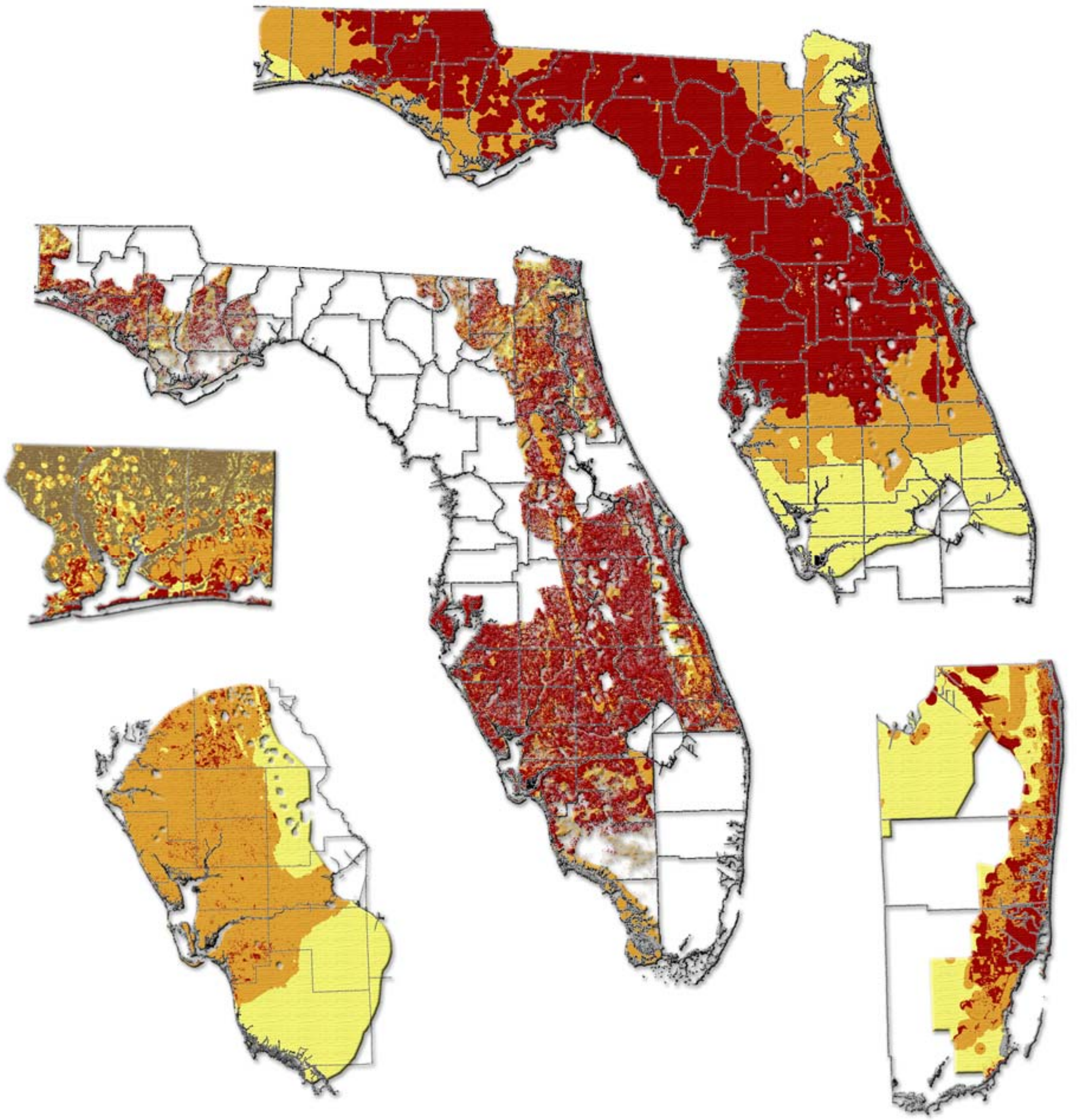
FLORIDA AQUIFER VULNERABILITY ASSESSMENT (FAVA II)

A Ground-Water Protection and Management Tool



Prepared for the Florida Department of Environmental Protection by Advanced GeoSpatial Inc.

FLORIDA AQUIFER VULNERABILITY ASSESSMENT

Prepared For:
The Department of Environmental Protection as part of the Florida Aquifer Vulnerability Assessment (FAVA) Phase II Project, Contract No.RM-059

Prepared by

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September 2009

PROFESSIONAL GEOLOGIST CERTIFICATION

I, Alan E. Baker, P.G., no. 2324, have read and agree with the findings in this report titled FLORIDA AQUIFER VULNERABILITY ASSESSMENT (FAV II) and do hereby certify that I currently hold an active professional geology license in the state of Florida. The model and report were prepared by Advanced GeoSpatial Inc., a State of Florida Licensed Geology Business (GB491), and have been reviewed by me and found to be in conformance with currently accepted geologic practices, pursuant to Chapter 492 of the Florida Statutes.

Alan E. Baker, P.G.
Florida License No. 2324

September 14, 2009
Date

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For additional information regarding this project, please refer to the associated 24” x 36” interpretive poster of the same title as this report, and/or the GIS project data and associated metadata. At the time of this report, these GIS files may be accessed using ArcMap™, version 9.x.

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INTRODUCTION

During FAVA version 1.0 it was recognized that additional data could improve the predictive capabilities of the model. FAVA phase II was developed to address this need. Training point and evidential theme improvements were the main focus of phase II. The changes that were made are described in the paragraphs that follow. New models were also created to account for important potable groundwater sources. The surficial aquifer system (SAS) was divided into three models; the sand-and-gravel aquifer, the Biscayne/Surficial aquifer and the SAS. The sand-and-gravel and Biscayne/Surficial models where cut out of the original SAS model because they represent important potable water sources. Modeling these SAS aquifers separately will help identify the relative vulnerability of these systems in their regional context rather than on a statewide scale.

Data Improvements

Training Points

The FDEP Background Groundwater Quality Monitoring Network has now been incorporated into a new database known as the STAUS Network. The STATUS network has removed some wells from the Background Network and added new monitoring well locations. All wells that were sampled for dissolved oxygen and dissolved nitrogen (nitrate + nitrite, dissolved as N), were possible training point locations from this database. All models had training point locations developed for them using the procedure in the FAVA version 1.0 model. The major difference was that all wells had water quality parameters that were measured through the 2006 calendar year. In addition to the STATUS network, all water management district water quality databases were examined to see if it was suitable to use any of their wells in the training point process. Again, all the wells had water quality parameters that were measured through the 2006 calendar year. The result was a water quality database with more well locations and more water quality measurements. Information on each models training points can be found in the project results section of this report.

Intermediate Confining Unit/ Overburden Thickness

Improved resolution of the Intermediate Confining Unit (ICU) was developed by the Florida Geological Survey of the Florida Department of Environmental Protection. Using the most recent well cuttings and core data, Florida Geological Survey staff developed a surface for the top of the IAS. To create an ICU thickness surface, the top of Floridan aquifer system (FAS) surface developed during FAVA version 1.0 was subtracted from the top of IAS surface. Likewise, overburden thickness was calculated by subtracting the top of the IAS surface from the latest Digital Elevation model (DEM). These layers were used in the modeling of the Floridan aquifer system and the intermediate aquifer system.

Depth to Water

In FAVA version 1.0 one depth to water layer was created for the entire State and the SAS was modeled on a statewide scale. For this project, the SAS was divided into three models; the sand-and-gravel, the Biscayne/Surficial and the SAS for the remainder of the State. As a result, three separate depth to water layers were created. The sand-and-gravel depth to water layer used the same methodology as version 1.0 of the FAVA model, but incorporated new data. The National Hydrography Dataset 1:24000 was used to develop the minimum water table layer and new water level data from the Northwest Florida Water Management District (NWFWMD) aided in the creation of a new linear regression equation. The results of this new data decreased the range of error by as much as 50%.

Two methods were utilized to create a depth to water coverage for the Biscayne/Surficial aquifer. The first was the same as the method described above (linear regression method) and incorporated the National Hydrography Dataset 1:24000 and water level data from the South Florida Water Management District (SFWMD). The second method used surficial aquifer system water level measurements from SFWMD databases and used kriging to create a surface. After comparing both surfaces, the surface that relied strictly on water level measurements had a smaller range of errors and correlated better with the actual measurements.

For the remainder of the State, the DEM was used to assess potential elevation discrepancies near water bodies and correct significant errors. The depth to water surface for this layer included the statewide surficial aquifer system minus the Biscayne/Surficial aquifer and the sand-and-gravel aquifer. Based on the new improvements the range of errors was reduced by 50% and the correlation between measured and regressed values was increased.

Soil Hydraulic Conductivity/ Soil Pedality

FAVA version 1.0 did not include Soil Survey Geographic (SSURGO) soil data for four counties (Holmes Washington, Taylor and Liberty) at the time of its completion. Since then the National Resource Conservation Service (NRCS) has improved the county soil data by digitally mapping every county in Florida and placing these GIS datasets in geodatabase format. They also improved the tabular data for soil hydraulic conductivity. As a result, the entire soil hydraulic conductivity data layer was reproduced rather then just updating the four missing counties.

During the modeling process for the Sand-and-gravel aquifer system, a large discrepancy in soil hydraulic conductivity values was noticed along the Santa Rosa/ Okaloosa County line. The Lakeland soil polygons on the Santa Rosa County side had a soil hydraulic conductivity value of 423 micrometers/sec, while the Lakeland soil polygons on the Okaloosa County side had a soil hydraulic conductivity value of 92 micrometers/sec. To remedy this situation, data from the Florida Soil Characterization Data Retrieval System was used. Based on this information, a median soil hydraulic conductivity value of 225 micrometers/sec was assigned to the polygons in the area that represent Lakeland soils.

Topography

The digital elevation model (DEM) currently in use by FDEP/FGS has minor problems that were recognized during FAVA version 1.0 of the process. These included the omission of hilltop attributes for the peninsula, providing curvature for flat areas where depressions and hilltops occur and updating two quadrangle maps.

Hilltops were attributed using an automated process in ArcView. All (topographic) polygons that touched more than two polygons were selected. The unselected polygons were either depressions or hilltops. Since depressions are already attributed a simple query was constructed to select all polygons that were not depressions. These remaining polygons were then attributed as hilltops.

Flat areas in the DEM are the result of closed contour lines. Since these features contain one elevation value, a centroid had to be established to add ½ contour intervals and provide curvature to these features. Centroids were developed based on the automated selection of hilltops/depressions described above. Elevation values were assigned to each centroid by extracting values from the original DEM grid. One-half the contour interval (rounded to 3 feet because it's an integer grid) was added to each centroid value to provide needed curvature in the DEM.

Two quadrangles in the St. Johns River Water Management District (Bostwick and Green Cove Springs) were based on the 1949 topographic survey. A later survey done in 1991 revealed that these contour lines were inaccurate. To fix this problem AGI scanned and digitized the two newer quad sheets for Bostwick and Green Cove Springs. Hilltops and depressions were attributed and then the new lines were edge matched with the surrounding quad sheets. Unfortunately edge matching issues were not exclusive to the new contours that were added. Significant errors were located just north of the Bay/Washington County due to a substantial number of two-meter interval quadrangle maps. To make matters worse this is an area that is characterized by intense karst. The contour lines associated with closed depressions along this border were matched with the nearest equivalent across the boundary. While this is not an accurate way to characterize elevation it did allow for the inclusion of many closed depressions that straddle the border of the two different quadrangle maps that had been missing from previous analyses.

Karst and Closed Topographic Depressions

Karst features are a very important part of the FAS model and it is in this model that the term is used. In the other models, IAS, SAS, SNG and Biscayne/Surficial models closed topographic depressions are used as an evidential theme. While developing the proximity to karst feature dataset for the FAVA version 1.0 project several problems were encountered. First of all not every closed depression is a karst feature. Second, the FGS sinkhole database was not used in the phase I vulnerability analysis because of its strong bias towards land use.

To address the issue of excluding non-karst features from the FAS model, AGI developed a filtering process based on index of circularity or circular index (Denizman, 2003). Closed depressions are filtered based on the ratio of circularity of a polygon to the circularity of a circle where 1 is a perfect circle and 0 is a line that never forms a polygon. Values for ratios ranged from of 0.9967 to 0.0003 the mean was 0.7665. Several evidential themes were generated based on circular index scores. These values were; 0.90, 0.85, 0.80, 0.75, 0.70 and 0.65. Each was evaluated individually for inclusion into the model based on the evidential theme's association with the training point set. More information on the circularity index method and the potential karst features evidential theme can be found in the FAS model section.

The FGS sinkhole database which indicates areas of the state where recent karst activity has occurred was investigated for inclusion into the model. The sinkhole database was originally excluded from the model because of its inherent bias towards land use. The sinkhole database is more of a predictor of where structures are built and not a predictor of aquifer vulnerability. A thorough review of the latest sinkhole database reveals that of the reported 2,939 sinkholes less than 7% fall in the land use categories of forest or wetland. All of the other land use codes are urban or agricultural land. Further, there is no way to perform a circularity index calculation on the features and 98% of the reported sinkholes were within the 3,000 meter buffer of existing features and therefore did not add to the analysis.

Aquifer Vulnerability

All groundwater and therefore all aquifer systems are vulnerable to contamination to some degree (National Research Council, 1993) and, as a result, different areas overlying an aquifer system require different levels of protection. An aquifer vulnerability assessment provides for the identification of areas which, based on predictive spatial analysis, are more vulnerable to contamination from land surface. AGI uses a definition of aquifer vulnerability similar to that of the FDEP in the version 1.0 of the FAVA report which is: the tendency or likelihood for a contaminant to reach the top of a specified aquifer system after introduction at land surface based on best available data representing the natural hydrogeologic system (Arthur et al., 2005). As a result, model output is considered an estimate of intrinsic vulnerability because it relies only on physical hydrogeologic factors and does not include natural and human sources of contamination or behavior of specific contaminants.

APPROACH

FAVA Technical Advisory Committee

An advisory committee was formed to provide technical review and support during the development of the FAVA Phase II project. This committee consists of professionals in the water resource, planning, engineering, hydrogeology and other environmental fields. Members, listed below, participated in workshop meetings, provided technical review of model progress and final results.

Table 1. FAVA Technical Advisory Committee members.

Name	Organization
Jonathan Arthur, Ph.D., P.G.	Florida Geological Survey of FDEP
Rodney Dehan, D.V.M.	Florida Geological Survey of FDEP
Allan Stodghill, P.G.	Florida Department of Environmental Protection
Gary Maddox, P.G.	Florida Department of Environmental Protection
Eberhard Roeder, Ph.D., P.E.	Florida Department of Health
Richard Deadman	Florida Department of Community Affairs
Tony Countryman, P.G.	Northwest Florida Water Management District
Chris Richards, P.G.	Northwest Florida Water Management District
Dave Dewitt, P.G.	Southwest Florida Water Management District
Jeff Davis	St. Johns Water Management District
Carlos Herd	Suwannee River Water Management District
Sam Upchurch, Ph.D., P.G.	SDII Global, Inc.
Timothy Hazlett, Ph.D.	Hazlett-Kincaid Inc.
Harley Means, P.G.	Florida Geological Survey of FDEP
John Lockwood	South Florida Water Management District
Keith Wilkins	Escambia County

Weights of evidence methodology, and weighted logistic regression methodology, were employed in FDEP's FAVA project (refer to Arthur et al., 2005). Use of these methods involves combination of diverse spatial data that are used to describe and analyze interactions and generate predictive models (Raines et al., 2000). This section provides an overview of the methodology.

Weights of Evidence

Weights of evidence was used in the FAVA phase II project to develop aquifer vulnerability assessment models of the SAS (Biscayne/Surficial and sand-and-gravel), IAS and FAS. These modeling techniques are based in a geographic information system (GIS) and executed using Arc Spatial Data Modeler (Arc-SDM), an extension to ESRI's ArcGIS software package (available for ArcView 3.x, and ArcGIS 8.x and 9.x). For more information on these methods please refer to Arthur et al. (2007), Kemp et al. (2001), Raines et al. (2000), and Bonham-Carter (1994). Primary benefits of applying these techniques to the FAVA project are that they are data-driven methods, rather than expert-driven, and model generation is dependent upon a training dataset resulting in a self-validated model output.

Weights of evidence involves the combination of diverse spatial data used to describe and analyze interactions and generate predictive models. Weights of evidence utilizes known occurrences (*training points)* to create maps from weighted continuous input data layers (*evidential themes*), which are in turn combined to yield an output data layer, or *response theme* (Raines, 1999).

Data Acquisition and Development

The initial phase of an aquifer vulnerability assessment project comprises acquisition, development and attribution of various GIS data representing natural hydrogeologic conditions for use as input into the model. The input data chosen during this phase determines the level of detail, accuracy, and confidence of final model output, i.e., vulnerability maps. Examples of data typically used in an aquifer vulnerability assessment include:

- Digital Elevation Data
- Aquifer Confinement or Overburden Thickness
- Karst Features/Topographic Depressions
- Water-Quality Data
- Soil Hydraulic Conductivity/Soil Pedality

Vulnerability Modeling

Upon completion of the development and adaptation of the necessary data coverages for the vulnerability assessment, the modeling phase using weights of evidence is initiated to generate aquifer vulnerability response themes, which, for the FAVA project, are expressed as probability maps.

Study Area and Training Points

The initial step in the vulnerability modeling phase is the identification and delineation of a study area extent. The study areas for each separate aquifer system are described below. Training points are locations of known occurrences of an event. In an aquifer vulnerability assessment, groundwater wells with water quality indicative of high recharge are selected as known occurrences. Dissolved oxygen or dissolved nitrogen analytical concentrations from ambient monitor well networks were used to develop training point datasets. The occurrence of a training point does not directly correspond to a site of aquifer system contamination, but is indicative of aquifer vulnerability.

Evidential Themes (Model Input)

Evidential themes are defined as sets of continuous spatial data that are associated with the location of training points and are analogous to data layers listed and described above, such as soil hydraulic conductivity or thickness of confinement. Weights are calculated for each evidential theme based on the location of training points with respect to the study area and spatial associations between training points and evidential themes are established. Themes are then generalized to determine the threshold or thresholds that maximize the spatial association between the evidential theme and the training points (Bonham-Carter, 1994).

Response Theme (Vulnerability Maps)

Following generalization of evidential themes, output results (response themes) are generated and display the probability that a unit area contains a training point based on the evidential themes provided (for more on generalization of evidential themes, see Arthur et al., 2005). The response theme generated in this project is a probability map displayed in classes of relative vulnerability.

Sensitivity Analysis and Validation of Model Results

Sensitivity analysis and validation are a significant component of any modeling project as they allow evaluation of the accuracy of results. Sensitivity analysis is applied during development of each evidential theme and validation exercises are applied to assess model strength and confidence.

PROJECT RESULTS

SURFICIAL AQUIFER SYSTEM

SAND-AND-GRAVEL AQUIFER SYSTEM

Study Area

The Counties of Escambia, Santa Rosa and Okaloosa were used as the sand-and-gravel aquifer system (SNG) model study area extent (Figure 1). Because of the sizes of some polygons representing soil data, a grid cell size of approximately 30 meter squares (or 900 m^2) was selected for evidential theme development. This grid cell size, while necessary to capture resolution available in some input data layers, does not reflect appropriate resolution of final model output. Appropriate scale of use of model results is discussed in *Model Implementation and Limitations*.

Training Point Theme

In the SNG analysis, training points are groundwater wells tapping the SAS with water quality data indicative of high recharge. Dissolved nitrogen analytical values served as training point data for the SNG model. Dissolved oxygen concentrations could not be used as a training point set because too many outliers were removed during statistical analysis to provide a viable training point theme. These extremely high dissolved oxygen values may be the result of where the samples were taken (at the tank rather than the wellhead). Naturally occurring oxygen and nitrogen are generally considered ubiquitous at land surface as primary components of the atmosphere; moreover, relatively low concentrations of these analytes occur in well protected – or less vulnerable – aquifer systems. Accordingly, where these analytes occur in elevated concentrations in groundwater, yet are not attributable to human activity, they are good indicators of aquifer vulnerability (Arthur et al., 2007).

Water quality data sources explored include the FDEP background water quality network, FDEP STATUS network and NWFWMD databases. From these data sources, 57 wells measured for dissolved nitrogen were identified as being potential candidates for training points. Statistical analyses revealed 5 samples were considered statistical outliers. The upper 25th percentile of this set – or all wells with median dissolved nitrogen values greater than or equal to 0.655 milligrams per liter (mg/L) – served as the training point theme and consists of thirteen wells. Figure 2 displays the distribution of water wells used to derive training points and the resulting training point theme across the study area. Training points are used to calculate prior probability, weights for each evidential theme, and posterior probability of the response theme (see *Glossary*). Prior probability (training point unit area divided by total study area) is the probability that a training point will occupy a defined unit area within the study area, independent of any evidential theme data. The prior probability value, a unitless parameter, for the SNG model is 0.0019 ([1 km^2 model unit area * 13 training points] / 6813.9 km^2 = 0.0019). Posterior probability values generated during response theme development are interpreted relative to the value of prior probability with higher values generally indicating areas with higher probability of containing a training point.

Figure 1. Sand-and-Gravel Aquifer Vulnerability Assessment project study area corresponds to the County's political boundaries.

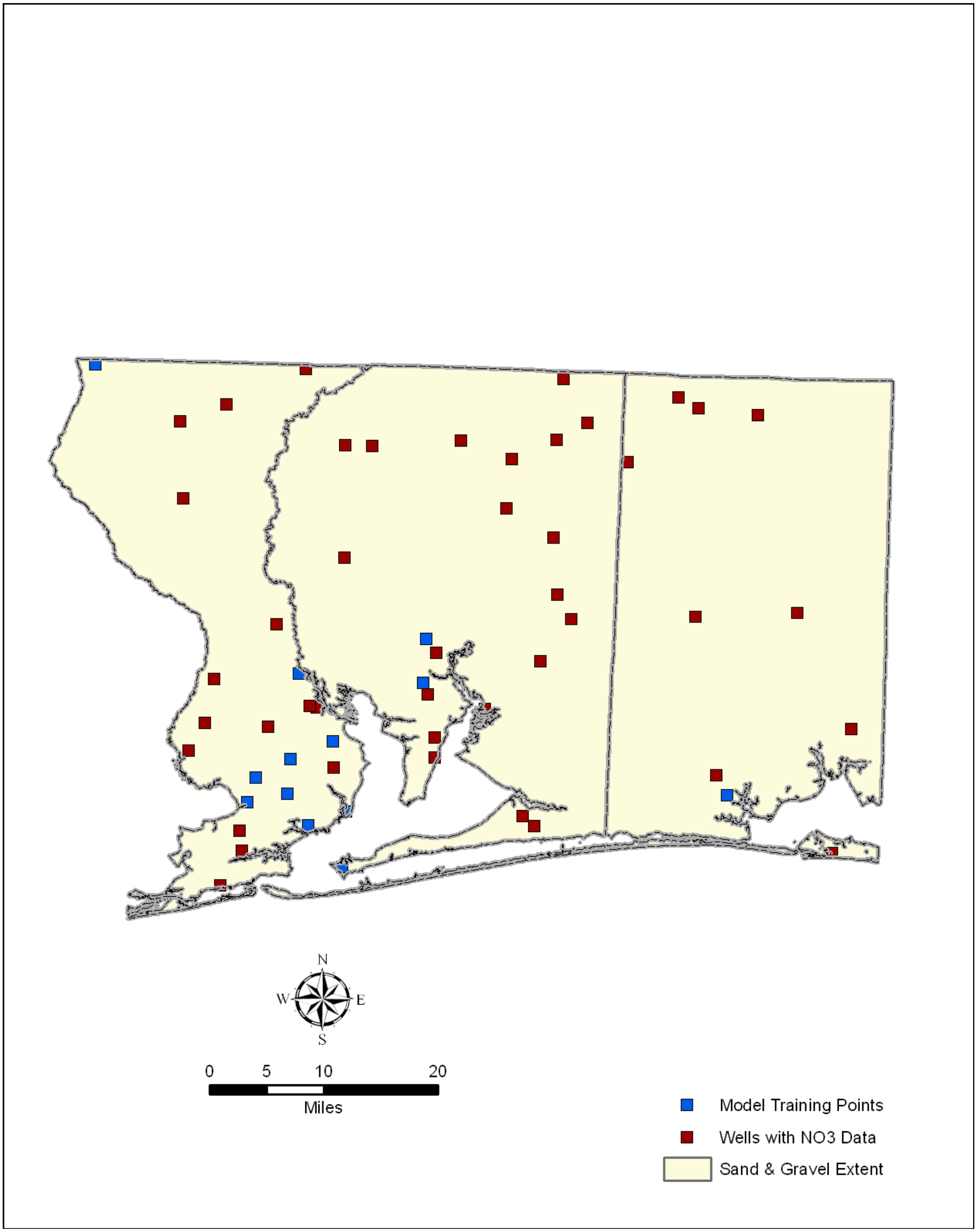

Figure 2. Location of all wells measured for Nitrate NO3 (dark red boxes), and locations of training point wells with median nitrate values greater than 0.655 mg/L (blue boxes).

Evidential Themes – Model Input Layers

Input data layers, or evidential themes, representing hydrogeologic factors controlling the location of training points, and thereby vulnerability, were developed for model input. Because of the local scale nature of the SNG project and the availability of new data, all model inputs represent previously unavailable datasets. The factors considered for the SNG project include closed topographic depressions, depth to water, soil pedality, and soil hydraulic conductivity.

Soil Hydraulic Conductivity and Soil Pedality Themes

The rate that water moves through soil is a critical component of any aquifer vulnerability analysis, as soil is literally an aquifer system's first line of defense against potential contamination (Arthur et al., 2005). Two parameters of soils were evaluated for input into the SNG model: *soil hydraulic conductivity*, which is the "amount of water that would move vertically through a unit area of saturated soil in unit time under unit hydraulic gradient" (U.S. Department of Agriculture, 2005); and *soil pedality*, which is calculated based on soil type, soil grade, and soil pedon size, and is a unitless parameter. Soil pedality is a relatively new concept used to estimate the hydrologic parameter of soil and is generated for SNG using the pedality point method developed by Lin et al. (1999).

Countywide datasets representing soil hydraulic conductivity and soil pedality were developed for use as input into the SNG model. Multiple empirical values are reported in soil surveys representing various zones in each soil column underlying a particular soil polygon. Representative values for each horizon in a column are combined using a sum of the weighted mean. This is completed for both hydraulic conductivity and soil pedality. Figure 4 displays values of soil hydraulic conductivity.

Depth to Water Theme

Depth to water is another critical layer in determining aquifer vulnerability. Where the depth to water is greatest (larger vadose zone), aquifer vulnerability is generally lower, whereas in areas where the depth to water is nearer to the surface, the vulnerability of the aquifer is generally higher.

To estimate the water-table elevation, and thus be able to derive depth to the water table, a multiple linear regression equation was generated based on the following datasets:

- Land surface altitude
- Monitor well water-level data
- Minimum water-table elevation

Land surface altitude (LSA) was based on the FDEP DEM. Elevations from 1:24,000 USGS maps for water bodies including streams, lakes and shorelines were used to interpolate a minimum water table (MINWT). Water-level data were compiled from NWFWMD and FDEP for the period of record between 1990 and 2006. The water table was calculated based on the following equation from Sepulveda (2002):

$$WT_i = \beta_1 \, MINWT_i + \beta_2 \, (LSA_i - MINWT_i)$$

Where:

WT_i is water-table measurement for the period of record at well i, in feet

$MINWT_i$ is the minimum water table interpolated at well i, in feet

LSA_i is the land surface altitude interpolated at well i, in feet

$\beta 1$ and $\beta 2$ are dimensionless regression coefficients of the multiple linear regression.

The water table grid for the study area was calculated from the equation:

$$WT = 1.01MINWT + 0.253(LSA – MINWT)$$

The root-mean-square residual between the regressed and measured water-table elevation resulted in a weighted mean of 4.82 feet and exhibited a strong correlation coefficient of 0.99 (Figure 3). The final depth to water evidential theme was calculated by subtracting the water table elevation values from the FDEP DEM values (Figure 5).

Table 2. Linear regression coefficients for MINWT and difference between DEM and MINWT.

Number of sand and gravel wells	Regression coefficient of minimum water table (β_1)	Regression coefficient of difference between LSA & MINWT (β_2)	Root mean square residual (ft)	Value range for difference between regressed & measured water table (ft)	Correlation coefficient
103	1.01	0.253	4.82	[-10.13, 9.05]	0.99

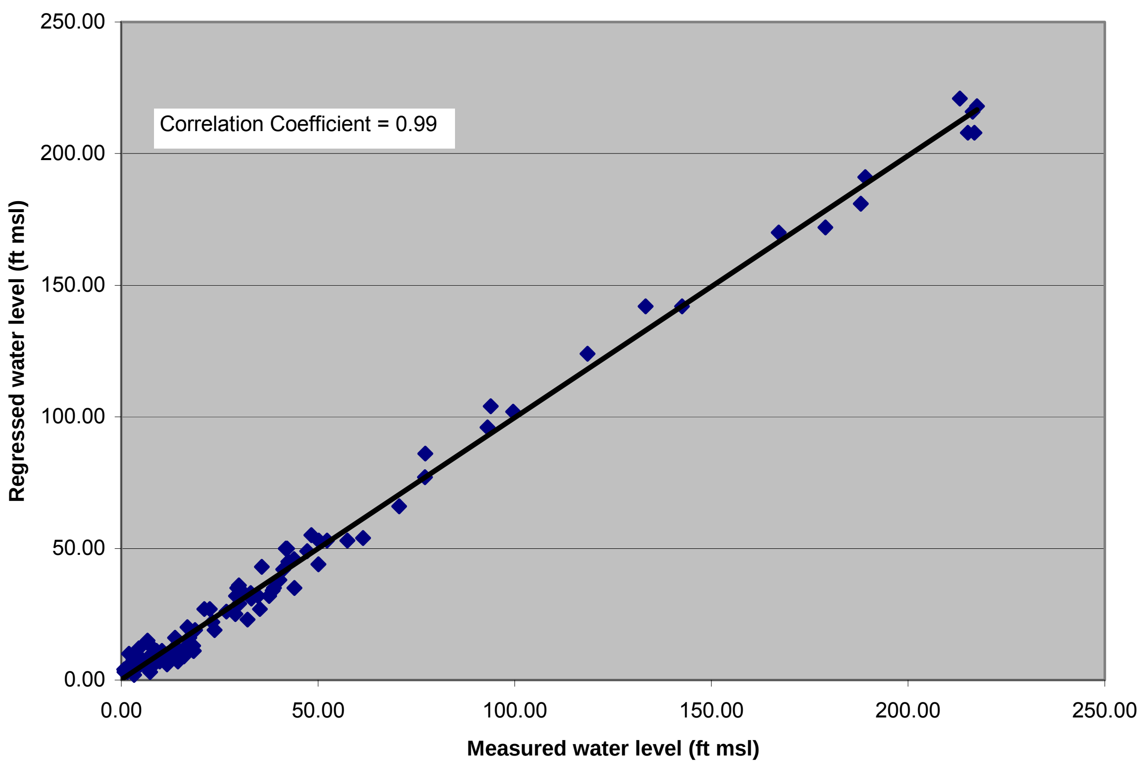

Figure 3. Regressed and measured water level for sand-and-gravel aquifer.

Closed Topographic Depressions

Karst features, or sinkholes and depressions, can provide preferential pathways for movement of surface water into the underlying aquifer system and enhance an area's aquifer vulnerability where present. The closer an area is to a karst feature, the more vulnerable it may be considered. Closed topographic depressions extracted from U.S. Geological Survey 7.5-minute quadrangle maps served as the dataset from which to estimate closed topographic depressions in the study area (Figure 6).

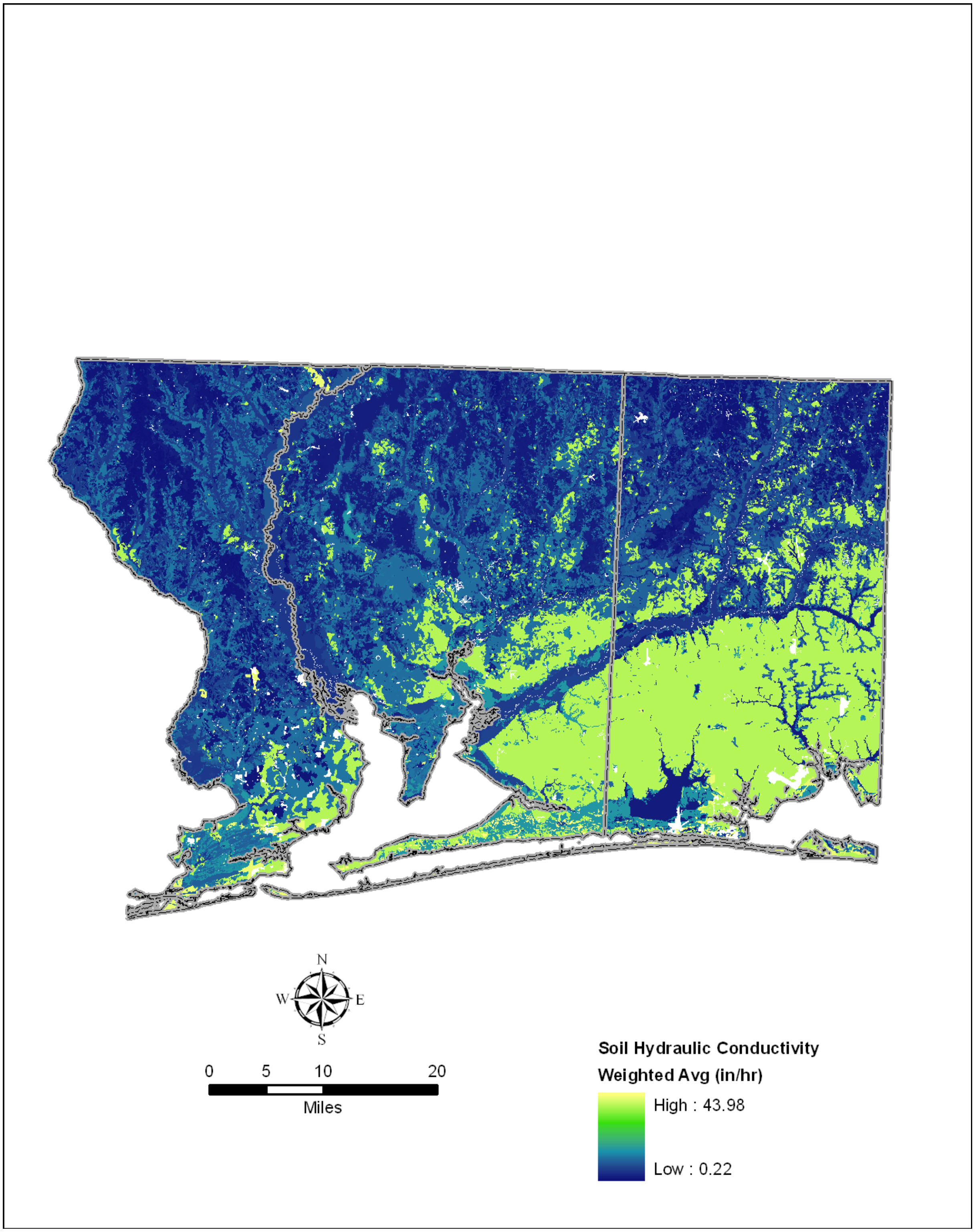

Figure 4. Distribution of soil hydraulic conductivity values across the SNG study area. White areas represent 'no data' areas in the soil survey data or locations of water bodies.

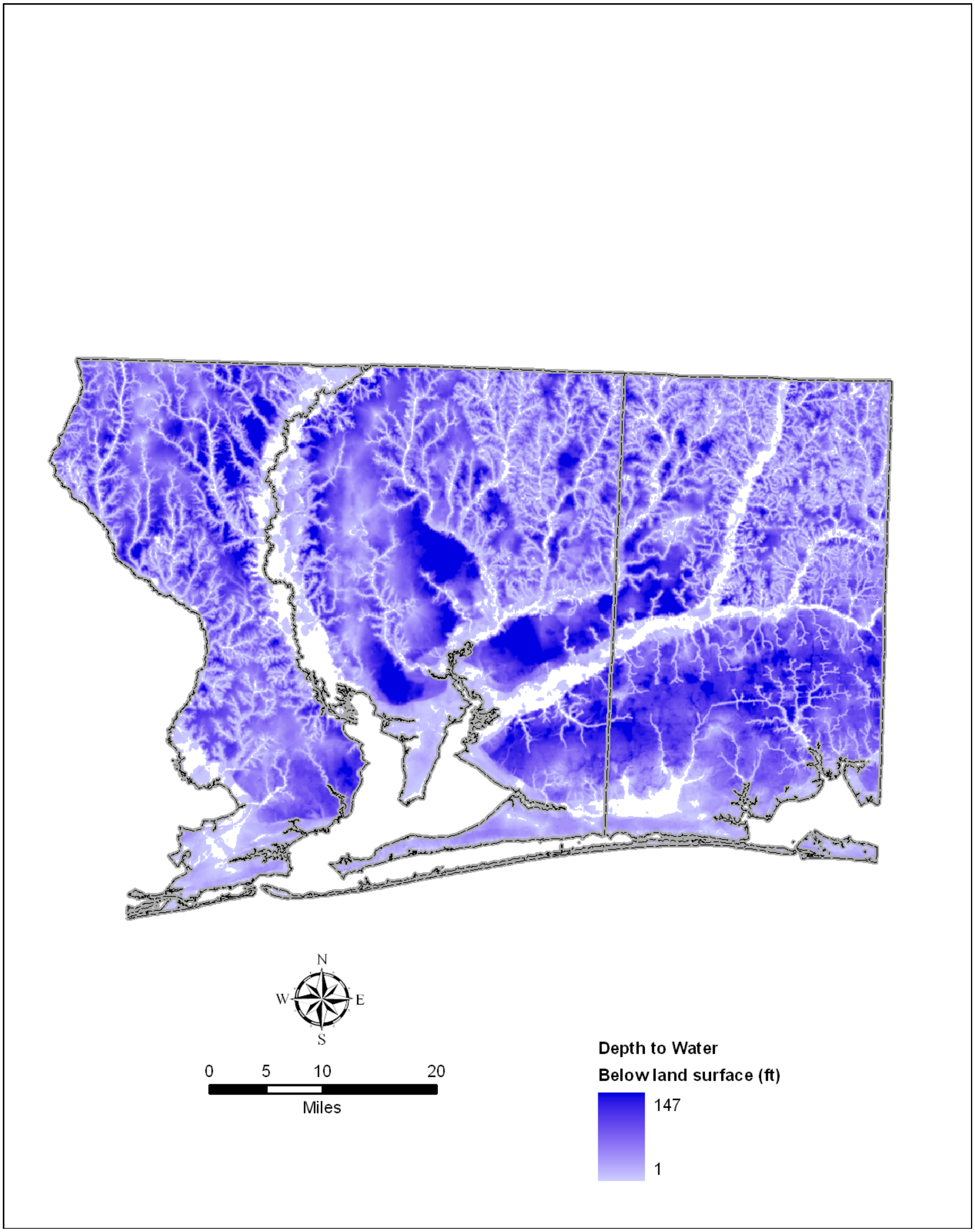

Figure 5. Distribution of depth to water values across the SNG study area. White areas represent 'no data' areas (where depth to water equals zero) or locations of water bodies.

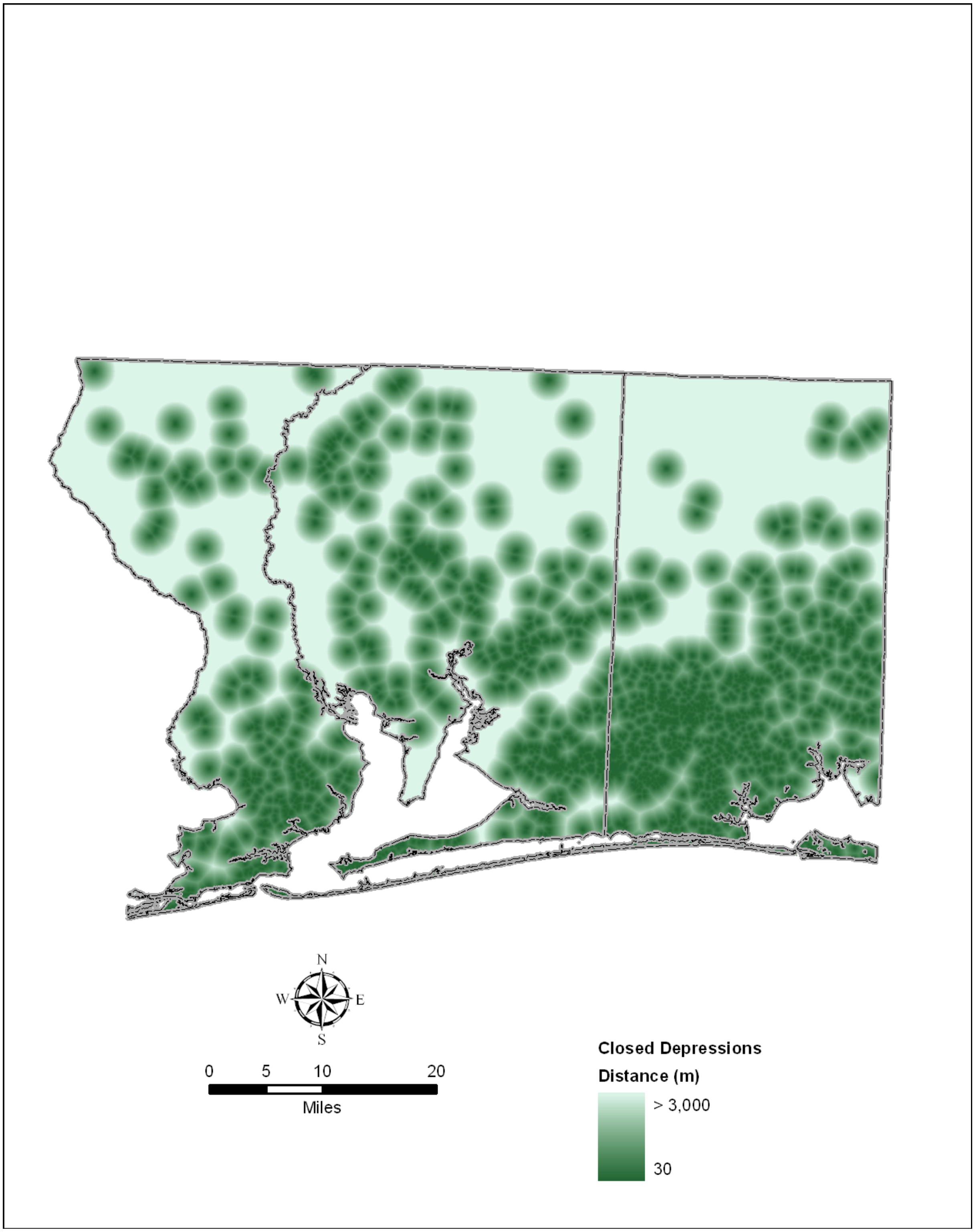

Figure 6. Proximity to closed topographic depressions extracted from U.S. Geological Survey 7.5-minute topographical contour lines.

Sensitivity Analysis/Evidential Theme Generalization

Sensitivity analysis allows decisions to be made about proposed evidential themes by evaluating each theme's association with training points – or aquifer vulnerability – and ultimately helps determine model input. For example, soil hydraulic conductivity and soil pedality were both developed to represent soil properties; sensitivity analysis allows, through statistical analysis, determination of which of these two layers served as the most appropriate input representing soil properties for the final SNG analysis. Results of this process indicate that soil hydraulic conductivity, depth to water, and closed topographic depressions were the best suited evidential themes for use in final modeling.

Following sensitivity analysis and selection of evidential themes to be input into the SNG model, themes were generalized to assess which areas of the evidence share a greater association with locations of training points. During calculation of weights for each theme, a contrast value was calculated for each class of the theme by combining the positive and negative weights. 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). Contrast and weights are described in more detail below in *Discussion*.

Contrast values were used to determine where to sub-divide evidential themes into generalized categories prior to final modeling. The simplest and most accepted method used to subdivide an evidential theme is to select the maximum contrast value as a threshold value to create binary generalized evidential themes. In other models, categorization of more than two classes may be justified (Arthur et al., 2005). For the SNG project, a binary break was typically defined by the weights of evidence analysis for each evidential theme creating two spatial categories: one with stronger association with the training point theme and one with weaker association.

Soil Hydraulic Conductivity/ Soil Pedality

Weights calculated during sensitivity analysis for soil hydraulic conductivity were stronger (i.e., had higher absolute value) than weights calculated for soil pedality. As a result, soil hydraulic conductivity was chosen as the better predictor of aquifer vulnerability because it shared the best association with training points.

Soil hydraulic conductivity, ranges from 0.22 to 43.98 in/hr across the study area. Test modeling indicated that areas greater than or equal to 9.20 in/hr were more associated with the training points, and therefore associated with higher aquifer vulnerability. Conversely, areas less than 9.20 in/hr were less associated with the training points, and therefore lower aquifer vulnerability. Based on this analysis, the evidential theme was generalized into two classes as displayed in Figure 7.

Depth to Water

The depth to water ranges from zero to 147 feet deep across the study area. The analysis revealed that areas less than or equal to 33 feet deep were more associated with the training points, and therefore associated with higher aquifer vulnerability. Areas with a depth to water greater than 33 feet were less associated with the training points, and therefore lower aquifer vulnerability. Based on this analysis, the evidential theme was generalized into two classes as displayed in Figure 8.

Closed Topographic Depressions

As mentioned above, areas closer to a depression are normally associated with higher aquifer vulnerability. Based on this, features were buffered into 30 meter zones to allow for a proximity analysis. The analysis indicated that areas within 1,470 meters of a closed topographic depression were more associated with the training points, and therefore with higher aquifer vulnerability.

Conversely, areas greater than 1,470 meters from a closed topographic depression were less associated with the training points, and therefore lower aquifer vulnerability. Based on this analysis, the evidential theme was generalized into two classes as displayed in Figure 9.

Response Theme

Using evidential themes representing soil hydraulic conductivity, depth to water, and closed topographic depressions, weights of evidence was applied to generate a response theme, which is a GIS raster consisting of *posterior probability* values ranging from 0.00003 to 0.0099 across the study area. These probability values describe the relative probability that a unit area of the model will contain a training point – i.e., a point of aquifer vulnerability as defined above in *Training Points* – with respect to the prior probability value of 0.0019 or ([1.0 km^2 model unit area * 13 training points] / 6813.9 km^2 = 0.0019). Prior probability is the probability that a training point will occupy a defined unit area within the study area, independent of evidential theme data. Probability values at the locations of twelve of the thirteen training points are above the prior probability, indicating that this model is a strong predictor of training point locations.

The response theme was broken into classes of relative vulnerability based on the prior probability value and on inflections in a chart in which cumulative study area was plotted against posterior probability (Figure 10). Higher posterior probability values correspond with more vulnerable areas, as they essentially have a higher chance of containing vulnerability based on the definition of a training point. Conversely, lower posterior probability values correspond to less vulnerable areas as they essentially have a lower chance of containing vulnerability based on the definition of a training point.

As described in *Introduction*, the SNG model was based on the modeling technique used in the FAVA project. The FAVA project identified relative vulnerability of Florida's principal aquifer systems broken into three classes: more vulnerable, vulnerable and less vulnerable zones. This naming technique was applied to the SNG results, along with addition of an extra vulnerability class, to define the relative vulnerability classes as displayed in Figure 11.

As expected, the SNG response theme indicates that areas of highest vulnerability are associated with areas where the depth to water is lowest, in areas of dense closed topographic depressions, and areas of higher soil hydraulic conductivity. Conversely, areas of lowest vulnerability are determined by high depth to water values, sparse closed topographic depression distribution, and lower soil hydraulic conductivity values.

Discussion

Prior to discussion of weights calculations during model execution, two components of a weights of evidence analysis are described to assist in interpretation of SNG model results: *Conditional Independence* and *Model Confidence*.

Conditional Independence

Conditional independence is a measure of the degree that evidential themes are affecting each other due to similarities between themes. Evidential themes are considered independent of each other if the conditional independence value is around 1.00, and conditional independence values within the range of 1.00 ± 0.15 generally indicate limited to no dependence among evidential themes (Bonham-Carter, 1994). Values significantly outside this range can inflate posterior probabilities resulting in unreliable response themes.

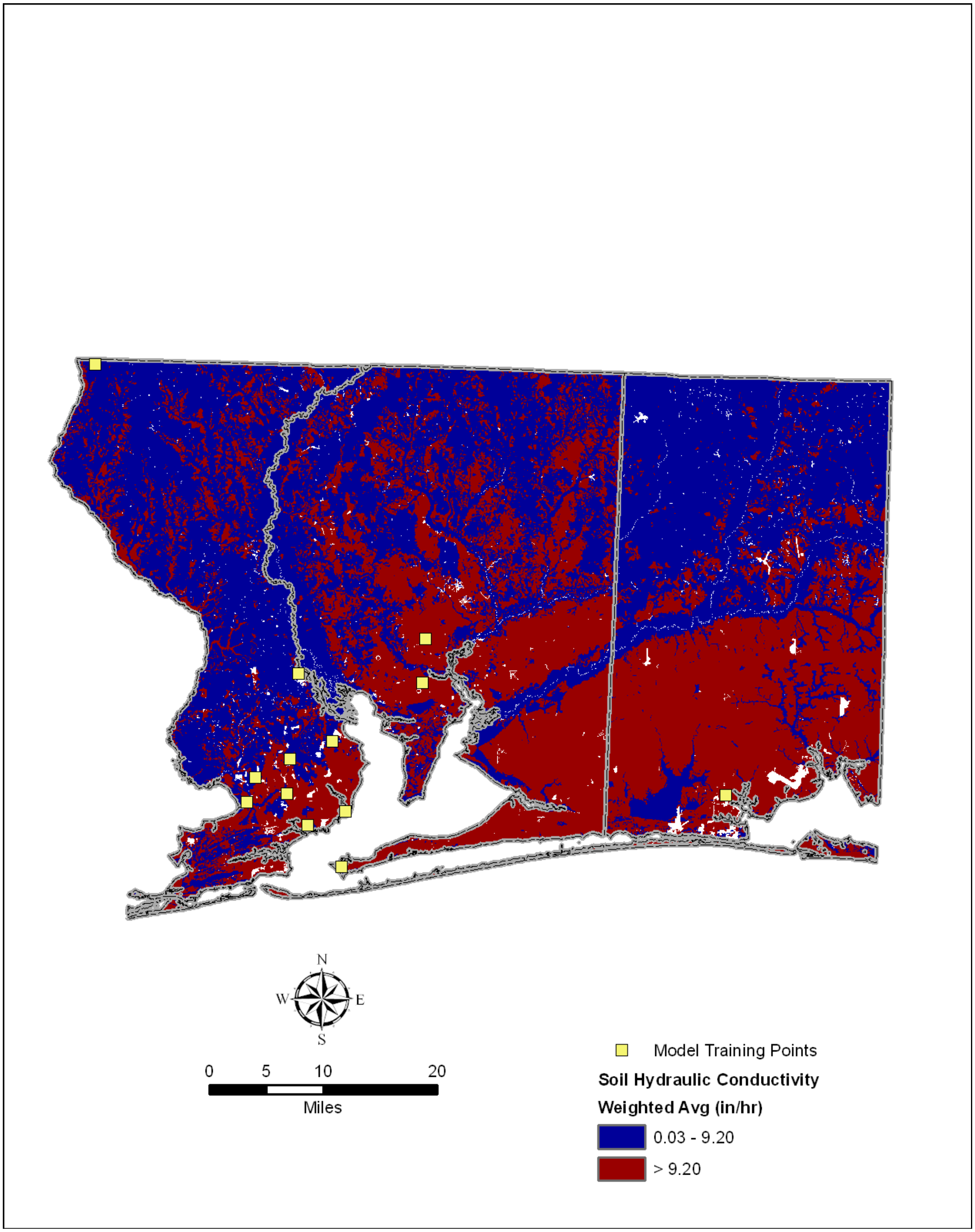

Figure 7. Generalized soil hydraulic conductivity evidential theme; based on calculated weights analysis blue areas share a weaker association with training points and thereby relatively lower aquifer vulnerability, whereas red areas share a stronger association with training points.

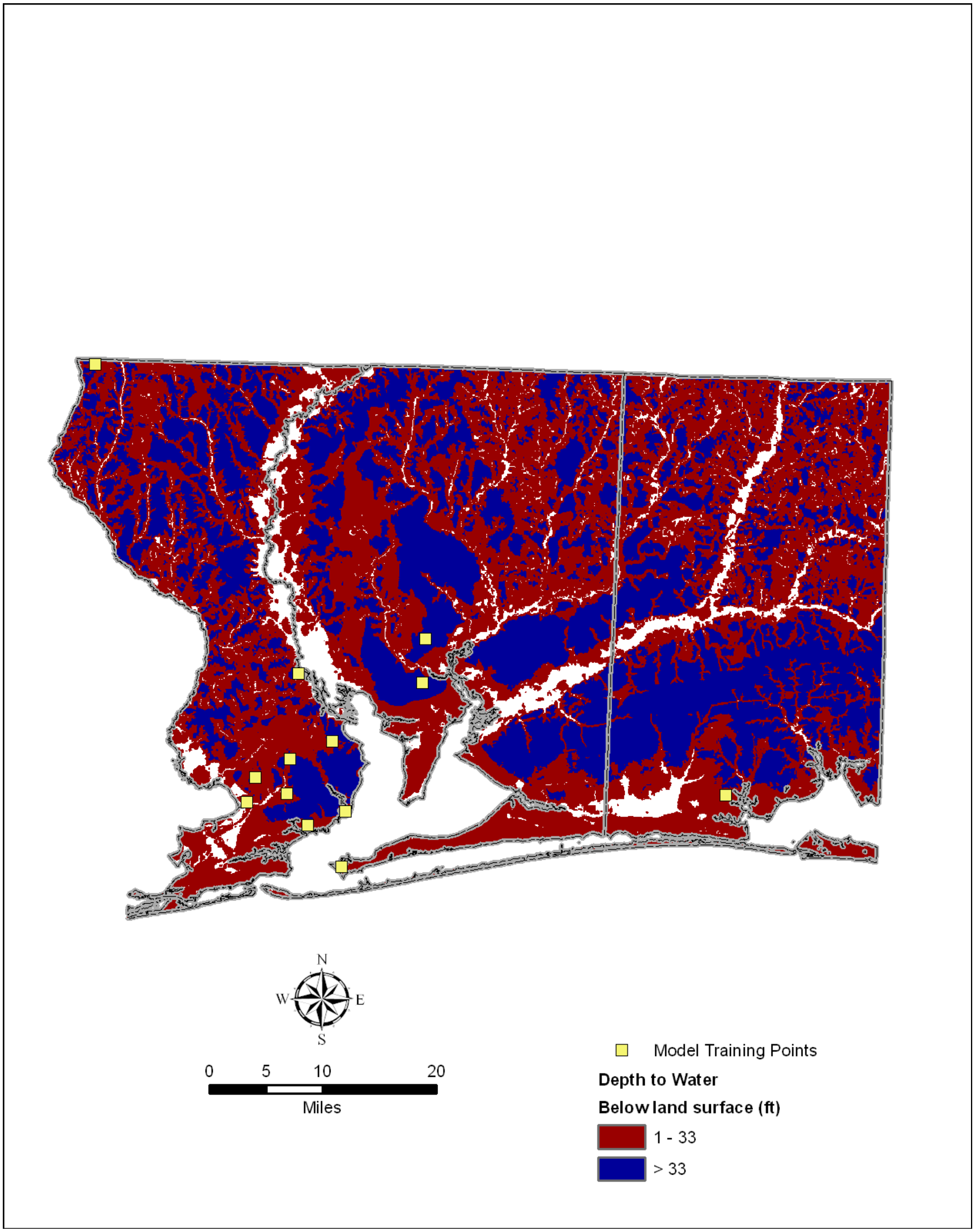

Figure 8. Generalized depth to water evidential theme; based on calculated weights analysis blue areas share a weaker association with training points and thereby relatively lower aquifer vulnerability, whereas red areas share a stronger association with training points.

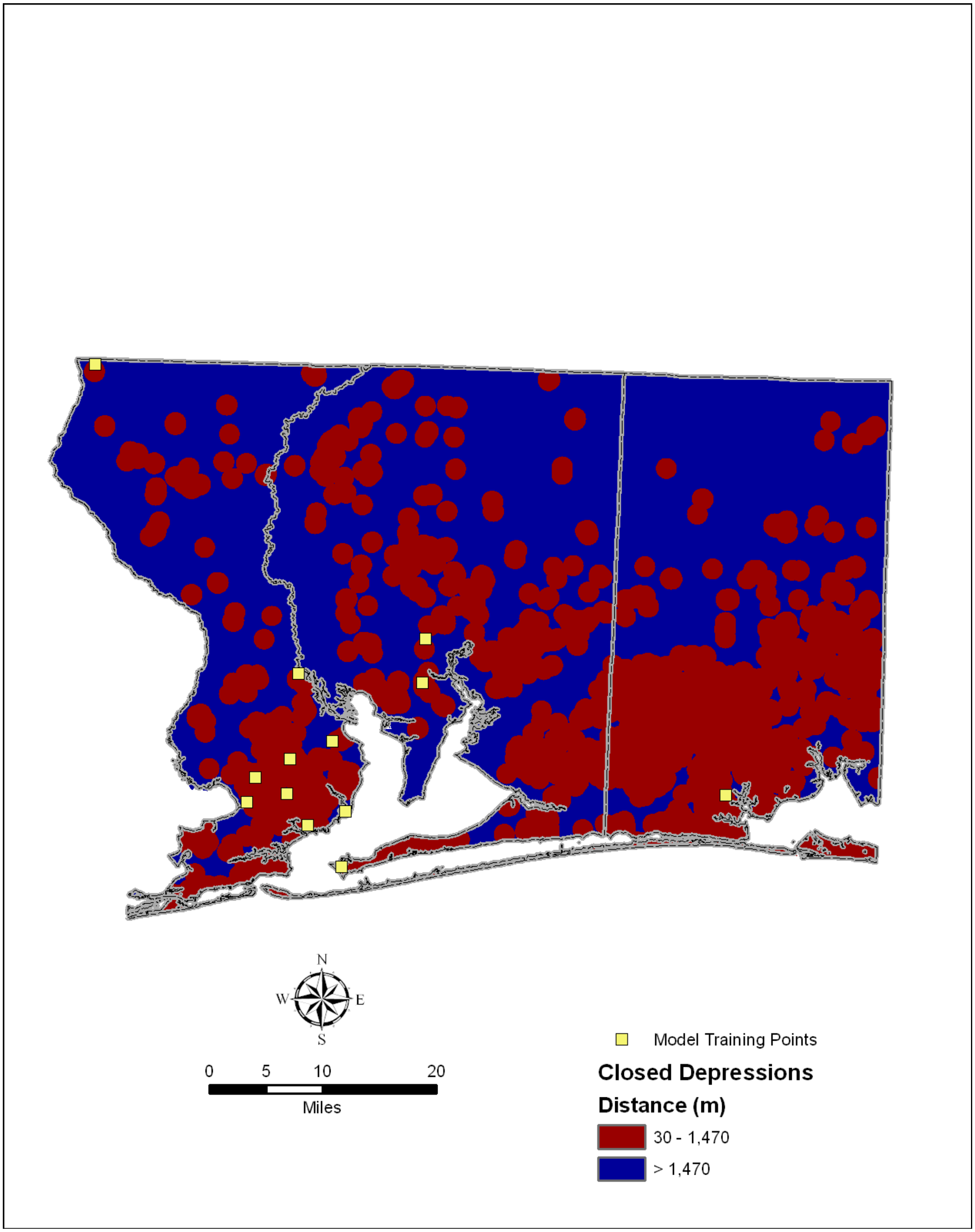

Figure 9. Generalized closed topographic depressions evidential theme; based on calculated weights analysis blue areas share a weaker association with training points and thereby relatively lower aquifer vulnerability, whereas red areas share a stronger association with training points.

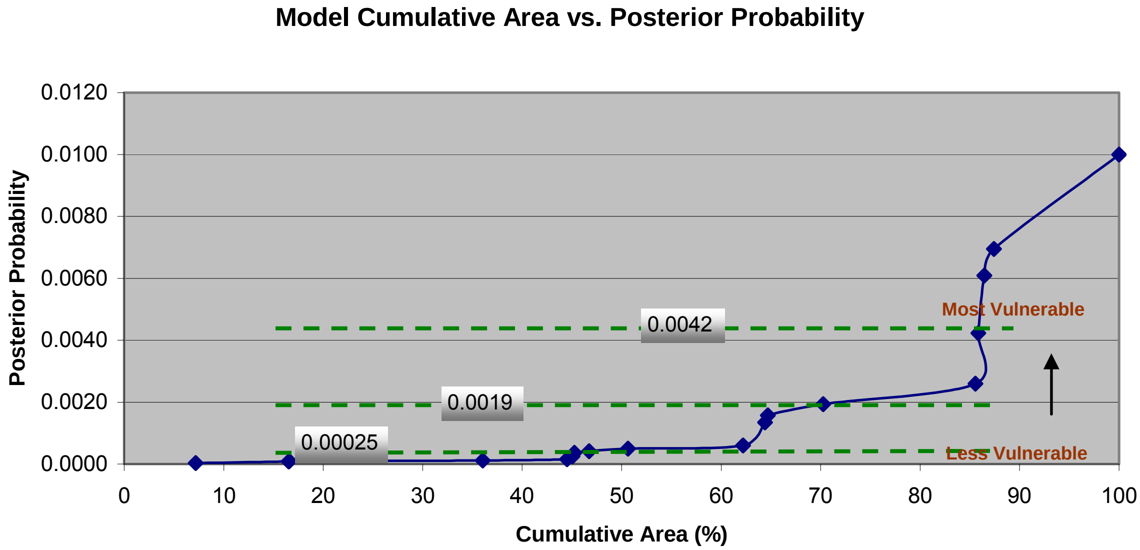

Figure 10. Vulnerability class breaks are defined by selecting where a significant increase in probability and area are observed.

Conditional independence was calculated at 0.93 for the SNG project indicating that evidential themes had virtually no conditional dependence.

Model Confidence

During model execution, confidence values are calculated both for each generalized evidential theme and for the final response theme. Confidence values approximately correspond to the statistical levels of significance listed in Table 3.

Table 3. Test values calculated in weights of evidence and their respective studentized T values expressed as level of significance in percentages.

Studentized T Value	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

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 test value of 1.7644 corresponds to a greater than 95% confidence – or level of significance – and was the minimum calculated confidence level for the SNG project evidential themes (see Table 4 below for evidential theme confidence values).

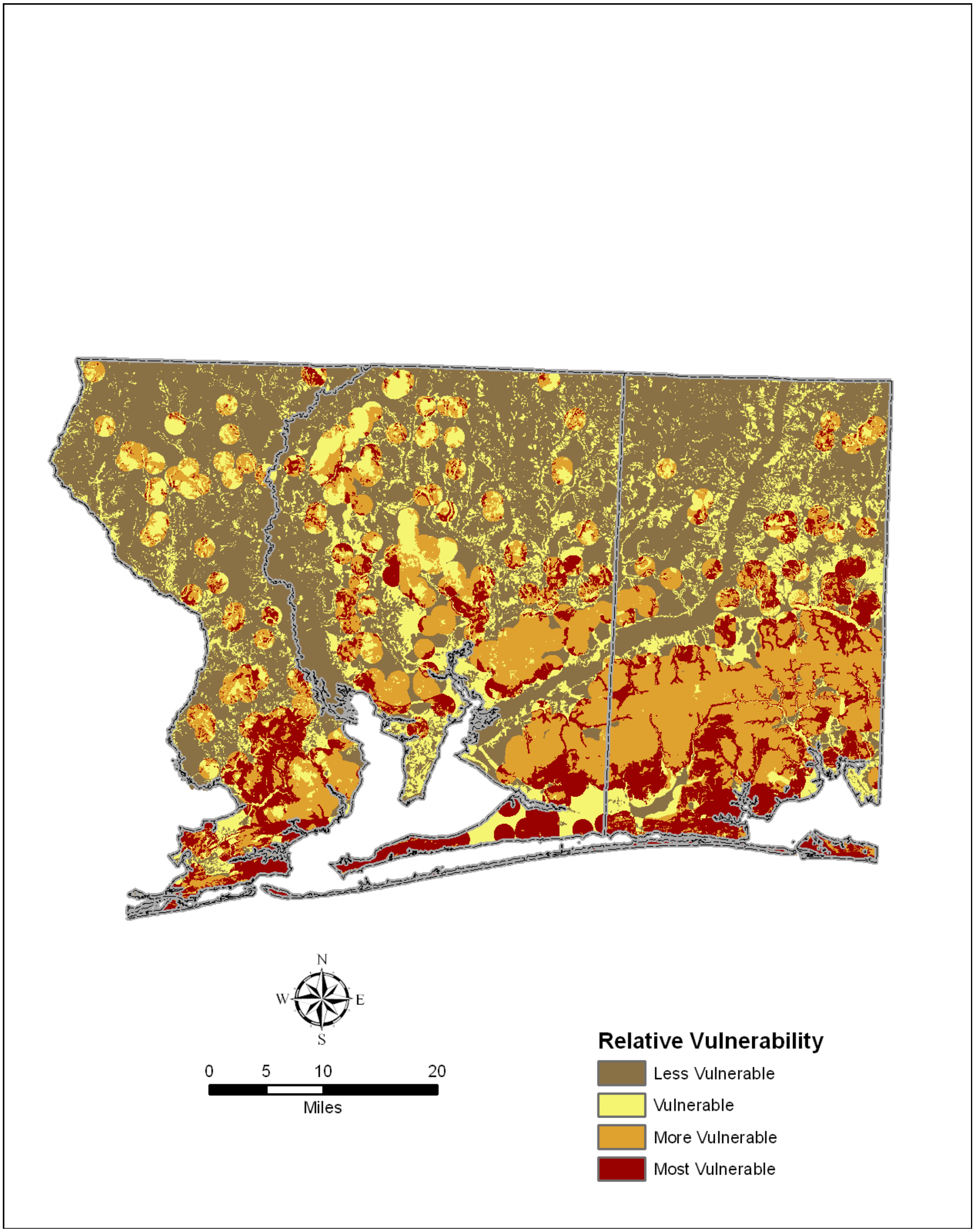

Figure 11. Relative vulnerability map for the Sand-and-Gravel Aquifer Vulnerability Assessment project. Classes of vulnerability are based on calculated probabilities of a unit area containing a training point, or a monitor well with water quality sample results indicative of vulnerability.

A confidence map is also calculated for a response theme by normalizing the theme's posterior probability by its total uncertainty (standard deviation). A confidence map can be generated based on these calculations. The confidence map for the SNG response theme is displayed in Figure 12. Areas with high posterior probability values typically correspond to higher confidence values and as a result have a higher level of certainty with respect to predicting aquifer vulnerability.

Weights Calculations

Table 4 displays evidential themes used in the SNG model, weights calculated for each theme, along with contrast and confidence values. Positive weights indicate areas where training points are likely to occur, while negative weights indicate 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. Confidence of the evidential theme is also calculated and is equal to the contrast divided by its standard deviation (a student T test). Confidence is a measure of significance due to uncertainties of the weights and missing data (Raines, 1999). A positive contrast that is significant, based on its confidence, suggests that a generalized evidential theme is a useful predictor.

Table 4. Weights of evidence 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
Soil Hydraulic Conductivity	0.4997	-1.1516	1.6513	2.147
Depth to Water	0.3673	-0.9898	1.3571	1.7644
Closed Topographic Depressions	0.7972	-2.0272	2.8244	2.7128

Because negative weights (W2) values for all evidential themes are stronger (have greater absolute values) than the positive weights (W1), they are better predictors of where training points were *less* likely to occur. Based on contrast values, closed topographic depressions theme has the strongest (highest absolute value) weight and is the primary determinant in predicting areas of vulnerability in the SNG model.

Validation

The weights of evidence approach, because it relies on a set of training points, which by definition are known sites of vulnerability, is essentially self-validated. Twelve of Thirteen training points were predicted in zones of posterior probability greater than the prior probability (in other words, classified accurately). Further strengthening the results were the evaluation of a minimum confidence threshold for evidential themes, and generation of a confidence map of the response theme. In addition to these exercises, and in the style of previous aquifer vulnerability assessments (Cichon et al., 2005; Baker et al., 2005; Arthur et al., 2005), additional validation techniques were applied to the SNG model to further strengthen its defensibility, and, ultimately, its utility: (1) comparison of dissolved nitrogen values to posterior probability and evaluation of an associated trend; and (2) generation of a test response theme based on a subset of training points and comparison of points not used in subset to model results.

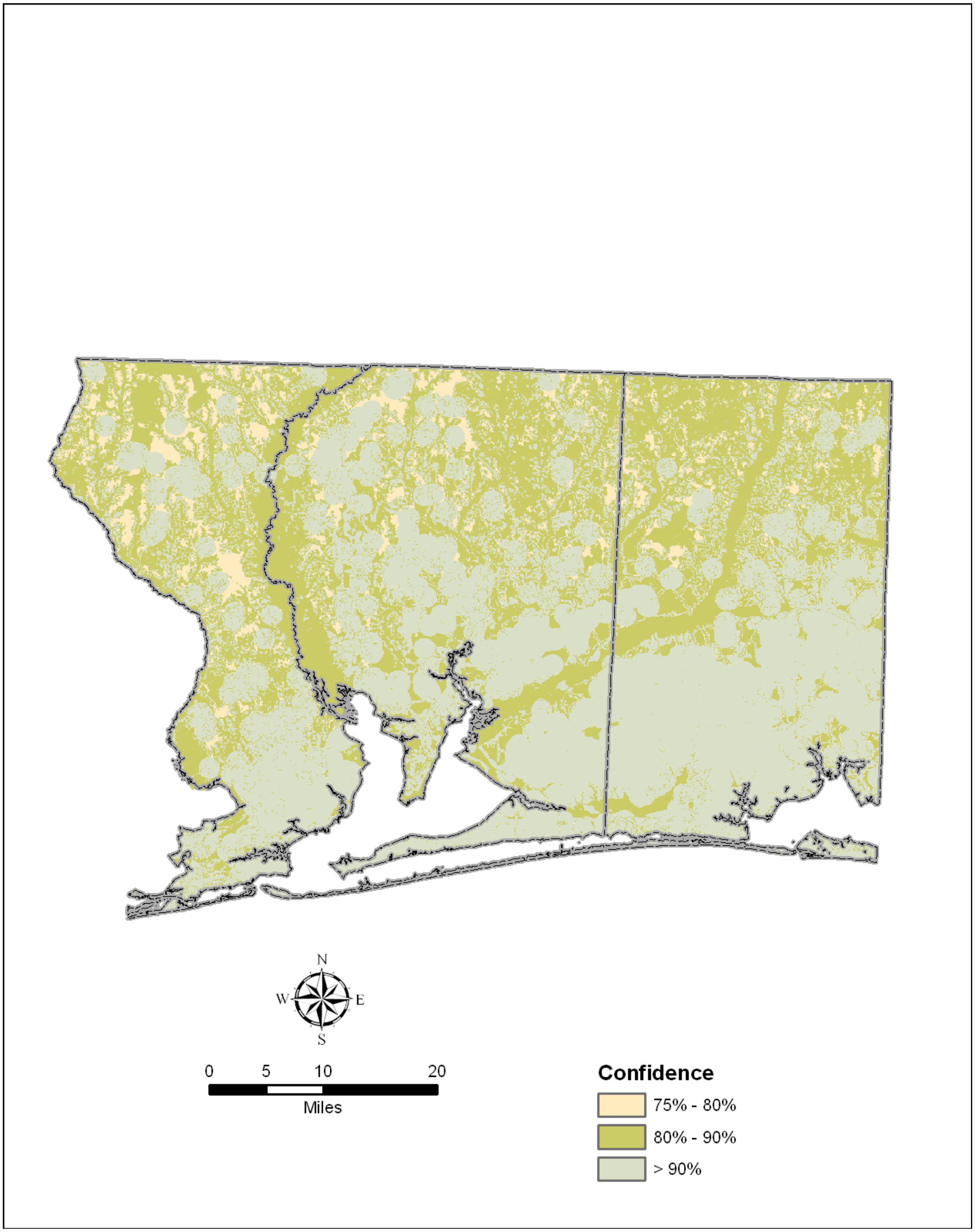

Figure 12. Confidence map for the SNG model calculated by dividing the posterior probability values by the total uncertainty for each class to give an estimate of how well specific areas of the model are predicted.

Dissolved Nitrogen Data vs. Posterior Probability

It was expected that comparison of posterior probability values to the dissolved nitrogen dataset from which the training point theme was extracted would reveal a proportional trend, in other words, as dissolved nitrogen values increase, so should posterior probability values. Dissolved nitrogen median concentrations were binned and averaged for each posterior probability value calculated in model output. The average values were plotted in a chart against posterior probability values (Figure 13) and a positive trend was observed.

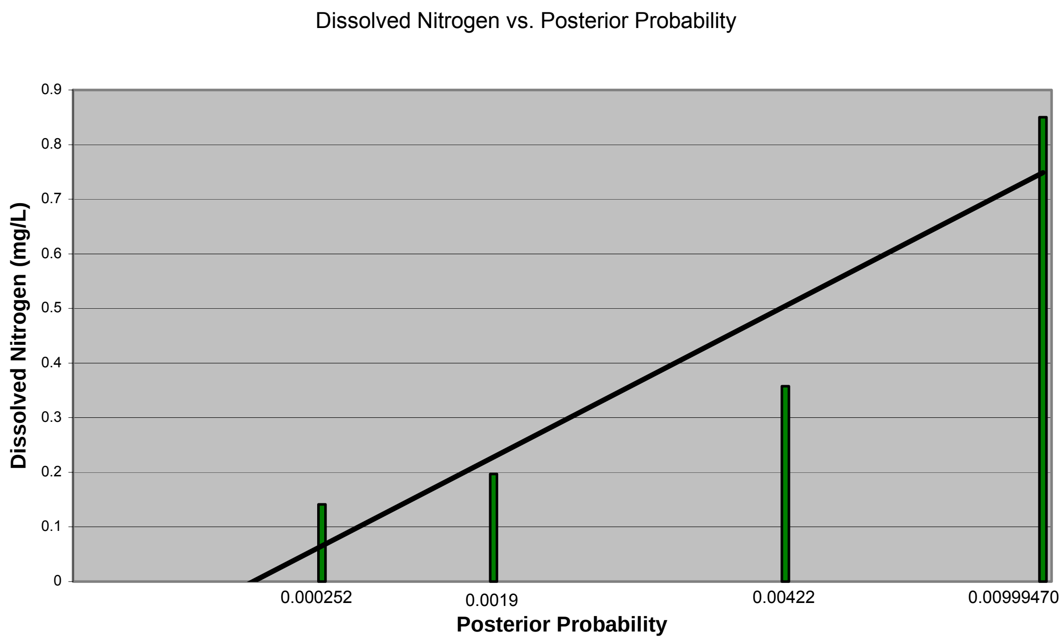

Figure 13. Dissolved nitrogen values (averaged per posterior probability class) versus probability values to reveal trend between increasing dissolved nitrogen concentrations and posterior probability.

An additional test involved applying a Pearson's correlation coefficient (r) test to all dissolved nitrogen values versus posterior probability values. This test revealed a value of 0.60 indicating more than a 99% degree of statistical significance between the response theme values and the dissolved nitrogen data.

Subset Response Theme

Another meaningful validation exercise similar to the exercise above is to use the existing training point dataset to develop two subsets: one to generate a test response theme, and one to validate output from this test response theme. Results from this exercise helped to further assess whether the dissolved nitrogen training points are reasonable predictors of aquifer vulnerability.

From the SNG training point theme, a subset of 75% (ten wells) were randomly selected and used to develop a test response theme; the remaining 25% (three wells) of the training points were used as the validation dataset for the test response theme. This comparison revealed that the three test wells in the validation subset, or 100%, occur in areas of the test response theme with predicted probability values higher than the prior probability value. In other words, 100% of the validation subset of training points were located in areas predicted to have a greater than chance probability of containing a training point in the test response theme (Figure 14). This further supports the conclusion that the SNG model response theme is a reasonable estimator of vulnerability.

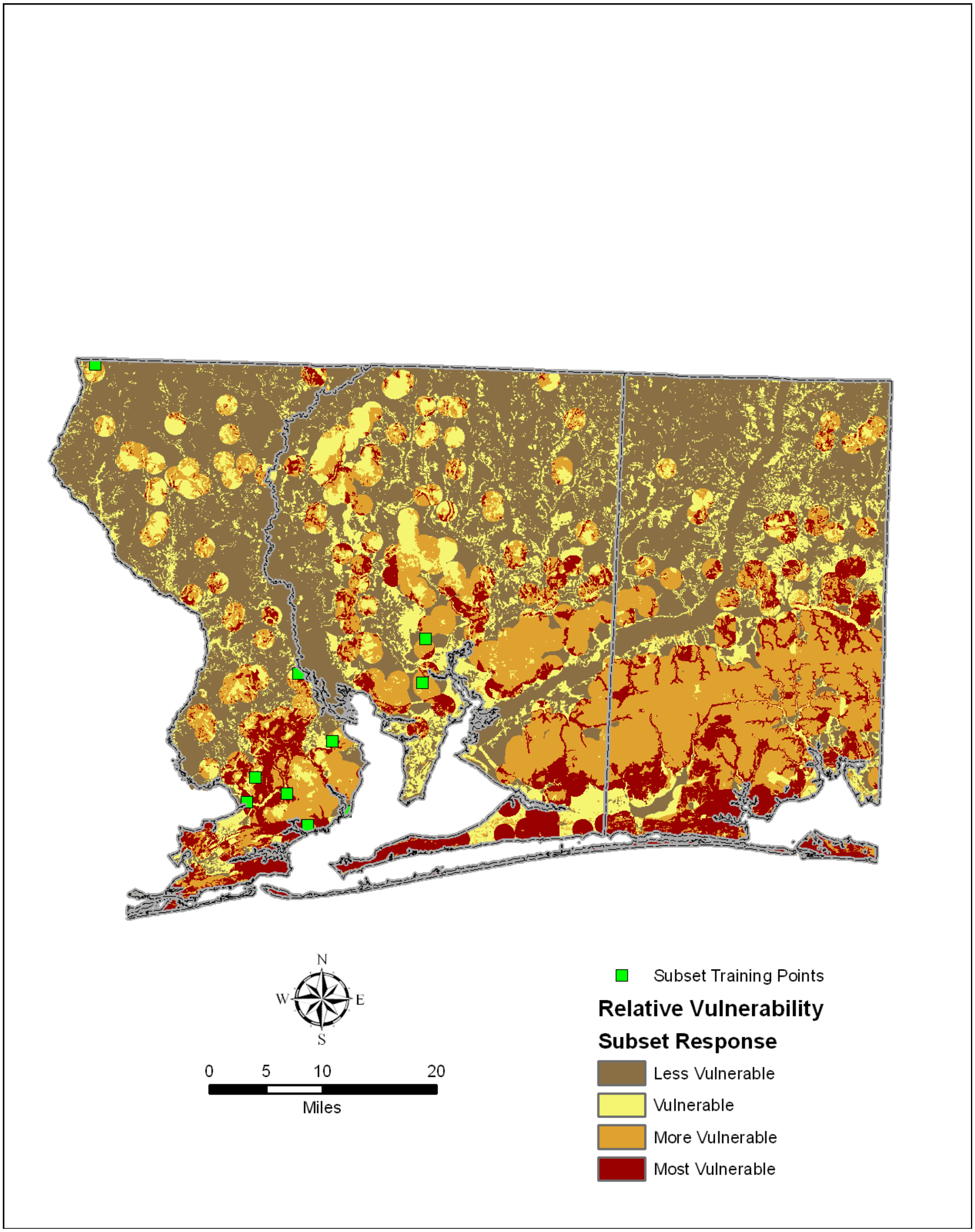

Figure 14. Subset response training points plotted in the dissolved nitrogen response theme.

BISCAYNE/SURFICIAL AQUIFER

Study Area

The Counties of Miami-Dade, Broward and Palm Beach were used as the Biscayne/Surficial aquifer system model study area extent (Figure 15). This boundary extends slightly outside the range of the Biscayne aquifer but does represent a valuable surficial aquifer system potable water source and conforms to political boundaries similar to the way the SNG boundary was developed. Because of the sizes of some polygons representing soil data, a grid cell size of approximately 30 meter squares (or 900 m^2) was selected for evidential theme development. This grid cell size, while necessary to capture resolution available in some input data layers, does not reflect appropriate resolution of final model output. Appropriate scale of use of model results is discussed in *Model Implementation and Limitations*.

Water bodies were omitted from the model extent for two main reasons: first, the main goal of this project is to estimate vulnerability of the surficial aquifer system (SAS) and not vulnerability of surface water features, and second, data for water bodies is typically not available – i.e., Everglades or wells are not drilled in water bodies. Also, soil surveys normally don't contain information regarding lake and stream bottoms.

Training Point Theme

In the model analysis, training points are groundwater wells tapping the SAS with water quality data indicative of high recharge. Dissolved nitrogen (ammonia plus total dissolved nitrogen) analytical values served as training point data for the Biscayne/Surficial model. Ammonia concentrations were incorporated into the Biscayne/Surficial training point data set to account for areas of the State with a high water table. In these areas, nitrogen in the form of ammonia can be more prevalent where the high water table and organic soils create a reducing environment. Naturally occurring oxygen and nitrogen are generally considered ubiquitous at land surface as primary components of the atmosphere; moreover, relatively low concentrations of these analytes occur in well protected – or less vulnerable – aquifer systems. Accordingly, where these analytes occur in elevated concentrations in groundwater, yet are not attributable to human activity, they are good indicators of aquifer vulnerability (Arthur et al., 2007).

Water quality data sources explored include the FDEP background water quality network, FDEP STATUS network and SFWMD databases. From these data sources, 115 wells measured for dissolved nitrogen were identified as being potential candidates for training points. Statistical analyses revealed 14 samples were considered statistical outliers. The upper 25th percentile of this set – or all wells with median dissolved nitrogen values greater than or equal to 0.955 milligrams per liter (mg/L) – served as the training point theme and consists of 24 wells. Figure 16 displays the distribution of water wells used to derive training points and the resulting training point theme across the study area.

Training points are used to calculate prior probability, weights for each evidential theme, and posterior probability of the response theme (see *Glossary*). Prior probability (training point unit area divided by total study area) is the probability that a training point will occupy a defined unit area within the study area, independent of any evidential theme data. The prior probability value, a unitless parameter, for the Biscayne/Surficial model is 0.003 ([1 km^2 model unit area * 24 training points] / 8841.9 km^2 = 0.003). Posterior probability values generated during response theme development are interpreted relative to the value of prior probability with higher values generally indicating areas with higher probability of containing a training point.

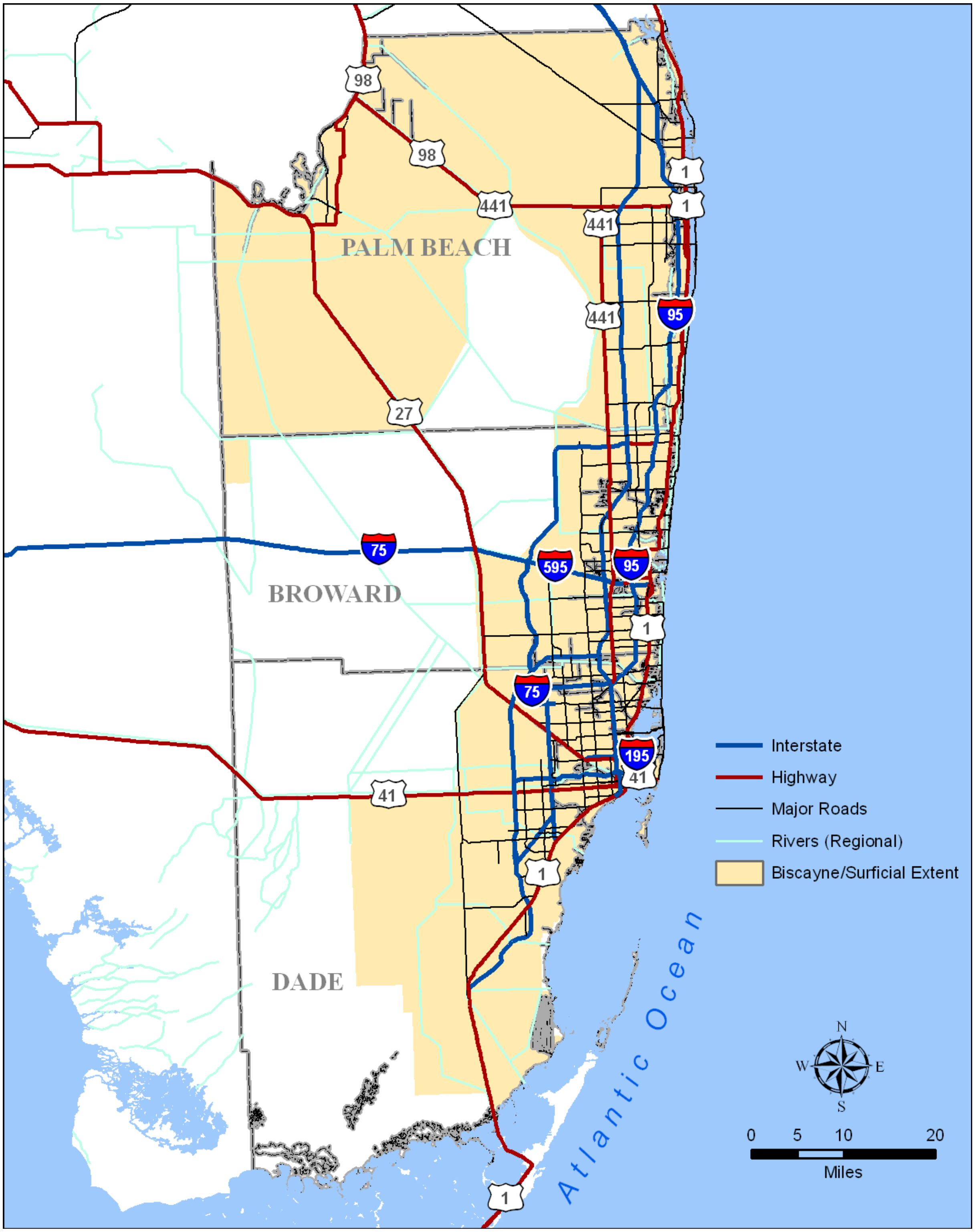

Figure 15. Biscayne/Surficial Aquifer Vulnerability Assessment project study area extent.

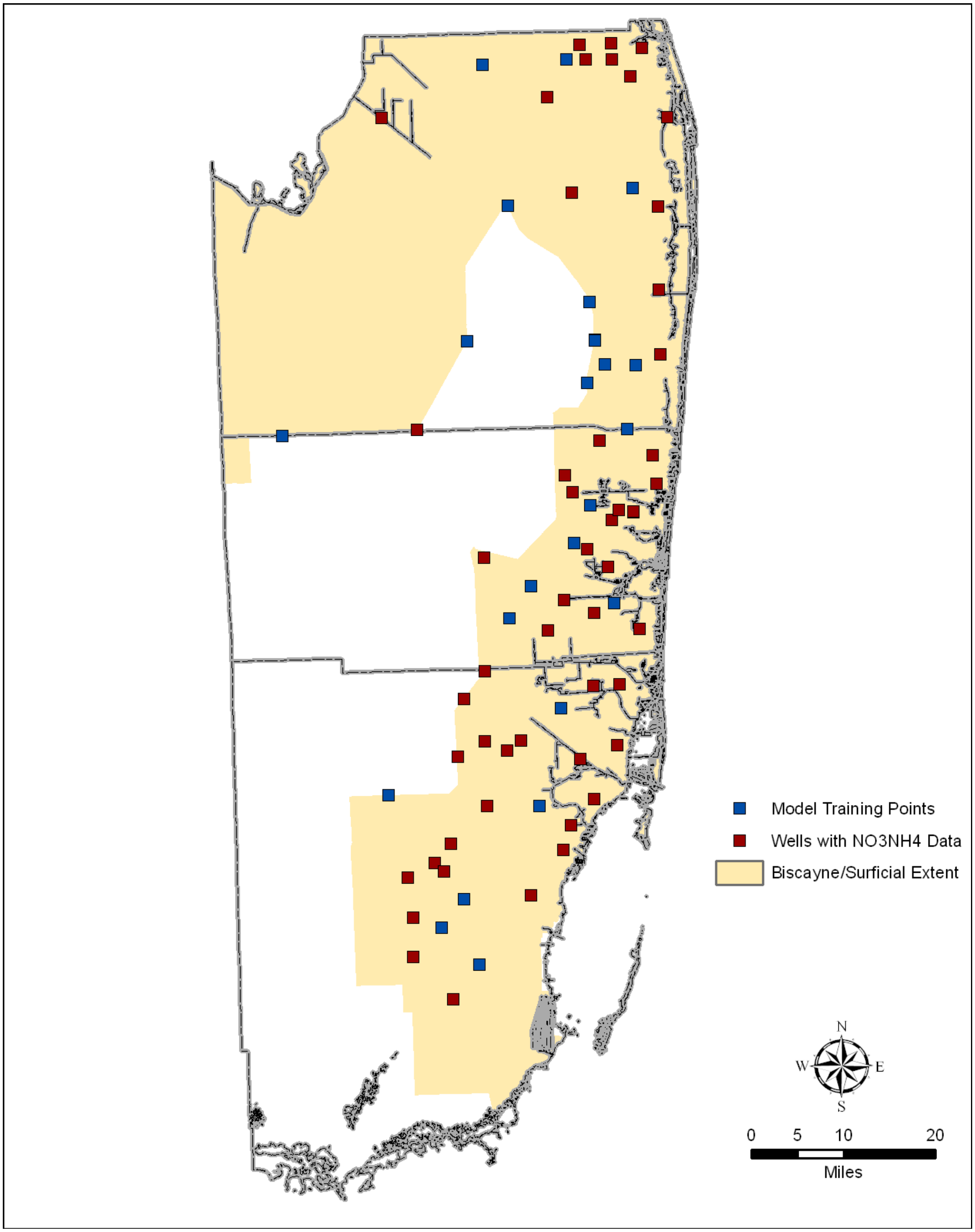

Figure 16. Location of all wells measured for ammonia + nitrate (dark red boxes), and locations of training point wells with median ammonia + nitrate values greater than 0.955 mg/L (blue boxes).

Evidential Themes – Model Input Layers

Input data layers, or evidential themes, representing hydrogeologic factors controlling the location of training points, and thereby vulnerability, were developed for model input. Because of the local scale nature of the Biscayne/Surficial project and the availability of new data, all model inputs represent previously unavailable datasets. The factors considered for the Biscayne/Surficial project include closed topographic depressions, depth to water, soil pedality, and soil hydraulic conductivity.

Soil Hydraulic Conductivity and Soil Pedality Themes

The rate that water moves through soil is a critical component of any aquifer vulnerability analysis, as soil is literally an aquifer system's first line of defense against potential contamination (Arthur et al., 2005). Two parameters of soils were evaluated for input into the Biscayne/Surficial model: *soil hydraulic conductivity*, which is the "amount of water that would move vertically through a unit area of saturated soil in unit time under unit hydraulic gradient" (U.S. Department of Agriculture, 2005); and *soil pedality*, which is calculated based on soil type, soil grade, and soil pedon size, and is a unitless parameter. Soil pedality is a relatively new concept used to estimate the hydrologic parameter of soil and is generated for the Biscayne/Surficial aquifer system using the pedality point method developed by Lin et al. (1999).

Countywide datasets representing soil hydraulic conductivity and soil pedality were developed for use as input into the Biscayne/Surficial model. Multiple empirical values are reported in soil surveys representing various zones in each soil column underlying a particular soil polygon. Representative values for each horizon in a column are combined using a sum of the weighted mean. This is completed for both hydraulic conductivity and soil pedality. Figure 18 displays values of soil hydraulic conductivity.

Depth to Water Theme

Depth to water is another critical layer in determining aquifer vulnerability. Where the depth to water is greatest (larger vadose zone), aquifer vulnerability is generally lower, whereas in areas where the depth to water is nearer to the surface, the vulnerability of the aquifer is generally higher.

The multiple linear regression equation method was not used to create the depth to water for the Biscayne/Surficial aquifer system. During testing of this method, the lack of good topographic data enhanced errors making the use of well data a more viable option. The SFWMD has a multitude of wells that measure water level of the surficial aquifer system. After examining all wells and removing outliers, 308 wells were used to create a water table elevation layer that was generated using the kriging interpolation technique.

The root-mean-square residual between the regressed and measured water-table elevation resulted in a weighted mean of 0.63 feet and exhibited a strong correlation coefficient of 0.99 (Figure 17). The final depth to water evidential theme was calculated by subtracting the water table elevation values from the FDEP DEM values (Figure 19).

Table 5. Linear regression coefficients for MINWT and difference between DEM and MINWT.

Number of surficial wells	Root mean square residual (ft)	Value range for difference between interpolated & measured water table (ft)	Correlation coefficient
308	0.626	[-3.65, 3.11]	0.99

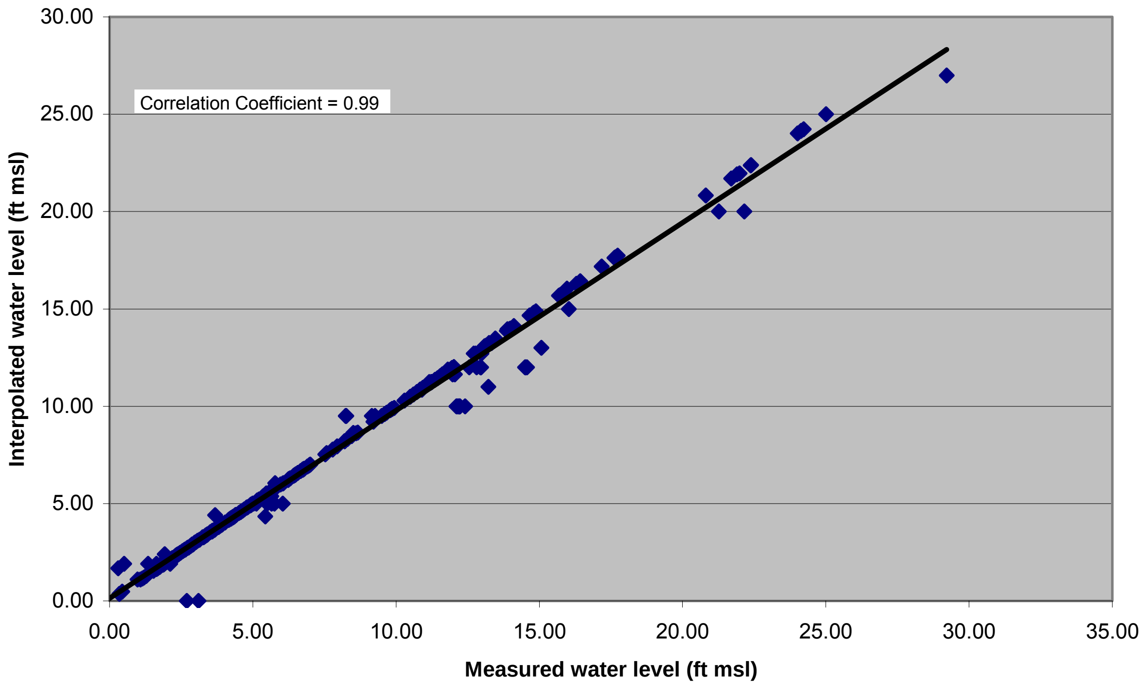

Figure 17. Regressed and measured water level for Biscayne / Surficial Aquifer.

Closed Topographic Depressions

Karst features, or sinkholes and depressions, can provide preferential pathways for movement of surface water into the underlying aquifer system and enhance an area's aquifer vulnerability where present. The closer an area is to a karst feature, the more vulnerable it may be considered. Closed topographic depressions extracted from U.S. Geological Survey 7.5-minute quadrangle maps served as the dataset from which to estimate closed topographic depressions in the study area (Figure 20).

Sensitivity Analysis/Evidential Theme Generalization

Sensitivity analysis allows decisions to be made about proposed evidential themes by evaluating each theme's association with training points – or aquifer vulnerability – and ultimately helps determine model input. For example, soil hydraulic conductivity and soil pedality were both developed to represent soil properties; sensitivity analysis allows, through statistical analysis, determination of which of these two layers served as the most appropriate input representing soil properties for the final Biscayne/Surficial analysis. Results of this process indicate that soil hydraulic conductivity, depth to water, and closed topographic depressions were the best suited evidential themes for use in final modeling.

Following sensitivity analysis and selection of evidential themes to be input into the Biscayne/Surficial model, themes were generalized to assess which areas of the evidence share a greater association with locations of training points. During calculation of weights for each theme, a contrast value was calculated for each class of the theme by combining the positive and negative weights. 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). Contrast and weights are described in more detail below in *Discussion*.

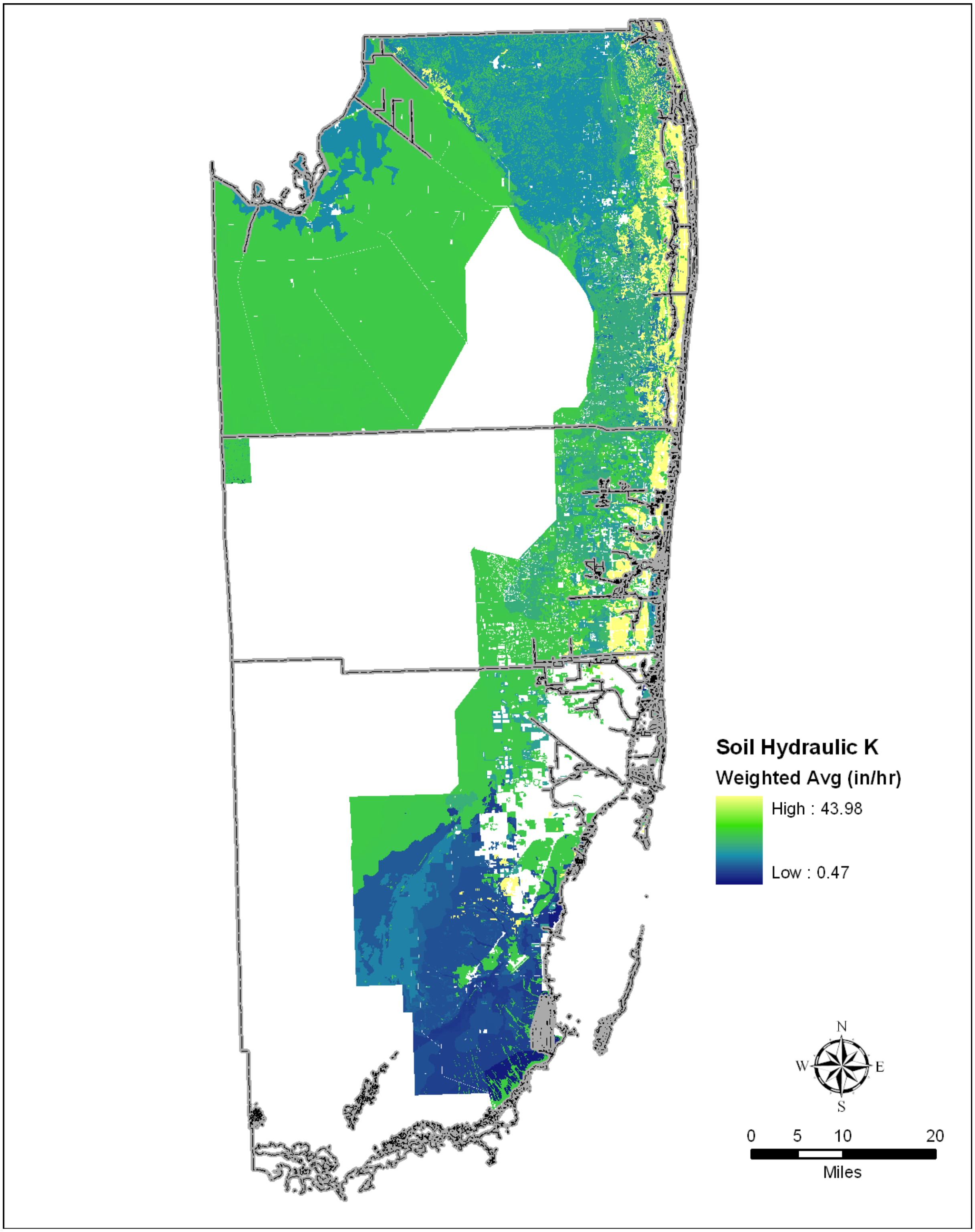

Figure 18. Distribution of soil hydraulic conductivity values across the Biscayne / Surficial study area. White areas represent 'no data' areas in the soil survey data or locations of water bodies.

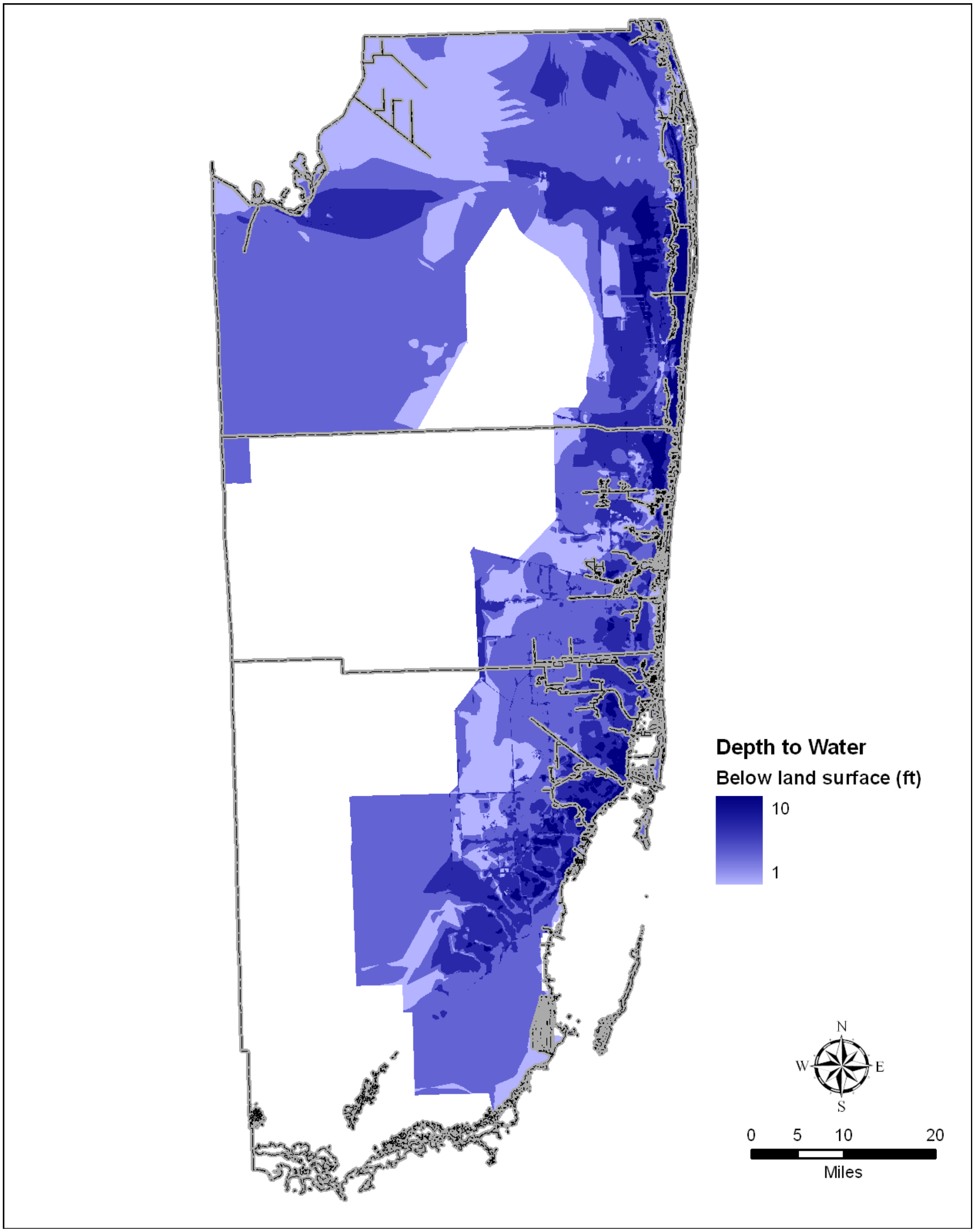

Figure 19. Distribution of depth to water values across the Biscayne / Surficial study area. White areas represent 'no data' areas or locations of water bodies.

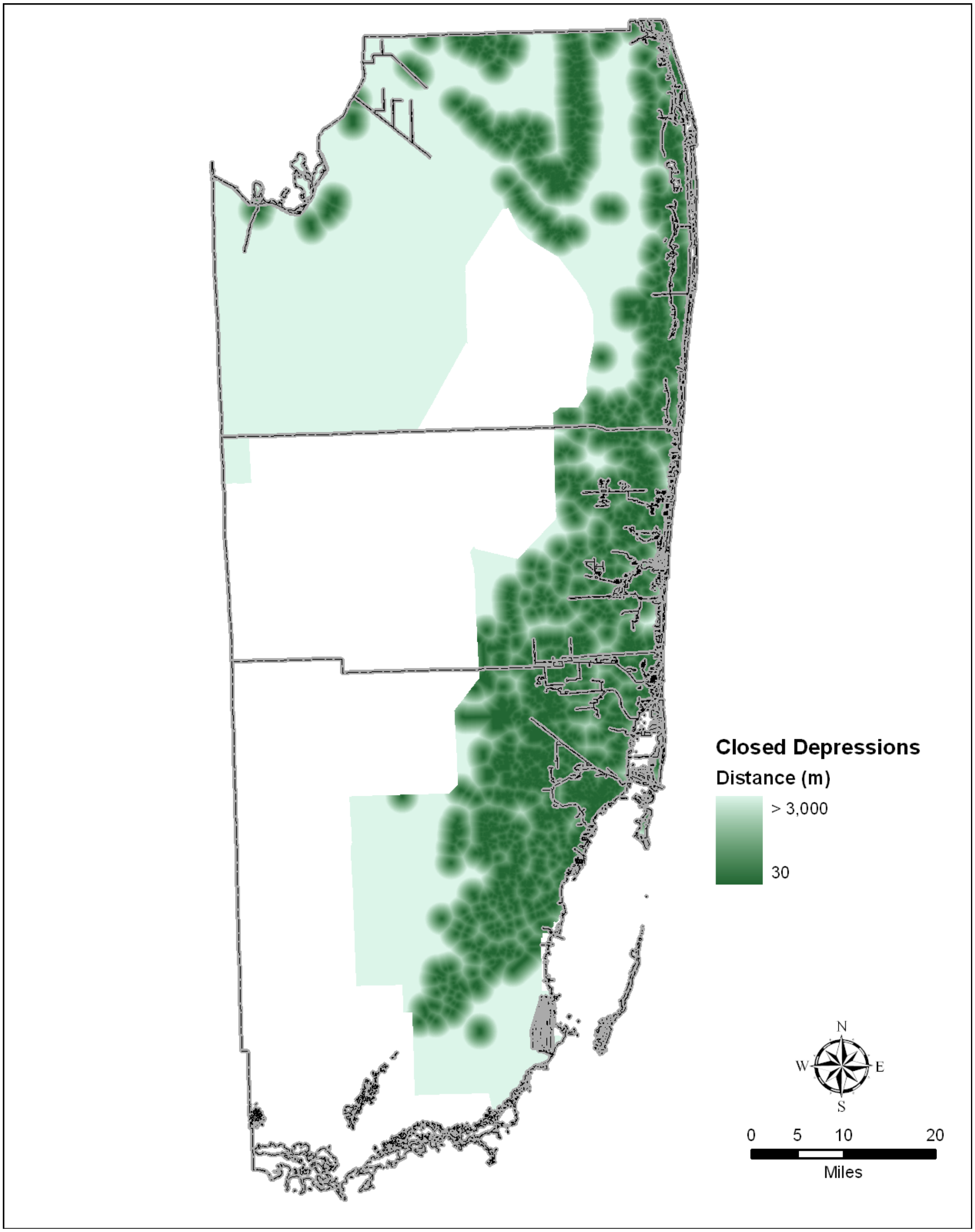

Figure 20. Proximity to closed topographic depressions extracted from U.S. Geological Survey 7.5-minute topographical contour lines.

Contrast values were used to determine where to sub-divide evidential themes into generalized categories prior to final modeling. The simplest and most accepted method used to subdivide an evidential theme is to select the maximum contrast value as a threshold value to create binary generalized evidential themes. In other models, categorization of more than two classes may be justified (Arthur et al., 2005). For the Biscayne/Surficial project, a binary break was typically defined by the weights of evidence analysis for each evidential theme creating two spatial categories: one with stronger association with the training point theme and one with weaker association.

Soil Hydraulic Conductivity/ Soil Pedality

Weights calculated during sensitivity analysis for soil hydraulic conductivity were stronger (i.e., had higher absolute value) than weights calculated for soil pedality. As a result, soil hydraulic conductivity was chosen as the better predictor of aquifer vulnerability because it shared the best association with training points.

Soil hydraulic conductivity, ranges from 0.47 to 29.71 in/hr across the study area. Test modeling indicated that areas greater than or equal to 13.02 in/hr were more associated with the training points, and therefore associated with higher aquifer vulnerability. Conversely, areas less than 13.02 in/hr were less associated with the training points, and therefore lower aquifer vulnerability. Based on this analysis, the evidential theme was generalized into two classes as displayed in Figure 21.

Depth to Water

The depth to water ranges from zero to 83 feet deep across the study area. The analysis revealed that areas less than or equal to one foot deep were more associated with the training points, and therefore associated with higher aquifer vulnerability. Areas with a depth to water greater than one foot were less associated with the training points, and therefore lower aquifer vulnerability. Based on this analysis, the evidential theme was generalized into two classes as displayed in Figure 22.

Closed Topographic Depressions

As mentioned above, areas closer to a depression are normally associated with higher aquifer vulnerability. Based on this, features were buffered into 30 meter zones to allow for a proximity analysis. The analysis indicated that areas within 2,430 meters of a closed topographic depression were more associated with the training points, and therefore with higher aquifer vulnerability. Conversely, areas greater than 2,430 meters from a closed topographic depression were less associated with the training points, and therefore lower aquifer vulnerability. Based on this analysis, the evidential theme was generalized into two classes as displayed in Figure 23.

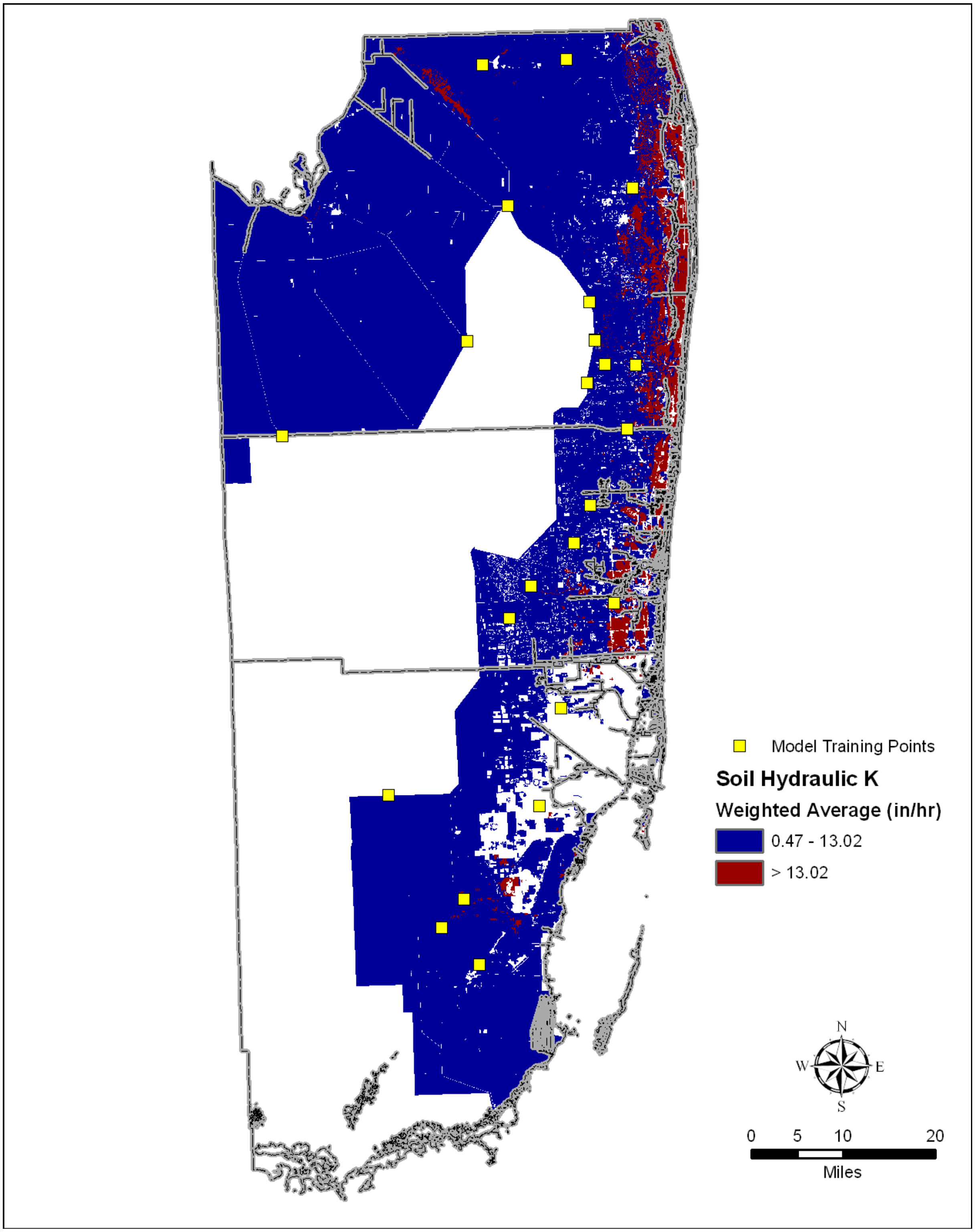

Figure 21. Generalized soil hydraulic conductivity evidential theme; based on calculated weights analysis blue areas share a weaker association with training points and thereby relatively lower aquifer vulnerability, whereas red areas share a stronger association with training points.

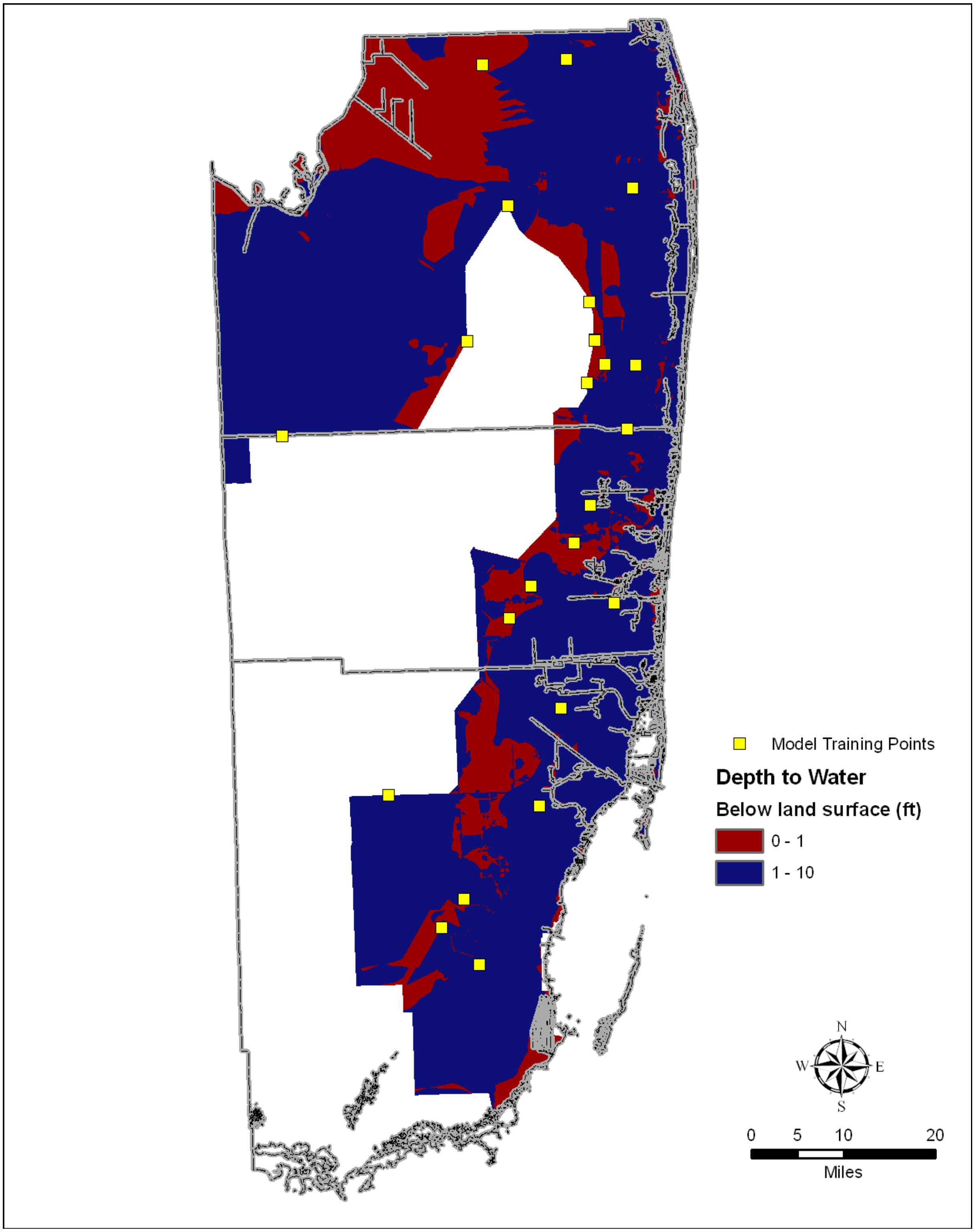

Figure 22. Generalized depth to water evidential theme; based on calculated weights analysis blue areas share a weaker association with training points and thereby relatively lower aquifer vulnerability, whereas red areas share a stronger association with training points.

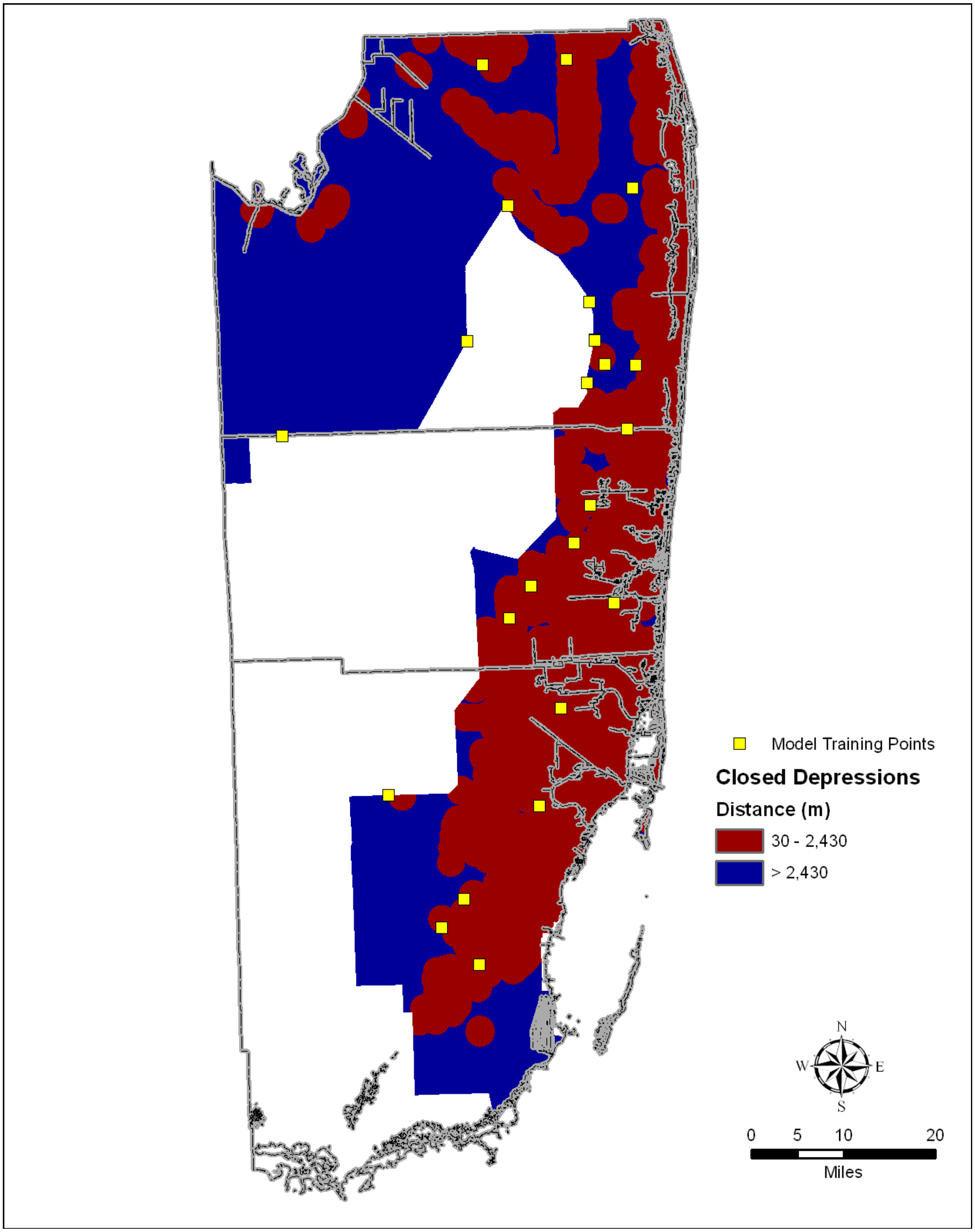

Figure 23. Generalized closed topographic depressions evidential theme; based on calculated weights analysis blue areas share a weaker association with training points and thereby relatively lower aquifer vulnerability, whereas red areas share a stronger association with training points.

Response Theme

Using evidential themes representing soil hydraulic conductivity, depth to water, and closed topographic depressions, weights of evidence was applied to generate a response theme, which is a GIS raster consisting of *posterior probability* values ranging from 0.0011 to 0.0146 across the study area. These probability values describe the relative probability that a unit area of the model will contain a training point – i.e., a point of aquifer vulnerability as defined above in *Training Points* – with respect to the prior probability value of 0.003 or ([1.0 km^2 model unit area * 24 training points] / 8841.9 km^2 = 0.003). Prior probability is the probability that a training point will occupy a defined unit area within the study area, independent of evidential theme data. Probability values at the locations of 22 of the 24 training points are above the prior probability, indicating that this model is a strong predictor of training point locations.

The response theme was broken into classes of relative vulnerability based on the prior probability value and on inflections in a chart in which cumulative study area was plotted against posterior probability (Figure 24). Higher posterior probability values correspond with more vulnerable areas, as they essentially have a higher chance of containing vulnerability based on the definition of a training point. Conversely, lower posterior probability values correspond to less vulnerable areas as they essentially have a lower chance of containing vulnerability based on the definition of a training point.

As described in *Introduction*, the Biscayne/Surficial model was based on the modeling technique used in the FAVA project. The FAVA project identified relative vulnerability of Florida's principal aquifer systems broken into three classes: more vulnerable, vulnerable and less vulnerable zones. This naming technique was applied to the Biscayne/Surficial results, to define the relative vulnerability classes as displayed in Figure 25.

As expected, the Biscayne/Surficial response theme indicates that areas of highest vulnerability are associated with areas where the depth to water is lowest, in areas of dense closed topographic depressions, and areas of higher soil hydraulic conductivity. Conversely, areas of lowest vulnerability are determined by high depth to water values, sparse closed topographic depression distribution, and lower soil hydraulic conductivity values.

Discussion

Prior to discussion of weights calculations during model execution, two components of a weights of evidence analysis are described to assist in interpretation of Biscayne/Surficial model results: *Conditional Independence* and *Model Confidence*.

Conditional Independence

Conditional independence is a measure of the degree that evidential themes are affecting each other due to similarities between themes. Evidential themes are considered independent of each other if the conditional independence value is around 1.00, and conditional independence values within the range of 1.00 ± 0.15 generally indicate limited to no dependence among evidential themes (Bonham-Carter, 1994). Values significantly outside this range can inflate posterior probabilities resulting in unreliable response themes.

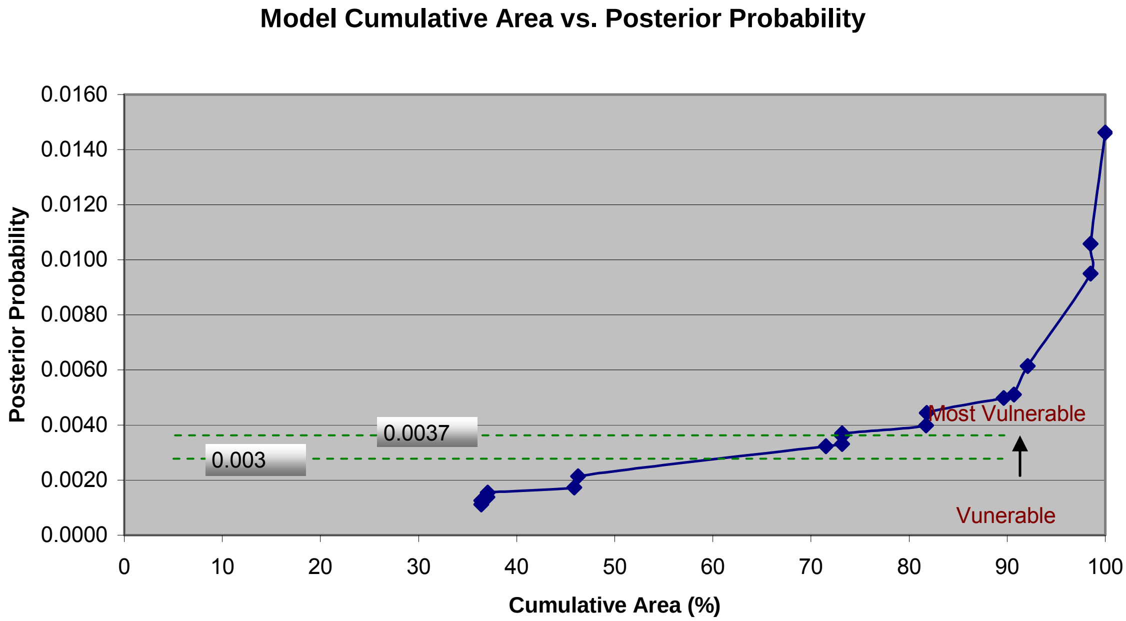

Figure 24. Vulnerability class breaks are defined by selecting where a significant increase in probability and area are observed.

Conditional independence was calculated at 0.96 for the Biscayne/Surficial project indicating that evidential themes had virtually no conditional dependence.

Model Confidence

During model execution, confidence values are calculated both for each generalized evidential theme and for the final response theme. Confidence values approximately correspond to the statistical levels of significance listed in Table 3.

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 test value of 0.9691 corresponds to approximately 85% confidence – or level of significance – and was the minimum calculated confidence level for the Biscayne/Surficial project evidential themes (see Table 6 below for evidential theme confidence values).

A confidence map is also calculated for a response theme by normalizing the theme's posterior probability by its total uncertainty (standard deviation). A confidence map can be generated based on these calculations. The confidence map for the Biscayne/Surficial response theme is displayed in Figure 26. Areas with high posterior probability values typically correspond to higher confidence values and as a result have a higher level of certainty with respect to predicting aquifer vulnerability.

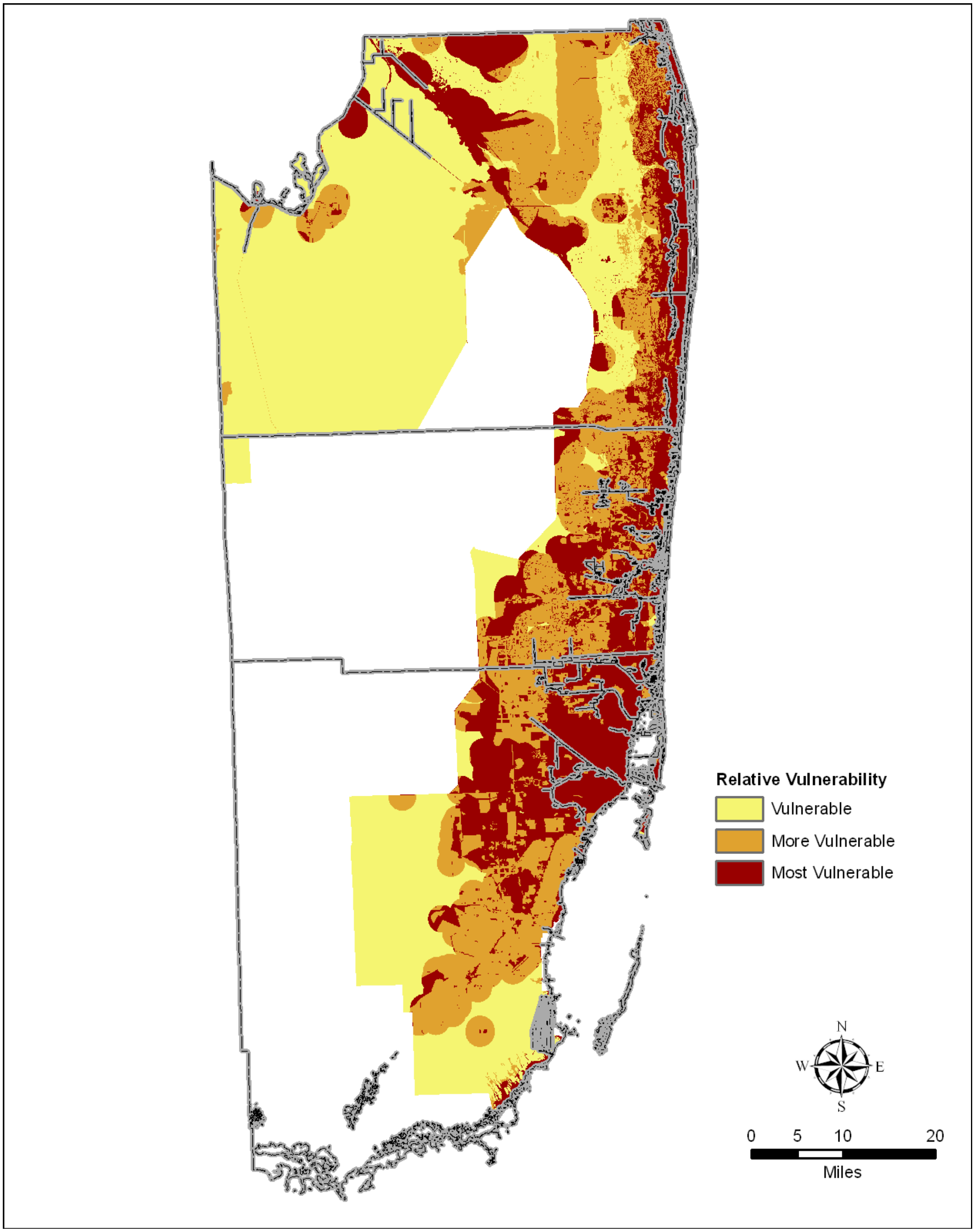

Figure 25. Relative vulnerability map for the Biscayne/Surficial Vulnerability Assessment project. Classes of vulnerability are based on calculated probabilities of a unit area containing a training point, or a monitor well with water quality sample results indicative of vulnerability.

Weights Calculations

Table 6 displays evidential themes used in the Biscayne/Surficial model, weights calculated for each theme, along with contrast and confidence values. Positive weights indicate areas where training points are likely to occur, while negative weights indicate 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. Confidence of the evidential theme is also calculated and is equal to the contrast divided by its standard deviation (a student T test). Confidence is a measure of significance due to uncertainties of the weights and missing data (Raines, 1999). A positive contrast that is significant, based on its confidence, suggests that a generalized evidential theme is a useful predictor.

Table 6. Weights of evidence 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
Soil Hydraulic Conductivity	0.8763	-0.2098	1.0861	2.2420
Depth to Water	0.3273	-0.1088	0.4360	0.9691
Closed Topographic Depressions	0.3866	-0.6740	1.0606	2.2473

Because positive weights (W1) values for soil hydraulic conductivity and depth to water are stronger (have greater absolute values) than the negative weights (W2), they are better predictors of where training points are likely to occur, whereas the closed topographic depression theme is a better indicator of where training points are less likely to occur. Based on contrast values, the soil hydraulic conductivity theme has the strongest (highest absolute value) weight and is the primary determinant in predicting areas of vulnerability in the Biscayne/Surficial model.

Validation

The weights of evidence approach, because it relies on a set of training points, which by definition are known sites of vulnerability, is essentially self-validated. Twenty-two of twenty-four training points were predicted in zones of posterior probability greater than the prior probability (in other words, classified accurately). Further strengthening the results were the evaluation of a minimum confidence threshold for evidential themes, and generation of a confidence map of the response theme. In addition to these exercises, and in the style of previous aquifer vulnerability assessments (Cichon et al., 2005; Baker et al., 2005; Arthur et al., 2005), additional validation techniques were applied to the Biscayne/Surficial model to further strengthen its defensibility, and, ultimately, its utility: (1) comparison of dissolved nitrogen values to posterior probability and evaluation of an associated trend; (2) generation of a test response theme based on a subset of training points and comparison of points not used in subset to model results and (3) comparison of dissolved oxygen values with vulnerable zones of the response theme.

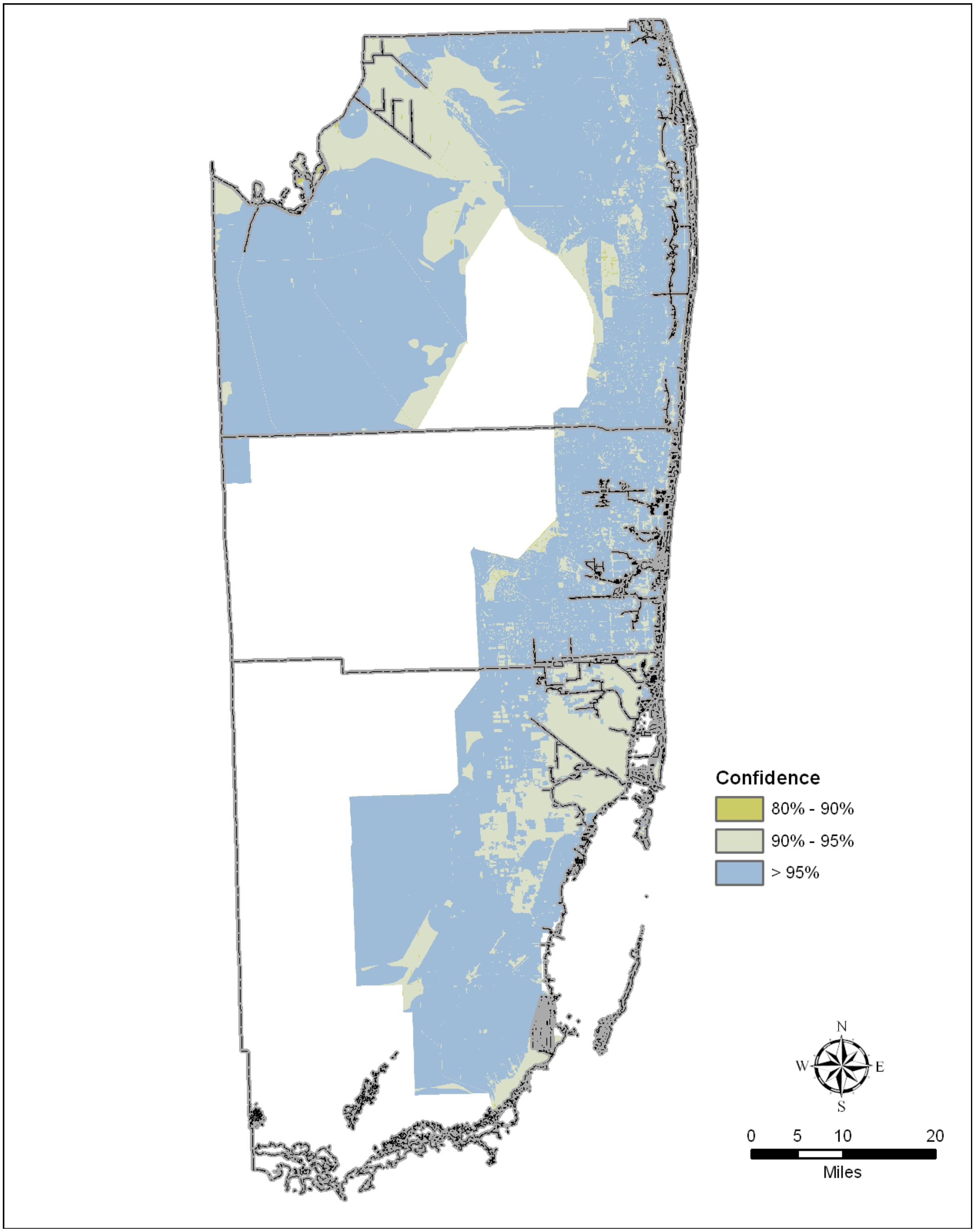

Figure 26. Confidence map for the Biscayne/Surficial model calculated by dividing the posterior probability values by the total uncertainty for each class to give an estimate of how well specific areas of the model are predicted.

Dissolved Nitrogen Data vs. Posterior Probability

It was expected that comparison of posterior probability values to the dissolved nitrogen dataset from which the training point theme was extracted would reveal a proportional trend, in other words, as dissolved nitrogen values increase, so should posterior probability values. Dissolved nitrogen median concentrations were binned and averaged for each posterior probability value calculated in model output. The average values were plotted in a chart against posterior probability values (Figure 27) and a slight positive trend was observed.

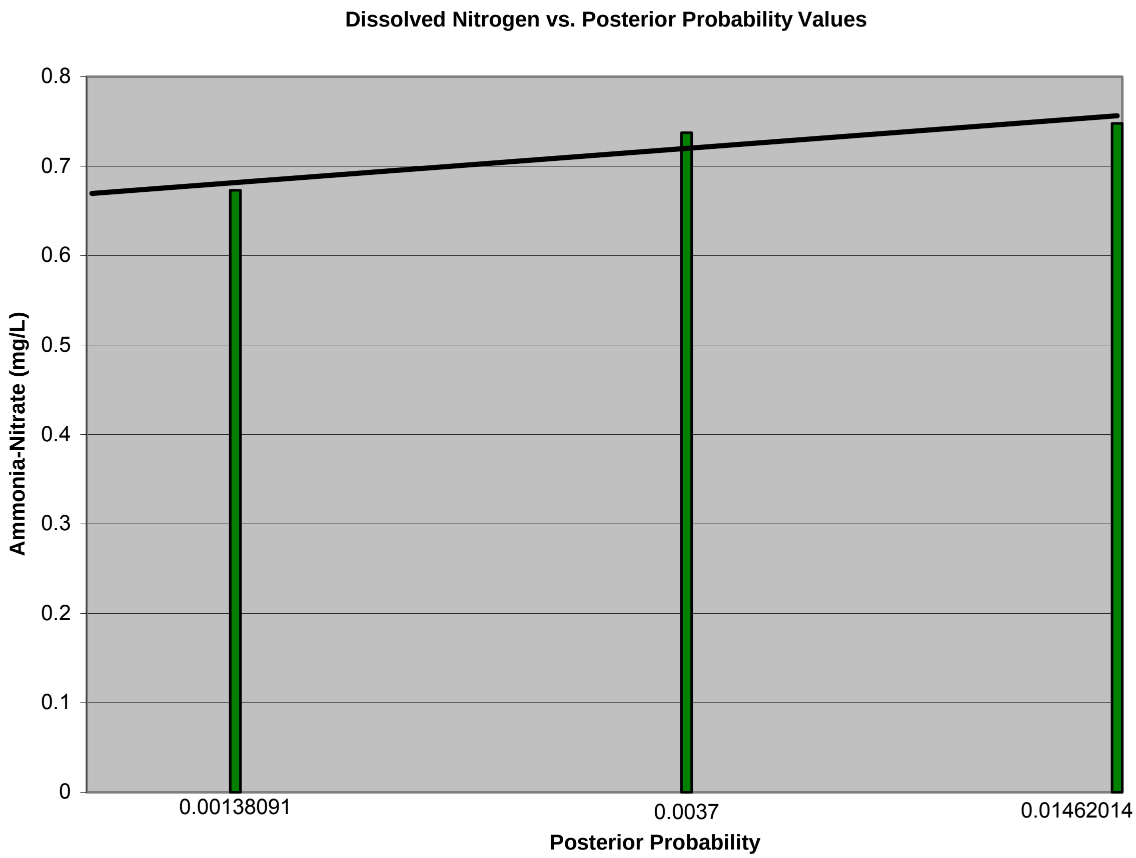

Figure 27. Dissolved nitrogen values (averaged per posterior probability class) versus probability values to reveal trend between increasing dissolved nitrogen concentrations and posterior probability.

Subset Response Theme

Another meaningful validation exercise similar to the exercise above is to use the existing training point dataset to develop two subsets: one to generate a test response theme, and one to validate output from this test response theme. Results from this exercise helped to further assess whether the dissolved nitrogen training points are reasonable predictors of aquifer vulnerability.

From the Biscayne/Surficial training point theme, a subset of 75% (18 wells) were randomly selected and used to develop a test response theme; the remaining 25% (6 wells) of the training points were used as the validation dataset for the test response theme. This comparison revealed that four of the six test wells in the validation subset, or 67%, occur in areas of the test response theme with predicted probability values higher than the prior probability value. The other two wells were within four meters of an area with predicted probability values higher than the prior probability. This further supports the conclusion that the Biscayne/Surficial model response theme is a reasonable estimator of vulnerability.

Dissolved Oxygen Data

Perhaps the most rigorous validation exercise used to evaluate quality of model-generated output is to compare predicted model values with independent test values not used in the model. For the Biscayne/Surficial model, this was accomplished by comparison of a separate well dataset based on dissolved oxygen. As mentioned above in *Training Point Theme*, dissolved oxygen is indicative of aquifer vulnerability, but is independent of dissolved nitrogen. Applying the methodology described in *Training Point Theme* to dissolved oxygen data (obtained from the same data sources as dissolved nitrogen data) resulted in a dissolved oxygen dataset of 32 wells each indicative of aquifer vulnerability.

These 32 points were evaluated against posterior probability values of the Biscayne/Surficial model output. Extracting the value of posterior probability from the dissolved nitrogen response theme for the location of each of the 32 dissolved oxygen training points revealed that 28 of the 32 dissolved oxygen training points occur in areas of the dissolved nitrogen model with predicted probability values higher than the prior probability value. In other words, 87.5% of the dissolved oxygen wells were located in areas predicted to have a greater than chance probability of containing a training point. Based on this test, the dissolved nitrogen model is not only a good predictor of vulnerability as defined by the training point theme, it is also a good predictor of the location of an independent parameter also representing aquifer vulnerability. Figure 29 displays dissolved oxygen data points plotted on the dissolved nitrogen response theme.

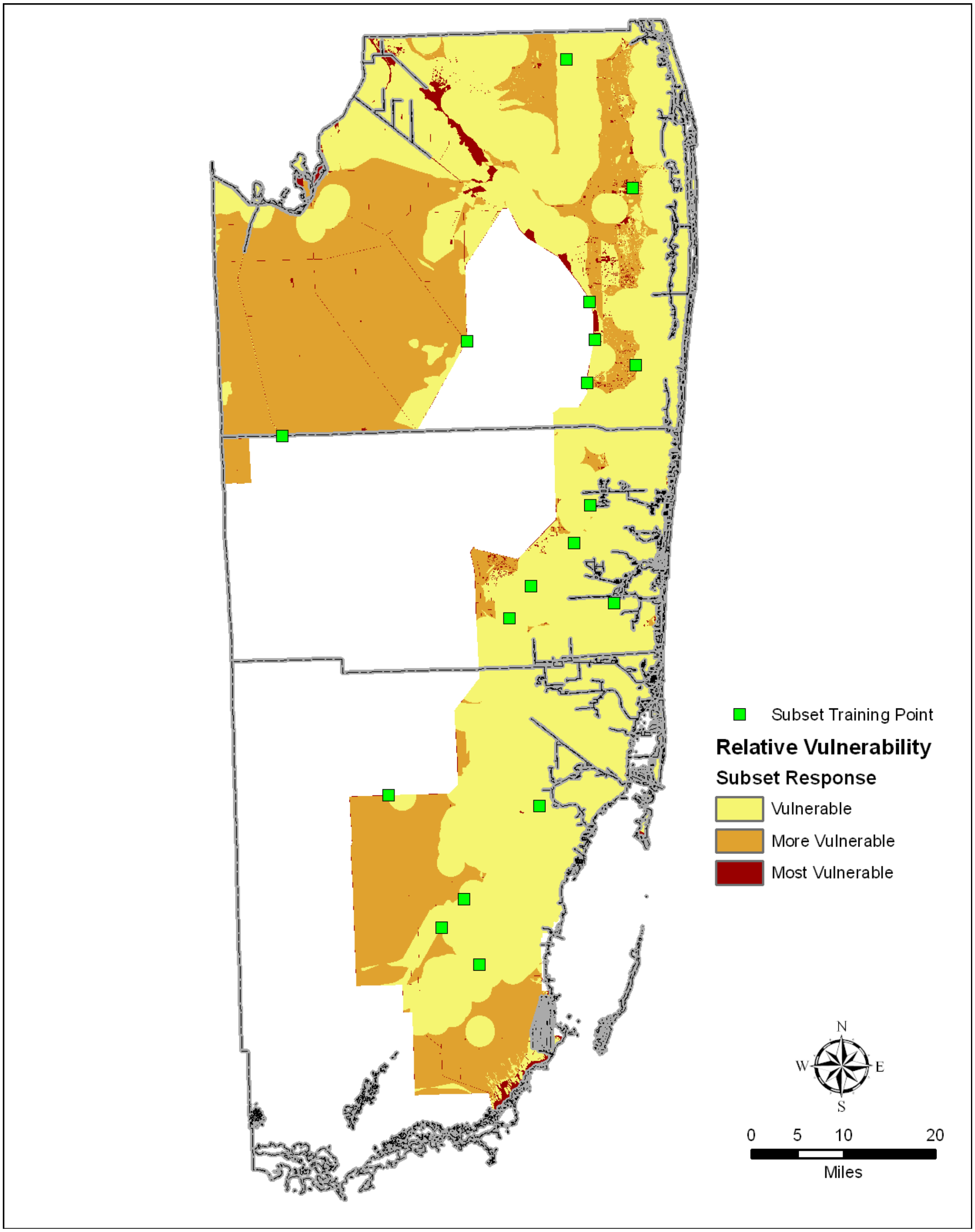

Figure 28. Subset response training points plotted in the dissolved nitrogen response theme.

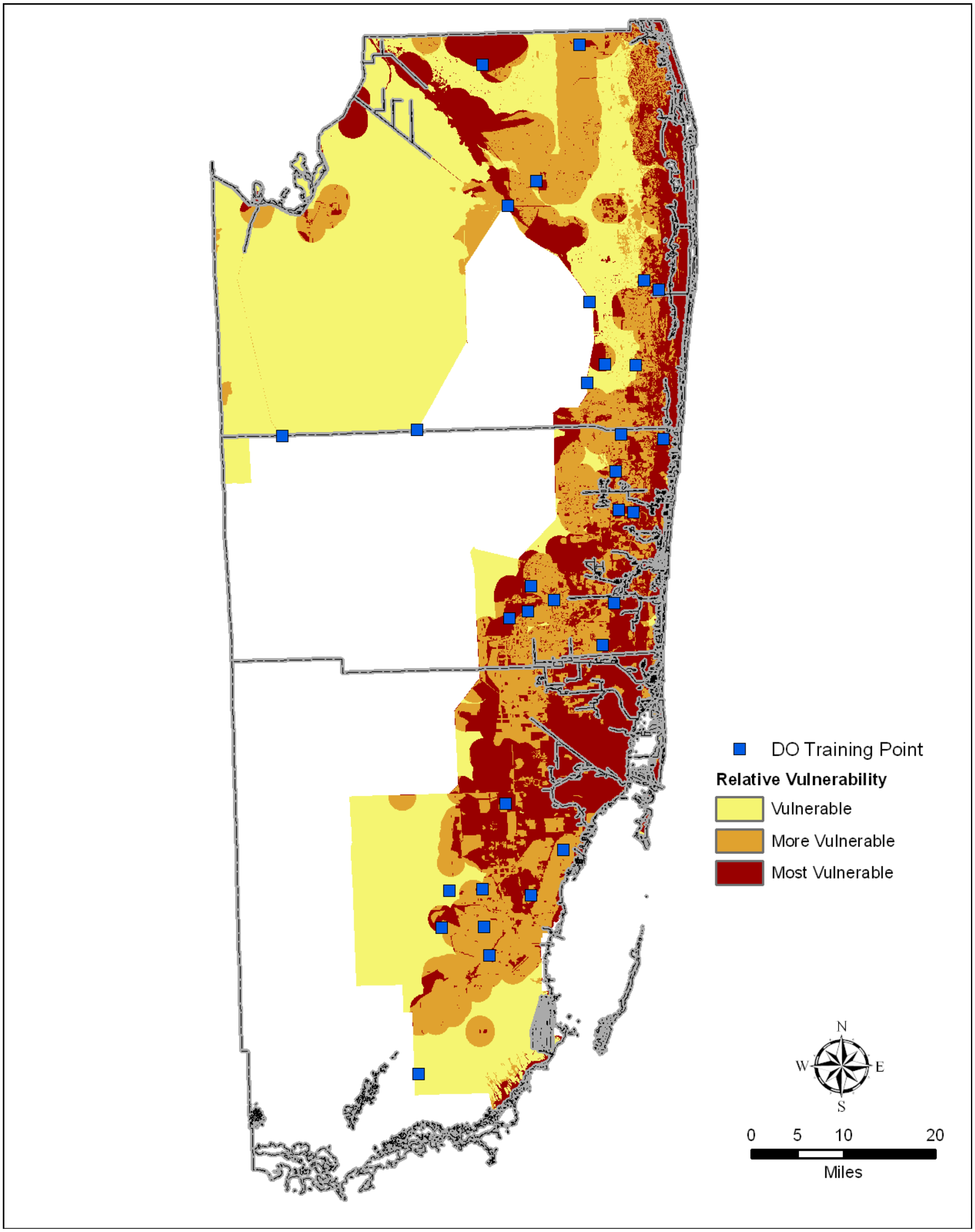

Figure 29. Dissolved oxygen validation training points plotted in the dissolved nitrogen response theme. Comparison reveals 28 of 32 wells (87.5%) of the independent water quality dataset are located in areas with predicted probability values higher than the prior probability value.

SURFICIAL AQUIFER SYSTEM

Study Area

The study area is the same as the FAVA version 1.0 model extent except that the Biscayne/Surficial and SNG model extents have been removed (Figure 30). Because of the sizes of some polygons representing soil data, a grid cell size of approximately 30 meter squares (or 900 m^2) was selected for evidential theme development. This grid cell size, while necessary to capture resolution available in some input data layers, does not reflect appropriate resolution of final model output. Appropriate scale of use of model results is discussed in *Model Implementation and Limitations*.

Water bodies were omitted from the model extent for two main reasons: first, the main goal of this project is to estimate vulnerability of the SAS and not vulnerability of surface water features, and second, data for water bodies is typically not available – i.e., wells are not drilled in water bodies, nor do soil surveys normally contain information regarding lake and stream bottoms.

Training Point Theme

In the model analysis, training points are groundwater wells tapping the surficial aquifer system (SAS) with water quality data indicative of high recharge. Dissolved oxygen analytical values served as training point data for the SAS model. Naturally occurring oxygen and nitrogen are generally considered ubiquitous at land surface as primary components of the atmosphere; moreover, relatively low concentrations of these analytes occur in well protected – or less vulnerable – aquifer systems. Accordingly, where these analytes occur in elevated concentrations in groundwater, yet are not attributable to human activity, they are good indicators of aquifer vulnerability (Arthur et al., 2007).

Water quality data sources explored include the FDEP background water quality network and FDEP STATUS network. From these data sources, 474 wells measured for dissolved oxygen were identified as being potential candidates for training points. Statistical analyses revealed 62 samples were considered statistical outliers. The upper 25th percentile of this set – or all wells with median dissolved oxygen values greater than or equal to 0.655 milligrams per liter (mg/L) – served as the training point theme and consists of 99 wells. Figure 31 displays the distribution of water wells used to derive training points and the resulting training point theme across the study area.

Training points are used to calculate prior probability, weights for each evidential theme, and posterior probability of the response theme (see *Glossary*). Prior probability (training point unit area divided by total study area) is the probability that a training point will occupy a defined unit area within the study area, independent of any evidential theme data. The prior probability value, a unitless parameter, for the SAS model is 0.0019 ([1 km^2 model unit area * 99 training points] / 52919.2 km^2 = 0.0019). Posterior probability values generated during response theme development are interpreted relative to the value of prior probability with higher values generally indicating areas with higher probability of containing a training point.

Figure 30. Surficial Aquifer System Vulnerability Assessment project study area extent.

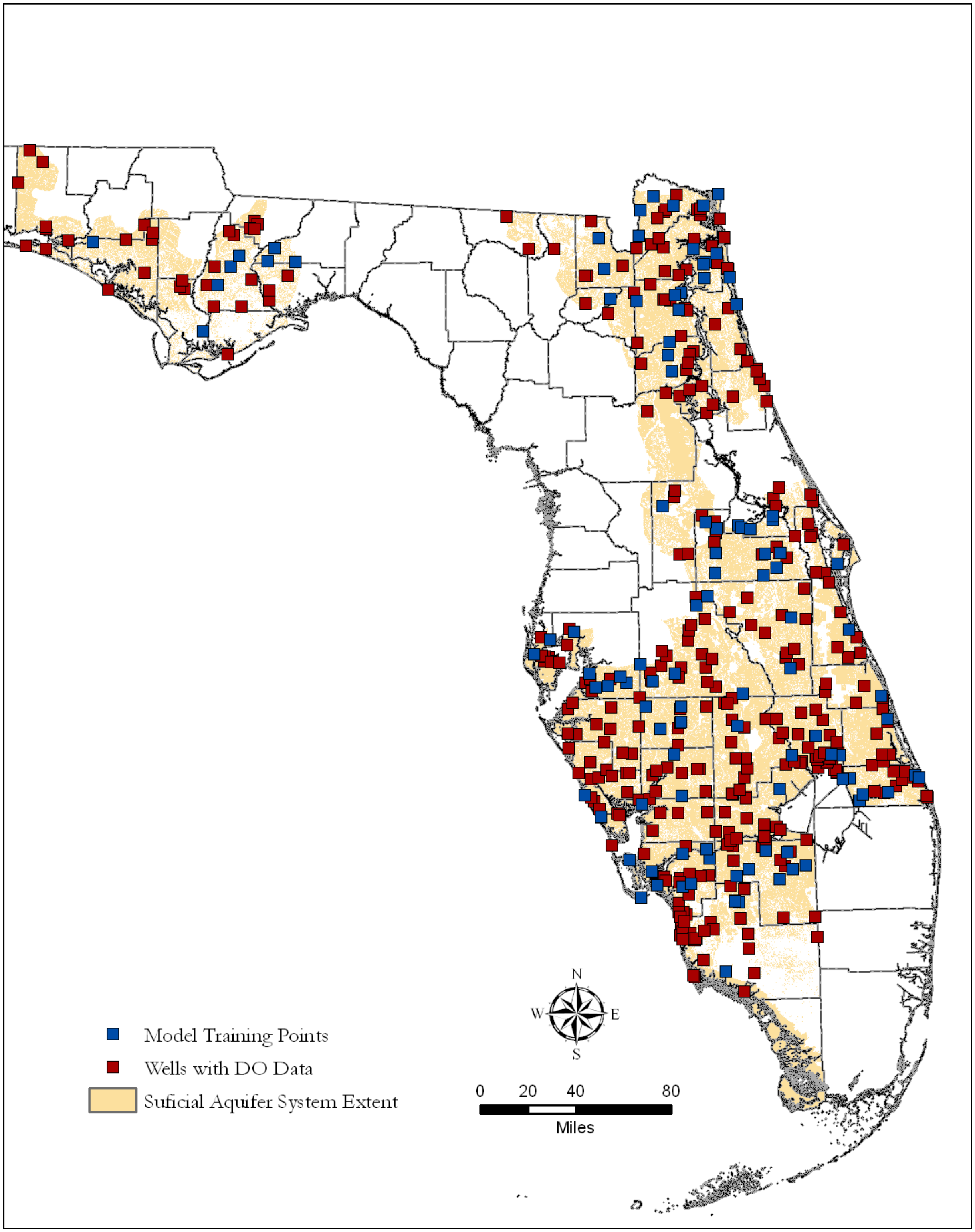

Figure 31. Location of all wells measured for dissolved oxygen (dark red boxes), and locations of training point wells with median dissolved oxygen values greater than 0.655 mg/L (blue boxes).

Evidential Themes – Model Input Layers

Input data layers, or evidential themes, representing hydrogeologic factors controlling the location of training points, and thereby vulnerability, were developed for model input. The factors considered for the SAS project include closed topographic depressions, depth to water, soil pedality, and soil hydraulic conductivity.

Soil Hydraulic Conductivity and Soil Pedality Themes

The rate that water moves through soil is a critical component of any aquifer vulnerability analysis, as soil is literally an aquifer system's first line of defense against potential contamination (Arthur et al., 2005). Two parameters of soils were evaluated for input into the SAS model: *soil hydraulic conductivity*, which is the "amount of water that would move vertically through a unit area of saturated soil in unit time under unit hydraulic gradient" (U.S. Department of Agriculture, 2005); and *soil pedality*, which is calculated based on soil type, soil grade, and soil pedon size, and is a unitless parameter. Soil pedality is a relatively new concept used to estimate the hydrologic parameter of soil and is generated for the SAS using the pedality point method developed by Lin et al. (1999).

Countywide datasets representing soil hydraulic conductivity and soil pedality were developed for use as input into the SAS model. Multiple empirical values are reported in soil surveys representing various zones in each soil column underlying a particular soil polygon. Representative values for each horizon in a column are combined using a sum of the weighted mean. This is completed for both hydraulic conductivity and soil pedality. Figure 33 displays values of soil hydraulic conductivity.

Depth to Water Theme

Depth to water is another critical layer in determining aquifer vulnerability. Where the depth to water is greatest (larger vadose zone), aquifer vulnerability is generally lower, whereas in areas where the depth to water is nearer to the surface, the vulnerability of the aquifer is generally higher.

Using the newly corrected DEM, errors in the SAS water table surface were corrected to produce a more accurate evidential theme layer. The original water table surface had an average error of 6.58 feet and an error range between regressed and measured values of -33.96 to 30.70. The newly created water able surface has an average error of 4.82 feet and an error range between regressed and measured values of -15.82 to 16.72 (Table 7). A strong correlation coefficient of 0.99 was exhibited between the regressed and measured water-table elevation (Figure 32). The final depth to water evidential theme was calculated by subtracting the water table elevation values from the FDEP DEM values (Figure 34).

Table 7. Linear regression coefficients for MINWT and difference between DEM and MINWT.

Number of surficial wells	Root mean square residual (ft)	Value range for difference between interpolated & measured water table (ft)	Correlation coefficient
656	4.82	[-15.82, 16.72]	0.99

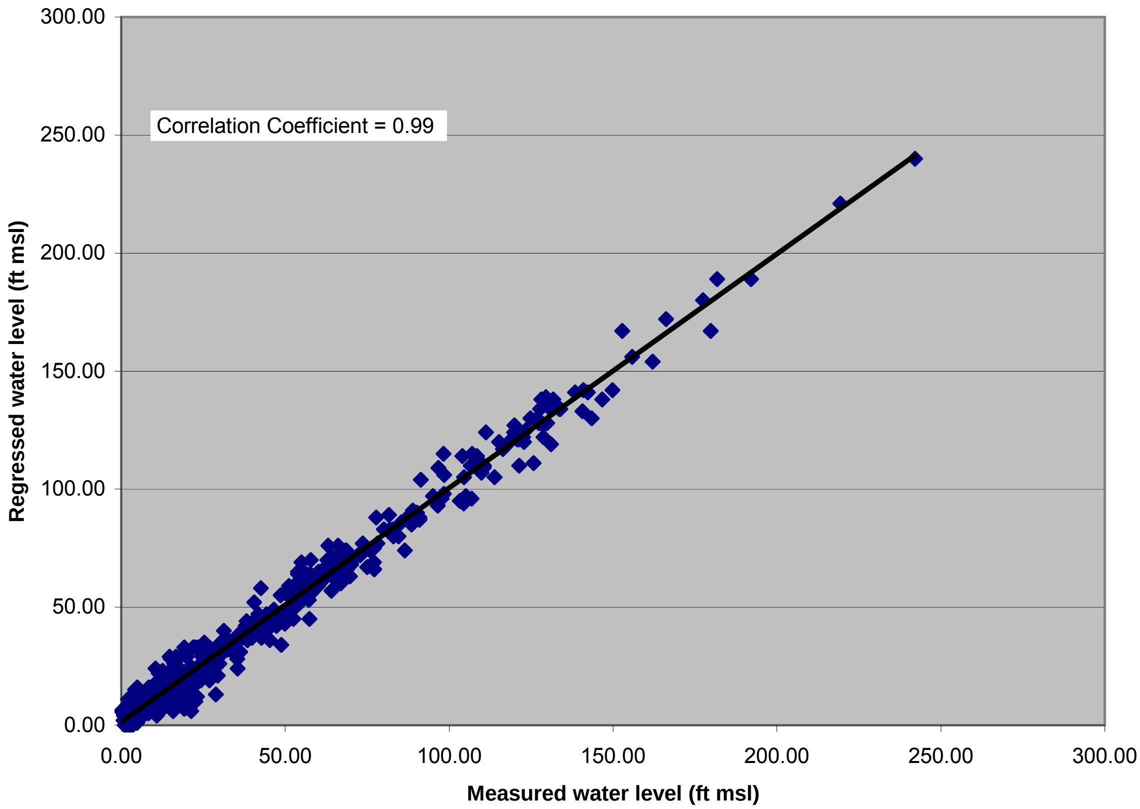

Figure 32. Regressed and measured water level for Surficial Aquifer.

Closed Topographic Depressions

Karst features, or sinkholes and depressions, can provide preferential pathways for movement of surface water into the underlying aquifer system and enhance an area's aquifer vulnerability where present. The closer an area is to a karst feature, the more vulnerable it may be considered. Closed topographic depressions extracted from U.S. Geological Survey 7.5-minute quadrangle maps served as the dataset from which to estimate closed topographic depressions in the study area (Figure 35).

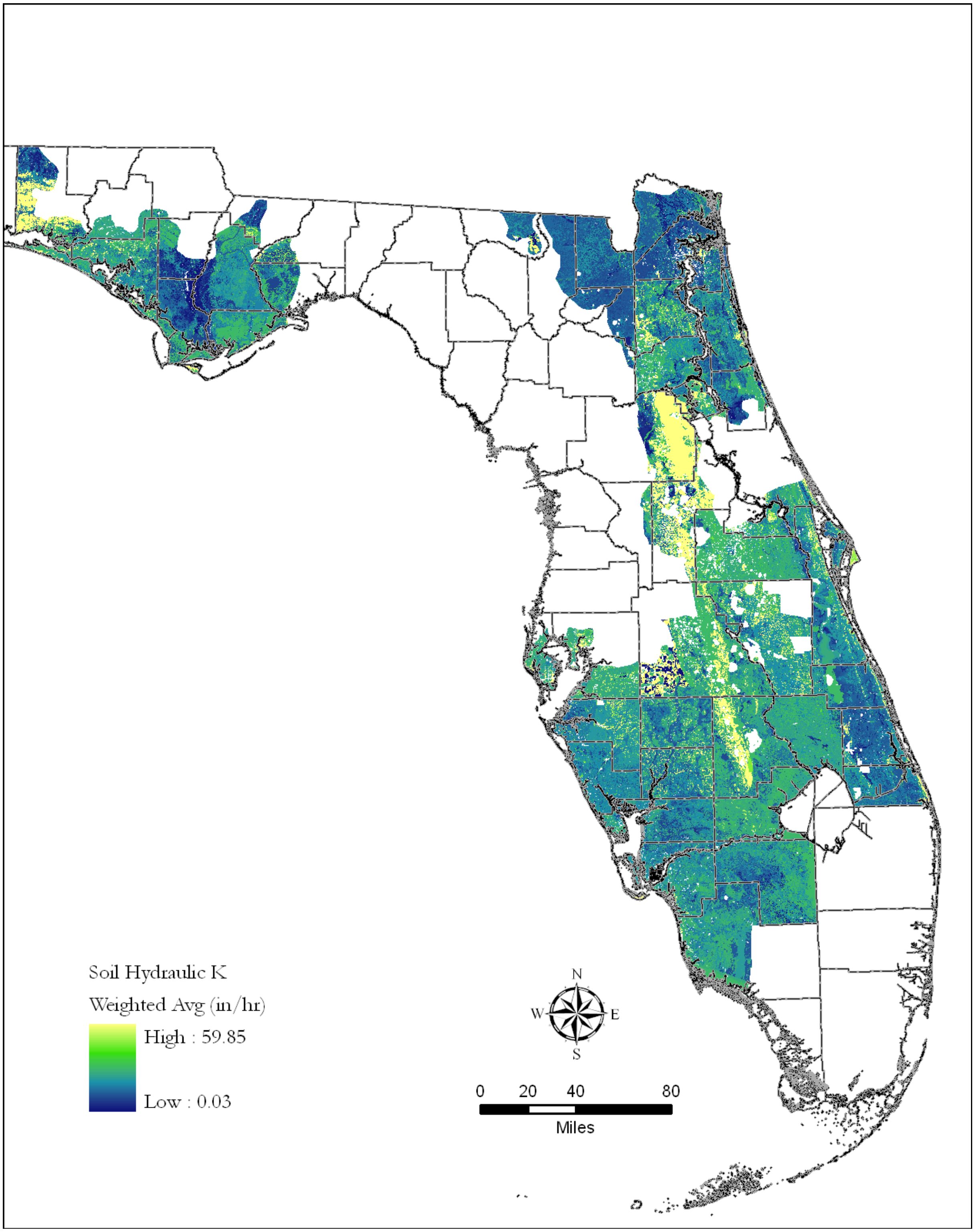

Figure 33. Distribution of soil hydraulic conductivity values across the Surficial Aquifer study area. White areas represent 'no data' areas in the soil survey data or locations of water bodies.

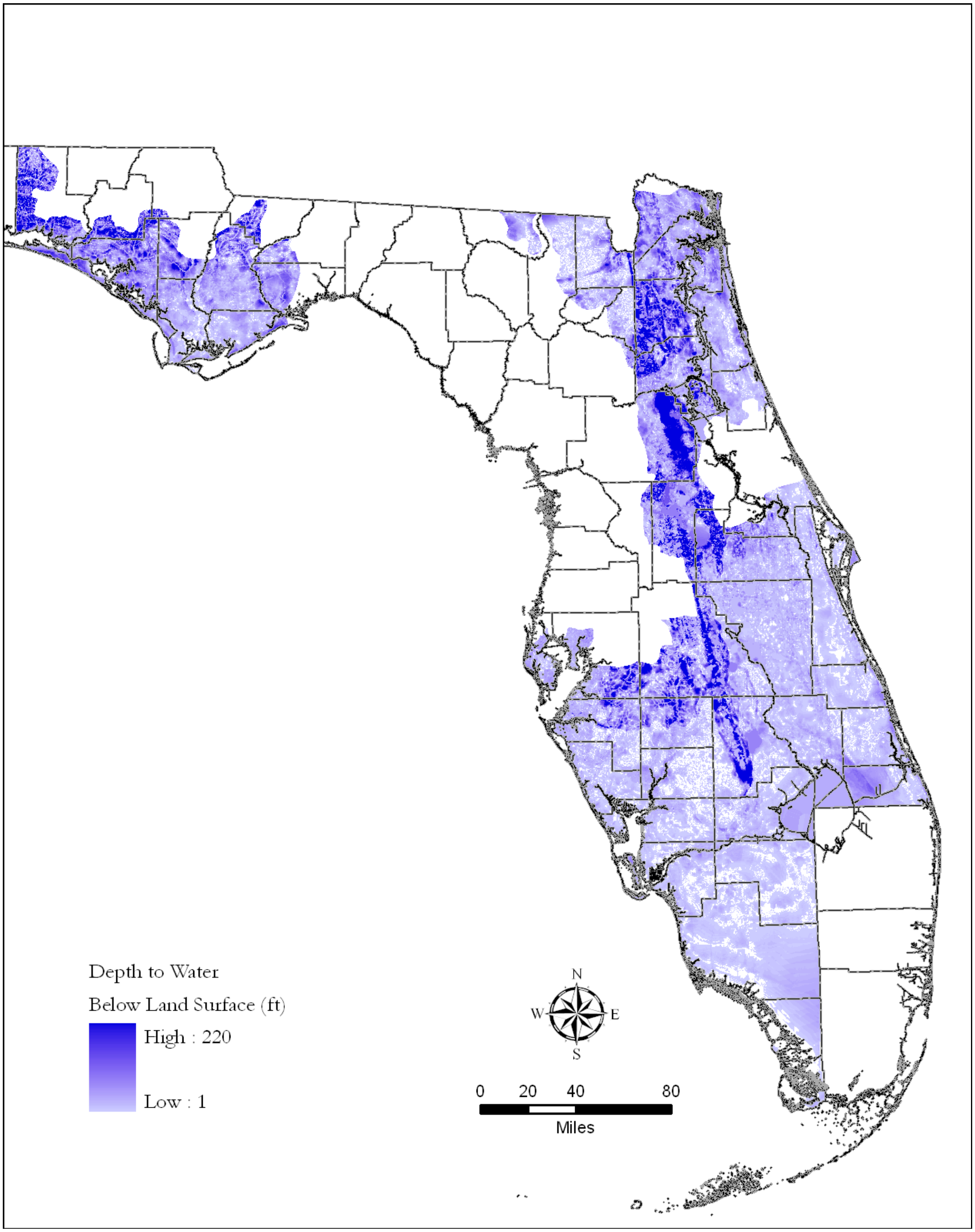

Figure 34. Distribution of depth to water values across the Surficial Aquifer study area. White areas represent 'no data' areas or locations of water bodies.

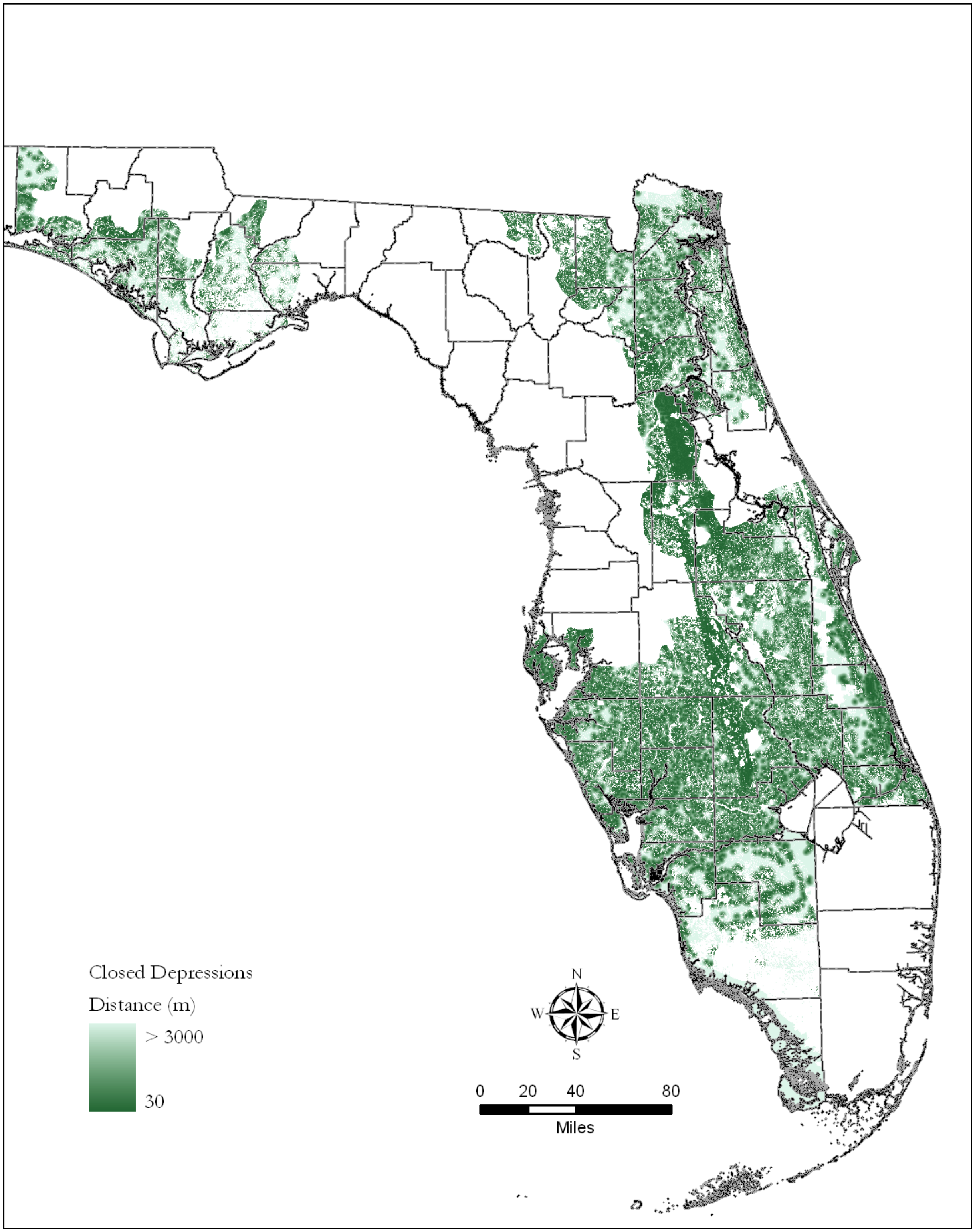

Figure 35. Proximity to closed topographic depressions extracted from U.S. Geological Survey 7.5-minute topographical contour lines.

Sensitivity Analysis/Evidential Theme Generalization

Sensitivity analysis allows decisions to be made about proposed evidential themes by evaluating each theme's association with training points – or aquifer vulnerability – and ultimately helps determine model input. For example, soil hydraulic conductivity and soil pedality were both developed to represent soil properties; sensitivity analysis allows, through statistical analysis, determination of which of these two layers served as the most appropriate input representing soil properties for the final SAS analysis. Results of this process indicate that soil hydraulic conductivity, depth to water, and closed topographic depressions were the best suited evidential themes for use in final modeling.

Following sensitivity analysis and selection of evidential themes to be input into the SAS model, themes were generalized to assess which areas of the evidence share a greater association with locations of training points. During calculation of weights for each theme, a contrast value was calculated for each class of the theme by combining the positive and negative weights. 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). Contrast and weights are described in more detail below in *Discussion*.

Contrast values were used to determine where to sub-divide evidential themes into generalized categories prior to final modeling. The simplest and most accepted method used to subdivide an evidential theme is to select the maximum contrast value as a threshold value to create binary generalized evidential themes. In other models, categorization of more than two classes may be justified (Arthur et al., 2005). For the SAS project, a binary break was typically defined by the weights of evidence analysis for each evidential theme creating two spatial categories: one with stronger association with the training point theme and one with weaker association.

Soil Hydraulic Conductivity/ Soil Pedality

Weights calculated during sensitivity analysis for soil hydraulic conductivity were stronger (i.e., had higher absolute value) than weights calculated for soil pedality. As a result, soil hydraulic conductivity was chosen as the better predictor of aquifer vulnerability because it shared the best association with training points.

Soil hydraulic conductivity, ranges from 0.03 to 59.85 in/hr across the study area. Based on calculated weights, this theme had justification for a multiple class generalization. Test modeling indicated that areas greater than or equal to 36.43 in/hr were most associated with the training points, areas that are greater than or equal to 6.17 in/hr and less than 36.43 in/hr were less associated with training points and areas less than 6.17 in/hr were least associated with the training points. Based on this analysis, the evidential theme was generalized into three classes as displayed in Figure 36.

Depth to Water

The depth to water ranges from zero to 220 feet deep across the study area. The analysis revealed that areas less than or equal to 34 feet deep were more associated with the training points, and therefore associated with higher aquifer vulnerability. Areas with a depth to water greater than 34 feet were less associated with the training points, and therefore lower aquifer vulnerability. Based on this analysis, the evidential theme was generalized into two classes as displayed in Figure 37.

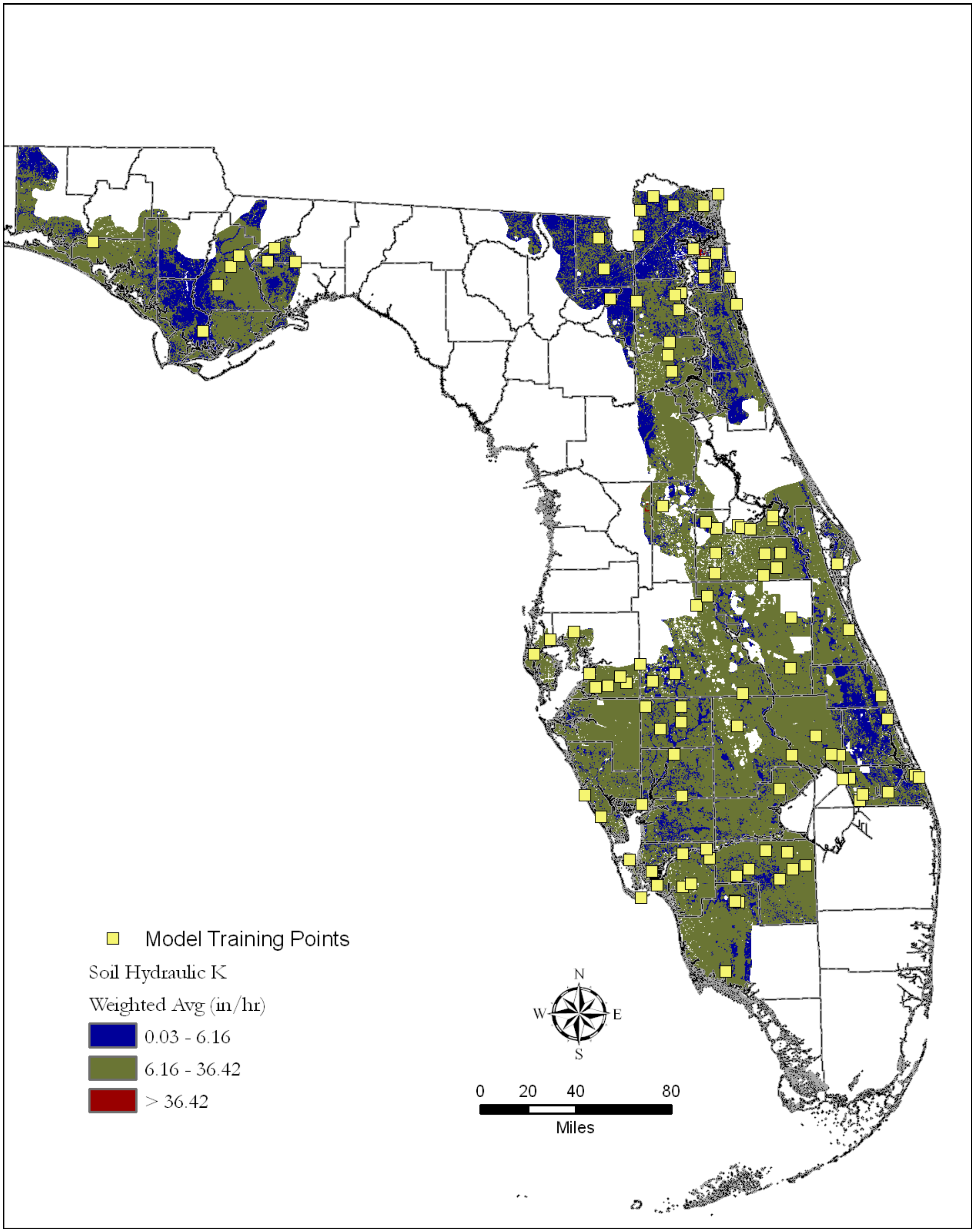

Figure 36. Generalized soil hydraulic conductivity evidential theme; based on calculated weights, a multi-class generalization with a break at a value of 6.16 and 36.42 in/hr was defined by the analysis. Based on the location of training points, blue areas share a weaker association with training points and thereby relatively lower aquifer vulnerability, whereas red areas share a stronger association with training points.

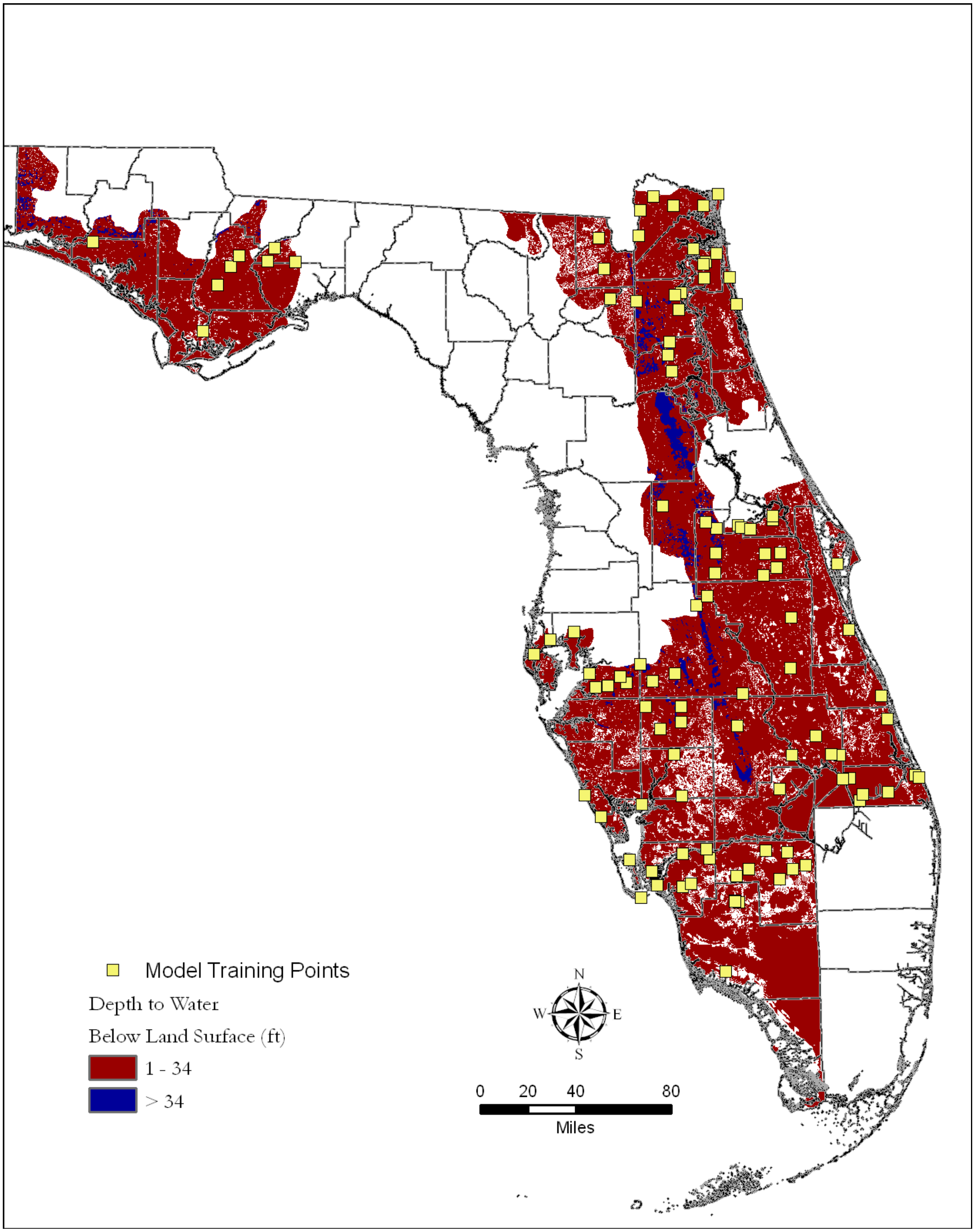

Figure 37. Generalized depth to water evidential theme; based on calculated weights analysis blue areas share a weaker association with training points and thereby relatively lower aquifer vulnerability, whereas red areas share a stronger association with training points.

Closed Topographic Depressions

As mentioned above, areas closer to a depression are normally associated with higher aquifer vulnerability. Based on this, features were buffered into 30 meter zones to allow for a proximity analysis. The analysis indicated that areas within 2,760 meters of a closed topographic depression were more associated with the training points, and therefore with higher aquifer vulnerability. Conversely, areas greater than 2,760 meters from a closed topographic depression were less associated with the training points, and therefore lower aquifer vulnerability. Based on this analysis, the evidential theme was generalized into two classes as displayed in Figure 38.

Response Theme

Using evidential themes representing soil hydraulic conductivity, depth to water, and closed topographic depressions, weights of evidence was applied to generate a response theme, which is a GIS raster consisting of *posterior probability* values ranging from 0.00019 to 0.0166 across the study area. These probability values describe the relative probability that a unit area of the model will contain a training point – i.e., a point of aquifer vulnerability as defined above in *Training Points* – with respect to the prior probability value of 0.0019 or ([1.0 km^2 model unit area * 99 training points] / 52919.2 km^2 = 0.0019). Prior probability is the probability that a training point will occupy a defined unit area within the study area, independent of evidential theme data. Probability values at the locations of 83 of the 99 training points are above the prior probability, indicating that this model is a strong predictor of training point locations.

The response theme was broken into classes of relative vulnerability based on the prior probability value and on inflections in a chart in which cumulative study area was plotted against posterior probability (Figure 39). Higher posterior probability values correspond with more vulnerable areas, as they essentially have a higher chance of containing vulnerability based on the definition of a training point. Conversely, lower posterior probability values correspond to less vulnerable areas as they essentially have a lower chance of containing vulnerability based on the definition of a training point.

As described in *Introduction*, the SAS model was based on the modeling technique used in the FAVA project. The FAVA project identified relative vulnerability of Florida's principal aquifer systems broken into three classes: more vulnerable, vulnerable and less vulnerable zones. This naming technique was applied to the SAS results to define the relative vulnerability classes as displayed in Figure 40.

As expected, the SAS response theme indicates that areas of highest vulnerability are associated with areas where the depth to water is lowest, in areas of dense closed topographic depressions, and areas of higher soil hydraulic conductivity. Conversely, areas of lowest vulnerability are determined by high depth to water values, sparse closed topographic depression distribution, and lower soil hydraulic conductivity values.

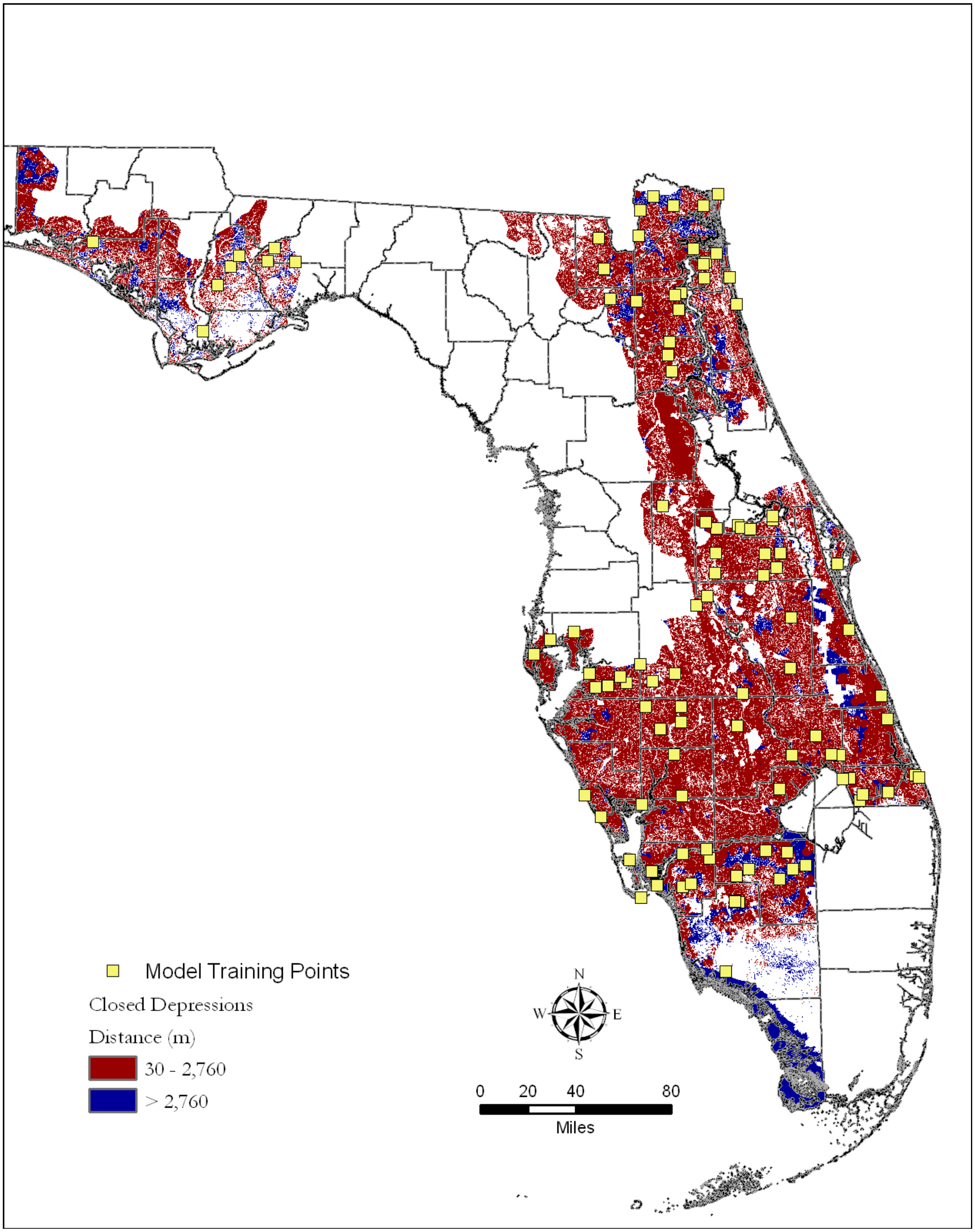

Figure 38. Generalized closed topographic depressions evidential theme; based on calculated weights analysis blue areas share a weaker association with training points and thereby relatively lower aquifer vulnerability, whereas red areas share a stronger association with training points.

Discussion

Prior to discussion of weights calculations during model execution, two components of a weights of evidence analysis are described to assist in interpretation of SAS model results: *Conditional Independence* and *Model Confidence*.

Conditional Independence

Conditional independence is a measure of the degree that evidential themes are affecting each other due to similarities between themes. Evidential themes are considered independent of each other if the conditional independence value is around 1.00, and conditional independence values within the range of 1.00 ± 0.15 generally indicate limited to no dependence among evidential themes (Bonham-Carter, 1994). Values significantly outside this range can inflate posterior probabilities resulting in unreliable response themes.

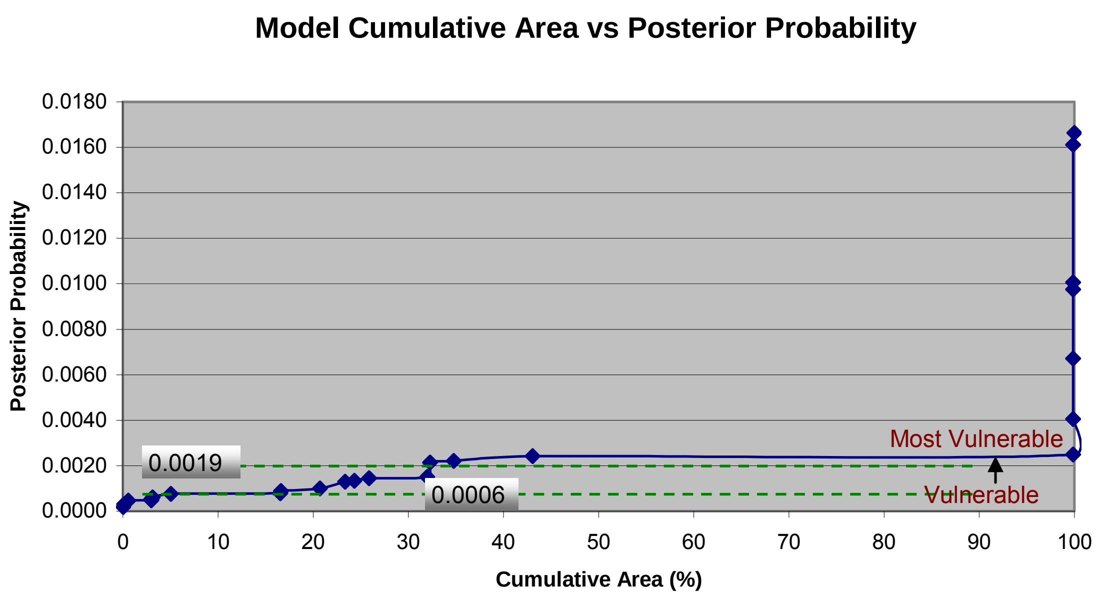

Figure 39. Vulnerability class breaks are defined by selecting where a significant increase in probability and area are observed.

Conditional independence was calculated at 1.00 for the SAS project indicating that evidential themes had virtually no conditional dependence.

Model Confidence

During model execution, confidence values are calculated both for each generalized evidential theme and for the final response theme. Confidence values approximately correspond to the statistical levels of significance listed in Table 3.

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 test value of 1.2814 corresponds to approximately 90% confidence – or level of significance – and was the minimum calculated confidence level for the SAS project evidential themes (see Table 8 below for evidential theme confidence values).

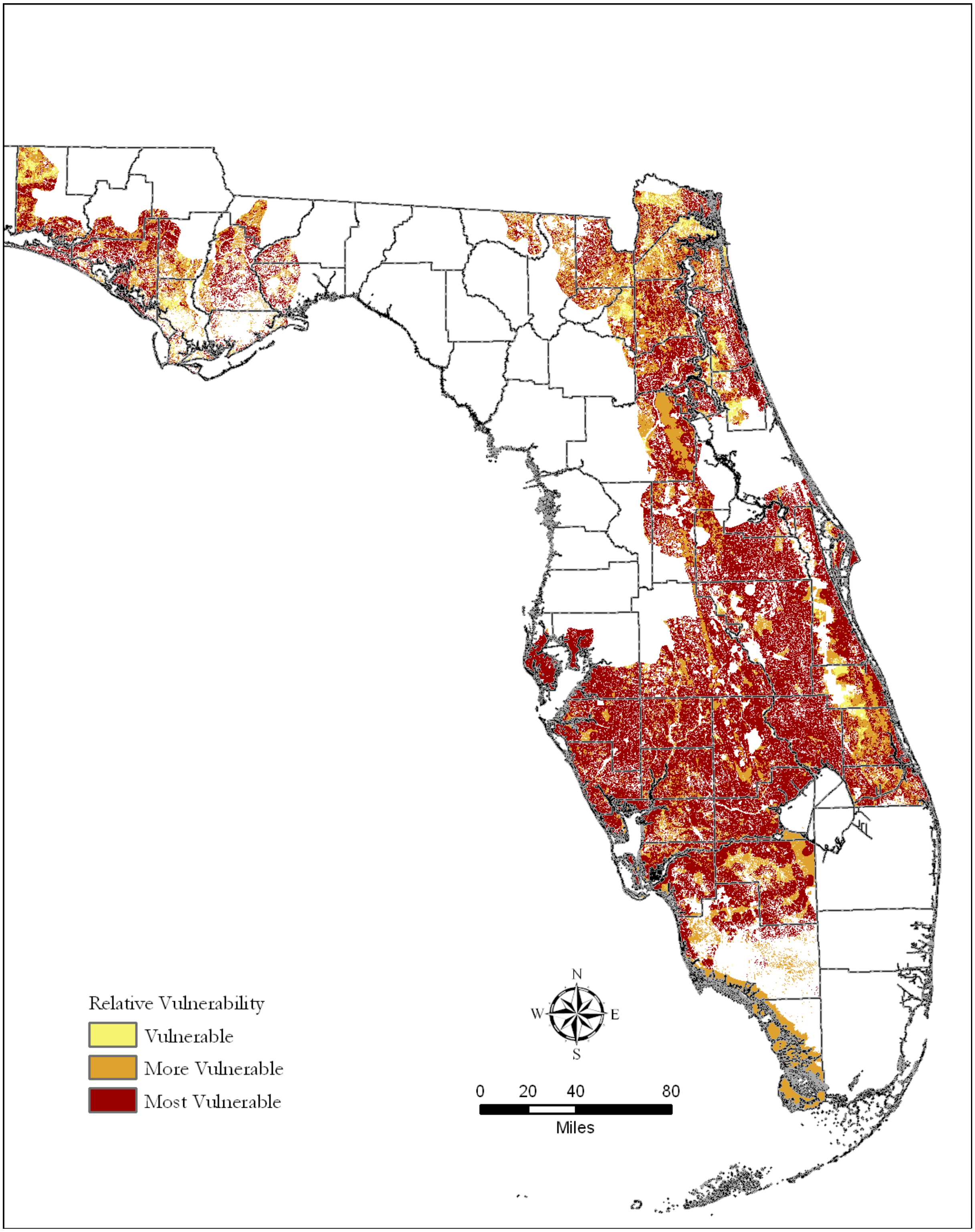

Figure 40. Relative vulnerability map for the Surficial Aquifer Vulnerability Assessment project. Classes of vulnerability are based on calculated probabilities of a unit area containing a training point, or a monitor well with water quality sample results indicative of vulnerability.

A confidence map is also calculated for a response theme by normalizing the theme's posterior probability by its total uncertainty (standard deviation). A confidence map can be generated based on these calculations. The confidence map for the SAS response theme is displayed in Figure 41. Areas with high posterior probability values typically correspond to higher confidence values and as a result have a higher level of certainty with respect to predicting aquifer vulnerability.

Weights Calculations

Table 8 displays evidential themes used in the SAS model, weights calculated for each theme, along with contrast and confidence values. Positive weights indicate areas where training points are likely to occur, while negative weights indicate 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. Confidence of the evidential theme is also calculated and is equal to the contrast divided by its standard deviation (a student T test). Confidence is a measure of significance due to uncertainties of the weights and missing data (Raines, 1999). A positive contrast that is significant, based on its confidence, suggests that a generalized evidential theme is a useful predictor.

Table 8. Weights of evidence 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	W3	Contrast	Confidence
Soil Hydraulic Conductivity	2.0316	0.1195	-1.0353	3.0669	2.8214
Depth to Water	0.0318	-0.8847		0.9164	1.2814
Closed Topographic Depressions	0.0586	-0.4507		0.5094	1.456

Because positive weights (W1) values for soil hydraulic conductivity are stronger (have greater absolute values) than the negative weights (W3), they are better predictors of where training points are likely to occur, whereas the depth to water and closed topographic depression themes are better indicators of where training points are less likely to occur. Based on contrast values, the soil hydraulic conductivity theme has the strongest (highest absolute value) weight and is the primary determinant in predicting areas of vulnerability in the SAS model.

Validation

The weights of evidence approach, because it relies on a set of training points, which by definition are known sites of vulnerability, is essentially self-validated. Eighty-three of ninety-nine training points were predicted in zones of posterior probability greater than the prior probability (in other words, classified accurately). Further strengthening the results were the evaluation of a minimum confidence threshold for evidential themes, and generation of a confidence map of the response theme. In addition to these exercises, and in the style of previous aquifer vulnerability assessments (Cichon et al., 2005; Baker et al., 2005; Arthur et al., 2005), additional validation techniques were applied to the SAS model to further strengthen its defensibility, and, ultimately, its utility: (1) comparison of dissolved oxygen values to posterior probability and evaluation of an associated trend; and (2) generation of a test response theme based on a subset of training points and comparison of points not used in subset to model results and (3) comparison of dissolved nitrogen values with vulnerable zones of the response theme.

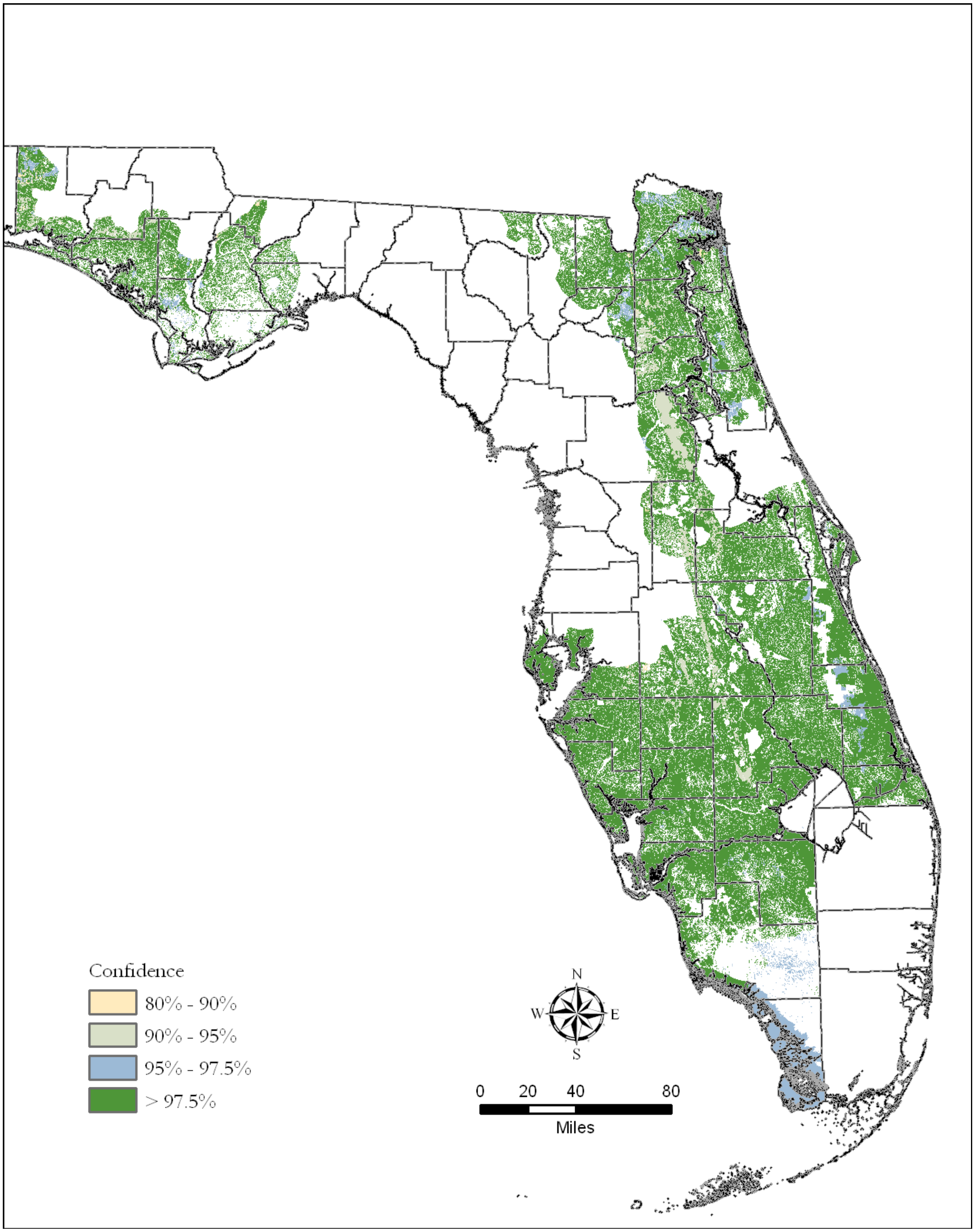

Figure 41. Confidence map for the Surficial Aquifer model calculated by dividing the posterior probability values by the total uncertainty for each class to give an estimate of how well specific areas of the model are predicted.

Dissolved Oxygen Data vs. Posterior Probability

It was expected that comparison of posterior probability values to the dissolved oxygen dataset from which the training point theme was extracted would reveal a proportional trend, in other words, as dissolved oxygen values increase, so should posterior probability values. Dissolved oxygen median concentrations were binned and averaged for each posterior probability value calculated in model output. The average values were plotted in a chart against posterior probability values (Figure 42) and a slight positive trend was observed. Only one well was observed in the first class so it was averaged into the next higher class.

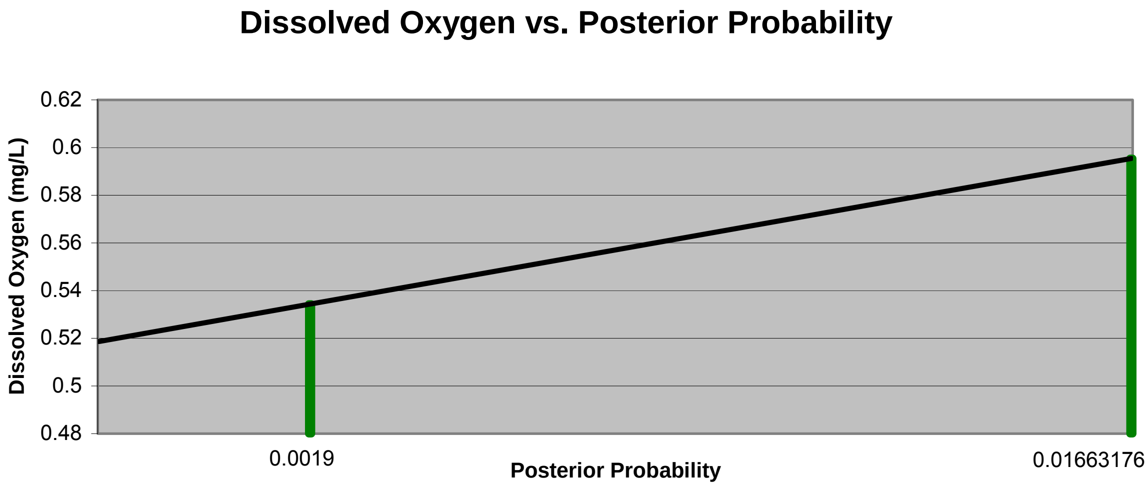

Figure 42. Dissolved oxygen values (averaged per posterior probability class) versus probability values to reveal trend between increasing dissolved oxygen concentrations and posterior probability.

Subset Response Theme

Another meaningful validation exercise similar to the exercise above is to use the existing training point dataset to develop two subsets: one to generate a test response theme, and one to validate output from this test response theme. Results from this exercise helped to further assess whether the dissolved oxygen training points are reasonable predictors of aquifer vulnerability.

From the SAS training point theme, a subset of 75% (81 wells) were randomly selected and used to develop a test response theme; the remaining 25% (26 wells) of the training points were used as the validation dataset for the test response theme. This comparison revealed that twenty-three of the twenty-six test wells in the validation subset, or 88.5%, occur in areas of the test response theme with predicted probability values higher than the prior probability value (Figure 43). This further supports the conclusion that the SAS model response theme is a reasonable estimator of vulnerability.

Dissolved Nitrogen Data

Perhaps the most rigorous validation exercise used to evaluate quality of model-generated output is to compare predicted model values with independent test values not used in the model. For the SAS model, this was accomplished by comparison of a separate well dataset based on dissolved nitrogen. As mentioned above in *Training Point Theme*, dissolved nitrogen is indicative of aquifer vulnerability,

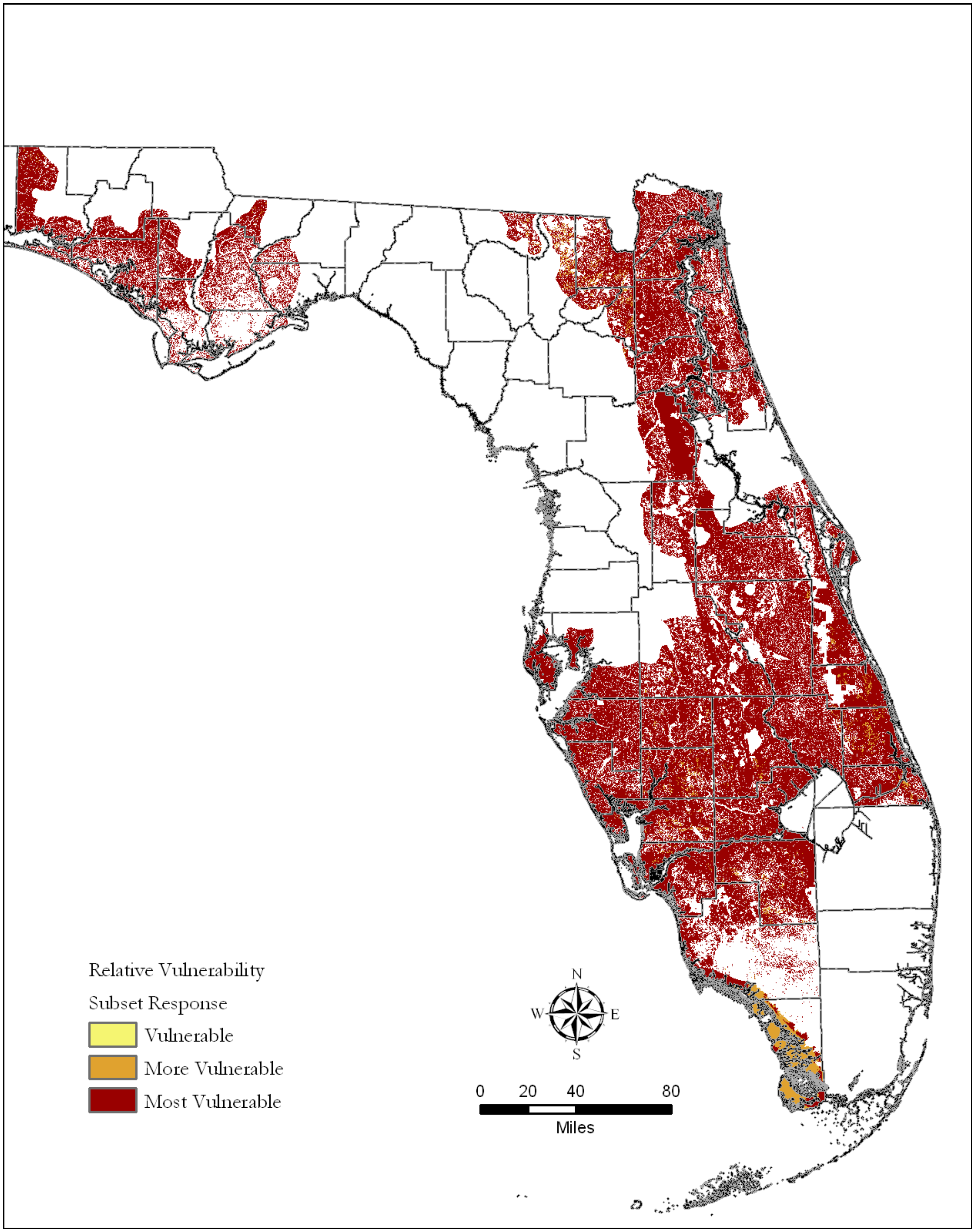

Figure 43. Subset response training points plotted in the dissolved oxygen response theme.

but is independent of dissolved oxygen. Applying the methodology described in *Training Point Theme* to dissolved nitrogen data (obtained from the same data sources as dissolved oxygen data) resulted in a dissolved nitrogen dataset of 63 wells each indicative of aquifer vulnerability.

These 63 points were evaluated against posterior probability values of the SAS model output. Extracting the value of posterior probability from the dissolved oxygen response theme for the location of each of the 63 dissolved nitrogen training points revealed that 53 of the 63 dissolved nitrogen training points occur in areas of the dissolved oxygen model with predicted probability values higher than the prior probability value. In other words, 84% of the dissolved nitrogen wells were located in areas predicted to have a greater than chance probability of containing a training point. Based on this test, the dissolved oxygen model is not only a good predictor of vulnerability as defined by the training point theme, it is also a good predictor of the location of an independent parameter also representing aquifer vulnerability. Figure 44 displays dissolved nitrogen data points plotted on the dissolved oxygen response theme.

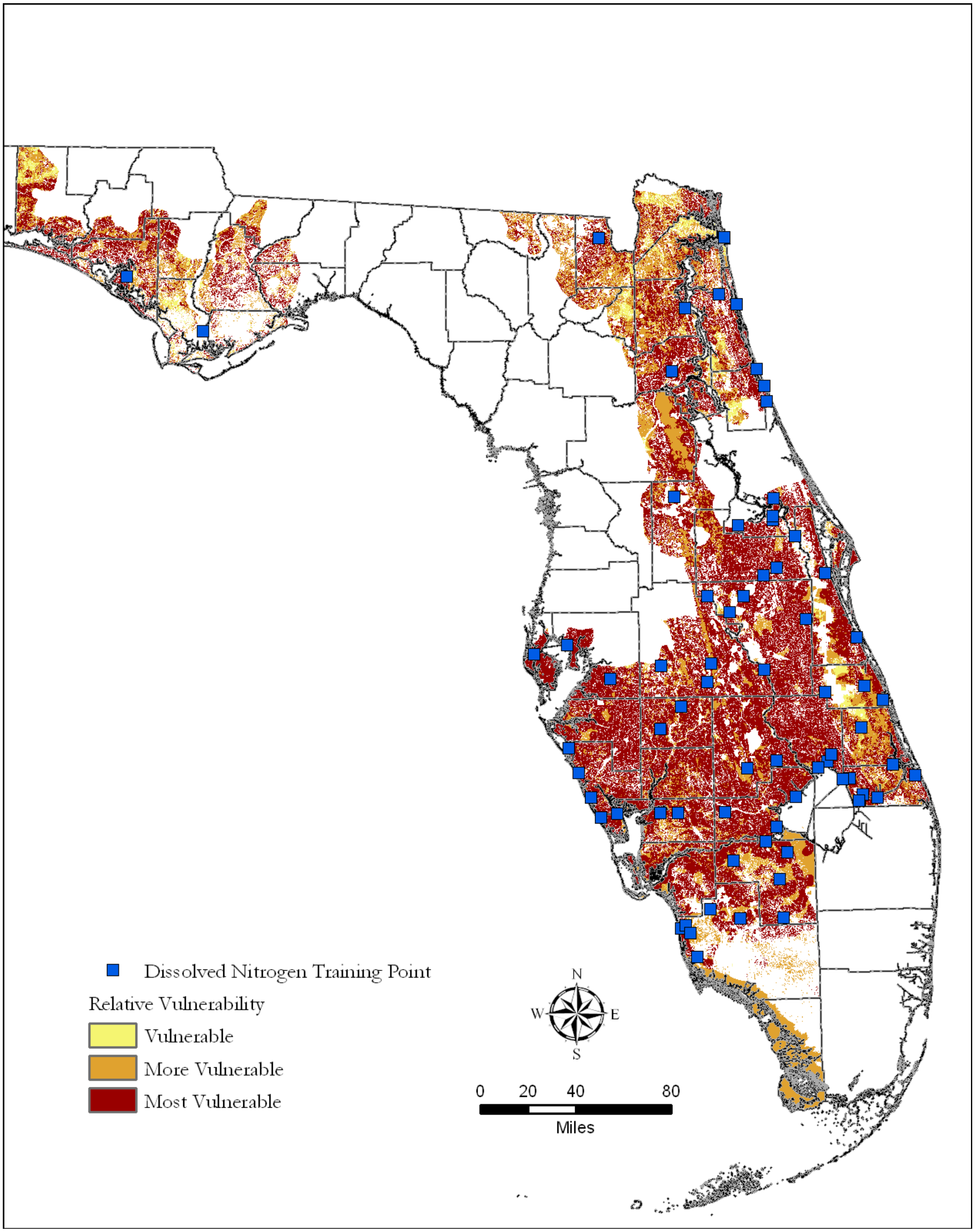

Figure 44. Dissolved nitrogen validation training points plotted in the dissolved oxygen response theme. Comparison reveals 53 of 63 wells (84%) of the independent water quality dataset are located in areas with predicted probability values higher than the prior probability.

INTERMEDIATE AQUIFER SYSTEM

Study Area

The study area is the same as the original FAVA model extent (Figure 45). Because of the sizes of some polygons representing soil data, a grid cell size of approximately 30 meter squares (or 900 m^2) was selected for evidential theme development. This grid cell size, while necessary to capture resolution available in some input data layers, does not reflect appropriate resolution of final model output. Appropriate scale of use of model results is discussed in *Model Implementation and Limitations*.

Water bodies were omitted from the model extent for two main reasons: first, the main goal of this project is to estimate vulnerability of the intermediate aquifer system (IAS) and not vulnerability of surface water features, and second, data for water bodies is typically not available – i.e., wells are not drilled in water bodies, nor do soil surveys normally contain information regarding lake and stream bottoms.

Training Point Theme

In the model analysis, training points are groundwater wells tapping the IAS with water quality data indicative of high recharge. Dissolved nitrogen (ammonia plus total dissolved nitrogen) analytical values served as training point data for the IAS model. Ammonia concentrations were incorporated into the IAS training point data set to account for areas of the State with a high water table. In these areas, nitrogen in the form of ammonia can be more prevalent where the high water table and organic soils create a reducing environment. Naturally occurring oxygen and nitrogen are generally considered ubiquitous at land surface as primary components of the atmosphere; moreover, relatively low concentrations of these analytes occur in well protected – or less vulnerable – aquifer systems. Accordingly, where these analytes occur in elevated concentrations in groundwater, yet are not attributable to human activity, they are good indicators of aquifer vulnerability (Arthur et al., 2007).

Water quality data sources explored include the FDEP background water quality network and FDEP STATUS network. From these data sources, 120 wells measured for dissolved nitrogen were identified as being potential candidates for training points. Statistical analyses revealed 4 samples were considered statistical outliers. The upper 25th percentile of this set – or all wells with median dissolved nitrogen values greater than or equal to 0.477 milligrams per liter (mg/L) – served as the training point theme and consists of 29 wells. Figure 46 displays the distribution of water wells used to derive training points and the resulting training point theme across the study area.

Training points are used to calculate prior probability, weights for each evidential theme, and posterior probability of the response theme (see *Glossary*). Prior probability (training point unit area divided by total study area) is the probability that a training point will occupy a defined unit area within the study area, independent of any evidential theme data. The prior probability value, a unitless parameter, for the IAS model is 0.0011 ([1 km^2 model unit area * 29 training points] / 27,458.4 km^2 = 0.0011). Posterior probability values generated during response theme development are interpreted relative to the value of prior probability with higher values generally indicating areas with higher probability of containing a training point.

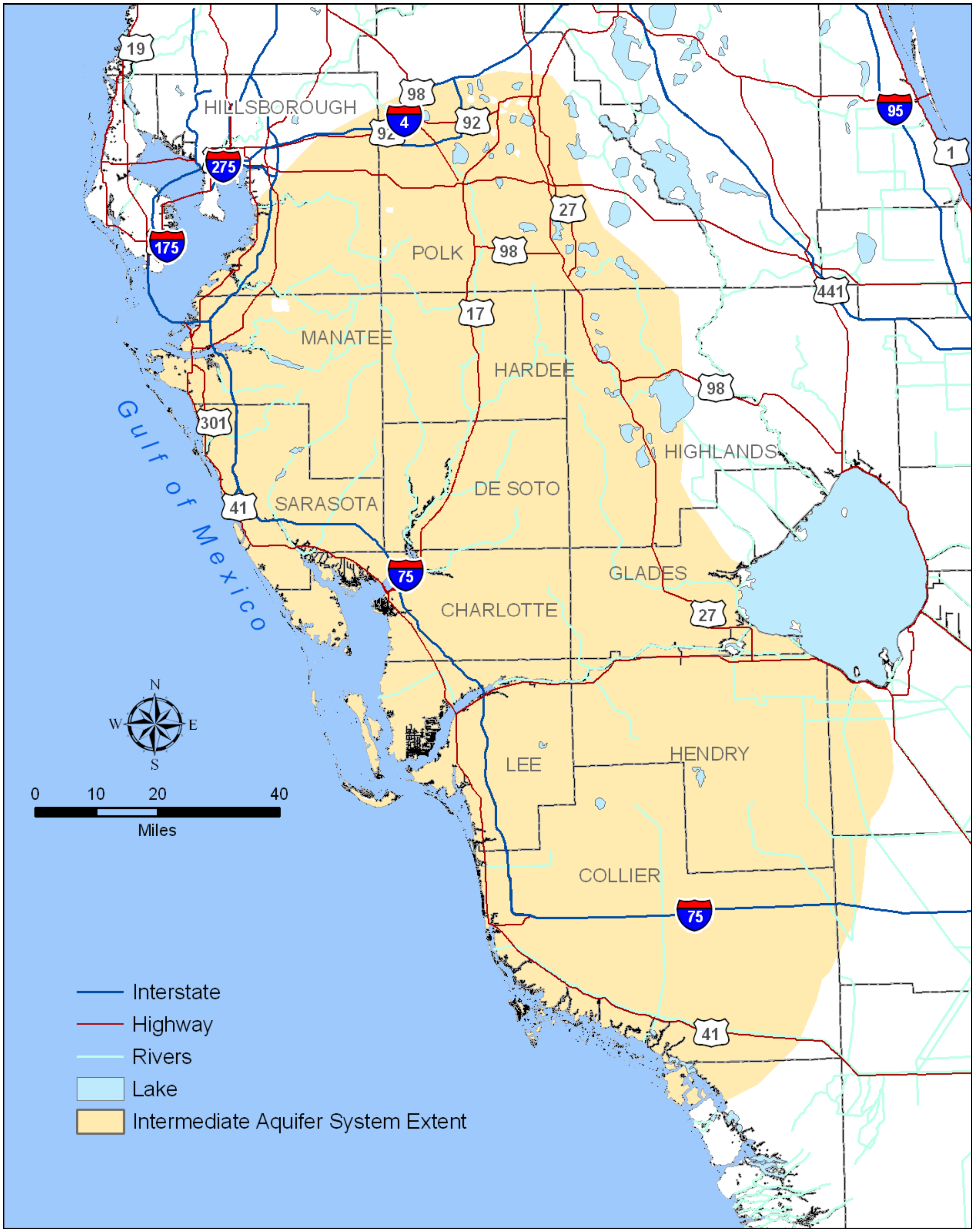

Figure 45. Intermediate Aquifer System Vulnerability Assessment project study area extent.

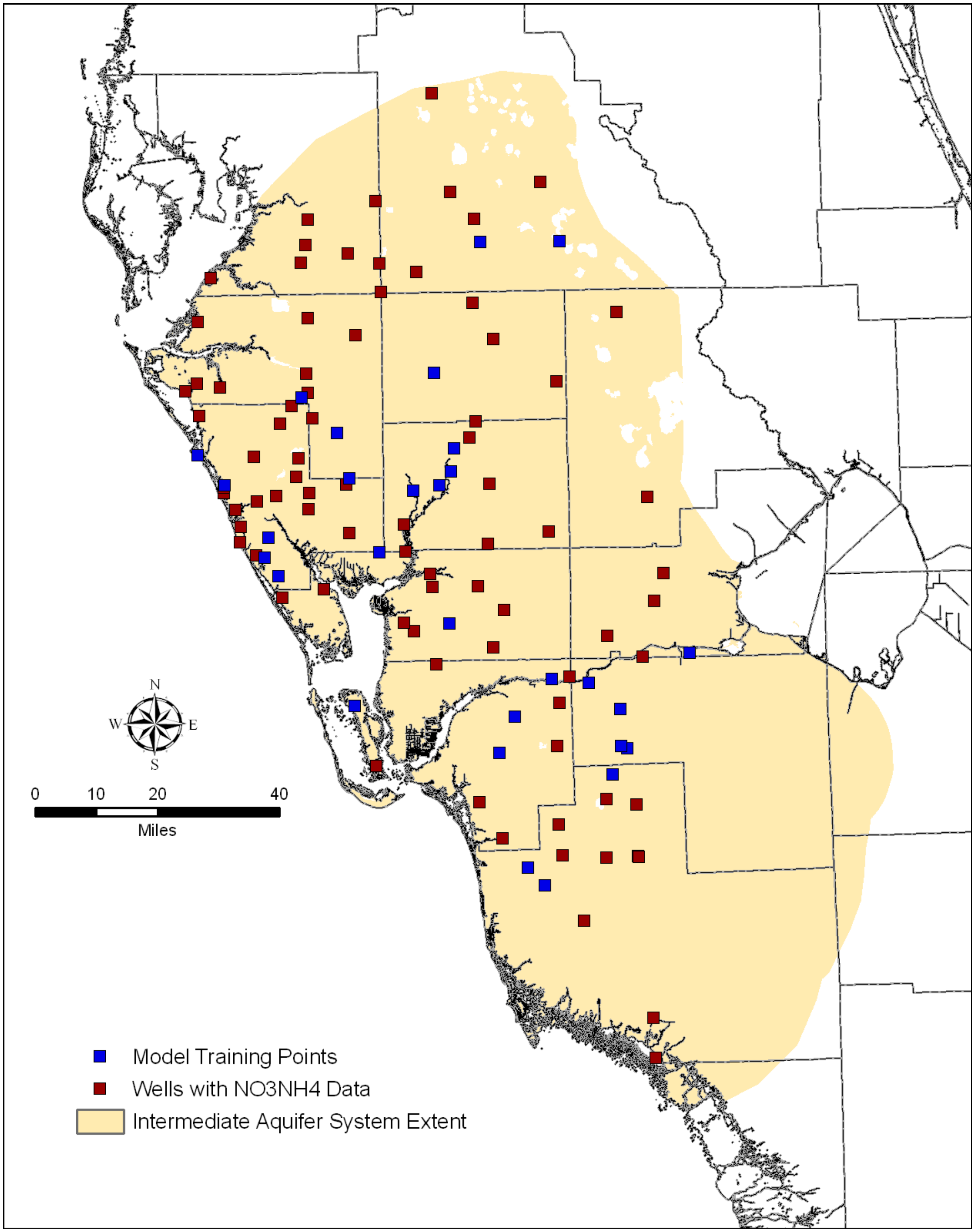

Figure 46. Location of all wells measured for ammonia + nitrate (dark red boxes), and locations of training point wells with median ammonia + nitrate values greater than 0.477 mg/L (blue boxes).

Evidential Themes – Model Input Layers

Input data layers, or evidential themes, representing hydrogeologic factors controlling the location of training points, and thereby vulnerability, were developed for model input. The factors considered for the IAS project include closed topographic depressions, IAS overburden, soil pedality, and soil hydraulic conductivity.

Soil Hydraulic Conductivity and Soil Pedality Themes

The rate that water moves through soil is a critical component of any aquifer vulnerability analysis, as soil is literally an aquifer system's first line of defense against potential contamination (Arthur et al., 2005). Two parameters of soils were evaluated for input into the IAS model: *soil hydraulic conductivity*, which is the "amount of water that would move vertically through a unit area of saturated soil in unit time under unit hydraulic gradient" (U.S. Department of Agriculture, 2005); and *soil pedality*, which is calculated based on soil type, soil grade, and soil pedon size, and is a unitless parameter. Soil pedality is a relatively new concept used to estimate the hydrologic parameter of soil and is generated for the IAS using the pedality point method developed by Lin et al. (1999).

Countywide datasets representing soil hydraulic conductivity and soil pedality were developed for use as input into the IAS model. Multiple empirical values are reported in soil surveys representing various zones in each soil column underlying a particular soil polygon. Representative values for each horizon in a column are combined using a sum of the weighted mean. This is completed for both hydraulic conductivity and soil pedality. Figure 47 displays values of soil pedality.

Intermediate Aquifer System Overburden Thickness Theme

Aquifer confinement – in the form of overburden overlying the IAS – is another critical layer in determining aquifer vulnerability. Where aquifer overburden is thick and the IAS is deeply buried, aquifer vulnerability is generally lower, whereas in areas of thin to absent confinement, the vulnerability of the IAS is generally higher.

A GIS model was developed of the surface of the IAS. The intent of this model was to allow the calculation of aquifer confinement thickness in various study areas. The surface model was developed using a dataset of borehole records from the Florida Geological Survey. The surface was used to calculate thickness of overburden overlying the IAS (Figure 48) in the study area.

Closed Topographic Depressions

Karst features, or sinkholes and depressions, can provide preferential pathways for movement of surface water into the underlying aquifer system and enhance an area's aquifer vulnerability where present. The closer an area is to a karst feature, the more vulnerable it may be considered. Closed topographic depressions extracted from U.S. Geological Survey 7.5-minute quadrangle maps served as the dataset from which to estimate closed topographic depressions in the study area (Figure 49).

Sensitivity Analysis/Evidential Theme Generalization

Sensitivity analysis allows decisions to be made about proposed evidential themes by evaluating each theme's association with training points – or aquifer vulnerability – and ultimately helps determine model input. For example, soil hydraulic conductivity and soil pedality were both developed to represent soil properties; sensitivity analysis allows, through statistical analysis, determination of which of these two layers served as the most appropriate input representing soil properties for the final IAS analysis. Results of this process indicate that soil pedality, IAS overburden, and closed topographic depressions were the best suited evidential themes for use in final modeling.

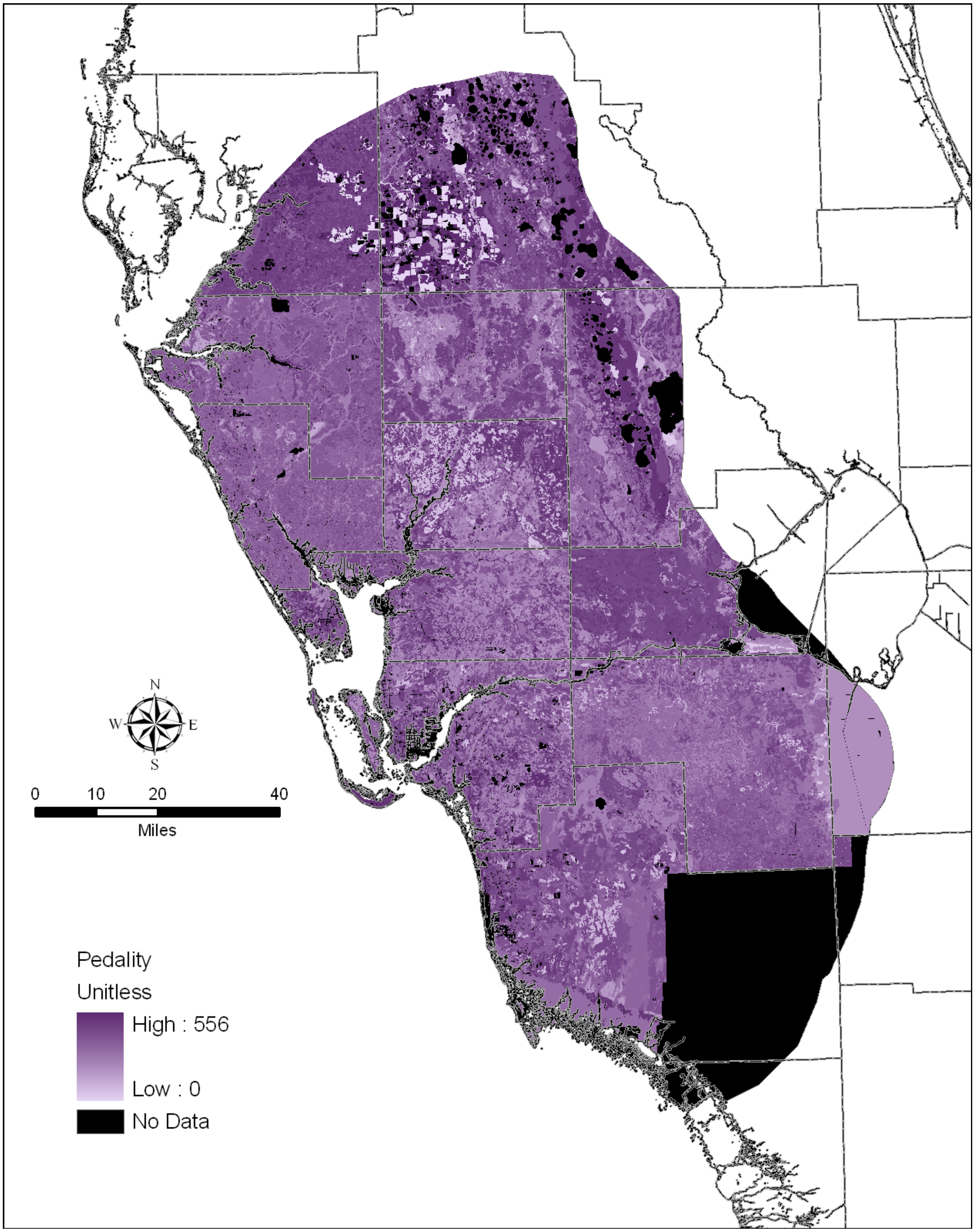

Figure 47. Distribution of soil pedality values across the Intermediate Aquifer study area. Black areas represent 'no data' areas in the soil survey data or locations of water bodies.

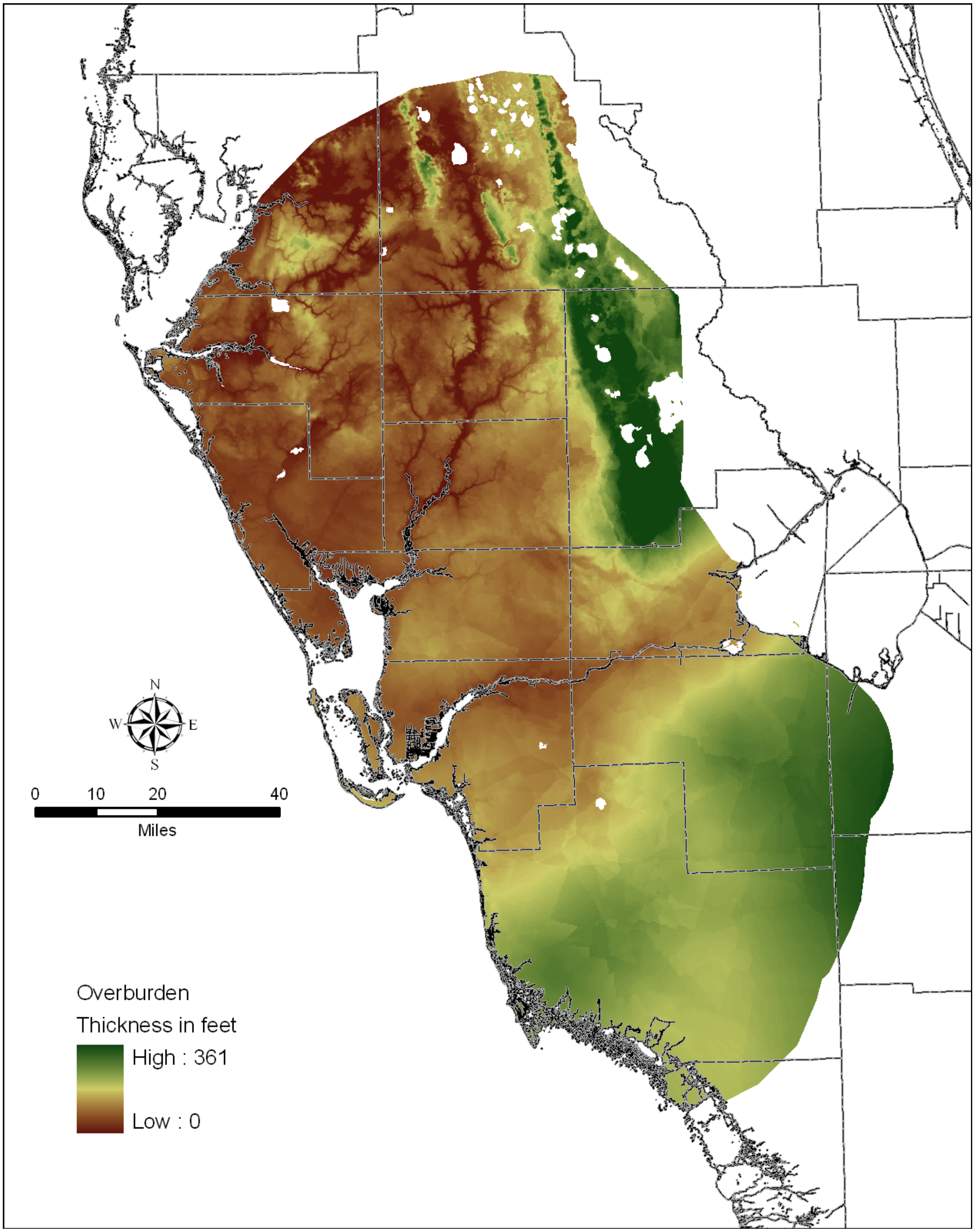

Figure 48. Thickness of IAS overburden calculated by subtracting predicted top of IAS surface (generated by FGS/FDEP) from digital elevation model.

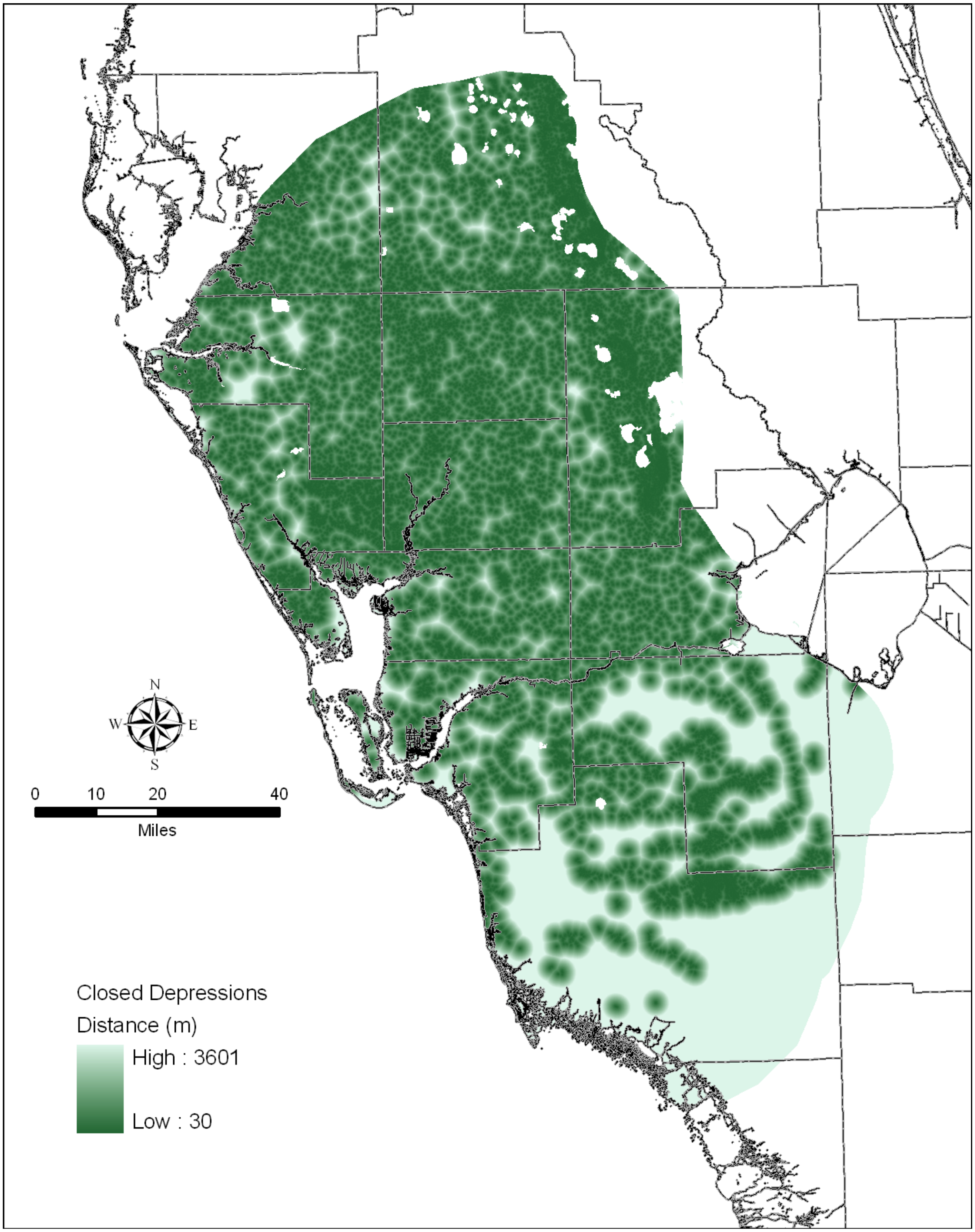

Figure 49. Proximity to closed topographic depressions extracted from U.S. Geological Survey 7.5-minute topographical contour lines.

Following sensitivity analysis and selection of evidential themes to be input into the IAS model, themes were generalized to assess which areas of the evidence share a greater association with locations of training points. During calculation of weights for each theme, a contrast value was calculated for each class of the theme by combining the positive and negative weights. 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). Contrast and weights are described in more detail below in *Discussion*.

Contrast values were used to determine where to sub-divide evidential themes into generalized categories prior to final modeling. The simplest and most accepted method used to subdivide an evidential theme is to select the maximum contrast value as a threshold value to create binary generalized evidential themes. In other models, categorization of more than two classes may be justified (Arthur et al., 2005). For the IAS project, a binary break was typically defined by the weights of evidence analysis for each evidential theme creating two spatial categories: one with stronger association with the training point theme and one with weaker association.

Soil Hydraulic Conductivity/ Soil Pedality

Weights calculated during sensitivity analysis for soil pedality were stronger (i.e., had higher absolute value) than weights calculated for soil hydraulic conductivity. As a result, soil pedality was chosen as the better predictor of aquifer vulnerability because it shared the best association with training points.

Soil pedality, ranges from 0 to 556 across the study area. Test modeling indicated that areas greater than or equal to 538 were most associated with the training points, and therefore associated with higher aquifer vulnerability. Conversely, areas less than 538 were less associated with the training points, and therefore lower aquifer vulnerability. Based on this analysis, the evidential theme was generalized into two classes as displayed in Figure 50.

Intermediate Aquifer System Overburden Thickness Theme

The overburden thickness ranges from absent to 361 feet thick across the study area. The analysis revealed that areas underlain by 86 feet or less of overburden thickness were more associated with the training points, and therefore associated with higher aquifer vulnerability. Areas underlain by greater than 86 feet of overburden thickness were less associated with the training points, and therefore lower aquifer vulnerability. Based on this analysis, the evidential theme was generalized into two classes as displayed in Figure 51.

Closed Topographic Depressions

As mentioned above, areas closer to a depression are normally associated with higher aquifer vulnerability. Based on this, features were buffered into 30 meter zones to allow for a proximity analysis. The analysis indicated that areas within 30 meters of a closed topographic depression were more associated with the training points, and therefore with higher aquifer vulnerability. Conversely, areas greater than 30 meters from a closed topographic depression were less associated with the training points, and therefore lower aquifer vulnerability. Based on this analysis, the evidential theme was generalized into two classes as displayed in Figure 52.

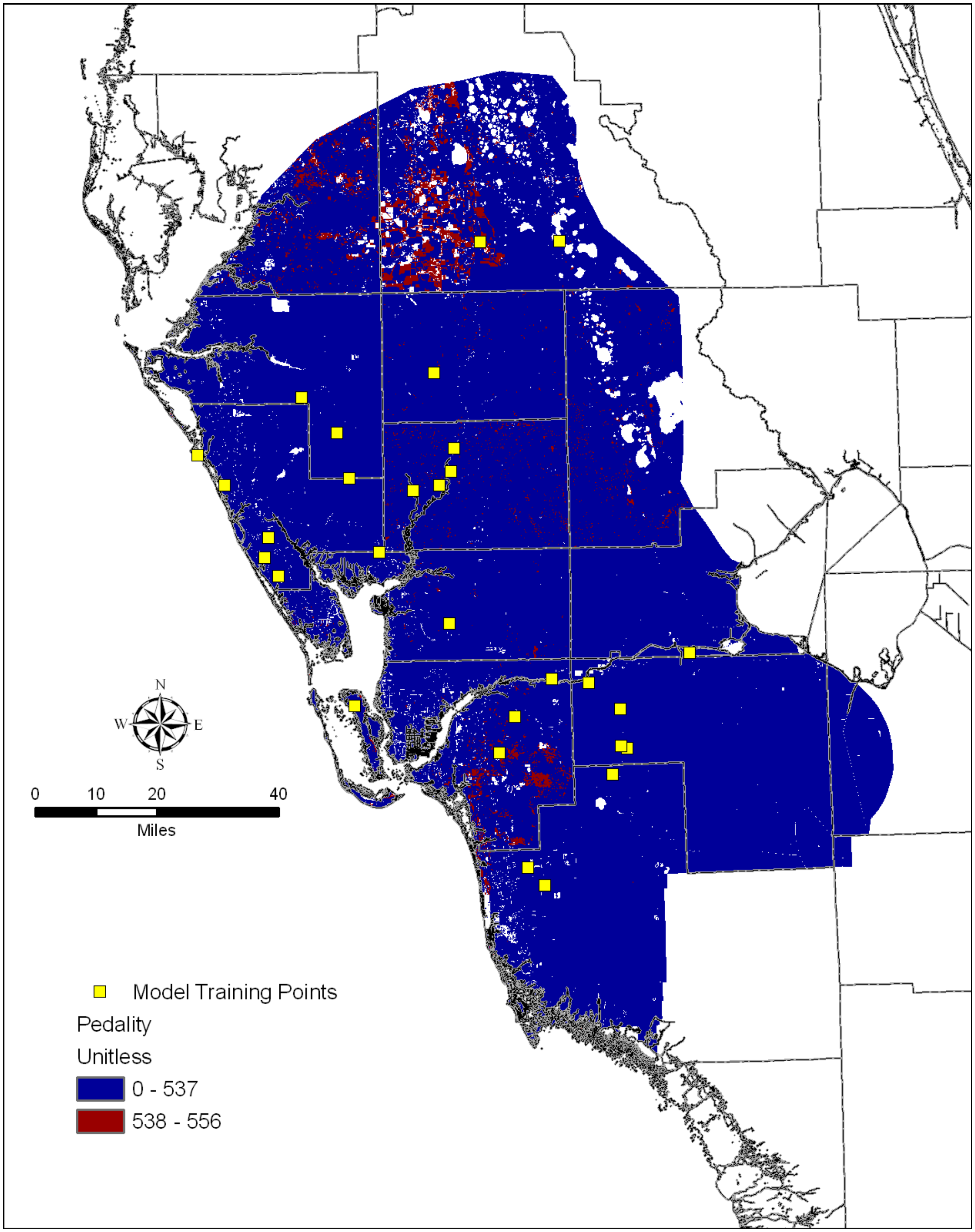

Figure 50. Generalized soil pedality evidential theme; based on calculated weights analysis blue areas share a weaker association with training points and thereby relatively lower aquifer vulnerability, whereas red areas share a stronger association with training points.

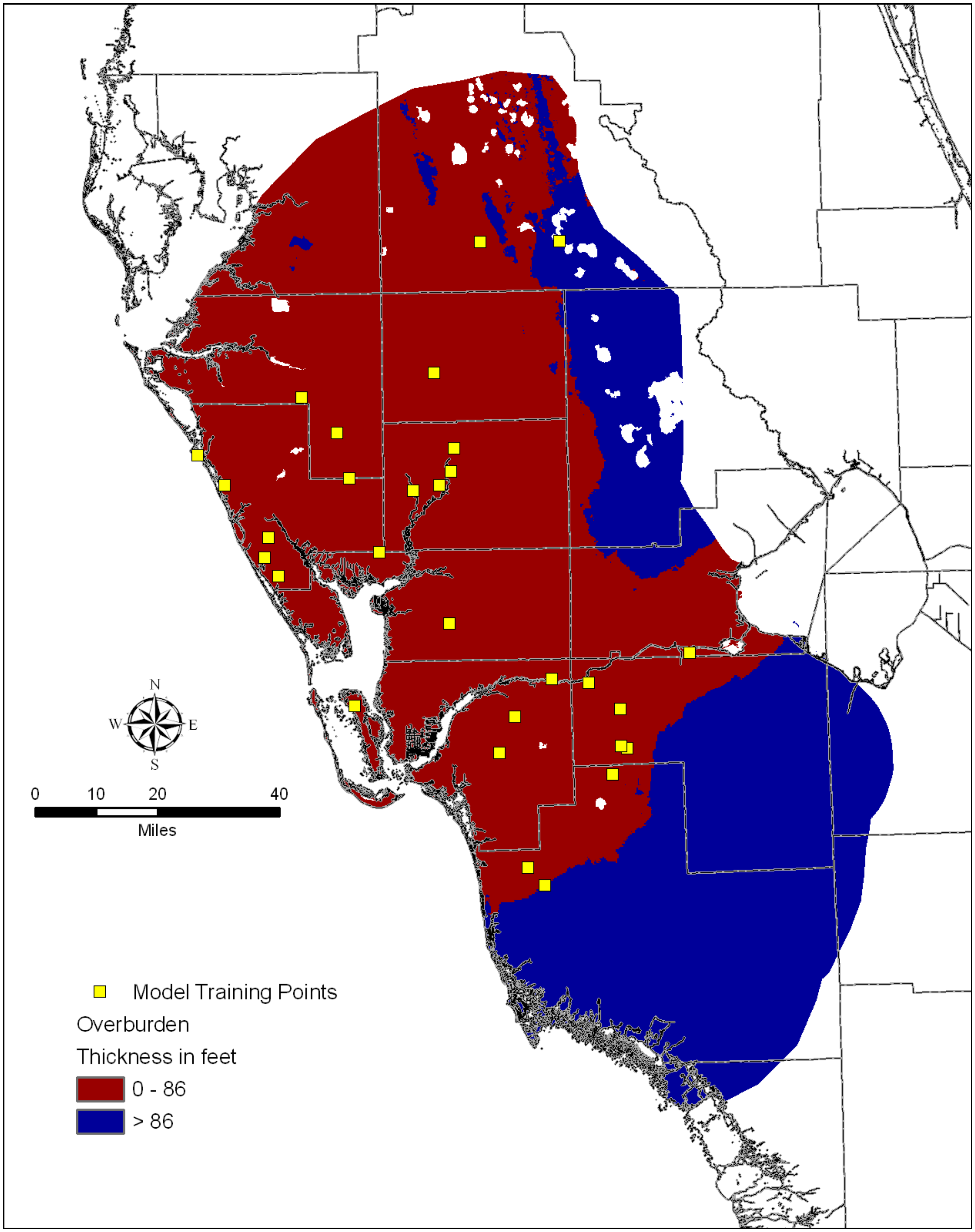

Figure 51. Generalized IAS overburden evidential theme; based on calculated weights analysis blue areas share a weaker association with training points and thereby relatively lower aquifer vulnerability, whereas red areas share a stronger association with training points.

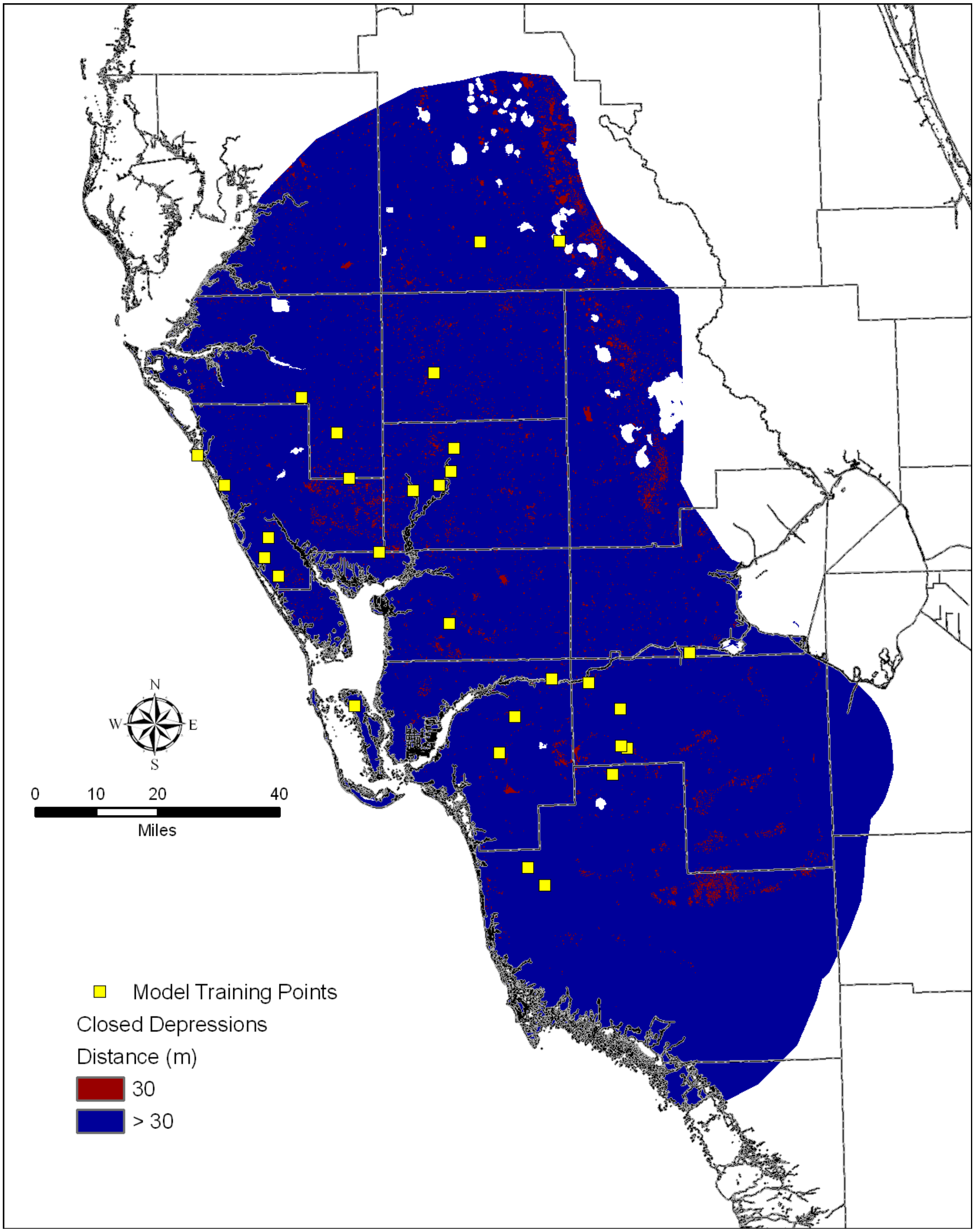

Figure 52. Generalized closed topographic depressions evidential theme; based on calculated weights analysis blue areas share a weaker association with training points and thereby relatively lower aquifer vulnerability, whereas red areas share a stronger association with training points.

Response Theme

Using evidential themes representing soil pedality, IAS overburden thickness, and closed topographic depressions weights of evidence was applied to generate a response theme, which is a GIS raster consisting of *posterior probability* values ranging from 0.000088 to 0.016892 across the study area. These probability values describe the relative probability that a unit area of the model will contain a training point – i.e., a point of aquifer vulnerability as defined above in *Training Points* – with respect to the prior probability value of 0.0011 ([1 km^2 model unit area * 29 training points] / 27,458.4 km^2 = 0.0011). Prior probability is the probability that a training point will occupy a defined unit area within the study area, independent of evidential theme data. Probability values at the locations of 28 of the 29 training points are above the prior probability, indicating that this model is a strong predictor of training point locations.

The response theme was broken into classes of relative vulnerability based on the prior probability value and on inflections in a chart in which cumulative study area was plotted against posterior probability (Figure 53). Higher posterior probability values correspond with more vulnerable areas, as they essentially have a higher chance of containing vulnerability based on the definition of a training point. Conversely, lower posterior probability values correspond to less vulnerable areas as they essentially have a lower chance of containing vulnerability based on the definition of a training point.

As expected, the IAS response theme indicates that areas of highest vulnerability are associated with areas where the IAS overburden is thinnest, in areas of dense closed topographic depressions, and areas of higher soil pedality. Conversely, areas of lowest vulnerability are determined by thick IAS overburden values, sparse closed topographic depression distribution, and lower soil pedality values. Relative vulnerability classes are displayed in Figure 54.

Discussion

Prior to discussion of weights calculations during model execution, two components of a weights of evidence analysis are described to assist in interpretation of IAS model results: *Conditional Independence* and *Model Confidence*.

Conditional Independence

Conditional independence is a measure of the degree that evidential themes are affecting each other due to similarities between themes. Evidential themes are considered independent of each other if the conditional independence value is around 1.00, and conditional independence values within the range of 1.00 ± 0.15 generally indicate limited to no dependence among evidential themes (Bonham-Carter, 1994). Values significantly outside this range can inflate posterior probabilities resulting in unreliable response themes.

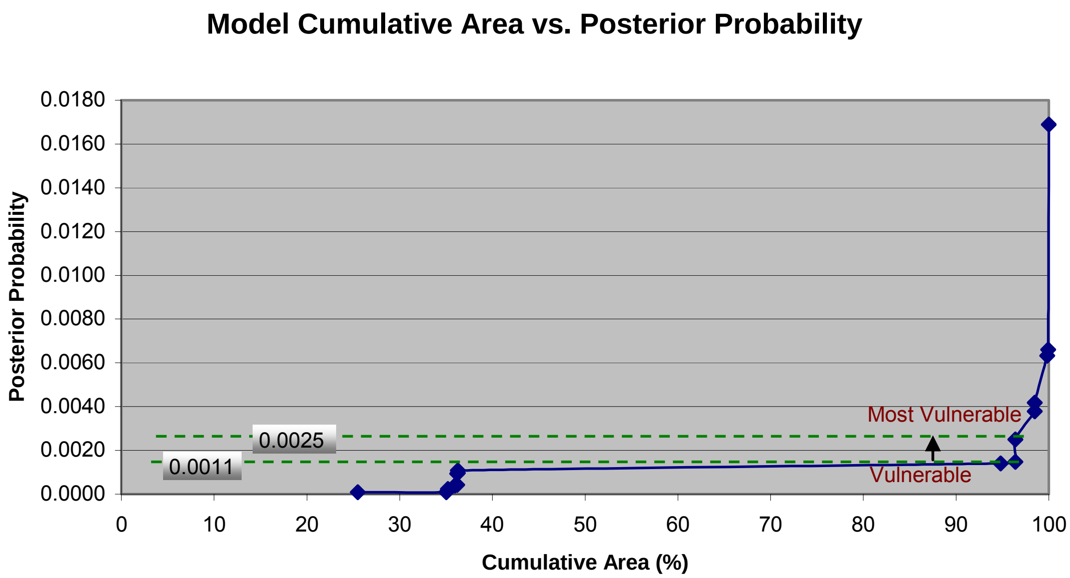

Figure 53. Vulnerability class breaks are defined by selecting where a significant increase in probability and area are observed.

Conditional independence was calculated at 0.98 for the IAS project indicating that evidential themes had virtually no conditional dependence.

Model Confidence

During model execution, confidence values are calculated both for each generalized evidential theme and for the final response theme. Confidence values approximately correspond to the statistical levels of significance listed in Table 3.

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 test value of 1.3537 corresponds to approximately 90% confidence – or level of significance – and was the minimum calculated confidence level for the IAS project evidential themes (see Table 9 below for evidential theme confidence values). A confidence map is also calculated for a response theme by normalizing the theme's posterior probability by its total uncertainty (standard deviation). A confidence map can be generated based on these calculations. The confidence map for the IAS response theme is displayed in Figure 55. Areas with high posterior probability values typically correspond to higher confidence values and as a result have a higher level of certainty with respect to predicting aquifer vulnerability.

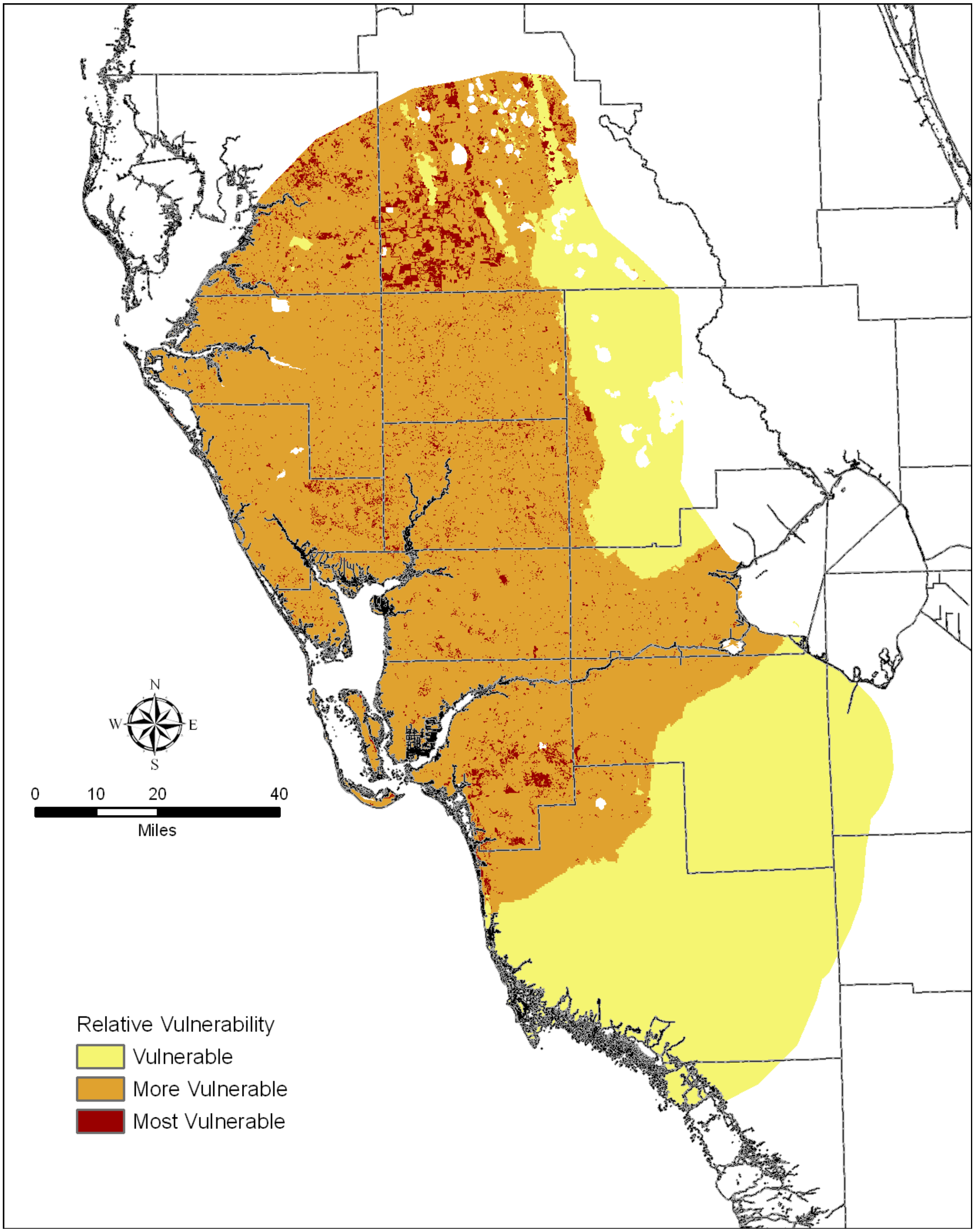

Figure 54. Relative vulnerability map for the Intermediate Aquifer Vulnerability Assessment project. Classes of vulnerability are based on calculated probabilities of a unit area containing a training point, or a monitor well with water quality sample results indicative of vulnerability.

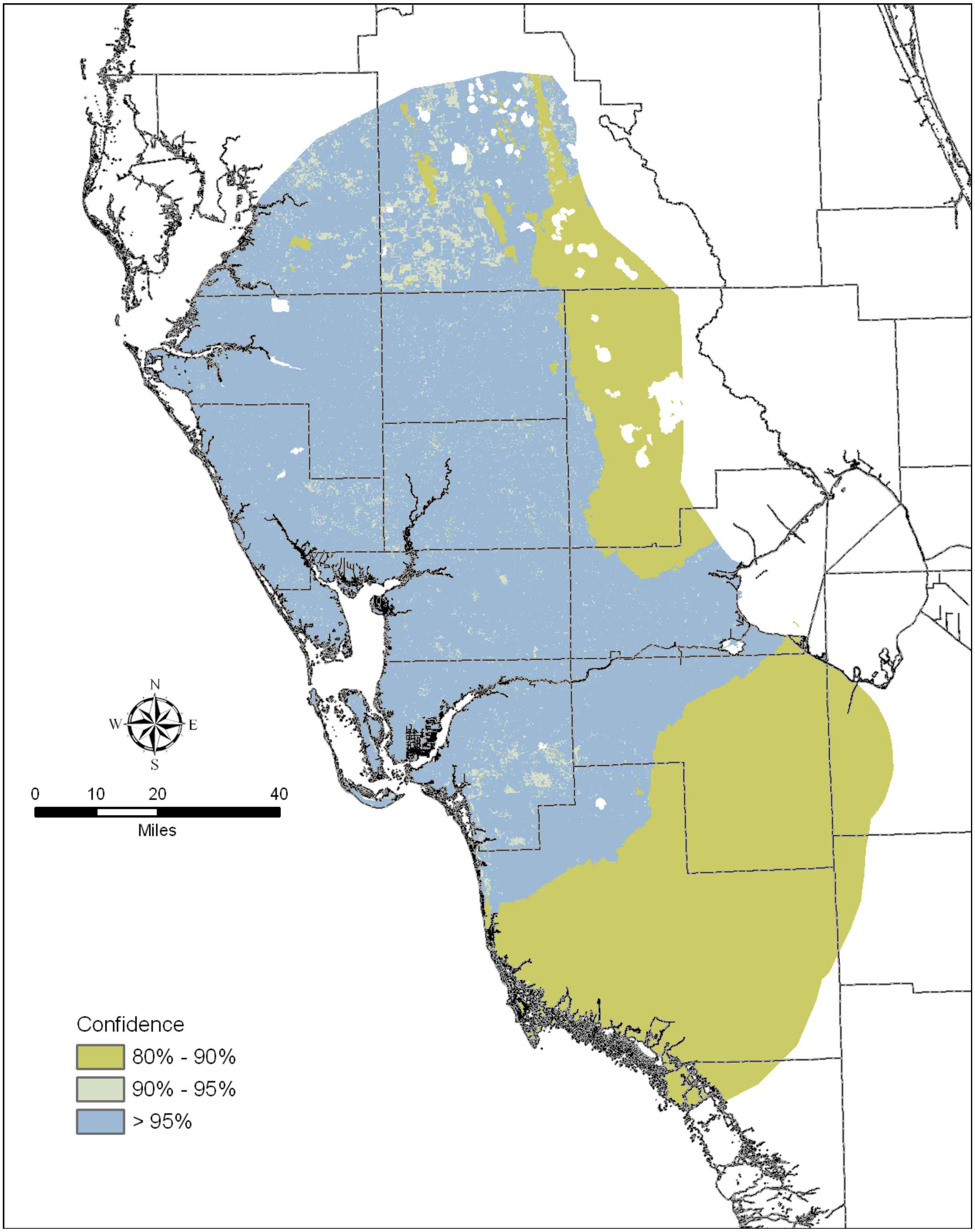

Figure 55. Confidence map for the Intermediate Aquifer model calculated by dividing the posterior probability values by the total uncertainty for each class to give an estimate of how well specific areas of the model are predicted.

Weights Calculations

Table 9 displays evidential themes used in the IAS model, weights calculated for each theme, along with contrast and confidence values. Positive weights indicate areas where training points are likely to occur, while negative weights indicate 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. Confidence of the evidential theme is also calculated and is equal to the contrast divided by its standard deviation (a student T test). Confidence is a measure of significance due to uncertainties of the weights and missing data (Raines, 1999). A positive contrast that is significant, based on its confidence, suggests that a generalized evidential theme is a useful predictor.

Table 9. Weights of evidence 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
Soil Pedality	0.9491	-0.0444	0.9935	1.3537
IAS Overburden	0.4154	-2.353	2.7684	2.72
Closed Topographic Depressions	1.4237	-0.084	1.5077	2.4677

Because positive weights (W1) values for soil pedality and closed topographic depressions are stronger (have greater absolute values) than the negative weights (W2), they are better predictors of where training points are likely to occur, whereas the IAS overburden theme is a better indicator of where training points are less likely to occur. Based on contrast values, the IAS overburden theme has the strongest (highest absolute value) weight and is the primary determinant in predicting areas of vulnerability in the IAS model.

Validation

The weights of evidence approach, because it relies on a set of training points, which by definition are known sites of vulnerability, is essentially self-validated. Twenty-eight of twenty-nine training points were predicted in zones of posterior probability greater than the prior probability (in other words, classified accurately). Further strengthening the results were the evaluation of a minimum confidence threshold for evidential themes, and generation of a confidence map of the response theme. In addition to these exercises, and in the style of previous aquifer vulnerability assessments (Cichon et al., 2005; Baker et al., 2005; Arthur et al., 2005), additional validation techniques were applied to the IAS model to further strengthen its defensibility, and, ultimately, its utility: (1) comparison of dissolved nitrogen values to posterior probability and evaluation of an associated trend; and (2) generation of a test response theme based on a subset of training points and comparison of points not used in subset to model results and (3) comparison of dissolved oxygen values with vulnerable zones of the response theme.

Dissolved Nitrogen Data vs. Posterior Probability

It was expected that comparison of posterior probability values to the dissolved nitrogen dataset from which the training point theme was extracted would reveal a proportional trend, in other words, as dissolved nitrogen values increase, so should posterior probability values. Dissolved nitrogen median concentrations were binned and averaged for each posterior probability value calculated in model output. The average values were plotted in a chart against posterior probability values (Figure 56) and a positive trend was observed.

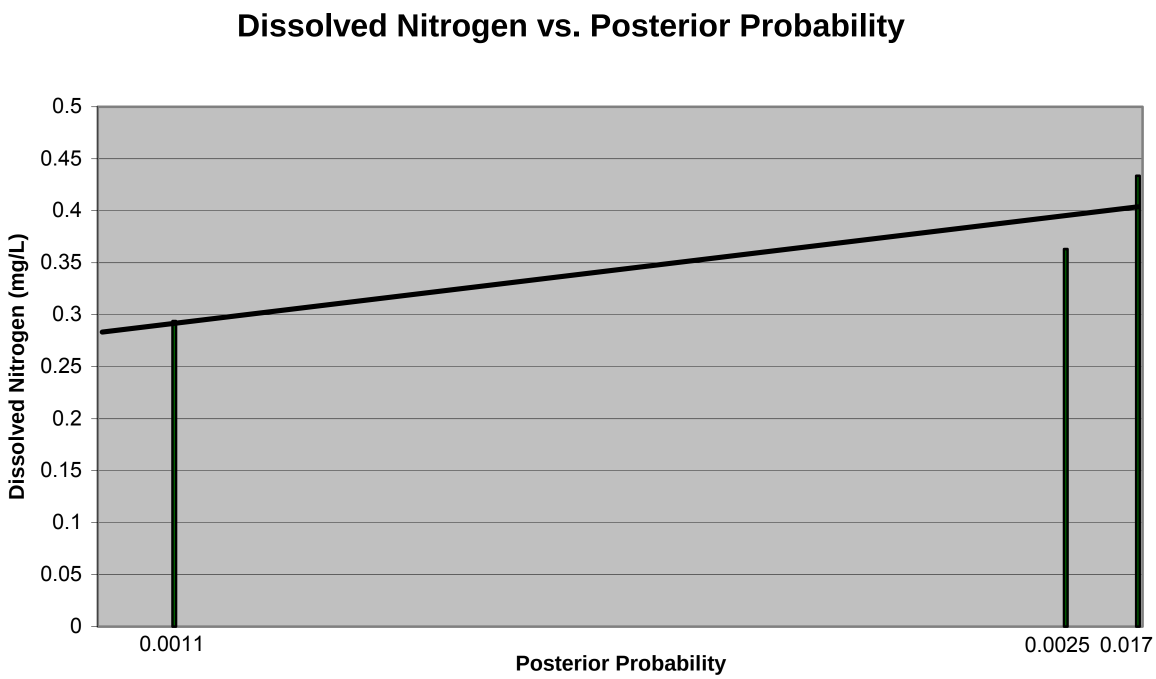

Figure 56. Dissolved nitrogen values (averaged per posterior probability class) versus probability values to reveal trend between increasing dissolved nitrogen concentrations and posterior probability.

Subset Response Theme

Another meaningful validation exercise similar to the exercise above is to use the existing training point dataset to develop two subsets: one to generate a test response theme, and one to validate output from this test response theme. Results from this exercise helped to further assess whether the dissolved nitrogen training points are reasonable predictors of aquifer vulnerability.

From the IAS training point theme, a subset of 75% (22 wells) were randomly selected and used to develop a test response theme (Figure 57); the remaining 25% (7 wells) of the training points were used as the validation dataset for the test response theme. This comparison revealed that seven of the seven test wells in the validation subset, or 100%, occur in areas of the test response theme with predicted probability values higher than the prior probability value. This further supports the conclusion that the IAS model response theme is a reasonable estimator of vulnerability.

Dissolved Oxygen Data

Perhaps the most rigorous validation exercise used to evaluate quality of model-generated output is to compare predicted model values with independent test values not used in the model. For the IAS model, this was accomplished by comparison of a separate well dataset based on dissolved oxygen. As mentioned above in *Training Point Theme*, dissolved oxygen is indicative of aquifer vulnerability, but is independent of dissolved nitrogen. Applying the methodology described in *Training Point Theme* to dissolved oxygen data (obtained from the same data sources as dissolved nitrogen data) resulted in a dissolved oxygen dataset of 35 wells each indicative of aquifer vulnerability.

These 35 points were evaluated against posterior probability values of the IAS model output. Extracting the value of posterior probability from the dissolved nitrogen response theme for the location of each of the 35 dissolved oxygen training points revealed that 32 of the 35 dissolved oxygen training points occur in areas of the dissolved nitrogen model with predicted probability values higher than the prior probability value. In other words, 91.4% of the dissolved oxygen wells were located in areas predicted to have a greater than chance probability of containing a training point. Based on this test, the dissolved nitrogen model is not only a good predictor of vulnerability as defined by the training point theme; it is also a good predictor of the location of an independent parameter also representing aquifer vulnerability. Figure 58 displays dissolved oxygen data points plotted on the dissolved nitrogen response theme.

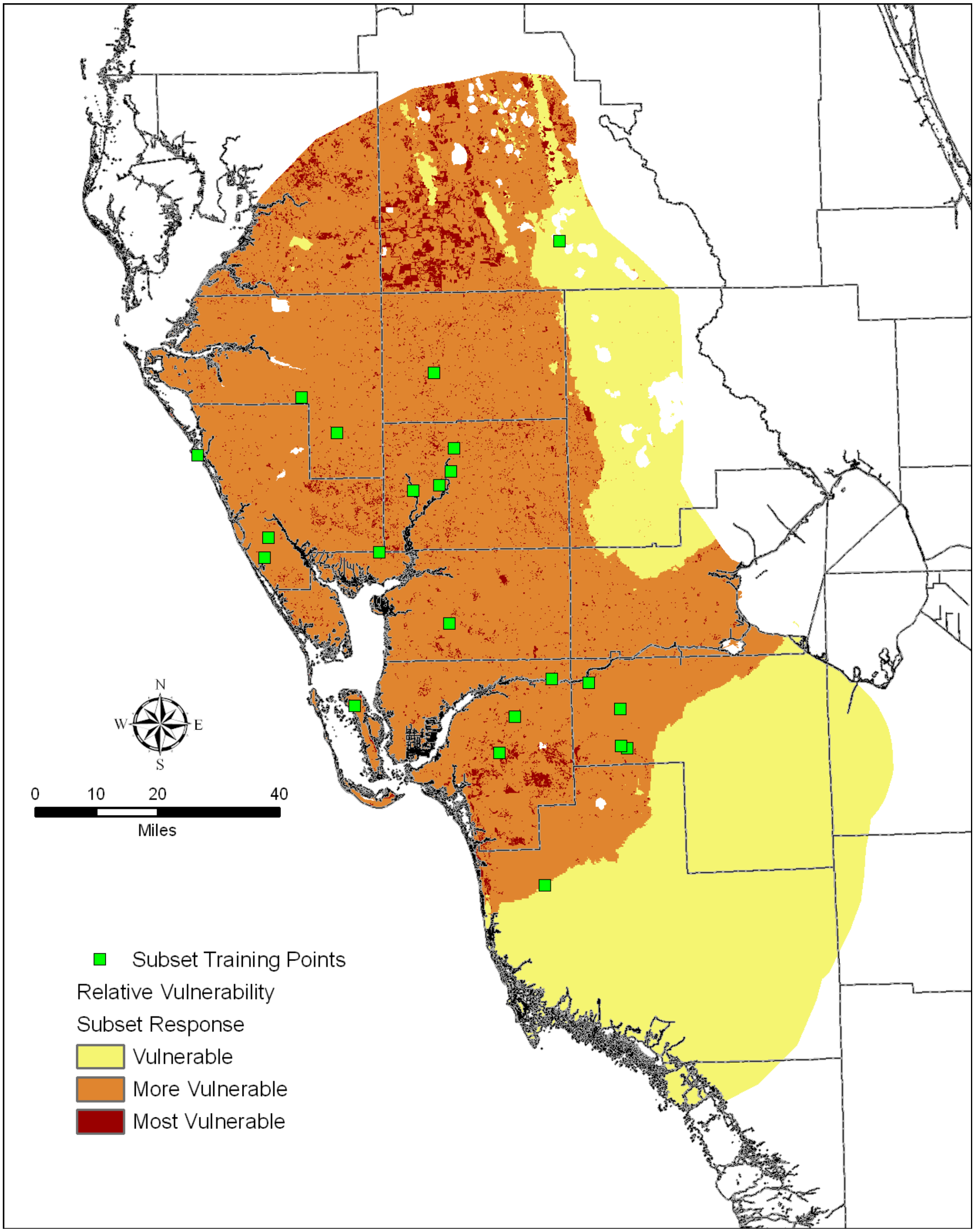

Figure 57. Subset response training points plotted in the dissolved oxygen response theme.

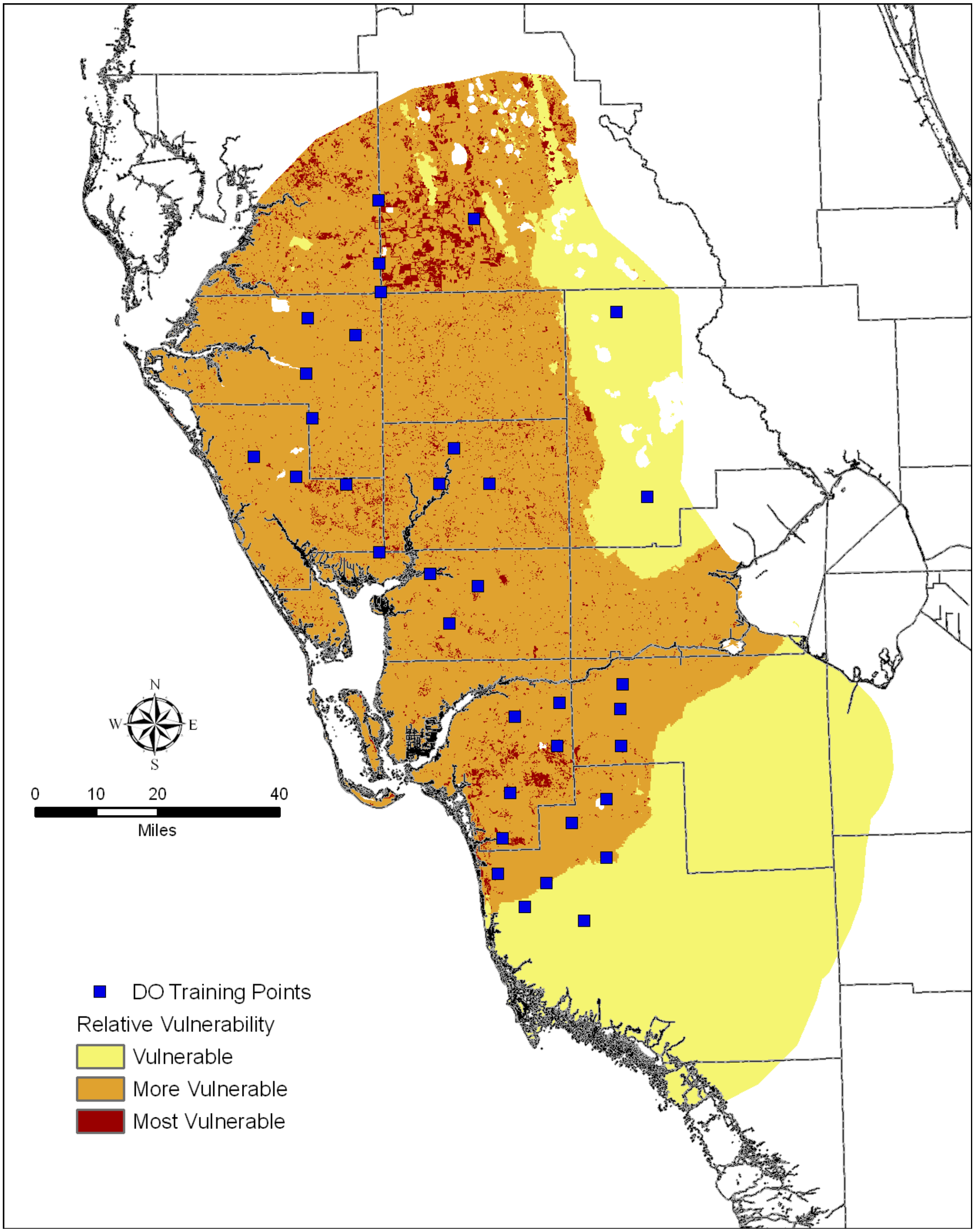

Figure 58. Dissolved oxygen validation training points plotted in the dissolved nitrogen response theme. Comparison reveals 32 of 35 wells (91.4%) of the independent water quality dataset are located in areas with predicted probability values higher than the prior probability.

FLORIDAN AQUIFER SYSTEM

Study Area

The study area is the same as the original FAVA model extent (Figure 59). Because of the sizes of some polygons representing soil data, a grid cell size of approximately 30 meter squares (or 900 m^2) was selected for evidential theme development. This grid cell size, while necessary to capture resolution available in some input data layers, does not reflect appropriate resolution of final model output. Appropriate scale of use of model results is discussed in *Model Implementation and Limitations*.

Water bodies were omitted from the model extent for two main reasons: first, the main goal of this project is to estimate vulnerability of the Florida aquifer system (FAS) and not vulnerability of surface water features, and second, data for water bodies is typically not available – i.e., wells are not drilled in water bodies, nor do soil surveys normally contain information regarding lake and stream bottoms.

Training Point Theme

In the model analysis, training points are groundwater wells tapping the Floridan aquifer system (FAS) with water quality data indicative of high recharge. Dissolved nitrogen analytical values served as training point data for the FAS model. Naturally occurring oxygen and nitrogen are generally considered ubiquitous at land surface as primary components of the atmosphere; moreover, relatively low concentrations of these analytes occur in well protected – or less vulnerable – aquifer systems. Accordingly, where these analytes occur in elevated concentrations in groundwater, yet are not attributable to human activity, they are good indicators of aquifer vulnerability (Arthur et al., 2007).

Water quality data sources explored include the FDEP background water quality network and FDEP STATUS network. From these data sources, 1,068 wells measured for dissolved nitrogen were identified as being potential candidates for training points. Statistical analyses revealed 252 samples were considered statistical outliers. The upper 25th percentile of this set – or all wells with median dissolved nitrogen values greater than or equal to 0.42 milligrams per liter (mg/L) – served as the training point theme and consists of 192 wells. Figure 60 displays the distribution of water wells used to derive training points and the resulting training point theme across the study area.

Training points are used to calculate prior probability, weights for each evidential theme, and posterior probability of the response theme (see *Glossary*). Prior probability (training point unit area divided by total study area) is the probability that a training point will occupy a defined unit area within the study area, independent of any evidential theme data. The prior probability value, a unitless parameter, for the FAS model is 0.0017 ([1 km^2 model unit area * 192 training points] / 115,364.72 km^2 = 0.0017). Posterior probability values generated during response theme development are interpreted relative to the value of prior probability with higher values generally indicating areas with higher probability of containing a training point.

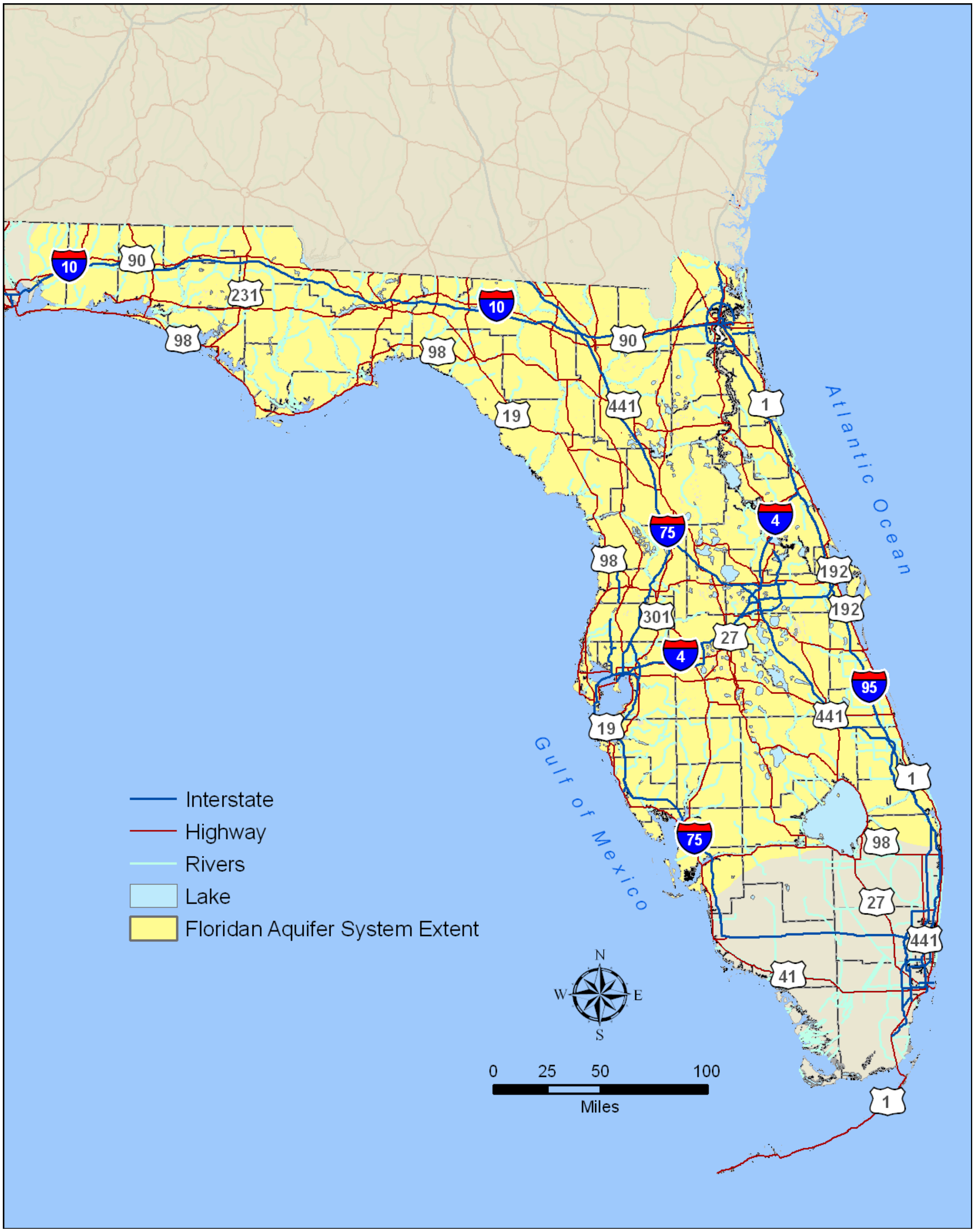

Figure 59. Floridan Aquifer System Vulnerability Assessment project study area extent.

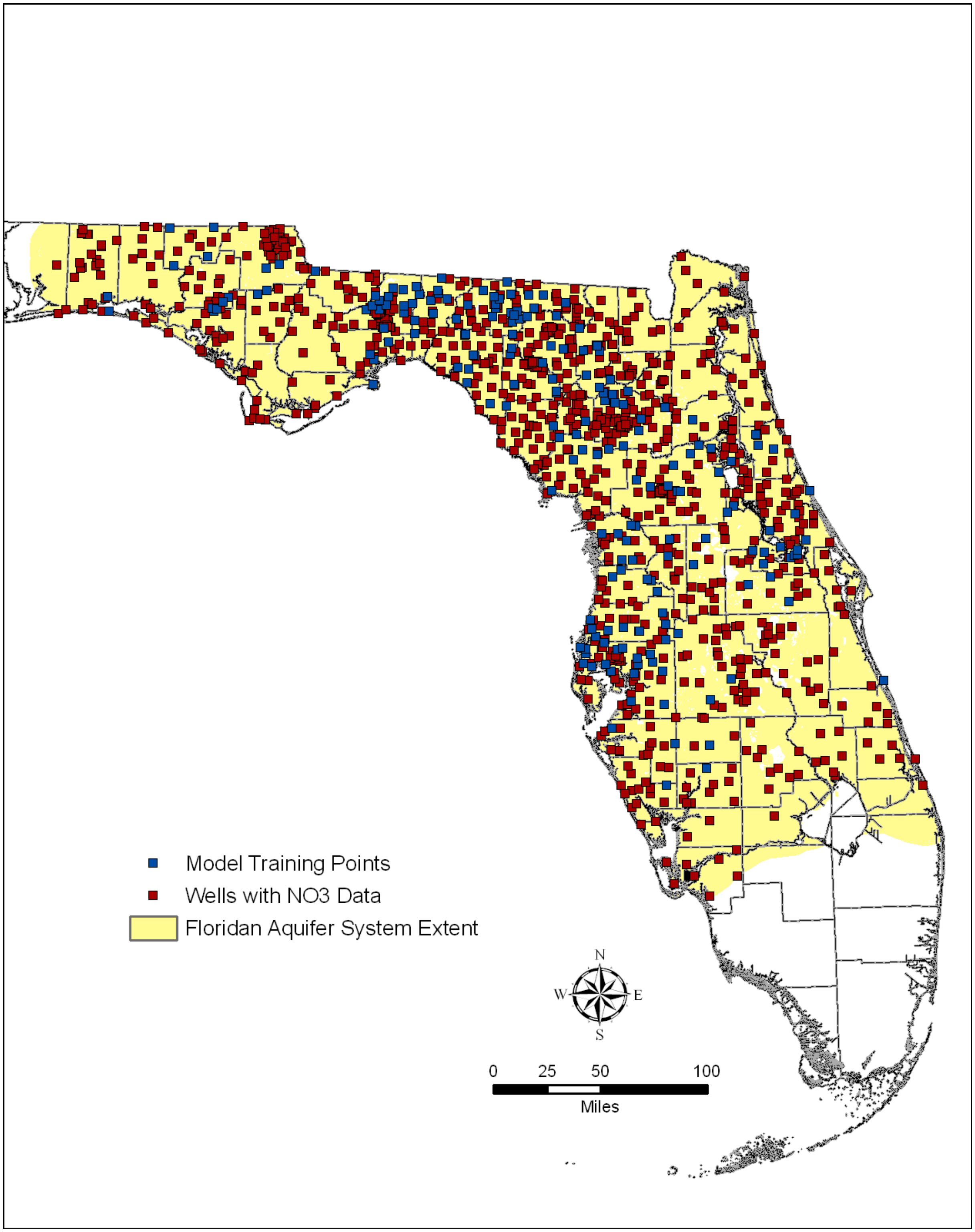

Figure 60. Location of all wells measured for dissolved nitrogen (dark red boxes), and locations of training point wells with median dissolved nitrogen values greater than 0.42 mg/L (blue boxes).

Evidential Themes – Model Input Layers

Input data layers, or evidential themes, representing hydrogeologic factors controlling the location of training points, and thereby vulnerability, were developed for model input. The factors considered for the IAS project include closed topographic depressions, intermediate confining unit, IAS overburden, soil pedality, and soil hydraulic conductivity.

Soil Hydraulic Conductivity and Soil Pedality Themes

The rate that water moves through soil is a critical component of any aquifer vulnerability analysis, as soil is literally an aquifer system's first line of defense against potential contamination (Arthur et al., 2005). Two parameters of soils were evaluated for input into the FAS model: *soil hydraulic conductivity*, which is the "amount of water that would move vertically through a unit area of saturated soil in unit time under unit hydraulic gradient" (U.S. Department of Agriculture, 2005); and *soil pedality*, which is calculated based on soil type, soil grade, and soil pedon size, and is a unitless parameter. Soil pedality is a relatively new concept used to estimate the hydrologic parameter of soil and is generated for the FAS using the pedality point method developed by Lin et al. (1999).

Countywide datasets representing soil hydraulic conductivity and soil pedality were developed for use as input into the FAS model. Multiple empirical values are reported in soil surveys representing various zones in each soil column underlying a particular soil polygon. Representative values for each horizon in a column are combined using a sum of the weighted mean. This is completed for both hydraulic conductivity and soil pedality. Figure 61 displays values of soil hydraulic conductivity.

Intermediate Confining Unit and Overburden Thickness Themes

Aquifer confinement – either in the form of overburden overlying the FAS, or the ICU – is another critical layer in determining aquifer vulnerability. Where aquifer confinement is thick and the FAS is deeply buried, aquifer vulnerability is generally lower, whereas in areas of thin to absent confinement, the vulnerability of the FAS is generally higher.

GIS models were developed of the top of the FAS and top of the IAS. The intent of these models was to allow the calculation of aquifer confinement thickness in the study area. Surface models were developed using a dataset of borehole records from the Florida Geological Survey. These surfaces were used to calculate thickness of the ICU (Figure 62) and thickness of overburden overlying the FAS in the study area. These two layers were tested for input in the model as described in *Sensitivity Analysis*.

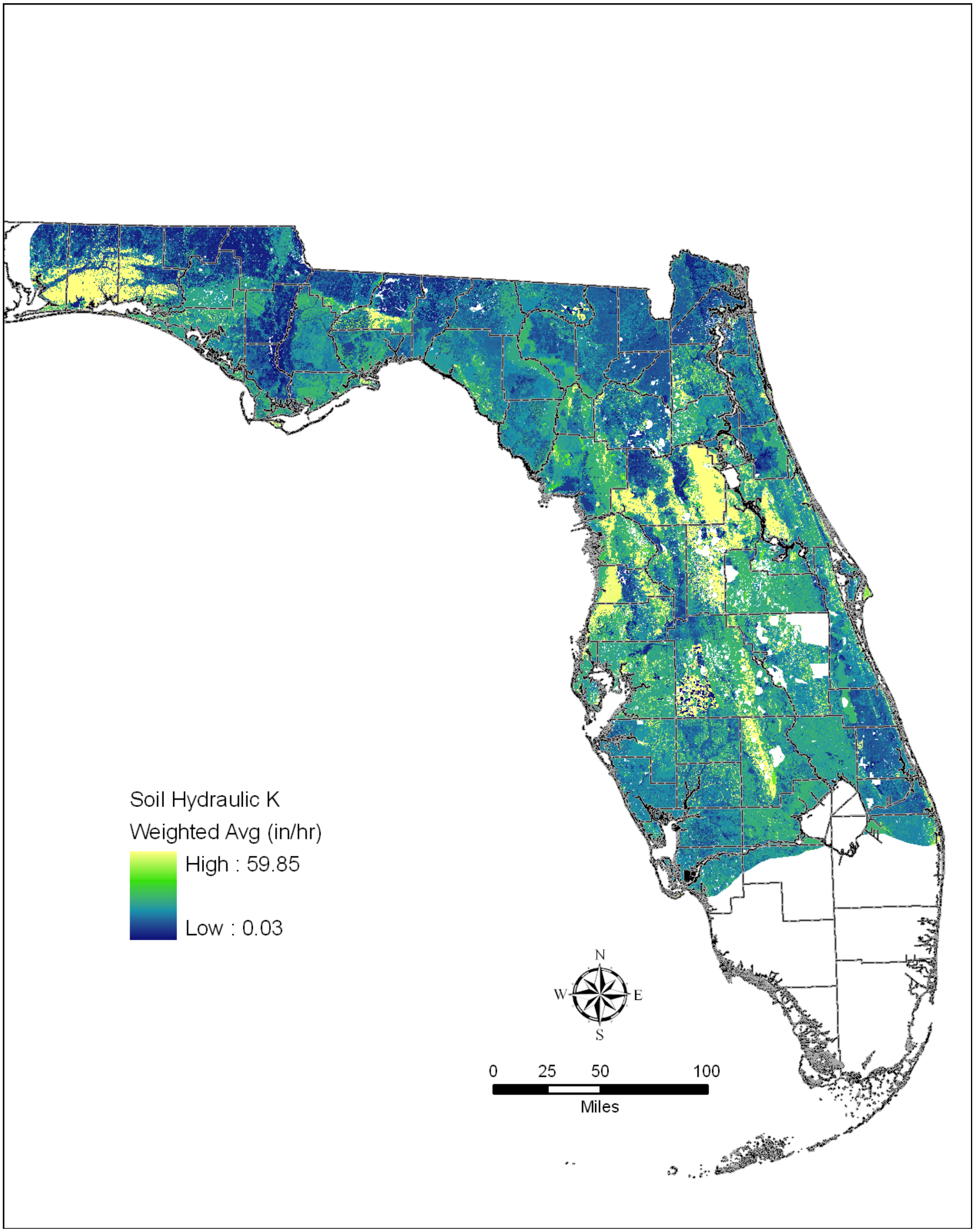

Figure 61. Distribution of soil hydraulic conductivity values across the Floridan Aquifer study area. White areas represent 'no data' areas in the soil survey data or locations of water bodies.

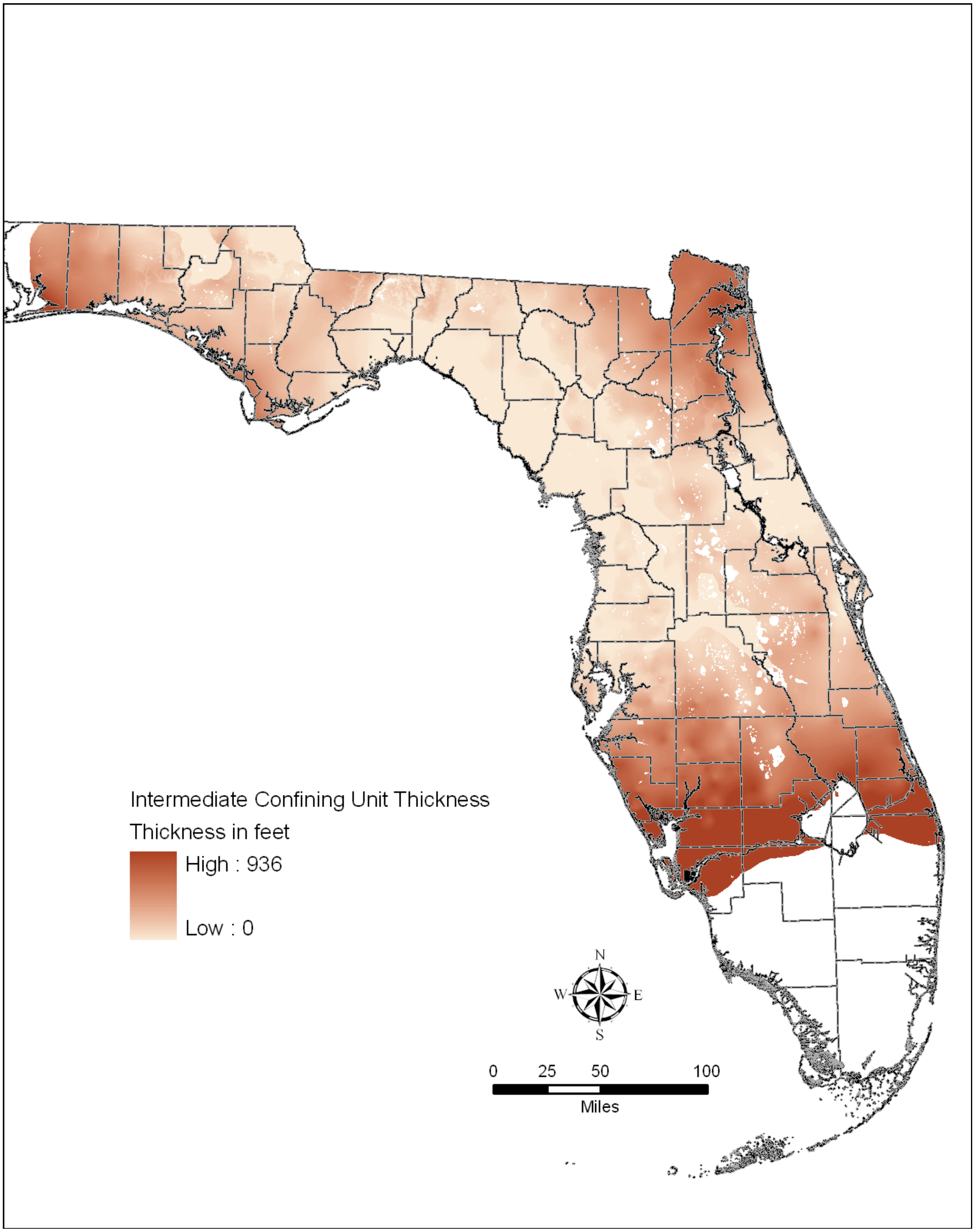

Figure 62. Thickness of intermediate confining unit calculated by subtracting predicted top of IAS surface (generated by FGS/FDEP) from predicted top of FAS surface.

Potential Karst Feature Theme

Karst features, or sinkholes and depressions, can provide preferential pathways for movement of surface water into the underlying aquifer system and enhance an area's aquifer vulnerability where present. The closer an area is to a karst feature, the more vulnerable it may be considered. Closed topographic depressions extracted from U.S. Geological Survey 7.5-minute quadrangle maps served as the initial dataset from which to estimate potential karst features in the study area.

It is recognized that using closed topographic depressions to develop a potential karst features theme may or may not represent all true karst features, however, application of analytical processes to digital elevation maps and models to estimate karst has been successfully completed in numerous projects (Baker et al., 2007; Arthur et al., 2005; Cichon et al., 2005; Baker et al., 2005; and Denizman, 2003). grid and only selecting those areas where that were less than or equal to 140 feet in thickness.

The most statistically significant and defensible method evaluated for this project is the circular index method described below. Once the circular index calculation is completed for all closed depressions a secondary filter was applied to remove those areas that are not karst. This was completed by taking the ICU thickness grid and only selecting those areas that were less than or equal to 140 feet in thickness.

Circular index method

Karst features, which form as the result of the dissolution of carbonate rocks and subsequent collapse of overlying material, are generally circular in nature. In contrast, non-karstic depressional features are common in near-shore modern terrains, relic dune terrains and other provinces, and tend to have a non-circular shape. To filter these features and other types of non-karst features in the study area, a circular index shape analysis (Denizman, 2003) was used to compare the roundness of depressional features to an ideal circle. The area of each closed depression was divided by the area of an ideal circle with the same perimeter as the depression. This resulted in a "roundness ratio", representing the degree of similarity between two such features. Several roundness ratio values were evaluated for use in the model; normally values of 0.75 to 0.80 are found to be most suitable for study areas of this size. Further filtering occurred by removing those potential karst features (Figure 63) that were in areas where the ICU thickness was greater than 140 feet.

Sensitivity Analysis/Evidential Theme Generalization

Sensitivity analysis allows decisions to be made about proposed evidential themes by evaluating each theme's association with training points – or aquifer vulnerability – and ultimately helps determine model input. For example, soil hydraulic conductivity and soil pedality were both developed to represent soil properties; sensitivity analysis allows, through statistical analysis, determination of which of these two layers served as the most appropriate input representing soil properties for the final FAS analysis. Results of this process indicate that soil hydraulic conductivity, intermediate confining unit thickness, and potential karst features depressions were the best suited evidential themes for use in final modeling.

Following sensitivity analysis and selection of evidential themes to be input into the FAS model, themes were generalized to assess which areas of the evidence share a greater association with locations of training points. During calculation of weights for each theme, a contrast value was calculated for each class of the theme by combining the positive and negative weights. 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). Contrast and weights are described in more detail below in *Discussion*.

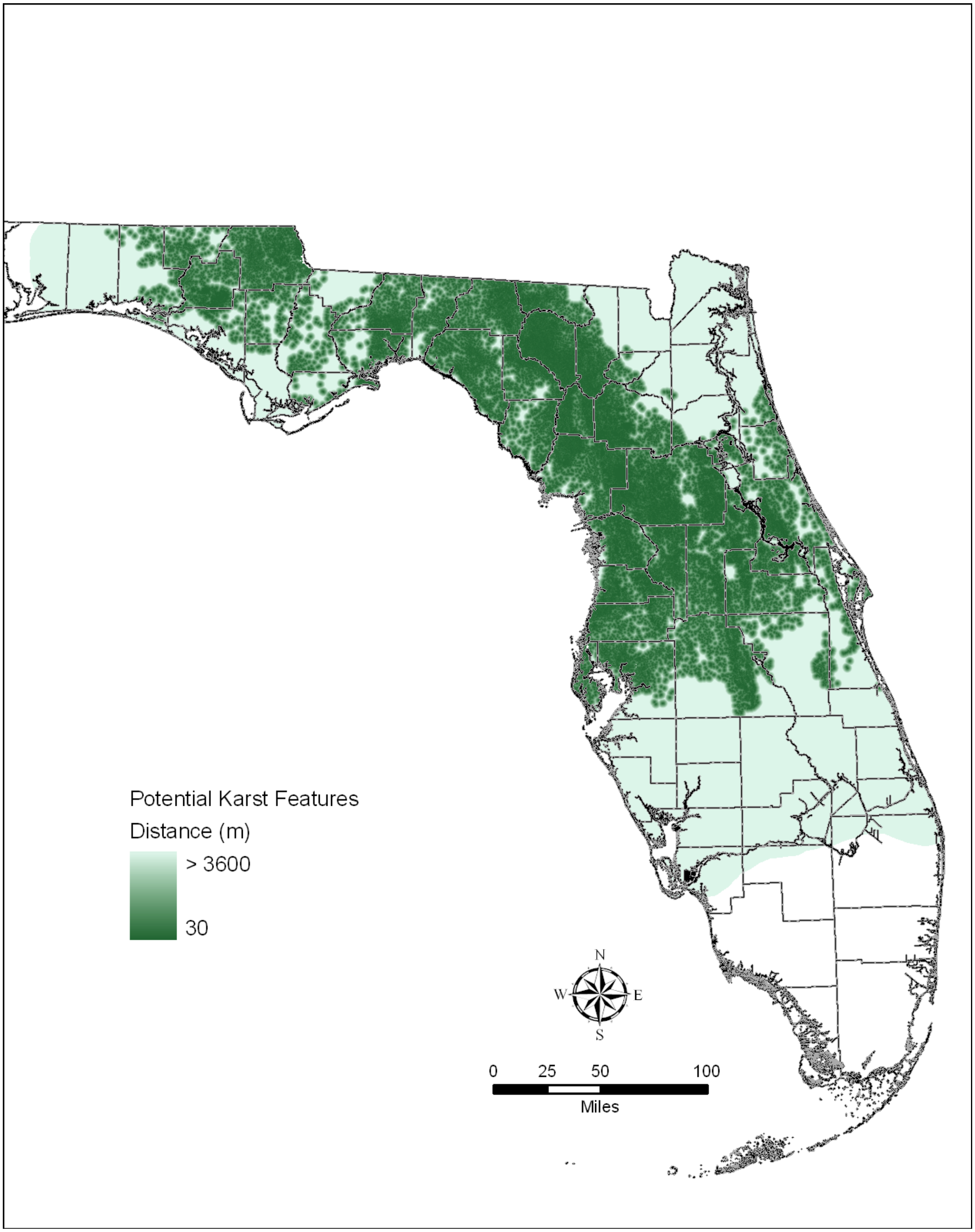

Figure 63. Potential karst features resulting from circular index method applied to U.S. Geological Survey 7.5 minute topographical contour lines and filtered by ICU thickness.

Contrast values were used to determine where to sub-divide evidential themes into generalized categories prior to final modeling. The simplest and most accepted method used to subdivide an evidential theme is to select the maximum contrast value as a threshold value to create binary generalized evidential themes. In other models, categorization of more than two classes may be justified (Arthur et al., 2005). For the FAS project, a binary break was typically defined by the weights of evidence analysis for each evidential theme creating two spatial categories: one with stronger association with the training point theme and one with weaker association.

Soil Hydraulic Conductivity/ Soil Pedality

Weights calculated during sensitivity analysis for soil hydraulic conductivity were stronger (i.e., had higher absolute value) than weights calculated for soil pedality. As a result, soil hydraulic conductivity was chosen as the better predictor of aquifer vulnerability because it shared the best association with training points.

Soil hydraulic conductivity, ranges from 0.03 to 59.85 in/hr across the study area. Based on calculated weights, this theme had justification for a multiple class generalization. Test modeling indicated that areas greater than or equal to 40.63 in/hr were most associated with the training points, areas that are greater than or equal to 14.80 in/hr and less than 40.63 in/hr were less associated with training points and areas less than 14.80 in/hr were least associated with the training points. Based on this analysis, the evidential theme was generalized into three classes as displayed in Figure 64.

Intermediate Confining Unit and Overburden Thickness Themes

Weights calculated during sensitivity analysis for the ICU thickness were stronger (i.e., had higher absolute value) than weights calculated using overburden thickness. As a result, the ICU thickness was chosen as the better predictor of aquifer vulnerability because it shared the best association with training points.

The ICU thickness ranges from absent to 1,209 feet thick across the study area. The analysis revealed that areas underlain by 364 feet or less of ICU thickness were more associated with the training points, and therefore associated with higher aquifer vulnerability. Areas underlain by greater than 364 feet of ICU thickness were less associated with the training points, and therefore lower aquifer vulnerability. Based on this analysis, the evidential theme was generalized into two classes as displayed in Figure 65.

Potential Karst Features

As mentioned above, areas closer to a karst feature are normally associated with higher aquifer vulnerability. Based on this, features were buffered into 30 meter zones to allow for a proximity analysis. The analysis indicated that areas within 3,480 meters of a closed topographic depression were more associated with the training points, and therefore with higher aquifer vulnerability. Conversely, areas greater than 3,480 meters from a karst feature were less associated with the training points, and therefore lower aquifer vulnerability. Based on this analysis, the evidential theme was generalized into two classes as displayed in Figure 66.

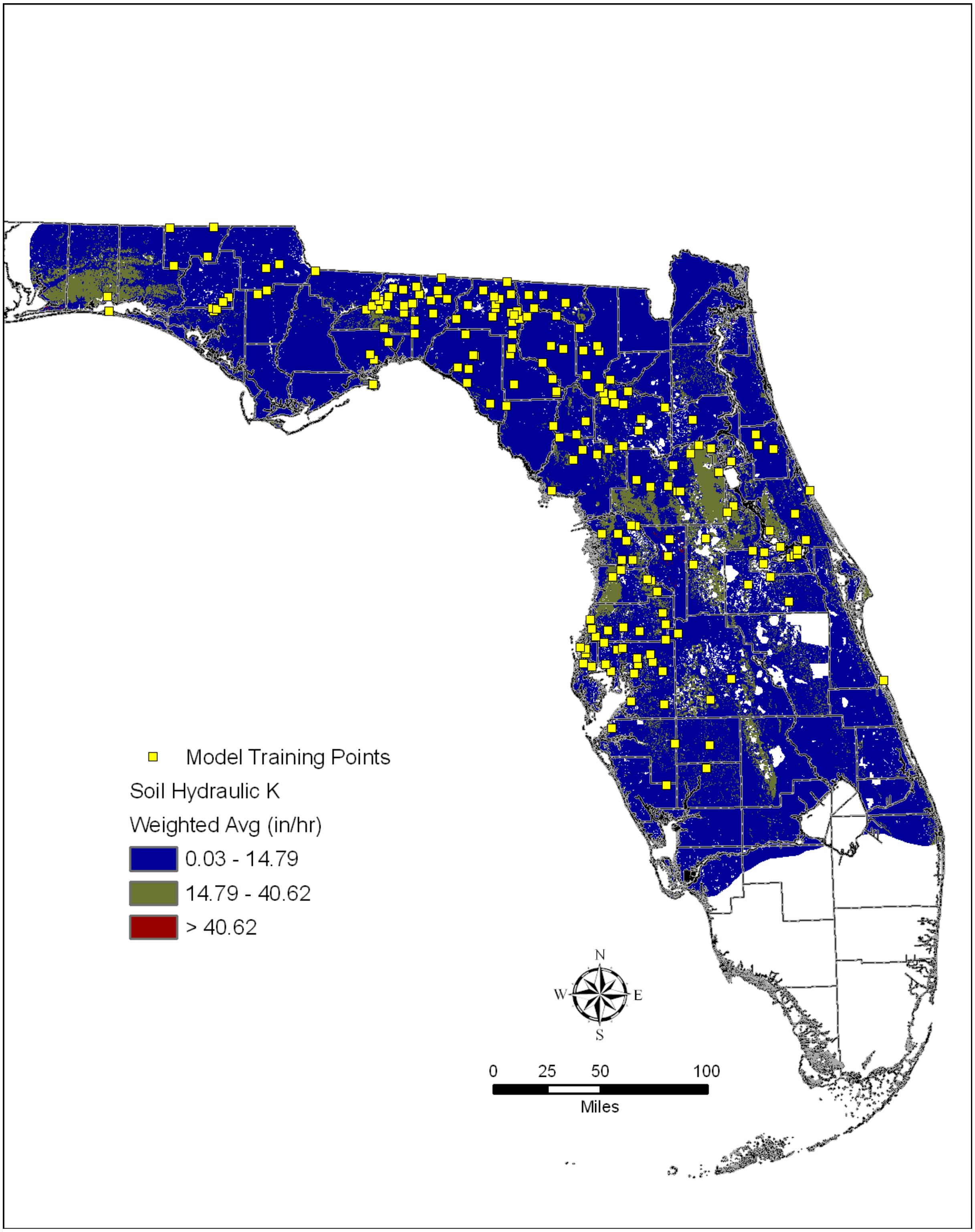

Figure 64. Generalized soil hydraulic conductivity evidential theme; based on calculated weights, a multi-class generalization with a break at a value of 14.79 and 40.62 in/hr was defined by the analysis. Based on the location of training points, blue areas share a weaker association with training points and thereby relatively lower aquifer vulnerability, whereas red areas share a stronger association with training points.

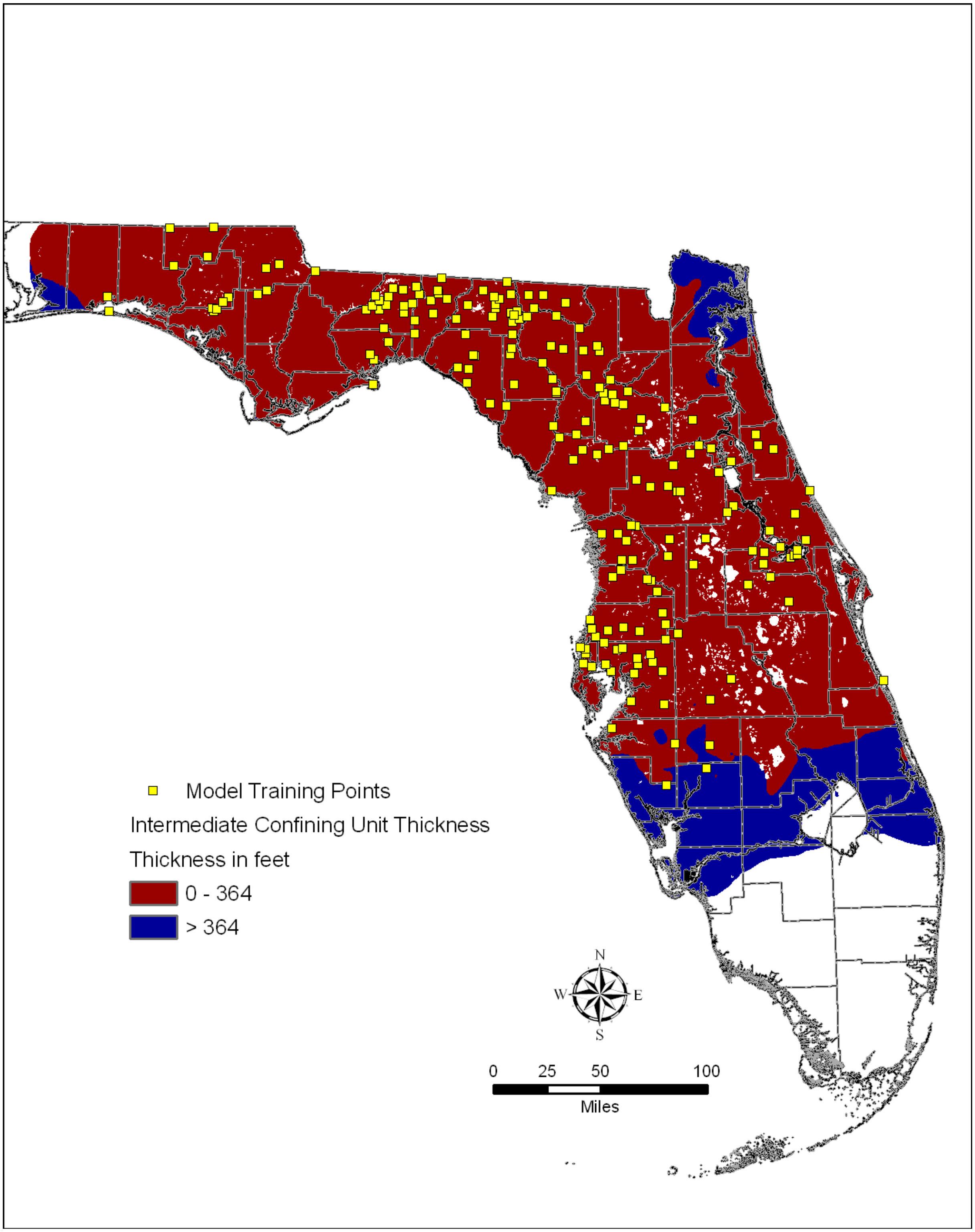

Figure 65. Generalized ICU evidential theme; based on calculated weights analysis blue areas share a weaker association with training points and thereby relatively lower aquifer vulnerability, whereas red areas share a stronger association with training points.

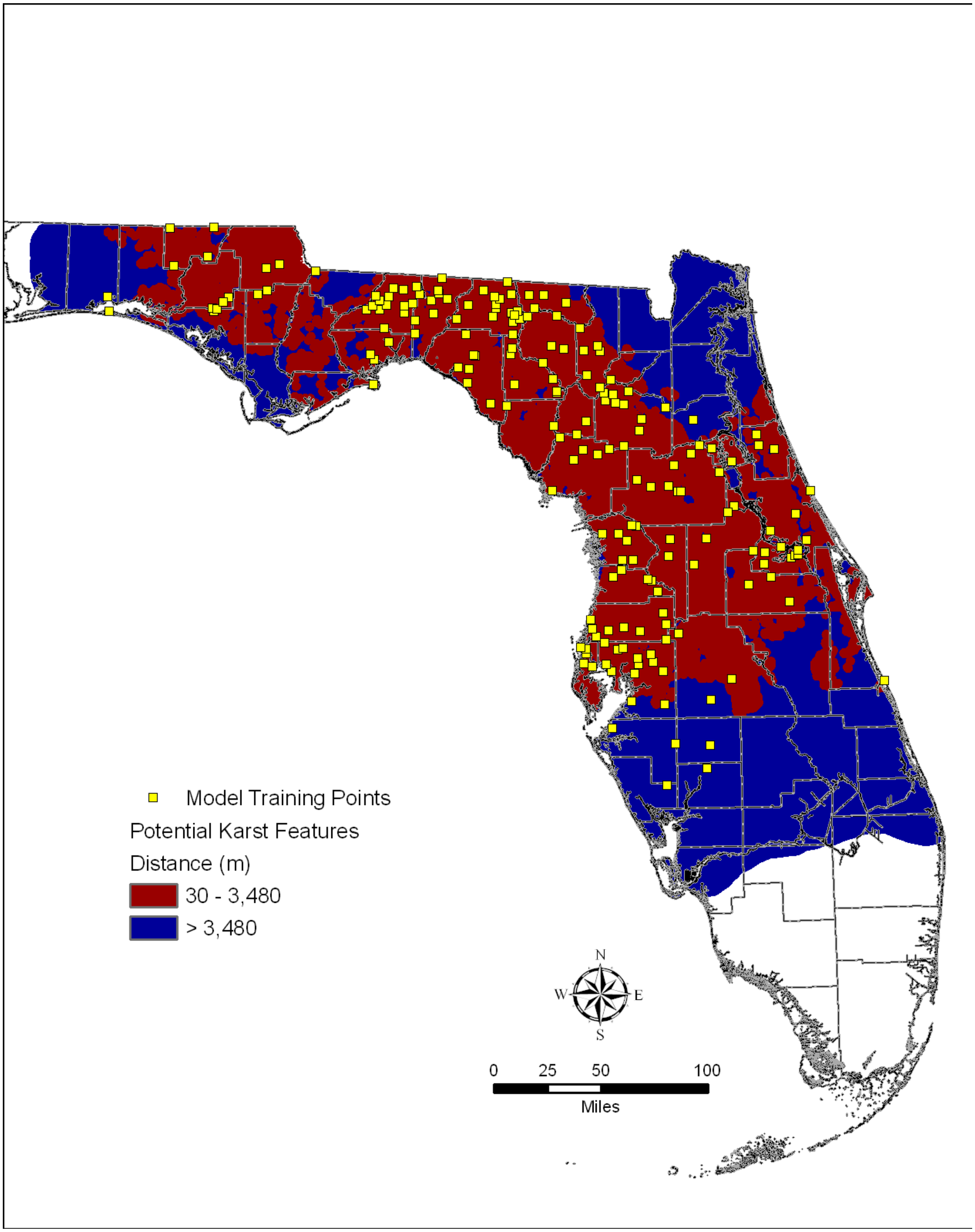

Figure 66. Generalized potential karst features evidential theme; based on calculated weights analysis blue areas share a weaker association with training points and thereby relatively lower aquifer vulnerability, whereas red areas share a stronger association with training points.

Response Theme

Using evidential themes representing soil hydraulic conductivity, ICU thickness, and potential karst, weights of evidence was applied to generate a response theme, which is a GIS raster consisting of *posterior probability* values ranging from 0.00000739 to 0.02732 across the study area. These probability values describe the relative probability that a unit area of the model will contain a training point – i.e., a point of aquifer vulnerability as defined above in *Training Points* – with respect to the prior probability value of 0.0017 ([1 km^2 model unit area * 192 training points] / 115,364.72 km^2 = 0.0017). Prior probability is the probability that a training point will occupy a defined unit area within the study area, independent of evidential theme data. Probability values at the locations of 179 of the 192 training points are above the prior probability, indicating that this model is a strong predictor of training point locations.

The response theme was broken into classes of relative vulnerability based on the prior probability value and on inflections in a chart in which cumulative study area was plotted against posterior probability (Figure 67). Higher posterior probability values correspond with more vulnerable areas, as they essentially have a higher chance of containing vulnerability based on the definition of a training point. Conversely, lower posterior probability values correspond to less vulnerable areas as they essentially have a lower chance of containing vulnerability based on the definition of a training point.

As expected, the FAS response theme indicates that areas of highest vulnerability are associated with areas where the ICU is thinnest, in areas of dense karst features, and areas of higher soil hydraulic conductivity. Conversely, areas of lowest vulnerability are determined by thick ICU values, sparse karst feature distribution, and lower soil hydraulic conductivity values. Relative vulnerability classes are displayed in Figure 68.

Discussion

Prior to discussion of weights calculations during model execution, two components of a weights of evidence analysis are described to assist in interpretation of FAS model results: *Conditional Independence* and *Model Confidence*.

Conditional Independence

Conditional independence is a measure of the degree that evidential themes are affecting each other due to similarities between themes. Evidential themes are considered independent of each other if the conditional independence value is around 1.00, and conditional independence values within the range of 1.00 ± 0.15 generally indicate limited to no dependence among evidential themes (Bonham-Carter, 1994). Values significantly outside this range can inflate posterior probabilities resulting in unreliable response themes. Conditional independence was calculated at 0.85 for the FAS project indicating that evidential themes had little conditional dependence.

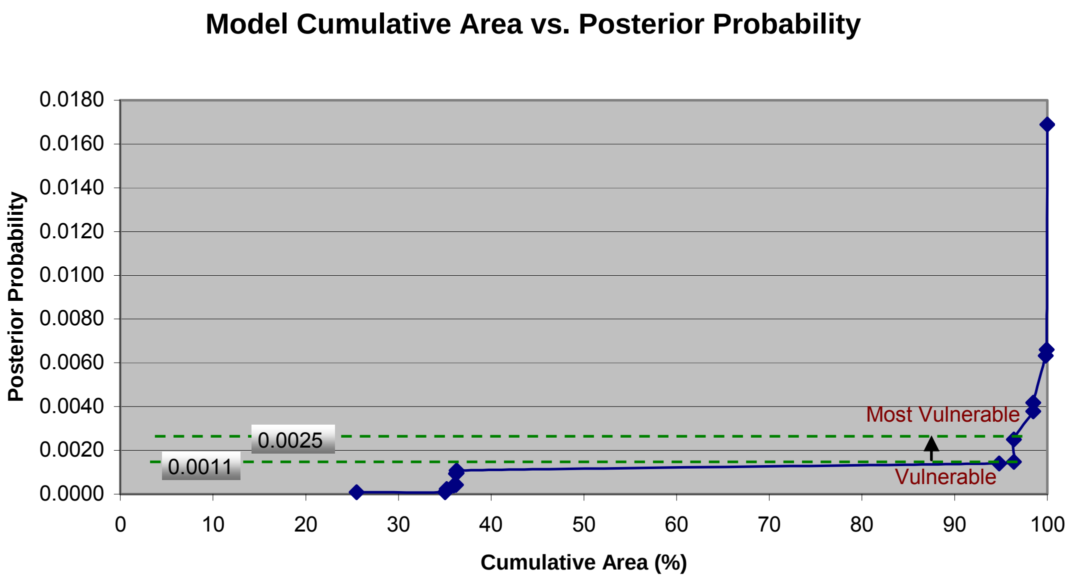

Figure 67. Vulnerability class breaks are defined by selecting where a significant increase in probability and area are observed.

Model Confidence

During model execution, confidence values are calculated both for each generalized evidential theme and for the final response theme. Confidence values approximately correspond to the statistical levels of significance listed in Table 3.

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 test value of 2.2259 corresponds to approximately 97.5% confidence – or level of significance – and was the minimum calculated confidence level for the FAS project evidential themes (see Table 10 below for evidential theme confidence values).

A confidence map is also calculated for a response theme by normalizing the theme's posterior probability by its total uncertainty (standard deviation). A confidence map can be generated based on these calculations. The confidence map for the FAS response theme is displayed in Figure 69. Areas with high posterior probability values typically correspond to higher confidence values and as a result have a higher level of certainty with respect to predicting aquifer vulnerability.

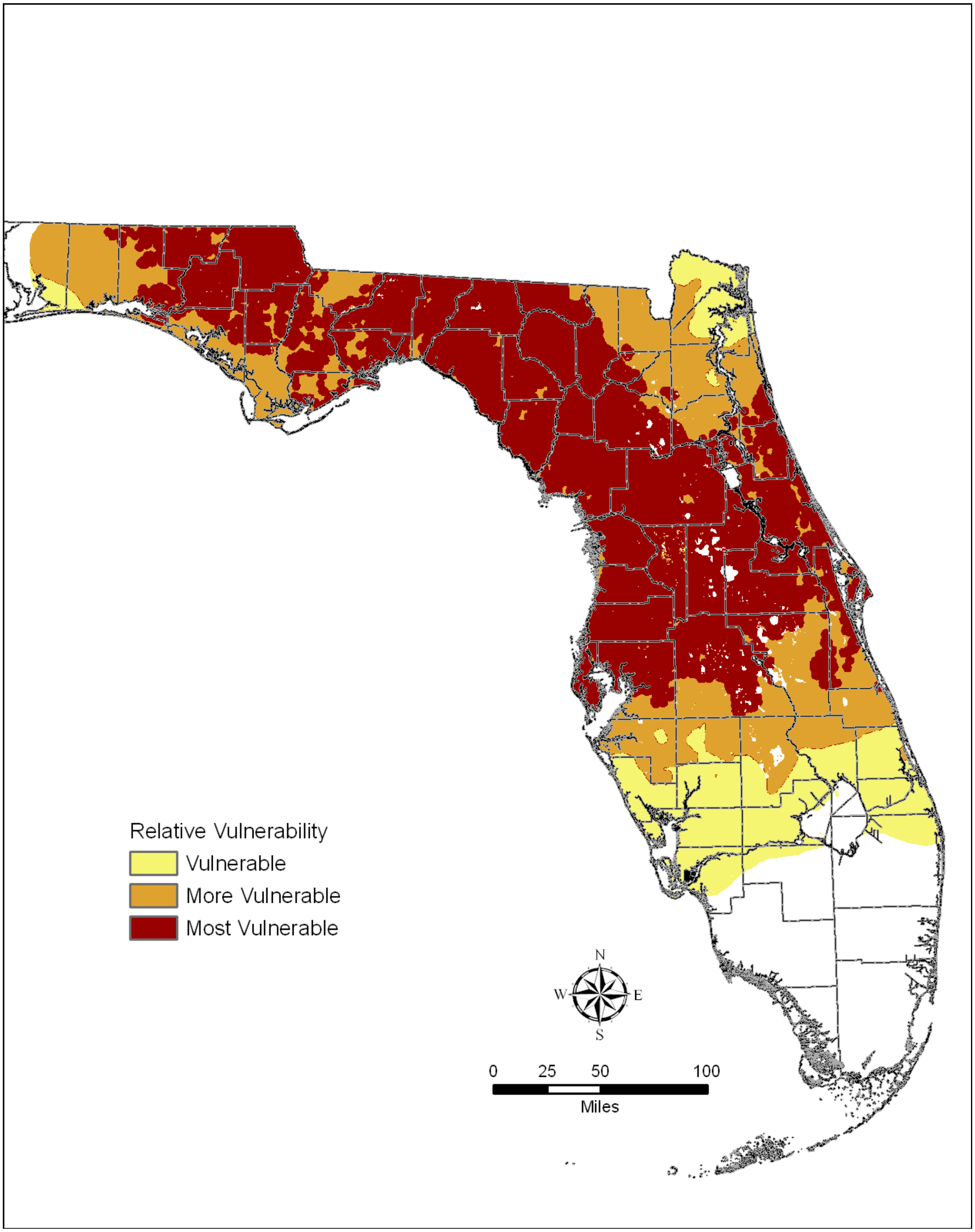

Figure 68. Relative vulnerability map for the Floridan Aquifer Vulnerability Assessment project. Classes of vulnerability are based on calculated probabilities of a unit area containing a training point, or a monitor well with water quality sample results indicative of vulnerability.

Weights Calculations

Table 10 displays evidential themes used in the FAS model, weights calculated for each theme, along with contrast and confidence values. Positive weights indicate areas where training points are likely to occur, while negative weights indicate 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. Confidence of the evidential theme is also calculated and is equal to the contrast divided by its standard deviation (a student T test). Confidence is a measure of significance due to uncertainties of the weights and missing data (Raines, 1999). A positive contrast that is significant, based on its confidence, suggests that a generalized evidential theme is a useful predictor.

Table 10. Weights of evidence 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	W3	Contrast	Confidence
Soil Hydraulic Conductivity	2.1478	0.5368	-0.1016	2.2193	2.2259
ICU Thickness	0.1753	-3.4569		3.6323	3.6227
Potential Karst Features	0.5012	-1.8606		2.3618	8.2205

Because positive weights (W1) values for soil hydraulic conductivity are stronger (have greater absolute values) than the negative weights (W3), it is a better predictor of where training points are likely to occur, whereas the ICU thickness and potential karst feature themes are better indicators of where training points are less likely to occur. Based on contrast values, the ICU thickness theme has the strongest (highest absolute value) weight and is the primary determinant in predicting areas of vulnerability in the FAS model.

Validation

The weights of evidence approach, because it relies on a set of training points, which by definition are known sites of vulnerability, is essentially self-validated. One hundred seventy nine of 192 points were predicted in zones of posterior probability greater than the prior probability (in other words, classified accurately). Further strengthening the results were the evaluation of a minimum confidence threshold for evidential themes, and generation of a confidence map of the response theme. In addition to these exercises, and in the style of previous aquifer vulnerability assessments (Cichon et al., 2005; Baker et al., 2005; Arthur et al., 2005), additional validation techniques were applied to the FAS model to further strengthen its defensibility, and, ultimately, its utility: (1) comparison of dissolved nitrogen values to posterior probability and evaluation of an associated trend; and (2) generation of a test response theme based on a subset of training points and comparison of points not used in subset to model results and (3) comparison of dissolved oxygen values with vulnerable zones of the response theme.

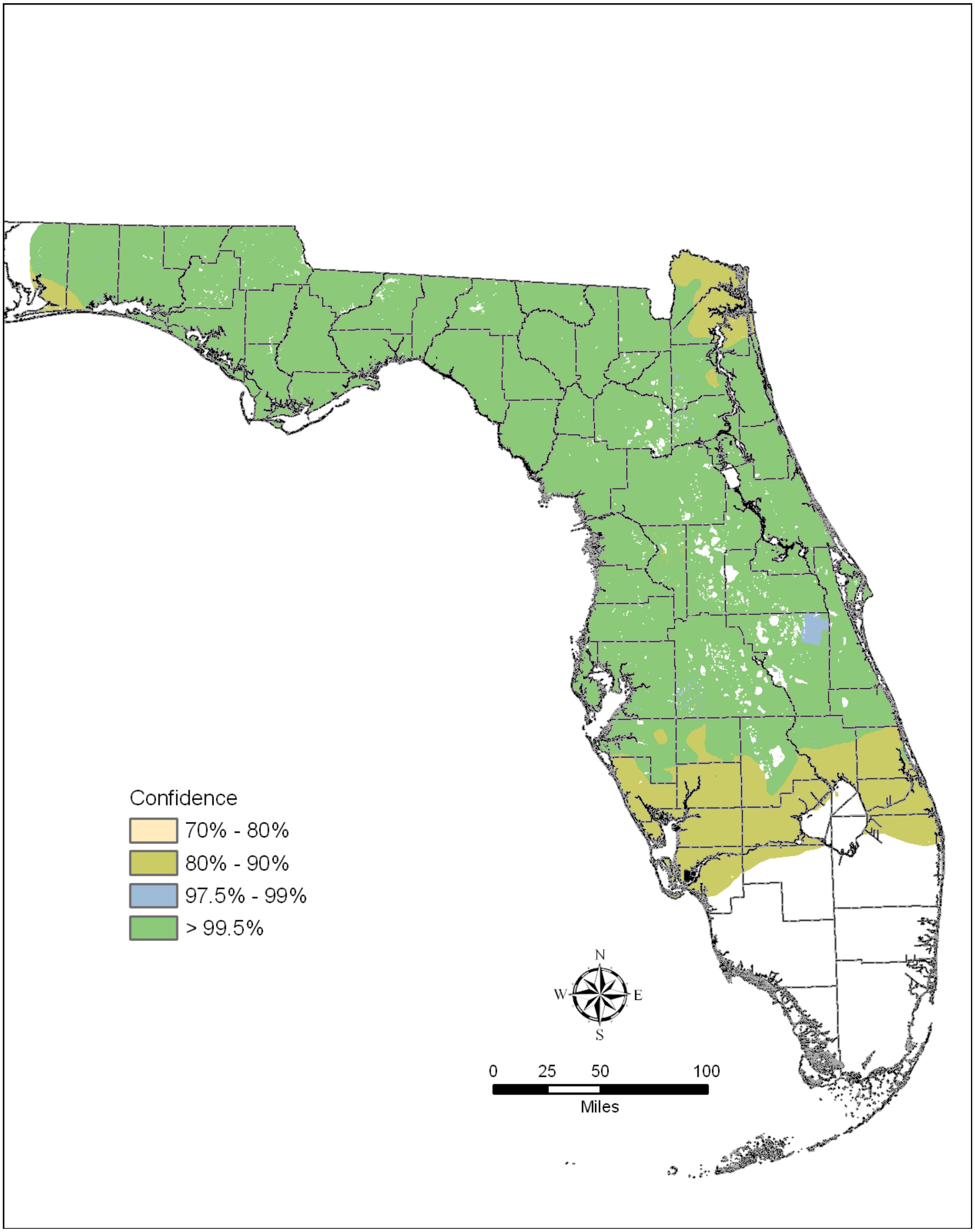

Figure 69. Confidence map for the Floridan Aquifer model calculated by dividing the posterior probability values by the total uncertainty for each class to give an estimate of how well specific areas of the model are predicted.

Dissolved Nitrogen Data vs. Posterior Probability

It was expected that comparison of posterior probability values to the dissolved nitrogen dataset from which the training point theme was extracted would reveal a proportional trend, in other words, as dissolved nitrogen values increase, so should posterior probability values. Dissolved nitrogen median concentrations were binned and averaged for each posterior probability value calculated in model output. The average values were plotted in a chart against posterior probability values (Figure 70) and a positive trend was observed.

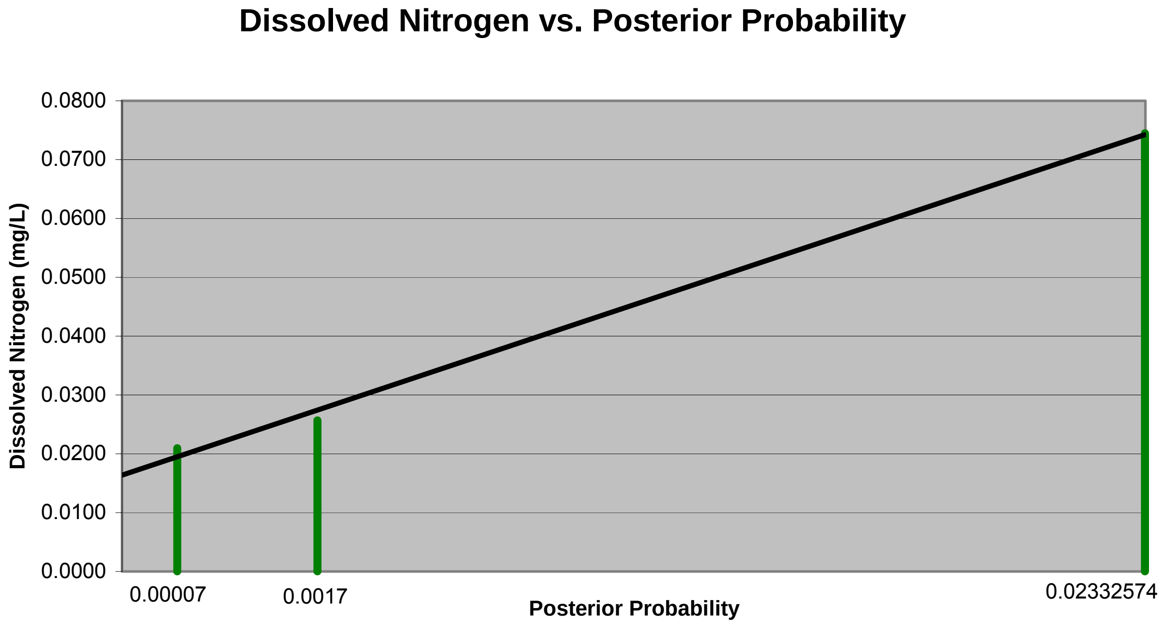

Figure 70. Dissolved nitrogen values (averaged per posterior probability class) versus probability values to reveal trend between increasing dissolved nitrogen concentrations and posterior probability.

An additional test involved applying a Pearson's correlation coefficient (r) test to all dissolved nitrogen values versus posterior probability values. This test revealed a value of 0.22 indicating more than a 95% degree of statistical significance between the response theme values and the dissolved nitrogen data.

Subset Response Theme

Another meaningful validation exercise similar to the exercise above is to use the existing training point dataset to develop two subsets: one to generate a test response theme, and one to validate output from this test response theme. Results from this exercise helped to further assess whether the dissolved nitrogen training points are reasonable predictors of aquifer vulnerability.

From the FAS training point theme, a subset of 75% (144 wells) were randomly selected and used to develop a test response theme; the remaining 25% (48 wells) of the training points were used as the validation dataset for the test response theme (Figure 71). This comparison revealed that 44 of the 48 test wells in the validation subset, or 92%, occur in areas of the test response theme with predicted probability values higher than the prior probability value. This further supports the conclusion that the FAS model response theme is a reasonable estimator of vulnerability.

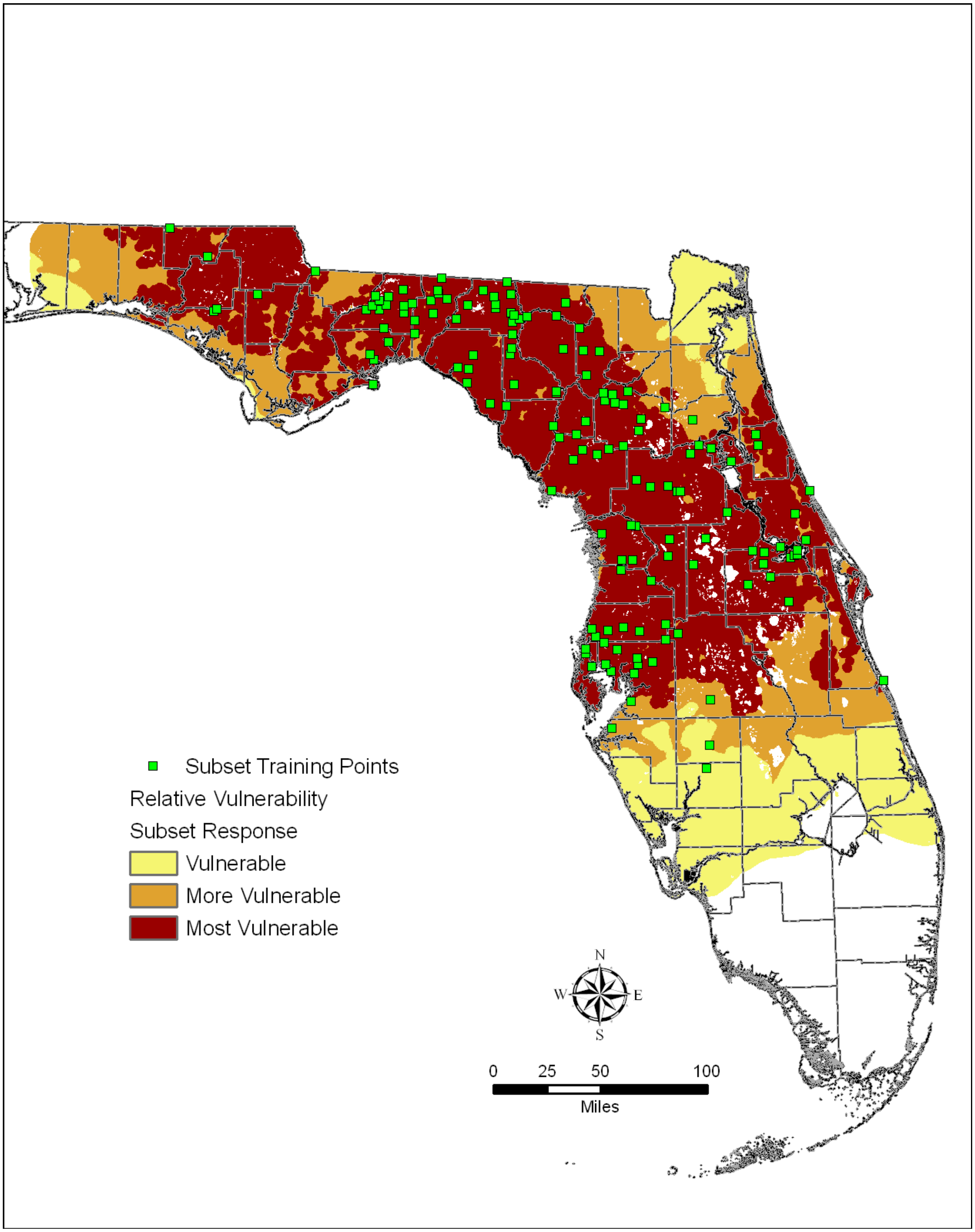

Figure 71. Subset response training points plotted in the dissolved nitrogen response theme.

Dissolved Oxygen Data

Perhaps the most rigorous validation exercise used to evaluate quality of model-generated output is to compare predicted model values with independent test values not used in the model. For the FAS model, this was accomplished by comparison of a separate well dataset based on dissolved oxygen. As mentioned above in *Training Point Theme*, dissolved oxygen is indicative of aquifer vulnerability, but is independent of dissolved nitrogen. Applying the methodology described in *Training Point Theme* to dissolved oxygen data (obtained from the same data sources as dissolved nitrogen data) resulted in a dissolved oxygen dataset of 245 wells each indicative of aquifer vulnerability.

These 245 points were evaluated against posterior probability values of the FAS model output. Extracting the value of posterior probability from the dissolved nitrogen response theme for the location of each of the 245 dissolved oxygen training points revealed that 214 of the 245 dissolved oxygen training points occur in areas of the dissolved nitrogen model with predicted probability values higher than the prior probability value. In other words, 87.3% of the dissolved oxygen wells were located in areas predicted to have a greater than chance probability of containing a training point. Based on this test, the dissolved nitrogen model is not only a good predictor of vulnerability as defined by the training point theme, it is also a good predictor of the location of an independent parameter also representing aquifer vulnerability. Figure 72 displays dissolved oxygen data points plotted on the dissolved nitrogen response theme.

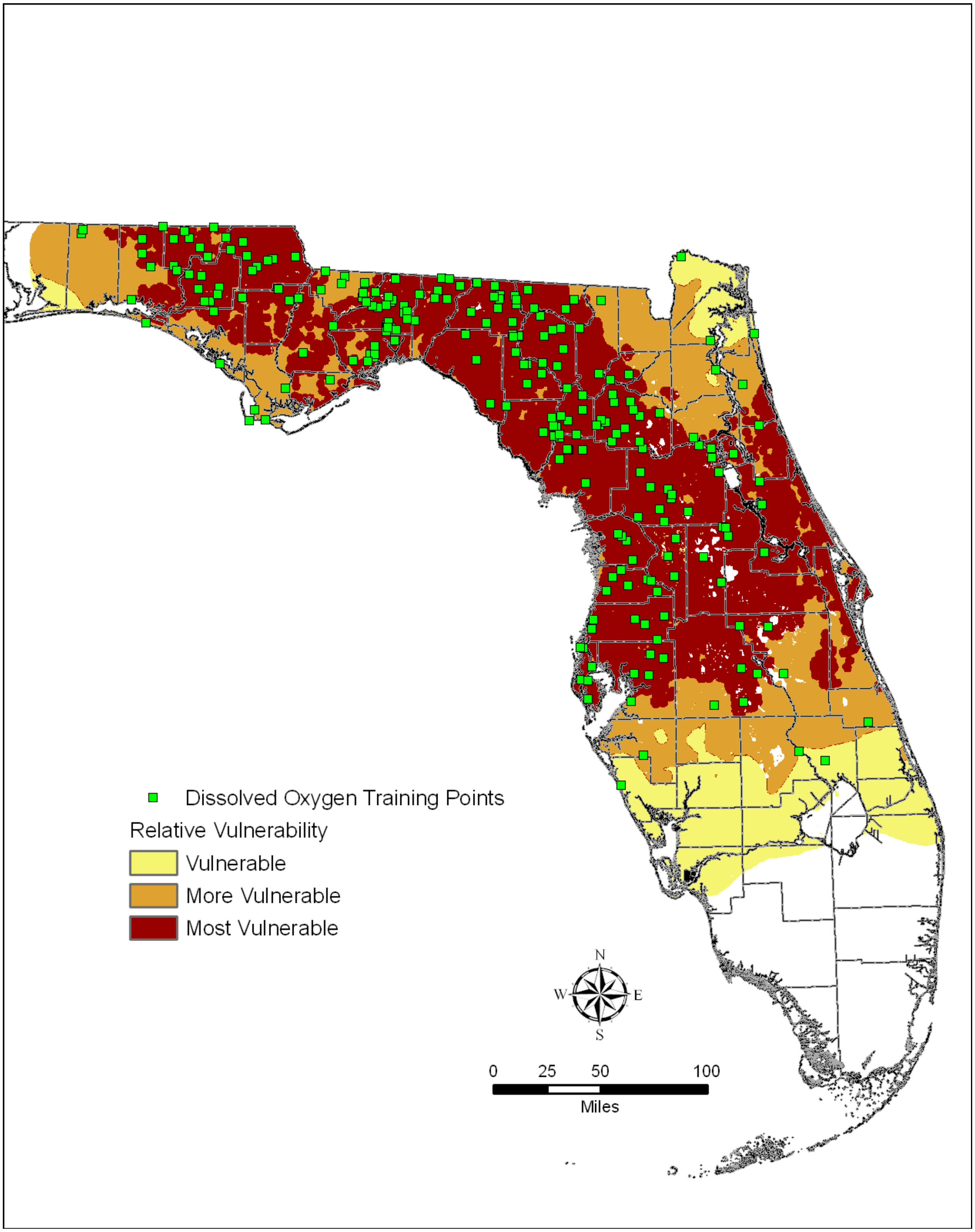

Figure 72. Dissolved oxygen validation training points plotted in the dissolved nitrogen response theme. Comparison reveals 214 of 245 wells (87.3%) of the independent water quality dataset are located in areas with predicted probability values higher than the prior probability.

Model Implementation and Limitations

When implementing the project results, it is essential to remember that all aquifer systems in Florida, to some degree, are vulnerable to contamination; an invulnerable aquifer does not exist. Further, model results are based solely on features of the natural system that have significant association with the location of training points and thereby aquifer vulnerability. The project results provide a probability map that identifies zones of relative vulnerability in the study area based on these input data; as a result the model output is an estimation of intrinsic or natural aquifer vulnerability. Additionally, model results do not account for human activities at land surface, take into consideration contaminant types, or estimate groundwater flow paths or fate/transport of chemical constituents.

Confidence Map

As mentioned above, a confidence map of the model's posterior probability values can be calculated by dividing the posterior probability by its total uncertainty. This essentially applies an informal student T-test (as in Table 3) to the posterior probability values. The higher the confidence values, the greater the certainty is with regard to the posterior probability. This map essentially indicates the degree of confidence to which the posterior probabilities are meaningful and should be referenced when interpreting and implementing the model results. In other words, the confidence map should be used to help guide implementation of the vulnerability map as it reveals the confidence level associated with each vulnerability class (Mihasky and Moyer, 2004).

Recommendations on Scale of Use

Use of highly detailed evidential theme data as model input results in highly resolute model output as can be seen in the model response theme. These resolute features are reflections of real data used as input; however, the final maps should not be applied to very large scales such as to compare adjacent small parcels.

Model output is, in a sense, as accurate as the most detailed input layer, and as inaccurate as the least detailed layer. Every raster cell of the model output coverage has significance per the model input as discussed above. However, it is important to note that aquifer vulnerability assessments are predictive models and no assumptions are made that all input layers are accurate, precise or complete at a single-raster cell scale. As mentioned above, the confidence map, because it is an indicator of the meaningfulness of the vulnerability classes, should be used to help guide implementation of the vulnerability map. For example, in the FAS confidence map (Figure 69), land-use decisions might be more defensible with the higher vulnerability class since these areas are usually associated with the highest confidence values.

Ultimately, accuracy of the maps does not allow for evaluation of aquifer vulnerability at a specific parcel or site location. It is the responsibility of the end users of the model output to determine specific and appropriate applications of these maps. In no instance should use of aquifer vulnerability assessment results substitute for a detailed, site-specific hydrogeological analysis (see FAVA version 1.0 for additional recommendations).

CONCLUSION

As demands for fresh groundwater increase resulting from continued population growth, identification of zones of relative vulnerability becomes an increasingly important tool for implementation of a successful groundwater protection and management program. The results of the project provide a science-based, water-resource management tool allowing for a pro-active approach to protection of the aquifer system, and, as a result, have the potential to increase the value of protection efforts. Model results will enable improved decisions to be made about aquifer vulnerability based on the input selected, including focused protection of sensitive areas such as springsheds and groundwater recharge areas.

The results of the vulnerability model are useful for development and implementation of groundwater protection measures; however, the vulnerability output map included in this report should not be viewed as a static evaluation of the vulnerability of the aquifer system. Because the assessments are based on snapshots of best-available data, the results are static representations; however, a benefit of this methodology is the flexibility to easily update the response themes as more refined or new data becomes available. In other words, as the scientific body of knowledge grows regarding hydrogeologic systems, this methodology allows the ongoing incorporation and update of datasets to modernize vulnerability assessments thereby enabling end users to better meet their objectives of protecting these sensitive resources. The weights of evidence modeling approach to aquifer vulnerability is a highly adaptable and useful tool for implementing ongoing protection of Florida's vulnerable groundwater resources.

QUALIFICATIONS

Disclaimer

Maps generated as part of this project were developed by Advanced GeoSpatial Inc. (AGI) to provide FDEP with a ground-water resource management and protection tool to carry out responsibilities related to natural resource management and protection regarding Florida's aquifer systems. Although efforts were made to ensure information in these maps is accurate and useful, neither, the Florida Department of Environmental Protection nor AGI assumes responsibility for errors in the information and does not guarantee that the data is free from errors or inaccuracies. Similarly the Florida Department of Environmental Protection and AGI assume no responsibility for consequences of inappropriate uses or interpretations of the data on these maps. Accordingly, these maps are distributed on an "as is" basis and the user assumes all risk as to their quality, results obtained from their use, and performance of the data. the Florida Department of Environmental Protection and AGI further make no warranties, either expressed or implied as to any other matter whatsoever, including, without limitation, the condition of the product, or its suitability for any particular purpose. The burden for determining suitability for use lies entirely with the end user. In no event shall the Florida Department of Environmental Protection and AGI, or their respective employees have any liability whatsoever for payment of any consequential, incidental, indirect, special, or tort damages of any kind, including, but not limited to, any loss of profits arising out of use of or reliance on the project results. The Florida Department of Environmental Protection and AGI bear no responsibility to inform users of any changes made to this data. Anyone using this data is advised that resolution implied by the data may far exceed actual accuracy and precision.

Because this data was developed and collected with FDEP funding, no proprietary rights may be attached to it in whole or in part, nor may it be sold to FDEP or any other government agency as part of any procurement of products or services.

Ownership of Documents and Other Materials

This project represents significant effort and resources on both the part of FDEP and AGI to establish peer-reviewed, credible and defensible aquifer vulnerability model results. Unauthorized changes to results can have far reaching implications including confusing end users with multiple model results, and discrediting validity and defensibility of original results.

A main goal of the project is to maintain the integrity and defensibility of the final model output by preserving its data-driven characteristics. Modification or alteration of the model or its output can only be executed by trained professionals experienced with the project and with weights of evidence.

To protect both FDEP and AGI from potential misuse or unauthorized modification of the project results, all input and output results of aquifer vulnerability assessments, and the aquifer vulnerability assessment models, along with project documents, reports, drawings, estimates, programs, manuals, specifications, and all goods or products, including intellectual property and rights thereto, created under this project or developed in connection with this project will be and will jointly remain the property of FDEP and AGI.

For additional information regarding this project, please refer to the associated 24” x 36” interpretive poster of the same title as this report, and/or the GIS project data and associated metadata. At the time of this report, these GIS files may be accessed using ArcMap™, version 9.x.

WEIGHTS OF EVIDENCE GLOSSARY

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 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.

Data Driven – Refers to a modeling process in which decisions made in regard to modeling input are driven by empirical data. Examples include the weights of evidence approach or logistic regression approach as in the FDEP's FAVA project (Arthur et al., 2005).

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

Expert Driven – A scientific approach which relies on the expertise and knowledge of one or more specialists to drive decisions in a modeling project. An example is the EPA's index ranking method known as "DRASTIC".

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 probability to contamination (i.e., this area is more vulnerable than that area). The response theme is the relative vulnerability map.

Spatial Data – Information about the location and shape of, and relationships among, geographic features, usually stored as coordinates and topology.

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. A weight is 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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