REDEFINING FOREST STOCKING IN THE NEW JERSEY PINELANDS: FOREST EVAPOTRANSPIRATION, UNDERSTORY LIGHT AVAILABILITY, AND A QUANTITATIVE FRAMEWORK TO BALANCE CONTEMPORARY MANAGEMENT GOALS

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ABSTRACT OF THE DISSERTATION
Redefining forest stocking in the New Jersey Pinelands:
forest evapotranspiration, understory light availability, and a quantitative framework to
balance contemporary management goals
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In establishing the Pinelands National Reserve, the United States Congress and the
Legislature of the State of New Jersey articulated the primacy of protecting the forests,
water resources, and rare species of this region. Though largely successful in preventing
active losses from development, these legal protections and their cultural effects have
coincided with significant passive changes to the condition of the region’s natural
resources. We sought to develop a quantitative framework for these pitch pine (Pinus
rigida) forests to relate forest condition to the stated goals for the land. We evaluated the
effect of forest attributes and management on evapotranspiration (ET), the effect of forest
occupancy on light availability and survival of open woodland understory plants, and
developed a density management diagram (DMD) for pitch pine. ET was higher in stands
with more pine and a more closed canopy; management also reduced ET: Regeneration
harvests caused a greater and longer reduction than thinning, while prescribed burns
caus ed a short and small-to-nonsignificant reduction in ET. There was a nonlinear
relationship between stand density index (SDI) and understory light availability that was
best described by the Michaelis-Menten equation. Our fitted Michaelis constant was
equal to 1/3 of a published maximum stand density index for pitch pine, corresponding well with the theoretical onset of full site occupancy. We were able to describe upper thresholds of stand density index for survival of some of the open woodland understory species, which were mostly eliminated around SDI = 230. Our DMD can be used to illustrate the tradeoffs between live aboveground carbon mass, habitat suitability for open-canopy species, risk of southern pine beetle outbreak, crowning index, and ET. Much of the pine forests of the Pinelands are nearing the maximum size-density boundary, which places the aboveground live carbon pool at greater risk of loss from southern pine beetle and wildfire, reduces the available habitat for open-canopy species, and reduces groundwater recharge. We propose the opportunity to manage forest density on the landscape for multiple concurrent objectives and emphasize that maximizing aboveground live carbon comes with decreased stability from density-dependent threats.
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1: Section I: Overview

New Jersey’s outer coastal plain landscape is dominated by the Pinelands ecosystem.

Today, this forest is largely composed of pitch pine (*Pinus rigida*), with components of shortleaf pine (*P. echinata*), black oak (*Quercus velutina*), white oak (*Q. alba*), chestnut oak (*Q. prinus*), post oak (*Q. stellata*), southern red oak (*Q. falcata*), scarlet oak (*Q. coccinea*), sassafras (*Sassafras albidum*), and Virginia pine (*P. virginiana*) in the uplands. Lowlands are also composed largely of pitch pine, with sizeable fractions of Atlantic white cedar (*Chamaecyparis thyoides*), red maple (*Acer rubrum*), and blackgum (*Nyssa sylvatica*). Excessively-drained uplands grade down into poorly drained lowlands, with often-gradual transitions in plant community composition determined by the depth to the water table (Laidig et al., 2010). The pinelands constitute the northern terminus of the coastal plain pine ecosystem (McNab et al., 2007) as well as the largest concentration of pitch pine in its range. In the United States, pitch pine extends from Georgia and Kentucky to Maine, but it rarely achieves dominance. The exception is in pine barrens communities like those of southern New Jersey, Long Island, New York, Cape Cod, Massachusetts.

In some ways, the forests of the Pinelands have been relatively stable for thousands of years, in that there has been a constant interaction between pine/oak forests and human interests. Pollen profiles establish that *Pinus* and *Quercus* have been dominant tree genera on the New Jersey Coastal plain throughout the Holocene (Buell, 1970; Florer, 1972; Potzger, 1952), and for much of the Oligocene and Miocene (Kotthoff et al., 2014), though it is not likely that the same species within these genera have been dominant throughout. Similarly, humans have been present on the coastal plain of New Jersey for at least 10,000 years (Chesler, 1982; Regensburg, 1978), and for that time our species has been witness to and a contributing factor in the condition of that landscape. Evidence of fire on the landscape can be found in pollen cores (Potzger, 1952) at their earliest dates of circa 8,000-10,000 years (Buell, 1970), and widespread evidence of purposeful indigenous use of fire was noted by early European accounts (Stewart, 2002).
Upon settlement by Europeans, the coastal plain forest was repeatedly consumed for timber, fuel, naval stores, and other uses (Muntz, 1959). As early as 1748 Peter Kalm noted that the area around Philadelphia exported prodigious quantities of goods to England, and decried the condition of the state’s forests:

“...They send both West India goods, and their own productions to England; the latter are all sorts of woods, especially black walnut, and oak planks for ships; ships ready built, iron, hides, and tar. Yet this latter is properly bought in New Jersey, the forests of which province are consequently more ruined than any others.” - Peter Kalm, 1748

Subsequent to Kalm’s observations a limonite-based iron industry was established in the pines. At its peak, as much as half of the forest acreage of the Pinelands was in a harvest rotation to supply fuel for the iron industry (Pierce, 1957). Though the industry eventually collapsed due to competition and a shortage of fuel, the Pinelands forests still experienced widespread anthropogenic pressures through harvest to support the Industrial Revolution in and around the state (Muntz, 1959). Neglect of silvicultural planning left the landscape in a generally young and heterogeneous condition, with all areas having been clearcut multiple times (Little, 1978).

After 300 years of continuous and intensive use, sparks of interest in conservation began to compete with sparks from railroad fires. Early conservation efforts emphasized ‘protection’ of the resource to limit the damaging effects of fire, enhancement of forest productivity, and management of the forest to provide water resources (Pinchot, 1899; Vermuele, 1900). Clearly, the historical goals for which the state legislature established the New Jersey Forest Park Reservation Commission were not so very different with the management goals of society today.

New Jersey’s 21st century objectives for the forest can be determined by looking at the legal and cultural institutions that have arisen in relation to society’s needs. Title 13 of the New Jersey Statutes Annotated instructs the executive branch through the structure of several state agencies to work towards a number of natural resource goals, including:


5. Providing technical support for other forest owners in efficient utilization of wood products (NJ Revised Statute § 13:1L-15 (2013))


7. Utilizing state forest wood resources (NJ Revised Statute § 13:1L-13 (2013))


Within the statutes there are other authorities granted to the Department of Environmental Protection pertinent to Pinelands landscapes, including but not limited to:

11. Protecting and enhancing populations of rare wildlife via the Endangered and Nongame Species Program (NJ Revised Statute § 23:2A-2)

12. Assuring the supply of water (NJ Revised Statute § 58:1A-5)

13. Prohibiting the transport of Pinelands water outside of the Pinelands (NJ Revised Statute § 58:1A-7.1)

Further, the Pinelands Protection Act explicitly calls out the forests and water resources of the landscape, as well as the biodiversity of the land as being critical resources (Pinelands Commission, 1979). As our society attempts to deal with climate change, new efforts are being discussed at multiple levels and across multiple jurisdictions to use the forest for carbon sequestration (Angarone et al., 2021). Finally, the proliferation of 501c-3 non-profit organizations devoted to environmental issues, particularly in the Pinelands, reflects a growing
interest in satisfying the social-emotional needs of the voting public. Clearly, there are a wide suite of goals for this forest, and management to achieve such diverse goals is an exercise in balance.

This dissertation is an attempt to examine the tradeoffs associated with some of those interests and to place them in a quantitative framework. We choose to examine two specific management concerns, casting them in a wider context: the effects of forest composition, disturbance, and structure on forest evapotranspiration, and the effects of forest site occupancy on habitat for open-canopy woodland plant species.

Water yield and quality is cited as far back as the 19th century as a concern for the Pinelands region. Evapotranspiration is the largest component of the water budget of the landscape, and changes to the forest over the preceding decades and century are manifest. Our first study seeks to connect the composition of the forest to the water budget, as well as to parameterize the intensity and duration of hydrologic changes resulting from forest management activities.

Our second study combines an examination of light availability as a function of forest occupancy and a determination of the thresholds for occurrence of open canopy taxa. Several conservation groups have called for restoration of a more open forest condition, citing scarcity of habitat for those species that thrive on disturbance. While advancement of these general objectives is worthwhile, it is of great importance to define the conditions that make such habitats. We seek in this study to first determine the relationship between forest occupancy and understory light availability, to determine the specific thresholds for the occurrence of open-canopy ground-level plant taxa, and to use instances of those taxa to validate modeled thresholds for plant survival. In this way we seek to define shade intolerance for indicator open-canopy plants, in the hope that knowledge of thresholds for their survival enables management to support them.
Our third study is an effort to develop a density management diagram (DMD) that describes pitch pine forests using forestry biometric methods. While these have been developed for species and forests where commercial products are a major consideration, the lack of economic attention to pitch pine has prevented the development of these sorts of tools for pinelands forests. DMDs are not restricted to commercially pertinent attributes like stand volume and height growth; several have been developed specifically for wildlife habitat and other objectives. We seek to place locally germane management objectives onto the DMD we create for pitch pine so that the tradeoffs inherent in local management concerns are clear to policymakers, decision makers, and land managers. This includes fire risk, live aboveground carbon mass, effects of forest stand attributes on evapotranspiration, and other forest traits.

The last section is a discussion of the implications of the different sections. It is our hope that through these studies we can improve the scientific and technical understanding of the pitch pine forest of southern New Jersey, as well as to characterize the consequences of both action and inaction.
2: Section II: The Effects of Forest Composition and Management on Evapotranspiration in the New Jersey Pinelands

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Abstract

Forests have contrasting roles in ecosystem services with relation to water, both provisioning it through filtration and recharge, and consuming it through evapotranspiration. Understanding forest evapotranspiration is critical for landscapes purchased and managed for the social benefits of their water provisioning ecosystem services. We used the flux disaggregation algorithm for the Atmosphere-Land Exchange Inverse model (DisALEXI) to characterize landscape-scale evapotranspiration over the forested coastal plain Pinelands of southern New Jersey, USA. We examined changes in evapotranspiration due to forest compositional and cover differences, then evaluated the effects of three common management actions (thinning, seed tree regeneration, and prescribed burning) on stand evapotranspiration. Upland oak forests had the lowest annual evapotranspiration, while Atlantic white cedar had the highest. In uplands, increasing proportions of conifers increased evapotranspiration, as did increased canopy cover. Seed tree harvests reduced evapotranspiration for about 13 years, while thinning reduced forest water use for roughly 5 years. Prescribed fires had variable effects, but their typical application did not reduce evapotranspiration for a complete growing season. Our research can help to inform decision-making about managing this or other forests for water yield.
2.1 Introduction

Forests are the dominant source of water yield across the United States (Brown et al., 2008; Sun et al., 2015) and have long been recognized for their critical role in water provisioning. Precipitation falling on a forest soil not only works its way downstream for human or ecosystem use but is also consumed by forest vegetation through evapotranspiration (ET). In the Pinelands of the southern coastal plain of New Jersey, ET is the largest component of the water budget (Clark et al., 2012; Sloto and Buxton, 2005; Walker et al., 2011), and it is a dominant factor in water budgets wherever natural vegetation includes forests. Even in the densely-populated human landscape of New Jersey, forest still covers 40% of the land area (Crocker et al., 2017), so understanding forest ET is a critical component of water planning.

Management of the natural resources of the Pinelands is currently dictated by multiple resource priorities. There are federal and state laws that dictate specific goals for the land (Public Law 95-625, Title V § 502, 1978; NJSA 13:18A et seq. 1979; NJSA 23:2A et seq. Endangered and Nongame Species Act; NJSA 13:9B et seq. Freshwater Wetlands Protection Act; NJSA 13:1B-15.5 Establishment of State Natural Areas), and those intersect with policies from various government agency jurisdictions, including those of municipal governments (Galloway, NJ, Revised Ordinances § 233-52 (2006)), county governments, and even different agencies within state government (NJAC 7:7A Freshwater Wetlands Rules; NJAC 7:13 Flood Hazard Area Control Act Rules; NJAC 7:19 Water Supply Allocation Permit Rules; NJSA 13:1L-16 Forest Fire Protection). Given the overlapping purview of these human factors, as well as the intersection of drivers of these natural systems themselves, management actions should ideally attempt to balance a variety of tradeoffs.

For data-driven decision-making, it is important to constrain the parameters of ecosystem services. Forest hydrologists have long sought to connect forest management to water yield (Douglass and Swank, 1972), with implications for the seasonality of flow, concern for the effects of flow changes on stream habitat, and for downstream human water use. Reductions in forest
stand ET resulting from varying management applications have been observed previously (Bosch and Hewlett, 1982; Stednick, 1996) and have been used in predictive modeling for water yield management (Sun et al., 2016, 2015). Models and policies that attempt to account or manage for ecosystem services should be sensitive to the hydrologic behavior of different forest disturbance events. Along with managing for carbon storage (Griscom et al., 2017) interest in water will be a major driver in this century of how societies manage their forest resources (Vose et al., 2011), and ET is an essential metric for understanding both forest carbon allocation and water resources.

Remote sensing can provide fine-grained spatially-continuous geospatial information on ET that is not possible with other methods. Flux towers provide measurements over a relatively small area and are capital intensive. Basin gauges integrate data over areas that may exist at a broader scale than the phenomenon of interest, introducing additional measurement variability. Sap flux measurements can evaluate transpiration from single trees, but must be corrected for the contributions of understory, interception, and evaporation (Ford et al., 2007). These factors make remote sensing-derived ET an attractive alternative for examination of processes that continuously vary across the landscape.

To date, most remotely sensed ET products have provided information at coarse spatial resolution on the order of kilometers using moderate resolution sensors like MODIS (Running et al., 2017) or GOES (Anderson et al., 2007). These sensors provide fine-scale temporal resolution (hourly to daily) but are too spatially coarse to characterize all but the most extensive forest stands. In contrast, Landsat-scale spatial resolution (30m) provides data that can be examined at the scale of a forest patch, enabling investigation of details such as the behavior of different species, forest inventory attributes, and other fine-scale traits. However, the temporal resolution of Landsat (8-16 day revisit interval) may be too infrequent to capture seasonal and management-induced changes in ET, particularly in cloudy regions.

In this study we use a data fusion method that combines the temporal characteristics of moderate resolution sensors with the fine spatial detail of Landsat to create daily ET products at
30m resolution. ET estimates from both sensor classes are obtained from the disaggregated Atmosphere-Land Exchange Inverse (DisALEXI, Norman et al., 2003) surface energy balance algorithm, driven primarily by thermal-infrared remote sensing estimates of land-surface temperature. Thermal methods are particularly advantageous for ET monitoring because of their sensitivity to the relationship between transpiration, vegetation health, and canopy temperature. The DisALEXI data fusion approach has been successfully applied in agricultural landscapes (Cammalleri et al., 2013; Semmens et al., 2016) as well as forests (Yang et al., 2020, 2017) to characterize fine-scale ET.

Our intent in this study is to use this ET data fusion system to provide hydrologic decision support for forest and water management. The New Jersey Pinelands are a good testbed for demonstrating the value of isolating the effects of management on ET. This region is underlain by an unconfined aquifer, blanketed in forest, ostensibly managed for a balance of ecosystem services, and has a well-documented history. Here, we seek to examine how forest composition affects ET and to describe the effects of land management actions on forest ET.

We hypothesized that forest ET in this area is related to both forest type and cover, with wetlands using more water than uplands, evergreen conifers using more water than deciduous species, and closed-canopy forests using more water than open-canopy forests. We expect the impact of forest management on ET would be related to the intensity of and time since most recent disturbance rather than to forest age. We expected that regeneration harvest should yield the largest dip in ET rates and the longest recovery period, by virtue of near-total removal of leaf area; forest thinning should cause an intermediate dip with an intermediate length of recovery, and prescribed fires should have the smallest effect with the shortest time to return to pre-fire ET.

2.2 Materials & Methods

2.2.1 Study Area

The study site covers the central and northern portions of New Jersey’s Coastal Plain physiographic province, within the Atlantic Coastal Pine Barrens Ecoregion (Woods et al., 2007)
(Figure 2-1). This area is characterized by warm, humid summers and moderately cold and occasionally snowy winters (Runkle et al., 2017). The dominant land cover is forest, much of which is jurisdictionally located within the Pinelands National Reserve. Most of the forest in the area is publicly owned (Crocker et al., 2017; Hewes et al., 2014). Thirty-year (1981-2010) mean annual precipitation for the county covering the largest portion of the study area is 1148mm. January mean temperature is 0.2 °C, and July mean temperature is 24.4 °C.

Like other areas of southeastern coastal plain pine forests, both upland and wetland forests are dominated by southern yellow pine species. While pitch pine (*Pinus rigida*) is dominant, shortleaf pine (*P. echinata*), Virginia pine (*P. virginiana*), black oak (*Quercus*
velutina), white oak (Q. alba), chestnut oak (Q. prinus), post oak (Q. stellata), and associated species are also found throughout the upland area. Transitional and seasonal wetlands are dominated by pitch pine, with wetter sites occupied by Atlantic white cedar (Chamaecyparis thyoides), red maple (Acer rubrum), and blackgum (Nyssa sylvatica). Ericaceous shrubs are extensive throughout both uplands and wetlands, with Vaccinium and Gaylussacia genera dominant.

Soils of the region are sandy, with excessively drained uplands. The Kirkwood Cohansey Aquifer, a subset of the wider Potomac-Raritan-Magothy regional aquifer, underlies much of the study area. Inputs to this aquifer come through the sandy, well- to excessively-drained upland soils of the region. The water budget is dominated by evapotranspiration, with precipitation that is not consumptively used going mainly to groundwater recharge (Sloto and Buxton, 2005; Walker et al., 2011).

2.2.2 DisALEXI Model
The DisALEXI model is derived from the broader-scale ALEXI model (Anderson et al., 1997), a spatial version of the Two-Source Energy Balance developed by (Norman et al., 1995). The two-source aspect partitions surface fluxes into vegetation and soil components. ALEXI applies the two-source energy balance at a coarse spatial resolution (GOES imagery scale, 4km) twice over a time-differential to determine a time-integrated sensible heat flux to the atmosphere, allowing the surface energy budget to be closed (Anderson et al., 2007). Spatial disaggregation of DisALEXI is achieved by running the two-source energy balance model at higher spatial resolution using finer-scale thermal and vegetation-fraction data (Gao et al., 2012; Norman et al., 2003). This is iteratively aggregated and compared to the broader ALEXI pixel scale and adjusted until the fine-scale fluxes are consistent with the broader-scale fluxes. To achieve Landsat-scale resolution, DisALEXI is run at both the MODIS and Landsat scale; on dates when it is possible to run the fine-scale DisALEXI model, the paired fine-scale data and moderate-scale
data are used as training sets for temporal and spatial gap filling using the Spatial and Temporal Adaptive Reflectance Fusion Model (Gao et al., 2006). The fine scale results are validated using local flux tower data; for this study we used the Silas Little Experimental Forest flux tower data, operated by the USDA Forest Service within Brendan T. Byrne State Forest (Clark, 2016). The steps used here to construct the ET model are detailed in Yang et al. (2017).

The DisALEXI model has been successfully used to characterize partition the energy budget in agricultural landscapes (Anderson et al., 2012; Semmens et al., 2016), grasslands (Norman et al., 2003), and southeastern coastal plain pine ecosystems (Yang et al., 2020, 2017). In the latter the total annual difference between flux-based measurements of ET and the model-derived estimates was <1%. Nevertheless, our efforts in the study landscape did not include additional local model validation to quantitatively determine the relationship between flux measurements from the eddy covariance technique and the DisALEXI-derived values beyond the visual agreement in Figure 2-2. Disagreement between these datasets does not necessarily imply that the remote-sensing based approach is inaccurate, however. For one, the size and location of the contributing area to the eddy covariance-measured fluxes varies with windspeed and direction (Burba, 2013). Such variation introduces discrepancies in the comparison with remote sensing-derived values of ET based on the choice of which pixels to include in the comparison. Some of this variance can be mitigated by integrating over greater lengths of time. Additionally, although eddy-covariance data can produce high-quality measurements of fluxes like evapotranspiration, they are still subject to limitations. For instance, characterizing ET through eddy covariance commonly requires gap-filling for timesteps when atmospheric conditions produce low-quality measurements, violate assumptions of the instrumentation, and when instruments fail. Despite a diversity of empirical approaches for gap-filling, it still introduces additional error (Moffat et al., 2007) that may disagree with true values and other methodologies. Considering these inherent discrepancies between ET observations of different types, as well as prior validation of the DisALEXI model in similar landscapes, we anticipate future efforts to corroborate the model
estimates of ET with those from flux towers will support our analyses even if there are discrepancies due to systematic biases.

2.2.3 Forest Inventory Data

Forest inventory data were collected from 2017-2019 in Wharton and Penn State Forests as part of New Jersey Forest Service’s process for developing forest management stewardship plans. For each of these three years a contractor measured 2000 inventory plot clusters, each with nested plot measurements to assess the plant community at different scales and resolutions: (a) a variable-radius overstory plot, (b) a 1/50th acre fixed area advanced-regeneration plot, and (c) a 1/500th acre fixed area ground-cover plot. The inventory plots were distributed among forest types identified by NJFS through heads-up digitization, where the number of plots were allocated among different forest types to achieve smaller sampling error in basal area estimates.
Plot clusters were allocated amongst the forest types to minimize type-level variance in basal area per acre, as predicted from an overstory pre-cruise conducted in the same area. For overstory plots in the Atlantic white cedar type, the contractor used a basal area factor (BAF) – 30 (ft²/acre), but for all other overstory plots the contractor used BAF-10 (ft²/acre). This was done to maintain the scale of plot-level sample variance, as Atlantic white cedar stands in the New Jersey Pinelands typically achieve basal areas that are more than triple the basal areas of adjacent uplands. All plots were located in Wharton State Forest and Penn State Forest, both owned by the New Jersey Department of Environmental Protection, and are under the management of the Division of Parks and Forestry.

Plot clusters were considered ‘pure’ when 80% of the total live basal area for the plot cluster was occupied by the proportions of the species in the type (Table 1). For example, a plot cluster would be labeled ‘pure pine’ if the sum of the basal area of pitch pine, shortleaf pine, Virginia pine, and loblolly pine was equal to or greater than 80% of the total living basal area for all species on the plot. For the purposes of this analysis, white pine was not counted towards the relative basal area of pines, as we were more interested in the behavior of more abundant southern yellow pines.

Table 1: Overstory tree species in typic Forest Types

<table>
<thead>
<tr>
<th>Forest Type</th>
<th>Atlantic White Cedar</th>
<th>Swamp Hardwood</th>
<th>Pine</th>
<th>Oak</th>
</tr>
</thead>
<tbody>
<tr>
<td>Species</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Atlantic White Cedar (Chamaecyparis thyoides)</td>
<td>Atlantic White Cedar (Chamaecyparis thyoides)</td>
<td>Red Maple (Acer rubrum)</td>
<td>Pitch Pine (Pinus rigida)</td>
<td>Black Oak (Quercus velutina)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Blackgum (Nyssa sylvatica)</td>
<td>Shortleaf Pine (P. echinata)</td>
<td>White Oak (Q. alba)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Sweetbay Magnolia (Magnolia virginiana)</td>
<td>Virginia Pine (P. virginiana)</td>
<td>Chestnut Oak (Q. prinus)</td>
</tr>
<tr>
<td></td>
<td>Gray Birch (Betula populifolia)</td>
<td>Lobolly Pine (P. taeda)</td>
<td>Post Oak (Q. stellata)</td>
<td>Southern Red Oak (Q. falcata)</td>
</tr>
</tbody>
</table>
A summary of forest type attributes can be found in Table 2. Overstory summary data included basal area per acre (ft²/ac), trees per acre, quadratic mean diameter (QMD), and Stand Density Index (SDI). Forest attributes were similar across vegetation types, other than for Atlantic white cedar. Relative density (current Stand Density Index / maximum theoretical Stand Density Index) was calculated using the methods in Dixon and Keyser (2019).

Table 2: Inventory plot characteristics by plot type grouping. Means (standard deviations)

<table>
<thead>
<tr>
<th>Forest Type</th>
<th>Basal Area (m²/ha)</th>
<th>Trees per Hectare</th>
<th>Stand Density Index (SDI)</th>
<th>Relative Density Index (SDI/SDIₘₐₓ)</th>
<th>Quadratic Mean DBH (cm)</th>
<th>Canopy Height (m)</th>
<th>Median Age (years)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Atlantic White Cedar</td>
<td>54.0 (29.0)</td>
<td>1295 (959)</td>
<td>398 (231)</td>
<td>0.52 (0.30)</td>
<td>25.9 (11.1)</td>
<td>16.5 (4.6)</td>
<td>91 (30)</td>
</tr>
<tr>
<td>Swamp Hardwood</td>
<td>20.7 (9.9)</td>
<td>581 (427)</td>
<td>163 (80.0)</td>
<td>0.38 (0.18)</td>
<td>24.4 (8.8)</td>
<td>15.0 (3.5)</td>
<td>83 (32)</td>
</tr>
<tr>
<td>Lowland Pine</td>
<td>24.4 (11.9)</td>
<td>873 (595)</td>
<td>209 (102)</td>
<td>0.42 (0.21)</td>
<td>20.9 (6.1)</td>
<td>13.5 (3.5)</td>
<td>70 (27)</td>
</tr>
<tr>
<td>Upland Pine</td>
<td>22.1 (8.4)</td>
<td>691 (456)</td>
<td>184 (75.0)</td>
<td>0.38 (0.15)</td>
<td>22.2 (5.3)</td>
<td>14.2 (2.8)</td>
<td>75 (26)</td>
</tr>
<tr>
<td>Oak</td>
<td>17.5 (5.9)</td>
<td>513 (345)</td>
<td>143 (49.6)</td>
<td>0.38 (0.13)</td>
<td>23.0 (6.1)</td>
<td>15.4 (2.9)</td>
<td>84 (24)</td>
</tr>
</tbody>
</table>

2.2.4 Land Use 2015 Dataset

We used the New Jersey Department of Environmental Protection’s (NJDEP) Land Use/Land Cover of New Jersey 2015 (LULC15) dataset (New Jersey Department of Environmental Protection, 2019) to sample and later stratify the DisALEXI model outputs. This dataset is the latest in a series commissioned by NJDEP’s Bureau of Geographic Information Systems to represent the landscape of New Jersey. The LULC15 data uses a modified hierarchical Anderson Land Use code to designate different cover types, with general cover designations for
forest. An example of the dataset beside a DisALEXI model output can be found in Figure 2-3.

Figure 2-3: Comparison of land use, 2016 annual evapotranspiration, and aerial imagery for a selected area in Wharton State Forest.
2.2.5 Forest Management Data

Forest management cutting history was reconstructed from NJFS activity records, aerial images, field reconnaissance, and consultation with private-lands foresters. We digitized polygons around each management activity using contemporaneous aerial imagery; prior to the 1990s there was approximately one set of images per decade, with at least two sets each decade since. We matched the paper records and the appearances of the sites in aerial images to determine the type of forest management that occurred for each polygon, although for many activities, the evidence of prior management can be witnessed through current stand structure. For instance, seed trees left from old cuts can today be found amidst their own offspring, made obvious by their drastically different crown architecture, height, and girth. Though there was significant diversity in the intent and execution of silvicultural prescriptions applied, some treatments were more common than others. Most regeneration treatments were seed tree harvests, and most intermediate treatments designed to increase accrual (not ingrowth) were considered to represent applications of thinning rather than other management techniques (like selection harvests). Clearcuts (meant to regenerate a new stand), clearings (intentional and permanent conversion to a non-forest land cover type), selective harvests, and shelterwoods were also recorded, though there were too few of these or they occurred too far in the past to make inferences about ET recovery patterns immediately following management. Since 1958 there have been 89 seed-tree harvests and 55 thinning events for which we had records in the study area. After removing pixels for which there had been multiple types of closely timed disturbance events, we had data for analysis on 71 seed tree harvests and 43 thinning events, yielding 10,077 and 8,227 pixels respectively.

Records of prescribed burns and wildfires were obtained from the New Jersey Forest Fire Service for the years 2015-2017. For prescribed burning records prior to 2015, we located & digitized burns using a combination of Landsat imagery, aerial imagery, LiDAR, and available paper records. LiDAR-derived ground surface elevation data were useful to locate plow lines,
which are used in this region to assist in the deployment and control of prescribed fire; their presence indicates an area has been or will be burned. All burn prescriptions in southern New Jersey occurred between November 1 and March 31, during the dormant season. We recorded 616 instances of prescribed burning in the study area from 2001 through 2014, along with 166 areas provided by the NJFFS for 2015-2017. After removing pixels for which there had been multiple types of disturbance events, we were left with 63,572 pixels for analysis across 113 different events (for 2015-2017) to characterize prescribed burning.

Other disturbances were noted but not analyzed for their effects on ET, but they were used to screen for overlapping disturbance events. These included wildfires, gypsy moth defoliation, and southern pine beetle mortality. Wildfire data were obtained from the New Jersey Forest Fire Service, while the insect pest data were extracted from the USDA Forest Service Damage Causing Agent data (USDA Forest Service, 2018).

### 2.2.6 Analyses

We filtered out pixels that had experienced additional recent disturbances so that overlapping events would have less influence in modelling. Pixels that had (in the prior 15 years) experienced other management activities or a wildfire were excluded, as were pixels that had (in the preceding five years) experienced a prescribed fire, damage caused by *Lymantria dispar* or *Dendroctonus frontalis*. Using the included data, we performed three sets of analyses:

1) Comparison of ET for Upland Forest Types from DEP Land Use 2015
2) Comparison of ET for five major forest types of NJ Pinelands from Inventory Data
3) Fit functions to the effect of different forest management actions on ET

#### 2.2.6.1 ET and Forest Inventory Points

We used forest inventory data collected for the New Jersey Forest Service to examine the five major forest types of the NJ Pinelands. There were three dominant wetland types in these
data: Atlantic white cedar forest, swamp hardwoods, and pine lowland, along with a pair of major upland forest types: upland pine, and upland oak.

For each inventory plot, we calculated the total live basal area of the type species for that forest type. Only plots where the typic species occupied more than 80% of total living basal area were considered in this analysis. Upland and lowland pine were distinguished by whether the inventory plot was located within an area demarcated as wetlands from the LULC15 data. From these groups and across four years of data, we used the LME4 package in R to fit a hierarchical mixed effects model to predict annual ET as a function of composition. We compared the AIC (Akaike Information Criterion), BIC (Bayesian Information Criterion), and residual variance of potential models to select the most appropriate model to describe ET as a function of composition.

2.2.6.2 ET and DEP LULC15

We selected upland forest types from the LULC15 dataset to examine the effects of composition and canopy cover on ET. There were four composition types in the dataset: Coniferous, Mixed (Coniferous dominated), Mixed (Deciduous dominated), and Deciduous. These categories were further subdivided into two canopy cover groupings (either 10-50% canopy or >50%). We evaluated a range of mixed-effect candidate models for the canopy cover and composition types on annual ET. As with the model selection process for the forest inventory points, we compared the AIC, BIC, and residual variance of potential models to select the most appropriate model to describe ET as a function of the land cover type.

For this analysis, only pixels within Wharton State Forest and Brendan T. Byrne State Forest were examined. The deciduous upland forest types on these properties are mainly oak-dominated with an ericaceous understory, making them distinct from other deciduous upland forests elsewhere in the inner coastal plain. This reduced some of the variance in the classes described in the Land Use data so that we could make Pinelands-specific comparisons.
2.2.6.3 ET as a Function of Management

We applied non-linear least squares models at different time steps to determine the behavior of forest ET in response to different types of management. Analysis was restricted to those activities that were frequent enough in the study area to have a sufficient sample size to enable modeling: seed-tree harvests, thinning, and prescribed burning. To account for annual differences in the magnitude of the water budget between years, as well as differences in ET between forest types, we performed a stratified standardization of annual pixel ET values (Figure 2-5). Strata were the cover types from LULC15 dataset. To ensure that the cover types corresponded to consistent physical forest types, we used only pixels over Wharton and Brendan T. Byrne State Forests to determine class-wise means/standard deviations. Forested pixels across the study area were standardized based on their Land Cover 2015 type. In this way, we were able to determine a pixel’s ET ‘divergence’ in standard deviations from the for that pixel’s type for a given time span. For thinning and seed tree harvests, we compared standardized annual ET to time since disturbance, while for prescribed fire we evaluated standardized daily, weekly, monthly, and annual ET. For most forest pixels, the DisALEXI data had missing values for about 7% of the dates. We filled these values by finding monthly average ET for each pixel, and gap-filling missing dates with the appropriate monthly average. With this gap-filling we calculated annual ET as the summation of ET for a calendar year for those analyses that used annual totals, but we did not use the gap-filled data for monthly, weekly, or daily analysis of prescribed fires.

From these data we fit a model of the form in equation (A) to describe the ET divergence due to management, using the ‘stats’ package for R:

\[
ET = \left( \frac{\beta_1}{1 + \exp(\beta_2(t - \beta_3))} \right) - 10
\]

(A)

where ET represents a pixel’s standardized evapotranspiration, \(\beta_1\) represents the maximum value of post-disturbance ET, \(\beta_2\) represents the slope of the recovery of ET post-disturbance, \(\beta_3\) represents the inflection point or time of most rapid recovery in ET, and \(t\) represents time in the units of the analysis. The offset (10) for ET was used to ensure that sign did not affect model
behavior when crossing zero. For each management activity, we pooled the data from all 4 years, drew a random 50% subsample of points, and recorded the model parameters, repeating this process 10,000 times. We used the resulting distribution for each model term to describe an overall effect of each management type. Prediction intervals were determined using the ‘propagate’ package in R.

To determine the duration of the effects on evapotranspiration, we used the model simulations to mark the point in time at which only 5% of the post-disturbance anomaly remained. From time = 0 to this endpoint, we calculated the integral of the model to determine the amount of water yield subsequent to the management activity. When the model’s maximum value ($\beta_1$) was less than 0, we calculated the integral below the maximum value, rather than to zero.

Figure 2-4: DisALEXI daily 30m Landsat-like ET (left) on May 16, 2016, and the same image standardized by class means/standard deviations from NJDEP LULC2015 classes (right). Non-forest is masked from the standardized ET on right and appears white. Wetlands are prominent features on the left, highlighting their elevated water consumption at this time of year. Upland pine forests with large components of planted white pines are distinct from wetlands in the standardized image, on right, adjacent to the north side of NJ Route 72.
2.3 Results

2.3.1 ET and DEP LULC15

A visual evaluation of the evapotranspiration model outputs along with the land use data can be found in Figure 2-2. Comparison of the patterns of ET (Figure 2-5) among the NJDEP Land Use 2015 upland forest types showed meaningful differences from composition and canopy cover. ET increased with increasing proportion of conifers, in both closed-canopy polygons (>50% canopy cover) and open-canopy polygons (10-50% canopy cover).

We used the following model to describe ET in these categories:

\[
ET = (1{\mid year}) + (1{\mid pixel}) + Forest Type + Canopy Cover
\]

where \( ET \) represents total annual evapotranspiration of a specific pixel in units of mm/year, \((1{\mid year})\) represents a random effect for the year of the observation, \((1{\mid pixel})\) represents a random effect for each pixel, \( Forest Type \) represents the first three digits of the land use code of the NJDEP Land Use 2015 data, and \( Canopy Cover \) represents the fourth digit, level of canopy cover. This model was a significant improvement upon the null and nested less-complex models (Table 3). Model effects and estimates can be found in Table 4.

Table 3: Likelihood ratio test for candidate models to predict annual evapotranspiration by selected Land Cover 2015 codes. Significance of *** indicates model significance at <0.001.

<table>
<thead>
<tr>
<th>Likelihood Ratio Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model 1: ET ~ 1</td>
</tr>
<tr>
<td>Model 2: ET ~ ForestType</td>
</tr>
<tr>
<td>Model 3: ET ~ ForestType + CanopyCover</td>
</tr>
<tr>
<td>Model 4: ET ~ ForestType + CanopyCover + (1{\mid year})</td>
</tr>
<tr>
<td>Model 5: ET ~ ForestType + CanopyCover + (1{\mid year}) + (1{\mid pixel})</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Model</th>
<th>Df</th>
<th>Log Likelihood</th>
<th>( X^2 )</th>
<th>( Pr(&gt;X^2) )</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2</td>
<td>-6160470</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>5</td>
<td>-6043709</td>
<td>233521</td>
<td>&lt; 2.2e-16</td>
<td>***</td>
</tr>
<tr>
<td>3</td>
<td>6</td>
<td>-6029400</td>
<td>28618</td>
<td>&lt; 2.2e-16</td>
<td>***</td>
</tr>
<tr>
<td>4</td>
<td>7</td>
<td>-5913026</td>
<td>232749</td>
<td>&lt; 2.2e-16</td>
<td>***</td>
</tr>
<tr>
<td>5</td>
<td>8</td>
<td>-5651019</td>
<td>524014</td>
<td>&lt; 2.2e-16</td>
<td>***</td>
</tr>
</tbody>
</table>

Coniferous upland forest (green lines in Figure 2-5) used roughly 145mm (18-20%) more water per year than deciduous upland forest (brown lines). Higher canopy cover (the solid lines) also corresponded with higher ET, with an increase of roughly 51mm for polygons labeled
as having >50% canopy cover. Within-pixel variance (model residual) was about the same size as the effect of the year, but less than variance between pixels.

Figure 2-5: Distributions of annual evapotranspiration, 2015-2018, for four forest compositions and two levels of canopy cover, as identified by the New Jersey Department of Environmental Protection Land Use/Land Cover 2015 dataset. Upland forests with more conifers and more closed canopies use significantly more water than more open forests and those with deciduous trees.
Table 4: Mixed effects model results examining evapotranspiration as a function of NJDEP Land Use/Land Cover 2015 categories.

2.3.2 ET and Forest Inventory Points

We found clear differences between most of the major Pinelands forest types in each of the study years (Figure 2-6). Relative ET differences among groups were consistent between years; oak uplands had the lowest annual ET (782 mm/year), Atlantic white cedar had the highest annual ET (1062 mm/year), and pine types had intermediate ET (918 mm/year and 908 mm/year for lowlands and uplands, respectively). Swamp hardwoods were both intermediate (918 mm/year) and variable, and their place in the order of ET varied by year.

The mixed effects model in Equation (C) produced estimates for the variation in total annual evapotranspiration in mm/yr introduced from annual differences (1|year term, random effect), variation between plots (1|plot term, random effect), and the fixed effects of the different forest types (ForestType term).

\[
ET = (1|year) + (1|plot) + Forest Type
\]  

(C)
Forest Types for this analysis were derived from the state forest inventory data. This model had by far the lowest AIC, BIC, and residual variance of any of the models evaluated. This model was a significant improvement upon the null and nested less-complex models (Table 5). Model effects and estimates can be found in Table 6.

**Forest Inventory: Pure Plots**

Wharton SF Inventory

![Kernel Density Distribution for Annual Evapotranspiration, 2015-2018](image)

**Figure 2-6:** Distributions of annual evapotranspiration, 2015-2018, for five different forest types identified through the New Jersey Forest Service inventory data of Wharton and Penn State Forests.

**Table 5:** Likelihood ratio test for candidate models to predict annual evapotranspiration by inventory-derived cover type. Significance of *** indicates model significance at <0.001.

<table>
<thead>
<tr>
<th>Model</th>
<th>Df</th>
<th>Log Likelihood</th>
<th>$X^2$</th>
<th>$Pr(&gt;X^2)$</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model 1: ET ~ 1</td>
<td>2</td>
<td>-78514</td>
<td>0</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Model 2: ET ~ ForestType</td>
<td>6</td>
<td>-77002</td>
<td>3023.4</td>
<td>&lt;2.2e-16</td>
<td>***</td>
</tr>
<tr>
<td>Model 3: ET ~ ForestType + (1</td>
<td>year)</td>
<td>7</td>
<td>-76039</td>
<td>1926.1</td>
<td>&lt;2.2e-16</td>
</tr>
<tr>
<td>Model 4: ET ~ ForestType + (1</td>
<td>year) + (1</td>
<td>pixel)</td>
<td>8</td>
<td>-72462</td>
<td>7154.2</td>
</tr>
</tbody>
</table>
As for random effects, variance among plots was greater than that among years. Within-plot variance (model residual) was greater than the effect of the year, but less than the variance between plots. Within-plot variance involves such features as spatial variation in annual rainfall, which is heterogeneous across the landscape, especially at the spatial resolution of an inventory plot. The between-plot (plot) term incorporates variation in forest structure such as varying occupancy of growing-space, different understory characteristics, changing groundcover, variation in mean canopy height, and any number of other forest attributes that vary among inventory plots, any combination of which can impact ET.

Table 6: Mixed effects model results examining evapotranspiration as a function of forest types identified in Wharton State Forest Inventory data, 2017-2019.

<table>
<thead>
<tr>
<th>Forest Type</th>
<th>Sample Size (n plots)</th>
<th>Predicted ET (mm/yr)</th>
<th>Confidence Intervals for Predictions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>2.5%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Random &amp; Fixed Effects</td>
</tr>
<tr>
<td>Atlantic White Cedar</td>
<td>233</td>
<td>1061.8</td>
<td>894.2</td>
</tr>
<tr>
<td>Swamp Hardwoods</td>
<td>182</td>
<td>917.7</td>
<td>750.0</td>
</tr>
<tr>
<td>Lowland Pine</td>
<td>726</td>
<td>917.7</td>
<td>750.4</td>
</tr>
<tr>
<td>Upland Pine</td>
<td>1928</td>
<td>907.8</td>
<td>740.6</td>
</tr>
<tr>
<td>Oak</td>
<td>141</td>
<td>782.5</td>
<td>614.8</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Fixed Effects</th>
<th>Est.</th>
<th>Std. Error</th>
<th>t value</th>
<th>Random Effects</th>
<th>Variance</th>
<th>SD</th>
<th>+/- 1.96 SD (mm/yr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Atlantic white cedar</td>
<td>-1061.8</td>
<td>21.0</td>
<td>50.65</td>
<td>Year</td>
<td>1658</td>
<td>40.7</td>
<td>79.8</td>
</tr>
<tr>
<td>Swamp Hardwoods</td>
<td>-144.0</td>
<td>5.73</td>
<td>-25.15</td>
<td>Plot</td>
<td>5208</td>
<td>72.2</td>
<td>141.4</td>
</tr>
<tr>
<td>Oak</td>
<td>-279.2</td>
<td>8.09</td>
<td>-34.52</td>
<td>Residual</td>
<td>2548</td>
<td>50.5</td>
<td>98.9</td>
</tr>
<tr>
<td>Lowland Pine</td>
<td>-144.2</td>
<td>7.52</td>
<td>-19.17</td>
<td>Residual</td>
<td>2548</td>
<td>50.5</td>
<td>98.9</td>
</tr>
<tr>
<td>Upland Pine</td>
<td>-153.9</td>
<td>5.27</td>
<td>-29.20</td>
<td>Residual</td>
<td>2548</td>
<td>50.5</td>
<td>98.9</td>
</tr>
</tbody>
</table>

We found temporal differences in evapotranspiration that corresponded to the life history of the dominant species in the inventory plots (Figure 2-7). For all years, oak-dominated plots had lower average daily evapotranspiration rates in March, April, and May. In most months, cedar plots had high ET rates, but during spring and autumn the increased ET rate
of cedar was more pronounced. The only year for which cedar did not have higher ET rates in the fall was 2018, which was the wettest year on record in the study area.

Figure 2-7: Daily average evapotranspiration by month, 2015. Data from NJFS inventory of Wharton State Forest. Delay in leaf-out until May coincides with the lower evapotranspiration rates for oak-dominated plots versus pine.

2.3.3 ET as a Function of Management

2.3.3.1 Effect of Thinning

Thinning affected forest evapotranspiration in the years immediately following cutting but after 5-10 years, thinning had little discernable impact on ET (Figure 2-8, Figure 2-9). After 5.6 years, the anomaly in ET had diminished to 5% of the original maximum effect size post-cutting (Table 7). In the time between cutting and when the model reached that point, the integral of ET showed a net accumulated effect of thinning of -3.92 annual standard deviations. As the model maximum value was less than 0, we subtracted this offset from the integral to determine the total water yield from thinning.
Coniferous forest with >50% canopy cover was by far the most common undeveloped land cover type in the study area; we used this cover type to convert the effect size back to a depth of water. For this cover type, of the four years modeled, 2015 had the smallest standard deviation, of 83.1mm/year. Using this smallest size to be conservative, we converted the integral (which we report in units of annual standard deviations) into a cumulative effect on evapotranspiration over the period of ET recovery following the management activity. This resulted in a cumulative reduction in ET of 326mm resulting from thinning.

Table 7: Simulation results for the effect of thinning on evapotranspiration. Simulations used a 50% subsample of the original data to fit the model, for which multiple terms were recorded. 10,000 model runs to get a distribution.

<table>
<thead>
<tr>
<th>Term</th>
<th>Mean</th>
<th>SD</th>
<th>2.5% quantile</th>
<th>97.5% quantile</th>
</tr>
</thead>
<tbody>
<tr>
<td>$B_1$ ($B_1-10$)</td>
<td>-0.322</td>
<td>0.00566</td>
<td>-0.333</td>
<td>-0.311</td>
</tr>
<tr>
<td>$B_2$</td>
<td>-0.574</td>
<td>0.0134</td>
<td>-0.601</td>
<td>-0.548</td>
</tr>
<tr>
<td>$B_3$</td>
<td>-2.25</td>
<td>0.083</td>
<td>-2.45</td>
<td>-2.09</td>
</tr>
<tr>
<td>Years until 5% left to recover</td>
<td>5.63</td>
<td>0.126</td>
<td>5.38</td>
<td>5.88</td>
</tr>
<tr>
<td>Integral of Model from $t_0$ to $t_{5%}$ (units are $\sigma$ of annual ET)</td>
<td>-3.92</td>
<td>0.067</td>
<td>-4.05</td>
<td>-3.79</td>
</tr>
<tr>
<td>Water Yield from Activity (# of $\sigma \times \sigma$ for annual ET of LULC15 Coniferous Forest &gt;50% canopy in 2015)</td>
<td>-325.8 mm</td>
<td>5.55 mm</td>
<td>-336.7 mm</td>
<td>-315.0 mm</td>
</tr>
</tbody>
</table>
Figure 2-8: Effect of thinning on evapotranspiration. Model fit using all four years of data; dotted lines are 95% prediction intervals.

Figure 2-9: Example of the duration and intensity of the effect of thinning on forest evapotranspiration. Selected area is in Brendan T. Byrne State Forest, Woodland Township, New Jersey.
2.3.3.2 Effect of Seed Tree Harvest

Seed tree harvests depressed evapotranspiration more and for a longer duration than did thinning (Figure 2-10, Figure 2-11). Model term $B_2$ was smaller following seed tree harvests than it was for thinning, highlighting this slower pace of recovery (Table 8). Further, the anomaly immediately after treatment was lower for seed tree harvests than thinning, with ET reduced by twice as many standard deviations in the seed tree harvest. To recover to the same 5% of effect size for a seed tree harvest took 13.1 years. From immediately after the cut until that point of recovery, the integral of the model was $-29.6$ standard deviations.

Using the same standard deviation size as for thinning ($83.1\text{mm/year}$, the standard deviation of ET for coniferous forest with $>50\%$ canopy cover in 2015), the accumulated effect of reduced ET due to the seed tree harvest was $2461$ mm. For comparison, in this region, total annual precipitation averages roughly $1150$ mm/year (Walker et al., 2011).

Table 8: Simulation results for the effect of seed tree harvest on evapotranspiration. Simulations used a 50\% subsample of the original data to fit the model, for which multiple terms were recorded. 10,000 model runs to get a distribution.

<table>
<thead>
<tr>
<th>Term</th>
<th>Mean</th>
<th>SD</th>
<th>2.5% quantile</th>
<th>97.5% quantile</th>
</tr>
</thead>
<tbody>
<tr>
<td>$B_1$ ($B_1 - 10$)</td>
<td>0.241</td>
<td>0.00559</td>
<td>0.230</td>
<td>0.252</td>
</tr>
<tr>
<td>$B_2$</td>
<td>-0.294</td>
<td>0.00308</td>
<td>-0.300</td>
<td>-0.288</td>
</tr>
<tr>
<td>$B_3$</td>
<td>1.17</td>
<td>0.0788</td>
<td>1.02</td>
<td>1.33</td>
</tr>
</tbody>
</table>

| Years until 5% left to recover            | 13.1 | 0.100 | 12.9            | 13.3            |

| Integral of Model from $t_0$ to $t_{0.05}$ (units are $\sigma$ of annual ET) | -29.6 | 0.325 | -30.3           | -29.0           |

| Water Yield from Activity ($\#$ of $\sigma \ast \sigma$ for annual ET of LULC15 Coniferous Forest $>50\%$ canopy in 2015) | -2461 mm | 27.0 mm | -2514 mm       | -2409 mm        |
Figure 2-10: Effect of seed tree harvesting on evapotranspiration. Model fit using all four years of data; dotted lines are 95% prediction intervals.

Figure 2-11: Effect of seed tree harvests on forest evapotranspiration. Note that the recovery of ET for thinned areas (open polygons) occurred at roughly the same time as seed tree harvests (diagonal hatching), though the seed tree harvests happened 7-9 years earlier. Private land in Washington Township, Burlington County, New Jersey.
2.3.3.3 Effect of Prescribed Fire

Direct impacts to evapotranspiration from prescribed fire were variable. We were unable to fit a recovery function of the same form as Equation (A) to the prescribed burn data, but a visual evaluation of the data showed an effect lasting roughly 22 weeks (Figure 2-12). Most burns occurred in February and March, meaning that forest ET returned to normal near the beginning of August.

When each instance of prescribed fire was plotted separately we observed event-specific patterns (see Appendix 2A). For some burns there was a modest effect of ET depression, while for others, prescribed fire had no effect or coincided with increased ET. Even for those fires that were followed by a negative ET anomaly, however, the effect generally did not last longer than a single growing season.

Prescribed fires that demonstrated a decrease in ET for part of the growing season were those burns where canopy leaf area was burned off. An example of a set of a range of burn intensities can be seen in Figure 2-13 and Figure 2-14. Burn blocks ‘A’ and ‘B’ were burned more gently than blocks ‘C’ and ‘D’. Flame heights largely did not reach tree crowns in ‘A’ and ‘B’; heat from the flames killed but did not consume foliage. In contrast, blocks flame heights in ‘C’ and ‘D’ consistently exceeded the height of the crown so that most to all leaf tissue was consumed; this can be seen from the photo in lower left panel of Figure 2-13, showing the condition of block ‘D’ roughly one month post-burn. Although there was significant overstory mortality in ‘D’ and some mortality in ‘C,’ a plot of weekly mean standardized ET (Figure 2-14) shows that the reduction in ET from these burns only persists in cases of the highest intensity. Prescribed fires as are more commonly applied elsewhere on the landscape were not observed to widely cause a reduction in ET lasting through the growing season immediately after burning (Figure 2-12).
Figure 2-12: Effect of prescribed fire on evapotranspiration. Data shown area for prescribed fires from 2015 through 2017. Broken line represents the weekly average standardized ET post-fire, and shading density corresponds to the density of pixel observations.

Figure 2-13: Spatial example of the varying effects of prescribed fire on evapotranspiration after disturbance; each gray polygon represents a discrete prescribed burn block. Clockwise from top left: standardized ET pre-fire, standardized ET immediately post-fire, standardized ET roughly 20 weeks post-fire, and a photo of site D post-fire showing the severity of the burn and the edge of the ‘pine plains’ forest type. Penn State Forest, New Jersey. Photo by the authors.
2.4 Discussion

Use of the DisALEXI model enabled characterization both of the effects of stand-level management on evapotranspiration and the impact of plot/stand-level forest type & canopy cover on ET. We were able to take advantage of its extensive spatial coverage to substitute space for time in generalizing the ET effects of forest management activities. Functional differences in water use due to forest type could be clearly identified (oak vs. pine upland) by the phenological expression of ET. The fine temporal and spatial scale also allowed a more thorough exploration of the effects of prescribed fire on ET, where the variations in fire intensity could be better discerned at weekly rather than annual scales. These characteristics make DisALEXI especially
suitable for examining the interactions of seasonality, disturbances, and forest attributes on forest evapotranspiration.

2.4.1 Effects of Composition

Our observed ET rates were somewhat higher than recorded in other studies. Clark et al. (2012) measured ET with the eddy covariance method in the same landscape in 2005-2009, finding lower absolute ET, and lower evapotranspiration/precipitation (ET:P) rates. Those observations occurred during a gypsy moth defoliation outbreak, however, along with a prescribed burn applied to the study site, both of which exerted downward pressure on annual ET. Further, annual precipitation totals for the US-Slt site are consistently lower than totals from North American Land Data Assimilation System-2 (NLDAS-2) data (Cosgrove et al., 2003). Table 9 shows annual ET:P rates by the means for the inventory cover types, sorted by year. ET/P values are comparable to those reported by Clark et al. (2012) for oak, but are higher for the other forest types. This may be due to our larger sample size capturing more of the variability within the landscape, a bias of the DisALEXI model in this landscape, the flux tower data underrepresenting ET of other forest types, or a mixture of these causes. Walker et al. (2011) observed slightly lower ET/P in the same region but did so using catchment basins, which incorporate the lower ET values of non-forest cover types. ET/P ratios using NLDAS-2 precipitation data overlapped with those observed by Sun et al. (2008) in northern Wisconsin.

Table 9: Total Annual Evapotranspiration/Precipitation for the five inventory forest types across study years 2015-2018. Cell numbers are expressed as forest type’s mean annual ET as a percentage of total annual precipitation

<table>
<thead>
<tr>
<th>Forest Type</th>
<th>Model ET / Precipitation from Silas Little Station (US-Slt)</th>
<th>Model ET / Precipitation from National Land Data Assimilation System</th>
</tr>
</thead>
<tbody>
<tr>
<td>Atlantic white cedar</td>
<td>111</td>
<td>136</td>
</tr>
<tr>
<td>Swamp Hardwood</td>
<td>99.9</td>
<td>111</td>
</tr>
<tr>
<td>Lowland Pine</td>
<td>95.8</td>
<td>112</td>
</tr>
<tr>
<td>Upland Pine</td>
<td>93.6</td>
<td>108</td>
</tr>
<tr>
<td>Oak</td>
<td>84.3</td>
<td>86.7</td>
</tr>
</tbody>
</table>
Differences between upland functional groups observed from the inventory data comported with our expectations (Figure 2-5, Figure 2-6, Figure 2-7). Increasing proportions of conifers increased ET (Figure 2-5, Table 4), and upland inventory plots dominated by oaks had the lowest ET of the forest types we examined (Figure 2-6, Table 6). Oaks are the last tree species to leaf out in the study area; prior to leaf out in May, inventory plots dominated by oaks had the lowest ET of the forest types we examined. In contrast, coniferous evergreens transpire in the shoulder months of spring and autumn if leaf and soil temperatures are high enough to support photosynthesis, hence plots dominated by these species had higher ET rates in the spring and fall. Contrasting our results, Komatsu et al. (2007) found that broadleaved forests have the same or higher ET than coniferous forests. However, the broadleaf forests they considered included broadleaf evergreens, which don’t have the same phenology as the deciduous oaks in our study area. Though there is an evergreen shrub component to forests in our study area, all the broadleaf overstory species are deciduous, seasonally removing canopy leaf area. Using sap flux measurements in northern Wisconsin, Mackay et al. (2002) and Ewers et al. (2002) noted that transpiration rates of different species varied based on their physiology; differences in species composition were important for parameterizing approaches to determine landscape ET, though environmental controls like vapor pressure deficit still drove most of the variance in water use. Though the coniferous forests in our area originate largely from natural reproduction, they exhibit the same higher ET compared to deciduous trees witnessed in conifer plantations elsewhere (Ford et al., 2011; Komatsu et al., 2008; Swank and Douglass, 1974). The upland pine type had slightly higher ET/P than that observed for planted white pine in the mountains of North Carolina (Ford et al., 2007). This has implications in the water budget for the region: disturbance effects and cultural conditions that favor dense pine regeneration will, over time, increase the proportion of the water budget consumed by forest.

Upland forest areas identified as having higher canopy cover also had higher ET rates. For the extensive coniferous forest types (Coniferous forest with either 10-50% cover or >50%
cover), more open crown caused about a 5% decrease in ET (Table 4). Though there was no
cover parameter in the inventory plot model, the pixel random effect in Table 4 and the plot effect
in Table 6 were larger than the effect of year or model residual (within-pixel or within-plot effect)
for both the NJDEP LULC 2015 dataset and the forest inventory data. This implies that there are
differences between pixels of the same forest type that have a greater effect on ET rates than
indicated by the effect of annual variation or within-plot model residuals. While it is unsurprising
that greater canopy cover increases ET, this gives a foundation to examine how differences in
forest structure, like stocking, impact ET. Forest inventory data could be used to investigate the
role of forest structure or other variables on ET.

Wetland forests were observed to have higher ET rates than uplands, and Atlantic white
cedar forests consistently had the highest annual ET rates. Walker et al. (2011) similarly reported
lower ET for uplands compared to wetlands, though measurements occurred only at one point for
each, and there was no differentiation as to composition. In other coastal plain wetland forests,
ET nearly equals precipitation (P) in the water budget, partially due to the availability of soil
moisture and surface ponding during portions of the year (Gholz and Clark, 2002; Liu et al.,
2018). ET/P higher than 100% is reasonable for the wetland types, in particular the cedar type, as
they typically occupy landscape positions where groundwater discharges (Laderman, 1989). This
is similar to the observations of Liu et al. (2018) and Sun et al. (2010), who, studying the same
ditched loblolly pine wetlands as each other, observed an evaporative index approaching or above
1 (e.g. 100%).

We observed similar ET rates for upland and lowland pine, though the credible interval
approach (at 95% confidence) showed a meaningful, if modest difference between them. The
small difference in ET rates between pine types is at least partially due to the difficulty in making
a binary distinction of wetland status. For this analysis, we used the LULC15 dataset, labeling
plots that fell in wetlands as such. However, the gradual topography and fluctuating water table of
this landscape make the line between pine upland and lowland blurry. Wetland forest types have
water tables closer to the surface but unlike cedar and hardwood swamps, pitch pine lowlands rarely have ponded water above the soil surface (Laidig et al., 2010). Free evaporation from standing water is less likely for this type, and the increase in ET probably had to do with more accessible soil water and the longer-term increases in forest density it has permitted.

Atlantic white cedar was consistently observed to have the highest average ET rates across all years and months, but particularly so in the spring (March-May). Cedar forests have long been known to create a moderated microclimate (Harshberger, 1916), with thick crowns and high stand densities that create low understory light availability. Cedar forests achieve much higher stand density index values than any of the other forest types in this landscape and have higher LAI, as well.

Oaks had the lowest mean basal area as well as the lowest stand density index, both of which are associated with lower leaf area. However, the relative density index (current stand density index/maximum possible stand density index for a species) for oak plots was comparable with that of upland pine, indicating comparable site occupancy for oaks and pines. Further investigations into type-specific relationships between inventory structural attributes and water use are warranted.

### 2.4.2 Effects of Management

#### 2.4.2.1 Thinning

For our purposes, we defined as thinning any cutting meant to concentrate growth in the remaining trees. In this region, most thinning was either low thinning or a variant of variable-density thinning (McIntyre et al., 2008). With low thinning in the Pinelands, the trees that are removed are the smallest-diameter trees and those stems considered unacceptable as growing stock. Low thinning results in a more uniform canopy and removes suppressed/intermediate trees that contribute little to the overall leaf area. In contrast, variable-density thinning removes trees of all diameter classes and results in a residual of variable-density in the treated area. This method increases spacing between residual crowns more than does low thinning. It also removes
trees whose crowns make larger contributions to canopy leaf area, so it is more impactful to the residual canopy than low thinning.

For the thinning activities in the study area, residual basal area was usually around 13.8-18.4 m²/ha (60-80 ft²/acre), down from levels around 23-27.6 m²/ha (100-120 ft²/acre) or higher. In portions of sites thinned with variable-density methods, some pockets were cut to as low as 6.9 m²/ha (30 ft²/acre), a feature designed to spur reproduction in small, dispersed patches. These, however, represented the extreme low-end of the distribution of residual BA in thinned sites. By and large, thinning activities left the majority of canopy intact and resulted in a small reduction in site utilization. Such moderate disturbance to the canopy structure caused a moderate, medium-duration dip in evapotranspiration in our study.

The speed at which ET recovered in thinned areas is reflective of the growth response in thinned stands, where residual trees only have to increase their individual growth to capture newly available resources. The organs for an individual tree to take advantage of increased water availability are present and are activated by the stimulus of thinning, governed by their growth rate. We observed a somewhat longer duration of effect of thinning on ET than other studies in coastal pine forests (Liu et al., 2018), but it is worth noting that trees in the commercial sites observed in other studies are managed to re-occupy vacated growing space as rapidly as possible to realize economic gain. The use of fertilizer and improved genetic stock in commercially-managed sites probably increases the rate at which trees re-occupy vacated growing space.

In contrast to other areas, the regulatory body for forest management in the New Jersey Pinelands proscribes the use of fertilizer and most varieties of improved seedlings that have been used to boost growth in other regions (New Jersey Pinelands Commission, 2020). Though the soils in our study area can capably support vigorous growth, tree growth rates are mostly unmanaged in this area and are generally slower than in more intensively-managed locales, which is probably responsible for some of the slower recovery of local ET here, following thinning. Additionally, the shorter growing season in our study area (compared with pine forests further
south along the coastal plain) provides less time per year for a forest to grow in response to disturbance, which would increase the number of years needed for recovery.

### 2.4.2.2 Seed Tree Harvest

Sites regenerated through seed tree harvests experienced a longer duration of reduced ET than thinned sites, with a slower recovery rate and a larger absolute reduction (Figure 2-8, Figure 2-10). We interpreted this to be the result of these sites needing new trees to get started before they can grow into vacated growing space. Most of the seed tree harvests in this area left similar residuals: large, vigorous pitch and shortleaf pines, with a total residual basal area of <3.4 m²/ha (<15 ft²/acre). The new generation of trees on these sites was usually a mix of artificial and natural regeneration of native pine species. Sites were often planted with seedlings, but residual trees, neighboring stands, and the existing seed bank stimulated additional natural regeneration. In many cases there was additional site preparation post-harvest to kill competing vegetation, such as drum-chopping or dispersing whole-tree chip skid trails throughout a site. This would additionally depress ET rates as existing shrubs and seedlings would not be available on site to grow into vacated space. Conversely, such preparation is usually used to speed the capture of the site by trees by eliminating competition. We did not attempt to partition the effect on ET of each step in the harvest (cutting overstory, moving material, site preparation, planting). The duration of the ET anomaly for regeneration harvests (seed tree cuts, here) of roughly 13 years was faster than in some studies (Ford et al., 2011; Komatsu et al., 2008), slower than some (Gholz and Clark, 2002), and in line with others (Sun et al., 2008).

### 2.4.2.3 Prescribed Fire

The mild but somewhat variable effect in site response after prescribed burning fits with the applications of prescribed burning in this study area. Fire is intentionally applied to this landscape only when very tightly controlled conditions exist, as the weather must be within the prescription and within the seasonal window allowed by policy. Burns must occur between
October 15th and March 15th; in the study area plants are largely dormant during this interval. Additionally, air temperature must be between 0 and 60 °F, with relative humidity between 30-60% and winds no more than 20 mph. For most of the burns applied during 2015-2017, these requirements precluded most overstory mortality from fire so that there was little significant structural change to burned areas. In hotter fires, hot air killed some of the existing canopy leaf area, but the spring flush of growth restored leaf tissue shortly thereafter. Only in the most intense prescribed burns was there significant enough mortality or branch dieback to cause lingering effects on ET from structural change (Figure 2-13 & Figure 2-14). Instead, prescribed fire’s effects on ET, like cutting, was dependent on the purpose of the activity. Where the burn boss intended to kill some overstory stems, ET impacts persisted for as long as a few growing seasons. For the vastly more common application of prescribed fire, with the fire intended to reduce fuel loads but not kill overstory, modest reductions in stand-level ET lasted less than the duration of a single growing season. On the surface this seems to contrast with Renninger et al. (2013), who observed sap flux increases across all tree diameter classes following prescribed fire. For that study competition from the shrub layer was removed and tree, not site, transpiration was measured, which was probably the reason for increased ET rates of canopy trees.

We did not quantify the indirect effects of repeated prescribed fire applied over time, which may impart a slightly different pattern on ET. Some areas of strategic vulnerability within the study area are repeatedly burned (on a 3-7 year interval) to forestall hazards, causing suppression of tree seedlings. As regeneration is repeatedly burned back to the ground, ingrowth into the canopy stratum is significantly reduced over time. After a few cycles, these areas are called ‘trained ground,’ where ladder fuels have been intentionally eliminated between the surface and crown. As these sites experience overstory disturbances (such as blowdowns, insect/fungi infestations, etc.) that outpace the ability of remaining trees to recapture vacated growing space, the effects of prescribed fire on ET may be realized many years later.
Repeated surface fires may also impact soil characteristics, causing longer-term shifts in ET. The upper horizons of upland soils in the Pinelands are generally sandy and loose, with little water-holding capacity (Tedrow, 1986). Organic matter provides much of the capacity of these soils to hold water, and it is partially generated from duff and other matter being deposited on the soil surface. Water held by soil organic matter steadies stream yield during the intervals between precipitation events (Moore et al., 2011), so a decrease in soil organic matter ought to make stand hydrological processes more dynamic. If repeated burning affects soil organic matter formation and water holding capacity, it may increase a forest’s drought susceptibility by reducing a site’s soil water capacity.

2.5 Conclusion
Application of the DisALEXI model in the forested coastal plain landscape of southern New Jersey provided a detailed and promising characterization of evapotranspiration. We consistently observed differences in forest evapotranspiration from forest composition and canopy cover and used these differences to better characterize the effects of forest management on ET. There was a variable effect of management on water yield, where the intensity and duration of the ET anomaly was qualitatively related to the intensity of overstory disturbance. These findings suggest that it should be possible to establish a relationship between some metrics of forest occupancy and forest ET across this landscape. Further, the Pinelands forest is changing through growth and maturation; as these factors are also changing metrics of forest occupancy, it is possible that such broad-scale changes may also be subtly changing landscape-scale ET rates.
2.6 Appendix 2A: Individual Prescribed Burn Effects

Figure 2-15: Line concentration plots of the effect of individual prescribed fires on evapotranspiration for the year 2015. Each panel represents a single burn block. Each semi-transparent line represents the daily z-score for a single pixel, calculated as the daily ET for that pixel minus the mean daily ET for that cover type, divided by the daily standard deviation of ET for that cover type. Green lines are rolling averages.
Figure 2-16: Line concentration plots of the effect of individual prescribed fires on evapotranspiration for the year 2016. Each panel represents a single burn block. Each semi-transparent line represents the daily z-score for a single pixel, calculated as the daily ET for that pixel minus the mean daily ET for that cover type, divided by the daily standard deviation of ET for that cover type. Green lines are rolling averages. Empty plots are the result of color density automatically set too low.
Figure 2-17: Line concentration plots of the effect of individual prescribed fires on evapotranspiration for the year 2017. Each panel represents a single burn block. Each semi-transparent line represents the daily z-score for a single pixel, calculated as the daily ET for that pixel minus the mean daily ET for that cover type, divided by the daily standard deviation of ET for that cover type. Green lines are rolling averages.
3: Section III: Understory Light Availability in the New Jersey Pinelands and its Influence on Plant Communities

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Abstract
Defining the parameters within which desired plant communities can grow is a critical first step for natural resource managers. In the pitch pine (Pinus rigida) dominated coastal plain of New Jersey, open canopy habitats represent the context for meaningful biodiversity, so we sought to define ‘open canopy’ using Stand Density Index (SDI), a common metric of forest occupancy. Using forest inventory data and leaf area index (LAI) measurements we found a non-linear relationship between overstory SDI and LAI, best described by a Michaelis-Menten equation. We used forest inventory measures of the understory to define upper limits of SDI for somewhat-common ‘open-canopy’ taxa, above which a manager will not find these plants. Our methods found credible thresholds in overstory density for four of five taxa, placing hard boundaries on the envelope of suitable conditions for these open-canopy community members. Native warm-season grasses (subfamily Panicoideae) were limited above SDI 225, sedge (genus Carex) above SDI 238, scrub oak (Quercus ilicifolia) above SDI 267 and blackjack oak (Q. marilandica) above SDI 226. Results for heather (Hudsonia) were not reliable due to the spotty frequency of the species in the dataset but qualitatively suggest lower SDI levels needed for survival. Abundant understory competitors, mainly in the tribe Vaccinieae, could produce as much shade as the overstory, showing the sizeable influence of shade-tolerant shrubs on ground-layer community composition. Management to create open-canopy habitat in this landscape should deploy treatments that keep SDI below 225 until the next management entry, and address ground-layer competition where appropriate.
3.1 Introduction

The Pinelands of New Jersey is a forested landscape on the outer coastal plain of southern New Jersey, currently dominated by pitch pine (*Pinus rigida*). Most of the forest is publicly owned, and due to the sociopolitical importance of the forest resource it is governed by a special set of rules (Pinelands Commission, 2020, 1979; United States Congress, 1978). This governing reality reflects the diversity of parties interested in the natural resource conditions on the landscape. In this fire- and disturbance-dependent region, biodiversity hotspots are those patches of the landscape where woody overstory is kept in check. Many of the endangered plants of this landscape are dependent on open, sunny conditions, such as Pickering’s morning glory (*Stylisma pickeringii* var. *pickeringii*), broom crowberry (*Corema conradii*), American chaffseed (*Schwalbea americana*), and eastern silvery aster (*Symphyotrichum concolor*) (CU Maurice River, 2010; NatureServe, 2021; Peters, 1995). Open, sunny ground conditions also provide much-needed habitat for rare wildlife, such as Northern Pine Snake (*Pituophis melanoleucus melanoleucus*) (David M. Golden et al., 2009), northern bobwhite quail (*Colinus virginianus*) (Castelli et al., 2011), and frosted elfin (*Callophrys irus*) (Albanese et al., 2007). From the standpoint of enhancing biodiversity, actions that keep the woody growth in check and limit the growth of trees are beneficial.

When considered simplistically, other common goals for the Pinelands conflict with this notion. With a growing awareness of the magnitude of the effects of climate change, policy goals at the state level involve increasing carbon storage in the forest (New Jersey Department of Environmental Protection and New Jersey Department of Agriculture, 2021). Further, there are entire journals dedicated to exploring the psychological benefits of interaction with natural spaces (see *Journal of Environmental Psychology* and *Environment and Behavior*). Studies from this field almost invariably assert that the preservation of ‘natural’ environments is imperative for human psychological well-being in an era of increased urbanization (Bratman et al., 2019). This burdens the landscapes of the Pinelands with meeting the psychological needs of the highly
urbanized regional population. There is a popular conception that reduction of woody overstory would constitute human interference with the ‘natural’ character of the forest, as well as negatively impacting goals to mitigate climate change. Together, this creates an unfortunate state of antinomy between the objectives of the parties most interested in the resource. Practical forest management policies must make tradeoffs to balance the divergent needs of such opposing agendas.

Achieving balance requires a keen understanding of the decision boundaries involved. It is imperative that land managers be able to translate desired conditions into measurable metrics of success, requiring an understanding of tradeoffs prior to management intervention. For instance, specifying that an activity should ‘open up the canopy’ is not specific enough to provide certainty that a planned management action will be effective in providing the light environment required by shade intolerant plants. Moreover, the human dimensions of resource management can become more complicated in the absence of clear metrics. Using empirical guideposts to justify management choices is a key component of trust between stakeholders and managers, a critically-important component of successful land management (Moffat et al., 2016).

Towards that goal, we sought to empirically define the light resources needed for open-canopy plant species in the Pinelands. Further, we aimed to describe the required forest structure by using metrics that are both easily measured and biophysically connected to light availability. To do this we asked two questions: (1) Is there a relationship between overstory occupancy and the light environment experienced by ground-layer plants? (2) Can a metric of overstory occupancy be used to predict the distributions of indicator taxa for open woodland communities? Successfully determining the conditions conducive to taxa of interest is likely to provide the conditions conducive to other desired plant communities. We hypothesized a nonlinear relationship between overstory occupancy and understory light availability, with a threshold imposed by the trees competing against one another for light. Above this density we expected to see decreasing frequency of open-canopy taxa.
3.2 Methods
3.2.1 Data Sources
3.2.1.1 Forest Inventory Data

Forest Inventory data were collected in Wharton State Forest and Penn State Forest between 2017 and 2019 as part of the New Jersey Forest Service (NJFS) process for developing forest management plans (Figure 3-1). NJFS staff delineated forest types by aerial photo interpretation; type boundaries were used to stratify the spatial distribution of plot locations, maintaining random spatial placement while reducing type-level variance in basal area per acre. LandVest, Inc. of Ridgway, Pennsylvania placed the plots and acquired the data, which was randomly checked by NJFS for accuracy by re-measurement.

Plots used a nested sampling design. Overstory was assessed using a variable radius point sampling of either BAF 10 or 30 (ft²/acre), advanced regeneration was measured using a 1/50th acre (1/123.5th hectare) fixed radius plot, and ground cover was measured using a 1/500th acre (1/1325th hectare) fixed radius plot. All three levels of sampling used the same plot center point. For all plots except those placed in the Atlantic white cedar forest type, the contractor used a basal area factor (BAF) of 10 (ft²/acre); for cedar plots the contractor used BAF 30. This was done to keep the plot-level sample variance proportional, as Atlantic white cedar stands in the New Jersey Pinelands typically achieve basal areas ≥3x the level of adjacent forests.

On trees counted ‘in’ as part of the overstory plots, the contractor recorded species, diameter at breast height, total height, merchantable height, and other tree attributes. In advanced regeneration plots, only tree species were counted, and only those stems taller than 4.5ft (1.37m) in height and less than 4 inches (10.2cm) in diameter. Ground cover was assessed as a percentage of the plot area over which leaf coverage was superimposed, by taxon. Plots could have a sum of more than 100% cover in the ground data, which was often the case in plots with mixed composition or multiple layers of vegetation. Woody species were identified in ground plots, but for some taxa a coarser grouping was recorded at the scale of genus, tribe, or growth form.
We collected additional partial inventory points at Greenwood Wildlife Management Area (WMA), which is located roughly 13km NNE of Penn State Forest. These points consisted solely of the variable-radius overstory plot, collected at BAF 10 (English). These supplemental points were needed to capture lower-density overstory; there are exceedingly few places in Wharton and Penn State Forests that exhibit low overstory density, while portions of Greenwood WMA have been managed for this very attribute.

![Figure 3-1: Map of study locations, forest inventory points, and leaf area index (LAI) measurements. As only a subset of the inventory data points was used for this analysis, only pure pine plots are shown.](image)

### 3.2.1.2 Forest Management Data

Forest management cutting history was reconstructed from NJFS activity records, aerial images, field reconnaissance, and consultation with private-lands foresters. We digitized polygons around each management activity using contemporaneous aerial imagery. These data were obtained from the New Jersey Department of Environmental Protection’s Bureau of Geographic Information Systems. There was approximately one set of leaf-off images per decade.
prior to the 1990s, with at least two sets each decade since. We matched the paper records and the appearances of the sites in aerial images to determine the type of forest management that occurred for each polygon, although for many activities, the evidence of prior management can be seen though current stand structure.

Records of prescribed burns and wildfires were obtained from the New Jersey Forest Fire Service (NJFFS) for the years 2015-2017. For prescribed burning records prior to 2015, we located & digitized burns using a combination of Landsat imagery from the US Geological Survey, as well as aerial imagery, LiDAR, and available paper records from the New Jersey Department of Environmental Protection. LiDAR-derived ground surface elevation data were useful to locate plow lines, which are used in this region to assist in the deployment and control of prescribed fire; their presence indicates an area has been or will be burned. All burn prescriptions in southern New Jersey occurred between November 1 and March 31, during the dormant season.

Other recorded disturbances include wildfires, *Lymantria dispar* defoliation, and mortality from *Dendroctonus frontalis* infestation. NJFFS provided wildfire data, while we selected out the insect disturbances from the USDA Forest Service Damage Causing Agent dataset (USDA Forest Service, 2018).

### 3.2.1.3 Leaf Area Index Measurements

We collected optical estimates of Leaf Area Index (LAI) data across a range of Stand Density Index values during August 2020 and June 2021 (Figure 3-1). For each plot measurement, we visited pure or nearly pure plots of pitch pine (*Pinus rigida*), defined as those stands where *P. rigida* comprised >90% of the living relative basal area of the plot. Other observed tree species included black oak (*Q. velutina*), blackjack oak (*Q. marilandica*), post oak (*Q. stellata*), southern red oak (*Q. falcata*), and scarlet oak (*Q. coccinea*), though these were restricted to have cumulatively less than 10% of the total basal area on a plot. Measurements were
recorded with a LI-COR 2200c Plant Canopy Analyzer and processed using FV2200 software (version 2.1). Plots were measured on cloudless days, starting at dawn or close to dusk. When the sun was above the horizon, we collected K records every 60-90 minutes to perform bright sky scattering corrections (Kobayashi et al., 2013), and where possible, used the closest two K readings to interpolate appropriate scatter corrections. Both above- and below-canopy measurements were collected with the 90° sensor field of view cap, facing north. Above-canopy (A) measurements were collected using a second wand logging every 30s in a grassy field with at least 80m to the nearest trees in the sensor field of view. Mean canopy height surrounding the fields varied between 15m and 20m.

We measured below-canopy (B) observations at overstory inventory plot locations, with 13 measurements on and around the forest inventory plot center (Figure 3-2), each collected at 1.7m off the ground. We collected an additional 9 ground-level measurements on and around the plot center, measured at 5-15cm off the ground; these skipped the 4 readings taken at 45° angles from the plot center. To scale the records, for all B readings we used the A value that was closest-in-time. Ring 5 was excluded from analysis for all records, as the BAF 10 (ft²/acre) limiting distance of a tree of the quadratic mean diameter and mean canopy height for each plot usually corresponded to the projected amount of canopy observed by rings 3-4. For the few observations where noise caused readings from the B sensor to slightly exceed the A readings, we clipped B readings at 1, the level of the A readings. Where the shrub layer was above the height
of the upper measurement, we dropped the observation, as we sought to relate the light
environment to metrics of overstory occupancy.

3.2.1.4 Validating Observations for Select Taxa
We also collected below-canopy LAI measurements where we found isolated and less
vigorous individuals of three indicator species: broomsedge bluestem (*Andropogon virginicus*),
switchgrass (*Panicum virgatum*), and golden-heather (*Hudsonia ericoides*). Vigor was visually
estimated by the overall density and size of culms for the grasses; we considered plants with
sparse, small culms to be of low vigor. Where these individuals were found, we took at least 6
and as many as 9 measurements corresponding to the inner ring of measurements taken on the
overstory plot, both at 1.7m and 5-15cm height. We took fewer observations when there was a
large competing plant within the measurement area, because its inclusion in LAI measurements
would have exaggerated the shade experienced by the indicator species. By sampling isolated,
low-vigor individuals of these indicator species, we speculated that these measurements would
indicate the upper limit of competition, or the location of the shade constraint on their realized
niches.

3.2.2 Analysis
3.2.2.1 Plot Summary Statistics
To summarize overstory characteristics we calculated forest occupancy metrics following
the protocols from the US Forest Service (USFS) Forest Vegetation Simulator (FVS, Dixon and
Keyser, 2019). Stand Density Index (SDI) calculations used in this analysis followed the form of
Zeide (Shaw, 2006; Zeide, 1983):

\[
\text{StandDensityIndex}_j = \sum_{i}^{n} \left( TPA_i \ast \left( \frac{\text{DBH}_i}{10} \right)^{1.605} \right)
\]

(A)

where \( TPA_i \) represents the number of trees per acre represented by observation \( i \), \( \text{DBH}_i \) represents
diameter at breast height (1.37m or 4.5feet) of tree \( i \) in inches, and \( n \) represents all of the
overstory tree observations at point \( j \). For plots where advanced regeneration was observed, we
used the area of the plot to expand observations to a per-acre number. All advanced regeneration stems were assumed to have a diameter of 0.5 inches, and their cumulative contribution to SDI was added to the overstory SDI. For this study, we restricted all analysis to those plots where southern yellow pines (Pitch pine, *Pinus rigida*; Shortleaf pine, *P. echinata*; Virginia pine, *P. virginiana*; Loblolly pine, *P. taeda*) together represented at least 90% of total live Basal Area.

### 3.2.2.2 Modeling SDI & LAI

To describe the effect of SDI on LAI, we fit five candidate models and compared their performance through simulated subsets of our data. We broke the dataset into random training and testing halves, fit each candidate model to the training half, recorded the standard deviation of the model residuals and the model’s Bayesian Information Criterion (BIC). Applying the models to the withheld testing half of the data, we recorded the root mean squared error of the model’s predictions. We repeated this process 10,000 times and compared model performance using the relative distributions of the model parameters. The five candidate models were as follows:

\[
\text{Linear} \quad \text{LAI} = \beta_1 \cdot SDI + \beta_2
\]

\[
\text{Logarithmic} \quad \text{LAI} = \beta_1 \cdot \log_{10}(SDI) + \beta_2
\]

\[
\text{Asymptotic} \quad \text{LAI} = \beta_1 - \beta_2 \cdot \left(1 - 10^{(-\beta_3 \cdot SDI)}\right)
\]

\[
\text{Log-Log} \quad \text{LAI} = 10^{(\beta_1 + \beta_2 \cdot \log_{10}(SDI))}
\]

\[
\text{Michaelis-Menten} \quad \text{LAI} = (\beta_1 \cdot SDI)/(\beta_2 + SDI)
\]

### 3.2.2.3 Maximum SDI for Taxa of Interest

We also attempted to use the inventory data to describe the light environment of the realized niche for different taxa for the ground plot observations. We chose five taxa that were well-represented in the understory data and that are viewed as evidence of more open canopy conditions: native warm-season grasses (subfamily *Panicoideae*), sedges (genus *Carex*), heather (genus *Hudsonia*), scrub oak (*Quercus ilicifolia*), and blackjack oak (*Q. marilandica*).
For each taxon, we plotted two variables against SDI: total percent cover of that taxon found in the ground plot (0-100 scale), and the proportion of the total ground cover for a plot occupied by that taxon (0-1 scale). Starting at the highest observed SDI and working down to lower SDI values, we evaluated whether the $y$ value of an observation was equal to or greater than the second highest $y$ observation already encountered. If the value met that criterion, we included it; if not, the point was excluded. These points were considered the upper envelope of suitability for the taxon in question. To each set of points we fit a logistic model of the form:

$$y = \frac{B_3}{1 + \exp(B_2(x - B_3))}$$

(B)

where $B_1 = 100$ or $B_1 = 1$ depending on whether we were looking at the percent of ground cover for that species or the proportion of total plot cover coming from that species.

This process was conducted on a random 50% subsample of the ground-level plot data, repeated 10,000 times. The model parameter values ($B_2$ and $B_3$) for each run were recorded, the distributions of which were used to describe a likely upper-envelope threshold.

3.2.2.4 Validation Observations for Select Taxa

We thought that a robust method for testing the models from sections 3.2.2.2 and 3.2.2.3 would be to compare models of maximum LAI to occurrences of the plants on the ground. If our model for the relationship of LAI–SDI was accurate, and if our model finding the maximum SDI suitable for a species was accurate, we could define a threshold LAI that, if exceeded, would make a site unsuitable for one of our taxa of interest. To this end we located low-vigor individuals of *Panicoideae* and *Hudsonia* and measured overstory and ground-level LAI around them, as over- and understory shade combine to influence the light environment. We expected that a robust model would have all our LAI measurements of weak individuals occurring within the product of the prediction intervals for the two functions (1: LAI–SDI, and 2: maximum SDI for survival).
3.2.2.5 Estimated Gamma Distributions
To ensure that the modeled SDI upper limits were not just a function of the sampling rate of SDI values from the full dataset, we also tested whether the distributions of observed SDI values for each species were different than a similarly sized random drawing of the full inventory data. For this evaluation, we took a random 50% subsample of the plots where each taxon of interest occurred and estimated a gamma distribution from the corresponding SDI values. We then took a similarly sized random sample of SDI values from the full dataset and estimated a gamma distribution for this ‘null’ dataset, repeating the subsampling routine 10,000 times. Calculating the difference between the taxon’s and the null’s modeled parameters (\(\text{shape}_{\text{taxon}} - \text{shape}_{\text{null}}; \text{scale}_{\text{taxon}} - \text{scale}_{\text{null}}\)), we evaluated whether 0 was included in the interval between the 2.5% and 97.5% quantiles of the difference (the credible interval).

3.3 Results
3.3.2 Modeling SDI & LAI
There was a non-linear relationship between SDI and LAI, with lower LAI corresponding with lower SDI (Figure 3-3). The interval over which the effect was dynamic was concentrated at lower levels of SDI; adding SDI when less growing space was occupied made a bigger difference in LAI than adding the same amount of SDI when there was already much more growing space occupied (Figure 3-3a). Of the candidate models used (Table 10), we found that a Michaelis-Menten equation was the most robust predictor of LAI based on SDI alone. When applied to the subsampled data, the Michaelis-Menten equation, the asymptotic model, and the logarithmic model had the lowest RMSE (Figure 3-3b). These three models also had the lowest standard deviation of residuals on the training data (Figure 3-3d). However, the logarithmic and Michaelis-Menten formulations had the lowest Bayesian Information Criteria across all subsamples, with the asymptotic model paying a penalty for its third parameter (Figure 3-3c). We chose the Michaelis-Menten formulation because its origin at 0,0 matches the phenomenon
being modeled. With no trees in the overstory (SDI of 0), there should be no leaf area in the overstory (LAI of 0), and a model describing this should not expend a model term on an additional intercept term to force it through the origin.

We were concerned with heteroscedasticity in the observed data and evaluated the performance of a log-log transformation for modeling, as this was the only model formulation that did not appear to have patterned variance. Indeed, such a transformation reduced some of the pattern of variability of the variance within the range sampled (Figure 3-4a). However, the

Figure 3-3: Evaluations of model performance to describe the effect of Stand Density Index on Leaf Area Index in pure Pitch Pine. (a) shows the model fit on the observed data, while (b-d) show the performance of each candidate model assessed using randomly subsampled replicates.
The overall appearance of the linear model residuals on the log-log transformed data was more strongly patterned than from the Michaelis-Menten model (Figure 3-5). Further, when back-transformed into the original observation units, the prediction intervals for the log-log model were poorly constrained around the data at the higher end of the observed SDI range (Figure 3-4b), while they more closely matched the data for the Michaelis-Menten formulation (Figure 3-4c). The distribution of the model formulations from the simulations for the log-log model and the Michaelis-Menten formulation can be seen in Figure 3-6.

**Figure 3-4:** Linear model fit to log-log transformation of the data to deal with heteroskedasticity (a), transformed into original measurement units (b), versus Michaelis-Menten model (c). Green lines are best fit, blue field is 95% confidence interval for model terms, dotted lines indicate 95% prediction interval.

**Figure 3-5:** Comparison of model residuals for log-log model vs. Michaelis-Menten equation.
Table 10: Mean model parameters and 95% quantiles for the five candidate models to predict leaf area index from stand density index. Each model was fit on 10,000 subsamples of the data.

<table>
<thead>
<tr>
<th>Model</th>
<th>Model Term</th>
<th>2.5% Quantile</th>
<th>Mean</th>
<th>97.5% Quantile</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 - Linear</td>
<td>$\beta_1$</td>
<td>0.623</td>
<td>0.928</td>
<td>1.27</td>
</tr>
<tr>
<td></td>
<td>$\beta_2$</td>
<td>$5.44\times10^{-3}$</td>
<td>$7.24\times10^{-3}$</td>
<td>$9.37\times10^{-3}$</td>
</tr>
<tr>
<td>2 - Logarithmic</td>
<td>$\beta_1$</td>
<td>-3.43</td>
<td>-2.64</td>
<td>-1.97</td>
</tr>
<tr>
<td></td>
<td>$\beta_2$</td>
<td>1.92</td>
<td>2.24</td>
<td>2.62</td>
</tr>
<tr>
<td>3 - Asymptotic</td>
<td>$\beta_1$</td>
<td>-1.22</td>
<td>-0.469</td>
<td>-1.18$\times10^{-2}$</td>
</tr>
<tr>
<td></td>
<td>$\beta_2$</td>
<td>-4.04</td>
<td>-3.40</td>
<td>-2.98</td>
</tr>
<tr>
<td></td>
<td>$\beta_3$</td>
<td>$3.13\times10^{-3}$</td>
<td>$5.21\times10^{-3}$</td>
<td>$7.55\times10^{-3}$</td>
</tr>
<tr>
<td>4 - Log-Log</td>
<td>$\beta_1$</td>
<td>-1.01</td>
<td>-0.742</td>
<td>-0.500</td>
</tr>
<tr>
<td></td>
<td>$\beta_2$</td>
<td>0.387</td>
<td>0.492</td>
<td>0.612</td>
</tr>
<tr>
<td>5 - Michaelis-Menten</td>
<td>$\beta_1$</td>
<td>3.51</td>
<td>4.18</td>
<td>5.29</td>
</tr>
<tr>
<td></td>
<td>$\beta_2$</td>
<td>82.4</td>
<td>131</td>
<td>209</td>
</tr>
</tbody>
</table>

Figure 3-6: Model simulations on subsampled replicates. For each 50% subsample of the original data, the best-fit line is shown as a gray line; concentration of color indicates the range of the model formulations.
### 3.3.3 Maximum SDI for Taxa of Interest

#### 3.3.3.1 Panicoideae

![Figure 3-7: Modeled upper limit of Stand Density Index for warm-season grasses, using original collection units (0-100% coverage of the ground in the 1/500th acre subplot). Transparent gray lines each represent one of 10,000 model runs to fit a logistic curve to the data. Vertical lines for inflection point statistics: green – median; blue – middle 68%; red – middle 95%.](image1)

![Figure 3-8: Modeled upper limit of Stand Density Index for warm-season grasses using proportion of plot observations (Proportion, 0-1, of the total ground observations in the 1/500th acre subplot). Transparent gray lines each represent one of 10,000 model runs to fit a logistic curve to the data. Vertical lines for inflection point statistics: green – median; blue – middle 68%; red – middle 95%.](image2)
Grasses showed the variable models for the relationship between SDI and cover. From the original % cover observations (0-100), the median inflection points for grasses occurred at 225 (middle 68% quantiles spanning 214 to 233) (Figure 3-8). However, scaled as a proportion of the total plant coverage on the plot, the inflection point occurred at SDI 269 (middle 68% quantiles 252-289) (Figure 3-8). Some of the variation between these two evaluations stems from a few plots that had a grass component in the SDI 300-400 range. These plots had less than 100% total coverage in the ground data, so that the importance of grass became exaggerated when the data were rescaled from the original collection units (0-100) to a proportion of the plot coverage (0-1). The outsize influence of these points can easily be seen above SDI 360 in Figure 3-8.

3.3.3.2 Carex

![Upper SDI Limit: Carex](image)

*Figure 3-9: Modeled upper limit of Stand Density Index for sedges, using original collection units (0-100% coverage of the ground in the 1/500th acre subplot). Transparent gray lines each represent one of 10,000 model runs to fit a logistic curve to the data. Vertical lines for inflection point statistics: green – median; blue – middle 68%; red – middle 95%.*
The scatter for *Carex* showed nearly no observations above SDI 350, and wide variation within and between the distributions of the modeled inflection points. When considered from the original measurement units (0-100) the modeled inflection points for sedges varied widely (Figure 3-9): the simulated median was 178, with a range across the middle 68% from 138 to 216. Scaled to the proportion of total ground cover (0-1), the median was 238, with a narrower range for the middle 68% between 227 and 246 (Figure 3-10).
3.3.3.3 Hudsonia

Figure 3-11: Modeled upper limit of Stand Density Index for heather, using original collection units (0-100% coverage of the ground in the 1/500th acre subplot). Transparent gray lines each represent one of 10,000 model runs to fit a logistic curve to the data. Vertical lines for inflection point statistics: green – median; blue – middle 68%; red – middle 95%.

Figure 3-12: Modeled upper limit of Stand Density Index for heather, using proportion of plot observations (Proportion, 0-1, of the total ground observations in the 1/500th acre subplot). Transparent gray lines each represent one of 10,000 model runs to fit a logistic curve to the data. Vertical lines for inflection point statistics: green – median; blue – middle 68%; red – middle 95%.
None of our plots showed that heather was a significant component of the understory, nor did it cover more than 75% of any single plot. For this reason, the middle 68% of the modeled data for % ground cover extended into a negative range of SDI, which is nonsensical. The median simulated inflection point for the genus occurred at SDI 22 when looking at the recorded % ground cover (0-100, Figure 3-11), and at SDI 49 when using the proportion of total plot cover (0-1, Figure 3-12). For % ground cover and the proportion of plot cover, the middle 68% ranges of the simulated inflection points were between -12 and 39, and 37 to 60, respectively.

3.3.3.4 Quercus ilicifolia

Figure 3-13: Modeled upper limit of Stand Density Index for scrub oak, using original collection units (0-100% coverage of the ground in the 1/500th acre subplot). Transparent gray lines each represent one of 10,000 model runs to fit a logistic curve to the data. Vertical lines for inflection point statistics: green – median; blue – middle 68%; red – middle 95%.

*Figure 3-13: Modeled upper limit of Stand Density Index for scrub oak, using original collection units (0-100% coverage of the ground in the 1/500th acre subplot). Transparent gray lines each represent one of 10,000 model runs to fit a logistic curve to the data. Vertical lines for inflection point statistics: green – median; blue – middle 68%; red – middle 95%.*
Scrub oak seldom occurred at the lowest SDI levels but did reach a threshold of SDI where it was no longer present. Using % total ground cover (original units, 0-100%, Figure 3-13), the median inflection point occurred at SDI 275, with the middle 68% of the simulations placing the inflection point between 257 and 300. Scaled as a proportion of the total plot cover (0-1, Figure 3-14), the median inflection point occurred at 267, with a middle 50% of simulations fitting an inflection point of 256-279.
3.3.3.5 *Quercus marilandica*

**Figure 3-15:** Modeled upper limit of Stand Density Index for blackjack oak, using original collection units (0-100% coverage of the ground in the 1/500th acre subplot). Transparent gray lines each represent one of 10,000 model runs to fit a logistic curve to the data. Datapoints selected for model fitting were chosen by starting at the highest SDI value and working downwards, where observations were only included if the y value was equal to or greater than the second highest y value already encountered. Vertical lines for inflection point statistics: green – median; blue – middle 68%; red – middle 95%.

**Figure 3-16:** Modeled upper limit of Stand Density Index for blackjack oak, using proportion of plot observations (Proportion, 0-1, of the total ground observations in the 1/500th acre subplot). Transparent gray lines each represent one of 10,000 model runs to fit a logistic curve to the data. Datapoints selected for model fitting were chosen by starting at the highest SDI value and working downwards, where observations were only included if the y value was equal to or greater than the second highest y value already encountered. Vertical lines for inflection point statistics: green – median; blue – middle 68%; red – middle 95%.
Blackjack oak showed a wide range for the simulations based on total ground cover, as there was only one plot where blackjack oak cover exceeded 55% of the ground plot data (Figure 3-15); since the maximum value was set to 100, this made for inherently unstable fits. Still, from the simulations using the % ground cover (original units, 0-100) there was a median inflection point of 203, with a range of middle 68% values between 116 and 224. From the simulations based on the data scaled as a proportion of plot cover (0-1, Figure 3-16), the median inflection point was 226, with a middle 68% range between 215 and 231.

Table 11: Modeled parameter values for logistic curves of upper Stand Density Index limits for five taxa. Summary quantiles collected from 10,000 simulated subsamples of the data. This table uses the original collection units, 0-100% of the ground plot area covered by the taxon. B2 is the slope of the curve, B3 is the inflection point. 10% columns show the SDI quantiles when the logistic curves reach 1/10th amplitude, e.g. the toe of the curve.

<table>
<thead>
<tr>
<th>Taxon</th>
<th>B2 16%</th>
<th>Median</th>
<th>B2 84%</th>
<th>B3 16%</th>
<th>Median</th>
<th>B3 84%</th>
<th>B3 10%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panicoideae</td>
<td>0.0318</td>
<td>0.0401</td>
<td>0.0500</td>
<td>214.5</td>
<td>224.6</td>
<td>233.1</td>
<td>268.7</td>
</tr>
<tr>
<td>Carex</td>
<td>0.0155</td>
<td>0.0190</td>
<td>0.0269</td>
<td>137.8</td>
<td>177.9</td>
<td>212.6</td>
<td>269.8</td>
</tr>
<tr>
<td>Hudsonia</td>
<td>0.0222</td>
<td>0.0266</td>
<td>0.0513</td>
<td>-12.4</td>
<td>21.8</td>
<td>39.1</td>
<td>64.3</td>
</tr>
<tr>
<td>Quercus ilicifolia</td>
<td>0.0216</td>
<td>0.0277</td>
<td>0.0402</td>
<td>256.9</td>
<td>275.1</td>
<td>300.4</td>
<td>338.4</td>
</tr>
<tr>
<td>Quercus marilandica</td>
<td>0.0162</td>
<td>0.0276</td>
<td>0.0467</td>
<td>116.4</td>
<td>203.1</td>
<td>223.9</td>
<td>254.6</td>
</tr>
</tbody>
</table>

Table 12: Modeled parameter values for logistic curves of upper Stand Density Index limits for five taxa. Summary quantiles collected from 10,000 simulated subsamples of the data. This table uses the scaled units, 0-1, the proportion of the ground plot observations occupied by the taxon. B2 is the slope of the curve, B3 is the inflection point. 10% columns show the SDI quantiles when the logistic curves reach 1/10th amplitude, e.g. the toe of the curve.

<table>
<thead>
<tr>
<th>Taxon</th>
<th>B2 16%</th>
<th>Median</th>
<th>B2 84%</th>
<th>B3 16%</th>
<th>Median</th>
<th>B3 84%</th>
<th>B3 10%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panicoideae</td>
<td>0.0357</td>
<td>0.0450</td>
<td>0.134</td>
<td>251.7</td>
<td>268.8</td>
<td>288.9</td>
<td>287.5</td>
</tr>
<tr>
<td>Carex</td>
<td>0.0250</td>
<td>0.0286</td>
<td>0.0344</td>
<td>227.1</td>
<td>237.9</td>
<td>246.1</td>
<td>296.7</td>
</tr>
<tr>
<td>Hudsonia</td>
<td>0.0251</td>
<td>0.0272</td>
<td>0.0310</td>
<td>36.7</td>
<td>48.8</td>
<td>59.6</td>
<td>116.1</td>
</tr>
<tr>
<td>Quercus ilicifolia</td>
<td>0.0177</td>
<td>0.0204</td>
<td>0.0246</td>
<td>256.0</td>
<td>267.4</td>
<td>279.4</td>
<td>358.0</td>
</tr>
<tr>
<td>Quercus marilandica</td>
<td>0.0254</td>
<td>0.0323</td>
<td>0.0442</td>
<td>215.0</td>
<td>225.7</td>
<td>230.5</td>
<td>274.9</td>
</tr>
</tbody>
</table>

For all but Q. ilicifolia, the inflection point of the modeled curves is higher when looking at the proportion of total plot cover (0-1) than it is for the recorded percent ground cover (0-100).
Also, for all five taxa, the span of the distribution was wider when the total % cover observations were used (Figure 3-17, Table 11) than when the proportional observations were used (Figure 3-18, Table 12).

**Figure 3-17:** Modeled upper limit of Stand Density Index for five taxa, using original collection units (0-100% coverage of the ground in the 1/500th acre subplot).

**Figure 3-18:** Modeled upper limit of Stand Density Index for five taxa, using scaled units (0-1, proportion of total ground observations in the 1/500th acre subplot).
3.3.4 Estimated Gamma Distributions

We wanted to test whether the observed upper limits for each taxon were coincident with the upper SDI limit for the rest of the data. Given that each taxon of interest only occurred on a subset of the plots, and that the overall distribution of plot SDIs was centered just below 200 (mean & median ≈189) (Figure 3-19), for uncommon taxa it could be possible that the modeled upper limit was an artifact of the infrequency of all observations above certain SDI levels, rather than an indication of that taxon being shade intolerant. Put another way, was our upper SDI limit for a taxon real, or could we reproduce it simply by drawing any small sample from the overall dataset?

For four of the taxa, there were differences in the parameters of the species-based gamma and the ‘null’ gamma distribution (based on the rest of the pure pine plot data) (Table 13). For significance we used the ‘credible-interval’ approach, where significance was determined by whether the middle 95% quantiles of the parameter differences included zero (not significant) or excluded zero (significant). For grasses and sedges, the shape parameter was significantly smaller than the null shape parameter, while scrub oak showed a significantly larger shape parameter than the null. For scrub oak and blackjack oak, the scale parameter was significantly smaller than the null. Only for heather was there no significant difference in the gamma distribution parameters compared to the null, most likely due to the small sample size of plots with heather (Figure 3-20).
Table 13: Estimated gamma distribution parameters (shape and scale) for SDI observations on plots where taxon occurred. Taxon-specific distributions were fitted for 10,000 random subsamples of the observations. These were compared to random subsamples of SDI values for all pure pine plots, with sample sizes corresponding to the specific taxon. Bolded values show where credible interval for difference between taxon and null does not include 0, indicating significance.

<table>
<thead>
<tr>
<th>Taxon</th>
<th>n</th>
<th>Shape (quantiles)</th>
<th>Delta Against Null</th>
<th>Scale (quantiles)</th>
<th>Delta Against Null</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>2.5% Median 97.5%</td>
<td></td>
<td>2.5% Median 97.5%</td>
<td></td>
</tr>
<tr>
<td>Panicoideae</td>
<td>117</td>
<td>2.01 2.31 2.74</td>
<td>-3.32 -0.70</td>
<td>50.8 59.8 68.4</td>
<td>-2.38 28.5</td>
</tr>
<tr>
<td>Carex</td>
<td>64</td>
<td>2.02 2.48 3.31</td>
<td>-4.06 -0.12</td>
<td>52.7 67.5 81.5</td>
<td>-2.37 43.3</td>
</tr>
<tr>
<td>Hudsonia</td>
<td>27</td>
<td>2.16 2.64 3.41</td>
<td>-6.54 0.35</td>
<td>29.4 39.7 50.0</td>
<td>-35.7 20.5</td>
</tr>
<tr>
<td>Q. ilicifolia</td>
<td>285</td>
<td>5.58 6.35 7.38</td>
<td>1.12 3.52</td>
<td>25.5 29.3 33.3</td>
<td>-26.0 -8.51</td>
</tr>
<tr>
<td>Q. marilandica</td>
<td>135</td>
<td>4.63 5.62 7.18</td>
<td>-0.17 3.37</td>
<td>23.8 30.0 36.0</td>
<td>-30.2 -3.58</td>
</tr>
</tbody>
</table>

Figure 3-20: Estimated gamma distribution parameters for null datasets, by taxon. Each density line represents 10,000 random subsamples from the Stand Density Index (SDI) values of the pure pine plot observations, with the size of the subsamples corresponding to 50% of the displayed n for each taxon.
Figure 3-21: Estimated gamma distributions for SDI observations on plots with the presence of a given taxon in the ground plot data from 10,000 50% subsamples of the dataset. Null distributions are drawn from the total plot SDI observations, of a sample size corresponding to the number of observations from each taxon, respectively. Column 1 shows the difference between the shape parameter for the estimated gamma distribution for the taxon and the estimated null distribution. Column 2 shows the differences in the scale parameter. Vertical dotted lines show the 2.5% and 97.5% confidence intervals for the difference, with the red line showing zero. The third column shows the taxon (green) and null (grey dotted) distributions, using the median shape and scale parameters for each.

Figure 3-21 shows the differences between the estimated gamma distribution for the taxa and the null. The rightmost column shows that a random sample of the overall dataset (gray dotted) produces more high SDI values than random samples of observations for the indicator taxa (green solid). This confirms that the absence of observations of these taxa at high SDI values is not an artefact of the overall distribution of SDI values. While the credible interval
approach did not show significant differences for the parameters estimated for *Hudsonia*, Figure 3-20 shows that this probably had much to do with the small sample size of plots observed with this taxon.

### 3.3.5 Validation for Select Taxa

On those plots where we had understory LAI measurements in addition to overstory observations, we saw no pattern of understory LAI with overstory LAI (Figure 3-22). Notably, the ground-layer component of LAI could as much as double total plot LAI (overstory + understory).

We plotted the product of the SDI~LAI function and the modeled SDI for both grasses (Figure 3-23) and heather (Figure 3-24), as well as the select observations of low-vigor individuals we made for these taxa. These plots were used as a visual validation to see if our models of maximum SDI and our model of LAI based on SDI were corroborated by field observations.

For grasses, the low-vigor individuals we measured fell within the prediction interval based on the multiplicative error between the maximum SDI function (Figure 3-23), using both the 0-100% ground coverage data, as well as the 0-1 proportional data. This interval was calculated as the 2.5% & 97.5% quantiles for the model parameters of maximum SDI (based on the 10,000 subsampled datasets) and the Michaelis-Menten LAI~SDI function’s prediction interval; the minimum bound was the 2.5% prediction interval for the LAI value based off the resulting SDI value using the 2.5% quantiles of the max SDI function parameters. The maximum bound was the 97.5% prediction interval for the LAI value based off the 97.5% quantiles of the maximum SDI function parameters.
For heather, observations of low-vigor plants did not correspond with the predicted region of suitability (Figure 3-24). For the 0-100% ground cover interval, 6 of 14 observations fell outside the suitable LAI interval, while 7 of 14 observations were outside the region using the 0-1 proportional cover interval.

Figure 3-23: Overstory LAI vs Understory LAI for grasses; left panel corresponds to the 0-100% coverage of the ground, right panel corresponds to the 0-1 proportion of the ground data. Shaded region corresponds to SDI levels below the maximum SDI threshold using the 2.5% quantiles of the simulated model parameters, fading color corresponds to the downward slope of the same, with no color indicating SDI values above the 97.5% quantiles of the simulated model parameters. All SDI values have been converted to LAI values using the Michaelis-Mentern formulation of the LAI~SDI function. The dotted lines correspond to the 2.5% and 97.5% prediction intervals for the LAI~SDI function, using the same quantiles of the max SDI function parameters. If the SDI~LAI model and the SDI upper survival limit are accurate, we would expect to see the low-vigor individual grasses occurring between the prediction intervals.
3.4 Discussion

3.4.1 LAI as function of SDI

Our observations showed that stand density index (SDI) is a useful attribute to assess the understory light environment in pitch pine forests. Though there is significant variation in the data, leaf area index (LAI) can be modeled as a non-linear function of SDI. This has been previously formulated as a linear relationship in uneven-aged Ponderosa Pine forests (Ex and Smith, 2013), though over a narrower and lower range of SDI values. In contrast, we found that at lower values of SDI, LAI rapidly accumulates; at higher values, LAI is less responsive to changes in SDI. Others have noted non-linear relationships between under-canopy light
availability and stand variables like Basal Area (Hale et al., 2009; Palik et al., 1997) and the uncommon Overstory Abundance Index (Battaglia et al., 2003).

The Michaelis-Menten formulation seemed to be the most reasonable model to use SDI to predict LAI, from both a theoretical and empirical basis. Based on the cross-validated testing data, the log, asymptotic, and Michaelis-Menten formulations had the lowest RMSE for model predictions. Similarly, they had the lowest residual standard deviation for the training data. However, the distributions of differences of BIC values compared to the linear model was highest for the Michaelis-Menten and log models. The Michaelis-Menten formulation had the added benefit of starting at the origin, which makes more physical sense; at an SDI of 0, there should be no foliage to contribute leaf area to the canopy, and no progress in the reaction.

Our formulation for the relationship between SDI and LAI is empirical for this forest type and in this landscape. Our observations were made for sites dominated by a single species (P. rigida) on unmanaged sites with light, acidic soils, yet species, site, and management all play a role in the relationship. Maximum LAI (our model term $\beta_1$ for the Michaelis-Menten formulation) is dependent on the photosynthetic physiology of the species of interest and is not uniform even amongst the closely-related southern yellow pines (Gonzalez-Benecke et al., 2011; Sharma et al., 2012). Further, site-level LAI for pine can be increased through fertilization (Gholz et al., 1991; Jokela et al., 2004), indicating a strong influence of site quality on the parameters of the relationship. There is, however, a strong relationship between stem increment and total leaf area at lower levels of LAI that becomes noisier at higher LAI (Jokela et al., 2004), indicating that stand occupancy is the limiting factor for light harvesting at lower LAI.

The reduced responsiveness of LAI to SDI at higher levels of the latter indicates that above a threshold, increasing occupancy does little to increase the amount of light harvested by a stand. This is consistent with the idea of full site occupancy, which Long (1985) placed at a relative density of 0.35, or 35% of maximum possible SDI for a species. The mean value for the Michaelis-Menten constant (model term $B_2$) occurred at SDI 131, almost exactly 1/3 of the
maximum SDI (398) used in contemporary forest growth modeling software (Dixon and Keyser, 2019). To place this point of site occupancy in the context of basal area observations from the plot data, SDI values of 126-136 were observed to have a mean BA of 15.3 m²/ha with a standard deviation of 1.8 (English: 66.8 ft²/ac, σ = 7.9, n=128). However, the physiological basis for using SDI to quantify the use of growing space is somewhat tenuous in uneven-aged stands (Long and Daniel, 1990), and not all of our plots were tested for even-agedness. Although sapwood area is proportional to site utilization in even-aged systems, SDI underpredicts site utilization in older trees and overpredicts for young trees in uneven-aged stands (Woodall et al., 2003).

Several factors could be responsible for heteroskedastic relationship between SDI and LAI. Errors around the model predictions for LAI may be due to the effects of tree clumping and canopy depth. We did not account for the spatial arrangement of trees within plots in impacting light transmittance, though clumping is widely known to impact the Beer-Lambert law homogeneity assumption in LAI measurements, particularly in open-canopy pine forests (Battaglia et al., 2002; Davi et al., 2008; Gholz et al., 1991; Sharma et al., 2012). While this should increase the variance in LAI at low to medium SDI values, we saw the opposite: residual error increased with higher values of SDI. SDI is calculated using trees/unit area and by doing so it inherently assumes tree spatial uniformity for point measurements. When derived as values from a set of inventory plots across a stand its use can reflect the variability in tree density one encounters across the stand. In this study we instead used point measurements of both LAI and SDI, but transect-based measurements aggregated at the stand level might reduce much of the variability we observed.

Abiotic latent variables that affect all trees on a site might also be responsible for the pattern of the residuals that we observed here. The higher SDI plots were collected across a wide range of sites spanning roughly 20km, while the lowest SDI plots were collected in a narrow range across 0.5km. This was the unfortunate consequence of difficulty in locating low SDI/low LAI plots anywhere on this landscape, which is suggestive of the relative paucity of habitat for
shade-intolerant species. Other factors that could have increased variability include the sky conditions during our measurements. All plots were measured under clear sky conditions, but not all plots could be measured during times of low solar elevation. However, there was no relationship between residual size and time of collection.

3.4.2 Light Needs of Indicator Taxa

As expected, shade-tolerant taxa (such as Gaylussacia) were more abundant at higher SDI values (Appendix C: General Overview of Understory Data), while shade-intolerant species were more abundant at lower SDI levels. Of the two models (0-100 vs. 0-1), the proportional model (0-1) was more consistent for four of the five taxa, while the total cover model (0-100) was more consistent for the Panicoideae. The total cover model produced lower estimates for the upper limit of SDI suitability for most species because of incomplete dominance.

3.4.2.1 Panicoideae

As there were many more plots where Panicoideae (grasses) were dominant, the maximum SDI model using the 0-100 data fit the data more consistently. An outlier plot with a small number of grasses amongst little cover of anything else skewed the results with the proportional (0-1) model. The estimated gamma distributions showed that the SDI values at which grass was found were lower than the dataset as a whole. Using the 0-100 data, the median inflection points for the upper limit of SDI occurred at 225; the 95% prediction interval for LAI at this SDI is 1.63-3.63 (modeled mean of 2.63). All the plant measurements for validation fell within this LAI interval when considering overstory and understory LAI together.

There is overlap between our results and previous investigations into grass yield for agroforestry purposes. For example, Albaugh et al. (2014) used greenhouse studies to experimentally determine biomass yield for switchgrass in the context of intercropping with loblolly pine, noting that significant reductions in biomass would become apparent at LAI values between 1.95 and 2.25. Using our modeled relationship with SDI, those values correspond to an
SDI range of 113-152. It is important to note, however, that the number from Albaugh et al. (2014) was for a modeled 50% reduction in biomass, not a limit for survival. Mulligan et al. (2002) underplanted wiregrass (*Aristida beyrichiana*) in a longleaf pine plantation across a thinning gradient. Some plants survived at all overstory densities (25, 16, and 8 m²/ha; 109, 70 and 35 ft²/acre), but survival increased with any level of thinning, and almost all reproduction occurred in the treatment with the lowest residual density. Wolters (1981) examined herbage production for silvopasture under longleaf pine with grass species seen in this study; that work recommended target basal areas of 12-20m²/ha (52-87 ft²/ac) for productive balance of timber and grazing, with basal areas above 28m²/ha (122 ft²/ac) eliminating production of grass herbage entirely. Though basal area does not map exactly to SDI, plots from our study within the basal area interval for productive grazing (in Wolters, 1981) had a mean SDI of 141 ($\sigma = 23$, $n=665$), and plots close to Wolters' (1981) basal area threshold for survival of grass (27-29 m²/ha) had a mean SDI of 238 ($\sigma =22$, $n=263$). This threshold for survival agrees well with our result for survival of local *Panicoideae* species.

The two grasses we used for validation (broomsedge bluestem, *Andropogon virginicus*; switchgrass, *Panicum virgatum*) are not only different species, but are also not an exhaustive representation of the full breadth of species of grass that can be found in this landscape. Other common native warm season grasses that can be found in the study landscape include little bluestem (*Schizachyrium scoparium*) and Indiangrass (*Sorghastrum nutans*). Different forage species have unique abilities to adjust to life in the partial-shade (Pang et al., 2019), although the species we observed in the New Jersey Pinelands landscape do have some physiology in common, being taxonomically grouped and all using C4 photosynthesis.

Our results suggest that management of pitch pine forests in this landscape should keep overstory occupancy below a maximum SDI of about 225 if goals include the presence of native warm-season grasses. At this level of overstory occupancy, the variance in light availability as
function of SDI leaves enough small openings for at least sparse survival of the grasses we considered.

3.4.2.2 Carex

Of the proportional (0-1) or the total cover (0-100) models, the proportional model produced more consistent estimates of the upper SDI limit for Carex spp. (sedges). This was likely because sedge was dominant on only a handful of plots. In contrast to the data for heather, sedges occurred at lower SDI values than the overall dataset, as evidenced by the estimated gamma distributions. An upper limit of SDI centered at 237 can be interpreted as sedge having intermediate shade tolerance – the prediction interval for LAI at this SDI level was 1.68-3.68. This agrees with previous qualitative assessments of the species surviving at middling levels of shade, but being a better competitor in brighter sunlight (Abrams and Dickmann, 1982; Crins and Ball, 1983; Houseman and Anderson, 2002). As far as surviving as a component of the plant community in these forests, our results indicate that sedges can remain in the understory below a pine overstory SDI of around 237.

3.4.2.3 Hudsonia

Hudsonia spp. (heather) had the lowest SDI limit by the logistic models, with both models centered on inflection points below SDI 100. That result was primarily an artefact of heather not being dominant on any of the plots. In addition, the estimated gamma distributions of SDI values for the null (full dataset) and the plots with occurrence of heather overlapped due to the small sample size for observations of this species. For this reason we cannot say that the SDI values under which heather was observed were any different from the overall observations, further undermining the upper SDI limit we determined from the logistic models.

Indeed, the validation data showed that heather occurred at higher LAI than calculated from the prediction interval for LAI based on the maximum SDI inflection point (Figure 3-24). The observed distribution of heather in this environment, while strongly light-dependent,
probably has more to do with other factors, such as soils. Heather is a component of the plant community on the driest sites and sites with abundant bare soil. These observations point to edaphic and disturbance effects as alternative explanations for the distribution of heather in the Wharton State Forest inventory data. Though we expect there is a bounding limit for the amount of shade that heather can tolerate, this study was unable to determine that limit with certainty. The validation observations showed that heather can occur under higher LAI levels than was predicted by our SDI limit model and SDI–LAI model.

3.4.2.4 *Quercus ilicifolia*

Our modeled inflection point for scrub oak was relatively consistent when using the proportional model (0-1). In contrast, the total cover (0-100) model was somewhat more unstable in that it produced a wider range for the inflection point. However, the median inflection points of both models were close to each other (SDI of 267 and 275, respectively).

Our observations of survival at this moderate level of shade is somewhat different from published descriptions of the species. Smith (1992) described the species as ‘very intolerant’ of shade, and it has been described as ‘light demanding’ (Halls, 1977). Survival under shade does not necessarily translate to productivity under shade, though. Little et al. (1958) observed that shaded scrub oak produced fewer acorns than open-grown plants, but Wolgast (1978) demonstrated that genetic differences are also responsible for the size of an individual’s acorn crop. There could also be an interaction between the two, where some individuals trade persistence under sub-optimal conditions for increased reproductive output.

3.4.2.5 *Quercus marilandica*

The modeled inflection point for blackjack oak was relatively consistent between the models using the proportional (0-1) and total (0-100) values. The latter model was somewhat unstable because there were no plots where blackjack oak reached 100% cover of the understory, leaving the upper end of the modeled curve to ‘float’ without support from data at the enforced
upper limit value of 100. The proportional model was relatively stable in producing an upper-SDI inflection point limit between SDI 215 and 230. This suggests a somewhat higher shade tolerance for blackjack oak than is qualitatively assumed in many sources.

Several authors have documented disappearance of blackjack oak in forested lands of the inland southeastern US, with complementary explanations of shade exclusion (Clark et al., 2005), lack of appropriate fire (Brewer, 2001), and both acting together (DeSantis et al., 2010; Surrette et al., 2008). Contemporaneous to this disappearance from forestlands has been blackjack oak recruitment into grasslands and savannahs, attributable to climatic effects (Rogers and Russell, 2014). It may be that there are interacting controls on the occurrence of blackjack oak: appropriate climatic and fire effects for recruitment, followed by shade requirements for persistence. Qualitative assessments of shade tolerance for this species are biased towards its current distribution (Smith, 1992), but its current occurrence in much of its range may not reflect its physiological abilities. Surrette et al. (2008) noted in reference to an observation from Hilgard (1860, p.289) that blackjack oak may be more flexible in response to shade than is typically thought - on fertile loams, blackjack oak:

“forms large, well shaped spreading trees, sometimes fifty feet and more in length, with trunks comparatively straight – or at least, not whimsically knotty like those of the Pine Hills;” (Hilgard, 1860)

While anecdotal, this account from two centuries ago highlights the difference between the realized niche today and the fundamental niche that a species might be capable of living in. Changes in land use on the more fertile sites where blackjack oak once grew may have removed from its range the sites where it was best able to tolerate moderate shade through expression of other growth forms.

Interestingly, the USDA Forest Service Forest Vegetation Simulator uses a maximum SDI for post oak (Q. stellata) of 311 (Dixon and Keyser, 2019), about 40% higher than our mean modeled inflection point for blackjack oak. These two species co-occur in the Cross Timbers
region, but post oak has seen less decline in importance on sites undergoing mesophication (DeSantis et al., 2010; Hoff et al., 2018). Though there is clearly a relationship with fire, some of the difference in trajectory for the two species may be attributable to shade tolerance differences. At least in the pitch pine forest type within Wharton State Forest, management to include blackjack oak should aim to keep SDI below 225.

3.4.3 LAI contribution from understory

There was no relationship between overstory and understory LAI (Figure 3-22), reflecting the diversity of understory composition with regard to their light-use needs. The most common understory taxon in the data were the Vaccinieae (huckleberry and blueberry), which demonstrated shade tolerance in our data (Appendix A: Shade-tolerant species). In lower-light environments, shade-adapted species contribute significant leaf area, as they’re less constrained by light. The maximum LAI that we observed at ground level corresponded with the values reported by Clark et al. (2012).

In the majority of the plots for which we collected LAI measurements, cumulative LAI at ground level was well beyond the limits for grass (Figure 3-23). In contrast, a significant proportion of the pure pine plots were below the SDI limit (median inflection point) for grasses (Figure 3-17 & Figure 3-19). This demonstrates that while there is top-down control on the distribution of warm-season grasses, in much of the landscape (by % of plots in Wharton State Forest) it is not solely overstory but also understory that limits light availability. For the establishment and survival of the ground-level pine barren taxa that we evaluated, shrub competition exerted a strong influence. In a similar environment with a notable absence of trees, clonal expansion of black huckleberry alone was enough to replace the more diverse sandplain grassland community (Harper, 1995). Thus, management to improve habitat for open-canopy species must include actions to diminish shrubs in addition to overstory.
3.4.4 Other factors that explain species abundance

A core assumption our approach is that maximum SDI for a taxon reflects the upper limit of shade under which that taxon can grow. It is possible that the competition experienced at higher SDI values could be constricting the use of other resources, such as water or nutrients. It may be that competition for these other resources is responsible for the disappearance of different taxa at higher SDI values. However, water is not limited in pitch pine lowlands, and these species are all adapted to the acidic conditions of these soils.

Our modeling approach was also contingent on there being plots where a taxon is limited by light; if no plots were located on or near the upper light limit, then there would be no data available for a model. This happened with heather: there were too few observations in the wider dataset to capture the upper limit of density for the species. Alternative approaches to deal with this shortcoming in our approach could be to measure SDI for a stand and count instances of the taxon of interest, repeating the process over multiple stands. A stronger method for determining the compensation point for the species would be greenhouse studies with varying levels of shade cloth, but these do not account for the effects of competition on survival, thus limiting the utility for land managers.

It would be unwise to neglect discussion of disturbance, as it plays an enormous role in the traits of this ecosystem. Disturbance is a broad term that covers many different events and mechanisms. Even within a type of disturbance event there are variations in intensity of effect, both within and between events. For instance, wildfires can occur at different times of year, at different intensities, at different spatial and temporal scales, all of which determine the ecosystem effects. In the case of intermediate disturbance that fails to replace a stand, residual SDI is not necessarily affected or reduced to zero. On sites where disturbance is intense enough to restart stand initiation, the trajectory of stand occupancy is sensitive to starting conditions: seed bank size, seed bank diversity, distance to new seed sources, time of year, precipitation, availability of
germination microsites, etc. For these reasons, the relationship between SDI and time since disturbance is not a simple relationship (see Appendix B: Time Since Disturbance).

If the presence of open canopy plant communities was solely due to succession, we would expect to see a trend in time since disturbance and the proportion of at least some of the indicator species we examined. We did not see such a trend (Appendix B: Time Since Disturbance) but examining the data this way did demonstrate that not all disturbances of the same type were equally inviting for colonization by our taxa of interest. As with SDI, the variance in site effects within each disturbance type is large; some defoliations by *Lymantria dispar* created the conditions for recruitment of specific taxa, while others did not. Though succession is a useful framework for understanding some plant communities, the successional behavior of a specific taxon may vary by site or associates. Though broomsedge is an old-field colonizer in the southeast, it can persist in pine forests (Grelen and Hughes, 1984), possibly as a result of allelopathy against certain competitors (Rice, 1972). Similarly, our taxa of interest were not all lost in undisturbed sites. We did not seek to answer whether SDI is more important than a specific type of or time since disturbance in predicting the presence of a taxon. Our method was instead an attempt to determine one of the boundaries to the niche space for select taxa in this community, not to explain the entire niche space.

We did attempt to classify points (presence/absence) by fitting general linear models (binomial), linear discriminant analysis, support vector machines, and neural networks to a set of predictors (stand variables, disturbance history variables, soil variables). These classifiers were very poor predictors of the occurrence of select taxa with these methods, partially due to asymmetry in the datasets, but also due to an incomplete set of predictors. It will take further study to determine the relative strength of different factors in determining presence/absence of these taxa in this landscape. Instead, our study showed that there are limits to the amount of overstory shade associated with these open-canopy indicator taxa. Additionally, community members shorter than the main shrub layer of the Vaccinieae are subject to increased competition
for light, which suggests management actions to benefit shade-intolerants should consider controlling huckleberries and blueberries.

### 3.5 Conclusions

This research linked a common forest occupancy metric, Stand Density Index (SDI), to leaf area index (LAI) using a model developed for enzyme reaction kinetics. We demonstrated upper limits of stand density for several taxa present in the ground layer within a coastal plain pitch pine forest. These upper limits were for survival and inclusion in the plant community, but not necessarily productivity. Management actions that aim to promote these taxa should bring overstory occupancy below their corresponding SDI levels, generally around SDI 230. Understory competition, often from shade-tolerant shrubs, could contribute as much shade as the overstory, highlighting the need for additional consideration of the shrub layer when planning management to increase ground-level light. Further analysis is needed to determine the relative importance of overstory occupancy and disturbance history on the distribution of the studied taxa.
3.6 Appendix A: Shade-tolerant species

Figure 3-25: Scatterplots of ground cover of greenbrier against Stand Density Index. Lower pane is in the original measurement units (0-100), percent of the 1/500th acre ground plot covered by the species. Upper pane is scaled to be a proportion of the total % cover observations for a plot.
Figure 3-26: Scatterplots of ground cover of inkberry against Stand Density Index. Lower pane is in the original measurement units (0-100), percent of the 1/500th acre ground plot covered by the species. Upper pane is scaled to be a proportion of the total % cover observations for a plot.
Figure 3-27: Scatterplots of ground cover of blue huckleberry against Stand Density Index. Lower pane is in the original measurement units (0-100), percent of the 1/500th acre ground plot covered by the species. Upper pane is scaled to be a proportion of the total % cover observations for a plot.
Figure 3-28: Scatterplots of ground cover of black huckleberry against Stand Density Index. Lower pane is in the original measurement units (0-100), percent of the 1/500th acre ground plot covered by the species. Upper pane is scaled to be a proportion of the total % cover observations for a plot.
Figure 3-29: Scatterplots of ground cover of sweetpepperbush against Stand Density Index. Lower pane is in the original measurement units (0-100), percent of the 1/500th acre ground plot covered by the species. Upper pane is scaled to be a proportion of the total % cover observations for a plot.
3.7 Appendix B: Time Since Disturbance

Figure 3-30: Scatterplots of proportional cover of grasses versus the time since the last known disturbance.

Figure 3-31: Scatterplots of proportional cover of sedges versus the time since the last known disturbance.
Figure 3-32: Scatterplots of proportional cover of heather versus the time since the last known disturbance.

Figure 3-33: Scatterplots of proportional cover of scrub oak versus the time since the last known disturbance.
Figure 3-34: Scatterplots of proportional cover of blackjack oak versus the time since the last known disturbance.
Figure 3-35: Effect of time since disturbance on Stand Density Index for the most common disturbance types observed in Wharton State Forest. Blue dots represent plots that have not experienced any disturbances in the time interval we examined. Red dots represent those plots where specified disturbances occurred.
3.8 Appendix C: General Overview of Understory Data

We examined the proportion of different taxa found in the ground plot along a gradient of SDI values. At lower SDI values, taxa such as genus *Carex* (sedges) and the subfamily *Panicoideae*, *Xerophyllum aspheloides* (turkeybeard), and the genus *Hudsonia* (heather) were present in the inventory data, but the abundance of both tapered and disappeared as SDI increased.

Conversely, species such as *Ilex glabra* (Inkberry holly) and *Gaultheria procumbens* (Wintergreen), the genus *Smilax* (greenbriers), and the tribe Vaccinieae (blueberries and huckleberries) all became more abundant as SDI increased. Shrubby oaks such as *Quercus ilicifolia* (scrub oak) and *Q. marilandica* (blackjack oak) were most

![Figure 3-36: Proportion of all ground layer observations for four taxa across a range of Stand Density Index values: warm-season grasses (subfamily Panicoideae), sedges (genus Carex), eastern turkeybeard (Xerophyllum aspheloides), and heather (genus Hudsonia). Bin ranges are units of 25 SDI (0-25, 25-50, etc.). Data for all the pure pine plots (relative live Basal Area of pine >90%).](image)

![Figure 3-37: Proportion of all ground layer observations for four taxa across a range of Stand Density Index values: sheep laurel (Kalmia angustifolia), mountain laurel (Kalmia latifolia), scrub oak (Quercus ilicifolia), and blackjack oak (Q. marilandica). Bin ranges are units of 25 SDI (0-25, 25-50, etc.). Data for all the pure pine plots (relative live Basal Area of pine >90%).](image)
abundant in the low- to middle-range of SDI values. *Kalmia angustifolia* (sheep laurel) had roughly steady abundance throughout the range of observed SDI values, while *K. latifolia* (mountain laurel) was most abundant at the extreme high range of SDI values. Lichen abundance tapered off above SDI values of around 300, with nearly no recorded lichens above this threshold.

Figure 3.38: Proportion of all ground layer observations for six taxa across a range of Stand Density Index values: black huckleberry (*Gaylussacia baccata*), blue huckleberry (*G. frondosa*), unidentified huckleberry (genus *Gaylussacia*), lowbush blueberry (*Vaccinium angustifolium*), highbush blueberry (*V. corymbosum*), and blue ridge blueberry (*V. pallidum*). Bin ranges are units of 25 SDI (0-25, 25-50, etc.). Data for all the pure pine plots (relative live Basal Area of pine >90%).

Figure 3.39: Proportion of all ground layer observations for lichen growth forms across a range of Stand Density Index values: crustose lichen, foliose lichen, and fruticose lichen. Fruticose lichen includes reindeer moss, genus Cladonia. Bin ranges are units of 25 SDI (0-25, 25-50, etc.). Data for all the pure pine plots (relative live Basal Area of pine >90%).
Figure 3-40: Total ground cover of select understory taxa in pure pine inventory plots, by Stand Density Index.

Figure 3-41: Proportion of ground cover of select understory taxa in pure pine inventory plots, by Stand Density Index.
4: Section IV: A density management diagram to balance local management objectives for pitch pine (*Pinus rigida*) forests of southern New Jersey

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Abstract

Pitch pine (*Pinus rigida*) can be found across a broad range in eastern North America but only becomes locally-dominant on poor soils in northeast, areas culturally referred to as ‘pine barrens.’ Contemporary management goals of pitch pine barrens are focused on non-commercial benefits of forests, and managers have not had the benefit of recent silvicultural studies of the species. We present a density management diagram that empirically articulates the size-density limits of even-aged pitch pine stands. Included in the diagram are some of the stated objectives for forests in this region, namely wildfire risk and carbon density. We also include a mixed-effects model of forest water use to relate stand attributes with evapotranspiration. Maximum possible aboveground live tree carbon begins to decline at quadratic mean diameters greater than 9”, while crown fire risk remains high along the size-density limit until quadratic mean diameters above 12” are achieved. Stand evapotranspiration was responsive to canopy height and understory cover, but we failed to reject the hypothesis that Stand Density Index (SDI) had no effect on stand water use. Canopy height and SDI were linked, however, as a result of our data filtering process and the limited amount of forest management in this landscape. Future research is proposed to discern the effects of stand variables on evapotranspiration.
4.1 Introduction

Overstory occupancy by trees exerts a top-down control on the light environment within a forest, so that the survival and growth of different organisms is bounded by the available resources not used by overstory trees. Purposeful management for a variety of ecosystem attributes requires an understanding of how growing space is allocated in a forest.

Foresters have long sought to define the bounds of available growing space to assess competition and stocking. Reineke’s Stand Density Index (SDI) (Reineke, 1933) defined the maximum relationship between the number and size of trees in a stand, representing one early but robust index of competition used in North American forestry. Renewed interest in SDI has stoked debate within forestry and ecology about the proper theoretical constructs to define the slope and location of the maximum size-density relationship for plant species (Jack and Long, 1996; Osawa and Sugita, 1989; Pretzsch and Biber, 2005; Weller, 1990, 1987). However, empirical approaches that use generally similar methods to have also been used to describe the limits forest of growth (Cao et al., 2000; Long and Shaw, 2005; Vacchiano et al., 2013, 2008; Wilson et al., 1999).

Forest biometricians have developed different tools to take advantage of this empirical work to describe growing space utilization, such as ‘Gingrich’ stocking diagrams and density management diagrams for even-aged stands (Drew and Flewelling, 1979; Jack and Long, 1996; Roach and Gingrich, 1968). Though these tools are often used to understand tradeoffs in a wood production context, they are by no means limited to parameters of economic interest. Density management diagrams have been used to visualize conditions and plan management trajectories for elk (Smith and Long, 1987), red-cockaded woodpecker (Shaw and Long, 2007), and goshawks (Lilieholm et al., 1994).

The process of land management decision-making turns descriptive goals from management objectives into prescriptive treatments to achieve a desired condition. Biometric
tools help to translate descriptive goals of conditions into prescriptive approaches to management, which greatly increases the flexibility of the manager to achieve specific goals (Lilieholm et al., 1994; Vacchiano et al., 2013, 2008). Articulated goals for the pitch-pine dominated forests of New Jersey’s coastal plain include water provisioning, protection of life and property from wildfire, protection of forest health, habitat for rare plants and wildlife, net carbon sequestration, and attention to the emotions of urbanized public that is unfamiliar with forest management (New Jersey Forest Service, 2020).

Despite these interests, biometric forestry tools have largely not yet been developed for the Pinelands landscape, nor have the limits of site occupancy been characterized for pitch pine, presenting an opportunity to do both. This paper seeks to create a density management diagram for pitch pine that characterizes local management objectives. To do this we define the maximum size-density relationship for pitch pine as the upper boundary of the diagram, and we further ask how forest occupancy impacts fire risk, stand height, aboveground live tree carbon, and forest evapotranspiration. These attributes provide a framework on which to place ecosystem attributes, so that tradeoffs in management can be easily visualized.

4.2 Methods

4.2.1 Grouping State Inventory Data into Stands

The New Jersey Forest Service data measured over Wharton and Penn State Forests was collected at the plot-scale, with the intention of summarizing the plot data by forest type for stewardship planning. For our analysis we sought to group the data into stands, rather than the broader forest types. However, as the data were not collected with respect to stands, we needed to determine a method to group the data.

Grouping the plots into stands has the benefit of smoothing some of the sampling error. As the proportion of the stand sampled decreases, it becomes possible for pockets of higher-density trees to have an outsize influence on the estimated stand attributes. (with a small enough plot that randomly falls within a tree, one could erroneously conclude that the whole stand is
occupied by a block of pure wood). The variable-radius point samples collected by NJFS each cover a relatively small footprint: the overall mean QMD observed across 5999 plots was 8.6” and the limiting distance for a tree of this size is 23.28’ (to the face of the tree on flat ground if measuring in BAF 10-English). This corresponds to the radius of an FIA subplot (24’), but because of size alone it skews towards higher-densities. Sampling a greater proportion of the stand itself would be more likely to capture the inherent variability within a stand. For this reason, grouping the data into stands is a more consistent use of the Stand Density Index (Shaw and Long, 2010).

We set out to group the plots into stands using a supervised classification approach. We downloaded Sentinel 2A L1C images (top-of-atmosphere reflectance) for five dates (Table 14) from the USGS via Earth Explorer, selecting from the two tiles that covered our study area (T18SWJ & T18TWK; Figure 4-1). We attempted to use images that were close in time to each other, as well as close to the actual time of forest inventory data collection. For each of these dates and footprints, we stacked the Multi-Spectral Instrument (MSI) bands with 10m spatial resolution (Blue, Green, Red, Near-Infrared), and mosaicked date-pair tiles together to cover our study area. These images were stacked together, and to improve the classification model, we added NDVI images for each date to the stack.

We used 2015 CIR aerial imagery and on-the-ground experience of the study area to select training areas for use in the model. In addition, we used local knowledge of more recent fires (wildfire and prescribed burning) to ensure that areas burned during the interval between the
images would not be included in the training datasets. As the purpose of this classification was for stratification that would isolate pure pine stands, we chose cover classes that generally corresponded to the dominant tree functional groups for the area: pine and oak in the uplands, cedar and swamp hardwoods in the wetlands.

Table 14: Supervised classification training data overview.

<table>
<thead>
<tr>
<th>Cover Type</th>
<th># of pixels</th>
<th>Training areas</th>
<th>Sentinel 2A Image Dates</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pine</td>
<td>4565</td>
<td>8</td>
<td>2016-03-11</td>
</tr>
<tr>
<td>Oak</td>
<td>1213</td>
<td>6</td>
<td>2016-07-17</td>
</tr>
<tr>
<td>Cedar</td>
<td>1925</td>
<td>4</td>
<td>2016-09-28</td>
</tr>
<tr>
<td>Swamp Hardwood</td>
<td>1044</td>
<td>9</td>
<td>2016-11-09</td>
</tr>
<tr>
<td>Shrub</td>
<td>109</td>
<td>1</td>
<td>2018-01-01</td>
</tr>
<tr>
<td>Herbaceous</td>
<td>758</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>Water</td>
<td>1661</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

We carried out the classification using the ERDAS Imagine Supervised Classification tool (Hexagon Geospatial, 2016). Within the options of the software, we used a parallelepiped non-parametric decision rule, but maximum likelihood for the parametric decision rule. Overlap and unclassified pixels were classified using the parametric rule.

After classification we recoded portions of the raster to remove errors resulting from spectral similarities between classes. To do this we included two additional datasets: a rasterized version of the New Jersey Department of Environmental Protection’s Land Use 2015 dataset, and a heads-up digitized polygon coverage of the pine plains. Pixels classified as swamp hardwoods but occurring in uplands according to the Land Use 2015 data were recoded to oak. Similarly, pixels classified as oak but occurring in wetlands were recoded to swamp hardwood. Pixels classified as herbaceous and occurring in wetlands were relabeled to swamp hardwood if the Land Use 2015 data labeled them as forest. A significant portion of the inventory points collected within Penn State Forest occurred in the pine plains, a unique pitch-pine dominated community with very different genetics from the rest of the pitch pine-dominated forest in the area. Any upland pixels classified as pine in the area marked as part of the pine plains were recoded to a new class, ‘Plains.’ Burned areas were erroneously classified as oak by the model, but this was acceptable for our purposes, as we sought to separate out higher-density pure pine: a non-target class that captures borderline data is helpful.
We then masked the classified raster to the extent of Wharton and Penn State Forests. We clumped the raster into unique groups of homogenous pixels using the 8-neighbor rule, then eliminated any groups with fewer than 100 pixels, replacing their values with that of the largest neighbor. As each pixel represented 100 m², our minimum mapping unit then became one hectare (Figure 4-2).

![Figure 4-2: Raster of classified forest types for Wharton State Forest and Penn State Forest. Note that recently burned areas are mis-classified as oak, which is helpful for selecting out only undisturbed, homogenous pitch pine.](image)

We used this classification map to stratify the points into forest types. Then, we further split these points by the BAF in which they were originally collected. Using cover type and BAF, we grouped the plots into spatial clusters using the k-means clustering in the base R ‘stats’ package. We used the X and Y coordinates of the plots as the inputs, a starting number of 25 clusters, and the Hartigan-Wong algorithm. For any clusters with more than 6 plots, we repeated the clustering to separate plots into smaller groups. In this way, all of the points collected in the
same cover type and at the same BAF were grouped into ‘stands’ of 1-6 points located together. We refer to these synthesized stands as ‘clusters’ throughout this document, in contrast to their original collection scale of inventory ‘points.’

4.2.2 State Forest Inventory Data

We summarized NJFS forest inventory data at two scales: the cluster, and the point. For most of the analysis, we used cluster-level data, lumping points into synthesized stands with the clustering approach described above. Only for the maximum size-density relationship portion did we use the point-level data. For each cluster and point we calculated stand attributes, including metrics like quadratic mean diameter (QMD), trees per acre (TPA), Stand Density Index (SDI), relative basal area of each tree species, stand height, and more. Descriptions of other inventory attributes collected on the state inventory plots can be found in section 2. For SDI, we calculated both the Dq formulation and the summation version, for the purpose of evaluating the degree of even-agedness of datapoints (Shaw, 2006, 2000).

Similar to SDI, we calculated height using two methods. The first uses the Forest Vegetation Simulator methodology for determining stand height: find the 40 trees per acre in the stand with the greatest diameter considering the expansion factor (how many trees per acre are represented by each plot observation) and calculate their average height. Alternatively, since the NJFS inventory data included height, we used the height of the 40 tallest trees per acre in the stand, again considering the expansion factor for each tree.

Figure 4-3: Distribution of limiting distance for trees of each plot’s quadratic mean diameter.
As a check on the comparability of the state point-scale data with USFS FIA data, we looked to verify that the sampled area was comparable between the two datasets. However, unlike the fixed-radius FIA data, the state point-scale data used variable-radius sampling, so that the sampled area varied according to the diameter of the nearby trees. For each point, we determined QMD then used the basal area factor of the prism to find the maximum distance from the plot center that a tree of such size could be and still be counted in the plot (limiting distance). In the state point-scale data we used, the median limiting distance for trees of each point’s QMD was 22 feet (Figure 4-3). This is slightly smaller than the 24-foot radius of the FIA fixed-area subplots, showing that the state point-scale data sampled approximately the same area as the FIA subplot data.

We used two filters on both the point and the stand-scale cluster data, with a third filter applied to just the clusters. First, we eliminated any clusters (at the stand-level) and points (at the point-level) where the relative basal area of pitch pine was less than 90%, considering this an acceptable level of purity. Next, we attempted to restrict the analysis to even-aged data by using the ratio of SDI (summation) to SDI (Dq): we considered only clusters and points with a ratio of at least 0.95 to be even-aged. The third filter, applied only to the stand-scale cluster data, was to drop any clusters that ended up with only one point, as that would make them no different from the point-scale data. These criteria left us with 455 clusters and 2,256 points with which to conduct analysis (Table 15).

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Scale</th>
<th>n</th>
<th>Age at breast height (of dominant/co-dominant trees)</th>
<th>Quadratic Mean Diameter (in.)</th>
<th>Trees per Acre</th>
<th>Basal Area (ft²/acre)</th>
<th>Stand Height (ft.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Central Pines</td>
<td>Point</td>
<td>2256</td>
<td>67 (11-154)</td>
<td>8.2 (4-17.7)</td>
<td>316</td>
<td>94 (10-230)</td>
<td>48.7 (5-77.3)</td>
</tr>
<tr>
<td></td>
<td>Stand (Cluster)</td>
<td>455</td>
<td>68 (21-146)</td>
<td>7.6 (4-15)</td>
<td>320</td>
<td>92 (3-195)</td>
<td>50.0 (15-71.3)</td>
</tr>
<tr>
<td>FIA</td>
<td>Stand (Condition)</td>
<td>91</td>
<td>n/a</td>
<td>6.3 (2.8-11.3)</td>
<td>467</td>
<td>83 (2.1-155)</td>
<td>42.8 (14.6-63.8)</td>
</tr>
<tr>
<td></td>
<td>Point (Subplot)</td>
<td>455</td>
<td>n/a</td>
<td>8.1 (1.3-20.3)</td>
<td>297</td>
<td>77.5 (3.6-210.5)</td>
<td>43.7 (10-91)</td>
</tr>
</tbody>
</table>

Table 15: Inventory characteristics for stand- and point-scale datasets.
4.2.3 USFS FIA Data

To increase both the size of our dataset and the range of the geography of analysis, we also utilized USFS Forest Inventory Analysis data. Using the ‘rFIA’ package we downloaded the FIA databases for states with populations of pitch pine (Stanke et al., 2020), from New Hampshire to Georgia, and west to Kentucky. For each state we used a series of filters to locate pitch pine dominated ‘conditions’ that could be treated as stands.

We used the PLOT table first to subset to those FIA plots that had some amount of forest on them (where PLOT_STATUS_CD == 1) and were of the current plot design (DESIGN_CD == 1). Of these, we made a table of unique XY locations of the points (using the LAT and LON fields from the same table), recording the plotID and year of each plot measurement. We subset the COND table to these plotIDs. Recognizing that not every subplot within a forested plot was actually forested, we subset the COND table to just forested conditions (where COND_STATUS_CD == 1). We also recognized that there were some cases where subplots were incompletely sampled, so we eliminated conditions that didn’t have a CONDPROP_UNADJ of 0.25, 0.5, 0.75, or 1.

At this point our use of FIA data forked. Though we first summarized FIA data using the condition-level data only (treating the condition as the stand), we repeated our procedure with subplot-level data (treating the subplot as the stand). At the condition level, we sorted through the TREE table observations and summarized the data using the unique PLT_CNs to calculate the same stand-level attributes calculated for the State Forest Inventory data. For subplots, we identified unique combinations of PLT_CN and SUBP in the selection of the TREE table; these became the unique stands with which we calculated the same stand-level attributes. This left us with two datasets at different scales: the point scale, summarizing FIA subplots, and the stand scale, summarizing FIA conditions. As with the state inventory data, we filtered out datapoints where the observation had less than 90% relative basal area of pitch pine. To focus on even-aged datapoints, we also filtered out those subplots where the ratio of SDI (summation) to SDI (Dq)
was less than 0.95, and those conditions where this ratio was less than 0.90. A final filter on the conditions removed those conditions with only a single subplot. This left us with 91 pure, even-aged FIA conditions and 455 pure, even-aged pitch pine subplots.

A geographic review of these data show that most of the pure pine FIA subplots occurred in New Jersey (Figure 4-4). There are also clusters on the southeastern coast of Massachusetts, the eastern portion of Long Island, New York, and scattered plots in the Appalachian Mountains in Virginia, West Virginia, and Pennsylvania. Notably, many of the plots are not independent: some of them are re-measurements of the same location, separated only by time. Due to the paucity of data on pure pitch pine outside of New Jersey, we included re-measured plots in this dataset.

Figure 4-4: Approximate locations of FIA subplots and conditions used in analysis. All locations are at least 90% Pinus rigida by relative basal area of live trees. Only even-aged locations considered. All locations approximate.
4.2.4 Stand Carbon

We compared two different models for determining tree carbon to visualize on the density management diagram. Both models are referenced by the National Biomass Estimator Library for estimating aboveground tree biomass for pitch pine (Wang, 2019).

The first carbon model is from Whittaker and Woodwell (1968), developed from biomass measurements on 15 pitch pine trees in Long Island, New York:

$$\log(Biomass) = 2.0171 + 2.3373 \times \log(DBH)$$

(A)

where $DBH$ is diameter in cm at 1.37m off ground, $Biomass$ is aboveground dry weight in grams.

The second carbon model comes from Jenkins et al. (2003). The broader goal of that document blended biomass estimates from multiple studies on pine for a more general model for any species in the pine group:

$$\ln(biomass) = -2.5356 + 2.4349 \times \ln(DBH)$$

(B)

where DBH is diameter in cm at 1.37m off ground, and biomass is total aboveground biomass in kilograms. The Jenkins pine model’s sole reference for pitch pine is actually the Whittaker and Woodwell (1968) study in New York, though it includes multiple studies of many other pine species.

We converted these tree-level biomass estimates to stand-level estimates using the TPA and QMD numbers for the range of

Figure 4-5: Isolines for aboveground tree carbon using the Jenkins equation for pine and the Whittaker & Woodwell equation for pitch pine. Bold numbers at top left indicate metric tonnes of carbon per acre.
values in the density management diagram. Stand-level biomass values were converted to carbon by multiplying by 0.5 (Burrill et al., 2021). We chose to display isolines for 1, 2, 4, 8, 12, 18, 24, and 32 metric tonnes of aboveground tree carbon per acre (Figure 4-5). Notably, as none of these published equations for biomass for pine include tree height, we did not include the effect of site height on the isolines.

4.2.5 Modeling Stand Height

We compared four different models to predict stand height to include it in the density management diagram.

\[
\text{Height} = \left( \frac{QMD - b_1}{b_2 - (b_3 \cdot TPA^{b_4})^{b_5}} \right)^{1/b_5} \\
\text{Height} = \left( \frac{(b_1 + QMD)}{b_2 \cdot TPA^{b_3}} \right)^{1/b_4} \\
\text{Height} = \left( \frac{QMD}{b_1 \cdot TPA^{b_2}} \right)^{1/b_3} \\
\text{Height} = \frac{QMD}{(b_1 - b_2 \cdot \log_{10} TPA)}
\]

We fitted these models using the nlsLM function in the ‘minpack.lm’ package (Elzhov et al., 2016). We compared model performance across the two different stand height metrics (FVS approach using largest 40 largest diameter trees per acre; second approach using tallest 40 trees per acre) from a combined stand-scale dataset of state clusters and FIA conditions. Combining the datasets was supported by the complementary distributions of the stand heights in the two datasets.

4.2.6 Crowning Index

Fire is an integral component of the pine forests of the coastal plain. We sought to include in our analysis a metric that would separate ecosystem conditions that would lead to differences of fire behavior. For that we used the Crowning Index, or the windspeed at 20 ft height that supports an active crown fire. Determined from forest type, crown spacing, and
canopy bulk density, crowning index is calculated as part of the model outputs of the Forest Vegetation Simulator’s (FVS) (Dixon, 2021; Dixon and Keyser, 2019) Fire and Fuels Extension (Rebain, 2021). Rather than duplicate the calculation of crowning index, we formatted the state inventory data for input into FVS (Crookston, 2021) for use in other projects. We ran all state inventory clusters through FVS, with the only model adjustment being to modify the fuels behavior. We selected the ‘new’ fuels model logic for fire behavior calculations, which uses the 40 Scott and Burgan fuel models (Scott and Burgan, 2005).

From the FVS output database we queried the ‘potential_fire’ table to obtain crowning index for all of our clusters. We used only the initial crowning index for each cluster, obtained from the model run for the inventory year. As there were multiple plots in each cluster, and those plots may have been collected in different years (data were collected 2017-2019), we assigned the most recent inventory year for any of the plots for the cluster. Using solely the even-aged, pure pine clusters, we then used linear models to regress SDI(summation) and other inventory variables against crowning index.

\[
\log(Crowning \ Index) = \beta_1 + \beta_2 \times \log(SDI) + \beta_3 \times HT + \beta_4 \times RP \tag{C}
\]

Where SDI = Stand Density Index (summation); HT = Stand height (ft); RP = relative Basal area of pine (0-1).

4.2.7 Placing the Maximum Size-Density Boundary

We sought to place the maximum size-density boundary on our density management diagram to define the upper limit of site occupancy possible for pure pitch pine stands. To cover a wider range of site occupancy conditions we attempted to fit the boundary using state clusters alone, FIA conditions alone, both stand-level datasets combined, and with subplot-level data. We selected the upper boundary of the point cloud by sorting in decreasing size all observations by trees per acre. The first three observations are the points with the top three most TPA; working down the dataset, each observation is compared to the QMD of the third-highest
QMD yet seen. If an observation has a QMD equal to or greater than the third-highest QMD yet
seen, it is included in the ‘upper envelope’ of points.

To fit a line to these data we used a model from Shaw and Long (2007) of the following
form on the stand level data:

\[ QMD = \beta_1 + \beta_2 (e^{\beta_3 TPA^{\beta_4}}) \]  

(D)

where QMD is quadratic mean diameter (in inches), and TPA is trees per acre. We fit this model
using the stand-scale data, then shifted the predicted values upward to circumscribe the upper
envelope data. First, we found the proportion of the predicted values divided by the observed
values for each of the upper envelope points used to fit the model. The smallest of these became
the adjustment value: to shift the full curve, we divided all of the fitted y values by this
adjustment value.

As determining the appropriate adjustment value is highly sensitive to the underlying
data, we sought an additional approach for comparative purposes. Since we sought to determine
the boundaries of stand occupancy at larger diameters, we looked to the larger dataset underlying
the stand-scale data: the point-scale data that was pooled into clusters and conditions. Combining
the FIA subplot-level data and the state forest inventory point data, we found the upper envelope
of the observations using the same approach described above, but only used the top two highest
TPA points, as there were many more subplot-level datapoints. We used the following model:

\[ QMD = \beta_1 + \beta_2 (\log_{10} TPA) \]  

(E)

but did not apply any adjustment factor to ensure the fit was above all of the point-scale
observations. Instead, we superimposed this curve on the stand data to evaluate its performance.

4.2.8 Effect of Inventory Variables on Forest Evapotranspiration

We further refined the state clusters for analysis of effects on forest evapotranspiration.

To select only those clusters where there could be a polygon, we subset to those clusters with at
least 3 plots, then used the vertices of the points within the cluster to find the minimum convex
polygon. These were joined with the cluster-level inventory data, which were filtered to only include clusters collected in BAF 10 and having at least 90% relative basal area of pitch pine. These clusters were further refined to exclude odd-shaped or excessively-large clusters. We eliminated clusters whose ratio of perimeter (in m) to area (in hectares) was greater than 350, removing from analysis clusters with a long, skinny shape. We also removed clusters larger than 25 hectares.

In addition to geometric filters, we sought to remove other sources of variability that we expected would complicate the analysis. Based off the work in chapter 1, which showed a relationship between forest management and evapotranspiration over time, we filtered out recently-disturbed polygons by intersecting the polygons with a layer containing disturbance history. We eliminated clusters that had any portions silviculturally treated in the last 15 years, burned by a wildfire in the last 15 years, burned with prescribed fire in the last 5 years, defoliated by *Lymantria dispar* in the last 5 years, or infested with *Dendroctonus frontalis* in the last 5 years. We also eliminated plots occurring in the pine plains as these stands are characteristically distinct from other pitch pine forests. At the finest scale, we removed clusters that incidentally included major roads, ponds, or strips of land not covered with pine forest, such as farm field edges and hardwood swamps. The cumulative effect of these filters left 156 cluster-based stand polygons (Figure 4-6).
For each of these polygons we extracted annual total evapotranspiration values from the same datasets created in chapter 1. We summarized stand ET with the mean for the stand and used the stand sizes as weights in our regression models. Using the ‘lme4’ package in R (Bates et al., 2015) we fit various mixed-effects models to describe stand mean annual ET using the inventory variables. Stand attributes like SDI, percent pine, stand height, quadratic mean diameter, trees per acre, and metrics of understory and ground cover were treated as fixed effects, when used. We treated year and stand as random effects because we had repeated measures of ET that reflected random temporal and spatial variation in the annual water budget. More specifically, rainfall varies between years, as well as between positions on the landscape. Our initial evaluation of model performance was based on the BIC value for each model.
From the overall set of possible term combinations for the models, we chose ten of the best-performing models for bootstrapping. We ran 10,000 bootstrapped replicates (with replacement) on the following ten models to evaluate stability and the relative magnitude of different factors on annual stand ET.

\[
ET_{\text{annu}t} = \beta_1 \log_{10} SDI + \beta_2 HT + (1|\text{stand}) + (1|\text{year})
\]

(F)

\[
ET_{\text{annu}t} = \beta_1 \log_{10} SDI + \beta_2 HT + \beta_3 RP + (1|\text{stand}) + (1|\text{year})
\]

(G)

\[
ET_{\text{annu}t} = \beta_1 \log_{10} SDI + \beta_2 HT + \beta_3 GC + (1|\text{stand}) + (1|\text{year})
\]

(H)

\[
ET_{\text{annu}t} = \beta_1 \log_{10} SDI + \beta_2 HT + \beta_3 RP + \beta_4 GE + (1|\text{stand}) + (1|\text{year})
\]

(I)

\[
ET_{\text{annu}t} = \beta_1 \log_{10} SDI + \beta_2 HT + \beta_3 RP + \beta_4 GC + (1|\text{stand}) + (1|\text{year})
\]

(J)

\[
ET_{\text{annu}t} = \beta_1 \log_{10} SDI + \beta_2 \log_{10} HT + (1|\text{stand}) + (1|\text{year})
\]

(K)

\[
ET_{\text{annu}t} = \beta_1 \log_{10} SDI + \beta_2 \log_{10} HT + \beta_3 RP + (1|\text{stand}) + (1|\text{year})
\]

(L)

\[
ET_{\text{annu}t} = \beta_1 \log_{10} SDI + \beta_2 \log_{10} HT + \beta_3 GC + (1|\text{stand}) + (1|\text{year})
\]

(M)

\[
ET_{\text{annu}t} = \beta_1 \log_{10} HT + \beta_2 GC + (1|\text{stand}) + (1|\text{year})
\]

(N)

\[
ET_{\text{annu}t} = \beta_1 \log_{10} HT + \beta_2 RP + (1|\text{stand}) + (1|\text{year})
\]

(O)

Where SDI = Stand Density Index (summation); HT = Stand height (ft); RP = relative Basal area of pine (0-1); GC = standardized total percent ground cover (z-score from $\mu = 89.1\%$ with $\sigma = 33.6\%$); GE = relative proportion of evergreen species in ground cover data (0-1).

### 4.2.9 Constructing the Density Management Diagram

Using the relationships developed in the previous sections, we assembled a density management diagram framework for pure pitch pine stands. This uses logarithmic axes for trees per acre (x-axis) and quadratic mean diameter (y-axis, in inches). To reflect contemporary management concerns in New Jersey, we included the following on the figure:

- **Stand Density Index** lines of 100, 200, 300, and 400;
- **Crowning Index** lines for windspeeds of 20, 30, 40, 50, & 60 miles per hour;
- **Aboveground Live Tree Carbon** in metric tonnes of carbon per acre of 1, 2, 4, 8, 12, 18, 24 using the Jenkins equations for pines;
- **Stand Height** at 20, 30, 40, 50, 60, 70 (feet) using model 2 developed from combined state and FIA condition data;
- Marginal **Evapotranspiration** from the fixed effect components of our selected ET model, relative to the mean SDI and mean stand height we observed in our data (199 and 50.4’, respectively), but assuming average ground cover; and
- Maximum size-density boundary.

### 4.3 Results

#### 4.3.1 Stand height

The FIA data had a slightly wider dispersion of stand heights, whereas the state data were heavily clustered across a much narrower range of heights (Figure 4-7). State inventory data had a median height of 52.5’, with the middle 95% occurring between 25’ and 66’. FIA conditions had a median height of 43.8’, with the 2.5% and 97.5% quantiles occurring at 17.8’ and 59’, respectively.

Model parameter estimates and standard errors can be found in Table 16. Goodness-of-fit evaluations of the four models show uniform better performance for the 5-term model with decreasing model quality with increasing model number (Table 17). Observed versus predicted plots show similar performance for the models (Figure 4-8), although models 3 and 4 seem to consistently overpredict height on the lower end of the distribution.
The 5-term model showed consistently lower deviance, AIC, BIC, and residual standard deviation. Though these evaluations would indicate that the 5-term model (model 1) is a more accurate predictor of stand height, a plot of isolines for fitted heights exhibits nonsensical behavior for the 5-term model (Figure 4-9). At high levels of density where trees per acre exceeds 2000, isolines of height begin to cross over each other, which has an absurd implication: stands with a high sapling density will achieve heights in excess of 70’ prior to reaching 20’ in height. The isolines for stand height appeared to be more realistic for model two. For this reason we chose the next best model for predictions (model 2) of heights on the density management diagram.

Table 16: Model parameters and standard errors for height models

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>b_1</td>
<td>2.27</td>
<td>-1.735</td>
<td>0.805</td>
<td>0.350</td>
</tr>
<tr>
<td></td>
<td>0.264</td>
<td>0.370</td>
<td>0.0822</td>
<td>0.0068</td>
</tr>
<tr>
<td>b_2</td>
<td>15.38</td>
<td>0.269</td>
<td>-0.231</td>
<td>0.0814</td>
</tr>
<tr>
<td></td>
<td>182.7</td>
<td>0.0937</td>
<td>0.00682</td>
<td>0.0027</td>
</tr>
<tr>
<td>b_3</td>
<td>15.28</td>
<td>-0.301</td>
<td>0.903</td>
<td>0.0814</td>
</tr>
<tr>
<td></td>
<td>182.7</td>
<td>0.0221</td>
<td>0.0233</td>
<td></td>
</tr>
<tr>
<td>b_4</td>
<td>0.0008001</td>
<td>0.00964</td>
<td>0.823</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.0669</td>
<td></td>
<td></td>
</tr>
<tr>
<td>b_5</td>
<td>1.28</td>
<td></td>
<td></td>
<td>0.0827</td>
</tr>
</tbody>
</table>

Table 17: Goodness-of-fit evaluations for height models.

<table>
<thead>
<tr>
<th>Model</th>
<th>N</th>
<th>AIC</th>
<th>BIC</th>
<th>Sigma</th>
<th>Deviance</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>545</td>
<td>3287</td>
<td>3312</td>
<td>4.90</td>
<td>12981</td>
</tr>
<tr>
<td>2</td>
<td>545</td>
<td>3315</td>
<td>3337</td>
<td>5.04</td>
<td>13750</td>
</tr>
<tr>
<td>3</td>
<td>545</td>
<td>3324</td>
<td>3341</td>
<td>5.08</td>
<td>14008</td>
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<tr>
<td>4</td>
<td>545</td>
<td>3336</td>
<td>3349</td>
<td>5.15</td>
<td>14384</td>
</tr>
</tbody>
</table>
4.3.2 Crowning index

Of the different inventory variables we included in the model to predict FVS’s crowning index there was a strong linear
relationship between the logarithm of crowning index and the logarithm of SDI. Including other terms in the model improved fit meaningfully, although $\log_{10}({\text{SDI}})$ alone explained 92% of the variation in $\log_{10}({\text{crowning index}})$ (Figure 4-10).

When we added other terms to test mode complex models, we found that crowning index was slightly better predicted by using height and the proportion of pine. Model parameters can be found in Table 18; $R^2$ for the selected model was 0.94.

The isolines used in the density management diagram show modeled crowning index for pure pine stands, with the height component of the crowning index model filled using the stand height relationship from section 4.3.1. Figure 4-11 shows these isolines for crowning index increments of 10 miles per hour, as well as the current condition of the land inventoried as part of the state forest inventory. The mass of the stands measured in 2017-2019 have a crowning index between 20 and 40; median crowning index is currently 32.

Table 18: Crowning Index linear model parameters

| Model Term         | Estimate | Std. Err. | Pr(>|t|) |
|--------------------|----------|-----------|---------|
| Intercept          | 3.25     | 7.60x10^-2 | <2x10^-16 |
| Log10(SDI)         | -0.675   | 8.76x10^-3 | <2x10^-16 |
| Stand Height       | 2.09x10^-3 | 2.28x10^-4 | <2x10^-16 |
| Relative BA Pine   | -0.326   | 7.20x10^-2 | 7.33x10^-6 |
4.3.3 Maximum Size-Density Boundary

Although the model did a good job characterizing our datasets at the stand scale, the tails of our observed data distribution exerted undue influence on the final fit (Figure 4-12). This was apparent from the maximum size-density boundary curving so far away from parallel with SDI as to suggest that it was not possible to have mature pitch pine stands with QMD greater than 17”. We felt that rather than this being a physical upper limit to the species, that instead it was a limitation of the data – out of 545 stand-level datapoints (of the combined state cluster and FIA condition data), only one had a QMD greater than 12.5”. This absence of large-diameter observations in the stand scale data spurred our fitting the same model, without an adjustment factor, on the point-scale data.

When the stand-scale adjusted curve was plotted together with the unadjusted point-scale curve, the two curves tracked each other closely until about 15” QMD. Above this value, the point-scale curve continues to increase where the adjusted stand-level curve does not.

Both models were sensitive to the limited number of observations in the higher diameter range. The models failed to converge when we removed the most obvious points below the curve and tried to re-fit the model; those datapoints were included because of our process to describe

Figure 4-11: Crowning index isolines and current state inventory cluster data. Crowning Index isolines are shown at 10mph intervals; predictions were made using the fitted height ~ f(QMD, TPA) function.
the upper envelope. This precluded attempts to describe the potential variability in the model terms through bootstrapping. Model terms can be found in Table 19.

Figure 4-12: Method for determining maximum size-density boundary. Top panel datapoints show the stand-level observations; black dots represent stands selected as the upper-envelope points. Bottom panel shows the NJFS point-level and FIA subplot-level datapoints, with black dots representing the selected upper-envelope points. Curve fitted to stand-level data is solid black line; the dotted line represents the same curve shifted up using the adjustment factor to circumscribe all observations. The blue curve fitted to the point-level observations is not shifted, and overlaps with the shifted stand-level curve.
### 4.3.4 Stand Evapotranspiration

Stand evapotranspiration was not tightly related to any of the inventory metrics, though it did show responsiveness to a few of them. Plots of local regression on both stand density index (Figure 4-13) and stand height (Figure 4-14) showed a generally positive relationship with annual evapotranspiration: denser and taller stands appeared to have higher evapotranspiration rates than shorter and sparser stands. The data from 2015 did not show much relationship between ET and SDI, though 2016-2018 showed more responsiveness. In contrast, all four years showed a positive relationship for the local regression of ET plotted against stand height.

However, not only was there much variance in the pattern, but a confounding relationship between height and stand density, as well. Figure 4-15 shows that there were very few tall-but-sparse stands, and a complete absence of short-and-dense stands in the inventory dataset used in this analysis.

<table>
<thead>
<tr>
<th></th>
<th>Stand-Level Data</th>
<th></th>
<th>Point-Level Data</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>SE</td>
<td>Mean</td>
<td>SE</td>
</tr>
<tr>
<td>$\beta_1$</td>
<td>0.554</td>
<td>2.25</td>
<td>29.6</td>
<td>0.284</td>
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<tr>
<td>$\beta_2$</td>
<td>14.4</td>
<td>2.73</td>
<td>-7.83</td>
<td>0.111</td>
</tr>
<tr>
<td>$\beta_3$</td>
<td>-9.28x10^{-3}</td>
<td>5.44x10^{-3}</td>
<td>-7.83</td>
<td>0.111</td>
</tr>
<tr>
<td>$\beta_4$</td>
<td>0.702</td>
<td>0.119</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adjustment factor</td>
<td>0.841</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Figure 4-13: Stand-wise evapotranspiration for 2015-2018, plotted against stand density index. Blue lines represent a rolling average calculated using the loess() function in R, with a span of 0.4.

Figure 4-14: Stand-wise evapotranspiration for 2015-2018, plotted against stand canopy height (ft.). Blue lines represent a rolling average calculated with the loess() function in R, with a span of 0.4.
Figure 4-15: Relationship between stand density index and stand height in the state forest inventory cluster dataset.

Table 20: Table of BIC comparisons between bootstrapped models. Comparisons show the credible intervals (middle 95% quantiles) of the change in BIC ($\Delta$BIC). Credible intervals that include 0 are shown in gray. Comparisons where the model on the left has a lower BIC than the model on the top (negative $\Delta$BIC) are shown in bold.

<table>
<thead>
<tr>
<th>BIC of This Model</th>
<th>Minus the BIC of this Model</th>
<th>G</th>
<th>H</th>
<th>I</th>
<th>J</th>
<th>K</th>
<th>L</th>
<th>M</th>
<th>N</th>
<th>O</th>
</tr>
</thead>
<tbody>
<tr>
<td>F</td>
<td>-0.5-10.7</td>
<td>5.8-12.2</td>
<td>8.4-17.4</td>
<td>7.4-10.2</td>
<td>13.5-17.8</td>
<td>8.3-20.5</td>
<td>4.1-16.1</td>
<td>8.8-14.2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>G</td>
<td>-7.2-4.3</td>
<td>2.4-4.9</td>
<td>-0.5-10.8</td>
<td>0.0-4.0</td>
<td>7.4-10.1</td>
<td>1.5-14.1</td>
<td>9.8</td>
<td>2.5-6.9</td>
<td></td>
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<tr>
<td>H</td>
<td>-11.2-10.6</td>
<td>5.8-8.7</td>
<td>2.1-9.6</td>
<td>4.4-16.4</td>
<td>7.8-10.9</td>
<td>1.5-7.5</td>
<td>0.4-13.0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I</td>
<td>-3.8-7.5</td>
<td>-3.6-11.1</td>
<td>3.6-7.3</td>
<td>1.8-10.8</td>
<td>5.9-6.6</td>
<td>0.9</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>J</td>
<td>-8.6-3.4</td>
<td>-2.0-9.6</td>
<td>0.3-4.7</td>
<td>-2.1-1.3</td>
<td>-5.2-6.0</td>
<td>6.0</td>
<td>6.3</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>K</td>
<td>-5.8-8.6</td>
<td>-0.4-11.5</td>
<td>-0.4-7.2</td>
<td>0.1-5.0</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>L</td>
<td>-7.1-5.1</td>
<td>-11.4-0.8</td>
<td>-6.3-2.9</td>
<td>-7.1-3.7</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>N</td>
<td>-4.3</td>
<td>-7.1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
</tbody>
</table>

Table 20: Table of BIC comparisons between bootstrapped models. Comparisons show the credible intervals (middle 95% quantiles) of the change in BIC ($\Delta$BIC). Credible intervals that include 0 are shown in gray. Comparisons where the model on the left has a lower BIC than the model on the top (negative $\Delta$BIC) are shown in bold.
Table 21: Table of AIC comparisons between bootstrapped models. Comparisons show the credible intervals (middle 95% quantiles) of the change in AIC (ΔAIC). Credible intervals that include 0 are shown in gray. Comparisons where the model on the left has a lower AIC than the model on the top (negative ΔAIC) are shown in bold.

<table>
<thead>
<tr>
<th>AIC of This</th>
<th>Minus the AIC of this→</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>G</td>
</tr>
<tr>
<td></td>
<td></td>
<td>H</td>
</tr>
<tr>
<td></td>
<td></td>
<td>I</td>
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<td></td>
<td></td>
<td>J</td>
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<td></td>
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<tr>
<td></td>
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<td>L</td>
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<td></td>
<td></td>
<td>N</td>
</tr>
<tr>
<td></td>
<td></td>
<td>O</td>
</tr>
</tbody>
</table>

Bootstrap replicates showed that Models L and M generally had the lowest BIC and AIC amongst the models (Table 20 and Table 21). BIC differences (ΔBIC) for model L was consistently stronger when compared to models F through H, with slightly weaker evidence of improvement when compared to models I, K, and O. For model L, the credible interval for delta BIC (2.5% to 97.5% quantiles for each coefficient, with the red line representing the mean observation.

![Figure 4-16: Distribution of model coefficients for fixed effects to predict stand evapotranspiration for models 7 (L) and 8 (M). Distribution determined from bootstrap replicates, n=10,000. Dotted lines represent the 2.5% and 97.5% quantiles for each coefficient, with the red line representing the mean observation.](image-url)
quantiles) for the comparison with models J, M, and N included 0, meaning that there were not meaningful differences between these models in their ability to predict stand-level ET. AIC comparisons followed a similar path; there was strong evidence of improvement for model L over models F, H, and K, with more moderate evidence of improvement over models G, K, N, and O. There was no difference in ΔAIC between model and models I, J, and M.

Model M showed strong improvement over models F and H using BIC, with weak-to-moderate improvement over models G, J, and N. For model M ΔBIC, the credible interval included 0 for the differences with models I, K, L, and O. For AIC comparisons, model M had strong evidence of improvement over models F, H, and N, with more moderate improvement over models G, K, and O. There was no difference in ΔAIC compared to models I, J, and L.

Despite this general improvement in model performance from using models L and M, the modeled parameter terms for model L were not consistent with our mechanistic understanding of the biology involved. Model L included a term for the relative basal area of pine, which only had a range in the models between 0.9 and 1 due to the filters we applied to the dataset prior to analysis. We observed in chapter 1 that increasing proportion of pine increases annual stand

![Figure 4-17: Model 8(M) fixed effect parameter estimates. Dotted lines represent the 2.5% and 97.5% quantiles of the bootstrapped distributions for the parameter's coefficient; solid black lines represent the mean coefficient of the bootstrapped distributions. Only the observed range of the data are shown on the x-axes. Note that the marginal effect of an increase of 10’ in stand height is roughly 45-25 mm/yr. Ground cover was standardized before fitting the model.](image)
evapotranspiration, but the sign of the coefficient for the relative basal area of pine in model L was predominantly negative. The middle 95% quantiles of the data did include, 0, however (Figure 4-16).

Table 22: Likelihood ratio test for candidate models to predict annual evapotranspiration by selected forest inventory attributes codes. Significance of *** indicates model significance at <0.001, significance of * indicates <0.05.

<table>
<thead>
<tr>
<th>Model Term</th>
<th>Mean Effect</th>
<th>2.5%</th>
<th>97.5%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>301</td>
<td>166</td>
<td>428</td>
</tr>
<tr>
<td>Log10(SDI)</td>
<td>35.9</td>
<td>30.3</td>
<td>97.3</td>
</tr>
<tr>
<td>Log10(Height)</td>
<td>310</td>
<td>199</td>
<td>418</td>
</tr>
<tr>
<td>Ground Cover</td>
<td>12.6</td>
<td>5.0</td>
<td>19.9</td>
</tr>
</tbody>
</table>

Table 23: Model parameter estimates for model 8 (M).

In contrast, simulated parameters for model M were more sensible, although the middle 95% quantiles excluded 0 only for two of the fixed effect terms: log10(height) and ground cover. The net effect of these on annual forest ET can be seen in Figure 4-17.

While the mean effect of changes in SDI was positively related to annual evapotranspiration, bootstrap replicates sometimes resulted in dataset replicates where denser forests had lower ET rates. This happened with enough frequency to prevent changes in SDI from being significant. We saw a positive relationship with stand height: taller stands had higher ET rates. Similarly, stands with a higher percentage of ground cover exhibited higher ET.

At the mean parameter estimate, and over the range of values in our data, the effect of an increase from SDI 100 to SDI 200 was about 11mm/yr (95% confidence interval for the fixed
effect: -9.1 to 29.3 mm/yr). The effect of increasing stand height from 40’ to 50’ was an increase in evapotranspiration of about 30 mm/yr (95% confidence interval for the fixed effect: 19.3 to 40.5 mm/yr). Increasing the percentage of the ground cover from 50 to 100% caused an increase of about 18.1 mm/yr (95% confidence interval for the fixed effect: 7.5 to 30.0 mm/yr).

A likelihood ratio test for nested versions of model M can be found in Table 22, while confidence intervals for model M parameters (from bootstrap replicates) can be found in Table 23. The random effects of stand and year were of smaller magnitude than the effect of height on the annual estimate of ET. The model had a large residual variance, however, indicating that predictions for any single stand are quite variable (Figure 4-18). Overall, model M appears to be able to noisily characterize the effects of forest traits on stand evapotranspiration.

4.3.5 Density Management Diagram

Our density management diagram can be found in Figure 4-19. It incorporates the isolines for aboveground tree carbon, stand height (model 2), our model for predicting crowning index, our maximum size-density boundary using the point-scale-derived boundary, and our estimates of mean marginal differences in evapotranspiration. All the stand-level datapoints from both the state inventory data and the FIA condition data fall within the area bounded by the maximum size-density boundary.
Figure 4-19: Density management diagram for pitch pine. Isolines for water are relative to the mean stand height and mean stand SDI for the dataset; ground cover is set to the mean for the dataset, so the effect of changes to ground cover is not included in this plot.
Figure 4-20: Density management diagram for pitch pine, with points representing current data for stands in Wharton State Forest, Penn State Forest, and FIA conditions. Evapotranspiration isolines have been removed for clarity.

The diagram shows that stands can achieve the lowest crowning index (highest wildfire risk) below a QMD of 7”. At QMD values between 5.5” and 13.5”, stands at the highest possible density achieve greater than 24 metric tonnes of aboveground live tree carbon per acre, and the maximum appears to be possible at 7” to 10” QMD. Aside from that maximum there are
different stable points for large masses of carbon: the same mass of carbon can be stored at QMD of 15” at the maximum size-density boundary as at 4” at the boundary, but crowning index at the higher QMD is around 45, instead of less than 20.

4.4 Discussion

To our knowledge this is the first density management diagram constructed for pitch pine, as the species has not received the level of attention paid to its more commercially-utilized cousins. We included in our diagram attributes of the ecosystem of stated importance to the local decision-making process for setting forest policy: risk of damaging wildfire, the size of the carbon pool, and the role of forest attributes in the water cycle (Angarone et al., 2021; New Jersey Forest Service, 2020). The utility of this diagram is that it adds dimensionality to assessment of the resource.

The state forest inventory data used to develop this tool were not collected for this purpose, and our method for grouping them into clusters for stand-scale analysis may have introduced error. The variable-radius point samples of this dataset were clustered using their proximity, not by being within the extent of the same delineated stand, as there were no stand maps to be used. We may have inappropriately lumped together point samples that were dissected by actual stand boundaries. Further, we did not estimate within-cluster variance of inventory metrics to see if the clusters were well-characterized by the collection of datapoints, nor did we check to see that each cluster met any standards for sampling error. Normally, a forester would aim to collect more than two-to-six point samples to properly characterize a stand, particularly if those point samples were collected at a rate of 1 point per 20 acres, as was the case with this dataset. The practical effect of our cluster assignment method would be to smooth out the extremes in the dataset, so the clusters we used might not have come as close to the maximum size-density boundary. However, since we used the point-scale data to fit the boundary line, and point data is capable of achieving higher densities than stand-level data (Shaw and Long, 2010),
we felt that our point clustering was successful in characterizing the maximum size-density boundary. Error from clustering certainly impacted the precision of model fit for other attributes we modeled.

There were shortcomings of the state inventory process itself that diminished precision but benefitted our ability to characterize the landscape overall through a larger dataset. State forest inventory protocols required tree heights for individual trees to be measured only to the nearest 5-foot increments, rather than to the nearest foot. At the scale of the individual point, this introduced additional error in characterizing stand height: the tallest 40 trees per acre in the sample were used for determining stand height, but for a BAF10 (English) point sample, a 7” diameter tree represents nearly 40 trees per acre. Thus, ‘stand’ height for a point in a smaller-diameter stand could be calculated from a single tree, subjecting the ‘stand’ attribute to unnecessary imprecision. For clusters with very open forest, small-diameter trees, or fewer inventory points, precision was greatly diminished. On the DMD, this would lead to imprecision on the left side and bottom of the figure for stand height lines, which explains the large variance in height model predictions in these regions of Figure 4-8.

Another limitation of the underlying dataset came from the ground data included in evaluating forest evapotranspiration. The stand-level cluster observations for ground cover were the average of the fixed-area ground cover plots co-located with each overstory point sample; each of the ground plots covered 1/500th acre. These qualitatively determined data were intended to indicate the general abundance of shrub and forb taxa, not for precise numerical use in regression modeling. About ¼ of the clusters used in the evapotranspiration analysis contained three point samples. For these clusters we characterized the understory across each approximately 8-acre polygon with 3/500th acres-worth of data, without consideration of the variance between the three points. If the scale of the response size for the fixed effects in the model to predict stand evapotranspiration is realistic, then imprecision in characterizing stand understory likely has a large effect on the noise within the model to predict evapotranspiration. Future work to examine
the effect of understory on evapotranspiration rates could be improved by transect-based methods to sample greater portions of a stand’s understory.

Our approach for placing stand carbon onto the diagram was to use the equations from Jenkins et al. (2003) which do not account for tree height, being based solely on tree diameter. The equations compiled in Jenkins et al. (2003) are not specific to pitch pine, but to the pine genus. It would be possible to come up with local volume equations based off state inventory data, but these would need to be scaled to biomass with some estimator function, as there are no known local measurements of tree biomass. In fact, the efforts of Whittaker and Woodwell (1968) appear to be the only biomass estimates specific to *Pinus rigida*, and that study was already included as a datapoint in the development of the Jenkins et al. (2003) equations.

We used metrics like AIC, BIC, and the residual standard deviation to choose our stand height model but selected the second-best model by these attributes. In the region of the DMD where most of the datapoints occurred, this introduced some unnecessary error. However, the data were not uniformly distributed across the DMD ‘space’ due to the current condition of the landscapes characterized by the data. At the highest tree densities possible with small trees, model one produced paradoxical results. Using model two for height meant that, particularly at lower densities, the isolines for stand height were notably steeper than those fitted from model 1, but sensible at higher densities. Locating lower-density stands would help mitigate the few high-leverage points that we had to fit the height model. Unfortunately, low-density stands are uncommon in the Pinelands landscape at this time.

In the more populated portion of our DMD, all our models produced similar height estimates. Our expected mean diameter at 100 TPA and 40’ height (7.6”) was on the larger end in comparison to predictions for other southern yellow pines: 4.6” for longleaf pine (Shaw and Long, 2007), 5.7” for slash pine (Dean and Jokela, 1992), and 8.2” for loblolly pine (Dean and Baldwin, 1993). It was however, smaller than for ponderosa pine (10.5”, Long and Shaw, 2005) and Scots pine (10.5”, Vacchiano et al., 2008), and very close to the numbers for other forest
types: 8” for mixed-conifer Sierra Nevada stands (Long and Shaw, 2012), 7.4” for mixed red spruce-balsam fir (Wilson et al., 1999), 7.3” for Norway spruce (Vacchiano et al., 2013), and 6.2” for lodgepole pine (Smith and Long, 1987). The model we chose to use was generally consistent with the behavior of height models developed for other species.

We had few examples of smaller-diameter stands, as the state data placed trees <4” DBH into the advanced regeneration plot, not the overstory plot. While the total number of stems of each species in each advanced regeneration plot was counted, the diameter of individual stems was not. In this way, small-diameter stands were systematically excluded from our analysis. This shortage of datapoints on the low end of the maximum size density relationship probably led us to slightly underestimate the maximum possible number of stems below QMD of 5”. With relation to the management objectives outlined in Section I, this would have an effect on two: aboveground carbon biomass and crowning index. Assuming that the maximum SDI line represents the maximum possible density below some mature threshold QMD, as it does for other species, we believe our DMD probably underestimates the maximum possible carbon at QMD smaller than 5”. We estimate the error to be about 2-3 metric tonnes of C per acre, or a 12-16% underestimation at 4” and 3” QMD. For crowning index, the expected change in windspeed would be on the order of a few miles per hour, but at a crowning index below 20 mph, this is relatively meaningless because the forest is already at such high risk of crown fire.

We were limited in the number of large diameter stands, as well, but for different reasons that reduce our willingness to make strong inferences about the behavior of the maximum size-density boundary at the largest diameters. Though we believe the boundary to be well-supported below a QMD of about 12”, above this diameter we are less confident that the boundary is an accurate depiction of possible density in larger-diameter stands. In the absence of more data from large-diameter stands, we have little support to ‘bend’ this portion of the curve. There are several explanations for the data gap on this end of the maximum size-density boundary.
It could be that such stands are infrequent in any of the southern yellow pine forest types, but for less-common forest types, like pitch pine, they become multiplicatively less common. Rarity today could be the result of the landscape history of southern New Jersey, where industrial use of the forest from the 18th through the 19th century wiped out all large-diameter pine stands (Muntz, 1959). The absence of large diameter stands in the dataset could be the result of less-intense sampling outside of Wharton and Penn State Forests, since pitch pines in other portions of the range may not have experienced the same intensity of utilization. The FIA subplot data covered a broader geographic region but at two orders of magnitude less intensity, so rare thick-stemmed stands may have been missed. A nugget of evidence supporting this are the three datapoints in Figure 4-12 at TPA of 25 and QMD of roughly 19” and 20”. These datapoints are FIA subplot data, and hint at the possibility of larger diameter stands at much lower densities located elsewhere in the range of the species.

It is also possible that the maximum size-density boundary we fit is close to the natural even-aged stand-scale limits of the species. Pitch pines are not thought to be particularly long-lived, and do not achieve as large diameter or height as do their more abundant relatives (Burns and Honkala, 1990), though some stands in Pennsylvania have been reported to achieve higher diameter than this DMD would indicate (Illick and Aughanbaugh, 1930; Little, 1959). Also, we only considered even-aged stands in the construction of our diagram, implying that the upper limit does not reflect a limit on the size or longevity of individual trees, but instead is really a limit on the upper size of a cohort. Older stands with larger trees may be present on the landscape but would have to be evaluated as part of a multi-aged structure. There are examples of the application of this management approach with other southern yellow pines which hinge on an understanding of the partitioning of growing space (Baker et al., 1996; McIntyre et al., 2008); many of these concepts are relevant and suitable in New Jersey’s pitch pine forest.

Our choice of using the subplot-based curve instead of the shifted stand-based curve was based, in part, on the arbitrariness of the amount by which to shift the stand-based curve to
delineate the maximum size-density boundary. The magnitude of the shift was dependent on which portions of the data range we included in locating the upper envelope of the data, so we sought to find a more defensible boundary, hence our use of a model not found elsewhere in the literature. In contrast to the shifted stand-based curve, using the subplot-scale data placed the boundary in a similar location, and belted all the stand-scale datapoints. This seemed to be as good of an approximation of the size-density boundary as the adjusted stand-based approach. Our other reason for adopting the point-scale approach was that there were more data in higher diameters with which to fit the curve.

Our density management diagram has a maximum SDI for pitch pine at 450, but the maximum size-density boundary is only close to that level at QMD of 5” to 6.5”. We saw subplot-scale data over SDI 400 to over 9” QMD, but there were no point-scale data above 10” QMD with an SDI over 400. At smaller diameters the maximum size-density model fit our data well, but there were probably too few small-diameter subplots to accurately characterize the boundary below QMD of 5”. Cao et al. (2000) used a different model to fit the upper envelope data that was more appropriate for smaller diameter stands, but in our case it would have come at the cost of underestimating the maximum possible stand density in larger-diameter stands. Assuming that pitch pine is like other tree species, below around 10” QMD the slope of the maximum size-density relationship should be constant, indicating that we probably had insufficient datapoints in smaller diameter stands. Our maximum observed SDI is somewhat higher than the maximum SDI for pitch pine used in the Forest Vegetation Simulator Northeast Variant (Dixon and Keyser, 2019). Set at 398 for Pitch pine, this is the only instance of a specified maximum size density parameter for pitch pine we were able to locate. A max SDI of 450 is in alignment with the levels used for other southern yellow pines: 490 for *P. echinata*, 499 for *P. virginiana*, 480 for *P. taeda*, and 310 for *P. serotina*.

We had previously found that the general degree of overstory removal corresponded with the amplitude of reduction in annual stand ET. We had interpreted this as an indication that
manipulation of growing space was responsible, and that inventory metrics like SDI might explain the pattern. Consequently, our models to explain stand ET included a term that was based on SDI. The model we ended up selecting included a term for SDI, but the credible interval approach for its model coefficient included 0, meaning that we failed to reject the null hypothesis that SDI had no role in determining stand ET.

In place of SDI, we found stand height explained as much or more of the variation in annual ET across stands. Confoundingly, height was a previously unconsidered latent variable generally correlated with SDI in the stand-level dataset used in this study. Although in undisturbed stands one would expect these variables to be related, they should not be related in the case of older, managed stands (taller trees but with low SDI from management activities), or thick, young stands (short heights but high SDI). Unfortunately, the features of this landscape as well as our own methods removed the handful of instances where such conditions could be met.

Our filtering of stands to exclude recently disturbed areas from the analysis is partially responsible for the pattern of SDI against height, while some responsibility is borne by current patterns of land management. We removed the few young regenerating stands that exist in this landscape because they were the result of recent disturbance. If we had included those disturbed stands in our analysis while knowing that there is a relationship between ET, time since disturbance, and disturbance intensity, it would not have been clear whether changes in ET were the result of the density changes incurred via the disturbance, or some other factor associated with the disturbance. To test whether SDI was responsible for annual ET behavior we would need to have inventory data on young stands that experienced similar disturbance (cleared and site prepped the same way) but regenerated at different densities, so that stocking could be isolated as a separate variable. Such stands do not currently exist on public land in this landscape, and we do not have inventory data on the few private properties which have experienced such management. Similarly, today there are vanishingly few examples of low-density, tall, managed stands in this landscape. Those older stands with naturally low density are typically shorter in stature, not
having had to add height growth to compete for light or are the result of a relatively recent disturbance like wildfire that caused them to be filtered out by our process. Bounded by these two issues, we were largely unable to disentangle the effects of SDI and height on ET. Future research is needed on separating the role of site occupancy from height in affecting ET.

Height is sensible as a factor for predicting ET, both from the biophysics of forest ET as well as from the model used to determine pixelwise ET. Canopy height is used in the formulation of the DisALEXI model as a component in the aerodynamic resistance term to calculate flux of sensible heat from both the ground and the canopy (Anderson et al., 2007, 1997; Li et al., 2005), although the number used in the model is assumed as a uniform value across all pixels with the same cover type; all pixels covering needleleaf evergreen forest are assumed to have a height of 15.0m. If we assume that height is truly responsible for changes in annual ET (as opposed to SDI), then our finding demonstrates the sensitivity of the DisALEXI to subtle changes in thermal properties of vegetative canopies.

Maximum possible stand height is tied to landscape position in the Pinelands, where pitch pine lowlands tend to have higher site indices than pine uplands, as well as commonly achieving higher stem densities (Johnson, 1978; Little, 1978). We also found in our previous work that wetland pine tended to use slightly more water than upland pine, which we believed had to do with more freely available water in wetland sites. Boundaries between uplands and wetlands in this landscape can be difficult to distinguish, however, as the difference between lowland pine and upland pine can be just a change in the depth to water table (Laidig et al., 2010), which already fluctuates seasonally and interannually (Walker et al., 2011).

Aguilos et al. (2021) and Yang et al. (2017) found that age was strongly linked with stand ET, but both of these studies were conducted in the same highly-instrumented commercially-managed landscape. In the former, stand ET was responsive to age for the first 10 years of the rotation; in the latter ET was responsive to age for the first 15 years. Aguilos et al. (2021) also found that the site’s LAI was relatively insensitive to thinning. All these behaviors of the stand
can be explained by considering concepts of stocking/growing space. The sites in both of those studies are being managed to maintain full site occupancy for as much of the rotation length as is possible. Thinning in this context is applied in such a way to have the smallest impact on overall stand volume growth, but the largest effect on the growth increment of the trees remaining for the whole rotation length. In stands that are being managed for economic return, it is an ordinary management objective to work to achieve ‘full’ stocking at as young an age as possible, and to keep the site at ‘full’ stocking levels during thinning operations. We believe that the responsiveness that other studies have found between age and ET only in young stands can be better explained by site occupancy or stocking.

Our model for explaining evapotranspiration has random effects terms for year and stand that show that stand-level ET is highly sensitive to differences in annual rainfall as well as spatial variability on the landscape. The stand-level random term may at least partially be explained by spatial variability of rainfall, which varies at a finer spatial scale than the size of our study area: the total size of the water budget within any year was probably different between our more widely spaced clusters. However, there are also other traits of each stand that likely influence ET, meaning that the random effect for the stand could be partitioned into more precise fixed and random effects if finer-scale data become available. The thickness and water-holding capacity of the soil litter and duff layers mitigates the effects of weather variability on water supply for plants (Moore et al., 2011). These layers are also reduced by prescribed fire in this and similar pine forest types (Parresol et al., 2012; Welch et al., 2000). Areas that have experienced fire longer ago than our filters (15 years for wildfire, 5 years for prescribed fire) are expected have soil organic layers with less water-holding capacity than undisturbed stands where soil organic matter has accumulated without interruption. We treated these differences as random effects because we did not measure soils at any of the state inventory plots, but improved models to explain forest ET might perform better with measurements and a fixed-effect term for surface litter, duff thickness, or some other measure of soil moisture capacity not already included in SSURGO data.
Though this is similar to previous findings where environmental effects were more important drivers than forest management effects (Gholz and Clark, 2002), we found evidence for changes in ET resulting from forest characteristics that can be manipulated by management. Our model coefficients in section 3.4 showed that a change in height from 40’ to 60’ would cause a marginal increase of about 55mm/year in stand ET (95% CI 35-74mm/yr). Similarly, a marginal increase from SDI 100 to SDI 200 would cause a mean effect of an increase in 11mm/year (95% CI: -9 to 29mm/yr). For comparative purposes, EVALIDator queries of timberland in the pitch pine forest type of NJ record a change in mean SDI (Dq method) from 178 in 1989, to a mean of 231 in 2019 (USDA Forest Service, 2019).

For our density management diagram water isolines we used mean total ground cover to estimate this component of the model. At this level of ground cover, the cumulative effect on ET was 0, as the input data was standardized prior to fitting. However, Table 23 shows that a decrease of one standard deviation for ground cover (a decrease of 33.6% total ground cover) would reduce ET by 12.6 mm/yr (95% CI 5.0-19.9mm/yr). That is an effect similar in size to what the model predicted for changes in SDI from 100 to 200, but the difference is statistically meaningful in the case of understory.

4.5 Conclusion
This study characterized the maximum size-density relationship for pitch pine, the dominant tree species of the New Jersey coastal plain. Local management considerations like fire risk, aboveground live carbon storage, forest evapotranspiration, and site occupancy are included in our management diagram, though it is possible to include other traits once they have been described. Though the tradeoffs inherent in management decisions may already be clear to land managers, tools like this DMD are needed for the most productive engagement of the great diversity of stakeholders interested in forest policy. This density management diagram illustrates
how different objectives are balanced in making choices for forest stands and can be used to
determine different trajectories for stand development.
5: Section V: Interpretation of Findings

Taken together, our findings illustrate a forest experiencing changes whose implications have not been fully grasped. Over the last century the Pinelands forest has re-grown much of the timber that was repeatedly exhausted since European settlement. This is a remarkable achievement of conservation, but it should not be accompanied with the assumption that the current state of the pine forest is stable. Rather, our density management diagram, light thresholds for open-canopy species, and lessons about forest evapotranspiration all show indications that the forest is sub-optimally achieving many of the sundry goals our society expects from it.

The concept of ‘stocking’ is usually considered as a function of the possible volume growth of a stand (Nyland, 2002) but it can be defined according to any number of management objectives. Drew and Flewelling (1979) defined ‘relative density’ as the current Stand Density Index (SDI) level divided by the maximum possible SDI for a species. Even though we found the maximum size-density relationship to be curvilinear, especially at higher levels of quadratic mean diameter (QMD), the framework of relative density as a function of maximum SDI is useful. Starting with a site uninhabited by trees (relative density of 0), Drew and Flewelling (1979) considered values below 0.15 to allow all trees free growth; below this level individual tree growth is independent of density. Long (1985) and Long and Shaw (2005) place the onset of competition or initial crown closure slightly higher, at 0.25, and place the lower limit of full site occupancy at 0.35. Arriving at densities of 0.55 to 0.6 the forest sees the onset of density-dependent mortality, the result of competition between trees (Drew and Flewelling, 1979; Long, 1985; Long and Shaw, 2005). Volume growth is maximized at levels of 0.6 to 0.8, but mortality deducts volume above this level so that stand net volume increment peaks around 0.6 (Mar:Möller, 1954; Nyland, 2002). Relative density levels from 0.8-1 place substantial stress on all the trees, killing many and constricting the growth of most of the survivors.
‘Full’ stocking in Gingrich—style diagrams corresponds to the area between the ‘A’ and ‘B’ lines, where trees are fully utilizing the growing space available on the site (Roach and Gingrich, 1968) and net volume growth is maximized (Mar:Möller, 1954). Calling this region ‘full’ is a cultural concept, however, and this region might be more correctly named ‘fully stocked with trees,’ rather than just ‘fully stocked.’ By clearly stating that trees are occupying the growing space, such phrasing begs the question of what might be the characteristics of a site fully stocked with respect to some other attribute of forests, instead of only trees. In the context of a forest landscape being managed for multiple non-timber objectives, this definition becomes attractive. Kara et al. (2018) shows an example of such a re-definition for an ecological approach to longleaf pine, where the lower limit of full site occupancy is considered the ‘B’ line, occurring at relative densities of 0.30-0.38, depending on QMD.

Wildfire risk is an enormous consideration for forest management in the pine region of New Jersey, with a long history of both forest fires and efforts to control wildfire (Pinchot, 1899). Wildfire risk to a stand can in part be explained by our DMD and we can redefine the subjective part of ‘full’ stocking based on what we consider to be acceptable thresholds of risk. For instance, if a stand is above a certain crowning index, we might consider it to be ‘overstocked’ with respect to damaging fire risk. Perhaps we could determine an acceptable level of risk by fixing a tolerable proportion of hourly windspeed measurements over a time interval that could exceed some reference level of crowning index. For instance, strategic planning to mitigate fire danger might aim to achieve crowning index values that don’t dip below the windiest x% of windspeeds during fire season. This could also vary depending on location, so that an acceptable crowning index might vary between forest interiors and the Wildland-Urban Interface. Setting such targets would need to occur in close consultation with fire managers, as crowning index is but one variable to assess fire risk; it just happens to be the one we used, here.

Habitat is another important consideration in NJ, with longstanding attention to rare plants and animals (Pinelands Commission, 2020, 1979). DMDs have been used previously to
articulate habitat management goals for elk (Smith and Long, 1987), red-cockaded woodpecker (Shaw and Long, 2007), and goshawk nests (Lilieholm et al., 1994), and ours can be similarly used for this purpose. Many of the rare plants in the pinelands landscape are believed to be dependent on full-sun to partial-sun conditions, and their decline is thought to be due in part to changes in the land that have reduced the extent of such habitats (Peters, 1995). There is limited data on the threshold levels of sunlight needed for survival and fecundity of individual rare plant species, in part because they are rare to begin with. However, management to create suitable conditions for plant communities associated with rare plant species would be a reasonable place to begin. We found that SDI values above 230 were a hard boundary, above which we did not see instances of open-canopy taxa such as Panicoideae. Keeping SDI levels below this critical threshold would likely be beneficial for shade-intolerant, disturbance-dependent plant species, as well as wildlife associated with open-canopy plant communities (Figure 5-1). By this standard, we could consider a stand to be ‘overstocked’ if SDI exceeds 230.

We can also examine stocking as a function of forest evapotranspiration, albeit without having fully isolated the role of density versus height. Regardless of the interactions responsible...
for the positive correlations between height and SDI, we expect that both have increased in the roughly 70 years since the State of New Jersey acquired the Wharton estate and the 115 years since the state acquired the Penn property. Rather than remaining in equilibrium, several lines of evidence support the idea that the pine forest of the New Jersey coastal plain have grown older, thicker, and taller, in the past several decades. Over the interval 1989-2019 FIA data for timberland show an increase in basal area per acre for growing stock trees (>1” DBH) from 66.8 ft²/ac to 101.7 ft²/ac (USDA Forest Service, 2019). Native wildlife species that depend on open, rather than closed forests, like pine snakes (*Pituophis melanoleucus*), bobwhite quail (*Colinus virginianus*), and ruffed grouse (*Bonasa umbellus*) have experienced population declines that are partially explained by increased forest occupancy (Chanda et al., 2011; David M Golden et al., 2009; New Jersey Division of Fish and Wildlife, 2019). Although not collected within the same State Forest properties, forest inventory data collected by New Jersey Forest Service in pine-dominated stands in Brendan T. Byrne State Forest over 1980-83 shows an increase in SDI, relative density index, total height, and basal area when compared to the dataset used in this analysis (NJFS, unpublished data). Though they are different properties, they are governed by all the same organizational policies, managed by the same individuals, exist in the same economic context, and occur in the same landscape. Volume of merchantable wood has increased substantially over the last 60 years (Cumming, 1966; USDA Forest Service, 2019), indicating more and larger trees are present. Generally, this could be represented by moving up and to the right on the DMD, in the direction of higher stand evapotranspiration.

The effect of these changes on forest ET is relatively small when compared for any two years, or locations, or even when compared to the annual water budget. However, when considered as part of long-term changes in the attributes of the forest over the landscape, the significance of such an increase is apparent. There are 334,000 acres of pine forest on the land above the Kirkwood-Cohansey aquifer (NJDEP Bureau of GIS, 2019). Applied to this area, a marginal change in height from 40’ to 60’ would be an annual change in ET of roughly 59,800
acre-feet (38,400-80,600), or 19,500 million gallons (12,500-26,300). This is of the same order of magnitude as the statewide total water withdrawn for agricultural and irrigation use (New Jersey Department of Environmental Protection, 2017). Of course, not all of the water used statewide for irrigation and agriculture is sourced from the Kirkwood-Cohansey aquifer, nor does the unconfined surface layer of the Kirkwood-Cohansey recharge all of the bodies tapped for groundwater (Gordon et al., 2021). Also, the forest has not uniformly changed in height since the time of germination of the current canopy-dominant trees, but we recognize that there have been profound shifts in the appearance of the Pinelands forest, including changes in average stand height. Rather than making the case that there has been a specific change in forest attributes that is causing a finite amount of ET, we make this point to illustrate the magnitude of the effects of changes in forest attributes on the overall water budget. Changes in the structure of the forest are not simply a natural process, but the result of policy choices made by our society; these policies are mainly the province of government in the Pinelands landscape of New Jersey, with multiple overlapping jurisdictions accompanied by extensive and growing public landholdings. Over time, subtle, passive changes can have effects similar in size to active choices and understanding their effects on water supply are important. Extractive use is not the only way we are using water: we are also using water to support the growth of a thicker, older forest.

Diminishing the shrub layer has the potential to significantly reduce total site LAI. In our study of light availability, we measured overstory and ground-level LAI and observed that in these pitch pine forests understory vegetation could have as much leaf area as the canopy. Interestingly, the patches of seed-tree and clearcut harvests studied in our first project did not just vary from the rest of the forest in that they were younger, or shorter: they also experienced site preparation to reduce shrub competition against tree seedlings. The effect that we saw from overstory harvest may not have been solely due to changes in overstory occupancy, but an amplified response to the reduction in LAI from site preparation activities. This evidence suggests
that management of the shrub layer could be as impactful to evapotranspiration as overstory thinning or a regulated forest management regime.

Being close to the size-density boundary indicates that a stand is experiencing increasing density-dependent mortality; as a stand approaches maximum density competition stress kills trees. Overall stand carbon growth is divided between trees, so that an individual tree with more competition experiences diminished radial growth. On its own, this causes the carbon stored in the trees that lose the battle for resources to be lost from the aboveground live pool. What’s more, the increased intraspecific competition reduces individual vigor and increases the probability of insect and disease outbreaks. Amongst several models for assessing stand risk of Southern Pine Beetle (SPB) infestation, specific stand attributes have been consistently linked to larger SPB populations. Stands with higher relative and total basal area of pine and reduced individual growth increment are at a higher risk of infestation (Birt, 2011) and have been consistently linked to larger SPB populations (Weed et al., 2017).

SPB is native to the southeastern US with a wide distribution and vast economic impact (Coulson and Klepzig, 2011). SPB outbreaks historically caused massive mortality across pine-growing areas, but over the last several decades such losses have been successfully managed throughout the range where SPB outbreaks were most common (Asaro et al., 2017; Nowak et al., 2015). Although several cultural factors have been shown to reduce the overall extent of SPB outbreaks, silviculture that mitigates forest density is strongest predictor of localized risk of SPB, with lower-density stands being most resistant (Clarke, 2012; Fettig et al., 2007; Guldin, 2011; Nowak et al., 2015).

Figure 5-2: Acres of southern pine beetle infestation in New Jersey, 2003-2019. Data from USFS Insect and Disease Detection Surveys, https://www.fs.fed.us/foresthealth/applied-sciences/mapping-reporting/detection-surveys.shtml
The northern limit of SPB is likely determined by minimum winter temperatures (Lesk et al., 2017; Ungerer et al., 1999). When cold winters increase the annual probability of larval stages freezing to death, population growth is constrained, reducing the likelihood of landscape-scale outbreaks (Tran et al., 2007). New Jersey has been experiencing SPB mortality since 2002; from 2003-2019 (inclusive), a cumulative area of more than 62,000 acres has been infested, with a peak of more than 14,000 acres in 2010 alone (Figure 5-2). Mortality from SPB was detected in the Long Island pine barrens in 2014 (New York Department of Environmental Conservation, 2016), and in subsequent years monitoring traps caught beetles in Connecticut, Rhode Island, and Massachusetts, all areas that have not previously had historic outbreaks or any detections of beetles (Dodds et al., 2018). Winter minimum temperatures are expected to rise with climate change, lifting the historic controls on this species in New Jersey (Lesk et al., 2017).

In an era predicted to have higher SPB risk in the pitch pine communities of the northeastern US we could also redefine stocking for this forest type to correspond to risk of SPB

![Figure 5-3: Portrayal of current forest occupancy with respect to southern pine beetle risk. Yellow field indicates areas below the 80ft²/acre basal area level, above which beetle risk rises. Gray dots represent clusters in Wharton State Forest used for the analysis in this paper. The red, brown, and green circles represent mean TPA and QMD by ownership category for the Pitch Pine forest type in the 2019 FIA data for New Jersey. Size of the FIA circles corresponds to area; there are roughly 26,000 acres in the federal (red) class, 268,000 in the state & local (brown) class, and 125,000 in the private (green) class.](image-url)
outbreak. A traditional guideline in commercially-managed pine stands recommends a maximum basal area of 80 ft²/acre for resistance to SPB (Nowak et al., 2008), with stands above 100 ft²/acre being at drastically higher risk (Belanger and Malac, 1980). Though BA does not correspond exactly with SDI, the region between 80-100 ft²/acre corresponds to SDI values between ~130-160 in larger-diameter stands (15” QMD), to SDI values of ~200-260 at QMD of 4”. The majority of the clusters in Wharton and Penn State Forests that we considered for this analysis were above this threshold (Figure 5-3). In the wider landscape, queries on New Jersey’s 2019 FIA dataset for pitch pine show that across ownership types, average TPA-QMD values exceed the SPB risk threshold.

Carbon is likely to be a leading management objective for the future of the forests of New Jersey (Barr et al., 2020). In the pitch pine forests of New Jersey, the same carbon density can be achieved with many small trees or fewer large trees (Figure 4-19). However, at the same mass of aboveground forest carbon, different attributes of the forest are benefitted. A stand stocked with 1,000 saplings per acre can achieve an aboveground carbon mass greater than 24 metric tonnes per acre by reaching a QMD of about 5.5”, but once there, the carbon is subject to a higher wildfire and SPB risk (Figure 4-19). Indeed, in the absence of actions to prevent carbon losses to wildfire or pest infestation, it is not guaranteed that a stand is always able to grow or maintain such a high carbon density in the aboveground live tree pool.

The maximum size-density boundary shows that there is no evidence that pitch pine stands can exceed a maximum level of aboveground live carbon. Upon reaching this saturation level, primary productivity is shifted into other carbon pools through mortality losses. Though some carbon from dead trees moves to the soil carbon pool, soil organic carbon receives more inputs from roots than from aboveground inputs (Berhongaray et al., 2019), and the vast majority of aboveground carbon in the aboveground dead pool is eventually lost as respiration, although the lag time in decay is an important consideration in determining carbon residence time in this pool. Maximizing the size of the live aboveground carbon pool in a pitch pine stand, then,
forces net sequestration close to zero after the aboveground carbon maximum is achieved. This illustrates the tradeoff between the size of the aboveground carbon pool and the rate of carbon sequestration.

Just considering the carbon isolines and maximum size-density relationship does not take into account management objectives for ecosystem function mentioned previously. At the same carbon isoline, risk of carbon loss is lower when there are fewer large trees than when there are more small trees. Both the risk of damaging wildfire and the risk of SPB outbreak are lower as one moves from bottom right to top left along the carbon isolines. These same risks are also lower as one moves from right to left along the same QMD value, though carbon is also lower along this same vector. Thus, there is a tradeoff between the size of the aboveground pool and the stability of that pool; in coniferous fire-dependent forest ecosystems, management that reduces aboveground live tree carbon also reduces mortality from damaging wildfires, increasing the stability of the pool (Hurteau et al., 2016; North and Hurteau, 2011).

Figure 5-4: Density management diagram for pitch pine with two possible management trajectories. Both trajectories start in the same location, between the TPA and QMD averages for state forest inventory dataset and the FIA pitch pine forest type, to roughly approximate current conditions. Scenario A shows a no-management path, while scenario B shows the expected path for a thin-from-below prescription that reduces TPA to roughly 140.
Forest management choices should recognize both pool size and stability, particularly when considered at the scale of the landscape. The choice to follow any one pathway to management objectives depends on the goals of the landowner, the size of the holdings, traits of the landscape, willingness to accept risk, the regulatory constrictions on management options, the availability of different management tools, the economics of each choice, and other factors.

Figure 5-4 shows two future general pathways for a stand at about 420 TPA and 7.3” QMD, slightly denser and smaller than the current means for the state forest inventory data, but less dense and larger than the current means for the pitch pine forest type in New Jersey using FIA data. Path A (dashed line) represents one management trajectory, assuming no action. Trees per acre remains stable and diameter increases for only a short time, before significant mortality begins. Crowning index decreases until significant mortality accrues, as does the aboveground live carbon pool, so that carbon losses and decreased fire risk are paired. Like the aboveground carbon pool, SPB outbreak risk remains high, only decreasing when there has been significant density-dependent mortality. The stand remains unsuitable for open-canopy species until somewhat less than 1/3 of trees are lost to mortality, but there will have been no disturbance that frees up growing space at ground-level, so utilization of the site by open-canopy species may not occur. Evapotranspiration increases slightly, then plateaus. The time it takes to follow this trajectory was not assessed, and it may require decades to accrue sufficient mortality to reduce wildfire risk, reduce beetle risk, and increase sunlight at the ground.

Alternatively, path B (solid line) shows the trajectory for one of many possible management paths. In this scenario, density is reduced to about 135 TPA via a thinning from below, keeping the largest and most vigorous trees. The immediate effects are that carbon drops from roughly 19 to 10 metric tonnes per acre, while crowning index increases to over 45 mph. Risk of SPB outbreak drop below the critical density threshold, and enough sunlight reaches the ground to make available habitat for open-canopy species. To that end, running equipment to perform the removal will probably disturb the existing shrub root mat, increasing the chance that
open-canopy plants can utilize the growing space. Evapotranspiration initially declines, but as the residual trees grow, it returns to pre-thinning levels. The increased growth of remaining trees eventually lowers the crowning index again and pushes the stand above 80 ft²/ac of BA, but density-dependent mortality kicks in before the stand can achieve 100 ft²/ac of BA, capping the risk of SPB outbreak. Carbon on the site is concentrated in the remaining trees, nearly returning to the pre-thinning level at about 18 metric tonnes per acre before density-dependent mortality restarts.

These examples, as well as the DMD itself, illustrate that management to maximize the positive attributes of any one trait comes at the expense of other traits – for example, maximizing stored carbon comes at the risk of increased fire risk until the trees get sufficiently large. However, hugging the maximum size-density boundary at high stocking levels places the stand at loss from damaging wildfire and predisposes it to eruptive pest outbreaks from unnecessary stress. Habitat for open-canopy species will come at the expense of stored carbon in most stands. These tradeoffs are inherent in making choices for land management; hopefully this diagram assists land managers and forest policymakers in their understanding of these tradeoffs. In the words of Long (1985): “…management objectives involve some form of compromise between the mutually exclusive goals of maximizing either stand or individual tree growth.”
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