Mapping and identifying drivers of crop production in space and time using interpretive machine learning.

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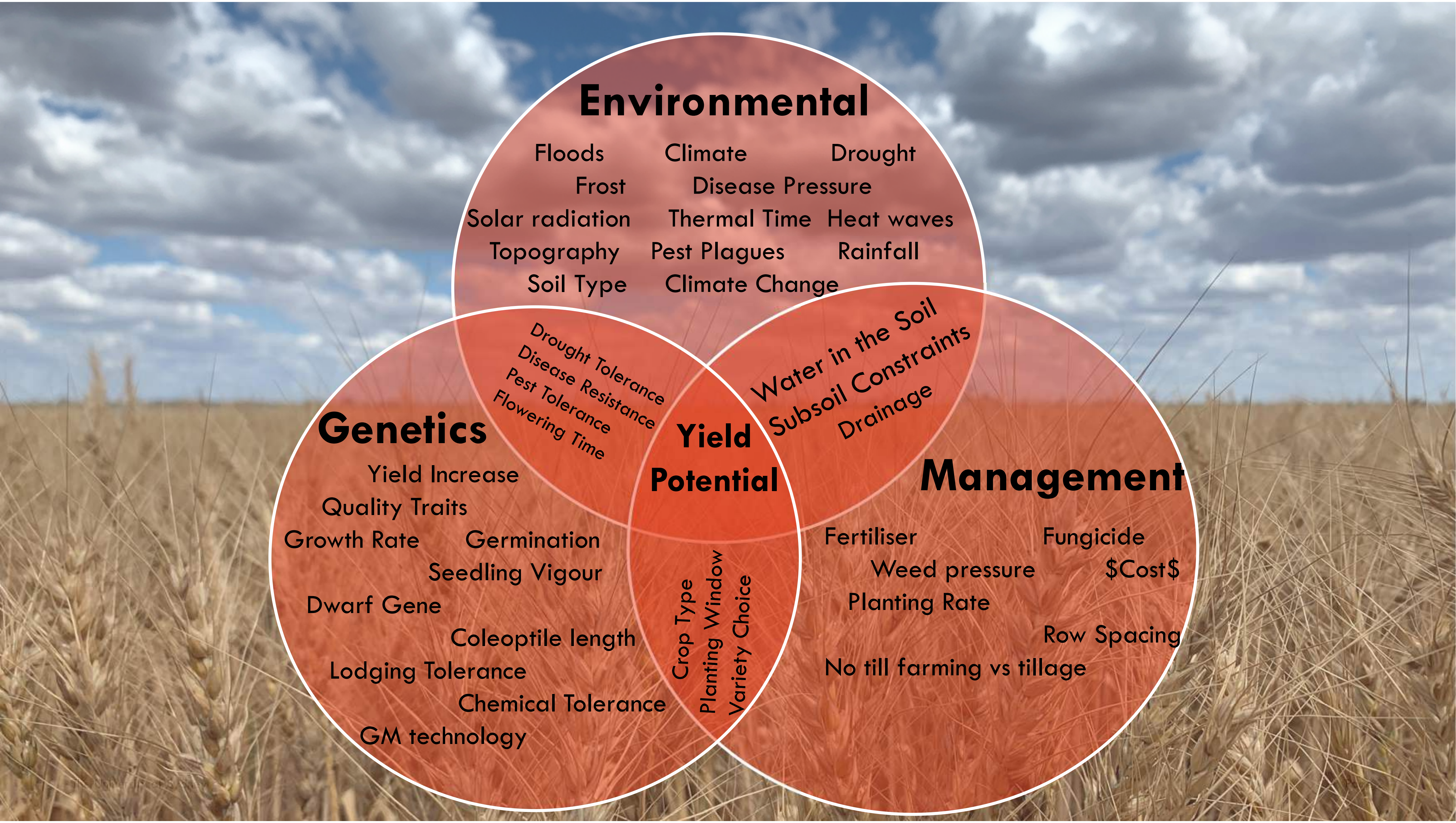
Environmental
Floods
Climate
Drought
Frost
Disease Pressure
Solar radiation
Thermal Time
Heat waves
Topography
Pest Plagues
Rainfall
Soil Type
Climate Change
Drought Tolerance
Disease Resistance
Pest Tolerance
Flowering Time
Water in the Soil
Subsoil Constraints
Drainage
Yield Potential
Genetics
Yield Increase
Quality Traits
Growth Rate
Germination
Seedling Vigour
Dwarf Gene
Coleoptile length
Lodging Tolerance
Chemical Tolerance
GM technology
Crop Type
Planting Window
Variety Choice
Management
Fertiliser
Fungicide
Weed pressure
$Cost$
Planting Rate
Row Spacing
No till farming vs tillage

Slide 2

PF0 This whole slide might be too much information. I think the next slide is OK on its own

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Outline

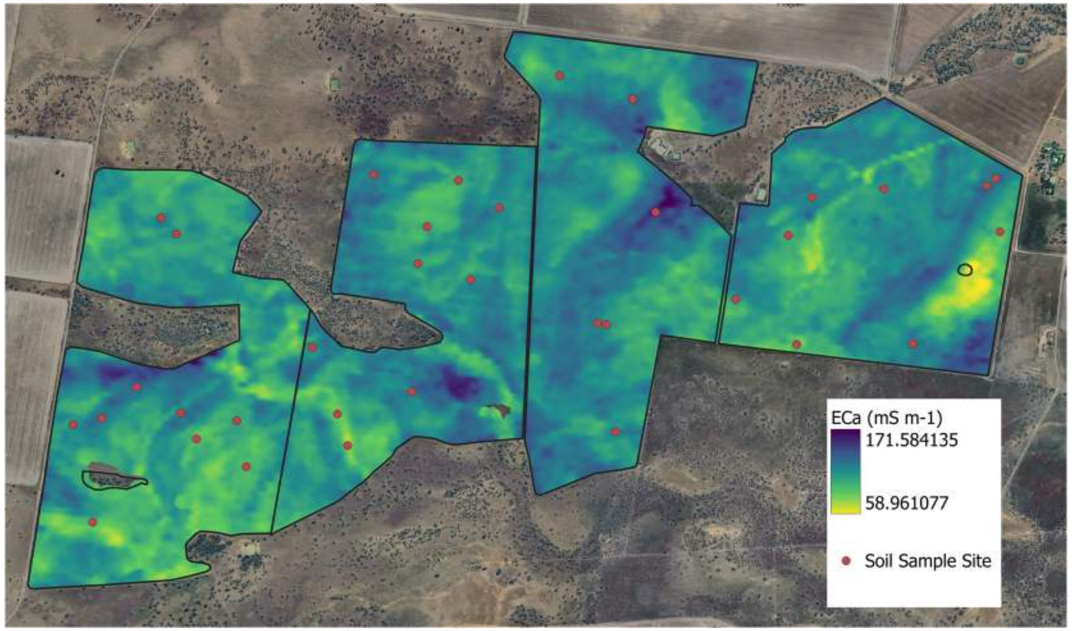
- Correlation analysis

- Interpretative machine learning
  - Individual seasons
  - Between crop types
  - Between seasonal type

- Variable rate case study season

Study Site and Data

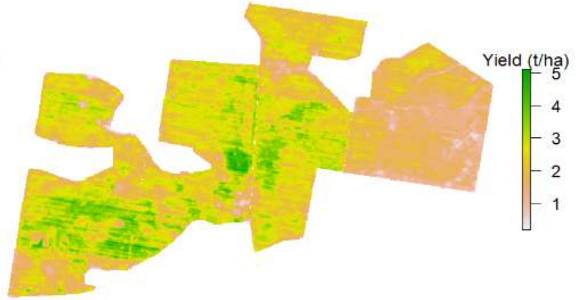
- 1099 ha field located 40km west of Moree.
- 10+ years of yield data
- Proximal electromagnetic induction and gamma radiometric data was collected in 2021.
- High resolution elevation data was collected using Lidar in 2019.
- 35 soil cores were taken across the field, located predominantly using a Latin hyper cube.
- Soil samples at the depths of 0-15cm, 15-30cm, 30-60cm, 60-90cm.
- Digital soil maps of soil properties were created using a splined random forest model.
- Soil water holding properties were modelled using a Pedotransfer function.



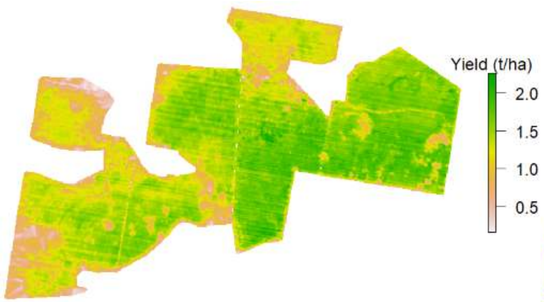
Yield maps 2010-2023

a) Cotton 2011

(b) Wheat 2012



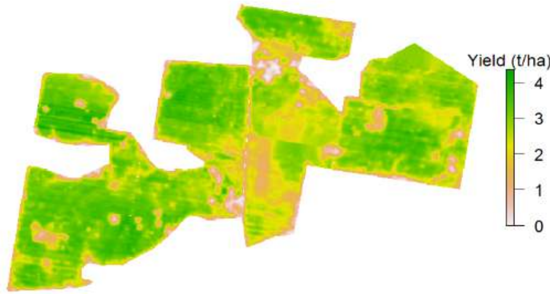
(c) Chickpeas 2013



(d) Wheat 2014

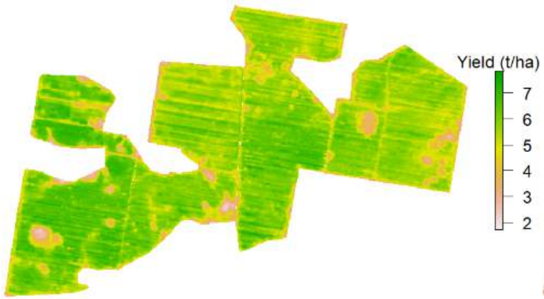
(e) Chickpeas 2016

(f) Wheat 2017



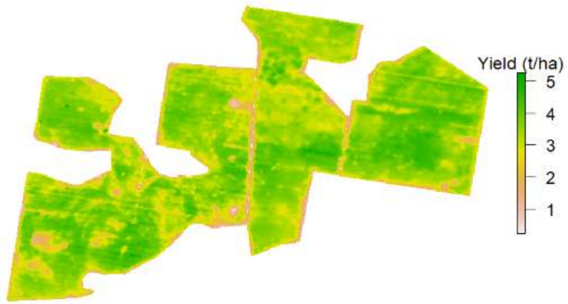
(g) Chickpeas 2019

(h) Wheat 2021



(i) Wheat 2022

(j) Wheat 2023

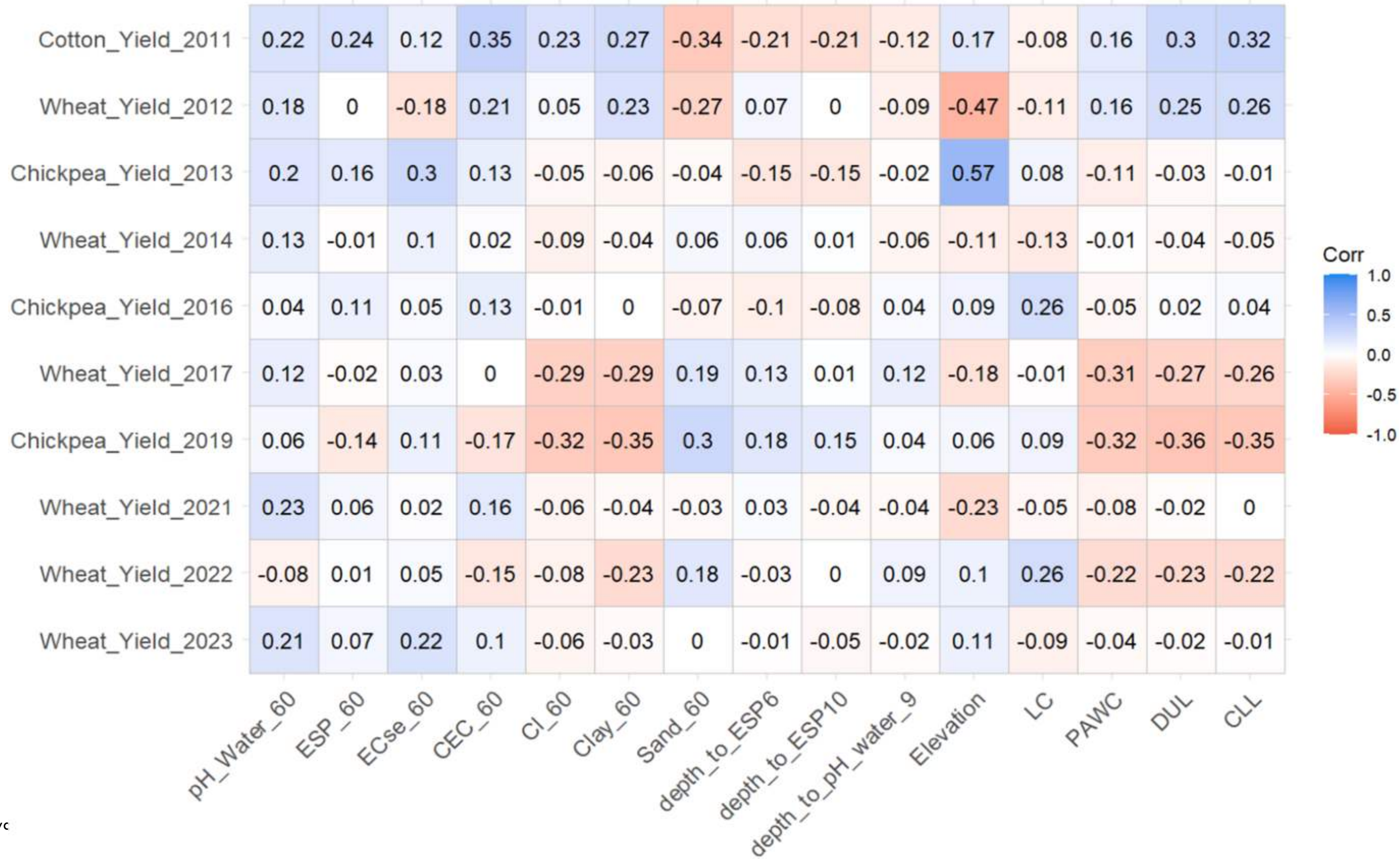


Yield Correlations

	2023 – Wheat – dry	2022 – Wheat – wet	2021 – Wheat – wet	2019 – Chickpeas – dry	2017 –Wheat – dry	2016 – Chickpeas – wet	2014 - Wheat – dry	2013 – Chickpeas – wet	2012 – Wheat – wet
2011 - Cotton – wet	0.24	-0.15	0.31	-0.01	0.16	0.22	0.1	0.37	0.34
2012 – Wheat – wet	0.25	-0.09	0.48	0.11	0.3	0.27	0.28	0.08	
2013 – Chickpeas – wet	0.41	0.05	0.34	0.43	0.3	0.33	0.16		
2014 - Wheat – dry	0.43	-0.16	0.44	0.2	0.42	-0.15			
2016 – Chickpeas – wet	0.09	0.36	0.22	0.19	0.1				
2017 –Wheat – dry	0.5	0.03	0.58	0.47					
2019 – Chickpeas – dry	0.35	0.24	0.32						
2021 – Wheat – wet	0.55	-0.04							
2022 – Wheat – wet	-0.15								

Corr
1.0
0.5
0.0
-0.5
-1.0

Yield and soil properties correlations



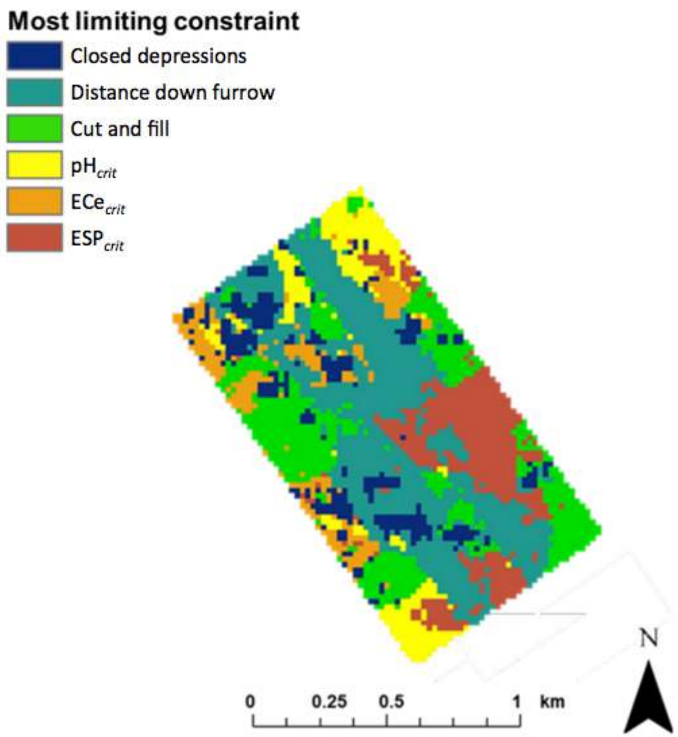
Using IML to understand the drivers of yield

Digital soil maps of subsoil constraints, soil water, and topography.

Yield = *f*(soil constraint maps + soil water maps + topography)

SHapley Additive exPlanations (SHAP) values were calculated for each factor at each point.

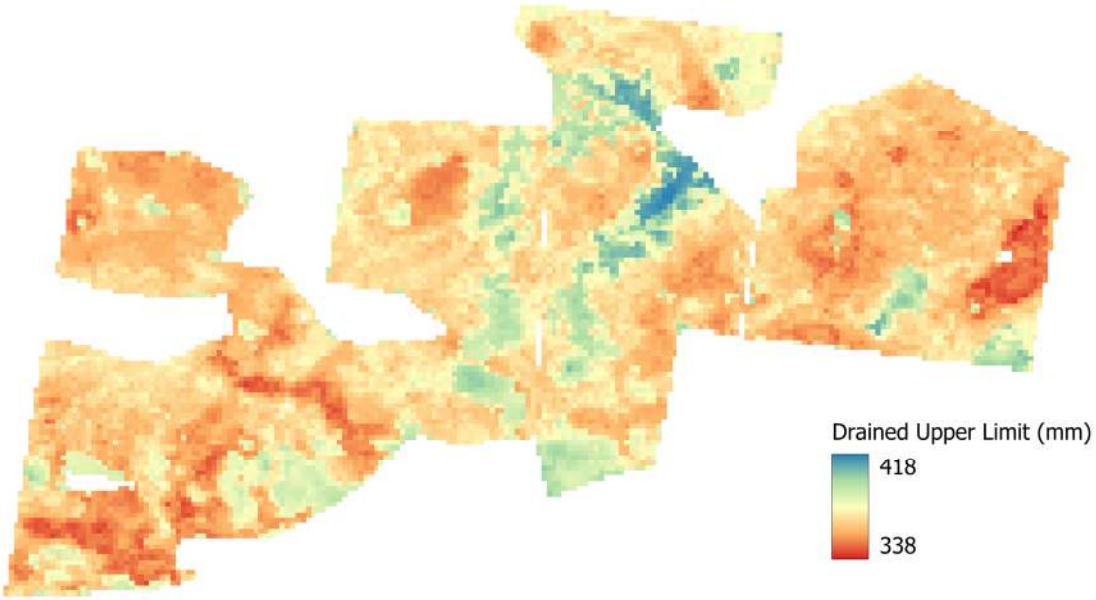
The factor with the lowest SHAP for each point is plotted creating a map of most limiting drivers of yield.



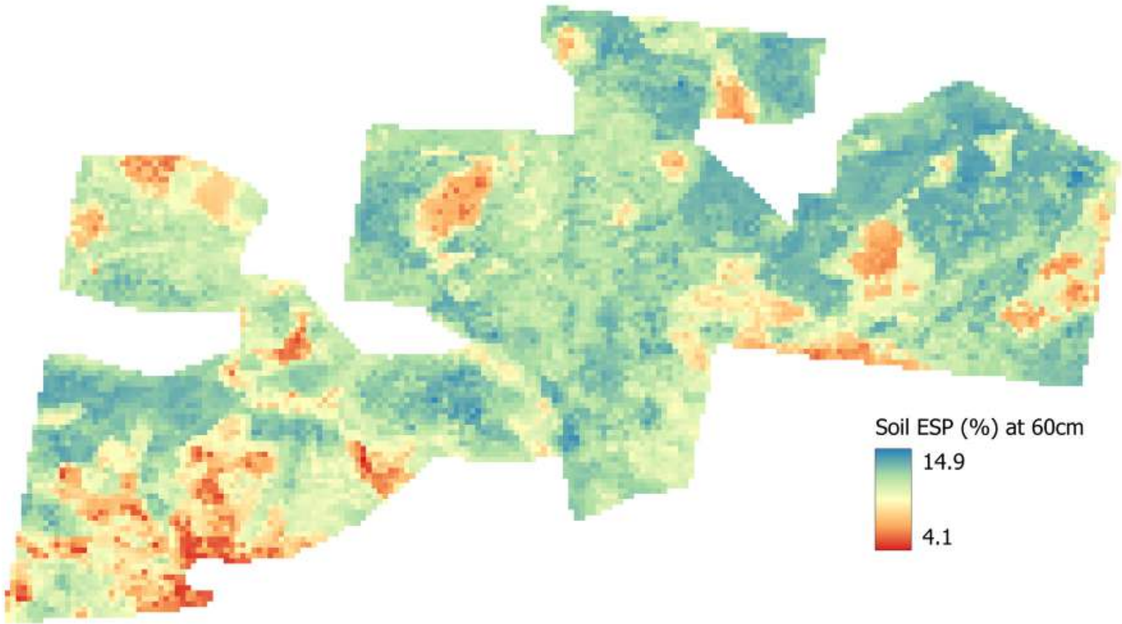
Source: Jones et al, 2022

Spatial Predictor Variables

Soil Drained Upper Limit (mm)

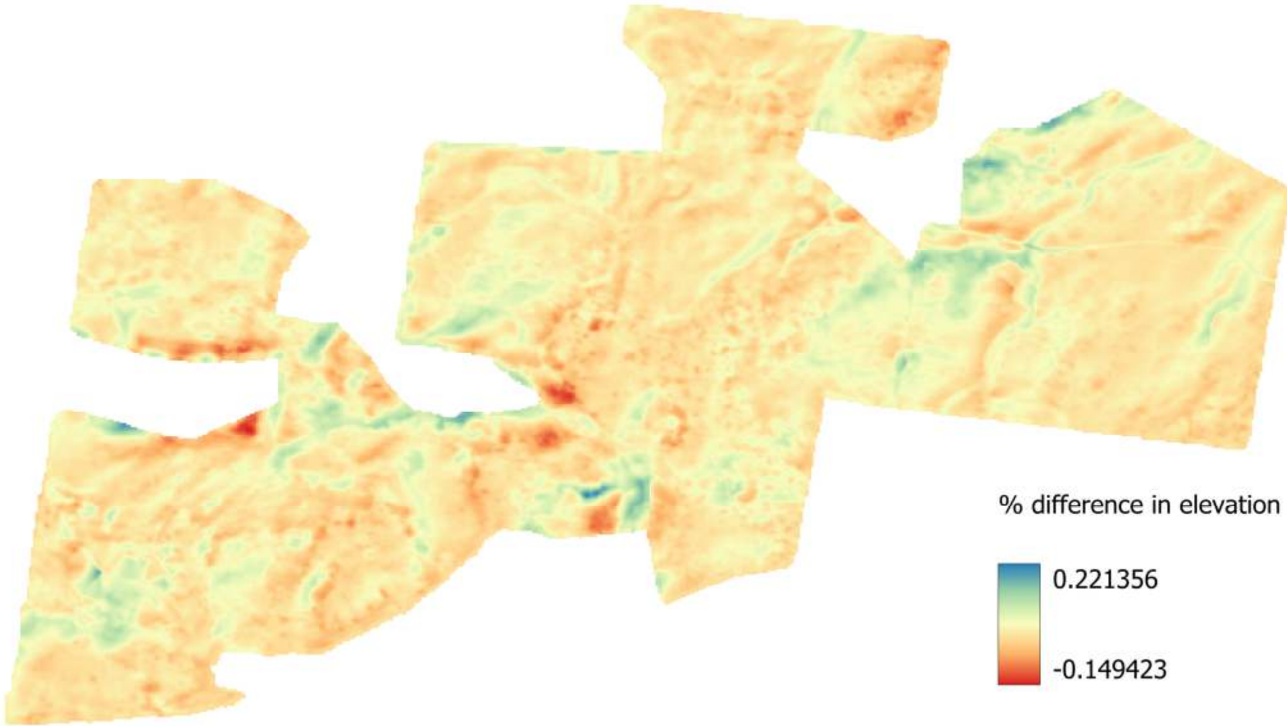


Soil Exchangeable Sodium Percentage (%)



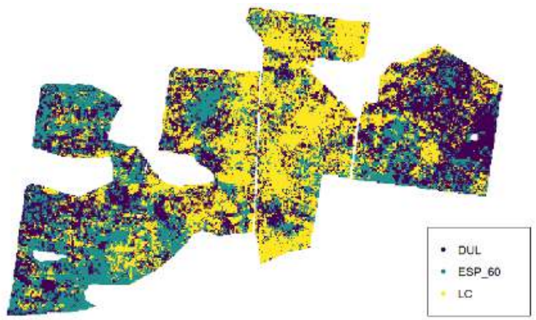
Spatial Predictor Variables

- Created from high resolution LiDAR data of the field.
- To represent localised variability in topography and likely water flows.
- Created using a moving windows of 90x90m and calculating the percentage difference between the point and the average elevation.



IML across all individual seasons – the most limiting factor on yield

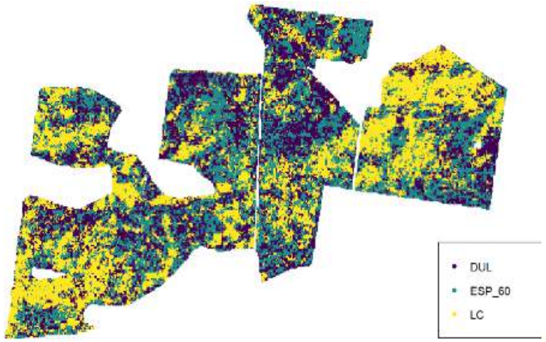
2011 Cotton – wet year



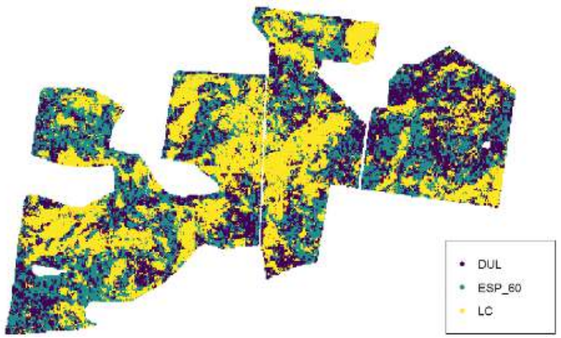
2012 Wheat – wet year

2013 Chickpeas - wet year

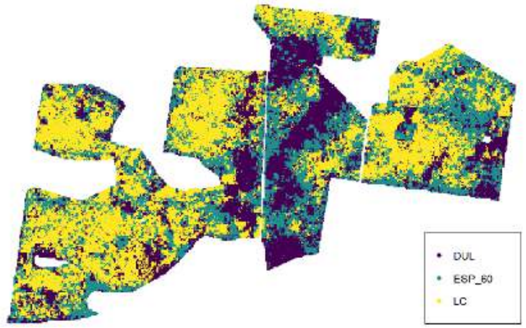
2014 Wheat – dry year



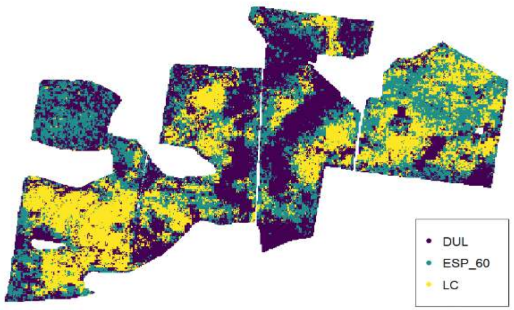
2016 Chickpeas - wet year



2017 Wheat – dry year

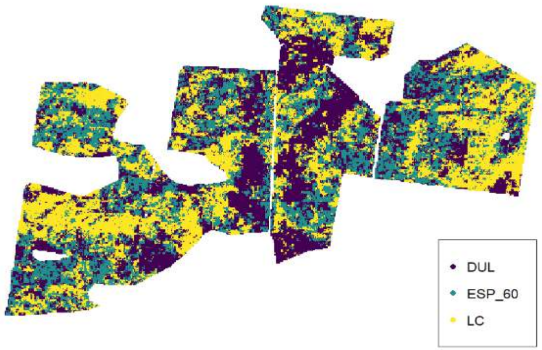


2019 Chickpeas - dry year

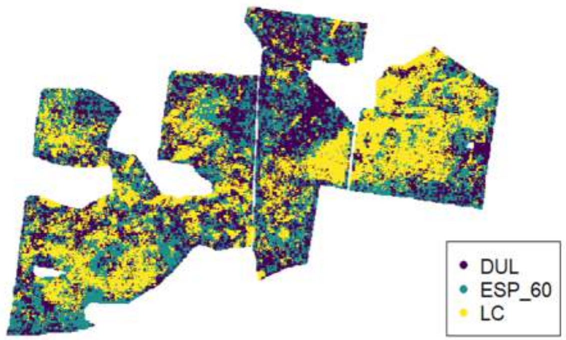


2021 Wheat – wet year

2022 Wheat – wet year

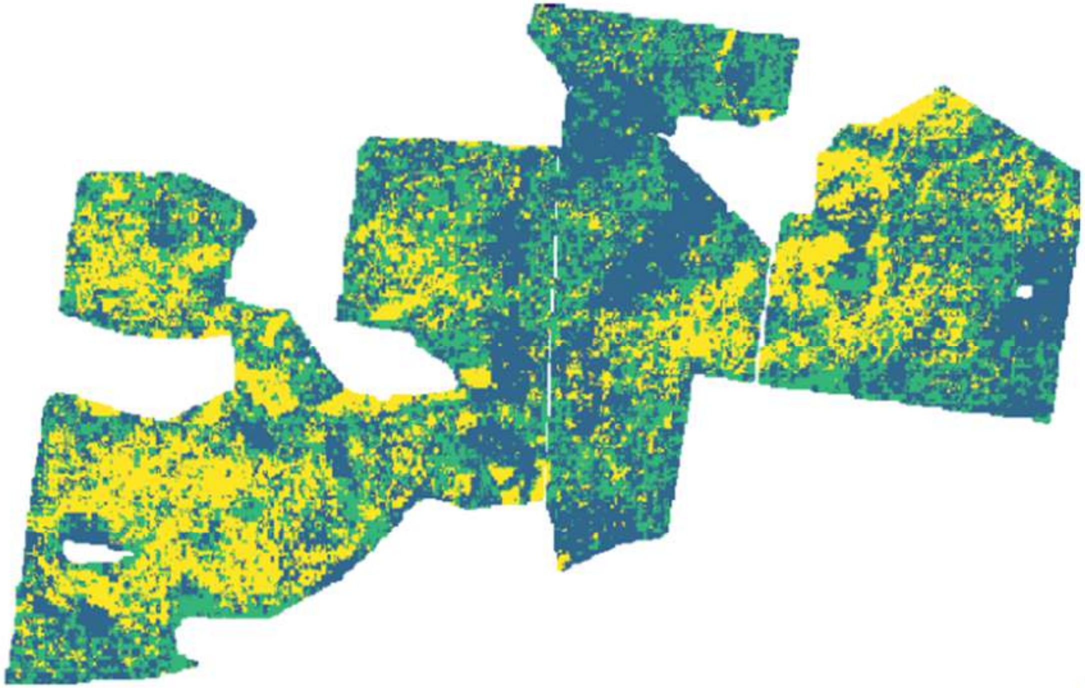


2023 Wheat – dry year

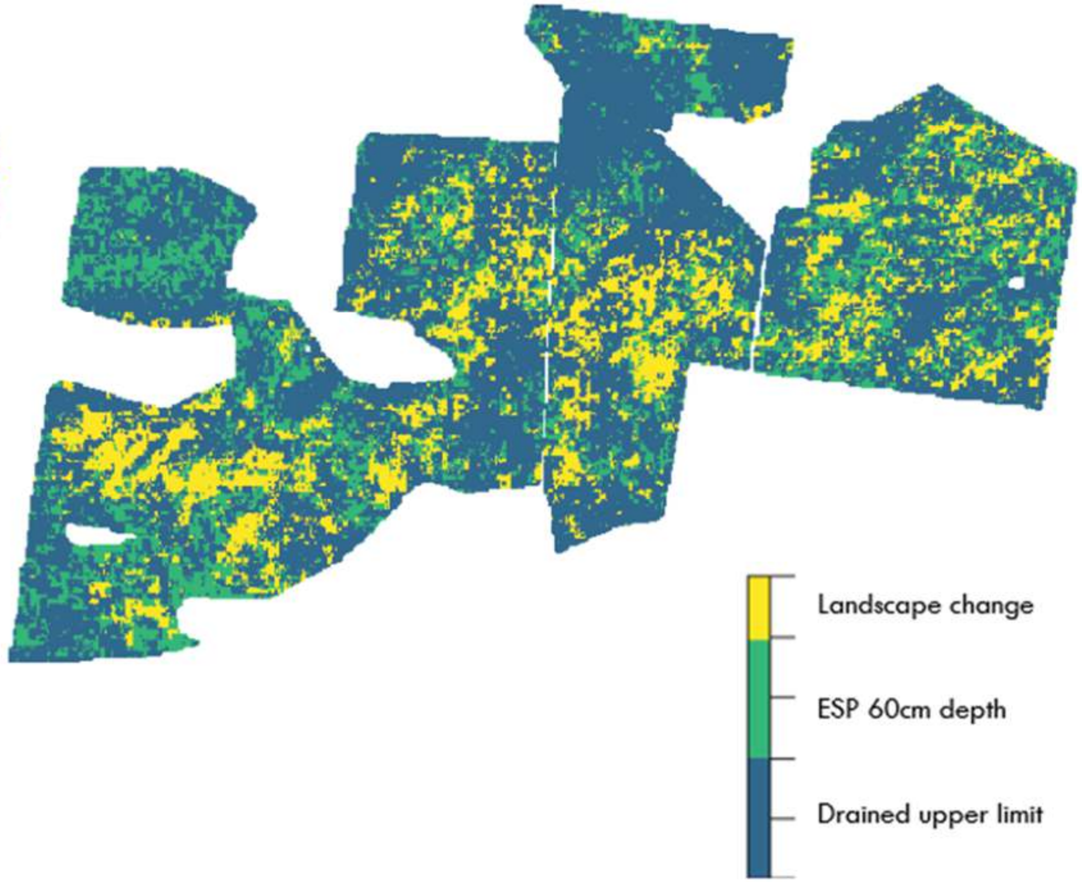


Most limiting variable on different crop types

Wheat

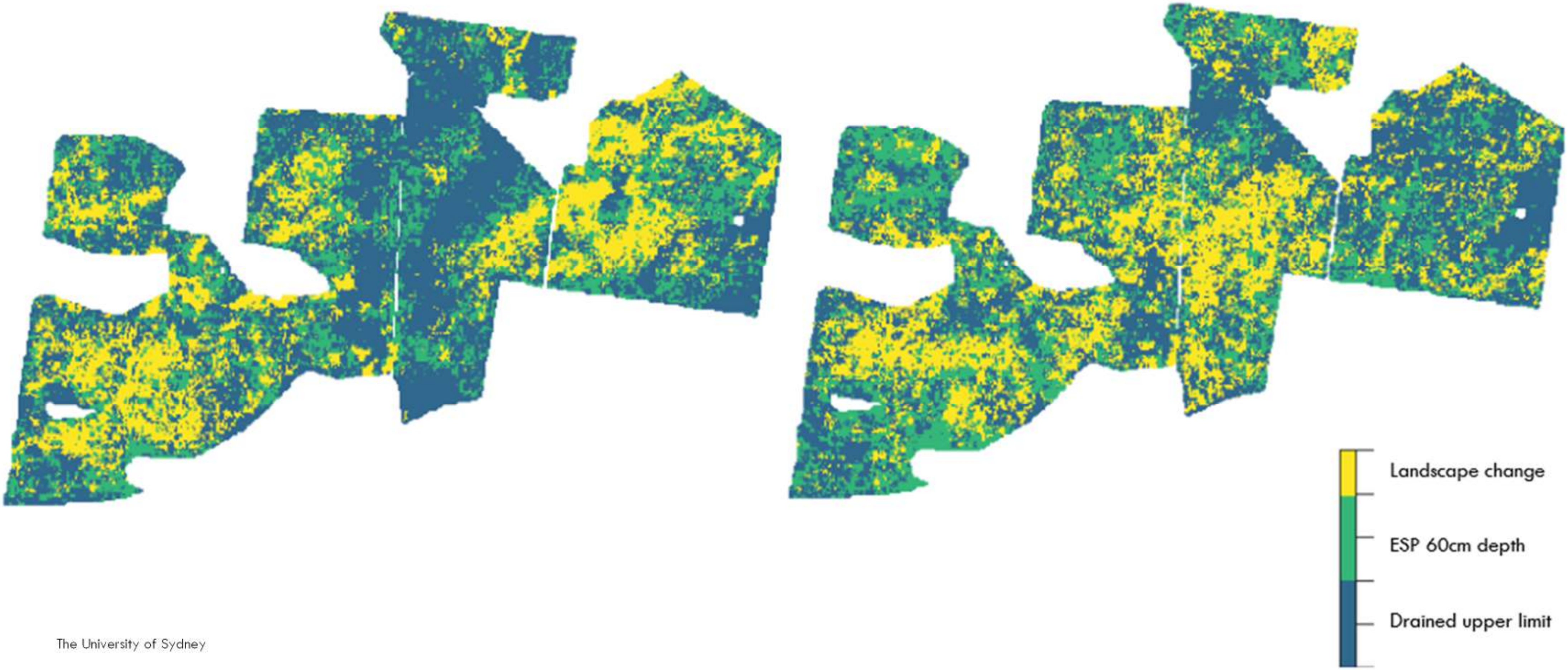


Chickpeas



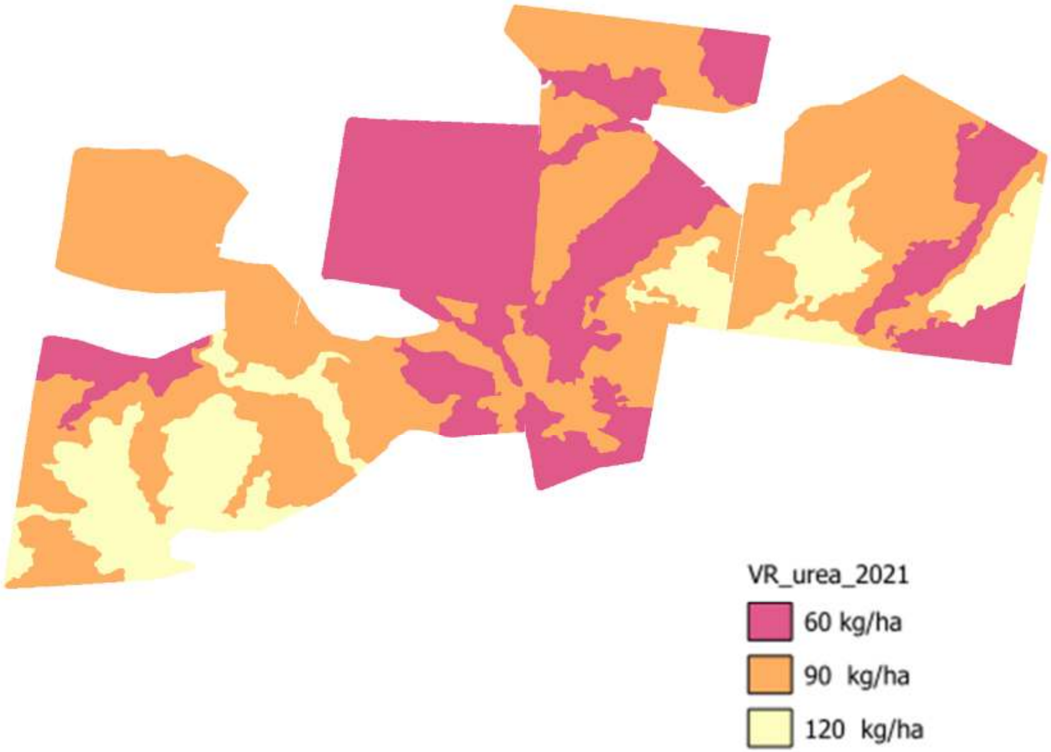
Most limiting variable on different crop types

Dry Season **Wet Season**

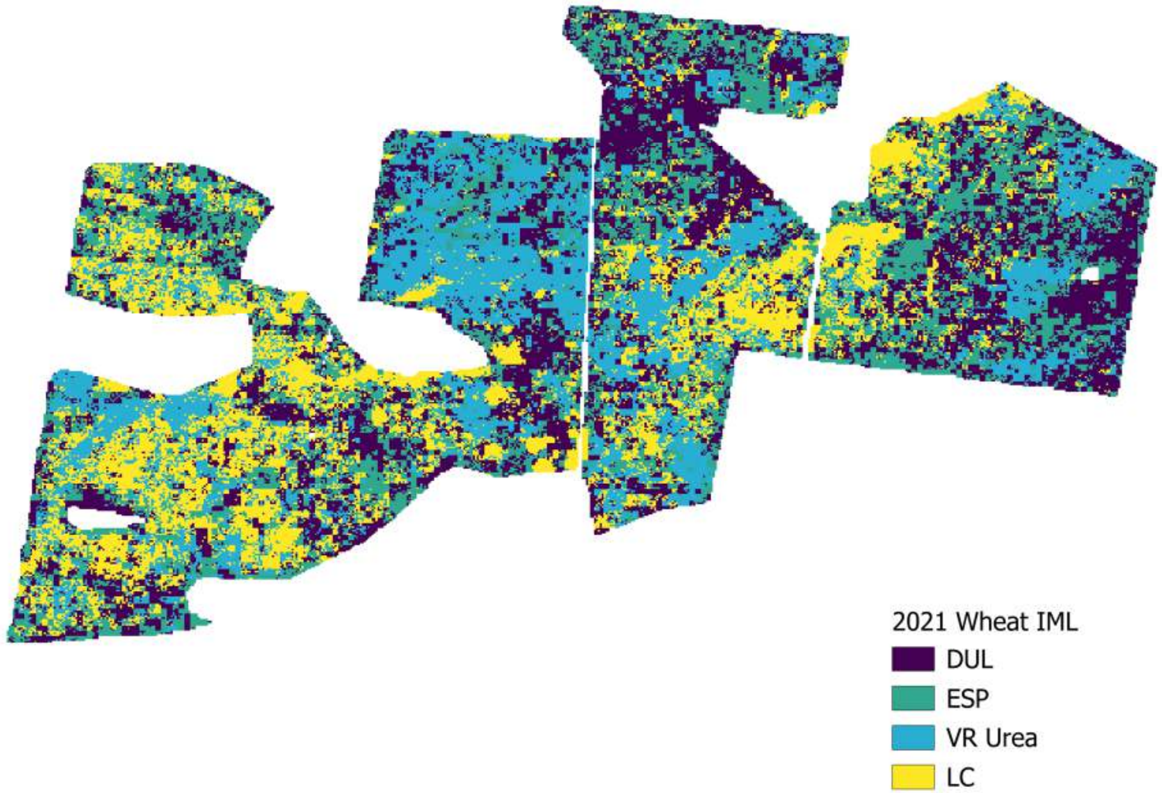


2021 most decreasing variable on yield – influence of a VR urea decisions

Variable Rate Urea map

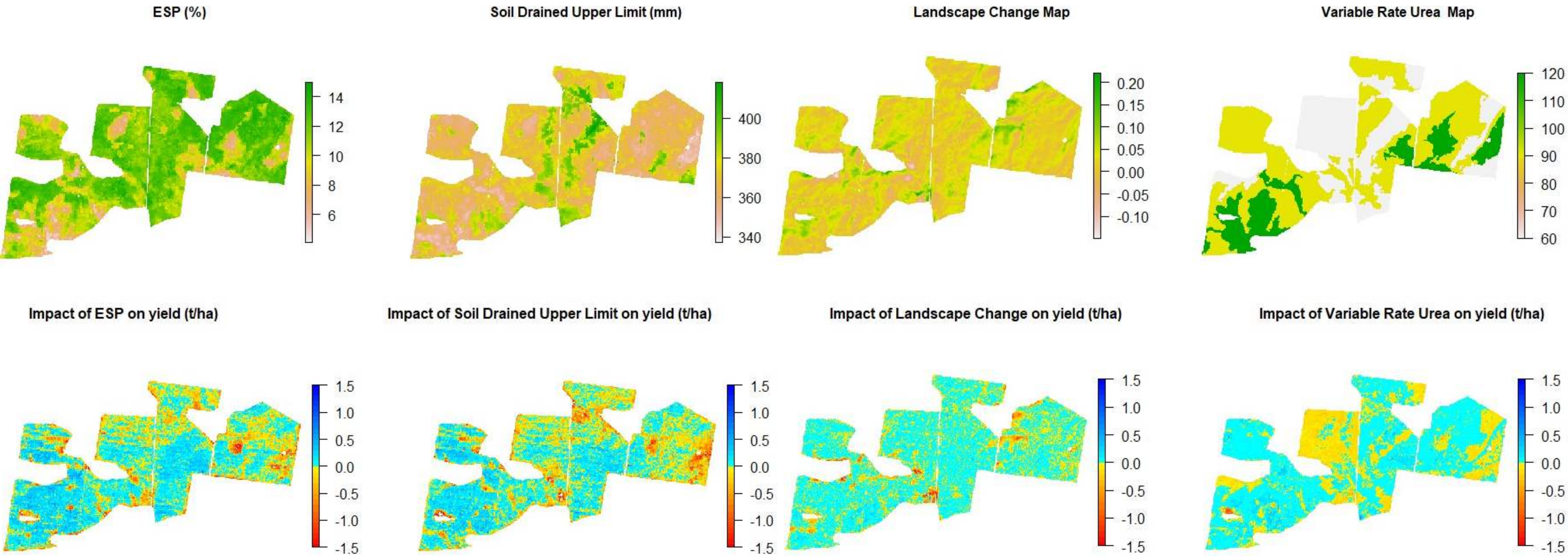


2021 Most limiting variable on yield



2021 most decreasing variable on yield – influence of a VR urea decisions

Wheat yield 2021



Conclusion

- Interpretive machine learning offers a way of understanding the spatial and temporal drivers of yield.
- Visualising the plotted SHAP values on maps helps with the interpretability of results. This will helps agronomists and farmers understand how these variables influence crop yield.
- The addition of variable rate management decisions and other spatial data layers such as pest, disease and management layers may further improve the model’s ability to predict and map limitations to crop yield.
- From this understanding of the spatiotemporal drivers of crop variability, new agronomic management decisions can be tailored to reduce the limitation of these drivers on future crop production and reduce the yield gap.