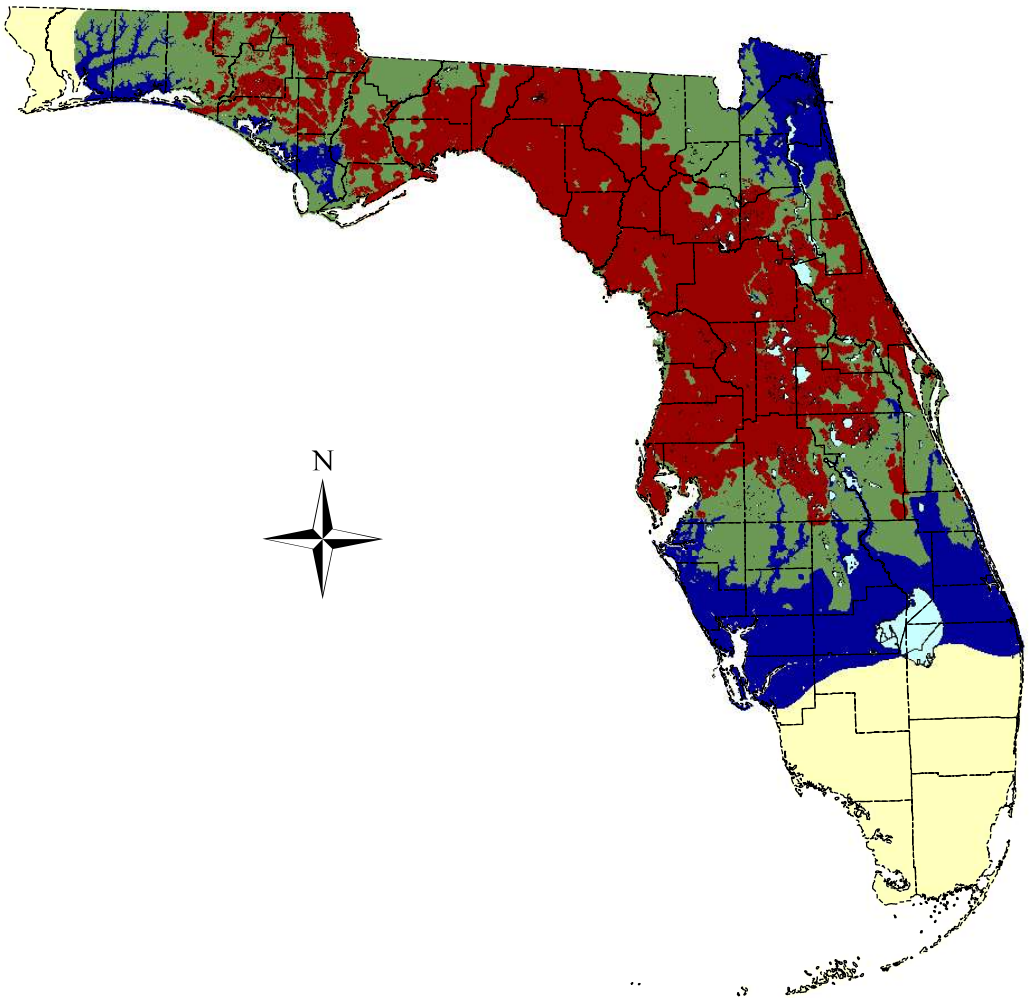
# Florida Aquifer Vulnerability Assessment (FAVA): Contamination potential of Florida's principal aquifer systems




## A report submitted to the Division of Water Resource Management Florida Department of Environmental Protection

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Division of Resource Assessment and Management
Florida Geological Survey

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**LIST OF ACRONYMS**

AVAM ..... Aquifer Vulnerability Assessment Model
DEM ..... Digital Elevation Model
DWRM ..... Division of Water Resource Management
FAS ..... Floridan Aquifer System
FAVA ..... Florida Aquifer Vulnerability Assessment
FDEP ..... Florida Department of Environmental Protection
FGS ..... Florida Geological Survey
ft* ..... Feet
GIS ..... Geographic Information System
GLEAMS ..... Groundwater Loading Effects of Agricultural Management
IAS ..... Intermediate Aquifer System
LSA ..... Land-Surface Altitude
m* ..... Meters
MINWT ..... Minimum Water Table
msl ..... mean sea level
NRCS ..... Natural Resources Conservation Service
NRC ..... National Research Council
NWFWMD ..... Northwest Florida Water Management District
NWI ..... National Wetlands Inventory
NWWA ..... National Water Well Association
SAS ..... Surficial Aquifer System
SEAMS ..... Soil, Environmental, and Agricultural Management Systems
SEEPAGE ..... System for Early Evaluation of Pollution Potential of Agricultural Environments
SSURGO ..... Soil Survey Geographic Database
STATSGO ..... State Soil Geographic Database
TAC ..... Technical Advisory Committee
TIN ..... Triangulated Irregular Network
USDA ..... United States Department of Agriculture
USEPA ..... United States Environmental Protection Agency
USGS ..... United States Geological Survey
WofE ..... Weights of Evidence
WT ..... Water Table

*It is acknowledged that both metric and standard units are used throughout this report. Metric is used with regard to spatial data, while standard is used in regard to well, potentiometric, depth-to-water, and permeability data.

**ACKNOWLEDGMENTS**

This project has been an immense and diverse undertaking that could not have been accomplished without the support, assistance and guidance of many people. The concept of developing a model of the contamination potential of Florida's principal aquifer systems has been the focus of the Florida Department of Environmental Protection's (FDEP) Aquifer Vulnerability Subcommittee of the Recharge Protection Committee for several years. Recognizing the caveats of applying the DRASTIC model in Florida, these committee members were forward-thinking in their collective vision to develop a tool for scientists, environmental managers and planners that would facilitate the stewardship and sustainability of Florida's ground-water resources.

On behalf of the authors of this study, I thank these committee members for their dedication, especially subcommittee chair, Gary Maddox and committee chair, Donnie McClaugherty. Since conceptualization of the Florida Aquifer Vulnerability Assessment (FAVA) in 1995, the model has evolved significantly. It began as a GIS-based index-type model advanced by the committee and then was revised by John Passehl (FDEP) as the Aquifer Vulnerability Assessment Model (AVAM). Upon completion of pilot counties using AVAM, funds to support a statewide modeling effort became available through the FDEP Division of Water Resource Management (DWRM) Ground Water Assessment Section. This Section, led by Jim McNeal administered funds from the EPA Source Water Assessment and Protection (SWAP) program. The SWAP program, now administered by the Ground Water Regulatory Section in the Bureau of Water Facilities Regulation is led by Donnie McClaugherty. Tremendous gratitude is extended to Gary, Jim and Donnie, as well as DWRM senior management for giving the Florida Geological Survey the opportunity to modify and complete the statewide FAVA project. Allan Stodghill (my project manager counterpart in DWRM) and Dr. Paul Lee are thanked for their insight, support and enthusiasm throughout the project. I also thank Mark Dietrich (DWRM) not only for his work in support of AVAM, but also for his guidance and assistance in our development of the statewide digital elevation model (DEM) used in the project.

Several part-time staff of the Florida Geological Survey Hydrogeology Section are appreciated for their productive and meticulous work involving development of databases and GIS coverages, as well as many other activities in support of the FAVA project: Brandon Ashby, Kristy Baker, Roberto Davila, Shawn Ferguson, Cindy Fischler, Suvrat Kher, Clint Kromhout, Lori Millonzi, Elizabeth Moulton, Rupa Sharma, and Jeff Thelen.

I also thank the state's five Water Management Districts, and the U.S. Geological Survey for contribution of digital hydrogeologic and topographic data. These agencies, as well as the Florida Department of Community Affairs and the two private firms, SDII Global Corporation. and Hazlett-Kincaid, Inc. are thanked for their support by allowing technical and scientific staff to participate in the FAVA Technical Advisory Committee (TAC). Members of the FAVA TAC (see *Introduction – Approach, Table 2*) contributed invaluable expertise and guidance in nearly every major phase of the FAVA project. Their contributions have significantly enhanced the scientific defensibility and utility of FAVA. I am deeply grateful for their time, wisdom, candor and in-depth review of the FAVA report. In addition to the TAC, I also thank other reviewers of the report: Drs. Walter Schmidt and Tom Scott (FGS) and Dr. Gary Raines (US Geological Survey, Reno, NV).

Dr. Raines is the co-developer of the Weights of Evidence (WofE) Spatial Data Modeler on which the FAVA maps are based. With support from his agency, Dr. Raines traveled to Tallahassee three times: first to teach the FAVA team in use of the WofE extension, which includes fuzzy logic modeling, second to participate in a FAVA TAC meeting, and third to work closely with the FAVA team as we addressed the finer points of the model. Sincere appreciation is extended to Dr. Raines, who has been a gracious and effective teacher and supporter of the project.

As mentioned earlier, the acknowledgements above are written on behalf of all authors of this report. Although perhaps unconventional, I also wish to acknowledge my co-authors with sincerity and utmost respect. Whether it involved data mining, data-coverage generation, or developing FAVA model outputs, every member of this team played a large and critical role toward completion of the project. I regret that it is not possible to list multiple "first authors" for this report. Andrew Rudin supervised GIS staff and led the development of the DEM, which was an immense and critical undertaking that involved editing and attribution of hundreds of thousands of contour lines. I appreciate Andrew's hard work and pleasant demeanor.

I often describe the other co-authors, Alan Baker, Jim Cichon and Alex Wood as my "three right arms" in this project and I deeply appreciate their diligence and determination as they developed supporting data coverages and the three aquifer vulnerability models presented herein. Alex, Jim and Alan are the type of employees/researchers that every scientific supervisor wishes they could clone. These three individuals are adept as GIS analysts and as hydrogeologists. Their competitive spirit, attention to detail and self-motivation created a synergy that helped FAVA far exceed original expectations and become a reality. As these three individuals move on from the FGS to try their hand in the private sector and I wish them every success with their new company, Advanced GeoSpatial Incorporated.

-Jon Arthur

## INTRODUCTION

Ground water is one of the most important and sensitive components of Florida's dynamic ecosystems. It is present throughout the framework of Florida's natural systems from deep underground to just below land surface. More than 700 springs that are known to exist in Florida are vivid examples of ground water flowing into surface water bodies (Scott, 2004). Less obvious, but equally important are surface-water – ground-water interactions occurring beneath dry uplands, and in lakes, rivers, streams, and along the coast. Regardless of where ground water exists and flows, it plays a major role in ecosystem health and almost every aspect of our lives.

In Florida, we depend on ground water for domestic, municipal, agricultural, recreational and industrial needs. The average Floridian uses more than 140 gallons of ground water per day (Solley et al., 1995; U.S. Census, 2005) and more than 90% of Florida's drinking water comes from ground water (Berndt et al., 1998). With the population of Florida growing at a rate of almost 900 people per day, demands on this resource continue to intensify. Human activities can degrade ground-water resources and it has required enormous effort to mitigate the damage. To ensure the sustainability of Florida's ground-water resources, a balance between human needs and environmental needs is essential.

Due to Florida's hydrogeologic setting, all of Florida's ground water is vulnerable to contamination. In fact, this statement, in a more broad sense, is considered the "First Law of Ground Water Vulnerability" by the National Research Council (NRC, 1993) which states: "All ground water is vulnerable." Furthermore, the NRC defines the phrase "ground-water vulnerability to contamination" as the tendency or likelihood for contaminants to reach a specified position in the ground-water system after introduction at some location above the uppermost aquifer. In this report, we adopt a similar definition of aquifer vulnerability: *the tendency or likelihood for contaminants to reach the top of the specified aquifer system after introduction at land surface based on existing knowledge of natural hydrogeologic conditions*.

Although many hydrogeological characteristics naturally protect Florida's ground-water resources, variations in these characteristics are also the reason some areas are more vulnerable than others. Natural processes or human activities can introduce contaminants to ground water either through pollution of surface-water bodies or by infiltration through soils and sequences of sediments and rocks that overly Florida's aquifer systems. Sinkholes, lack of overlying confinement, and permeable soils are a few characteristics that can increase the likelihood of contaminants (i.e., from runoff) entering an aquifer system. On the other hand, low-permeability soils and thick clay-rich sediments overlying an aquifer system help protect it from contamination introduced at land surface. Biological, chemical and physical aspects of plants, soils, sediments and rock units also help limit the types and amounts of contaminants reaching the subsurface aquifer systems.

Recognizing the ubiquitous vulnerability of Florida's aquifer systems, the Florida Aquifer Vulnerability Assessment (FAVA) was developed to identify areas of relative aquifer vulnerability based on the local hydrogeologic setting. Specifically, the FAVA project was designed to provide a detailed distribution of relative vulnerability which is based solely on natural properties of Florida's hydrogeology and does not include anthropogenic factors such as land use and contaminant loading (Maddox and Arthur, 1996). Technically, this approach defines the FAVA project as an estimate of intrinsic vulnerability because it includes only the physical factors affecting flow and does not include natural and human sources of contamination or behavior of specific contaminants (Focazio et al., 2003).

The primary goal of the FAVA project is to provide a scientifically defensible water-resource management and protection tool that will facilitate planning of human activities to help in minimizing adverse impacts on ground-water quality. More specific applications of the FAVA project include well-head protection, source-water protection, watershed and ecosystem comprehensive planning, land-use planning/zoning, land conservation and as a component of ground-water susceptibility models. These models, unlike vulnerability (as defined herein), address movement of a contaminant through the ground-water flow system. Results of the FAVA project also serve as valuable educational resources to promote stewardship of Florida's ground water and aquifer systems.

The FAVA project is not the first science-based resource designed to serve as a tool for evaluating ground-water contamination potential. In 1985, the U.S. Environmental Protection Agency (EPA) and the National Water Well Association (NWWA) developed a method to estimate the contamination potential of ground water by incorporating various components of the natural hydrogeologic system. This model, known as DRASTIC (see *Introduction – Background – Previous Studies* for more information), was an important first step toward a resource protection tool designed to identify areas of relative vulnerability.

DRASTIC was developed as a nationwide model, and as such, it has limitations when applied to more localized areas of the country with relatively unique hydrogeologic settings. For example, in Florida, use of the DRASTIC model placed an overemphasis on topography and did not account for the significant role of karst features in aquifer vulnerability. Karst features, such as sinkholes, often function as uninhibited shortcuts for contamination to enter an aquifer system and therefore should be an essential input into any aquifer vulnerability assessment in Florida. Moreover, DRASTIC maps were based on a subjective ranking method, generally highly-variable data quality, and the resulting scores yielded sharp angular boundaries that generally did not reflect natural conditions (Figure 1).

Implementation of DRASTIC began in Florida in 1986, which pre-dated readily available geographic information systems (GIS). DRASTIC was initially put into practice by utilizing paper map overlays and was later converted for use in a GIS platform in 1998 with the DRASTIC index values and weighted scores included in the data attribution. DRASTIC index values range from 1-276 and higher values indicate areas of higher aquifer vulnerability. In several studies completed more recently, the DRASTIC method has been applied to take full advantage of the GIS platform (see *Introduction – Background – Previous Studies*). The FAVA method was specifically designed for the GIS platform, which facilitates calculation and management of highly complex and resolute data. This platform also allows the achievement of three requisite objectives of the FAVA method, which are that the model be scalable, updateable, and flexible. The GIS platform allows the combination of a series of input data layers within a statistical model to yield a derivative output map that represents predicted areas of relative aquifer vulnerability.

Attempts to develop a predictive tool such as the FAVA method have been limited by the availability of data upon which the model was based. As one would expect, greater accuracy and higher resolution of input data layers allows for a more accurate and highly resolved output (i.e., map of relative aquifer vulnerability). The assumption was made that the input data were appropriate with respect to addressing the defined problem: where are Florida's aquifer systems most and least vulnerable to surface sources of contamination? Perhaps equally important to the process is that data layers should be consistently and continually developed, especially over such a large study area as the entire State of Florida.

It should be noted that significantly more detailed data layers can be generated at a local scale, such as a county or a springshed. For example, at the statewide scale, it was not time or cost-effective to

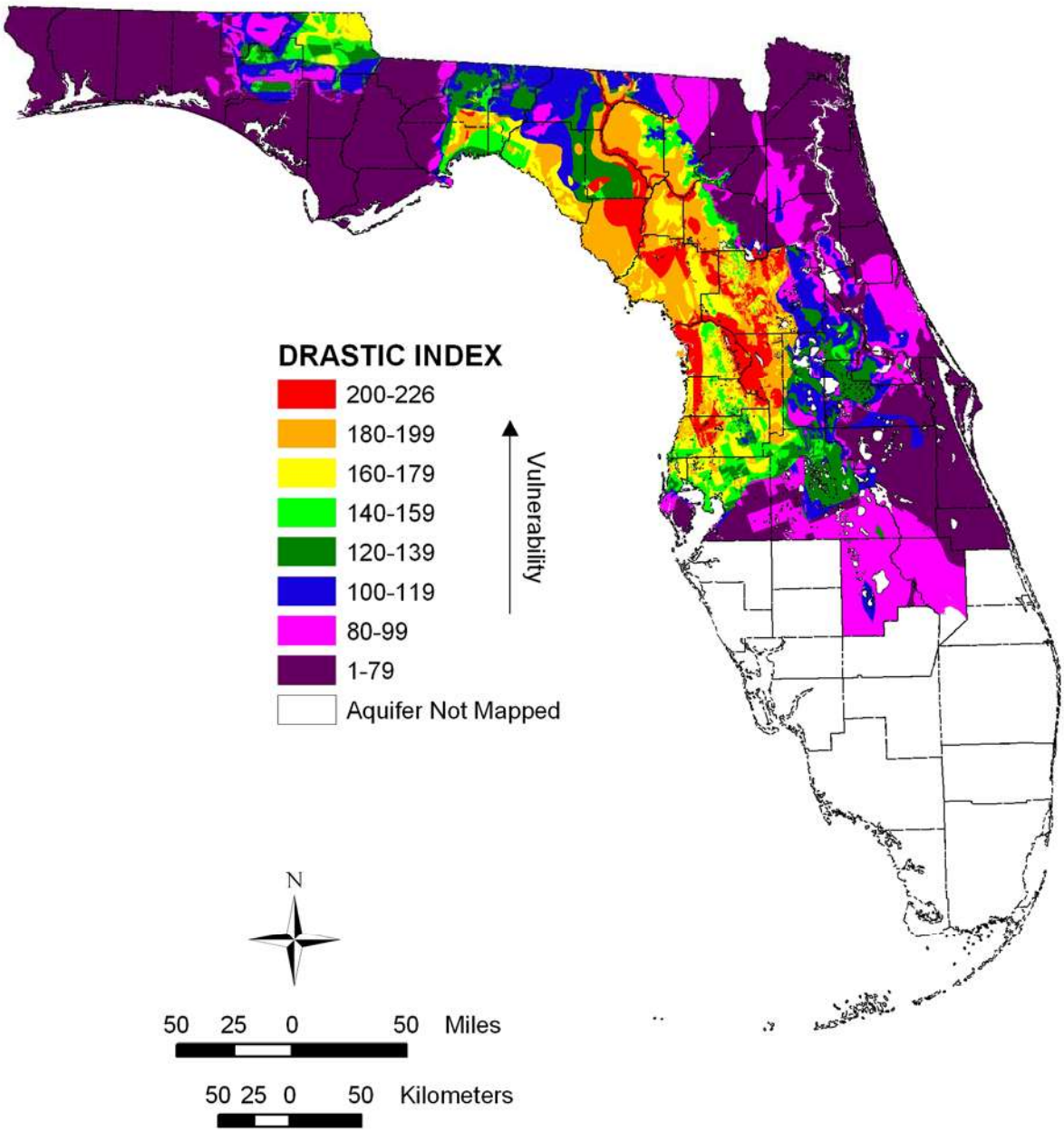


**Figure 1. DRASTIC map of vulnerability of the Floridan Aquifer System in Florida (Aller et al., 1985) designed to estimate the contamination potential of ground water by incorporating various components of the natural hydrogeologic system. The higher DRASTIC scores indicate areas of higher aquifer vulnerability.**

attempt to classify all topographic depressions (of which there are more than 200,000) into various karst types; however, this effort may not be cost-prohibitive at a local scale. Cave conduit maps and lineaments are other examples of input data layers that should be included in a local-scale FAVA project.

This report generally follows the FAVA project management plan. The *Introduction* describes background information, previous works, and the role of the Technical Advisory Committee (TAC). A description and assessment of each model considered for application in the FAVA project is also presented in the *Introduction*. Although only one model technique was ultimately selected and used for the production of the FAVA maps, the other modeling techniques were used as tools for validating the results. *Results* contains two major parts: 1) details regarding all data layers (even those used for validation purposes) developed as input for the FAVA project and 2) results of the modeling efforts (model output) for the three principal aquifer systems in Florida, which are, as defined by Southeastern Geological Society (1986), the:

- Surficial Aquifer System (SAS), including the Biscayne Aquifer in southeastern Florida and the Sand and Gravel Aquifer in the Florida panhandle,
- Intermediate Aquifer System (IAS) where it forms a major regional aquifer system in southwestern Florida, and,
- Floridan Aquifer System (FAS).

In the *Discussion*, model validation is presented along with *Application of the FAVA Maps*, perhaps the most important part of this report aside from the FAVA maps themselves. Due to the statewide focus of the FAVA project, application of the results at a local scale should be carried out with caution. FAVA maps are predictions based on statistical probability and should be used only as a guide for relative vulnerability, but not as a definitive statement of vulnerability at a site-specific location. Although FAVA maps were developed in an attempt to reduce uncertainty regarding aquifer vulnerability, only site-specific hydrogeologic data and interpretation by a licensed Professional Geologist can be used to provide site-specific information on contamination potential of the aquifer system(s) on a local basis.

## Background

### Previous Studies

Aquifer vulnerability models generally fall into four categories: index models, simulation models, statistical (i.e., probabilistic, experimental) models and hybrid models (Metz, 1993; NRC, 1993; Bonham-Carter, 1994; Rupert, 1997; Rupert 1999; Focazio et al., 2002). A fifth more qualitative technique involves the subjective comparison of hydrogeological characteristics of a given area. Index models combine spatial data layers (i.e., maps showing different parameters) by calculating a weighted score. Simulation models are used to consider the role of hydrologic and hydrogeologic processes such as transport and dispersion. Multivariate methods, fuzzy logic, and probability analyses are among the statistical group of models. Hybrid models, as the name implies, comprise a combination of these other methods.

Another aspect of aquifer vulnerability modeling pertains to the source of information on which the model is based. In this regard, the model is either considered knowledge driven or data driven. Knowledge-driven models (also known as “expert” models) rely on expert scientific opinion, insight and perhaps even anecdotal information, whereas data-driven models are based on measured observations. This section highlights a few of the many publications that have addressed aquifer contamination modeling.

Perhaps the most widely known and applied index model is the DRASTIC model (Aller et al., 1985), which was developed in a cooperative effort between the EPA and the NWWA. This ground-water vulnerability assessment tool allows application of hydrogeological characteristics to produce an index score of aquifer vulnerability to contamination from land surface. The components of DRASTIC include: Depth-to-water table, net Recharge, Aquifer media, Soil media, Topography, Impact of the vadose zone, and hydraulic Conductivity of the aquifer.

Wurm (1992) used the DRASTIC method in Ohio to assess the relative vulnerability of a confined aquifer. Merchant (1994) provided a critical assessment of the DRASTIC method where he not only made recommendations for improvements to the DRASTIC model, but also reviewed methods of utilizing GIS in its implementation. Navulur et al. (1995) evaluated the vulnerability of aquifers to non-point source pollution. They analyzed soils data in a GIS platform using both DRASTIC and the SEEPAGE (System for Early Evaluation of Pollution potential of Agricultural Groundwater Environments) index model. The models were modified to include land use and fertilizer application data layers. Results were validated using known locations of nitrate contamination. Navular et al. (1995) recognized the strength of their modified method at the smaller scale and recommended that more detailed simulation models such as Groundwater Loading Effects of Agricultural Management Systems (GLEAMS; Leonard et al., 1987) be applied at the field scale.

Rupert et al. (1991) developed a map of aquifer vulnerability in Idaho using a modified form of the DRASTIC method which depended upon only three of the seven DRASTIC parameters: depth-to-water, net recharge, and soil media. Rupert (1997) later used a point rating scheme for measured nitrite plus nitrate as nitrogen ($NO_2$+$NO_3$–N) in ground water to calibrate the DRASTIC mapping technique based on statistical correlation between $NO_2$+$NO_3$–N concentrations, land use, soils, and depth-to-water table. Calibration of this method and an overall summary is presented in a U.S. Geological Survey (USGS) Fact Sheet (Rupert, 1999). Witkowski et al. (2003) coupled a DRASTIC index approach with MODFLOW to assess aquifer vulnerability as defined herein plus some degree of transport within the aquifer. During MODFLOW calibration, recharge, hydraulic conductivity and flow velocities in the aquifer were determined, and then applied in the index model to produce a vulnerability map.

As mentioned in the *Introduction* of this report, one of the shortcomings of the DRASTIC model in limestone terrains pertains to a lack of consideration of karst processes, which are very significant hydrogeologic features in Florida. Doerfliger et al. (1999) developed a weighted-index, GIS-based method called EPIK. This approach utilizes the following parameters: epikarst, protective cover, infiltration conditions and karst network development. Potential refinements could be made to this method, such as characterization of the cation exchange capacity of soils in the protective cover, or further characterization the epikarst with tracer tests and geophysics; the EPIK method, however, is a valuable resource for delineating ground-water protection zones.

At least three qualitative vulnerability assessments have been completed in Florida. A statewide map of recharge to the Floridan Aquifer System (Stewart, 1980) can be considered a surrogate for relative aquifer vulnerability (and vice versa). Recharge areas delineated in his study were generally based on regional observations of potentiometric surfaces, depth to the aquifer, confinement thickness and karst. Beck and Jenkins (1988) provide a subjective estimation of ground-water pollution potential based on hydrogeologic characteristics including karst, surface drainage, and types of overburden. They utilized an Environmental Geology Map Series published by the Florida Geological Survey [FGS (see *Results – Data Coverages – Environmental Geology* for more information and full reference)] delineated areas of vulnerability into 11 major classes divided into two groups to distinguish between internally drained areas and areas that were drained by surface water.

A statistical method for assessing aquifer sensitivity/vulnerability within a glacio-hydrogeologic system was conducted by Chidester (1993). Nolan (2001) applied logistic regression to USGS National Water-Quality Assessment data to assess aquifer susceptibility to contamination. He reported that the most significant factors contributing to nitrate contamination of ground water in the United States are: 1) nitrogen fertilizer loading, 2) percent cropland/pasture, 3) population density, 4) percent well-drained soils, 5) depth to minimum water table, and 6) presence/absence of fracture zones within an aquifer. Bekesi and McConchie (2000) conducted an empirical assessment of vulnerability in the vadose zone. Their models focused on sorption capacity within geologic media comprising the unsaturated aquifer. An R-mode factor analysis was used by Lawrence and Upchurch (1982) to associate water-quality analytes in terms of processes affecting aquifer recharge. The resulting factors were attributed to regional carbonate dissolution, localized dissolution and ion exchange in confining sediments, and land use. Dixon et al., (2001) are among researchers applying a neural network approach to predicting vulnerability with an emphasis on soil structure.

Use of GIS to predict ground-water vulnerability to pesticide contamination was accomplished by Tim et al. (1996). Their study was driven by a need to combine an integrated and interactive modeling system entirely within a GIS platform. Hoogeweg and Hornsby (1998) developed an interactive GIS-based simulation model called SEAMS (Soil, Environmental, and Agricultural Management Systems). This program allows for the estimation of pesticide risk to the ground water beneath application sites by combining digitized soil data, pesticide fate, toxicity data, cultural practices, and weather data. Other simulation models, which some may also consider hybrid models, include the works of Stewart and Loague (2003), Connell and van den Dale (2003) and Huaming and Wang (2004). This cross section of studies underscores the diversity in approach and scale of vulnerability mapping. Processes that are included in these modeling/mapping efforts address sorption, advection-dispersion, recharge, leaching potential and contaminant degradation (and non-degradation).

Another approach to ground-water vulnerability mapping emphasizes point-source versus non-point-source contaminants. These contaminant-specific studies are considered "specific vulnerability" assessments (NRC, 1993). For non-point sources, Roux et al. (1986) address pesticides, Sauriol (1982) evaluates the effects of septic systems, Edmunds and Kinniburgh (1986) and Holmberg et al. (1987) both focus on acid deposition, and Carter et al. (1987) address nitrates. Point-source studies include LeGrand (1983), who developed a vulnerability mapping technique to evaluate landfills, while DeSmedt et al. (1987) and Porcher (1988) developed vulnerability mapping for use with both point and non-point sources of pollution.

### Laws of Ground-Water Vulnerability

In 1993, the NRC (1993) presented three laws of ground-water vulnerability: 1) all ground water is vulnerable, 2) uncertainty is inherent in all vulnerability assessments, and 3) the obvious may be obscured and the subtle indistinguishable. As noted above, the first law was adopted earlier in this section of the report. The second and third laws are hereby adopted for application of the FAVA method as well. These laws underscore the basic principals regarding application of FAVA maps for environmental decision making (see also *Discussion – Appropriate Use of FAVA Maps*).

The NRC (1993) also presented six vulnerability assessment case studies (including Florida) to provide examples of the diverse techniques available and the factors that influenced the selected method for assessment. The NRC offered ways to understand the inherent substantial uncertainties in various vulnerability assessment methods and provided implementation recommendations for policy-makers and managers. Similarly, Focazio et al. (2002) presented common approaches used to determine ground-water vulnerability. The authors present examples of ground-water vulnerability

modeling approaches with a focus on hydrogeological processes as well as ways to assess scientific defensibility of assessments.

## APPROACH

The FAVA project was initiated after a series of meetings within the Florida Department of Environmental Protection (FDEP) on the subject of recharge protection and aquifer vulnerability in Florida. The name FAVA was introduced and adopted at a meeting of the FDEP Aquifer Vulnerability Subcommittee of the Recharge Protection Committee in April, 1995. As the FAVA project began at the FGS, several key issues were identified and addressed during the early stages of project management. These included: stating the problem, identifying the end users of the model, data gathering and processing, prioritization of data refinement, addressing data scale, data resolution and quality issues, model assessment and selection, and model validation.

An important goal of the FAVA project was to model or estimate the natural vulnerability of Florida's aquifer systems to contamination from land surface. In other words, the FAVA project is a pre-development model and the results do not take into consideration different land uses or altered natural systems (i.e., soil alteration, or cones of depression). As a result, the use of pre-development data for input into the model was appropriate. For example, when estimating the difference in hydraulic head between the water table and the FAS, a map of the predevelopment potentiometric surface was used (see *Results – Hydraulic Head Difference between Water Table and Floridan Aquifer System* for more information).

The initial phase of the project involved identifying all spatial data potentially relevant to aquifer vulnerability in Florida. These data were evaluated in terms of availability, accuracy, format, consistency, statewide coverage and source. During this data acquisition and evaluation phase, it became apparent that most of the relevant spatial data layers (i.e., GIS coverages) were 1) not readily available, 2) less accurate than desired, 3) had poor resolution, or 4) required patching data together from disparate sources of different scales and resolutions. Additional data coverage issues pertained to how to address missing data, and how to apply the data (i.e., what is being asked of the data).

The USGS 30-meter (m) horizontal-resolution digital elevation model (DEM) is one example where these attributes were recognized. Numerous differences exist between the USGS DEM and the USGS 7.5-minute quadrangle maps, many exceeding 50 feet. For the FAVA project, accuracy of a DEM was of paramount importance in the development of model input data coverages which were based on land-surface elevations including: thickness of IAS, thickness of overburden sediments on IAS, closed topographic depressions and water-table elevation. To develop a seamless statewide, highly-accurate topographic coverage, significant resources were dedicated toward development of a new statewide FDEP DEM at the resolution of USGS 7.5-minute quadrangle maps (see *Results – Data Coverages – Topography*).

Another example of where these attributes were recognized was the IAS thickness map. Although some IAS thickness maps have been published for parts of the State, the raw data upon which the maps were based was not readily available. Moreover, significant and irresolvable edge-matching problems occurred upon attempting to splice these maps together. As a result, another priority of the FAVA project was to generate a new statewide thickness of confinement map (see *Results – Data Coverages – Intermediate Aquifer System thickness*) based on data in the FGS lithologic database. A similar scale effort was dedicated to the development of the water-table elevation coverage (see *Results – Data Coverages – Water-Table Elevation*).

Data sources for all water-quality and spatial data used in the FAVA project are listed in Table 1 (Specific publications are referenced in *Results*). Considerable effort was made to standardize these data across agency formats and measures for quality control were implemented. As all data types were accumulated, evaluated and refined for application in the FAVA project, data and file management became a priority, as well as the data sources and related information. Extensive metadata were recorded for the input data layers used to develop the final FAVA output data layers. *Appendix I* provides an example of metadata for the new FDEP DEM, which was developed at the FGS in cooperation with the Division of Water Resource Management (DWRM) at the FDEP and Florida's water management districts. Metadata for other coverages used in the FAVA project will be available from the FDEP website (see http://www.dep.state.fl.us/gis/datadir.asp).

Throughout the development of the FAVA project, a policy of adaptive management was implemented. Part of this process involved the assembly and collective input from a multi-agency Technical Advisory Committee (TAC). FAVA TAC members (Table 2) participated alongside the FAVA research team (i.e., authors of this report) in four workshops, provided technical review of interim text and maps, and generally served as a sounding board as the project progressed. The TAC members were also points of contact for agency resources (i.e., GIS coverages and raw data). Expertise among TAC members included water quality, hydrologic modeling, hydrogeology and some contributed first-hand experience in development of the Florida DRASTIC model. As feedback from the TAC was received, "course corrections" in the data development and project plans were made.

Dr. Gary Raines of the USGS office in Reno, Nevada is a co-developer and expert in the use and application of the modeling technique used in the development of FAVA vulnerability maps. Dr. Raines generously provided his time and expertise throughout the entire development of this project. Dr. Raines made several visits the FGS office to guide the project, provide technical expertise and assist with the modeling. Dr. Raines provided invaluable support and feedback on the project and attended TAC meetings as well to provide input and assist in explaining the modeling technique to the TAC members.

As noted at the beginning of this section, one of the goals of the FAVA project involved identifying potential end-users of the FAVA maps. The FAVA research team was fortunate to include Shaun Ferguson, a part-time FGS staff member with expertise in planning and needs assessments. During his tenure on the FAVA project, Shaun completed a Delphi study, which was comprised of three surveys utilizing broad questions with open-ended answers, each building on the results of the prior survey. Many TAC members participated in the study. The goal of the Delphi study was to reach consensus regarding the FAVA approach, the relative benefits of the FAVA project as compared to DRASTIC, and FAVA end-product design (i.e., maps and scale). Among the many useful aspects of the Delphi study was this list of the most important features that should be included in the FAVA approach to make the final product more useful:

- Appropriate list of parameters
- Sensitivity of scale (e.g., GIS grid-cell size adequate to represent karst)
- Address and reduce uncertainties
- Well-documented methodology
- Easy to upgrade given future data
- Easy to comprehend
- Clarity in presentation of results
- Use of existing data

**Table 1. FAVA point and spatial data sources.**

| Name | Source |
|---|---|
| Wells and water-level data for water-table elevation | Florida Department of Environmental Protection (FDEP), Florida's Water Management Districts, U.S. Geological Survey (USGS) |
| National Hydrography Dataset (streams, lakes and coastline) | USGS |
| Soil Survey Geographic database | U.S. Department of Agriculture (USDA) Natural Resource Conservation Service (NRCS) |
| State Soil Geographic database | USDA NRCS |
| USGS 7.5-minute quadrangle maps | FDEP, Florida's Water Management Districts, USGS |
| Well core and cuttings samples | FDEP/Florida Geological Survey (FGS) |
| Potentiometric surface (predevelopment) | USGS |
| Physiographic provinces | FDEP/FGS |
| Geologic map of the State of Florida | FDEP/FGS |
| Environmental geology of the State of Florida | FDEP/FGS |
| Background Water Quality Monitoring Network well data | FDEP |
| Generalized Water Information System Database | FDEP |
| Land use data | Florida’s Water Management Districts; FDEP |

**Table 2. Members of the FAVA TAC and their associated organizations.**

| Name | Agency/Company |
|---|---|
| Rick Copeland | FDEP-FGS |
| Richard Deadman | Florida Department of Community Affairs |
| Rodney DeHan | FDEP-FGS |
| Eric Dehaven | Southwest Florida Water Management District |
| Mark Dietrich | FDEP |
| Tim Hazlett | Hazlett-Kincaid, Inc. |
| Jeff Herr | South Florida Water Management District |
| Paul Lee | FDEP |
| Gary Maddox | FDEP |
| James McNeal | FDEP |
| Multiple | USGS – Trudy Phelps, Nicolas Sepulveda |
| Tom Pratt | Northwest Florida Water Management District |
| Allan Stodghill | FDEP |
| David Toth | St. Johns River Water Management District |
| Sam Upchurch | SDII Global Corporation, Inc. |
| Warren Zwanka | Suwannee River Water Management District |

In general, Ferguson (2002) reported overwhelming agreement that the FAVA method, as being developed at that time, would be a significant improvement over the DRASTIC model. Moreover, he found that the FAVA project meets all criteria for scientific credibility as defined in the Delphi study; however, several "practical utility credibility criteria" at the time of the survey in 2001 were not yet achieved. FAVA researchers anticipate that this is primarily due to the timing of the survey, which was conducted when the FAVA project was two years from completion.

In a related assessment of end-user needs, a survey instrument was distributed at the 2001 Annual meeting of the Florida Chapter of the American Planning Association. Highlights of the survey results, based on the 37 respondents include: 1) 92% agreed that they would consider the FAVA project as a resource in their decision-making process, 2) 95% state that their agency or company uses GIS applications, 3) 86% preferred to be able to use the FAVA maps at a scale between 1:24,000 and 1:150,000; however, others agreed that regional and statewide scales would be beneficial, and 4) respondents agreed that to make the end-product more useful, data delivery (i.e., Internet and compatible file formats) and education/outreach opportunities (i.e., training workshops) are needed.

Model - A representation of reality used to simulate a process, understand a situation, predict an outcome, or analyze a problem. A model is structured as a set of rules and procedures, including spatial modeling tools that relate to locations on the Earth's surface.

– EPA Mid-Atlantic Integrated Assessment Program Glossary

**Models Considered**

Several models were evaluated as potential frameworks upon which FAVA maps would be constructed. To help guide the model selection process, the FAVA TAC assisted in the development of selection criteria. Similar in some ways to the Delphi study, the TAC recommended that the model should have the following characteristics:

- Easy to explain
- Meet identified end-users needs
- GIS format (scaleable, updateable and flexible)
- Scientifically-defensible results
- Results can be validated by geochemistry

Models considered for application in the FAVA project included the Aquifer Vulnerability Assessment Model (AVAM), Travel Time, Fuzzy Logic, and Weights of Evidence (WofE). In this section, these models are described and reviewed. Although only one model was selected as the basis for the FAVA method, the other methods were used as independent methods to validate the FAVA results. As a result, all methods initially considered for application are described and compared in this section.

Four Florida counties, selected for their diverse hydrogeological settings, were used as pilot areas for preliminary FAVA modeling. The pilot areas included Leon, Alachua, Hillsborough, and Polk counties. These counties were selected for use in determining which model technique would produce results meeting the goals of the FAVA project identified in the Delphi study and by the TAC. Preliminary data was used as input for these models as many of the data coverages were still under development at this stage of the project. It was considered important to select the FAVA model technique prior to completing the development of the final input data coverages because the type of model chosen would ultimately affect the types of input data required. Because preliminary data were used, pilot county model results were not included in this report as they were not directly comparable to final FAVA model results and did not provide any meaningful analysis. The TAC was instrumental in assisting the FAVA research team regarding assessment of preliminary model results developed for these counties.

### Aquifer Vulnerability Assessment Model

The Aquifer Vulnerability Assessment Model (AVAM) was the first post-DRASTIC method to be developed by Florida environmental managers at the State level. The method was generated by FDEP staff in the late 1990's based on a concept that improved DRASTIC by taking full advantage of a GIS platform. Additionally, AVAM was designed to use readily-available, statewide GIS data. Upon evaluation, however, the methodology was not used because, like DRASTIC, it was a knowledge-driven index-type model subject to bias. Many of the input layers were based on the Natural Resource Conservation Service (NRCS) soil surveys, including depth-to-water, leakance, permeability and clay content. The FGS Environmental Geology Map Series data (see *Results – Data Coverages – Environmental Geology* for more information) was also to be used as a layer. Although it was considered to be an improvement over the DRASTIC model, it was not without its share of concerns. For example, it was designed to run different models for the unconfined versus confined FAS. As a result, a county having both confined and unconfined FAS conditions would require two models. Results for the two different models would have varied greatly (i.e., have significant "edge effects"). Moreover, the model was to be calibrated for one county and then weights were to be applied to other areas with significantly differing hydrogeologic conditions. On the other hand, the development and design of AVAM helped lay the groundwork for implementing the FAVA project.

### Travel Time Model

The travel time model is based on a "top down" conceptual model of a confined aquifer system, where aquifer vulnerability is calculated as a measure of the time required for a contaminant at land surface to reach the saturated zone of the target aquifer. Although the approach was carefully planned and the concept is easy to understand, the methodology relies heavily on detailed vertical hydraulic conductivity data of the vadose zone, which is very limited in availability.

The travel time model was developed by Drs. Paul Lee and Jonathan D. Arthur based on the following parameters: geologic sediment thickness, estimated hydraulic conductivity of these sediments and a factor accounting for reduction of potential travel time due to the influence of karst topography. The travel time model is a stochastic estimate of aquifer vulnerability based on the following equation and the conceptual framework in Figure 2:

$$\text{Travel Time} = (T_s/K_s + T_{eg}/K_{eg} + T_{ias}/K_{ias}) * K_f$$

where:

$T_s$ is soil thickness
$T_{eg}$ is environmental geology thickness
$T_{ias}$ is IAS thickness
$K_s$ is soil hydraulic conductivity (weighted average)
$K_{eg}$ is environmental geology hydraulic conductivity
$K_{ias}$ is IAS hydraulic conductivity
$K_f$ is the karst factor

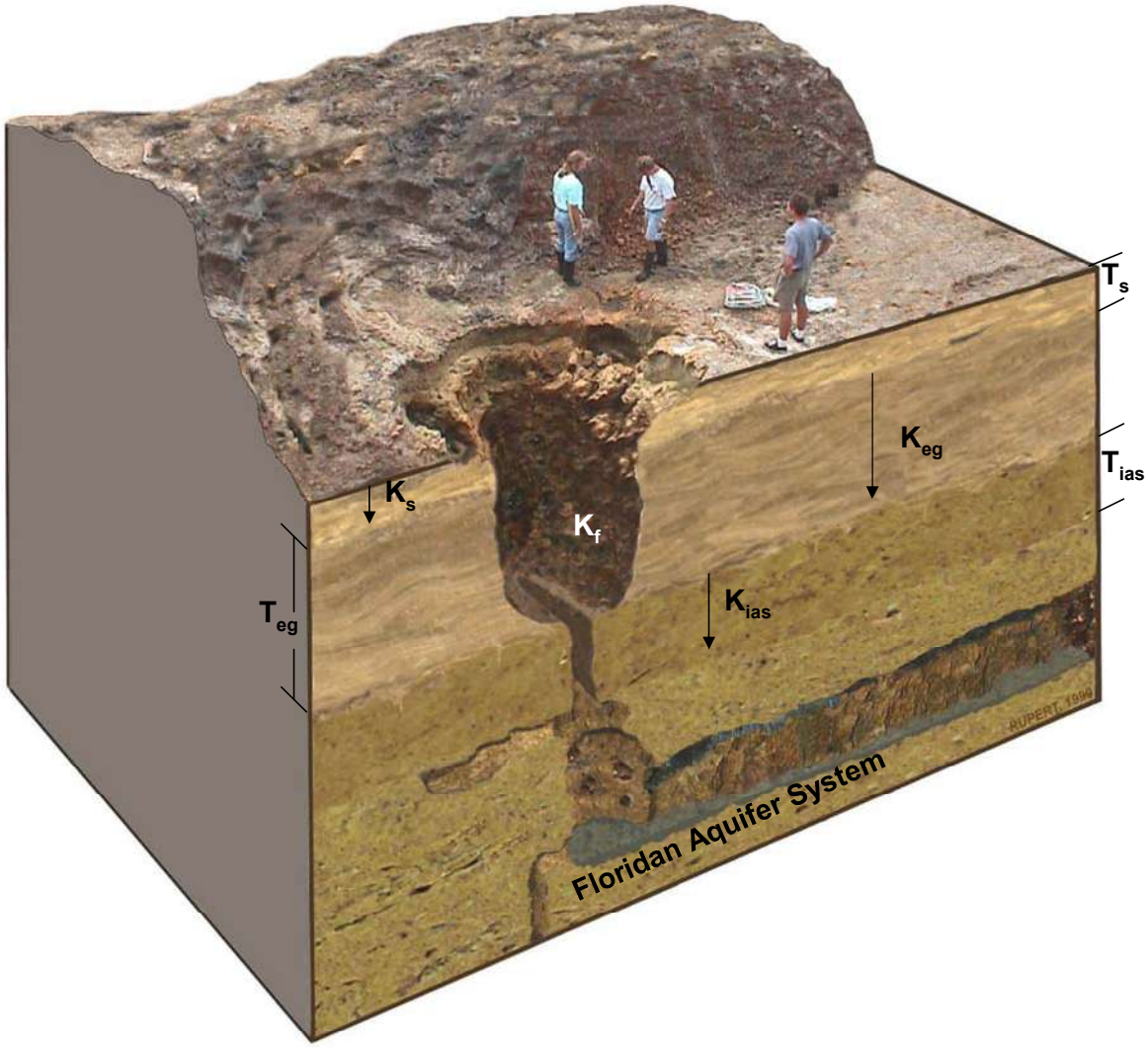


**Figure 2. Conceptual framework for travel time model where aquifer vulnerability is calculated as a measure of the time required for a contaminant at land surface to reach the saturated zone of an aquifer. This model uses geologic sediment thickness, estimated hydraulic conductivity of these sediments and a factor accounting for influence of karst.**

Sediment thicknesses applied in this model technique are obtained from the following sources:

$T_s$ NRCS SSURGO and STASTGO databases.

$T_{eg}$ Calculated difference between the bottom of the soil layer and the top of the IAS.

$T_{ias}$ Thickness of the IAS based on FGS well core and cuttings data.

The function of the $K_f$ is to decrease the calculated travel time if a sinkhole intersects the grid cell. $K_f$ represents the fraction of a grid cell area intersected by a topographic depression (i.e., sinkhole): [1 – (% Area * 0.01)]. If $K_f = 1$, then no topographic depression intersects the grid cell. If $K_f = 0$, then 100 percent of the grid cell includes a topographic depression.

The soil hydraulic conductivity values chosen for input into the travel time model came from the NRCS soil tables. The hydraulic conductivity values for environmental geology (i.e., lithotypes from the FGS Environmental Geology Map Series) and IAS input data layers represent average values for lithotypes based on Freeze and Cherry (1979). The FGS hydraulic conductivity database was also a source of data. The values chosen for the environmental geology and IAS layers were as follows:

| | |
|---|---|
| Limestone | $10^{-2}$ cm/sec |
| Medium fine sand and silt | $10^{-3}$ cm/sec |
| Clayey sand | $10^{-4}$ cm/sec |
| IAS | $10^{-5}$ cm/sec |

The major disadvantage in attempting to use the travel time method for FAVA was the lack of continuous, reliable hydraulic conductivity values for the IAS and environmental geology layers. In order to accurately develop a reliable input data layer representing hydraulic conductivity for these layers, it would have been necessary to generate a continuous statewide coverage of hydraulic conductivity. This was not feasible due to limited data availability concerning hydraulic conductivity. In addition, use of the hydraulic conductivity values listed above for each layer of geological material in the conceptual model was a gross oversimplification and did not accurately represent the natural system. For example, the FGS hydraulic conductivity database indicated that the value for limestone in Florida may vary from $10^{-3}$ to $10^{-8}$ cm/sec. As a result, the travel time model was not selected for use in the development of FAVA models; however, travel time model results were used for validation of FAVA pilot areas.

### Fuzzy Logic Model

Fuzzy logic is used to quantify conceptual processes because it emulates the flexibility of human reasoning by drawing conclusions from imprecise and incomplete information (Fang, 1997). This modeling technique is particularly useful when applied to evaluate fuzzy inputs because they tolerate imprecision and uncertainty and show marked reduction in information loss (Burrough et al., 1992).

Fuzzy logic is a model that takes into account expert scientific knowledge to relate datasets and their relative level of importance with respect to the desired output. Fuzzy set theory uses gradational membership values to characterize continuous data, where the membership values reflect the degree of truth of some pre-position.

Fuzzy logic is comparable to Boolean logic (e.g., “and” and “or”) because it addresses the concept of partial truths. The fuzzy logic model can be described as the process of assigning values to events using a gradational or continuous scale between 1 and 0, which represent true and false respectively. Fuzzy logic is an expert-driven progression in which the developer of the model assigns membership values based on their experience and knowledge of the data. Fuzzy set theory or fuzzy memberships address partial truths where 1 is full membership and 0 is full non-membership. For example, a partial truth using this method to define its membership can have a value of 0.8.

As an example, fuzzy membership assignment to the FAVA input data layer, “proximity to karst,” (see *Results – Data Coverages – Closed Topographic Depressions* and *Results – FAVA Model Outputs – Intermediate Aquifer System* and *Floridan Aquifer System* for more detail of karst as applied in FAVA) is provided. An area’s proximity to a karst feature is an important factor in determining its relative vulnerability. Distance to karst, for example, can be categorized into 100-m intervals and fuzzy logic can be used to assign values to those intervals. A value of 1 representing full

membership would be assigned to areas closest to a karst feature. Areas that are farthest away from a karst feature would be given a value of 0 to represent full non-membership. Values between would then be interpolated from 1 and 0 (Figure 3).

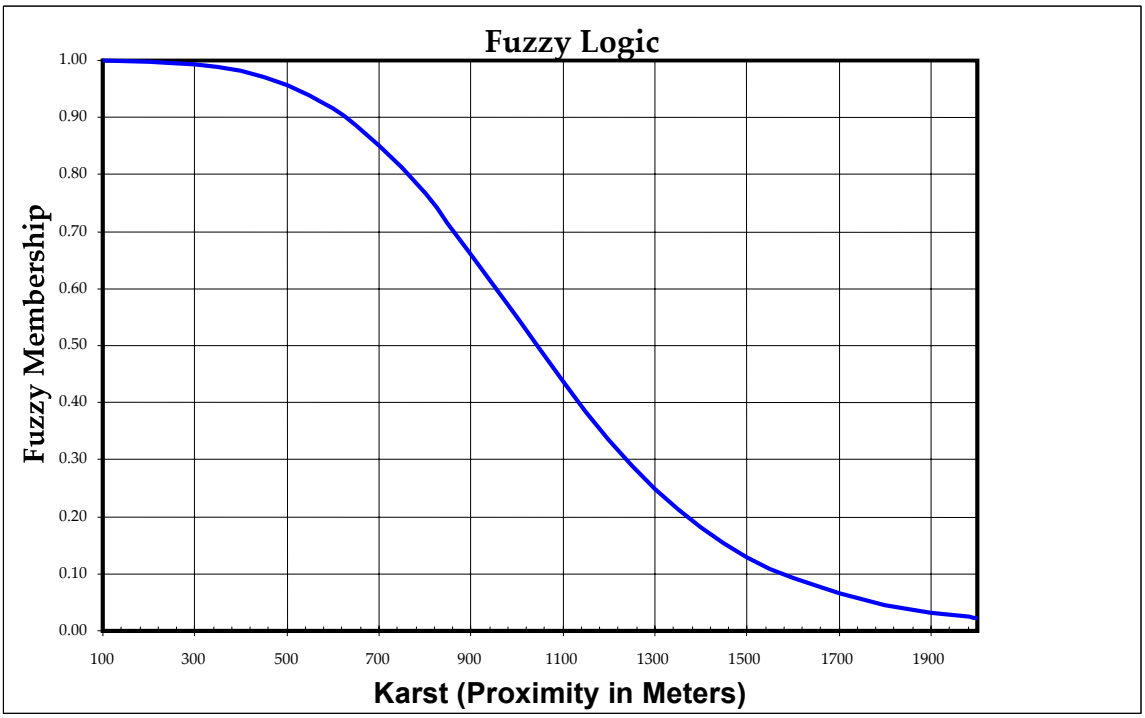


**Figure 3. Fuzzy membership values relative to "proximity to karst" where areas within 100 m of a karst feature represent full membership and areas located 2,000 m from a karst feature is full non-membership. Figure for informational purposes only, data not used in FAVA results.**

Two or more maps with fuzzy memberships can be combined using a variety of fuzzy operators. They can be combined in a relational sense using Boolean operators to calculate the new data layer. The operators include: AND, OR, ALGEBRAIC and GAMMA. Each one of these operators has very different effects on a set of values.

Fuzzy Operator AND

The fuzzy operator AND is used to combine input data layers resulting in a new data layer which is controlled by the smallest fuzzy membership value occurring at a given location. The AND operation is appropriate where two or more pieces of evidence for a hypothesis must be present together for the hypothesis to be true (Bonham-Carter, 1994). This conservative operation involves the intersection of a set of values for which only the smallest of the membership values for a particular location are considered:

Fuzzy AND operator

Minimum (value 1, value 2)

Minimum (0.8, 0.45) = 0.45

### Fuzzy Operator OR

The fuzzy operator OR involves the union of a set of values where maximum input data layer values control the output. The membership value in this case is limited by the best of the input data layers. It should be noted that both the operators AND and OR assign values for the new data layer from only one of the input data layers:

Fuzzy operator OR

Maximum (value 1, value 2)

Maximum (0.8, 0.45) = 0.8

### Fuzzy Operator ALGEBRAIC (SUM & PRODUCT)

The fuzzy ALGEBRAIC operator comprises SUM and PRODUCT (PRD) functions. The fuzzy ALGEBRAIC operator SUM is an increasing association between two input data layers where two pieces of evidence that favor a hypothesis strengthen each other. The combined evidence is more supportive than the input data layers are individually and the new data layer is greater or equal to the largest contributing membership value:

Fuzzy SUM operator

$$1 - [(1 - \text{value } 1) * (1 - \text{value } 2)]$$

$$1 - [(1 - 0.8) * (1 - 0.45)]$$

$$1 - [(0.2)(0.55)]$$

$$1 - (0.11) = 0.89$$

The fuzzy ALGEBRAIC operator PRD is the decreasing association between two input data layers and is calculated by multiplying the fuzzy values to produce a new data layer. Because fuzzy input data layer values will be between 1 and 0, when these values are multiplied to produce a new data layer, their product will be equal to or lesser than the input data layer values. An example is below:

Fuzzy PRD operator

(value 1 * value 2)

(0.8 * 0.45) = 0.36

### Fuzzy Operator GAMMA ($\gamma$)

The gamma operation is a combination of the ALGEBRAIC PRD and the ALGEBRAIC SUM where the $\gamma$ is a parameter in the range of (0, 1). The function is defined as the fuzzy ALGEBRAIC SUM factored by $\gamma$, multiplied by the fuzzy algebraic PRD factored by 1- $\gamma$.

$$\text{GAMMA} = (\text{Fuzzy algebraic SUM})^{\gamma} * (\text{Fuzzy algebraic PRD})^{1-\gamma}$$

When the $\gamma = 1$ the outcome of the operation is the same as the ALGEBRAIC SUM, when $\gamma = 0$ the outcome is the same as the ALGEBRAIC PRODUCT. A $\gamma$ value between 0 and 1 allows for variable compromises between the SUM and PRODUCT outputs. For example, if $\gamma = 0.7$ with the combination of (0.8, 0.45), the result equals 0.677. In this example the combination of the two grids decreases the output. Conversely, using a $\gamma = 0.9$ to combine the two layers using (0.8, 0.45) yields 0.813, which increases the association between the two layers. These examples are shown below:

If $\gamma = 0.7$,

and results from Fuzzy SUM and Fuzzy PRD

calculated above (0.89 and 0.36) are used, then:

$$[(0.89)^{0.7} * (0.36)^{1-0.7}]$$

$$[(0.92) * (0.74)] = 0.677$$

If $\gamma = 0.9$, then

and results from Fuzzy SUM and Fuzzy PRD

calculated above (0.89 and 0.36) are used, then:

$$[(0.89)^{0.9} * (0.36)^{1-0.9}]$$

$$[(0.90) * (0.90)] = 0.813$$

Fuzzy logic modeling technique was employed in the development of the IAS FAVA model to generate one of the input data layers (see *Results – FAVA Model Outputs – Intermediate Aquifer System*). Fuzzy logic was also used during the development of the FAVA project to help validate output data layers from other model techniques. This method was not used, however, in the calculation of the final FAVA output data layers for any of the aquifer systems because it is a knowledge-driven model technique. Further, this model did not meet the first model technique selection criteria of being easy to explain.

### Weights of Evidence Model

Use of the Weights of Evidence (WofE) modeling technique involves the combination of diverse spatial data that are used to describe and analyze interactions and generate predictive models (for a detailed discussed of this statistical modeling technique see Bonham-Carter, 1994 and Raines et al., 2000). WofE is a data-driven process that utilizes known occurrences as model *training sites* to create maps from weighted continuous input data layers. These input data layers, known as *evidential themes*, are then combined to yield an output data layer (or result of the model), known as a *response theme* (Raines, 1999). WofE was adapted to mineral potential mapping in a GIS and is based on the application of Bayes' Rule of Probability, with an assumption of *conditional independence* (Raines et al., 2000). Although Bayesian theory has been applied to ground-water related issues in recent years (e.g., Soulsby et al., 2003; Meyer et al., 2003; and Feyen et al., 2004), the specific application of WofE to ground-water issues is very limited to date (Cheng, 2004). See also *Appendix I – Glossary* for more information on WofE terms.

When applied in the FAVA project, WofE was used to generate aquifer vulnerability response themes (expressed in probability maps). These response themes were generated in the Environmental Systems Research Institute (ESRI) ArcView 3.x environment. WofE was executed using the Arc Spatial Data Modeler (ArcSDM) which is available free of charge as an internet download (Kemp, et al., 2001). ArcSDM is also available to implement in the ESRI ArcGIS software suite. Versatility of the WofE model is demonstrated by its ability to utilize data inputs resulting from other numerical and modeling techniques such as fuzzy logic. The fundamental approach and basic nomenclature of WofE is described in the following sections.

### Study Area

The initial step in implementing a WofE model is the identification and delineation of a study area extent (i.e., aquifer system areal extent). This is a critical step because the area identified is used in the calculation of weights and probabilities throughout the modeling process.

### Training Sites Theme and Prior Probability

Training points are locations of known occurrences. In mining applications for example, existing mines are known occurrences. In an aquifer vulnerability assessment, wells with water quality indicative of high recharge are potential known occurrences. Training points are used in WofE to calculate the following parameters: *prior probability*, weights for each *evidential theme*, and posterior probability of the *response theme*. The italicized terms are defined below, and in *Appendix I – Glossary*.

Training points are converted to represent a unit area of the study area, such as a grid cell within a GIS application. The prior probability is calculated by dividing the training point unit area by the total study area and represents the probability that a training point will occupy any given unit area within that study area, independent of any evidential theme data. In less complex terms, the prior probability is based on prior knowledge of the problem without the benefit of supporting evidence. In the mining example, prior probability could be described as the proportion of known deposits within the study area.

### Evidential Themes

An evidential theme is defined as a set of continuous spatial data that is associated with the location and distribution of known occurrences, i.e., training points. In GIS terms, an evidential theme is analogous to a data layer or coverage. Evidential themes in the mining example might include the location of hydrothermal ore deposits or proximity to faults. In the FAVA project, soil permeability and thickness of confinement are examples of evidential themes. Weights calculated in WofE establish spatial associations between training points and evidential themes. Depending on the data comprising an evidential theme, in order to deal with random processes and small number of training points, it may be necessary to reclassify the data into categories prior to analysis. This is completed by grouping large sets of data into fewer, more manageable categories that have statistical significance. For example, if an evidential theme consisted of a data layer of confining unit thickness divided into one-foot thickness intervals, it might be necessary to classify the data into 10 or 20 feet intervals to make it more manageable and statistically significant.

Weights are calculated for each evidential theme based on the presence or absence of training points with respect to the study area. A positive weight is calculated for areas that have more points than would be expected by chance; the weight is associated with occurrence of evidence. Conversely, a negative weight would be calculated for areas that have fewer points than expected; the weight is not associated with occurrence of evidence (or non-evidence). A weight of zero indicates that there is no association between training points and the evidential theme, or that the evidential theme is not a discriminating layer. In order for an evidential theme to be a valid WofE input, it must be a discriminating data layer and have statistical significance.

Weights can be calculated using three distinct methods: categorical, cumulative ascending or cumulative descending. The categorical method is used to calculate weights for evidential themes where the theme's values are not ordered (e.g., a geologic map). The cumulative ascending method is used to calculate cumulative weights in a proximity analysis. In this method, areas represented by smaller values of an evidential theme have a stronger association with training points, and those represented by larger values of an evidential theme have a weaker association with training points. Area and number of points are determined cumulatively from the first class to the last class. This method is applicable for themes where the points are mainly associated with the lower values of the evidential theme (e.g., confinement thickness). The cumulative descending method is used to calculate the cumulative weights from the last class to the first class in the opposite way of cumulative ascending. This method is applicable for themes where the points are mainly associated with the higher values of the evidential theme (e.g., soil permeability).

### Generalization of Evidential Themes

Generalization of evidential themes follows calculation of weights in the WofE modeling process. Themes are generalized in an effort to establish which areas of the evidence share a greater association with locations of training points. During calculation of weights for each evidential theme, a contrast value is calculated, which is a combination of the positive and negative weights (positive weight – negative weight) described above. Contrast is a measure of a theme's significance in predicting the location of training points and helps to determine the threshold or thresholds that maximize the spatial association between the evidential theme map pattern and the training point theme pattern (Bonham-Carter, 1994).

Confidence of the evidential theme is also calculated for each class, and equals the contrast divided by its standard deviation (a student T test) for a given evidential theme. Confidence provides a useful measure of significance of the contrast due to the uncertainties of the weights and areas of possible missing data (Raines, 1999). Also, a contrast value that is significant, based on its confidence, suggests that an evidential theme is a useful predictor of training points. A confidence value of 0.674 corresponds to a 75% level of significance (see Table 3). This confidence value was the minimum acceptable confidence level selected for the FAVA project evidential themes. Evidential themes that did not meet this test of significance were not included in the FAVA models. Confidence values approximately correspond to the statistical levels of significance listed in Table 3.

Following calculation of weights, contrast is used as a threshold to generalize or break evidential themes into categories. These breaks delineate which areas of the model study area have more association with the training points. The simplest and most common method of categorizing an ordered evidential theme is to select the maximum contrast as a threshold to determine where to place a binary break in the evidential theme data thereby creating two categories: one with stronger association with the training point theme and one with weaker association with the training point theme (see *Results – FAVA Model Outputs* for specific examples). In some cases, more complex

statistical contrast patterns are inherent in the data and may justify the creation of multiple classes in the evidential theme data. To create multiple classes, contrast thresholds must correspond to a 75% level of significance.

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

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

Response Theme

Following the generalization of evidential themes, WofE output results are generated and are known as response themes. A response theme is an output data layer showing the probability (posterior probability) that a unit area contains a training point based on the evidence (evidential theme) provided. Areas of higher posterior probability indicate that an area is more likely to contain a training point, whereas areas of lower posterior probability indicate that an area is less likely to contain a training point. For the FAVA project, a response theme can be a probability map that is displayed in classes of relative vulnerability based on selected water-quality analytes in training point wells.

A response theme table is generated during calculation of each response theme (Table 4) and contains a list of evidential themes and their respective weights, contrast and confidence (of the evidential theme generalized break). In general, a positive weight (W1) for an evidential theme indicates areas where training points are likely to occur, while a negative weight (W2) for an evidential theme indicates areas where training points are not likely to occur. Contrast is the difference between the highest and lowest weights and is a measure of how well an evidential theme predicts training points. Contrast is also used to rank the evidential themes. Higher contrast values indicate those evidential themes that best predict training point locations and which are more important in the model. For example, in the table below, Evidential Theme C was the best predictor among the evidential themes because it had the highest contrast and a relatively high confidence. Moreover, because the negative weight was stronger than the positive weight, Evidential Theme C was a better predictor of where

training points were not likely to occur (i.e., low vulnerability) as opposed to where they were likely to occur.

**Table 4. Sample response theme table generated during calculation of a response theme. W1 and W2 are weights calculated for the evidential themes, contrast is a combination of the two weights, and confidence equals the contrast divided by its standard deviation. Confidence provides a useful measure of significance.**

| Evidential Theme | W1 | W2 | Contrast | Confidence |
|---|---|---|---|---|
| Evidential Theme A | 0.7336 | -0.0529 | 0.7865 | 2.7967 |
| Evidential Theme B | 0.4794 | -1.1573 | 1.6367 | 7.0812 |
| Evidential Theme C | 0.2736 | -1.5470 | 1.8206 | 5.2923 |

Confidence of the evidential theme, as defined above, equals the contrast divided by the standard deviation (a student T test) for a given evidential theme. Confidence can also be calculated for each response theme by dividing the theme's posterior probability by its total uncertainty (standard deviation). This calculation produces a confidence map which allows the spatial display of confidence for the response theme and an assessment of the quality of the response theme.

### Conditional Independence

Validity of the posterior probability values is dependent upon the assumption that conditional independence is met, which is a calculation performed during execution of WofE. A conditional independence concern exists when the probability of occurrence of one evidential theme influences the occurrence of another evidential theme. An example of when conditional independence would fall outside this range would be if environmental geology (lithotypes) and geologic map units were used as evidential themes in the same model, because both of these datasets share similar characteristics. This occurred in the FAVA project during the development of two evidential themes for use in the IAS FAVA model (see *Results – FAVA Model Outputs – Intermediate Aquifer System* for further explanation).

The conditional independence ratio is calculated by taking the product of the sum of each unique condition's area (created by the intersection of all input evidence) multiplied by its corresponding posterior probability. This number equals the number of training sites predicted by each model. A ratio of the actual training sites used in the model versus the predicted points from the response theme is the conditional independence ratio. When conditional independence is violated it can cause the model to over-predict probabilities where map patterns overlap one another. Evidential themes were considered independent of each other for the FAVA project if the conditional independence value calculated was within the range 1.00 ± 0.15 (Raines, 2001). Values that significantly deviate from this range can over inflate the posterior probabilities resulting in unreliable response themes. A ratio of 1.00 indicates that the evidential layers used in the model are conditionally independent. Conversely, a ratio lower than 0.85 indicates that there is a conditional independence problem (Raines, 2001).

### Logistic Regression

As stated above, WofE assumes that conditional independence exists among evidential themes. When conditional independence problems do arise, yet there is expert-knowledge justification that the evidential themes do not produce circular reasoning, there are three solutions that can be employed to compensate for this and still produce usable WofE model results:

- Combine the evidential themes of concern into a single theme using one of several methods, such as fuzzy logic
- Present the WofE results (response theme) as a favorability map instead of a probability map
- Employ use of logistic regression

Utilizing fuzzy logic, one can combine "dependent" evidential themes into a single unitless evidential theme, which can then be input into the WofE model, thus representing both of the original evidential themes. This technique was employed in the development of the IAS FAVA map for the evidential themes IAS overburden and effective karst features (see *Results - FAVA Model Output – Intermediate Aquifer System* for a full discussion).

The second option is simply to recognize the WofE response theme as an output data layer reflecting "favorability" rather than probability. In a favorability map, the response theme pattern alone is used to report whether certain areas are more favorable or less favorable to contain a training point than others. The actual probability values calculated by WofE are not used because they over-predict the response (i.e. aquifer vulnerability).

The third option, logistic regression, is an optional function in the ArcSDM extension that can be used to account for the inflated probabilities associated with conditional independence problems. In WofE, the extension breaks down multi-class evidential layers into binary layers. Logistic regression is similar to linear regression; however, because the evidence is reduced into binary themes, the response variable can only be divided into two classes, (i.e., presence or absence of training points) whereas linear regression can have continuous values ranging from 0 to 1. WofE model results using logistic regression do not differ greatly from standard WofE model results. The main difference is that the posterior probabilities of a response theme with conditional independence problems are much higher when logistic regression is not used compared to when it is used. Overall, the patterns of the response themes case are extremely similar. In the FAVA project, logistic regression was used in the calculation of the response theme for the FAS because conditional independence problems did occur in this model (see *Results – FAVA Model Outputs– Floridan Aquifer System* for more information).

### Selected Primary Model Technique

Based on a comparison of the advantages and disadvantages of each model considered for application in the FAVA project, the WofE modeling technique was selected. Although WofE is not strong with respect to the "easy to explain" criterion, it has several advantages over the other models. For example, WofE is data-driven rather than knowledge-driven, the latter being more subject to experts' preconceptions. WofE is also the most empirical and the least subjective model of those being evaluated for this project. As noted above, WofE is used to calculate confidence (posterior probability divided by total uncertainty), which can be displayed spatially as a confidence map. Moreover, as presented in the *Discussion* section of this report, use of WofE facilitates post-modeling validation (see *Discussion – Model Validation Techniques*). Other models presented in this section were used during the FAVA pilot studies as sources of output comparison as well as initial validation.

In addition, some of the modeling techniques, such as Fuzzy Logic, have been used in combination with WofE to maximize the accuracy of the WofE modeling results.

As an example, the Wekiva River area was used as a sample study area to apply WofE to generate a response theme for the FAS (Figure 4). Four evidential themes were used: soil permeability, proximity to karst features, and thickness of confining sediments overlying the FAS, and hydraulic head difference between the water table and the FAS. The vertical lines in Figure 4 represent the location of training points, which are wells from which water samples exceed an established threshold (see *Results – Data Coverages – Training Points* for a full discussion). The bottom layer in Figure 4 is the response theme representing relative vulnerability with red areas representing the more vulnerable areas.

### Future Considerations

A fourth modeling technique under consideration is a hybrid between expert-driven fuzzy logic and a data-driven neural network. This technique uses neural network theory as another way of determining fuzzy membership rules. Neural networks "learn" from the associated spatial patterns of data layers by using exploratory problem-solving techniques. These models have the ability to address uncertainty and imprecise or incomplete data; however, many consider them "black box" in nature and they are difficult to explain and understand (Dixon et. al. 2001). As such, this modeling technique is not applied herein. The FGS, however, is currently funding research in this area.

## RESULTS

### Introduction

Prior to developing FAVA response themes for assessing relative aquifer system vulnerability, it was necessary to identify and develop data coverages to be used as evidential themes. The *Results* section of this report is therefore divided into two main parts: *Data Coverages* (potential evidential themes), and *FAVA Model Outputs* (response themes).

At the onset of the FAVA project, it became apparent that many good evidential theme candidates either did not exist or were not of sufficient detail to serve as model inputs. For example, although all water management districts have at one time generated maps of IAS thickness, no recent statewide seamless digital coverage was available. Of the existing maps, significant edge-matching problems occurred along district boundaries. Moreover, for nearly all of the available maps, data on which the maps were based were not readily available, and did not exist in a GIS format. As a result, a data coverage defining IAS thickness was created using FGS well coring and cuttings data. Significant effort was put forth in the development of other data coverages as well.

A requirement of data coverages which were considered as evidential themes for input into the WofE – FAVA model was that they:

- were relevant to hydrogeological processes that affect aquifer vulnerability,
- were well documented (i.e., GIS metadata), and/or published,
- covered the entire extent of the aquifer system being modeled,
- were consistently developed, and
- were of sufficient accuracy for use in a statewide model.

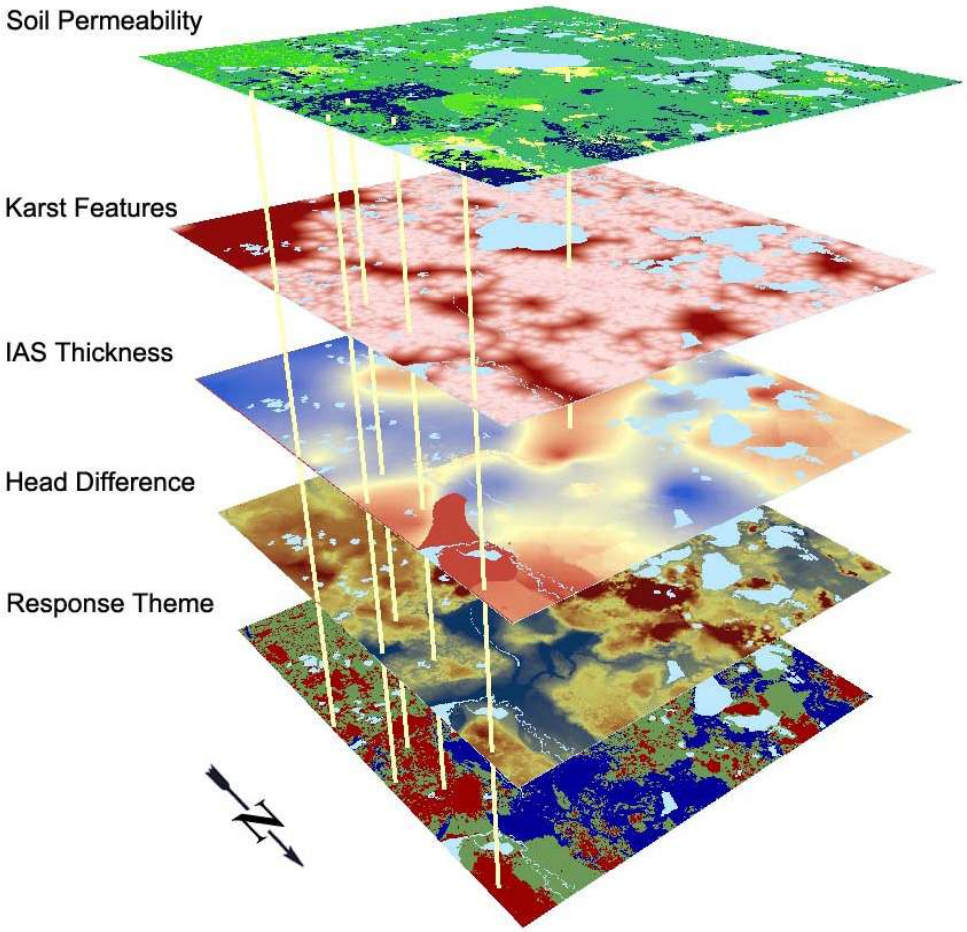


**Figure 4. WofE conceptual model of the FAS. The top four layers are evidential themes and the bottom layer is the response theme. Yellow lines represent training points (wells) projected throughout the layers. Red regions of the response theme indicate more vulnerable regions of the FAS whereas the blue areas are less vulnerable areas.**

"Not everything that counts can be counted, and not everything that can be counted counts."

– Albert Einstein

As the details of the WofE models for each aquifer system are introduced later in this section, it will become apparent that not all of the evidential themes presented herein were utilized in the final FAVA response theme development. There were two primary reasons for this approach. First, although significant effort was required to develop a specific evidential theme, the results of the WofE model may have indicated that this evidential theme correlated strongly with another evidential theme. This undesirable correlation contributed to inflation of the posterior probability of the response theme. Second, an evidential theme might have had no association with the training points, or the weights may have had no relevance from a hydrogeologic standpoint. The significance of all evidential themes may not generally be known until the weights are calculated using WofE. Once weights were calculated for the FAVA evidential themes, then "added value" of the evidential theme was determined. If the evidential theme was not a discriminatory layer and weights calculated using WofE were meaningless or not statistically significant, then it was not included in the final FAVA model.

The following data coverages were either used to develop evidential themes, or were themselves considered for use as evidential themes in the WofE – FAVA model:

- Soil permeability and drainage
- Topography
- Closed topographic depressions
- Water-table elevation
- IAS thickness and extent as a confining unit
- Overburden on the IAS
- Difference in hydraulic head between the water table and the FAS
- Geologic map of the State of Florida
- Environmental geology

## Data Coverages

### Soil Drainage and Permeability

The rate at which ground water moves through soil is an important factor with respect to ground-water contamination potential. As such, soils and their hydrologic properties are critical components of any aquifer vulnerability analysis, as soil is literally the aquifer system's first line of defense against potential contamination. Two main characteristics of soils were considered for use in the WofE – FAVA model: soil drainage and soil permeability. In more local studies, other soils properties, such as bulk density, may be useful evidential themes. To represent these soil characteristics in the FAVA model, continuous statewide digital GIS coverages of soils data were developed for the project.

Soils coverages and their corresponding data tables were obtained from two sources: Florida Geographic Data Library [FGDL (2003)] and U.S. Department of Agriculture (USDA) NRCS (2003). The data were downloaded from these agencies' respective internet websites (see *References* for full website addresses). The Soil Survey Geographic database (SSURGO), obtained from both FGDL (2003) and NRCS (2003) websites, consists of specific soils data modeled at a scale of 1:24,000. State Soil Geographic database (STATSGO), obtained from the FGDL (2003) website, consists of generalized soils data modeled at a scale of 1:250,000. For this project, SSURGO data were preferred over the STATSGO because of the more resolute scale at which the soils were modeled.

Digital SSURGO data were not available for the entire State at the time of this project. Counties that were still under review by the NRCS included Taylor, Washington, Holmes and Liberty. Furthermore, SSURGO data were unavailable for the Everglades area. For the FAVA project, the FGS used the 1:24,000 scale data from published county soil survey books to attribute soil drainage data tables for Washington, Holmes and Taylor counties (Huckle et al., 1965; Sullivan, 1975; Watts, 2000, respectively). Digital STATSGO drainage data were used for Liberty County and the Everglades area to complete the soil drainage coverage. Due to time and funding constraints, it was not feasible to attribute soil permeability data for the same regions; STATSGO permeability data were used for Washington, Holmes, Taylor, and Liberty counties and the Everglades area as a result. Areas for which no soils data were available included a number of urban areas. To compensate, a nearest neighbor GIS function was employed, which was used to apply spatial statistics (Euclidean distance functions) to predict soils data values for these areas.

### Soil Drainage

The USDA (2002) defines natural drainage classes as the frequency and duration of wet periods under conditions similar to those during which the soil developed. Alteration of the water regime through drainage or irrigation is not a consideration unless the alterations have significantly changed the morphology of the soil. The classes, as defined by USDA are as follows:

- Excessively drained
- Somewhat excessively drained
- Well drained
- Moderately well drained
- Somewhat poorly drained
- Poorly drained
- Very poorly drained

Soil drainage (Figure 5) was initially used as an evidential theme in the WofE – FAVA model for all aquifer systems; however, it was replaced with vertical permeability of soil (hereafter, soil permeability) for two important reasons. First, there were areas mapped as “poor” or “very poor” soil-drainage, whereas soil permeability for the same areas was listed as extremely high (e.g., 20 in/hr). These soil characteristics may occur in swamps underlain by coarse, sandy soils. Though the soils are considered permeable, water remains at or near the surface due to a high water table, causing characterization of the drainage as poor. In the SAS FAVA response theme, for example, areas with a high water table would appear to be less vulnerable, which could lead to misinterpretation and misuse of the FAVA model results. Second, there were occurrences where soil drainage for a specific area was listed as “excessively drained,” whereas the soil permeability was listed as very low (e.g., 1.8 in/hr) for the same area. This could occur on a hilltop underlain by clay-rich soils. Although water would be removed from this soil rapidly due to topographic relief, the soil is not permeable. As a result, preliminary results of the FAS FAVA response theme, for example, would appear more vulnerable in areas with low-permeable soils, which also contradicted the hydrogeologic basis of the model.

### Soil Permeability

As defined by the USDA (1951), “soil permeability is that quality of the soil that enables it to transmit water or air. It can be measured quantitatively in terms of rate of flow of water through a

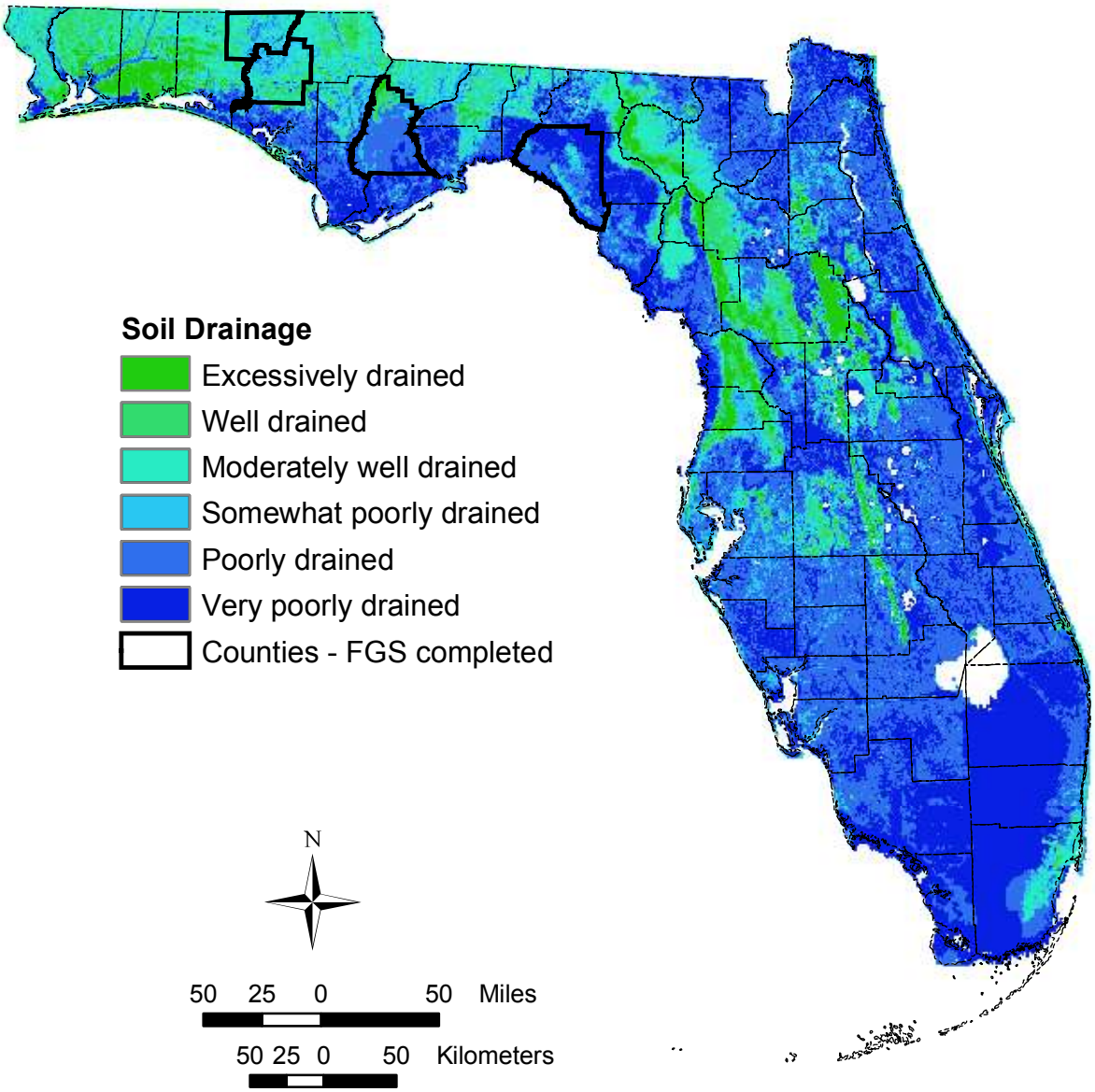


**Figure 5. Soil drainage map of the State of Florida compiled using soil survey books [Washington, Holmes, Taylor counties (Huckle et al., 1965; Sullivan, 1975; Watts, 2000)], STATSGO data [Liberty County and Everglades area (FGDL 2003)], and SSURGO data [remainder of State (FGDL 2003; NRCS 2003)].**

unit cross section of saturated soil in unit time." In STATSGO and SSURGO datasets, rates of permeability (vertical) were expressed in inches per hour (in/hr), and each separate soil-horizon layer was assigned high and low permeability values.

In the development of a soils statewide data coverage for the FAVA project, average soil permeability values were calculated for each soil horizon layer using STATSGO and SSURGO permeability values. Then, based on soil horizon thicknesses, weighted-average permeability values were calculated for the entire soil column. This allowed the generation of a statewide data coverage of soils containing a single permeability value per soil polygon. Average weighted soil permeability values calculated for the State of Florida range from 0.1 in/hr to 20.0 in/hr (Figure 6).

Permeability data were not available in the STATSGO and SSURGO datasets for some areas representing dumps, pits, urban land and water. To compensate, a nearest neighbor GIS function was employed as described above to assign approximated permeability values to these areas.

### Topography

The development of an accurate digital land surface data coverage was of critical importance with regard to generation of evidential themes required for the FAVA project. These evidential themes include karst features, hydrostratigraphic surfaces, and water-table elevation. USGS 30-meter DEMs are available for the entire contiguous United States; however, erroneous elevation values exist throughout the USGS DEM for Florida.

In addition, the USGS DEM resolution is too coarse for use as a baseline for development of some evidential themes. Currently, the best-available statewide source for elevation data is the USGS 7.5-minute quadrangle Topographic Map Series. These maps existed only in paper form in Florida until the 1980's when the State's water management districts [excluding Northwest Florida Water Management District (NWFWMD)] began digitizing the maps into a GIS format. This digitizing process was the first stage in the development of a statewide digital 1:24,000 scale contour data coverage. Several issues with the data, however, remained, such as a lack of splicing between adjoining maps, merged contours along road embankments, and erroneous elevation values for some contour lines.

In an effort to address these problems, the FDEP DWRM and the FGS began the significant and time-consuming task of correcting and refining the digital contours (Rudin et al., 2003). DWRM scanned and digitized all 7.5-minute quadrangle maps in the NWFWMD and implemented a detailed quality assurance plan. The FGS also implemented a detailed quality assurance plan for contour lines, edge-matched digital maps for the remainder of the State, and improved the locational accuracy for contour lines. The FGS effort involved visually checking digitized contour line values against USGS 7.5-minute quadrangle topographic maps and developing custom software programs to expedite identification of inconsistencies and errors to be corrected.

Once the corrections were made, the FDEP DEM was generated. Two GIS functions were considered in this step: Triangulated Irregular Networks (TIN) and TOPOGRID, a tool in ArcInfo Workstation. Each function provided unique benefits to the output surface. The TIN function's main drawback was that it would not extend elevation values beyond attributed contour lines. In areas of closed depressions or hilltops, development of a TIN therefore caused the creation of false plateaus in areas which should have rounded hilltops. Further, in areas of valleys and depressions, the TIN function caused inaccuracies in drainage systems. The TOPOGRID function can be used to extrapolate elevation values beyond attributed contour lines and into valley bottoms; however these

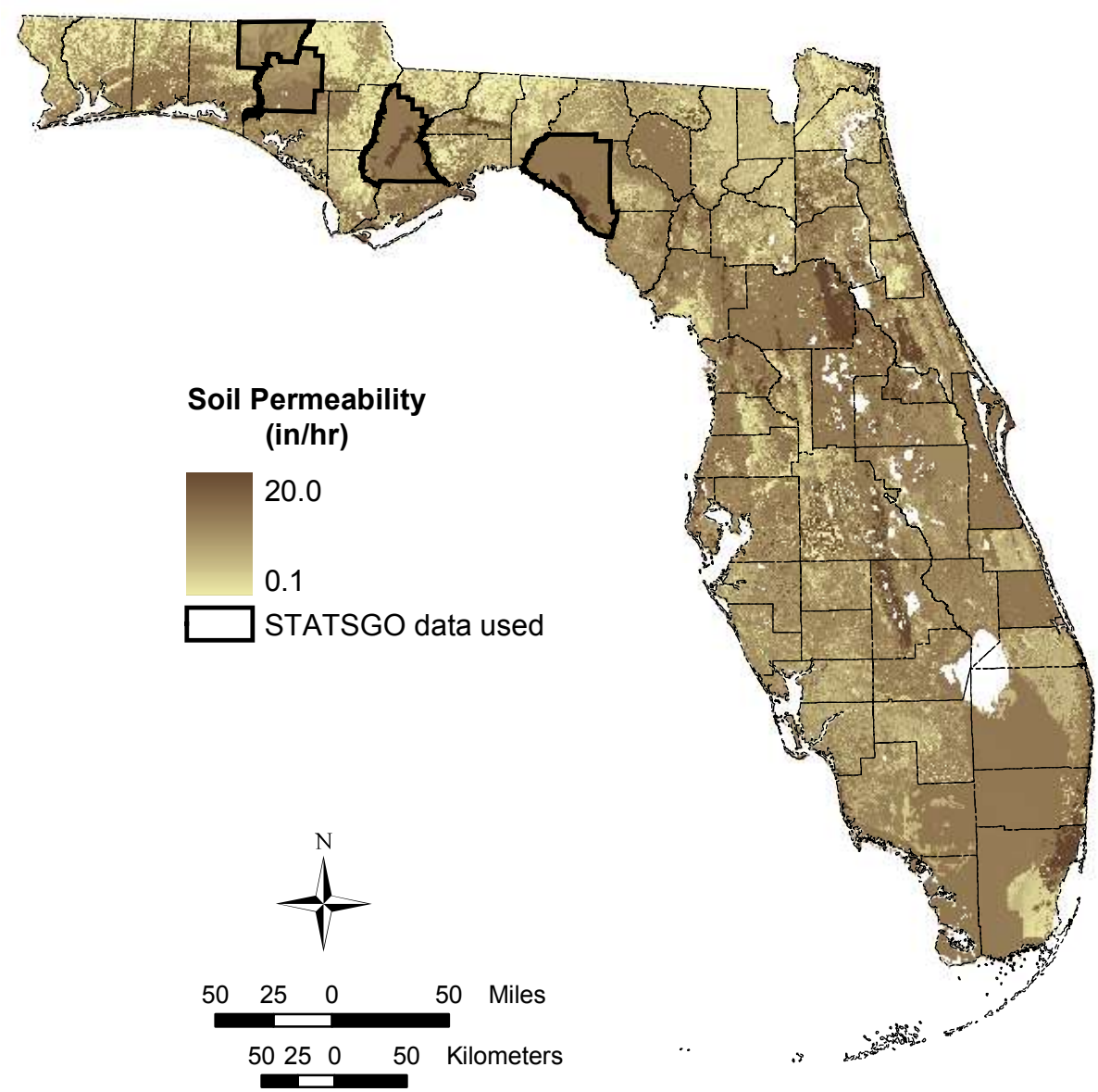


**Figure 6. Soil permeability map of the State of Florida compiled using, STATSGO data [Washington, Holmes, Taylor and Liberty counties and Everglades area (FGDL 2003)], and SSURGO data [remainder of State (FGDL 2003; NRCS 2003)].**

extrapolations extended far beyond the designated contour interval creating inaccurately high hilltops and false depressions. Although, TOPOGRID function is typically used to create a more visually appealing surface, overall the TIN function returned more accurate elevation values and was used for the final generation of the statewide FDEP DEM. Figure 7 displays the statewide FDEP DEM, and Figure 8 is a close-up view of the detailed topographic coverage. This represents a significant increase in resolution over the USGS DEM; differences between the more resolute FDEP DEM and the USGS DEM were noted as exceeding 50 feet in a few cases

### Closed Topographic Depressions

Ground-water vulnerability is dependent upon the rate at which water reaches the aquifer system. In Florida, sinkholes generally provide preferential pathways for water and contaminants to travel to aquifer systems more rapidly from land surface. As a result, aquifer vulnerability increases in areas of relatively dense karst topography. It is well beyond the scope of this study to map every sinkhole or karst-related feature in Florida; however, a surrogate data coverage was available from the FDEP DEM that reflects areas with a high population of karst features. During development and enhancement of FDEP DEM, closed hachured topographic depressions were attributed. For areas with multiple encircling hachured contour lines, only the outermost depression was selected. These lines were converted to polygons which were used to create a statewide data coverage of closed topographic depressions (Figure 9). This coverage was filtered for each aquifer system and used as input into the WofE – FAVA model. These filtering processes are described in *Results – FAVA Model Outputs* for each aquifer system.

Although not all closed topographic depressions are karst features, there is a strong correlation between the density of depressions on USGS 7.5-minute quadrangle maps and areas that include sinkholes of various types. In addition to spatial filtering for the IAS and FAS, other enhancements to this coverage are yet to be completed. These enhancements, however, are not expected to significantly change the results of the FAVA response themes. For more details, see *Discussion – FAVA Maps: Data Limitations and Applications.*

### Water-Table Elevation Map

At present, there are few maps depicting the water-table elevation on a statewide basis. Most water-table elevation maps that exist cover relatively small regions (multi-county areas), with the recent exception of Sepulveda (2002) who generated a water-table elevation model for much of the Florida peninsula using a terrain-following method. In the present study, Sepulveda's method was adopted and implemented statewide.

#### Water-Table Elevation Development

An initial step toward generation of water-table elevation data coverage (i.e., a depth-to-water evidential theme) involved grouping Florida's physiographic provinces (White, 1970 and Puri and Vernon, 1964) into eleven regions (Figure 10). The basis of this technique was that each major physiographic region has unique hydrogeological characteristics that justified the correlation of water levels solely within that region

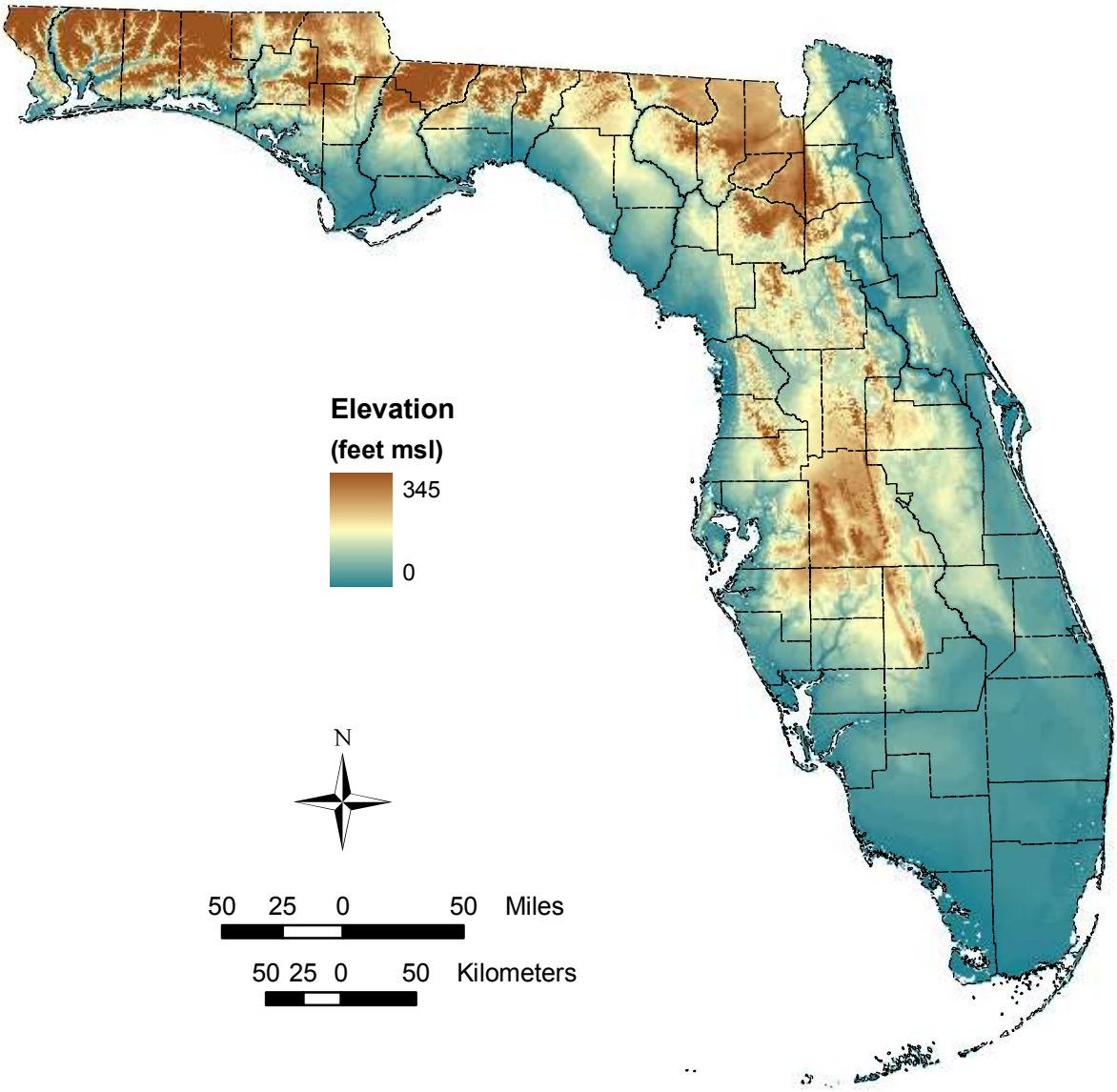


**Figure 7. Statewide digital elevation model developed using scanned USGS 7.5-minute quadrangles. This model of topography is a 15-m grid cell size and was used to develop many evidential themes for use in the FAVA project.**

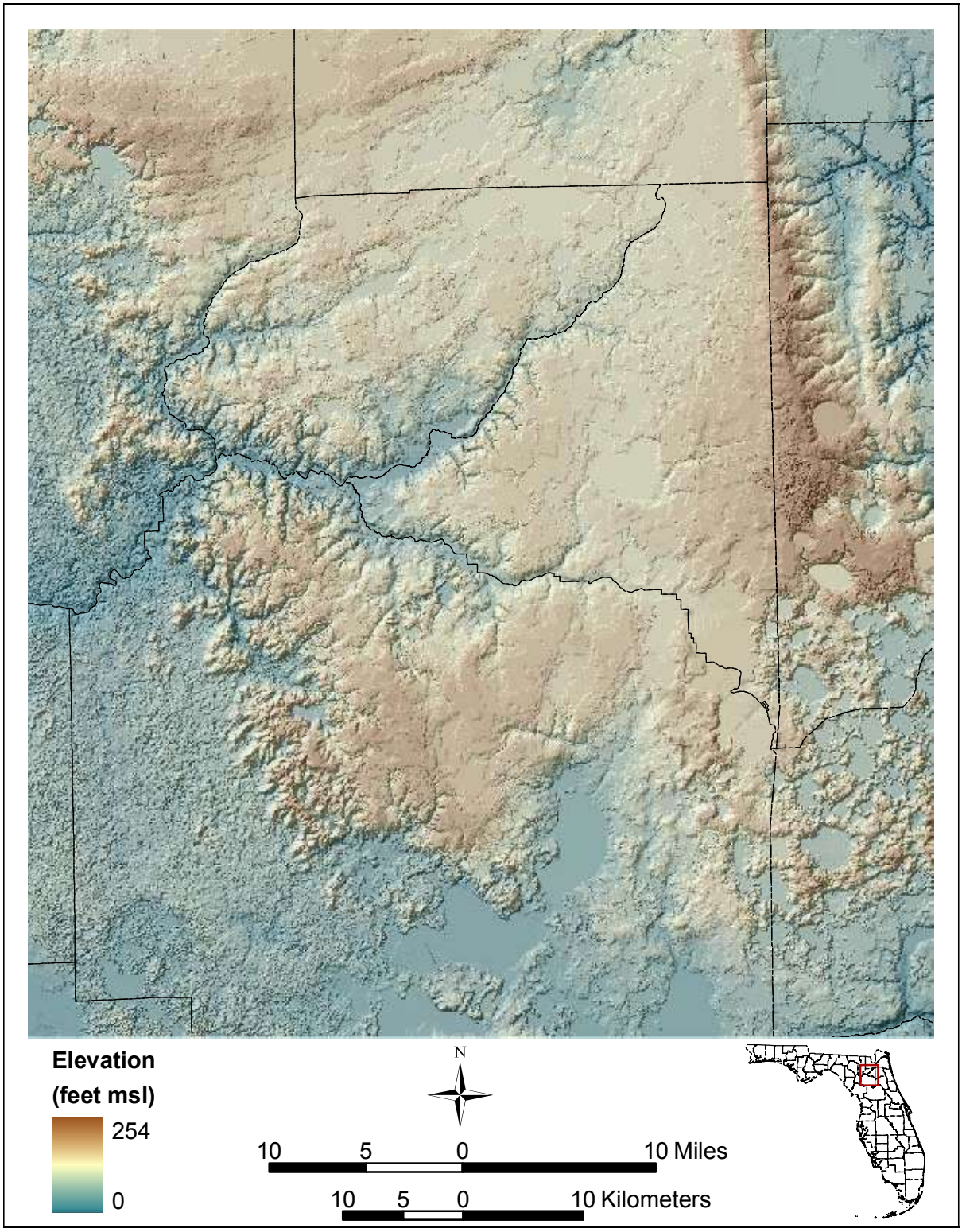


**Figure 8. Detail view of statewide digital elevation model coverage with shaded relief for the Alachua, Bradford, and Union county region. Significant topographic features are apparent at this scale.**

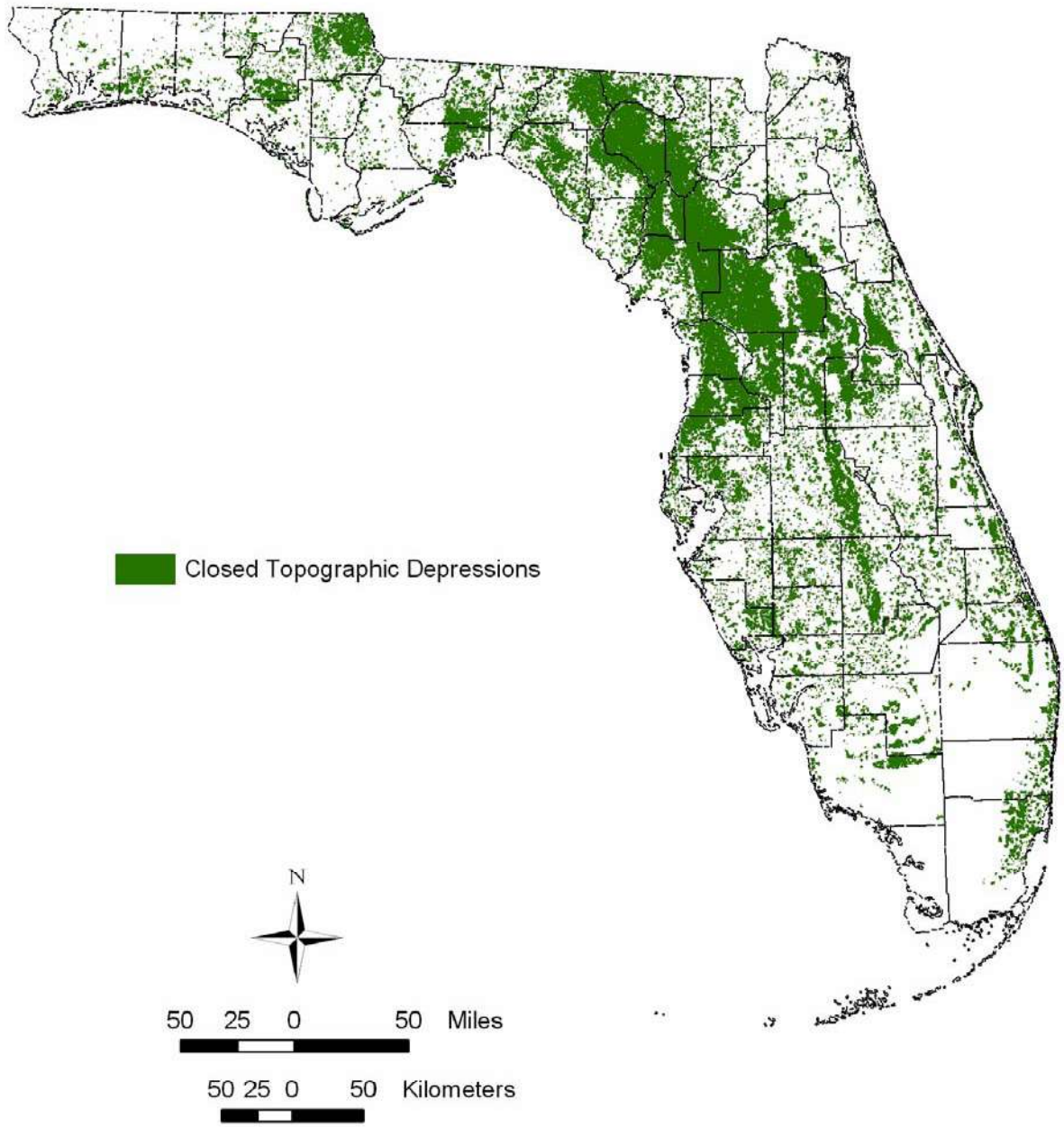


**Figure 9. Map showing location of closed topographic depressions used to reflect the hydraulic role of karst features in the WofE – FAVA model. The green polygons represent closed hachured depressions extracted from the FDEP DEM developed for this project.**

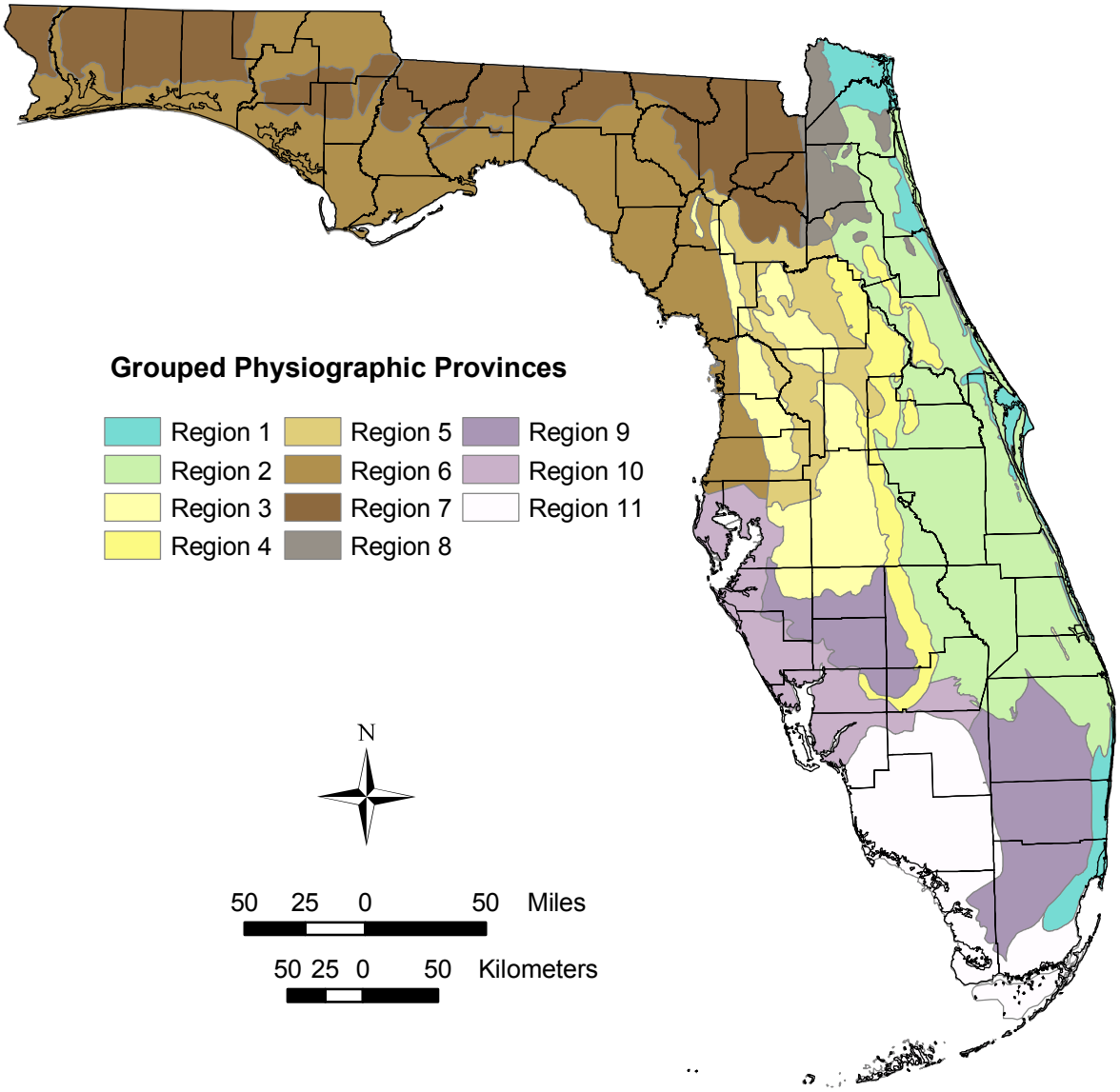


**Figure 10. Grouped physiographic regions (adapted from White, 1970, and Puri and Vernon, 1964) used to estimate water-table elevation throughout the State.**

To estimate the water-table elevation, and thus be able to derive depth to the water table, a multiple linear regression equation for each physiographic province 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 1:100,000 USGS maps for water bodies within each physiographic province including streams, lakes and shorelines (Figure 11) were used to interpolate a minimum water table (MINWT). Water-level data were compiled from the period of record between 1990 and 2000. A minimum of four water-level readings during this period were required for the well data to be included in the dataset. Sources of this data include Florida's five water management districts, the FDEP, and the USGS. The interactions between these components are displayed in the water-table conceptual model (Figure 12).

For those areas where the water table follows land-surface topography, the vertical difference between land surface and the minimum water table (LSA – MINWT) is added as a variable to the regression (Sepulveda, 2002).

Streams (as arcs) and lakes (as polygons) were obtained from the USGS National Hydrography Dataset. To allow for an accurate interpolation of the MINWT, stream arcs were digitized in the downstream direction. The coastline was given a value of zero and the streams and lakes were assigned elevation values based on the FDEP DEM. The DEM used in the creation of the water-table elevation was developed using the ArcInfo program TOPOGRID. It should be noted that this DEM is different than what was used in other FAVA applications, but was still based on the scanned USGS 7.5-minute quadrangle maps. Streams, lakes, the coastline and contour lines were used in TOPOGRID to create a hydrologically-correct grid, meaning that the contour rules were met with respect to surface-water flow and drainage. Where the MINWT, land surface and measured water table coincide, the water table was defined as the minimum water table.

Wells were grouped by physiographic region and an average water-level value over the ten-year period of record (1990-2000) was calculated for each well. The final water-table elevation surface was calculated by applying a multiple linear regression equation to data from within each physiographic region. Values from the MINWT surface were assigned to each monitor well, and the wellhead elevation was taken from the DEM. Multiple linear regressions for each physiographic region were 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 ten-year 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. |

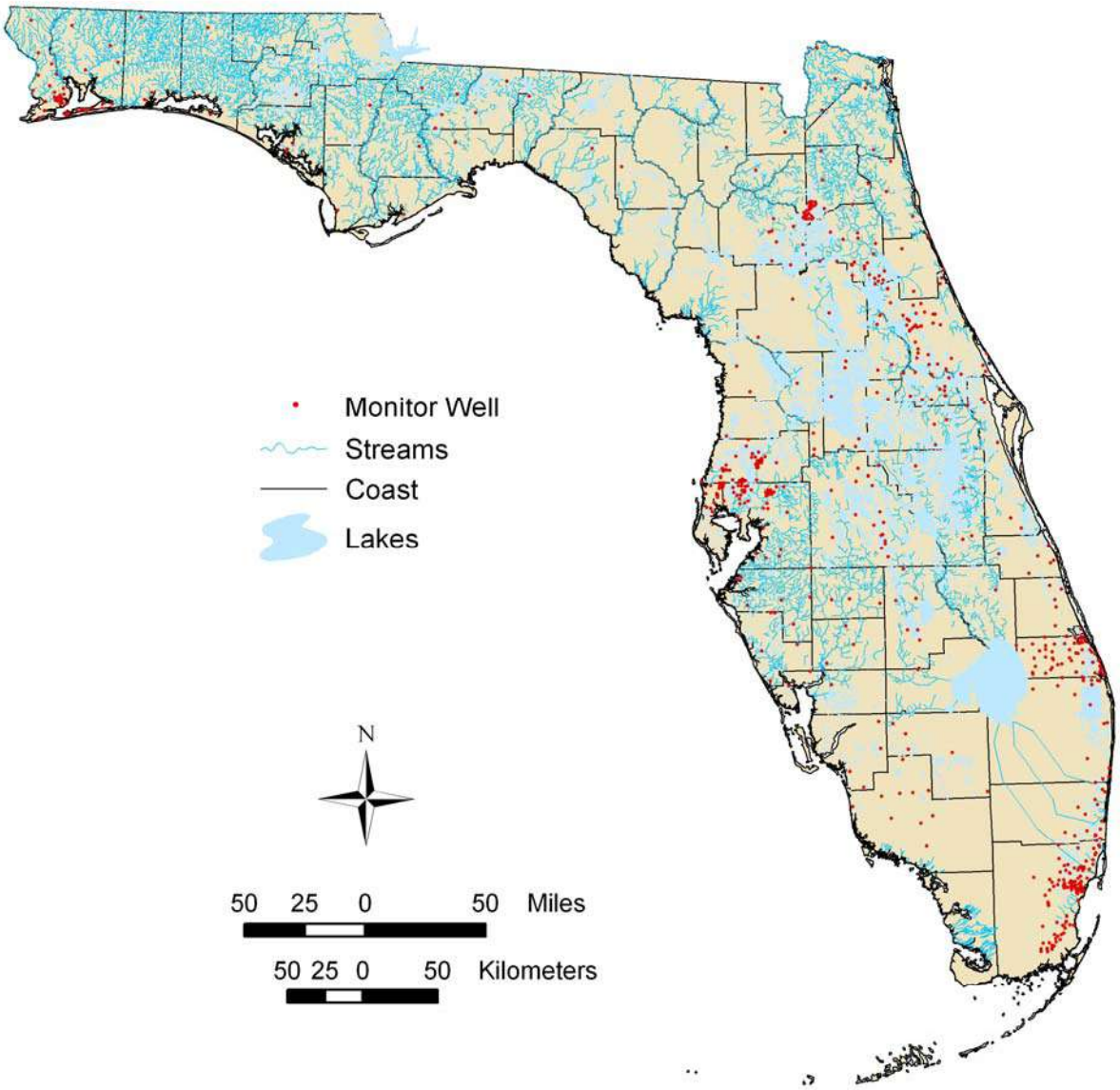


**Figure 11. Surface hydrology and wells used to estimate the water-table elevation.**

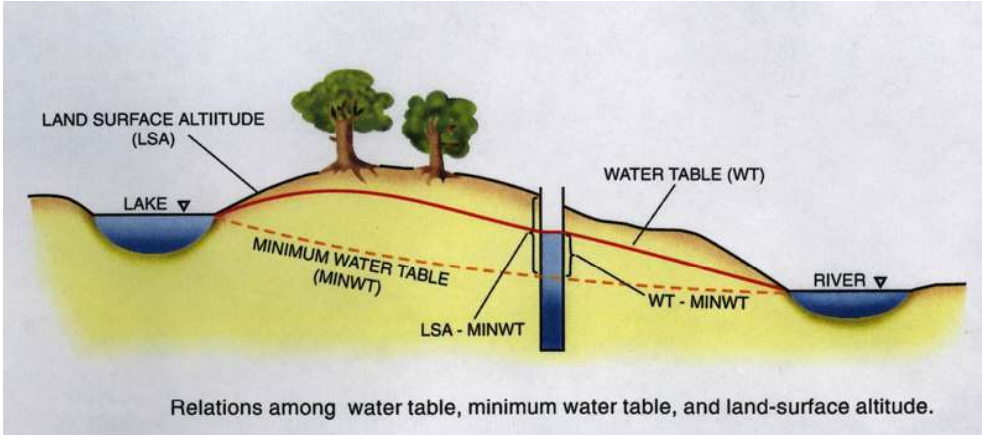


**Figure 12. Idealized cross-section displaying the components of the terrain-following linear regression equation (from Sepulveda, 2002).**

Table 5 summarizes the results of the correlations for each physiographic region. The root-mean-square residual between the regressed and measured water-table elevation for all physiographic regions resulted in a weighted mean of 6.58 feet and a range from 2.60 to 13.91 feet. The resulting water-table elevation surface ranged from zero to 328 feet above mean sea level (Figure 13). Some physiographic regions were predicted better than others; areas with high root-mean-square residuals contain provinces that were classified as ridges and uplands. These areas were located in the western panhandle and upper-central peninsula of Florida. A leaky IAS or a high SAS hydraulic conductivity may result in a poor correlation between the water table and the land surface in these areas (Sepulveda, 2002). A strong correlation existed between the regressed and measured water table throughout the State as is shown in Figure 14 and indicated by the correlation coefficient of 0.98

### Intermediate Aquifer System Thickness and Extent

According to the Florida Geological Survey's Special Publication No. 28 (Southeastern Geological Society 1986), the intermediate aquifer system/intermediate confining unit consists of highly-variable siliciclastic and carbonate deposits that are relatively low-permeability, fine-grained sediments and collectively retard the exchange of water between the overlying SAS and the underlying FAS. The term "intermediate confining unit" applies to those areas where this unit is poorly to non-water yielding, whereas the term "intermediate aquifer system" applies to those areas where one or more low to moderate-yielding aquifers occur. Special Publication No. 28 is currently under review, and the forthcoming version suggests the use of the term "Intermediate Aquifer System" for this entire unit and calls for the elimination of the use of "intermediate confining unit." Instead, the "intermediate confining unit" is considered to be confining beds within the IAS. This newer convention currently under review is hereby adopted for the FAVA report.

The IAS helps protect the underlying FAS from potential contamination where it is thick and low in permeability; however where the IAS is thin to absent or breached by sinkholes, the vulnerability of the FAS to contamination from land surface is greatly increased. As a result, the IAS extent and thickness was mapped and used as an evidential theme for input in the FAS FAVA model.

**Table 5. Multiple linear regression coefficients for MINWT and difference between DEM and MINWT.**

| Physiographic Region as grouped in Figure 10 | No. wells | Regression coefficient of MINWT (β1) | Regression coefficient of difference between DEM& MINWT(β2) | Root mean square residual (ft) | Value range for difference between regressed& measured water table (ft) | Correlation coefficient |
|---|---|---|---|---|---|---|
| 1 | 88 | 1.18 | 0.578 | 2.94 | [-14.76, 7.92] | 0.80 |
| 2 | 143 | 0.978 | 0.465 | 5.30 | [-15.29, 19.47] | 0.93 |
| 3 | 22 | 1.01 | 0.0325 | 10.18 | [-23.97, 17.01] | 0.96 |
| 4 | 50 | 0.919 | 0.301 | 13.91 | [-32.38, 23.23] | 0.87 |
| 5 | 30 | 0.967 | 0.603 | 5.56 | [-11.89, 16.85] | 0.96 |
| 6 | 163 | 0.926 | 0.314 | 7.71 | [-18.48, 30.70] | 0.93 |
| 7 | 24 | 1.03 | 0.431 | 13.56 | [-19.73, 30.58] | 0.96 |
| 8 | 38 | 0.876 | 0.417 | 12.38 | [-33.96, 11.24] | 0.87 |
| 9 | 59 | 1.06 | 0.772 | 3.07 | [-9.33, 10.86] | 0.99 |
| 10 | 40 | 0.951 | 0.895 | 3.53 | [-7.32, 11.48] | 0.98 |
| 11 | 39 | 1.01 | 0.345 | 2.60 | [-5.69, 7.85] | 0.98 |
| weighted mean | 696 | | | 6.58 | [-33.96, 30.70] | |

Though the IAS is primarily a confining unit overlying the FAS, this aquifer system also provides usable quantities of ground water in various areas of the State, particularly in the southwest peninsula. As a result, the vulnerability of the IAS was modeled for this report, and the extent of where the IAS is primarily used as a source of drinking water is defined and discussed further in *Results – FAVA Model Outputs – Intermediate Aquifer System*.

The FAS is confined to varying degrees throughout its extent in the State of Florida. Local confinement can exist in the form of thin, discontinuous low-permeability lenses which occur in the SAS, or it may be in the form of thick, laterally-extensive, low-permeability beds of the IAS. Due to the statewide scale of the FAVA project and the difficulty in mapping discontinuous SAS basal confining layers, the confinement of the FAS was based solely on the presence or absence of laterally extensive IAS sediments. Geologic units (Table 6) comprising the IAS were identified in borehole samples, cataloged and interpolated to simulate the IAS surface, which was then used to develop an IAS thickness map.

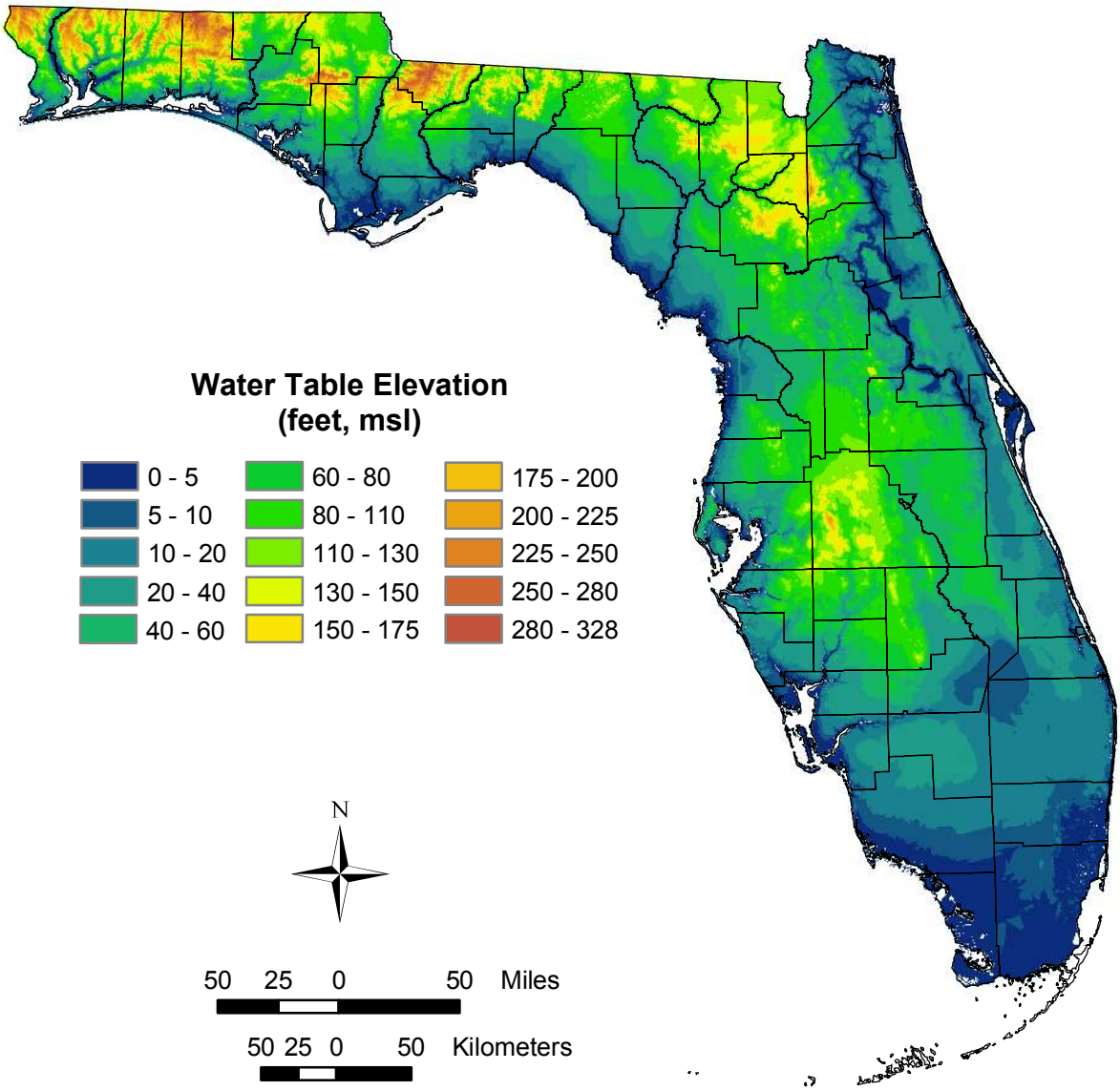


**Figure 13. Calculated water-table elevation for the State of Florida in feet referenced to mean sea level.**

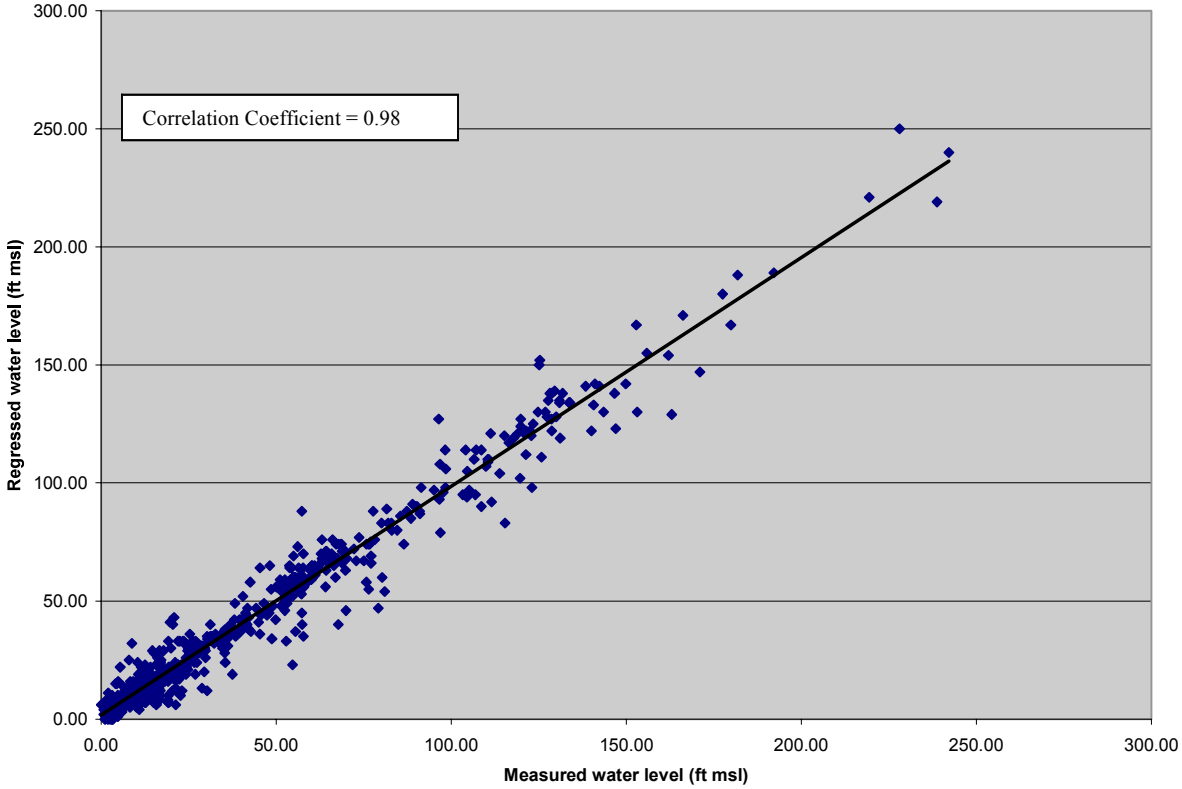


**Figure 14. Regressed and measured water level for all physiographic regions.**

**Table 6. Geologic units comprising the IAS (Scott, 1988; Schmidt, 1984; Pratt et al., 1996).**

| Panhandle | | Northern Peninsula | | | Southern Peninsula | | |
|---|---|---|---|---|---|---|---|
| Miccosukee Formation | | Hawthorn Group | Statenville Formation | | Hawthorn Group | Peace River Formation | |
| Jackson Bluff Formation | | | | | | | |
| Intracoastal Formation | | | Coosawhatchie Formation | | | | Bone Valley Member |
| Chipola Formation | | | | Charlton Member | | | |
| Pensacola Clay | | | Markshead Formation | | | Arcadia Formation | |
| Alum Bluff Group | | | | | | | |
| Hawthorn Group | Torreya Formation | | Penney Farms Formation | | | | Tampa Member |
| | | | | | | | Nocatee Member |

The IAS map was developed on a statewide basis and well samples were included only if they penetrated or encountered geologic formations as identified in Table 6. This method, while appropriate for the FAVA project, may not account for where the FAS is overlain by thin sediments that provide some degree of confinement in localized areas that occur beyond the extent of the IAS as mapped herein. This confinement can occur in the form of discontinuous clay lenses in the basal SAS or areas of reworked undifferentiated Hawthorn Group sediments that are not well constrained by the location of boreholes. In Pasco County for example, Arthur and others, (2005, in preparation)

identified areas where local confining sediments overlie and provide some degree of confinement to the FAS based on detailed study. Though this is a different extent than that developed for the FAVA project, the difference does not affect the FAS FAVA model output. During weights calculation for the IAS (see *FAVA Model Outputs – Floridan Aquifer System* for more information) categories were defined by the analysis in which IAS sediments ranging from 0 to 160 feet thick were grouped into one generalized category. That is, IAS sediments between 0-160 feet thick have a strong association with the training point theme. It is inconsequential to the response theme whether an area is underlain by one foot or 20 feet of confining IAS sediments.

Though numerous mapping projects define the thickness and extent of the IAS, most studies focused on a local area or region such as a water management district (e.g., Copeland et al., 1991 and references therein; Pratt et al., 1996). Overlap problems between regions and variable spatial resolutions of adjacent study areas were significant obstacles toward development of a statewide digital map of the IAS based on existing publications. Further, most IAS maps that do exist were typically created by hand and no digital datasets were available for manipulation (i.e., splicing or interpolation). As a result, a continuous, statewide thickness map of the IAS was developed for the FAVA project (Wood et al., 2003), building in part on the Southwest Florida Water Management District hydrostratigraphic database developed by Arthur et al. (2005, in preparation).

The initial effort was to develop a database of wells from FGS and water management district files for which core samples had been collected and described. Formational descriptions based on core samples were the most detailed descriptions available, and were therefore chosen over other well samples. In several areas of the State, however, no detailed core samples were available so the core data were supplemented with descriptions based on well cuttings. The cuttings data, while more abundant, were thought to have a greater margin of error with regard to formational depths and thicknesses. These wells from which cores and cuttings were available for study were compiled into a database that included locational data and detailed lithologic and stratigraphic information. The wells were then plotted in a GIS to begin development of the IAS thickness and extent. A total of 1,346 wells were evaluated as control points for the map; 643 wells penetrated the tops of both the IAS and FAS and 296 wells penetrated the top of the IAS only. The remaining 407 wells penetrated the top of the FAS, however, data for the top of the IAS for these wells was unreliable or unavailable (Figure 15).

Through the use of the well data and the State of Florida geologic map (Scott et al., 2001), the spatial extent of the IAS was established. In areas where the IAS sediments were thin to absent, the well data would sometimes conflict with the geologic map data. In these cases, the well data were preferred over the map, as the wells were considered to be more accurate on a local scale than the geologic map data due to the scale of the geologic map.

The well database was then used to create a hydrostratigraphic surface for the top of the IAS and the top of the FAS (which coincides with the base of the IAS). The surfaces were interpolated using the ArcGIS Geostatistical Analyst package. Kriging was the preferred method of interpolation because it allows for prediction of a surface using values from known measured locations, and it relies on similarity of nearby data points to create a surface much like an inverse distance weighted method. Kriging is unique, however, in that it allows cross validation of the results and assessment of uncertainty of the predicted surfaces. The surfaces of the IAS and FAS are displayed in Figures 16 and 17, respectively.

Following creation of the hydrostratigraphic-unit surface models, it was necessary to resolve the interpolated surfaces with land-surface elevation. In some localized areas where the IAS is at or near

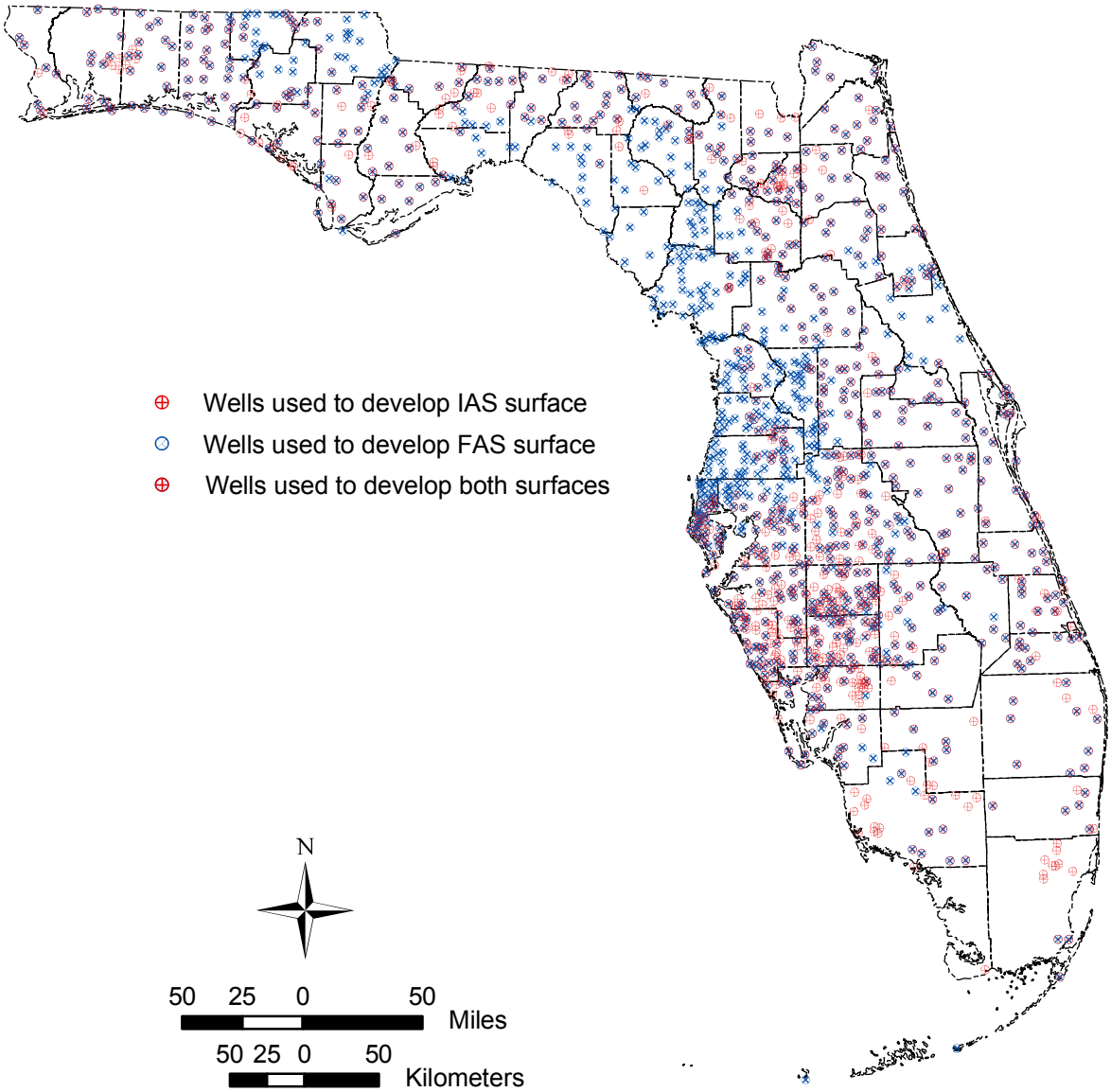


**Figure 15. Distribution of wells extracted from FGS and water management district files used to define the thickness and extent of the IAS. A total of 1,346 wells were used; 643 wells penetrated the tops of both the IAS and FAS, 296 wells penetrated the top of the IAS only, and 407 wells penetrated the top of the FAS only.**

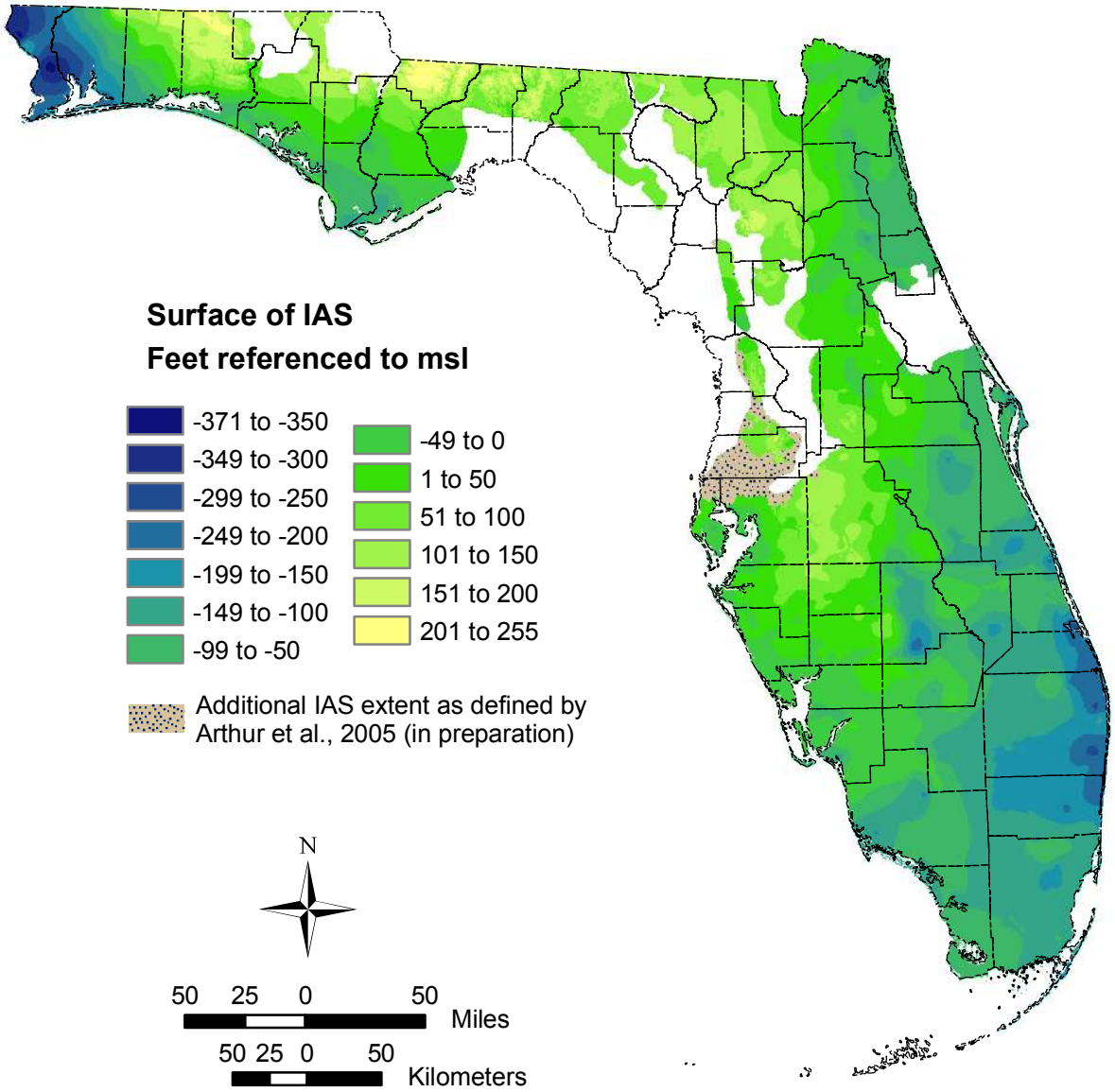


**Figure 16. Elevation of the calculated surface of the IAS in feet referenced to mean sea level, based on data from 939 wells. The extent defined by Arthur et al. (2005, in preparation) is based on a more detailed study. For the more generalized mapping effort in FAVA, a different method was used that was internally consistent on a statewide scale. Due to the different project approaches and scales, differences exist between the two IAS extents.**

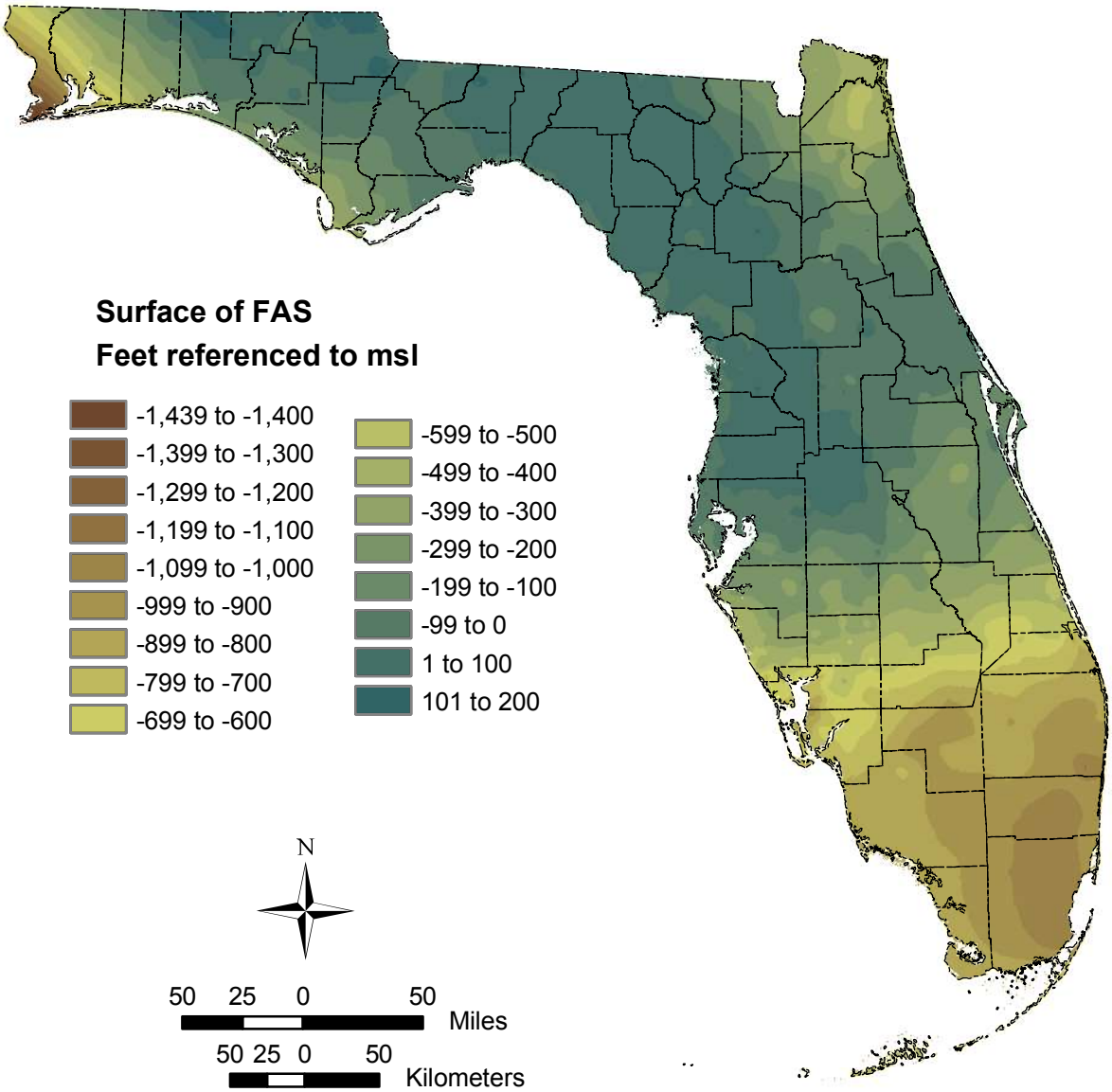


**Figure 17. Elevation of the calculated surface of the FAS in feet referenced to mean sea level based on 1,050 wells. Areas of the FAS in this model which extend more than 1,100 feet below mean sea level are restricted to the extreme southwest corner of the panhandle in Escambia County where the FAS dips deeply to the southwest.**

land surface, the IAS surface interpolation may extend above land-surface elevation due to the limited amount of control data as compared to the topographic maps on which the FDEP DEM is based. The IAS hydrostratigraphic surface was therefore digitally trimmed vertically against the FDEP DEM. This resulted in an interpolated IAS surface that did not falsely extend above land surface. The same issue was also encountered when predicting the FAS surface, and therefore, the same process was applied.

After the hydrostratigraphic surfaces were developed, calculation of a thickness map was completed by carrying out a simple grid subtraction of the IAS hydrostratigraphic surface from the FAS hydrostratigraphic surface. It was then necessary to further resolve certain areas (i.e., lake and stream bottoms where the IAS is very thin) where the thickness of the IAS was calculated at slightly less than zero. The final output was a continuous thickness map of the IAS as displayed in Figure 18, which is included as an evidential theme for input into the FAS FAVA model and is employed in the development of the SAS extent.

#### Data-Poor Areas for IAS

As mentioned above, well core-sample descriptions were initially preferred in the development of the database used to define the thickness and extent of the IAS. In areas for which core samples were sparse or unavailable, well cuttings sample descriptions were added to supplement the database. In some more remote areas of Florida, however, such as the Everglades, few wells have been drilled, and as a result, extremely limited core and cuttings samples were available for these areas. When predicting hydrostratigraphic surfaces based on these wells, prediction errors can be higher for these remote areas containing fewer wells.

The accuracy of predicting surfaces is highly dependent upon the regularity and density of data point spacing. In areas of densely spaced data points, a predicted surface based on these points will be more reliable and have a higher confidence than an area with sparsely spaced data points. In certain areas of the IAS thickness map, therefore, where data points were sparse, such as the Everglades, the IAS map is much less accurate, and therefore less reliable, than in areas of more highly concentrated data points. In general, the vertical resolution of the IAS thickness is approximately 30 feet.

### Intermediate Aquifer System Overburden

Where the IAS is a major regional and productive aquifer system in southwest Florida (Figure 19), overlying sediments form an important protective layer. The materials include undifferentiated sands and clays, shelly sediments of Plio-Pleistocene age, including the uppermost permeable sediments of the Tamiami Formation. To calculate the thickness of sediments overlying the IAS, the surface of the IAS was subtracted from the FDEP DEM. This grid was clipped to the extent of the IAS and used as input into the IAS FAVA model. The thickness of the overburden ranged from a few feet in the northwestern area of the IAS extent to 429 feet along the eastern edge in Highlands County. The thickest part is limited to a small area and is believed to be the result of a deep trough or depression in the surface of the IAS overlain by thick sandy deposits of the southern end of the Lake Wales Ridge. This observation is reflected in the well core and cuttings descriptions. In general the IAS overburden thickens toward the south. Figure 19 displays the thickness map of the IAS overburden. Refer to *Results – FAVA Model Output – Intermediate Aquifer System – Study Area and Extent* for more detail on the delineation of the IAS extent as a source of ground water for purposes of this study.

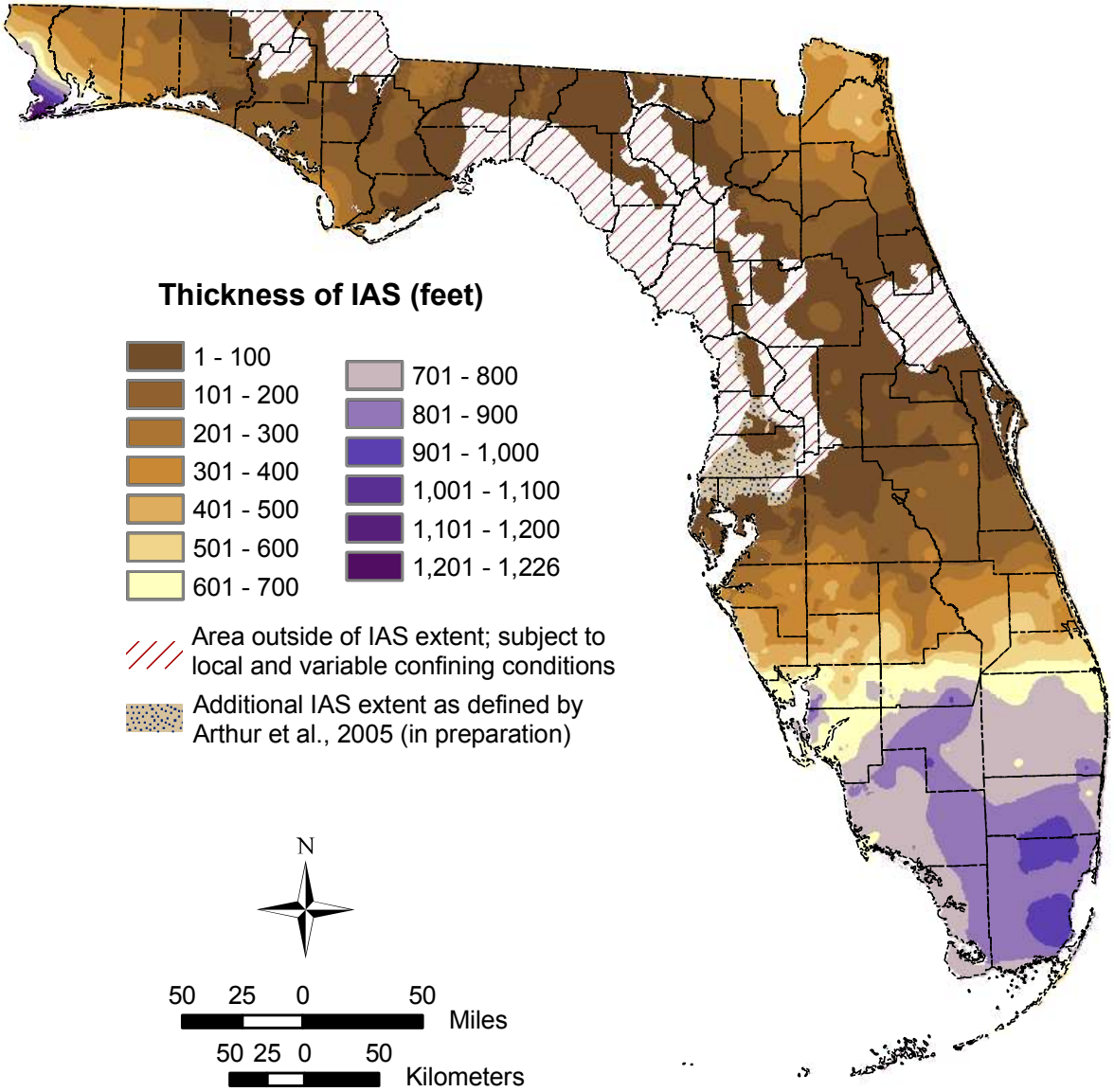


**Figure 18. Thickness and extent of the IAS in feet. The red-lined pattern and the stippled IAS extent from Arthur, et al. (2005; in preparation) indicates areas that may be under local confining conditions, but were not mapped for this project. The omission of these locally confined areas did not impact final FAVA model results.**

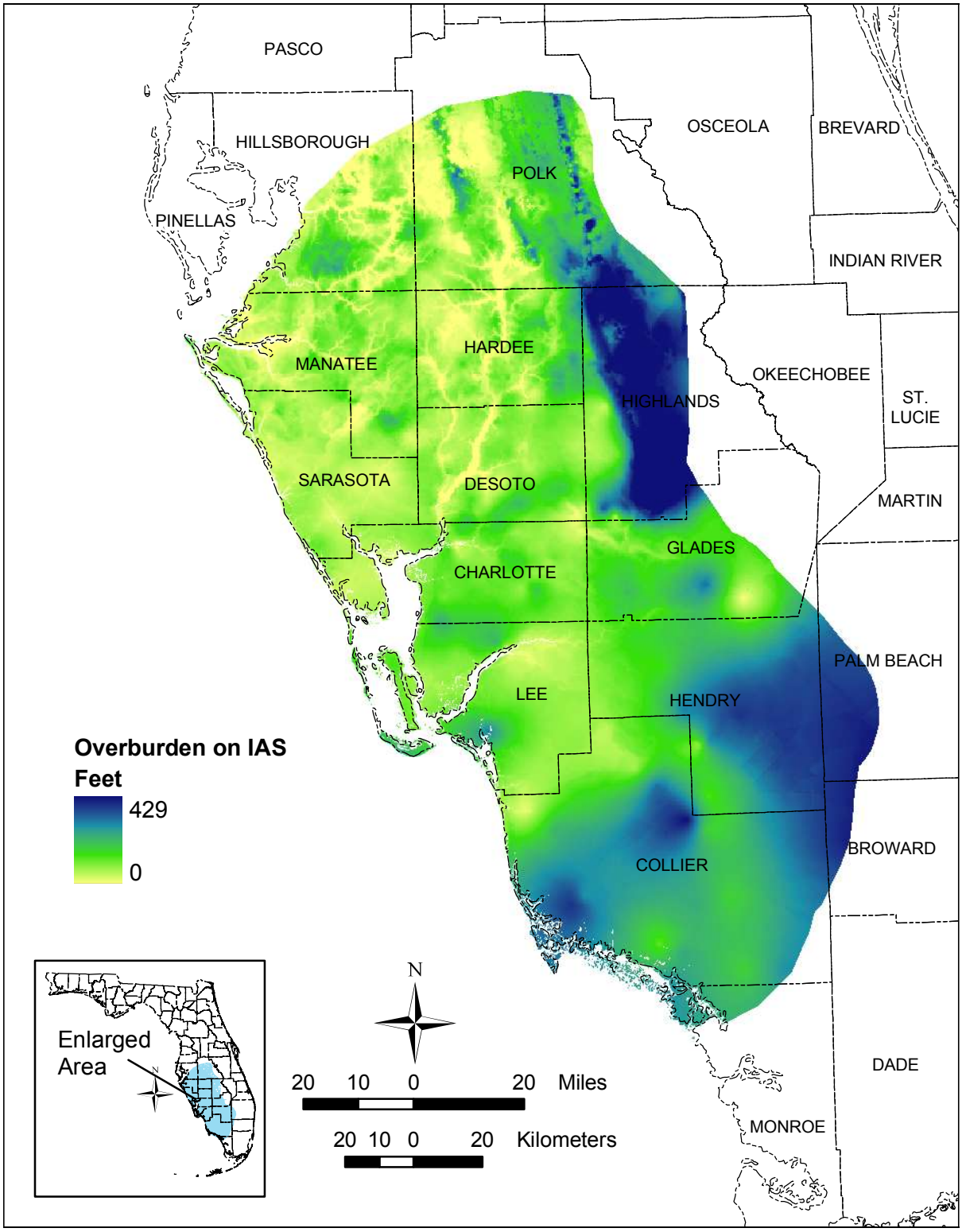


**Figure 19. Thickness of sediments overlying the IAS where it forms a major regional aquifer system in southwestern Florida. This evidential theme was calculated by subtracting land surface (FDEP DEM) from the top of FAS surface developed as part of the IAS thickness map.**

### Hydraulic Head Difference between the Water Table and Floridan Aquifer System

The hydraulic head difference between the uppermost water-level and FAS is an important factor for use in the prediction of vulnerability of the FAS. In areas where the water-table surface is greater (higher in elevation) than the FAS potentiometric surface, the direction of ground-water flow is assumed to be downward, thereby potentially increasing the contamination potential in the underlying FAS, depending on the thickness of the IAS. An evidential theme depicting the hydraulic head difference between the water-table surface and the FAS potentiometric surface was developed for incorporation into the FAS FAVA model (Figure 20).

Hydraulic head difference was calculated by subtracting the FAS predevelopment potentiometric surface (Johnston, et al., 1980) from the water-table surface described previously (see *Results – Data Layers – Water-Table Elevation*). Areas where the head difference is a positive value indicates where the FAS is receiving recharge, whereas areas with a negative value indicate the FAS has the potential to discharge to the overlying aquifer system (Figure 21).

The predevelopment potentiometric surface has poor resolution due to limited data; however, its use in creating a hydraulic head difference evidential theme was more appropriate for use in the FAVA project than any of the recent potentiometric surface maps. The more recent maps include cones of depression created by major well fields, which in some areas result in potentiometric levels as much as 180 feet lower than predevelopment levels. If current potentiometric surface maps were used in the calculation of a hydraulic head difference evidential theme, the resulting evidential theme would inaccurately show major well fields as areas of high potential recharge for the FAS, which may not be true due to the presence of thick (over 400 feet) IAS sediments. Further, this has the affect of biasing this evidential theme in those areas and is less reflective of the natural system being evaluated in the FAVA project.

### Geologic Map

The geologic map of the State of Florida (Scott et al., 2001) was considered as an evidential theme for the FAVA models (Figure 22). To a great extent, Florida's geologic units are overlain by a thin cover of Pliocene and younger, undifferentiated sediments. To maximize detail, the geologic map identifies the uppermost recognizable lithostratigraphic units occurring within 20 feet of land surface.

Attributed polygons from the geologic map were used as input into each model, and weights of evidence were calculated; however, the geologic map data were ultimately omitted from the final FAVA analyses for a number of reasons. For example, in the FAS FAVA model, Undifferentiated Quaternary (Qu) sediments overlie a wide variety of other sediments ranging from carbonates to thick sequences of low permeability siliciclastics of the IAS. Correlations calculated using WofE between the distribution of training points and the total area of Qu sediment distribution were therefore not of meaningful value to the model.

Use of the geologic map was inappropriate for the SAS FAVA model as well because the top of the SAS can occur several feet above the uppermost recognizable lithostratigraphic unit (within 20 feet of land surface). As a result, and due to the design of the geologic map, it would poorly reflect SAS hydrogeological characteristics in many areas.

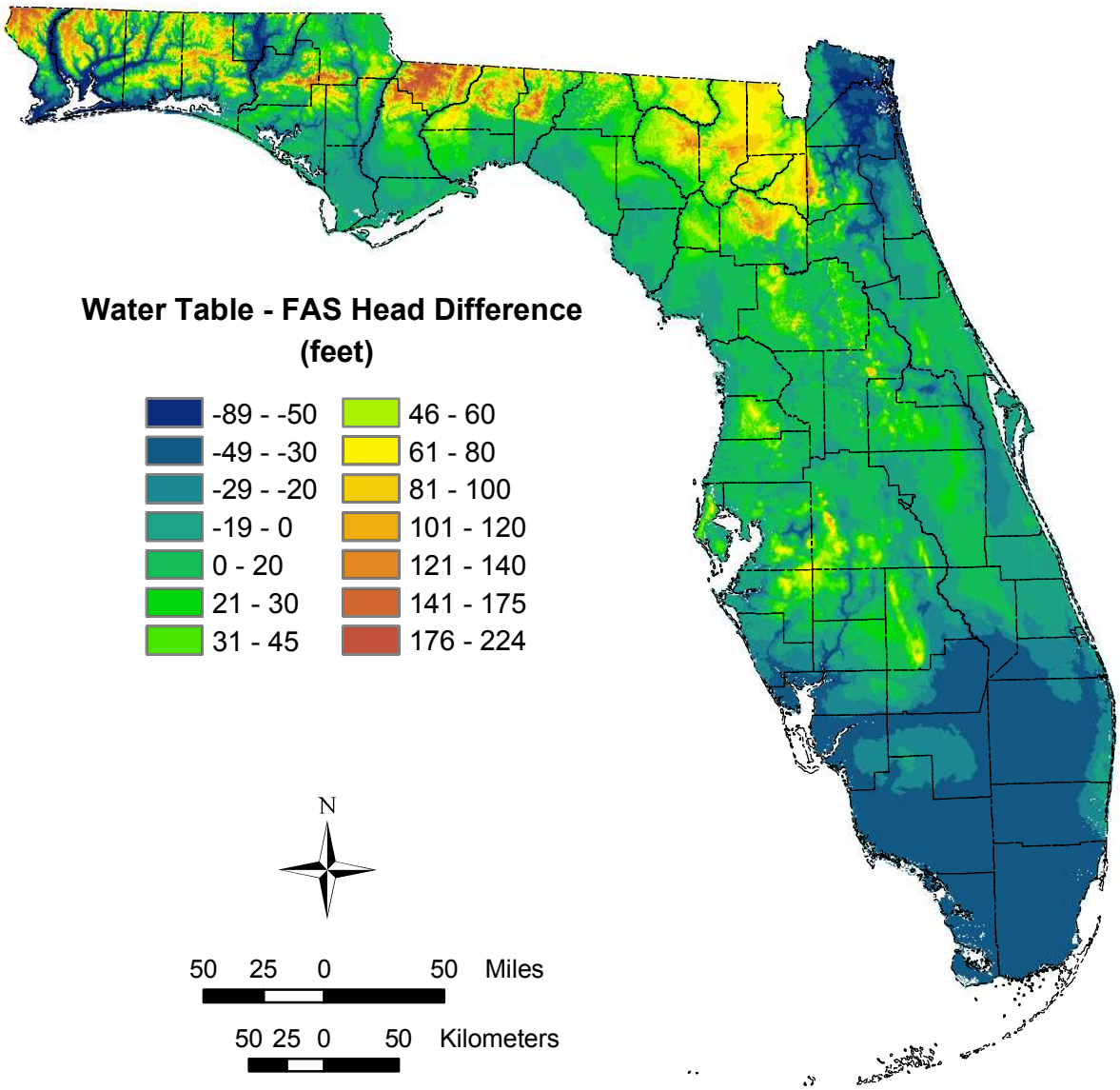


**Figure 20. Hydraulic head difference between the water-table surface and the FAS potentiometric surface in feet (i.e., hydraulic head difference = water table – FAS). Negative values indicated where the FAS potentiometric surface exceeds the overlying water-table elevation.**

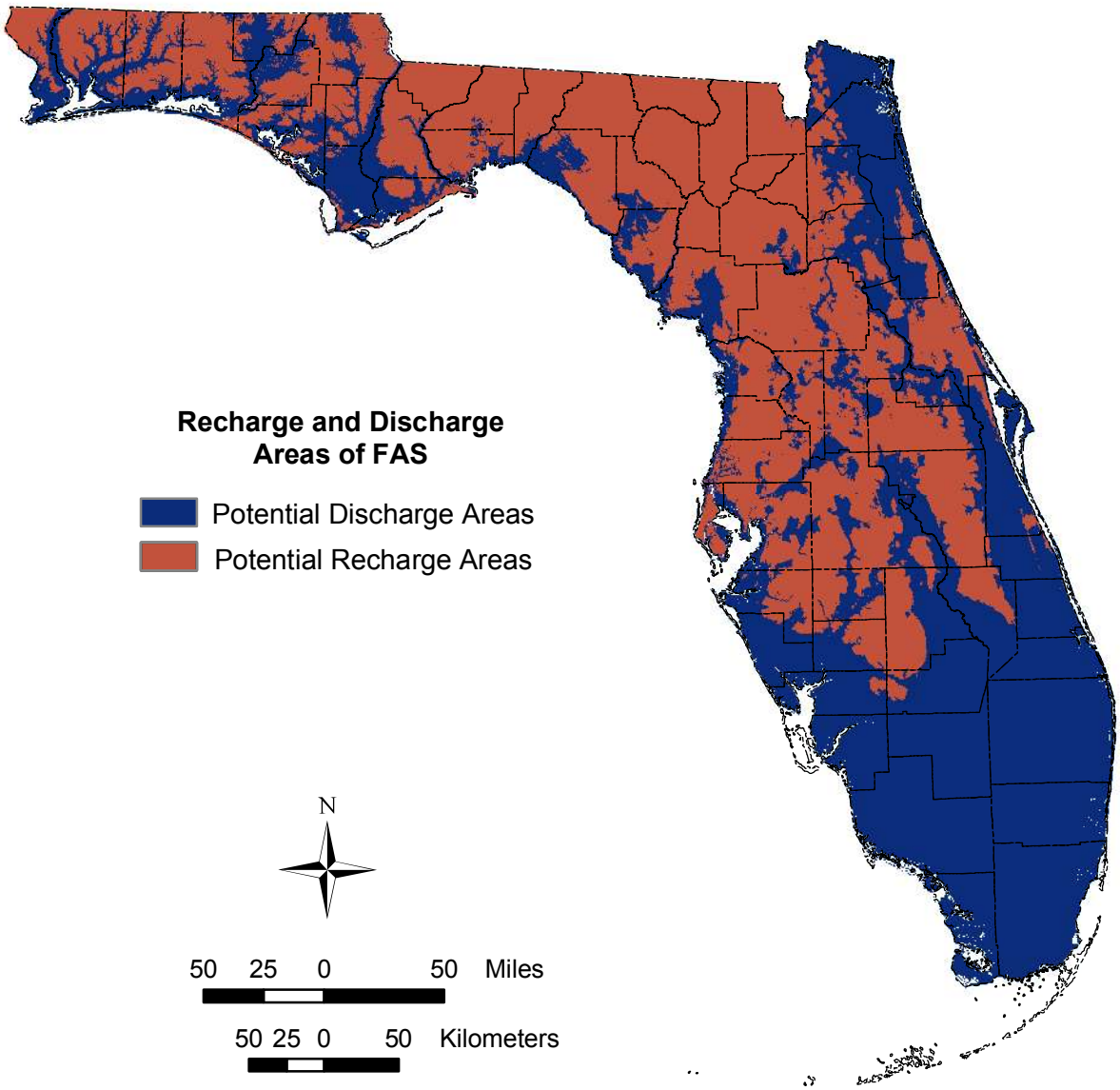


**Figure 21. Map showing relative areas of potential recharge and discharge based on calculation of subtracting the water table from the FAS potentiometric surface.**

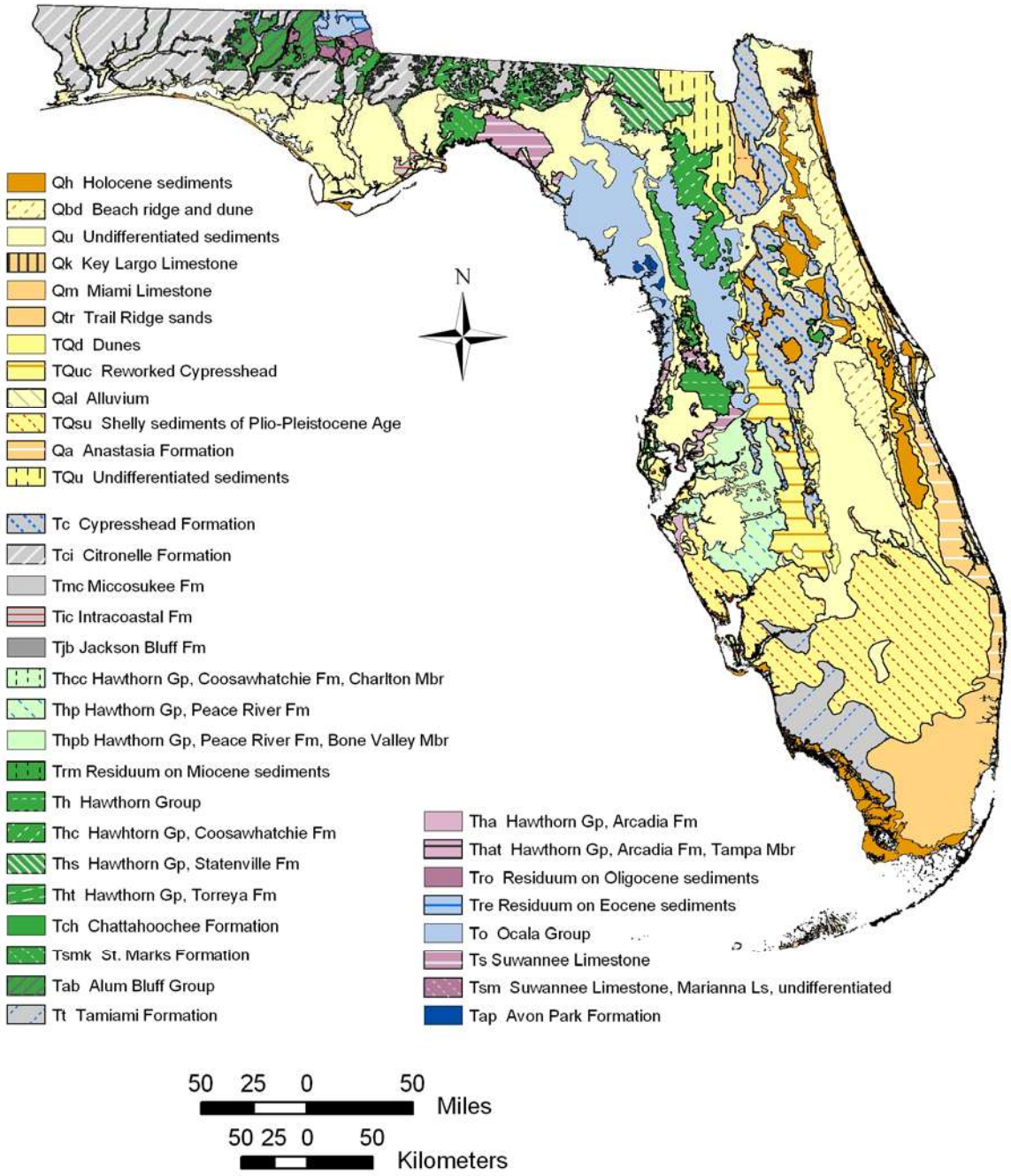


**Figure 22. Geologic Map of the State of Florida (Scott et al., 2001) originally published at a scale of 1:750,000.**

The geologic map was also applied to the IAS FAVA model; however, because of the limited geographic extent of the IAS model, few geologic units were represented. Moreover, weights calculated for the IAS for the geologic map units were not usable because they did not meet the test of significance for the FAVA project (i.e., none of the calculated confidence values reached the minimum acceptable level for FAVA of 0.674, or 75%), and the weights were counterintuitive with regard to hydrogeologic processes and vulnerability.

### Environmental Geology

The Environmental Geology Map Series (Schmidt, 1978a; Schmidt, 1978b; Scott, 1978a; Scott, 1978b; Knapp, 1978a; Knapp, 1978b; Schmidt, 1979; Scott, 1979; Lane et al., 1980; Knapp, 1980; Lane, 1980; Deuerling, 1981; Lane, 1981) was created to provide a series of lithology and sediment-type reference maps for professionals working in fields such as waste disposal, water resources management, land management, highway construction, geologic hazards, soils mapping, mining, and reclamation.

Environmental geology maps represent the dominant geologic material present just below the soil horizon (within 10 feet of land surface). These maps were intended to be used by professionals who do not necessarily have specific training in the field of geology yet require knowledge of the distribution and composition of geologic material. The maps are therefore more simplified than the geologic map of the State of Florida (Scott et al., 2001).

The Environmental Geology Map Series was compiled into a GIS layer as a continuous statewide coverage (Figure 23). During model sensitivity analyses, this statewide data coverage was evaluated as a potential evidential theme in the FAVA models for the three major aquifer systems. Ultimately, this data coverage was not included in the final FAVA model input primarily because common rock types were not necessarily grouped based on their hydrogeologic properties. As such, calculated weights return results indicating that the data layer provides no significant contribution to the FAVA response themes. On the other hand, the environmental geology layer was useful in the travel time model, which was used during the pilot phases of the FAVA project as a validation tool.

### Training Points

In WofE models, training points are a set of locations reflecting the presence of an analyte used to calculate weights for each evidential theme, one weight per class, using the overlap relationships between points and the various classes (Raines, 1999). For the FAVA project, the training point wells used in the WofE – FAVA model were obtained from the FDEP background water quality monitoring network (Figure 24). The statewide network, which consisted of over 2,600 wells, was designed to monitor the ambient ground-water quality of Florida's three major aquifer systems. The well locations were selected to avoid association with any particular land use or uses. Ground-water quality data for the monitoring wells were obtained from the FDEP Generalized Water Information System (GWIS) database provided by the Ambient Monitoring Section at FDEP. This database provided ground-water quality data through August, 1999.

Several water-quality analytes were measured for these wells, however, only a few have geochemical characteristics that yielded information regarding vulnerability and/or recharge rates of Florida's aquifer systems. Moreover, it was required for this project that any analytes selected for the training point data set must have a large number of wells in all aquifers that could support meaningful statistical analyses. Further, ideal water-quality analytes should generally have been considered ubiquitous at land surface, have very low background or native ground-water concentrations, and be geochemically conservative (i.e., easily transported, and not absorbed or adsorbed by aquifer media).

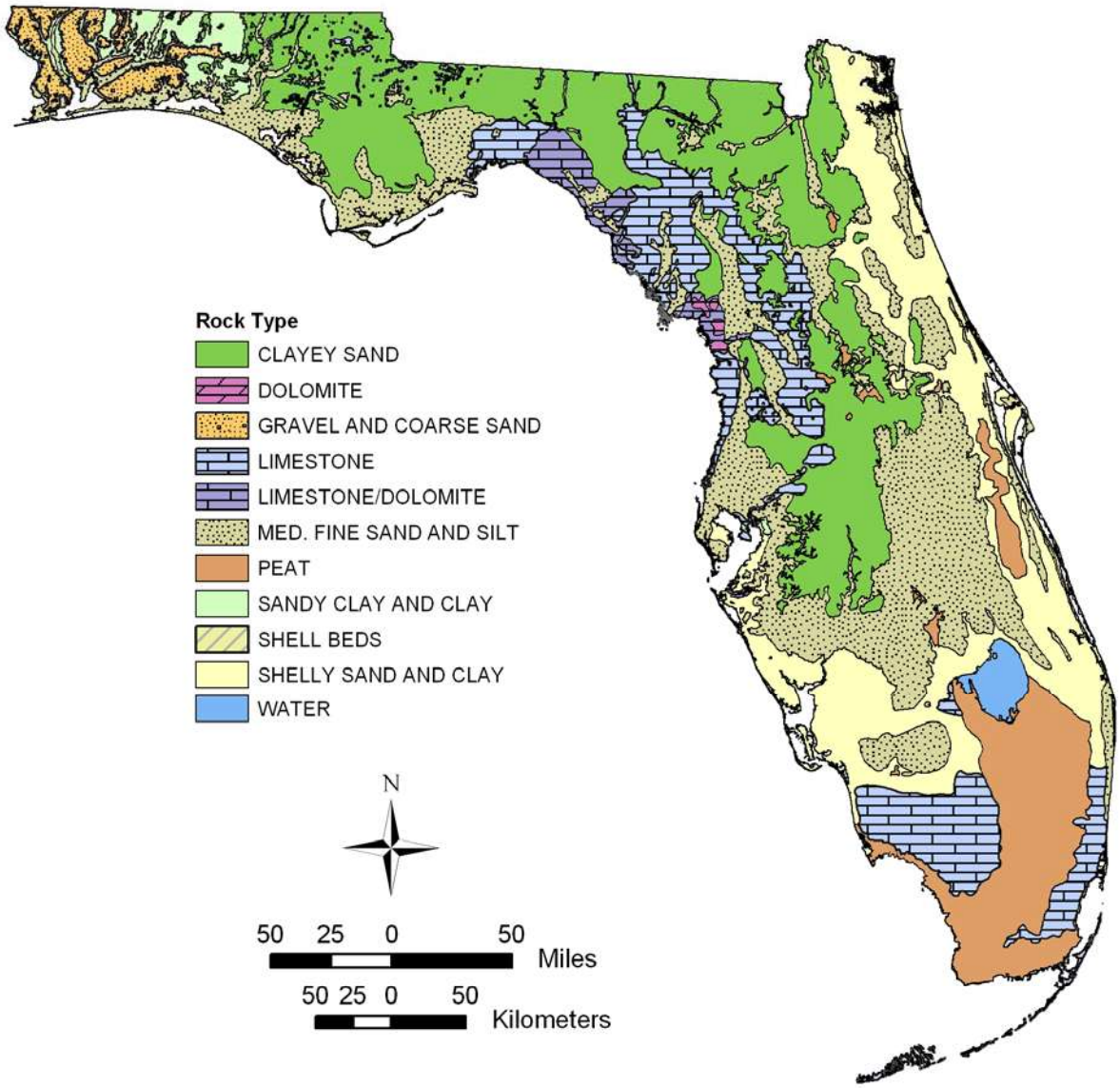


**Figure 23. Environmental Geology map of Florida (see text for references from which map was compiled). Polygons represent the dominant geologic material present just below the soil horizon (within 10 feet of land surface).**

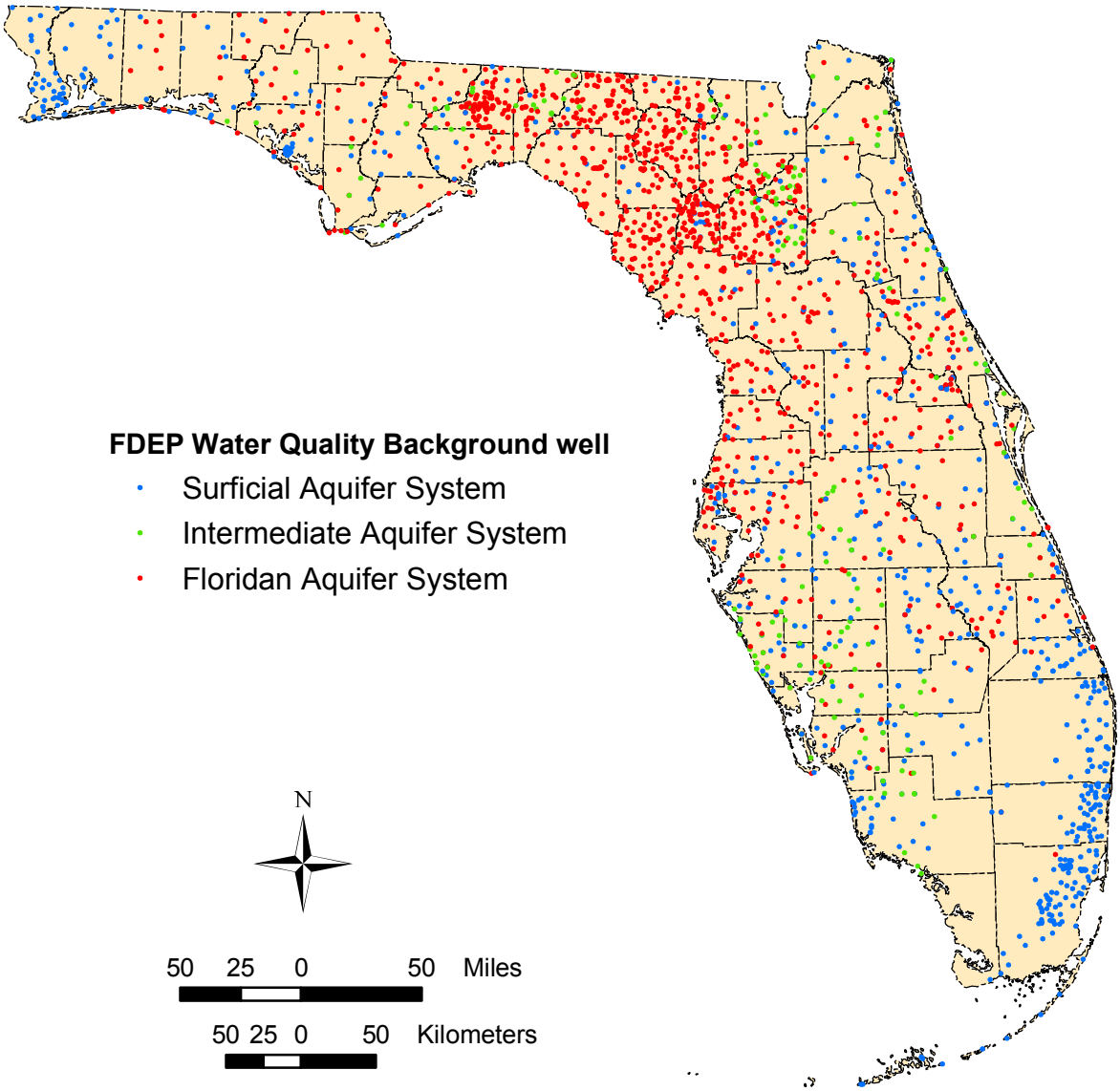


**Figure 24. Location of wells and their respective hydrogeologic unit in the FDEP background water quality monitoring network. These wells were used to develop the training points themes for input into the WofE – FAVA models.**

The water-quality analytes selected for the FAVA training data set included nitrogen and oxygen. Background levels of nitrogen and oxygen in Florida's aquifer systems are naturally low where the aquifer system is not affected by activities at land surface. Therefore, where dissolved nitrogen, ammonia and dissolved oxygen occur at concentrations significantly above background levels in an aquifer system, one can generally assume a relatively greater hydrologic connection between land-surface activities and ground water. Other analytes, such as tritium provide an indication of the age of water recharging the aquifers, and can provide an estimate of relative recharge – an approximate method of assessing vulnerability. These analytes, however, were not in abundance in the water quality database and would not provide adequate statewide coverage and representation of the many hydrogeologic settings in Florida. As a result, ammonium, nitrogen, and dissolved oxygen, were selected to develop training sets for WofE – FAVA models.

It is acknowledged that factors exist that may affect the concentration of these model training analytes, such as land use and the potential for dilution due to rainfall events prior to sample collection. These factors, however, were addressed to some degree by: 1) use of, where possible, median values of multiple analyses of these analytes to comprise the training point data set in order to reduce the possible influence of anomalous values, 2) use of statistical methods, described below, to remove anomalies that may have resulted from these factors, and 3) assessment of potential land-use bias during model output validation.

Water-quality measurements that included nitrate-plus-nitrite dissolved as nitrogen ($NO_3^-$ + $NO_2^-$ dissolved as N; hereafter, dissolved nitrogen), ammonia ($NH_3^-$), and dissolved oxygen from January 1991 through August 1999 were extracted from the FDEP database for use in development of training point themes for each aquifer system model. Measurements prior to 1991 were excluded due to the lack of consistent quality assurance. The background water quality monitoring network program was reorganized into another program (STATUS Network Program) in 2000 and due to the development of a new computer system, data from the STATUS network were not available for later dates. Future calculations of the FAVA response themes will be able to benefit from water quality analyses in the STATUS Network.

For the SAS and IAS FAVA model output, dissolved nitrogen and ammonia data were used to develop training point themes, whereas, for the FAS model output, only dissolved nitrogen was used (see *Results – FAVA Model Outputs* for each aquifer for further details and justification). Dissolved oxygen data were used to develop training point themes for validation of the FAVA models.

Many of the wells extracted from the GWIS database have multiple water-quality measurements taken over time for the analytes of concern. To develop training point themes for each aquifer system with a single analyte value per well, the median value of the multiple analyses was chosen to represent the well. An "upper fence" was calculated for the set of median values for each aquifer system to identify and omit outlier wells. This conservative approach was taken based on the possibility that outliers represented either erroneous water-quality measurements or were associated with nitrogen loading from a particular land use rather than representing general native ground-water quality.

The remaining sets of wells were further statistically analyzed to establish a 75th percentile value for each aquifer system's dataset. Wells with values of the analytes of concern occurring above the 75th percentile median value were selected to be the training point themes for input into the WofE model. These points represent the upper 25th percentile of wells with detected levels of analytes of concern. All aquifer systems in Florida are vulnerable to contamination to some degree throughout their extents and therefore some level of interconnectedness exists between land surface and all aquifer systems.

It is important to note that the occurrence of a training point in an area does not correspond to a site of aquifer system contamination. Rather, a training point is an indication of the degree of interconnectedness between the land surface and the top of the aquifer system in question. By choosing the upper 25$^{th}$ percentile for this report, we identified those areas where the connection is greatest, and therefore, are most vulnerable to contamination from land surface based on analytes that are considered to be ubiquitous in the Florida landscape. This method is also significant because instead of choosing a drinking water standard for a particular analyte threshold, the upper 25$^{th}$ percentile was used, ensuring that with any set of water quality data, a training point theme can be developed. The FAVA models are therefore models of vulnerability and not contamination.

## FAVA Model Outputs

### Introduction

As described in the *Introduction – Background – Models Considered* section, Weights of Evidence (WofE) was selected as the model on which to base the FAVA maps. Use of WofE requires the combination of diverse spatial data which are used to describe and analyze interactions and generate predictive models (Raines et al., 2000). A primary benefit of applying WofE to the FAVA project is that it is data-driven, rather than expert-driven. The data that "drive" or "train" the model consist of known occurrences of analytes that reflect relative aquifer vulnerability, such as levels of dissolved nitrogen and/or ammonia that exceed native ground-water conditions in wells. These wells are the training points used to calculate relative weights for laterally continuous input data layers (evidential themes), which are then combined to yield a response theme (Raines, 1999).

When reviewing the model results, it is important to note that all aquifers, to some degree, are vulnerable to contamination from land surface. The model results simply identify those areas within the study area that are more vulnerable or less vulnerable based on the evidential themes and training points used in the model. FAVA model results for Florida's three primary aquifer systems using WofE are broken down by aquifer system and discussed in the following sections. Each section describes the model extent (study area), training point selection, evidential themes, and response theme for that particular aquifer system. Although the details of the WofE modeling technique were described in the *Introduction*, additional general comments regarding how WofE was applied to the FAVA project are presented below.

### FAVA Evidential Themes

As described in the *Introduction – Approach – Models Considered* of this section of the report, several evidential themes were considered for use in the WofE – FAVA model. Themes were generalized in an effort to establish which areas of the evidence shared a greater association with locations of training points. During calculation of weights for each evidential theme used in the FAVA project, a contrast value was calculated for each class of the theme by combining the positive and negative weights (positive weight – negative weight). Contrast is a measure of a theme's significance in predicting the location of training points and helps to determine the threshold or thresholds that maximize the spatial association between the evidential theme map pattern and the training point theme pattern (Bonham-Carter, 1994).

Confidence of the evidential theme equals the contrast divided by the standard deviation (a student T test) for a given evidential theme and provides a useful measure of significance of the contrast due to the uncertainties of the weights and areas of possible missing data (Raines, 1999). A confidence

value of 0.674, which corresponds to a 75% level of significance, was the minimum acceptable level selected for the FAVA project evidential themes. Evidential themes that did not meet this test of significance were not included in the FAVA models. Confidence values approximately correspond to the statistical levels of significance listed in Table 7.

Contrast values were used to determine where to sub-divide evidential themes into generalized categories. The most common method of categorizing an ordered evidential theme was to select the maximum contrast as a threshold value to create a binary generalized evidential theme. For most evidential themes used for the FAVA project, this binary break was typically defined by the WofE analysis thereby creating two spatial categories: one with stronger association with the training point theme and one with weaker association with the training point theme. In some instances, more complex statistical contrast patterns were calculated and the creation of multiple classes in the evidential theme data was justified by the analysis. As mentioned in the *Introduction,* to create multiple classes, contrast thresholds chosen to create multi-class themes must also correspond to a level of significance, or confidence, greater than or equal to 0.674

Iterative model runs were completed to perform sensitivity analyses in relation to these evidential themes (for more information on model validation and sensitivity analyses see *Discussion – Model Validation and Sensitivity Analysis*). Given their importance in the overall process of developing FAVA maps, they are all described in this report; however, not all were applied within each aquifer system model. Evidential themes ultimately not used as WofE model inputs for two main reasons: they did not meet the test of significance for the FAVA project, or the resulting weights were counterintuitive with regard to hydrogeologic processes and vulnerability.

**Table 7. Test values calculated in WofE and their respective studentized T values expressed as level of significance in percentages.**

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

### FAVA Response Themes

The FAVA response themes are output maps calculated using WofE for each aquifer system showing the probability that a unit area would be vulnerable to contamination from land surface based on the evidence provided. The response themes are portrayed as relative vulnerability maps and were classified into probability classes which were selected based on the inflections in charts in which cumulative study area was plotted against the posterior probability for each model. The breaks for these vulnerability zones were selected where a notable stepwise increase in posterior probability relative to cumulative area occurred. The more vulnerable areas corresponded with higher posterior probabilities, while the less vulnerable areas were associated with lower posterior probabilities. In essence, a higher posterior probability indicated that an area was more likely to contain a training point, or more likely to be contaminated, and therefore more vulnerable to contamination from land surface.

Further, implications of the Delphi study results, as well as feedback from the FAVA TAC suggest that too many (or too few) classes of relative vulnerability may complicate application of the FAVA model results. As a result, the posterior probabilities were divided into three classes:

- less vulnerable,
- vulnerable, and
- more vulnerable.

These three class designations were used in the model results of the SAS, IAS, and FAS. The color codes and class designations were kept the same throughout the models for simplification. They should not be assumed, though, to mean the same thing between model results for all three aquifer systems. Each response theme was unique to each aquifer system and was dependent on the evidential theme and training point data used for input for that model only.

Typically, the break between the *vulnerable* and *more vulnerable* zone corresponded to the prior probability value for each model. The three sections that follow discuss the model results for the SAS, IAS, and FAS, and the response themes for each aquifer system are presented at the end of each section at a scale of 1:4,800,000. The response themes are also included in Plates 1, 2, and 3 at a scale of 1:1,267,200. The Plates allow the display of more detail in the response themes and also include information about training points and evidential themes. These three-class vulnerability maps are provided as a potential resource for decision making, development of rules, or policies regarding environmental conservation, protection, growth management and planning.

As mentioned above, all aquifers are vulnerable to contamination to some degree; i.e., no aquifer can be considered to be truly invulnerable to contamination. It follows then that the probability that an aquifer system is vulnerable to contamination can never be equal to zero because this would indicate that it has no probability of being contaminated (e.g., containing a training point). This was supported by the model results; the posterior probability values for none of the models was zero, indicating that all the aquifer systems in Florida are to some degree, vulnerable to contamination.

An assumption is made when using WofE that there is conditional independence between the layers used as predictors. Conditional independence is violated when the presence of one evidential theme influences the probability of another evidential theme. The validity of a posterior probability value is dependent upon the degree of conditional independence calculated for each model. If an evidential theme does not significantly affect the probability of another evidential theme then conditional independence is satisfied. Evidential themes are considered independent of each other if the conditional independence value is around 1.00. For the FAVA project, appropriate conditional

independence values fell within the range of 1.00 ± 0.15 (Raines, 2001). Values outside of this range could have over inflated the posterior probability values and yielded misleading results. In this study, the only model that violated the assumption of conditional independence was the FAS FAVA model. As a result, the FAS FAVA model response theme was calculated using logistic regression (see *Introduction – Approach – Models Considered* for a detailed discussion of logistic regression).

A response theme table was generated for each FAVA response theme. This table displays the evidential themes used, weights calculated for those evidential themes, as well as the theme contrast and confidence of the evidential themes. Refer to *Introduction – Approach – Models Considered – Weights of Evidence Model* for an explanation of the components listed in the response theme table.

### Confidence Maps

As mentioned in the *Introduction – Approach – Models Considered – Weights of Evidence Model*, there are two types of confidence used on the WofE model. Confidence of the evidential theme, as reported in the response theme tables, equals the contrast divided by the standard deviation for a given evidential theme. Confidence maps were also generated for the response themes by dividing a response theme's posterior probability distribution by the total uncertainty for the model. Confidence maps help the end-user to assess the certainty of each FAVA response theme. Areas with a high posterior probability tend to have higher confidence values and therefore have a higher level of certainty with respect to predicting aquifer vulnerability. Areas with missing data raise the total uncertainty, which in turn lowers the confidence value. Confidence maps are displayed with the response theme for each aquifer system below.

### Surficial Aquifer System

#### Study Area and Extent

The Surficial Aquifer System (SAS) is the permeable hydrostratigraphic unit in Florida contiguous with land surface that comprises principally unconsolidated siliciclastic deposits, and to a lesser extent, carbonate rocks. The lower limit of the SAS coincides with less permeable sediments of the top of the IAS (Southeastern Geological Society, 1986). The SAS occurs throughout much of the State and is used extensively in the western panhandle (Sand and Gravel Aquifer) and the southeastern peninsula (Biscayne Aquifer) as a principal source of drinking water.

The preliminary extent (i.e., WofE study area) of the SAS for the FAVA project was based on the extent of the IAS. Modifications of this preliminary extent were based on the distribution of Miocene-Pliocene clay-rich sediments as mapped by Scott et al. (2001). In areas where sediments of the IAS were not mapped on a regional scale, the SAS was not mapped for this project (see *Results – Data Coverages – Intermediate Aquifer System Thickness* for additional information). Further refinement of the SAS extent was accomplished by omitting areas where laterally continuous SAS sediments were calculated at less than ten feet thick and where IAS sediments were at or near land surface. In some instances, SAS sediments greater than ten feet in thickness were omitted from the extent because they represented isolated, discontinuous, local packages of sediment which do not form part of a major regional aquifer system. In some of these areas, hydraulic heads in the FAS and surficial sediments differ, justifying a local water-table aquifer in the areas; however, these local occurrences are generally discontinuous. Given the statewide scale of the FAVA project, attempting to map and model these isolated areas was beyond the scope of this project. Maps showing the SAS

extent in this report reflect only areas where the SAS is present in a laterally continuous and regional extent.

For modeling purposes, the extent of the SAS was further revised to exclude all areas covered by both permanent and seasonal wetlands (Figure 25). These wetlands were identified using the National Wetlands Inventory (NWI) database (US Fish and Wildlife Service, 1988-1993). Wetlands were omitted from the SAS extent because they were poorly represented by training points, i.e., few wells existed in wetland areas. During sensitivity analyses, model outputs for the SAS that included wetlands yielded misleading evidential theme weights and poorly predicted vulnerability of the SAS in wetland areas. It is important to note that this NWI differs significantly from wetlands identified in land use data used later in this report to compare land use to relative vulnerability.

### Training Points

There were a total of 916 wells in the FDEP background water quality monitoring network that were completed in the SAS. Of these wells, 442 were measured during the same sampling event for both ammonia and dissolved nitrogen concentrations. This was a criterion for selecting SAS training point wells. The measured values were then combined (dissolved nitrogen plus ammonia; hereafter referred to as "total dissolved nitrogen") to provide a single analyte value per well on which statistical analyses could be completed.

Ammonia concentrations were incorporated into the SAS training point data set to account for areas of the State with a high water table, primarily in the southern part of the study area. 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. If ammonia was not used in conjunction with dissolved nitrogen, the SAS model results were biased toward areas with a thick vadose zone (i.e., Sand and Gravel Aquifer).

Using statistical methods described in *Results – Data Coverages –Training Points*, 52 wells were identified as outliers and subsequently removed from the dataset leaving 390 wells for additional analysis. Further statistical analysis returned a 75$^{th}$ percentile combined median value for a total dissolved nitrogen concentration of 0.619 milligrams per liter (mg/L). There were 92 wells occurring in the dataset with a total dissolved nitrogen value greater than 0.619 mg/L. These 92 wells were used to create the training point theme for input into the SAS FAVA model. The resulting prior probability was calculated at 0.0014, which represents the chance that a training point will occupy any given unit area within the study area, independent of any evidential theme data. The distribution of these wells is displayed in Figure 26.

### Generalization of Evidential Themes

Several evidential themes were considered for input into the SAS FAVA model:

- Soil drainage
- Soil permeability
- Closed topographic depressions
- Depth-to-water
- Environmental geology map
- Geologic map of the State of Florida

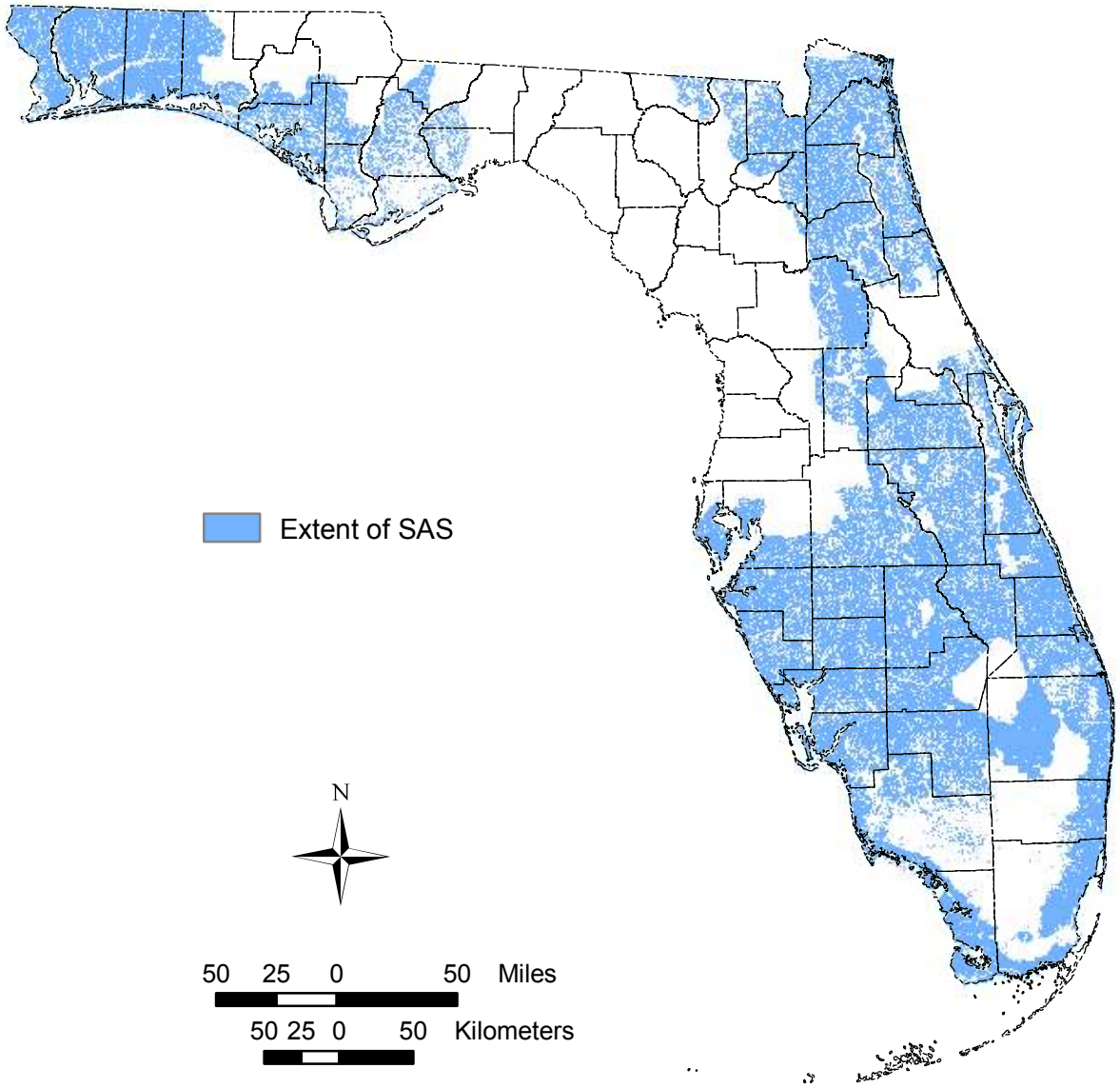


**Figure 25. Extent of the SAS where it forms a major regional aquifer system throughout Florida. Wetlands and large water bodies have been omitted from this study area based on the National Wetlands Inventory to avoid biasing the model.**

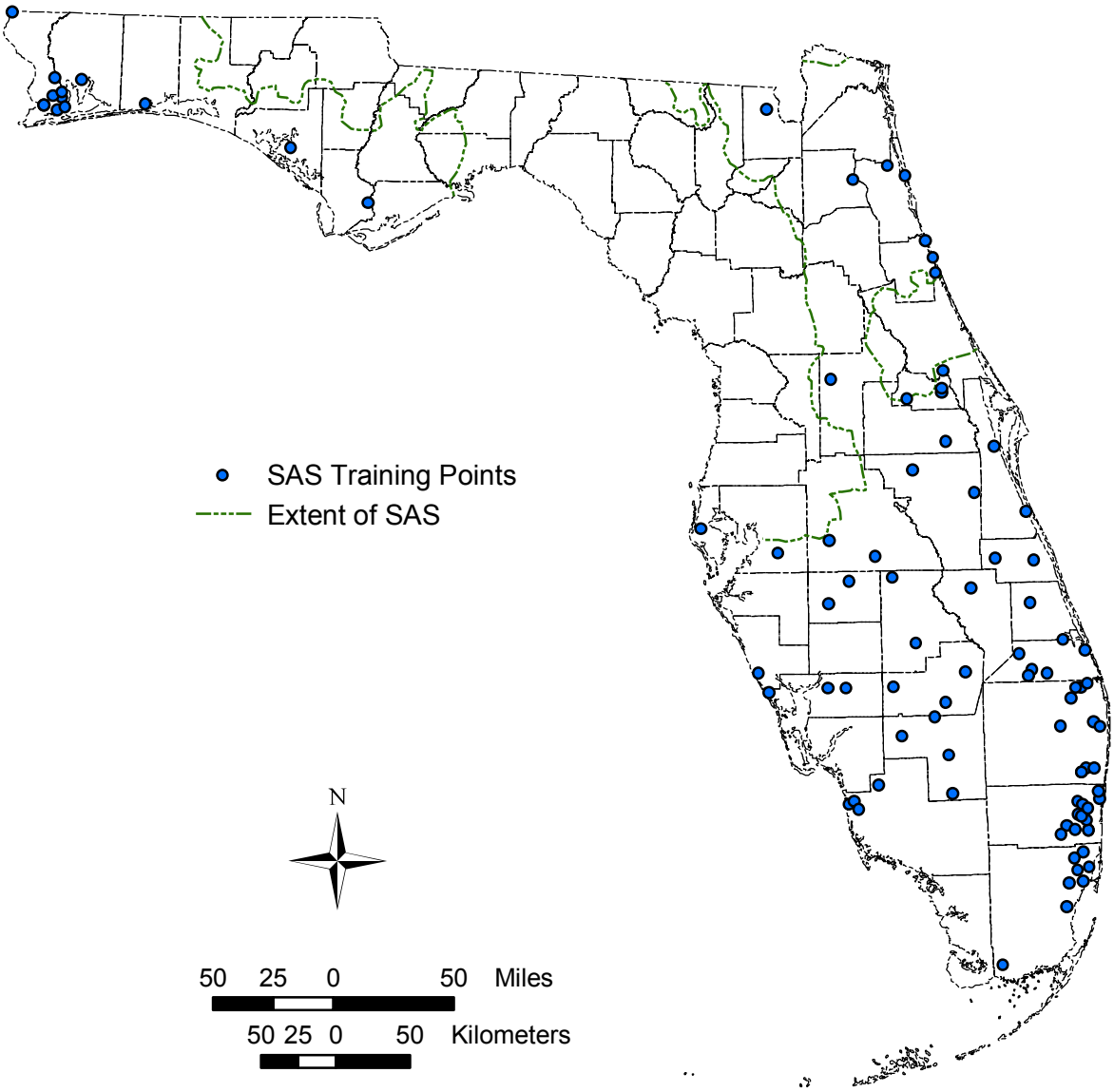


**Figure 26. Map showing location and distribution of the 92 training points consisting of wells completed in the SAS, which were simultaneously measured for both ammonia and dissolved nitrogen. These wells had a measured total dissolved nitrogen value greater than 0.619 mg/L.**

Ultimately, three of the above evidential themes were used for the SAS model: depth-to-water, soil permeability and closed topographic depressions. The other evidential themes were not used because they either did not meet the test of significance for the FAVA project, or the resulting weights were counterintuitive with regard to hydrogeologic processes and vulnerability. For a full discussion on the limitations of evidential themes refer to *Results – Data Coverages*. Modifications were made to the evidential themes to calculate weights and then generalize the evidential themes for input into the SAS FAVA models. The modifications and generalizations are discussed below.

Soil Permeability

Soil permeability is a measure of the rate at which water travels through the upper vadose zone. Areas with high soil permeability values are normally associated with higher aquifer vulnerability. Weights were therefore calculated for soil permeability using the cumulative descending method. The highest contrast (see *Results – FAVA Model Outputs – FAVA Evidential Themes* and *Introduction – Approach – Models Considered – Weights of Evidence Model* for more information on use of contrast to generalize evidential themes) of any class was calculated at 6.3 in/hr (Figure 27).

The calculated weights did not justify the selection of a multi-class theme because neither contrast nor confidence calculated for other classes was statistically significant enough to support delineation of more breaks. As defined by the analysis of this evidential theme, the most appropriate break in the soil permeability evidential theme was at 6.3 in/hr creating a binary generalized theme for input into the SAS FAVA model. In other words, this analysis indicated that areas underlain by soils with permeability values ranging from 0.1 to 6.3 in/hr were, based on the location of training points, associated with areas of lower vulnerability. Conversely, the analysis indicated that areas underlain by soils with permeability values ranging from 6.3 to 20.0 in/hr were, based on the location of training points, associated with areas of higher vulnerability. The generalized theme is displayed in Figure 28.

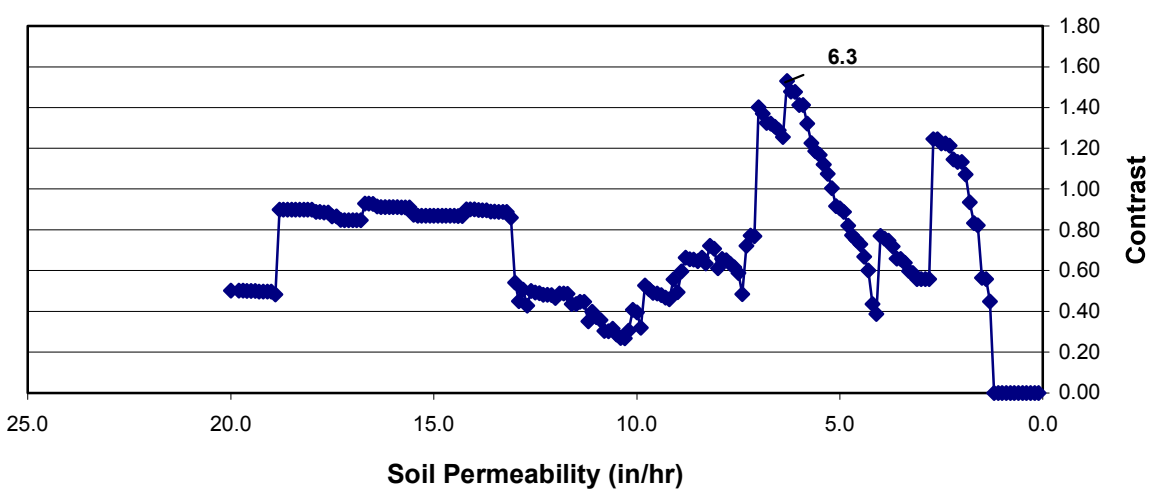


**Figure 27. Cumulative-descending soil permeability values (in/hr) plotted against contrast values calculated using WofE. The highest cumulative contrast value was calculated at 6.3 in/hr, which indicated that areas of the evidential theme with permeabilities higher than this value are the best predictor of training points.**

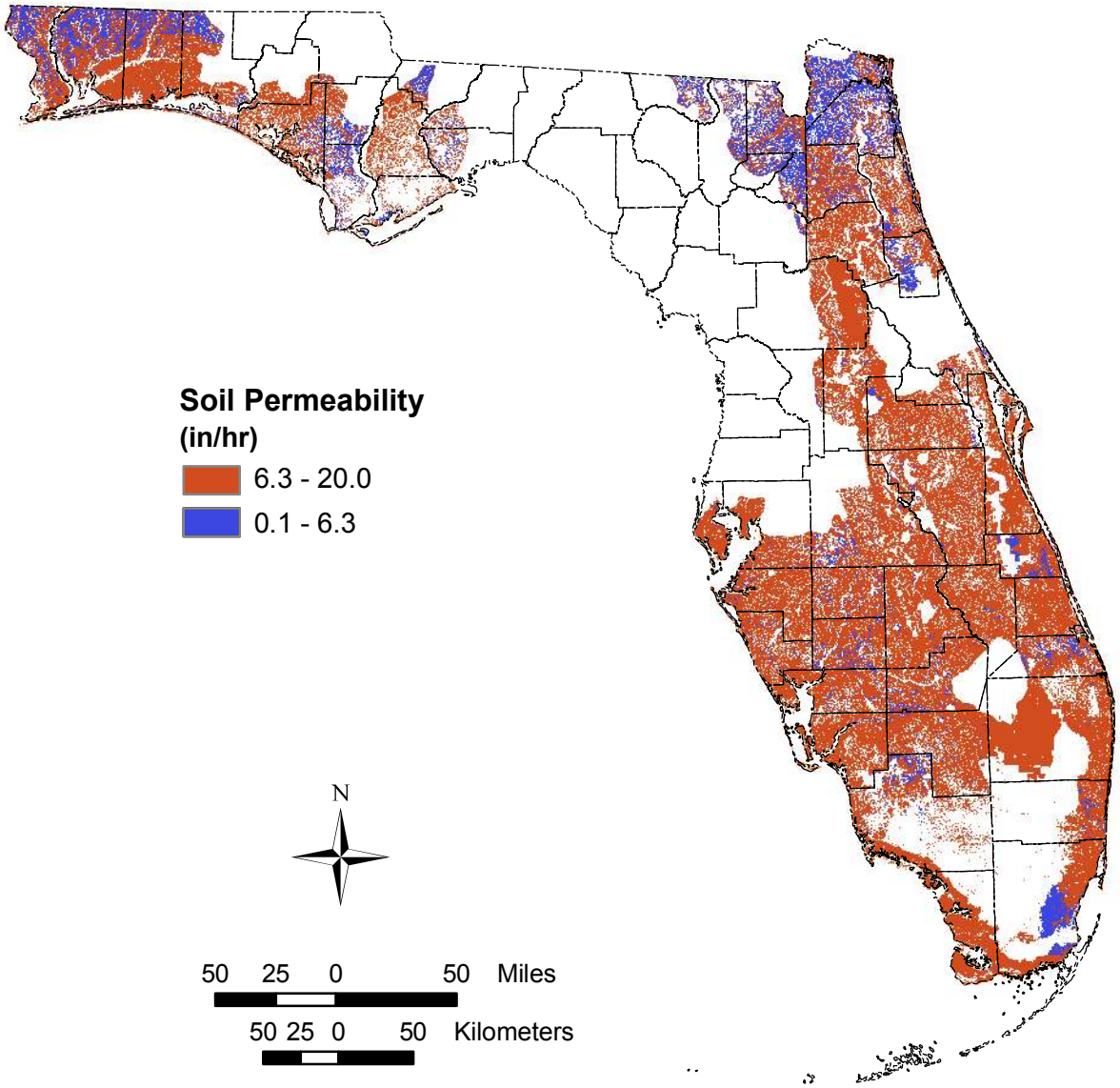


**Figure 28. Map showing generalization of soil permeability evidential theme. Based on calculated weights, a binary generalization with a break at a value of 6.3 in/hr was defined by the analysis. Based on the location of training points, blue areas were associated with areas of lower vulnerability, while red areas were associated with areas of higher vulnerability.**

### Closed Topographic Depressions

In the FAVA project, closed topographic depressions were typically prominent in areas of high karst feature density. Water generally collects and recharges the underlying aquifers beneath closed topographic depressions. Because areas nearer to a karst feature are considered more vulnerable to contamination than areas further away, a proximity analysis was completed for the closed topographic depressions theme by creating a 2,700-m buffer zone around each topographic depression within which equally-spaced 90-m intervals were delineated. The outermost interval contained all areas of the SAS extent which lie 2,700 m or further from a topographic depression. Based on spatial analysis, all training points occurred within 2,700 m from a closed topographic depression, thereby lending support to that radial distance as a lateral threshold for the delineation of intervals within the buffer zone.

As stated above, areas closer to a closed topographic depression are normally associated with higher aquifer vulnerability, and, as a result, weights were calculated for the closed topographic depressions evidential theme using the cumulative ascending method. The highest contrast of any class was calculated at a distance of 2,340 m from a depression. The calculated weights did not justify the selection of a multi-class theme because neither contrast nor confidence calculated for the other classes supported delineation of more breaks. As defined by the analysis of this evidential theme, the most appropriate break in the closed topographic depressions evidential theme was at 2,340 m creating a binary generalized theme for input into the SAS FAVA model. In other words, this analysis indicated that areas beyond 2,340 m of a closed topographic depression were, based on the location of training points, associated with areas of lower vulnerability. Conversely, the analysis indicated that areas within 2,340 m of a closed topographic depression were, based on the location of training points, associated with areas of higher vulnerability. The generalized theme is displayed in Figure 29.

### Depth-to-Water

The depth-to-water evidential theme used in the SAS FAVA model was calculated by subtracting the water-table elevation values from the FDEP DEM values. Areas where the depth-to-water was equal to zero occurred over a large part of the SAS study area and, for the most part, coincided with wetlands and water bodies. These areas were considered surface water and for the purpose of modeling were converted into “missing data” values. These areas did not directly correspond to the mapped NWI database because depth-to-water values were based on interpolated values calculated from water-table elevation. It is important to note that designation of these areas as “missing data” was done for this evidential theme only and did not change the model study area that was based on the NWI database and identified in Figure 25. Weights were still calculated for this evidential theme, but “missing data” areas were assigned a weight of zero. In addition, during preliminary model iterations, it was determined that if areas calculated at a depth-to-water value of zero were included, calculated weights and their associated confidence values did not meet the test of significance for the FAVA project. The FAVA approach was not designed to address vulnerability of surface water bodies, all of which are vulnerable to contamination. The depth-to-water evidential theme values ranged from one to 220 ft below land surface, and, for over 50% of the study area, were less than eight feet deep.

Aquifer vulnerability for the SAS is normally associated with areas of high-water table (i.e., shallow depth-to-water). A pattern identifying where the water table is closest to land surface would therefore be a good predictor of training points. As a result, weights were calculated for depth-to-water using the cumulative ascending method of the WofE analytical technique. The highest contrast calculated

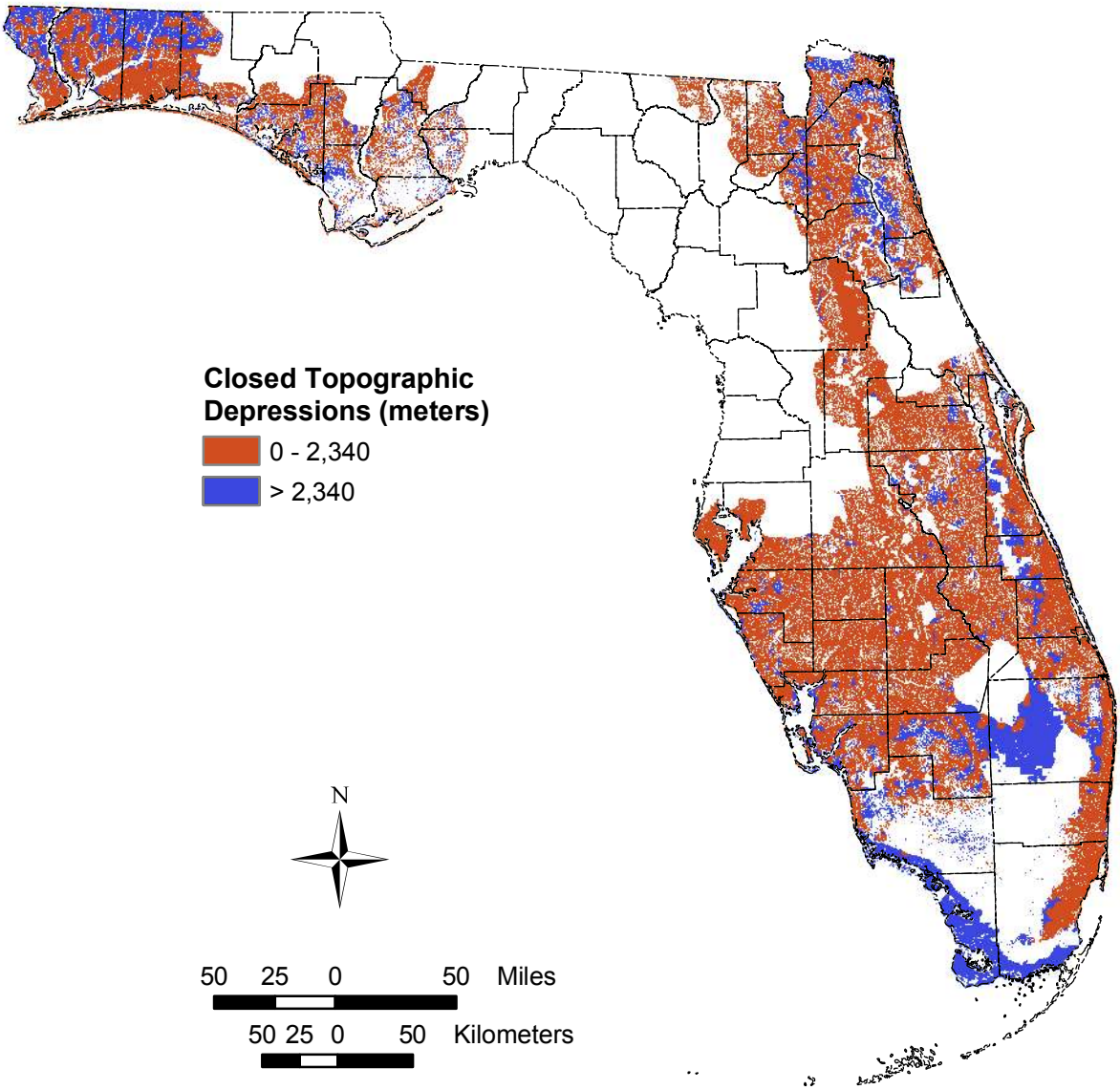


**Figure 29. Map showing generalization of closed topographic depressions evidential theme. Based on calculated weights, a binary generalization with a break at a distance of 2,340 m was defined by the analysis. Based on the location of training points, blue areas were associated with areas of lower vulnerability, while red areas were associated with areas of higher vulnerability.**

for any class was calculated at a depth-to-water value of 48 feet. The calculated weights did not justify the selection of a multi-class theme because neither contrast nor confidence calculated for the other classes supported delineation of more breaks. As defined by the analysis, the most appropriate break in the depth-to-water evidential theme equals 48 feet, thus creating a binary generalized theme for input into the SAS FAVA model. In other words, this analysis indicated that areas in which the depth-to-water exceed 48 ft were, based on the location of training points, associated with areas of lower vulnerability. Conversely, the analysis indicated that areas in which the depth to water is less than 48 ft were, based on the location of training points, associated with areas of higher vulnerability. The generalized theme is displayed in Figure 30

Response Theme

Using the three evidential themes discussed above, a response theme (Figure 31) was generated showing the posterior probability that a unit area contained a training point based on the evidential themes used as input. The posterior probabilities of the response theme ranged from 0.000119 to 0.001870 across the model domain. Plotting posterior probability against cumulative area as a percentage (Figure 32) allowed the delineation of class breaks for display of vulnerability zones in the final response theme. The breaks for these vulnerability zones were selected where a notable stepwise increase in posterior probability relating to cumulative area occurred. The first break, which delineated the *less vulnerable* zone from the *vulnerable* zone, occurred at a posterior probability value of 0.00047. The *less vulnerable* zone represents approximately 5% of the study area. The second break delineating the *vulnerable* zone from the *more vulnerable* zone occurred at the next significant stepwise increase in posterior probability at a value of 0.0014, which also corresponded with the prior probability. The *vulnerable* zone represents approximately 29% of the study area. The remainder of the study area fell into the *more vulnerable* zone and represents approximately 66% of the study area. This *more vulnerable* zone contained the greatest probability of containing a training point. Plate 1 (back pocket) provides a more detailed display of the relative vulnerability zones.

The response theme (Figure 31) indicated that the areas of highest vulnerability tended to be associated with areas of high soil permeability, shallow depth-to-water zones and, to a lesser degree, high density of closed topographic depressions. Conversely, areas of lowest vulnerability tended to be characterized by relatively low soil permeability values, sparse closed topographic features, and deeper depth-to-water zones.

The study area contains a multitude of surface water features, which can represent areas of discharge and may be predicted with low posterior probability values. These discharging surface waters are not considered part of the aquifer, although they can originate from it. The FAVA project was designed to focus on the ability for a contaminant to travel through soils, overburden, karst features, etc. to enter into the aquifer system. As a result, it is very important that the FAVA model never be applied to assess contamination of surface waters or discharge areas.

Weights calculated for the evidential themes used in the SAS model are listed in Table 8. The soil permeability evidential theme had a greater association with the training points (higher contrast) than the other themes and was therefore the primary determinant in predicting areas of vulnerability. The larger absolute value of the negative weights (W2) in Table 8 indicated that the response theme was a better predictor of where training points were not likely to occur. In other words, the SAS FAVA model more strongly predicted where the SAS is less vulnerable to contamination than it predicted where it was more vulnerable to contamination. See *Introduction – Approach – Models Considered – Weights of Evidence* for a more detailed discussion of the significance of this table. Confidence values for the evidential themes all fell above the target value of 0.674. Conditional independence was calculated at 1.00 indicating no dependence between evidential themes.

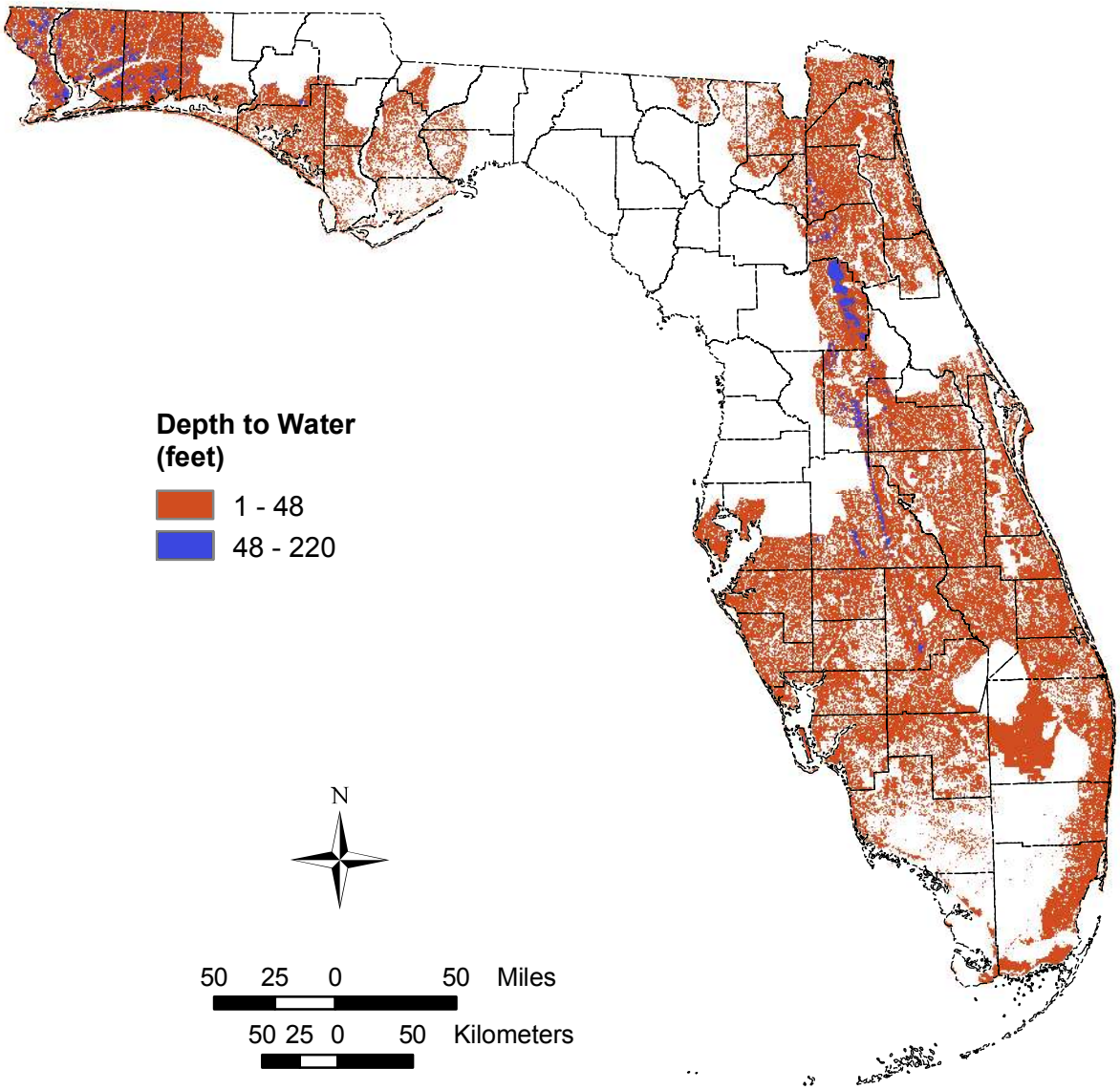


**Figure 30. Map showing generalization of depth-to-water evidential theme. Based on calculated weights, a binary generalization with a break at a depth of distance of 48 ft was defined by the analysis. Based on the location of training points, blue areas were associated with areas of lower vulnerability, while red areas were associated with areas of higher vulnerability.**

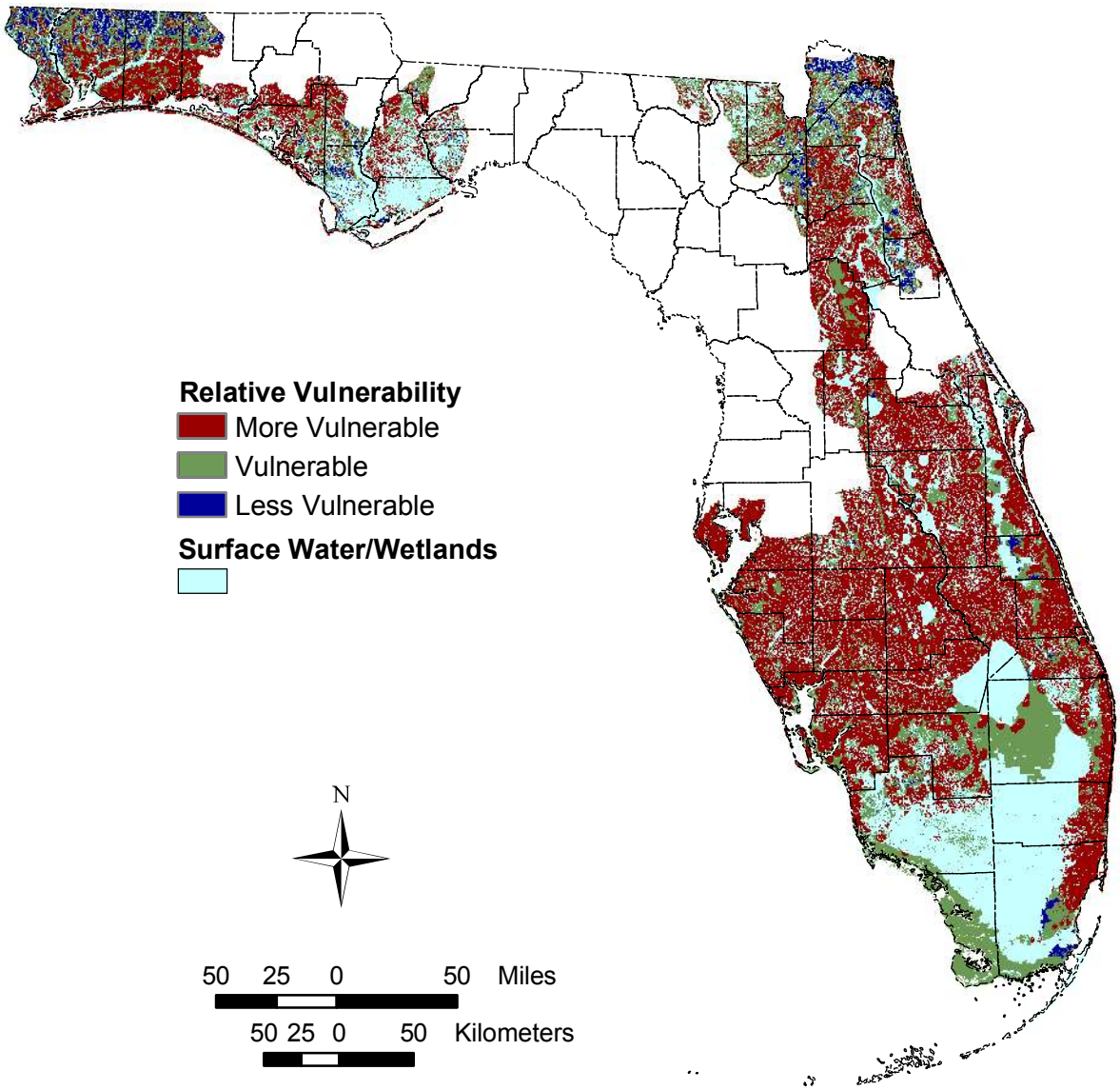


**Figure 31. Relative vulnerability of the SAS divided into three zones based on posterior probability values displayed in Figure 32. Total dissolved nitrogen concentrations were used as a training point theme. See Plate 1 (back pocket) for a more detailed display and discussion of the vulnerability zones.**

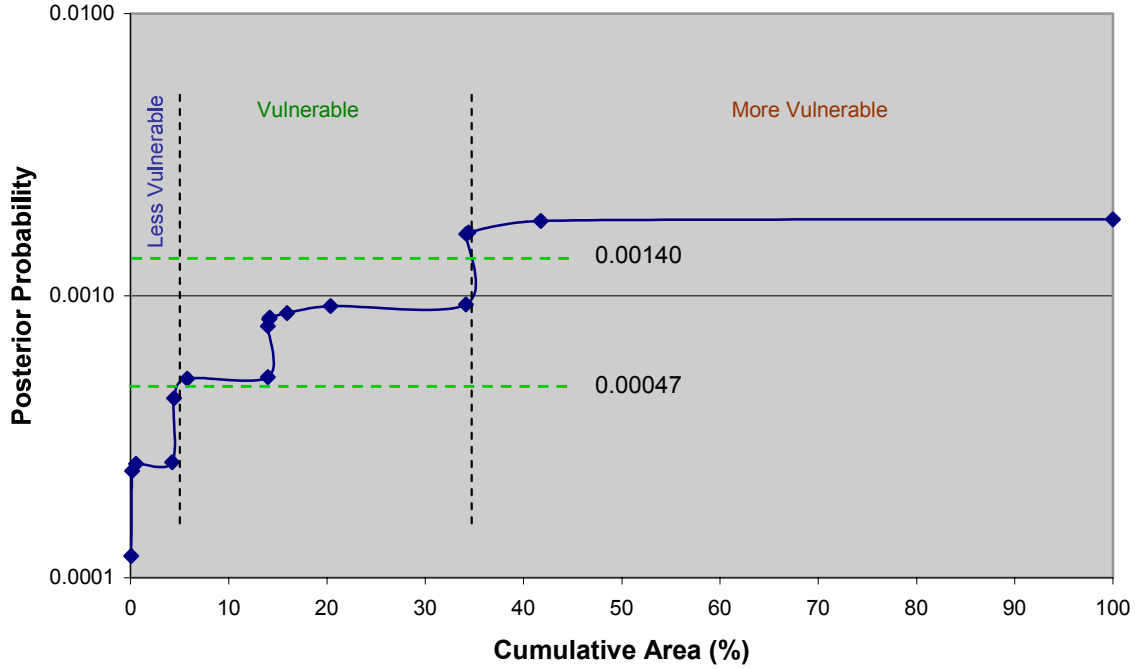


**Figure 32. Class breaks, represented by green dashed lines, were placed where both a significant increase in probability and area were observed. These boundaries correspond with relative vulnerability zones delineated in Figure 31 and are indicated in this chart by vertical black dashed lines.**

Confidence Map

The confidence values calculated by dividing posterior probability by its total uncertainty (standard deviation) for the SAS model area ranged from 0.862 to 5.810. The higher confidence areas corresponded with higher vulnerability areas whereas lower confidence areas corresponded to lower vulnerability areas. These values indicated that the confidence level was above 97.5% for most of the model study area, and was greater than 80% for the entire model domain. Areas of lower confidence also corresponded with areas that lack training points. The confidence map for the SAS model response theme is displayed in Figure 33.

**Table 8. Response theme table listing weights calculated for each evidential theme and their associated contrast and confidence values.**

| Evidential Theme | W1 | W2 | Contrast | Confidence |
|---|---|---|---|---|
| Soil Permeability | 0.1061 | -1.1830 | 1.2891 | 2.5220 |
| Closed Topographic Depressions | 0.1210 | -0.5760 | 0.6970 | 2.2541 |
| Depth-to-Water | 0.0132 | -0.7531 | 0.7663 | 0.7616 |

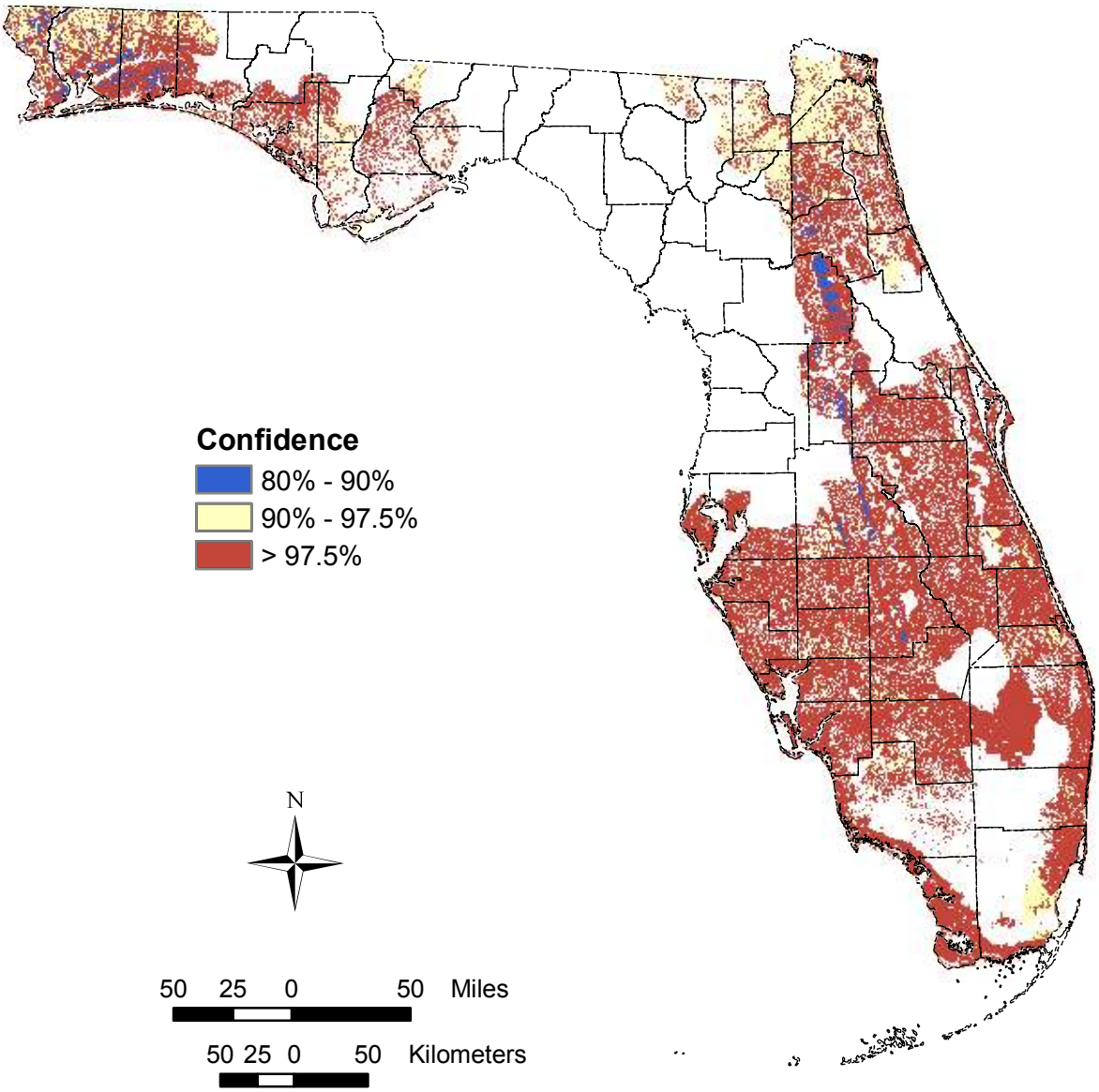


**Figure 33. Distribution of confidence values calculated for SAS response theme.**

### Intermediate Aquifer System

Study Area and Extent

The Intermediate Aquifer System (IAS) includes all rocks and sediments that lie between and collectively restrict the exchange of water between the overlying SAS and underlying FAS (Southeastern Geological Society, 1986). This unit generally acts as a confining unit for the FAS where it is present, but also contains minor, moderate-yielding aquifers throughout the State. It is, however, a major source of ground water only in the southwestern part of Florida, and is the region selected for the IAS FAVA study area. Figure 34 displays the study area used by the FGS to assess the relative vulnerability of the IAS.

The IAS in southwestern Florida comprises a major regional aquifer system providing ground water to municipalities, industries and agriculture. Various researchers have identified several production zones (aquifers) within this aquifer system (e.g., Metz, 1993, Torres et al., 2001). Due to the complex and discontinuous nature of these zones, it was not feasible to map them or model their individual vulnerability within the scope of this project.

The extent of the IAS was based on the combination of the distribution of FDEP public water supply wells and an extent proposed by Miller (1986). FDEP wells were plotted in a GIS with a 20-km buffer. This method accounted for major production zones of the IAS in the southern part of the region, but did not adequately represent areas where the IAS is a principal aquifer system for domestic supply in Polk, Sarasota, Manatee, and Hardee Counties. For this region, Miller's (1986) extent was applied. By combining the polygons for these two areas, a comprehensive extent of the IAS where it is predominantly used for public supply was developed for input into the FAVA model.

Large water bodies (those covering greater than approximately 50 acres) were omitted from IAS FAVA model because a well would never be drilled in these areas – therefore, they would never contain a training point. If the lakes were left in the model, the surface area is increased with no chance of increasing the number of training points. This would unnecessarily bias the model, and further, large water bodies typically have no soils or other input data associated with them.

Training Points

There were a total of 295 wells in the FDEP background water quality monitoring network that were completed in the IAS. These wells were located throughout the State, but for this project, only those falling within the IAS study area defined in Figure 34 were used. Criteria for selecting IAS training point wells also included that the wells be sampled for both ammonia and dissolved nitrogen during the same sampling event. There were 130 wells that met these criteria. The measured values were then combined to provide a single analyte value per well, total dissolved nitrogen, on which statistical analyses could be completed.

Ammonia concentrations were incorporated into the IAS training point dataset because nitrogen in the form of ammonia can be more prevalent than dissolved nitrogen in deeper parts of the IAS where lack of dissolved oxygen creates a reducing environment. If ammonia was not used in conjunction with dissolved nitrogen, weights calculated for evidential themes using WofE did not produce significant contrast values for use in generalizing the themes.

Using statistical methods described in *Results – Data Coverages –Training Points*, 32 wells were identified as outliers and subsequently removed from the dataset leaving 98 wells for additional analysis. Further statistical analysis returned a 75$^{th}$ percentile combined median value for a total

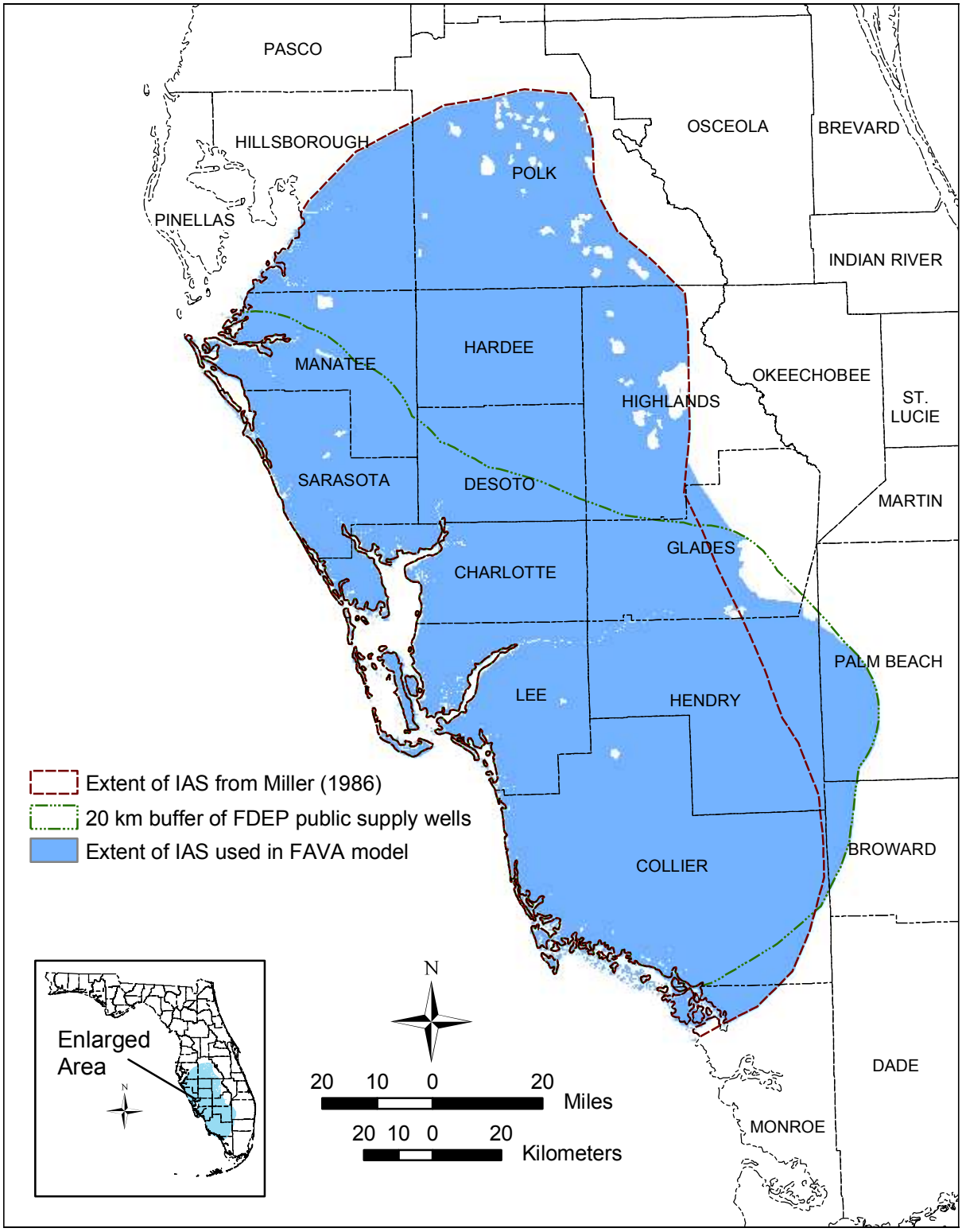


**Figure 34. Extent of the IAS where it forms a major regional aquifer system in southwest Florida. Large water bodies have been omitted from the analysis to avoid biasing the model.**

dissolved nitrogen concentration of 0.457 mg/L. There were 26 wells occurring in the dataset with a total dissolved nitrogen median value greater than 0.457 mg/L. These 26 wells were used to create the training point theme for input into the IAS FAVA model. The resulting prior probability was calculated at 0.0009, which represents the chance that a training point will occupy any given unit area within the study area, independent of any evidential theme data. The distribution of these wells is displayed in Figure 35.

### Generalization of Evidential Themes

Several evidential themes were considered for the IAS FAVA model:

- Soil drainage
- Soil permeability
- Karst features (derived from closed topographic depressions data layer)
- Thickness of overburden on IAS
- Environmental geology map
- Geologic map of the State of Florida

After extensive sensitivity analyses, three of the above evidential themes were used in the IAS model: soil permeability, karst features, and thickness of overburden. The other evidential themes were not used because they either did not meet the test of significance for the FAVA project, or the resulting weights were counterintuitive with regard to hydrogeologic processes and vulnerability. For a full discussion on the limitations of evidential themes refer to *Results – Data Coverages*. Modifications were made to the evidential themes to calculate weights and then generalize the evidential themes for input into the IAS FAVA models. The modifications and generalizations are discussed below.

### Soil Permeability

Soil permeability is a measure of the rate at which water travels through the vadose zone. Areas with high soil permeability values are normally associated with higher aquifer vulnerability. Weights were calculated for soil permeability using the cumulative descending method of the WofE model technique. The highest contrast of any class was calculated at 7.3 in/hr. The calculated weights did not justify the selection of a multi-class theme because neither contrast nor confidence calculated for other classes was significant enough to support delineation of more breaks. As defined by the analysis of this evidential theme, the most appropriate break in the soil permeability evidential theme was at 7.3 in/hr creating a binary generalized theme for input into the IAS FAVA model. In other words, this analysis indicated that areas underlain by soils with permeability values ranging from 0.1 to 7.3 in/hr were, based on the location of training points, associated with areas of lower vulnerability. Conversely, the analysis indicated that areas underlain by soils with permeability values ranging from 7.3 to 20.0 in/hr, based on the location of training points, were associated with areas of higher vulnerability. The generalized theme is displayed in Figure 36.

### Effective Karst Features

Effective karst is defined herein as those closed topographic depressions which are believed to increase hydrologic communication between land surface and the underlying aquifer system. To develop an appropriate representation of karst features in the IAS model, an effective karst GIS grid was created based on closed topographic depressions and thickness of IAS overburden. This was accomplished by filtering out those depressions underlain by more than 100 feet of IAS overburden.

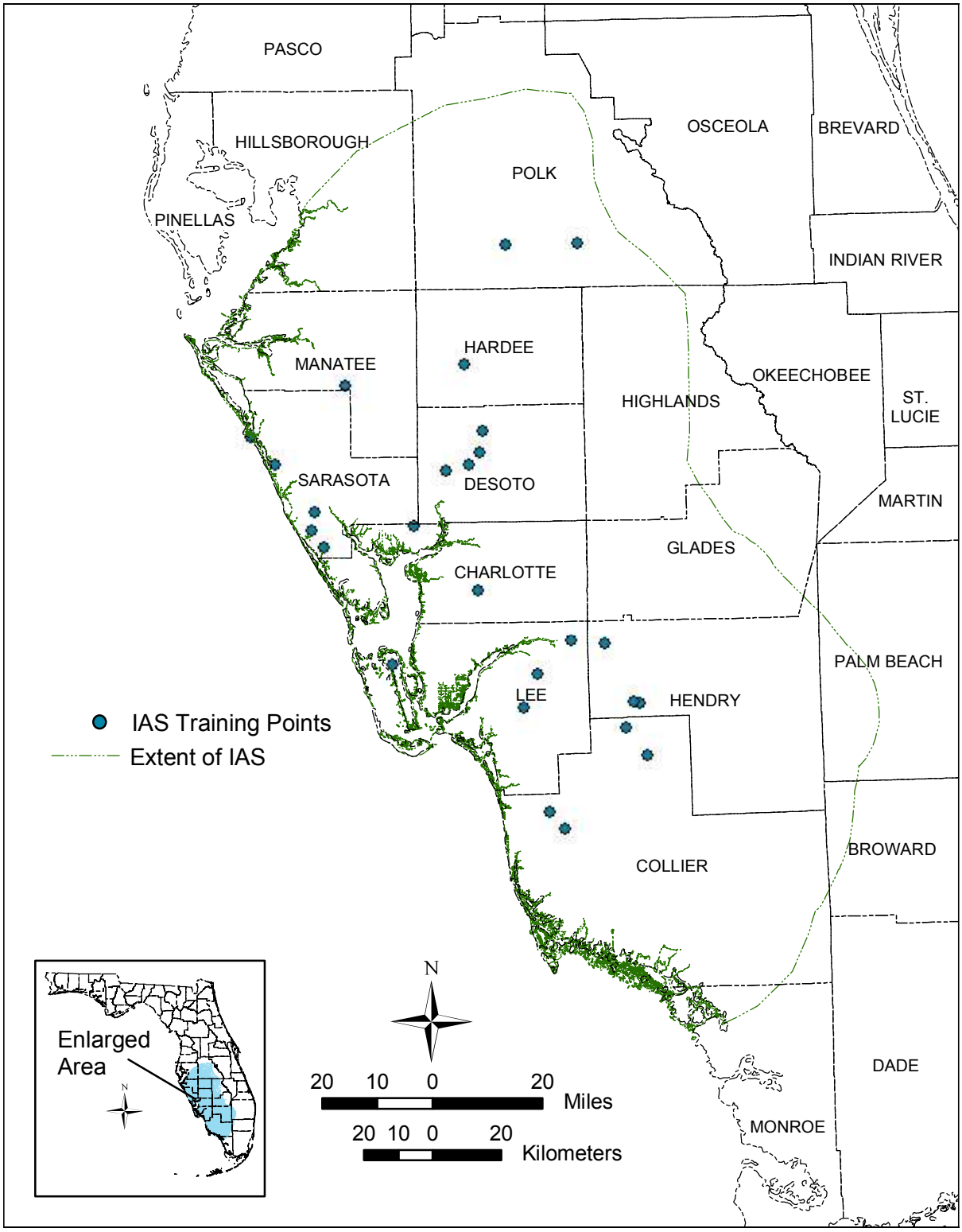


**Figure 35. Map showing location and distribution of the 26 training points consisting of wells completed in the IAS, which were simultaneously measured for both ammonia and dissolved nitrogen. These wells had a measured total dissolved nitrogen median value greater than 0.457 mg/L.**

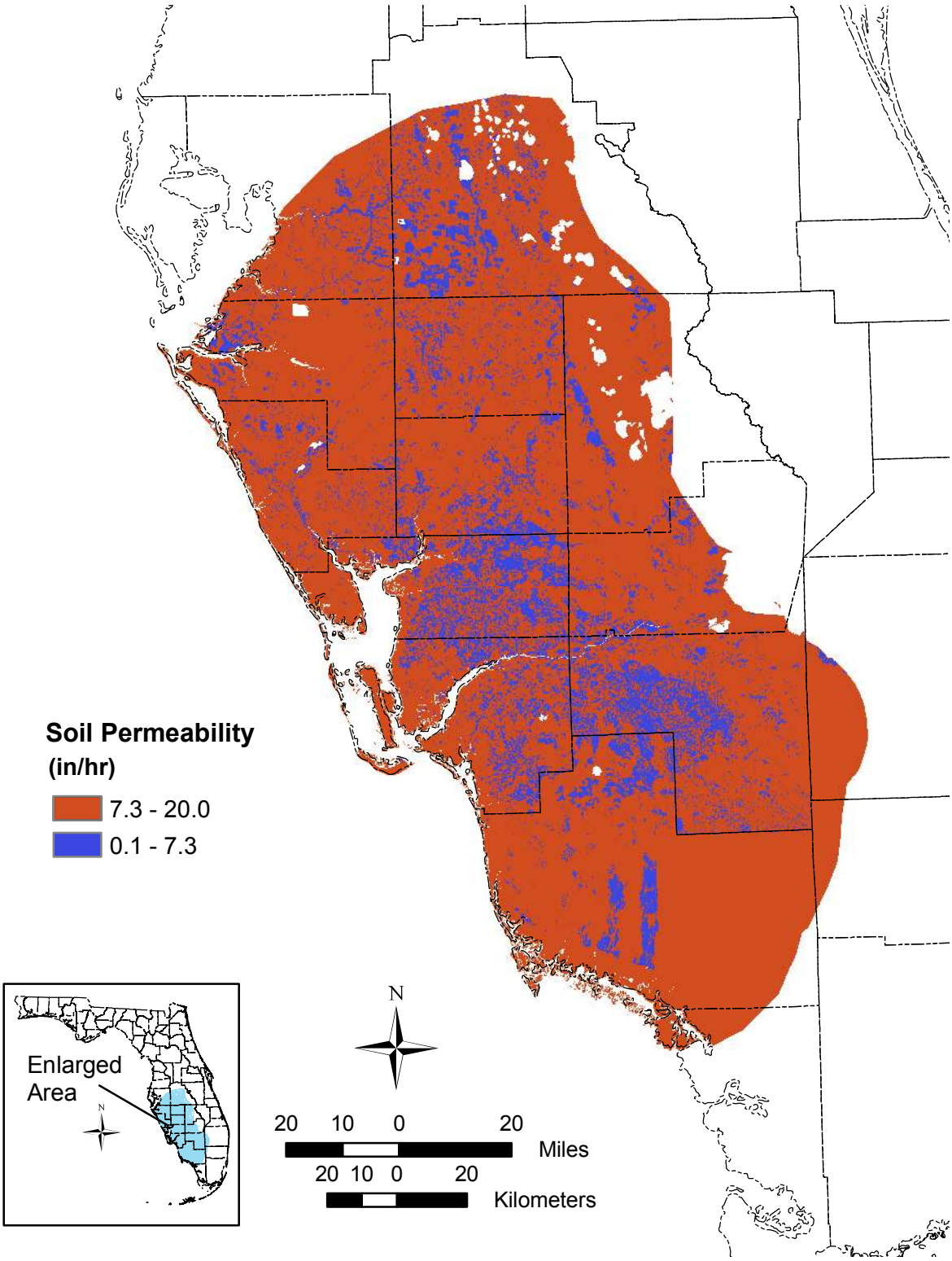


**Figure 36. Map showing generalization of soil permeability evidential theme. Based on calculated weights, a binary generalization with a break at a value of 7.3 in/hr was defined by the analysis. Based on the location of training points, blue areas were associated with areas of lower vulnerability, while red areas were associated with areas of higher vulnerability.**

The 100-ft threshold of overburden thickness has been used to identify karst-prone areas by Cichon et al. (2004) and Wright (1974). Though the location of training points was not used to select this filter threshold, the lack of their occurrence in areas underlain by more than 100 feet of overburden thickness lends support to the use of this filter. This calculation provided an effective karst evidential theme for use in the IAS FAVA model. Moreover, this filtering procedure removed several karst "sags" formed by the dissolution of shell material in shallow sediments. Removal of sags from this evidential theme was appropriate because the features do not provide deep vertical preferential pathways to allow surface water to more rapidly reach the IAS.

Because areas nearer to a karst feature are considered more vulnerable to contamination than areas further away, a proximity analysis was completed for the effective karst evidential theme by creating a 6,000-m buffer zone around each karst feature within which equally-spaced 60-m intervals were delineated. The outermost interval contained all areas of the IAS extent which lie 6,000 m or further from a karst feature. Based on spatial analysis, all training points occurred within 6,000 m from an effective karst feature, thereby lending support to that radial distance as a lateral threshold for the delineation of intervals within the buffer zone.

IAS Overburden and Effective Karst Feature Interdependence – Fuzzy Logic

In the IAS model, IAS overburden and karst were statistically related because the overburden evidential theme was used to develop the effective karst layer – karst features were removed based on the presence of more than 100 feet of IAS overburden thickness. When both themes were input into the IAS model separately, conditional independence problems arose for the model output. As a result, fuzzy logic was utilized to combine the effective karst and IAS overburden into a single evidential theme. As discussed in *Introduction – Approach – Models Considered*, fuzzy logic handles the concept of partial truths and can be described as the process of assigning values to events using a gradational or continuous scale between 0 and 1, where 1 represents full membership and 0 is full non-membership.

In the effective karst feature evidential theme, a fuzzy membership value of 1 was assigned to all areas that were within 60 meters of an effective karst feature. These areas represent full membership. A fuzzy membership value of 0 was assigned to the class representing areas 6,000 m or greater from karst features, representing full non-membership. Intermediate values were then interpolated in a linear manner.

For the IAS overburden evidential theme, areas where the overburden was calculated at zero were assigned a fuzzy membership value of 1 representing full membership and areas where the overburden was thickest (429 feet) were assigned a value of 0, or full non-membership. Intermediate values were then interpolated in a linear manner.

Using these fuzzy membership values the two evidential themes were combined using the fuzzy logic Boolean operator OR. This operator was chosen because it involves the union of a set of values where the maximum input controls the output. The result is an output map, used as evidence, where the values are the "best" of both pieces of evidence. The fuzzy logic output was converted to a GIS integer grid to be consistent with other evidential themes; and, to preserve data resolution, all values were multiplied by 100. The final fuzzy logic output values therefore ranged from 0-100. The new IAS overburden/effective karst features evidential theme is displayed in Figure 37.

Areas of the IAS overburden/effective karst features evidential theme with higher values corresponded with dense karst feature distribution and thin IAS overburden sediments and were associated with higher aquifer vulnerability. For these reasons, weights were calculated for this

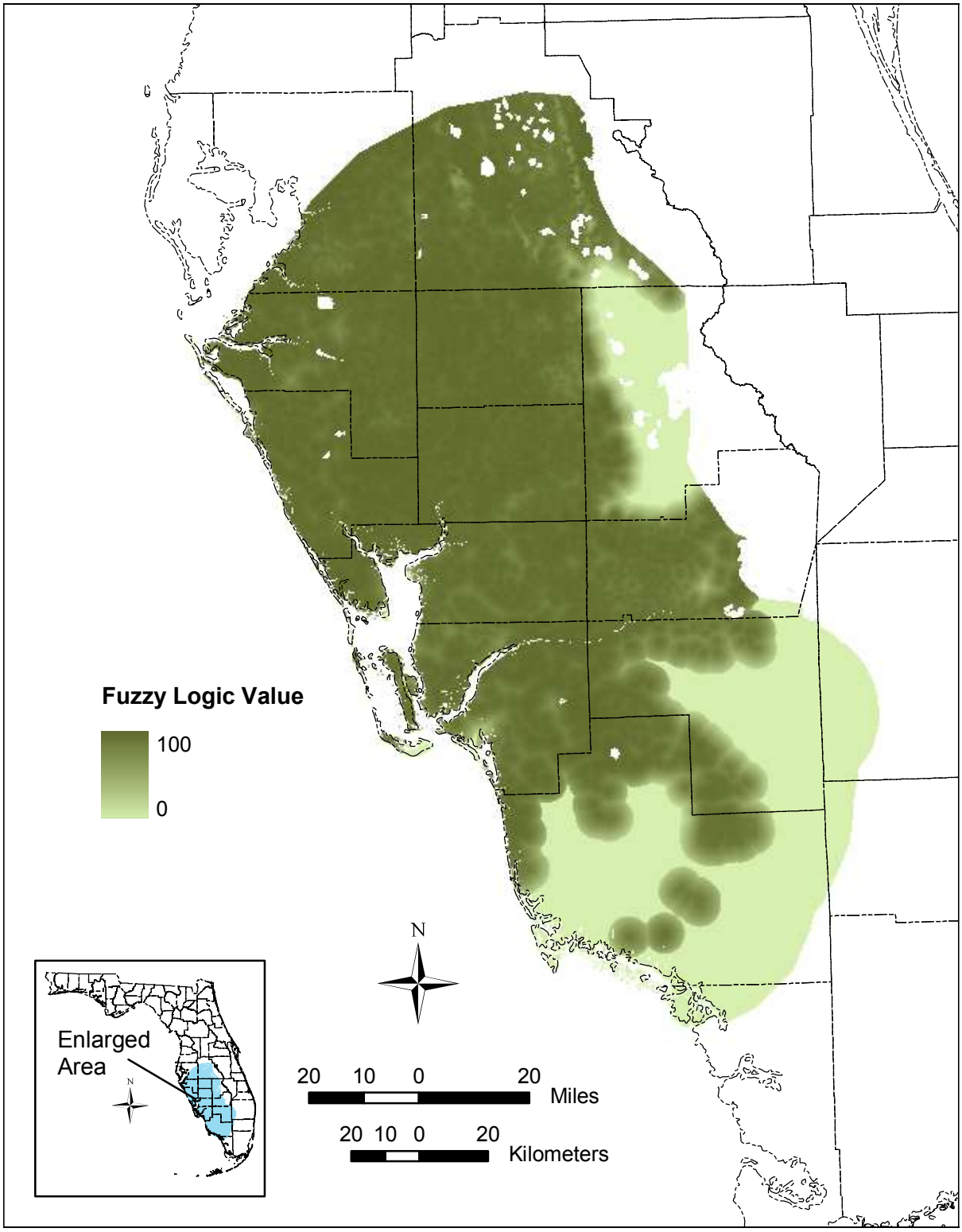


**Figure 37. Evidential theme produced by combining overburden on IAS with proximity to karst features using fuzzy logic. Higher values correspond to thinner overburden and denser karst features.**

evidential theme using the cumulative descending method of the WofE analytical technique. The highest contrast of any class was calculated at a fuzzy logic value of 87. The calculated weights did not justify the selection of a multi-class theme because neither contrast nor confidence calculated for the other classes supported delineation of more breaks. As defined by the analysis of this evidential theme, the most appropriate break in the IAS overburden/effective karst features evidential theme was at 87 creating a binary generalized theme for input into the IAS FAVA model. In other words, this analysis indicated that areas where fuzzy logic exceeded 87 (i.e., thin overburden and dense effective karst) were, based on the location of training points, associated with areas of higher vulnerability. Conversely, the analysis indicated that areas where the fuzzy logic value was less than 87 (i.e., thicker overburden and sparse effective karst) were, based on the location of training points, associated with areas of lower vulnerability. Figure 38 displays the break for this evidential theme.

Response Theme

Using the two evidential themes discussed above, a response theme (Figure 39) was generated showing the posterior probability that a unit area contained a training point based on the evidential themes used as input. The posterior probabilities of the response theme ranged from 0.00003 to 0.00163 across the model domain. Plotting posterior probability against cumulative area as a percentage (Figure 40) allowed the delineation of class breaks for display of vulnerability zones in the final response theme. The breaks for these vulnerability zones were selected where a notable stepwise increase in posterior probability relative to cumulative area occurred. The first break, which delineated the *less vulnerable* zone from the *vulnerable* zone, occurred at a posterior probability value of 0.000062. The *less vulnerable* zone represents approximately 3.5% of the study area. The second break delineating the *vulnerable* zone from the *more vulnerable* zone occurred at the next significant stepwise increase in posterior probability at a value of 0.0009, which also corresponded with the prior probability. The *vulnerable* zone represents approximately 43.5% of the study area. The remainder of the study area fell into the *more vulnerable* zone and represents approximately 53% of the study area. This *more vulnerable* zone contained the greatest probability of containing a training point. Plate 2 (back pocket) provides a more detailed display of the relative vulnerability zones.

The response theme (Figure 39) indicated that the areas of highest vulnerability (high probabilities) tended to be associated with areas of dense karst-feature distribution, thinner IAS overburden sediments, and, to a lesser degree, high soil permeability. Conversely, areas of lowest vulnerability (low probabilities) tended to be determined by sparse karst feature distribution, thicker overburden sediments, and low soil permeability values.

The study area contained a multitude of surface water features, which can represent areas of discharge and may have been predicted with low posterior probability values. These discharging surface waters are not considered part of the aquifer, although they can originate from it. The FAVA project was designed to focus on the ability for a contaminant to travel through soils, overburden, karst features, etc. to enter into the aquifer system. As a result, it is very important that the FAVA model never be applied to assess contamination of surface waters or discharge areas.

Weights calculated for the evidential themes used in the IAS model are included in Table 9. The IAS overburden/effective karst features evidential theme had a greater association with the training points (higher contrast) than the soil permeability evidential theme and was therefore the primary determinant in predicting areas of vulnerability. The larger absolute value of the negative weights (W2) in Table 9 indicated that the response theme was a better predictor of where training points were not likely to occur. In other words, the IAS FAVA model more strongly predicted where the IAS is less vulnerable to contamination than it predicted where it is more vulnerable to contamination. See *Introduction – Approach – Models Considered – Weights of Evidence* for a more detailed discussion

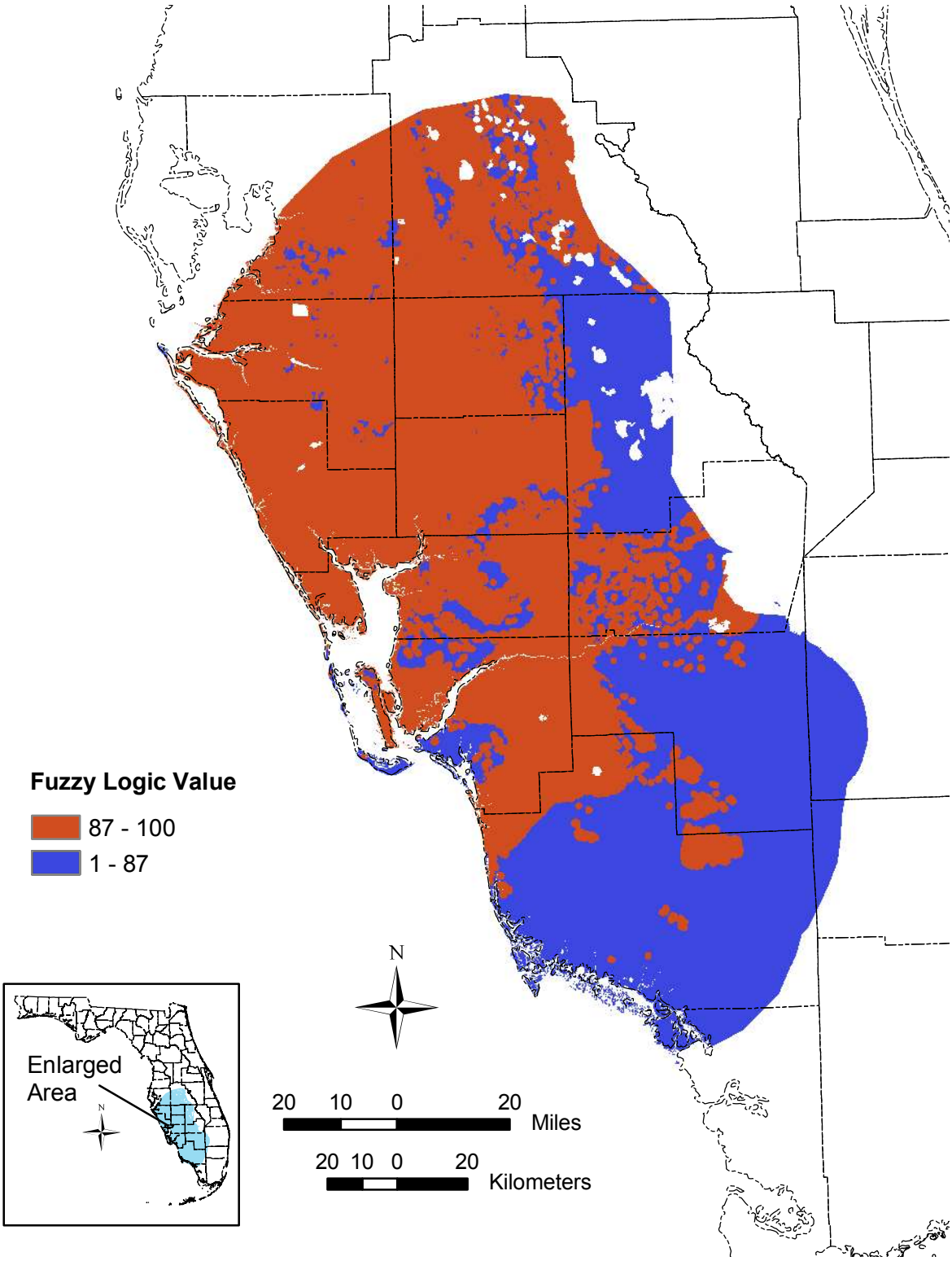


**Figure 38. Map showing generalization of IAS overburden/karst feature evidential theme. Based on calculated weights, a binary generalization with a break at a value of 87 was defined by the analysis. Based on the location of training points, blue areas were associated with areas of lower vulnerability, while red areas were associated with areas of higher vulnerability.**

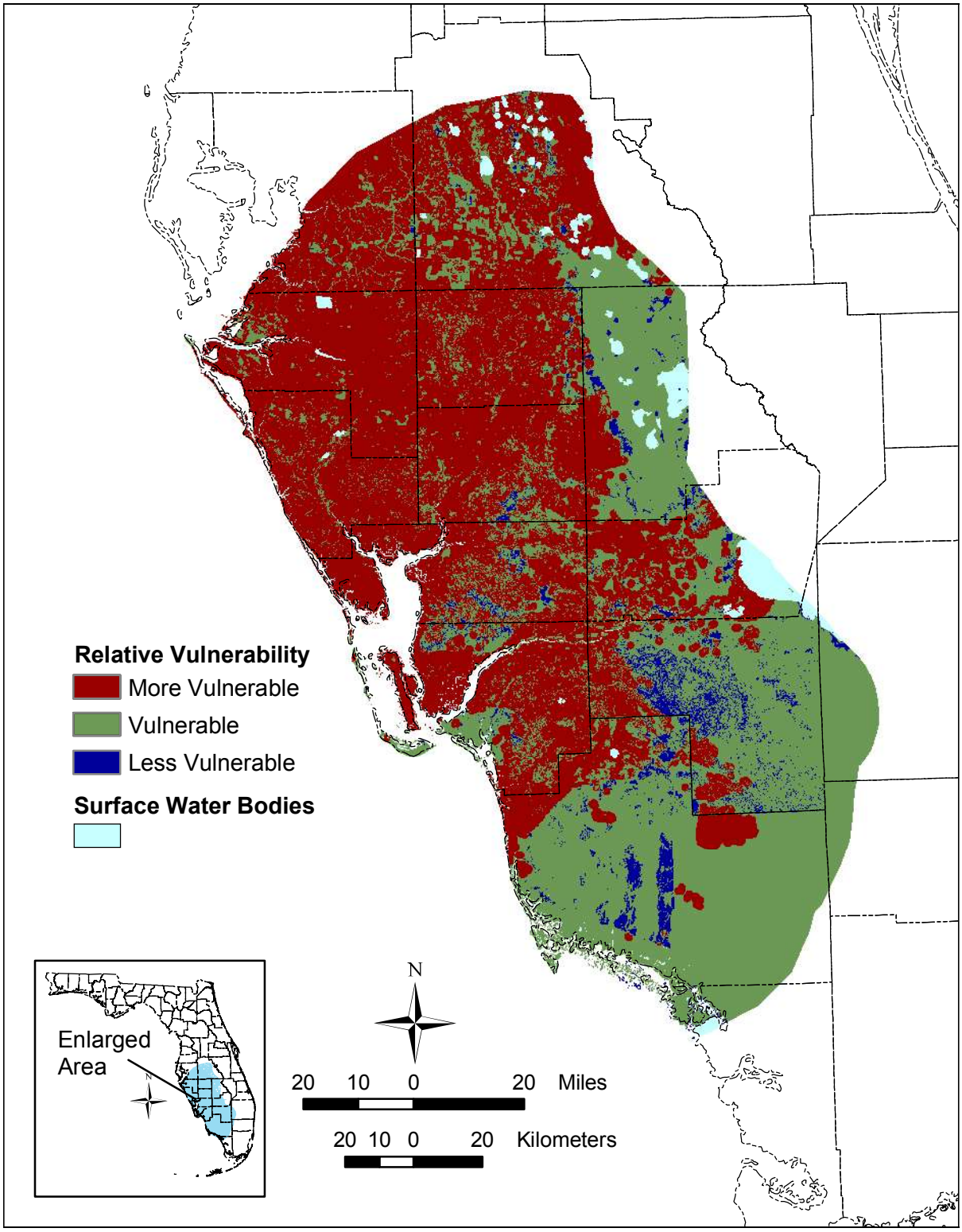


**Figure 39. Relative vulnerability of the IAS divided into three zones based on posterior probability values displayed in Figure 40. Total dissolved nitrogen concentrations were used as a training point theme. See Plate 2 (back pocket) for a more detailed display and discussion of the vulnerability zones.**

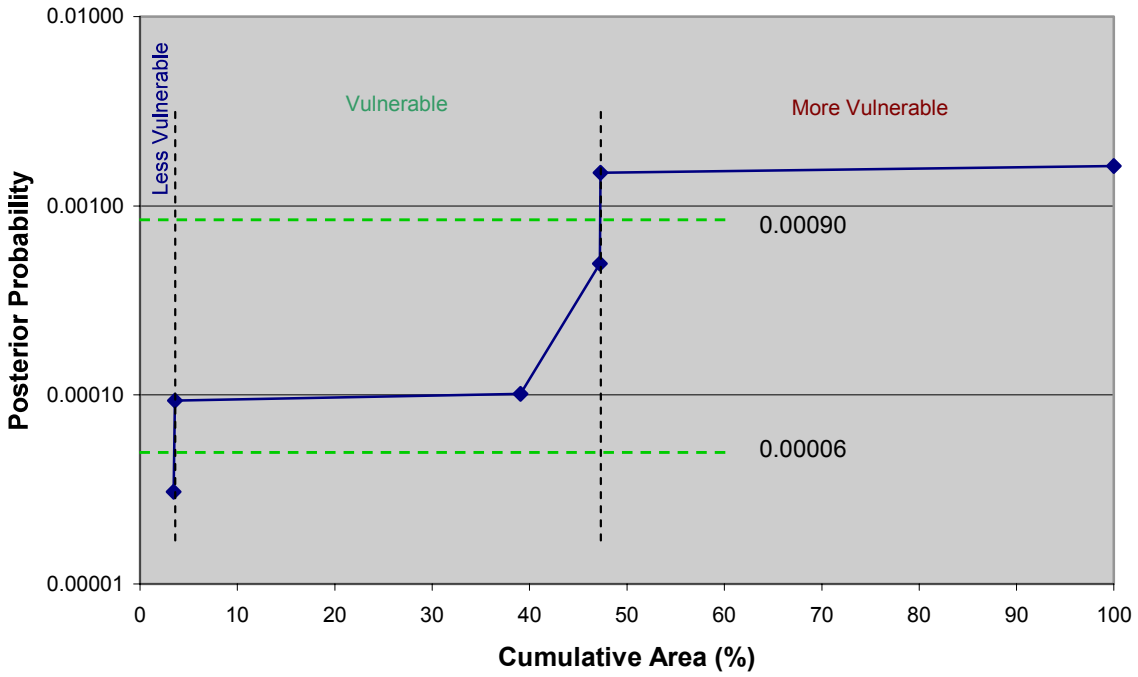


**Figure 40. Class breaks, represented by green dashed lines, were placed where both a significant increase in probability and area were observed. These boundaries correspond with relative vulnerability zones delineated in Figure 39 and are indicated in this chart by vertical black dashed lines.**

**Table 9. Response theme table listing weights calculated for each evidential theme and their associated contrast and confidence values.**

| Evidential Theme | W1 | W2 | Contrast | Confidence |
|---|---|---|---|---|
| Karst/Overburden | 0.4569 | -2.3194 | 2.7763 | 2.7222 |
| Soil Permeability | 0.0844 | -1.1063 | 1.1907 | 1.1674 |

of the significance of this table. Confidence values for the evidential themes all fell above the target value of 0.674. Conditional independence was calculated at 1.01 indicating no dependence between evidential themes.

Confidence Map

The confidence values for the IAS model area ranged from 0.70 to 2.90. Like the SAS response theme, the higher confidence areas corresponded with higher vulnerability areas whereas lower confidence areas corresponded to lower vulnerability areas. These values indicated that the confidence level was above 90% for the majority of the model domain, and was greater than 75% for the entire model domain. Areas of lower confidence corresponded with areas that lack training points. The confidence map for the IAS FAVA model is displayed in Figure 41.

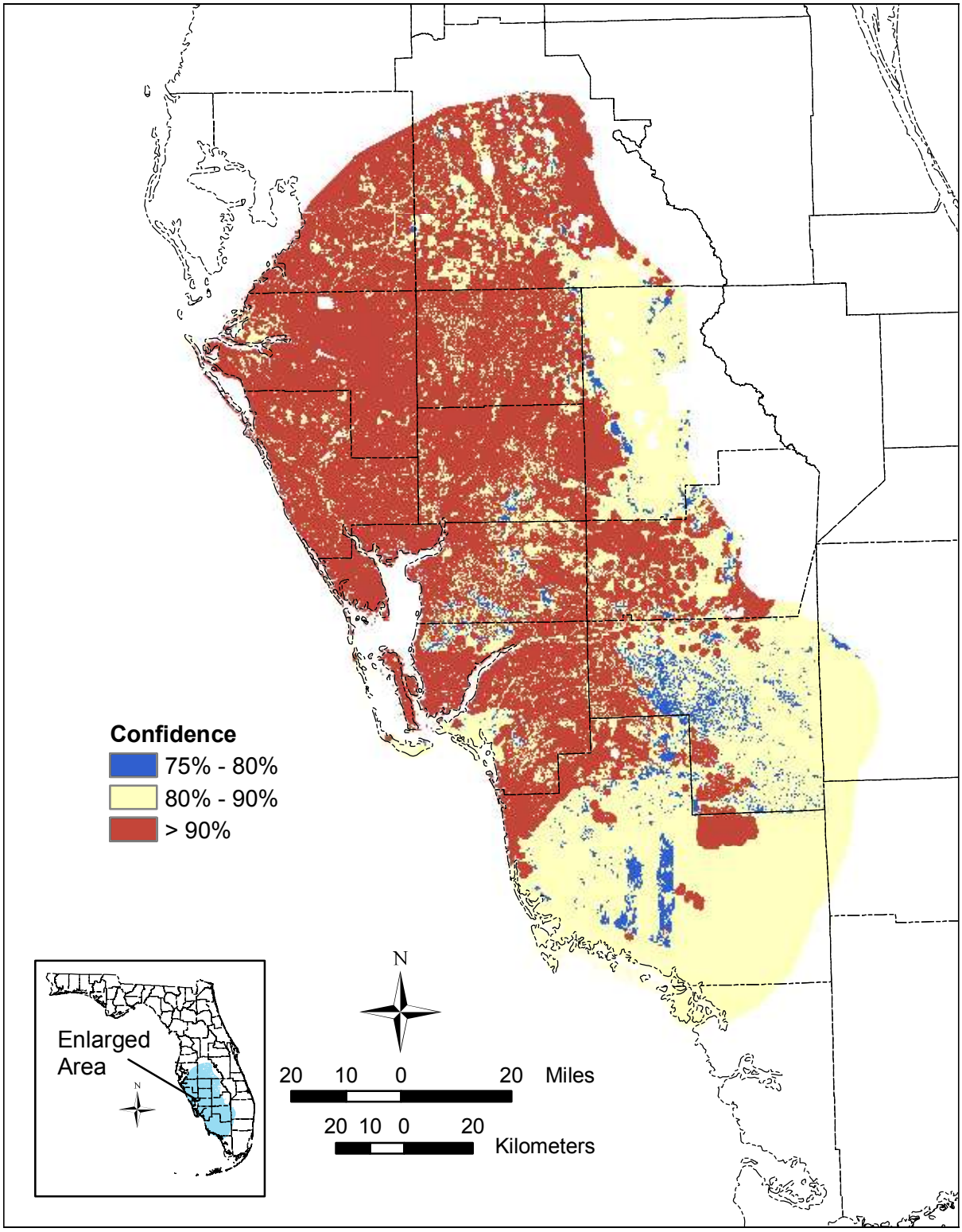


**Figure 41. Distribution of confidence values calculated for IAS response theme.**

### Floridan Aquifer System

#### Study Area and Extent

The Floridan Aquifer System (FAS) comprises a thick sequence of carbonate rocks which function regionally as a major aquifer system. It ranges from a fully-confined aquifer system where overlain by the IAS to an unconfined aquifer system in areas where it is at or near land surface. The FAS extends throughout the entire State of Florida, however, in the southern peninsula and western panhandle, it is not used as a source of public water supply due to high salinity of ground water (Southeastern Geological Society, 1986).

The extent of the FAS used for input into the FAVA model was based on the distribution of FDEP public water supply wells. FDEP wells were plotted in a GIS with a 20-km buffer to develop a study area extent for the FAS. This extent represented areas where this aquifer system is used as a principal aquifer system. The extent is displayed in Figure 42.

Large water bodies (those covering greater than approximately 50 acres) were omitted from FAS FAVA model because a well would never be drilled in these areas – therefore, they would never contain a training point. If the lakes were left in the model, the surface area was increased with no chance of increasing the number of training points. This unnecessarily biased the model, and, further, large water bodies typically have no soils or other input data associated with them.

#### Training Points

There were a total of 1,297 wells in the FDEP background water quality monitoring network that were completed only in the FAS (i.e., open-hole portion of well open to the FAS only). Of these wells, 781 were measured for dissolved nitrogen. Ammonia concentrations were not used to develop the training point theme for the FAS models as they were in the SAS and IAS models. Because thin peat and lignite beds are present within the Avon Park Formation of the FAS (Vernon, 1951) there was a potential for *in situ* introduction of ammonia as opposed to from land surface.

Using statistical methods described in *Results – Data Coverages –Training Points*, 152 wells were identified as outliers and subsequently removed from the dataset leaving 629 wells for additional analysis. Further statistical analysis returned a 75$^{th}$ percentile median value for dissolved nitrogen concentration of 0.0355 mg/L. There were 148 wells occurring in the dataset with a measured median dissolved nitrogen value greater than 0.0355 mg/L. These 148 were used to create the training point theme for input into the FAS FAVA model. The resulting prior probability was calculated at 0.0013, which represents the chance that a training point will occupy any given unit area within the study area, independent of any evidential theme data. The distribution of these wells is displayed in Figure 43.

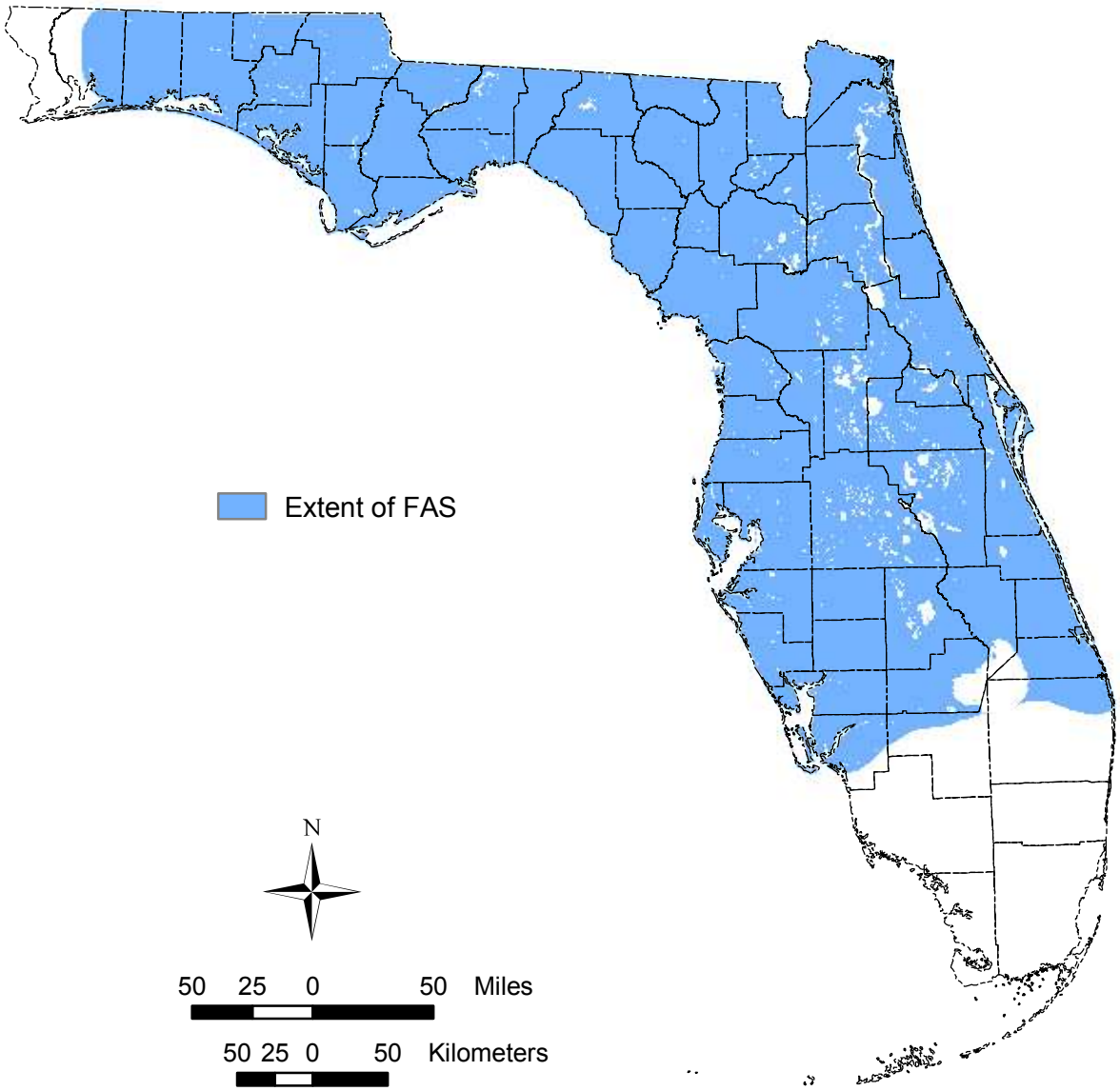


**Figure 42. Extent of the FAS where it forms a major regional aquifer system throughout Florida. Large water bodies were omitted from the analysis to avoid biasing the model.**

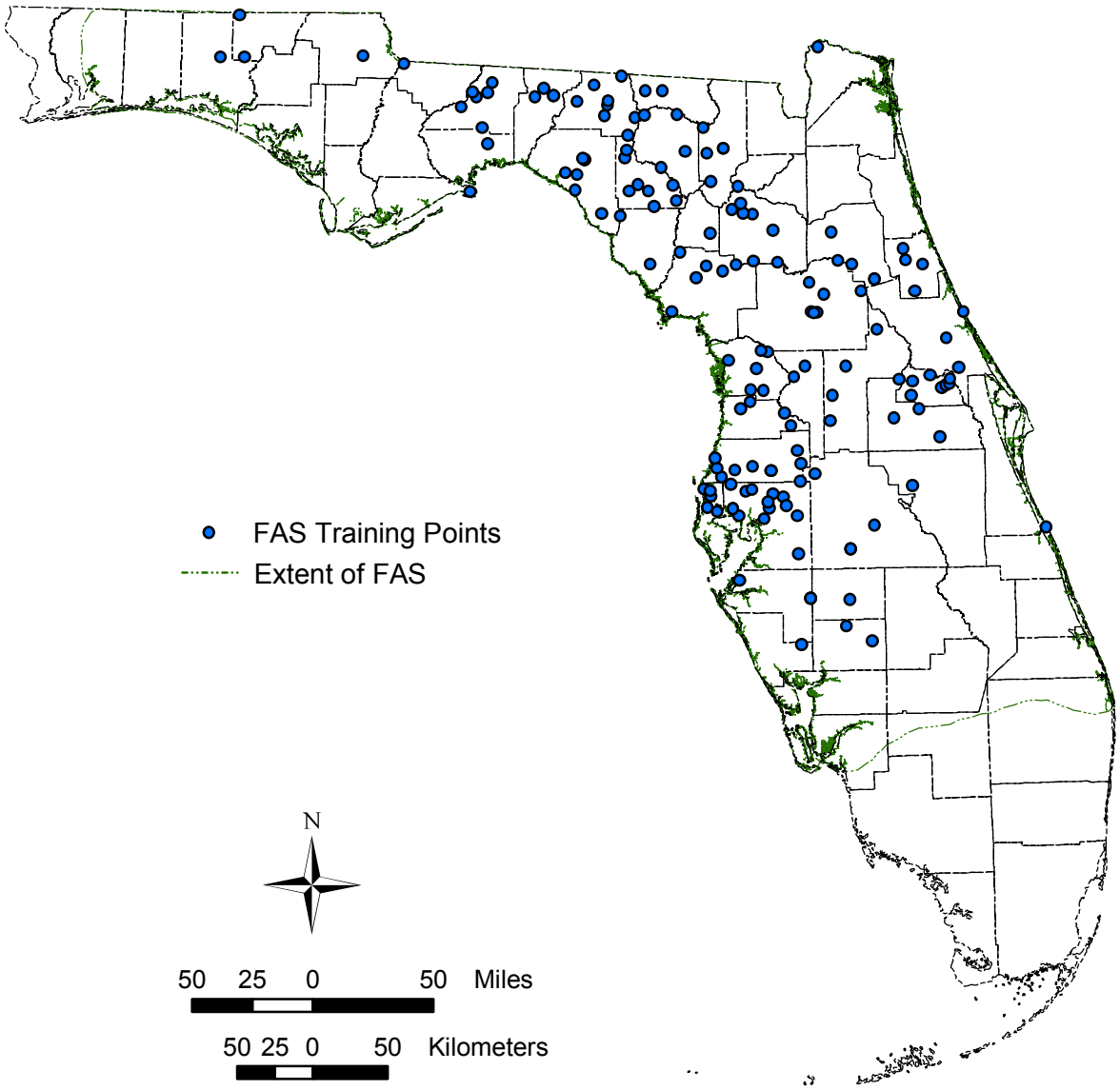


**Figure 43. Map showing location and distribution of the 148 training points consisting of wells completed in the FAS, which were measured for dissolved nitrogen. These wells had a measured dissolved nitrogen value greater than 0.0355 mg/L.**

### Generalization of Evidential Themes

Several evidential themes were considered for input into the FAS FAVA model:

- Soil drainage
- Soil permeability
- Karst features (derived from closed topographic depressions data layer)
- Thickness of IAS
- Depth-to-water
- Potentiometric surface of the FAS
- Hydraulic head difference between water table and FAS
- Environmental geology map
- Geologic map of the State of Florida
- Leakance of the IAS

For the FAS FAVA model four of the above evidential themes were ultimately used: soil permeability, karst features, hydraulic head difference, and IAS thickness. The other evidential themes were not used because they either did not meet the test of significance for the FAVA project, or the resulting weights were counterintuitive with regard to hydrogeologic processes and vulnerability. While not discussed in *Results – Data Coverages,* leakance of the IAS was considered as an evidential theme for the FAS. Data needed to complete leakance coverage of the IAS for the extent of the FAS was not available at the time of this report. For a full discussion on the limitations of evidential themes refer to *Results – Data Coverages*. Modifications were made to the evidential themes to calculate weights and then generalize the evidential themes for input into the FAS FAVA models. The modifications and generalizations are discussed below.

### Soil Permeability

Soil permeability is a measure of the rate at which water travels through the vadose zone. Areas with high soil permeability values are normally associated with higher aquifer vulnerability. Weights were calculated for soil permeability using the cumulative descending method of the WofE model technique. The highest contrast of any class was calculated at 19.7 in/hr. The calculated weights did not justify the selection of a multi-class theme because neither contrast nor confidence calculated for other classes was significant enough to support delineation of more breaks. As defined by the analysis of this evidential theme, the most appropriate break in the soil permeability evidential theme was at 19.7 in/hr creating a binary generalized theme for input into the FAS FAVA model (Figure 44). In other words, this analysis indicated that areas underlain by soils with permeability values ranging from 0.1 to 19.7 in/hr were, based on the location of training points, associated with areas of lower vulnerability. Conversely, the analysis indicated that areas underlain by soils with permeability values ranging from 19.7 to 20.0 in/hr were, based on the location of training points, associated with areas of higher vulnerability. The generalized theme is displayed in Figure 44.

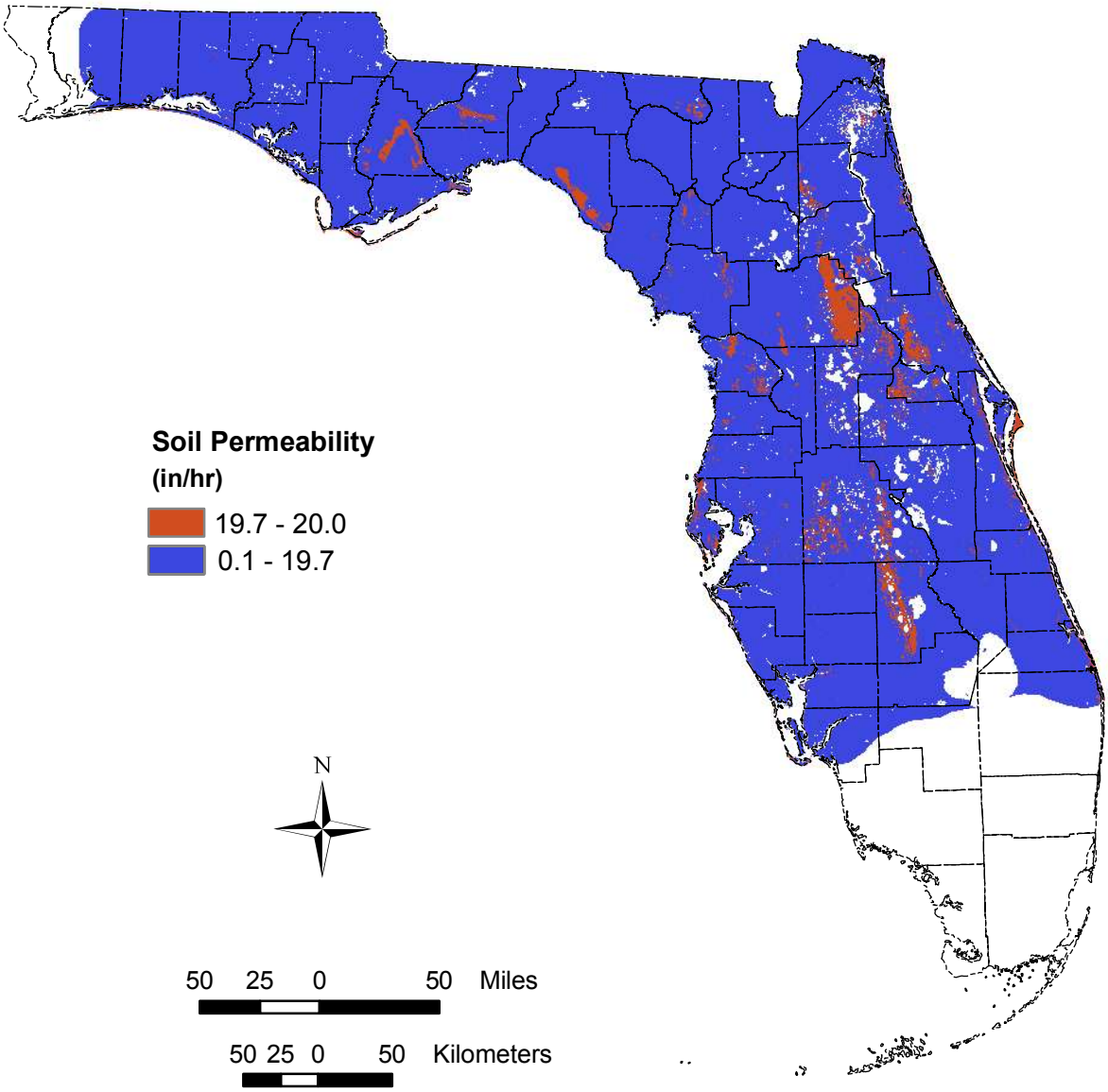


**Figure 44. Map showing generalization of soil permeability evidential theme. Based on calculated weights, a binary generalization with a break at a value of 19.7 in/hr was defined by the analysis. Based on the location of training points, blue areas were associated with areas of lower vulnerability, while red areas were associated with areas of higher vulnerability.**

### Effective Karst Features

Effective karst is defined as in *Results – FAVA Model Outputs – Intermediate Aquifer System* – those closed topographic depressions which are believed to increase hydrologic communication between land surface and the underlying aquifer system. Features were selected by intersecting the IAS thickness grid with the locations of closed topographic depressions. Based on expert hydrogeologic knowledge, areas that were underlain by 140' or less of IAS-type sediments were selected. Additional features were included for those areas where the IAS was not mappable by selecting those depressions that were underlain by 100 feet or less of surficial sediment thickness. Cichon et al. (2004) and Wright (1974) have used the 100-ft threshold of overburden thickness to identify karst prone areas. This calculation provided an effective karst evidential theme for use in the FAS FAVA model. Moreover, this filtering technique also removed sags as described in *Results – FAVA Model Outputs – Intermediate Aquifer System – Effective Karst Features*.

Because areas nearer to a karst feature are considered more vulnerable to contamination than areas further away, a proximity analysis was completed for the effective karst evidential theme by creating a 3,600-m buffer zone around each karst feature within which equally-spaced 60-m intervals were delineated. The outermost interval contained all areas of the FAS extent which lie 3,600 m or further from a karst feature. Based on spatial analysis, nearly 90% of all training points occurred within 3,600 m from an effective karst feature, thereby lending support to that radial distance as a lateral threshold for the delineation of intervals within the buffer zone.

As stated above, areas closer to an effective karst feature are normally associated with higher aquifer vulnerability, and, as a result, weights were calculated for the effective karst feature evidential theme using the cumulative ascending method. The highest contrast of any class was calculated at a distance of 3,420 m from an effective karst feature. The calculated weights did not justify the selection of a multi-class theme because neither contrast nor confidence calculated for the other classes supported delineation of more breaks. As defined by the analysis of this evidential theme, the most appropriate break in the effective karst feature evidential theme was at 3,420 m creating a binary generalized theme for input into the FAS FAVA model. In other words, this analysis indicated that areas beyond 3,420 m of an effective karst feature were, based on the location of training points, associated with areas of lower vulnerability. Conversely, the analysis indicated that areas within 3,420 m of an effective karst feature were, based on the location of training points, associated with areas of higher vulnerability. The generalized theme is displayed in Figure 45.

### IAS Thickness

Areas underlain by thinner IAS sediments are normally associated with higher aquifer vulnerability. Weights were therefore calculated for the IAS evidential theme using the cumulative ascending method. The highest contrast of any class was calculated at a thickness interval of 451 feet. The second highest contrast of any class was calculated at a thickness interval of 160 feet (Figure 46).

The calculated weights therefore justified the selection of a multi-class theme because the contrast values for both of these breaks are statistically significant at a 75% confidence level. As defined by the analysis of this evidential theme, the most appropriate breaks in the IAS thickness evidential theme were at 160 ft and 451 ft creating a multi-class generalized theme for input into the FAS FAVA model. In other words, this analysis indicated that areas underlain by greater than 451 feet of IAS were, based on the location of training points, associated with less vulnerable zones, areas underlain by between 160 and 451 feet of IAS were associated with vulnerable zones, and areas

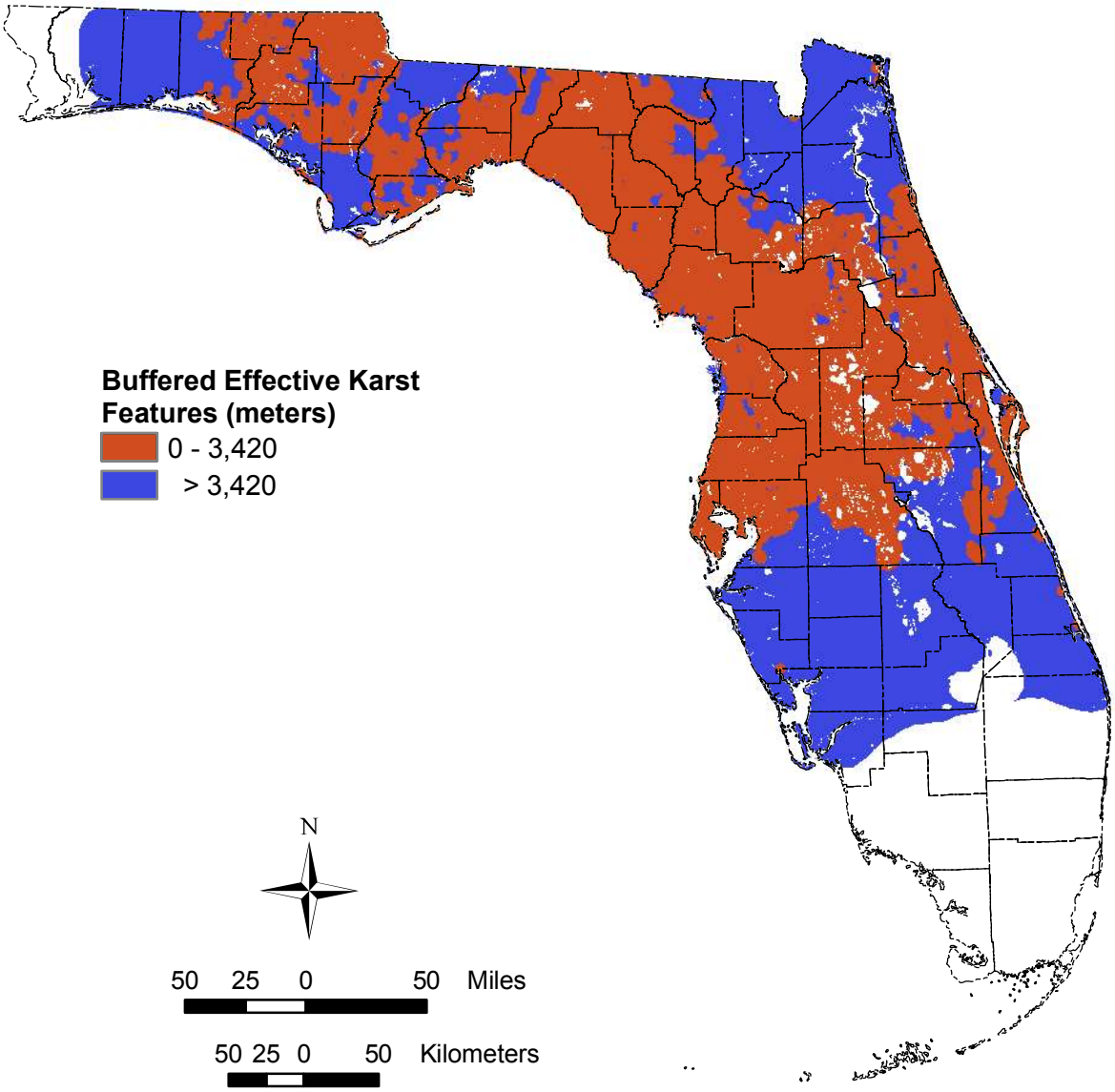


**Figure 45. Map showing generalization of effective karst features evidential theme. Based on calculated weights, a binary generalization with a break at a distance of 3,420 m was defined by the analysis. Based on the location of training points, blue areas were associated with areas of lower vulnerability, while red areas were associated with areas of higher vulnerability.**

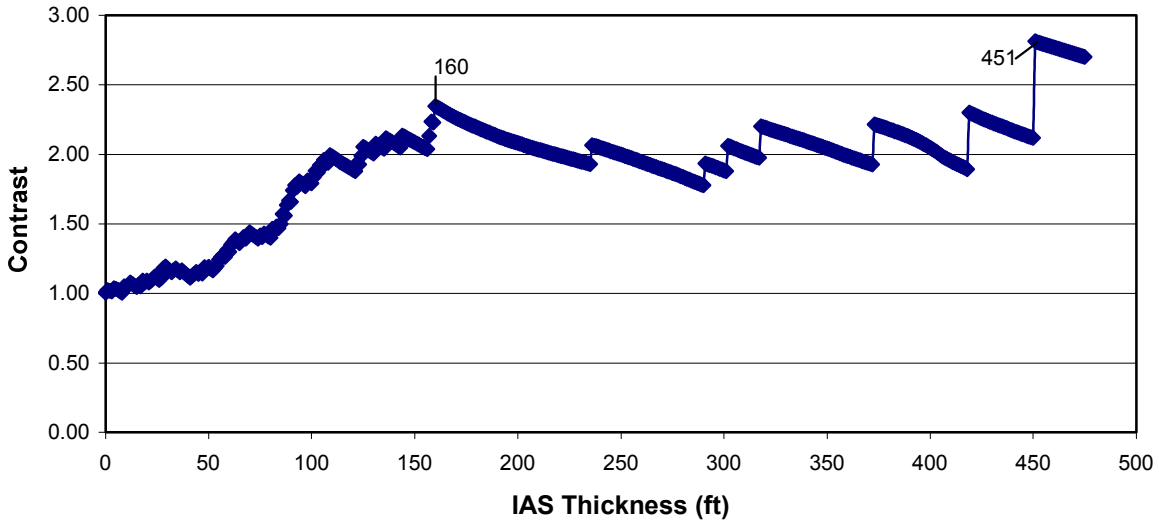


**Figure 46. IAS thickness in feet plotted against contrast values calculated using WofE. Statistically significant high contrast values were calculated at 160 ft and 451 ft defining a multi-class theme with generalized breaks at these values.**

underlain by less than 160 feet of IAS were associated with more vulnerable zones. The generalized theme is displayed in Figure 47.

Hydraulic Head Difference between the Water Table and the FAS

Areas where the hydraulic head difference between the water table and the FAS is great, indicating the potential for downward recharge to the FAS, are generally associated with higher aquifer vulnerability. Weights were therefore calculated for the hydraulic head difference evidential theme using the cumulative descending method. The highest contrast for any class was calculated at a hydraulic head difference value (i.e., water-table elevation minus FAS potentiometric surface) of -8 feet. The calculated weights did not justify the selection of a multi-class theme because neither contrast nor confidence calculated for the other classes supported delineation of more breaks. As defined by the analysis, the most appropriate break in the hydraulic head difference evidential theme equals -8 feet, thus creating a binary generalized theme for input into the FAS FAVA model. In other words, this analysis indicated that areas in which the hydraulic head difference is greater than -8 ft were, based on the location of training points, associated with areas of higher vulnerability. Conversely, the analysis indicated that areas in which the hydraulic head difference was less than -8 ft were, based on the location of training points, associated with areas of lower vulnerability. The generalized theme is displayed in Figure 48.

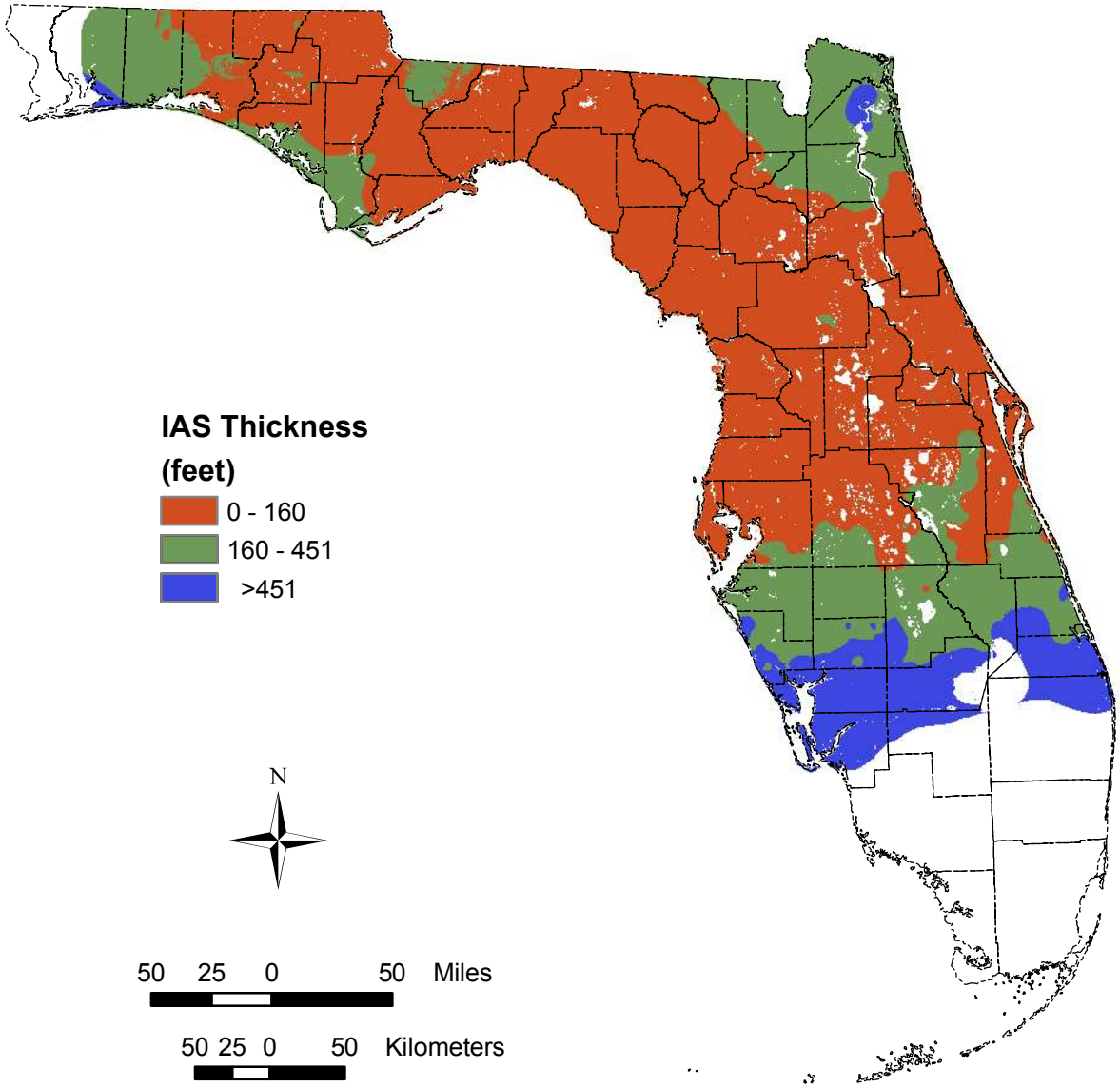


**Figure 47. Map showing generalization of IAS thickness evidential theme. Based on calculated weights, a multi-class generalization with a break at a value of 160 and 451 ft was defined by the analysis. Based on the location of training points, blue areas were associated with areas of lower vulnerability, while red areas were associated with areas of higher vulnerability.**

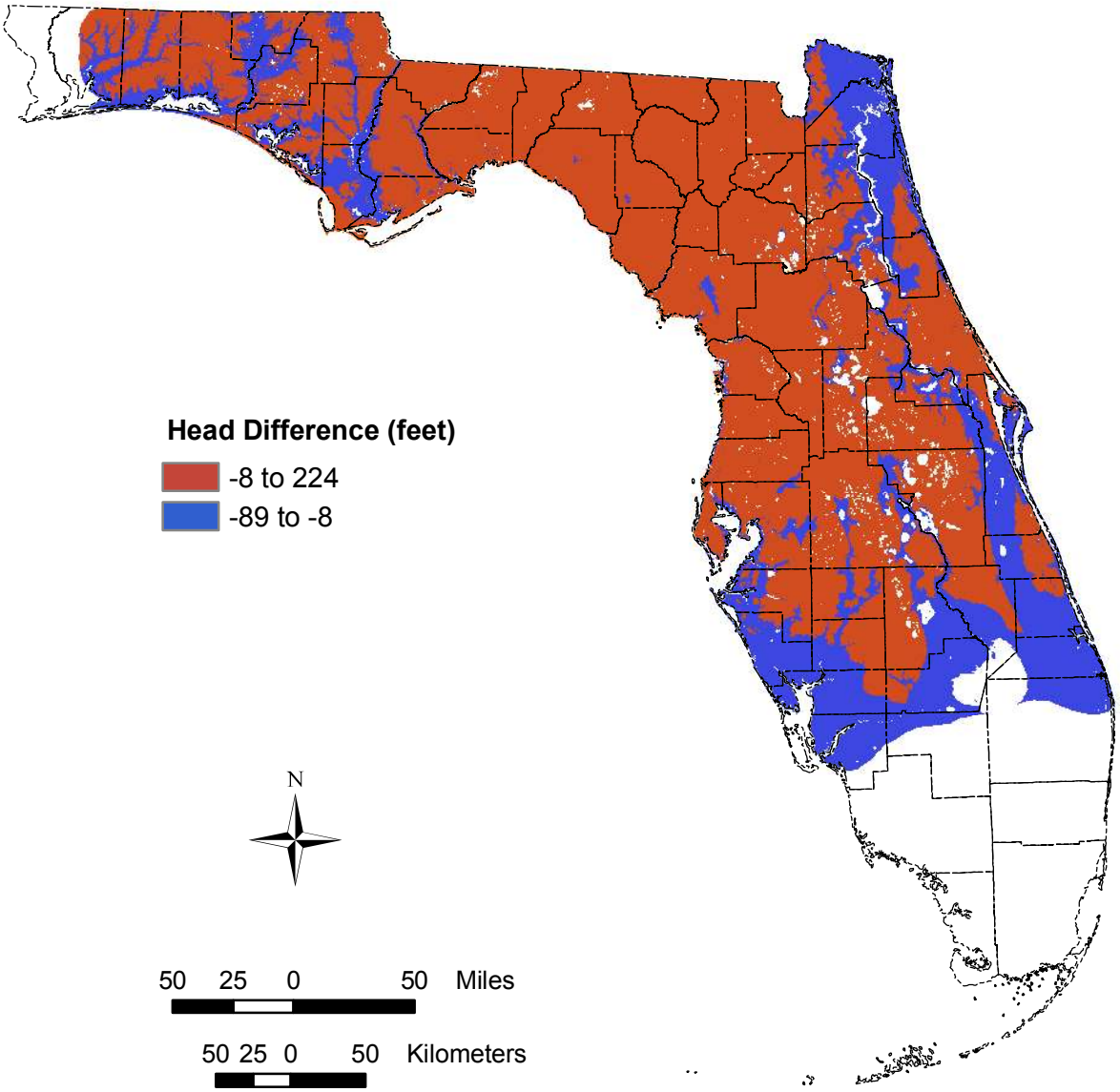


**Figure 48. Map showing generalization of hydraulic head difference evidential theme. Based on calculated weights, a binary generalization with a break at a value -8 ft was defined by the analysis. Based on the location of training points, blue areas were associated with areas of lower vulnerability, while red areas were associated with areas of higher vulnerability.**

Response Theme

Using the four evidential themes discussed above, a response theme (Figure 49) was generated showing the posterior probability that a unit area contained a training point based on the evidential themes used as input. The posterior probabilities of the response theme ranged from 0.00003 to 0.00371 across the model domain. Plotting posterior probability against cumulative area as a percentage (Figure 50) allowed the delineation of class breaks for display of vulnerability zones in the final response theme. The breaks for these vulnerability zones were selected where a notable stepwise increase in posterior probability relative to cumulative area occurred. The first break, which delineated the *less vulnerable* zone from the *vulnerable* zone, occurred at a posterior probability value of 0.00029. The *less vulnerable* zone represents approximately 21% of the study area. The second break delineating the *vulnerable* zone from the *more vulnerable* zone occurred at the next significant stepwise increase in posterior probability at a value of 0.0013, which also corresponded with the prior probability. The *vulnerable* zone represents approximately 34% of the study area. The remainder of the study area fell into the *more vulnerable* zone and represents approximately 45% of the study area. This *more vulnerable* zone contained the greatest probability of containing a training point. Plate 3 (back pocket) provides a more detailed display of the relative vulnerability zones.

Conditional independence was calculated at 0.64, which fell outside the target range of 1.00 ± 0.15 indicating dependence between evidential themes. This was resolved by using the logistic regression option described in *Introduction – Approach – Models Considered – Weights of Evidence Model*.

The response theme (Figure 49) indicated that the areas of highest vulnerability (high probabilities) tended to be associated with areas of thinner IAS sediments, dense karst-feature distribution, positive hydraulic head difference, and, to a lesser degree, high soil permeability. Conversely, areas of lowest vulnerability (low probabilities) tended to be determined by thick IAS sediments, sparse karst-feature distribution, negative (less than -8 ft) hydraulic head difference, and low soil permeability values.

The study area contains a multitude of surface water features, which can represent areas of discharge and may be predicted with low posterior probability values. These discharging surface waters were not considered part of the aquifer, although they can originate from it. The FAVA project was designed to focus on the ability for a contaminant to travel through soils, overburden, karst features, etc. to enter into the aquifer system. As a result, it is very important that the FAVA model never be applied to assess contamination of surface waters or discharge areas.

Weights calculated for the evidential themes used in the FAS model are included in Table 10. The IAS thickness evidential theme had a greater association with the training points (higher contrast) than the other evidential themes and was therefore the primary determinant in predicting areas of vulnerability. The larger negative weights for IAS thickness (W2 and W3), proximity to karst (W2), and hydraulic head difference (W2) also indicated where training points were not likely to occur because the negative weights were stronger than the positive weights (i.e., have a higher absolute value). Conversely, soil permeability indicated where training points were likely to occur because of the stronger positive weight (W1). See *Introduction – Approach – Models Considered – Weights of Evidence* for a more detailed discussion of the significance of this table. Confidence values for all evidential themes fell above the target value of 0.674; in fact, all confidence values for the FAS fell above a value of 2.576 which corresponds to a confidence level of approximately 99.5% (see *Introduction – Approach – Models Considered – Weights of Evidence* and *Discussion – Validation of Models* for further discussion of confidence).

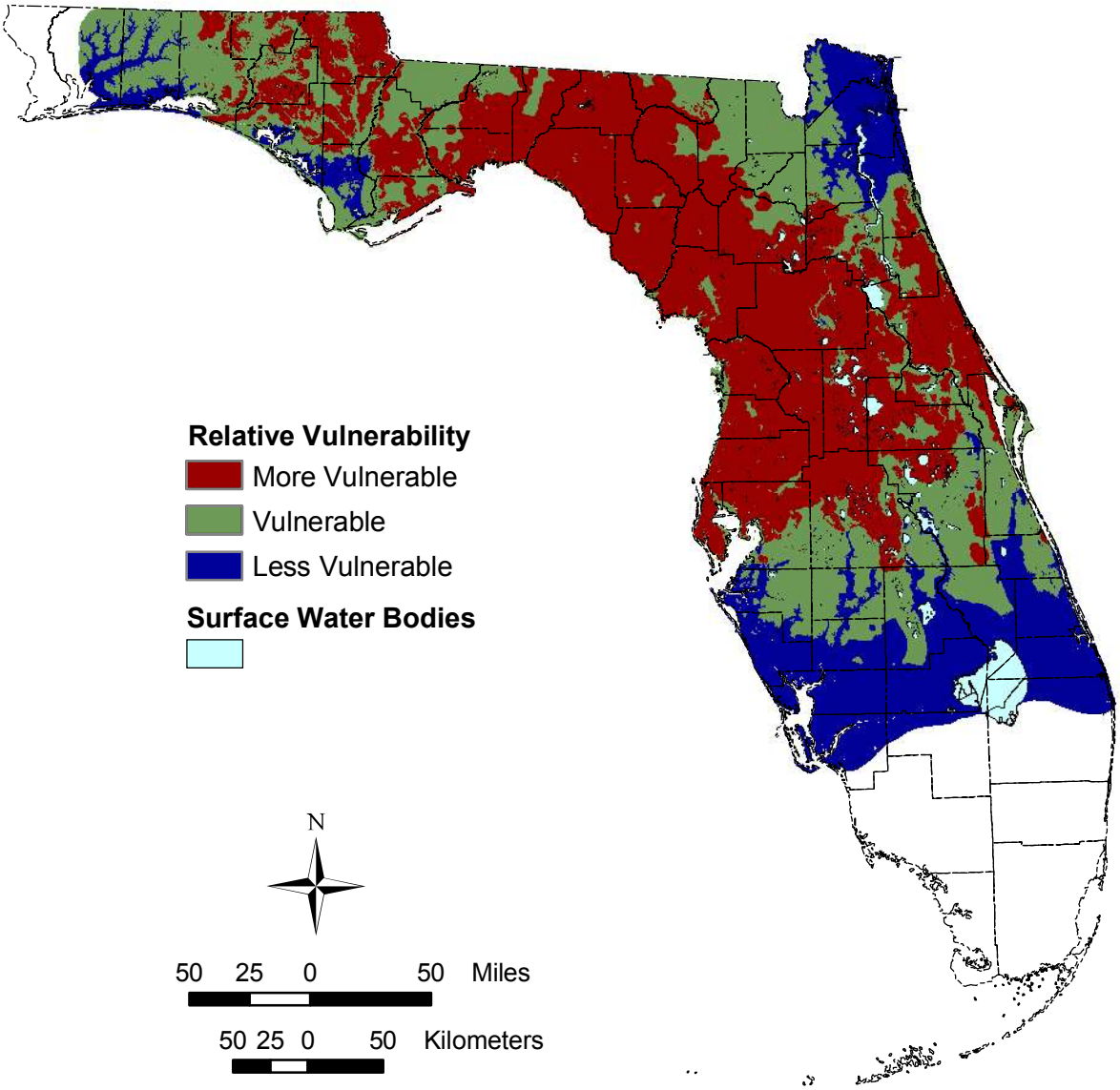


**Figure 49. Relative vulnerability of the FAS divided into three zones based on posterior probability values displayed in Figure 50. Dissolved nitrogen concentrations were used as a training point theme. See Plate 3 (back pocket) for a more detailed display and discussion of the vulnerability zones.**

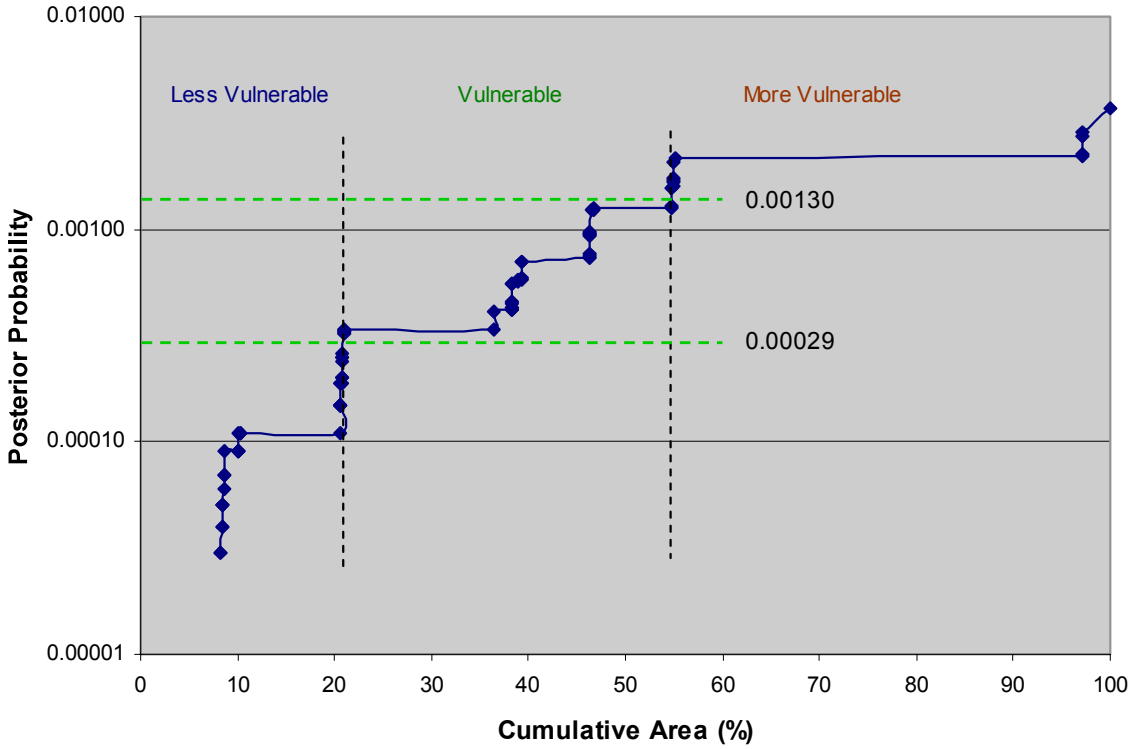


**Figure 50. Class breaks, represented by green dashed lines, were placed where both a significant increase in probability and area were observed. These boundaries correspond with relative vulnerability zones delineated in Figure 49 and are indicated in this chart by vertical black dashed lines.**

**Table 10. Response theme table listing weights calculated for each evidential theme and their associated contrast and confidence values.**

| Evidential Theme | W1 | W2 | W3 | Contrast | Confidence |
|---|---|---|---|---|---|
| IAS Thickness | 0.4127 | -1.7500 | -2.7121 | 3.1248 | 3.1136 |
| Proximity to Karst | 0.4794 | -1.1573 | | 1.6367 | 7.0812 |
| Hydraulic Head Difference | 0.2736 | -1.5470 | | 1.8206 | 5.2923 |
| Soil Permeability | 0.7336 | -0.0529 | | 0.7865 | 2.7967 |

Confidence Map

The confidence values for the FAS model area ranged from 1.18 to 10.76. The higher confidence areas corresponded with higher vulnerability areas whereas lower confidence areas corresponded to lower vulnerability areas. These values indicated that the confidence level was above 99.5% for the majority of the model domain, and was greater than 90% for all but a few areas across the entire model domain. Areas of lower confidence also corresponded with areas that lack training points. The confidence for the FAS model response them is displayed in Figure 51.

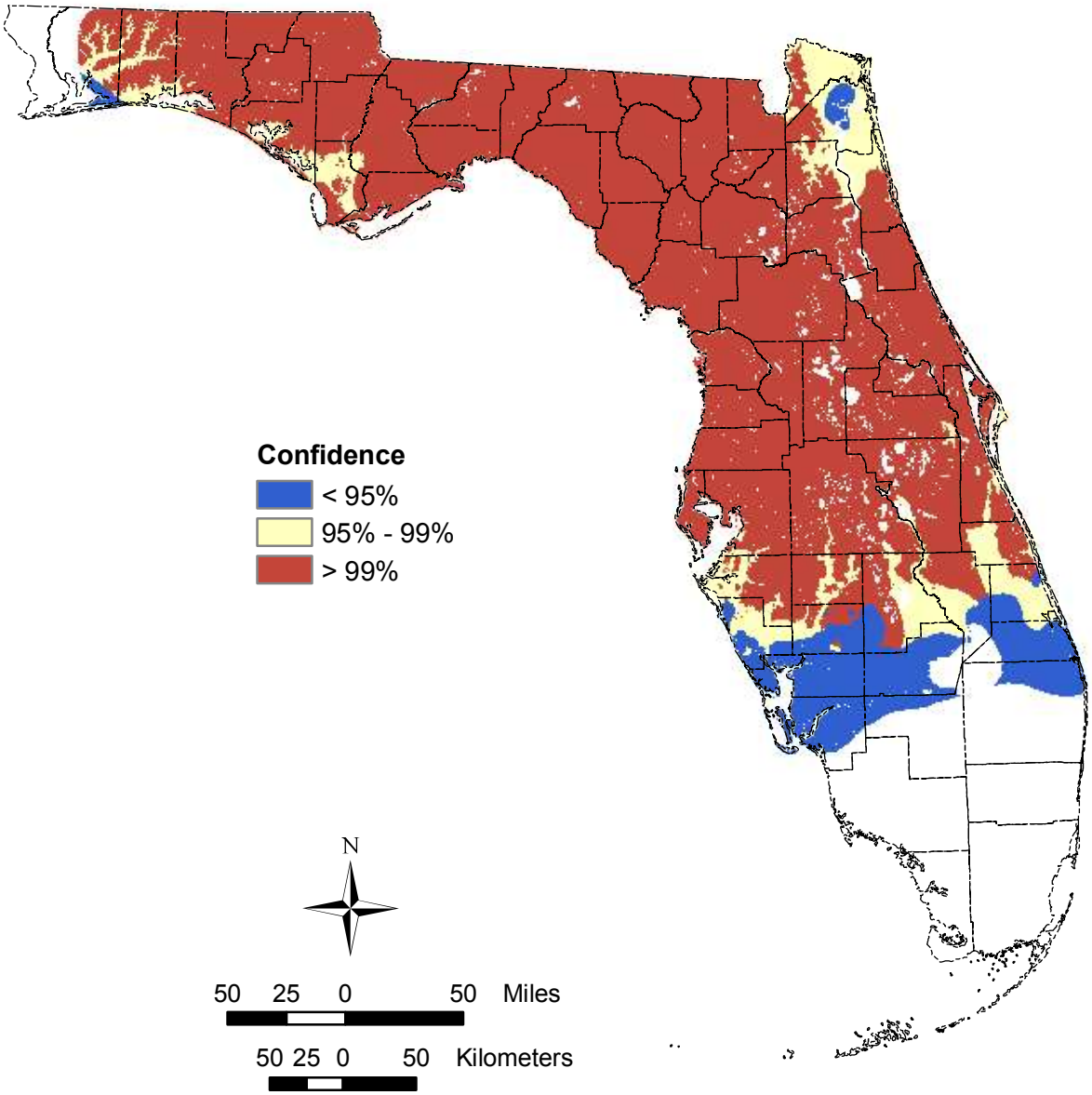


**Figure 51. Distribution of confidence values calculated for FAS response theme.**

## DISCUSSION

### Introduction

Although numerous hydrogeological aspects of the FAVA evidential themes and response themes are of significant interest, such an evaluation is beyond the scope of this study. Instead, the focus of this *Discussion* section is more applied in nature. Four primary focus areas are presented in the following pages: 1) methods of model validation for each aquifer system, 2) resolution of evidential themes, 3) potential refinement of evidential themes, and 4) appropriate use of the FAVA maps.

Maintaining high standards of data quality was of paramount importance in the development of the FAVA project's evidential themes and response themes. A few examples of how data quality was addressed include: 1) use of peer-reviewed published data, 2) utilizing the expertise of the TAC, i.e., hydrogeology, modeling, statistics, environmental planning, 3) TAC review of evidential themes, methodologies, model comparisons, pilot study results, and response themes, 4) continued feedback from a broader pool of experts through presentations of FAVA results at professional meetings, for example, Arthur et al. (2002), Baker et al. (2002), Baker et al. (2003), Cichon et al. (2003), and Wood et al., (2003) 5) implementation of a detailed quality assurance/quality control program during the development of the FDEP DEM, and 6) maintenance of accurate and complete records for metadata (for an example, see *Appendix II*).

Aside from data-quality challenges that may exist with regard to a project of this magnitude, another potential limiting factor exists regarding application of the model results that involves the evidential themes. Resolution is a measure of the level of detail of a given set of data. For example, at the onset of this study, the only available dataset reflecting surface topography, the USGS DEM, had a lateral resolution of 30 m. This level of resolution allowed for changes in topography to be seen only at 30 m. Not only is this a coarse model of topography by some standards, surface elevation errors exceeding 50 feet were also discovered within the dataset (see *Results – Data Coverages – Topography*). As a result, a new, more accurate and more highly resolved DEM was needed. During the course of this project, the FGS worked with other FDEP programs and water management districts to develop a statewide FDEP DEM with a lateral resolution of 15 m and vertical resolution equal to that of the USGS 7.5-minute quadrangle maps (± 5 or 10 feet, depending on each map's contour interval).

During the course of the FAVA project, every effort was made to maximize use of existing data and produce new data coverages needed for the modeling effort while maintaining the highest possible accuracy and precision of those coverages. The new data coverages (e.g., thickness of IAS, statewide environmental geology, top of FAS, and the FDEP DEM) are derivative FAVA products that alone are important contributions to the geological, planning and environmental management community.

### Model Validation and Sensitivity Analysis

Validation and sensitivity analyses comprise a significant phase of any modeling project as they allow evaluation of the optimization of model parameters and accuracy of the results. Most of the sensitivity analyses were spatial in nature; they involved developing FAVA response themes for individual counties, and then for a region encompassing both counties to assess the differences. Other sensitivity analyses helped select and refine evidential themes to minimize the amount of requisite data inputs while maximizing the results of the models as measured through statistical assessment. During this process, for example, it was discovered that soil permeability, rather than soil drainage, was a better representation of aquifer vulnerability in the model. Moreover, during iterations through the modeling process, techniques were explored with respect to data consolidation such as the "fuzzy

combination" of proximity to karst features with IAS overburden thickness in the IAS WofE model. Other sensitivity analyses were completed throughout the development of this project; as a result, some evidential themes originally considered for use were omitted. This occurred for two main reasons: the evidential themes did not meet the test of significance (0.674, or 75%) for the FAVA project, or the resulting weights were counterintuitive with regard to hydrogeologic processes and vulnerability.

Among the many strengths of applying WofE to estimate aquifer vulnerability is that this technique is, in a general sense, self-validating due to the training point component of the process. FAVA model output validation and sensitivity was accomplished via several methods:

- Use of random 75% subset of training points
- Comparing land use with posterior probability
- Comparing dissolved nitrogen values with posterior probability
- Using a different training point set (dissolved oxygen)

In the sections that follow, these methods are discussed relative to the three FAVA response themes (SAS, IAS and FAS).

**Random 75% Subset of Training Points**

If the FAVA evidential themes and training points are robust (i.e., not sensitive to subtle changes in the training data set), one would expect the response theme patterns for the full training data set and a subset to be similar. For this sensitivity test, a training point theme consisting of a random subset of 75% of the original training points was generated and the models were re-executed. Response themes generated for each aquifer system using the random subset of points were divided into three vulnerability classes using the methodology described in the *Results* section. The subset response themes were then compared to the original response themes. Two statistical tests – kappa coefficient and Spearman's rank – were used to evaluate the degree of correlation between the FAVA response theme and the subset response theme.

The kappa coefficient was used to measure the amount of spatial agreement between response themes while taking into account agreement that could have occurred by chance. Additionally, conditional kappa values were calculated to determine the amount of agreement between each vulnerability class of the two response themes. A cross-tabulation matrix was used to classify the response themes by area (in square meters) and aided in the calculation of observed and expected proportions (i.e., agreement). Values along the diagonal in this table (upper left to lower right) reflect the amount of agreement between response themes cells. The other values in the table reflect where the response themes were mismatched. Table 11 is an example of the cross-tabulation matrix.

Kappa coefficient results can range between -1 (perfect disagreement) and 1 (perfect agreement). A value of zero indicated that the agreement was no better than that expected due to chance (Bonham-Carter 1994). Kappa coefficients calculated in the FAVA project were all positive values. Positive kappa coefficients can be interpreted using Table 12.

The area-weighted Spearman's Rank correlation coefficient was used to determine if a significant correlation existed between the two response themes. The FAVA response themes were ranked by sorting the posterior probability values in ascending order and assigning integer values. The response themes were then combined to create a unique-conditions grid to compare the ranks for the same areas. The Spearman's Rank correlation coefficient is always between 1 and -1 as with the kappa

coefficient. A value of 1 indicated perfect positive correlation between response themes and a value of -1 indicated there was perfect negative correlation between response themes. A value of zero represented no correlation between response themes.

**Table 11. Example cross-tabulation matrix of the area in square meters per class of a FAVA response theme and 75% subset response theme. Values along the diagonal reflect the amount of agreement.**

| Class | | 75% Subset Response Theme | | | |
|---|---|---|---|---|---|
| | | More Vulnerable | Vulnerable | Less Vulnerable | Total |
| FAVA Response Theme | More Vulnerable | 42,096,002,400 | 524,043,900 | 0 | 42,620,046,300 |
| | Vulnerable | 761,423,400 | 18,469,155,600 | 122,436,900 | 19,353,015,900 |
| | Less Vulnerable | 0 | 39,979,800 | 2,696,742,000 | 2,736,721,800 |
| | Total | 42,857,425,800 | 19,033,179,300 | 2,819,178,900 | 64,709,784,000 |

**Table 12. Kappa coefficient values and their associated interpretation (Landis and Koch, 1977).**

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

### Land Use vs. Posterior Probability

A GIS-based tool known as "zonal statistics" allows comparison of model results with other map-based information. A concern exists regarding validation because the results of the aquifer vulnerability assessment may correlate with human activities on the land surface, despite efforts in the FAVA approach to only utilize and predict characteristics of the natural system. Zonal statistics were used to evaluate possible associations between land use and the distribution of mean posterior probabilities. Land use data was obtained from FDEP GIS website for each of Florida's five water management districts and then compiled into a single GIS coverage of the State (NWFWMD, 1995; SFWMD, 1995; SJRWMD, 1995; SFWMD, 1995; SRWMD, 1995; SWFWMD, 1995). If a strong correlation existed between certain types of land use and higher vulnerable areas (i.e., areas of high posterior probabilities), one may conclude that there was bias in the results due to anthropogenic activities. Elimination of this potential correlation was crucial in validating the objectivity of the FAVA response themes.

### Dissolved Nitrogen Data Distribution vs. Posterior Probability

The presence of dissolved nitrogen was used in the FAVA modeling process as a proxy indicator of aquifer system vulnerability (see *Results – FAVA Model Outputs*). Once outlier wells with anomalous values were removed to yield water-quality values that represent the least human-impacted conditions, it follows that areas of higher concentrations of these constituents should correspond to areas of high vulnerability. In other words, higher total dissolved nitrogen in the aquifer systems should generally correlate with areas of higher posterior probabilities in the response themes.

To assess this hypothesis and provide another method of model validation for each aquifer system, training point median values were averaged and plotted against their respective posterior probability values for each probability class in the aquifer vulnerability response themes. Although this is a qualitative validation, there is value in the technique in that a positive correlation should exist.

### Using a Different Training Point Theme

Models were ultimately validated by creating a training point theme based on a parameter that reflects vulnerability yet is independent of nitrogen. Based on data availability, dissolved oxygen was chosen for this validation method. For each aquifer system, weights were re-calculated for each evidential theme using a dissolved oxygen training point set and a new response theme was generated. The model results were compared with the results of the dissolved nitrogen-based FAVA models. If the original FAVA response theme was valid, one would expect that the vulnerability maps produced using training data set would produce similar results. Comparison of the two response themes was achieved using the same two statistical tests as applied in the 75% subset methods: kappa coefficient and Spearman's rank correlation coefficient.

## Sensitivity and Validation of the SAS FAVA map

### Random 75% Subset of Training Points (SAS)

A subset of the SAS total dissolved nitrogen training point theme was generated using a random selection process. This random subset included 75% of the original wells for a total of 70 training points and yielded a prior probability of 0.0011. Weights were then recalculated for each evidential theme, class breaks were selected, and a response theme was generated (Figure 52). The pattern of posterior probabilities was nearly identical to the original total dissolved nitrogen response theme.

The kappa coefficient was used to measure the amount of spatial agreement between the random subset response theme and the SAS FAVA response theme. The kappa coefficient between the response themes was calculated at 0.953. Additionally, conditional kappa values were calculated to determine the amount of agreement between each vulnerability class of the two response themes being compared. Table 13 displays the conditional kappa coefficient between each vulnerability class of the two response themes. Both the agreement between each class and the overall agreement between the two response themes was almost perfect (Table 12). The area-weighted Spearman's Rank correlation coefficient for the SAS FAVA response theme and the random subset response theme was calculated at 0.798 indicating a very strong positive correlation between the response themes. This value corresponds to a level of confidence of 99% for the correlation of the two response themes.

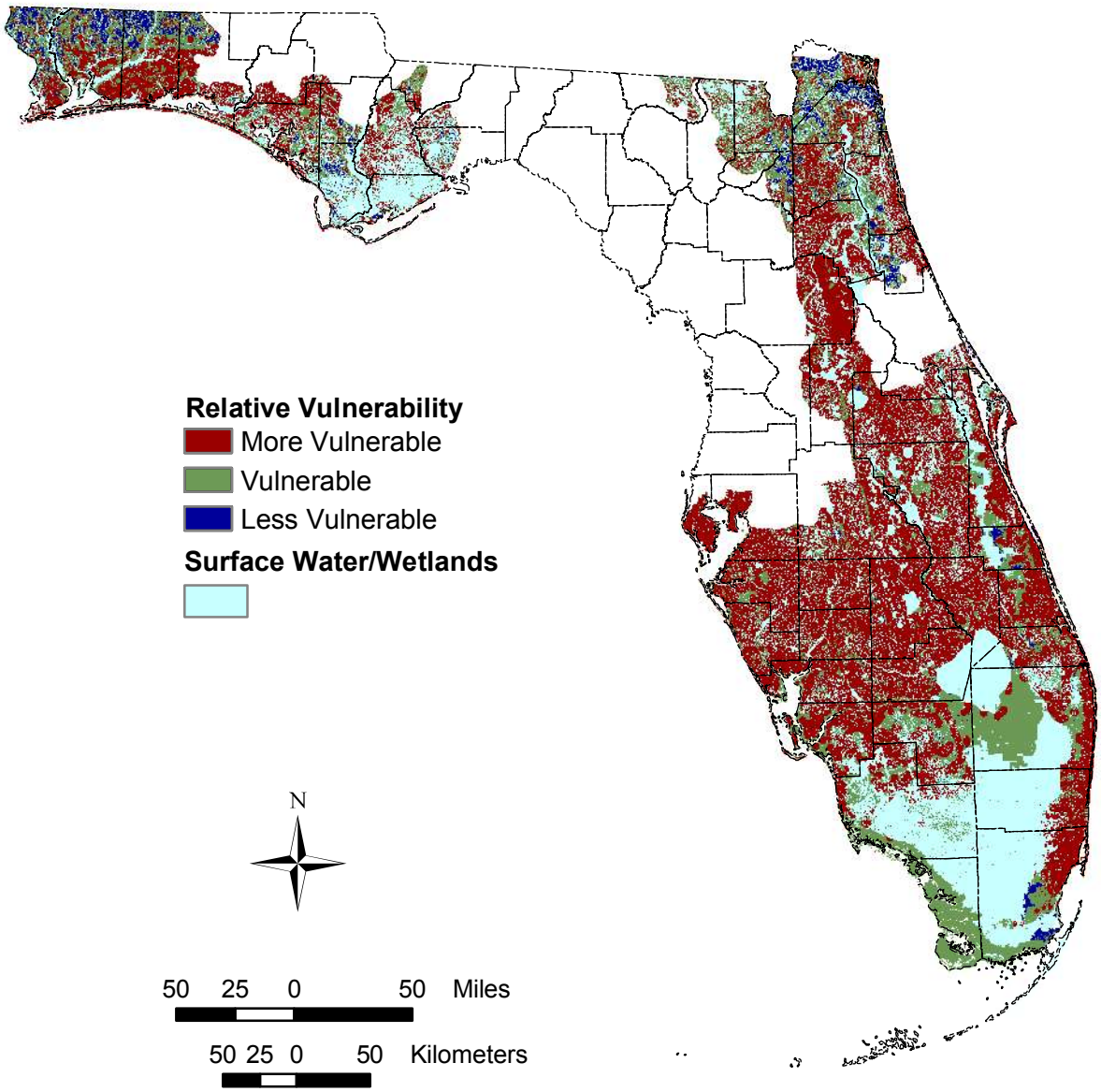


**Figure 52. Relative vulnerability of the SAS divided into three zones based on posterior probability values using a random 75% subset of the original total dissolved nitrogen training point theme. The same methodology used in the Results – FAVA Model Output was used herein to determine vulnerability class breaks.**

**Table 13. Conditional kappa coefficient values between the random 75% subset response theme and the FAVA response theme for the SAS model. Kappa coefficient values are reported between each vulnerability class.**

| Agreement | Conditional Kappa ($K_f$) values |
|---|---|
| More Vulnerable Classes | 0.964 |
| Vulnerable Classes | 0.935 |
| Less Vulnerable Classes | 0.985 |

**Land Use vs. Posterior Probability (SAS)**

Zonal statistics were calculated to compare the statewide land use GIS coverage to the distribution of the posterior probability values for the SAS FAVA response theme (Figure 53). Wetlands and upland forests had slightly lower mean posterior probability values, but overall, no strong association could be drawn between any one type of land use and average posterior probability values. This indicated that land use was not influencing the distribution of the training point set, and, therefore, did not significantly affect the response theme for the SAS FAVA model.

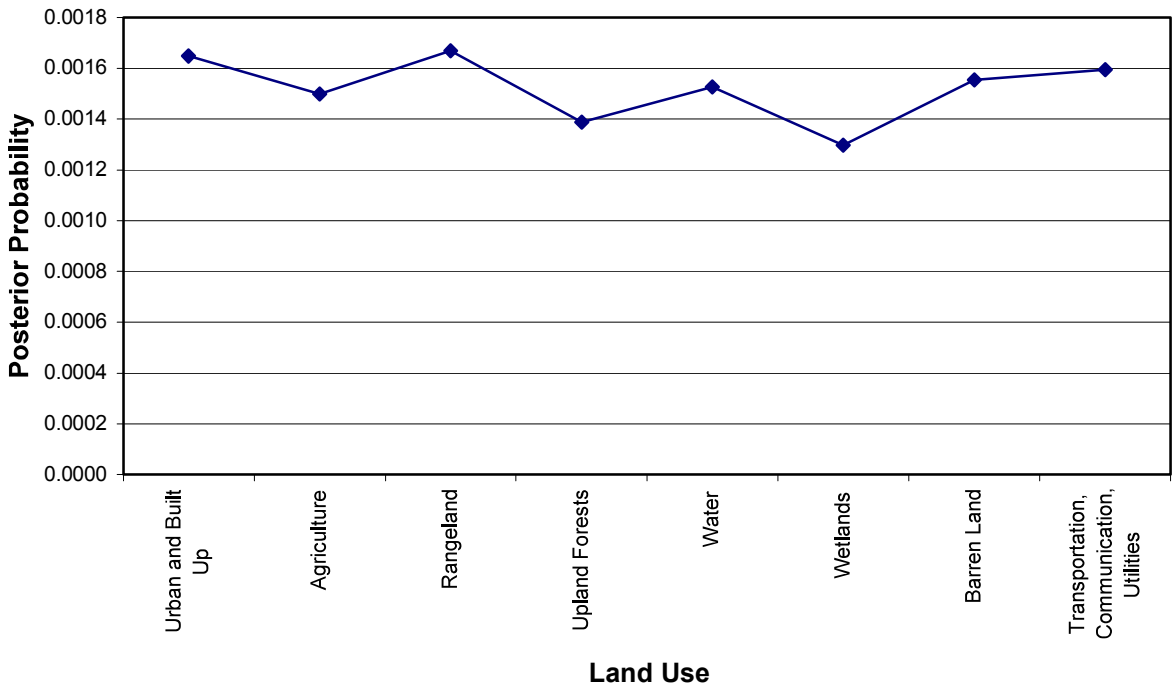


**Figure 53. Land use plotted against posterior probability values in the SAS FAVA response theme. Though Rangeland and Urban and Built-Up areas have a slightly stronger association with land use, no strong association could be drawn between any land use type and the distribution of posterior probability.**

### Total Dissolved Nitrogen Data versus Posterior Probability (SAS)

Posterior probability values were compared with total dissolved nitrogen dataset from which the training point theme was extracted. Average total dissolved nitrogen median concentrations for each posterior probability class in the response theme were plotted versus posterior probability values (Figure 54). As expected, a positive trend was observed between posterior probability and total dissolved nitrogen values.

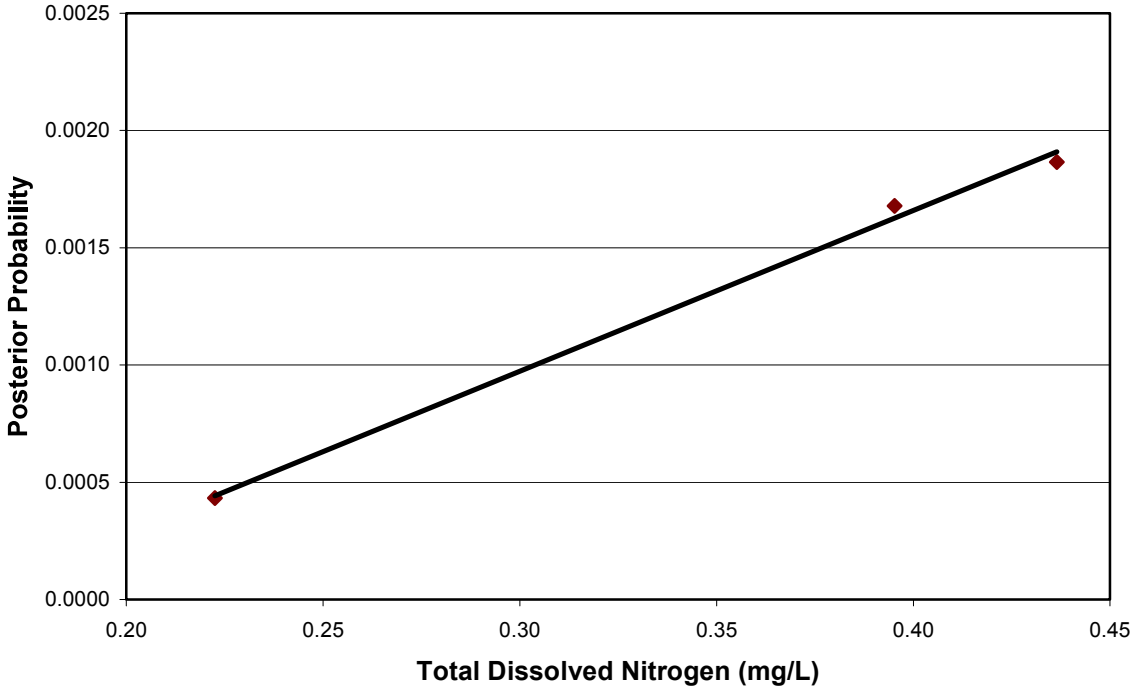


Figure 54. Relationship between average total dissolved nitrogen median concentrations and posterior probability classes of the SAS response theme. Note the positive correlation between increasing total dissolved nitrogen and posterior probability.

### Using a Different Training Point Set (SAS)

A training point set was developed for the SAS study area from wells measured for dissolved oxygen in the FDEP background water quality monitoring network. Outliers were removed and statistical analysis returned a 75$^{th}$ percentile median value for dissolved oxygen concentration of 1.03 mg/L. There were 91 wells occurring in the dataset with a measured median dissolved oxygen value greater than 1.03 mg/L, which yielded a prior probability of 0.0014. Using this dissolved oxygen training point set, a validation response theme was developed to compare to the total dissolved nitrogen model. The same input themes were used, and weights were calculated for each theme. The response

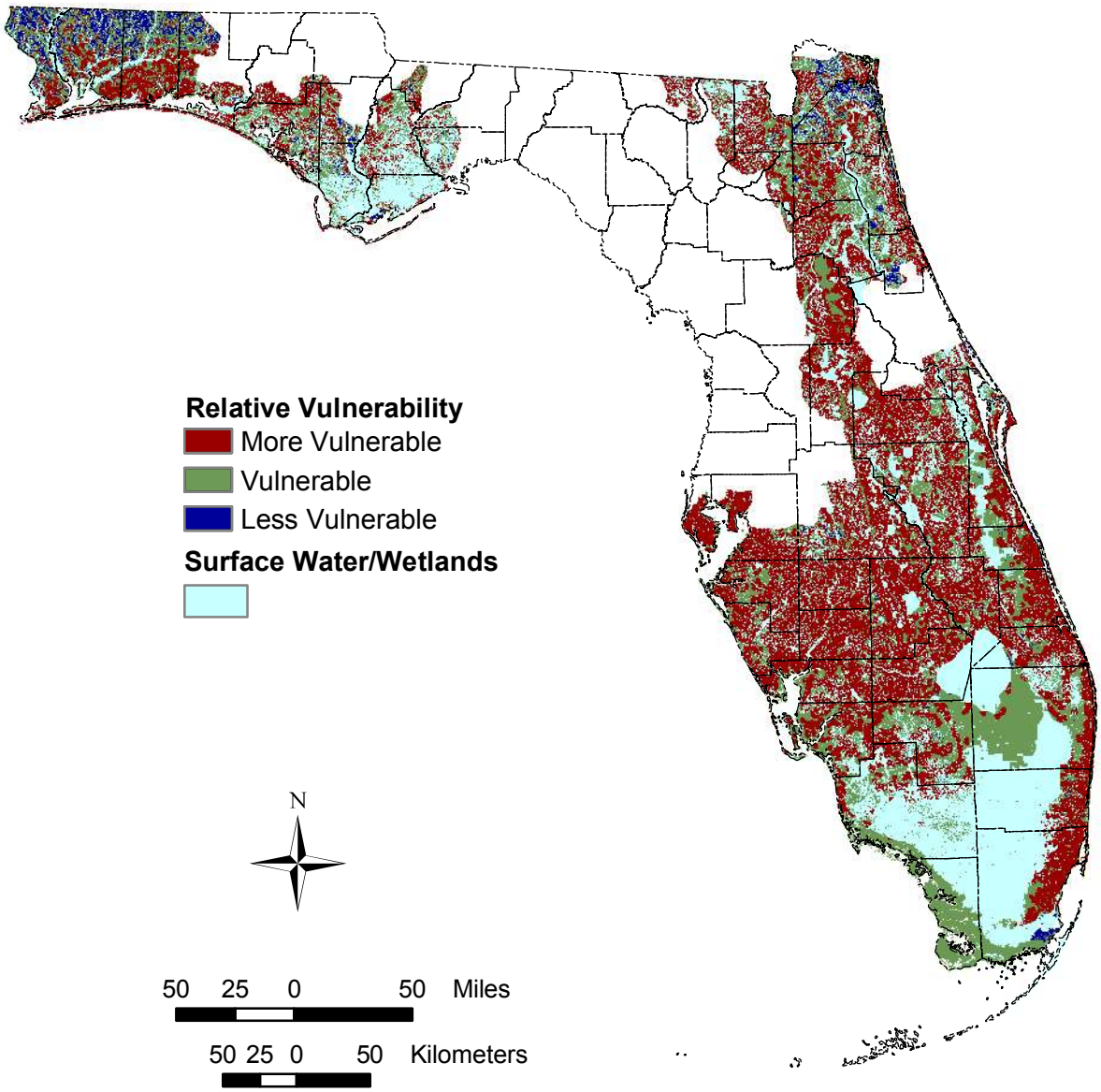


**Figure 55. Relative vulnerability of the SAS divided into three zones based on posterior probability values using training point theme based on dissolved oxygen. The same methodology used in the *Results – FAVA Model Output* was used to determine vulnerability class breaks.**

theme is shown in Figure 55. The pattern of posterior probabilities was nearly identical to the SAS FAVA response theme. The dissolved oxygen model predicts higher vulnerability in the northeast part of the State, a small section of the Biscayne Aquifer, and the southern tip of Florida.

The kappa coefficient was used to measure the amount of spatial agreement between the dissolved oxygen response theme and the SAS FAVA response theme. The kappa coefficient between the response themes was calculated at 0.670. Additionally, conditional kappa values were calculated to determine the amount of agreement between each vulnerability class of the two response themes being compared. Both the agreement between each class and the overall agreement between the two response themes was substantial. Table 14 displays the kappa coefficient between each vulnerability class of the two response themes.

**Table 14. Conditional kappa coefficient values between the dissolved oxygen response theme and the FAVA response theme for the SAS model. Kappa coefficient values are reported between each vulnerability class.**

| Agreement | Conditional Kappa ($K_f$) values |
|---|---|
| More Vulnerable Classes | 0.643 |
| Vulnerable Classes | 0.714 |
| Less Vulnerable Classes | 0.632 |

The area-weighted Spearman's Rank correlation coefficient for the original SAS response theme and the dissolved oxygen response theme was calculated at 0.985 indicating a very strong positive correlation between the response themes. This value corresponds to a level of confidence of 99% for the correlation of the two response themes.

**Sensitivity and Validation of the IAS FAVA model**

**Random 75% Subset of Training Points (IAS)**

A subset of the IAS total dissolved nitrogen training point theme was generated using a random selection process. This random subset included 75% of the original wells for a total of 20 training points and yielded a prior probability of 0.0007. Weights were then recalculated for each evidential theme, class breaks were selected, and a response was theme generated (Figure 56). The pattern of posterior probabilities was nearly identical to the original total dissolved nitrogen response theme.

The kappa coefficient was used to measure the amount of spatial agreement between the random subset response theme and the IAS FAVA response theme. The kappa coefficient between the response themes was calculated at 0.833 indicating that the overall agreement between the two response themes was almost perfect. Additionally, conditional kappa values were calculated to determine the amount of agreement between each vulnerability class of the two response themes being compared. Table 15 displays the kappa coefficient between each vulnerability class of the two response themes. According to Table 12, the conditional kappa values for the 75% subset response theme and the IAS FAVA response theme indicated almost perfect agreement between the more vulnerable and less vulnerable classes. The conditional kappa value for the vulnerable classes indicated substantial agreement between the two response themes.

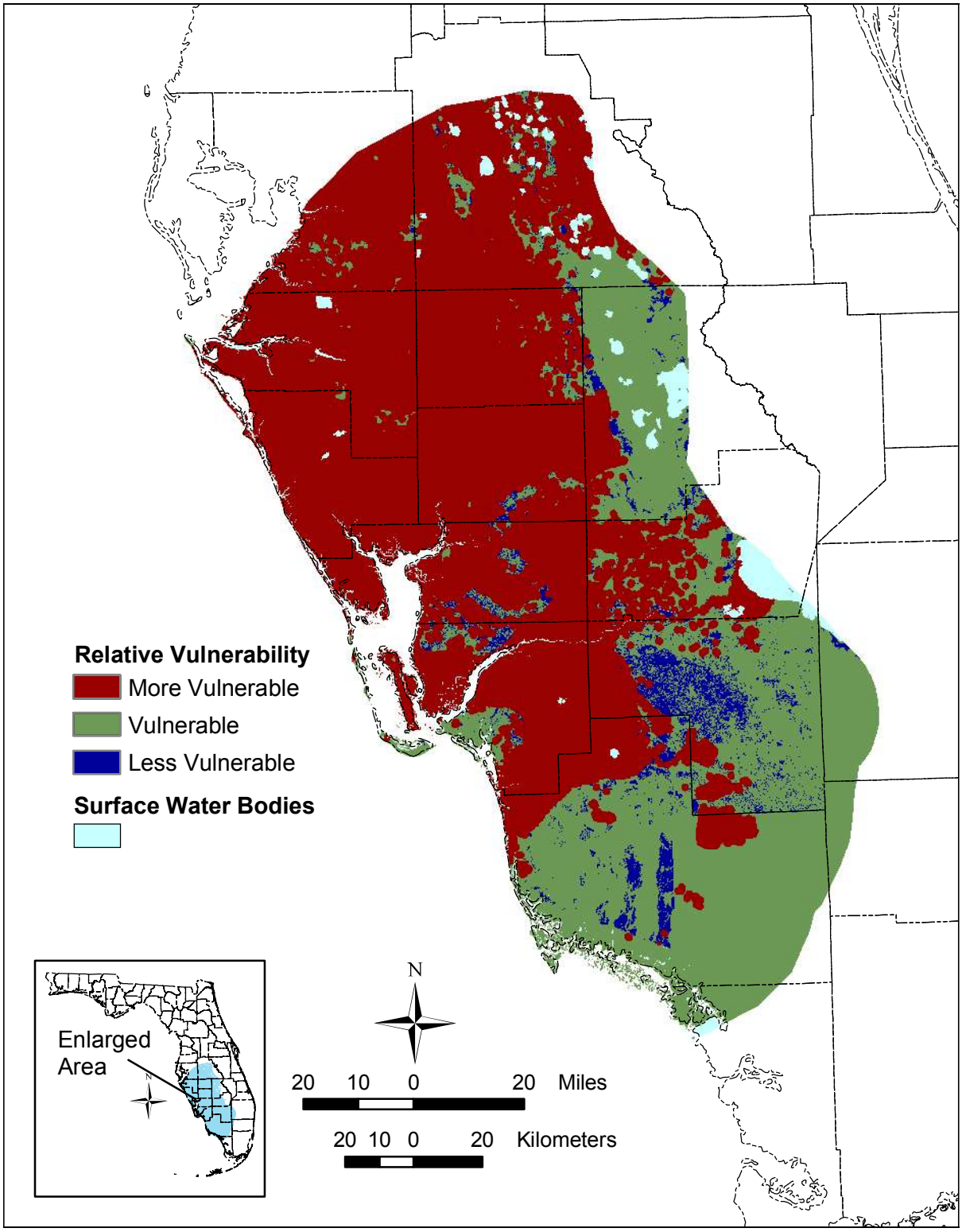


**Figure 56. Relative vulnerability of the IAS divided into three zones based on posterior probability values using a random 75% subset of the original total dissolved nitrogen training point theme. The same methodology used in the *Results – FAVA Model Output* was used herein to determine vulnerability class breaks.**

**Table 15. Conditional kappa coefficient values between the random 75% subset response theme and the FAVA response theme for the IAS model. Kappa coefficient values are reported between each vulnerability class. The asterisk indicates these values have been rounded.**

| Agreement | Conditional Kappa ($K_f$) values |
|---|---|
| More Vulnerable Classes | 1.000* |
| Vulnerable Classes | 0.691 |
| Less Vulnerable Classes | 1.000* |

The area-weighted Spearman's Rank correlation coefficient for the IAS FAVA response theme and the random subset response theme was calculated at 0.999 indicating a near-perfect positive correlation between the response themes. This value corresponds to a level of confidence of 98% for the correlation of the two response themes.

**Land Use vs. Posterior Probability (IAS)**

Zonal statistics were calculated to compare the statewide land use GIS coverage (compiled as described in *Discussion – Model Validation Techniques*) to the distribution of the posterior probability values for the IAS FAVA response theme (Figure 57). Wetlands and barren lands had lower mean posterior probability values, but overall, no strong association was observed between any one type of land use and average posterior probability values. Wetlands and barren lands (i.e., sandy areas, beaches, exposed rock) likely have lower posterior probability due to fewer wells having been drilled in these areas. These two land uses, which comprise only 0.4% of the total study area land use are therefore underrepresented by training points.

**Total Dissolved Nitrogen Data versus Posterior Probability (IAS)**

Posterior probability values were compared with total dissolved nitrogen dataset from which the training point theme was extracted. Average total dissolved nitrogen median concentrations for each posterior probability class in the response theme were plotted versus posterior probability values (Figure 58). As expected, a positive trend was observed between posterior probability and total dissolved nitrogen values.

**Using a Different Training Point Set (IAS)**

A training point set was developed for the IAS study area from wells measured for dissolved oxygen in the FDEP background water quality monitoring network. Outliers were removed and statistical analysis returned a 75$^{th}$ percentile median value for dissolved oxygen concentration of 0.93 mg/L. There were 22 wells occurring in the dataset with a measured median dissolved oxygen value greater than 0.93 mg/L, which yielded a prior probability of 0.0008. Using this dissolved oxygen training point set, a validation response theme was developed to compare to the total dissolved nitrogen model. The same input themes were used, and weights were calculated for each theme. The response theme is shown in Figure 59. The pattern of posterior probabilities was nearly identical to the IAS FAVA response theme.

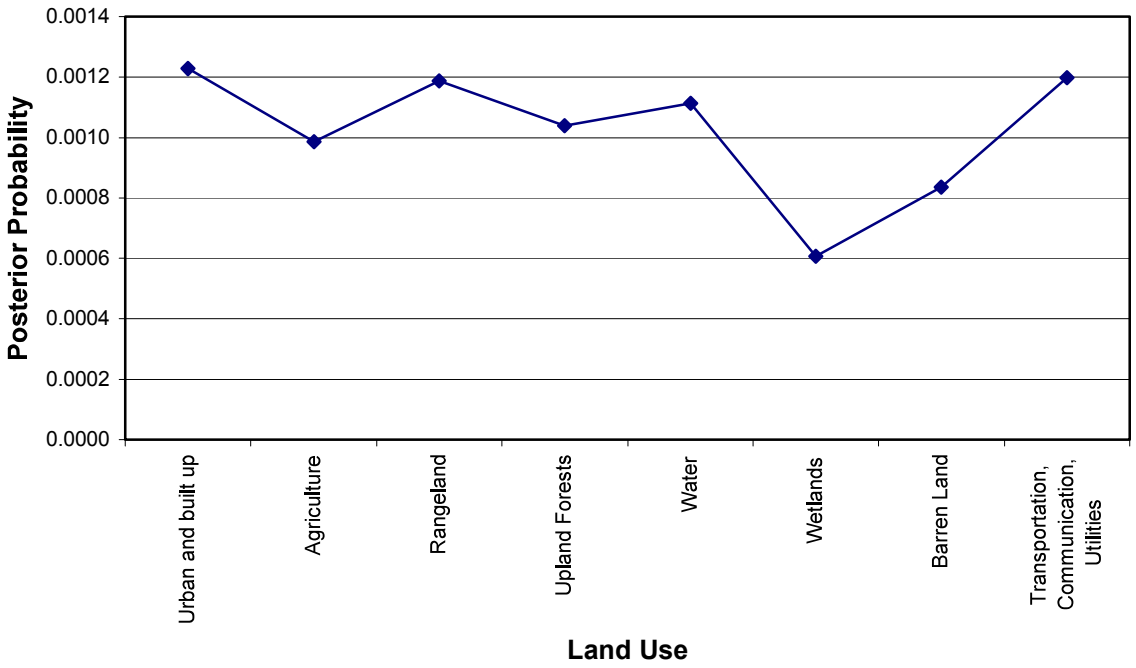


**Figure 57. Land use plotted against posterior probability values in the IAS FAVA response theme. Though Wetland and Barren Land areas had a weaker association with land use, no strong association could be drawn between any land-use type and the distribution of posterior probability.**

The kappa coefficient was used to measure the amount of spatial agreement between the dissolved oxygen random subset response theme and the IAS FAVA response theme. The kappa coefficient between the response themes was calculated at 0.802 indicating that the overall agreement between the two response themes was almost perfect. Additionally, conditional kappa values were calculated to determine the amount of agreement between each vulnerability class of the two response themes being compared. Table 16 displays the kappa coefficient between each vulnerability class of the two response themes.

According to Table 12, the conditional kappa values for the dissolved oxygen response theme and the IAS FAVA response theme indicated almost perfect agreement between the more vulnerable classes, substantial agreement between the vulnerable classes, and moderate agreement between the less vulnerable classes. The less vulnerable class in the IAS model was extremely small so a moderate agreement between these classes had little effect on the overall agreement between the maps. Approximately half of the less vulnerable area in the IAS FAVA response theme was overlain by the vulnerable class of the dissolved oxygen response theme causing the lower kappa value between these two classes and corresponding lower agreement level.

The area-weighted Spearman's Rank correlation coefficient for the IAS FAVA response theme and the dissolved oxygen response theme was calculated at 0.997 indicating a near-perfect positive correlation between the response themes. This value corresponds to a level of confidence of 98% for the correlation of the two response themes.

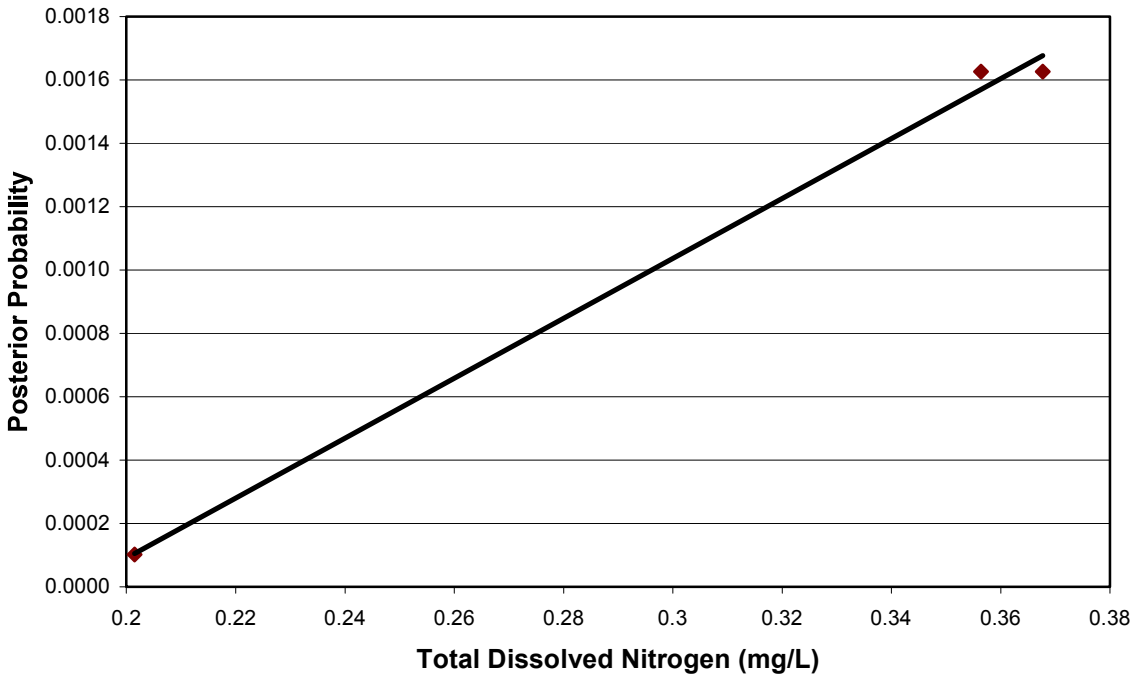


**Figure 58. Relationship between average total dissolved nitrogen median concentration data and posterior probability classes of the IAS response theme. Note the positive correlation between increasing total dissolved nitrogen and posterior probability.**

**Table 16. Conditional kappa coefficient values between the dissolved oxygen response theme and the FAVA response theme for the IAS model. Kappa coefficient values are reported between each vulnerability class.**

| Agreement | Conditional Kappa ($K_f$) values |
|---|---|
| More Vulnerable Classes | 0.961 |
| Vulnerable Classes | 0.717 |
| Less Vulnerable Classes | 0.482 |

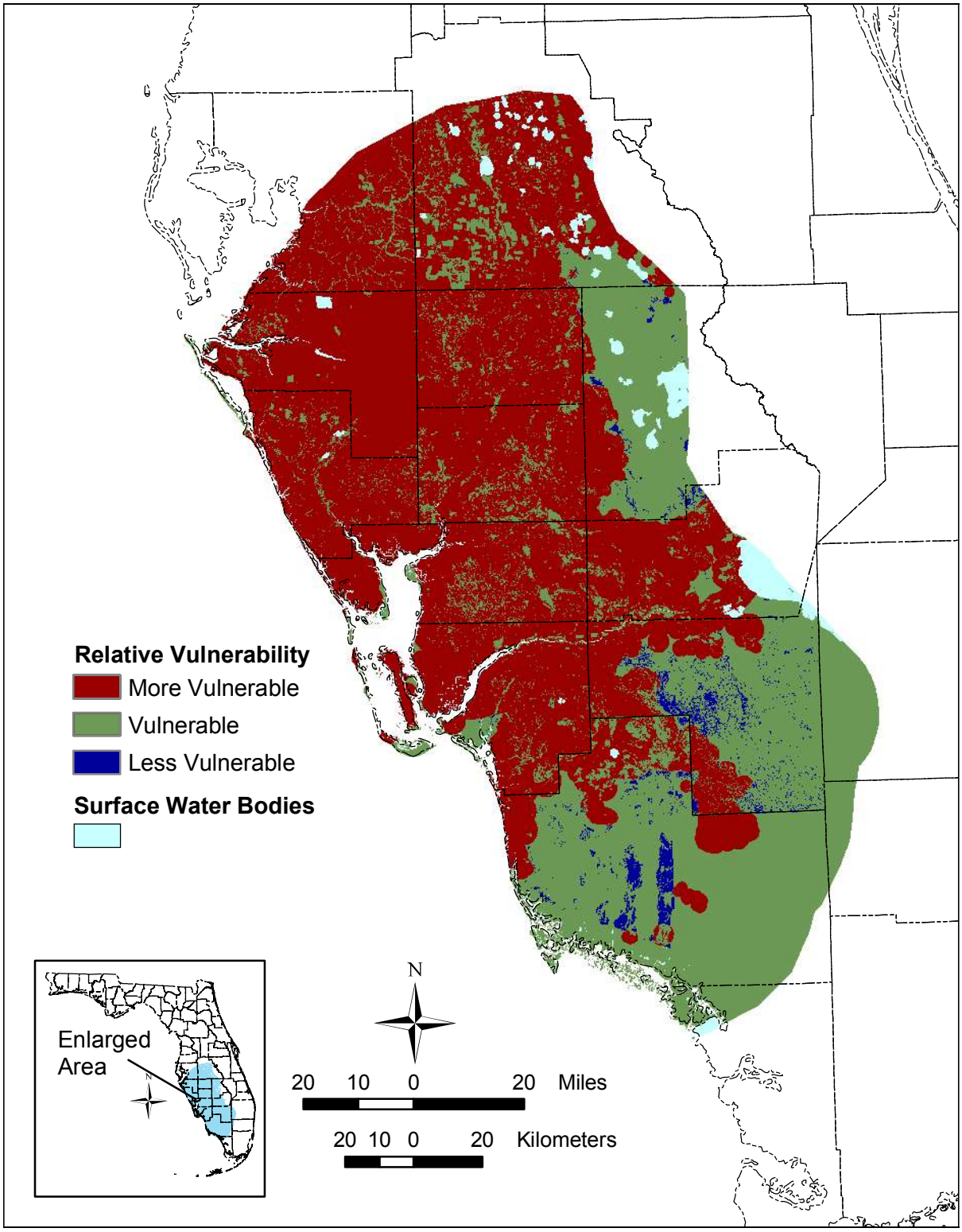


**Figure 59. Relative vulnerability of the IAS divided into three zones based on posterior probability values using training point theme based on dissolved oxygen. The same methodology used in the *Results – FAVA Model Output* was used herein to determine vulnerability class breaks.**

## Sensitivity and Validation of the FAS FAVA Model

### Random 75% Subset of Training Points (FAS)

A subset of the FAS dissolved nitrogen training point theme was generated using a random selection process. This random subset included 75% of the original wells for a total of 118 training points and yielded a prior probability of 0.0010. Weights were then recalculated for each evidential theme, class breaks were selected, and a response theme was generated (Figure 60). The pattern of posterior probabilities was nearly identical to the original dissolved nitrogen response theme.

The kappa coefficient was used to measure the amount of spatial agreement between the random subset response theme and the FAS FAVA response theme. The kappa coefficient between the response themes was calculated at 0.840 indicating that the overall agreement between the two response themes was almost perfect. Additionally, conditional kappa values were calculated to determine the amount of agreement between each vulnerability class of the two response themes being compared. Table 17 displays the kappa coefficient between each vulnerability class of the two response themes.

According to Table 12, the conditional kappa values for the 75% subset response theme and the FAS FAVA response theme indicated almost perfect agreement between the more vulnerable and less vulnerable classes. The kappa value for the vulnerable classes indicated substantial agreement between the two response themes. A small area of the more vulnerable class from the subset response theme overlapped the vulnerable class causing the lower kappa value between these two classes and corresponding lower agreement level.

**Table 17. Conditional kappa coefficient values between the random 75% subset response theme and the FAVA response theme for the FAS model. Kappa coefficient values are reported between each vulnerability class. The asterisk indicates these values have been rounded.**

| Agreement | Conditional Kappa ($K_f$) values |
|---|---|
| More Vulnerable Classes | 1.000* |
| Vulnerable Classes | 0.611 |
| Less Vulnerable Classes | 1.000* |

The area-weighted Spearman's Rank correlation coefficient for the original FAS response theme and the random subset response theme was calculated at 0.985 indicating a very strong positive correlation between the response themes. This value corresponds to a level of confidence of 99% for the correlation of the two response themes.

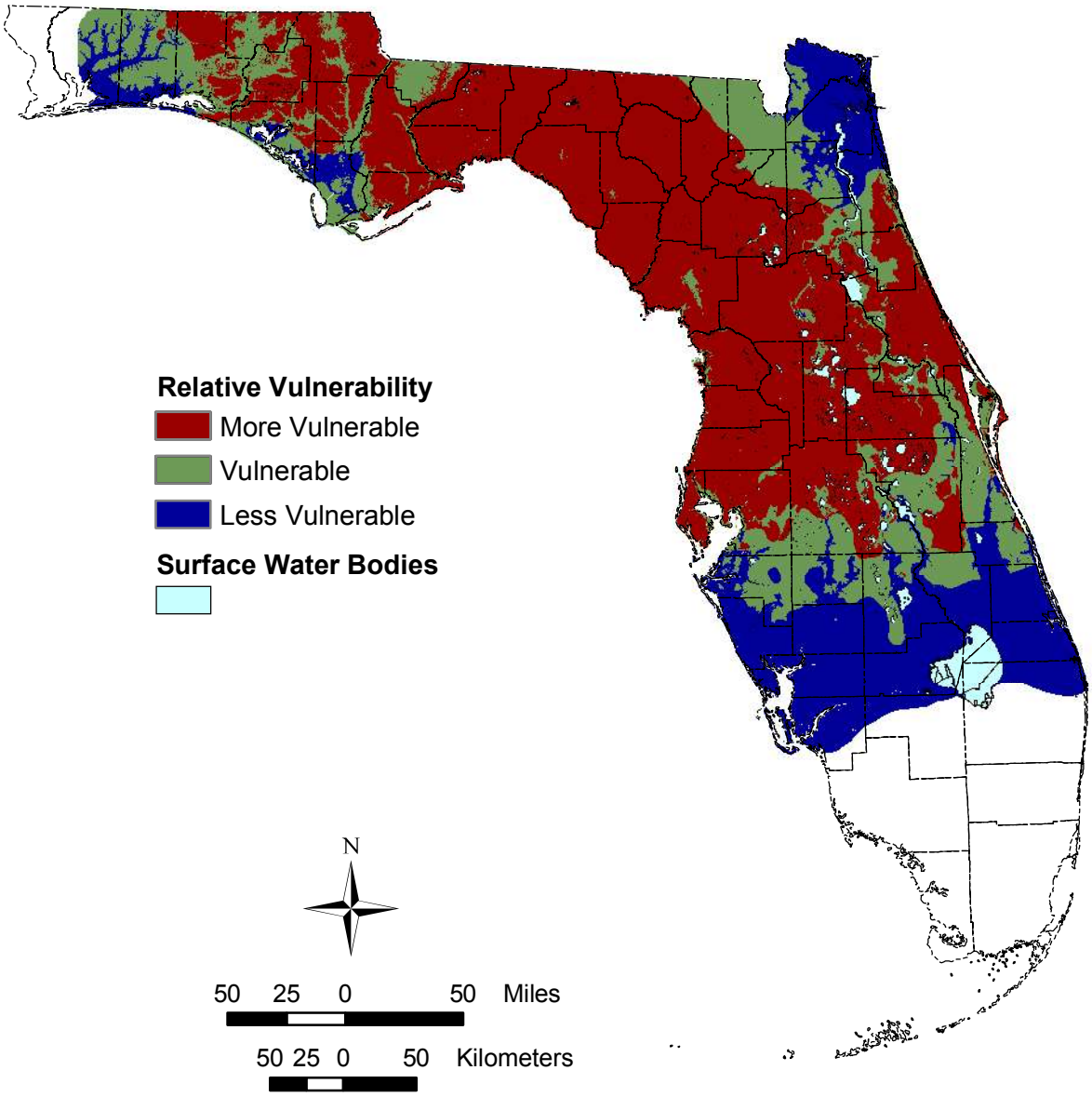


**Figure 60. Relative vulnerability of the FAS divided into three zones based on posterior probability values using a random 75% subset of the original dissolved nitrogen training point theme. The same methodology used in the *Results – FAVA Model Output* was used herein to determine vulnerability class breaks.**

### Land Use vs. Posterior Probability (FAS)

Zonal statistics were calculated to compare the statewide land use GIS coverage (compiled as described in *Discussion – Model Validation Techniques*) to the distribution of the posterior probability values for the FAS FAVA response theme (Figure 61). Rangeland and barren land had slightly lower mean posterior probability values, but overall, no strong correlation was observed between any one type of land use and average posterior probability values. With the exception of perhaps barren land, which represents 0.3% of the total land use in the study area, this generally indicated that land use was not influencing the distribution of the training point set, and, therefore, did not affect the response theme for the FAS FAVA model.

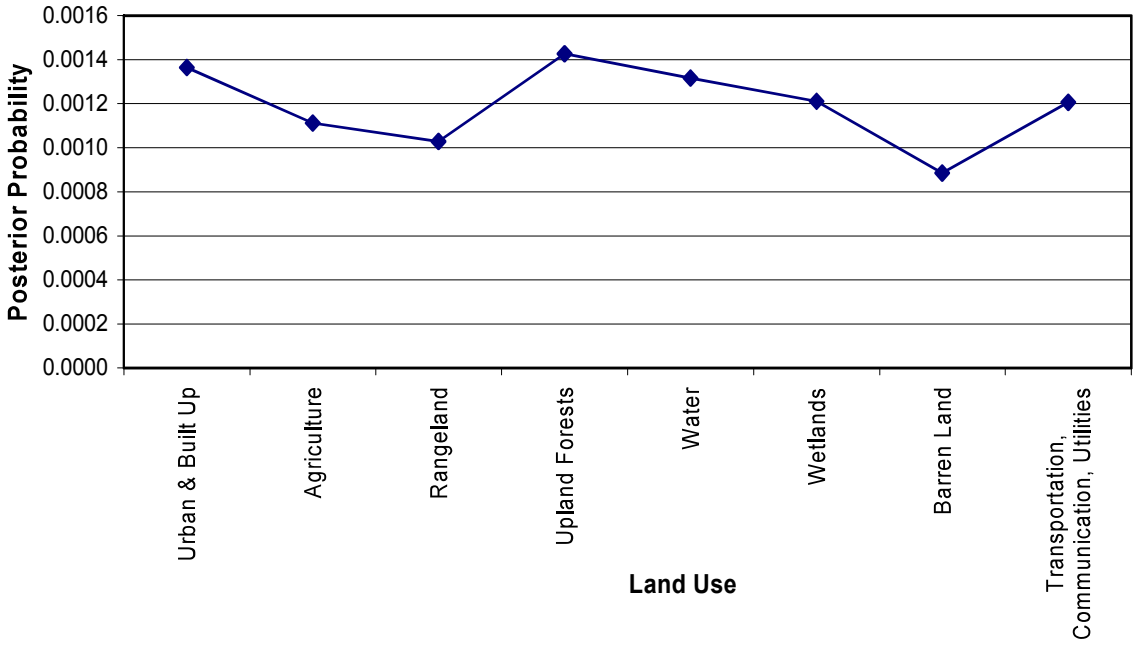


**Figure 61. Land use plotted against posterior probability values in the FAS FAVA response theme. Though Rangeland and Barren Land areas have a slightly weaker association with land use, no strong association could be drawn between any land use type and the distribution of posterior probability.**

### Dissolved Nitrogen Data versus Posterior Probability (FAS)

Posterior probability values were compared with dissolved nitrogen dataset from which the training point theme was extracted. Average dissolved nitrogen median concentrations for each posterior probability class in the response theme were plotted versus posterior probability values (Figure 62). As expected, a positive trend was observed between posterior probability and dissolved nitrogen values.

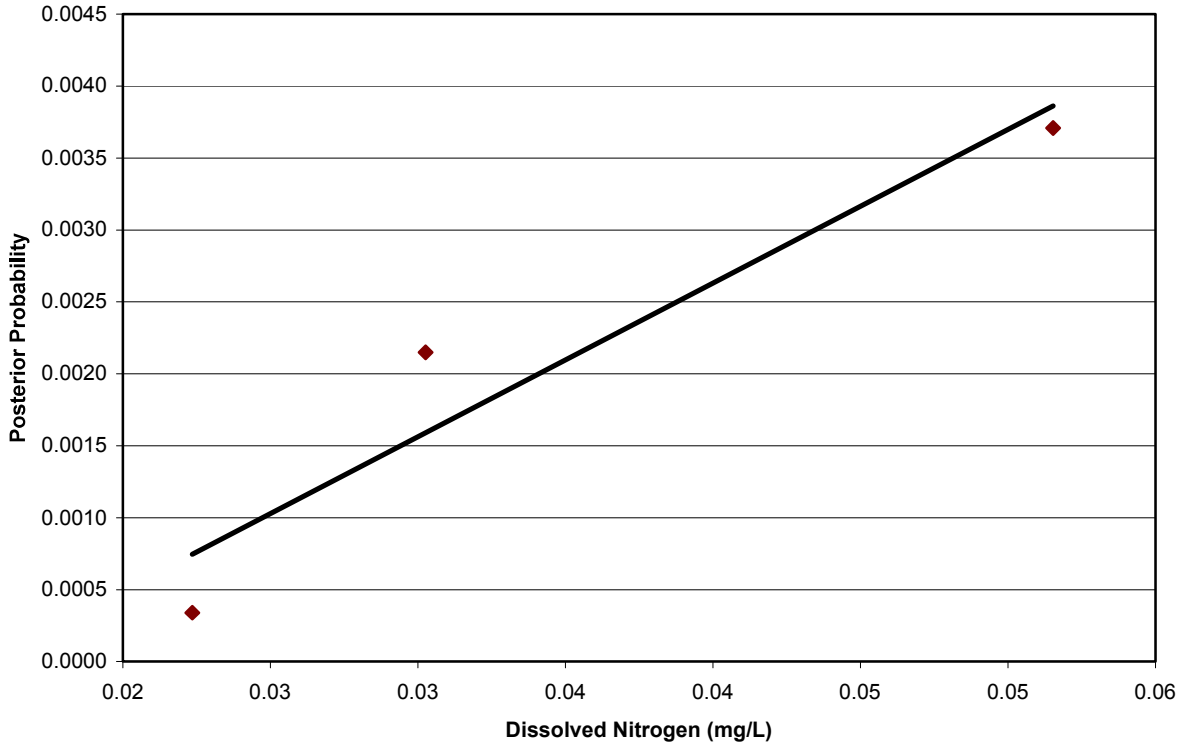


**Figure 62. Relationship between average dissolved nitrogen median concentration data and posterior probability classes of the FAS response theme. Note the positive correlation between increasing dissolved nitrogen and posterior probability.**

### Using a Different Training Point Set (FAS)

A training point set was developed for the FAS study area from wells measured for dissolved oxygen in the FDEP background water quality monitoring network. Outliers were removed and statistical analysis returned a 75$^{th}$ percentile median value for dissolved oxygen concentration of 1.00 mg/L. There were 150 wells occurring in the dataset with a measured median dissolved oxygen value greater than 1.00 mg/L, which yielded a prior probability of 0.0012. Using this dissolved oxygen training point set, a validation response theme was developed to compare to the dissolved nitrogen model. The same input themes were used, and weights were calculated for each theme. The response theme is shown in Figure 63. The pattern of posterior probabilities was nearly identical to the original response theme.

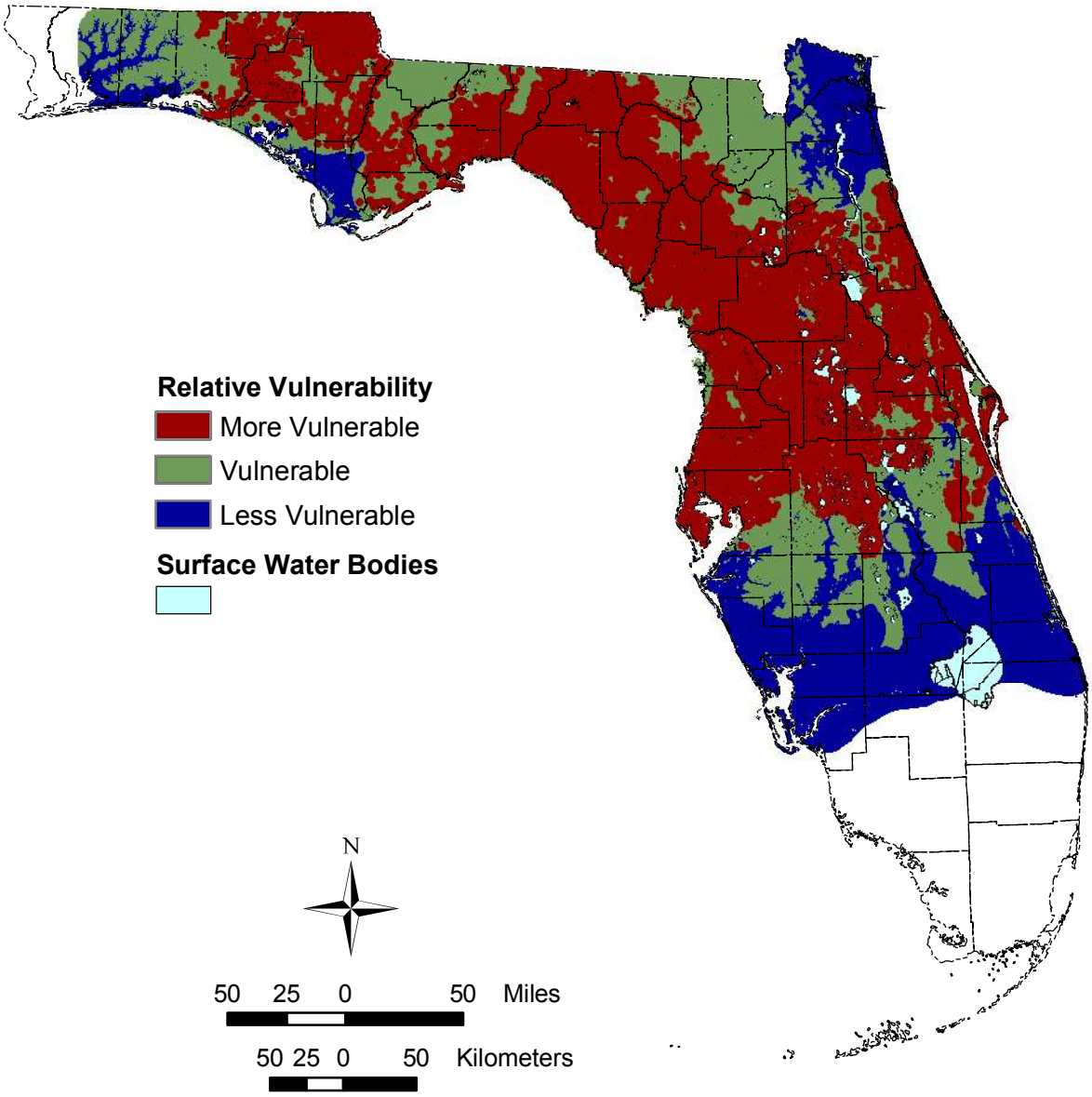


**Figure 63. Relative vulnerability of the FAS divided into three zones based on posterior probability values using training point theme based on dissolved oxygen. The same methodology used in the *Results – FAVA Model Output* was used herein to determine vulnerability class breaks.**

The kappa coefficient was used to measure the amount of spatial agreement between the dissolved oxygen response theme and the FAS FAVA response theme. The kappa coefficient between the response themes was calculated at 0.811 indicating that the overall agreement between the two response themes was almost perfect. Additionally, conditional kappa values were calculated to determine the amount of agreement between each vulnerability class of the two response themes being compared. Table 18 displays the kappa coefficient between each vulnerability class of the two response themes.

**Table 18. Conditional kappa coefficient values between the dissolved oxygen response theme and the FAVA response theme for the FAS model. Kappa coefficient values are reported between each vulnerability class.**

| Agreement | Conditional Kappa ($K_f$) values |
|---|---|
| More Vulnerable Classes | 0.911 |
| Vulnerable Classes | 0.607 |
| Less Vulnerable Classes | 0.991 |

According to Table 12, the conditional kappa values for the dissolved oxygen response theme and the FAS FAVA response theme indicated almost perfect agreement between the more vulnerable and less vulnerable classes. The kappa value for the vulnerable classes indicated substantial agreement between the two response themes. A small area of the more vulnerable class from the dissolved oxygen response theme overlapped the vulnerable class causing the lower kappa value between these two classes and corresponding lower agreement level.

The area-weighted Spearman's Rank correlation coefficient for the FAS FAVA response theme and the dissolved oxygen response theme was calculated at 0.997 indicating a near-perfect positive correlation between the response themes. This value corresponds to a level of confidence of 99% for the correlation of the two response themes.

"Scientists can provide water-resource decision makers scientifically defensible information for the assessment of ground-water vulnerability and (or) intrinsic vulnerability. To the extent that uncertainties in the assessment can be elucidated either qualitatively or quantitatively, the scientific defensibility and usefulness of the product will increase."

– Focazio, Reilly, Rupert and Helsel, 2002

**FAVA Maps: Data Limitations and Applications**

Although several qualitative and quantitative validation methods support the results of the FAVA maps, important factors exist regarding appropriate end-user application of the maps. These factors involve understanding input-data resolution, missing data, model precision, and what the maps and associated statistics indicate regarding vulnerability at a given location.

The FAVA maps reflect predictions based on scientific models. These models were structured to represent interrelationships between relevant components of Florida's hydrogeologic framework as they pertain to aquifer vulnerability. Of critical importance to the accuracy of these predictive maps is the quality and type of data input into the model. If data of poor quality (i.e., inaccurate or imprecise) is used in a model, output from the model will be of equally poor quality and thus of limited or no value.

The response theme tables (Tables 8, 9, and 10) that were generated along with each aquifer system's vulnerability map were useful in assessing the quality of data used as evidential themes. The contrast values reported in the response theme tables were used to rank the importance of the evidential themes and were used to indicate the quality of the evidential themes. Further, the response theme tables were also central in determining which evidential themes were most important to improve for future modeling. This was revealed by evaluating the significance of the weights (W1, W2….etc.) reported in these tables. These weights indicated which evidential themes were good predictors of training point locations (vulnerable areas). The response theme tables, in effect, help to demonstrate that some evidential themes could be improved to be better representations of reality or considered for removal from future modeling projects.

A number of techniques have been employed to resolve many of the data gaps and inconsistencies within the statewide data coverages. These approaches are described in *Results – Data Coverages*. For example, the technique to address missing soils data is discussed in *Results – Data Coverages – Soil Drainage and Permeability*. In the sections that follow, aspects of data resolution and issues regarding data quality are presented and related to the FAVA model results. The FDEP and the FGS are working together to address many of these issues.

### Topography

The FDEP DEM developed for the FAVA project was based on USGS 7.5-minute quadrangle maps. The accuracy of the FDEP DEM is therefore, in theory, as good as the maps on which it was based. Data quality and consistency issues related to the FDEP DEM stem from the method by which the FDEP DEM was created, as well as from the use of these 7.5-minute quadrangle maps as a data source.

FDEP DEM elevation values have a ±5 feet or ±10 feet vertical accuracy, depending on whether a 5-feet or 10-feet contour interval was used in the 7.5-minute quadrangle map.

Coastlines used for a "zero line" (mean sea level) were taken from 1:40,000 Florida Marine Research Institute datasets. In some areas, the scale difference between the inland contours (at 1:24,000) and the shoreline created contour overlaps.

When developing the 7.5-minute quadrangle maps, the USGS generally displayed levees preferentially over the display of contour lines. Interpolation in these areas was completed, where possible, to determine the contour line path over the levee. In some areas, however, the amount of error potentially involved in choosing one of many possible routes for a contour line resulted in termination of the contour at the levee. In these cases, contour lines were appropriately flagged so they could be omitted from the final digital topographic grid interpolation which was used to generate the FDEP DEM.

Quality assurance on the NWFWMD digital contour line work had not been completed at the time FGS acquired the data. Misattribution of many digital contour lines was evident. Contour line data from this region continue to be corrected and cleaned; however at the time this report was written, some minor errors still exist in the NWFWMD area of the FDEP DEM. In northeastern Florida, quadrangles 4714 (Bostwick) and 4814 (Green Cove Springs) are both comprised of contour lines which were surveyed in 1949. Although they were resurveyed for the 1991 map, the new contour lines have not been re-digitized, and thus not used in the FDEP DEM presented herein.

To create a DEM for the entire State, interpolated elevation decimal values were truncated during the process of edge-matching multiple digital maps. On FDEP DEM visualizations, this yields a stair-step appearance where one elevation value meets another in low relief areas. During development of the FDEP DEM, errors were present in the Everglades region due to a lack of contour lines; most of the relief in the Everglades varied less than five feet and much of the higher elevations are anthropogenic in origin (e.g., an interstate overpass, or levee).

The FDEP DEM contains flat surfaces for hilltops and depressions because hilltops and depressions were not attributed. The flat surfaces are a relic of the TIN method used to generate the grid. It was not within the project scope and timeline to interpolate the digital elevation between the uppermost contour line on a hilltop and the true hilltop elevation; the same applies for topographic depressions.

The FDEP DEM was a major factor in the development of all the evidential themes excluding soil permeability. This is shown by the higher contrast values reported for the evidential themes based on topography in the response theme tables generated during modeling. The quality of the FAVA response themes are, as a result, very dependent on the accuracy and quality of the FDEP DEM data.

### Karst Features

In the WofE – FAVA model, a modified closed topographic depressions coverage served as the proxy for karst feature density. This method of identifying karst may have overestimated the number of features that actually meet the definition of karst. For example, parts of dune fields appeared on topographic maps as depressions. In addition, storm-water ponds and berms around agricultural fields appeared as topographic depressions. Some of these types of features were included in the closed topographic depressions coverage; as a result, non-karst depressions were included in the development of a karst coverage. Many of these "false positive" features, however, were eliminated through spatial filtering prior to input into the IAS and FAS FAVA models.

Another aspect of the closed topographic depressions coverage pertains to the data source: USGS 7.5-minute quadrangle maps. These maps were originally created between 1953 and 2002. It is likely that thousands of sinkholes have occurred in recent decades, yet they are not reflected on the topographic maps. Alternatively, the sinkholes may never have been identified during the topographic map-making process because of the limited resolution of the maps. For example, implementation of a recently developed light detection and ranging (LIDAR) coverage for Alachua County (2002) allowed the detection of numerous sinkholes not represented on USGS topographic maps. Figure 64 is a comparison of the Rochelle 7.5-minute quadrangle map (last revised in 1993) to the LIDAR imagery. Blue polygons representing closed topographic depressions of the LIDAR data greatly outnumber the closed topographic depressions, shown as red hachured contour lines, of the 7.5-minute quadrangle maps. The LIDAR data has a resolution of approximately two feet. The red hachured depressions which are not also represented by blue polygons of the LIDAR data may be the result of inaccurately located depressions during development of the 7.5-minute quadrangle map.

More than 2,600 sinkholes are recorded in the FGS sinkhole database (FGS, 2004); however, the database contains only sinkholes that have been reported. Further, the sinkhole database is also biased towards population centers – there is a strong correlation between reported sinkholes and built-up urban areas. Moreover, the FGS sinkhole database provides only locations (points), whereas the closed topographic depressions coverage applies polygons (i.e., areas of sinkholes). As a result, the FGS sinkhole database could not be represented in the closed topographic depressions coverage unless significant assumptions regarding sinkhole size and depth were made. A comparison of the FAVA closed topographic depressions coverage and the FGS sinkhole database (Figure 65) reveals that the area of western Polk and eastern Hillsborough counties are under-represented in the FAVA model with respect to karst. On the FAVA maps, these areas could be more vulnerable to contamination than what was indicated by the response themes.

The response theme tables indicated that proximity to karst was the most important evidential theme in the IAS (proximity to karst/IAS overburden thickness evidential theme) and third most important theme in the FAS FAVA model. Further, the absolute value of the negative weight (W2) for both IAS and FAS FAVA models was much higher than the positive weight (W1). This indicated that the evidential theme was a better predictor of where training points would not occur and a weaker predictor of where training points would occur. In other words, proximity to karst was a better predictor of where less vulnerable areas occurred as opposed to where more vulnerable areas occurred. Improving this theme by addressing some of the above-mentioned limitations and potential problems could result in this evidential theme being a better predictor of vulnerable areas in future model iterations.

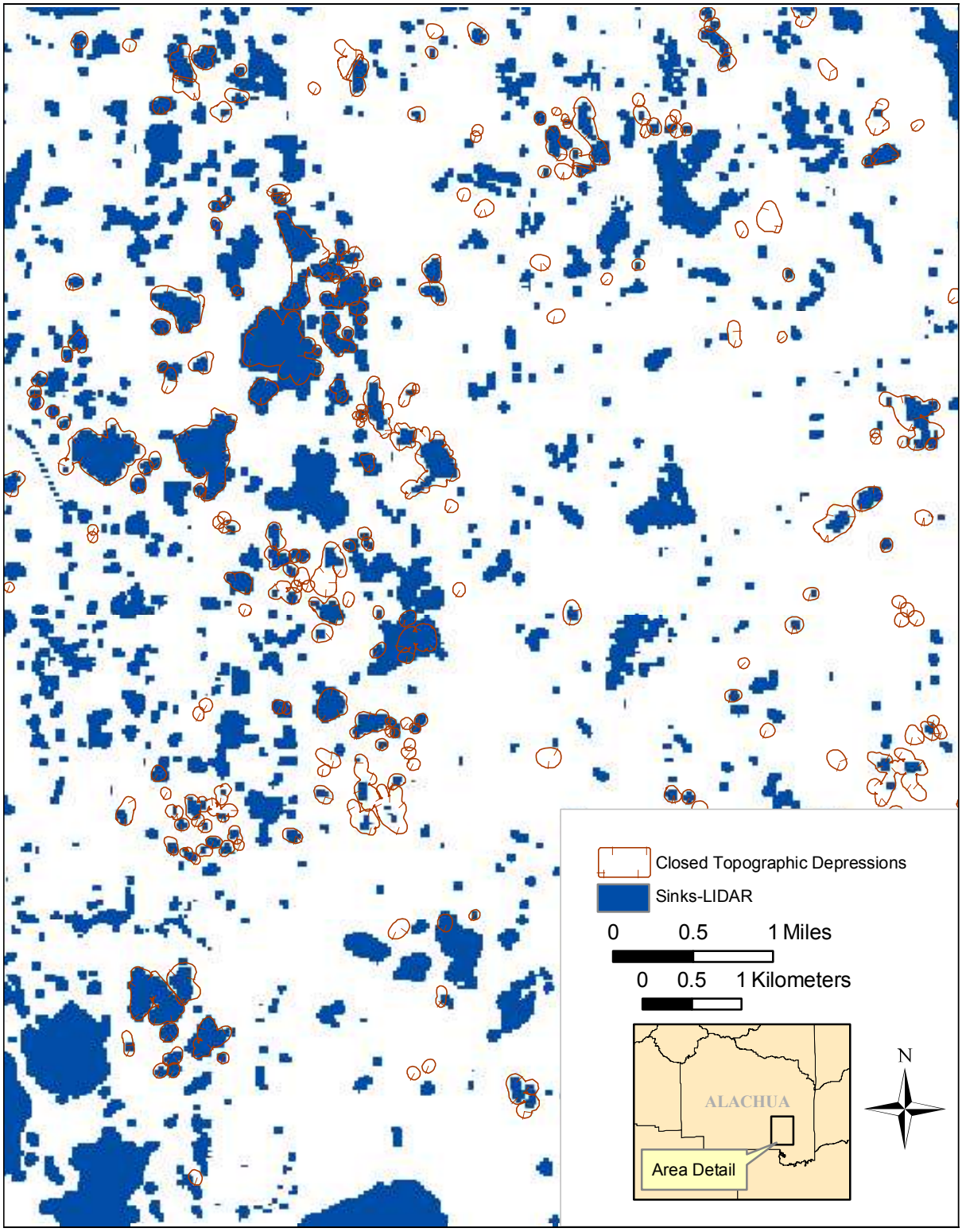


**Figure 64. Closed topographic depressions extracted from the Rochelle 7.5-minute quadrangle map used to develop the FDEP DEM overlain on the Alachua County LIDAR data. Alachua County LIDAR data contour interval is approximately two feet.**

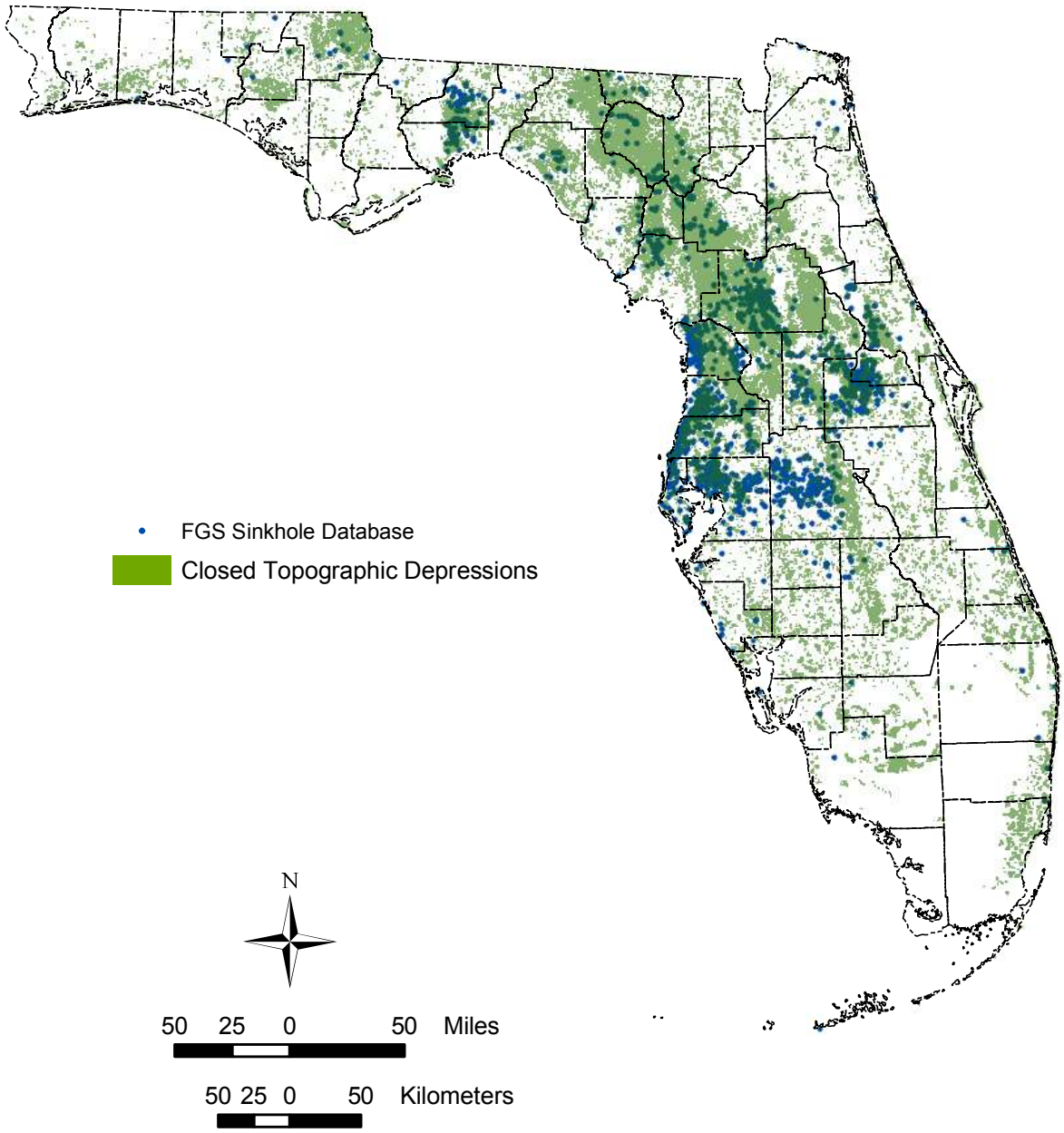


**Figure 65. Comparison of closed topographic depressions (extracted from the FDEP DEM based on USGS 7.5-minute quadrangles) with sinkhole locations in the FGS sinkhole database (FGS, 2003). The map demonstrates that some sinkhole-prone areas are not well represented by the topographic depression coverage.**

### Depth-to-Water and Hydraulic Head Difference

Stream and lake water levels were extracted from 1:100,000 scale maps, however, contour lines used in the development of the depth-to-water layer were taken from 7.5-minute (1:24,000) quadrangle maps. As a result of these differing resolutions, errors occurred when assigning digital elevation values to some surface water bodies. In addition, the relation between depth-to-water and physiographic province may be inconsistent if a leaky IAS exists within a ridge or upland. Vertical uncertainty in the depth-to-water evidential theme averages approximately seven feet, with a maximum error ranging from -34 feet to +31 feet (Table 5, *Results – Data Coverages – Water-Table Elevation*).

The potentiometric head difference coverage was created by subtracting the FAS "pre-development" potentiometric surface (Johnston et al., 1980) from the depth-to-water. The pre-development surface was produced from limited data and is therefore not as highly resolved as more recent potentiometric maps. In consideration of the vertical uncertainty in the depth-to-water surface and the Johnston et al. (1980) map, the hydraulic head difference has an estimated uncertainty on the order ± 17 feet.

As indicated by the contrast values included in the response theme tables, depth-to-water was the second most important evidential theme in the SAS FAVA model. Likewise, hydraulic head difference ranked second most important in the FAS FAVA model. Further, the absolute value of the negative weight (W2) for both evidential themes in both the SAS and FAS FAVA models was much higher than the positive weight (W1). This indicated that these evidential themes were better predictors of where training points would not occur and a weaker predictor of where training points would occur. In other words, depth-to-water and hydraulic head difference were both better predictors of where less vulnerable areas occurred as opposed to where more vulnerable areas occurred. Improving these themes by addressing some of the above-mentioned limitations and potential problems could result in the themes being better predictors of vulnerable areas in future modeling projects.

### Soils

STATSGO soils data were used for Washington, Holmes, Taylor, Liberty Counties and the Everglades because SSURGO data for these areas was incomplete. Disturbed lands such as dumps, pits, urban land and water were either not mapped or were assigned "no data" values because of the absence of data. Permeability values of these "no data" areas were interpolated using GIS neighborhood statistics. The NRCS (2002) states "Since measurements are difficult to make and are available for relatively few soils, estimates of permeability are based on soil properties." In other words, the NRCS assigned many soil types to permeability classes based on soil structure, clay content, etc, and then assigned estimated permeability values to the classes. The permeability of some soils was based on actual measurements taken from representative soil profiles (pedons). For each of these selected soil types, generally less than five pedons were measured, and their characteristics are taken to represent every occurrence of that particular soil type throughout the State (USDA, 1951).

In the development of the permeability data layer for the FAVA project, the NRCS weighted average of the permeability values for each layer in a given soil profile were calculated. Further, in calculation of the weighted average permeability of each soil type, the entire soil pedon column (or the entire column of estimated permeability) was used rather than attempting to intersect the column thickness with the depth-to-water for that location. If the depth-to-water was intersected with the representative soil columns, some soil layers would not be used in the permeability calculation and

thus the values would change. This difference could significantly change the permeability values in the soils evidential theme for use in the SAS FAVA model. However, accomplishing this water-soil column intersection would produce questionable results at best because the depth-to-water data coverage was not of high enough resolution, and the difficulty of completing this intersection was beyond the scope of this project.

As indicated by the contrast values included in the response theme tables, soil permeability was the most important evidential theme in the SAS FAVA model, whereas soil permeability was the least important evidential theme in both the IAS and FAS FAVA models. This is to be expected as soil characteristics are generally assumed to have greater impact on SAS vulnerability as it is contiguous with land surface and less of an influence on deeper aquifer systems. The absolute value of the negative weight (W2) for soil permeability in both the SAS and IAS FAVA models was much higher than the positive weight (W1) indicating that this evidential theme was a better predictor of where training points would not occur and a weaker predictor of where training points would occur (i.e., a better predictor of where less vulnerable areas occurred). For the FAS FAVA model, the absolute value of the positive weight (W1) for soil permeability was much higher than the negative weight (W2) indicating that this evidential theme was a better predictor of where training points would occur and a weaker predictor of where training points would not occur (i.e., a better predictor of where more vulnerable areas occurred). Improving these themes by addressing some of the above-mentioned limitations and potential problems could result in the evidential themes being better predictors of vulnerable areas in future modeling projects.

### Thickness of Overburden on IAS and Thickness of the IAS

These layers were created from well data that is based on well samples from the FGS well database and the NWFWMD well database. The wells were chosen for input into a database if they penetrated the top of the IAS or the top of the FAS or both. Surfaces developed with these data points were then used to calculate hydrostratigraphic unit thicknesses.

Locational information for generally older wells may be limited to a "center of section" designation. Further, aquifer and formational picks, especially if based on well cuttings samples alone, can have an error of up to ±20 feet depending on the interval of the well cuttings descriptions. Finally, the surfaces created based on well data are much less reliable in areas lacking in well data, such as the Everglades where few wells have been drilled. Comparisons of well data with interpolated grid cell values revealed the surface of the IAS and FAS have standard deviations of 9 feet and 2 feet, respectively. Data from 1,346 wells contributed to the development of the IAS thickness model. The extent of the IAS, as defined in this report, covers an area of approximately 45,400 square miles. As a result, each well is taken to represent 33 square miles in the IAS thickness map. It should be noted however, that this value is an average statewide well density; some areas are much better represented with wells, while others are very poorly represented and have a much smaller well density (e.g., the Everglades area).

As indicated by the contrast values included in the response theme tables, IAS thickness was the single most important evidential theme in the FAS FAVA model. Likewise, IAS overburden thickness (proximity to karst/IAS overburden evidential theme) ranked as the most important in the IAS FAVA model. Additionally, the absolute value of the negative weight (W2 for IAS, and W3 for FAS) for both evidential themes in both the IAS and FAS FAVA models was much higher than the positive weight (W1). This indicated that these evidential themes were better predictors of where training points would not occur and a weaker predictor of where training points would occur. In other words, IAS thickness and IAS overburden thickness were both better predictors of where less

vulnerable areas occurred as opposed to where more vulnerable areas occurred. Improving these themes by addressing some of the above-mentioned limitations and potential problems could result in the themes being better predictors of vulnerable areas in future model considerations.

### Extent of IAS as Confining Unit

The extent of the IAS was based on FGS and NWFWMD well data and the geologic map of the State of Florida (Scott et al., 2001). It was based on relatively continuous geologic formations officially recognized as part of the IAS. These formations are listed in Table 6. The IAS extent does not include localized basal SAS confinement that may or may not be laterally continuous. Though these sediments do provide effective confinement to the underlying FAS in various localized settings, such mapping detail was not required by the WofE technique or possible within the scope of the FAVA project. Further refinement of the IAS in areas of little or no confinement would not be relevant to the FA.

### Anthropogenic Features Affecting Topography and Water Quality

Although the FAVA response themes are based on data coverages (evidential themes) characterizing the natural system, some anthropogenic features can affect natural hydrologic or hydrogeologic characteristics of the aquifer systems. The features can "override" the predicted results of relative vulnerability. Storm-water ponds are currently not accounted for in the FAVA model. If these structures are poorly designed or maintained, or become damaged (i.e., penetrated by a sinkhole), ground-water vulnerability may be affected. The features may become sites of preferential pathways into the aquifer system. Rapid infiltration basins are sites that promote localized aquifer recharge and perhaps should be addressed in the FAVA model similar to closed topographic depressions. A complete statewide coverage of these features, however, was not available at the time of this study. Pumping near municipal well fields can change local hydrogeologic conditions to the extent that recharge is induced. In these localized areas, results of FAVA modeling may under-predict vulnerability. To provide a broad representation of where these well fields have most significantly affected the FAS potentiometric surface, an image was used from Bush and Johnston (1988) which depicts areas that have experienced significant net decline in the potentiometric surface. These areas are included in Figure 66 to show other areas where vulnerable areas might be under-predicted.

Mined areas and reclaimed areas (Figure 66) also create potential issues for the accuracy of the FAVA maps because in some cases, the mining activities have thinned or removed the confinement, increasing aquifer vulnerability in those areas. In addition, contour lines on 7.5-minute quadrangle maps generally stop at mined areas making it difficult to calculate accurate thicknesses for evidential themes such as IAS thickness and overburden. Soils in mined areas are reworked and have no assigned permeability values. During FAVA modeling, permeability values in mined areas (or other disturbed lands, such as municipal areas) were interpolated using the nearest neighbor selection method.

Drainage wells are also constructed features that affect local recharge and therefore vulnerability. During the FAVA project, an attempt was made to compile drainage well locations (Figure 66), however, the coverage is not complete because the information regarding the installation and location of many of these wells is not publicly recorded or otherwise available. Similar to reasons for excluding the FGS sinkhole database, the drainage well coverage was not suited as an evidential theme in the WofE – FAVA models because assumptions would have to be made about area of influence, depth of penetration, and a potentially large amount of missing data. Figure 66 is provided

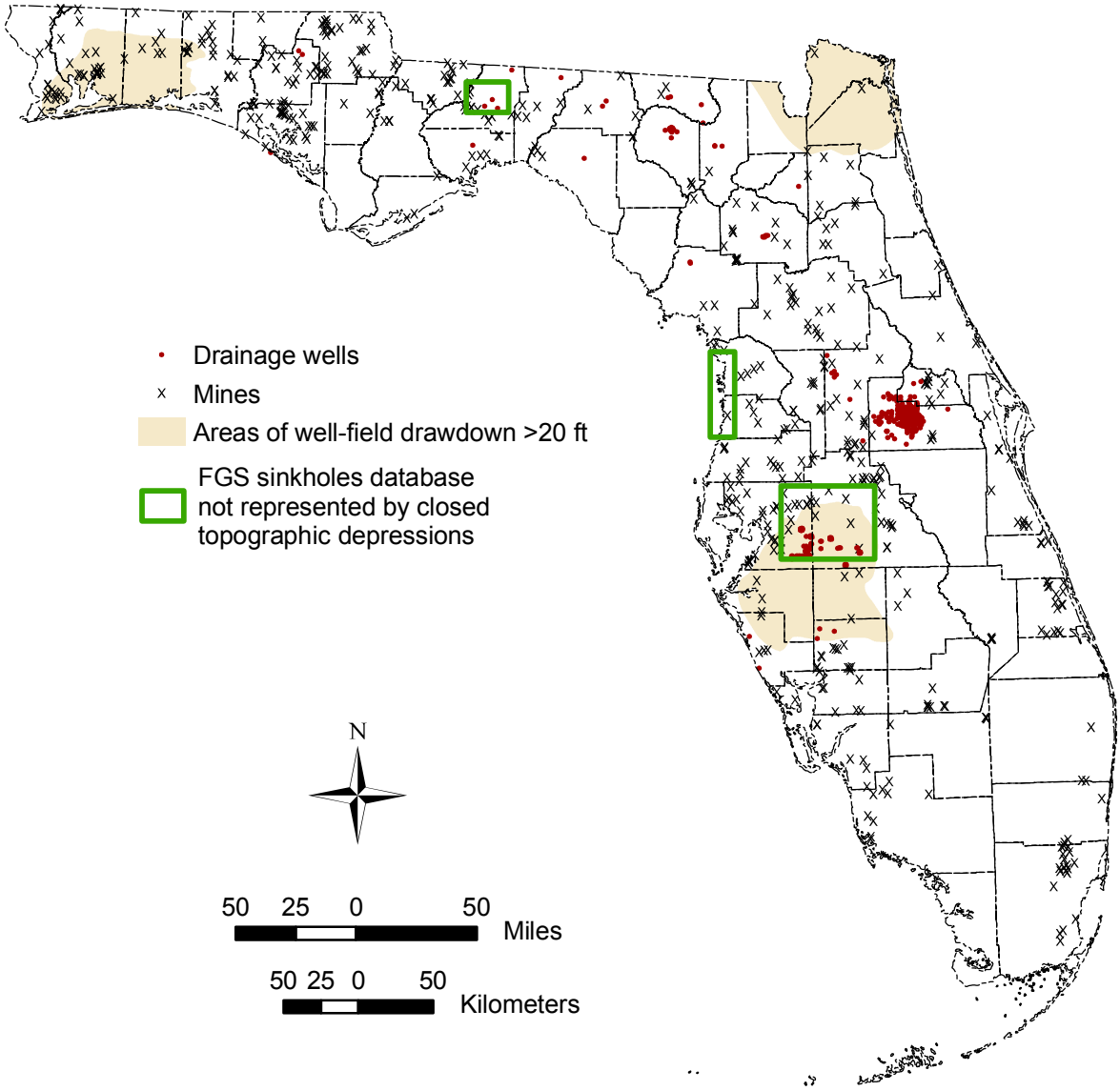


**Figure 66. Summary of features that may have caused under-representation of vulnerability in the FAVA maps: Drainage wells, known mines, areas representing significant (greater than 20 ft) differences between the FAS pre-development and recent (1980s) potentiometric surfaces, sinkholes not represented by closed topographic depressions. Location of mines is a point theme and does not accurately represent the actual areas of the mined areas.**

as a map to be used together with FAVA maps to represent localities where the FAVA results may have under-predicted vulnerability.

### Application of the FAVA maps

Appropriate use of the FAVA maps may not be readily apparent given the large amounts of data on which the maps were based, the modeling technique used, the qualitative and quantitative validation of the results, the oversight of the entire project by technical experts, and the obvious limitations of the data (including missing data). The purpose of this section is to address the question of how one should use the maps. Much of the answer to this question is related to resolution. In the FAVA maps, the finer detail in the vulnerability patterns of the response themes is directly related to the detail of some of the evidential themes (e.g., soil permeability, effective karst features). In the IAS and FAS FAVA maps, the coarser, more obvious patterns are related to overburden or confinement thickness.

Close inspection of the FAVA maps in their digital form revealed that some of the predicted vulnerabilities are as small as a single grid cell (i.e., 30 $m^2$) in the response theme. Technically speaking, this cell size dictates that the resolution of the FAVA maps is 30 m. This value is based on the resolution of the most highly resolved evidential theme, which is soil permeability (see *Results – Data Coverages – Soil Drainage and Permeability* for further explanation). All evidential themes – including IAS thickness, despite having originated from less detailed resolutions – were required to be re-sampled to a consistent 30-m grid cell size resolution for input into the WofE models (it is important to note, however, that the data were not changed during this process, just the number of grid cells).

One may ask if land use or environmental management decisions can be made based on a unit cell (30 m by 30 m) of the FAVA map. Although the resolution of some evidential themes is 30 $m^2$, the answer to this question is "no." If a unit cell of the FAVA response theme differs in predicted vulnerability as compared to nearby cells, the difference is real and is based on real hydrogeologic evidence, such as a nearby closed topographic depression or a change in soil permeability. On the other hand, it is important to keep in mind the limitations in the data. For example, interpolation of soil properties are made statewide based on few site specific observations and/or measurements. Another degree of uncertainty pertains to the closed topographic depression features: not all closed topographic depressions are karst related, and even if one assumes they are, many different types of karst exist. One closed topographic depression may reflect a clay-filled sinkhole that reduces the vulnerability of the underlying aquifer system, whereas another closed topographic depression may be a karst window, which can maximize the underlying aquifer system vulnerability.

Another consideration when evaluating the results of WofE – FAVA models pertains to the training point data set. As described in *Results* for each aquifer system, either dissolved nitrogen or total dissolved nitrogen was applied as training point data. Strictly speaking the WofE – FAVA response themes are "specific vulnerability" maps because they reflect the probability of aquifer vulnerability to nitrogen. If dissolved oxygen had been used as the primary training data set, the maps would specifically reflect the probability of aquifer vulnerability to dissolved oxygen. In either case, both of these parameters are considered appropriate surrogates for vulnerability.

Whether using the FAVA response themes in Figures 31, 39, and 49 or Plates 1, 2 and 3, suggestions by the authors regarding guidelines for applications are the same. To recap, the FAVA maps were developed from a wide range of data-coverage resolutions, both vertically and horizontally, and in this report the known strengths and weaknesses of the input data (evidential themes) are described, as well as knowledge of data not represented in the FAVA models. In consideration of these factors, we suggest that the FAVA maps be used at scales of sufficient size to preclude the comparison of individual parcels to the FAVA response themes. For example, use of a scale of 1:200,000 or smaller (i.e., 1:500,000) is suggested. Plates 1, 2 and 3 are provided at a scale of 1 inches = 20 miles (1:1,267,200).

For those with a need to apply these statewide FAVA maps at the local scale, we suggest application greater than or equal to one square mile (~2.5 $km^2$). Again, this is not to imply that results less than that area are meaningless; on the contrary. Every 30-m grid cell has significance as discussed above; however, this is a predictive model and the authors make no assumption that all input layers are accurate or precise or even complete at that scale. Application of the FAVA maps does not replace the need for site-specific studies.

One may suggest that the maps should be generalized to a resolution that would not allow end-users to see detail finer than the recommended scale. This generalization however would have the negative effect of masking areas of higher vulnerability and would not allow the end-user to see meaningful patterns in the maps. Rather than coarsen the resolution of the FAVA maps, they are presented in the best possible and most scientifically and technically defensible level of resolution. In a sense, the maps are as accurate as the most detailed input layer, and as inaccurate as the least detailed layer. For example, the wells used to define the IAS thickness represent, on average, about 40 $mi^2$. For several reasons already discussed, this does not at all imply the maps should only be used at that scale. Accuracy of the maps is not sufficient for evaluating aquifer vulnerability at a specific location. It is the responsibility of the end-users of these maps to determine specific and appropriate applications of these maps.

Standing surface water bodies are also highly vulnerable to contamination; however those waters do not reflect waters residing in an aquifer system. Instead, those waters reside "on" an aquifer system. Due to the geostatistical framework and evidential layers (spatial hydrogeological data) of FAVA, aquifer systems near point or diffuse (i.e. seeps) discharge areas were sometimes predicted by the output model to be low in vulnerability, even though the discharging surface waters are highly vulnerable to contamination. Those discharging waters are not part of the aquifer, although they originate from it. The FAVA project was designed to focus on the ability for a contaminant to travel through soils, overburden, karst features, etc. to enter into the aquifer system. As a result, it is very important that the FAVA model never be applied to assess contamination of surface waters or ground-water discharge areas, such as seeps or springs. Major water bodies are included as overlays on the FAS and IAS FAVA generalized maps (Plates 2 & 3) and all water bodies (wetlands included) are shown as map overlays on the SAS FAVA map (Plate 1).

Application of these maps may be useful to meet the requirements of Florida codes and laws, such as Comprehensive Plan requirements described in Rule 9J-5.005(2)(c), F.A.C. for purposes of defining and mapping high aquifer recharge areas as required by 163.3177(6)(c) F.S. The latter states that the Comprehensive Plan should include a "…natural groundwater aquifer recharge element correlated to principles and guidelines for future land use, indicating ways to provide for future potable water, drainage, sanitary sewer, solid waste, and aquifer recharge protection requirements for the area." 163.3177(6)(c) F.S. further states "The element shall also include a topographic map depicting any areas adopted by a regional water management district as prime groundwater recharge areas for the Floridan or Biscayne aquifers, pursuant to s. 373.0395. These areas shall be given special

consideration when the local government is engaged in zoning or considering future land use for said designated areas." Moreover, in Chapter 373.0395 F.S., it states: "Each water management district shall develop a groundwater basin resource availability inventory covering those areas deemed appropriate by the governing board. This inventory shall include, but not be limited to, the following: (1) A hydrogeologic study to define the groundwater basin and its associated recharge areas. (2) Site specific areas in the basin deemed prone to contamination or overdraft resulting from current or projected development. (3) Prime groundwater recharge areas..." The FAVA maps are also relevant to aspects of the EPA Source Water Assessment Program (SWAP) and the Safe Drinking Water Act, for which the FAVA method may be applied to refine "critical aquifer protection areas."

In addition to the potential applications related to Florida law, the FAVA maps have valid and useful applications in the following areas of environmental management, protection and conservation as well as in land-use planning:

- Wellhead protection
- Source-water protection
- Recharge protection
- Vulnerability indices
- Contaminant-specific maps
- Land conservation acquisition
- Total maximum daily loads (TMDLs)
- Surface-water–ground-water interactions
- Precursors to susceptibility predictions
- Water-quality management tool
- Resource planning strategies and policies
- Prioritization of areas of critical concern
- Design of monitoring plans
- Best Management Practices

**Disclaimer**

The FAVA maps were developed by the FDEP/FGS to carry out agency responsibilities related to management, protection, and responsible development of Florida's natural resources. Although efforts have been made to make the information in these maps accurate and useful, the FDEP/FGS assumes no responsibility for errors in the information and does not guarantee that the data are free from errors or inaccuracies. Similarly FDEP/FGS assumes no responsibility for the consequences of inappropriate uses or interpretations of the data on these maps. As such, these maps are distributed on an "as is" basis and the user assumes all risk as to their quality, the results obtained from their use, and the performance of the data. FDEP/FGS further makes 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 user. In no event shall the FDEP/FGS or its 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 maps or support by FDEP/FGS. FDEP/FGS bears 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.

Comments on this data are invited and FDEP/FGS would appreciate that documented errors be brought to the attention of our staff. Because part of this data was developed and collected with U.S.

Government and/or State of Florida funding, no proprietary rights may be attached to it in whole or in part, nor may it be sold to the U.S. Government or the Florida State Government as part of any procurement of products or services.

### Sub-regional FAVA Modeling

During the course of the FAVA project, there have been requests for preliminary results of the maps at the scale of a county. While the FAVA maps herein are certainly useful at this scale, the smaller the area of interest, the more evidence required to create higher-resolution FAVA maps. If FAVA maps were to be generated at the scale of a county or springshed, or a need exists to apply FAVA results at the sub-kilometer level, several additional evidential themes may be required, as well as the need to refine existing evidential themes. Moreover, application of models designed for the field scale such as SEAMS may become more appropriate. Potential local-scale refinements and additions include, but are not limited to the following:

- use of LIDAR data rather than the FDEP DEM to define surface topography,
- subdivision of closed topographic depressions into different classes (i.e., water-filled sinkholes, possible sinkholes, karst windows, cover-collapse sinkholes, etc.),
- application of combinations of soil properties,
- addition of more data on which evidential themes (i.e., IAS thickness and extent, water-table elevation etc.) are based to improve resolution,
- addition of more wells in the training data set,
- use of a different training set analyte, such as dissolved oxygen or tritium,
- use of results of lineament studies, and
- cave maps, and
- refinement of training point data sets to include only averages of water quality analytes collected during the dry season.

"… a key starting point for assuring a sustainable future for any ground-water system is the development of a comprehensive hydrogeologic data base over time."

– Alley, Reilly and Franke, 1999

**CONCLUSIONS**

All aquifer systems in Florida are vulnerable to contamination due to the natural hydrogeologic setting or human influences that modify the natural system, such as mining, urban development and agriculture. Other anthropogenic factors can increase vulnerability in certain areas due to the installation of large impermeable barriers (i.e., parking lots that runoff into areas of potentially focused recharge), poorly constructed wells and drainage wells, retention ponds and rapid infiltration basins, poor land-use practices, and activities that can induce sinkhole formation. Recognizing the need for a science-based, defensible, flexible resource on which to base environment protection/conservation and growth management decisions, the FAVA project was initiated. The FAVA project provides statewide maps that predict relative aquifer vulnerability for Florida's three principal aquifer systems: the Surficial Aquifer System, Intermediate Aquifer System, and Florida Aquifer System.

The FAVA project was designed with the end-user in mind. With the help of a multi-agency Technical Advisory Committee (TAC) that provided a broad range of expertise and resources to the project, a set of characteristics for the FAVA project was developed which required any modeling effort to be:

- Scalable
- Updateable
- Flexible
- Easy to understand
- Easy to apply
- Scientifically defensible

While most of these requirements were met, the modeling technique is admittedly not readily easy to understand. On the other hand, the final FAVA maps are, in fact, easy to understand. Several modeling approaches were considered for the development and validation of the FAVA maps. Bayesian statistics, specifically utilizing WofE (Raines et al., 2000) in a GIS platform, in combination with fuzzy logic and logistic regression were applied to the input data. When applying this technique, much of the subjectivity and potential bias inherent in many models is removed. Moreover, by applying the WofE model, the results are in a sense, self-validated. This, however, does not take the place of further model validation, which was extensively performed for each model

output. Application of the WofE technique also allowed the FAVA project to provide "specific vulnerability" maps that are contaminant specific. For example, because nitrogen is used in the training data set, the FAVA maps are technically vulnerability maps with respect to surface sources of nitrogen. But because nitrogen (i.e., dissolved nitrates, nitrites and ammonia) is adopted herein as a conservative indicator of contamination potential, the FAVA maps provide estimates of intrinsic vulnerability (i.e., any contamination in general; Focazio et al. 2002). Although Bayesian statistics have been applied to ground-water resource studies, the WofE model has never before been applied to assess aquifer vulnerability, with possible exception of Cheng (2004), who applied WofE to assess characteristics of flowing wells.

Large amounts of data were processed and utilized in order to generate the FAVA maps. These data sets not only have limitations with respect to resolution, accuracy and completeness, but many also reflect a mere snapshot in time. Consequently, the FAVA maps are time-sensitive; as new data become available, the FAVA maps should be periodically revised. The frequency of this revision may serve well to correspond with program needs within the State of Florida. For example, the FDEP "Ground water basin rotation" cycles every four years, and the Water Management District's Regional Water Supply plans are revisited every five years. Periodic updates (e.g. every four to five years) of the FAVA maps will strengthen the accuracy and value of the FAVA response themes as predictive tools.

Within this report, aquifer vulnerability maps represent probabilities of vulnerability. These probabilities have been separated into three categories of relative vulnerability: less vulnerable, vulnerable and more vulnerable. These three-class vulnerability maps are provided as a resource for science-based decision making; the development of rules or establishment of policies regarding environmental conservation, protection, and land-use planning.

Several valuable derivative data coverages were developed throughout the course of the FAVA project, including:

- FDEP DEM seamless statewide topography at a 15-m resolution; applications include slope calculations, more accurate delineation of drainage and drainage basins, identification of land subsidence primarily due to karst processes, 3D visualizations, etc.
- Depth-to-water table – a derivative product of the FDEP DEM; applications include a resource for well drilling, hydrologic models, estimation for recharge and discharge areas.
- Closed topographic depressions – a derivative product of the FDEP DEM; applications include estimation of karst feature densities per unit area, buffer zones, sinkholes that penetrate underlying confinement and those that intersect the water table.
- Thickness and extent of IAS; applications in hydrogeologic framework studies, water resource assessment and protection, ground-water modeling.
- Seamless soil characterization of permeability and drainage; nearly statewide data for application in local scale vulnerability assessments, agriculture, etc.
- Hydraulic head difference between the water table and the FAS; applications include estimation of recharge and discharge areas of the FAS.
- Extents of Florida's principal aquifer systems; applications in hydrologic and hydrogeologic models, land-use planning, consumptive use and water-resource protection.
- Overburden on the IAS (as defined in this study); applications include consumptive use and water-resource protection.
- Environmental geology; applications include characterization of the geologic material present just below the soil horizon unsaturated to a depth of expected use, material for mineral resource identification, and localized vulnerability studies.

While not recharge maps per se, FAVA maps may be considered probability-based recharge models (i.e., proxy for recharge maps) that consider characteristics of the hydrogeological framework as well as ambient water quality data. It is important to note that the FAVA project response themes are not contaminant-transport or susceptibility models.

Appropriate application of the FAVA maps is important and is discussed thoroughly in this report. In general, it is recommended that the maps should be applied at scales smaller than 1:200,000 thereby eliminating the ability to compare relative probability values to individual land parcels. On the other hand, much of the data on which the maps were based are accurate to the minimum GIS grid-resolution of the FAVA maps (30 m). Use of the maps at that scale is not suggested, however, application of the maps on the order of one square mile may be appropriate as long as conditions outlined in *Discussion – Disclaimer* are met. Most importantly, the FAVA maps are not of sufficient detail to provide site specific information regarding relative aquifer vulnerability.

This project and the vulnerability maps provided herein underscore the importance of the need to further our understanding of Florida's aquifer systems, both in terms of hydrogeologic data and ambient (or background) water quality data. As our knowledge increases regarding Florida's natural and highly complex hydrogeologic systems, so does our ability to serve as better stewards of these precious resources.

## REFERENCES


Alachua County Property Appraiser's Office, 2002, Digital Elevation Model (ArcInfo lattice), SPCS of 1983 Florida North Zone, Alachua County Property Appraiser's Office, 2002.

Aller, L., Bennett, T., Lehr, J.H., and Petty, R.J., 1985, DRASTIC: A Standardized System for Evaluation of Ground Water Pollution Potential Using Hydrogeologic Settings: U.S. Environmental Protection Agency, EPA/600/2-85/018, 63 p.

Alley, W.M., Reilly, T.E., and Franke, O.L., 1999, Sustainability of Ground-Water Resources: U.S. Geological Survey Circular 1186, 79 p.

Arthur, J.D., Fischler, F., Kromhout, C., Clayton, J., DeWitt, D., Kelley, M., Lee, R.A., Li, L., O'Sullivan, M., Green, R., Thompson, R., and Werner, C., 2005, in preparation, Hydrogeologic Framework of the Southwest Florida Water Management District: Florida Geological Survey Bulletin.

Arthur, J.D., Cichon, J., Baker, A., Marquez, J., Rudin, A., and Wood, A., 2002, Hydrogeologic mapping and aquifer vulnerability modeling in Florida: 2D and 3D data analysis and visualization, *in*: Thorleifson, L.H., and Berg, R.C., (convenors), Three-dimensional geological mapping for groundwater applications, Workshop extended abstracts, Denver, Colorado – October 26, 2002, Geological Survey of Canada, Open File 1449, p. 1-4.

Baker, A.E., Cichon, J.R., Arthur, J.D., and Raines, G.L., 2002, Florida Aquifer Vulnerability Assessment (FAVA): Geological Society of America Annual Meeting October, 2002, Denver CO, Abstracts with Programs, v. 34, no. 6, p. 346.

Baker, A.E., Cichon, J.R., Arthur, J.D, and Wood, H.A.R., 2003, Application of the weights of evidence method to assess aquifer vulnerability in Florida, *in* Florida Academy of Sciences 67th annual meeting program issue, v. 66, p. 50-51.

Beck, B.F., and Jenkins, D.T., 1988, Potential for Groundwater Pollution of the Floridan Aquifer, Based upon Surficial Drainage, Karst Development, and Overburden Characteristics: Florida Sinkhole Research Institute, University of Central Florida, Map Series 87-88-1, scale 1:250,000, 15 sheets.

Bekesi, G., and McConchie, J., 2000, Empirical Assessment of the Influence of the Unsaturated Zone of Aquifer Vulnerability, Manawatu Region, New Zealand: Ground Water, v. 38, n. 2., p. 193-199.

Berndt., M.P., Oaksford, E.T., Mahon, G.L., and Schmidt., W., 1998, Groundwater, *in* Fernald, E.A., and Purdum, E. D., ed., Water Resources Atlas of Florida: Florida State University, Institute of Public Affairs, 312 p.

Bonham-Carter, G. F., 1994, Geographic Information Systems for Geoscientists, Modeling with GIS: Oxford, Pergamon, 398 p.

Burrough, P.A., MacMillan, R.A. and Van Deursen, W., 1992, Fuzzy classification methods for determining land suitability from soil profile observations: Journal of Soil Science, v. 43, p. 193-210.

Bush, P.W., and Johnston, R.H., 1988, Ground-Water Hydraulics, Regional Flow, and Ground-Water Development of the Floridan Aquifer System in Florida and in Parts of Georgia, South Carolina, and Alabama: U.S. Geological Survey Professional Paper 1403-c, 80 p.

Carter, A.D., Palmer, R.C., and Monkhouse, R.A., 1987, Mapping the Vulnerability of Ground Water to Pollution from Agricultural Practice, Particularly with Respect to Nitrate in Vulnerability of Soil and Ground Water to Pollutants, Proceedings and Information no. 38, International Conference, Noodwijk aan zee, National Institute of Public Health and Environmental Hygiene, The Hague, The Netherlands, p. 333-342.

Cichon, J.R., Arthur, J.D., Baker, A.E., and Wood, H.A.R., 2003, Florida Aquifer Vulnerability Assessment (FAVA): Utilizing Geologic Mapping Data to Predict Aquifer Vulnerability: Geological Society of America Annual Meeting November, 2003, Seattle, WA, Abstracts with Programs, v. 35, no. 6, p. 65.

Cichon, J.R., Wood, H.A.R., Baker, A.E., and Arthur, J.A., 2004, Application of Geologic Mapping and Geographic Information Systems to Delineate Sensitive Karst Areas for Land-Use Decisions, American Geological Institute website, http://www.agiweb.org/environment/publications/mapping/graphics/florida.pdf, 2004.

Cheng, Q., 2004, Application of Weights of Evidence Method for Assessment of Flowing Wells in the Greater Toronto Area, Canada: Natural Resources Research, v. 13, no. 2, p. 77-85.

Chidester, S.D., 1993, A study of aquifer sensitivity and vulnerability in Kalamazoo County, Michigan based on hydrogeologic and agricultural factors [Thesis]; Kalamazoo, Western Michigan University, 163 p.

Connell, L.D., and van den Daele, G., 2003, A quantitative approach to aquifer vulnerability mapping: Journal of Hydrology, v. 276, p. 71-88.

Copeland, R., Scott, T.M., Lloyd, J.M., and Maddox, G.L., 1991, Florida's Ground Water Quality Monitoring Program, Hydrogeologic: Florida Geological Survey Special Publication No. 32, 97 p.

DeSmedt, P., DeBreuck, W., Loy, W., Van Autenboer, T., and Dijck, E., 1987, Ground Water Vulnerability Maps: Aqua, v. 5, p. 264-267.

Deuerling, R., 1981, Environmental Geology Series – Tarpon Springs Sheet, MS 99, size: 22 x 36 inches, scale: 1:250,000, 1 sheet.

Dixon, B., Scott, H.D., Brahana, J.V., Mauromoustakos, A., and Dixon, J.C., 2001, Application of Neuro-Fuzzy Techniques to Predict Ground Water Vulnerability in Northwest Arkansas: Arkansas Water Resource Center, University of Arkansas, Publication No. PUB-183, 64 p.

Doerfliger, N., Jeannin, P.-Y., and Zwahlen, F., 1999, Water vulnerability assessment in karst environments: a new method of defining protections areas using a multi-attribute approach and GIS tools (EPIK method): Environmental Geology, v. 39, no. 2, p. 165-176.

Edmunds, W.M. and Kinniburgh, R.E., 1986, The Susceptibility of United Kingdom Ground Waters to Acidic Deposition: Journal of the Geological Society, v. 143, p. 707-720.

Fang, J.H., 1997, Fuzzy Logic and Geology: Geotimes: News and Trends in Geoscience, v. 42, no. 10, p. 23-26.

Ferguson, S., 2002, DRASTIC vs. FAVA - A comparison of two available methodologies for aquifer protection in Florida: A case study in Orange County [Master of Science research paper]: Tallahassee, Florida State University, 67 p.

Feyen, L., Dessalegn, A.M., DeSmedt, F., Gebremeskel, S., and Batelaan, O., 2004, Application of a Bayesian Approach to Stochastic Delineation of Capture Zones: Ground Water, v. 42, no. 4, p. 542-551.

Florida Geographic Data Library (FGDL), GeoPlan Center, Gainesville, University of Florida, www.fgdl.org/, 2003.

Florida Geological Survey, 2004, Florida Sinkhole Database, Florida Geological Survey website, http://www.dep.state.fl.us/geology/gisdatamaps/sinkhole_database.htm, 2004.

Focazio, M.J., Reilly, T.E., Rupert, M.G., and Helsel, D.R., 2002, Assessing Ground-Water Vulnerability to Contamination: Providing Scientifically Defensible Information for Decision Makers: U.S. Geological Survey Circular 1224, 33 p.

Freeze, A. R., Cherry, J. A., 1979, Groundwater: Englewood Cliffs, Prentice Hall, 604 p.

Holmberg, M., Johnston, J., and Maxe, L., 1987, Assessing Aquifer Sensitivity to Acid Depositions in Vulnerability of Soil and Ground Water to Pollutants, *in* Proceedings and Information No. 38, International Conference, Noodwijk aan zee, National Institute of Public Health and Environmental Hygiene, The Hague, The Netherlands, p. 373-380.

Hoogeweg, C. G., and Hornsby, A.G., 1998, Soil, environmental and agricultural systems, SEAMS Version 1.0 Users Manual, Circular SW112: Florida Cooperative Extension Service, Institute of Food and Agricultural Sciences, Gainesville, University of Florida, 57 p.

Huaming, G., and Wang, Y., 2004, Specific vulnerability assessment using the MLPI model in Datong city, Shanzi province, China: Environmental Geology, v. 45, p. 401-407.

Huckle, H.F., and Weeks, H.H., 1965, Soil Survey of Washington County, Florida: Natural Resources Conservation Service, U.S. Department of Agriculture, Series 1962, n.2., 119 p.

Johnston, R.H., Krause, R.E., Meyer, F.W., Ryder, P.D., Tibbals, C.H., and Hunn, J.D., 1980, Estimated Potentiometric Surface for the Tertiary Limestone Aquifer System, Southeastern United States, Prior to Development: U.S. Geological Survey Open-File Report 80-406, scale 1 in. = approximately 15 mi., 1 sheet.

Kemp, L.D., Bonham-Carter, G.F., Raines, G.L. and Looney, C.G., 2001, Arc-SDM: Arcview extension for spatial data modeling using weights of evidence, logistic regression, fuzzy logic and neural network analysis, http://ntserv.gis.nrcan.gc.ca/sdm/, 2002.

Knapp, M.S., 1978a, Environmental Geology Series – Gainesville Sheet: Florida Geological Survey Map Series 79, scale 1:250,000, 1 sheet.

Knapp, M.S., 1978b, Environmental Geology Series – Valdosta Sheet: Florida Geological Survey Map Series 88, scale 1:250,000, 1 sheet.

Knapp, M.S., 1980, Environmental Geology Series – Tampa Sheet: Florida Geological Survey Map Series 97, scale 1:250,000, 1 sheet.

Landis, J.R. and Koch, G.G., 1977, The measurement of observer agreement for categorical data: Biometrics, v. 33, p. 159-174.

Lane, E., Knapp, M.S., and Scott, T., 1980, Environmental Geology Series – Ft. Pierce Sheet: Florida Geological Survey Map Series 80, scale 1:250,000, 1 sheet.

Lane, E., 1980, Environmental Geology Series – West Palm Beach Sheet: Florida Geological Survey Map Series 100, scale 1:250,000, 1 sheet.

Lane, E., 1981, Environmental Geology Series – Miami Sheet: Florida Geological Survey Map Series 101, scale 1:250,000, 1 sheet.

Lawrence, F.W., and Upchurch, S. B., 1982, Identification of recharge areas using factor analysis: Groundwater, v. 20, no. 6, p. 680-687.

LeGrand, H.E., 1983, A Standardized Method for Evaluation Waste Disposal Sites: Worthington, National Water Well Association, 49 p.

Leonard, R.A., Knisel, W.G., and Still, D.A., 1987, GLEAMS: Groundwater loading effects of agricultural management systems, Transactions of American Society of Agricultural Engineers, v. 31, no. 4, p. 1128-1134.

Maddox, G.L., and Arthur, J.A., 1996, Florida aquifer vulnerability assessment: An overview [abs]: Florida Scientist, v. 59, iss. 1, p. 24.

Merchant, J.W., 1994, GIS-based groundwater pollution hazard assessment; a critical review of the DRASTIC model: Photogrammetric Engineering and Remote Sensing, v. 60, iss. 9, p. 1117-1127.

Metz, P.A., 1993, Hydrogeology and Simulated Effects of Ground-Water Withdrawals for Citrus Irrigation, Hardee and De Soto Counties, Florida: U.S. Geological Survey Water-Resurces Investigations Report 93-4158, 83 p.

Meyer, P.D., and Nicholson, T.J., 2003, Analysis of hydrogeologic conceptual model and parameter uncertainty, *in* Mishra, S., ed, Symposium on Groundwater quality modeling and management under uncertainty: Reston, VA, American Society of Civil Engineers, Conference Proceedings, p. 47-57.

Miller, J.A., 1986, Hydrogeologic Framework of the Floridan Aquifer System in Florida, and in Parts of Georgia, Alabama and South Carolina: U.S. Geological Survey Professional Paper 1403-B, 90 p.

National Research Council, 1993, Ground Water Vulnerability Assessment: Predicting Relative Contamination Potential under Conditions of Uncertainty: Washington, National Academy Press, 204 p.

Navulur, K.C.S., Engel, B.A., and Mamillapalli, S., 1995, Groundwater Vulnerability Evaluation to Nitrate Pollution on a Regional Scale Using GIS, *in* Applications of GIS to the Modeling of Non-Point Source Pollutants in the Vadose Zone, SSSA Special Publication No. 48, ASA-CSSA-SSSA Bouyoucos Conference, Mission Inn, Riverside, CA. 20 p.

Nolan, B.T., 2001, Relating Nitrogen Sources and Aquifer Susceptibility to Nitrate in Shallow Ground Waters of the United States: Ground Water, v. 39, no. 2, p. 290-299.

Northwest Florida Water Management District, 1995, Land Use Data, Florida Department of Environmental Protection, Bureau of Information Systems/GIS Section website, http://www.dep.state.fl.us/gis/, 2004.

Pratt, T.R., Richards, C.J., Milla, K.A., Wagner, J.R., Johnson, J.L., and Curry, R.J., 1996, Hydrogeology of the Northwest Florida Water Management District: Northwest Florida Water Management District Water Resources Special Report 96-4, 97 p.

Porcher, E., 1988, Ground Water Contamination Susceptibility in Minnesota, Program Development Section, Ground Water and Solid Waste Division, Minnesota Pollution Control Agency, St. Paul, Minnesota, 36 p.

Puri, H.S., and Vernon, R.O., 1964, Summary of the Geology of Florida and a Guidebook to the Classic Exposures: Florida Geological Survey Special Publication No. 5 (revised), 312 p.

Raines, Gary L., 1999, Evaluation of Weights of Evidence to Predict Epithermal-Gold Deposits in the Great Basin of the Western United States: Natural Resources Research, vol. 8, no. 4, p. 257-276.

Raines, G. L., Bonham-Carter, G. F., and Kemp, L., 2000, Predictive Probabilistic Modeling Using ArcView GIS: ArcUser, v. 3, no.2, p. 45-48.

Raines, G. L., 2001, Resource Materials for a GIS Spatial Analysis Course: U.S. Geological Survey Open File Report 01-221, 216 p.

Roux, P., Demartinis, J., and Dickson, G., 1986, Sensitivity analysis for Pesticide Application on a Regional Scale, in Proceedings, Conference on Agricultural Impacts on Ground Water, Dublin, Ohio, National Water Well Association, p. 145-158.

Rudin, A., Baker, A.., Wood, A., Cichon, J., Arthur, J., and Ashby, B., 2003, Creating a statewide digital elevation model (DEM) from U.S. Geological Survey 1:24000 topographic map contour lines, *in* Florida Academy of Sciences 67th annual meeting program issue, v. 66, p. 51-52.

Rupert, M.G., Dace, T., Maupin, M.A., and Wicherski, B., 1991, Ground-water vulnerability assessment, Snake River Plain, southern Idaho: Boise, Idaho Department of Health and Welfare, Division of Environmental Quality, 25 p.

Rupert, M.G., 1997, Nitrate ($NO_2$+$NO_3$–N) in ground water of the upper Snake River Basin, Idaho and western Wyoming, 1991-95: U.S. Geological Survey Water Resources Investigations Report 97-4174, 47 p.

Rupert, M.G., 1999, Improvements to the DRASTIC Ground-Water Vulnerability Mapping Method: U.S. Geological Survey Fact Sheet FS-066-99, 6 p.

St. John's River Water Management District, 1995, Land Use Data, Florida Department of Environmental Protection, Bureau of Information Systems/GIS Section website, http://www.dep.state.fl.us/gis/, 2004.

Sauriol, J.J., 1982, Terrain Suitability Rating for the Attenuation of Septic System Effluents, *in* Proceedings, National Ground Water Quality Symposium, 6th, Dublin, Ohio, National Water Well Association, p. 270-275.

Schmidt, W., 1978a, Environmental Geology Series – Pensacola Sheet: Florida Geological Survey Map Series 78, scale 1:250,000, 1 sheet.

Schmidt, W., 1978b, Environmental Geology Series – Apalachicola Sheet: Florida Geological Survey Map Series 84, scale 1:250,000, 1 sheet.

Schmidt, W., 1979, Environmental Geology Series – Tallahassee Sheet: Florida Geological Survey Map Series 90, scale 1:250,000, 1 sheet.

Schmidt, W., 1984, Neogene Stratigraphy and Geologic History of the Apalachicola Embayment, Florida: Florida Geological Survey Bulletin No. 58, 146 p.

Scott, T., 1978a, Environmental Geology Series – Orlando Sheet: Florida Geological Survey Map Series 85, scale 1:250,000, 1 sheet.

Scott, T., 1978b, Environmental Geology Series – Jacksonville Sheet: Florida Geological Survey Map Series 89, scale 1:250,000, 1 sheet.

Scott, T., 1979, Environmental Geology Series – Daytona Beach Sheet: Florida Geological Survey Map Series 93, scale 1:250,000, 1 sheet.

Scott, T.M., 1988, The Lithostratigraphy of the Hawthorn Group (Miocene) of Florida: Florida Geological Survey Bulletin No. 59, 148 p.

Scott, T.M., Campbell, K.M., Rupert, F.R., Arthur, J.D., Missimer, T.M., Lloyd, J.M., Yon, J.W., Duncan, J.G., 2001, Geologic Map of the State of Florida: Florida Geological Survey Map Series 146, Scale 1:750,000, 1 sheet.

Scott, T.M., Means, G.H., Meegan, R.P., Means, R.C., Upchurch, S.B., Copeland, R.E., Jones, J., Roberts, T., and Willet, A., 2004, Springs of Florida: Florida Geological Survey Bulletin No. 66, 377 p.

Sepulveda, N., 2002, Simulation of Ground-Water Flow in the Intermediate and Floridan Aquifer Systems in Peninsular Florida: U.S. Geological Survey Water-Resource Investigation Report 02-4009, 130 p.

Solley, W.B., Pierce, R.R., and Perlman, H.A., 1998, Estimated Use of Water in the United States: U.S. Geological Survey Circular 1200, 71 p.

Soulsby, C., Petry, J., Brewer, M. J., Dunn, S. M., Ott, B., and Malcolm, I.A., 2003, Identifying and assessing uncertainty in hydrological pathways; a novel approach to end member mixing in a Scottish agricultural catchment: Journal of Hydrology, v. 274, iss. 1-4, p. 109-128.

South Florida Water Management District, 1995, Land Use Data, Florida Department of Environmental Protection, Bureau of Information Systems/GIS Section website, http://www.dep.state.fl.us/gis/, 2004.

Southeastern Geological Society Ad Hoc Committee, 1986, Hydrogeological Units of Florida: Florida Geological Survey Special Publication No. 28, 8 p.

Southwest Florida Water Management District, 1995, Land Use Data, Florida Department of Environmental Protection, Bureau of Information Systems/GIS Section website, http://www.dep.state.fl.us/gis/, 2004.

Stewart, I.T., and Loague, K., 2003, Development of type transfer functions for regional-scale nonpoint source groundwater vulnerability assessments: Water Resources Research, v., 39, no., 12, SBH17.

Stewart, J.W., 1980, Areas of Natural Recharge to the Floridan Aquifer in Florida: Florida Geological Survey Map Series 98, scale 1 in. = 30 mi., 1 sheet.

Sullivan, J.L., Weeks, H.H., Duffee, E.M., Thomas, B.P., Ammons, H.C., and Harrell, M.L., 1975, Soil Survey of Holmes County, Florida: Natural Resources Conservation Service, U.S. Department of Agriculture, 61 p.

Sullivan III, M., 2004, Annotated Instructor's Edition, Statistics: Informed Decisions Using Data: Upper Saddle River, Pearson Education, Inc., 823 p.

Suwannee River Water Management District, 1995, Land Use Data, Florida Department of Environmental Protection, Bureau of Information Systems/GIS Section website, http://www.dep.state.fl.us/gis/, 2004.

Tim, U.S., Jain, D., Liao, H.H., 1996, Interactive modeling of ground-water vulnerability within a geographic information system: Ground Water, v. 34, iss. 4, p. 618-627.

Torres, A.E., Sacks, L.A., Yobbi, D.K., Knochenmus, L.A., 2001, Hydrogeologic framework and geochemistry of the intermediate aquifer system in parts of Charlotte, De Soto, and Sarasota Counties, Florida: U.S. Geological Survey Water-Resources Investigations Report 01-4015, 74 p.

U.S. Census Bureau: State and County Quick Facts, 01-Feb-2005, 15:48:47 EST, ww.census.gov.

United States Department of Agriculture, 1951, Soil Survey Manual, USDA Handbook No. 18, 503 p.

United States Department of Agriculture, Natural Resource Conservation Service, 2002, National Soil Survey Handbook, title 430-VI, USDA website, http://soils.usda.gov/technical/handbook/, 2003.

United States Department of Agriculture, Natural Resource Conservation Service, Soil Data Mart, USDA website, http://soildatamart.nrcs.usda.gov/State.aspx, 2003.

United States Fish and Wildlife Service, 1988-1993, National Wetlands Inventory, Florida Department of Environmental Protection, Bureau of Information Systems/GIS Section website, http://www.dep.state.fl.us/gis/, 2004.

Vernon, R.O., 1951, Geology of Citrus and Levy Counties, Florida: Florida Geological Survey Bulletin 33, 256 p.

Watts, F.C., Readle, E.L., Dearstyne, D.A., and Weatherspoon,, R.L., 2000, Soil Survey of Taylor County, Florida: Natural Resources Conservation Service, U.S. Department of Agriculture, 311 p.

White, W.A., 1970, The Geomorphology of the Florida Peninsula: Florida Geological Survey Bulletin 51, 164 p.

Witkowski, A.J., Rubin, K., Kowalczyk, A., Różkowski, A., and Wróbel, J., 2003, Groundwater vulnerability map of the Chrzanów karst-fissured Triassic aquifer (Poland): Environmental Geology, v. 44, p. 59-67.

Wright, A.P., 1974, Environmental Geology and Hydrology of the Tampa Area, Florida: Florida Geological Survey Special Publication No. 19, 93 p.

Wood, H.A.R., Arthur, J.D., Ashby, B.N., Baker, A.E., and Cichon, J.R., 2003, Mapping the intermediate confining unit/ intermediate aquifer system in Florida, *in* Florida Academy of Sciences 67th annual meeting program issue, v. 66, p. 53.

Wurm, C.M., 1992, Ground-water pollution potential in Putnam County, Ohio utilizing the DRASTIC mapping system and geographical information system [Master's Thesis]: Bowling Green, Bowling Green State University, 33 p.

Yuedong Wang and Sunwei Guo, 2004, Statistical Methods for Detecting Genomic Alterations through Array-Based Comparative Genomic Hybridization (CGH): Frontiers in Bioscience, v. 9, p. 540-549.

## APPENDIX I – GLOSSARY

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

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

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

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

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

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

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

Extent – the amount of space or surface area that something occupies or the distance over which it extends.

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

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

Prior Probability – The probability that a unit cell contains a training point before considering the evidential themes. Normally it is assumed to be a constant 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 contains 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.

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

Studentized Contrast (Confidence of evidential theme) – contrast divided by its estimated standard deviation; provides a useful measure of significance of the contrast.

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

Training Points – A set of locations (points) reflecting a parameter used to calculate weights for each evidential theme, one weight per class, using the overlap relationships between points and the various classes. In an aquifer vulnerability assessment, wells with water quality indicative of high recharge are potential known occurrences.

Vulnerability – the tendency or likelihood for contaminants to reach the top of the specified aquifer system after introduction at land surface based on existing knowledge of natural hydrogeologic conditions.

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.

## APPENDIX II – SAMPLE METADATA: DIGITAL ELEVATION MODEL

**Digital Elevation Model (DEM)**

**Metadata:**

- Identification_Information
- Data_Quality_Information
- Spatial_Data_Organization_Information
- Spatial_Reference_Information
- Entity_and_Attribute_Information
- Distribution_Information
- Metadata_Reference_Information

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Identification_Information:
*Citation:*
*Citation_Information:*
*Originator:*
Florida Geological Survey, Florida Department of Environmental Protection
*Publication_Date:* Unpublished Material
*Title:* Digital Elevation Model (DEM)
*Geospatial_Data_Presentation_Form:* raster digital data
*Online_Linkage:* \\fgs04\fgs\Projects\FAVA\FAVA_Model\metadata\dem1_04
*Description:*
*Abstract:* Digital Elevation Model for the State of Florida
*Purpose:*
Data created/updated for use in the development of evidential layers used in the Florida Aquifer Vulnerability Assessment (FAVA) Model.
*Supplemental_Information:*
Explanation and further description can be found in Florida Aquifer Vulnerability Assessment (FAVA): Contaminant potential of Florida's principal aquifer systems, Florida Geological Survey Bulletin No. 67
*Time_Period_of_Content:*
*Time_Period_Information:*
*Single_Date/Time:*
*Calendar_Date:* unknown
*Time_of_Day:* unknown
*Currentness_Reference:* ground condition
*Status:*
*Progress:* Complete
*Maintenance_and_Update_Frequency:* None planned
*Spatial_Domain:*
*Bounding_Coordinates:*
*West_Bounding_Coordinate:* -87.649870
*East_Bounding_Coordinate:* -79.800996
*North_Bounding_Coordinate:* 31.219123
*South_Bounding_Coordinate:* 24.376234
*Keywords:*
*Theme:*
*Theme_Keyword:* Digital Elevation Model
*Theme_Keyword:* Florida
*Theme_Keyword:* DEM

*Theme_Keyword:* Contours
*Theme_Keyword:* Elevation
*Theme_Keyword:* Topography
*Place:*
*Place_Keyword:* Florida
*Place_Keyword:* Peninsula
*Place_Keyword:* South East
*Place_Keyword:* United States of America
*Stratum:*
*Stratum_Keyword:* Elevation
*Stratum_Keyword:* Topography
*Access_Constraints:* None
*Use_Constraints:*
This geologic data was developed by the Florida Department of Environmental Protection (FDEP) - Florida Geological Survey (FGS) to carry out agency responsibilities related to management, protection, and development of Florida's natural resources. Although efforts have been made to make the information accurate and useful, the FDEP/FGS assumes no responsibility for errors in the information and does not guarantee that the data are free from errors or inaccuracies. Similarly FDEP/FGS assumes no responsibility for the consequences of inappropriate uses or interpretations of the data. As such, these digital data are distributed on "as is" basis and the user assumes all risk as to their quality, the results obtained from their use, and the performance of the data. FDEP/FGS bears no responsibility to inform users of any subsequent changes made to this data. Anyone using this data is advised that precision implied by the data may far exceed actual precision. Comments on this data are invited and FDEP/FGS would appreciate that documented errors be brought to staff attention. The development of these data sets represents a major investment of staff time and effort. As a professional responsibility, we expect that the FDEP/FGS will receive proper credit when you utilize these data sets. Further, since part of this data was developed and collected with U.S. Government or State of Florida funding, no proprietary rights may be attached to it in whole or in part, nor may it be sold to the U.S. Government or the Florida State Government as part of any procurement of products or services.

*Point_of_Contact:*
*Contact_Information:*
*Contact_Person_Primary:*
*Contact_Person:* Jonathan Arthur, PhD., P.G.
*Contact_Organization:* Florida Geological Survey
*Contact_Position:* Professional Geologist Supervisor
*Contact_Address:*
*Address_Type:* mailing and physical address
*Address:* Florida Geological Survey
*Address:* Gunter Building MS# 720
*City:* Tallahassee
*State_or_Province:* FL
*Postal_Code:* 32304-7700
*Country:* U.S.A.
*Contact_Voice_Telephone:* 850.488.4191
*Contact_Facsimile_Telephone:* 850.488.8086
*Contact_Electronic_Mail_Address:* Jonathan.Arthur@dep.state.fl.us
*Browse_Graphic:*
*Browse_Graphic_File_Name:* dem1_04_image.TIF
*Browse_Graphic_File_Description:*

Figure No. 7 Included in the Florida Aquifer Vulnerability Assessment (FAVA): Contaminant potential of Florida's principal aquifer systems
*Browse_Graphic_File_Type:* TIFF
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*Browse_Graphic_File_Name:* dem1_04_image_zoom.TIF
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Large scale image of the Trail Ridge area in Northern peninsular Florida
*Browse_Graphic_File_Type:* TIFF
*Data_Set_Credit:* Florida Geological Survey
*Native_Data_Set_Environment:*
Microsoft Windows 2000 Version 5.1 (Build 2600) Service Pack 2; ESRI ArcCatalog 8.3.0.800
*Cross_Reference:*
*Citation_Information:*
*Originator:* Florida Geological Survey
*Publication_Date:* November 2003
*Publication_Time:* Unknown
*Title:*
fl_contoursalb 1:24000 Topographic Contour Lines for the Florida Peninsula
*Geospatial_Data_Presentation_Form:* vector digital data

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*Data_Quality_Information:*
*Attribute_Accuracy:*
*Attribute_Accuracy_Report:*
Elevations based on the USGS 7.5-minute quadrangle maps. Elevation values have a 5-foot or 10-foot vertical accuracy and is dependent on the contour interval reported on the quadrangle maps. Horizontal accuracy is the same as reported on the paper maps.
*Quantitative_Attribute_Accuracy_Assessment:*
*Attribute_Accuracy_Value:* Value
*Attribute_Accuracy_Explanation:* Elevation of the cell is in feet above mean sea level
*Lineage:*
*Source_Information:*
*Source_Citation:*
*Citation_Information:*
*Title:* United States Geological Survey Topographic Maps
*Source_Scale_Denominator:* 1:24 000
*Type_of_Source_Media:* paper
*Source_Time_Period_of_Content:*
*Source_Currentness_Reference:* publication date
*Process_Step:*
*Process_Description:*
1. All the contours were merged into one large coverage. 2. A directory was made for each county (counties parallel and south of Lake Okeechobee were merged together due to the lack of contours there. The Florida Keys were also completed separately. 3. The contours for each county were clipped based on a six-kilometer buffer of the county. 4. Shoreline (zero contour line) was created by converting the detailed counties shapefile to an outline then clipping the Georgia border and also clipped by the six kilometer buffer. 5. A triangular irregular network (TIN) was then created from the two coverages and was then clipped to a one kilometer buffer of the each county or area polygon. 6. The TINs for each county or area polygon were then converted to grids. 7. The grids were then combined using the MOSAIC command, to create the statewide elevation model.
*Process_Date:* Unknown
*Process_Step:*

*Process_Description:* Dataset copied.
*Source_Used_Citation_Abbreviation:* U:\Projects\FAVA\fava_data\dem_elev\dem1_04

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*Spatial_Data_Organization_Information:*
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*Row_Count:* 50205
*Column_Count:* 49860
*Vertical_Count:* 1

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*Standard_Parallel:* 31.500000
*Longitude_of_Central_Meridian:* -84.000000
*Latitude_of_Projection_Origin:* 24.000000
*False_Easting:* 400000.000000
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*Planar_Coordinate_Information:*
*Planar_Coordinate_Encoding_Method:* row and column
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*Ordinate_Resolution:* 15.000000
*Planar_Distance_Units:* meters
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*Denominator_of_Flattening_Ratio:* 298.257222

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*Attribute:*
*Attribute_Label:* ObjectID
*Attribute_Definition:* Internal feature number.
*Attribute_Definition_Source:* ESRI
*Attribute_Domain_Values:*
*Unrepresentable_Domain:*
Sequential unique whole numbers that are automatically generated.
*Attribute:*
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*Attribute_Definition:* Elevation in feet above mean sea level
*Attribute:*
*Attribute_Label:* Count

*Distribution_Information:*
*Resource_Description:* Downloadable Data
*Standard_Order_Process:*
*Digital_Form:*
*Digital_Transfer_Information:*
*Transfer_Size:* 259.560

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*Metadata_Reference_Information:*
*Metadata_Date:* 20050107
*Metadata_Review_Date:* 20041028
*Metadata_Contact:*
*Contact_Information:*
*Contact_Organization_Primary:*
*Contact_Organization:* Florida Geological Survey (FGS)
*Contact_Person:* Alan Baker
*Contact_Position:* Professional Geologist I
*Contact_Address:*
*Address_Type:* mailing and physical address
*Address:* Gunter Building MS #720
*Address:* 903 W. Tennessee St.
*City:* Tallahassee
*State_or_Province:* Florida
*Postal_Code:* 32304-7700
*Country:* U.S.A.
*Contact_Voice_Telephone:* 850.488.4191 x 122
*Contact_Facsimile_Telephone:* 850.488.8086
*Contact_Electronic_Mail_Address:* Alan.Baker@dep.state.fl.us
*Metadata_Standard_Name:* FGDC Content Standards for Digital Geospatial Metadata
*Metadata_Standard_Version:* FGDC-STD-001-1998
*Metadata_Time_Convention:* local time
*Metadata_Extensions:*
*Online_Linkage:* <http://www.esri.com/metadata/esriprof80.html>
*Profile_Name:* ESRI Metadata Profile

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