Modelling Shallow Groundwater Risk in New Zealand Using Categorical Machine Learning Models

Future Coasts Aotearoa

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## The Challenge

- Rising sea levels threaten coastal communities
- Groundwater shoaling a hidden risk
- PREMISE 1: Need to know vulnerable areas
- Critical knowledge gap: Where is groundwater already shallow?
- PREMISE 2: Acceptable prediction error is dependent on



Bosserelle, A. L., Morgan, L. K., & Hughes, M. W. (2022). Groundwater rise and<br>associated flooding in coastal settlements due to sea-level rise: A review of pro associated flooding in coastal settlements due to sea-level rise: A review of processes and methods. *Earth's Future*, 10, e2021EF002580. <https://doi.org/10.1029/2021EF002580>

## What do we have to work with:

- Depth to groundwater dataset
	- 5.7M observations from ~113,000 locations available
	- 2.4M observations used from ~70,000 locations that met criteria (well depth, unconfined, non-artesian)
	- Cleaned and standardized
	- This dataset is in publication and will (hopefully) be freely available  $\rightarrow$  In the interim contact us if you need it
- 199 predictor variables –precip, et, distance to coast…

### How:

- Random Forest classification
- Multiple depth thresholds 0.5 m 5.0 m
- Multiple probability thresholds



## Rethinking the Problem – what's different about our approach?



(b) Depth to water estimates from Koch et al. 2019 Figure 3

#### Traditional Approach:

- Predictions precise depths to groundwater (regression | modelling)
- Struggles with shallow groundwater (not a much monitoring here)
- Uncertainty is presented in +- depth
- Decision makers need to interpret uncertainty and decide what this means for their planning objectives

*Huston, we have a problem…*

### Rethinking the Problem – what's different about our approach?

#### Our Approach

- Answer the question (**classify**): *is groundwater shallower than x m (e.g., 1 m)*
- Classification lets us handle uncertainty as **Type I and Type II errors**







#### **Variables of Importance**

**Well Depth** 

· Distance to wetlands

• Distance to rivers

**Distance to Wetlands** 

 $\wedge$   $\wedge$   $\wedge$ 

• Well depth



2.5

 $2.0$ 

Recall

ROC-AUC

Accurac

 $P<sub>rec</sub> is$ 

Our model's ROC-AUC (0.823 - 0.962) indicates strong predictive power

# Error Classification

- Trade-off between:
	- **Precision (depth),**
	- **Type I error (sky is falling),**
	- **Type II error (this is fine)**
	- Red: 10% probability of Type 1, 30% probability of Type II
	- Purple: 18% probability of Type 1, 18% probability of Type II
	- Blue: 25% probability of Type 1, 10% probability of Type II



## Results – within 10 km of coast

- Assuming "shallow gw" =  $\leq$ 2 m depth and we want 10% Type II error
	- 10% of our deep groundwater is shallow
	- ⁻ 25% of what's marked shallow is deep
	- ⁻ Exposed area = **1060 km²** (**0.6%** of NZ ex conservation estate)
- ≤2 m depth and 30% Type II error
	- ⁻ 30% of our deep groundwater is shallow
	- 10% of our shallow groundwater is actually deep
	- ⁻ Exposed area = **85 km²** (**0.05%** of NZ ex conservation estate)





Easting (m)

## Flips the adaptation script



#### **Coastal Adaptation Planning Framework**

Scientific Input Assessment Pro is Planning Output

#### **Current Limitations & Future Directions**



 $\begin{matrix} \circledR \\ \circledR \end{matrix}$  $\frac{1}{\sqrt{2}}$ 

2100 2050 **Now** 

2100

### **Conclusions**



## What are your questions?

- Thank you for your attention
- Contact: patrick@komanawa.com

Get out your calculators! We're going to talk machine learning, linear algebra and detailed model performance