AAGI
Analytics for the Australian Grains Industry

Case Studies in Advanced Analysis of Large Strip On-farm Experiments

Zhanglong Cao
Jordan Brown, Suman Rakshit, Mark Gibberd

GRDC Grains Research & Development Corporation | Curtin University | The University of Queensland Australia | The University of Adelaide

What is OFE

These are field trials conducted in consultation with the growers using their machinery and tools to answer questions relevant to their farming practices.

The main objective is to model the spatial relationship between the response (e.g. crop yield or profit) and the treatment factor.

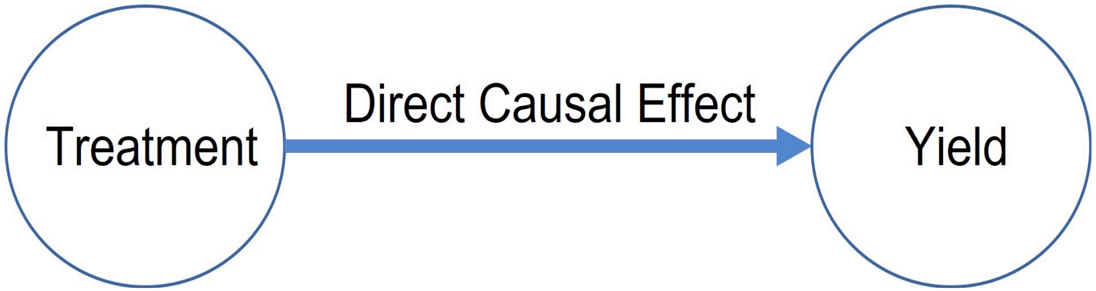
Why OFE

It allows farmers to test different agronomic questions using their equipment and management practices on their own fields. [Kyveryga, P. M., et al, 2018]

It is farmer-centric, where farmers work with consultants and/or researchers to design and implement large-scale experiments on their farms to test management practices. [Evans, F. H., et al, 2020]

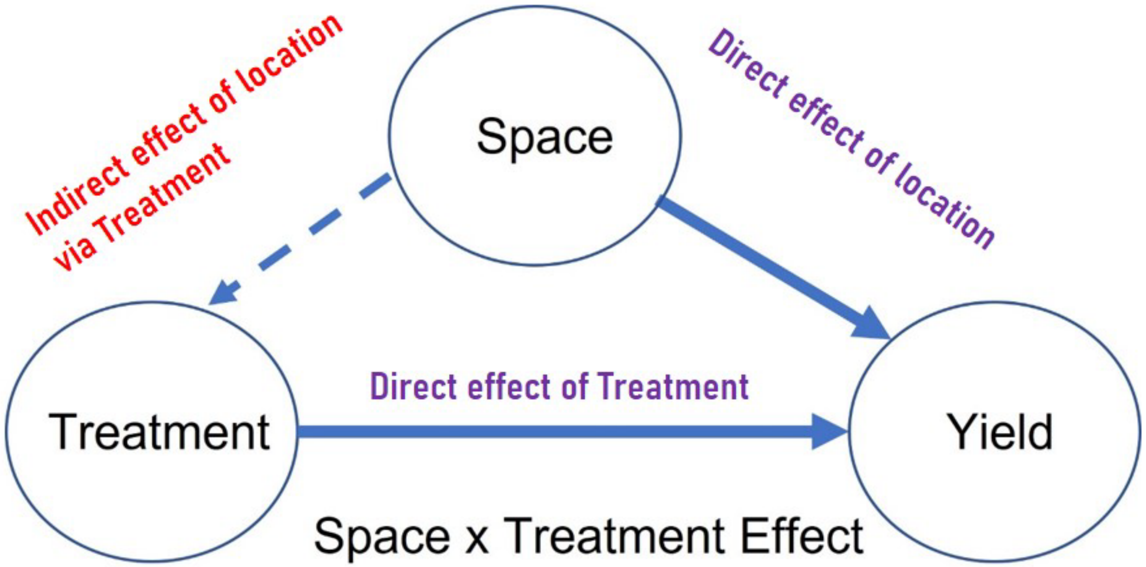
Motivation behind small plot trials

- The main objective of a small plot trial is to obtain an unbiased estimate of the treatment effect.



Motivation behind OFE

- Growers want to test new treatments in their paddock, and the main objective is to determine the location-specific optimal treatments.



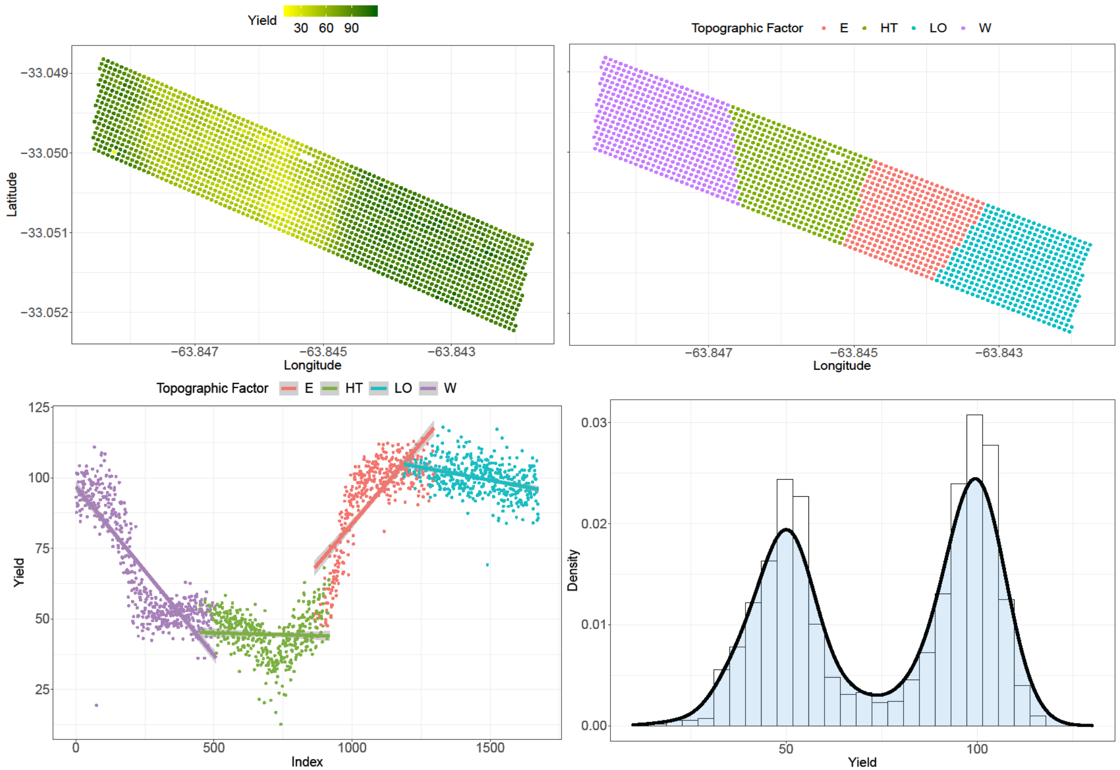
Two types of OFE trials

Local estimation: the shape of the response to a variable input, and optimal input level, vary spatially within the field.

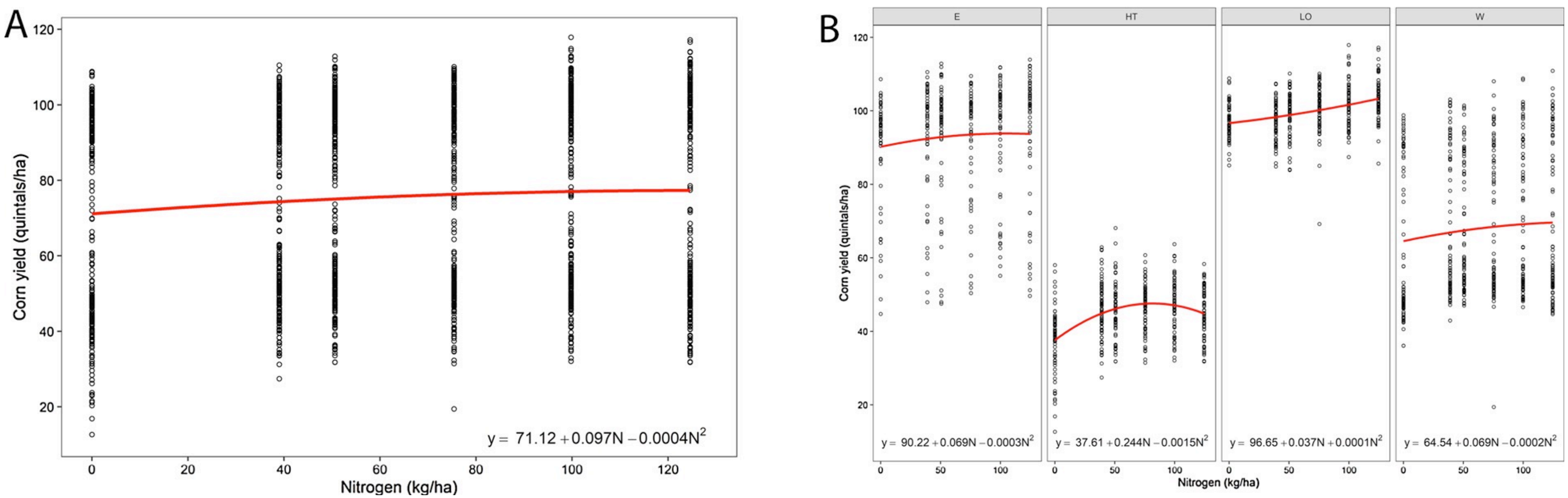
Global estimation: it globally assess the performance of site-specific crop management (SSCM) treatments and possibly compare them to a control treatment.

Case 1: Las Rosas corn yield data

Large strip experiment (18 strips) with 3 replications incorporating 6 nitrogen rates in a systematic design.



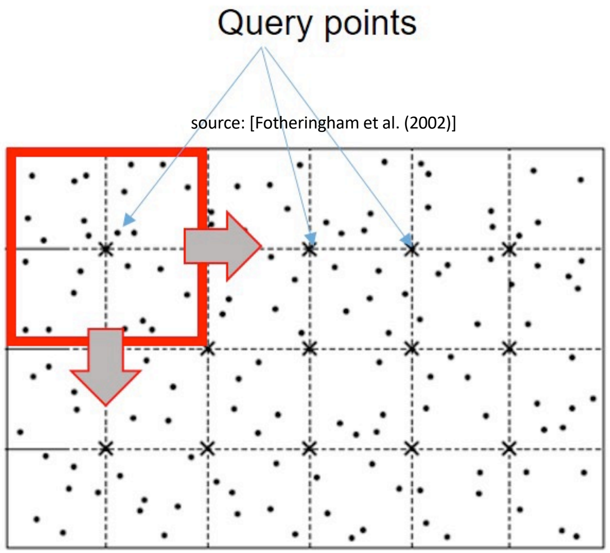
Case 1: Las Rosas corn yield data



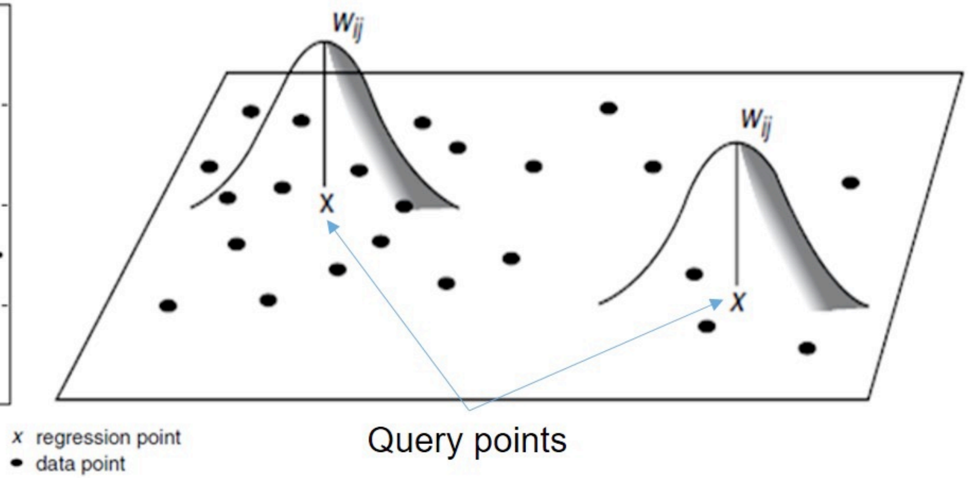
Source: Rakshit et al. (2020)

Solution: geographically weighted regression (GWR)

Moving window regression



GWR with kernel function

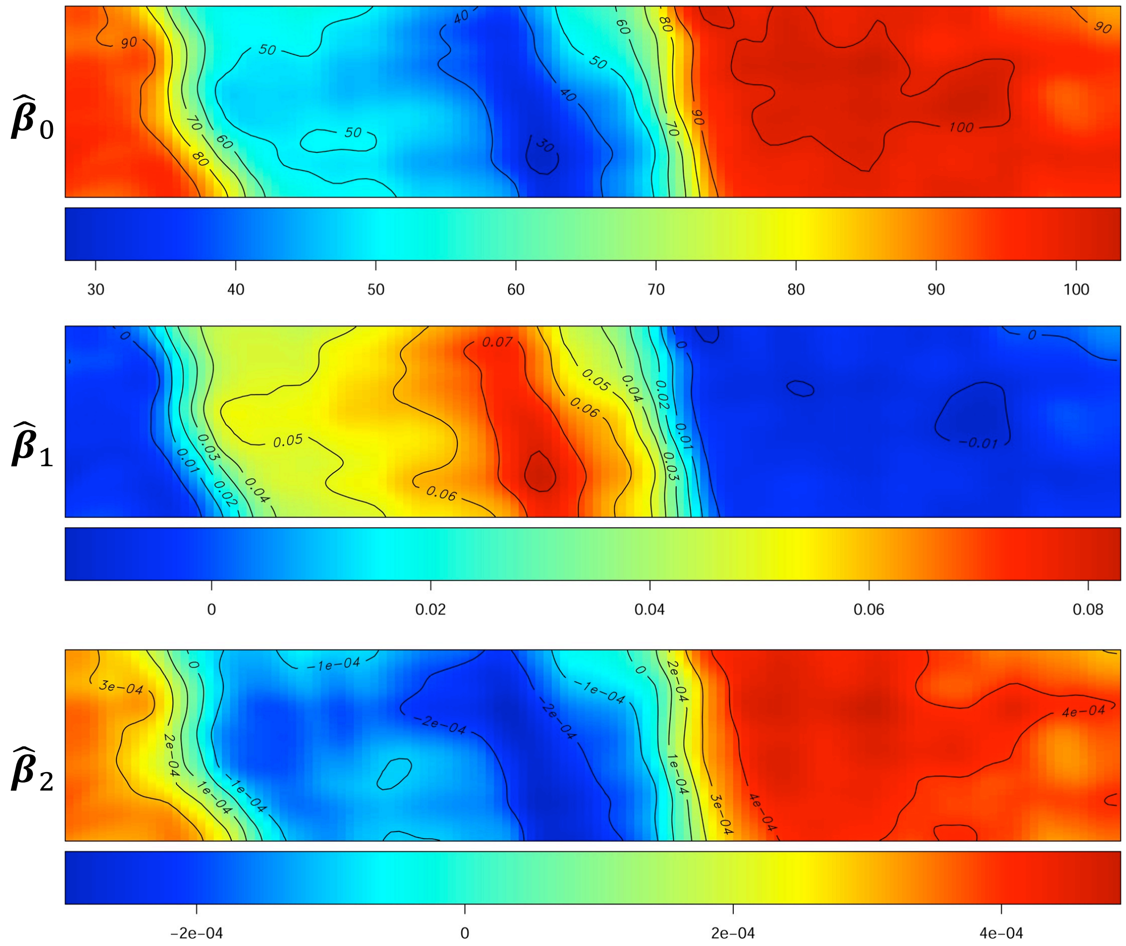


source: [Fotheringham et al. (2002)]

Outcome

Ideally, we would like to find optimal Nitrogen N_i for each grid i.

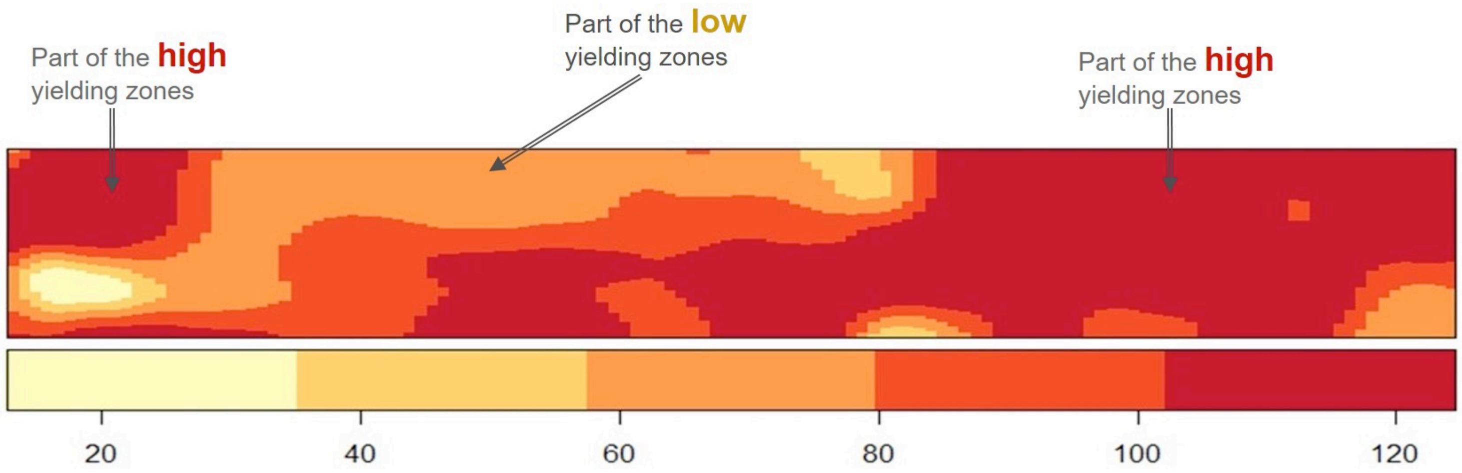
$$y_i = \beta_{0i} + \beta_{1i}N_i + \beta_{2i}N_i^2 + \varepsilon_i$$



Rakshit, S., et al. "Novel approach to the analysis of spatially-varying treatment effects in on-farm experiments." Field crops research 255 (2020): 107783.
Cao, Z., et al. "Bayesian inference of spatially correlated random parameters for on-farm experiment." Field Crops Research 281 (2022): 108477.

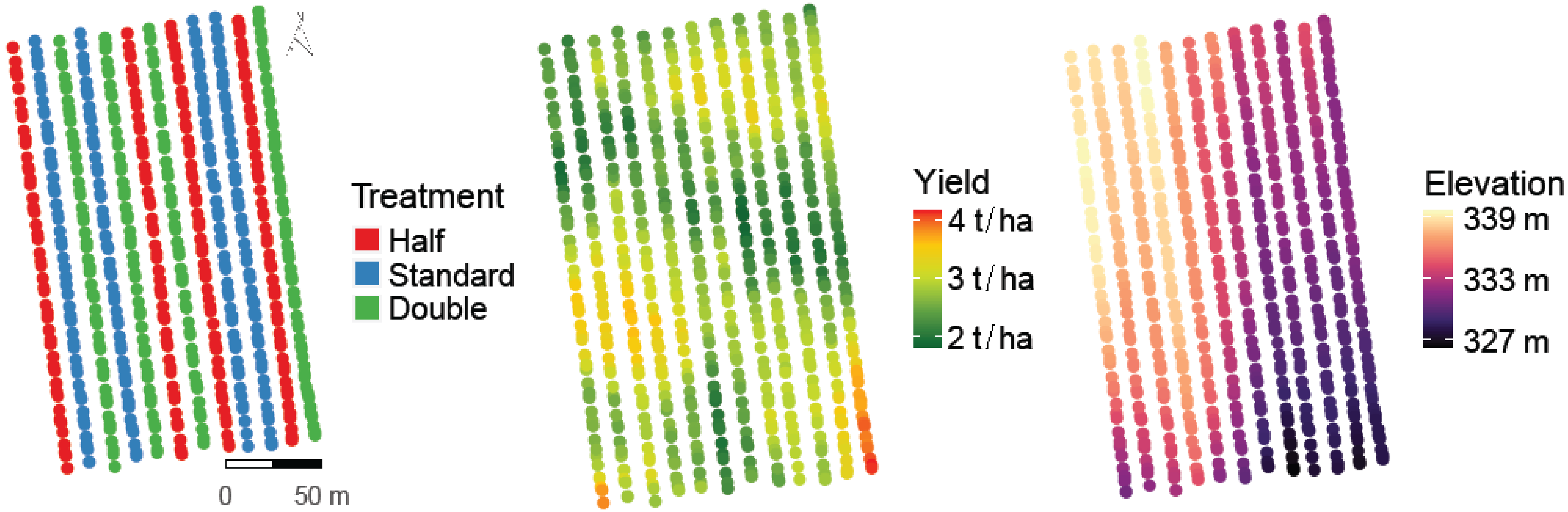
Outcome

Spatial map of the optimum nitrogen levels: $\widehat{N}_i = -\hat{\beta}_{1i}/(2\hat{\beta}_{2i})$

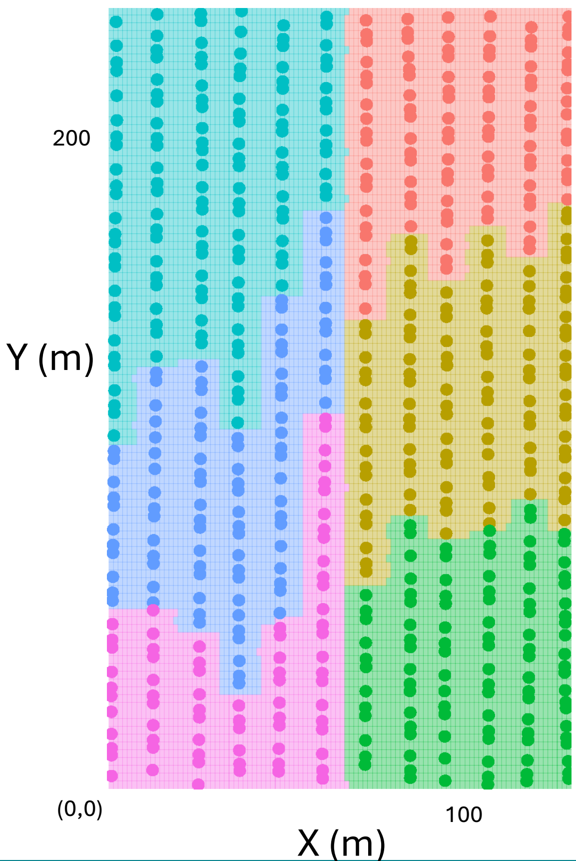


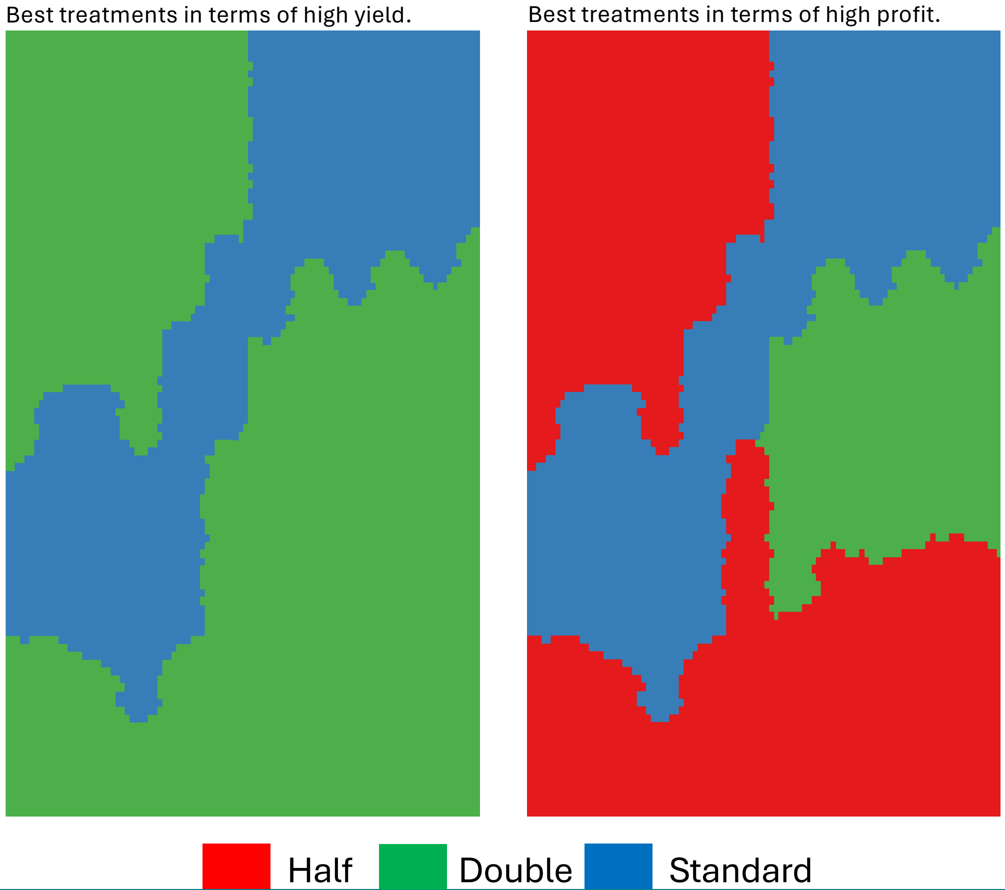
Case 2: winter wheat agronomy for grain growers in the Western region

Large strip experiment (12 strips) with 4 replications incorporating 3 treatment levels in a randomised design.



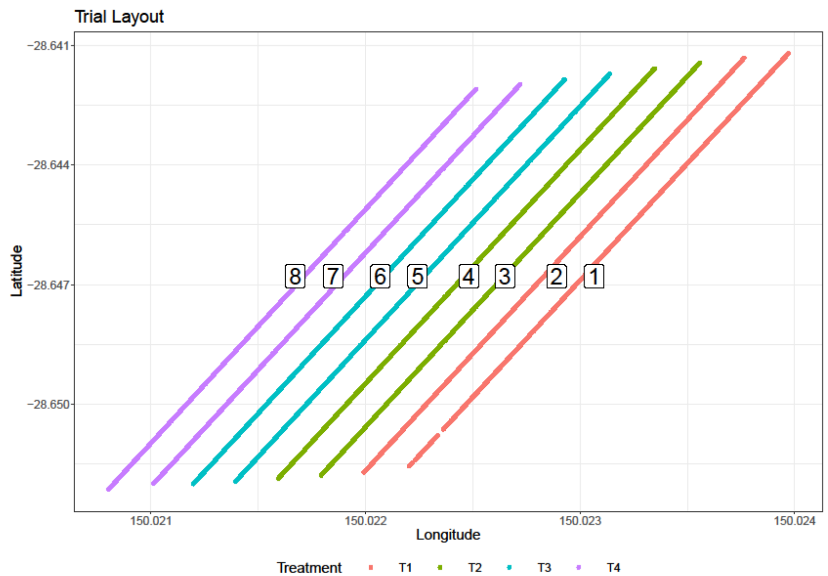
Solution: partition into pseudo-environments using clusters



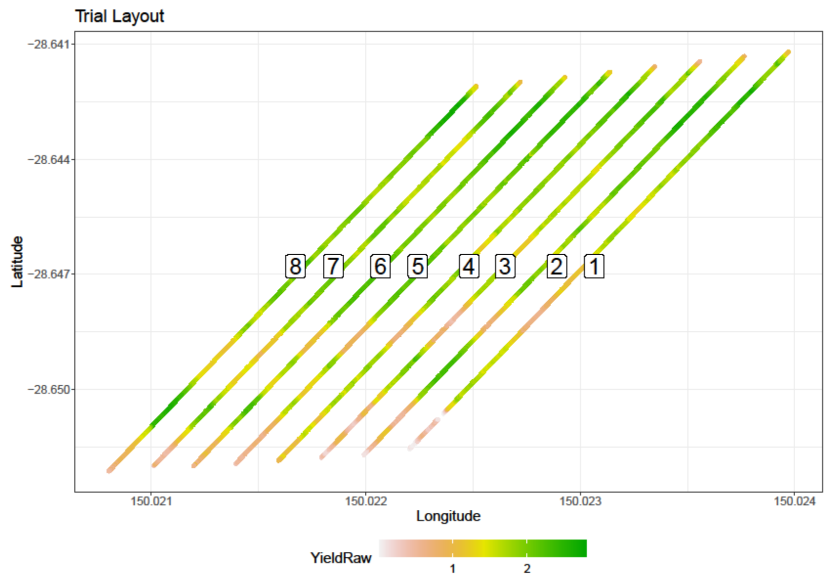


Case 3: economic thresholds and management of faba beans

Large strip experiment (4 strip plots with samples taken from 2 strips per plot) and NO replications incorporating 4 treatments.



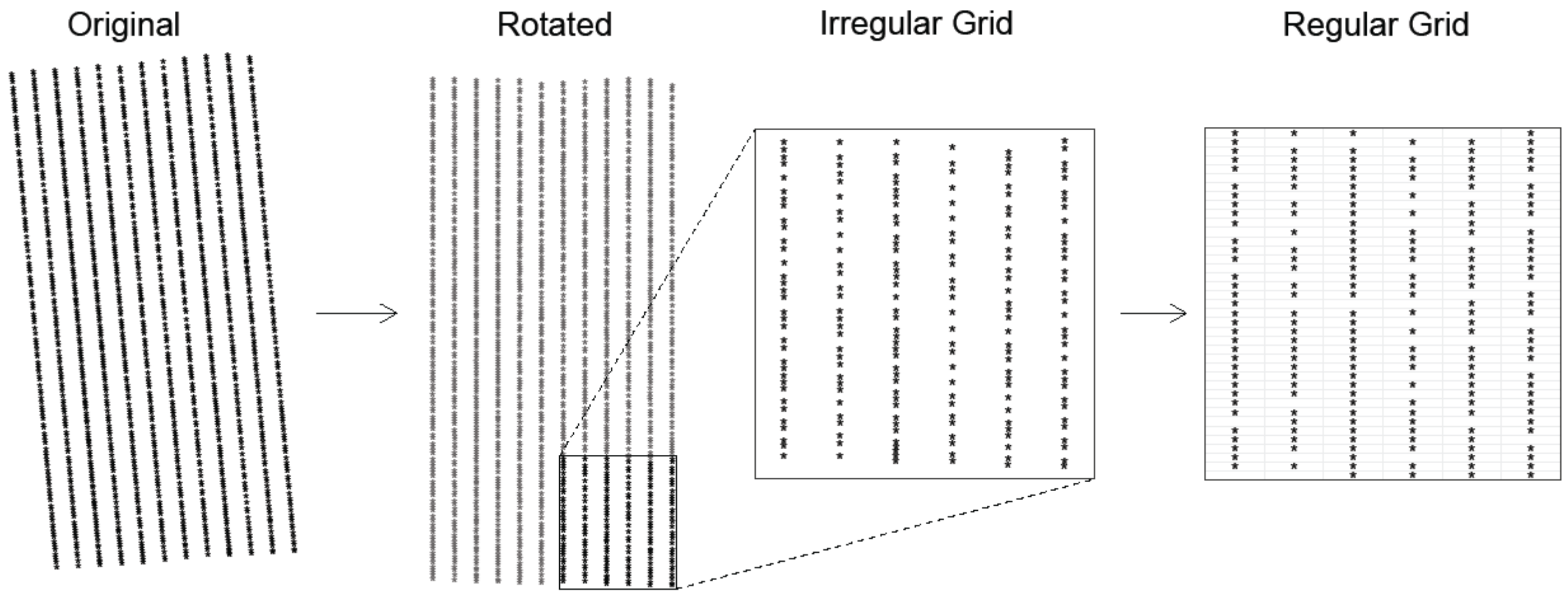
Fungicide treatment map



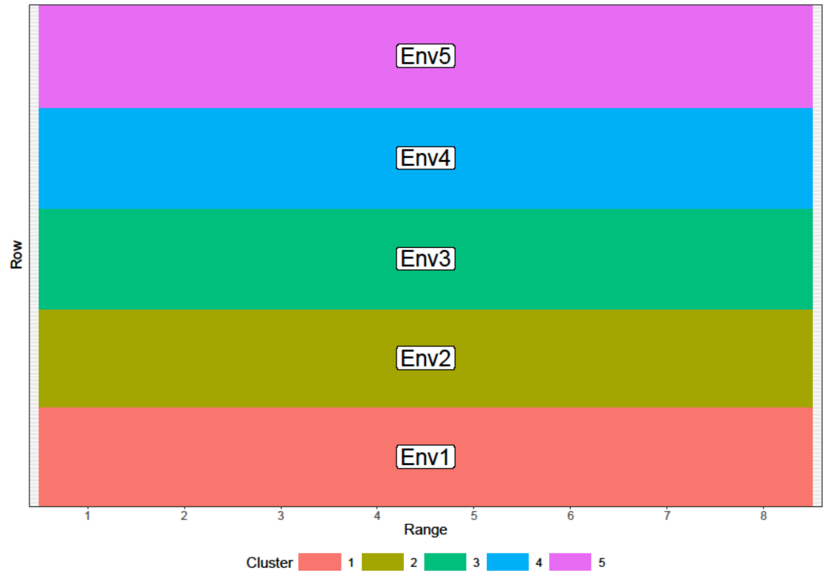
Yield map

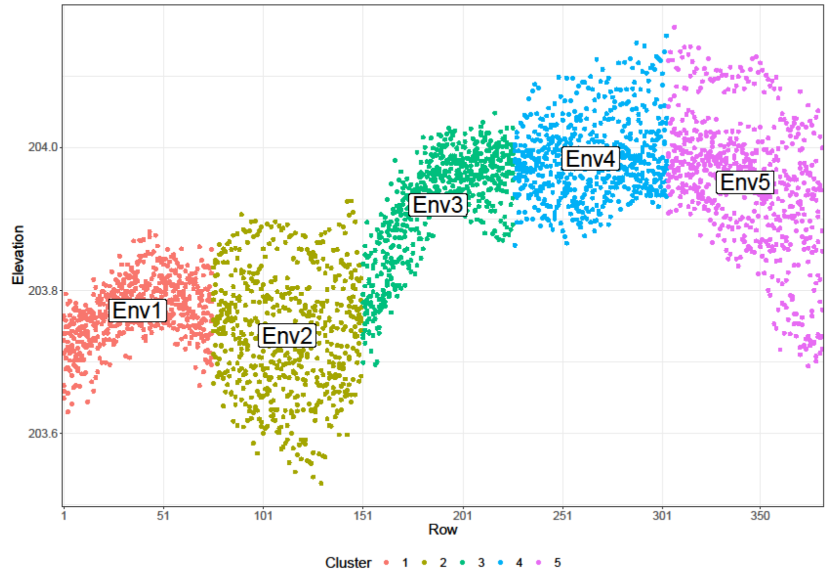
Solution: step 1 - rotation

A MET idea is implemented (Katia, S., et al, 2023).

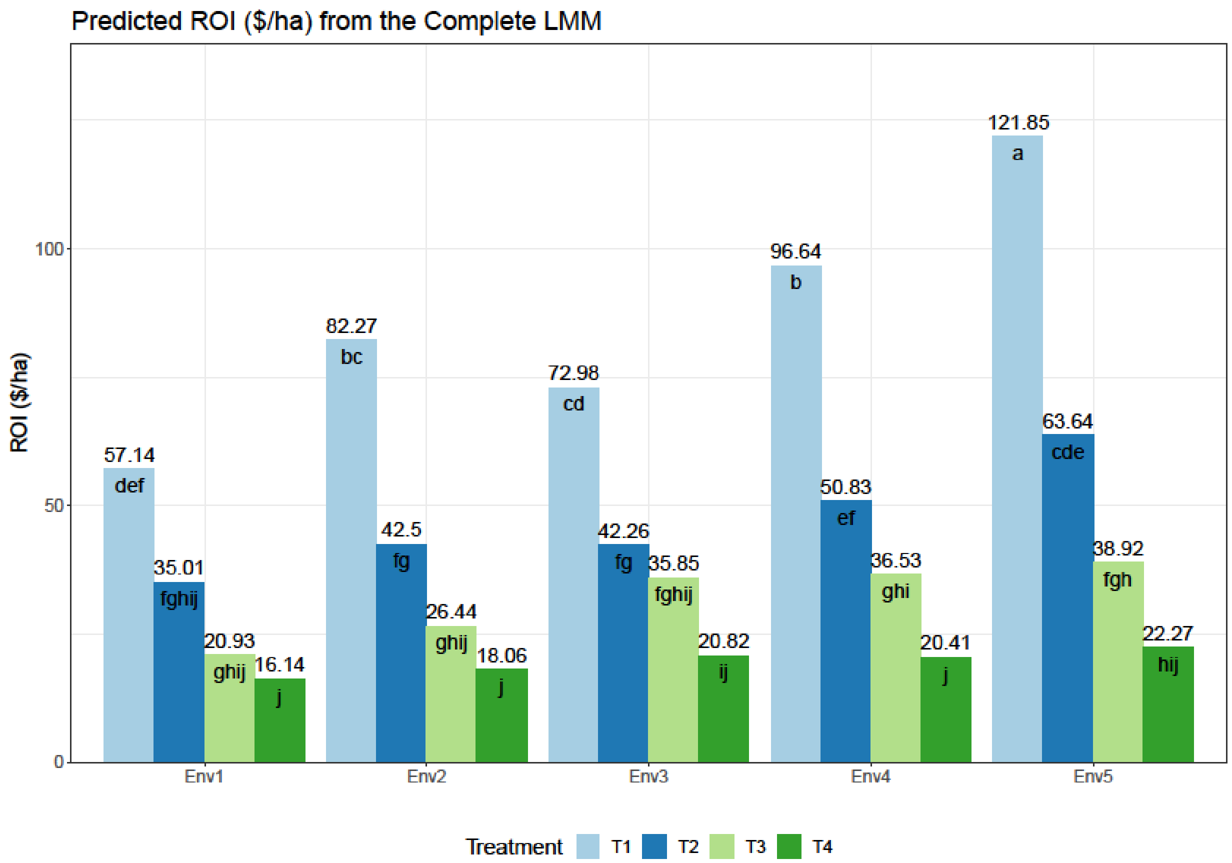


Solution: step 2 - partition into PE





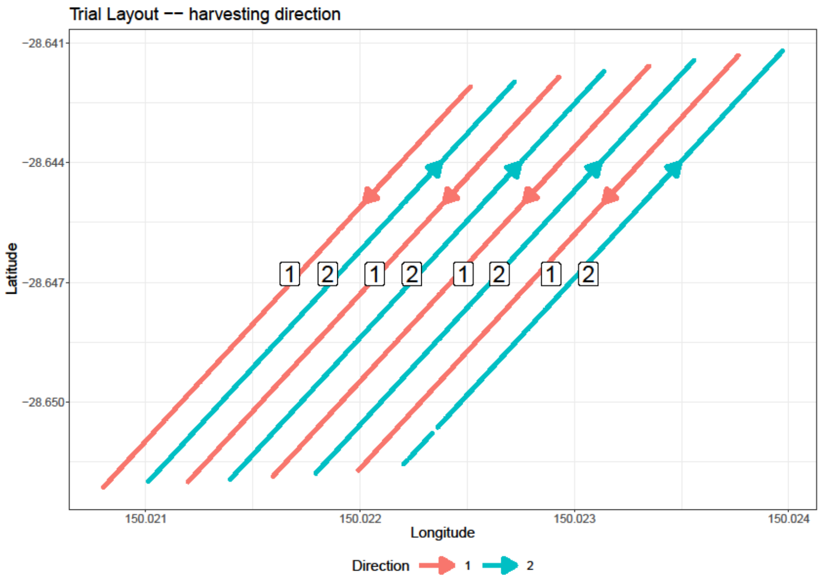
Outcome

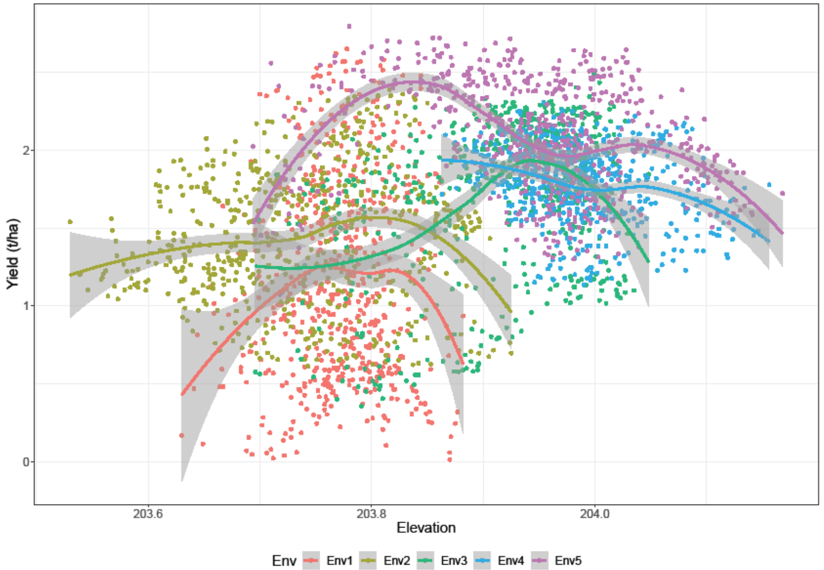

Predicted ROI ($/ha) from the Complete LMM
ROI ($/ha)
100
50
0
57.14
def
35.01
fghij
20.93
ghij
16.14
j
82.27
bc
42.5
fg
26.44
ghij
18.06
j
72.98
cd
42.26
fg
35.85
fghij
20.82
ij
96.64
b
50.83
ef
36.53
ghi
20.41
j
121.85
a
63.64
cde
38.92
fgh
22.27
hij
Env1
Env2
Env3
Env4
Env5
Treatment
T1
T2
T3
T4

Solution without transformation

Generalised Additive Models (GAM) (Wood, S., 2017; Wood, S., 2006), which can capture non-linear relationships and spatial variations between predictor variables and the response variable.

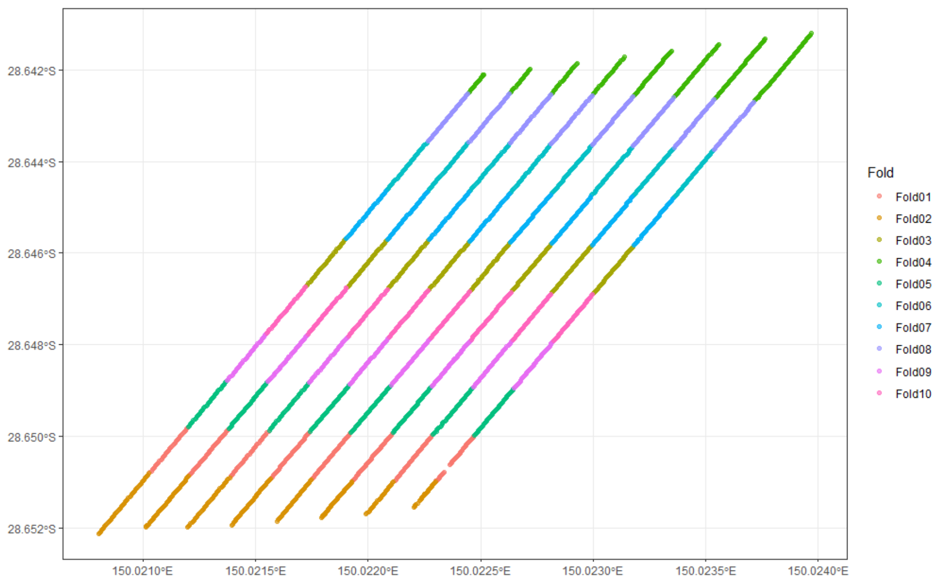
$$y = t + f(e) + h + g(s) + \varepsilon$$

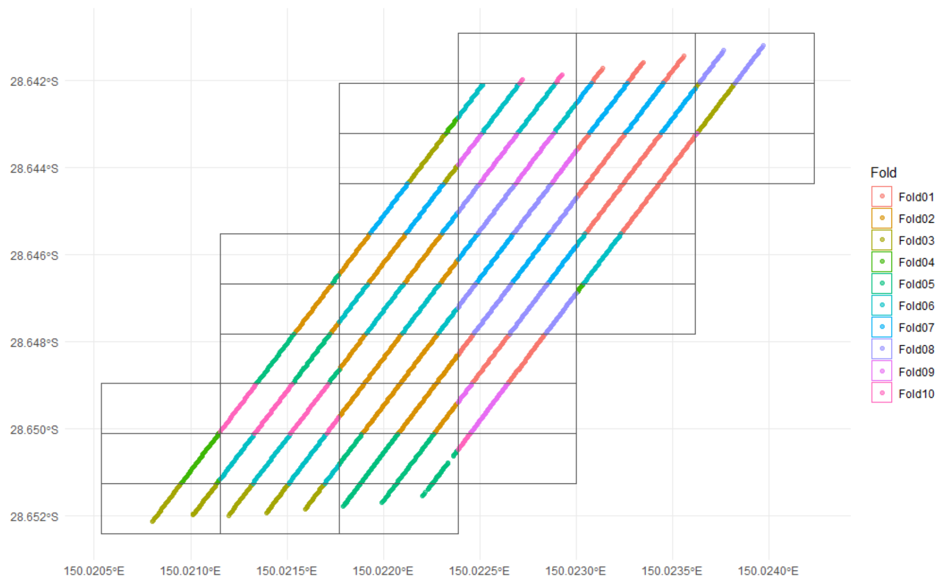




Solution without transformation

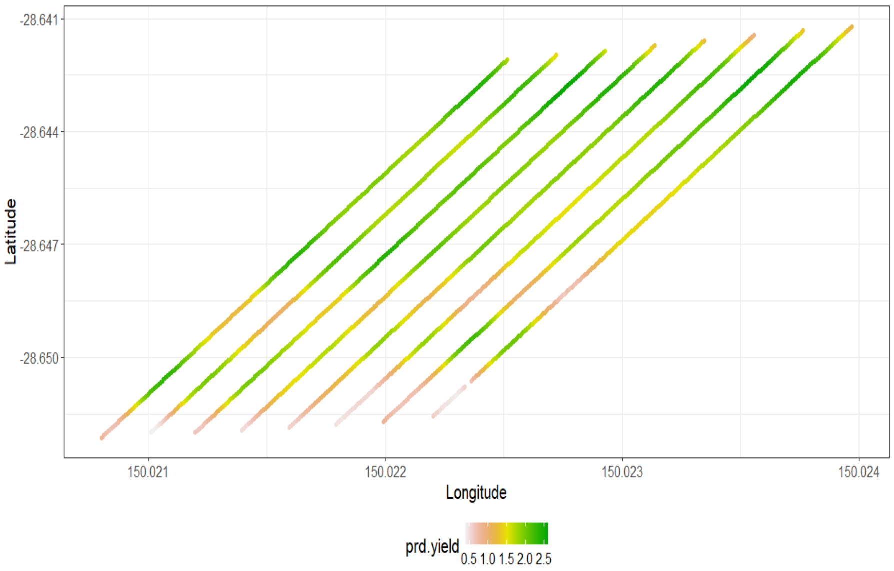
Two spatial cross-validation approaches.

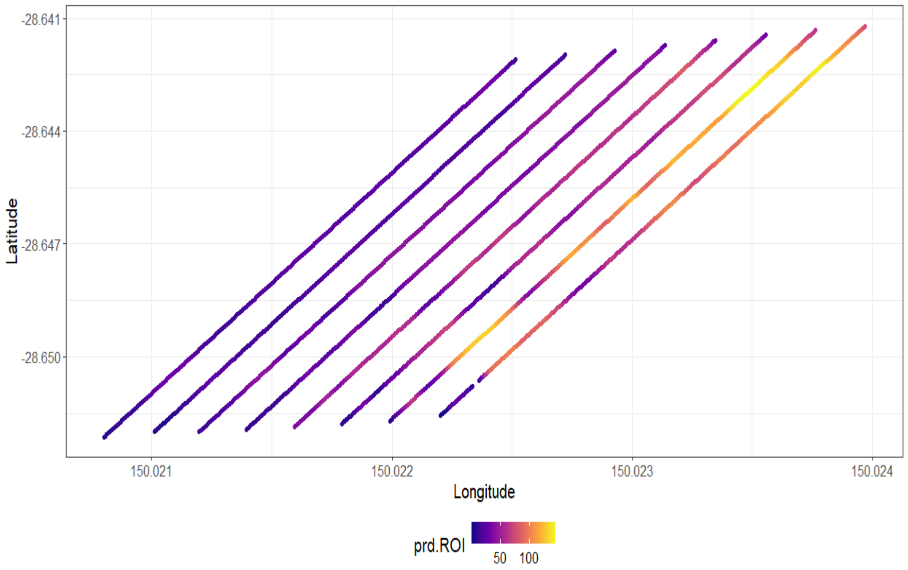




Outcome

Predicted yield and ROI





Outcome

P-values of single factor.

Source	Yield	Profit	ROI
T1	< 0.01	< 0.01	< 0.01
T2	< 0.01	< 0.01	< 0.01
T3	< 0.01	< 0.01	0.043
T4	0.006	0.011	NS
hdir2	NS	NS	NS
s(Elevation)	0.003	0.004	< 0.01
ti(Longitude,Latitude)	< 0.01	< 0.01	< 0.01

P-values of pairwise comparison.

Contrast	Yield	Profit	ROI
T1 - T2	NS	NS	< 0.001
T1 - T3	NS	NS	0.001
T1 - T4	NS	NS	0.009
T2 - T3	NS	NS	NS
T2 - T4	NS	NS	NS
T3 - T4	NS	NS	NS

NS: not significant

Take home message

Approaches

- **Local Estimation:** Determines optimal input levels, varying spatially within the field.
- **Global Estimation:** Assesses overall performance of site-specific crop management (SSCM) treatments compared to a control.

Approach	Weaknesses	Strengths
GWR	Reliance bandwidth	Simplifies local estimation
MET (cluster)	Sensitive to spatial covariates	Robust performance
MET (rotation)	Potential loss of information	Robust performance
GAM	Sensitive to knots and basis functions, risk of underestimating	Flexible modelling of nonlinear relationships

Acknowledgements

Mark Gibberd, Julia Easton, Adam Sparks, Suman Rakshit, Kefei Chen, Jordan Brown, Kristina Gagalova, Irina Kuznetsova, Matthew Nguyen.

Jordy Medlen, Ben Whisson, Justine Tyson, Garren Knell

Leigh Norton, Tom McGillivray,

Nicole Dron, Joop Van Leur

References

1. Rakshit, S., et al. "Novel approach to the analysis of spatially-varying treatment effects in on-farm experiments." Field crops research 255 (2020): 107783.
2. Cao, Z., et al. "Bayesian inference of spatially correlated random parameters for on-farm experiment." Field Crops Research 281 (2022): 108477.
3. Stefanova, K. T., et al. "Statistical analysis of comparative experiments based on large strip on-farm trials." Field Crops Research 297 (2023): 108945.
4. Cao, Z., et al. "Optimal design for on-farm strip trials--systematic or randomised?."
5. Kyveryga, Peter M., Tristan A. Mueller, and Daren S. Mueller. "On-farm replicated strip trials." *Precision agriculture basics* (2018): 189-207.
6. Evans, Fiona H., et al. "Assessment of the use of geographically weighted regression for analysis of large on-farm experiments and implications for practical application." *Agronomy* 10.11 (2020): 1720.
7. Wood, S.N. (2006) Low rank scale invariant tensor product smooths for generalized additive mixed models. Biometrics 62(4):1025-1036
8. Wood S.N. (2017) Generalized Additive Models: An Introduction with R (2nd edition). Chapman and Hall/CRC Press. doi:10.1201/9781315370279
9. A. Brenning, "Spatial cross-validation and bootstrap for the assessment of prediction rules in remote sensing: The R package sperrorest," 2012 IEEE International Geoscience and Remote Sensing Symposium, Munich, 2012, pp. 5372-5375, doi: 10.1109/IGARSS.2012.6352393.
10. D. R. Roberts, V. Bahn, S. Ciuti, M. S. Boyce, J. Elith, G. Guillera-Arroita, S. Hauenstein, J. J. Lahoz-Monfort, B. Schröder, W. Thuiller, D. I. Warton, B. A. Wintle, F. Hartig, and C. F. Dormann. "Cross-validation strategies for data with temporal, spatial, hierarchical, or phylogenetic structure," 2016, Ecography 40(8), pp. 913-929, doi: 10.1111/ecog.02881.

AAGI
Analytics for the Australian Grains Industry

Thank you!

GRDC GRAINS RESEARCH & DEVELOPMENT CORPORATION

Curtin University

The University of Queensland Australia

The University of Adelaide