

Advancing LiDAR and machine-learning applications for managing wildfires and cultural resources on public lands

Case studies in collaborative research with federal and academic partners

Dr. Grant Snitker
Cultural Resource Sciences Program
New Mexico Consortium
Feb. 28, 2024



New Mexico Consortium



- Connects the Los Alamos National Laboratory (LANL) and other federal research with the three research universities in New Mexico (UNM, NMSU, NMTech)
- Non-profit educational institute to foster collaboration and cross-disciplinary science.

Cultural Resource Sciences Program

- Initiated in 2022 as one pillar of the **Center for Applied Fire and Ecosystem Science (CAFES)**
- Mission of the CRS program is to advance technology and data science to support archaeological research on public lands.



The CRS team



Dr. Grant Snitker
Director; Research Scientist



Dr. Claudine Gravel-Miguel
Research Scientist



Katherine Peck
Junior Research Scientist
Current UNM Graduate Student



Jayde Hirniak
Archaeology Technician
Current ASU Graduate Student



Alexis Malone
Archaeology Technician
Current US Forest Service Tech



CRS projects

- Advancing methods and technologies for managing fire risk to cultural resources
- LiDAR (terrestrial/aerial) data collection and modeling in archaeology
- Fire effects on archaeological sites
- Paleofire/cultural burning in restoration ecology

Our Motivation

- Ecological, geographical, and other physical sciences well represented in federal research initiatives and investments.
- Archaeology less represented, despite legislative obligation to manage and non-renewable resource...not to mention tangible and intangible cultural importance.

The Challenge

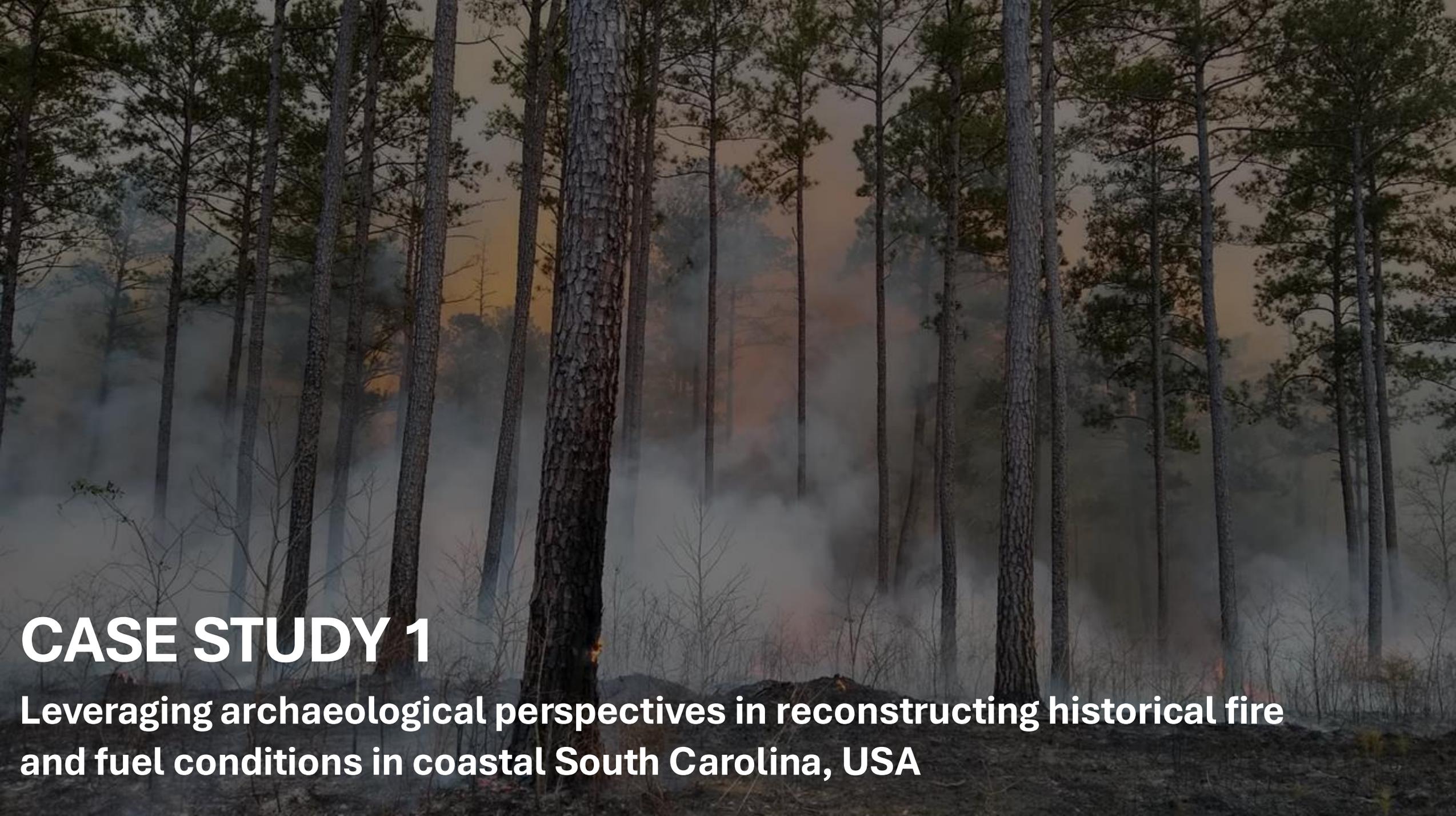
- Develop archaeological science and technology to support cultural resource management and research on public lands.
- How do we design actionable science, interdisciplinary approaches, and direct management implications?

Case study 1:

Leveraging archaeological perspectives in reconstructing historical fire and fuel conditions in coastal South Carolina, USA

Case study 2:

Deep learning approaches to archaeological object detection for enhancing site inventorying and wildfire protection measures



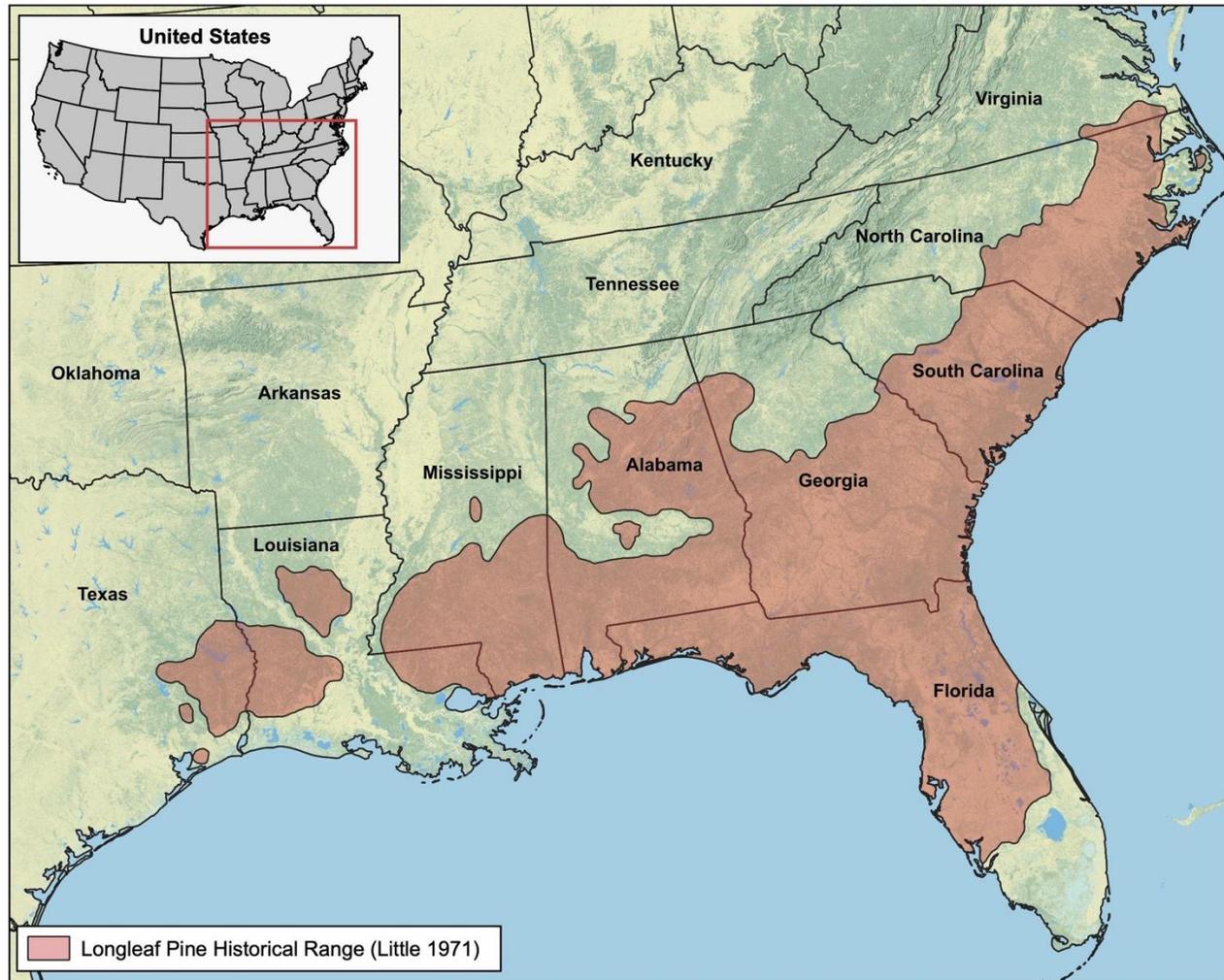
CASE STUDY 1

Leveraging archaeological perspectives in reconstructing historical fire and fuel conditions in coastal South Carolina, USA



Restoring Longleaf pine Ecosystems

Longleaf pine (*Pinus palustris*) ecosystems cover about 2 million acres of the US Southeast — which some suggest is **4%** of their original range.



Multitude of federal, state, private, and academic institutions involved in initiatives to restore and manage these ecosystems.

Fire is a **fundamental** component of
Longleaf pine life history

Restoration includes regular **Rx burning**





Restoration ecology points to **historical baselines** to justify fire frequency, fire intensity, and stand structure...

**Which
landscapes?**

When?

Why?

Bibliometric analysis to determine how the current Longleaf pine restoration literature use historical baselines

1. Introduction

Longleaf pine (*Pinus palustris* Mill.) forests once dominated the southeastern Coastal Plain in the United States (US), occupying 36 million hectares (ha) prior to the arrival of European settlers (Frost, 1993). Currently, 3% of the historical area of longleaf pine forests (1.3 million ha) remains in the Florida Panhandle, southern Alabama, Georgia and Mississippi, primarily in private ownership and as natural forest (Oswalt et al., 2012). The primary reasons behind this intensive decline include land use change for agriculture and human occupation, suppression of natural fire regimes, and conversion to economically more attractive southern pines (Frost, 1993; Landers et al., 1995).

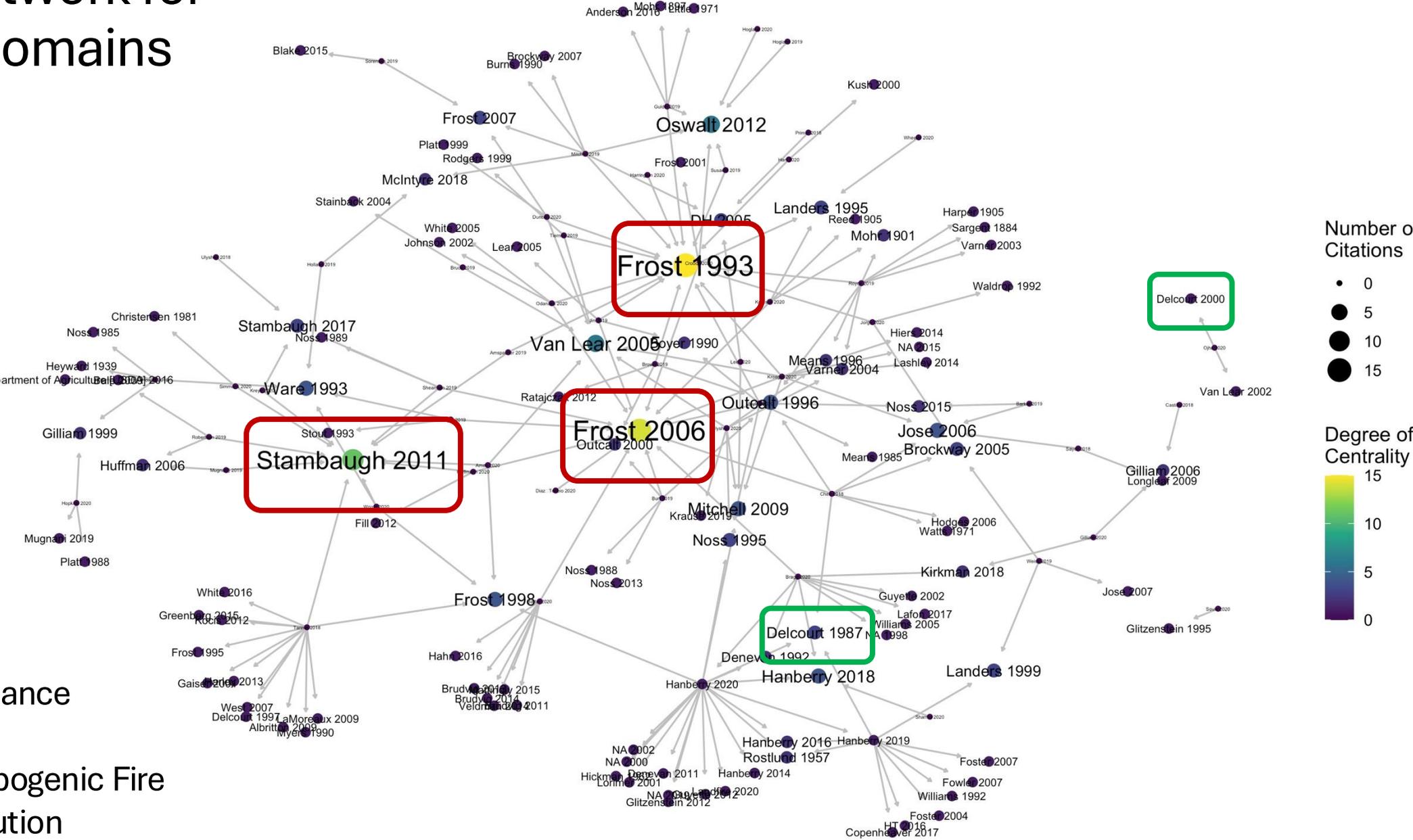
Domain Codes

Historic Distribution

Historic Disturbance

Historic Disturbance

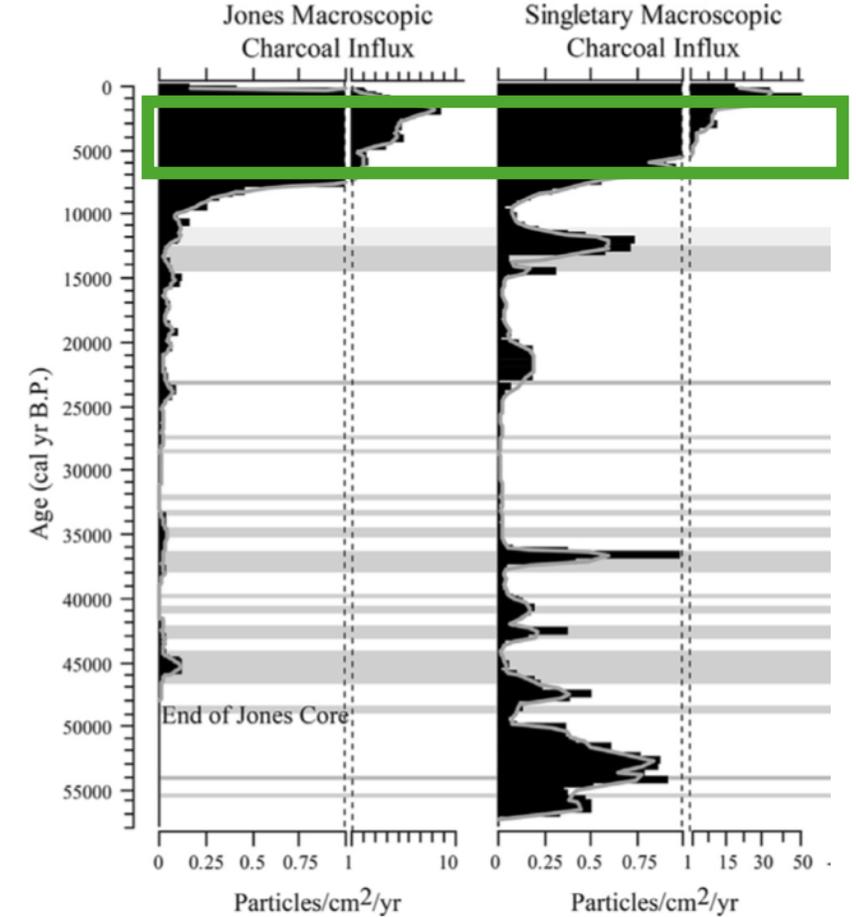
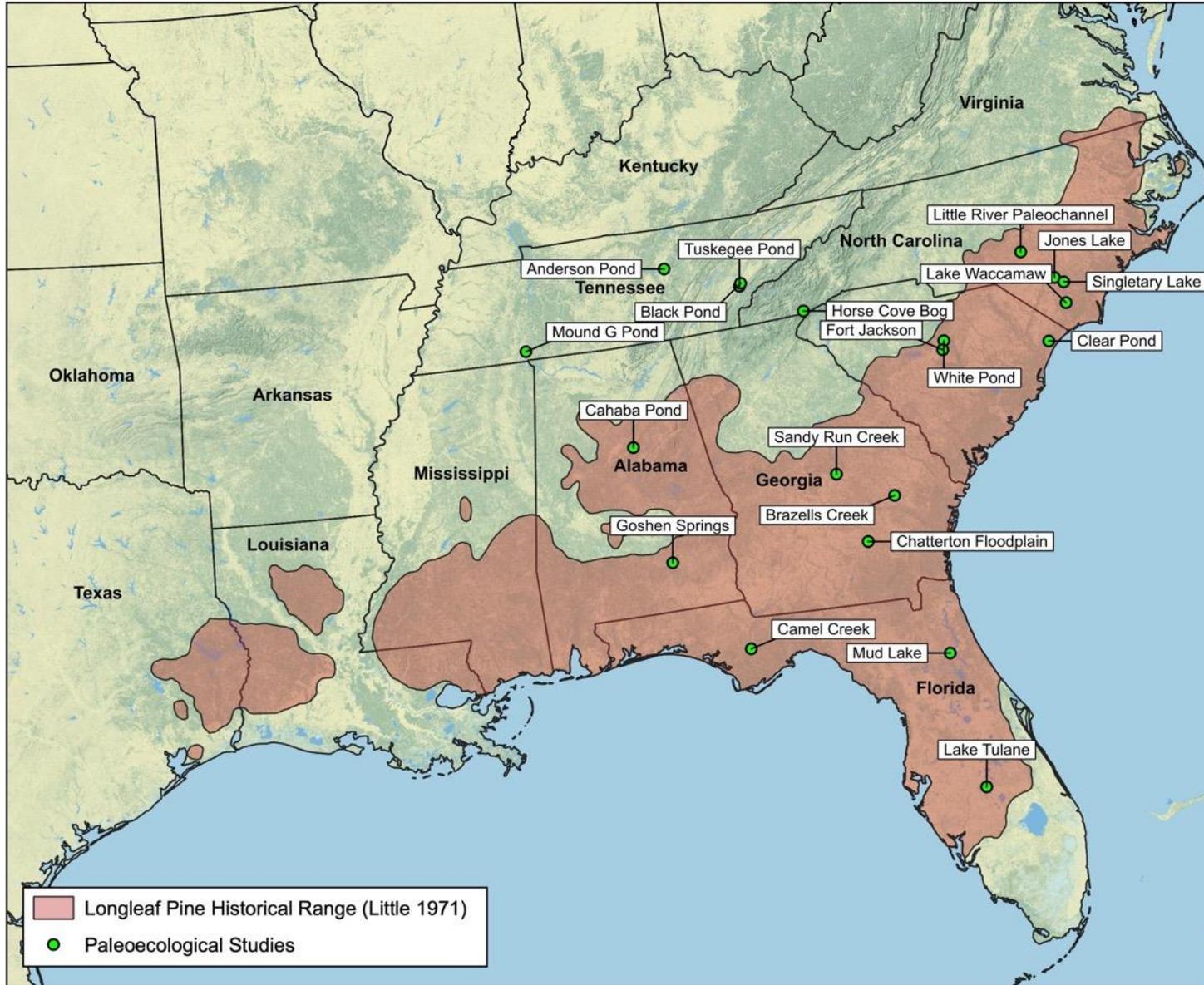
Citation network for all coded domains



Domains

- Historic Disturbance
- Historic FRI
- Historic Anthropogenic Fire
- Historic Distribution
- Historic Longleaf Ecosystem Condition

What about **palynology** and **charcoal** studies?



Challenges of **resolution** and **scale**.

Spencer, J., Jones, K.B., Gamble, D.W., Benedetti, M.M., Taylor, A.K., Lane, C.S., 2017. Late-Quaternary records of vegetation and fire in southeastern North Carolina from Jones Lake and Singletary Lake. *Quaternary Science Reviews* 174, 33–53. <https://doi.org/10.1016/j.quascirev.2017.09.001>

Historical baseline extends back to the Pleistocene, but lacks fine temporal resolution in recent centuries



Palynology
Charcoal Studies
Climate Proxies

Fundamental Gap in Knowledge



Historic Timber Inventories
Travelogues
Historical Photos
Fire-Scarred Trees

Historical baseline extends back 100-250 years, but well after European colonization

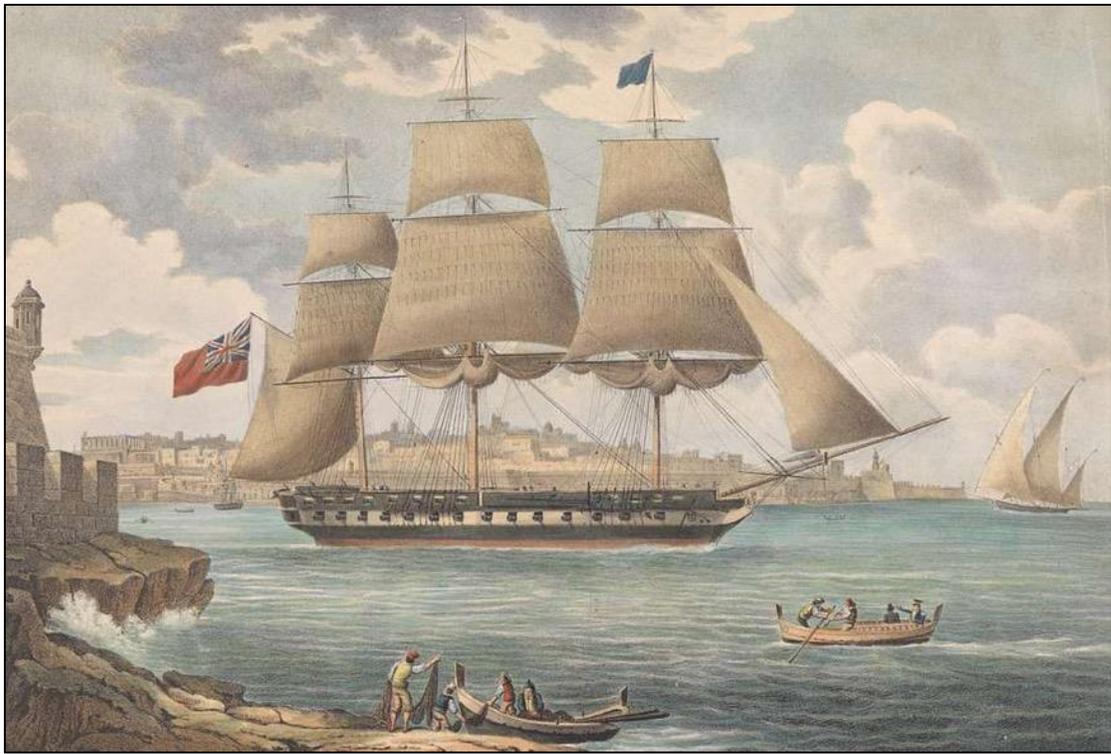


Time

Identifying the **challenge** and **recognizing** opportunities for archaeological approaches



**Leveraging Archaeology:
*The Naval Stores Industry and Longleaf Pines***



Naval stores and the myth of *'pristine forests'*

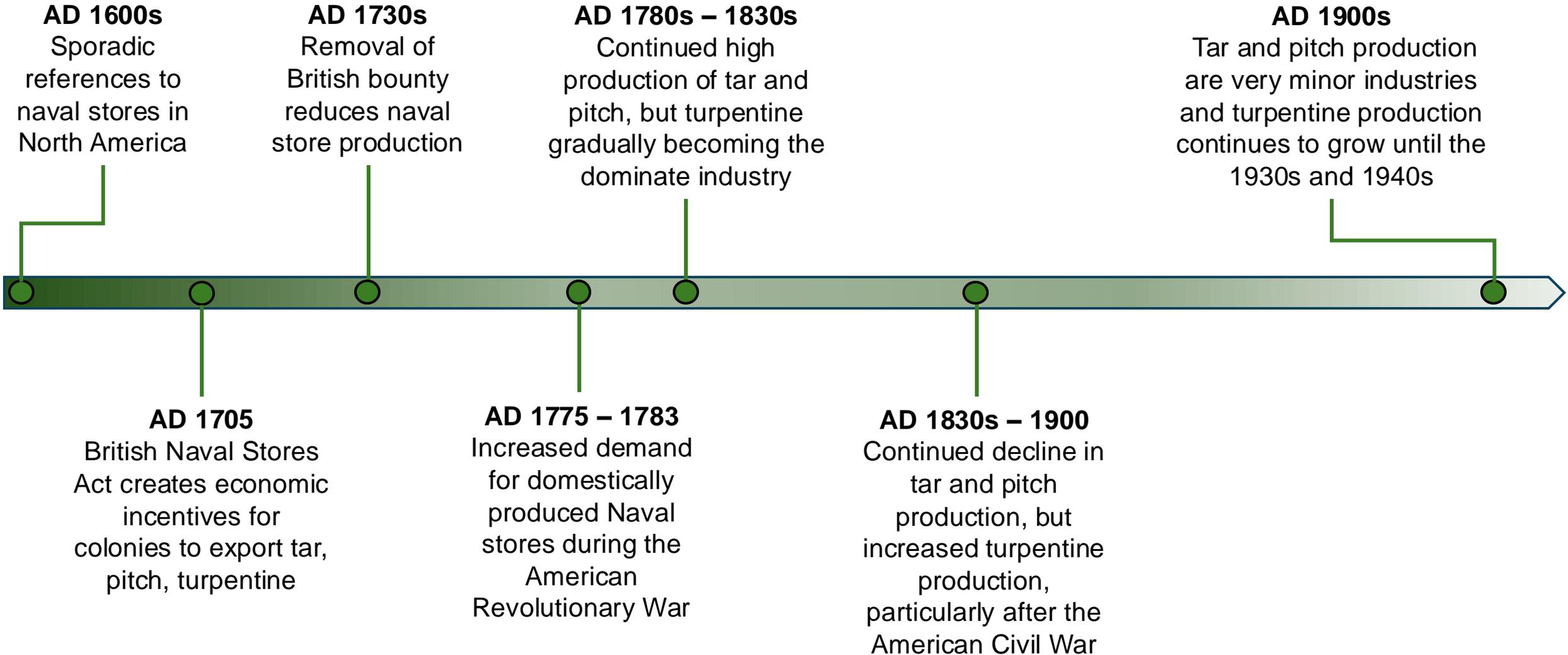
Tar / pitch production in kilns

Turpentine (box cutting / cat faces)

Wood/stump distilling



A Brief History of the Naval Stores Industry in the Southeast US



What is a **tar kiln** in the Southeast US?

Tar Kiln Schematic

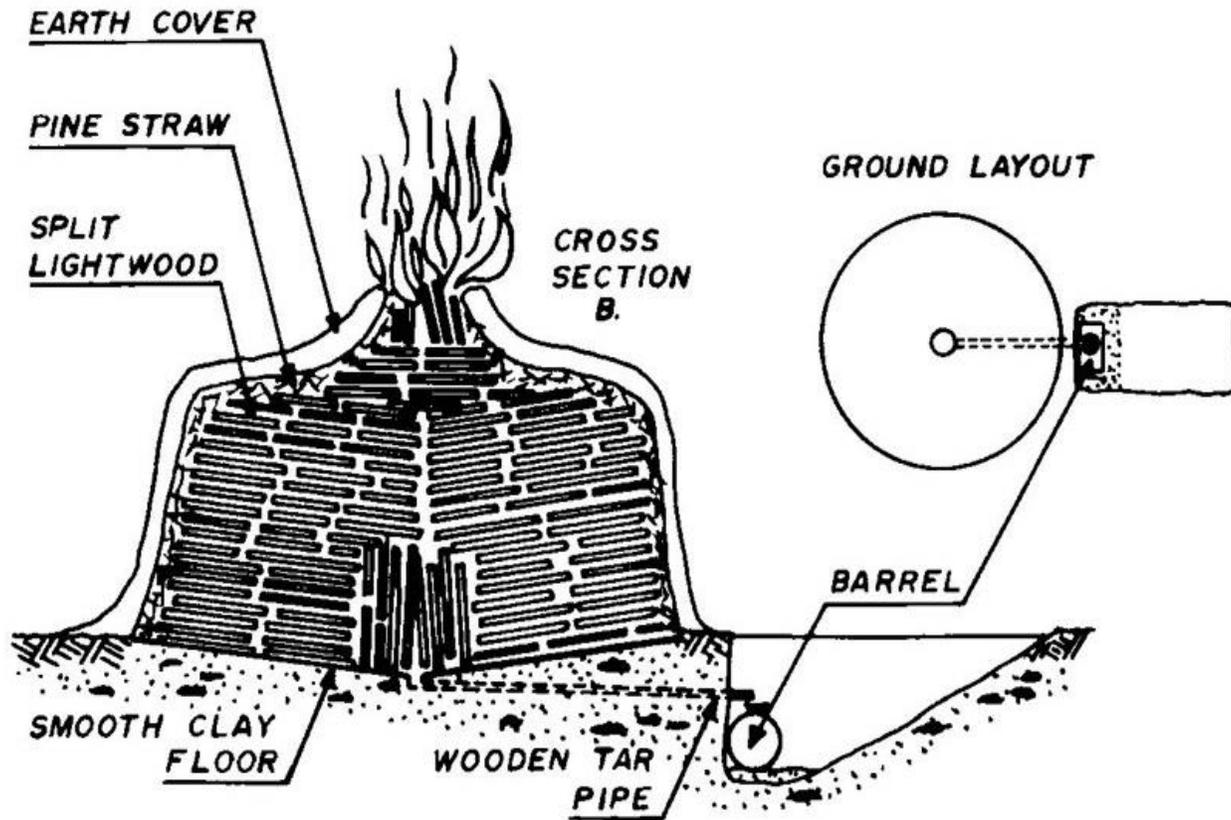


Figure is reproduced from Combes 1974



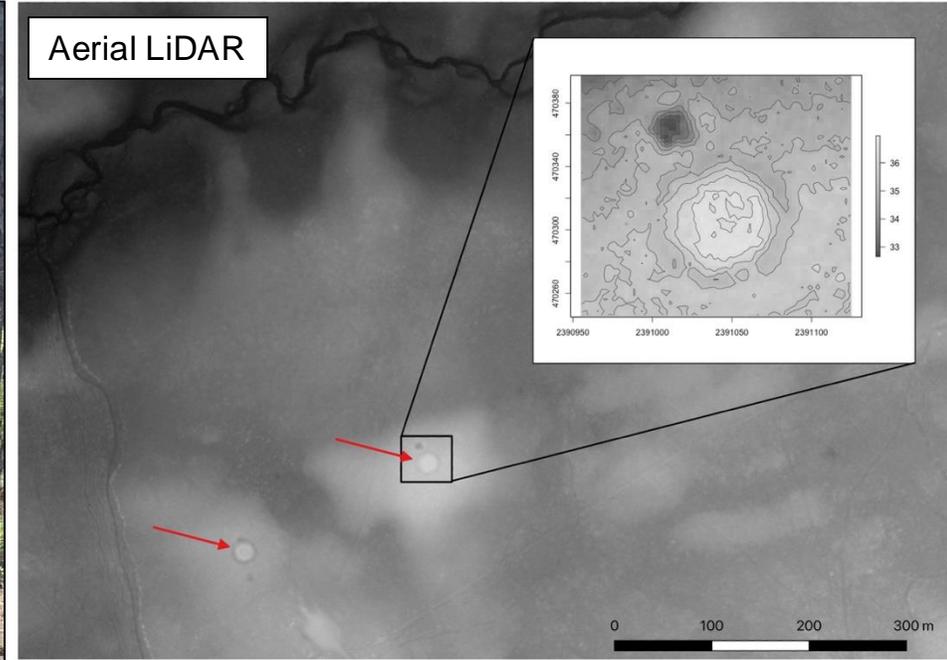
Tar Kiln Examples



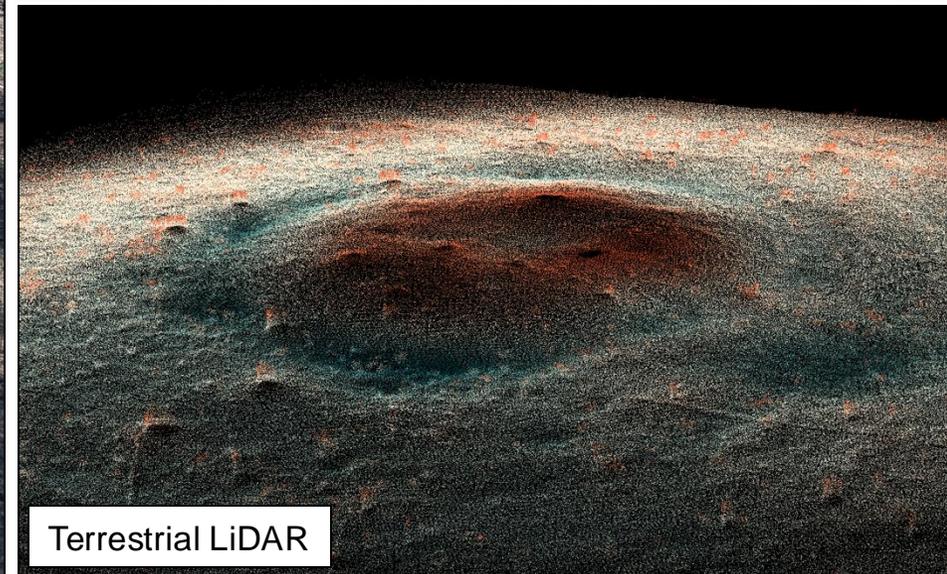
What do tar kilns look like in the field?



Photograph of archaeological tar kiln (April 2021)



Aerial LiDAR



Terrestrial LiDAR

Connecting tar kilns to **fire** and **fuels**

- Kiln-produced tar required large quantities of Longleaf pine “light wood”
- Primary accounts suggest ~400 cubic meters of lightwood needed per kiln...**about 10 standard shipping containers**
- Implications for Longleaf pine stand density, coarse woody debris, and fuel connectivity — all factors that shape our historical baselines





Project Objectives

1. Utilize remote sensing datasets to identify tar kiln production sites
2. Quantify tar kiln sites / attributes within 170,000-hectare study area in collaboration with USFS
3. Validate dataset with archaeological survey and previously known sites
4. Connect tar kilns to the emergence of largescale exploitation of Longleaf pine ecosystems and influence on fire and fuel conditions to support management objectives

Project Objectives

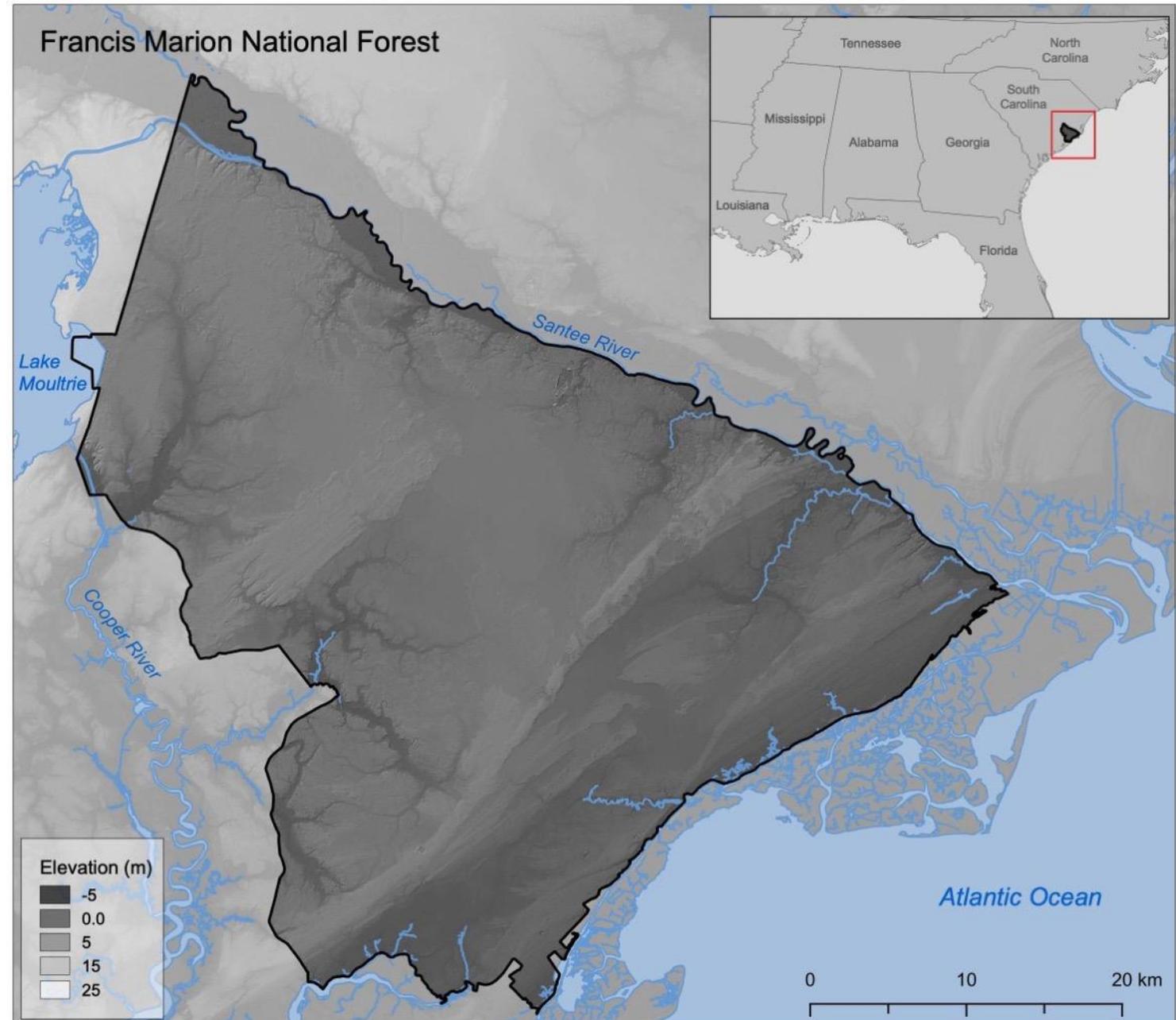
Specific metrics important for restoration ecology

- Local spatial variability in historical Longleaf pine stands
- Quantity of fuels removed from these systems
- Extent of human impacts on fuels in these systems from ~ AD 1670 - 1900.

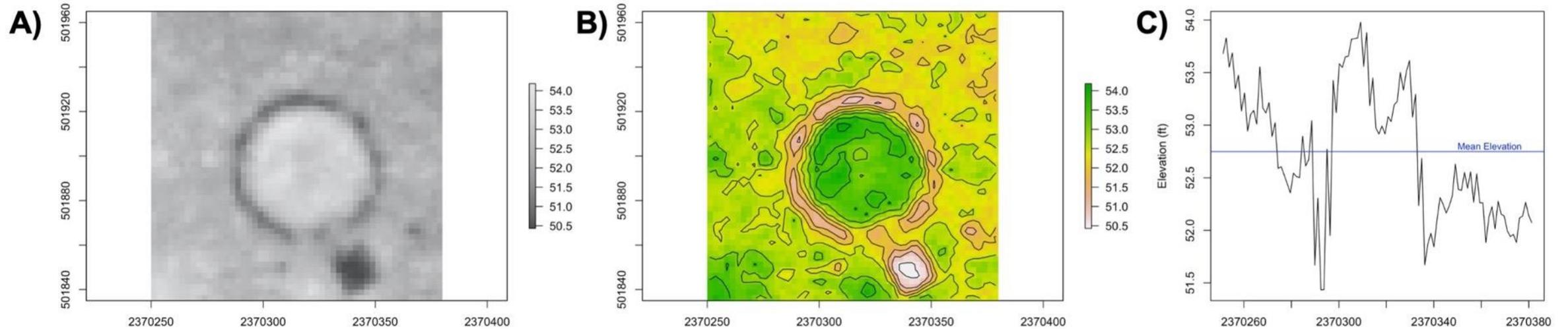
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The Francis Marion National Forest serves as the study area for this project

- Managed by the US Forest Service (170,000-hectares)
- 50 km northeast of Charleston, SC
- Euro-American land-use since the founding of Charles Town in AD 1670.



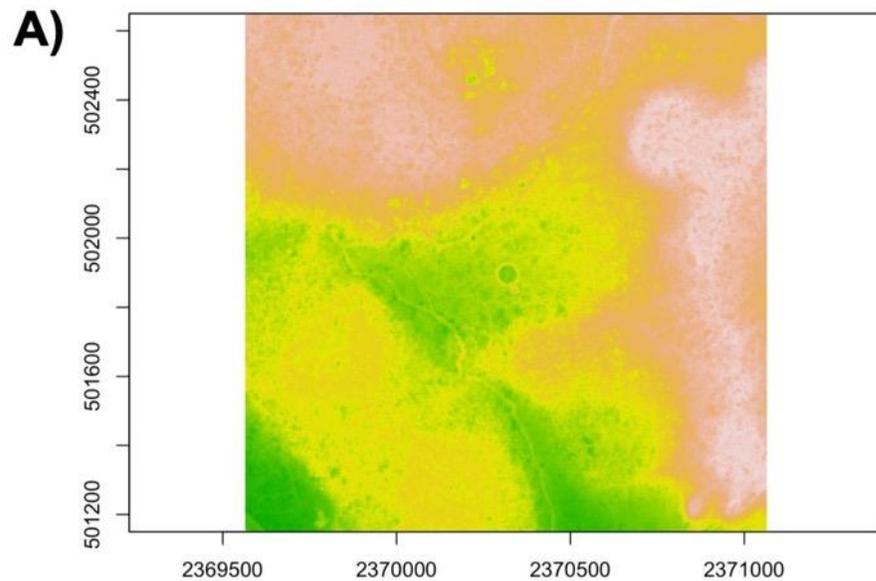
The Tar Kiln Feature Detection (TKFD) workflow



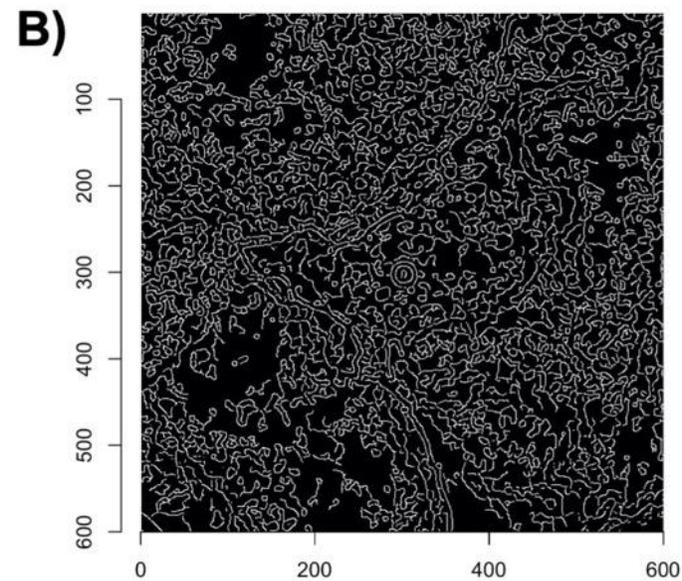
- Scripted, open-source workflow linking R and FIJI
- Computer vision technique to extract archaeological features that might not be highly visible in the field
- Relies on tar kiln morphology for detection: **[A]** circular, **[B]** slightly mounded, and **[C]** surrounding trench

The Tar Kiln Feature Detection (TKFD) workflow

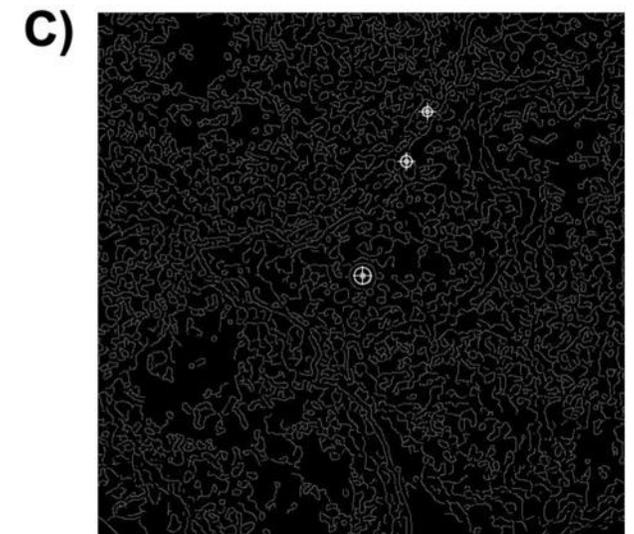
Brief overview



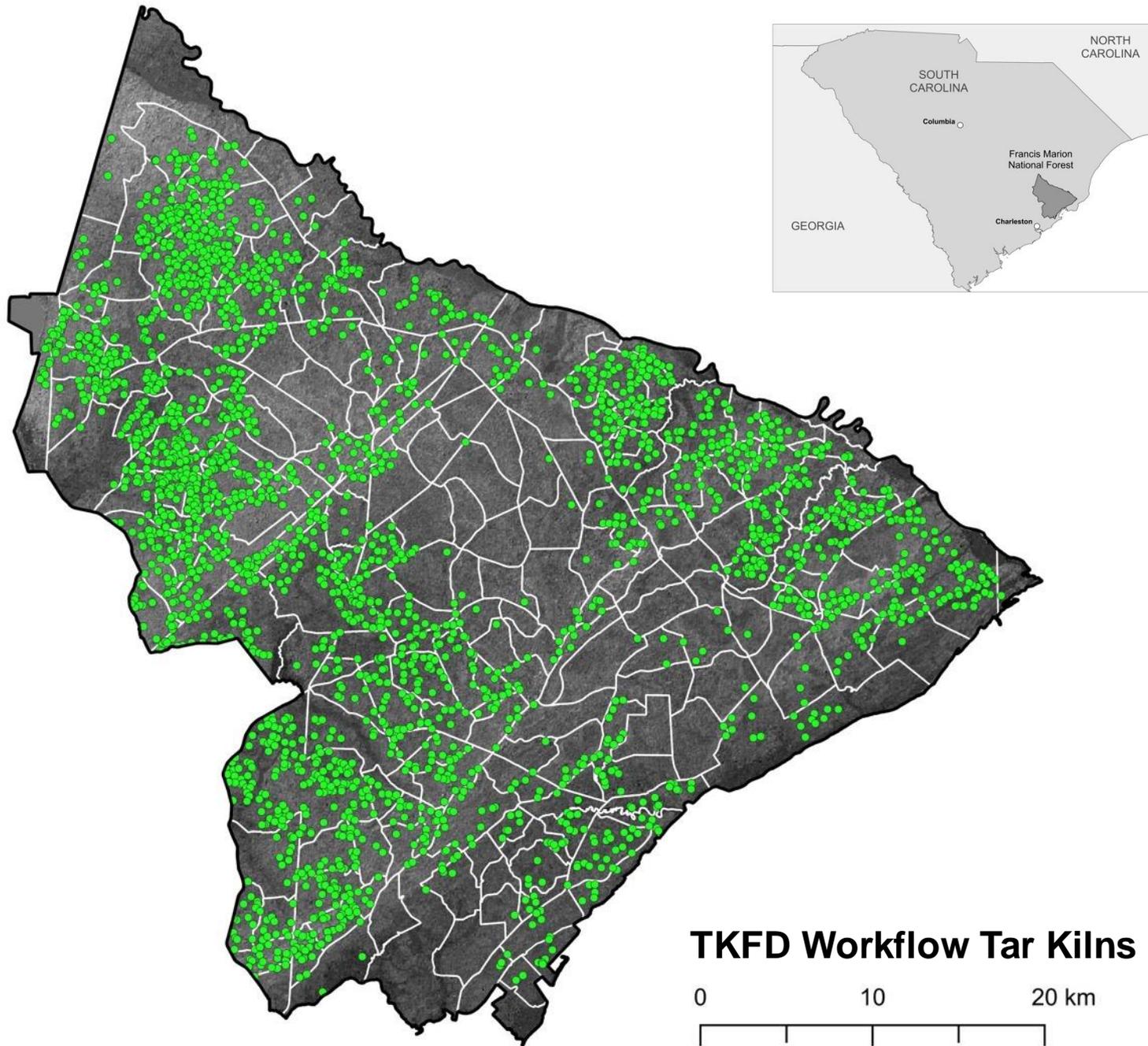
1-meter DEM from
aerial Lidar



Canny edge detector to
extract image structure



Circle Hough Transform
to detect circular objects



Distribution of
tar kilns
according to
the **TKFD**
workflow,
but how do
we verify
these results?

Validation of **Tar Kilns** detection

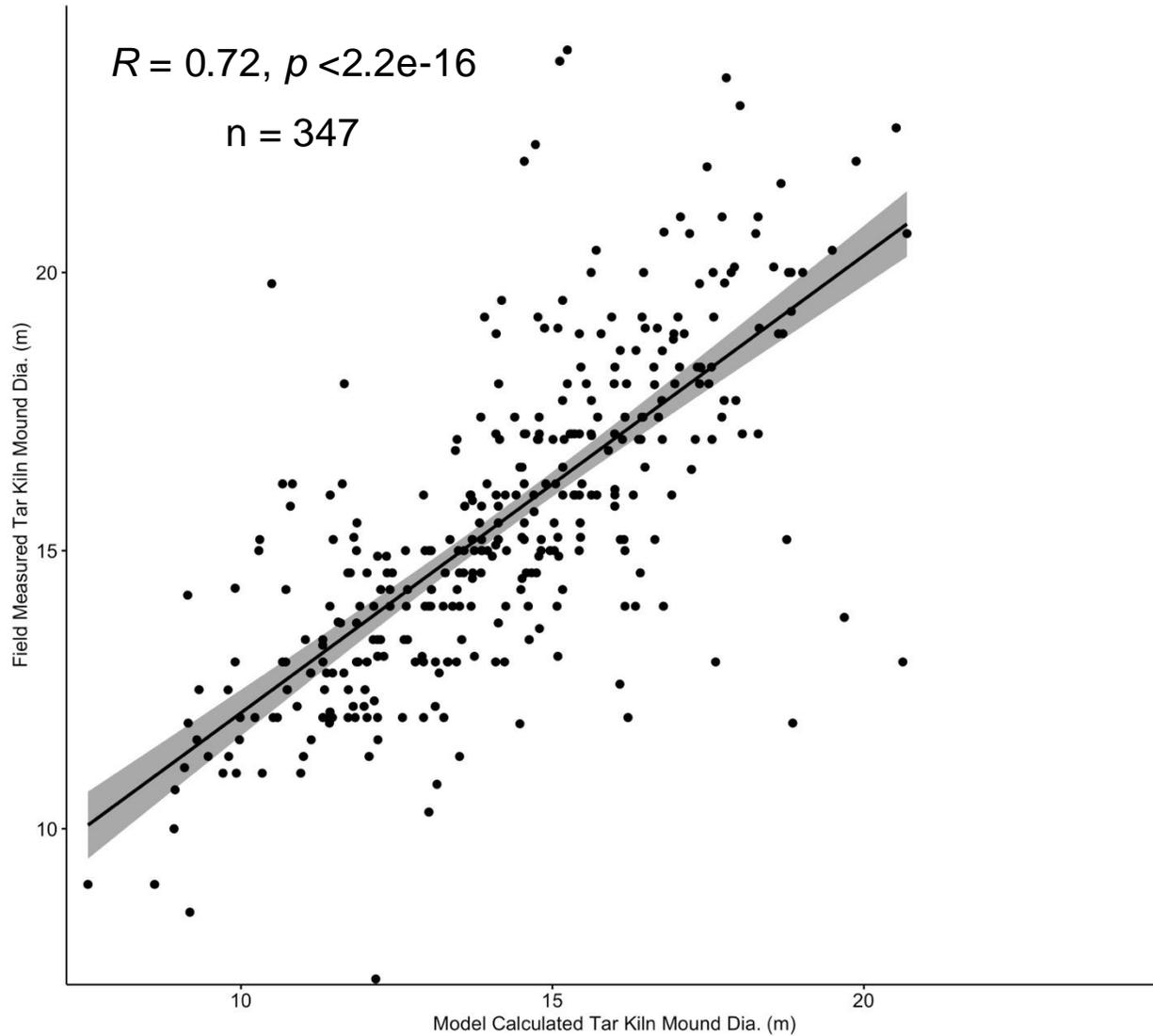
Previously
known tar kilns,
fieldwork, and
random points

**Balanced
Accuracy:**
90.6%

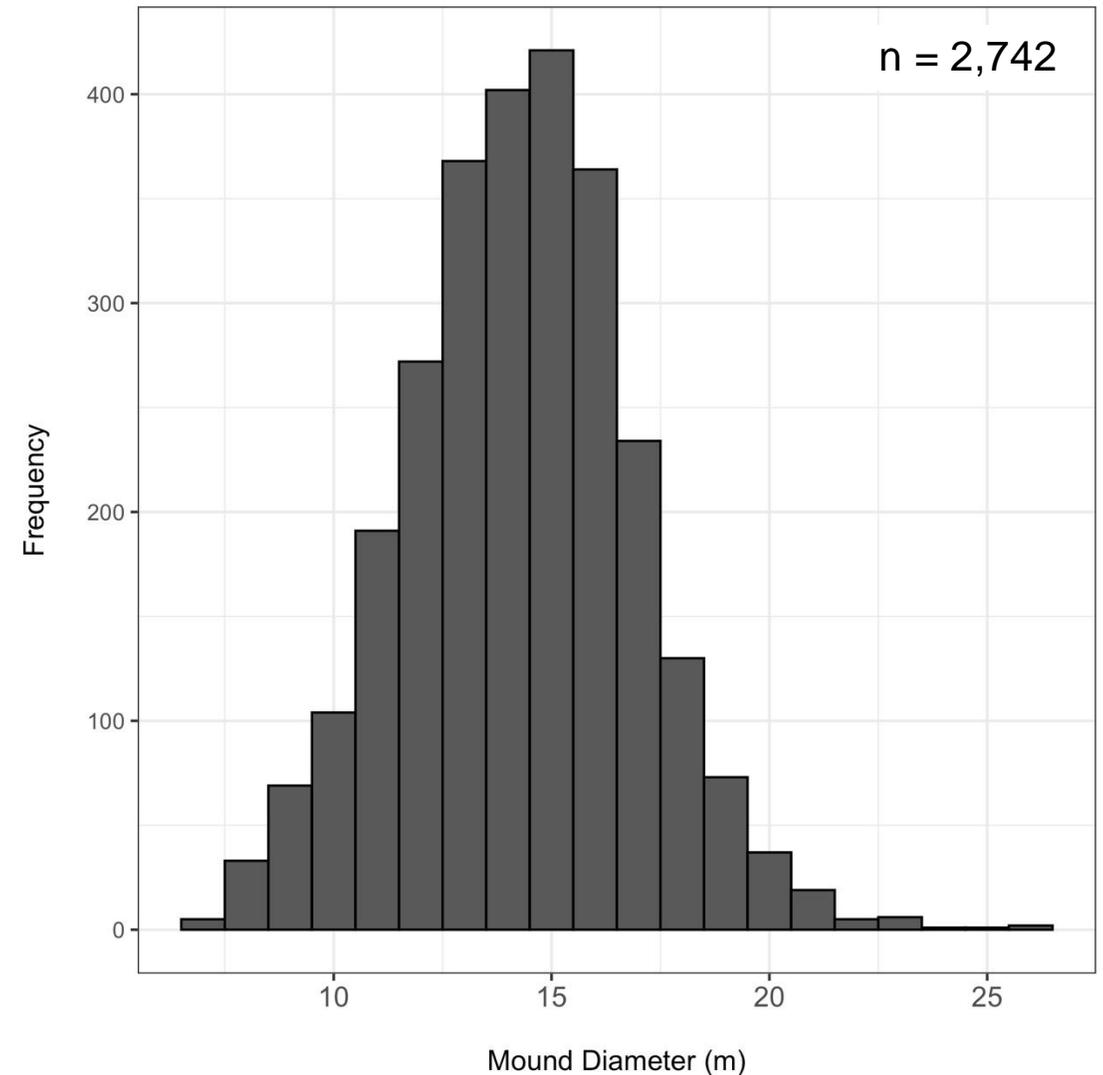


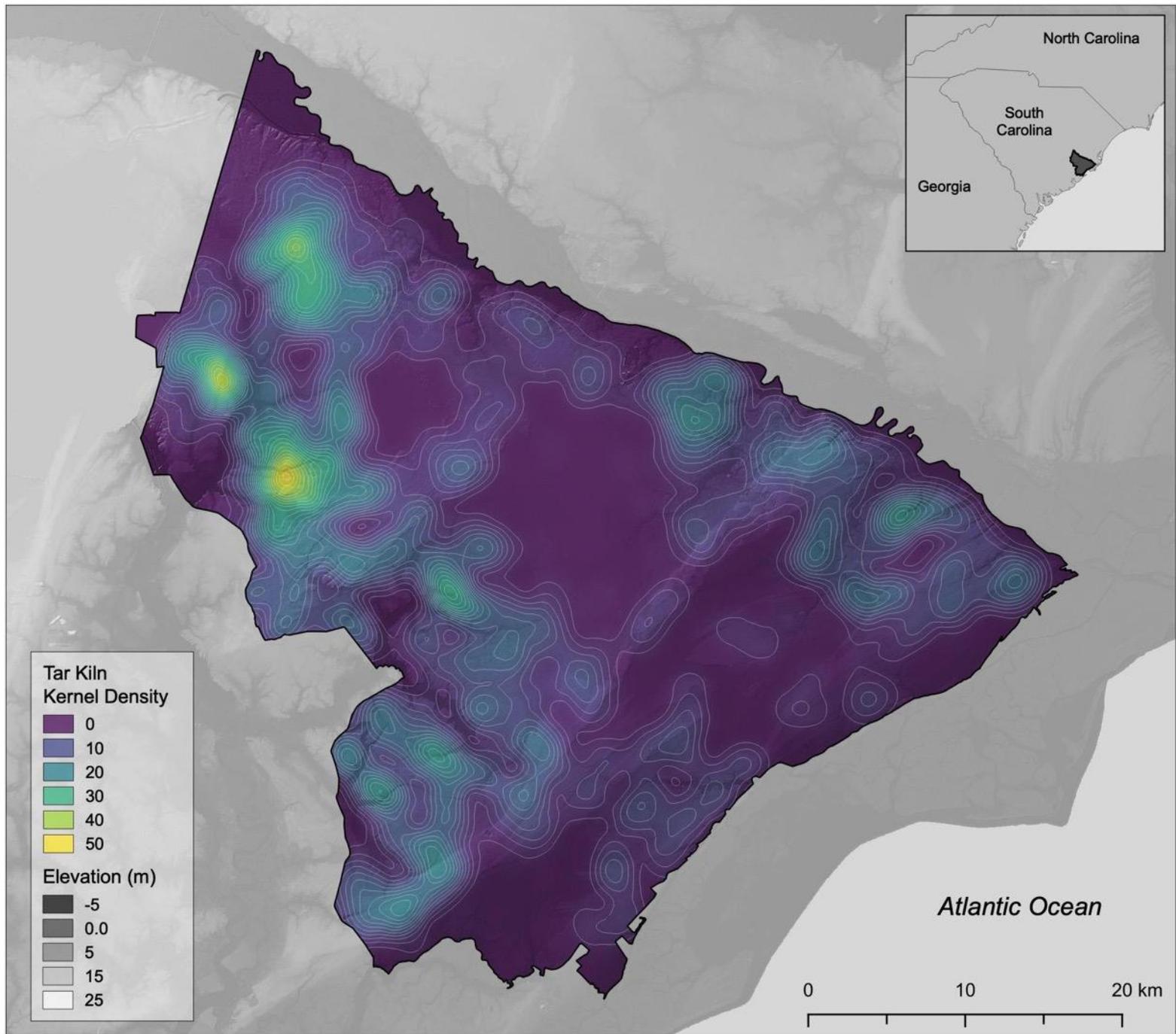
Measuring and validating of tar kiln diameter

Comparison to field measured kilns



Tar Kiln Diameter (m) Distribution

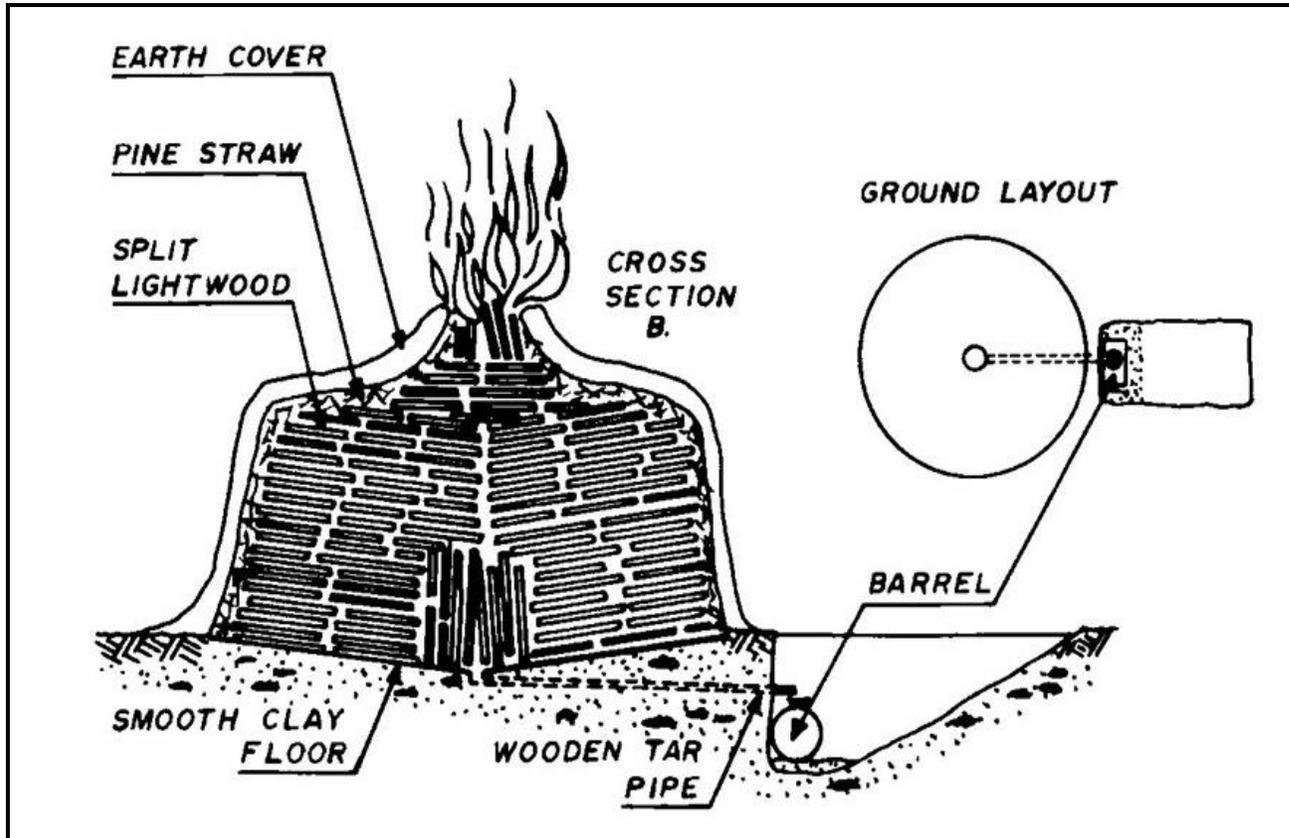




Tar kilns as a proxy
for the local
distribution of
Longleaf Pine
stands

**Heterogeneous
and patchy,
rather than
uniform**

Estimating the **quantity** of Longleaf pine removed from the Francis Marion National Forest



- Kiln volume calculated from diameter

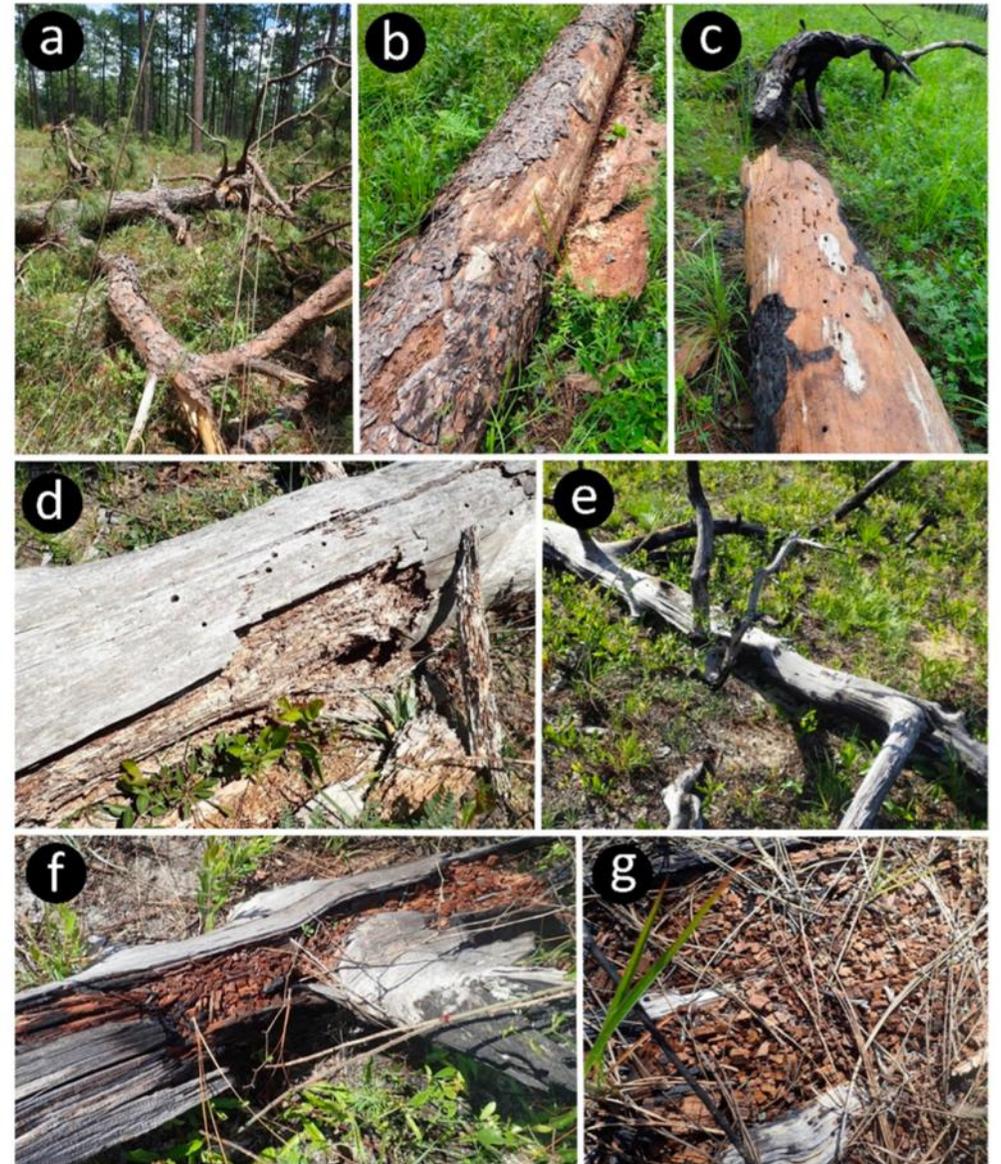
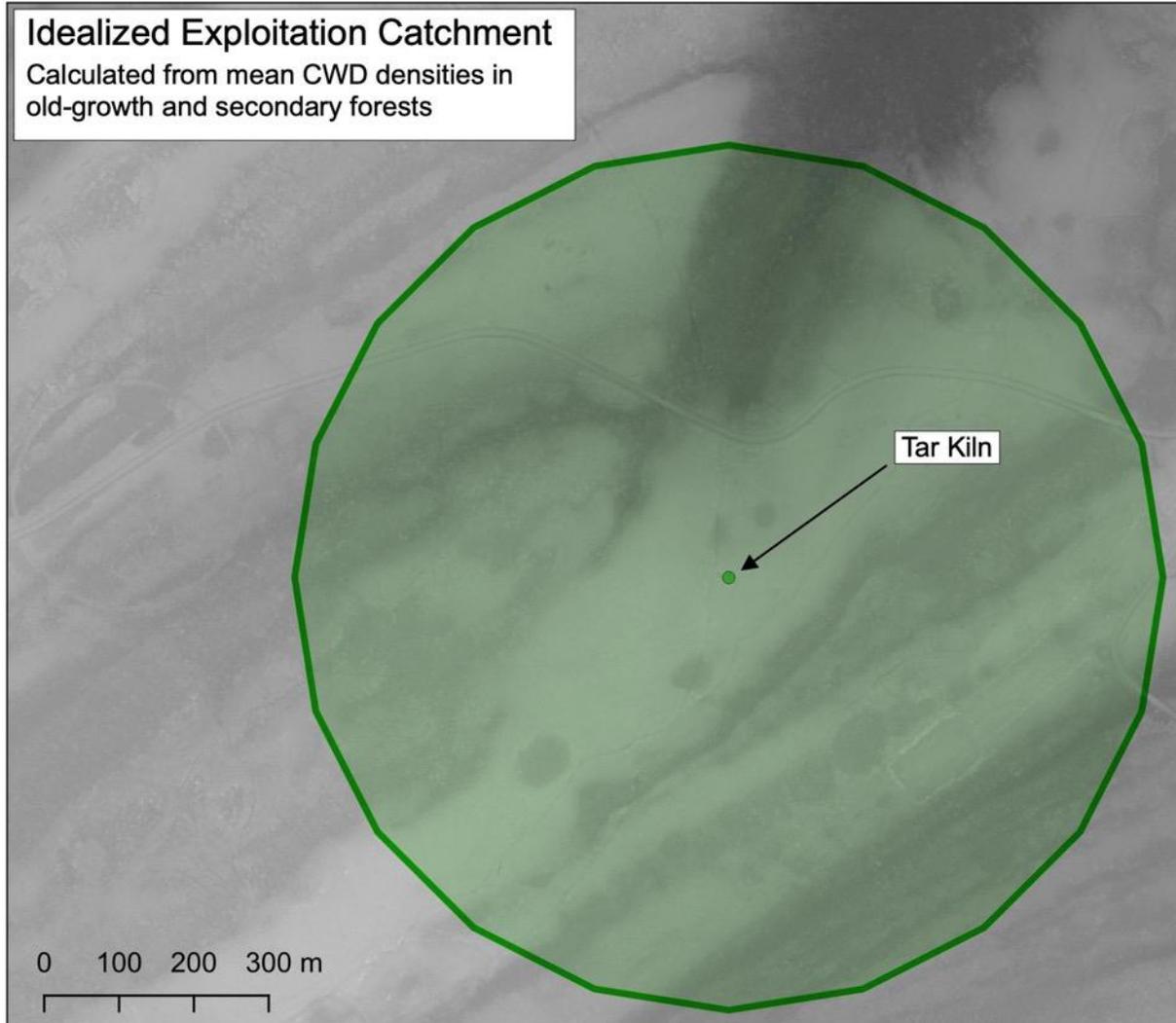
$$V = \pi r^2 \frac{h}{3}$$

If each kiln were used only once...

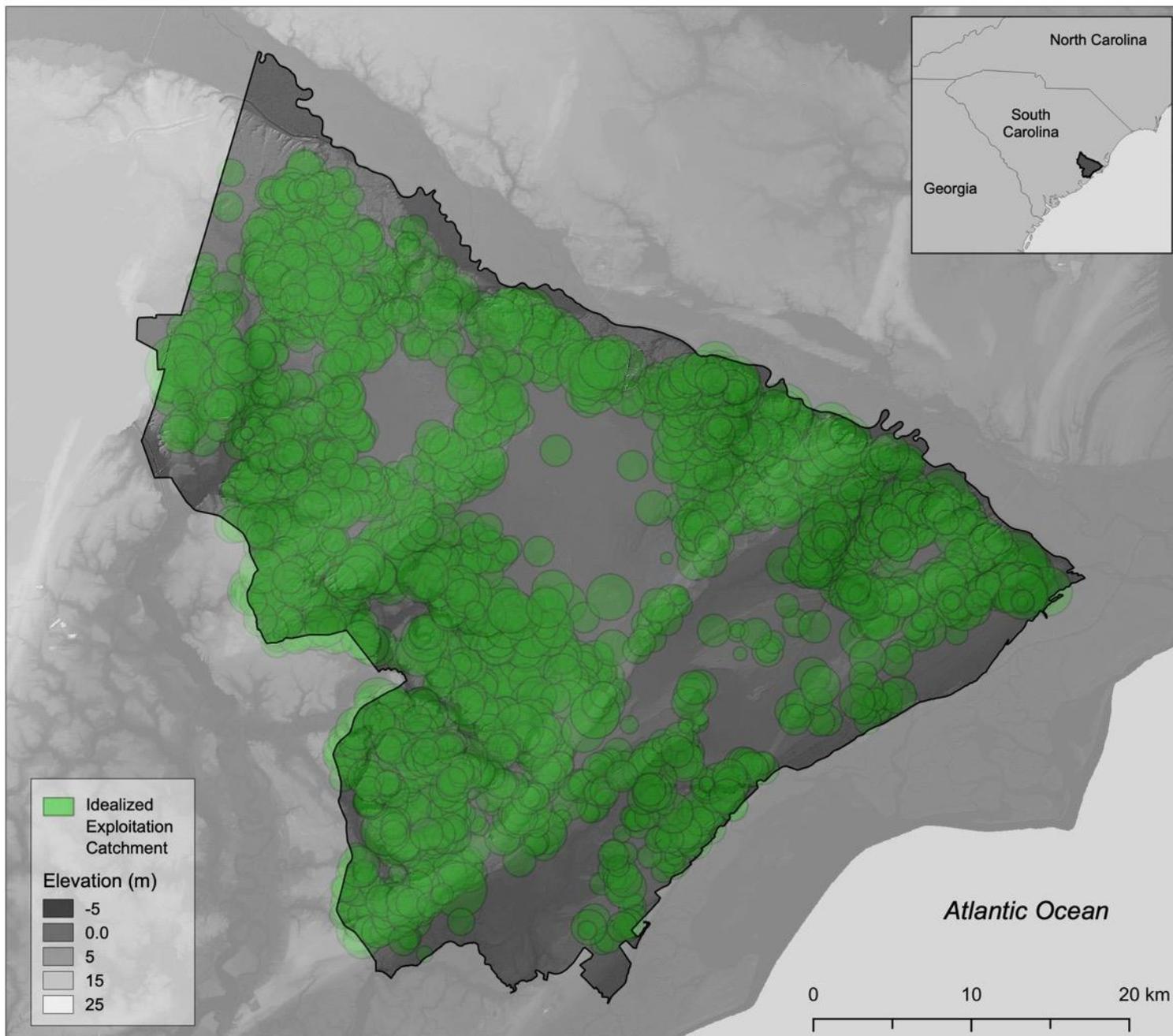
- Almost **1.2 million cubic meters** of lightwood needed
- Equivalent of over **750,000** mature, old-growth Longleaf pines removed

Lightwood calculations based on: Gonzalez-Benecke, C.A., Gezan, S.A., Martin, T.A., Cropper, W.P., Samuelson, L.J., Leduc, D.J., 2014. Individual Tree Diameter, Height, and Volume Functions for Longleaf Pine. Forest Science 60, 43–56. <https://doi.org/10.5849/forsci.12-074>

Quantifying the extent of **human impacts** on fuels in these systems from ~ AD 1670 - 1900



Ulyshen, M.D., Horn, S., Pokswinski, S., McHugh, J.V., Hiers, J.K., 2018. A comparison of coarse woody debris volume and variety between old-growth and secondary longleaf pine forests in the southeastern United States. *Forest Ecology and Management* 429, 124–132. <https://doi.org/10.1016/j.foreco.2018.07.017>



Estimated that **76%** of the Francis Marion National Forest was impacted by coarse woody debris collection for tar production between ~ **AD 1670 - 1900**



The Archaeology of Fire and Fuels

What does this all mean for the restoration of **Longleaf pine ecosystems**?

- Acknowledging that these are, and have been, intensively modified landscapes
- Bias in historical reference conditions
- Situating historical fire regimes into a context of historical fuels

A Social Ecology of Fuels





Where do we go from here?

- Recognize these as social-ecological systems—restoration to a “pristine” condition is not possible or helpful
- How do humans, fire, and fuels interact in these forests in the context of climate change
- Leverage archaeological perspectives and remote sensing techniques (Aerial LiDAR) to understand the social ecology of fire and fuels elsewhere

A topographic map showing terrain elevation with a color gradient from purple (low) to yellow (high).

CASE STUDY 2

Deep learning approaches to archaeological object detection for enhancing site inventorying and wildfire protection measures



Meeting the challenges of CRM on public lands

The Kisatchie National Forest Heritage LiDAR Project

- Three-year project to collect and process **LiDAR data** on the Kisatchie National Forest and to develop heritage feature detection tools to improve predictive models, site identification, and cultural resource management.
- Develop analytical products for the Heritage Program to aid in monitoring the effects of disturbance (e.g. wildfire) for use throughout the Southern Region.
- Partners include both **USFS and USFWS**





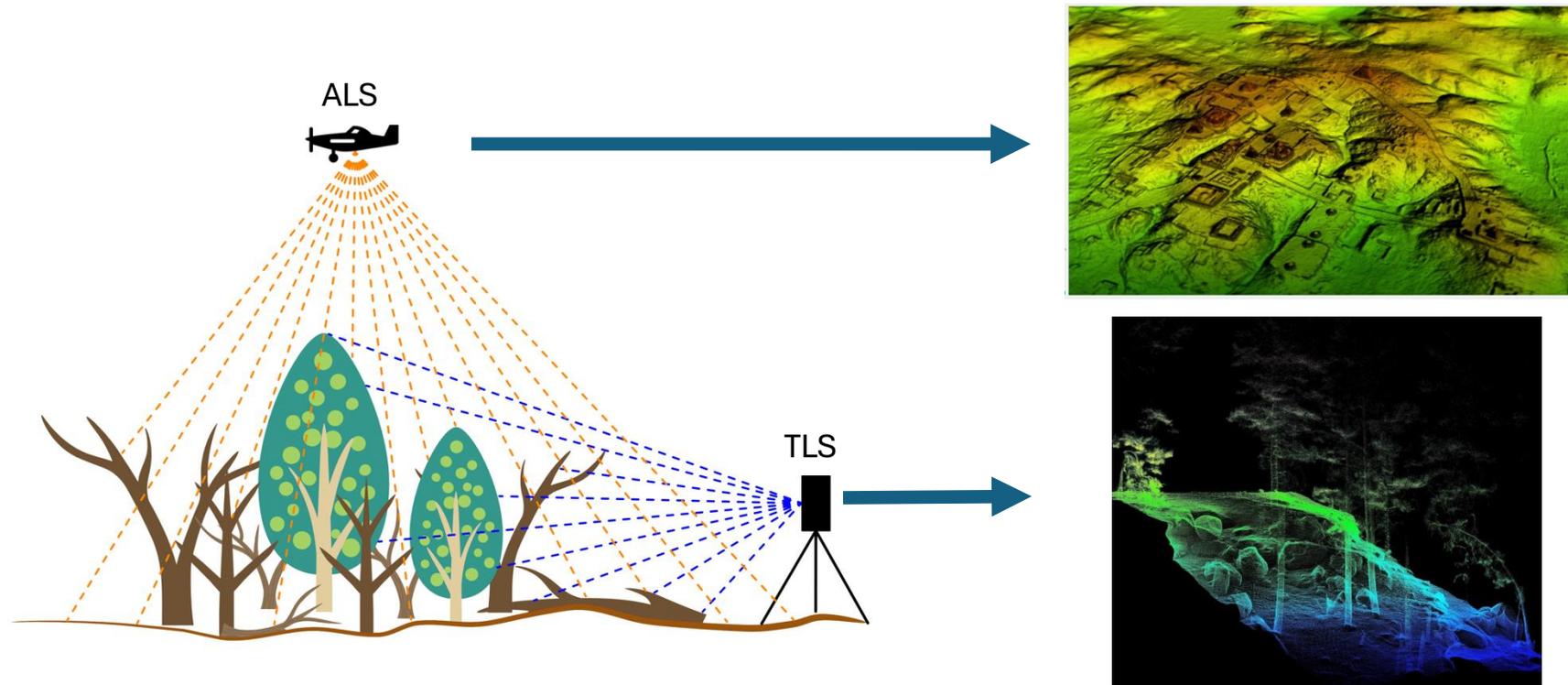
- **Kisatchie National Forest** is the only national forest in Louisiana
- Over **600,000 acres** of public land, intermixed with private inholdings and DoD property
- Diverse landscapes (dry upland conifers, wet lowland swamps) and diverse archaeology spanning the late Pleistocene to the 20th century



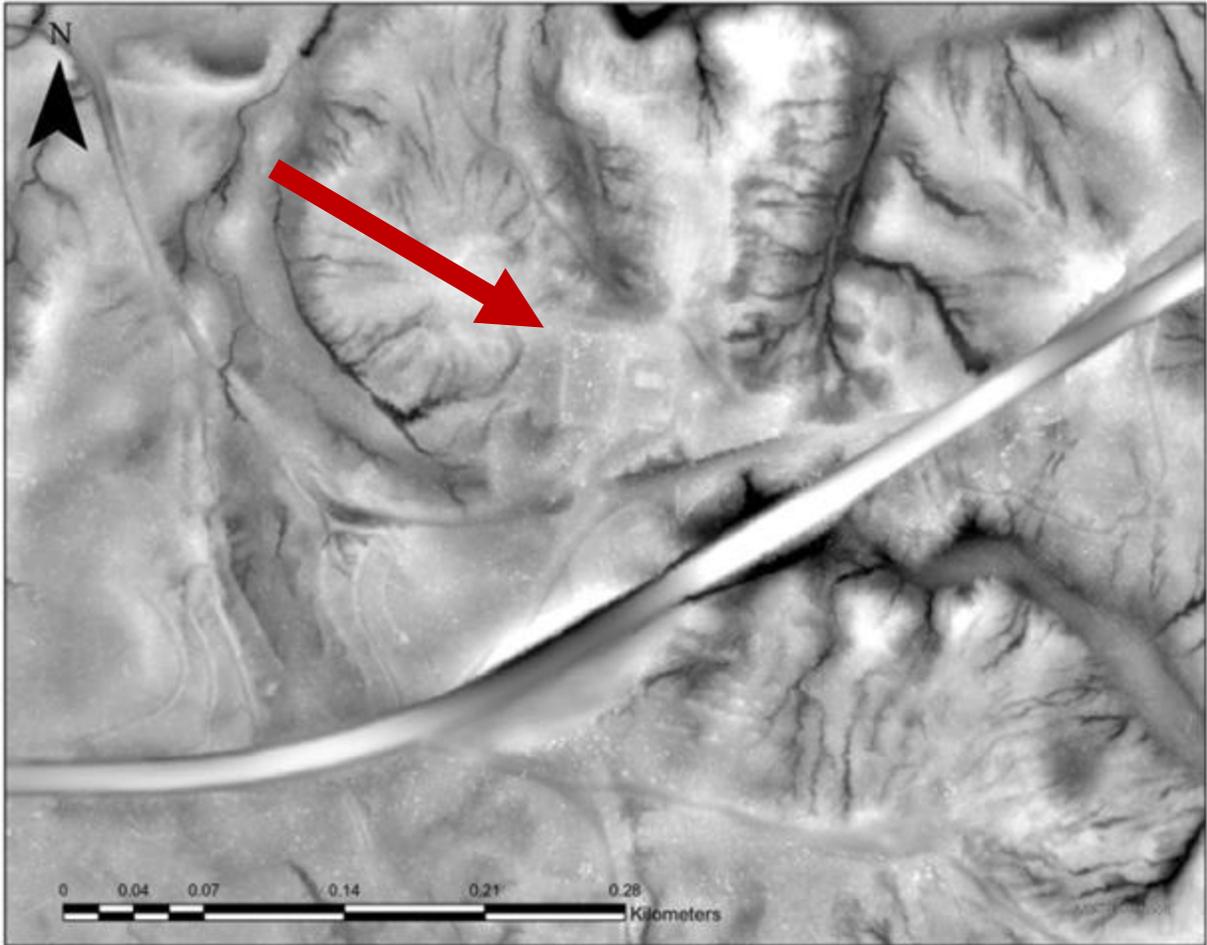
LiDAR and deep learning for archaeological inventorying and risk mitigation

Aerial and Terrestrial LiDAR for CRM

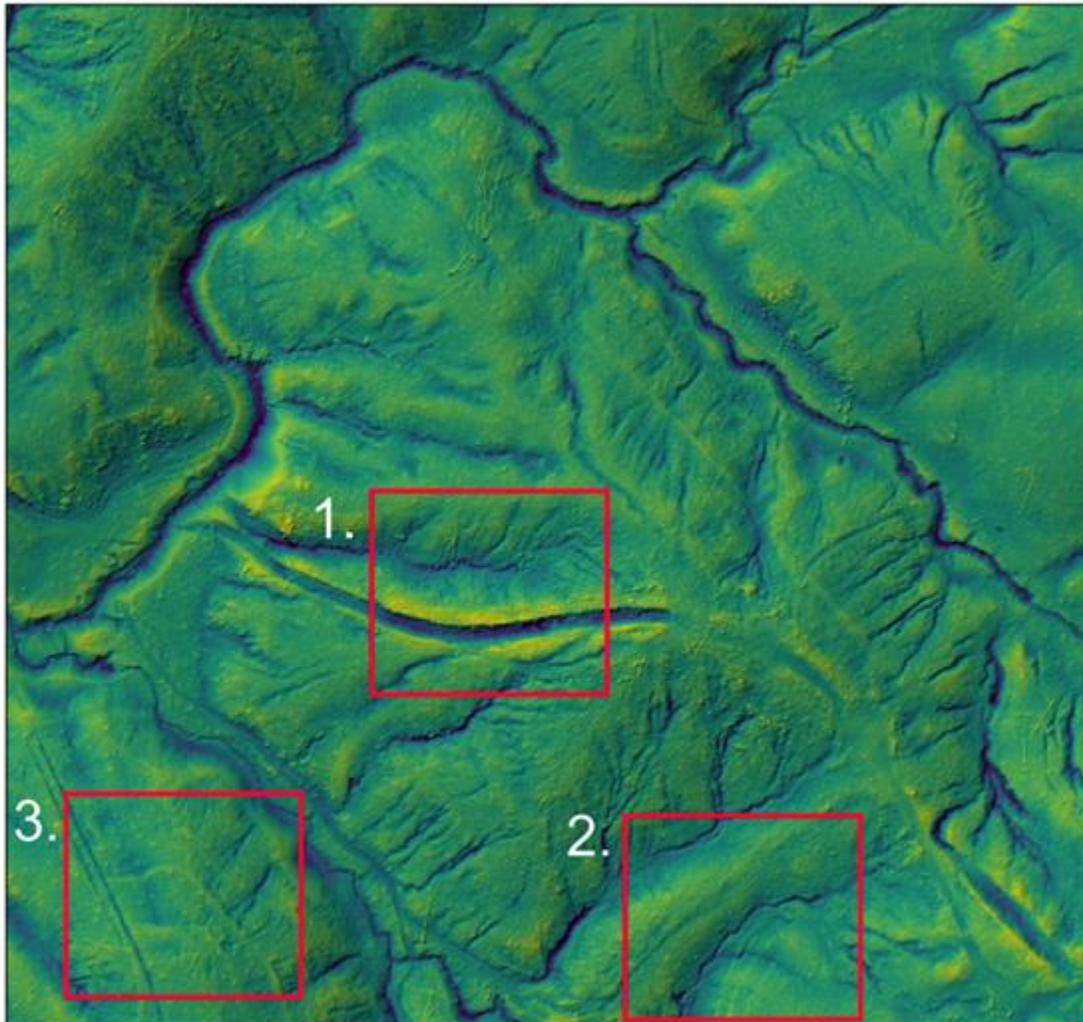
- ALS (aerial LiDAR) and TLS are remote sensing techniques that use calibrated laser returns to create 3D representations of topography, vegetation, structures, etc.
- Opportunities for cultural resource monitoring, wildland fire risk, fuel monitoring, etc.



Identifying archaeological features

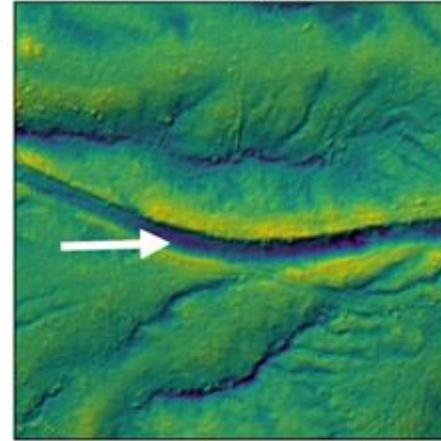


Deep learning to inventory archaeological features

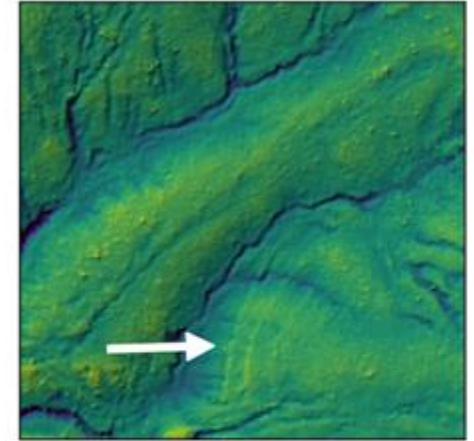


0 100 200 m

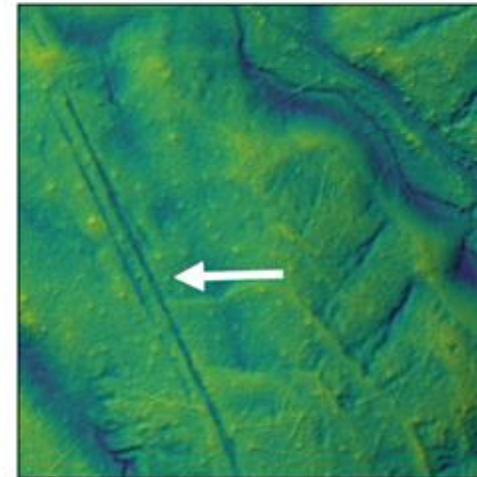
1. Historic narrow gauge railway grade



2. Historic terracing



3.



Two-track not visible in satellite imagery

Brief overview of Deep Learning

How can Apple/Google create 'magic' folders of just images of your dog/cat?

Object detection

Algorithm creates a box around the object detected in an image.

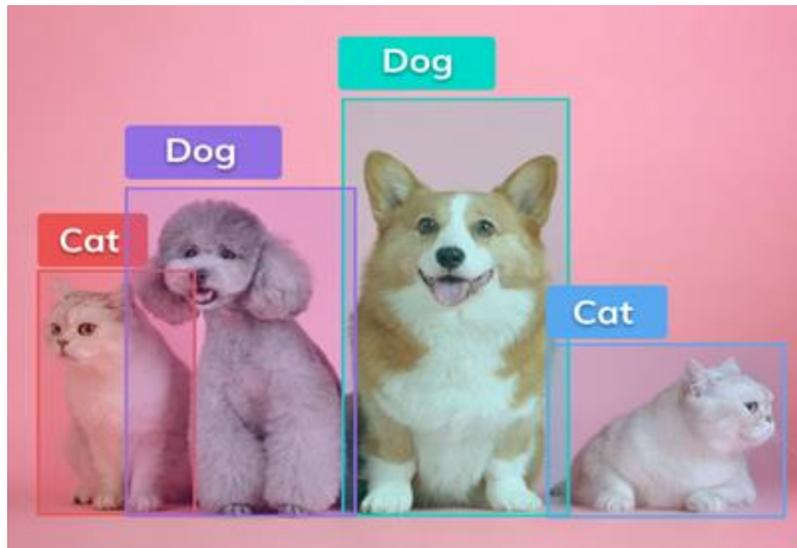
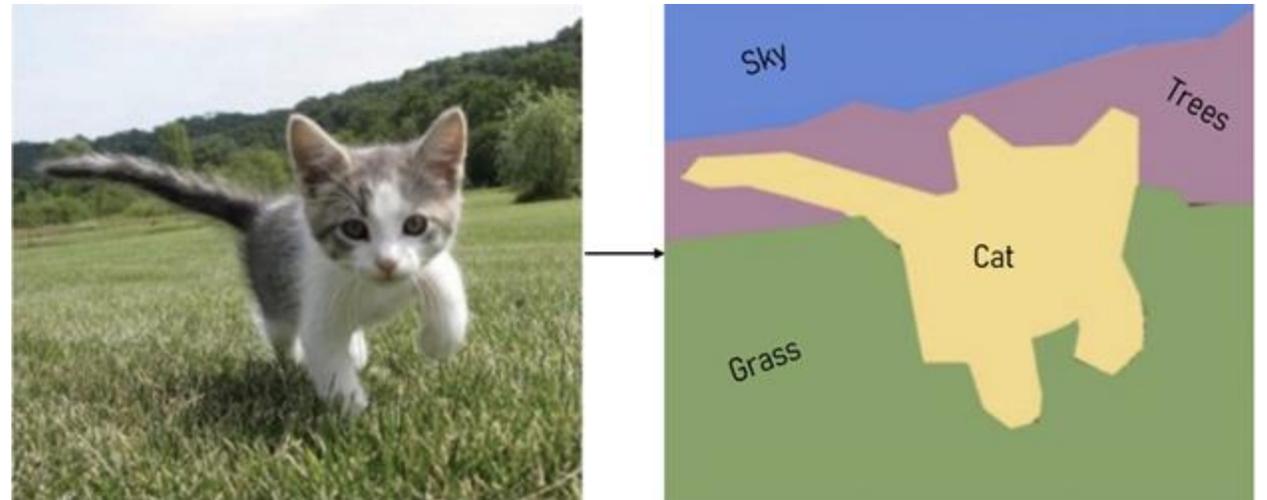


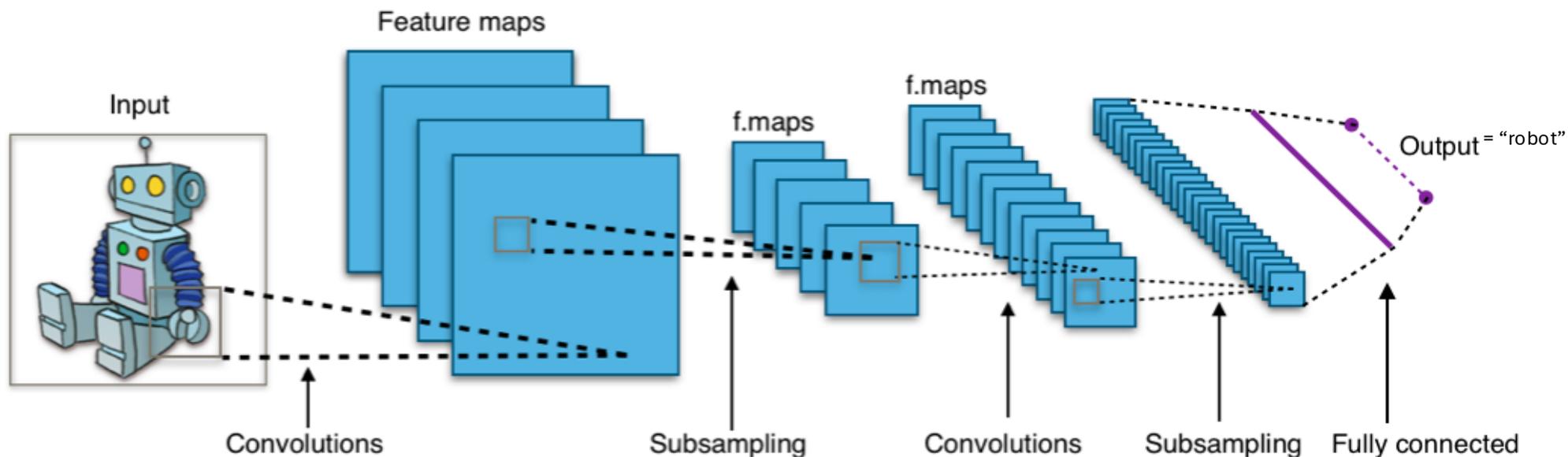
Image segmentation

Algorithm classifies all pixels of an image.

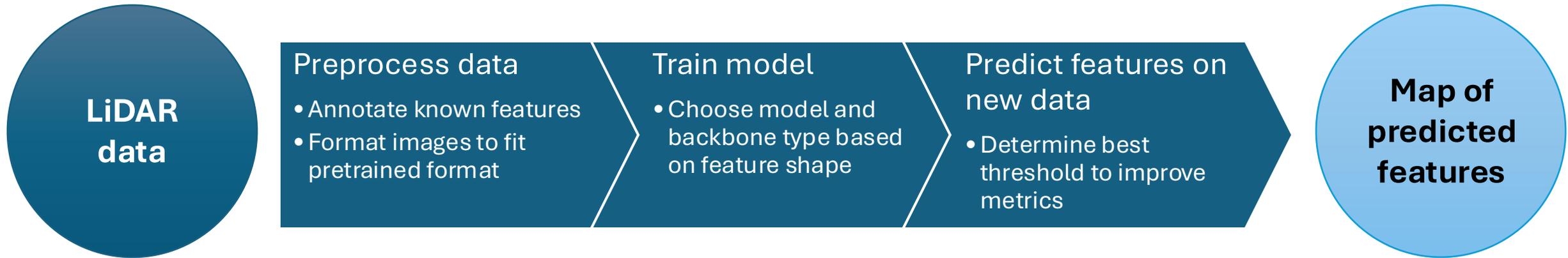


Convolutional Neural Networks (CNN)

- Deep Learning machine learning algorithms that specialize in detecting features in visual contexts (images).
- CNNs are relatively recent but have taken over the world. They are everywhere (self-driving cars, facial recognition, medical image analysis, etc.)



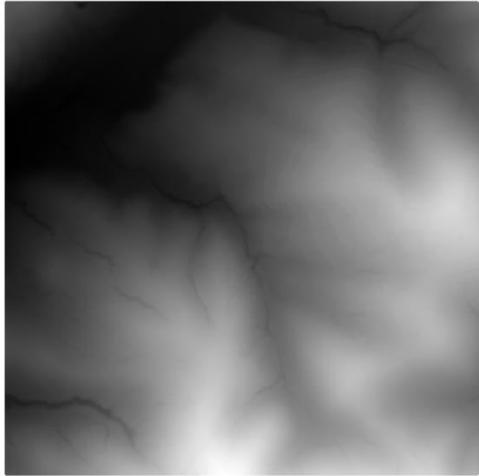
Developing a Deep Learning Model Library for Public Lands



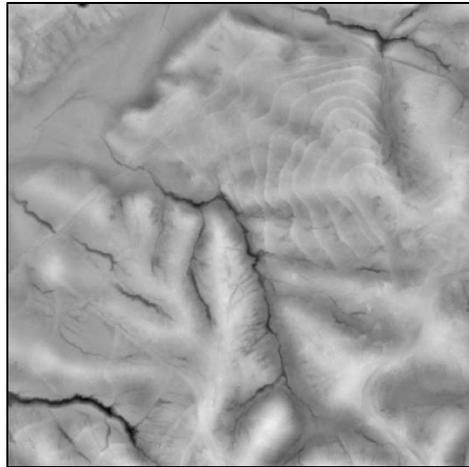
- Develop, train, and deploy CNN models to inventory and monitor diverse types of archaeological sites and features across the Kisatchie NF.
- Multiple architectures (U-Net, Mask R-CNN, YOLO, etc.) and backbones to meet needs of multiple site types.
- Currently advancing models to detect historical structures, historical trails, pre-contact earthworks, pre-contact village sites, terraces, legacy roads, and others.

Data formatting and visualizations

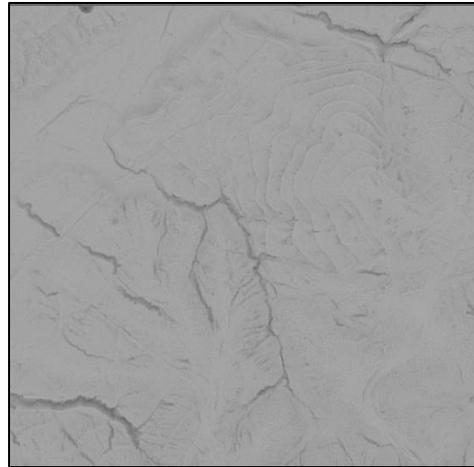
DSM



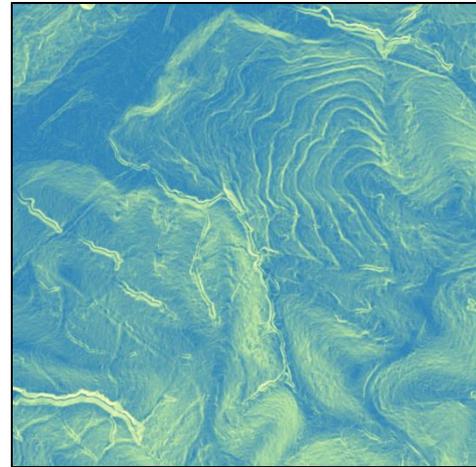
Simple Local Relief Model



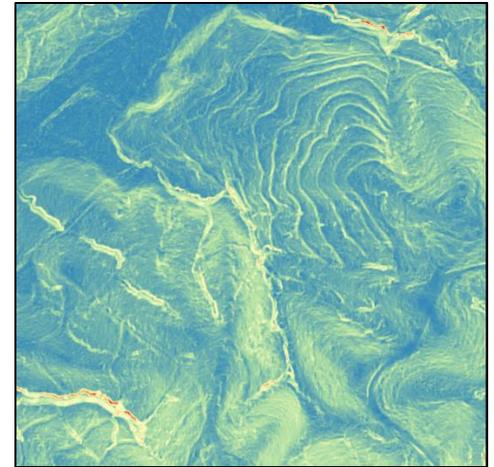
Positive openness



Slope



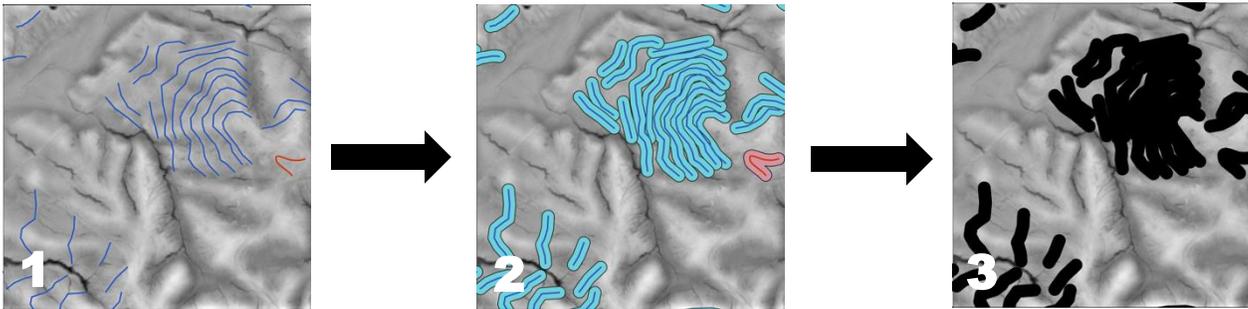
Terrain Ruggedness Index



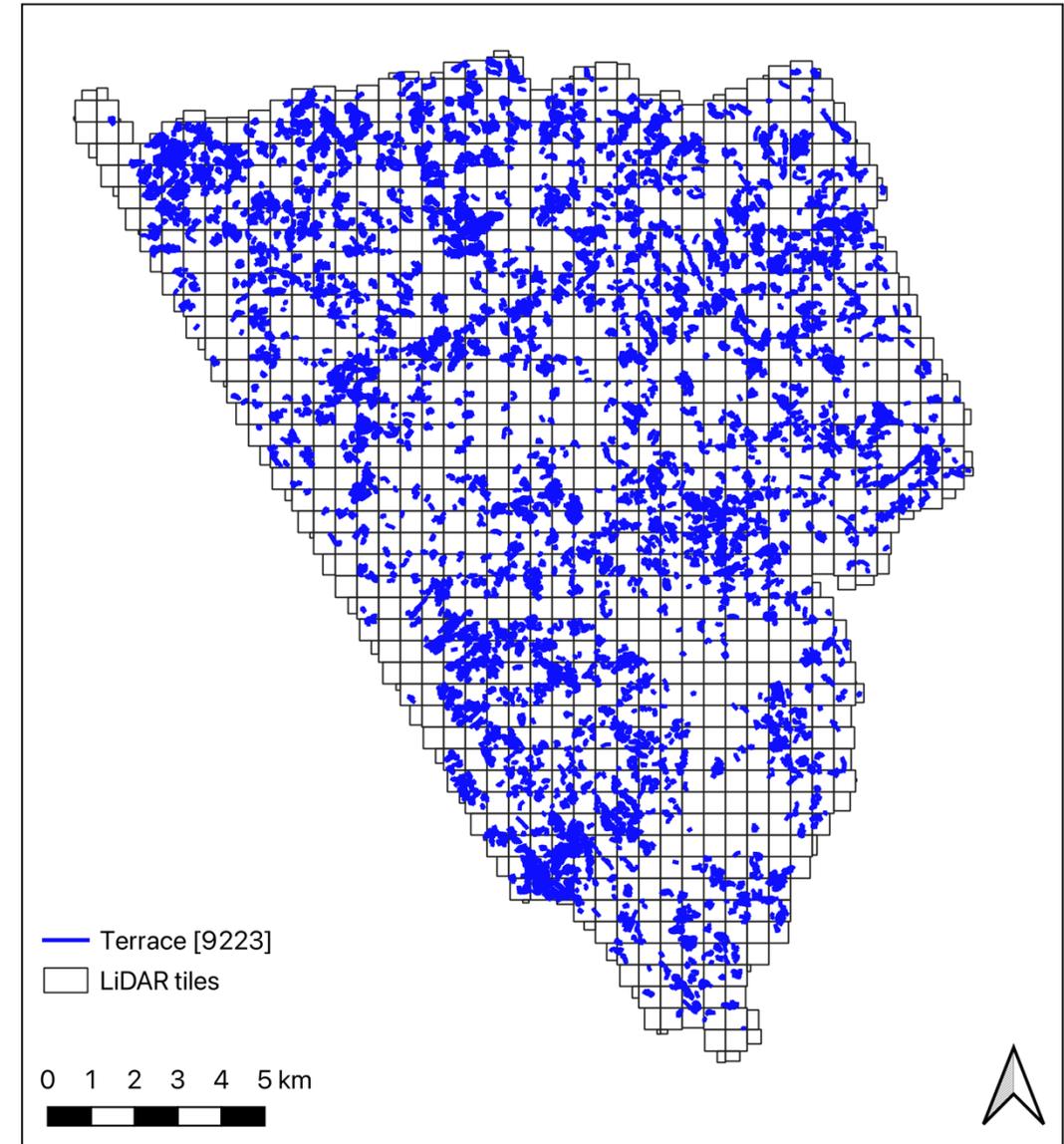
Multiple visualizations of the DSM to enhance the visibility of a wide diversity of archaeological features.

Annotating archaeological sites and features

- Manual digitizing of existing features, synthesis of existing datasets from agencies, and SHPO records.
- Transform annotations into buffered vectors to capture geographic context (tried 5m, 10m, and 20m).

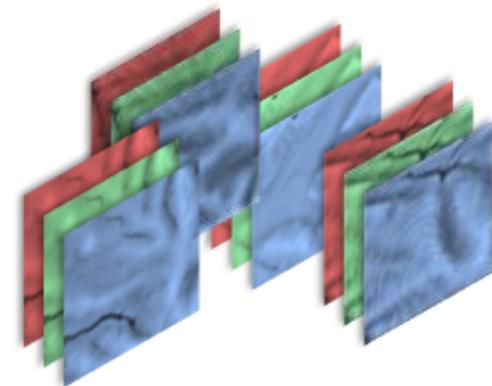
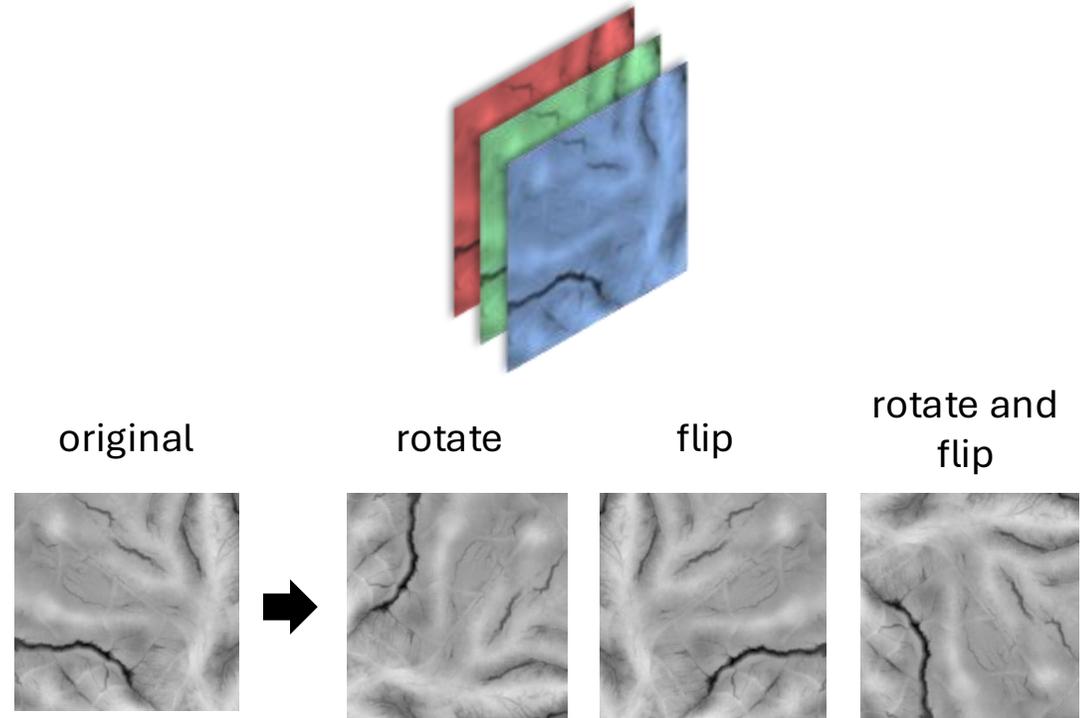


Examples from Piedmont National wildlife Refuge, GA.

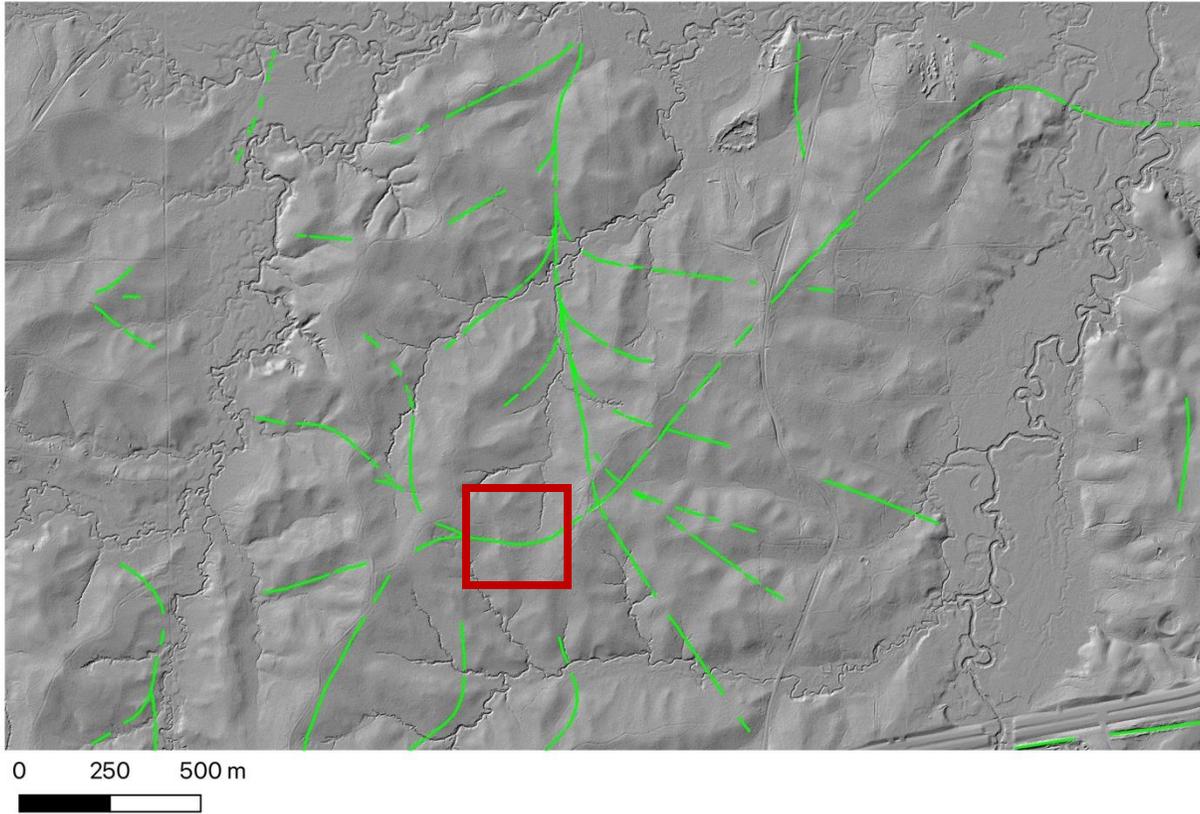


Augmenting inputs to enhance training

- 3-bandi input tiles by combining 3 visualizations to fit the model pretrained backbone requirements.
- Augmentations to increase the number of different images seen by the model.
- Fed the 3-band images in batches, adjusted to increase model performance.



Simulated features to extend training sets

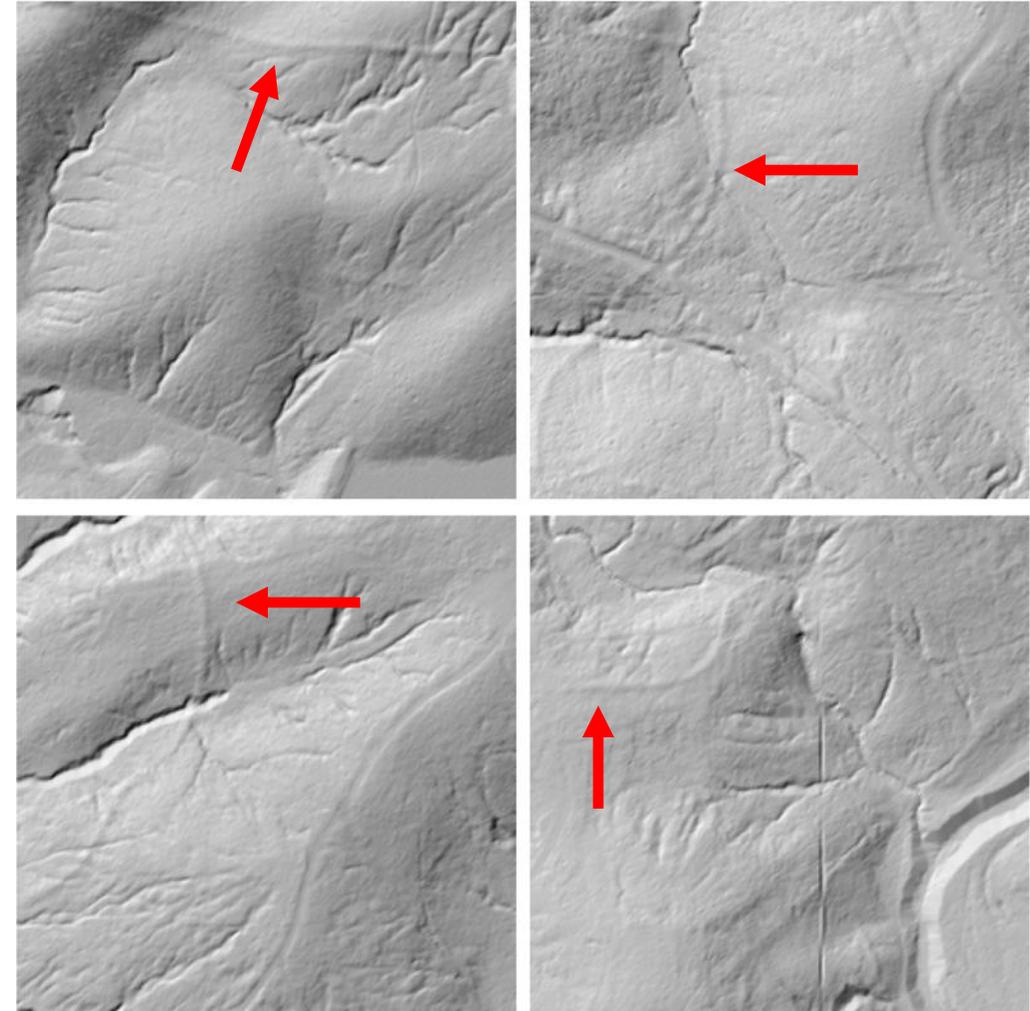


Examples of grade features on the Kisatchie NF

- Detecting features requires a large training dataset
- Some features are relatively rare
- **Potential solution:** Create simulated features for training

Simulated features to extend training sets

- To mimic this feature, generate a least-cost path from two random points on the tile edges
- Buffer, simplify, and smooth feature to match examples observed in DEMs and field.
- Add to landscape and annotate for training.
- **Amplify training sets for model development**



Above-grade simulated features across test tiles

What have we learned; how do we continue?

- Building research objectives and products that can scale to the mission area of the agency
 - Not working at the scale of a site or landscape, rather a region consisting of **100,000 acres or more.**
- Finding the intersection between research and management
 - Emphasis on **multiple resource benefits**
- Designing tools and products that prioritize the needs of Heritage programs and integrate into existing infrastructures
 - Agency partners have limitations on time, resources, and authorizations
 - Cannot easily adopt technologies or products like the academic community

Moving forward

- New experiments to understand compounding disturbances on archeological sites (hurricanes, wildfires, grazing, etc.)
- Expanding deep learning to new regions, archaeological site types, and management needs
- Develop training opportunities for the next generation of archeologists interested in academic-agency partnerships to support archeological science



Pile burning experiment on the Plumas NF, 2024

**Many thanks to my agency
collaborators, funders, and the
Mizzou Anthropology Department**

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This material is based upon work supported by the U.S. Geological Survey under Cooperative Agreement No. G22AC00496.
This material is based upon work supported by the U.S. Department of Agriculture, Forest Service award 22-PA-11080600-228.
Any opinions, findings, and conclusions or recommendations expressed in this publication are those of the author(s) and do not necessarily reflect the views of the USDA Forest Service.