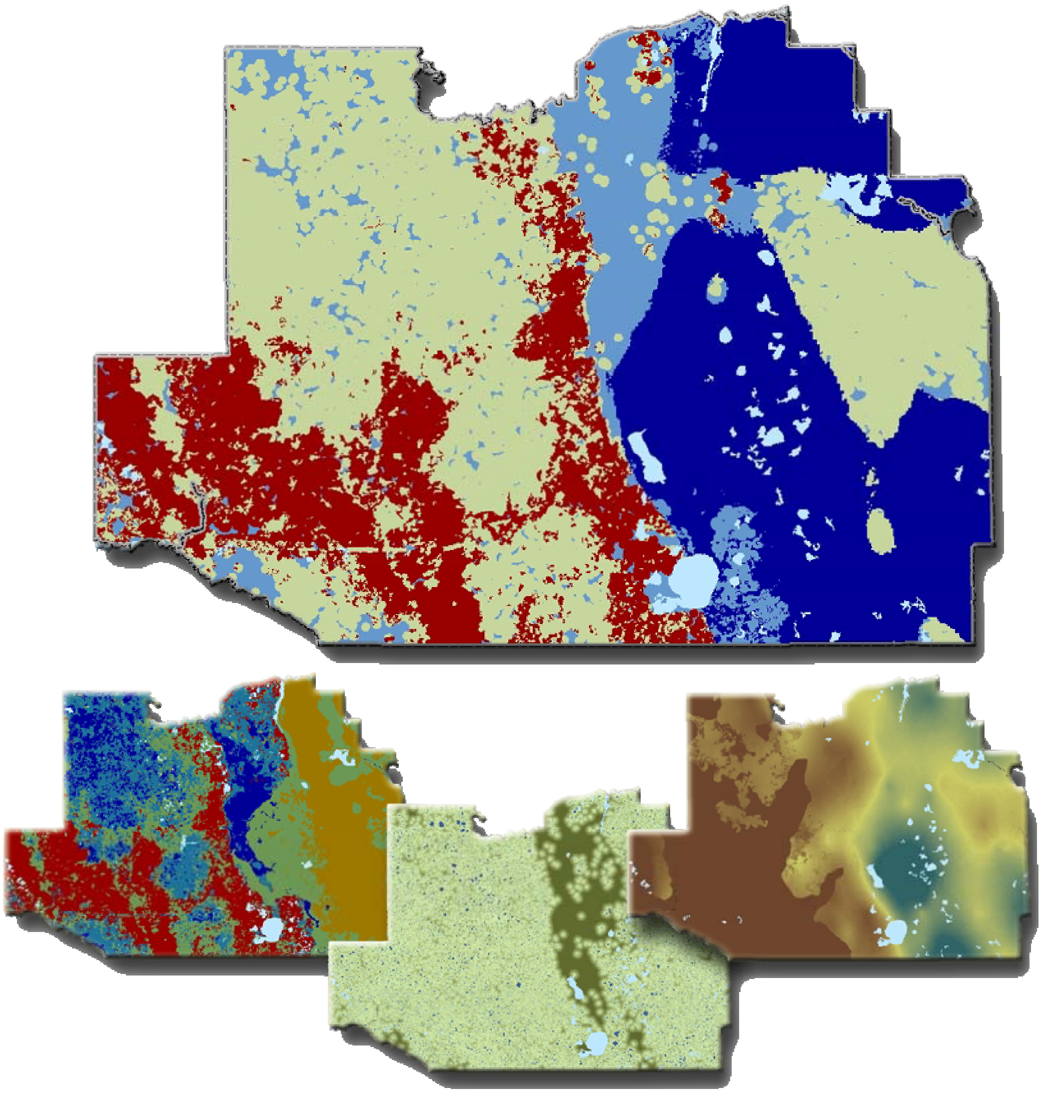
THE MARION COUNTY AQUIFER VULNERABILITY ASSESSMENT

A Ground-Water Protection and Management Tool



Prepared for the Marion County Board of County Commissioners by Advanced GeoSpatial Inc. in fulfillment of SS06-01

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THE MARION COUNTY AQUIFER VULNERABILITY ASSESSMENT

Prepared For:
The Marion County Board of County Commissioners
In fulfillment of Marion County Project No. SS06-01

Prepared by

Alan E. Baker, P.G. 2324, Alex R. Wood, and James R. Cichon of
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March 2007

PROFESSIONAL GEOLOGIST CERTIFICATION

I, Alan E. Baker, P.G., no. 2324, have read and agree with the findings in this report titled THE MARION COUNTY AQUIFER VULNERABILITY ASSESSMENT 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

March 15, 2007
Date

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THE MARION COUNTY AQUIFER VULNERABILITY ASSESSMENT

Alan E. Baker, P.G. 2324, Alex R. Wood, and James R. Cichon

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INTRODUCTION

The Floridan Aquifer System is the most important and prolific source of fresh water in Marion County. Ground water use from the Floridan Aquifer System in Marion County is an estimated 56 million gallons of water per day for public supply, agriculture, domestic (self-supply wells), and other uses (SJRWMD, 2006; SWFWMD, 2006). Population of Marion County increased from approximately 194,833 to 258,916 residents between 1990 and 2000, and the 2005 population is estimated at 303,442 (U.S. Census Bureau, 2007). As a result, demands on the Floridan Aquifer System underlying Marion County are increasing on a significant scale every year as each additional resident requires an estimated 110 gallons of water per day (SWFWMD, 2006). In addition, numerous fresh water springs and spring groups arise from the Floridan Aquifer System in Marion County and some or all of their springshed boundaries are contained within the county. These valuable resources include Silver, Rainbow, Silver Glen, Indian Creek, Juniper and many others (Scott et al., 2004).

Identifying areas of Marion County where the Floridan Aquifer System is more vulnerable to contamination from activities at land surface is a critical component of a comprehensive ground-water management program. Protection of the Floridan Aquifer System is an important measure to take in helping ensure viable, fresh water is available from the Floridan Aquifer System for continued future use in the Marion County study area. Aquifer vulnerability modeling allows for a pro-active approach to protection of aquifer systems, which can save significant time and increase the value of protection efforts. Successful implementation of an aquifer vulnerability assessment benefits:

- Wellhead protection
- Source-water protection
- Land-use planning
- Environmental protection
- Sensitive land acquisition

Project Objective

Marion County contracted with Advanced GeoSpatial Inc. (AGI) in September of 2006 to develop the Marion County Aquifer Vulnerability Assessment (MCAVA) model characterizing the natural (or intrinsic) vulnerability of the Floridan Aquifer System (FAS). The primary purpose of this project is to provide Marion County with a scientifically-defensible, water-resource management tool that can be used to help minimize adverse impacts on ground-water quality. The project intent is to allow Marion County to make improved decisions about aquifer vulnerability with regard to model input selected, including focused protection of sensitive areas such as springsheds and ground-water recharge areas.

Derivative Products: Protection Zones

Relative vulnerability zones defined in this project may be applied to develop derivative maps, such as a protection-zone map, for use in planning or regulation. Ideally, data layers not included as input in the aquifer vulnerability model would be considered to help in defining such protection zones and may include ground-water flow modeling, stream-sink features, induced drawdown areas from large well fields, and distribution of drainage wells. These layers, while important to aquifer vulnerability, do not form usable input into this aquifer vulnerability assessment project.

Aquifer Vulnerability

All ground water 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 Florida Department of Environmental Protection (FDEP) in the Florida Aquifer Vulnerability Assessment (FAVA) report: 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 coverages representing the natural hydrogeologic system (Arthur et al., 2005).

APPROACH

AGI is currently the *single source* provider of aquifer vulnerability assessment analysis using *weights of evidence* as defined by both FDEP and Marion County. The weights of evidence methodology was employed in FDEP's FAVA project (for detailed information please refer to Arthur et al., 2005). Use of this method involves combination of diverse spatial data which are used to describe and analyze interactions and generate predictive models (Raines et al., 2000). The following sections provide brief overview of this methodology; project-specific and more detailed information is presented in *Project Results*.

Weights of Evidence

Weights of evidence was used in the MCAVA project to develop an aquifer vulnerability assessment model of the FAS. The modeling technique is based in a geographic information system (GIS) and is executed using Arc Spatial Data Modeler (Arc-SDM), an extension to ESRI's ArcGIS software package. For more information on weights of evidence please refer to Arthur et al. (2005), Kemp et al. (2001), Raines et al. (2000), and Bonham-Carter (1994). Primary benefits of applying weights of evidence technique to the MCAVA project is that it is a data-driven method, rather than expert-driven, and model generation is dependent upon a training dataset resulting in self-validated model output.

Data Acquisition and Development

The initial phase of the MCAVA project comprised acquisition, development and attribution of various GIS data coverages 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 Recharge
- Confinement or Overburden Thickness
- Karst Features/Topographic Depressions
- Water-Quality Data
- Soil Hydraulic Conductivity

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 are expressed as probability maps.

Study Area and Training Points

The initial step in implementing the vulnerability modeling phase is the identification and delineation of a study area extent. Marion County political boundary served as the model study area. Training points are locations of known occurrences. In an aquifer vulnerability assessment, ground-water wells with water quality indicative of high recharge are selected as known occurrences. Dissolved oxygen or dissolved nitrogen analytical concentrations 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 it is indicative of aquifer vulnerability.

Evidential Themes (Model Input)

An evidential theme is defined as a set of continuous spatial data that is associated with the location of the training points and is analogous to the 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 presence or absence 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 theme provided. The response theme generated in this project is a probability map displayed in classes of relative vulnerability for the FAS in Marion County.

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 the results. Sensitivity analysis was applied during development of each evidential theme and validation exercises were applied to model results to assess strength and confidence.

MCAVA Technical Advisory Committee

An advisory committee was formed to provide technical review and support during the development of the MCAVA project and consisted of professionals in the water resource, planning, engineering, hydrogeology and other environmental fields. Members participated in three workshop meetings, provided technical review of model progress and final results and report. Members and their organization are listed in Table 1 below.

Table 1. MCAVA Technical Advisory Committee members.

Name	Organization
Jonathan Arthur, Ph.D., P.G.	Florida Geological Survey of FDEP
Jeff Davis, P.G.	St John’s River Water Management District
David Dewitt, P.G.	Southwest Florida Water Management District
William Wise, Ph.D., P.E.	University of Florida
Gail Mowry, P.E.	Marion County Engineering
Troy Kuphal	Marion County Planning
Tracy Straub, P.E.	Marion County Transportation
Evan Shane Williams, Ph.D., P.E.	Marion County Engineering
Alan Toms	Marion County Engineering
Sam Marstolf	Marion County Planning
Melissa Northey	Marion County Information Systems
Robin Hallbourg	Alachua County Environmental Protection

PROJECT RESULTS

Study Area

The political boundary of Marion County was used as the MCAVA model study area extent (shown in Figure 1 along with training points as described below). Because of the sizes of some polygons representing soil data and because LIDAR data was used to develop model input, a grid cell size of 100 ft^2 was selected for evidential theme development. This grid cell size does not reflect appropriate resolution of final model output.

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 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 MCAVA analysis, training points are ground-water wells tapping the FAS with water quality data indicative of high recharge. Dissolved oxygen analytical values served as training point data for the MCAVA model, and dissolved nitrogen concentrations were used for validation of model output. Natural 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 the ground-water system, they are good indicators of aquifer vulnerability (Arthur et al., 2007a, in press).

Water quality data sources explored include the FDEP background water quality network, FDEP STATUS network, St. John's River Water Management District (SJRWMD), Southwest Florida Water Management District (SWFWMD), and U.S. Geological Survey (Phelps, 2004). From these data sources, 72 wells measured for dissolved oxygen were identified as being potential candidates for training points. Statistical analyses revealed that there were no wells considered statistical outliers. The upper 25th percentile of this set – or all wells with median dissolved oxygen values greater than 5.51 milligrams per liter (mg/L) – served as the training point theme and consists of 18 wells. Figure 2 displays the distribution of water wells used to derive training points and the resulting training point theme across the study area.

In the weights of evidence module, training points are used calculate prior probability, weights for each evidential theme, and posterior probability of the response theme (see Glossary for more information). 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 MCAVA model is 0.00428. Posterior probability values generated during response theme development are interpreted relative to the value of prior probability with higher values generally indicating higher probability of containing a training point.

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. Factors considered for the MCAVA project include karst features, thickness of aquifer confinement, aquifer recharge, and soil hydraulic conductivity. In an effort to take advantage of recently-collected data and the most resolute data available, such as LIDAR and recently constructed wells, new data coverages not previously available were developed representing both aquifer confinement and karst features. Further, datasets

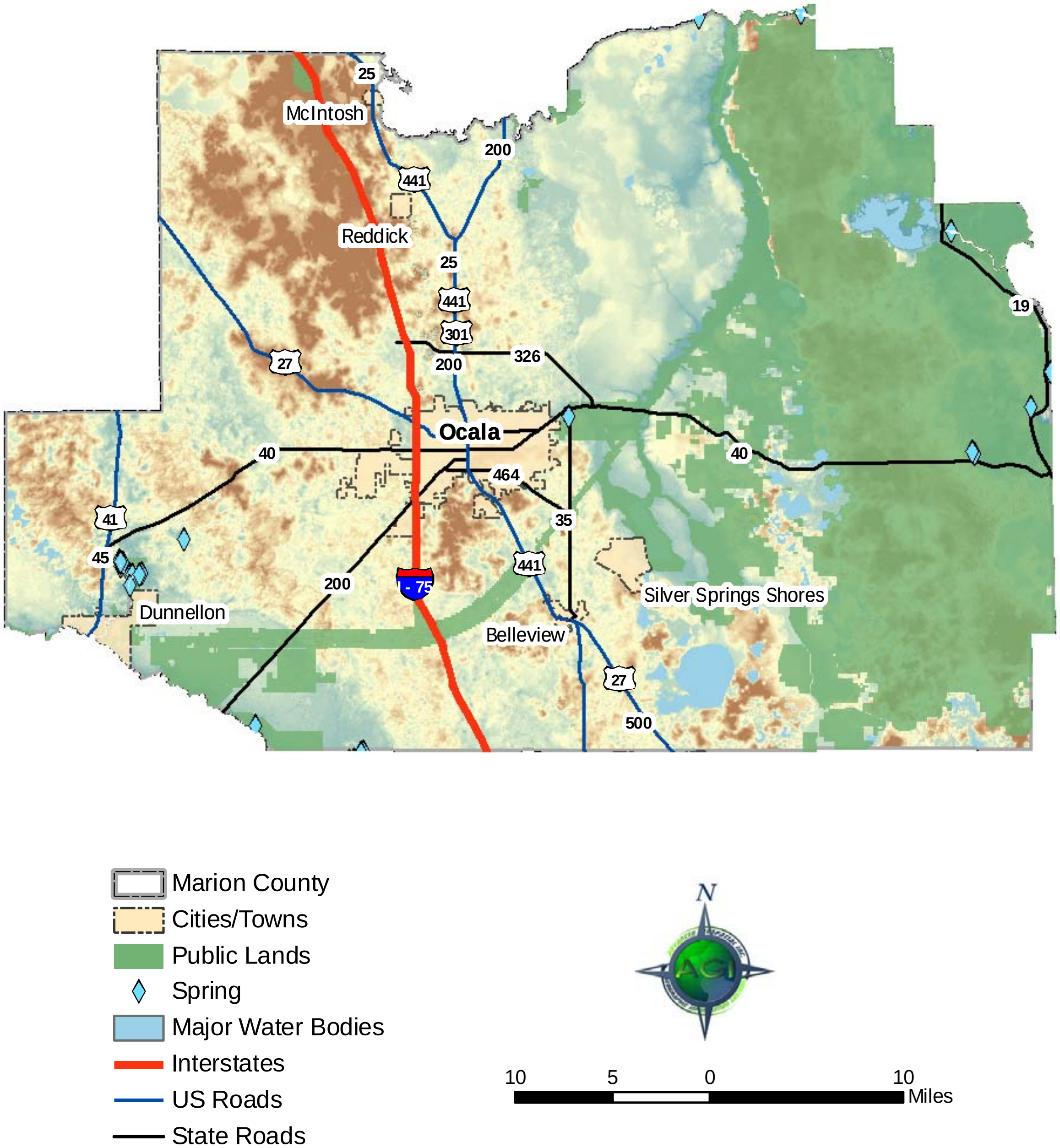

Figure 1. Marion County Aquifer Vulnerability Assessment project study area corresponds to the County's political boundary.

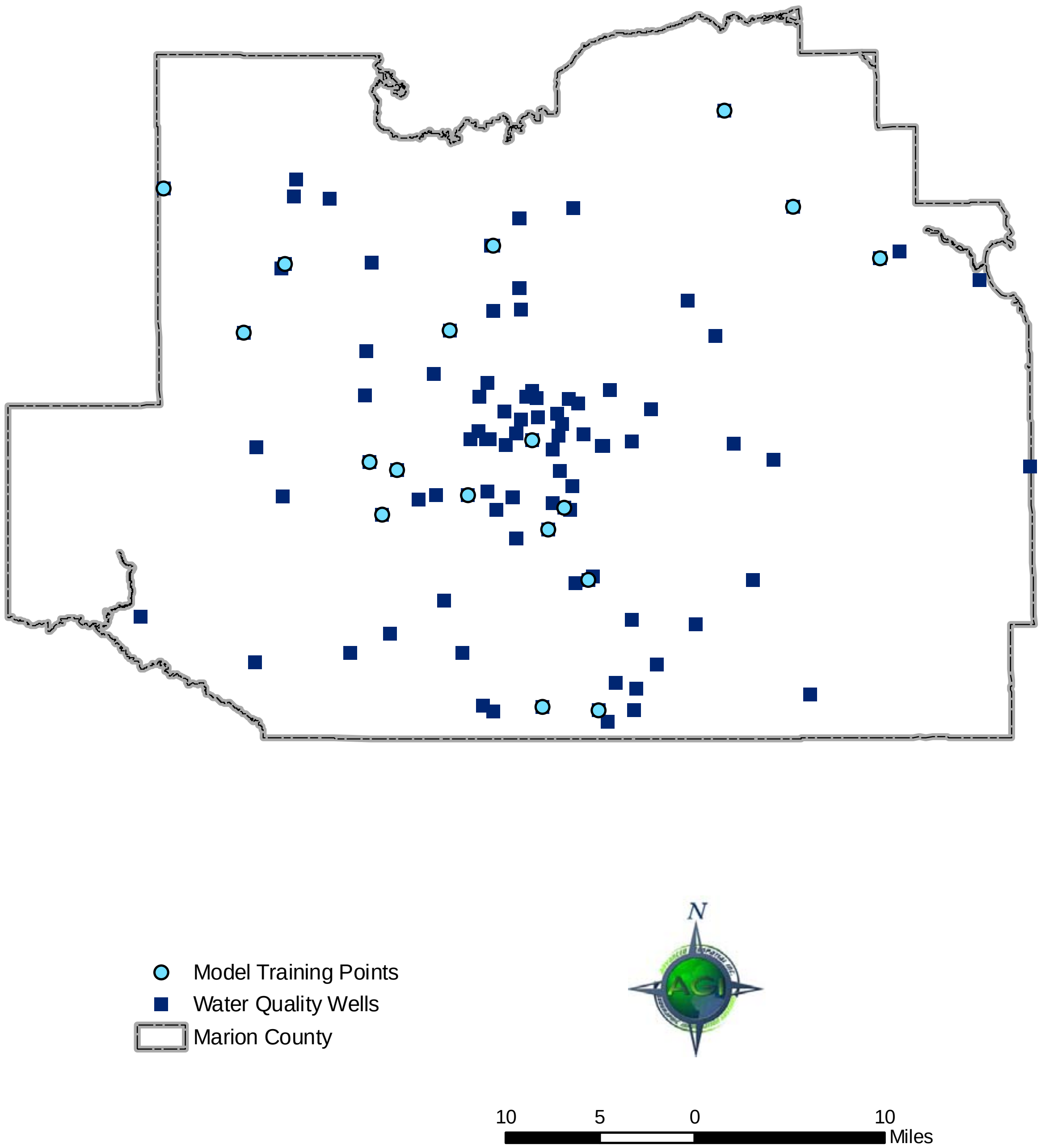

Figure 2. Location of all wells measured for dissolved oxygen in dark blue boxes, and locations of wells with median dissolved oxygen values higher than 5.51 mg/L which comprise training point dataset.

representing soils and recharge were adapted from existing data for use in the MCAVA model and now represent previously unavailable countywide datasets.

Soil Hydraulic Conductivity Theme

The rate that water moves through soil is a critical component of any aquifer vulnerability analysis, as soil is an aquifer system's first line of defense against potential contamination (Arthur et al., 2005). According to the National Soil Survey Handbook (U.S. Department of Agriculture, 2003) saturated hydraulic conductivity is defined as "the amount of water that would move vertically through a unit area of saturated soil in unit time under unit hydraulic gradient."

A countywide dataset representing soil hydraulic conductivity was developed to represent this hydrogeologic parameter in the MCAVA model. In 2006, soils data of the area west of the Ocklawaha was redesigned by the NRCS in Marion County, whereas areas east of the River were completed in 1979. There is, as a result, a difference in dataset resolution for the county coverage developed. The soil surveys report multiple conductivity values for any given soil column underlying a particular soil polygon. To generate a continuous coverage of soil hydraulic conductivity across the study area site, each column's weighted average was summed into a single value. Figure 3 displays the soil hydraulic conductivity coverage across the study area.

Intermediate Confining Unit / Overburden Thickness Themes

Aquifer confinement – either in the form of overburden overlying the FAS, or the Intermediate Confining Unit (ICU) – is another critical layer in determining aquifer vulnerability. The rate water moves through the confining units overlying an aquifer, or conductivity, is an important measure of degree of confinement. However, reliable data representing conductivity is limited across the study area, while detailed information regarding thickness of confinement is generally more readily available in borehole and gamma logs from wells. Where aquifer confinement is thick and the FAS is deeply buried, aquifer vulnerability is lower, whereas in areas of thin to absent confinement, the vulnerability of the FAS is generally higher.

As part of the MCAVA project, AGI developed models of both overburden overlying the FAS, and the ICU using a dataset of borehole records combined with well gamma logs that contain descriptions of subsurface materials. Sources of these datasets included the Florida Geological Survey, SJRWMD, and SWFWMD. Data points were analyzed to identify potential statistical outliers and erroneous data points. Because the ICU is discontinuous across the study area, it was necessary to estimate the areas where ICU was absent. Data points were used in conjunction with the State of Florida geologic map (Scott et al., 2001), Marion County LIDAR data, and extents used in previous works (Arthur et al., 2005; Arthur et al., 2007b, in review) to estimate the areal extent of the ICU. The well dataset and areal extent of ICU are identified in Figure 4.

The point dataset was then used to predict two hydrostratigraphic surfaces: top of FAS (Figure 5) and top of ICU (Figure 6). These were used in conjunction with LIDAR data to calculate thickness of ICU and thickness of overburden. Ordinary kriging was selected as the surface prediction method because of its flexibility and data exploration options. A sensitivity analysis was completed to determine the best modeling protocol for creating surfaces. These surfaces were combined with LIDAR data to resolve areas where the prediction technique estimated values above land surface. Resulting surfaces were used to calculate thickness of the ICU (Figure 7) and thickness of material overlying the FAS (Figure 8). These two layers were tested for input in the model as described in *Sensitivity Analysis*.

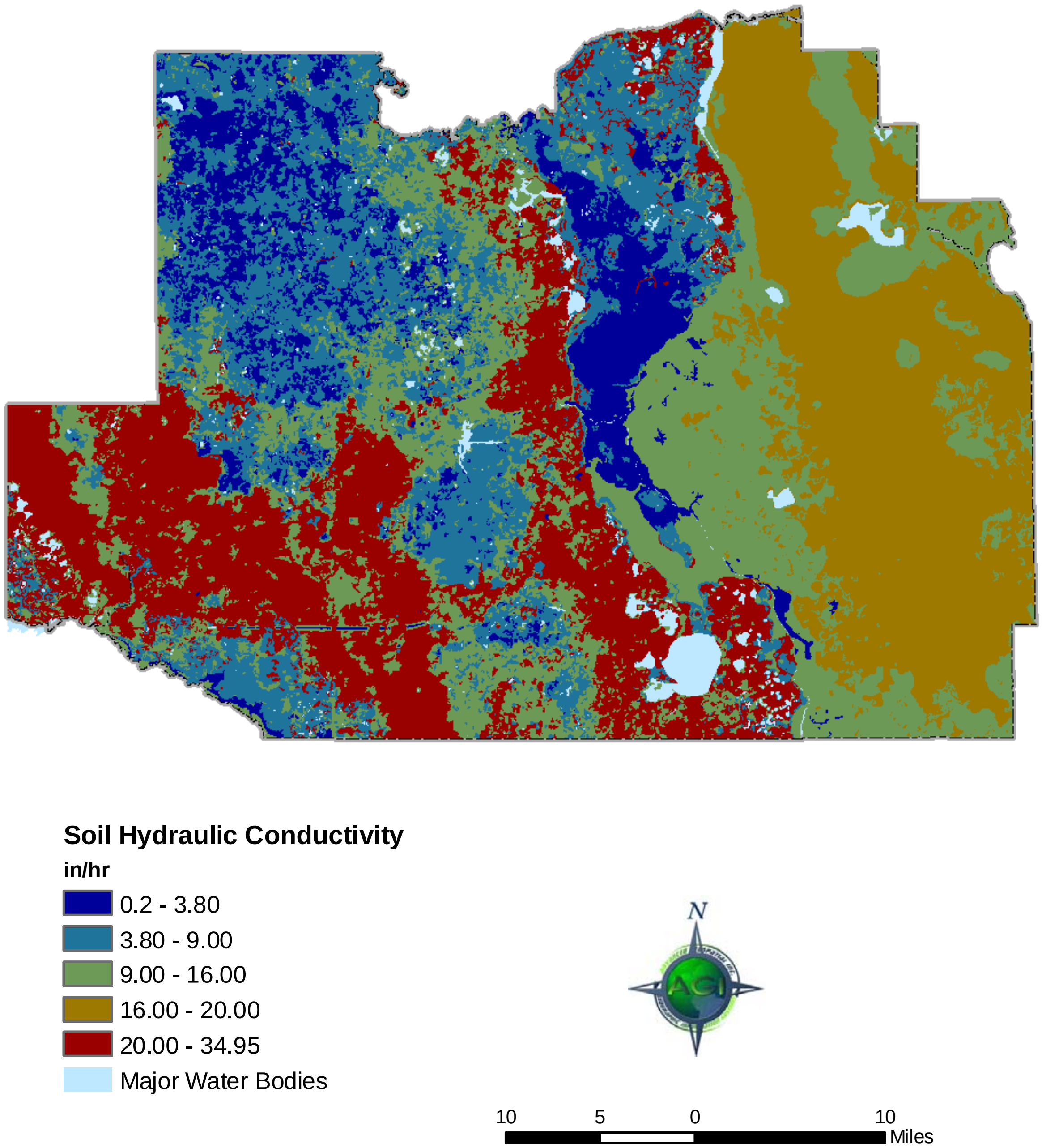

Figure 3. Distribution of soil hydraulic conductivity values across the MCAVA study area.

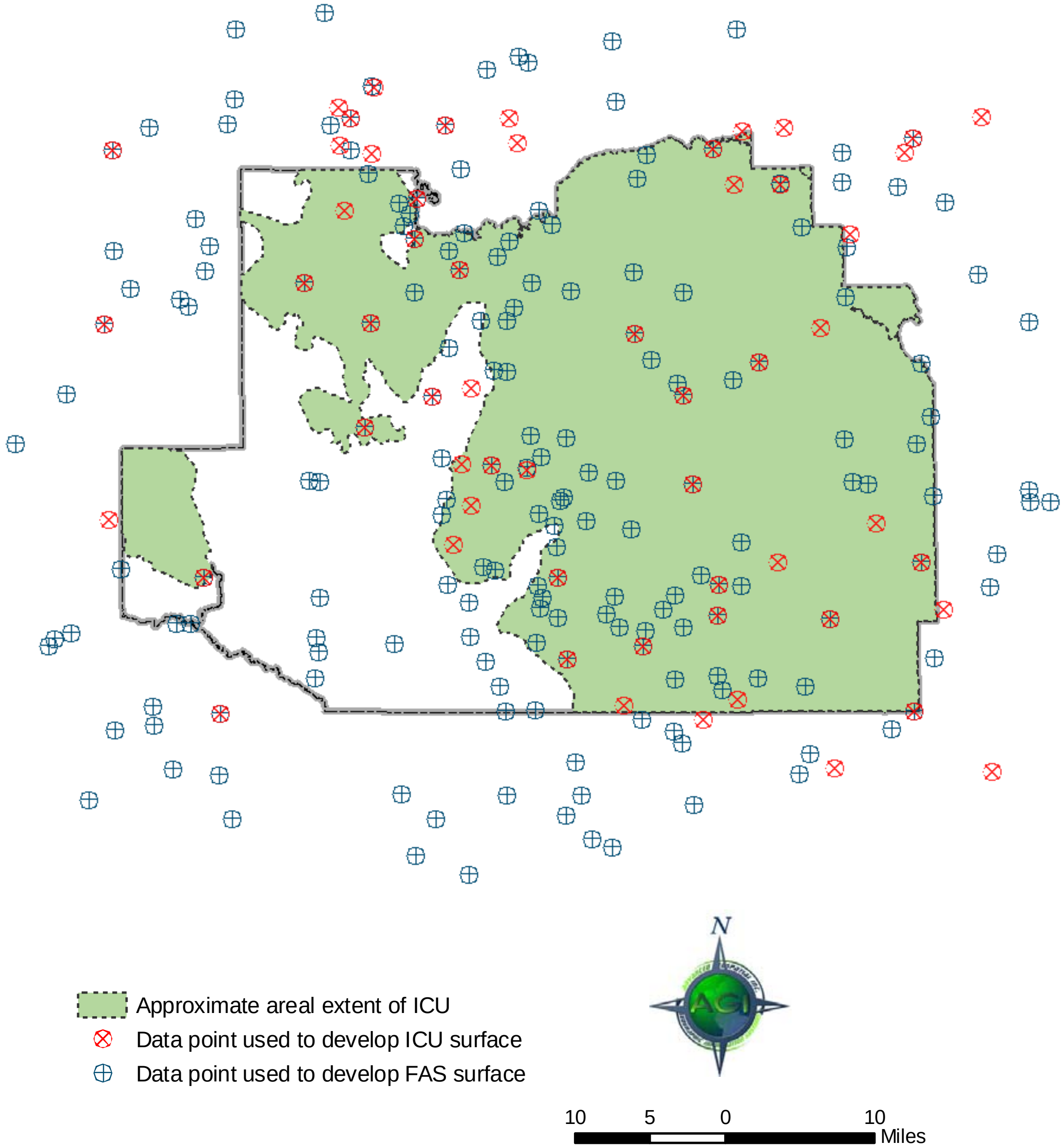

Figure 4. Data points used to develop surfaces representing the FAS and ICU surfaces. Several data points contained information about both surfaces. Areal extent of ICU is based on extent of Hawthorn Group deposits.

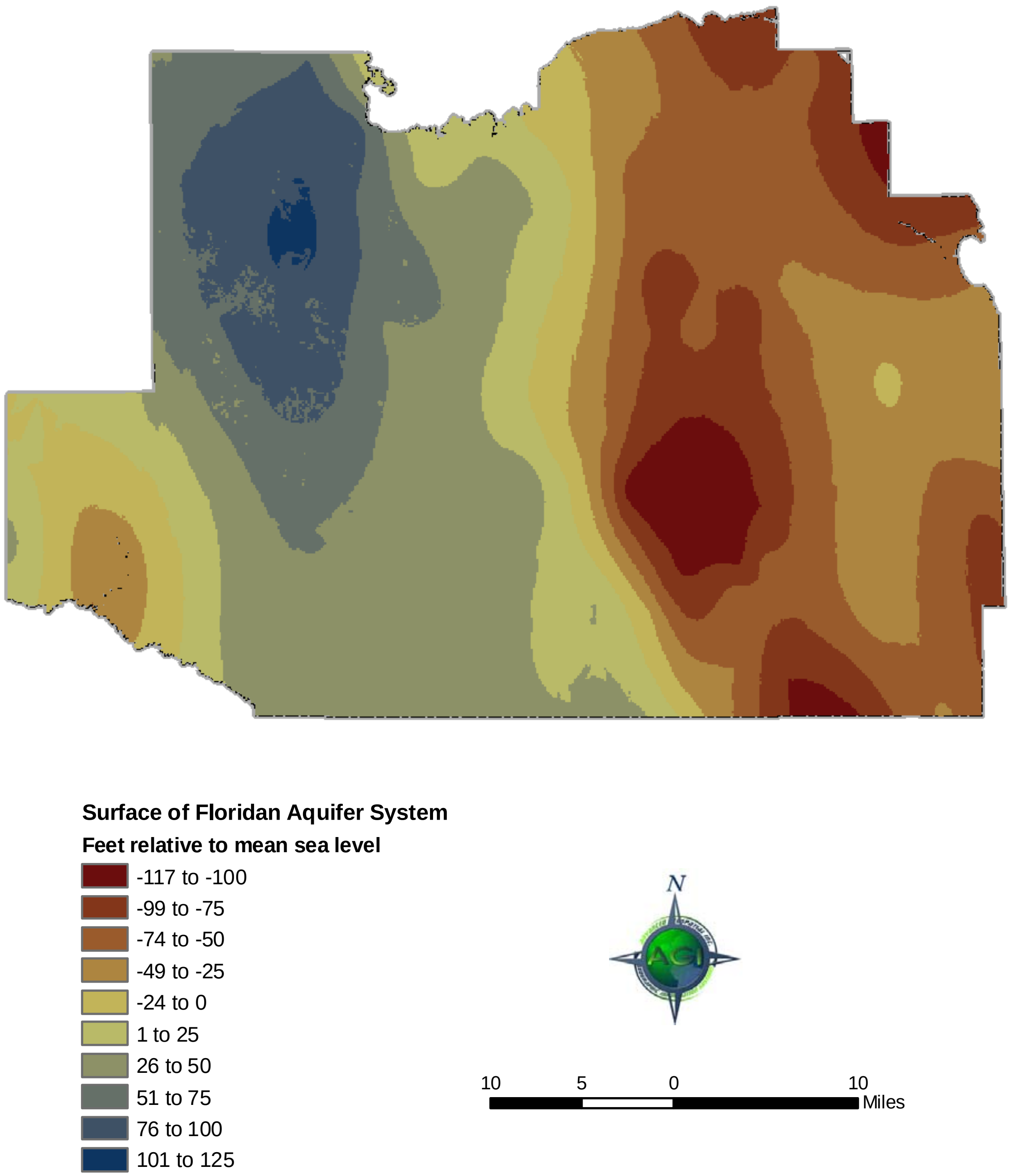

Figure 5. Predicted surface of the FAS in Marion County.

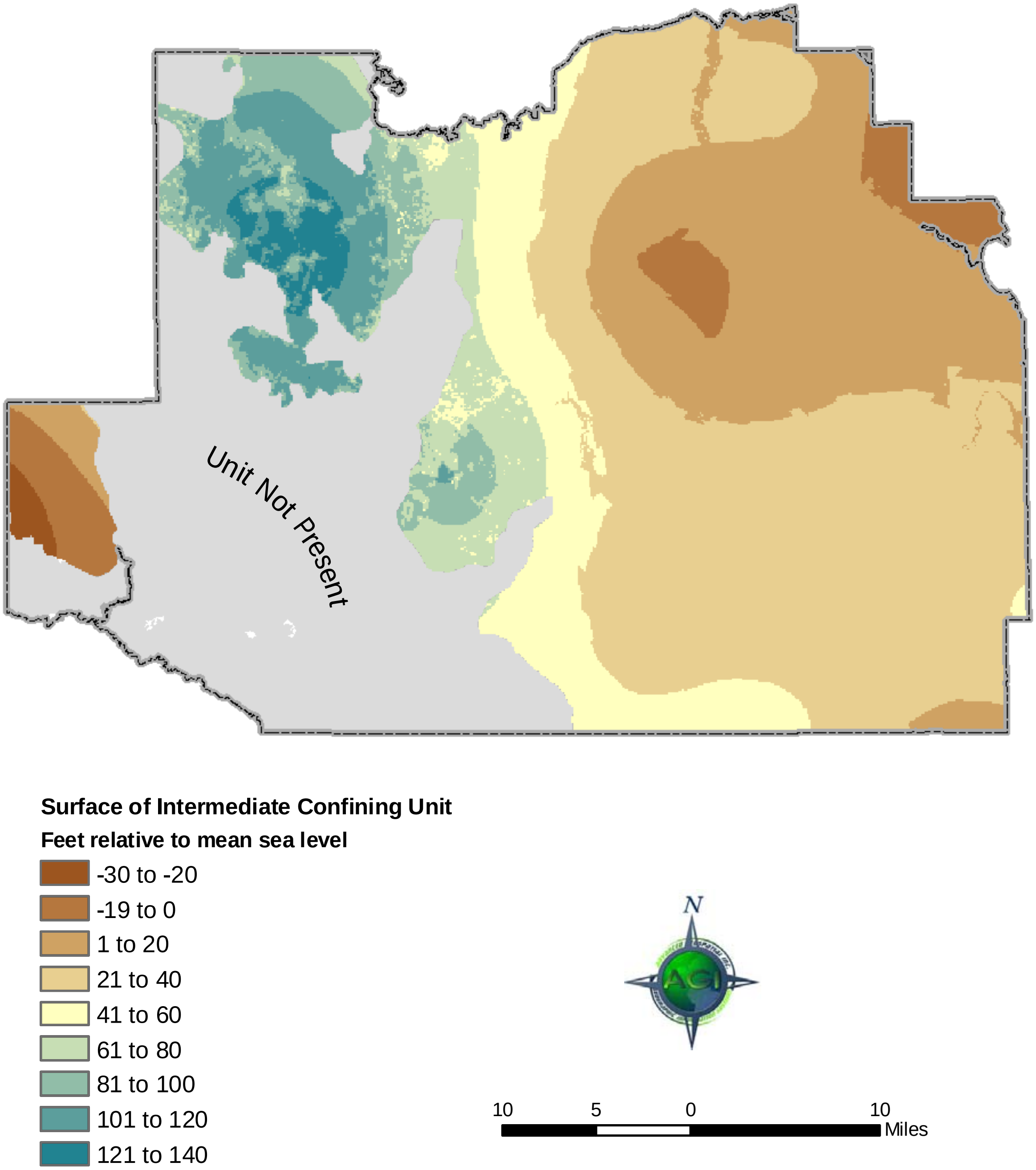

Figure 6. Predicted surface of the ICU in Marion County.

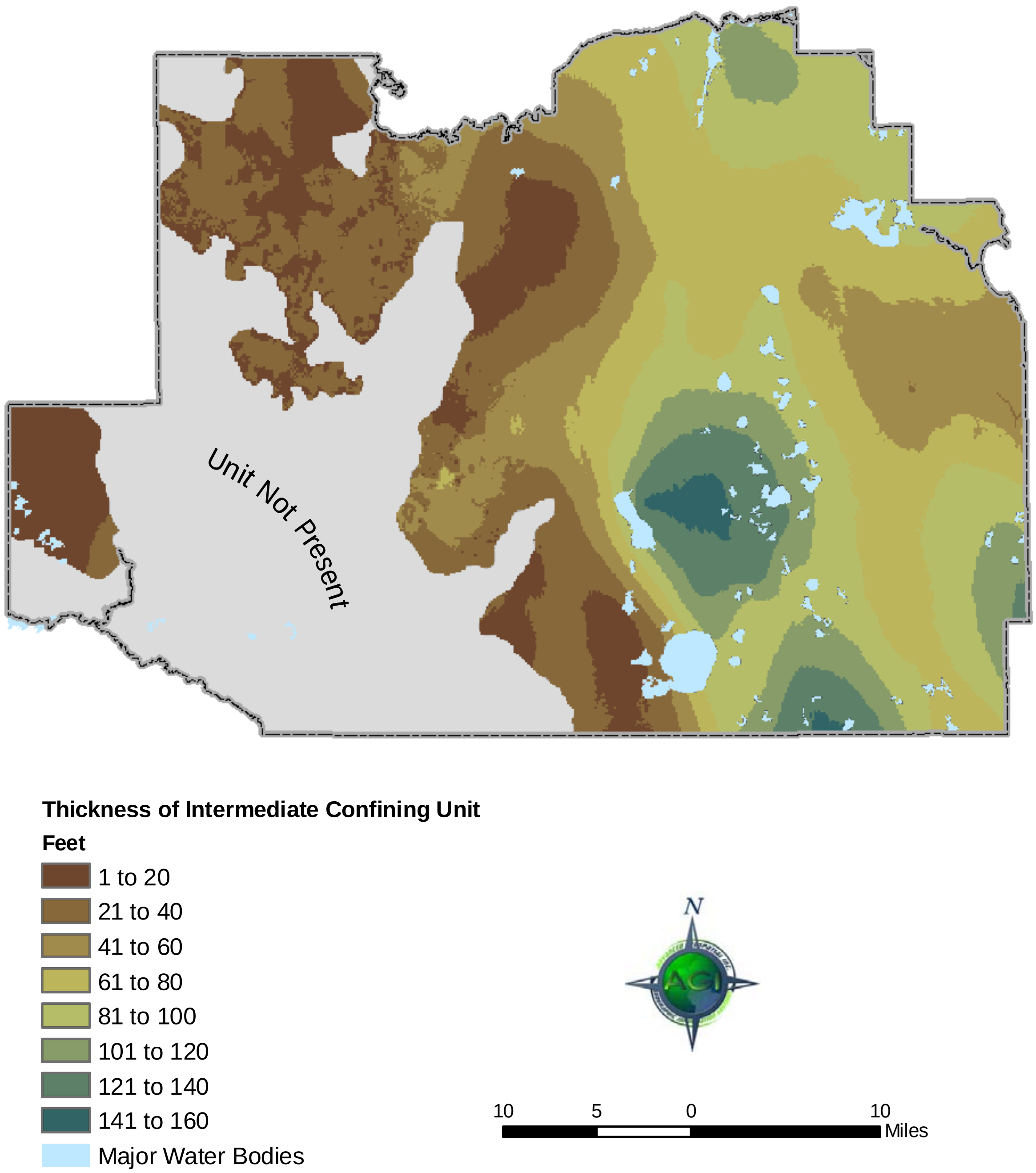

Figure 7. Thickness of the ICU calculated by subtracting predicted surface of ICU (Figure 6) from predicted surface of FAS (Figure 5). Major lakes and water bodies were omitted for input into final model.

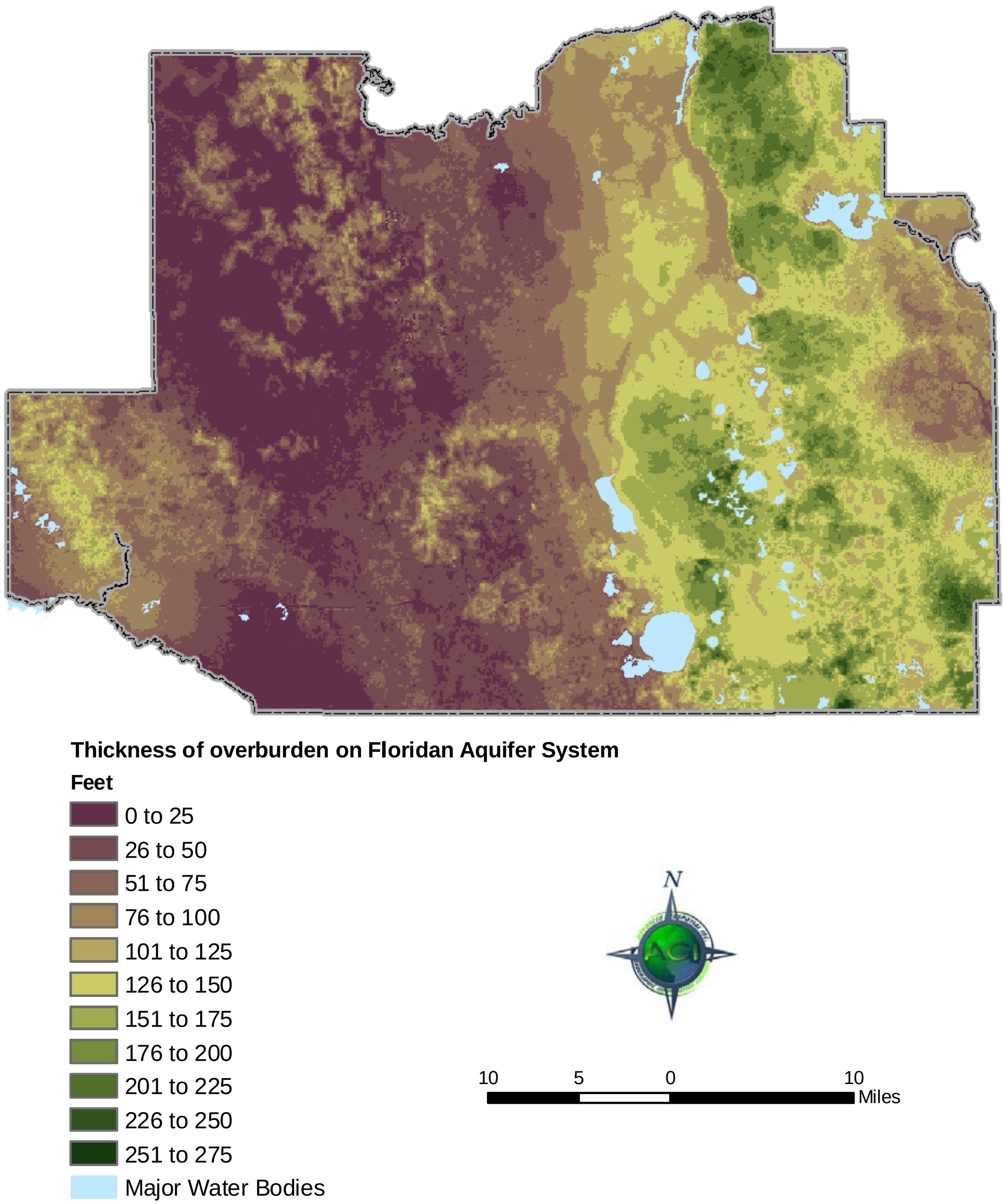

Figure 8. Thickness of sediments overlying the FAS calculated by subtracting digital elevation data (LIDAR) from predicted surface of FAS (Figure 5). Major lakes and water bodies were omitted for input into final model.

Effective Karst Feature Theme

Karst features, or sinkholes and depressions, can provide preferential pathways for movement of ground 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 the county's LIDAR dataset (raster format) served as the initial dataset from which to estimate karst features in the study area. It is recognized that closed topographic depressions may or may not be true karst features. For example, some karst features known as solution pipes offer direct pathways to the FAS and are typically very small in size, possibly below the feature size threshold restrictions applied in this project. In lieu of an exhaustive field-karst survey, applying GIS techniques to closed topographic depressions results in a defensible method for estimating karst in the county. Application of analytical processes to digital elevation maps and models to estimate karst was successfully completed in numerous projects (Arthur et al., 2005, Cichon et al., 2005, Baker et al., 2004, and Denizman, 2003).

Analytical processes were applied to the closed topographic depressions dataset to filter out features which are considered to have little or no impact on the underlying aquifer system, and may not be true karst features. The first step involved extraction of closed topographic depressions from both the 10-ft and 25-ft LIDAR raster-format datasets. To establish the best source for estimating karst, sensitivity analyses were completed for both datasets and revealed the 25-ft LIDAR dataset as a better estimator of karst for the MCAVA project (Figure 9). The primary factor is the tendency of the 10-ft dataset to over predict karst features. The following analyses were applied to the closed topographic depressions dataset to develop an *effective karst features* evidential theme for model input.

Feature size and depth restriction

LIDAR data reveals highly resolved and detailed information about an area's surface elevation, including the characterization of very small or very shallow depressional features. These minor features are real, but may not be karstic in nature. Use of the 25-ft raster LIDAR dataset to develop a closed topographic depressions coverage greatly reduces the number of these minor depressional features. To further eliminate minor, potentially non-karstic features, a size restriction was applied to exclude features less than 2,500 ft^2, and a depth restriction was set to exclude features with a depth of three feet or less.

Circular index method

Karst features, which form as the result of the dissolution of carbonate material, are generally circular in nature. Further, non-karstic depressional features are common in Florida in near-shore modern or relic dune terrains, such as in eastern Marion County, which is underlain by a geologic province known as the beach ridge and dune province (Scott et al., 2001). Depressions of this province have a common elongate shape not typical of karst features.

To filter these features and other types of non-karst features in the study area, a circular index (Denizman, 2003) shape analysis was applied. Circular index was used to compare the roundness of depressional features to an ideal circle with the same perimeter as the depressional feature. A ratio value representing the degree of similarity between two such features was used as a threshold to evaluate how closely each depression approximates a true circle, and thereby, a true karst feature. Features outside this ratio were eliminated. To avoid removal of nested karst features within larger, possibly non-karstic (non-circular) depressions, this analysis was completed on five-foot topographic intervals within every topographic depression.

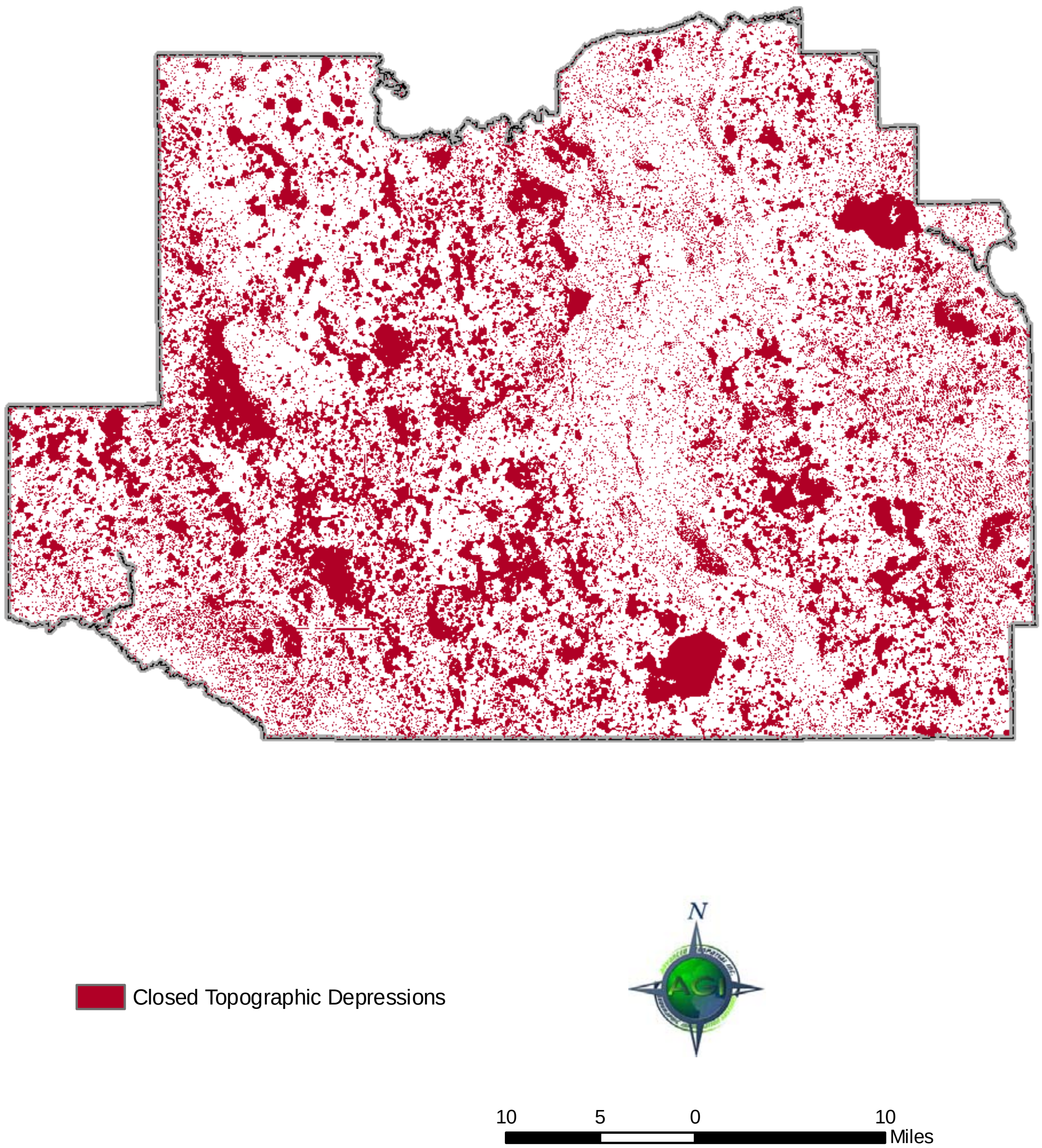

Figure 9. All closed topographic depressions extracted from the Marion County 25-foot LIDAR digital elevation model.

Separation from aquifer analysis

The thickness of material separating a depression from the top of the underlying aquifer system has bearing on its connectivity to the aquifer system. Features separated from the underlying aquifer system by more than 100 feet of overburden material may have little or no impact on that system (Wright, 1974; Cichon, 2003). Excluding closed topographic depressions separated by greater than 100 feet of aquifer overburden provided an additional method for extracting effective karst from closed topographic depressions.

It was expected that use of an overburden filter described above might have an impact on conditional independence of the final model result (see *Conditional Independence* in *Discussion* below). As a result, two evidential themes were used for testing in the sensitivity analysis phase of MCAVA: one in which an overburden filter of 100 feet was applied along with feature size and depth restriction and circular index method (Figure 10), and one in which an overburden filter was not applied (Figure 11).

Aquifer Recharge

Aquifer recharge data layers are estimates of the amount of water infiltrating to the FAS. Aquifer recharge data may provide some control over the location of training points as areas where the recharge values are higher are generally associated with higher aquifer vulnerability. Florida Statues require water management districts to map recharge areas for the FAS and these recharge datasets were evaluated for input in to the MCAVA model.

Boniol et al. (1993) developed district-wide recharge maps for SJRWMD. As an extension to this project, recharge was also mapped for the part of Marion County that falls outside its jurisdiction for the same time period (Figure 12). In 2005, SJRWMD updated the recharge map using recent data and a modernized technique for modeling the water table, an important parameter used in recharge calculations. The 2005 work included only that part of the county which lies in SJRWMD jurisdiction plus an overlapping area (totaling approximately 67% of the county). Consequently, for this 2005 data to be tested for use in MCAVA, the 1993 map was merged with the 2005 map to create a countywide continuous coverage (Figure 13). A USGS recharge dataset (Sepulveda, 2002) displayed in Figure 14 was tested as well.

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, thickness of ICU and thickness of overburden themes were both developed to represent aquifer confinement; sensitivity analysis allows, through statistical analysis, determination of which of these two layers served as the most appropriate input representing confinement for the final MCAVA analysis. Results of this process indicate that soil hydraulic conductivity, thickness of intermediate confining, and effective karst features were the best suited evidential themes for use in final modeling.

Following sensitivity analysis and selection of evidential themes to be input into the MCAVA 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*.

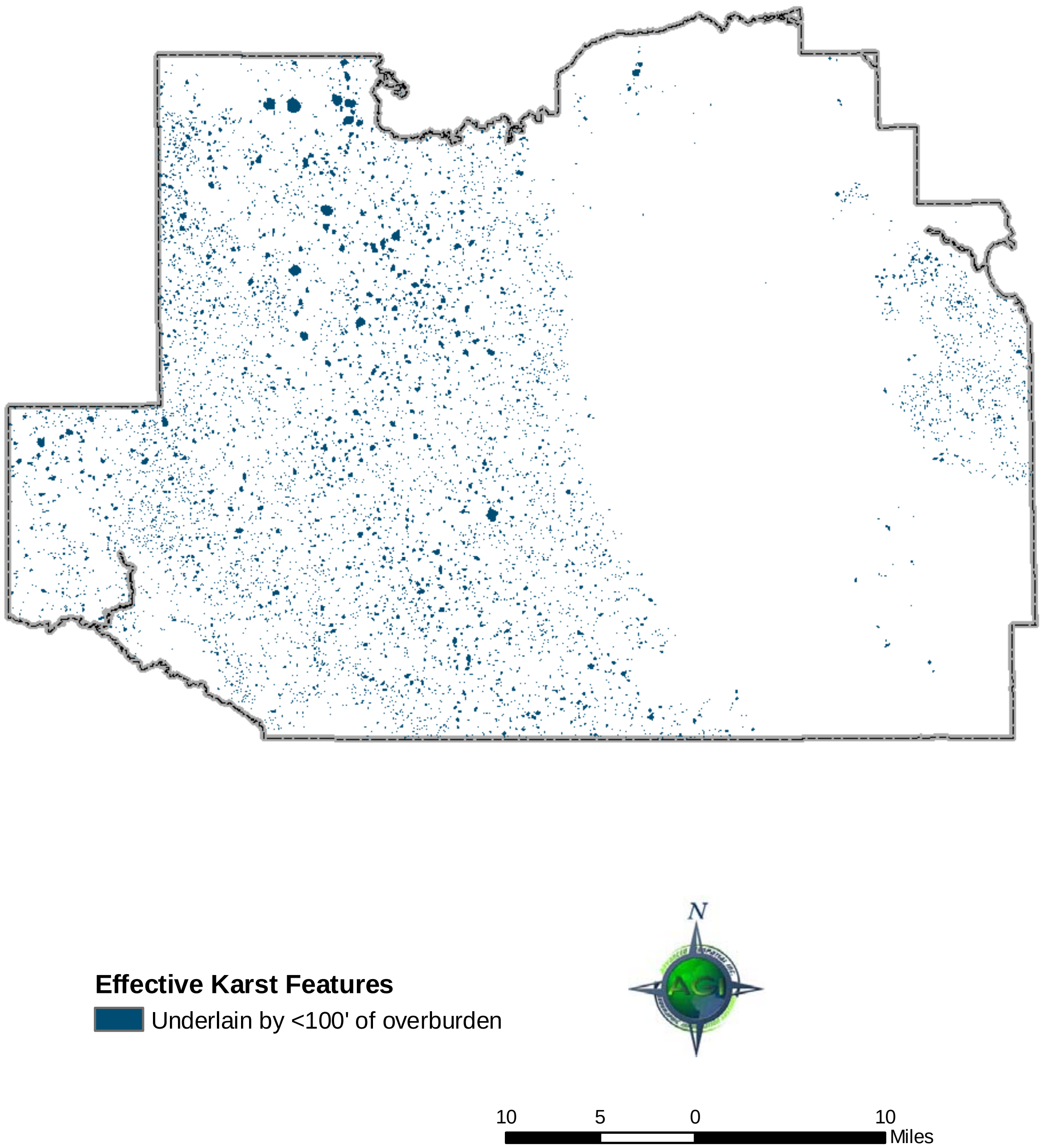

Figure 10. Effective karst features dataset derived from LIDAR based closed topographic depressions. Filters applied include feature size and depth restriction, circular index method, and exclusion of features underlain by more than 100 feet of aquifer overburden.

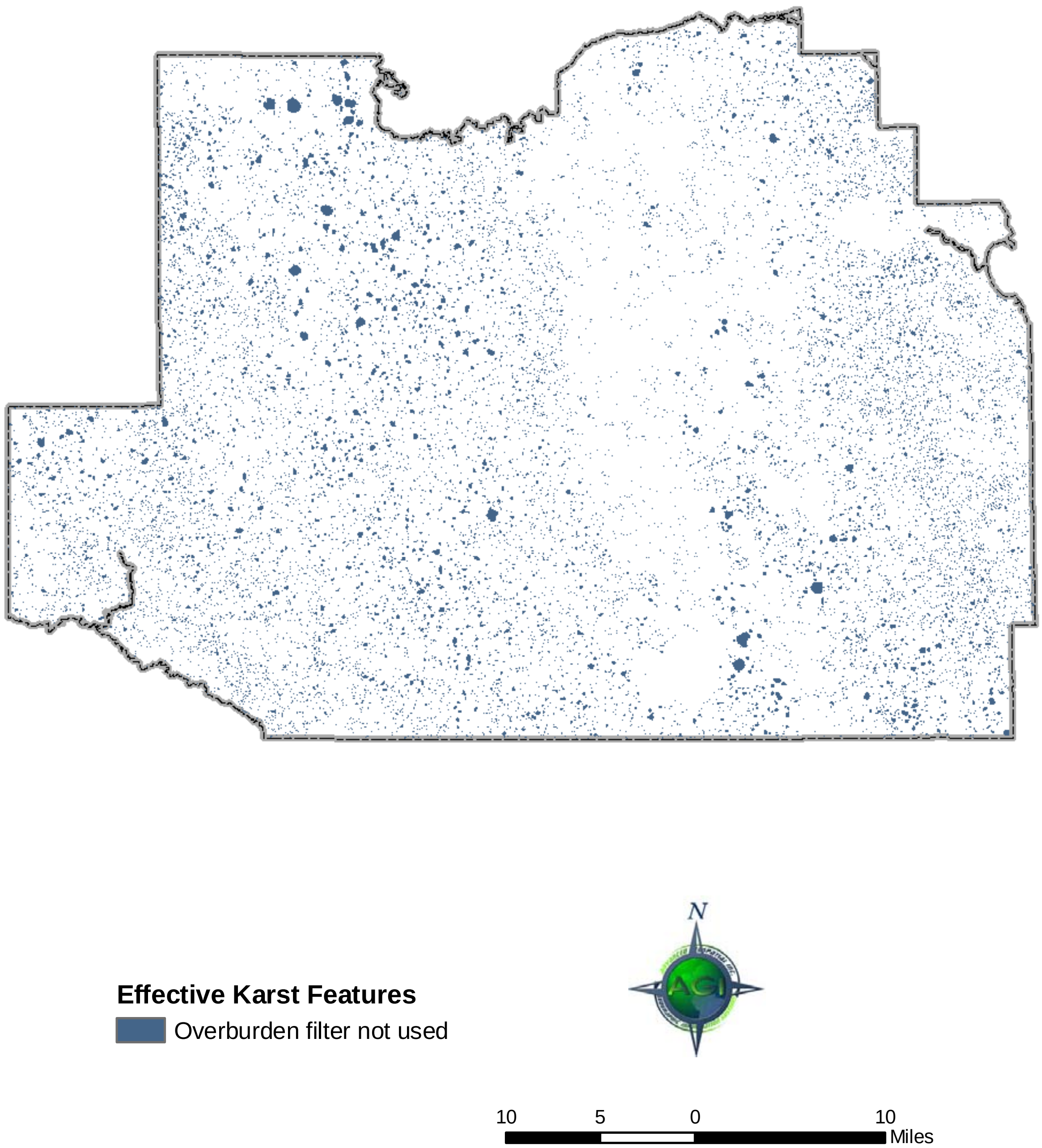

Figure 11. Effective karst features dataset derived from LIDAR based closed topographic depressions. Filters applied include feature size and depth restriction and circular index method only.

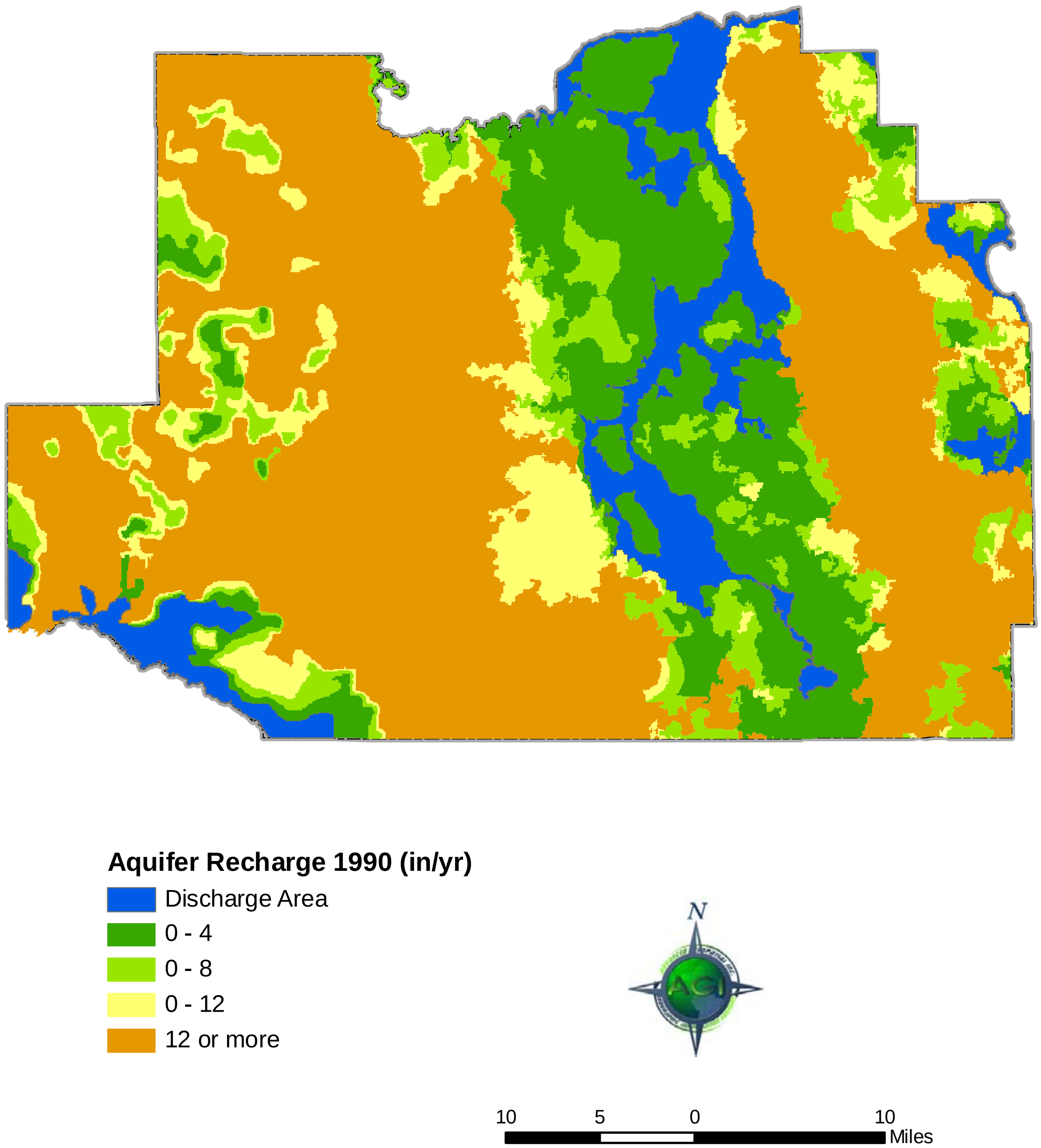

Figure 12. Aquifer recharge for the FAS in Marion County developed by SJRWMD (Boniol et al., 1993).

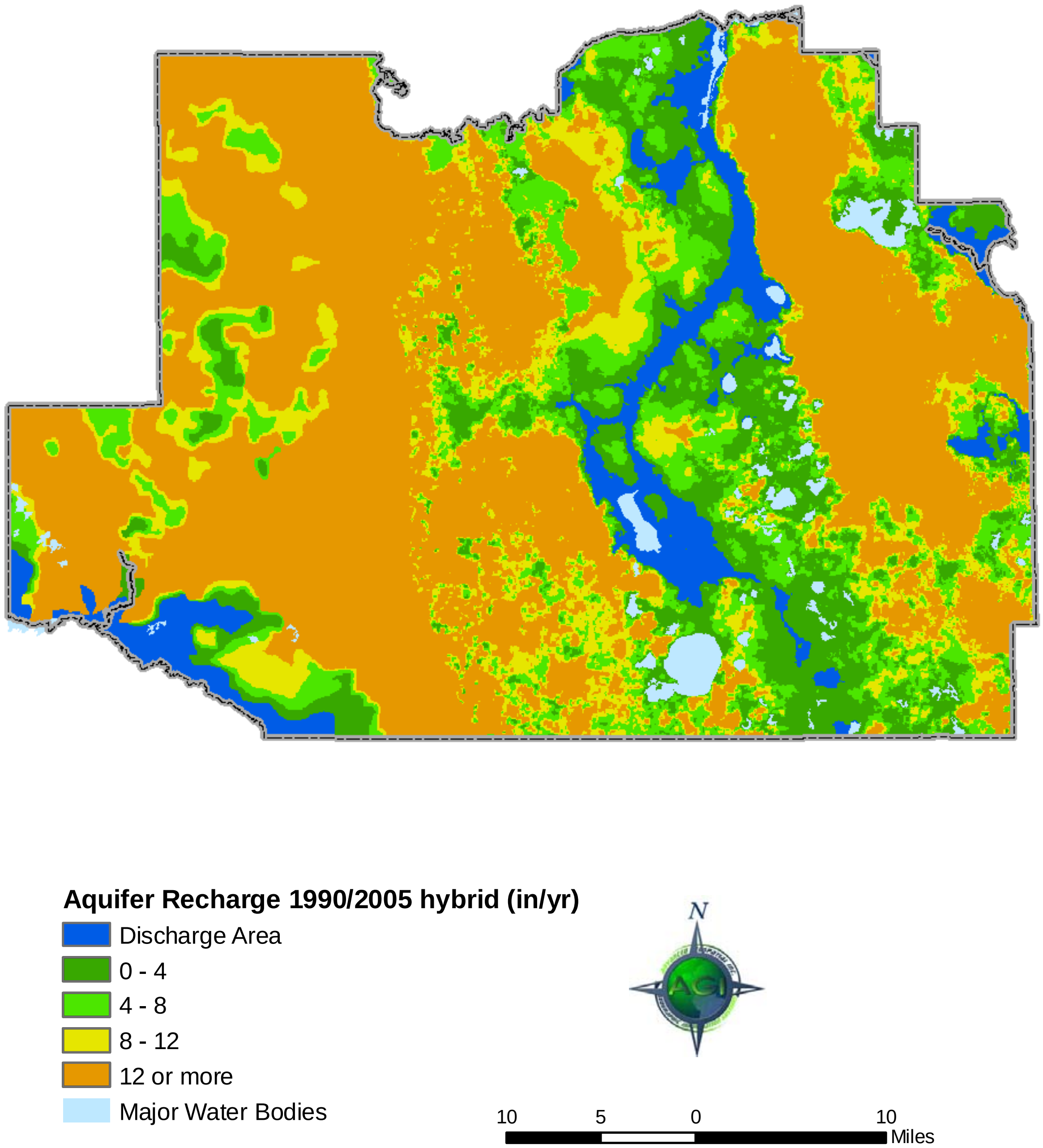

Figure 13. Aquifer recharge to the FAS in Marion County. Datasets from 1990 (Boniol et al., 1993) and 2005 were merged into a single countywide theme for testing in the MCAVA model.

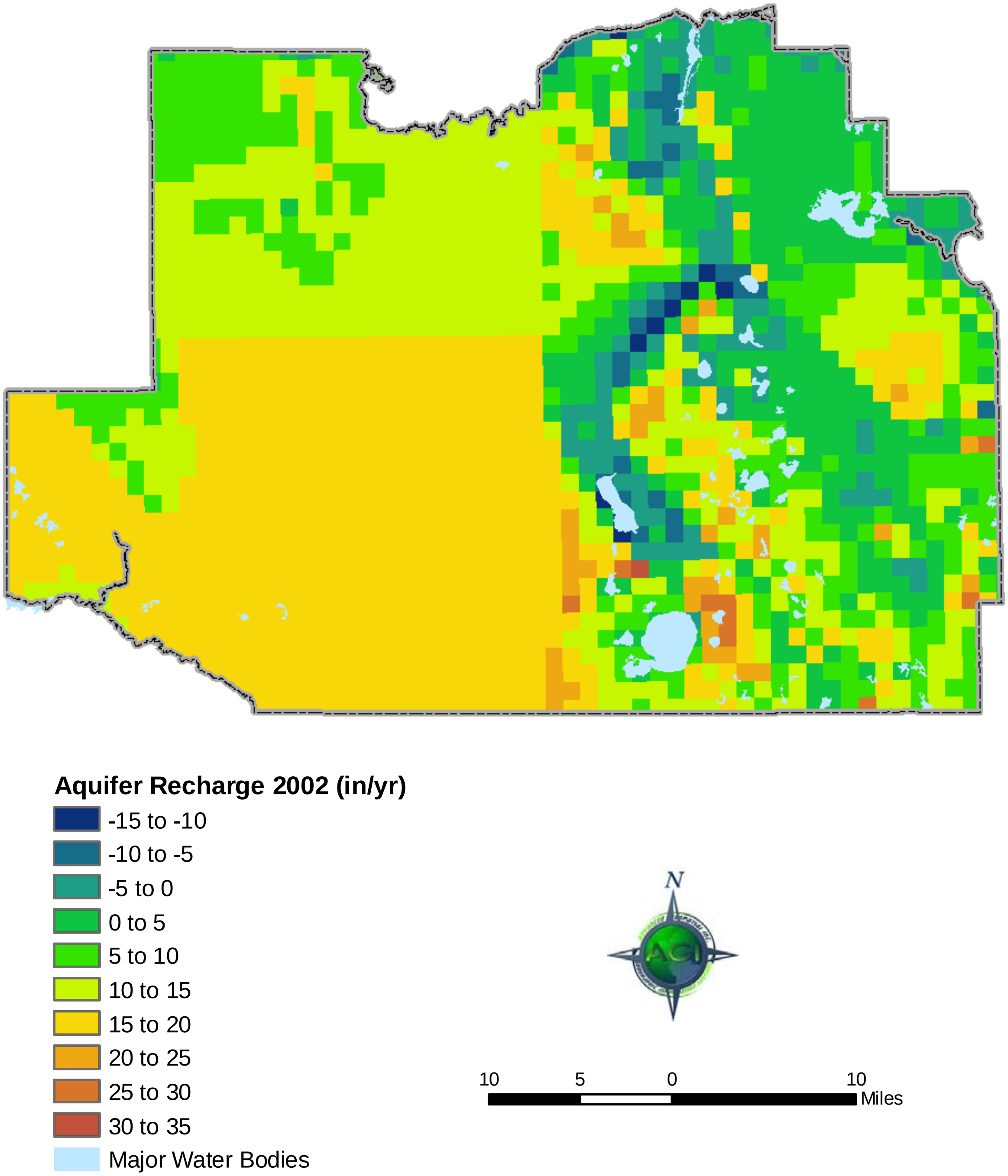

Figure 14. Aquifer recharge to the FAS in Marion County developed by U.S. Geological Survey (Sepulveda, 2002).

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(s) as a threshold value or values to create binary generalized evidential themes. In other models, categorization of more than two classes may be justified (Arthur et al., 2005). For the MCAVA project, a binary break was typically defined by the WofE 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 hydraulic conductivity ranges from 0.20 to 34.95 inches per hour (in/hr) across the study area. Test modeling indicated that areas underlain by 34.95 to 31.37 in/hr were more associated with the training points, and therefore associated with higher aquifer vulnerability. Conversely, areas underlain by 31.36 to 0.20 in/hr soil hydraulic conductivity 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 15.

Intermediate Confining Unit / Overburden Thickness Themes

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

The ICU ranges from absent to 145 feet thick across the study area. The analysis revealed that areas underlain by less than 72 feet of ICU were more associated with the training points, and therefore associated with higher aquifer vulnerability. Areas underlain by greater than 72 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 16.

Effective Karst Features

As mentioned above, two versions of the effective karst features evidential theme were tested for input in the MCAVA project: one in which feature size and depth restriction, circular index method, and a overburden filter were applied to the closed topographic depressions coverage, and one in which only feature size and depth restriction and circular index method were applied. Sensitivity analysis reveals that use of the latter evidential theme provided more defensible model input. More specifically, including the overburden filter returned a conditional independence value of 0.81 for the resulting response theme, which is outside of the commonly accepted range of 1.00 ± 0.15 (refer to *Conditional Independence* below in *Discussion* and to Arthur et al., 2005). Using the karst theme not filtered for overburden to generate a response theme revealed a conditional independence value 0.91, which is within the acceptable range above. This difference in conditional independence is caused by using overburden as a filter in the karst layer and using the ICU thickness as a separate evidential theme, both of which are representations of aquifer confinement.

As mentioned above, areas closer to an effective karst feature are normally associated with higher aquifer vulnerability. Based on this, features were buffered into 25-ft zones to allow for a proximity analysis. The analysis indicated that areas within 1,375 feet of a karst feature were more associated with the training points, and therefore with higher aquifer vulnerability. Conversely, areas greater than 1,375 feet 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 17.

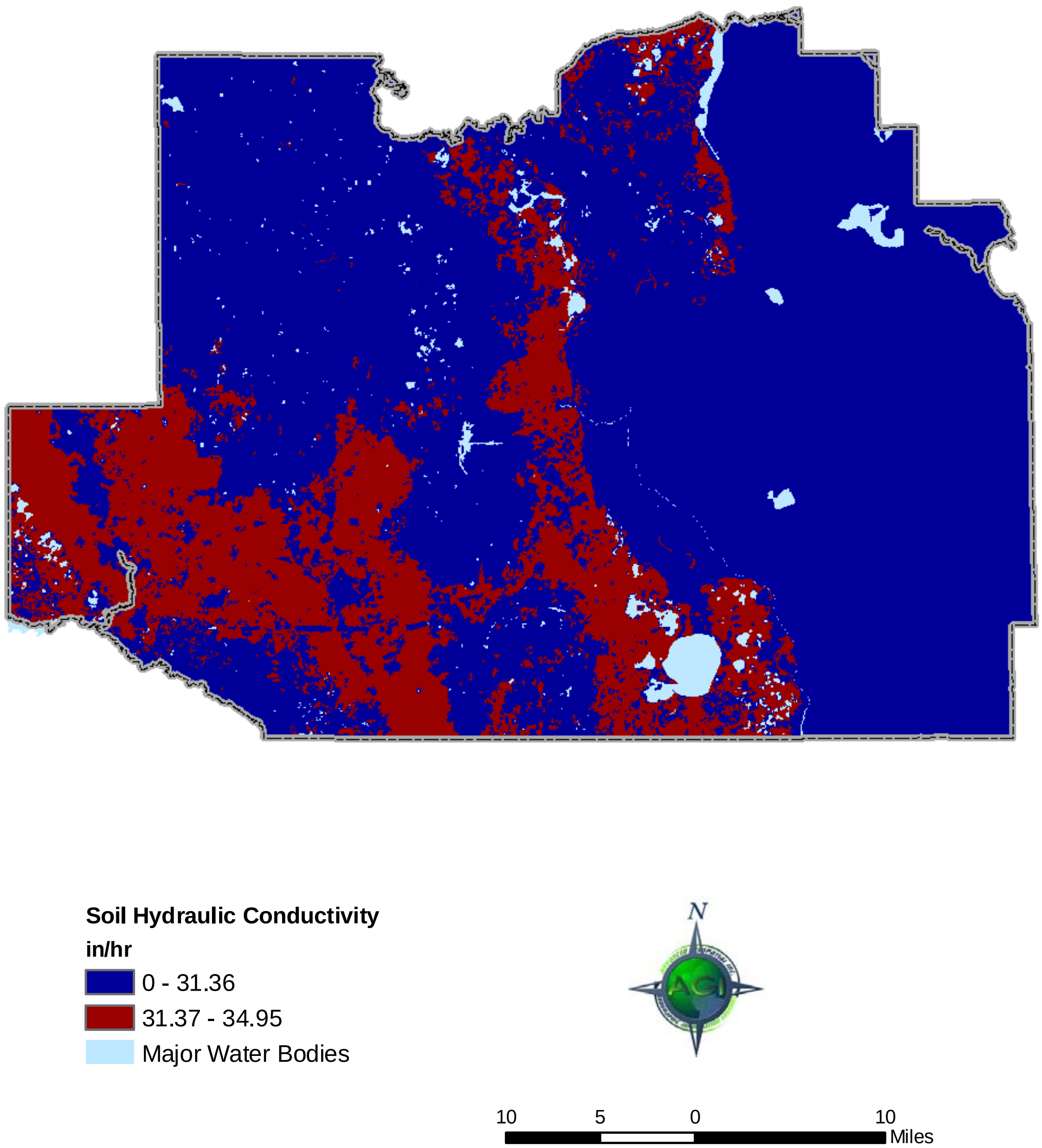

Figure 15. Generalized soil permeability evidential theme; based on calculated weights analysis blue areas share a weaker association with training points and thereby aquifer vulnerability, whereas red share a stronger association with training points.

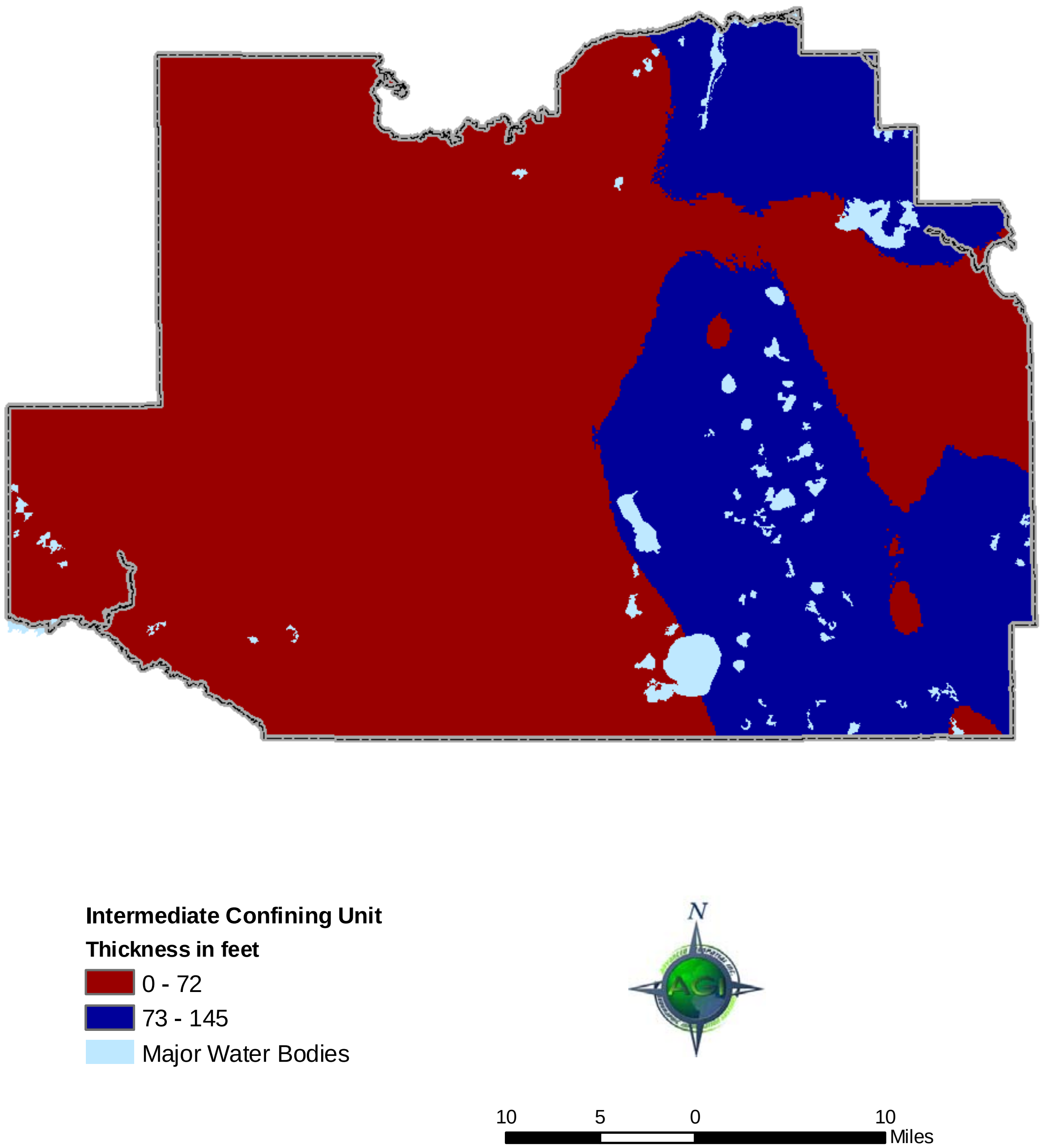

Figure 16. Generalized ICU evidential theme; based on calculated weights analysis blue areas share a weaker association with training points and thereby aquifer vulnerability, whereas red share a stronger association with training points.

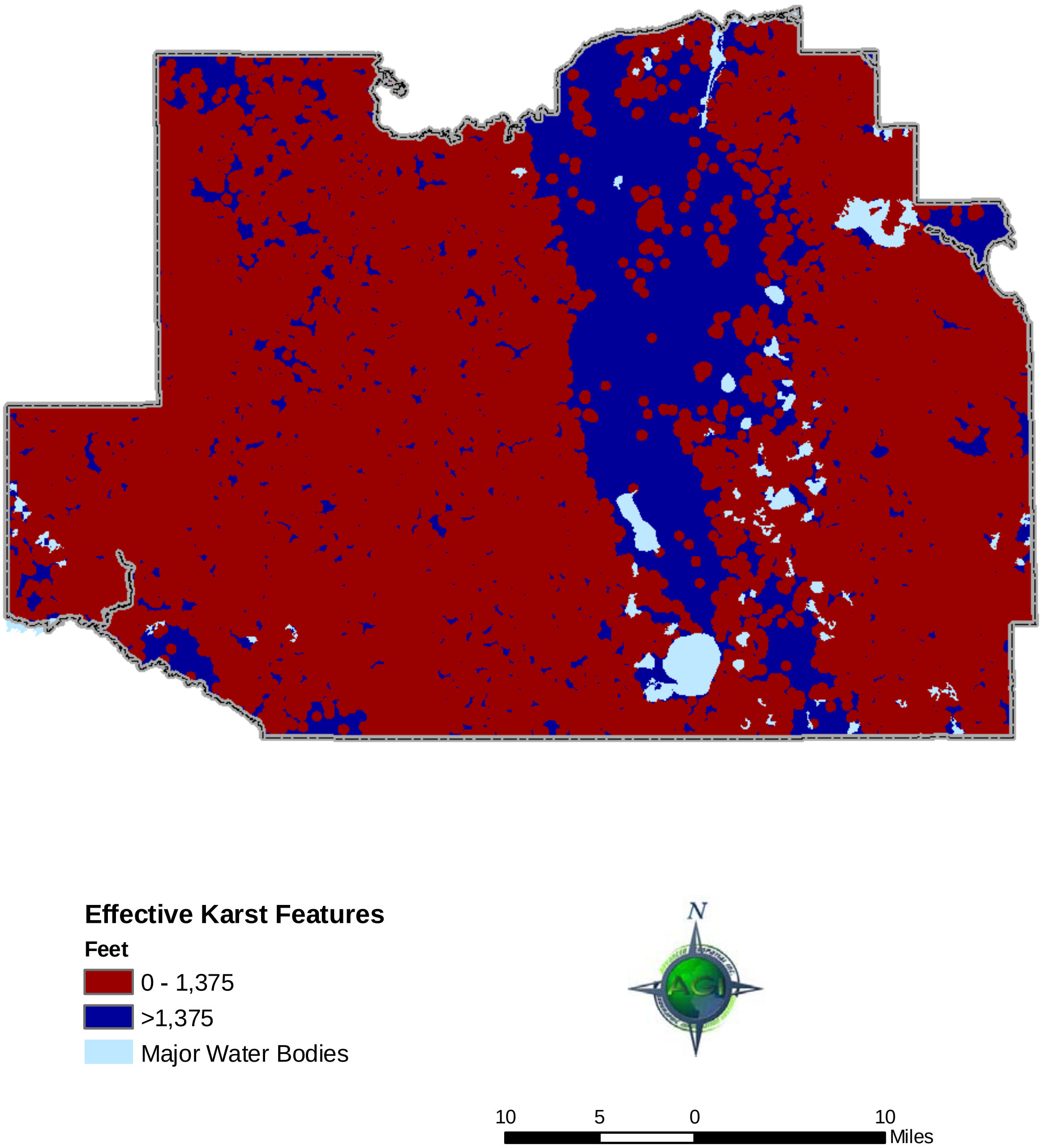

Figure 17. Generalized effective karst feature evidential theme; based on calculated weights analysis blue areas share a weaker association with training points and thereby aquifer vulnerability, whereas red share a stronger association with training points.

Aquifer Recharge

Aquifer recharge datasets were tested for use in the MCAVA model and ultimately were omitted from the MCAVA model because recharge maps share similar input parameters with aquifer vulnerability assessments. For example, ICU thickness was used both in the calculation of aquifer recharge and is a major evidential theme in the MCAVA model. As a result, using recharge maps as input into an aquifer vulnerability assessment can affect conditional independence of the aquifer vulnerability assessment (more on conditional independence is included below in *Discussion*).

Response Theme

Using evidential themes representing effective karst, ICU, and soil hydraulic conductivity, 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 0.01037 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 0.00428. 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 17 of the 18 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 18). 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 MCAVA 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 MCAVA results as well to define the relative vulnerability classes as displayed in Figure 19.

As expected, the MCAVA model response theme indicates that the areas of highest vulnerability are associated with areas where the ICU is thin to absent, dense effective karst-feature distribution, and higher soil hydraulic conductivity. Conversely, areas of lowest vulnerability are determined by thicker ICU sediments, sparse karst-feature distribution, and lower soil hydraulic conductivity values.

Interpretation of Results in Context of FAVA

Results of the MCAVA project have allowed delineation of new and unique zones of relative vulnerability for the FAS in Marion County, based on the county-specific model boundary used, incorporation of LIDAR data, use of numerous well points for aquifer confinement characterization, incorporation of most recent soils data, and application of recently-developed approaches for karst estimation in a GIS. These new results, though refined and highly detailed, do not replace results of previous studies. In other words, the FDEP's regional FAVA results (Arthur et al., 2005) for the FAS indicate that the Marion County study area occurs in primarily a "more vulnerable" zone relative to other areas in Florida (Figure 20); as a result the new MCAVA model output should be interpreted in the context of this major regional project.

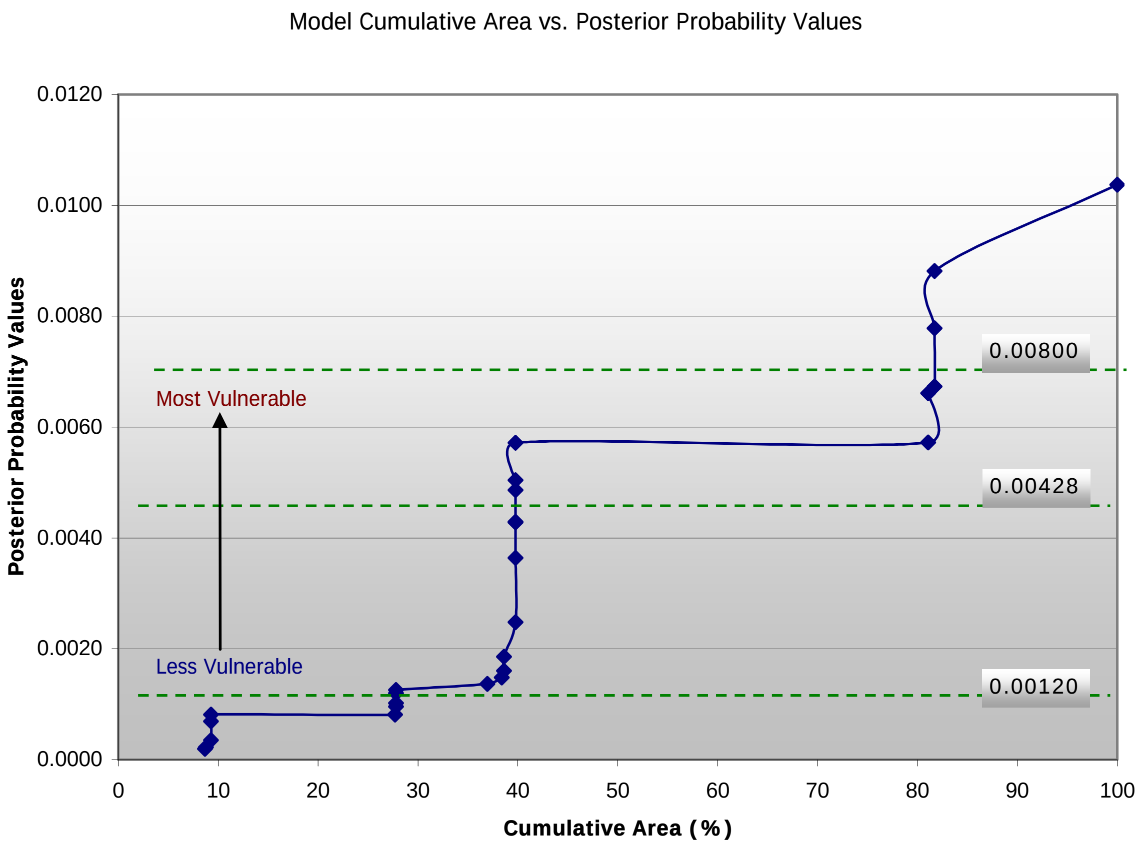

Figure 18. Vulnerability class breaks are defined by selecting where a significant increase in probability and area are observed.

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 MCAVA 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 (Gary Raines, personal communication, 2003) generally indicate limited to no dependence among evidential themes. Values significantly outside this range can inflate posterior probabilities resulting in unreliable response themes. Conditional independence was calculated at 0.91 for the MCAVA project indicating minimal dependence between evidential themes.

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 2.

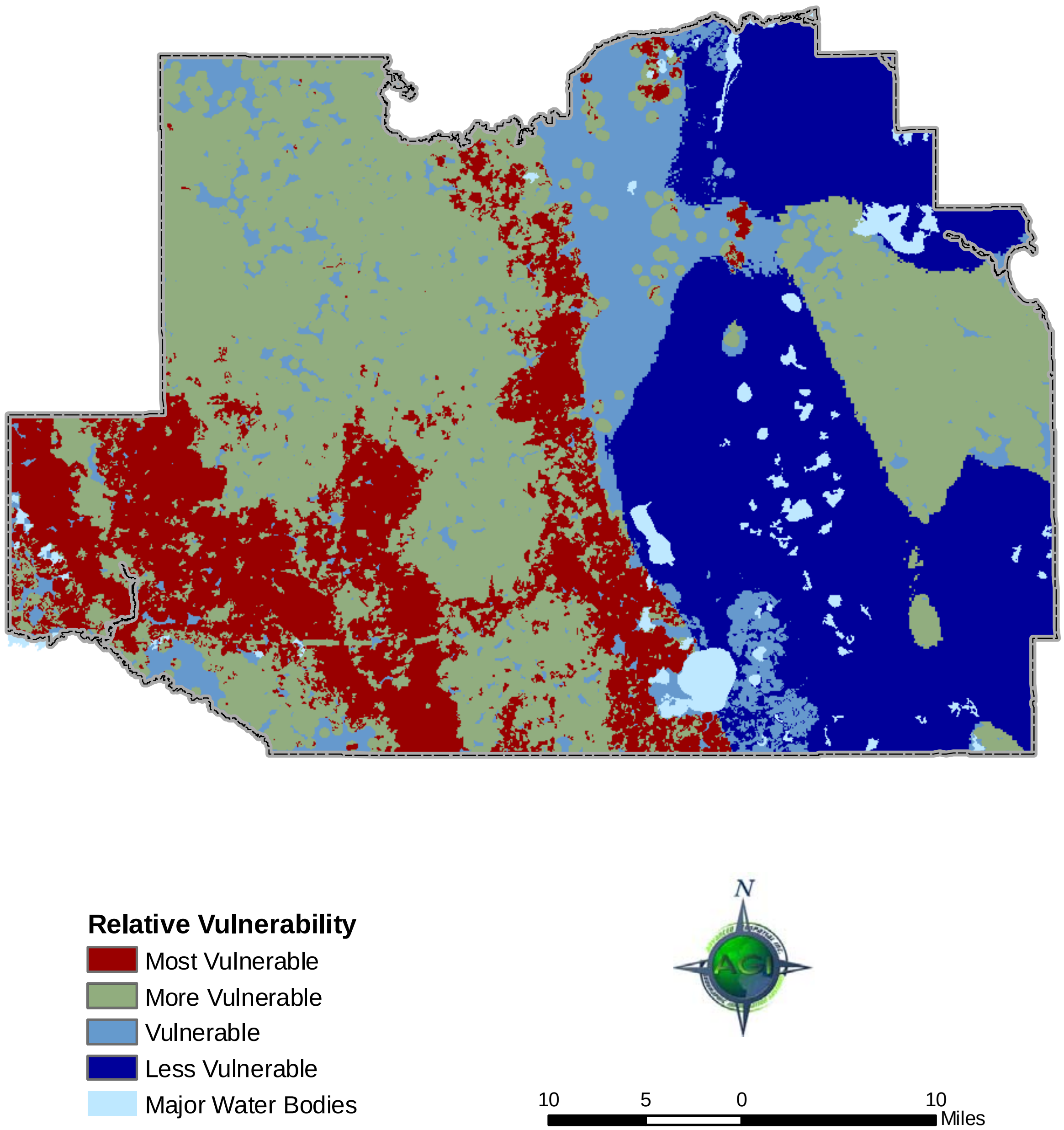

Figure 19. Relative vulnerability map for the Marion County Aquifer Vulnerability Assessment project. Classes of vulnerability are based on calculated probabilities of a unit area containing a training point, or a monitor well with water quality sample results indicative of vulnerability.

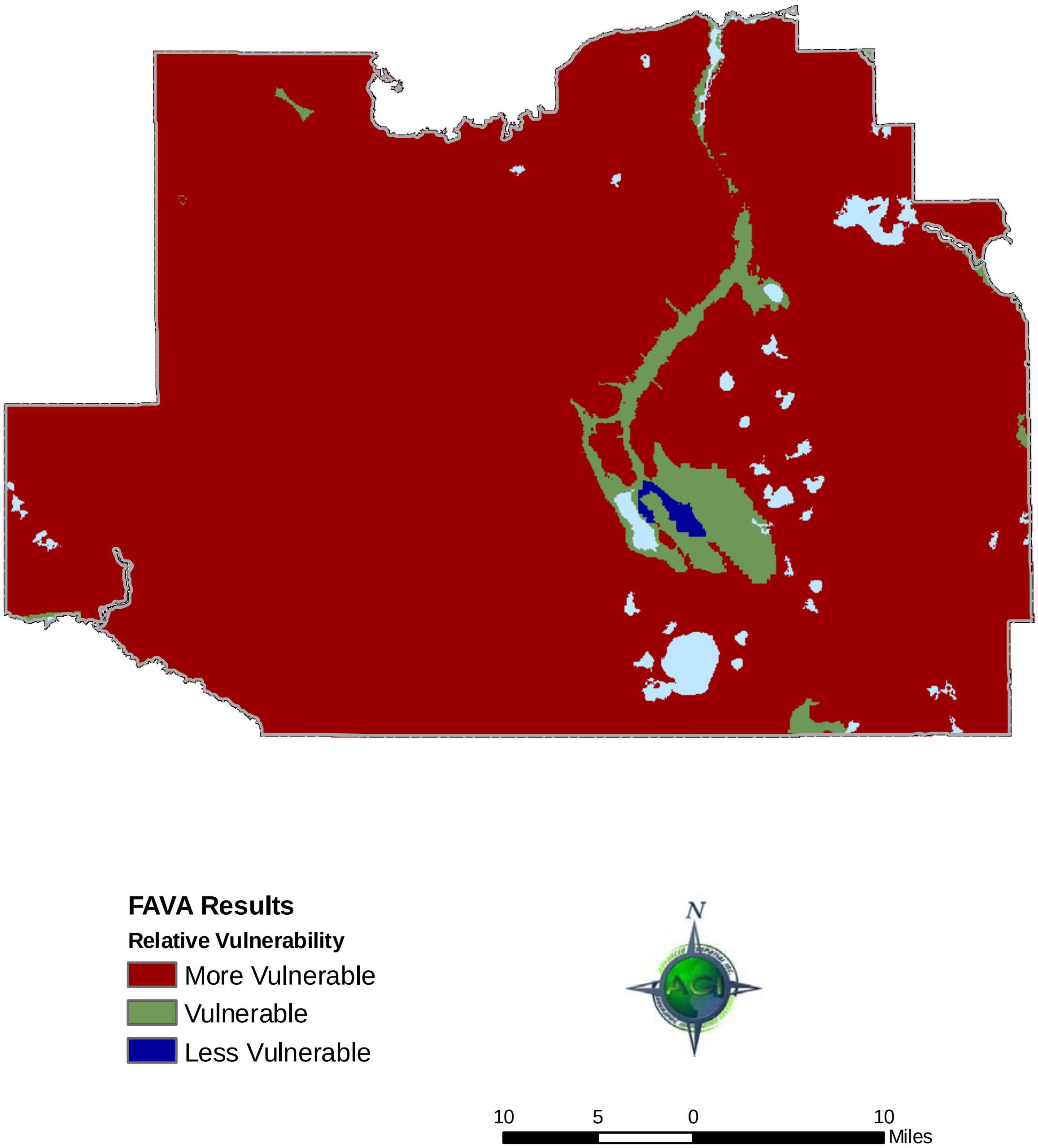

Figure 20. Results of the Florida Aquifer Vulnerability Assessment project (Arthur et al., 2005) for the FAS in Marion County. The MCAVA model relative vulnerability zones, while based on more refined data than the FAVA project, still occur within the context of this regional model.

Table 2. Test values calculated in WofE 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 confidence value of 1.1942 corresponds to an approximate 88% test value – or level of significance – and was the minimum calculated confidence level for MCAVA project evidential themes (see Table 3 below for evidential theme confidence values).

Confidence is also calculated for a response theme by dividing the theme's posterior probability by its total uncertainty (standard deviation). A confidence map can be generated based on these calculations. The confidence map for the MCAVA response theme is displayed in Figure 21. 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 3 displays evidential themes used in the MCAVA model, weights calculated for each theme, along with contrast and confidence values. Positive weights indicate areas where training points were likely to occur, while negative weights indicate areas where training points were not likely to occur. The contrast column is a combination of the highest and lowest weights (positive weight – negative weight) and is a measure of how well the generalized evidential themes predict training points. A positive contrast that is significant, based on its confidence, suggests that a generalized evidential theme is a useful predictor.

Table 3. WofE final output table listing weights calculated for each evidential theme and their associated contrast and confidence values of the evidential themes.

Evidential Theme	W1	W2	Contrast	Confidence
Intermediate Confining Unit	0.2902	-1.6643	1.9544	1.8983
Effective Karst Features	0.1642	-1.2737	1.4379	1.3964
Soil Hydraulic Conductivity	0.4361	-0.1627	0.5988	1.1942

Based on contrast values, the ICU theme had the strongest association with the training points and is the primary determinant in predicting areas of vulnerability in the MCAVA model. Because negative weights (W2) values for ICU and effective karst themes are stronger (have greater absolute values) than the positive weights (W1), these two evidential themes are better predictors of where training points were *less* likely to occur. In contrast, soil hydraulic conductivity is a better predictor of where training points are *more* likely to occur, as W1 is stronger than W2.

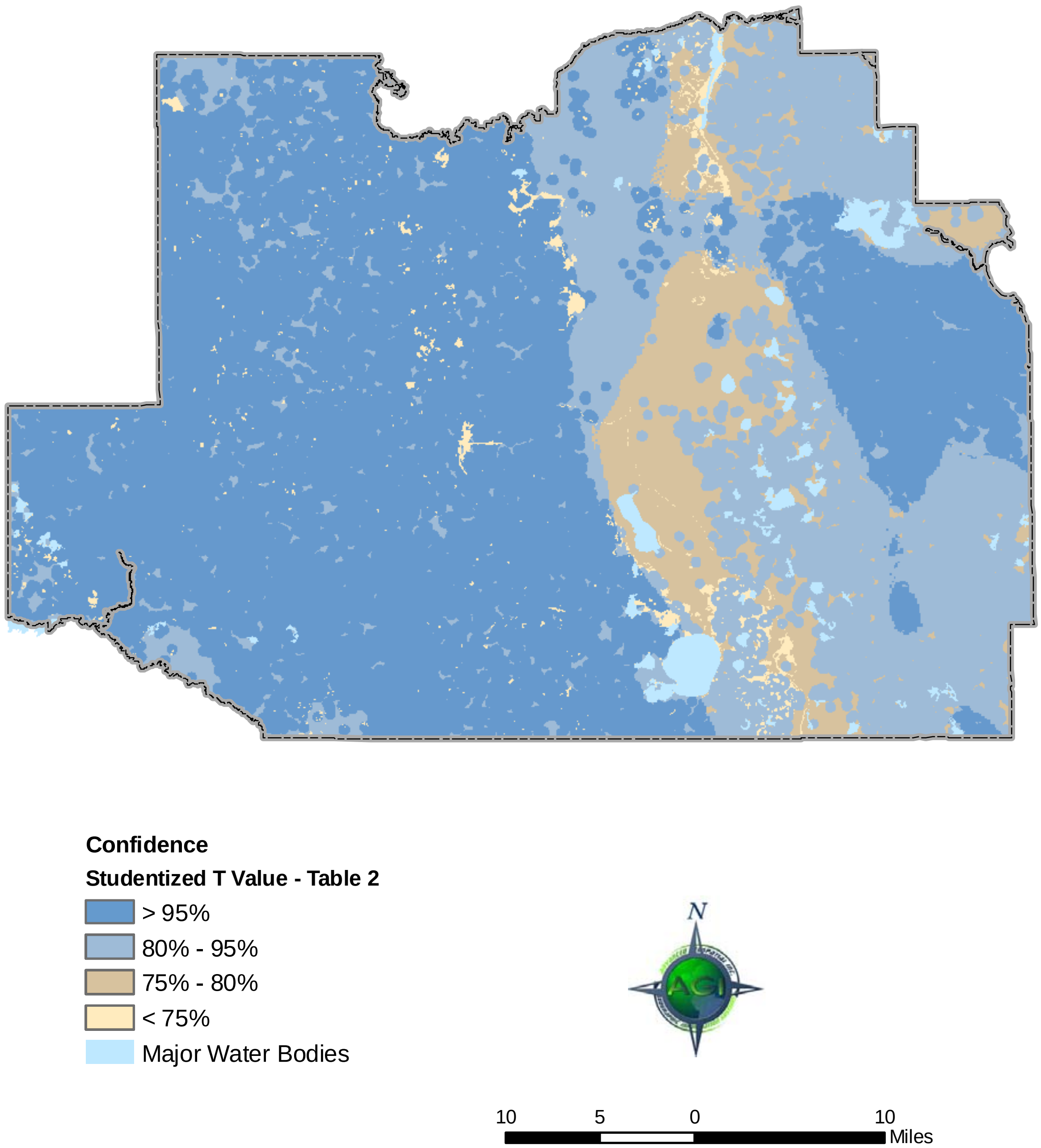

Figure 21. Confidence map for the MCAVA model calculated by dividing the posterior probability values by the total uncertainty for each class to give an estimate of how well specific areas of the model are predicted.

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. All but one training point (17 of 18) were predicted in zones of posterior probability greater than the prior probability. Further strengthening the results were the evaluation of a minimum confidence threshold for evidential themes, generation of a confidence map of the response theme, and evaluation of conditional independence within an acceptable range. 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 MCAVA model to further strengthen its defensibility, and, ultimately, its utility: (1) generation of an additional response theme based on dissolved nitrogen to compare with the dissolved oxygen training points and response theme; (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 to posterior probability and evaluation of an associated trend.

Dissolved Nitrogen Response Theme

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 MCAVA model, this was accomplished by generation and comparison of a separate response theme using a new training point set based on dissolved nitrogen data. Dissolved nitrogen data is abundantly available, and indicative of aquifer vulnerability, but is independent of dissolved oxygen. Applying the methodology described in *Training Points* to dissolved nitrogen data (obtained from the same data sources as dissolved oxygen data) resulted in a new training point theme of 22 wells. Using the same three evidential themes as in the dissolved oxygen model, a response theme was generated using the dissolved nitrogen training points. Figure 22 displays the distribution of nitrogen training points and the resulting nitrogen response theme.

The dissolved nitrogen response theme and training points were compared to the MCAVA model output in three ways: (1) evaluation of posterior probability values of the dissolved oxygen response theme (main MCAVA model) with location of the nitrogen training points (2) evaluation of posterior probability values of the dissolved nitrogen response theme with the location of the dissolved oxygen training points, and (3) spatial comparison of the two response themes to evaluate pattern similarity.

Figure 23 displays dissolved nitrogen training points plotted on the dissolved oxygen response theme. By extracting the value of posterior probability from the dissolved oxygen response theme for the location of each of the 22 dissolved nitrogen training points, a comparison was made to see where the independent dataset point locations fall in the dissolved oxygen model. This comparison revealed that 20 of the 22 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, 91% 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 24 displays the results of the inverse test as described above; dissolved *oxygen* training points plotted on the dissolved *nitrogen* response theme. Though the dissolved nitrogen theme was used only for validation, this cross-validation revealed further useful information about the training points. Comparison as above revealed that 15 of the 18 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, 83% of the dissolved nitrogen wells are located in areas predicted to have a greater than

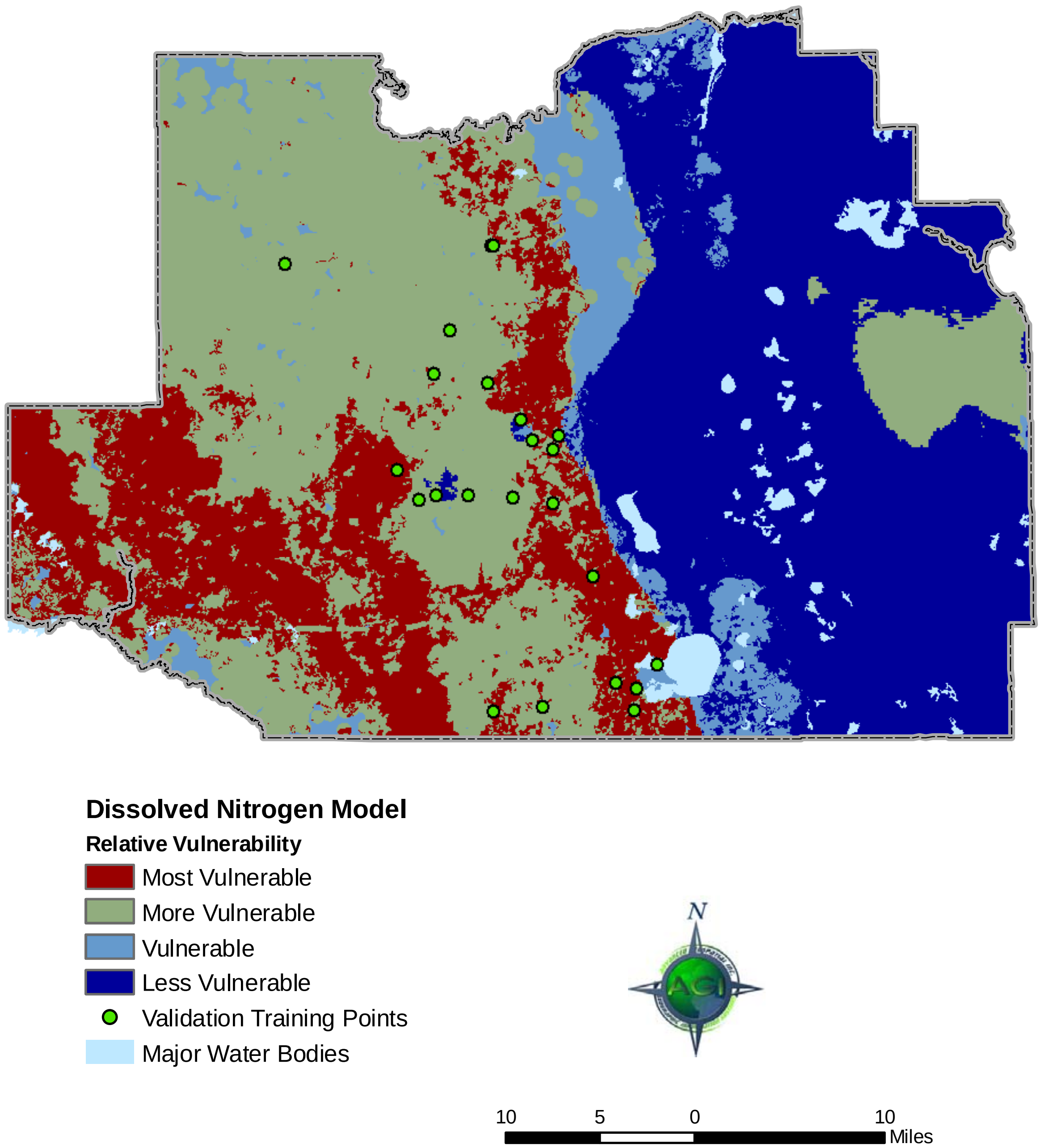

Figure 22. Relative vulnerability map for validation exercises based on dissolved nitrogen concentrations.

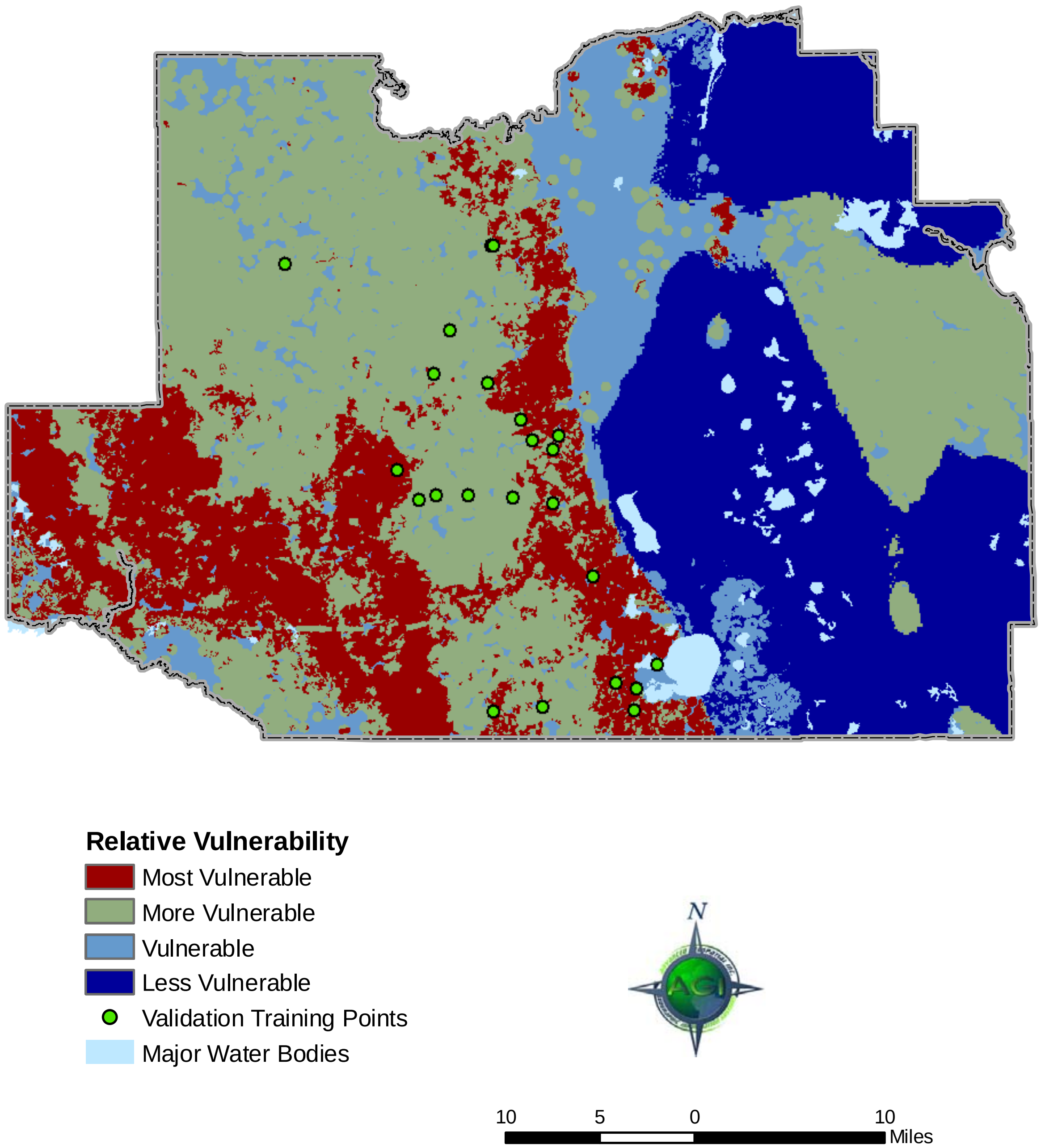

Figure 23. Dissolved nitrogen validation training points plotted in the dissolved oxygen response theme. Comparison reveals 20 of 22 wells, or 91% are located in vulnerable or more vulnerable areas.

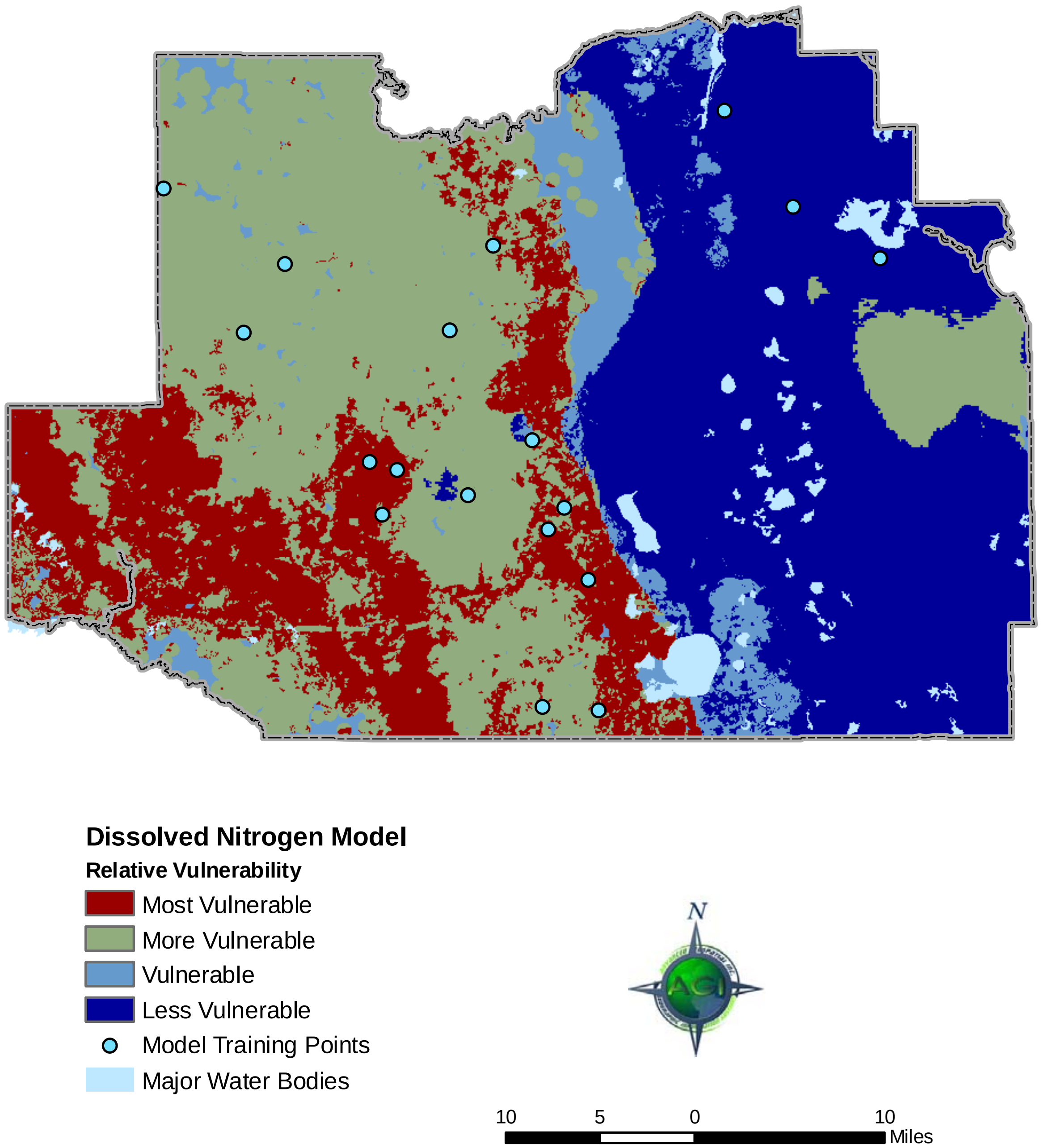

Figure 24. Dissolved oxygen training points plotted in the dissolved nitrogen response theme. Comparison reveals 15 of 18 wells, or 83% are located in vulnerable or more vulnerable areas.

chance probability of containing a training point (for comparison, 94%, or 17 out of 18 of dissolved oxygen points occur in areas of the dissolved oxygen model above the prior probability).

Spatial comparison of the dissolved oxygen and dissolved nitrogen response themes was completed to reveal similarity of the response theme patterns, and was accomplished by applying a kappa coefficient (Cohen, 1960) test. Kappa values were calculated to assess overall agreement between both response themes and to determine the amount of agreement between each vulnerability class of the two response themes. Kappa coefficient results range between -1 (perfect disagreement) and 1 (perfect agreement). A value of zero indicates the agreement is no better than that expected due to chance (Bonham-Carter 1994). Kappa coefficients calculated in the MCAVA project were all positive values and are interpreted using Table 4.

Table 4. Kappa coefficient values and their associated interpretation (Landis and Koch, 1977).

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

Application of this test to overall agreement between response themes revealed a kappa coefficient value between overall response themes of 0.814 indicating that the response themes are in “almost perfect agreement.” Applying this to each vulnerability class of the response theme revealed the values displayed in Table 5, indicating “almost perfect agreement” between most vulnerable, vulnerable, and less vulnerable classes, with “substantial agreement” between the least vulnerable classes.

Table 5. Conditional kappa coefficient values calculated to compare vulnerability classes between dissolved oxygen and dissolved nitrogen response themes.

Agreement	Conditional Kappa (K_f) value
More Vulnerable Classes	0.966
Vulnerable Classes	0.904
Less Vulnerable Classes	0.860
Least Vulnerable Classes	0.645

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 assess whether the dissolved oxygen training points are reasonable predictors of aquifer vulnerability.

From the MCAVA training point theme, a subset of 75% (14 wells) were randomly selected and used to develop a test response theme; the remaining 25% (four wells) of the training points were used as the validation dataset for the test response theme. This comparison revealed that all four of these wells in the validation subset 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. This further increases the conclusion that the MCAVA model response theme is a reasonable estimator of vulnerability.

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 25) and a positive trend was observed.

An additional test involved applying a Pearson's correlation coefficient (r) test to all dissolved oxygen values versus posterior probability values. This test revealed a value of 0.223 indicating more than a 90% degree of statistical significance between the response theme values and the dissolved oxygen data.

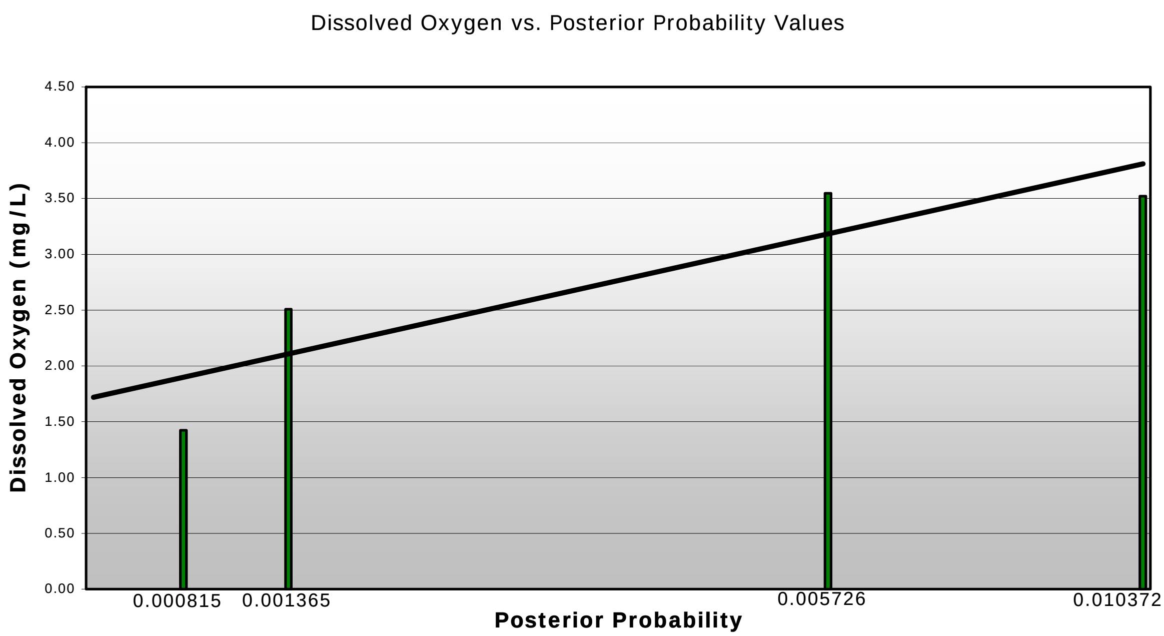

Figure 25. Dissolved oxygen values (averaged per posterior probability class) versus probability values to reveal trend between increasing dissolved oxygen concentrations and posterior probability.

Model Limitations and Scale of Use

When implementing the MCAVA 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 MCAVA 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 MCAVA 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 ground-water flow paths or fate/transport of chemical constituents.

Surface Water Areas

In addition to large surface-water bodies omitted from the analysis, there are many other surface-water features which were not removed. Many of these features may represent areas of ground-water discharge; however, these discharging surface waters are not part of the aquifer, although they originate from it. Accordingly, the MCAVA model is not intended to be used to assess contamination potential of surface waters, though the discharging surface waters are highly vulnerable to contamination.

Recommendations on Scale of Use

Use of highly detailed evidential theme and LIDAR 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. Recognizing the need of these maps to be applied to regulation and decisions made at the parcel scale, the following usage recommendations are made.

MCAVA model output is, in a sense, as accurate as the most detailed input layer, and as inaccurate as the least detailed layer. Wells used to define confinement thickness represent an area up to 15 square miles (mi^2), for example; on the other hand, soils polygons or karst features derived from LIDAR data represent an area as small as 2,500 square feet (ft^2).

Reports on past projects recommended that model results be applied on a local scale of greater than or equal to approximately 1.0 mi^2 for statewide studies (Florida Aquifer Vulnerability Assessment) or approximately 0.75 mi^2 for localized studies (Wekiva Aquifer Vulnerability Assessment). Based on similarities to larger scale projects, AGI recommends that the MCAVA model output be used for implementation on the order of greater than 0.75 mi^2, or an approximate 4,500-ft grid cell size. In other words, decisions using this tool made within a 0.75 mi^2 area (approximate 4,500-ft x 4,500-ft area) is not recommended, however, use of the MCAVA results on smaller scales is recommended.

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. 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 MCAVA 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.

CONCLUSION

As demands for fresh ground water from the Floridan Aquifer System underlying Marion County increase resulting from continued population growth, identification of zones of relative vulnerability becomes an increasingly important tool for implementation of a successful ground-water protection and management program. The results of the MCAVA project provide a science-based, water-resource management tool allowing for a pro-active approach to protection of the FAS, 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 ground-water recharge areas.

The results of the MCAVA vulnerability model are useful for development and implementation of ground-water protection measures; however, the vulnerability output map included in this report should not be viewed as a static evaluation of the vulnerability of the Floridan 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 ground-water resources.

QUALIFICATIONS

Disclaimer

Maps generated as part of this project were developed by Advanced GeoSpatial Inc. (AGI) to provide Marion County with a ground-water resource management and protection tool to carry out agency responsibilities related to natural resource management and protection regarding the Floridan Aquifer System. Although efforts were made to ensure information in these maps is accurate and useful, neither Marion County nor AGI assumes responsibility for errors in the information and does not guarantee that the data is free from errors or inaccuracies. Similarly, AGI and Marion County 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. AGI and Marion County 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 AGI or Marion County, 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. AGI and Marion County 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 Marion County funding, no proprietary rights may be attached to it in whole or in part, nor may it be sold to Marion County or 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 Marion County 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 Marion County 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 Marion County and AGI.

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.

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

Kappa Coefficient – Allows statistical comparison of map patterns. It is a multivariate accuracy assessment technique developed by Cohen (1960) to determine if one error matrix is significantly different than another.

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

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

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

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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