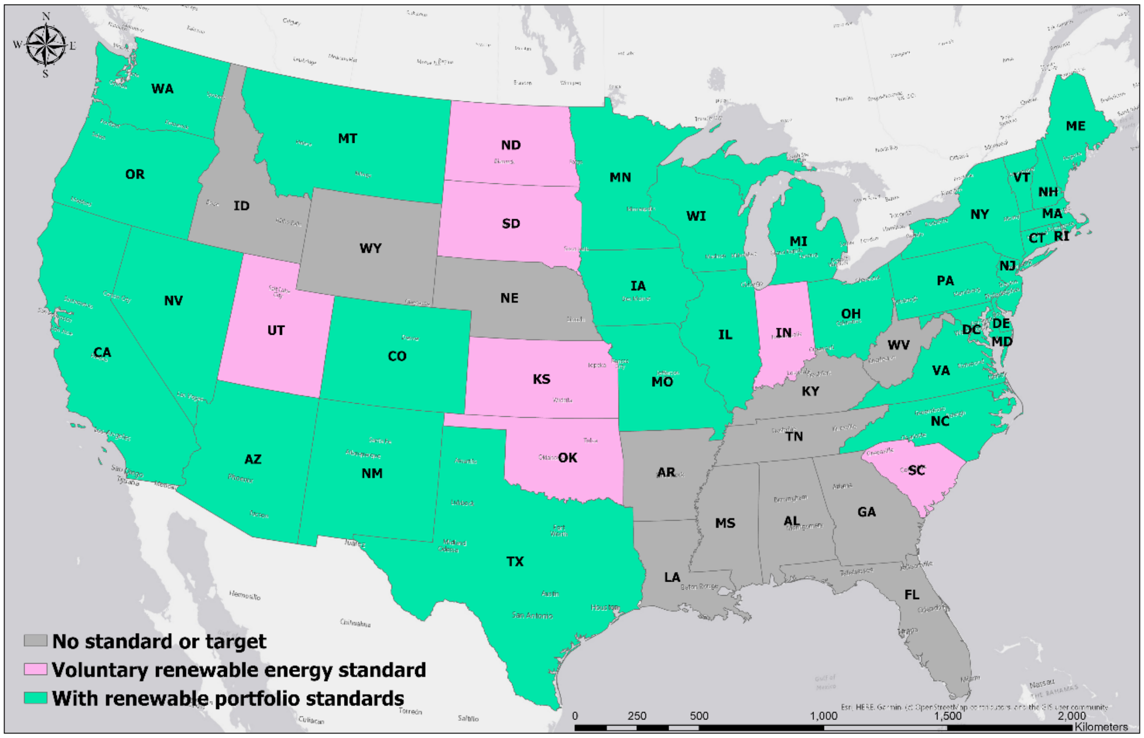

Figure 11. Renewable Portfolio Standards in the United States.

Energy efficiency and renewable energy impact can be valuable factors in determining future policies. EPA has a guideline to estimate the future impact of energy efficiency and renewable energy, which includes three main steps: (1) Development of business as usual (BAU) forecast of demand and supply, which analyses the historical demand and supply portfolio and how policies can cause any change, (2) Estimation of potentials and (3) Creation of an alternative policy forecast (EPA, 2018). “In the case of energy efficiency, the electricity savings estimates developed in Step 2 are subtracted from the BAU energy forecast developed under Step 1 to create a new policy forecast (EPA, 2018, p.37).”

In that sense, and drawing on the instructive literature summarized above, an HEI’s commitment to sustainable energy is hypothesized to be a function of at least four interacting variables: (1) Financial feasibility, (2) energy savings, (3) State priorities and policy supports, and (4) Local/community preferences, values, and priorities. According to this view, HEIs are most likely to invest in sustainable energy when all four of the above factors are favorable (i.e., sustainable energy investments are profitable; the investments demonstrably save energy; the state is strong on climate action and energy, and residents prioritize sustainability goals). Simultaneously, the view suggests that even when projects are financially feasible and save energy, investments might not occur if states and communities are not particularly strong on environmental protection issues and sustainability.

3.2.1 GEOGRAPHICAL CONTEXT AND CLUSTER ANALYSIS

As a slight tangent, note that reducing numerous data points down to succinct descriptions of an HEI's geographical context is no simple task. While there are many strategies for engaging with such a challenge, one of the most common data sciences approaches is to rely on multivariate analytical methods. More specifically, massive amounts of data are meaningful only when "one can extract the hidden information inside them" (Shih et al., 2010, p.1). Clustering is a powerful tool for automated data analysis and data mining (Aloise et al., 2009; Shih et al., 2010; Ralambondrainy, 1995; Huang, 1997), revealing interesting groups with similar features (Huang, 1998). Clustering aims to discover the natural grouping(s) of patterns, points, or objects (Jain, 2010). Clustering is also helpful when and where the researcher wants to take action based on the location of one or more clusters (Mitchel, 2005). Useful patterns can be extracted by analyzing each cluster (Shih et al., 2010). A comparison between the extent of energy sustainability and the public's opinion about sustainability will be applied by identifying clusters, including a given university, which is part of the study. For instance, grouping block groups with their population into several clusters and based on their attitudes towards the environment may lead to further knowledge and patterns.

Cluster analysis emerged in the 1960s and 1970s when the monograph ’Principles of numerical taxonomy’ by Sokal and Sneath (1963) encouraged research on clustering methods. Although MacQueen (1967) is known as the first author to use K-means' term, Hans-Herman (2008) retraces the origin back to 1950. Organizing data into a more specific grouping is of the most fundamental modes of understanding and learning. It is also prevalent in any discipline that involves the analysis of multivariate data (Jain, 2010). Identifying clusters of people with a higher level of sustainability attitudes may explain why a university falling close to that cluster is more energy conscious than the others.

“Mapping features based on how similar they are to surrounding features [clustering] is different [and more significant] than simply mapping the values of features [graduate color map]” (Mitchel, 2005, p.163). By comparing the geographical locations of clusters, it is possible to examine and identify the potential contributing factors to sustainability commitment in HEIs. In other words, it is feasible to describe the essential aspects of an HEI’s geographic context.

Statistical cluster analysis helps to minimize subjectivity in making maps and delineating one “type” of geographic context from another. Namely, cluster analysis uses mathematical algorithms and inferential statistics to reveal (a)spatial patterns in data. Clustering groups like features together in data space and, if appropriate, in geographic space, which allows the analyst to understand critical ways in which places differ on a range of relevant variables. In this dissertation, the relevant variables will be drawn primarily from consumer studies that ask adults their attitudes and opinions regarding the environment.

In practice, cluster analysis is similar to Multidimensional Scaling (MDS), where the proximity (distance) between observations is taken into account to organize them (Davison, 1983). Cluster analysis does not include testing any null hypothesis (DiStefano, 2012), and different clustering algorithms can result in different partitions, even with the same data (Jain, 2010). The outcome of cluster analysis is an exploratory result with the best structuring approach (Meyers et al., 2016). Rogerson (2010) and Ralambondrainy (1995) believe that cluster analysis should be considered a data reduction technique. From this perspective, the researcher seeks to reduce the number of original observations n into g groups, where:

$$1 \leq g \leq n \qquad \textit{Equation 2}$$

The goal is to minimize the variation within groups and maximize the variation between groups (Rogerson 2010). The basic idea is that the algorithm "finds [group] centroids of a fixed number of clusters of points in a high-dimensional space" (Peng, 2012, p.111). In a two-dimensional approach—given by two variables– it is possible to look at the data and figure out where the centroids are. Still, when there are more than two dimensions, the researcher needs an algorithm (Peng, 2012, p.111). Most clustering algorithm looks at the data as a point in a multidimensional space, and that is why in the literature they are represented as vectors (x_1, x_2, …x_d) (Shih et al., 2010) and shown in figures where they are represented with x and y-axis (e.g., see the methodology section). In the present context, one goal of cluster analysis is therefore to leverage complex, multivariate data in a way that "reduces" a large amount of information (e.g., environmental preference variables) into a smaller handful of "groups"—or similar *contexts*—that can be described more succinctly (e.g., Rogerson, 2010).

Geodemographics is one field study where cluster analysis has been used frequently toward this end (Rogerson, 2010). Cluster analysis in geodemographics tries to reduce many subregions (given by block groups in this dissertation) by grouping them into a smaller number of types (Rogerson, 2010). Approaches to cluster analysis can be categorized into (1) *agglomerative* or *hierarchical* and (2) *non-agglomerative* or *nonhierarchical* methods (Rogerson, 2010; Hans-Hermann, 2008; Meyers et al., 2016; Jain, 2010; Shih et al., 2010). The agglomerative method is used to sort a small number of cases into clusters based on quantitative variables (Hans-Herman, 2008). In the agglomerative method, there are n clusters composed of the number of observations. This means that each observation will be assigned to the respective cluster. Two initial clusters will be merged so that $n -1$ clusters are left, and the iteration continues until one cluster remains (Rogerson, 2010). Hierarchical clustering is an agglomerative mode where each point (value) is assigned to its cluster one by one (Jain, 2010; Shih et al., 2010). "The Hierarchical clustering algorithm takes numeric data as the input and generates the hierarchical partitions as the output" (Shih et al., 2010, p. 5). The approach can also be in a divisive process where all the points are initially assigned to one cluster. Eventually, similar points will be divided into smaller clusters until no point is left (Jain, 2010). The merger of two clusters cannot be undone in further steps—making more clusters— and the clustering of two observations will remain intact. Hence, this is why this process is hierarchical (Rogerson, 2010; Meyers et al., 2016).

In the non-hierarchical process, there is a pre-established number of *g* [clusters]. "Then one begins with either an initial set of *g* seed points or an initial partition of the data into *g* groups" (Rogerson, 2010, p. 342). *Seed points* will determine the assignment of observations to the nearest seed point. In contrast, if the researcher begins the algorithm with a partition of data into *g* groups (clusters), *g* seed point locations will be calculated as the centroids of the pre-established *g* groups, and this process repeats until no observation is moved from one cluster to another (Rogerson, 2010). The non-hierarchical process has the advantage of being computationally less time-consuming and the disadvantage of establishing the number of clusters even though the optimal number of clusters can be determined after a few tries (Rogerson, 2010) by looking at the pseudo-F statistics chart. One of the challenging steps in clustering is determining the optimized number of clusters (Jain, 2010). There is a top-down option where the analysis starts with many clusters and gradually merges them if the Minimum Message Model (MML) is decreased by the merger process (Jain, 2010). Other approaches are the Gaussian mixture model (GMM), Minimum Description Length (MDL), Bayes Information Criterion (BIC), Akiake Information Criterion (AIC), Gap statistics, and the Dirichlet Process (DP) (Jain. 2010). Non-hierarchical clustering, which is also called a *partitional* clustering by Jain (2010), finds all clusters simultaneously without imposing a hierarchy (Jain, 2010). Partitional algorithms are preferred in pattern recognition (Jain, 2010). A distinction is made between a *clustering method* and a *clustering algorithm* where the method is a strategy to solve a clustering problem, and the algorithm is only an instance of the method (Jain, 2010). “For instance, minimizing the squared error is a clustering method” (Jain, 2010, p.9), and K-means is just one of the algorithms used to minimize the squared error method.

K-means clustering is known as an *iterative-agglomerative* clustering procedure (Meyers et al., 2016), partitional and non-hierarchical (MacQueen, 1967), and a *distance-based* algorithm (Shih et al., 2010) whose purpose is to “identify from a relatively large sample a few subgroups of cases based on a relatively small set of variables” (Meyers et al., 2016, p.819). MacQueen (1967) named the K-means clustering algorithm, where at each step of the iteration, the mean of *k* groups represents the new mean of the respective number of iteration (*K-means*). However, the version of the algorithm most often used today was developed by Harington and Wong (1979). The areas where K-means is applied are identified by MacQueen (1967) and Jain (2010): (1) similarity grouping (clustering) where the goal is to obtain a qualitative and quantitative understanding of large amounts of N-dimensional data, (2) Relevant classification, (3) Approximating a general distribution, (4) A scrambled dimension test for independence among several variables, (5) Distance-based classification trees, (6) A two-step improvement procedure (7) Underlying structure detection, and (8) Compression as a method of summarizing.

Cluster analysis emerged in the 1960s and 1970s in response to Sokal and Sneath’s (1963) call for research on clustering methods. The advantage of cluster analysis is that it uses statistical methods such as K-means to take the guesswork out of grouping like records (e.g., places) together (Mitchel, 2005). In other words, if the goal is to identify “types” of places based on their geographic context(s), then clustering can help the researcher avoid making guesses about which places to group as being the same “type.”

One significant advantage of using clustering to help summarize essential aspects of a place’s geographic context is that it can be applied to any analysis level at which data are collected. In that sense, clusters detected at multiple spatial resolutions can be combined into a multi-level framework for specifying and evaluating context. Using a specific example, consider a dataset on environmental policies and practices measured at the state level of analysis in the U.S. and a consumer survey that provides data on the environmental attitudes and preferences of a place’s residents down to the census tract unit of analysis. Performing cluster analyses on both datasets and combining the results would facilitate an investigation that identifies where (in geographic space) neighborhood environmental values and state environmental values and actions are aligned/congruent or at odds/incongruent. HEIs in neighborhoods with congruent pro-environment policies, preferences, and attitudes are arguably more likely to take strong action on alternative energy than HEIs where state policies are comparably anti-environment, and community preferences are comparably neutral, for example. Stated another way, clustering states and neighborhoods into groups based on their environmental preferences, actions, and attitudes offers a valuable, multi-level interpretive lens through which to examine HEI energy practices. Recognizing which of those practices are relatively “sustainable” and aimed at reducing carbon emissions is taken up in the next subsection.

3.3 SUSTAINABLE ENERGY OPTIONS FOR HEIs

To this point, interdisciplinary literature streams have been synthesized to make the case that: (1) HEIs are massive energy consumers, with campuses resembling small cities (Gormally et al., 2019; Amber et al., 2017; Chung and Rhee, 2014; Alshuwaikhat

& Abubakar, 2008;); (2) HEIs tend to have growth imperatives, suggesting that their energy demands and consumption levels are likely to continue rising as Universities continue to expand under business-as-usual practices (Gormally et al., 2019; Chung and Rhee, 2014); (3) HEIs, particularly those that are publicly owned and funded, have a specific social mission and responsibility that private multinational corporations or similarly-scaled actors do not necessarily have (Shek and Hollister, 2017; Fonseca et al., 2018; FHKPS, 2019); (4) at least part of that social mission manifests in the form of sustainability-related research and education (FHKPS, 2019; Amaral et al, 2019); (5) there are gains to be made from HEIs putting that research and education into practice, and leading by example in replacing fossil fuel-intensive energy infrastructure with more sustainable infrastructure (Buffel et al., 2017; Gormally et al., 2019; Pearce and Miller, 2006); (6) however, HEIs face numerous barriers and constraints to sustainable energy implementation, including but not limited to massive upfront costs vis-à-vis short-term profitability mandates, as well as manifold state and local contextual factors (Amaral et al, 2019).

While prior research has studied individual aspects of these dynamics in detail, a more comprehensive, spatially based approach has the potential to clarify how those pieces come together to result in sustainable energy (in)decisions at HEIs. More precisely, by evaluating the financial attractiveness of concrete sustainable energy projects at real-world HEIs, while simultaneously engaging with the state/policy and local/community influences that bear on HEI decision-making, it is possible to reveal pathways to successful implementation as well as roadblocks that can be targeted for removal. To round out the literature review and finish setting the stage for such an investigation, it is necessary to conceive a "concrete sustainable energy projects" menu for real-world HEIs. This section creates such a menu, though observe that it is non-exhaustive by necessity. Projects reviewed herein were selected for their regular appearance in the literature and their probable familiarity with institutional energy decision-makers. In other words, whereas previous sections reviewed the barriers to sustainable development in HEIs, this section discusses potential practical *solutions* offered in the literature.

The shrinking budgets, climate change, internal and external obligations push HEI towards implementing energy-efficiency programs (Fonseca et al., 2018). Amaral et al. (2019) identify renewable energy generation sources as the most substantial sustainable energy initiative in HEIs, accounting for 12% of scientific papers in the literature. This is in line with the global trend to comply with climate change, but, as Amaral et al. (2019) stated, the implementation percentage has remained low. The desired implementation happens in university buildings that perform as demonstration sites of sustainable renovation (Fonseca et al., 2018). One example of the international surge for energy-efficient buildings was introduced by the 2010 Energy Performance of Buildings Directive (EPBD) on behalf of the European Union (EU). According to this directive, buildings are considered crucial for achieving the EU's energy and environmental goals. EPBD is supposed to change the EU members' building stock to highly energy-efficient and decarbonized by 2050. "The Directive requires that by the end of 2020, all new buildings should be nearly zero [emission] energy, being the deadline even sooner (by the end of 2018) for the buildings occupied or owned by public authorities" (Fonseca et al., 2018, p.791). Such energy efficiency measurements require establishing a numerical indicator of energy consumption (Fonseca et al., 2018). The average numerical indicator for a zero-emission building in the European Union is set to 110 kWh/m^2 by Fonseca et al. (2018). While this number indicates the total energy consumption, it is possible to extract the electricity portion from it by using factors or looking at the portions of energy consumed at the building level (Mohammadalizadehkorde & Weaver, 2020). This dissertation uses the Commercial Buildings Electricity Consumption Survey (CBECS) issued by the U.S. Energy Information Administration (EIA) to create the numerical indicator of electricity consumption. The data for expenditure and use in commercial buildings shows (partially) the energy consumption of higher education facilities.

Schneider Electric Organization identifies other areas that influence energy use as:

- Controls
- Operations and Maintenance
- Employee Awareness

Promoting the individual participation of professors, staff, and students across the campus is another solution to achieve better energy use (Fonseca et al., 2018). Mtutu and Thondhlana (2016) have studied individual energy (Employee Awareness) use practices on the Likert scale questioning the habits related to energy conservation, such as turning off the light and computers when there is no need for use. However, personal values do not always reflect the reported behavior in pro-environmental studies (Mtutu and Thondhlana, (2016), and the best combination for achieving a pro-environment change is given by the personal and institutional change of values (Steg & Vlek, 2009).

Following the preceding paragraph, a possible and immediate option may consist of institutional (rather than individual) changes. Among other things, people are more likely to engage with environmental issues if they see the active involvement of other community members (Mtutu and Thondhlana, 2016), which again speaks to the importance of geographical context in promoting alternative energy.

One reason for the low uptake of renewable energy technologies in large institutions is the long-term payback period (Mohammadalizadehkordeh & Weaver, 2020). In line with a significant body of literature, renewable energy implementation is not a profitable investment in many places (Kalkan et al., 2011), mainly because of non-favorable climatic conditions—e.g., low irradiance and low wind power. However, several authors consider it an instrument for improving the cost even with a long payback period of 8 years or the fact that the microgrid benefits can surpass the cost (Paudel and Sarper, 2013; Machamint et al., 2108).

One way to achieve energy-efficient buildings is to implement renewable energy. Renewable energy is energy generated in part or exclusively from non-depleting energy sources (EPA, 2018). However, renewable energy definition varies by state but often includes wind, solar, and geothermal energy. “Some states also consider low-impact or small hydro, biomass, biogas, and waste-to-energy to be renewable energy sources (EPA, 2018).” In the United States, renewable energy generated to achieve 2013 RPS requirements and obligations possibly moved the supply curve for electricity distribution, “reducing wholesale electricity prices and yielding an estimated $0 to $1.2 billion in savings to electricity consumers across the United States (Wiser et al., 2016, p.39). Renewable energy implementation also can contribute to the economy: RPS compliance obligations have supported nearly 200,000 U.S.-based jobs and over $20 billion in GDP (Wiser et al., 2016, p.50). Does this urge a global investment in clean energy? Bloomberg's report on *Clean Energy Investment Trends* confirms this desire to achieve a high investment volume in clean energy. Renewable power generation even continued to grow in 2020 amid the COVID-19 pandemic (IRENA, 2020). The IRENA data shows that solar PV projects commissioned in 2021 could have an average price of just USD 0.039/kWh. "This represents a 42% reduction compared to the global weighted-average Levelized cost of capital (LCOE) of solar PV in 2019 and is more than one-fifth less than the cheapest fossil-fuel competitor, namely coal-fired plants (IRENA, 2020, p.14)." The global weighted-average LCOE of utility-scale solar PV and onshore wind potentially will drop to USD 0.039/kWh and USD 0.043/kWh in 2021 (IRENA, 2020). This means renewable power projects are cheaper than "the marginal operating costs of an increasing number of existing coal-fired power plants, raising the risk of a growing number of stranded assets (IRENA, 2020, p.15)." Also, wind and solar accounted for about 27% of U.S. non-carbon electricity generation in 2019 (EIA, 2020). This is while hydropower had the largest share of renewable electricity generation in the United States. With other renewables' growth, the hydropower share has declined from 34% in 1997 to 18% in 2019 (Figure 12). Following Figures 12-15 Show the number of investments in the United States.

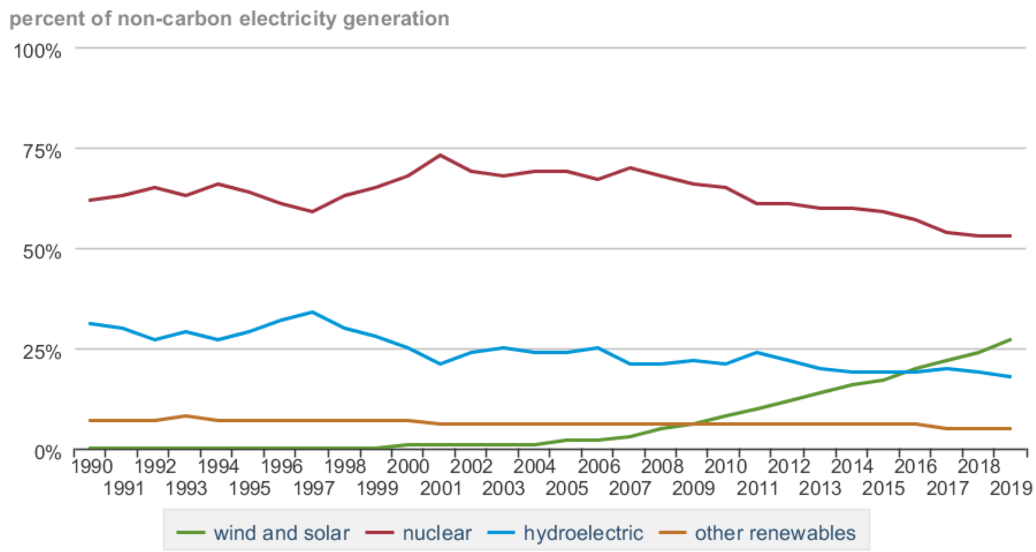

Figure 12. Share of non-carbon electricity generation in the U.S

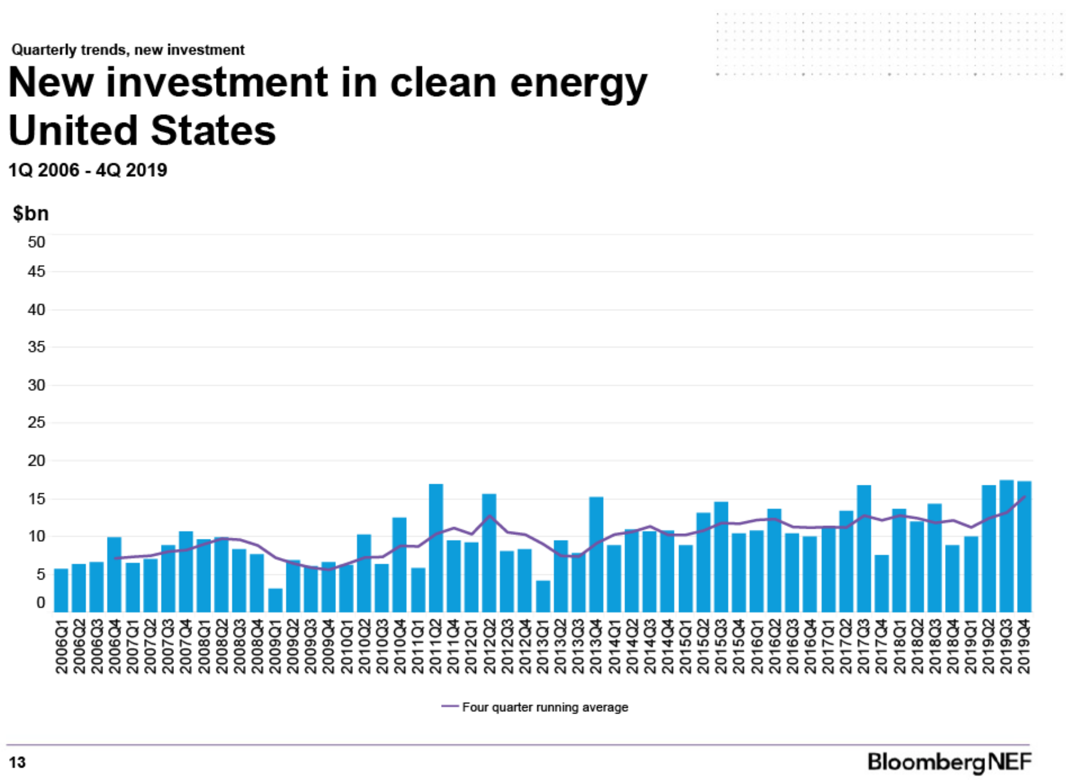

Figure 13. Clean energy investment in the United States

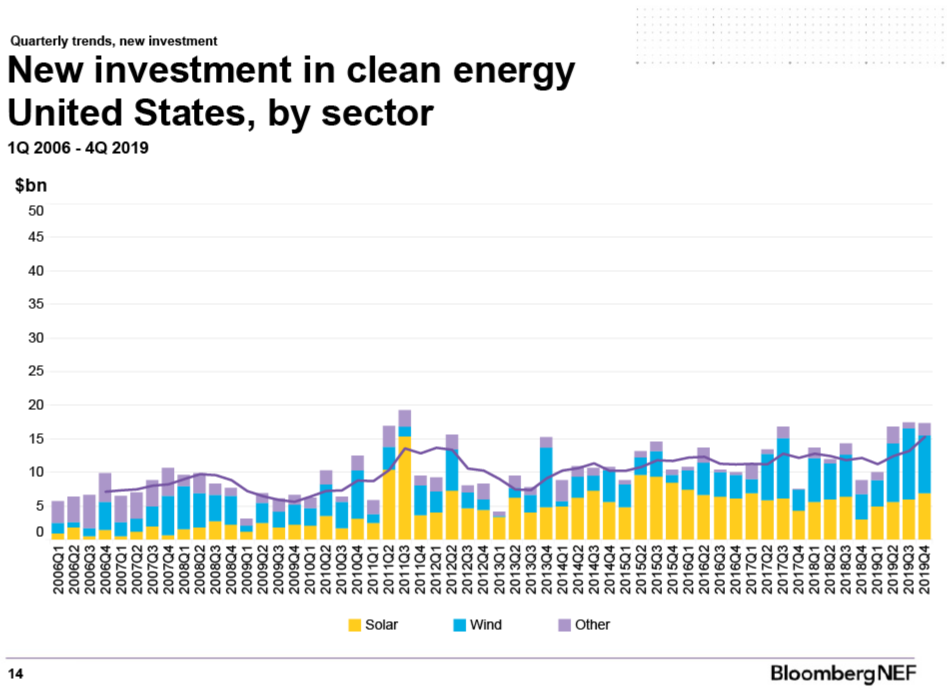

Figure 14. Clean energy investment by sector in the United States

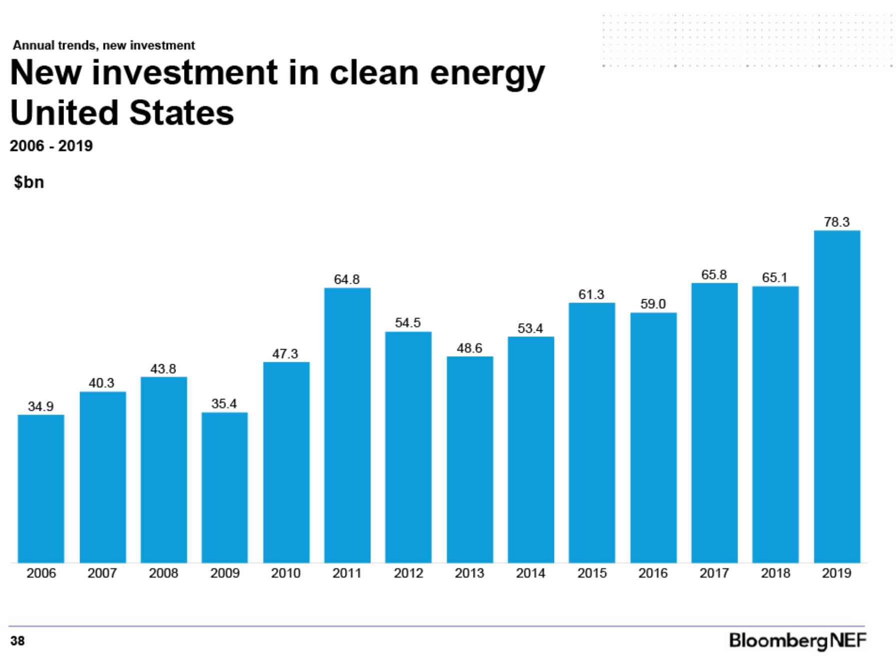

Figure 15. Investment in clean energy in the United States 2006-2019

The latest cost data from the International Renewable Energy Agency (IRENA) shows that the global weighted-average Levelized cost of electricity (LCOE, also discussed in section 5.2.3) of utility-scale solar photovoltaics (PV) fell 82% between 2010 and 2019 (IRENA, 2020).

With the preceding points in mind, the following subsections discuss specific projects that HEIs might consider to reduce their fossil fuel dependencies (and, by extension, ecological footprints).

3.3.1 SMALL WIND TURBINE IMPLEMENTATION

Wind energy is a transformed type of solar energy (Tong, 2010) and occurs due to the unequal distribution of solar radiation, which causes unequal heating and wind power around the globe (Aydin et al., 2009; Hawken, 2017). Wind energy has relatively low impacts on the environment and has been actively used by human societies for at least the past 3,000 years (Akpinar & Akpinar, 2005). A wind turbine has no fuel cost, and, once installed, the only fee to pay is the cost of maintenance and operations.

In 2009, the global annual installed wind generation capacity touched 37 GW bringing the world capacity to 158 GW (Tong, 2010). Nearly four percent of global electricity is provided by 314,000 wind turbines (Hawken, 2017). In the United States, wind power recently saw 8,203 MW of newly added capacity relative to 2016 and $13 billion in new investment, reaching 2,611 MW (2016 wind technologies market report). In 2018 Cumulative U.S. distributed wind installed capacity reaches over 1.1 GW until the end of 2018 (2018 Distributed Wind Market Report, U.S. Department of Energy).

According to the American Wind Energy Association (AWEA), Texas is ranked first for installed wind capacity with 12,494 installed wind turbines. During 2016, wind energy provided 12.63% of all in-state electricity production (American Wind Association). Although wind power technology has been available for decades, more than 90% of all wind power capacity on a global range has been installed between 2002 and 2012 (Bolinger and Wiser, 2012). 91% of turbine units in 2015 were deployed to power off-grid sites or charge batteries (Orrell & Foster 2016). According to many studies, this happens while the cost of renewable energy has been falling in the past decade (Gielen et al., 2019; Al Badi et al., 2009; American Wind Energy Association). Onshore and offshore wind projects experienced a 9% year-on-year drop in price in 2019, reaching USD 0.053 kWh and USD 0.115 kWh of cost, respectively (IRENA, 2020).

In some cases, the capital cost has been announced between 75% and 90% of the total (Kaygusuz. 2002). According to AWEA, since wind energy implementation has zero fuel cost, utilities, and corporate customers can sign long-term contracts called power purchase agreements (PPA) with known electricity costs for 20 to 30 years.

A total of 1.5 MW of small wind turbines (with a maximum of 100 kW capacity) were deployed in the United States in 2018. This capacity is down from 1.7 MW in 2017, driven by changing federal and state environmental policy and competition from low-cost solar PV (2018 Distributed Wind Market Report, U.S. Department of Energy). Architects have suggested installing small wind turbines on high buildings' rooftops as a means of sustainable energy generation (Tabrizi et al., 2014). Selecting a suitable site is the primary factor in leading a renewable energy project towards success and starting a wind energy project. Wind turbines can be categorized as small, medium, and large. A small wind turbine can be used for on-site generation, and a large one can be used for utility applications (Akpinar, & Akpinar, 2005). The literature on wind turbine site selection is rich, especially for large-scale implementations (e.g., a wind farm).

In contrast, small or medium-size wind turbine studies are more frequent in guideline format (e.g., Stokes et al., 2011). Regardless of the environmental impact, much thought must be given to the economic output of the installation. Adding a financial analysis to the site selection analysis will help decision-makers adopt renewable energy wisely while keeping account of the needed amount of investment, payback, and avoided CO_2 emission.

Wind farm location analysis can be considered a Multi-Criteria Decision Making (MCDM) problem (Al-Yahyai et al., 2012). A variety of MCDM exists in the literature that can be used for different purposes, such as choosing, ranking, sorting, and describing (Baban & Parry 2001; Atici et al., 2015). Azizi et al. (2014) used an analytic network process (ANP) to assign the weight of each criterion and decision-making trial and evaluation laboratory (DEMATEL) method to determine the criteria relationship. "Analytic network process (ANP) proposed by Saaty (1996) is one MCDM method that is a generalization of the analytic hierarchy process (AHP)" (Azizi et al., 2014 p. 6696). Tegou et al. (2010) have applied GIS to evaluate land suitability for wind farm site selection. Atici et al. (2015) apply a pre-elimination of infeasible sites and evaluate available ones. The lack of accurate calculations—caused by the instability of wind discussed in the next paragraphs— creates a major difficulty in the effective deployment of micro-wind turbines in urban areas. Some of these methodologies to calculate the mean wind speed include Weibull analysis, micrometeorology data, experimental measurements, and computational fluid dynamics (CFD) (Yang et al. 2016). Site selection's economic aspect in several studies consists of calculating the environmental factors such as distance from roads, slope, and the possibility of connecting the system to the grid in large-scale wind turbine installation. Wind power density calculation and power output in small-scale implantation are other parameters in this study.

Parameters used in wind turbine analysis can be classified in (1) economic parameters, such as slope, terrain, distance to road, distance to the grid, (2) social factors, such as urban area and its implications for noise, aesthetic concerns, vibration, and electromagnetic interference, (3) environmental factors, such as bird flyways, historical sites, wildlife, natural reserves and (4) technical parameters, such as wind speed, wind power density, elevation, capacity factor and forecast of electricity production (Azizi et al., 2014; Atici et al., 2015; Aydin et al., 2009). Note well, however, that these classifications are non-mutually exclusive and non-exhaustive. For example, Azizi et al. (2014) refer to the slope, elevation, river, and protected areas as environmental parameters, while Baban & Parry (2000) call them topographic factors. In other studies, like Al_Yahyai et al. (2012), technical variables are given more weight than socio-economic-environmental variables. Atici et al. (2015)—bearing in mind their goal to create a wind turbine farm—the elevation below 1500 meters is excluded from being considered as a suitable area for wind turbines. The maximum terrain slop is 10% in Al yahyai et al. (2012) because slopes with a higher percentage can cause turbulence while the cost can still differ considerably between two sites with slopes of 1% and 10% (Atici et al., 2015). The capacity factor is another crucial criterion highly correlated to elevation and wind speed (Atici et al., 2015). Other parameters, such as land cover, land value, and electricity demand, have been considered in studies such as Tegou et al. (2010).

There are few detailed methodologies for conducting wind resource assessment in the built environment (Tabrizi et al., 2014), where the distance to roads, slope, bird flyways, wildlife, and terrain have less importance due to the tendency of wind turbines implementation on rooftops.

Purchasing small wind turbines is a long-term investment, and like most renewable energy projects, it might not have a fast payback. In Al Badi et al. (2009), it is mentioned that a 50-kW wind turbine installation can have an 8.5 year of simple payback and 15.6 years as discounted payback at a 10% discount rate. It is necessary to remember that for every doubling in cumulative production or installation of wind turbines, there is a significant reduction in cost (Bolinger and Wiser 2012) considering the average lifetime of renewable energy technology —like wind turbines and solar panels— of 20-25 years. This study will assess the degree of the economic and financial output of such an energy efficiency project.

Installation cost varies depending on local zoning, permitting, and utility interconnection costs and eventually based on the size and components. In 2011 "a reliable small wind electric system and tower in Tennessee and Kentucky used to cost, on average \$5000-\$8000 per kilowatt capacity installed" (Stokes, 2011 p.7). The average cost reaches \$5,760 per kilowatt installed in 2015, and compared to 2014, the price dropped almost 8% (Orrell & Foster 2016). "A 2.4 kW system, including the tower, inverter, and installation, can cost approximately \$18,000 (\$7500 per kilowatt). Larger systems will be less costly per kilowatt; a system rated 10kW will cost about \$60,000, or

$6000 per kilowatt" (Stokes, 2011 p.7), while the capacity factor varies for different types of wind turbines. Environmental Defense Fund (EDF) establishes a capacity factor percentage from 20 to 40. In contrast, according to Cory & Schwabe (2009), the capacity factor ranges from 22 to 48 in three different scenarios (Table 6), and for Mathew (2006), it ranges from 0.25 to 0.4.

Table 6. Variables for financial Analysis (Adapted from Cory & Schwabe, 2009)

Scenario	Capacity Factor (%)	Installed Cost ($/kW	Operations & Maintenance ($/MWh)	Levelized Replacement Cost ($000)
High-Cost	22	2,600	17	25,600
Base-Case	34	1,710	6	12,800
Low-Cost	48	1,240	3	0

*These ranges were based on estimates of a realistic wind project

The cost trend for wind turbines has changed in the past decade. The lowest registered price is around $800/kW from 2000 to 2002 while the price increased to $1600/kW by the end of 2008, and recent market data suggest that the price will range from $800 to $1,100/kW, hitting the historically low price (2016 wind technologies market report). The price drops in concert with technological improvements and favorable terms for turbine purchases (2016 wind technologies market report). In 2015, "4.3 MW of small wind was deployed in the United States, representing 1.695 units and over $21 million in investment" (Orrell & Foster (2016). The installed MW in 2015 is slightly higher than in 2014 (3.7 MW) and lower than in 2013 with 5.6 MW and $36 million of investment (Orrell & Foster 2016).

It is necessary to bear in mind that the cost ratio for wind power decreases with each year of operation while the minimum useful period reaches 20 years and more.

Wind turbines made with the last generation of technology cost more but require less maintenance and can improve the scenario's financial output. The levelized cost of energy (LCOE) allows alternative technologies to be compared to fossil fueled generating unit and, if assigned to every unit of energy produced (or saved) by the system over the analysis period, will equal the total life-cycle cost (TLCC) when discounted back to the base year (Short et al., 1995).

Universities can implement wind power and benefit from power purchase agreements with utilities without a significant initial investment. However, there is little literature on the implementation of wind power in HEIs. The U.S. Department of Energy is one of the few federal departments funding the Wind for Schools project. However, such programs' focus is educational and aimed to engage communities in wind energy applications without an explicit reference to saving energy or environmental improvement in the short term. In 2004 Carleton College became the first college in the United States to possess an active utility-grade wind turbine, located out of campus and to supply more than 50% of college’s electricity (Environment America, 2020, on-campus wind energy, moving toward 100% clean, renewable energy on campus). Ball State University is another example of HEI that has implemented a wind study to assess wind power implementation feasibility with the economic earnings for a 20-year life span (Hedin and Pentecost, 2016). While the little available literature on wind power implementation mainly focuses on a payback period and commercial wind turbine, this dissertation will attempt to study the options given by small wind turbines.

3.3.2 PHOTOVOLTAIC SOLAR PANEL INSTALLATION

Much of the recent literature on the “Anthropocene” epoch of history implicates a need to curb large-scale fossil fuel consumption all over the world (e.g., Castree 2015). “Among renewable energy sources, solar energy is the most promising due to its tremendous potential” (Gençer & Agrawal, 2016). Currently, there are two different technologies capable of capturing solar energy: (1) photovoltaic solar panels and (2) heliothermic electric generation (Conde et al., 2019). In an hour, the quantity of power from the sun that strikes the Earth (supply) is more than the total world consumption (demand) in a year (Lewis & Nocera 2006). Yet, current technology cannot capture and convert this amount of energy into a usable format. Solar power has received remarkable attention and growth in recent years. Electricity costs from utility-scale solar PV decreased by 13% in 2019 compared to 2018, reaching USD 0.068 kWh (IRENA, 2020). The falling price is driven by a 90% reduction in module prices between 2010 and 2019 (IRENA, 2020). However, residential and commercial rooftop solar PV—the subject of this study—have a higher cost structure than utility-scale projects, which will be discussed in this dissertation's result section. Tax incentives (i.e., policy/geographic context) play an influential role in this process, and projections show that the solar PV industry continues to experience a significant cost reduction (Comello & Reichelstein 2016).

It can be argued that the most crucial factor in photovoltaic electricity generation is the amount of solar radiation received by a surface. Not all the energy received by the surface can be converted to electricity. The potential for photovoltaic electricity generation on rooftops depends on several global, local, temporal, and spatially variable conditions (Redweik et al., 2011). Therefore, there is a need to narrow down the calculation, including environmental conditions such as the amount of direct normal irradiation (DNI), available building footprint, the mean value of sun azimuth, and its angle in a given geographical space.

Solar radiation comprises three components: direct beam, diffuse, and reflected radiation (Perez et al. 1987). The amount of solar energy reaching the Earth's surface depends on location, atmospheric effects, and topography. Solar radiation is measured at ground level, but since solar irradiation levels can vary dramatically with the terrain, vegetation, ground structures, and weather, in most cases, it is not accurate to be implemented in the analysis (Carl, 2014). Studies have revealed that solar irradiance data from distant stations (20-30 kilometers) can have a root mean square error reaching 25 percent (Perez et al., 1997).

"Technical potential is a metric that quantifies the generation available from a particular technology in a given region" (Gagnon et al. 2016 p.1). In other words, the technical potential is an estimation of how much of a given resource of energy can be captured by the available technology. In contrast, resource potential is the total energy available in a geographical entity. Previous estimates at the regional and national levels have lacked a rigorous foundation in geospatial data and statistical analysis to estimate rooftop PV potential at the individual building level (Gagnon et al., 2016). Most previous estimates have relied on rough engineering rules of thumb. However, there are three main approaches to calculate the suitable area for PV installation (Melius et al. 2013): 1) constant value method, 2) manual selection, 3) GIS-based methods. In this study, a GIS-based approach will be applied to calculate the potential electricity production by the available rooftops in a higher education institution's sample of buildings. Eventually, the obtained number will be compared to the constant-value method to assess the accuracy of calculations.

Constant-value estimation methods calculate a percentage of building rooftop areas suitable for implementing PV (Chaudhari et al. 2004). According to this approach, 22%-27% of the residential rooftop area is suitable for PV. Manual selection evaluates buildings individually and is the most precise estimation among three types of methods to estimate potential PV on rooftops. PVWatts and System Advisor Model (SAM) from NREL are examples of manual calculation of potential electricity production via solar panels. At the same time, large-scale estimates are usually based on GIS and LiDAR data.

As stated in the literature, HEIs are often identified as ideal *testbeds* for pilot studies to evaluate and adapt decarbonization technologies (Horan et al., 2019). As this dissertation focuses on the HEIs, the quantification of possibilities may provide insight for the aimed transition from traditional energy consumption to renewable resources. Although it is difficult for state schools to find funding for such projects, previous studies have shown that implementing solar panels in state-funded universities is financially and technically feasible (Jo et al., 2017).

3.3.3 ENERGY EFFICIENCY SOLUTIONS AT THE BUILDING LEVEL

3.3.4 LIGHTING SYSTEM

While the prior solutions (wind and solar) were focused at the campus level, HEIs can also take more nuanced scale actions at the level of individual buildings. This section enumerates several such options. Lighting systems are indispensable components that ensure comfort, productivity, and safety at the building level (Mahila et al., 2011). Lighting is one of the primary sources of energy consumption in buildings by representing 20-30 percent of total demand at the building level (Habash et al., 2014). Rapid enhancement of lighting efficiency in existing buildings is essential to reduce the community or even at a global level (Ma et al., 2012). “Electricity saving over time is significant enough to not only pay for the new lighting but also produce a return on the investment” (Mahlia et al., 2005). A heuristic evaluation of bulbs used at any HEI will provide information on the most recent technology replaced with the non-efficient system (Fonseca et al., 2006). Different studies have considered upgraded lighting systems to assess the electricity savings in residential and commercial sections (Mahila et al., 2011; Heffernan et al., 2007; Mahila et al., 2005; Franconi & Rubinstein, 1992) While Pavlov et al. (2019), Fonseca et al. (2006), and Pearce and Miller (2006) have studied the options in HEI settings.

The characteristics of an efficient lighting system consist of (1) operating cost, (2) light output, (3) bulb life, and (4) light quality (Fonseca et al., 2006). In the absence of efficiency in any of the characteristics mentioned above, the whole system is eligible for replacement (Fonseca et al., 2006). The traditional fluorescent and compact fluorescent bulbs (CFL) often use more energy—in the form of heat— than needed, causing over-illumination or under-illumination (Fonseca et al., 2006). Fluorescent tubes have been considered by Heffernan et al. (2007) and Mahila et al. (2011) as the primary lighting system at the industrial, commercial, and institutional levels. The same lighting system was identified as the primary type at Texas State University despite more than a decade has passed since Heffernan et al.'s study (Mohammadalizadehkorde and Weaver, 2020). Several drawbacks make this traditional way of lighting a non-sustainable technology: (1) sensitivity to supply disturbance causing flicker, (2) non-dimmable options, (3) non-ideal spectral power distribution, and (4) sub-optima color rendering (Heffernan et al., 2007). One way to improve energy efficiency at the indoor level is to use energy-efficient light sources such as LED lightbulbs (Pavlov et al., 2019; Heffernan et al., 2007). The artificial lighting must replicate the natural sunlight since human vision has adapted to conditions under specific light radiation (Pavlov et al., 2019), which is not represented by the traditional lighting system based on fluorescent or incandescent technology.

Several types of lighting systems are available in the market, and the selection of the light bulb, ballasts, fixture, and the distance between each fixture depends on the type of task executed by the users (Mahila et al., 2011), which is accounted in the model used to study the lighting system in this dissertation. Table 21 summarizes different usage types and the amount of light needed to execute specific tasks, calculating energy consumption and demand. Fonseca et al. (2006) have considered the cost of bulb, ballast, fixture, and labor to calculate the annual savings in energy, cost, and demand while calculating the time to recoup the money invested in a simple payback period. This dissertation will provide a breakdown of all the investment's financial returns on a yearly basis and for the entire needed time to recoup all the money invested in the chosen study area.

3.3.5 MOTOR REPLACEMENT

Global climate change has been pushing governments at various scales and across the globe to pass laws to reduce greenhouse gas emissions (Soleimani et al., 2018). As a result, motors will be more efficient based on different national and international standards (Soleimani et al., 2018; (Kaya et al., 2008).

At the industrial level, the energy consumed by electric motors in plants can reach 65% of total energy consumption (Kaya et al., 2008). Not all the energy consumed by a motor can be converted to mechanical energy (Kaya et al., 2008). A well-designed and well-maintained motor can convert over 90% of its input energy into useful shaft power for decades (Nadel, 1991), which is also verifiable in Mohammadalizadehkorde and Weaver (2020). Under normal conditions and correct size selection, a motor can last for 15 years (Soleimani et al., 2018). Nadel (1991) believes that it is possible to save 9-23% of electricity by optimizing electric motors' performance, wiring, power conditioning, and components. The motors' efficiency decreases by aging, while motor winding failure has been subject to a crucial question: should a non-efficient motor be replaced or repaired? (Soleimani et al., 2018). It is known that the replacement of heavily used motors brings more economic profit than retrofitting them (Nadel, 1991), but also a rewound motor can cause a 1% - 2% loss in efficiency (Soleimani et al., 2018).

Rewinding motors consume more energy than a new one (Rai et al., 2017). The Department of Energy (DOE) suggests that even the best rewinding causes a loss of motor efficiency, and motors with less than 70 HP should not be rewound but replaced. “A motor’s efficiency tends to decrease dramatically below about 50% load” (Fact Sheet, Motor Challenge, Determining Electric Motor Load and Efficiency. US-DOE Program). If the energy efficiency motor is still in a serviceable state, there is no need to change the motors. The high volume of the motor duty cycle is an essential factor in the process of retrofitting. Deviations from ideal electricity distribution on a circuit can reduce the efficiency and, eventually, the useful life of a motor or other electric component (Nadel, 1991). In an ideal and theoretical condition, the voltage should flow without turbulence, but in reality, the ideal condition of electricity distribution is never achieved due to system inefficiencies (Nadel, 1991).

The payback gap results as the primary impediment to investing in efficient equipment (Nadel, 1991), although a motor's efficiency can be reduced by 10% because of aging (Soleimani et al., 2018). A replacement decision is usually taken after ensuring that the payback period is not more than the motor's lifespan (Soleimani et al., 2018). In Germany, the U.K., and the United States, with a small loss in efficiency, the motors are usually replaced (Soleimani et al., 2018). It is also known that motors operating at full load—which is the case of many universities— offer good efficiency (Rai et al., 2017; Kaya et al., 2008). In the past decade, the efficiency of motors has been improved: According to Kaya et al. (2008), while a motor's efficiency was 90% when fully loaded, it reached 87% when it was half loaded and 80% when it is 1/4 loaded. Table 7 shows the average efficiency and power factor of motors in different loads in recent years, demonstrating a slight improvement in efficiency (Soleimani et al., *2018).*

Table 7. Average efficiency and power factor of motors (Soleimani et al., 2018)

Load	Efficiency	Power Factor
25%	90.41%	0.55
50%	94.93	0.75
75%	95.6%	0.83
100%	95.7%	0.87

3.3.6 VARIABLE FREQUENCY DRIVE

A significant portion of electrical power in industries is consumed by electrical motors (Bhas and Lathkar, 2015). Most motors applied in the higher education system are designed to provide constant energy consumption continuously. At the same time, "Modern technology requires different speeds in many applications where electric motors are used (Saidur et al., 2012, p. 1)". Traditional and non-efficient ways of speed control, such as switching it on and off in two-speed motors, can waste a significant amount of energy (Saidur et al., 2012). One of the best practices to meet energy efficiency measures in motors is to apply VFDs on the motors with constant speed induction. A variable-speed or frequency drive is a device that regulates the speed and rotational force or output torque of pumps, fans, motors, or other industrial equipment (Saidur et al., 2012; Alsofyani and Idris, 2013).

VFDs can represent a potential solution because motors contribute to more than 60% of total industrial electricity consumption, and they cover 85% of the world's market (Alsofyani and Idris, 2013). For Bhase and Lathkar (2015), more than two-thirds of electrical energy is fed to motors to convert AC induction into mechanical energy. Motors supplied with AC power have a significant potential for energy savings when operated by variable frequency drives (Alsofyani and Idris, 2013). The output flow in the case of fans and pumps changes by seasonal change and hours of operation of the buildings (Mohammadalizadehkorde and Weaver, 2020), and that is why a speed regulator is required as a possible way of energy saving. If the load demand decreases, significant energy saving can be achieved by decreasing the motor's rotational speed (Saidur et al., 2012).

There are different terminologies used to describe the speed control in motors: (1) variable frequency drive (VFD), which will be used in this dissertation, (2) Variable speed drive (VSD), and (3) Adjustable speed drive (ASD) (Saidur et al., 2012). While there are small differences between all three types, the concept remains the same. “VSDs and VFDs are electronic devices, which match motor speed to the required speed of the application (Saidur et al., 2012, p. 3)”.

Because VFDs' cost has dropped around 50% since 1995 (Bhas and Lathkar, 2015), the application of VFDs or other types of speed control systems can improve the cost of implementation in HEIs. It is also known that a 20% reduction in the speed of induction motor can reduce 45% of energy consumption (Bhas and Lathkar, 2015). Figure 16 compares the power consumption between fans with VFDs and fans without it (Mohammadalizadehkorde & Weaver, 2020).

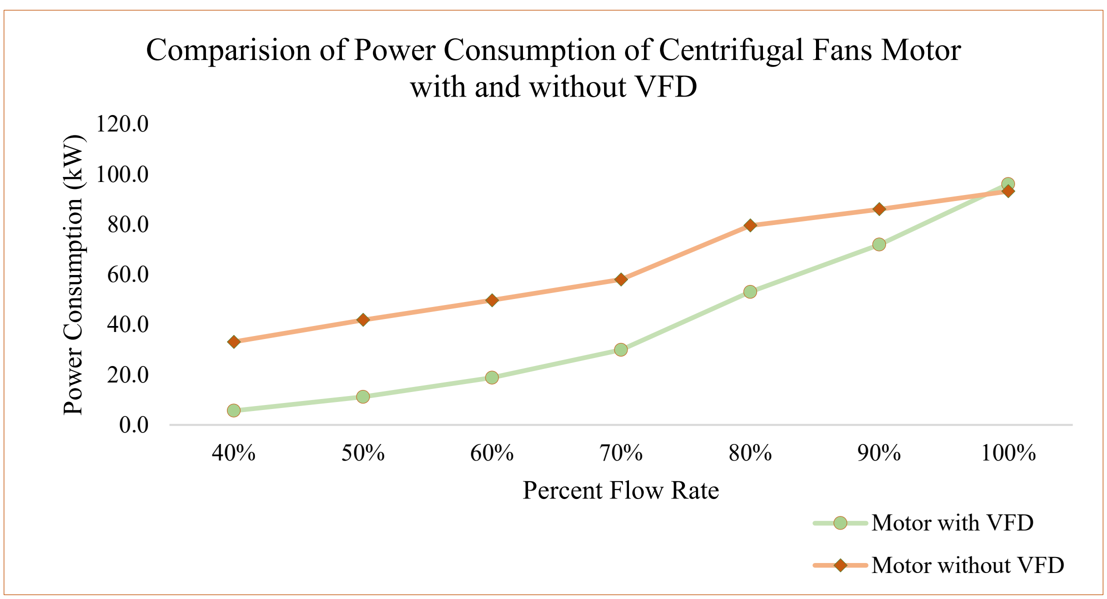

Figure 16. Comparison of power consumption in fans

Some of the benefits of VFDs are listed by Bhas and Lathkar (2015) as follows:

1. Substantial energy costs (due to direct speed control)
2. Improves Process by smooth speed control
3. Energy costs by reducing maximum utility demand charges
4. Increase Life of mechanical equipment (due to soft starting)
5. Reduce Motor stress (lower heat, vibration, and transient torques)
6. Lower chances of System disruptions (by lowering current inrush from 600 percent to 100-150 %)
7. Substantially brings down [the] downtime and maintenance costs
8. Smooth start and perfect control
9. Complete motor protection against overvoltage, overload, motor stalling, short circuit, transients, phase loss, etc.

VFD can be applied in two levels: first, at thermal plants where the needed flow rate is produced, and secondly, in HVAC systems inside each building to optimize the components' output.

3.3.7 PUMP REPLACEMENT

Another potential energy savings option at building scale is pumping systems (Kaya et al., 2008), especially when they are at the end of their lifespan. Thirty percent of the energy consumed by pumps could be saved through good design (Kaya et al., 2008). The performance loss at the operation stage of pumps arises from operating at part load (Kaya et al., 2008). A significant loss of efficiency can be experienced in pumps with a decrease in flow rate (Kaya et al., 2008). In case there is no need of replacing the pump, an elimination of clogs in the pipelines, revision of impermeability, “regular maintenance of belts, pulleys, bearings and filters, insulation of the heating circuit and prevention of vibration will assure energy saving and financial economy (Kaya et al., 2008, p. 3)”. However, efficient pumps will cut the operation cost and improve any institution's ecological footprint (Tverdokhleb et al., 2017). In recent years, the primary approach to increasing pumps' efficiency consisted of upgrading hydraulics and increasing the drives' efficiency (Tverdokhleb et al., 2017).

The design of the most used type of pumps manufactured in recent years has an efficiency very close to the maximum achievable efficiency (Tverdokhleb et al., 2017). The last generations of pumps, motors, and drives can save between 3%-5% of energy (Tverdokhleb et al., 2017) compared to 30% of potential energy saving at the end of the first decade of 2000 (Kaya et al., 2008).

This study will assess the Life Cycle Cost (LCC) of pumps used in higher education institutions. According to the American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE), despite the consequences of the fact that pumps have been under a scheduled maintenance plan, they are at the end of their lifespan of 15 to 20 years. Moving to more efficient pumps during replacement processes is an essential step in reducing energy consumption.

3. 4 FROM PROPER COUPLING TO PROPER *N-TUPLING*?

In an influential article published in *Systems Dynamics Review*, scholar Jack Harich (2010, p. 36) noted that a *proper coupling* "occurs when the behavior of one system affects the behavior of other systems desirably, using the appropriate feedback loops, so the systems work together in harmony in accordance with design objectives (Harich and Rosas, 2020, p, 9)." While Harich applies this concept to the connections between human and environmental systems—and their current *improper* coupling—for present purposes, a proper coupling might be thought of as a situation in which the behavior of HEI systems affect the behavior of other systems (e.g., communities and local environments) in a desirable, or more environmentally sustainable, manner. Isolating just one aspect of this relationship, the proper coupling between HEI energy decisions and local environmental sustainability arguably exists when HEIs replace fossil fuel-intensive energy infrastructure with lower impact alternatives (see, for example, the menu of possible solutions in the preceding subsection).

As the literature reviewed in this chapter suggests, this sort of HEI decision-making problem is embedded in broader cultural, policy, and community (i.e., spatial) contexts that either enhance or impede (or are neutral toward) a proper coupling between HEI and environmental systems. Among the cultural variables that most impede progress on alternative energy implementation are the deep-seated values or norms that guide decision-making. Put another way, "policy-making is reproductive based on the dominant ideas which become institutionalized over time (Marginson, 2013, p. 2)". In the present case, there is ample evidence to suggest that HEIs tend to be driven by growth imperatives, and, as such, often operate like private firms in their efforts to maximize revenues (e.g., from larger student enrollments) while minimizing costs (Mitchell et al., 2015). Like all entrenched mental models, changing this predominant business-as-usual approach may require a crisis (Hay, 2001). As indicated in the literature reviewed in this Chapter, many scholars—who are based at prominent HEIs—now see the adverse effects of climate change as constituting a crisis (e.g., Aronoff et al., 2019). Thus, the timing is arguably right for HEIs to begin displacing extant mental models rooted in the competitive market economy and have played such a central role in many countries throughout the past 50 years (Dill, 1997).

To be sure, the notion of a climate crisis is leading to an increasingly ambitious state and local energy policy (e.g., Soleimani et al., 2018). Consequently, state-owned and funded HEIs are likely to face increasing pressure to reduce energy consumption internally and externally (i.e., due to their mandate to abide by state policies and priorities) (Mitchell et al., 2015). Relatedly, HEIs that are committed to strong Town-Gown relationships may wish to make decisions that are consistent with local (popular) priorities and values, suggesting that increasingly pro-environmental community attitudes and priorities can exert further pressure on HEIs to break away from business-as-usual decision-making models (Butterfield and Soska, 2013).

For all of these reasons and more, if the desired outcome (i.e., the "design objective," to use Harich's [2010] terminology) of scholars and practitioners in the campus sustainability discourse is that a given HEI replaces existing "dirty" energy infrastructure with "cleaner" alternatives, then there are more than two systems that must be properly coupled together—namely: HEIs must commit to a "clean" energy agenda; "clean" energy projects must be financially feasible; state policy must support (or, at minimum, not impede) an HEI’s “clean” energy agenda; and local communities must demand (or, at minimum, be neutral toward) lower and “cleaner” energy use from their large HEI neighbors. In this stylized sense, the challenge is to arrange not a proper coupling but a *proper quadrupling* of HEI, environment, state, and local systems. Even more realistically, the ultimate task involves a *proper n-tupling* of countless interacting (sub)systems. To the extent that mapping out that terrain is a constant and evolving project, a single dissertation can neither achieve such an ambitious end nor provide all the answers. As such, the remainder of this research focuses more narrowly on the relationships sketched out above. That is, the dissertation will draw on case studies of four public HEIs to unpack how financial analysis, state policy, and multilevel geographic context(s) interact to result in the implementation (failure) of selected sustainable energy projects in universities.

4. CONCEPTUAL FRAMEWORK

Grounded in the research summarized in Chapter III, to evaluate the extent to which a *proper coupling*, or, more accurately, a *proper n-tupling* (see above), of interacting systems to reduce fossil fuel consumption in large public higher education institutions (HEIs) is possible, it is necessary to engage explicitly with (1) HEI goals, objectives, and actions in the domain of energy use, (2) the goals and objectives of local and state policies that affect HEI energy decisions, and (3) local/community preferences, values, and priorities related to energy use. Conceptually, then, a proper coupling is evaluated as the intersections between university (internal - financial) motivations, community values (external – fine-scale), state (external – coarse scale) policies and directives, and positive environmental impacts. With that being said, recall the first research question posed in the introductory chapter of this dissertation:

1. Are selected alternative energy investments characterized by long-run profitability in the HEIs under investigation? In other words, is there evidence that a proper coupling between lower energy consumption and economic profitability can be achieved?

This first question aims to identify synergy between HEI goals and objectives related to economic efficiency and broader societal goals related to energy efficiency and positive environmental impacts. As noted above, these two goals are not strictly incompatible (Altan, 2010). However, without empirical evidence of coupling between them, new investments by large institutions or governments into energy efficiency are unlikely (Altan, 2010). Thus, quantifying potential financial savings from these investments can encourage internal (HEI) decision-makers to make investments that produce external (pro-environmental) benefits (Elliot & Wright, 2013). On that backdrop, the first research question from above requires financial analysis and energy audits to document, empirically, the levels of (1) financial attractiveness of and (2) energy savings from investing in selected alternative energy projects at specific public HEI study areas.

Next, recall the second through fourth research questions from earlier:

2. To what extent are sustainability goals prioritized by residents and municipalities in each HEI's local spatial context?
3. What is the nature of the relationship(s) between state-level policy, state Sustainable Development Goal performance, and alternative energy investments at the selected HEIs?
4. To what extent do (in)congruent state and local/regional spatial contexts promote (inhibit) alternative energy implementation in HEIs?

As noted in the preceding chapter, compared to physical, environmental, and engineering factors, energy researchers have paid less attention to the social and behavioral aspects of investing in alternative energy technologies (Hoppe & de Vries, 2018). To begin filling this gap, the dissertation will address research questions 2-4 by following a relational approach that grapples with "how energy relates to and interacts with the political, social, cultural, economic, ecological and technological spheres in specific locales" (Broto & Baker, 2018 p.3). More precisely, studying HEI energy decisions through the lens of their unique multilevel spatial contexts (e.g., community values and state-level policies and programs) will allow the dissertation to generate new insights about how state policy and community preferences (fail to) work together to advance alternative energy agendas in selected public HEIs.

Figure 17 integrates these considerations into a bridging framework represented here by way of a conceptual radar chart. According to the figure, and following the reasoning laid out to this point in the dissertation, specific alternative energy projects can be evaluated empirically according to their financial attractiveness and potential energy savings. Financial attractiveness and energy savings are both quantitative values that can be grouped into classes for comparative purposes. More explicitly, for clarity and ease of exposition, Figure 10 illustrates a case wherein these dimensions collapse into four broad categories—those that are associated with (1) *low*, (2) *medium/moderate*, or (3) *high* financial feasibility and/or energy savings, and (4) those that are *not feasible* due to their lack of energy savings, lack of economic return, or both.

Next, Figure 17 suggests that HEI communities and states can likewise be classified according to the strengths of their sustainability-related values and preferences (for local communities) and sustainable energy policy supports (for states or other levels of government). Once again, to facilitate exposition, consider the case wherein multivariate analyses can be used to group HEI communities and states into three classes: those that are associated with (1) *low*, (2) *medium/moderate*, or (3) *high* values, preferences, priorities, and/or policy supports for sustainability-related goals and alternative energy investments. When these spatial contextual dimensions are combined with the two HEI- and project-scale dimensions described in the preceding paragraph (i.e., financial attractiveness and energy savings), a *proper coupling* of HEI-environment-social systems can be visualized as the outermost envelope in Figure 17, where projects are characterized by high financial feasibility and high potential energy savings, residents in HEI communities hold and exhibit strong sustainability-related preferences and values, and HEI states provide strong policy supports and leadership in the area of alternative energy.

Perhaps the most immediate implication of this framework for the current dissertation—and for future research that seeks to build on or replicate it—is that empirical analysis can be used to map any given alternative energy project (see, for example, the menu of options reviewed in Chapter III), at any given public HEI, onto the landscape delimited in Figure 17. The nearer a project falls to the outer envelope of the diagram, the more *properly coupled* are the HEI-environmental-social systems in which the project exists—and, as such, the more likely the project is to be implemented.

In addition to this potential predictive function of the framework (i.e., identifying projects that are most likely to be selected for implementation), Figure 17 also offers at least one crucial observable implication for studying and explaining past actions and decisions. Namely, sustainable energy projects that are implemented by selected HEIs are likely to fall closer to the outer envelope of Figure 17 than projects that receive consideration but do not get implemented. In other words, variation in the extent to which HEI-environmental-social systems are properly coupled plausibly explains at least some of the variation in patterns of HEI investments into sustainable energy.

The remainder of the dissertation draws on this framework for both of the previous paragraph's purposes. More precisely, the following chapters propose and will subsequently carry out methods to evaluate the same menu of alternative energy projects for all four case study HEIs. Each project from that menu will be analyzed through the lens of Figure 17 to measure the extent to which any given project is embedded in a relatively *properly coupled* state of nature. The results from those analyses will be unpacked toward two ends. First, projects for which there is evidence of implementation, or, at minimum, consideration, at the case study HEIs will be used to evaluate the alternative hypothesis that proximity to the proper coupling envelope is positively associated with implementation (as opposed to consideration but no implementation). Second, projects with no history of implementation or consideration at the case study HEIs will be ranked according to their proximity to the proper coupling envelope. The projects nearest to that envelope will be highlighted as the ones that the HEIs should immediately pursue to lead by example on the issue of emissions reduction (thereby fulfilling part of their social missions; see Ch. III). Over time, as HEIs continue to move toward these projects and away from business-as-usual decision-making, the aggregation of their place-based sustainable energy investments will help to more *properly couple* local, regional, and, eventually, global landscapes of social-economic-environmental systems. As an example, Figure 17 shows an HEI represented by the red dot where the institution shows strong community values by the placement of the red dot close to the green line and weak financial feasibility by being close to the red line.

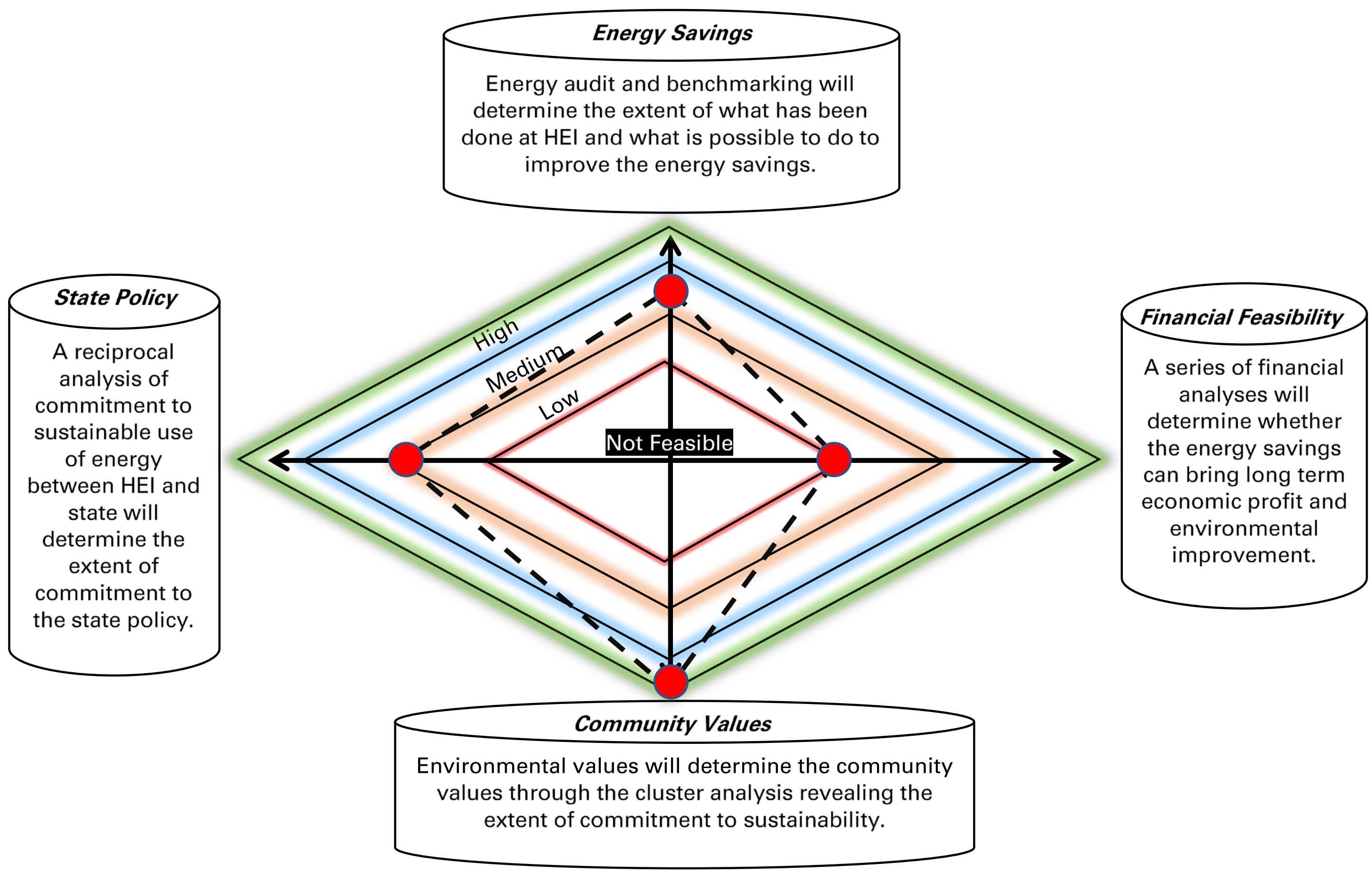

Figure 17. The conceptual landscape of properly coupled environment-social systems

5. METHODOLOGY

Although several benefits of renewable energy implementation and energy efficiency policies are clear, some states faced initial resistance in implementing them since the benefits were not fully understood or transformed into a quantitative comparison of cost and benefit (EPA 2018). Research suggests that evidence of demonstrable financial savings can help to overcome internal barriers that stand in the way of sustainable energy initiatives (Elliot & Wright, 2013). More specifically, financial analyses can plausibly convince decision-makers to invest in sustainable energy projects using the same language of costs and benefits that tends to underwrite executive budgeting processes. A financial analysis aims to identify the options with the highest economic returns from a set of alternatives. In this case, alternatives are business as usual technology versus selected, comparably sustainable energy investments that would reduce energy consumption. The goal of the analysis, therefore, is to determine the level of attractiveness of investing in new technologies—for example, replacing compact fluorescent lamps (CFL) with light-emitting diodes (LED)—in terms of money saved every year (simple payback) or more extended period (e.g., 20 years).

This dissertation's proposed approach also outlines the *system improvement process* (SIP) defined by Harich and Rosas (2020). In the SIP perspective, a problem should be tackled in 4 main steps: (1) Problem definition, (2) Analysis, (3) Solution convergence, (4) Implementation. The main problem discussed in this dissertation, environmental sustainability, is eventually divided into subproblems explained in the introduction and methodology sections. Subproblems, in general, include three questions: (1) How to overcome change resistance, (2) How to achieve proper coupling, and (3)

How to avoid excessive model drift (Harich and Rosas, 2020). “Excessive solution model drift occurs when a solution model works at first and then does not (Harich and Rosas, 2020, p. 9).” It is challenging to avoid excessive drift since the system is continuously evolving. For example, the change in GSF, enrollment rate, hotter summers, colder winters, or pandemics could easily cause an excessive drift. EPA has several recommendations and key considerations for energy analysis, which are incorporated in this dissertation. These steps comprise:

1. Determining the scope of strategy for the analysis.
2. Defining the expected or actual direct electricity impacts of the initiative(s).
3. Quantifying the electricity system, emissions, health, and/or economic benefits of interest.
4. Use of information to support a balanced comparison of costs and benefits during decision-making processes.

The sustainability problem is casual, and it could be solved only by solving its root causes (Harich and Rosas, 2020). This dissertation will be part of the ongoing series of analyses that assess the sustainability problem's roots and the costs, benefits, and effects of different sustainable measurements. The first portion of this study builds on an earlier Environmental Defense Fund-supported empirical financial analysis of energy efficiency measures at Texas State University. It draws on the established financial analysis methods used in the earlier study (Mohammadalizadehkorde & Weaver, 2020). While the earlier research focused exclusively on the profitability of certain alternative energy investments at a single university, which can be considered as superficial problem-solving in Harich and Rosas (2020) point of view, this dissertation offers a more nuanced study that analyzes renewable energy implementation (failure) in four public universities through the lens of the conceptual framework spelled out in Chapter IV. The proposed method will apply a root cause analysis by involving the spatial context representing the first step in creating a national-level evaluation.

HEIs selected for this study are (1) state-owned and funded, (2) similar in size to Texas State University, (3) have had similar growth trajectories as Texas State, (4) are similar in institutional aspects, (5) may have had more success in implementing sustainable energy projects. The second portion of the dissertation generates national geographic profiles of (1) block groups based on resident/community environmental values and preferences, and (2) states based on their policies, plans, and performance with respect to selected Sustainable Development Goals (SDGs). Generating those profiles from secondary data sources will involve cluster analysis.

5. 1 STUDY AREA AND DATA

The HEIs suggested for this study are Texas State University (TSU), Texas A&M, UC Berkeley, and Colorado State University. Table 8 summarizes the proposed study areas needed to establish the benchmark or run the comparison.

Table 8. Summary of sample HEIs

University	Enrollment	Building Number	Building Gross Square Meter (Study Area)	Total annual consumption (kWh) Main Campus	Energy Efficiency Improvement Type at Building Level	Energy Improvement in the Master Plan	Local Government's Energy Consideration
Texas State University, San Marcos	38,187	250	762,635	122,386,158	Sensors/controls, cool roof, measurement/verification, appliances/equipment/electronics, lighting, benchmarking, water/wastewater, water heating, and water conservation	Yes	Yes
Texas A&M, College Station	68,726	686	629,238	323,314,727	Building Energy Optimization	Yes	Yes
UC Berkeley	43,204	257	393,246	213,638,553	On-campus renewable electricity, Energy Efficiency	Yes	Yes
Colorado State University	33,877	91	1,114,836	119,854,978	Utility Services supervises energy and water consumption and costs and promotes energy and water conservation.	Yes	Yes

Table 9. Data sources

Description	Type of Data	Provider	Last Update	Link
GIS data	point data of universities	Geoplatform		https://hifld-geoplatform.opendata.arcgis.com/datasets/colleges-and-universities
GIS data	University Campuses (Boundary)	Geoplatform		https://hifld-geoplatform.opendata.arcgis.com/datasets/colleges-and-universities-campuses
JSON data	Building Footprint	Microsoft		https://github.com/microsoft/USBuildingFootprints
Raster data	Direct Normal Irradiation	SOLARGIS	2019	https://solargis.com/maps-and-gis-data/overview
Raster data	Global Digital Surface Model 30x30 m	Earth Observation Research Center (EORC), Japan Aerospace Exploration Agency (JAXA)		https://www.eorc.jaxa.jp/ALOS/en/aw3d30/
The National Solar Radiation Database (NSRDB) is a serially complete collection of hourly and half-hourly values of meteorological data and the three most common measurements of solar radiation: global horizontal, direct normal, and diffuse horizontal irradiance.	Meteorological data	NREL	2016-2017	https://nsrdb.nrel.gov/
As part of a local educational outreach initiative, a simpler web page was developed, which allows you to find the Closest Weather Station to your location.	Meteorological data	University of Utah	2020	https://mesowest.utah.edu/

The Commercial Buildings Energy Consumption Survey (CBECS) is a national sample survey that collects information on U.S. commercial buildings' stock, including their energy-related building characteristics and energy usage data (consumption and expenditures).	Commercial Building Energy Consumption	U.S Energy Information Administration	2012	https://www.eia.gov/consumption/commercial/
Fugro USA Land, Inc. acquired this orthoimagery dataset in January 2019 during leaf-off conditions in Bastrop, Blanco, Brazos, Burnet, Caldwell, Fayette, Hays, Lee, Llano, Travis, and Williamson counties and portions of Burleson and Grimes counties. Aerial orthoimagery flown during leaf-off conditions allows the data user to 1) identify human-made features through the deciduous tree canopy and 2) distinguish between evergreen and deciduous vegetation.	Satellite/Areal Imagery	TNIRS	2019	https://data.tnris.org/collection/aa2cd74e-9c2d-4f00-bae5-609b5e898093 Other links: https://www.tnris.org/stratmap/stratmap-contracts/ https://www.fugro.com/about-fugro/locations/north-america/united-states
DEM	DEM 10x10 m spatial resolution	USGS	2019	https://viewer.nationalmap.gov/basic/
Lidar Data	LiDAR	USGS	2019	https://prd-tnm.s3.amazonaws.com/LidarExplorer/index.html#/
Lidar Data	LiDAR	USGS		https://www.usgs.gov/core-science-systems/ngp/3dep/data-tools
Lidar Data	LiDAR	USA Government	2017-2019	https://data.ca.gov/dataset/delta-lidar-2017
Sustainability Report	Report	Sustainable Development Solutions Network	2018	https://sdgindex.org/reports/sustainable-development-report-of-the-united-states-2018/
Utility Report	Report	A&M	2020	https://utilities.tamu.edu/2014/12/17/campus-building-cost-usage-october-2014/
Sustainability Report	Report	A&M	2020	http://sustainability.tamu.edu/Data/Sites/1/downloads/2018SMP.PDF

Utility consumption at Texas A&M	Report	A&M	2020	https://utilities.tamu.edu/epi-data/
Texas A&M Building directory	Report	A&M	2020	https://aggiemap.tamu.edu/directory
Texas A&M GIS data	GIS data	A&M	2020	https://msi.tamu.edu/maps/gis-data/
Utility rate by commodity at A&M	Report	A&M	2020	https://utilities.tamu.edu/utility-rates/
Utility consumption at UC Berkeley	Report	UCB	2020	https://engagementdashboard.com/ucb/ucb
Utility consumption at Colorado State University	Report	CSU	2020	https://www.fm.colostate.edu/energy
Building Floor Number at Colorado State University	Report	CSU	2020	https://www.fm.colostate.edu/floorplans

5.1.1 DATA FOR PROFILING LOCAL SPATIAL CONTEXT

One of the geographic resolutions in this study is represented by the Simmons consumer survey, one of the oldest and most reliable consumer behavior authorities. The SimmonsLOCAL US captures in-depth information on consumer attitudes and consumption in nearly 600 categories. SimmonsLOCAL ends late fall and is released to the market in the spring, 2018. The survey is distributed to between 25,000 and 30,000 participants across 210 American DMAs (Designated Market Areas). From there, Simmons/Experian analysts apply proprietary geo-behavioral models to the survey data – where models rely on Census Bureau and related data for validity – to extrapolate the survey responses for the overall adult (18 years and over) populations in various geographic units across the United States, down to the block group level of analysis. Among other information, the extrapolated data allow researchers to explore and analyze detailed patterns of consumer and media usage behavior. SimmonsLOCAL is sourced from trusted respondents, National Consumer study/Simmons National Hispanic Consumer Study (NCS/NHCS), using a probability sample to measure all American adults – Hispanics/Latinos and non-Hispanics, English speaking, and Spanish- speaking (SimmonsLOCAL Methodology Overview). SimmonsLOCAL leverages the 12-month Simmons NCS/NHCS study from the same time frame that corresponds to the SimmonsLOCAL dataset being compiled. “In addition to the NCS/NHCS study, over 200 data points are compiled from various well-known data sources to create profiles of each U.S. Census block group, the smallest geographic area for which the U.S. Census provides population estimates” (SimmonsLOCAL Methodology Overview). SimmonsLOCAL delivers robust sample sizes at all geographic levels, which means greater reliability and accuracy (SimmonsLOCAL Methodology Overview).

A significant portion of Simmons's collected data is represented by a Likert scale that provides convertible quantitative data. Cluster analysis of subjects will create some groups based on the 15 chosen variables. Higher is the average and R^2 of the group, the more distant is that group from the center of the conceptual framework representing a better opportunity for coupling. The demographics for those groupings will be related to the case study's local demographics (e.g., block groups) based on the similarity of surveyed subjects and census demographics. The block group population data can eventually normalize the number of people agreeing with a variable to create further comparisons. In that case, the aggregate demography for the chosen variables is given by the sum of the +18 of male and female respondents in each block group.

Using Simmons's data, it is possible to assess selected environmental and sustainability values held by residents at various levels of geographic aggregation, from local (block groups) to city, state, and national scales. The most recent Simmons dataset available relates to consumer behavior and preferences in 2018, with variables ranging from demography, media preferences, food consumption, expenditure on sustainable products, and how likely the individuals support sustainability initiatives in different places. Attitudes towards the environment give one portion of the available data by asking people whether they agree or disagree with certain products, management, attitudes, and measures the likelihood of purchasing environmentally friendly products. However, the Likert scale includes different agreement levels, such as “agree a little” or “agree a lot.” This dissertation will draw on any agreement level for consistency, thereby aggregating all the positive responses in one category. The specific variables used for creating geographic profiles of HEI communities in this dissertation, therefore, include the fraction of residents who agree with the following statements: (1) I make a conscious effort to recycle, (2) packaging for products should be recycled, (3) environmentally sound practices are good business. (4) companies should help consumers to become environmentally responsible, (5) I have a personal obligation towards environmental responsibility, (6) others must see me environmentally conscious, (7) I would buy less expensive eco-friendly products, (8) eco-friendly products should be higher quality products, (9) tell companies to stop sending catalogs, (10) I am more likely to purchase environmentally-friendly products, (11) I am more likely to choose environmentally-friendly methods of transportation, (12) I use recycled products, (13) I worry about the pollution caused by cars, (14) people must recycle, and (15) I belong to environmental organizations.

5.1.2 DATA FOR MEASURING STATE POLICY CONTEXT

America's Goals are seven goals and twenty-one targets, offering achievable objectives for the United States. These goals are measured on a state-by-state basis. America's Goals: Report Card analysis looks at the baseline conditions across all states compared to each other. At the same time, future reports will analyze whether each state is progressing rapidly enough to achieve the 2030 goals and targets. The 2018 report is presented as a ranking. Three specific variables can be used to create the State-level profile: (1) under goal 6B; a categorical variable indicates whether a State has a climate action plan or is in the process of creating one (Figure 18), (2) under goal seven, two variables show the rate of renewable energy consumption and production as continuous variables (Figures 19 and 20).

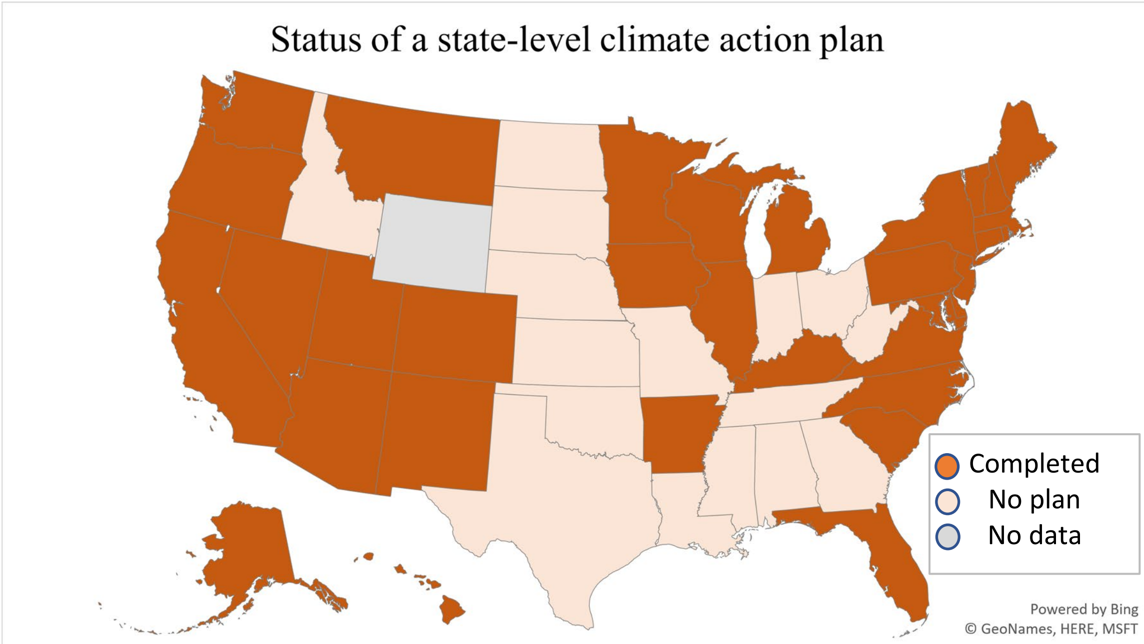

Figure 18. Status of climate action in the United States

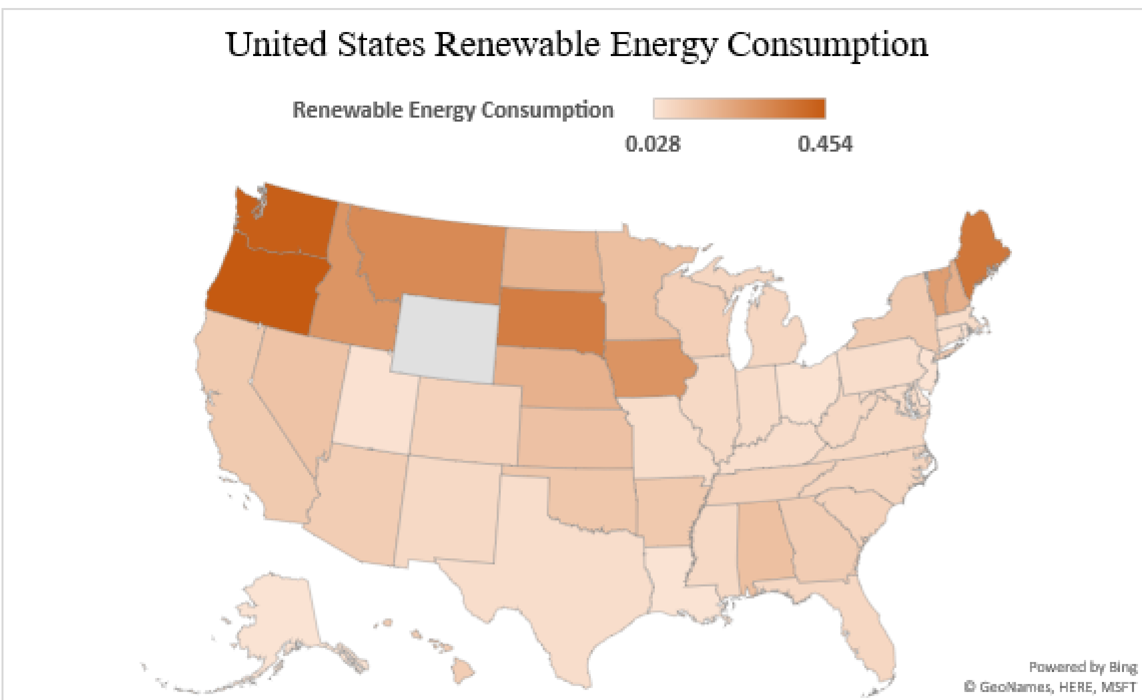

Figure 19. United States renewable energy consumption

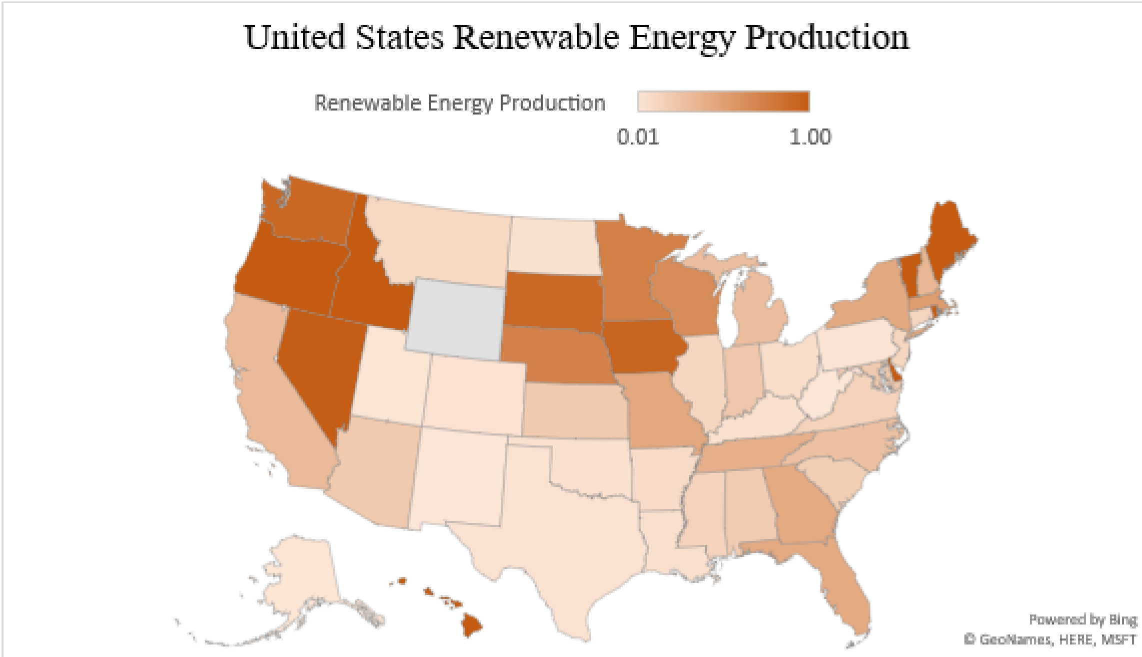

Figure 20. The United States renewable energy production

While previous figures showed a categorized visualization of data, a typical visualization of America's Goals is represented using a cartogram (Figure 21) in which the rankings do not indicate necessarily that the top-ranked states (green color) have reached the targets; instead, the green symbology is typically used to indicate "relatively good" performance.

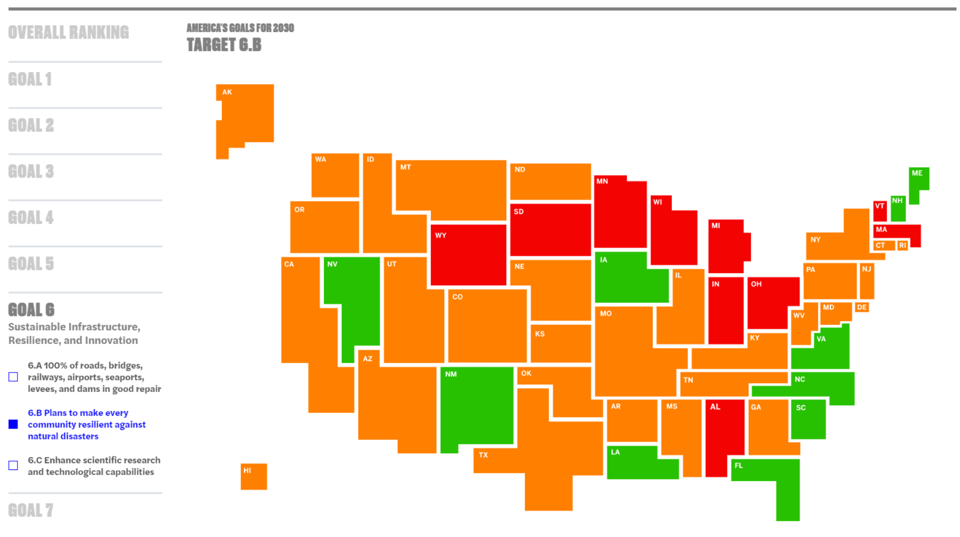

Figure 21. Visualization of Goal 6.B in America's Goals web site

According to the methodology described by the authors:

> "Every state is ranked on an absolute scale of 1-50, with 1 being the best, for each indicator, target, goal, and overall. Ranks were not normalized, and 1 does not indicate that a state has achieved, or made the most progress toward, a goal, only that the state outperforms other states on the same measure" (America's Goals Methodology, 2018, p. 2).

State climate action plan uses 2017 data from the Center for Climate Strategies and assigns number 2 "if a state plan is completed, 1 if a state plan is in progress, and 0 if a state plan does not exist" (America's Goals Methodology, 2018, p. 12). However, the score does not assess the quality of the climate action plan. Renewable energy consumption and production indicators are taken from the sources included in the EIA State Energy Data System (SEDS): fuel ethanol, wood, waste, hydroelectric, geothermal, solar, and wind energy, as a share of state total primary energy consumption and production.

5.2 METHODS

5.2.1 ENERGY AUDIT

An energy audit evaluation will be applied to benchmark the actual performance of a plant's energy using systems and equipment compared against the current industry standards' best performance level. The difference between observed performance and best practice is the potential for energy and cost-saving. The energy audit should provide (1) clear visibility on energy consumption and cost. This means it should include a simple, comprehensive overview of all the types of energy used and their cost. It should also break out the energy consumption by users to know where and when the energy is being used. Moreover, this is where the number of students can help calculate the ratio of energy consumption in an HEI. (2) it should identify energy conservation opportunities. It does this by showing how energy is used or wasted and describing the energy-saving alternatives that could be adopted. (3) the audit will also provide an energy management plan including recommendations with cost-benefit analysis and prioritization of best practices, quick wins, and easily implemented solutions. Common opportunities to apply this approach in HEIs are identified by SEO:

- Lighting
- Pumping
- Ventilation
- Compressed Air
- Steam
- Refrigeration
- HVAC
- Vacuum
- Process Machinery

Each area's performance depends on the geographical area, but HVAC systems and lighting are often the largest energy wasters in commercial buildings.

This dissertation's financial analysis will be assessed using an Excel-based model built on discounted cash flow analysis (DCF), including a relatively wide range of energy efficiency projects. A profitability index will be drawn against the NPV to visually detect the best option in the same building, geographical area, or other aggregate projects. Figure 22 shows the amount of money invested with the circles' volume, while the horizontal distance from the origin of the chart draws the ratio of profitability. In the case of Figure 22, even though the lighting system has the greatest NPV, the pump replacement has the highest profitability ratio.

It is possible to look at the same outputs from another perspective (Figure 23). Figure 23 shows capital investment against annuity in dollars. The amount of money invested is given by the horizontal distance from the origin of the chart. In contrast, the vertical distance from the origin of the chart indicates the amount of annuity. The volume of the circle indicates the annual savings in kWh.

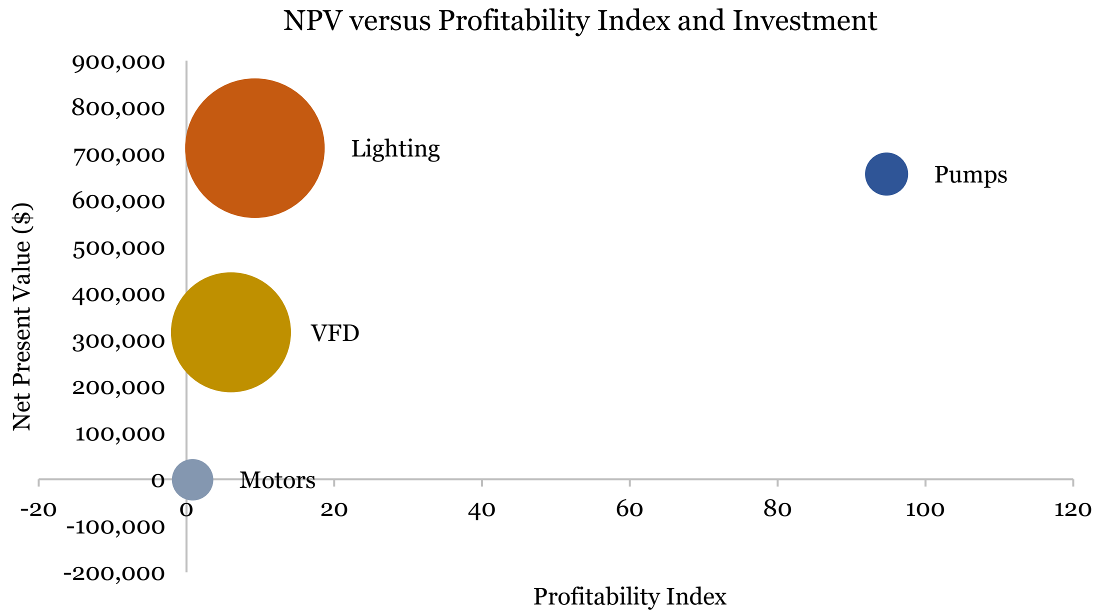

Figure 22. Profitability against NPV

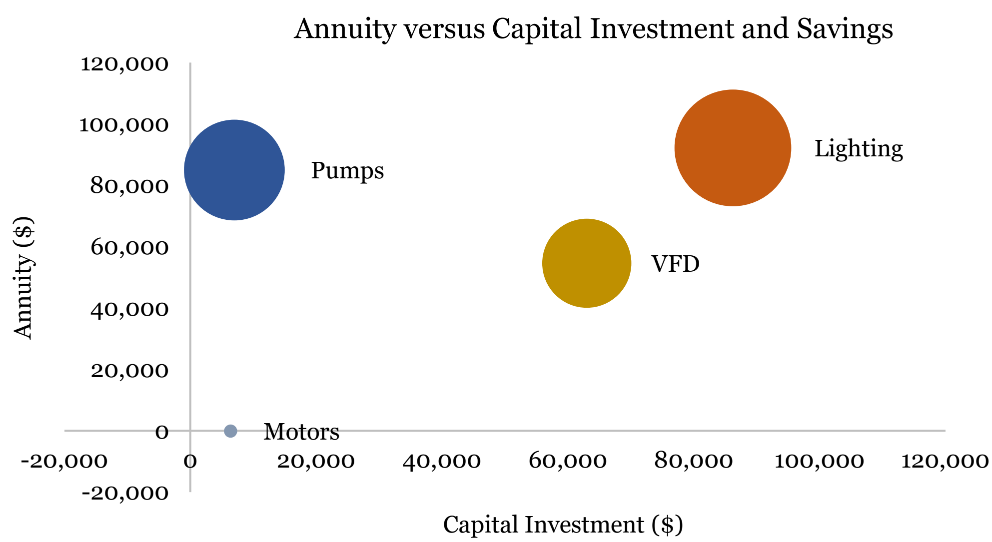

Figure 23. Capital investment against the annuity

Several factors in the 2016 report and Mohammadalizadehkorde & Weaver (2020) retraced their origin from pre-calculated numbers based on regressions (such as potential irradiation taken from available online tool kits, the weighted average cost of capital, or efficiency rates mentioned on the nameplate in motors). In this study, an empirical approach will calculate those numbers to provide a more accurate estimation. The policy assessment, residential attitudes, and consumer behavior will also give a significant and informative categorization of universities based on the geographical context.

5.2.2 BENCHMARKING

Buildings are considered the first target in campus sustainability, and they are often measured by how much electricity they consume every year to determine the extent of sustainable energy consumption. Fonseca et al. (2018) give a recent example of looking at building consumption by choosing the Electrical Engineering Department at the University of Coimbra, Portugal mentioning its total area, the year of construction, and total electricity consumed in a year. A similar approach was used in Mohammadalizadehkorde & Weaver (2020), where a sample of buildings was chosen to study electricity consumption at the building level. It is possible to conduct a comparative study of HEIs energy consumption in the Commercial Buildings Electricity Consumption Survey (CBECS) issued by the U.S. Energy Information Administration (EIA). The data for expenditure and use in commercial buildings show (partially) the energy consumption of higher education facilities. A conventional baseline is offered by EIA's survey on consumption, which will be used to compare the energy consumption in universities to the national standard of energy usage based on different parameters such as area, year of construction, and climate of the region. Also, the CBECS survey will be used to assign the principal activity of buildings even though, in some cases, the chosen facility cannot represent the specific activity of the space caused by a mixed usage of space. (Mohammadalizadehkorde and Weaver, 2020). Table 10 retraces an example of benchmarking for Texas State University from Mohammadalizadehkorde & Weaver (2020) based on CBECS 2012. Similar tables for other study areas are available in chapter 6.10.

Table 10. Sample building baseline comparison

Building Name	Electricity Cost (2014-2015)	% of Total Electricity Consumed Based on the Sample Size	EUI	CBECS EUI Based on Area (table C14 of CBECS)	CBECS EUI by Building Size and Activity (Table C21)	CBECS EUI by the Year of Construction (Table C21)
Alkek L.	$252,358.72	3.93%	10	17	10.8	17,8
JC Kellam	$147,370.88	2.30%	9	17	19.4	16,4
LBJ Center	$173,722.56	2.71%	10	17	NA	NA
Jowers	$134,860.80	2.10%	12	15	10.8	18,1
McCoy Hall	$55,321.44	0.86%	5	15	10.8	18,5
ELA	$55,129.84	0.86%	6	15	10.8	13,1
Health C.	$19,131.20	0.30%	9	11	24.1	12,4
Roy Mitte	$267,190.64	4.17%	22	15	10.8	16,2
San Jacinto	$69,212.72	1.08%	6	15	15	18,5
Rec Center	$54,723.12	0.85%	4	15	20	17,8
Supple Sci.	$13,920.00	0.22%	2	15	10.8	17,8
C. Plant	$4,981,587.36	77.66%	1,336*	12	NA	NA
East Chiller	$189,907.28	2.96%	197.49*	11.7	17.1	12.6

*Not significant since it belongs to the industrial section

5.2.3 CASH FLOW AND DISCOUNTED CASH FLOW

Several authors, such as Abraham & Plourde (2014), tried to give an example of a cash flow model for energy efficiency projects like small scale wind turbines (Table 10) where the only negative value after implementation is the price paid for maintenance:

Table 11. Cash flow model for small-scale wind turbines (Abraham & Plourde 2014)

Cash Flow Model	**Initial**	**Year 1**	**Year 2**	**Year 3**	**Year (*n*)**
Cost of the system	−				
Rebates	+				
Shipping	−				
Assembly	−				
Installation	−				
Maintenance		−	−	−	−
Energy reduction		+	+	+	+
Utility buyback		+	+	+	+
Tax credit		+	+	+	+
Subsidies		+	+	+	
Energy credits		+	+	+	
Carbon credits		+	+	+	

Another example is provided by a case study in Abraham & Plourde (2014, p. 29), where the authors assume that a wind system generates 0.5 kW continuously—which is very unlikely to happen given the fluctuation in wind power— with 12 kWh of daily production. The total cost of energy being replaced is $0.45/kWh, then the daily savings provided by the system reach $5.40, which makes this investment a reliable one in the long-term period. This study will provide a comparative analysis of the implementation of different potential energy efficiency projects—discussed in the methodology— in several universities, offering more robust and dynamic tables and visualizations of the GIS output.

Although there are many barriers to achieve a more sustainable university, the use of positive and demonstrable financial savings can encourage decision-makers to overcome difficulties (Elliot & Wright, 2013). The energy efficiency assessment in this dissertation is based on a financial-economic approach. A financial analysis aims to provide the information needed to propose the best options to reduce energy consumption. This method must determine the level of attractiveness of investing in new technology like replacing compact fluorescent lamps (CFL) with light-emitting diodes (LED) in terms of money saved every year (simple payback) or more extended period like more than 20 years in the case of solar panel installation (cash flow model).

"There are many ways to define cash flow and free cash flow resulting in problems of consistency and comparability" (Mills et al., 2002, p.37). Most companies and institutions produce the annual *Statement of Cash Flows.* The authors of *Defining free cash flow* (2002) state that since there is no consensus on a unique definition of cash flow and free cash flow, there is a need to reach this consensus. This becomes important when many analysts and investors use this criterion to assess investments' attractiveness (Mills et al., 2002). Here, two of these definitions are mentioned from Mills, J et al. (2002): In equation 4, EBITDA stands for Earnings before interest, taxes, depreciation, and amortization.

$$Cash\ Flow = Net\ Profit + Depreciation \qquad \text{Equation 3}$$

$$Cash\ Flow\ = (EBITDA) \qquad \text{Equation 4}$$

Also, the authors of *Defining free cash flow* provided an extensive table of definitions for cash flow taken from different sources shown in Table 12:

Table 12. Cash flow definition in different sources. Source: Mills et al., 2002

Station Casino	EBITDA plus operating leases
Accounting for Dummies	Net income plus depreciation, plus or minus changes in short-term operating assets and liabilities
Barron's Accounting Handbook	Net income plus non-cash charges (such as depreciation) plus or minus changes in accounts receivable, inventory, repaid expenses, accounts payable, and accrued liabilities
Financial Accounting: An Introduction to Concepts, Methods, and Uses	Net income plus depreciation, depletion, and amortization
Handbook of Common Stocks	Net income plus non-cash depreciation charges less preferred dividends
Standard and poor's Stock Report	Net income (before extraordinary items and discontinued operations and after preferred dividends) plus depreciation, depletion, and amortization
Forbes Magazine	Net income after taxes but before interest depreciation and rental expense
Harry Domash's Winning Investing	Net income after taxes minus preferred dividends and general partner distributions plus depreciation, depletion, and amortization
Investorama	Net income after taxes plus non-cash charges
Money Magazine	Net income before depreciation, amortization, and non-cash charges

In the first place, cash flow is the measure of producing money from an investment. However, there are many factors to be subtracted from or added to the investment, and this is why we can have different definitions. EBITDA, one of the standard definitions for cash flow, has several shortcomings. First of all, it ignores many non-cash adjustments and the need to fund working capital changes (Mills et al., 2002).

Free cash flow represents the available cash after meeting all current commitments. The lack of a unique definition applies to FCF, as well. Some analysts argue that FCF should represent cash availability after subtracting the operations expenses (Mills et al., 2002). Based on International Accounting Standard (IAS 7) (1992), "dividends and mandatory debt payments should not be subtracted to arrive at FCF" (Mills et al., 2002 p.39). There are different definitions for FCF, as well. These definitions are presented by Mill et al. (2002) in Table 13.

Table 13. Definitions of Free Cash Flow (FCF) according to different sources

Bell Canada	CFO minus investing activities minus dividends
Coca-Cola	CFO minus business reinvestments
Gerdau Steel	EBITDA minus debt service cost, minus income taxes incurred and actually paid, minus capital expenditures incurred
Money Magazine	Operating income minus capital expenditures minus the change in working capital
Forbes Magazine	Net income plus depreciation and amortization plus or minus working capital adjustments, minus maintenance capital expenditures
Harry Domash's Winning Investing	CFO minus cash paid for property and equipment minus dividends
The Motley Fool	Net income plus depreciation and amortization minus the change in working capital plus or minus cash outlay for taxes
Valueline	Net income plus depreciation minus dividends, minus capital expenditures, minus required debt repayments, minus any other scheduled cash outlays
InvestorLinks	Operating cash flow (net income plus, amortization and depreciation) minus capital expenditures minus dividends
Advisors Inner Circle Fund	Net income plus depreciation and amortization minus capital expenditures
Financial Management, Theory, and Practice	CFO minus gross investment in operating capital
Financial Accounting: An Introduction to Concepts, Methods, and Users	CFO plus interest expense plus income tax expense

The cash flow model may differ based on the type of analysis (e.g., after-tax cash flows, before-tax cash flows, incremental cash flows, etc.). For some universities, such as Texas State University, there is no tax rate included, and in all parts of the calculation, the value 0 will be considered for tax rate. This is because some universities are part of a public sector governed by the State governing that university. The same rate should be applied to other universities, given their public nature.

A cash flow model can be thought of in terms of three different activities performed by a company (Short et al., 2005): (1) operating, (2) investing, and (3) financing. Cash flows from operating activities include all revenues captured, minus operating and maintenance expenses. Cash flows from investments are given by capital expenditure minus expenses, and financing cash flows include repayment of debt. The specific type of cash flow studied in this research is a discounted-investing cash flow model (DCF).

Actual cash flows observed in the market are called current dollar cash flows, representing the actual number of dollars required in the year the cost is incurred (Short et al., 2005). Constant dollar cash flows stand as F_n. Cash flow in current dollars in year *m* is F_m. In this approach, where *n* stands for the base year and *e* stands for constant inflation, we have:

$$F_n = \frac{F_m}{(1+e)m-n} \qquad \textit{Equation 5}$$

DCF analysis discounts the future cash flows to the expenses to assess the attractiveness of an investment. The underlying assumption in DCF is that the value of DCF should be positive and higher than the initial investment discounted to the expenses:

$$DCF = \frac{CF_1}{(1+r)^1} + \frac{CF_2}{(1+r)^2} + \cdots \frac{CF_n}{(1+r)^n} \qquad \textit{Equation 6}$$

$$NPV = \sum_{n=0}^{N} \frac{F_n}{(1+d)^n} = F_0 + \frac{F_1}{(1+d)^1} + \frac{F_2}{(1+d)^2} + \cdots \cdot \frac{F_N}{(1+d)^N} - investment \qquad \textit{Equation 7}$$

Where:

$\mathrm{F_n} = \text{net cash flow in year n}$

N = analysis period

d = annual discount rate

Time value is another crucial factor that assumes that today's value of money is higher than the value of money made next year. This is because the money earned today can be invested as soon as possible to produce a profit.

$$FV = PV\left(1 + \left(\frac{i}{n}\right)\right)^{(n*t)}$$ *Equation 8*

FV = Future value of money

PV = Present value of money

i = interest rate

n = number of compounding periods per year

t = number of years

The discount rate acts as a measure of time value and central to calculate the present value. Also, the discount rates are often used to account for the risk inherent in an investment (Short et al., 2005). When it comes to assessing the future value of investments, it is common to use the weighted average cost of capital (WACC) as the discount rate (Investopedia). In universities' case, the discount rate has been fixed for 5% in all projects, which is very common in higher education systems and recommended by EDF and used in Mohammadalizadehkorde & Weaver (2020). In case the model's user wants to calculate the WACC, the formula is provided by (Cucchiella and Rosa, 2015):

$$WACC = \omega_e * r_e + \omega d * r_d * (1 - t_f)$$ *Equation 9*

Where:

ω_e = equity percentage

r_e = opportunity cost

ωd = debt percentage

r_d = interest rate on the loan

t_f = tax rate

According to Short et al., “real discount rates and dollars cash flows exclude inflation,” and nominal discount rates include inflationary effects, and the following formula can calculate them: (Short et al., 2005).

$$(1 + \mathrm{d_n}) = (1 + \mathrm{d_r})(1 + e)$$

$$d_n = [(1 + d_r)(1 + e)] - 1$$ *Equation 10*

$$\mathrm{d_r} = [(1 + \mathrm{d_n})/(1 + \mathrm{e})] - 1$$

Where:

d_n = nominal discount rate

d_r = discount rate in the absence of inflation(real)

e = inflation rate

The Internal Rate of Return is another parameter used in this study, given by the rate at which the NPV will be zero (no loss and no profit). IRR should always be higher than the discount rate.

$$0 = N\rho v = \sum_{n=0}^{N}[F_n \div (1 + d)^n]$$ *Equation 11*

Where:

NPV = net present value of the capital investment
F_n = cash flows received at time n
d = rate equates the current value of positive and negative cash flows when used as a discount rate.

As mentioned by Short et al. (2005), "there is no absolute standard as to which costs are included in operation and maintenance costs." O&M costs can be broken into the following categories:

- Costs during the operation
- Variable O&M costs
- Fixed costs

Energy costs are typically variable costs, and labor costs are frequently fixed O&M costs, and they tend to increase since the system gets older and more maintenance is required (Short et al., 2005).

The Equivalent Annual Annuity (EAA) is calculated based on this formula:

$$EAA = \frac{WACC(NPV)}{1-(1+WACC)^{-T}} \qquad \text{Equation 12}$$

Where:

EAA= Equivalent Annual Annuity

WACC= Weighted Average Cost of Capital

NPV=Net Present Value

T= Project's useful life

This study will assess the minimum cost of renewable energy based on the current cost of electricity and the cost-based tariff escalation rate, which is the projected increase or decrease in the cost of renewable energy in the future over the project's duration. According to the Environmental Defense Fund (EDF), the cost-based tariff escalation rate can be between 2 to 5 percent. The cost of energy is calculated based on the formula provided by (Fingersh et al. 2006 p.4):

$$COE = \frac{(FCR \times ICC)}{AEP_{net}} + AOE \qquad \text{Equation 13}$$

Where:

$\text{COE} = \text{levelized cost of energy}(/\text{kWh})$

FCR = fixed charge rate (constant \$) (1/yr)

ICC = initial capital cost (\$)

$\text{AEP}_{\text{net}} = \text{ net annual energy production } \left(\frac{\text{kWh}}{\text{yr}}\right)$

$\text{AOE} = \text{ annual operating expenses } = \text{LLC} + \frac{(\text{O\&M}+\text{LRC})}{\text{AEP}_{\text{net}}}$

Where:

$\text{LLC} = \text{ land lease cost}$

$\text{O\&M} = \text{ levelized O\&M cost}$

$\text{LCR} = \text{ Levelized replacement/overhaul cost}$ (10.7/kW in Fingersh et al., 2006)

The payback period (PBP) is calculated based on the following formula taken from Abraham & Plourde (2014):

$$Payback\ Period = \frac{Capital\ Expenditure}{Net\ Change\ in\ Periodic\ Cash\ Flow} \qquad \text{Equation 14}$$

PBP is a simple calculation used commonly to evaluate the attractiveness of an investment. PBP's acceptable range varies based on geographical location or application and ranges from 5 years in less-developed areas with a high electricity price —typically over \$0.30/kWh— to 8 years (Abraham & Plourde, 2014). BPB greater than ten years is generally ignored as a reliable investment.

5.2.4 GREENHOUSE GAS CALCULATION

The quantification of avoided emission accompanies several studies of renewable energies. For example, the study of Wiser et al. (2016) estimates a 3.6% reduction in fossil fuel generation due to renewable energy implementation. In this study, the calculation of emission driven by electricity consumption is based on the Scope 2 method. Scope 2 represents a "policy-neutral, collaborative solution guided by GHG Protocol principles" (GHG Protocol Scope 2 Guidance, 2014). There are two methods included in Scope 2: (1) Location-based method, which reflects the average emission intensity of grid retrievable from (Emission) & Generation Resources Integrated Database (eGRID), calculated by the emission factor provided by the distributor of electricity which in Texas is Electric Reliability Council of Texas ERCOT and (2) Market-based method which calculates the emission from electricity distributed from a third party (company). The second method's emission factors are provided by a contract, which includes attributes about the energy generation. The new GHG Protocol states that companies shall report both location-based and market-based Scope 2 GHG emissions. The calculation of market-based GHG emission is dependent on the possibility of obtaining market-based emission factors. Since it was not possible to gather this information, the first method (location base) has been chosen to calculate the emissions at Texas State University, which is given from the saved kWh multiplied by the emission factors. Emission factors are fundamental to create and control inventories of GHG emissions and eventually for air quality management. EPA has a specific definition for emission factor:

> An emissions factor is a representative value that attempts to relate the quantity of a pollutant released to the atmosphere with an activity associated

with the release of that pollutant. These factors are usually expressed as the weight of pollutant divided by a unit weight, volume, distance, or duration of the activity emitting the pollutant (e.g., kilograms of particulate emitted per megagram of coal burned). Such factors facilitate [the] estimation of emissions from various sources of air pollution. In most cases, these factors are simply averages of all available data of acceptable quality and are generally assumed to be representative of long-term averages for all facilities in the source category (i.e., a population average) (from www.EPA.gov retrievable in https://goo.gl/9kI9BS).

Hence, the general equation for emission calculation is:

$$E = A * EF * (1 - ER/100) \quad \text{Equation 15}$$

Where:

E = emissions
A = activity rate
EF = emission factor
ER = overall emission reduction efficiency

The electricity emission factors provide the emission factors for location-based calculation on the EPA web portal (https://goo.gl/gP8Idw), where table 6 presents the needed factor for CO_2, CH_4, and N_2O in Texas. The ERCT (ERCOT ALL) emissions are shown in Table 14.

Table 14. Electricity emission factors in Texas

	Total Output Emission Factors			Non-Baseload Emission Factors		
eGRID Subregion	**CO_2 (lb CO_2/MWh)**	**CH_4 (lb CH_4/ MWh)**	**N_2O (lb N_2O /MWh)**	**CO_2 (lb C_2/MWh)**	**CH_4 (lb CH_4/ MWh)**	**N_2O (lb N_2O /MWh)**
ERCT (ERCOT ALL)	1,143.04	0.0167	0.01233	1,280.59	0.02153	0.01071

So, we have:

$$Scope\ 2\ Emission\ =\ Electricity\ Consumption\ (MWh) *\ Emission\ Factor \qquad \text{Equation 16}$$

Other emission factors for the rest of the United States are shown in Table 15 and Figure 24. It is also possible to use a custom emission factor given by the last row of Table 15. In case the location of an institution falls around the boundaries of a sub-region, making it hard to find which eGRID should be used, the user can refer to the interactive model using the institution's zip code —or any building— to find the appropriate eGRID.

Table 15. Electricity emission factors in the United States

eGRID Subregion[1]	lb CO_2e /kWh
U.S. Average	1.509
AKGD: ASCC Alaska Grid	1.375
AKMS: ASCC Miscellaneous	1.539
AZNM: WECC Southwest	1.391
CAMX: WECC California	0.946
ERCT: ERCOT All	1.410
FRCC: FRCC All	1.193
HIMS: HICC Miscellaneous	1.540
HIOA: HICC Oahu	1.648
MORE: MRO East	1.751
MORW: MRO West	1.834
NEWE: NPCC New England	0.980
NWPP: WECC Northwest	1.534
NYCW: NPCC NYC/Westchester	1.063
NYLI: NPCC Long Island	1.341
NYUP: NPCC Upstate NY	1.022
RFCE: RFC East	1.441
RFCM: RFC Michigan	1.816
RFCW: RFC West	1.947
RMPA: WECC Rockies	1.698
SPNO: SPP North	2.004
SPSO: SPP South	1.671
SRMV: SERC Mississippi Valley	1.191
SRMW: SERC Midwest	1.967
SRSO: SERC South	1.461
SRTV: SERC Tennessee Valley	1.768
SRVC: Virginia/Carolina	1.430

	CO2	CH4	N2O
Global Warming Potential[2] (CO_{2e})	1	25	298
Custom Emissions Factor (lbs CO_2/kW	0.000		

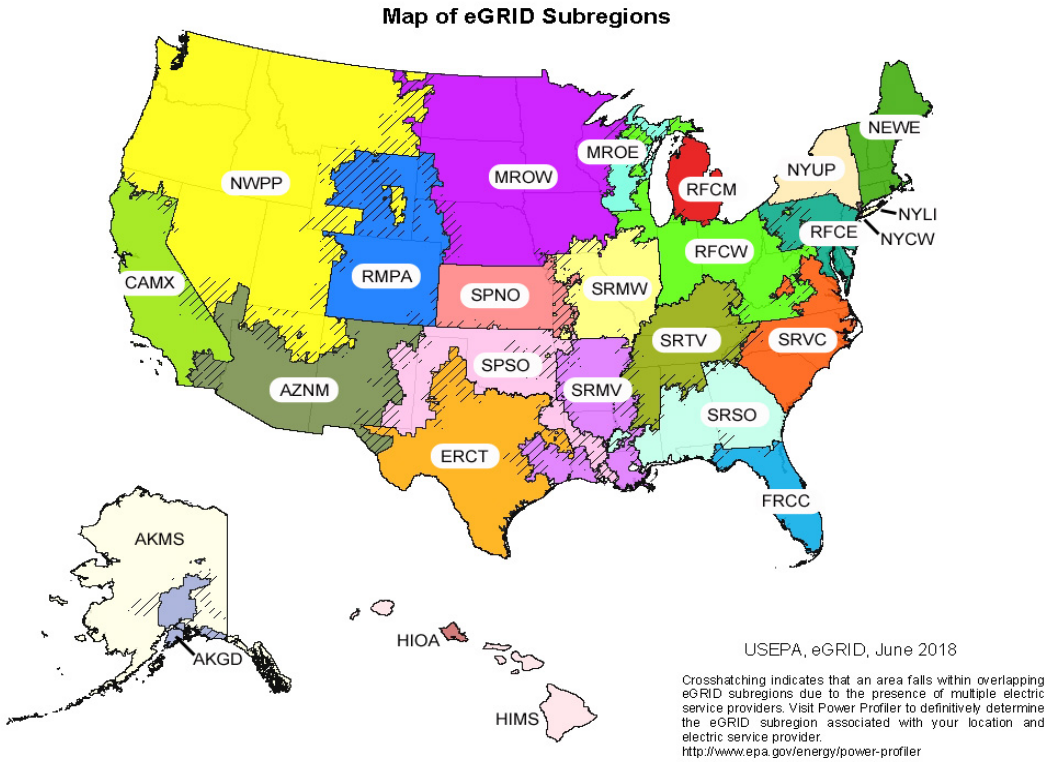

Figure 24. United States eGRID subregions

Other methods might calculate the value of energy supplied by the heating system in different units such as MJ, Kg, m^3, or L (Nesticò and Pipolo, 2015). This dissertation uses the most common consumption measurement unit (kWh or MWh) found on electrical bills. However, units are convertible to kWh or MWh and vice versa.

5.3 RENEWABLES IN FORMS OF WIND AND SOLAR

5.3.1 WIND

The average wind speed is a critical factor in calculating how much electricity can be produced by a given type of wind turbine, which, in turn, will determine the rate of return in financial analysis. Wind speed is a crucial factor in wind power generation, and it is subject to variation in time and space (Tong 2010; Elliott et al. 1987; Al Yahyai et al. 2012). The periodic change of wind due to the local climate, landscape, and building shape in urbanized areas can affect wind speed and turbulence in the process of site selection (Yang et al., 2016). Mean wind speed measured in hourly time series format is a determinative parameter in location analysis for wind turbine installation (Akpinar, & Akpinar, 2005). Wind power density (WPD) and wind speed are very useful in wind resource analysis. In some studies (such as Al-Yahyai et al., 2012), wind power was given a relatively higher weight than other factors (Al Yahyai et al., 2012). "Power density of wind is a cubic function of wind speed. Double the speed, and power increases eight times" (Gipe, 2005, p.35).

A wind turbine can support high or low wind conditions based on other economic factors mentioned in previous paragraphs. The air density variation impacts the power output and kilowatt/hour of electricity production from the wind turbine. It is known that there is a significant seasonal variation in wind energy resources with high intensity in winter and spring and reduced intensity in summer and autumn in the United States (Elliott et al. 1987). Despite that, the variation in intensity is not global and changes in different parts of the world: A 10-year study of wind in Iran shows that a higher wind power occurs in summer (Azizi et al. 2014). The cut-in gives the wind speed threshold (5 m/s) and cut-off (20 m/s) of wind speed (Al-Yahyai et al. 2012; Al Yahyai et al. 2011). Wind power density relatively increases in higher atmospheric elevation (Al Yahyai et al. 2012). On average, in higher height, the wind shear is positive, and the wind speed tends to increase, but there are some real-world experiences where the speed increase has not occurred (Gipe, 2005 p.40).

The wind is classified according to wind power classes based on wind speed (Akpinar, & Akpinar, 2005). According to National Renewable Energy Laboratory (NREL), areas designated as class 3 or higher are suitable for large wind turbine installation (NREL), while small wind electric systems work best in wind power class 2 with an average speed of 4.5 m/s (Stokes, 2011).

While the following paragraphs are focused on Texas State University's case, a similar consideration of potentials will be taken into account for every chosen university. NREL wind power classification at 50 meters and *Wind Energy Resource Atlas of the United States* categorization of wind (see map 2-6 on the report) show that central and east Texas are not qualified for large-scale wind turbine installation (Figure 25). "The NREL-produced map applies only to areas with a low surface roughness (e.g., grassy plains) and excludes areas with slopes higher than 20%. Although, table 1-2 from the *Wind Energy Resource Atlas of the United States* shows that the same wind speed at three different sites can have different power class output, demonstrating the difficulty of having high percentage confidence of class assignment to the wind power (Table 16).

Given the uncertainty of wind power classification, the question is whether any part of a campus can be qualified for any wind power installation? According to maps 2-12 of the *Wind Energy Resource Atlas of the United States* during winter, central Texas switches to wind power classes 2 and 3 with an average speed of wind above 5.6, which makes these areas suitable for small wind turbine implementation. In the wind atlas, the wind resource assessment is based on surface wind data, coastal marine area data, and upper-air data. This opportunity is not reflected in NREL-produced data and maps (Figure 25-26). On the other hand, Figure 26 shows the annual average wind speed at 30 meters, adopted from NREL. Indeed, on this map, many parts in central Texas show an average wind speed above 4.4 m/s, which is the threshold for class number 2 (Table 16). Another resource to assess the wind speed is the National Climatic Data Center (NCDC) report on wind data, including the wind data summary 1930 – 1960. According to this document, both Austin and San Antonio areas (San Marcos is located between these two areas) have an average annual speed of 9 mph (4.0-meter per second). Table 17 shows the classes of wind power density adapted from Tong (2010, p.11).

Table 16. Wind Speed and Wind Power Comparison (Elliott et al., 1987)

Site	Annual Average Wind Speed (m/s)	Annual Average Wind Power Density (W/m^2)	Wind Power, Power Class (10 m)
Culebra, Puerto Rico	6.3	220	4
Tiana Beach, New York	6.3	285	5
San Gorgonio, California	6.3	365	6

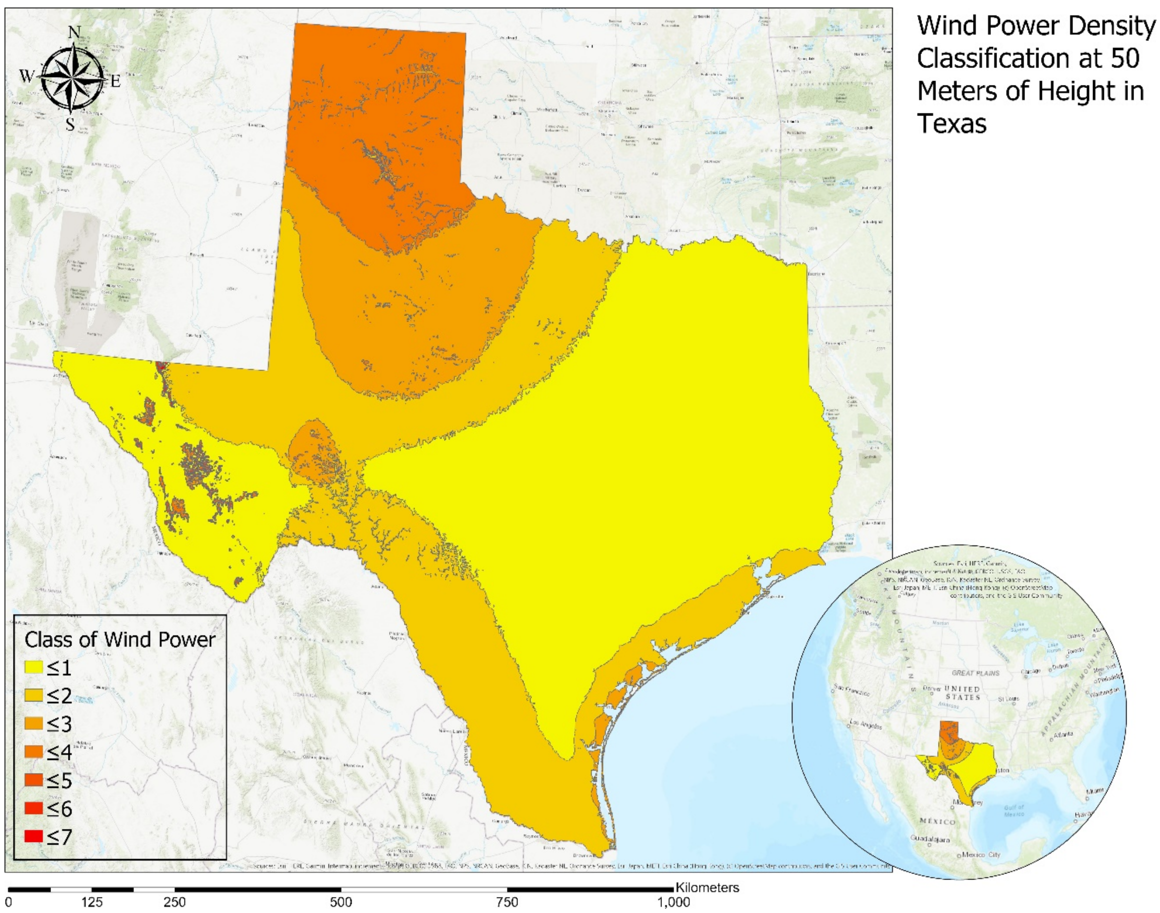

Figure 25. Wind Power Density Classification at 50 Meters based on NREL data

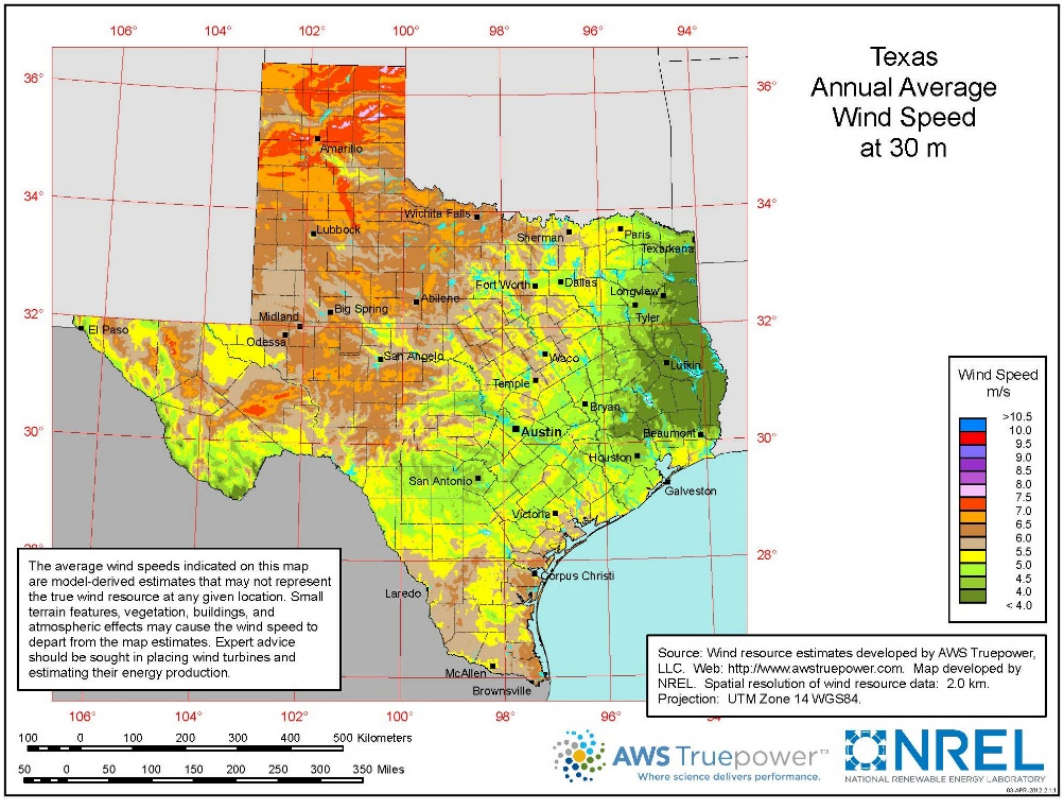

Figure 26. Texas Annual Average Wind Speed at 30 Meters, adopted from NREL

Table 17. Classes of wind power density adapted from Tong (2010 p.11)

Wind power class	10 m height		50 m height	
	Wind power density (W/m^2)	Mean wind speed (m/s)	Wind power density (W/m^2)	Mean wind speed (m/s)
1	<100	<4.4	<200	<5.6
2	100-150	4.4-5.1	200-300	5.6-6.4
3	150-200	5.1-5.6	300-400	6.4-7.0
4	200-250	6.6-6.0	400-500	7.0-7.5
5	250-300	6.0-6.4	500-600	7.5-8.0
6	300-350	6.4-7.0	600-800	8.0-8.8
7	>400	>7.0	>800	>8.8

As mentioned in previous paragraphs, wind power is subject to change with a significant variation. Past experiences show that wind classification can change drastically. The composite analysis of new wind data obtained for the South-Central region in the United States resulted in a change of class for southern High Plains from north of Amarillo, Texas, to extreme southwestern Kansas, which were categorized as class 5, and after revision, they were assigned as class 4 and 3 (Elliott et al. 1987). The change has been verified in other places as well; The annual mean wind speed decreases from 1970 to 1983 at Dhahran, Saudi Arabia (Siddiqi, Khan, & Rehman, 2005), while Mahbub et al. (2011) showed that Saudi Arabia experienced a 2% increase in wind speed from 2007 to 2008.

There are four ways to obtain the data on wind resources: 1) Data gathered from weather stations, 2) Using the NCDC report on wind data including the wind data summary between 1930 – 1960, 3) Using grids produced by other organizations such as NREL which are based on ground measurements and then used to generate the desired wind maps (Al Yahyai et al., 2012) and 4) Using the following formula (Stokes, 2011) to estimate the wind speed at a different elevation:

$$V_2 = V_1(h_2/h_1)^{\alpha} \qquad \textit{Equation 17}$$

Where:

V_2 = wind speed at height 2
V_1 = wind speed at height 1
h_2 = height 2
h_1 = height 1
α = shear factor

However, the level of uncertainty with this equation is high because of present surface features like buildings, parking lots, and trees (Stokes, 2011), which in its turn causes a lower shear factor with minimum surface roughness and a high shear factor with maximum surface roughness disturbing the flow (Gipe, 2005). The interpolation of wind speed from lower annual mean speed (10m) to higher height (80m) has been applied by Yang (2013) using the formula developed by Davenport (1960):

$$\frac{\bar{V}_Z}{\bar{V}_G} = \left[\frac{Z}{Z_G}\right]^{\alpha} \qquad \textit{Equation 18}$$

Where:

$\bar{V}_z$ = wind speed at height1(known)
$\bar{V}_G$ = wind speed at height 2
Z = the height at $\bar{V}_z$
Z_G = the height at the interpolated $\bar{V}_G$
α = wind shear exponent

In this study, to have a more accurate wind speed assessment, a set of meteorological data will be gathered through nearby weather stations close to the chosen campus. In the pilot study, the closest station to San Marcos is Municipal Airport (KHYI). This data reports the wind speed in miles/hour in an interval of 5 min 24/7. A mean speed has been calculated for 12 months in 2017 (Figure 28), which confirms the result from the NCDC report and NREL analysis, where the average wind speed does not exceed 9 miles per hour (the equivalent of 4 meters per second). However, the peak wind speed occurs in August, which contrasts with the findings of Elliott et al. 1987, where the strongest winds are supposed to happen in winter. At the same time, this finding confirms the study of Azizi et al. (2014), where the highest wind power was detected during the summer in Ardabil province in Iran. The other shortcoming of wind speed assessment is that the weather station is located at 597 feet above sea level. There will be an addition of 10 meters (32 feet) of height for the wind speed station—the standard height for a typical meteorological station (Yang, Z. 2013) — while Texas State University's main campus elevation ranges from 174 ft to 243 ft. Nevertheless, while the increase in wind speed with height is unspecified, it is commonly assumed that the 1/7 power law fits many sites (Gipe, 2005 p.41). For example, a wind speed of 4.7 m/s at 9.1 meters of height registered in Huron, South Dakota, will increase in wind speed to 6.8 at the height of 45.7 meters with a shear factor equivalent to 0.23, resulting in 1.45 times bigger wind speed (Gipe, 2005 p.41). In the first step, the average wind speed is measured based on a higher elevation from the meteorological station (Figure 27), which shows the local level's average wind speed. Consequently, the wind speed at the given campus is calculated adapting Davenport (1960) formula with a wind shear exponent equal to 0.25 because of the type of surface roughness, including buildings and different types of constructions:

$$V = 4\,(E/629)^{0.25}$$ *Equation 19*

Where:

V = wind speed
4 = mean wind speed in San Marcos
E = elevation in a given point on campus (DEM)
629 = height in reference point
0.25 = wind shear exponent

The result of this formula is reflected in Figure 27. Comparing the results, the average wind speed on campus level is below the average suggested by reports and studies mentioned in previous paragraphs. A lower elevation of campus causes this compared to the weather station as the reference point.

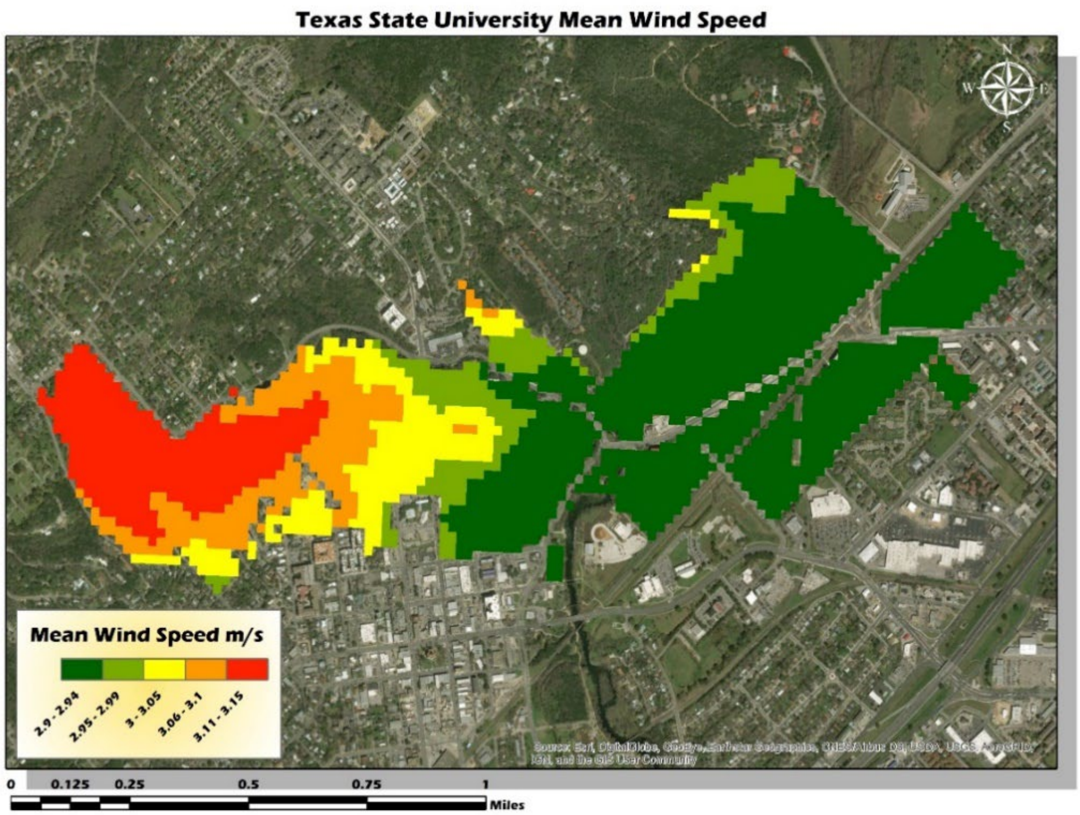

Figure 27. Calculated mean speed based on elevation and shear factor at TSU

In summary, all these findings demonstrate that urban wind regimes are characterized by low wind speed, increased turbulence due to high surface roughness, atmospheric instability, and sudden change in direction and speed (Goodfield et al., 2017).

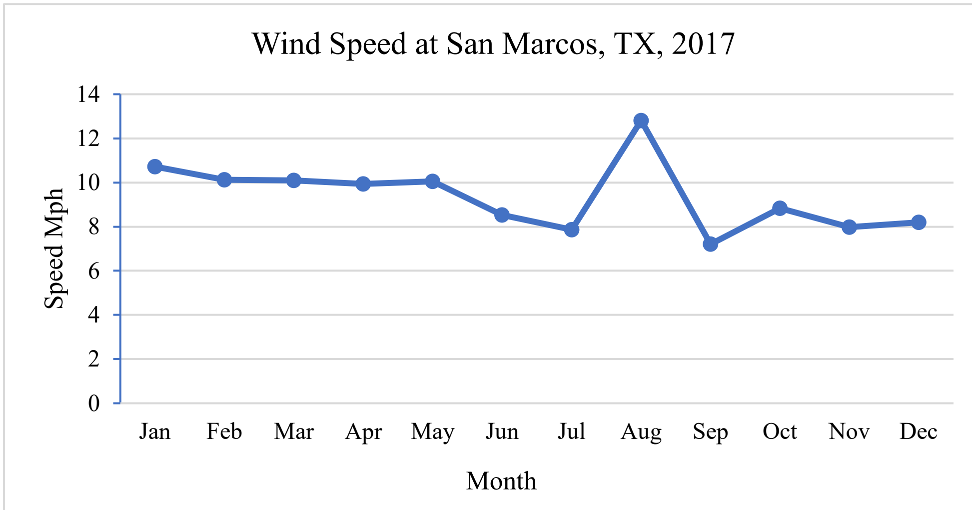

Figure 28. Mean wind speed at San Marcos based on the nearest weather station

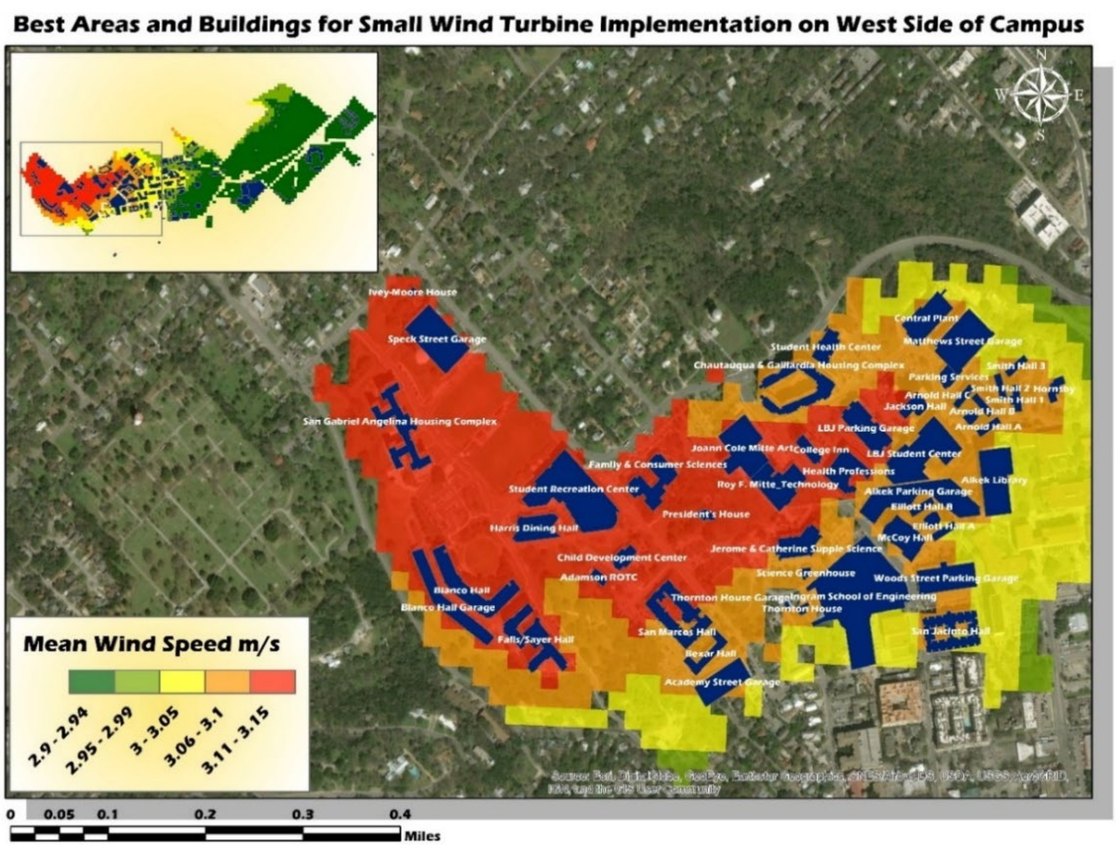

Figure 29. Proposed buildings for implementation of a small wind turbine at TSU

Manufacturers often provide the estimated annual energy output (AEO), but in case of the lack of such information, it is possible to calculate AEO based on Gipe's formula (2005). There are multiple factors to be considered in AEO calculation: (1) wind power at the site and at the height where the wind turbine will operate. (2) Annual average of wind speed at a given location and height and (3) Area swept by the wind turbine. (4) Efficiency rate.

$$AEO = (P/A) \times (A) \times (Ef) \times (8760h/yr) \times (1.000W/kw) \qquad \text{Equation 20}$$

Where:

P = power density
A = rotor diameter in square meter
Ef = efficiency %

The capacity factor has been set to 30% and is given by "the ratio of the energy produced by the system to the energy that could have been produced by it" (Mathew 2006 p.155). The annual energy production varies based on different types of VAWT. In this study, an average of 4000 kWh will be set as the yearly kWh produced, and it is calculated based on the formula provided by Mathew (2006):

$$\textit{Annual Production (kWh/year)} = \textit{Rated Power} \times \textit{Capacity factor} \times 8760 \qquad \text{Equation 21}$$

One other factor that should be considered while working with wind and solar energy is the difference between capacity and generation, which might also be confusing in this dissertation's financial model. The (EIA) refers to capacity as the "maximum output of electricity that a generator can produce under ideal conditions." On the other hand, electricity generation refers to the amount of electricity produced over a specific period (time).

5.3.2 WIND TURBINE TYPE SELECTION

According to Orrell & Foster (2016), in 2015, there were 24 different types of wind turbines ranging from 160 W to 2.85 MW from 15 manufacturers in the United States. Fifteen different small turbine models are certified to AWEA standard 9.1-2009 (Orrell et al., 2017). As stated by Tabrizi et al. (2014), "small wind turbines are often sited in more complex environments than the open terrain sites assumed in relevant installation guidelines or in the international small wind turbine design standard IEC61400-2" (IEC 61400-2:2013 is the most recent standard). The certified small wind turbines can range from 3,400 to 64,920 kWh of rated annual energy with five m/s of wind speed and a Rayleigh wind speed distribution, sea-level air density, and 100% availability (Orrell et al., 2017).

The financial and economic factors should be considered prior to the purchase and after site analysis to implement a micro wind system. For Abraham & Plourde (2014), the initial capital and setup costs are the most critical factors. In this study, both variables are included in the calculations as the total installed cost ($/kW). A fixed operational and maintenance expense has been considered for a kW of production every year ($/kW/yr).

Wind turbines can be categorized as small, medium, or large (Orrell & Foster, 2016). According to Abraham & Plourde (2014), "while there is no universal definition of small-scale wind power, it generally refers to systems that produce only a few kilowatts, can be installed in constrained spaces, and have a small footprint" (Abraham & Plourde 2014 p.2). Also, small wind turbine refers to wind turbines rated from 400 watts to 100 kilowatts (100,000 watts) when running at full capacity (Stokes, 2011; Orrell &

Foster, 2016). According to the international standard IEC 61400-2, "a small wind turbine system includes the wind turbine itself including support structures, the turbine controller, the charge controller/inverter (if required), wiring and disconnects, the installation and operation manual(s) and other documentation."

"Wind turbines designed for low wind conditions are characterized by a large rotor swept area and an increased hub height" (Al Badi et al., 2009 p.2737). Small wind turbines are less efficient, and many have an efficiency of less than 30%. "The average capacity factor for a small wind turbine sample size of 3.6 MW from 66 projects in 12 states was 32%" (Orrell & Foster, 2016, executive summary). If the manufacturer has not provided the potential output, it is possible to calculate it based on parameters used in output calculation: wind speed, swept area, power curve, efficiency, and height.

A microturbine with a swept area of 1 m^2 and potential capacity of 2200 kWh yearly and an efficiency of 20 percent can produce 440 kWh/m^2 /yr with the best technology integrated into the wind turbine (Gipe, 2005, p. 57):

$$\left(P_{kWh/year}\right) \times E_f \qquad \textit{Equation 22}$$

Where:

$P_{kWh=\text{Potential interception of wind}}$

E_f = Efficiency

Due to social and environmental reasons discussed in previous paragraphs, it is recommended to implement small or medium-size wind turbines on campus and specifically on areas assessed by GIS as the most suitable places. A small-scale wind turbine system at any campus must be connected to a battery array. It is often the case that power is available when not needed by the user or vice versa; the electricity is required but not produced because of the low wind power (Abraham & Plourde 2014). The goal of implementing renewable energies, such as wind turbines or solar panels, is to cover a portion of all needed electricity at the building level. Obstruction reduces the wind speed near the ground; hence, it is recommendable to install small or medium wind turbines either on the west part of campus or on top of the buildings on the west side of campus where elevation is higher (at TSU). On campuses, small wind turbines installed in open areas might be narrow pole towers supported by wires. This wind turbine demands more space (due to the wire support), and they are usually more expensive (Stokes, 2011). The manufacturer must provide the power curve and meet the criteria for a mean wind speed of 4 to 6 meters per second and support higher wind speed without damaging parts. The vertical axis wind turbine (VAWT) is proposed due to its independence from wind direction (Mertens 2002).

Also, small wind turbines tend to be less dependent on turbulence and wind direction than large-scale wind turbines (Abraham & Plourde, 2014). As mentioned previously, buildings, trees, and landforms can disrupt the wind's flow, and wind close to the ground is turbulent. Therefore, the higher is the wind turbine smother is the flow of current captured by the turbine. Building Augmented Wind Turbine (BAWT) was introduced in Mertens (2002). Mertens suggests that the concentrator effect is likely to be present for a small wind turbine close to the buildings. Table 18 summarizes several characteristics of wind turbines.

Table 18. Wind turbine size and capacity comparison

	Small	Large
Capacity rate	400 watts to 100 kW	More than 1 MW
Capacity Factor	30%	20% to 45%
Height from ground	10 to 50 meters/ rooftops	50 to 80 meters
Output kWh	1.7 to 100	Higher than 1 MW
Placement	Sides or top of buildings	Large area with slope < 20-30%
Swept area	1 to 10 m^2	Greater than 10 m^2
Weight	< 1000 kg	> 1000 kg
Type	VAWT(Darrieus)-HAWT	HAWT
Wind direction dependency	VAWT is independent of wind direction	Should be positioned in the direction of the wind
Building modification	No	No
Grid Connection	No	Yes
Levelized cost(¢/kWh)	10 to 30 (¢/kWh)	0.6 to 7.1(¢/kWh)

The ultimate performance of turbines occurs with a steady wind speed extended in long periods (Abraham & Plourde, 2014), which is unlikely to happen. Implementation of a small wind turbine on top of the buildings implies a "low tip speed of the blades, which brings about a low Reynolds number of the flow on the blades" (Mertens 2002). The Darrieus has a lower aerodynamic efficiency compared to a lift-driven HAWT. Some of the buildings in the designated area with the highest wind power might be excluded because of physical insufficiency present in water tanks, chillers, and fire pump houses. Some of the buildings, such as the Central Plant at TSU, would not support additional weight due to the type of rooftop.

5.4 SOLAR PANEL IMPLEMENTATIONS

The quality of solar data is critical for the economic assessment of solar implementation. Accounting of uncertainty and managing weather-related variables are essential for successfully planning and operating solar electricity assets. According to SOLARGIS, two approaches can obtain high-quality solar data and meteorological data: (1) high-accuracy solar instruments installed at a meteorological station and (2) complex models based on satellite data collection. The latter are typically less accurate than the meteorological stations, but their advantage is given by continuous geographical coverage and the possibility of collecting data for any location within decades. However, satellite data are also validated by ground measurements (SOLARGIS; Cebecauer and Suri, 2015).

While solar irradiance consists of solar power falling on a unit of area per a given unit of time (W/m^2), solar irradiation is the amount of solar energy falling on a unit area over a stated time interval (Wh/m^2 or kWh/m^2). Primary solar resources are categorized as Global Horizontal Irradiance (GHI) and Direct Normal Irradiance (DNI). Some institutions may also provide Diffuse Horizontal Irradiance (DIF) derived from GHI and DNI and Global Tilted Irradiance (GTI), the sum of DNI, and DIF. In this dissertation, I will be using or creating the DNI, the irradiation used for solar thermal power plants (CSP), and photovoltaic concentrating technologies (PV). Alternatively, it is also possible to use a third party to produce DNI based on multi-year satellite data. The solar radiation tools in ArcGIS Pro calculates irradiation throughout geography or for specific places, based on the hemispherical viewshed algorithm built by Rich et al. (1994) and further developed by Fu and Rich (2000, 2002).

DNI for a given location with at least 80 degrees of zenith is the aggregation of the direct insolation ($Dir_{\theta,\alpha}$) from all sun map sectors (Rich et al., 1994; Fu and Rich, 2000, 2002):

$$Dir_{tot} = \Sigma\, Dir_{\theta,\, \alpha} \qquad \textit{Equation 23}$$

The following equation determines the Dir_{tot} (DNI) from all sun map sector ($Dir\theta,\alpha$) with a centroid at zenith angle (θ) and azimuth angle (α):

$$Dir_{\theta,\alpha} = S_{Const} * \beta^{m(\theta)} * SunDur_{\theta,\alpha} * SunGap_{\theta,\alpha} * cos(AngIn_{\theta,\alpha}) \qquad \textit{Equation 24}$$

where:

S_{Const} = The solar flux beyond the atmosphere at the average earth-sun distance, known as a solar constant, is equivalent to 1367 $W/m^{2,}$ consistent with the World Radiation Center (WRC) solar constant.

β = The transmissivity of the atmosphere (averaged over all wavelengths) for the shortest path (in the zenith) direction. The amount of radiation received by a surface is only a portion of what is received outside the atmosphere. Values range from 0 (no transmission) to 1 (complete transmission). Typically observed values are 0.6 or 0.7 for very clear sky conditions and 0.5 for only a generally clear sky.

m(θ) = The relative optical path length, measured as a proportion relative to the zenith path length calculated by the solar zenith angle and elevation above sea level.

SunDurθ,α = The time duration is characterized by the sky sectors. It can be equal to the day interval multiplied by the hour interval.

SunGapθ,α = The gap for the sun map sector.

AngInθ,α = The angle of incidence amongst the centroid of the sky sector and the axis normal to the surface.

In the first phase, three approaches are considered to assess the resource potential of solar energy in this study: 1) using the Solar Radiation toolset in ArcGIS and 2) using the third-party data from SOLARGIS, which consists of a raster layer of potential kWh/m^2 on a daily and yearly basis and 3) calculation of potential based on System Advisor Model (SAM). These three methods will provide potential solar radiation across a given area without considering the available rooftop, tilt, azimuth, and shading. Hence, in this study, LiDAR data based on the reflective surface return will be used, which correlates to the first object's elevation to create a digital surface model and building footprint.

Area Solar Radiation calculation in ArcGIS can be done based on a whole year with monthly intervals, within a day, special days, and multiple days in a year. The DEM used to run the Area Solar Radiation may have different resolutions for different study areas. For example, for a pilot study, a spatial resolution of 15 meters was used for Texas State University using the available data in the USGS repository. However, the elevation model can also be produced based on the LiDAR (Texas A&M solar case). Whenever LiDAR is not available, it is possible to use High-resolution DEM. However, results are not as accurate as when LiDAR produces them.

To compare the result from the ArcGIS Area Solar Radiation tool, the analysis will be applied based on the SOLARGIS raster layer s well. The SOLARGIS raster layer is based on an average daily/yearly sum of direct normal irradiation covering a period from 1994/1999/2007 (depending on the geographical region) to 2015. The solar model produced by SOLARGIS is based on atmospheric and satellite data, with a 15-minute and 30- minute time step, respectively. The spatial resolution of SOLARGIS is 1 kilometer, which makes it hard to process for small geographic units such as building footprint. The range of global Direct Normal Irradiance (DNI) is <1.0 to 10.0 kWh/m^2. The lower average of DNI does not mean that it is not qualified for solar panel installation.

Table19 shows the result from the solar radiation tool included in ArcGIS Pro, calculation of potential electricity based on the SOLARGIS grid, LiDAR-based calculation, and the numbers coming from SAM. It is expected that in table 19, the potential kWh differs in various methods but not drastically since all methods are based on scientific approaches. Modeling the potential in SAM will provide a single floating number with minimum and maximum (Lopez et al., 2019).

Table 19. Comparison of Potential kWh

Method	Potential (kWh/m2/day) for DNI	Spatial resolution
SOLARGIS potential	?	1 kilometer
ArcGIS potential	?	Based on the available DEM
LiDAR	?	1 and 0.5 meter
SAM	?	N/A

Now the question is how to assign the value of DNI to each building footprint? The goal is to have a more accurate estimation of potential electricity production for each rooftop. Without building footprint extraction, the potential output will be a generalized layer accompanied by low-level accuracy. The process of creation of building footprint and the value extraction can include:

1. (If a prepared DNI is available), The Raster to Polygon tool can only process integer input raster. Hence, a floating type raster must be converted to an integer type raster before using the tool. One possible way is to use the *Int* tool (Spatial Analysis) or multiply the float number to the number of decimals (in our case, three decimals) in the map algebra. So DNI * 1000 will solve the problem.

2. To calculate the potential kilowatt on the available rooftops, a point cloud LiDAR dataset will create the building footprint. If LiDAR does not cover the chosen area, an editing process will be applied to develop the building footprint, or an algorithm-based approach provided by Microsoft's building footprint will be used.

3. The LiDAR data often includes the LiDAR data Exchange File (LAS) grids. To extract the needed LAS files, we need first to overlay the files and then choose the ones covering the area of interest. After getting the LiDAR, it is possible to extract values falling on building footprints. This is useful because the different range of colors stands for multiple ranges of elevation. The following picture (Figure 30) shows an example of LiDAR output from West Bank, Buffalo, New York, where streets and generally low elevation objects are shown in green color, and building footprints are shown in orange and red:

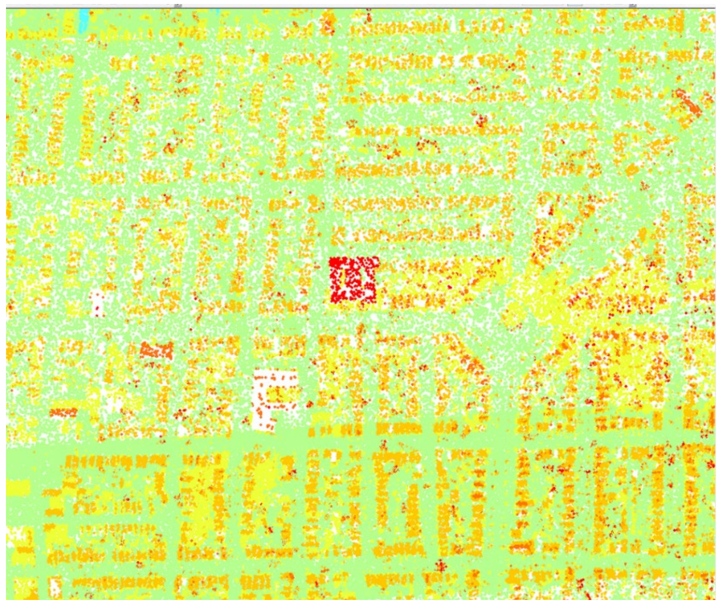

Figure 30. Example of LAS files in West Bank Buffalo, New York

There is a problem of noise, which means that not all the orange points stand for the rooftop. However, I will estimate the number of rooftops and their perimeter using these points, which will let me use the previous paragraphs' Constant-value methods.

4. The next step consists of converting LAS to raster (Figure 31).

Figure 31. Example of converting LAS to Raster

The sampling value in the process of LAS to Raster conversion defines the spatial resolution of the output. In most cases, the cell size—and the sampling value—are set to 1 meter to extract the best possible output. Also, the output data type is set to an integer.

5. The next step consists of extracting the pixels in the building footprint and converting them to polygons or simply extracting the raster by the mask if a building footprint is already prepared.

6. After depicting the building footprint, it is possible to use the *Regularize Building Footprint* tool to smooth the footprint.

The other factor in depicting the best buildings to implement solar PV is the rooftop's illumination. Hillshade can help create shaded relief, considering the illumination distributing an integer value in the range of 0 to 255, representing the most shaded areas to the brightest. The shaded area is calculated by considering the local horizon at each cell. An only shaded layer can be eventually created by extracting 0 values (or small integers). The azimuth is set to 180 in all modeling, which means the south-facing fixed array. The altitude is set to 45 to keep an average value for all models. The Z factor may change depending on the type of DEM used, but in most cases, it will be set on 1, which means the unit of measurement for x,y, and z is in the same unit (meter). Calculating the real potential will be possible by extracting shaded areas and measuring the area covered by solar PV arrays.

The Area Solar Radiation tool can calculate the solar potential based on the received solar radiation and the DEM's elevation. Parameters will be set as the following Table 20. However, depending on the geographical area of interest, some parameters, such as the latitude, may change.

Table 20. Solar radiation calculation parameters

Parameter	Value	Description
Latitude	Based on the geographic unit	The latitude for the site area. The units are decimal degrees, with positive values for the northern hemisphere and negative for the southern. The analysis is designed only for local landscape scales, so it is generally acceptable to use one latitude value for the whole DEM.
Sky size/resolution	200-10000	
Time	Whole year	
Year	2019	The year value for time configuration is used to determine a leap year. It does not have any other influence on the solar radiation analysis as the calculations are a function of the period determined by Julian's days.
Hour interval	0.5	
Z factor	1	Since the analysis is applied on a projected dataset, therefore, the Z is set to 1. A z-factor is essential for correcting calculations when the surface z units are expressed in units different from the ground x,y units. The z units should be the same as the x,y ground units to get accurate results. If the units are not the same, use a z-factor to convert z units to x,y. For example, if your x,y units are meters and your z units are feet, you could specify a z-factor of 0.3048 to convert feet to meters.
Calculation direction	32	The number of azimuth directions. The number of calculation directions needed is related to the resolution of the input DEM. Natural terrain at 30-meters resolution is usually quite smooth, so fewer directions are sufficient for most situations (16 or 32). With finer DEMs, particularly with human-made structures incorporated in the DEMs, the number of directions needs to increase. Increasing the number of directions will increase accuracy but will also increase calculation time.
Zenith division	8	
Azimuth division	8	

Diffuse proportion	0.3	The diffuse proportion is the fraction of global normal radiation flux that is diffuse. Values range from 0 to 1. This value should be set according to atmospheric conditions. Typical values are 0.2 for very clear sky conditions and 0.3 for generally clear sky conditions.
Transmittivity	0.5	The amount of solar radiation received by the surface is only a portion of what would be received outside the atmosphere. Transmittivity is a property of the atmosphere that is expressed as the ratio of the energy (averaged overall wavelengths) reaching the earth's surface to that which is received at the upper limit of the atmosphere (extraterrestrial). Values range from 0 (no transmission) to 1 (complete transmission). Typically observed values are 0.6 or 0.7 for very clear sky conditions and 0.5 for only a generally clear sky.

To identify suitable rooftops for solar panels, it is possible to consider a series of criteria:

1. Rooftops with a slope of 45 degrees or less.

2. Suitable sections of rooftops should receive at least 800 kWh/m^2 of solar radiation. This criterion will be assessed based on the ASR output.

3. Since north-facing rooftops in the northern hemisphere receive less sunlight, they will be removed.

4. The area with less than 800 kWh/m^2 of annual radiation will be removed.

5. Create a zonal statistic for each building with the average value and join the result to the building layer.

6. Find suitable buildings by determining If a building has less than 30 square meters of suitable roof surface (See the previous paragraphs for the minimum needed area).

7.Calculate the average potential of kWh production for each building by multiplying the mean solar radiation in an area.

8. Convert the usable solar radiation values from the previous step to electric power production potential based on average efficiency and the installation's performance ratio. The EPA provides a conservative best estimate of 15 percent efficiency and an 86 percent performance ratio. These values mean that the solar panels can convert 15 percent of incoming solar energy into electricity, and 86 percent of that electricity is maintained throughout the installation.

*kWh or MWh potential for each building * 0.15 * 0.86* Equation 25

9. A zonal statistic can help calculate the average solar radiation for each building and eventually join the result to the building layer.

10. The next step consists of removing buildings with less than 30 m^2 of the available rooftop (which means a non-feasible condition for the minimum number of the array installation equal to one). As discussed previously, considering the setback on the available area for security reasons, 30 m^2 will not suffice to implement the minimum solar PV.

11. Next, we can calculate the total average of annual kWh potential production for each building based on the AREA and MEAN fields' values. After the

previous step, we can convert the usable solar radiation values to electric power production potential based on average efficiency and the installation's performance ratio according to equation 25 (discussed in 5.4).

All the classifications on final radiation outputs are based on Natural Breaks (Jenks) for unevenly distributed data. Jenks is a data clustering method designed to determine the best arrangement of values into different classes to normalize data more accurately. The number of classes can vary from 3 to 7.

As mentioned in previous paragraphs, constant-value estimation methods calculate a percentage of building rooftop areas suitable for implementing PV equal to 22%-27% (Chaudhari et al. 2004). Besides, "Due to a 4 to 6 feet fire code setback requirement for solar installations, a portion of the rooftop along the perimeter cannot be used to host solar panels" (How to calculate building's rooftop area, Report for U.S. Department of Housing and Urban Development). Since the rooftop homogeneity is non-existent in the entire area, the setback should be calculated separately for each building to narrow down the calculation.

Solar panel installation at different higher education institutions will be studied only for buildings with a significant flat and even roof. The rooftops give the best condition with no shadow area where the sunlight can be absorbed for the entire day, and panels can point toward the south without any obstacles. Usable roofs should support the addition of 5-6 pounds per square foot to avoid substantial construction costs. The average cost of electricity purchased from the local utility will be taken in the calculations as well. The criteria for converting Direct Current (DC) (produced by panels) to Alternating Current (AC) will be applied to the calculations. It is necessary to bear in mind that the installation can be a grid-connected system to benefit from Renewable Energy Credit (REC) (Renewable Energy Credit can be sold or purchased in compliance or voluntary markets) in the case of excess in electricity production.

After the detection of available rooftop through the process of GIS, the financial output calculation will be based on the Cost of Renewable Energy Spreadsheet Tool (CREST) version 1.4; this is an economic cash flow model created on behalf of the partnership between major energy organizations in the U.S (National Renewable Energy Laboratory (NREL), the U.S. Department of Energy (DOE) Solar Energy Technologies Program (SETP), and the National Association of Regulatory Utility Commissions (NARUC). The model was developed by Sustainable Energy Advantage (SEA) under the direction of NREL).

The tariff escalation rate is the projected increase or decrease in the cost of renewable energy in the future throughout the project. It can be between 2 to 5 percent. The generation capacity has been calculated using the PV Watts calculator, an online toolkit provided by National Renewable Energy Laboratory (NREL). It is necessary to bear in mind that the roof tilt and sun azimuth cannot be automatically determined from the aerial imagery, and consequently, the estimated system capacity may not reflect what is possible. To increase the accuracy of estimation, the sun azimuth and roof tilt will be calculated using GIS. The solar PV capacity factor is taken from EIA. The capacity factor is the percentage of actual energy produced after removing all the losses. The percentage of product degradation is due to the natural aging of mechanical components, and it can be between 0 to 2 percent.

We also need to bring in the average condition given by total irradiance production of 1000 W/m2 at 25 degrees Celsius, also known as the Standard Test Condition (STC).

The kW_{DC} system size is the DC (direct current) power rating of the photovoltaic array in kilowatts (kW) at standard test conditions (STC). For a system with 16% efficient PV modules (which is the average capacity factor of Texas), the default PV system size is 4 kW. However, in many cases, the 15% capacity factor is used upon the EPA recommendation. This corresponds to an array area of approximately 25 m^2 (269 ft^2): 4 kW ÷ 1 kW/ m^2 ÷ 16% = 25 m^2. This array area is the total module area, not the total area required by the system that might include space between modules and space for inverters and other parts of the system.

By default, and in many calculation tools such as PVWatts®, a DC-to-AC size ratio is 1.1 or 1.2 so that the arrays DC nameplate size at STC is 1.1 times the inverters AC (alternating current) size. The large-scale systems can reach high ratios as 1.50. The DC to AC size ratio is the array's DC rated size to the inverters AC rated size. For the default value of 1.2, a 4 kW system size would be for a 4 DC kW array at standard test conditions (STC) and 4 DC kW / 1.2 = 3.33 AC kW inverter.

The best value depends on the system's geographical location, azimuth, and the costs of technology. For example, the default 4 kW system has an array size of 4 DC kW and an inverter size of 3.63 AC kW. The default DC-to-AC ratio value is appropriate for most analyses, but you can change it under Advanced Parameters. It is possible to estimate the system size based on the area available for the array or calculate it from the module nameplate size at STC and the number of modules in the array:

$$\textit{Size (kW)} = \textit{Array Area } (m^2) \times 1\ kW/m^2 \times \textit{Module Efficiency (\%)} \qquad \text{Equation 26}$$

or

$$\textit{Size (kW)} = \textit{Module Nameplate Size (W)} \times \textit{Number of Modules} \div 1{,}000\ W/kW \qquad \text{Equation 27}$$

5.5 ENERGY EFFICIENCY IN BUILDINGS

5.5.1 LIGHTING SYSTEM REPLACEMENT

Each fixture often contains two bulbs and, in some cases, three lamps. Measurements for recommended illuminance should be applied to ascertain that lighting conditions are adequate for the chosen space. A light meter to measure lux (foot-candles) should be conducted at the working surface in a horizontal plane 76.2 centimeters (30 inches) above the floor. Since the objective is to measure the task illuminant, daylight should be excluded. Therefore, in an occupied area with windows, readings should be taken with the full use of interior shading to reduce direct solar gain.

Illuminance is referred to as a measurement unit for the amount of light evaluated on a plane surface. Illuminance is measured in foot candles (ftcd, fc,fcd) or lux (metric system) in the international system of units (SI). A foot-candle is equal to one lumen of light per square foot, and one lux is one lumen per square meter. The outdoor light level is approximately 1,000. There has been a rapid change in recommended illuminance levels since the 1930s (Mills and Borg, 1999). The needed amount of lumens varies based on the main activity of the space used for lighting, the proximity to the window during the day, and the building's physical properties, and the office's physical properties. However, illumination can be calculated as:

$$I = L_I C_u L_{Lf} / A_I \qquad \text{Equation 28}$$

Where:

I = illumination (lux, lumen/m^2)
L_l = lumens per lamp (lumen)
C_u = coefficient of utilization
L_{LF} = light loss factor
Al = area per lamp (m^2)

Different space usage assumptions are delivered in Table 21, provided by the Illuminating Engineering Society (IES) and the Environmental Defense Fund (EDF). There are various online calculators to calculate the needed amount of lumen, and many of them reach the average lumen represented in the last column of Table 21.

Table 21. Average needed lumen for an indoor activity

Illumination Required (lumen/m2)		
Activity	**Illumination** ***(lux, lumen/m²)***	**Average Lumen**
Public areas with dark surroundings	20 – 50	40
Simple orientation for short visits	50 – 100	75
Working areas where visual tasks are only occasionally performed	100 – 150	125
Warehouses, Homes, Theaters, Archives	150	150
Easy Office Work, Classes	250	250
Normal Office Work, PC Work, Study Library, Groceries, Show Rooms, Laboratories	500	500
Supermarkets, Mechanical Workshops, Office Landscapes	750	750
Normal Drawing Work, Detailed Mechanical Workshops, Operation Theatres	1,000	1000
Detailed Drawing Work, Very Detailed Mechanical Works	1500 – 2000	1750
Performance of visual tasks of low contrast and very small size for prolonged periods of time	2000 – 5000	2250
Performance of very prolonged and exacting visual tasks	5000 – 10000	7500
Performance of very special visual tasks of extremely low contrast and small size	10000 – 20000	15000

The next important step consists of the calculation of fixture number, which is given by the following formula:

$$F = L^{*}S_f/MF * UF * L_f \quad \text{Equation 29}$$

Where:

F = required number of fixtures

L = required Lux

S_f = Square feet (converted to square meter in calculations)

MF = maintenance factor

UF = utilization factor

L_f = lumen per fixture (lumen per watt * each fixture watt)

It is possible to calculate the cost of new fixtures for LED bulbs and ballast as well. The ballast price will be introduced to the formula with an average price of $10.00, but the average price will be verified before submitting the final version of the dissertation. Also, the assumption is that there is no need to remodel the distance between each fixture.

5.5.2 MOTORS

The nameplate of the motor includes factors needed to apply the energy efficiency calculation. If it is not possible to read the factors, the vendor or producer will be contacted to obtain information. The NEMA definition of energy efficiency is given by the ratio of its useful power output to its total power input, shown in percentage (Fact Sheet, Motor Challenge. Determining Electric Motor Load and Efficiency. US-DOE Program):

$$\eta=(0.7457*hp*Load)/\rho_i \qquad \textit{Equation 30}$$

Where:

η = Efficiency as operated in %
hp = Nameplate horsepower
Load = Output power as % of rated power
ρ_i = Three-Phase power in kW

Power factor is calculated by:

$$PF = (Volt*Current*1.732)/((HP)*0.7457*1000) \qquad \textit{Equation 31}$$

5. 5.3 PUMP REPLACEMENT

The primary proposed measure consists of replacing the oversized standard pump with energy efficiency pumps. The nameplate provides factors to apply calculations. In the case of nonexistence, the vendor or producer will be contacted to obtain the needed information. The calculation of efficiency is similar to the calculation of efficiency in motors and VFDs, and other parameters for flow rate are retrievable through charts provided by vendors. Total head in feet is often provided by the plot of total head vs. flow. However, it is possible to calculate the total head by:

$$HT = Hd - hs \qquad \text{Equation 32}$$

Where:

HT = Total head
Hd = Suction head
hs = Discharge head

Pump hydraulic power is calculated as:

$$Ph(hp) = Ph(kW) / 0.746 \qquad \text{Equation 33}$$

Where:

Ph (hp) = hydraulic horsepower (hp)
Ph (kW) = hydraulic power (kW)

5.6 FINANCIAL ANALYSIS MODEL

This dissertation's financial model aggregates several models incorporating discounted cash flow analysis (DCF) for some common types of energy projects. The models used to create the customized version for this dissertation are:

- the Cost of Renewable Energy Spreadsheet Tool (CREST) version 1.4; CREST is an economic cash flow model created on behalf of the partnership between major energy organizations in the U.S: National Renewable Energy Laboratory (NREL), the U.S. Department of Energy (DOE) Solar Energy Technologies Program (SETP), and the National Association of Regulatory Utility Commissions (NARUC). The prototype CREST model was developed by Sustainable Energy Advantage (SEA) under the direction of NREL.
- EDF Climate Corps Financial analysis version 2.0
- Greenhouse Gas Protocol GHG emission from purchased electricity version 4.7
- NREL PV Operations and Maintenance Cost Model and Cost Reduction
- NREL System Advisor Model version 2020.2.29
- TRM401-Technical Reference Manual for Pumps and VFDs

To showcase a populated model in the following section, a completed model is represented (Figure 32). Tables 22 to 24 review the sample of evaluations.

Table 22. Key Assumption for a certain building or project

Key Assumptions	
Electricity Rate ($/kWh)	$0.08
Demand Rate ($ /kW/month)	
Electricity Growth Rate (%)	1%
Tax Rate (%)	0%
Discount Rate (WACC) (%)	5%
Total Annual Energy Spend of Alkek Library, (kWh)	3,154,484
Location-Based Emissions factor (eGrid)	ERCT: ERCOT All
Market-Based Emissions Factor (lbs CO_2/kWh)	0.000
Market-Based Emissions Factor (lbs CH_4/kWh)	0.00000000
Market-Based Emissions Factor (lbs N_2O/kWh)	0.00000000
Social Cost of Carbon or Internal Carbon Price?	Social Cost of Carbon
Internal Carbon Price ($/MT CO2)	N/A

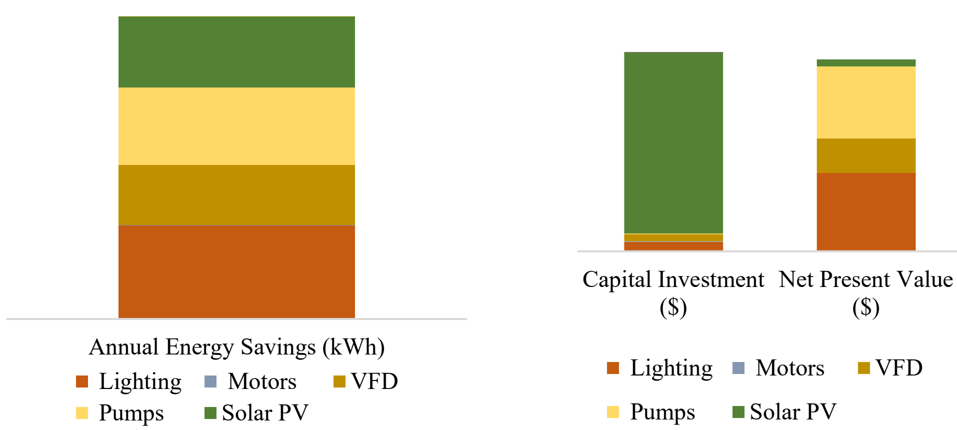

Figure 32. Bar charts for annual energy savings, capital investment, and NPV

Table 23. Project overview sample

Projects	Lighting	Motors	VFD	Pumps	Solar PV
Energy Efficiency Measure	**Replacement of T8 lamp with LED**	**Replacement of Same Size Standard Motor with EE Motor**	**Installation of VFD in Centrifugal Fans**	**Replacement of Oversized Standard Pump with EE Pump**	**On-Site Solar PV Energy Generation**
Unit Installed (No.)	4247	2	6	2	
Annual Energy Savings (kWh)	1227587	8126	788094	1020055	934217
Annual Energy Savings (% of total spend)	39%	0%	25%	32%	30%
GHG Savings Location-Based Method (metric tons CO_2e)	715	5	459	594	544.24
GHG Savings Market-Based Method (metric tons CO_2e)	0	0	0	0	0.17
Useful Life (Yrs.)	10	15	7	10	20
Capital Investment ($)	$86,214	$6,400	$63,000	$7,000	$1,650,000
Net Present Value ($)	$711,905	-$1,117	$315,969	$656,192	$62,560
Profitability Index	9.26	0.83	6.02	94.74	1.04
Internal Rate of Return (%)	116%	-1%	101%	1178%	7%
Equivalent Annual Annuity ($)	$92,195	-$108	$54,606	$84,980	$5,678
Payback Period (Yrs.)	0.87	9.35	0.99	0.08	9.42

Table 24. Sample of evaluation

Potential EEMs								
Energy Efficiency Measure		**Source of Savings**	**Annual Energy Savings (kWh)**	**Annual Energy Savings ($)**	**NPV**	**Potential Barriers to Implementation**	**Potential Additional Benefits to Implementation**	**Recommend?**
1	Replacing LFB with LEDs	LEDs can provide the same amount of Lumens with a lower level of Watts. Also, the average expected life of LEDs is 50000 hours compared to 10000 hours of CFL.	1,227,587	$24,972	$711,905	The total number of LFB to change can represent a problem, but they can be replaced gradually (after being burned) or sold with a substantial rebate on each bulb.		YES
2	Replacement of Motors	Energy-efficient motors also called premium or High-efficiency motors are 2 to 8% more efficient than standard motors. Motors qualify as “energy-efficient if they meet or exceed the efficiency levels listed in the National Electric Manufacturers Associations (NEMA’s) MG1-1993 publication.	8,126	$650	$1,117	No economic benefit.		NO

5.7 MEASURING STATE CONTEXT

In their recent *Sustainable Development Report of the United States*, Jeffrey Sachs and colleagues (2018) developed and measured a composite Sustainable Development Goal (SDG) index for each state using numerous indicator variables that the authors grounded in the United Nations (UN's) SDG framework. Both the overall state-level SDG index values and the underlying indicator variable values are available in public-facing datasets. Among the indicators used to construct the composite index are a state's: (1) CO_2 intensity in the electric supply, (2) energy-related CO_2 emissions, (3) effective carbon rate, (4) presence or absence of a climate action plan, (5) percentage of adults who are aware of climate change, (6) energy efficiency, (7) renewable energy production, and (8) renewable energy consumption. Drawing on these variables, this dissertation will create state-level energy/energy policy profiles that will be used to describe the state-level energy context in which each HEI study area is located.

5.8 MEASURING LOCAL CONTEXT: K-MEANS CLUSTERING OF CONSUMER SURVEY DATA

This dissertation will attempt to situate concrete alternative energy projects at selected HEIs in their state policy and local/community contexts. Whereas the preceding section proposed data and methods for measuring/describing state context, this section provides details on how the local context will be approximated.

To assess the geographical context, I will rely on two valuable data sources: (1) the SimmonsLOCAL annual consumer survey and (2) America's Goals Report. The indicator sources were chosen to be as up-to-date as possible and based on data availability for the most significant number of States. The purpose of further analysis of geographical context is to represent the interests to which university decision-makers are accountable and in which they are embedded. The assumption is that university administrators make decisions consistent with state priorities, especially when they are state-owned and funded. Therefore, by looking at the extent of sustainability in public/state HEIs' plans, it is possible to assess whether current priorities reflect state policy.

Similarly, it is possible to draw on data obtained from local (home) populations to determine how aligned HEI energy priorities are with their neighbors' attitudes towards the environment. In that sense, and drawing on the instructive literature summarized above, an HEI's commitment to sustainable energy is hypothesized to be a function of at least three interacting variables: (1) Financial feasibility (i.e., whether there is a proper coupling), (2) State priorities, and (3) Local priorities. One argument could be that universities are most likely to invest in sustainable energy when all three of the above factors are favorable (i.e., it is profitable; the state is strong on climate action and energy, and local residents prioritize sustainability goals). On the other hand, even when projects are financially feasible, we might expect inaction if states and localities are not particularly strong on environmental protection sustainability issues.

"Mapping features based on how similar they are to surrounding features [clustering] is different [and more significant] than simply mapping the values of features [graduate color map]" (Mitchel, 2005, p.163). By comparing the geographical locations of clusters, it is possible to examine and identify the possible contributing factors to sustainability commitment in HEIs.

To perform a cluster analysis, two problems have to be solved: (1) efficient partitioning with homogeneous groups and (2) effective interpretation (Huang, 1997). The Multivariate Clustering tool in ArcGIS Pro uses the k-means algorithm by default. If the number of clusters is not defined, they will be determined by Calinski-Harabasz pseudo-F-statistics, a ratio of the variance between and within clusters. While it is possible to use nominal data, the variable used in K-means should be numeric because the algorithm does not yield satisfactory results with binary (categorical) variables (ArcGIS Pro help) unless a two-step approach is used. In addition to a summary statistic for each variable, the R^2 will also be calculated (Equation 35).

The similarity between features is determined by the value assigned to them. In the k-means approach, higher values in multiple features will be associated with higher values in other features through a highly algorithmic process that cannot be summarized in a single formula (Peng, 2012). K-means clustering is a partitioning approach based on multiple rounds of iteration (Peng, 2012, p.111; MacQueen, 1967; Meyers et al., 2016). One requirement is that the number of clusters should be decided, and when the number of clusters is left empty, the algorithm may produce a high number of clusters even with one variable selected.

The process called k-means appears to provide partitions that are "reasonably efficient in the sense of within-class variance" (MacQueen 1967, p.1). The k-means clustering is *agglomerative* since observations are added to a cluster after completing a phase and is *iterative* since the next step is based on previous ones (Meyers et al., 2016). The exact appropriate number of clusters cannot be known in advance, even though some statisticians tried to examine strategies to calculate the correct number of clusters before starting the iteration (Meyers et al., 2016). The number of clusters will be determined after several attempts and by comparison between the researcher's best results or by using the results of Pseudo F statistics (Peng, 2012; Meyers et al., 2016).

The k-means also represent a generalization of the ordinary sample mean (MacQueen, 1967). Given a set of numeric X and an integer number of clusters (K), the K-means algorithm tries to find a partition of X into K clusters that minimize the within-group sum of squared errors (WGSS) (Huang, 1998). To achieve that, the variables should be in z-score, the standardization of data should be applied before starting the algorithm (Meyers et al., 2016), and data should be screened for outliers to avoid their selection as the central point in the clustering step (Norusis, 2011; Shih et al., 2010). The outline of the algorithm is defined by Peng (2012), Meyers (2016), ArcGIS help center (2019), MacQueen (1967), Shih et al. (2010), Ralambondrainy (1995), Huang (1998), and Jain (2010) as follows:

1. Classification: identifies the number of clusters at some integer greater than or equal to 2.
2. Selection of a sample number of centroids (seeds): this step is also known as the *seed point* step, where some random points will be drawn as the center of clusters (see appendix 1).
3. Assigning the points (objects, values) to the centroids of features
4. Assign the center points of each feature to the belonging cluster: After a point is added, “the mean of the group will be adjusted to take account of the new point” (MacQueen, 1967, p.283).
5. Recalculation of centroid position and repetition of the iteration: The modified

centroid involves calculating Euclidean distance between center points. The smallest distance then will determine which cluster the center point belongs to. One key criterion is given by “the minimum sum of squared Euclidean distances from each entity to the centroid of the cluster to which it belongs” (Aloise et al., 2009, p.245).

Therefore, the number of clusters is given by:

$$\frac{\left(\frac{R^2}{n_e-1}\right)}{\left(\frac{1-R^2}{n-n_e}\right)} \qquad \textit{Equation 34}$$

Where:

$$R^2 = \frac{TSS-ESS}{TSS} \qquad \textit{Equation 35}$$

TSS is the total sum of squares, and ESS is the explained sum of squares. TSS is calculated by squaring and then summing deviations from the global mean value for a variable. ESS is calculated the same way, except deviations are group by group: every value is subtracted from the mean value for the group it belongs to and is then squared and summed. TSS is a reflection of *between-cluster* difference, and ESS reflects within-cluster similarity.

$$TSS = \sum_{i=1}^{n_e} \sum_{j=1}^{n_t} \sum_{k=1}^{n_v} \left(V_{ij}^k - \overline{V^k}\right)^2 \qquad \textit{Equation 36}$$

$$ESS = \sum_{i=1}^{n_e} \sum_{j=1}^{n_t} \sum_{k=1}^{n_v} \left(V_{ij}^{k} - \overline{V_t^{k}}\right)^2 \qquad \text{Equation 37}$$

Where:

n = the number of features

n_i = the number of features in cluster i

n_e = the number of classes (clusters)

n_v = the number of variables used to cluster features

V_{ij}^{k} = the number of the k^{th} variable of the j^{th} feature in the i^{th} cluster

V^{k} = the mean value of the k^{th} variable

V_{t}^{k} = the mean value of the k^{th} variable in cluster *I*

The k-means algorithm is classified as an NP-complete and also known as *non-deterministic polynomial-time* hardness (NP-hard), which means that to maximize the within-group similarity and between-group differences, the algorithm must try all the possible combinations among features (variables) (Aloise et al., 2009; Mahajan et al., 2009; ArcGIS Pro Help, 2020).

The 15 variables used in this dissertation are coming from different data sets available on SimplyAnalytics, and they include people who agree with the following statements: (1) make a conscious effort to recycle, (2) packaging for products should be recycled, (3) environmentally sound/good business. (4) companies should help consumers to become environmentally responsible, (5) personal obligation towards environmental responsibility, (6) others must see me environmentally conscious, (7) would buy less expensive eco-friendly products,

(8) eco-friendly products should be higher quality products, (9) tell companies to stop sending catalogs, (10) more likely to purchase from the environmentally-friendly company, (11) to choose environmentally-friendly methods of transportation, (12) they have used recycled products, (13) worried about the pollution caused by cars, (14) people have to recycle, and (15) people who belong to environmentalists organizations. The acronyms correspond to the same variables, and they are shown in Table 25.

Table 25. Variable acronyms

Acronym	Variable (Number of Adults Who Agree with the Statement)
PAKSHLDREC	Packaging for products should be recycled
COMCONENV	Companies help consumers to be environmentally responsible
USEDRECPRD	They have used recycled products
PRSOBENVRE	personal obligation/environment responsible
MAKCONTORE	I make a conscious effort to recycle
PEPLDTYTTOR	People have a duty to recycle
PRCHENVFRC	More likely to purchase/environmentally friendly products
ENVGOODBUS	Environmentally sound/good for business
WORCARPOLLU	Worried about pollution caused by cars
LESEXPECFP	Would buy less expensive eco-friendly products
OTHSEEMRE	Others must see me as environmentally conscious
CSMETRPENF	Choose methods of transport/environment-friendly
ECOFHIQPPR	Eco-friendly products/higher quality products
STPSENDCAT	Tell companies to stop sending me catalogs
BLNGSTOENOR	Belong to an environmentalist organization

Source: SimmonsLOCAL U.S. 2018, via SimplyAnalytics

K-modes is used for categorical clustering data (Huang, 1997), and K-prototype (Huang, 1997) can cluster categorical and numerical variables together against the standard K-means algorithm, which is exclusively used for numerical variables. The dissimilarity measure in K-modes is calculated by the mismatch of the two objects' corresponding attribute categories. “The smaller the number of mismatches is, the more similar the two objects” (Huang, 1998).

The outline of K-prototype is defined by Huang (1997):

1. Select k initial prototypes for each cluster.
2. Assign each object to the nearest cluster according to the following formula:

$$d(X_i, Q_1) = \sum_{j=1}^{m_r} \left(x_{ij}^r - q_{lj}^r\right)^2 + \gamma l \sum_{j=1}^{m_c} \delta\left(x_{ij}^c, q_{ij}^c\right) \qquad \textit{Equation 38}$$

Where “x_{ij}^r and q_{lj}^{r} are values of numeric attributes, whereas x_{ij}^c and $q_{lj}^{\ c}$ are values of categorical attributes for object i and the prototype of cluster l. m_r and m_c are the numbers of numeric and categorical attributes. γl is a weight for categorical attributes for cluster l” (Huang, 1997, p.4).

3. Retest the similarity of objects against the prototypes and re-assign an object to the correct cluster if needed.
4. Repeat until no change occurs.

In K-Prototypes, the dissimilarity between a categorical and numerical variable is calculated by computing first, the Euclidean distance between numeric attributes, and secondly by matching dissimilarity measure on the categorical attributes (Huang, 1998). The following formula shows a linear formulation of K-prototype implementation:

$$d_2(X,Y) = \sum_{j=1}^{P} \left(x_j - y_j\right)^2 + \gamma \sum_{j=\rho+1}^{m} \delta\left(x_j, y_j\right) \qquad \textit{Equation 39}$$

Where γ is used as a weight "to avoid favoring either type of attribute" (Huang, 1998, p.9), the first term is the squared Euclidean distance calculation only for the numeric attributes, and the second term is the matching dissimilarity measure on the categorical attribute (Huang, 1998). The dissimilarity measure without weighting and only for two categorical objects can be measured by the following formula where smaller is the number of mismatches more similar are the two objects:

$$d_1(x,y) = \sum_{j=1}^{m} \delta\left(x_j, y_j\right) \qquad \textit{Equation 40}$$

Where,

$$\delta\left(x_j, y_j\right) = \begin{cases} 0 (x_j = y_j) \\ 1 (x_j \neq y_j) \end{cases} \qquad \textit{Equation 41}$$

A Python implementation of K-prototype is offered by Nico de Vos (Copyright, 2016 Nico de Vos, njdevos@gmail.com), which is retrievable in appendix 3. However, it is possible to run K-prototypes in R using the *kproto* function. As opposed to other R packages in *kproto*, the categorical variables "do not need to be preprocessed in advance, and the order of variables does not matter (Szepannek, 2018, p.2).

6. RESULTS AND OUTCOMES

The results from performing the analyses described above will allow classifying every alternative energy project under investigation along four dimensions: (1) *financial feasibility* (i.e., is the energy-saving project a financially sound investment?); (2) *community environmental preferences* (i.e., to what extent are residents in the HEI's local spatial context positively, neutrally, or negatively predisposed to sustainable energy investments?); (3) *state energy policy arena* (i.e., to what extent are the HEI state's policy and Sustainable Development Goal performance strong, neutral, or weak with respect to reducing energy consumption?); and (4) *energy savings* (i.e., how much energy will the investment save?).

With this classification framework (see Figure 17 in Ch. IV for a visual representation), I can evaluate actual HEI decision-making practices and alternative energy (non)implementation to look for *proper couplings* between these dimensions. My overarching expectation is that any alternative energy projects that have been implemented will exist in more properly coupled HEI-environment-social systems than those that have not been implemented.

For projects that have neither been implemented nor (openly) deliberated at the case study HEIs, the dissertation will offer vital information for strategic decision-making. Namely, projects that are shown (empirically) to exist in relatively properly coupled HEI-environment-social systems are ones that have the highest likelihood of achieving institutional, community, state, and broader environmental objectives in the long run—alternatively stated, the dissertation will generate actionable knowledge that the case study Universities can integrate directly into their sustainability and energy use agendas and planning processes going forward. By following the methodology described in this dissertation, future researchers will likewise generate novel findings that can be used to motivate large institutional or governmental actors and decision-making bodies to take financially feasible, energy-saving actions. Over time, the aggregation of these place-based actions and decisions will help to more *properly couple* local, regional, and, eventually, global landscapes of social-economic-environmental systems.

6.1 TEXAS STATE UNIVERSITY SOLAR POTENTIAL

The Digital Surface Model (DSM) for Texas State University is produced by mosaicking separate LiDAR files (LAS) with a spatial resolution of 0.5 meters. The LiDAR used for this section of the study is last updated in 2017. The building footprint was already digitalized for TSU; hence no processing is needed to create the building footprint.

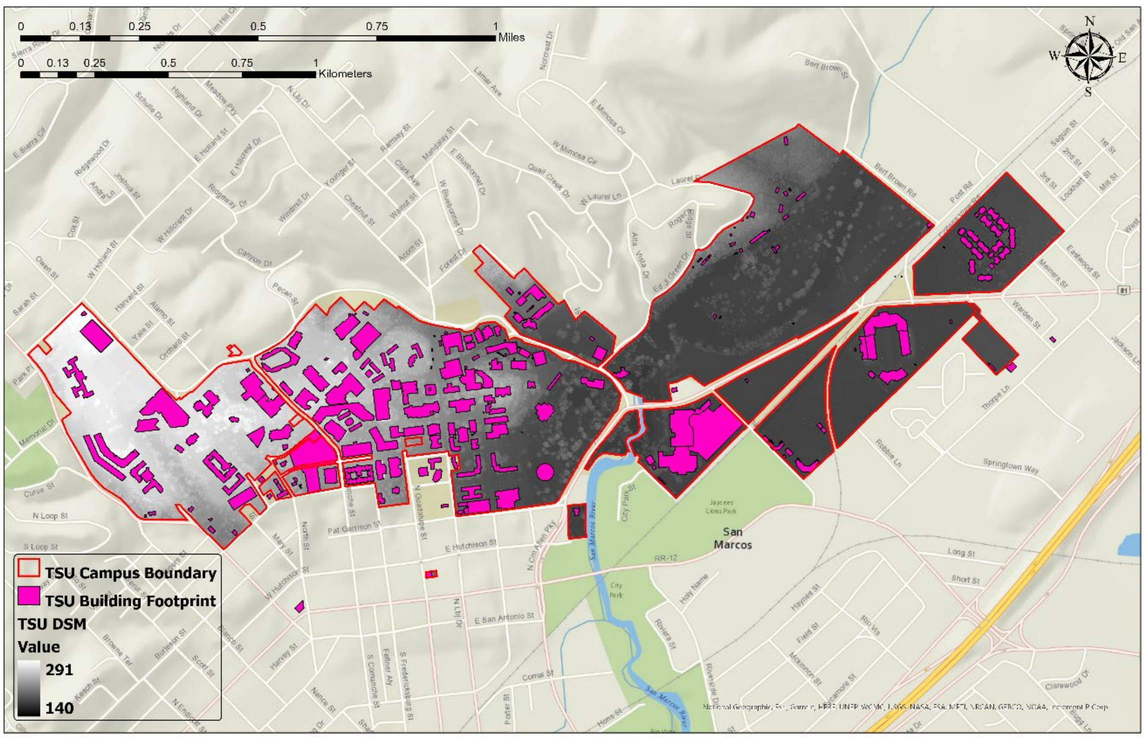

Figure 33. Texas State University building footprint, and digital surface model

According to the weather file obtained from NSRDB, the average daily radiation potential (DNI) at San Marcos, Texas, reaches 5.18 kWh/m^2. Figure 34 shows the monthly potential, which is similar to the output for Texas A&M and College Station, Texas (Figure 48), given the proximity of these two chosen study areas.

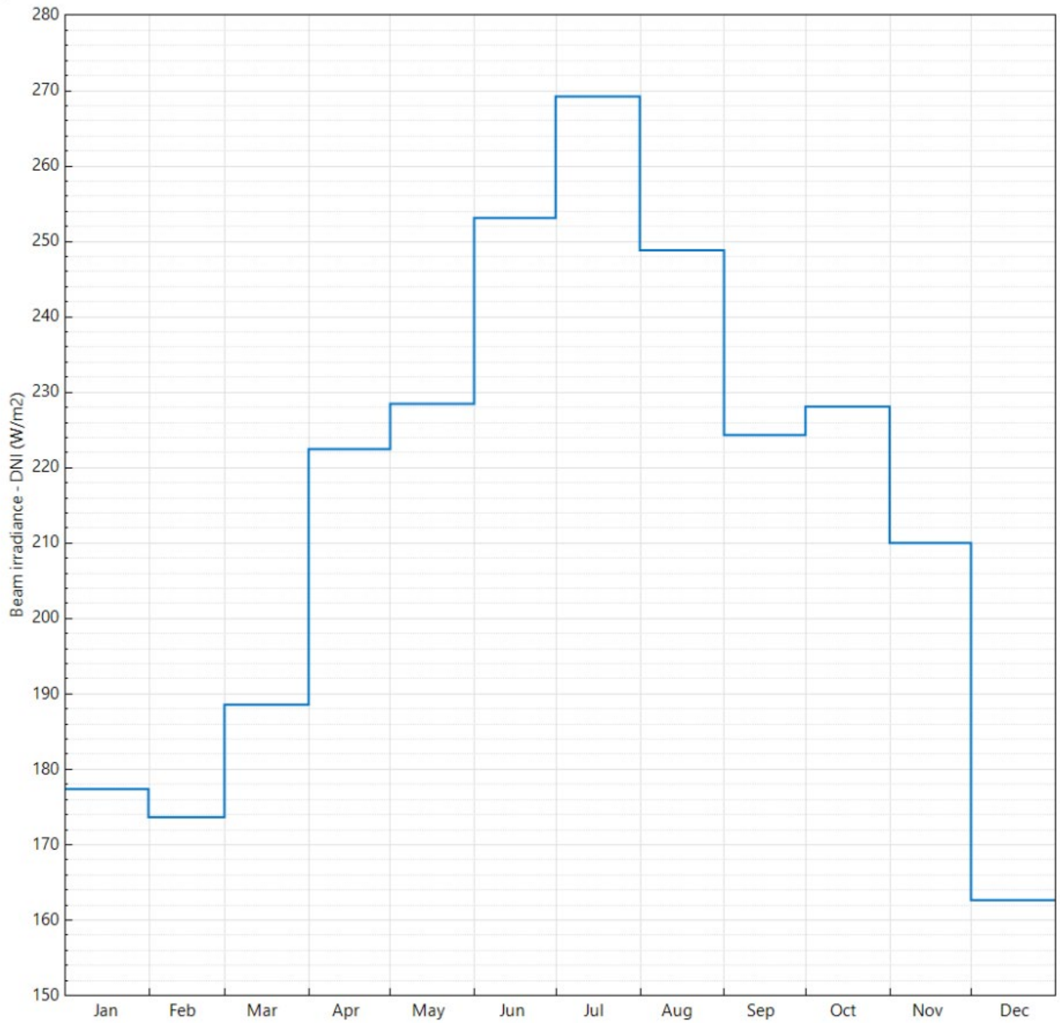

Figure 34. Monthly DNI (W/m^2) at Texas State University

The output radiation raster is a floating-point type and has watt-hours units per square meter (WH/m^2). The latitude for the study area is in the decimal degree unit. It will be positive for the northern hemisphere and negative for the southern hemisphere. The latitude is also used to calculate solar declination and solar position (ArcGIS Pro documentation). The following figure shows the radiation output potential. The annual irradiation based on this method reaches the maximum of 1582 kWh/m^2 for the best location (Figure 35).

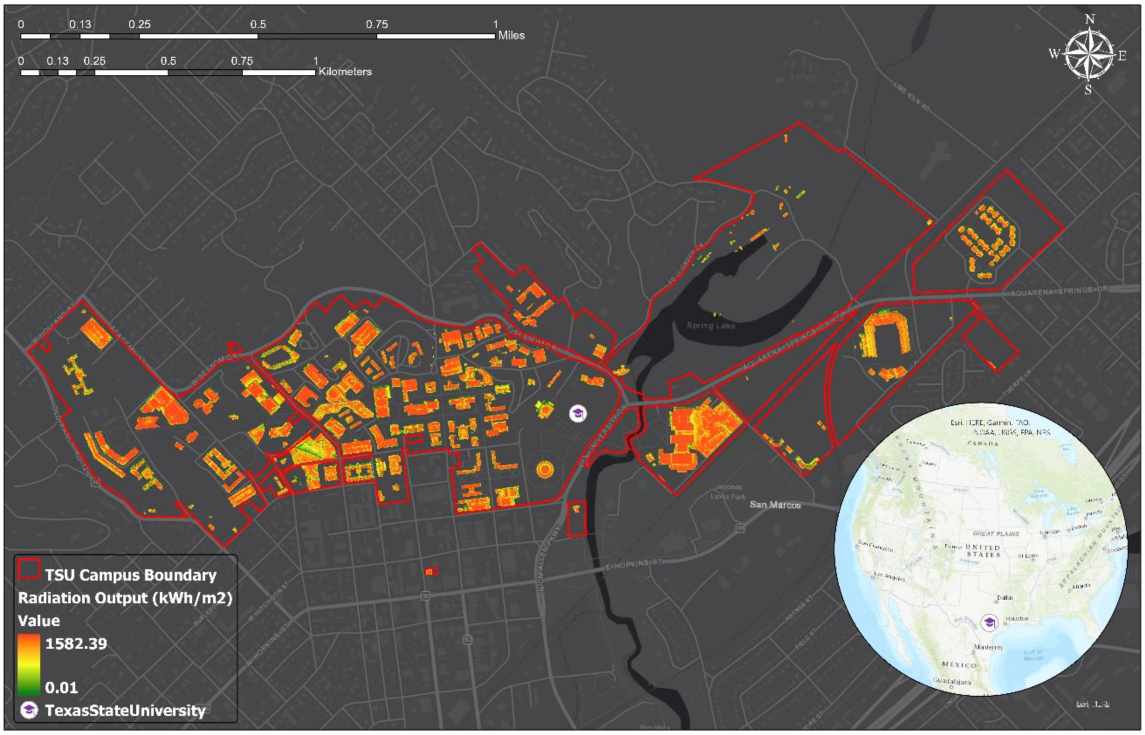

Figure 35. Solar radiation potential at TSU based on Area Solar Radiation

By having the total area of building footprint (337.778 m^2) and an average of radiation (5.18 $kWh/m^2/day$), it is possible to calculate the daily potential based on extracted building footprint:

$$337.778\ m^2 * 5.18\ kWh/m^2/day = 1{,}749{,}690.04\ kWh/m^2/day \qquad \text{Equation 42}$$

Hence a yearly potential can be calculated as follows:

$$1{,}749{,}690.04\ kWh/m^2/day * 365 = 638{,}636{,}864.6 \qquad \text{Equation 43}$$

However, the obtained number is the total potential absorbed by the building footprint area and not the energy produced. Depending on the kind of technology and the capacity factor discussed in chapter 5.4, the produced kWh will be drastically lower than the potential. As mentioned previously, a percentage of building rooftop areas suitable for implementing PV equal to 22%-27% (Chaudhari et al. 2004). Also, "Due to a 4 to 6 feet fire code setback requirement for solar installations, a portion of the rooftop along the perimeter cannot be used to host solar panels" (How to calculate building's rooftop area, Report for U.S. Department of Housing and Urban Development). Hence the calculation should be based on only 70% of the available rooftop to meet the standard conditions. Also, since the rooftop's homogeneity is non-existent in the entire area, the setback could be calculated separately for each building to narrow down the calculation.

Seventy percent (70%) of the total building area at TSU is equal to 236444.59 m^2. Considering that a 4kW capacity requires 25 m^2 of the array as discussed in chapter 5.4, we can have 9,457.76 m^2 of array dedicated to solar PV, producing 37,828 kW of DC energy. This number can be used as the financial model's input (Figure 36) but is still not significant since further processing is needed.

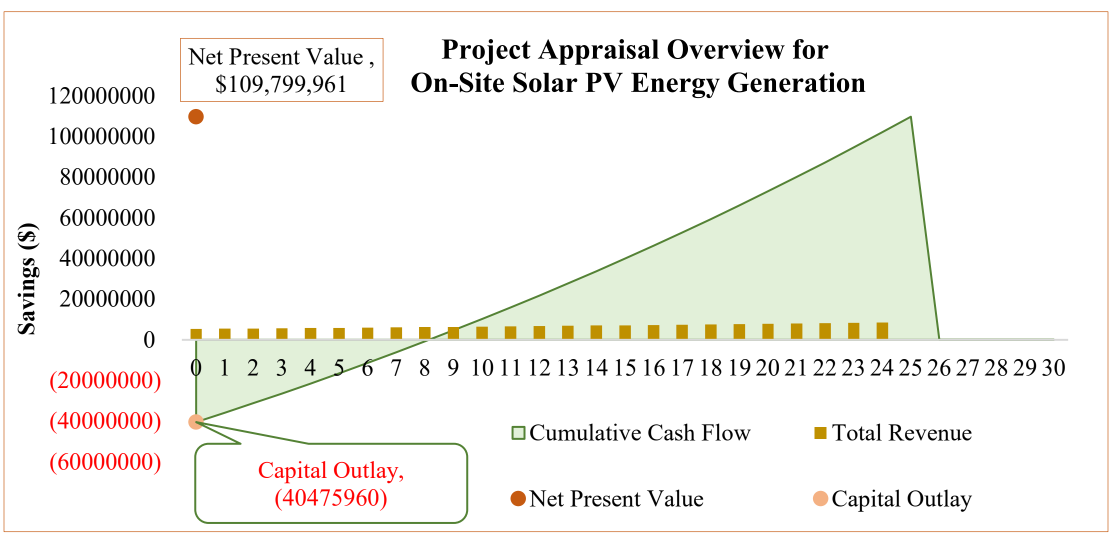

Figure 36. Project appraisal overview for a 4 kWDC on-site solar PV

Table 26. Project evaluation for solar potential at Texas State University

Project Valuation	
Annual Energy Production (kWh)	53,544,764
GHG Savings Location-Based (metric tons CO2e)	34239.36
GHG Savings Market-Based (metric tons CO2e)	0.00
Capital Investment (excluding Rebate/Incentive)	75,960
Net Present Value	$109,799,961
Internal Rate of Return (IRR)	13%
Payback Period (Years)	8.14
Profitability Index/BCR Ratio	3.71
Debt Service Coverage Ratio	-
Equivalent Annual Annuity	$4,391,998

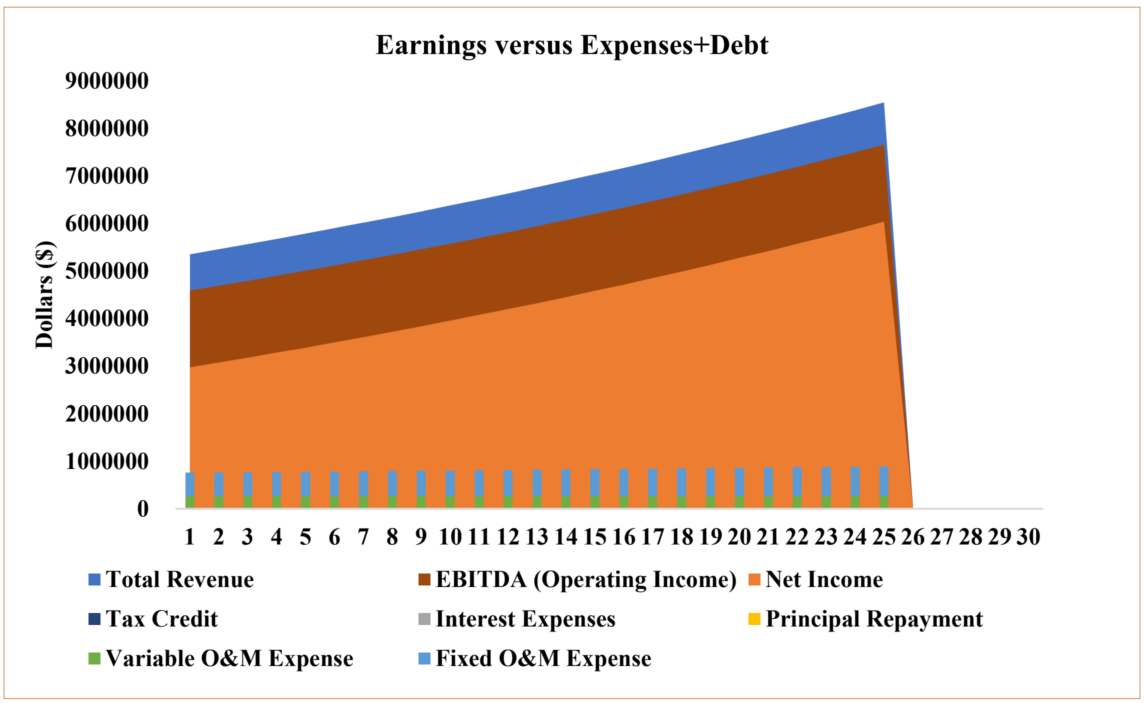

Figure 37. Earnings vs. expenses with 37,828 kWDC potential generation capacity

As discussed in the methodology section, suitable rooftops should have a slope of 45 degrees or less since steep slopes tend to receive less radiation. Suitable rooftops should also receive at least 800 kWh/m^2 of solar radiation. Suitable rooftops ought to not face north, as north-facing rooftops in the northern hemisphere receive less sunlight. Hence a calculation of slope, aspect, and reassignment of potential is needed as the next step. However, there is not much change between the conditional assignment and the ASR since almost all the Texas State University rooftops are flat (Figure 38).

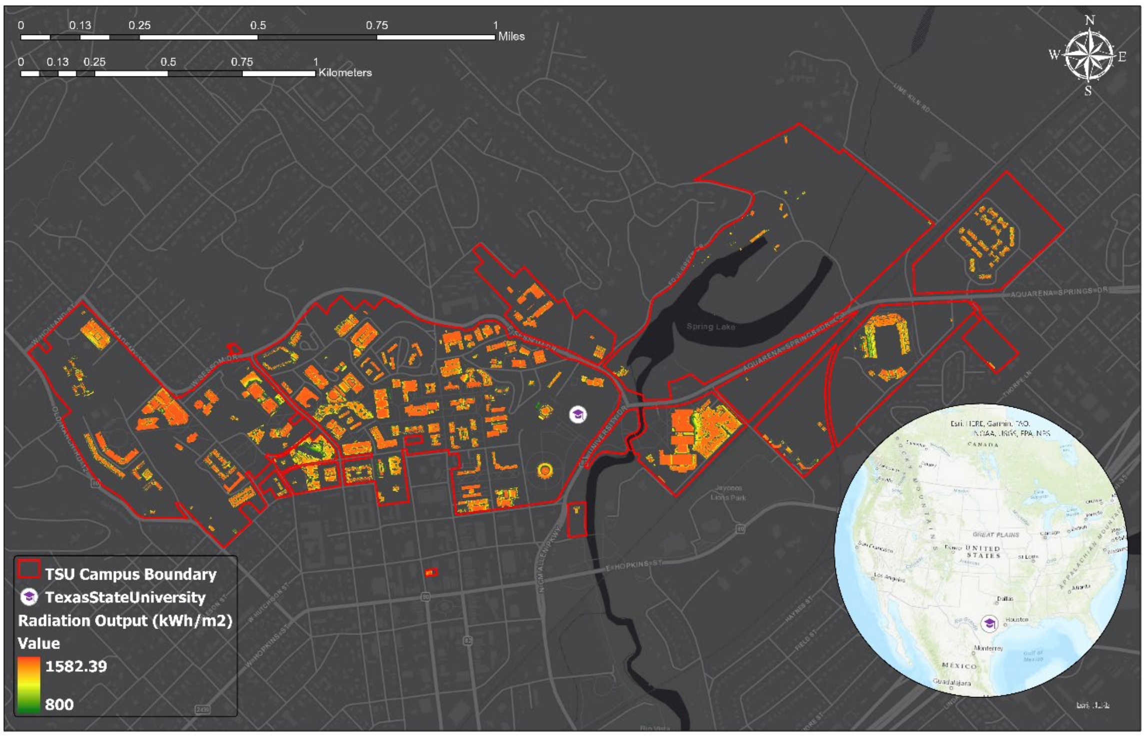

Figure 38. Solar radiation potential at TSU after minimum kWh/m2 condition

The majority of north-facing surfaces were already removed by conditional assignment of minimum radiation; however, a few remain. Slopes that face north should contain a value less than 22.5 degrees or more than 337.5 degrees in the aspect raster layer. Eventually, flat slopes will be kept, regardless of their aspect. To achieve the condition above, the Con tool will determine areas with low slopes (less than 10 degrees) and determine areas facing north.

A zonal statistic approach will assign the potential to the building footprint by determining the mean value of the potential. The table contains fields for the number of cells, the area in square meters, and the average solar radiation in kWh/m^2 for each building. Next, we remove buildings with less than 30 square meters of area, and by doing that, 210 out of 294 buildings will be selected. Next, we convert the potential to MWh by the following equation:

$$Area * Mean / 1000 \qquad \text{Equation 44}$$

Moreover, as the final step, the potential will be converted to power based on equation 23. Figure 39 shows the final output with the chosen buildings and potential electricity produced in MWh.

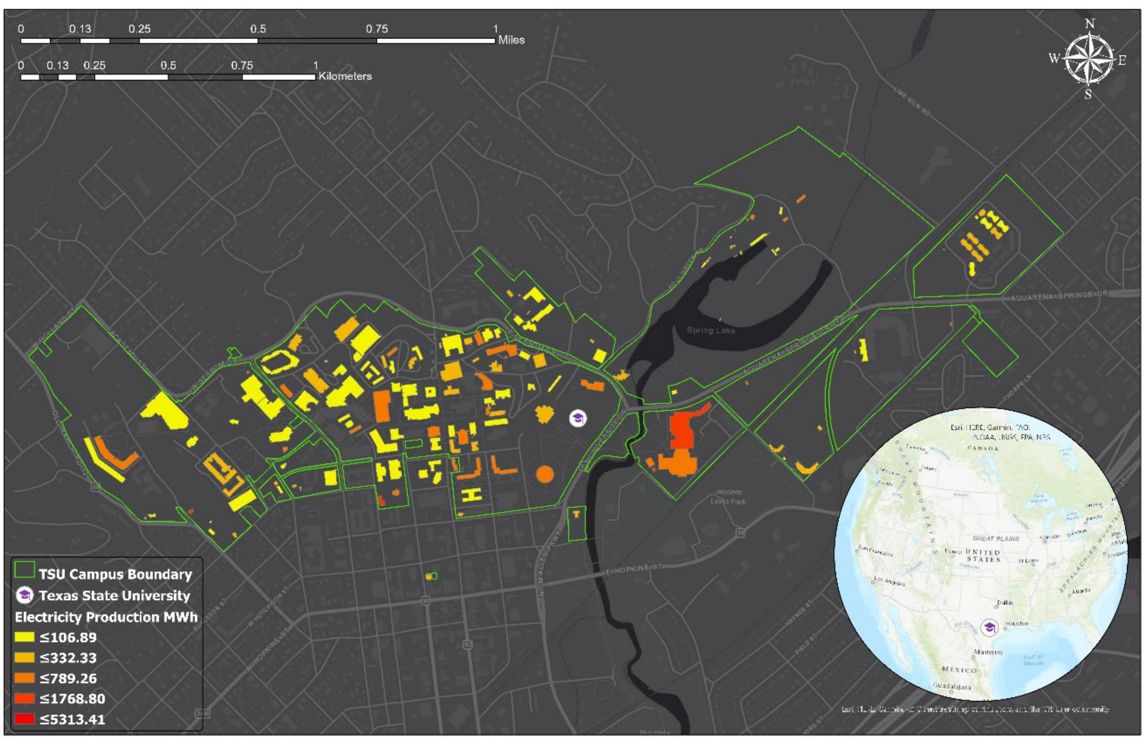

Figure 39. Final potential production at Texas State University

The applied methods offer a more detailed and accurate output. The total possible output reaches 45518000 kWh (45518 MW) or 17.63% less than the initial assessment based only on the available rooftop area.

6.2 TEXAS STATE UNIVERSITY WIND POTENTIAL

There are 306 constructed buildings around Texas State University's main campus, with an average height of 23.5 feet. The mean wind speed at Texas State University’s main campus is calculated and discussed in section 5.3.1 and reaches four m/s. However, more generalized studies or different data sources may report drastically different average speeds, as discussed in 5.3.1. For example, Figure 40 calculates an average wind speed equivalent of 2.9 meters per second (m/s) based on NSRDB data from the station with ID number 671993 (Lat: 29.89, Long: -97.94 Elevation: 200 meters).

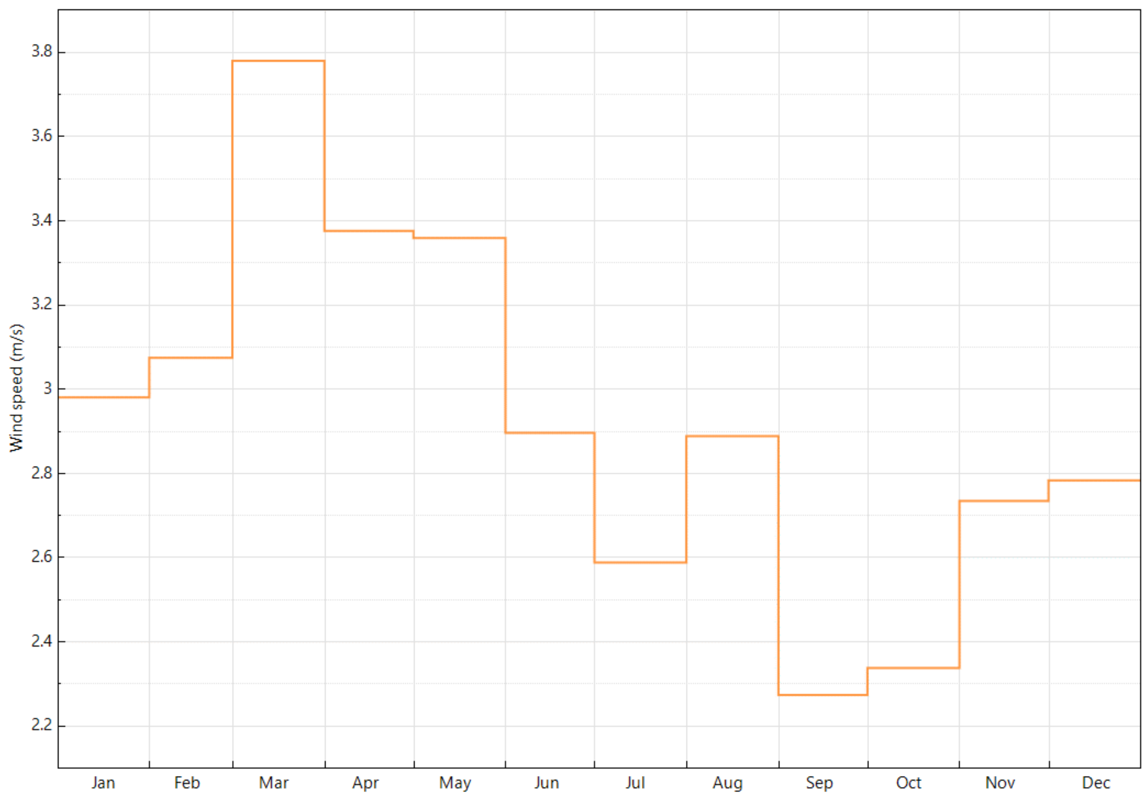

Figure 40. Average monthly wind speed at Texas State University

In this study, wind power was assessed based on data for the four seasons from the nearest methodological station to San Marcos. The variation in seasonal mean in 2017 ranged from 7 Mph to 13 Mph (Figure 28). The limited rate of change in mean wind speed causes a low wind power class (Class 1 or 2) in central Texas, where Texas State University is located. As mentioned, there is a high rate of fluctuation in wind speed depending on surface roughness. Power density can vary from season to season (Akpinar, & Akpinar, 2005). The energy output is given by fixed numbers while having an exact estimation of wind turbine output is difficult due to wind power and wind speed instability.

On the other hand, studies show that higher wind speed occurs in higher elevations. Hence, having different buildings with different heights will impact the calculation of output. "The cut-in speed, which is the minimum speed at which the wind turbine will generate usable power, is typically between 3 and 5 m/s" (Al Yahyai et al., 2011 p.154). There is some peak of high wind speed registered in data, such as the one during August 2017, which can partially compensate for the low wind power in other seasons. The following Figure 41 shows the elevation of rooftops at TSU.

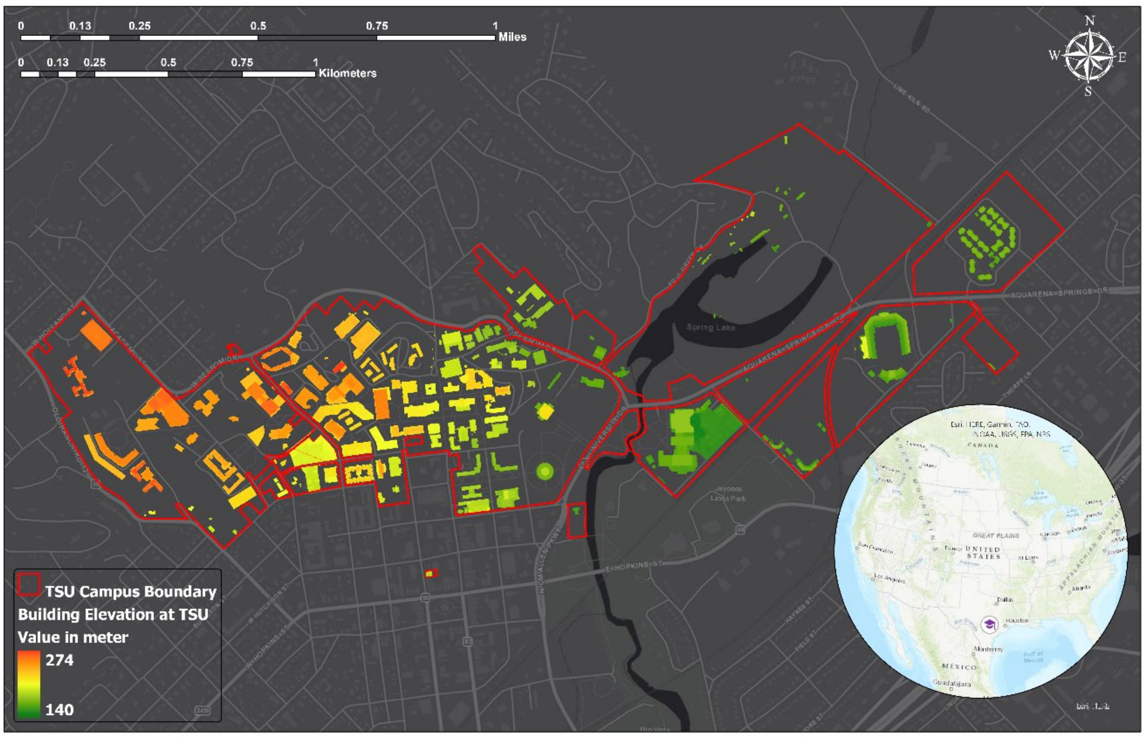

Figure 41. Rooftop elevation at Texas State University

After determining the elevation of available rooftops (via LiDAR), we can calculate the average wind speed based on Equation 17 discussed in chapter 5.3.1.

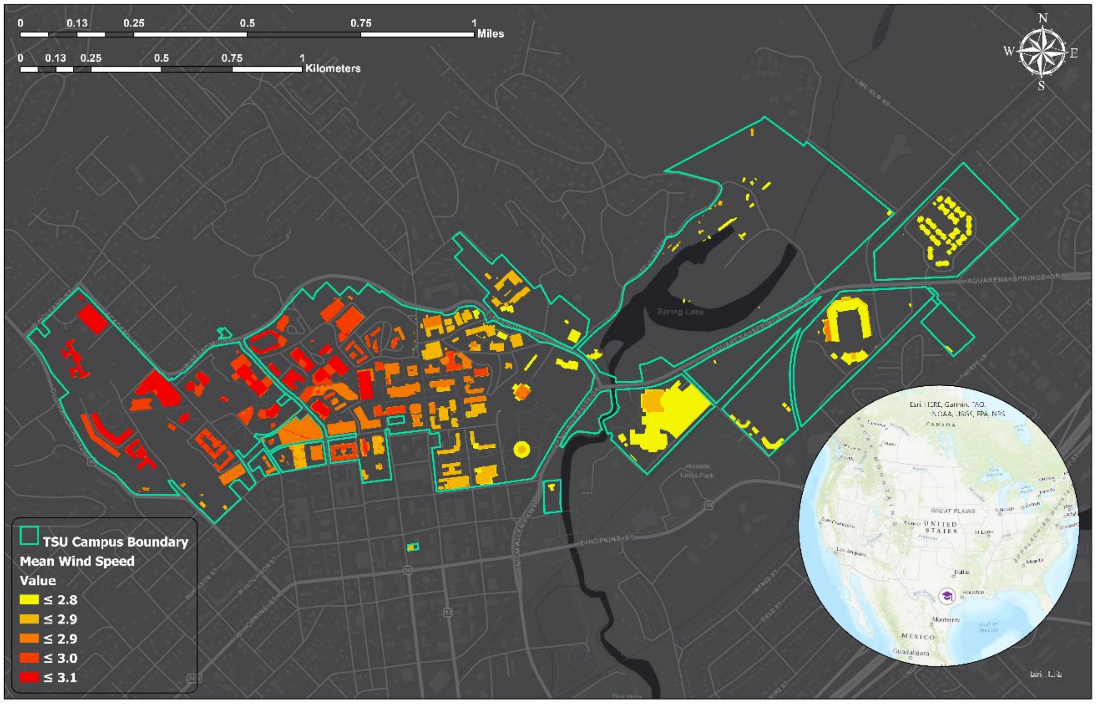

Figure 42. Mean wind speed based on rooftop elevation at Texas State University

Since the minimum cut-in speed is set to 3 to 5 meters per second (Al Yahyai et al., 2011 p.154), only the buildings falling inside that range will be kept. The chosen 33 buildings at TSU are shown in Figure 43.

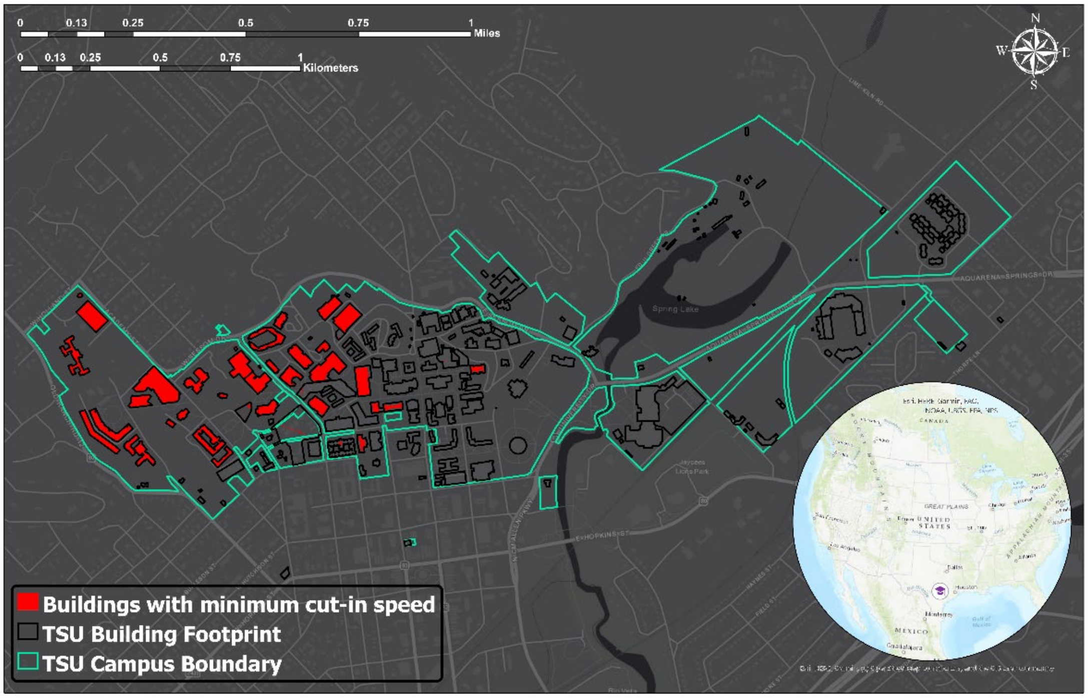

Figure 43. Buildings with minimum cut-in wind speed at Texas State University

The total available perimeter for chosen buildings reaches 10,017 meters. Considering a 5-meter distance between each wind turbine, we can have 2003 installed wind turbines. If each wind turbine produced 2500 kWh yearly, the generation capacity would be more than 3 million kWh, which can be used as the input for the financial model, as shown in table 27 and Figure 44.

Table 27. On-site wind turbine energy generation at Texas State University

Project Valuation	
Annual Energy Production (kWh)	3,285,000
GHG Savings Location-Based (metric tons CO2e)	1913.70
GHG Savings Market-Based (metric tons CO2e)	0.00
Capital Investment (excluding Rebate/Incentive)	$18,500,000
Net Present Value	($11,349,211)
Internal Rate of Return (IRR)	-8%
Payback Period (Years)	N/A
Profitability Index/BCR Ratio	0.39
Debt Service Coverage Ratio	N/A
Equivalent Annual Annuity	($567,461)

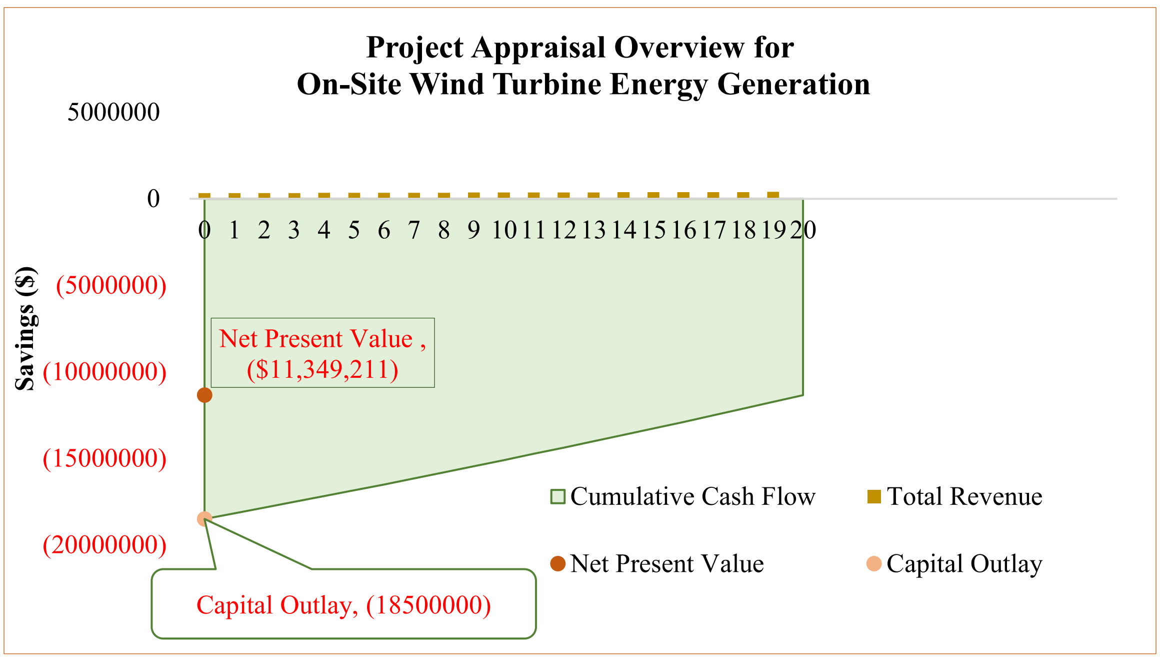

Figure 44. Project appraisal overview for on-site wind generation at TSU

6.3 TEXAS A&M SOLAR POTENTIAL

To obtain an initial assessment, the DEM for Texas A&M was extracted from the ALOS Global Digital Surface Model "ALOS World 3D" with 27.5 meters of spatial resolution and eventually clipped based on the campus profile (Figure 46). The Microsoft building footprint produces the building footprint for this study section with a low inaccuracy rate. However, solar potential GIS processing will detect most of the rooftops (Figure 45).

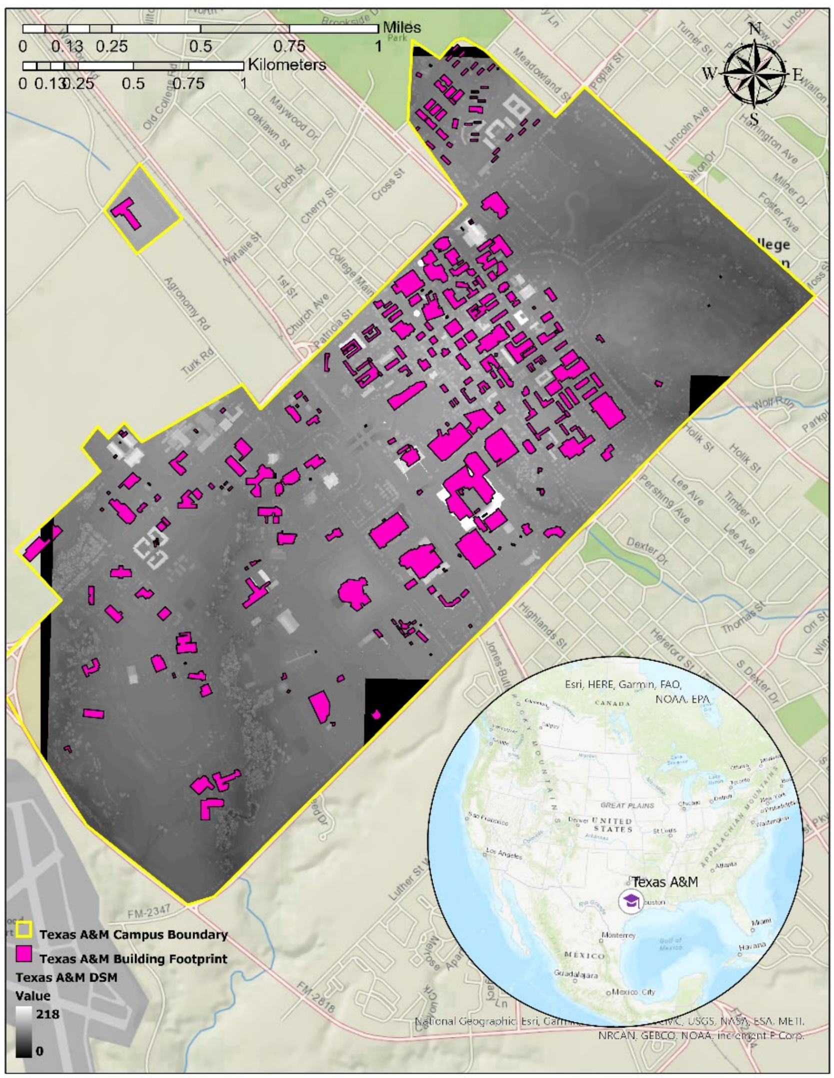

Figure 45. Texas A&M main campus, building footprint, and digital surface model

The output radiation raster is a floating-point type and has watt-hours units per square meter (WH/m^2). The latitude for the study area is in the decimal degree unit. It will be positive for the northern hemisphere and negative for the southern hemisphere. The latitude is also used to calculate solar declination and solar position (ArcGIS Pro documentation). The annual irradiation based on this method reaches the maximum of 82821 WH/m^2 for the best location and a minimum of 18572 WH/m^2 for low and shaded areas, as shown in Figure 46, where the potential is converted to kWh/ m^2 using a LiDAR-based digital elevation model (1-meter spatial resolution). The purpose of assessing the irradiation in two different resolutions is to highlight feature recognition ability between low-medium (Figure 46) and high spatial resolution (Figures 45 and 47) and provide an initial assessment for non-rooftop solar systems.

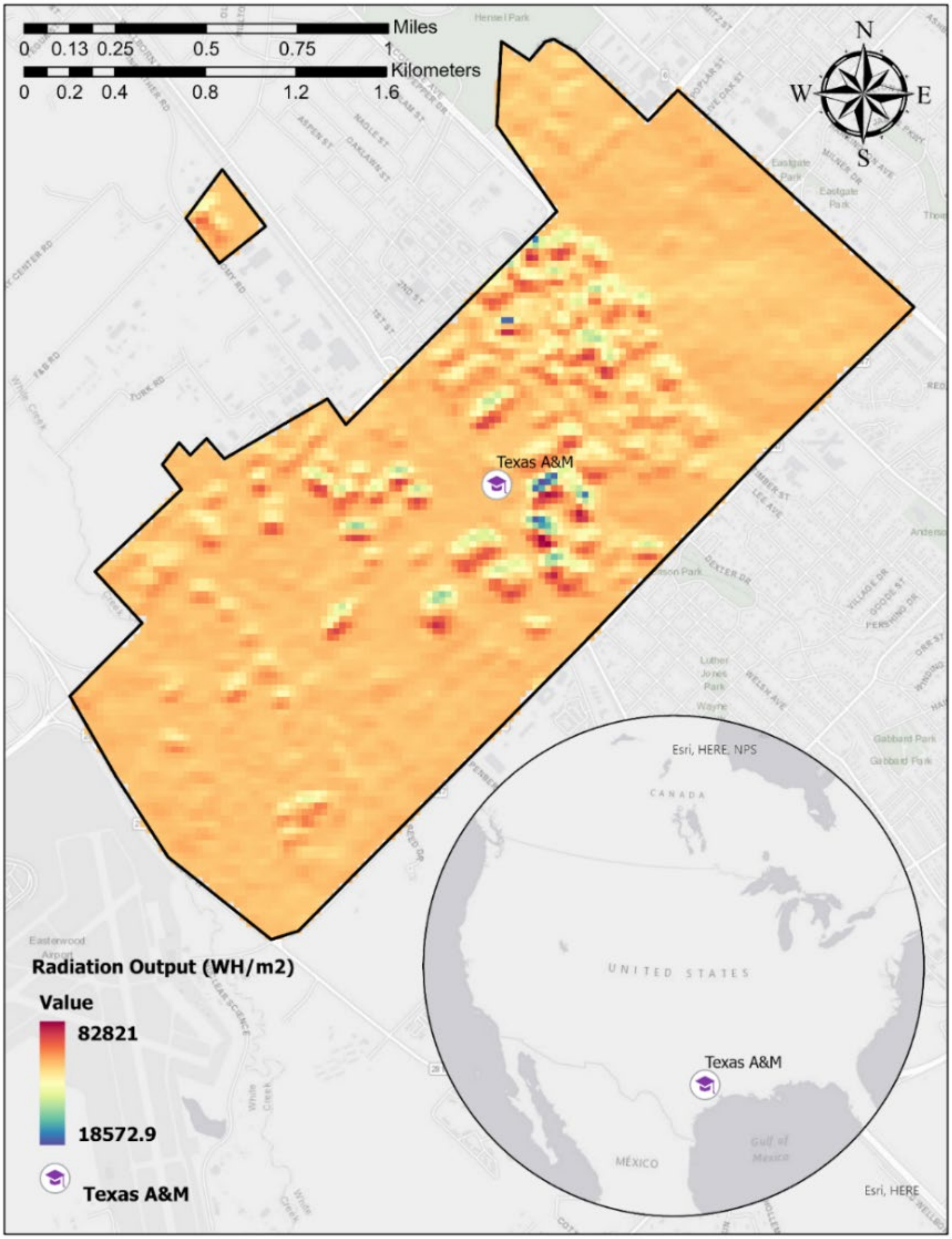

Figure 46. Solar radiation potential at A&M, based on 30-meter spatial resolution

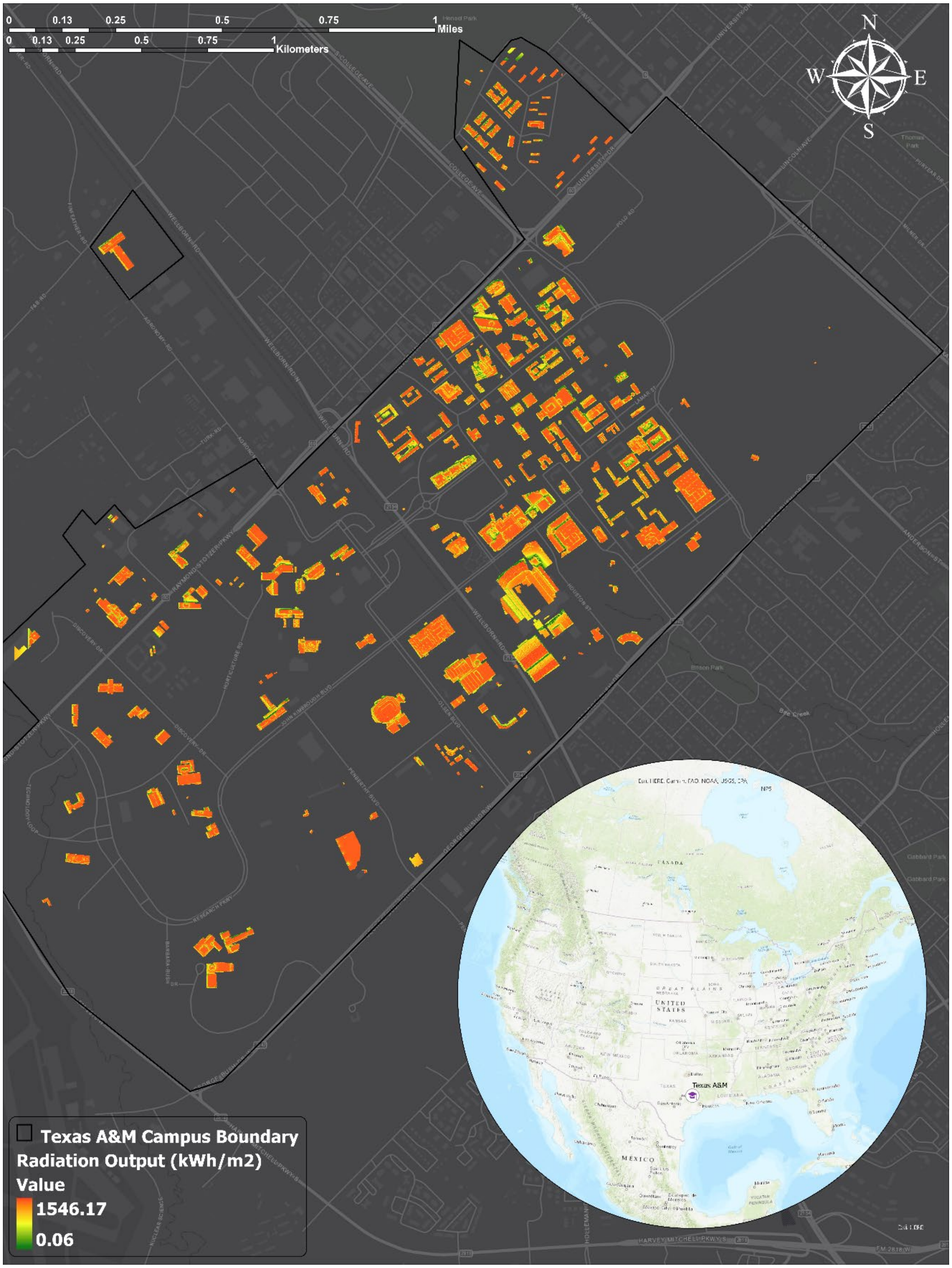

Figure 47. Solar radiation potential at A&M, based on 1-meter spatial resolution

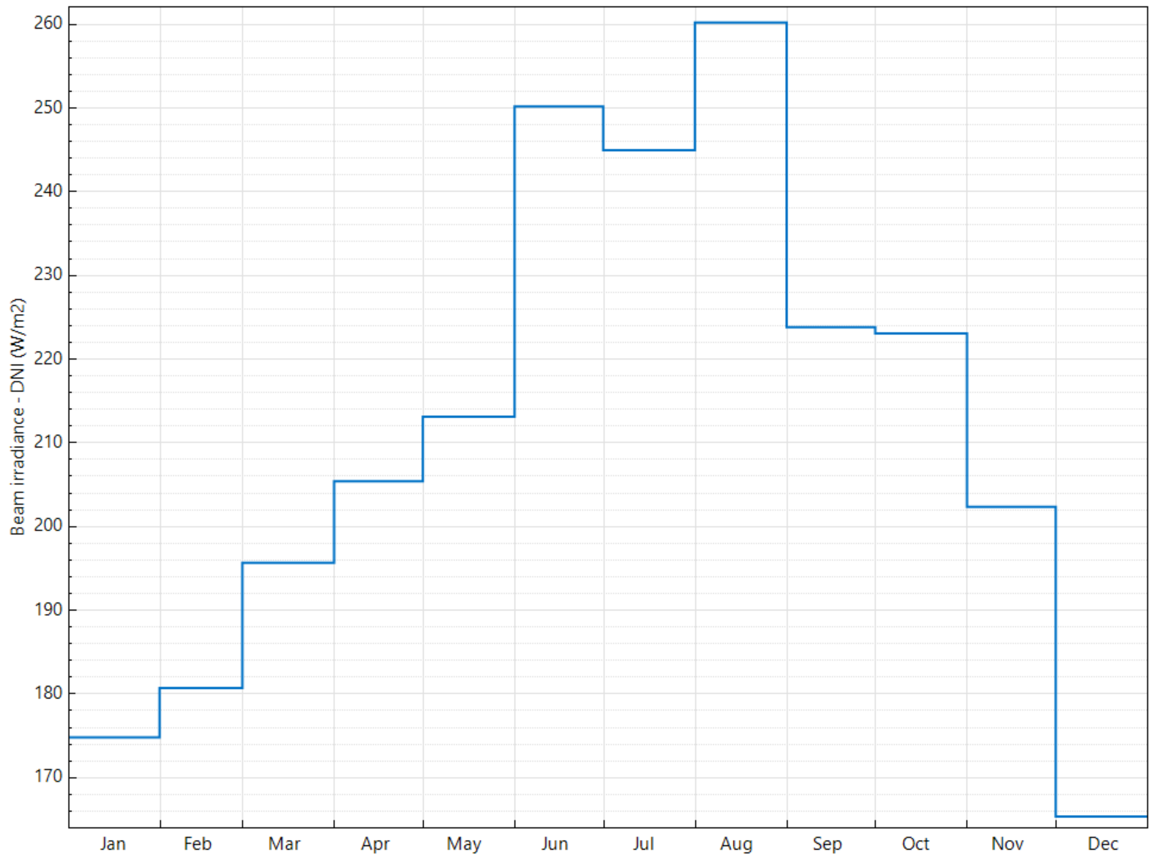

Figure 48. Monthly DNI (W/m^2) at Texas A&M College Station

Comparing the radiation outputs based on the proposed methods (ArcGIS, SolarGIS, and SAM), the average potential solar radiation within the Texas A&M campus reaches a daily 4.5 kWh/m^2. The average potential is slightly larger in SAM and reaches 5.08 kWh/m^2/day (Figure 48). The next question is that the building footprint includes how much of this potential? By having the total area of building footprint (629,235 m^2) and an average of radiation (4.5 kWh/m^2/day), it is possible to calculate the daily potential based on extracted building footprint:

$$629.235\ m^2 * 4.5\ kWh/m^2/day = 2,831,557\ kWh/m^2/day \qquad \text{Equation 45}$$

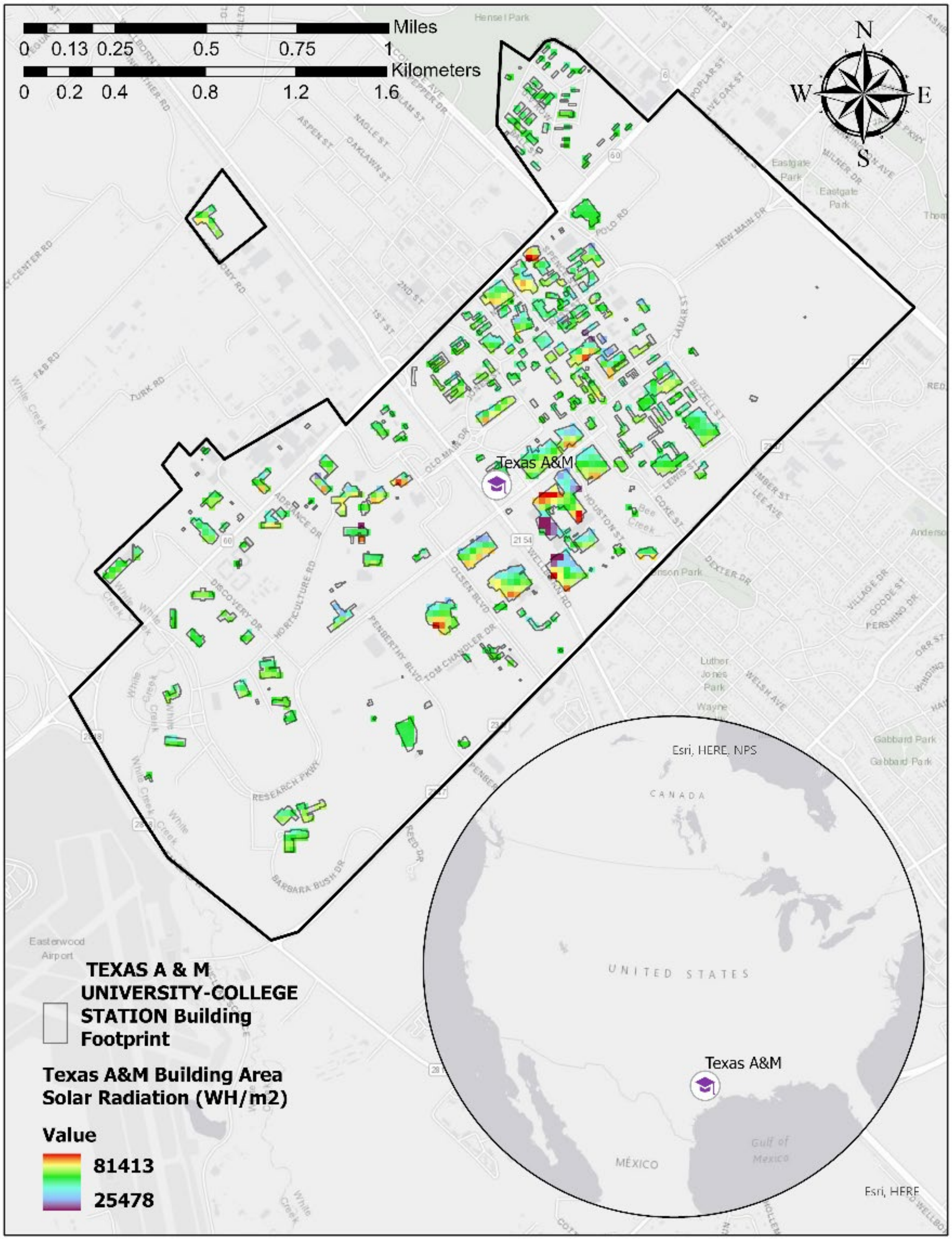

Figure 49. Solar radiation potential at Texas A&M, based on the building footprint

Hence a yearly potential can be calculated as follows:

$$2,831,557\ kWh/m^2/day * 365 = 1,033,518,487 \qquad \text{Equation 46}$$

However, this number is the total potential absorbed by the building footprint area and not the energy produced. Depending on the kind of technology and the capacity factor discussed in chapter 5.4, the produced kWh will be drastically lower than the potential. As mentioned previously, a percentage of building rooftop areas suitable for implementing PV equal to 22%-27% (Chaudhari et al. 2004). Also, "Due to a 4 to 6 feet fire code setback requirement for solar installations, a portion of the rooftop along the perimeter cannot be used to host solar panels" (How to calculate building's rooftop area, Report for U.S. Department of Housing and Urban Development). Hence the calculation should be based on only 70% of the available rooftop to meet the standard conditions. Also, since the rooftop's homogeneity is non-existent in the entire area, the setback could be calculated separately for each building to narrow down the calculation. Hence, 70% of the total building area at Texas A&M is equal to 440464.5 m^2. Considering that a 4kW capacity requires 25 m^2 of the array as discussed in chapter 5.4, we can have 17,618.58 m^2 of array dedicated to solar PV, producing 70,474.32 kW of DC energy. The following figures, 50 and 51, show the project appraisal for a 4 kW_{DC} array, while Table 28 depicts financial and environmental outputs.

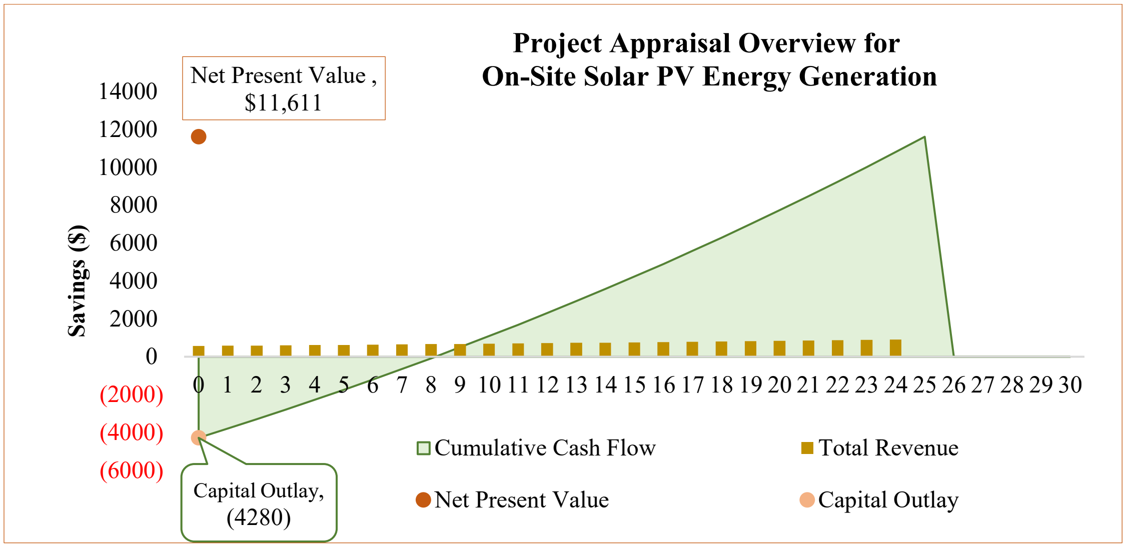

Figure 50. Project appraisal overview for a 4 kWDC on-site solar PV at Texas A&M

Table 28. Project evaluation for solar potential at Texas A&M

Project Valuation	
Annual Energy Production (kWh)	5,662
GHG Savings Location-Based (metric tons CO2e)	3.62
GHG Savings Market-Based (metric tons CO2e)	0.00
Capital Investment (excluding Rebate/Incentive)	$4,280
Net Present Value	$11,611
Internal Rate of Return (IRR)	13%
Payback Period (Years)	8.14
Profitability Index/BCR Ratio	3.71
Debt Service Coverage Ratio	N/A
Equivalent Annual Annuity	$464

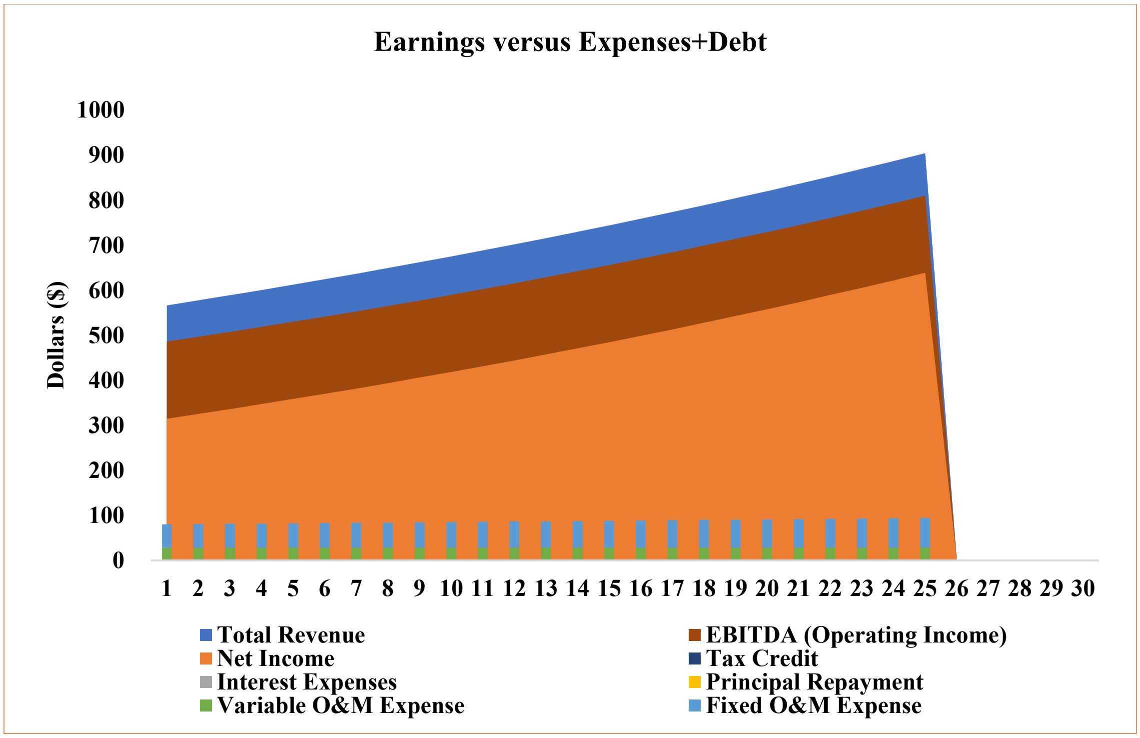

Figure 51. Earnings vs. expenses for a 4 kWDC array on Texas A&M campus

Considering the dynamic nature of the model, any number can be introduced for generation capacity in kW_{DC}. However, the shape of the cumulative cash flow, net income, EBITDA, and total revenue will not change, meaning that any volume of capacity will require at least eight years to recoup the initial investment.

Now we know that not all the building footprints have the optimal condition to implement solar PV. As discussed in the methodology section, suitable rooftops should have a slope of 45 degrees or less since steep slopes tend to receive less radiation. Suitable rooftops should also receive at least 800 kWh/m2 of solar radiation. Suitable rooftops should not face north, as north-facing rooftops in the northern hemisphere receive less sunlight. Hence, a calculation of slope, aspect, and potential reassignment is needed as the next step. Figure 52 shows the extracted area by applying a slope simulation based on the discussion in chapter 5.4.

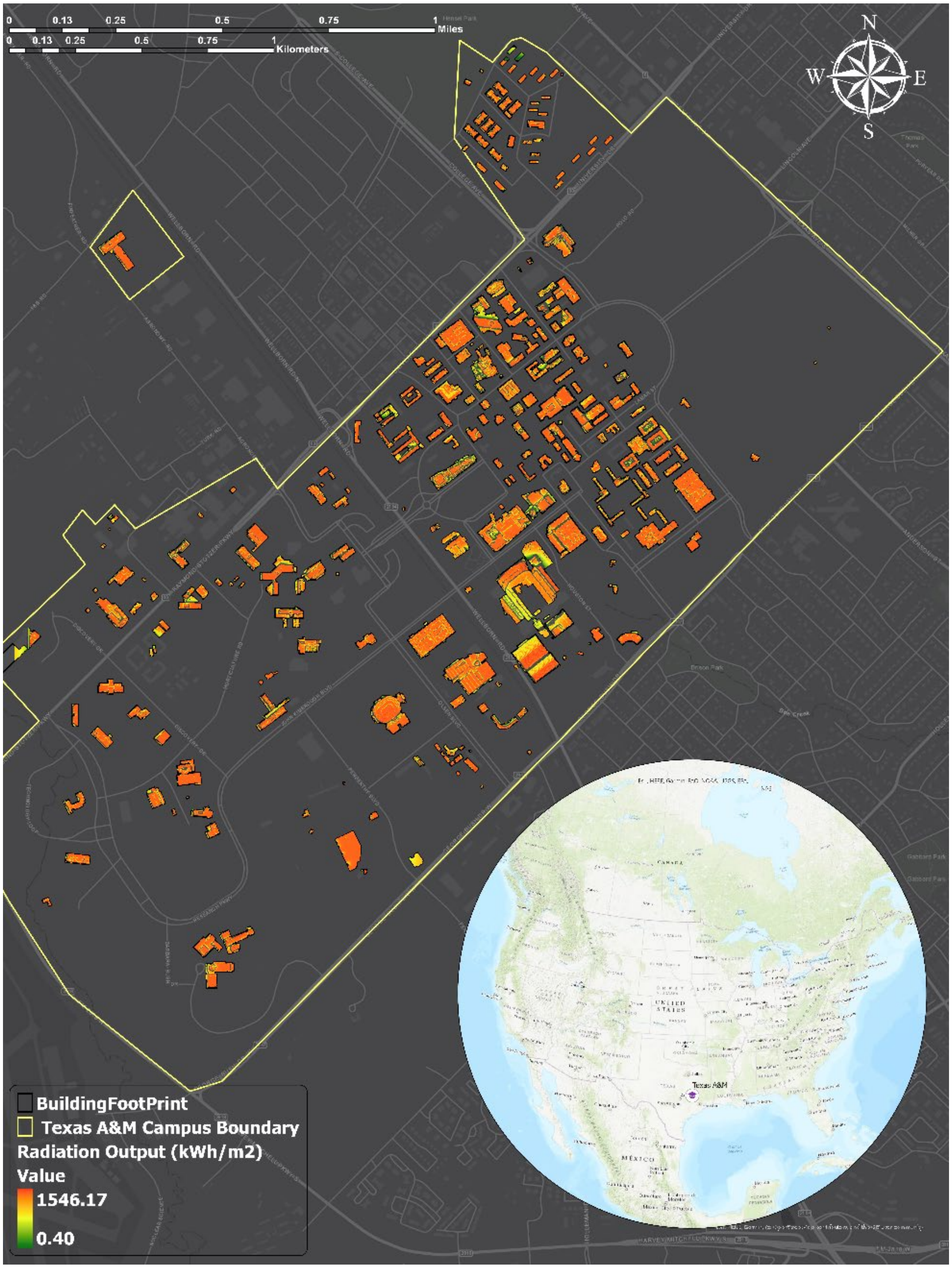

Figure 52. Solar radiation potential at Texas A&M, based on slope simulation

In the next step, we move forward with removing areas with low solar radiation. Rooftop surfaces should receive at least 800 kWh/m^2 in solar radiation if solar panels are installed (Figure 53). This step removes all the pixels with radiation less than 800 kWh/m^2 in a year.

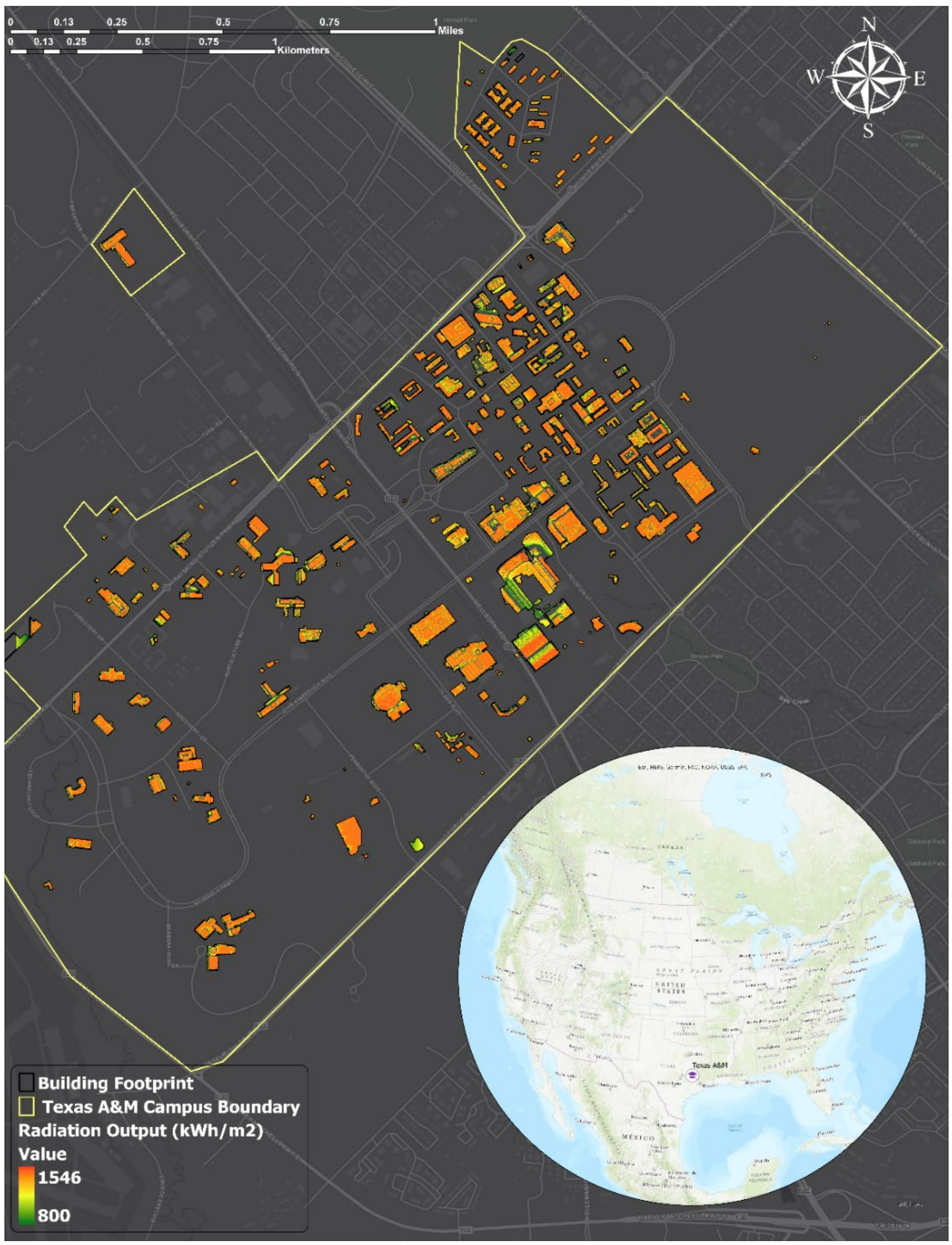

Figure 53. Total radiation after removing unsuitable areas

The majority of north-facing surfaces were already removed by conditional assignment of minimum radiation; however, a few remain. Slopes that face north have a value less than 22.5 degrees or more than 337.5 degrees in the aspect raster layer. Eventually, flat slopes are kept, regardless of their aspect. To achieve the condition above, the Con tool is used first to determine areas with low slopes (less than 10 degrees) and then to determine areas facing north. However, the change is not drastic compared to the previous figure.

A zonal statistic can help calculate the average solar radiation for each building and eventually join the result to the building layer. The next step consists of removing buildings with less than 30 m^2 of the available rooftop (which means a non-feasible condition for the minimum number of the array installation equal to one). As discussed previously, considering the setback on the available area for security reasons, 30 m^2 will not suffice to implement the minimum solar PV. However, all the chosen buildings at Texas A&M have an area greater than 30 m^2.

Next, we can calculate the total average of annual kWh potential production for each building based on the AREA and MEAN fields' values. After the previous step, we can convert the usable solar radiation values to electric power production potential based on average efficiency and the installation's performance ratio according to equation 23 (discussed in 5.4).

The following map (Figure 54) depicts the annual available production capacity on all the building footprints after applying the methodology discussed in chapter 5.4. However, some building footprints are given by parking lots, stadiums, and in some cases, by a portion of not entirely flat objects such as water tanks. These footprints are not removed to provide an estimation of the rooftop creations matching the given available area. Also, the values classification is based on Jenks's natural brakes discussed in the methodology section. Total production after applying all the methods reaches 108,667 MWh in a year.

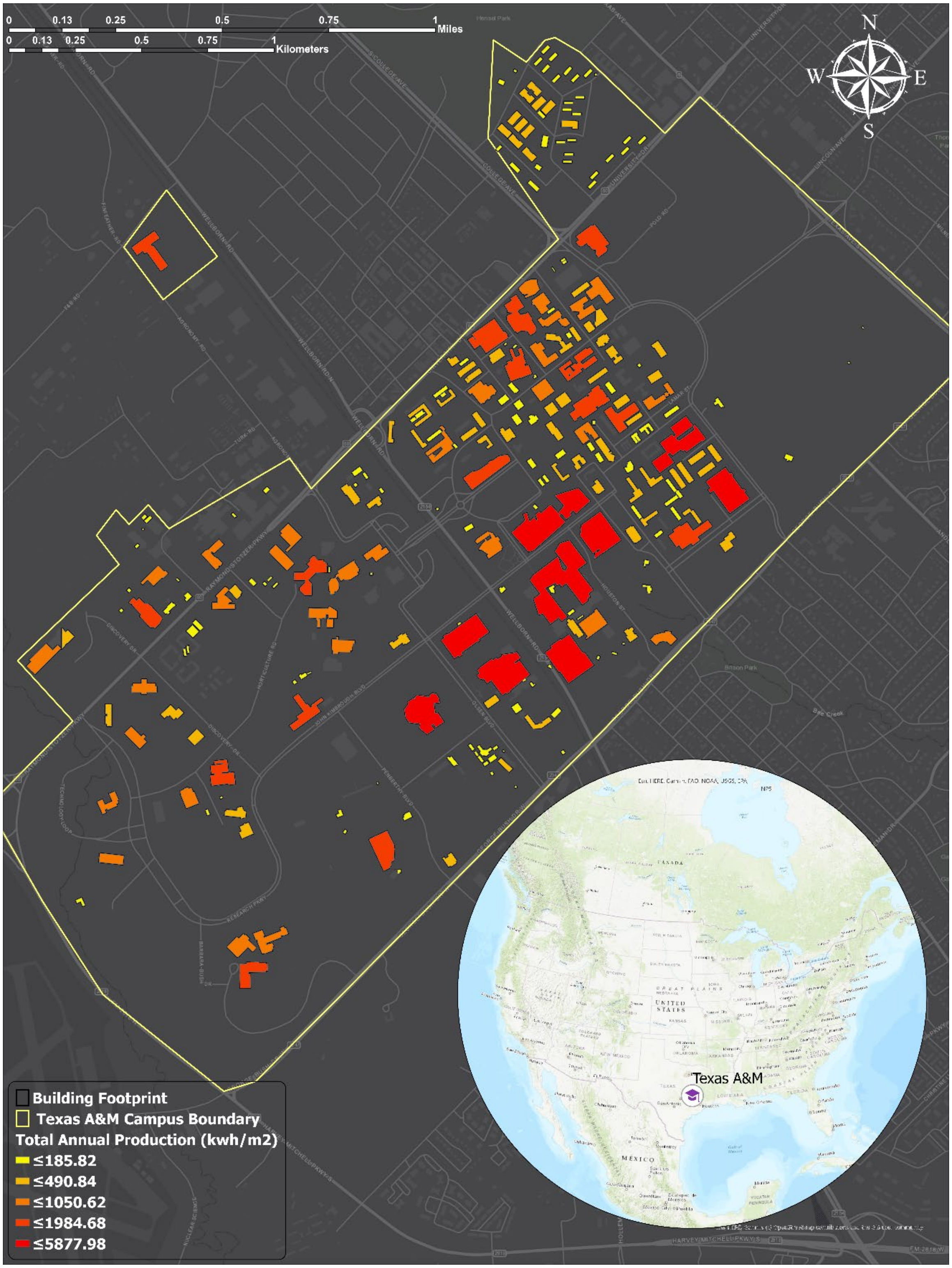

Figure 54. Final potential production at Texas A&M

6.4 TEXAS A&M WIND POTENTIAL

There are 264 constructed buildings around Texas A&M University's main campus, with an average height of 122 meters. The average wind speed in College Station, Texas, where Texas A&M is located, is calculated based on the NSRDB station 712655 (Figure 55). In this study, wind power was assessed based on data for the four seasons from the nearest methodological station to the campus. The seasonal mean variation in 2019 ranged from 1.5 m/s to 3.2 m/s (Figure 55). The limited rate of change in mean wind speed causes a low wind power class (Class 1 or 2) at North Central Texas, where Texas A&M is located. As mentioned, there is a high rate of fluctuation in wind speed depending on surface roughness. Power density can vary from season to season (Akpinar, & Akpinar, 2005). The energy output is given by fixed numbers while having an exact estimation of wind turbine output is difficult due to wind power and wind speed instability.

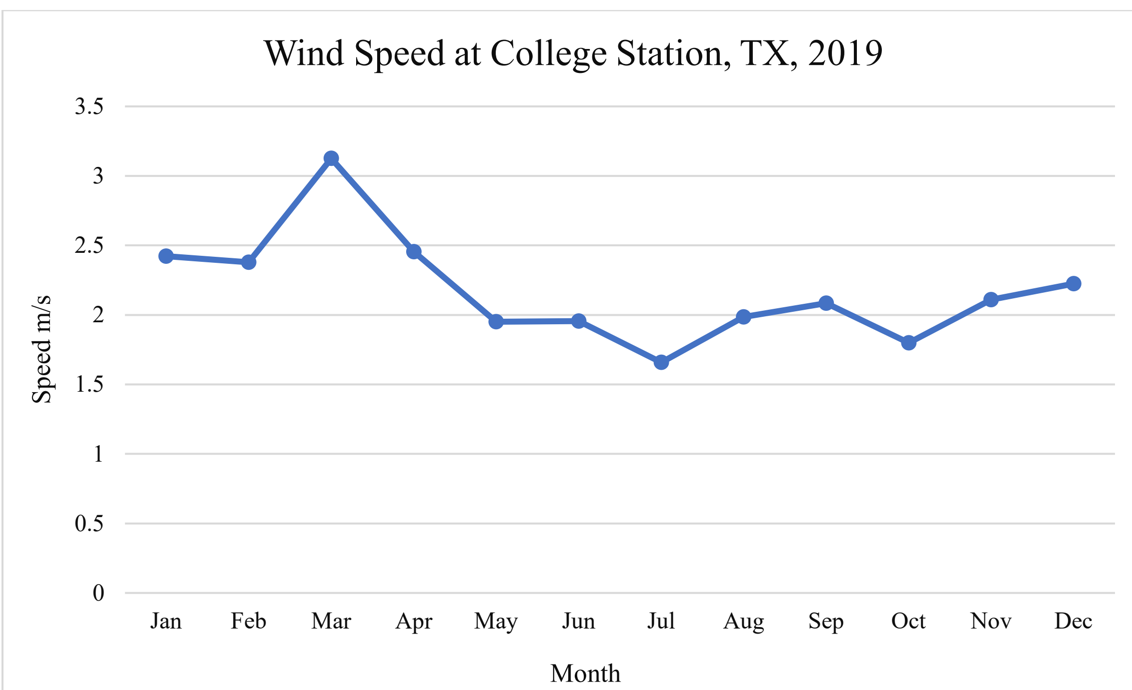

Figure 55. Mean wind speed at College Station based on the nearest weather station

On the other hand, studies show that higher wind speed occurs in higher elevations. Hence, having different buildings with different heights will impact the calculation of output. “The cut-in speed, which is the minimum speed at which the wind turbine will generate usable power, is typically between 3 and 5 m/s” (Al Yahyai et al., 2011 p.154). There is some peak of high wind speed registered in data, such as the one during March 2019, which can partially compensate for the low wind power in other seasons. Figure 57 shows the elevation in a generalized way produced by the digital elevation model.

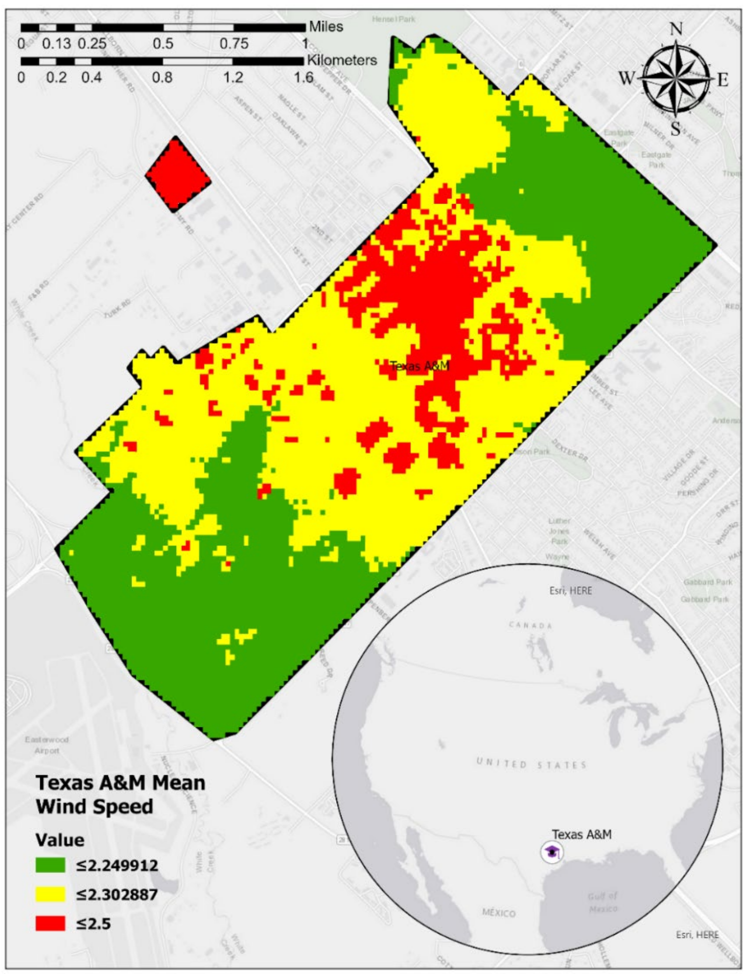

Figure 56. Texas A&M mean wind speed

Figure 57 shows the elevation of rooftops at Texas A&M based on LiDAR. Texas A&M's main campus elevation ranges from 89 meters to 218 meters on top of the buildings (Figure 57).

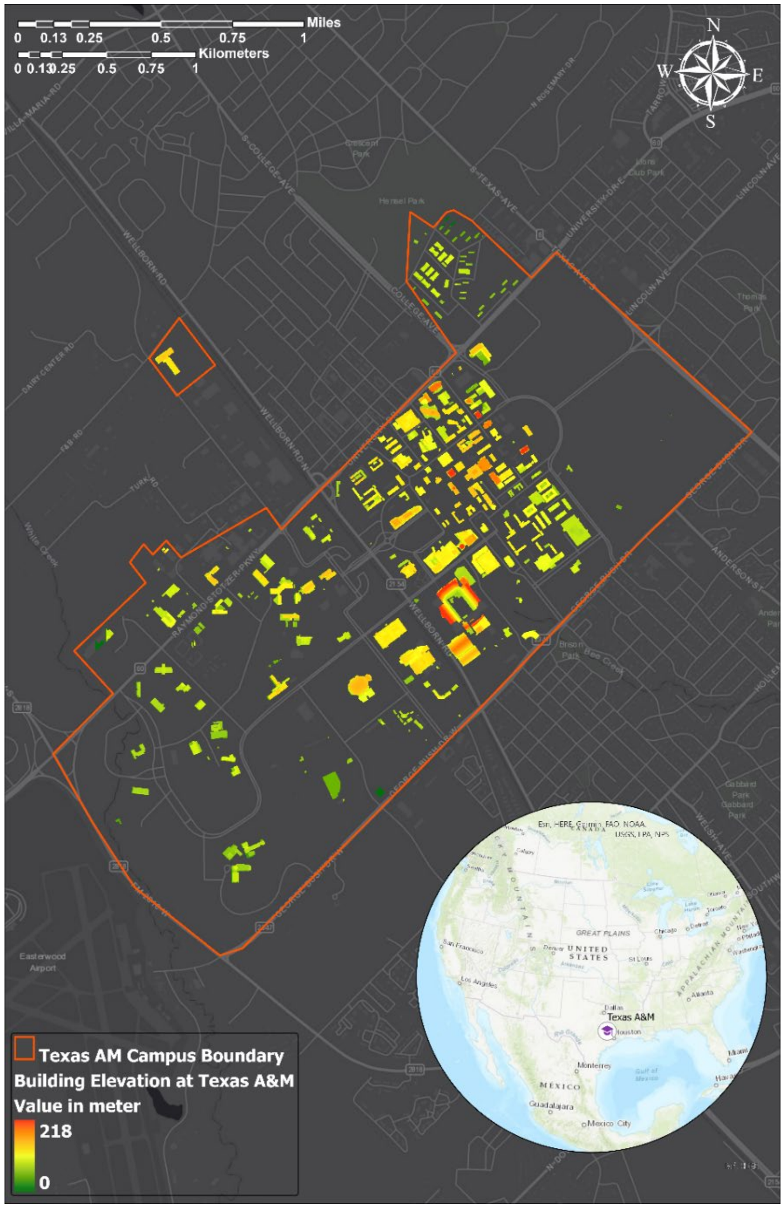

Figure 57. Rooftop elevation at Texas A&M

The difference between figures 56 and 57 is given by the inclusion of buildings on the map for mean wind speed at the College Station campus. However, the difference between the wind speed on top of the buildings and the ground is not significant.

By inserting values in equation 17 and including the average wind speed of 2.2 m/s, the reference elevation at 99 meters (Station ID: 712655, Lat: 30.61, Long: -96.34), and a shear factor of 0.25 then we have the following figure with average wind speed for Texas A&M campus.

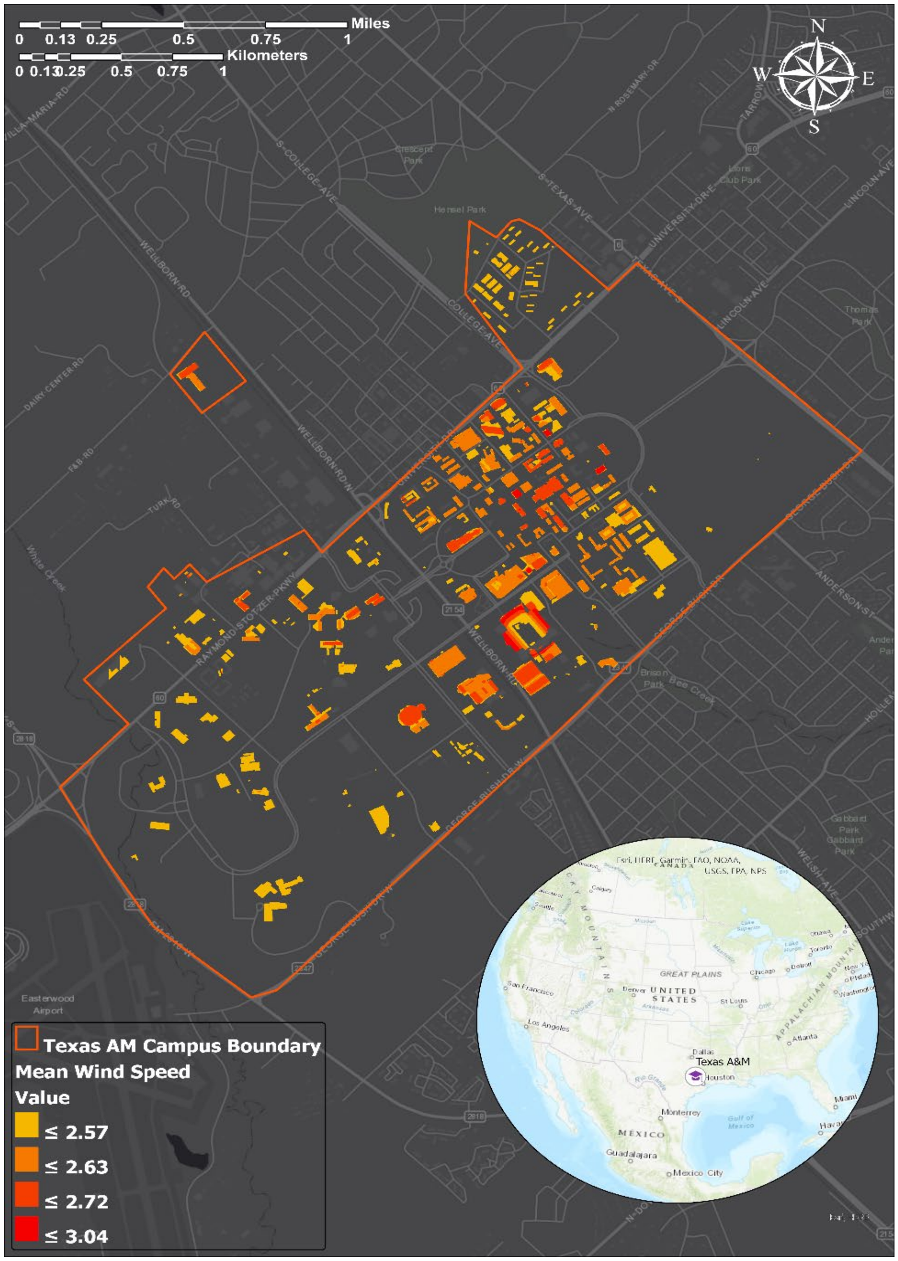

Figure 58. Mean wind speed based on rooftop elevation at Texas A&M

Since the minimum cut-in speed is set to 3 to 5 meters per second (Al Yahyai et al., 2011 p.154), only the buildings falling inside that range must be kept. However, none of the buildings at Texas A&M reaches the cut-in speed unless a seasonal study is applied, such as one focused on March with a higher than three m/s wind speed. It is clear that with a low-class power of wind, no small wind project will be feasible even if federal help and credits are added to the project. However, to provide an example of negative NPV, Figure 59 shows the project appraisal for a single small wind turbine with 100 kW daily of capacity.

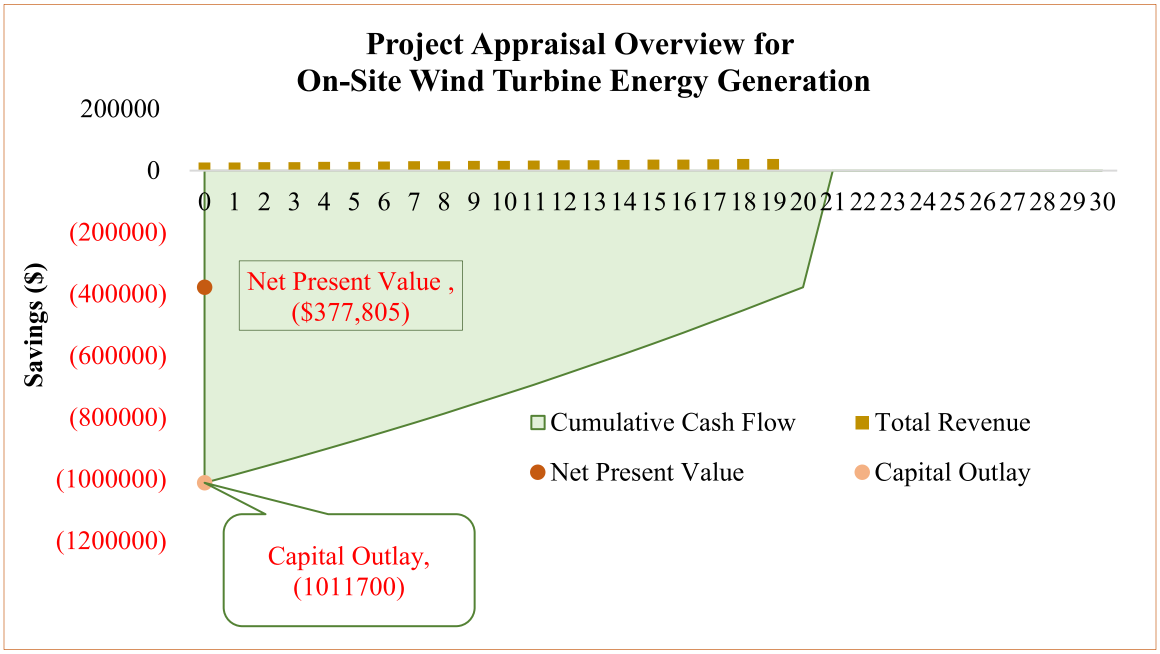

Figure 59. Project appraisal overview for on-site wind generation at Texas A&M

6.5 UC BERKELEY SOLAR POTENTIAL

The Digital Surface Model (DSM) for UC Berkeley is produced by mosaicking separate LiDAR files (LAS) with a spatial resolution of 1 meter. The LiDAR used for this section of the study is last updated in 2018. The building footprint was already digitalized for UCB; hence no processing is needed to create the building footprint (Figure 60).

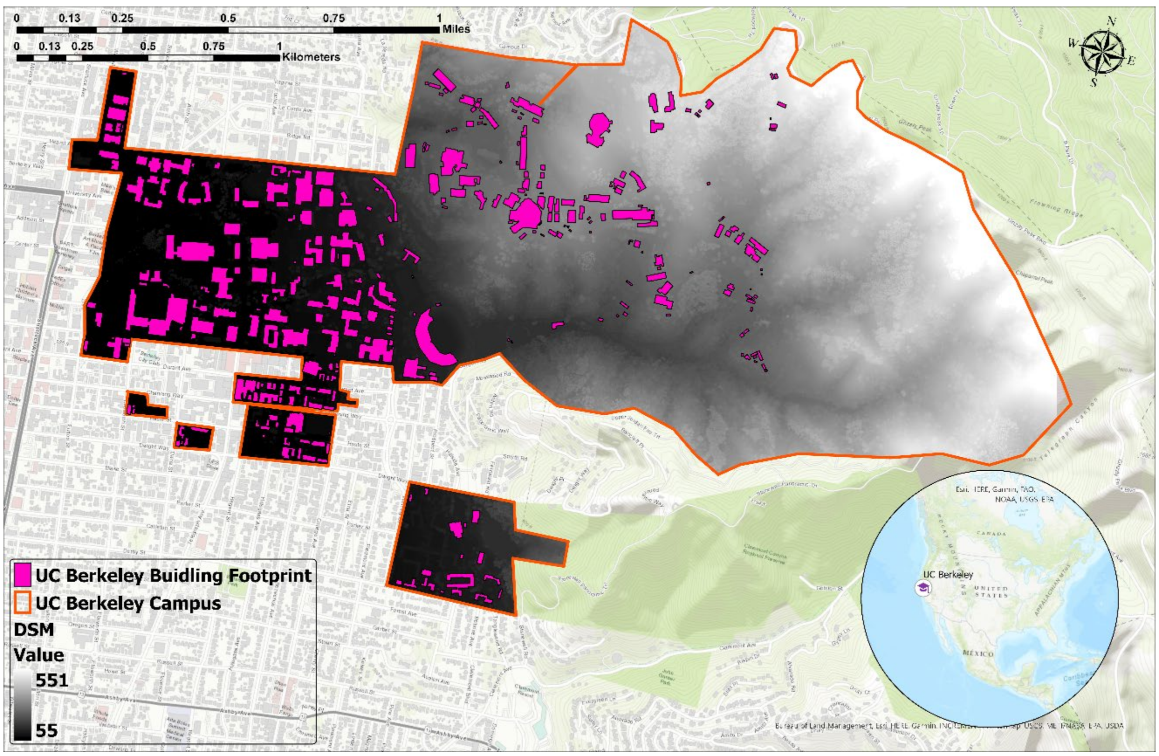

Figure 60. UC Berkeley main campus, building footprint, and digital elevation model

According to the NSRDB weather file (Station ID: 62944, Lat: 3152, Long: -106.18, elevation: 1099 meters), the average daily radiation potential (DNI) for San Fransisco bay reaches 7.59 kWh/m^2. Figure 61 shows the monthly potential.

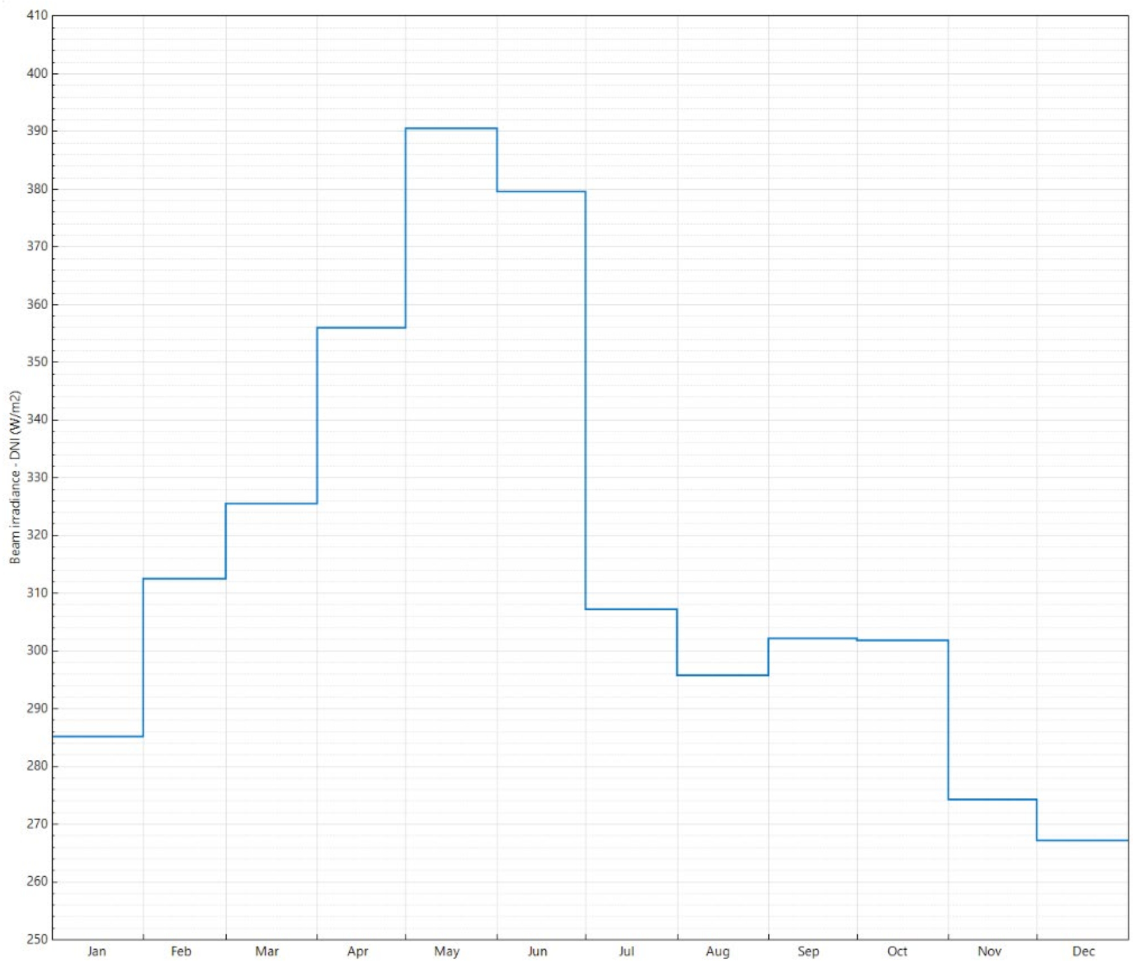

Figure 61. Monthly DNI (W/m²) at UC Berkeley

The output radiation raster is a floating-point type and has units of watt-hours per square meter (WH/m^2); however, in cases where there is a need to use a Zonal Statistic, the user can convert the float numbers to an integer. The latitude for the study area is in the decimal degree unit. It will be positive for the northern hemisphere and negative for the southern hemisphere. The latitude is also used to calculate solar declination and solar position (ArcGIS Pro documentation). The annual output based on this method reaches the maximum of 1456 kW/m^2 for the best location and a minimum of 0.15 kW /m^2 for low and shaded areas, as shown in Figure 62.

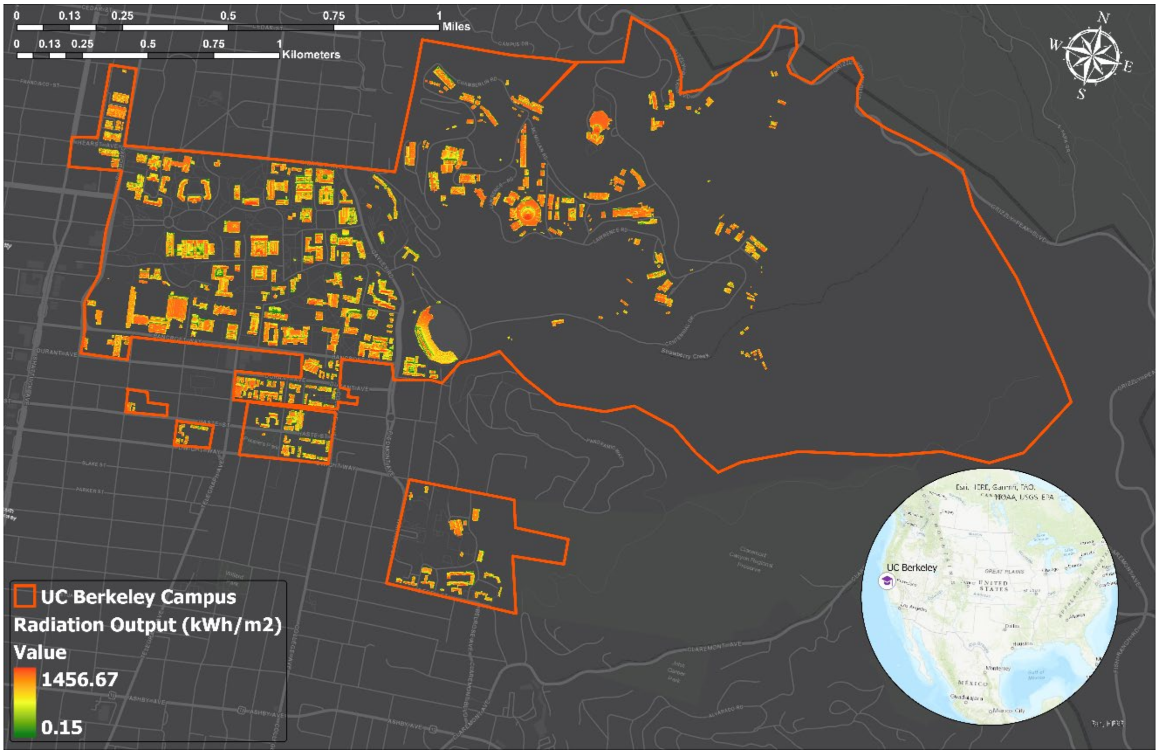

Figure 62. Solar radiation potential at UC Berkeley, based on the building footprint

Having the total area of building footprint (393,246 m^2) and an average of radiation 7.59 (DNI) kWh/m^2/day, it is possible to calculate the daily potential based on extracted building footprint:

$$393{,}246\ m^2 * 7.59\ kWh/m2/day = 2{,}977{,}147.14\ kWh/m2/day \qquad \text{Equation 47}$$

Hence a yearly potential can be calculated as follows:

$$2{,}977{,}147.14\ kWh/m2/day * 365 = 1{,}086{,}658{,}706.1 \qquad \text{Equation 48}$$

However, the obtained number is the total potential absorbed by the building footprint area and not the energy produced. Depending on the kind of technology and the capacity factor discussed in chapter 5.4, the produced kWh will be drastically lower than the potential. As mentioned previously, a percentage of building rooftop areas suitable for implementing PV equal to 22%-27% (Chaudhari et al. 2004). Also, “Due to a 4 to 6 feet fire code setback requirement for solar installations, a portion of the rooftop along the perimeter cannot be used to host solar panels” (How to calculate building’s rooftop area, Report for U.S. Department of Housing and Urban Development). Hence the calculation should be based on only 70% of the available rooftop to meet the standard conditions. Also, since the rooftop's homogeneity is non-existent in the entire area, the setback could be calculated separately for each building to narrow down the calculation.

70% of the total building area at UC Berkeley is equal to 275272.19 m^2. Considering that a 4kW capacity requires 25 m^2 of the array as discussed in chapter 5.4, we can have 11,010.88 m^2 of array dedicated to solar PV, producing 44,043.52 kW of DC energy. This number can be used as the financial model's input (Figure 63) but is still not as accurate as it should be since further processing is needed. As seen in the figure, the number of years required to recoup the initial investment is very similar to the previous case studies, and on average, it reaches 7-8 years.

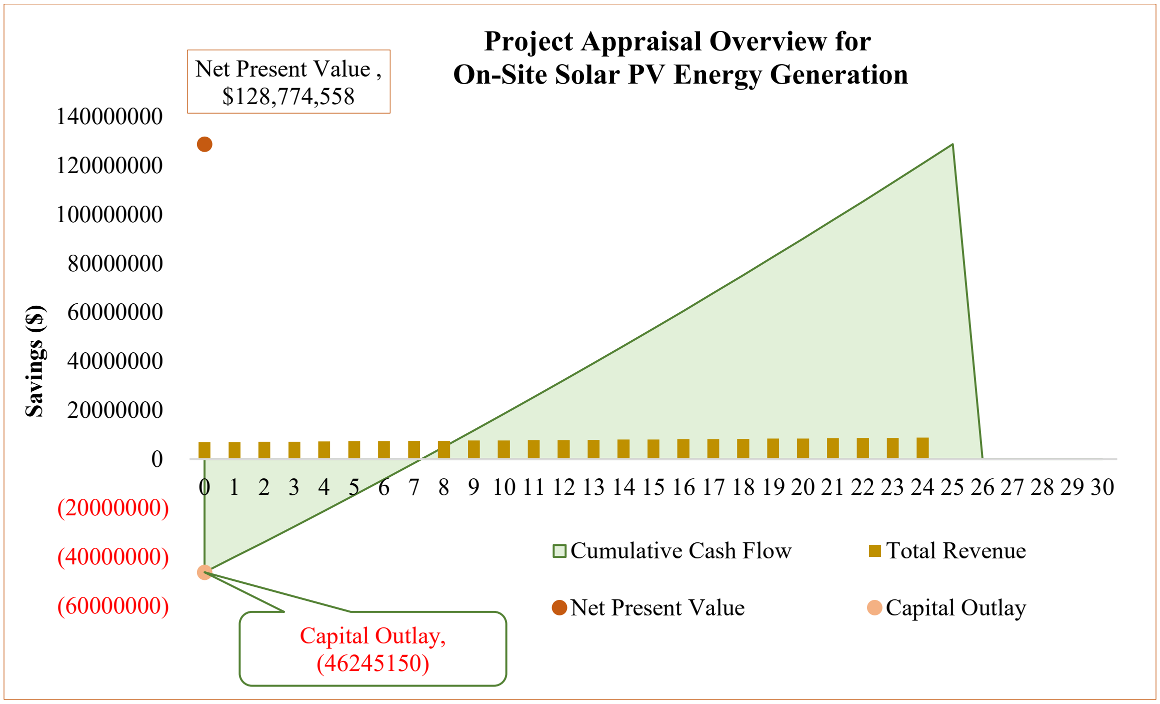

Figure 63. Project appraisal overview for on-site solar PV at UC Berkeley

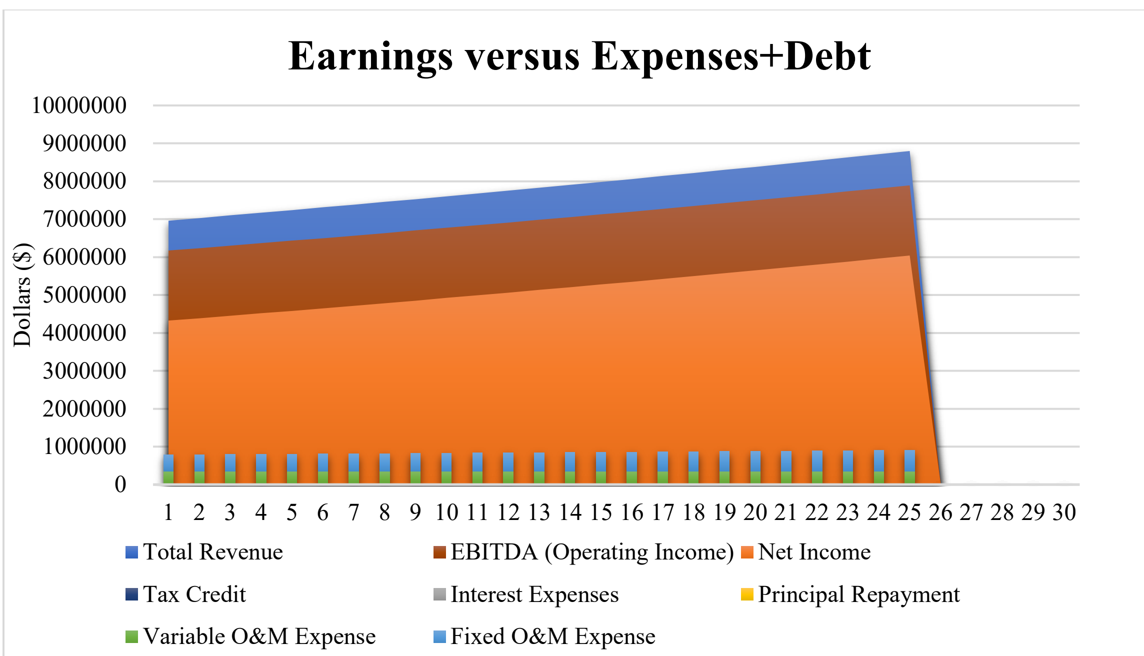

Figure 64. Earnings vs. expenses based on potential generation capacity at UCB

Table 29. Project evaluation for solar potential at UC Berkeley

Project Valuation	
Annual Energy Production (kWh)	69,623,112
GHG Savings Location-Based (metric tons CO2e)	29862.79
GHG Savings Market-Based (metric tons CO2e)	0.00
Capital Investment (excluding Rebate/Incentive)	$46,245,150
Net Present Value	$128,774,558
Internal Rate of Return (IRR)	14%
Payback Period (Years)	7.25
Profitability Index/BCR Ratio	3.78
Debt Service Coverage Ratio	N/A
Equivalent Annual Annuity	$5,150,982

As discussed in the methodology section, suitable rooftops should have a slope of 45 degrees or less since steep slopes tend to receive less radiation. Suitable rooftops should also receive at least 800 kWh/m^2 of solar radiation. Suitable rooftops should not face north, as north-facing rooftops in the northern hemisphere receive less sunlight. Hence, a calculation of slope, aspect, and potential reassignment is needed as the next step (Figure 65).

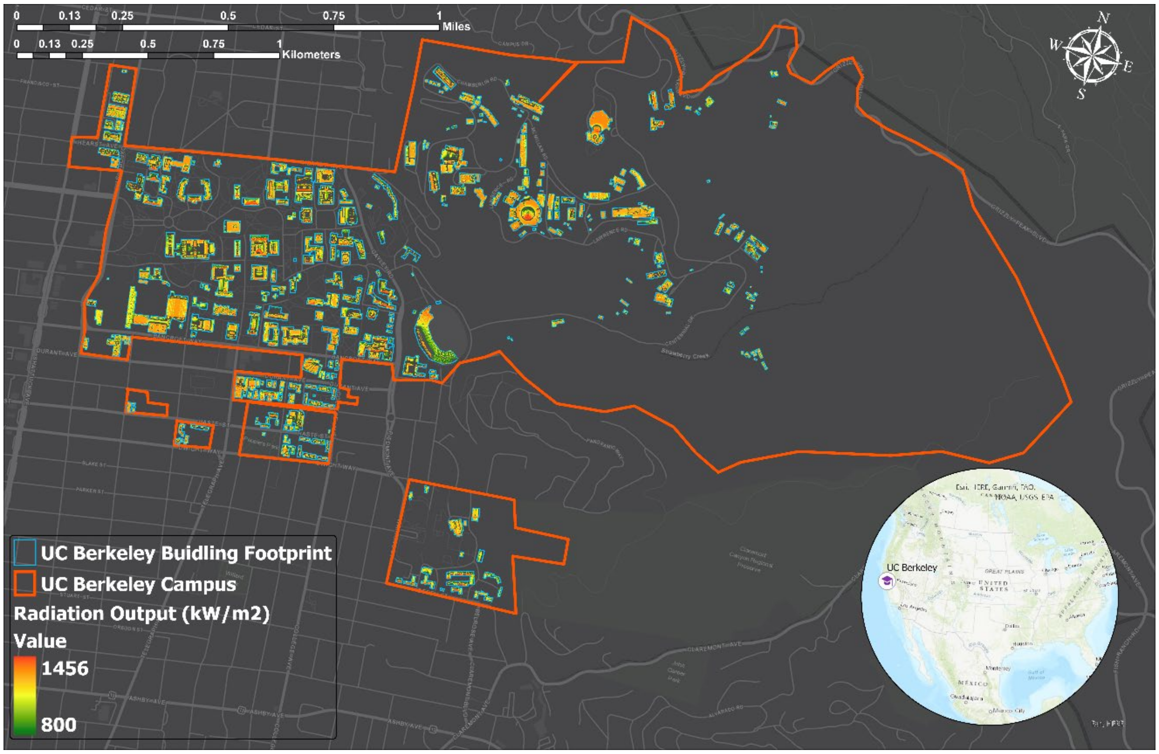

Figure 65. Solar radiation potential at UCB after minimum kWh/m² condition

The majority of north-facing surfaces were already removed by conditional assignment of minimum radiation. Slopes that face north have a value less than 22.5 degrees or more than 337.5 degrees in the aspect raster layer. Eventually, flat slopes will be kept, regardless of their aspect. To achieve the condition above, the Con tool will be used first to determine areas with low slopes (less than 10 degrees) and then to determine areas facing north.

A zonal statistic approach will assign the potential to the building footprint by determining the mean value of the potential. The table contains fields for the number of cells, the area in square meters, and the average solar radiation in kWh/m2 for each building. Next, we remove structures with less than 30 square meters of area, and by doing that, 292 out of 316 buildings will be selected.

Next, we convert the potential to MWh according to equation 44, and as the final step, the potential will be converted to power based on equation 23. Figure 66 shows the final output with the chosen buildings and potential electricity produced in MWh.

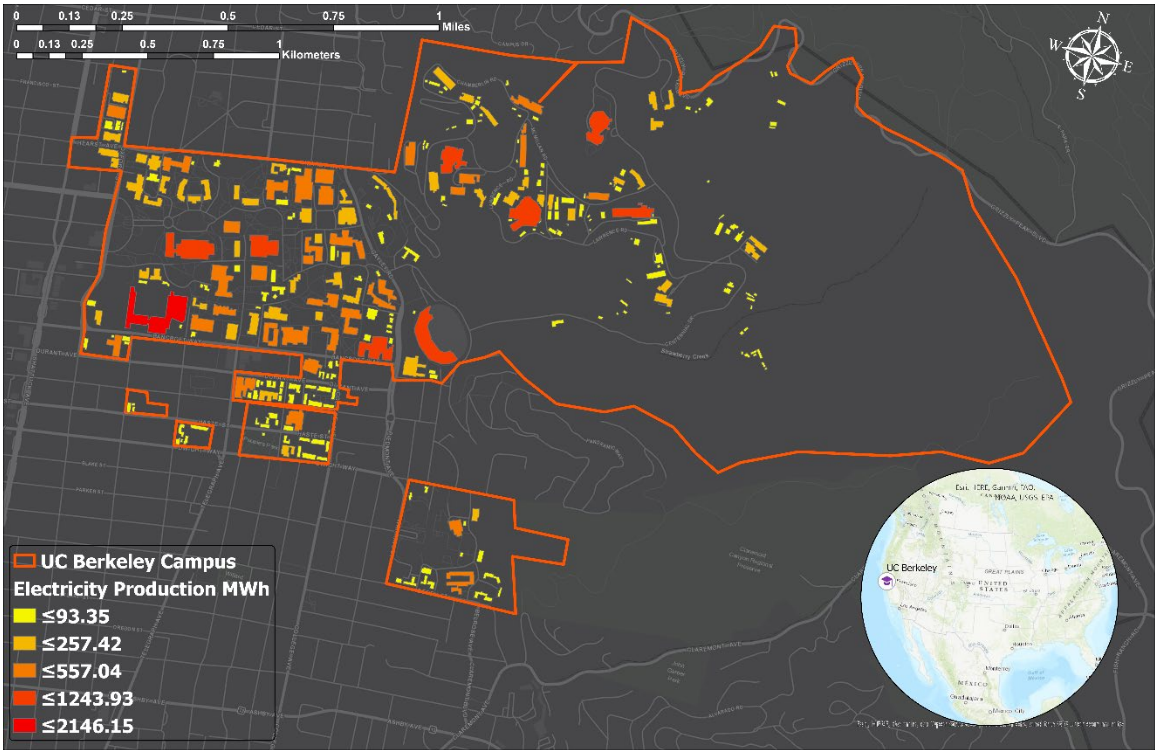

Figure 66. Final potential production at U.C Berkeley

The applied methods offer a more detailed and accurate output. The total possible output reaches 35,609 MWh.

6.6 UC BERKELEY WIND POTENTIAL

There are 316 constructed buildings within the U.C Berkeley main campus, with an average height of 130 meters above sea level. The average wind speed in San Francisco Bay, where U.C Berkley is located, is calculated based on the NSRDB station 62944 (Figure 67). The wind power is assessed based on data for the four seasons from the nearest methodological station to the campus. The seasonal mean variation in 2019 reached three m/s (Figure 67).

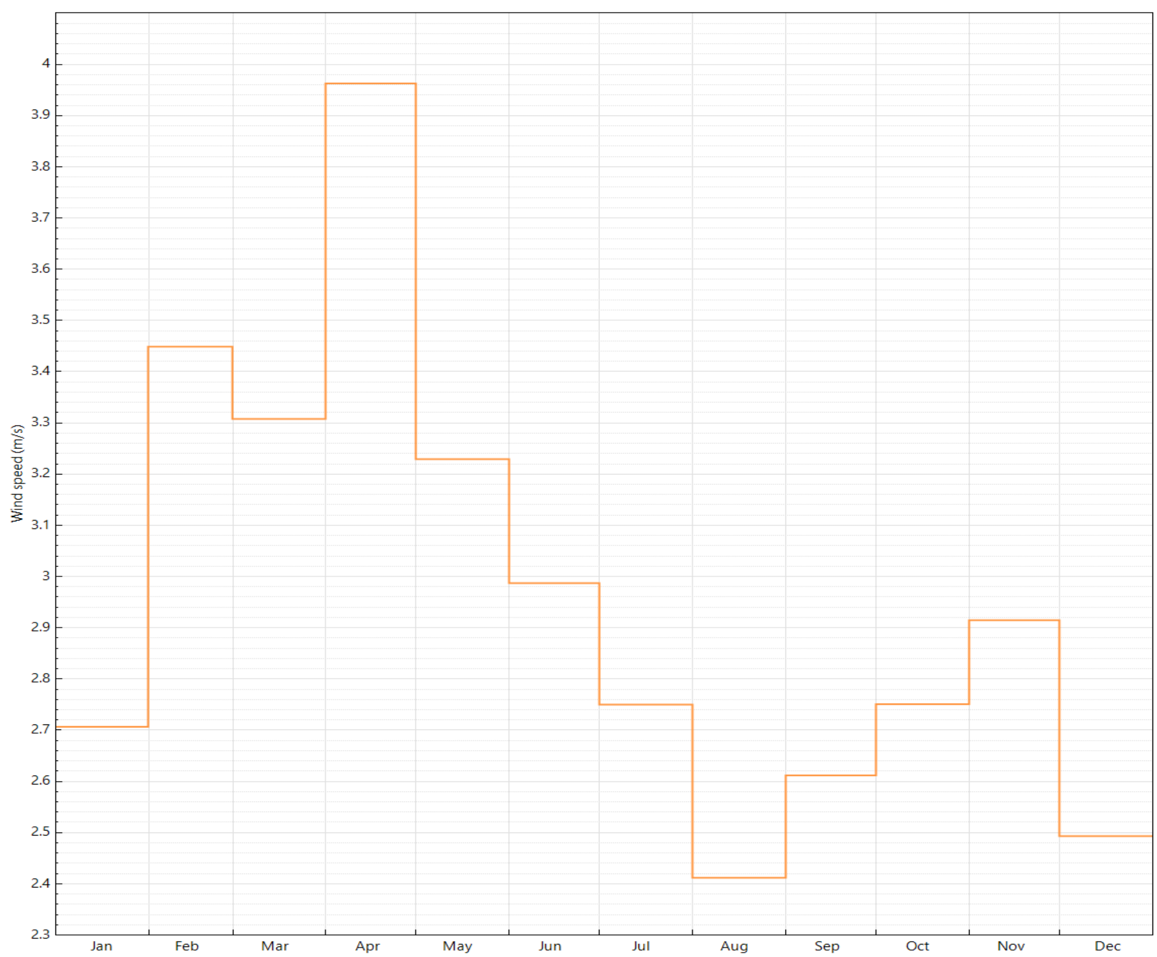

Figure 67. Mean wind speed at San Francisco Bay in 2019

The limited rate of change in mean wind speed causes a low wind power class (Class 1 or 2) at San Francisco Bay. As mentioned, there is a high rate of fluctuation in wind speed depending on surface roughness. Power density can vary from season to season (Akpinar, & Akpinar, 2005). The energy output is given by fixed numbers while having an exact estimation of wind turbine output is difficult due to wind power and wind speed instability.

On the other hand, studies show that higher wind speed occurs in higher elevations. Hence, having different buildings with different heights impacts the calculation of output. “The cut-in speed, which is the minimum speed at which the wind turbine generates usable power, is typically between 3 and 5 m/s” (Al Yahyai et al., 2011 p.154). There is some peak of high wind speed registered in data, such as the one during April 2019, which can partially compensate for the low wind power in other seasons. Figure 68 shows the elevation of rooftops at Colorado State University.

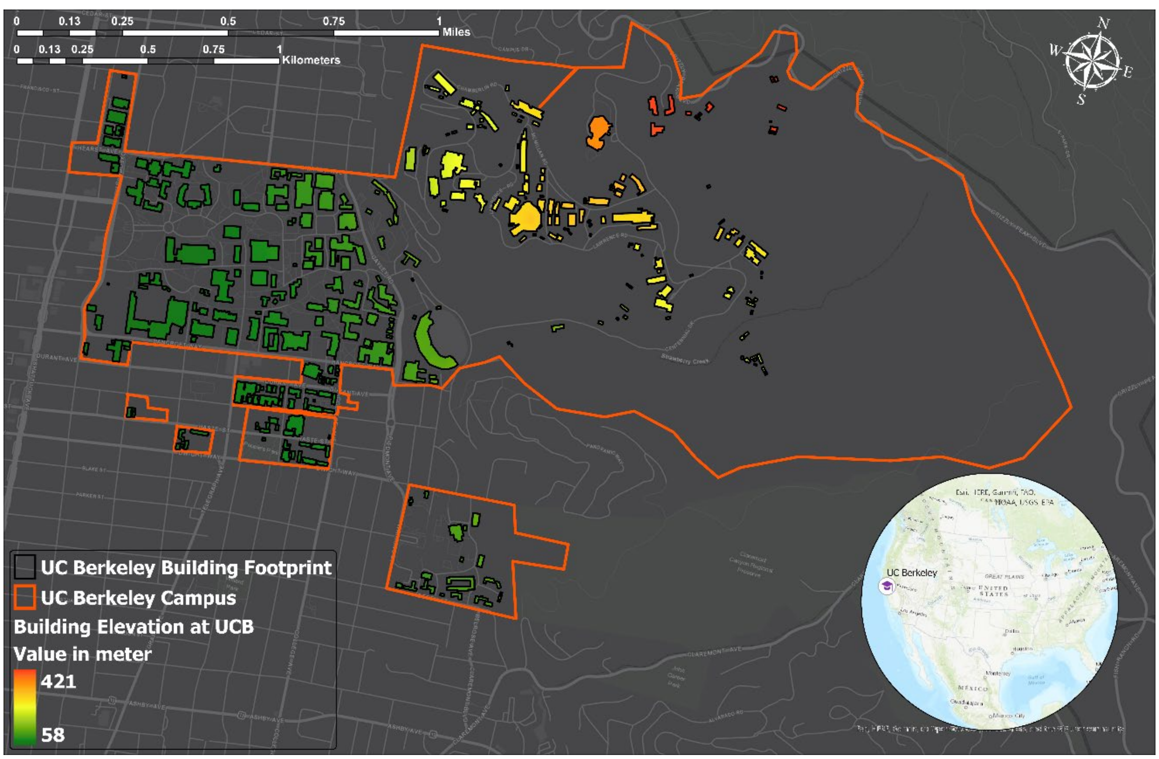

Figure 68. Rooftop elevation at UC Berkeley

After determining the elevation of available rooftops (via LiDAR), we can calculate the average wind speed based on Equation 17, discussed in chapter 5.3.1 (Figure 69). However, the range of change is minimal; hence three categories are chosen based on Natural Breaks (Jenks).

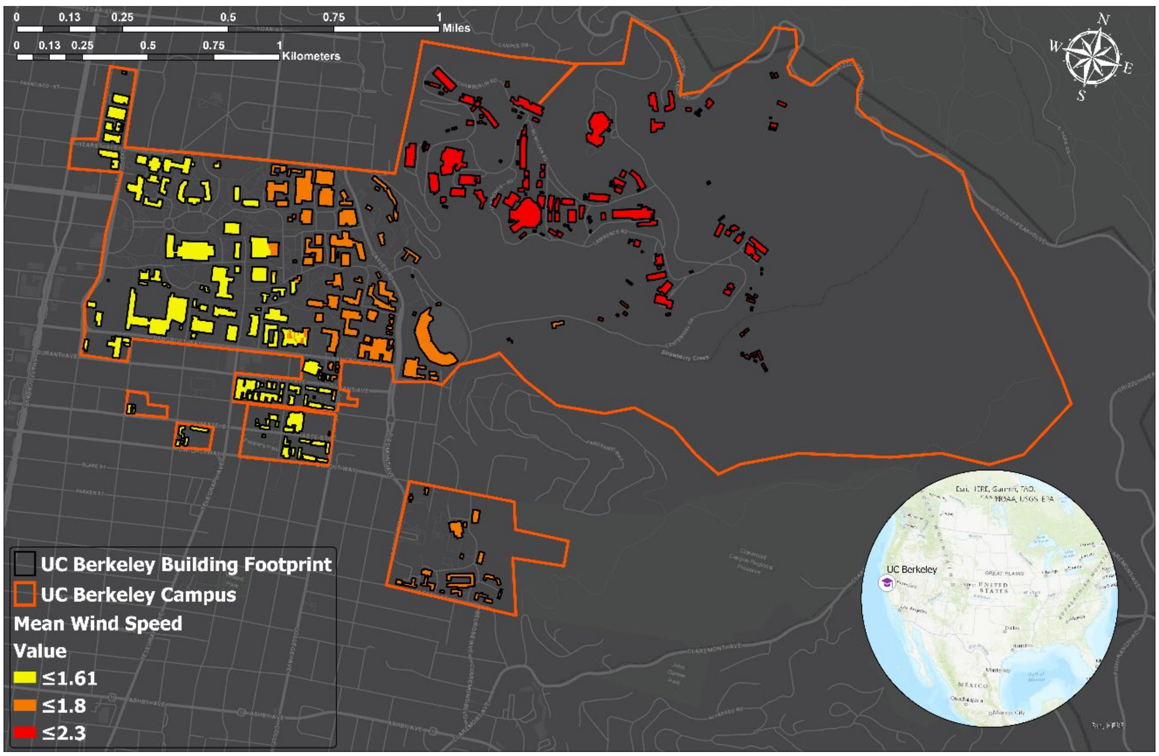

Figure 69. Mean wind speed based on rooftop elevation at UCB

Since the minimum cut-in speed is set to 3 to 5 meters per second (Al Yahyai et al., 2011 p.154), only the buildings falling inside that range must be kept. However, none of the buildings at UC Berkeley reaches the cut-in speed unless a seasonal study is applied, such as one focused on April with a higher than three m/s wind speed. It is clear that with a low-class power of wind, no small wind project will be feasible even if federal help and credits are added to the project.

6.7 COLORADO STATE UNIVERSITY SOLAR POTENTIAL

The Digital Surface Model (DSM) for Colorado State University (CSU) is produced by mosaicking separate LiDAR files (LAS) with a spatial resolution of 1 meter. The LiDAR used for this section of the study is last updated in 2015. The building footprint was already digitalized for CSU; hence no processing is needed to create the building footprint. The criteria for delineating the building footprint consisted of selecting buildings intersecting with the campus boundary to include the buildings not falling completely inside the campus boundary (Figure 70).

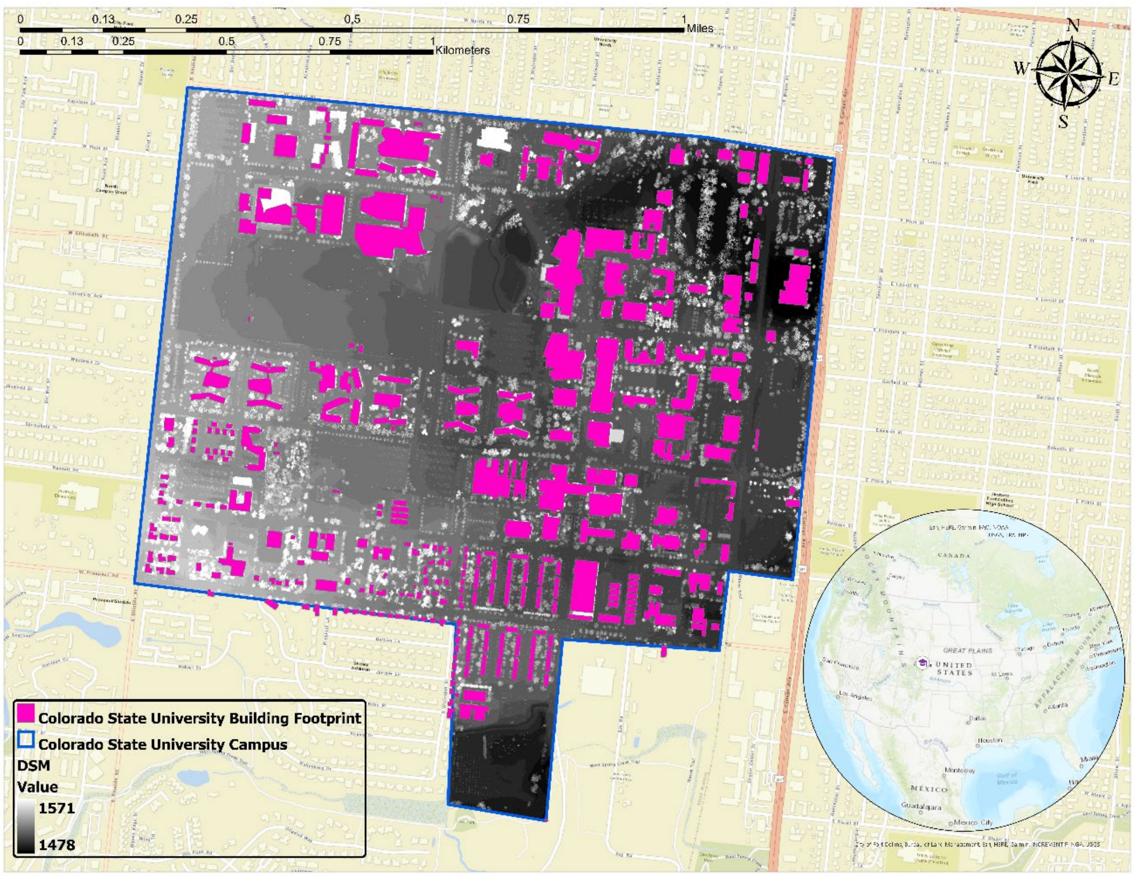

Figure 70. CSU main campus, building footprint, and digital surface model

According to the weather file obtained from NSRDB, the average daily radiation potential (DNI) at Fort Collins, Colorado, reaches 5.36 kWh/m^2 daily. Figure 70 shows the monthly potential at Fort Collins, where the CSU is located.

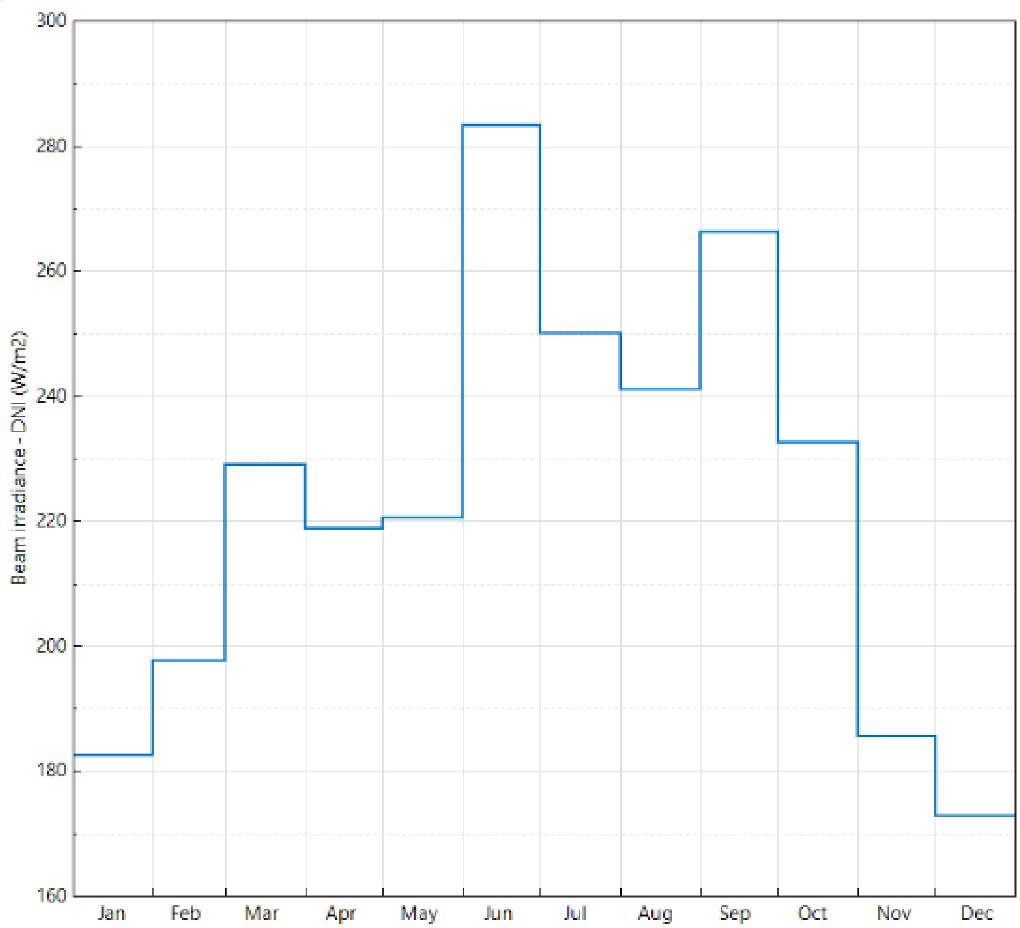

Figure 71. Monthly DNI (W/m²) at Fort Collins, Colorado State University

The latitude has changed to 40, and it is interesting to compare the Colorado case study and Texas cases. Figure 72 shows the radiation output potential based on the available rooftop detected through the LiDAR processing. The annual irradiation based on this method reaches the maximum of 1602.8 kWh/m^2 for the best location (Figure 72).

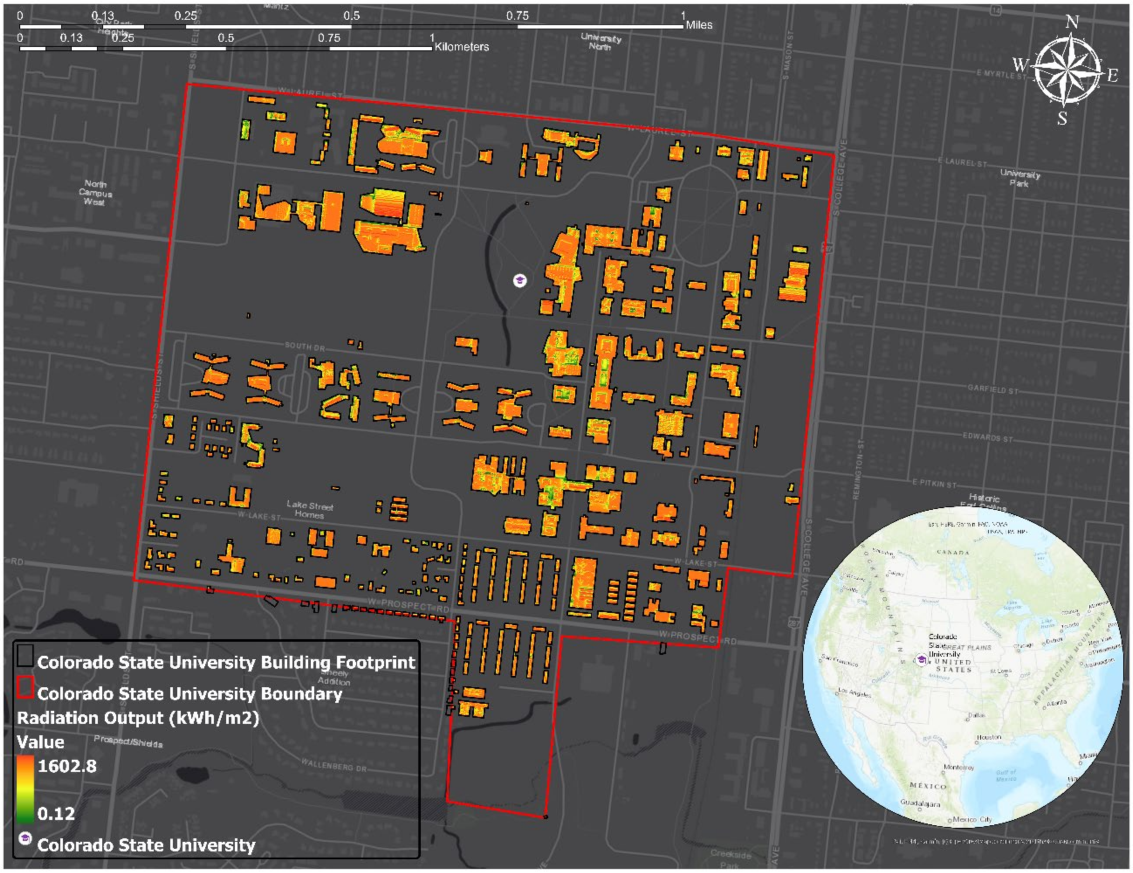

Figure 72. Solar radiation potential at Colorado State University

Having the total area of building footprint at Colorado State University Campus (323,363 m^2) and an average of radiation (5.36 kWh/m^2/day), it is possible to calculate the daily potential based on extracted building footprint:

$$323363\ m^2 * 5.36\ kWh/m^2/day = 1{,}733{,}225.68\ kWh/m^2/day \qquad \text{Equation 49}$$

Hence a yearly potential can be calculated as follows:

$$1{,}733{,}225.68\ kWh/m^2/day * 365 = 632{,}627{,}373.2 \qquad \text{Equation 50}$$

However, the obtained number is the total potential absorbed by the building footprint area and not the energy produced. Depending on the kind of technology and the capacity factor discussed in chapter 5.4, the produced kWh will be drastically lower than the potential. As mentioned previously, a percentage of building rooftop areas suitable for implementing PV equal to 22%-27% (Chaudhari et al. 2004). Also, “Due to a 4 to 6 feet fire code setback requirement for solar installations, a portion of the rooftop along the perimeter cannot be used to host solar panels” (How to calculate building’s rooftop area, Report for U.S. Department of Housing and Urban Development). Hence the calculation should be based on only 70% of the available rooftop to meet the standard conditions. Also, since the rooftop's homogeneity is non-existent in the entire area, the setback could be calculated separately for each building to narrow down the calculation.

70% of the total building area at CSU is equal to 226354 m^2. Considering that a 4kW capacity requires 25 m^2 of the array as discussed in chapter 5.4, we can have 9,054.28 m^2 of array dedicated to solar PV, producing 36,217 kW of DC energy. This number can be used as the financial model's input (Figure 73) but is still not significant since further processing is needed.

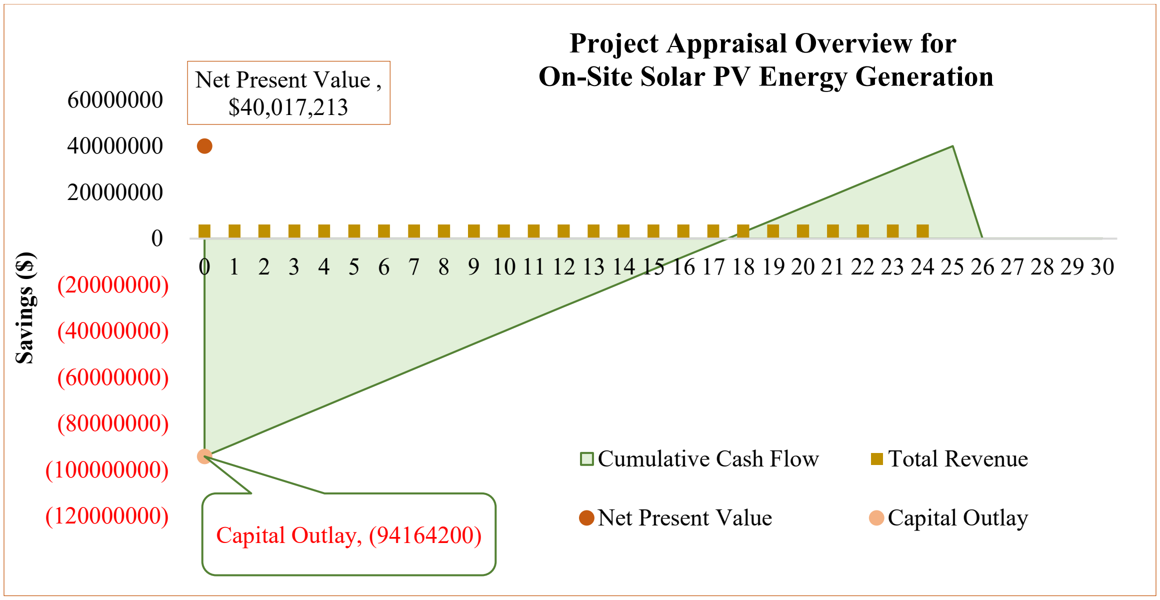

Figure 73. Project appraisal overview for on-site solar PV energy generation at CSU

Table 30. Project evaluation for solar potential at Colorado State University

Project Valuation	
Annual Energy Production (kWh)	56,160,868
GHG Savings Location-Based (metric tons CO2e)	43252.01
GHG Savings Market-Based (metric tons CO2e)	0.00
Capital Investment (excluding Rebate/Incentive)	$94,164,200
Net Present Value	$40,017,213
Internal Rate of Return (IRR)	3%
Payback Period (Years)	17.48
Profitability Index/BCR Ratio	1.42
Debt Service Coverage Ratio	N/A
Equivalent Annual Annuity	$1,600,689

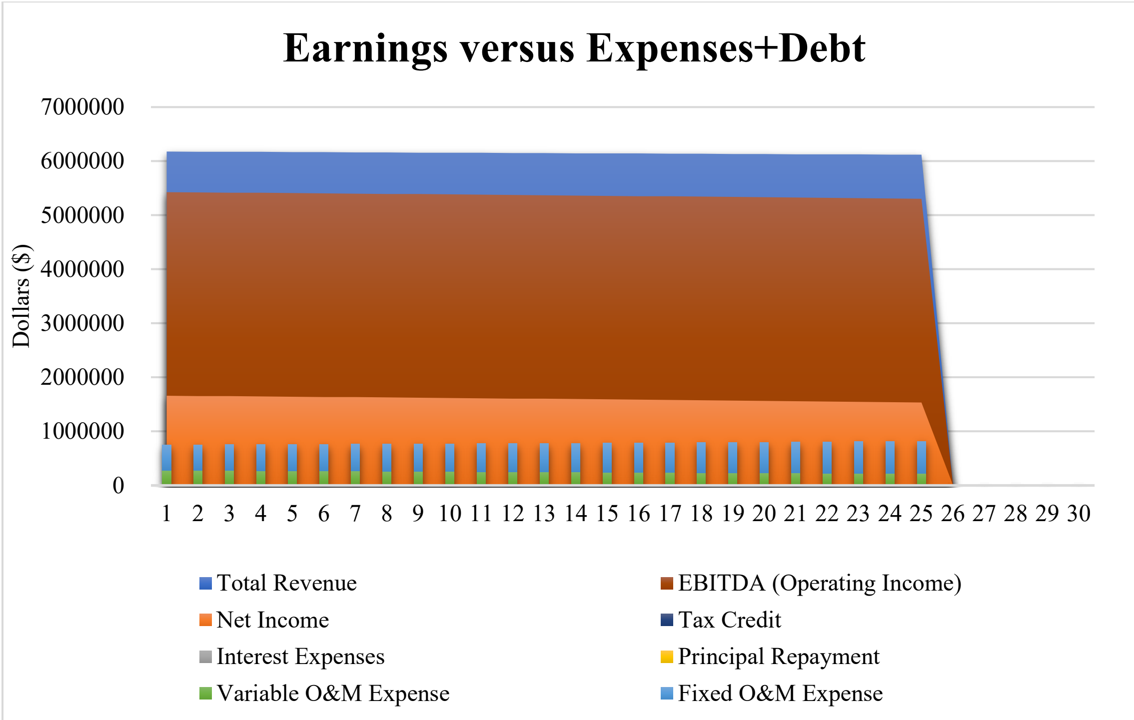

Figure 74. Earnings vs. expenses with 37,828 kWDC potential generations at CSU

As discussed in the methodology section, suitable rooftops should have a slope of Forty-five degrees or less since steep slopes tend to receive less radiation. Suitable rooftops should also receive at least 800 kWh/m^2 of solar radiation. Suitable rooftops should not face north, as north-facing rooftops in the northern hemisphere receive less sunlight. Hence a calculation of slope, aspect, and reassignment of potential is needed as the next step. Following Figure 75, exclude areas with less than 800 kWh of radiation.

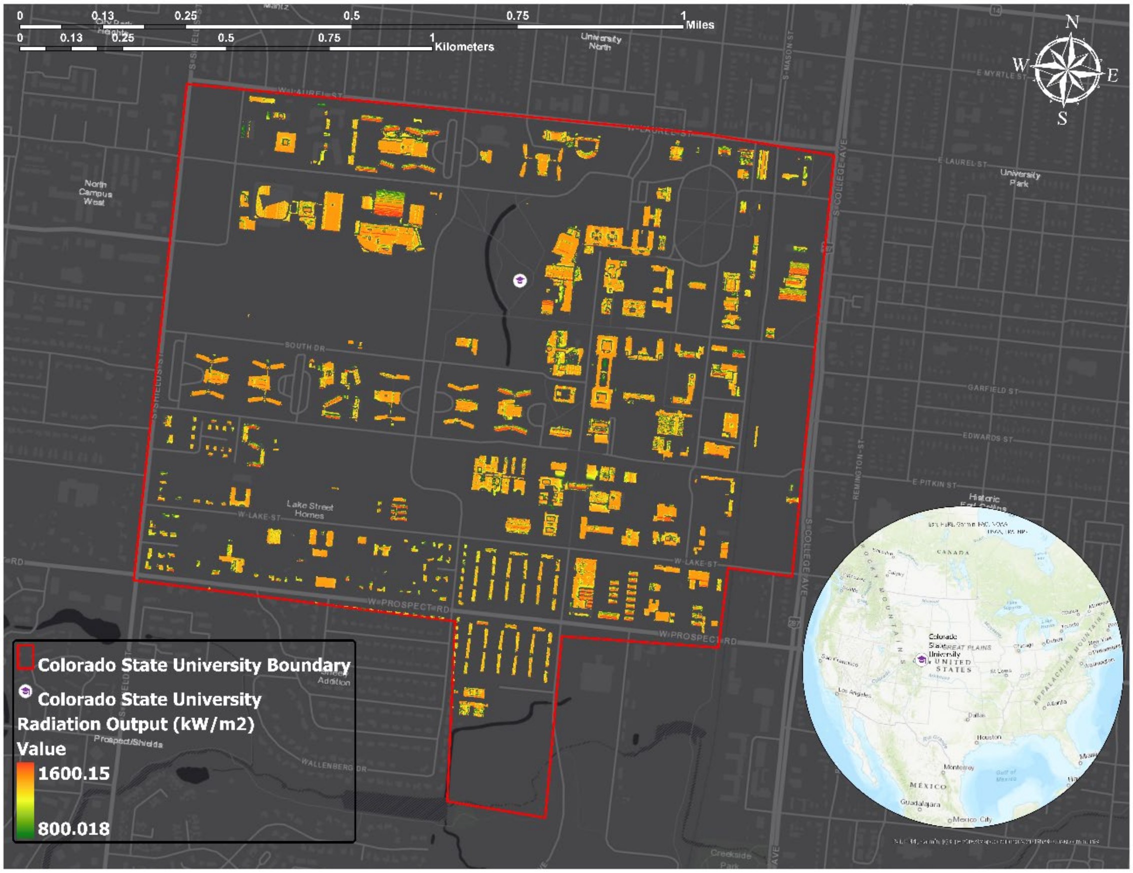

Figure 75. Solar radiation potential at CSU after minimum kWh/m² condition

The majority of north-facing surfaces were already removed by conditional assignment of minimum radiation. Slopes that face north have a value less than 22.5 degrees or more than 337.5 degrees in the aspect raster layer. Eventually, flat slopes are kept, regardless of their aspect. To achieve the condition above, the Con tool is used first to determine areas with low slopes (less than 10 degrees) and then to determine areas facing north (Figure 76). However, the change is not drastic compared to the previous figure.

Figure 76. Solar radiation potential at CSU

A zonal statistic approach assigns the potential to the building footprint by determining the mean value of the potential. The table contains fields for the number of cells, the area in square meters, and the average solar radiation in kWh/m^2 for each building. Next, we remove buildings with less than 30 square meters of area, and by doing that, 270 out of 302 buildings are selected.

Next, a field will contain the total amount of solar radiation received per year by each building's usable area. This field is calculated by multiplying each building's suitable area by its average solar radiation (Equation 42). The same method was used initially for each building based on the city's average radiation where the campus is located. Now by introducing the GIS, the result is more accurate and calibrated. Also, to avoid large numbers, it is possible to convert the solar radiation from kilowatt-hours per square meter to megawatt-hours per square meter.

Equation 25 provides the amount of converted potential to produce power based on EPA average efficiency and performance ratio (Figure 77). The total amount of production reaches 36,353.34 MWh at Colorado State University.

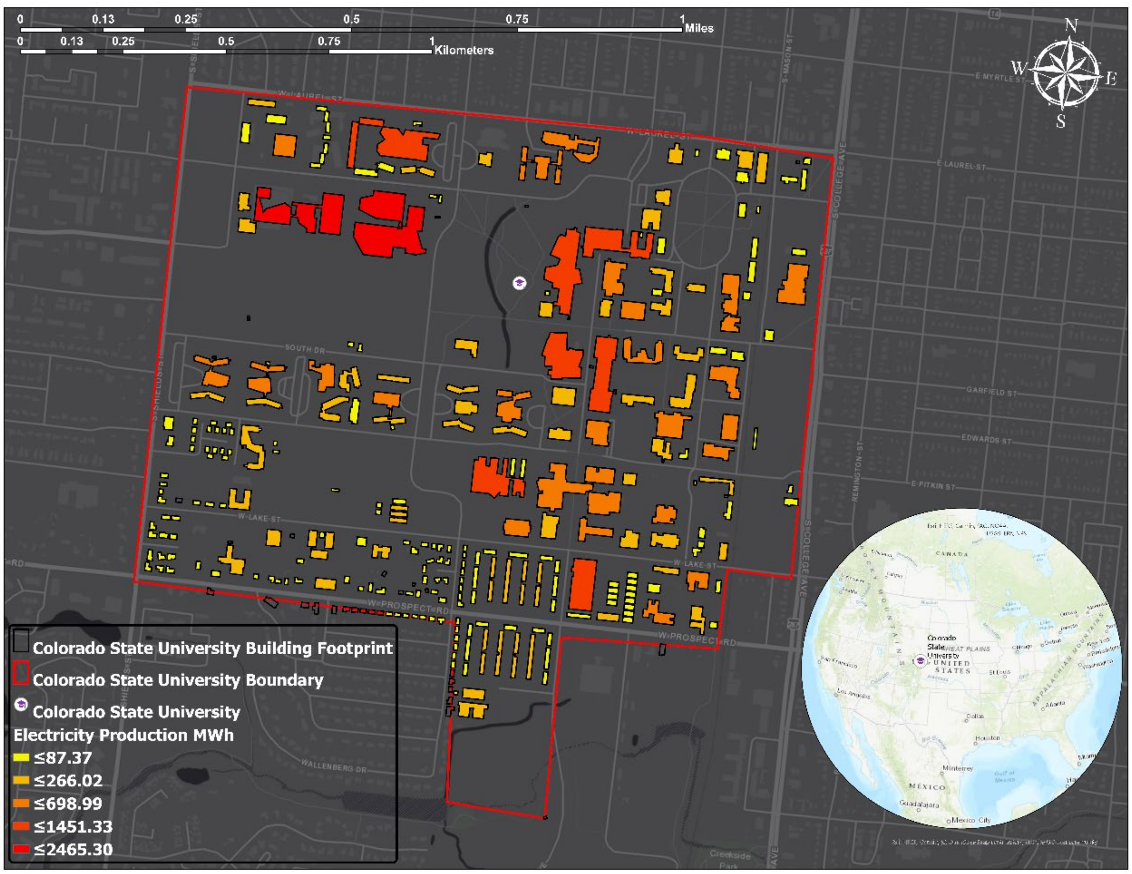

Figure 77. Final solar electricity potential production at Colorado State University

6.8 COLORADO STATE UNIVERSITY WIND POTENTIAL

There are 302 constructed buildings around Colorado State University's main campus, with an average height of 90 meters. The average wind speed in Fort Collins, Colorado, where Colorado State University is located, is calculated based on the NSRDB station 156050 (Figure 78). In this study, wind power was assessed based on data for the four seasons from the nearest methodological station to the campus. The seasonal mean variation in 2019 reached 2.7 m/s (Figure 78).

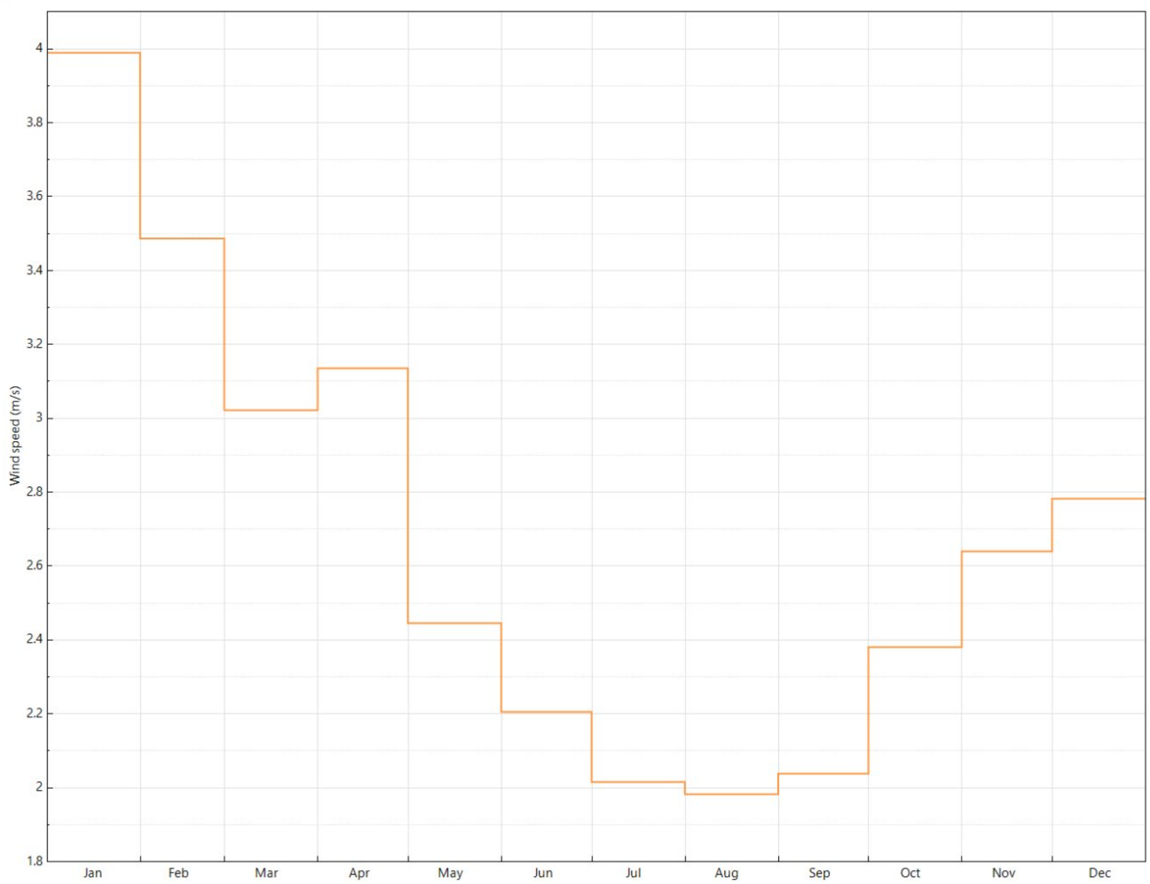

Figure 78. Mean wind speed at Fort Collins based on the nearest weather station

The limited rate of change in mean wind speed causes a low wind power class

(Class 1 or 2) at Fort Collins. As mentioned, there is a high rate of fluctuation in wind speed depending on surface roughness. Power density can vary from season to season (Akpinar, & Akpinar, 2005). The energy output is given by fixed numbers while having an exact estimation of wind turbine output is difficult due to wind power and wind speed instability.

On the other hand, studies show that higher wind speed occurs in higher elevations. Hence, having different buildings with different heights impacts the calculation of output. “The cut-in speed, which is the minimum speed at which the wind turbine generates usable power, is typically between 3 and 5 m/s” (Al Yahyai et al., 2011 p.154). There is some peak of high wind speed registered in data, such as the one during January 2019, which can partially compensate for the low wind power in other seasons. Figure 79 shows the elevation of rooftops at Colorado State University.

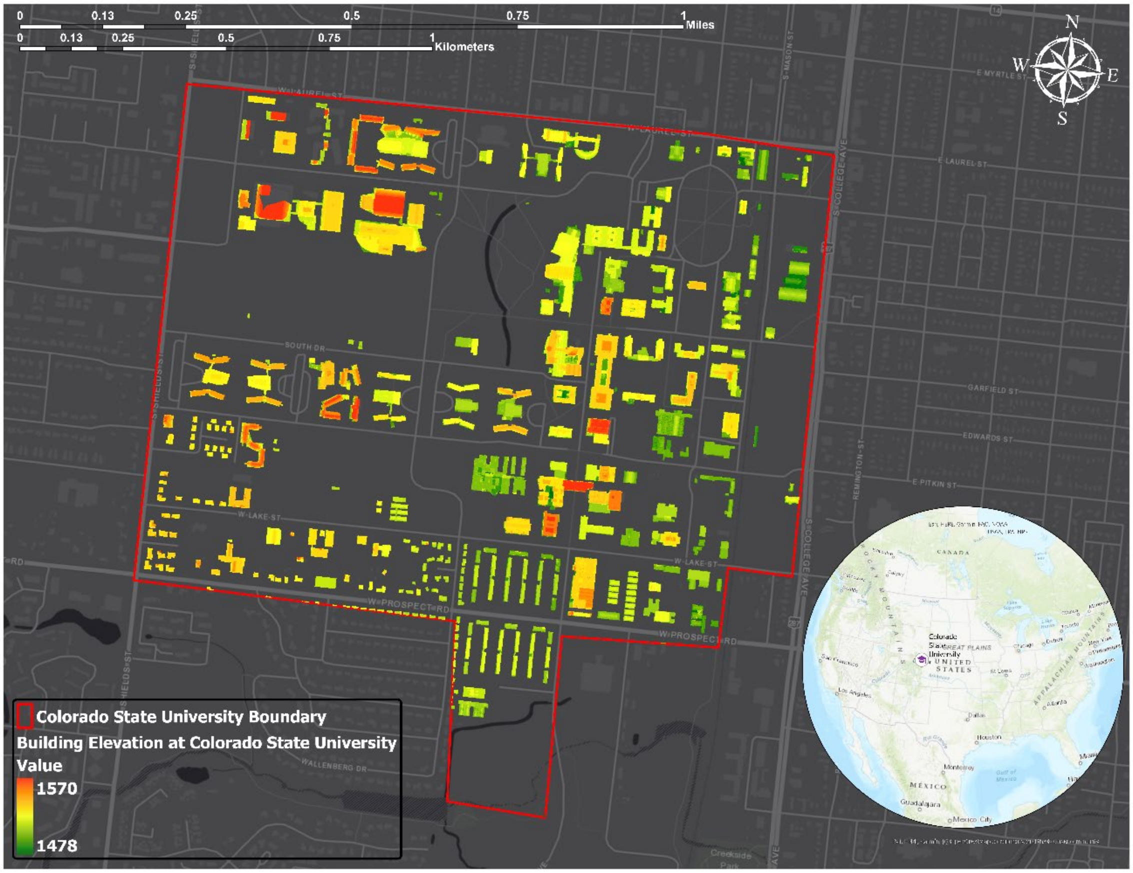

Figure 79. Rooftop elevation at Colorado State University

After determining the elevation of available rooftops (via LiDAR), we can calculate the average wind speed based on Equation 17, discussed in chapter 5.3.1 (Figure 80). However, the range of change is minimal; hence two categories are chosen based on Natural Breaks (Jenks).

Figure 80. Mean wind speed based on rooftop elevation at Colorado State University

Since the minimum cut-in speed is set to 3 to 5 meters per second (Al Yahyai et al., 2011 p.154), only the buildings falling inside that range must be kept. However, none of the buildings at Colorado State University reaches the cut-in speed unless a seasonal study is applied, such as one focused in January with a higher than three m/s wind speed. It is clear that with a low-class power of wind, no small wind project will be feasible even if federal help and credits are added to the project.

6.9 CLUSTER ANALYSIS

6.9.1 TEXAS

Figure 81 shows an example of wrong clustering where the number of clusters is not defined; hence the algorithm produces 30 different clusters.

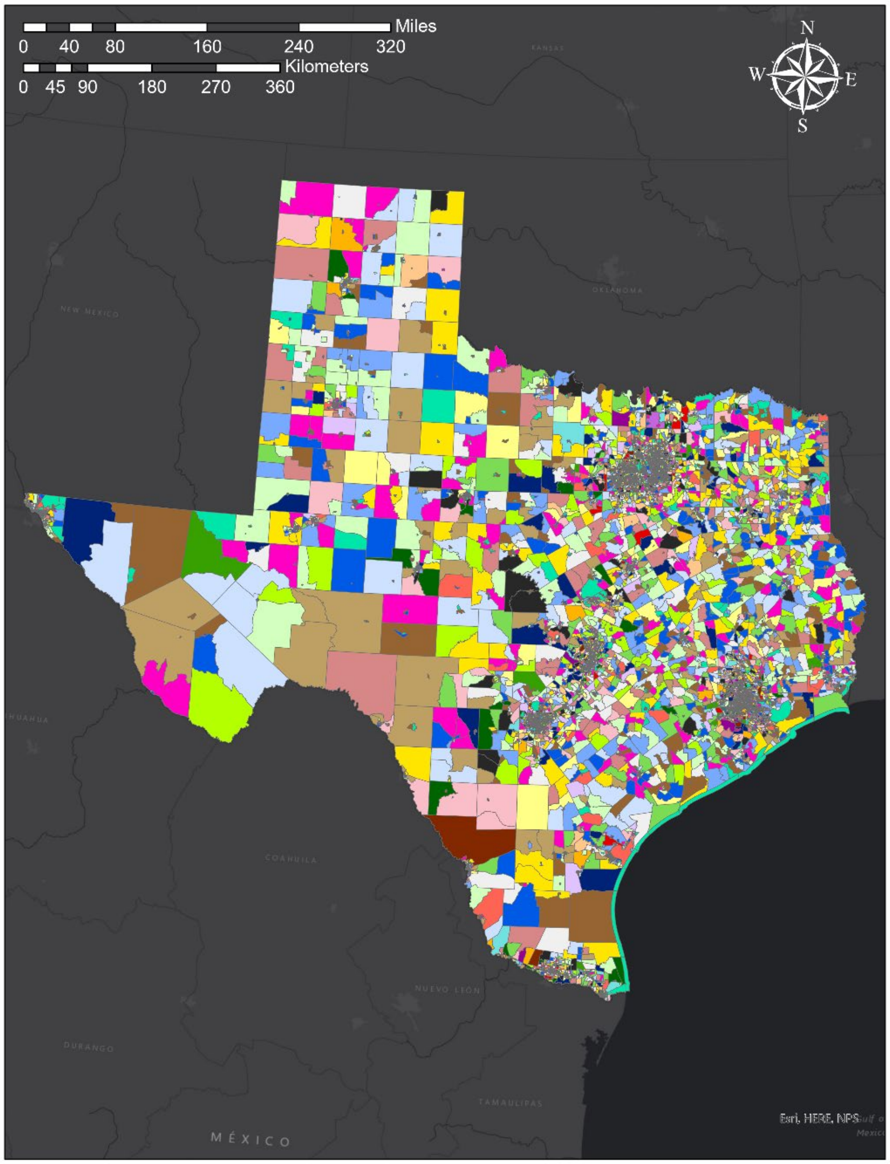

Figure 81. Example of incorrect cluster number

The maximum number of iterations is set to 100 in ArcGIS and R *kproto* function.

However, if R or any other customized script in Python is used to apply K-means clustering, at some point, the cluster centroids will stabilize and stop moving with each iteration. The cluster centroid will move less with higher numbers of iterations until fixed. Between each iteration, we can keep track of the distance change between the new position of the centroid and the previous position (Figure 82). “Once this distance is relatively small, we can stop the algorithm” (Peng, 2012, p. 117). A “stop snippet” is mentioned in the Python algorithm in appendix 1. The next step consists of assigning the points close to the centroid (Figure 83).

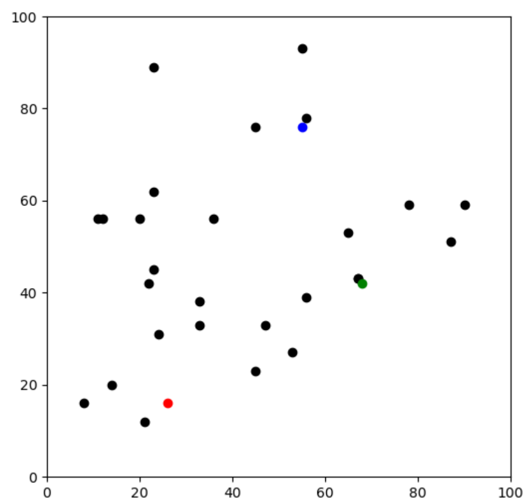

Figure 82. Selection of random seed points as centroids of initial clusters

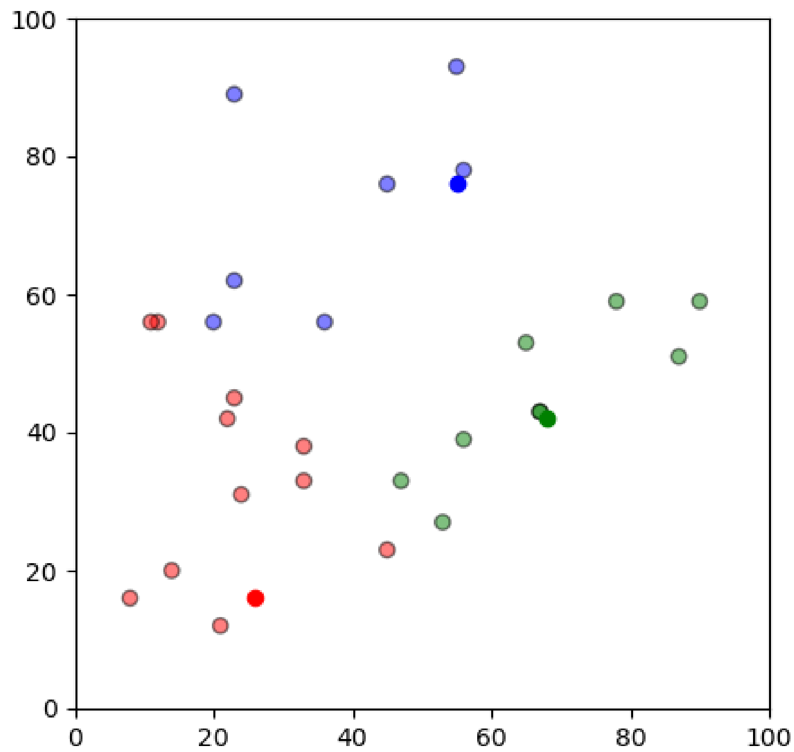

Figure 83. Assigning points to the respective clusters

Table 31 shows a sample of distance calculation from the centroid of clusters for the first 5 points:

Table 31. Distance calculations form the centroid of clusters

X	Y	distance from k1	distance from k2	distance from k3	closest	color
14	20	12.64	58.30	69.40	1	r
20	56	40.44	50	40.31	3	b
47	33	27.01	22.84	43.73	2	g
36	56	41.23	34.92	27.58	3	b
56	78	68.87	37.94	2.23	3	b

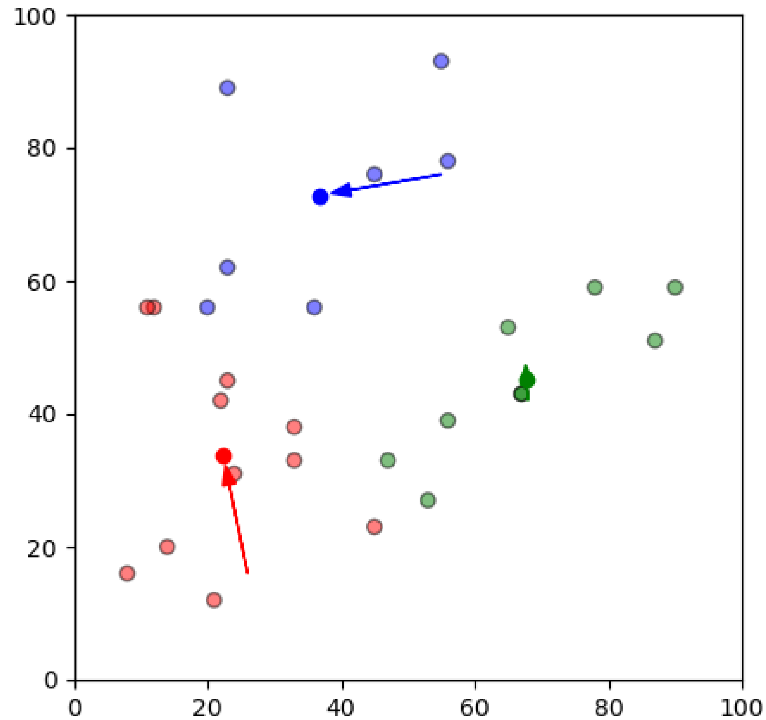

Figure 84. Updated center of clusters after recalculation

Figure 83 updates the center of clusters after recalculation (Step 5). Clusters have been identified at this stage, but the algorithm is set to more than one iteration so that it continues until no point is moved from one cluster to another (Figure 84). The highlighted point in Figure 85 is now red, while it was blue in the first iteration (Figure 84).

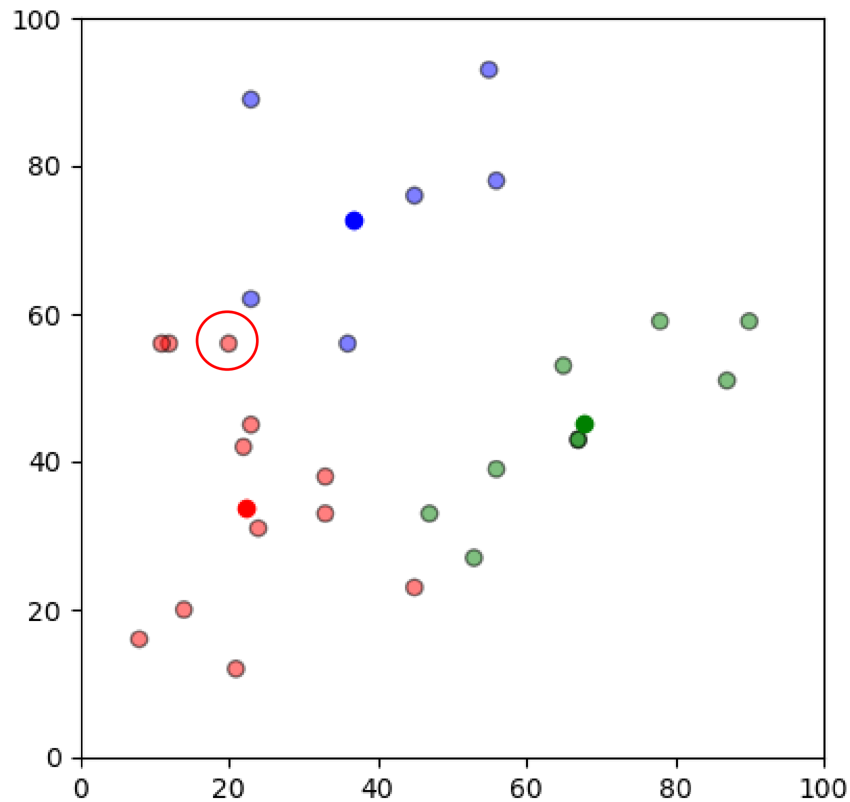

Figure 85. Change of cluster assignment after repeated iteration

The K-means algorithm requires three inputs on behalf of the user: (1) the number of clusters, (2) initialization mode, and (3) distance metric, which is usually set to Euclidean distance. If the number of clusters is specified, a table will be created containing the pseudo-F-statistic for clustering solutions 2 through 30, calculated to evaluate the clusters' optimal number. Figure 86 shows the output for running the K-means on 15 aforementioned environmental variables in Texas at the block group level with five pre-established clusters. The summary statistics are shown in Table 32.

Table 32. Summary statistics with 5 clusters in Texas

Variable	Mean	Std. Dev.	Min	Max	R2
PAKSHLDREC	1260.387895	1501.445	0	47484	0.857615
COMCONENV	1075.803997	1299.049	0	41997	0.854736
USEDRECPRD	1099.796977	1312.985	0	42237	0.853953
PRSOBENVRE	1275.253621	1530.819	0	50781	0.853321
MAKCONTORE	1207.520903	1447.01	0	48075	0.852783
PEPLDTYTTOR	1088.674657	1307.174	0	43377	0.852295
PRCHENVFRC	931.911391	1116.819	0	34599	0.848288
ENVGOODBUS	1037.810575	1273.775	0	38232	0.846742
WORCARPOLLU	956.218392	1158.461	0	34506	0.845718
LESEXPECFP	1127.016444	1363.19	0	47517	0.837735
OTHSEEMRE	738.103346	903.6934	0	26169	0.820191
CSMETRPENF	496.751818	660.7856	0	17757	0.732823
ECOFHIQPPR	559.973879	720.5262	0	21576	0.730778
STPSENDCAT	418.565556	560.2972	0	14895	0.716951
BLNGSTOENOR	26.515021	91.31169	0	1728	0.120902

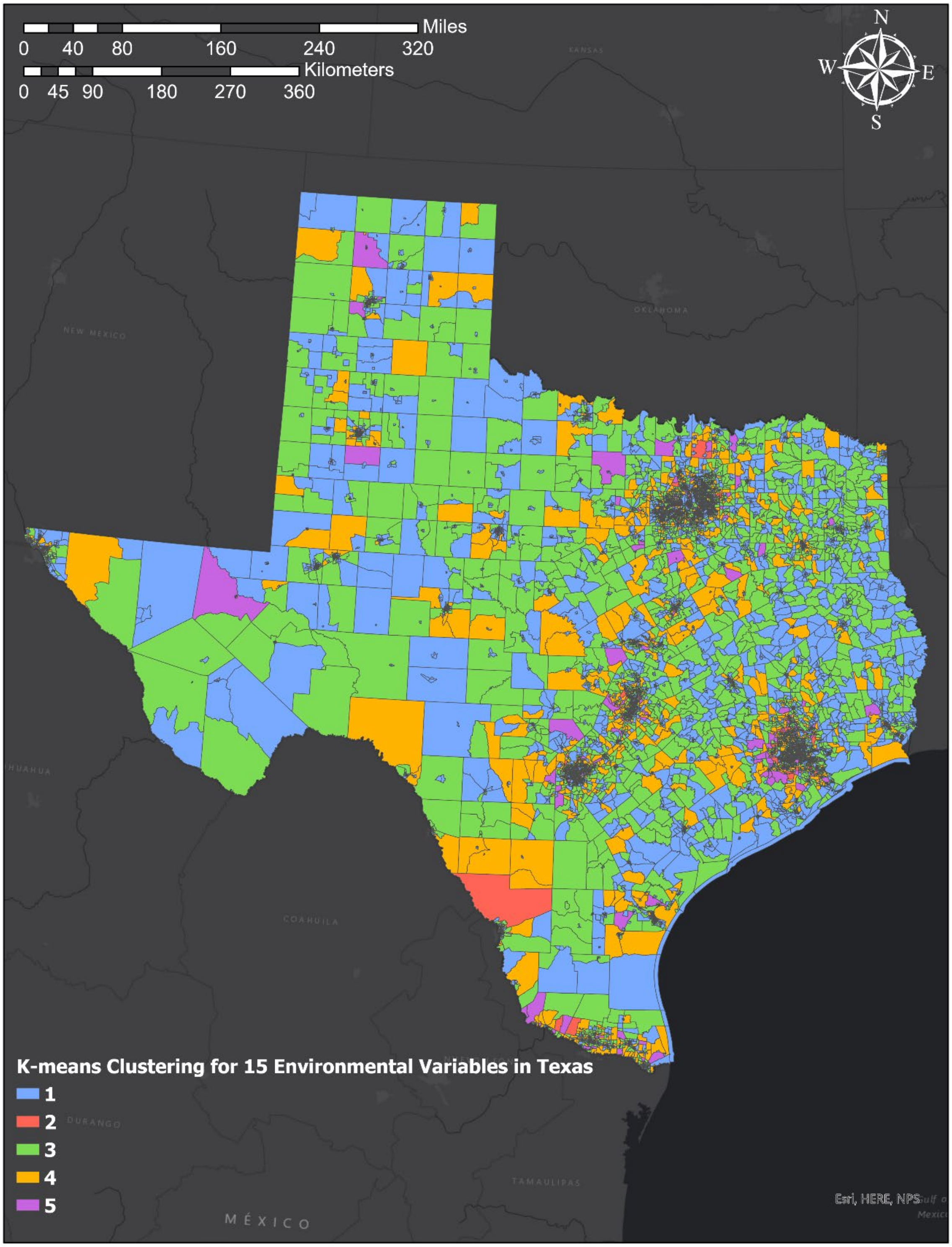

Figure 86. K-means on 15 environmental variables in Texas with 5 clusters

Multiple charts will be produced to summarize the information about clusters. The feature per cluster chart (Figure 87) shows the count of features (block groups) in each cluster. Box plots shown in Figure 88 provide statistical information about clusters and variables. The same information can be shown as a mean line in Figure 89. The values for Box-Plot are standardized to avoid the influence of variables with large variances. Standardization requires a z-transformation by subtracting the mean for all values from each value and dividing it by the standard deviation for all values.

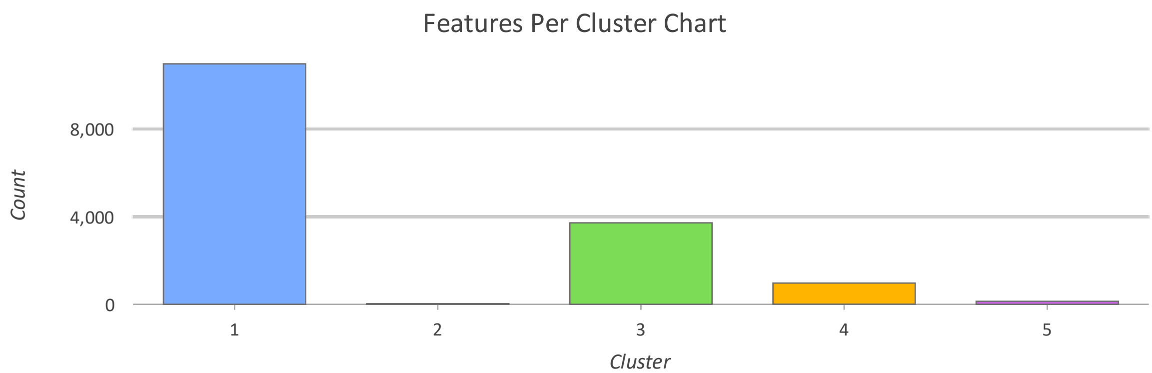

Figure 87. Feature per cluster count for Texas

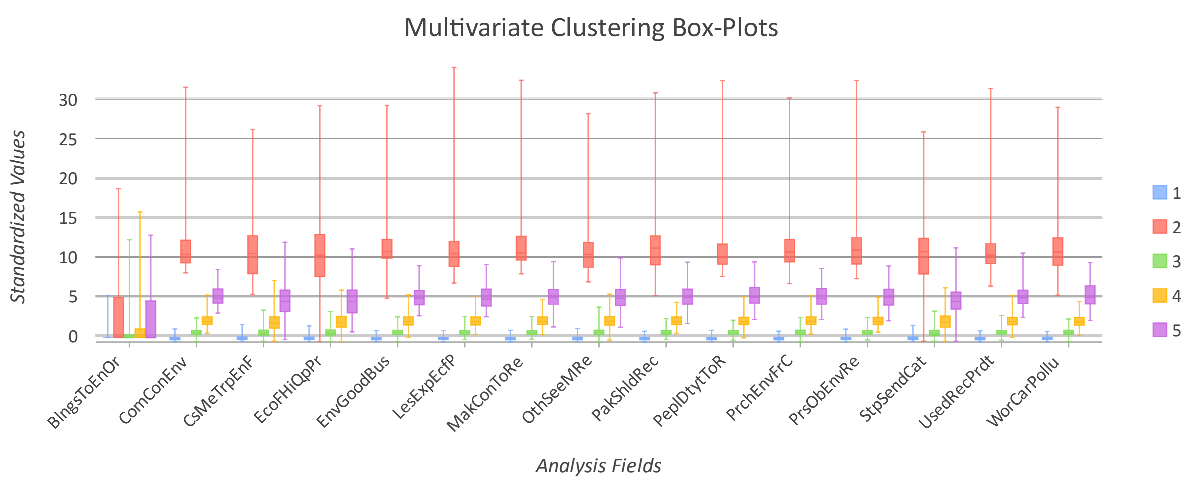

Figure 88. Multivariate clustering box-plots side by side for Texas

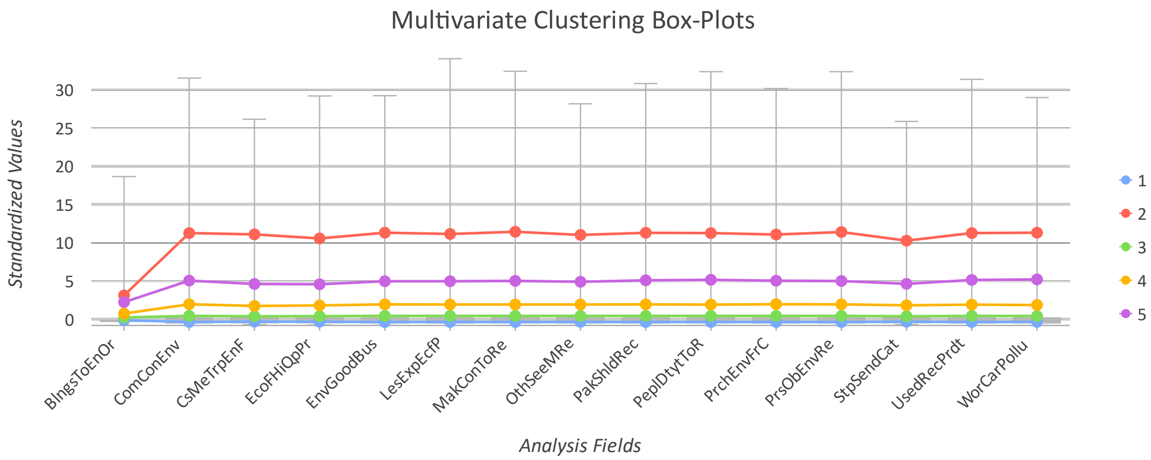

Figure 89. Multivariate clustering box-plots as a mean line for Texas

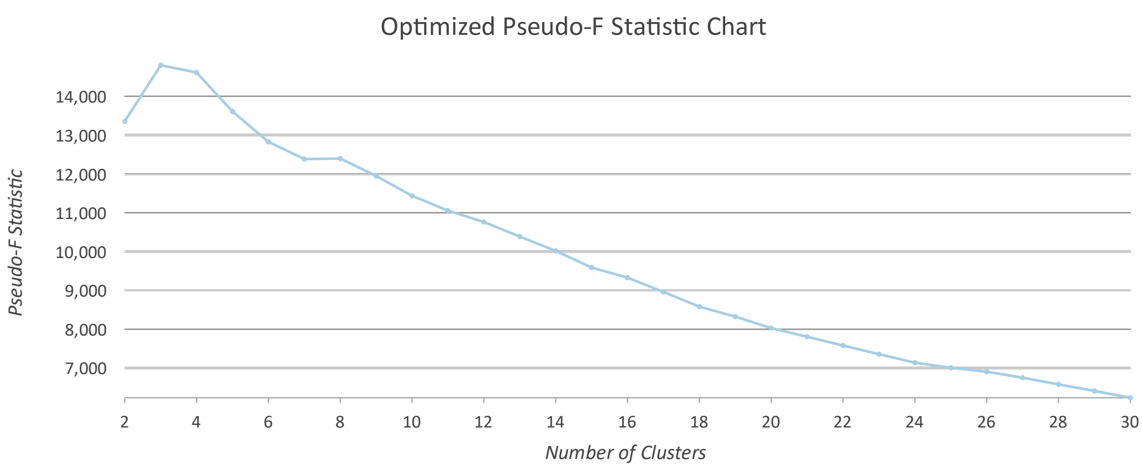

Figure 90. Optimized Pseudo-F statistics for Texas

The highest peak on the optimized pseudo-F statistics shows the optimum number of clusters coinciding with number 3 (Figure 90). There is no need to produce another optimized pseudo-F statistic since, by referring to Figure 90, we know that the optimized number of clusters for our study area is 3. The following figures and tables show the result for the same study area in Texas with 3 clusters:

Table 33. Summary statistics with 3 clusters in Texas

Variable	Mean	Std.Dev.	Min	Max	R^2
PAKSHLDREC	1260.388	1501.445	0	47484	0.722484
USEDRECPRDT	1099.797	1312.985	0	42237	0.71956
COMCONENV	1075.804	1299.049	0	41997	0.719044
WORCARPOLLU	956.2184	1158.461	0	34506	0.717967
PRSOBENVRE	1275.254	1530.819	0	50781	0.717608
PEPLDTYTTOR	1088.675	1307.174	0	43377	0.717419
PRCHENVFRC	931.9114	1116.819	0	34599	0.715505
MAKCONTORE	1207.521	1447.01	0	48075	0.715374
ENVGOODBUS	1037.811	1273.775	0	38232	0.71083
LESEXPECFP	1127.016	1363.19	0	47517	0.706133
OTHSEEMRE	738.1033	903.6934	0	26169	0.688909
ECOFHIQPPR	559.9739	720.5262	0	21576	0.619608
CSMETRPENF	496.7518	660.7856	0	17757	0.617494
STPSENDCAT	418.5656	560.2972	0	14895	0.593344
BLNGSTOENOR	26.51502	91.31169	0	1728	0.097195

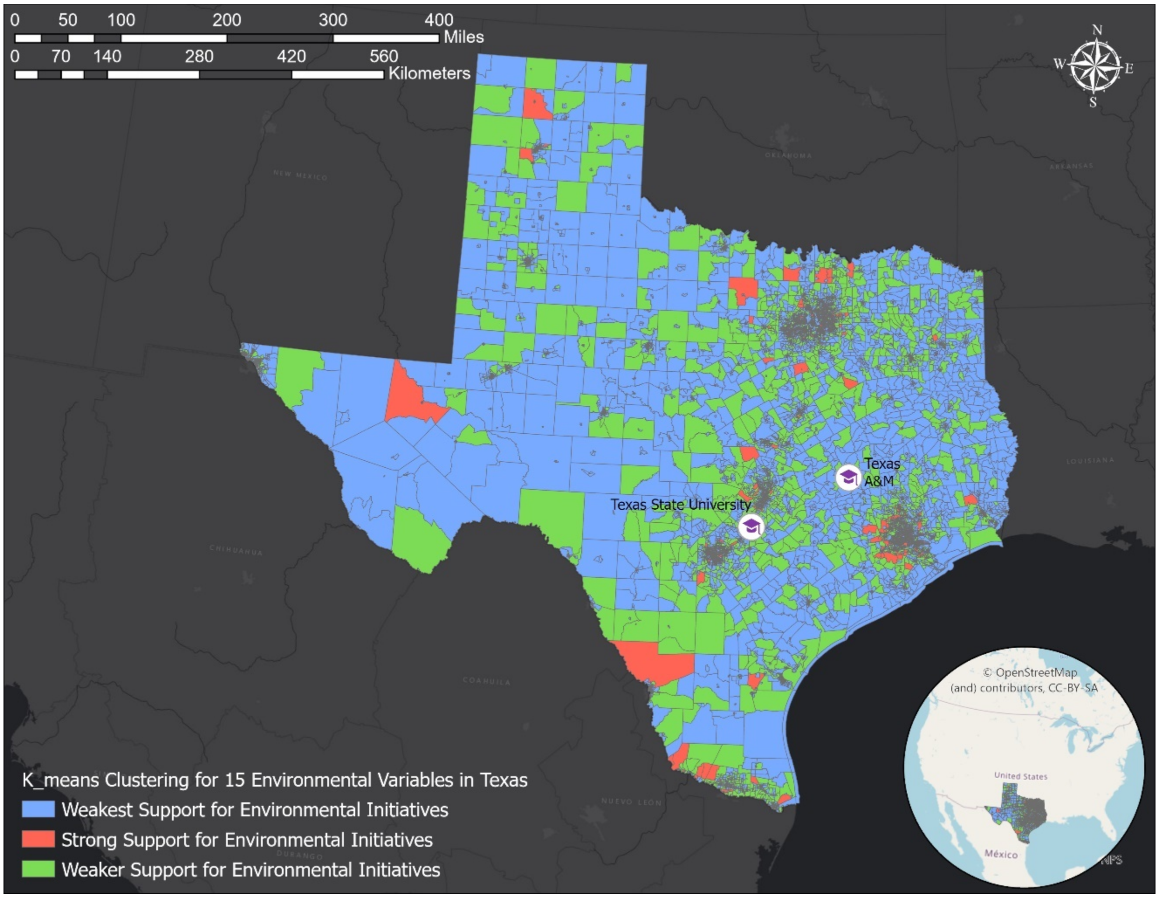

Figure 91. K-means on 15 environmental variables in Texas with 3 clusters

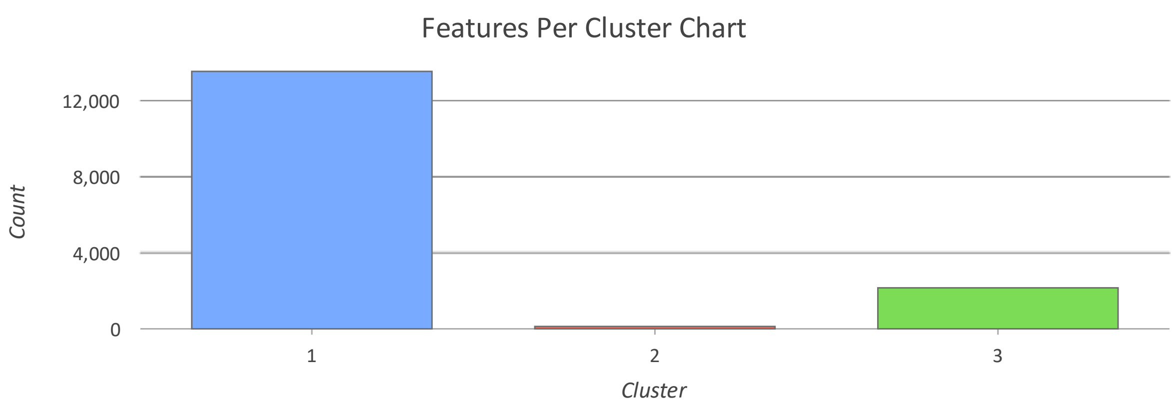

Figure 92. Feature per cluster count for Texas with 3 clusters

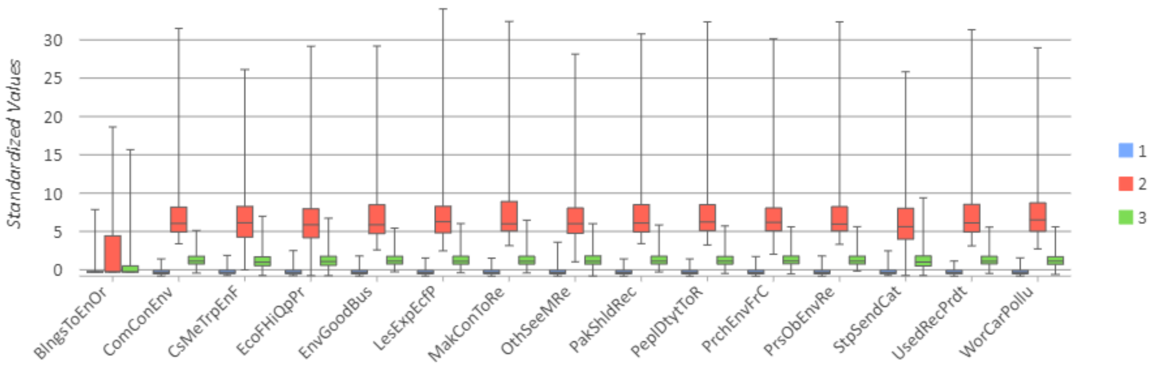

Figure 93. Multivariate clustering box-plots side by side for Texas

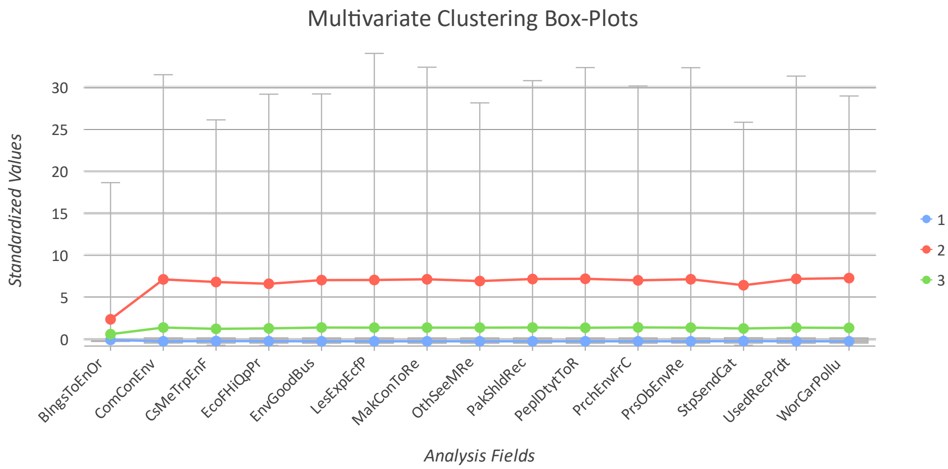

Figure 94. Multivariate clustering box-plots as a mean line for Texas

An implementation of K-means in R is represented in Appendix 2 with 1000 seed points from the same data set with 15 environmental variables in Texas at the block group level with 3 clusters. The difference between running the algorithm in R and other platforms such as ArcGIS Pro and Python is the possibility of visualization of each step in R and a smaller coding amount (Figure 95).

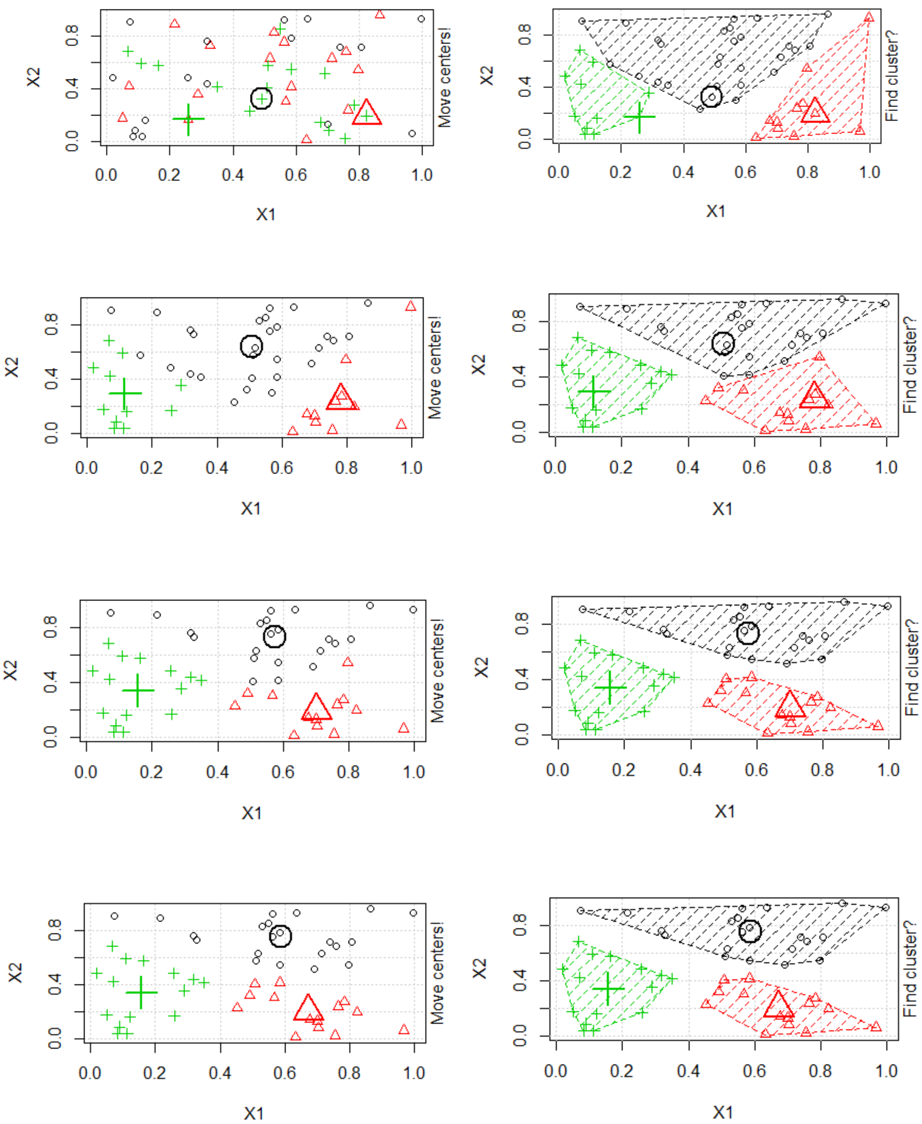

Figure 95. K-means clustering implementation in R with Texas data set

Depicting the output of cluster analysis helps to answer question number two and four in chapter 4:

2. To what extent are sustainability goals prioritized by residents and municipalities in each HEI's local spatial context?

4. To what extent do (in)congruent state and local/regional spatial contexts promote

(inhibit) alternative energy implementation in HEIs?

Thirteen thousand five hundred thirty-five block groups are clustered in cluster number 1(blue color) in Texas. This is equivalent to 85.6% of all block groups. These block groups have the lowest frequency of positive answers among all 15 environmental variables and are scattered throughout Texas. Cluster number 2 (orange color) has 125 features (0.7% of all), showing the highest standardized values, which fall above 5 for most environmental variables. The exception in cluster number 2 is given by the number of people who belong to an environmental organization with a decreased standardized value. Block groups falling inside cluster 2 do not fall in each other's vicinity except in the west Houston metropolitan area. Cluster number 3 (green color) has 2151 block groups (13.6% of all features), with a standardized value falling between cluster number 1 and number 2. Cluster number 3 is scattered around big metropolitan areas.

Texas State University falls inside cluster 1—with a few isolated green clusters—with the lowest rate of standardized values (Figure 96), including a direct consequence of putting the university and the community in the inner rings of the conceptual framework and specifically for *Community Values and Priorities* as one of the pillars of the conceptual framework (Figure 17). This positioning in the conceptual framework is not necessarily a direct result of State policy. As shown in Figure 11, Texas is one of the States *with Renewable Portfolio Standards* that will position the state in the outer lines of the conceptual framework for *State Policy and Priorities.* Also, at the census block and bigger geographical units such as County, there is no unit categorized with cluster 2 (highest rate of environmental attitudes). Indeed, the entire Hays County includes clusters 1 and 3 only.

Figure 96. TSU campus position compared to the environmental clusters

Texas A&M falls in cluster 3 (Figure 97), with characteristics explained in previous paragraphs. This fact put the university in the middle positions of the conceptual framework (Figure 17), making it more reliable for reaching a landscape of properly coupled HEI-environment-social systems than Texas State University.

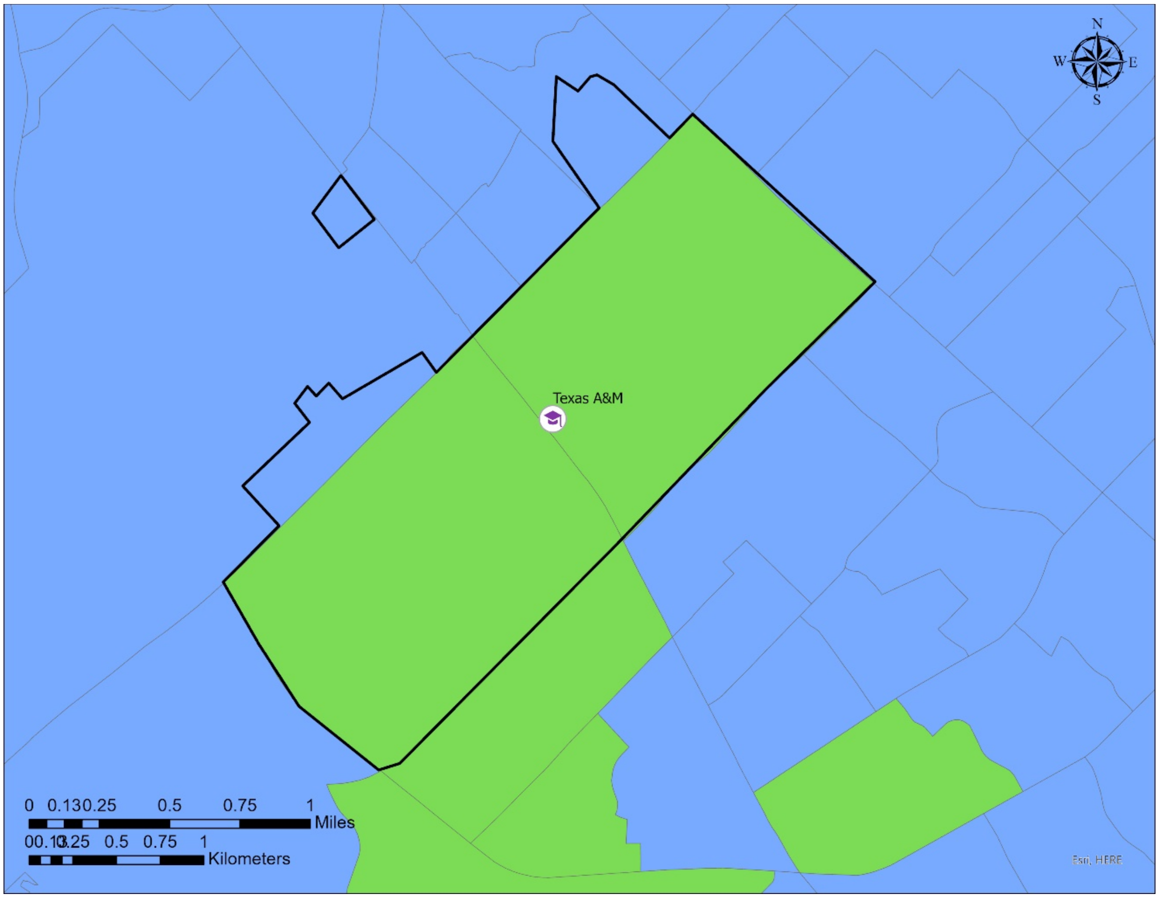

Figure 97. Texas A&M campus position compared to the environmental clusters

6.9.2 COLORADO

Figure 98 shows the clustering output for Colorado environmental variables. The optimized Pseudo-F Statistic (Figure 99) determines the best number of clusters as 5.

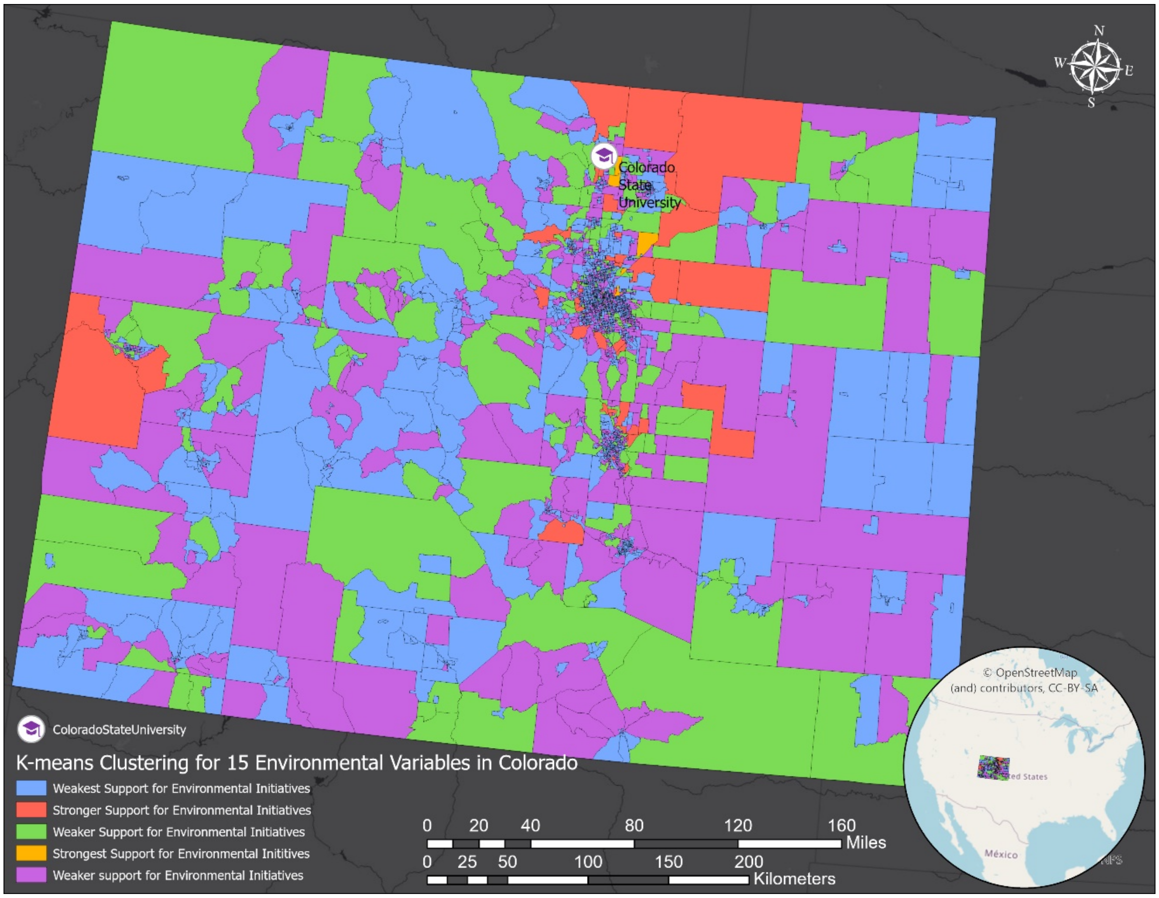

Figure 98. K-means on 15 environmental variables in Colorado with 5 clusters

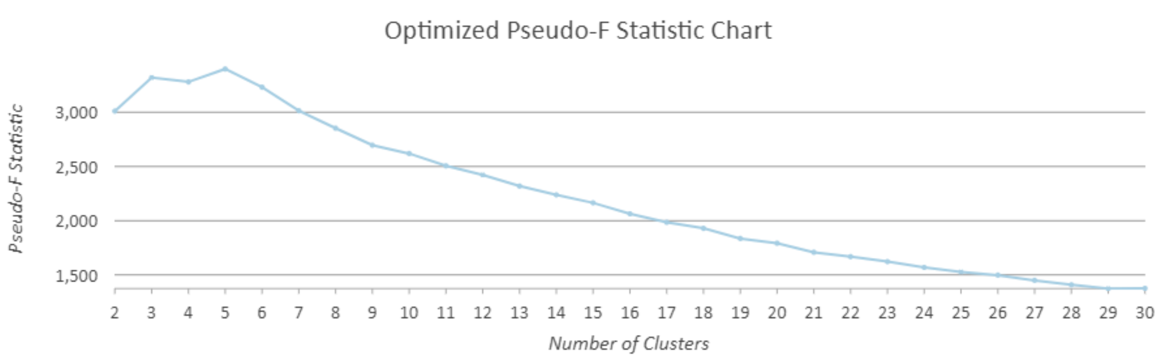

Figure 99. Optimized Pseudo-F statistics for Colorado

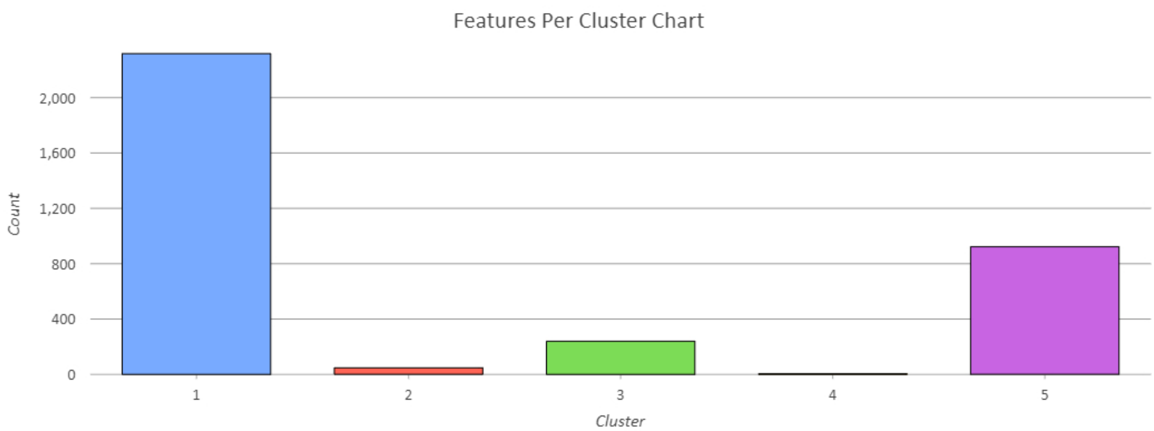

Figure 100. Feature per cluster count for Colorado

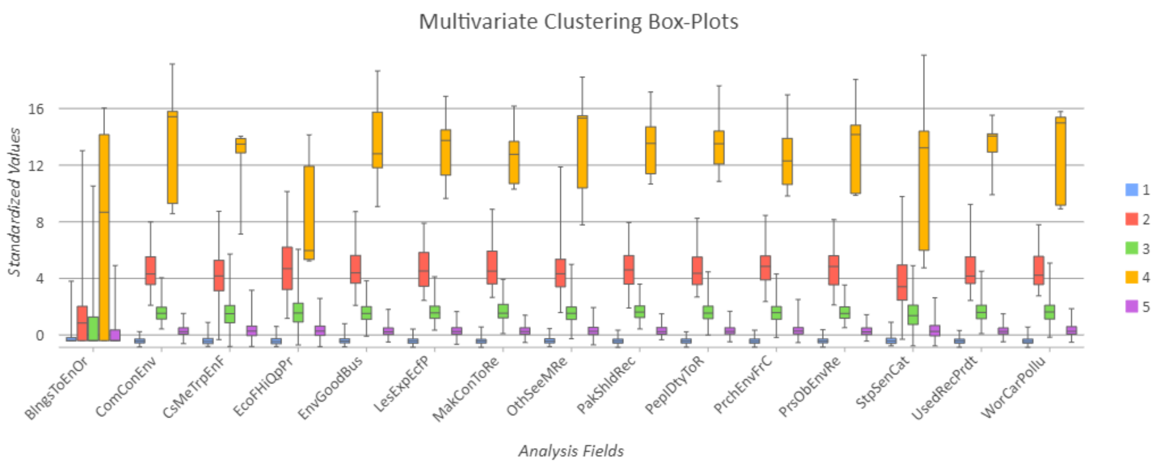

Figure 101. Multivariate clustering box-plots for Colorado

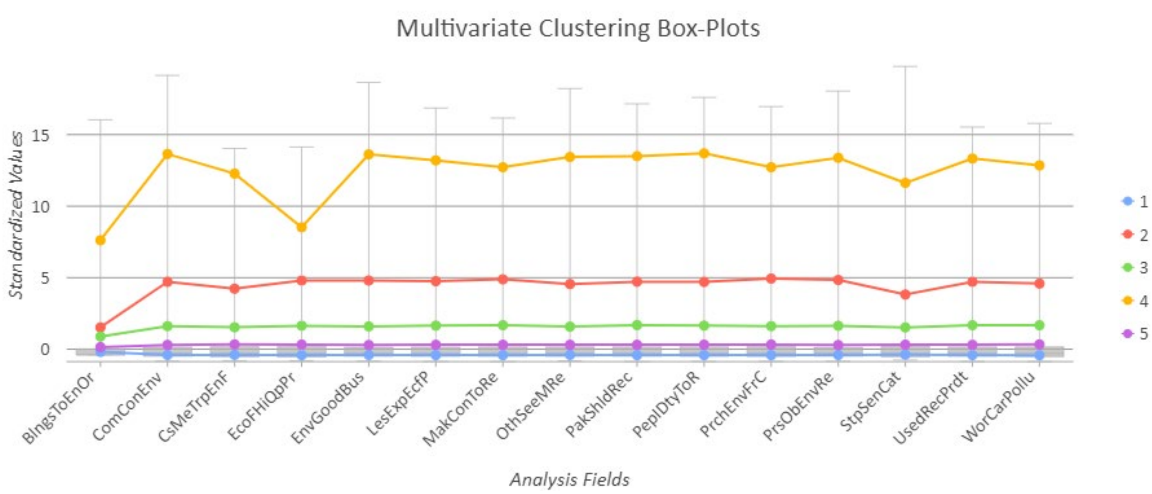

Figure 102. Multivariate clustering box-plots as the mean line for Colorado

Two thousand three hundred eighteen block groups out of 3532 are categorized as cluster 1(blue color) in Colorado. This number comprises 65.6% of the total number of features clustered with the algorithm. These block groups have the lowest frequency of positive answers among all 15 environmental variables. The geographical distribution of cluster 1 is scattered across Colorado State with some groups at the central, east, southwest, and northeast, as shown in Figure 98. Cluster 5 has the second-highest number of features, including 922 block groups (26%). A low frequency of positive answers also characterizes this cluster. However, the standardized values for cluster 5 are slightly higher than cluster 1(Figure 101). Cluster 5 groups occur at the central-east, northeast, southwest, and central west (Figure 98). Cluster 3(green color) is characterized as a low standardized value. However, the numbers are slightly higher than in clusters 1 and 5.

Block groups with the highest standardized values are categorized as cluster 4 (yellow color). Only five block groups clustered as cluster 4 fall at the central north part of Colorado, two of them being close to the Colorado State University. Cluster number 2 (red color) with 47 block groups comprises the second-highest standardized value, including some of Colorado's largest block groups. The occurrence of cluster 2 is verifiable at the north-central part of Colorado except for three block groups located in Colorado's west-central part. Colorado State University falls inside cluster 1 with the lowest rate of standardized values, including a direct consequence of putting the university and the community in the inner rings of the conceptual framework and specifically for Community Values and Priorities as one of the pillars of the framework (Figure 17). Nevertheless, Colorado State University is relatively close to higher rank clusters for standardized values (Clusters 2 and 4). The proximity to higher rank clusters may cause geographical assimilation in the future based on Tobler's first law of geography.

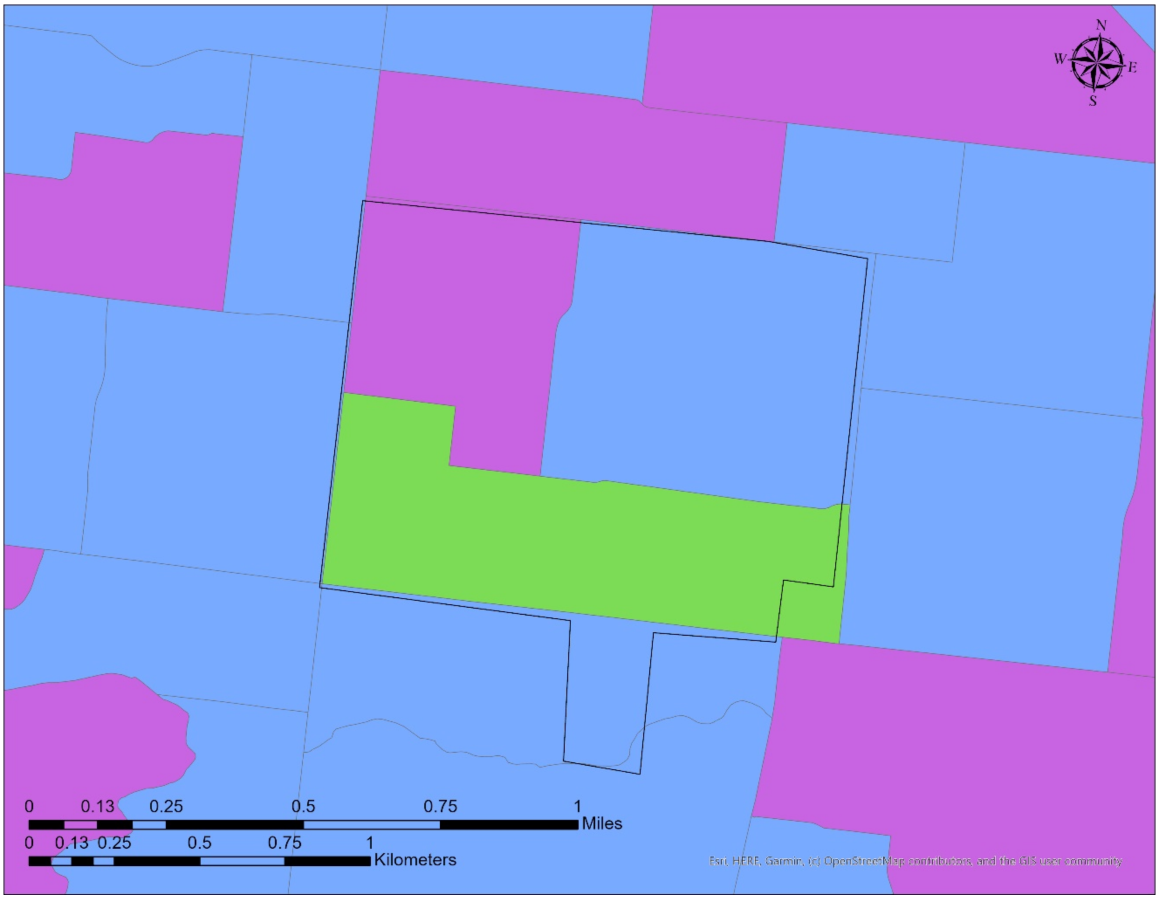

Figure 103. CSU campus position compared to the environmental clusters

6.9.3 CALIFORNIA

Figure 104 shows the optimized Pseudo-F Statistic, which determines the best number of clusters as 2.

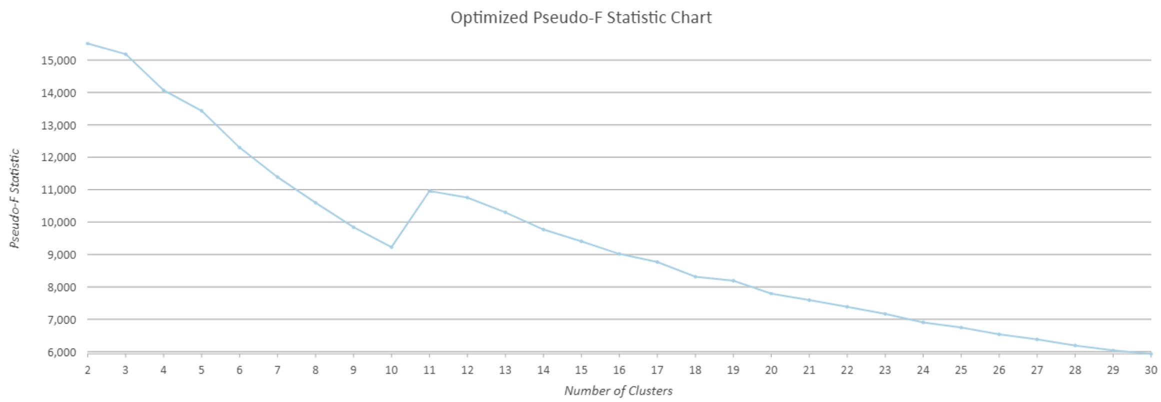

Figure 104. Optimized Pseudo-F statistics for California

The number of features (block groups) per clustering output is shown in Figure 105, while Figures 106 and 107 show the Box-Plot for clusters.

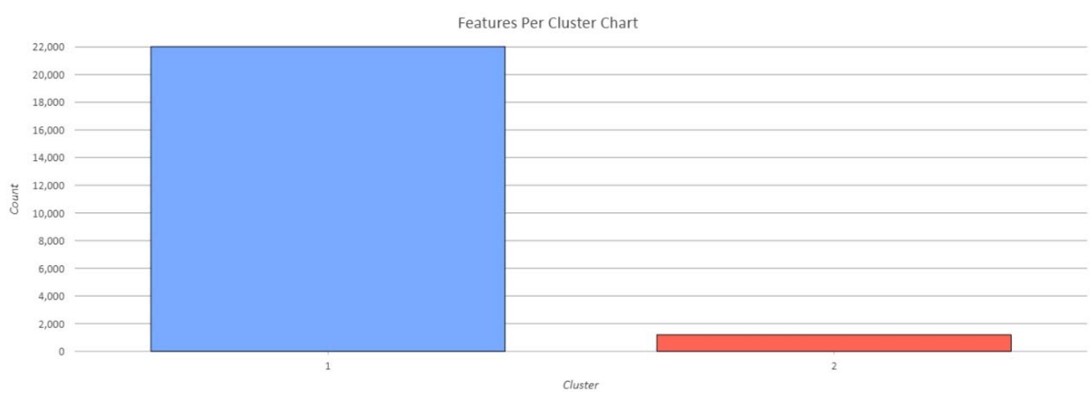

Figure 105. Feature per cluster count for California

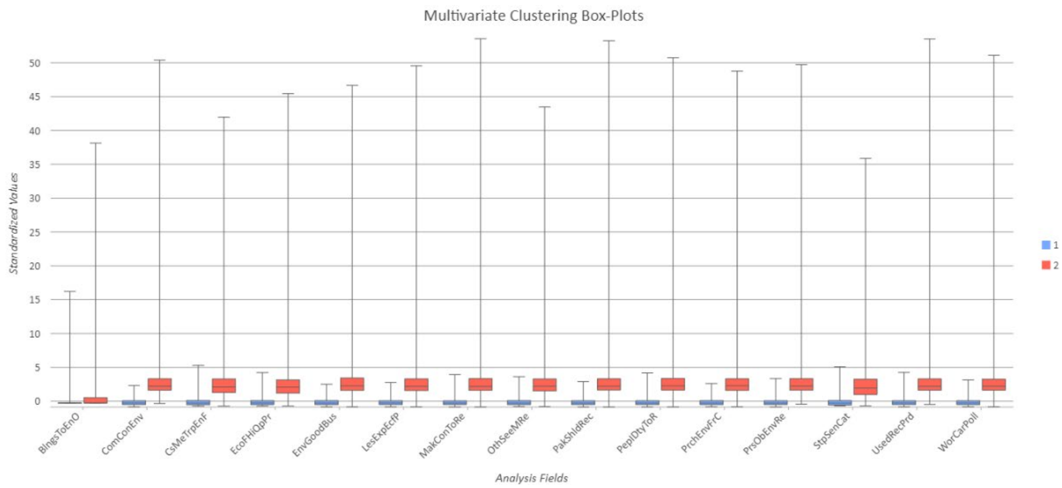

Figure 106. Multivariate clustering box-plots for California

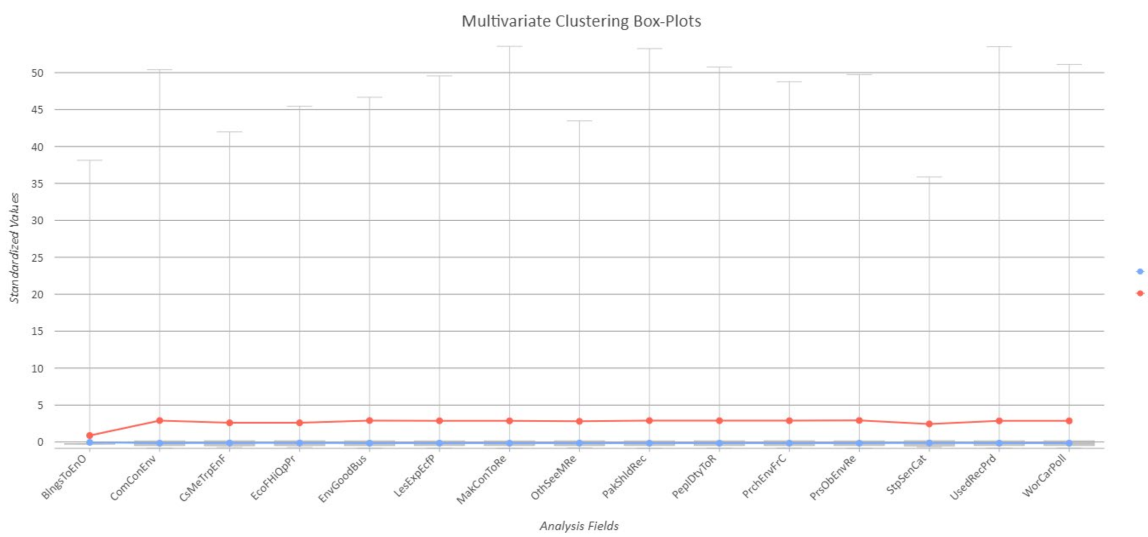

Figure 107. Multivariate clustering box-plots as the mean line for California

Figure 108 shows the clustering output for California environmental variables with three insets trying to magnify the high concentration areas with small block groups.

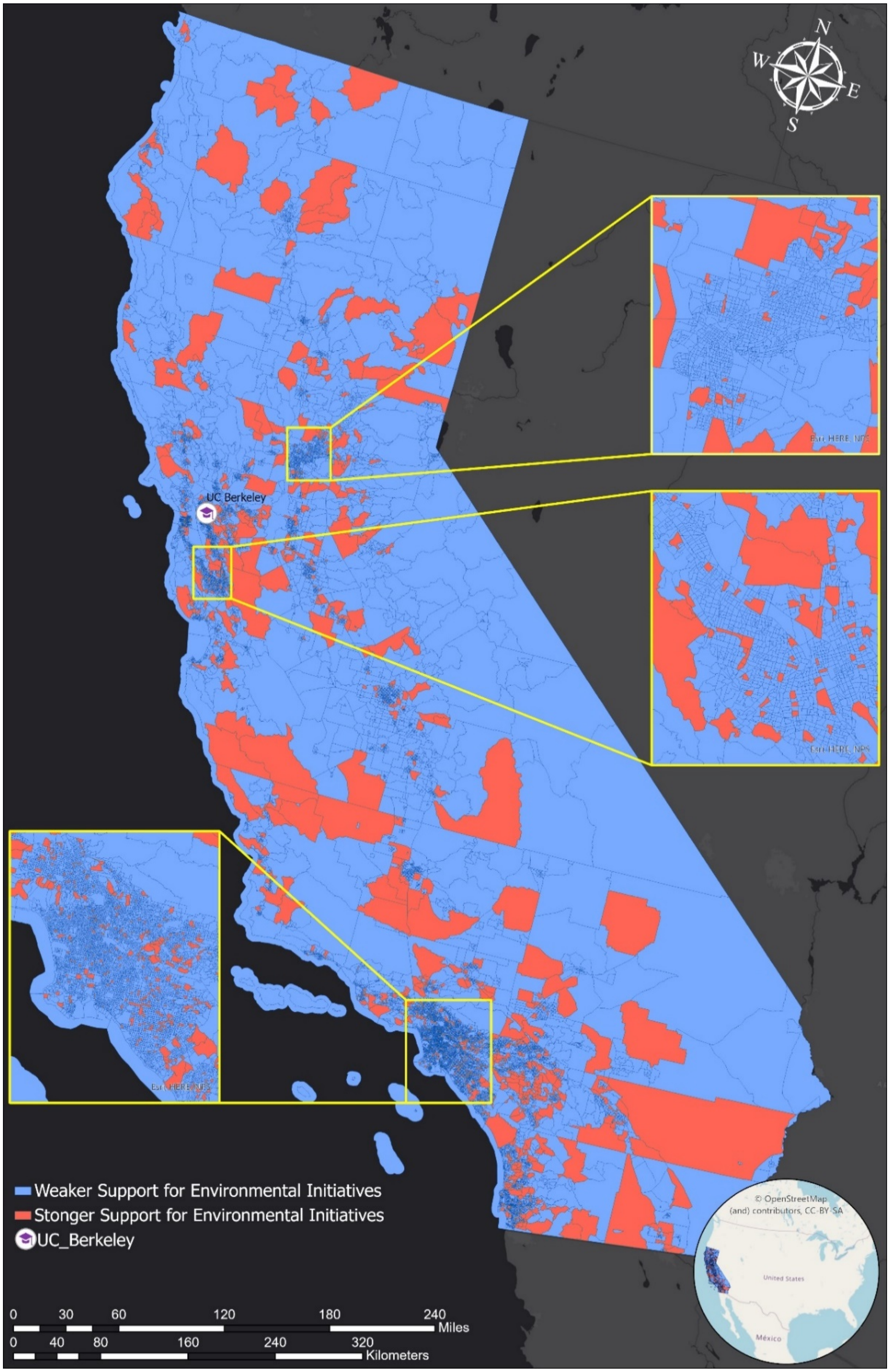

Figure 108. K-means on 15 environmental variables in California

The number of clusters in California drops to only two among 23212 census blocks. Cluster 1 comprises 94.8% of all features in California. These block groups have the lowest frequency of positive answers among all 15 environmental variables scattered throughout California. Cluster number two includes 6.2% of census blocks, reaching 1189 features distributed through California. Even though the standardized value of cluster 2 is slightly higher than cluster 1, they both are very close in values, as shown in Figures 106 and 107. None of the 15 environmental variables shows a distinction in terms of importance compared to other variables.

UC Berkeley's main campus is divided between clusters 1 and 2 (Figure 109). Although a non-matching campus shape causes this compared to the census block, it is challenging to allocate the campus in either of the clusters with a high statistical confidence level. The university is surrounded by many block groups clustered with blue color (Cluster 1) while neighboring two block groups clustered as 2. Either way, the university will be positioned in the framework's inner lines due to the low levels of standardized value in both clusters.

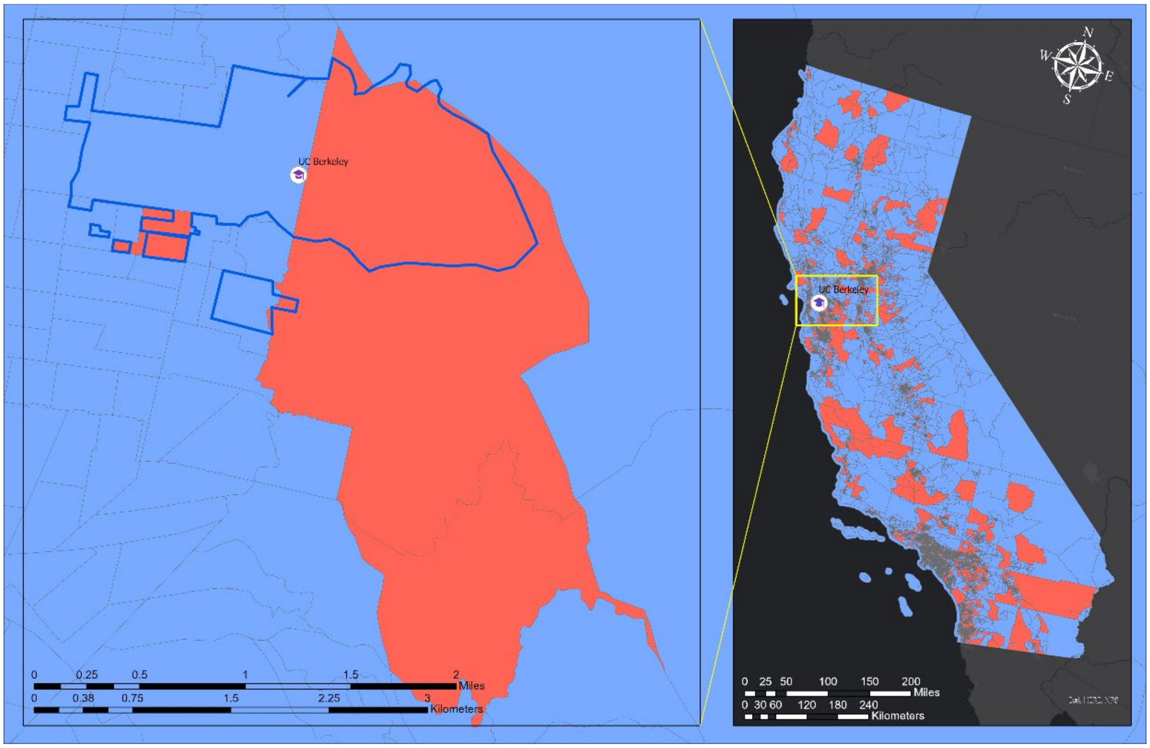

Figure 109. UC Berkeley campus position compared to the environmental clusters

6.10 ENERGY CONSUMPTION

This section will answer research question #3 in chapter 4:

3. What is the nature of the relationship(s) between state-level policy, state Sustainable Development Goal performance, and alternative energy?

6.10.1 TEXAS A&M

In favor of the Texas A&M University Vision 2020: Creating a Culture of Excellence and Core Values, the Energy Action Plan (EAP) 2020 has been established to continue improving mission-critical utilities' efficiency and effectiveness energy services. Continuing upon energy efficiency improvement of 47 percent for Source EUI FY02 through FY18, EAP 2020 aims to continue improving services while reducing Source

EUI by an additional 3 percent (with a target of 182) for the period from FY18 through FY20. This goal is challenging but can be accomplished by implementing and managing the following comprehensive EAP 2020 plan. Figures 110-112 show the relationship between campus size and energy consumption.

Initiative 1: Energy Stewardship Program (ESP)
Initiative 2: Energy Awareness, Education, Outreach, and Engagement
Initiative 3: Comprehensive Building Automation Management
Initiative 4: Comprehensive Utility Metering, Data Management, Billing, and Reporting
Initiative 5: Building Energy Optimization
Initiative 6: Server Room Consolidation and Virtualization
Initiative 7: Utilities and Energy System Capital Planning
Initiative 8: Utility Production and Distribution Optimization
Initiative 9: Academic and Research Collaboration and Partnering
Initiative 10: Building Energy Efficiency Upgrades and Optimization
Initiative 11: Sustainability (Environmental Benefit) and GHG Reduction
Initiative 12: Energy Performance Improvement (EPI) Program

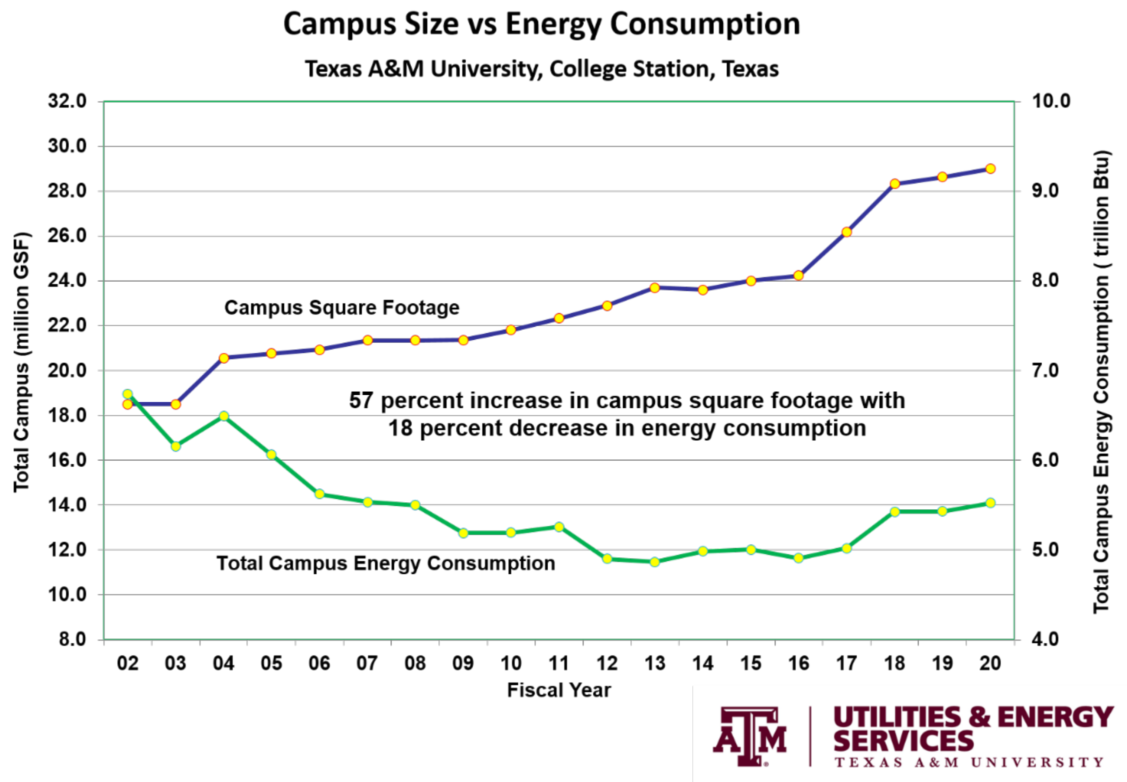

Figure 110. Texas A&M Campus size vs. energy consumption

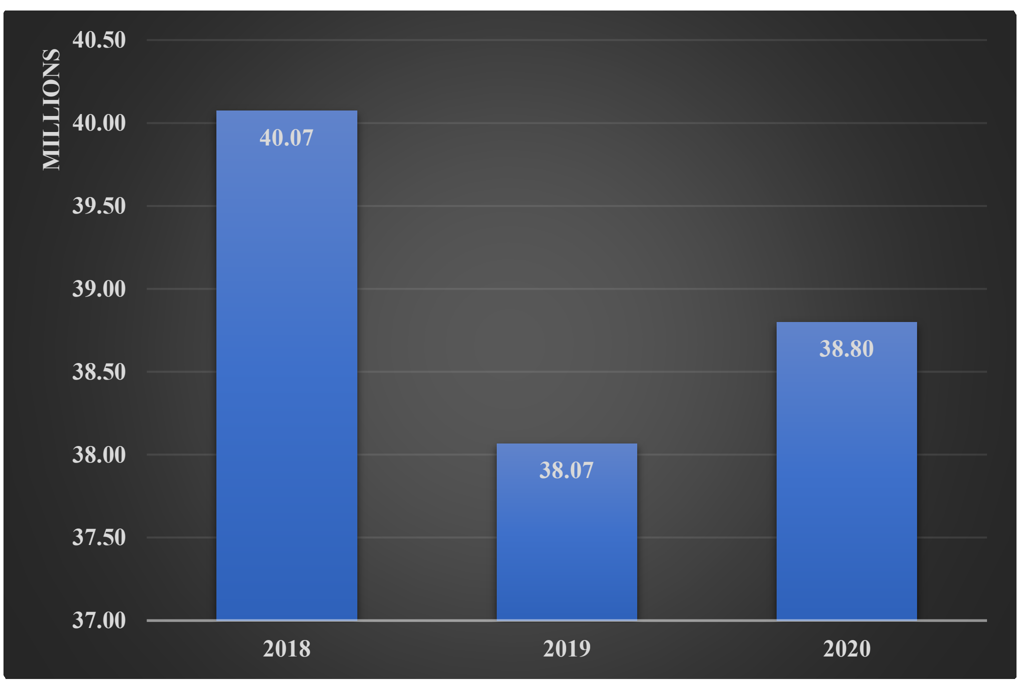

Figure 111. The total cost of energy at Texas A&M (in a million dollars)

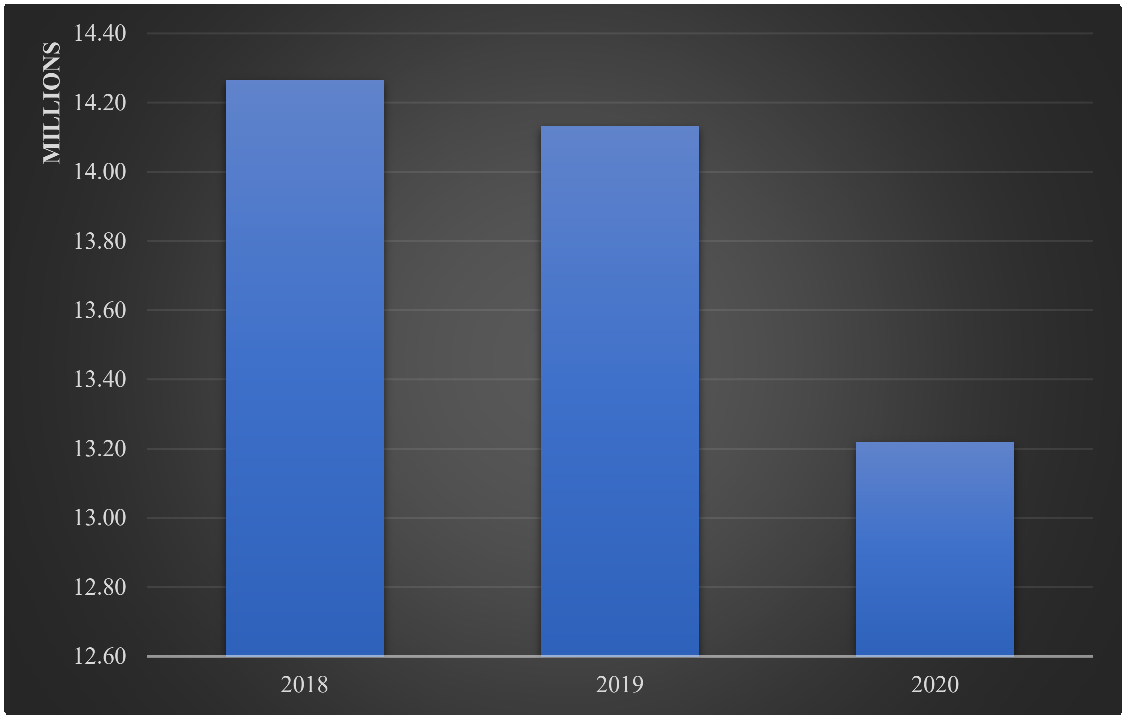

Figure 112. Cost of electricity at Texas A&M

Table 34. Texas A&M sample building baseline comparison

Building Name	Total Floor Area sq.ft	Total Electricity Used in kWh (2019)	Electricity Cost (2019)	% of Total Electricity Consumed Based on the Sample Size	EUI (kWh)	CBECS EUI Based on sq.ft (table C21 of CBECS)	Activity	Year of Construction
Evans Library	712,093	7,391,241	$576,516	43.9%	10.4	10.8	Library	N/A
Anthropology	51,592	342,433	$26,709	2.0%	6.6	11.1	Classroom	N/A
Chemistry	115,797	4,069,693	$317,436	24.2%	35.1	10.8	Research	N/A
C. Engineering	56,537	462,234	$36,054	2.7%	8.2	11.1	Research	N/A
SBISA Dining	94,233	2,752,993	$214,733	16.3%	29.2	31.0	Dining	N/A
Uti.Cen.Office	46,110	104,534	$8,154	0.6%	2.3	14.6	Office	N/A
Health Center	63,318	86,2678	$67,289	5.1%	13.6	24.1	Health	N/A
Neeley Hall	69,668	542,630	$42,325	3.2%	7.8	15.7	Residence	N/A
The Gardens	33,535	280,038	$21,843	1.7%	8.4	15.7	Residence	N/A
Bush Park.Lot	N/A	29,470	$2,299	0.2%	10.4	28.2	Parking Lot	N/A
Total	**1,242,883**	**16,837,944**	**$1,313,358**	**100%**				

6.10.2 UC BERKELEY

Table 35. UC Berkeley sample building baseline comparison

Building Name	Total Floor Area sq.ft	Total Electricity Used in kWh (2020)	Electricity Cost (2020)	% of Total Electricity Consumed Based on the Sample Size	EUI (kWh)	CBECS EUI Based on sq.ft (Table C21 of CBECS)	Activity	Year of Construction
Hertz Hall	31,362	99,000	$889,020	0.39%	3.2	11.1	Col/Uni	1958
Campbell Hall	81,600	2,136,000	$19,181,280	8.35%	26.2	11.1	Laboratory	2014
Minor Hall	46,225	1,111,000	$9,976,780	4.35%	24.0	11.1	Col/Uni	1941
Tang Health Center	77,369	1,174,000	$10,542,520	4.59%	15.2	24.1	Health	1993
Oxford Tract	10,535	2,180,000	$19,576,400	8.53%	206.9	11.1	Laboratory	1960
Kroeber Hall	119,001	649,000	$5,828,020	2.54%	5.5	37.5	Facility	1959
Energy Biosciences	124,175	3,914,000	$35,147,720	15.31%	31.5	10.8	Laboratory	2012
Sutardja Dai Hall	141,000	4,914,000	$44,127,720	19.22%	34.9	10.8	Col/Uni	2009
Bancroft Parking	38,986	8,938,000	$80,263,240	34.96%	229.3	28.2	Parking lot	N/A
O'Brien Hall	41,822	451,000	$4,049,980	1.76%	10.8	14.6	Office	1959
Total	**712,075**	**25,566,000**	**$229,582,680**	**100%**				

* The average industrial electricity rate in Berkeley is 8.98¢/kWh
* Data collected on Dec 7, 2020

UC Berkeley has a goal for each campus to reduce its energy consumption by 2% each year. The Energy Office is continually working on projects to make significant improvements in campus energy efficiency and save 4 million kWh this year. UC Berkeley is now producing 1 MW of solar PV through recent installations at five locations on campus: the MLK Student Union, Eshleman Hall, the Recreational Sports Facility field house, the University Village carport solar system, and Jacobs Hall.

Table 36. UC Berkeley Energy Goals

Goal	Status
Energy Efficiency: reduce energy use intensity by 2% annually.	In progress
On-campus renewable electricity: add 2.5 MW of solar.	In progress
Off-campus clean electricity: by 2025, procure 100% clean electricity.	In progress
On-campus combustion: by 2025, 40% of natural gas will be replaced by biogas.	In progress

* Source: Energy Office, Facilities Services at UC Berkeley

6.10.3 COLORADO STATE UNIVERSITY

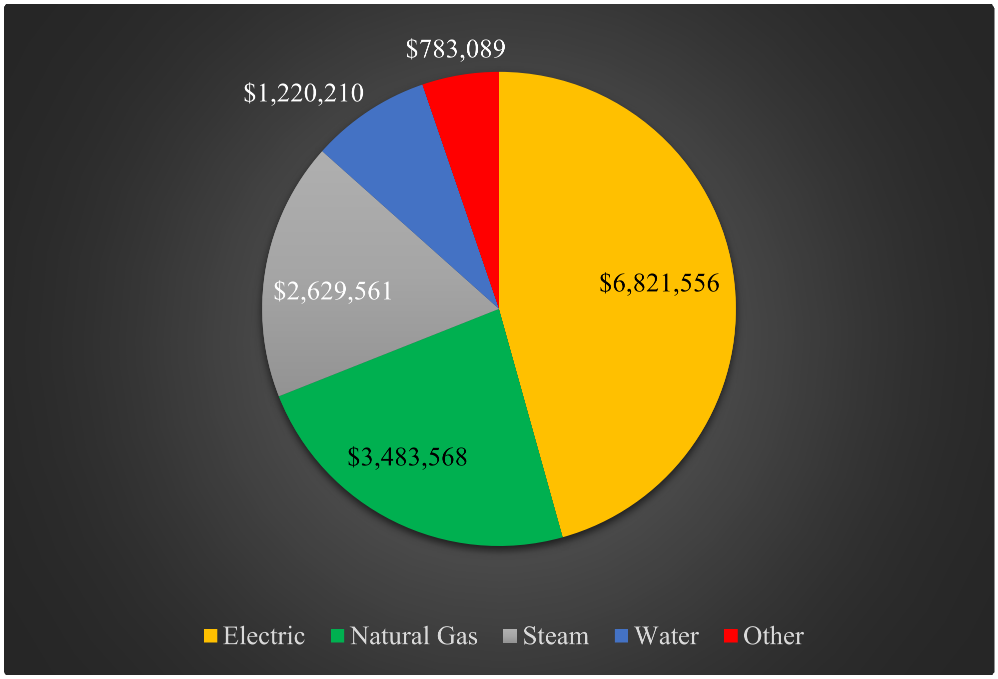

Figure 113. Annual energy cost at Colorado State University, main campus

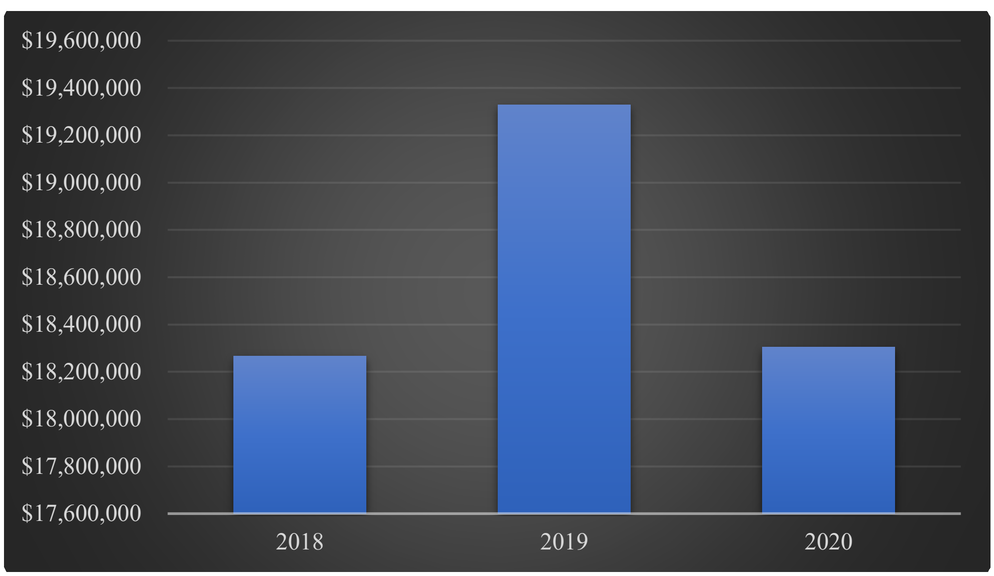

Figure 114. Cost of energy at Colorado State University

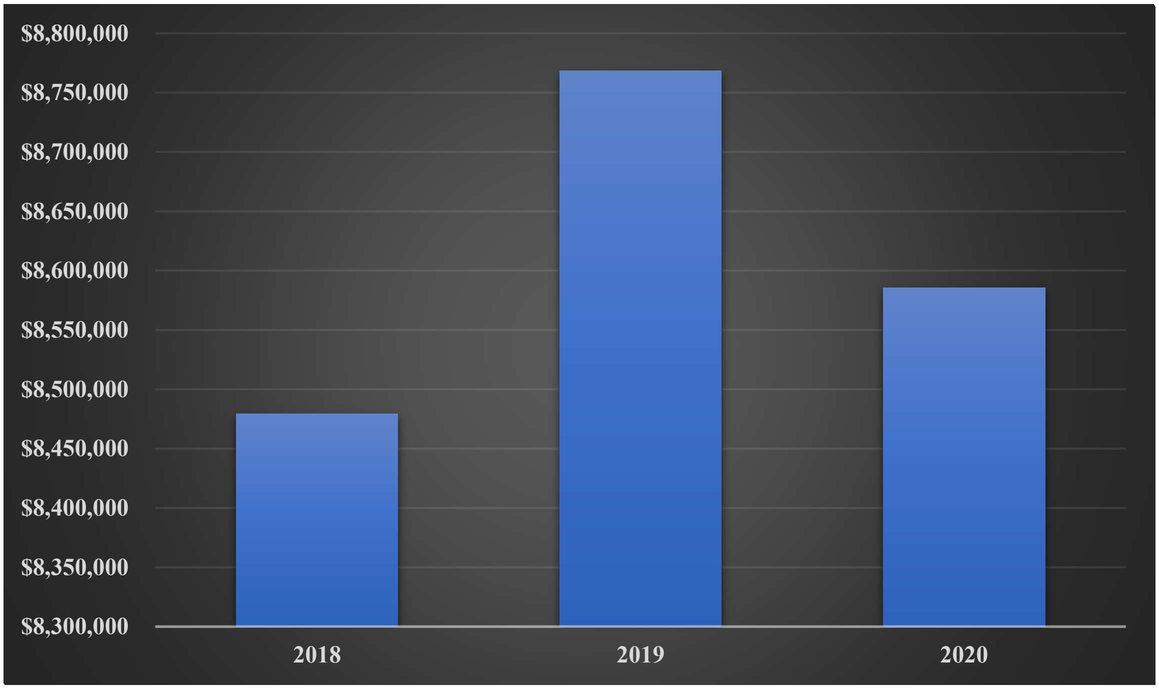

Figure 115. Cost of electricity at Colorado State University

Table 37. Colorado State University sample building baseline comparison

Building Name	Total Area sq.ft	Total Electricity Used in kWh (2019)	Electricity Cost (2019)	% of Total Electricity Consumed Based on the Sample Size	EUI (kWh)	CBECS EUI Based on sq.ft (Table C21)	Activity	Year of Construction
A. Village Aspen	67,093	434,167	$31,432	3%	6.4	15.7	Dormitory	2009
Ingersoll Hall	98,888	307,756	$22,115	2.13%	3.1	15.7	Dormitory	1964
Administration 0080	33,919	246,013	$17,877	1.70%	7.2	14.6	Office	1924
Centennial Hall	43,677	213,788	$15,645	1.48%	4.8	14.6	Office	1950
Animal Science	100,469	1,264,743	$91,946	8.74%	12.5	10.8	Research	1959
Biology	148,654	3,346,731	$243,142	23.11%	22.5	10.8	Research	2017
Chemistry	166,127	5,052,555	$366,328	34.90%	30.4	10.8	Research	1971
Eddy Hall	86,598	434,449	$31,492	3%	5.0	11.1	Classroom	1963
Clark Building	255,493	2,017,539	$146,566	13.93%	7.8	10.8	Classroom	1967
Health Center	162,061	1,161,008	$98,593	8.02%	7.1	29.1	Health	2017
Total	**1,162,979**	**14,478,749**	**$1,065,136**	**100%**				

*Electricity rate: 0.072/kWh
*Data collected on Dec 9, 2020

6.11 FRAMEWORK PLACING

6.11.1 TEXAS STATE UNIVERSITY

1. Are selected alternative energy investments characterized by long-run profitability in the HEIs under investigation? In other words, is there evidence that a proper coupling between lower energy consumption and economic profitability can be achieved?

According to the results discussed in chapter 6, at least in some cases, such as solar panel implementation or as shown in Mohammadlizadehkorde and Weaver (2020), it is possible to achieve long-term profitability despite the high costs of upfront investment. The results in chapter 6 define the extent of possible coupling by providing empirical evidence in terms of financial and geographical feasibility. The energy audit based on the sample can also reveal another pillar of the framework given by the extent of possible energy savings. Texas State University shows a low EUI based on the total area compared to the results from CBECS calculated based on the area, the activity type, and the year of construction (Table 10). This data put the university in the high-medium range of coupling diagram for *energy savings* and *financial feasibility*, as shown in Figure 116. Other components of the framework, such as *state policy* and *community values,* tend to reach the diagram's inner circles affected by the results of cluster analysis (chapter 6.9) and other studies taken into account.

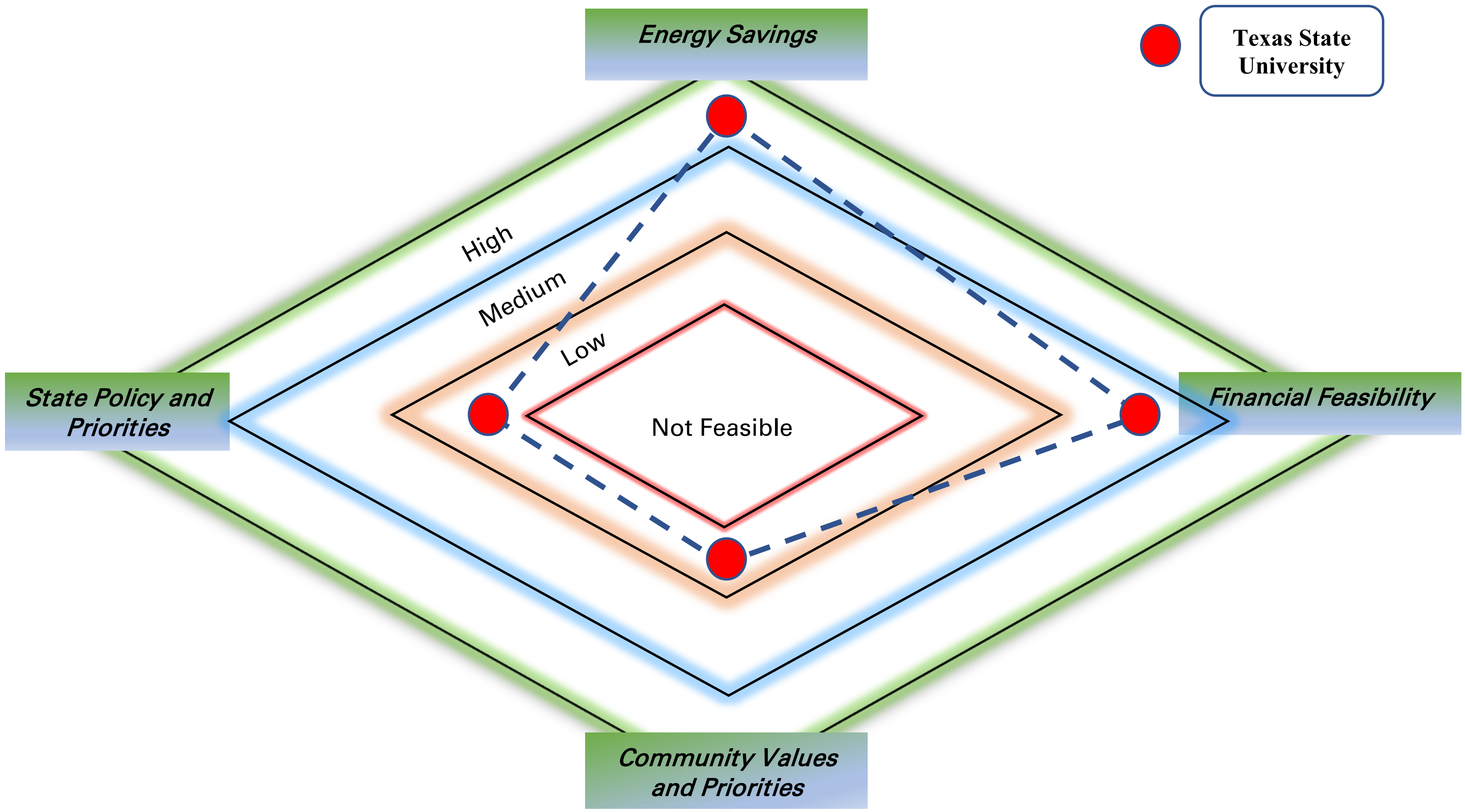

Figure 116. The conceptual landscape of properly coupled HEI-environment-social systems for TSU

6.11.2 TEXAS A&M

According to the results discussed in chapter 6, at least in some cases, such as solar panel implementation, it is possible to achieve long-term profitability despite the high costs of upfront investment. The results in chapter 6 define the extent of possible coupling by providing empirical evidence in terms of financial and geographical feasibility. The energy audit based on the sample can also reveal another pillar of the framework given by the extent of possible energy savings. Texas A&M shows a good EUI based on the total area compared to the results from CBECS calculated based on the area, the activity type, and the year of construction (Table 34). This data put the university in the high-medium range of coupling diagram for *energy savings* and *financial feasibility*, as shown in Figure 117. Other components of the framework, such as *state policy* and *community values,* tend to reach the diagram's inner circles affected by the results of cluster analysis (chapter 6.9) and other studies considered.

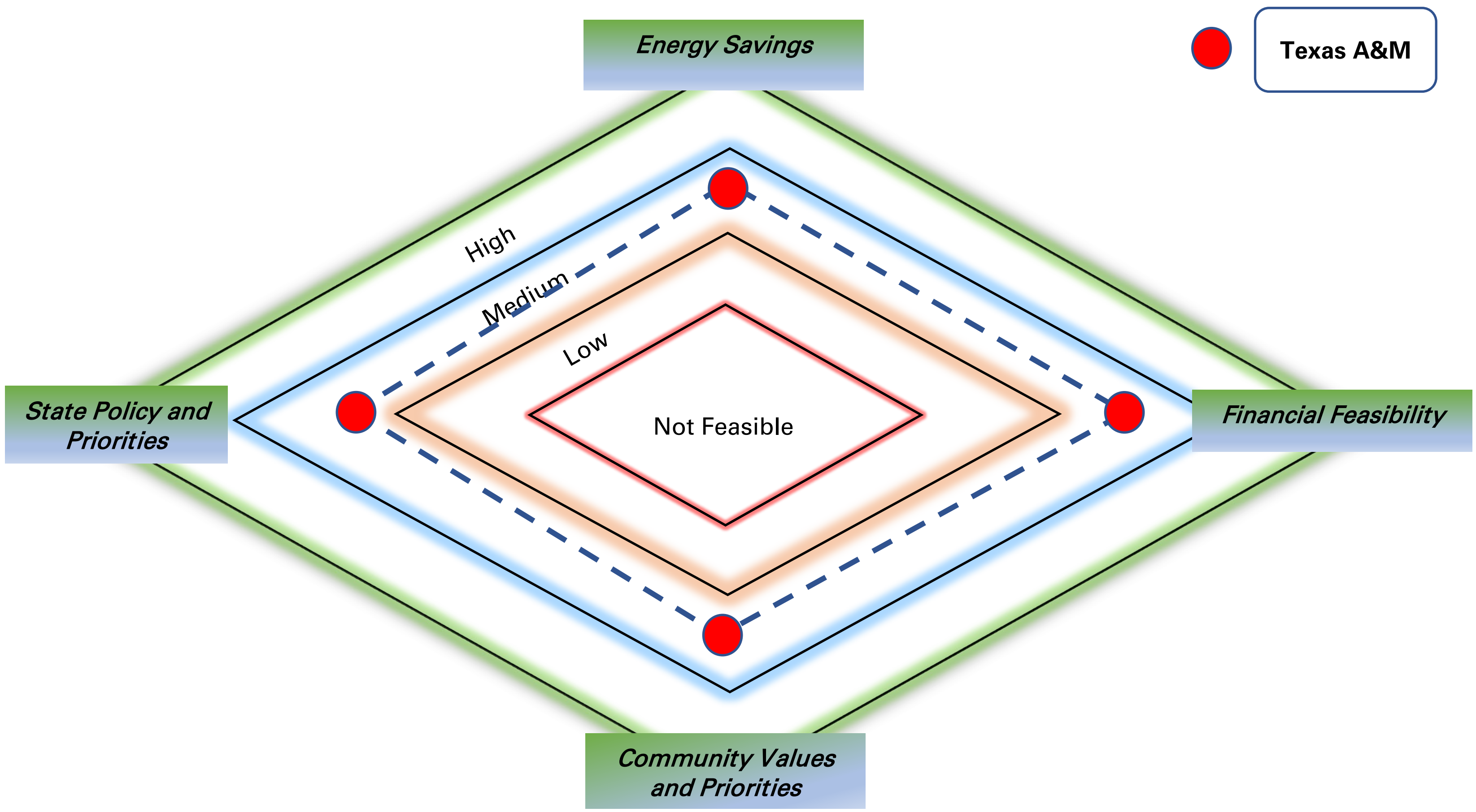

Figure 117. The conceptual landscape of properly coupled HEI-environment-social systems for A&M

6.11.3 UC BERKELEY

According to the results discussed in chapter 6, at least in some cases, such as solar panel implementation, it is possible to achieve long-term profitability despite the high costs of upfront investment. The results in chapter 6 define the extent of possible coupling by providing empirical evidence in terms of financial and geographical feasibility. The energy audit based on the sample can also reveal another pillar of the framework given by the extent of possible energy savings. UC Berkeley shows a high EUI based on the total area compared to the results from CBECS calculated based on the area, the activity type, and the year of construction (chapter 6.10.2). This data put the sample building at UC Berkeley in the coupling diagram's inner range for *energy savings* and *financial feasibility*, as shown in Figure 118. Other components of the framework, such as *state policy* and *community values,* tend to reach the diagram's inner circles affected by the results of cluster analysis (chapter 6.9) and other studies considered.

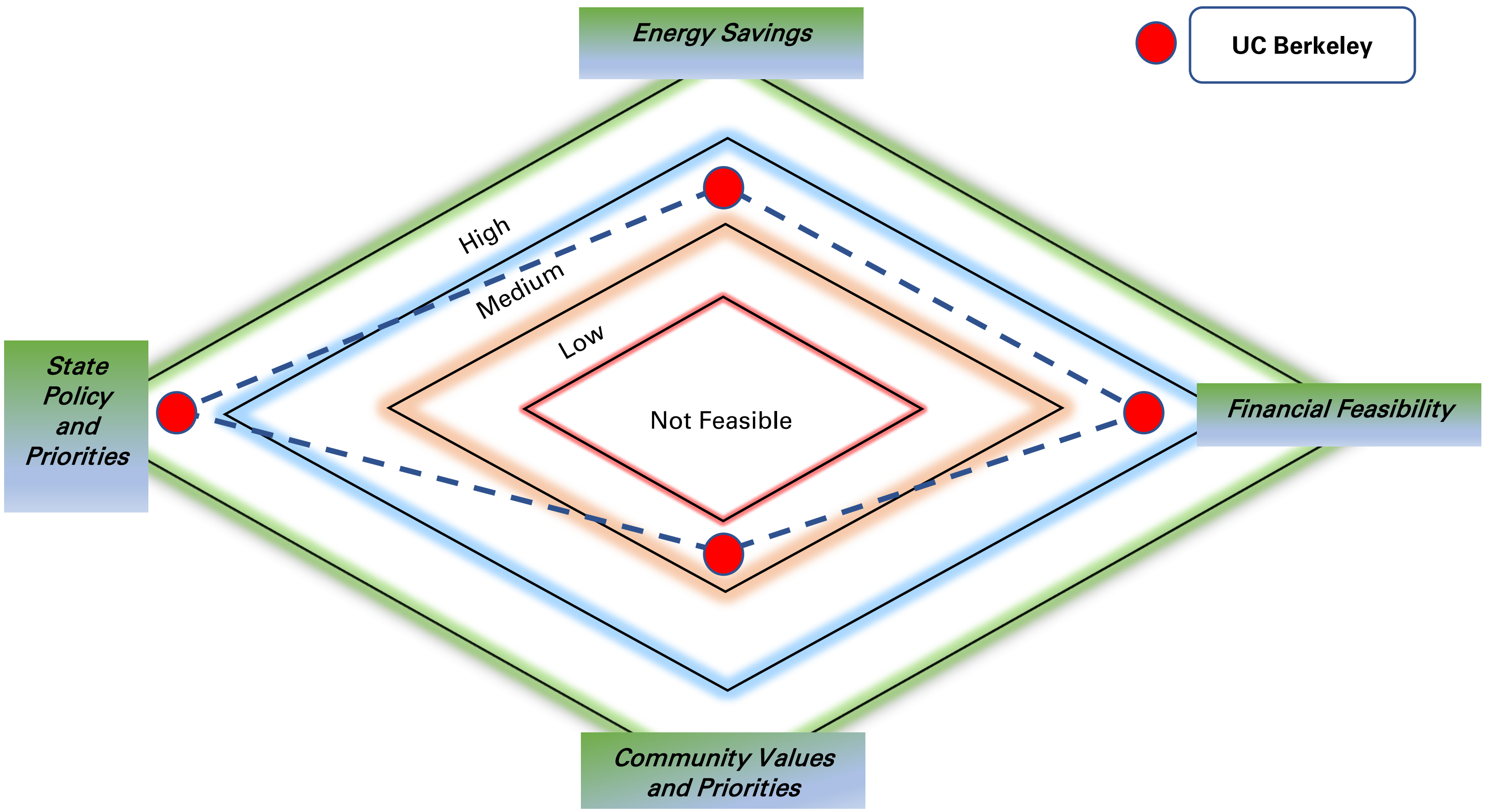

Figure 118. The conceptual landscape of properly coupled HEI-environment-social systems for UCB

6.11.4 COLORADO STATE UNIVERSITY

According to the results discussed in chapter 6, it is implausible to achieve long-term profitability through either a solar project or wind turbine implementation at Colorado State University. The results in chapter 6 define the extent of possible coupling by providing empirical evidence in terms of financial and geographical feasibility. The energy audit based on the sample can also reveal another pillar of the framework given by the extent of possible energy savings. UC Berkeley shows a high EUI based on the total area compared to the results from CBECS calculated based on the area, the activity type, and the year of construction (chapter 6.10.2). This data put the sample building at Colorado State University in the coupling diagram's exterior range for *energy savings* and *financial feasibility*. Hence a better output than other cases, as shown in Figure 119. Other components of the framework, such as *state policy* and *community values,* tend to reach the diagram's outer circles and inner circles affected by cluster analysis (chapter 6.9) and other studies considered.

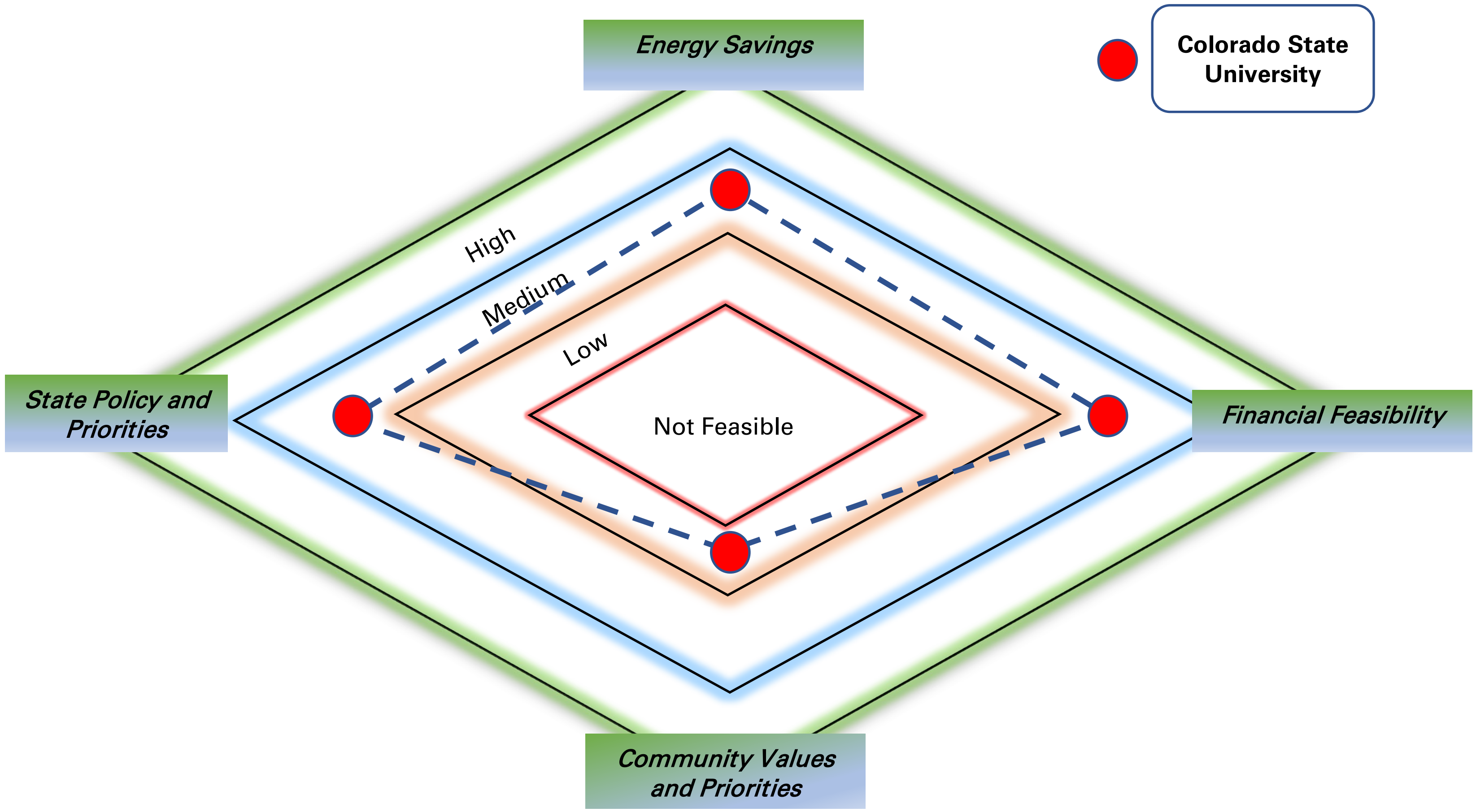

Figure 119. The conceptual landscape of properly coupled HEI-environment-social systems for CSU

7. CONCLUSION AND DISCUSSION

Many countries, local governments, and even higher education institutions have already integrated renewable energy systems into their long and short-term policymaking process. Many of the master plans (at universities), State bills, standards, and international agreements such as the Paris agreement (2016) make their cosigners responsible for adhering to alleviate the environmental degradation caused by traditional forms of energy production. Although in 2020 there has been a slight improvement in terms of CO_2 emission (EIA, 2020), the energy-related CO_2 is expected to increase in 2021, which is in line with the world energy consumption trends shown in Figure 2. The correlation between energy consumption and the warming climate is considered a leverage point for intervention at many levels, including HEIs. The short-term cost and pursuing growth seem to be the most convenient explanations for the low rate of sustainable use of renewable energy, as discussed in Chapters 1 and 3. The pursuit of *economic success* (e.g., Weaver et al., 2015) and *economic efficiency* (Timmons et al., 2019) prevents systems from reaching *properly coupled* goals in conjunction with environmental systems, with a few exceptions (Obama, 2017).

Considering the convoluted labyrinth of sustainability, the pursuit of growth, and the social responsibility of HEIs, how might society in the aggregate overcome this incentive trap in ways that mobilize actors toward short-term sacrifices for the long-term benefit of local and global environmental integrity? This dissertation answered this question by including a series of multiple questions discussed in Chapter 4. Financial analysis is one aspect of this equation covered in many studies shown in Chapter 3 and improved by taking GIS into account (Chapters 5 and 6). A renewable investment's numerical aspect is discovered by combining financial methods based on different tools developed by the most accredited environmental organizations (Chapter 5.6). Through using a multicriteria decision-making process, it was possible to detect the best place and time for the chosen renewable energy implementation (e.g., solar and wind in Chapter 6) in addition to its financial output. Simultaneously, many formal studies merely focus on financial aspects without including the geographical factor (Mohammadalizadehkorde & Weaver., 2020). In this dissertation, a combination of financial analysis and the geographical study was provided through a series of GIS methods to improve financial analysis accuracy.

As discussed in Chapters 3.2 and 5.8, a radical change of structure with the capacity to alter current society rules is needed to enable proper coupling (N-tupling). As such, after determining the financial feasibility of selected alternative energy interventions in four case study universities, the dissertation zeroes in on spatial context as a potential determinative factor (Chapters 5.8 and 6.9). This dissertation shows the spatial context of at least two of Howe and colleagues' (2017) three categories discussed in Chapter 1 (structural factors and knowledge/scope). With respect to structural factors, embeddedness in a neighborhood or region where residents and leaders prioritize sustainability goals might positively influence HEI sustainable energy implementation. However, through cluster analysis, a discrepancy was found between the community attitude towards sustainability and the HEI master plan toward the same goals, where the University is placed among the most sustainable institutions even without significant support on behalf of the community. This is in contrast with the assumption discussed in Chapter 2. While issues of HEI leadership and strategic planning are likely to be some of the more determinative factors at play in institutional energy investment decisions, it is reasonable to assume that leadership and decision-making in public HEIs will at least partially reflect the preferences and values of their local communities or regions (shown by the cluster analysis), insofar as most HEIs strive to be upstanding citizens who maintain effective Town-Gown relations (Broto & Baker, 2018; Pasqualetti, 2011; Cupples, 2011).

To classify the institution's placement in the sustainability constellation and based on the suggested conceptual framework, a series of key terms and ideas are developed to show the extent of proper coupling in each institution shown in Table 38.

Table 38. The implication of forces in proper N-tupling and possible outputs

Internal Forces/External Forces	***Proactive***	***Reactive***
Supportive	*Proper coupling*	*Greenwashing*
Neutral	*Trendsetting*	*Business-as-usual*
Inhibitive	*Radical innovation*	*Cost minimization*

Proactive: commitment to sustainability/sustainable energy use is evident in actions; is apparent with or without government mandates; predates government mandates.

Reactive: commitment to sustainability/sustainable energy use is either not present or present only in words, not actions; is superseded by economic considerations; would probably not exist if government mandates were absent.

Proper coupling: internal and external motivations are congruent; both the university and the state and local community that funds it has taken demonstrable actions to reduce energy use.

Trend-setting: universities are taking actions that contribute to sustainable energy use without evident external support and in the absence of external pressure—it is possible that these "trend-setters" could inspire or otherwise motivate governments to take actions that would attempt to "scale up" the university's sustainability initiatives, which could eventually lead to a "proper coupling."

Radical innovation: despite a policy/government context that incentivizes short-term cost-minimization and creates artificial barriers to sustainable energy regimes, universities are internally motivated to reduce energy consumption and invest in sustainable energy technology.

Supportive: state and local government: has adopted policies, funded initiatives that demonstrate a commitment to sustainable energy use; offers technical support to other levels of government or public institutions to achieve sustainability goals.

Neutral: commitment to sustainability/sustainable energy use is either not present or present only in words, not funded programs or enforceable policies; is superseded by economic considerations.

Inhibitive: government incentivizes economic efficiency and cost-savings above all else; no commitment to sustainability or sustainable energy use.

Greenwashing: the relevant state and local community are supportive, but, internally, the university does not demonstrate a genuine commitment to sustainable energy use. Rather than taking bold actions or investing in new technologies, the university modifies business-as-usual in marginal ways to give it the appearance of being more sustainable (what critical geographers have called "greenwashing"); might include rhetoric within a university strategic plan that is not acted on.

Business-as-usual: self-explanatory; because there is no push or compelling external force, the university continues following standard operating procedure.

Cost minimization: where the primary objective is economic efficiency, actions will be oriented toward minimizing the short-term (e.g., fiscal year) budget without accounting for the externalities that those actions generate (and how they work against sustainability agendas).

Texas State University will be categorized as a *reactive-business as usual* institution since the commitment to the sustainable use of energy does not appear in the master plan (2017-2027) concretely. The use of renewable energy is almost absent except for research purposes in the engineering department. The expression "alternative energy" is used in different parts of the plan with no direct reference to renewable options. The master plan refers to "Assure that architectural designs and building sites consider energy efficiency (Master plan 2017-2027, p.17)." This is in line with the scope of cost minimization based on the standard retrofitting techniques applied at the building level. The local government does not require any specific renewable implementation for the higher education system and limits its policy to reduce electricity consumption by at least 5% each year beginning in 2011 and extended in 2019 (Senate Bill 898 and Senate Bill 241). On the other hand, there is no specific State-level climate action in the act, as shown in Figure 18, and both renewable energy consumption and production are relatively low (Figures 19, 20).

Texas A&M shares several aspects of this categorization, with Texas State University being located in the same geographical context. Although the institution itself has a specific commitment to energy efficiency at the building level (see Chapter 6.10.1), it fails to bring up the renewable energy implementation into its long-term plan (reflected at the State level). The total campus area is growing steadily, but the energy consumption has been contained, as shown in Figure 110. Also, the EUI in sample buildings is lower than CBECS values in many cases (Table 34). On the other hand, the study of wind and solar potential does not show a significant and reliable investment potential (Chapters 6.3 and 6.4), which is probably why the priority is not given to renewable energy implementation. That is why Texas A&M can be categorized as a *reactive-cost minimization* institution.

UC Berkeley has a goal for each campus to reduce its energy consumption by 2% each year. Compared to Texas, the goal at UCB is set for a lower percentage of saved energy yearly. However, the average EUI shows a higher electricity consumption for most of the sample buildings. Still, UC Berkeley is the only one with a significant renewable energy implementation among the four study areas. UC Berkeley is now producing 1 MW of solar PV through recent installations at five locations on campus: the MLK Student Union, Eshleman Hall, the Recreational Sports Facility field house, the University Village carport solar system, and Jacobs Hall. This occurs while the solar energy study does not show a better output than other case studies (Chapter 6.5). While State policy is supportive of the transition towards a more sustainable energy future by having a completed climate action (Figure 17), the community does not show substantial support to reach the goal based on the results of cluster analysis (Chapter 6.9.3). Indeed, the cluster analysis shows the lowest rate of positive attitude towards sustainability among all 4 cases. Therefore, UC Berkeley can be considered as a *supportive-trendsetting* institution.

Colorado is another example of a State with a complete climate action (Figure 18). Colorado State University has added several large new buildings increasing the institution's total square footage in recent years. However, the total energy consumption related to the buildings remains relatively flat. The institution has no direct reference to implementing renewable resources in the master plan even though Colorado aims at 100% clean energy by 2050 for utilities serving 500,000 or more customers. Nevertheless, according to Colorado State University's facilities management, several cost minimizations and energy efficiency programs are in progress. Colorado State University falls inside cluster 1 with the lowest rate of standardized values, including a direct consequence of putting the university and the community in the inner rings of the conceptual framework and specifically for Community Values and Priorities as one of the pillars of the framework. Therefore, the institution can be categorized as *cost minimization and business as usual* HEI.

Acquisition of viable plans is one of the requirements of sustainability implementation in HEIs (Leal Filho et al., 2018). This dissertation provides a feasible framework to cover this sustainability aspect at HEIs and, to a bigger extent, communities or cities. The chosen universities as a sample are aware of their unique opportunity to be sustainability leaders with or without being advised of their *proactive* or *reactive* response to sustainability. They introduce multiple opportunities to save energy or adhere to bills, declarations, and other non-binding measures. Although the administrations see growth as a means of remaining competitive and economically successful, this culture will change under climate change's critical conditions. The social mission of HEIs suggests that they arguably have a responsibility not only to teach and research sustainable practices (Stough et al., 2018) but also to practice sustainability in their daily operations. In this dissertation, I attempt to provide the needed practices and approaches that shift the attention from exclusively a business-as-usual institution to a thriving organization to be coherent to their social responsibility.

However, the decisive factor remains the lack of a long-term governance model capable of forcing measurements. The resistance to replacing fossil fuel-intensive energy systems results reasonably convincing due to insufficient renewable energy potential shown in the result section. This dissertation reviewed only wind and solar power, the most obvious options, while every geographic context (place) can represent a diverse potential given by geothermal, hydropower, biofuel, and biogas.

Renewable energy, however, is not the only choice since building-level energy efficiency options can significantly reduce consumption (Mohammadalizadehkorde & Weaver, 2020). This dissertation reviews a series of energy efficiency measurements at the building level with their respective financial output, which is replicated in an Excel-based model to be used by other researchers. In combination with renewable energy options, these opportunities can extend the planning process's horizon without necessarily relying on renewable energy.

As this dissertation demonstrated, tackling the sustainability problem from multiple fronts can result in a more holistic solution for HEIs. Behavioral interventions have a significant role in this process, as well. “The transition to low carbon energy systems cannot solely rely on technological innovation,” and there are social and behavioral barriers that need to be overcome to make the energy transition possible (Hoppe and de Vries, 2018). That is why in this dissertation, I Introduced the community dimension. The relationship between community and energy has been studied scarcely, and it is at its initial stage, as stated in the literature review. This dissertation has tried to show whether the community's attitude contributes to how HEI faces sustainability. The low or high level of sustainability attitude—shown by cluster analysis— among the citizens of a place might reflect how an institution adopts its social responsibility. The assumption is that a demanding society—with higher sustainable expectations— can overcome the barrier of *reactive* response, transforming a university into a *proactive* organization. However, cases like the University of California at Berkley show the exact opposite of this assumption where despite a low level of sustainable attitude on behalf of citizens, the university is one of the pioneers of sustainability implementation. A non-business-as-usual political establishment could cause this diverse attitude on behalf of the university. In other cases, such as Texas State University, state legislation prompted sustainability planning; however, inconsistent enforcement over time has weakened the effects.

As centers of research and education, colleges and universities have a unique opportunity to help their local communities create and maintain more sustainable urban environments. Beyond research, instruction, and credentialing, HEIs can model best practices for sustainability planning, lead in the development of sound financial projections associated with sustainability initiatives, demonstrate the values of emerging sustainable technologies, and illustrate the need for equitable, socially just community engagement. I argue that sustainability objectives at HEIs can only be achieved by integrating the needs and voices of the local community into the objectives. Therefore, a sustainable HEI certainly sets and achieves robust internal managerial goals, but it is also one that acknowledges its influence on the broader urban environment and successfully engages and improves its local community.

8. LIMITATIONS

8.1 TIME AND RESOURCE CONSTRAINTS

Due to the dissertation's goal of evaluating the financial feasibility of substantial alternative energy investments in their multi-level spatial contexts, it is necessary to select both specific projects and specific study areas. In other words, it is essential to perform case studies. This case study approach has limitations for generalization, and it looks past any projects or alternative energy innovations that are not included in the preidentified menu of options created by the author. However, it is worth pointing out that much of the recent research on sustainable energy in HEIs involves small-scale investigations (Mohammadalizadehkorde and Weaver, 2020). In that sense, this dissertation aligns with the contemporary literature, but it also meaningfully advances that literature by taking a comparatively holistic approach that interrogates connections between feasible energy projects, financial attractiveness, community priorities, and state policies. In other words, the dissertation takes up the challenge of attempting to "understand complex inter-relationships" between decision-makers, decision-making contexts, and decisions (Hadkinson, P. and Hadkinson, H., 2001). It does so by using a methodological framework that can be replicated on other University campuses or entire communities, given that the former tends to function and operate much like the latter.

More generally, case studies, although focused on specific study areas, "are fertile grounds for conceptual and theoretical development (Hodkinson, P. and Hodkinson, H., 2001, p. 7). The application of case studies on a large scale is expensive and time-consuming if attempted on a large scale (Hodkinson, P. and Hodkinson, H., 2001). An example is given by the number of organizations covered by EDF to identify sustainable measures since 2008. Currently, only 450 organizations—including TSU— have benefitted from the EDF Climate Corps program that provides a network of qualified graduate students as sustainability experts. The identified potential projects by nearly 1000 graduate students reach 2.1 million metric tonnes on CO_2 reduction in 12 years. All these significant efforts go along with the fact that per the International Energy Agency, even if nations fulfill the Paris Agreement goals, it is still unlikely to keep the warming climate below 1.5°C of increase on the average global temperature (World Energy Outlook, 2016).

8.2 CLUSTER ANALYSIS

Clustering is an exploratory method with no single optimal approach. Clustering algorithms also occasionally find clusters even when there are no natural clusters present in the data (Jain, 2010). *Cluster validity* refers to evaluating the result regarding the quality of clustering, which invites the user to verify whether data have any *clustering tendency* (Jain and Dubes, 1988).

Clustering algorithms work best on either numeric data or exclusively categorical data (Shih et al., 2010). One way to overcome this problem is to apply a two-step clustering method to find clusters among numeric and categorical data (Shih et al., 2010). Nevertheless, the existing clustering algorithms involve some disadvantages or weaknesses such as sensitivity to outliers or the initial selection of clusters; the two-step method integrates hierarchical and partitioning clustering algorithms with adding attributes to cluster objects (Shih et al., 2010). The shortcoming of two-step clustering for the k-prototype algorithm is defined by Shih et al. (2010) as follows: (1) After applying a binary distance, if the object pairs with the value of the numeric data, the distance between them is zero, otherwise it is one. However, this will not work on categorical data types such as “high,” “low,” and “medium” because there is a degree of difference between high-medium and high-low pairwise. (2):

> “Only one attribute value is chosen to represent [the] whole attribute in [the] cluster center. Therefore, the categorical value with less appearance seldom gets the chance to be shown in [the] cluster center, though these items may play an important role during [the] clustering process. Additionally, since k-prototype inherits the ideas of k means, it will retain the same weakness of k-means” (Shih et al., 2010, p. 2)

The exclusivity of k-means on numeric data type is caused by optimizing a cost function defined with Euclidean distance measure between data points and means of clusters (Huang, 1997), measured only on numerical data types.

The use of constructed and artificial data sets is suggested to validate clustering algorithms (Huang, 1998). The advantage of artificial data sets is given by the ability to control the data set structure. However, artificial data sets may not represent the real world, and they are mainly focused on numeric data generation, while the interest should be focused on mixed-type data (Huang, 1998).

An alternative to clustering is given by visualization techniques (Huang, 1998). However, visualization may not be useful when there is no point (coordinate or observation) involved, like when only a number is assigned to a block group. Also, the weight γ assigned to attributes to avoid favoring them may add additional problems to the

K-means method's limitations in the K-prototype. The average standard deviation of numeric attributes may be used as a guidance in specifying γ, but it may not be considered as a general rule (Huang, 1998). As stated by Huang (1998), "The user's knowledge of the data is important in specifying γ" (Huang, 1998, p. 20). If the researcher thinks there is a need to favor a given numeric attribute, that attribute needs a small γ. If the categorical attributes are essential, the researcher should set a large γ for that categorical attribute.

8.3 NET PRESENT VALUE

The selection among multiple energy investments in HEIs is a laborious job involving numerous factors, conflicting priorities, different scenarios, and methods. Making the same decision *sustainable* is a more difficult task, which might be affected by local and governmental policies. At least one correlate of observations at TSU while decreasing electrical consumption might not be reducing its overall energy consumption footprint as effectively as possible. Put another way, a potential weakness of SB 898— and maybe several other master plans in HIEs— is that it only restricts electrical consumption. Indeed, gas consumption accounts for a significant portion of energy use at TSU (24%). Thus, while the Bill acts as somewhat of a regulatory mechanism for moving TSU's commitment to sustainability beyond words and into action, it might not go far enough. Accordingly, financial analyses aimed at quantifying the attractiveness of investments into sustainable energy technologies could benefit from being more inclusive than SB 898 and incorporating additional forms of energy consumption into their calculations. The present dissertation heeds this call and considers both electrical and natural gas consumption in its analyses. Consequently, the case studies and their findings have to value TSU and other universities and Texas state legislators who might consider drafting a new bill that applies to all fossil fuel-based energy consumption, rather than electricity alone.

A financial analysis protocol always requires a cost-benefit analysis to detect the optimal investment choice and estimate the economic value of avoided CO_2 (Nesticò and Pipolo, 2015). Mastering the concept of net present value is at the core of many financial analyses. “The simplest statement of the NPV rule is that you should discard projects with negative NPVs and undertake all projects with positive NPVs” (Ross, 1995). When the financial analysis is not based on NPV, other economic indicators such as IRR or payback period are considered. Simultaneously, taking a single project should not prevent us from undertaking other projects (Ross, 1995). This is very likely to happen since a single lighting system replacement can have the highest NPV value.

In contrast, other smaller projects, such as replacing motors and pumps, have lower values, but in aggregate, they can surpass the NPV value of lighting replacement (Mohammadalizadehkorde & Weaver, 2020). Therefore, the question is which project should be rejected among the projects with positive NPV? The rules of NPV are subject to many other variables. Ross (1995) made it clear with the story of *The Good, the bad, and the ugly of the NPV.* In his paper, a $100 million upfront investment with $10 million of profit in a year and a negative $300,000 NPV was rejected by the management (Probably because of negative NPV). The same project reached a negative 200,000 NPV (better NPV) after a few exchanges of the right to the project (sold by the company) and less than a 1% decrease in a one-year interest rate.

A thorough accounting of costs is essential, but it does not cover all the details regarding how a new policy or measurement affects a state or community. Some researchers believe that renewable energy sources, even without incentives, are cost-effective compared to fossil fuels (Johnson et al., 2013). Still, once the time factor is added, they might not seem appealing to decision-makers. Therefore, it is crucial to be aware that cost-effectiveness is achievable on both axes of economy and time, as shown in solar panel installations at Texas State University in 2016 (Mohammadlizadehkorde & Weaver, 2020). Also, equal renewable energy policies might not lead to higher efficiency in the implementation process (Hafeznia et al., 2017). Hence, the process of site selection should precede financial analysis. Other factors, such as the index of readiness, should be included in the study (Hafeznia et al., 2017). Depending on the researchers' methodology, the analysis may not include a balanced comparison of costs and benefits (EPA, 2018). For example, it may include the costs and the quantity of electricity savings but exclude the health benefits of emissions reductions (EPA, 2018). Quantifying these benefits would accurately highlight the broader value of energy efficiency or renewable energy programs.

8.4 DATA CONFIDENTIALITY

Energy consumption data is, in many cases, subject to confidentiality. For example, the buildings that participated in the U.S. Energy Information Administration's CBECS survey are kept anonymous, and CBECS respondent information is rigorously confidential. To guarantee confidentiality, all building identifiers are deleted from the data file before the public use microdata file is created, and the location of each building is made available only at the Census division level (groups of four to nine states). Also, building features that could identify a particular responding building, such as the number of floors, building square footage, and the number of workers in the building, are masked to protect the respondent's identity. This shortcoming negatively affected the process of identifying energy consumption in comparing HEI to the buildings represented in CBECS.

APPENDIX SECTION

Appendix 1

```
"""
#K-means in Python
"""


#Initialization


import pandas as pd
import numpy as np
import matplotlib.pyplot as plt


#%matplotlib inline


df = pd.DataFrame({


    'x': [14, 20, 47, 36, 56, 23, 12, 45, 23, 45, 23, 67, 78, 67, 90, 33, 22, 65, 33, 56, 87, 55,
53, 24, 21, 11, 8],
    'y': [20, 56, 33, 56, 78, 45, 56, 76, 89, 23, 62, 43, 59, 43, 59, 33, 42, 53, 38, 39, 51, 93,
27, 31, 12, 56, 16]
```

```
})


np.random.seed(200)

k = 3

# centroids[i] = [x, y]

centroids = {

    i+1: [np.random.randint(0, 100), np.random.randint(0, 100)]

    for i in range(k)

}


fig = plt.figure(figsize=(6, 6))

plt.scatter(df['x'], df['y'], color='k')

colmap = {1: 'r', 2: 'g', 3: 'b'}

for i in centroids.keys():

    plt.scatter(*centroids[i], color=colmap[i])

plt.xlim(0, 100)

plt.ylim(0, 100)

plt.show()


#Assignment


def assignment(df, centroids):
```

```
    for i in centroids.keys():
        # sqrt((x1 - x2)^2 - (y1 - y2)^2)
        df['distance_from_{}'.format(i)] = (
            np.sqrt(
                (df['x'] - centroids[i][0]) ** 2
                + (df['y'] - centroids[i][1]) ** 2
            )
        )
    centroid_distance_cols = ['distance_from_{}'.format(i) for i in centroids.keys()]
    df['closest'] = df.loc[:, centroid_distance_cols].idxmin(axis=1)
    df['closest'] = df['closest'].map(lambda x: int(x.lstrip('distance_from_')))
    df['color'] = df['closest'].map(lambda x: colmap[x])
    return df


df = assignment(df, centroids)
print(df.head())


fig = plt.figure(figsize=(5, 5))
plt.scatter(df['x'], df['y'], color=df['color'], alpha=0.5, edgecolor='k')
for i in centroids.keys():
    plt.scatter(*centroids[i], color=colmap[i])
plt.xlim(0, 100)
plt.ylim(0, 100)
```

```
plt.show()

## Update Stage

import copy

old_centroids = copy.deepcopy(centroids)

def update(k):
    for i in centroids.keys():
        centroids[i][0] = np.mean(df[df['closest'] == i]['x'])
        centroids[i][1] = np.mean(df[df['closest'] == i]['y'])
    return k

centroids = update(centroids)

fig = plt.figure(figsize=(5, 5))
ax = plt.axes()
plt.scatter(df['x'], df['y'], color=df['color'], alpha=0.5, edgecolor='k')
for i in centroids.keys():
    plt.scatter(*centroids[i], color=colmap[i])
plt.xlim(0, 100)
plt.ylim(0, 100)
```

```
for i in old_centroids.keys():
    old_x = old_centroids[i][0]
    old_y = old_centroids[i][1]
    dx = (centroids[i][0] - old_centroids[i][0]) * 0.75
    dy = (centroids[i][1] - old_centroids[i][1]) * 0.75
    ax.arrow(old_x, old_y, dx, dy, head_width=2, head_length=3, fc=colmap[i],
ec=colmap[i])
plt.show()

## Repeat Assignment Stage

df = assignment(df, centroids)

# Plot results
fig = plt.figure(figsize=(5, 5))
plt.scatter(df['x'], df['y'], color=df['color'], alpha=0.5, edgecolor='k')
for i in centroids.keys():
    plt.scatter(*centroids[i], color=colmap[i])
plt.xlim(0, 100)
plt.ylim(0, 100)
plt.show()

# Continue until all assigned categories don't change any more
```

```
while True:
    closest_centroids = df['closest'].copy(deep=True)
    centroids = update(centroids)
    df = assignment(df, centroids)
    if closest_centroids.equals(df['closest']):
        break

fig = plt.figure(figsize=(5, 5))
plt.scatter(df['x'], df['y'], color=df['color'], alpha=0.5, edgecolor='k')
for i in centroids.keys():
    plt.scatter(*centroids[i], color=colmap[i])
plt.xlim(0, 100)
plt.ylim(0, 100)
plt.show()
```

Appendix 2

```
"""
K-means clustering in R
"""
#install bindr
#install animation
```

```
library(dplyr)

PATH <-"C:/Users/milad/Desktop/Database_15_Variables.csv"

df <- read.csv(PATH)

glimpse(df)


#Get rid of all non-numeric variables


df$spatial_id <- NULL

df$Shape_Length <- NULL

df$Shape_Area <- NULL


glimpse(df)


summary(df)


set.seed(1000)

library(animation)

kmeans.ani(df, 3)

plot (kmeans.ani())
```

Appendix 3

```
"""

K-prototypes clustering for mixed categorical and numerical data

"""
```

```
# pylint: disable=super-on-old-class,unused-argument,attribute-defined-outside-init

from collections import defaultdict

import numpy as np
from joblib import Parallel, delayed
from scipy import sparse
from sklearn.utils import check_random_state
from sklearn.utils.validation import check_array

from . import kmodes
from .util import get_max_value_key, encode_features, get_unique_rows, \
    decode_centroids, pandas_to_numpy
from .util.dissim import matching_dissim, euclidean_dissim

# Number of tries we give the initialization methods to find non-empty
# clusters before we switch to random initialization.
MAX_INIT_TRIES = 20
# Number of tries we give the initialization before we raise an
# initialization error.
RAISE_INIT_TRIES = 100
```

```
def move_point_num(point, to_clust, from_clust, cl_attr_sum, cl_memb_sum):
    """Move point between clusters, numerical attributes."""
    # Update sum of attributes in cluster.
    for iattr, curattr in enumerate(point):
        cl_attr_sum[to_clust][iattr] += curattr
        cl_attr_sum[from_clust][iattr] -= curattr
    # Update sums of memberships in cluster
    cl_memb_sum[to_clust] += 1
    cl_memb_sum[from_clust] -= 1
    return cl_attr_sum, cl_memb_sum


def _split_num_cat(X, categorical):
    """Extract numerical and categorical columns.
    Convert to numpy arrays, if needed.
    :param X: Feature matrix
    :param categorical: Indices of categorical columns
    """
    Xnum = np.asanyarray(X[:, [ii for ii in range(X.shape[1])
                          if ii not in categorical]]).astype(np.float64)
    Xcat = np.asanyarray(X[:, categorical])
    return Xnum, Xcat
```

```
def _labels_cost(Xnum, Xcat, centroids, num_dissim, cat_dissim, gamma, membship=None):
    """Calculate labels and cost function given a matrix of points and
    a list of centroids for the k-prototypes algorithm.
    """

    n_points = Xnum.shape[0]
    Xnum = check_array(Xnum)

    cost = 0.
    labels = np.empty(n_points, dtype=np.uint16)
    for ipoint in range(n_points):
        # Numerical cost = sum of Euclidean distances
        num_costs = num_dissim(centroids[0], Xnum[ipoint])
        cat_costs = cat_dissim(centroids[1], Xcat[ipoint], X=Xcat, membship=membship)
        # Gamma relates the categorical cost to the numerical cost.
        tot_costs = num_costs + gamma * cat_costs
        clust = np.argmin(tot_costs)
        labels[ipoint] = clust
        cost += tot_costs[clust]
```

```
    return labels, cost


def _k_prototypes_iter(Xnum, Xcat, centroids, cl_attr_sum, cl_memb_sum, cl_attr_freq,
                       membship, num_dissim, cat_dissim, gamma, random_state):
    """Single iteration of the k-prototypes algorithm"""
    moves = 0
    for ipoint in range(Xnum.shape[0]):
        clust = np.argmin(
            num_dissim(centroids[0], Xnum[ipoint]) +
            gamma * cat_dissim(centroids[1], Xcat[ipoint], X=Xcat, membship=membship)
        )
        if membship[clust, ipoint]:
            # Point is already in its right place.
            continue

        # Move point, and update old/new cluster frequencies and centroids.
        moves += 1
        old_clust = np.argwhere(membship[:, ipoint])[0][0]

        # Note that membship gets updated by kmodes.move_point_cat.
        # move_point_num only updates things specific to the k-means part.
        cl_attr_sum, cl_memb_sum = move_point_num(
```

```
    Xnum[ipoint], clust, old_clust, cl_attr_sum, cl_memb_sum
)
cl_attr_freq, membship, centroids[1] = kmodes.move_point_cat(
    Xcat[ipoint], ipoint, clust, old_clust,
    cl_attr_freq, membship, centroids[1]
)

# Update old and new centroids for numerical attributes using
# the means and sums of all values
for iattr in range(len(Xnum[ipoint])):
    for curc in (clust, old_clust):
        if cl_memb_sum[curc]:
            centroids[0][curc, iattr] = cl_attr_sum[curc, iattr] / cl_memb_sum[curc]
        else:
            centroids[0][curc, iattr] = 0.

# In case of an empty cluster, reinitialize with a random point
# from largest cluster.
if not cl_memb_sum[old_clust]:
    from_clust = membship.sum(axis=1).argmax()
    choices = [ii for ii, ch in enumerate(membship[from_clust, :]) if ch]
    rindx = random_state.choice(choices)
```

```
        cl_attr_sum, cl_memb_sum = move_point_num(
            Xnum[rindx], old_clust, from_clust, cl_attr_sum, cl_memb_sum
        )
        cl_attr_freq, membship, centroids[1] = kmodes.move_point_cat(
            Xcat[rindx], rindx, old_clust, from_clust,
            cl_attr_freq, membship, centroids[1]
        )

    return centroids, moves


def k_prototypes_single(Xnum, Xcat, nnumattrs, ncatattrs, n_clusters, n_points,
                        max_iter, num_dissim, cat_dissim, gamma, init, init_no,
                        verbose, random_state):
    # For numerical part of initialization, we don't have a guarantee
    # that there is not an empty cluster, so we need to retry until
    # there is none.
    random_state = check_random_state(random_state)
    init_tries = 0
    while True:
        init_tries += 1
        # _____ INIT _____
        if verbose:
```

```
    print("Init: initializing centroids")
if isinstance(init, str) and init.lower() == 'huang':
    centroids = kmodes.init_huang(Xcat, n_clusters, cat_dissim, random_state)
elif isinstance(init, str) and init.lower() == 'cao':
    centroids = kmodes.init_cao(Xcat, n_clusters, cat_dissim)
elif isinstance(init, str) and init.lower() == 'random':
    seeds = random_state.choice(range(n_points), n_clusters)
    centroids = Xcat[seeds]
elif isinstance(init, list):
    # Make sure inits are 2D arrays.
    init = [np.atleast_2d(cur_init).T if len(cur_init.shape) == 1
            else cur_init
            for cur_init in init]
    assert init[0].shape[0] == n_clusters, \
        "Wrong number of initial numerical centroids in init " \
        "({}, should be {}).".format(init[0].shape[0], n_clusters)
    assert init[0].shape[1] == nnumattrs, \
        "Wrong number of numerical attributes in init ({}, should be {})." \
        .format(init[0].shape[1], nnumattrs)
    assert init[1].shape[0] == n_clusters, \
        "Wrong number of initial categorical centroids in init ({}, " \
        "should be {}).".format(init[1].shape[0], n_clusters)
    assert init[1].shape[1] == ncatattrs, \
```

```
        "Wrong number of categorical attributes in init ({}, should be {})." \
        .format(init[1].shape[1], ncatattrs)
    centroids = [np.asarray(init[0], dtype=np.float64),
                 np.asarray(init[1], dtype=np.uint16)]
else:
    raise NotImplementedError("Initialization method not supported.")

if not isinstance(init, list):
    # Numerical is initialized by drawing from normal distribution,
    # categorical following the k-modes methods.
    meanx = np.mean(Xnum, axis=0)
    stdx = np.std(Xnum, axis=0)
    centroids = [
        meanx + random_state.randn(n_clusters, nnumattrs) * stdx,
        centroids
    ]

if verbose:
    print("Init: initializing clusters")
membship = np.zeros((n_clusters, n_points), dtype=np.uint8)
# Keep track of the sum of attribute values per cluster so that we
# can do k-means on the numerical attributes.
cl_attr_sum = np.zeros((n_clusters, nnumattrs), dtype=np.float64)
```

```
# Same for the membership sum per cluster
cl_memb_sum = np.zeros(n_clusters, dtype=int)
# cl_attr_freq is a list of lists with dictionaries that contain
# the frequencies of values per cluster and attribute.
cl_attr_freq = [[defaultdict(int) for _ in range(ncatattrs)]
            for _ in range(n_clusters)]
for ipoint in range(n_points):
  # Initial assignment to clusters
  clust = np.argmin(
    num_dissim(centroids[0], Xnum[ipoint]) + gamma *
    cat_dissim(centroids[1], Xcat[ipoint], X=Xcat, membship=membship)
  )
  membship[clust, ipoint] = 1
  cl_memb_sum[clust] += 1
  # Count attribute values per cluster.
  for iattr, curattr in enumerate(Xnum[ipoint]):
    cl_attr_sum[clust, iattr] += curattr
  for iattr, curattr in enumerate(Xcat[ipoint]):
    cl_attr_freq[clust][iattr][curattr] += 1

# If no empty clusters, then consider initialization finalized.
if membship.sum(axis=1).min() > 0:
  break
```

```
    if init_tries == MAX_INIT_TRIES:
        # Could not get rid of empty clusters. Randomly
        # initialize instead.
        init = 'random'
    elif init_tries == RAISE_INIT_TRIES:
        raise ValueError(
            "Clustering algorithm could not initialize. "
            "Consider assigning the initial clusters manually."
        )

# Perform an initial centroid update.
for ik in range(n_clusters):
    for iattr in range(nnumattrs):
        centroids[0][ik, iattr] = cl_attr_sum[ik, iattr] / cl_memb_sum[ik]
    for iattr in range(ncatattrs):
        centroids[1][ik, iattr] = get_max_value_key(cl_attr_freq[ik][iattr])

# _____ ITERATION _____
if verbose:
    print("Starting iterations...")
itr = 0
labels = None
```

```
converged = False

_, cost = _labels_cost(Xnum, Xcat, centroids,
                       num_dissim, cat_dissim, gamma, membship)

epoch_costs = [cost]
while itr <= max_iter and not converged:
    itr += 1
    centroids, moves = _k_prototypes_iter(Xnum, Xcat, centroids,
                                          cl_attr_sum, cl_memb_sum, cl_attr_freq,
                                          membship, num_dissim, cat_dissim, gamma,
                                          random_state)

    # All points seen in this iteration
    labels, ncost = _labels_cost(Xnum, Xcat, centroids,
                                 num_dissim, cat_dissim, gamma, membship)
    converged = (moves == 0) or (ncost >= cost)
    epoch_costs.append(ncost)
    cost = ncost
    if verbose:
        print("Run: {}, iteration: {}/{}, moves: {}, ncost: {}"
              .format(init_no + 1, itr, max_iter, moves, ncost))
```

```
    return centroids, labels, cost, itr, epoch_costs



def k_prototypes(X, categorical, n_clusters, max_iter, num_dissim, cat_dissim,
                 gamma, init, n_init, verbose, random_state, n_jobs):
    """k-prototypes algorithm"""
    random_state = check_random_state(random_state)
    if sparse.issparse(X):
        raise TypeError("k-prototypes does not support sparse data.")

    if categorical is None or not categorical:
        raise NotImplementedError(
            "No categorical data selected, effectively doing k-means. "
            "Present a list of categorical columns, or use scikit-learn's "
            "KMeans instead."
        )
    if isinstance(categorical, int):
        categorical = [categorical]
    assert len(categorical) != X.shape[1], \
        "All columns are categorical, use k-modes instead of k-prototypes."
    assert max(categorical) < X.shape[1], \
        "Categorical index larger than number of columns."
```

```
ncatattrs = len(categorical)
nnumattrs = X.shape[1] - ncatattrs
n_points = X.shape[0]
assert n_clusters <= n_points, "Cannot have more clusters ({}) " \
                               "than data points ({}).".format(n_clusters, n_points)

Xnum, Xcat = _split_num_cat(X, categorical)
Xnum, Xcat = check_array(Xnum), check_array(Xcat, dtype=None)

# Convert the categorical values in Xcat to integers for speed.
# Based on the unique values in Xcat, we can make a mapping to achieve this.
Xcat, enc_map = encode_features(Xcat)

# Are there more n_clusters than unique rows? Then set the unique
# rows as initial values and skip iteration.
unique = get_unique_rows(X)
n_unique = unique.shape[0]
if n_unique <= n_clusters:
    max_iter = 0
    n_init = 1
    n_clusters = n_unique
    init = list(_split_num_cat(unique, categorical))
    init[1], _ = encode_features(init[1], enc_map)
```

```
# Estimate a good value for gamma, which determines the weighing of
# categorical values in clusters (see Huang [1997]).
if gamma is None:
    gamma = 0.5 * Xnum.std()

results = []
seeds = random_state.randint(np.iinfo(np.int32).max, size=n_init)
if n_jobs == 1:
    for init_no in range(n_init):
        results.append(k_prototypes_single(Xnum, Xcat, nnumattrs, ncatattrs,
                                           n_clusters, n_points, max_iter,
                                           num_dissim, cat_dissim, gamma,
                                           init, init_no, verbose, seeds[init_no]))
else:
    results = Parallel(n_jobs=n_jobs, verbose=0)(
        delayed(k_prototypes_single)(Xnum, Xcat, nnumattrs, ncatattrs,
                                     n_clusters, n_points, max_iter,
                                     num_dissim, cat_dissim, gamma,
                                     init, init_no, verbose, seed)
        for init_no, seed in enumerate(seeds))
all_centroids, all_labels, all_costs, all_n_iters, all_epoch_costs = zip(*results)
```

```
    best = np.argmin(all_costs)
    if n_init > 1 and verbose:
        print("Best run was number {}".format(best + 1))

    # Note: return gamma in case it was automatically determined.
    return all_centroids[best], enc_map, all_labels[best], all_costs[best], \
        all_n_iters[best], all_epoch_costs[best], gamma


class KPrototypes(kmodes.KModes):
    """k-protoypes clustering algorithm for mixed numerical/categorical data.
    Parameters
    -----------
    n_clusters : int, optional, default: 8
        The number of clusters to form as well as the number of
        centroids to generate.
    max_iter : int, default: 300
        Maximum number of iterations of the k-modes algorithm for a
        single run.
    num_dissim : func, default: euclidian_dissim
        Dissimilarity function used by the algorithm for numerical variables.
        Defaults to the Euclidian dissimilarity function.
    cat_dissim : func, default: matching_dissim
```

Dissimilarity function used by the kmodes algorithm for categorical variables.

Defaults to the matching dissimilarity function.

n_init : int, default: 10

Number of time the k-modes algorithm will be run with different

centroid seeds. The final results will be the best output of

n_init consecutive runs in terms of cost.

init : {'Huang', 'Cao', 'random' or a list of ndarrays}, default: 'Cao'

Method for initialization:

'Huang': Method in Huang [1997, 1998]

'Cao': Method in Cao et al. [2009]

'random': choose 'n_clusters' observations (rows) at random from

data for the initial centroids.

If a list of ndarrays is passed, it should be of length 2, with

shapes (n_clusters, n_features) for numerical and categorical

data respectively. These are the initial centroids.

gamma : float, default: None

Weighing factor that determines relative importance of numerical vs.

categorical attributes (see discussion in Huang [1997]). By default,

automatically calculated from data.

verbose : integer, optional

Verbosity mode.

random_state : int, RandomState instance or None, optional, default: None

If int, random_state is the seed used by the random number generator;

If RandomState instance, random_state is the random number generator;

If None, the random number generator is the RandomState instance used

by `np.random`.

n_jobs : int, default: 1

The number of jobs to use for the computation. This works by computing

each of the n_init runs in parallel.

If -1 all CPUs are used. If 1 is given, no parallel computing code is

used at all, which is useful for debugging. For n_jobs below -1,

(n_cpus + 1 + n_jobs) are used. Thus for n_jobs = -2, all CPUs but one

are used.

Attributes

----

cluster_centroids_ : array, [n_clusters, n_features]

Categories of cluster centroids

labels_ :

Labels of each point

cost_ : float

Clustering cost, defined as the sum distance of all points to

their respective cluster centroids.

n_iter_ : int

The number of iterations the algorithm ran for.

epoch_costs_ :

The cost of the algorithm at each epoch from start to completion.

```
gamma : float
    The (potentially calculated) weighing factor.
Notes
-----
See:
Huang, Z.: Extensions to the k-modes algorithm for clustering large
data sets with categorical values, Data Mining and Knowledge
Discovery 2(3), 1998.
"""

def __init__(self, n_clusters=8, max_iter=100, num_dissim=euclidean_dissim,
             cat_dissim=matching_dissim, init='Huang', n_init=10, gamma=None,
             verbose=0, random_state=None, n_jobs=1):

    super(KPrototypes, self).__init__(n_clusters, max_iter, cat_dissim, init,
                                      verbose=verbose, random_state=random_state,
                                      n_jobs=n_jobs)
    self.num_dissim = num_dissim
    self.gamma = gamma
    self.n_init = n_init
    if isinstance(self.init, list) and self.n_init > 1:
        if self.verbose:
            print("Initialization method is deterministic. "
```

```
                "Setting n_init to 1.")
            self.n_init = 1

    def fit(self, X, y=None, categorical=None):
        """Compute k-prototypes clustering.
        Parameters
        ----------
        X : array-like, shape=[n_samples, n_features]
        categorical : Index of columns that contain categorical data
        """
        if categorical is not None:
            assert isinstance(categorical, (int, list, tuple)), "The 'categorical' \
                argument needs to be an integer with the index of the categorical \
                column in your data, or a list or tuple of several of them, \
                but it is a {}.".format(type(categorical))

        X = pandas_to_numpy(X)

        random_state = check_random_state(self.random_state)
        # If self.gamma is None, gamma will be automatically determined from
        # the data. The function below returns its value.
        self._enc_cluster_centroids, self._enc_map, self.labels_, self.cost_, \
        self.n_iter_, self.epoch_costs_, self.gamma = k_prototypes(
```

```
            X,
            categorical,
            self.n_clusters,
            self.max_iter,
            self.num_dissim,
            self.cat_dissim,
            self.gamma,
            self.init,
            self.n_init,
            self.verbose,
            random_state,
            self.n_jobs
        )

        return self

    def predict(self, X, categorical=None):
        """Predict the closest cluster each sample in X belongs to.
        Parameters
        ----------
        X : array-like, shape = [n_samples, n_features]
            New data to predict.
        categorical : Indices of columns that contain categorical data
```

```
        Returns
        -------
        labels : array, shape [n_samples,]
            Index of the cluster each sample belongs to.
        """
        assert hasattr(self, '_enc_cluster_centroids'), "Model not yet fitted."

        if categorical is not None:
            assert isinstance(categorical, (int, list, tuple)), "The 'categorical' \
                argument needs to be an integer with the index of the categorical \
                column in your data, or a list or tuple of several of them, \
                but it is a {}.".format(type(categorical))

        X = pandas_to_numpy(X)
        Xnum, Xcat = _split_num_cat(X, categorical)
        Xnum, Xcat = check_array(Xnum), check_array(Xcat, dtype=None)
        Xcat, _ = encode_features(Xcat, enc_map=self._enc_map)
        return _labels_cost(Xnum, Xcat, self._enc_cluster_centroids,
                            self.num_dissim, self.cat_dissim, self.gamma)[0]

    @property
    def cluster_centroids_(self):
        if hasattr(self, '_enc_cluster_centroids'):
```

```
    return [
        self._enc_cluster_centroids[0],
        decode_centroids(self._enc_cluster_centroids[1], self._enc_map)
    ]
else:
    raise AttributeError("'{}' object has no attribute 'cluster_centroids_' "
                         "because the model is not yet fitted.")
```

LITERATURE CITED

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