EFFECTS OF ENVIRONMENTAL PARAMETERS AND PRECIPITATION DYNAMICS ON INFILTRATION AND RECHARGE INTO THE TRINITY AQUIFER OF CENTRAL TEXAS

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EFFECTS OF ENVIRONMENTAL PARAMETERS AND PRECIPITATION DYNAMICS ON INFILTRATION AND RECHARGE INTO THE TRINITY AQUIFER OF CENTRAL TEXAS

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December 2012

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ABSTRACT

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SUPERVISING PROFESSOR: Benjamin F. Schwartz

Good predictive models of infiltration and recharge through the vadose zone in karst systems are required for improving groundwater models and sustainable management policies in karst regions. The goal of this study was to estimate annual recharge rates and quantify how cumulative environmental effects, and their timing, influence epikarst infiltration and recharge in the karstic Trinity Aquifer of the central Texas Hill Country. The Trinity Aquifer is the most important groundwater resource for communities and private well owners in the region, and as the region's population grows, increased demands for groundwater are causing spring-fed streams to cease flowing, wells to run dry, and large portions of the population are facing water shortages, especially during drought periods.

Stable isotope and hydrologic data from Cave Without A Name, near Boerne, TX, allowed me to quantify relationships between recharge and antecedent moisture conditions, environmental parameters, and rainfall characteristics. A mixed effects logistic regression model incorporating precipitation sum from rainfall events, antecedent soil moisture, and the sum of potential evapotranspiration for eight weeks prior to rainfall events is successful approximately 85% of the time at predicting whether or not a precipitation event will result in a hydrologic response in the cave. Data were randomly divided into a test set to build the final model, and then validated on the remaining data: both performed equally well. Additionally, a multiple linear regression model was found to be moderately successful (Adj. R²=0.67, P<0.01) at predicting the magnitude of hydrologic responses in an in-cave stream which drains a large groundwater basin. Combined, these models enable me to predict if a recharge response will occur, and if it does, what its magnitude will be.

Chloride mass balance calculations were also made using nearly two and a half years of precipitation and in-cave groundwater samples. These calculations produce an average recharge rate of around 8%, which is consistent with previously published literature for the region. As a check, measured discharge from an in-cave stream over the same time period was combined with recharge estimates to calculate a watershed area of \sim 27 km², which is realistic given the known extent of the associated cave system and the local geology.

CHAPTER 1

INTRODUCTION

A better understanding of controls on karst recharge processes is essential for developing resource management strategies in regions where populations rely on karstic groundwater (Jones et al. 2000). Ford and Williams (2007) estimated that 15% of the continental globe is karst and that these regions supply more than 20% of the world population with drinking water. Much of central Texas relies heavily on karst groundwater (Ashworth 1983), and my project is focused on the karstic Trinity Aquifer of central Texas (Figure 1), which supplies water to all or parts of Comal, Travis, Hays, Gillespie, Kendall, Bexar, Kerr, Bandera, Medina, Blanco, and Uvalde county (Mace et al. 2000).

With projected increases in demand, parts of the Trinity Aquifer are expected to have water level declines of up to 100 ft (30.48 m) by 2050 (Mace et al. 2000). This would not only severely impact many ranchers and communities that rely on the Trinity Aquifer, but also users of the adjacent Edwards Aquifer, which has been classified as a sole source aquifer by the EPA (EPA 2012). Water level declines in the Trinity will affect the Edwards because many surface streams that contribute to the Edwards as they cross its recharge zone are formed and supported by groundwater from the Trinity Aquifer (Barker, Bush, and Baker Jr. 1994). Additionally, cross-

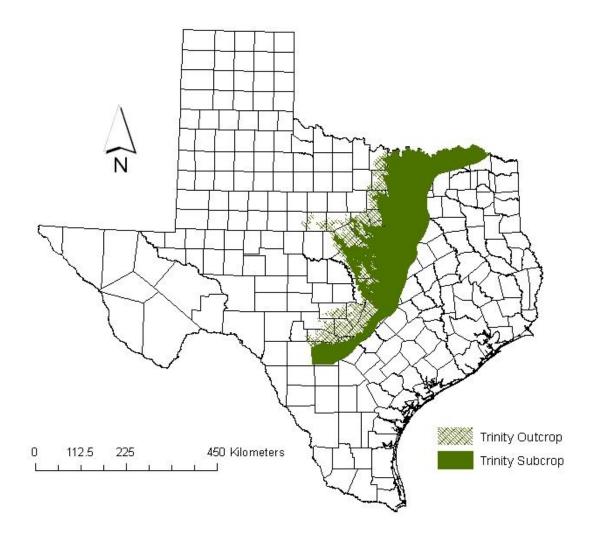


Figure 1. Map of the Trinity Aquifer in Texas.

formational flow from the Trinity Aquifer directly into the Edwards Aquifer is estimated to be about 97,500 acre ft/yr (120,264,479m³/yr) (Kuniansky and Holligan 1994), which is about 17% of the median annual recharge to the Edwards (Edwards Aquifer Authority 2010). In recent years, many springs have ceased to flow during drought (USGS 2012), and without better management of groundwater in the Trinity Aquifer, many more spring-fed streams will cease to flow and large portions of the population may face water shortages during drought periods (Mace et al. 2000).

In this thesis I examine recharge dynamics in upland areas overlying the Trinity Aquifer by expanding on previous cave drip studies (Arbel et al. 2009; Baker and Brunsdon 2003; Fernandaz-Cortes and Calaforra 2008) and examining the complex relationship between precipitation events, environmental parameters, and recharge in an attempt to better understand what variables most affect the occurrence and amount of recharge into the system. I use multi-year cave drip monitoring coupled with weather station and soil moisture data to predict in the region. Additionally, I use the chloride mass balance method to investigate recharge rates at the site, and I also use deuterium and a two end-member mixing model to explore the changes in recharge source-water composition, including the percentage of rainfall event water contributing to rapid recharge, over varying antecedent moisture conditions, rainfall amounts, and rainfall intensities. The purpose of this study is to quantify how cumulative environmental effects and their timing influence epikarst storage and recharge. The ultimate goal is to improve predictive groundwater models and facilitate the development of sustainable

management policies in the central Texas Hill Country as the region's population and stress on the aquifer system continue to grow.

Literature Review

Trinity Aquifer

The Trinity Aquifer lies under an area of approximately 21,308 mi² (55,188 km²)(George, Mace, and Petrossian 2011) and is classified as a major aquifer by the state of Texas (Ashworth and Hopkins 1995). At its southernmost extent, the Trinity Aquifer begins in Uvalde and Medina County and stretches northeasterly through the state of Texas before crossing under the Red River into Oklahoma (Figure 1). The Trinity is one of the most utilized aquifers in Texas (George, Mace, and Petrossian 2011) and is the dominant groundwater system of the central Texas Hill Country (Ashworth 1983).

The Trinity Aquifer of the Hill Country, which is the focus area of this study, is present in rocks of the Trinity Group (Figure 2). The Trinity Group is subdivided into the upper, middle, and lower aquifer units by two relatively impermeable strata (Ashworth 1983a; Barker and Ardis 1996; Barker, Bush, and Baker Jr 1994). The Upper Trinity Aquifer consists of the upper member of the Glen Rose Limestone, and its use is typically limited to livestock and domestic production because of low yields and poor water quality due to the presence of evaporite beds (Ashworth 1983). The Middle Trinity Aquifer is composed of the lower member of the Glen Rose Limestone, the Hensel Sand, and the Cow Creek Limestone, and it is separated

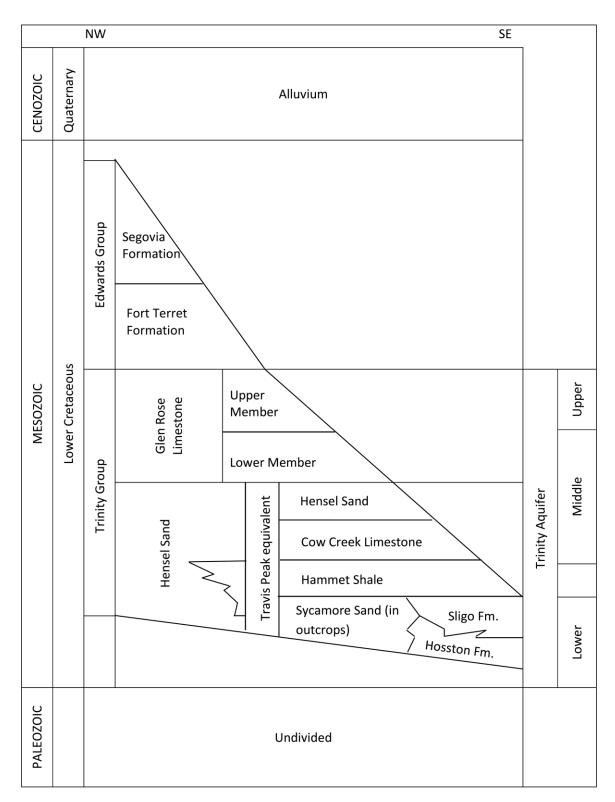


Figure 2. Stratigraphy and hydrostratigraphy of the Trinity Aquifer in the central Texas Hill Country (after Ashworth 1983; Barker, Bush, and Baker Jr. 1994; Mace et al. 2000).

from the Upper Trinity by thin to medium bedded less permeable rocks in the upper to middle parts of the Glen Rose Limestone. The Middle Trinity is the most utilized zone because of its accessibility and good water quality (Ashworth 1983), and it supplies water to approximately 85% of the wells in the Hill Country (Jennings et al. 2001). The Lower Trinity Aquifer, which is separated from the Middle Trinity by the Hammet shale confining unit, is comprised of the Sycamore Sand, the Sligo members of the Travis Peak Formation, and the Hosston Formation. The Hosston and Travis Peak Formations of the Lower Trinity are heavily relied upon by the cities of Kerrville and Bandera, but water quality in this zone is variable and the cost of drilling to the required depth has resulted in less production in this zone (Ashworth 1983).

Recharge to the Hill Country's Trinity Aquifer is primarily via direct and diffuse infiltration into exposed units of the Trinity, mainly the Glen Rose Limestone and the Hensell Sand, which are exposed through much of the Hill Country (Ashworth 1983; Mace et al. 2000). Recharge estimates (Table 1) for the Hill Country Trinity range from 1.5% (Muller and Price 1979) to 11% of precipitation (Kuniansky 1989).

<u>Karst</u>

A karst system is a region defined by an underground drainage system with extensive tertiary porosity formed by the dissolution of rock by chemically aggressive water (Ford and Williams 2007). For most karst systems this tertiary permeability develops in carbonate rocks as meteoric waters become mildly acidic

Table 1. Summary of published recharge estimates for the Middle Trinity Aquifer of the central Texas Hill Country (after Jennings et al. 2001; Mace et al. 2000).

Source	Recharge as a Percent of Rainfall
Muller and Price (1979)	1.5%
Ashworth (1983)	4.0%
Kuniansky (1989)	11.0%
Bluntzer (1992)	6.7%
Mace et al. (2000)	4%; 6.6%
Kuniansky and Holligan (1994)	7.0%

from reacting with atmospheric $CO_2(g)$, and more importantly, $CO_2(g)$ in soils, to form carbonic acid:

$$CO_2(g) \leftrightarrow CO_2(aq)$$
 [1]

$$CO_2(aq) + H_2O \leftrightarrow H_2CO_3^0(carbonic\ acid)$$
 [2]

This weak acid then reacts with calcite and dolomite in carbonate rocks and dissolves it. In the case of limestone, calcite dissociates into bicarbonate and calcium ions.

$$CaCO_3(s) + H_2CO_3(aq) \leftrightarrow Ca^{2+} + 2HCO_3^-$$
 [3]

It is this reaction which causes the dissolution and formation of near-surface and subsurface flow paths that create the complexity of karst hydrogeology. The rate at which dissolution occurs is mainly a factor of rainfall intensity and rock geometry at the surface, and $CO_2(aq)$ concentrations and water retention times in the subsurface (Gabrovsek 2009).

Epikarst

Located at the top of most karst systems and controlling many recharge processes is the epikarst. It is a zone of highly weathered carbonate rock reaching from the bottom of the soil zone, or the surface when soil is not present, to a depth of around 10-15 meters (Klimchouk 2004). The epikarst is structurally different from the lower unsaturated zone; its porosity and permeability are more homogenously dispersed, and an almost uniform system of enlarged fractures and conduits exists, creating high permeability and hydraulic conductivity (Trček 2007).

Klimchouk (2004) estimated the hydraulic conductivity of a generalized epikarst system to generally be two to three orders of magnitude higher than that of the rock below. Because of this, a perched aquifer unit often exists at the base of the epikarst due to the convergence high permeability epikarst with the less permeable rock below. Within the perched aquifer, pooled water slowly migrates downwards through micro-fissures or horizontally toward larger but widely spaced vertical fractures and conduits (Klimchouk 2004; Pronk et al. 2009; Smart and Friederich 1986). As a result of these features and properties, the epikarst has the ability to both store water for long periods of time and quickly transfer water towards the lower vadose or phreatic zone (Klimchouk 2004; Smart and Friederich 1986; Williams 2008).

Cave Drips

Fed by a combination of draining epikarst storage and fast infiltration from storm events, cave drip waters are an excellent and commonly used tool to investigate and characterize processes controlling the infiltration and chemical evolution of infiltrating precipitation and stored epikarstic waters (Musgrove and Banner 2004; Pronk et al. 2009; Tooth and Fairchild 2003). Use of cave drips however can be complicated by the extreme heterogeneity of the epikarst. This heterogeneity typically causes high variability in drip characteristics between multiple dripping speleothems, as well as high variability between and within speleothems drip locations in responses to rainfall events.

Arbel et al. (2009) classified cave drips into four types of flow regimes describing the variety of speleothem drip types; though some drip sites may experience more than one of these flow regimes over a given period of time. The four regime types are perennial, seasonal, post storm, and overflow. Perennial flows are generated from slow draining of the epikarst matrix, seasonal flows are those that drip intermittently only after a seasonal precipitation threshold has been reached in the wet season, post storm flows are a result of infiltrating storm water and can begin at varying times following a rainfall event, and overflow occurs as a result of lateral flow from nearby locations that have reached their maximum drip rate capacity due to relatively low hydraulic conductivity.

Because of the lack of quantitative data at a small-basin scale, much of my thesis is focused on examining recharge responses, particularly during post-storm flow regimes when most recharge occurs. Previous research has found post-storm flows to be non-linearly related to precipitation amount (Baker, Barnes, and Smart 1997). Non-linearity in the relationship was attributed to periods where increased evapotranspiration, and therefore increased soil moisture deficit, caused little or no drip response to a rainfall event. Pronk et al. (2009) used a two-end-member mixing model (Equation 4), a technique used to separate the components of flow in a hydrologic system into their respective contributions, to characterize post storm flows using a controlled application of water to the surface above a cave. Using the concept that drip responses to rainfall are comprised of event water (water being discharged from the drip site that originated as precipitation from the rainfall event causing the response) and pre-event water (water that was stored in the epikarst

prior to the event), the contribution of event water for any given time during the response can be determined using:

$$Q_{e} = Q_{d} \frac{C_{d} - C_{pe}}{C_{e} - C_{pe}}$$
 [4]

where Q_e is the amount of event water discharging from the drip site, Q_d is the total water discharging from the drip site, and C_d , C_e , and C_{pe} are the concentrations of a conservative tracer (typically a stable isotope or a relatively inactive specific ion) in the drip water, the event water, and the pre-event water, respectively. Using this technique and chloride as the selected tracer, Pronk et al. (2009) was able to separate drip responses into three phases. Phase one is the lag phase in which the storm has begun but no response has occurred, phase two is the piston flow phase in which the drip rate is responding to the storm event with old water being forced out of the matrix by newer infiltrating water, and phase three is the well-mixed phase where the drip response is fed by a mix of event and pre-event water until the drip rate has returned to near base flow.

The Water Balance in Semi-Arid Regions

The water balance equation provides the fundamental framework for studying any hydrologic system. The general equation is:

$$I - O = \frac{dS}{dt} \tag{5}$$

where $\frac{dS}{dt}$ is the change in the system's storage, *I* comprises all inputs into the system, and *O* comprises all outputs from the system. In the Texas Hill Country,

inputs to shallow karst systems are dominated by precipitation (P), and outputs are dominated by evapotranspiration (ET), runoff (RO), groundwater discharge (D), and pumping withdrawals (W).

$$P-ET-RO-D-W = \frac{ds}{dt}$$
 [6]

In semi-arid environments, evapotranspiration, which comprises all processes that cause water to change from liquid phase to gas phase, including evaporation from litter or plant surfaces, evaporation from soil, and transpiration by vegetation, returns a large proportion of rainfall to the atmosphere (Wilcox, Breshears, and Seyfried 2003). In the Texas Hill Country, potential evapotranspiration typically exceeds precipitation, and recharge, the infiltration of meteoric waters into the phreatic or saturated zone, occurs only during extreme rainfall events (Hibbert 1983; Phillips, Hogan, and Scanlon 2004; Wilcox et al. 2006). Previous research has found that 65-99% of rainfall in the Edwards Plateau region is removed from the system via evapotranspiration (Dugas, Hicks, and Wright 1998; Wilcox et al. 2006), and that recharge is mainly caused by winter rainfall, because of lower ET, and very large rainfall events (>120 mm) (Seyfried and Wilcox 2006; Wilcox et al. 2006).

Recharge Characterization/Prediction and Regression Models

A regression is a statistical analysis used to estimate the relationship of one variable to another, or others, in terms of a function, and can be used to fit a model to establish or explain a relationship and/or predict variation in a response variable due to changes in one or more independent variables (Sokal and Rohlf 1995). A regression model's ability to establish or explain a relationship generally increases

as more predictor variables are added to the model, but there is a point of diminishing returns where additional predictor variables explain less and less of the variance in the response variable. The goal for many researchers using this technique, therefore, is to limit the model to the most easily measured variables that explain the most variation in the response variable.

Regression models have often been used in hydrogeology to understand recharge dynamics and to predict and quantify recharge with potentially only a few easily obtainable and inexpensive variables (Hodgson 1978; Pérez 1997). Izuka, Oki, and Engott (2010) developed regression models that related computed recharge values from soil water budget data, which requires large amounts of spatial and historical data, to mean annual rainfall, soil infiltration, and infiltration minus potential evapotranspiration. They found that a simple rainfall model differed from the soil water budget recharge estimates by -25% to 47%, a model using infiltration data differed by -11% to 8%, and an infiltration minus potential evapotranspiration model differed by -8% to 11%. Lorenz and Delin (2007) estimated basin wide groundwater recharge in sub-humid regions using a regional regression model. Their model was based on stream base flow estimates using the Rorabaugh method, and was developed using precipitation, growing degree days for the basin, and average basin specific yield. Sanz and López (2000) found a relationship between cave drip rates, rainfall, and outside air temperature; the significance of air temperature was attributed to the presence of a clay layer over the cave exposing infiltrating water to increased evapotranspiration during warmer days. Pérez (1997) developed a multiple regression model to estimate groundwater recharge,

based on hydrograph recessions of local streams, using rainfall and air temperature data. Examples like these demonstrate the use of regression models as a tool for predicting recharge, but careful consideration must be used when choosing predictor variables.

CHAPTER II

METHODOLOGY

Study Site

This study was conducted in the central Texas Hill Country at Cave Without A Name (CWAN). CWAN (29°53'10.88"N, 98°37'02.78W) is a commercial cave in the southeastern portion of the Edward's Plateau physiographic province, near Boerne, Texas in Kendall County; approximately 35 km northwest of San Antonio, Texas (Figure 3). CWAN is a branchwork stream cave that likely began forming in the carbonate lower member of the Glen Rose Limestone formation around 880 ka B.P (Veni 1994). The cave passage used in this study (Figures 4 and 5) is approximately 20 to 30 meters below the surface, and is overlain by shallow or absent Eckrant soil, which is described as having moderately low permeability and little ability to store water (Dittemore and Hensell 1981). The surface of the site is representative of the region, with vegetation being dominated by a mix of Plateau Live Oak (Quercus fusiformus) Texas Oak (Quercus buckleyi), Shin Oak (Quercus sinuata), Cedar Elm (Ulmus crassifolia), Ashe Juniper (Juniperus ashei), and sparse grass cover. The climate is classified as sub-humid to semi-arid (Mace et al. 2000), and the area is subject to frequent droughts (Carr 1967). In most years, much of the area does not receive enough rainfall to offset evapotranspiration (Carr 1967). Precipitation in the

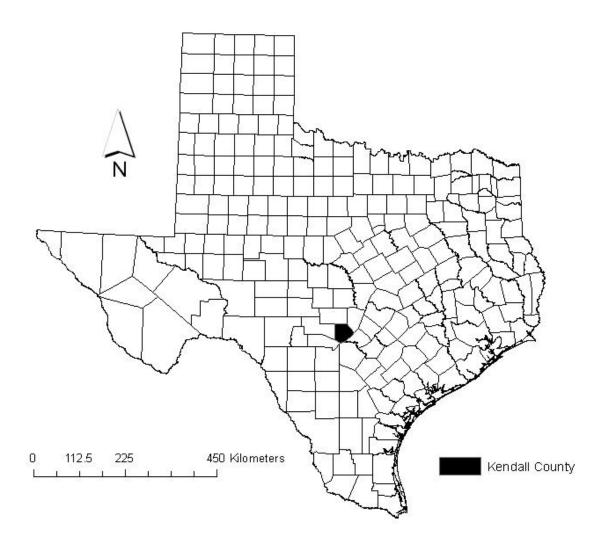


Figure 3. Map of Texas with Kendall County.

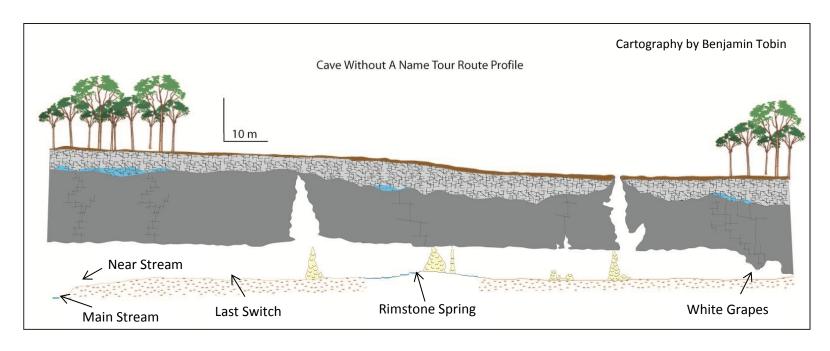


Figure 4. Profile diagram of the Cave Without A Name tour route and the monitoring locations.

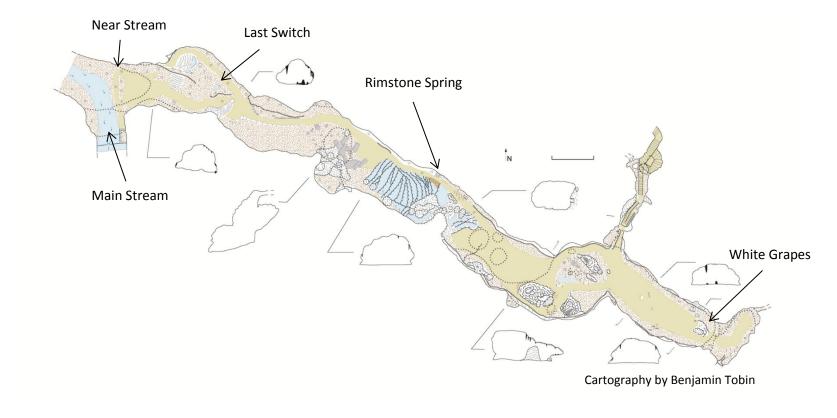


Figure 5. Plan view diagram of the Cave Without A Name tour route and the monitoring locations.

region, as with most of the interior of Texas, tends to be bimodally distributed with periods of maximum precipitation occurring in May and September (Carr 1967). In addition, annual precipitation amounts are variable and are strongly influenced by El Niño and La Niña conditions, with the former generally resulting in above average rainfall and the later resulting in drought conditions. According to data collected in the San Antonio region by NOAA between 1885 and 2012, the average rainfall is approximately 737 mm and average temperatures range from ~ 10 °C in the winter to ~ 27 °C in the summer (NOAA 2012).

Data for this project was collected between November 2009 and March 2012, it includes environmental variables collected at a weather station on the surface, incave drip rate data from three speleothem drip locations, and discharge or stage data collected from an in-cave stream and an in-cave spring. Soil moisture data was also collected.

Weather Station

The weather station is a HOBO H21-001 unit (ONSET Computer Corp, Bourne, MA, USA) and is located directly above the cave and adjacent to the entrance. The weather station records rainfall, solar radiation, temperature, wind speed and direction, and barometric pressure at one second intervals, which are logged as ten minute averages. Additionally, precipitation samples have been collected from a rain collection device attached to the weather station. These samples were analyzed for liquid water stable isotopes (δD and $\delta^{18}O$) using a Los Gatos Research DLT 100 Liquid Water Isotope Analyzer (Los Gatos Research, Inc.,

Mountain View, Ca, USA), as well as major anions and cations using a Dionex ICS 1600 Liquid Ion Chromatograph (Thermo Fischer Scientific, Walther, Ma, USA).

Soil Moisture

Soil moisture is measured at 30 second intervals by a ECH $_2$ O EC-5 soil moisture sensor (Decagon Devices, Pullman, WA, USA) 25 cm below the surface and \sim 40 m from the weather station. A Campbell Scientific data logger records these measurements at 15 minute averages. Soil samples have also been collected for analysis using the gravimetric method in order to verify and/or calibrate the soil moisture sensor data collected in the field.

In-Cave Data

Three in-cave speleothem drip sites are instrumented to continuously record drip rate. These locations, White Grapes, Last Switch, and Near Stream, have a PVC and plastic tarp structure situated under the dripping speleothem which collects the drips and drains them through a PVC pipe to a HOBO rain gauge (ONSET Computer Corp, Bourne, MA, USA) connected to a HOBO micro-station data logger H21-002 (ONSET Computer Corp, Bourne, MA, USA). Prior to reaching the tipping bucket at the White Grapes drip site, water flows through a sealed flowcell containing a Hanna HI-9828 multi-parameter water quality meter (HANNA Instruments, Woonsocket, RI, USA) which continuously records dissolved oxygen (DO), specific conductivity (SC), barometric pressure, temperature, pH, and oxidation reduction potential (ORP) at 10-minute intervals.

Two other in-cave sites, Rimstone Spring and Main Stream, are instrumented with Schlumberger CTD-Diver pressure transducers (Schlumberger Limited, Tucson, AZ, USA) that continuously record pressure, temperature, and specific conductance. A Schlumberger Baro-Diver barometric logger (Schlumberger Limited, Tucson, AZ, USA) at the Near Stream monitoring station records in-cave barometric pressure and is used in conjunction with either of the other pressure transducers to determine true water depth at the given location. Utilizing periodic discharge measurements, rating curves were created for both Rimstone Spring and Main Stream to convert stage data to discharge. All data collected in the cave is recorded at ten minute intervals that are synchronized with the surface instrumentation. Additionally, periodic water samples from all in-cave sites have been collected on a weekly to monthly basis and analyzed for liquid water stable isotopes using a Los Gatos Research DLT 100 Liquid Water Isotope Analyzer (Los Gatos Research, Inc., Mountain View, Ca, USA), anions and cations using a Dionex ICS 1600 Liquid Ion Chromatograph (Thermo Fischer Scientific, Walther, Ma, USA), and alkalinity by titration.

Model Selection/Regression Analyses

 AIC_c and regression analyses were performed to investigate the relationship(s) between selected predictor variables and recharge responses from rainfall events, and also to create predictive models for recharge at three monitoring sites. White Grapes, Rimstone Spring, and Mainstream are the only sites studied using regression analysis because they are the only sites that clearly respond to

rainfall events (Figures 6,7, and 8). All regression analyses were performed using the statistical analysis program R.

Logistic regression analyses were performed for White Grapes, Rimstone Spring, and Main Stream. The presence or absence of a response was the dependent variable, and the proposed predictors for all three sites were precipitation amount (sum of precipitation from an individual event (characterized as a period of rain separated from another by ~ 10 hours, the average response time for the three locations), for each event over 5.5 mm; the minimum threshold for a response observed during the study) (P_s), precipitation duration (P_d), soil moisture prior to the rainfall event (θ), and the sum of potential evapotranspiration for the eight weeks prior to the event calculated using the Penman- Monteith equation(Allen 2005; Allen et al. 1998; Howell and Evett 2004; Snyder and Eching) (PET_8), which was found by prior analyses to have a stronger relationship with response than two, four, and six week sums. Drip rate or discharge values immediately preceding a rainfall event (Q_{prev}) were also used as proposed predictors for each location's regression.

A mixed effects logistic regression analysis was performed on a combined data set from all three locations. Site was considered a random effect and all other variables were considered fixed effects. Dependent and proposed independent variables were the same as previously mentioned for the site specific logistic regressions. A model validation analysis was also performed by randomly selecting half the data and then running the same analysis (mixed effects logistic regression).

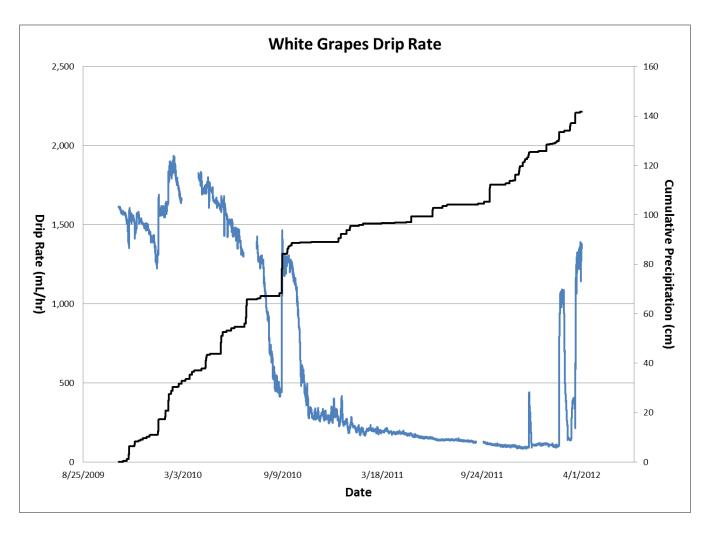


Figure 6. Drip rate (mL/hr) at White Grapes and the cumulative precipitation (cm) during the period of investigation.

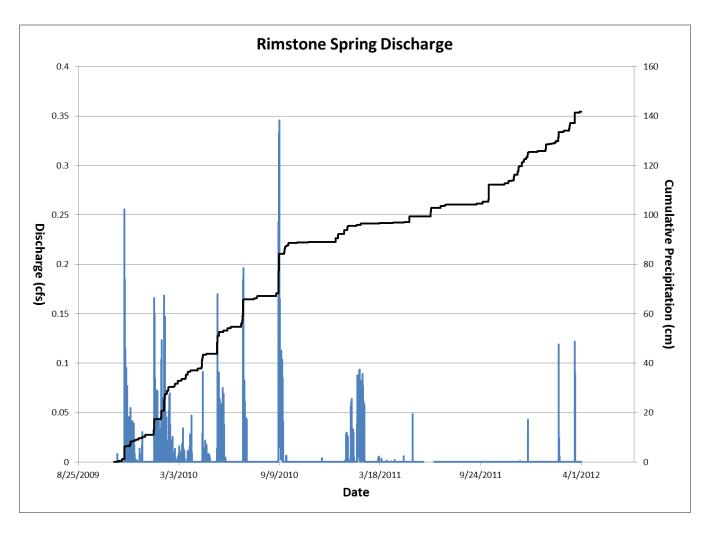


Figure 7. Discharge at Rimstone Spring (cfs) and the cumulative precipitation (cm) during the period of investigation.

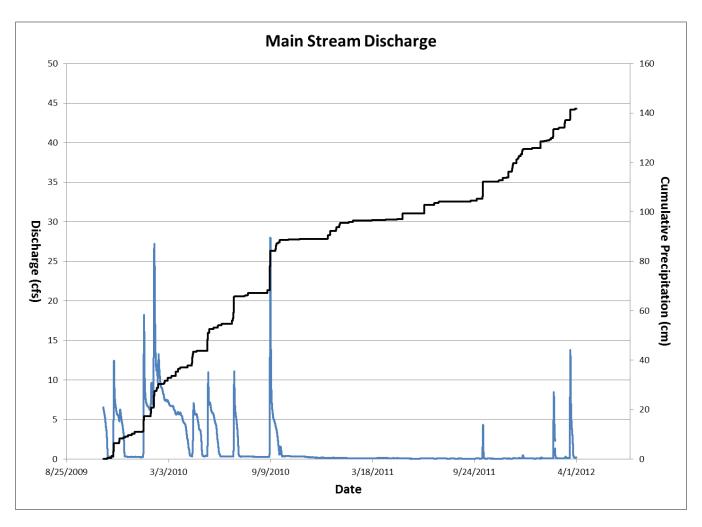


Figure 8. Discharge at Main Stream (cfs) and the cumulative precipitation (cm) during the period of investigation.

The model derived from this random subset was then used to predict an outcome for the remaining data.

Using discharge data from Main Stream, a multiple regression analysis was also performed to investigate the relationship between previously discussed proposed predictors and response magnitude, or the difference between the maximum discharge due to the rainfall event and the discharge immediately preceding the event; the response variable for this analysis. Because the goal of this analysis was to investigate potential relationships between predictor variables and response magnitude, only data from events that caused a response were included. Additionally, the response characteristics of the Main Stream made this site the only suitable candidate for this analysis. The site responds with a sharp spike in flow that is easily determined, while responses at White Grapes and Rimstone Spring are much more convoluted and can be difficult to determine.

Mixing Model Analysis

Hydrograph separation curves were created using Equation 4 and stable isotope data (δ D) from samples collected before, during, and after recharge responses from two back-to-back rainfall events on September 7 and 8, 2010, and another rain event on March 19, 2012. Once again, because of the lack of detectable responses at Last Switch and Near Stream, only White Grapes, Rimstone Spring, and Main Stream were analyzed. Water samples for the September 7 and 8, 2010 rainfall event response were collected on a weekly basis beginning on September 8, 2010. Samples were collected at this interval until flow at each site returned to base level.

Water samples for the March 19, 2012 rainfall event were collected on approximately one hour to two hour intervals until noon on March 20, 2012. Following this, samples were collected every few days until flows returned to base levels.

Chloride Mass Balance

The chloride mass balance method was used in this study to estimate groundwater recharge for the area. The average recharge flux to a system can be calculated using:

$$Q(Cl_{gw}) = P(Cl_{wap})$$
 [7]

where Q is the groundwater recharge, Cl_{gw} is the average chloride concentration in groundwater (in this case in cave drip water), and Cl_{wap} is the weighted average chloride concentration in precipitation (P). The average weighted chloride concentration in precipitation was found using:

$$Cl_{wap} = \frac{\sum_{i=1}^{n} P_{i} * Cl_{pi}}{\sum_{i=1}^{n} P_{i}}$$
 [8]

where $\mathcal{C}l_{pi}$ is the chloride concentration in the ith sample, P_i is the precipitation sum of the ith sample, and n is the number of rainfall events. This equation was modified to also weight drip water concentrations using drip flow summations prior to sample collection. This was done to more accurately assess drip water concentrations. The modified equation appears as:

$$q(Cl_{wadw}) = P(Cl_{wap})$$
 [9]

where ${\it Cl}_{\it wadp}$ is the weighted average drip water concentration of chloride. These calculations were performed to estimate recharge for the region, utilizing data from White Grapes, Last Switch, Near Stream, and Main Stream. Rimstone Spring was not used in this analysis because of the intermittency of flow at the site and the lack of water samples collected there because of this.

CHAPTER III

RESULTS AND DISCUSSION

General Observations and Extremes in Response Data

During the period of investigation, November 2009 to March 2012, White Grapes responded to 11 rainfall events, Rimstone Spring responded to 15, and Main Stream responded to 22 (Figures 6, 7, and 8). Last Switch and Near Stream had no clear responses to any rainfall event. The smallest event that produced a response at any of the monitoring sites was 5.5 mm in December 2009, and it was only detected at Rimstone Spring. The smallest rainfall events that caused responses at White Grapes and Main Stream were 14.3 mm in February 2010 and 5.6 mm in December 2011, respectively. During the period of investigation there were 55 rainfall events greater than 5.5 mm, the minimum response threshold observed during the study period. The largest of these events that caused no response at White Grapes, Rimstone Spring, or Main Stream was 24.1 mm in May 2011.

Further examination of the timing and environmental conditions associated with these results reveal that, as predicted, environmental conditions exert a strong influence on in-cave responses to rainfall events. The smallest rainfall event that caused a response at any of the sites, 5.5 mm in December 2009, occurred during a time when calculated PET was low (approximately 174 mm over the previous eight weeks) and soil moisture was 26%, which is slightly above the mean average value

recorded prior to any of the 55 rainfall events (24%). Because of the non-linear relationship between moisture content and unsaturated hydraulic conductivity, these relatively wet conditions allowed a small rain event to infiltrate and transmit a signal to the drip site in the cave.

Similar conditions existed during the 14.3 mm rain event in February 2010 and the 5.6 mm rain event in December 2011. The February 2010 event was preceded by eight weeks of low PET (143 mm) and high rainfall (174.9 mm).

Additionally, soil moisture prior to the event was relatively high, 35%. The December 2011 event was also preceded by conditions highly conducive to recharge; eight weeks of low PET (222 mm), and soil moisture was 39% (the highest value prior to any of the 55 rainfall events). The sum of rain over the preceding eight weeks was slightly below the average for the data set, but the rainfall sum for two weeks prior to the event was the highest recorded for the data set, 56.26 mm, and likely assisted in 'priming' the system.

Conditions preceding the 24.1 mm rainfall event in May 2011 that caused no response were quite opposite of those for the previously mentioned events. PET for the eight weeks prior to this event was 479 mm, and considering that this event occurred during mid-spring when canopy density is generally highest, high canopy interception and evaporation are also likely to have occurred. In the preceding eight weeks, CWAN received only 4.0 mm of rainfall, and prior to the event soil moisture was only 13%. The combined effects of high PET, high canopy interception, and low

soil moisture resulted in no recharge response from this relatively large rainfall event.

Regression Models

For binary response data from White Grapes, an AIC_c indicated that the best fitting model for predicting the probability of a response (Prob.) was one that incorporated P_s , θ , and PET₈ (Table 2). This model was found to be significantly better than the null model (Model χ^2 = 32.16, P<0.01), and analysis of the Wald statistics for these variables shows that P_s and θ are both significant, and that PET₈ is slightly insignificant with a p-value of 0.08 (Table 2). The prediction success of the model (Equation 10) is 89.8% and the Nagelkerke R² value is 0.73, indicating that the model is rather successful at predicting response at the site.

$$Prob. = \frac{e^{-6.08 + 0.19(P_S) + 0.20(\theta) - 0.02(PET_8)}}{1 + e^{-6.08 + 0.19(P_S) + 0.20(\theta) - 0.02(PET_8)}}$$
[10]

Analysis of an AIC_c performed on predictive models for the Rimstone Spring data set did not reveal one model that was decisively better (Table 3). Erring on the side of caution, the chosen model includes only P_s and is likely the best model because of its mediocre Akaike weight, and because it has the fewest (only one) predictor variables out of the competing models. This model was found to be significantly better than the null model (Model χ^2 = 23.04, P<0.01), and analysis of the Wald statistic for P_s indicates that it is a significant variable for predicting response at the site (Table 3). The prediction success of this model (Equation 11) is

Table 2. Summary of logistic model selection results and analysis of the chosen model (in bold and highlighted) for White Grapes.

Model NPar AlC AlC Akaike Wt.		Logistic Regression Analysis for White Grapes (n=49)							
Model nPar AIC AIC, Akaike Wt. Prob.=1 1 54.19 54.27 0.00 Prob.=P _S 2 40.31 40.57 0.00 Prob.=P _S +P _d 3 42.11 42.64 0.00 Prob.=P _S +P _d 3 34.66 35.20 0.01 Prob.=P _S +P _d +PET ₈ 3 29.78 30.31 0.12 Prob.=P _S +Q _{prev} 3 42.14 42.68 0.00 Prob.=P _S +Q _{prev} 4 36.66 37.57 0.00 Prob.=P _S +P _d +PET ₈ 4 30.76 31.67 0.06 Prob.=P _S +P _d +PET ₈ 4 30.76 31.67 0.00 Prob.=P _S +P _d +PET ₈ 4 28.03 28.93 0.25 Prob.=P _S +P _d +PeT _R +Q _{prev} 4 35.92 36.83 0.00 Prob.=P _S +PET ₈ +Q _{prev} 4 31.43 32.34 0.05 Prob.=P _S +PET ₈ +Q _{prev} 5 37.88 39.28 0.00 Prob.=P _S +PET ₈ +Q _{prev} +P _d +D fs									
Prob.=1 1 54.19 54.27 0.00 Prob.=P₅ 2 40.31 40.57 0.00 Prob.=P₅+P₀ 3 42.11 42.64 0.00 Prob.=P₅+θ∈Tѕ 3 34.66 35.20 0.01 Prob.=P₅+PETѕ 3 29.78 30.31 0.12 Prob.=P₅+Pdqprev 3 42.14 42.68 0.00 Prob.=P₅+Pd+PeTѕ 4 36.66 37.57 0.00 Prob.=P₅+Pd+PeTѕ 4 30.76 31.67 0.06 Prob.=P₅+Pd+Qprev 4 44.00 44.91 0.00 Prob.=P₅+θ+PETѕ 4 28.03 28.93 0.25 Prob.=P₅+θ+PETѕ 4 28.03 28.93 0.25 Prob.=P₅+θ+Qprev 4 35.92 36.83 0.00 Prob.=P₅+PeTҕ+Qprev 4 31.43 32.34 0.05 Prob.=P₅+PeTҕ+Qprev 5 37.88 39.28 0.00 Prob.=P₅+PeTҕ+Qprev+P₀ 5 32.52 33									
Prob.=P _S 2 40.31 40.57 0.00 Prob.=P _S +P _d 3 42.11 42.64 0.00 Prob.=P _S +θ 3 34.66 35.20 0.01 Prob.=P _S +PET _B 3 29.78 30.31 0.12 Prob.=P _S +P _d +PeT _B 3 42.14 42.68 0.00 Prob.=P _S +P _d +PET _B 4 36.66 37.57 0.00 Prob.=P _S +P _d +PET _B 4 30.76 31.67 0.06 Prob.=P _S +P _d +Q _{prev} 4 44.00 44.91 0.00 Prob.=P _S +9+HET _B 4 28.03 28.93 0.25 Prob.=P _S +0+Q _{prev} 4 35.92 36.83 0.00 Prob.=P _S +PET _B +Q _{prev} 4 31.43 32.34 0.05 Prob.=P _S +PET _B +Q _{prev} 4 36.66 37.57 0.00 Prob.=P _S +PeT _B +Q+PetQ _{prev} 5 37.88 39.28 0.00 Prob.=P _S +PeT _B +Q-Q _{prev} +P _d 5 32.52 33.91 0.02					•				
Prob.=P _S +P _d 3 42.11 42.64 0.00 Prob.=P _S +θ 3 34.66 35.20 0.01 Prob.=P _S +PET ₈ 3 29.78 30.31 0.12 Prob.=P _S +P _{Qprev} 3 42.14 42.68 0.00 Prob.=P _S +P _d +PET ₈ 4 36.66 37.57 0.00 Prob.=P _S +P _d +PET ₈ 4 30.76 31.67 0.06 Prob.=P _S +P _d +PET ₈ 4 28.03 28.93 0.25 Prob.=P _S +P _d +PET ₈ 4 28.03 28.93 0.25 Prob.=P _S +P _d +PET ₈ 4 35.92 36.83 0.00 Prob.=P _S +P+PET ₈ +Q _{prev} 4 31.43 32.34 0.05 Prob.=P _S +P _d +θ+PET ₈ 4 36.66 37.57 0.00 Prob.=P _S +P _d +θ+Q _{prev} 5 37.88 39.28 0.00 Prob.=P _S +PeT ₈ +Q _{prev} +P _d 5 32.52 33.91 0.02 Prob.=P _S +PET ₈ +Q _{prev} +P _d +θ 6 27.53 29.53 0.18 </td <td></td> <td></td> <td></td> <td></td> <td></td> <td></td>									
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Prob.=P _S +Q _{prev} 3 42.14 42.68 0.00 Prob.=P _S +P _d +θ 4 36.66 37.57 0.00 Prob.=P _S +P _d +PET ₈ 4 30.76 31.67 0.06 Prob.=P _S +P _d +Q _{prev} 4 44.00 44.91 0.00 Prob.=P _S +θ+PET ₈ 4 28.03 28.93 0.25 Prob.=P _S +θ+PET ₈ 4 35.92 36.83 0.00 Prob.=P _S +θ+Q _{prev} 4 31.43 32.34 0.05 Prob.=P _S +P+B _T +Q _{prev} 4 36.66 37.57 0.00 Prob.=P _S +P _d +θ+PET ₈ 4 36.66 37.57 0.00 Prob.=P _S +P _d +θ+PET ₈ 4 36.66 37.57 0.00 Prob.=P _S +P _d +θ+PET ₈ +Q _{prev} 5 37.88 39.28 0.00 Prob.=P _S +PET ₈ +Q _{prev} +P _d 5 32.52 33.91 0.02 Prob.=P _S +PET ₈ +Q _{prev} +P _d +θ+θ 6 27.53 29.53 0.18 Variables in Selected Model Coefficients <td>Prob.=P_S+θ</td> <td></td> <td>3</td> <td>34.66</td> <td>35.20</td> <td>0.01</td>	Prob.=P _S +θ		3	34.66	35.20	0.01			
Prob.=P _S +P _d +θ 4 36.66 37.57 0.00 Prob.=P _S +P _d +PET ₈ 4 30.76 31.67 0.06 Prob.=P _S +P _d +Q _{prev} 4 44.00 44.91 0.00 Prob.=P _S +P _d +PET ₈ 4 28.03 28.93 0.25 Prob.=P _S +θ+PET ₈ 4 35.92 36.83 0.00 Prob.=P _S +PET ₈ +Q _{prev} 4 31.43 32.34 0.05 Prob.=P _S +PET ₈ +Q _{prev} 4 36.66 37.57 0.00 Prob.=P _S +PeT ₈ +Q _{prev} 5 37.88 39.28 0.00 Prob.=P _S +PeT ₈ +Q _{prev} 5 37.88 39.28 0.00 Prob.=P _S +PeT ₈ +Q _{prev} +P _d 5 32.52 33.91 0.02 Prob.=P _S +PET ₈ +Q _{prev} +P _d +θ 6 27.53 29.53 0.18 Variables in Selected Model Coefficients Estimate Standard Error Wald P-value Intercept -6.08 3.88 -1.57 0.12 P _S	Prob.=P _S +PET _S	3	3	29.78	30.31	0.12			
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Prob.=P _S +θ+Q _{prev} 4 35.92 36.83 0.00 Prob.=P _S +PET ₈ +Q _{prev} 4 31.43 32.34 0.05 Prob.=P _S +P _d +θ+PET ₈ 4 36.66 37.57 0.00 Prob.=P _S +P _d +θ+Q _{prev} 5 37.88 39.28 0.00 Prob.=P _S +θ+PET ₈ +Q _{prev} 5 27.22 28.62 0.29 Prob.=P _S +PET ₈ +Q _{prev} +P _d 5 32.52 33.91 0.02 Prob.=P _S +PET ₈ +Q _{prev} +P _d +θ 6 27.53 29.53 0.18 Variables in Selected Model Coefficients Estimate Standard Error Wald P-value Intercept -6.08 3.88 -1.57 0.12 P _S 0.19 0.07 2.70 < 0.01	Prob.=P _S +P _d +0	Q_{prev}	4	44.00	44.91	0.00			
Prob.=P _S +PET ₈ +Q _{prev} 4 31.43 32.34 0.05 Prob.=P _S +P _d +θ+PET ₈ 4 36.66 37.57 0.00 Prob.=P _S +P+P _d +θ+Q _{prev} 5 37.88 39.28 0.00 Prob.=P _S +θ+PET ₈ +Q _{prev} 5 27.22 28.62 0.29 Prob.=P _S +PET ₈ +Q _{prev} +P _d 5 32.52 33.91 0.02 Prob.=P _S +PET ₈ +Q _{prev} +P _d +θ 6 27.53 29.53 0.18 Variables in Selected Model Variables in Selected Model Intercept -6.08 3.88 -1.57 0.12 P _S 0.19 0.07 2.70 < 0.01	Prob.=P _s +0+P	ET ₈	4	28.03	28.93	0.25			
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Prob.=P _S +P _d +θ+Q _{prev} 5 37.88 39.28 0.00 Prob.=P _S +θ+PET ₈ +Q _{prev} 5 27.22 28.62 0.29 Prob.=P _S +PET ₈ +Q _{prev} +P _d 5 32.52 33.91 0.02 Prob.=P _S +PET ₈ +Q _{prev} +P _d +θ 6 27.53 29.53 0.18 Variables in Selected Model Variables in Selected Model Intercept -6.08 3.88 -1.57 0.12 P _S 0.19 0.07 2.70 < 0.01	Prob.=P _S +PET ₈	3+Q _{prev}	4	31.43	32.34	0.05			
Prob.=P _S +θ+PET ₈ +Q _{prev} 5 27.22 28.62 0.29 Prob.=P _S +PET ₈ +Q _{prev} +P _d 5 32.52 33.91 0.02 Prob.=P _S +PET ₈ +Q _{prev} +P _d +θ 6 27.53 29.53 0.18 Variables in Selected Model Variables in Selected Model Intercept -6.08 3.88 -1.57 0.12 P _S 0.19 0.07 2.70 < 0.01	Prob.=P _s +P _d +6)+PET ₈	4	36.66	37.57	0.00			
Prob.=P _S +PET ₈ +Q _{prev} +P _d 5 32.52 33.91 0.02 Prob.=P _S +PET ₈ +Q _{prev} +P _d +θ 6 27.53 29.53 0.18 Variables in Selected Model Variables in Selected Model Use of the problem of th	Prob.=P _S +P _d +6)+Q _{prev}	5	37.88	39.28	0.00			
Prob.=P _S +PET ₈ +Q _{prev} +P _d +θ	Prob.= $P_S+\theta+P$	ET ₈ +Q _{prev}	5	27.22	28.62	0.29			
Variables in Selected Model Coefficients Estimate Standard Error Wald P-value Intercept -6.08 3.88 -1.57 0.12 Ps 0.19 0.07 2.70 < 0.01	Prob.=P _S +PET _S	$_{3}+Q_{prev}+P_{d}$	5	32.52	33.91	0.02			
Coefficients Estimate Standard Error Wald P-value Intercept -6.08 3.88 -1.57 0.12 P _s 0.19 0.07 2.70 < 0.01	Prob.=P _S +PET ₈	$_{3}+Q_{prev}+P_{d}+\theta$	6	27.53	29.53	0.18			
Coefficients Estimate Standard Error Wald P-value Intercept -6.08 3.88 -1.57 0.12 P _s 0.19 0.07 2.70 < 0.01 θ 0.20 0.11 1.77 0.08 PET ₈ -0.02 0.01 -2.14 0.03 Classification Table Predicted Observed No Response Response % Correct No Response 36 2 94.7% Response 3 8 72.7%				100 11					
Intercept	Coefficients				P-value				
P _s 0.19 0.07 2.70 < 0.01 θ 0.20 0.11 1.77 0.08 PET ₈ -0.02 0.01 -2.14 0.03 Classification Table Predicted Observed No Response Response % Correct No Response 36 2 94.7% Response 3 8 72.7%									
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Classification Table Predicted Observed No Response Response % Correct No Response 36 2 94.7% Response 3 8 72.7%	PET ₈		0.01	-2.14					
Predicted Observed No Response Response % Correct No Response 36 2 94.7% Response 3 8 72.7%									
ObservedNo ResponseResponse% CorrectNo Response36294.7%Response3872.7%	Classification Table								
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Response 3 8 72.7%			•	•	_				
		·							
I Overall % Correct I 89.8% I		Overall % Correct		0	89.8%				

Table 3. Summary of logistic model selection results and analysis of the chosen model (in bold and highlighted) for Rimstone Spring.

Logistic Regression Analysis for Rimstone Spring (n=55)							
		Model Selection					
<u>Model</u>		<u>nPar</u>	<u>AIC</u>	AIC _c	Akaike W		
Prob.=1		1	66.45	66.53	0.00		
Prob.=P _S		2	45.42	45.65	0.09		
Prob.=P _S +P _d		3	45.51	45.98	0.08		
Prob.= $P_S+\theta$		3	44.59	45.06	0.13		
Prob.=P _S +PET ₈		3	44.77	45.24	0.12		
Prob.=P _S +Q _{prev}		3	47.26	47.73	0.03		
$Prob.=P_S+P_d+\theta$		4	45.16	45.96	0.08		
Prob.=P _S +P _d +PI	ET ₈	4	46.01	46.81	0.05		
Prob.=P _S +P _d +Q	prev	4	47.43	48.23	0.03		
Prob.=P _S +θ+PE	T ₈	4	44.83	45.63	0.09		
Prob.= $P_S+\theta+Q_0$	rev	4	45.61	46.41	0.06		
Prob.=P _S +PET ₈ +	+Q _{nrev}	4	46.65	47.45	0.04		
Prob.=P _S +P _d +θ-	p	4	45.16	45.96	0.08		
Prob.=P _S +P _d +θ-		5	46.42	47.64	0.03		
Prob.=P _S +θ+PE	r -	5	45.83	47.05	0.05		
Prob.=P _S +PET ₈ +		5	47.94	49.16	0.02		
Prob.=P _S +PET ₈ +		6	47.31	49.06	0.02		
	Vai	riables in Selected N	/lodel				
Coefficients	<u>Estimate</u>	Standard Error	<u>Wald</u>	P-value			
Intercept	-3.35	0.78	18.42	< 0.01			
P_s	0.11	0.04	10.56	< 0.01			
Classification Table							
		Predic					
	Observed	No Response	Response	% Correct			
	No Response	39	1	97.5%			
	Response Overall % Correct	7	8	53.3% 85.5%			

85.5% and the Nagelkerke R² value is 0.50, indicating that the model is moderately successful at predicting response at the site.

$$Prob. = \frac{e^{-3.35 + 0.11(P_S)}}{1 + e^{-3.35 + 0.11(P_S)}}$$
[11]

Analysis of an AIC_c performed on predictive models for Main Stream indicated that a model incorporating P_s , θ , and PET₈ is the best model for predicting response at the Main Stream (Table 4). This model was found to be significantly better than the null model (Model χ^2 = 59.87, P<0.01), and analysis of the Wald statistics for these variables shows that both P_s and θ are significant, and that PET₈ is somewhat insignificant with a P-value of 0.19 (Table 4). The prediction success of the model (Equation 12) is 92.7% and the Nagelkerke R² value is 0.90, indicating that the model is quite successful at predicting response at the site.

$$Prob. = \frac{e^{-21.58 + 0.58(P_S) + 0.61(\theta) - 0.02(PET_8)}}{1 + e^{-21.58 + 0.58(P_S) + 0.61(\theta) - 0.02(PET_8)}}$$
[12]

Analysis of an AIC_c performed on logistic mixed effect models for a data set incorporating all three sites revealed that a model including P_s , θ , and PET₈ best predicts a recharge response at the sites (Table 5) and was found to be significantly better than the null model (Model χ^2 = 52.20, P<0.01). For all proposed models, the variable 'site' (White Grapes, Rimstone Spring, and Main Stream) was considered a random effect, and all other variables were considered fixed effects. Analysis of the Wald statistics for P_s , θ , and PET₈ shows that all three predictor variables are highly significant (Table 5). The prediction success of the model (Equation 13) is 84.9%, indicating that the model is quite successful at predicting responses in the cave.

Table 4. Summary of logistic model selection results and analysis of the chosen model (in bold and highlighted) for Main Stream.

	Logistic Re	gression Analysis fo	or Main Stream (ı	1=55)				
		Model Selec	tion					
Model		<u>nPar</u>	AIC	AIC _c	Akaike Wt			
Prob.=1		1	76.03	76.11	0.00			
Prob.=P _S		2	49.78	50.01	0.00			
Prob.=P _S +P _d		3	51.74	52.21	0.00			
Prob.= $P_S+\theta$		3	24.80	25.27	0.11			
Prob.=P _S +PET ₈		3	39.63	40.10	0.00			
Prob.=P _S +Q _{prev}		3	44.96	45.43	0.00			
Prob.=P _S +P _d +θ		4	26.32	27.12	0.04			
Prob.=P _S +P _d +PET ₈		4	39.92	40.72	0.00			
Prob.=P _S +P _d +Q _{prev}		4	46.95	47.75	0.00			
Prob.=P _s +θ+PET ₈		4	22.16	22.96	0.35			
Prob.= $P_S+\theta+Q_{prev}$		4	26.56	27.36	0.04			
Prob.=P _S +PET ₈ +Q _o	rev	4	39.45	40.25	0.00			
Prob.= $P_S+P_d+\theta+PE$	T ₈	4	26.32	27.12	0.04			
Prob.= $P_S+P_d+\theta+Q_d$	orev	5	28.19	29.41	0.01			
Prob.= $P_s+\theta+PET_8+$	Q _{prev}	5	24.05	25.28	0.11			
Prob.=P _S +PET ₈ +Q ₀		5	40.23	41.45	0.00			
Prob.=P _S +PET ₈ +Q _p	$_{rev}+P_d+\theta$	6	21.53	23.28	0.30			
		Variables in Select	ted Model					
Coefficients	<u>Estimate</u>	Standard Error	<u>Wald</u>	P-value				
Intercept	-21.58	8.66	6.21	0.01				
P_s	0.58	0.25	5.33	0.02				
θ	0.61	0.24	6.39	0.01				
PET ₈	-0.02	0.01	1.73	0.19				
Classification Table Predicted								
1	0/ 0							
	Observed No Response	No Response 31	Response 2	% Correct 93.9%				
	Response	2	20	90.9%				
	Overall % Correct		20	92.7%				

Table 5. Summary of logistic mixed effects model selection results and analysis of the chosen model (in bold and highlighted) for the combined data set (including all data from White Grapes, Rimstone Spring, and Main Stream).

	Mixed Effect Model (n=159)							
		Model Select	ion					
<u>Model</u>		<u>nPar</u>	<u>AIC</u>	AIC _c	Akaike Wt.			
Prob.=1		2	198.59	198.67	0.00			
Prob.=P _S		3	135.80	135.95	0.00			
Prob.=P _S +P _d		4	136.48	136.74	0.00			
Prob.=P _S +θ		4	111.20	111.46	0.00			
Prob.=P _s +PET _s	8	4	114.39	114.65	0.00			
Prob.=P _S +P _d +6	Э	5	112.83	113.22	0.00			
Prob.=P _S +P _d +F	PET ₈	5	115.94	116.34	0.00			
Prob.=P _s +θ+P	ET ₈	5	100.19	100.58	0.99			
Prob.=P _S +P _d +6	9+PET ₈	6	101.64	113.22	0.00			
		riables in Selecto						
<u>Coefficient</u>	<u>Estimate</u>	Standard Error	<u>Wald</u>	<u>P-value</u>				
Intercept	-6.62	1.81	-3.66	< 0.01				
P_s	0.17	0.03	5.35	< 0.01				
θ	0.18	0.05	3.70	< 0.01				
PET ₈	-0.01	0.00	-3.00	< 0.01				
	Classification Table							
		Predic		T .				
	Observed	No Response	Response	% Correct				
	No Response	102	9	91.9%				
	Response	15	33	68.8%				
	Overall % Correct			84.9%				

$$Prob. = \frac{e^{-6.62 + 0.17(P_S) + 0.18(\theta) - 0.01(PET_8)}}{1 + e^{-6.62 + 0.17(P_S) + 0.18(\theta) - 0.01(PET_8)}}$$
[13]

To further test the predictive capabilities of a logistic mixed effects model, a cross validation assessment was performed. A test data set was created by randomly selecting half (79 of 159) of the data from the combined data set. AIC_c analysis indicated that a model including P_s, θ, and PET₈ best predicts a recharge response at the sites (Table 6) and was found to be significantly better than the null model (Model χ^2 = 51.70, P<0.01). The proposed models were all coded as previously discussed, 'site' was coded as a random effect, and all other dependent variables were coded as fixed effects. Analysis of the Wald statistics shows that both P_s and θ are significant, and that PET₈ is slightly insignificant with a p-value of 0.07 (Table 6). The prediction success of the test model (Equation 14) is 88.6%. To validate the predictive strength of the model, it was then applied to the remaining half of the data that were not randomly selected to create the test model. The model was found to be significantly better at predicting response in this data set than the null model (Model χ^2 = 18.78, P<0.01), and correctly predicted response in this data set 86.3% of the time, indicating that the model is quite successful at predicting recharge responses in the cave for events that were not used in building the model.

$$Prob. = \frac{e^{-7.17 + 0.20(P_S) + 0.17(\theta) - 0.01(PET_8)}}{1 + e^{-7.17 + 0.20(P_S) + 0.17(\theta) - 0.01(PET_8)}}$$
[14]

Results of linear regression and AIC_c analysis of Main Stream response data with the magnitude of change in discharge after a rain event (Resp.) as the dependent variable, and the same independent variables as were used in the logistic

Table 6. Summary of logistic mixed effects cross validation model selection results and analysis of the chosen model (in bold and highlighted) for the combined data set (including all data from White Grapes, Rimstone Spring, and Main Stream).

Mixed Effect Model (n=79)									
	Model Selection								
<u>Model</u>		<u>nPar</u>	<u>AIC</u>	AIC _c	Akaike Wt.				
Prob.=1		2	102.62	102.78	0.00				
Prob.=P _S		3	68.49	68.81	0.00				
Prob.=P _S +P _d		4	70.47	71.01	0.00				
Prob.=P _S +θ		4	59.38	59.92	0.15				
Prob.=P _S +PE	8	4	61.83	62.37	0.04				
Prob.=P _S +P _d +	-θ	5	61.29	62.11	0.05				
Prob.=P _S +P _d +	·PET ₈	5	62.57	63.40	0.03				
Prob.=P _s +0+F	PET ₈	5	56.92	57.74	0.45				
Prob.=P _S +P _d +	·θ+PET ₈	6	57.53	58.70	0.28				
	Vari	ables in Selected	Model						
Coefficient	<u>Estimate</u>	Standard Error	<u>Wald</u>	<u>P-value</u>					
Intercept	-7.17	2.59	-2.76	< 0.01					
P_s	0.20	0.05	3.68	< 0.01					
θ	0.17	0.07	2.40	0.02					
PET ₈	-0.01	0.00	-1.83	0.07					
	Classificati	on Table (Genera Predict							
	Observed			0/ Cours at					
		No Response	Response	% Correct					
	No Response	53 8	1 17	98.1% 68.0%					
Response		0	17	88.6%					
	Overall % Correct			88.0%					
	Classification Table (Non-Generating Data Set)								
Predicted									
	Observed	No Response	Response	% Correct					
	No Response	51	6	89.5%					
	Response	5	18	78.3%					
	Overall % Correct			86.3%					

regression, indicates that the best model for predicting the magnitude of response is one that includes P_s and PET_8 (P<0.01))(Table 7 and Equation 15).

$$Resp. = 0.63 + 1.26(P_s) - 0.62(PET_8)$$
 [15]

While P_s was a significant predictor variable in the model, PET₈ was moderately insignificant with a p-value of 0.15 (Table 7). The adjusted R^2 value for the model is 0.67, indicating a moderately good fit with the data (Figure 9).

These results show that a logistical regression model that includes the effects of P_s , θ , and PET₈ is capable of predicting whether or not a recharge response will occur. Additionally, a linear regression model that incorporates only P_s and PET₈ can successfully be used to predict the magnitude of a recharge response at the Main Stream site. The significance of P_s in all models is expected, because the magnitude of a rainfall event is the main factor controlling infiltration and, ultimately, recharge. The significant positive correlation between θ and recharge response in all but one of the logistic regression models is due to the fact that this parameter is effectively a measure of the soil moisture deficit that must be overcome before recharge can occur. During periods with little or no rainfall, this deficit is caused by the combined effects of evaporation, transpiration, and downward drainage. The higher the soil moisture is, the lower this deficit is, which increases the probability that a rainfall event will infiltrate or push residual water past this zone and cause a recharge response.

The significant and near significant negative correlation between PET_8 and response at many of the sites is likely because PET_8 is a proxy for deeper epikarst

Table 7. Summary of linear model selection results and analysis of the chosen model (in bold and highlighted) for the Main Stream response magnitude data set.

Reg	Regression Analysis for Main Stream Response Pulse (n=19)							
Model Selection								
Model		<u>nPar</u> 2	<u>AIC</u> 60.84	<u>AIC</u> 134.43	Akaike Wt. 0.00			
Resp.=1 Resp.=P _s		3	46.49	110.21	0.00			
Resp.=P _s +P _d		4	48.00	113.09	0.02			
. 3 4		•						
Resp.=P _s +θ		4	47.83	113.43	0.00			
Resp.=P _s +PET ₈		4	45.18	104.06	0.50			
Resp.=P _S +Q _{prev}		4	48.38	113.46	0.00			
Resp.= $P_S+P_d+\theta$		5	49.11	116.84	0.00			
Resp.=P _S +P _d +PET ₈		5	47.01	105.64	0.23			
Resp.=P _S +P _d +Q _{prev}		5	49.90	116.84	0.00			
Resp.= $P_S+\theta+PET_8$		5	46.36	107.73	0.08			
Resp.= $P_S+\theta+Q_{prev}$		5	49.59	117.18	0.00			
Resp.=P _S +PET ₈ +Q _{prev}		5	47.16	107.51	0.09			
Resp.= $P_S+P_d+\theta+PET_8$		6	48.02	110.02	0.03			
Resp.= $P_S+P_d+\theta+Q_{prev}$		6	50.85	121.22	0.00			
Resp.= $P_S+\theta+PET_8+Q_{prev}$		6	48.26	111.85	0.01			
Resp.=P _S +PET ₈ +Q _{prev} +P _c	ı	6	48.99	109.66	0.03			
Resp.=P _S +PET ₈ +Q _{prev} +P _o		7	49.91	114.84	0.00			
, s s piet e								
Variables in Selected Model								
<u>Coefficients</u>	Estimate	Standard Error	<u>t value</u>	<u>P-value</u>				
Intercept	0.63	1.97	0.32	0.75				
P_s	1.26	0.21	5.96	< 0.01				
PET ₈	-0.62	0.41	-1.52	0.15				
					,			

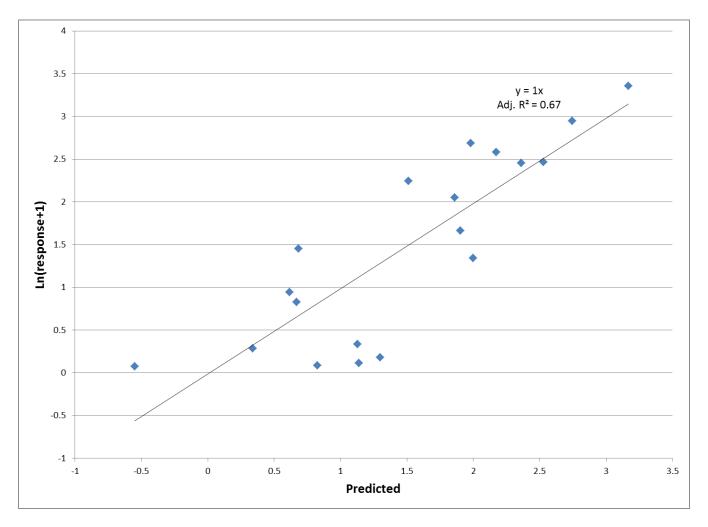


Figure 9. Observed (natural logarithmically transformed)vs. predicted (calculated using the selected regression model) response magnitude from rainfall events at Main Stream.

moisture that is not measured by the soil moisture sensors at a depth of 25 cm. Relatively high PET_8 is linked to greater actual transpiration and less deep infiltration, when all other variables are held constant. From a modeling perspective, this proxy for deeper moisture content is moderately useful for predicting response at the sites, and response magnitude at the Main Stream site.

PET₈ is also an indirect measure of water available to be forced out of the system by piston flow when deep infiltration occurs. Analysis of the response magnitude model (Equation 15) for Main Stream indicates that this parameter is nearly significant, but that θ is no longer a useful parameter in the model. This indicates that once a response occurs, θ is no longer important. Instead, the magnitude of the response is related to the amount of deep epikarst moisture available to be pushed downward by piston flow.

The importance of θ and PET₈ for all logistic models but Rimstone Springs is probably due to site-specific flow and storage dynamics. Rimstone Spring likely has more open-conduit vadose flow paths that allow water to more easily infiltrate and directly recharge via open fractures at the surface. This is consistent with the fact that the site responds to smaller rainfall events than any of the other sites. Additionally, the site does not flow continuously, as do White Grapes and Main Stream, which suggests that either there is less long-term epikarst storage connected to this monitoring site, or that the site may simply be an overflow route for some other unknown flowpath. The cave manager has observed that running a hose into a depression on the surface will cause the site to respond within a few

hours, which is further evidence that direct recharge and overland flow influence this site more strongly than either of the others.

The site specific logistic regression model that has the highest success at predicting responses is the model for Main Stream. This is probably due to the fact that Main Stream has a much larger drainage basin than White Grapes and Rimstone Spring, and integrates the signals produced by a wide range of flow paths with variable recharge and storage properties throughout the system. This suggests that the model for the Main Stream site is more representative of the whole system than either White Grapes or Rimstone Spring, individually.

The prediction success, the larger sample size, and the fact that the mixed effects models include data from three in-cave sites, makes it probable that these models have the most potential for predicting responses in the system, and may be more appropriate for understanding regional responses to recharge in the Trinity Aquifer. The ability of the cross validation model to predict a response with >80% accuracy for both halves of the data, suggests that the model may be appropriate for use in larger scale resource management applications. In addition to the similar accuracy in prediction, both the model for the full data set and the validation model produce very similar intercept and coefficient estimates. However, a larger sample size with additional data from this and other sites in the Trinity Aquifer will result in a more robust predictive model.

Recharge Estimates Using Chloride Mass Balance

Using the chloride mass balance method and multiple samples collected from CWAN monitoring sites between January 2010 and March 2012 (Table 8), recharge estimates over the period of study range from 4.3% of precipitation, calculated at Last Switch, to 11.1%, calculated at Near Stream (Table 9). Annualized and period-of-study recharge estimates from the Near Stream site tend to be higher than these estimates from any of the other locations and may not be representative of the entire system. The contributing zone for this site may experience faster infiltration rates than the other locations. This would cause less mixing with partly evaporated shallow soil or epikarstic water (with higher chloride concentrations) and result in lower chloride values for the drip water. Essentially, if water is able to quickly infiltrate to depths below the zone in which evapotranspiration has a strong influence, chloride will not be as concentrated in recharge water, resulting in a locally higher actual and calculated recharge rate.

Recharge estimates from White Grapes and Last Switch are similar and are more reasonable estimates of recharge for the climate and geology of this system. The estimated recharge at White Grapes from January 2010 to March 2012 is 4.3%. The estimated recharge at Last Switch over the same period is 6.6%. These results are similar to many published recharge estimates for the region (Table 1).

Evaluation of yearly recharge estimations reveals that 2011 has the highest estimated recharge at all studied locations. This is likely not a true increase in

Table 8. Summary of chloride concentrations for rainfall samples and in-cave samples at Cave Without A Name.

	Number of Samples	Avg. chloride concentration (mg/L)	Avg. weighted chloride concentration (mg/L)
Precipitation	55	1.82	1.48
White Grapes	69	20.16	22.48
Last Switch	56	31.68	34.56
Near Stream	57	12.4	12.68
Main Stream	65	15.48	not calculated

Table 9. Summary of recharge estimates for the Trinity Aquifer of the central Texas Hill Country using the chloride mass balance method and water samples collected from Cave Without A Name.

Last Switch						
	Recharge %					
Year	Using avg. chloride concentration	Using weighted chloride concentration				
2010	4.1	3.5				
2011	6.7	6.6				
2012 (Jan 1st- Mar 30th)	3.4	3.3				
Full Data Set	4.7	4.3				
	White Grapes					
	Recha	arge %				
	Using avg. chloride	Using weighted chloride				
Year	concentration	concentration				
2010	5.8	4.9				
2011	9.2	7.8				
2012 (Jan 1st- Mar 30th)	7.4	7.8				
Full Data Set	7.3	6.6				
	Near Stream					
	Recha	arge %				
	Using avg. chloride	Using weighted chloride				
Year	concentration	concentration				
2010	10.5	8.6				
2011	18.5	21.1				
2012 (Jan 1st- Mar 30th)	7.8	11.9				
Full Data Set	11.9	11.7				
		7				
Main	Main Stream					
	Recharge %					
	Using avg. chloride					
Year	concentration	_				
2010	9.6					
2011	14.1					
2012 (Jan 1st- Mar 30th)	6.0					
Full Data Set	9.6					

recharge because 2011 was a drought year with approximately 381 mm of rainfall (~50% of the average). Factors such as residence time are not taken into account using this method, and therefore estimates of yearly recharge may not be accurate. From analysis of hydrographs during this time period and the lack of rainfall responses recorded at the monitoring locations during 2011, it is likely that all, or at least a large percentage, of the water dripping from speleothems and flowing in the stream is from precipitation during previous years. Although this study did not attempt to measure or model average residence time in the epikarst, this result indicates that residence time is likely one or more years.

Measurements of chloride deposition from comparable National Atmospheric Deposition Program (NADP) locations (Table 10)(NADP 2012) indicate that concentrations measured at CWAN are relatively consistent with expected values. At our site, other than aerial deposition, there are no known sources of chloride deposition to this system. In other settings, agriculture, septic systems, road salts, or chloride containing geologic units are potential sources. None of these are known to be present at our field site. As a further check of recharge estimations calculated using chloride data from CWAN, a basin size was derived for the Main Stream. By dividing Main Stream's average yearly discharge between January 1, 2010 and April 1, 2012 (1,283,163.6 m³) by the product of 0.08 (8%, the approximate average of annualized recharge estimates from White Grapes, Rimstone Spring, and Last Switch) and the average yearly rainfall recorded during the same period (0.5844 m), the basin size is estimated to be ~27 km², which is realistic given the known extent of the associated cave system and the local geology.

Table 10. Summary of chloride concentrations reported by NADP (NADP 2012) for locations nearby or comparable to Cave Without A Name.

Bee County, Texas						
	Weekly	Sample Conce		Yearly Average		
	Minimum	Average	Maximum	Precipitation Weighted Mean		
Year	(mg/L)	(mg/L)	(mg/L)	Concentration (mg/L)	Dry Deposition (Kg/ha)	
2008	0.19	1.94	10.23	0.88	3.83	
2009	0.03	1.00	9.95	0.52	3.95	
2010	0.13	1.35	9.29	0.71	7.22	
2011	0.14	2.84	12.75	1.34	3.92	
			Edwards C	ounty, Texas		
	Weekly Sample Concentration			Yearly Ave	erage	
	Minimum	Average	Maximum	Precipitation Weighted Mean		
Year	(mg/L)	(mg/L)	(mg/L)	Concentration (mg/L)	Dry Deposition (Kg/ha)	
2008	0.06	0.49	1.96	0.38	1.09	
2009	0.04	0.45	5.93	0.20	0.87	
2010	0.03	0.29	1.60	0.18	0.98	
2011	0.05	0.75	8.65	0.22	0.85	
			Hinds Count	ty, Mississippi		
	Weekly	Sample Conce	ntration	Yearly Ave	erage	
	Minimum	Average	Maximum	Precipitation Weighted Mean		
Year	(mg/L)	(mg/L)	(mg/L)	Concentration (mg/L)	Dry Deposition (Kg/ha)	
2008	0.02	0.41	1.50	0.33	4.89	
2009	0.02	0.44	4.21	0.23	3.55	
2010	0.02	0.52	8.72	0.27	2.86	
2011	0.05	0.30	0.84	0.24	3.09	

Two-End-Member Mixing Model Results

Analysis of high-frequency liquid water stable isotope data from White Grapes, Rimstone Spring, and Main Stream revealed differences in event water contributions between sites and between two rain events. The first samples and data were collected during and following rainfall events on September 7 and 8, 2010. These events occurred approximately 9.5 hours apart, but produced only one distinct response at the White Grapes site (Figure 10), and two responses at both Rimstone Spring (Figure 11) and Main Stream (Figure 12). The first event produced 98.8 mm of rainfall over 14 hours, and the second event produced 58.9 mm over 8 hours. Event water contributions from these two events contributed to approximately 28% of the recharge response at White Grapes, and approximately 78% of the response at both Rimstone Spring and Main Stream.

Stable isotope data were also collected before, during, and after a rainfall event on March 19, 2012. This event lasted approximately 4.5 hours, produced 41.9 mm of rain, and contributed to approximately 58% of the recharge response at White Grapes (Figure 13), 40% at Rimstone Spring (Figure 14), and 16% at Main Stream (Figure 15).

Differences in event water contributions at specific sites between the two events are likely due to differences in the rainfall dynamics and antecedent conditions. The high event water contribution at White Grapes from the smaller rain event on March 19, 2012 is likely due to the occurrence of another small rainfall event, 3.6 mm, which fell on March 28. While the event was too small to cause a

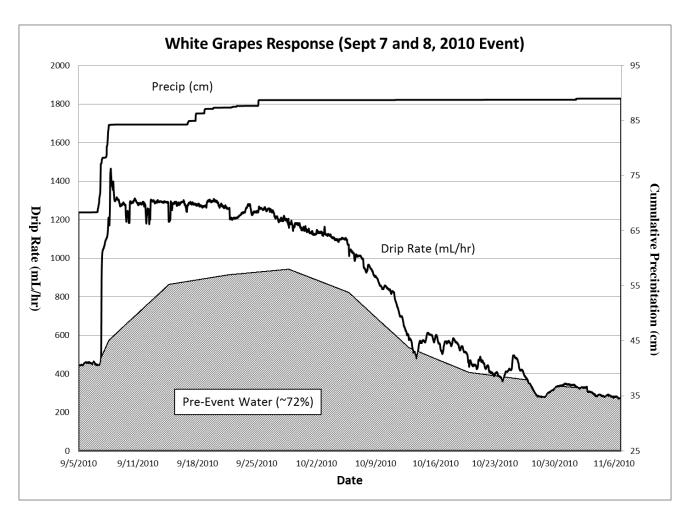


Figure 10. Hydrograph separation of drip water discharge at White Grapes following rain events on September 7 and 8, 2010 using δD as a tracer.

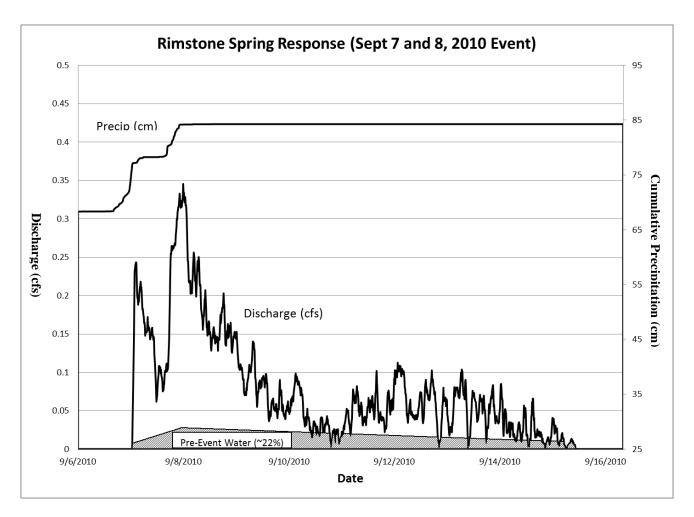


Figure 11. Hydrograph separation of discharge at Rimstone Spring following rain events on September 7 and 8, 2010 using δD as a tracer.

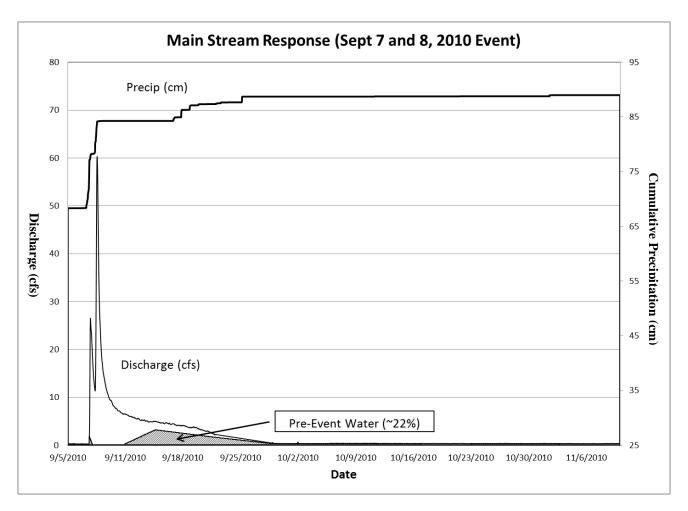


Figure 12. Hydrograph separation of discharge at Main Stream following rain events on September 7 and 8, 2010 using δD as a tracer.

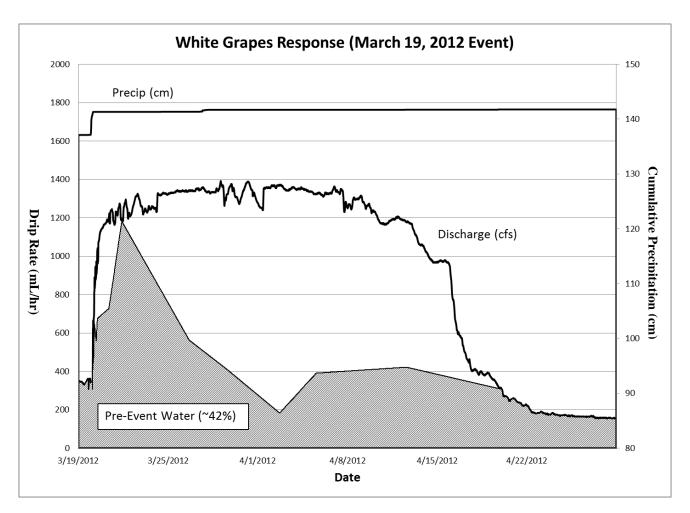


Figure 13. Hydrograph separation of drip water at White Grapes following a rain event on March 19, 2012 using δD as a tracer.

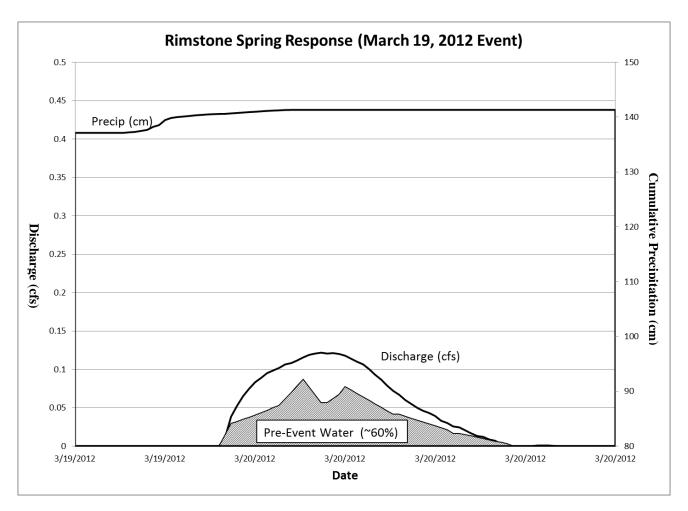


Figure 14. Hydrograph separation of discharge at Rimstone Spring following a rain event on March 19, 2012 using δD as a tracer.

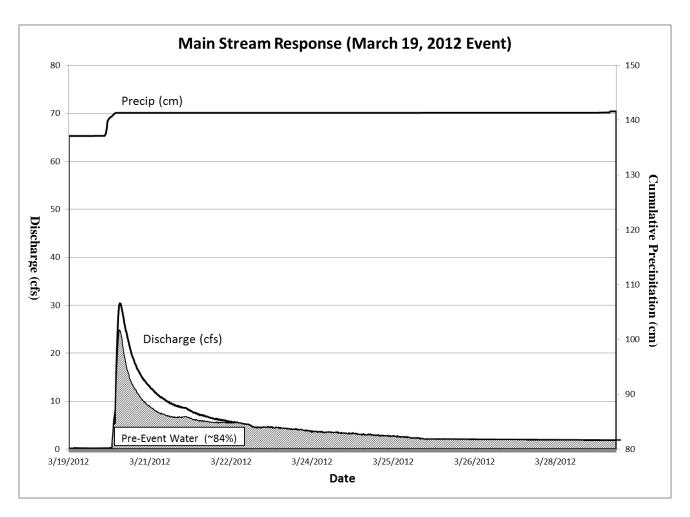


Figure 15. Hydrograph separation of discharge at Main Stream following a rain event on March 19, 2012 using δD as a tracer..

response, the drip rate was still high from the event on March 19, and that enabled this small event to force a pulse of event water out of the epikarst. This piston flow signal was not observed at other sites because they had already receded back to base flow.

The much larger event water contributions at Rimstone Spring and Main Stream from the September 2010 events are likely simply due to the much larger rainfall sum. As previously mentioned, the Rimstone Spring site has been found by the cave manager to respond when a hose on the surface flows into a closed depression. This, and the fact that the site quickly ceases to flow after rain events, suggests that the spring is mainly, or at least substantially, supplied by recharge via a preferential pathway directly from the surface. The higher rain amount during September 2010 contributed to a substantial amount of surface runoff, as noted by the cave manager that day, which would have allowed large amounts of overland flow to enter the depression, causing an event-water fueled response at both the Rimstone Spring and Main Stream sites. This large event, and the overland flow produced by it, resulted in a large volume of direct recharge into factures, conduits, and sinkholes. Some of these features are known and visible at the surface in the estimated drainage basin for the stream. Because many of these are assumed to have direct connections between the surface and tributaries to the Main Stream, this resulted in the large event-water contribution to Main Stream during the storms of September 2010. Evidence for this direct connection includes airflow observations, large amounts of coarse organic debris being washed in, and tannic water being observed both on the surface and in the cave after storm events.

CHAPTER IV

CONCLUSION

A strong and quantifiable relationship exists between recharge and antecedent moisture conditions, environmental parameters, and rainfall characteristics. This relationship was shown to exist through the use of stable isotope mixing models and regression analyses. Regression modeling showed that a relationship between event rainfall sum, soil moisture, and the sum of PET over the eight weeks prior to an event is quite successful at predicting whether a response will or will not occur in this system. Additionally, a model that includes event rainfall sum and the sum of PET over the eight weeks prior to an event is successful at predicting response magnitude at the Main Stream location. This site has the largest drainage basin and is most likely to be representative of the whole system.

These regression models are not only useful for predictive analysis of responses and response magnitude in this system, but may be useful in predicting recharge responses and magnitudes in the larger Hill Country recharge zone for the Trinity Aquifer System. However, because they have only been tested in one karst watershed, caution must be used when applying these models outside of similar geologic and climatological conditions present in this study area. Additionally,

further investigation may be needed to verify and increase the power of predictability of these models.

Recharge estimates made using the chloride mass balance method in this system are a first pass and provide a reasonable approximation of recharge in the system. However, the lack of dry aerial deposition instrumentation for sampling chloride warrants caution in interpreting their applicability over large areas. This method was simply used as another technique to compare with other recharge estimates made in the region. However, results do support many other recharge estimates for the Trinity Aquifer of central Texas which have reported values of around 3-12%.

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