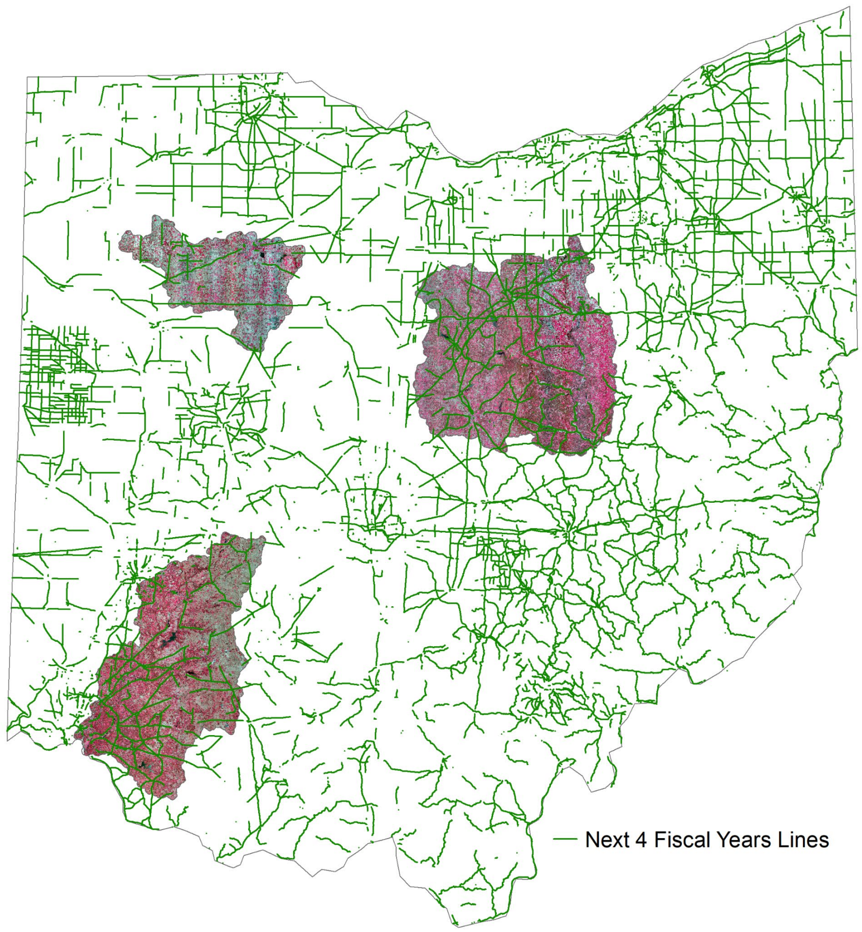
Stream & Wetland Mitigation Forecasting: Developing a Predictive Model for Faster Project Delivery and Cost-Savings



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Wetlands and streams provide significant ecological and societal services. Accurate mapping of their locations is necessary for ODOT to plan for avoidance or mitigation efforts and costs. The National Wetland Inventory (NWI) provides the best nationwide spatial database of wetlands, but the database has not been updated for up to four decades and misses many smaller, vegetated wetlands. To address these problems, we developed a method for identifying wetlands and stream channels from publicly accessible data including aerial images and lidar point clouds. We applied both image classification and terrain analysis to identify potential wetlands and streams in five test watersheds across Ohio. Overall accuracy of the method ranged from 64.5% to 85.6% when compared to known points and decreased with increasing watershed size. With an overlay of project data, we identified potential ODOT projects over the next four fiscal years that could impact nearby streams or wetlands.		
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The faculty and staff within the School of Environment and Natural Resources (SENR) at The Ohio State University holds great respect for the land and original peoples of Ohio. As we strive to honor the resiliency of these tribal nations and recognize the historical contexts that have and continue to affect American Indians, we recognize that we are visitors and hope to become gracious guests that honor Indigenous past, present, and future.

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List of Commonly Used Acronyms

CHM	Canopy Height Model
CIR	Color Infrared, refers to an image that displays the NIR band as the red band
CNN	Convolutional Neural Network
DEM	Digital Elevation Model (interchangeable with DTM)
DSM	Digital Surface Model
DTM	Digital Terrain Model
GEE	Google Earth Engine
GIS	Geographic Information Systems
HUC	Hydrologic Unit Code
LIDAR	Light Detection and Ranging
NAIP	National Agriculture Imagery Program
NDVI	Normalized Difference Vegetation Index
NIR	Near Infrared
NLCD	National Land Cover Database (of the Multi-Resolution Land Characteristics Consortium)
NOAA	National Oceanic and Atmospheric Association (of USDC)
NRCS	Natural Resource Conservation Service (of USDA)
NSRS	National Spatial Reference System (of NGS)
NWI	National Wetlands Inventory (of USFWS)
ODOT	Ohio Department of Transportation
OEPA	Ohio Environmental Protection Agency
OES	Office of Environmental Services
OGRIP	Ohio Geographically Referenced Information Program (of Ohio OIT)
OIT	Office of Information Technology
OSIP	Ohio Statewide Imagery Program
SSURGO	Soil Survey Geographic Database (of NRCS)
TIMS	Transportation Information Mapping System
USACE	United States Army Corps of Engineers
USDA	United States Department of Agriculture
USDC	United States Department of Commerce
USEPA	United States Environmental Protection Agency
USFWS	United States Fish and Wildlife Service
USGS	United State Geological Survey

Problem Statement

Wetlands and surface water bodies were once a dominant feature across the landscape in Ohio with the Great Black Swamp covering much of what is northwestern Ohio today. Although the coverage of these features has drastically diminished in the past two centuries (Fretwell et al. 1996) the ecosystem services that they provide are innumerable. Wetlands provide habitat for endangered species, regulate stormwater runoff, and provide water purification services in agricultural areas. Indeed, some researchers believe that restoring the Great Black Swamp would solve the algal bloom issues in Lake Erie (see Mitsch 2017). Streams also provide benefits in the form of habitat, recreation, food (fish), and as a source for municipal water. It is for these reasons and more that wetlands and streams are protected under sections 404 and 401 of the Clean Water Act and the Ohio Isolated Wetlands Law (Ohio Revised Code 6111). These regulations require permits when fill material is discharged into regulated streams and wetlands, which also can require compensatory mitigation.

Permitting and mitigation efforts are often time-consuming and, depending on the quality of resources and quantity of impact, require review and approval from the US Army Corps of Engineers (USACE) and/or the Ohio Environmental Protection Agency (OEPA). Additionally, identification and boundary determination of a jurisdictional wetland requires vegetation identification and inspection from US Army Corps personnel *during the growing season*. The overall permitting process could take months to years to complete. Credits can be purchased from mitigation banks or in lieu fee providers within the impacted watershed to offset impacts to streams or wetlands, but credits are not always available in the timeframe or location needed and can be difficult to identify ahead of time. The credits required to offset impacts to wetlands and streams are determined by the size and quality of the wetland or stream and often this is unknown until field verification occurs. If existing mitigation credits are not available, the cost and complexity of mitigation becomes much more significant (Koncelik, 2020).

Road construction and maintenance projects can impact a wetland or stream through a variety of activities, such as culvert or bridge installation, new road construction, temporary access, rock channel protection, and building retaining walls. To mitigate these disturbances, the Ohio Department of Transportation (ODOT) often secures mitigation credits within a project's watershed. Project construction cannot begin until impacted streams and wetlands are identified, permits have been obtained, and mitigation is secured; thus, the mitigation process can result in substantial delays in the Project Development Process (PDP). In addition to planning timelines, ODOT plans ahead for project costs within budget periods. For ODOT to develop accurate budgets, mitigation requirements and costs (including mitigation credits or need for a new mitigation site) must be identified. Projects within the revolving four-year plan are chosen with regard to many factors, stream and wetland mitigation among them, but because waterway permitting and mitigation efforts can be so costly and time consuming, they must be identified early in the PDP.

ODOT has previously made efforts to predict mitigation needs of the four-year plan by using data available in ODOT's Transportation Information Mapping System (TIMS); however, this method does not incorporate environmental factors such as topography, soil type, or vegetation but instead relies on the number of past mitigation efforts in the watershed as well as information on the mitigation bank and in lieu fee credits available within the project watershed, size of the watershed, and land use within the watershed. This method is limited and does not provide the level of detail needed for ODOT to predict future mitigation needs with much clarity.

A GIS-based analysis method that could quickly and remotely forecast the location and boundaries of streams and wetlands would be of great benefit to ODOT. A methology that would aid in the planning of the budget and timeline of projects, as well as identifying watersheds that will require large mitigation efforts for advanced credit purchasing is desired. Such a tool would provide cost and time savings to ODOT for not only the current four-year planning period but would continue to be of use as it is updated with future remotely sensed data.

Research Background

Traditional wetland delineation requires the on-site inspection of soils, vegetation, and hydrology. This process was originally described by Cowardin et al. (1979) and their classification of types of wetlands is still used today. Presently, a wetland is identified and delineated using the 1987 *Corps of Engineers Wetlands Delineation Manual* and the relevant regional supplements (US Army Corps of Engineers 1987, US Army Corps of Engineers 2010). This method requires on the ground determination of soil type, vegetation species (during the growing season), and hydrologic features. The protocol for steam assessment varies by state and in Ohio it is determined by OEPA guidelines.

The National Wetlands Inventory (NWI) of the USFWS is a common preliminary tool used to identify the locations of wetlands. The NWI was developed using the traditional field indicators for wetlands of hydrophytic vegetation, hydric soils, and hydrology as identified by visual interpretation of high-altitude aerial photography at a large spatial scale. Although the tool has a high accuracy rate for identifying wetland location (90% and greater as reported by Kudray and Gale 2000 for forested wetlands in Michigan), it is known for conveying inaccurate wetland boundaries (Matthews et al. 2016), possibly due to differences in scale and spatial resolution, and studies have found that the NWI completely omits 84% to 90% of smaller, isolated forested wetlands and almost all agricultural wetlands (Hodgson et al. 2017, Stolt and Baker 1995). Furthermore, the maps used to create the NWI for many regions in the country are outdated, with the original imagery taken in the early 1980s. In 2008, Ducks Unlimited updated the NWI for Ohio using digital orthophotography from 2006-2007 collected as part of the Ohio Statewide Imagery Program (OSIP; Ducks Unlimited 2008). However, even these data have become outdated in areas with rapid land development. A final complication is that the NWI maps have a target mapping unit which is defined as the estimate of the minimum sized wetland that should be consistently mapped. The target mapping unit varies by location due to aerial photography used, wetland type, and funding available during the development of the specific map (Tiner 1997). These differences can create huge discrepancies in the coverage of wetlands shown in neighboring maps.

While field surveys provide the most accurate wetland identification, they are usually costly, seasonal, time-consuming, spatially limited, and less practical in remote areas. Methods and tools that use remote sensing can aid in the delineation process for wetlands and identify probable stream location. Aerial imagery can identify changes in vegetation, digital elevation models (DEMs) can determine locations of topographic concavity, and the return of wavelengths from Light Detection and Ranging (lidar) can distinguish locations of surface water. In addition, online databases can provide information on soil type for specific locations. Improving the mapping of wetlands has been the interest of wetland scientists for decades (see Guo 2017, Mahdavi 2018, Ozesmi and Bauer 2002, Rundquist 2001).

To be a jurisdictional wetland under the Clean Water Act, a wetland area must have adequate hydrology, hydric soils, and hydrophytes. Remote observation of soil properties is challenging, and thus existing studies usually focused on wetland hydrology and vegetation communities. Wetland hydrology refers to visual evidence of surface inundation at some point in time and can be observed remotely by open water, water under canopy, or saturated soil conditions (Schlaffer 2016).

Open water is relatively easier to identify by the near-infrared band in multispectral sensors. Inundation under canopy is challenging to identify, but radar remote sensing can help to some extent (e.g., Schlaffer 2016). Mapping soil moisture is also possible with radar sensors (e.g., Jensen et al. 2018). Hydrophytes can be mapped either as broad categories such as forest, scrub-shrub, and emergent, or as individual species depending on the available spectral information (e.g. Jacome et al. 2013, Townsend and Walsh 2001, de Almeida Furtado et al. 2016).

Recent advancements in image processing techniques and data availability allow for more insights to this discipline. There is not a unique way of mapping wetlands, but supervised image classification is a common method (Mahdianpari et al. 2020). Open access to satellite data including Landsat and Sentinel has also contributed to the development of recent wetland mappings. Recent studies often combine optical, radar, and topographic data for a more comprehensive observation of wetland hydrology and vegetation (e.g. Mahdianpari et al. 2020, Wu et al. 2019, Du et al. 2020, Morandeira et al. 2016).

The rapid growth in resolution and quality of aerial imagery has increased the difficulty of image analysis. Unlike multispectral sensors, aerial images usually only contain three (red, green, and blue, RGB) to four bands (RGB + near-infrared, NIR). The compromised spectral information may not allow for detailed hydrophyte identification. However, they have value in identifying small and isolated wetlands which are typically ignored by satellite data (e.g. Wu et al. 2019, Lang et al. 2013).

Encouraged by the technological advancements in this field, regulatory agencies have more recently become interested in remotely predicting the location of wetlands and stream channels. Indeed, Departments of Transportation for individual states have started to develop their own tools. The North Carolina Department of Transportation developed a regression-based model using 12 variables including soil, topography, and land use, and used Random Forest, a machine learning algorithm, to improve the prediction results (Wang et al. 2015). Maryland, Mississippi, and Colorado Departments of Transportation have all developed GIS tools or methods to identify and map wetlands based largely on satellite imagery and aerial photography for land cover, land use, and digital elevation.

A study supported by the South Carolina Department of Transportation (SCDOT) adopted a slightly different approach from many other states. Rather than directly classifying spatial attributes into wetland classes, SCDOT combined three existing layers—wetlands (NWI), soils (SSURGO), and land cover—to generate a wetland likelihood map using a weighted bookkeeping method, improving the NWI data accuracies from 51% to 83% (Hodgson et al. 2017). Their results highlight the large uncertainties in NWI as well as the values of combining several imperfect maps to a better map. Their research particularly emphasizes the value of high-resolution imagery and lidar to characterize certain types of wetlands.

We have highlighted many of the methods and products currently used to remotely identify wetlands and stream channels; additional results from the literature review can be seen in Appendices A and B. While most recent wetland mapping studies still focus on satellite images, we contend that automatically classifying aerial images provides more meaningful spatial details for transportation agencies. Furthermore, cloud free aerial imagery collected in the early spring is widely available.

The overall goal of this research was to provide ODOT with a GIS-based methodology that can more accurately predict the location of wetlands and streams within an eight-digit Hydrologic Unit Code (HUC) watershed in Ohio to aid in avoiding impacts to these resources as well as planning and budgeting for mitigation efforts. This study improved on the work done for SCDOT by going beyond the rule-based combination of multi-sourced wetland maps to directly ingest high-quality lidar and aerial photos into the refinement and correction of NWI wetland products and overlaying these results with ODOT's four-year plan. Our specific objectives and tasks to meet this goal were to:

1. Evaluate the existing tools and methods for mitigation forecasting used by other researchers and agencies with a thorough review of recent literature pertaining to the remote identification of wetlands and stream channels (Task 1).
2. Develop a GIS-based methodology, or tool, to remotely identify wetlands and streams using existing watershed-specific data regarding soil properties, surface topography, vegetation, and surface water bodies. To meet this objective, we first gathered and processed available data (Task 2) and then used established methods and developed new processes to analyze the data (Task 3).
3. Validate and refine the new tool using existing wetland delineation maps, including NWI, and ground-truthing the locations of remotely-identified wetlands and streams (Task 4).
4. Determine the wetlands and streams that could be impacted by ODOT projects within the four-year planning period and that will require mitigation (Task 5).
5. Mentor key ODOT employees on the use and upkeep of the new tool and disseminate the results of this research via presentations and publications (Task 6).

Research Approach

Literature Review

Using keyword searches in research databases including Web of Science and TRID (Transport Research International Documentation) we identified relevant refereed publications and gray literature. We limited our search to recent (past decade) publications to identify methods that use current databases and methodologies. We assessed the strengths and weaknesses of the methodologies of each publication and identified the specific aspects that we felt were appropriate to the objectives of this research. We created a searchable database of the findings in Microsoft Excel (Appendix A). We used the findings from the literature review regarding the specific data requirements, methods, and tools identified in other research to guide the development of a methodology for this project.

Tool Development, Test Study Sites

We selected five watersheds in Ohio to guide the development of our remote sensing methods for wetland classification and stream extraction. These watersheds were selected to represent a range of land use and land cover in Ohio and be easily accessible for ground truthing efforts. Four of the watersheds (Mohican, Walhonding, Blanchard, and Little Miami) were analyzed at the HUC 8 level while the fifth (Thomas Ditch – Little Darby Creek) was analyzed at the HUC 12 level (Figure 1).

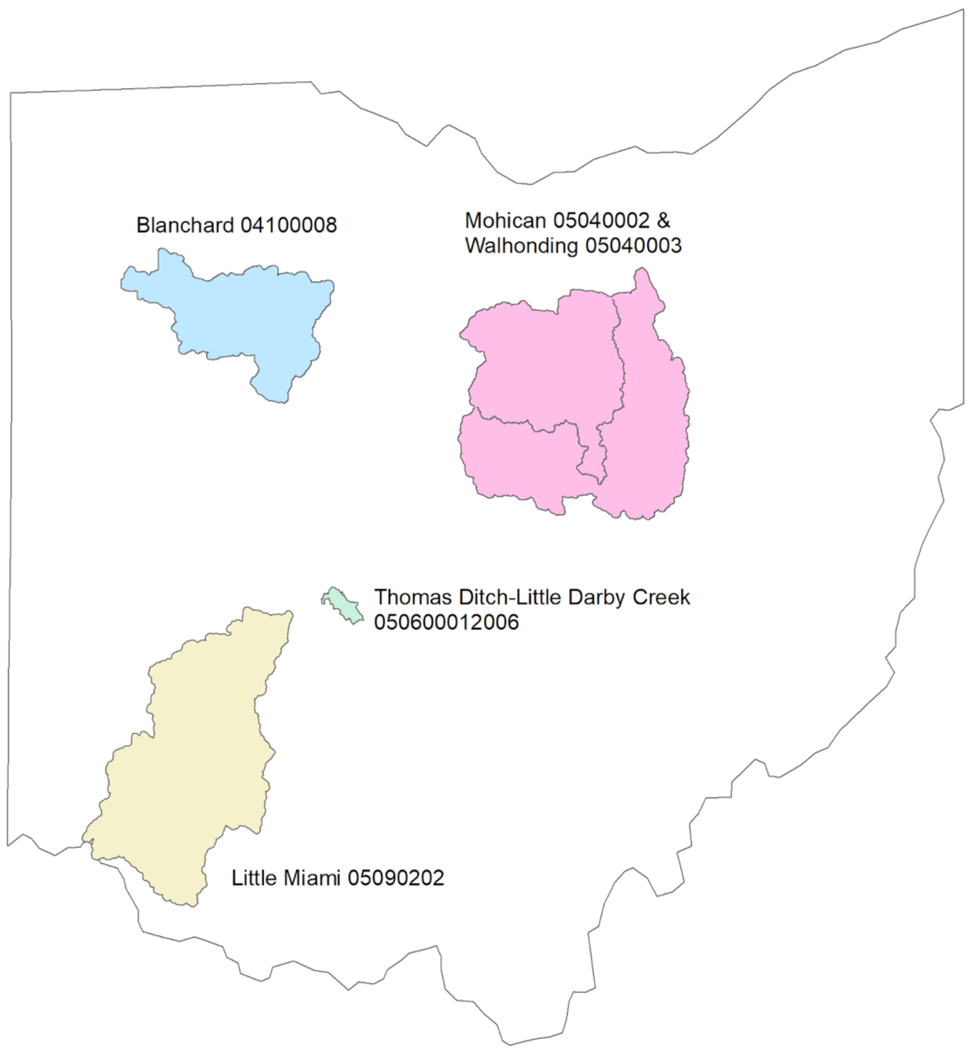

Figure 1. Location map of the test watersheds and their associated hydrologic unit code (HUC).

Data Collection and Analysis

Remote identification of stream channels and wetlands used both imagery and lidar data. In all test watersheds, we began the analysis with the three-band color-infrared (CIR) aerial images that were collected during the Ohio Statewide Imagery Program (OSIP) Phase I (2006-2010). These leaf-off images show the difference between forested wetlands and forested uplands because the former appear darker. For some watersheds, we also included a three-band true color image collected during the OSIP Phase III which captured recent land cover changes (Table 1). Sentinel-2 images were only included in the Thomas Ditch – Little Darby HUC12 watershed (Xu et al. 2022). Meanwhile, we derived a digital elevation model (DEM) and a digital surface model (DSM) from lidar point clouds. The DEM (topography) was created by the triangulation interpolation method from ground returns only and was used to extract stream channels. The DSM captures the highest elevations of the surface and typically represents either the highest vegetation elevation or ground elevation. Thus, the difference between DSM and DEM gives the canopy height information, known as canopy height model (CHM). Canopy height information is helpful in separating forested wetlands and non-forested wetlands (Xu et al., 2018) and was combined with other spectral bands for the image classification. Texture information was added to the input bands. First, we conducted principal component analysis (PCA) of the spectral bands and picked the top three principal component (PC) bands which usually contain the majority of information. Next, focal standard deviation was calculated using a moving circle with the radius of 3 m across the entire study site. The three standard deviation bands were then added to the original spectral bands as the classification input (Table 1). All images and lidar derivatives were sampled to 1 m spatial resolution.

Table 1 Watershed characteristics and methods used for wetland classification in each watershed.

Watershed & HUC	**Area (km^2)**	**Method**	**Bands**
Blanchard 04100008	1999	RF, 5 classes	CIR (3), NDVI (1), CHM (1), PCAStd (3)
Little Miami 05090202	4553	RF, 5 classes	CIR (3), NDVI (1), CHM (1), PCAStd (3)
Mohican 05040002 & Walhonding 05040003	5843	RF, 6 classes	True Color (3), CIR (3), NDVI (1), CHM (1), PCAStd (3)
Mohican 05040002 & Walhonding 05040003	5843	RF, 5 classes	True Color (3), CIR (3), NDVI (1), CHM (1), PCAStd (3)
Thomas Ditch – Little Darby 050600012006	94	CNN, 7 classes	True Color (3), CIR (3), NDVI (1), CHM (1), Sentinel NDVI (1), Sentinel NIR (1)

Note: RF = random forest, CNN = convolutional neural network, CIR = color infrared, NRI = near infrared, NDVI = normalized difference vegetation index, CHM = canopy height model. PCAStd is calculated as the focal standard deviation of the first three principal components of the above spectral bands, with the focal radius of 3 m. Numbers in parentheses denote the numbers of bands. See Xu et al. (2022) for the details of the Thomas Ditch – Little Darby *watershed classification, which included shadow as an additional (7^{th}) class.*

Supervised image classification was used for wetland extraction. Five to seven classes were defined: forested wetland, emergent wetland, open water, forested upland, non-forested upland, developed land, and shadow (Table 1). Shadow was only included in the analysis of the Thomas Ditch – Little Darby HUC 12 watershed (Xu et al., 2022). Emergent wetlands are not common in some watersheds, so the Blanchard and Little Miami only included five classes (without shadow and emergent wetland). We used random forest (RF) as the default classifier. This is a common method that has been adopted by numerous recent studies (Mahdianpari et al., 2020). For the Thomas Ditch – Little Darby watershed we used convolutional neural network (CNN); a deep learning classifier. Both classifiers were implemented in MATLAB software (The Mathworks, Inc.).

To automatically extract stream channels, we used the classic D8 algorithm which is based on topographically driven flow direction and flow accumulation and determines channel networks across a landscape (see Garbrecht and Martz, 1997). The input for the D8 is the digital terrain model (DTM) of the complete watershed from the headwaters, and the output is a channel network. The D8 algorithm has been validated in numerous studies in natural channels except in landscapes with very low elevation gradient (Xu et al., 2020). Dependent upon the size of the threshold drainage area, the D8 algorithm can extract all drainage channels including roadside and agricultural ditches. These drainage features are not considered as streams for regulatory purposes and therefore the results of the D8 algorithm will be hereafter be referred to as "channels" rather than "streams" to differentiate. The threshold drainage area represents the largest area that could drain to a single starting point for a headwater stream. A threshold drainage area of 10^4 m^2 was chosen because the channels identified by this value generally agree with the streams visible on the imagery. Bridges and culverts were identified on the aerial imagery and were burned onto the DTM for hydraulic enforcement. The raw output of the channel extraction is a single-pixel wide raster map. We improved the mapped result by setting the channel width as two times (unit: meter) the Strahler stream order (where headwater streams have a Strahler value of 1 and downstream of every junction of tributaries the Strahler value increases by 1). The result is a binary raster map which includes pixels of channels and non-channels.

Sample Selection, Field Verification, and Accuracy Assessment

Within each test watershed we remotely identified wetland sample points through visual inspection of high resolution, leaf-off aerial imagery from Google Earth. During the growing season, we field verified these wetlands by performing "quick wetland checks" that determined hydrologic features, vegetation species, and, when needed, soil type and features. The purpose of the quick checks was not to delineate wetland boundaries but to confirm the presence of a wetland at each sample point. In addition, we field verified the presence of a selection of streams and wetlands that were identified by the NWI within each test watershed (Figure 2).

The training and testing samples for wetland classification were separately selected. For the image classification, we first selected forested wetlands based on the NWI. All forested wetland polygons were assigned a random number and were ranked from smallest to largest in area. From the polygon with the smallest value, we either confirmed it as a wetland sample or discarded it if it could not be confirmed on imagery. Once the confirmed samples reached twenty (or another desired number), we stopped the selection and discarded all remaining polygons. The same procedure was used to collect emergent wetland samples, though in some watersheds emergent wetlands are not abundant and therefore not defined as a class. For the classes except forested and emergent wetlands, training samples were manually selected across the study site. This is because those classes are easier to identify on imagery.

The testing samples first included all field validated wetland points. Those samples typically focused on forested and emergent wetlands, because they are usually difficult to be confirmed remotely. The field surveys were conducted in June through September, 2021. Wetland hydrology, soil condition, and hydrophytes were assessed to confirm each wetland sample. For each studied watershed, an equal number of upland sample points were randomly generated. The upland points were determined remotely by comparing CIR image, NWI, and other sample points. After combining the wetland and upland points, a circle with the radius of 3 m was generated around each point in order to generate more testing sample pixels. The testing samples were then compared to the binary classification maps to calculate the accuracies.

The accuracy was calculated by Equation 1 below. Here *N* is the total number of all testing samples. N_{ii} is the number of correctly classified samples for class ***i***. We only conducted the land use / land cover accuracy assessment for the Thomas Ditch – Little Darby HUC 12 (see Xu et al. 2022). For the four HUC8 watersheds, we combined the classification map and channels to a binary classification (wetland and upland) and calculated accuracies for the two classes.

$$Accuracy = \frac{\Sigma N_{ii}}{N} \text{ (Equation 1)}$$

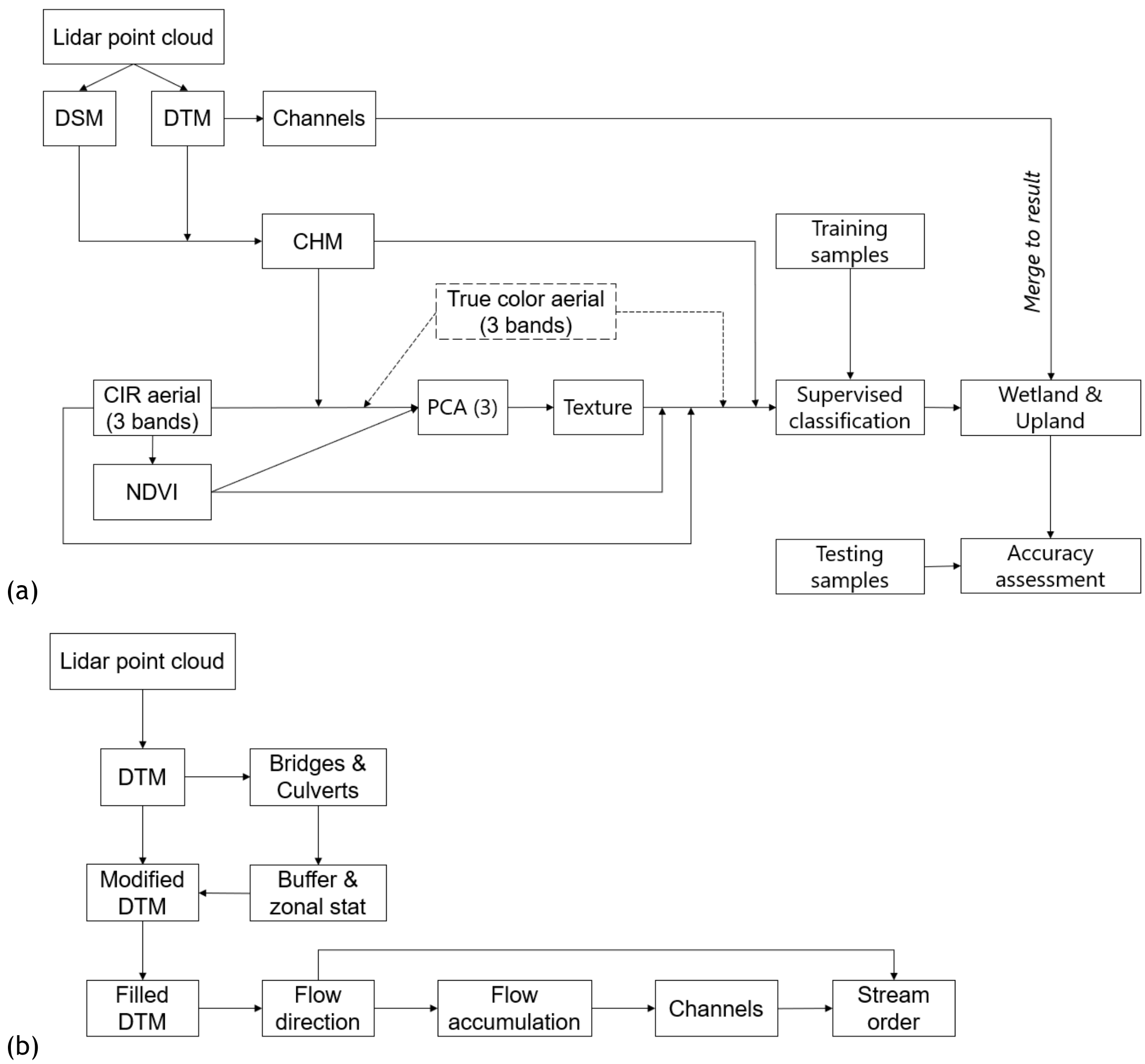

Figure 2. Flowcharts of the methods used in this research. (a) Flowchart of the image classification. The dashed box for true color aerial imagery is an optional input. (b) Flowchart of the topography-based channel extraction.

Integration with ODOT four-year plan

The combined maps of classified wetlands and extracted channels and the ODOT four-year plan were used to predict future impacts to wetlands and streams. Ideally, the future project layer would include the road centerlines and two attribute fields, the number of lands and the functional class. With such information, accurate projected areas (polygons) can by automatically created (e.g., Hodgson et al., 2017). However, the ODOT four-year plan layer currently only provides centerlines and so we conducted a simpler analysis with the assumption of a fixed road width, 50 m buffer distance from the centerlines. The entire buffer polygon is considered as new construction area.

The combined wetland and channel maps were then clipped by the buffers. Wetlands and channels within the buffers are considered potential impacts. However, due to the uncertainty (misclassification) in the wetland maps, we do not recommend interpreting the impacts at the pixel scale but at the focal or zonal scale. Specifically, we detected the impact hotspots 1) focally with a moving window and a user-defined radius and 2) zonally within each project buffer.

Research Findings and Conclusions

Literature Review

We identified over sixty publications in which the researchers identified wetlands or open bodies of water including streams from remotely sensed data. We documented the landscape type, sources of data, main methods utilized, and other noteworthy features of each publication in a searchable database. A snapshot of the search function of this database is shown in Appendix A and the macro-enabled file was delivered to ODOT. We also identified land features in the literature such as slope, wetness, texture, etc., that were extracted or derived from remotely sensed data and organized these features by source of data and method of extraction (Appendix B). From this meta-analysis, we determined that using both lidar and optical imagery was important for remote stream and wetland identification. While there was no standard method for computer-based identification of wetlands, supervised classification of optical imagery, mainly satellite imagery, was the most common method used in the literature and provided good results. Vegetated wetlands, whether classified as emergent, scrub-shrub, or forested, were found to be the most difficult wetlands to identify remotely. Additional research showed that deep-learning methods such as Convolutional Neural Network (CNN) could improve classification results for wetland identification.

Channels and Wetlands at Test Watersheds

The combined analysis of lidar and optical imagery with the methodology presented in Figure 2 above resulted in maps with the location of wetlands (emergent, scrub/shrub, and forested combined) and channels within each test watershed. These results are shown in an overview map of Ohio in Figure 3 below and in more detail for each watershed in Appendix C. The wetlands that were identified by this process were dominated by forested wetlands located mostly in the floodplains of stream channels. Emergent wetlands were less common but found throughout the study watersheds. The extracted channels were consistent with streams identified by the NWI and/or the USGS Stream Stats online tool in each watershed and, in addition, included smaller channels such as field drainage ditches and headwater tributaries.

Field verification

Through the growing season of May to October 2021, 311 sites within the test watersheds were visited to confirm the presence or absence of a wetland or channel. Site characteristics and photographs were recorded using ArcGIS Collector Classic phone app (Esri). An example data collection form is shown in

Appendix D. Of the 311 sites, 194 were verified as wetlands, 68 were channels, 6 were ponds, and 12 were identified as upland (not a wetland) land cover. In addition, 17 sites were noted as locations where NWI had indicated the presence of a wetland, but we did not find wetland indicators on site; often these were locations that had been developed with parking lots, structures, or lawn. The field verified sites were used for both the training and testing samples in the classification analysis. Separately, nearly 1000 sample points were chosen by remote inspection of leaf-off, high resolution imagery by our wetland delineation expert. These points were combined with the field-verified samples and used as testing samples for an accuracy assessment.

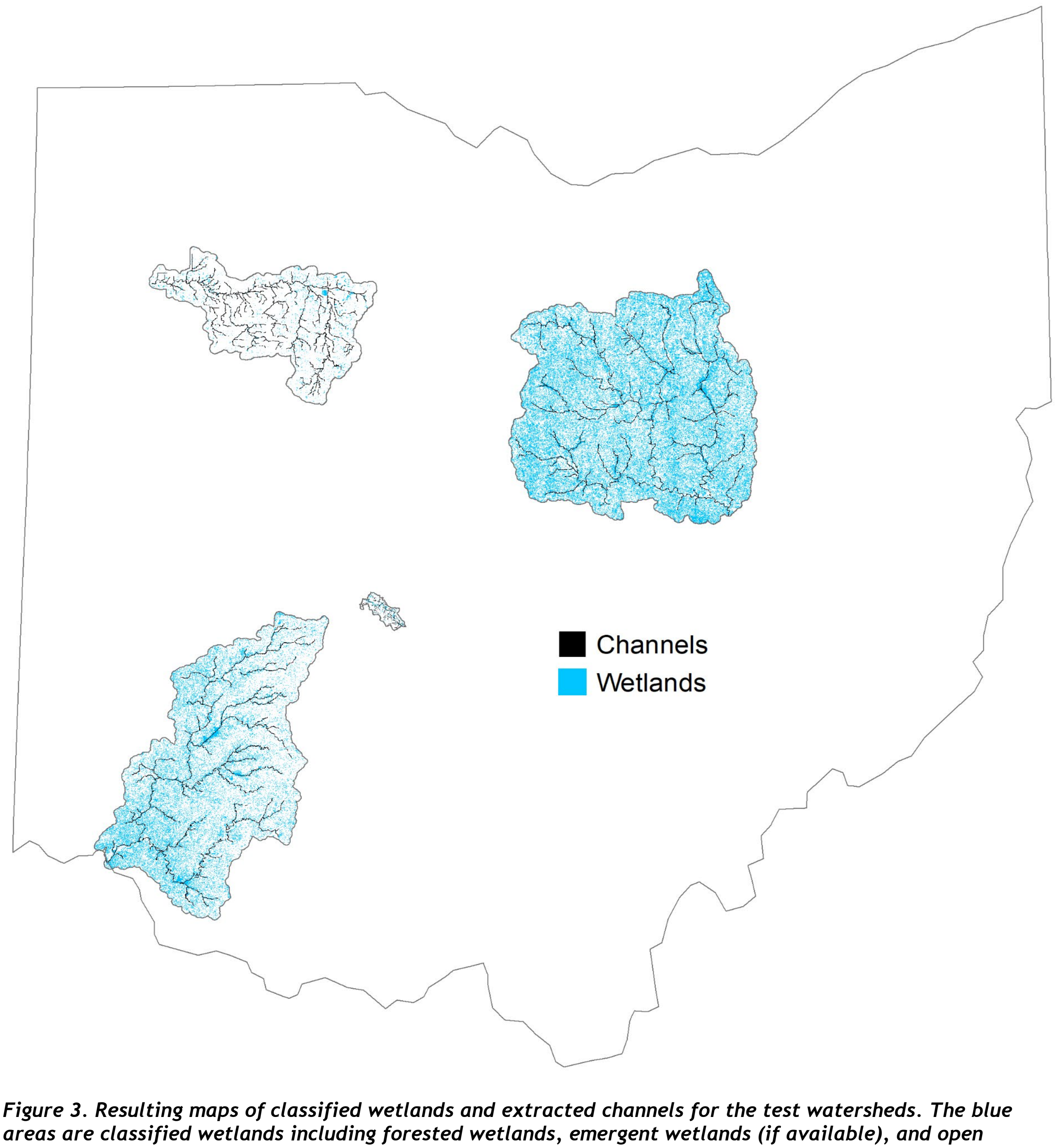

Figure 3. Resulting maps of classified wetlands and extracted channels for the test watersheds. The blue areas are classified wetlands including forested wetlands, emergent wetlands (if available), and open water. The black lines are extracted channels based on lidar topography. Channels with low Strahler orders are not displayed but are included in the detailed maps (Appendix C).

Comparison with Existing Data

Our method mapped significantly more vegetated wetlands than provided by NWI within our test watersheds. In the Thomas Ditch-Little Darby Creek watershed our procedure identified 5.1 km^2 forested wetlands while NWI only provided 2.9 km^2, giving an increase of 76% in area. Figure 4 visually describes the discrepancies between the NWI and the results from our procedures at a site located west of South Charleston, Ohio. In an agricultural area in the northern reaches of the Little Miami watershed, small wetlands have been left unfarmed or conserved as vegetated areas. These fragmented areas are easy to identify as dark patches with the CIR imagery from OSIP Phase I due to increased soil moisture (Figure 4b) and thus our process that relies on spectral differences within the CIR bands classifies them correctly (Figure 4a). When compared to the NWI information provided for the same area, we can see how many of these smaller, vegetated wetlands are omitted by the NWI (Figure 4c).

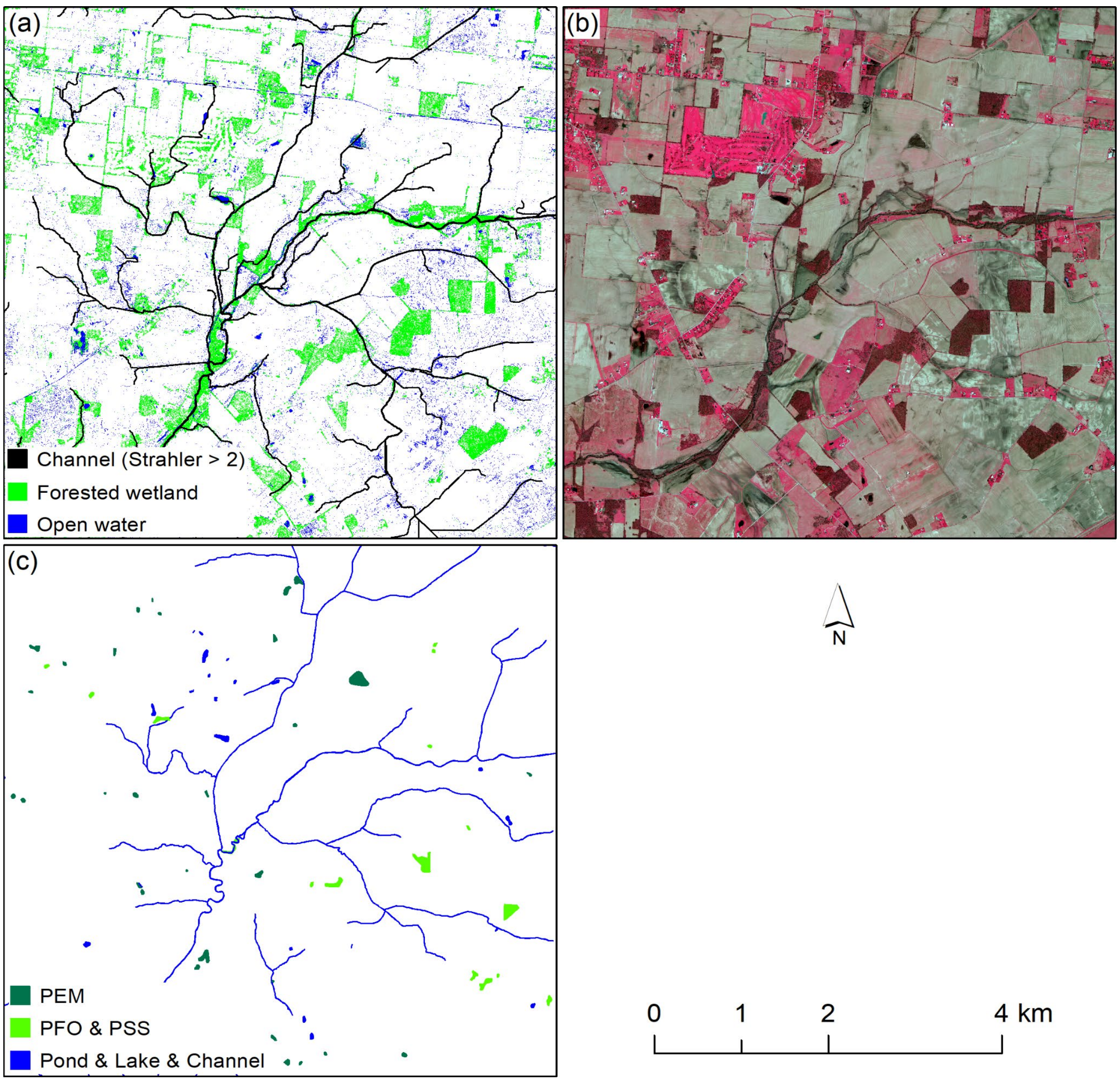

Figure 4. Mapping vegetated wetlands omitted by NWI. This site is located west of South Charleston, Ohio, in the Little Miami watershed. (a) Predicted wetlands and extracted channels. (b) CIR image from OSIP Phase I. (c) NWI wetlands and channels.

Our method also mapped significantly more channels than provided by either NWI or the USGS Stream Stats online tool. In the Thomas Ditch – Little Darby watershed alone our methods extracted 181.8 km of additional channel length within the watershed over NWI, giving an 168% increase in channels. The additional channels are a combination of low Strahler order streams, irrigation or drainage ditches for agricultural areas, and roadside drainage. Any of which could become captured streams if located within a road project area or regulated channels as the definition of these resources is continually revised. An example is given in Figure 5 at an interchange east of Mansfield, Ohio. At this location our methods extracted a channel that originated in an agricultural field, flowed alongside the south-bound lanes of Interstate 71 for approximately 225 m, crossed under the interstate and eventually flowed into a larger order stream. Our ground truthing efforts verified the path of this channel. In addition, in some locations our method corrected for recent changes in stream location for higher order streams due to development or other land use change.

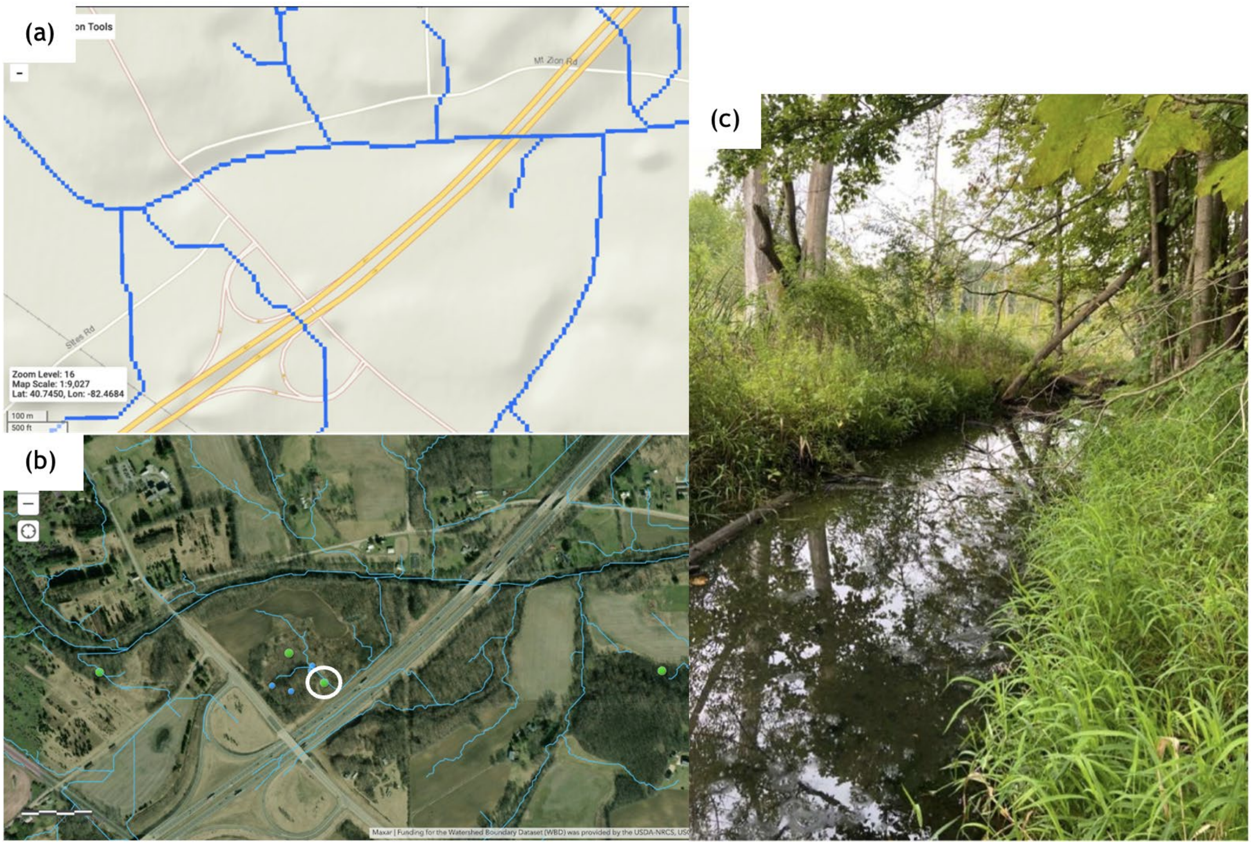

Figure 5. Comparison of extracted channels with streams delineated by the USGS Stream Stats online tool near an interchange at Interstate 70 and State Highway 39 east of Mansfield, Ohio, in the Mohican watershed. (a) Output from streamstats.usgs.gov for streams at this location. (b) Extracted stream channels and field sample points. (c) Existing channel at circled sample point in 5b.

Accuracy Assessment

The accuracies, based on our independent testing samples, span a wide range from 64.53% to 85.60% (Table 2). Accuracies typically decrease as the watershed size increases. For example, the smallest Thomas Ditch – Little Darby HUC 12 has the highest accuracy of 85.6% and the largest watershed has only 68.69% accuracy. This is usually because of more heterogeneous ground features in large study sites, and more overlapping of spectral information between different classes. Detailed explanation is given below and in Figure 6. Noteworthily, the combined Mohican and Walhonding are the only HUC 8 watersheds that included emergent wetlands in the analysis, but substantial commission error in emergent wetland occurred in the classification result (Appendix C). The issue is caused by the confusion with agricultural fields, which essentially have the same spectral signature to emergent wetlands. Therefore, we conducted two classifications (with and without emergent) for this study site.

***Table 2 Classification accuracies for the wetland classification in each watershed*.**

Watershed & HUC	Area (km^2)	Accuracy (Binary)	Kappa	Method
Blanchard 04100008	1999	79.46%	0.59	RF, 5 classes
Little Miami 05090202	4553	73.50%	0.47	RF, 5 classes
Mohican 05040002 & Walhonding 05040003	5843	68.69%	0.37	RF, 6 classes
Mohican 05040002 & Walhonding 05040003	5843	64.53%	0.29	RF, 5 classes
Thomas Ditch – Little Darby 050600012006	94	85.60%	0.70	CNN, 7 classes

Note: RF = random forest, CNN = convolutional neural network, See Xu et al. (2022) for the details of the Thomas Ditch – Little Darby *watershed classification, which included shadow as the 7th class.*

Additional Considerations to Improve Results

Each of the test watersheds had physical features or data characteristics that were unique and required additional data processing or analysis efforts, especially regarding the classification methods for wetland prediction. Here we describe common challenges and suggestions to improve the wetland classification results.

Data Quality. The most common challenge for the automated classification of wetlands from optical imagery was the difference in quality between images. Unlike aerial imagery, watershed boundaries are not the same as geo-political boundaries nor are they linear. To analyze a complete watershed at once, multiple images were combined to create a mosaic that covers the full watershed area and clipped to the watershed boundaries. Adjacent images were often taken during different seasons or months, displaying differences in soil moisture and vegetation color or cover. For our processing efforts, which rely on spectral differences between wetland, upland, open water, and developed areas, the spectral differences within the same land cover across imagery were confounding. For example, the mosaic CIR image shown in Figure 6b has an alternating vertical pattern between dark (wet) and bright (dry). This issue can be more common if the study site is big enough, because precipitation is more likely to be non-uniform. This issue can cause misclassification to both wetlands and uplands. For example, the forested wetlands at the center & left of Figure 6b were classified as uplands (Figure 6a), while the NWI has a more consistent delineation (Figure 6c).

To overcome these differences in data quality, we recommend that wetland classification be conducted at a smaller scale, perhaps analysis should occur at the county level. Especially when adjacent imagery is taken during different seasons, the boundaries for the area of analysis should follow the available imagery. The methods for channel extraction, however, rely on the analysis of the full watershed at once with complete elevation differences from headwaters to the point of interest, therefore this process should still be analyzed on the watershed scale.

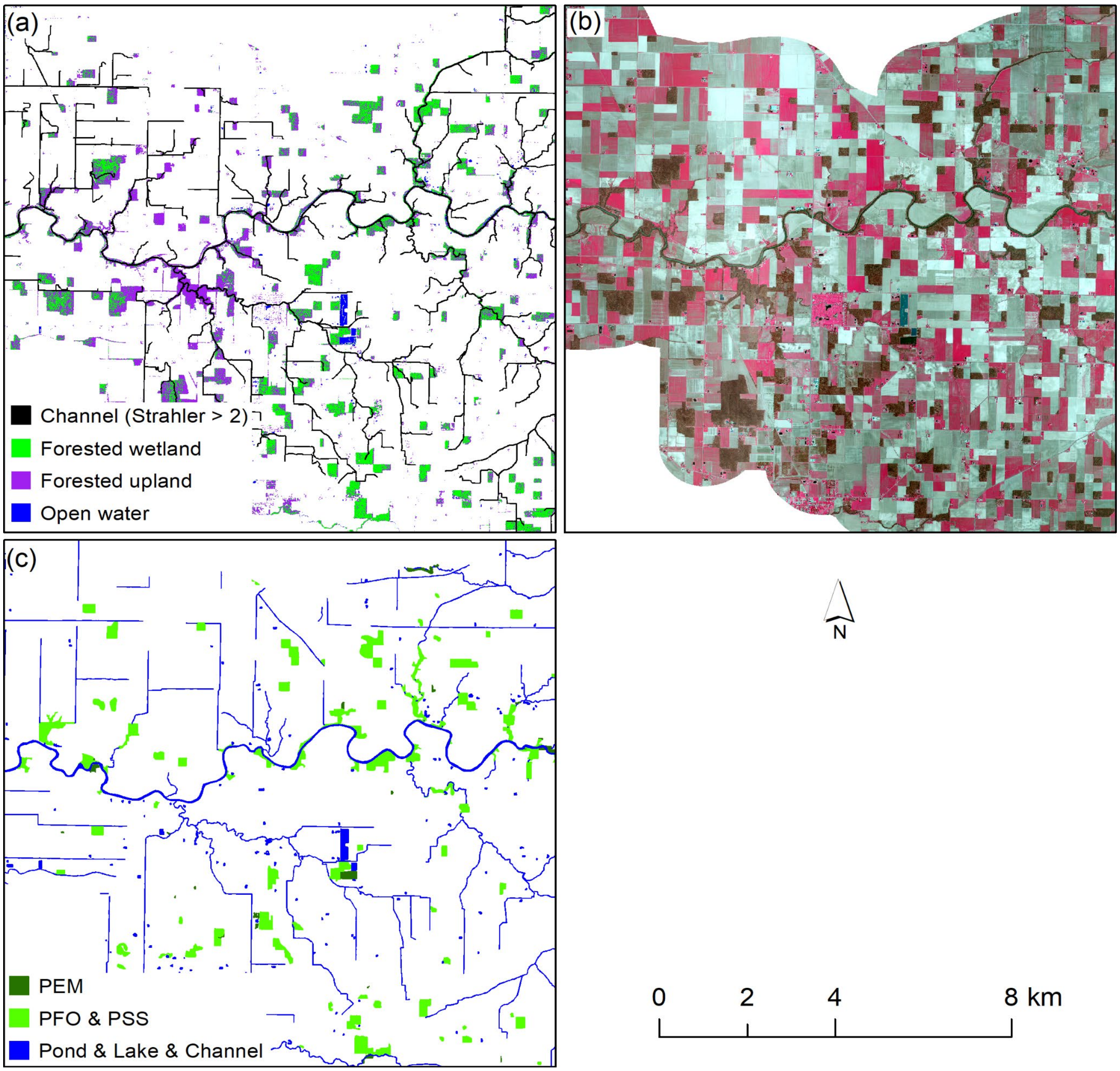

Figure 6. Influence of data quality on mapping wetlands. The location is along the lower Blanchard River, near Cuba, Clinton County, Ohio, in the Blanchard watershed. (a) Predicted forested wetlands, forested uplands, open water, and extracted channels. (b) CIR image from OSIP Phase I. (c) NWI wetlands and streams.

Emergent vs Forested Wetlands. One difficulty with classifying wetlands came in distinguishing between type of wetland (ie. forested, scrub-shrub, or emergent as defined by the Cowardin classification system). The primary characteristic that differentiates types of inland (palustrine) wetlands is the type of vegetation. Optical aerial imagery typically does not provide information that is useful to determine specific characteristics of vegetation other than spectral difference due to moisture level or color. Lidar data, however, can provide information on vegetation height. Our methods merged the canopy height model, a product of lidar data, with the CIR imagery before the classification of wetlands to incorporate data on vegetation height. This allowed us to train the supervised classifiers using forested and emergent wetland samples. The result identified more emergent wetlands from the combined spectral and elevation information (Figure 7a), while the NWI based on visual interpretation of imagery alone identified less emergent wetland (Figure 7c).

As classification between wetland and non-wetland land cover was based on spectral differences, many agricultural fields that were wet at the time of imagery (due to irrigation, recent precipitation, or season) were incorrectly classified as emergent wetland. As we have included the CHM in our analysis, we can resolve this error by removing the emergent wetland class and only identifying wetlands as wet areas with vegetation height greater than some given value. This method will omit all emergent wetlands from the results and should only be used in watersheds/areas where emergent wetlands are scarce. See the watershed maps C4 and C5 provided in Appendix C for a comparison of the combined Mohican and Walhonding watersheds with and without the emergent watershed class.

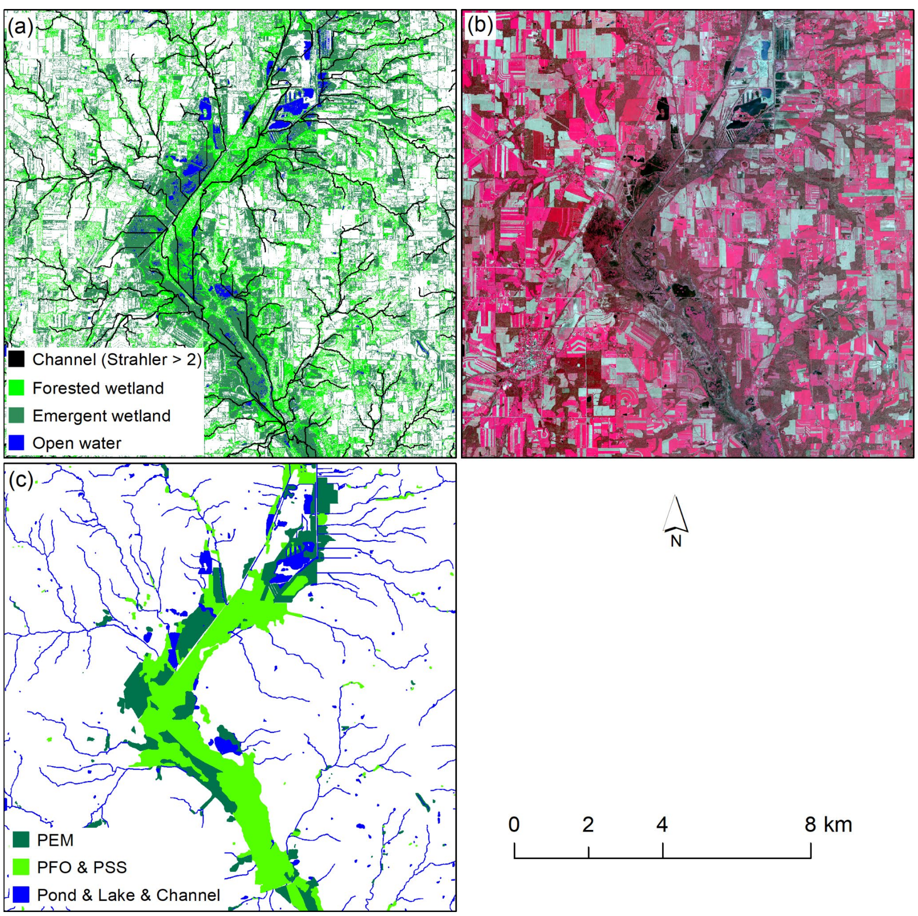

Figure 7. Mapping emergent wetlands highlighted in the Killbuck Marsh Wildlife Area, south of Wooster, Ohio, in the Walhonding watershed. This site is among the largest emergent wetlands of all tested watersheds. (a) Classified forested wetlands, emergent wetlands, open water, and extracted stream channels. (b) CIR image from OSIP Phase I. (c) NWI wetlands and streams.

Recent changes in land cover or land use. Outdated imagery does not capture recent changes to land cover or land use due to development or land conversion. This was confirmed with our ground truthing efforts to verify NWI wetlands. We found no evidence of wetland presence at 17 locations where the NWI indicated a wetland. These errors were all due to development changes that have occurred since the NWI was produced. The use of up-to-date imagery in the analysis can rectify these discrepancies. Figure 8 describes an area in the Mohican watershed where the NWI shows a large patchwork of emergent and forested wetlands that are artificially and seasonally flooded and surrounded by open water (8c). The CIR imagery shows some of this area has been drained and converted to agricultural land, especially in the northern arm (8b). Our classification methods based on the CIR imagery predict much of the wetland area has remained intact (greens) while the seasonal lake and ponding has been reduced to smaller ponds located in the floodplain of the streams (8a).

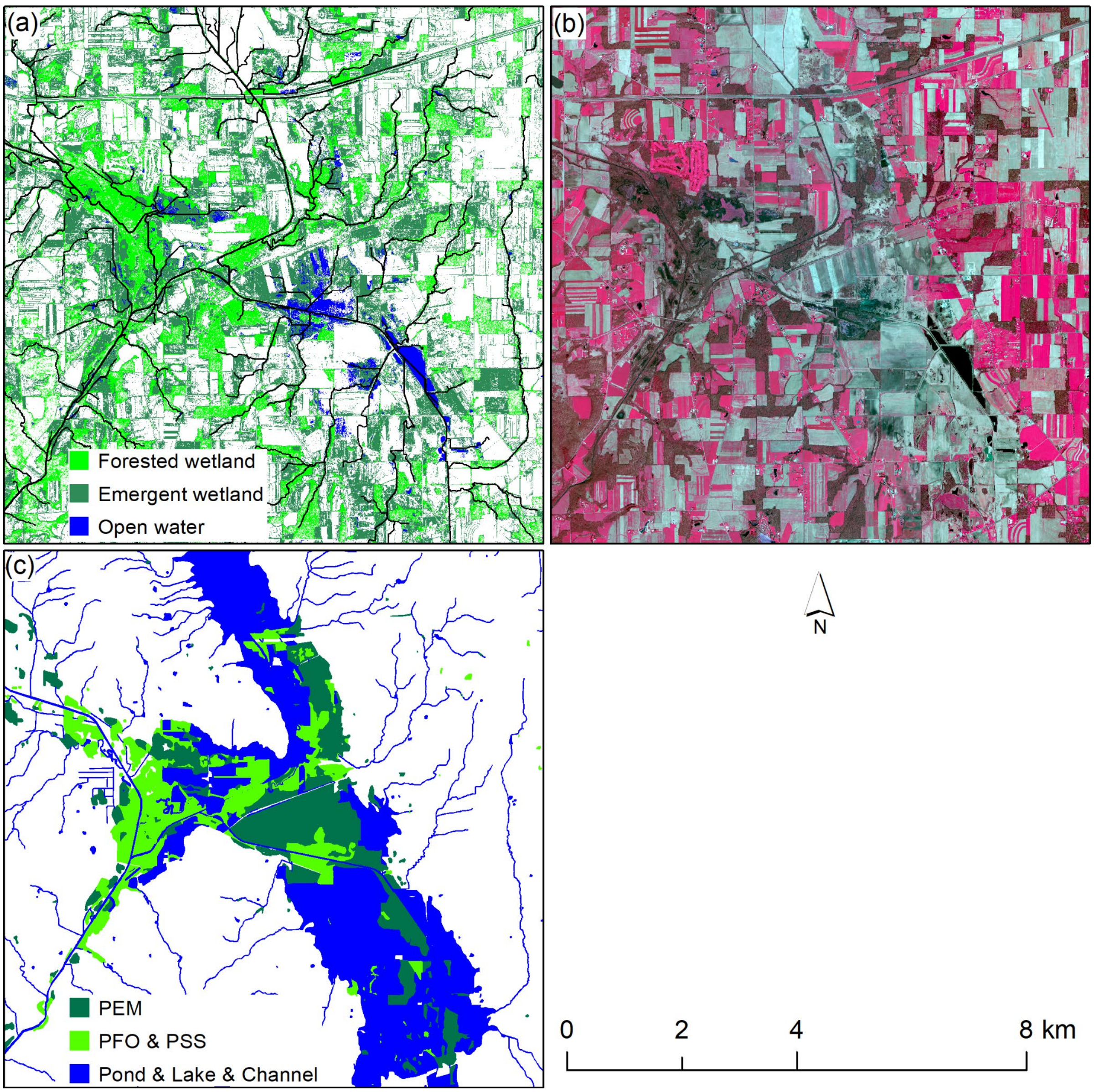

Figure 8. Outdated wetland information due to land use change highlighted in the Funk Bottoms Wildlife Area, west of Wooster, Ohio, in the Mohican watershed. (a) Predicted forested wetlands, emergent

wetlands, open water, and extracted channels. (b) CIR image from OSIP Phase I. (c) NWI wetlands and streams.

The CIR imagery from OSIP Phase I were collected during 2006-2010. Although more recent than the NWI maps, this imagery may still miss changes in land cover during the past decade. Adding bands from the true color imagery taken during OSIP Phase III in 2019 improved results in the Mohican and Walhonding combined watersheds. However, true color imagery lacks enough spectral information to correctly classify open water bodies because these features often have the same color as green vegetation and therefore will miss recent additions of water features including wetlands and ponds. The added NIR band from Sentinel-2 (2019) in Thomas Ditch – Little Darby Creek watershed improved results and captured the recent construction of detention ponds in one example area.

Open Water Bodies. Wind across the surface of an open water body such as a lake or pond as well as water with high turbidity can appear bright with spectral similarities to bare ground or hard surfaces. This effect causes misclassification of open water bodies as developed areas (concrete, asphalt, roof). Figure 9 shows a reservoir along a river with adjacent connected ponds. The main channel has high turbidity due to muddy receiving waters while the floodplain ponds have much lower turbidity due to low connectivity with the main channel or possibly settling of sediments. There is, however, evidence of wind creating waves in these side ponds. Much of the main channel of the reservoir is classified as developed due to high turbidity levels. While the side ponds are correctly classified as open water, they have "clouds" or pixelated areas where the waves can be seen that are misclassified as developed land.

Incorporating a height threshold would not be helpful in this situation because developed areas can be located at ground level (roads). The solution for this error must be human interpretation of the final classification results. Visual comparison with the imagery and classification results can quickly identify open water bodies and recognize this type of error.

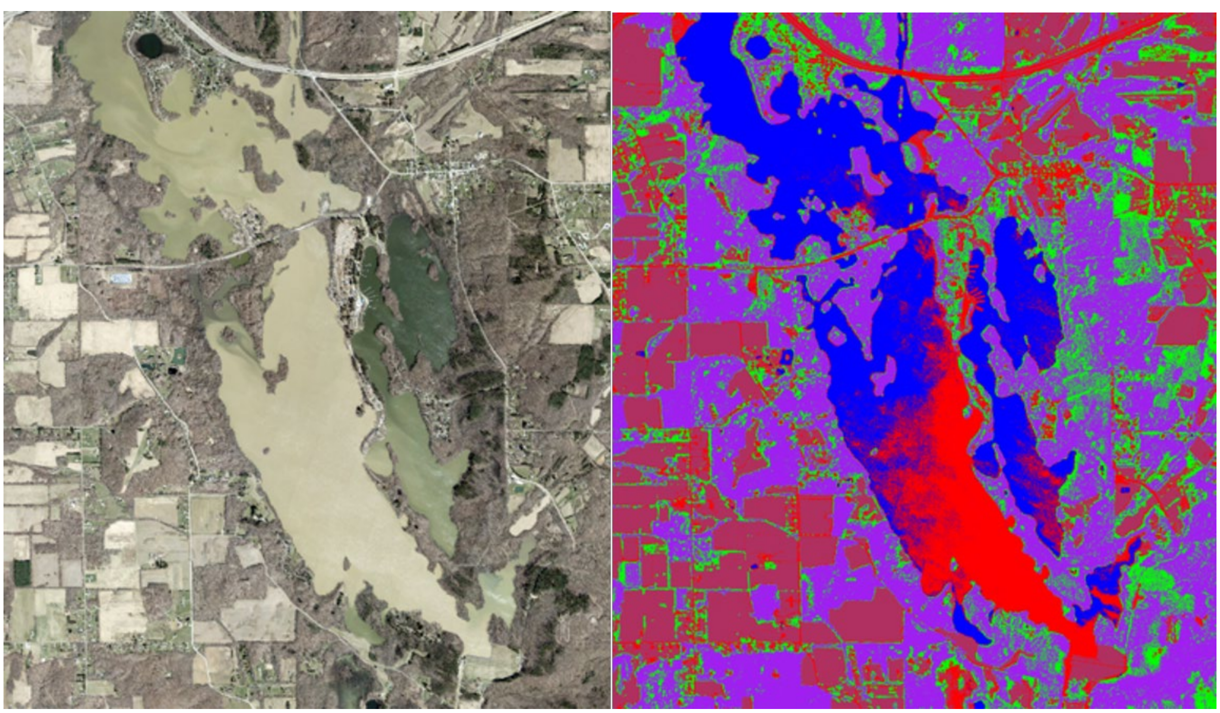

Figure 9. Effects of wind or sediments in open water bodies. Left image is a true color image from OSIP Phase I while the right image shows the classification results for this same area. Classification results should show blue for open water and red for developed areas (roofs, asphalt, concrete).

Tree Shadows and Canopy Cover over Roads. A noticeable limitation of our method for wetland classification is the influence of tree shadows. The shadows are more obvious on high resolution imagery than satellite imagery with moderate resolution. Tree shadows can be incorrectly classified as forested wetlands due to their spectral similarity. This is especially true along roadways where there is canopy cover over a dark asphalt surface or along property boundaries where there is a single row of trees. The tree canopy over roadways can cause significant errors when identifying ODOT projects that interact with wetlands. In the example presented in Figure 10, the roadway (OH-520) is classified as forested wetland due to canopy coverage from the forest on the west side of the road. Our process identified all road projects along this segment of the road as impacting wetlands due to the mis-identified forested wetland within the road right-of-way as well as the emergent wetland alongside the road to the east. In reality, only road widening and other projects that extend beyond the right-of-way of OH-520 would impact wetland areas. Human interpretation will be required at this step to visually compare the classification results and the impacted ODOT projects to confirm impacted wetlands.

To correct for the shadow effect, additional deep learning methods were applied in the Thomas Ditch – Little Darby Creek watershed. By including a shadow class, the CNN classifier correctly identified most tree shadows, usually along the northern edge of forests or buildings. However, the tradeoff is a potential decrease in the classification accuracy for forested wetlands. This is because of the limited spectral information provided by the aerial imagery, typically three 8-bit bands. Open water, saturated soil, and shadow have very similar spectral signatures and thus cause confusions. The CNN method, which utilizes the contextual information, improves the pixel based maximum likelihood. This method is very time and resource heavy and therefore was not applied in the larger watersheds.

Figure 10. Effect of tree lines and canopy cover over roads near Kilbuck, Ohio, in the Walhonding watershed. (a) NWI wetlands and streams. (b) Predicted wetlands (greens), open water (blue), and other land classifications. (c) ODOT project segment identified on OH-520. (d) Project segment that could impact wetlands or streams.

Impacted ODOT Projects in Test Watersheds

The analysis of the results from this research on the projects of ODOT's four-year plan within the test watersheds are shown in Figure 11. All watersheds will have impacts but the high impacts (e.g., deep blue) are only within Little Miami, Mohican, and Walhonding watersheds. The Blanchard watershed has generally less (below 3/8). One explanation is the bias in the image classification towards more uplands, because Blanchard CIR images show a repetitive wet and dry pattern (cover image of this report). Another explanation is that in areas where the primary land use is agriculture, wetlands do not widely occur except along streams and in isolated forests (Figure C2).

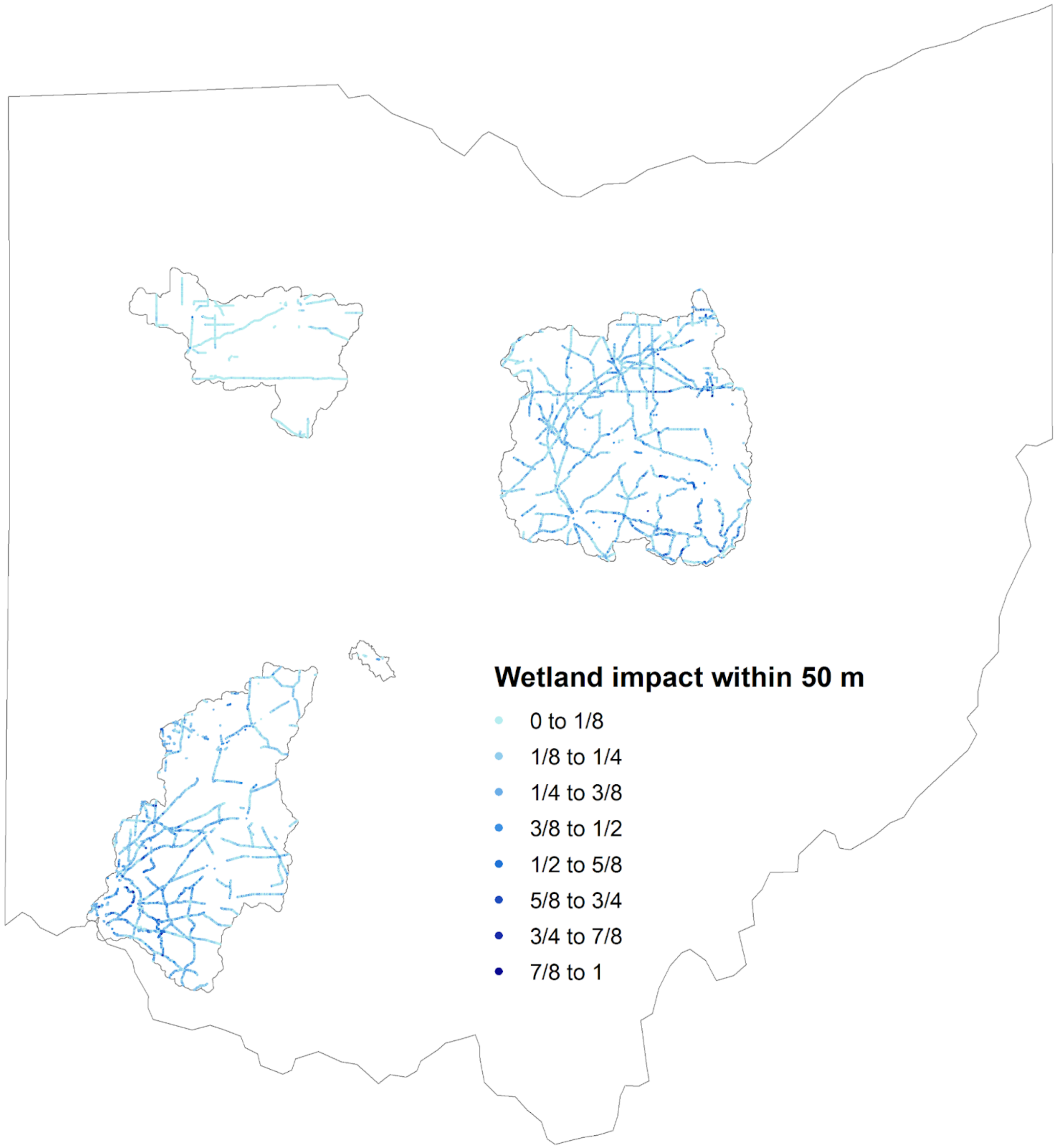

Figure 11. Wetland and stream impacts caused by the ODOT next four-year construction plan. Ratio represents the portion of wetlands and streams within 50 m buffer distance.

Knowledge Transfer

Initial results from the analysis of the Thomas Ditch – Little Darby watershed and the subsequent mapping methodology that was developed for that location were presented at the Annual Meeting of the Transportation Research Board of the National Academies of Science in Washington, D.C. in January 2022. The accompanying paper was accepted for publication in the Transportation Research Record (Hu et al., 2022 *In Press)*.

We developed a user manual that includes step-by-step instructions on how to apply this methodology and the algorithms to future areas in Ohio. The user manual provides screen views of each of the software and tools used to analyze data as well as code. A snapshot of the user manual is provided in Appendix E. The manual was provided to ODOT in June 2022.

Research Conclusions

This study proposed and tested a cost-effective framework for mapping wetlands and channels with aerial imagery and lidar derivatives. All the data used in this study are publicly accessible. Early spring aerial imagery is widely available in the US and some parts of the world. To identify wetlands, the CIR images provide essential information. Lidar point clouds are also available for most areas in the US and other countries. The importance of lidar observation of forested landscapes have been highlighted in recent studies (e.g. Xu et al. 2020, Xu et al. 2021) where optical satellites can omit substantial inundated areas and subtle channels.

We purposely chose a simple process and selected a small number of training polygons, in order to make the wetland classification method more adaptable to other areas. Although increasing the training sample size and choosing a more complex deep learning network could potentially increase the accuracy, they could also overfit the dataset and make the methods less universal.

The framework was validated in five watersheds of varying sizes in Ohio. The merged wetland class achieved 64.5% to 85.6% accuracy. Field surveys confirmed that NWI misses small, vegetated wetlands and low-order streams. The findings demonstrated a cost-effective way of identifying ODOT project areas that could interact with wetlands or streams during early planning before field studies are undertaken. The transportation community can benefit from the updated wetland maps by reducing potential environmental impacts from their future development projects and aid in project planning, specifically budgeting. Additionally, the results could be used by conservation groups or regulatory agencies for wetland mitigation by predicting sites with potential wetland hydrology.

Recommendations for Implementation

We have developed a method to predict the location of wetlands and channels in a format that can be combined with existing TIMS data regarding road projects in the revolving four-year plan. We recommend that ODOT apply our method and continue the analysis for additional areas throughout Ohio. The method is such that ODOT can continue to implement these procedures as new imagery becomes available. The resulting wetlands and channel maps can continue to be overlaid with planned projects in the four-year window to prioritize and budget for mitigation efforts in perpetuity.

Based on the challenges that we encountered in our five test watersheds as outlined in the “Additional Considerations to Improve Results” section of this report, we recommend the following for implementation of the research methods by ODOT:

- Conduct the wetland analysis at a smaller scale to avoid differences in image quality. We recommend that ODOT consider differences in image dates before mosaicking adjacent images and conduct the wetland analysis on images taken at the same time. This is only an issue with optical imagery; channel analysis should occur at a watershed scale and include the full watershed from headwaters.
- Combine vegetation height (from lidar) with optical imagery to allow for the differentiation of wetland type. This is a defining step in our methodology that sets it apart from methods that other researchers have used. This step allows ODOT to distinguish between emergent and forested wetlands and provides a means to remove wet agricultural land that has been mis-classified as emergent wetland.
- Use up-to-date imagery to detect recent land cover changes. Our process for wetland classification relies on the thermal bands of aerial imagery. If an area only has CIR images from OSIP Phase I (2006-2010) available, we recommend including a thermal band from recent satellite coverage to provide details on recent land cover changes.

- Human interpretation of the results, especially the verification of ODOT projects interacting with wetland areas, is recommended. While we have worked to automate the prediction of wetlands and channels on the landscape as much as possible, remote sensing and artificial intelligence cannot yet replace the understanding and visual abilities of humans. The common problems to be aware of when interpreting the results are: tree lines and road right-of-ways classified as forested wetland due to shadows and larger open water bodies (ponds, lakes, reservoirs) classified as developed land.

ODOT personnel were taught key steps in this methodology through a hands-on training session in April 2022. The user manual provides additional guidance as ODOT continues to implement our methods across the state and with future projects.

One of the main products from this analysis is a GIS map that identifies the location of wetlands and channels. This file can be exported as a stand-alone map or as a layer that can be incorporated into other maps. This type of information could be beneficial to many other agencies and entities, especially those that are involved in the conservation or regulation of wetlands and streams. We have already had interest from the Ohio Environmental Protection Agency and Ohio-Kentucky-Indiana Regional Council of Governments (OKI).

We developed this methodology to rely on publicly accessible data and work with software programs that ODOT already has access to (ArcGIS, MATLAB) or that could be obtained for free (QGIS, R, LAStools, and Visual Studio Community). Other than ODOT employee time, no additional resources will be required to implement this methodology.

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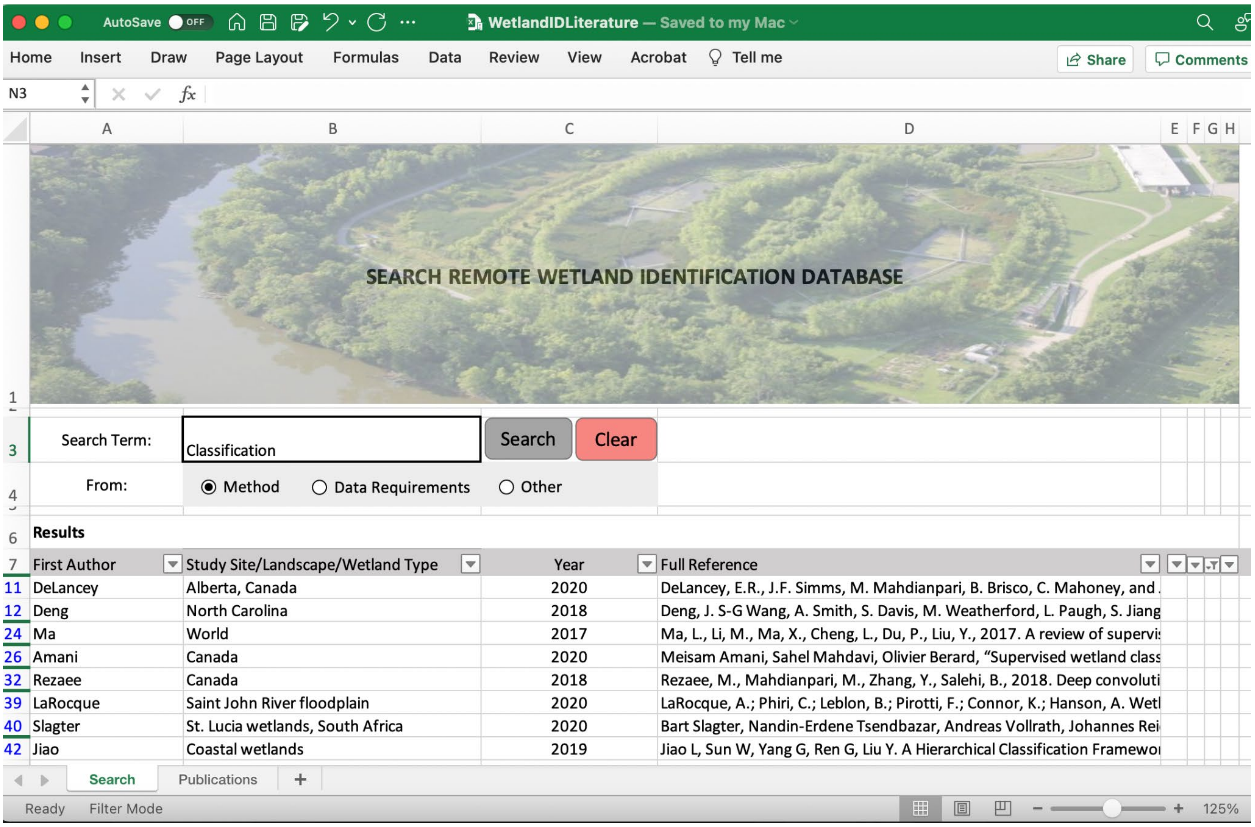
Appendix A: Database of Literature Regarding Remote Wetland Identification

Image of the search tool for the remote wetland identification database after searching the keyword “classification” within the “methods” of all publications in the database:



First Author	Study Site/Landscape/Wetland Type	Year	Full Reference
DeLancey	Alberta, Canada	2020	DeLancey, E.R., J.F. Simms, M. Mahdianpari, B. Brisco, C. Mahoney, and
Deng	North Carolina	2018	Deng, J. S-G Wang, A. Smith, S. Davis, M. Weatherford, L. Paugh, S. Jiang
Ma	World	2017	Ma, L., Li, M., Ma, X., Cheng, L., Du, P., Liu, Y., 2017. A review of supervis
Amani	Canada	2020	Meisam Amani, Sahel Mahdavi, Olivier Berard, “Supervised wetland class
Rezaee	Canada	2018	Rezaee, M., Mahdianpari, M., Zhang, Y., Salehi, B., 2018. Deep convoluti
LaRocque	Saint John River floodplain	2020	LaRocque, A.; Phiri, C.; Leblon, B.; Pirotti, F.; Connor, K.; Hanson, A. Wetl
Slagter	St. Lucia wetlands, South Africa	2020	Bart Slagter, Nandin-Erdene Tsendbazar, Andreas Vollrath, Johannes Rei
Jiao	Coastal wetlands	2019	Jiao L, Sun W, Yang G, Ren G, Liu Y. A Hierarchical Classification Framewo

Appendix B: Summary of Feature Extraction from the Literature

The tables below show the features used for mapping wetlands and channels in the literature. Those features can be derived based on individual pixels or image objects (aggregates of pixels). Most features are defined and derived based on multispectral satellite images. This project, however, focused on high-resolution aerial images which typically contain three to four bands. Thus, only NDVI was utilized and it helped separate green vegetation from other ground features. Nevertheless, when better images (e.g., high-resolution multispectral images) are available in the future, more features can be derived and tested in the applications.

Features derived from optical imagery

Group	Name	Equation	Purpose	Reference
Spectral bands	Spectral bands	DN value	Spectral information	
Indices	Simple ratio (SR) or ratio vegetation index (RVI)	$\mathrm{SR\ or\ RVI} = \frac{\mathrm{NIR}}{\mathrm{R}}$	Green vegetation	
	Normalized difference vegetation index (NDVI)	$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{R}}{\mathrm{NIR} + \mathrm{R}}$	Green vegetation	Liu & Huete 1995
	Renormalized difference vegetation index (RDVI)	$\mathrm{RDVI} = \frac{\mathrm{NIR} - \mathrm{R}}{\sqrt{\mathrm{NIR} + \mathrm{R}}}$	Reduce effects of soil and sun angle	Roujean & Breon 1995
	Triangular vegetation index (TVI)	$\mathrm{TVI} = 0.5 * [120 * (\mathrm{NIR} - \mathrm{G}) - 200 * (\mathrm{R} - \mathrm{G})]$	Estimating green LAI	
	Enhanced vegetation index (EVI)	$\mathrm{EVI} = \frac{2.5 * (\mathrm{NIR} - \mathrm{R})}{(\mathrm{NIR} + 6 * \mathrm{R} - 7.5 * \mathrm{B}) + 1}$	Lead area index or chlorophyll	Gao et al. 2000
	Normalized difference water index (NDWI)	$\mathrm{NDWI} = \frac{\mathrm{NIR} - \mathrm{SWIR}}{\mathrm{NIR} + \mathrm{SWIR}}\ \mathrm{or}\ \frac{\mathrm{G} - \mathrm{NIR}}{\mathrm{G} + \mathrm{NIR}}$	Water, soil moisture, wet vegetation	Gao 1996; McFeeters 1996
	Modified Normalized Difference Water Index (MNDWI)	$MNDWI = \frac{G - SWIR}{G + SWIR}$	Enhance open waters	
	Soil adjusted vegetation index (SAVI)	$SAVI = \frac{NIR - R}{NIR + R + L} * (1 + L)$	Correct influence of soil brightness	
	Modified soil adjusted vegetation index-2 (MSAVI2)	$MSAVI2 = \frac{2 * NIR + 1 - \sqrt{(2 * NIR + 1)^2 - 8 * (NIR - R)}}{2}$	Minimize effect of bare soil on SAVI	
	Normalized burn ratio (NBR)	$NBR = \frac{NIR - SWIR}{NIR + SWIR}$	Identify burned areas	
	Normalized burn ratio 2 (NBR2)	$NBR2 = \frac{SWIR1 - SWIR2}{SWIR1 + SWIR2}$	Highlight water sensitivity in vegetation	
	Atmospheric resistant vegetation index (ARVI)	$ARVI = \frac{NIR - R - y(R - B)}{NIR + R + y(R - B)}$	Minimizes effects of atmospheric scattering	
	Soil adjusted and atmospheric resistant vegetation index (SARVI)	$SARVI = \frac{NIR - R - y(R - B)}{NIR + R + y(R - B) + L}(1 + L)$	Minimizes influences of soil and atmosphere	
	Thiam's transformed NDVI (TTVI)	$TTVI = \sqrt{\lvert NDVI + 0.5 \rvert}$	Transform of NDVI	
	Global environmental monitoring index (GEMI)	$GEMI = eta * \left(1 - \frac{eta}{4}\right) - \frac{R - 0.125}{1 - R}$	Nonlinear vegetation index. Reduces atmospheric effects	
		$eta = \frac{2 * (NIR^2 - R^2) + 1.5 * NIR + 0.5 * R}{NIR + R + 0.5}$		
	Tasseled cap (TC) transform	Spectral Bands * Transform Matrix = TC Bands	Brightness; greenness; wetness	
Attribute profiles	Morphological attribute profiles (MAP)		Multilevel structural information	Mura et al. 2010
	Extended multi-attribute profile (EMAP)			Zhang et al. 2019
Image texture	Entropy	$-\sum_i \sum_j P(i,j) * lnP(i,j)$	randomness of greyscale distribution	
	Homogeneity			
	Contrast			
	Correlation			
	Dissimilarity			
Dimensionality reduction	Principal Component Analysis (PCA)		Orthogonal linear transformation	
	Minimum Noise Fraction (MNF)		Maximize S/N ratio	

Features derived from lidar point cloud

Group	Name	Equation	Purpose	Reference
Canopy	Canopy height model (CHM)	DSM - DEM	Vegetation canopy height	Jahncke et al. 2018

Features derived from DEM/lidar

Group	Name	Equation	Purpose	Reference
Elevation	Elevation	z	Elevation information	Correll et al. 2019
	Roughness	$\sqrt{std(Z)}$	Roughness of local topography	Riley et al. 1999
	Dissection	$\frac{Z - Z_{min}}{Z_{max} - Z_{min}}$	Dissection of landscape index	Evans 1972
1st derivatives	Slope	$\sqrt{(dz/dx)^2 + (dz/dy)^2}$	Max local slope	
	Catchment slope		Average catchment slope	
	Aspect	$\arctan(dz/dy, -dz/dx)$	Direction of max local slope	
2nd derivative	Curvature	$Z = Ax^2y^2 + Bx^2y + Cxy^2 + Dx^2 + Ey^2 + Fxy + Gx + Hy + I$	Equation of local topography	Moore et al. 1991
		$Profile\ curvature = -2\frac{DG^2 + EH^2 + FGH}{G^2 + H^2}$	Parallel to max slope. Concave or convex up.	
		$Planform\ curvature = 2\frac{DH^2 + EG^2 - FGH}{G^2 + H^2}$	Normal to max slope. Convergence or divergence.	
		$Standard\ or\ Laplacian\ curvature = 2D + 2E$	Combination of profile and planform curvature	
Indices	Topographic wetness index (TWI)	$\ln(a/\tan(b))$, a: contributing area, b: local slope angle	Steady state wetness	
	SAGA wetness index (SWI)			
	Topographic position index (TPI)	$z - \bar{z}$, $\bar{z}$: average focal elevation	Relative topographic position	
	Terrain ruggedness index (TRI)	$\sqrt{\sum(z_{0,0} - z_{i,j})^2}$, $z_{0,0}$: central elevation, $z_{i,j}$: neighbor elevation	Focal elevation difference	Riley et al. 1999
	Depth to water index (DTW)	$DTW = \left[\sum \frac{dz_i}{dx_i} a\right] * cellSize, a = 1\ or\ \sqrt{2}$	Cumulative slope along the least-cost pathway	Oltean et al. 2016

Features derived from image objects

Group	Name	Equation	Purpose	Reference
Statistics	Max		Max DN value / elevation	Zhang et al. 2018
	Min		Min DN value / elevation	
	Mean		Mean DN value / elevation	
	Std		Standard deviation of DN / elevation	
Geometry	Area	$N * Area\ of\ pixel, N: \#\ of\ pixels\ in\ object$		
	Width	$\sum Width_i / N$	Mean width measured at each pixel	Jiao et al. 2020
	Length	$Area/Width$	Mean length	
	Length-width ratio	$Length/Width$	L-W ratio	
	Shape index	$Perimeter/(4\sqrt{Area})$	Shape: circular or elongated	
	Density	$\sqrt{N}/(1 + \sqrt{var(X) + var(Y)})$		

Appendix C: Results of Watershed Classification and Channel Extraction in Test Watersheds

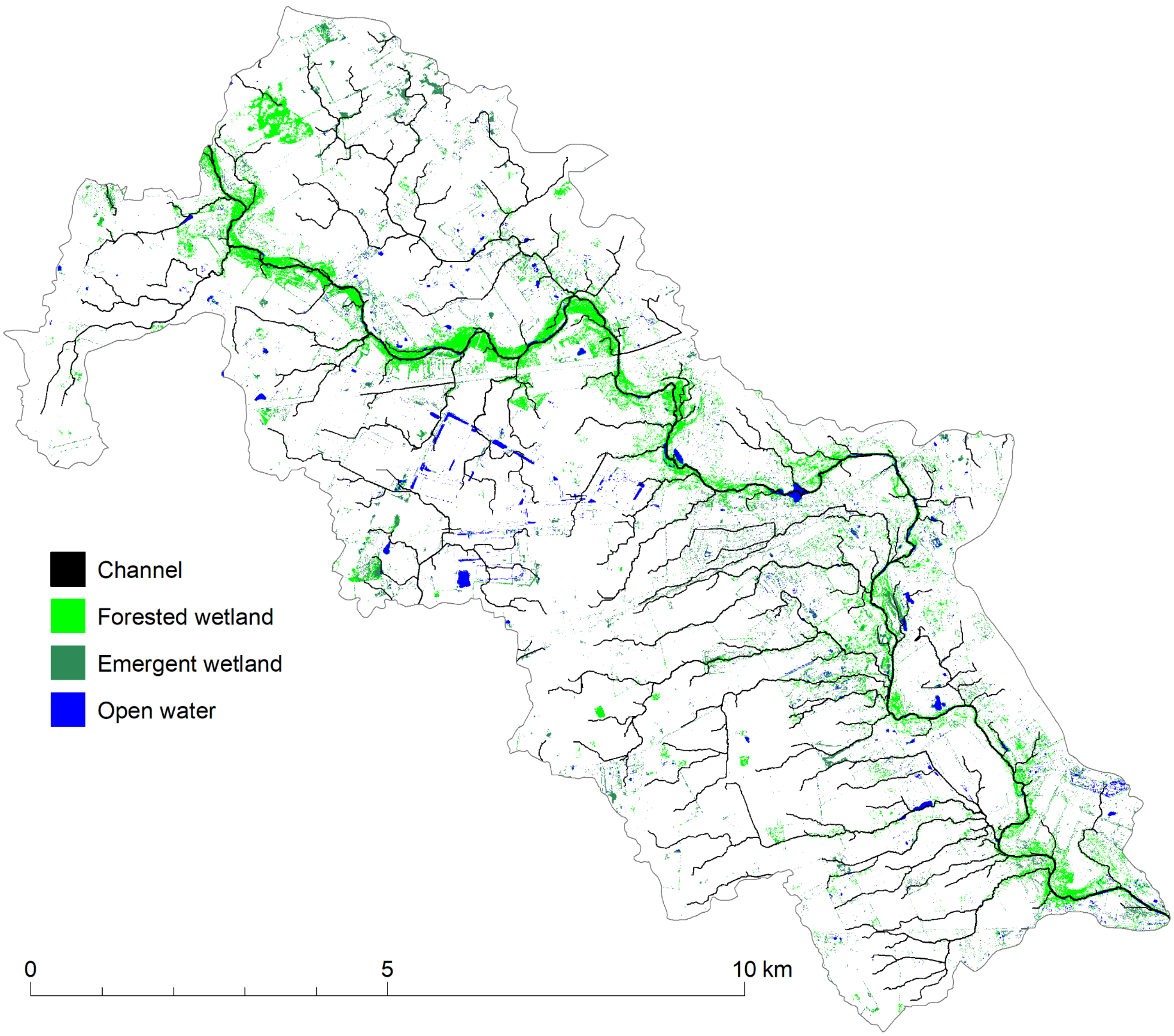


Figure C1. *Wetlands and channels for the Thomas Ditch – Little Darby Creek HUC 12 watershed.*

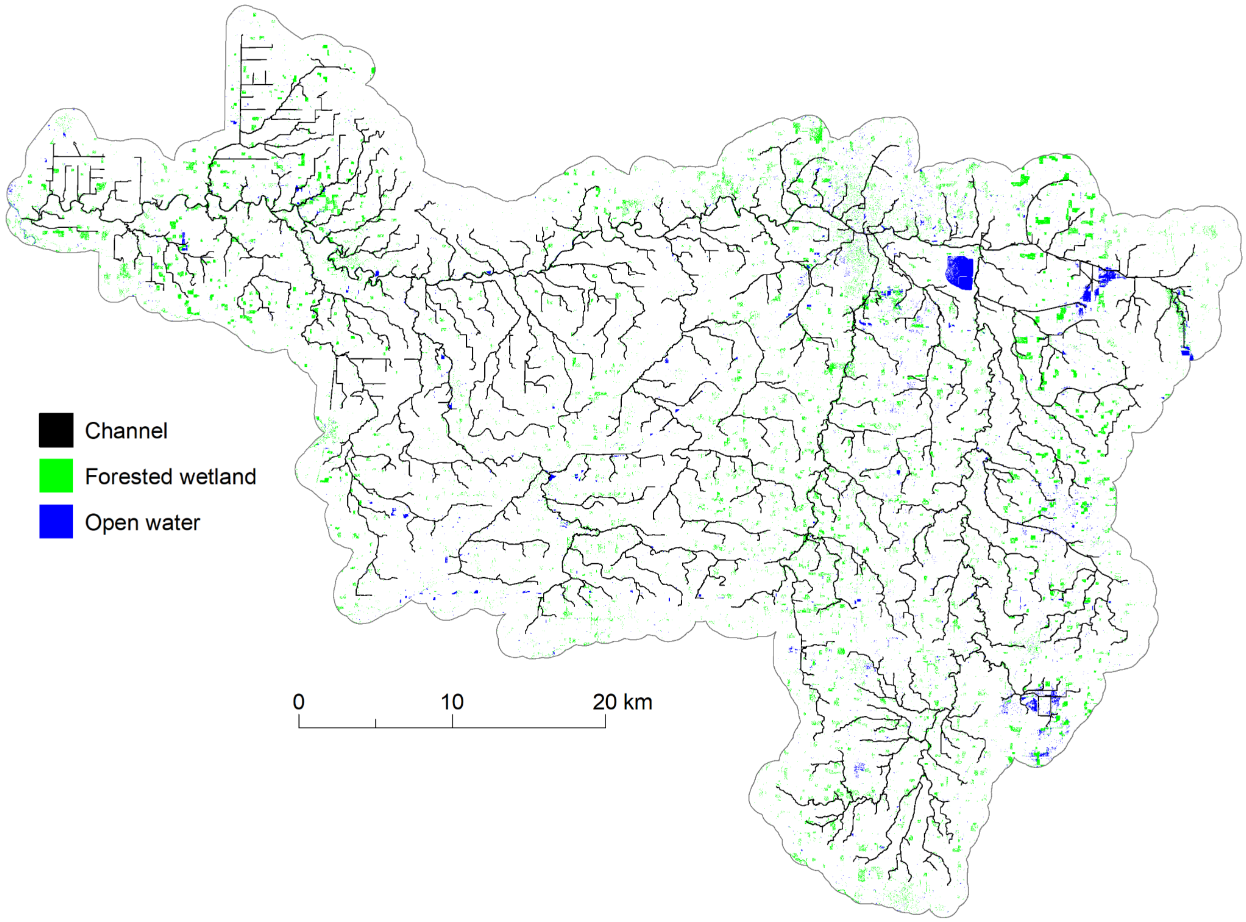


Figure C2. *Wetlands and channels for the Blanchard HUC 8 watershed. Emergent wetlands were not mapped due to their scarcity.*

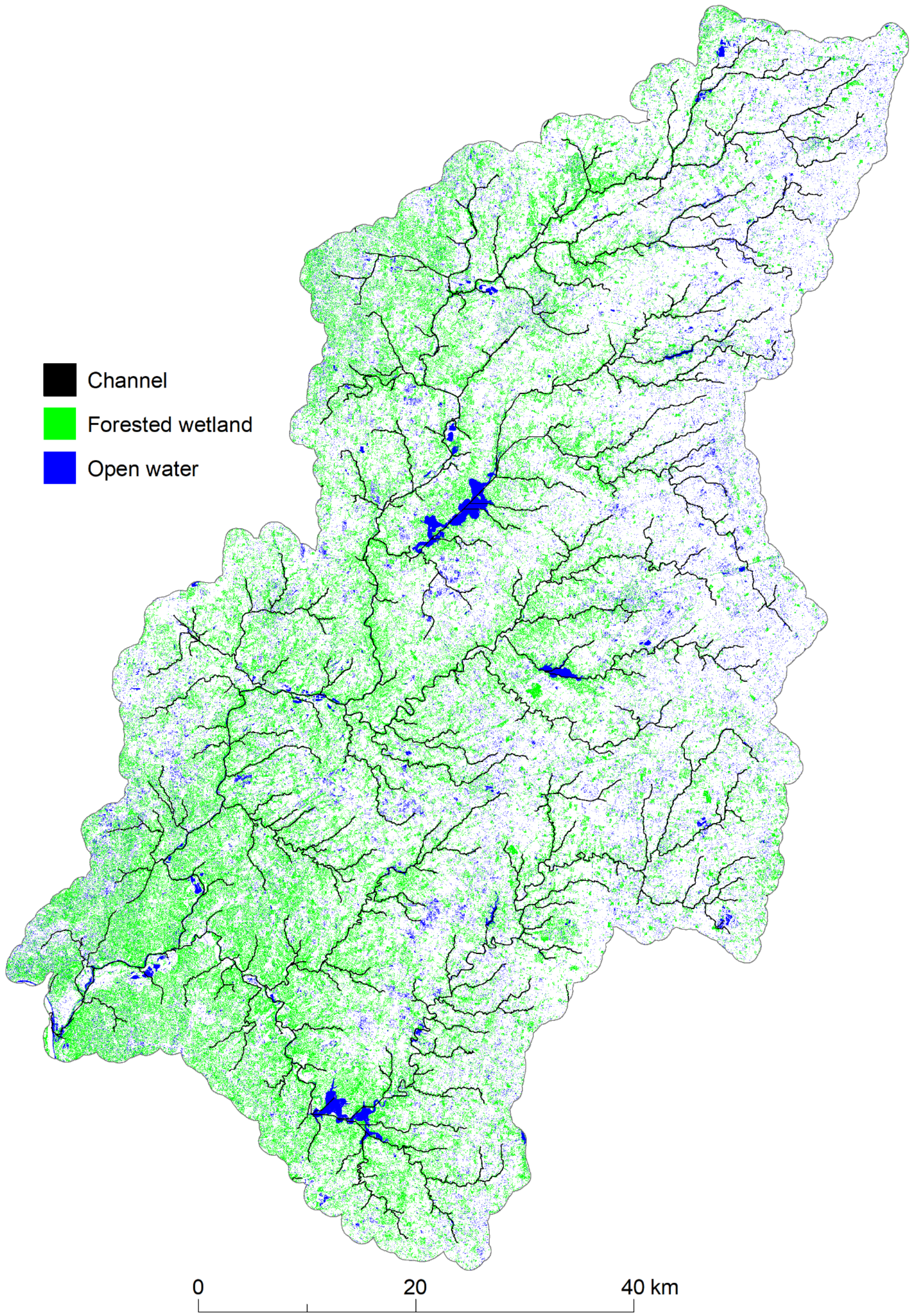


Figure C3. *Wetlands and channels for the Little Miami HUC 8 watershed. Emergent wetlands were not mapped due to their scarcity.*

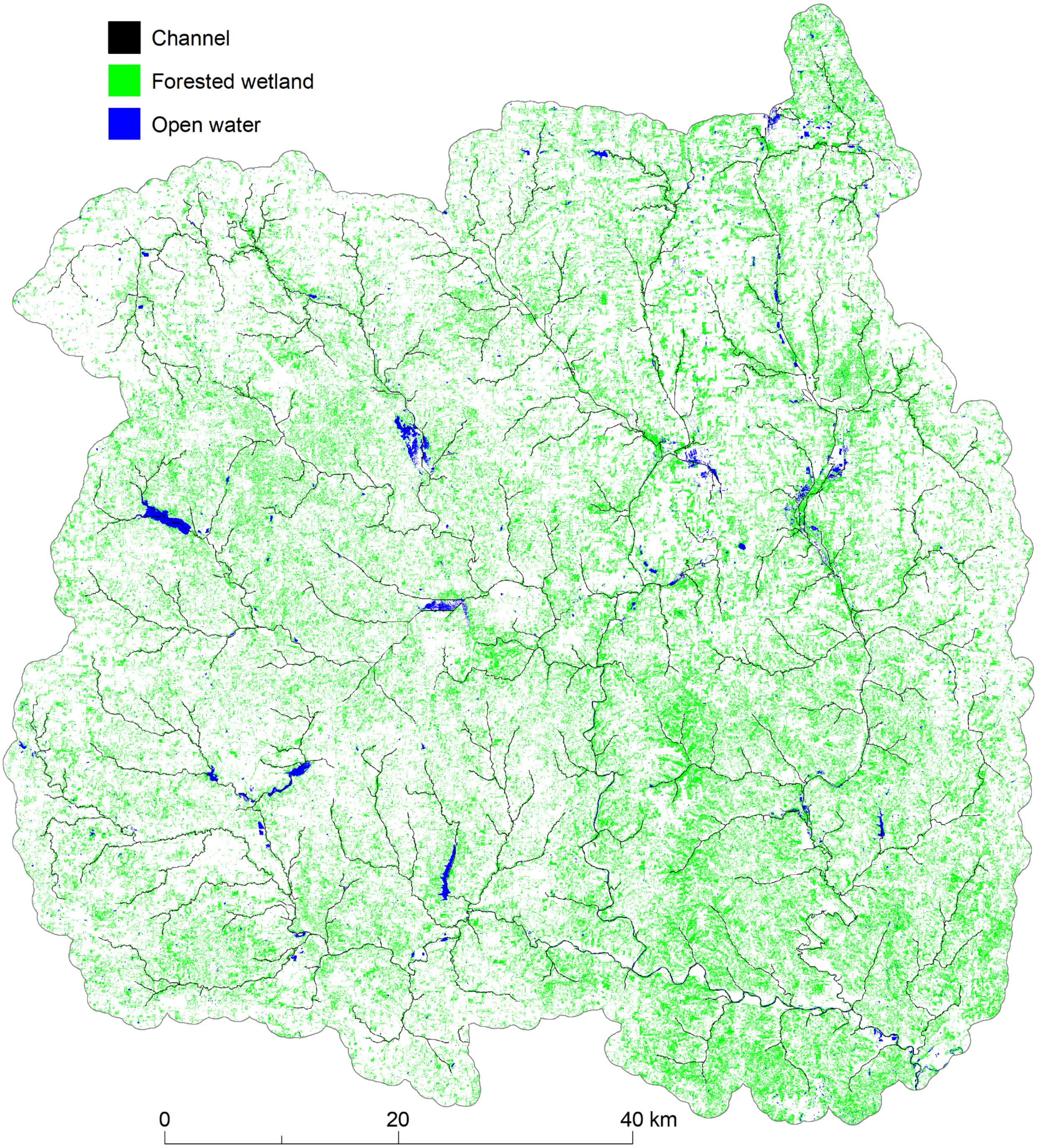


Figure C4*. Wetlands and channels for the Mohican HUC 8 and Walhonding HUC 8 watersheds without emergent wetlands.*

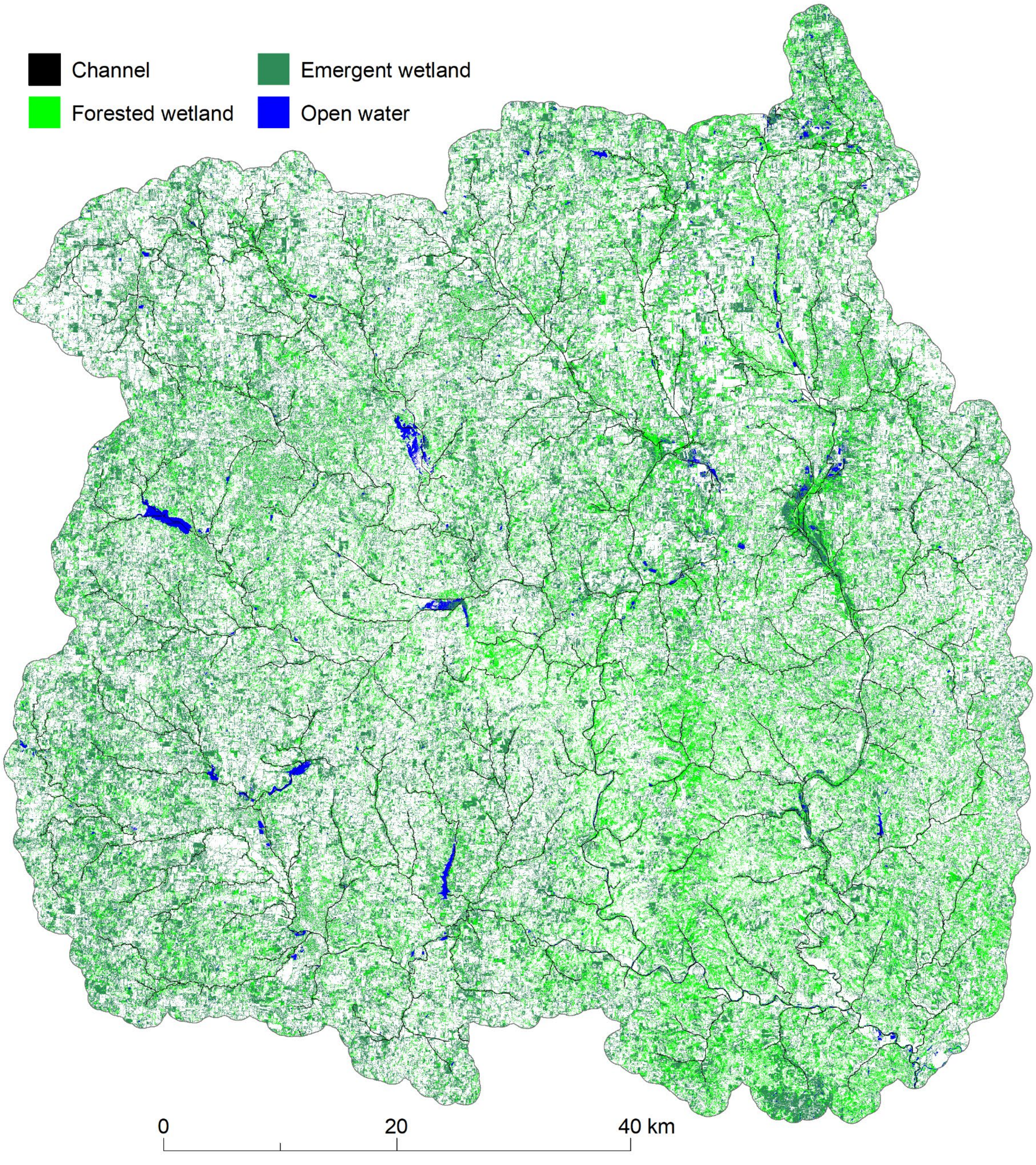
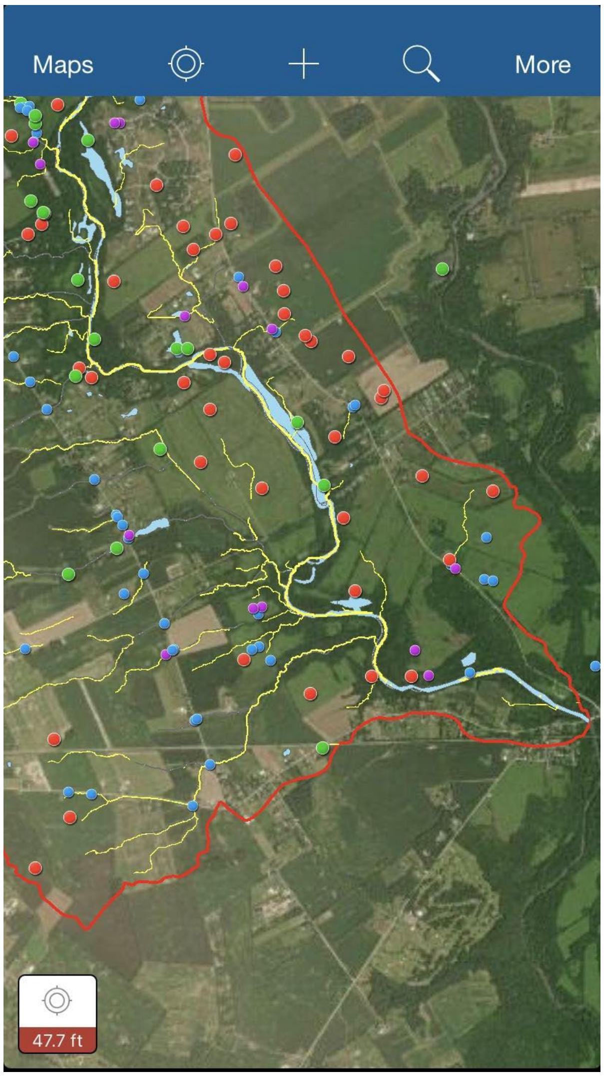


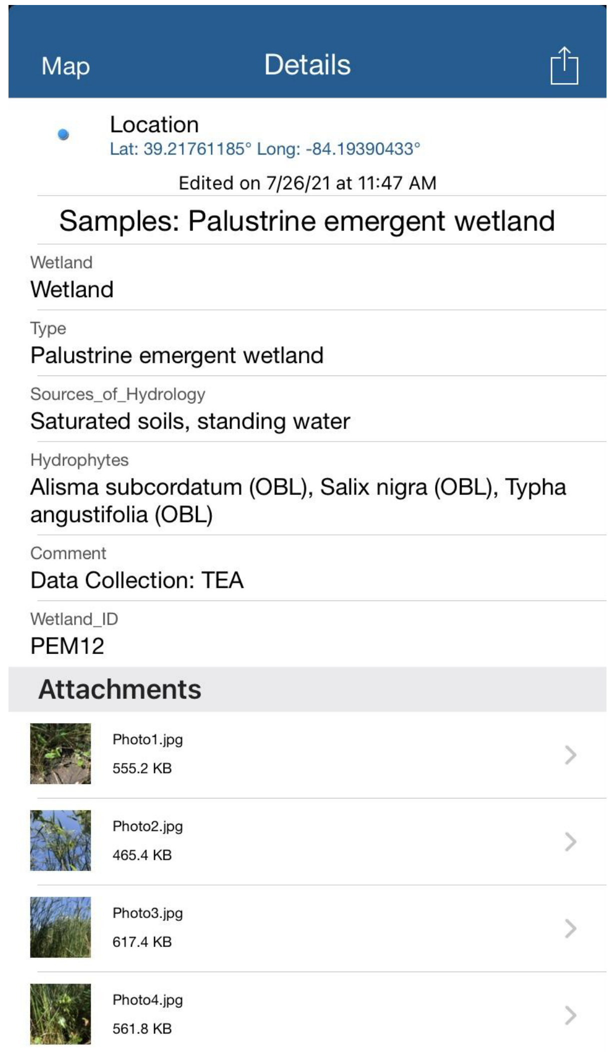
***Figure C5**. Wetlands and channels for the Mohican HUC 8 and Walhonding HUC 8 watersheds including emergent wetlands.*

Appendix D: Example Field Data Collection Form

Screenshots from ArcGIS Collector Classic application (ESRI) for iPhone.

Left: location map with watershed boundaries, channels, and sample points identified. Right: completed data collection form for one of the wetland sample points.





Map
Details

Location
Lat: 39.21761185° Long: -84.19390433°

Edited on 7/26/21 at 11:47 AM

Samples: Palustrine emergent wetland

Wetland
Wetland

Type
Palustrine emergent wetland

Sources_of_Hydrology
Saturated soils, standing water

Hydrophytes
Alisma subcordatum (OBL), Salix nigra (OBL), Typha angustifolia (OBL)

Comment
Data Collection: TEA

Wetland_ID
PEM12

Attachments

Photo1.jpg
555.2 KB

Photo2.jpg
465.4 KB

Photo3.jpg
617.4 KB

Photo4.jpg
561.8 KB

Appendix E: Example Page from the User Manual

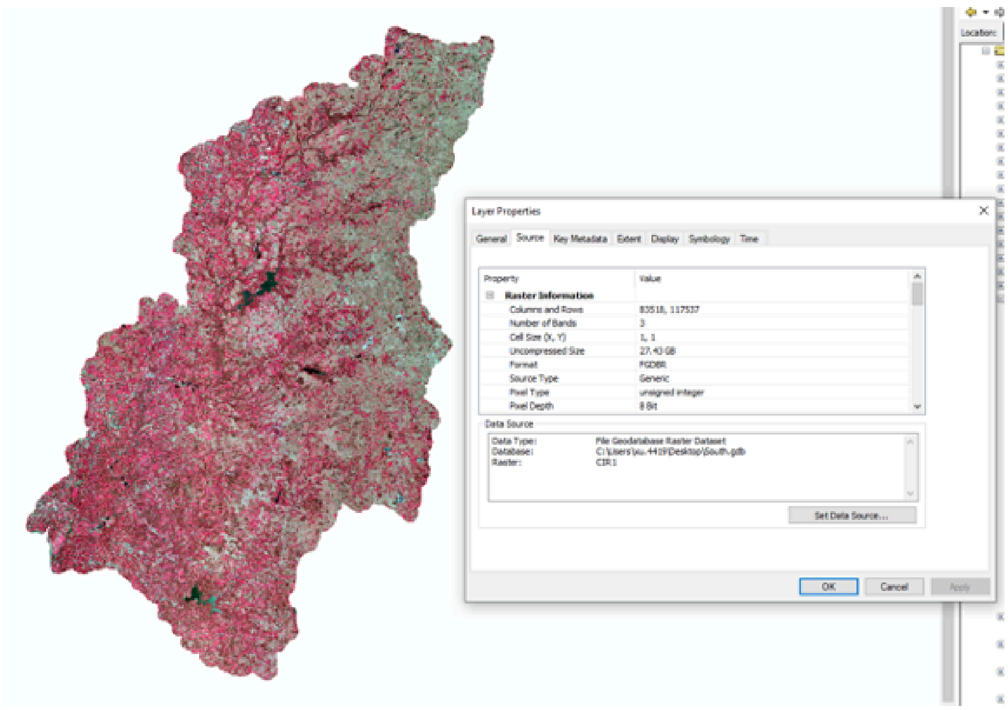


Figure 10. The final mosaicked and clipped CIR image for the Little Miami HUC8 watershed. Note the large size of the image even using UINT8 data type. UINT8 is typically the data type using the least amount of space. If using floating number (32 bit), the file size will be four times of UINT8.

Calculating NDVI

The normalized difference vegetation index (NDVI) is a common feature for differentiating ground features. NDVI is a ratio involving the near-infrared (NIR) band and the red band, defined as below.

$$NDVI = \frac{NIR - Red}{NIR + Red}$$

The Phase 1 CIR images has three bands: the first two being NIR and red, respectively. Therefore, the NDVI is calculated in the Raster Calculator tool in Figure 11 (https://desktop.arcgis.com/en/arcmap/latest/tools/spatial-analyst-toolbox/raster-calculator.htm). Note there are two bands in Figure 11, this is because them were loaded in ArcMap separately. Do not load the entire multi-band image, instead, unfold the bands, and load the required bands.

Note the Float() function is enforced because the default data type is associated with the input image (UINT8). If Float() was ignored, then the output layer has only two values: 0 and 1. The correct output raster layer is a floating number layer (32-bit) with the range [-1, 1]. The user may check the zero-denominator issue (NIR + Red = 0), but it rarely occurs.