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ARTICLE

Calculating the Ecosystem Service of Water Storage in Isolated Wetlands using LiDAR in North Central Florida, USA

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Abstract We used remotely-sensed Light Detection and Ranging (LiDAR) data to estimate potential water storage capacity of isolated wetlands in north central Florida. Data were used to calculate the water storage potential of >8500 polygons identified as isolated wetlands. We found that isolated wetlands in this area stored 1619 m^3/ha on average, with a median measure of 876 m^3/ha. Significant differences in average storage capacity were found depending on wetland type, ranging from 1283 m^3/ha in palustrine scrub-shrub wetlands to 2906 m^3/ha in palustrine aquatic bed wetlands. Our study tested LiDAR-derived volume measures and volumes calculated using currently available equations in landscapes with differing surficial geology formations (e.g., clayey sand, limestone) and found that accuracy improved when basin morphology, a function of near-surface geology, was included. An exponential equation was developed that accurately correlated isolated wetland area and volume in our study area, but overestimated volume by an average of 45% when tested with a small independent dataset from the same ecoregion. Results from this study can be used in hydrologic modeling at the landscape scale to estimate ecosystem services and may prove useful in determining the significant nexus between isolated wetlands and navigable waters.

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Introduction

Since Costanza et al. (1997) published their groundbreaking and controversial report on the value of ecosystems, there have been numerous efforts to provide resource managers and decision makers with accurate information on the ecosystem services provided by wetlands (e.g., Woodward and Wui 2001; de Groot et al. 2002; Millennium Ecosystem Assessment 2005). Wetlands perform many ecosystem services, including aquifer recharge, carbon sequestration, biogeochemical processing, floodwater attenuation, improvement and maintenance of water quality and quantity, food and fiber provisioning, and maintenance of wildlife refugia (Millennium Ecosystem Assessment 2005; Brauman et al. 2007; Reddy and DeLaune 2008). The very real issues associated with assigning value to non-market functions in wetlands aside (see Woodward and Wui 2001; Boyer and Polasky 2004), there remain gaps in our knowledge of wetland ecosystem functions and processes that in turn affect the provisioning of ecosystem services (Carpenter et al. 2006). Quantification of ecosystem services provisioning by different wetland types (e.g., Cowardin et al. 1979) in different landscape settings (e.g., Brinson and Malvarez 2002) remains a fruitful and timely avenue of applied research, as does the effect of anthropogenic disturbance on ecosystem processes and flows (Carpenter et al. 2006).

Isolated wetlands, those completely surrounded by uplands (Tiner 2003), include prairie potholes, California vernal pools, New England seasonal ponds (Brooks 2009), flatwoods ponds and cypress domes, and other unique habitats (Tiner et al. 2002). In the eastern United States, isolated wetlands provide critical habitat for dependent amphibians (e.g., Gibbons et al.

2006), endemic macroinvertebrate taxa (Colburn et al. 2008), and rare and endangered plants (Comer et al. 2005). Recent studies on other ecosystem services provided by depressional wetlands have documented the sequestration of carbon in prairie pothole wetlands (Euliss et al. 2006); assimilation and processing of nutrients such as phosphorous (P) and nitrogen (N) in emergent marsh systems (Whitmire and Hamilton 2005; Dunne et al. 2007); pesticide degradation/sequestration in isolated wetlands in farmed landscapes (Skagen et al. 2008); and water storage capacity in urban landscapes and agricultural settings (Gamble et al. 2007; Gleason et al. 2007).

Water storage in wetlands has far-reaching effects. Hydrology in a given site or suite of sites drives the creation and maintenance of vegetation structure and wildlife habitat, redoximorphic potential and microbial activities, and organic matter concentration for sorption of pesticides and other contaminants. Small-scale studies on water storage in wetlands also provide opportunities to aggregate research from individual study sites to the watershed level (Lindsay et al. 2004; Rains et al. 2006). For instance, understanding the volume of water stored in wetlands can lead to the development of regression equations between wetland area, storage, and downstream receiving waters to determine the minimum number of wetlands needed to provide particular ecosystem services, such as denitrification, at a watershed scale (Seitzinger et al. 2006).

Wetland area data used as input in calculating the potential ecosystem service of water storage can be acquired most accurately by delineating the study area on the ground, although this option is not always available. Aerial photography or other data sources, such as the National Wetlands Inventory (NWI) can also be used for wetland area. Although NWI data were not created to remotely delineate wetlands *per se* (Tiner 1997), Haag et al. (2005) found that georectified NWI data was only 2% off from their on-site delineations.

Efforts to map the bathymetry of isolated wetlands and calculate storage potential have typically involved establishing laser transects in the field, collecting sufficient depth data points for contour development, and developing regression equations between wetland area, depth, and size (Brooks 2005). Haag et al.'s (2005) morphometric surveys of cypress domes and marshes in southern Florida found that stage-area and stage-volume relationships differed by 50–100% when lower depth data point densities were used. Wilcox and Huertos (2005) developed rapid morphometric measures for California vernal pools that incorporated irregularities in wetland shape, and urban isolated and riverine wetlands in Ohio were assessed for storage capacity and hydrologic influence on downstream systems by Gamble et al. (2007). Gleason et al. (2007) explored the capacity of existing and potentially restorable isolated Prairie Pothole wetlands to hold rainwater.

Recently, aircraft-borne Light Detection and Ranging (LiDAR) data have been used to provide fine-scale elevation data in wetland studies (Lillesand et al. 2004; Töyrä and Pietroniro 2005; Hogg and Holland 2008; Maxa and Bolstad 2009), eliminating the need for on-site laser transects and costs associated with field visits. LiDAR data are collected via an aircraft-mounted laser that sends 100,000 pulses per second downward within a narrow field of view and measures the time of pulse return (Lillesand et al. 2004). LiDAR data generally include 30–50% overlap of paths and extremely dense layering of points (i.e., 250,000 to 600,000 points per square kilometer). While LiDAR is an expanding resource for aquatic research (Power et al. 2005), there are limitations to the data, including the need for expensive aircraft, computer systems, and expansive data storage, as well as various sources of error (Hodgson and Bresnahan 2004; Lillesand et al. 2004).

Upon completion of morphometric and areal data collection, volume can be calculated using several methods and/or parameters. Hayashi and van der Kamp (2000) used morphometric data to develop mathematical equations relating area and volume to depth in shallow depressions, and Brooks and Hayashi (2002) improved upon these equations to include maximum depth for greater accuracy in measuring depression volume. The Brooks and Hayashi (2002) equation for maximum volume (V_{max}) includes maximum area (A_{max}), depth (d_{max}), and a p–coefficient, which represents the basin shape:

$$V_{\max} = \frac{(A_{\max} \times d_{\max})}{(1 + (2/p))} \quad (1)$$

Coefficient values of $p<1.0$ indicate a convex basin profile (e.g., a raised bog), p–coefficients >1.0 suggest a concave basin shape typical of isolated wetlands formed in a karst landscape (Hayashi and van der Kamp 2000). In their study of ephemeral pools in New England, Brooks and Hayashi (2002) found the dimensionless p–coefficient ranged from 0.60 to 2.24, with an average value of 1.02 over 34 sites.

Gamble et al. (2007) used a similar approach, generating an equation relating wetland area (A_{max}), depth (d_{max}), and volume (V_{max}) for wetland depressions. They found that incorporating depth resulted in better correlations than with area and volume alone:

$$V_{\max} = 0.3219 A_{\max} \times d_{\max} \quad (2)$$

The depressional wetlands in the Gamble et al. (2007) study area averaged over 6,000 m^3 of water storage when full—a value that does not include interstitial storage, evaporation, or transpiration (Krasnostein and Oldham 2004).

Gleason et al. (2007) created multiple equations relating wetland basin volume and area in prairie potholes. The particular equation used depended on the prairie pothole physiographic region. They found that existing and restorable wetlands were able to store 47,059,507 m^3 of water in their 52,758 ha study area.

In this study, we explored the use of remotely-sensed LiDAR data to calculate isolated wetland water storage capacity in north central Florida. We used Cowardin et al. (1979) class data to explore potential differences in LiDAR-based storage capacities of different wetland types and hypothesized that because hydrology is a driving force in the development of wetland structure (David 1996; Casanova and Brock 2000), significant differences would be found in storage capacity among wetland classes. We compared our volume results, calculated using spatial modeling of LiDAR data, to area, depth, and volume calculations developed by Brooks and Hayashi (2002) and Gamble et al. (2007) for wetland depressions. Finally, because LiDAR data are not readily available throughout the country and the existing formulas require time consuming field work and/or inputs, we created a regression equation between area and volume for isolated wetlands in north central Florida and tested the equation using a small independent dataset from the same ecoregion.

Methods

Site Selection and Pre-processing of Data

Reif et al. (2009) and Frohn et al. (2009) used a combination of GIS and remotely-sensed (Landsat ETM+) data to identify >12,500 potential isolated wetlands in Alachua County, Florida, USA (Fig. 1). They reported that for wetlands >0.20 ha, the Reif et al. (2009) and Frohn et al. (2009) (hereafter Reif/Frohn) dataset had high producer accuracy (93%), which measures the ability of their analysis to correctly classify target features, and high user accuracy (86%), which measures the proportion of their identified target class that exists on the ground (Lillesand et al. 2004). The Reif/Frohn dataset was acquired from the authors and further analyzed for false positives using a combination of land use and color aerial imagery analysis. Three land use datasets were used to identify and rectify errors in which land was incorrectly classified as wetlands: the St. Johns River Water Management District 2000 Land Use/Land Cover (available through www.fgdl.org, accessed May 2009), the 2001 National Land Cover Dataset (available at http://www.epa.gov/mrlc/nlcd-2001.html, accessed May 2009), and the Florida Department of Transportation Generalized Land Use Derived from Parcels dataset (available at http://www.fgdl.org/metadata/fgdc_html/d2_lu_gen_2007.fgdc.htm, accessed May 2009). Initial analyses identified quarry and mining land use features as a source of classification error. Reif/Frohn polygons located in any mining, quarry, barren land, or similar land use/land cover classification scheme were compared against high resolution 1-m georectified 1999 and/or 2004 color infrared aerial photographs acquired from the Florida Department of Environmental Protection Land Boundary Information System (available at http://www.labins.org, accessed multiple dates in 2009) to confirm land use class.

In a final pre-processing analysis step, the Reif/Frohn dataset was checked for overlapping and/or nested polygons, as well as very small "orphaned" polygons. Overlapping and nested polygons were merged, and potentially "orphaned" polygons within ≤1 m of nearby polygons were combined with those nearby polygons to remove the threat of double counting during the volume analysis. Following these steps, the pre-processed Reif/Frohn dataset consisted of 8,927 isolated wetland polygons across the Alachua County study area.

LiDAR Data

Bare earth LiDAR data were acquired from the Alachua County GIS Division (http://www.acpafl.org, acquired 2007) as a Triangulated Irregular Network dataset, or TIN. The Alachua County LiDAR survey was flown in January 2001, during the season with the least rainfall in north central Florida (Chen and Gerber 1990). Flights were made at approximately 2.4 km above ground level and data collected using an Aeroscan/ALS40 Airborne Laser Scanner (Leica Geosystems, Heerbrugg, Switzerland), which recorded five return pulses per second at a pulse rate of 33 kHz. Following data collection, Shrestha et al. (2003) examined the Alachua County LiDAR data for data voids and swath errors. As isolated wetlands are typically shallow, intermittently dry systems (Ewel and Odum 1984, Kushlan 1990), especially during the dry season of the flight period (Chen and Gerber 1990), we deemed the effect of voids, which often occur when the LiDAR laser is unable to penetrate standing water, to be negligible in our analysis. Evidence of a single swath error was found by Shrestha et al. (2003), which caused the data to be vertically off-set by approximately 24 cm in that swath. Because volume calculations of wetlands straddling the boundary of this swath could be affected by the offset, these wetlands (n=168) were removed from the pre-processed Reif/Frohn dataset, leaving 8,759 polygons in the final isolated wetland dataset used for volume calculations and deriving area and volume relationships.

TIN Volume Calculations in GIS

Volume was calculated using the TIN Polygon Volume model in ArcGIS 3D Analyst (ESRI Inc., Redmond, CA,

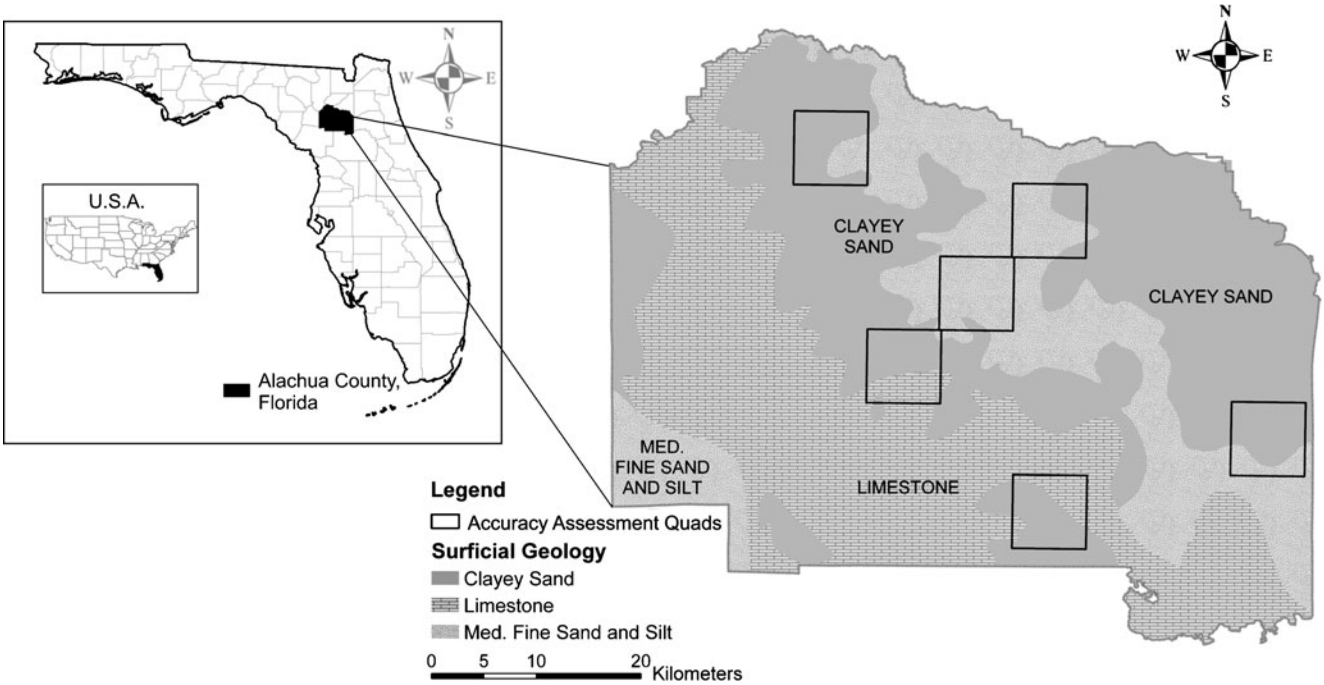


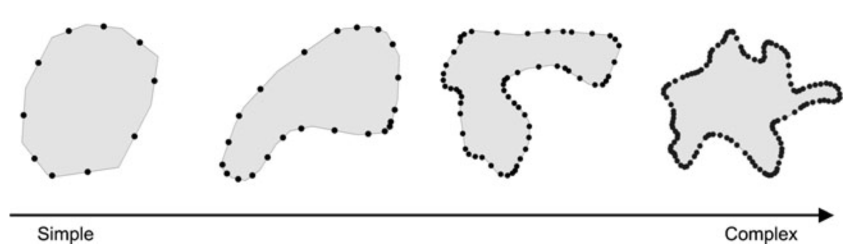
Fig. 1 Study area: Alachua County, Florida, with a schematic of the underlying near-surface geology. The black squares represent the accuracy assessment quads randomly selected by Reif et al. (2009) and Frohn et al. (2009). Wetlands throughout the entire county area were used in volume calculations and the development of a regression equation between wetland area and volume stored; a subset of wetlands within the accuracy assessment quads was used for comparison of volume by wetland type and in the assessment of storage capacity using derived volume equations

versions 9.2 and 9.3), which calculates volume below a given elevation plane. A stage-height elevation plane was calculated for each isolated wetland polygon using average perimeter elevation (i.e., averaging LiDAR-derived elevation points from around the edge of each wetland polygon). The number of points averaged was directly proportional to the complexity of the wetland shape, as determined by the number of vertices in the polygon perimeter (i.e., a more complex shape has a greater number of vertices; Fig. 2). Once the stage-height elevation plane was calculated for each wetland polygon in the final isolated wetland dataset, the volume of the wetland polygon was calculated; areal information was provided by the final isolated wetland dataset. The final volume (m^3), surface area (m^2), average perimeter elevation (m), and minimum elevation (m) of each wetland in the final isolated wetland dataset (n=8,759) were then tabulated for further analysis.

Differences in Wetland Volume by NWI Type

Digital georectified NWI data were acquired for the study area from the National Wetlands Inventory (http://www.fws.gov/wetlands/, accessed various dates fall 2008). NWI data includes the Cowardin et al. (1979) classification, which classifies wetlands based on hydrologic, geomorphic, chemical, and/or biological factors. To compare the effect of wetland type on isolated wetland storage capacity, the final isolated wetland dataset (n=8,759) was attributed with wetland characteristics from the NWI dataset. A total of 4,035 polygons were found across the study area that overlapped between the final isolated wetland dataset and the NWI; some of the final isolated wetland polygons did not overlap a NWI polygon, possibly a result of the higher spatial resolution targeted in the original Reif/Frohn assessment (Reif et al. 2009). To minimize ambiguity when comparing volume calculations among wetland

Fig. 2 Example of relationship between wetland shape complexity and elevation points used in determining wetland stage-height elevation plane. The more complex the shape, the more vertices the shape has, resulting in a higher number of points to average for elevation



types, only final isolated wetland polygons with a single Cowardin et al. (1979) class (e.g., palustrine emergent marsh or palustrine forested) were considered, and of those, only polygons with the more common wetland classes (i.e., classes occurring in >50 instances) were used in analysis. This resulted in 3,622 polygons with LiDAR-derived volumes, areal estimates, and wetland class information (Table 1). Differences in median storage between the six most commonly occurring Cowardin et al. (1979) classes were tested in SAS (SAS Institute, Cary, NC, version 9.2) with the Kruskal-Wallis test, followed by the post-hoc Tukey's Honest Significance Difference test when significant (p<0.05) differences were found.

Applying Derived Volume Equations

The derived volume equations of Brooks and Hayashi (2002) and Gamble et al. (2007) [Eqs. 1 and 2, respectively] were applied to a subset of the final isolated wetland polygons within the six Reif/Frohn 7.5-minute accuracy assessment quads (n=1,597; see Fig. 1) to calculate volume. The accuracy assessment quads were randomly selected by Reif/Frohn and the polygons within these areas checked for wetland presence using various ancillary data sources (see Reif et al. 2009 and Frohn et al. 2009 for additional information). Areal and depth values used in the derived equation calculations were acquired from the final isolated wetlands and LiDAR TIN datasets, respectively. Multiple p–coefficients (1.0, 1.5, and 2.0) were used in the Brooks and Hayashi (2002) Eq. 1, as basin morphology can differ substantially across the landscape. Preliminary analyses suggested a value between 1.0 and 1.5 would provide additional accuracy in volume calculations, so a p–coefficient of 1.25 was used in the final analysis as well. As basin morphology is a function of near surface geology (Hayashi and van der Kamp 2000), a surficial geology GIS data layer (available through the Florida Geographic Data Library, www.fgdl.org, accessed spring 2007) was used to explore the influence of near surface geology (i.e., clayey sand, limestone, and medium fine sand and silt; see Fig. 1) on p–coefficient accuracy (n=1,597).

Linear correlations and percent difference from the LiDAR-derived volume measures were calculated for each derived volume equation (Eq. 1, p=1.0, 1.25, 1.5, and 2.0; and Eq. 2). The relative accuracy of the volumes calculated from the derived equations was also compared to the LiDAR-derived volumes for each major surficial geology type.

Table 1 Cowardin et al. (1979) classification for a subset of polygons in the final isolated wetland dataset used in this study

Wetland Class	Number of Polygons in Dataset	Average Area (ha)	Area Standard Deviation (ha)
Palustrine Aquatic Bed	207	1.2	±2.0
Palustrine Emergent Marsh	1059	1.0	±2.9
Palustrine Forested	1992	2.0	±4.3
Palustrine Open Water	98	0.9	±1.1
Palustrine Shrub-Scrub	114	0.9	±1.7
Palustrine Unconsolidated Bottom	152	0.8	±1.9

Developing Area and Volume Relationships

Wetland polygon area in the final isolated wetland dataset (n=8,759) was not distributed normally, but ranged from <0.10 ha to 1,337.2 ha. Therefore, we calculated an exponential equation using Microsoft Excel (Microsoft, Inc., Redmond, WA, version 2007) to describe the relationship between volume and area in our study area, with potential application to the Southern Coastal and Middle Atlantic Coastal Plains (Omernik 1987). The resulting equation was then compared to volume data available from a study of isolated wetlands in west central Florida (n=10) by Haag et al. (2005).

Results

Using LiDAR data with the TIN Polygon Volume model (ArcGIS), isolated wetlands within the study area (n=8,759) were found to store on average 1619 m^3/ha of water (±2864 m^3/ha) at stage height, with a range from <1 m^3/ha to 64,701 m^3/ha. The median volume stored per hectare was 876 m^3/ha, while total volume stored by isolated wetlands (n=8,759) equaled 156,251,112 m^3. In terms of the maximum volume of water that can be stored, isolated wetlands within the study area stored on average 17,839 m^3 of water (±924,593 m^3), with storage capacity ranging from <0.01 m^3 to 85,834,141 m^3. Due to the high number of smaller wetland polygons (i.e., 4,232 were less than 0.20 ha in size), the median volume stored was 186 m^3. A single very large wetland feature (1,337 ha) deemed to be isolated by Reif et al. (2009) was responsible for 55% of the water stored in the study area. Ten other large polygons (1,561 ha in total) were collectively responsible for another 15% of the volume (m^3) stored, and the remaining polygons, which averaged 1.3 ha in size, were each responsible for <1.75% of the volume. Recalculating the average storage without the 11 largest polygons resulted in a mean water storage capacity of 5,351 m^3 (±43,063 m^3) and a maximum capacity of 2,565,421 m^3; mean storage per hectare decreased to 1,593 m^3/ha (±2,664 m^3/ha), and the median changed slightly to 875 m^3/ha.

Kruskal-Wallis tests found that the six different wetland classes analyzed stored significantly different volumes per hectare of water (F=8.7, $p<0.0001$). Post-hoc Tukey's Honest Significant Difference test indicated that there were two main groups—a high volume storage group (palustrine aquatic bed, palustrine open water, and palustrine unconsolidated bottom wetlands) and a low volume storage group (palustrine forested, palustrine emergent marsh, and palustrine shrub-scrub wetlands) (Fig. 3). Palustrine unconsolidated bottom (high storage) and palustrine forested (low storage) wetlands were not significantly different and formed a third, overlapping group. While palustrine aquatic bed systems were found to store the most water (2,906 m^3/ha ±3,242 m^3/ha), the two most commonly occurring isolated wetland types, palustrine forested and palustrine emergent marsh, were found to store 1,925 m^3/ha (±2,519 m^3/ha) and 1,852 m^3/ha (±3,061 m^3/ha), respectively.

Volume calculations using Brooks and Hayashi (2002) and Gamble et al. (2007) varied from −14% to 31% of the LiDAR value (Table 2), depending on the equation and p–coefficient. Using Brooks and Hayashi (2002) and a p–coefficient of 1.25 resulted in values that were within 3% of the LiDAR-measured value. All the linear Pearson correlations were highly significant (r>0.988, see Table 2).

While using a p–coefficient of 1.25 resulted in an average value that was within 3% of the LiDAR-derived volume, the deviation in volume calculations differed substantially depending on the surficial geology (Table 3), which likely affected the shape of the basin. For instance, using a p–coefficient of 1.25 in areas of limestone surficial geology provided values that were on average 14% different from the actual value, while using the same coefficient in areas of high clay concentration resulted in values that were −2% different. In areas where limestone was close to the surface, a p–coefficient of 1.0 produced the most accurate volume estimates; however, the Brooks and Hayashi (2002) equation performed best in all other areas using a p–coefficient of 1.25. Recalculating the difference between the LiDAR-based value and the dataset without the 160 limestone underlain wetland polygons (n=1,437) resulted in a volume measure that was only 1.9% different from the LiDAR-based calculations (data not shown).

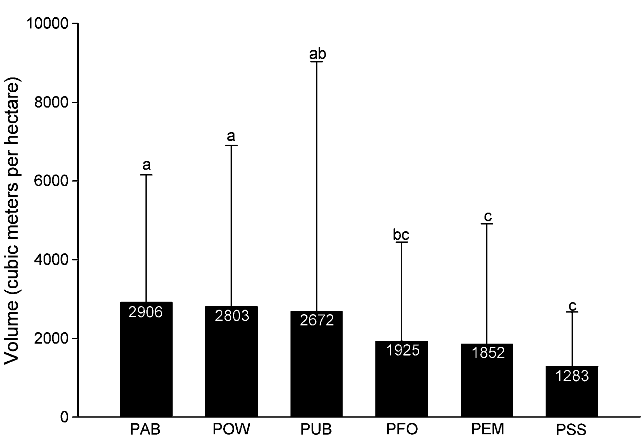


Fig. 3 Results of Tukey's Honest Significant Difference test for average volume (m^3/ha) among six classes of wetlands. The Cowardin et al. (1979) wetland classes used, in order of decreasing average volume (given as m^3/ha in vertical bar), are palustrine aquatic bed (PAB), palustrine open water (POW), palustrine unconsolidated bottom (PUB), palustrine forested (PFO), palustrine emergent marsh (PEM), and palustrine scrub-shrub (PSS). Classes that do not share a letter (a, b, c) are significantly different ($p<0.05$)

When the LiDAR-based volume data was coupled with areal data from the final isolated wetland dataset, an equation was derived based on an exponential relationship between volume and area (r=0.959, $p<0.0001$):

$$V_{\max} = 0.0195 A_{\max}{}^{1.3061} \quad (3)$$

where V_{max} is volume in m^3 and A_{max} is area in m^2. Removing a possible outlier from the equation (i.e., the 1,337-ha wetland) resulted in an area exponent of 1.3059, but no change in the strength of the relationship. Using Eq. 3 and the volume and area data available in Haag et al. (2005; n=10) resulted in an average error of 45% (±73%; Table 4), while using the Brooks and Hayashi (2002) equation that incorporates depth and a p–coefficient of 1.25 (Eq. 1) resulted in an average error of 6% (±32%). Applying the Gamble et al. (2007) algorithm (Eq. 2) resulted in an error value of −12% (±27%; Table 4).

Discussion

Through water storage and associated ground-water recharge, evaporation and transpiration, as well as biogeochemical processing, wetlands provide numerous ecosystem services that have the potential for significant cost avoidance through the use of natural ecological capital to freely perform functions that are costly for humans to recreate (Millennium Ecosystem Assessment 2005). For example, costs associated with managing stormwater—rainwater that does not percolate, evaporate, or become transpired—have an impact on local economies both in terms of damages from floodwaters and from degradation of recreation and drinking waters from entrained pollutants. The US Federal Emergency Management Agency estimated the annual property damage from all types of flooding averages US$2 billion (as cited by the National Research Council (NRC) 2008). Constructing retention basins to manage stormwater on site can attenuate flooding events, but can add significant costs to construction. The NRC (2008) estimates wetland construction for water storage to range from $100 to $3,000 per acre, while Randolph et al. (2006) estimated stormwater and sediment controls added between $1,500 and $9,000 to the cost of new dwellings constructed in North Carolina. Stormwater also entrains

Table 2 Linear correlation coefficients and errors associated with different derived volume equations when compared to the LiDAR-derived volume measures. Significant correlations at $p<0.0001$ are denoted with an asterisk

		Equation 1 (Brooks and Hayashi 2002)			
		Basin Morphology Coefficient			
Wetland Polygons (n=1597)	Equation 2 (Gamble et al. 2007)	p=1.0	p=1.25	p=1.5	p=2.0
Average difference from LiDAR-derived volume (%)	−14	−11	3	18	31
Standard deviation (%)	±53	±55	±63	±79	±74
Minimum error (%)	−98	−98	−98	−98	−97
Maximum error (%)	1464	1519	1768	2329	1982
Pearson linear correlation	0.992*	0.992*	0.992*	0.993*	0.988*

pollutants that can negatively affect downstream water quality (Havens and Schelske 2001; Paul and Meyer 2001; Benham et al. 2005) and cause economic loss from the closure of recreational areas (e.g., Rabinovici et al. 2004). Houck (1999) estimated the costs for the development and implementation of TMDLs to be approximately $4 billion per state. Maintaining wetlands on the landscape to perform ecological services could limit the impact of flooding and entrained pollutants on downstream systems. While the United States demonstrated a net gain of 77,000 hectares in the latest assessment (1998–2004) through the construction, restoration, and enhancement of wetland systems, wetland losses continued: 61% of the net wetland loss between 1998 and 2004 was due to urban and rural development (Dahl 2006).

However, wetland ecosystem services are difficult to quantify, and it is further difficult to scale the loss of numerous individual wetlands to effects at the watershed scale (Brinson 1988; Power et al. 2005). Results from this research on wetland water storage capacity could be used to improve watershed models that incorporate isolated wetland recharge, discharge, and flow-through hydrodynamic processes (Winter and LaBaugh 2003). On an areal basis, isolated wetlands in the study area stored approx-

Table 3 Linear correlation coefficients and errors associated with different derived volume equations (stratified by surficial geology) when compared to the LiDAR-derived volume measures. Significant correlations at $p<0.0001$ are denoted with an asterisk

		Equation 1 (Brooks and Hayashi 2002)			
		Basin Morphology Coefficient			
	Equation 2 (Gamble et al. 2007)	p=1.0	p=1.25	p=1.5	p=2.0
Clayey Sand (n=705)					
Average difference from LiDAR-derived volume (%)	−18	−15	−2	13	24
Standard deviation (%)	±31	±32	±36	±43	±46
Minimum error (%)	−98	−98	−98	−98	−97
Maximum error (%)	201	211	259	367	300
Pearson linear correlation	0.962*	0.962*	0.962*	0.966*	0.955*
Limestone (n=160)					
Average difference from LiDAR-derived volume (%)	−5	−2	14	40	35
Standard deviation (%)	±138	±143	±165	±215	±184
Minimum error (%)	−94	−94	−93	−91	−93
Maximum error (%)	1464	1519	1768	2329	1982
Pearson linear correlation	0.999*	0.999*	0.999*	0.999*	0.999*
Medium Fine Sand and Silt (n=732)					
Average difference from LiDAR-derived volume (%)	−12	−8	6	18	38
Standard deviation (%)	±32	±33	±38	±42	±49
Minimum error (%)	−95	−95	−94	−94	−93
Maximum error (%)	123	131	166	197	246
Pearson linear correlation	0.967*	0.967*	0.967*	0.967*	0.967*

Table 4 Volume results and percent error using Eq. 1 (Brooks and Hayashi 2002) and the exponential equation developed in this paper (Eq. 3), when compared to morphologic and volume data published by Haag et al. (2005)

Haag et al. (2005)				Equation 1 (p=1.25)		Equation 2		Equation 3	
Wetland Name	Area (m^2)	Max. Depth (m)	Volume (m^3)	Volume (m^3)	Error (%)	Volume (m^3)	Error (%)	Volume (m^3)	Error (%)
Duck Pond Marsh	21003.2	2.5	20488.3	20017.8	−2	16753.7	−18	8617.3	−58
GS Cypress	6758.3	0.5	999.1	1331.0	33	1114.0	11	1959.7	96
GS Marsh	6596.4	0.3	1245.8	827.4	−34	692.5	−44	1898.6	52
HRSP Marsh	8943.6	0.8	1825.6	2778.4	52	2325.4	27	2825.5	55
S-63 Cypress	5099.0	0.4	900.4	878.7	−2	735.4	−18	1356.4	51
S-68 Cypress	23431.3	0.5	5637.0	4257.6	−24	3563.4	−37	9940.9	76
W-03 Marsh	29865.8	1.7	17207.2	19046.5	11	15940.8	−7	13647.7	−21
W-05 Cypress	35531.4	0.6	5649.4	8788.9	56	7355.8	30	17123.4	203
W-19 Cypress	8417.5	0.8	2787.7	2664.3	−4	2229.9	−20	2610.4	−6
W-29 Marsh	26385.5	0.8	11619.5	8537.2	−27	7145.1	−39	11608.6	0
Average					6		−11		45

imately 1,619 m^3/ha on average, while the total storage capacity of the isolated wetlands in the study area was approximately 156,000,000 m^3. These figures suggest that isolated wetlands' influence on watershed level hydrodynamics through water storage and processes mediated by redoximorphic conditions, such as methanogenesis, phosphate sorption and desorption kinetics, and denitrification, could be substantial.

In addition to implications on process modeling and the provisioning of ecosystem services, results of this study may be useful in addressing limitations to isolated wetland protection in the wake of the Solid Waste Agency of Northern Cook County (SWANCC) v. U.S. Army Corps of Engineers [531 U.S. 159 (2001)] and the Rapanos v. United States [126 S. Ct. 2208 (2006)] U.S. Supreme Court decisions. Following those decisions, arguments for federal protection of isolated wetlands under the Clean Water Act (33 U.S.C. §1251 et seq.) typically hinge on establishing a 'significant nexus' to downstream waters. While this research alone does not demonstrate such a nexus, it may provide data useful for watershed models that effectively link upland sinks and downstream flows via different pathways (including transpiration and evaporation from wetlands; Leibowitz and Nadeau 2003; Lindsay et al. 2004; Leibowitz et al. 2008). Incorporating hydrogeomorphic landscape settings into the watershed models (e.g., Brinson 1993; Gwin et al. 1999) may further elucidate the influence and relative importance of isolated wetlands as a class to downstream navigable waters.

There are several limitations of this modeling approach. For example, the wetland morphology was established by LiDAR data, which in essence treated each wetland bottom as a concrete basin. Interstitial spaces were not measured to establish average volume, yet Sun et al. (1995) and Tsuboya et al. (2001) have shown that the interstitial volume measurements in wetlands are not inconsequential. Reutebuch et al. (2003) reported that the vertical accuracy of LiDAR in open canopies is within 0.15 m, while in closed canopies (such as those found in a substantial proportion of the forested wetlands in the study area) its accuracy drops to 0.30 m. Additional sources of potential error in morphometric measures might include dense ground cover that can affect LiDAR pulse returns (Wang et al. 2009). In addition, while the Reif/Frohn dataset used in our assessment was reported as generally accurate, with producer accuracies of 93% and user accuracies of 86% (Frohn et al. 2009; Reif et al. 2009), the Reif/Frohn wetland polygons were not ground truthed and their accuracy decreased with decreasing wetland size.

Like Brooks and Hayashi (2002) and Gamble et al. (2007), we found Eq. 1, which included maximum depth and the p–coefficient related to basin morphology, performed admirably when comparing equations used in this study to the data collected by Haag et al. (2005; see Table 4). Incorporating the depth and basin shape profile through LiDAR-based GIS TIN analyses provided accurate volume results, but LiDAR data are not currently available throughout the U.S., nor indeed throughout the southeastern U.S. (see USGS LiDAR Information Coordination and Knowledge website, http://lidar.cr.usgs.gov). The results suggest, however, that when LiDAR data are available, wetland volumes can be calculated quickly, accurately, and with little or no need for fieldwork.

In the absence of depth information, we found very strong correlations with our regression equation (Eq. 3) in the Alachua County study area, but the equation over-estimated storage by 45% when using the limited data available in Haag et al.

(2005; Table 4). These results suggest the need for additional analyses in other physiographic regions and with other landscape variables in order to develop a unified model for area and depth calculations.

Results further suggest that greater accuracy may be had when a surficial geology layer is used to inform underlying structure affecting basin shape. A basin shape p–coefficient of 1.0 has a very shallow to non-existent slope (Hayashi and van der Kamp 2000) and worked best for areas with limestone near-surface geology. Wetlands underlain by clayey sands and medium fine sand and silt performed better with p–coefficients with steeper sides and flatter basins. The geological mechanisms that underpin these relationships remain unknown. Future research relating measured basin bathymetry to p–coefficients for greater accuracy in volume studies appears warranted.

It is axiomatic that hydrologic controls affect the vegetation within wetlands (van der Valk 1981; Sharitz and Gresham 1998). While our study found significant differences in water storage per hectare among the six most common wetland classes (see Fig. 3), it was unexpected that there were no differences found between the Cowardin et al. (1979) classes that had significant and varied vegetative structure, namely palustrine forested, palustrine emergent marsh, and palustrine shrub-scrub. While our study analyzed storage potential in isolated wetlands, we did not model the timing, depth, or duration of the inundation, which along with fire frequency can have a strong effect on vegetative structure in isolated wetlands (Ewel 1990; Kushlan 1990; Sharitz and Gresham 1998; Cronk and Fennessy 2001).

Conclusion

Using LiDAR data, we found that isolated wetlands in our study area stored 1,619 m^3/ha on average, although significant differences were found depending on wetland type. The total volume of water that could be stored in isolated wetlands in the study area was >156,000,000 m^3. We developed an exponential equation that accurately correlated wetland area and volume, but when applying this equation to a small independent dataset in the same ecoregion, it tended to overestimate volume. Established equations that require depth and basin shape information (i.e., Brooks and Hayashi 2002) were calculated and found to be highly accurate, although the accuracy could be improved when surficial geology was taken into account. The results from this study might be used in hydrologic modeling at the landscape scale to quantify ecosystem services and may prove useful in determining the significant nexus between isolated wetlands and navigable water bodies.

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