Upland Microtopography and Implications to Surface Water Detention in Maine

Bea Van Dam[1,3], Sean Smith[1,3], and Kate Beard[2,3]

University of Maine

1. School of Earth and Climate Sciences 2. School of Computing and Information Science

3. Senator George J. Mitchell Center for Sustainability Solutions

Microtopography and Upland Storage

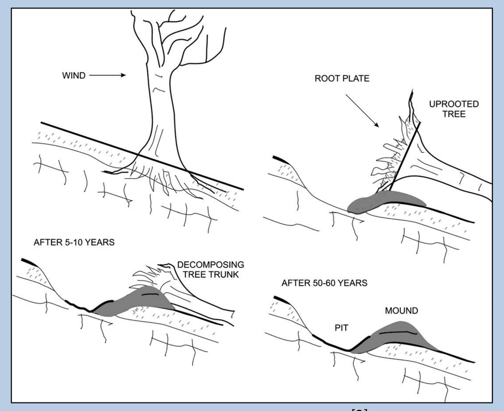


Figure 1. Illustration of tree throw[2]

Tree throw is not the only driver of pit/mound formation in forested landscapes, but is likely the dominant one.

A notable characteristic of Maine's forested landscape is the pit-mound microtopography caused by a combination of factors related to surficial geology and tree fall. These features are often on the scale of single meters wide and decimeters to a meter in depth[3], appearing as "puddles" in the landscape during significant precipitation events.

Figure 2. Surface water storage in shallow pit feature after rain event. Webhannet River Watershed, Wells

Surface water detention in by these depressions can be substantial at the scale of a watershed and measurably affect runoff rates in low order streams.

Little is known about how microtopography and related detention varies in Maine's dominant physiographic settings defined by slope, surficial geology, and land cover conditions. With the increasing availability of high resolution elevation data, it has become possible to remotely evaluate the extent of these depressions and quantify the total upland storage capacity they may represent.

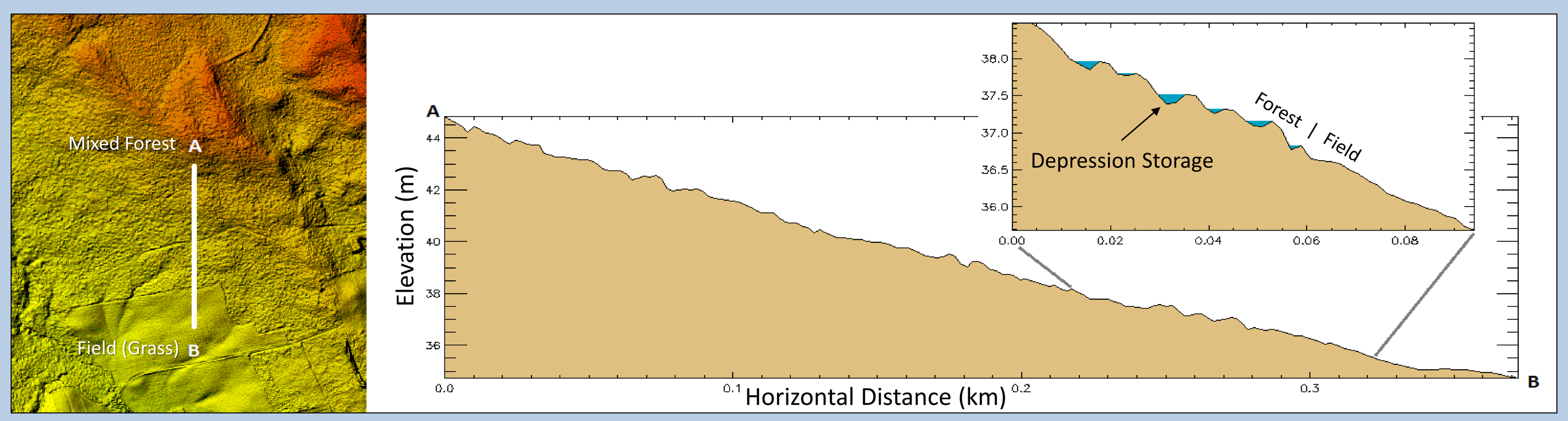
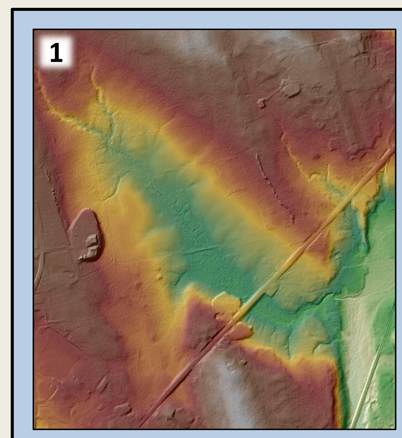


Figure 3. Cross-section of a forest-field transition from LiDAR data, showing potential depression storage in pit-mount microtopography

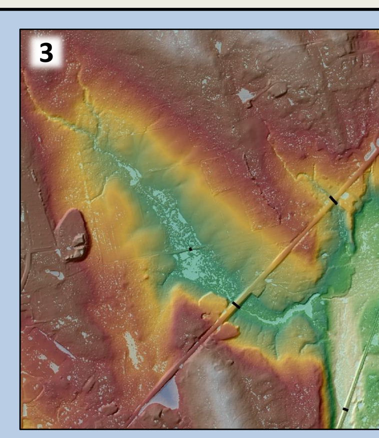
Remote Detection Methods

Direct Calculation from LiDAR

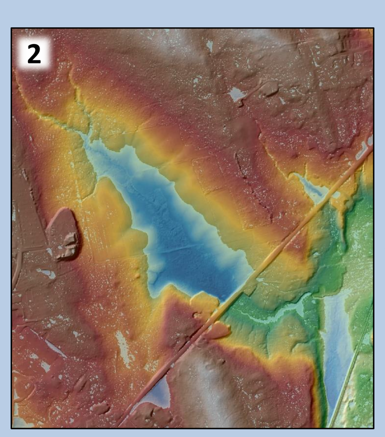


A hillshade view of a 2m cell size, bare-earth elevation raster interpolated from airborne LiDAR (**L**ight **D**etection **A**nd **R**anging).

The prominent linear feature is a road across a wetland area, with a culvert to allow a low-order stream to reach the Penobscot River.

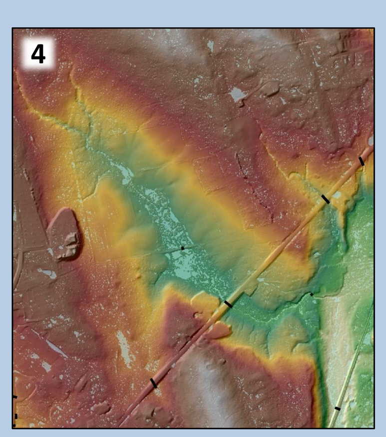


To remove artificial fills, culverts (black) are "burned" into the elevation raster, allowing the water to bypass the artificial dam.



A fill process is performed on the 2m DEM, creating fill depths for each cell[1] (light-dark blue scale).

Because the LiDAR cannot "see" the culvert below the road surface, the road acts as an artificial dam, causing fill depths up to 4+ meters.



Through multiple iterations, artificial fills are removed until only likely "natural" potential storage locations remain.

Figure 4. Illustration of direct detection of potential depression storage from LiDAR DEM

Indirect from LiDAR Derivatives

Due to the time and effort involved in direct detection of storage using the fill method, it is not feasible to perform over large areas without existing culvert data.

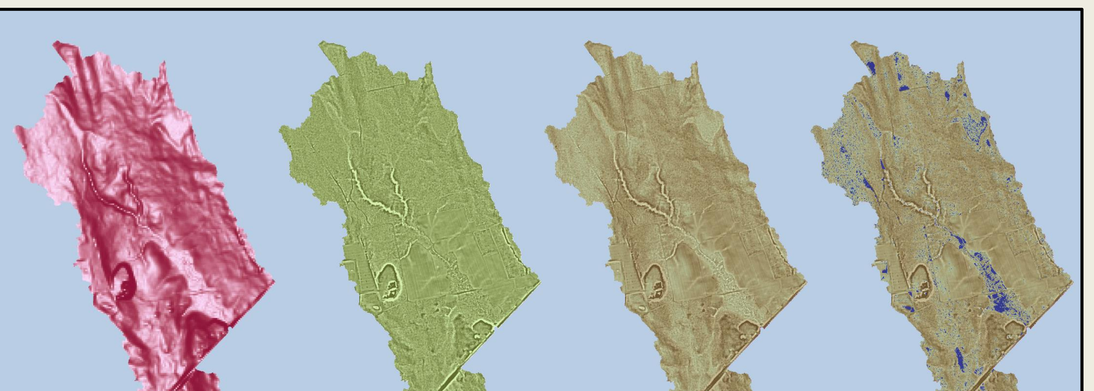


Figure 5. LiDAR derivative layers showing slope (low-high: light-dark purple), TPI (low-high: light-dark green), and slope-TPI visual overlay (lightest browns are flattest slopes and lowest TPIs), plus overlay with storage

Slope and Topographic Position Index (TPI), a measure of local prominence in a landscape calculated by comparing a cell's elevation to the average elevation of its neighbors[4], were identified as likely predictors of storage locations. However, multiple regression analyses of storage vs slope * TPI at several scales never achieved $R^2 > 0.15$. (See Terrain-Storage Correlations)

Terrain Categorization

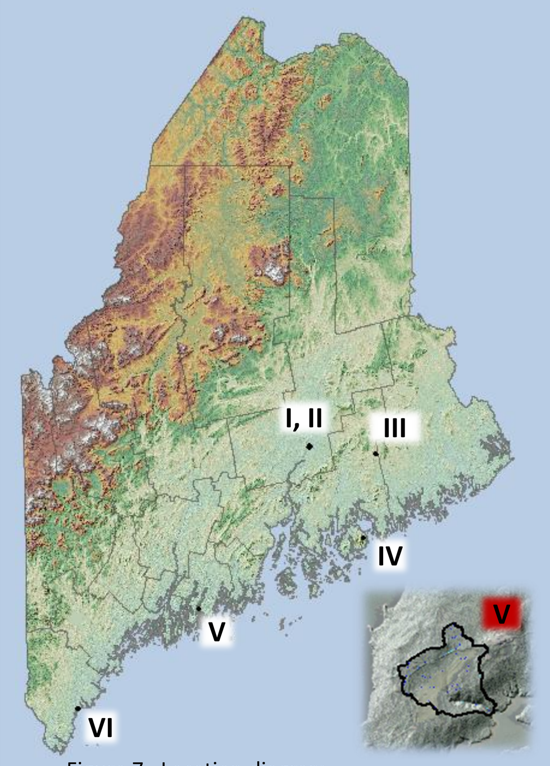


Figure 7. Location diagram (State of Maine)

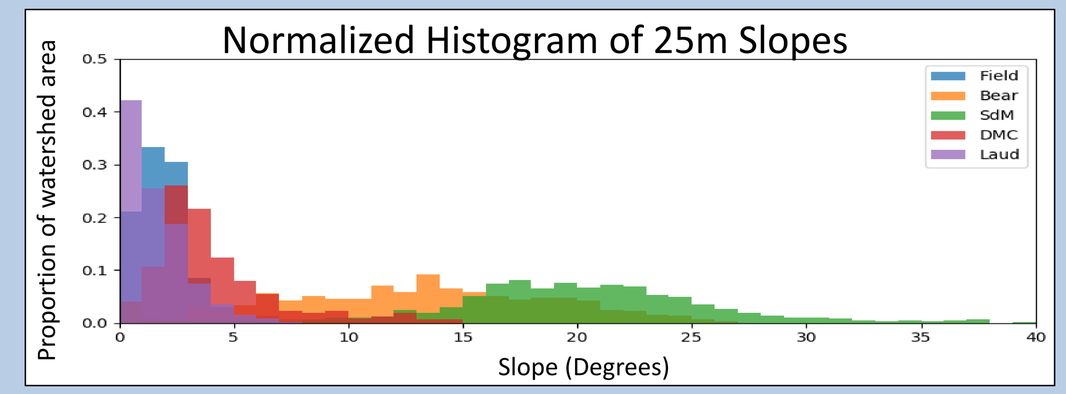
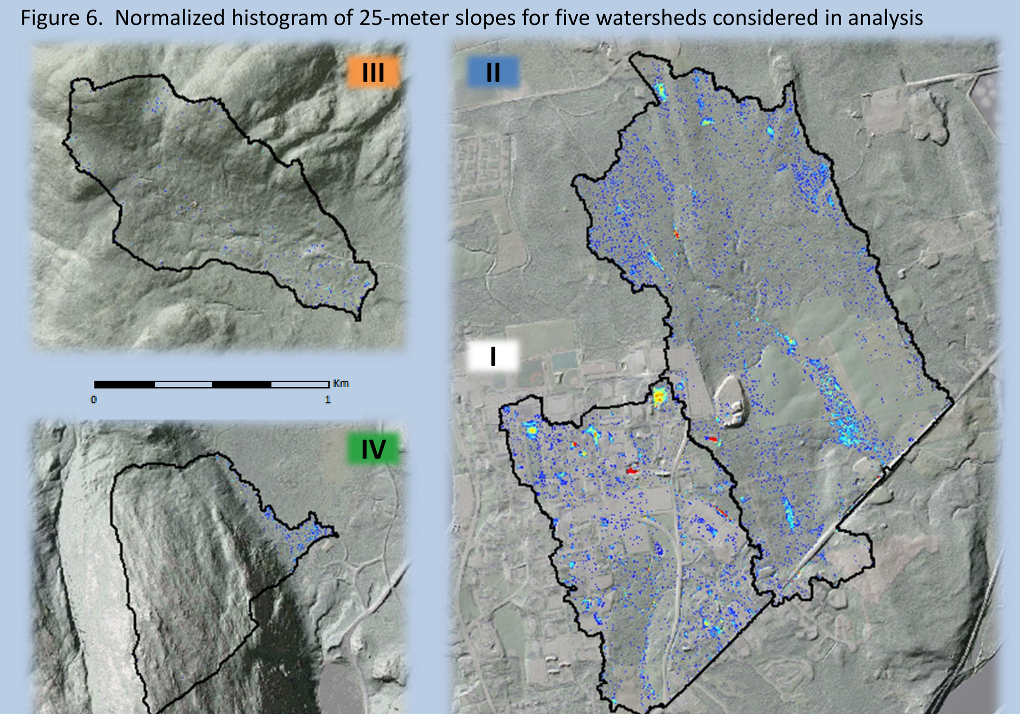


Figure 6. Normalized histogram of 25-meter slopes for five watersheds considered in analysis



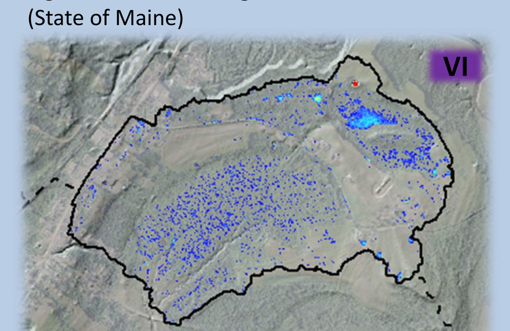


Figure 8. Hillshade maps of study watersheds with potential storage depth overlaid (light blue to red)

Watershed Name	Location	General Setting	Relief	Dominant Land Cover(s)	Avg Storage Depth	Notes
I. "Campus"	Marsh Is., Orono	River Island	Low	Developed	-	Extensive subsurface storm-water management ***Excluded from Analysis***
II. "Field"	Marsh Is., Orono	River Island	Low	Evergreen, Mixed Forest	4.78 mm	Relatively undeveloped neighbor of "Campus" watershed.
III. "Bear"	East Hancock	Mountainside	High	Deciduous Forest	0.16 mm	Bear Brook research watershed. DEM is interpolated from 1m LiDAR DEM (see Discussion)
IV. "SdM"	Bar Harbor	Mountainside	Very High	Mixed Forest, Shrub/Scrub	0.61 mm	Storage overwhelmingly in Great Meadow near Sieur de Monts spring
V. "DMC"	South Bristol	Coastal	Low-Mod.	Forest, Hay/Pasture	0.67 mm	On campus of Darling Marine Center
VI. "Laud"	Wells	Coastal	Very Low	Hay/Pasture, Woody Wetland	2.73 mm	Within Webhannet River watershed; eastern uplands incl. portion of Wells Reserve at Laudholm

Table 1. Basic site description of watersheds

Terrain-Storage Correlations

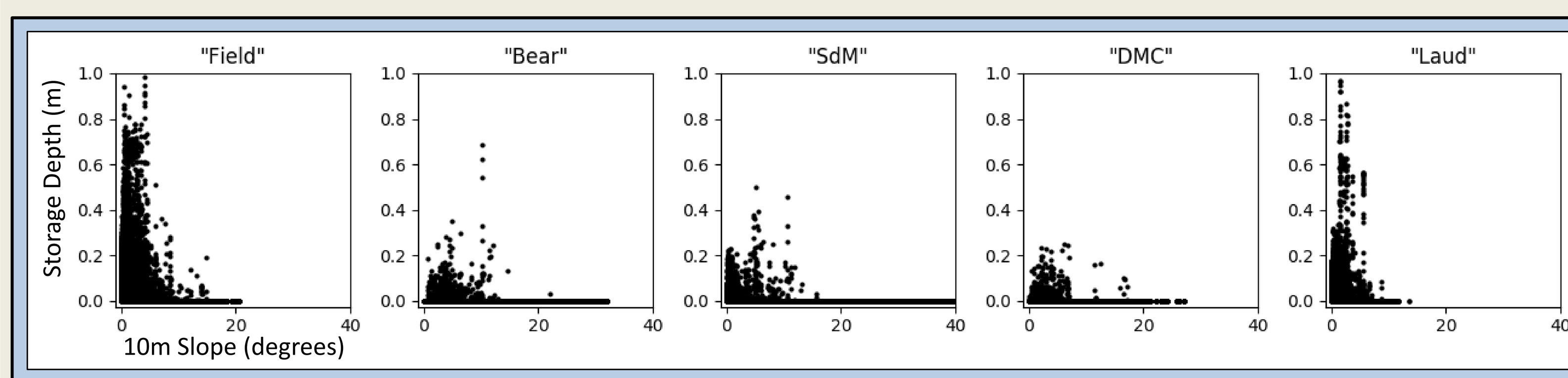


Figure 9. Scatter plots of Storage Depth vs 10m Slope for watersheds

Of fillable surface depressions across all test watersheds:
- 96% occur where 10m Slope < 3°
- 92% occur where 10m TPI < 0
- 88% occur where both 10mTPI < 0 & 10mSlope < 3°

However:
- 83% of all cells where 10mTPI < 0 & 10mSlope < 3° have zero surface depressions

Low slope and negative TPI appear to be necessary but not sufficient conditions for the occurrence of microtopographic depressions.

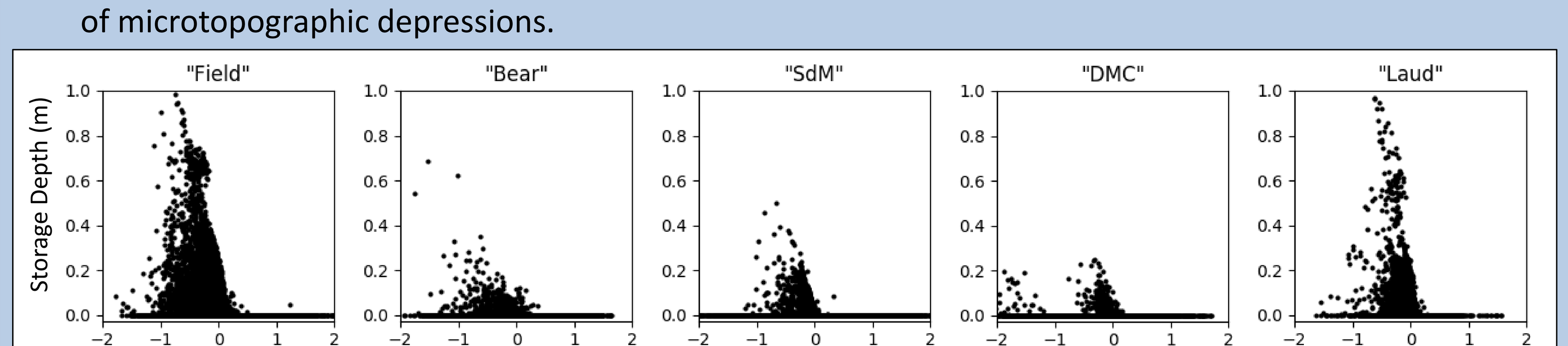


Figure 10. Scatter plots of Storage Depth vs 10m TPI for watersheds

Land Cover and Soils

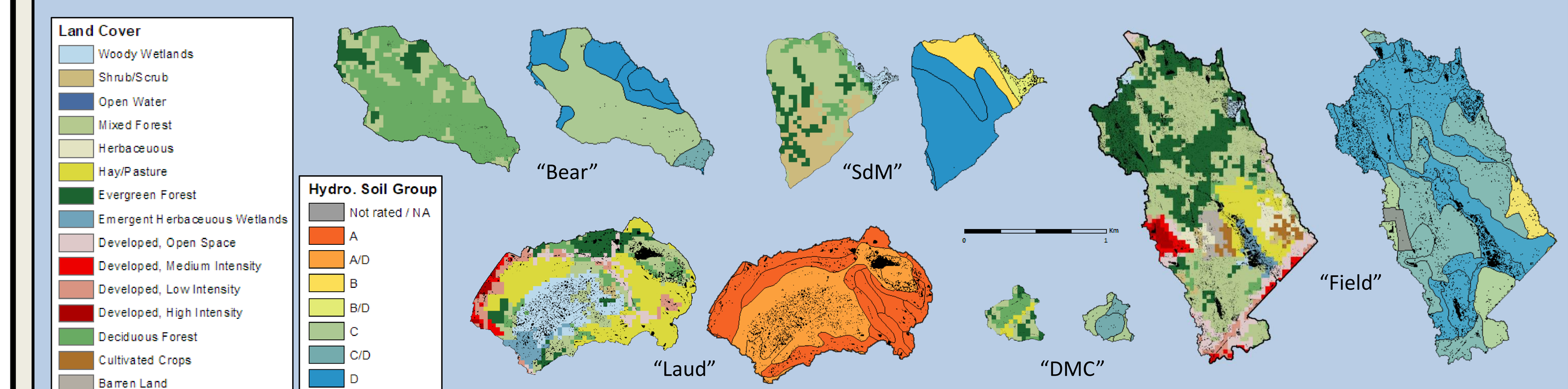
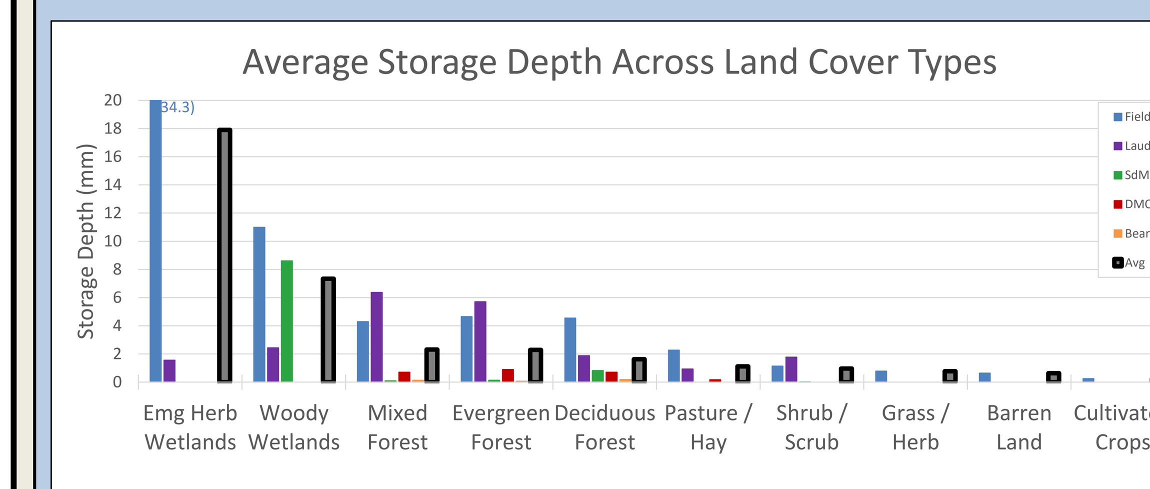


Figure 11. NLCD Land Cover (left) and NRCS Hydrologic Soil Group (right) for each watershed, storage overlaid in black



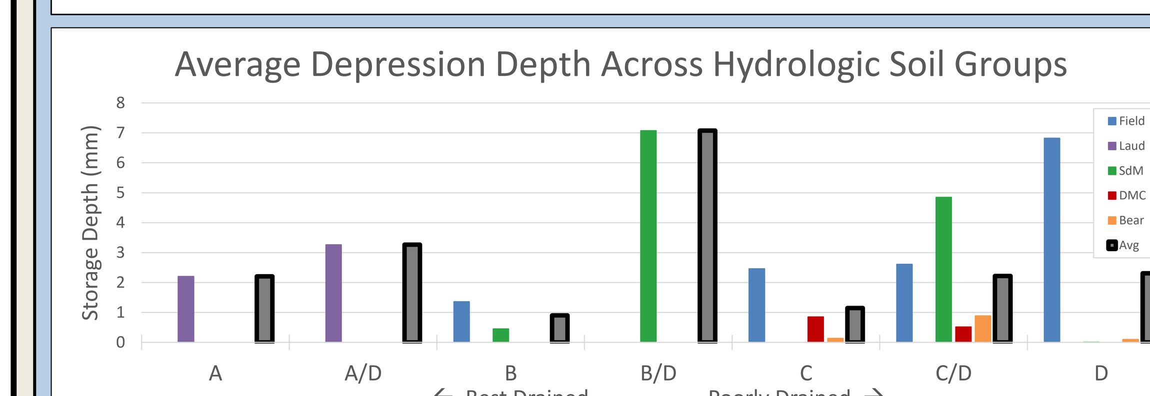


Figure 12. Bar charts of average potential storage across Land Cover types (top) and Hydrologic Soil Groups (bottom)

Among non-developed, upland (non-wetland) land cover types, depression storage decreases from forest cover types through pasture, grass, and finally cultivated cropland as humans increasingly smooth out microtopographic features.

No clear trend exists in average potential storage depth across hydrologic soil groups. It is important to note, however, that soil characteristics, particularly infiltration capacity, are key in determining whether surface water storage will actually occur in depressions during rain events.

Discussion

Unexpected Results

Slope and TPI showed surprisingly little predictive power for storage. Future work will focus on identifying additional predictive factors, likely beginning with forest cover type.

"Bear" watershed produces notably low potential surface storage in this analysis, even given its relatively steep slopes. Unlike the other four watersheds, for which 2m LiDAR DEMs were already available, the 2m DEM for "Bear" was created from an existing 1m LiDAR DEM.

"Field" watershed generated relatively high storage depths for developed cover types (not shown in chart). It is generally accepted that surface storage decreases with development, as surfaces are smoothed and drainage measures are installed. It is likely that these may be spurious / due to artificial fills that were missed, compounded by the small areal extent of developed area. Field checks will be required.

Implications

Knowledge of the location and extent of microtopography and related surface storage is important for accurately modeling the hydrologic response of a landscape during precipitation events. Pit features intercept overland flow, channeling it into shallow subsurface flow or holding it as surface storage, to evaporate or infiltrate later. This natural state results in a drawn-out, less "peaky" hydrograph downstream.

As humans remove forest and smooth the landscape, this storage capacity is diminished (Figures 3, 12, 13). In 465-acre "Field" watershed, converting all forested land to "pasture/hay" type would remove on the order of $3000 m^3$, or almost 800,000 gallons, of potential surface storage.

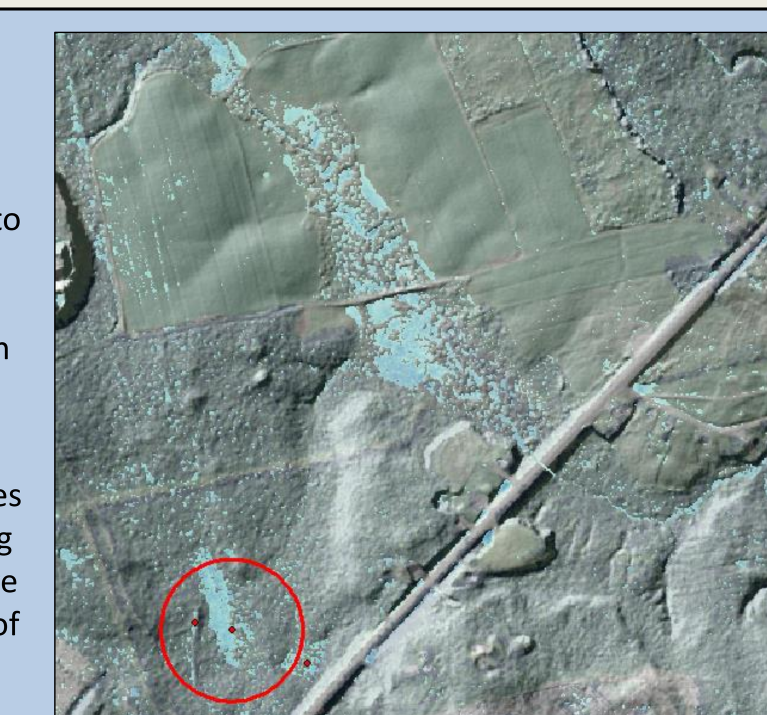


Figure 13. Lower end of "Field" watershed, with vernal pools (circled)

Beyond hydrology: Methods used to locate microtopographic pit fills could also be useful for locating larger depressions, such as vernal pools and other key habitat areas (Figure 13).

References: [1] Brubaker et al. (2013); [2] Pawlik (2013); [3] Roering et al. (2010); [4] Weiss (2001)