

On Design-Based, Model-Assisted and Model-Based Forest Biomass Estimation

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Lead partners



Norwegian Ministry
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EARTH OBSERVATIONS**

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Traditional Forest Inventory

Estimating forest biomass in a project area (design-based estimation)

1. Select field plot locations using probabilistic sampling
2. Measure the amount of carbon on each plot
3. Estimate carbon for the project area
4. Estimate the standard error

Advantages

- Estimators are unbiased
- Error is easy to estimate and interpret based on sampling design

Disadvantages

- Expensive to collect field data



Incorporating remotely sensed data

Estimators can be constructed to bring in remote sensing data to increase precision

- Lidar height metrics related to forest height
 - Airborne and spaceborne platforms (e.g., GEDI Lidar, IceSat-2)
- Optical remote sensing related to forest cover
 - NASA Landsat and Sentinel-2
- Aboveground biomass map products
 - ESA CCI Biomass maps
 - GEDI Biomass Maps



Incorporating remotely sensed data

How do we incorporate remote sensing products into forest carbon estimation?

- Model-assisted estimation (design-based)
 - Use assisting model to relate remote sensing data to field observations
 - Estimate biomass/carbon and standard error based on field sampling design
- Model-based estimation
 - Use model to relate remote sensing data to field observation
 - Estimate biomass/carbon and standard error based on model assumptions



Incorporating remotely sensed data

Model-assisted approach

Emick, E., Babcock, C., White, G., Hudak, A., Domke, G. & Finley, A. An approach to estimating forest biomass while quantifying estimate uncertainty and correcting bias in machine learning maps. *Remote Sensing of Environment* **295**, 113678 (2023).

$$\hat{\bar{y}} = \frac{1}{N} \sum_{i \in U} \hat{y}_i + \frac{1}{n} \sum_{i \in s} (y_i - \hat{y}_i)$$

$$\hat{y}_i = \hat{\beta}_0 + \hat{\beta}_1 x_i$$

$$\hat{V}(\hat{\bar{y}}) = \frac{1}{n(n-1)} \sum_{i \in s} (y_i - \hat{y}_i)^2$$



Incorporating remotely sensed data

Model-based approach

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Posterior Predictive
Distribution samples
(PPD)

$$\hat{\tilde{y}}^l = \frac{1}{N} \sum_{i \in U} \tilde{y}^l(\mathbf{s}_i)$$

Mean of PPD

$$\hat{\bar{y}} = \frac{1}{M} \sum_{l=1}^M \hat{\tilde{y}}^l$$

Variance of PPD

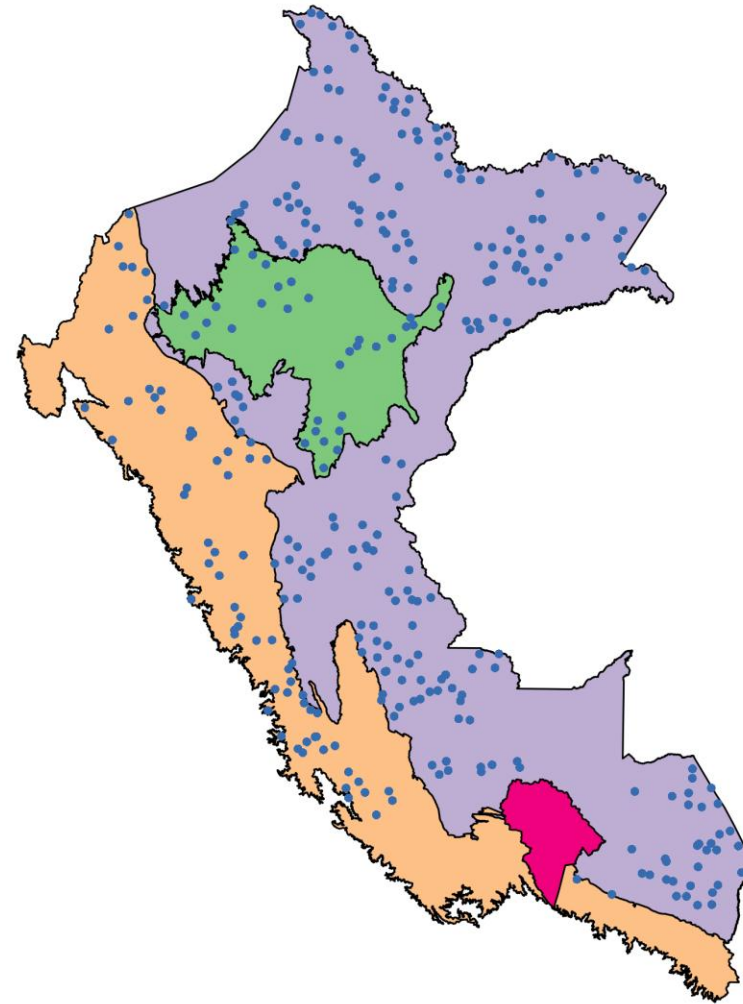
$$\hat{V}(\bar{y}) = \frac{1}{M} \sum_{l=1}^M (\hat{\tilde{y}}^l - \hat{\bar{y}})^2$$



Case Study in Peru

Goals:

- Estimate forest biomass for:
 - Amazon Region in Peru
 - Each Strata
 - del Manu (Pink Region)
- Incorporate remote sensing to reduce uncertainty



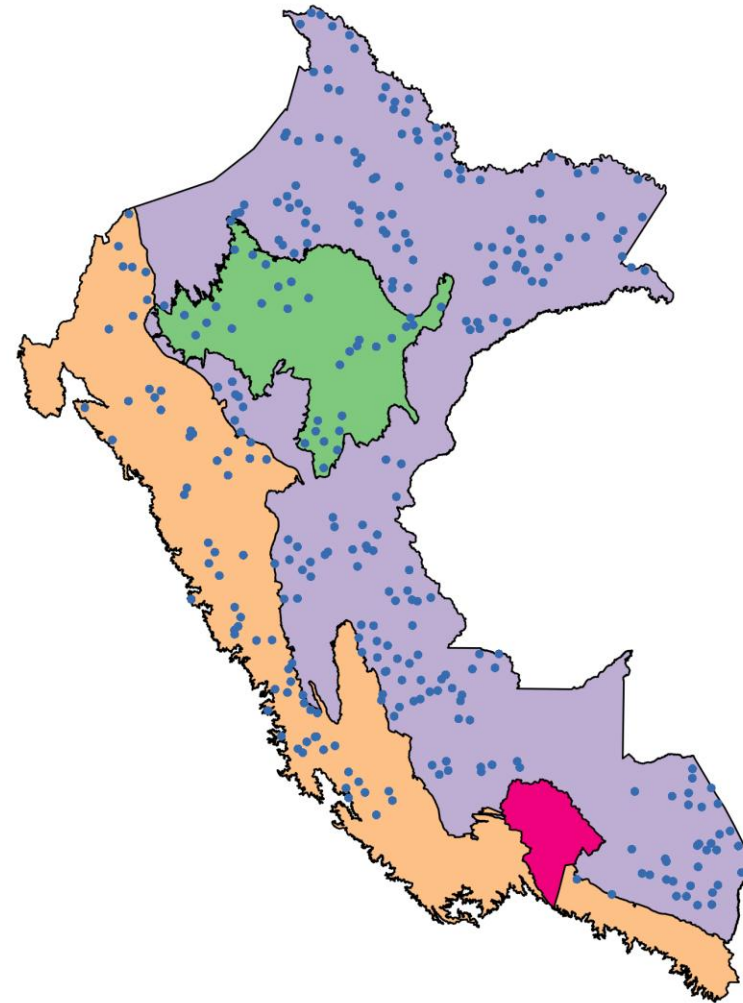
Case Study in Peru

Field Data:

- Field plot data collected through Peru's National Forest Inventory
- Amazon = 320 plots
- Purple = 221 plots
- Green = 32
- Orange = 67
- Pink = 0

Remote Sensing Data:

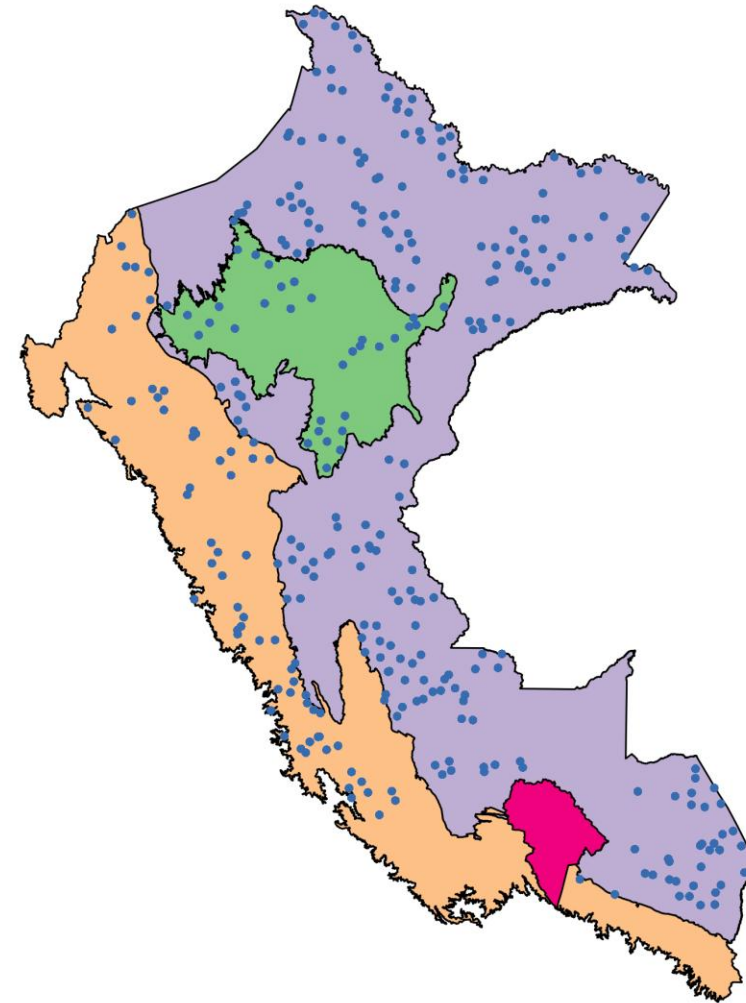
- ESA CCI Biomass Map



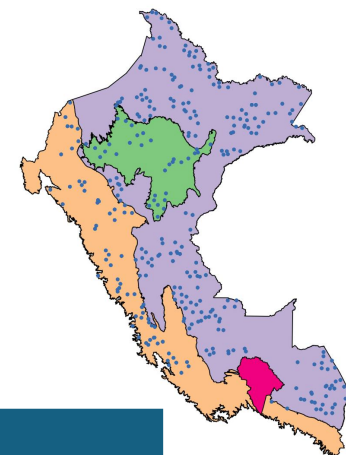
Case Study in Peru

Estimators:

- **Design-based Estimator**
 - Only field data
- **Model-assisted GREG Estimator**
 - Field and remote sensing data
 - Design-based paradigm
 - linear regression assisting model
- **Spatial Model-based Estimator**
 - Field and remote sensing data
 - Model-based paradigm
 - Spatial random effect included
- **Null Spatial Model-based Estimator**
 - Only field data
 - Model-based paradigm
 - Spatial random effect included



Case Study in Peru



Strata	Design Based (No CCI Map)	Model Assisted (Yes CCI Map)	Null Spatial Model (No CCI Map)	Spatial Model (Yes CCI Map)
Amazon (320 plots)	218.66 (6.39)	216.25 (5.90)	226.68 (6.94)	228.84 (5.80)
Purple (221 plots)	255.24 (7.12)		243.92 (7.60)	253.17 (6.84)
Green (32 plots)	221.26 (16.21)		239.76 (15.87)	217.69 (10.36)
Orange (67 plots)	161.98 (12.32)		183.81 (12.64)	181.11 (7.33)
Pink (0 plots)	---	---	194.12 (36.04)	240.09 (24.78)



Case Study in Peru

Concluding Remarks

- Model-assisted and geostatistical model-based estimators can improve forest biomass estimation by incorporating remote sensing data
- Both approaches can produce useful estimates of uncertainty
- Both approaches can lower inventory costs by reducing the number of plots need to get a reliable estimate
- Spatial model-based approach does not require plots within area-of-interest to generate estimates with uncertainty



Forest Carbon Framework

Extend Spatial Model Based Estimator for Dynamic AOI Estimation

<https://forestcarbonframework.com/>

