**Monitoring of Wetland Inundation Dynamics in the Delmarva Peninsula
using Landsat Time-Series Imagery from 1985 to 2011**

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Abstract

Wetlands provide important ecosystem services, the provision of which is largely controlled by fluctuations in inundation and soil saturation. Inundation is highly dynamic and can vary substantially through time in response to multiple drivers, including precipitation and evapotranspiration. This research focused on developing a practical and effective framework for regional, long-term monitoring of wetland inundation dynamics using airborne LiDAR intensity data (Lang et al., 2013) and Landsat time-series imagery. Subpixel water fraction (SWF) maps indicating the percent of surface water within each 30-m pixel were generated on an annual basis over the entire Delmarva Peninsula on the East Coast of the United States from 1985 to 2011. Comprehensive accuracy assessments of the SWF maps were conducted using historical high-resolution aerial photography to determine the reference condition. The assessment resulted in an estimated root mean square error (RMSE) of 7.78% for the sample of open water areas (mean SWF was ~40% for this region of the map). Moreover, a separate accuracy assessment targeting inundation in wetlands (i.e. presence or absence of water) yielded an overall accuracy of 93%. Accuracies derived indicated that Landsat data can be calibrated to accurately extract long-term water information at the regional scale. Characteristics of inundation were examined with respect to different wetland types defined by water regime and dominant vegetation types, as well as different physical drivers. Results showed that tidal wetlands typically exhibited more intensive inundation than nontidal wetlands, and a higher degree of inundation was associated with emergent wetlands compared to wetland areas dominated by woody vegetation. Analysis of change drivers revealed that tide exerted a statistically significant influence on coastal inundation with r^2 values of 32–36% and $p < 0.01$, whereas inundation changes in inland wetland areas were in part driven by precipitation with r^2 values of 25–34% and $p < 0.08$. Because an up-to-date

archive of Landsat imagery is globally available and LiDAR data are becoming increasingly more affordable, the developed framework can be easily implemented to generate a continuous inundation record in many regions of the globe to assist in ongoing and future studies focused on wetland hydrology and wetland management.

Keywords

Wetlands; Inundation mapping; Accuracy assessment; Interannual change; Subpixel water fraction (SWF); Landsat time-series; Delmarva

1. Introduction

Wetlands are unique ecosystems where terrestrial and aquatic habitats intermix (Mitsch&Gosselink, 2007). The wet to dry transition along wetland ecotones supports a diverse biological community that is often not present elsewhere in the landscape (Carter et al., 1994; Chapman et al., 1996). Wetlands are tremendously productive, providing a variety of ecosystem services, such as water purification, flood regulation, erosion control, coastline protection, and sediment and nutrient transport (Gosselink& Turner, 1978; Keddy, 2000; de Groot et al., 2006). With the importance of wetlands as a natural resource being increasingly recognized, reliable information on wetland condition and functioning is required to help promote effective management decisions that will improve the resilience and sustainability of human-environment systems.

A key factor controlling the functioning of a wetland area is its inundation extent (Nestler& Long, 1997). Inundated areas can change rapidly in response to tide, precipitation, snowmelt, human alteration, and other factors (Millar, 1971; Johnson et al., 2005). Recent studies show that inundated areas play critical roles in many Earth system processes, including land-atmosphere energy balance (Krinner, 2003), carbon and nitrogen cycling (Shindell et al., 2005; Fox et al., 2014), and surface- and groundwater interchange (Winter, 1999; Becker, 2006). Despite their broad impact, wetlands are among the least well characterized in current land cover products (e.g. Wickham et al., 2010; 2013). Long-term, routine monitoring of inundation dynamics is needed to improve understanding of the health and functioning of wetland ecosystems.

Remotely sensed data can provide a spatially continuous and highly consistent map-like representation of the Earth's surface (Foody, 2002), and therefore, it has been recognized as an

important data source for monitoring wetland inundation dynamics (Huang et al., 2014). Satellite imagery in particular has the potential to capture large-scale, up-to-date wetland information in a repetitive manner, making it possible to obtain temporal trends at regional to global scales. Optical images from a variety of satellite sensors have been applied extensively to study wetlands (Lang et al., 2015), including Landsat MSS/TM/ETM+ (e.g. Jensen et al., 1986; Lunetta & Balogh, 1999; Huang et al., 2011; Tulbure et al., 2016), SPOT (e.g. Davranche et al., 2010), and AVHRR (e.g. Ramsey et al., 1997). The utility of Synthetic Aperture Radar (SAR) imagery has also been explored in many wetland studies (e.g. Townsend, 2001; Kasischke et al., 2003; Lang et al., 2008), taking advantage of its day-and-night, all-weather observation capability and its sensitivity to soil moisture (Fung, 1994; Ulaby et al., 1986). Recently, there has been increasing interest in the use of airborne Light Detection and Ranging (LiDAR) intensity data to detect inundation beneath the forest canopy (e.g. Lang & McCarty, 2009). Despite the demonstrated use of LiDAR intensity data to produce highly accurate inundation maps, LiDAR inundation monitoring over large areas or at fine temporal scales is greatly constrained by limited data availability.

Much effort has been devoted to generating regional or global scale inundation maps at coarse to moderate spatial resolutions, ranging from 1° longitude by 0.5° latitude (e.g. Brakenridge et al., 2013), 25 km (e.g. Prigent et al., 2007; Papa et al., 2010), 1 km (e.g. Friedl et al., 2010), to 250 m (e.g. Carroll et al., 2009). Because the majority of individual inundated areas are smaller than 0.01 km² (Downing et al., 2006; Verpoorter et al., 2014), these maps cannot provide the spatial details necessary to fully characterize inundation status. Some recent studies used Landsat imagery to map water bodies at a finer spatial resolution (e.g. Liao et al., 2014; Verpoorter et al., 2014; Carroll et al., 2016; Feng et al., 2016). However, these studies

weremainly focused onopen water areas such as lakes and rivers, and little emphasis has been placed on woody wetlands(swamps) with intermittent inundation.Moreover, most inundation maps at the 30-m pixel scale lack subpixel information, and therefore, may be of limited use over wetlands and other shallow and periodically inundated areas where partial inundation is common.An additionalconcern associated with nearly all existing Landsat-derived regional to global inundation products is theirextremely limited temporal resolution, as they were created only once (e.g. Verpoorter et al., 2014; Feng et al., 2016) or every ten years (e.g. Liao et al., 2014; Carroll et al., 2016), which makethe monitoring of inundation dynamics unrealistic even onan annual basis.

The value of a map constructed from remotely sensed data is largely a function of its quality (Foody, 2002). Compared to the validation of other land cover products, assessing the accuracy of inundation maps is a more challenging task due to the highly dynamic nature of inundation extent in most wetland areas. Because of the dynamics, it is best to collect reference data at or close to the time of image acquisition. For example, Hess et al. (2003)primarily used digital videographyacquired simultaneously with SAR mosaic scenesfor locatingvalidation sitesto assess map accuracy of wetland inundation and vegetation over the central Amazon basin. Nonetheless, little investigation has focused on accuracy assessment of long-term inundation productscreated at the regional scale. Neither has the use of archived historical high-resolution data to extract reference information on wetland inundation been intensively explored.

The diversity among differentwetland types is significant from the perspective of land surface process modeling (Lafleur, 1990). Wetlands represented as a single category can introduce considerable uncertainty into climate models (Comer et al., 2000),as their carbon storage capacity varies with soil and vegetation type and coverage. Differences in energy

exchange among wetland types can be greater than differences between wetland and non-wetland surfaces (Desjardins et al., 1994; Roulet et al., 1997). Because inundation is crucial to wetland functioning including carbon storage, understanding how it varies among major wetland types is necessary to support management and policy decisions.

Dramatic changes have occurred in the inundated area of many of the world's aquatic ecosystems during the past several decades. These changes are driven by a wide range of biophysical, socioeconomic and political factors (Millennium Ecosystem Assessment, 2005). However, most existing studies on the assessment of inundation dynamics were performed over relatively easy to map and less dynamic aquatic ecosystems (e.g. lakes), and irrespective of wetland type or the characteristics of the study site. Because the role of a specific factor may differ substantially by the location and type of wetland, it is important to investigate possible drivers of local inundation change with respect to different wetland types.

The main objective of this study was to develop a practical and effective framework for regional, long-term monitoring of wetland inundation dynamics. The study was conducted over the Delmarva Peninsula, which is adjacent to the Chesapeake Bay along the East Coast of the United States. This region is recognized for its rich network of wetlands, and the important ecosystem services that they provide. The approach proposed by Huang et al. (2014) to map localized inundation in forested wetland areas using LiDAR intensity and Landsat data was refined and adapted for use over a long time period and a much larger area with a rich array of wetland types. Landsat time-series images were acquired over the entire study area during the leaf-off season in early spring from 1985 to 2011. The refined approach was applied to these data to generate a set of temporally consecutive maps of subpixel water fraction (SWF), indicating the percent of surface water within every 30-m Landsat pixel at each timestep. A comprehensive

accuracy assessment evaluated the quality of the SWF maps. A key focus of this research was the examination of wetland inundation patterns and long-term dynamics with respect to different wetland types as well as the factors that may cause inundation changes. The large area and long temporal period investigated allows for better understanding of wetland dynamics than can be accomplished by examining only a small wetland area for a short period of time.

2. Study area

The study area is the Delmarva Peninsula on the East Coast of the United States, occupied by most of the State of Delaware and portions of Maryland and Virginia (Fig. 1). The area of the peninsula is 14,230 km². The peninsula is bounded by the Chesapeake Bay to the west, Delaware Bay and the Atlantic Ocean to the east, and the Elk River and its isthmus to the north. This area is distinguished by flat topography with a maximum elevation of 31 m above sea level. Temperature ranges from an average of about 2°C in January and February to 25°C in July and August (Shedlock et al., 1999). Rain and snow are two major forms of precipitation on the peninsula. Average precipitation is about 112 cm per year (Hamilton et al., 1993). Approximately 50% of annual precipitation is lost to the atmosphere due to evapotranspiration. The remaining precipitation recharges groundwater or enters streams via surface flow (Ator et al., 2005). According to National Land Cover Database (NLCD) 2011 (Homer et al., 2015), land cover of this area is dominated by agriculture (~42%), followed by wetlands (~31%) and forest (~11%). Agriculture plays an important role in the Delmarva's economy. Most of the area is rural, except for a few large population centers such as Dover, Delaware and Salisbury, Maryland.

Fig. 1. The Delmarva Peninsula on the East Coast of the U.S. and footprints of remotely sensed data used in this study. The underlying layer consists of two Landsat scenes at path 14, row 33 and path 14, row 34 (RGB bands 5, 4, and 3).

Fig. 2 illustrates the spatial distribution of different wetland types depicted by the U.S. Fish and Wildlife Service (FWS) National Wetlands Inventory (NWI, see more details in Section 3.4). A large area of tidal wetlands has formed close to the estuaries that line the coast of the

176 Delmarva. These wetlands are dominated by marsh plants that are adapted to the brackishwater
177 and fluctuating water levels. With a flat landscape, close proximity to groundwater and relatively
178 high precipitation-evapotranspiration ratio, this region also has numerous nontidal wetlands
179 distributedover the inland portion of the Delmarva beyond the reach of tides(includingnon-
180 vegetatedshallow water zones and aquatic beds, marshes and wet meadows dominated by
181 emergent plants, and swamps with evergreen and deciduous shrubs or trees). Unlike tidal
182 wetlands where water comes mainly from ocean-driven tides, the major sources of water in
183 nontidal wetlands are precipitation, river overflow and groundwater. Although wetland
184 hydroperiod varies with weather conditions, maximum hydrologic expression in nontidal
185 wetlands (i.e. highest groundwater level and most area inundated) typically occurs in or around
186 March before evapotranspiration substantially increases with rising temperatures and leaf out.
187 Forested wetlands (or woody swamps) are the primary inland wetland type in the study area.

Fig. 2. Spatial distribution of different wetland types on the Delmarva Peninsula. To facilitate a clearer interpretation of wetland types, all pixels that NWI identified as tidal wetland are displayed in a dark blue. Definitions of wetland types are provided in Section 3.4. The points

represent locations of the weather stations and tide gauges used in Section 4.3. The watershed boundaries and 15-km buffers indicate the local areas where change drivers were analyzed.

3. Data and preprocessing

Three types of remotely sensed data were collected for modeling, prediction and validation of subpixel percent of surface water, namely LiDAR intensity data, Landsat imagery, and historical aerial photos (Table 1). NWI data were invoked to identify wetland areas, as shown in Fig. 2, where further analyses on inundation extent and change drivers were carried out. Routine preprocessing was performed on each dataset(e.g. LiDAR point rasterization, Landsat atmospheric correction, etc.).Details are provided in the following sections.

3.1. *LiDAR intensity data*

A LiDAR system provides both elevation and intensity data that reflect material properties of objects (Song et al., 2002). LiDAR intensity (or amplitude) is defined as the amount of energy returned relative to that transmitted by the sensor per laser pulse (Chust et al., 2008). Two LiDAR intensity datasets were collected over a 51 km² area consisting of dense forested wetlands in the headwaters of the Choptank River watershed (Fig. 1), one on 27 March 2007 and the other on 24 March 2009. These dates were selected to correspond with the average period of maximum nontidal hydrologic expression and the beginning of the growing season. Both LiDAR campaigns were conducted under normal-dry conditions to reduce signal attenuation by the atmosphere. Specifically, no precipitation occurred for four days prior to the 2007 acquisition and six days prior to the 2009 acquisition. An Optech ALTM 3100 LiDAR sensor with a wavelength of 1064 nm was used to collect LiDAR data. The 2007 dataset was collected at a height of 610 m

above the Earth's surface with a scan angle of $\pm 20^\circ$, a pulse rate of 100,000 Hz and a scan frequency of 50 Hz. The 2009 dataset was collected at about the same height, but with a scan angle of $\pm 10^\circ$, a pulse rate of 100,000 Hz and a scan frequency of 70 Hz. Average point densities were 2.5 pts/m² (0.40 m post spacing) and 11 pts/m² (0.09 m post spacing) for the 2007 and 2009 datasets, respectively. For more detailed descriptions of the sensor and the datasets, the reader is referred to Lang & McCarty (2009) and Lang et al. (2013).

A 1-m gridded intensity image was generated for each of the two dates. Because water absorbs nearly all energy at near infrared wavelengths, inundated areas were easily detected as very dark pixels on the intensity images. Two 1-m inundation maps were created, one for each year, where each pixel was classified as non-inundated, transition (partly inundated), or inundated (Lang & McCarty, 2009). An overall classification accuracy of 96.3% was attained for the 2007 inundation map based on field data collected concurrently with LiDAR at over 1000 random locations regardless of tree species (Lang & McCarty, 2009). Although no ground data for validation were collected in March-April 2009, the 2009 inundation map was deemed to have a similar level of accuracy because both maps were derived from very similar intensity datasets using the same method (Huang et al., 2014). Non-inundated and inundated 1-m pixels were assigned 0% and 100%, respectively, and partly inundated 1-m transition pixels were assigned an average inundation value of 50%. With each 1-m pixel assigned an appropriate inundation value, subpixel water fraction (SWF) at a 30-m resolution was calculated by averaging all 1-m pixels inside of each 30-m Landsat grid. Both SWF maps, as shown in Fig. 3, were used to extract training data.

Fig. 3. (a) 2007 and (b) 2009 SWF maps generated from LiDAR intensity data collected on 2007/3/27 and 2009/3/24, respectively. The two Landsat images were acquired on (c) 2007/3/29 and (d) 2009/3/18, providing an overview of ground conditions close to the two dates of LiDAR acquisition. Inundation patterns shown on the LiDAR-derived SWF maps visually matched those observed in the Landsat images. More inundated areas existed in 2007 relative to 2009.

3.2. Landsat imagery

The study area falls in Landsat path 14/row 33 (centered at 38°53' 32"N, 75° 19' 8"W) and path 14/row 34 (centered at 37° 28' 25"N, 75° 44' 56"W) (Fig. 1). At each path/row, Landsat Thematic Mapper (TM)/Enhanced Thematic Mapper Plus (ETM+) scenes acquired in early spring (late-February to mid-April) close to the LiDAR acquisition dates were collected for 27 years from 1985 to 2011, among which those with minimal cloud and cloud shadow contamination and no snow cover were further selected. Four years (1990, 1992, 1993 and

1997) were excluded due to the lack of Landsat data that met both the aforementioned seasonal and cloud/snow cover requirements. This resulted in a collection of 46 Landsat scenes, one per year for each path/row (Table 1). To minimize radiometric differences across the study area, same-date Landsat scenes acquired consecutively within a few seconds at the two adjacent rows were used. The only exception was the year of 1999, where the two scenes were acquired 16 days apart due to data gaps in the Landsat imagery archive (Loveland & Dwyer, 2012; Wulder et al., 2012).

All selected images were downloaded from the U.S. Geological Survey (USGS) Earth Resources Observation and Science Center (EROS) website (source: <http://glovis.usgs.gov>). Atmospheric correction was conducted using the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS), which converts digital number (DN) to surface reflectance (SR) (Maseket al., 2006). Cloud and cloud shadow were identified using the vegetation change tracker (VCT) algorithm (Huang et al., 2010). The percentages summarized in Table 1 showed that 17 of the 23 image pairs had 5% or less cloud cover over the study area, and only one had cloud cover of slightly more than 10%. To reduce the temporal variability of the spectral signature of water pixels that may be attributable to factors such as changes in water turbidity (Schott, 2007; Yeo et al., 2014), a normalization process similar to a dark object subtraction approach (Chavez, 1996), was undertaken based on a set of digitized water samples that had SWF values of 100%. Several indices were derived from each normalized image, including tasseled cap brightness, greenness, wetness, wetness-greenness difference, and greenness-brightness angle, as well as normalized difference vegetation index (NDVI), two forms of normalized difference wetness index (NDWI), an infrared-visible ratio index, and an infrared ratio index. These indices were subsequently used

as model inputs along with SR of the six reflective bands. Details on the indices and their calculation are provided in Huang et al. (2014).

3.3. Aerial photos (validation data)

Color-infrared (CIR) Digital Orthophoto Quarter Quadrangles (DOQQs) produced by the USGS at a 1-m resolution were used to extract reference data for accuracy assessment. DOQQs are scanned aerial photos corrected for image displacement and camera tilt, each covering an area of 3.75-min longitude by 3.75-min latitude at a map scale of 1:12,000 (USGS, 2001). The DOQQs in the Delmarva region that most closely matched the dates of Landsat overpass were from the years 1989 and 1995, creating the opportunity to assess the derived SWF products for these two years. In 1989, a set of 17 DOQQ photos along the southeast coast of Maryland's Eastern Shore were acquired on the same day as the 1989 Landsat images. In 1995, 109 photos over the western portion of Maryland's Eastern Shore were acquired within two weeks of the acquisition of the 1995 Landsat scenes (Fig. 1, Table 1). All ortho photos were converted to the WGS-84 datum and UTM Zone 18 North coordinate system and coregistered to Landsat scenes to facilitate a direct overlay.

Table 1. Summary of remotely sensed data used in this study. Percent cloud cover corresponds with the date/time of Landsat data collection.

Year	Landsat Date (Sensor)	LiDAR	DOQQ (number of photos)	Cloud cover (%) calculated with VCT
1985	04/17 (TM)			0.47
1986	04/20 (TM)			5.50
1987	03/06 (TM)			1.14
1988	03/08 (TM)			1.16
1989	04/12 (TM)		04/12 (17)	2.93
1991	03/17 (TM)			1.47
1994	04/26 (TM)			9.45
1995	03/12 (TM)		03/25 (109)	6.89
1996	03/30 (TM)			10.45
1998	04/21 (TM)			1.00
1999	04/08& 04/24 (TM)			1.78
2000	02/22 (TM)			1.93
2001	03/28 (TM)			0.24
2002	03/23 (ETM+)			0.48
2003	03/10 (ETM+)			4.56
2004	04/05 (TM)			1.71
2005	02/19 (TM)			0.56
2006	04/11 (TM)			1.20
2007	03/29 (TM)	03/27		1.12
2008	02/28 (TM)			1.82
2009	03/18 (TM)	03/24		5.02
2010	04/06 (TM)			4.10
2011	03/08 (TM)			6.21

3.4. National Wetlands Inventory (NWI)

The National Wetlands Inventory (NWI) was used to identify wetlands in this study (source: <https://www.fws.gov/wetlands/>). NWI polygons were delineated based on vegetation, visible hydrology, and geography through the combined use of aerial photography, field verification and collateral data (Federal Geographic Data Committee, 1992), representing the location, extent, and types of wetlands and deepwater habitats. Currently, NWI is considered one of the most commonly relied upon databases of wetland information in the U.S., and has been

widely used by local, state, and federal agencies, as well as by private industry and other organizations (Wilensky & Bates, 1995). We recognize that NWI can contain significant errors, especially in forested wetland areas (Stolt & Baker, 1995; Kudrinsky & Gale, 2000), but it is the best available nationwide wetland product that provides a unique opportunity to distinguish types of wetland habitats affected by different environmental or biotic influences (U.S. Fish and Wildlife Service, 2002).

A NWI layer containing nearly 120,000 wetland polygons within the study area was downloaded from the FWS's website (source: <http://www.fws.gov/wetlands>). Since we were more interested in several generalized wetland types in accordance with major hydrological and biological variables, the original classification scheme was simplified and wetlands were grouped into eight classes with respect to two different water regimes (i.e. tidal and nontidal) and four different vegetation types (i.e. evergreen, deciduous, emergent, and non-vegetated). Table 2 shows that nontidal wetlands have a slightly larger presence than tidal wetlands, and nearly 75% of wetlands on the Delmarva Peninsula are dominated by deciduous and emergent plants.

314 Table 2. NWI wetland types grouped by vegetation type and water regime.

		Water regime				
		Tidal		Nontidal		
		NWI codes ¹	Area (km ²) (and class percent)	NWI codes	Area (km ²) (and class percent)	Total
Vegetation type	Evergreen forest/scrub-shrub	PFO/PSS E2FO/E2SS	124 (3.1%)	PFO/PSS	527 (13.2%)	651 (16.3%)
	Deciduous forest/scrub-shrub	PFO/PSS E2FO/E2SS	151 (3.8%)	PFO/PSS	1,316 (33.0%)	1,467 (36.8%)
	Emergent	PEM E2EM R1EM L2EM	1,382 (34.7%)	PEM R(2-5)EM L2EM	120 (3.0%)	1,502 (37.7%)
	Non-vegetated	All other E, R1 All other L, P with tidal classes	284 (7.1%)	All other R(2-5) All other L, P with nontidal classes	79 (2.0%)	363 (9.1%)
	Total		1,941 (48.7%)		2,041 (51.3%)	3,982 (100%)

315 ¹P (palustrine), E (estuarine), R (riverine), L (lacustrine), FO (forested), SS (scrub-shrub), and
316 EM (emergent). NWI codes apply the hierarchical classification system defined by Cowardin et
317 al. (1979). Subclasses based on the predominant plant life form are used to distinguish vegetation
318 types. Water regimes are designated by different class modifiers in the hierarchy. A complete
319 description of the letter codes is provided by the FWS (U.S. Fish and Wildlife Service, 2015).

320

321 4. Methods

322 The inundation monitoring framework developed consisted of three major steps. Time-
323 series SWF maps were first produced over Delmarva using Landsat data and a training sample
324 set. The quality of the maps was then assessed using reference data collected independently from

high-resolution aerial photos. Finally, inundation dynamics were investigated with respect to different wetland types.

4.1. Time-series SWF map production

This study followed the approach developed in Huang et al. (2014), who used Landsat and LiDAR intensity data to map wetland inundation in a 324 km² subwatershed of the upper Choptank River Basin during the leaf-off season of 2005, 2007, 2009 and 2010. However, we used a ten-times larger set of training samples to capture the potentially more diverse spectral signature of different land cover types at the regional scale over a near 30-year period. A total of 121,818 pixels formed the training set of this study, including a simple random sample of 51,467 pixels from each of the two LiDAR-based 30-m SWF maps, and 18,884 pixels within a collection of reference polygons digitized for agriculture, evergreen forest, soil, and water classes. Relationships between SWF and Landsat-derived SR and spectral indices were established using the training samples and a regression tree model (Breiman et al., 1984). The constructed model was then applied to each radiometrically normalized image to generate SWF maps over the entire Delmarva from 1985 to 2011.

Because land-cover proportions of cloudy areas can be considered approximately the same as land-cover proportions in nearby surrounding cloud-free areas (Achard et al., 2014), SWF for each contaminated pixel identified by VCT was estimated as the average of the predicted SWF values of all uncontaminated pixels under the same land cover category in a particular year. Such spatial interpolation was performed for each of the seven climate divisions within the study area defined by the National Oceanic and Atmospheric Administration (NOAA). We recognize that heterogeneity in weather (e.g. temperature, precipitation),

hydrology (e.g. stream flow), and topography (e.g. spatial gradients) may still exist and impact wetland inundation at the local scale. However, cloud and cloud shadow pixels comprised less than 5% of the area at most dates (Table 1). Interpolation of SWF values for this small proportion of area, using a method that takes into account the difference in inundation patterns among climate divisions and land cover types, allowed for generation of a series of SWF maps without gaps.

4.2. Accuracy assessment

Accuracy assessment was conducted by comparing a map of SWF to reference data collected independently of the training samples. Both qualitative and quantitative assessments were undertaken to evaluate the performance of the SWF prediction model. Because it is generally more difficult to determine a quantity than it is to determine a category, obtaining reference data for a continuous product is more challenging than for a categorical product (Stehman & Foody, 2009). As a result, considerable time and effort was devoted in the collection of SWF reference data.

Quantifying percent cover of water within a pixel requires interpretation of imagery at finer spatial resolutions relative to the original Landsat images. Validation of the SWF map time series is further complicated by the lack of conventional reference data sources with the required temporal characteristics. High-resolution satellites, such as GeoEye IKONOS, were not in orbit until the late 1990s, and thus cannot provide relevant information for the earlier years mapped. Similarly, LiDAR intensity data that proved helpful in detecting inundation under the tree canopy have been available only in the most recent decades (Lang & McCarty, 2009). Historical high-resolution aerial photography has been the primary source of reference imagery in the

assessments of large-scale land cover products such as NLCD1992 and 2001 (Stehman, et al., 2003; Wickham et al., 2004, 2010), and was also extensively employed in this study for assessing the accuracy of the SWF maps. Of the historical aerial photos archived by the USGS and other agencies, only a few were temporally relevant when acquisition dates were constrained to be close to the acquisition dates of the selected Landsat imagery. This date constraint was necessary because the SWF, particularly in wetland areas, may vary substantially through time following precipitation, snow melt, sea-level fluctuation, or other hydrologic events (e.g. flood).

Two quantitative assessments were conducted to evaluate the prediction accuracy and associated errors of SWF. The reference data were derived from DOQQ photos obtained in 1989 and 1995, targeting open water areas (as described in Section 4.2.1) and inundation in wetlands (as described in Section 4.2.2). Different sample designs and validation approaches were applied for the two years of data because of different availability of DOQQs and the practical realities of observing water in different water-formed land cover types (i.e. open water vs. wetlands).

4.2.1. Accuracy of open water areas

The first assessment of SWF was based on 17 DOQQ photos acquired on 12 April 1989 along the southeast coast of Maryland's Eastern Shore (Fig. 1). These DOQQs had the same acquisition date as the 1989 Landsat imagery, so accuracy of the 1989 SWF map for the corresponding area was assessed. On-screen interpretation and manual digitization techniques were implemented to delineate the boundary between land and a body of water (subsequently referred to as "land-water boundary"). Despite the availability of high-resolution aerial photos at the most desired date, quantifying the proportion of water is still challenging if the land-water

boundary is not visually identifiable within the 30-m pixel examined. High uncertainties are often associated with digitization performed on inundated pixels covered by forest canopy (Fig. 4a) and emergent vegetation (Fig. 4b), or in agricultural areas shortly after irrigation (Fig. 4c). Although intuitively the presence of water can be confirmed due to the much darker appearance, SWF for small areas as shown in Fig. 4a–c cannot be properly extracted by digitizing aerial photos.

Fig. 4. Examples of sample pixels for which the land-water boundary cannot (upper row) and can (lower row, blue outline) be digitized from aerial photos within the 90-m by 90-m window. Grids represent the location of 3 by 3 Landsat pixels.

Most effort was therefore devoted to assessing the accuracy in or close to open water areas where the land-water boundary was easier to distinguish (e.g. Fig. 4d–f). Specifically, a

simple random sample of 300 30-m pixels was selected from the area with aerial photos available in 1989. After excluding pixels similar to those shown in Fig. 4a–c, we used the remaining 169 sample pixels for the accuracy assessment. The land-water boundary was manually digitized within a window of 3 by 3 pixels (or 90-m by 90-m). Proportion of water, as the reference data, was calculated based on the digitized water polygons inside of each window examined. The corresponding predicted SWF values for 1989 were also aggregated to the 90-m resolution through spatial averaging. Although aggregating map products of spatial density variables like SWF to coarser resolutions could smooth out the errors of adjacent pixels at the original resolution (Huang, 1999), aggregation permits some allowance for slight misregistration or shifts between Landsat and DOQQs at the subpixel level that may cause significant disparity when percentages are examined. This assessment was also motivated in the context of hydrological modeling, as the percentage composition of water is often a key input variable and currently most hydrologic models are grid-based with cell sizes of 100-m by 100-m or more (e.g. Abbott et al., 1986; Niehoff et al., 2002; Nelson & Palmer, 2007). The root mean square error (RMSE) was then calculated to quantify the difference between predicted and reference SWF values.

4.2.2. *Accuracy of inundation in wetlands*

To further evaluate the quality of the resultant SWF maps, an accuracy assessment was conducted over the western portion of Maryland's Eastern Shore using 109 DOQQ photos acquired on 25 March 1995 (Fig. 1). A 30-m by 30-m pixel was chosen as the sampling unit.

To eliminate areas of overlap of the DOQQs, we first created a tessellation of the population based on the interior and non-overlapping areas of the 109 DOQQ photography

frames. To complement the assessment of coastal regions (Section 4.2.1), we focused this assessment on the inland Delmarva DOQQs. Because of the time and cost of DOQQ preprocessing to achieve exact alignment with Landsat data, we selected a simple random sample of 10 DOQQs from those including area of the inland Delmarva. Preliminary analysis of the 1995 SWF predictions showed that the majority of pixels in the sampled DOQQs were assigned zero or very low SWF values. To accommodate such a highly unbalanced distribution and assess the quality of the map for different SWF intervals, we defined 11 SWF classes as strata, including one stratum comprised of pixels deemed to have no water component ($\text{SWF} = 0\%$), and the remaining separated by 10% intervals up to 100% for pixels with $\text{SWF} > 0\%$. From the pixels available in the 10 sampled DOQQs, 100 pixels of each class were selected via stratified random sampling. The sampling design achieved two desirable criteria typically sought for large-area accuracy assessments (Stehman et al., 2003; Wickham et al., 2010): 1) restricting the sample pixels spatially to 10 DOQQs reduced processing costs; and 2) stratification by SWF classes ensured that sample sizes were large enough to represent the rare water class at different SWF intervals, particularly in inundated wetland areas, and therefore yield precise class-specific estimates of user's accuracy.

Each sample pixel was located on the DOQQs using the spatial coordinates specified by the sampling design. Photo interpretation was done using a blind format in that *a priori* knowledge of the predicted SWF values was not provided to the interpreters. Because of the randomization invoked in the sampling design, the sample pixels were spread over different land cover types so that digitization would be challenging under most circumstances due to the lack of explicit land-water boundary. However, the presence (or absence) of water within a 30-m pixel can be qualitatively determined by cross-referencing the 1-m DOQQs, local expert knowledge

and field experiences. Although DOQQs were acquired approximately two weeks after the acquisition of the 1995 Landsat scenes, evident precipitation did not occur during this period according to daily meteorological data collected at two nearby weather stations. Impact of sea-level fluctuation driven by tides on wetland inundation was also negligible due to the minimal footprint of tidal wetlands in the region assessed. Therefore, it is reasonable to assume similar ground conditions would be observed at the two dates, and the discrepancy, if any, was considered marginal in the context of binary labeling to indicate the presence or absence of water at each sample pixel. Among the 1100 30-m pixels collected for validation, 860 pixels had water present when examined on DOQQs at the 1-m resolution. The remaining 240 pixels were found to have no presence of water. Agreement was defined to occur when a pixel with SWF=0% had no presence of water according to the photointerpretation (reference classification), or when water was present according to the photointerpretation for a pixel with SWF>0%.

The analysis was informed by the general estimation theory of probability sampling (cf. Särndal et al., 1992), which requires knowing the probability of each pixel being included in the sample (i.e. inclusion probability). The two-stage structure of the sampling design generates inclusion probabilities for each stage. The first-stage inclusion probability of pixel u was $\pi_{1u} = k/K$, resulting from the selection of a simple random sample of $k=10$ from $K=109$ photography frames. At the second stage, pixels in the first-stage sampled frames were stratified by H classes defined on SWF predicted values ($H = 11$). The second-stage inclusion probability for each pixel of class h was $\pi_{2.1hu} = n_h/N_h^*$, where n_h is the number of pixels sampled per class h ($n_h = 100$) and N_h^* is the number of pixels per class h in the sampled frames. Consequently, the inclusion probability of pixel u , incorporating both stages of sampling (Särndal et al., 1992, Chapter 9), was

$$\pi_{hu} = \pi_{2.1hu}\pi_{1u} = (n_h/N_h^*)(k/K) \quad (1)$$

π_{hu} varies by SWF strata. Higher inclusion probabilities are associated with pixels in rarer classes (i.e. smaller N_h^*). When constructing the error matrix (Story & Congalton, 1986), each sample pixel was weighted inversely to its inclusion probability to account for different sampling intensities among strata. Because the 11 strata established using SWF 10% intervals for validation sample selection do not correspond to the two aggregated classes of SWF prediction (i.e. SWF = 0% and SWF > 0%), accuracy estimators applicable to this situation described by Stehman (2014) were used. Particularly, overall accuracy was derived by summing cell proportions of the error matrix that indicate an agreement occurred. Producer's and user's accuracies were calculated for the two visually labeled reference classes and the two aggregated prediction classes, respectively. Accuracies for 10% intervals defined by the SWF prediction were also estimated to further disaggregate the description of agreement and assess the quality of particular intervals.

4.3. *Analyses of wetland inundation dynamics*

Whereas the proportion of surface water within a 30-m by 30-m pixel was estimated over the entire region covered by the two Landsat path/rows, we concentrated on investigating inundation characteristics and dynamics of wetland areas in the Delmarva Peninsula (Fig. 2). To initially characterize inundation patterns over time, the average of SWF and total inundated area for each year were calculated with respect to the different wetland types defined in Table 2. Total inundated area was computed by summing water portions of all pixels of a specific wetland type based on the predicted SWF values. Changes in coastal and inland inundation were compared against tide and precipitation at the subregional and local scale. Because tide and precipitation

data were recorded at fixed stations on an hourly or daily basis, they were used to characterize the hydrologic and meteorological condition at the time of Landsat overpass.

Tides are usually considered the largest driver of short-term sea-level fluctuations. Tides are semi-diurnal on the Delmarva with a period of about 12 hours and 25.2 minutes, exactly half of a tidal lunar day. The stage or phase of a tide at a specific time and location varies throughout the year. Because tidal range is affected by the topography of a local area and its proximity to the coast, sea water level measured at one gauge station may not be representative of that observed elsewhere. To accommodate such temporal and spatial variability, we evaluated the relationship between tide and inundation changes at the subregional scale. More specifically, inundated areas of tidal wetlands in both Eastern and Western Delmarva were calculated using watershed boundaries delineated by the 12-digit Hydrologic Unit Code (HUC-12) product (see Fig. 2). Meanwhile, the Verified Hourly Height Water Level data collected at Lewes and Solomons Island by NOAA's Center for Operational Oceanographic Products and Services (CO-OPS, <http://tidesandcurrents.noaa.gov/>) were adopted as an indicator of local tide conditions. Water levels observed at 0:00 to 10:00 am local time on the Landsat acquisition dates immediately prior to the overpass were extracted at each station. Whereas the Lewes station has a continuous record during the observation period, no data were archived at Solomons Island in 1994 and 1995.

The relationship between precipitation and wetland inundation was examined at the local scale due to spatial heterogeneity in precipitation and hydrologic conditions. Precipitation data were collected at two stations of NOAA's National Climatic Data Center (NCDC, <http://www.ncdc.noaa.gov/>) near Chestertown and Salisbury on the upper and lower Eastern Shore of Maryland (see locations in Fig. 2). Cumulative precipitation with different time lags

before Landsat acquisitions was calculated at both short-term (2, 5, 10 days) and long-term scales (30, 45, 60 days, and all days back to November 1 of the previous year). This was done because both short-term (daily scale) and long-term (seasonal scale) precipitation may influence wetland inundation. Recent precipitation events have a direct impact on wetland water budgets, in part via surface water runoff, and fall-spring cumulative precipitation is indicative of longer-term weather conditions that affect inundation primarily via snow meltwater, shallow groundwater and antecedent surface water storage in catchment and wetland areas.

Two study areas were defined by delineating a circular region with radius of 15 km surrounding each weather station. Wetlands cover a greater area at the Salisbury site, where soils are rich in clay and more capable of retaining groundwater. In contrast, wetlands are less extensive at the Chestertown site, where the landscape has a steeper slope (Clearwater et al., 2000). Most wetlands in the two study sites are nontidal and dominated by deciduous plants. Nontidal non-vegetated and tidal wetlands have minimal footprints at both sites. Moderate presence of nontidal evergreen and emergent wetlands can be observed at Salisbury. However, as viewed using remotely sensed data, these areas are less responsive to precipitation events due to the largely reduced signal transmission by evergreen canopy and emergent plants. Therefore, multiple linear regression was used to examine the association of both short-term and long-term precipitation (predictor variables) with the inundated area of nontidal deciduous wetlands (response variable) within each of the two 15-km study sites (Chestertown and Salisbury).

5. Results

5.1. Visual assessment

The derived SWF maps were first evaluated qualitatively through visual comparison with Landsat images. Although we conducted an intensive inspection at different locations, only two small areas were displayed as examples of forested and emergent wetland in Figs. 5a and 5b, respectively. Four acquisition dates were selected, as represented by the four columns, showing substantial differences in the extent of inundation in each wetland area. Compared to the years of 1999 and 2006, more pixels with medium or high inundation were identified in the forested wetland area in 1989 and 2010. This is consistent with the inundation pattern observed from the corresponding Landsat images. Similarly, the emergent wetland area exhibited more inundation in 1999 and 2010, which was properly captured as the resultant maps contained a larger amount of highly inundated pixels with $SWF > 50\%$. Complete presence of water was assigned to most pixels in open water areas such as streams (marked as 'A' in Fig. 5), whereas residential ('B') and cropland ('C') pixels were predicted to have little or no water. This qualitative assessment revealed that the model developed using locally collected 2007 and 2009 LiDAR intensity data can generate visually reliable SWF maps over different land cover types for multiple years with varying extents of inundation.

(a) Forested Wetland

(b) Emergent Wetland

SWFValue (%) 0 100

Fig. 5. Visual comparison of Landsat imagery and predicted SWF maps for areas of (a) forested and (b) emergent wetland on the dates of 1989.04.12 (1st column), 1999.04.08 (2nd column), 2006.04.11 (3rd column), and 2010.04.06 (4th column). Each map consists of 40 by 40 Landsat pixels, covering an area of 1.2-km by 1.2-km. The color of the SWF maps ranges from white to blue and black, indicating a gradually increasing proportion of water within the 30-m pixels. Examples of open water, residential and cropland areas identified using Google Earth imagery were marked as A, B and C, respectively.

5.2. Accuracy of the SWF maps

Fig. 6 shows the comparison of Landsat-derived SWF with SWF obtained from digitization of aerial photos over open water areas in coastal Maryland in 1989. For over 85% of the sampled pixels (145 out of 169), the SWF prediction error was less than 10% in absolute value. The greater number of sample pixels below the lower 10% error boundary indicates potential overestimation of Landsat-derived SWF. The RMSE was 7.78%, relative to a mean of 40% water estimated from the reference sample, yielding a relative RMSE of 19%.

Fig. 6. Comparison of 1989 SWF derived from Landsat modeling and aerial photo digitization when aggregated from 30-m to 90-m resolution. The solid line is the 1:1 line, indicating an exact match between prediction and reference. The dashed lines represent the upper and lower 10% error bounds. Sample pixels within the error bounds have a prediction error of less than 10%.

Table 3. Error matrix and accuracy estimates (%) for inundation in wetlands defined by the presence of water. Overall accuracy is 93%.

SWF-based prediction class		Reference class			Total	User Acc.	P_w
		N_{wc}	W_{wc}	Subtotal			
Predicted SWF (%)	= 0	80.376	4.230		84.606	95	5
	0 < SWF ≤ 10	2.047	1.544	3.590			43
	10 < SWF ≤ 20	0.553	1.176	1.730			68
	20 < SWF ≤ 30	0.157	1.150	1.307			88
	30 < SWF ≤ 40	0.125	0.914	1.039			88
	40 < SWF ≤ 50	0.085	0.767	0.852			90
	50 < SWF ≤ 60	0.070	0.704	0.773			91
	60 < SWF ≤ 70	0.039	0.733	0.772			95
	70 < SWF ≤ 80	0.041	0.783	0.824			95
	80 < SWF ≤ 90	0.014	0.699	0.714			98
	90 < SWF ≤ 100	0.038	3.755	3.793			99
	Subtotal	3.169	12.225		15.394	79	
	Total	83.545	16.455		100		
	Prod. Acc.	96	74				

Note: N_{wc} and W_{wc} denote *no water component* and *with water component*, respectively. Cell entries displayed in bold represent agreement between the prediction and reference data. The column subtotal represents the proportion of area on the created SWF map for each 10% interval, and the row subtotal represents the area proportion of the N_{wc} and W_{wc} classes in the reference data. P_w indicates the percent of pixels with water presence confirmed through aerial photointerpretation. Cell entries are expressed as percent area such that a value of 10 would translate to 10% of the region's area.

Overall accuracy of the binary water classification assessing accuracy of inundation was 93% (Table 3). User's and producer's accuracies were higher for the N_{wc} class relative to the W_{wc} class. Omission error of the W_{wc} class was an estimated 26%, whereas the commission error rate for W_{wc} was 21%. A substantial contributor to the commission error was the

disagreement at $0\% < \text{SWF} \leq 10\%$ and $10\% < \text{SWF} \leq 20\%$, where only 43% and 68% of the pixels indeed contained water and the remaining were located in forest, cropland or developed areas. As predicted SWF increased, the proportion of pixels with water identifiable at the subpixel scale through aerial photointerpretation (denoted as P_w in Table 3) increased reaching 99% at the highest SWF interval, indicating that water was typically present within pixels that were assigned higher SWF values. Nearly all pixels with $\text{SWF} \geq 50\%$ were covered, or at least partially covered, by open water (e.g. lakes, streams) or inundated wetlands. These results revealed that our prediction model was more accurate for areas with moderate to high levels of inundation.

5.3. *Inundation characteristics*

Higher values of averaged SWF and inundated area were associated with tidal wetlands (Fig. 7), suggesting a more substantial inundation in terms of both subpixel inundation degree and ground extent relative to nontidal wetlands. Considerable changes were identified in Figs. 7a and 7b for both wetland types throughout the years. Extremely high levels of tidal wetland inundation occurred in 1986, as total inundated area was nearly doubled compared to that in the following three years. For nontidal wetlands, inundated areas in 2004 and 2005 were six to nine times higher than in 1994 and 1998. The overall trend (increase or decrease) in tidal and nontidal inundation was generally consistent, but differences are to be expected and did occur between the two wetland types. For example, while tidal inundation reached a peak in 1986, inundated area of nontidal wetlands was below average for that time period. Such inconsistency may be attributable to the different drivers of tidal and nontidal inundation changes, as will be discussed in Section 5.4.

Fig. 7. (a) Average of SWF and (b) inundated area for tidal and nontidal wetlands. Lines displayed in light gray in (a) and vertical dashed lines in (b) indicate gaps of the years that were not included in the analysis.

Fig. 8. (a) Average ofSWF and (b) inundated areafor evergreen, deciduous, emergent, and non-vegetated wetlands.Lines displayed in light gray in (a) and vertical dashed lines in (b) indicate gaps of the years.

Fig. 8 shows inundation dynamics of four wetland types determined by the predominant plant life form, including evergreen, deciduous and emergent vegetation, and non-vegetated materials. Averaged SWF values for non-vegetated wetlands were always considerably higher than those of the three vegetated wetland types, indicating a consistently stronger degree of inundation in non-vegetated wetland areas. Also, little variation across the years was observed in the inundated area of non-vegetated wetlands. In contrast, vegetated wetlands exhibited more

apparent changes in terms of both subpixel inundation degree and ground extent. Evergreen and deciduous wetlands have slightly different averaged SWF values, and a more substantial difference occurs in the inundated area due to the overwhelming coverage of forested/scrub-shrub deciduous wetlands relative to evergreen wetlands (37% vs. 16% of total wetland areas, see Table 2). Among the three vegetated wetland types, a greater degree of inundation always occurred in emergent wetland areas (i.e. higher average of SWF). Accordingly, emergent wetlands that account for 38% of the wetlands in Delmarva held much more extensive inundated area on the ground. Because more than 90% of emergent wetlands belong to the tidal system, and emergent plants dominate nearly 72% of tidal wetland areas (Table 2), similar inundation patterns were observed between emergent wetlands (Fig. 8) and tidal wetlands (Fig. 7).

5.4. Drivers of inundation change

The strongest tide-inundation correlation was observed between water level at 10 am at Solomons Island and the inundated area of tidal wetlands adjacent to the Chesapeake Bay in Western Delmarva (Fig. 9a, Fig. 10a), and between averaged water level at Lewes five hours prior to Landsat overpass (i.e. 5–10 am) and the inundated area of tidal wetlands along the Delaware Bay in Eastern Delmarva (Fig. 9b, Fig. 10b). The use of water level data with different time lags may be explained by spatial characteristics of tidal wetlands in the two regions. Tidal wetlands in Western Delmarva are located close to the outlet (Fig. 2) and thus are quickly reached by ocean-driven tides, whereas it requires a much longer time for tides to travel up along the coastal estuaries in Eastern Delmarva. A generally consistent trend was found when subregional inundation and local water levels were compared in the temporal dimension (Fig. 9). Specifically, a higher water level was observed at the Landsat overpass in 1986, giving rise to the more severe

655 inundation in tidal wetland areas. Due to the considerable cloud cover along the east coast of
656 Delaware on the 1994 Landsat scene at path 14/row 33, SWF in tidal wetlands was significantly
657 underestimated in Eastern Delmarva, and thus a large discrepancy between tide and inundation
658 occurred in 1994 (Fig. 9b). As the discrepancy was mainly attributable to the contaminated
659 Landsat data rather than model performance or other factors that may cause inundation changes
660 (e.g. precipitation), 1994 was taken out of Fig. 10b and the regression analysis. An r^2 value of
661 0.36 and 0.32 was obtained in Western and Eastern Delmarva (Figs. 10a and 10b),
662 respectively, indicating that more than 30% of the variance of coastal inundation can be explained
663 by a linear model using a single variable of tide. Small p values ($p < 0.01$) at both stations
664 demonstrated the existence of a statistically significant association between tide and wetland
665 inundation.

Fig. 9. Comparison of Landsat-derived inundated area of tidal wetlands and water surface heights observed at or close to Landsat overpass in (a) Western and (b) Eastern Delmarva. Lines displayed in light gray and vertical dashed lines indicate gaps of the years.

671

672 Fig. 10. The relationship between inundated area of tidal wetlands and observed water surface
 673 heights in (a) Western and (b) Eastern Delmarva. Note that 1994 and 1995 were not displayed on
 674 (a) due to the lack of water level data at the Solomons Island station, and that 1994 was not
 675 displayed on (b) as the Landsat scene was largely contaminated by clouds in Eastern Delmarva.

The coefficient of determination (r^2) of the precipitation-inundation relationship varied with the different time lags used to extract cumulative precipitation (Fig. 11). For both Chestertown and Salisbury sites, the highest r^2 value was attained when precipitation was calculated for a 5-day period (i.e. short-term) and over several months (i.e. long-term). Further investigation of the role of each variable (Table 4) showed that daily scale short-term precipitation led to a stronger and statistically more significant correlation. This is consistent with the general expectation that precipitation that occurred most recently would have an immediate effect on inundation in nontidal wetland areas. Seasonal scale long-term precipitation was also related to wetland inundation, albeit to a less significant degree (i.e. higher p values), indicating the gradual impact of antecedent precipitation on the groundwater system and surface water storage over the months. Using the two variables concurrently resulted in a higher r^2 value compared to the exclusive use of either one, suggesting both short-term and long-term precipitation influence inundation status. The relationships were weaker at the Salisbury site, where wetlands are more likely to remain saturated and thus less responsive to precipitation events due to the clay-rich soils that have slow drainage and help to store groundwater (Clearwater et al., 2000).

Fig. 11. Coefficient of determination (r^2) between inundated area of nontidal deciduous wetlands (y) and short-term(x_1) and long-term (x_2) cumulative precipitation at the (a) Chestertown and (b) Salisbury sites.

Table 4. Coefficient of determination (r^2) of the multiple linear regression models established between inundated area of nontidal deciduous wetlands and short-term (Pcp_s , 5 days) or long-term (Pcp_l , all days back to November 1 of the previous year) cumulative precipitation or both (Pcp_s & Pcp_l). The corresponding p values are reported in parentheses.

	Pcp_s	Pcp_l	Pcp_s & Pcp_l
Chestertown	0.27 ($p = 0.01$)	0.14 ($p = 0.08$)	0.34 ($p = 0.02$)
Salisbury	0.18 ($p = 0.05$)	0.13 ($p = 0.10$)	0.25 ($p = 0.07$)

6. Discussion

The SWF maps created over the entire Delmarva Peninsula provided a novel characterization of inundation patterns of different wetland types, a result that could not have been accomplished via investigation of a smaller study area. Moreover, continuous monitoring of wetland inundation on an annual basis over a near 30-year period allowed us to investigate possible drivers of inundation dynamics. Assessment of drivers would not be possible using existing large-scale inundation maps produced only for one date or at much lower temporal resolutions (e.g. every ten years). Our products can potentially serve as baseline data to judge future inundation changes in the Delmarva Peninsula by quantifying deviations of individual wetlands from the norm as a measure of the severity of the drought/flood conditions, and may also be used as a key input to model wetland hydrology and ecosystem function of local landscapes.

Assessing the accuracy of a continuous product in which the output is a quantity, such as percent composition of land cover classes, requires high-resolution imagery, which can be difficult to obtain due to constraints on data availability, accessibility and costs (Congalton, 1991). Validation of SWF products is even more challenging, as SWF may vary substantially within days responding rapidly to changes in weather condition and local hydrology. To minimize temporal disparity, reference data need to be acquired close to the time of Landsat overpass. However, this requirement is difficult to satisfy because continuous temporal coverage of historical high-resolution imagery with acquisition dates specified rarely exists. Also, little investigation has focused on assessing accuracy of regional categorical or continuous wetland products created for multiple dates spanning a long period of time.

Despite the challenges, comprehensive validation was performed on the created SWF maps using historical 1-m DOQQ photos for two years covering different regions of Delmarva. Compared to the SWF values obtained by digitizing land-water boundaries on the DOQQs acquired concurrently with the 1989 Landsat scenes, SWF of more than 85% of the pixels sampled in the coastal region had a prediction error of smaller than 10% when evaluated at the 90-m resolution. Although in this assessment more emphasis was placed on open water areas, aerial photo digitization allowed us to quantitatively assess the prediction accuracy of SWF in terms of percentages over a broader area for a historical year in the 1980s. The accuracy assessment over a large portion of Delmarva for the year 1995 showed that an overall accuracy of 93% was achieved when predicted SWF values were aggregated to two classes of SWF = 0% and SWF > 0%. Such aggregation was equivalent to a conversion of continuous water proportions to a binary presence/absence indicator of water using a threshold of zero, which may be a potential use of the SWF maps produced. This binary indicator assessment opportunistically took advantage of the extremely limited resource of historical high-resolution aerial photos and allowed us to assess accuracy over a large area consisting of different land cover types. Pixels with SWF at every 10% interval were adequately represented in the validation sample, thereby permitting more detailed evaluation of model performance compared to typical two-class map assessments. With subpixel mapping (or soft/fuzzy classification) of land cover and land use (LCLU) using remotely sensed data being increasingly explored, the accuracy assessment protocol employed in this study may act as a guide on how to evaluate the quality of regional and long-term continuous products, especially percentage maps of LCLU that change rapidly.

Wetland classification is complicated, as wetlands can be categorized by water chemistry, plant assemblage, microtopography, and hydrological character. However, these are

generally too detailed for climate modeling purposes (Comer et al., 2000). The simplified classification scheme we adopted can capture both the primary sources of water in wetland areas and the dominant vegetation layer that controls evapotranspiration and defines surface roughness. The eight wetland types assessed are suited for modeling.

A broad range of factors may contribute to changes in wetland inundation. Expecting inundated area extracted from remotely sensed data to be highly correlated with one particular variable is therefore unrealistic. The two physical factors of tide and precipitation examined in this study were demonstrated to be associated with inundation change in coastal and inland wetland areas, respectively, as around 30% of the variance of inundation change was explained by a linear model with the exclusive use of observed tide or precipitation data. Other factors include, but are not limited to, sea-level rise, wetland loss and degradation caused by logging, and drainage for agriculture and urban development, as well as wetland impoundment and restoration (Millennium Ecosystem Assessment, 2005). The correlation analyses conducted provide insights into the potential applicability of the SWF maps to the assessment of the role of different factors in driving inundation change.

The proposed framework is most effective to map inundation during the leaf-off season. Identifying surface water in wetland areas using Landsat data acquired in the leaf-on season is more difficult because dense plant canopies would obscure the ground surface from being observed by optical sensors. Because longer wavelength radar signals can penetrate the tree canopy and interact with the underlying ground (Ulaby et al., 1986; Le Toan et al., 1992), the use of multi-polarization SAR data for the detection of below canopy inundation is also worth investigating to facilitate intra-annual inundation monitoring. With the successful launch of Landsat-8 and Sentinel-1/2 missions, future opportunities may arise by integrating optical and

SAR data to track inundation dynamics on a seasonal or even monthly basis. Techniques developed for Unmanned Aerial Vehicles (UAVs) also make it possible to collect high-resolution photos at a specified time and location, providing an opportunity for more targeted field assessments to help validate the inundation mapping products.

7. Summary and conclusions

This study developed a practical and effective framework for long-term, routine monitoring of inundation dynamics on an annual basis over the Delmarva Peninsula from 1985 to 2011. Time-series SWF maps were reproduced, indicating the percent of surface water within each 30-m pixel during the observation period. Analysis of inundation patterns with respect to different wetland types revealed that tidal wetlands consistently exhibited more intensive inundation than nontidal wetlands, and a higher degree of inundation was always associated with emergent wetlands compared to wetland areas dominated by deciduous and evergreen forest and scrub-shrub. It was also demonstrated that tide exerted a statistically significant influence on coastal inundation, whereas inundation changes in inland wetland areas were strongly driven by short-term and long-term precipitation at daily and seasonal scales. Our fine-tuned model was established using a small amount of calibration data, and yet it showed high-level robustness when applied to a large region over a long time period. The derived inundation products have the potential to assist in ongoing and future research focused on wetland hydrology and wetland management across the Delmarva Peninsula. Further, with an up-to-date archive of Landsat imagery globally available and LiDAR data becoming increasingly more affordable, the developed framework can be easily implemented to generate a continuous inundation record in

many regions throughout the United States and elsewhere for improved understanding of wetland health and functioning to ensure sustainability of ecosystem services.

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LIST OF FIGURE CAPTIONS

Fig. 1. The Delmarva Peninsula on the East Coast of the U.S. and footprints of remotely sensed data used in this study. The underlying layer consists of two Landsat scenes at path 14, row 33 and path 14, row 34 (RGB bands 5, 4, and 3).

Fig. 2. Spatial distribution of different wetland types on the Delmarva Peninsula. To facilitate a clearer interpretation of wetland types, all pixels that NWI identified as tidal wetland are displayed in a dark blue. Definitions of wetland types are provided in Section 3.4. The points represent locations of the weather stations and tide gauges used in Section 4.3. The watershed boundaries and 15-km buffers indicate the local areas where change drivers were analyzed.

Fig. 3. (a) 2007 and (b) 2009 SWF maps generated from LiDAR intensity data collected on 2007/3/27 and 2009/3/24, respectively. The two Landsat images were acquired on (c) 2007/3/29 and (d) 2009/3/18, providing an overview of ground conditions close to the two dates of LiDAR acquisition. Inundation patterns shown on the LiDAR-derived SWF maps visually matched those observed in the Landsat images. More inundated areas existed in 2007 relative to 2009.

Fig. 4. Examples of sample pixels for which the land-water boundary cannot (upper row) and can (lower row, blue outline) be digitized from aerial photos within the 90-m by 90-m window. Grids represent the location of 3 by 3 Landsat pixels.

Fig. 5. Visual comparison of Landsat imagery and predicted SWF maps for areas of (a) forested and (b) emergent wetland on the dates of 1989.04.12 (1st column), 1999.04.08 (2nd column), 2006.04.11 (3rd column), and 2010.04.06 (4th column). Each map consists of 40 by 40 Landsat pixels, covering an area of 1.2-km by 1.2-km. The color of the SWF maps ranges from white to blue and black, indicating a gradually increasing proportion of water within the 30-m pixels. Examples of open water, residential and cropland areas identified using Google Earth imagery were marked as A, B and C, respectively.

Fig. 6. Comparison of 1989 SWF derived from Landsat modeling and aerial photo digitization when aggregated from 30-m to 90-m resolution. The solid line is the 1:1 line, indicating an exact match between prediction and reference. The dashed lines represent the upper and lower 10% error bounds. Sample pixels within the error bounds have a prediction error of less than 10%.

Fig. 7. (a) Average of SWF and (b) inundated area for tidal and nontidal wetlands. Lines displayed in light gray in (a) and vertical dashed lines in (b) indicate gaps of the years that were not included in the analysis.

Fig. 8. (a) Average of SWF and (b) inundated area for evergreen, deciduous, emergent, and non-vegetated wetlands. Lines displayed in light gray in (a) and vertical dashed lines in (b) indicate gaps of the years.

Fig. 9. Comparison of Landsat-derived inundated area of tidal wetlands and water surface heights observed at or close to Landsat overpass in (a) Western and (b) Eastern Delmarva. Lines displayed in light gray and vertical dashed lines indicate gaps of the years.

Fig. 10. The relationship between inundated area of tidal wetlands and observed water surface heights in (a) Western and (b) Eastern Delmarva. Note that 1994 and 1995 were not displayed on (a) due to the lack of water level data at the Solomons Island station, and that 1994 was not displayed on (b) as the Landsat scene was largely contaminated by clouds in Eastern Delmarva.

Fig. 11. Coefficient of determination (r^2) between inundated area of nontidal deciduous wetlands (y) and short-term (x_1) and long-term (x_2) cumulative precipitation at the (a) Chestertown and (b) Salisbury sites.