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Article

An Effective Method for Detecting Potential Woodland Vernal Pools Using High-Resolution LiDAR Data and Aerial Imagery

Qiusheng Wu [1,3,*], Charles Lane [2] and Hongxing Liu [3]

1 Dynamac Corporation c/o U.S. Environmental Protection Agency, 26 W. Martin Luther King Dr., Cincinnati, OH 45268, USA

2 U.S. Environmental Protection Agency, Office of Research and Development, 26 W. Martin Luther King Dr., Cincinnati, OH 45268, USA; E-Mail: Lane.Charles@epa.gov

3 Department of Geography, University of Cincinnati, Cincinnati, OH 45221, USA; E-Mail: Hongxing.Liu@uc.edu

* Author to whom correspondence should be addressed; E-Mail: Wu.Qiusheng@epa.gov; Tel.: +1-513-569-7983.

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Abstract: Effective conservation of woodland vernal pools—important components of regional amphibian diversity and ecosystem services—depends on locating and mapping these pools accurately. Current methods for identifying potential vernal pools are primarily based on visual interpretation and digitization of aerial photographs, with variable accuracy and low repeatability. In this paper, we present an effective and efficient method for detecting and mapping potential vernal pools using stochastic depression analysis with additional geospatial analysis. Our method was designed to take advantage of high-resolution light detection and ranging (LiDAR) data, which are becoming increasingly available, though not yet frequently employed in vernal pool studies. We successfully detected more than 2000 potential vernal pools in a ~150 km^2 study area in eastern Massachusetts. The accuracy assessment in our study indicated that the commission rates ranged from 2.5% to 6.0%, while the proxy omission rate was 8.2%, rates that are much lower than reported errors of previous vernal pool studies conducted in the northeastern United States. One significant advantage of our semi-automated approach for vernal pool identification is that it may reduce inconsistencies and alleviate repeatability concerns associated with manual photointerpretation methods. Another strength of our strategy is that, in addition to detecting the point-based vernal pool locations for the inventory, the boundaries of vernal pools can be extracted as polygon features to characterize their geometric properties, which are not available in the current statewide vernal pool databases in Massachusetts.

Keywords: geographically isolated wetlands; seasonal wetlands; depression analysis; Massachusetts

1. Introduction

Vernal pools are frequently considered a type of so-called "geographically isolated wetland", temporary or semi-permanent pools typically defined as occurring in a confined basin depression without a permanently flowing outlet [1–3]. These systems can become inundated pools in the fall, winter, or spring, and frequently dry completely in the summer [3,4]. Vernal pools are also known as ephemeral ponded wetlands, temporal ponds, or seasonal woodland ponds and are common in the glaciated portions of North America. Normally free of reproducing fish populations, vernal pools and vernal pool complexes are important breeding habitat for numerous amphibians and reptiles adapted to reproduction in temporary and fishless habitats. However, due in part to their small size and short hydroperiods, as well as the relative lack of resilience to hydrologic alterations to the surrounding landscape, vernal pool wetlands are at risk of destruction across the northeastern United States [2,5–7].

Some geopolitical entities of the United States have developed guidance and regulations for vernal pool protection, including New Jersey [4], Maine [8], and Massachusetts [9,10], as well as smaller municipalities such as towns of Farmington, Simsbury, and Suffield in Connecticut [11,12]. Massachusetts provides a useful model for vernal pool protection. The protection of vernal pools in Massachusetts involves a certification process in which biological data are collected by citizens to demonstrate that a wetland provides vernal pool functions. The Massachusetts Wetland Protection Act does not specifically protect vernal pools unless they are certified by a field verification process to ascertain that they serve as habitat for obligate or facultative vernal pool amphibian species [5,10]. Once certified, regulatory restrictions are placed on the development and other activities affecting a pool [13]. However, the protection of vernal pools and other small, geographically isolated wetlands suffers from a lack of effective methods for identifying these features in the landscape. Current methods for identifying potential vernal pools include visual interpretation and digitization on aerial photographs and subsequent field verification [4,8,10,14–17], as well as statistical modeling approaches to map or predict vernal pool locations [5–7,18]. Several studies have been conducted in the northeastern United States to map potential vernal pools on aerial photographs, yet their accuracy has been highly variable. The reported commission errors ranged from 3% to 90%, as the visual interpretation process was largely dependent on the skill of the photo interpreters, imagery types, imagery acquisition dates, minimum mapping unit size, extent and type of forest cover, and topography [14,19].

Recent advances in remote sensing technology hold great potential for enhanced local, regional and national wetland mapping and inventory. High-resolution light detection and ranging (LiDAR) data can facilitate the detection of wetlands that are normally difficult to identify, such as vernal pools. A number of studies have demonstrated the promise of LiDAR for enhanced wetland mapping and inventory [20–24];

however, few studies have specifically used LiDAR data for identifying small, geographically isolated wetlands, such as vernal pools. In this paper, we propose an efficient and effective method for identifying potential vernal pools with high-resolution LiDAR data and near-infrared aerial photographs. We accepted the vernal pool definition of Calhoun *et al.* [3] and Carpenter *et al.* [14], namely that a vernal pool is a geospatially isolated or depressional basin with no permanent inlet or outlet and is typically not connected through surface water to or immediately adjacent to other water bodies (see Section 2.5 below). Vernal pool habitats generally have a water regime of seasonally to semi-permanently inundated, meaning that they hold water for at least two continuous months (though we note that vernal pools do, on occasion, stay inundated year-round [3]). To standardize the types of habitats that were designated as vernal pools across our study area, we defined vernal pools as confined surface depressions with no permanent surface inflow or outflow with a total surface area larger than 50 m^2 (the minimum size that could be confidently identified using our datasets), which is much smaller than the reported minimum mapping unit (200–250 m^2) that has been reliably identified with leaf-off color-infrared (CIR) aerial photographs in previous studies on vernal pools [4,6,15]. A stochastic depression analysis method [25] using a Monte Carlo approach was developed to extract surface depressions from a 1-m resolution LiDAR digital elevation model (DEM). By applying a Monte Carlo approach, we estimated the likelihood of a topographic depression actually occurring in the landscape, given the degree of uncertainty in the LiDAR DEM. With this methodology, actual surface depressions can be distinguished from artifact depressions. These derived actual surface depressions can then be further refined using ancillary data, such as depression area, the National Hydrography Dataset (NHD) [26], land use and land cover type, and the Normalized Difference Water Index (NDWI) [27], to identify potential vernal pools. Successful application of this approach to other portions of the glaciated northeastern North America, using data and methods developed from the localities of Norton and Attleboro in eastern Massachusetts, would suggest that potential vernal pools can be detected efficiently and objectively with high accuracy and low commission and omission errors, thereby increasing our understanding of the extent of these important ecosystems.

2. Study Area and Data

2.1. Study Area

Currently, the Natural Heritage and Endangered Species Program (NHESP) in Massachusetts maintains two statewide databases concerning vernal pool habitats, Certified Vernal Pools (CVPs) and Potential Vernal Pools (PVPs). Once a vernal pool has been officially certified by the Massachusetts Division of Fisheries and Wildlife, it receives protection under several state wetland protection regulations [10]. However, the NHESP does not establish a physical, on-the-ground vernal pool boundary during the certification process, but rather identifies vernal pools as points. As of April 2014, there were 6807 certified vernal pools in Massachusetts. The dates of vernal pools certified range from 31 May 1988 to 31 January 2014, and the number certified per year varies (Figure 1). The statewide PVP database developed by Burne [10] in 2001 contains 29,723 potential vernal pools and is used as the primary source of information to locate possible vernal pools across Massachusetts [14]. The NHESP conducted this statewide survey by interpreting potential vernal pools from 1:12,000-scale CIR leaf-off aerial photographs from the spring of 2000 [10]. The estimated statewide average precipitation in April 2000 was 15.21 cm, which was 57 percent higher than the long-term average of the month (9.65 cm) [28], indicating 2000 was a wet spring for representing wetlands. It should be noted that the potential vernal pools identified in this survey do not automatically receive protection under the Massachusetts Wetlands Protection Act Regulations, nor under any other state or federal wetlands protection laws that have specific language protecting certified vernal pools. Evidence of amphibians or invertebrates using a vernal pool, in addition to proof that the pool does not support a reproducing fish population, must be presented to the NHESP for certification to obtain official standing as a certified vernal pool under state wetlands protection laws [10]. Both the CVP and PVP layers can be obtained from the Massachusetts Office of Geographic Information (MassGIS) website [29]. The data layers were prepared in ESRI shapefile format, where each point in the data represents the location of a vernal pool. The combined vernal pool (CVP + PVP) density map for all towns of Massachusetts is shown in Figure 2 (note, in this part of the Northeast United States, all lands within the boundaries of a state are allocated to towns).

Our study area included two towns (Attleboro and Norton) of Bristol County in eastern Massachusetts (Figure 3), with a total land area of 147.9 km^2. The two towns share similar physiographic characteristics, including extensive forest and wetlands, urban/suburban development, and elevations ranging from 10 to 81 m above mean sea level. We chose these two towns as our study area because they have the highest total number of certified and potential vernal pools in eastern Massachusetts. As of June 2014, the study area contained 192 CVPs and 721 PVPs (Table 1). The distribution of these CVP and PVP locations is widespread throughout the study area (Figure 4). In addition, high-resolution LiDAR data and CIR aerial photographs were available for this area.

Figure 1. The number of vernal pools certified by the Natural Heritage and Endangered Species Program (NHESP) in Massachusetts.

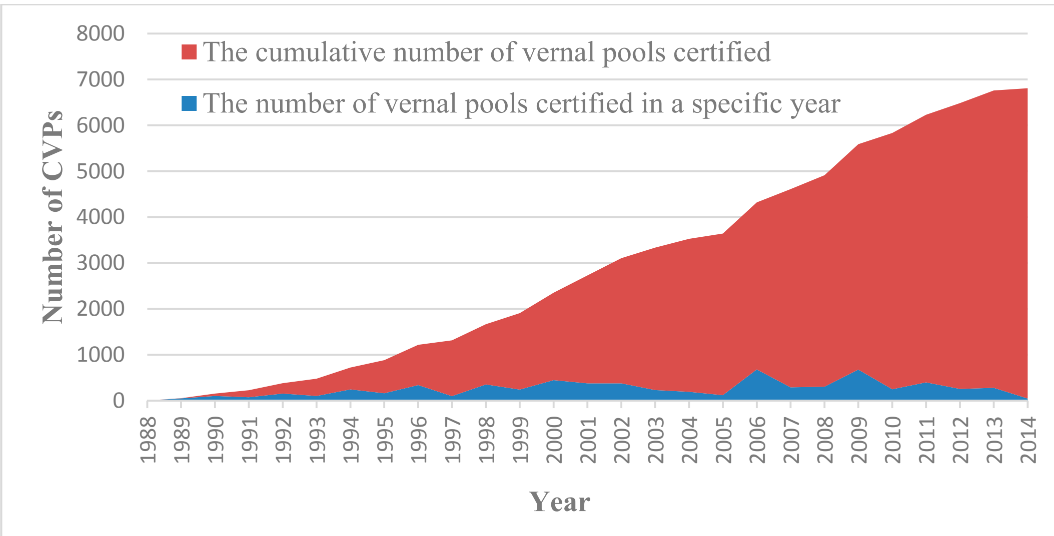


Figure 2. The combined vernal pool (CVP + PVP) density map in towns of Massachusetts. CVPs—certified vernal pools; PVPs—potential vernal pools; NHESP—Natural Heritage and Endangered Species Program.

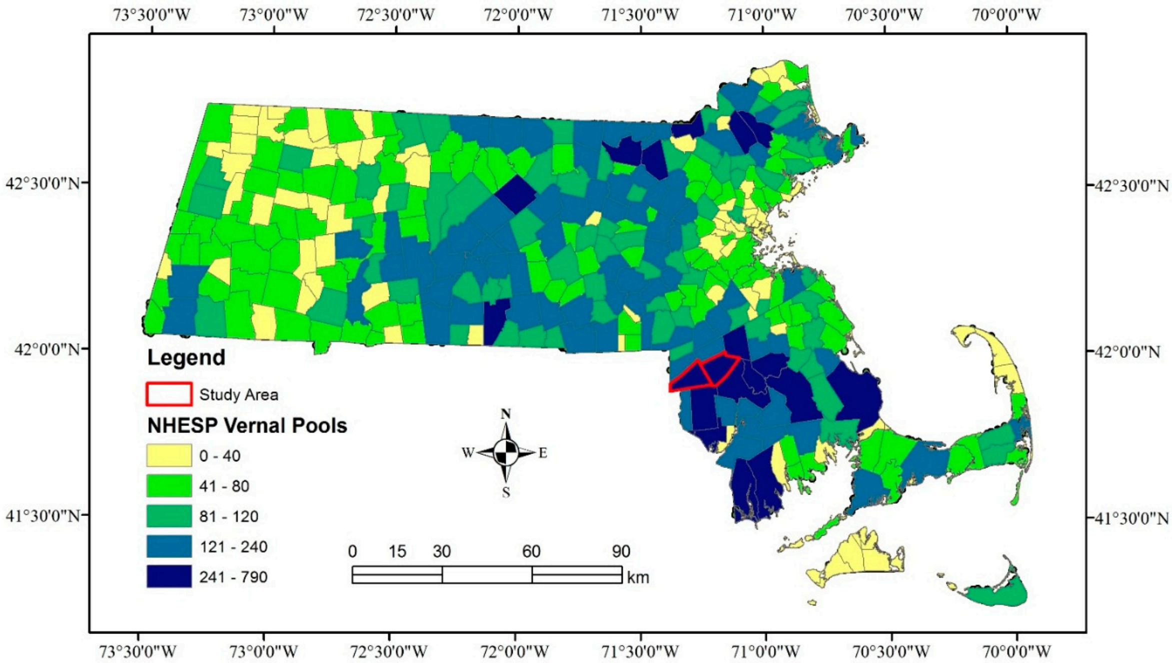


Figure 3. Location of the study area—towns of Attleboro and Norton, in Bristol County, Massachusetts. The imagery is a false-color composite image mosaic from U.S. Geological Survey color orthoimagery acquired in April 2013.

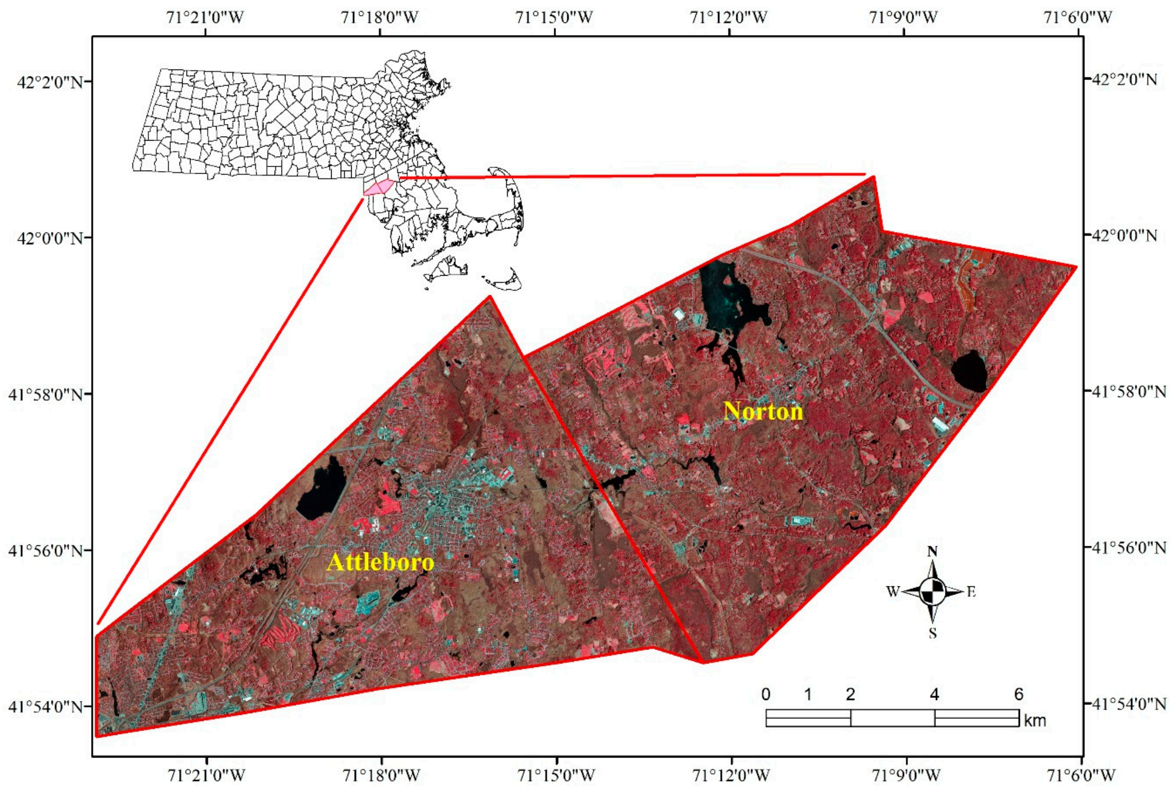


Figure 4. The distribution of Natural Heritage and Endangered Species Program (NHESP) certified/potential vernal pool locations across the study area.

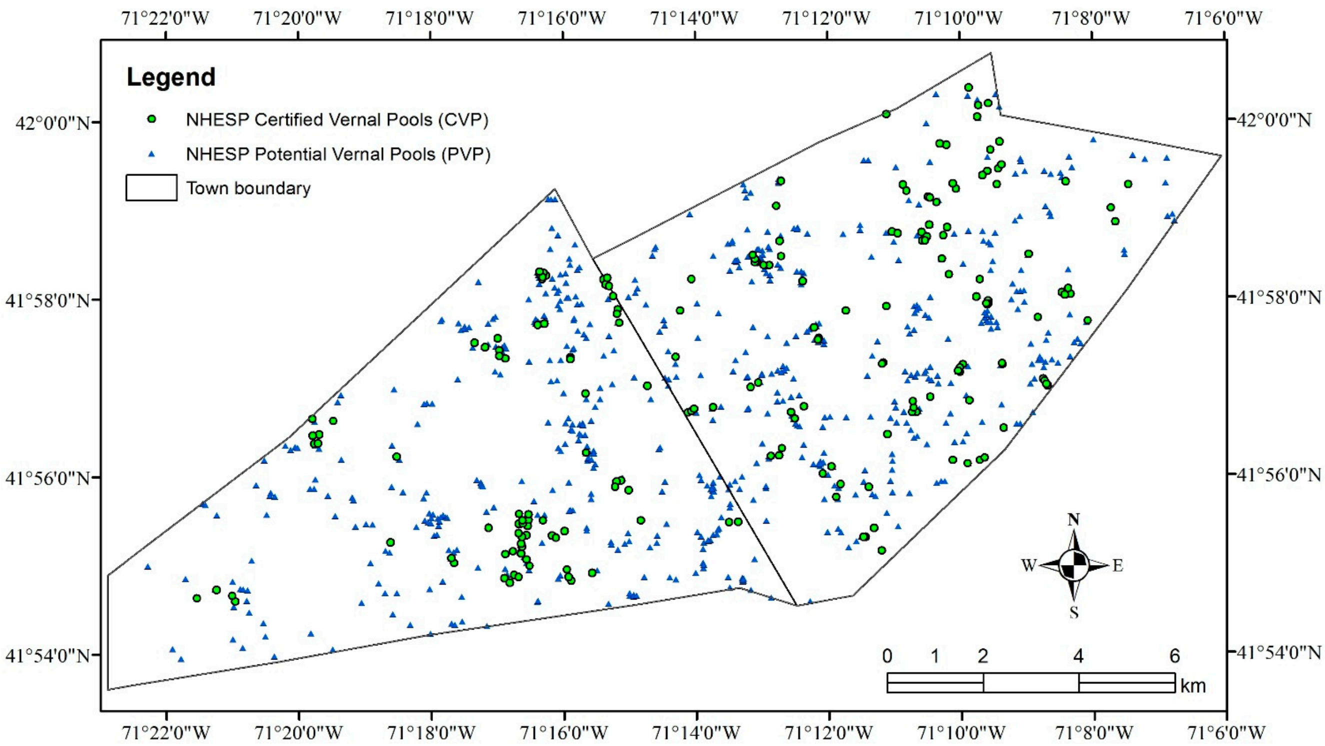


Table 1. The number of CVPs and PVPs in towns of Attleboro and Norton, Massachusetts. CVPs—certified vernal pools; PVPs—potential vernal pools.

	Norton	Attleboro	Total
CVPs	115	77	192
PVPs	369	352	721
Total	484	429	913

In addition to the NHESP CVP and PVP layers we used a number of other layers in the analysis, including 1-m LiDAR DEM (collected in 2010), 0.3-m U.S. Geological Survey (USGS) color orthoimagery (collected in 2013), land use (developed in 2005) [30], and the NHD. The NHD data were obtained from the USGS website [31], while all the other data layers were obtained from the Massachusetts GIS website [29]. All these acquired datasets were projected to the common spatial reference system: Transverse Mercator Projection (UTM) Zone 19 N in the North American Datum of 1983 (NAD83). A summary of the data sets used in our study is given in Table 2.

Table 2. Summary of data sets used in our study.

Data Set	**Acquisition Dates**	**Precipitation (% of Long-Term Normal of the Month)**	**Application**
1-m LiDAR DEM	8–12 December 2010	6.78 cm (69%)	deriving surface depressions
0.3-m color orthoimagery	April 2013	4.93 cm (51%)	refining surface depressions
Land use data	April 2005	12.95 cm (136%)	refining surface depressions
National Hydrography Dataset (NHD)	2005–2009	N/A	refining surface depressions
Certified vernal pool (CVP) database	May 1988–January 2014	N/A	validating results
Potential vernal pool (PVP) database	April 2000	15.21 cm (157%)	validating results

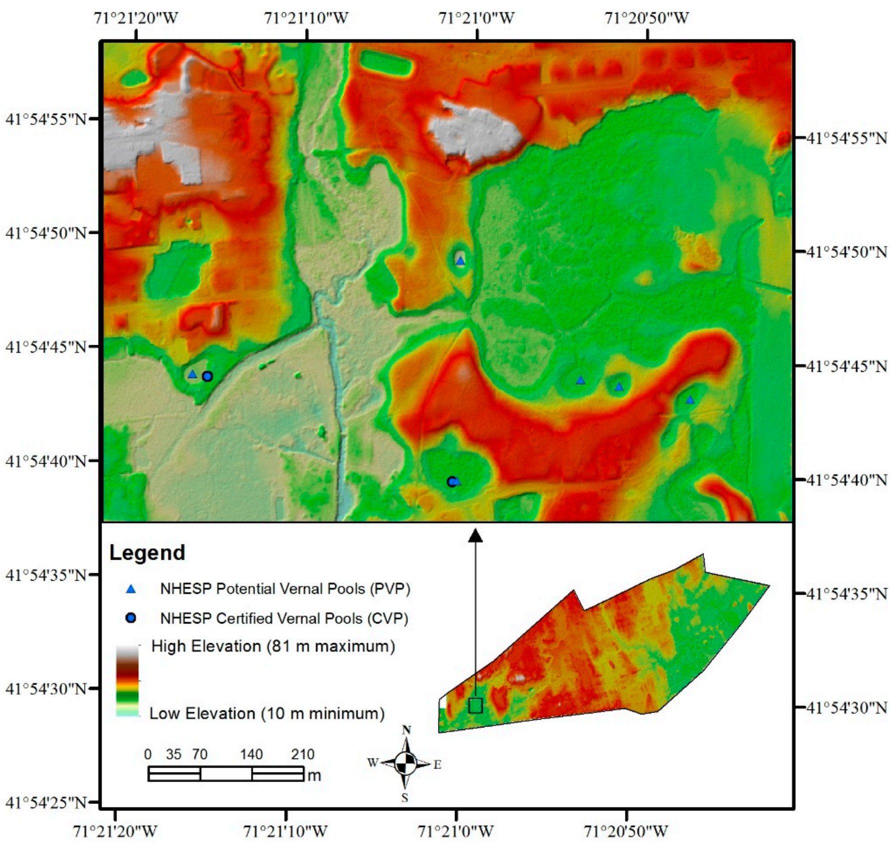
2.2. 1-m LiDAR DEM

The LiDAR data were collected by the Federal Emergency Management Agency (FEMA) for its 5-year program for Risk Mapping, Assessment, and Planning (Risk MAP) [32]. FEMA has made a commitment through Risk MAP to work closely with its National Digital Elevation Program partners to obtain and support the collection of terrain data throughout the United States. Using an Optech Gemini LIDAR system, 44 flight lines of highest density (Nominal Pulse Spacing of 1.0 m) were collected over the Narragansett area in eastern Massachusetts, which encompasses 217 square miles. A total of six missions were flown on 8 December 2010 and 10 December 2010, with one-meter nominal spacing that tested at 0.095 m fundamental vertical accuracy at a 95% confidence level [32]. The bare-earth LiDAR DEM are available for download in GeoTiff format as 1500 m × 1500 m tiles with one-meter pixel resolution. Our study area (Attleboro and Norton) was composed of 96 tiles. The Dynamic Raster Mosaicking function in ArcGIS (ESRI, Redlands, CA, version 10.2) was used to create a mosaicked dataset that combined the 96 DEM tiles as a seamless 1-m raster for all subsequent image analysis and map generation (Figure 5). Prior to the surface depression detection, a 3 × 3 median morphological operator was used to smooth the LiDAR DEM. DEM smoothing is desirable since it produces a more realistic surface while retaining detailed topographic characteristics of the landscape [33]. The median operator is an edge-preserving filter [34] that is used to remove data noise and suppress small artifact depressions without distorting the boundaries of true surface depressions, and is considered better than a mean (averaging) filter [35,36].

2.3. 0.3-m USGS Color Orthoimagery (2013)

Cloud-free 0.3-m USGS color orthoimagery (2013) was acquired in generally leaf-off conditions during mid- to late April 2013. The estimated statewide precipitation in April 2013 was 4.93 cm, which was 51 percent of the long-term average for the month (9.65 cm) [28]. Images were downloaded in JPEG2000 format, 20:1 compression ratio, four-band (red, green, blue, and near-infrared), 1500 m × 1500 m tiles with 0.3-m pixel resolution. Our study area was composed of 96 tiles. To facilitate the analysis, the Dynamic Raster Mosaicking function in ESRI ArcGIS 10.2 was used to create a mosaicked dataset that combined the 96 image tiles as a seamless four-band, 0.3-m image, which was used for all subsequent image analysis and map generation (Figure 3). The CIR orthoimagery was used both for visual assessment of vernal pool locations and to create NDWI images from the spectral bands to identify water features associated with pools.

Figure 5. The bare-earth LiDAR DEM shaded relief of Attleboro and Norton, Massachusetts.



2.4. Land Use Data (2005)

MassGIS provides a statewide seamless digital dataset of land cover/land use, created using semi-automated methods and based on 0.5-m resolution four-band orthoimagery acquired in 2005. The original MassGIS land use data layer has 40 land use categories, which were aggregated into five general classes for our study, including developed, forest, grassland, wetlands, and water (Table 3).

Table 3. The land use composition of the study area.

Class	Area (km^2)	Percentage
Developed	52.2	35.3%
Forest	59.7	40.4%
Grassland	4.0	2.7%
Water	5.5	3.7%
Wetlands	26.5	17.9%

2.5. National Hydrography Dataset (NHD)

Following Lane *et al.* [37], buffer zones were created from the NHD data to delimit potentially "geographically isolated" depressions from depressions assumed to be hydrologically connected to downstream systems, based solely on proximity or adjacency. This was performed while noting that the so-called "geographically isolated" wetlands are indeed frequently hydrologically, biologically, and/or biogeochemically connected to other waters, though this varies in terms of magnitude, duration, frequency, and intensity [38,39]. To identify potential vernal pools from surface depressions assumed to be at least intermittently connected to other water bodies, we used a series of buffered overlays. Using the 1:24,000-scale NHD data as the source data for hydrology, we created 10-m distance buffer zones from the NHD flowlines, waterbody, and area data layers, replicating Lane *et al.* [37] and Reif *et al.* [40]. The three buffered data layers were then merged as a single data layer to intersect with the depression layer. Any depressions located inside the NHD buffered layer were excluded from further analysis.

3. Methods

3.1. Stochastic Depression Analysis

As mentioned in the Introduction, we defined vernal pools as confined surface depressions with no permanent surface inflow or outflow and a total surface area larger than 50 m^2 to standardize the types of habitats that were designated as vernal pools across our study area. Our vernal pool identification methods involved extracting surface depressions from the bare-earth LiDAR DEM, followed by further refining the depression set and eliminating those that occurred on developed lands or were identified as permanent waterbodies. We eliminated depressions on developed lands as these features were frequently slight depressions in parking lots and/or yards with no otherwise discernable vernal pool features. Those surface depressions located in forest, wetland, or grassland with identifiable water features would be designated as potential vernal pools for subsequent analyses.

The Stochastic Depression Analysis Tool in Whitebox Geospatial Analysis Tools (GAT) [41] was used to derive surface depressions from LiDAR DEM. Whitebox GAT is an open-source GIS and Remote Sensing software package [41,42] developed at the University of Guelph's Centre for Hydrogeomatics and distributed under the GNU General Public License. The program and its source code can be downloaded from the Whitebox website [43]. The Stochastic Depression Analysis Tool can be used to map topographic depressions in a DEM, taking into account the uncertainty in depression shape resulting from DEM error [28]. The tool uses a Monte Carlo approach to map depressions. Based on the Monte Carlo procedure, each grid cell in a DEM is assumed to follow a Gaussian error probability distribution function (PDF) with a mean of zero and a specified standard deviation (error magnitude) [25]. The LiDAR data root mean squared error (RMSE) value can be used to represent the error magnitude of the data. The RMSE value of the LiDAR in our study area is 0.095 meters, which was specified in the metadata [32]. We used the Gaussian probability function (mean = 0, standard deviation = 0.095 m) to create a distribution of the probability of LiDAR data error (Figure 6).

Once the distribution of the probability of LiDAR data error was created, a random sample was drawn from the Gaussian error PDF of each grid cell and added to the original DEM. Depressions in the error-added DEM were then filled using the highly efficient depression filling algorithm developed by Wang and

Liu [44] and a new random draw completed. With each iteration, grid cells affected by the depression filling process were flagged and entered into a cumulative grid. The probability of a grid cell belonging to a depression feature, given the uncertainty in the DEM, was mapped using an 80% probability as the threshold. In other words, for a depression to be delineated as a "true depression", it must be identified as a depression for at least 8 out of 10 iterations. The Stochastic Depression Analysis tool was tested on a LiDAR DEM tile (1500 m × 1500 m) with various numbers of iterations ranging from 10 to 100. Figure 7 shows the number of detected depression pixels using the 80% probability threshold increased with increasing number of iterations from 10 to 30. After 30 iterations, the number of detected depression pixels became relatively stable, with approximately 516,000 pixels. Of course, with more iterations, there is a higher possibility that a "true depression" will be detected; however, based on excessive computational run-time (about one minute per iteration per tile) for 96 LiDAR DEM tiles, we determined that 50 iterations (with a critical value of ≥ 40 for "true depressions") was acceptable for our study. We subsequently applied the morphology operator [45] to remove small areas of erroneous pixels (e.g., tiny holes inside a depression) and smooth the boundary between depression zones. The Region Group tool in ArcGIS was then used to group depression pixels as objects, which were labeled and indexed incrementally with a unique integer number. These uniquely identified raster objects were then converted to vector format (ESRI shapefile) and the boundaries of the depression features were extracted for subsequent analysis.

Figure 6. Probability distribution of LiDAR data error.

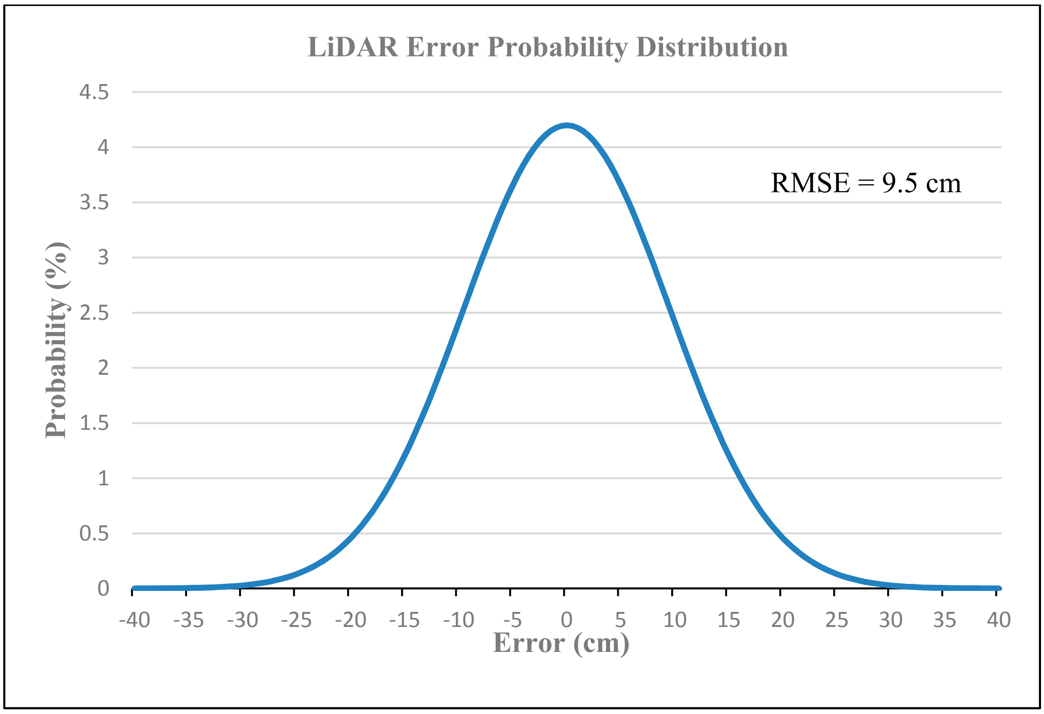
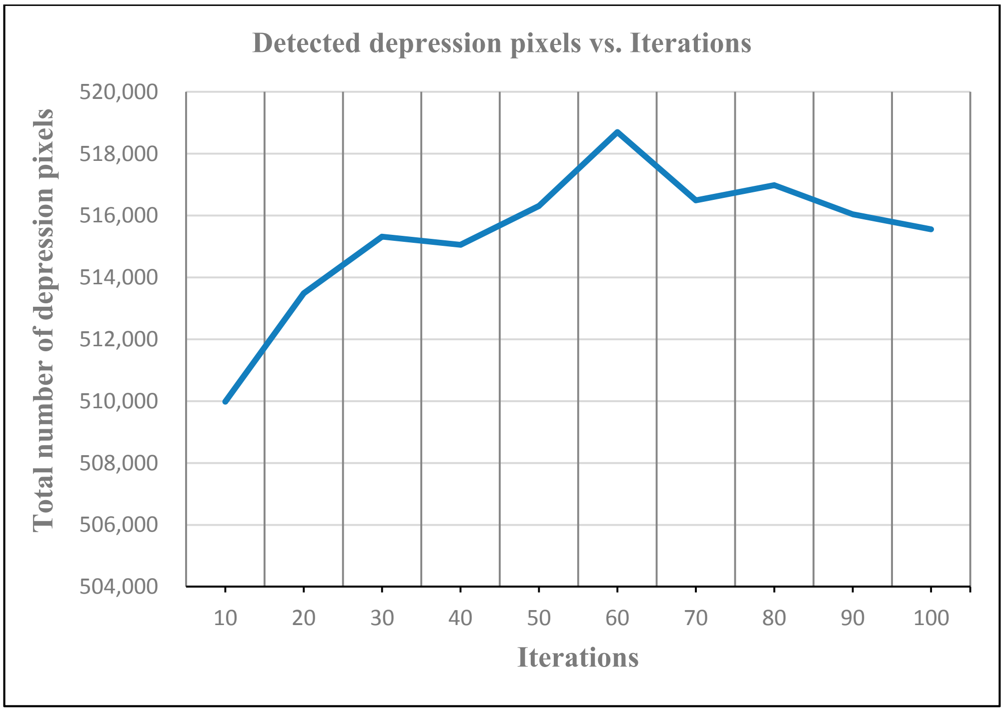


Figure 7. The number of detected depression pixels with corresponding number of iterations.



3.2. Eliminate Depressions Occurring in Permanent Waterbodies and Developed Land

As one type of geographically isolated wetland, vernal pools are defined as occurring in "isolated" basins with no permanent inlet or outlet. In other words, vernal pools should not be connected via a discernable bed-and-bank hydrologic feature with any permanent hydrologic features, such as rivers, streams, lakes, and reservoirs. The 10-m buffered NHD waterbody layer was used to intersect the depression polygon layer output from the Stochastic Depression Analysis. Depressions not overlapping any NHD water features were retained for further analysis, while the others were considered adjacent or connected waters and removed from further analysis or consideration as possible vernal pools [37]. We intersected the remaining depressions with the reclassified land use data layer (developed, forest, grassland, wetlands, and water land use types) and calculated the land use modality for each depression. The maximum percentage land use within each depression was designated as the dominant land use type. Only those depressions with forest, grassland or wetlands as their dominant land use types were retained for further analysis. Visual inspection showed the depression overlay analysis with the land use data layer was highly effective in eliminating numerous false positive depressions in urban/suburban areas.

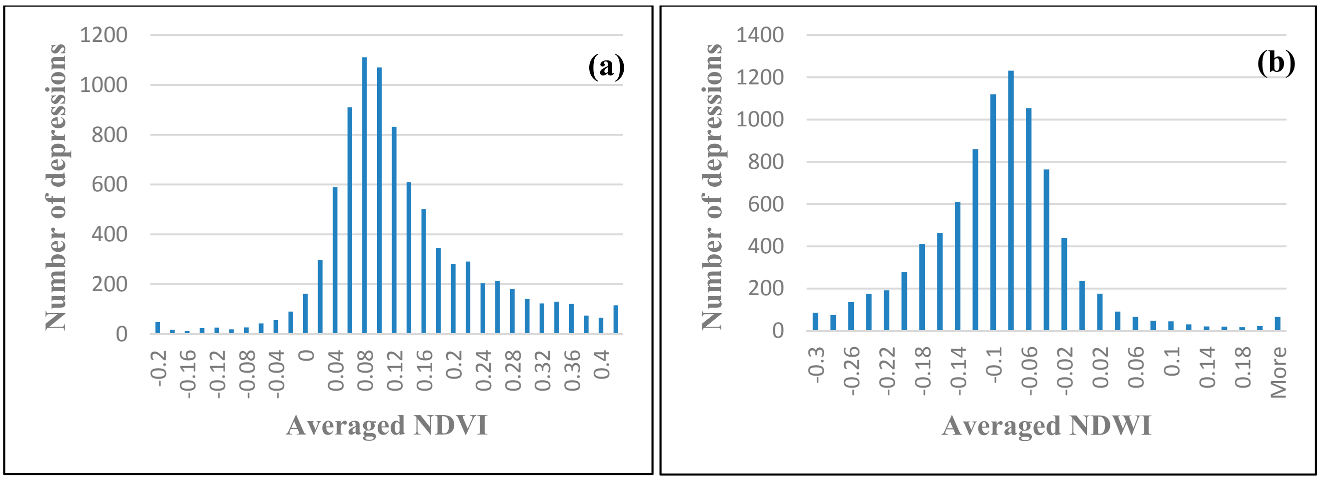
3.3. Refine Depressions Using the Normalized Difference Water Index (NDWI)

The NDWI was first proposed by McFeeters [27] to delineate open water features in wetland environments with remotely sensed imagery. The NDWI makes use of reflected near-infrared radiation and visible green light to enhance the presence of such features while eliminating the presence of soil and terrestrial vegetation features [27]. Similar to the principles used to derive the Normalized Difference Vegetation Index (NDVI) [46], the NDWI is calculated as follows:

$$NDWI = \frac{Green - NIR}{Green + NIR} \tag{1}$$

In the resultant NDWI image, the water features will have positive values while soil and vegetation have zero or negative values [47]. In our study, the CIR orthoimagery (2013) was used to derive both the NDVI and NDWI images. The Zonal Statistics tool in ESRI ArcGIS 10.2 was used to derive the maximum NDWI (NDWI MAX), averaged NDWI (NDWI AVG), and averaged NDVI (NDVI AVG) values for each of 8733 depressions from the depression polygon layer and the NDWI and NDVI images (Figure 8). The distribution patterns of the NDVI AVG and NDWI AVG were relatively symmetric and complementary, which met our expectations. Depressions with high NDVI AVG tend to have low NDWI AVG, and vice versa. To segment the depressions further and isolate only potential vernal pools with identifiable water features, NDWI MAX was used in conjunction with NDWI AVG to ensure that water pixels existed inside depressions. The use of NDWI MAX can extract those depressions with water pixels, while the use of NDWI AVG can ensure sufficient abundance of water pixels inside depressions, which was effective in eliminating depressions with only a few water pixels. By examining some typical depressions on the CIR orthoimagery, we chose NDWI MAX > 0.3 and NDWI AVG > −0.15 as the selection criteria. Depressions that met these criteria were designated as potential vernal pools.

Figure 8. The histograms of averaged NDVI (**a**) and NDWI (**b**) for 8733 depressions.



4. Results

4.1. Validation/Classification with the NHESP, CVP, and PVP Databases

We compared our depression detection results to the NHESP statewide vernal pool databases, including both the certified vernal pools and potential vernal pools. Although the potential vernal pools mapped by Burne [10] for the study area were not field-verified, the PVP database can still serve as a source of information for validating our methods for vernal pool identification. For this comparison, vernal pool overlap was performed by overlaying the statewide vernal pool databases and our mapped vernal pools in ArcGIS onto the USGS color orthoimagery (2013).

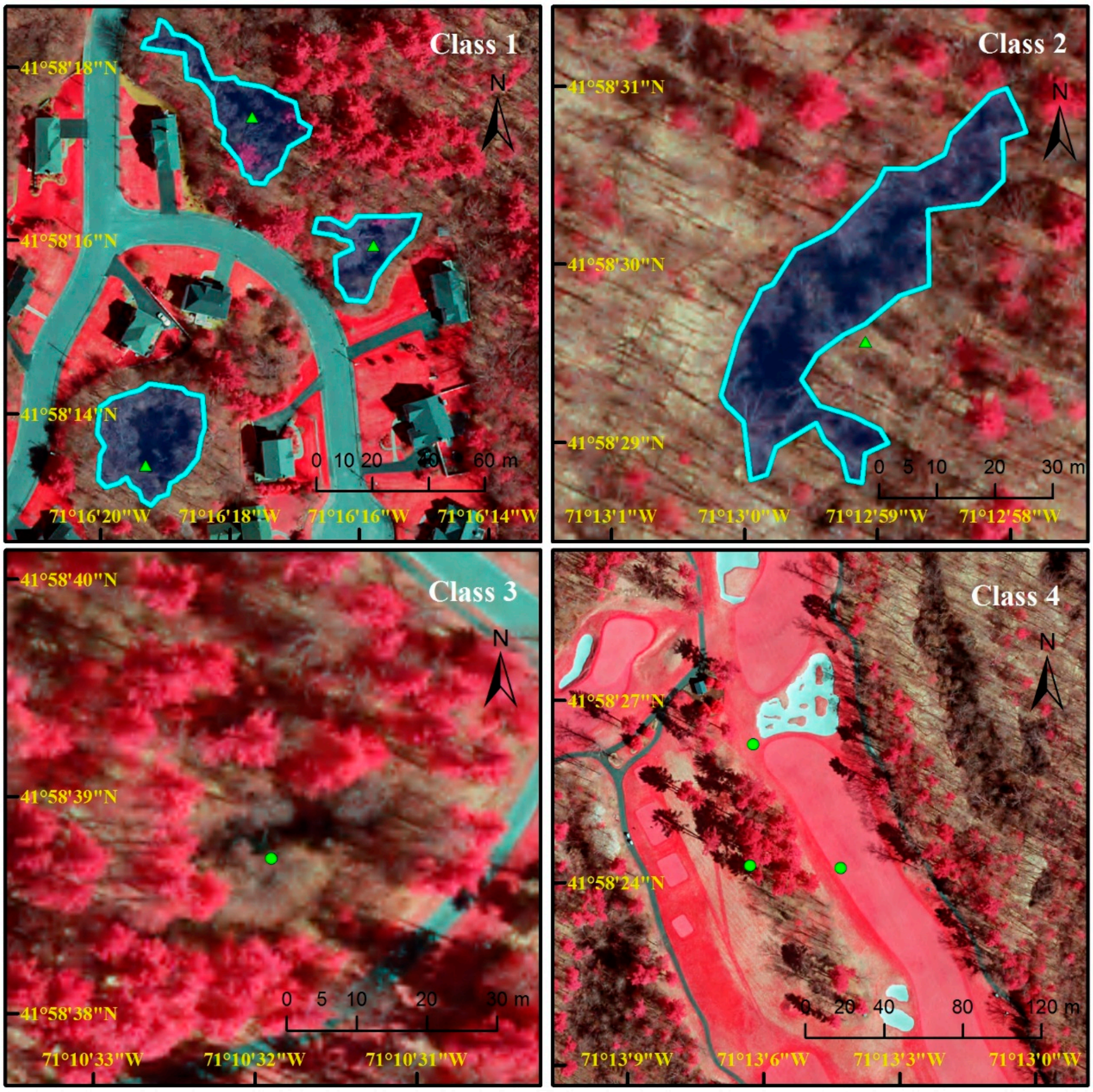
As noted by Burne [10], there were considerable differences in the precision with which the locations of vernal pools were mapped in both PVP and CVP data layers. The points representing potential vernal pools have a precision of ≤ 5 m or so from the center of an interpreted pool, while the locations of certified vernal pools have a precision of approximately 15 m in any direction. When relating the vernal pools to depressions in our study, we handled the certified and potential vernal pools separately. A certified vernal pool was related to its nearest depression within a 15-m buffer, while a potential vernal pool was related to its nearest depression within a 5-m buffer. By considering their presence and absence on the CIR orthoimagery (2013) and their spatial relationships to the detected depressions, the statewide vernal pools were classified into four categories (Table 4): Class 1, present vernal pools that were directly located inside our detected depressions; Class 2, present vernal pools that were not contained by any depressions, but were within the 15-m/5-m buffer distance; Class 3, present vernal pools that were not detected by our methods; Class 4, vernal pools that were absent or not identifiable from the CIR orthoimagery (2013). The determination of which CVP/PVP points were to be classified into which class was done by photo interpretation of CIR orthoimagery. By overlaying the vernal pool databases onto the imagery, it was possible to determine if each vernal pool was still present or absent. National Wetland Inventory (NWI) [48] and land use data layers were used as supplemental layers in decision-making for identifying CVPs/PVPs for Class 4. Only data points with an identifiable water feature present on the orthoimagery were considered as an extant vernal pool. If a CVP/PVP vernal pool was not contained by any depression, a 15-m/5-m radius (respectively) around the point was analyzed to determine if there was any depression within the buffer distance. If there was more than one depression within a 15-m/5-m buffer distance of the point, the closest one was chosen to be correlated with the vernal pool. Points were classified as "absent" if there was certainty that a vernal pool was not present; such locations included areas of significant development, new residential or commercial buildings, roads, parking lots, or golf courses (Figure 9).

Of the 913 statewide CVPs and PVPs in the study area, 415 (45.5%) were located inside our detected depressions, and 64 (7.0%) were located within 15 m/5 m of depressions. Our methods did not detect 212 (23.2%) pools visually confirmed to be present, while 222 (24.3%) CVP + PVP vernal pools were considered as absent (or "missing"), as no identifiable water features could be observed from the 2013 orthoimagery. Combing Class 1 and Class 2 indicated that there was an overlap of 479 (52.5%) pools between our detected depressions and the statewide vernal pool databases.

Table 4. The classification of certified vernal pools (CVPs) and potential vernal pools (PVPs).

Class ID	Class Description	Count	Percentage	Cumulative Percentage
1	Present CVPs/PVPs located inside depressions	415	45.5%	45.5%
2	Present CVPs/PVPs within buffer distance (15 m/5 m) of depressions	64	7.0%	52.5%
3	Present CVPs/PVPs not related to any depressions	212	23.2%	75.7%
4	Absent vernal pools	222	24.3%	100.0%

Figure 9. Examples of different certified vernal pools (CVPs) and potential vernal pools (PVPs) overlaid on color-infrared aerial photographs (2013). The green circular dots represent CVPs and the green triangles represent PVPs. The polygons with blue outlines represent our detected depressions.



4.2. Depression Detection Result Analysis

Initially, 12,774 depressions with area > 50 m^2 were detected in the first step with Stochastic Depression Analysis. After eliminating depressions occurring in permanent waterbodies and developed lands in the second step, 8733 depressions remained. Further parsing the data using the NDWI MAX and NDWI AVG criteria resulted in a final 2370 depressions selected as putative vernal pools in our study area. Each output depression polygon (representing where vernal pools were predicted to be present) was examined and overlaid with layers, such as CVP, PVP, a LIDAR shaded relief map, and CIR orthoimagery, to determine detection success.

Through the overlay analysis and visually checking the occurrences on the CIR orthoimagery (2013), these 2370 depressions were further classified into nine categories according to their spatial relationships with the statewide CVP and PVP databases (Table 5). Polygons (Class 1–5) overlaid or geospatially proximal to CVPs or PVPs were considered as successful identifications—this accounted for approximately 17% of the depressions in our dataset. The goal of this study was to identify not only the vernal pools already existing in the statewide vernal pool databases (e.g., Classes 1–5), but also to detect new pools in the landscape including those not identified within the statewide inventory. We identified an additional 1832 depressions (Class 6) that were considered successfully identified vernal pools based on criteria that we described above, suggesting a substantial number of vernal pools might be underestimated by the photo interpretation methods used in previous studies (as noted by Carpenter *et al.* [14]). Depressions of Class 7 (n = 70) were considered as uncertain vernal pools, as the structure of the system could not be ascertained via aerial imagery. Thirteen depressions (Class 8) were deemed to be too large to be vernal pools and were considered as errors. Although the true boundaries of vernal pools technically were not detected for Classes 7 and 8, these classes were distinguished by the presence of water and a topographic depression on the landscape. Polygons in Classes 7 and 8 were considered as "partially successful" detections, as they could be examples of orthoimagery interpretation error on our part (Class 7) or large vernal pool complexes [8] within a topographic depression (Class 8). If we assume Classes 7 and 8 were correct, then 98% of the depressions correctly identified vernal pools in the landscape. Conversely, assuming that none of the Class 7 or Class 8 polygons were vernal pools reduced our detection accuracy to about 94%. We were able to discern that 2.5% (n = 59) of the depressions we identified were, indeed, not vernal pools (Class 9). This provided a rough estimate of commission errors for our methods, though the uncertainty associated with Classes 7 and 8 suggests that our errors may be as high as 6.0% (see Section 4.3, below). Visual assessment of the incorrect depressions revealed that shadows were most often confused with water and accounted for the majority of errors (see Class 9 in Figure 10).

The descriptive statistics of 2228 detected depressions (Classes 1 to 6) are shown in Table 6, including area, perimeter, averaged elevation, averaged NDVI, and averaged NDWI. The median size of detected vernal pools was 337 m^2 and the median perimeter was 102 m.

4.3. Accuracy Assessment (Commission and Omission Errors)

The accuracy assessment was evaluated by errors of commission and errors of omission. Within the context of surface depressions, errors of commission were those depressions that were incorrectly identified as vernal pools. Errors of omission were vernal pools that were overlooked. In other words, these existing vernal pools could not be detected with surface depression analysis. The commission rate was 2.5% when Classes 7 and 8 were considered as successful detections and 6.0% when they were considered to be incorrect. The number of the present CVPs and PVPs that were not identified by our methods can be used as a proxy for omission rate, which was defined as the ratio between the omitted vernal pools and the total number of vernal pools (detected vernal pools + omitted vernal pools). There were 2370 detected depressions and 212 omitted vernal pools, and the proxy omission rate was calculated to be 8.2%.

Figure 10. Examples of different depression classes, as described in Table 5, overlaid on color-infrared aerial photographs (2013). The green circular dots represent certified vernal pools (CVPs), and the green triangles represent potential vernal pools (PVPs). The polygons with blue outlines represent detected depressions.

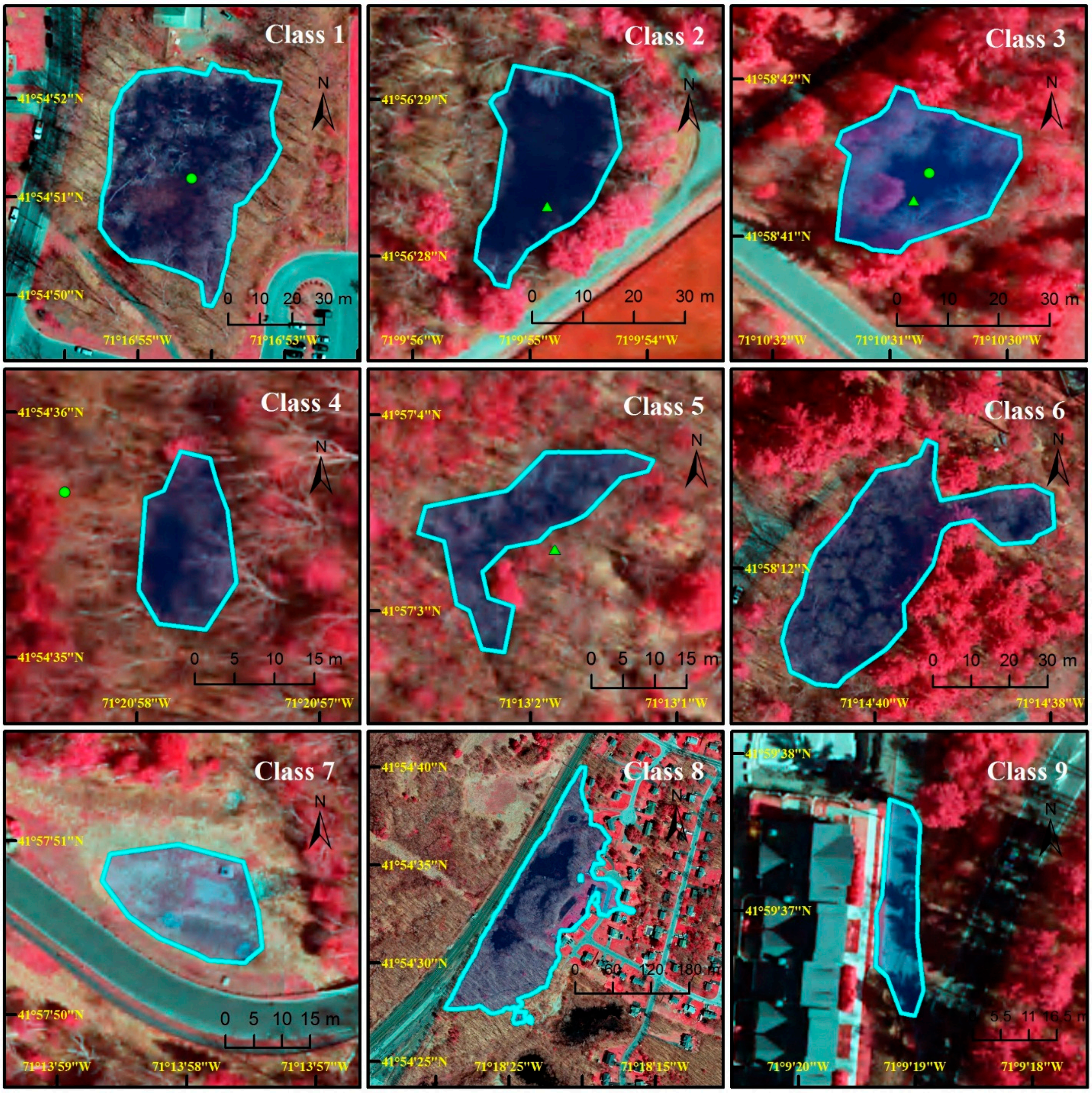


Table 5. Depression types and their relationships to statewide vernal pool databases. CVPs—certified vernal pools; PVPs—potential vernal pools.

Class ID	Class Description	Count	Percentage	Cumulative Percentage
1	Depressions that contain CVPs	29	1.2%	1.2%
2	Depressions that contain PVPs	268	11.3%	12.5%
3	Depressions that contain both CVPs and PVPs	48	2.0%	14.6%

Table 5. *Cont.*

Class ID	Class Description	Count	Percentage	Cumulative Percentage
4	Depressions within 15m buffer distance of CVPs	13	0.6%	15.1%
5	Depressions within 5m buffer distance of PVPs	38	1.6%	16.7%
6	Depression considered as certain vernal pool but not related to a CVP/PVP	1832	77.3%	94.0%
7	Depressions considered as uncertain vernal pools and not related to a CVP/PVP	70	3.0%	97.0%
8	Depressions whose boundaries are bigger than vernal pools	13	0.6%	97.5%
9	Depressions not considered as vernal pools	59	2.5%	100.0%

Table 6. Descriptive statistics of 2228 detected depressions (Classes 1–6). ELEV AVG—averaged elevation; NDVI AVG—averaged normalized difference vegetation index; NDWI AVG—averaged normalized difference water index.

Index	Median	Minimum	Maximum	Sum
Area (m^2)	337	50	126,428	3,832,255
Perimeter (m)	102	28	4493	435,427
Volume (m^3)	151	12	34,692	1,421,789
Depth (m)	0.42	0.10	1.75	N/A
ELEV AVG (m)	31.07	9.23	54.00	N/A
NDVI AVG	0.07	−0.62	0.26	N/A
NDWI AVG	−0.05	−0.15	0.70	N/A

5. Discussion

Vernal pools are important landscape elements that contribute to amphibian metapopulation dynamics [49–51], the maintenance of threatened and endangered plant and animal species [52], water storage [53,54], and local biogeochemical reactions [55,56]. However, wetlands are also typically small and shallow systems that are easily overlooked and frequently unprotected by local, state, and federal regulations [57]; thus, they are often disturbed and destroyed [58,59]. Understanding the location of these systems is frequently the first step towards better understanding of their functions, connections to other waters and systems [60], and potential impacts of human alterations on the maintenance of system integrity.

In the past, aerial photography was the best available data for discerning vernal pools, but with the advent of readily available LIDAR data and increasingly robust geostatistical processes [5,6], as well as increasing availability of repeated satellite imagery (though not applied in this study; see [61]), we have an improved opportunity to discern extant vernal pools of formerly glaciated terrain. Our approach was successful in identifying over 1800 additional vernal pools in the study area, which (assuming their veracity as extant systems) would almost triple the number of potential vernal pools previously identified in the study area (when coupled with the work by Burne *et al.* [10]). As shown in Table 5, 1832 depressions in Class 6 were identified as putative vernal pools with our method, but not related to any vernal pool in the statewide vernal pool databases. The 1832 putative vernal pools mapped by our stochastic depression analysis method were in part related to differences in minimum mapping units. Most authors concluded that only pools greater than 200–250 m^2 circular area (0.020–0.025 ha) could be reliably identified with leaf-off CIR aerial photographs [4,6,15]. As pointed out by Burne [10] in his statewide potential vernal pool database, only pools of 125 feet (38.1 meter) in diameter and larger on the photographs could be reliably identified when photos were of fair to excellent quality, and where evergreen trees were not dominant. The New Jersey vernal pool database developed by Lathrop *et al.* [4] used the minimum detectable pool size of 200 m^2. Only the pool centroid point location was digitized on-screen based on the CIR aerial photographs. As stated in the NHESP's vernal pool certification guidelines [13], the NHESP does not establish a physical, on-the-ground vernal pool boundary during the certification process. The minimum mapping unit for our depression analysis method was 50 m^2. Of the 1832 depressions detected in Class 6914 (50.0%) were within the area from 50 m^2 to 250 m^2. This means that our method was able to detect small vernal pools (< 250 m^2) that could not be reliably identified in previously studies. This also indicated that photographic interpretation may considerably underestimate the number of vernal pools.

The 59 (2.5%) false positive identifications of vernal pools in Class 9 could have resulted in part from the confusion between tree shadows and water bodies, due to their similar spectral signatures derived from the CIR aerial photographs. As apparent from an example of Class 9 systems (see Figure 10), the depression had tree shadows in it, which appeared as dark features on the CIR aerial orthoimagery. This resulted in positive NDWI values in the depression that caused it to be falsely identified as a vernal pool.

The acquisition date differences between LIDAR, CIR aerial photographs, and land use data may have also contributed to the false identification of vernal pools. The LIDAR data and CIR aerial photographs used in our study were acquired in 2010 and 2013, respectively. The land use data were derived from the four-band orthoimagery acquired in 2005. For the purposes of our study we assumed that depressional vernal pools occur infrequently on developed land [5], and the land use data in 2005 was used to refine the depressions. In this case, land use and land cover change after 2005 would not be reflected in the 2005 land use data. Human development and land use practices, including new residential or commercial development since 2005, could have resulted in removal of some pools.

The extraction of vernal pool boundaries from remotely sensed imagery is highly dependent on the water level at the time of image acquisition. Although the CIR aerial photographs used in our study were acquired in generally leaf-off conditions during mid- to late April 2013, it should be noted that not all potential vernal pools were flooded or holding water during the imagery acquisition time. Some pools might already have dried out in the early spring or were just beginning to form in the early summer. The estimated statewide average precipitation in April 2013, was only 4.93 cm, which was 51 percent of the long-term average for the month (9.65 cm). According to the National Drought Mitigation Center's 30 April 2013, Drought Monitor Map, 70% percent of Massachusetts was in abnormally dry conditions [28]. As a result, many small intermittent pools that normally stay saturated during the spring seasons were dry. In other words, our method might not have captured all the vernal pools solely based on the dry conditions represented in the aerial photographs.

In contrasting our results with that of the statewide CVP/PVP databases, we determined that approximately 52% of the 913 CVPs + PVPs within the study area occurred within discrete depressions. However, 23% of the CVPs + PVPs were not associated with depressions, but were visually confirmed based on the 2013 CIR orthoimagery (see Table 4) and were therefore considered as errors of omission in our study. By inspecting these omitted pools and their associated LIDAR DEM, NHD, and depression layers, these omissions could be subdivided into two types. The first type were depressions associated with omitted pools that were not detected with our stochastic depression analysis in the first step (see Section 3.1). These could be considered true errors of omission and may have been due to the RMSE error for the LIDAR data (0.095 m) being greater than the average depth of the vernal pool system. We found that 152 vernal pools belonged to this case, which accounted for 71% of the undetected vernal pools. The second type are omissions which emanate from analytical processes in which these omitted pools were initially detected using the stochastic depression analysis method, then eliminated because as they did not meet our refining criteria (see sections 3.2 and 3.3). In particular, the adjacency criteria of > 10 m from NHD features seemed to account for most of these eliminations. Through our stepwise process, we identified and removed 32 vernal pools that were within 10-m buffer zones of NHD features, which could have accounted for up to 15% of our errors of omission. We note that Lang *et al.* [62] found that the horizontal accuracy of NHD maps was > 18 m, which is substantially greater than the 10-m buffer distance of NHD flowlines and areas used by Reif *et al.* [40] and Lane *et al.* [37] and applied in this study. However, Lane *et al.* [37] doubled the buffer width to 20 m in a 8600 km^2 subsample of their study extent and reported an areal change in GIWs of approximately 3%, suggesting that the horizontal accuracy error in the NHD may play a small (though not insignificant) role in the outcome of the current study. Further refinement of our data required an abundance of water pixels to be identified within each depression. If this criterion was not met, the depression was rejected as a potential vernal pool.

Coupling our depression analyses with soil wetness features, along with other ancillary GIS data sets and algorithms, such as performed by Grant (2005) [5], could result in increased precision in the number of CVPs and PVPs identified. However, the majority of the vernal pools in our study were located within depressions (or within 15 m/5 m of a depression), suggesting that focusing on depression systems can improve the precision of the studies and better discern extant vernal pools on the changing landscape.

6. Conclusions

Effective conservation of vernal pools depends on locating and mapping these pools accurately. We developed and applied an efficient and effective method for detecting and mapping potential vernal pools using stochastic depression analysis with additional geospatial analysis. Our method was designed to take advantage of high-resolution LIDAR data, which are becoming increasingly available, though not yet frequently employed in vernal pool studies. We successfully detected more than 2000 putative vernal pools in our ~150 km^2 study area in eastern Massachusetts, substantially increasing the record of potential resource abundance for resource management. The accuracy assessment in our study indicated that commission rates might range from 2.5% to 6.0%, while the proxy omission rate was 8.2%. These rates were much lower than generally reported errors of previous vernal pool studies conducted in the northeastern United States, though there is potential for continued improvement of our methods. One significant advantage of our semi-automated approach for vernal pool identification is that it may reduce inconsistencies and alleviate repeatability concerns associated with manual photointerpretation methods. Another strength of our strategy is that in addition to detecting the point-based vernal pool locations, the boundaries of vernal pools can be extracted as polygon features to characterize their geometric properties, which are not available in the current statewide vernal pool databases in Massachusetts. Ultimately, integrating LIDAR and depression analysis with a physiographic/GIS-based approach might prove particularly effective in discerning vernal pool ecosystems. In conclusion, our results demonstrated the potential of using high-resolution LIDAR data along with CIR aerial photographs for vernal pool mapping and inventory. With the increasing availability of these sources of high-resolution remotely sensed data, our methods of vernal pool identification can be easily adopted to meet the geospatial data needs of individual towns (or counties) to entire states. A regional putative vernal pool database would become increasingly valuable in enhancing our understanding of the current status of vernal pools in the northeastern United States under increasing anthropogenic pressure.

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Author Contributions

All authors have made significant contributions to the manuscript. Charles Lane developed the original idea, supervised the study, and contributed in manuscript revision. Qiusheng Wu is the main author who processed the data, developed the methodology, analyzed the results and wrote the manuscript. Hongxing Liu provided the depression filling algorithm and contributed with ideas and discussions. All authors shared equally the editing of the manuscript.

Conflicts of Interest

The authors declare no conflict of interest.

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