

Where the (urban) palms are: potential impact of a palm pest on the US mainland

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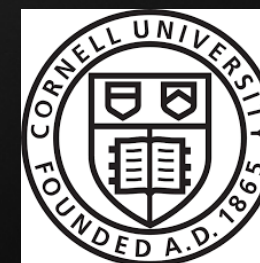
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Introduction

- ▶ Urban forests are gateways for alien forest pests
 - ▶ Not well characterized
 - ▶ Few are inventoried
- ▶ Koch et al. 2018:
 - ▶ Modeled urban distributions of 3 tree genera: ash, maple, oak
 - ▶ For ≈24000 communities in eastern and central USA
 - ▶ From limited sample of existing urban forest inventories (n=842)

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Modeling urban distributions of host trees for invasive forest insects in the eastern and central USA: A three-step approach using field inventory data

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ABSTRACT

Despite serving as invasion gateways for non-native forest pests, urban forests are less well understood than natural forests. For example, only a fraction of communities in the USA and Canada have completed urban forest inventories, and most have been limited to street trees; sample-based inventories that provide valid community-wide estimates of urban forest composition are much rarer. As a proof of concept, we devised a three-step approach to model urban tree distributions regionally using available street tree and whole-community inventory data. We illustrate the approach for three tree genera – ash (*Fraxinus* spp.), maple (*Acer* spp.), and oak (*Quercus* spp.) – that are hosts for high-profile insect pests. The objective of the first step was to estimate, for communities with only street tree inventories, the proportion of the community's total basal area (BA) in each host genus. Utilizing data from communities with paired street tree and whole-community inventories, we applied polynomial regression to estimate whole-community BA proportion per genus as a function of a community's street tree BA proportion and its geographic location. The objective of the second step was to estimate per-genus BA proportions for communities in our prediction region (eastern and central USA) with no urban forest inventory. We used stochastic gradient boosting to predict these proportions as a function of environmental and other variables. In the third step, we developed a generalized additive model for estimating the total BA of a community as a function of its canopy cover, geographic location, and area. We then combined the outputs from the second and third steps to estimate ash, maple, and oak BA for the nearly 24,000 communities in our prediction region. By merging these estimates with similar information on natural forests, we can provide more complete representations of host distributions for pest risk modeling, spread modeling, and other applications.

1. Introduction

Invasive species have tremendous impacts globally, including disruption of ecosystem functions, loss of important agricultural crops, declines and extinctions of native species, damage to infrastructure, and direct as well as indirect (e.g., as a vector) effects on human health (Parker et al., 1999; Allen and Humble, 2002; Clavero and Garcia-Berthou, 2005; Bradshaw et al., 2016). These impacts are challenging to specify in economic terms. For example, insects, which comprise one of the largest classes of invasive species, recently were estimated to have an annual impact of US\$77 billion worldwide in terms of direct losses of goods and services, control costs, and associated human health costs (Bradshaw et al., 2016). However, because there have been few dedicated assessments of the economic impacts of insects, this number likely underestimates the true costs by a large margin (Bradshaw et al., 2016). Forest pests (i.e., insects and diseases that affect trees) account for a considerable fraction of the impacts of all invasive pests of plants (Liebhold et al., 1995; Kenis et al., 2009; Paine et al., 2016). For instance, more than 450 non-native forest insect species have become established in the continental USA since European settlement (Aukema et al., 2010). Out of these, a subset of 62 high-impact species were estimated to cost nearly US\$1.7 billion annually in government expenditures for management and control, and another US\$830 million in lost residential property values (Aukema et al., 2011). By changing

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Example: Maple (*Acer*)

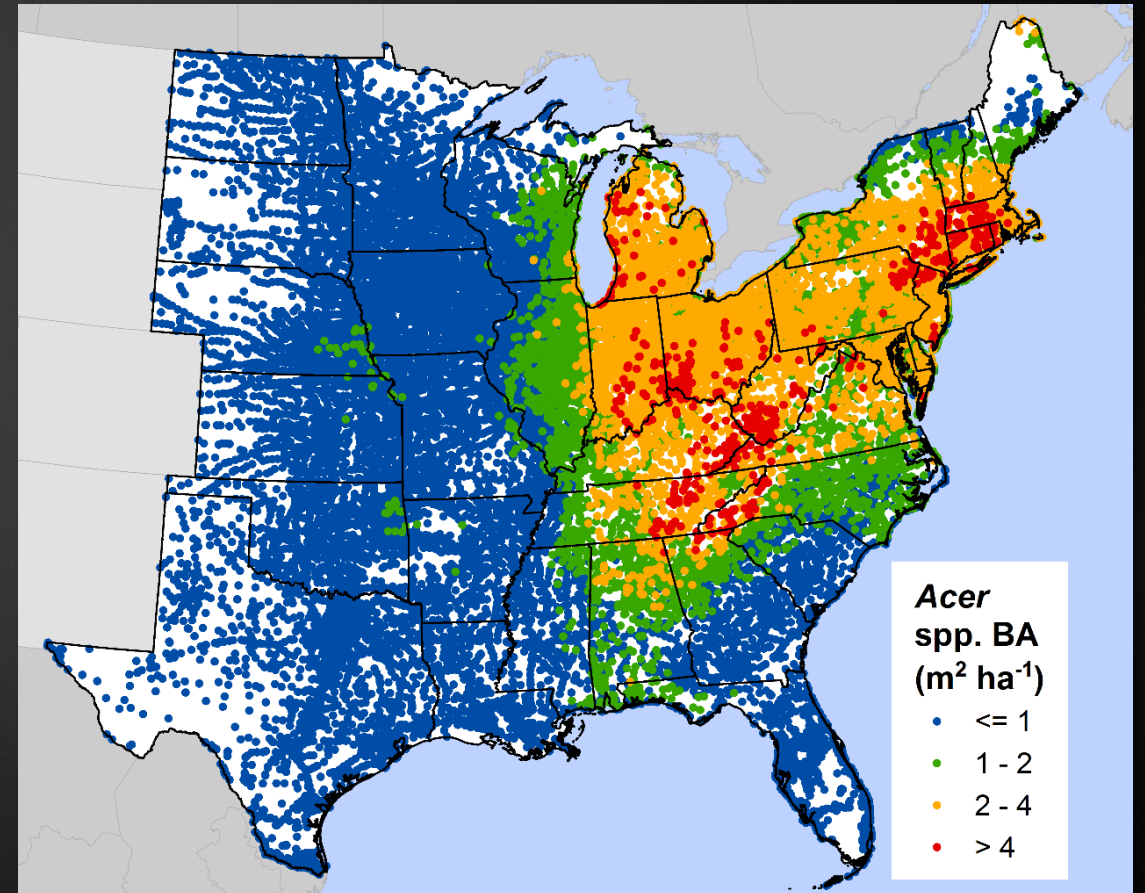
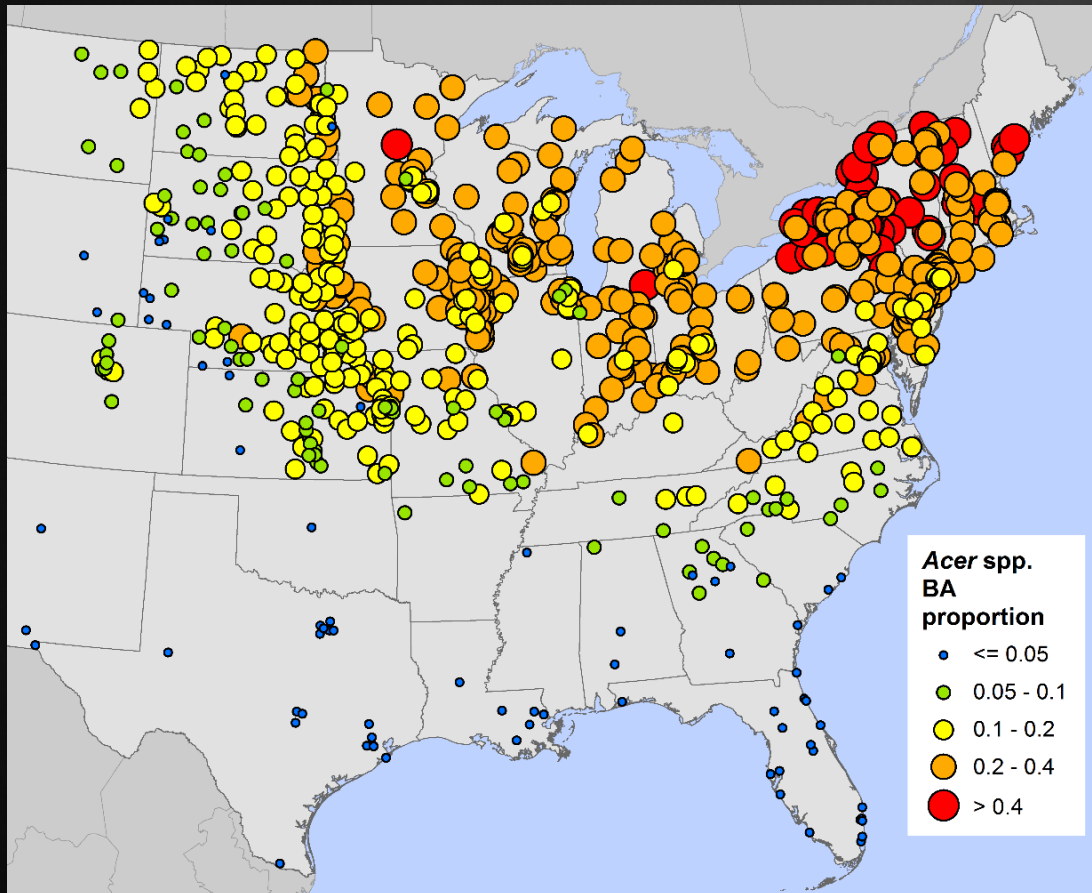
Estimated proportion of community's urban basal area that is maple



Community's estimated total basal area, all trees



Community's estimated maple basal area



Modeling Street Palm Distributions in the Continental USA

- ▶ Building on Koch et al. 2018
- ▶ Objective: estimate potential losses if coconut rhinoceros beetle (*Orycytes rhinoceros*) were to invade mainland USA
 - ▶ Discovered in Guam (2007) and Hawaii (2013)
 - ▶ Major pest of coconut palm, African oil palm, date palm
- ▶ Little agricultural palm production in mainland USA
- ▶ But widely used in urban areas for landscaping
 - ▶ Largest palms are usually street “trees”

Coconut Rhinoceros Beetle (*Oryctes rhinoceros*)

- ▶ Native to China and South Asia
- ▶ Why so worrisome as potential urban pest?
 - ▶ Adults attack crowns of palms
 - ▶ Larvae develop in green waste
 - ▶ Infests a variety of palms and palm-like plants



Can kill palm if eats into apical meristem



Urban Street Palms: Examples



Palm Beach, Florida



Salisbury, North Carolina



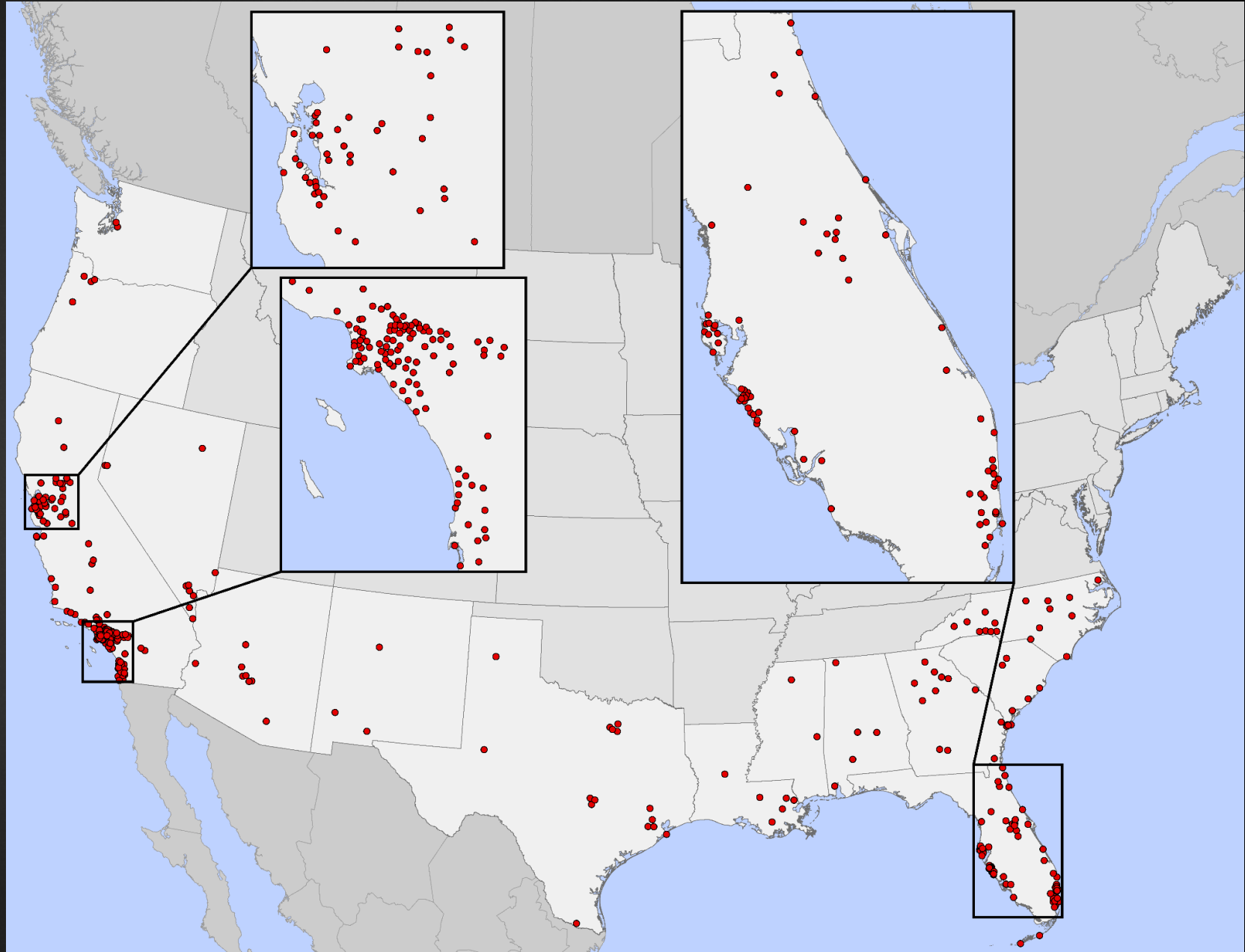
Beverly Hills, California

General Approach

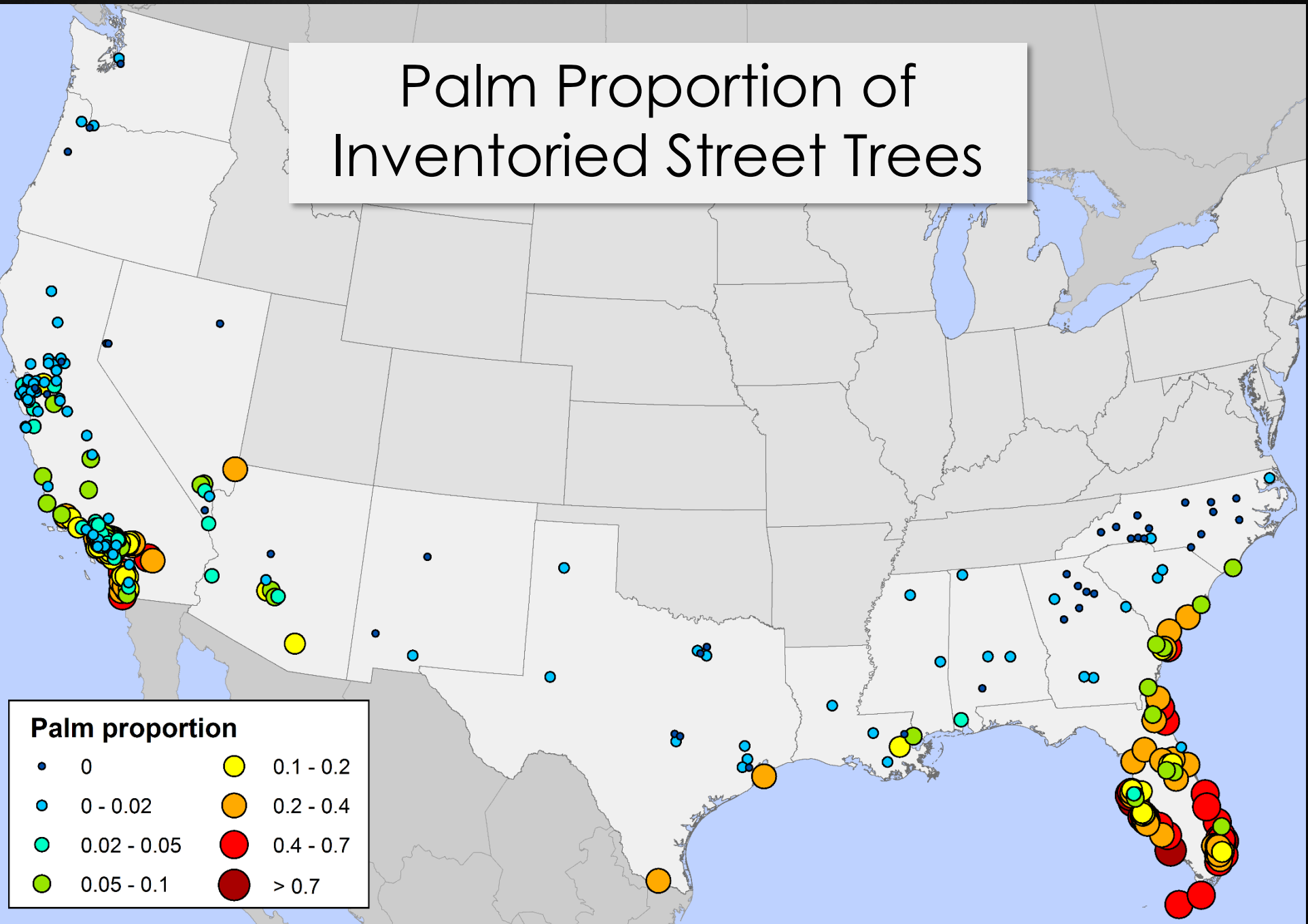
- ▶ Based on sample of street tree inventories:
 - ▶ Model to estimate palm proportion of a community's street trees
 - ▶ Model to predict a community's average street tree density (trees / km)
- ▶ Measure of the community's total street length
- ▶ With these, can estimate total number of palms in communities without inventories

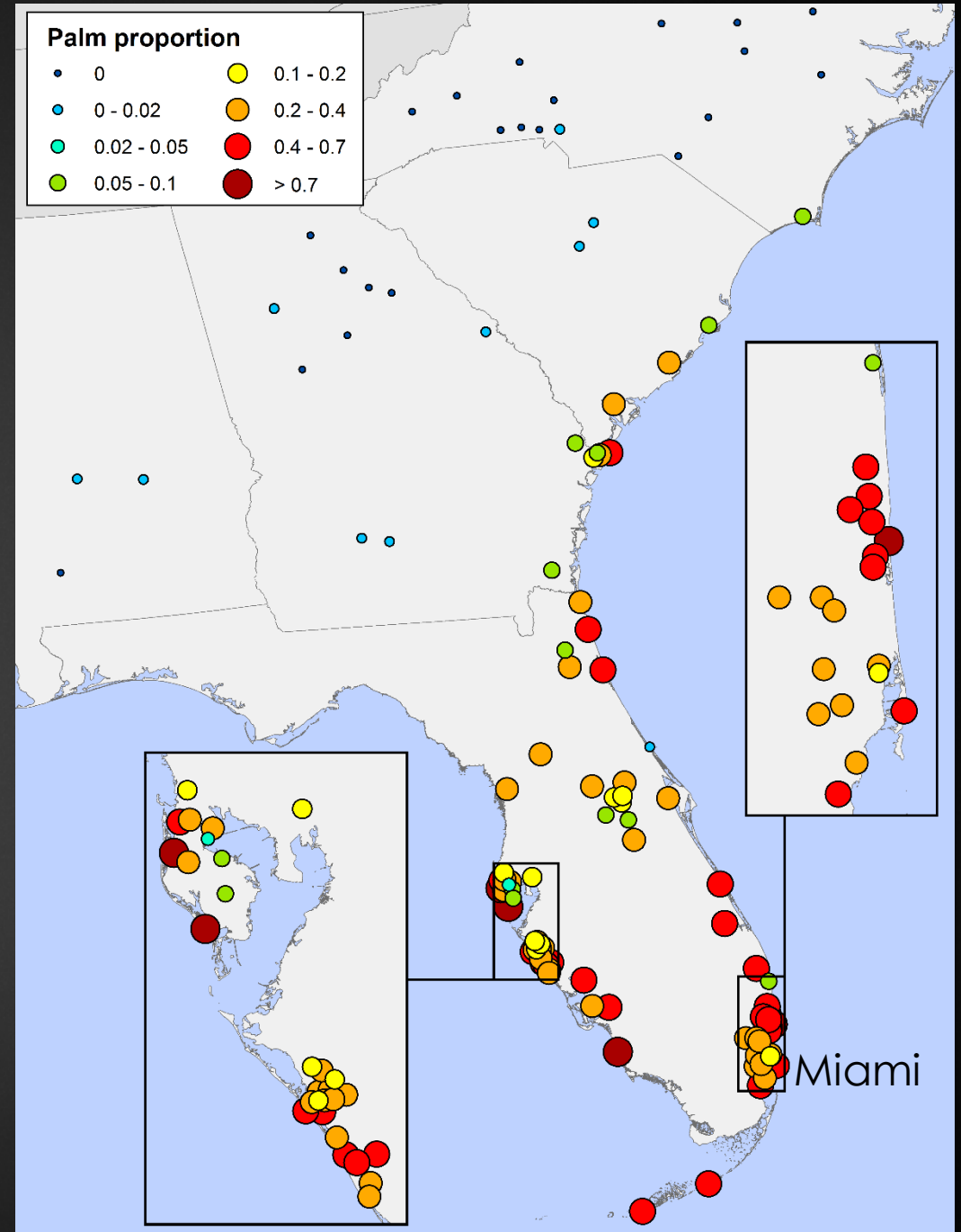
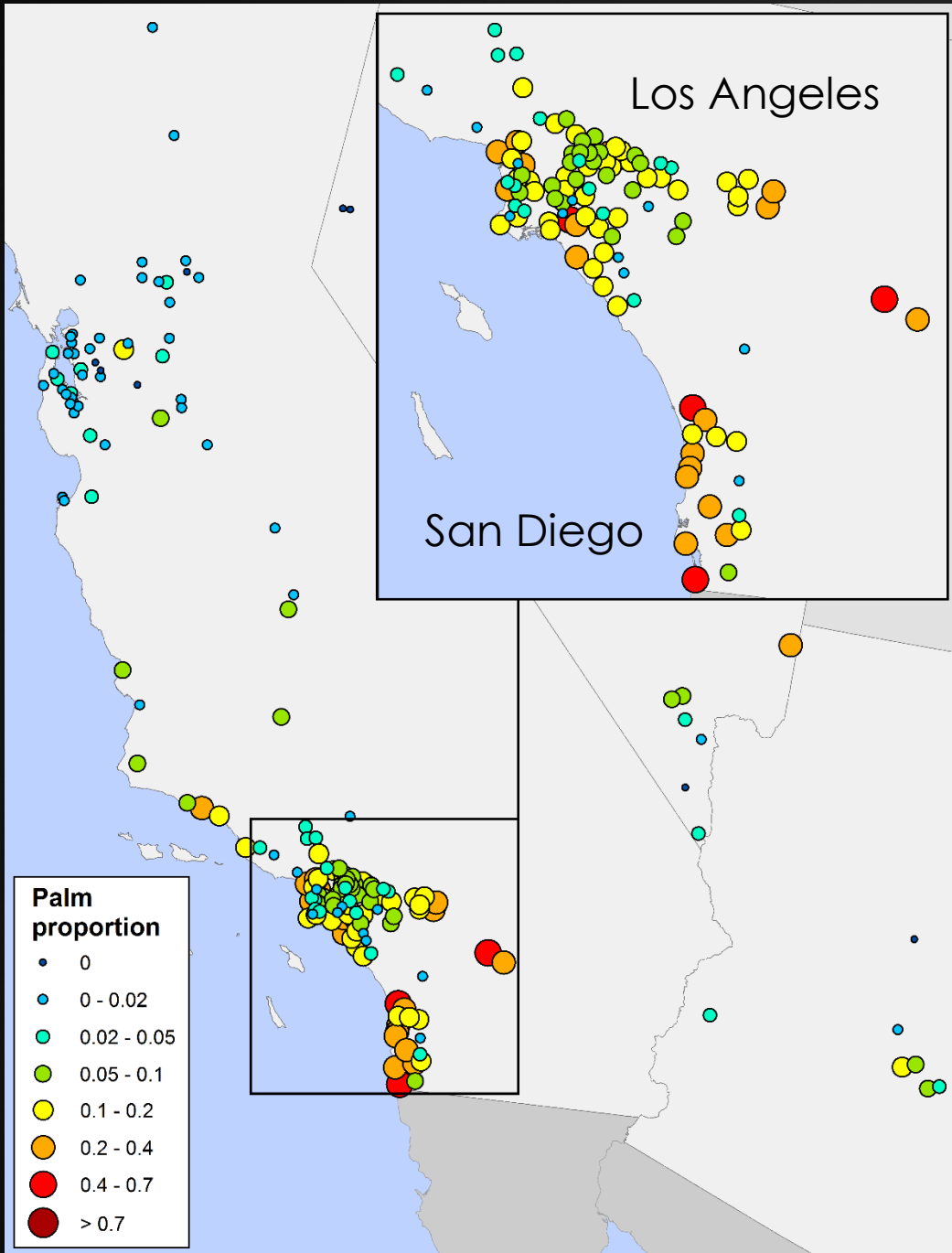
Street Tree Inventory Data

- ▶ 341 inventories across 14 states
 - ▶ Effective range of palms in continental USA
- ▶ Best represented states are California and Florida



Palm Proportion of Inventoried Street Trees





Step 1: Modeling Street Palm Proportion

- ▶ Generalized additive models (GAMs)
- ▶ Separate GAMs for eastern USA ($n = 138$) and western USA ($n = 203$)
- ▶ Candidate predictor variables
 - ▶ Categories: geographic, environmental, socioeconomic, land cover / land use
- ▶ Generalized cross validation for model selection
 - ▶ Correlation / concavity

Eastern USA Model Results

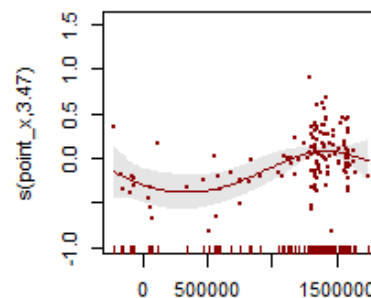
Parametric coefficients:

| | Pr(> t) |
|-------------|------------|
| (Intercept) | <0.001 *** |

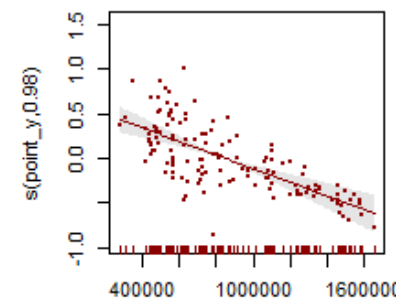
Approximate significance of smooth terms:

| | p-value |
|---------------------------------|------------|
| s(x-coordinate) | <0.001 *** |
| s(y-coordinate) | <0.001 *** |
| s(coastal proximity) | <0.001 *** |
| s(prop. developed open space) | 0.081 . |
| s(prop. developed med. intens.) | <0.001 *** |
| s(mean year home built) | 0.068 . |
| s(mean home value) | 0.003 ** |

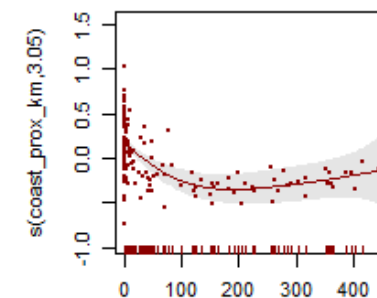
R-sq.(adj) = **0.817**, deviance explained = 84.7%



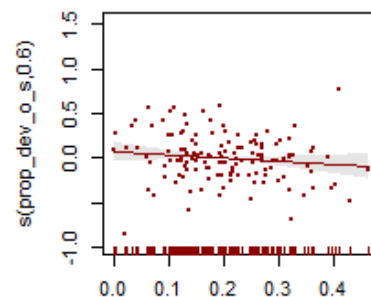
X



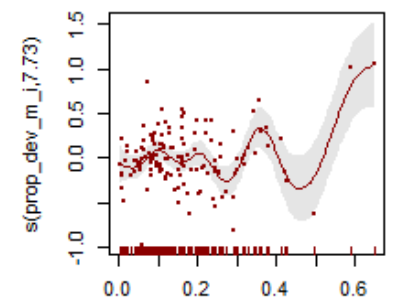
Y



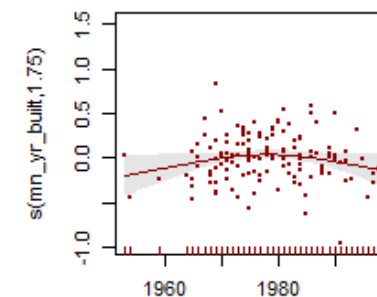
Coastal Proximity



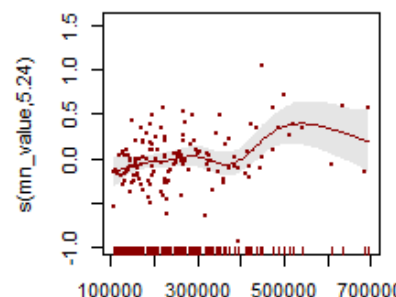
Prop. Dev. Open Space



Prop. Dev. Medium Intensity

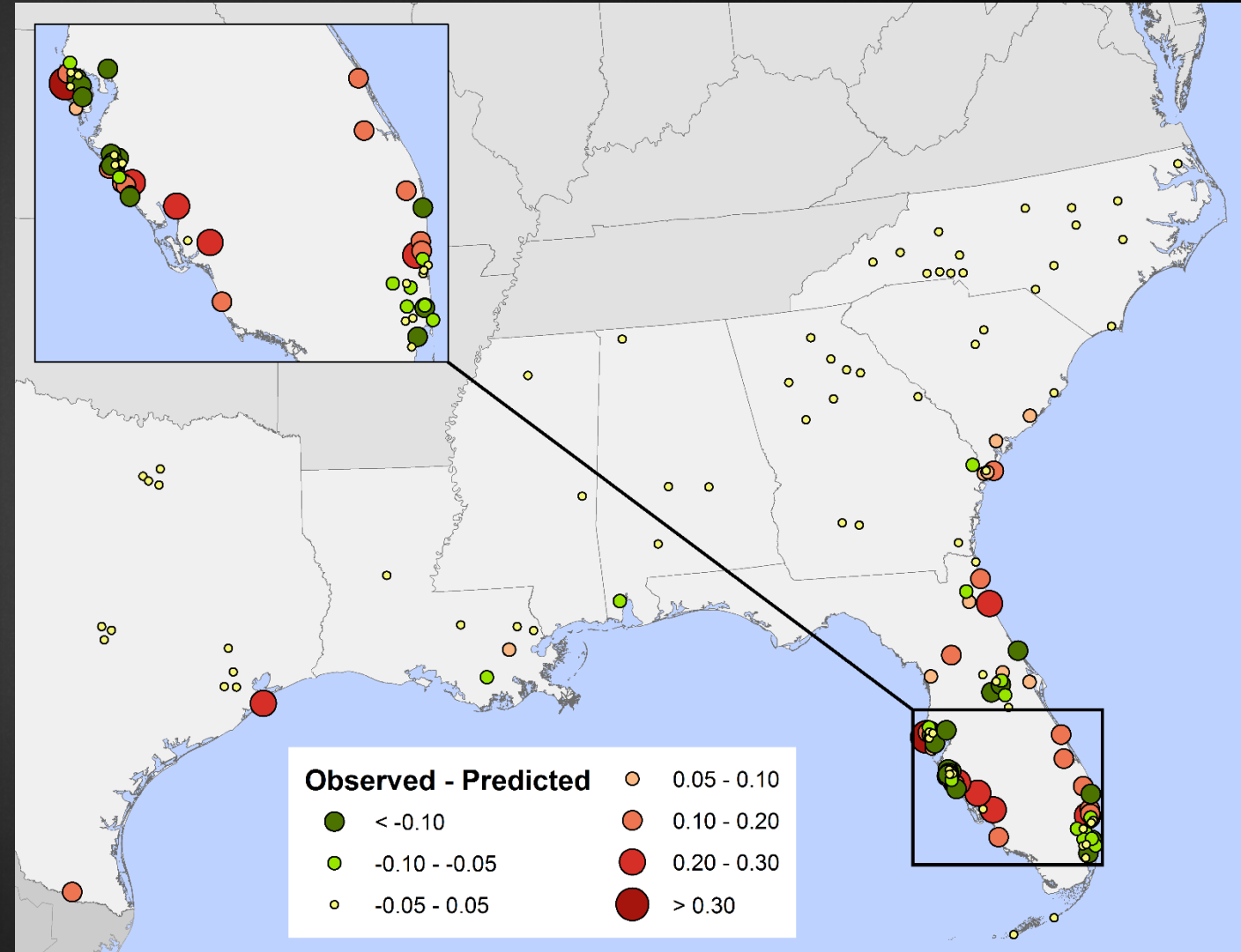
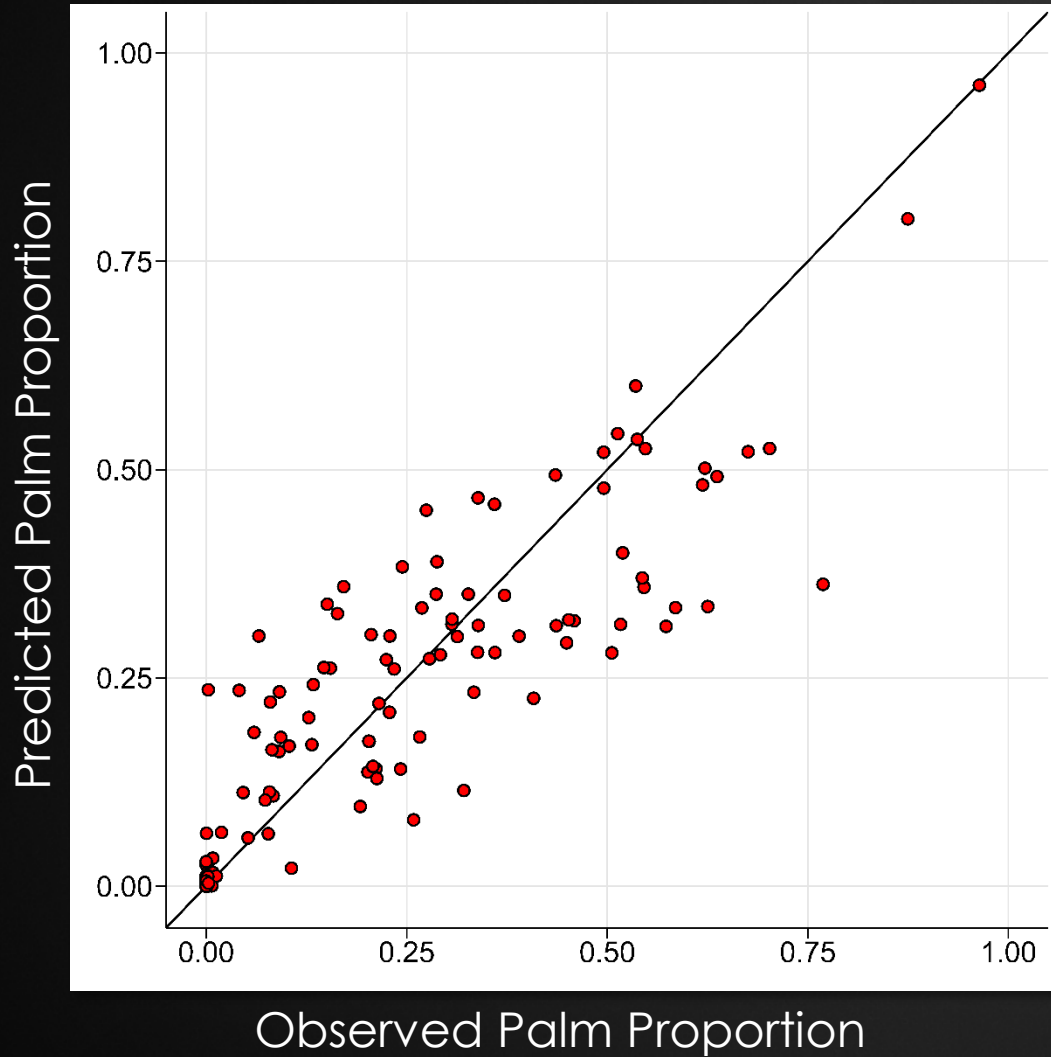


Mean Year Home Built



Mean Home Value

Eastern USA: Observed vs. Predicted



Western USA Model Results

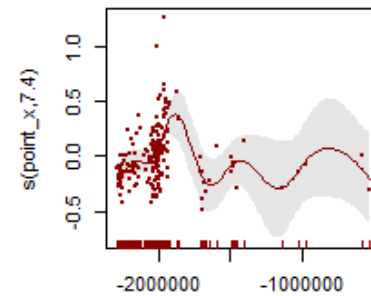
Parametric coefficients:

| | Pr(> t) | |
|-------------|-----------|-----|
| (Intercept) | <0.001 | *** |

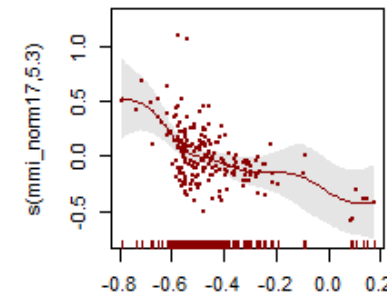
Approximate significance of smooth terms:

| | p-value | |
|----------------------------------|---------|-----|
| s(x-coordinate) | <0.001 | *** |
| s(moisture index) | <0.001 | *** |
| s(mean extreme min. temp.) | <0.001 | *** |
| s(prop. developed open space) | <0.001 | *** |
| s(prop. developed low intensity) | 0.001 | ** |
| s(prop. forest land) | 0.029 | * |
| s(prop. agricultural land) | 0.033 | * |
| s(pct. below poverty level) | 0.005 | ** |
| s(mean year home built) | <0.001 | *** |

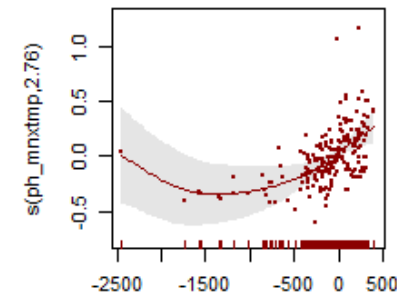
R-sq.(adj) = **0.623**, deviance explained = 68.9%



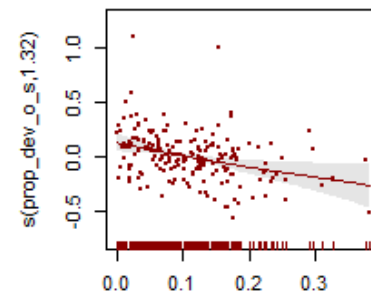
X



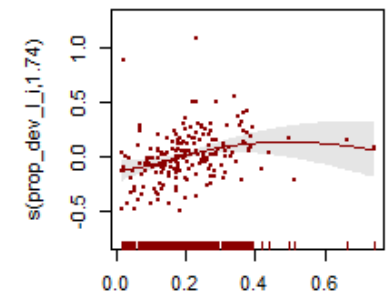
Moisture Index



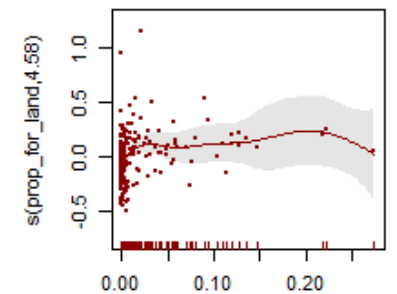
Mean Ext. Min. Temp.



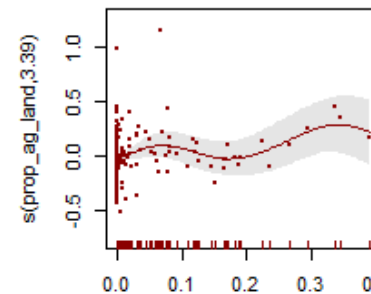
Prop. Dev. Open Space



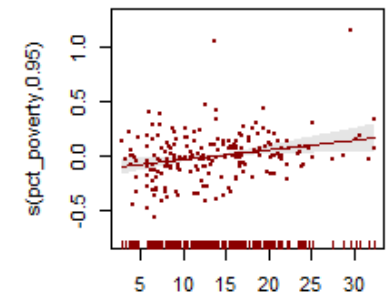
Prop. Dev. Low Intensity



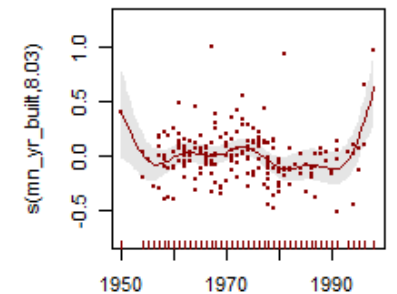
Prop. Forest Land



Prop, Agric. Land

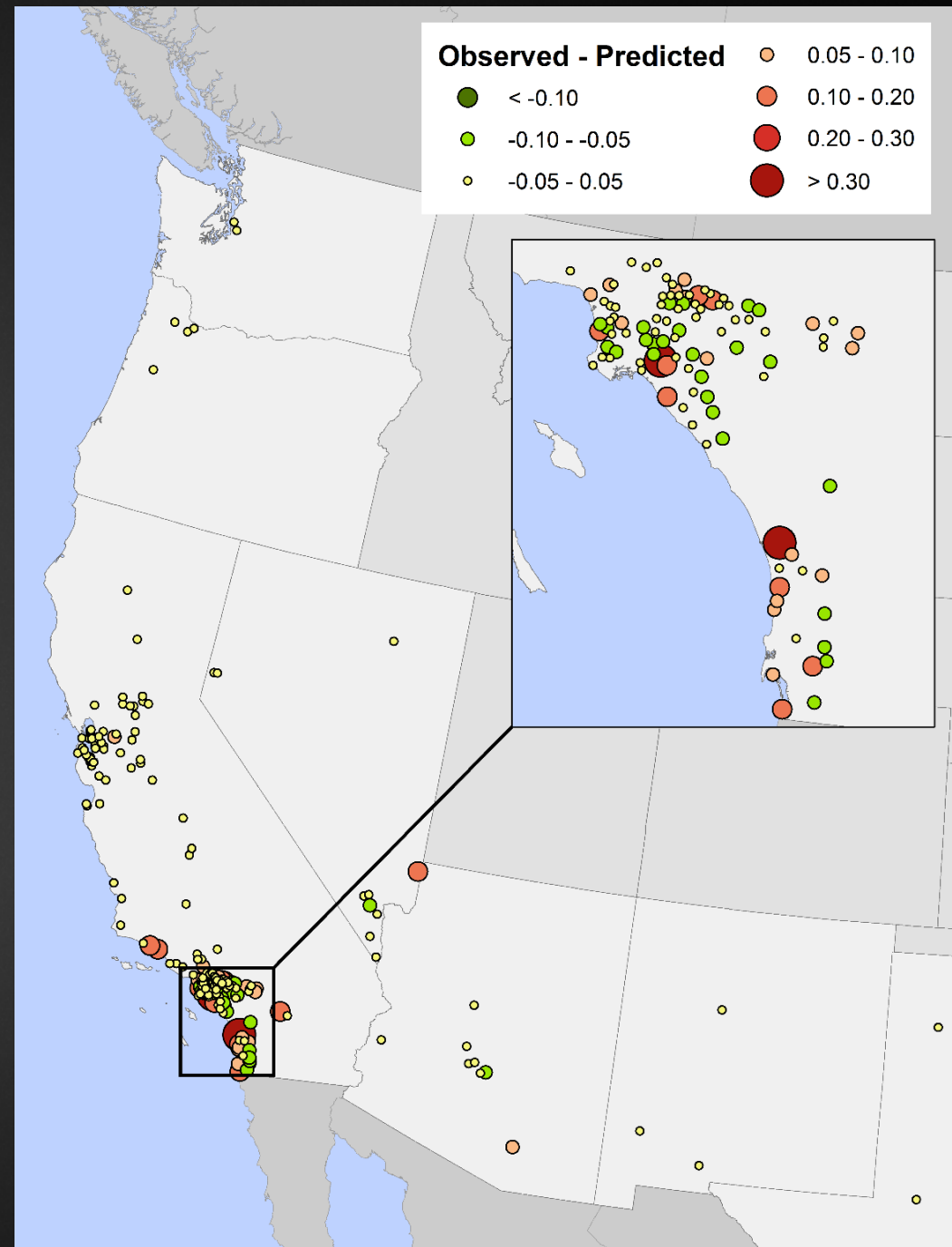
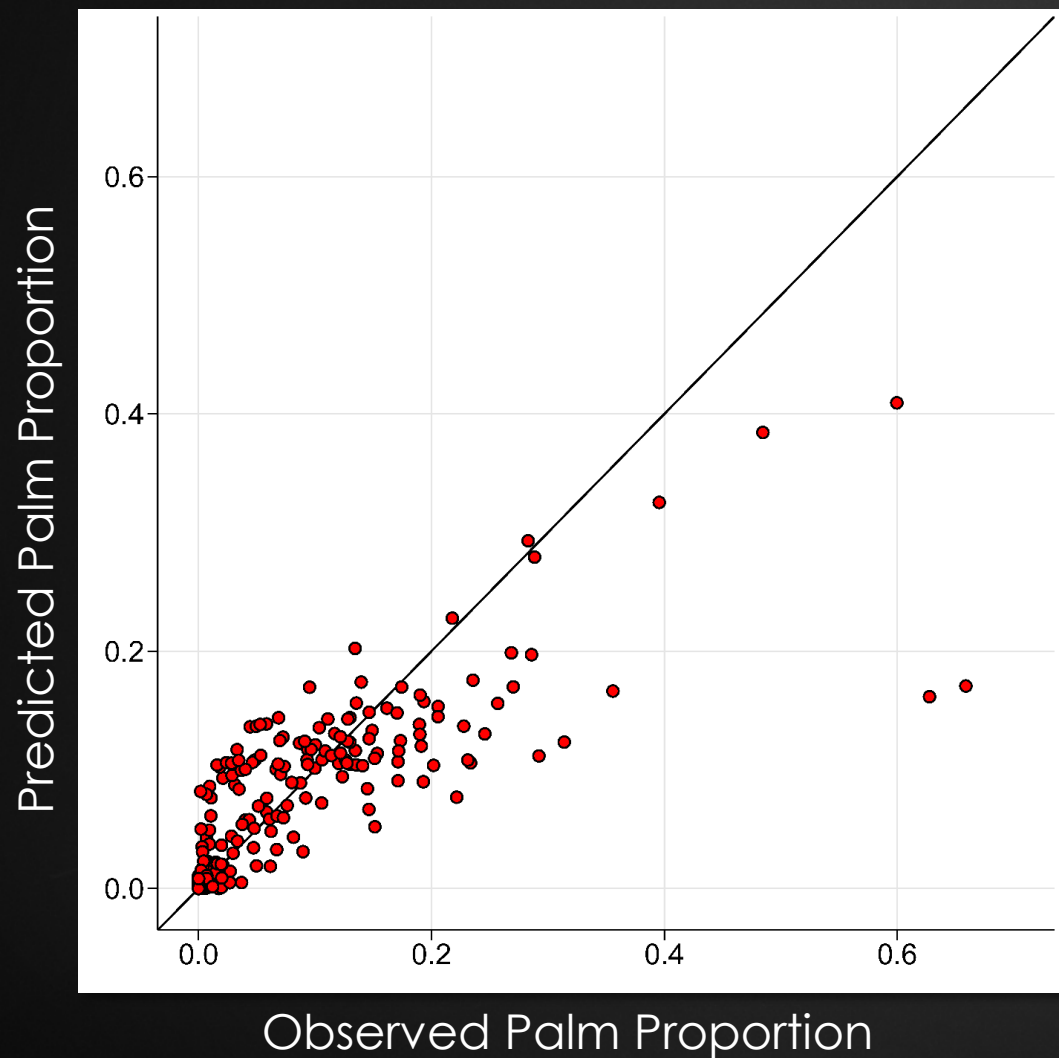


Pct. Below Poverty Level



Mean Year Home Built

Western USA: Observed vs. Predicted



Step 2: Modeling Street Tree Density

- ▶ Across USA, street tree density usually 40-55 trees / km
- ▶ Some communities have much greater density
 - ▶ City of Miami Beach, Florida \approx 140 trees / km (!)
 - ▶ Very high street palm proportion



- ▶ Density data are difficult to acquire
- ▶ Can't develop robust model with few data
- ▶ **Assume density = simple function of street palm proportion?**

Final Points

- ▶ Palm proportion modeling results are preliminary but promising
 - ▶ Must apply to 1000s of communities without inventories
- ▶ Street tree density is more difficult
 - ▶ May have to assume very simple model
 - ▶ Density appears related to street palm proportion
- ▶ Approach seems feasible overall
- ▶ Additional work to translate to economic impact
 - ▶ Other palm pests?

Questions?

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