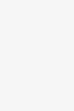
# Optimal Policy Learning Under Spatial Dependence With Applications to Groundwater in Wisconsin

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## Introduction

- Motivation: Data-Driven, Cost-Efficient Groundwater Policy
  - A necessary trade-off: increasing water well depth improves groundwater quality but increases installation costs.
  - **Goal:** Determine the *minimum well depth* required to meet the *public health standards* for contaminants in groundwater.
- Method: Spatial Minimum Resource Threshold Policy (spMRTP)
  - A Gaussian process model for **spatial dependence** of contaminants in groundwater.
  - Policy learning via risk minimization with a novel, doubly robust loss function.
  - Computational efficiency via the Vecchia approximation.
- Application: Nitrates in Wisconsin Groundwater

### Framework

#### • Notations

- $\circ \mathcal{S} = \{s_1, s_2, ..., s_n\} \subset \mathcal{D} \subset \mathbb{R}^2$ : set of spatial locations where n observations are measured.
  - $\circ$   $Y_s$ : observed concentration of contaminate at location s
  - $A_s \in \mathcal{A} \subset \mathbb{R}$ : observed well depth at location s
  - $Y_s(a)$ : potential concentration of contaminants at location s and depth  $a \in \mathcal{A} \subset \mathbb{R}$
  - $\circ$   $X_s$ : measured spatial covariates at location s
  - $\circ$   $U_s$ : unmeasured spatial covariates at location s

#### • Assumptions

- Causal consistency:  $Y_s = Y_s(A)$  almost surely.
- Strong ignorability:  $A_s \perp Y_s(a) \mid X_s \text{ and } p(a \mid X_s = x) > 0 \text{ for all } a, x$ .
- Spatial unconfoundedness:  $U_s \perp A_s \mid X_s$ .
- Additive, semiparametric, spatial structural model:  $Y_s = \mu(X_s, A_s) + U_s + \epsilon_s$ .
  - $\circ \mu(X, A)$ : nonparametric, monotonically decreasing function w.r.t. A for all X.
  - $U_s$ : mean-zero, Gaussian process, i.e.,  $E[U_s \mid A_s, X_s] = 0$
  - $\circ$   $\epsilon_s$ : mean-zero, i.i.d. measurement error, i.e.,  $E[\epsilon_s | A_s, X_s, U_s] = 0$

### • Definition of spMRTP $\theta^*(x_s)$

- $\mathcal{T}$ : target threshold for the outcome (e.g., nitrate concentration is less than  $\mathcal{T}=10 \text{ mg/L}$ )
- o Given measured covariates at new location  $s_0$  (i.e.,  $x_{s_0}$ ), the spMRTP is defined as

$$\theta^*(x_{s_0}) = \arg\min_{a \in \mathcal{A}} a$$
, such that  $E[Y_{s_0}(a) | X_{s_0}] + U_{s_0} \leq \mathcal{T}$ .

# Identification and Estimation

#### **Identification**

- Under assumptions above, we have the following identification results

  - $U_{s_0}$  can be approximated by conditional mean  $E[U_{s_0} | \{U_s\}_{s \in \mathcal{S}}]$

#### **Doubly Robust Nonparametric Estimation**

- Assume  $\theta \in \Theta$  where  $\Theta$  is a function class defined on  $\mathcal{D} \mapsto \mathcal{A}$ .
- STEP 1: Estimation of nuisance parameters
  - Estimate  $\hat{\mu}$  and  $\hat{p}(a|x)$  —> Estimate covariance function with  $Y \hat{\mu}$  —> Estimate  $\hat{E}[U(s)|\mathcal{S}]$  by kriging.
- STEP 2: Doubly robust risk minimization

$$\hat{\theta} = \arg\min_{\theta \in \Theta} \sum_{i=1}^{n} \left( \mathcal{T} - \hat{\mu}(X_i, \theta(s_i)) - \hat{E}[U(s_i) \mid \mathcal{S}] - \frac{\{Y_i - \hat{\mu}(X_i, \theta(s_i)) - \hat{E}[U(s_i) \mid \mathcal{S}]\}K_{\delta}(A_i - \theta(s_i))}{\hat{p}(A_i \mid X_i)} \right)^2.$$

### Simulation Studies

#### • Simulation Setting

- Let  $\mathcal{D} = [0,1]^2$  and  $\mathcal{S}$  be a uniform  $50 \times 50$  grid on  $\mathcal{D}$ .
- $\circ$   $(X_1,...,X_5)$  are i.i.d. normally distributed.
- $\circ$   $A | X_1, ..., X_5$ : beta distributed with logistic mean model.
- $\circ$  U(s): gaussian process with range = 0.2.
- $\circ Y | A, X_1, ..., X_5$ : normal distribution with non-linear mean.

#### Completing Methods

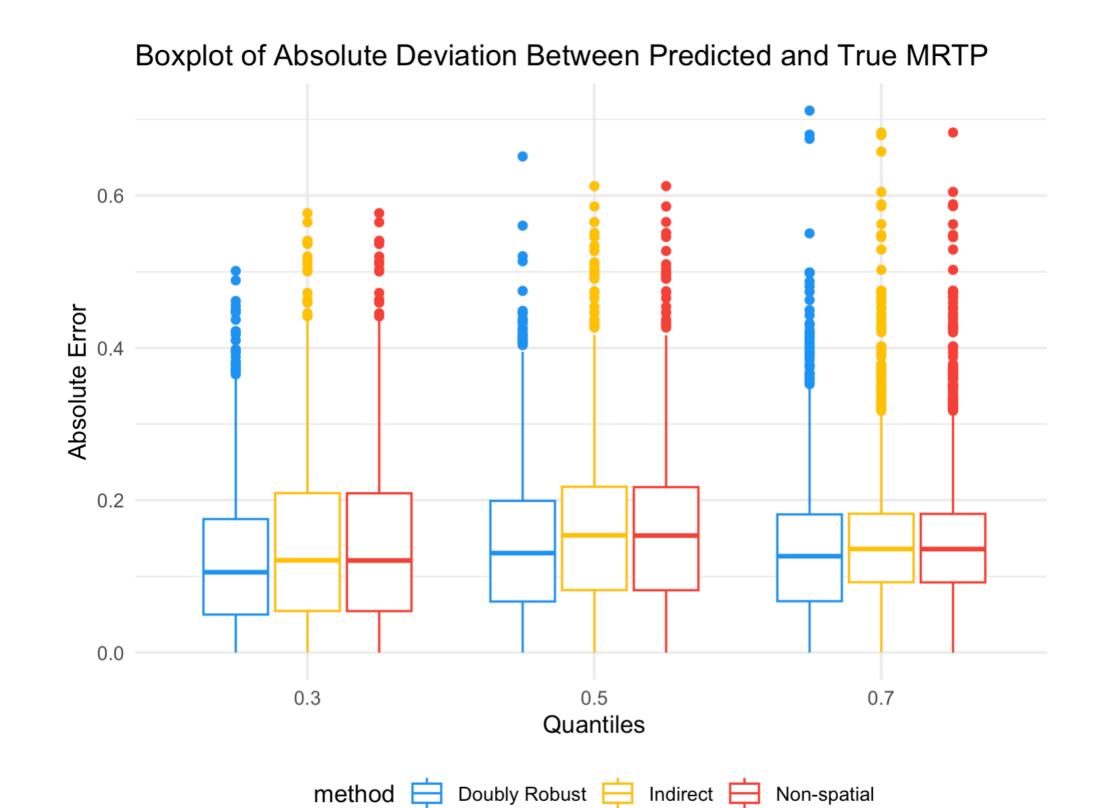
• Indirect method:

$$\hat{\theta}(s) = \inf_{a \in \mathcal{A}} \left\{ a \, | \, \hat{\mu}\{X(s), a\} + \hat{E}\left[U_s \, | \, \{U_s\}_{s \in \mathcal{S}}\right] \right\}.$$

 $\circ \text{ Non-spatial MRTP: } \hat{\theta}(s) = \inf_{a \in \mathcal{A}} \left\{ a \mid \hat{\mu}\{X(s), a\} \right\}.$ 

#### Implementation

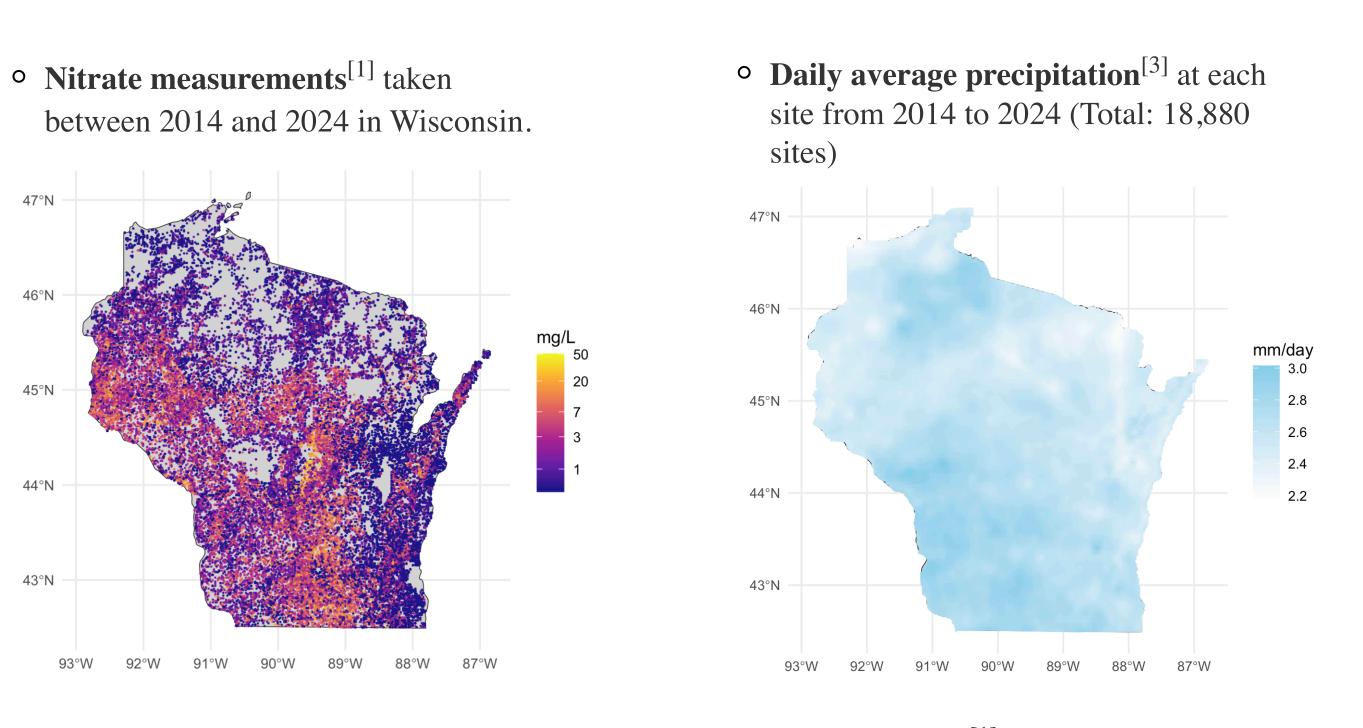
- Tuning parameters are selected via cross-fitting.
- $\circ$  Use generalized linear regression to estimate  $p(a \mid x)$ .
- Use linear regression to estimate  $\mu(x, a)$ .

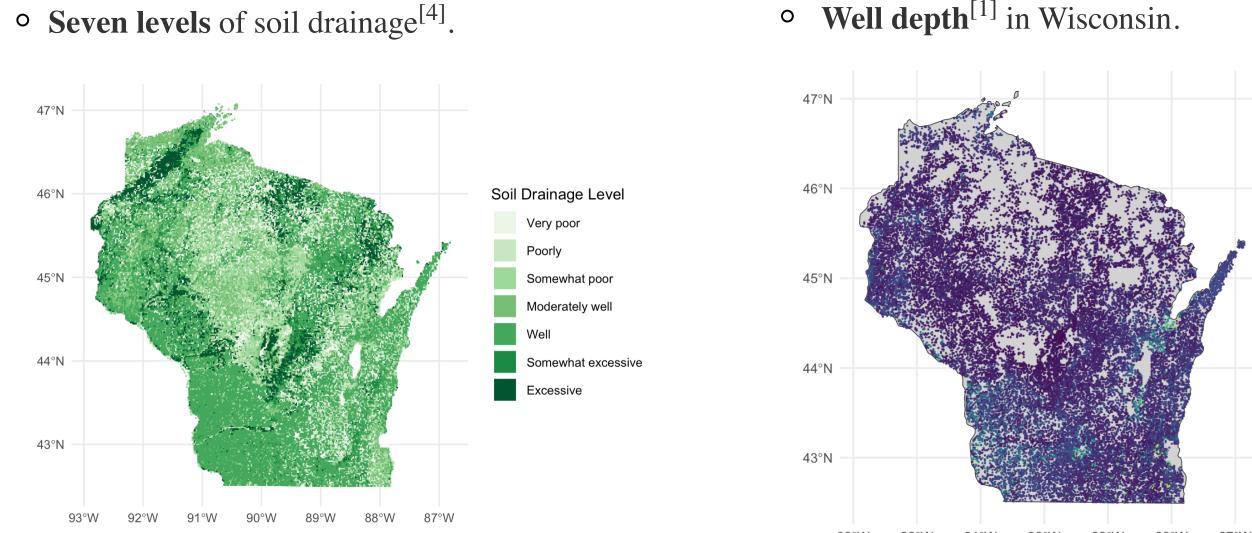


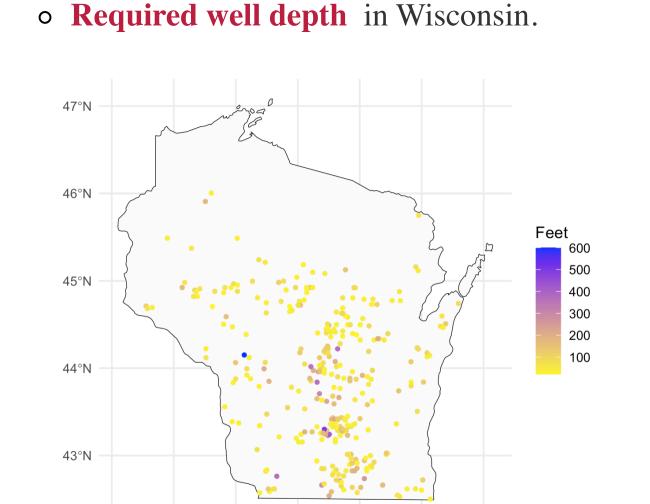
**Figure:** boxplot of absolute error between the predicted spMRTP and true spMRTP. Doubly robust: our doubly robust estimation. Indirect: indirect method using outcome regression. Nonspatial: indirect method that ignores the spatial dependency term U(s).

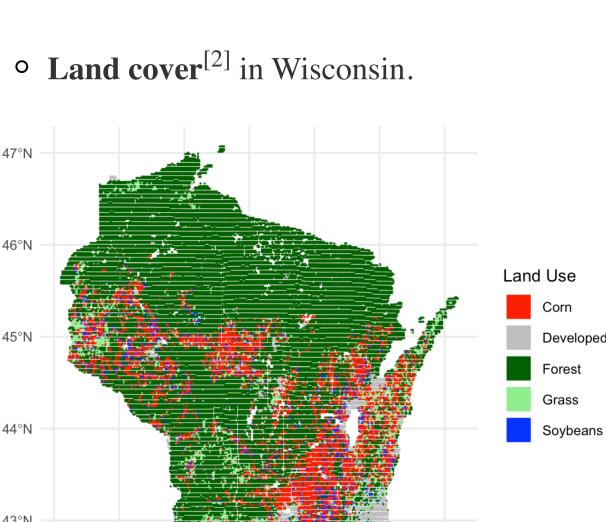
# Application: Nitrate in Wisconsin Groundwater

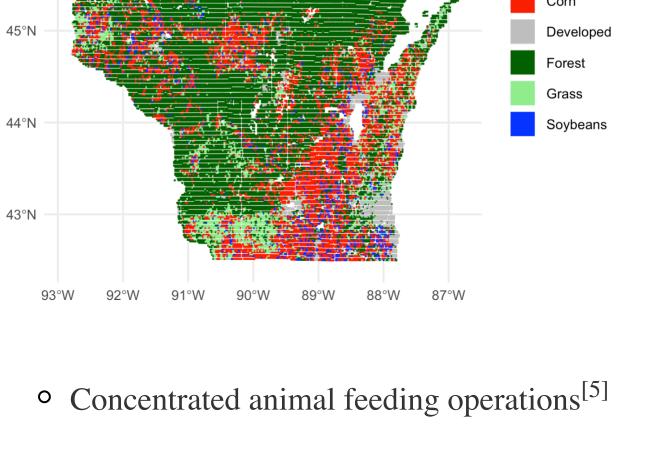
- Nitrate remains the most widespread groundwater contaminant in Wisconsin.
- Millions of dollars<sup>[6]</sup> are spent to meet the 10mg/L public health standard.
- We aim to estimate minimum well depth to meet the 10mg/L health standard.
- We use publicly available groundwater nitrate measurements and environmental variables that are hypothesized to predict nitrate contamination.

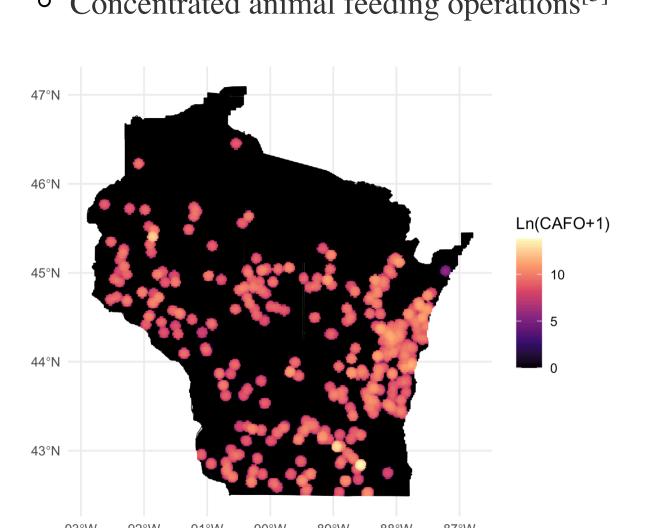












References: [1] Groundwater Retrieval Network (GRN). [2] Cropland Data Layer (CDL). [3] United States Geological Survey (USGS). [4] Soil Survey Geographic Database (SSURGO). [5] Wisconsin Pollutant Discharge Elimination System (WPDES). [6] Estimates of Recoverable and Non-Recoverable Manure Nutrients Based on the Census of Agriculture, USDA. [6] Wisconsin Groundwater Coordinating Council Report to the Legislature, 2024

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