The RITAS algorithm

A constructive yield monitor data processing algorithm

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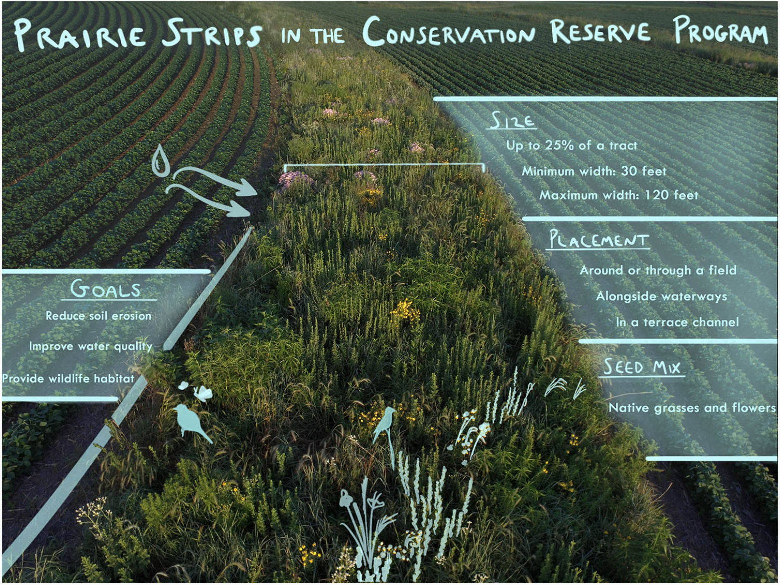
2020-10-21

Department of Statistics
Iowa State University

Road map

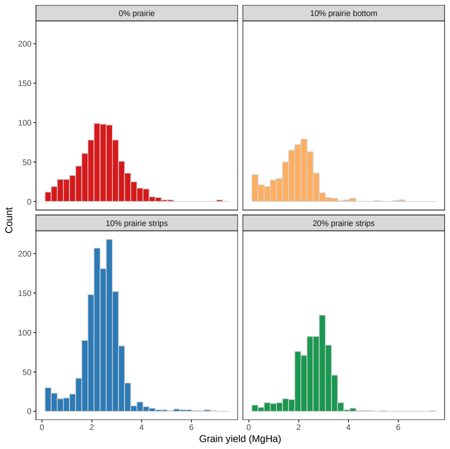
Introduction

Context


PRAIRIE STRIPS IN THE CONSERVATION RESERVE PROGRAM
SIZE
Up to 25% of a tract
Minimum width: 30 feet
Maximum width: 120 feet
PLACEMENT
Around or through a field
Alongside waterways
In a terrace channel
SEED MIX
Native grasses and flowers
GOALS
Reduce soil erosion
Improve water quality
Provide wildlife habitat

Context

What is the magnitude of crop grain yield decrease associated with the presence of prairies?



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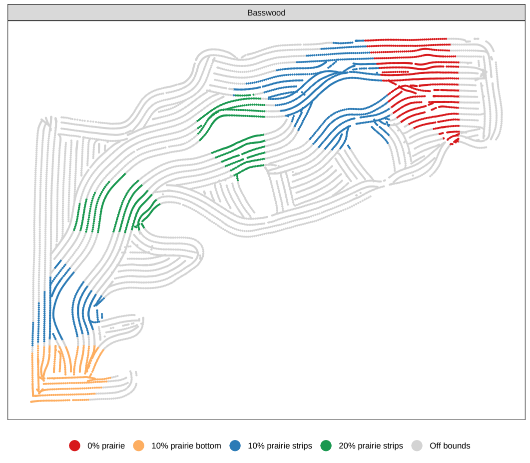


Data acquisition

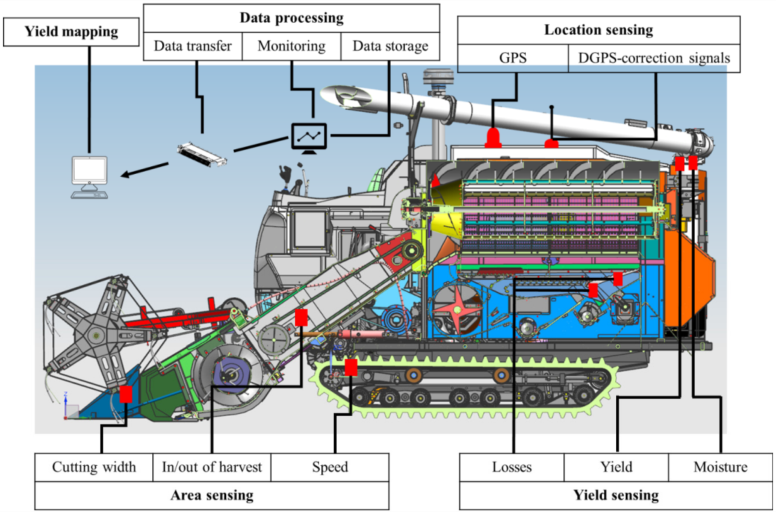
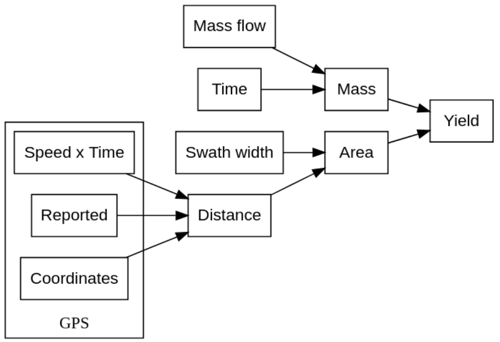


Figure 1: Yield monitoring component diagram from **??**

Uncertainty map



Modeling challenges

- Harvesting dynamics (time lag, start-pass and end-pass delay)
- Continuous measurements (local harvest circumstances)
- Positioning information (GPS receiver accuracy, repeated locations)
- Operator-induced errors (short segments, sudden speed changes, narrow finishes and overlaps, sharp turns, calibration)

Current analysis methodology

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- Normality vs non-normality

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- Spatial vs non-spatial analysis

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- Spatial vs non-spatial analysis
- Heuristics

The RITAS algorithm

Notation

RITAS

Notation

Time-ordered observations for $t = 0, \ldots, T,\ T \in \mathbb{N}$

RITAS

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RITAS

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RITAS

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[1] Not included in the writing, but it allows for a nice tweak next

RITAS

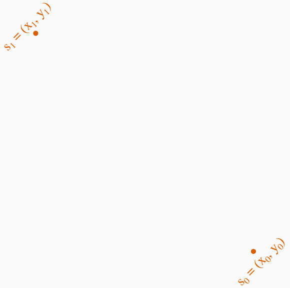
Rectangles

RITAS

Rectangles

Consider two subsequent locations

$\mathbf{s_t}, \mathbf{s_{t-1}}$



Rectangles

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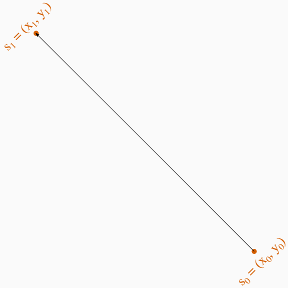
$$b_t = \frac{(y_t - y_{t-1})}{(x_t - x_{t-1})}$$



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$$dx_t = w_t(1 + b_t^{-2})^{-\frac{1}{2}}$$
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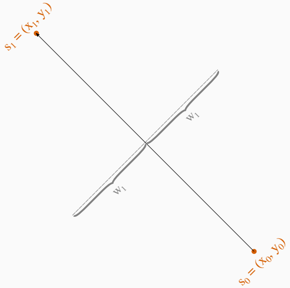

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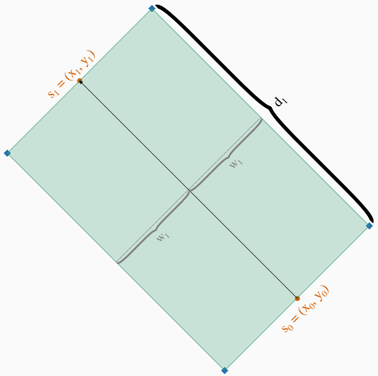

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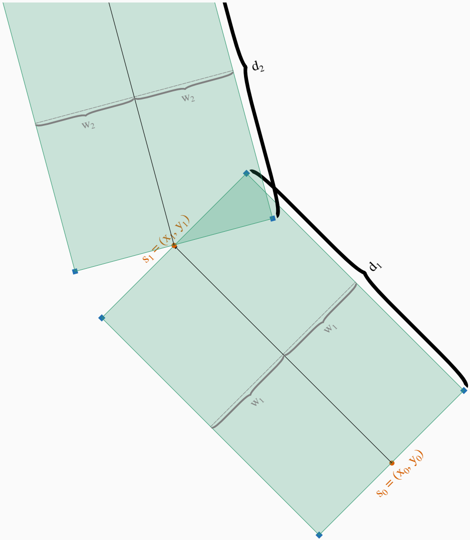
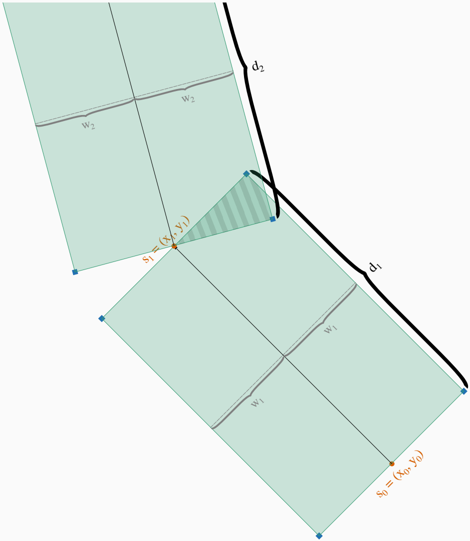
Rectangle collection

$\mathcal{P} = \{P_\tau \colon \tau \in \{1, \ldots, T\}\}$

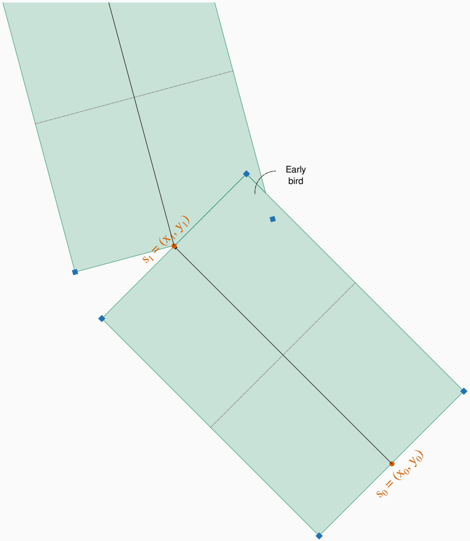


Intersection



RITAS

Tessellation

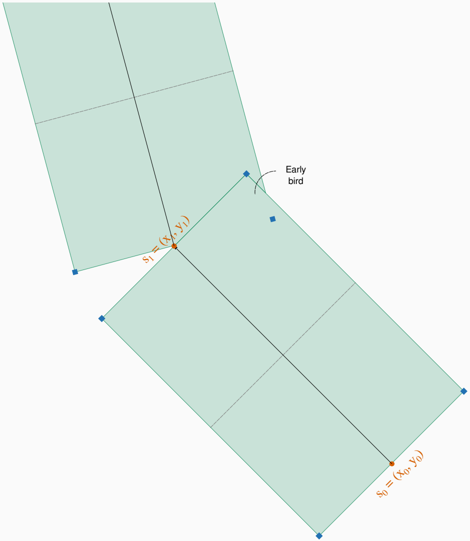


RITAS

Tessellation

Define the time-ordered relative complement

$$\tilde{P}_\tau = P_t \setminus \left(\bigcup_{i=1}^{t-1} P_i \right)$$



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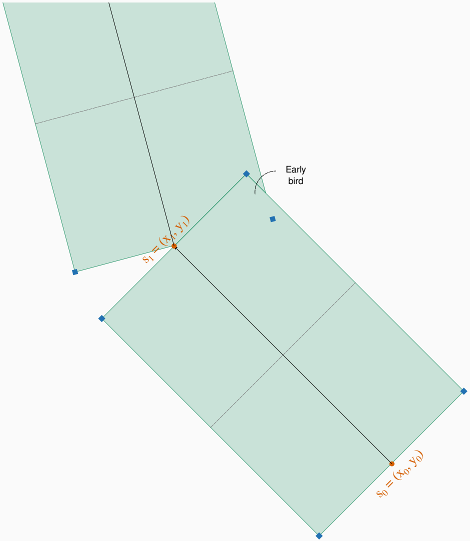

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RITAS

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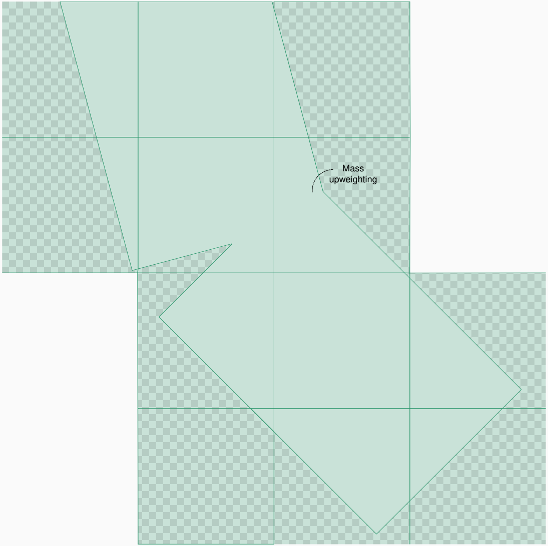
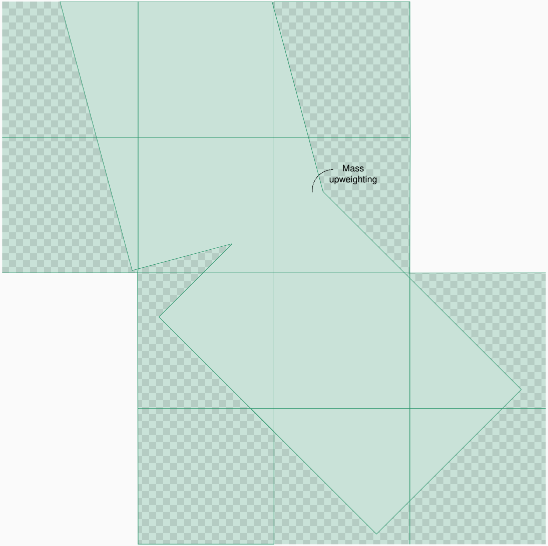


Apportioning

Fix $N \in \mathbb{N}$



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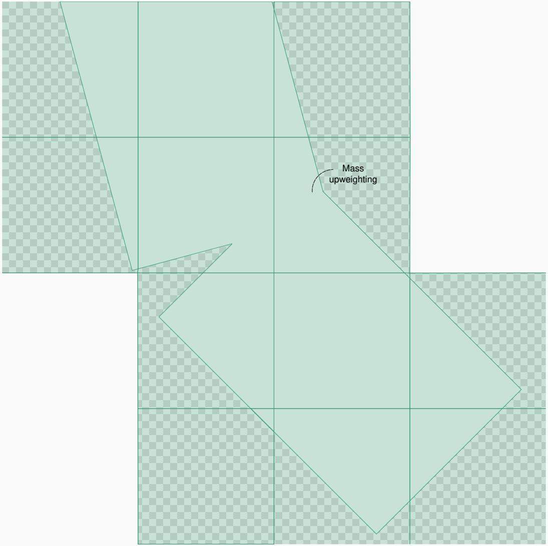
Fix $N \in \mathbb{N}$

Create N equally-sized, non-overlapping, contiguous squares covering $\tilde{\mathcal{P}}$



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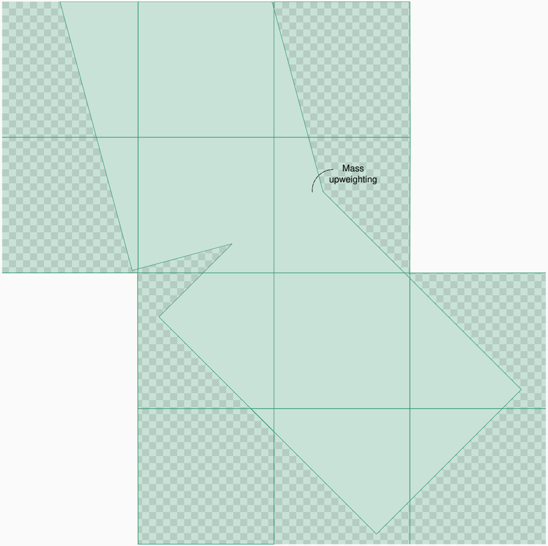

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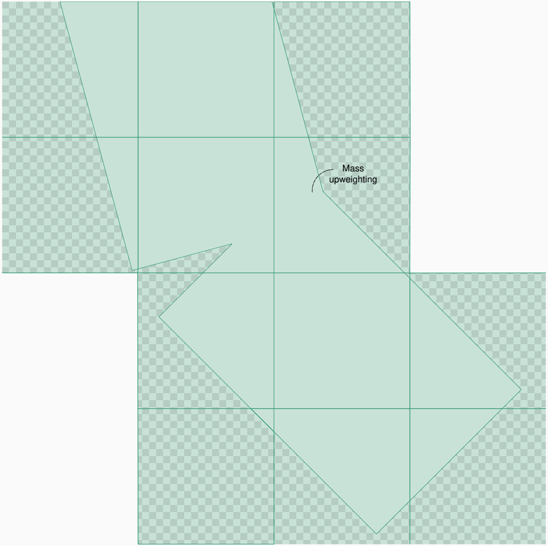
Assign $m_n^* = \sum_{\tau=1}^{T} \pi_{\tau,n} m_\tau$ to the n-th pixel



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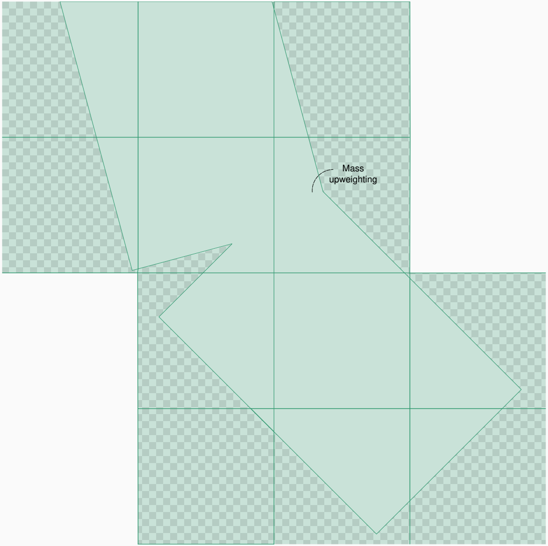

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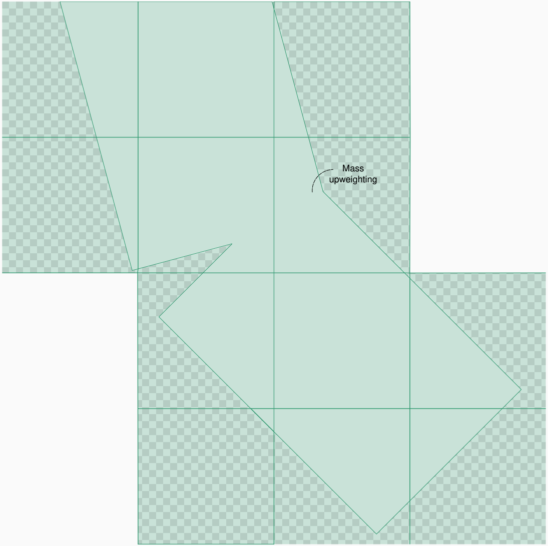
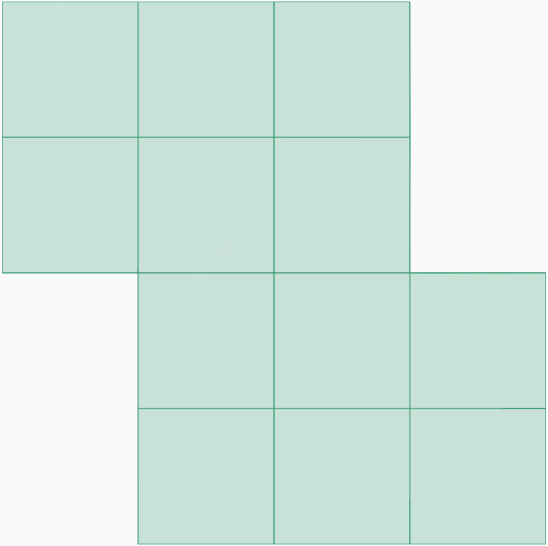


Grid collection

$\mathcal{P}^* = \{P_\tau^* \colon \tau \in \{1, \ldots, T\}\}$

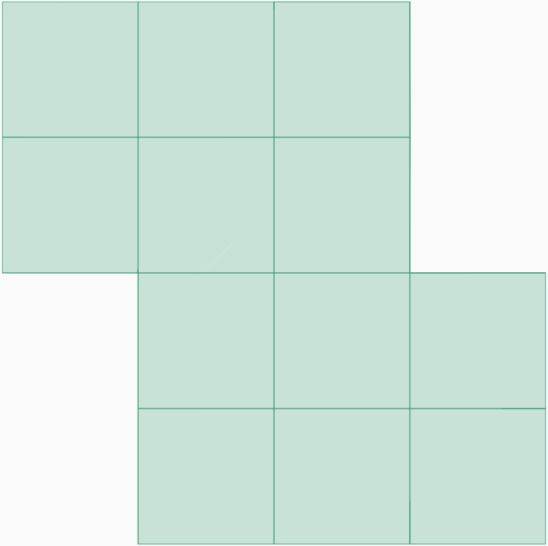
Smoothing



RITAS

Smoothing

- Model



Smoothing

- Model
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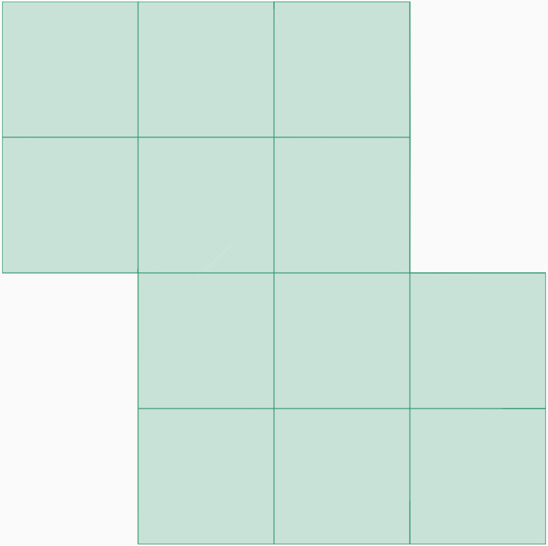

RITAS

Smoothing

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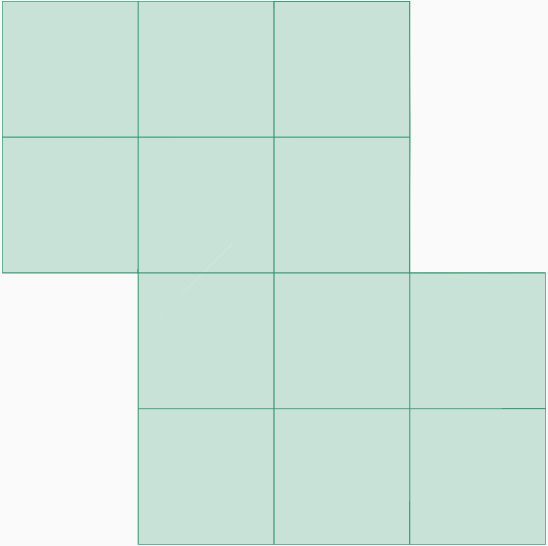

RITAS

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Model

$$f(\mathbf{S}) \triangleq \log(\mathbf{m}) \sim \mathcal{GP}\left(m(\mathbf{S}), k\left(\mathbf{S}, \mathbf{S}'\right)\right)$$

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$$k(d) = \frac{2^{1-\nu}}{\Gamma(\nu)} \left(\frac{\sqrt{2\nu}d}{\ell}\right)^{\nu} K_{\nu}\left(\frac{\sqrt{2\nu}d}{\ell}\right)$$

for $d \geq 0$ known and fixed, $\ell, \nu > 0$ unknown

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Log marginal likelihood

$$\log p(\mathbf{m} \mid \mathbf{S}) = -\frac{1}{2}\mathbf{y}^{\top}\left(K + \sigma_n^2 I\right)^{-1}\mathbf{y} - \frac{1}{2}\log\left|K + \sigma_n^2 I\right| - \frac{n}{2}\log 2\pi$$

for $K = k\left(\mathbf{S}, \mathbf{S}'\right)$

RITAS

Smoothing

Predictive distribution

$$\left[\begin{array}{c}\mathbf{m}\\ \mathbf{f}_*\end{array}\right] \sim \mathcal{N}\left(\mathbf{0}, \left[\begin{array}{cc} K(S,S)+\sigma_n^2 I & K\left(S,S_*\right)\\ K\left(S_*,S\right) & K\left(S_*,S_*\right)\end{array}\right]\right)$$

Smoothing

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$$\begin{bmatrix} \mathbf{m} \\ \mathbf{f}_* \end{bmatrix} \sim \mathcal{N}\left(\mathbf{0}, \begin{bmatrix} K(S,S) + \sigma_n^2 I & K\left(S, S_*\right) \\ K\left(S_*, S\right) & K\left(S_*, S_*\right) \end{bmatrix}\right)$$

$\mathbf{f}_* \mid S, \mathbf{m}, S_* \sim \mathcal{N}\left(\mu_\ell, \sigma_\ell^2\right)$, where

$$\mu_f = K\left(S_*, S\right)\left[K(S,S) + \sigma_n^2 I\right]^{-1} \mathbf{y}$$

$$\sigma_f^2 = K\left(S_*, S_*\right) - K\left(S_*, S\right)\left[K(S,S) + \sigma_n^2 I\right]^{-1} K\left(S, S_*\right)$$

RITAS

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$$\mathbf{f}_* \mid S, \mathbf{m}, S_* \sim \mathcal{N}\left(\mu_\ell, \sigma_\ell^2\right), \text{ where}$$

$$\mu_f = K(S_*,S)\left[K(S,S)+\sigma_n^2 I\right]^{-1}\mathbf{y}$$

$$\sigma_f^2 = K(S_*,S_*) - K(S_*,S)\left[K(S,S)+\sigma_n^2 I\right]^{-1} K(S,S_*)$$

$$\mu_m = \exp\left(\mu_f + \sigma_f^2/2\right) \quad \text{and} \quad \sigma_m^2 = \exp\left(2\mu_f + \sigma_f^2\right)\left[\exp\left(\sigma_f^2\right) - 1\right]$$

Implementation

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- R package, documentation at about 80%

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  - Has issues with small $\nu < 0.3$

Code snippet

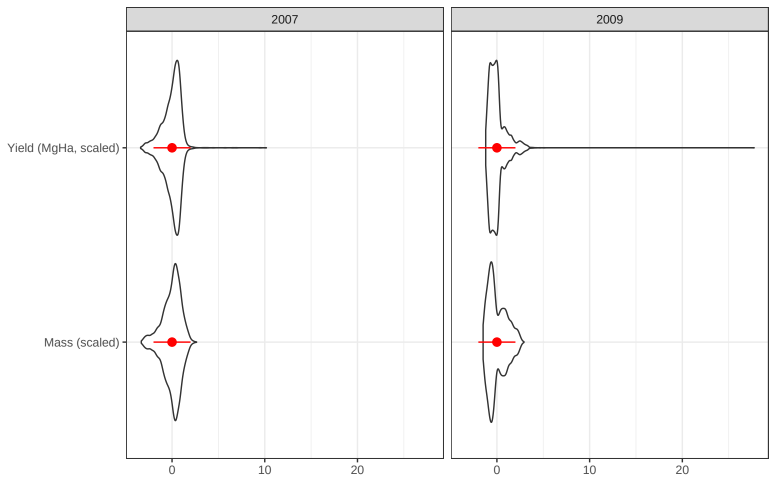
```
proj4string <-
  "+proj=utm +zone=15 +datum=WGS84 +units=m +ellps=WGS84 +towgs84=0,0,0"

> head(DF)
      site year record        x       y  mass swath    d
1 Basswood 2012      0 476877.0 4598424  3.67  6.09   NA
2 Basswood 2012      1 476879.5 4598424  7.87  6.09 1.87
3 Basswood 2012      2 476881.8 4598424  2.65  6.09 2.33
4 Basswood 2012      3 476882.6 4598424  9.26  6.09 0.76
5 Basswood 2012      4 476884.8 4598424 11.68  6.09 2.26
6 Basswood 2012      5 476887.0 4598424 18.14  6.09 2.23

ritas(DF, proj4string, "Basswood", 2012, res = 5, nmax = 0.4, nCores = 16)
```

STRIPS

Data set



Results


Basswood 2012 (corn)
Harvested yield (mg/ha)
0.0 3.7 6.8 10.1 29.5
W 119th St S
S 112th Ave W

Results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Harvested yield (mg/ha)
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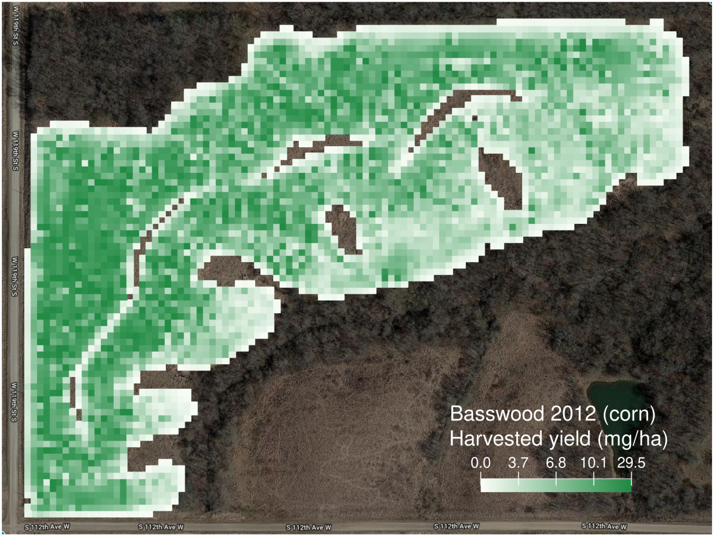

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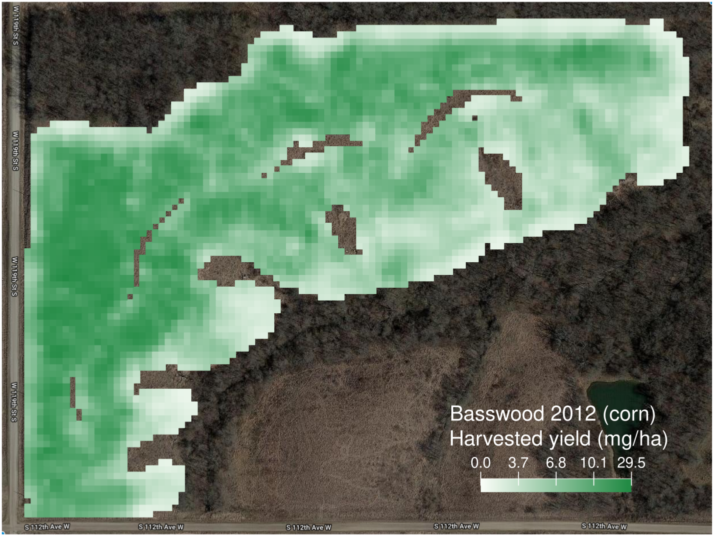
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0.0 3.7 6.8 10.1 29.5
S 112th Ave W
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Discussion

The YAYs!

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- No observations were harmed during the making of this film.
- Apportioned observations are aligned for spatio-temporal analysis (spatial registration).

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- Tessellation, if improved naively, involves $(N-1)!$ operations.
- Time lag processing rules sold separately.

Future work

Variability quantification

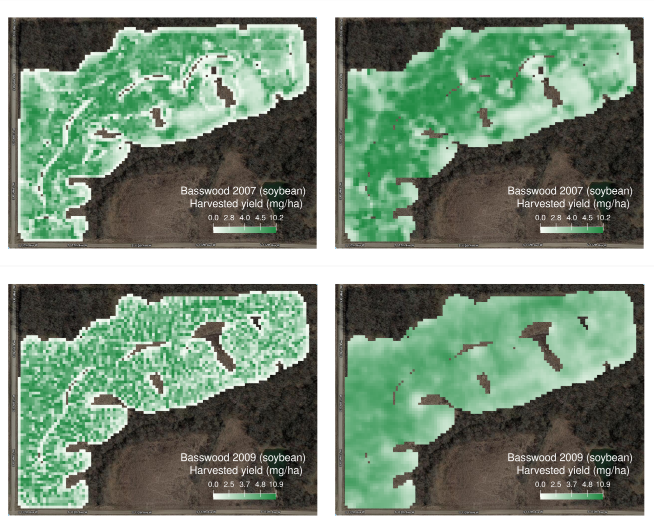

Figure 2: Apportioned (left) and smoothed (right) maps for two datasets with an apparent difference in variability.

Improvement quantification

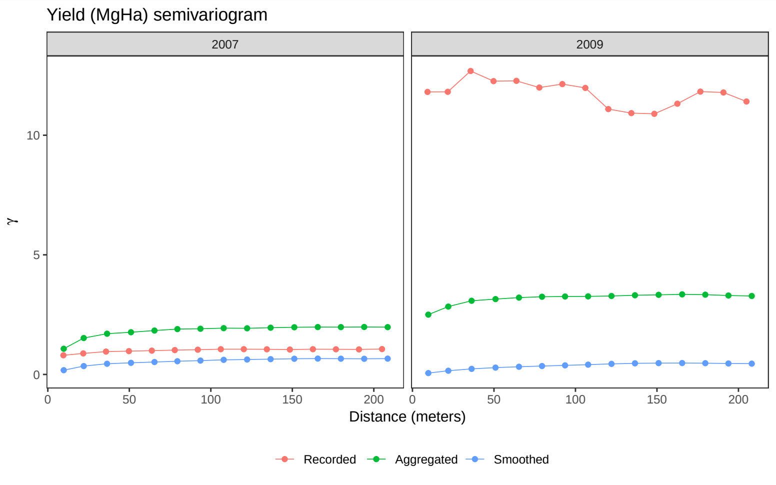

Figure 3: Semivariogram of the yield monitor data

Resolution selection

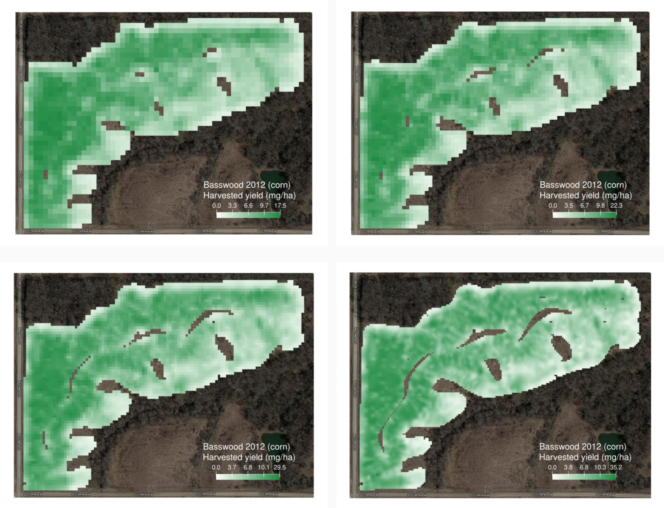

Figure 4: Smoothed map at four different resolutions. Top: 9m, 7m; bottom: 5m, 3m.

References

References i

See Creative Component writing.