

# From Pedo to Pedon: Towards the next generation of transfer functions to estimate saturated hydraulic conductivity

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# Why you should stay in this presentation?

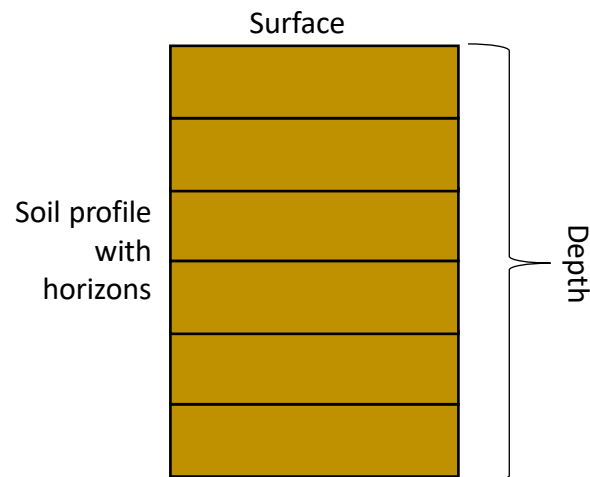
Here we present a new framework to predict  $K_{sat}$  using transfer functions

From Pedotransfer Function  
(PTF)

Common PTFs (usually used)

- Soil material arising from different soil horizons are treated as independent samples.
- Highly dependent of soil textural information

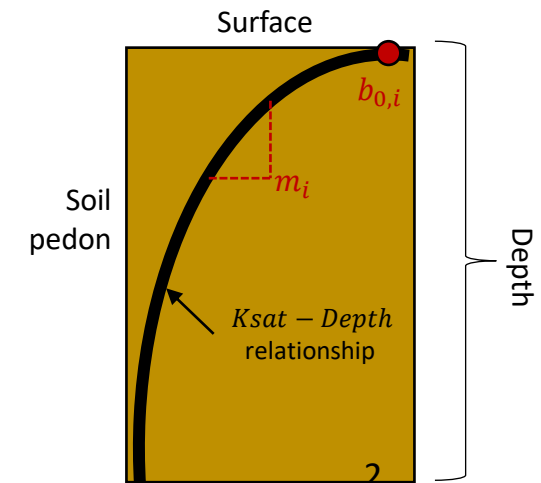
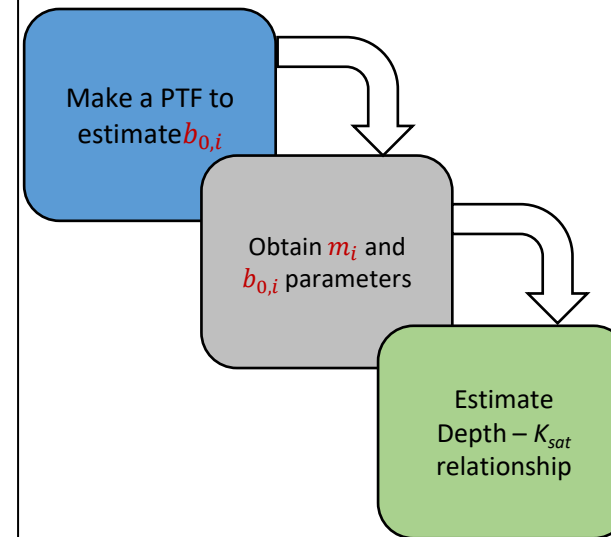
$$K_{sat} = f(\text{clay}) + f(\text{sand}) + f(\text{bulk density})$$



To Pedontransfer Function  
(PnTF)

This work (what we propose)

- We present a framework to predict  $K_{sat}$  that incorporates its depth dependency.
- We show that we can predict  $K_{sat}$  at an arbitrary depth from surface information.
- Our best predictors incorporates time-varying information (i.e., meteorological data).



# Different models need PTFs at different spatial scales



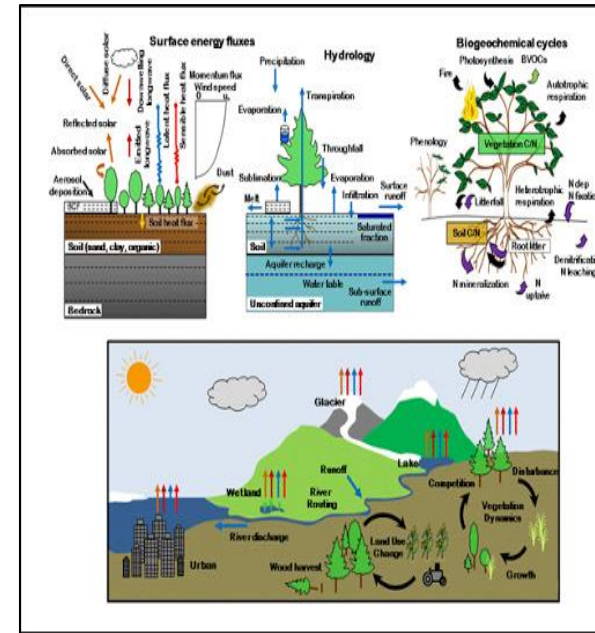
Single-point  
scale



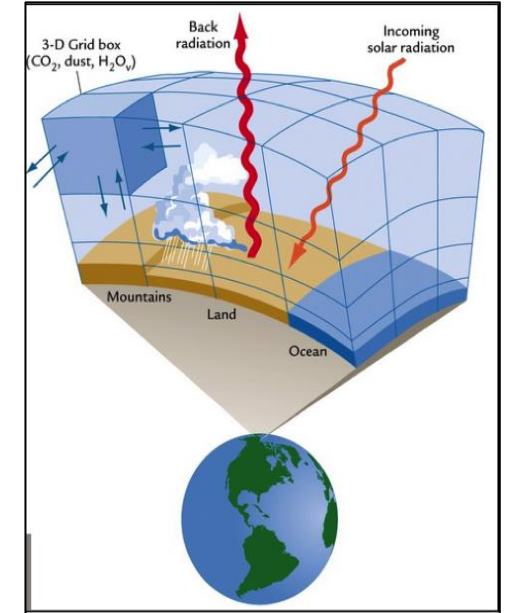
Field  
scale



Landscape  
scale



Land Surface  
Model



Global Climate  
Model



Small scale

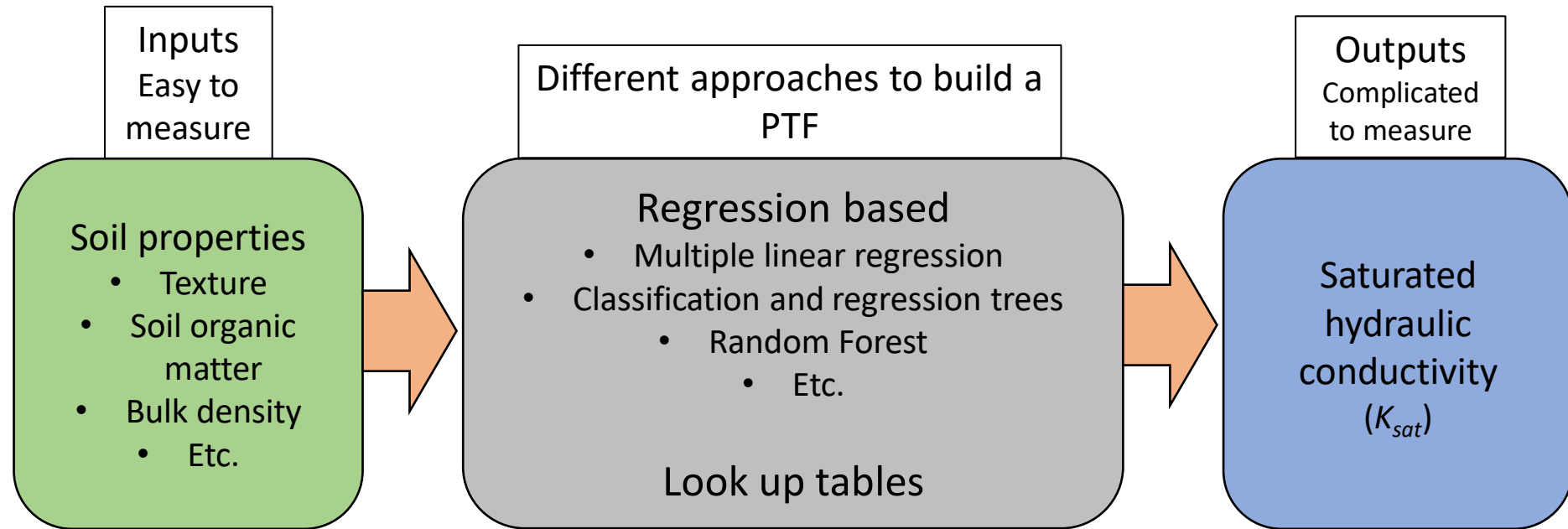
Agriculture, water,  
solute transport

Energy and mass  
balance

Climate  
change

Large scale

# Common PTFs are simple to implement



Soil material arising from different soil horizons are treated as independent samples despite the depth dependency that exists for horizons within individual profiles.

## Limitations

PTFs remain highly dependent of soil textural information rather than incorporating time varying biotic or climatological variables.

# Common PTFs are simple to implement

Examples from Zhang & Schaap (2019)

(2) Two independent variables to estimate  $K_s$  in Cosby et al. (1984)

$$K_s = 60.96 \times 10^{0.0126 \times \text{sand} - 0.0064 \times \text{clay} - 0.6} \quad (\text{B3})$$

(3) Wösten et al. (1999)

$$\begin{aligned} K_s &= \exp[7.755 + 0.0352 \times \text{silt} + 0.93 \times \text{topsoil} - 0.967 \times BD^2 - 0.000484 \times \text{clay}^2 - 0.000322 \times \text{silt}^2 + 0.001/\text{silt} - 0.0748/OM - 0.643 \times \ln(\text{silt}) \\ &\quad - 0.01398 \times BD \times \text{clay} - 0.1673 \times BD \times OM + 0.02986 \times \text{topsoil} \times \text{clay} - 0.03305 \times \text{topsoil} \times \text{silt}] \end{aligned} \quad (\text{B4})$$

where topsoil and subsoil are qualitative variables having the value of 1 or 0, respectively.

Soil material arising from different soil horizons are treated as independent samples despite the depth dependency that exists for horizons within individual profiles.

**Limitations**

PTFs remain highly dependent of soil textural information rather than incorporating time varying biotic or climatological variables.

# From Pedo to Pedon

Is there a depth-dependency of  $K_{sat}$  and can we incorporate the depth-dependency of  $K_{sat}$  in PTFs?

- Need to incorporate time-varying variables to predict  $K_{sat}$   
Time varying variables usually are available/influence soil surface  
(Precipitation, VPD, LAI, NDVI)

## Motivation:

- Could  $K_{sat}$  at an arbitrary depth be predicted from the surface?

# What data did we used?

## Pedogenic and Environmental DataSet (PEDS)

Includes climatological and field-based pedon information from >300,000 soil horizons across the globe. We used USA data only.

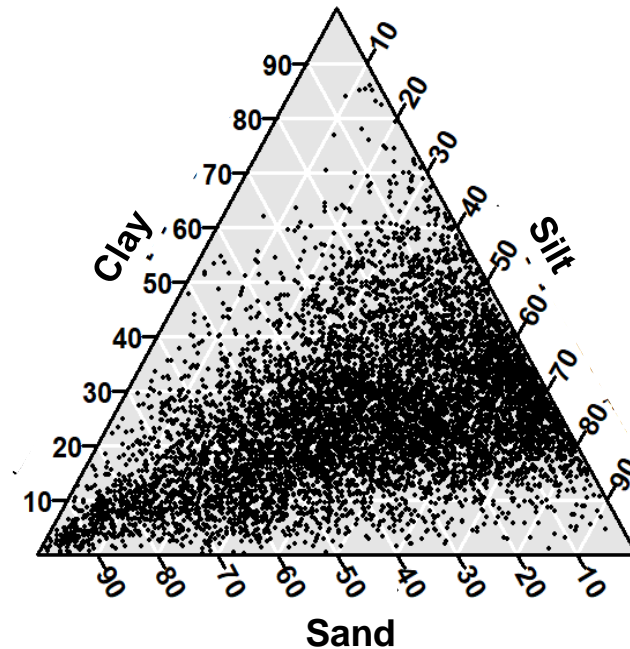
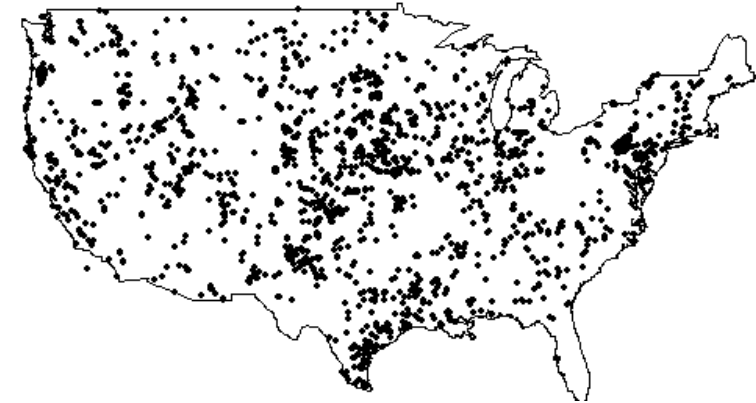
$K_{sat}$  was estimated using a Kozeny-Carman equation:

$$K_{sat} = 1930EP^{3-D}$$

where:

D = Slope of the water retention curve

EP = Effective porosity



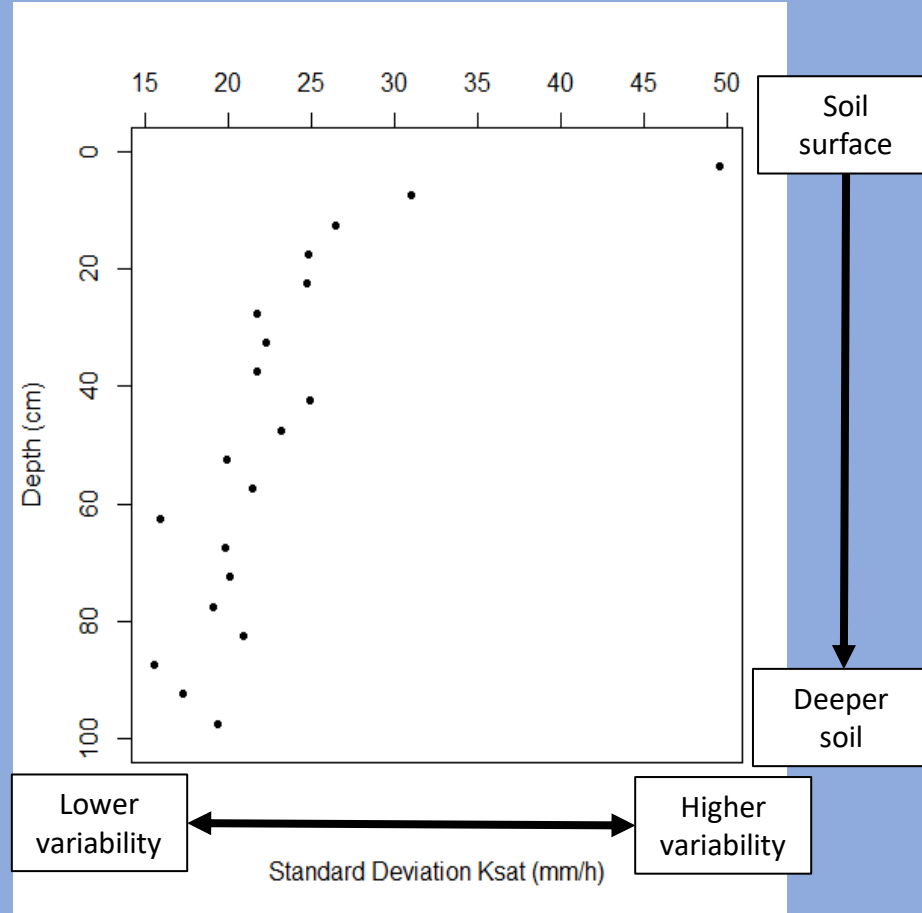
# Is there a depth-dependency of $K_{sat}$ ?

## Variability of $K_{sat}$ decreases at depth

- Higher variability of  $K_{sat}$  at surface, lower variability of  $K_{sat}$  at depth
- The magnitude of  $K_{sat}$  decreases with depth

### Potential reasons:

- Macroporosity constrained by overburden pressure
- Lessivage of soil fine particles





# Is there a depth-dependency of $K_{sat}$ ?

Could  $K_{sat}$  at an arbitrary depth be predicted from the surface?

$$K_{sat} = b_{0,i}(Z)^{m_i} \quad \text{Left panel}$$

$$\ln K_{sat} = \ln b_{0,i} + m_i \ln Z \quad \text{Right panel}$$

where:

$K_{sat}$  = Saturated hydraulic conductivity

$Z$  = Soil depth

$b_{0,i}$  = Intercept or  $K_{sat}$  at 1 cm below land surface in the  $i$ th soil profile

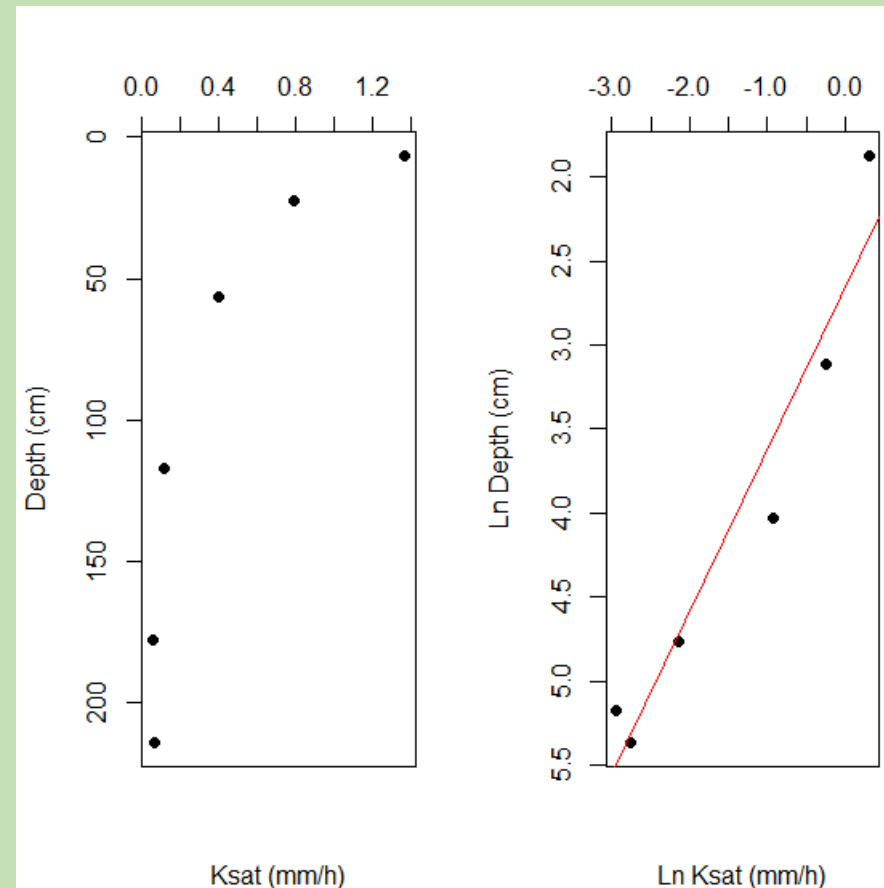
$m_i$  = Slope of the linearized  $K_{sat}$ - $Z$  function for the  $i$ th soil profile

We estimated the  $b_{0,i}$  and  $m_i$  parameters for each soil profile

Regular units



Ln scale units



# Is there a depth-dependency of $K_{sat}$ ?

Could  $K_{sat}$  at an arbitrary depth be predicted from the surface?

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$$\ln K_{sat} = \ln b_{0,i} + m_i \ln Z$$

where:

$K_{sat}$  = Saturated hydraulic conductivity

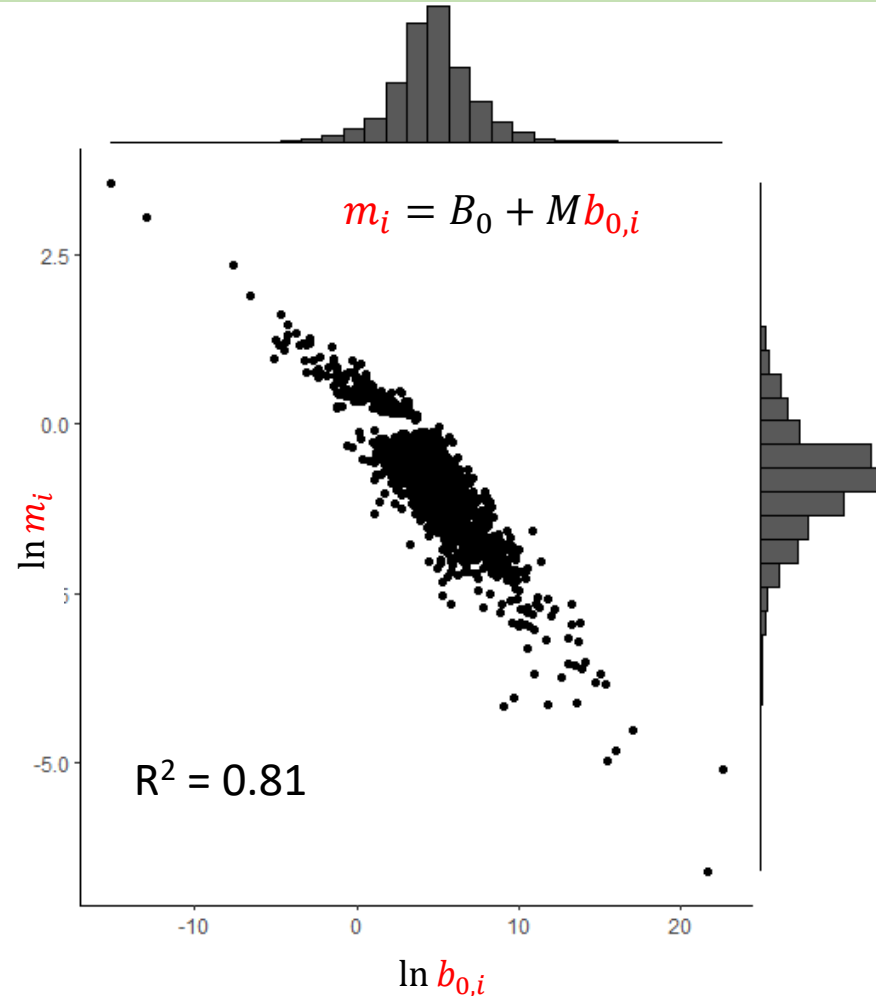
$Z$  = Soil depth

$b_{0,i}$  = Intercept or  $K_{sat}$  at 1 cm below land surface in the  $i$ th soil profile

$m_i$  = Slope of the linearized  $K_{sat}$ - $Z$  function for the  $i$ th soil profile

We estimated the  $b_{0,i}$  and  $m_i$  parameters for each soil profile

We found a negative linear relationship that exists between the intercept and the slope of the regressions

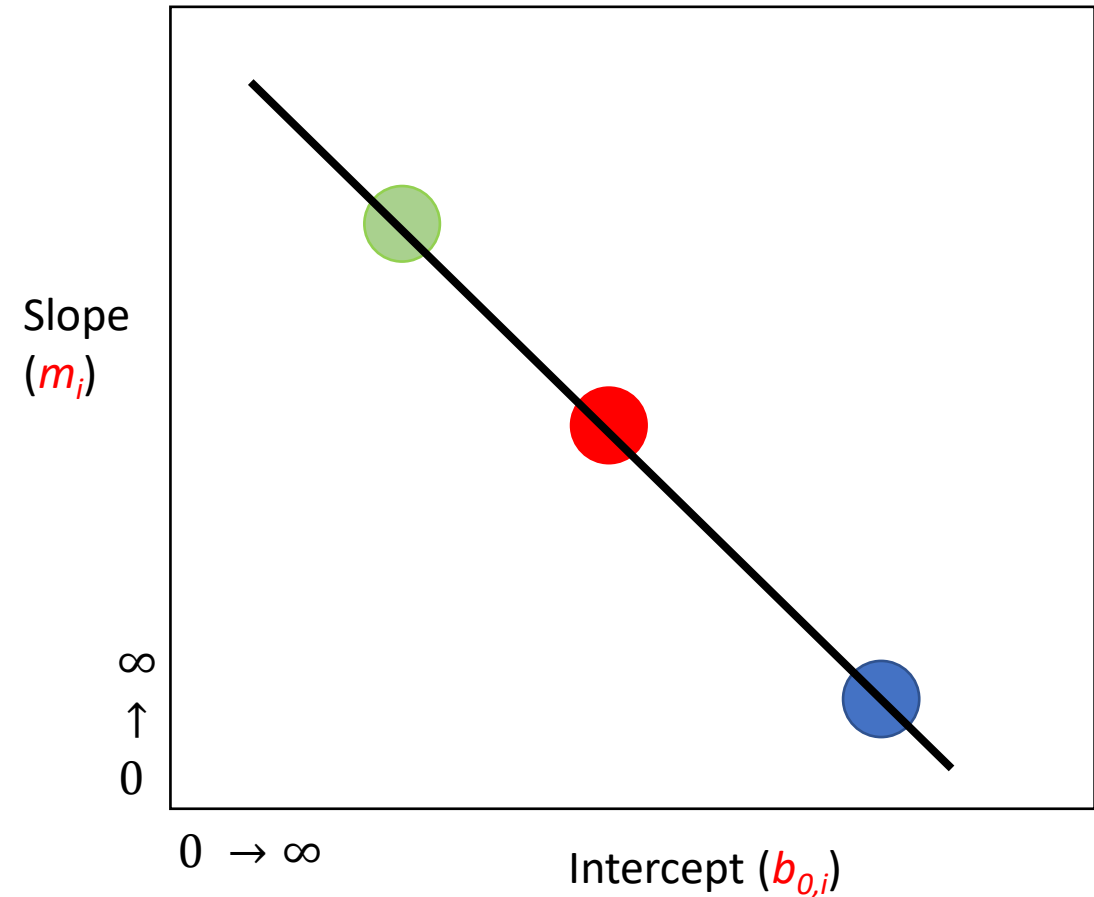
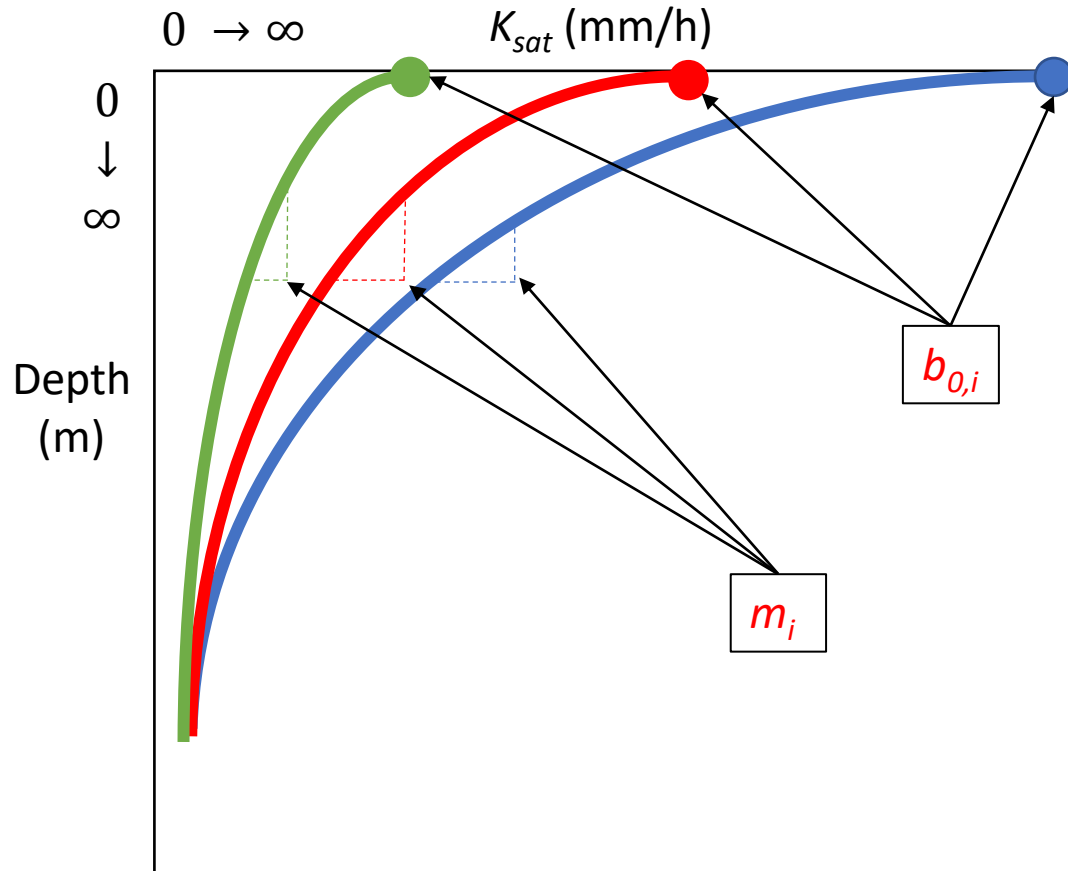


This suggests that we can use  $K_{sat}$  at surface ( $b_{0,i}$ ) to predict its rate of change in relation to depth

$B_0$  = Intercept from a population of profile-derived parameters

$M$  = Corresponding slope

# Example for the negative linear relationship between the intercept and the slope of the regressions



$b_{0,i}$  = Intercept or  $K_{sat}$  at 1 cm below land surface in the  $i$ th soil profile

$m_i$  = Slope of the linearized  $K_{sat}$ -Z function for the  $i$ th soil profile

The higher the intercept, the higher the rate of decrease

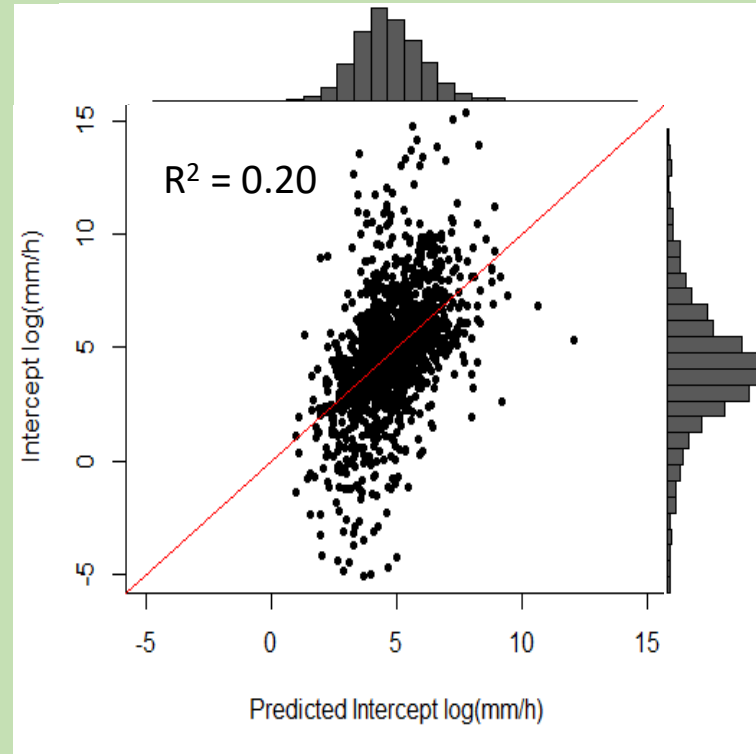
# Can we predict $K_{sat}$ at surface ( $b_{0,i}$ )?

- We build a common PTF to predict  $b_{0,i}$
- We used a stepwise multiple linear regression (MLR) to predict  $b_{0,i}$
- Initial predictor variables:
  - Bulk density (BD)
  - Sand
  - Clay
  - pH
  - Coefficient of linear extensibility (COLE)
  - Mean annual precipitation (MAP)
  - Mean annual temperature (MAT)
  - Vapor pressure deficit (VPD)

\*Soil data is for the upper horizon

$b_{0,i}$  = Intercept or  $K_{sat}$  at 1 cm below land surface in the  $i$ th soil profile

$m_i$  = Slope of the linearized  $K_{sat}$ -Z function for the  $i$ th soil profile



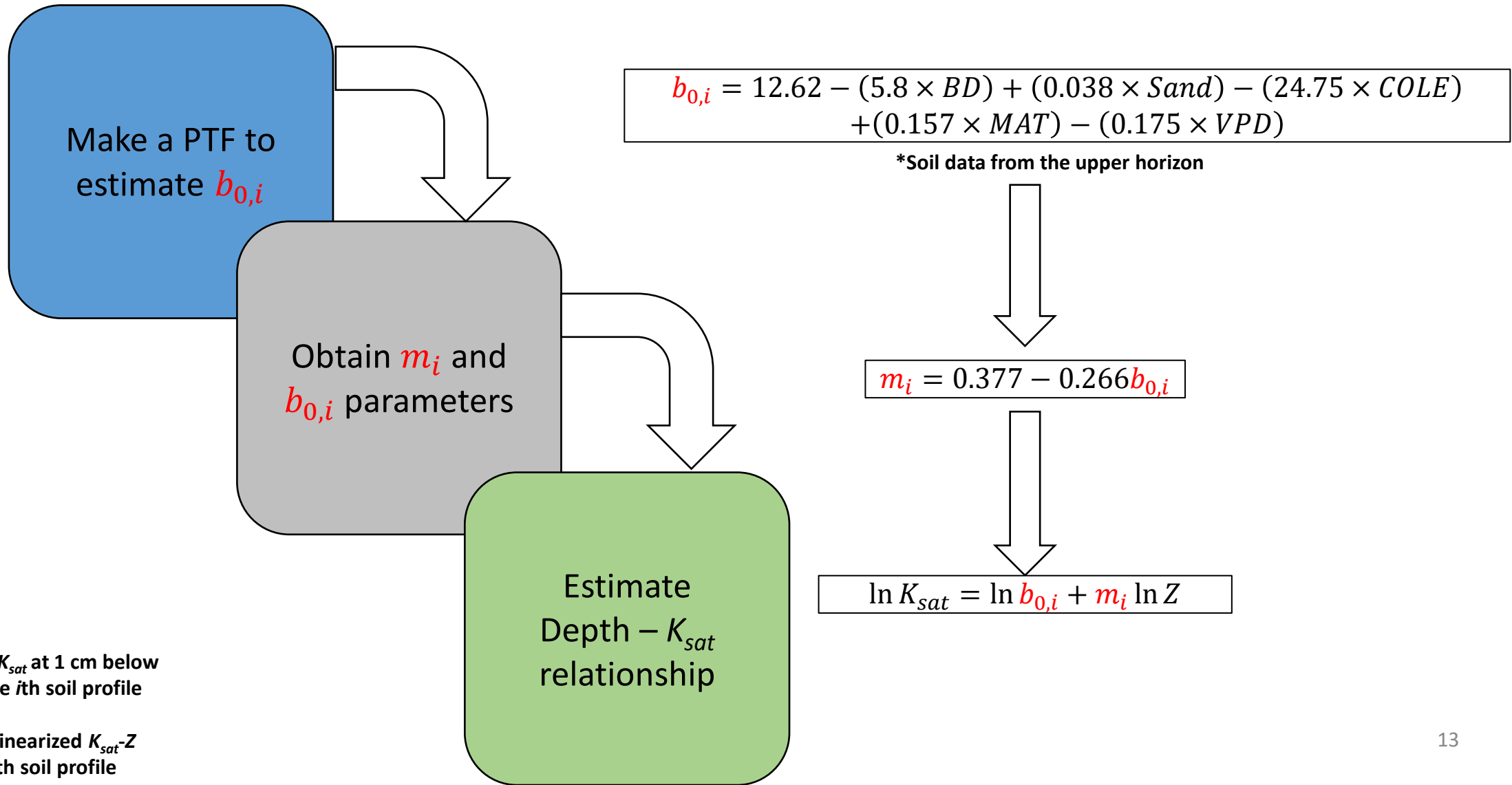
## Final predictor variables:

- Bulk density
- Sand
- Coefficient of Linear Extensibility (COLE)
- Mean annual temperature (MAT)
- Vapor pressure deficit (VPD)

$$\begin{aligned} b_{0,i} &= 12.62 - (5.8 \times BD) + (0.038 \times Sand) - (24.75 \times COLE) \\ &\quad + (0.157 \times MAT) - (0.175 \times VPD) \end{aligned}$$

\*Soil data is for the upper horizon

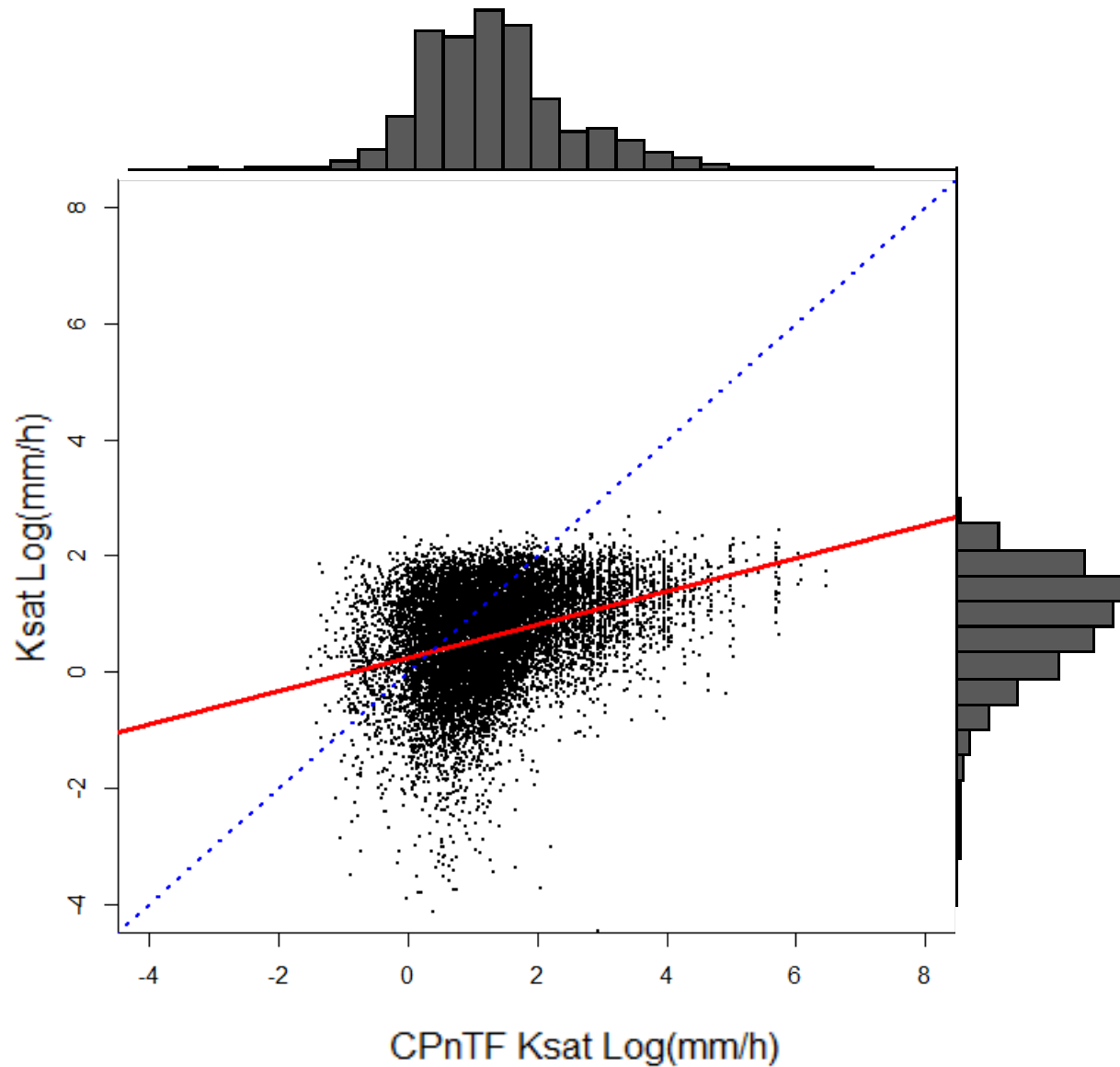
# Workflow - Pedontransfer Function (PnTF)



$b_{0,i}$  = Intercept or  $K_{sat}$  at 1 cm below land surface in the  $i$ th soil profile

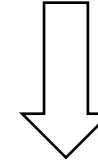
$m_i$  = Slope of the linearized  $K_{sat}$ - $Z$  function for the  $i$ th soil profile

# Pedontransfer Function (PnTF)

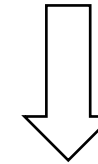


$$b_{0,i} = 12.62 - (5.8 \times BD) + (0.038 \times Sand) - (24.75 \times COLE) + (0.157 \times MAT) - (0.175 \times VPD)$$

\*Soil data from the upper horizon



$$m_i = 0.377 - 0.266b_{0,i}$$



$$\ln K_{sat} = \ln b_{0,i} + m_i \ln Z$$

$b_{0,i}$  = Intercept or  $K_{sat}$  at 1 cm below land surface in the  $i$ th soil profile

$m_i$  = Slope of the linearized  $K_{sat}$ - $Z$  function for the  $i$ th soil profile

# Summary and conclusions

## Limitations

- There are overestimations at high and low extremes of  $K_{sat}$
- There is a low explained variability of the 1:1 relationship of the predicted VS observed  $K_{sat}$

## Future work

- Improve the prediction of  $b_{0,i}$ 
  - Classification and regression trees
  - Random forests
  - Artificial Neural Networks
- Explore new predictors for  $b_{0,i}$
- Use taxonomic information to find where the performance of PnTF is good/bad

$b_{0,i}$  = Intercept or  $K_{sat}$  at 1 cm below land surface in the  $i$ th soil profile

$m_i$  = Slope of the linearized  $K_{sat}$ -Z function for the  $i$ th soil profile

# Summary and conclusions

- We presented a framework to predict  $K_{sat}$  that incorporates its depth dependency.
- We have shown that, at a modest level, we can predict  $K_{sat}$  at an arbitrary depth from surface information.
- Our best predictors incorporates time-varying information (i.e., meteorological data).



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## Questions?

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