# Geographic Information System (GIS) Desktop Identification of Wetland Areas

*A Literature Review, Review of a Utility Model, and A Discussion on Moving from Research to Tool Design*

**3002016545**

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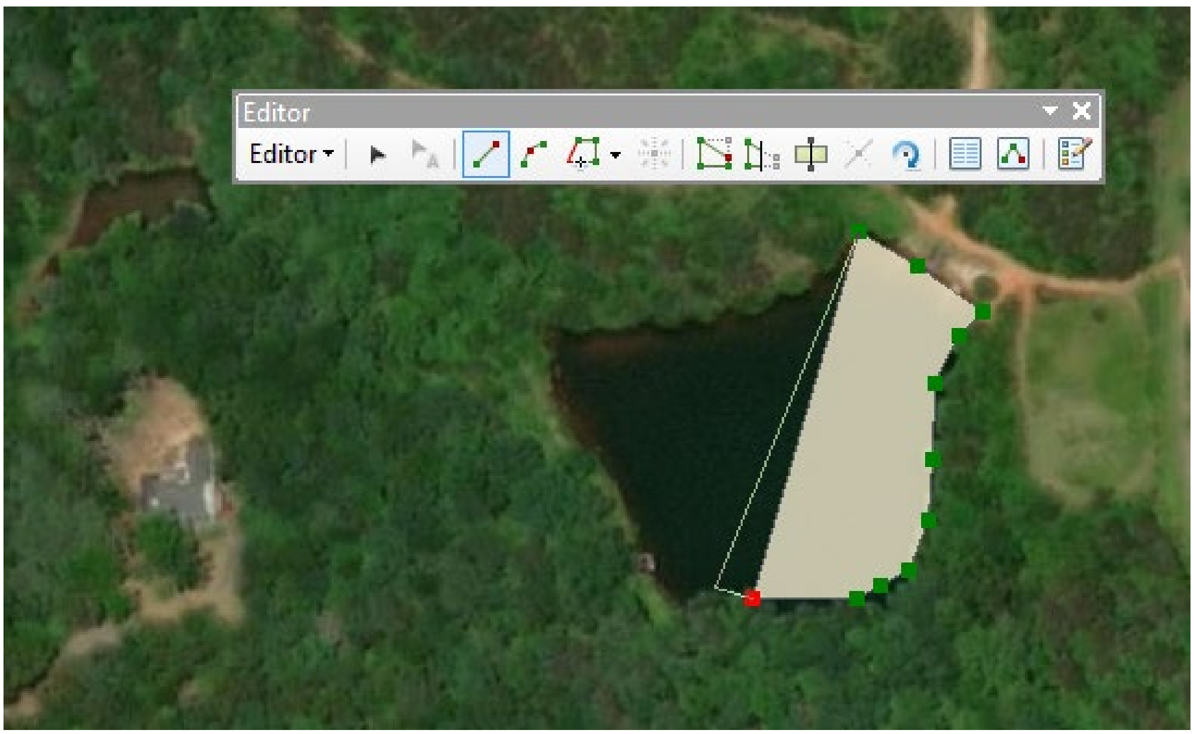


*Digitizing a wetland*

# Geographic Information System (GIS) Desktop Identification of Wetland Areas

*A Literature Review, Review of a Utility Model, and A Discussion on Moving from Research to Tool Design*

**3002016545**

Technical Update, December 2019

EPRI Project Manager

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# ABSTRACT

Siting electric utility infrastructure is an expensive and resource-intensive operation that requires extensive planning before a project commences. The ability to accurately and efficiently identify suitable sites with minimal constraints (e.g., wetlands) is paramount to the success of a project. Identifying wetland locations in the early stages of a project is critical as it can prevent unexpected complications and delays in project siting. Fortunately, the use of desktop Geographic Information Systems (GIS) and related remote sensing tools have improved dramatically over the last decade and can be used effectively to identify wetlands before a project starts, saving time and money for everyone involved. Previous EPRI research, *Wetlands Identification using Desktop GIS: An Overview* (EPRI report 3002013698, 2018), identified and explained standard approaches for desktop identification of wetlands. Adding to that research, this report addresses the following research questions:

- What improvements are recommended for an existing desktop wetland identification model/methodology in use by an electric power company?
- Could desktop identification get to 90% accuracy and what does the literature tell us?
- What might a new wetland identification tool look like?

### Keywords

Wetland
Delineation
Geographic Information Systems (GIS)
Stream
Riparian area

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## Product Title: Geographic Information System (GIS) Desktop Identification of Wetland Areas: A Literature Review, Review of a Utility Model, and A Discussion on Moving from Research to Tool Design

**PRIMARY AUDIENCE:** Environmental managers and staff working on wetland issues

**SECONDARY AUDIENCE:** Other corporate managers, staff, and interested researchers and agency staff working on wetland &/or geographic information systems (GIS) issues

### KEY RESEARCH QUESTION

Three related research questions are addressed in this report: 1) What improvements are recommended for an existing desktop wetland identification model/methodology in use by an electric power company?; 2) Could desktop identification get to 90% accuracy and what does the literature tell us?, and 3) What might a new wetland identification tool look like?

### RESEARCH OVERVIEW

The use of desktop GIS and related remote sensing tools have improved dramatically over the last decade and can be used effectively to identify wetlands before a project starts, saving time and money for everyone involved. A previous EPRI factsheet “Wetlands Identification using Desktop GIS: An Overview” (3002013698, 2018) identified and explained standard approaches for desktop identification of wetlands. Adding to that research, this report addresses the research questions noted above.

### KEY FINDINGS

- There are many ways to use geospatial data, maps and GIS software to identify potential wetlands locations within an area of interest (Section 2). Some broad categories of GIS-based wetlands identification methods are the following, rank ordered by technical difficulty from lowest to highest: digitizing wetlands, imagery classification, geospatial modeling, or a combination of the methods (recommended if possible). The selection of a method will depend on the scope and size of the project area, the accuracy of delineation required, data accessibility and relevancy, availability of GIS software and skills, and staff or financial resources available. Barriers to implementing GIS-based methods for wetlands identification include lack of GIS expertise, the accuracy of the resulting maps, and the transient nature of wetlands (extents can change from year to year).
- The case study in Section 3 of this report provides environmental managers with a working example of how one utility company uses desktop GIS to identify wetlands prior to transmission line siting. The recommended improvements could be helpful for companies reviewing their own current practices.
- In our review of peer-reviewed literature (Section 4), object-based Imagery Analysis is the most accurate technique used for identifying wetlands using desktop GIS software. However, this technique also requires the most expertise and expensive software.
- As discussed in Section 4, there are many different desktop GIS software solutions available for use in wetland identification. Trimble’s ECognition, Hexagon’s ERDAS Imagine, SPRING and Esri’s ArcGIS Desktop are the most widely used. Software cost and required level of expertise can vary greatly, with Trimble’s ECognition and Hexagon’s ERDAS Imagine being the most expensive and difficult to use. Peer-reviewed literature suggests that ECognition is the most accurate of available software. ArcGIS Desktop, which is easily the most widely used Desktop GIS software in the world, is substantially less costly and easier to use.

EXECUTIVE SUMMARY

**WHY THIS MATTERS**

Siting electric utility infrastructure is an expensive and resource-intensive operation that requires extensive planning before a project commences. The ability to accurately and efficiently identify suitable sites with minimal constraints (e.g., wetlands) is paramount to the success of a project. Identifying wetland locations in the early stages of a project is critical as it can prevent unexpected complications and delays in project siting.

**HOW TO APPLY RESULTS**

Information provided in this document can serve as a guide to choosing an appropriate method for identification of wetlands using tools available from a desktop computer (Section 2). The recommended improvements in the case study could be helpful for companies reviewing their own current practices (Section 3). The literature review and discussion provides a foundation for scoping and designing a potential new tool or software to enhance desktop wetland identification (Sections 4 and 5).

**LEARNING AND ENGAGEMENT OPPORTUNITIES**

- Wetlands Identification using Desktop GIS: An Overview (3002013698, 2018)
- No desktop GIS software is solely designed to identify wetlands. This research provides a foundation for scoping and designing a potential new tool or software to enhance desktop wetland identification. This work might include identification of potential tool users, use cases, and functionality desired, in addition to analysis of whether existing tools meet those needs.
- The following agencies and groups have various resources (webinars, fact sheets, etc.) related to wetlands:
  - American Society of Wetland Scientists (https://www.sws.org/)
  - Association of Wetland State Managers (https://www.aswm.org/)
  - Environmental Protection Agency (https://www.epa.gov/wetlands)

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**IMPLEMENTATION CATEGORY:** NA

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# 1 INTRODUCTION

The use of desktop Geographic Information Systems (GIS) and related remote sensing tools have improved dramatically over the last decade and can be used effectively to identify wetlands before a project starts, saving time and money for everyone involved.

Many useful desktop methods exist for locating wetland features, varying in both accuracy and amount of effort required. As environmental managers, the need to effectively manage resources is critical for the success of any project and balancing the need for accuracy with available resources is one of the key aspects in determining the best method for identifying wetlands in an infrastructure project.

A previous EPRI factsheet “Wetlands Identification using Desktop GIS: An Overview” (3002013698, 2018) identified and explained standard approaches for desktop identification of wetlands. The information from that fact sheet is provided in Section 2 as background for the remainder of the report.

Adding to that research, this report:

- Reviews an existing desktop wetland identification model/methodology in use by an electric power company and provides recommendations for improvements (Section 3);
- Investigates the question “Could desktop identification get to 90% accuracy?” by reviewing leading-edge research and technology that could improve desktop accuracy (Section 4);
- Provides a discussion on moving from research to tool design, including a “wireframe”/mock-up for a new tool that could be developed to improve accuracy of desktop wetland identification (Section 5); and
- Concludes with a summary of the research and potential next steps (Section 6).

# 2
# AN OVERVIEW OF WETLANDS IDENTIFICATION USING DESKTOP GIS

*This section is sourced from the EPRI fact sheet "Wetlands Identification using Desktop GIS: An Overview" (3002013698, 2018).*

GIS is a combination of computer hardware and software that links mapped features to databases that describe them, while simultaneously providing tools for analysis, storage and retrieval, and visualization of data. Over the last 20 years, desktop GIS systems have become quite powerful tools for mapping, managing, analyzing, and visualizing large volumes of spatial data, including wetlands. Having in-house, robust GIS capabilities is increasingly becoming the "norm" for electric utility companies, especially large companies, and can help save time and money by having GIS work done internally as opposed to work done by external consultants. GIS is also commonly used for asset management and project planning after an initial geospatial database containing features of interest is created.

## GIS Data

The primary source for mapped wetland features is the National Wetlands Inventory (NWI) dataset. This layer, created by tracing wetland features seen in aerial imagery, is the starting point for avoiding wetlands in infrastructure projects. However, for site specific studies and more detailed analyses, the NWI dataset may be out of date, incomplete, or inadequate for the specific needs of the project. In order to bolster this free resource and derive additional information, other datasets can be incorporated to produce a more complete picture of probable unmapped wetlands. A great quantity of GIS data (e.g., topography, hydrography, soils, land cover, elevation, etc.) is freely available from government agencies like the U.S. Geological Survey (USGS), the U.S. Natural Resource Conservation Service (NRCS), and the U.S. Fish and Wildlife Service (USFWS), all of which are based on geospatial standards promoted by the Federal Geographic Data Committee (FDGC). Many of these supplemental data sources can be used in conjunction with NWI data to determine the likelihood of an area being identified as a protected wetland under the Clean Water Act (CWA) §404 or state wetland regulations. In addition, commercial services are available to capture further information at a specific site or higher resolution than is otherwise freely available. One of the many benefits of the GIS platform is the ability to consume data derived from both manual field collection and remote sensing. Drone, airplane, and satellite based sensors are able to capture information over a much broader area than can be reasonably covered by a survey team on the ground and can be easily incorporated into a company's GIS database.

## Common Methods and Tools

There are many ways to use geospatial data, maps and GIS software to identify potential wetlands locations within an area of interest. The selection of a method will depend on the scope and size of the project area, the accuracy of delineation required, the familiarity of the team with GIS tools, and the resources available to the project manager. Some broad categories of GIS-based wetlands identification methods are described below, rank ordered by technical difficulty from lowest to highest.

- Digitizing Wetlands: Using existing maps to delineate wetlands features in a process known as 'heads-up digitization.' This method requires knowledge of what to look for on a map to correctly identify wetlands before tracing over features to create a new data layer. Tracing existing features can be quite expedient and as mentioned previously, is the method used by the USFWS to create the NWI. This technique does not require much prior GIS knowledge or expertise and one can easily be trained to digitize wetlands.
- Imagery Classification: Categorizing satellite and aerial photos into distinct land classes is a technique known as image classification. This technique groups pixels in an image into distinct classes based on their similarities. Supervised, Unsupervised, and Object-Based Imagery classification are the most common types of imagery classification, utilizing machine learning techniques to differentiate between land cover classes. Supervised or unsupervised imagery classification are the most common methods used to identify classes of land over large areas and can be highly accurate when high-resolution (< 1m) imagery is used. Imagery classification is not terribly difficult, though it does require a good base knowledge of GIS and remote sensing.
- Geospatial Modeling: An increasingly common technique used to determine which areas have properties most consistent with wetlands, especially for utility companies with an in-house GIS team or with adequate financial resources, is a "likelihood" GIS model, where multiple geospatial datasets are overlaid and weighted to determine which areas are most likely wetlands. It is a very subjective technique and requires numerous, high-resolution datasets to accurately identify probable wetland areas. This method requires expert GIS knowledge to design, build, run, and manage the model and data. However, once created, the model can usually be easily modified and run for other project locations. It is a very flexible and cost-effective technique yet can be extremely complex and definitely requires someone one with strong GIS skills to successfully run the model.

In the process of accurately determining wetland locations, these methods may be used in isolation or combination, as needed. To improve the confidence of delineated wetland areas, one method is often used to supplement and reinforce the results from another.

### Pitfalls and Pain Points

If the project team does not already have experience working with GIS, the learning curve for commercial software may seem daunting. Luckily one does not need to know the complete GIS toolset in order to perform wetland delineation and mapping. Technical documentation, existing method guidelines, and customer support for commercially licensed packages are all useful resources for getting started with GIS software. However, limited knowledge of GIS will undoubtedly hinder the success of any effort to use desktop GIS to identify probable wetlands.

Another barrier to implementing GIS-based methods for wetlands identification is the accuracy of the resulting maps. Both the spatial location of features determined to be wetlands, and the confidence with which those features are delineated, must be accurate to a high standard to comply with federal, state, and local regulations regarding the protection of wetland ecosystems. In cases where there is uncertainty in the presence of discovered wetlands and the identified area is unavoidable for project purposes, permitting agencies may require site visits to verify wetland boundaries before issuance of approval. Quantifying the accuracy of a wetland delineation method can be difficult and time consuming, however it is an important component of the procedure.

One final consideration that makes accurate delineation of wetlands difficult is the transient nature of the features themselves. Wetlands may be permanent features in certain areas, and only infrequently inundated elsewhere. The amount of rainfall received, dam release schedules, and atmospheric conditions will influence the amount of surface water in a wetland. Since the extents can change from year to year, it is advisable to obtain historical data if possible to confirm delineated boundaries.

## Ideal Procedure

Choosing the best method for a given site will depend on several factors. Beyond the availability of GIS software and skills, data accessibility and relevancy will be the most important aspects to consider when selecting a method. If possible, it is recommended to use a combination of the methods listed above to verify mapped features. For example, heads-up digitizing may be supplemented with site visits to confirm the existence of wetlands and verify their boundaries. Similarly, older datasets containing wetland features can be checked with more recent imagery to ensure the dataset is still accurate. Ultimately, project resources will dictate which methods and tools will be used for a project and hopefully, the information provided in this brief can help environmental managers make informed decisions regarding the use of desktop GIS for the identification of probable wetlands on project sites.

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# 3
# CASE STUDY – REVIEW OF MODEL

This section reviews an existing desktop model/methodology, which estimates the probability of forested wetlands used by an electric power company and provides recommendations for improvements. The review was requested by a volunteer power company in the United States (herein Utility A) which was interested in an objective review of and recommendations for improving its methodology of desktop wetland identification. The case study provides insight and learning opportunities for the electric power industry as well as other sectors.

## Case Study Background

Transmission line siting is a routine endeavor undertaken by utility companies around the world. In the Unites States, impacts to wetlands and streams are regulated under the Clean Water Act (CWA) and requires avoidance and minimization whenever possible, and compensatory mitigation when unavoidable. Therefore, avoidance of federally regulated wetlands during transmission line siting can reduce the time and challenges associated with obtaining a CWA §404 permit. Consequently, the ability to accurately predict or identify the presence of wetlands during transmission line siting is extremely important to utility companies as it saves them time as well as costs for compensatory mitigation of impacted wetlands. Prior to transmission line siting, many, if not most utility companies, use desktop GIS to identify wetlands located in a given project area. EPRI has interviewed multiple utilities about their use of tools and methods for desktop wetland identification and found no commonly accepted industry standard for desktop identification of wetlands (see EPRI report 3002017470, 2019). The GIS methods and techniques used to identify wetlands by utilities vary by company. Many of the methods described in Sections 2 and 3 are utilized by utility companies (Gallant, 2015; Kumar et al., 2015; Mahdavi et al., 2017).

Utility A, a large electric power company located in the United States, routinely constructs new transmission lines to meet area demand for electricity. Inevitably, these transmission line corridors run through or are proximate to sensitive wetland areas, primarily forested wetlands. In order to minimize impacts to these areas, over the last ten years Utility A has developed and utilizes publicly available GIS data as inputs to a custom-built GIS model that identifies potential forested wetlands prior to transmission line siting. The result of this predictive model, a GIS layer containing potential forested wetland areas ranked by their likelihood of containing a wetland, is provided to siting engineers for constraint mapping in support of selecting alternative routes for new transmission lines. Siting transmission line routes with this additional knowledge supports avoidance and minimization of forested wetland conversion resulting from construction of overhead transmission lines. Similarly, planning for wetland permitting schedules and mitigation costs may be better anticipated when using results from this model.

## Model Design

Forested Wetland Predictive Model (FWPM) is Utility A's GIS model built using ESRI's Model Builder, a standard modeling tool that comes with the ArcMap module of the ArcGIS Desktop software suite. FWPM is a vector-based model that includes overlays and weighted rankings of

GIS datasets that, when used in combination, are thought to indicate the presence of previously unmapped forested wetlands. The model process begins with assignment of the study area or potential site area to the wetlands modeling team. Using the study area as a locational guide, the wetlands modeling team then compiles all the necessary FWPM GIS data, almost all of which are publicly available, and are listed in Table 3-1.

**Table 3-1**
**Model input data**

| Data Type | Source | Scale |
|---|---|---|
| National Wetlands Inventory | USFWS | 1:24,000 |
| Hydric Soils | SSURGO* | 1:12,000 – 1:63,360 |
| Flood Frequency | SSURGO | 1:12,000 – 1:63,360 |
| Pond Frequency | SSURGO | 1:12,000 – 1:63,360 |
| Drainage Class | SSURGO | 1:12,000 – 1:63,360 |
| Floodplains | FEMA** | 1:24,000 |
| Land Cover | USGS | 1:60,000 |
| Canopy Cover | USGS | 1:60,000 |
| Marsh/Swamp | USGS 24k Topo Maps | 1:24,000 |
| Depressions | USGS 24k Topo Maps | 1:24,000 |
| Groundwater Features | USGS 24k Topo Maps | 1:24,000 |
| Shoreline Management Initiative Polygons | Internal | 1:24,000 |
| Sensitive Area Review Polygons | Internal | 1:24,000 |

*SSURGO = Soil Survey Geographic database

**FEMA = Federal Emergency Management Agency

Once the GIS data is retrieved from the relevant website or prepared in-house, various preparatory functions (e.g., ArcGIS functions such as clip, reproject, and vectorization) are performed on the data as needed. Separated quality assurance checks throughout the creation and use of GIS data ensures that the end products are acceptable for their intended purpose. Dedicating resources to these tasks is an often-overlooked component of environmental modeling and is critical in preventing the misuse of resulting data.

After data prep, the model inputs are loaded into the model (Figure 3-1) and the overlay processes are run.

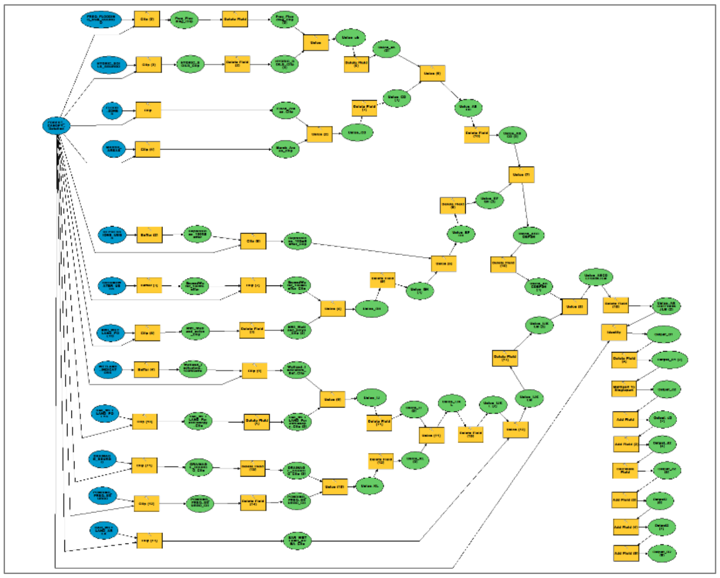

**Figure 3-1**
**FWMP model thumbnail**

Essentially, the data layers noted in Table 3-1 are combined into one layer via a union process with specified input attributes (i.e., wetland classification category) carried over to the model output. The result of the model is a polygon GIS layer with multiple features (polygons) having concatenated (joined) attributes describing each location. For example, the polygon's concatenated attributes would look something like this (Figure 3-2).

| |
|---|
| - - - - Floodway - - Occasional Flooding - - - - Disappearing Stream (USGS) - - Canopy (NLCD 2001) - 90. Woody Wetlands - 11-100% Canopy |
| - - - - Floodway - - Occasional Flooding - - - - Disappearing Stream (USGS) - - Canopy (NLCD 2001) - 21. Developed, Open Space - 11-100% Canopy |
| - - - - Floodway - - Occasional Flooding - - - - Disappearing Stream (USGS) - - Canopy (NLCD 2001) - 21. Developed, Open Space - 11-100% Canopy |
| - - - - Floodway - - Occasional Flooding - - - - Disappearing Stream (USGS) - - Canopy (NLCD 2001) - 90. Woody Wetlands - 11-100% Canopy |
| - - - - Floodway - - Occasional Flooding - - - - Disappearing Stream (USGS) - - Canopy (NLCD 2001) - 90. Woody Wetlands - 11-100% Canopy |
| - - - - Floodplain (100 Year) - - Occasional Flooding - - - - Disappearing Stream (USGS) - - Canopy (NLCD 2001) - 95. Emergent Herbaceous Wetlands - 11-100% Canop |
| - - - - Floodplain (100 Year) - - Occasional Flooding - - - - Disappearing Stream (USGS) - - Canopy (NLCD 2001) - 90. Woody Wetlands - 11-100% Canopy |
| - - - - Floodplain (100 Year) - - Occasional Flooding - - - - Disappearing Stream (USGS) - - Canopy (NLCD 2001) - 90. Woody Wetlands - 11-100% Canopy |
| - - - - Floodplain (100 Year) - - Occasional Flooding - - - - Disappearing Stream (USGS) - - Canopy (NLCD 2001) - 90. Woody Wetlands - 11-100% Canopy |
| - - - - Floodplain (100 Year) - - Occasional Flooding - - - - Disappearing Stream (USGS) - - Canopy (NLCD 2001) - 90. Woody Wetlands - 11-100% Canopy |
| - - - - Floodplain (100 Year) - - Occasional Flooding - - - - Disappearing Stream (USGS) - - Canopy (NLCD 2001) - 90. Woody Wetlands - 11-100% Canopy |
| - - - - Floodplain (100 Year) - - Occasional Flooding - - - - Disappearing Stream (USGS) - - Canopy (NLCD 2001) - 90. Woody Wetlands - 11-100% Canopy |
| - Wooded Marsh/Swamp (USGS) - - - Floodway - - Occasional Flooding - - - - Disappearing Stream (USGS) - - Canopy (NLCD 2001) - 90. Woody Wetlands - 1-10% Can |
| - Wooded Marsh/Swamp (USGS) - - - Floodway - - Occasional Flooding - - - - Disappearing Stream (USGS) - - Canopy (NLCD 2001) - 90. Woody Wetlands - 11-100% C |

**Figure 3-2**
**Example of concatenated attributes**

The resultant layer is then given to the team's wetlands biologist who takes the concatenation and breaks it into individual columns, categorizing, sub categorizing, scoring and ranking each polygon based on the presence or absence of a geographic feature and therefore its probability of being a potential forested wetland (Figure 3-3).

| Flood Frequency SSURGO | Hydric Soil Map SSURGO | Flood-plain FEMA | NWI | Drainage Class SSURGO | Ponding Frequency SSURGO | LULC | Canopy Percent NLCD | SUM HYDRO | SUM SOILS | SUM VEG | SCORE | WEIGHT |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | 0 | | | 36 | 36 | 0 | 0 | 72 | 24 | LOW |
| | | | 0 | | | 18 | 36 | 0 | 0 | 54 | 18 | LOW |
| | | | 0 | | | 0 | 36 | 0 | 0 | 36 | 12 | LOW |
| | | | 0 | | | 0 | 36 | 0 | 0 | 36 | 12 | LOW |
| | | 30.3 | | | | 0 | 36 | 30.3 | 0 | 36 | 22.1 | LOW |
| | | 30.3 | | | | 0 | 36 | 30.3 | 0 | 36 | 22.1 | LOW |
| | | 30.3 | | | | 36 | 36 | 30.3 | 0 | 72 | 34.1 | MEDIUM |
| | | 30.3 | | | | 36 | 36 | 30.3 | 0 | 72 | 34.1 | MEDIUM |
| | | 30.3 | | | | 36 | 36 | 30.3 | 0 | 72 | 34.1 | MEDIUM |

**Figure 3-3**
**Potential wetland scoring and weighting**

The three main weighting categories and their associated sub-categories are listed below:

- Vegetation (USGS Wetland Habitat, National Wetland Inventory, Land Cover, Land Use)
- Soils (Drainage Class, Wetland Soil Mapping)
- Hydrology (Ponding Frequency, USGS Hydrology Indicators, Flooding Frequency, Floodplain)

For more detail about the scoring and ranking system, see Appendix A.

The probable forested wetland data layer is then provided to the transmission siting team for use in their constraint mapping. A right of way is chosen, partially based on results from the Forested Wetland Model. Surveyors then verify and delineate the wetlands through on the ground fieldwork before line construction commences. The steps in the model are summarized in Figure 3-4.

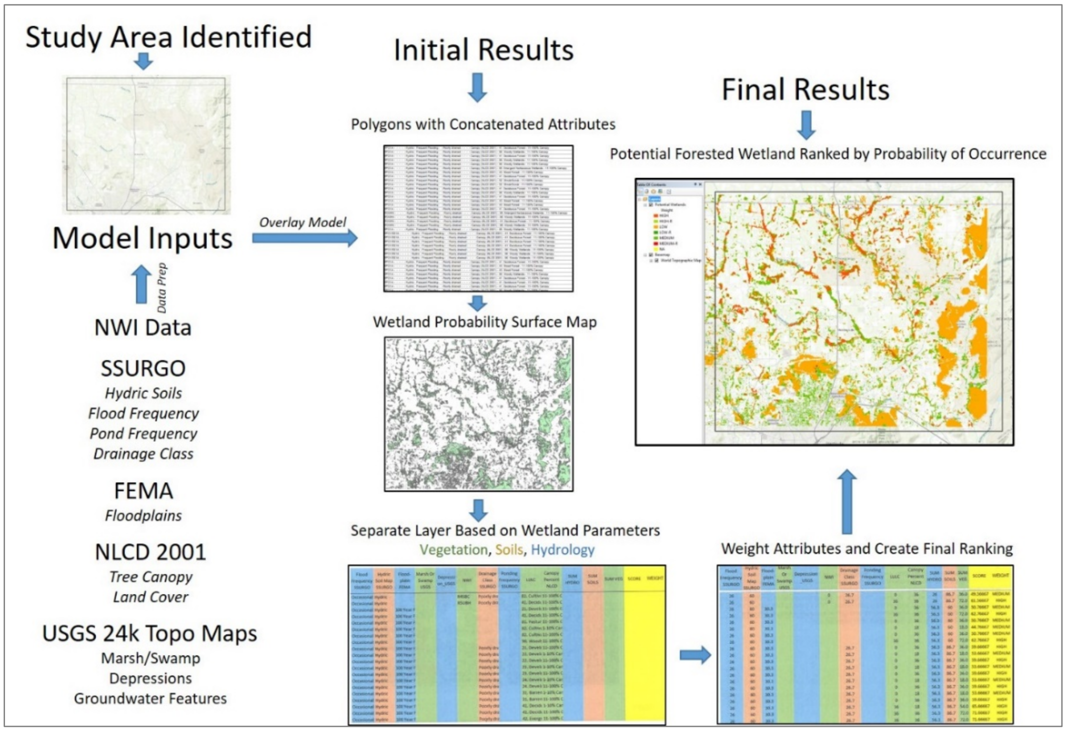


**Figure 3-4**
**FWPM model summary**

## Benefits of the Modeling Procedure

The model and methods developed by Utility A are tools that aid in project site selection and location of constructed assets. Inputs to the model are widely available, with internal layers developed to enhance these initial datasets with more region-specific features. This procedure can be employed independent of location, with little additional effort required for additional localization. Since this model is used only as a guide for Utility A's line siting constraint models, the modeling process can be conducted entirely by office staff. Thorough documentation of the process allows for new team members to assist with modeling and serves to free up resources for more technical and advanced analysis.

The data layers used by the agency are widely available, grounded in theory, and have a longstanding acceptance by the remote sensing and conservation communities. Despite known limitations with federal datasets (e.g., NWI data accuracy and currency), they offer the ability to identify features at potential sites without time and manpower invested in field excursions. In addition to this base data, the agency has developed standardized internal procedures for the creation of supporting layers that expand on the scope and detail of the NWI and related datasets to include localized information derived from USGS topographic maps such as springs, seeps, and waterfalls, which are not found in national GIS layers.

## Suggestions for Model Improvement

There are no conceptual issues with the wetlands identification process as currently implemented, rather areas for time or cost savings and improvement of accuracy are noted below. Of course, all of these suggestions have associated costs that must be considered.

Theoretically, each suggestion would benefit the utility, resulting in more effective and accurate identification of wetlands. However, it is quite difficult to estimate the exact cost and subsequent savings gained through implementation of these suggestions. Therefore, we have labeled each suggestion with a categorical estimate of cost/benefit (low cost/high benefit, etc.) achieved through implementation of a suggestion. The specific cost-benefit calculations and implications are left to the reader to determine for his/her company and will certainly vary from utility to utility.

1. ***Elimination of redundancy induced by simplification and standardization of the procedure.***

   The format in which the model was created (ESRI ArcMap Model Builder) is a very approachable form of GIS automation. However, scripting with graphic code blocks is limiting when compared to fully coded logic implementation and requires user effort and oversight where none is strictly required. There are stages of the model that could be consolidated into a larger routine, and further steps that could be taken to reduce user effort. The Model Builder format is less flexible than a fully scripted solution (such as could be developed in the Python scripting language) but is easily diagnosable by those unfamiliar with programming and troubleshooting computer code. The tradeoff between ease of access (using Model Builder) and advancing automation (such as using Python) is worth consideration if a major update to the procedure is planned.

   <u>Cost:</u> Low to medium costs depending on in-house capabilities.

   <u>Benefit:</u> High savings in the long run as time and resources can be reallocated.

2. ***Validate the Model***

   Currently, Utility A does not have a process for determining the accuracy of its FWMP model results. While a modest examination of model accuracy is explored In Appendix B, (Validation Exercise for Subset of Utility A's Service Territory), a full accuracy assessment is beyond the scope of this project. Directing resources to site specific calibration of the model could benefit the overall procedure, however a one-time accuracy assessment is a significant step and requires field collection of data beyond Utility A's currently available data resources.

   As an example of the efforts involved in an accuracy assessment, the Food and Agriculture Organization (FAO) of the United Nation's Practical Guide to Map Accuracy Assessment and Area Estimation identifies four critical steps in an accuracy assessment (Figure 3-5).

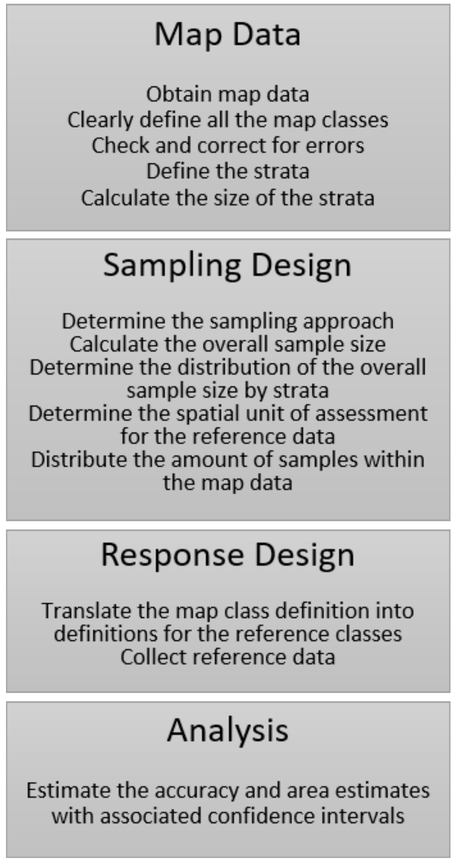


**Figure 3-5**
**FAO accuracy assessment steps**

*A complete accuracy assessment for this model would require defining a sampling approach, creating a sample size, comparison of the sample to reference data, which in this case would likely need to be surveyed wetlands at pre-identified sample sites, and finally estimate the accuracy at associated confidence intervals using statistical analysis. For illustration purposes, we provide a sketch of such an analysis in Appendix B, Validation Exercise for Subset of Utility A's Service Territory.*

Verification of locations identified as wetlands with high confidence with field data collection would further increase the reliability of the model. A one-time project aimed at refining modeling procedures through field data collection and comparison could benefit the utility company.

Cost: High; extensive fieldwork required.

Benefit: High; this will validate the model and ultimately dictate whether the model weighting works effectively or should be redesigned.

3. ***Improved Data Inputs***

Spatial resolution used in the model is coarse by current standards; a 30-meter grid cell size for raster data (NLCD and Land Use) is acceptable for preliminary planning purposes but inadequate for more detailed analysis, especially having confidence identifying unmapped wetlands in an area as narrow as a transmission line corridor, which ranges from 50-250 ft (15-76m). The same is true for data collected at a scale of 1:24,000 (e.g., one inch on a map represents 2,000ft / 1cm represents 240m). Utility A might consider using Landsat data, which in addition to being free, may shed light on average conditions for the past 10 years.

Much of the federally produced free data used in the FWMP model is currently out of date as well. By using primarily free federally produced data, the utility company is limited in what they should expect out of their model: developments and natural changes may have occurred on the landscape that are not reflected in the data.

Increasing the resolution of input data would require additional budgeting for image purchases and would require more effort in recreating the datasets currently available at the 30-meter resolution. To balance these points, a final stage could be included wherein remote sensing data at a higher resolution is collected for wetland areas identified with high confidence by the existing model.

<u>Cost:</u> High – good data is costly.

<u>Benefit:</u> High; the use of high-resolution aerial imagery, Landsat and LIDAR data would undoubtedly increase the accuracy of any wetland delineation project.

4. ***Raster is Faster***

Conversion of all data to a raster (e.g., pixel-based) format would speed up the model run time and speed of data drawing. It is also a much more accepted form of overlay analysis as it is fast and efficient. There would be no need for concatenation of attributes as the attributes could be converted into numeric representation and combined with the weighted variable using the ArcMap tool Raster Algebra. Please see Appendix C for an example.

<u>Cost:</u> Low; this could be done in-house by a person with moderate GIS expertise.

<u>Benefit:</u> High: model run-time would be significantly diminished.

5. ***Variable Weighting***

The model weighting scheme could potentially be improved. Currently, the weights are based on the frequency of occurrence of an input variable. A more comprehensive examination of the weighting scheme is warranted as the literature does not support the current weighting scheme (for a review of recommended practices in spatial prioritization - including weighting of variables - see Game et al. 2013). The weighting scheme needs validation, and this could be achieved in tandem with a detailed accuracy assessment.

<u>Cost:</u> Low; could be done in-house in a few hours

<u>Benefit:</u> No benefit until an accuracy assessment is conducted.

### Comparison to Other Common Methods

One of the difficulties preventing the implementation of other wetlands identification methods is the specific objective of Utility A's modeling procedure. Unmapped wetlands occurring on forested land and under a tree canopy are difficult to identify through photointerpretation of top-down imagery. Methods that make use of a single source of imagery excel at classifying land cover over the full scope of the image but are of limited benefit for identifying surface water *under* tree cover. Leaf-off imagery or the use of 3D remote sensing data (LiDAR*) may provide a better source for identification of these obscured wetland features. Object-based classification* of the desired features may be a promising alternative to traditional image classification methods but is the most technical and difficult to implement. Heads-up digitization* of features (image tracing) faces many of the same challenges as automated classification in terms of uncertainty in identifying wetland features under tree canopy. When compared to field data collection, the modeling method is significantly less costly and more immediately implementable, but offers less certainty in delineated features. The use of field survey teams to verify areas identified by the model as wetlands would be the primary supplemental method for ensuring accuracy of model results.

*For more on these techniques, see Section 2.

### Next Steps for Improvement of the Modeling Procedure

A point of consideration when developing a long-term method for wetlands identification is future changes in the GIS platform. Although the current stack of GIS tools provided by ESRI will likely receive support for many years to come, ESRI is transitioning its development resources to a new iteration of the software. The creation of a fully scripted modeling procedure or a standalone program to perform modeling tasks may be worth the initial time and financial investment if the model will be in use beyond the life-cycle of commercial GIS platforms.

Incorporation of a calibration or validation step would be of significant benefit in terms of quantifying the accuracy of a remote, site-independent modeling procedure. The level of resources devoted to this aspect of the method would depend on the intended use for model output. Conceptual and preliminary planning efforts may receive only marginal benefits from further confirmation of initially mapped wetlands. However, the further quality checks provided by this verification step would allow the model output to be used in later project stages and would reinforce the confidence with which model results are used in early phases.

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# 4

# LITERATURE REVIEW ON ACCURACY OF GIS DESKTOP IDENTIFICATION OF WETLANDS

This section investigates the question “Could desktop identification of wetlands reach a goal of 90% accuracy?” In other words, is it possible to use desktop GIS and remote sensing software to delineate wetlands with enough confidence to reduce risk/cost of regulatory compliance, and to avoid or reduce field verification at the planning phase. Field verification and delineation of wetlands is almost always required by regulators at the permitting stage.

This section will summarize findings from a review of literature focused on identifying research to improve accuracy of desktop wetland identification. Based on the articles reviewed, we identified a few key themes:

- Data source(s),
- Wetland classification approaches and their reliability,
- Commonly used software for wetlands delineation, and
- Recommendations for improving accuracy in wetland classification.

A total of fifteen articles were identified that discuss use of remotely sensed data in wetland delineation, focusing on articles that review the latest research, methods, and technology. Several articles (Mahdavi et al. 2018, Guo et al., 2017, Dronova 2015) provided a synthesis of peer-reviewed research relevant to the topic, while the remaining twelve articles touched on specific topics such as use of UAS and the efficacy of new classification algorithms.

This information could be useful to environmental managers as it provides a clear idea of current practices and their successes for delineation of wetlands using desktop GIS.

## Data Sources

The level of accuracy attained by desktop GIS wetland delineation is dependent on the quality and suitability of data used. The value of a particular dataset can only be assessed based on the spatial scale and objective of the task at hand. Time and costs of data acquisition and processing also play a role in the choice of data source.

Data sources that have been successfully used in desktop GIS wetland delineation include:

**Aerial photographs** - imagery taken from manned vehicles in the air.

**Multispectral satellite data** - multiple bands capture information both within the visible spectrum and often in the infrared and thermal ranges as well.

**Hyperspectral data** - data with very high spectral resolution, where data comes from imaging spectrometers and consists of continuous spectral information, sometimes hundreds of bands. There are satellite, airspace, and hand-held sources.

**SAR data** - Synthetic Aperture and Radar uses the long-range propagation characteristics of radar signals to provide imagery that can be taken at any time of day and is not affected by cloud cover.

**LiDAR data** - Light Detection and Ranging measures distance between the sensor and target. Products have been used in combination with other imagery to improve classification (i.e. Chadwick, 2011). Data has traditionally been collected from aircraft, sometimes collected from UAS as well.

**UAS data** - UAS stands for unmanned autonomous systems and describes multicomponent systems that include hardware and software elements supporting navigation and control for data collection.

See summary of data sources in Table 4-1 below.

**Table 4-1**
**Sources of remotely sensed data frequently used for wetland delineation. Table compiled using information found in Adam et al. 2010, Chadwick 2011, Guo et al. 2017, Mahdavi et al. 2018, Tiner et al. 2015.**

| Data Source | Cost of Acquisition | Pre-processing work | Notes | Example data sources |
|---|---|---|---|---|
| Aerial photographs | High | Usually performed by user | NA | Locally obtained |
| Multispectral Satellite Data | Ranges from free for some low and medium resolution data sources to quite expensive for high resolution data | Imagery often available with pre-processing already performed, saving time and requiring less expertise | Clouds impact image quality, so images must be chosen carefully | LandSat, IKONOS, WorldView |
| Hyperspectral Data | Data can be expensive to obtain | Both pre-processing and processing can be time-consuming and takes a lot of memory due to volume of data | High spectral resolution can be useful when differentiating between different classes of wetlands | HYMAP |
| SAR Data | Some datasets freely available | More time-consuming than for optical imagery | Can retrieve information through clouds and vegetation, unlike optical systems | RadarSAT, ASTER, Sentinel |

**Table 4-1 (continued)**
**Sources of remotely sensed data frequently used for wetland delineation. Table compiled using information found in Adam et al. 2010, Chadwick 2011, Guo et al. 2017, Mahdavi et al. 2018, Tiner et al. 2015.**

| Data Source | Cost of Acquisition | Pre-processing work | Notes | Example data sources |
|---|---|---|---|---|
| LiDAR data | Some LiDAR products, such as medium-resolution DEM, are freely available; high resolution products often need to be purchased or collected by user, which can be very expensive | Some products of LiDAR are available pre-processed | Cannot be used alone, must be combined with other data products. LiDAR and LiDAR products such as DEMs can also be used to roughly predict where wetlands should occur. | DEMs available from USGS |
| UAS Data | Lower than many other methods of obtaining high spatial res data | Data requires pre-processing for geometric correction, and full radiometric correction can be difficult | Images taken below cloud cover means cloud interference is a non-issue. Potential for very high accuracy - 95% accuracy reached in one study (Zaman et al. 2011) | Usually obtained by user |

Often, several of these data sources are combined to identify wetlands. Vector data can also be used alongside remotely sensed data in some analyses to increase accuracy of wetlands identification. Considerations when choosing a data source include spatial resolution, temporal resolution, spectral resolution, cost to obtain data, and pre-processing costs (see cost column of Table 4-1 and summary of resolution properties in Table 4-2). Spatial, temporal, and spectral resolution are defined as follows:

**Spatial resolution** – the smallest feature detected by a sensor, usually the size of a pixel in an image. The spatial resolution of data used must be appropriate for the level of precision needed for the identification. For example, if wetlands need to be classified with a 5 m level of precision at the planning stage, using LandSat data would be inappropriate because LandSat imagery has a spatial resolution of 30 m.

**Temporal resolution** - the time interval between images. Generally, it applies more to satellites, which have a revisit time, than to UAS or aerial imagery, which may be collected at the request of the user. The date and season when data was obtained is also important as wetlands are dynamic and can appear quite different depending on the stage of growth of vegetation and change in water levels from season to season (Gallant, 2015). Though there is no universal optimal date for collecting data to be used for wetland delineation, summer images are typically best, followed by spring and fall (Mahdavi et al. 2018).

**Spectral resolution** - the bandwidth of the bands and the range of wavelengths over which a sensor can receive information (e.g., bands of light: visible, infrared, etc.). It is generally less important than spatial resolution in identifying wetlands, but higher spectral resolution can provide valuable information when differentiating between types of wetlands, as different types of vegetation have different spectral signatures.

**Table 4-2**
**Resolution properties of data sources frequently used for wetland delineation.**

| Data Source | Spatial Resolution | Spectral Resolution | Temporal Resolution |
|---|---|---|---|
| Aerial photographs | Relatively high | Low | Determined by user; generally low |
| Multispectral Satellite Data | Variable; Low, medium, and high available | Medium, most sources will be good enough for wetland identification | Variable; for most sources this is a tradeoff with spatial resolution |
| Hyperspectral Data | Highly variable depending on how data is collected | Very high | Variable; satellite sources often have moderate temporal resolution while other devices collect data only once |
| SAR Data | Varies | N/A | Varies, similar to multispectral satellite data in this regard |
| LiDAR Data | Varies from medium to high | N/A | Usually temporally irregular without planned revisits as data is collected from the air rather than using satellites |
| UAS Data | High | Generally lower spectral resolution than satellite imagery | Usually temporally irregular without planned revisits as data is collected from the air rather than using satellites |

Cost of acquisition is an obvious consideration when determining a data source for wetland identification (Table 4-1). Another consideration is pre-processing time. Often prior to wetlands identification, imagery data must be geo-corrected and radiometrically corrected. Geometric correction simply means to adjust the imagery to its proper location on the earth. Radiometric correction takes the raw digital number values provided by the sensor (satellite, etc.) and converts them to radiance by accounting for sun elevation and solar zenith angle as well as sensor-specific rescaling factors. Some data sources provide higher-level products where this work has already been done (i.e. geometric correction in Landsat Level products), but for others, especially for aerial and UAS imagery, this work will be done by the user and can be extremely time-consuming and challenging for inexperienced users.

## Classification Approaches

The data sources listed above are inputs into desktop wetland identification, which is generally accomplished through a process called image classification, where images are broken into or classified as separate classes (wetlands, developed, barren land, etc.) based on various image characteristics. Imagery is almost always classified using one of two general approaches:

**Object-based Image Analysis (OBIA)** – image is segmented into a series of objects based on their location and then each object is classified based on its properties as well as its context within the image.

**Pixel-based classification** – each individual image pixel is assigned to a class (wetland or not wetland) based on the spectral characteristics of that pixel

Object-based Image analysis (OBIA) was developed specifically to deal with classification of high resolution images (Guo et al. 2017) but has been applied to images ranging from 250 m to .02 m resolution (Dronova 2015). In comparison to pixel-based analysis, it smooths local noise and allows inclusion of non-spectral features (elevation, texture) in the classification process (Dronova 2015. In several studies, object-based image analysis has resulted in a higher classification accuracy than a pixel-based analysis (Grenier et al. 2007, Vo et al. 2013). However, it is not completely automated and requires the user to have sufficient knowledge to make decisions about inputs, including: spatial scale and spectral properties of image data inputs to segmentation, segmentation parameters to generate objects as classification units, object attributes to discriminate among classes, and classification approach and statistical algorithm (Dronova 2015).

## Classification Algorithms

After the level of classification has been chosen (e.g., object-based or pixel-based), a classification algorithm is identified, and the classification is carried out. According to the literature, most classification algorithms used in wetland delineation use machine learning, though rule-based approaches are used as well, and deep learning approaches are being explored. The most common machine learning algorithms used for wetland classification are K nearest neighbors (KNN), Maximum Likelihood (ML), support vector machine (SVM), and random forest (RF) (Mahdavi et al. 2018). Each of these have advantages and disadvantages, and their utility depends on the context. SVM is a nonparametric algorithm that may be useful if the user has a reasonable amount of remote sensing background, because it can reach higher classification accuracy than other algorithms with a smaller amount of training data (Qian et al. 2015). The use of deep learning networks for classification has also been explored, but preliminary investigation shows that they offer improvements over traditional machine learning methods only when the training sample size is large (Liu et al. 2018).

## Software Packages Used

In addition to using leading-edge data sources and classification techniques, it is important to be aware of the software options for implementing wetland identification using remotely sensed data. There are many software packages that have been used to identify wetlands, including open source solutions and add-ons to commonly used GIS platforms such as ArcMap and ERDAS IMAGINE. eCognition is the most commonly used software for object-based image analysis, because it is highly customizable, but choice of software may also be impacted by user familiarity and budget. Table 4-3 gives a list of software that have been used in wetland delineation as identified in Dronova's 2015 review. A current (2019) online search for wetland identification software using remotely sensed data yielded no additional major software packages. However, it did reveal numerous companies, mostly engineering or technology based firms like Upstream Tech, that claim to be able to accurately identify wetlands, though they do not mention software used. This is likely because their software is proprietary or they use customized versions of the software listed in Table 4-3.

**Table 4-3**
**Software packages used in OBIA for wetland delineation**

| Software Used | Description | Cost | User Experience |
|---|---|---|---|
| eCognition | Most commonly used software for OBIA in wetland delineation User can develop custom algorithm sequences that combine segmentation, classification, and other steps | Available for purchase (~$10k) | Fully utilizing customization may take some learning |
| VLS Feature Analyst | Available as a plug-in for ArcGIS and other GIS platforms. Gives a selection of trainable algorithms with analyst reinforcing extraction by selecting correct and incorrect extractions. | Available for purchase (~$5k) | Not too difficult for user familiar with ArcGIS environment. |
| ArcMap using rule-based and thresholding procedures | Uses ArcMap to perform identification based on rule-based and thresholding procedures rather than traditional machine learning algorithms | Available with ArcMap Spatial Analyst license | Not too difficult for user familiar with ArcGIS environment |
| SPRING | Allows integration of vector and raster data in classification. | Open-source | Less user-friendly than some other options, especially for user without experience coding. |
| Objective add-on for ERDAS IMAGINE | Available as an add-on to ERDAS IMAGINE. | IMAGINE expansion pack must be purchased in addition to basic ERDAS IMAGINE software (~3$k) | Not too difficult for user familiar with ERDAS IMAGINE environment. |

## Synthesis of the Literature Relating to Accuracy in Desktop Identification of Wetlands

The goal of selecting the correct data source, classification approach, algorithm, and software for desktop identification of wetlands is to improve the accuracy of the classification, which subsequently will save costs and time for environmental managers in electric utility companies. When done well, desktop classification regularly achieves an overall accuracy over 80% (i.e. Dronova et al. 2015), and often over 90% (i.e. Zweig et al. 2015). If differentiating between classes of wetlands or identifying a particular class is the primary objective, additional research should be conducted, as classification accuracy for each class is not the same as overall accuracy.

### *Methods for improving accuracy*

#### Use an object-based approach over pixel-based

When possible (and expertise is sufficient), use object based-image analysis over pixel-based analysis. Dronova analyzed the results of 61 studies using OBIA for wetland classification and found that there was a mean of 84.6% overall accuracy and a median of 85.9% accuracy for all of the studies, with accuracy values below 85% increasing for studies using more than 4 classes.

### Consider UAS as a data source

UAS can provide high spatial resolution data at a lower cost than high-resolution commercially available satellite imagery (e.g., from Airbus' Pleiades or Digital Globe's WorldView 2 and 3) and can be especially cost effective if the task is general wetland delineation, where a sensor recording only within the visible spectrum can provide sufficient data (Tiner et al. 2015). Classifications using UAS imagery and an objected-based approach have reached overall accuracy above 90% (i.e. Zweig et al. 2015).

### Don't forget about precision

Ensure that the spatial resolution of data is appropriate for the level of precision you are trying to achieve. For example, 30-m resolution data would not be appropriate for identifying wetlands in a transmission corridor, which range from 15-76m (50-250 ft).

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# 5

# MOVING FROM RESEARCH TO TOOL DESIGN: A DISCUSSION AND WIRE FRAME MOCK-UP FOR A WETLANDS IDENTIFICATION TOOL

Initially, we went into this research looking for methods, examples, and tools on the feasibility of achieving 90% accuracy for wetlands identification using desktop GIS. We examined the literature on this question and while not reaching a direct answer, identified commonly used methods for identifying land features using imagery and vector data as well as improving accuracy.

We found and summarized what the research tells us about improving accuracy.

We also found that while there are some add-on and stand-alone software tools commonly used to identify wetlands, the expertise and cost required to use these tools varies greatly.

Something that was beyond the scope of this research was an assessment of the accuracy or functionality of existing tools. Do these existing tools claim/achieve good accuracy? Do they have the functionality and meet the needs of desktop wetlands identification for electric power sector purposes? Based on those questions, is the development of a new wetland identification tool justified?

These are remaining questions that are being investigated in a Phase II of research.

Understanding that those questions are at present unanswered, we pulled together a potential wireframe of a tool – the outlines for how a tool might look and function for the identification of wetlands.

One question that has come up is: Is wetland law too variable to pursue developing a tool? The box below provides background of ongoing changes to the definition of Waters of the United States.

**A note about recent changes to the extent of the "Waters of the United States" (WOTUS)**

In February of 2019 the EPA and U.S. Army Corps of Engineers released a proposed new definition of WOTUS. EPA CWA applies only in areas that fall under the definition of WOTUS, and therefore what is defined as WOTUS affects whether impacts to wetlands would require a §404 permit. The new proposed definition of WOTUS excludes ephemeral streams and wetlands without a surface connection to jurisdictional waters (Environmental Protection Agency: Revised Definition of the Waters of the United States, 2019). Additionally, some states have different definitions of wetlands for regulatory purposes at the state level. A WIT could identify wetlands on an ecological basis (e.g., including Cowardin classification) regardless of Federal or State legal definitions of WOTUS.

While the legal definition of WOTUS may shift one way or another over time, the underlying ecosystem-focused Cowardin classification system for wetlands does not change. Beyond the ecological identification of a wetland could be an additional exercise of determining whether it is legally considered a wetland. Some recent research has pointed out a way of creating ‘scenarios’ roughly linked to potential future legal definitions of WOTUS that could be considered as an add-on to an identification exercise or tool (Meyer and Robertson 2019).

### Wetlands Identification Tool Overview

This section provides a “wireframe”/mock-up for a new tool, a wetlands identification tool (WIT), that could be developed to improve accuracy of desktop wetland identification. Currently, this is simply a high-level, conceptual description of a tool that could potentially be further refined, designed, and developed.

The objective of this WIT is accurate identification of wetlands using an easy to use, customized GIS toolkit.

Accurate identification of wetland areas is achievable through a combination of remote sensing-based, machine learning techniques and vector spatial models that may incorporate weighted overlay analysis that are made available to a user through customized GIS software and tools such as an ESRI ArcMap Extension, stand-alone, custom-built desktop software, or an online, cloud-based interface and toolkit. Using publicly available and/or proprietary data, and by following a series of prescribed steps detailed below, WIT users will be able to identify any type of wetland (based on Cowardin NWI Classification) and subsequently create a spatially and thematically accurate wetland GIS layer for any given area in the U.S.A.

### WIT Data Inputs

Several GIS datasets are needed to run the WIT. While use of all the datasets listed below is not absolutely required, the inclusion of these datasets is highly desired and directly related to the level of accuracy achieved. WIT users will, at minimum, need internet access to obtain and compile the following publicly available datasets for use in the WIT spatial model: (NWI data, SSURGO soils, FEMA Q3, USGS Digital Raster Graphics, National Hydrography Data (NHD), Elevation (DEM), and Land Cover (NLCD).

While not requisite, WIT users will also have the option to incorporate additional datasets into the model to help improve the accuracy of the wetlands identification. Some examples of supplemental data that could be incorporated into WIT are: Public (NAIP Imagery, LiDAR, NWI Plus) and Private (High-resolution satellite imagery [4-band, 8-band, hyperspectral], LiDAR, Air Photos, and ground survey data)

### WIT Workflow

The draft WIT workflow is described below. The workflow is intended to rank areas based on their probability of containing a wetland. This is achieved through a series of vector overlay analyses (weighted suitability) between various wetland probability-ranked vector data layers combined with raster potential wetland data derived from imagery using remote sensing techniques utilizing machine learning algorithms. Prior to overlay, vector data layers are given wetland probability scores (scores could be user defined or pre-defined). Ranked vector layers are overlaid or “unioned” to produce a final potential wetland vector layer containing scores for areas based on weighted overlay of the input vector layers. When available, imagery data is classified into land cover using supervised classification techniques (machine learning) that utilize wetland training samples contained in WIT libraries. The classified raster data is then converted to vector format and unioned with the final vector probability layer. The result is a final ranked wetland probability layer.

**Steps in the WIT workflow:**

1. Area of Interest (AOI) delineated by user
2. Publicly available data compiled for AOI and user directory created
3. Supplemental data added to working directory
4. Data converted to raster and recoded for model input.
5. Run Data Prep Model: clips all data to AOI
6. Run Vector Overlay Model: geospatial weighted overlay model that combines all vector data into one layer and subsequently ranks areas based on their probability of containing a wetland.
7. Run Supplemental Data Models: object-based imagery analysis (OBIA) using machine learning techniques is performed on supplemental high-resolution imagery (spatial and spectral) and subsequently combined with additional layers such as digital elevation models, and normalized difference vegetation index. The output is a wetland land cover raster.
8. Run Final Wetland Probability Model: Vector model output combined with OBIA outputs, resulting in a layer showing areas rank ordered based on their wetland probability.

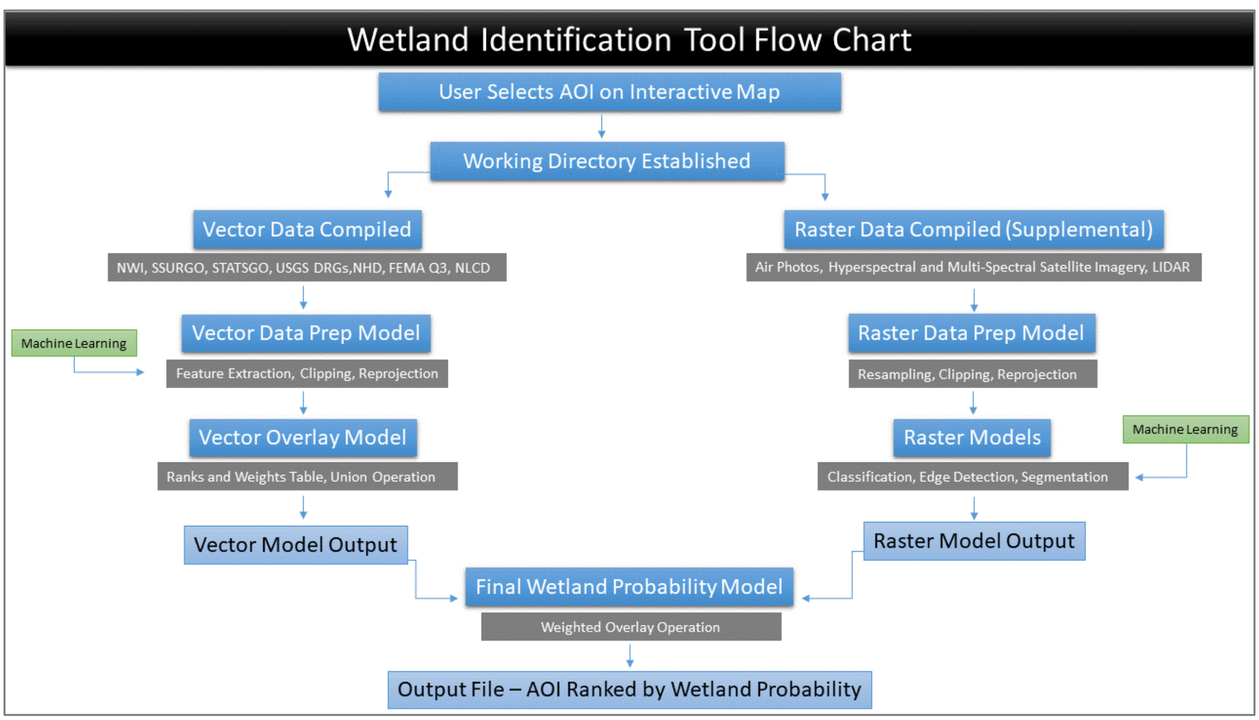


**Figure 5-1**
**Wetlands identification tool flow chart**

## Potential Delivery Systems

WIT could be potentially made available to users through multiple delivery systems, each having their own distinct advantages and disadvantages. Three potential options are listed below. The work flow and outputs for each delivery systems would essentially be the same, with minor modifications as needed.

### *Desktop Extension to ArcGIS*

An ESRI "Add-in" or ArcMap extension is a tool that is manually added to ESRI's ArcMap software and generally contains tools that add functionality to ArcMap. A WIT extension would provide users with a set of python-based scripts, tools, and models that allow users to identify wetlands for any given area. This would likely be the least expensive option to produce yet it limits users to only those who use ArcGIS. This option does not require approval from ESRI and can be freely available or licensed for a fee.

### *Online Web Application*

This option is a cloud-based WIT, where users would visit an online site to conduct their wetlands identification. Tools and data would be hosted by EPRI or the development team on a server, with all GIS processing, data creation and analysis done using ArcGIS Server or other server software. Users would be able to download their identified wetlands data as a shapefile, geodatabase or other type of GIS file. The benefit of this option is that it requires only an internet connection. This option would be costly to develop and maintain and would certainly require ongoing maintenance. However, this option would likely reach more users than any of the other options.

### *Stand-Alone Software*

This is a traditional software development route, where all functionality is bundled and delivered as stand-alone software. The WIT software could be made available through EPRI's website. The cost of this would likely be equivalent to development of an online web application.

## References

Meyer, R., and A. Robertson. 2019. Clean Water Rule spatial analysis: A GIS-based scenario model for comparative analysis of the potential spatial extent of jurisdictional and non-jurisdictional wetlands. Saint Mary's University of Minnesota, Winona, Minnesota.

# 6
# CONCLUSION

This report addressed the following:

- Reviewed an existing desktop wetland identification model/methodology in use by an electric power company and provided recommendations for improvements (Section 3);
- Investigated the question "Could desktop identification get to 90% accuracy?" by reviewing leading-edge research and technology that could improve desktop accuracy (Section 4); and
- Provided a "wireframe"/mock-up for a new tool that could be developed to improve accuracy of desktop wetland identification (Section 5).

Some key findings gathered over the course of research includes the following:

- There are many ways to use geospatial data, maps and GIS software to identify potential wetlands locations within an area of interest. The selection of a method will depend on the scope and size of the project area, the accuracy of delineation required, the familiarity of the team with GIS tools, and the resources available to the project manager (Section 2);
- Some broad categories of GIS-based wetlands identification methods are the following, rank ordered by technical difficulty from lowest to highest: digitizing wetlands, imagery classification, geospatial modeling, or a combination of the methods, which is recommended, if possible (Section 2);
- Selecting the best method for a site depends on several factors: availability of GIS software and skills, data accessibility and relevancy, and staff or financial resources available (Section 2);
- Barriers to implementing GIS-based methods for wetlands identification include lack of GIS expertise, the accuracy of the resulting maps, and the transient nature of wetlands as extents can change from year to year (Section 2);
- The case study (Section 3) provides environmental managers with a working example of how one utility company uses desktop GIS to identify wetlands prior to transmission line siting. The recommended improvements could be helpful for companies reviewing their own current practices;
- There are many different desktop GIS software solutions available for use in wetland identification. Trimble's ECognition, Hexagon's ERDAS Imagine, SPRING and ESRI's ArcGIS Desktop are the most widely used (Section 4);
- While software capabilities and functionalities are not starkly different, the cost and required level of expertise can vary greatly, with Trimble's ECognition and Hexagon's ERDAS Imagine being the most expensive and difficult to use. ArcGIS Desktop, which is easily the most widely used Desktop GIS software in the world, is substantially less costly and easier to use (Section 4);
- According to recent peer-reviewed literature, ECognition is the most accurate and commonly used software for wetlands identification using high-resolution imagery. However, its use

requires the most training and remote sensing knowledge when compared to other software discussed in Section 4 (ArcGIS, SPRING, ERDAS Imagine);

- Object-based Imagery Analysis is the most accurate technique used for identifying wetlands using desktop GIS software. However, this technique also requires the most expertise and expensive software (Section 4).

Siting electric utility infrastructure is an expensive and resource-intensive operation that requires extensive planning before a project commences. The ability to accurately and efficiently identify suitable sites with minimal constraints (e.g., wetlands) is paramount to the success of a project. Identifying wetland locations in the early stages of a project is critical as it can prevent unexpected complications and delays in project siting.

Information provided in this document can serve as a guide to choosing an appropriate method for identification of wetlands using tools available from a desktop computer. This research provides a foundation for scoping and designing a potential new tool or software to enhance desktop wetland identification. Some next steps could include:

- Stakeholder input to identify intended users, their needs &/or use cases, and functionality that this tool could bring above and beyond current data and tools available.
- A comparative analysis of the delineations of publicly available datasets that indicate location of wetlands versus wetland identification via satellite imagery &/or machine learning.
- Ongoing tracking of peer review literature to identify relevant new research in this topical area.

# A
# ADDITIONAL DETAIL OF CASE STUDY UTILITY'S SCORING AND RANKING SYSTEM

The maximum score for each of the three categories is 100; that is, it is 100 for vegetation, 100 for soils, and 100 for hydrology. Once the overall scores per each of these three categories is calculated, they are summed and divided by three to get a final numeric score for each polygon. The numeric score is translated to a categorical ranking and subsequently ranked as follows: Low (0-29), Medium (30-59), High (60-100). The figure below shows the conceptual design of the wetland probability scoring.

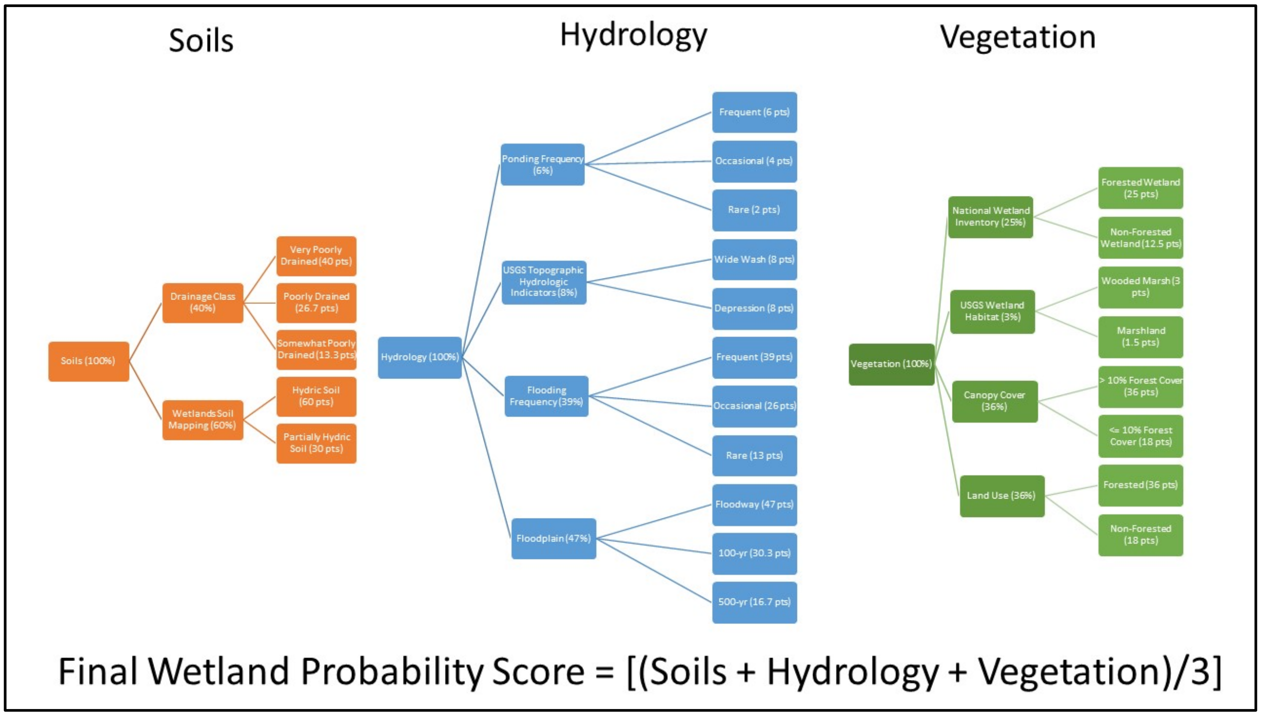


**Figure A-1**
**Wetland probability scoring diagram**

Next, we describe how the calculations within each category—vegetation, soils, and hydrology—is performed. The score for each of the three categories is based on the percentage of total occurrences of different sub-categories within each category. For example, as indicated above, the Soils score is based on two sub-categories; Drainage Class and Wetland Soil Mapping. The Drainage Class scoring weight is 40% because 40% of all occurrences of soil variables in the concatenation table include Drainage Class data. The Wetland Soil Mapping scoring weight is 60% because 60% of all occurrences of wetland soil variables in the concatenation table include Wetland Soil Mapping data. Therefore, there is a maximum of 40 points possible for Drainage Class and 60 maximum points possible for Wetland Soil Mapping, totaling 100 points.

Next, we look within each of the subcategories using the same Soils example as above, with two subcategories of Drainage Class and Wetland Soil Mapping. The possible Drainage Class values and associated scores are: Very Poorly Drained (40 points), Poorly Drained (40/3 *2) and Somewhat Poorly Drained (40/3). The possible Wetland Soil Mapping values and associated scores are: Hydric Soil (60 points) and Partially Hydric Soil (60/2). Scoring for other sub-categories and the associated values are calculated similarly. (That is, sub category percentages based on percent of total occurrences - sub category values are divided equally.) The overall approach is depicted in Figure 3-4 (see Section 3).

# B

# ILLUSTRATION OF A VALIDATION EXERCISE FOR A SUBSET OF CASE STUDY UTILITY'S SERVICE TERRITORY

*Disclaimer: This is a modest and partial accuracy assessment for illustration purposes only. The drawback to this approach is that this approach has not been fully implemented, detailed, or validated. The benefit of this approach is simply to provide an initial level of understanding of what could be pursued.*

## Single Right of Way (ROW)

If we take a look at existing model outputs and field verified data for a single ROW for Utility A, we see that the current model overestimated the wetlands in this particular ROW (Figure B-1). The model predicted fifty-three wetland polygons (8.4 acres of wetland) were predicted to occur in this ROW (Figure B-1C). A ground survey of the same ROW identified two wetland polygons (1.5 acres of wetland) (Figure B-1D). This was a single attempt to verify the model outputs, and more data would be needed to do a similar assessment across the entire work zone.

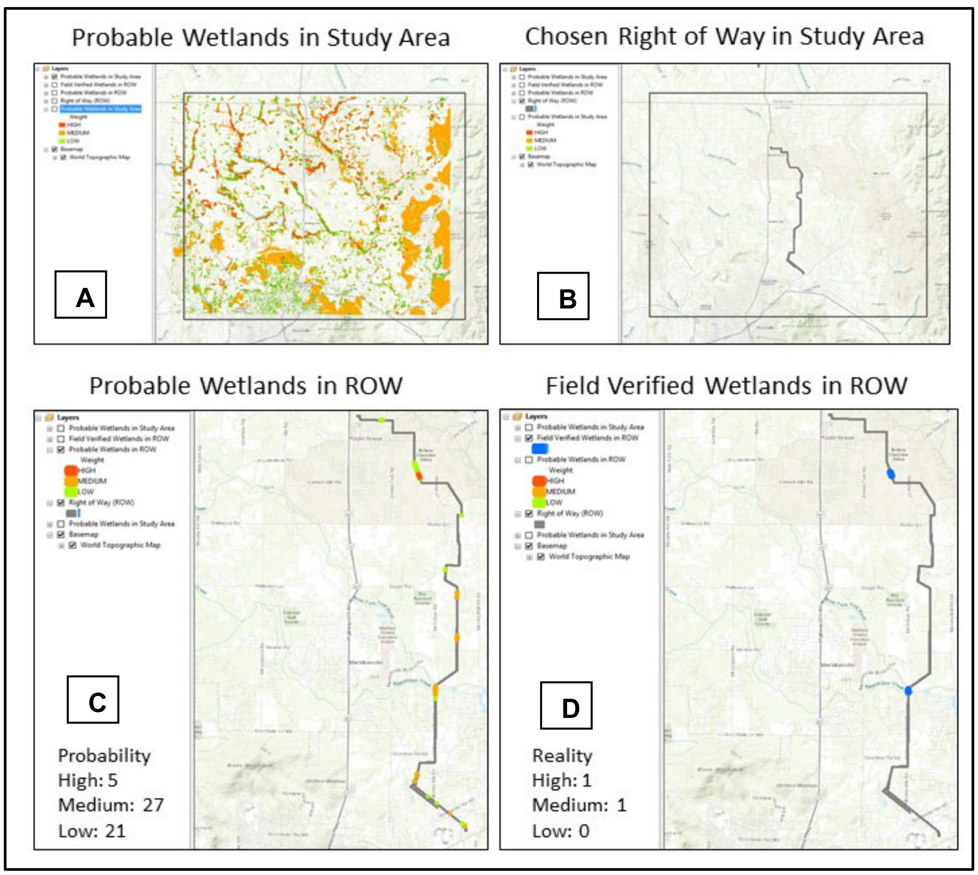


**Figure B-1**
**Estimate of accuracy for one ROW**

## Set of ROWs

Examining results for 30 ROWs for which data was provided, the FWP model predicted roughly 1,305 acres of wetlands, of which the model categorized 103 acres as high probability for being wetlands (Table B-1).

**Table B-1**
**Predicted wetland area for selected ROWs**

| Probability | Number of Polygons | Acres |
|---|---|---|
| High | 316 | 103 |
| Medium | 1,909 | 540 |
| Low | 1,743 | 662 |
| Total | 3,968 | 1305 |

Ground survey for wetlands along these 30 ROWs found only 92 acres of wetlands, of which the surveyors characterized 48 acres as highly probable. Thus, for this attempt to examine 30 ROWs, the model overpredicted both the wetland acreage and the wetland acreage of high probability.

Although these two examples are not fully vetted, they provide an initial indication that the model overestimates wetland presence. Further analysis to explore the overestimation might include understanding what data sets might contribute more to the results, and if data thresholds within the data sets are also contributing.

Utility A might consider conducting a true accuracy assessment as described above in Figure B-1. For example, a series of at least 100 random points would be generated for the predicted wetlands in a given study area (Figure B-2) and then field verification of these random points performed, with the results run through an error matrix to determine the true accuracy of the model.

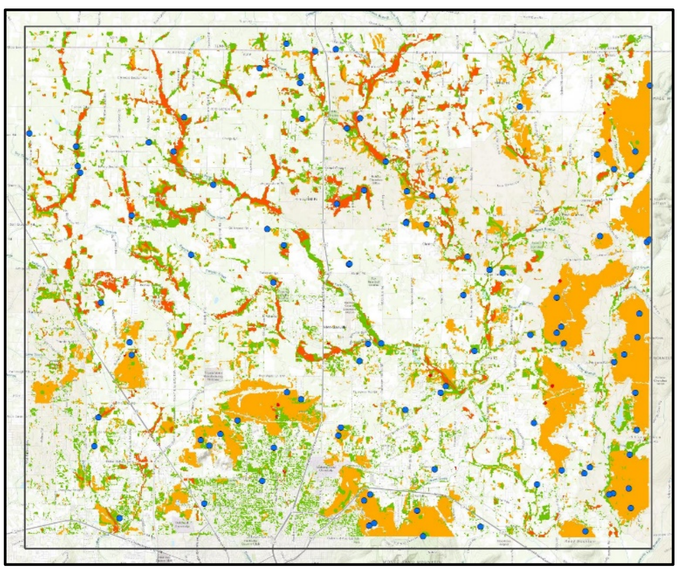

**Figure B-2**
**Example of random points for accuracy assessment**

# C
# ADDITIONAL DETAIL OF RASTER ALGEBRA

As we noted above in Section 3, Conversion of all data to a raster (e.g., pixel-based) format would speed up the model run time and speed of data drawing. It is also a much more accepted form of overlay analysis as it is fast and efficient. There would be no need for concatenation of attributes as the attributes could be converted into numeric representation and combined with the weighted variable using the ArcMap tool Raster Algebra.

For example, each variable (drainage class, flood frequency, etc.) would be converted to a raster and cells in the raster that contain the variable would be assigned a score of 1 and then multiplied by the relative weight to receive a final score per each variable raster, ranging from 0-1. Then, using Raster Algebra, all rasters would be added together and a final overlay raster created. The final raster scores would then be reclassified into low, medium and high probability based on a numeric classifications scheme developed by the wetlands biologist. For example, if there are twenty input variables or rasters, the maximum score would be a 20 for an area. The raster could be classified as 12-20 = high probability, 6-11 = medium probability, and 0-5 low probability.

Here's an example. Soil data has two input variables; Drainage class and Wetland Soil Mapping. Drainage class is worth 40% and Soil Mapping is 60% of the Soils category. Drainage class has three sub categories (Very poorly drained = 40 points, Poorly Drained = 40/3 *2 or 26.7 points, Somewhat Poorly Drained = 40/3 or 13.3 points) and Wetland Soil Mapping has two sub categories (Hydric soil = 60 points and Partially Hydric Soil (60/2 = 30 points). So, if this data was converted to a raster, a raster cell containing Hydric Soils would receive a score of .6, Partially Hydric would score .3, etc. This processing would be extremely fast and efficient. Model conversion from the existing vector framework to a raster framework would likely take a week or two of person hours to achieve but once completed, would save time and effort for future model runs.

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