How Do We Assess the Performance of Our Small Area Estimators?

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Forest Inventory and Analysis Science Stakeholder Meeting **Nov 17, 2022**

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  - EBLUP?
  - Hierarchical Bayes?
  - Spatial?

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Priors?

Fitting method?

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How do we choose?

In order to address these choices, we have designed a unique simulation study using k nearest neighbors (kNN) and hot deck imputation.

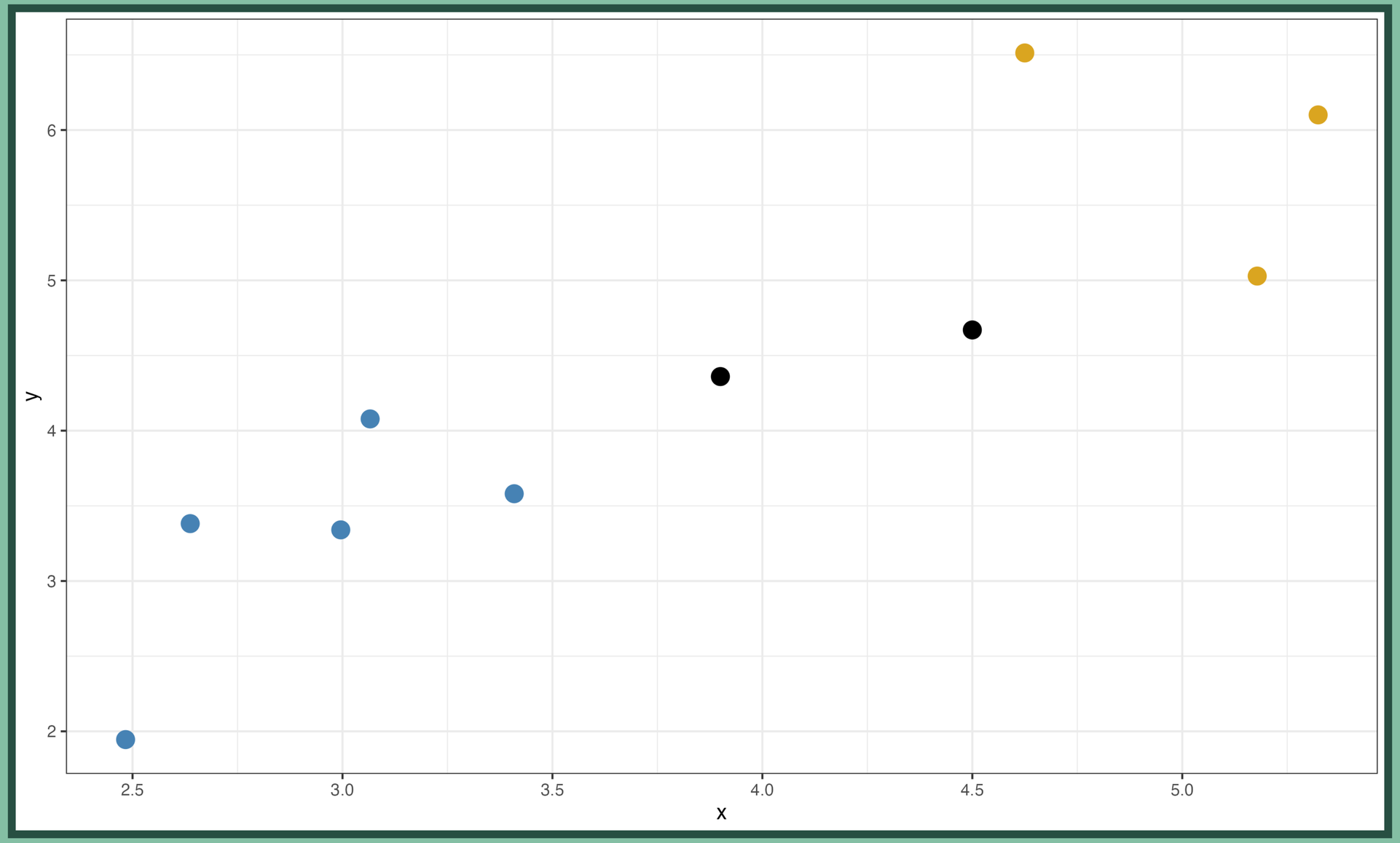
kNN

A non-parametric algorithm for finding the k "closest" observations to a given observation.

Hot deck imputation

A method for filling in missing data, where each new value is picked at random from a set of possible new values.

A brief overview of kNN



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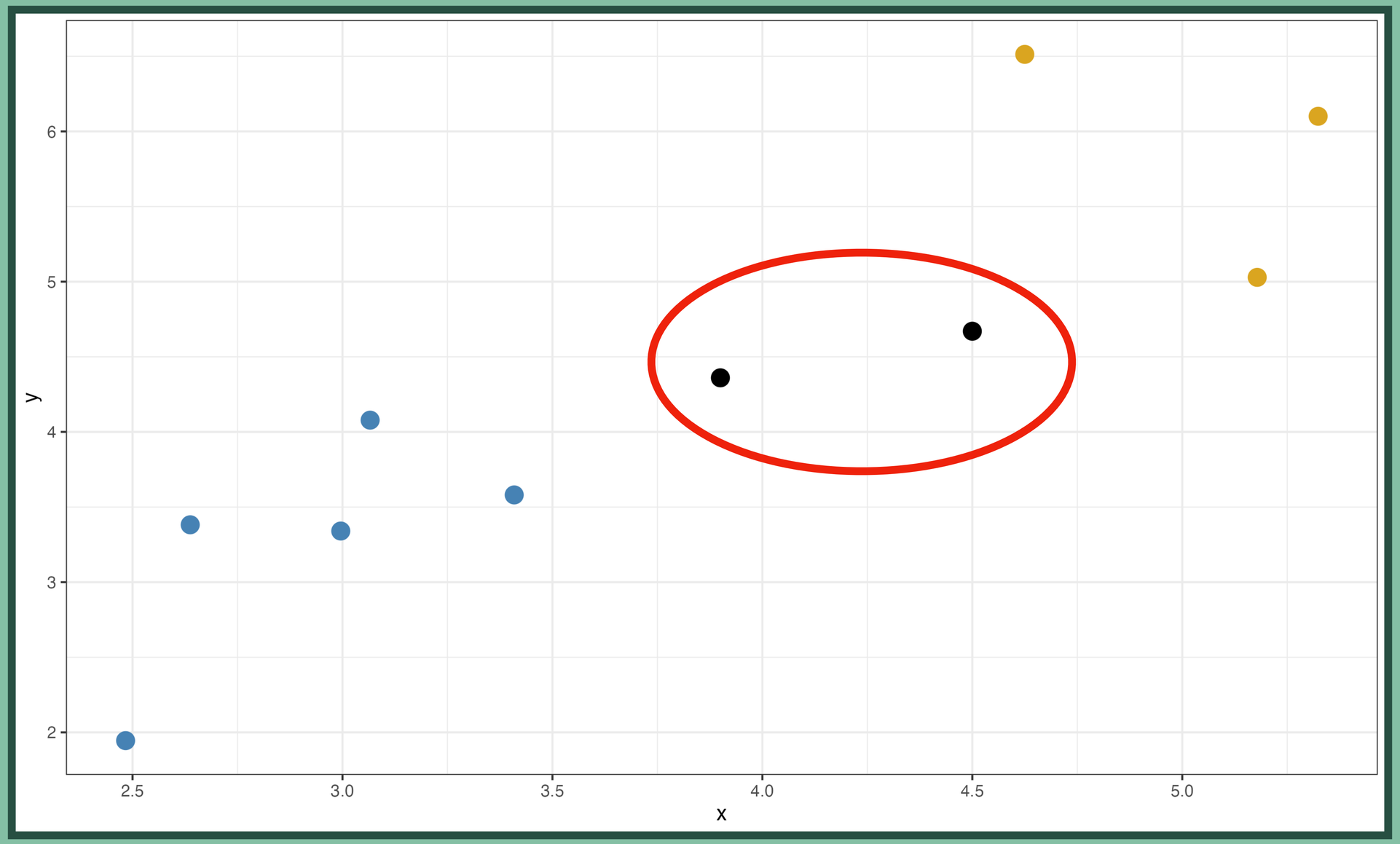

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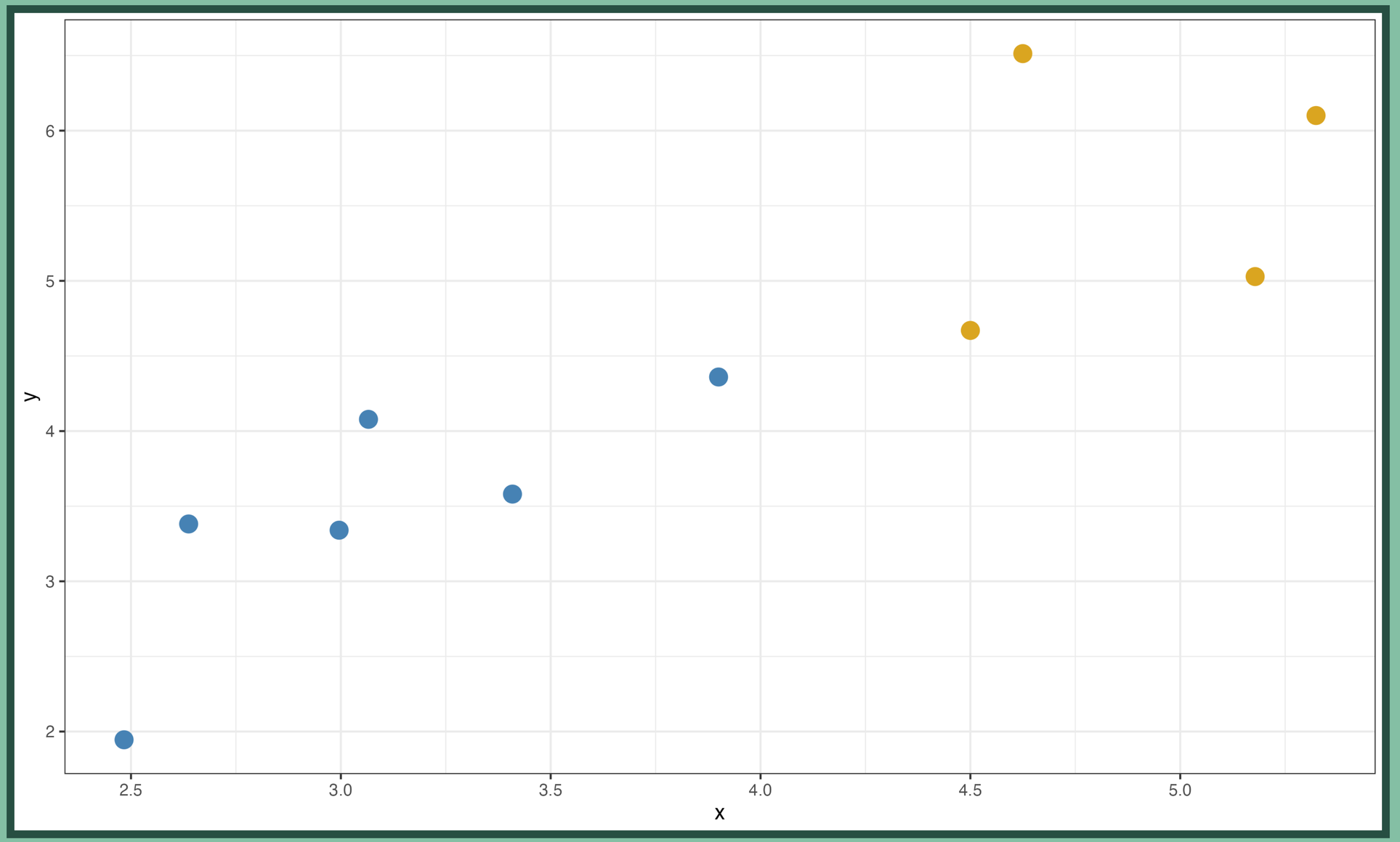
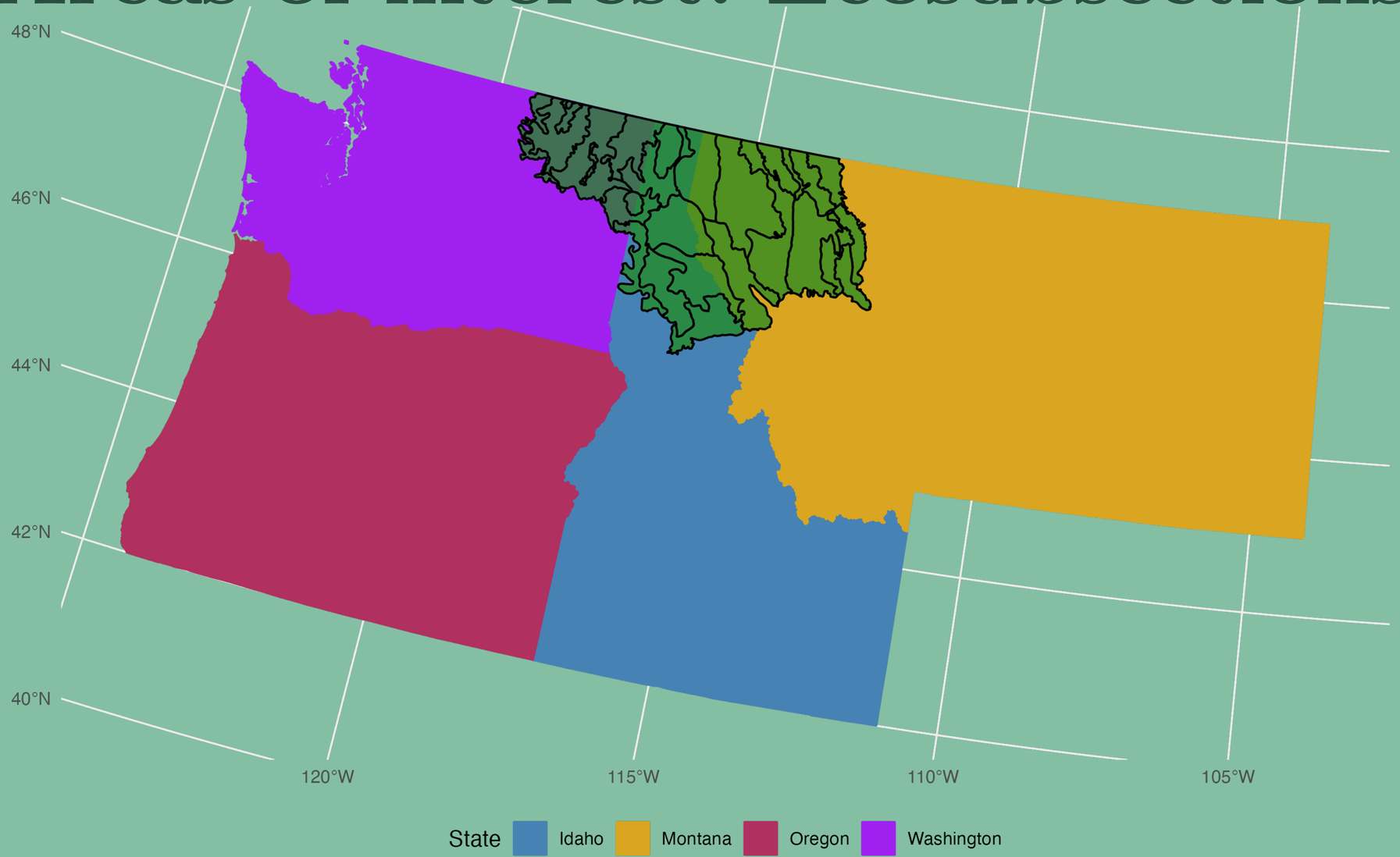


Simulation Design

Orcas Island, Washington

Lansing, Michigan

Study region: Ecoprovince M333, Areas of interest: Ecosubsections



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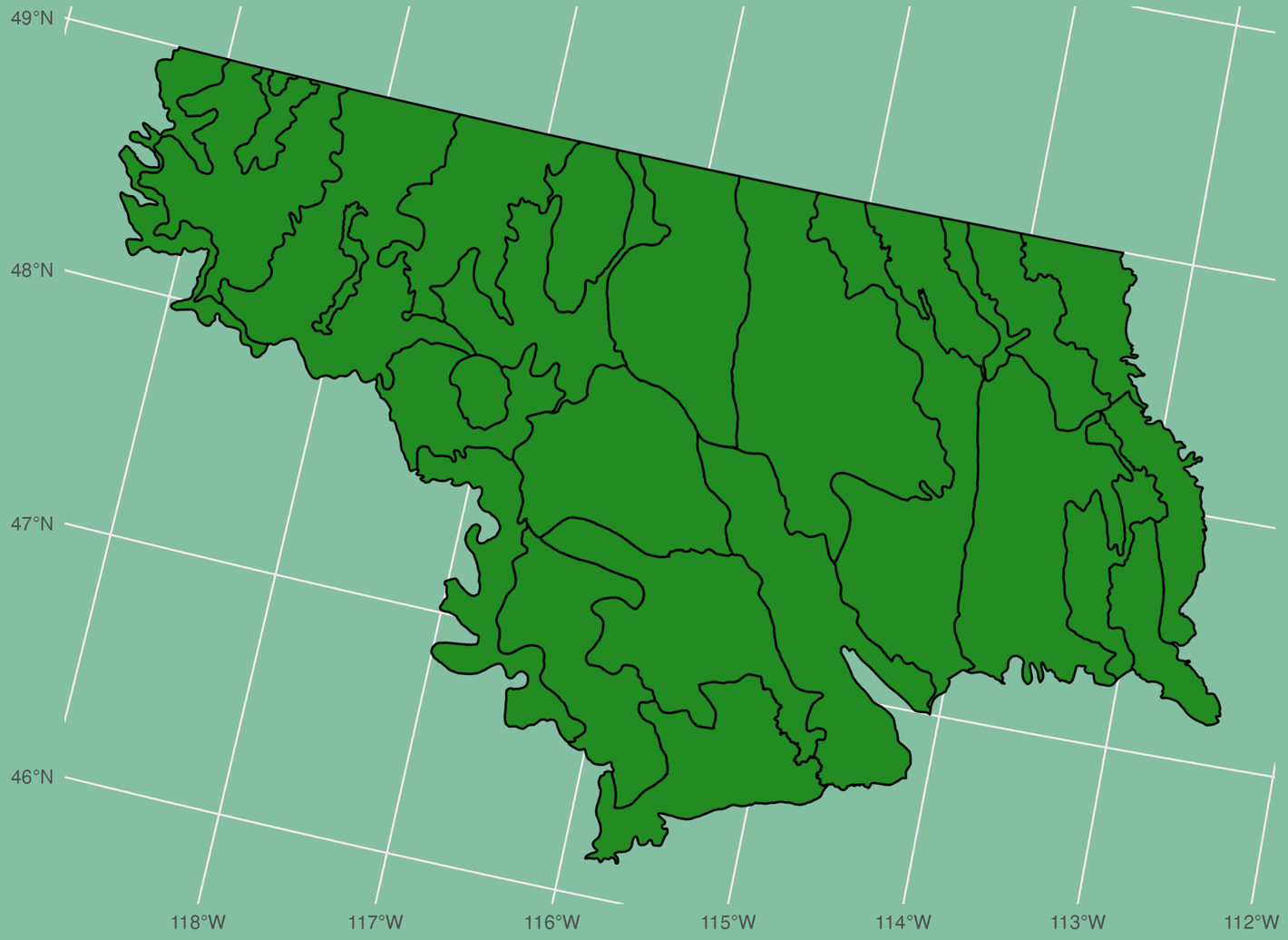
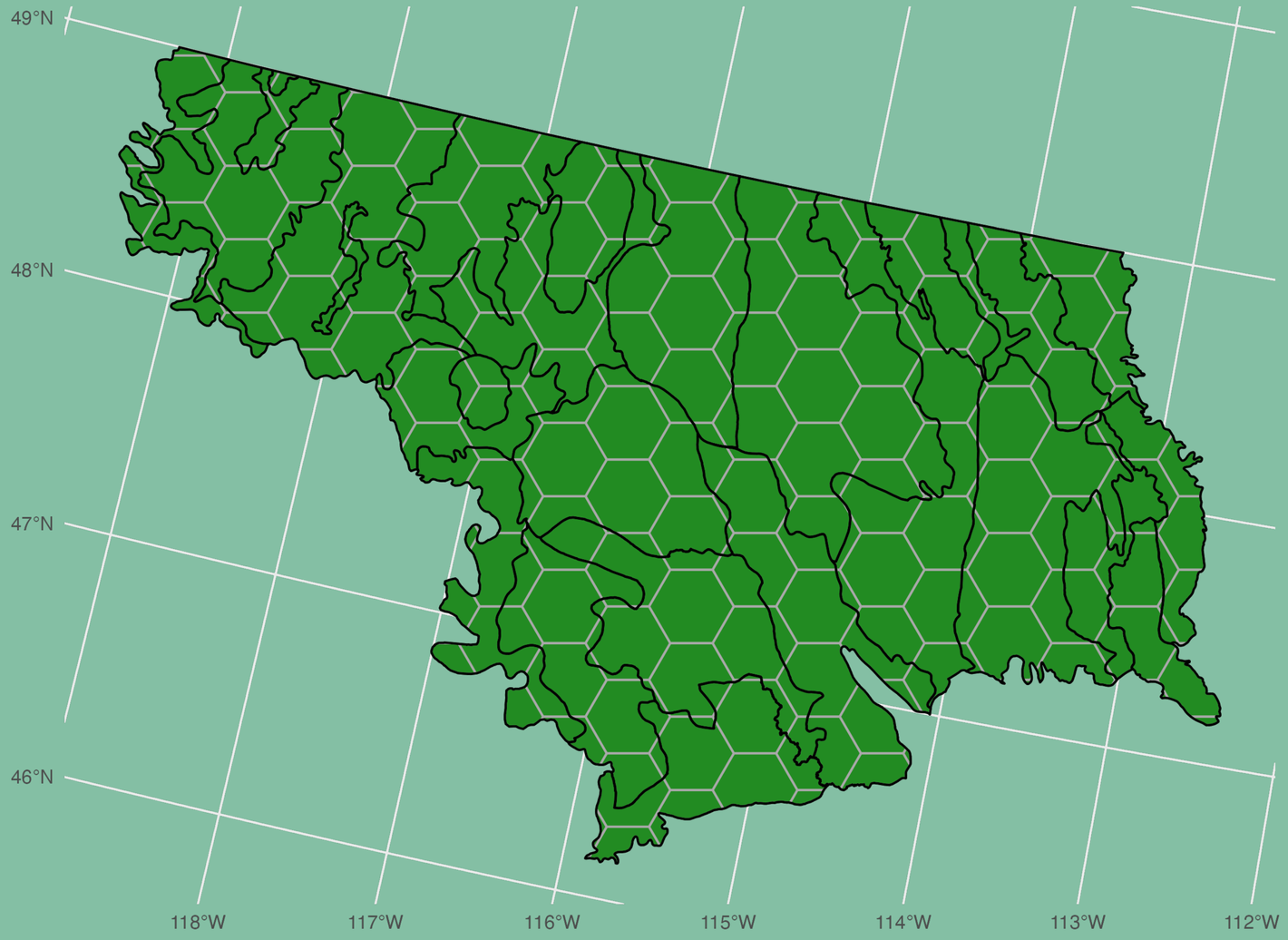
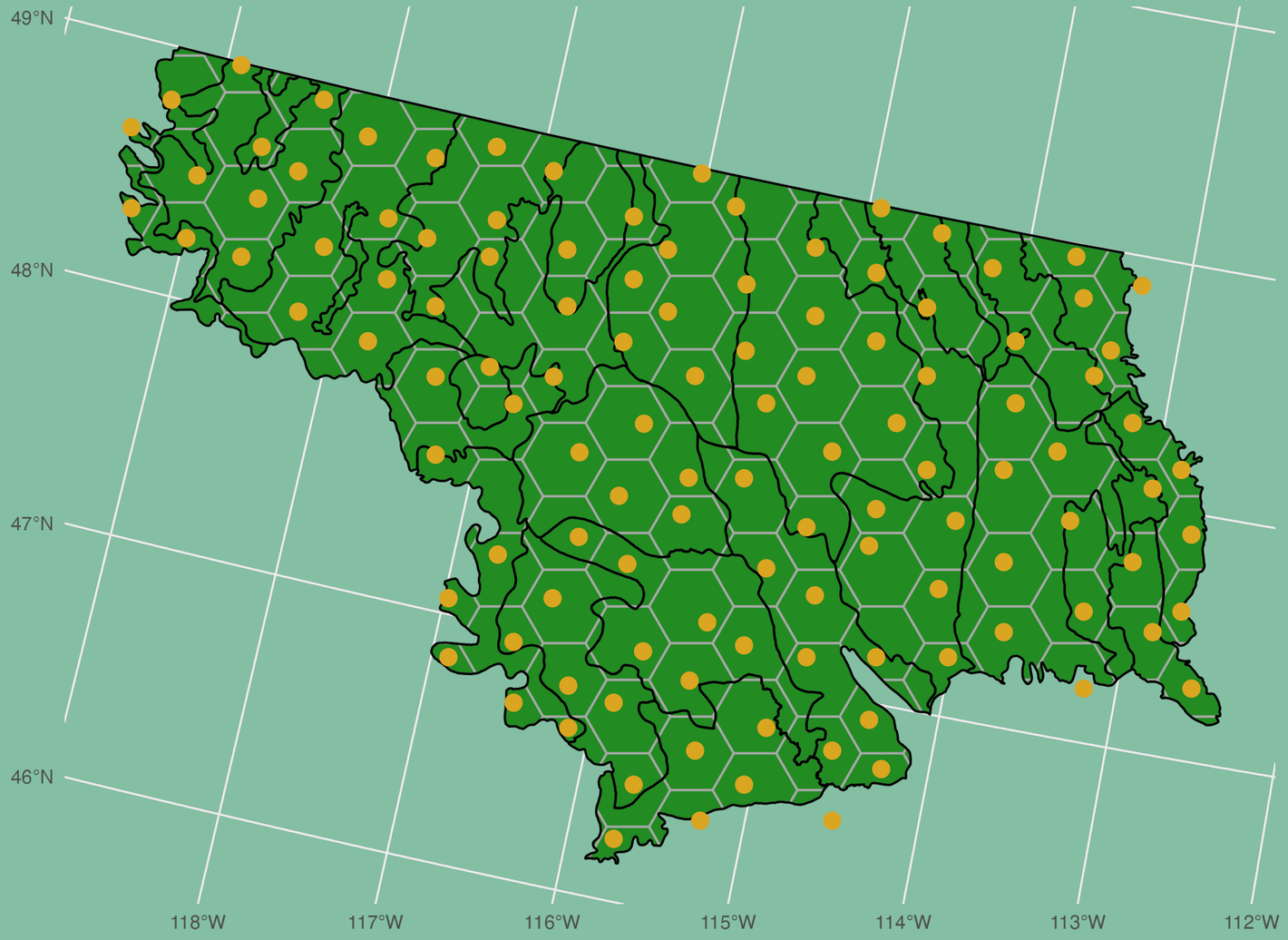


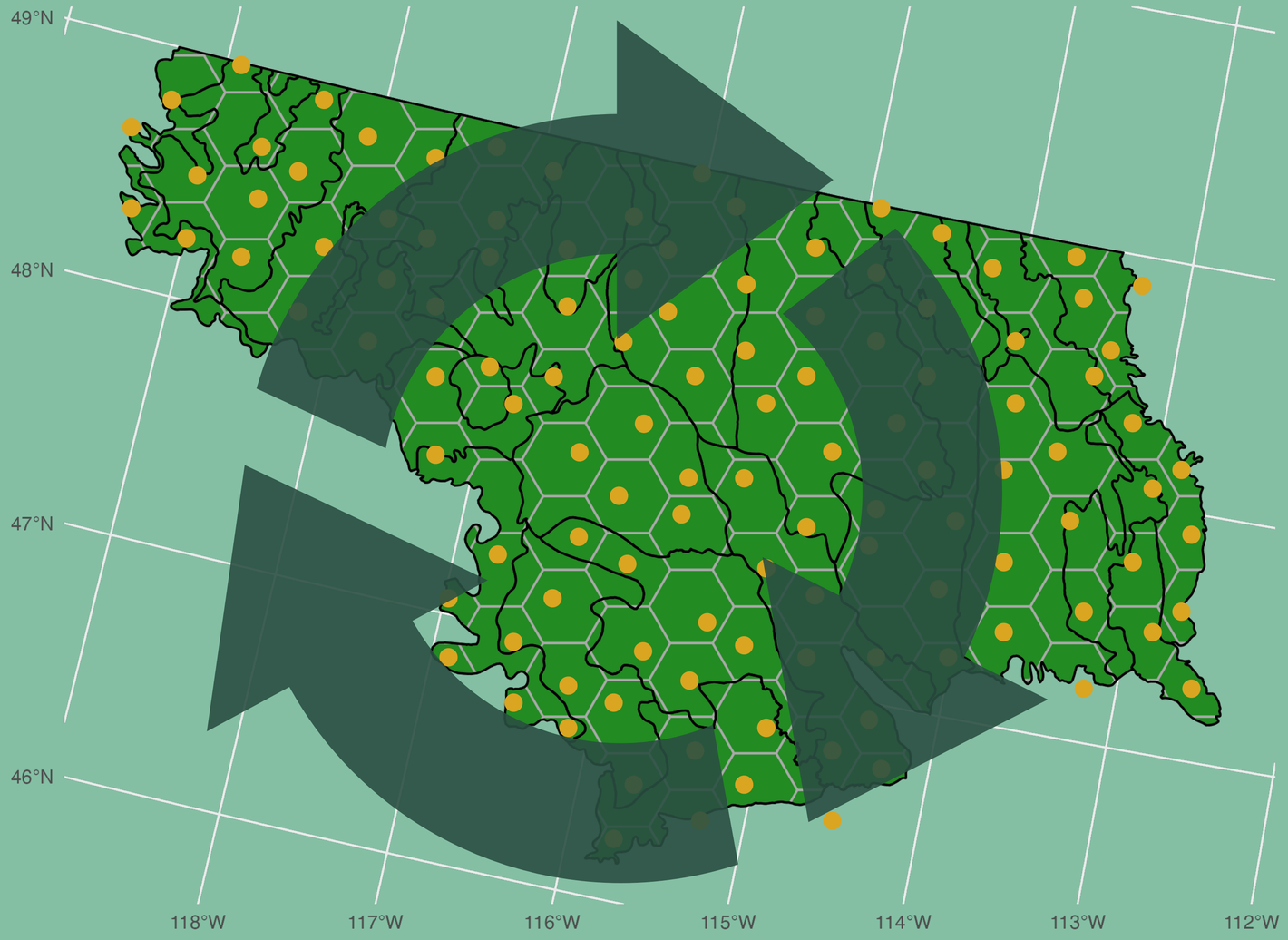
Creating Artificial Samples: Overlay FIA's Hexagonal Grid



Creating Artificial Samples: Randomly Select 90m Pixel Within Each Hex



Creating Artificial Samples: Repeat Pixel Selection Many Times



kNN Hot Deck Imputation: Step-by-step

Recipient row

tcc	tri	def	tnt
63	18.4	198	1

Step 1: select a recipient row of data

kNN Hot Deck Imputation: Step-by-step

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62	15.4	147	1	185
59	19.8	242	1	148
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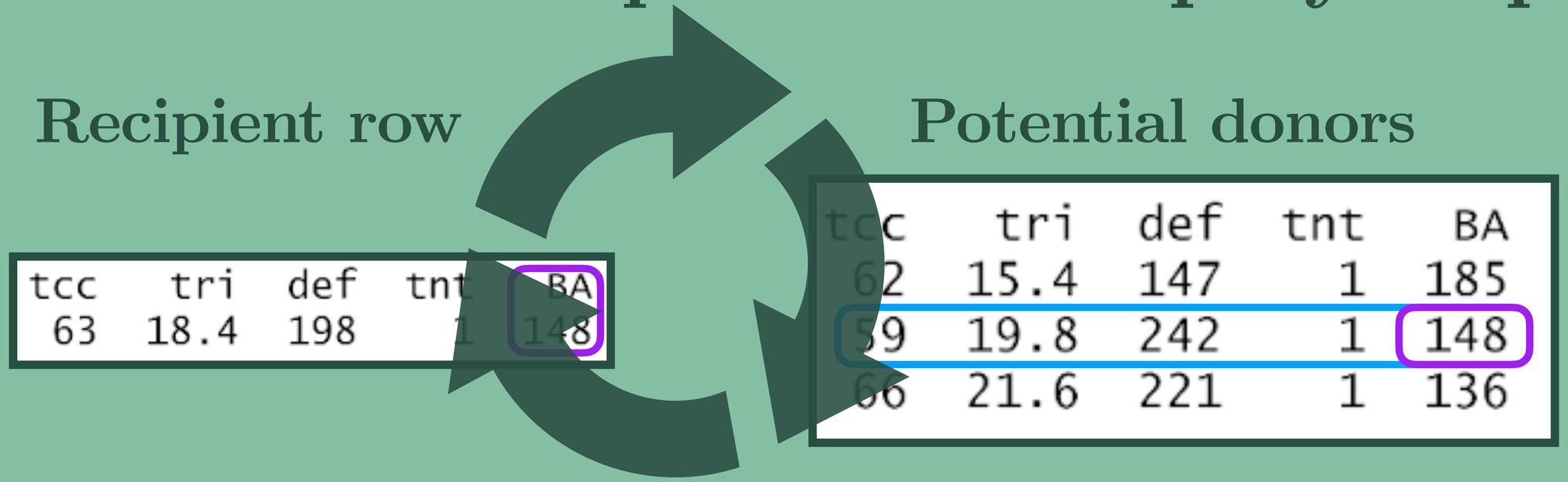

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Step 5: Repeat many times to generate simulation datasets

Why not a simpler alternative to kNN Hot Deck Imputation?

How else could we have generated our response variable values?

(1) Through fitting a regression model, or

(2) By treating an auxiliary variable as the response

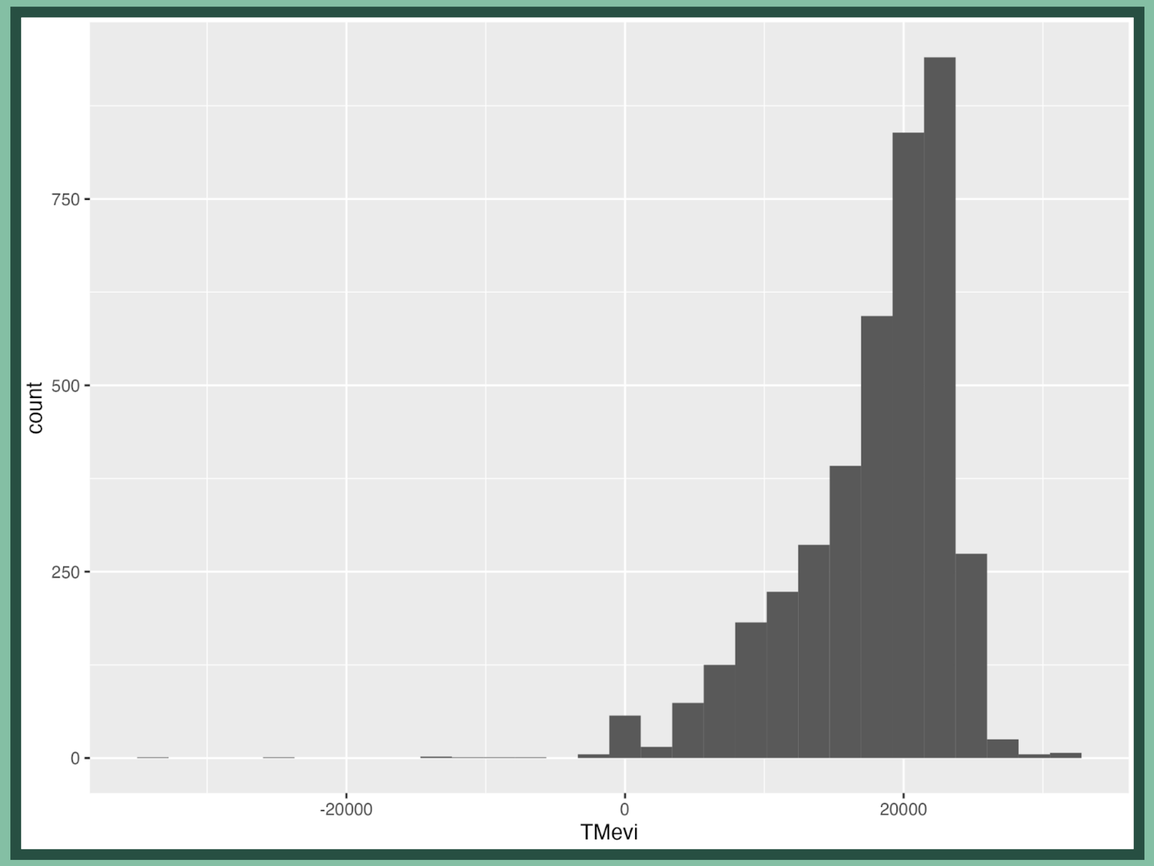
Both (1) and (2) have issues!

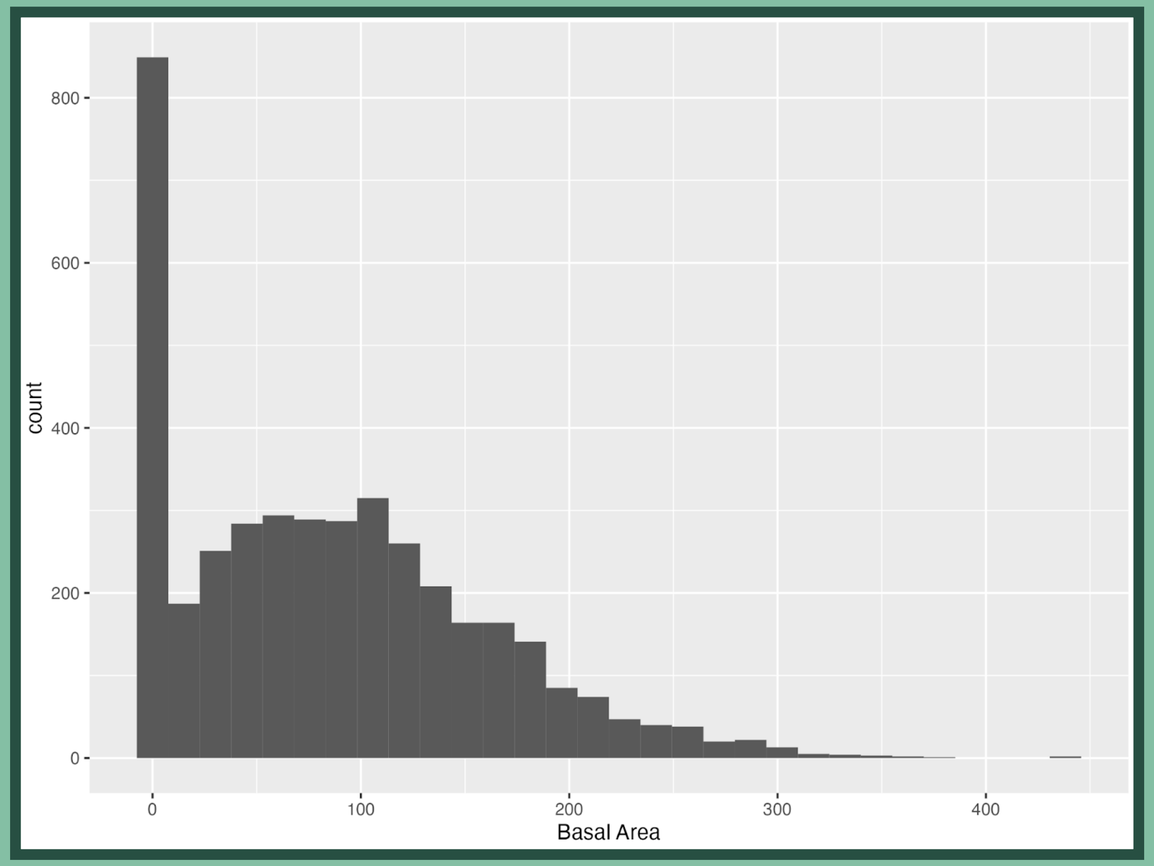
(1) Regression as Response:

Issue: If we fit a regression model and generated response values from it, our simulation study would be over-optimistic when evaluating estimators built on similar regression models.

(2) Auxiliary as Response

Issue: Our auxiliary variables are not "shaped" liked our response variables.





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Thank you!

Get in touch:

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Website: www.graysonwhite.com

Slides/other work available: www.github.com/graysonwhite