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REMOTE DETECTION OF EPHEMERAL WETLANDS IN MID- ATLANTIC COASTAL PLAIN ECOREGIONS: LIDAR AND HIGH- THROUGHPUT COMPUTING

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REMOTE DETECTION OF EPHEMERAL WETLANDS IN MID-ATLANTIC COASTAL PLAIN ECOREGIONS: LIDAR AND HIGH-THROUGHPUT COMPUTING

A Thesis
Presented to
the Graduate School of
Clemson University

In Partial Fulfillment
of the Requirements for the Degree
Master of Science
Wildlife & Fisheries Biology

by
Paul Brandon Leonard
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Accepted by:
Dr. Robert F. Baldwin, Committee Chair
Dr. Jessica A. Homyack
Dr. Christopher J. Post

ABSTRACT

Ephemeral wetlands are ecologically important freshwater ecosystems that occur frequently throughout the Atlantic coastal plain ecoregions of North America. Despite the growing consensus of their importance and imperilment, these systems historically have not been a national conservation priority. They are often cryptic on the landscape and methods to detect ephemeral wetlands remotely have been ineffective at the landscape scales necessary for conservation planning and resource management. Therefore, this study fills information gaps by employing high-resolution light detection and ranging (LiDAR) data to create local relief models that elucidate small localized changes in concavity. Relief models were then processed with local indicators of spatial association (LISA) in order to automate their detection by measuring autocorrelation among model indices. Following model development and data processing, field validation of 114 predicted wetland locations was conducted using a random stratified design proportional to landcover, to measure model commission (α) and omission (β) error rates. Wetland locations were correctly predicted at 85% of visited sites with α error rate = 15% and β error rate = 5%. These results suggest that devised local relief models captured small geomorphologic changes that successfully predict ephemeral wetland boundaries in low-relief ecosystems. Small wetlands are often centers of biodiversity in forested landscapes and this analysis will facilitate their detection, the first step towards long-term management.

DEDICATION

I would like to dedicate this thesis to my wife Jennifer who endured my compulsive hours and often fragmented brain with grace, forgiveness, and love.

ACKNOWLEDGMENTS

I would like to thank the National Council for Air and Stream Improvement (NCASI) and Weyerhaeuser NR Company for funding and support throughout this project. I would like to thank Paul Hulker and Dr. Paula Mitchell for encouragement and clarity while helping to shape my academic pursuits. Sincere thanks are offered to Dr. Robert Baldwin for his tireless optimism, guidance, ideas, and support. I extend gratitude to committee members Dr. Jessica Homyack and Dr. Christopher Post who eagerly edited manuscripts and presentations while offering insightful ideas. An additional acknowledgment is in order for Dr. Baldwin and Dr. Homyack who contributed to chapter two of this thesis. I would like to thank Dr. Amber Pitt and Dr. T. Bently Wigley for their support and advice. Lastly, I would like to thank my parents for instilling independence and acceptance, and for offering perspective.

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CHAPTER ONE

REMOTE DETECTION OF EPHEMERAL WETLANDS

INTRODUCTION

Ephemeral wetlands are common features of the Atlantic coastal plain (Sutter and Kral 1994) and are often widely distributed in managed forest landscapes (Kirkman et al. 1999). These wetlands (i.e., vernal pools, seasonal pools, isolated wetlands, temporary ponds) are typically small, shallow, seasonally inundated, and lack predatory fish (Colburn 2004, Brown and Jung 2005). Such characteristics foster a unique blend of biodiversity (Russell and Guynn 2002, Comer et al. 2005, Mitchell et al. 2008) by providing critical habitat to hydroperiod sensitive organisms (Snodgrass et al. 2000) while performing an assortment of other ecosystem functions (Van der Kamp and Hayashi 1998, Leibowitz 2003).

In 2002 the United States Fish and Wildlife Service (USFWS) declared freshwater forested wetlands among the most imperiled wetland type in the country (U.S. Fish and Wildlife U.S. 2002). This broad characterization incorporates many of the ephemeral wetland settings which are frequently found in the southeastern United States (Messina 1989). Despite the growing literature describing ephemeral wetlands as ecologically important systems, they historically have not been subject to the same regulations as other wetlands thereby hindering conservation efforts. Federal regulation is authorized by section 404 of the Clean Water Act that states wetlands must have a “significant nexus” to “navigable water,” and is frequently interpreted as excluding isolated wetlands. This ambiguous language was featured in the 2006 U.S. Supreme

Court opinion in the Rappanos case. Although isolated wetlands are not federally protected, an earlier supreme court decision (*Solid Waste Authority of Northern Cook County (SWANNC) v. Army Corps of Engineers (USACE)*, 531 U.S. 159 (2001)) delegated regulatory authority over isolated wetlands to each state. The response of states in the Atlantic Coastal plain has varied greatly from requiring a permit to fill wetlands (Virginia and North Carolina), to no systematic attempt to protect them (Georgia). South Carolina has proposed legislation several times but has failed to adopt protections (Munoz et al. 2009). However, a South Carolina Supreme Court ruling in July of 2011 (*Georgetown League of Women Voters v. Smith Land Company, Inc.*, No. 27006) provides the impetus for future protection under the S.C. Pollution Control Act, which is enforced by the Department of Health and Environmental Control (DHEC). Additionally, ephemeral wetland management is being litigated across multiple levels of government and regions, and thus management practices are likely to be affected by future legislation and increased social awareness (Mahaney and Klemens 2008, Hart and Calhoun 2010).

In addition to the ambiguous nature of ephemeral wetland regulation, inherent difficulties in finding and mapping these ecosystems also contributes to their pretermission (Burne and Lathrop 2008). Because identifying such small temporary features, with ground surveys, is often cost prohibitive at landscape scales, recent efforts have been focused on remote detection. However, even in regions where remote detection has been implemented (e.g., Maine, New Jersey, Massachusetts), local geographic conditions, pool variation, availability of high-resolution large extent remotely sensed data, and coniferous canopy often confound detectability (Burne 2001,

Calhoun et al. 2003, Colburn 2004, Lathrop et al. 2005). Moreover, multiple third-party forest sustainability certification schemes are offering new language pertaining to isolated wetland management. The most recent Sustainable Forestry Initiative (SFI) standard requires the “identification and protection of ... vernal pools of ecological significance” (Sustainable Forestry Initiative, Inc. 2010). The American Tree Farm System (ATFS) certification classifies vernal pools as “special sites” and requires land owners to make a reasonable effort to locate and protect these areas (American Tree Farm Systems 2010). Other certification standards, such as the Forest Stewardship Council (FSC), characterize “vernal pools” as streamside management zones (SMZs) that should be buffered accordingly (Forest Stewardship Council 2010). These three standards certify more than 200 million acres of timber in North America alone. In summary, forest certifications are an important way the forest products industry communicates their commitment to sustainability; however, historical methods for detection and mapping (see below) are omitting many ephemeral wetlands, hindering their ability to comply with these voluntary conservation initiatives.

In order to directly address these needs, this study will encompass landscapes in the Atlantic coastal plain that are predominated by privately-owned and managed coniferous forests. Managed, forested landscapes may provide the quickest route to landscape-scale ephemeral wetland conservation (de Maynadier and Houlahan 2008) in at least three ways: (1) timber companies have incentives to voluntarily satisfy sustainable forestry initiatives, (2) planning and implementation of policy may be more efficient with fewer land owners (Baldwin and deMaynadier 2009), and (3) commercial timberlands

comprise a large portion of total southeastern forested lands; 201 million acres (94%) in 1999 (Wear and Greis 2002).

Historically Employed Methods

Historically, wetlands were identified opportunistically by field researchers or through topographic and soil map interpretation. However, in 1954 the USFWS began a rudimentary national wetland survey that eventually encompassed nearly 40 percent of the conterminous United States at a scale of 1:250,000 (Shaw and Fredine 1956). Another nationwide survey was attempted 25 years later when the USFWS was mandated to establish a more comprehensive database describing wetlands. By 1979, the National Wetlands Inventory (NWI) began creating 1:24,000 scale wetland maps that currently encompass >90 percent of the conterminous United States (Wilén and Bates 1995, Tiner 2009). These maps were generated and updated using high-to-mid-level aerial photography (1:130,000 to 1:80,000) and satellite imagery (i.e., Landsat) followed by manual delineation and site visits. In later years, technology advances made larger-scale imagery and analysis more practicable and many of the current southeastern NWI maps were made from mid 1980's color infrared (CIR) photography (1:58,000) or 1970's black and white imagery (1:80,000) (Tiner 2009). However, variation in topography, canopy cover, passive sensors, and seasonality contribute to highly variable results in forested landscapes (Turner et al. 1999). By design, NWI targets features >1 acre (4,046m²) although it may be accurate to 0.1 acre (405m²) under optimal conditions (Dahl and Bergeson 2009). Again, results vary greatly as the inventory missed 88 percent of ephemeral wetlands smaller than 0.25 acres in one Delaware study (Snyder et al. 2005)

and 55 percent smaller than 0.11 acres in another southern Maine study (Baldwin and deMaynadier 2009). In this study's area, all wetlands smaller than 0.13 acre are absent from the NWI database.

To date the most successful method for detecting ephemeral wetlands is using low-level, high water, leaf off, CIR imagery to photo-interpret inundation (Calhoun et al. 2003, Burne and Lathrop 2008, Carpenter et al. 2011). Although this method works well, it is time and labor intensive and inherits the same problems exhibited by all passive sensors such as confounding tree shadow and/or canopy cover. Recently, active sensor technologies such as Light Detection and Ranging (LiDAR) (see, Means et al. 1999, Lefsky et al. 2002) and Interferometric Synthetic Aperture Radar (IFSAR) (see, Bamler and Hartl 1998, Balzter 2001) have been used for mapping forested landscapes due to their ability to pass through openings in canopy cover and detect the underlying earth. These sensors can provide data necessary for sub-meter resolution digital elevation model (DEM) creation and are quickly becoming essential tools in remote sensing applications ranging from natural resource management to archaeology (e.g., Devereux et al. 2005, Reutebuch et al. 2005).

High resolution DEMs that represent complex topography and geomorphology offer researchers an efficient method to display and model terrain. Light Detection and Ranging is best suited to create these models due to existing data, resolution capabilities and the widespread adoption of the technology for forestry applications (Dubayah and Drake 2000, Wulder et al. 2008). Furthermore, a number of studies have demonstrated the promise of LiDAR for wetland detection (e.g., Hogg and Holland 2008, Julian et al.

2009, Lang and McCarty 2009, Maxa and Bolstad 2009), but few have employed the technology for predicting small ephemeral wetlands in forested landscapes. However, Lichvar et al. (2006) combined multispectral satellite imagery data with LiDAR-derived DEMs to predict vernal pools on federal lands in northern California. The study produced landscape-scale prediction maps but authors did not estimate rates of commission and/or omission with ground-validation, thus their approach is difficult to compare with other methods.

Many LiDAR studies extract terrain derivatives from DEMs to build indices that model their target features. Wetland-related studies often use multiple surface-water indices (Hjerdt et al. 2004, Summerell et al. 2004) such as the topographic wetness index (TWI), first described by Beven and Kirby (1979). This index operates under the premise that topography is an adequate proxy for hydraulic gradients. However, TWI is less successful in low-relief areas (e.g., Atlantic Coastal Plain ecoregions) due to unpredictability of water flow across subtle elevation changes (Schmidt and Persson 2003) and the fact that low-relief groundwater gradients often differ significantly from surface slopes (Grabs et al. 2009). Another common method of characterizing wetland landscapes is by modeling surface shape (e.g., Lichvar et al. 2006, Shaeffer 2008, Maxa and Bolstad 2009, Richardson et al. 2010). These techniques are often modifications of the terrain shape index (TSI) first described by McNab (1989) and are more widely referred to as elevation residual analysis (Wilson and Gallant 2000). These indices attempt to model local elevation changes to highlight curvature and may be very useful in

predicting forested ephemeral wetlands in low-relief areas where hydrology modeling is often spurious.

Objectives and Research Questions

The primary goal of this study was to further develop remote sensing methods to aid in the management and conservation of ephemeral wetlands in low-relief forested landscapes. This was accomplished by using high-resolution LiDAR data to create custom local-relief models. These models were then subjected to a workflow of spatial statistics and vector analytics to facilitate remote detection, and ultimately to provide an inventory of pools to collaborators. The entire model was developed for use in a high-throughput computing environment to speed automated wetland detection on landscape scales. This study focused on wetlands $\leq 600\text{m}^2$ which are commonly omitted by NWI for the study area. The research questions were:

- 1.) Can high-resolution LiDAR DEMs predict location and characteristics of small ephemeral wetlands in low-relief managed forests?
- 2.) Are LiDAR models more successful at predicting small ephemeral wetlands with higher accuracy than existing methods?
- 3.) Can spatial statistics be used to help automate feature extraction and landscape characterization?

METHODS

Study Area

The study area covered approximately 55,000 hectares of low-relief (~10m) privately owned timberlands within the Middle Atlantic Coastal Plain Ecoregion (Fig. 1). Most (98%) of the area was in the Mid-Atlantic Flatwoods with the remaining 2% in the Mid-Atlantic Floodplains and Low Terraces level IV ecoregions. This area was historically forested with longleaf pine (*Pinus palustris*) and dominated by ephemeral hydrology. In the late nineteenth and early twentieth centuries, these forests underwent a drastic anthropogenic intervention to facilitate agriculture, timber management, and human habitation (Loehle et al. 2009). These interventions required extensive draining and ditching of the antecedent hydrology which ultimately contributed to wetland decline (Cashin et al. 1992). Today much of this area is privately owned timberland composed of planted loblolly pine (*Pinus taeda*) forests. However, a great number of wetland remnants persist in these low-relief areas including; Carolina bays, pocosin wetlands, pine flats, and other ephemeral pools (Earley 2001).

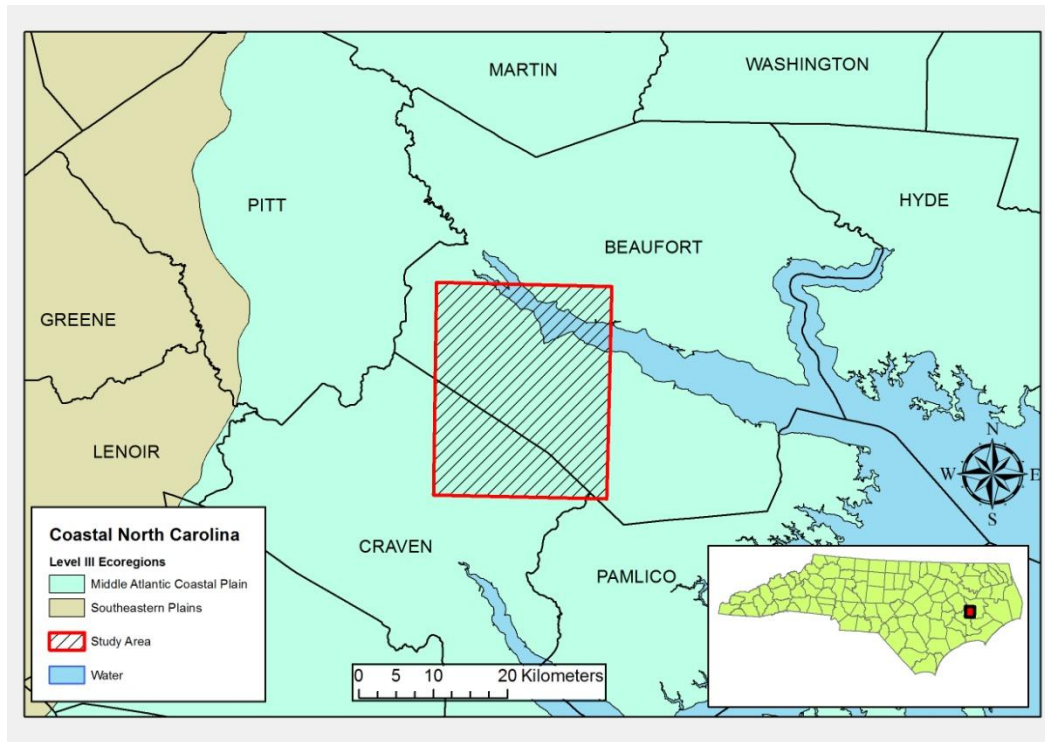


Figure 1.1. Study Area Encompassed by the Middle Atlantic Coastal Plain Ecoregion in Coastal North Carolina.

Data and Processing

Pre-processed proprietary digital elevation models (2m spatial resolution) were obtained directly from private land holders for this study. These data were captured using a Leica ALS-50 II scanner at a nominal flight level of 1500m above ground level with an average of 1.07 ground strikes per square meter from a fixed-wing aircraft. From this altitude the LiDAR instrument may attain a vertical accuracy near 10cm and a horizontal accuracy near 18cm (assuming a 40° field of view and a nominal 5cm global positioning error) in optimal conditions (Leica 2007).

LiDAR DEMs are among the most efficient and accurate representation of topography at landscape scales (Hodgson et al. 2003, Hodgson and Bresnahan 2004, Forlani and Nardinocchi 2007) and demonstrate a marked improvement of resolution in conifer dominated forests over traditional photogrammetry (Reutebuch et al. 2003) (Fig. 2). In addition, small changes in geomorphology can be extracted from terrain derivatives such as slope, and curvature that are unparalleled by other approaches (Töyrä and Pietroniro 2005). Because wetlands mostly occur where concave and convex geomorphologies converge, these characteristics should prove useful for predicting wetland locations. Therefore, simple local relief models (LRMs) were created to elucidate localized changes in concavity that can be applied over a landscape-scale.

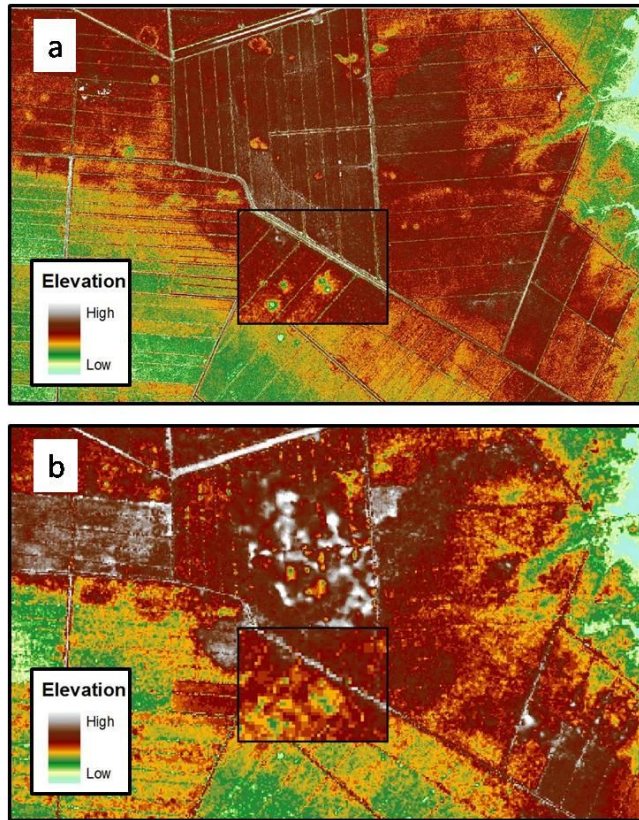


Figure 1.2. Digital elevation model (DEM) comparison of 2m LiDAR (a) and 10m National Elevation Dataset (NED) (b). Small wetlands (green) visible in the LiDAR DEM inlay are ambiguous in the NED inlay. In addition, large errors (white) are evident in the scene just above the inlay.

These LRMs, unlike other common differential indices, create an elevation ratio using a defined area or scanning “neighborhood” around a central cell in which the neighborhood elevations are compared to the central cell’s elevation such that:

$$LRM = \frac{Z_0}{\bar{Z}}$$

Where Z_0 = DEM Elevation
 \bar{Z} = Mean elevation of neighborhood

Values may range between 0 and ∞ , and all values <1 indicate concave morphology.

This model, like all ratios, exhibits bias against raw difference in elevation values, making it inherently difficult to compare across neighborhoods. To account for the variance of raw elevation in a landscape the values can be normalized before development of the LRMs. This method follows a typical rescaling equation so that all elevation data ranges between 0, and 1 but retains their relative order:

$$\frac{(Z - B)(a)}{(A - B) + b}$$

Where Z = DEM Elevation
 A = Maximum DEM Elevation
 B = Minimum DEM Elevation
 a = Maximum scale value (1)
 b = Minimum scale value (0)

LRMs, like all neighborhood analyses, are subject to another type of bias introduced by scale. Derived values are often highly dependent on the chosen size of the scanning neighborhood. The appropriate neighborhood size will vary for both landscape and target topographic feature and may be inversely related to relief. Thus, as the terrain variability inside the neighborhood increases, the mean becomes less diagnostic in relation to the value of one pixel. The following three factors need to be considered before assigning a neighborhood size:

- 1.) Amount of relief represented in the landscape
- 2.) Target size of the topographic features in question

3.) Computational resources and expense

In this study, the elevation range was very low and the targeted topographic features were small ephemeral wetlands $\leq 600\text{m}^2$; for reference, NWI rarely detected wetlands smaller than 600m^2 in the study area. Sensitivity analysis (analysis of variance) of neighborhood size on LRM values indicated that with low-relief, neighborhood size had minimal effect on LRM (Table 1). Thus for this study the appropriate neighborhood size is likely related to target feature size. If neighborhood size is too small, the model will calculate values that fall completely within the target features (e.g, Fig. 3a) and therefore fail to detect concavity. As neighborhood size increases, the model becomes coarser, more similar to the original DEM, and exponentially more computationally expensive (Fig. 4). In theory, the total neighborhood area should be at least $\frac{1}{2}$ the area of the largest target feature. This increases the likelihood that peripheral neighborhoods encapsulate both the center of the feature as well as its perimeter (Fig. 5). Thus, I selected neighborhoods of 150 pixels (300m^2) to encompass the target features (i.e., small ephemeral wetlands) while maintaining a reasonable computation expense. Many wetlands larger than 600m^2 were readily visible in the original LiDAR DEM and needed no further processing for detection.

Table 1.1. Affect of neighborhood size on 1,000 randomly generated LRM values, $F_{7, 1000} = 0.110, p = 0.998$. Area demonstrates very low-relief (mean LRM of 1 = no curvature).

Neighborhood Size (pixels)	Mean LRM	Variance
15	0.999582	0.000300
25	0.999530	0.000305
50	0.999552	0.000326
75	0.999551	0.000334
100	0.999510	0.000342
150	0.999311	0.000358
200	0.999206	0.000375
300	0.999065	0.000406

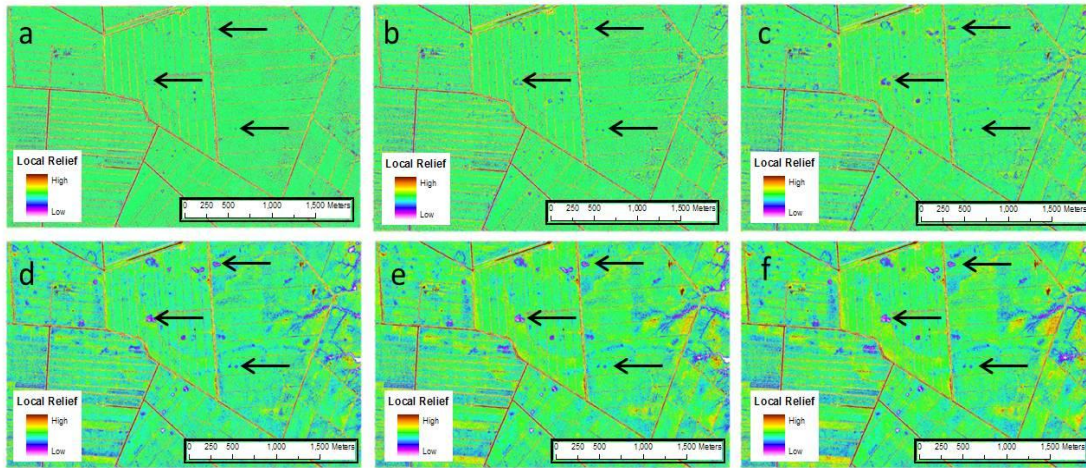


Figure 1.3. Visual examples of neighborhood size on local relief models at 25m² (a), 50m² (b), 100m² (c), 200m² (d), 300m² (e), 400m² (f). Black arrows indicate ephemeral wetland locations.

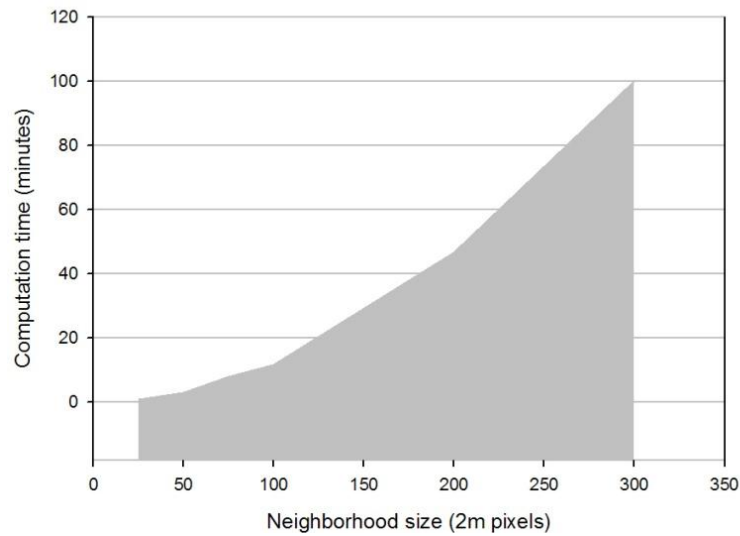


Figure 1.4. Neighborhood size vs. computation time for area = 1225 ha using Pentium 4 3.4Ghz 2GB RAM.

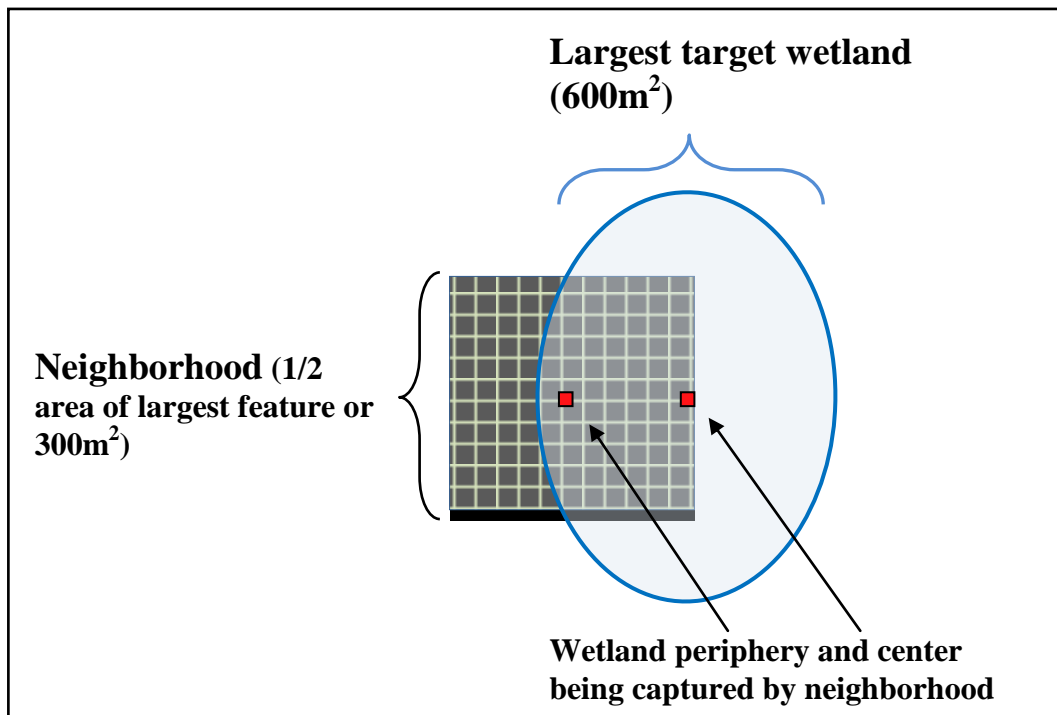


Figure 1.5. Depiction of neighborhood size relative to target feature size. Most likely to capture entire range of concavity.

Original DEM versus LRM

To compare the original LiDAR DEMs with the LRMs, I conducted a moving window correlation analysis using the same neighborhood size as the LRMs (Fig. 6). Areas with little relief produced similar model results; however, as the terrain undulated the correlation with LRM decreased. The most obvious decrease occurred along river corridors although it was also noticeable with smaller changes in relief likely characterizing the upland/wetland interface. Another method of visualizing the difference between the two models is by using a profile analysis. A profile line illustrates relief sensitivity of LRM in relation to the DEM surface model across the same areal area (Fig. 7).

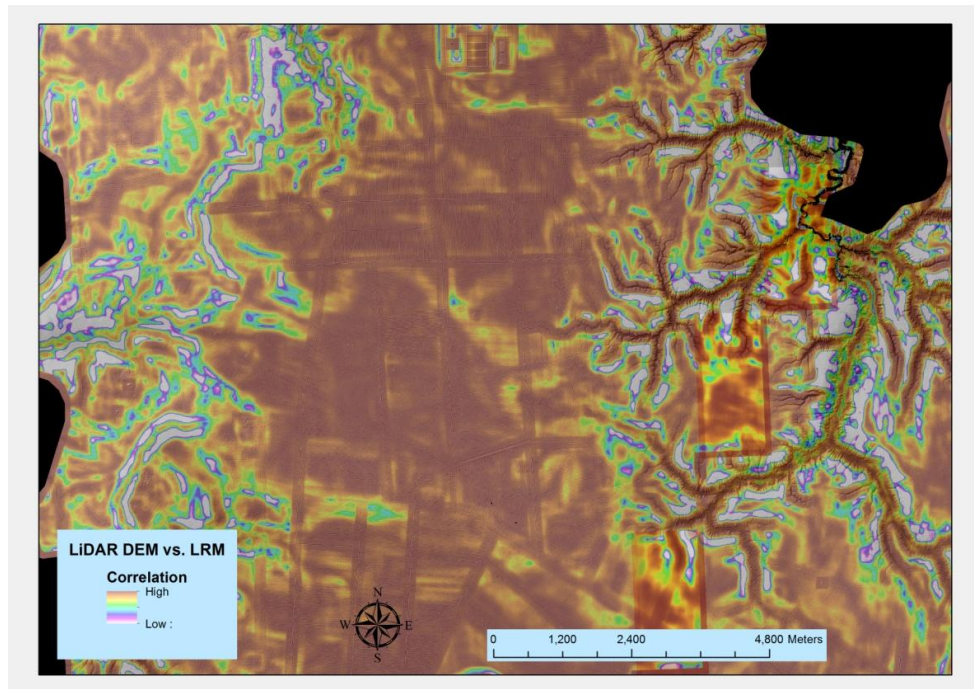


Figure 1.6. Moving window correlation analysis between the original LiDAR DEM and LRM.

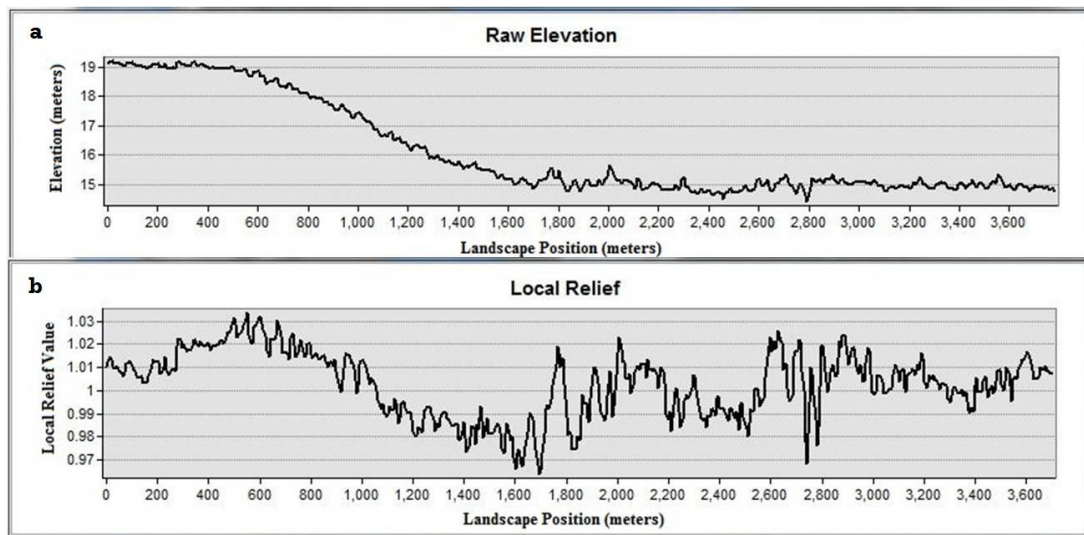


Figure 1.7. Profile lines analysis across 3.6 km comparing raw elevation (a) and local relief values (b) which captures more micro-variation across the landscape.

LISA

Outputs from the LRM models were further processed with Local Indicators of Spatial Association (LISA), using local Moran's I (see, Anselin 1995), to investigate the underlying spatial structure of local relief. This process elucidates clusters and outliers of LRM values and tests them against a randomized spatial distribution hypothesis. The 5 possible outputs from this algorithm are as follows:

1. Low-relief surrounded by low-relief (LrLr: significantly clustered)
2. Low-relief surrounded by high-relief (LrHr: significant outlier)
3. High-relief surrounded by low-relief (HrLr: significant outlier)
4. High-relief surrounded by high-relief (HrHr: significantly clustered)

5. No apparent spatial pattern (NA: Non-significant distribution of values)

These clustering results were then grouped into regions and filtered into targeted features creating a shapefile of polygons that signify high probability depressional areas (i.e., likely ephemeral wetlands). This entire workflow was modeled with Python scripting language in ArcGIS (version 10.0, Redlands, CA.) and processed using high-throughput computing via Condor (version 7.6, Madison, WI.). The study area was partitioned into tiles of 2km² for more economical processing and executed using idol GIS computer laboratory workstations and servers (*see chapter 2*).

Ground Truthing

I visited 114 unique sites spanning two consecutive seasons (summer and winter) in 2010 and 2011. With no *a priori* knowledge of ephemeral wetland locations omitted by NWI, I used current best practices (CIR photo interpretation) to locate 19 potential sites in 2010. These sites were not chosen at random but were stratified by measures commonly confounding detection ([e.g., size, land-cover, and canopy cover (Table 2)]). Land cover was derived from the National Land Cover Dataset of 2006 (<http://www.epa.gov/mrlc/nlcd-2006.html>) and distilled into pine, deciduous, and mixed cover classes. Canopy cover was estimated by photo-interpretation of foliage directly over a pool and classified as open (<40%), partial (40-70%), closed (>70%). These sites were later included with 2011 data and tested by the model to measure rates of omission (α error) and commission (β error).

I visited 95 sites in the winter of 2011 during high water. Commission error was tested using a random stratified design proportional to land cover at 50 sites. The strata were as follows; developed (6), grassland (5), managed forest (19), shrub (10), wet (10). Omission error was tested using best methods (CIR photo-interpretation) on 32 sites in areas not previously subjected to the model. In addition, 13 sites were found opportunistically during field validation and were included in model error testing. Sites were confirmed ephemeral wetlands upon visual inspection of inundation and presence of indicator species (e.g., *Vaccinium spp.*, *Ilex spp.*, *Lyonia lucida*). Ephemeral wetland sizes were first estimated remotely and later corrected with field-derived GPS data where possible.

Table 1.2. Experimental design for ground truthing of 19 sites in June 2010.

Surrounding Landcover	Canopy Cover								
	Open			Partial			Closed		
Pine	1	1	1		1	1	1	1	1
Deciduous		1				1	1	1	1
Mixed		1		1		1	1	1	1
<div> <div>Area < 50m²</div> <div>Area < 100m²</div> <div>Area > 100m²</div> <div>Area < 50m²</div> <div>Area < 100m²</div> <div>Area > 100m²</div> <div>Area < 50m²</div> <div>Area < 100m²</div> <div>Area > 100m²</div> </div>									

Biases and Limitations

Although active sensors commonly overcome obstacles of passive sensors, they are subject to multiple forms of bias. LiDAR returns are commonly affected by atmospheric conditions, sensor type, and/or land cover type and the resulting errors are

not uniform across the landscape (Hodgson and Bresnahan 2004, Fisher and Tate 2006). In coastal North Carolina many pocosin wetlands exist and dense understory vegetation such as fetterbush (*Lyonia lucida*), holly (*Ilex spp.*), and other shrubs (*Vaccinium spp.*) (Sharitz and Gibbons 1982) may reduce point spacing of LiDAR ground returns. In addition, areas of open or deep water will absorb light from the sensor or create a weak and inconsistent return (i.e., data voids). However, biases were somewhat minimized by the small forested focal features in this study and the use of LiDAR acquired before absolute high water in early January 2007.

The processing of raw points also requires multiple choices for interpolation based on terrain and spacing. As a consequence, LiDAR DEMs and resultant models may vary greatly (Liu 2008). Furthermore, DEM derivatives (e.g., slope analysis, hydrological modeling and topographic indices) using roving windows are inherently scale-dependent (MacMillan and Shary 2009) and sensitivity analysis may be necessary to ascertain an appropriate sized window for any given study area and/or focal features. Finally, roving windows lose resolution around the perimeter of DEMs where fewer neighbors are available for computation. This problem was overcome by overlapping tiles by twice the distance of the neighborhood.

Local indicators of spatial association, based on local Moran's I, typically only approximates asymptotic distributions (Anselin 1995). As a result, ArcGIS tests the LISA statistic against a randomizing algorithm where the cell being analyzed in a neighborhood remains fixed and is not randomly permuted while the surrounding cells are randomized. This process will arrive at a pseudo-significance level that may inflate

spatial dependence (i.e., overestimate clustering) thereby introducing α error. Although characterizing wetlands with a conservative approach is desired, the effect of α error on very small wetlands was diminished by targeting a minimum cluster size threshold of at least 15 cells (30m^2). This size threshold was chosen because no smaller confirmed wetland was detected in this study and it may represent a more appropriate size for management.

RESULTS

Local relief models derived from fine-scale LiDAR DEMs, captured small changes in local geomorphology that helped characterize small wetland sites in low-relief ecosystems. Mean area of NWI delineated wetlands ($n = 1,621$) was 9.06 ha with a median of 2.32 ha. In contrast, probable wetlands ($n = 4,610$) detected in this study exhibited a mean area of 0.37 ha with a median of 0.13 ha. Ground-verified wetlands averaged $323\text{m}^2 \pm 316\text{m}^2$. The frequency distribution of NWI wetlands versus those detected with the semi-automated model indicated that NWI only approached sensitivity of the model when wetland area was approximately two ha (Fig. 8).

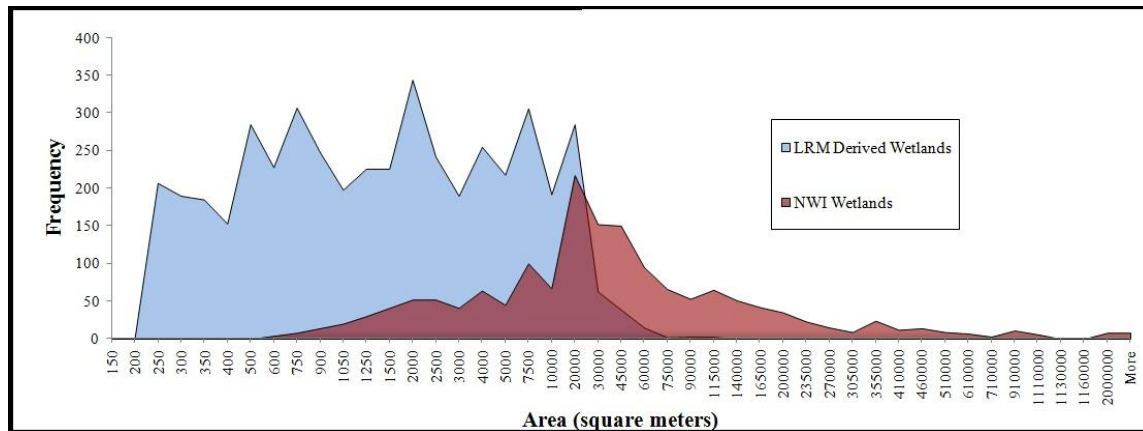


Figure 1.8. Frequency distribution of NWI wetlands versus likely wetlands detected in this study.

Depressions (summer) or inundation (winter) were correctly described at 97 of 114 sites, obtaining a mapping accuracy of 85%. Commission and omission errors were estimated to be 15%, and 5%, respectively. The majority of errors occurred in managed forest and shrub land covers, however these errors were not disproportionate to percent land cover (Table 3). In addition, commission ($\bar{X} = 134\text{m}^2 \pm 173\text{m}^2$) and omission ($\bar{X} = 415\text{m}^2 \pm 500\text{m}^2$) errors varied greatly in size but did not differ in mean area from ground-verified sites, $t_{52} = 2.00$, $p = 0.13$, and $t_{47} = 2.01$, $p = 0.69$ respectively. Recent forestry operations had altered 15% (19:114) of visited sites (clear-cut and not yet replanted or recently replanted) accounting for 29% of the total error (5:17). However, a Chi-squared test with Yates continuity suggests these sites were not a disproportionate contributor to model error, $\chi^2(1, N = 155) = 0.48$, $p = 0.49$.

Table 1.3. Model errors in relation to the land cover classes in which they were found.

Land cover classes:	Managed Forest	Shrub	Grassland/Open	Wet	Developed
Type I Error (n=14)	50.0%	21.5%	21.5%	7.0%	0.0%
Type II Error (n=3)	66.6%	33.3%	0.0%	0.0%	0.0%
% Total Area	38.0%	20.0%	12.0%	20.0%	10.0%
% Total Error	53.0%	23.5%	17.5%	6.0%	0.0%

DISCUSSION

This study has demonstrated that small localized changes in elevation are captured by high-resolution LiDAR and characterizing these changes is an effective method to identify ephemeral wetlands in low-relief managed ecosystems. Further, spatial statistics can be used to semi-automate a landscape-scale mapping effort. Mapping these cryptic fine-scale features is a necessary first step in promoting or implementing conservation and management strategies (Lang and McCarty 2008). In addition, this study highlights the limitations of coarse-filter landform detection such as the National Wetlands Inventory. Most small wetlands found in this study were systematically omitted by other mapping efforts (Fig. 8) despite the fact that these types of wetlands may be of high conservation value (Semlitsch and Bodie 1998, Gibbons et al. 2006). Although the NWI is a very important tool for monitoring wetland loss and estimating future trends (Cashin et al. 1992, Gibbs 2000, Tiner 2003), a fine-filter approach may be complimentary for individual land holders where NWI errors are relatively frequent. Using both coarse and fine-scale detection methods will likely decrease mapping error and increase the efficiency of management decisions (Franklin 2001). Interestingly, coarse and fine-filter analysis produced similar results when

wetland area was between 1.5-2.5 hectares. This likely occurs because wetlands of this size are difficult to miss upon visual inspection of CIR imagery and thus this range produces the smallest cumulative rate of detection error. Larger wetlands were not targeted by the fine-filter approach in this study but could likely accommodate mapping of these areas with larger neighborhood sizes.

Classification Errors

The mapping accuracy for this study indicates that small ephemeral wetlands may be identified successfully using LiDAR DEMs even in low-relief ecosystems. Furthermore, it is likely that other small features, which may be important for sustainable forest management, can be detected or monitored with similar technology. However, the estimated error rates in this study require further examination. Commission error rates were much higher than omission rates for several possible reasons. Perhaps most strikingly, LISA clusters are biased towards α error because of multiplicity (Anselin 1995) and overestimate wetland boundaries (Fig. 9). Secondly, α error occurs in heterogeneous wetlands where hummocks and hammocks are prevalent (i.e., wetland complexes, pine flats) and also in areas recently altered by forestry operations where clear-cutting, heavy machinery and ditching may alter hydrology and/or morphology (Lockaby et al. 1997). Lastly, the high spatial resolution data likely inflated α error because of the inverse relationship that exists between grain size and the number of detected depressions (Lindsay and Creed 2005, Zandbergen 2006). This phenomenon also likely contributed to the noticeably smaller commission error areas.

Reported omission error rates were likely artificially low because nearly 75% of wetlands tested for omission error were found by manual photo-interpretation of CIR images. It is often difficult to detect small wetlands using these methods at appropriate scales (1:1200) with the spatial resolution available (1m). Therefore, the test set may have been biased towards more obvious wetlands (i.e., those less obscured). New literature suggests using a minimum of 0.33 meter spatial resolution CIR photos for delineating these features manually (Pitt et al. 2011). In addition, some landscape features are likely to cause higher incidence of LiDAR laser return error (e.g., pocosin) and ~15% of the test set in these areas was inaccessible during high water in 2011. However, the region is known to contain many pocosin wetlands.

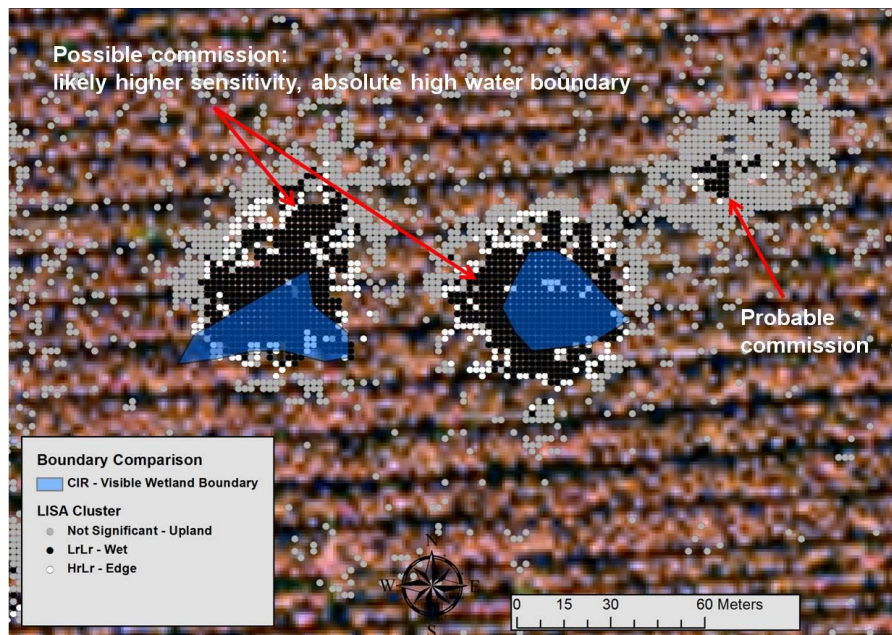


Figure 1.9. LISA clusters depicting wet areas not visible in CIR. Image likely contains areas of both commission error and absolute-high water boundaries based on higher sensitivity from morphology.

LISA Returns

The five possible outcomes from LISA clusters are explained as follows:

1. LrLr – returns appear to be the most likely predictor of wetlands. These are points that fall completely inside a depression and are surrounded by other similar points.
2. LrHr – returns most obviously delineate ditches. The study area is highly intersected with a network of drainage ditches and points falling inside ditches represent thin linear features where most surrounding points fall outside the ditch. These returns also may signify areas created by forestry operations (i.e., skidder ruts), small narrow pools, coves, or spill points which connect a larger complex of wetlands.
3. HrLr – returns are found around the boundary of depressional areas where high-relief areas are surrounded by low-relief. No error sites displayed these returns although they may also be found in small peninsulas or islands of vegetation commonly seen in pine flats.
4. HrHr – returns are classified as mostly flat points with little deviation. Only one ground-verified wetland returned this type of return and it was much larger (> 0.25 acre) than the targeted features although still omitted from NWI. This particular omission suggests the selected neighborhood may have been too small to correctly characterize some wetlands of this size.
5. NA – returns are typically areas where local relief values are >1 or that display a non-significant, non-autocorrelated spatial arrangement. One omitted site

displayed this return. This inundated area was part of a larger pine flat type wetland which was correctly mapped nearby and likely hydrologically connected by an overspill point which was difficult to identify *in-situ* due to water level.

Heuristic Thresholds for Small Wetlands

Because of inherent DEM error (Fisher and Tate 2006) and diversity of pool size, shape, and depth, (Tiner 2003, Rheinhardt and Hollands 2008), it is often difficult to separate actual ephemeral wetlands from spurious ones using remote methods. This problem may be compounded in flat areas (Martz and Garbrecht 1998) if hydrology modeling is used to predict these depressions. Furthermore, soil data are often too coarse to offer clarity for small wetlands (Bowen et al. 2010, Enwright et al. 2011). In fact, nearly 965 ha of wetlands delineated by NWI in the study area (7%) are found on non-hydric soils (Soil Survey Geographic Database); highlighting the coarseness of both datasets. Expectedly, the finer-scaled approach of this study led to a higher such percentage (22%), accounting for 374 ha.

Even ground surveys can be an unreliable method of separating confounding pools because there is inherent scale bias of field observes as to what constitutes a wetland, especially among small shallow pools (Li et al. 2011). Although Lindsay and Creed (2006) describe an automated modeling technique of separating confounding features, the method requires DEM error information which is seldom measured (Li et al.). Ultimately, management decisions will likely need to include depth thresholds, size thresholds, or probability thresholds in order to limit the expense associated with error

and to focus limited resources on productive pools. Ideally, these filtering decisions will use sensitivity analysis and local knowledge of features being mapped.

CONCLUSIONS

In addition to small landform detection, a micro-topographical approach may also be useful for landscape-scale conservation planning. Several tools used to characterize surrogates for biodiversity may perform poorly on parcels of land in low-relief areas. These tools include the Ecological Land Units and Land Facets (Anderson and Ferree 2010, Beier and Brost 2010). Difficulties occur in low-relief areas because subtle changes in elevation make hydrological modeling less reliable and ultimately flat areas are treated as homogeneous landscapes. Some, if not all, of the omitted heterogeneity may be captured by using higher resolution LiDAR datasets which can correctly characterize even very small changes in elevation. Therefore, incorporation of high-resolution LiDAR data in these planning tools is recommended where applicable.

In summary, high-resolution LiDAR data coupled with high-throughput computing holds promise for landscape-scale detection of important ecosystems. Although this study focused on detection of ephemeral wetlands in low-relief ecosystems, additional methods could be incorporated to characterize wetlands in areas exhibiting more relief. For example, LiDAR intensity returns (which is standard data collected by most modern LiDAR sensors) have been successfully used to separate in-pond habitat from upland (e.g., Julian et al. 2009) and elucidate coastal wetland boundaries (Brazank and Lohmann 2005). In addition, high-resolution multi-spectral data, if available, may be

included and modeled with an object-oriented approach to further reduce model error (e.g., Frohn et al. 2009, Sullivan et al. 2009).

Future Questions

Although this study provides an affordable (using existing data) and rapid method to map small ephemeral wetlands in low-relief areas, several important questions remain about prioritizing these features for management and conservation. Legislation, regulation, and management guidance (e.g., sustainable forestry certifications programs) often use ambiguous language to describe vernal pools leading to subjective interpretation. Questions about which vernal pools are “ecologically significant” may arise and could require biological surveys or access to existing survey data, to determine presence of sensitive species. However, significance may also be associated with the hydrological connectivity (i.e., spatial configuration) of wetland complexes, which has been examined extensively in more undulating terrain (e.g., Leibowitz 2003, Rains et al. 2006, Leibowitz and Brooks 2008, Wilcox et al. 2011). Hydrological connectivity is dynamic in managed landscapes and a shifting mosaic planning tool, which accounts for forestry operations while maintaining a degree of connectivity and diversity, could help to conserve the ecological value of these ecosystems (Gibbs 2000). Moreover, diversity of pool size and hydroperiod directly affects floral diversity (Casanova and Brock 2000, Battaglia and Collins 2006), invertebrates (Colburn et al. 2007), and amphibians (Semlitsch and Skelly 2007), which in turn likely affects avifauna (Scheffers et al. 2006).

In addition, optimization of LiDAR DEM grain-size should be explored for use in low-relief ecosystems to minimize data acquisition costs. It is likely there is a

diminishing returns threshold of spatial resolution that exists for detecting most vernal pools, as is widely seen in other remote sensing applications (e.g., Chaplot et al. 2000, Gessler et al. 2000). However, in managed coniferous landscapes where high-resolution LiDAR is most effective, this threshold is likely beyond the resolution of most publically available datasets. Although higher resolution data will increase sensitivity (decreasing omission) exponentially, it will simultaneously decrease specificity (increasing commission) (Li et al. 2011) likely requiring more field validation and/or heuristic rules for filtering.

Recommendations for Implementation of Methods

In order to apply these methods to a larger spatial extent (e.g., in the coastal plain), several factors should be considered. One important implementation objective is to define a “reasonable effort” to find vernal pools. Conservatively, such an effort would include a mapping approach where commission error is higher than omission error. Heuristic rules can be made about thresholds of size, depth, and connectivity to maintain optimal timber management while prioritizing conservation efforts on areas with high pool density.

While publically available datasets often lack high-resolution or large-extent products, proprietary LiDAR can be collected to befitting specifications. If using expensive and highly sensitive data, it may be prudent to hire in-house analysts with full access to remote sensing products. Disclosure of handling, and auxiliary data may prove quite useful for reducing mapping error of ephemeral wetlands (e.g., intensity data). In addition, it is possible to rent high-throughput or high performance computing resources

from outside sources to execute analyses. This can be done from a variety of sources but perhaps most affordably through a university with appropriate cyberinfrastructure (or commercial offerings; e.g., Amazon Elastic Cloud computing (<http://aws.amazon.com/ec2/>), Microsoft Azure (<http://www.microsoft.com/windowsazure/>)).

CHAPTER TWO

HIGH-THROUGHPUT COMPUTING OF HIGH-RESOLUTION, LARGE EXTENT DATA

INTRODUCTION

Landscape-scale analyses in ecology and conservation biology historically have been restricted to low-resolution datasets due to data availability/capture and computer hardware/software limitations. Although the associated technologies have advanced exponentially, analyzing large datasets remains computationally expensive. At landscape-scales, even coarse-resolution datasets become cumbersome in typical software applications and are time-intensive to interpret, when using a single desktop workstation. Moreover, modern high-resolution remote sensing technologies can produce millions of data points on local-scales. While such datasets offer tantalizing methods for remote sensing of landscape patterns (e.g., Asner et al. 2008) the data processing challenges are often daunting to ecologists with limited computer science background (Roberts et al. 2010). The field of ecology is increasingly reliant on computer based modeling and informatics (Jørgensen et al. 2009) and developing concise methods to process large datasets (with commonly available software and hardware) may help facilitate their exploration and exploitation by landscape ecologists and conservation planners.

Prior to the mid-1990s, high-resolution remotely-sensed datasets were sensor-limited, cost prohibitive, or computationally prohibitive (Armstrong 2000). While traditional landscape-scale analyses have utilized a range of spatial resolutions from 10m

(high) to 1km (low), they have typically been limited by the positive relationship between resolution and spatial extent (Woodcock and Strahler 1987). Although great advances have been made in passive remote sensing (e.g., hyperspectral imaging), active sensors are increasingly being used in natural resource management. Technologies such as Interferometric Synthetic Aperture Radar (IFSAR) and Light Detection and Ranging (LiDAR) are becoming more affordable and publically available (Maune 2007). These relatively new technologies are capable of capturing sub-meter resolution data at large extents (e.g., county, state, province).

Acquiring clusters or grids of workstations was cost prohibitive until the early 1990s (Buyya 1999). Today, however, large networks of computing resources are easily shared (e.g., NSF's TerraGrid) or rented (e.g., Amazon Elastic Cloud Computing: <http://aws.amazon.com/ec2/> or Microsoft Azure: <http://www.microsoft.com/windowsazure/>). Although commercial resources are expanding to fill computing needs, many of the largest networks exist in academic realms. Academic systems make up 16% of top 500 supercomputer resources in the world, and 13% of top US supercomputing sites are on college campuses (TOP500.Org 2011). The National Academy of Sciences and the National Research Council have recommended an increase in access to both public and commercial resources as many supercomputing projects have large social implications (e.g., climate modeling, national security, and geophysical exploration) (Graham et al. 2004).

In conservation biology, many modeling tasks rely on spatially focused analytical paradigms, which are shifting towards more complex algorithms (Armstrong et al. 2005).

These spatial analytics are commonly used to describe natural phenomena not easily measured (Liebhold and Gurevitch 2002, Wagner and Fortin 2005). Specifically, ecosystem function analyses, which incorporate high-resolution datasets, are becoming more frequent and are being applied at multiple large extents (Wulder et al. 2004). While coarse-grained geophysical variation captures much of the biogeographic variation and is useful for large landscape-scale conservation planning (Anderson and Ferree 2010, Beier and Brost 2010), high-resolution regional-scale connectivity modeling may unveil functional ecological requirements not captured under a coarse-grained umbrella effect (Minor and Lookingbill 2010). To that end, there is a need for fine-grained ecoregional conservation planning in general (Woolmer et al. 2008) as small reserves and protected areas have proven to significantly contribute to regional and local diversity (Shafer 1995, Falkner and Stohlgren 1997).

The primary goal of this study was to investigate high-throughput computing as a method to shorten processing time of computationally intensive spatial analyses for conservation biology. The current industry standard to explore spatial data in these fields is ESRI's ArcGIS software suite (Redlands, CA 2010). Therefore, our first objective was investigate native tools in ArcGIS (e.g., modelbuilder) for use in development of models for third-party open source grid middleware (*Condor*) management within the Python programming language. Python is an open source high-level programming language designed for readability, and it is the preferred language in ArcGIS 10.0. We explored the feasibility of using natively created Python code to execute custom models for non-programmers. A computationally expensive model was developed for use in a grid

computing environment and overall performance was compared to model execution on a similar local workstation. The second objective for this study was to provide evidence that high-throughput computing will save time and resources over conventional processing techniques for high resolution and large extent datasets. We provide herein two brief high-throughput computing (HTC) examples dealing with large extents: 1) a vector-based protected areas job which operates on a continental extent and 2) a landscape connectivity modeling job, using the emerging software *Circuitscape* (Shah and McRae 2008), operating at state-extent and processed using a supercomputer.

METHODS

In our primary example, we investigated HTC in the context of a landscape-scale study to identify small landforms. We used a high-resolution LiDAR-derived digital elevation model (DEM) covering 55,000 hectares at 2m spatial resolution to create custom relief models in ArcGIS modelbuilder using native toolboxes. These models were then divided into 2km tiles for further processing. The resultant DEMs contained more than 10 million points which were analyzed with local indicators of spatial association (LISA): a computationally expensive analysis (Armstrong et al. 1994). We used the LISA output to perform a multitude of vector tasks in order to map topographic depressions in low-relief landscapes. These small depressions were omitted from coarse-grain mapping efforts (National Wetlands Inventory) but may still provide critical habitat for herpetofauna and other hydroperiod sensitive organisms (Semlitsch and Bodie 1998,

Calhoun et al. 2003). This workflow was output to Python code using modelbuilder graphical user interface export options.

The resulting output Python code was optimized for execution on the local machine which exported the code (e.g., all file inputs and related toolboxes are referenced from the local hard drive). Therefore, slight alterations were required to clarify the model interaction with files (i.e., file paths) on remote machines (i.e., GIS equipped computer laboratory workstations). These path corrections required altering a few lines of code to reference the working directory on ArcGIS server from which the input files will be transferred (Fig. 1 step 4). Although the user had no interaction with the model while being executed on remote machines, *Condor* provided native functionality (i.e., pre-defined macros) to iterate through a sequence of files and/or folders which streamlined the workflow of jobs.

The following two examples involve using parallel processing to speed analysis of large-extent coarser-resolution data. First, we conducted a continent-scale human footprint analysis (see Sanderson et al. 2002) (1km resolution) that encountered multiple zonal statistics problems (see Lipscomb and Baldwin 2010) . Using ArcGIS 9.3 and custom Visual Basic (VB) geoprocessing scripts, we used *Condor* and grid HTC cyber infrastructure for processing (described below). These VB scripts can be directly exported from modelbuilder in version 9.3 similar to Python in 10.0. Lastly, we utilized an emerging connectivity modeling software (*Circuitscape*) to do a pairwise analysis of potential gene flow between 63 points (2,211 pairs) across South Carolina using a 100m resolution DEM of naturalness (see Theobald 2010). This analysis was executed within a

supercomputing system consisting of a heterogeneous cluster operating on the CentOS 5 platform, a Linux based distribution (Palmetto Cluster: <http://top500.org/system/9849>).

Condor and grid middleware

Grid middleware is a software application that manages a distributed workload for computationally expensive jobs. It facilitates dissemination of these jobs to remote machines while allowing the user to control job execution. Although there are a number of capable grid middleware applications, we chose *Condor* for this study for several reasons. *Condor* is open source and designed to handle complex task scheduling (Raman et al. 1998) such that might exist when utilizing a student ArcGIS computer laboratory at a university. In fact, scheduling can be the most difficult task in any embarrassingly parallel grid workflow (Afgan and Bangalore 2008) where processing cores or workstations do not communicate with one another during processing. Finally, The Condor Project (<http://www.cs.wisc.edu/condor/>), made up of a consortium of researchers from the University of Wisconsin, has been utilizing and developing the software for nearly two decades and it is well-known and maintained.

Cyberinfrastructure

The workstations (n=132) used to support the HTC were housed in several student computer laboratories equipped with ArcGIS Desktop version 9.3 and later 10.0. Although these resources were outfitted with heterogeneous hardware, they contained a minimum of Intel Core 2 Duo 2.4 GHz processors with 2GB RAM. In addition, these workstations interfaced with a ArcGIS Enterprise Server (v.10.0) and a dedicated server containing *Condor* software which handled pairing the jobs with available workstations

(i.e., matchmaking). Together, these 3 components (laboratory workstations, ArcGIS server, and *Condor* matchmaker) provided a high-throughput computing (HTC) environment which operated without the need for the user or remote machines to interact with a local machine during processing (Fig. 2.1).

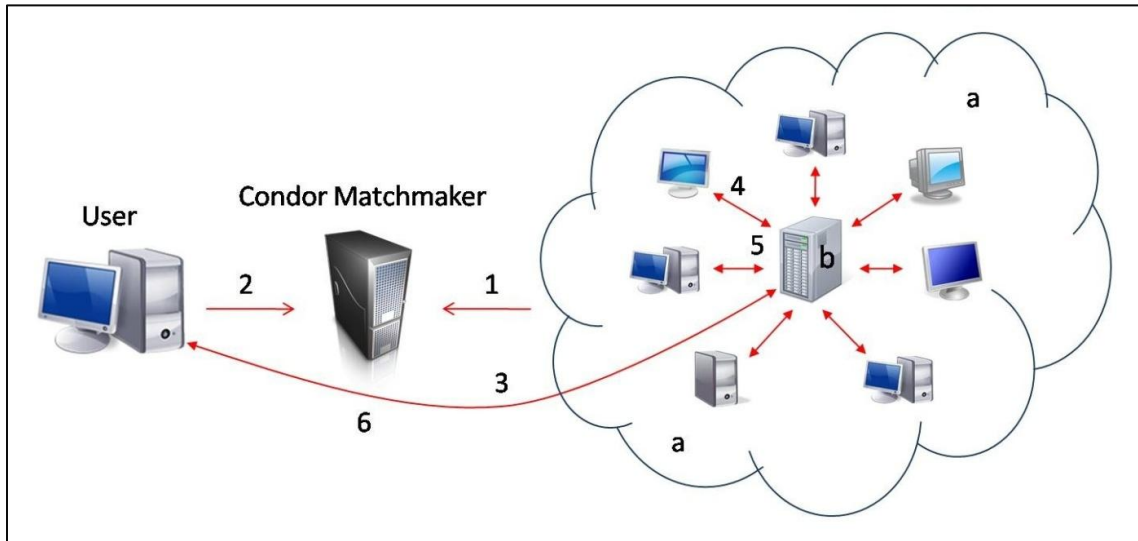


Figure 2.1. Cyberinfrastructure including Condor Pool (a), ArcGIS geodatabase (b), and workflow as follows: advertisement of available machines (1) user query of those machines (2) and then data transfer (3). Those data are sent to remote workstations for execution (4) and output is returned to geodatabase (5) where the end user retrieves the data (6).

Workflow

In the first step of *Condor* matchmaking, the pool of computers advertise themselves as available, along with other useful information about their operating system, hardware, installed software, etc. We used computers with Intel architecture, Windows NT operating system 6.1, and ArcGIS installed. In the second step, the user queries the

matchmaker for available machines and minimum requirements to execute a desired job. Using *Condor*, this is done by submitting a “class advertisement” which consists of a text file that describes jobs, required resources, when the resources are needed, and how many workstations are needed. In the third step of the workflow the user submits all necessary files required to execute the job to a remote ArcGIS geodatabase server, including class-ad, input files, and executable files. This initiates each matching workstation to start the calculation. The fourth step occurs as each workstation in the pool draws necessary input files to execute its portion of the overall job and stores these files on the local machine. This entire step is executed with an embarrassingly parallel workload. In the fifth step, each local workstation transfers its output back to the ArcGIS geodatabase. The sixth and final step occurs as all the output files are transferred back to the user’s machine for further analysis and display in a GIS.

Limitations

In order to maximize use of existing cyberinfrastructure, ArcGIS computer laboratories such as those that exist in many universities can be utilized. However, if these idle workstations are engaged by a user in the computer lab, *Condor* will stop processing and reassign the task to the next available workstation. Therefore, it is practical to execute models during low use times such as nights or weekends. Because *Condor* is able to leverage a heterogeneous assemblage of resources (e.g., servers and personal workstations), varied computing power will inherently be employed for individual task execution resulting in uneven performance. In addition, the workflows are not balanced on remote workstations because each processed tile contains a different

number of features to analyze with different spatial structures, despite the tiles being of the same areal size. These problems can be controlled by decomposing spatial domains using a curve-filling algorithm (Wang and Armstrong 2003, Wang et al. 2008). This approach will tile the input features based on estimated computational requirements of underlying spatial structure while facilitating dissemination of these tiles to individual processors (Wang and Armstrong 2009). In our study, strict optimization was not desired or necessary due to unrestricted access to the cyberinfrastructure, number of available workstations, and our focus on usability to the end user.

RESULTS

High-throughput computing of landscape-scale high resolution data offered massive wall time savings over traditional desktop workstation execution, displaying a near negative exponential relationship with number of workstations (Fig. 2.2). For one 2km square tile, processing time was cut 30% from 41 minutes 42 seconds (local) to 29 minutes 10 seconds (grid). However, the most appreciable savings were recognized when executing these tiles concurrently. Using a local machine to process the entire study area of roughly 55,000 hectares exhausted 205.25 hours of processing. That same workflow using our grid computing infrastructure consumed only 2.25 hours accounting for a 91x speedup when:

$$S_p = \frac{T_1}{T_p}$$

Where p = number of processors

T_1 = processing time of sequential execution with one workstation

T_2 = processing time in parallel execution

HTC and *Condor* managed to decrease our continental human footprint analysis wall time from an estimated 864 hours to fewer than 12, a 72x speedup. In addition, by parallelizing our state-wide *Circuitscape* job across 201 nodes at 11 calculations per node, use of the Palmetto cluster decreased processing wall time from 611 hours to just under 5 hours, a 122x speedup (A. Rose, “unpublished data”)

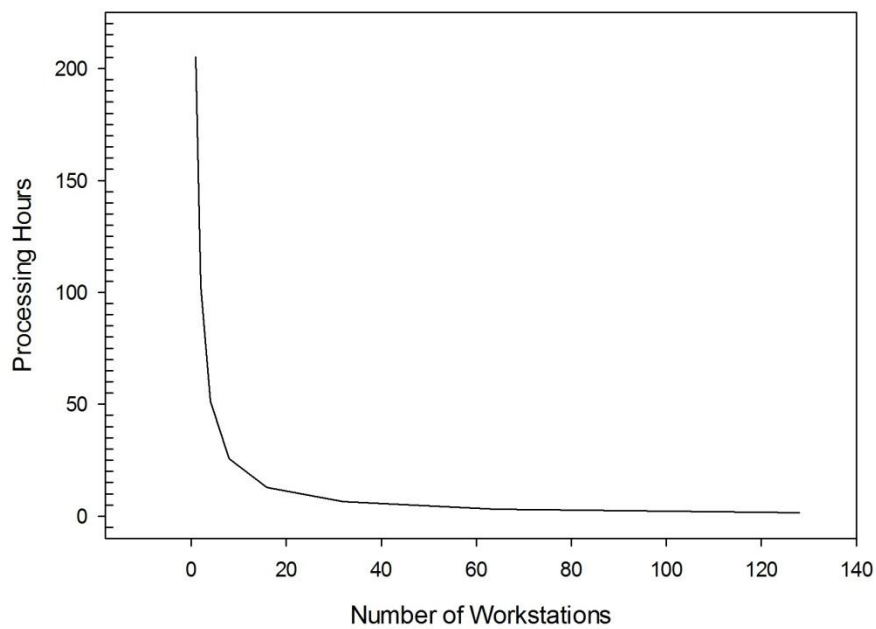


Figure 2.2. Optimized grid computing performance expressing exponential relationship. Infrastructure and workflow were not optimized although a very similar relationship was found. See Limitations.

DISCUSSION

Results from this study demonstrate the promise that HTC holds for landscape ecology and conservation planning using high-resolution spatial data. HTC can help reduce processing time by more than 100 fold. In an era when there are huge, global datasets and increasingly, high-resolution datasets available for analyzing pressing ecological problems, such improvements in processing time can facilitate several scientific advances. First, they can assist integration of high-resolution data at greater spatial extents. This can help test assumptions inherent in coarse-filter conservation planning (Anderson and Ferree 2010, Beier and Brost 2010) and other large-extent mapping projects common in sub-disciplines such as macroecology (Brown and Maurer 1989). Additionally fast computing will improve spatial ecology and conservation planning by enabling more iterations of models leading to more systematic analyses (e.g., sensitivity analyses) thereby arming researchers with the ability to ask more complex questions. Finally, these methods may help global and regional assessments integrate updated data and apply these data in a timelier manner.

Although ecological phenomena operate at multiple scales, they are often best characterized by a specific spatial resolution (Dungan et al. 2002). Perhaps most notably, direct biodiversity estimates are highly reliant upon spatial resolution (e.g., Palmer and White 1994, Hortal and Lobo 2005, Legendre et al. 2005). While high-resolution data typically capture more heterogeneity in the landscape (Wiens 1989), a diminishing returns threshold will likely exist when resolution is smaller than the features being remotely sensed (Gessler et al. 2000, Nagendra 2001) and data acquisition, handling, and

processing costs outweigh the benefit. Because availability of high-resolution datasets is not uniformly distributed for most studies, the data sets of highest spatial resolution can be used to concentrate on focal species (Cabeza et al. 2010) or provide validation areas for the broader coarse-filter approach which will likely cover most of the landscape. In addition, studies incorporating high-resolution analyses may further elucidate ecosystem phenomena that are resolution-dependent.

Conservation planning incorporates data at multiple grain sizes and extents to insure representation of diversity and incorporate resilience in reserve networks (Margules and Pressey 2000, Groves 2003). Ecological Land Units, and Land Facets used in coarse filter conservation planning are macro-scale land forms designed to represent biodiversity in reserve selection and climate corridor applications (Anderson and Ferree 2010, Beier and Brost 2010). Most conservation planning uses a combination of fine and coarse scale data; with examples of fine scale data including point locations for rare species or digitized local ecosystems of high value (e.g., floodplains, alpine zones) (Groves 2003, Anderson et al. 2006, Trombulak 2010). Still, geophysical variation is often employed as a biodiversity surrogate, capturing heterogeneity at regional scales (Anderson and Ferree 2010). Doing so is usually mandated by a lack of fine-scale data and/or computing limits and is supported by evidence that regional variation in biodiversity is indeed represented by underlying geophysical patterns (Anderson and Ferree 2010). Some aspects of conservation planning may greatly improve if higher-resolution data could be incorporated at greater spatial scales. For example land facets and ecological land units, common geophysical units employed in modeling “climate

corridors”, could be generated using fine-scale DEM’s and connectivity assessed over continental scales. Also, connectivity modeling using fine-scale resistance layers and involving multiple pairwise iterations over state and regional extents could become more practical (see above).

With high-resolution data sets becoming available at state extents (e.g., 6m DEM from North Carolina Floodplain Mapping Program: <http://www.ncfloodmaps.com/>) and moderate-resolutions of 30-90m at country-wide extents, conservation planning studies need only solve computational requirements to expand the extent of their analysis. For analyses that cannot be split into smaller jobs, high-performance computing (HPC) may be explored. High-performance computing may use hundreds or thousands of cores to simultaneously solve a problem. This process differs from HTC because workstations (i.e., nodes) communicate with one another while processing to effectively become one computer. However, because ArcGIS does not natively support multithreading, and is Microsoft Windows x86 based (i.e., 32 bit), it has serious limitations in a typical HPC environment (Fig. 3). Although there are workarounds to these problems (e.g., Microsoft HPC 2008 or operating system virtualization (see Faria et al. 2010)) they are not easily overcome by the typical end user.

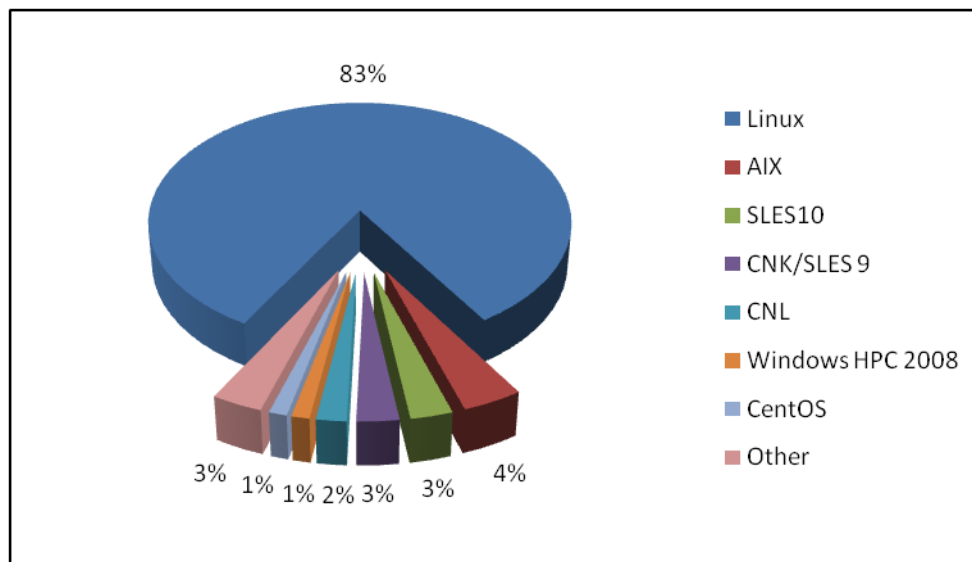


Figure 2.3. Operating system usage of top 500 supercomputers (<http://top500.org>).

However, many software packages (e.g., *Circuitscape*) maintain functionality with ArcGIS files but operate as stand-alone software and may be available for HPC. While HPC is the ‘future’ of high-resolution and/or large extent geoprocessing, it typically requires technical support from supercomputing administrators to implement various software packages. Access for non-profit organizations or non-government scientists with small computing budgets may be limited. For now the average ecology and conservation biology user will most likely need to rely on HTC until usability of these systems increases.

CONCLUSIONS

High-throughput computing is a viable option for everyday GIS users with access to grid resources, such as those available in an academic computer laboratory or other

networked GIS configurations. Although other HTC operations have been applied to natural resource modeling questions in the past (e.g., Mellott et al. 1999, Immanuel et al. 2005), these applications often deal with existing models and specialized modeling environments. This study highlights the flexibility of creating a custom workflow within ArcGIS modelbuilder and then executing these tools with HTC while requiring minimal programming knowledge. Ecologists and natural resource managers can now analyze regional-scale high resolution datasets quickly without the need to outsource the work to IT professionals or computer programmers and without burdening themselves with hours of training on the computational complexities of geoprocessing. In light of the availability of high-resolution data, computer hardware/software, and complex spatial analyses, it is possible that conservation biologists will be able to sway the resolution:area ratio trade-off.

Status and future development

Conservation biologists often rely on third-party software that is not routinely updated and loses functionality with each new ArcGIS version. Many of these defunct packages include connectivity and conservation planning software, statistical tools, and home range/movement analysis tools. Until existing tools are updated, or new ones are developed, many of the packages ecologists have relied upon in the past may not be available using the above methods. However, with ESRI's focus on the Python language for ArcGIS 10.0, it is likely that new third-party functionality will follow. Popular statistical software such as the R project (<http://www.r-project.org/>) and landscape connectivity software such as *Corridor Designer* (<http://corridordesign.org/>) have already

been integrated within multiple custom toolboxes of ArcGIS 10.0 and can be executed inside HTC using identical methods to those previously described. In addition, the newly developed *Geospatial Modeling Environment* (<http://www.spatialecology.com/gme/>) which provides the functionality of the former widely used *Hawth's Tools*, offers direct integration of both *R* and ArcGIS files. This integration is easily explored with Python scripting, similar to any other tool in the modelbuilder toolbox. These open source software projects provide a pathway for HTC execution utilizing a plethora of raster and vector analytics not natively accessible within ArcGIS.

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