Continuing Project

Assessing & Mapping Regional Variation in Site Productivity

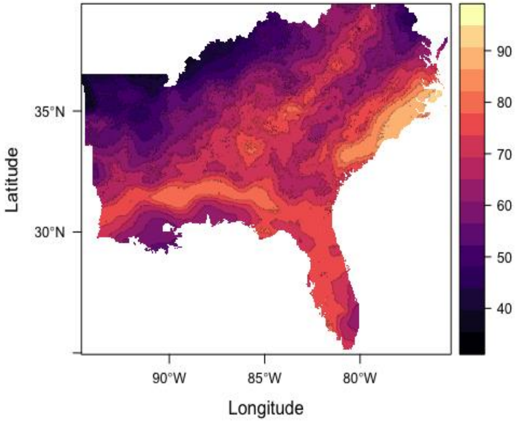
CAFS.19.75
June 2025

Investigators: Rachel Cook (NCSU), Cristian Montes (UGA), Aaron Weiskittel (UM), Jeff Hatten (OSU), Mark Coleman (UI), Doug Jacobs (Purdue), Mark Kimsey (UI), Doug Maguire (OSU), Kim Littke (UW)

Objectives

What drives site productivity and how do we make predictions?

1. Develop a consistent and biologically meaningful metric of potential site productivity
2. Relate soils, geology, and environmental variables to predict site productivity
3. Map productivity across major forest regions



Timeline - Updated

Year 1 (2020):

- ✓ Data gathering and compilation of forest soil map units and available stand data

Year 2-4 (2021-2023):

- ✓ Spatial modeling and model comparisons of site productivity and drivers

Year 4-5 (2023-2024)

- ✓ Collect USGS data across SEUS for large-scale site index mapping
- ✓ Map base and potential site productivity
- ✓ Develop web-based interface (see Pala @ 2:15)

Year 5 (2024-2025)

In Progress: Incorporate LAI into productivity modeling

Input Data…

1. Soils + Geology + Physiographic Province Data (**SPOT database**)
2. Climate (**PRISM 30 yr**)
3. Geolocated Site Index estimates
    1. Regionwide Trials - *Cook et al. 2024*
    2. FIA plots - *Ribas et al. 2024*
    3. FPC Member stands + USGS LiDAR

4. Next up: USGS LiDAR LAI Data

…Find Best Estimate of Loblolly SI across Southeast U.S.

Methods

Contents lists available at ScienceDirect

Forest Ecology and Management

journal homepage: www.elsevier.com/locate/foreco

ELSEVIER

FOREST ECOLOGY AND MANAGEMENT

Check for updates

Forest soil classification for intensive pine plantation management: "Site Productivity Optimization for Trees" system

Rachel Cook[a,*], Thomas R. Fox[b], Howard Lee Allen[c], Chris W. Cohrs[d], Vicent Ribas-Costa[a,e], Andrew Trlica[a], Matthew Ricker[f], David R. Carter[g], Rafael Rubilar[h], Otávio Campoe[i], Timothy J. Albaugh[g], Pete Kleto[j], Ed O'Brien[j], Kirk McEachern[b]

Major Soil Group	
A	Clay
B	Fine Loamy
C	Coarse Loamy
D	Spodic
E	Silty
F	Deep Subsoil (Grossarenic, > 40 in)
G	Deep Sand (> 80 in)
H	Histosol/ Organic

Depth Code (inches)	
0	unknown (0-20)
1	0 – 5
2	5 – 10
3	10 – 20
4	20 – 40
5	40 – 80
6	None within 80 in

Drainage	
E	Excessively Drained
D	Somewhat Excessively Drained
W	Well Drained
M	Moderately Well Drained
S	Somewhat Poorly Drained
P	Poorly Drained
V	Very Poorly Drained

Modifier 1: Nature of Surface	
d	Dark surface
y	Silty
e	Eroded
g	Gullied
r	Rocky
o	Other or NA

Modifier 2: Nature of Subsoil	
a	Alfic
m	Mica
x	Mixed
k	Kaolinitic
p	Plastic/ smectitic /vertic
i	Siliceous (sandy)
o	Other or NA

Modifier 3: Limitations (A or B Horizon)	
w	Ponded Water
f	Floods (fluvic)
l	Lamella
s t u	Root limited (densic, lithic, paralithic) (<10, 10-20, 20-40 in)
v	Root limited 40-80 in
q	Restrictions within 40 inches (fragic, cemented, plinthic)
c	Alkaline, calcareous
n	Salt affected (natric)
o	Other or NA

Geo Code
Pa
Al
Dw
Lb
Ws
Am
Au
Ct
Fl
Ch
Vk
Yg
Jk
Cb
Wx
Md
Bb
Ba
Av
Sa
Cs
Ms
Fs
Lo
Gg
Le
Sh
St
Lm
Sc
Bg
Um
Sr
Mr
Ui

Physiographic Province	
AF	Atlantic Coastal Plain Flatwoods
GF	Gulf Coastal Plain Flatwoods
SC	Southern Coastal Plain
WG	Western Gulf Coastal Plain
LP	Mississippi Valley Loess Plain
BP	Blackland Prairie
SH	Sandhills
PD	Piedmont
MT	Mountains
AA	Alluvium

"SPOT" v3.1.1 Soils data

Center for Advanced Forestry Systems

Methods

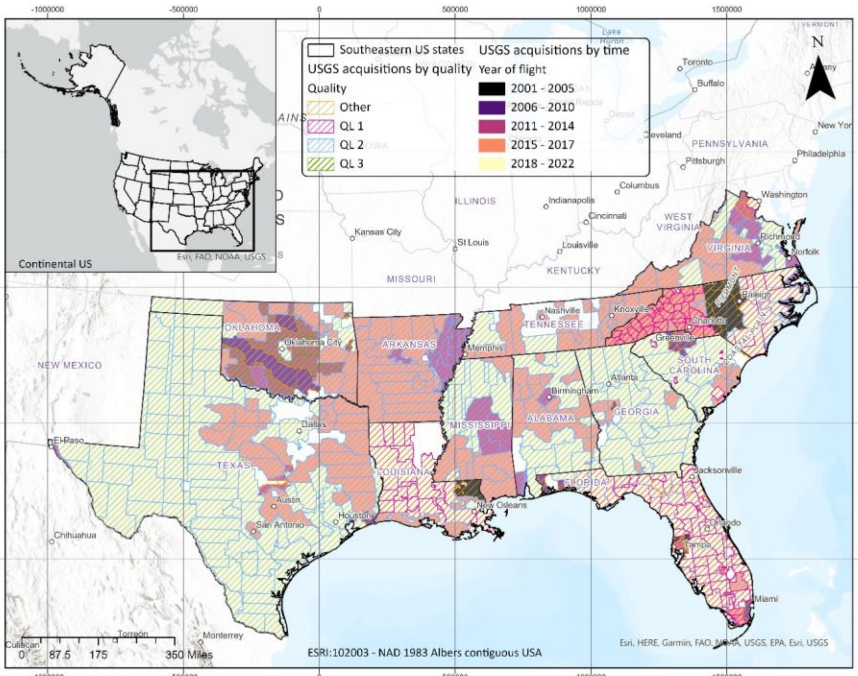
Random forest models of SI

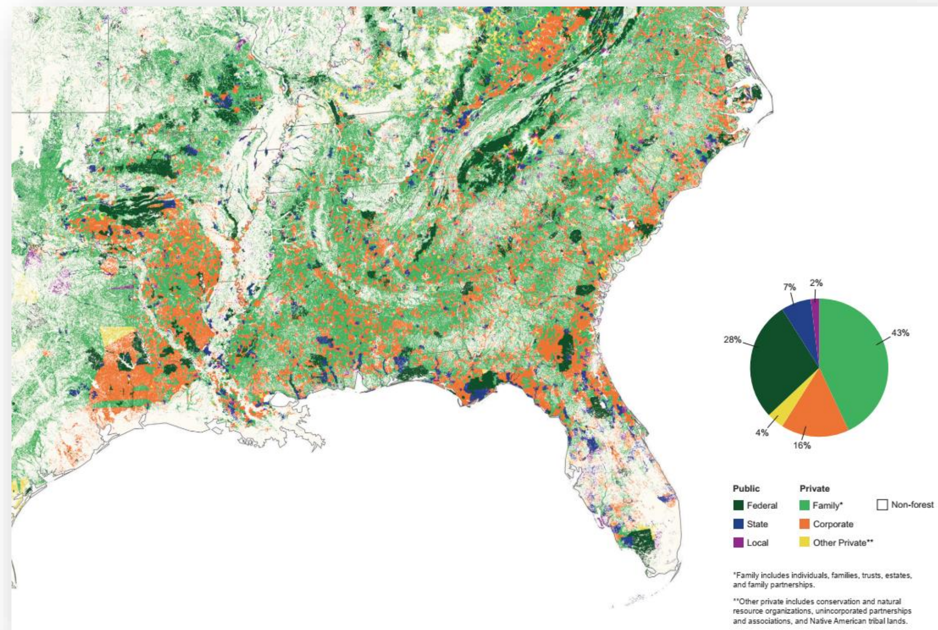
Ribas et al., 2024 (FEM)

Vicent Rubilar
Univ. Pol. Madrid

Industrial Site Index = Member stands + age + USGS LiDAR Data

FIA Data (Natural or Planted) = Site Index trees + intersection with SPOT code



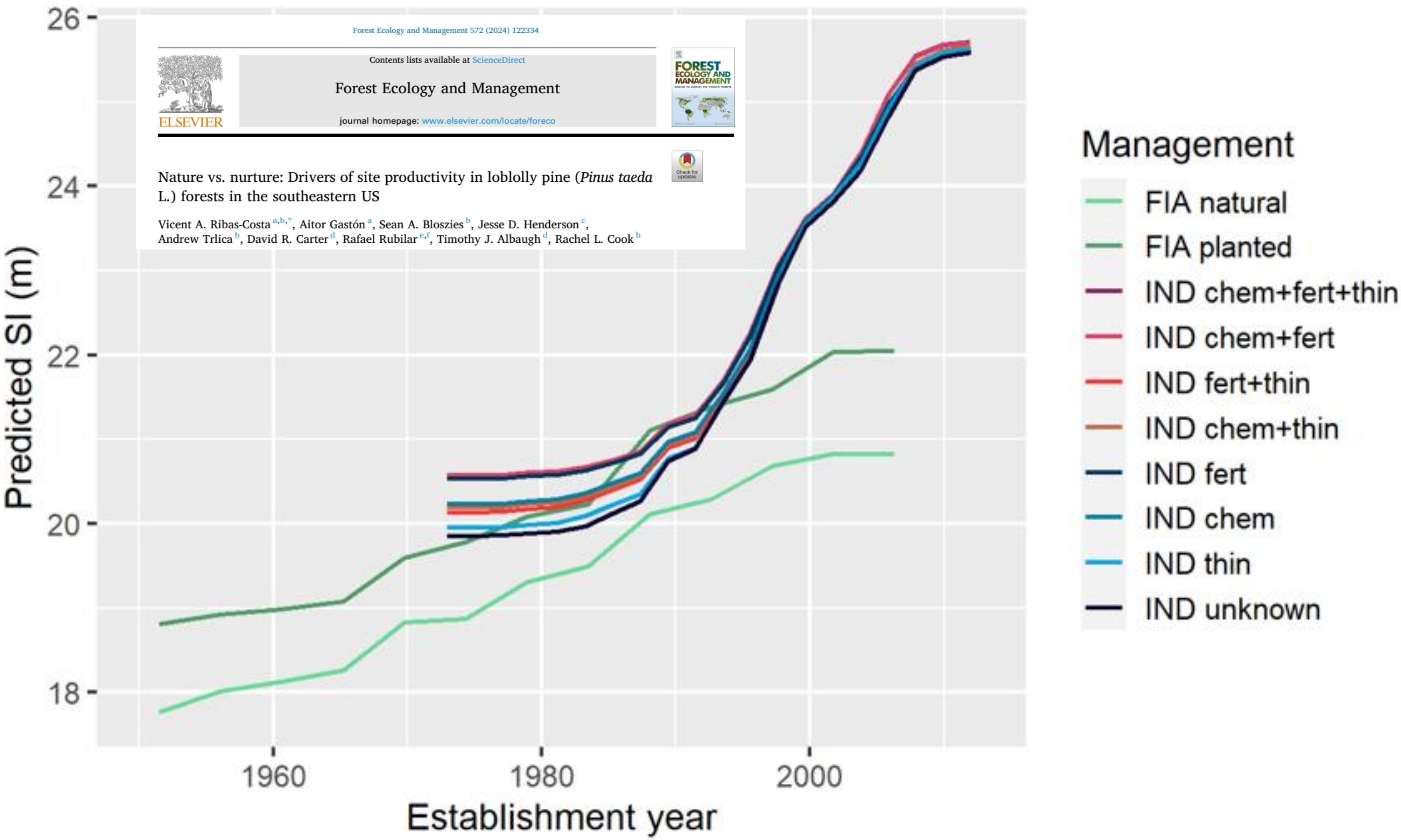


OXFORD Institute of Chartered Foresters
Forestry: An International Journal of Forest Research, 2024, 1–15
https://doi.org/10.1093/forestry/cpae034
Original Article

Modeling dominant height with USGS 3DEP LiDAR to determine site index in even-aged loblolly pine (*Pinus taeda* L.) plantations in the southeastern US

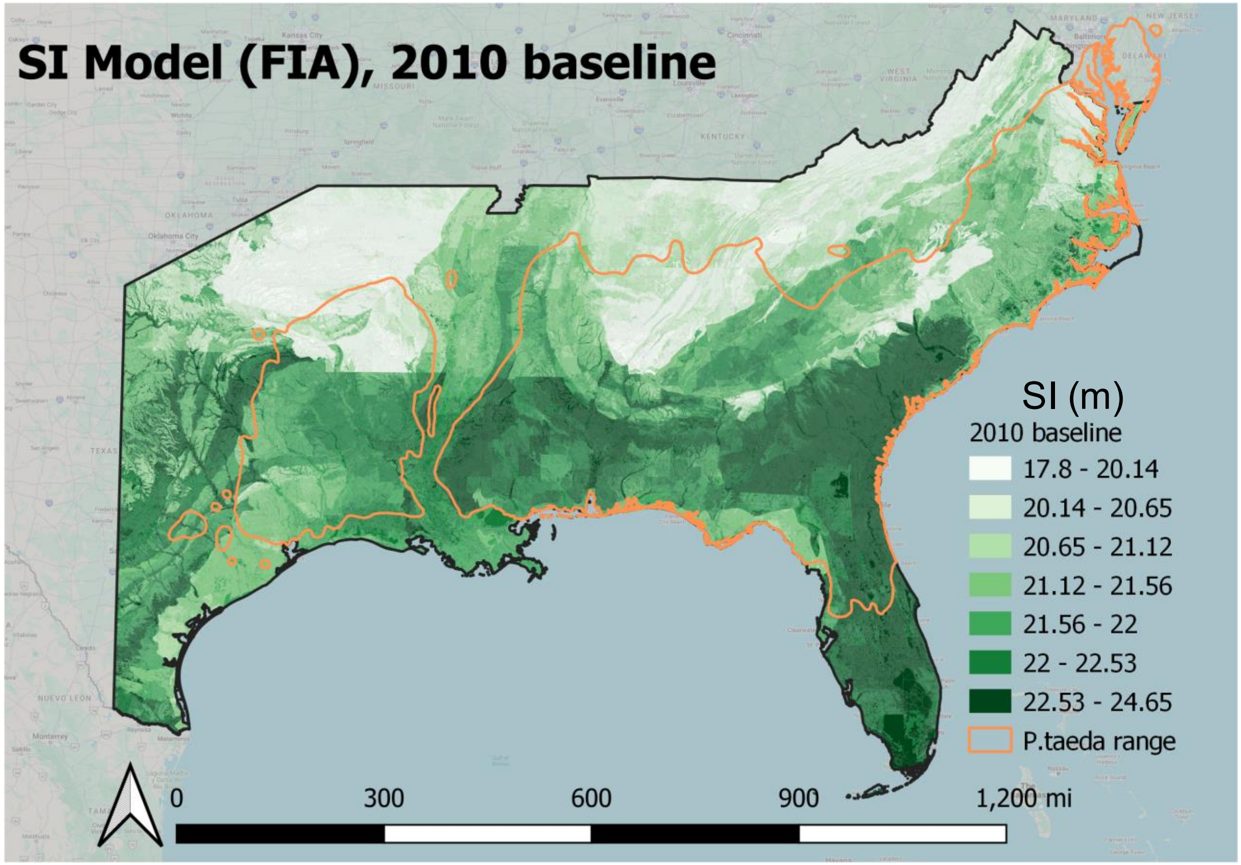
Vicent A. Ribas-Costa[1,2,*], Aitor Gastón[1], Rachel L. Cook[2]

[1]Departamento de Sistemas y Recursos Naturales, Centro para la Conservación de la Biodiversidad y el Desarrollo Sostenible (CBDS), ETSI Montes, Forestal y del Medio Natural, Universidad Politécnica de Madrid, Calle José Antonio Novais 10, 28040 Madrid, Spain
[2]Department of Forestry & Environmental Resources, NC State University, Raleigh, NC 27695, United States
*Corresponding author. E-mail: va.ribas@upm.es; vribasc@ncsu.edu; vicentribas11@gmail.com


Forest Ecology and Management 572 (2024) 122334
Contents lists available at ScienceDirect
Forest Ecology and Management
journal homepage: www.elsevier.com/locate/foreco
ELSEVIER
Nature vs. nurture: Drivers of site productivity in loblolly pine (*Pinus taeda* L.) forests in the southeastern US
Vicent A. Ribas-Costa [a,b,*], Aitor Gastón [a], Sean A. Bloszies [b], Jesse D. Henderson [c], Andrew Trlica [b], David R. Carter [d], Rafael Rubilar [e,f], Timothy J. Albaugh [d], Rachel L. Cook [b]
Predicted SI (m)
26
24
22
20
18
1960
1980
2000
Establishment year
Management
FIA natural
FIA planted
IND chem+fert+thin
IND chem+fert
IND fert+thin
IND chem+thin
IND fert
IND chem
IND thin
IND unknown

Major Findings

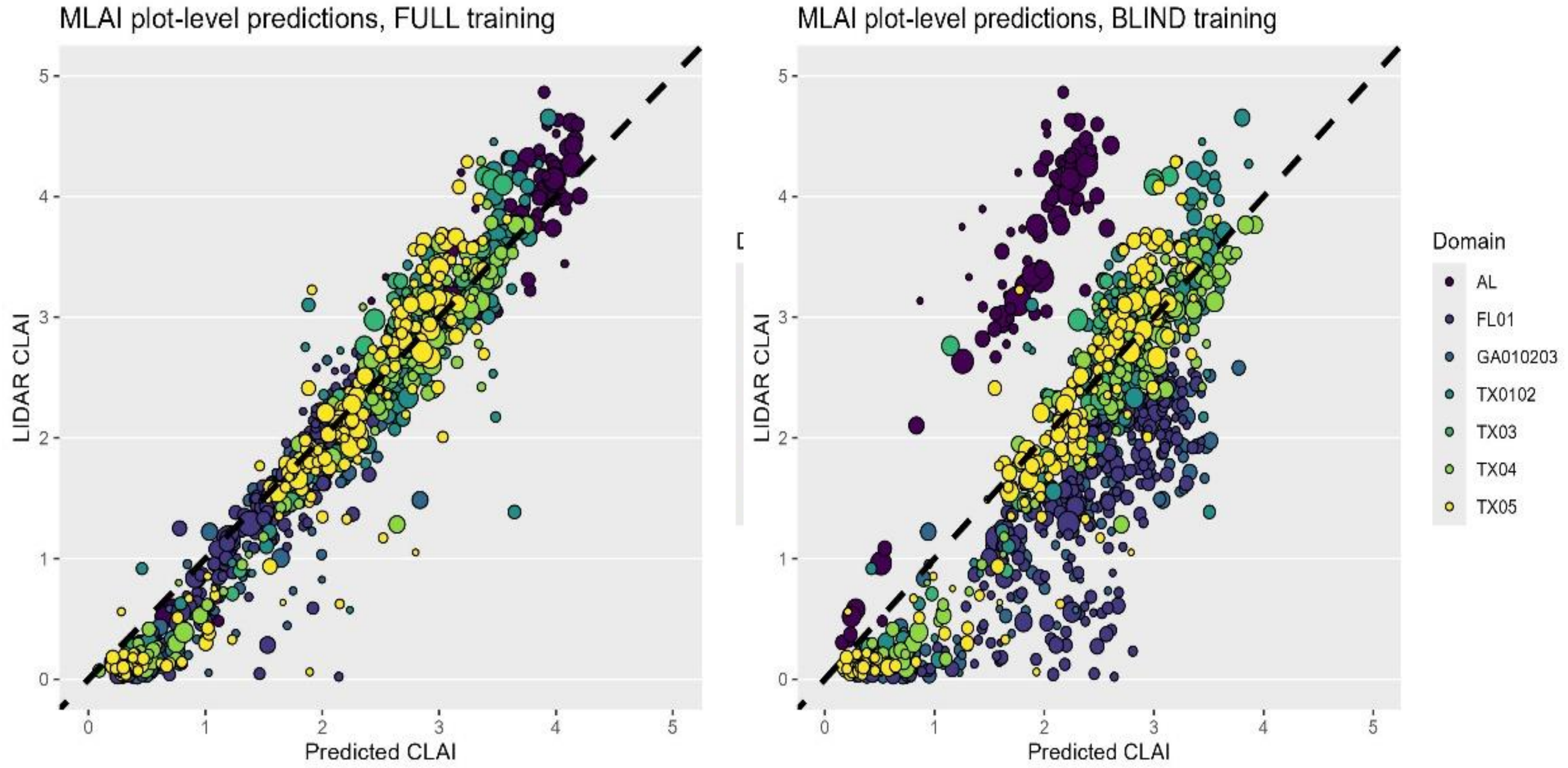
Predicted SI across Loblolly range



1. Planting year = 2010
2. All stands “planted”

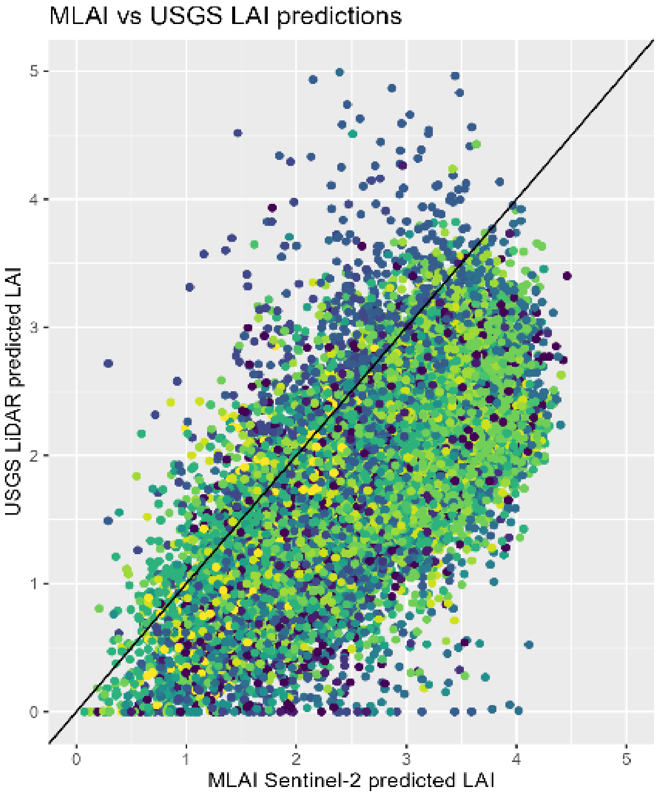
Building a new Machine Learning LAI Model

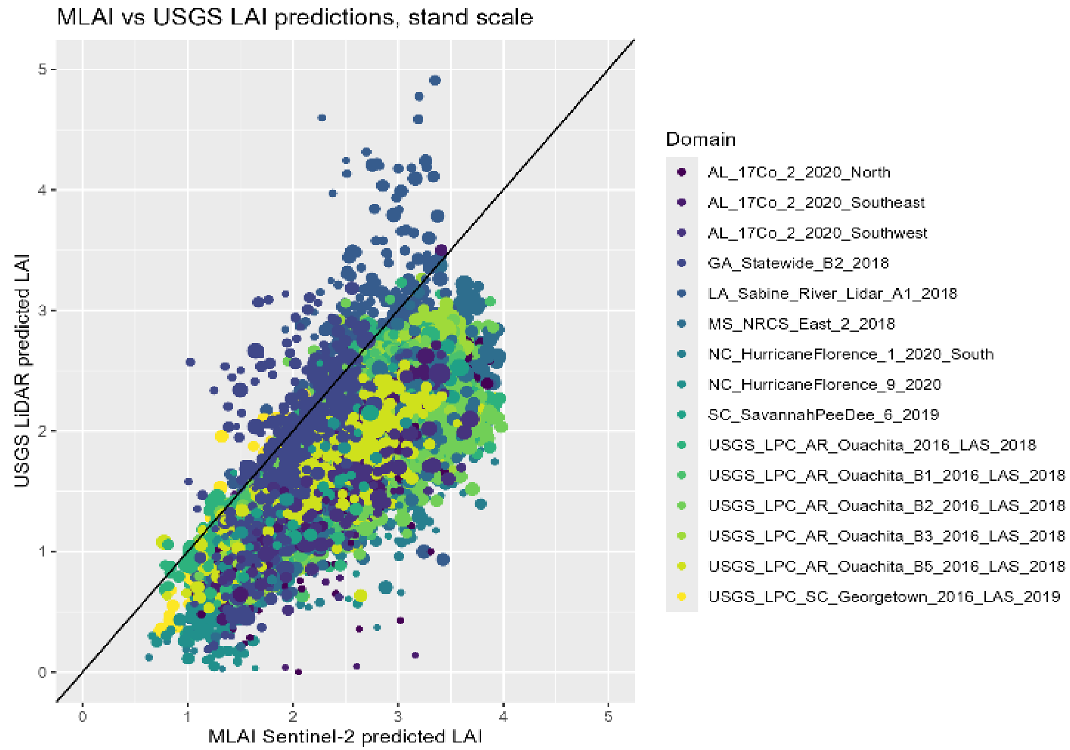
- Machine Learning models need a LOT of data



Machine Learning LAI model under predicting USGS LiDAR LAI

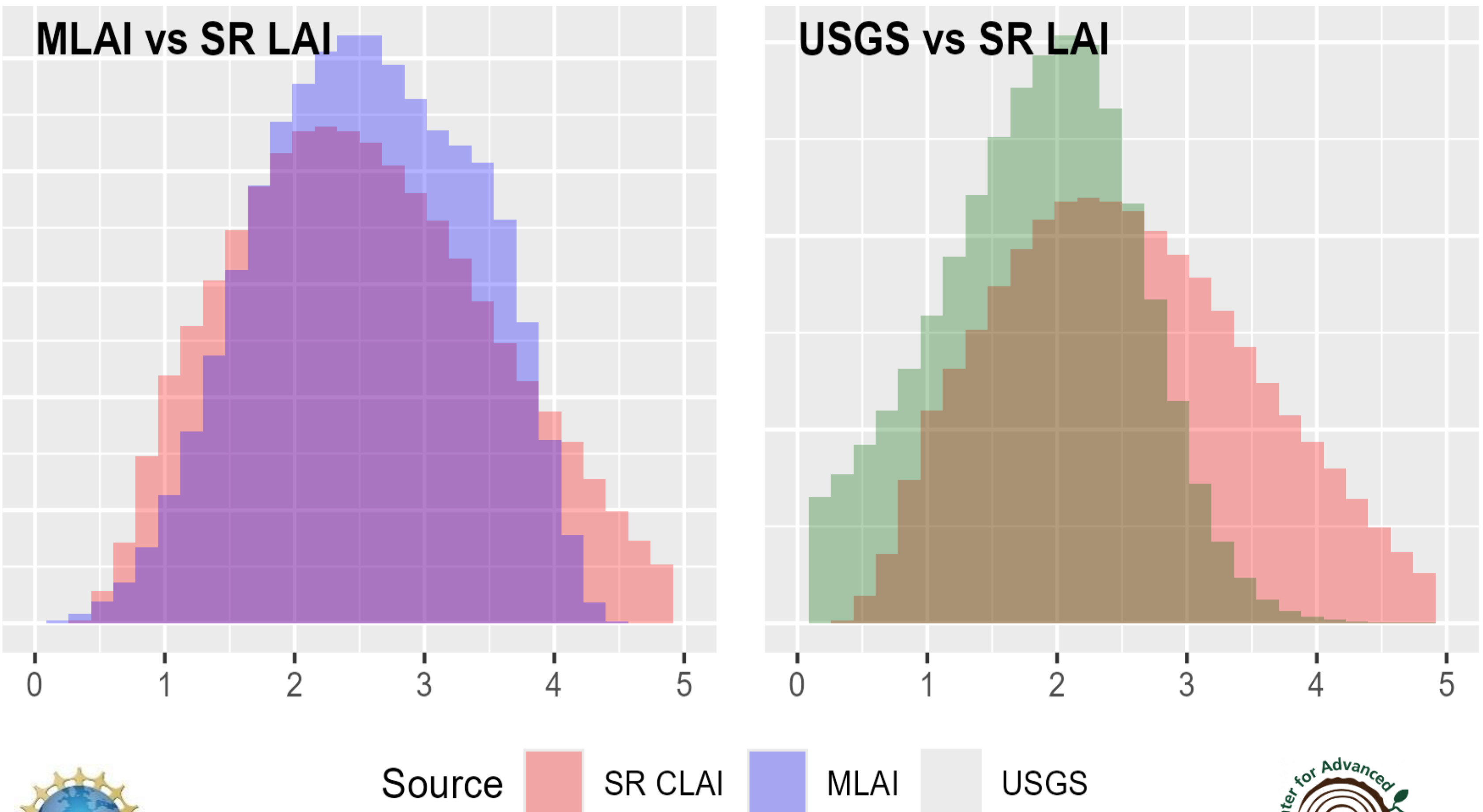
Pixel-level



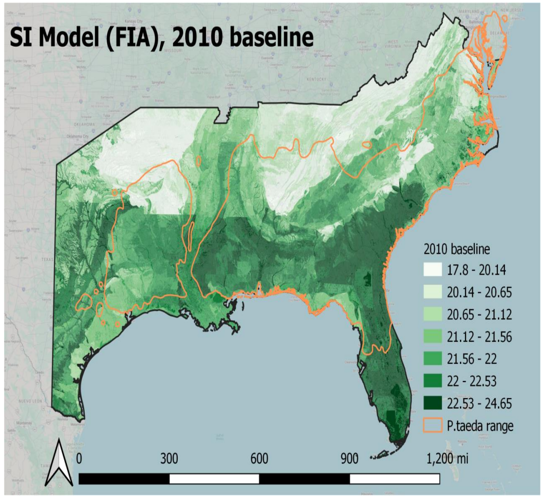


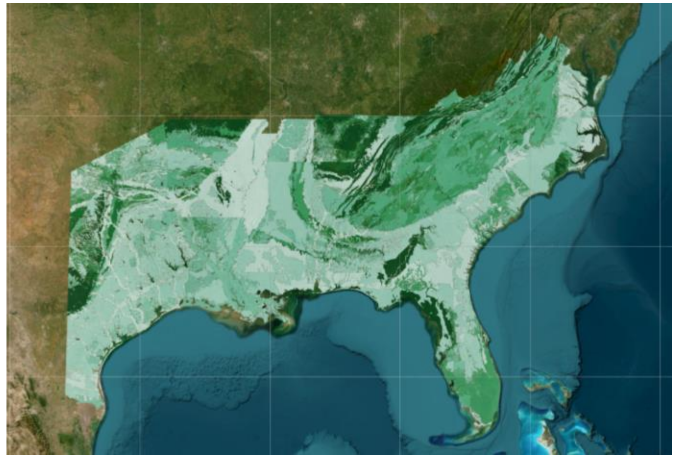
Currently Machine Learning LAI Overpredicts

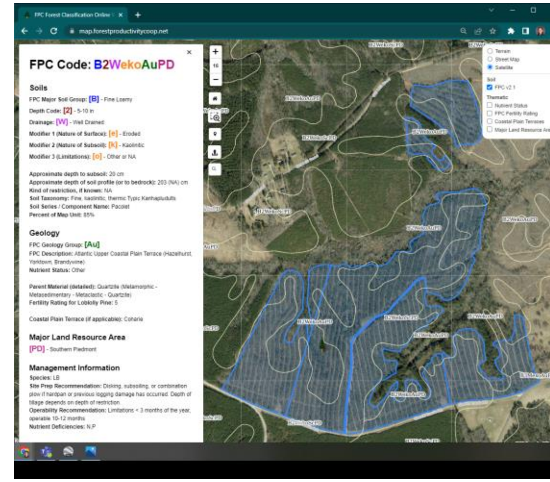
- Which one is “right”?



Company Benefits: How will it all fit together?

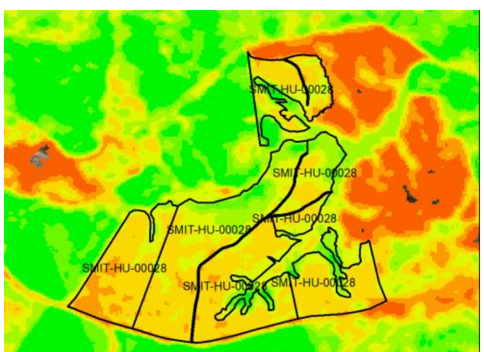


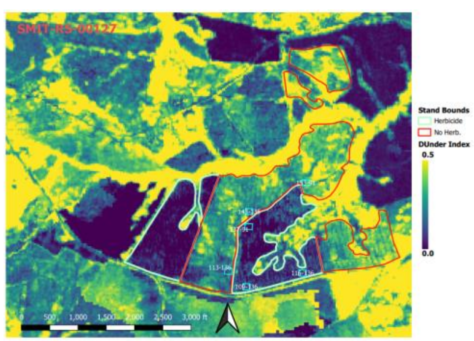


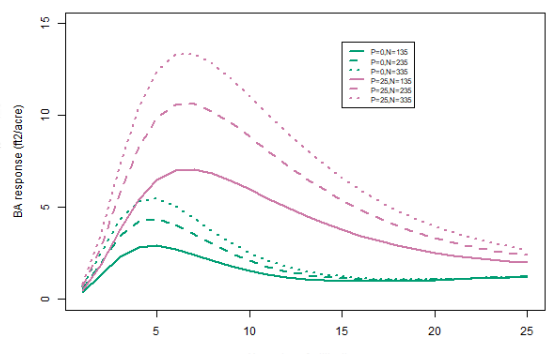


Base & Potential Site Index

Soils and Geology to predict site limitations







Optimize inputs to reduce risk and improve return on investment

Canopy and Understory LAI

Site Specific Response Models