Karst Landscape Influence on the Planetary Boundary Layer Atmosphere

Zachary S. Sullivan
Western Kentucky University, zachary.sullivan653@topper.wku.edu

Follow this and additional works at: http://digitalcommons.wku.edu/theses

Part of the Climate Commons, Geology Commons, and the Other Oceanography and Atmospheric Sciences and Meteorology Commons

Recommended Citation
http://digitalcommons.wku.edu/theses/1638

This Thesis is brought to you for free and open access by TopSCHOLAR®. It has been accepted for inclusion in Masters Theses & Specialist Projects by an authorized administrator of TopSCHOLAR®. For more information, please contact topscholar@wku.edu.
KARST LANDSCAPE INFLUENCE ON THE PLANETARY BOUNDARY LAYER ATMOSPHERE

A Thesis
Presented to the Faculty of the
Department of Geography and Geology
Western Kentucky University
Bowling Green, Kentucky

In Partial Fulfillment
of the Requirements for the Degree
Master of Geoscience

By
Zachary Sullivan

August 2016
KARST LANDSCAPE INFLUENCE ON THE PLANETARY BOUNDARY LAYER ATMOSPHERE

Date Recommended 07/15/2016

Dr. Xingang Fan, Director of Thesis

Dr. Jason Poll

Dr. Rezaul Mahmood

Dean, Graduate Studies and Research  Date

7/20/16
I dedicate this thesis to my mother, Deborah Sullivan, and grandmother, Daisy Harris, who are my greatest inspirations. Also, I dedicate this work to my dearest friends Trent White, Denise Constanza, and Megan Duke, for their continued support. Finally, I dedicate this thesis to my committee members, Drs. Xingang Fan, Jason Polk, and Rezaul Mahmood, for their critiques, inputs, and aid along the way.
ACKNOWLEDGMENTS

I would like to thank my committee members, Drs. Xingang Fan, Rezaul Mahmood, and Jason Polk for their continued input and aid throughout the development and synthesis of this thesis. My work under their supervision has allowed me to incorporate two of my passions in the field of science, geology and meteorology, which I had previously thought was not possible. I am very grateful for the critiques and mentoring that they have provided along the way, as it has helped to shape me towards the professional scientist and potential educator I wish to become. My sincerest gratitude goes out to each and every one of you. I hope to achieve as much success in my careers as each of you have.

I would also like to acknowledge several individuals whose help towards the development of this thesis was greatly appreciated. Thank you, William Rodgers, for your aid in my understanding of computer coding in meteorology and of meteorological models. Your help along the way was greatly appreciated. Thank you, Dr. Jun Yan, for your aid with and input on my GIS work and statistical analysis, which was also much appreciated.

Although not directly associated with my thesis work, there are several individuals I would like to thank for their support and aid throughout my thesis writing process. Thank you, Dr. Joshua Durkee, for providing me with the opportunity to grow as an instructor and a leader. I have grown so much through my work in the meteorology lab and through instructing, which has provided me with opportunities I did not have access to previously. Words cannot describe my gratitude. Dr. Leslie North, thank you for your input on my thesis work along the way, your aid in my professional development, and
your encouragement to get me to study abroad. My thanks also go to Robert Schaefer and Ellen Barringer, my graduate school family. You’re some of my best friends and I am blessed to have your support. Thanks to Trent White, Denise Constanza, and Megan Duke for being my support at home and cheering me on. You’re more than my best friends, you’re my family and I only hope to make you as proud as you make me.

Finally, I would like to thank my mother, Deborah Sullivan, my grandmother Daisy Harris, and my Uncle, Richard Harris, for their continued support throughout the process of obtaining my Master’s degree. It was tough, but you never let me quit and were there always to remind me of the light at the end of the tunnel. I am truly grateful to call you family. I hope to make you proud.
# TABLE OF CONTENTS

Chapter 1: Introduction ........................................................................................................1

1.1 Research Questions and Purpose ..............................................................................2

Chapter 2: Forecast Verification .........................................................................................5

2.1 Introduction .................................................................................................................5

2.2 Background ................................................................................................................6

2.3 Methodology ..............................................................................................................10

2.4 Results .......................................................................................................................14

2.4.1 Control Results ....................................................................................................14

2.4.2 Experimental Results .........................................................................................20

2.4.2.1 Daily Maximum/Minimum Temperatures ......................................................20

2.4.2.2 U/V winds .....................................................................................................24

2.4.2.3 Precipitation .................................................................................................26

2.5 Conclusions .............................................................................................................40

Chapter 3: Karst Parameters ............................................................................................44

3.1 Introduction .................................................................................................................44

3.2 Background ...............................................................................................................45

3.2.1 What is Karst .......................................................................................................45

3.2.2 Aspects of Karst ..................................................................................................46

3.2.3 Study Area .........................................................................................................47

3.3 Methodology .............................................................................................................51

3.4 Results .......................................................................................................................55

3.5 Conclusions .............................................................................................................60
Chapter 4: WRF Model Experiment

4.1 Introduction .................................................................................................................62
4.2 Background ....................................................................................................................63
  4.2.1 Soil Moisture ........................................................................................................63
  4.2.2 Vegetation ............................................................................................................65
  4.2.3 Atmospheric Modeling ........................................................................................67
4.3 Methods .........................................................................................................................68
4.4 Results ............................................................................................................................70
  4.4.1 Case 1 ....................................................................................................................71
  4.4.2 Case 2 ....................................................................................................................84
  4.4.3 Case 3 ....................................................................................................................93
  4.4.4 Case 4 ..................................................................................................................105
4.5 Conclusions ..................................................................................................................113

Chapter 5: Conclusions .................................................................................................118
References .......................................................................................................................122
LIST OF FIGURES

Figure 2.1 The 13 regions used to analyze statistically the performance of the NAM model ..................................................................................................................................................6

Figure 2.2 Example of a 2x2 Contingency table ..........................................................................................................................11

Figure 2.3 Location of the control regions selected for verification .................................................................................................15

Figure 2.4 Root Mean Square Error (RMSE) and BIAS scores associated with the daily maximum temperatures within controls ..........................................................................................................................16

Figure 2.5 Root Mean Square Error (RMSE) and BIAS scores associated with the daily minimum temperatures within controls ........................................................................................................................................17

Figure 2.6 Root Mean Square Error (RMSE) and BIAS scores associated with the U-component (west/east) of the winds within controls ........................................................................................................17

Figure 2.7 Root Mean Square Error (RMSE) and BIAS scores associated with the V-component (north/south) of the winds within the controls ..................................................................................18

Figure 2.8 ETS and fBias scores associated with the raw precipitation data within the control regions. ......................................................................................................................................................19

Figure 2.9 ETS and fBias scores associated with the standardized precipitation data within the control regions ......................................................................................................................................................20

Figure 2.10 Root Mean Square Error (RMSE) and BIAS scores associated with the daily maximum temperatures ..................................................................................................................................................22

Figure 2.11 Root Mean Square Error (RMSE) and BIAS scores associated with the daily minimum temperatures ..................................................................................................................................................23
Figure 2.12 Root Mean Square Error (RMSE) and BIAS scores associated with the U-component (west/east) of the winds ................................................................. 25

Figure 2.13 Root Mean Square Error (RMSE) and BIAS scores associated with the V-component (west/east) of the winds ................................................................. 26

Figure 2.14 $ETS$ and $fBias$ scores associated with raw precipitation data for a) WEST, b) SE, and c) CONUS. .............................................................................................................. 27

Figure 2.15 Root Mean Square Error (RMSE) associated with the raw precipitation data ..................................................................................................................... 29

Figure 2.16 $ETS$ and $fBias$ scores associated with raw precipitation data for a) Area 3, b) Area 7, and c) Area 8 ................................................................. 30

Figure 2.17 $ETS$ and $fBias$ scores associated with raw precipitation data for a) Area 2, b) Area 5, and c) Area 6 ................................................................. 31

Figure 2.18 $ETS$ and $fBias$ scores associated with raw precipitation data for a) Area 4, b) Area 9, and c) Area 10 ................................................................. 34

Figure 2.19 $ETS$ and $fBias$ scores associated with standardized precipitation data for a) WEST, b) SE, and c) CONUS. ................................................................. 35

Figure 2.20 $ETS$ and $fBias$ scores associated with standardized precipitation data for a) Area 3, b) Area 7, and c) Area 8 ................................................................. 37

Figure 2.21 $ETS$ and $fBias$ scores associated with standardized precipitation data for a) Area 2, b) Area 5, and c) Area 6 ................................................................. 38

Figure 2.22 $ETS$ and $fBias$ scores associated with standardized precipitation data for a) Area 4, b) Area 9, and c) Area 10 ................................................................. 39
Figure 2.23 Root Mean Square Error (RMSE) and BIAS scores associated with the standardized precipitation data .................................................................40

Figure 3.1 The geology of the Kentucky region .................................................................48

Figure 3.2 Land cover over the state of Kentucky .............................................................50

Figure 3.3 Map of the average annual precipitation over the Western Kentucky
Penryroyal Karst region ..........................................................................................51

Figure 3.4 Karst geology associated within the inner model domain for use within the experimental model runs ........................................................................59

Figure 3.5 Soil association with the karst geology placed within the geogrid data for the WRF model runs ........................................................................60

Figure 4.1 Model domains used for this research ..........................................................69

Figure 4.2 Soil changes made within the model domains for this research .................70

Figure 4.3: The RMSD scores generated over a two day period for each case study between an experiment and CTRL ...............................................................72

Figure 4.4 2m temperature results within the EXP domain for Case 1 ......................73

Figure 4.5 2m Temperature results within the BARREN_K domain for Case 1 ..........75

Figure 4.6 Sensible Heat (Q_h) results within the EXP domain for Case 1 ...............76

Figure 4.7 Sensible Heat (Q_h) results within the BARREN_K domain for Case 1 .........78

Figure 4.8 Latent Heat (Q_e) results within EXP domain for Case 1 .........................79

Figure 4.9 Latent Heat (Q_e) results within BARREN_K domain for Case 1 ..........81

Figure 4.10 Precipitation results within EXP domain for Case 1 ...............................82

Figure 4.11 Precipitation results within BARREN_K domain for Case 1 ...............83

Figure 4.12 2m temperature results within EXP domain for Case 2 ....................85
Figure 4.13 2m temperature results within BARREN_K domain for Case 2 .................86
Figure 4.14 Sensible Heat Flux (Q_h) results within the EXP domain for Case 2 ........88
Figure 4.15 Sensible Heat Flux (Q_h) results within the BARREN_K domain for Case 2.89
Figure 4.16 Latent Heat Flux (Q_e) results within the EXP domain for Case 2 ..........90
Figure 4.17 Latent Heat Flux (Q_e) results within the BARREN_K domain for Case 2 ...91
Figure 4.18 Precipitation results within the EXP domain for Case 2 .......................92
Figure 4.19 Precipitation results within the BARREN_K domain for Case 2 ..........93
Figure 4.20 2m Temperature results within the EXP domain for Case 3 ..................95
Figure 4.21 2m Temperature results within the BARREN_K domain for Case 3. ........96
Figure 4.22 Sensible heat (Q_h) results within the EXP domain for Case 3 ...............98
Figure 4.23 Sensible heat (Q_h) results within BARREN_K domain for Case 3 ..........99
Figure 4.24 Latent Heat Flux (Q_e) results within the EXP domain for Case 3 ...........101
Figure 4.25 Latent Heat Flux (Q_e) results within the BARREN_K domain for Case 3 ..102
Figure 4.26 Precipitation results within the EXP domain for Case 3 .......................103
Figure 4.27 Precipitation results within the BARREN_K domain for Case 3 ..........104
Figure 4.28 2m Temperature results within the EXP domain for Case 4 .................106
Figure 4.29 2m Temperature results within the BARREN domain for Case 4 ............107
Figure 4.30 Sensible Heat Flux (Q_h) results within EXP domain for Case 4 ..........109
Figure 4.31 Sensible Heat Flux (Q_h) results within the BARREN_K model domain for
Case 4 .................................................................................................................110
Figure 4.32 Latent Heat (Q_e) results within the EXP domain for Case 4 ...............112
Figure 4.33 Latent Heat (Q_e) results within the BARREN domain for Case 4 ..........113
Figure 4.34 Radar images ....................................................................................115
LIST OF TABLES

Table 2.1 P-Values and t-scores from the student’s t-test for TMAX/TMIN ..........21
Table 2.2 P-Values and T-scores for U-Winds/V-Winds ....................................25
Table 2.3 P-values generated with the raw precipitation data for ETS and fBias values...28
Table 2.4 P-values generated with the raw precipitation data for ETS and fBias values...32
Table 2.5 P-values generated with the standardized precipitation data for ETS and fBias
values ..................................................................................................................41

Table 3.1 The 19 soil classes and their associated parameter values used within the latest
version of the Noah LSM ...................................................................................53
Table 3.2 Values for the ten soil parameters given in the SOILPARM.TBL within WRF
.........................................................................................................................56
Table 3.3 Average values between regions of greater and less weathering/fracturing the
epikarst region of the karst terrain within Kentucky and Tennessee ......................56
Karst landscapes cover approximately 20% of the ice-free land area worldwide. The soluble nature of the bedrock within a karst landscape allows for the formation of caverns, joints, fissures, sinkholes, and underground streams, which affect the hydrological behavior of the region. Currently, the Noah Land-Surface Model (Noah-LSM), coupled with the Weather Research and Forecasting (WRF) model, does not provide a representation of the physical behavior of a karst terrain. Previous research has attempted to model karst behavior through soil moisture and land cover/land use changes to determine the influence this unique landscape may have on atmospheric phenomenon. This highlights the need to study the potential influence that karst landscapes may have on model simulations. For this study, several factors were taken into account while studying karst and meteorology: the verification of a current operational forecasting model against observational data over five years (2007 to 2011), the formation of a karst-like soil type for use within an operational forecasting model, and model behavior once this karst-like soil type was added to the operational forecasting model.

The verification of a currently operational forecasting model, the North American Mesoscale (NAM), indicated that, overall, the karst regions may exhibit an influence on local winds (greater error) and precipitation (frequency and forecasting). When developing a realistic karst-like soil proxy for use in the Noah-LSM, hydraulic conductivity values show a variation ranging from around $10^{-7}$ and $10^{-5}$ m s$^{-1}$ for the karst
bedrock within Tennessee and Kentucky. Sandy loam and clay soils were used, along with bedrock parameters, to determine an average soil parameter type for the epikarst bedrock located within this region. The model study demonstrated that the addition of karst highlighted the potential influence on precipitation distribution and energy fluxes, through RMSD and $R^2$ values taken at a 95% confidence interval.
CHAPTER 1: Introduction

Karst landscapes cover approximately 20% of the Earth’s ice-free land surface, with an estimated 40% of the United States east of Tulsa, Oklahoma, covered by karst (White et al. 1995; Ford and Williams 2007). Karst terrains consist of soluble rocks such as gypsum, limestone, marble, and dolomite, which, through dissolution, form caves, underground streams, sinkholes, and aquifers (Milanovic 1981). Epikarst, or the subcutaneous zone, refers to the upper-most 3 to 10 meters of the vadose zone within karst areas. This is characterized by higher porosities near the surface, due to weathering processes that decrease downward throughout the subsurface region (Ford and Williams 2007; Williams 2008). Karst regions are of interest when studying the influence that the karst land surface has on the surrounding planetary boundary layer atmosphere (PBLA). The PBLA is the portion of the lower troposphere in contact with the land surface. The height of the PBLA varies between day and night largely due to surface heating (Vasque 2003). Previous studies modeled the effects that karst landscapes have on PBLA by manipulating soil moisture contents of karst regions (Leeper et al. 2011; Johnson et al. 2014).

The subsurface plays an integral role in the hydrological process, by way of evaporation from exposed soil surface or through evapotranspiration. The partitioning of sensible and latent heat fluxes through soil moisture plays an important role in the weather and climate of a region with respect to air temperature, stability of the boundary layer, and precipitation (Seneviratne et al. 2010). Previous studies revealed that soil moisture can result in changes in wind patterns (Quintanar et al. 2009), severe weather development (Lanicci et al. 1987), and precipitation (Leeper et al. 2011) over a karst
region. The use of the Noah land-surface model (Noah-LSM) with respect to these variables over the Kentucky and Tennessee region allows for the simulation of potential influences of karst on the PBLA.

The Noah-LSM has been widely used throughout land-surface/atmospheric interaction studies due to its coupling within the Weather Research and Forecasting (WRF) model (Niu et al. 2011). The Noah-LSM simulates the upper two meters of a subsurface region taking into account the soil moisture, soil temperature, snow cover, canopy water content, heat, moisture, and CO₂ fluxes of this subsurface region (Chen and Dudhia 2001).

1.1 Research Questions and Purpose

As demonstrated in prior studies (Johnson et al. 2014), current operational forecasting models do not account for karst-like landscapes within the model’s parameters. This highlights the need to determine if inclusion of such information could be useful in modeling and forecasting. To conduct such an analysis, this research used forecast verification techniques to determine the performance of a current operational forecast model, the North American Mesoscale (NAM) model. The NAM forecasts were statistically analyzed using several skill scores, such as the Equitable Threat Score (ETS), frequency Bias (fBias), and Root Mean Square Error (RMSE) score. The objective of the NAM forecast verification was to determine whether the karst regions over- or underestimated these specific meteorological variables and the magnitude of error between simulations and observations.

The next important goal of this research was the development of a realistic representation of karst within a current operational forecasting model, the WRF model.
Due to prior research on karst geology/hydrogeology within the Tennessee and Kentucky region, this area was chosen to conduct the study. To formulate as realistically as possible representation of karst within the WRF model, I studied the literature on karst characteristics and rock properties (limestone/dolomite) to create a proper replacement for use in the soil classes of the Noah-LSM. The newly identified parameters were used to replace the previous bedrock class alongside several weather events to evaluate model sensitivity to the inclusion of a karst-like classification in the WRF model. The model estimates, along with statistical analysis of model simulations, were used to improve the understanding of the usefulness that these data may provide in forecasting and future research.

Using these methods discussed above, this study aimed to answer the following questions:

1. How well does a currently operational forecasting model, such as the NAM, perform over karst regions compared to non-karst regions?
2. Which proxy parameters can be used to model behavior accurately within the epikarst region of karst landscapes?
3. How does the performance of the WRF model, adjusted for karst terrains, compare to the original WRF model run?

In short, the underlying hypothesis of this study is that the subsurface characteristics of karst landscapes demonstrate an influence on atmospheric phenomenon. The results from this research provide further insight into the potential influence that karst landscapes have on atmospheric phenomenon. This research also provides validation of the NAM model, with respect to the forecast output and its relationship to karst/non-karst locations. This
method of verification and model sensitivity to karst can be implemented in future research related to this topic, as this study provides an outline of how to include a karst-like landscape into an operational forecasting model for evaluation. The results may also improve WRF model output, which, in turn, can be of use to a number of governmental and local agencies whose work is related to meteorology.
CHAPTER 2: Forecast Verification

2.1 Introduction

Current operational forecasting models do not include parameters associated with karst landscapes (Chen and Dudhia 2001; Johnson et al. 2014). Karst geology allows for the modification of the hydrology within a region, which could influence energy fluxes (heat and moisture) from the surface to the surrounding atmosphere (Leeper et al. 2011; Johnson et al. 2014). In order to determine the potential influence on meteorological phenomenon associated with karst landscapes, an analysis of the NAM against observational data was undertaken. NAM and PREPBUFR observational data were compiled for a five-year period (2007 – 2011) in order to evaluate the model’s performance over karst and non-karst landscapes. Within the contiguous United States, thirteen experimental and four control regions (discussed in detail below in Figure 2.1 and 2.3) were chosen due to their location and orientation of karst versus non-karst landscapes. In order to determine the model performance, an evaluation of five forecast variables, daily maximum temperature, daily minimum temperature, precipitation, U-component wind, and V-component wind, was undertaken. Five verification scores (Root Mean Square Error (RMSE), Equitable Threat Scores (ETS), frequency Bias (fBias), Mean Bias (MB), and Bias) were used in this research to evaluate the model performance (Fan and Tilley 2005; Wilks 2011; Wolff et al. 2011). The discussion of verification results is broken into groups as shown in Figure 2.1: Control regions (discussed below in Figure 2.3), Contiguous United States (CONUS), southeastern United Stated (SE), western United States (WEST), karst landscape located on the western side of the study region (Areas 1, 3, 7, 8), karst landscapes located on the eastern side of the study region.
(Areas 2, 5, 6), a region of non-karst surrounded by karst (Area 9), a region of karst surrounded by non-karst (Area 4) and, finally, a region consisting mostly of karst (Area 10).

**Figure 2.1.** The 13 regions used to analyze statistically the performance of the NAM model. The various data regions (colored rectangles) used in data analysis of the karst (hatched regions) and non-karst regions are shown. The numbers associated with each region correspond to the number of karst/non-karst points used within each region. The projection used for this map is NAD_1983_Albers. Source: Esri 2012; Weary and Doctor 2014).

2.2 - Background

Forecast verification is used in order to assess the quality of forecasts, which entails a comparison between the model-predicted variables with the observations (Warner 2011; Wilks 2011). The purpose behind forecast verification includes assessing forecasting and the recent trends in forecast quality, improving the procedure behind
forecasts and, ultimately, the forecasts themselves, and to provide information to make effective forecasts (Murphy and Winkler 1987). Forecast verification is important when conducting studies on physical processes, since the model is used as a proxy for the real atmosphere. The model solution must then be objectively verified against the observational data to see if these data correspond well enough to use in regions where observational data are missing (Warner 2011). Verification of forecast data consists of a collection of forecast and observational pairs, whose joint behavior can be characterized to see the relationship between these two variables (Wilks 2011). Examples of the joint distribution of forecasts include a simple dichotomous situation, such as precipitation/no precipitation, multiple categorical forecasts such as cloud cover, or even single variable forecasts such as maximum/minimum temperature or amount of precipitation (Murphy and Winkler 1987).

There are numerous methods for verifying forecasts. The verification of the accuracy of discrete variables can be determined if the variables have a yes-no value, such as precipitation of a certain amount, which can be verified through the use of a 2 x 2 contingency table (Warner 2011). A skill score is a measure of the accuracy of one forecast method with respect to a reference forecast with threat scores (TS) used as a basic accuracy measure and the TS of random forecasts used as the reference in this verification score (Warner 2011). The Equitable Threat Score (ETS), or Gilbert Skill Score, measures the skill in predicting a given threshold at a given location with a score of zero indicating no skill and a score of one indicating a perfect forecast (Mesinger 1996; Wilks 2011). The bias score is used to compare the average forecast to the average observations for a discrete variable (Warner 2011). The fBias is the measure of a ratio of
the number of “yes” forecasts to the number of “yes” observations regarding the discrete variable being tested, with a value of 1 indicating a perfect forecast, (<1) indicating a tendency to under-forecast and (>1) indicating a tendency to over-forecast for the frequency of occurrence of the discrete variable (Fan and Tilley 2005). The ETS and $fBias$ are based off a 2 x 2 contingency table, which tests any discrete variable to the number of its occurrences, while the Mean Square Error ($MSE$) is the average squared distance between the forecast and observation pairs, which is more sensitive to larger errors and outliers (Wilks 2011). The MSE is a scalar accuracy measure with regards to continuous variables, such as if the temperature alone is the prediction in question, with the square root of this variable ($RMSE$) having the same physical dimensions with respect to forecasts and observations (Warner 2011). The mean bias ($MB$) score, or mean error ($ME$), is a measure of the systematic error, which represents a comparison between the model values and the actual climatological values (Fan and Tilley 2005; Warner 2011).

The use of contingency tables and the ETS score shows that implementation of these techniques alone in order to verify the performance of WRF model simulations at two different resolutions, 4 km and 10 km respectively, for mesoscale convective systems (MCS) may yield an incomplete interpretation of model behavior (Done et al. 2004). Fan and Tilley (2005) coupled the use of the ETS, Bias, and $RMSE$ score to verify precipitation forecasts at various rainfall thresholds showing that the pairing of these two skill scores with the $RMSE$ score aids in the determination of systematic errors with respect to the magnitude of the precipitation forecast. Detail descriptions of the metrics used in this current work are provided below in section 2.3, where ETS, Bias, and $RMSE$ verification scores were of use when evaluating the overall preference of the NAM.
model’s response to variables, such as precipitation over both karst and non-karst regions. The \( RSME \) and \( MB \) scores were also of use when verifying the performance of operational models on variables such as 2m temperature, and 10m zonal (U) and meridional (V) vector winds (Fan and Tilley 2005). An understanding of this will provide an insight into a preliminary idea about how karst geologic terrains are behaving compared to the surrounding non-karst regions.

The forecast verification techniques are applied to a currently running operational model, the NAM. The NAM has a high grid resolution of 12 km and is a good for short-range forecasts (Vasque 2003). In June 2006, the NAM model transitioned into the use of the WRF model’s Non-hydrostatic Mesoscale Model (NMM) dynamic core (Janjic 2003; Clark et al. 2010; Bernardet et al. 2009). Verification between the NAM and NCAR-WRF demonstrates that the NAM model has a tendency to under-estimate heavy precipitation events (low bias) along with a decrease in forecast skill within heavier events (Clark et al. 2010). Verification research regarding the WRF-NMM model indicates that precipitation within 12.7 mm (0.5 inches), 19.1 mm (0.75 inches), and 25.4 mm (1 inch) displays an under-prediction of precipitation, with forecast skill decreasing as precipitation threshold increases (Bernardet et al. 2009). Pyle et al. (2004) found the WRF-NMM displayed several characteristics when verifying surface meteorological variables. The daily maximum displayed a warm bias and minimum temperatures a cool bias, with \( RMSE \) values of 3.6°C and 3.7°C for maximum and minimum temperatures, respectively. With respect to precipitation, the results from Pyle et al. (2004) indicated a weaker forecast skill within the WRF-NMM model with the exception of over the western United States. The NAM model has shown bias scores indicating a tendency to
under-estimate precipitation between the 2007 to 2011 time periods with respect to precipitation performance (Novak et al. 2014).

2.3 Methodology

The primary input data used in this study include five years (2007 – 2011) of operational forecasts from the NAM system with regards to precipitation, maximum temperature, minimum temperature, and U/V component winds. Traditional verification methods, including the ETS and the $f_{Bias}$, were used in order to check the accuracy of the precipitation forecasts across the karst/non-karst regions (Mesinger 1996; Fan and Tilley 2005; Wolff et al. 2011).

The $f_{Bias}$ are based off a 2 x 2 contingency table (Figure 2.2), in which any discrete variable can be tested to the number of its occurrences. Based on the contingency table, the $f_{Bias}$ score is simply a ratio of the number of “yes” forecasts to the number of “yes” observations regarding the discrete variable being tested and is calculated by the following (Wilks 2011):

\[ f_{Bias} = \frac{A + B}{A + C} \]  

Thus, the $f_{Bias}$ provides a score that indicates the frequency of the occurrence of a specific event for that threshold with a $f_{Bias}$ score of 1 indicating a perfect forecast, $f_{Bias} < 1$ indicating a tendency to under forecast and $f_{Bias} > 1$ indicating a tendency to over forecast for the frequency of occurrence of the discrete variable (Fan and Tilley 2005; Wolff et al. 2011). The ETS is calculated as:

\[ ETS = \frac{H - E}{F + O - H - E} = \frac{A - E}{A + B + C - E} \]  

where H is defined as the number of forecast “hits” in which a hit refers to the number of simulated and observed variables meeting or exceeding a given threshold at a point, F is
the number of forecasts at the observation station, O is the number of observation occurrences that meet or exceed the threshold, and E is calculated as:

\[
E = \frac{FO}{N} = \frac{(A + B)(A + C)}{N}
\]

where N refers to the number of points being verified (Mesinger 1996; Fan and Tilley 2005). ETS, also called the Gilbert Skill Score, measures the skill in predicting a given threshold at a given location with a score of zero indicating no skill and a score of one indicating a perfect forecast (Mesinger 1996; Wilks 2011; Wolff et al. 2011).

Figure 2.2 Example of a 2x2 Contingency table. Each square is associated with the occurrence of either a “yes” forecasted/observed or a “no” forecasted/observed occurrence for any discrete variable of interest. Adding up each \((A + B + C + D)\) gives the sample size \((n)\) for the type of event of interest. Source: Wilks (2011).

In order to check the performance of the NAM model, the ETS and fBias scores were calculated using the thresholds of 0.5, 1, 2.5, 5, 10, 15, 25, and 50 mm over a five-year time period (2007 -2011). The ETS and fBias scores only measure the model’s skills based on the frequency of the variable’s occurrence at or above a threshold; thus they do not calculate the magnitude of the forecasted error (Fan and Tilley 2005). In order to
check the forecasted error in regards to the variable in question, the RMSE is used between the forecast \((P_{\text{model},i})\) and observed \((P_{\text{obs},i})\). RMSE is calculated as:

\[
RMSE = \sqrt{\frac{1}{N} \sum_{i}^{N} (P_{\text{obs},i} - P_{\text{model},i})^2}
\]  

(2.4)

where \(N\) is the number of observation points utilized in the verification process (Fan and Tilley 2005). A RSME score of zero indicates a perfect forecast, and a score increasing from zero showing a greater magnitude of error (Fan and Tilley 2005; Wilks 2011). To check model performance further, a BIAS score has been associated with the RMSE to show if the models are underestimating or overestimating the variable. This BIAS score is achieved using this formula:

\[
\text{BIAS} = (a_{\text{mod}}) - (a_{\text{obs}})
\]  

(2.5)

where the \(a_{\text{mod}}\) is the average for the modeled events and \(a_{\text{obs}}\) is the average for the observed events.

Statistical analysis was completed using the ArcGIS version 10.2 zonal statistics tool in order to generate the overall average RMSE scores and ETS/fBias scores for the eight given thresholds. These average scores were used to verify the accuracy of the model simulations over karst regions in comparison to non-karst regions. Thirteen experimental and four control regions were used within this verification process.

In order to eliminate any discrepancies between regions with differing climatological patterns (i.e., the western portion of the U.S. receives less rainfall than the southeastern portion), a standardization of the data is achieved by subtracting the month’s average rainfall from daily precipitation values and then dividing this by the month’s standard deviation. The resulting values are unitless and show the intensity of the rainfall
over the U.S. The resulting threshold used in the calculation of the $ETS$ and $fBias$ scores is now 0, 0.5, 1, 1.5, 2, 3, 4, and 5 over the same five-year time period. The $RMSE$ score for this situation did not receive an associated BIAS score due to the assumption of zero discrepancy between the model and the observed dataset.

Model data for temperature and wind were obtained from the University Corporation of Atmospheric Research (UCAR) Computational and Information System Lab (CISL) Research Data Archive using NAM 12-km 18Z run using gridded data (614 x 428) at 12.19km resolution. These data gathered include: maximum 3 hourly temperatures, minimum 3 hourly temperatures, and U and V components of the wind (NCEP 2015). Observational data for maximum/minimum daily temperatures were obtained from the Global Historical Climatological Network (GHCN) database for the years of 2007 – 2011 (Menne et al. 2012). U/V component winds were obtained from NCEP ADP Global Upper Air and Surface Weather Observations (PREPBUFR format) data for the same years as the maximum/minimum daily temperatures (Menne et al. 2012). In order to check the performance of the NAM model for other variables, such as maximum/minimum daily temperature and U/V component, winds were analyzed using $RMSE$ and the Mean Bias ($MB$) score (Fan and Tilley 2005). The Mean Bias score is calculated as:

$$MB = \frac{1}{N} \sum_{i=1}^{N} (X_i - X_i^o)$$

(2.6)

where $(X_i)$ represents the forecasts, $(X_i^o)$ represents the observations and $N$ denotes the number of observations (Fan and Tilley 2005). Both the $RMSE$ and $MB$ scores were used to analyze the performance of the NAM model over the thirteen experimental and four control regions in the Contiguous United States with respect to karst/non-karst regions. This analysis will be of use to evaluate the current performance of working operational
forecasting models, such as the NAM, over karst/non-karst regions. In order to evaluate the overall significance of the verification results, a Student’s t-test and p values were gathered using the student’s t-test at a 0.05 significance level. Resulting p-values in excess of 0.05 indicate statistically insignificant data and were not included within the discussion of evaluation of model performance in these locations.

2.4 – Results

2.4.1 – Control Results

In order to evaluate the performance of the NAM model for karst/non-karst terrains, two sets of controls were analyzed that include two non-karst regions and two karst regions. The locations of the controls are depicted in Figure 2.3. These regions selected for the control comparisons were created at the same size in order to keep spatial differences to a minimum. Two non-karst locations, NK1 in Louisiana and NK2 in Nebraska, and two karst locations, K1 in Missouri and K2 in Tennessee, were chosen for analysis of the model output. While evaluating the performance of the NAM model within karst/non-karst regions, the assumption was that the control regions (non-karst to non-karst and karst to karst) should display near similar results with respect to model error. The U.S. Department of Commerce’s National Institute of Standards and Technology lists the accuracy limit for liquid-in-glass thermometers within around a 0.03°C range, as this is the common type of thermometer used within observational weather stations (NIST 1997). The observational instrument precision for wind speed indicates a +/- 0.1 m s⁻¹ error in wind speed up to 56 m s⁻¹, while the overall precision of observational precipitation events is within the 0.1 to 0.2 mm range (Burt 2012).
Figure 2.3 Location of the control regions selected for verification. Source: Esri (2012); Weary and Doctor (2014).

The resulting daily maximum temperatures indicate that location does play a role in model biases for both of the control regions (Figure 2.4). NK2 demonstrates a 0.62°C higher RMSE compared to NK1. Similarly, K2 demonstrates a 0.79°C higher RMSE compared to K1. When considering the MB scores, both non-karst locations displayed errors statistically similar to one another. The karst locations do indicate higher MB scores within K1 (with temperatures 0.24°C higher) compared to K2. This indicates that other factors, such as vegetation, might be at work within the discrepancies between model output and observational data. Mahmood et al. (2013) noted that conversion of land from the original land type to agricultural use (such as soybean or maize) displayed
a cooling effect on temperatures in the midwestern U.S.. Gallo et al. (1996) discussed that diurnal temperature ranges displayed the greatest range within a rural land use/land cover classification.

**Figure 2.4:** Root Mean Square Error (RMSE) and BIAS scores associated with the daily maximum temperatures within controls. The yellow highlighted locations indicate statistically significant results (p > 0.05): a) NK and NK, and b) K and K.

Source: Created by the Author.

Daily minimum temperatures display both NK2 and K2, demonstrating higher error in forecasted values (Figure 2.5). Minimum temperatures in NK2 indicate a 0.65 °C higher RMSE and a 0.44°C higher MB when compared against NK1. The differences are halved, 0.32°C higher within K2, within the karst regions when the RMSE values are taken into account. The MB, however, indicates a larger increase in minimum temperatures, by 0.51°C, within K2 compared against the NK2 results.

Regarding model performance with respect to winds, the U-component of winds display a 0.76 m s\(^{-1}\) higher RMSE within NK2 compared to that of NK1 (Figure 2.6). The winds display an overall over-estimation by 0.45 m s\(^{-1}\) compared to NK1. The karst locations display more similar RMSE values between the two locations compared to the non-karst regions. Overall, K2 displays a 0.06 m s\(^{-1}\) higher RMSE value compared to K1. The MB indicates an under estimation by 0.42 m s\(^{-1}\) within K2 compared to K1.
**Figure 2.5** Root Mean Square Error (*RMSE*) and BIAS scores associated with the daily minimum temperatures within controls. The yellow highlighted locations indicate statistically significant results (p > 0.05): a) NK and NK, and b) K and K. Source: Created by the Author.

**Figure 2.6** Root Mean Square Error (*RMSE*) and BIAS scores associated with the U-component (west/east) of the winds within controls. The yellow highlighted areas denote *RMSE*/BIAS scores of statistical significance (p > 0.05): a) NK and NK, and b) K and K. Source: Created by the Author.

Similar to the U-component of wind results, V-component of winds display a 5.3 m s\(^{-1}\) higher *RMSE* within NK2 compared to NK1, with an associated 0.1 m s\(^{-1}\) overestimation in winds (Figure 2.7). The karst landscapes display more variation in V-wind model output than U-wind between the two locations. K1 displays a 4.7 m s\(^{-1}\) higher *RMSE* compared to K2, with a 0.4 m s\(^{-1}\) lower over–estimation compared to that of K2.
The raw precipitation results display noticeable differences between the two control locations (Figure 2.8). NK2 consistently displays lower ETS throughout all thresholds compared to NK1. Variation is noted in the resulting karst region comparison. All thresholds from 1.0 to 15.0 mm thresholds display slightly higher ETS within K2, with the 5 mm threshold displaying the greatest ETS (0.08 higher for K2). The heaviest thresholds display means between the two karst locations, which are statistically similar to one another. The $f_{Bias}$ associated with the non-karst locations displays a general underestimation in precipitation frequency within NK1 from the 2.5 mm threshold upward. These differences become more pronounced by the 10.0 mm threshold. The $f_{Bias}$ within the karst locations indicates K1 with a greater propensity for the underestimation in precipitation frequency for precipitation events 2.5 mm or greater. The $f_{Bias}$ noted at the 25 mm thresholds displays values slightly higher than those noted in the Novak et al. (2014) study (between 0.8 and 1). The NK regions indicate a 0.4 decrease in $f_{Bias}$ scores compared to a 0.1 decrease in the K regions. The $f_{Bias}$ results coincide with that of the biases described within the Bernardet et al. (2009) study, with noted underestimation of precipitation within the NAM model displayed at higher thresholds. Regarding the

**Figure 2.7** Root Mean Square Error (RMSE) and BIAS scores associated with the $V$-component (west/east) of the winds within controls. The yellow highlighted areas denote RMSE/BIAS scores of statistical significance ($p > 0.05$): a) NK and NK, and b) K and K. Source: Created by the Author.
magnitude of error associated with two karst and non-karst locations, NK1 displays a 3.1 mm higher RMSE value compared to that of NK2. The karst locations demonstrate a 0.52 mm higher RMSE value within K1 compared to K2 (figure not shown).

Figure 2.8 ETS and fBias scores associated with the raw precipitation data within the control regions. The yellow highlighted areas denoted ETS/fBias scores of statistical significance (p > 0.05): a) NK and NK, and b) K and K. Source: Created by the Author.

The standardization of the precipitation data decreased the mean ETS results that display difference statistically from one another within the control locations (Figure 2.9). NK1 displays lower ETS values in comparison to NK2, indicating a decrease in precipitation skill, for thresholds 1.5, 4.0, and 5.0. The results between the karst landscapes indicate that the lighter events (0.5 to 1.5) display lower ETS values, by 0.02 to 0.04, within K1 compared to K2. The fBias score indicates a greater propensity for the under estimation in precipitation frequency within NK1. Similar to the raw precipitation results, K1 displays a greater propensity for the under estimation of precipitation compared to K2, with the exception of the heaviest events.
Figure 2.9 *ETS* and *fBias* scores associated with the standardized precipitation data within the control regions. The yellow highlighted areas denoted *ETS/fBias* scores of statistical significance (*p* > 0.05): a) NK and NK, and b) K and K. Source: Created by the Author.

2.4.2 Experimental Results

2.4.2.1 Daily Maximum/Minimum Temperatures

The evaluation of the verification results indicated several locations with associated *p*-values in excess of 0.05, demonstrating statistically insignificant results.

Daily maximum temperatures (TMAX) reveal Areas 1, 3, 4, 5, 8, WEST and CONUS to be insignificant, and daily minimum temperatures displaying Areas 1, 2, 4, 5, 6, and WEST as insignificant (*P*-value > 0.05). (Table 2.1).
<table>
<thead>
<tr>
<th>TMAX - RMSE</th>
<th>p-Value</th>
<th>T-Score</th>
<th>TMIN - RMSE</th>
<th>p-Value</th>
<th>T-Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Area 1</td>
<td>0.5253</td>
<td>0.6408</td>
<td>Area 1</td>
<td>0.9467</td>
<td>0.0672</td>
</tr>
<tr>
<td>Area 2</td>
<td>0.0001</td>
<td>4.8176</td>
<td>Area 2</td>
<td>0.744</td>
<td>0.3272</td>
</tr>
<tr>
<td>Area 3</td>
<td>0.8197</td>
<td>0.2285</td>
<td>Area 3</td>
<td>0.0004</td>
<td>3.6571</td>
</tr>
<tr>
<td>Area 4</td>
<td>0.0602</td>
<td>1.8876</td>
<td>Area 4</td>
<td>0.0964</td>
<td>1.6685</td>
</tr>
<tr>
<td>Area 5</td>
<td>0.2268</td>
<td>1.2182</td>
<td>Area 5</td>
<td>0.2962</td>
<td>1.0515</td>
</tr>
<tr>
<td>Area 6</td>
<td>0.0002</td>
<td>3.9088</td>
<td>Area 6</td>
<td>0.0526</td>
<td>1.9626</td>
</tr>
<tr>
<td>Area 7</td>
<td>0.0001</td>
<td>5.5922</td>
<td>Area 7</td>
<td>0.0001</td>
<td>5.0636</td>
</tr>
<tr>
<td>Area 8</td>
<td>0.4289</td>
<td>0.8028</td>
<td>Area 8</td>
<td>0.0023</td>
<td>3.346</td>
</tr>
<tr>
<td>Area 9</td>
<td>0.001</td>
<td>3.321</td>
<td>Area 9</td>
<td>0.0001</td>
<td>4.1997</td>
</tr>
<tr>
<td>Area 10</td>
<td>0.0108</td>
<td>2.5772</td>
<td>Area 10</td>
<td>0.0001</td>
<td>6.3847</td>
</tr>
<tr>
<td>WEST</td>
<td>0.114</td>
<td>1.5813</td>
<td>WEST</td>
<td>0.1261</td>
<td>1.5304</td>
</tr>
<tr>
<td>SE</td>
<td>0.0001</td>
<td>5.7592</td>
<td>SE</td>
<td>0.0001</td>
<td>4.3861</td>
</tr>
<tr>
<td>CONUS</td>
<td>0.1438</td>
<td>1.4622</td>
<td>CONUS</td>
<td>0.0001</td>
<td>11.1802</td>
</tr>
</tbody>
</table>

**Table 2.1** P-Values and t-scores from the student’s t-test for TMAX/TMIN. These results were derived from the comparison of the karst and non-karst landscapes within each of the thirteen study regions. Source: Created by the Author.

The orientation of the karst landscapes does not appear to suggest any preferential influence on daily maximum temperatures. The resulting daily maximum temperatures indicate a greater magnitude of forecasting error within non-karst landscapes overall, excluding the largely karst location (Area 10) and the southeastern United States (SE) (Figure 2.10). This indicates a preference for a larger maximum temperature range within the non-karst locations compared with karst landscapes. The highest RMSE differences are noted within Areas 6 and 7 with values of 0.81 and 0.88°C higher for both regions, respectively. The resulting MB scores indicate an overall 1.1 to 1.6°C temperature increase within the locations of non-karst landscapes in Areas 2, 6, 7, and 9. The highest MB score is noted within Area 2, with a 0.45°C higher error noted within non-karst landscapes compared to karst locations. Area 10 denotes the highest differences in RMSE.
values, 0.61°C, whereas the SE displays the greatest differences in MB values, 0.06°C. When compared to the control results, Areas 6 and 7 are the only locations that display higher difference in RMSE values (greater than 0.78°C), and Area 2 is the only location with MB differences above the control (greater than 0.24°C). The overall results from the TMAX analysis indicate that other factors within these locations display a stronger influence on maximum temperatures than karst terrains alone.

**Figure 2.10** Root Mean Square Error (RMSE) and BIAS scores associated with the daily maximum temperatures. The yellow highlighted locations indicate statistically significant results (p > 0.05). Source: Created by the Author.

Similar to the daily maximum temperatures, the orientation of the karst/non-karst terrains appears to display little preferential behavior in the resulting minimum temperatures. The daily minimum temperatures display an increase in the magnitude of error associated with karst terrains within Areas 3, 7, and 9 (Figure 2.11). The largest
RMSE differences are noted within Area 7 by 0.34°C. Within these locations, a 1.9 to 2.2°C positive bias is noted over the karst areas. The karst landscapes display a 0.14 to 0.35°C higher MB compared to the non-karst landscapes. The remaining locations display higher RMSE values within the non-karst landscapes. The MB values demonstrate a positive bias between 1.9 and 3.8°C associated within these non-karst regions. When compared against the control analysis, all differences in the RMSE results display values below that shown between regions of similar terrains (RMSE < 0.65°C). The MB result within Area 8 is the only location that demonstrates values above that noted in the control (MB > 0.51°C). Overall, this indicates that karst regions tend to demonstrate less influence on minimum temperatures than other factors within these locations.

Figure 2.11 Root Mean Square Error (RMSE) and BIAS scores associated with the daily minimum temperatures. The yellow highlighted areas denoted ETS/fBias scores of statistical significance (p > 0.05). Source: Created by the Author.
2.4.2.2 – U/V winds

The wind pattern within the thirteen study regions displays several locations of increased model error associated with karst terrains (Area 3, 8, 9, 10, WEST, and SE). All locations demonstrate errors above the instrument precision. The RMSE values indicate between 0.42 and 1.96 m s\(^{-1}\) higher errors within karst terrains compared to non-karst. The highest RMSE value is noted within Area 3, 1.96 m s\(^{-1}\). The MB scores indicate an underestimation of 0.6 and 1.4 m s\(^{-1}\) within Area 6 and 8, and an over-estimation of 0.39 and 2.4 m s\(^{-1}\) within Areas 10, SE and WEST (Figure 2.12). When compared to the control, the U-winds display larger error between karst and non-karst landscapes compared to the maximum and minimum temperatures. The RMSE values within Areas 2, 3, 8, and 10 display errors above those noted within the control (in excess of 0.76 m s\(^{-1}\)). The MB values display even more error than the controls, with all but Area 9 and the SE displaying values in excess of 0.45 m s\(^{-1}\). This indicates that there is the potential for karst landscapes to influence the U-wind patterns, with orientation playing less of a role in model error. Overall, the karst locations tend to indicate an underestimation in U-wind speed by 0.46 m s\(^{-1}\).

The V winds display higher RMSE within Areas 2, 4, 7, 9, and CONUS, with a range of 0.47 to 2.3 m s\(^{-1}\) within the karst landscapes compared to non-karst. The MB scores indicates an under estimation 0.36 and 1.36 m s\(^{-1}\) within Areas 8 and 9 and a northern bias 1.3 and 2.4 m s\(^{-1}\) within Area 10 and SE (Figure 2.13). Compared to the controls, the V-wind displays a higher MB between the karst and non-karst landscapes.
Table 2.2 P-values and T-scores for U-Winds/V-Winds. These results were derived from the comparison of the karst/non-karst landscapes within the thirteen study regions. Source: Created by the Author.

<table>
<thead>
<tr>
<th></th>
<th>p-value</th>
<th>T-Score</th>
<th></th>
<th>p-value</th>
<th>T-Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Area 1</td>
<td>0.1053</td>
<td>1.6573</td>
<td>Area 1</td>
<td>0.4874</td>
<td>0.701</td>
</tr>
<tr>
<td>Area 2</td>
<td>0.0001</td>
<td>6.5713</td>
<td>Area 2</td>
<td>0.0001</td>
<td>5.4429</td>
</tr>
<tr>
<td>Area 3</td>
<td>0.0001</td>
<td>5.1899</td>
<td>Area 3</td>
<td>0.0368</td>
<td>2.1131</td>
</tr>
<tr>
<td>Area 4</td>
<td>0.5362</td>
<td>0.6194</td>
<td>Area 4</td>
<td>0.0001</td>
<td>4.6838</td>
</tr>
<tr>
<td>Area 5</td>
<td>0.6038</td>
<td>0.521</td>
<td>Area 5</td>
<td>0.9419</td>
<td>0.0731</td>
</tr>
<tr>
<td>Area 6</td>
<td>0.0138</td>
<td>2.509</td>
<td>Area 6</td>
<td>0.0001</td>
<td>5.0958</td>
</tr>
<tr>
<td>Area 7</td>
<td>0.3135</td>
<td>1.0137</td>
<td>Area 7</td>
<td>0.0001</td>
<td>9.5863</td>
</tr>
<tr>
<td>Area 8</td>
<td>0.0001</td>
<td>6.2669</td>
<td>Area 8</td>
<td>0.2931</td>
<td>1.0715</td>
</tr>
<tr>
<td>Area 9</td>
<td>0.0184</td>
<td>2.3749</td>
<td>Area 9</td>
<td>0.0018</td>
<td>3.1637</td>
</tr>
<tr>
<td>Area 10</td>
<td>0.0001</td>
<td>5.2816</td>
<td>Area 10</td>
<td>0.0001</td>
<td>9.4535</td>
</tr>
<tr>
<td>WEST</td>
<td>0.0113</td>
<td>2.5348</td>
<td>WEST</td>
<td>0.5465</td>
<td>0.6031</td>
</tr>
<tr>
<td>SE</td>
<td>0.0001</td>
<td>7.1685</td>
<td>SE</td>
<td>0.3775</td>
<td>0.8829</td>
</tr>
<tr>
<td>CONUS</td>
<td>0.0001</td>
<td>5.2437</td>
<td>CONUS</td>
<td>0.0001</td>
<td>4.1397</td>
</tr>
</tbody>
</table>

Figure 2.12 Root Mean Square Error (RMSE) and BIAS scores associated with the U-component (west/east) of the winds. The yellow highlighted areas denoted ETS/Bias scores of statistical significance (p > 0.05). Source: Created by the Author.
2.4.2.3 Precipitation

ETS values within the CONUS study area indicate a decreased skill in precipitation prediction within non-karst landscapes. The overall increase noted within the mean ETS scores (Figure 2.14) indicates a slight (0.0065) decrease in prediction skill across the 0.5 to 15.0 mm and 50.0 mm thresholds over the five-year period (Figure 2.14a). The skill in predicting the frequency of precipitation indicates an underestimation in events between the 5.0 and 25.0 mm threshold within karst landscapes. When compared to the control results, the ETS values overall are much lower than those noted between the karst and karst or non-karst and not-karst locations. Similarly, the fBias scores indicate an overall underestimation in precipitation than displayed between the NK controls.
Figure 2.14  

ETS and fBias scores associated with raw precipitation data for a) WEST, b) SE, and c) CONUS. The yellow highlighted areas denoted ETS/fBias scores of statistical significance (p > 0.05). Source: Created by the Author.

The WEST demonstrates decreased precipitation prediction skill associated within karst landscapes, indicated by an average drop in ETS within karst terrains by 0.038 compared to non-karst landscapes. The skill of the frequency of precipitation displays a general improvement in the overestimation of precipitation, an average 0.19 decrease in fBias, within karst landscapes for moderate thresholds (5.0 to 15.0 mm) (Figure 2.14b). The ETS results are slightly higher (0.001) than indicated in the control verification; however, the fBias values demonstrate less overall discrepancies than that noted in the control regions.

Similar to the results within WEST, the SE displays an overall 0.021 decrease in ETS associated with the 0.5 to 25.0 mm thresholds within karst landscapes, compared to non-karst landscapes. The resulting fBias demonstrates an underestimation in the skill of
precipitation frequency within karst landscapes by 0.02 to 0.03. Similar to the results found in the CONUS location, the ETS and fBias scores within the SE are below the differences noted between the control regions. The resulting P-values associated with ETS and fBias scores within the CONUS, WEST, and SE are displayed in Table 2.3 below for the raw precipitation data.

The resulting RMSE errors display an increase in the magnitude of precipitation forecasting by 0.21 and 1.6 mm within the SE and CONUS, respectively (Figure 2.15). When compared against the controls, they indicate errors much greater than those noted between the karst and non-karst regions.

| PRECP | P-VALUES |  |  |
|-------|----------|-------|-------|-------|
|       | ETS      | WEST  | SE    | CONUS |
| 0.5 mm| 0.0005   | 0.5683| 0.0001|
| 1.0 mm| 0.0001   | 0.0001| 0.0001|
| 2.5 mm| 0.0006   | 0.0001| 0.0001|
| 5.0 mm| 0.0007   | 0.0001| 0.0001|
| 10.0 mm| 0.0027   | 0.0001| 0.2202|
| 15.0 mm| 0.0002   | 0.0001| 0.6924|
| 25.0 mm| 0.3333   | 0.0001| 0.3432|
| 50.0 mm| 0.1522   | 0.4262| 0.0337|

| PRECP |  |  |  |
|-------|  |  |  |
|       | fBias    | WEST  | SE    | CONUS |
| 0.5 mm| 0.908    | 0.0012| 0.0004|
| 1.0 mm| 0.9803   | 0.0006| 0.0001|
| 2.5 mm| 0.1899   | 0.0002| 0.0001|
| 5.0 mm| 0.0271   | 0.0001| 0.0001|
| 10.0 mm| 0.0298   | 0.0011| 0.0001|
| 15.0 mm| 0.009    | 0.0046| 0.0001|
| 25.0 mm| 0.6122   | 0.1735| 0.0001|
| 50.0 mm| 0.2102   | 0.4262| 0.4134|

Table 2.3 P-values generated with the raw precipitation data for ETS and fBias values. These results were derived from the comparison of the karst and non-karst landscapes within the WEST, SE, and CONUS regions. Source: Created by the Author.
Area 3 indicates an overall drop in ETS by 0.013 within karst landscapes compared to non-karst. The NAM model performance with respect to fBias indicates an overall increased skill within karst landscapes, which is demonstrated by 0.07 higher fBias (Figure 2.16a). Area 7 depicts a general decrease in ETS by 0.025 within karst landscapes. However, the non-karst locations display a drop in the skill of precipitation frequency by an underestimation shown by overall 0.12 lower fBias results. The smallest location indicates lower ETS within the lightest events (0.5 and 2.5 mm) by 0.028 and 0.013, respectively (Figure 2.16b). The moderate precipitation intensities indicate a minute 0.004 fBias difference in the forecasting of the frequency of precipitation events between the two landscapes. All locations indicate ETS and fBias scores below that noted between the control regions. The RMSE errors indicate a greater magnitude in error associated with precipitation forecasting within Area 7 by 0.43 mm. Area 3 indicates better forecast performance within karst landscapes by 1.1 mm (Figure 2.16), which are
below the values noted in the control. The resulting P-values for Areas 1 – 10 are displayed below in Table 2.4.

![Bar charts showing ETS and fBias scores for Areas 3, 7, and 8.]

**Figure 2.16** ETS and fBias scores associated with raw precipitation data for a) Area 3, b) Area 7, and c) Area 8. The yellow highlighted areas denoted ETS/fBias scores of statistical significance (p > 0.05). Source: Created by the Author.

Area 2 displays a drop in ETS within the non-karst landscapes for all thresholds by an overall 0.02 compared to non-karst landscapes. The fBias indicates worse skill associated with moderate events (2.5 to 10.0mm) by 0.04 to 0.05 results within karst landscapes (Fig. 2.17a). Area 5 demonstrates a slight decrease in ETS within the lightest events by 0.008 within karst terrains. The fBias results indicate slightly increased, 0.03 to 0.04, skill in precipitation frequency prediction as the karst terrains display less underestimation in precipitation frequency (Fig. 2.17b). A decrease in ETS is noted in non-karst by 0.022 overall compared to karst. The moderate precipitation events display a greater underestimation as shown by 0.057 lower fBias (Fig. 2.17c). Of interest within the orientation of karst to non-karst are the ETS values from Area 5, which are higher than
those noted within the control regions. Only Area 2 indicates significant results with respect to $RMSE$ values, with an overall 0.60 mm increase in the magnitude of forecasting error noted within karst. The resulting $RSME$ is higher than that noted between the karst locations (0.52 mm) but lower than that noted between the non-karst regions (3.1 mm) (Figure 2.23).

![Figure 2.17](image)

**Figure 2.17** $ETS$ and $fBias$ scores associated with raw precipitation data for a) Area 2, b) Area 5, and c) Area 6. The yellow highlighted areas denoted $ETS/fBias$ scores of statistical significance ($p > 0.05$). Source: Created by the Author.
Table 2.4 P-values generated with the raw precipitation data for *ETS* and *fBias* values. These results were derived from the comparison of the karst and non-karst landscapes within the ten study areas. Source: Created by the Author.
The location of karst surrounded by non-karst (Area 4) displays near similar results in precipitation prediction skill with karst landscapes indicating only 0.006 lower $ETS$ compared to non-karst. A slightly lower skill is noted within karst by a 0.041 lower $fBias$ overall (Figure 2.18a). The associated $RMSE$ score displays a 0.21 mm increase in error within karst landscapes (Figure 2.23). When compared to the control, Area 4 demonstrated $ETS$ and $fBias$ values are lower between karst and non-karst landscapes. The region of non-karst surrounded by karst (Area 9) displays slightly lower $ETS$, between 0.008 and 0.014, associated with non-karst landscapes. The non-karst landscapes also display worse skill as displayed by a lower $fBias$, 0.14, overall (Figure 2.18b). The resulting magnitude of error in precipitation forecasting indicates a 0.21 mm increase within the non-karst landscapes compared to karst. The location of largely karst landscapes (Area 10) displays an overall decreased $ETS$ by 0.031 within karst landscapes when compared to non-karst. Similarly, the moderate precipitation events indicate a decrease in $fBias$ by near 0.03 in karst locations (Figure 2.18c). Again, of special interest are the $ETS$ values within Area 10, which are higher than those within both controls.

In order to eliminate potential climatic influences within the thirteen study areas used within this research, a standardization of the precipitation data was performed to analyze model response within the two different landscapes. Similar to the raw precipitation results, Area 1 displays statistically insignificant results for all verification scores.
Figure 2.18 ETS and fBias scores associated with raw precipitation data for a) Area 4, b) Area 9, and c) Area 10. The yellow highlighted areas denoted ETS/fBias scores of statistical significance (p > 0.05). Source: Created by the Author.

Results from the standardized CONUS data display an overall decrease in ETS by 0.015 within karst terrains compared to non-karst. Similarly, the fBias displays a decrease within the same locations by 0.03, indicating a greater tendency to underestimate moderate events (1.5 to 3.0) (Figure 2.19a). The associated RMSE indicates a 0.022 increase in forecasting error (Figure 2.23). The BIAS score within the region displays a 0.26 rise compared to non-karst, indicating a tendency to overestimate precipitation. The WEST indicates a similar decrease in ETS within karst landscapes by 0.022 overall compared to non-karst. A decrease in fBias of 0.019 is noted within the same locations for the ETS scores, indicative of a decrease in skill associated with the prediction of precipitation frequency (Figure 2.19b). A 0.033 increase in forecast error is also noted within these landscapes. The BIAS score indicates a tendency to over predict
precipitation, as shown by a value of 0.39, within the karst landscapes compared to non-karst (Figure 2.23). The SE also displays decreased ETS within karst landscapes by 0.02 compared to non-karst landscapes. The fBias indicates decreased skill by a greater underestimation, 0.012, within the same landscapes. A similar result to the CONUS region is noted in the RMSE scores within karst landscapes, with a 0.028 increase in forecasting error noted (Figure 2.23). The BIAS score indicates a greater underestimation of precipitation, by 0.35, within the non-karst landscapes. When standardized, the precipitation data over each location indicate ETS values all above the overall average noted in between the control runs (0.009).

**Figure 2.19** ETS and fBias scores associated with standardized precipitation data for a) WEST, b) SE, and c) CONUS. The yellow highlighted areas denoted ETS/fBias scores of statistical significance (p > 0.05). Source: Created by the Author.
Area 3 demonstrates decreased $ETS$ within karst landscapes associated with the heaviest events, displaying a 0.02 to 0.3 increase. A decrease in $fBias$ is also noted within the same locations, by around 0.05, compared to non-karst (Figure 2.20a). The associated $RMSE$ score displays an increased error in forecasting within non-karst landscapes by 0.02 (Figure 2.23). The BIAS scores show nearly the same results between karst and non-karst locations. Area 7 indicates a lower $ETS$ demonstrated within karst terrains by 0.015 overall. Only one threshold, 1.0, displays statistically different results with a 0.032 lower $fBias$ within non-karst landscapes (Figure 2.20b). Area 8, the smallest location, also indicates only one threshold displaying a difference statistically between the two locations, 50.0, with a greater accuracy, by 0.11, noted by $ETS$ within karst landscapes compared to non-karst. Similarly, a generally higher $fBias$ by 0.053 is noted within karst landscapes, displaying near perfect ($fBias = 1$) skill (Figure 2.20c). Both Areas 7 and 8 display statistically similar results associated with $RMSE/BIAS$ values and, thus, are not included. All $ETS$ and $fBias$ results displayed within these locations are above those noted in the controls, with Area 3 and 8 displaying the greatest differences.

Area 2 displays a drop in prediction skill within the lowest threshold, by 0.018, within karst landscapes. The same locations display a higher accuracy compared to non-karst associated with the underestimation forecasted frequency by between 0.03 and 0.06 (Figure 2.21a). Area 5 only displays statistically different results associated with the $fBias$ score within the 1.0 threshold, with a 0.038 increase in $fBias$, displaying near perfect skill within karst landscapes (Figure 2.21b). Similarly, only one threshold, 2.0, displays statistically different results within Area 6 for $ETS$, which demonstrates that a 0.022 decrease in precipitation prediction skill is noted within the karst landscapes. Similarly,
around a 0.04 decrease in fBias within karst landscapes is indicative of a tendency to underestimate the frequency in precipitation (Figure 2.21c). An increase in forecast error is noted within the karst landscapes by 0.019, with BIAS scores indicating a drop in skill by 0.74 in karst landscapes (Figure 2.23). These locations display a higher ETS when compared against the control values, but indicate a lower fBias than the karst and karst control.

![Figure 2.20](image)

**Figure 2.20** ETS and fBias scores associated with standardized precipitation data for a) Area 3, b) Area 7, and c) Area 8. The yellow highlighted areas denoted ETS/fBias scores of statistical significance (p > 0.05). Source: Created by the Author.
The location of karst surrounded by non-karst, Area 4, indicates an overall increase in precipitation prediction skill within non-karst landscapes by 0.023. The skill in frequency of forecasted precipitation demonstrates minute differences overall, with a slight decrease, 0.0003, in fBias within non-karst landscapes. The largest events display fBias indicative of better skill, around 0.06 lower, within karst landscapes compared to non-karst (Figure 2.22a), which is above that noted in the control analysis. The results from Area 9, a location of non-karst surrounded by karst, displays only statistically different results associated with fBias scores. The fBias results display an overall 0.038 decrease within non-karst landscapes, which is indicative of an underestimation in precipitation frequency skill between the 0.5 and 1.5 thresholds (Figure 2.22b). These results display generally lower fBias between the karst and non-karst locations than that of the karst and karst regions. The location of mostly karst landscape, Area 10, displays
an overall drop in precipitation prediction skill by 0.23, with these landscapes compared to non-karst. Similarly, decreased skill is noted with a 0.04 decrease in fBias within karst landscapes (Figure 2.22c), which is just slightly under that noted between the two karst control regions (0.046). The magnitude of forecasting error displays a 0.025 increase within these same landscapes, and a tendency to underestimate precipitation more within karst landscapes noted by the BIAS (Figure 2.23).

Figure 2.22 ETS and fBias scores associated with standardized precipitation data for a) Area 4, b) Area 9, and c) Area 10. The yellow highlighted areas denoted ETS/fBias scores of statistical significance (p > 0.05). Source: Created by the Author.
2.5 Conclusions

The response in the NAM model displays errors not only between the karst and non-karst locations, but also between the controls (karst and karst or non-karst and non-karst). The comparison between the controls and the various karst/non-karst analyses indicates that karst landscapes may influence certain variables more so than others. The daily maximum and minimum temperature analysis indicates that karst landscapes alone do not appear to be a strong influence on temperatures, as all error is below that of the controls. Other factors, such as land use/land cover, may play a larger role in forecasting errors, as previous research has noted that rural locations (such as farm lands, forests, or small cities) show differences when compared to more urban locations (Gallo et al. 1996). The differences surrounding the land use/land cover types within the various study

Figure 2.23 Root Mean Square Error (RMSE) and BIAS scores associated with the standardized precipitation data. Source: Created by the Author.
regions selected may potentially be a greater influence on the temperatures when compared to the karst and non-karst locations.

<table>
<thead>
<tr>
<th>PRECP</th>
<th>p-values</th>
<th>ETS</th>
<th>WEST</th>
<th>SE</th>
<th>CONUS</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.001</td>
<td>0.001</td>
<td>0.7965</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.5</td>
<td>0.0011</td>
<td>0.0001</td>
<td>0.0001</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.0025</td>
<td>0.0001</td>
<td>0.0001</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1.5</td>
<td>0.0009</td>
<td>0.0001</td>
<td>0.0001</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>0.0021</td>
<td>0.0001</td>
<td>0.0001</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>0.0012</td>
<td>0.0006</td>
<td>0.0001</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>0.0149</td>
<td>0.2101</td>
<td>0.0001</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>0.008</td>
<td>0.3395</td>
<td>0.0015</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>PRECP</th>
<th>p-values</th>
<th>fBias</th>
<th>WEST</th>
<th>SE</th>
<th>CONUS</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.0001</td>
<td>0.0001</td>
<td>0.0002</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.5</td>
<td>0.4237</td>
<td>0.0001</td>
<td>0.0001</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.1684</td>
<td>0.0003</td>
<td>0.0001</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1.5</td>
<td>0.0892</td>
<td>0.0093</td>
<td>0.0001</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>0.5538</td>
<td>0.4744</td>
<td>0.0001</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>0.5767</td>
<td>0.8609</td>
<td>0.001352</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>0.3661</td>
<td>0.2787</td>
<td>0.0001</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>0.0427</td>
<td>0.9598</td>
<td>0.0011</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 2.5 P-values generated with the standardized precipitation data for $ETS$ and $fBias$ values. These results were derived from the comparison of the karst and non-karst landscapes within the WEST, SE, and CONUS locations. Source: Created by the Author.

The winds, however, displayed a more pronounced result between karst and non-karst regions when compared against the controls. The error between karst and non-karst locations indicated a tendency for greater errors in U/V winds than within the controls. This response may be due to soil moisture differences between the karst and non-karst locations generating local circulations between these two boundaries, thus affecting the resulting observed winds. Moisture differences within the sub-surface have previously
been described as generating a sea breeze-like effect, aiding in the generation of
mesoscale circulations (Ookouchi et al. 1984).

The raw precipitation data demonstrated only three locations where the
differences in the ETS values exceeded the 0.03 noted in the control (Areas 5, 10, and
WEST). The standardization of the precipitation data, however, did display more error
between the differing landscapes than that of the controls. Only ETS values within Area 2
display differences lower than those noted in the control (less than 0.009). Overall, the
precipitation data display a tendency for more error in forecasting over large areas
(WEST, SE, and CONUS) and within Areas 10 and 7. The orientation of the karst
terrains does not appear to affect ETS values in either location, as Area 3, 4, 6, 8, and 9
all display lower scores within non-karst landscapes. There is a slight preference for karst
locations on the west side of the study area to display greater underestimation than the
other orientations.

The results from this verification study did not differentiate between surface-
expressed karst landscapes and those buried under non-karst material, nor were different
types of karst such as carbonate, evaporate, or pseudokarst studied independently of one
another. Future work would benefit from analyzing the statistical difference between
these various locations in order to determine individual responses to these variables
within these differing landscapes. The control regions were selected so that the sizes of
both regions were the same and the location contained either entirely karst or non-karst
landscapes. Through this selection process, side-by-side regions were not used due to
these restrictions. This may have allowed for bias within the control results, as the
distance between the two karst and non-karst regions may allow for climatic differences
to play a role within these results. Future research would benefit from choosing control locations with a closer proximity to one another in order to reduce climatic differences between these two locations. The inclusion of additional variables, such as humidity and evaporation, would also be of use to determine if the potentially increased drainage within these locations varies, which may explain some of the variances between the thirteen study regions.

The results from this analysis show that karst terrains have some influence on winds and precipitation. It is of interest, then, to determine which physical characteristics are needed to add within a current operational forecast model to account for a karst terrain. The next chapter discusses the study and addition of these karst parameters to the WRF model and the response of precipitation and related variables.
CHAPTER 3: Karst Parameters

3.1 Introduction

Karst landscapes are currently not included within operational forecasting models, such as the WRF model. However, it is noted that the presence of a karst landscapes may influence lower atmospheric conditions over the surrounding regions (Leeper et al. 2011; Johnson et al. 2014). In this context, the interactions of karst characteristics, such as high porosity (Ford and Williams 2007; Palmer 2009), thin overlying soils, and dynamic vegetation cover are of specific interest (Pielke 2001; McPherson 2007; Chen et al. 2009; Seneviratne et al. 2010; Zhang et al. 2011). Vegetation within a karst region is an important contribution to the overall relationship between the surface and the PBLA. The moisture transport to the atmosphere via vegetation acts to reduce surface temperatures through evaporative cooling and, thus, may also play a role in boundary layer behavior (McPherson 2007). Vegetation cover can also act to reduce the albedo of the region (Anthes 1984; McPherson 2007).

The interactions of variables such as soil moisture (Seneviratne et al. 2010; Leeper et al. 2011; Zhang et al. 2011; Johnson et al. 2014), soil temperature (Fan 2009; Xue et al. 2012) and the amount of exposed rock (McPherson 2007; Zhang et al. 2011; Johnson et al. 2104) are important when considering how to model the interaction between karst systems and the PBLA. The relationship between surface energy fluxes through heat and moisture transfer aid in atmospheric instability (Pielke 2001; Fan 2009; Seneviratne et al. 2010). An understanding of the physical aspects related to the epikarst layer within a region of karst should provide insight into variables needed to model the climate surrounding a karst location properly. Proper modeling of karst geologic systems
could aid in precipitation prediction as well as provide a general understanding of atmospheric phenomena occurring over a karst system. Currently, land-surface models are not adapted to model karst landscapes (Chen and Dudhia 2001; Johnson et al. 2014); therefore, it is of interest to obtain adequate information on this system to aid in the development of a proper model of this region to improve forecast simulations and information.

3.2 Background

3.2.1 What is Karst?

Karst is defined as a landscape consisting of soluble rocks such as gypsum, limestone, marble, and dolomite, which, through dissolution, allow the formation of caves and extensive underground streams within a region (Jennings 1971; Milanovic 1981). Karst landscapes are found over approximately 20% of the Earth’s ice-free surface, with 40% of the U.S. east of Tulsa, Oklahoma, covered by a karst terrain (White et al. 1995; Ford and Williams 2007). The dissolution of karst regions occurs due both to the interaction of CO₂ gas in the atmosphere with rainwater/groundwater forming carbonic acid and carbonate rock dissociation into Ca²⁺ and HCO₃⁻ under aqueous conditions (Palmer 2007). This solubility allows for an enlargement in void spaces and, in many instances, increases the permeability of the system allowing for rapid transfer of water through the connection of joints within karst rocks (Jennings 1971). Over time, this process creates surface features, such as sinkholes, vertical shafts, and subterranean river systems, which can significantly alter the hydrological processes occurring in a karst region and created a well-drained landscape (Palmer 2007).

Epikarst, or the subcutaneous zone of a karst landscape, is located at the uppermost portion of the vadose (unsaturated) zone and is where the soil-rock interface exists (Ford and Williams 2007). Within this location, the expansion of fissures and pores through dissolution supports the formation of a solutionally enlarged network of openings
independent of the surficial soil cover (Palmer 2009). The subcutaneous zone is usually three to ten meters in depth, but characteristics vary with little-to-no soil in arid and glacially scoured regions and down to 30 meters or more in depth if the rock is especially massive with a low density of fissuring (Ford and Williams 2007). In some instances, the epikarst region is missing within a region of karst either due to lack of development, such as in regions with high primary porosities, or by removal through glacial scouring or other erosional processes (Williams 2008). Soils residing in widened fissures of a karst system strongly influence the water storage and permeability near the surface, so much so that water infiltration in thick soils may be the principal control of water flow into the underlying limestones (Williams 1983).

3.2.2 Aspects of Karst

The porosities of soluble rocks typically range from < 1% in well-consolidated telogenetic rocks to that of > 20% in poorly consolidated younger (eogenetic) karst rocks (Palmer 2009). Epikarst is a highly weathered near-surface layer with a secondary porosity of 10 – 30% that gradually gives way to the main massif of the unweathered vadose zone with a porosity of < 2% (Ford and Williams 2007; Williams 2008). This high porosity and permeability in the epikarst is a function of the greatest amount of chemical weathering occurring at the near surface portion of karst regions mainly by proxy of CO$_2$ production in the soil layer (Williams 2008). Within locations of relatively low porosity, where more compact telogenetic bedrock underlies the epikarst zone, water movement may slow, creating a perched water table in some cases at the boundary (Ford and Williams 2007). Storativity within the epikarst region is determined by three factors: thickness and continuity of the epikarst, average porosity, and relative inflow and outflow rate of water, with the first two factors determining the available storage space in the epikarst (Williams 2008). An increase of water volume in the epikarst during rainfall and snowmelt events aids in the transfer of water by increasing the hydraulic head of this
subsurface region (Williams 2008). The epikarst region has a relatively short residence time with respect to water infiltration, less than 1-3 months, due to its high secondary porosity (Aquilina et al. 2006). The storage within the epikarst can range anywhere from several months to a year in humid regions, to the order of many years to decades in semi-arid regions (Ford and Williams 2007; Williams 2008).

The quick infiltration of water into a karst system may play a role in atmospheric conditions by way of changes in the moisture and energy fluxes through altered hydrological processes (Leeper et al. 2011). The rapid infiltration of precipitation within karst areas can raise the water table as much as 100 meters in some areas, enhancing surface flooding and providing an increase in the atmospheric moisture variability in the root zone (Milanovic 1981; Johnson et al. 2014). The desertification of a karst region can alter the climate of a region by increasing surface albedo, reducing the latent heat flux, moisture flux, and evaporation, which thereby reduces the precipitation of that region creating a feedback in the soil moisture, vegetation, and phenology of the region (Gao and Wu 2014). The epikarst zone significantly decreases evapotranspiration loss and increases flood discharge of a region (Zhang et al. 2011). The energy exchange between the atmosphere and the land-surface may also enhance precipitation over a region. An example of possible precipitation enhancement is that of the May 1st-2nd, 2010, flooding event around the Tennessee and Kentucky regions, in which the hydrogeology of the karst region may have aided in the localized mesoscale circulations and subsequent wider circulation (Durkee et al. 2012). Prediction of the overall attributes of a karst system may aid in a more accurate understanding of the dynamic interplay between this type of geologic landform and atmospheric conditions, as well as assist in more accurate modeling of meteorological phenomenon that occur due to this interaction.

3.2.3 Study Area

The Green River and its associated tributaries drain the Mississippian plateau, or the Pennyroyal Plain, which is subtly controlled by the regional dip of the limestone beds
away from the Cincinnati Arch and into the Western Coal Field region (Newell 2001). This region is characterized by sinkholes, sinking streams, and extensive cave networks including Mammoth Cave (Newell 2001). The Western Kentucky Pennyroyal Karst region is part of a karstic limestone belt extending from southern Indiana into Tennessee and west of the Cumberland River along the eastern and southern reaches of the Western Kentucky Coal Field region (White et al. 1970; White 2007) (Figure 3.1).

Figure 3.1 The geology of the Kentucky region. This map shows the various geologic rock types across the state of Kentucky. Source: After USGS (2005); Esri (2012).

Conditions needed for long cave development exist throughout the study area, including thick amounts of pure limestone, high rainfall amounts, high elevation with drainage towards major streams, and large areas of limestone overlain by insoluble rocks
preventing surficial erosion (Currens 2002). The proximity of non-karst region surrounding this region will be useful when comparing the influence of karst regions to the surrounding non-karst regions, in addition to examining the behavior of model runs at these boundaries (Leeper et al. 2011).

The soil within Kentucky is the Crider soil system, which is formed in a mantle of loess and the underlying limestone residuum. This soil is suitable for agriculture with crops such as corn, small grains, soybeans, tobacco, and hay (USDA 2011a). This soil type corresponds with other soil in the karst regions of Kentucky. The upper 23 cm of the Crider soil type found throughout this region consists of a silt loam soil followed by a silty clay loam layer (23 - 71 cm), a silty clay loam layer (71 - 127 cm), and a clay layer (127 – 203 cm), which is well-drained and has depth to the water table of greater than 203 cm (USDA 2011b).

The characteristics of the overlying soil are of importance when developing an accurate land-surface model within the WRF model, especially when relating the influence that the karst regions of Kentucky have on the surrounding PBLA. This will potentially aid in improving irrigation techniques through the region, provide better precipitation forecasts, and assist in the prediction of possible drought and flooding events within the region.

The state of Kentucky comprises 55% farmland, encompassing 5.7 million hectares of Kentucky’s 10.3 million hectares, and accounts for $1.5 billion of net agricultural income (KFB 2013). Land cover over the state of Kentucky primarily consists of deciduous forests, pasture/hay, and cultivated cropland (Figure 3.2). The interior plateau region of the southeast, which includes the Pennyroyal region of Kentucky, has a land cover primarily of agriculture, forest, and developed lands (96%) (Drummond 2014). The interior plateau region, which encompasses the Western Kentucky Pennyroyal Plateau karst region, has experienced a 0.9% decrease in agriculture from 1973 to 2000 (50.9% to 50%), forest declining by 1.3% from 1973 to
2000 (39% to 37.7 %), and developed land expanded by 1.7% from 1973 to 2000 (6.9 to 8.6 %) (Drummond 2014).

**Figure 3.2** Land cover over the state of Kentucky. Source: After USDA (2011a,c); Esri (2012).

The southeastern portion of the United States, including the state of Kentucky, is characterized by a *Cfa* climate type on the Köppen climate classification scale (Peel et al. 2007). A *Cfa* climate type is characteristic of a temperate type climate without a dry season and with hot summers (temperatures ≥ 22°C) (Peel et al. 2007). The annual precipitation across the study area (Figure. 3.3) ranges from 1143 mm (45 inches) in the northern portion of the region to 1346 – 1397 mm (53 – 55 inches) in the southeastern portion of the study area. Precipitation is well distributed throughout the year over
Kentucky, with rainfall rates exceeding two and a half millimeters per hour not unusual. The annual temperature for Kentucky ranges from around 12°C (55°F) in the northeast to 15°C (59°F) in the southwest (KCC 2014).

![Kentucky Annual Precipitation](image)

**Figure 3.3** Map of the average annual precipitation over the Western Kentucky Pennyroyal Karst region. The annual precipitation data (in inches) are averaged from the years of 1971 to 2000. Source: After Luzio (2011); Esri (2012).

### 3.3 Methodology

For the purpose of this study, the Noah-LSM is of particular importance when taking into account the effects of karst landscapes on the surrounding atmosphere. The subsurface characteristics are the main focus for this study when attempting to account
for the unique hydrological characteristics of karst terrains. The soil characteristics within the Noah-LSM were adjusted in order to conform to what would be associated with a karst landscape. Then, the soil parameters within the Noah LSM were adjusted in order to properly account for karst subsurface conditions.

Table 3.1 shows the 10 parameters within the 19 soil classes used in the Noah-LSM. The BB stands for the “b” parameter in the hydraulic functions. DRYSMC refers to the top layer soil moisture threshold where direct evaporation from the soil ceases. MAXSMC refers to the maximum volumetric soil moisture amount or porosity of the soil. The REFSMC is the soil moisture threshold for the onset of some transpiration stress within the soil. SATPSI and SATDK refer to the saturated soil matric potential and the saturated soil hydraulic conductivity, respectively. The SATDW is saturated soil water diffusivity. The WLTSMC references the wilting point in association with the soil moisture at which transpiration ceases. QTZ refers to the content of quartz in the soil, which is used to compute the soil thermal conductivity (Mitchell 2005). Currently there are some difficulties in obtaining standardized values associated with karst landscapes. The difficulty in obtaining hydrological parameters characteristic of karst landscapes is due to the variable nature of the subsurface by differing secondary porosities and heterogenic spatial properties (Baedke and Krothe 2001).
<table>
<thead>
<tr>
<th>Category</th>
<th>Class</th>
<th>BB</th>
<th>DRYSMC</th>
<th>F11</th>
<th>MAXSMC</th>
<th>REFSMC</th>
<th>SATPSI</th>
<th>SATDK</th>
<th>SATDW</th>
<th>WLTSMC</th>
<th>QTZ</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sand</td>
<td>1</td>
<td>2.79</td>
<td>0.010</td>
<td>-0.472</td>
<td>0.339</td>
<td>0.236</td>
<td>0.069</td>
<td>1.07E-6</td>
<td>0.608E-6</td>
<td>0.010</td>
<td>0.92</td>
</tr>
<tr>
<td>Loamy Sand</td>
<td>2</td>
<td>4.26</td>
<td>0.028</td>
<td>-1.044</td>
<td>0.421</td>
<td>0.383</td>
<td>0.036</td>
<td>1.41E-5</td>
<td>0.514E-5</td>
<td>0.028</td>
<td>0.82</td>
</tr>
<tr>
<td>Sandy Loam</td>
<td>3</td>
<td>4.74</td>
<td>0.047</td>
<td>-0.569</td>
<td>0.434</td>
<td>0.383</td>
<td>0.141</td>
<td>5.23E-6</td>
<td>0.805E-5</td>
<td>0.047</td>
<td>0.60</td>
</tr>
<tr>
<td>Silt Loam</td>
<td>4</td>
<td>5.33</td>
<td>0.084</td>
<td>0.162</td>
<td>0.476</td>
<td>0.360</td>
<td>0.759</td>
<td>2.81E-6</td>
<td>0.239E-4</td>
<td>0.084</td>
<td>0.25</td>
</tr>
<tr>
<td>Silt</td>
<td>5</td>
<td>5.33</td>
<td>0.084</td>
<td>0.162</td>
<td>0.476</td>
<td>0.383</td>
<td>0.759</td>
<td>2.81E-6</td>
<td>0.239E-4</td>
<td>0.084</td>
<td>0.10</td>
</tr>
<tr>
<td>Loam</td>
<td>6</td>
<td>5.25</td>
<td>0.066</td>
<td>-0.327</td>
<td>0.439</td>
<td>0.329</td>
<td>0.355</td>
<td>3.38E-6</td>
<td>0.143E-4</td>
<td>0.066</td>
<td>0.40</td>
</tr>
<tr>
<td>Sandy Clay Loam</td>
<td>7</td>
<td>6.66</td>
<td>0.067</td>
<td>-1.491</td>
<td>0.404</td>
<td>0.314</td>
<td>0.135</td>
<td>4.45E-6</td>
<td>0.990E-5</td>
<td>.067</td>
<td>0.60</td>
</tr>
<tr>
<td>Silty Clay Loam</td>
<td>8</td>
<td>8.72</td>
<td>0.120</td>
<td>-1.118</td>
<td>0.464</td>
<td>0.387</td>
<td>0.617</td>
<td>2.04E-6</td>
<td>0.237E-4</td>
<td>0.120</td>
<td>0.10</td>
</tr>
<tr>
<td>Clay Loam</td>
<td>9</td>
<td>8.17</td>
<td>0.103</td>
<td>-1.297</td>
<td>0.465</td>
<td>0.382</td>
<td>0.263</td>
<td>2.45E-6</td>
<td>0.113E-4</td>
<td>0.103</td>
<td>0.35</td>
</tr>
<tr>
<td>Sandy Clay</td>
<td>10</td>
<td>10.73</td>
<td>0.100</td>
<td>-3.209</td>
<td>0.406</td>
<td>0.338</td>
<td>0.098</td>
<td>7.22E-6</td>
<td>0.187E-4</td>
<td>0.100</td>
<td>0.52</td>
</tr>
<tr>
<td>Silty Clay</td>
<td>11</td>
<td>10.39</td>
<td>0.126</td>
<td>-1.916</td>
<td>0.468</td>
<td>0.404</td>
<td>0.324</td>
<td>1.34E-6</td>
<td>0.964E-5</td>
<td>0.126</td>
<td>0.10</td>
</tr>
<tr>
<td>Clay</td>
<td>12</td>
<td>11.55</td>
<td>0.138</td>
<td>-2.138</td>
<td>0.468</td>
<td>0.412</td>
<td>0.468</td>
<td>9.74E-7</td>
<td>0.112E-4</td>
<td>0.138</td>
<td>0.25</td>
</tr>
<tr>
<td>Organic Material</td>
<td>13</td>
<td>5.25</td>
<td>0.066</td>
<td>-0.327</td>
<td>0.439</td>
<td>0.329</td>
<td>0.355</td>
<td>3.38E-6</td>
<td>0.143E-4</td>
<td>0.066</td>
<td>0.05</td>
</tr>
</tbody>
</table>

Table 3.1 The 19 soil classes and their associated parameter values used within the latest version of the Noah LSM. Source: Modified from Chen (2007).
In order to attempt to account for some of these challenges, research was conducted on the hydraulic conductivity and porosity associated with karst within the Tennessee and Kentucky regions in order to determine proper values for the model use. Hydraulic conductivity is described as a measure of how permeable a medium is, which in turn affects the overall transmission of a liquid’s movement under a hydraulic gradient (Kasenow 2002). An average value for the porosity of epikarst, that is the upper-most weather portion of a karst geologic terrain, is 20% (Ford and Williams 2007). This value was used as an average porosity throughout the karst landscape of the study region, MAXSMC = 0.20. For use within the model, the bedrock type was chosen to edit within the SOILPARAM.TBL in order to obtain the proper hydrological characteristics of karst geologic terrains. When considering the hydraulic conductivity of a karst region (SATDK), research was conducted into the hydraulic conductivities of three locations within the study area in order to obtain a proper average value for use within the model: East Tennessee, Louisville (KY), and the Mammoth Cave area (KY). Kishne (2013) showed several equations for calculating the parameters used in the Noah-LSM for soil characteristics:

\[
WLTSMC = DRYSMC
\]

\[
REFSMC = SATSMC \times \left( \frac{2}{3} \times \left( 5.79 \times \frac{10^{-9}}{SATDK} \right)^{1/2B+3} \right)
\]

\[
SATDW = SATDK \times SATPSI \times BB/SATSMC
\]

Using the bedrock type to obtain the B parameter, the REFSMC was calculated with the addition of the SATDK and SATSMC discussed above. The values associated with the WLTSMC and SATPSI were gathered using the SATSMC and the SATDK values as a guide to get proxy values near those with soils that showed similar properties. The data used to gather this proxy information are shown in Table 3.1.
3.4 Results

The hydraulic conductivity (SATDK) for the Tennessee and Kentucky region shows that, for a more highly fractured/weathered karst environment such as that associated with the Mammoth Cave region in Kentucky, the SATDK value is $3.0 \times 10^{-5}$ m/s (Worthington et al. 2000; Worthington 2008), and karst environments showing little in the way of fracturing/weathering, such as those located in the Louisville, KY, and Eastern Tennessee regions, show SATDK values at $6.39 \times 10^{-7}$ m/s (Connell and Bailey 1989; Taylor 2014). The values for the less fractured/weathered karst environment were averaged using hydraulic conductivity data from Charon’s Cascade ($1.86 \times 10^{-5}$ m/s), Eastern Tennessee ($1.02 \times 10^{-6}$ m/s), and the Mammoth Cave ($1.02 \times 10^{-6}$ m/s) region, respectively (Connell and Bailey 1989; Worthington et al. 2000; Worthington 2008). The values associated with the WLTSMC and SATPSI were gathered using the SATSMC and the SATDK values as a guide to get proxy values near those with soils that showed similar properties (Table 3.1). For the highly weathered karst environment, the best proxy for WLTSMC and SATPSI was a sandy soil. The less weathered/fractured karst environment showed SATSPI and WLTSMC proxies from clay soils. The values associated with limestone and dolomite were gathered and averaged in order to attain the thermal diffusivity (F11) value for karst. This method was chosen because both rock types are associated with the karst terrain located in the Tennessee and Kentucky regions. The values for limestone and dolomite are $10.54 \times 10^{-3}$ cm$^2$/s and $11.17 \times 10^{-3}$ cm$^2$/s, respectively (Eppelbaum et al. 2014), with a median value of $10.80 \times 10^{-3}$ cm$^2$/s used within this research. The values for both types of epikarst environments are given in Table 3.2.
Table 3.2 Values for the ten soil parameters given in the SOILPARM.TBL within WRF. The values in the second role represent the highly fractured epikarst environment and the values in the third role, assigned asterisks, denote the values unique to more unfractured/less weathered epikarst region. Source: Created by the Author.

<table>
<thead>
<tr>
<th>BB</th>
<th>DRYSMC</th>
<th>F11</th>
<th>SATSMC</th>
<th>REFSMC</th>
<th>SATPSI</th>
<th>SATDK</th>
<th>SATDW</th>
<th>WLT</th>
<th>QTZ</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.79</td>
<td>0.01</td>
<td>0.0108</td>
<td>0.3</td>
<td>0.448257</td>
<td>0.091</td>
<td>0.00003</td>
<td>0.00001925</td>
<td>0.01</td>
<td>0.07</td>
</tr>
<tr>
<td>2.79</td>
<td>0.138*</td>
<td>0.0108</td>
<td>0.1*</td>
<td>0.21361*</td>
<td>0.069*</td>
<td>0.000000687*</td>
<td>0.00000897*</td>
<td>0.138*</td>
<td>0.07</td>
</tr>
</tbody>
</table>

Table 3.3 Average values between regions of greater and less weathering/fracturing the epikarst region of the karst terrain within Kentucky and Tennessee. Source: Created by the Author.

<table>
<thead>
<tr>
<th>BB</th>
<th>DRYSMC</th>
<th>F11</th>
<th>SATSMC</th>
<th>REFSMC</th>
<th>SATPSI</th>
<th>SATDK</th>
<th>SATDW</th>
<th>WLT</th>
<th>QTZ</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.79</td>
<td>0.074</td>
<td>0.01054</td>
<td>0.2</td>
<td>0.331</td>
<td>0.2685</td>
<td>0.0000154</td>
<td>0.0000141</td>
<td>0.074</td>
<td>0.07</td>
</tr>
</tbody>
</table>

In order to determine an overall value for the study area, a midpoint value between the two different karst environments was determined in order to acquire the mean soil parameter for karst terrain over the study area, shown in Table 3.3. The overall values for the karst landscape within the Kentucky and Tennessee regions show WLTSMC and DRYSMC content similar to a silty or loamy type soil. The porosity, SATSMC, of the region is the same as shown in the soil parameter table for bedrock, 0.2 or 20%. The REFSTM shows a value similar to loamy or sandy clay soil. The SATPSI is similar to a clay loam soil type. The hydraulic conductivity shows an average value near a loamy sand soil type, with the SATDW showing an average value similar to a sandy type. The values for BB and QTZ were taken from the soil parameter table in WRF for a bedrock type. The results from this research experiment show that, overall, the karst
landscape behaves in a manner similar to a loamy soil type. Water movement through this system appears to be on the higher end of the spectrum when compared to the other values shown in Table 3.1. This shows the potential for faster water transfer through this system, which could lead to drier soils located within regions of karst. The WLTSME and DRYSMC depict some water retention with the epikarst region of karst geology. The epikarst region of a karst landscape can act as a perched water table, with residence time of the water within the portion of the bedrock being influenced by infiltrated water from rainfall or snowmelt due to hydraulic damming, which can increase the hydraulic head of the system flushing the water down in the karst system below (Ford and Williams 2007; Williams 2008). The water diffusivity through the system shows a high diffusion similar to a sandy soil type. The epikarst region of the karst system typically has a short residence time with respect to water storage, due to the higher amount of weathering in the portion of the bedrock, increasing its secondary porosity and, therefore, increasing the diffusion of water through this portion of the karst landscape (Aquilina et al. 2006). The potential from these results shows that karst landscapes could drain moisture rather quickly compared to various soil types given within the soil parameter type in the WRF with some moisture residence in the system. This behavior could affect the surface hydrology of the region by aiding in the drying of the soils.

Soil moisture contrasts have been shown potentially to induce circulations similar to those associated with a sea breeze along the boundary between these contrasting regions of soil moisture (Ookouchi et al. 1984). Drier soil conditions, such as those potentially found in this research, could influence the energy fluxes within the region through the modification of the hydrology due to the behavior of karst landscape. Drier
soil conditions have shown convective development similar to that discussed in Ookouchi et al. (1984), with development occurring around boundaries of higher and lower soil moisture content (Leeper et al. 2011; Mahmood et al. 2011). A decrease in soil moisture content in regions associated with karst landscapes could increase the sensible heat flux while decreasing the latent flux from the surface, which could potentially influence planetary boundary layer (PBL) development and may influence convective development associated with this type of surficial environment (Findell and Eltahir 2003; Suarez et al. 2014).

The addition of the karst parameters was implemented by editing the SOILPARM.TBL within the WRF model. This table is located within the em_real directory of the WRF model code and provides the soil characteristics that are used within the Noah-LSM model during the WRF run. The bedrock type was edited in order to change the values of DRYSMC, F11, SATSMC, REFSMC, SATPSI, SATDK, SATDW, and WLTSMC, which were obtained through research and analysis of karst terrains and other soil properties. In order to account for this within the model itself, the location of karst areas must be coded into the GEOGRID package of the WRF model system for use in implementing proper changes to the soil parameters. With respect to the vegetation parameters used within the Noah-LSM, previous research by Johnson et al. (2014) aimed to simulate properly the location of each karst grid point located on the surface of the study area. Johnson et al. (2014) used two types of land surface, a barren and forested land cover, in order to simulate the atmospheric effects of a completely exposed karst surface and a completely vegetated karst surface. In order to associate this information with the karst regions located within this study area, a GIS was implemented.
to create an ASCII text file in association with the spatial data for U.S. karst. The spatial information used for this research came from USGS data mapping karst geology across the United States and Puerto Rico (Weary and Doctor 2014). This karst gridded information provided the spatial information for where the karst subsurface data needed to be placed within the study area. This information was then converted into a readable format for WRF’s Geogrid program (Figure 3.4).

![Figure 3.4](image)

**Figure 3.4** Karst geology associated within the inner model domain for use within the experimental model runs. 20 categories of karst are associated with this data set with categories 7 through 11 being associated with that of carbonate karst geology. Source: Weary and Doctor (2014).

Using methods from Johnson et al. (2014), an NCL program was written to associate the specific karst spatial data with the newly edited bedrock soil type within the soil parameter table (Figure 3.5). Only surface-expressed karst geology was considered when inputting this spatial data into the WRF output file, as karst located beneath a non-karst layer was assumed to have less interaction with energy/moisture fluxes from the subsurface to the atmosphere compared to karst geology expressed from the surface.
Changes to the vegetation of the domain were implemented using methods outlined in Johnson et al. (2014).

Figure 3.5 Soil association with the karst geology placed within the geogrid data for the WRF model runs. The grey color within the figure above depicts that bedrock soil type, which was edited to show karst-like behavior. Source: Created by the Author.

3.5 Conclusions

This study was conducted in order to determine the proper characteristics for use within the soil parameter table in the WRF model. Currently, the WRF model is unable to account for the unique hydrological aspects of a karst environment. The fractured and weathered natured of a karst system allows for a higher rate of infiltration compared to other forms of geology. Several methods were used in order to calculate the most accurate parameters for the upper portion of a karst landscape, known as the epikarst.
Both heavily fractured and relatively unfractured karst environments were considered when calculating the average values for use in the soil parameter table in the WRF. The averaged values developed through this analysis show hydraulic conductivity and soil diffusivity values similar to those associated with sandy loam or sandy types of soil, showing signs of relatively fast water transport through the system. The values associated with the wilting point and field capacity of the epikarst show the potential for some moisture retention, which would be expected in the zone (Williams 2008). This could lead potentially to convective development along the boundaries between the karst regions, where soil moisture could be lower, and non-karst regions, which may have higher soil moisture values in comparison (Ookouchi et al. 1983; Leeper et al. 2011; Mahmood et al. 2011). This research only took into account the karst environment associated with the Tennessee and Kentucky regions.

Future work associated with developing parameters for use with other karst regions would benefit from looking further into the hydrologic characteristics of the karst environments when using the methods outlined within this research. The values gathered for use within this study were influenced by previous research (Connell and Bailey 1989; Worthington et al. 2000; Worthington 2008; Eppelbaum et al. 2014). The use of field studies related to these variables would provide more accurate results related to the behavior of the epikarst within the Tennessee and Kentucky regions. The use of the above data is discussed in Chapter 4 with respect to model performance. It is of interest to determine the overall influence these variables potentially show within an operational forecasting model, such as the WRF.
4.1 Introduction

Karst landscapes may potentially modify land-surface atmosphere interactions and, hence, meteorological phenomenon (Leeper et al. 2011). In order to determine the potential influence of karst landscapes on atmosphere and model simulations, incorporation of karst physical characteristics and subsequent model evaluation needs to be completed. Previous research related to the influence that karst landscapes display within a current operational forecasting model was constrained to only soil moisture modifications (Leeper et al. 2011) and land use/land cover alterations (Johnson et al. 2014) within forecast models. To expand obtain this previous research, the resulting parameters incorporated into the soil parameter table within the Noah-LSM were used, along with several other model configurations, to evaluate model sensitivity to the inclusion of karst. The aim of this research was to expand upon previous work through the inclusion of karst parameters within a current operational forecasting model to measure more effectively the potential influence these locations have on model results. The potential of the influence of karst being masked by vegetation was also taken into account within this study. Land use/land cover changes have displayed modifications of surface energy fluxes (Mahmood et al. 2014), temperature (Anthes 1984; McPherson 2007), and local climate (Pielke 2001). In order to analyze the potential influence karst landscapes may have on the model estimates, several different model experiments were conducted. Four different meteorological events were chosen for evaluation within the research: Case 1 – a convective precipitation event driven along a stationary frontal boundary between June 11th and 13th, 2006; Case 2 – a non-frontally forced convective
precipitation event between June 17th and 19th, 2006; Case 3 – a mesoscale convective complex generated along a cold frontal boundary between September 29th and October 1st, 2008; and Case 4 - a clear weather event with a region of high pressure present over the study area between June 14th and 16th, 2006 (Leeper et al. 2011; Johnson et al. 2014).

4.2 Background

4.2.1 - Soil Moisture

The potential influence karst landscapes could have on surrounding atmospheric phenomenon can be linked with research on soil moisture. Precipitation can be formed from three sources: 1) moisture within the atmosphere; 2) advected moisture brought in by way of converging winds; and 3) evaporation of moisture from the surface (Trenberth 1999). Soil moisture content is defined as the measure of the percentage by volume of moist soil occupied by water (Oke 1987). The hydrological processes of a specific region are affected by the amount of moisture retained within the soil. Soil moisture is a source of water to the atmosphere by way of evapotranspiration from the land through plant transpiration and evaporation from bare soils (Seneviratne et al. 2010). The moisture budget for bare and vegetated soils is a function of evaporation, transpiration, surface runoff, and infiltration (Pielke 2001). Evapotranspiration of soil moisture aids in the flux of moisture from the surface to the atmosphere, affecting, in turn, cloud development and precipitation over a region (Shukla and Mintz 1982). The forces that bind soil moisture are related to soil porosity, which are weakest within open textured wet soils such as sand at around 7%, and strongest for dry compacts soils such as clays at around 15% (Oke 1987). The thermal and hydraulic conductivities of soil are very sensitive to soil moisture changes and, thereby, affect soil heat and soil water transfer, which, in turn, results in runoff and water movement through the subsurface (Chen and Dudhia 2001). Soil moisture, by way of partitioning the incoming sensible and latent heat flux energy, plays
an important role on the climate with respect to air temperature, boundary-layer stability and, in some cases, precipitation (Seneviratne et al. 2010).

Numerous studies conducted on soil moisture examined its interaction and effects on the atmosphere (e.g., Ookouchi et al. 1984; Chen and Avissar 1994; Seneviratne et al. 2010; Leeper et al. 2011). Early research regarding soil moisture focused on the fact that large soil-moisture contrasts can induce circulations over flat terrain equivalent in magnitude to sea breezes, with slight soil-moisture contrasts significantly affecting mesoscale circulations and the boundary layer structure (Ookouchi et al. 1984). Chen and Avissar (1994) reported that the discontinuity of soil moisture affects the genesis of cloud formation, the spread and intensity of rainfall, and assists in the generation of mesoscale circulations. Changes in the subsurface moisture budget influence heat and moisture fluxes within the PBL, and the measures of deep cumulus activity. This can potentially change convective available potential energy and in turn storm development (Pielke 2001). Results from Findell and Eltahir (2003) indicated that convection is triggered in two ways when considering soil moisture: 1) when the temperature profiles are near the moist adiabatic rate, the latent heat from the wet soils is the trigger; and 2) when the temperature profile is near the dry adiabatic rate, the sensible heat flux from the dry soils is the trigger. Lanicci et al. (1987) stated that the relationship of severe weather environments to soil moisture content revealed that soil moisture influences the elevated mixed-layer, dryline development, instability, and the location and intensity of precipitation.

Looking more specifically into the effect of soil moisture on the PBL phenomenon, Quintanar et al. (2009) found decreasing positive vertical velocities associated with drier soil conditions aiding the development of horizontal divergence at lower levels, whereas more moist soils showed the opposite effect with an increase in positive vertical velocities and the development of low level horizontal convergence. Convergence at the lower levels is of interest when looking into the aspects of potential
storm development as it provides the lift needed to induce storms. Quintanar and Mahmood (2012) studied the overall sensitivity of ensemble forecasts to soil moisture, finding that soil moisture does have an effect on precipitation but is dependent on the antecedent moisture conditions. The effects of a decrease in soil moisture show an increase in potential temperature, instability, and larger changes in precipitation distribution and accumulation compared to an increase in soil moisture (Quintanar and Mahmood 2012; Suarez et al. 2014).

With respect to karst landscapes, a high secondary porosity within this terrain by way of joints, fractures, faults, bedding planes, and voids acts to increase infiltration, thereby decreasing the overall soil moisture. The hydraulic properties that can influence moisture content of the soil are dependent on the position and fracture of the rocks within the system with an increase in rock fragments in the soil aiding in water retention increasing the overall soil moisture (Chen et al. 2009). When attempting to simulate a karst landscape, Leeper et al. (2011) found that drier soil simulations showed preferential regions of convective development downwind of the karst and nonkarst boundary, and found the opposite to be true for wet soil simulations for summertime convective events with the Western Kentucky Pennyroyal Karst region. Johnson et al. (2014) found that soil moisture with respect to land cover in simulated karst-like regions may play a role in the near surface atmospheric conditions at a more local scale or microscale.

4.2.2 Vegetation

Land cover can modify lower atmospheric conditions by way of surface heat and moisture fluxes in association with vegetation (Taylor and Lebel 1998). Changes in land cover can alter the surface moisture, heat, and momentum fluxes within a region (Mahmood et al. 2014). Vegetated surfaces are able to intercept rainfall and allow for surfaces on which dew and frost may form (McPherson 2007). Increases in vegetated
surfaces decrease the overall albedo of a region, equivalent potential temperature, humidity, moisture contents, and minimum temperatures of a specific area (Anthes 1984; McPherson 2007). The primary attributes associated with the interaction of vegetation and the atmosphere include the response to incoming shortwave radiation and emission of longwave radiation, roughness length, transpiration from vegetation, which aids in the regulation of surface heat fluxes, and the generation of CO₂ from photosynthesis (McPherson 2007). Differences in land cover, therefore, play an important role on the local climate of a region (Pielke 2001). Changes in vegetation lead to changes in energy fluxes and partitioning, which, along with biophysical properties like roughness and albedo, enhance the development of convection and/or precipitation at the mesoscale (Mahmood et al. 2014).

Hong et al. (1995) reported an increase in cloud water with relation to vegetation forcing in conditionally unstable atmospheric conditions. With respect to dense vegetation, Anthes (1984) found that alternating bands of dense vegetation with bare soil aided in the generation of mesoscale circulations. Land-cover change effects on the local climate of a region are correlated with soil moisture modifications in such a way that shifts in vegetative cover may be a direct result in shifts in the soil moisture regime of a region (Seneviratne et al. 2010). This relationship is important when factoring in the potential for relatively quick infiltration of water through a karst landscape, as it may alter the vegetative cover and, thus, the energy budget. With respect to karst areas, Zhang et al. (2011) studied hydrological processes in southwestern China and found that karst regions with a forested ground cover have a higher soil moisture content at the upper layers of the soil than shrub or agricultural areas, and a lower soil moisture content at the
lower levels due to increased evapotranspiration from the root system at this region. More densely vegetated regions may be able to tap into the more saturated lower portion of the epikarst zone, which could increase the latent heat flux of a karstic region.

4.2.3 Atmospheric Modeling

The WRF model was developed as a next generation mesoscale model and data assimilation system to advance the understanding and prediction of mesoscale weather, as well as accelerate the transfer of research advances into operations (Skamarock et al. 2008). The WRF model allows for numerous options related to dynamics and physics packages, which can be tailored to a large degree (Vasque 2003). This model is widely used due to a broad range of applications that the forecasting model can perform, from mesoscale-sized events to global simulations (Skamarock et al. 2005). The Advanced Research WRF (ARW) is a subset of the WRF system, which includes physics schemes, numerical/dynamical options, initialization schemes, and a data assimilation package (Skamarock et al. 2005).

Numerical Weather Prediction (NWP) models, such as the WRF, cannot represent accurately all the physical processes due to the minute scale at which these processes take place, making them too computationally intensive, the complexity of the physical processes, or an insufficient knowledge of the process to represent explicitly in mathematical terms (Warner 2011). Due to this, parameterization schemes for clouds, precipitation, radiation, and exchanges in momentum, heat, and moisture fluxes at the surface of the earth are used within atmospheric models (DeCaria and Van Knowe 2014).

One such parameterization coupled with the WRF model is the Noah LSM model, which allows for proper analysis of the physical interactions between the land surface and
the lower atmosphere (Fan 2009; Niu et al. 2011). Due to the incorporation of land-surface modeling with this atmospheric model, it is useful in studies involving soil temperature and soil moisture interaction with the atmosphere (Fan 2009; Leeper et al. 2011; Johnson et al. 2014). This is of specific interest when researching the interaction between landscapes, such as karst, and the atmosphere.

4.3 Methods

For this study, simulations were conducted using the WRF version 3.7.1. The parameterization schemes used within this study include the Lin microphysics (Lin et al. 1983), the Rapid Radiative Transfer Model longwave radiation scheme (Mlawer et al. 1997), the Goddard shortwave radiation scheme (Chou et al. 1998), the Noah land surface model (Chen and Dudhia 2001), the YSU boundary layer scheme, and the Kain-Fritsch (new Eta) cumulus scheme (Kain and Fritsch 1993; Kain 2004). The RRTM is used to calculate the longwave clear-sky fluxes and cooling rates by way of using multiple bands of radiations and multiple trace gases present in the atmosphere (Mlawer et al. 1997; Rodgers 2014). The Dudhia shortwave radiation physics parameterization simply represent the scattering and absorption of downward solar radiation by clear-air and clouds (Chen and Dudhia 2000; Rodgers 2014).

The WRF model was configured with two one-way nested domains over the Tennessee and Kentucky region (Figure 4.1). The model resolution associated with the outer domain was 9 km and 3 km for the inner domain, with 49 vertical Eta levels extending from the surface upward to 100 hPa (Johnson et al. 2014). Due to the high resolution of the inner domain (< 5 km), the cumulus parameterization was not needed. Model simulations were initialized and driven using North American Regional Reanalysis (NARR-A) data. For the purpose of this research, several convective weather events were chosen due to previous research with these events and access to the data (Leeper et al. 2011; Johnson et al. 2014). Four different model simulations were run for
comparison in this research: a control run (CTRL) using the preset soil and land use types set up within WRF, and an experimental run using the data associated with the karst regions within the study area (EXP) (Figure 4.2). Of interest in this study, the effects of vegetation cover may also have influence over the changes to the soil characteristics. In order to account for this, a comparison between a completely barren landscape over the karst locations using the default soil parameters (a BARREN model run) and a barren landscape over karst landscapes with the addition of the karst soil parameters (a BARREN_KARST model run) were used to determine further the influence karst landscapes have on the surrounding atmosphere.

**Figure 4.1** Model domains used for this research. The outer domain has a 9-km resolution and the inner domain (d02) has a 3-km resolution. Source: Created by the Author.
Figure 4.2 Soil changes made within the model domains for this research. a) soil types within the CTRL, b) soil change (gray = karst) within EXP. Source: Created by the Author.

The use of NCL code was implemented in order to determine the overall average values and Root Mean Square Differences (RMSD) between the various experimental model runs (EXP, BARREN, and BARREN_K) and the CTRL. The NCL allows for the testing of average values, standard deviations, regression statistics, and statistical significance through the use of built-in functions within the code. In order to determine the statistical significance between the CTRL and the experimental model simulations, the student’s t-test was implemented using the built-in t-test function within the NCL. R² values, which denote the change in the dependent variable to the independent variable, were also generated through the NCL regline_stat function at a 95% confidence interval (NCAR 2014).

4.4 Results

The results for the case studies are broken down into sections within each case. As stated above, each case study is as follows: Case 1 (June 11th and 13th, 2006) – a convective precipitation event along a stationary frontal boundary; Case 2 (June 17th and
19th, 2006) – a non-frontally forced convective precipitation event; Case 3 (September 29th and October 1st, 2008) – a mesoscale convective complex along a cold frontal; and Case 4 (June 14th and 16th, 2006) – a clear weather event (Leeper et al. 2011; Johnson et al. 2014). Within each case study, the 2m temperature, sensible heat, latent heat, and precipitation (with the expectation of precipitation for Case 4) were evaluated for CTRL/EXP and BARREN/BARREN_K model simulations. The resulting RMSD scores for each of the following cases are outlined in Figure 4.3.

4.4.1 Case 1

The 2m temperature output demonstrates results that are statistically similar between EXP and CTRL during only two time periods (1200 UTC of day 1 and 2). When comparing the CTRL temperature results to the changes made in the existing soil within EXP, the overall temperature changes appear the same regardless of previous soil type in CTRL. The movement of a stationary frontal boundary appears to diminish the resulting influence from the karst locations at all time periods (Figure 4.4). Temperatures on the southern side of the boundary depict lower temperatures by upwards of 4°C and higher on the northern side by upwards of 2°C (Figure 4.4a). Differences in temperature in the northern portion of Kentucky, nearly 2°C lower, are most likely due to precipitation shifts between EXP and CTRL (discussed in Figure 4.10 below) at 1500 UTC (Figure 4.4b). Locations associated with karst within the model domain demonstrate a 1°C lower temperature at this time. The location of the boundary along the Tennessee and North Carolina border continued to influence temperature results, with 1 to 2°C higher temperatures noted just north of the boundary, in southern Tennessee, at 1500 UTC (Figure 4.4d).
Figure 4.3 The RMSD scores generated over a two day period for each case study between an experiment and CTRL. a) 2m Temperature (EXP), b) 2m Temperature (BARREN_K), c) Sensible Heat (EXP), d) Sensible Heat (BARREN_K), e) Latent Heat (EXP), f) Latent Heat (BARREN_K), g) Precipitation (EXP), Precipitation (BARREN_K). The time periods are as follows: Case 1 (June 11th to June 12th), Case 2 (June 17th to June 18th), Case 3 (September 29th to September 30th), and Case 4 (June 14th to June 15th). Source: Created by the Author.
The RMSD results display the greatest error in temperature noted at 0600 UTC of day 1 and 2. Day 2 displays the highest error, at 0.87°C. The least error in temperature is denoted at 1500 UTC on day 1 and 2, at 0.50 and 0.53°C, respectively. The low sensitivity to karst with regarding 2m temperature output is further displayed through the R² results at each time period (all 0.93 or greater) (Figure 4.3a). This indicates little in the way of difference between both EXP and CTRL.
The addition of karst parameters to the barren locations indicates less overall variation in model simulations compared to EXP. The temperature behavior at 0600 UTC of day 1 (Figure 4.5a) displays very slight differences (1°C) within the domain area. The karst regions display a slight correlation between these slightly higher temperatures within BARREN_K. At 1500 UTC of day 1 (Figure 4.5b), the karst regions of middle Tennessee and south Kentucky display 0 to 1°C lower temperatures within BARREN_K. The weakest correlation between temperature differences between model simulations and karst additions is noted at 0600 UTC of day 2 (Figure 4.5c). By 1500 UTC day 2, the karst locations display a slight spatial correlation with a drop in temperature (by 0 to 1°C) in BARREN_K compared to BARREN. In comparison to EXP, BARREN_K demonstrates a decrease sensitivity to the addition of karst between the BARREN and BARREN_KARST overall. The greatest sensitivity was displayed at 1500 UTC of day 1, with an RMSD score of 0.60°C (Figure 4.3b). The diminished changes in the 2m temperature model output are also noted in the R² values. Overall, the BARREN/BARREN_K models appear to display less sensitivity to the addition of karst between model simulations, with R² > 0.98 for all time periods.

The sensible heat (Q_h) results indicate statistically different estimates for all time periods, with the exception of 0600 UTC of day 2. The 1200 UTC of day 1 and day 2 were excluded due to anomalous noise generated by the model, which were not representative of the phenomenon. The spatially mapped Q_h results display the strongest influence to the addition of karst landscapes at 1500 UTC. The movement of a frontal boundary (Fig.4.6a) appears to greatly reduce the response from the karst locations.
Figure 4.5 2m Temperature results within the BARREN_K domain for Case 1. Differences between the BARREN_K and BARREN were calculated by BARREN_K – BARREN. A) 0600 UTC Day 1, b) 1500 UTC Day 1, c) 0600 UTC Day 2, and d) 1500 UTC Day 2. Source: Created by the Author.

At 0600 UTC of day 1 (Figure 4.6a), \( Q_h \) displays a 40 Wm\(^{-2} \) decrease on the southern side of the stationary boundary in southern Kentucky. With the movement of the boundary toward the south at 1500 UTC of day 1 (Figure 4.6b), \( Q_h \) demonstrates greater sensitivity to the addition of karst landscapes, noted by 20 to 40 Wm\(^{-2} \) lower \( Q_h \). This presence and absence of precipitation within northern Kentucky provides a much stronger influence on \( Q_h \) when the EXP and CTRL are compared. The movement of a frontal
boundary back into the study area at 1500 UTC of day 2 (Figure 4.6c) indicates a stronger decrease in $Q_h$ by as much as 100 Wm$^{-2}$ within southeastern Tennessee. The RMSD results display an initial 8.1 Wm$^{-2}$ sensitivity to the addition of karst at 0600 UTC. The RMSD reflects the increased sensitivity at 1500 UTC on day 1 and 2 (42 and 50 Wm$^{-2}$) when compared against the other time periods (Figure 4.3c). The $R^2$ values between CTRL and EXP indicate almost no correlation (results below 0.09), demonstrating a resulting influence on $Q_h$ within EXP.

**Figure 4.6** Sensible Heat ($Q_h$) results within the EXP domain for Case 1. Differences between the CTRL and EXP runs were calculated by EXP – CTRL. A) 0600 UTC Day 1, b) 1500 UTC Day 1, c) 1500 UTC Day 2. Source: Created by the Author.
The addition of the karst parameters within the BARREN model simulation displays a greater sensitivity to the karst landscapes with respect to \( Q_h \) in comparison to EXP. The strongest response in \( Q_h \) is demonstrated during days 1 and 2 at 1500 UTC (Figure 4.7b and c). The karst locations display 20 to 50 Wm\(^{-2}\) lower \( Q_h \) within BARREN_K. As noted in EXP, little to no preferential difference is noted between the changes in soil type between model simulations and spatial changes in \( Q_h \). Similar to EXP, no spatial correlation was displayed between higher and lower \( Q_h \) and the location to karst landscapes. A decrease in the overall sensitivity to the addition of karst landscapes is noted in RMSD values when compared to EXP. Similar to EXP, BARREN_K demonstrates the greatest sensitivity to changes in \( Q_h \) compared to the other case studies. The greatest sensitivity is noted overall during 1500 UTC on days 1 and 2 (29 Wm\(^{-2}\) on days 1 and 2) within RMSD results (Figure 4.3d). This response to \( Q_h \) is further noted in the \( R^2 \) results, with days 1 and 2 at 1500 UTC displaying the greatest differences (\( R^2 = 0.47 \) at 1500 UTC day 1 and \( R^2 = 0.43 \) at 1500 UTC day 2).
Figure 4.7 Sensible Heat ($Q_h$) results within the BARREN_K domain for Case 1. The differences between the BARREN_K and BARREN simulations were calculated by BARREN_K – BARREN. a) 0600 UTC Day 1, b) 1500 UTC Day 1, c) 1500 UTC Day 2

Source: Created by the Author.

The latent heat ($Q_e$) results indicate no statistically similar output between EXP and CTRL, with p-values > 0.05. Spatially, the stationary frontal boundary appears to have a greater influence on $Q_e$ during the time periods where the frontal boundary is positioned within the study area (Figure 4.8). Days 1 and 2 at 1500 UTC time indicate a stronger response to the karst locations south of precipitation on day 1 (Figure 4.4b) and north of the stationary front on day 2 (Figure 4.8d). During this simulation, the day 1 $Q_h$ model estimates display 20 to 40 Wm$^{-2}$ lower results within EXP than CTRL within the
karst locations of Tennessee and Kentucky. The karst locations of northern Kentucky and Indiana indicate as much as 60 Wm$^{-2}$ lower $Q_e$ output during 1500 UTC of day 2. Compared to the other case studies, case 1 displays the highest sensitivity within EXP for $Q_e$ (RMSD values of 42 and 53 Wm$^{-2}$ for day 1 and 2, respectively, at 1500 UTC) (Figure 4.3e). This increased sensitivity maybe due to the shift in precipitation on day 1, and the influence of the stationary frontal boundary on day 2. The influence on $Q_e$ is not as strong as the results noted in $Q_h$. The greatest sensitivity to the addition of karst on $Q_e$ is noted at days 1 and 2 at 1500 UTC ($R^2 = 0.16$ day 1, $R^2 = 0.20$ day 2).

![Figure 4.8](image)

**Figure 4.8** Latent Heat ($Q_e$) results within EXP domain for Case 1. Differences between CTRL and EXP were calculated by EXP – CTRL. a) 0600 UTC Day 1, b) 1500 UTC Day 1, c) 0600 UTC Day 2, and d) 1500 UTC Day 2. Source: Created by the Author.
The introduction of karst to the barren model provides an overall decrease in sensitivity to karst landscapes on $Q_e$ compared to EXP. The 0600 UTC time periods (Figure 4.9a and c) indicate the least overall correlation between $Q_e$ estimated changes and karst landscapes. These time periods also displayed the least change between model simulations (+/- 20 Wm$^{-2}$). The best correlation is noted at 1500 UTC of day 2 (Figure 4.9d), within northern Kentucky, indicating 40 to 100 Wm$^{-2}$ lower $Q_e$. The sensitivity to karst between BARREN and BARREN_K demonstrates nearly a quarter of the difference noted in the RMSD scores for EXP (Figure 4.3f). Of the RMSD values for each case study, Case 1 demonstrates the highest RMSD values within the BARREN_K results. The sensitivity noted in the spatial orientation at 1500 UTC of day 2 is further displayed within the RMSD values (22 Wm$^{-2}$). The spatial pattern noted at 0600 UTC is also in the RMSD values, all well below 10 Wm$^{-2}$. The drop in sensitivity to karst terrains is noted at 1500 UTC on days 1 and 2 and is also found in the $R^2$ values ($R^2 = 0.68$ at 15 UTC day 1 and 0.53 day 2).

Of the resulting model simulations for precipitation, only 1200 UTC of days 1 and 2 indicate statistically similar results between EXP and CTRL, with p-values > 0.05. The 0600 UTC time of day 1 indicates an overall 0.06 mm rise in precipitation within the model domain on average. Precipitation at the 0600 UTC time period of day 1 (Figure 4.10a) displays a southward shift in precipitation within Indiana and Kentucky compared to the CTRL. Additional rainfall is also noted within the karst region of Kentucky around the Louisville, KY, area. The precipitation shifts eastward in CTRL at the 1500 UTC of day 1 (Figure 4.10b) within southern Indiana and northern Kentucky.
Figure 4.9 Latent Heat ($Q_e$) results within BARREN_K domain for Case 1. Differences between BARREN_K and BARREN were calculated by BARREN_K – BARREN. a) 0600 UTC Day 1, b) 1500 UTC Day 1, c) 0600 UTC Day 2, and d) 1500 UTC Day 2

Source: Created by the Author.

The 1500 UTC time of day 2 (Figure 4.10c) indicates precipitation along the border of Tennessee and Georgia in response to the location of the frontal boundary. Of all the case studies, Case 1 displays the greatest sensitivity to karst within EXP for the resulting RMSD values. The 0600 UTC time period displays the greatest sensitivity, with a 3.4 mm RMSD (Figure 4.3g), and an $R^2 = 0.68$. 
Figure 4.10 Precipitation results within EXP domain for Case 1. Differences between CTRL and EXP were calculated by EXP – CTRL. a) 0600 UTC Day 1, b) 1500 UTC Day 1, c) 1500 UTC Day 2. Source: Created by the Author.

The BARREN_K run indicates a general shift in precipitation eastward compared to BARREN. The location of precipitation at the 0600 UTC time period of day 1 (Figure 4.11a) displays a shift eastward within Indiana and an increase in precipitation within northern Kentucky. A shift in precipitation southerly is noted around northern Kentucky and middle Indiana at 1500 UTC of day 1 (Figure 4.11b). By 1500 UTC of day 2 (Figure 4.11c), an increase in precipitation is demonstrated within eastern Tennessee and southwestern North Carolina when compared against EXP. A near similar response to
EXP is noted in the RMSD values within BARREN_K (Figure 4.3h). The greatest sensitivity to the addition of karst is noted with the onset of precipitation at 0600 UTC on day 1 at 2.3 mm. The spatial change between BARREN and BARREN_K demonstrates a greater variance in model simulations ($R^2 = 0.56$) compared to that of EXP.

Figure 4.11 Precipitation results within BARREN_K domain for Case 1. Differences between BARREN_K and BARREN were calculated by BARREN_K – BARREN. a) 0600 UTC Day 1, b) 1500 UTC Day 1, c) 1500 UTC Day 2. Source: Created by the Author.
4.4.2 Case 2

The 1200 UTC time of day 1 and 2 display similar model estimates statistically, when the EXP and CTRL are evaluated, with p-values > 0.05. Although there is a slight spatial association between the 1°C higher temperatures and locations of karst landscape at 0600 UTC of day 1 (Figure 4.12a), 0600 UTC of day 2 indicates little in the way of spatial association between the increase in model estimates temperatures and the inclusion of karst into the model. At 1500 UTC day 1 (Figure 4.12b), the EXP model estimates display the best correlation between temperature estimates changes and the addition of karst. When compared to the sensitivity of the other case studies, case 2 displays the lowest RMSD values at the 0600 UTC time period, at 0.45°C for day 1 and 0.60°C for day 2 (Figure 4.3a). The R² results (0.96 or greater) further reflect the low sensitivity to the addition of karst between EXP and CTRL. In association with the changes in soil type between model simulations, no changes in the spatial nature of the temperature are noted.

When the vegetation was removed from the karst locations in the model simulation, the behavior of the model simulation of 2m temperatures changed (Figure 4.13). At 0600 UTC of day 1, the temperatures display a slight correlation with karst locations in the model simulation. Overall, temperatures in BARREN_K demonstrate 0 to 1°C lower estimates compared to BARREN. This behavior is more evident at the 1500 UTC time (Figure 4.13b), where portions of the karst landscapes of Kentucky and northern Tennessee display a 1 to 2°C decrease in model temperature estimates. The pattern noted at 0600 UTC day 1 continues into the 0600 UTC day 2 time (Figure 4.13c).
Figure 4.12 2m temperature results within EXP domain for Case 2. Differences between CTRL and EXP were calculated by EXP – CTRL. a) 0600 UTC Day 1, b) 1500 UTC Day 1, c) 0600 UTC Day 2. Source: Created by the Author.

The spatial coverage of the 1 to 2°C model temperature decrease diminishes in comparison to the 15 UTC of day 1 estimates. The overall sensitivity to the addition to karst appears to be rather slight, with RMSD values (Figure 4.3b) displaying the greatest sensitivity at 1500 UTC day 1 (0.60°C) and 0600 UTC of day 2 (0.53°C). The R² values display a very slight difference in model variation (R² = 0.99 for EXP; R² = 0.96 for
BARREN_K) at the 1500 UTC of day 1, with the remaining times displaying near similar results to EXP.

**Figure 4.13** 2m temperature results within BARREN_K domain for Case 2. Differences between BARREN_K and BARREN were calculated by BARREN_K – BARREN. a) 0600 UTC Day 1, b) 1500 UTC Day 1, c) 0600 UTC Day 2.

Source: Created by the Author.

The $Q_h$ output displays model estimates of a statistically different nature for all but the 0600 UTC on day 2. At 0600 UTC of day 1 (Figure 4.14a), no preference in sensitivity of $Q_h$ output is noted between the karst and non-karst locations. The 1200 UTC time periods of days 1 and 2 (Figure 4.14b and d) began to display preferential
results with respect to $Q_h$ and the changes in the soil type in EXP. The locations of silty clay soil in the karst domain indicate 10 to 20 Wm$^{-2}$ lower $Q_h$ model estimates than the other locations within the EXP run., noted at 1500 UTC of day 1 (Figure 4.14c). The location of loam soils display 0 to 10 Wm$^{-2}$ higher $Q_h$ results within EXP. The decreased value in $Q_h$ is also stronger within the locations of previously loam soil type within northern Kentucky, where 50 to 60 Wm$^{-2}$ lower $Q_h$ results are noted. This sensitivity is further demonstrated through the associated RMSD values (Figure 4.3c), where results for day 1 display a 19 Wm$^{-2}$ difference between the model simulations. Model estimates at the 0600 and 1200 UTC time periods display the least sensitivity, lower than 5 Wm$^{-2}$, between CTRL and EXP. Corresponding to the RMSD results, the $R^2$ values display the greatest variance ($R^2 = 0.72$) between EXP and CTRL at 1500 UTC.

In comparison to EXP, the $Q_h$ output from BARREN_K displays a stronger spatial correlation between the addition of karst and changes in model simulations. The 1200 UTC time of day 1 and 2 (Figure 4.15b and d) demonstrate $Q_h$ output of 20 to 40 Wm$^{-2}$ lower than in BARREN. The greatest change is noted at 1500 UTC of day 1 (Figure 4.15c). Many of the karst locations display 40 to 50 Wm$^{-2}$ lower $Q_h$ model estimates compared to BARREN. The loam soils within BARREN_K display 10 Wm$^{-2}$ higher $Q_h$ compared to the other locations. Unlike EXP, the silty clay soil locations do not indicate lower $Q_h$ like that noted in EXP. The $Q_h$ estimates displays a greater sensitivity to the addition of karst in BARREN_K compared to EXP. The RMSD values display the greatest sensitivity at 1500 UTC of day 1, at 23 Wm$^{-2}$ (Figure 4.3d). The remaining times display much less sensitivity (below 10 Wm$^{-2}$). The $R^2$ values at 1500 UTC ($R^2 = 0.54$) reflect that in the spatial distribution of the model estimates and the RMSD results.
Figure 4.14 Sensible Heat Flux ($Q_h$) results within the EXP domain for Case 2. Differences between the CTRL and EXP were calculated by EXP – CTRL. a) 0600 UTC Day 1, b) 1200 UTC Day 1, c) 1500 UTC Day 1, and d) 1200 UTC Day 2. Source: Created by the Author.
Figure 4.15 Sensible Heat Flux ($Q_h$) results within the BARREN_K domain for Case 2. Differences between the BARREN and BARREN_K were calculated by BARREN_K – BARREN. a) 0600 UTC Day 1, b) 1200 UTC Day 1, c) 1500 UTC Day 1, and d) 1200 UTC Day 2. Source: Created by the Author.

The $Q_e$ displays little statistical difference between the model simulations. Only the 0600 UTC time period of days 1 and 2 indicated statistically different model outputs, with p-values < 0.05. The day 1 (Figure 4.16a) estimates indicate a slight spatial correlation between the addition of karst and changes in $Q_e$. The karst locations display a slight change in $Q_e$ with 20 Wm$^{-2}$ higher output within the EXP compared to the CTRL. This breaks down at day 2 (Figure 4.16b), with the locations experiencing precipitation at
this time recording as much as a 40 Wm$^{-2}$ increase in $Q_e$ values. The day 1 estimates display the least sensitivity with a 10 Wm$^{-2}$ RMSD, where the day 2 estimates display the greatest, 27 Wm$^{-2}$ RMSD, which may be due to the addition of precipitation at this time period. The sensitivity to $Q_e$ changes appears to be low when the $R^2$ value is taken into account ($R^2 = 0.97$) at 0600 UTC day1.

![Latent Heat Flux (Qe) results within the EXP domain for Case 2. Differences between the EXP and CTRL were calculated by EXP – CTRL. a) 0600 UTC Day 1, and b) 0600 UTC Day 2. Source: Created by the Author.](image)

**Figure 4.16** Latent Heat Flux ($Q_e$) results within the EXP domain for Case 2. Differences between the EXP and CTRL were calculated by EXP – CTRL. a) 0600 UTC Day 1, and b) 0600 UTC Day 2. Source: Created by the Author.

The $Q_e$ results display less spatial correlation when compared to EXP. At 0600 UTC of day 1 (Figure 4.17a), the karst locations display a smaller spatial coverage with 0 to 20 Wm$^{-2}$ higher $Q_e$ estimates compared to BARREN. The correlation further diminishes at 0600 UTC of day 2 (Figure 4.17b), with no clear association with increases and decreases in $Q_e$ to the karst locations. The sensitivity to the karst additions indicates very minute changes, with RMSD values all below 5 Wm$^{-2}$ (Figure 4.3f). This decreased sensitivity to karst for $Q_e$ is noted in the $R^2$ value ($= 0.96$) at 0600 UTC of day 1.
Figure 4.17 Latent Heat Flux ($Q_e$) results within the BARREN_K domain for Case 2. Differences between the BARREN_K and BARREN were calculated by BARREN_K – BARREN. a) 0600 UTC Day 1 and b) 0600 UTC Day 2. Source: Created by the Author.

Much like the $Q_e$ estimates, the precipitation results display little difference statistically between model estimates, with only 0600 UTC of day 2 demonstrating p-values < 0.05. The precipitation generated by the EXP at 0600 of day 2 (Figure 4.18) indicates a generation of greater precipitation in the northwest within central Illinois. The spatial nature of this precipitation has also decreased in size when compared to the CTRL. Both Case 2 and 3 display nearly similar RMSD values at 0600 UTC on day 2, with a 2.24 mm difference in EXP noted (Figure 4.3g). There is little similarity between the EXP/CTRL results as shown by the $R^2$ of 0.30 at this time period.

The results from BARREN_K demonstrate better spatial accuracy with respect to precipitation within western Tennessee, but do not capture precipitation occurring within western Kentucky and southern Illinois (Figure 4.19). The eastward shift in precipitation within BARREN_K indicates improved accuracy of observed precipitation within western Tennessee (discussed in section 4.5 in Figure 4.34). Unlike EXP, both BARREN/BARREN_K simulations do not capture precipitation at this time in western
Kentucky. This sensitivity is noted in the resulting RMSD value for this time period (2.3 mm), which is similar to the results noted in EXP (Figure 4.3h). The model sensitivity to karst with respect to precipitation changes does appear to increase when comparing the data from BARREN/BARREN_K ($R^2 = 0.02$).

**Figure 4.18** Precipitation results within the EXP domain for Case 2. Differences between the EXP and CTRL were calculated by EXP – CTRL. This graphic depicts precipitation at 0600 UTC Day 2. Source: Created by the Author.
Figure 4.19 Precipitation results within the BARREN_K domain for Case 2. Differences between the BARREN_K and BARREN were calculated by BARREN_K – BARREN. This graphic depicts precipitation at 0600 UTC Day 2. Source: Created by the Author.

4.4.3 Case 3

The 2m temperature results from Case3 indicate only one time period with statistically similar results at 15 UTC day 2, with p-values > 0.05. Both the 0600 and 1200 UTC time periods of day 1 (Figure 4.20a and b) demonstrate 1 to 2°C higher temperatures within the karst regions of middle Tennessee and southern Kentucky. Without the presence of a frontal boundary, the 1500 UTC time (Figure 4.20c) indicates a slight decrease in temperatures within EXP by 1°C. By 0600 UTC time period on day 2 (Figure 4.20d), the movement of the cold frontal boundary into the region begins to wash out any response to karst additions noted in the 2m temperatures previously. Overall, the EXP displays 2 to 4°C higher temperatures directly behind the front, with temperatures in
front of the boundary decreasing by 1 to 2°C. This response continues at 12 UTC (Figure 4.20e), with temperatures behind the front in eastern Tennessee demonstrating 2 to 4°C higher temperatures. Prior to frontal passage into the model domain, the 0600 and 1200 UTC time periods display near similar sensitivities to the addition of karst, indicated by a 0.52°C RMSD. This sensitivity is the least at 1500 UTC. The movement of the frontal boundary into the study area demonstrates a much greater influence, as noted in the rise in RMSD values at the 0600 and 1200 UTC time periods of day 2 (1.0 and 0.82°C) (Figure 4.3a). The passage of the frontal boundary at 0600 UTC on day 2 displayed the greatest change between EXP and CTRL ($R^2 = 0.75$). Prior to the movement of the cold front into the study area, the EXP and CTRL depict little sensitivity to the addition of karst in the 2m temperature results ($R^2 = 0.95$ or greater).

Within BARREN_K, the removal of vegetation from the model run displays an overall decrease in sensitivity to the inclusion of karst compared to EXP. The 0600 UTC of day 1 (Figure 4.21a) displays around 1°C higher temperatures within karst landscapes, a decrease from EXP. The spatial spread of 2°C higher temperatures in karst locations at 1200 UTC of day 1 (Figure 4.21b) has also diminished. Both EXP and BARREN_K display similar changes (1°C lower temperatures) within karst landscapes at 1500 UTC of day 1 (Figure 4.21c). The passage of the frontal boundary at 0600 UTC of day 2 (Figure 4.21d) also demonstrates a change in temperature patterns, with a decrease in both spatial coverage and a diminishment in the increase in temperature noted directly behind the front (2°C) at this time. The RMSD values also reflect this change, with all time periods displaying a near half decrease. The greatest sensitivity prior to the frontal passage is noted at 1200 UTC day 1, with an RMSD of 0.51°C (Figure 4.3b).
Figure 4.20 2m Temperature results within the EXP domain for Case 3. Differences between EXP and CTRL runs were calculated by EXP–CTRL. a) 0600 UTC Day 1, b) 1200 UTC Day 1, c) 1500 UTC Day 2, d) 0600 UTC Day 2, and e) 1200 UTC Day 2. Source: Created by the Author.
Figure 4.21 2m Temperature results within the BARREN_K domain for Case 3. Differences between BARREN_K and BARREN were calculated by BARREN_K–BARREN. a) 0600 UTC Day 1, b) 1200 UTC Day 1, c) 1500 UTC Day 2, d) 0600 UTC Day 2, and e) 1200 UTC Day 2. Source: Created by the Author.
Prior to the cold front moving into the study area, 1500 UTC day 1 displays a slight difference in $R^2$ values ($= 0.97$ for BARREN_K compared to 0.98 in EXP). A decrease in sensitivity to the addition of karst is noted in the 2m temperatures at 0600 and 1200 UTC ($R^2 = 0.91$ for both times) compared to EXP ($R^2 = 0.75$ at 0600 UTC and 0.86 at 1200 UTC). The results for $Q_h$ display statistically different model estimates for all times except 1200 UTC on days 1 and 2. Similar to the 0600 UTC EXP estimates in Case 2 for $Q_h$, the 0600 UTC of day 1 (Figure 4.22a) results demonstrates no correlation between $Q_h$ changes in EXP and spatial orientation of the karst addition. A clear response is noted at 1500 of UTC day 1 (Figure 4.22b), where 30 to 40 Wm$^{-2}$ lower $Q_h$ is demonstrated within the karst locations of EXP. The silty clay soil locations of CTRL indicate the lowest $Q_h$ values with the EXP: 50 to 60 Wm$^{-2}$ lower $Q_h$ within the EXP at 1500 UTC day 1. By 0600 UTC of day 2 (Figure 4.19c), the movement of the cold front through the domain masks any response from the karst landscape, indicating an increase in model $Q_h$ ahead of the boundary by 20 to 40 Wm$^{-2}$, and a decrease behind the boundary by 20 Wm$^{-2}$. In comparison to all other cases, the 1500 UTC RMSD values are the highest of the remaining case studies, demonstrating a 24 Wm$^{-2}$ difference between EXP and CTRL, with only Case 1 results of 1500 UTC demonstrating the higher values (Figure 4.3c). Along with the response noted in the RMSD values at 1500 UTC of day 1, the $R^2$ value (0.73) reflects this sensitivity to the addition of karst in $Q_h$. 

97
Figure 4.22 Sensible heat \((Q_h)\) results within the EXP domain for Case 3. Differences between the CTRL and EXP were calculated by EXP – CTRL. a) 0600 UTC Day 1, b) 1500 UTC Day 1, c) 0600 UTC Day 2. Source: Created by the Author.

The mixed nature of \(Q_h\) change noted at 0600 UTC of day 1 in EXP has diminished, with much of the model domain displaying 10 Wm\(^{-2}\) higher \(Q_h\) estimates. The most well-defined change between BARREN and BARREN_K is noted at 1500 UTC of day 1 (Figure 4.23b). The locations of loam soil type within the BARREN simulation demonstrate 10 Wm\(^{-2}\) higher values within BARREN_K. Overall, the conversion of the BARREN soils to karst displays a 20 to 40 Wm\(^{-2}\) decrease in the model estimates for \(Q_h\). As noted in the 2m temperature output for BARREN_K, the \(Q_h\) estimates displays a
change on either side of the frontal boundary (+/- 20 Wm$^{-2}$). This sensitivity is further displayed by the corresponding RMSD values, 15 Wm$^{-2}$ at 1500 UTC of day 1. Of the four case studies, Case 3 displays the lowest sensitivity to the addition of karst between model outputs for $Q_h$ prior to movement of the front into the study area at 0600 UTC of day 2 (Figure 4.3d). The sensitivity to the addition of karst to the $Q_h$ estimates between BARREN and BARREN_K displays an increased sensitivity with an $R^2 = 0.64$.

Figure 4.23 Sensible heat ($Q_h$) results within BARREN_K domain for Case 3. Differences between BARREN_K and BARREN were calculated by BARREN_K – BARREN. a) 0600 UTC Day 1, b) 1500 UTC Day 1, c) 0600 UTC Day 2. Source: Created by the Author.
Along the same lines as the results of the case 2 $Q_e$, little statistical difference is noted between the model simulations for case 3 (p-values < 0.05), with only 1500 UTC of days 1 and 2 displaying statistically different results. The response to the $Q_e$ values on day 1 for EXP indicates a slight spatial response by 40 to 60 Wm$^{-2}$ higher $Q_e$ estimates within the karst regions of the model domain at 1500 UTC (Figure 4.24a). This is negated by the movement of the frontal boundary into the region by 1500 UTC on day 2 (Figure 4.24b). The $Q_e$ response behind the front demonstrates a 40 to 60 Wm$^{-2}$ higher $Q_e$ estimate with values directly in front of the boundary (within the Tennessee and North Carolina region) indicating a 40 to 100 Wm$^{-2}$ decrease compared to the CTRL. The sensitivity to the addition of karst is the lowest (37 Wm$^{-2}$) of all case studies at 1500 UTC day 1 when the RMSD values are taken into account (Figure 4.3e). The movement of the frontal boundary into the study area appears to have a greater influence, increasing RMSD values on day 2 by 41 Wm$^{-2}$. Prior to the passage of the cold front, the $R^2$ values further indicate the changes noted in Figure 4.24 ($R^2 = 0.75$).
Figure 4.24 Latent Heat Flux ($Q_e$) results within the EXP domain for Case 3. Differences between the EXP and CTRL were calculated by EXP – CTRL. a) 1500 UTC Day 1 and b) 1500 UTC Day 2. Source: Created by the Author.

The $Q_e$ results display overall less sensitivity to the addition of karst compared to EXP. The 1500 UTC of day 1 simulation (Figure 4.25a) displays 20 Wm$^{-2}$ higher $Q_e$ compared to BARREN. At 1500 of UTC day 2 (Figure 4.25b), the karst locations display a slightly higher $Q_e$ by 20 to 40 Wm$^{-2}$, which may be associated with the precipitation that had previously moved through the region. Of all of the case studies, Case 3 demonstrates the lowest RMSD values, with the greatest sensitivity associated with 1500 UTC of day 2 (11 Wm$^{-2}$) (Figure 4.3f). The overall decrease model sensitivity to karst regarding $Q_e$ between BARREN and BARREN_K is noted in an increase in $R^2$ results ($R^2 = 0.87$) at 0600 UTC of day 1.
Figure 4.25 Latent Heat Flux ($Q_e$) results within the BARREN_K domain for Case 3. Differences between the BARREN and BARREN_K were calculated by BARREN_K – BARREN. a) 1500 UTC Day 1 and b) 1500 UTC Day 2. Source: Created by the Author.

The overall precipitation estimates within EXP displayed the most statistically different results, with all time periods of the model simulations displaying p-values < 0.05. The initialization of precipitation begins at 0600 UTC on day 2 (Figure 4.26b), which indicates precipitation to be mainly within the karst locations of the model domain at this time compared to the CTRL. The 1200 UTC time period (Figure 4.26c) demonstrates an increase in precipitation (6 to 8 mm) noted along the Kentucky and West Virginia border. By 1500 UTC, an increase in precipitation is noted within the West Virginia region by 4 to 8 mm (Figure 4.26d). The 0600 UTC of day 2 output displays the greatest sensitivity to the addition of karst with associated RMSD values of 2.24 mm (Figure 4.3g). This response decreases as the precipitation begins to move out the region by 1200 UTC. The response at the 0600 UTC of day 2 time period displays a $R^2$ of 0.03, which reflects an increased sensitivity between the CTRL and EXP.
Figure 4.26 Precipitation results within the EXP domain for Case 3. Differences between the CTRL and EXP were calculated by EXP – CTRL: a) 1500 UTC Day 1, b) 0600 UTC Day 2, c) 1200 UTC Day 2, and d) 1500 UTC Day 2.
Source: Created by the Author.

The onset of precipitation at 0600 UTC of day 2 (Figure 4.27b) displays spatial agreement with observed precipitation located within southern Kentucky and near the Kentucky and Indiana border. Both 1200 and 1500 UTC of day 2 (Figure 4.27c and d) display spatial agreement in the increased precipitation noted in BARREN_K, but do not capture the light precipitation noted in BARREN. This spatial shift in precipitation is also demonstrated in the RMSD values (2.5 mm), which demonstrates the increased
sensitivity to the addition of karst for precipitation (Figure 4.3h). The response noted at 0600 UTC of day 2 displays slightly more variance between BARREN and BARREN_K than in EXP, with an $R^2 = 0.02$.

**Figure 4.27** Precipitation results within the BARREN_K domain for Case 3. Differences between the BARREN_K and BARREN were calculated by BARREN_K – BARREN: a) 1500 UTC Day 1, b) 0600 UTC Day 2, c) 1200 UTC Day 2, and d) 1500 UTC Day 2. Source: Created by the Author.
4.4.4 – Case 4

The results from the 2m temperature model estimates from the clear day model simulation (Case 4) indicate estimates of a statistically similar nature, p-values > 0.05, during two time periods (1200 UTC on June 14th, 2006 and 1500 UTC on June 15th, 2006). Spatially, the 0600 UTC time of days 1 and 2 display 1 to 2°C higher temperatures (Figure 4.28a and c) within the karst locations. The 1500 UTC estimates (Figure 4.28b) display a clear 1°C decrease in temperatures within the karst regions added to the model. The 1200 UTC time period (Figure 4.28d) displays the least change throughout the model domain, where no geologic landscape demonstrates a clear influence on model output. The RMSD values associated with the model estimates indicate the greatest sensitivity associated with 0600 UTC on days 1 and 2 (0.54 and 0.67°C, respectively) (Figure 4.3a). The 1500 UTC results indicate the least sensitivity to karst with respect to temperature when compared against all other model estimates (0.12 and 0.16°C for days 1 and 2, respectively). Without the potential influence of any frontal boundaries, the temperature output continues to display little sensitivity to the addition of karst within the EXP simulation when the CTRL soil types are taken into account. The 1500 UTC time period displays the highest R² value out of all other cases (R² = 0.99). The most sensitive time period is indicated at 0600 UTC of day 2 (R² = 0.95), suggesting a very close similarity between the CTRL and EXP.
Figure 4.28 2m Temperature results within the EXP domain for Case 4. Differences between the CTRL and EXP were calculated by EXP – CTRL. a) 0600 UTC Day 1, b) 1500 UTC Day 1, c) 0600 UTC Day 1, and d) 1200 UTC Day 2.
Source: Created by the Author.

The 2m temperatures in BARREN_K display an overall similar model estimate compared to the EXP. Days 1 and 2 at 0600 UTC (Figure 4.29a and c) demonstrate no clear correlation between the slight (1°C) increase and decrease in temperatures with the addition of karst to the model simulation. The 1500 UTC (Figure 4.29b) model simulation demonstrates the closest correlation with 1°C lower temperatures within the karst locations. Case 4 demonstrates the lowest RMSD values of all of the case studies,
with the greatest sensitivity at 1500 UTC of day 1 (0.35°C) (Figure 4.3b). The change in
the spatial spread of lower temperature values at 1500 UTC of day 1 is reflected in the $R^2$
value ($R^2 = 0.95$). A decrease in model sensitivity to karst is noted between
BARREN/BARREN_K at both 0600 UTC time periods ($R^2 = 0.99$ at both time periods).

Figure 4.29 2m Temperature results within the BARREN domain for Case 4. Differences
between the BARREN_K and BARREN were calculated by BARREN_K – BARREN: a)
0600 UTC Day 1, b) 1500 UTC Day 1, c) 0600 UTC Day 1, and d) 1200 UTC Day 2.
Source: Created by the Author.
All times display estimates for sensible heat flux ($Q_h$) of a statistically different nature, with the exception of 0600 UTC of day 1. The strongest influence is noted at 1500 UTC (Figure 4.30b and e), where $Q_h$ values indicate 20 to 60 Wm$^{-2}$ lower results within EXP. The changes in the soil type display regional higher and lower $Q_h$ in model estimate outputs within EXP. Locations of loam soil display 10 Wm$^{-2}$ higher $Q_h$ estimates within EXP, whereas the silty clay soils of northern Kentucky show the greatest decrease in $Q_h$ estimates (60 Wm$^{-2}$). The 0600 UTC and 1200 UTC estimates display no clear influence on $Q_h$ within the model domain. The RMSD values indicate the lowest errors compared to the other case studies (Figure 4.3c). The greatest sensitivity is noted at 1500 UTC on days 1 and 2 by 15 and 14 Wm$^{-2}$, respectively. The 0600 UTC and 1200 UTC time periods display the least sensitivity, all under 5 Wm$^{-2}$. The response noted at 1500 UTC also displays the greatest variance between model simulations ($R^2 = 0.85$ at 1500 UTC of day 1 and 0.87 on 1500 UTC of day 2).

Similar to results noted in case 2, the $Q_h$ indicates well-defined changes within the karst locations of BARREN_K. The 1200 UTC time periods of days 1 and 2 (Figure 4.31a and d) demonstrate slightly (10 to 20 Wm$^{-2}$) decreased $Q_h$ values in BARREN_K. The greatest changes are noted at the 1500 UTC time periods (Figure 4.31b and e), with 20 to 50 Wm$^{-2}$ lower $Q_h$ model estimates all within karst landscapes. Similar to the 1500 UTC day 1 run of case 2, the 1500 UTC time periods of days 1 and 2 display areas of previously loam soil with near 10 Wm$^{-2}$ higher $Q_h$ estimates compared to all other locations within BARREN_K. These results are further reflected through the RMSD values (Figure 4.3d). The 1500 UTC time periods of days 1 and 2 display the greatest sensitivity (18 Wm$^{-2}$ for day 1 and 15 Wm$^{-2}$ for day 2). The response between BARREN
and BARREN_K displays greater variance ($R^2 = 0.69$ at 1500 UTC day 1 and 0.79 at 1500 UTC of day 2) compared to EXP.

**Figure 4.30** Sensible Heat Flux ($Q_h$) results within EXP domain for Case 4. Differences between CTRL and EXP runs were calculated by EXP – CTRL: a) 1200 UTC Day 1, b) 1500 UTC Day 1, c) 0600 UTC Day 2, d) 1200 UTC Day 2, and e) 1500 UTC Day 2. Source: Created by the Author.
Figure 4.31 Sensible Heat Flux (Q_h) results within the BARREN_K model domain for Case 4. Differences between the BARREN_K and BARREN were calculated by BARREN_K – BARREN: a) 1200 UTC Day 1, b) 1500 UTC Day 1, c) 0600 UTC Day 2, d) 1200 UTC Day 2, and e) 1500 UTC Day 2. Source: Created by the Author.
The latent heat flux ($Q_e$) results indicate two time periods with statistically similar results ($p$-values $> 0.05$): 1200 UTC on day 1 and day 2. The spatial nature of the $Q_e$ output indicates the greatest response at 1500 UTC (Figure 4.32b and d), with 20 to 60 Wm$^{-2}$ lower results within EXP. Similar to the $Q_h$ results, the soil types in CTRL do display an influence on model estimates in EXP. The silty clay soil location of northern Kentucky does display 20 Wm$^{-2}$ lower results than the surrounding locations in EXP. The remaining soil types do not display a noticeable change between model simulations. The 0600 UTC time periods of days 1 and 2 (Figure 4.32a and c) demonstrate slight differences in $Q_e$ output by 0 to 20 Wm$^{-2}$ higher estimates within EXP. The greatest sensitivity is demonstrated at 1500 UTC by 43 and 17 Wm$^{-2}$ RMSD values respectively (Figure 4.32e). Similar to the $Q_h$ RMSD results, the 0600 and 1200 UTC estimates display the least sensitivity, with results under 10 Wm$^{-2}$. The 1500 UTC day 1 time period displays the greatest sensitivity to the addition of karst on $Q_e$ with an $R^2 = 0.73$.

The $Q_e$ within BARREN_K displays a diminishment in the correlation between the changes in results and karst locations. The 0600 UTC time periods of days 1 and 2 indicate a slight correlation between 20 Wm$^{-2}$ higher $Q_e$ output within BARREN_K within day 1 (Figure 4.33a), which diminishes at day 2 (Figure 4.33c). Unlike EXP, BARREN_K demonstrates slightly higher (20 Wm$^{-2}$) $Q_e$ model estimates within karst terrains at 1500 UTC of day 1 (Figure 4.33b). Like the 0600 UTC results on day 2, this pattern breaks down by 1500 UTC of day 2 (Figure 4.33d). Also, unlike EXP, no preference is noted between the changes in the soil types and the inclusion of karst into BARREN_K. The greatest sensitivity is demonstrated at 1500 UTC of day 2 by 11 Wm$^{-2}$ RMSD (Figure 4.3f). The remaining time periods display the least sensitivity, all below
7.0 Wm$^{-2}$. A decrease in model sensitivity to the addition of karst for $Q_e$ is noted at 1500 UTC of day 1 with an $R^2 = 0.80$.

**Figure 4.32** Latent Heat ($Q_e$) results within the EXP domain for Case 4. Differences between the CTRL and EXP were calculated by EXP – CTRL: a) 0600 UTC Day 1, b) 1500 UTC Day 1, c) 0600 UTC Day 2, and d) 1500 UTC Day 2. Source: Created by the Author.
Figure 4.33 Latent Heat ($Q_e$) results within the BARREN domain for Case 4. Differences between the BARREN and BARREN_K were calculated by BARREN_K – BARREN: a) 0600 UTC Day 1, b) 1500 UTC Day 1, c) 0600 UTC Day 2, and d) 1500 UTC Day 2. Source: Created by the Author.

4.5 Conclusions

Overall, the case studies conducted for this research display a low sensitivity to the addition of karst when temperature is taken into account. This is not only reflected in the spatial nature of the temperature changes, but also with the RMSD scores generated with each case study, all generally 0.6°C. This is further reflected through the linear regression analysis between the experimental simulations, all denoting an $R^2 > 0.93$. 
Without vegetation within the model simulations, the resulting changes in the temperature estimates diminished, with the greatest differences between model simulations being only 0.6°C overall. This demonstrates that karst alone does not appear to be a strong influence on model estimates with respect to temperature. The influence of the vegetation may have a stronger influence than the karst landscapes alone. Across a one week time period, the relationship of the temperature results varied little outside of the movement of a front into the study area. The changes in temperature that were noted in the model simulations correlate with the decrease in $Q_h$ during the daylight hours within the karst landscapes.

The decrease in $Q_h$ varied between 20 to 50 Wm$^{-2}$ overall. Like the results between Case 1, 2, and 4, little change was noted in the resulting spatial orientation of the model estimates between EXP and CTRL, and BARREN and BARREN_K. The removal of the vegetation appears to increase model sensitivity to the addition of karst by about a 10 Wm$^{-2}$ decrease in $Q_h$. This demonstrates that karst alone does appear to influence the response in $Q_h$. The slight differences between the karst areas may be due to the changes in the thermal diffusivity (F11) among soils in the model simulations (karst = 0.01054, loam= 0.066, and silty clay loam = 0.012).

Overall, the $Q_e$ results demonstrate lower values during daylight hours (between 20 and 60 Wm$^{-2}$) when compared to the control simulations (CTRL and BARREN). The model sensitivity indicates that karst alone displays less change in $Q_e$, which is demonstrated through lower RMSD (generally less than 40 Wm$^{-2}$) and increased $R^2$ values (generally $R^2 > 0.7$). The response to precipitation is mixed. The BARREN_K displays better agreement with radar observations within all three time periods of the
most intense precipitation compared to EXP (Figure 4.34). This demonstrates that the addition of karst into the model does provide some improvement with the spatial distribution of precipitation.

![Radar images](image)

**Figure 4.34** Radar images: a) June 11th, 2006, 0600 UTC, b) June 18th, 2006 0600 UTC, c) September 30th, 2008 0600 UTC. The circled regions depict locations where the EXP model displays spatial agreement with radar observations. Source: After UCAR (2014).

The response between the cases reviewed within this study indicates that the greatest response to the inclusion of karst to the model simulation is associated with precipitation and surface energy fluxes. This reflects the results discussed previously with regard to soil moisture changes, where the distribution of precipitation improved when soil moisture was adjusted for karst-like behavior (Leeper et al. 2011). These changes may influence circulation at the surface, which may induce mesoscale convection to
develop between the karst and non-karst landscapes (Ookouchi 1984). The response to frontal activity appears to be greater (with larger RMSD and lower $R^2$ values) than karst influences alone.

Only one non-frontally forced event was included within this research (Case 4) due to the availability of the data and better understanding from previous studies (Leeper et al. 2011; Johnson et al. 2014). This study would benefit from the addition of other non-frontally forced events in order to determine the influence the addition of these karst parameters might have on model sensitivity. Additionally, only summer events were chosen within this location. This is due to more non-frontally forced convective precipitation events occurring during the summer months. The addition of spring and fall precipitation events would be of value in future work to determine if seasonality plays a role regarding model response. The location of study area was chosen due to previous research conducted within this area associated with karst and modeling studies. Future work related to the influence karst has with respect to atmospheric modeling would benefit from choosing different locations to determine if this response is similar or different within other locations. A full week was not analyzed within this study. Several events in conjunction with one another from June 11th to June 18th, 2006, were chosen for analysis. It may be valuable to add a full week-long period in future work, as it would allow for a better understanding of the evolution of the atmosphere in response to karst over time.

The overall model response displays a notable change in surface fluxes and a better distribution of precipitation with the addition of karst within the model simulations. The evolution in temperatures during June displayed little change associated with the
addition of karst. Removal of vegetation denoted an increased response in $Q_h$ and a decreased response in $Q_e$ and temperature, indicating the influence from vegetation in EXP may play a stronger role on temperature and moisture movement within the atmosphere. These results indicate a potential influence on precipitation and heat flux within modeling estimates, and thus might benefit from future analysis with observational information.
CHAPTER 5: Conclusions

The hydrological nature of karst landscapes, covering approximately 20% of the ice-free land surface, highlights their importance for determining their potential influence on atmospheric phenomena (Ford and Williams 2007). Prior to this research, only two previous studies, to the author’s knowledge, were conducted examining this potential relationship (Leeper et al. 2011; Johnson et al. 2014). Neither study had previously tested the spatial differences in model estimates between karst and non-karst locations, or attempted to create a karst-like soil type for use in modeling studies. Expanding on this previous research, the goals of this study were to answer several research questions.

The first question within this study was: what differences are noted between a currently operational forecast model and observational data? The comparison between the NAM model and observational data over a five-year period (2007–2011) indicates varied results between karst and non-karst landscapes, especially when two controls are taken into account. Overall, both the daily maximum and minimum temperatures appear to display less overall error between karst and non-karst locations than noted between regions of similar geologic type (karst and karst or non-karst and non-karst). This being stated, other factors may have greater influence on observed temperatures than karst alone. One such factor may be the varying land use/land cover within the various locations chosen for this study. Previous research has noted that varying land use classifications, such as rural/agricultural lands, may have a greater influence on diurnal temperatures within a region (Gallo et al. 1996; Mahmood et al. 2014). This may be the source of the larger model bias within the control locations. The wind patterns within the NAM displayed an increase in the forecast error within karst landscapes compared to the
controls. The karst landscapes displayed an error in forecasting winds between 0.42 and 1.96 m s$^{-1}$ associated with U winds and between 0.47 and 2.3 m s$^{-1}$ with V winds. These results may be in response to small-scale circulations developing between the karst and non-karst landscapes in these locations (Ookouchi 1984; Leeper et al. 2011). The raw precipitation data displayed better skill overall between karst/non-karst regions than the controls. When the precipitation data were standardized, they demonstrated a tendency for the greater forecasting error associated with larger regions (CONUS, WEST, and SE) and a slight preference in decrease model skill regarding the frequency of predicted precipitation, noted by a tendency to underestimate the frequency of precipitation within karst landscapes on the western-side of the study area.

The second question highlighted by this research was: which parameters are needed in order to determine the overall behavior of a karst landscape? Research conducted on the hydrological nature of karst demonstrates an overall sandy soil-like movement of moisture through the system, noted by an increased hydrologic conductivity (SATDK) to $1.5\times10^5$ m/s within the Noah-LSM. The resulting parameters calculated for use in the Noah-LSM displayed water retention similar to that of a silty-type of soil (Chen and Dudhia 2001). This retention of moisture is similar to the hydraulic damming noted within karst landscapes (Ford and Williams 2007; Williams 2008).

Lastly, what influence, if any, does the inclusion of karst into a currently working forecast model for this landscape show on modeled results? The model simulations, along with the statistical analysis of these results, taken at a 95% confidence interval, displayed mixed results regarding model sensitivity to the inclusion of karst. Overall, model estimates displayed little sensitivity to the inclusion of karst with respect to temperature.
The WRF model estimates displayed, on a case-by-case basis, little difference ($R^2 > 0.94$ and RMSD < 0.6°C) between the two model simulations (EXP and CTRL or BARREN and BARREN_K) for 2m temperature. These results echo the response noted in the verification study, where the control regions displayed greater error than karst to non-karst. The flux of latent and sensible heat demonstrated the greatest change during daylight hours, with decreases in both sensible heat and latent heat visible within the karst locations of the model domain. The greatest changes in sensible heat were noted in BARREN_K (10 Wm$^{-2}$ higher). The greatest sensitivity within the model simulations to the addition of karst was noted within non-frontal forced events or during time periods of clear weather. This influence is greatly decreased during the passage of a frontal system through the region, which is noted in previous work associated with the weather events chosen for this study (Leeper et al. 2011). Precipitation within these case studies did display sensitivity to the inclusion of karst within the model. The BARREN_K runs indicated better spatial agreement of model precipitation to observed radar composite data within case 1, 2, and 3 (UCAR 2014). This response with the barren simulation indicates that the inclusion of karst does display a stronger sensitivity, and thus may improve model estimates in the realm of precipitation forecasting.

Overall, karst landscapes displayed the potential influence on certain weather phenomena, winds and precipitation, at a more mesoscale level. This influence may induce local circulations within these locations, which may impact local precipitation development at a small scale. This research only took into account the influence karst landscapes exhibit on temperature, winds, energy fluxes, and precipitation. Future work would benefit from the addition of more variables, such as dew point and evaporation, to
determine further the influence these locations display on atmospheric phenomena. Additional field-based observations/data would also be of use when determining karst parameters, as this would aid in strengthening the understanding of the nature of karst landscapes and how best to develop the most realistic representation of these regions within an operational forecasting model. This study also used primarily summer precipitation events, as this time period is best suited for more non-frontally forced convective precipitation to form within the study area. The use of other meteorological events, such as during spring or fall, would provide additional information on the seasonal influence these regions have on the atmosphere. Finally, the use of other karst landscapes, such as evaporate or eogenetic (younger) karst regions, would provide new details on behavior similarities and differences between different karst regions and their influence on atmospheric processes.
References


Quintanar, A., Mahmood, R., 2012. Ensemble forecast spread induced by soil moisture changes over Mid-South and neighboring Mid-Western region of the USA. *Tellus A: Dynamic Meteorology and Oceanography* 64(1): DOI: 10.3402/tellusa.v64i0.17156.


