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1 **Evaluating the Potential for Site-Specific Modification of LiDAR DEM Derivatives to**
2 **Improve Environmental Planning-Scale Wetland Identification using Random Forest**
3 **Classification**

4 Gina L. O’Neil^a, Jonathan L. Goodall^{a,*}, Layne T. Watson^b

5 ^a Department of Civil and Environmental Engineering, University of Virginia, Charlottesville,
6 Virginia 22904, USA.

7 ^b Department of Computer Science, University of Virginia, Charlottesville,
8 Virginia 22904, USA; Departments of Computer Science, Mathematics, and Aerospace and
9 Ocean Engineering, Virginia Polytechnic Institute and State University,
10 Blacksburg, Virginia 24061, USA.

11 *Corresponding author. Tel.: (434) 243-5019

12 E-mail address: goodall@virginia.edu (J. Goodall)

13 Abstract

14 Wetlands are important ecosystems that provide many ecological benefits, and their
15 quality and presence are protected by federal regulations. These regulations require wetland
16 delineations, which can be costly and time consuming to perform. Computer models can assist in
17 this process, but lack the accuracy necessary for environmental planning-scale wetland
18 identification. In this study, the potential for improvement of wetland identification models
19 through modification of digital elevation model (DEM) derivatives, derived from high-resolution
20 and increasingly available Light Detection and Ranging (LiDAR) data, at a scale necessary for
21 small-scale wetland delineations is evaluated. A novel approach of flow convergence modeling

22 is presented where Topographic Wetness Index (TWI), curvature, and Cartographic Depth-to-
23 Water index (DTW), are modified to better distinguish wetland from upland areas, combined
24 with ancillary soil data, and used in a Random Forest classification. This approach is applied to
25 four study sites in Virginia, implemented as an ArcGIS model. The model resulted in significant
26 improvement in average wetland accuracy compared to the commonly used National Wetland
27 Inventory (84.9% vs. 32.1 %), at the expense of a moderately lower average non-wetland
28 accuracy (85.6% vs. 98.0 %) and average overall accuracy (85.6% vs. 92.0%). From this, we
29 concluded that modifying TWI, curvature, and DTW provides more robust wetland and non-
30 wetland signatures to the models by improving accuracy rates compared to classifications using
31 the original indices. The resulting ArcGIS model is a general tool able to modify these local
32 LiDAR DEM derivatives based on site characteristics to identify wetlands at a high resolution.

33 **KEYWORDS:** wetlands, LiDAR, topographic indices, Random Forest

34 1. Introduction

35 Wetlands are important ecosystems that not only provide habitat for many plant and
36 animal species, but also improve water quality, recharge groundwater, and ease flood and
37 drought severity (Guo et al., 2017). Despite the ecological value of wetlands, their quality and
38 presence are threatened by agricultural or development repurposing, pollutant runoff, and climate
39 change (Klemas, 2011). Current estimates are that roughly 50% of wetlands have been lost
40 globally since 1900 (Davidson, 2014) and approximately 53% of wetlands of the conterminous
41 U.S. have been lost since the early 1600s (Dahl et al., 1991). The historic loss of wetlands and
42 sustained threat to remaining wetlands has motivated increased efforts by scientists and
43 government to protect and maintain these ecosystems.

44 U.S. federal regulations play an important role in the abatement of further wetland loss.
45 One of the most important policies in support of this effort is Section 404 of the Clean Water
46 Act, which protects the nation's waters, including wetlands. According to Page and Wilcher
47 (1990), this law states that environmental planning entities must identify and assess
48 environmental impact due to land development and water resource projects. This requires
49 environmental planning entities, such as state departments of transportation (DOTs), to provide
50 wetland delineations that are ultimately jurisdictionally confirmed by the U.S. Army Corps of
51 Engineers (USACE). The USACE *Wetlands Delineation Manual* states that wetlands can be
52 identified by environmental characteristics shared among the many wetland types. The USACE
53 guidelines for wetland delineations use these common features and are based on the presence of
54 hydrologic conditions that inundate the area, vegetation adapted for life in saturated soil
55 conditions, and hydric soils (Environmental Laboratory, 1987).

56 Manual surveying by trained analysts will always be the most accurate method to
57 delineate wetlands, however carrying out detailed field surveys can be time consuming and
58 costly. According to estimates provided by representatives from the Virginia DOT (VDOT)
59 Environmental Division, the costs of these delineations range from \$60 to \$140 per acre (~0.4
60 ha) (personal communication, November 28, 2017). These estimates are based on recent VDOT
61 projects and can vary widely across projects. To offset these costs, the wetland permitting
62 process could potentially be streamlined by supplementing and guiding the manual delineations
63 with accurate digital wetland inventories. However, developing and updating wetland inventories
64 can be expensive and technically challenging due to the complexity of wetland features (Kloiber
65 et al., 2015). Furthermore, the existing national-scale wetland inventory in the U.S., the National
66 Wetland Inventory (NWI), is not ideal for assisting in the permitting process. Despite being one
67 of the most commonly used sources of wetland data in the U.S., NWI maps were never intended
68 to map federally regulated wetlands (Cowardin & Golet, 1995; Environmental Laboratory, 1987)
69 and research has shown that relying solely on the NWI may fail to protect a considerable fraction
70 of wetlands (Morrissey & Sweeney, 2006). Thus, a wetland inventory with the reliability
71 necessary to assist in the wetland permitting process is an unmet need.

72 Remote sensing has long been recognized as a powerful tool for identifying wetlands
73 (Environmental Laboratory, 1987) and may offer an accurate and cost-effective way to fulfill this
74 need (Guo et al., 2017; Lang et al., 2013; Lang & McCarty, 2014). Past studies have
75 incorporated remote sensing data such as multispectral imagery, radar, and Light Detection and
76 Ranging (LiDAR) for wetland identification. A review of wetland remote sensing studies of the
77 past 50 years shows that most researchers incorporate multispectral imagery in wetland
78 classifications (Guo et al., 2017). However, the incorporation of multispectral imagery can

79 weaken the potential for use during the wetland permitting process by introducing issues of
80 resolution or accessibility. For example, the commonly used Landsat multispectral imagery is
81 freely available on a national scale, but the 30 m resolution of this data can be too coarse to
82 detect wetlands at a scale relevant to environmental planning entities, which can require a spatial
83 accuracy of at least 1.5 m (VDOT Environmental Division, personal communication, November
84 28, 2017). While studies have shown higher resolution, multispectral data can result in accurate
85 wetland classifications (e.g., Kloiber et al., 2015) these data can be inaccessible due to cost.
86 Alternatively, LiDAR is remote sensing data that has been rapidly endorsed by the wetland
87 science and management community for its growing availability and technological benefit to
88 wetland mapping (Kloiber et al., 2015; Lang & McCarty, 2014). LiDAR sensors provide detailed
89 information on the Earth's landscape and bare surface by collecting x, y, and z data that can then
90 be interpolated to create digital elevation models (DEMs) (Lang & McCarty, 2014). LiDAR data
91 availability has increased rapidly over the past 20 years, and although current coverage in the
92 conterminous U.S. is at about one third, there is an ongoing effort by multiple federal agencies to
93 hasten the collection of LiDAR data throughout the entire U.S. (Snyder & Lang, 2012). LiDAR
94 derived DEMs have the ability to map wetlands by identifying areas of inundation based on
95 topographic drivers of flow convergence and offer widely available, high-resolution data that
96 could be utilized during the wetland permitting process. While conventional DEMs and their
97 derivatives have been shown to be useful for wetland delineation (e.g., Hogg & Todd, 2007),
98 LiDAR DEMs allow for more detailed mapping of topographic metrics (Lang & McCarty,
99 2014).

100 Previous research has shown that DEM derivatives have the potential to model spatial
101 patterns of saturated areas, and that LiDAR DEM derivatives improve the ability of these metrics

102 to do so (e.g., Hogg & Todd, 2007; Lang et al., 2013; Millard & Richardson, 2013). Among the
103 DEM derivatives found to be useful for this purpose are curvature, Topographic Wetness Index
104 (TWI) and the Cartographic Depth-to-Water index (DTW) (e.g., Ågren et al., 2014; Lang et al.,
105 2013; Murphy et al., 2009, 2011; Sangireddy et al., 2016). Curvature is defined as the second
106 derivative of the input surface and can describe the degree of convergence and acceleration of
107 flow (Moore et al., 1991). The TWI, developed by Beven and Kirkby (1979), relates the
108 tendency of a site to receive water to the tendency of a site to evacuate water and is defined as

$$TWI = \ln\left(\frac{\alpha}{\tan(\beta)}\right), \quad (1)$$

109 where α is the specific catchment area, or contributing area per unit contour length, and $\tan(\beta)$ is
110 the local slope. The DTW is a soil moisture index developed by Murphy et al. (2007) that is
111 based on an assumption that soils very close in elevation to their assigned surface water are more
112 likely to be saturated. The DTW model in grid form is calculated as

$$DTW (m) = \left[\sum \left(\frac{dz_i}{dx_i} \right) a \right] * x_c, \quad (2)$$

113 where $\frac{dz}{dx}$ is the downward slope of a pixel, i is a pixel along a calculated least cost (i.e., slope)
114 path to the assigned source pixel, a is 1 when the flow path is parallel to pixel boundaries or $\sqrt{2}$
115 when the flow crosses diagonally, and x_c is the pixel length (Murphy et al., 2007).

116 Although many studies have shown the benefit of using topographic indices to identify
117 wetted areas, and the added benefit of deriving these indices at higher resolutions, there are
118 unique challenges inherent to using LiDAR DEMs. Researchers have noted that LiDAR DEMs
119 used for purposes related to modelling landform characteristics must be resampled to coarser
120 resolutions and smoothed to overcome issues of increased “noise” from excessive topographic
121 detail (MacMillan et al., 2003), with this topographic noise arising from DEMs on the order of 1

122 m pixel size (Richardson et al., 2009). Moreover, variations in DEM resolution result in
123 significantly different spatial and statistical distributions of contributing areas and downslope
124 flow path lengths (Woodrow et al., 2016), and at high resolutions, micro-topographic features
125 can lead to highly variable slope values and provide unrealistic estimates of hydraulic gradients
126 (Grabs et al., 2009; Lanni et al., 2011). Previous studies have acknowledged the negative effect
127 that these micro-topographic features have on the ability of curvature (e.g., Sangireddy et al.,
128 2016) and TWI (e.g., Sørensen & Seibert, 2007) to identify hydrologic features of interest. For
129 example, Ågren et al. (2014) found that high-resolution DEMs (< 2 m) caused local TWI
130 variations that are too strong to separate wetlands from uplands, whereas deriving the index from
131 coarser (> 24 m) DEMs reduced these variations but resulted in poorly delineated flow channels
132 and local depressions. In contrast, the researchers also concluded that DTW derivations are not
133 sensitive to scale, but have suggested that the DTW could be further optimized (Ågren et al.
134 2014).

135 LiDAR DEM data and other remote sensing data are commonly used to map wetlands
136 through supervised classification algorithms. Random Forest (RF) classification is a relatively
137 new supervised classification method that is widely used for its ability to handle both continuous
138 and categorical, high-dimensional data and produce descriptive variable importance measures
139 (Millard & Richardson, 2015; Rodriguez-Galiano et al., 2012). RF has been shown to produce
140 higher accuracies than other classification techniques, such as maximum likelihood, when
141 incorporating multisource data (Duro et al., 2012; Miao et al., 2012; Rodriguez-Galiano et al.,
142 2012). Furthermore, studies have shown that LiDAR DEM metrics are suitable input variables
143 for the RF approach (e.g., Deng et al., 2017; Kloiber et al., 2015; Zhu & Pierskalla, 2016), and

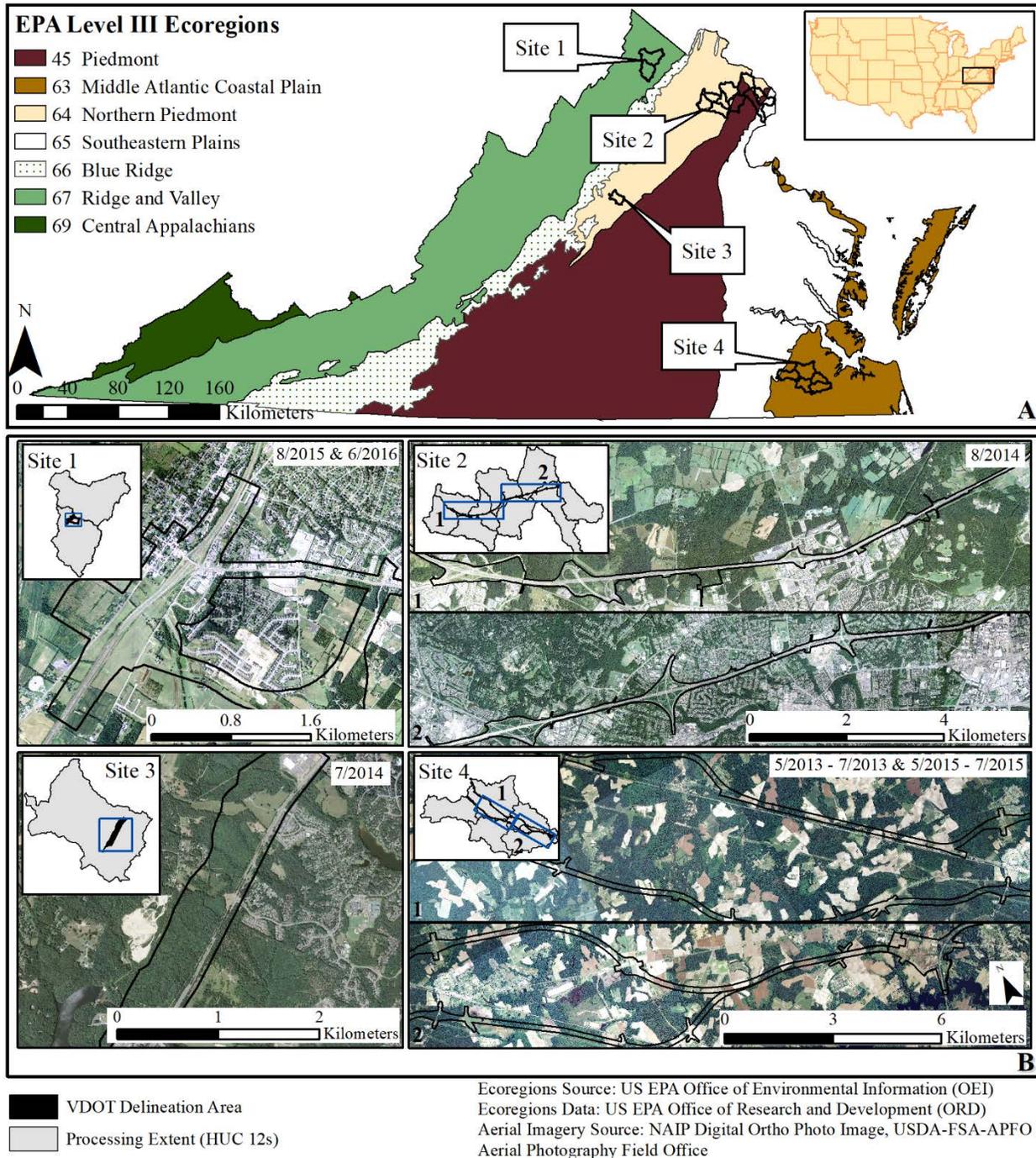
144 that using this classifier has strong potential to improve mapping and imagery classification of
145 wetlands (e.g., Millard & Richardson, 2013).

146 Many previous studies have relied primarily on ecological factors and spectral indices
147 provided by multispectral imagery to classify wetlands, and fewer studies have evaluated the
148 predictive power of LiDAR DEM data alone for this purpose. The primary objective of this study
149 was to further advance the application of LiDAR DEM derivatives to wetland mapping by
150 evaluating the potential of modified TWI, DTW, and curvature grids to address limitations noted
151 by researchers and identify small (i.e., environmental planning-scale) wetlands across varying
152 ecoregions. RF classifications of original and modified TWI, curvature, and DTW, where the
153 TWI and curvature were modified via smoothing and the DTW was modified via adjustments to
154 the input slope grid, along with ancillary national-scale soil data were assessed against field-
155 mapped test data and compared to NWI maps to identify the best performing models. Accuracy
156 assessments of these classifications provided a measure of the benefits and costs of modifying
157 these input data. This approach was applied to four study sites across varying ecoregions of
158 Virginia and implemented in ArcGIS with the potential for further refinement and utility by
159 environmental planning entities.

160 2. Study Areas

161 The four sites in this study were selected due to availability of VDOT wetland
162 delineations and LiDAR DEMs, and to have applications of this approach across varying
163 ecoregions of Virginia. As seen in Figure 1, the study sites span five of the seven level III EPA
164 ecoregions of Virginia: the Piedmont (45), the Mid-Atlantic Coastal Plain (63), the Northern
165 Piedmont (64), the Southeastern Plains (65), and the Ridge and Valley (67). According to the

166 EPA (2013), the Piedmont ecoregion is considered the non-mountainous region of the
167 Appalachians Highland and is comprised of transitional areas between the mountainous
168 Appalachians to the northwest and the relatively flat coastal plain to the southeast. The soils in
169 this region tend to be finer textured than in ecoregions 63 and 65. The Mid-Atlantic Coastal Plain
170 is characterized by low, nearly flat plains with many swamps, marshes, and estuaries. The region
171 has a mix of coarse and finer textured soils and poorly drained soils are common here. The
172 Northern Piedmont consists of low rounded hills, irregular plains, and open valleys. It is a
173 transitional region between the low mountains in ecoregion 66 and the flat coastal area of
174 ecoregions 63 and 65. The Southeastern Plains are irregular and have a mosaic of cropland,
175 pasture, woodland, and forest. The subsurface is predominantly sands, silts, and clays. The Ridge
176 and Valley ecoregion is relatively low-lying and characterized by alternating forested ridges and
177 agricultural valleys. Additional information describing the conditions of each study site can be
178 found in Table 1.



179

180 Figure 1. (a) Study site locations, outlined by watershed(s) used as site processing extent,
 181 spanning five of the seven ecoregions of Virginia, and (b) areas of each VDOT delineation site
 182 with orthoimagery corresponding to the time frame in which VDOT delineations were performed
 183 (M/YYYY).

184 Table 1. Conditions of the processing extent and VDOT delineation area for each study site;
 185 upper portion describes conditions of the processing extent and lower portion describes
 186 conditions of the VDOT delineation area.

	Site 1	Site 2	Site 3	Site 4
Processing Extent (HUC 12s) (km ²)	273	1208	65	547
LiDAR DEM Resolution (m)	1.00	1.50	0.76	0.76
HUC12 Max. Elevation (m)	458	417	223	37
HUC12 Min. Elevation (m)	140	0	96	0
HUC12 Mean Slope (%)	9.5	7.0	12.6	3.7
VDOT Delineation Total Area (km ²)	2.98	7.87	1.82	12.17
VDOT Delineation Max. Elevation (m)	241	147	178	34
VDOT Delineation Min. Elevation (m)	210	47	101	3
VDOT Delineation Mean Slope (%)	7.2	9.4	14.7	3.2
VDOT Wetland to Non-Wetland Ratio	0.02	0.02	0.02	0.42

187

188 3. Input Data

189 Freely available LiDAR elevation data, land cover data, national-scale hydrography data,
 190 national-scale soil data, and VDOT wetland delineations were used as inputs to the wetland
 191 identification model.

192 3.1. LiDAR Elevation Data

193 LiDAR-derived elevation data used in this study were provided by the Virginia
 194 Information Technologies Agency (VITA) in raster format (<http://vgin.maps.arcgis.com>). VITA
 195 LiDAR data products were freely available and included hydro-flattened, bare-earth DEMs. The
 196 LiDAR DEMs used in this study were collected and processed between 2010 and 2015 and have
 197 horizontal resolutions ranging from 0.76 m to 1.5 m. Tiles with different resolutions were
 198 merged and resampled to the coarsest resolution using the bilinear resampling method in
 199 ArcGIS, following the approach previously done by Ågren et al. (2014). Site 2 was unique in
 200 that LiDAR data were unavailable for approximately 230 km² (23%) of the processing extent and

201 0.8 km² (12%) of the VDOT delineation area. To fill the missing areas, 3 m elevation data from
202 the National Elevation Dataset were used (<https://viewer.nationalmap.gov>) and resampled to 1.5
203 m to match the dominating LiDAR data. While resampling to finer resolutions is not ideal,
204 maintaining consistency in the application of highest resolution LiDAR data across all study sites
205 was prioritized over the error introduced in the relatively small portion of the processing extent,
206 and even smaller portion of the delineation area.

207 3.2. Land Cover Data

208 Land cover data were used for post classification filtering. Land cover data used in this
209 study were provided by VITA in raster format (<http://vgin.maps.arcgis.com>). VITA land cover
210 data were derived from the Virginia Base Mapping Program 4 band orthophotography, collected
211 between 2011 and 2014. These data provided 12 land cover classifications with 85-95% accuracy
212 and have a horizontal resolution of 1 m (WorldView Solutions Inc., 2016).

213 3.3. National-Scale Datasets

214 National-scale soil and hydrography data were incorporated in the classification as
215 ancillary data. Soil data used in this study were obtained from the Soil Survey Geographic
216 database (SSURGO) and distributed by the Natural Resources Conservation Service's Web Soil
217 Survey in polygon vector format (<https://websoilsurvey.sc.egov.usda.gov>). The SSURGO hydric
218 rating, depth to water table, hydrologic soil group, surface texture, and soil drainage class were
219 used as indicators of saturated conditions. According to the Soil Survey Staff (2017), the hydric
220 rating attribute indicates the percentage of a map unit that meets the criteria for hydric soils.
221 Hydric soils are characteristic of wetlands and are defined as soil that is formed under conditions
222 of saturation, flooding, or ponding long enough during the growing season to develop anaerobic
223 conditions in the upper horizon (Federal Register, 1994). The surface texture attribute describes

224 the representative texture class according to percentage of sand, silt, and clay in the fraction of
225 the soil that is less than 2 mm in diameter. The drainage class attribute identifies the natural
226 drainage conditions of the soil and refers to the frequency of wet periods without considering
227 alterations of the water regime by human activities, unless they have significantly changed the
228 morphology of the soil. The hydrologic soils group assignment is based on estimates of the rate
229 of water infiltration when the soils are not protected by vegetation, are thoroughly wet, and
230 receive precipitation from long-duration storms. The depth to water table attribute indicates the
231 representative depth to the saturated zone in the soil.

232 Hydrography data used in this study were provided by the National Hydrography Dataset
233 (NHD) in polygon vector format (<https://viewer.nationalmap.gov>). NHD HUC 12 watersheds
234 intersected by the limits of VDOT delineations were combined to be used as the processing
235 extent for each study site in order to encompass the hydrologically connected area around VDOT
236 delineations. NHD streams and waterbodies within these processing extents were also used.

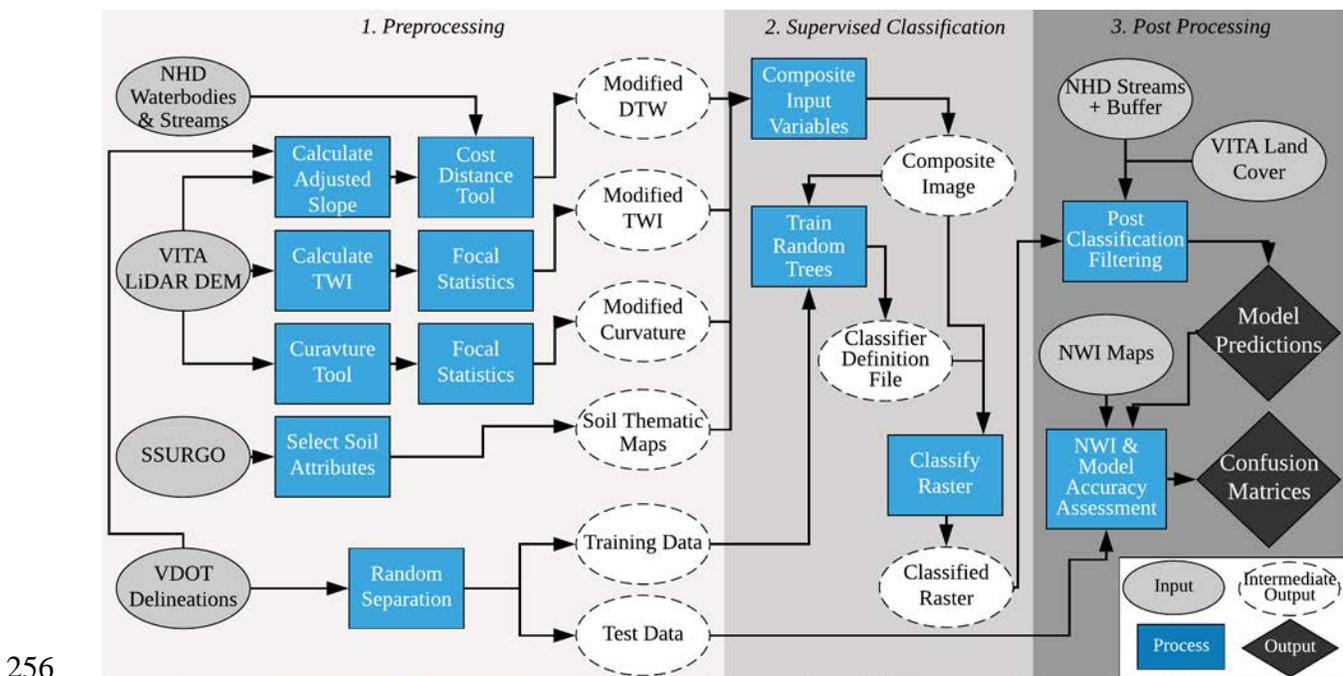
237 3.4. VDOT Wetland Delineations

238 Wetland delineations for each site were provided by VDOT and were used to create
239 training and testing datasets. The VDOT delineations in Site 2, Site 3, and Site 4 were
240 jurisdictionally confirmed by the USACE, and all study sites were produced through field
241 surveys conducted by professional wetland scientists. For these reasons, the VDOT delineations
242 were considered to be ground truth for the purpose of training and testing the wetland
243 identification model. VDOT delineations were provided in polygon vector format and included
244 both wetlands and streambeds. Both were included in subsequent processing because both are
245 considered waters of the state and therefore must be delineated during the wetland permitting
246 process. Although the delineations were categorized by wetland type by VDOT analysts, all

247 areas were merged into a single “wetland” category before application in this study.
 248 Additionally, limits of delineations were used to identify true non-wetland areas.

249 4. Methods

250 The workflow followed to implement the wetland identification approach consisted of
 251 three main parts: preprocessing, supervised classification, and post processing (Figure 2). The
 252 workflow was implemented in ArcGIS 10.4 and the ModelBuilder tool was used to automate
 253 processes that did not require user intervention. Outputs of the workflow were model predictions
 254 and confusion matrices used to assess the accuracy of those predictions. Components of the
 255 workflow are described in more detail in the following sections.



257 Figure 2. Workflow followed to implement the wetland identification approach as an ArcGIS
 258 model consisting of preprocessing, supervised classification, and post processing phases to create
 259 model predictions and confusion matrices used for accuracy assessment.

260 4.1. Preprocessing

261 The preprocessing phase consisted of a combination of automated and semi-automated
262 processes that required user intervention. Preprocessing steps not explicitly shown in Figure 2
263 include projection of input data to the appropriate North or South Virginia State Plane coordinate
264 system, clipping data to the HUC 12 processing extent, rasterizing input data originally in
265 polygon vector format by using the site LiDAR data as the pixel size constraint, and filling sinks
266 within the LiDAR DEM. Rasterizing the polygon vector layers mapped at larger scales assumes
267 that the information provided at the original scale (ranging from 1:24,000 to 1:12,000) is true for
268 each pixel of the output grid (ranging from 0.76 to 1.52 m). The LiDAR DEM was filled using
269 the depression filling algorithm of Planchon and Darboux (2002) that is implemented in ArcGIS.
270 Intermediate outputs created by the preprocessing phase were calibrated input variables, training
271 data, and testing data.

272 4.1.1. Modified Input Variable Creation

273 Input variables included the modified TWI, modified curvature, modified DTW, and
274 selected soil thematic maps. Input variables were modified based on site characteristics and
275 information provided by VDOT delineations in order to produce distinct wetland and non-
276 wetland signatures, and user intervention was necessary to execute some of the calibration
277 processes. Summarized modification parameters for topographic indices and information
278 relevant to their calculation are shown in Table 2 and the methods used to calculate these
279 parameters are described in the following sections.

280 Table 2. Modification parameters for topographic indices, and soil thematic maps determined to
281 be relevant for each study site. Site characteristics relevant to the calculation of modification
282 parameters are italicized and inclusion of a soil layer is indicated by an “X.”

	Site 1	Site 2	Site 3	Site 4
<i>LiDAR DEM Resolution (m)</i>	1.0	1.52	0.76	0.76
TWI Focal Statistic Window size (# pixels)	5	3	7	7
Curvature Focal Statistic Window size (# pixels)	5	3	7	7
TWI Focal Statistic Type	Median	Median	Median	Median
Curvature Focal Statistic Type	Mean	Mean	Mean	Mean
<i>Maximum Underlying Wetland Slope Value (m/m)</i>	0.751	1.134	1.652	1.403
<i>Representative Wetland Slope (m/m)</i>	0.088	0.168	0.41	0.115
DTW γ	11.42	5.95	2.44	8.70
DTW β	2	2	2	2
Hydrologic Soil Group	X	X		
Depth to Water Table	X			X
Surface Texture	X	X		
Hydric Rating		X		X
Soil Drainage Class		X		

283 *4.1.1.1. TWI Modifications*

284 The modified TWI grid is based on the TWI as defined in Equation (1). The TWI was
285 created in ArcGIS as a Map Algebra expression. The inputs required for this calculation were a
286 flow accumulation grid, to represent the α term, and a slope grid, to represent the $\tan(\beta)$ term,
287 both derived from the filled LiDAR DEM. The D8 method (Jenson & Domingue, 1988) was
288 used to generate flow direction and flow accumulation grids. A slope grid was generated with the
289 ArcGIS slope tool, calculated as the steepest downhill descent from each pixel in units of m/m
290 (Burrough & McDonell, 1998). A constant equal to 1 was added to flow accumulation grids so
291 that every pixel received flow from itself as well as upslope pixels to avoid undefined TWI
292 values, and a constant equal to 0.0001 (m/m) was added to slope grids to avoid dividing by zero.
293 An example of the resulting TWI grid, overlaid with VDOT wetland areas, for a portion of Site 1
294 is shown in Figure 4 (panel A1). This TWI grid models the presence wetter areas (high TWI
295 values) in locations of high flow accumulation and low slopes, and drier areas (low TWI values)
296 in locations of steep slopes and less flow accumulation. Larger clusters of relatively high TWI
297 values align with the VDOT delineated wetlands, however there is also a scattering of high TWI

298 values outside of these wetland boundaries, corroborating the challenges of high-resolution TWIs
299 previously described in the literature (e.g., Ågren et al., 2014; Sørensen & Seibert, 2007). Some
300 researchers recommend deriving TWIs from coarser DEMs (e.g., Ågren et al., 2014), but doing
301 so would sacrifice the rich detail provided by LiDAR DEMs that may be needed to precisely
302 model shape and size of environmental planning-scale wetlands.

303 Although these scatterings of relatively high TWI values may be modelling true micro-
304 topographic features, their location outside of the field-mapped wetlands suggest these flow
305 channels are not large enough to result in saturated conditions. Rather than lose hydrologic detail
306 of the LiDAR data by resampling, anomalous local variations were smoothed by applying a low-
307 pass filter over a moving NxN window to create the modified TWI. Applying a low-pass filter
308 searches over a user-defined window in which every pixel is replaced with the statistical value
309 from the surrounding pixels within the NxN window, as done by Ali et al. (2014), Buchanan et
310 al. (2014), and Lanni et al. (2011). The window size for the smoothing operation is significant in
311 that it is usually set with consideration of the average size of the feature of interest (Sangireddy
312 et al., 2016). In this study we estimated that areas of interest must be at least 5 m in width based
313 on the size of VDOT delineated wetlands. Therefore, window sizes were set to smooth over a
314 total area of approximately 25 m² (5 m x 5 m) with this window size varying slightly across
315 study sites depending on pixel length of the LiDAR data. Additionally, a median filter was
316 chosen to perform smoothing rather than the mean filter. Visual assessment of both statistic types
317 showed that the median filter better retained VDOT wetland edge features while removing
318 scattered high TWI values outside of these boundaries. TWI smoothing was implemented in the
319 ArcGIS model using the Focal Statistics tool. Window sizes used to calculate the modified TWI
320 grid for each site are shown in Table 2, and an example of applying this modification for a

321 portion of Site 1 is shown in Figure 4, panel A2. Compared to the unmodified TWI (panel A1),
322 this scene shows the larger cluster of relatively high TWI values within VDOT delineated
323 wetlands were maintained, but the discrete, small flow channels outside of the true wetland
324 boundaries have been smoothed via replacement of these pixels with relatively lower TWI
325 values.

326 *4.1.1.2. Curvature Modifications*

327 Curvature grids, as defined by Moore et al. (1991) were created from the filled LiDAR
328 DEM using the ArcGIS Curvature tool. Curvature has been shown to be a key component in the
329 process of identifying likely channelized pixels indicating flow convergence (Ågren et al., 2014;
330 Hogg & Todd, 2007; Kloiber et al., 2015; Millard & Richardson, 2013; Sangireddy et al., 2016).
331 It was anticipated that the high resolution of the LiDAR-derived curvature grids would assist in
332 separating small differences in concavity between nearly flat roadways and shallow local
333 depressions. However, visual assessment of the LiDAR-derived curvature grids showed a similar
334 issue of topographic noise as seen in the TWI, in that micro-topographic channels were also
335 mapped. An example of the output curvature grid for a portion of Site 1 is shown in Figure 4,
336 panel B1. This image shows negative and zero curvature values within VDOT wetland extents,
337 which correspond to concave and flat areas, respectively.

338 Similar to modified TWI creation, the curvature was modified by applying a statistical
339 smoothing process to curvature grids, following the approach of Sangireddy et al. (2016). When
340 choosing the window size for this calculation, the assumption of the average size of features of
341 interest was kept consistent with that of the TWI (i.e., at least 5 m in width). In this case a mean
342 filter was chosen to smooth the curvature data rather than a median filter due to a visual
343 inspection and perceived improvement in VDOT wetland edge retention resulting from the mean

344 smoothing. The modified curvature grid was created by applying the ArcGIS Focal Statistics
345 tool. Window sizes used to calculate the modified curvature grid for each site are shown in Table
346 2 and an example of applying this modification for a portion of Site 1 is shown in Figure 4, panel
347 B2. In this image one can see that the modified curvature grid has a smoother appearance but
348 maintains significant areas of concavity.

349 *4.1.1.3. DTW Modifications*

350 The modified DTW grid is based on the DTW as defined in Equation (2). This iterative
351 function finds the cumulative slope value along the least downward slope (i.e., “cost”) path to the
352 nearest surface water (i.e., “source”) pixel with which it is most likely to be hydrologically
353 connected (Murphy et al., 2009). To calculate the DTW, two input grids are required: a grid of
354 slope values and a grid of areas of open water (Murphy et al., 2009). In this study, slope grids
355 were derived from the filled LiDAR DEM using the ArcGIS slope function, as done in the
356 original formulation of the DTW model (e.g., Murphy et al., 2007, 2009, 2011), and the source
357 grids were created from rasterized NHD waterbodies and streams. While the publicly available
358 NHD was chosen in this study to maintain consistency between the four sites, there are
359 alternatives for researchers without publicly available open water data. The source grid can also
360 be generated directly from elevation data by deriving streams based on a designated flow
361 accumulation threshold (Murphy et al., 2009) or use of open source channel extraction software,
362 such as GeoNet (Sangireddy et al., 2016). The effects and limitations of using the relatively
363 coarsely mapped NHD as the source grid for the DTW are discussed in section 5.2. of this paper.
364 The ArcGIS Cost Distance tool was used to evaluate Equation (2) within the model using the
365 slope and NHD source grids as inputs. It was also necessary to add a small constant (0.0001
366 m/m) to all pixels in the slope grid to differentiate from source grid pixels, which are assigned a

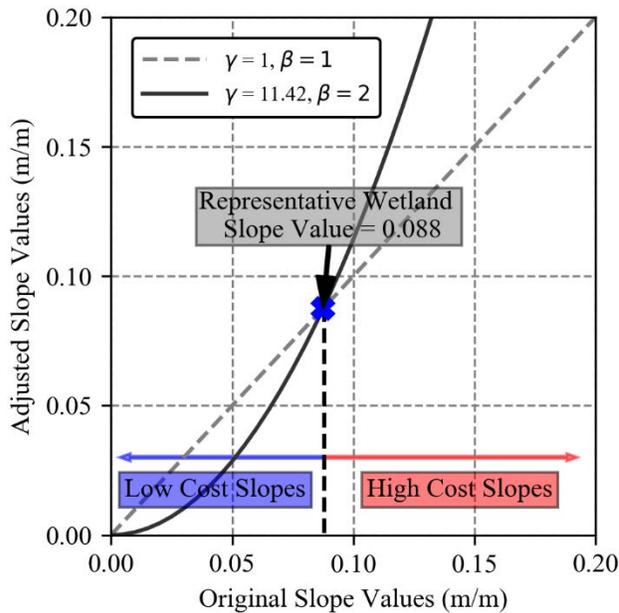
367 value of zero for the calculation. An example of the resulting DTW grid for a portion of Site 1 is
368 shown in panel C1 of Figure 4. As expected, low wetness (high DTW values) occurred in areas
369 further and higher along the terrain from surface water, and high wetness (low DTW values)
370 occurred in areas of low slopes that are closer to surface water. While wetted areas calculated by
371 the DTW correspond to VDOT delineated wetlands, the transition from wet to dryer areas is
372 gradual. We found this to result in lower non-wetland accuracy, or an overestimation of
373 wetlands, when using only the original DTW formulation to identify wetland areas.

374 Therefore, a modified DTW was created to accelerate the gradual transition from
375 wetlands to uplands in an effort to better distinguish wet from dry locations. The method outlined
376 above was used to calculate the modified DTW, except that the input slope grid was replaced
377 with an adjusted slope grid, defined as,

$$Y = \gamma * X^\beta, \tag{3}$$

378 where X is the slope (with a small constant added to all values, as described earlier), and γ and β
379 are calculated slope adjustment parameters. This adjustment to the slope values was intended to
380 create two distinct ranges of low cost areas, where wetlands are likely to exist, and high cost
381 areas, where wetlands are unlikely to exist, based on the observed distribution of wetland slope
382 values in each site. The γ parameter allows users to control the cutoff between the low and high
383 cost slope values, which corresponds to a designated representative wetland slope value. The β
384 parameter allows users to control the rate of increase in cost as the slopes increase throughout the
385 site. In this study, β was set to a value of 2 for all sites while γ was individually calibrated. We
386 hypothesized that setting the wetland slope value equal to the 95th percentile of all underlying
387 VDOT wetland slope values would result in a γ parameter that further flattens the terrain (i.e.,
388 reduces the cost) where most wetlands exist, disregarding assumed outliers, and further

389 steepening the terrain (i.e., increasing the cost) elsewhere. Representative slope values were
 390 calculated by extracting slope values within VDOT wetland boundaries, and calculating the 95th
 391 percentile of each array with the Numpy Python library. Figure 3 shows an example of this
 392 adjusted slope calculation and describes the effect of this adjustment for Site 1, where the 95th
 393 percentile was 0.088 m/m, which corresponded to a γ value of 11.42.



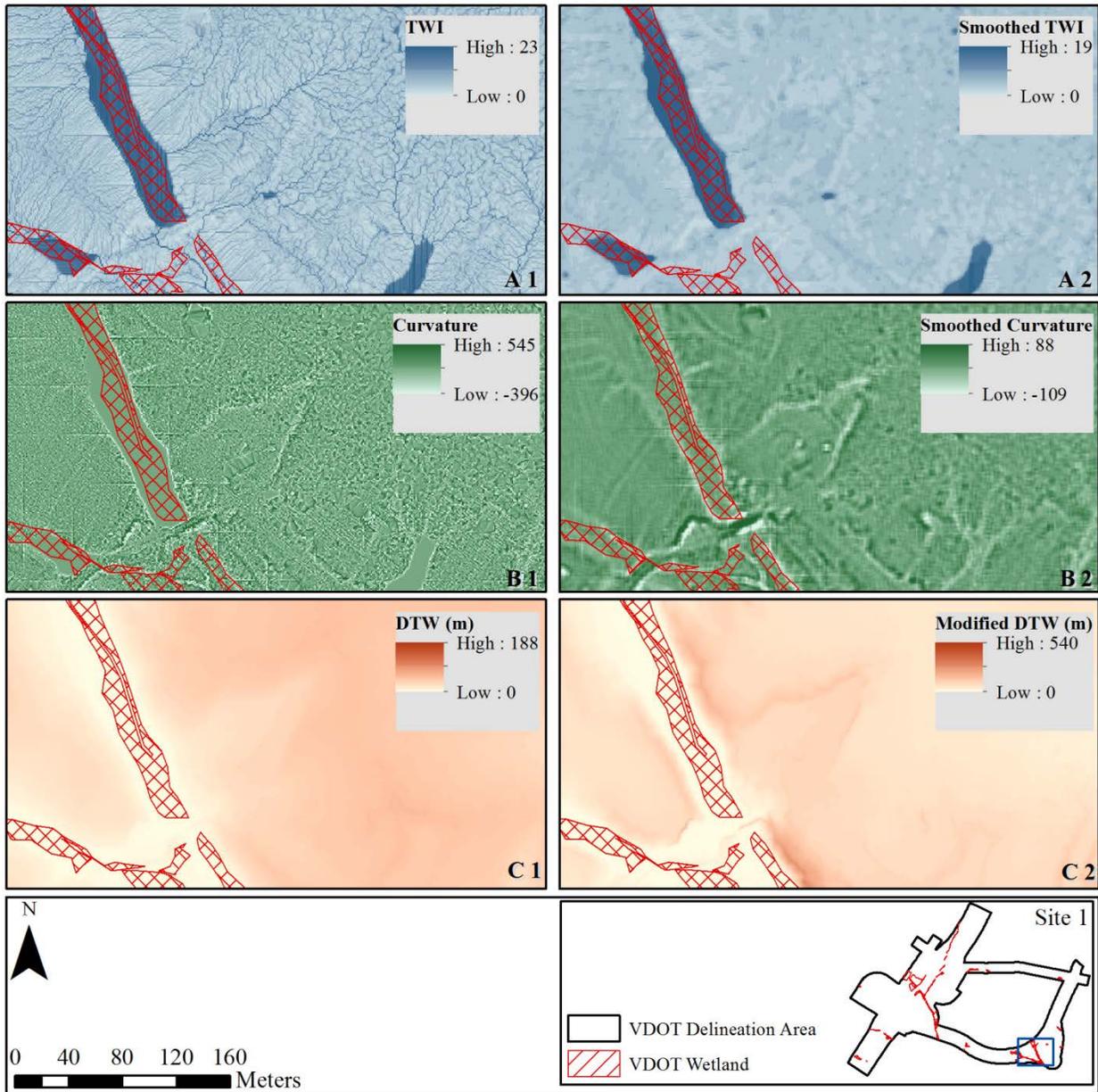
394
 395 Figure 3. Example calculation of the adjusted slope grid (solid line) for Site 1 where the β was
 396 set to a value of 2 and γ was calculated to be 11.42, corresponding to a representative slope value
 397 taken to be the 95th percentile of all underlying wetland slopes. These adjustments decrease
 398 slopes that are originally below 0.088 and increase slopes that are originally above 0.088,
 399 relative to a slope grid (dashed line) where γ and β are both equal to 1.

400 Note: Although maximum wetland slope value in Site 1 was 0.751 m/m, a smaller range of values is shown here for
 401 clarity.

402 With the adjustments to the slope grid applied, Equation (2) becomes

$$\textit{Modified DTW (m)} = \left[\sum \gamma \left(\frac{dz_i}{dx_i} \right)^2 a \right] * x_c, \quad (4)$$

403 where γ and $\beta=2$ are introduced. Slope adjustment parameters and relevant site characteristics
404 used to calculate these parameters are shown for each site in Table 2. An example of the effect of
405 modifying the DTW in Site 1 using this calculation is shown in panel C2 of Figure 4. In this
406 figure, the modified DTW (C2) shows relatively wetter areas within VDOT wetland boundaries
407 and an accelerated increase to drier values moving away from VDOT wetlands, compared to the
408 original DTW (C1).



409

410 Figure 4. Topographic input variables in Site 1, original TWI (A1), curvature (B1), and DTW

411 (C1), compared to modified versions each variable, shown in A2, B2, and C2, respectively.

412 Modification parameters used to calculate the modified topographic indices in Site 1 are shown

413 in Table 2.

414 Note: Panels A1 and B1 highlight anomalies in elevation data that are likely artifacts of LiDAR tile merging during

415 original processing of raw data.

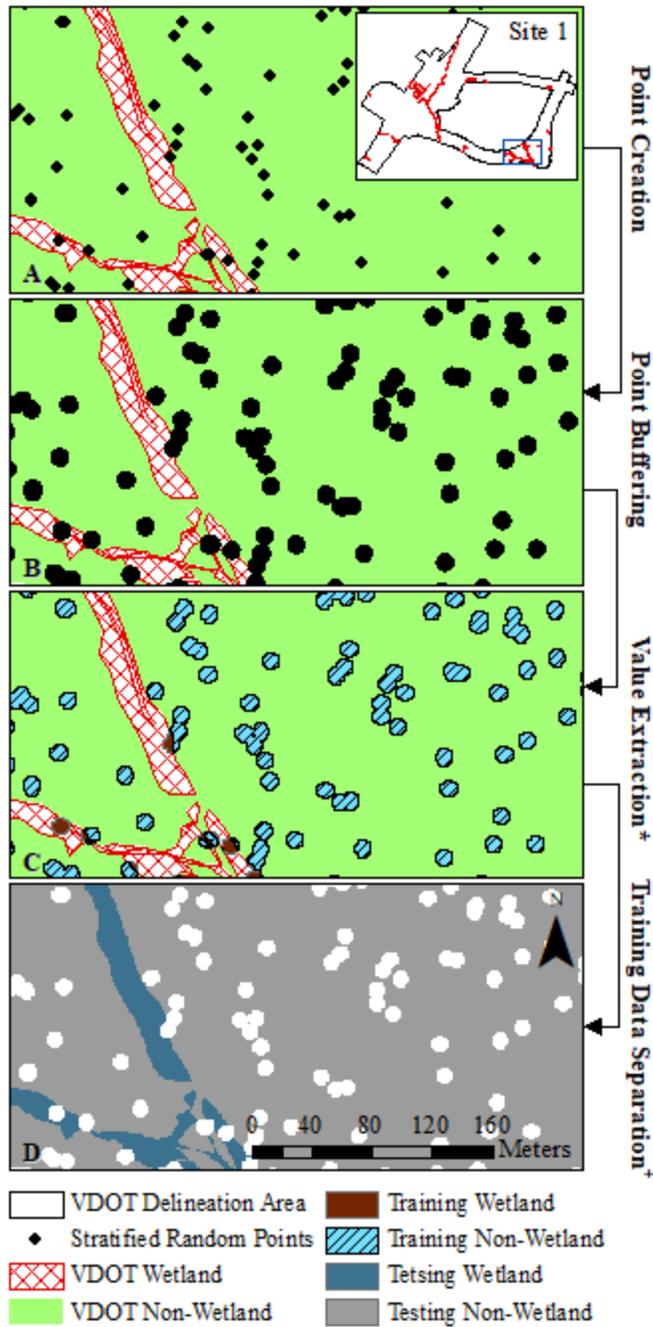
416 4.1.1.4. *Soil Thematic Maps*

417 The final input variables created in the preprocessing phase were soil thematic maps. Soil
418 thematic maps were created from the extensive SSURGO database using the Soil Data Viewer
419 ArcMap extension (NRCS, 2015). Although the Soil Data Viewer creates soil thematic maps
420 automatically, combinations of soil layers were manually chosen for each site based on
421 correspondence of the soil data to the current physical landscape. This correspondence was
422 assessed by visual comparison to VDOT delineations and VITA land cover data. Soil layers that
423 appeared too coarse, i.e. generally did not vary enough within the VDOT delineated area to
424 describe features of interest, were not selected.

425 4.1.2. Training and Testing Data

426 An automated process was used to randomly designate 10% of VDOT delineation area to
427 train the classifier and reserve the remaining 90% to test the classification results. It has been
428 noted that statistical classifiers and machine learning algorithms may be sensitive to imbalanced
429 training data or cases where rare classes are being classified (such as most cases of wetland
430 identification), and the sensitivity of RF, specifically, to training class proportions was
431 investigated by Millard and Richardson (2015). The researchers found that when training
432 samples were disproportionately higher or lower than the true distribution of that feature, the
433 final classification over or under predicted that class, respectively. They concluded that using a
434 sampling strategy that ensures representative class proportions, and minimal spatial
435 autocorrelation, minimized proportion-error in their results (Millard & Richardson, 2015). In this
436 study we took into account the findings of Millard and Richardson (2015) when designing the
437 methodology to randomly separate VDOT delineations into training and testing data. This
438 process consisted of 4 steps: random point creation, point buffering, value extraction, and

439 training data separation (Figure 5). A stratified random sampling method was used in the first
440 step to distribute a designated number training sample locations proportionately between wetland
441 and non-wetland areas (panel A). These randomly generated points were then buffered to create
442 circle polygons with an area of approximately 100 m² each (panel B). In the value extraction step
443 (panel C), training data, composed of approximately 10% of the delineated area and with
444 representative class proportions, were produced by rasterizing the buffered polygons with pixel
445 values extracted from VDOT delineations to correct cases of buffered polygons falling into both
446 wetland and non-wetland classes. The testing data were created by separating the training data
447 from the VDOT delineations, leaving approximately 90% of the delineated area to be used for
448 accuracy assessment (panel D). Statistics describing the training and testing datasets for each site
449 are found in Table 3.



450

451 Figure 5. Example of the process, shown for Site 1, used to randomly separate VDOT
 452 delineations into training and testing datasets, consisting of four steps: (A) point creation, (B)
 453 point buffering, (C) value extraction, and (D) training data separation. Asterisk indicates the
 454 phase in which training data are created and superscript “+” indicates the phase in which testing
 455 data are created.

456 Table 3. Statistics describing the training and testing data for each site.

	Site 1	Site 2	Site 3	Site 4
Training Wetlands (km ²)	0.007	0.015	0.003	0.347
Training Non-Wetlands (km ²)	0.271	0.745	0.172	0.816
Training Wetland to Non-Wetland Ratio	0.03	0.02	0.02	0.43
Training Area to VDOT Delineation Area Ratio	0.09	0.09	0.10	0.10
Testing Area (VDOT Delineation - Training Area) (km ²)	2.71	7.11	1.65	11.00

457 4.2. Supervised Classification

458 In the first phase of the supervised classification portion of the workflow, the input
 459 variables created during preprocessing were combined into a multidimensional, composite image
 460 where each dimension stores an independent input variable. Wetland and non-wetland signatures
 461 were extracted from this composite image and used to perform the supervised classification. RF
 462 classification was chosen as the supervised classification algorithm for its noted advantages in
 463 similar studies, as described previously (e.g., Duro et al., 2012; Miao et al., 2012; Millard &
 464 Richardson, 2013; Rodriguez-Galiano et al., 2012). According to Breiman (2001), RF is an
 465 ensemble classifier that produces many Classification and Regression-like trees where each tree
 466 is generated from different bootstrapped samples of training data, and input variables are
 467 randomly selected for generating trees. This algorithm also produces variable importance
 468 information, which measures the mean decrease in accuracy when a variable is not used in
 469 generating a tree.

470 The RF classification was executed in ArcGIS with the Train Random Trees and Classify
 471 Raster tools (ESRI, 2016). The Train Random Trees tool utilizes the OpenCV implementation of
 472 the RF algorithm (Bradski, G., 2000). Using Train Random Trees, the training data were used to
 473 extract class signatures from the dimensions (i.e., input variables) of the composite image,

474 creating an ESRI Classifier Definition file with variable importance measures. The Classifier
475 Definition file was subsequently used to classify the remainder of the composite image. The
476 result of these operations is a grid where each pixel has been classified as wetland or non-
477 wetland. As the focus of this study was to analyze the response of classification models to input
478 data, the RF parameters were not varied or calibrated to study sites. For this reason, the default
479 values of maximum number of trees, maximum tree depth, and maximum numbers of samples
480 per class were held constant at the recommended default values of 50, 30, and 1000,
481 respectively. Future work should perform a sensitivity analysis to test the effect of adjusting
482 these parameters.

483 4.3. Post Processing

484 The first phase of post processing was post classification filtering. The objective of the
485 post classification filtering was to account for areas that may be susceptible to water
486 accumulation due to its local topography, but cannot be wetland areas due to impervious land
487 cover. The post classification filtering algorithm first used a logical statement to determine if a
488 classified wetland pixel overlaps VITA land cover designated as impervious. If this was false,
489 the pixel classification was unchanged. If this was true, a second logical statement was used to
490 account for cases where wetlands may exist under bridges by determining if classified wetland
491 pixels are within 30 m of NHD streams. The 30-m buffer distance was an estimated value based
492 on visual inspection, and more precise measurements would increase effectiveness of post
493 classification filtering. If this second statement was false, the pixel was reclassified as non-
494 wetland, otherwise it was left unchanged. This process produced the model predictions.

495 The second phase of post processing was accuracy assessment. The model predictions
496 and NWI map for the study area were assessed for accuracy in terms of agreement with the test

497 dataset. Accuracy assessments were evaluated with confusion matrices, which summarized the
498 areas of wetland agreement, non-wetland agreement, false negative predictions (cases where true
499 wetland areas were predicted to be non-wetland), and false positive predictions (cases where true
500 non-wetland areas were predicted to be wetland). Confusion matrices for the model predictions
501 and NWI maps were used to calculate wetland accuracy, non-wetland accuracy, and overall
502 accuracy using Equations 5-7,

$$\text{Wetland Accuracy} = \frac{\text{wetland agreement (km}^2\text{)}}{\sum \text{test (actual) wetland (km}^2\text{)}} \quad (5)$$

$$\text{NonWetland Accuracy} = \frac{\text{nonwetland agreement (km}^2\text{)}}{\sum \text{test (actual) nonwetland (km}^2\text{)}} \quad (6)$$

$$\text{Overall Accuracy} = \frac{\text{wetland agreement (km}^2\text{)} + \text{nonwetland agreement (km}^2\text{)}}{\sum \text{test (actual) area (km}^2\text{)}}. \quad (7)$$

503 The use of these metrics to assess wetland classifications is common in literature (e.g., Ågren et
504 al., 2014; Millard & Richardson, 2013).

505 5. Results and Discussion

506 5.1. Highest Performing Models

507 To determine the highest performing models, classifications varying only topographic inputs
508 were first performed and assessed, and the input data that resulted in highest overall accuracy
509 were combined with relevant soil layers, if any. In the coming sections, the following results are
510 discussed: (1) scenes for each site comparing highest performing models and their level of
511 agreement with VDOT delineations, compared to NWI maps, (2) variable importance of highest
512 performing input data, and (3) the accuracy assessment of highest performing models compared
513 to the NWI. The input data used to produce the best performing models and the importance of
514 these inputs according to the ESRI Classifier Definition file are listed in Table 4. Although

515 accuracy assessments for each site only extend to testing dataset limits, scenes depicting
 516 predictions and VDOT delineations prior to the separation process are shown for clarity.
 517 Table 4. Input data that produced the highest performing wetland identification model in each
 518 site, in terms of overall accuracy, as well as variable importance and rank of each input variable
 519 according to the ESRI Classifier Definition file. Topographic inputs with an asterisk indicate the
 520 application of modifications using parameters from Table 2.

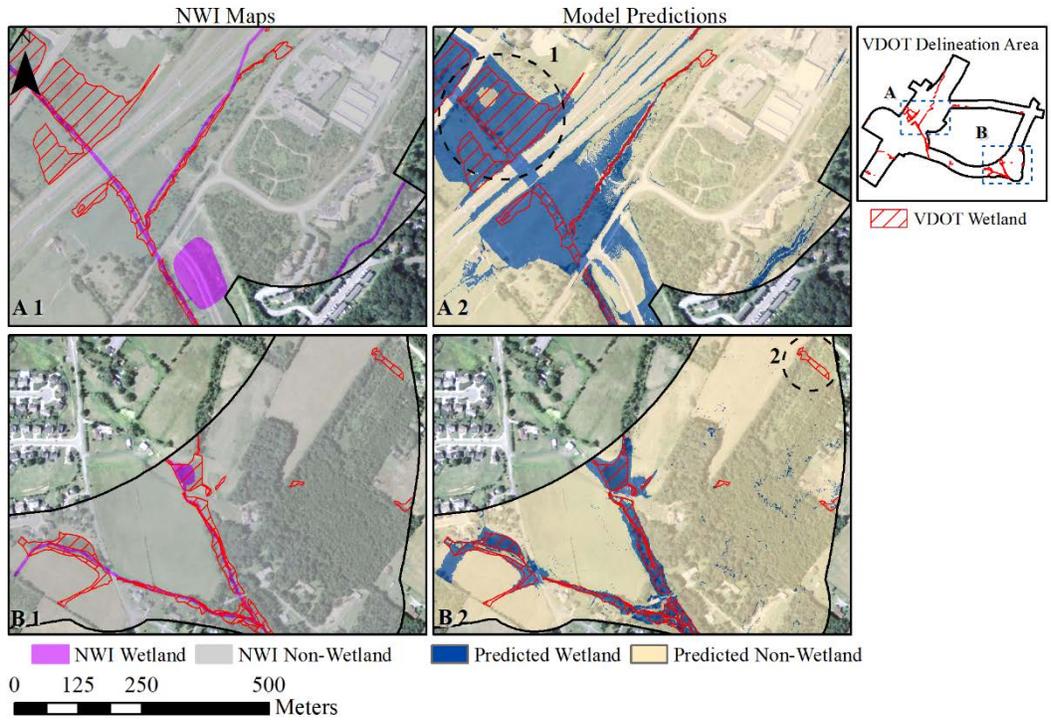
	Input 1	Input 2	Input 3	Input 4	Input 5	Input 6	Input 7	Input 8
Site 1	TWI*	Curvature*	DTW*	HSG ¹	Depth to WT ²	ST ³	-	-
VI ⁺	0.087	0.111	0.333	0.131	0.182	0.156	-	-
Rank	6	5	1	4	2	3	-	-
Site 2	TWI*	Curvature*	DTW	HSG ¹	-	ST ³	HR ⁴	DC ⁵
VI ⁺	0.078	0.107	0.156	0.208		0.126	0.177	0.150
Rank	7	6	3	1		5	2	4
Site 3	TWI*	Curvature*	DTW*		-	-	-	-
VI ⁺	0.158	0.325	0.516					
Rank	3	2	1		-	-	-	-
Site 4	TWI*	Curvature*	DTW*		Depth to WT ²		HR ⁴	
VI ⁺	0.076	0.114	0.215		0.338		0.257	
Rank	5	4	3		1		2	

521 ⁺Variable Importance; ¹Hydrologic soil group; ²Depth to water table; ³Surface texture; ⁴Hydric rating; ⁵Drainage
 522 Class

523 5.1.1. Site 1 Results

524 Wetland predictions and NWI data for Site 1 are shown in Figure 6. Both of the NWI
 525 scenes (A1 and B1) exemplify the tendency of the NWI to underestimate the size of VDOT
 526 delineated wetlands by mapping wetlands primarily along streams. While the narrow NWI
 527 wetlands precisely map the wetland areas that are in agreement with VDOT delineations, the
 528 NWI fails to match the contours or the size of larger wetland zones. These larger wetland zones
 529 were more fully mapped by wetland predictions produced by the model (A2 and B2). However
 530 the model also produced relatively higher overestimation of wetlands. Overestimation of

531 wetlands is especially prevalent in location 1. Underlying input variables indicated that
532 overestimation here was due to a depression that was filled to become a large, zero-slope area.
533 This flat zone resulted in a corresponding generalized area of high wetness values in the
534 modified TWI and modified DTW. In addition, the surface texture input indicated that silty clay
535 loam, which have relatively slow infiltration rates (~0.5 cm/h) (Soil Survey Staff, 2017), was
536 also present in this overestimated area, likely contributing to the wetland predictions here. It is
537 possible that the results in this site could be improved by using an alternative to the pit filling
538 (i.e., ArcGIS Fill) algorithm to avoid creation of generalized, flat areas, more severe adjustments
539 to the slope grid for the modified DTW, or higher resolution SSURGO data. Panel B2 shows
540 more precise model wetland predictions, represented by conformity of predicted wetlands to the
541 curvature of VDOT delineated wetlands. This panel encompasses the scene in Figure 4 (C2)
542 where the modification to the DTW was shown to more precisely map wetland areas. For that
543 reason, we attribute the relatively precise mapping of wetlands in B2 in part to the modifications
544 used for the DTW in this site. Location 2 shows one small wetland that was undetected by the
545 model. This may indicate a wetland formed due to conditions more strongly driven by vegetation
546 rather than topography or proximity to surface water.



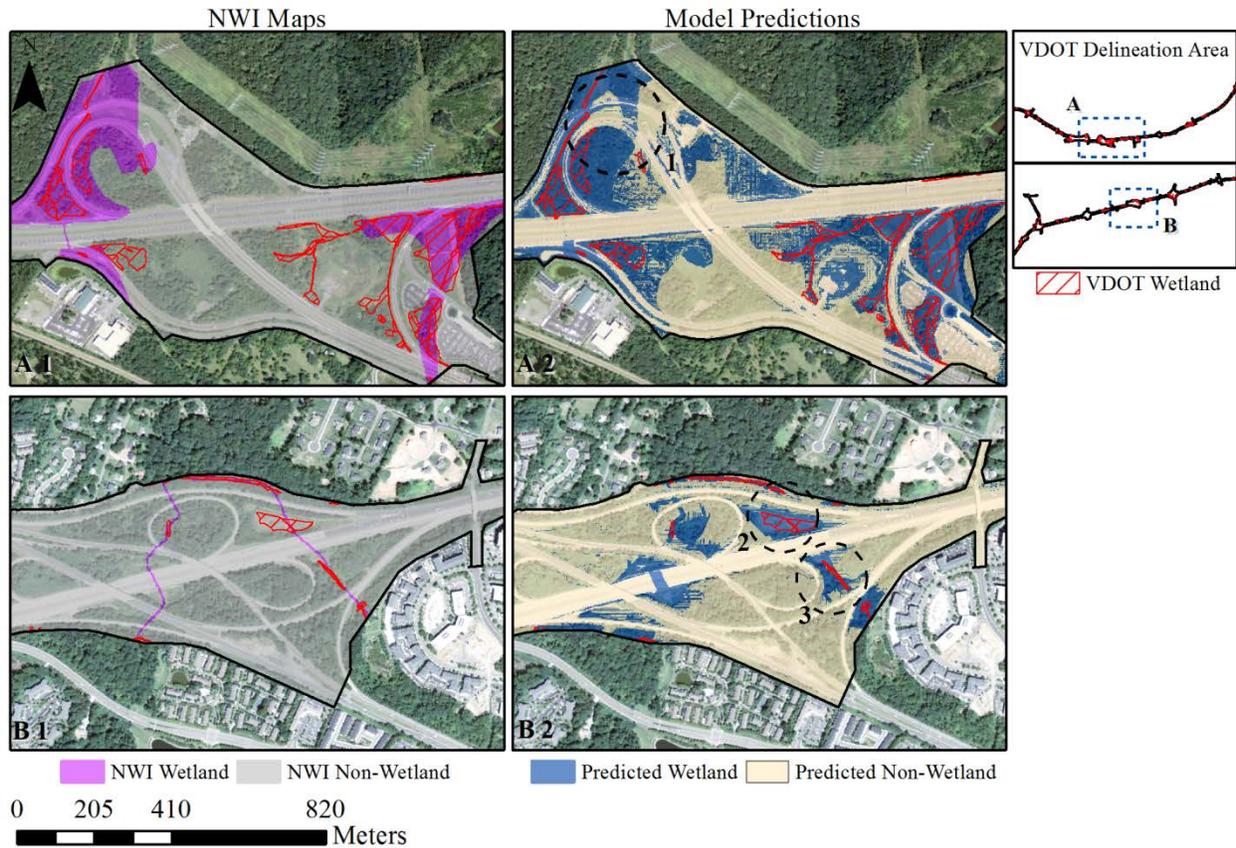
547

548 Figure 6. Examples of NWI maps (A1 and B1) and model predictions (A2 and B2) for Site 1,
 549 both compared to VDOT delineations.

550 5.1.2. Site 2 Results

551 Two scenes of the model predictions and NWI maps for Site 2 are shown in Figure 7. In
 552 panels A1 and A2, the NWI dataset and model predictions both show similar overestimation of
 553 wetland area, although the model resulted in higher overestimation. The false positive
 554 predictions in this area were due to flow convergence indicated by the topographic inputs, and
 555 the presence of hydric soils indicated by the SSURGO data. Also, many false positive
 556 predictions in this site were in locations overlapping road features (e.g., location 1). This may
 557 indicate a need for alternate modifications to topographic inputs, especially curvature, to better
 558 differentiate channelized areas due road features from channelized areas that are wetlands, as
 559 proposed by Sangireddy et al. (2016). Panel B1 shows another example of NWI wetland
 560 delineations following along streams, but failing to capture the extents of larger wetland zones.

561 For this same area, the model predicted wetlands further from the streambeds due to the gradual
 562 slopes surrounding them and better encompassed VDOT delineated wetlands (locations 2 and 3).

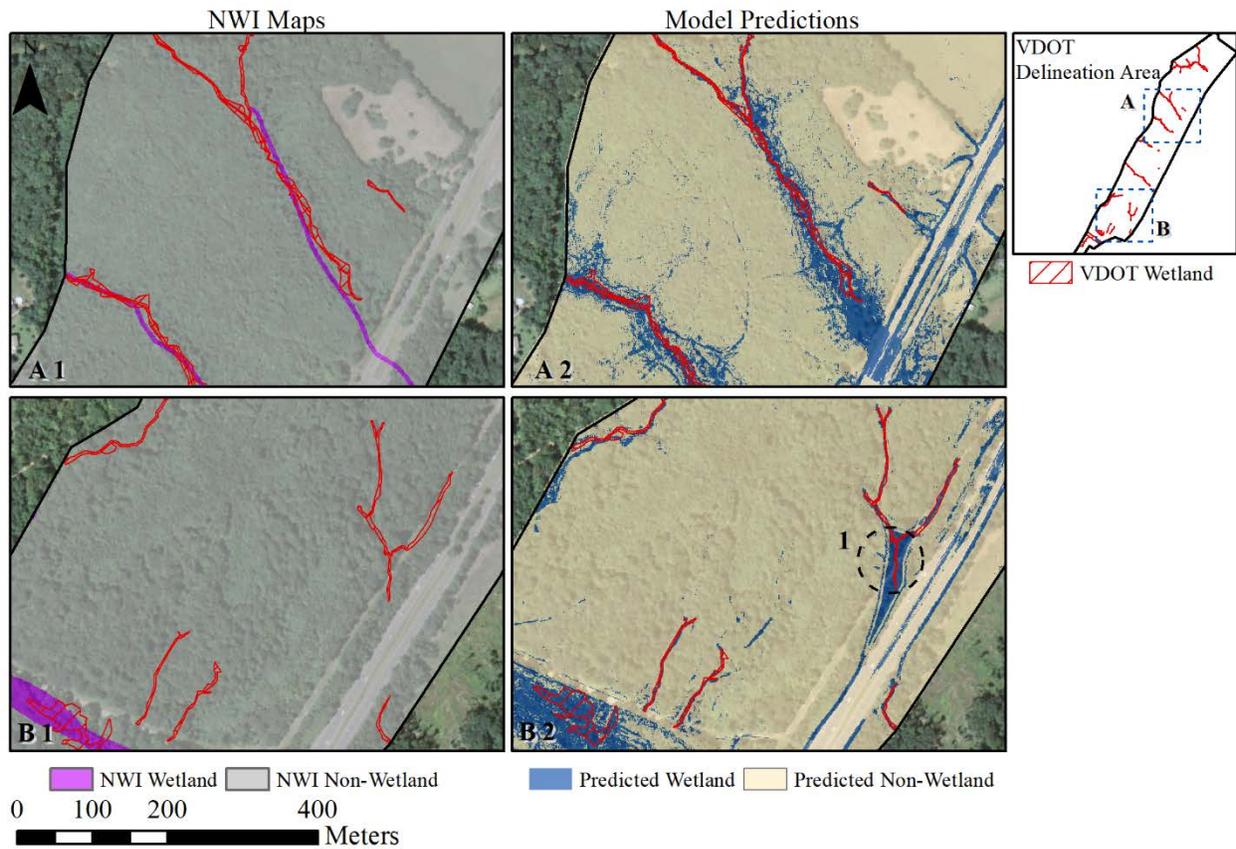


563
 564 Figure 7. Examples of NWI maps (A1 and B1) and model predictions (A2 and B2) for Site 2,
 565 both compared to VDOT delineations.

566 5.1.3. Site 3 Results

567 Examples of model predictions and NWI data for Site 3 are shown in Figure 8. As seen in
 568 Table 4, Site 3 was unique in that no soil layers were included in the best performing model.
 569 Visual assessment of relevant soil layers in this area showed that the SSURGO data did not vary
 570 in a way that effectively differentiated between features of interest. Site 3 was also unique for its
 571 wetlands which were typically narrow and located along small flow channels, rather than in
 572 larger wetland zones. The NWI data shown either do not conform to the bends along the length

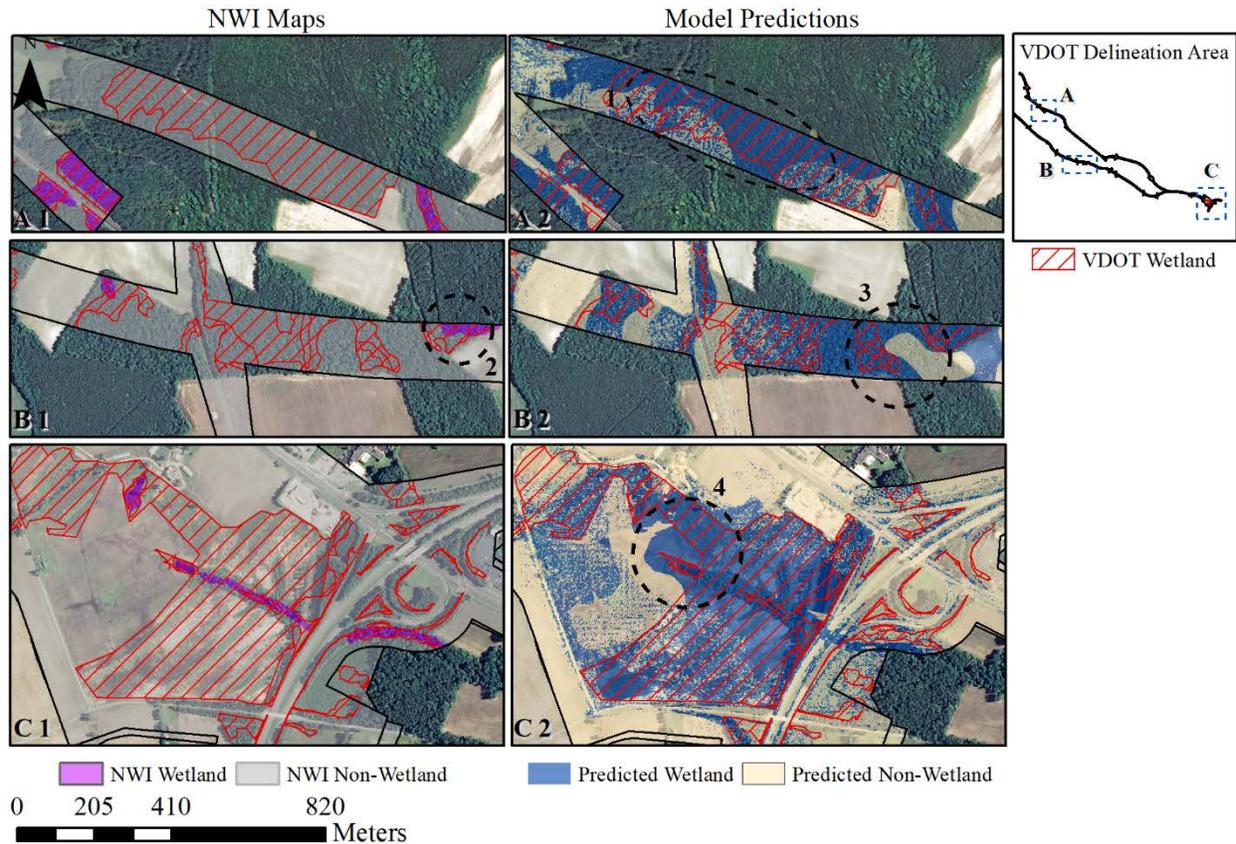
573 of wetlands (A1), or failed to map a number of wetlands in these channelized areas (B1). The
 574 model predicted a larger portion of the VDOT delineated wetlands in both scenes, however the
 575 wetland predictions often extended too far on either side of the narrow wetlands (A2). Location 1
 576 shows another example of a local depression filled to become a generalized, flat area, resulting in
 577 an overestimation due to the modified TWI and modified DTW indices. Additionally, both
 578 scenes A2 and B2 show that the model detected road edges and road medians as wetland areas.
 579 This is a shortcoming of the model that was observed in other sites, such as Site 2, and indicates
 580 a need for further modification to topographic indices.



581
 582 Figure 8. Examples of NWI maps (A1 and B1) and model predictions (A2 and B2) for Site 3,
 583 both compared to VDOT delineations.

584 5.1.4. Site 4 Results

585 Figure 9 shows three scenes from the NWI maps and model predictions for Site 4, which
586 was the largest site studied. Site 4 was also unique for having the largest distribution of VDOT
587 delineated wetlands, covering more than 40% of the surveyed area, as well as the mildest
588 average slope (see Table 1). NWI maps underestimated a large portion of VDOT delineated
589 wetlands, and the portions of these wetlands that were mapped were delineated with less
590 precision than typically seen by the NWI (e.g., location 2). The model predictions also resulted
591 in a large number of false negative predictions and imprecise wetland delineations. The well-
592 defined contours of model predictions (e.g., locations 1, 3, and 4) exemplify the heavy reliance
593 of the model on soil thematic layers. In these scenes, the primary drivers for wetland prediction
594 were the presence of hydric soils and shallow depth to water table, which both outlined the same
595 contours as these wetland predictions. The relatively lower reliance on topographic indices in
596 this site is likely due to the unchanging topography of the area, which is characteristic of the
597 Mid-Atlantic Coastal Plain, as there was often little to no flow convergence indicated by the
598 topographic indices where VDOT delineated wetlands were mapped. It is possible that
599 alternative filtering techniques or more severe adjustments to the slope grid could increase the
600 effectiveness of topographic indices to detect wetted areas, however the correspondence of the
601 model to the soil layers used and the relatively high occurrence of false negative predictions
602 imply that vegetation data would also be valuable in this region.



603

604 Figure 9. Examples of NWI maps (A1, B1, and C1) and model predictions (A2, B2, and C2) for
 605 Site 4, both compared to VDOT delineations.

606 5.1.5. Variable Importance

607 An important output from the RF classification was the ESRI Classifier Definition file,
 608 which provided the variable importance of each input used in classifications (see Table 4).
 609 Variable importance measures were used to gauge the ability of input variables to provide
 610 unique, significant information to the classifier. Table 4 shows that in Site 1, Site 3, and Site 4,
 611 the modified DTW was the most important topographic index, and in Site 2 the original DTW
 612 was the most important topographic index. In contrast, the modified TWI was the overall least
 613 important input variable in every study site. The low ranking of the modified TWI relative to the
 614 modified and original DTW suggests that some information was duplicated by these inputs, but

615 that the modified DTW provided more robust wetland and non-wetland signatures. This
616 corresponds to the findings of previous studies (e.g., Ågren et al., 2014; Murphy et al., 2009)
617 which stated that wet TWI values were restricted to discrete lines of flow accumulation within
618 wetted areas, whereas the DTW model effectively encompassed wetted areas as a whole and was
619 therefore more robust. For this same reason, it was unexpected that for Site 3 the modified DTW
620 ranked higher than the modified TWI, as the VDOT delineated wetlands here were primarily
621 restricted to narrow lines of flow accumulation. Soil data were among the most important
622 variables in all sites that included them. In Site 1 and Site 2, this is likely due to the heavy
623 presence of road features and the ability of the soil information to better distinguish these from
624 wetland features relative to the topographic indices, which were observed to detect water
625 accumulation near these features. The higher importance of soil layers in Site 4 is likely due to
626 the flat terrain, and is in line with the wetland predictions seen in Figure 9, which were dictated
627 primarily by areas of hydric soil and shallow depth to water table. The low importance of the
628 topographic indices in Site 4 also reinforces the claim that topographic indices that are static and
629 assume the local slope is an adequate proxy subsurface flow patterns, such as the TWI and DTW,
630 are less suitable in flat areas due to undefined flow directions that are likely to change over time
631 (Grabs et al., 2009). The lower importance of modified curvature relative to DTW inputs in all
632 sites may indicate that our application of the curvature was limited by the ArcGIS fill operation
633 and smoothing, which generalized potentially significant terrain features, since curvature has
634 been shown to strongly determine flow convergence in flat topography (Sangireddy et al., 2016).

635 5.1.6. Accuracy Assessment

636 The accuracy of model predictions was assessed using the testing data, and compared to
637 the accuracy achieved by the NWI maps. Table 5 shows the confusion matrices produced for the

638 best performing model and the NWI maps across all study sites. In each confusion matrix, test
639 data are represented along columns and NWI and model predictions are represented along rows.
640 Categorized pixels (expressed as total km²) in Table 5 were used to calculate wetland accuracy,
641 non-wetland accuracy, and overall accuracy using Equations 5-7. It is important to note that the
642 accuracy assessment only extended to the limits of the testing data, which as previously
643 described, are randomly selected subsets of the original VDOT delineations, and the effect of
644 varying testing and training data separation on model accuracy was not assessed.

645

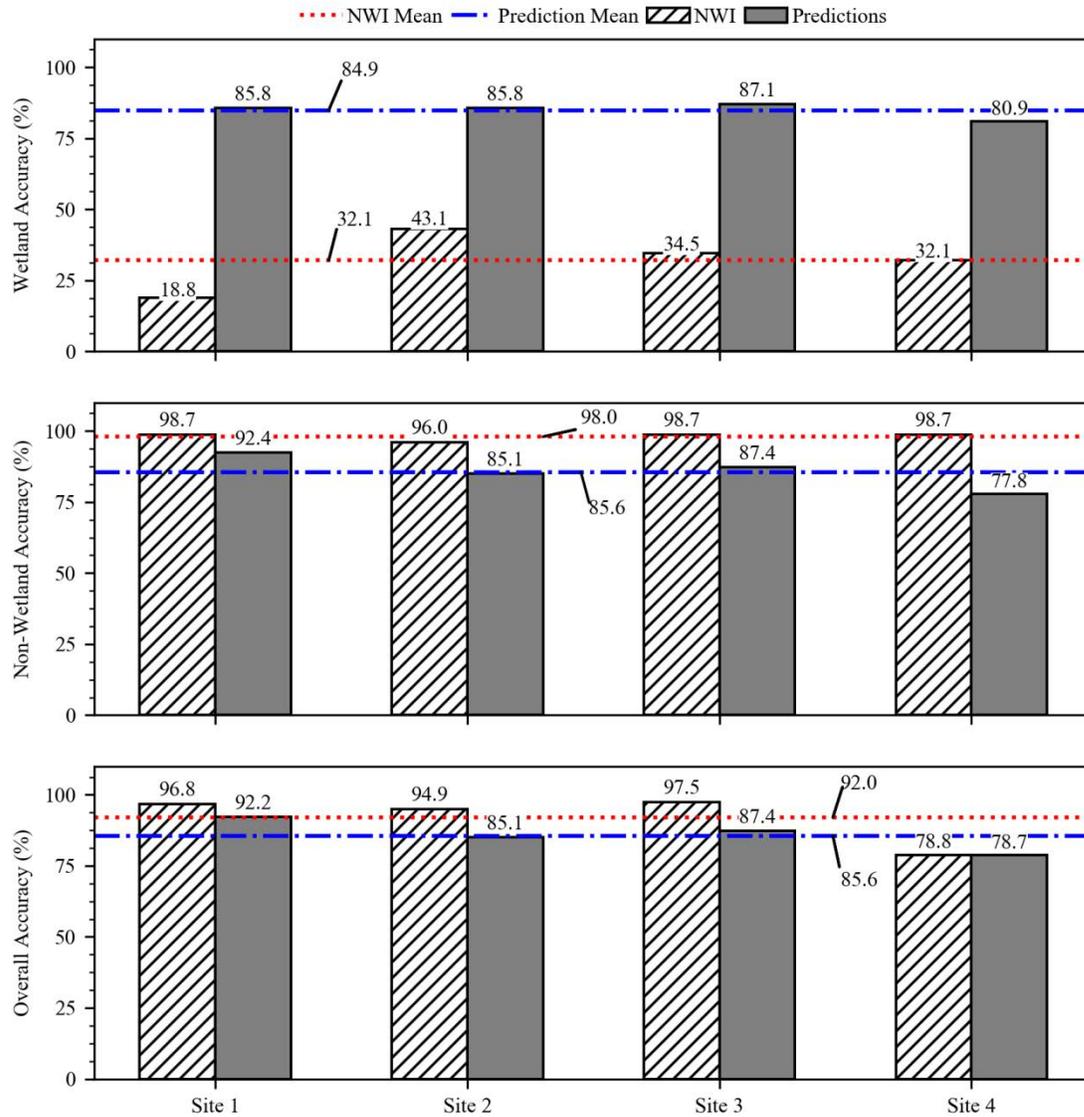
646 Table 5. Confusion matrices used to assess the accuracy of NWI maps (left) and best performing
 647 model predictions (right) compared to the test data, where predicted values are represented along
 648 rows and actual values are represented along columns. Wetland, non-wetland, and overall
 649 accuracy rates are derived from values in the confusions matrices using Equations 5-7.

<i>Site 1</i>									
<i>NWI (predicted)</i>	Test Data (actual)				<i>Model (Predicted)</i>	Test Data (actual)			
		Wetland (km ²)	Non-Wetland (km ²)	Σ=			Wetland (km ²)	Non-Wetland (km ²)	Σ=
	Wetland (km ²)	0.012	0.034	0.05		Wetland (km ²)	0.056	0.202	0.26
	Non-Wetland (km ²)	0.053	2.605	2.66		Non-Wetland (km ²)	0.009	2.441	2.45
Σ=	0.07	2.64	2.7	Σ=	0.07	2.64	2.7		
<i>Site 2</i>									
<i>NWI (predicted)</i>	Test Data (actual)				<i>Model (Predicted)</i>	Test Data (actual)			
		Wetland (km ²)	Non-Wetland (km ²)	Σ=			Wetland (km ²)	Non-Wetland (km ²)	Σ=
	Wetland (km ²)	0.064	0.280	0.34		Wetland (km ²)	0.127	1.038	1.16
	Non-Wetland (km ²)	0.084	6.673	6.76		Non-Wetland (km ²)	0.021	5.912	5.93
Σ=	0.15	6.95	7.1	Σ=	0.15	6.95	7.1		
<i>Site 3</i>									
<i>NWI (predicted)</i>	Test Data (actual)				<i>Model (Predicted)</i>	Test Data (actual)			
		Wetland (km ²)	Non-Wetland (km ²)	Σ=			Wetland (km ²)	Non-Wetland (km ²)	Σ=
	Wetland (km ²)	0.010	0.022	0.03		Wetland (km ²)	0.026	0.203	0.23
	Non-Wetland (km ²)	0.020	1.592	1.61		Non-Wetland (km ²)	0.004	1.411	1.41
Σ=	0.03	1.61	1.6	Σ=	0.03	1.61	1.6		
<i>Site 4</i>									
<i>NWI (predicted)</i>	Test Data (actual)				<i>Model (Predicted)</i>	Test Data (actual)			
		Wetland (km ²)	Non-Wetland (km ²)	Σ=			Wetland (km ²)	Non-Wetland (km ²)	Σ=
	Wetland (km ²)	1.052	0.116	1.16		Wetland (km ²)	2.648	1.717	4.37
	Non-Wetland (km ²)	2.220	7.596	9.81		Non-Wetland (km ²)	0.625	6.005	6.63
Σ=	3.27	7.71	11.0	Σ=	3.27	7.71	11.0		

650 Note: Values shown are rounded for clarity.

651 Figure 10 summarizes the accuracy achieved by the best performing model predictions
 652 and NWI maps. In the context of the wetland permitting process, it is important to have high
 653 values for all accuracy metrics. To uphold the objective of protecting existing wetlands, wetland
 654 accuracy is of high importance, and in order to provide realistic estimates of potentially impacted
 655 wetland areas in transportation and environmental planning, non-wetland accuracy is also

656 necessary. However, it is important to be aware of the potential for overall accuracy, which
657 measures the portion of the entire area that is correctly classified regardless of class, to be
658 misleading due to the uneven distribution of landscape classes. For example, the consistently
659 conservative wetland mapping by the NWI is reflected by the high average non-wetland
660 accuracy (98.0%). Due to the uneven distribution of wetland and non-wetland classes in all but
661 one of the study sites, the conservative nature of the NWI predictions also translated into high
662 average overall accuracy (92.0%), despite an average wetland accuracy of 32.1 %. In contrast,
663 the model predictions resulted in significantly higher average wetland accuracy (84.9%), but at
664 the expense of moderately lower average non-wetland and overall accuracy (85.6% and 85.6%,
665 respectively). As previously discussed, Site 4 was the lowest performing site. The low wetland
666 accuracy here may be due to a lack of vegetative signatures to distinguish wetland from upland
667 area, especially in this excessively flat area where terrain indices were found to be less
668 important.



669

670 Figure 10. Wetland, non-wetland, and overall accuracy produced by the best performing model
 671 predictions, compared to accuracy produced by NWI maps.

672 5.2. Response of Model to Input Data Modification

673 Iteration results in terms of wetland, non-wetland, and overall accuracy highlight the benefit
 674 and cost of applying the modifications described here, as well as including the coarser mapped
 675 (1:24,000 to 1:12,000) SSURGO data. Results of the analysis of model responses to
 676 classification iterations are shown in Table 6, where the highest performing iteration per

677 accuracy metric, not including iteration 5 which built off of top performing topographic inputs, is
 678 indicated with a “+” superscript and modified topographic inputs are indicated with an asterisk.
 679 Table 6. Wetland, non-wetland, and overall accuracy achieved by iterations of RF classification
 680 for each site. Asterisk indicates modifications with parameters from Table 2 were applied and
 681 “+” superscript indicates highest performing iteration per accuracy metric.

Iteration:		1	2	3	4	5
Input Data:		TWI, Curvature, DTW	TWI*, Curvature*, DTW*	TWI, Curvature, DTW*	TWI*, Curvature*, DTW	Best Performing of 1-4, plus soils
Site 1	Wetland Accuracy (%)	86.26 ⁺	83.65	84.47	85.97	85.84
	Non-Wetland Accuracy (%)	88.34	90.45 ⁺	87.77	89.15	92.36
	Overall Accuracy (%)	88.29	90.29 ⁺	87.69	89.08	92.20
Site 2	Wetland Accuracy (%)	67.57	69.85	71.33 ⁺	69.50	85.78
	Non-Wetland Accuracy (%)	83.58	83.87	81.14	84.26 ⁺	85.06
	Overall Accuracy (%)	83.25	83.58	80.94	84.13 ⁺	85.08
Site 3	Wetland Accuracy (%)	82.72	87.12	83.88	88.10 ⁺	-
	Non-Wetland Accuracy (%)	85.20	87.40 ⁺	83.49	86.72	-
	Overall Accuracy (%)	85.16	87.40 ⁺	83.50	86.74	-
Site 4	Wetland Accuracy (%)	55.15	57.11	62.67 ⁺	60.74	80.91
	Non-Wetland Accuracy (%)	69.31	78.03 ⁺	64.44	71.97	77.76
	Overall Accuracy (%)	65.09	71.80 ⁺	63.91	68.63	78.70

682

683 Shown in Table 6, non-wetland accuracy and overall classification accuracy from iteration
 684 1, where the original versions of all indices were used, improved in every site as a result of
 685 modifying all topographic indices (iteration 2). In addition, for three of the four sites, modifying
 686 all topographic indices resulted in the highest overall accuracy. These results suggest there is a
 687 benefit to applying the modifications presented here rather than using the indices as they are
 688 traditionally calculated, where this benefit is a reduction in false positive predictions and increase
 689 in overall accuracy. Furthermore, in every site that relevant soil layers were applicable, the
 690 inclusion of these soil layers with top performing topographic indices (i.e., iteration 5) further
 691 improved the RF classification. From this, we conclude that in these sites, the soil data provided
 692 important information to the classifier, despite its relatively coarse scale. Both Site 2 and Site 4
 693 saw relatively high increases in wetland accuracy resulting from iteration 5, which suggests the

694 topographic indices were not effective in encompassing flow convergence or subsurface
695 moisture conditions in order to detect wetlands. Iterations 3 and 4 were performed to determine
696 the effect of individual modifications on the classification. Note that for this evaluation, modified
697 TWI and modified curvature were generalized into a single category of modifications because of
698 their similar adjustment parameters and methods.

699 The purpose of modifying topographic indices was largely to reduce false positive
700 predictions in that TWI and curvature grids were modified to reduce unrealistic flow
701 convergence due to excess topographic detail, and the DTW was modified to accelerate the
702 transition from wetland to upland areas. Results in Table 6 show that the effect of modifying
703 only the TWI and curvature grids (iteration 4 vs. iteration 1) was an increase in non-wetland
704 accuracy in every study site, as well as an increase in wetland accuracy in all but Site 1. The
705 decrease in wetland accuracy in this site may indicate unintentional smoothing of some features
706 of interest (i.e., too large of a window size), and it is possible that in this study site a mean filter
707 or smaller window would have performed better. In sites 2, 3 and 4, results of iteration 4 suggest
708 the statistic type and window size were effective. Despite the improvements to classifications
709 with these modifications, the modified TWI and curvature grids can be further advanced. The
710 current approach should be expanded to test the effects of varying window sizes of smoothing
711 filters and statistic type, as well as the TWI formulation.

712 The effect of modifying only the DTW (iteration 3 vs. iteration 1) appeared to be an
713 increase in wetland accuracy in sites 2, 3, and 4, and an unexpected decrease in non-wetland
714 accuracy in every site. This suggests that while the modified DTW was effective in increasing
715 non-wetland accuracy when combined with modified TWI and modified curvature, the DTW
716 modification alone may not be sufficient for reducing false positive predictions. The limited

717 improvements provided by the DTW modification could be due to the designation of the
718 representative wetland slope value, which may not apply an effective cut off between low and
719 high cost areas. Additionally, improvements to the original DTW calculation before applying
720 modifications may enhance the results of iteration 3. The DTW calculation can be improved first
721 through slope calculation on a DEM corrected with an alternate method, and second by deriving
722 the source grid by extracting surface water features directly from the LiDAR data. In this study,
723 DTW source grids were generated from rasterized NHD data, which are mapped at a coarser
724 scale (1: 24,000 – 1: 12,000) compared to the LiDAR data and therefore, do not capture precise
725 curvature and locations of streams and open water.

726 6. Conclusions

727 This study evaluated the potential for modification of LiDAR DEM derivatives,
728 combined with ancillary national-scale soil data, to improve a RF classification of wetland areas
729 at a scale relevant for the wetland permitting process, over four study sites in Virginia. The
730 approach was implemented as a model in ArcGIS and performed a RF classification of input
731 variables that were modified to provide distinct wetland and non-wetland signatures. Model
732 predictions were assessed against field-mapped testing data, provided by the Virginia DOT, and
733 compared to NWI maps. Accuracy assessments showed that compared to NWI maps, the highest
734 performing models produced significantly higher average wetland accuracy (84.9% and 32.1%,
735 respectively), while resulting in moderately lower average non-wetland accuracy (85.6% and
736 98.0%, respectively) and overall accuracy (85.6% and 92.0%, respectively).

737 Through multiple iterations of input variable combinations, we concluded that there is
738 potential to improve classifications through modification of topographic indices. In every site,

739 the highest performing models included modified topographic indices, and the addition of
740 available soil layers further improved these classifications. Assessment of the variable
741 importance of the highest performing models showed that DTW inputs were of higher
742 importance, compared to the modified TWI in all study sites. This finding supports conclusions
743 of previous studies (e.g., Ågren et al., 2014; Murphy et al., 2009), which state the DTW model
744 provides more robust flow convergence information compared to the TWI. The low variable
745 importance of the TWI relative to the DTW also suggests that there is duplicate information
746 provided between these two indices. In addition, the heavy reliance of the model in Site 4 on soil
747 data reinforces previous findings that topographic indices like the TWI and DTW are less
748 effective in flat areas due to undefined flow directions that are likely to change over time,
749 whereas these indices typically model static conditions and assume local slope describes
750 subsurface flow patterns (Grabs et al., 2009; Murphy et al., 2009). Through classification
751 iterations, we found that non-wetland and overall classification accuracy increased in all sites
752 when all topographic indices were modified, compared to the accuracy achieved by using the
753 original versions of these indices. While modifications to the DTW alone did not reduce false
754 positive predictions, modifications to only the TWI and curvature did have this effect. However,
755 we believe the DTW modification approach could be further improved on. In addition, iteration
756 accuracies varied by small margins in many cases, and it is important to note that that RF
757 parameters and training and testing data separation were not varied or calibrated to sites in this
758 study. Completing this additional calibration step may produce different outcomes of iteration
759 comparisons.

760 Results from this study offer a starting point to the enhancement of the model
761 implementation in ArcGIS to include the capability of modifying LiDAR DEM derivatives based

762 on site characteristics to map small-scale wetlands in support of environmental planning and
763 conservation efforts. The results while successful, have also highlighted shortcomings that
764 should be addressed to further enhance the approach and model implementation. We found that
765 the topographic indices were limited by the use of the ArcGIS fill function, which removed local
766 depressions in the LiDAR DEM by creating larger areas of flat terrain. Studies have shown that
767 high-resolution elevation data could be filtered with more sophisticated methods (e.g., Besl et al.,
768 1989; Haralick et al., 1983; Lindsay et al., 2016; Mainguy et al., 1995; Sangireddy et al., 2016),
769 and exploring these methods could improve the accuracy of the topographic indices, especially in
770 low relief areas. The TWI modification can be further advanced on by assessing model responses
771 to alternate TWI formulations such as the D-infinity method for deriving flow accumulation
772 (Tarboton, 1997) and the Soil Topographic Index formulation which has been shown to improve
773 modelling of soil moisture patterns through inclusion of relevant soil properties (e.g., Buchanan
774 et al., 2014; Lanni et al., 2011). Alternate curvature modifications should also be explored, as
775 this index has been shown to effectively model flow convergence in low-relief and engineered
776 landscapes by applying automated filtering techniques (Sangireddy et al., 2016). Improvements
777 to the DTW modification should include deriving source data directly from LiDAR DEMs
778 through calibrated flow initiation thresholds, as shown by Ågren et al. (2014), and deriving flow
779 accumulation using the D-infinity method (Murphy et al., 2009, 2011), or incorporating the use
780 of other channel extracting software, such as GeoNet (Sangireddy et al., 2016). Furthermore,
781 variable importance indicated that the DTW and TWI may provide duplicate information in
782 many cases, and efforts should be made to effectively combine these indices through a
783 mathematical relationship to reduce feature space for the classifier. Future work should also
784 address the excessive computation times needed to process the high-resolution LiDAR data.

785 Implementing this approach using parallel computing could allow for reductions in runtime
786 needed to calculate γ and β parameters through an iterative calibration to study sites in the DTW
787 modification process. Alternative implementations of the RF algorithm should be tested as well,
788 as the ArcGIS implementation is limited in output data provided to users. Lastly, the approach
789 presented here should be applied to additional study areas to begin to identify modification
790 parameters that can be effectively generalized by site characteristics. While the prototype model
791 has produced more accurate wetland predictions for the study sites compared to NWI, these
792 improvements would strengthen the potential for this approach to be a useful tool for wetland
793 identification in support of environmental planning decision making in areas where wetland
794 maps are currently unavailable.

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800 8. References

- 801 Ågren, A. M., Lidberg, W., Strömberg, M., Ogilvie, J., & Arp, P. A. (2014). Evaluating digital
802 terrain indices for soil wetness mapping -- a Swedish case study. *Hydrology & Earth
803 System Sciences*, 18(9), 3623-3634. doi:10.5194/hess-18-3623-2014 .
- 804 Ali, G., Birkel, C., Tetzlaff, D., Soulsby, C., McDonnell, J. J., & Tarolli, P. (2014). A
805 comparison of wetness indices for the prediction of observed connected saturated areas
806 under contrasting conditions. *Earth Surface Processes and Landforms*, 39(3), 399-413.
807 doi: 10.1002/esp.3506 .
- 808 Besl, P. J., Birch, J. B., & Watson, L. T. (1989). Robust window operators. *Machine Vision and
809 Applications*, 2(4), 179-191. doi:10.1007/BF01215874 .
- 810 Beven, K., & Kirkby, M. J. (1979). A physically based, variable contributing area model of basin
811 hydrology/Un modèle à base physique de zone d'appel variable de l'hydrologie du bassin
812 versant. *Hydrological Sciences Journal*, 24(1), 43-69.
- 813 Bradski, G. (2000). The OpenCV Library. *Dr. Dobb's Journal: Software Tools for the
814 Professional Programmer*, 25(11), 120-123.
- 815 Breiman, L. (2001). Random forests. *Machine Learning*, 45(1), 5-32.
- 816 Buchanan, B. P., Fleming, M., Schneider, R. L., Richards, B. K., Archibald, J., Qiu, Z., &
817 Walter, M. T. (2014). Evaluating topographic wetness indices across central New York
818 agricultural landscapes. *Hydrology and Earth System Sciences*, 18(8), 3279.
819 doi:10.5194/hess-18-3279-2014

820 Burrough, P. A., and McDonell, R. A., 1998. Principles of Geographical Information Systems
821 (Oxford University Press, New York), 190 pp.

822 Cowardin, L., & Golet, F. (1995). US Fish and Wildlife Service 1979 Wetland Classification: A
823 Review. *Vegetatio*, 118(1/2), 139-152.

824 Dahl, T. E., Johnson, C. E., & Frayer, W. E. (1991). Wetlands, status and trends in the
825 conterminous United States mid-1970's to mid-1980's. US Fish and Wildlife Service.

826 Davidson, N. C. (2014). How much wetland has the world lost? Long-term and recent trends in
827 global wetland area. *Marine and Freshwater Research*, 65(10), 934-941. doi:
828 10.1071/MF14173 .

829 Deng, J., Smith, A. S., Davis, S., Weatherford, M., Paugh, L., & Wang, S. G. (2017).
830 Identification of NC Wetland Types by LiDAR Data and Tree Based Machine Learning
831 Methods (No. 17-01199).

832 Duro, D. C., Franklin, S. E., & Dubé, M. G. (2012). A comparison of pixel-based and object-
833 based image analysis with selected machine learning algorithms for the classification of
834 agricultural landscapes using SPOT-5 HRG imagery. *Remote Sensing of Environment*,
835 118, 259-272. doi:10.1016/j.rse.2011.11.020 .

836 Environmental Laboratory. (1987). Corps of Engineers wetlands delineation manual.

837 ESRI. (2016). Train Random Trees. Retrieved June 8, 2017, from
838 [http://desktop.arcgis.com/en/arcmap/10.4/tools/spatial-analyst-toolbox/train-random-](http://desktop.arcgis.com/en/arcmap/10.4/tools/spatial-analyst-toolbox/train-random-trees-classifier.htm)
839 [trees-classifier.htm](http://desktop.arcgis.com/en/arcmap/10.4/tools/spatial-analyst-toolbox/train-random-trees-classifier.htm).

840 Federal Register. July 13, 1994. Changes in hydric soils of the United States.

841 Grabs, T., Seibert, J., Bishop, K., & Laudon, H. (2009). Modeling spatial patterns of saturated
842 areas: A comparison of the topographic wetness index and a dynamic distributed model.
843 *Journal of Hydrology*, 373(1), 15-23. doi:10.1016/j.jhydrol.2009.03.031 .

844 Guo, M., Li, J., Sheng, C., Xu, J., & Wu, L. (2017). A Review of Wetland Remote Sensing.
845 *Sensors*, 17(4), 777. doi:10.3390/s17040777 .

846 Haralick, R. M., Watson, L. T., & Laffey, T. J. (1983). The topographic primal sketch. *The*
847 *International Journal of Robotics Research*, 2(1), 50-72.

848 Hogg, A. R., & Todd, K. W. (2007). Automated discrimination of upland and wetland using
849 terrain derivatives. *Canadian Journal of Remote Sensing*, 33, S68-S83. doi:10.5589/m07-
850 049 .

851 Jenson, S. K., & Domingue, J. O. (1988). Extracting topographic structure from digital elevation
852 data for geographic information system analysis. *Photogrammetric Engineering and*
853 *Remote Sensing*, 54(11), 1593-1600.

854 Klemas, V. (2011). Remote sensing of wetlands: case studies comparing practical techniques.
855 *Journal of Coastal Research*, 27(3), 418-427.
856 doi:10.2112/JCOASTRES-D-10-00174.1 .

857 Kloiber, S. M., Macleod, R. D., Smith, A. J., Knight, J. F., & Huberty, B. J. (2015). A semi-
858 automated, multi-source data fusion update of a wetland inventory for east-central
859 Minnesota, USA. *Wetlands*, 35(2), 335-348. doi:10.1007/s13157-014-0621-3 .

860 Lang, M. W., & McCarty, G. (2014). Light Detection and Ranging (LiDAR) for Improved
861 Mapping of Wetland Resources and Assessment of Wetland Conservation Practices
862 USDA, Natural Resources Conservation Service.

863 Lang, M., McCarty, G., Oesterling, R., & Yeo, I. (2013). Topographic metrics for improved
864 mapping of forested wetlands. *Wetlands*, 33(1), 141-155. doi:10.1007/s13157-012-0359-
865 8 .

866 Lanni, C., McDonnell, J. J., & Rigon, R. (2011). On the relative role of upslope and downslope
867 topography for describing water flow path and storage dynamics: a theoretical analysis.
868 *Hydrological Processes*, 25(25), 3909-3923. doi:10.1002/hyp.8263 .

869 Lindsay, J. B. (2016). Efficient hybrid breaching-filling sink removal methods for flow path
870 enforcement in digital elevation models. *Hydrological Processes*, 30(6), 846-857. doi:
871 10.1002/hyp.10648 .

872 MacMillan, R. A., Martin, T. C., Earle, T. J., & McNabb, D. H. (2003). Automated analysis and
873 classification of landforms using high-resolution digital elevation data: applications and
874 issues. *Canadian Journal of Remote Sensing*, 29(5), 592-606. doi:10.5589/m03-031 .

875 Mainguy, Y., Birch, J. B., & Watson, L. T. (1995). A robust variable order facet model for image
876 data. *Machine vision and applications*, 8(3), 141-162. doi:10.1007/BF01215810 .

877 Miao, X., Heaton, J. S., Zheng, S., Charlet, D. A., & Liu, H. (2012). Applying tree-based
878 ensemble algorithms to the classification of ecological zones using multi-temporal multi-
879 source remote-sensing data. *International Journal of Remote Sensing*, 33(6), 1823-1849.
880 doi: 10.1080/01431161.2011.602651 .

881 Millard, K., & Richardson, M. (2013). Wetland mapping with LiDAR derivatives, SAR
882 polarimetric decompositions, and LiDAR–SAR fusion using a random forest classifier.
883 Canadian Journal of Remote Sensing, 39(4), 290-307.

884 Millard, K., & Richardson, M. (2015). On the importance of training data sample selection in
885 random forest image classification: A case study in peatland ecosystem mapping. Remote
886 Sensing, 7(7), 8489-8515. doi:10.5589/m13-038 .

887 Moore, I. D., R. B. Grayson, and A. R. Landson. 1991. Digital Terrain Modelling: A Review of
888 Hydrological, Geomorphological, and Biological Applications. Hydrological Processes 5:
889 3–30.

890 Morrissey, L., & Sweeney, W. (2006). Assessment of the national wetlands inventory
891 implications for wetland protection. Proceedings of the 2006 AWRA Spring Specialty
892 conference: GIS and water resources IV. DR Maidment & JS Grounds III, Houston, TX,
893 139 papers/abstracts (May 8–10, 2006)(TPS-06-1)(ISBN 1-882132-70-X) CD-ROM
894 (Specialty Conference).

895 Murphy, P., Ogilvie, J., & Arp, P. (2009). Topographic modelling of soil moisture conditions: a
896 comparison and verification of two models. European Journal of Soil Science, 60(1), 94-
897 109. doi:10.1111/j.1365-2389.2008.01094.x .

898 Murphy, P. N., Ogilvie, J., Connor, K., & Arp, P. A. (2007). Mapping wetlands: a comparison of
899 two different approaches for New Brunswick, Canada. Wetlands, 27(4), 846-854. doi:
900 10.1672/0277-5212(2007)27[846:MWACOT]2.0.CO;2 .

901 Murphy, P. N., Ogilvie, J., Meng, F. R., White, B., Bhatti, J. S., & Arp, P. A. (2011). Modelling
902 and mapping topographic variations in forest soils at high resolution: A case study.
903 Ecological Modelling, 222(14), 2314-2332. doi:10.1016/j.ecolmodel.2011.01.003 .

904 Natural Resources Conservation Service (NRCS). (2015). Soil Data Viewer 6.2 User Guide.
905 Unpublished manuscript.

906 Page, R., & Wilcher, L. (1990). Memorandum of Agreement Between the Environmental
907 Protection Agency and the Department of the Army concerning the determination of
908 mitigation under the Clean Water Act, Section 404 (b)(1) Guidelines. Washington, DC,
909 USA.

910 Planchon, O., & Darboux, F. (2002). A fast, simple and versatile algorithm to fill the depressions
911 of digital elevation models doi:10.1016/S0341-8162(01)00164-3 .

912 Richardson, M. C., Fortin, M. J., & Branfireun, B. A. (2009). Hydrogeomorphic edge detection
913 and delineation of landscape functional units from lidar digital elevation models. Water
914 Resources Research, 45(10). doi:10.1029/2008WR007518 .

915 Rodriguez-Galiano, V. F., Ghimire, B., Rogan, J., Chica-Olmo, M., & Rigol-Sanchez, J. P.
916 (2012). An assessment of the effectiveness of a random forest classifier for land-cover
917 classification. ISPRS Journal of Photogrammetry and Remote Sensing, 67, 93-104.
918 doi:10.1016/j.isprsjprs.2011.11.002 .

919 Sangireddy, H., Stark, C. P., Kladzyk, A., & Passalacqua, P. (2016). GeoNet: An open source
920 software for the automatic and objective extraction of channel heads, channel network,
921 and channel morphology from high resolution topography data. Environmental Modelling
922 & Software, 83, 58-73. doi: 10.1016/j.envsoft.2016.04.026 .

923 Snyder, D., & Lang, M. (2012). Significance of the 3D Elevation Program to wetlands mapping.
924 National Wetlands Newsletter, 34(5), 11-15.

925 Soil Survey Staff, Natural Resources Conservation Service, United States Department of
926 Agriculture. Web Soil Survey. Retrieved August 7, 2017, from
927 <https://websoilsurvey.nrcs.usda.gov/>.

928 Sørensen, R., & Seibert, J. (2007). Effects of DEM resolution on the calculation of topographical
929 indices: TWI and its components. *Journal of Hydrology*, 347(1), 79-89.
930 doi:10.1016/j.jhydrol.2007.09.001 .

931 Tarboton, D. G. (1997). A new method for the determination of flow directions and upslope
932 areas in grid digital elevation models. *Water resources research*, 33(2), 309-319. doi:
933 10.1029/96WR03137 .

934 U.S. Environmental Protection Agency (EPA). (2013). Primary Distinguishing Characteristics of
935 Level III Ecoregions of the Continental United States.

936 Woodrow, K., Lindsay, J. B., & Berg, A. A. (2016). Evaluating DEM conditioning techniques,
937 elevation source data, and grid resolution for field-scale hydrological parameter
938 extraction. *Journal of Hydrology*, 540, 1022-1029. doi:10.1016/j.jhydrol.2016.07.018 .

939 WorldView Solutions Inc. (2016). Technical Plan of Operations: Virginia Statewide Land Cover
940 Data Development. Richmond, VA.

941 Zhu, J., & Pierskalla, W. P. (2016). Applying a weighted random forests method to extract karst
942 sinkholes from LiDAR data. *Journal of Hydrology*, 533, 343-352. doi:
943 10.1016/j.jhydrol.2015.12.012 .