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Field Validation of LiDAR-based Predictions of Riparian Buffer Zones

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FIELD VALIDATION OF LiDAR-BASED PREDICTIONS OF RIPARIAN BUFFER ZONES

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ABSTRACT

Riparian buffer zones (RBZ's) are critical for protecting water quality both in channel and downstream. High Resolution Light Detection and Ranging (LiDAR) provides a way to locate where water is flowing through a channel into an RBZ and then into a stream. The objectives of this study were to characterize riparian buffer zones around Lake Issaqueena, SC and streams flowing into the lake by channel presence: ephemeral, intermittent, and perennial; to relate channel presence to buffer width and buffer cover composition via soil moisture content and buffer width, and to validate potential differences in LiDAR versus field observations via soil moisture content and soil temperature. A LiDAR derived DEM was utilized in ArcGIS to define flow channels and determine forty locations for field measurements (soil moisture, buffer width, buffer composition, and a thermal image of the soil) around Lake Issaqueena. LiDAR indicated channels were ephemeral with large buffers generally ten meters or greater (except where locations were located on private property). High flow accumulation channels can be accurately predicted by LiDAR data, but not for low and moderate flow channels. Surface soil temperature measurements were relatively uniform with some extremes and showed no difference between sample locations and control locations indicating that channel presence cannot be accurately predicted using surface soil temperature. These presented methodologies can serve as a template for future efforts to quantify riparian buffers and their effects on protecting in-stream habitat and water quality.

(KEY TERMS: Geographic Information Systems (GIS), Riparian Buffer Zone (RBZ), Soil Moisture, Thermal Imagery, Water Quality, Watershed Management)

DEDICATION

This thesis is dedicated to my parents (Carol and Gibson), sister (Karen), and grandparents (Wayne, Evelyn, Elizabeth, and Sam Ben).

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CHAPTER ONE

Field Validation of LiDAR-based Predictions of Riparian Buffer Zones

INTRODUCTION

Most riparian buffer characterization efforts have focused on using low-resolution data to understand areas adjacent to streams. Typically, thirty-meter resolution Landsat satellite data is used for the characterization along with digital elevation models (DEMs) with a similar resolution. Using this relatively low-resolution data is problematic because the size of the buffer is typically similar to the size of each individual pixel (30 meters) and therefore fails to represent buffer characteristics in smaller areas. Stream buffer analysis also does not typically account for areas where water flows through the buffer zone to the stream (James *et al*., 2007). This source of error has been identified but field-testing and validation is needed using high accuracy high resolution spatial data. LiDAR data, which comes from plane mounted instruments, measures three-dimensional surface characteristics by determining the canopy, understory, and surface topography using reflected light from rapidly emitted laser pulses (Wasser *et al*., 2014). In order to better understand the RBZ dynamics and what constitutes each buffer, higher resolution and more accurate data need to be used. James *et al*. (2007) observed that buffer zones may be so heavily forested or otherwise covered that analysis by satellite imagery or conventional remote sensing means may not be effective or accurate. Use of LiDAR based data may be an effective way to identify channels that may be otherwise hidden from view (James *et al*., 2007).

Location and contribution of channels that flow through RBZs into streams is critical because they contribute to the overall health of the stream (Johansen *et al*., 2010a). Having a buffer around perennial or permanent streams is important but locating areas where water is flowing into the stream through RBZs is also a significant issue when considering stream health (Johansen *et al*., 2010a). Studies by Lee *et al*. (2000) and Sabater *et al*. (2002) demonstrated that RBZs are critical in preventing sediment, excess nutrients, and toxic metals from flowing into a stream. While the need to protect permanent or perennial streams is generally recognized and subject to numerous laws and regulations such as the Clean Water Act and other individual state regulations, the protection of ephemeral channels that are only present during or shortly after storm events is largely unregulated (Clean Water Act, 1972). These channels, which frequently go unnoticed, provide a direct path for sediments, nutrients, and other unwanted materials to flow into a stream during a storm event with little or no interaction with a riparian buffer. Locating these channels may assist with the protection of these channels which would then assist in the overall health of the stream and subsequent water quality.

Soil moisture levels may be a way to identify ephemeral channels (Creed *et al*., 2008). If soil moisture in a predicted channel location is statistically high in comparison to a location where a channel is not predicted may validate a LiDAR based analysis. Visible water may not be present on the soil surface but water may be maintained in the soil structure. Instruments for available moisture determination in the soil are becoming increasingly accurate. Modern moisture meters function by using an electromagnetic sensor to obtain data. The use of the soil moisture meter would be an effective and highly accurate way to analyze the water content present in the soil (Vaz *et al*., 2013).

Field evaluation and analysis of buffer zone characteristics of ephemeral, intermittent, or perennial streams is possible based on visual analysis of ground topography but other, newer techniques may be utilized to identify areas where water is flowing and where high soil moisture is present. Traditionally, the high cost of thermal cameras has been a hindrance to their use in mainstream scientific studies and overall availability, but recent technological advances have seen prices drop precipitously along with their size, weight, and ease of use. Ground-based thermal imagery collection has been used successfully in the field to identify areas of saturated soil and water connectivity and dynamics in the landscape (Pfister *et al*., 2010). In addition, laboratory studies of soil temperature have been successfully able to predict different types of soil permeability (de Lima *et al*., 2014). Thermal imaging is possible due to the effects of evaporative cooling which cools a surface as water evaporates from the surface. The use of low-cost thermal imagery is especially interesting when compared to the price of high-accuracy soil moisture meters.

The objectives of this study are: 1) to characterize riparian buffer zones around Lake Issaqueena and streams flowing into the lake by channel presence and predicted flow level: low, medium, and high; 2) to relate channel presence to buffer width and buffer cover composition via soil moisture content and buffer width (meters), and 3) to validate potential differences in LiDAR versus field observations via soil moisture content and soil temperature.

MATERIALS AND METHODS

Study area

Lake Issaqueena is located in the Savannah River Basin area of Pickens County in the upstate region of South Carolina (Figure 1). The lake is classified as being in the Piedmont region which follows the area south of Appalachian Mountains (USGS, 2012). The study area is predominantly a mixed hardwood forest with areas of planted pines (*Pinus spp*.). The land was reclaimed in the 1930's from poor farming practices with an almost total loss of topsoil. The study area is almost completely managed within the boundaries of the Clemson University Experimental Forest with the exception of a small amount of privately owned land. The lake is filled by one fourth-order stream, Six-Mile Creek, two third-order streams, Indian Creek and Wildcat Creek as well as numerous ephemeral streams. For the data collection, the majority of the sample points occur in the Clemson Forest, however, some selected points lie on private property. Four of the points on the eastern branch of Lake Issaqueena were outside of the boundaries of the Clemson Experimental Forest. The topography of the area is varied with slopes ranging from 5-25%. Vegetation is dense, especially around the streams where dense groves of mountain laurel (*Kalmia latifolia* L.) form a canopy over most of the streams.

LiDAR Data Processing

Light Detection and Ranging (LiDAR) based data was used to define both the topography and stream buffer characteristics for this study (Figure 2, Table 1). The LiDAR data (which was used for the buffer analysis and was the data source for the DEM) has an approximate spacing of 1 return/m^2 and a vertical accuracy of approximately 20cm. A pre-existing LiDAR based DEM was used to represent ground topography, while standard flow accumulation routines within the Spatial Analyst extension of ArcGIS 10.2.2 (ESRI, Redlands, CA) were used to map ephemeral channels . The flow accumulation channels flowing into the perennial streams were identified and arranged into three different categories based on the unique accumulation value of each identified pixel ArcMap provided (low, medium, and high accumulation). Potential sampling locations were placed in the map using ArcGIS wherever a channel intercepted a perennial stream identified by the USGS National Hydrology Dataset through an RBZ (USGS, 2012).

Sample Location Determination in ArcMap

Sampling locations (Figure 3) were determined by finding points where the LiDAR-DEM indicated water flow intercepting an identified stream from USGS NHD (Table 2). Each sample point had an assigned value correlating to the amount of flow accumulation that the LiDAR-DEM indicated. Of the 122 potential locations in the study area, forty were randomly determined. The sample area was divided into three zones: Zone 1, Zone 2, and Zone 3 (Figure 3). A representative number of predicted channel sampling locations were selected from each zone: 10 from “low” flow level 10 from “medium” flow level, and 20 from “high” flow level. A pivot table was created in Microsoft Excel to determine the number to sites per stream branch. Stratified sampling generation within SAS® (version 9.3) was conducted on stream branch and category with probabilities similar to the proportion of sites in each section and category. Ten samples were selected from Zone 1, 18 samples were selected from Zone 2, and 12 samples were selected from Zone 3. Sampling locations were randomly drawn from the stratified sample.

Data Entry with ArcCollector

The data obtained from the sampling map was loaded into a single geodatabase where it was then used as the base map for ArcCollector (ESRI, Redlands, CA) using an android tablet (Google Nexus 5, second generation; Table 3). A data entry form with attributes was created for the purpose of easily recording data measurements in the field. After setup of ArcCollector with the GIS data and custom form, the GPS-capable tablet recorded the current location for accurate sampling and data could be easily entered into the collection form (Figure 5).

Thermal Image Data Collection

Thermal images provided one of the critical components of the study. For the thermal imagery, a low-cost thermal camera Seek XR™ (about $300) was obtained. The camera connected to the Google Nexus tablet through its micro-USB connector and a free mobile application provided by Seek was used to access pictures from the camera. The thermal camera has a temperature range from -40°C to 330°C and an infrared range from 7.2µ to 13µ. (Seek Thermal™ 2015). A thermal picture was taken after surface debris was removed exposing bare soil. “Cooler” temperature colors, such as blue, indicated cooler temperatures on the soil surface. A “cool” temperature in comparison to a warmer control temperature indicates water is collecting or accumulating in the soil (Pfister *et al*., 2010). In addition to the color, a temperature value was given (ranging from 66°F - 95°F or 18.3°C – 35.0°C) which was uploaded into ArcCollector. The data were compared to control points, which were pre-determined to be 10 meters away from the actual sample location and away from LiDAR DEM-predicted flow channels. A control thermal picture was taken in the same way as at the sample locations.

RBZ Characteristics

The RBZs were characterized by estimating the density of vegetation around each of the stream channels. The channels were classified into four broad categories:

1. Vegetated buffer with dense overstory,
2. Vegetated buffer with moderately dense overstory,
3. Vegetated buffer with little or no overstory,
4. Predominately bare soil.

A significant amount of information was already known about the types of buffers surrounding the streams from analysis of LiDAR data, and previous visual analysis of site characteristics. The width of the immediate buffer zone was calculated in meters. A LiDAR derived Digital Terrain Model (DTM) using first-return data was used to estimate buffer presence in Arc GIS 10.2 to compare to the field measurements.

Channel Locations through RBZs

Perennial**,** intermittent and ephemeral stream channel locations were used to identify areas across the landscape where flow is predicted through stream buffers. In addition, other variables were measured including: soil moisture of the channel, buffer width, buffer composition/type, and bearing.

Determination of Channel Presence using Soil Moisture

Soil moisture was also used as a parameter to determine where flow accumulation was occurring. An electromagnetic soil moisture meter (FieldScout TDR 300®) with three-inch rods was used to determined soil water content as percent volumetric water content. At each sample location, a measurement was recorded and then a control sample was taken ten meters away in the same area as the control thermal image. The control data were collected in an area where LiDAR data indicated there was no flow accumulation. The soil moisture meter was calibrated after every ten sample measurements. In addition, the moisture meter data was georeferenced through an interfaced handheld GPS (Garmin 72H®) which attached to the meter. Once the data measurements were taken, the data, including latitude and longitude, were recorded in a spreadsheet that was subsequently uploaded into Microsoft Excel.

Statistical Methods

Soil moisture and temperature data were analyzed using SAS to compare site versus control averages for each category using paired sample tests. Tests of significance were evaluated with a 0.05 significance level.

RESULTS

Characteristics of Riparian Buffer Zones and Streams

Table 4 shows the number of channels that were observed in the field. Six channels out of a possible ten were observed in “low” and “medium” flow level. Eighteen out of a possible 20 channels were observed in “high” flow level. All channels that flow into the streams surrounding the lake were ephemeral channels (Table 5). The sampling zones had a mean width of 8.8 meters and a standard deviation of 2.5 meters. At the time of sampling, no LiDAR indicated channels had any water present on the surface. The weather around the time of sampling had been dry for several days leading to the lack of surface water.

Field Measurements

Table 6 shows the relationship between stream flow levels, buffer width and buffer cover composition around Lake Issaqueena. All channels were ephemeral and therefore no comparison can be made that relates channel type (ephemeral, intermittent, or perennial) to the buffer composition or buffer width. The buffers were generally wide with a mean of 8.8 meters and standard deviation of 2.4 meters and had dense vegetation cover, except where sample locations lied on private property. Buffer measurements based on a LiDAR canopy height model (CHM) were similar overall to the field measurements (Table 5). There were some difficulties identifying buffer width with the CHM because of the 3.3m resolution of the raster cells. There were several instances where one individual cell was identified as being without tree cover, surrounded by tree cover, which may have been in error.

LiDAR Data and Validation

Table 7 summarizes the data obtained from the observations. LiDAR based DEM data failed to accurately predict channels in low and medium flow accumulation channels using an alpha of 0.05 with p-values of 0.698 and 0.5721, respectively. In high flow accumulation channels, LiDAR was able to accurately predict channels using an alpha of 0.05 with a p-value of 0.0003.

Thermal Imagery

Table 8 shows descriptive statistics for the thermal imagery data. The observed locations had a mean of 77.3°F (25.2°C) and the control locations had a mean of 79.9°F (26.0°C). The standard deviations for the observed locations were 4.9°F (2.7°C) and the control locations had a standard deviation of 5.2°F (2.9°C). The thermal imagery failed to accurately predict channel presence as soil temperature was similar between observed sites and control sites with relatively large standard deviations. Figure 4 demonstrates the variability of temperatures when a sample site is illuminated by direct sunlight versus a similar location where the ground is shaded by canopy cover. As Figure 4 illustrates, sunlight has a powerful ability to heat soil when it is directly illuminated.

DISCUSSION

Several studies have linked LiDAR data to channel presence (Akay *et al*., 2012; James *et al*., 2006; Johansen *et al*., 2010a; Johansen *et al*., 2010b). These studies are conclusive in the fact that LiDAR data has the ability to accurately locate the location of streams, however, this study agrees with the work of James et al. (2006) in that smaller channels may be more difficult for LiDAR data to predict. This study differs from previous studies in that it seeks to identify smaller channels that feed into larger streams using soil moisture content and thermal imagery as validation techniques. Use of a soil moisture meter is a novel technique in this field of study as its use is generally intended for agricultural or horticultural use. Thermal imagery is also a novel technique in that it has only recently come into more mainstream use because of price reduction and higher ease of use.

LiDAR Predictions

LiDAR offers a unique and precise way to map ground characteristics when compared to conventional methods of using aerial and satellite photography and visual analysis of ground topography. This project found that only large channels can be accurately predicted by use of LiDAR data. James *et al*. (2006) noted that larger features are accurately predicted by LiDAR data but that smaller features are not accurately predicted especially when features are small in size or run parallel to other features (James *et al*., 2007). Buffer width estimations with a LiDAR canopy height model (CHM) seemed accurate overall, but there was likely some error because raster cells were identified as either have or not having tree cover and the 3.3m cell size limited the resolution of the measurement. One issue encountered that may contribute to error in this project is the mapping system used to collect the data, ArcCollector. Analysis of the information that ESRI provides about ArcCollector (ESRI, Redlands, CA) and experience with the program leads to a conclusion that ArcCollector may not be designed for projects where high accuracy data is required. It appears ArcCollector is designed for areas where only a general location is required and access to GPS satellites is minimally limited. In addition, the mapping system is not necessarily intended for high accuracy GPS points as the downloaded maps to the tablet have a limited zoom capability. In addition, the tablet GPS would frequently lose signal under the dense canopy of mountain laurel and taller vegetation around the streams which leads to a certain amount of supposition using visual analysis of ground topography.

Soil Moisture Data

The soil moisture data were easily obtained and provides a highly accurate way to assess the amount of moisture present in the soil. Issues with the sampling were the presence of rocks (which are characteristic of Piedmont soils) and differences in soil type. Some sampling locations on larger streams consisted of well-drained sand that produced low moisture values. The dominant soil type as classified by USDA-NRCS was Madison sandy loam (USDA, 2015). Variations in the soil type (composition and texture) could produce small sampling differences with the equipment readings (Vaz *et al*., 2013). Three inch (7.5 cm) rods were used on the moisture meter which is one of several rod lengths available. Longer rods will allow for a broader analysis of water deeper in the soil profile but under field conditions are not practical as longer rods are more easily bent and damaged when encountering heavy clay soils, compacted soils, or rocks.

Thermal Data

The collected data suggest that thermal data cannot, in this situation, be used as a predictor of channel presence. Pfister *et al*. (2010) noted that thermal imaging is potentially a valid way to locate water contributions in soil. Thermal imagery offers instantaneous data of surface soil temperature; however, care should be taken when conducting temperature observations. Thermal analysis of soil has been tested in controlled laboratory experiments where conditions are easily controlled (de Lima *et al*., 2014) but field-testing of thermal imagery of soil moisture to determine channel presence has not been fulfilled. Analysis of data from this project demonstrates that normal environmental conditions and deviations may prevent data from being accurately observed. The dominant problem is that direct sunlight has a powerful ability to heat a surface when compared to a similar shaded area which will lead to a significant error in data collection. Thermal observations should be performed when a desired sampling area is at uniform temperature. However, this may also lead to sampling error as the ambient humidity is often highest before sunrise which will diminish or negate the effects of evaporative cooling as the air may almost or completely be saturated with water.

SUMMARY AND CONCLUSIONS

Flow accumulation analysis using the LiDAR-based DEM was excellent (90% accurate) at locating "high" flow ephemeral or intermittent channels passing through the riparian buffer. For similar predicted channels with "low" or "medium" flow the identification was less successful (60% accurate). This accuracy of channel prediction and buffer width estimation will likely vary depending on the density of the LiDAR used (and related DEM resolution and accuracy), so the accuracy of this type of analysis may improve with higher resolution LiDAR data. Control sites were accurately predicted as not having channels in all cases. Soil moisture data was able to distinguish the 'high" flow channels from surrounding areas, but similarly were unable to identify "low" flow predicted channels. Analysis using a thermal camera was unsuccessful at finding ephemeral or intermittent channels with similar temperatures in the observed and control sites. There was also variation is soil temperature based on sun exposure of the sample site. Sampling times occurred in a generally dry period, and if it had been possible to sample directly after rain events, the thermal imagery may have been able to identify channels. Using a hand-held tablet with integrated GPS and data collection form worked well, but there was some uncertainly associated with the GPS accuracy, especially under heavy canopy. Future studies should consider incorporating a differentially corrected GPS.

APPENDICES

Appendix A

Figures

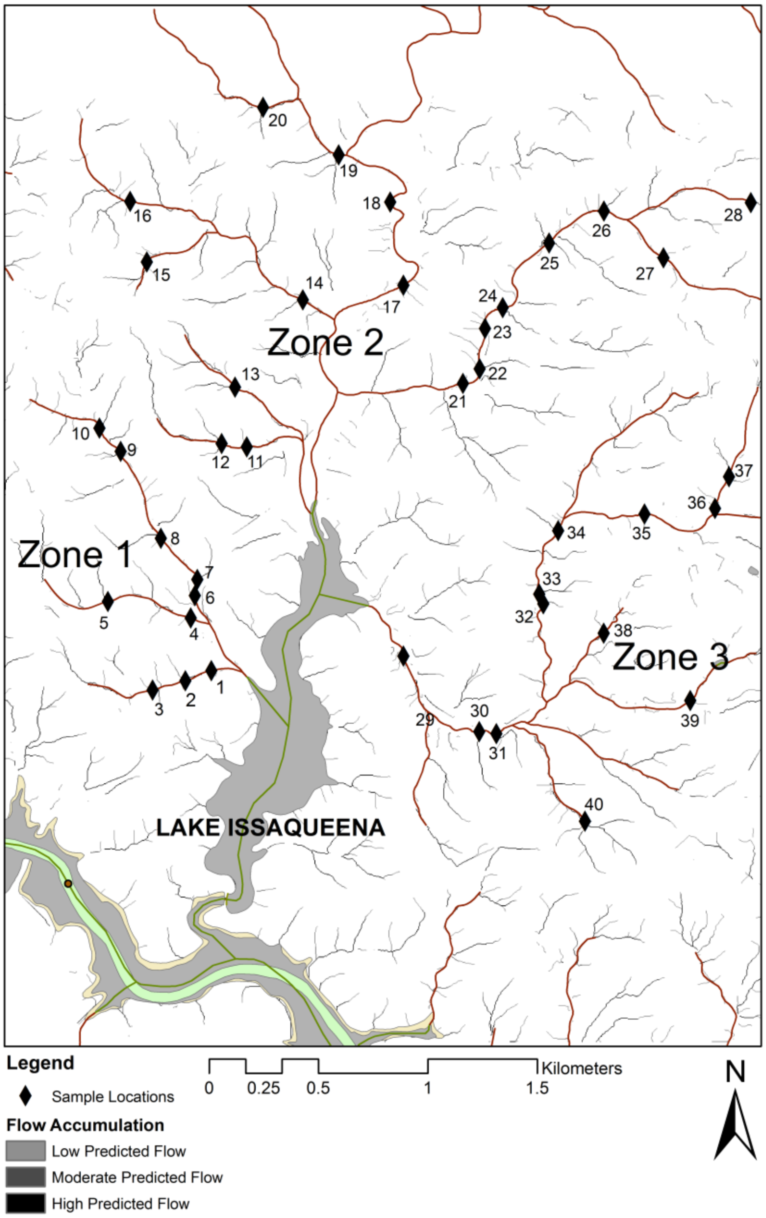

FIGURE 1. Lake Issaqueena study area.

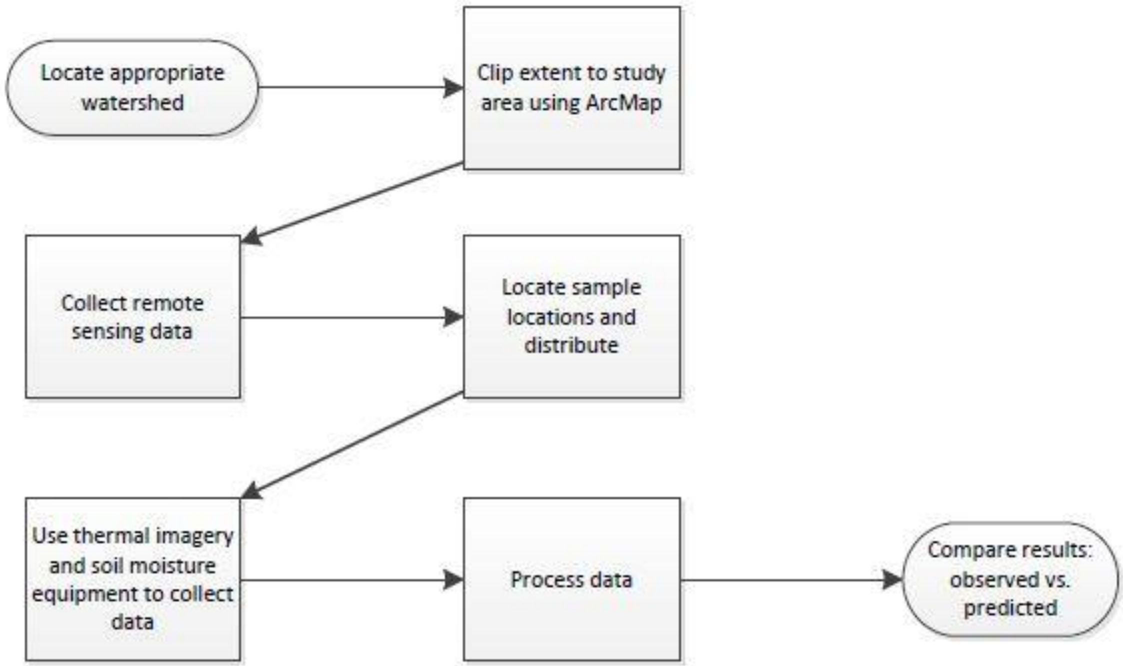

FIGURE 2. Flowchart of processes.

FIGURE 3. Example of category 3 channel.

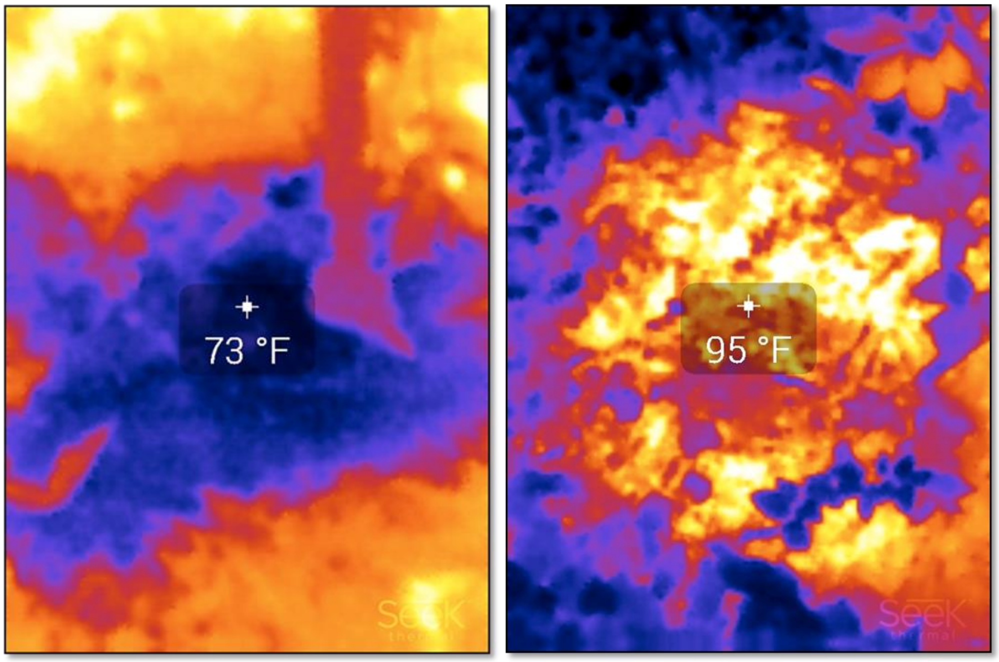

FIGURE 4. Comparison between thermal image in sunlight (left) and similar location in shade (right).

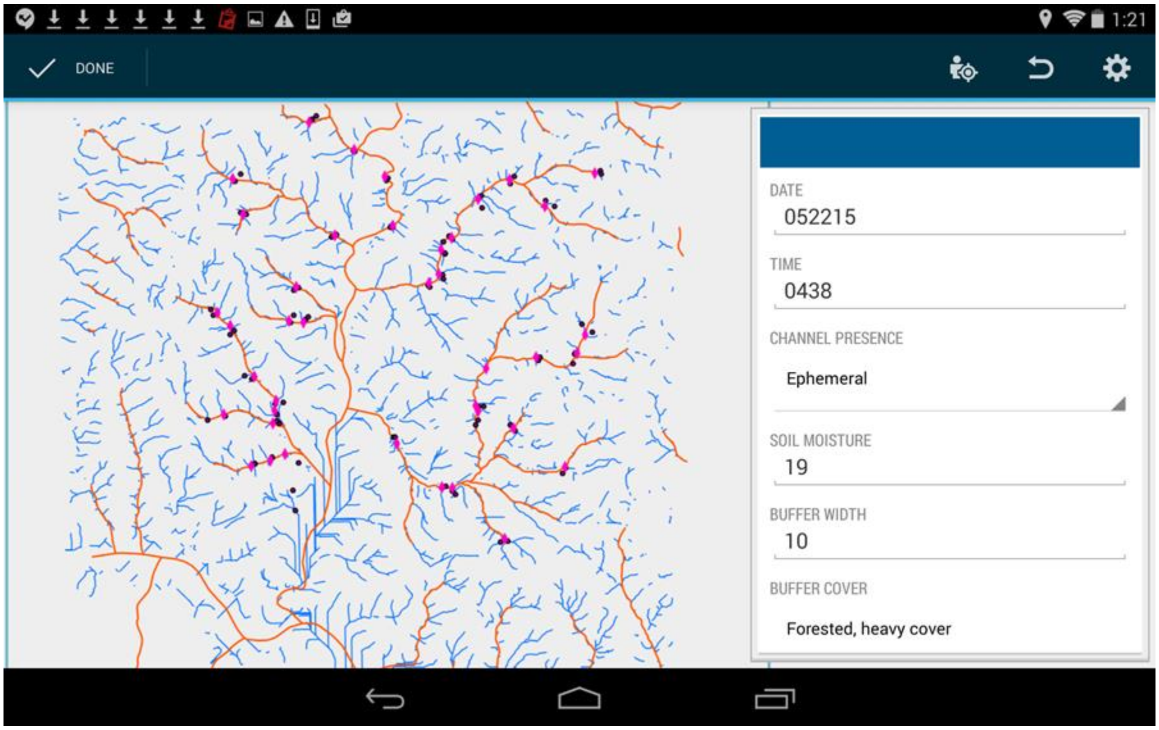

FIGURE 5. Example of ArcCollector interface.

Appendix B

Tables

TABLE 1. Data sources and descriptions.

Data Layer	Source	Coordinate System	Date
LiDAR (LAS) files	Pickens County GIS	NAD State Plane 1983 SC	2011
Lake Polygon	Pickens County GIS	NAD State Plane 1983 SC	2013
Hydrology Datasets	USGS NHD	NAD State Plane 1983 SC	2012

TABLE 2. Characterization of sample locations along streams near Lake Issaqueena, SC.

Parameters	Units	Zone 1	Zone 2	Zone 3
Stream Order	-	4th	3rd	3rd
Flow Level				
- Low	Cells drained (500 -1000)	4	4	2
- Medium	Cells drained (1000.01-1500)	2	4	4
- High	Cells drained (1500.01-99369)	4	10	6

TABLE 3. Field and GIS measured parameters, Lake Issaqueena, SC.

Parameter	**Units**	**Instrument**
Channel presence	Categorical data (1=ephemeral; 2=intermittent; 3=perennial)	Visual
Soil moisture of channel	Volumetric water content (1-100)	FieldScout TDR 300 Soil Moisture Meter
Soil moisture of control	Volumetric water content (1-100)	FieldScout TDR 300 Soil Moisture Meter
GPS Location	Latitude/Longitude	Garmin 72H GPS
Thermal image of channel	Fahrenheit	Seek Thermal XR
Thermal image of control	Fahrenheit	Seek Thermal XR
Bearing of thermal image*	Categorical data (1-10)	Suunto compass
Buffer width	Meter (m)	Meter stick
Buffer composition of channel	Categorical data	Visual
Field Data Entry	N/A	Google Nexus tablet with ArcCollector for Android

* Note: Used to identify sample location.

TABLE 4. Comparison of observed versus LiDAR predicted channels around Lake Issaqueena.

Ephemeral channel (predicted flow level)	LiDAR predicted	Number in field verification
Low	10	6
Medium	10	6
High	20	18
Control	0	0

TABLE 5. Width of the riparian buffer zones around Lake Issaqueena: visual versus LiDAR predicted.

Sampling zone	**Visual: Ephemeral**		**LiDAR predicted: Ephemeral**	
	(n)	Mean width (stdev) (m)	(n)	Mean width (stdev) (m)
Zone 1	10	8.4 (2.9)	10	8.0 (2.8)
Zone 2	12	7.8 (3.2)	12	8.4 (3.3)
Zone 3	18	9.5 (1.5)	18	8.9 (2.6)
Overall	40	8.8 (2.5)	40	8.4 (2.9)

TABLE 6. Stream category, buffer width, and buffer cover composition around Lake Issaqueena.

Flow level	**Mean width (stdev) (m)**	**Overall buffer composition**	
		Vegetative	**Bare**
Low	9.25 (2.05)	Dense	0
Medium	8.25 (2.76)	Dense	0
High	9.00 (2.38)	Dense	0
Overall	8.83 (2.40)	Dense	0

TABLE 7. Summary statistics for soil moisture comparisons between low, medium, and high stream flow (observed-predicted).

Flow level	**n**	**DF**	**t-value**	**Pr > t**	**Mean (volumetric water content)**	**Standard deviation**
Low	10	9	2.06	0.0698	25.70	15.68
Medium	10	9	0.59	0.5721	16.20	6.17
High	20	19	4.41	0.0003	21.65	8.84
Control	40	-	-	-	15.03	4.26

TABLE 8. Summary statistics for thermal imagery data.

Observed thermal mean (stdev)	Control thermal mean (stdev)
77.3°F (4.9°F)	79.9°F (5.2°F)
25.2°C (2.7°C)	26.0°F (2.9°C)

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