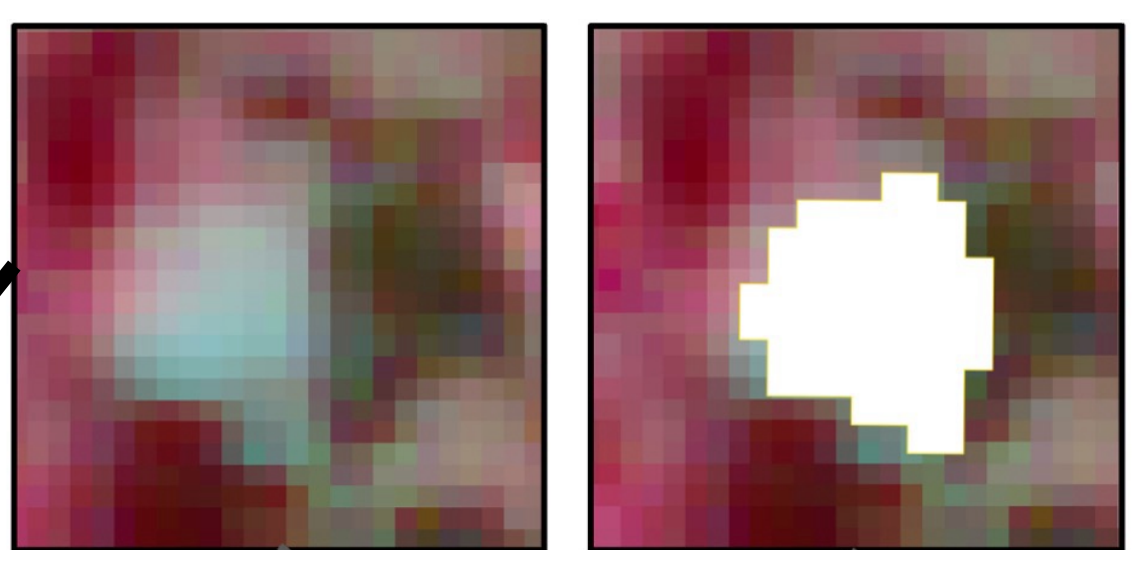


Tracking individual tree mortality across the US coasts

Henry C.H. Yeung^{1*}, Tamlin M. Pavelsky², Chao Wang², Nate G. McDowell^{3, 4}, Ryan E. Emanuel⁵, Emily S. Bernhardt^{5,6}, and Xi Yang^{1*}

(1) Department of Environmental Sciences, University of Virginia; (2) Department of Earth, Marine and Environmental Sciences, University of North Carolina, Chapel Hill; (3) Atmospheric Sciences and Global Change Division, Pacific Northwest National Lab; (4) School of Biological Sciences, Washington State University; (5) Nicholas School of the Environment, Duke University; (6) Department of Biology, Duke University (*) hchyeung@virginia.edu; (^) xiyang@virginia.edu



A ghost forest in Maryland (Dineen, 2025, *Science*; Photo by Henry Yeung)

Introduction

- Rising water tables have led to widespread **flooding** and **saltwater intrusion**
- Increased sighting of coastal tree mortality
- The 'true' mortality extent is poorly understood (Fig. 2), limiting our understanding of its drivers and trend

Purpose

- Track tree mortality at **individual-level**
- Domain: Great Lakes, Atlantic, Gulf, and Pacific coasts (10 km from coasts and 5 m above drainage)
- Time: 2010 to 2023

Method

- Individual standing dead trees were mapped with deep learning using **very-high-resolution (1m)** aerial imagery (NAIP; Fig. 3)
 - Dead tree location: heatmap regression
 - Dead tree crown size: Semantic segmentation
- To enhance generalizability, we used transfer-learning and geospatial-embedding during training
- We matched individuals with a nearest-neighbor approach (radius = 6m) to track them across years

Results

- Mapped **217 million** individual dead trees (Fig. 1) across 84,641 image tiles (> 25TB of data)
- Model generalized across regions and years (Fig. 4)
- We tracked individual trees temporally, alongside their individual crown sizes (Fig. 5)

Implications

- By tracking individual tree mortality, we reveal mortality that was severely underestimated by coarser resolution satellites (Not all are driven by flooding or saltwater intrusion, but also other agents (e.g., insect))
- Estimating individual crown size can offer insights into tree size-mortality patterns, and their decaying rate

Acknowledgements: NASA Coastal Resilience Team (grant no. 80NSSC23K0127) and UVA research computing

Tracing 217 million dead trees over the past decade reveal accelerating decline of coastal forests

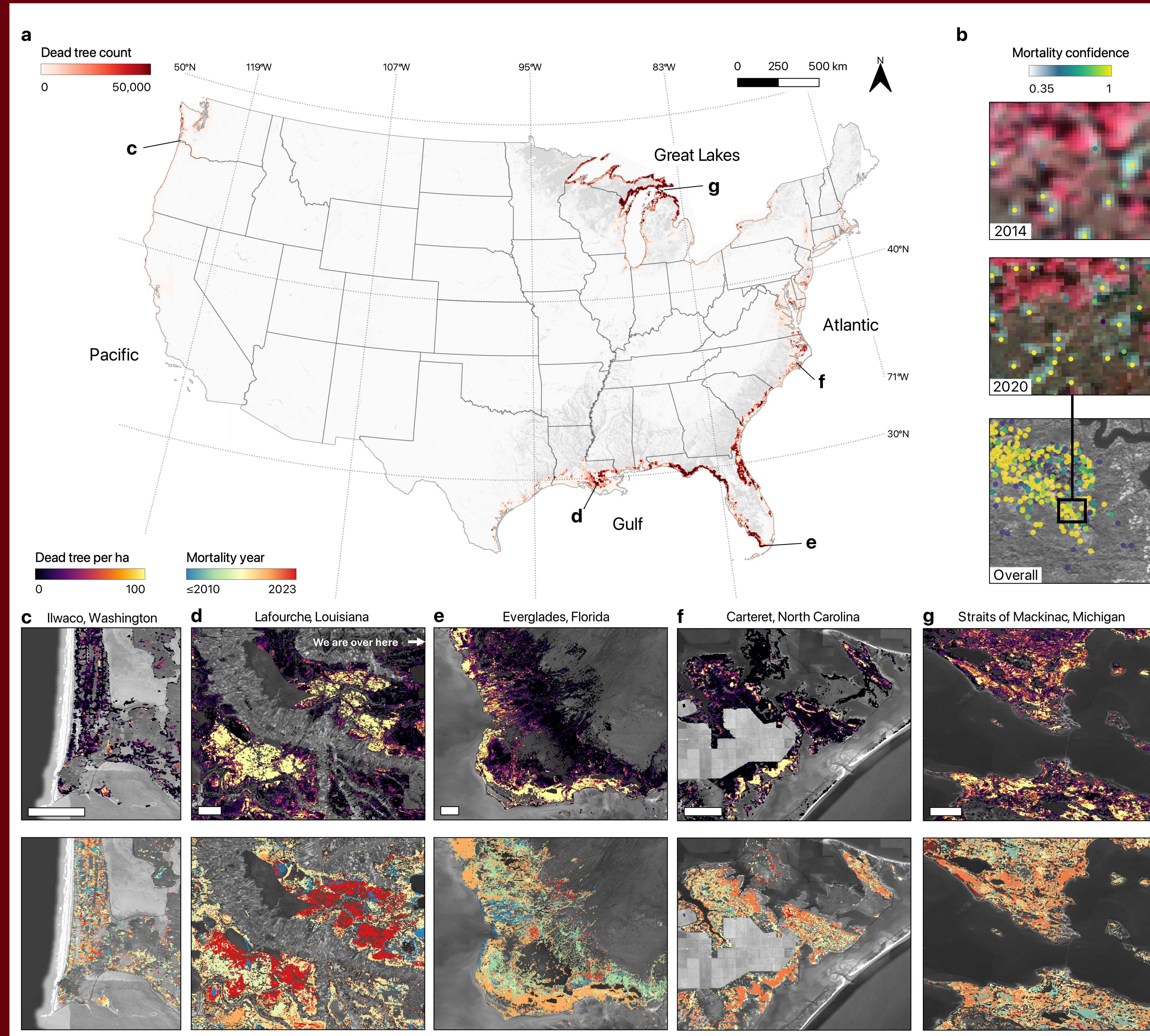


Fig. 1 | Hotspots of coastal tree mortality across the US. **a.** Spatial distribution of dead trees across the US coasts. Shaded area shows the extent of forested wetlands based on NLCD landcover. **b.** Detection of individual dead trees across years. **c-g.** Zoomed-in maps of mortality hotspots across the Pacific (**c**), Gulf (**d, e**), Atlantic (**f**), and Great Lakes (**b**). Images in **b** from NAIP (false color composite; NIR, R & G). Basemap in **b-g** from Esri with state boundaries from the US Census Bureau.



Fig. 2 | Coarser-resolution satellites severely underestimate coastal tree die-offs. False-color images where dead trees and healthy vegetation are displayed in white/grey and red, respectively (Yeung et al. 2025, *Nat. Sustain.*)

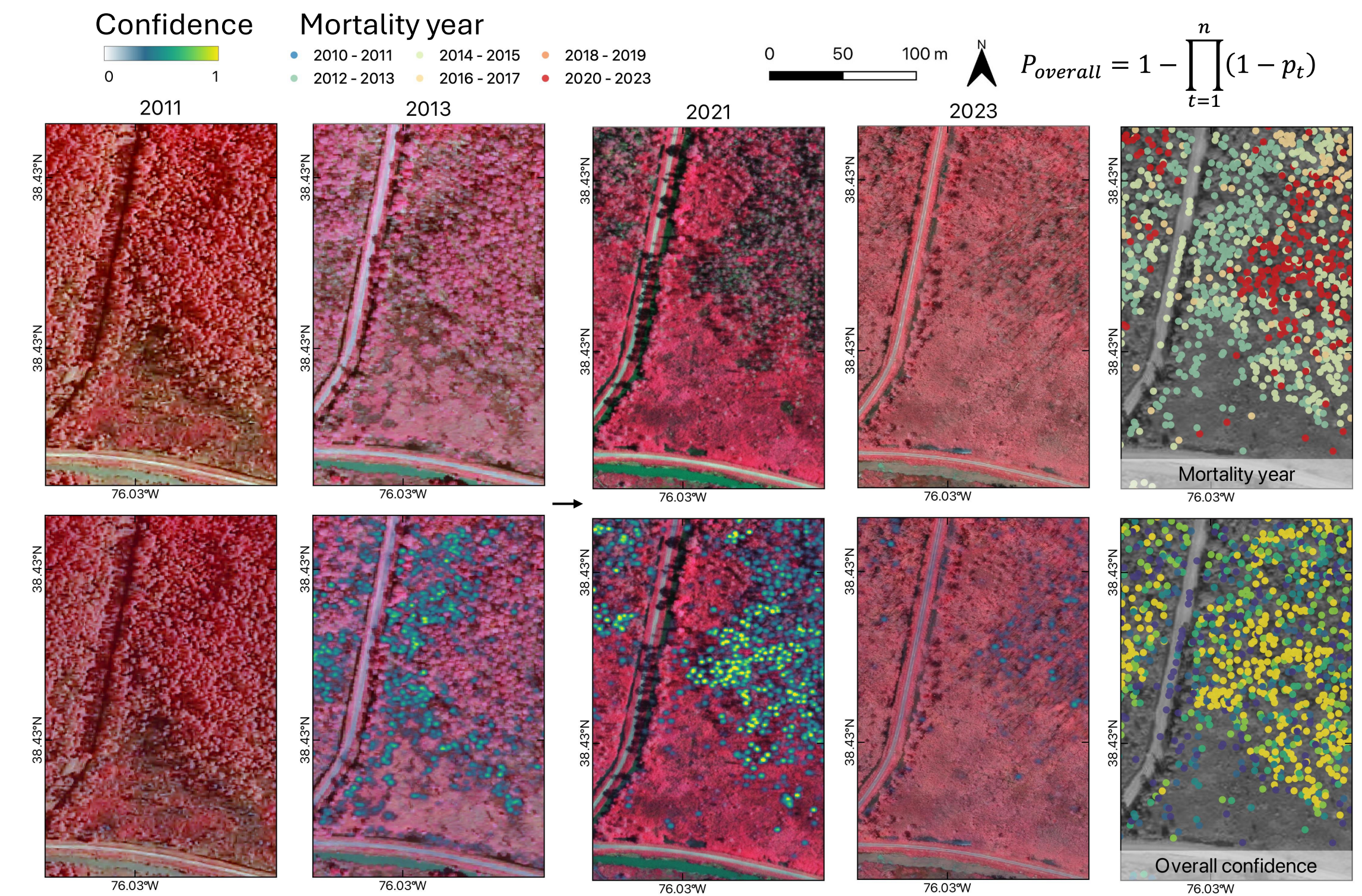


Fig. 3 | Tracking mortality timing biennially with deep learning. Example of NAIP images and heatmap-based deep learning predictions from 2011 to 2023. Mortality year is the first year a dead tree is detected; overall confidence is its cumulative confidence across years.

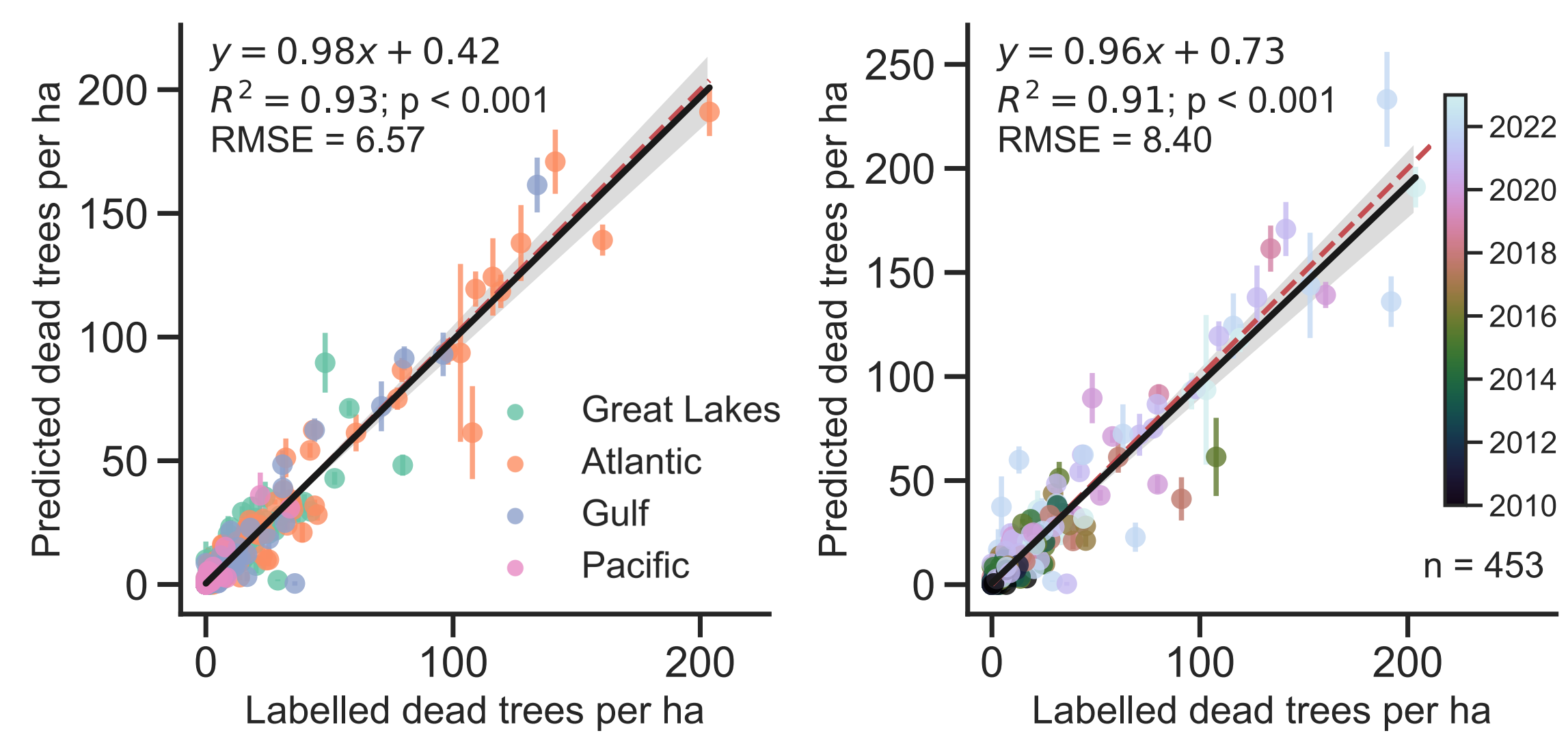


Fig. 4 | Model performance across US coasts. The dead tree counts from the heatmap-based models were compared with manual labels. Points and error bars are the ensemble mean and standard deviation, respectively. Colors denote different coasts and years.

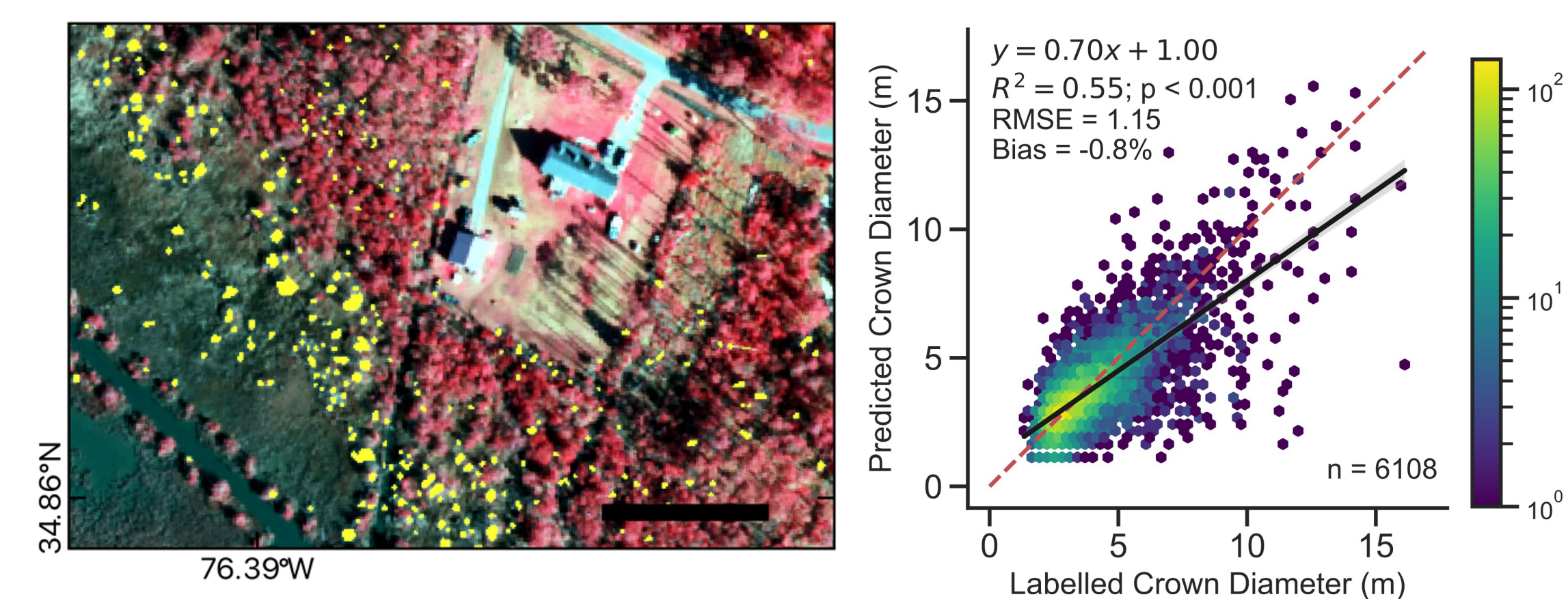


Fig. 5 | Measuring the crown sizes of detected dead trees. Manually labeled dead tree crowns were compared with segmentation-based model predictions ($n = 6,108$). We calculated diameter from crown area with the assumption of circular crown shape.