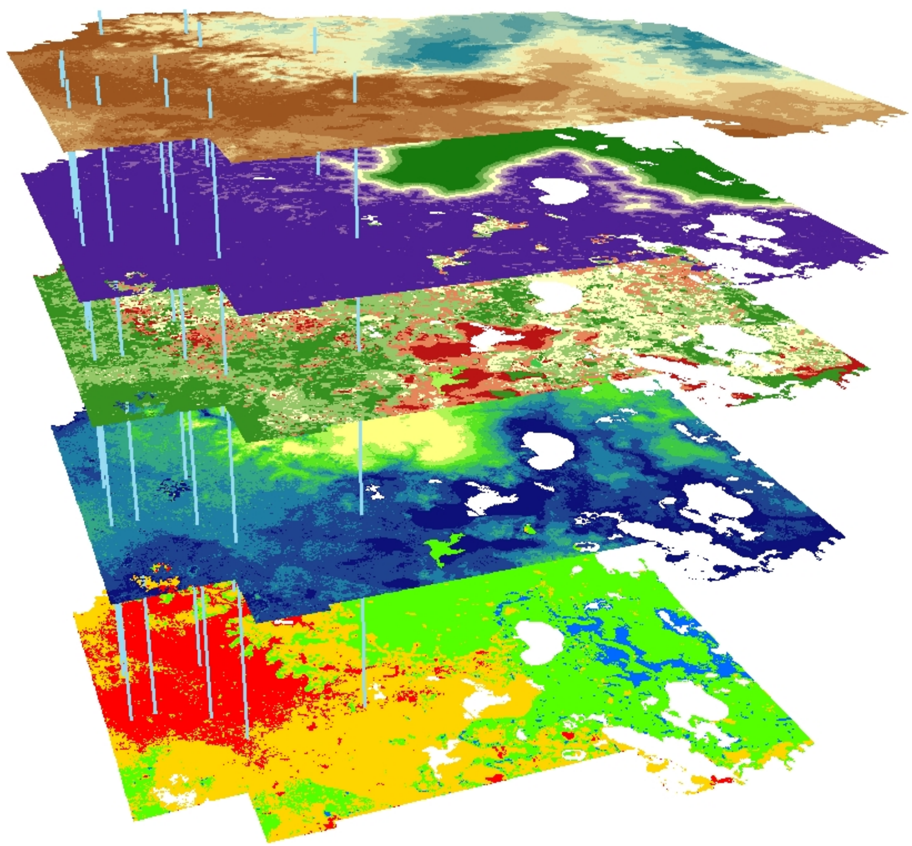
ALACHUA COUNTY AQUIFER VULNERABILITY ASSESSMENT



Report Submitted to the Alachua County Planning & Development Office

By the Florida Geological Survey of the Florida Department of Environmental Protection

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INTRODUCTION

The Florida Geological Survey (FGS) has conducted a comprehensive and detailed vulnerability analysis of the Floridan Aquifer System (FAS) in Alachua County using the methodologies developed for the statewide Florida Aquifer Vulnerability Assessment (FAVA). This analysis is more refined than the statewide model due to the higher resolution of data involved. The modeling technique used in the statewide FAVA model, Weights of Evidence (WofE), is summarized below. For a more thorough explanation of this method refer to FGS Bulletin 67, *Florida Aquifer Vulnerability Assessment: Contamination potential of Florida's principal aquifer systems* (Arthur et al., 2005, in preparation). Though both FAVA and the Alachua County aquifer vulnerability analysis (ACAVA) models were developed using the same methodology, considerably different data sets were used for input, because more detailed and comprehensive data were available for Alachua County as compared to complete statewide datasets. As a result, it is not possible to directly compare output from the two models. Results of the ACAVA model are a unique output based solely on the input data used in this analysis. On the other hand, FAVA FAS results serve as a baseline level of vulnerability that is normalized across the State. While not a recharge map, ACAVA may be used as a proxy for relative recharge in Alachua County.

WEIGHTS OF EVIDENCE

Use of WofE requires the combination of diverse spatial data which are used to describe and analyze interactions and generate predictive models (Raines et al., 2000). When applied in the ACAVA project, WofE was used to generate maps of aquifer vulnerability, or response themes. These response themes were generated in the Environmental Systems Research Institute ArcView 3.2 environment. WofE was executed using the Arc Spatial Data Modeler extension which is available as an internet download (Kemp, et al., 2001).

A primary benefit of applying WofE to the ACAVA project is that it is data-driven, rather than expert-driven. The data that "train" the model consist of known occurrences of parameters (water quality analytes) that reflect relative aquifer vulnerability, such as high levels of dissolved nitrogen in ground-water wells. These wells are the training points used to calculate weights for laterally continuous input data layers, or evidential themes, which are then combined to yield a response theme (Raines, 1999).

When reviewing the model results, it is important to note that all aquifers, to some degree, are vulnerable to contamination from land surface. The model results simply identify those areas within the study area that are more vulnerable or less vulnerable based on the evidential themes and training points used in the model. So, the vulnerable areas are assigned values <u>relative</u> to each other within the study area. These relative values would not be directly transferable or correlated to another study area.

Study Area

The initial step in the development of the ACAVA model was the delineation of a study area, which corresponded to the political boundaries of Alachua County. The study area, composed of 30 square meter (m^2) grid cells, was used in the calculation of weights and probabilities throughout the modeling process (Figure 1).

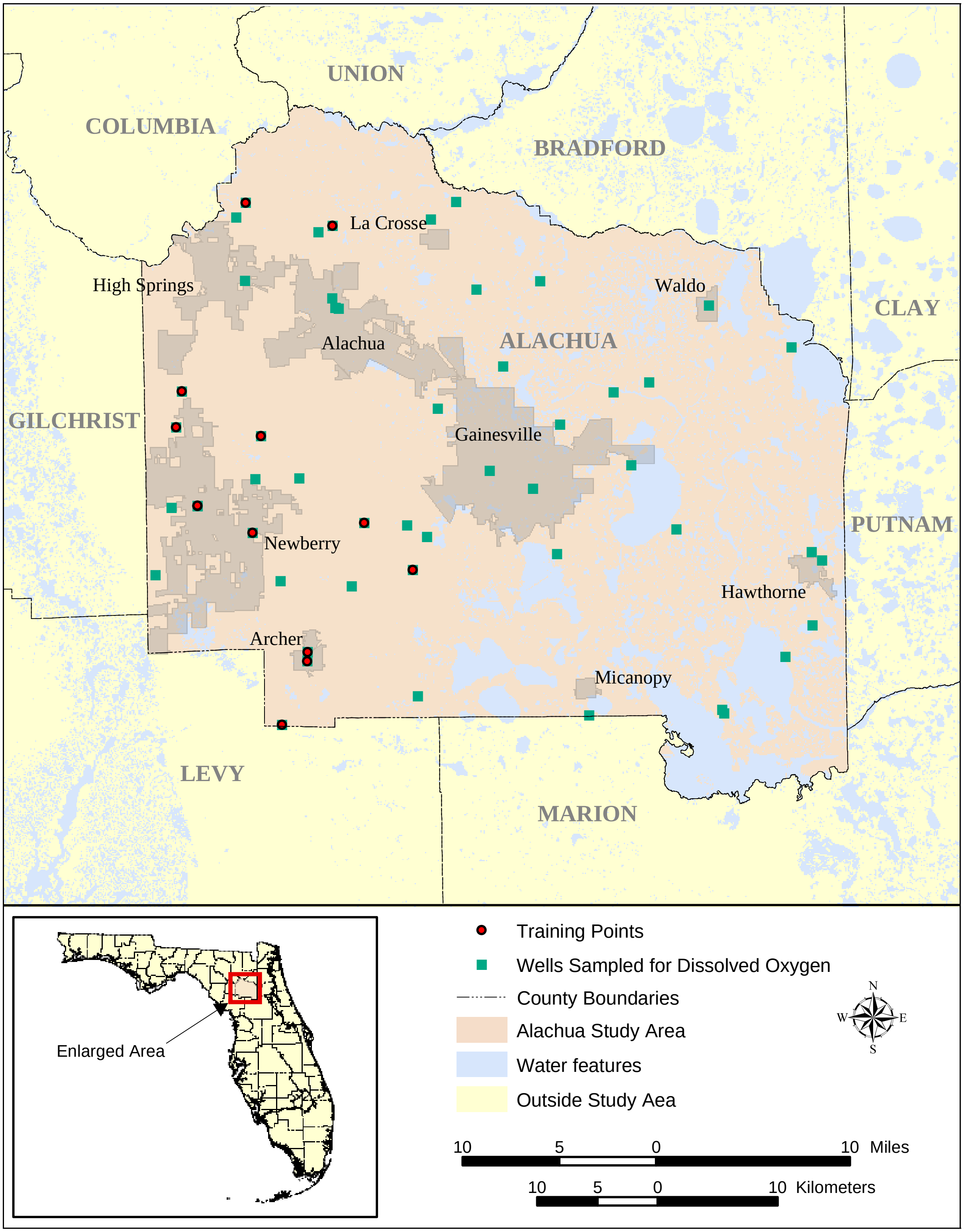

Figure 1. Extent of the ACAVA study area and training point set developed based on measured dissolved oxygen. Large water bodies have been omitted from the analysis to avoid biasing the model.

Large water bodies were omitted from the model because a well would never be drilled in these areas; as a result, they would never contain a training point. Additionally, if lakes were left in the model, the surface area was increased with no chance of increasing the number of training points. This would unnecessarily bias the model. Further, large water bodies typically have no soils or other input data associated with them, thus the model output omits these areas due to lack of data or potential bias in the calculated probabilities. The ACAVA project was designed to focus on the probability for a contaminant to travel through soils, aquifer system overburden, karst features, etc. to enter into the aquifer system. As a result, it is very important that the ACAVA model never be applied to assess contamination of surface waters or discharge areas.

Training Points – Model Input

Training points are locations of known measured occurrences. In an aquifer vulnerability assessment, wells with water quality indicative of high recharge are potential known occurrences (i.e., areas where a good connection exists between the top of the aquifer and land surface). Training points are used in WofE to calculate the following parameters: prior probability, weights for each evidential theme, and posterior probability of the response theme (see *Glossary* for an explanation of these terms).

The water-quality parameters selected for the ACAVA training data set included oxygen and nitrogen. Background levels of oxygen and nitrogen in the FAS are typically low where the aquifer system is not affected by activities at land surface. Therefore, where dissolved oxygen and $NO_3^- + NO_2^-$ dissolved as N (hereafter, referred to as dissolved nitrogen) occur at concentrations above background levels in an aquifer system, it can generally be assumed a relatively greater hydrologic connection exists between land-surface activities and ground water. Dissolved oxygen analytical values served as the training point set for the ACAVA model. Dissolved nitrogen analytical values were used to validate the results for the ACAVA model.

In the ACAVA study area, there were a total of 52 wells in the FDEP Background Water Quality Monitoring Network and the FDEP STATUS network that were completed only in the FAS (i.e., open-hole portion of well that is open only to the FAS) and measured for dissolved oxygen. Using statistical methods described in Arthur et al. (2005, in preparation), no wells were identified as statistical outliers and therefore none were removed from the dataset leaving all 52 wells for additional analysis. Further statistical analysis returned a 75th percentile median value for dissolved oxygen concentration of 4.8 mg/L. There were 13 wells occurring in the dataset with a measured median dissolved oxygen value greater than 4.8 mg/L, and these wells were used to create the training point theme for input into the ACAVA model.

The chance that a training point will occupy any given unit area within the study area, independent of any evidential theme data, is known as prior probability. The prior probability is the ratio of the number of training points (each representing 1 km^2 in area) to the total study area (in km^2). The prior probability for the ACAVA was calculated at 0.0051 and is a unitless value. The distribution of the wells meeting training point criteria are displayed in Figure 1.

Evidential Themes – Model Input

Several evidential themes were considered for use in the ACAVA model due to their potential influence on ground-water quality:

- Thickness of overburden on the FAS
- Effective karst features
- Soil bulk density
- Soil drainage
- Soil permeability
- Hydraulic head difference between water table and FAS
- Vertical leakage rate to and from the FAS

Soil drainage and soil bulk density were ultimately not used as an evidential theme in the ACAVA model for the following important reasons. First, there were areas mapped as "poor" or "very poor" soil drainage, whereas soil permeability for the same areas was listed as extremely high (e.g., 20 in/hr), such as in swamps underlain by coarse, sandy soils. Though the soils are considered permeable, water remains at or near the surface due to a high water table, thus characterizing the drainage as poor. Second, there were occurrences where soil drainage for a specific area was listed as "excessively drained," whereas the soil permeability was listed as very low (e.g., 1.8 in/hr) for the same area, such as on a hilltop underlain by clay-rich soils. Soil bulk density was originally considered to represent soils in the ACAVA model as weights calculated using bulk density were excellent predictors of vulnerable areas. However, bulk density is actually a measure of a soil's porosity and may not reflect how well a soil transmits water. Therefore, soil permeability was selected to represent that component of the hydrogeologic system characterized in the ACAVA model.

Vertical leakage rate to and from the FAS ultimately was not used because it was based on model simulations with a grid cell size of 1,000 meters, which was too coarse for this project; further there was large variability in the calculated leakage rate between adjacent grid cells. Weights were calculated for each of the other four evidential themes and generalized as discussed below.

Generalization of Evidential Themes

Evidential themes were generalized in an effort to assess which areas of the evidence shared a greater association with locations of training points. During calculation of weights for each evidential theme used in the ACAVA project, a contrast value was calculated for each class of the theme by combining the positive and negative weights (positive weight – negative weight). Contrast is a measure of a theme's significance in predicting the location of training points and helps to determine the threshold or thresholds that maximize the spatial association between the evidential theme map pattern and the training point theme pattern (Bonham-Carter, 1994).

Confidence of the evidential theme equals the contrast divided by the standard deviation (a student T test) for a given evidential theme and provides a useful measure of significance of the contrast due to the uncertainties of the weights and areas of possible missing data (Raines, 1999). A confidence value of 1.282 corresponds to a 90% level of significance (see Table 1), which was the value selected as the minimum acceptable confidence level for the ACAVA project evidential themes. Confidence values approximately correspond to the statistical levels of significance listed in Table 1.

Table 1. Test values calculated in WofE and their respective studentized T values expressed as level of significance in percentages.

Studentized T Value (confidence expressed as level of significance)	Test Value
99.5%	2.576
99%	2.326
97.5%	1.960
95%	1.645
90%	1.282
80%	0.842
75%	0.674
70%	0.542
60%	0.253

Contrast values were used to determine where to sub-divide evidential themes into generalized categories. The most common method of categorizing an ordered evidential theme was to select the maximum contrast as a threshold value to create a binary generalized evidential theme. In some WofE models, categorization of more than two classes may be justified (Arthur et al., 2005, in preparation). For evidential themes used for the ACAVA project, this binary break was typically defined by the WofE analysis thereby creating two spatial categories: one with stronger association with the training point theme and one with weaker association with the training point theme.

Thickness of Overburden on the FAS

Sediments overlying the FAS in Alachua County form an important protective layer with respect to contamination potential. Overburden materials include undifferentiated Plio-Pleistocene sediments, and sediments of the Miocene Coosawhatchie Formation of the Hawthorn Group. To calculate the thickness of sediments overlying the FAS, a grid representing the surface of the FAS was subtracted from the LIDAR (light detection and ranging) data obtained from Alachua County. The resulting thickness of the overburden ranged from thin to absent in the southwestern part of the county to over 200 feet in the northeastern area (Figure 2).

Areas underlain by thinner overburden sediments are normally associated with higher aquifer vulnerability. Weights were therefore calculated for the FAS overburden evidential theme using the cumulative ascending method (see *Glossary*). The highest contrast of any class was calculated at a thickness of 52 feet which allowed the creation of a binary generalized theme for input into the ACAVA model (Figure 3). In other words, the analysis indicated that this threshold of overburden thickness maximized the spatial association between the map pattern and the training point pattern.

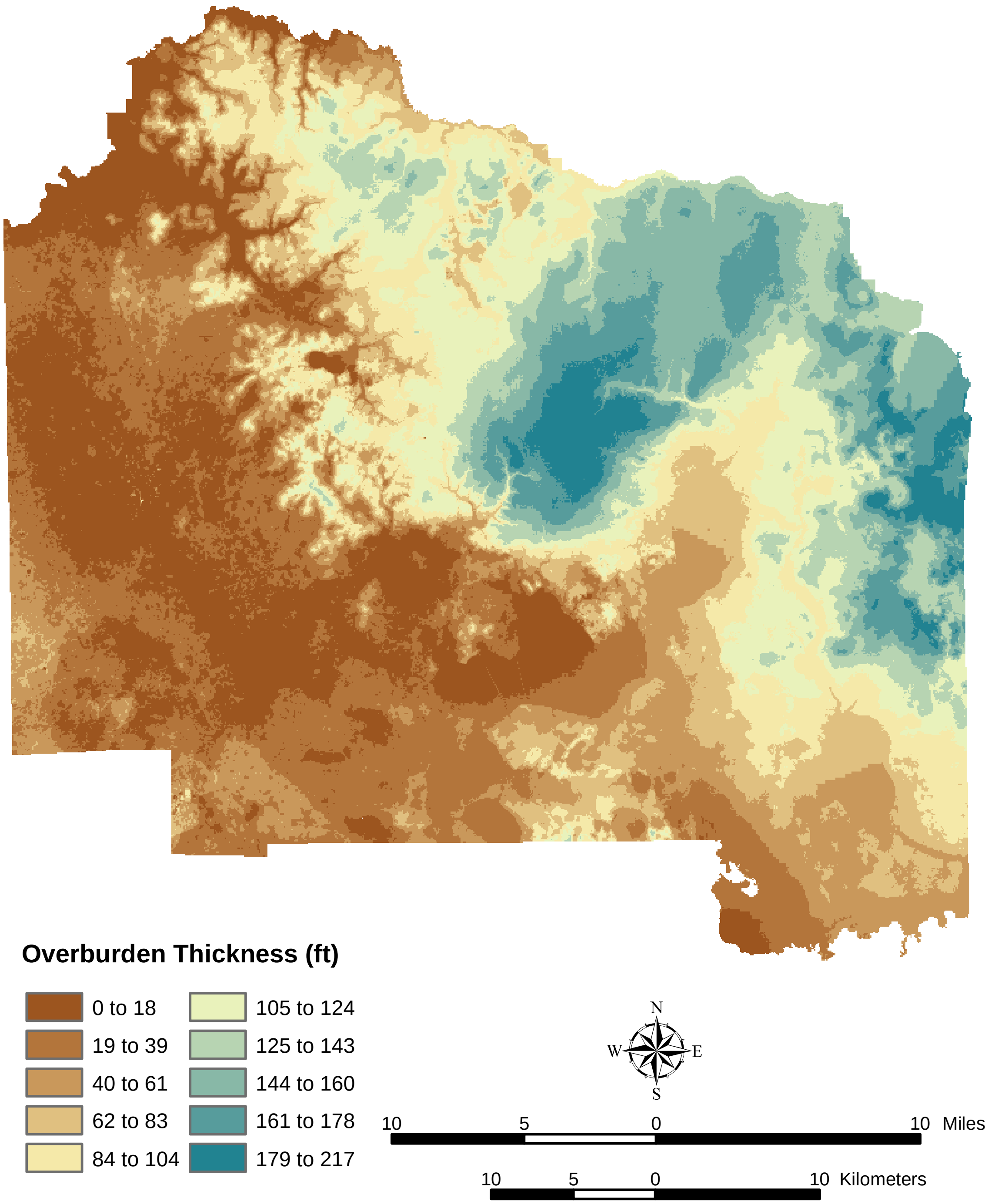

Figure 2. Thickness of FAS overburden in feet.

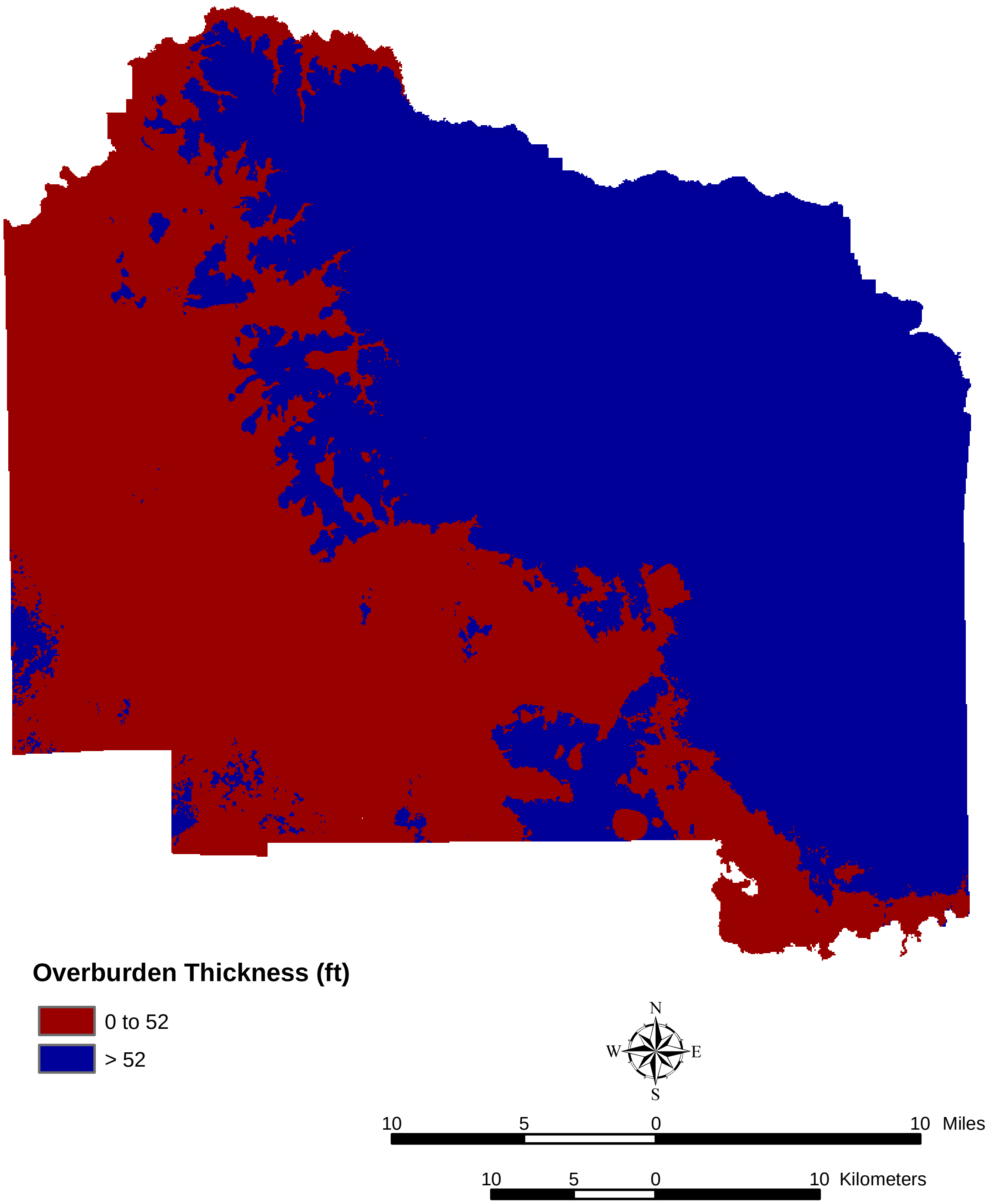

Figure 3. Map showing binary generalization of the FAS overburden thickness evidential theme. Based on calculated weights, a binary generalization with a break at a value of 52 ft was defined by the analysis. Based on the location of training points, dark blue areas were associated with areas of lower vulnerability, while red areas were associated with areas of higher vulnerability.

Buffered Effective Karst Features

To develop an appropriate representation of karst features in the ACAVA model, an effective karst data layer was created based on sinks identified in the LIDAR data and thickness of FAS overburden data coverage. The LIDAR data was processed and evaluated to locate all sink features in the data. A filter was used to remove anomalously small and linear features such as ditches along roadways and sinks smaller than 100 m^2. Further filtering was used to remove depressions underlain by more than 100 feet of FAS overburden. The 100-ft threshold of overburden thickness was used to identify karst-prone areas by Cichon et al. (2004) and Wright (1974). Though the location of training points was not used to select this filter threshold, the lack of their occurrence in areas underlain by more than 100 feet of overburden thickness lends support to the use of this filter. This calculation provided an effective karst evidential theme for use in the model (Figure 4).

Areas nearer to an effective karst feature are normally associated with higher aquifer vulnerability due to the increased chance of overland flow and infiltration into the depression. Therefore, a buffer zone of 3,000 m divided into 30-m intervals was generated around each karst feature, and weights were calculated for the effective karst feature evidential theme using the cumulative ascending method. The highest contrast of any class was calculated at a distance of 120 m from a depression creating a binary generalized theme for input into the ACAVA model. In other words, the analysis indicated that this threshold of proximity to karst maximized the spatial association between the map pattern and the training point pattern. The generalized theme is displayed in Figure 5.

Soil Permeability

As defined by the USDA (1951), "soil permeability is that quality of the soil that enables it to transmit water or air. Soil permeability values were obtained from the Soil Survey Geographic database (SSURGO), through both the Florida Geographic Data Library (2003) and United States Department of Agriculture, Natural Resource Conservation Service (2003) websites. This database was mapped at a scale of 1:24000 and contained the most detailed soil permeability data. The development of this layer included the calculation of weighted average soil permeability values for each soil horizon layer expressed in inches per hour (in/hr). Then, based on soil horizon thicknesses, weighted-average permeability values were calculated for the entire soil column. This allowed for the generation of a data coverage of soils containing a single permeability value per soil type polygon (Figure 6).

Areas with high soil permeability values are normally associated with higher aquifer vulnerability. Weights were calculated for soil permeability using the cumulative descending method. The highest contrast of any class was calculated at 9.9 inches per hour (in/hr). Therefore, as indicated by the analysis, the most appropriate break in the soil permeability evidential theme was at 9.9 in/hr (Figure 7), which yielded a binary generalized theme for input into the ACAVA model. This contrast break indicated that values exceeding 9.9 in/hr were strongly correlated with aquifer vulnerability as defined by the training point data, whereas values lower than 9.9 in/hr were less significant with respect to vulnerability. The generalized theme is displayed in Figure 7.

Hydraulic Head Difference between Water-Table Surface and FAS

Hydraulic head difference was calculated by subtracting the FAS 1993-1994 potentiometric surface (Sepulveda, 2002) from the water-table surface (Arthur et al., 2005, in preparation). Areas with a positive hydraulic head difference value indicated that the FAS is receiving recharge, whereas areas with a negative value indicated the FAS is discharging to the overlying aquifer system (Figure 8).

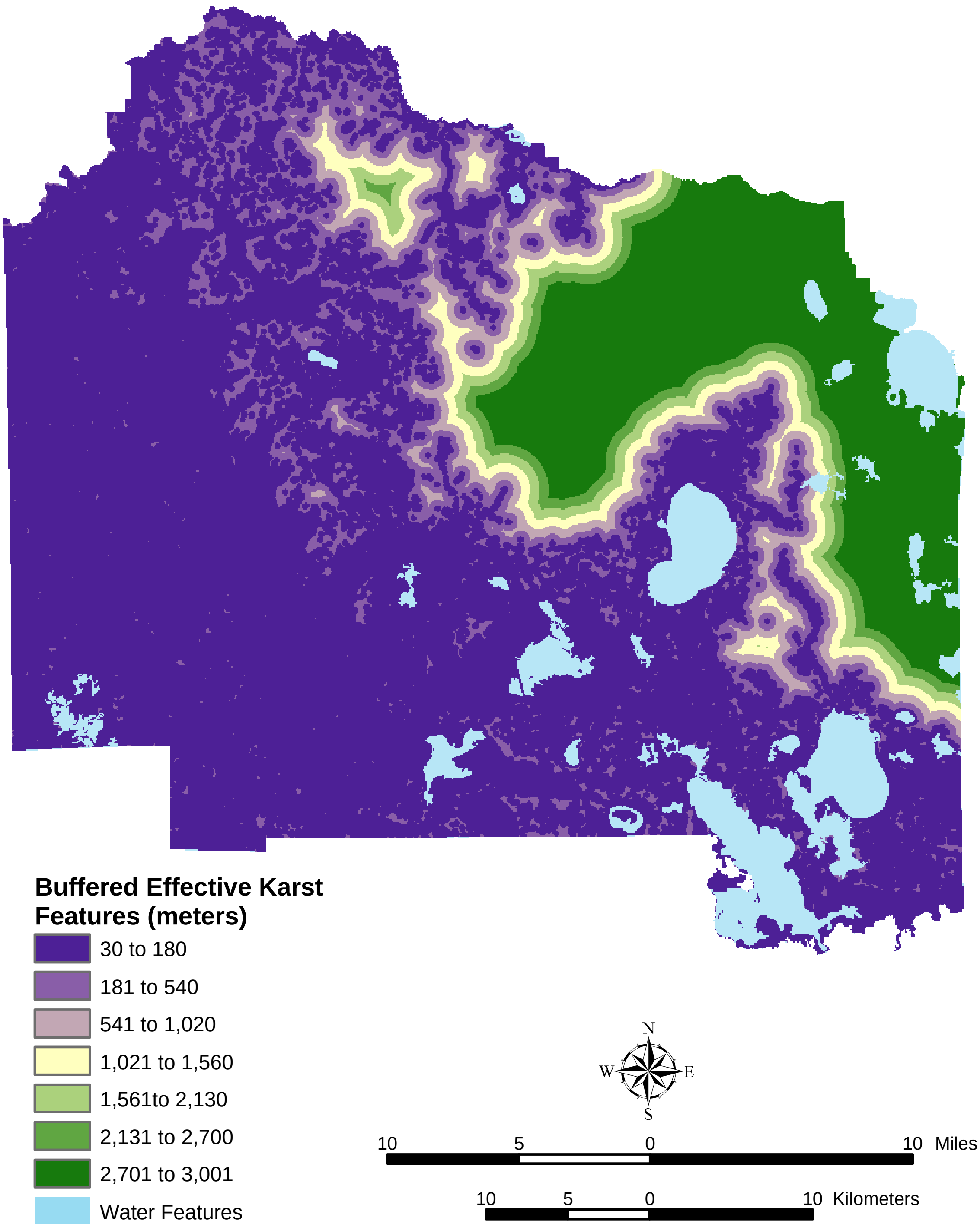

Figure 4. Buffered effective karst features as identified by extracting sinks from Alachua County LIDAR data.

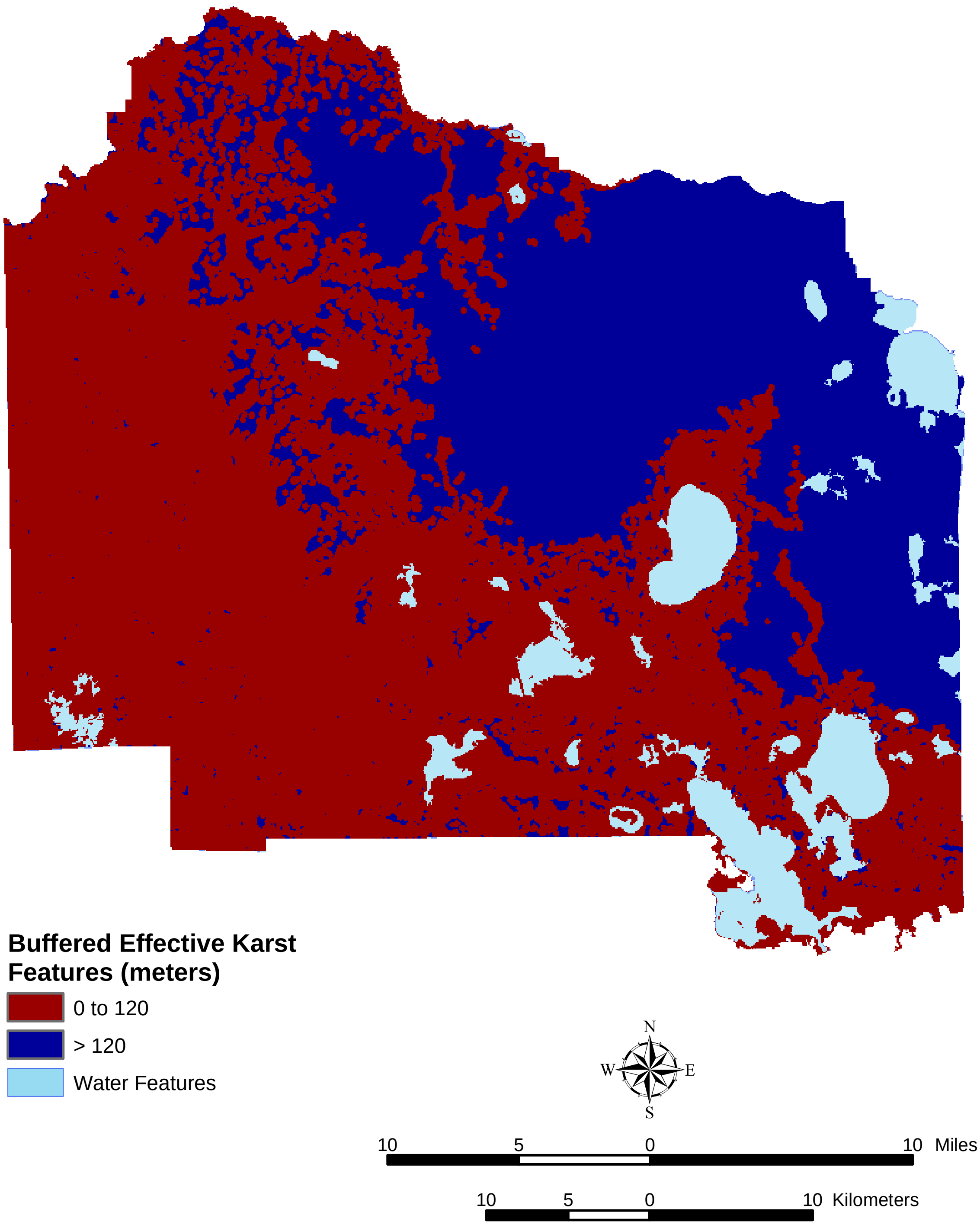

Figure 5. Map showing binary generalization of the buffered effective karst features evidential theme. Based on calculated weights, a binary generalization with a break at a distance of 120 m was defined by the analysis. Based on the location of training points, dark blue areas were associated with areas of lower vulnerability, while red areas were associated with areas of higher vulnerability.

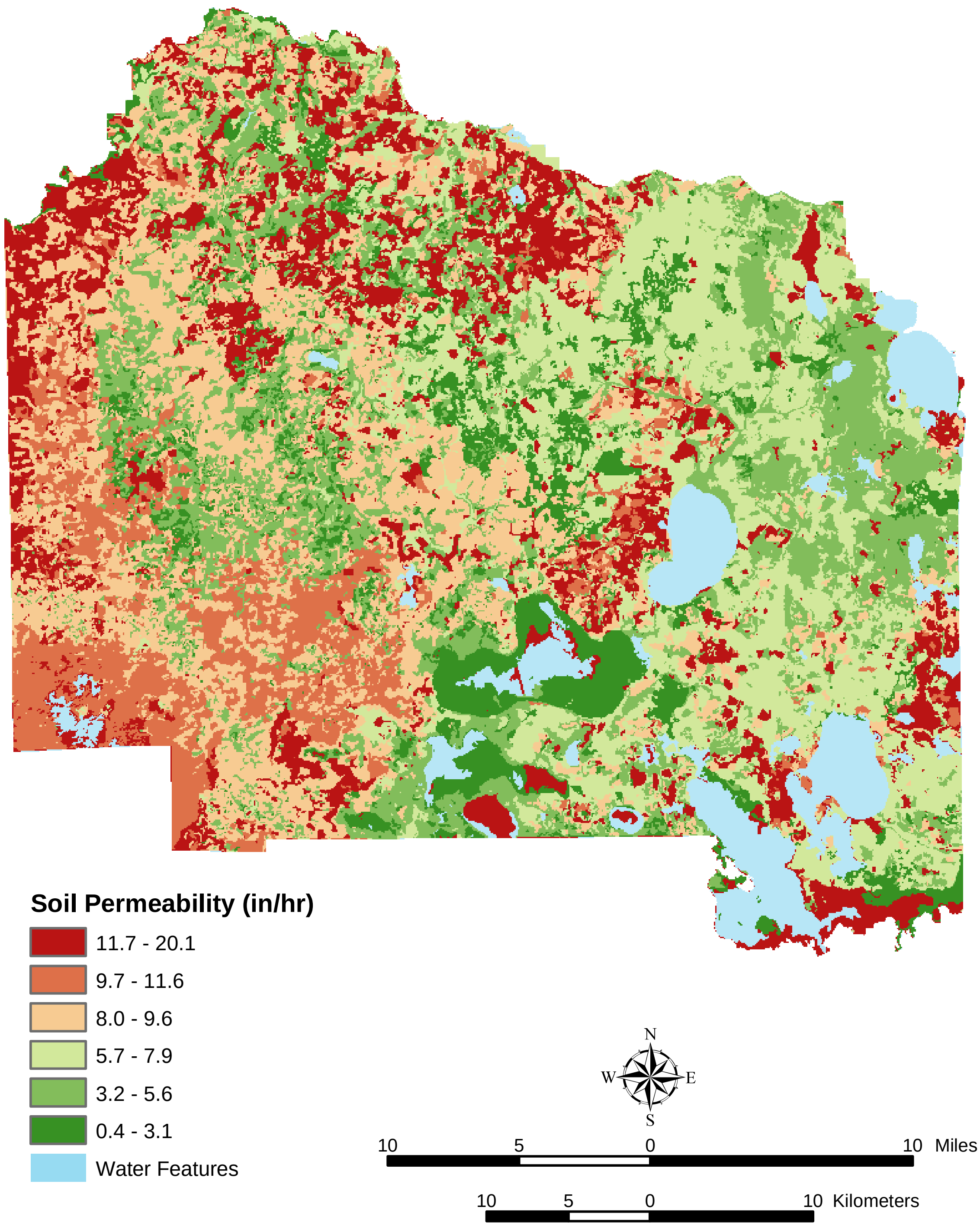

Figure 6. Soil permeability (weighted average) map of the ACAVA study area (FGDL, 2003).

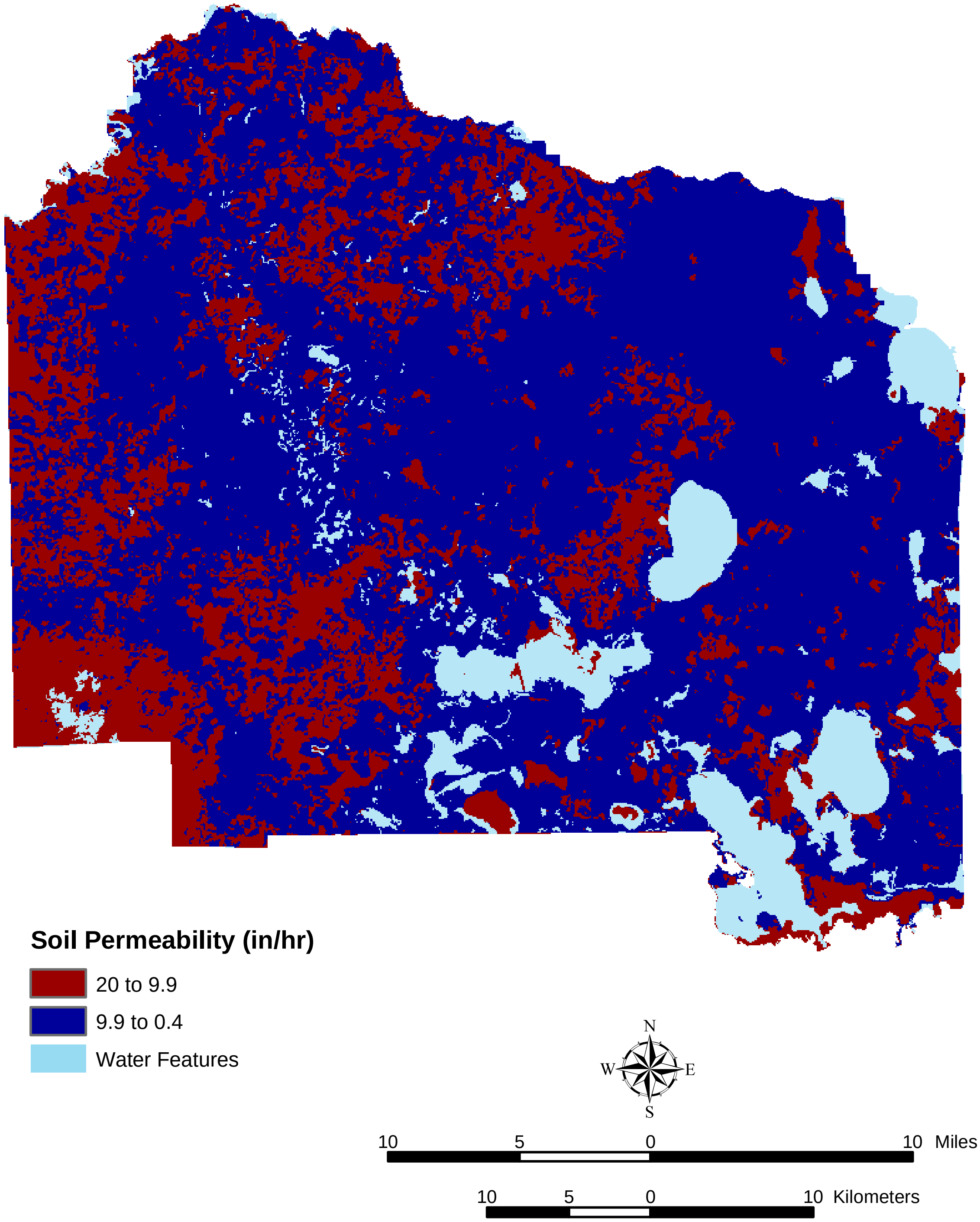

Figure 7. Map showing binary generalization of the soil permeability evidential theme. Based on calculated weights, a binary generalization with a break at a distance of 9.9 in/hr was defined by the analysis. Based on the location of training points, dark blue areas were associated with areas of lower vulnerability, while red areas were associated with areas of higher vulnerability.

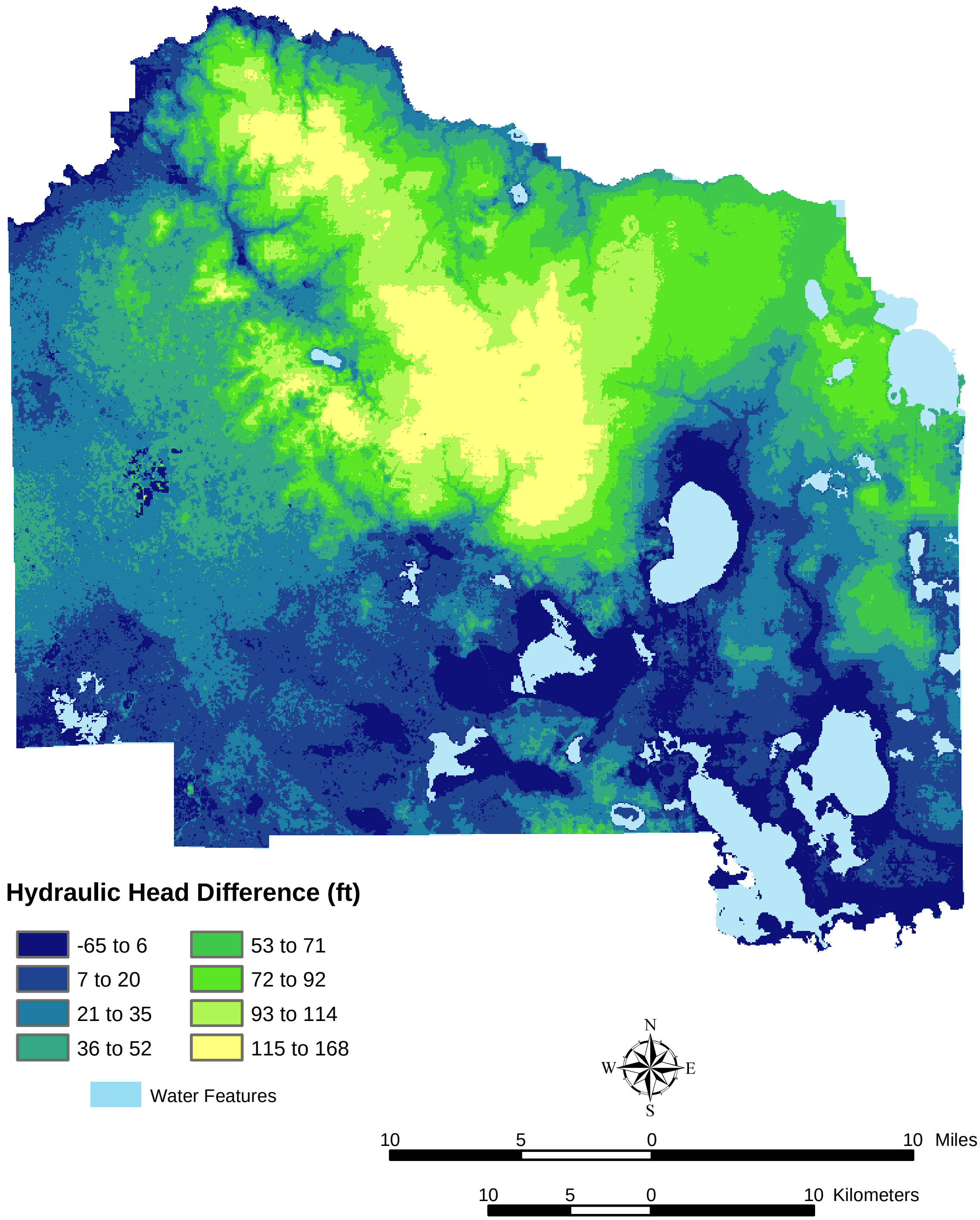

Figure 8. Hydraulic head difference between the water table surface (Arthur et al., 2005, in preparation) and the FAS potentiometric surface (Sepulveda, 2002).

Areas of greater hydraulic head difference between the water table and FAS indicate greater potential for downward recharge to the FAS, which is normally associated with higher aquifer vulnerability. Weights were therefore calculated for the hydraulic head difference evidential theme using the cumulative descending method (see *Glossary*). The highest contrast of any class was calculated at a hydraulic head difference value of 21 feet creating a binary generalized theme for input into the ACAVA model. In other words, the analysis indicated that this threshold of hydraulic head difference maximized the spatial association between the map pattern and the training point pattern. Figure 9 displays the binary generalization used for the hydraulic head difference evidential theme.

Response Theme – Model Results

The ACAVA response theme is an output map, calculated using WofE, showing the probability (posterior probability) that a unit area is vulnerable to contamination from land surface based on the evidence provided. A response theme (see *Glossary*) is portrayed as relative vulnerability and is classified based on the relationship between the cumulative study area and the posterior probability. Assessment of this relationship may allow for the selection of several classes of posterior probability. Most vulnerable areas correspond with highest posterior probabilities, while least vulnerable areas are associated with lowest posterior probabilities. In essence, a higher posterior probability indicates that an area is more likely to contain a training point, or more likely to be contaminated, and therefore more vulnerable to contamination from land surface.

As identified in the introduction, the ACAVA model is based on the WofE modeling technique used in the FAVA project. In the FAVA project, aquifer vulnerability was compared over the statewide extent of the FAS and consolidated vulnerability into three classes (more vulnerable, vulnerable and less vulnerable). The FAVA response theme for the FAS in the ACAVA study area (Figure 10) shows that the majority of the study area is located in the *more vulnerable* zone. A smaller part of the study area is located in the *vulnerable* zone and none of the study area is located in the *less vulnerable* zone. Through application of the FAVA modeling technique to the Alachua County area it is possible to identify new degrees of relative vulnerability by using more highly resolved evidential themes. By applying the FAVA model as a baseline for the ACAVA study area, all vulnerability zones should be interpreted in the context of the statewide FAVA results for the FAS. However, because of the use of different model boundaries, different evidential themes, and different training point themes between the two models, it is not possible to compare the FAVA model results for the FAS directly to the ACAVA model.

Using the four evidential themes discussed above, a response theme was generated showing the posterior probability that a unit area contained a training point based on the evidential themes provided. A conceptual model showing the association between the training points and the evidential themes is shown in Figure 11. The posterior probabilities of the response theme ranged from 0.00008 to 0.02250 across the model domain. As noted earlier, the bivariate relation between posterior probability and cumulative area as a percentage (Figure 12) allows the delineation of class breaks representing relative vulnerability zones in the final response theme (Figure 13). The class breaks for these vulnerability zones were selected where a notable stepwise increase in posterior probability relative to the cumulative study area occurred. Three breaks were identified using this method which created four relative vulnerability classes. These classes ranged from *least vulnerable* to *most vulnerable* and are displayed in Figure 13 and in Plate 1. This *most vulnerable* class has the greatest probability of containing a training point and therefore represents the highest vulnerability of the FAS in Alachua County, while the *least vulnerable* class has the lowest probability of containing a training point.

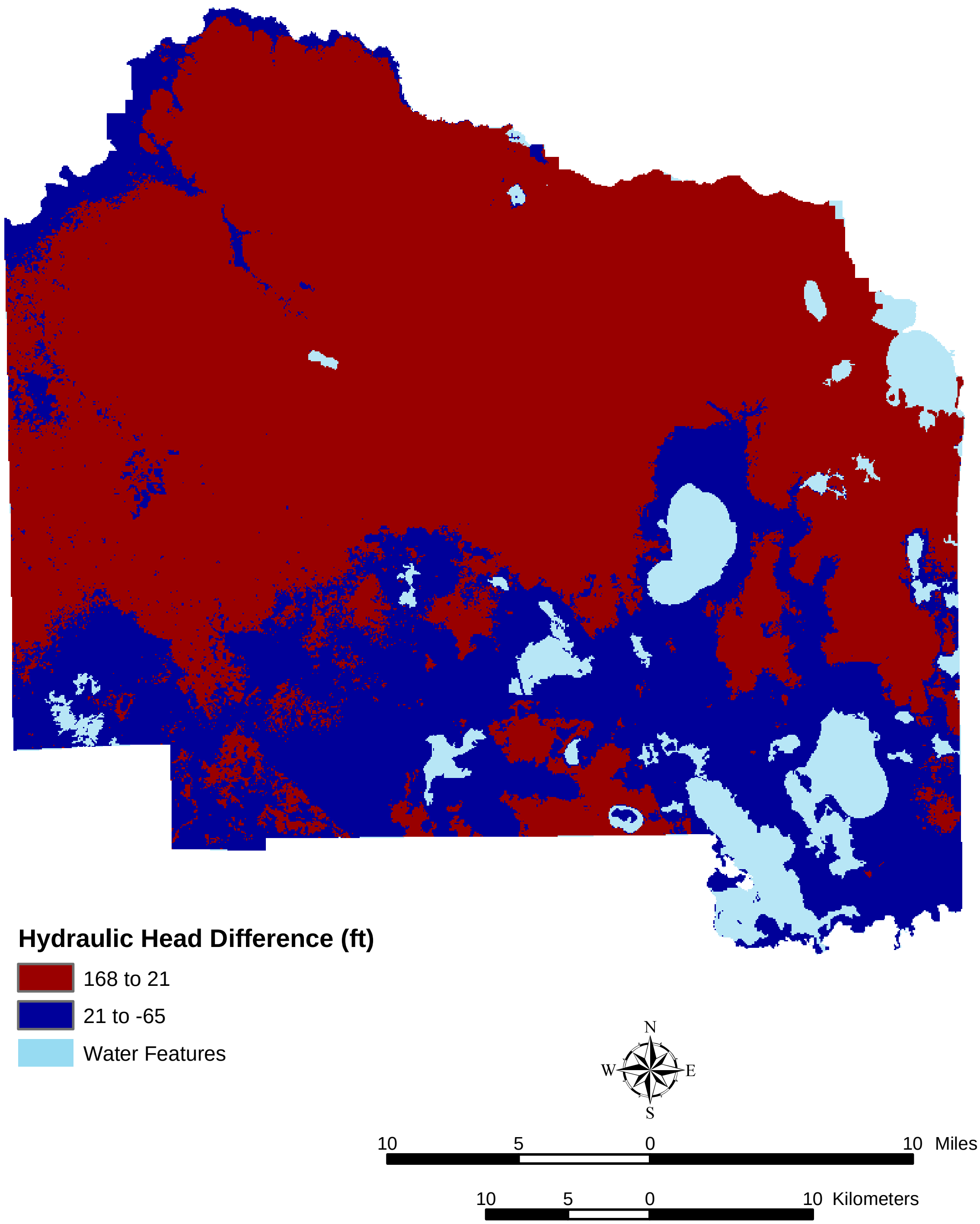

Figure 9. Map showing binary generalization of the hydraulic head difference evidential theme. Based on calculated weights, a binary generalization with a break at a distance of 21 ft was defined by the analysis. Based on the location of training points, dark blue areas were associated with areas of lower vulnerability, while red areas were associated with areas of higher vulnerability.

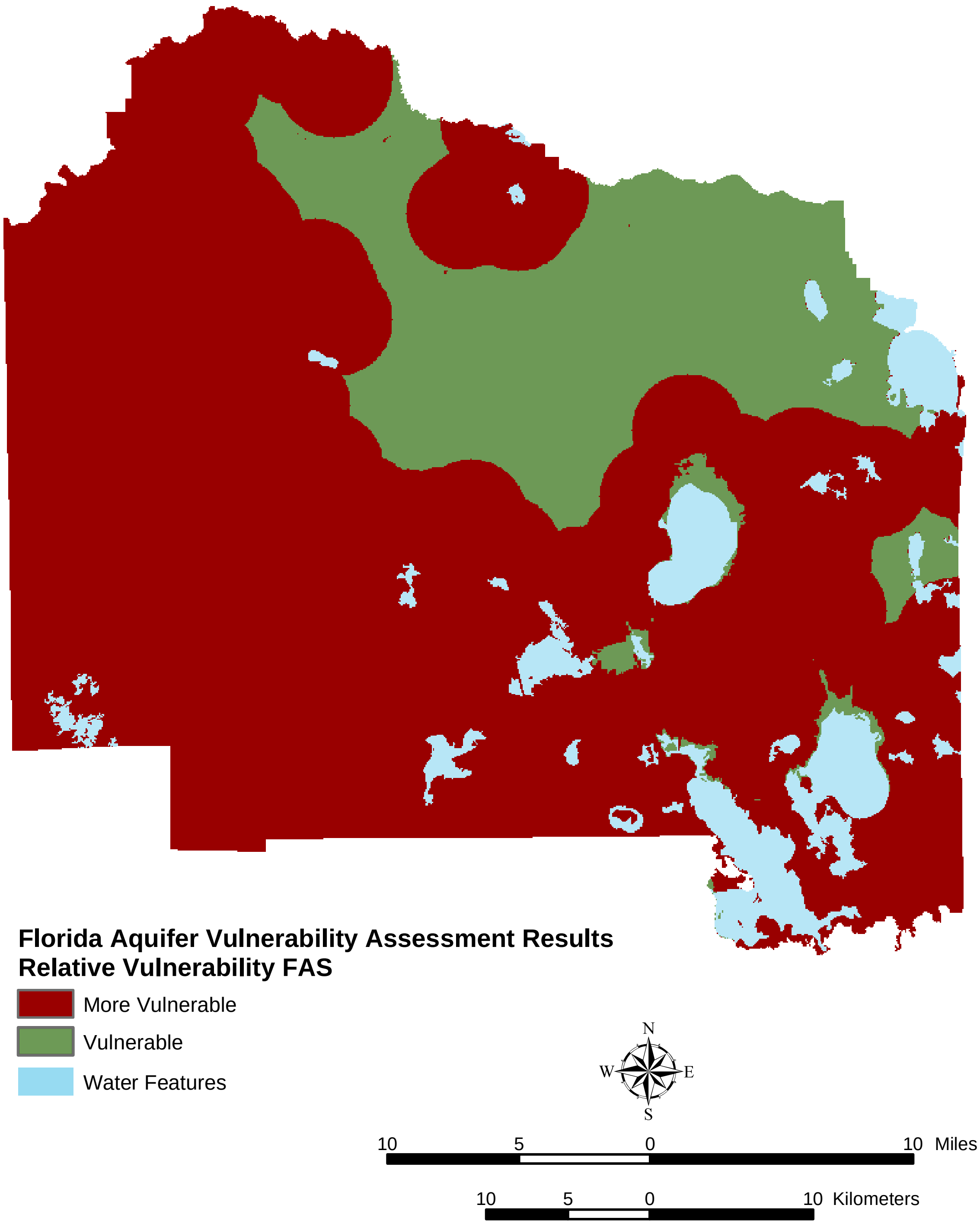

Figure 10. Relative vulnerability of the FAS FAVA model (Arthur et al., 2005, in preparation) showing zones of vulnerability based on the extent of the Floridan Aquifer System. Although a "less vulnerable" category exists in the FAVA model, no part of the Alachua County contained this category.

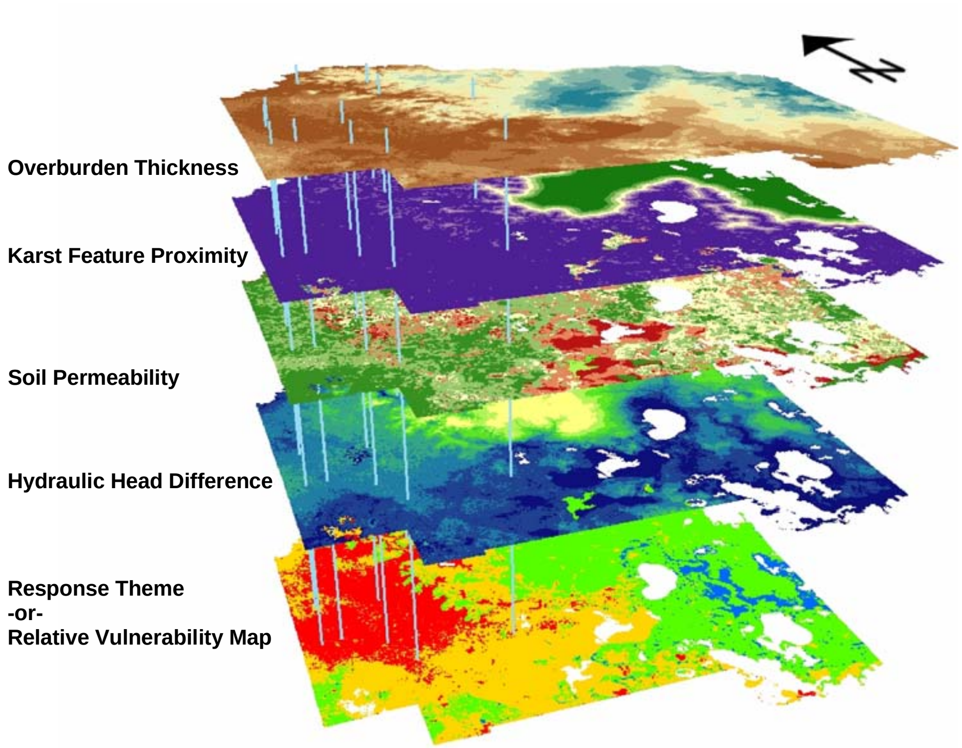

Figure 11. Conceptual model of the FAS in Alachua County. The top four layers are evidential themes and the bottom layer is the response theme. Blue lines are extruded training points.

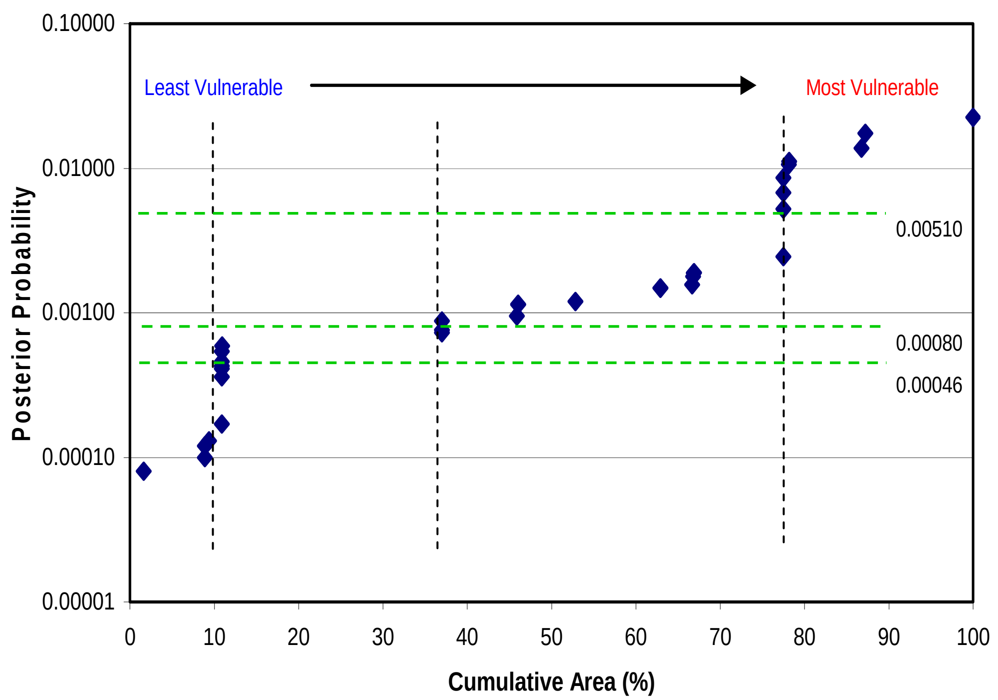

Figure 12. Relative vulnerability class breaks, represented by green dashed lines, were placed where both a significant increase in probability and cumulative area were observed.

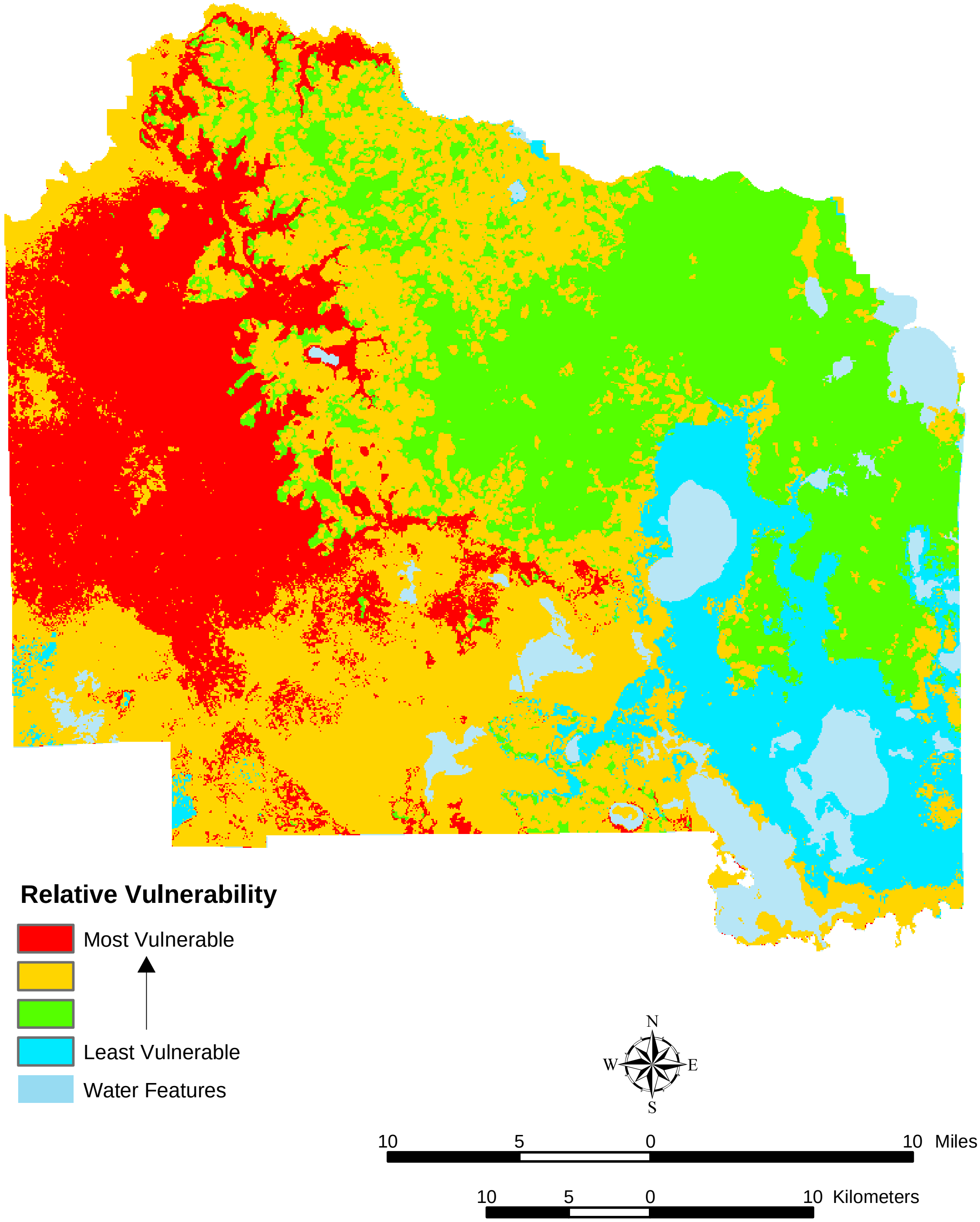

Figure 13. Relative vulnerability of the FAS divided into four zones based on posterior probability values displayed in Figure 12. Total oxygen concentrations were used as a training point theme. See Plate 1 for a more detailed display and discussion of the vulnerability zones.

The response theme indicated that the areas of highest vulnerability (high probabilities) tended to be associated with areas of thin to absent FAS overburden sediments, which are close in proximity to effective karst features, have high positive hydraulic head difference, and have high soil permeability. Conversely, areas of lowest vulnerability (low probabilities) tended to be associated with areas of thick FAS overburden sediments, that are spatially removed from areas influenced by karst, have hydraulic head difference less than 21 feet and have low soil permeability values.

An assumption is made when using WofE that there is conditional independence between the layers used as predictors. Conditional independence is violated when the presence of one evidential theme influences the probability of another evidential theme. The validity of posterior probability values depends upon the degree of conditional independence calculated for the model. Evidential themes are considered independent of each other if the conditional independence value is within the range of 1.00 ± 0.15 (Gary Raines, personal communication, 2003). When conditional independence is violated the model can over predict the vulnerability in some areas. For the ACAVA model, conditional independence was calculated at 0.73, which fell outside the target range of 1.00 ± 0.15 indicating dependence between evidential themes. This was resolved by using the logistic regression option described in Arthur et al. (2005, in preparation).

Logistic regression is an optional function that can be used to account for the inflated probabilities associated with conditional independence issues. Logistic regression is similar to linear regression; however, because the evidence is reduced into binary themes, the response variable can only be divided into two classes, (i.e., presence or absence of training points) whereas linear regression can have continuous values ranging from 0 to 1. WofE model results using logistic regression do not differ greatly from standard WofE model results. The main difference is that the posterior probabilities of a response theme with conditional independence problems are much higher when logistic regression is not used compared to when it is used. Overall, the patterns of the response themes are nearly identical, but use of logistic regression yielded better statistical support of the response theme

Weights calculated for the evidential themes used in the ACAVA model are included in Table 2. This table displays the evidential themes used, weights calculated for those evidential themes, as well as the contrast and confidence of the evidential theme. A positive weight indicates areas where training points are likely to occur, while a negative weight indicates areas where training points are not likely to occur. The contrast column is a combination of the highest and lowest weights (positive weight – negative weight) and is a measure of how well the generalized evidential themes predict training points. A positive contrast that is significant, based on its confidence, suggests that a generalized evidential theme is a useful predictor. The confidence of the evidential theme is the contrast divided by its standard deviation and provides a useful measure of significance of the contrast because of the uncertainties of the weights and areas of missing data (Raines, 1999). Confidence values for each evidential theme exceed 1.282, which approximately corresponds to a 90% level of significance.

The FAS overburden thickness evidential theme had a stronger association with the training points (i.e., highest contrast) than the other evidential themes and was therefore the primary determinant in predicting areas of vulnerability in this model. Effective karst was the second most important theme in predicting aquifer vulnerability. Hydraulic head difference and soil permeability were third and fourth most important, respectively. According to the WofE analysis, all the evidential themes indicated where training points were more likely not to occur because the negative weights (W2) were stronger (had a greater absolute value) than the positive weights (W1). This indicated that response theme was a better predictor of where training points were not likely to occur, than it was of where they were likely to occur. In other words, the model is a better predictor of areas of less vulnerability than it is of areas of higher vulnerability.

Table 2. WofE final output table listing weights calculated for each evidential theme and their associated contrast and confidence values of the evidential themes.

Evidential Theme	W1	W2	Contrast	Confidence
FAS Overburden Thickness	0.7493	-1.9170	2.6663	2.5507
Buffered Effective Karst	0.3672	-1.4773	1.8445	1.7645
Hydraulic Head Difference	0.3000	-1.3483	1.6483	1.5767
Soil Permeability	0.6055	-0.6463	1.2518	2.0391

Confidence Map

There are two types of confidence used on the WofE model. Confidence of the evidential theme, as reported in Table 1 and discussed above in *Generalization of Evidential Themes*, equals the contrast divided by the standard deviation (a student T test) for a given evidential theme (Raines, 1999). The second type of confidence can be calculated for each response theme by dividing the theme's posterior probability by its total uncertainty (standard deviation). A confidence map can be generated based on these calculations.

Areas with a high posterior probability tend to have higher confidence values and therefore have a higher level of certainty with respect to predicting aquifer vulnerability. The confidence map for the ACAVA response theme is displayed in Figure 14. A small population of training points along with missing data raises the total uncertainty for the response theme, which in turn lowers the confidence. A confidence (of posterior probability) map of the response theme can therefore contain a lower level of significance than those calculated for each separate evidential theme.

Sensitivity Analysis and Validation

Sensitivity analysis and validation are a significant component of any modeling project as they allow evaluation of the accuracy of the results. ACAVA model output sensitivity and validation was accomplished by use of a random 75% subset of training points, and use of a different training point set (dissolved nitrogen), respectively.

The kappa coefficient was used to measure the amount of spatial agreement between the ACAVA response theme and the response themes generated during sensitivity analysis and validation, while taking into account agreement that could have occurred by chance. A cross-tabulation matrix was used to classify the response themes by area (in square meters) and aided in the calculation of observed and expected proportions (i.e., agreement). Kappa coefficient results range between -1, indicating perfect disagreement, and 1, indicating perfect agreement. A value of zero would indicate that the agreement was no better than that expected due to chance (Bonham-Carter 1994). The Kappa coefficients calculated in the FAVA project were all positive values. Positive kappa coefficients can be interpreted using Table 3.

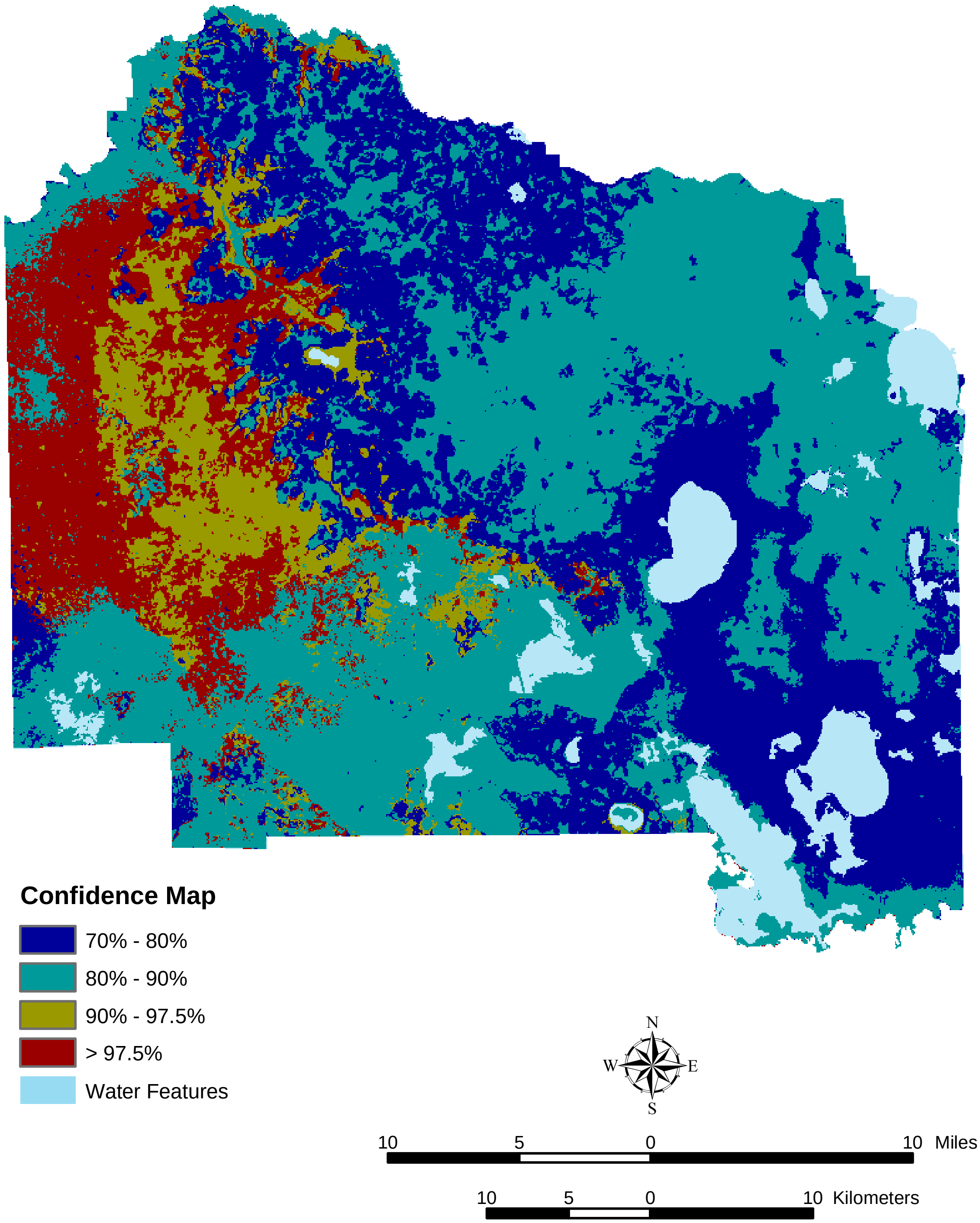

Figure 14. Distribution of confidence values calculated for ACAVA response theme.

Table 3. Kappa coefficient values and their associated interpretation (Landis and Koch, 1977).

Interpretation of kappa values	
Kappa	Interpretation
< 0	No agreement
0.0 – 0.19	Poor agreement
0.20 – 0.39	Fair agreement
0.40 – 0.59	Moderate agreement
0.60 – 0.79	Substantial agreement
0.80 – 1.00	Almost perfect agreement

Random 75% Subset of Training Points

A sensitivity analysis was completed by using a random subset of the original training point theme. This random subset included 75% of the original wells for a total of nine training points and yielded a prior probability of 0.0039. Weights were then recalculated for each evidential theme, class breaks were selected, and a response theme was generated (Figure 15). The pattern of posterior probabilities was nearly identical to the original total dissolved oxygen response theme. The kappa coefficient between the response themes was calculated at 0.8394, indicating almost perfect overall agreement between the response themes.

Using a Different Training Point Theme

Although the ACAVA WofE method, in a sense, pre-validates the model results through the use of water quality data, post-modeling validation was completed as well. The ACAVA model was validated by creating a training point theme based on a parameter that reflects vulnerability yet is independent of oxygen. Based on data availability, dissolved nitrogen was chosen for this validation method. A training point set was developed using the methods described above in *Weights of Evidence – Training Points – Model Input.* This training point set of wells measured for dissolved oxygen consisted of 13 wells and yielded a prior probability of 0.0051. Weights were then recalculated for each evidential theme, class breaks were selected, and a response theme was generated (Figure 16). The pattern of posterior probabilities closely resembles the original response theme. The kappa coefficient between the response themes was calculated at 0.588, indicating a moderate agreement between the two response themes.

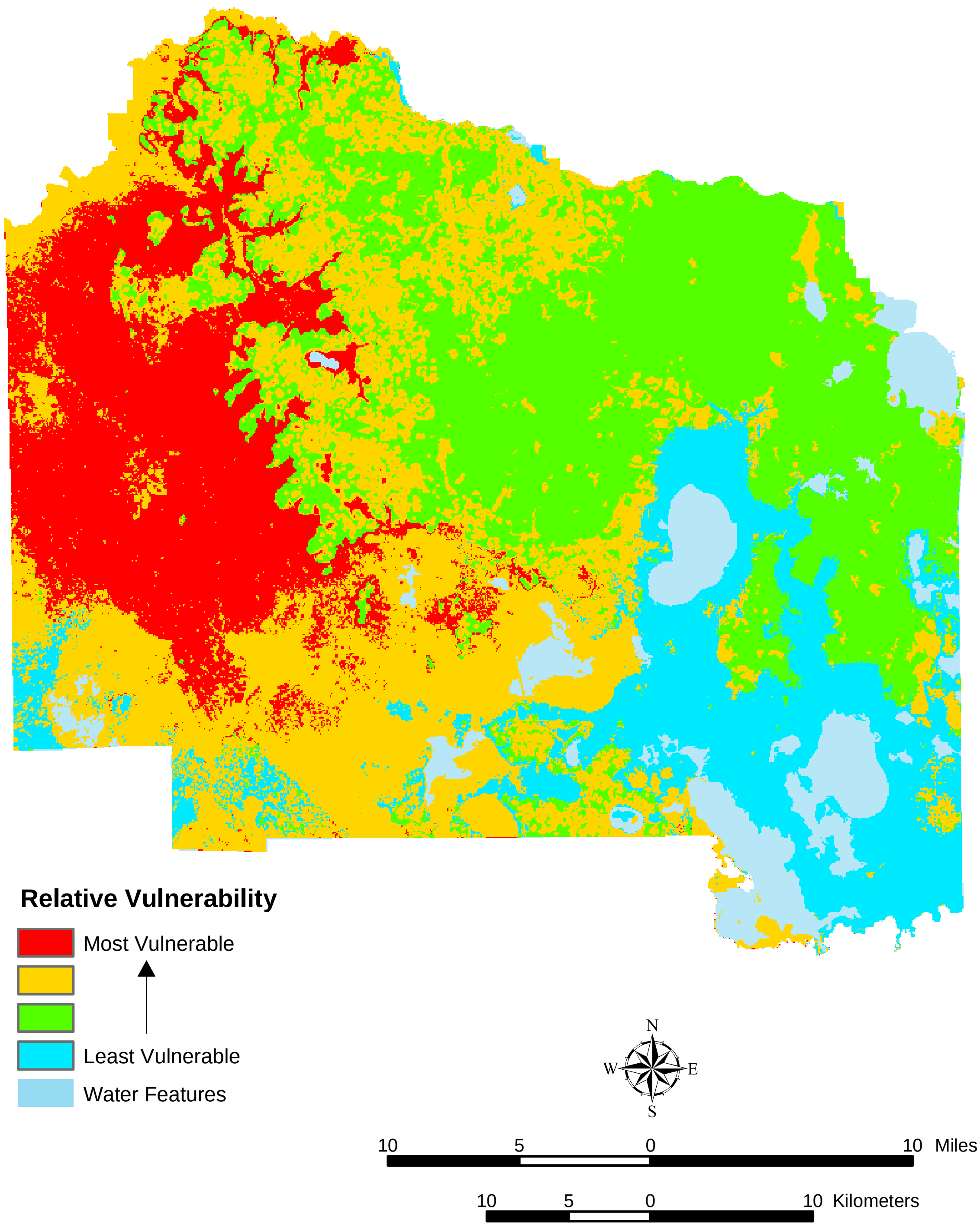

Figure 15. Relative vulnerability of the FAS generated using a random 75% subset of the original dissolved oxygen training point theme.

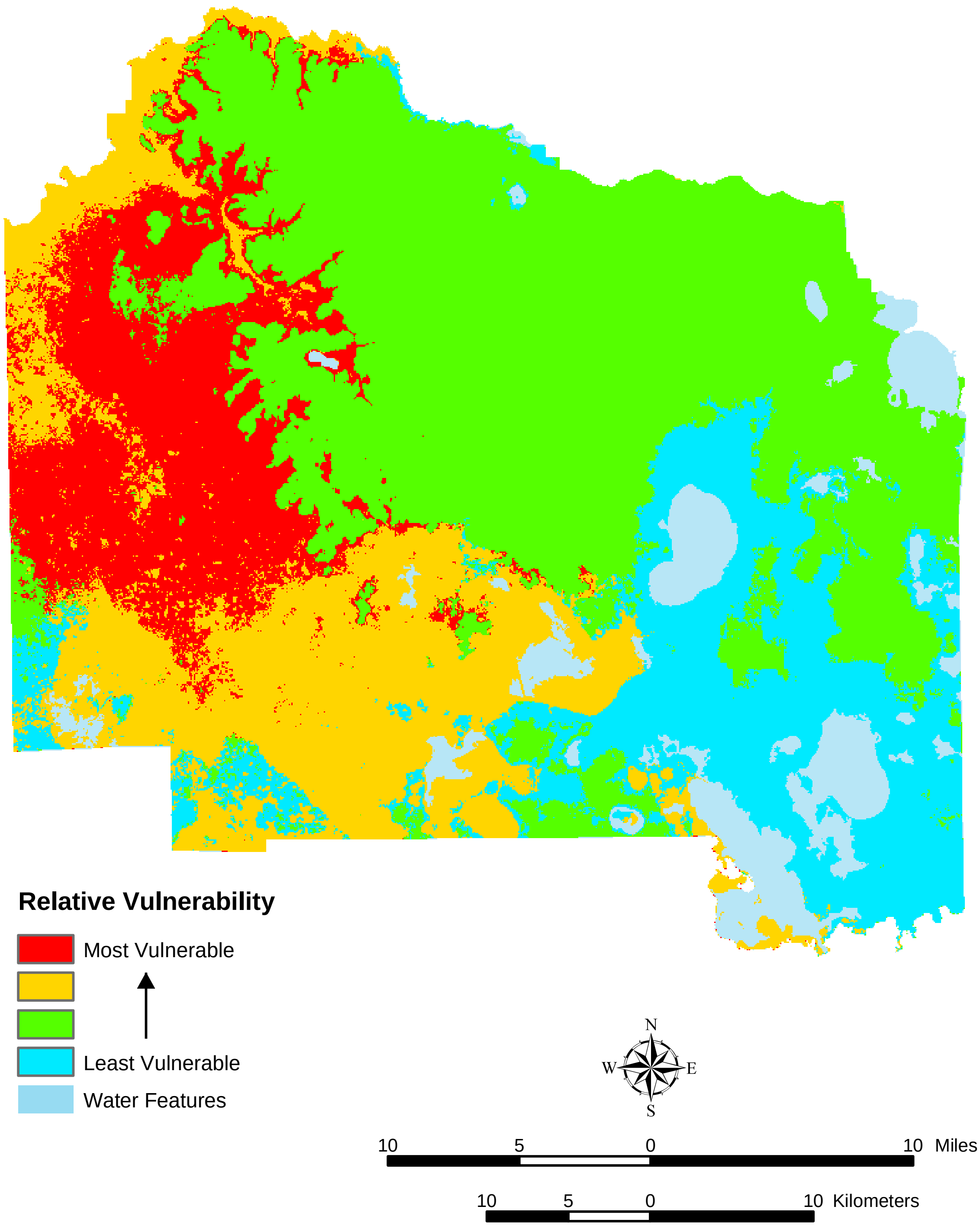

Figure 16. Relative vulnerability of the FAS generated using a dissolved nitrogen training point theme.

DISCLAIMER

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GLOSSARY

Binary – Refers to the generalization or simplification of evidential themes or data layers. Binary layers are reclassified from the original dataset into presence/absence type themes or into two classes.

Conditional Independence – Occurs when an evidential theme does not affect the probability of another evidential theme. Evidential themes are considered independent of each other if the conditional independence value calculated is within the range 1.00 ± 0.15 (Raines, personal communication, 2003). Values that significantly deviate from this range can over inflate the posterior probabilities resulting in unreliable response themes.

Confidence of Evidential Theme – Contrast divided by its estimated standard deviation; provides a useful measure of significance of the contrast.

Confidence of Posterior Probability – A measure based on the ratio of posterior probability to its estimated standard deviation.

Contrast – W+ minus W- (see weights), which is an overall measure of the spatial association (correlation) of an evidential theme with the training points.

Cumulative Ascending – Calculates the cumulative weights from the first class to the last class while increasing the area. Areas nearest a training point have a stronger association, and those farthest away have a weaker association. This method is applicable for themes where the training points are mainly associated with the lower values of the evidential theme (e.g., higher vulnerability correlates with lower confinement thickness).

Cumulative Descending – Calculates the cumulative weights from the last class to the first class while increasing the area (opposite of cumulative ascending). This method is applicable for themes where the training points are mainly associated with the higher values of the evidential theme (e.g., higher vulnerability correlates with higher soil permeability).

Evidential Theme – A set of continuous spatial data that is associated with the location and distribution of known occurrences (i.e., training points); these map data layers are used as predictors of vulnerability.

Model – The characteristics of a set of training points, and the relationships of the training points to a collection of evidential themes.

Posterior Probability – The probability that a unit cell contains a training point after consideration of the evidential themes. This measurement changes from location to location depending on the values of the evidence.

Prior Probability – The probability that a unit cell contains a training point before considering the evidential themes. It is a constant value over the study area equal to the training point density (total number of training points divided by total study area in unit cells).

Response Theme – An output map that displays the probability that a unit area would contain a training point, estimated by the combined weights of the evidential themes. The output is displayed in classes of relative aquifer vulnerability or favorability to contamination (i.e., this area is more vulnerable than that area) or favorability. The response theme is the relative vulnerability map.

Study Area – A grid theme that acts as a mask to define the area where the model is developed and applied. It may be irregular in outline and may contain interior holes (e.g., lakes and no data areas).

Training Points – A set of locations (points) reflecting a parameter used to calculate weights for each evidential theme, one weight per class, using the overlap relationships between points and the various classes. In an aquifer vulnerability assessment, training points are wells with one or more water quality parameters indicative of relatively higher recharge which is an estimate of relative vulnerability.

Weights – A measure of an evidential-theme class calculated for each theme class. For binary themes, these are often labeled as W+ and W-. For multiclass themes, each class can also be described by a W+ and W- pair, assuming presence/absence of this class versus all other classes. Positive weights indicate that more points occur on the class than due to chance, and the inverse for negative weights. The weight for missing data is zero. Weights are approximately equal to the proportion of training points on a theme class divided by the proportion of the study area occupied by theme class, approaching this value for an infinitely small unit cell.

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