AgWise

Collaborative and adaptive data analytics framework for tailored agronomy advice

EiA - transform work package

AgWise

Collaborative and **adaptive** data analytics product for measurable **impact** in **agronomy**

Collaborative: the economy of scale in access to expertise, data and in response time

Adaptive: responding to partners' demand, making use of available data and tools

Measurable impact: optimized to partner's target: yield/profit increase, support subsidy programs and government investments

Agronomy+ : precise fertilizer use to increase food security, improve soil health and foster climate resilience

AgWise fertilizer recommendation

Key features:

Tailored Fertilizer Recommendations: AgWise specializes in providing site- and context-specific fertilizer recommendations based on the unique conditions of each target area.

Advanced Data Analytics: The tool utilizes advanced data analytical techniques to model spatial variations in yield response to nutrient use. This approach ensures that recommendations are finely tuned to the specific needs of each field.

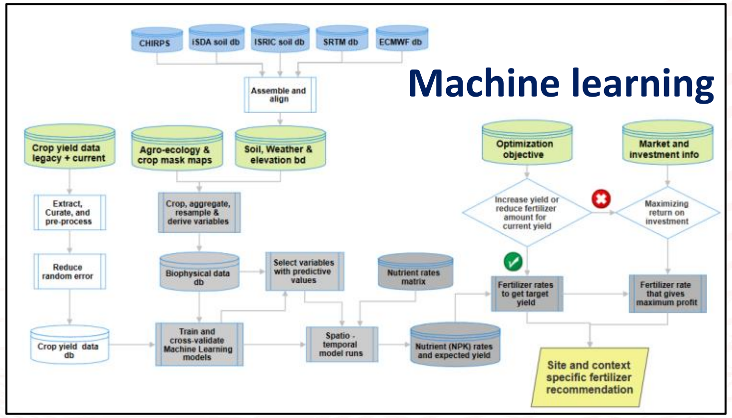
Comprehensive Inputs: AgWise integrates multiple factors into its models, including:

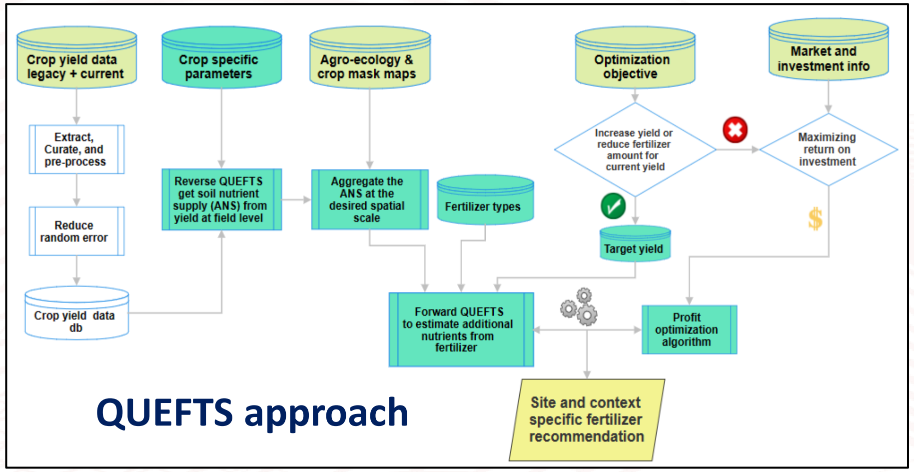
- Soil conditions
- Local weather patterns
- Crop-specific requirements
- Socio-economic conditions of the target farmers

Impact: AgWise aims to help farmers:

- Enhance crop productivity
- Maximize nutrient use efficiency
- Increase farm income either by saving cost of fertilizer and/or increasing return on investment

AgWise approaches for fertilizer recommendation

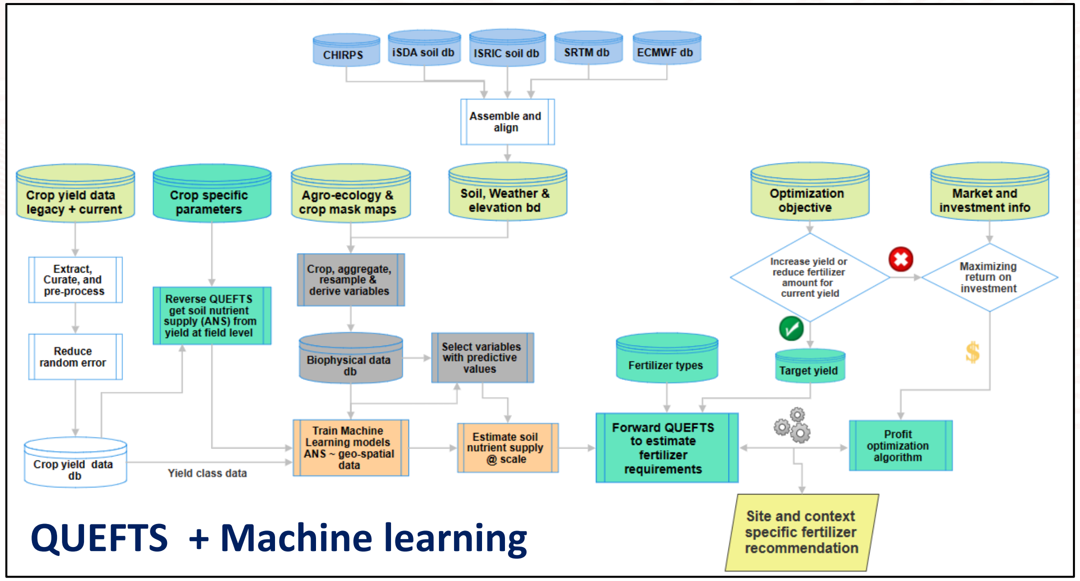


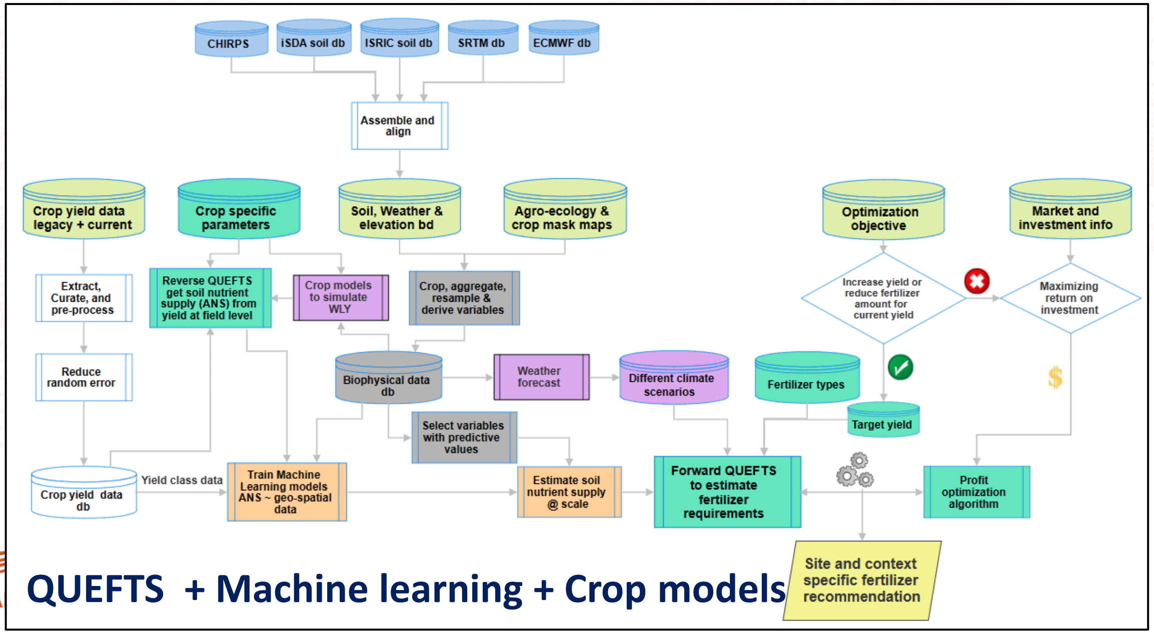


Pic and mix principle dictated by data & objective

Data:

- standardized legacy data (carob, CoW)
- Partners data
- Digital soil and weather info
- **Expert input**





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AgWise data needs

Agronomic data

Standardized new/legacy data:

Partners' data, Carob, Cow, data pool, …

Expert input

Target area characterization

Growing season, ag-input availability, market information, …

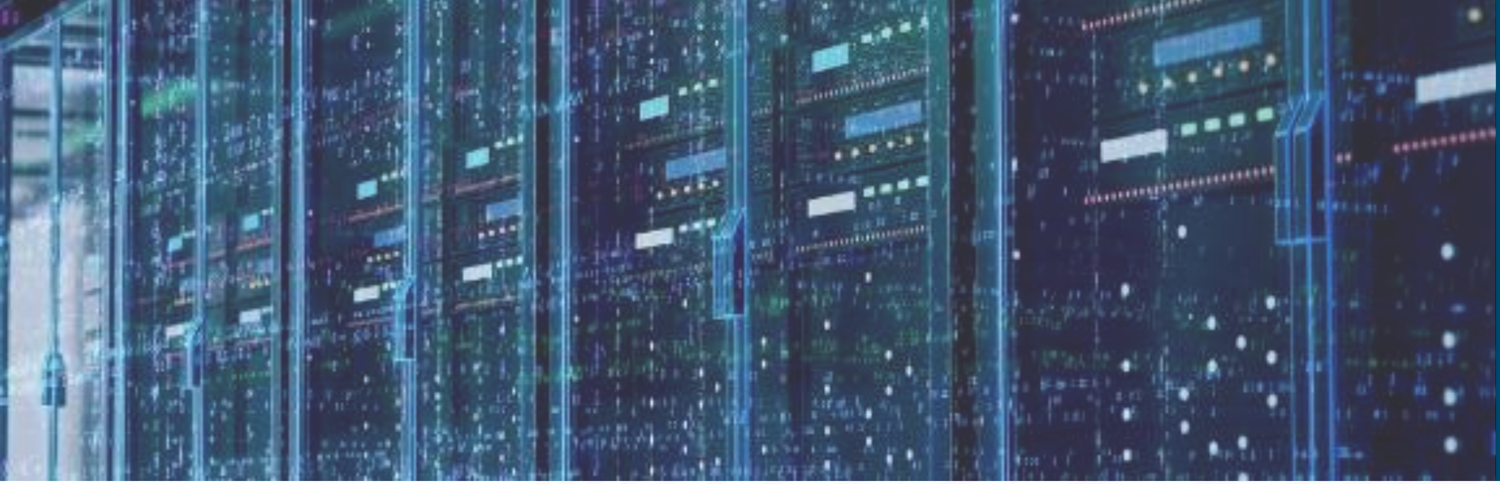
Data cube

Geo-spatial data @ scale

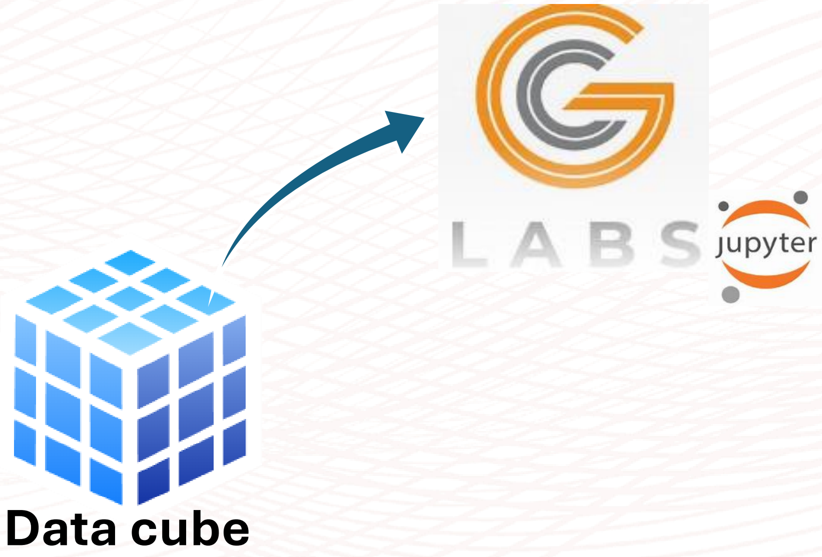
Soil information

Weather data

Satellite imagery



Computational infrastructure

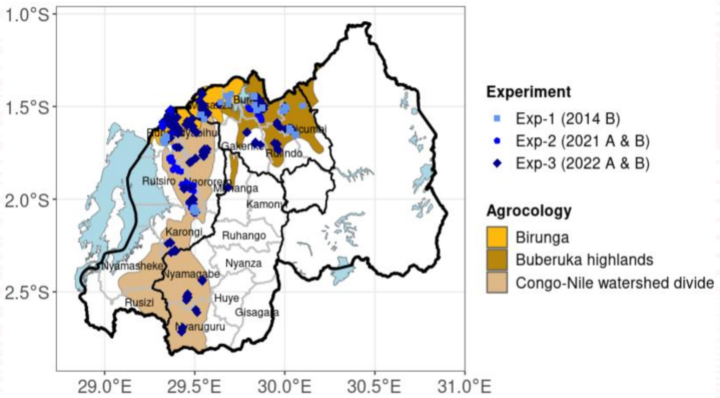


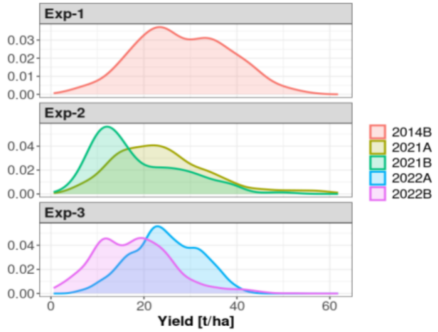
- Multi-core processors
- High-capacity RAM
- High-speed network
- Integrated data analytics software
- Comprehensive backup solutions

Exploring field trials data

Legacy data often from trails conducted using **different protocols**, through the **years** by different **institutes, etc = different quality**

It requires thorough **investigation** and **random error** reduction.





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Focus on structured variation

Difference in yield response is determined by the treatments effect conditioned by biotic and abiotic factors such as the soil and weather conditions.

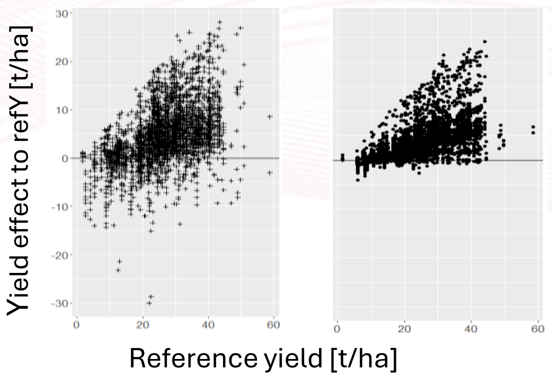
However, even in a very good quality data, there is yield difference that we can NOT attribute to differences in measured factors, and this is called **random error**.

$$\boldsymbol{Yield \sim treatment + season + AEZ + (1|site) + (0 + treatments|site)}$$

This mode allows different locations have their own baseline yield and different shapes of response curve

To increase the signal : noise ratio, it is important that the random error in the data is reduced.

AgWise uses linear mixed effects model to evaluate overall and location specific effects of fertilizer application on yield.



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Tailored for changing climate

Key features:

Optimal Planting Date Determination: AgWise analyzes soil and climate variability to recommend the best planting dates for different cropping systems, enhancing resource use efficiency and crop yield.

Variety Suitability Mapping: AgWise generates variety suitability maps, detailing the performance of long, medium, and short-duration crop varieties under different climate scenarios. These maps support better climate risk management and improved crop productivity.

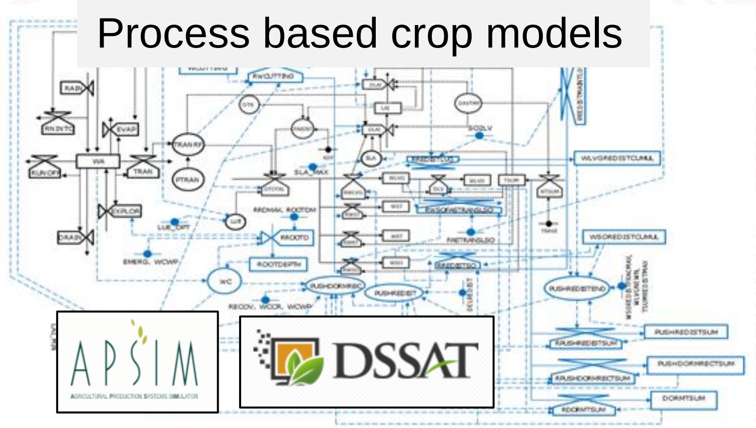
Climate Resilience: AgWise assesses the effects of different climate scenarios, helping farmers choose the most suitable crop varieties for their regions. The tool assesses weather patterns in relation to crop growth stages, helping to minimize climate risks during critical phases.

Crop Models Integration: The tool couples diverse crop models with spatially varying soil and weather data to provide accurate, site-specific recommendations.

Tailored for changing climate

Crop models

Soil, weather, phenology info



Model the **effect of soil and weather spatial variation** on crop production

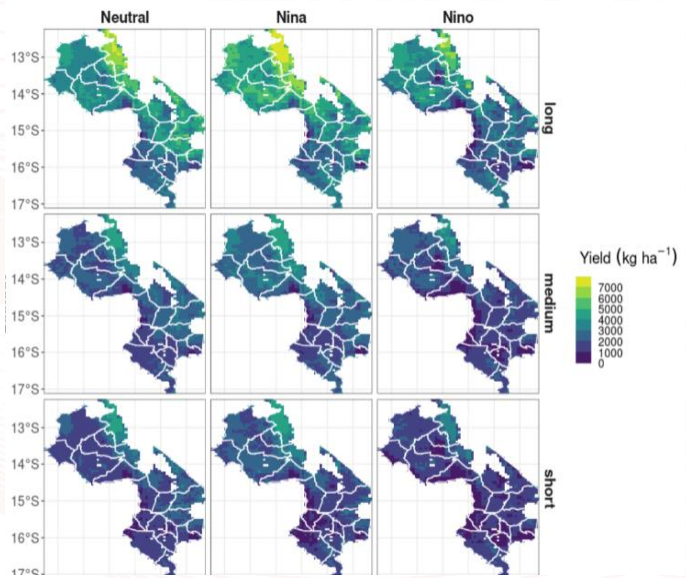
Yield potential map

Optimal planting dates

Best fit cultivar

Tailored for changing climate

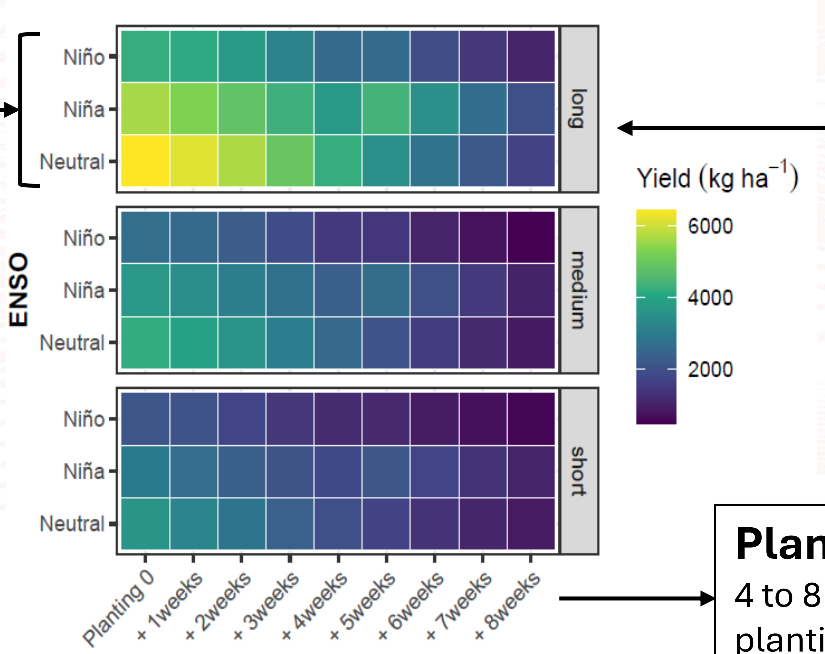
Yield potential map



Malawi, soybean water limited yield

3 Weather scenarios
Nino, Nina, neutral conditions

3 cultivar types
Long, medium, short



Planting weeks
4 to 8 weeks in planting period

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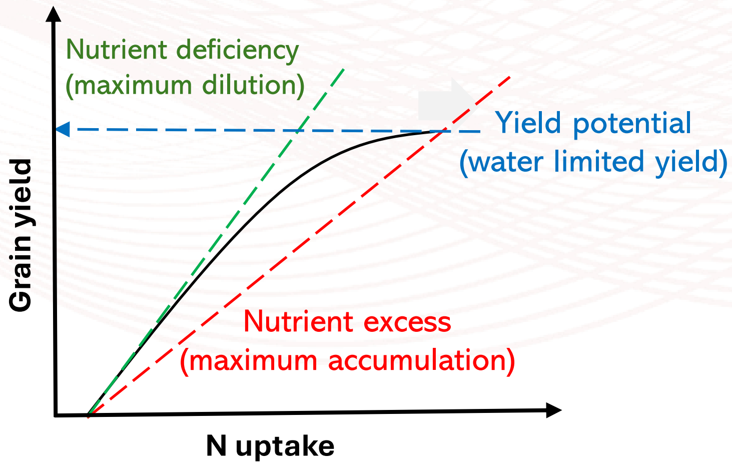
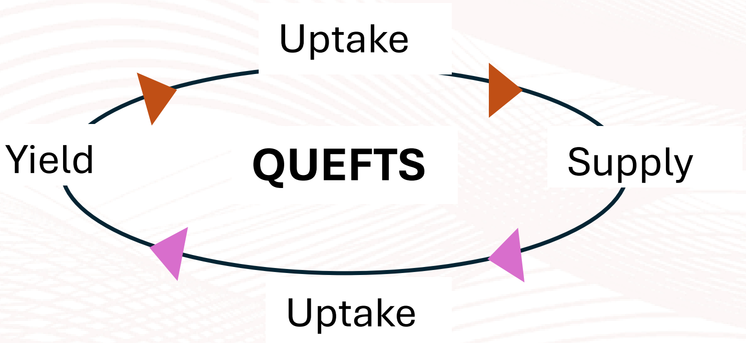
Determining soil nutrient supply

Because of the spatial variation in soil fertility, knowing the soil nutrient supply of a farm is important to provide site-specific fertilizer advice





The soil nutrient supply can be determined by soil sample analysis. Alternatively, if we have yield data measured from several treatments, it can be determined using **QUEFTS** (Quantitative Evaluation of Fertility of Tropical Soils) model.

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Determining soil nutrient supply

Available nutrient = (fertilizers added * recovery fraction) + soil nutrients supply or apparent (N_{soil}, P_{soil}, K_{soil})

Adjusted by crop specific parameters and yield potential, QUEFTS can determine the apparent soil nutrient supply for N, P & K by solving the following optimization algorithm.

$$NP_{yield} = f\{(N_{soil} + (N_{fertilizer} * N_{RF})), (P_{soil} + (P_{fetilizer} * P_{RF})), (K_{soil}), WLY\}$$

$$NK_{yield} = f\{(N_{soil} + (N_{fertilizer} * N_{RF})), (P_{soil}), (K_{soil} + (K_{fetilizer} * K_{RF})), WLY\}$$

$$PK_{yield} = f\{(N_{soil}), (P_{soil} + (P_{fertilizer} * P)), (K_{soil} + (K_{fetilizer} * K_{RF})), WLY\}$$

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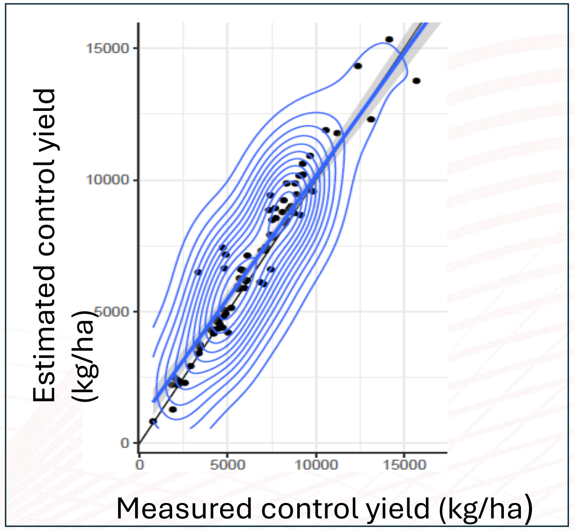
Assessing accuracy of QUEFTS prediction



1. Keep the control treatment data for validation

2. Use the remaining data to estimate the apparent soil nutrient supply (ANS) for every trial using QUEFTS

3. Use the estimated ANS and estimate what the yield with zero fertilizer would be at every trial

4. Compare the measured control yield in the validation set with the estimated control yield at step 3

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Machine learning

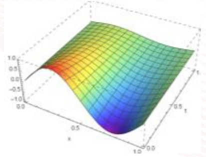
Estimating the soil nutrient supply with QUEFTS requires yield from fertilize rates at a location.

At farmers field there yield response to different rates of nutrient is **not** available.

We know the soil, weather and altitude of farmer's field using data from public databases

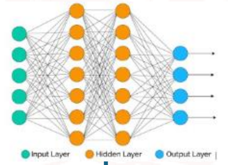
At farmer's field, AgWise uses **machine learning** models to predict soil nutrient supply using the secondary data.

Gradient boosting



Random forest

Artificial neural network



Ensemble learning

$$N_{soil\ supply} \sim soil + \ elevation + reference\ yield\ class$$

$$P_{soil\ supply} \sim soil + \ elevation + reference\ yield\ class$$

$$K_{soil\ supply} \sim soil + \ elevation + reference\ yield\ class$$

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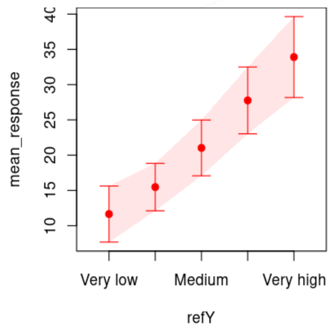
Machine learning in AgWise

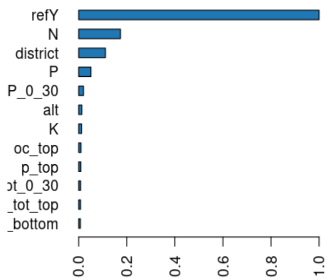
In the absence of sufficient data to run QUEFTS, it is not possible to determine the soil nutrient supply

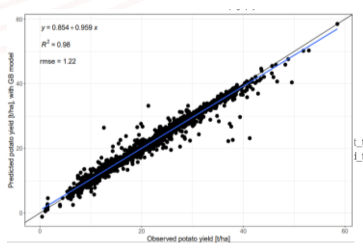
Alternatively

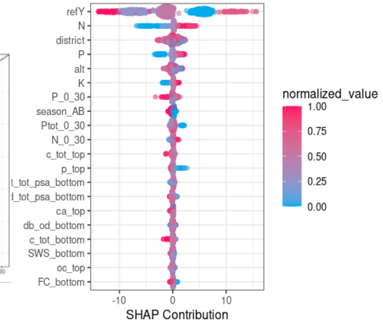
Machine learning techniques are used to model yield as a response to NPK added with the fertilizer and geospatial variables.

$$Yield \sim N_{fertilizer} + P_{fertilizer} + K_{fertilizer} + AEZ + Soil + Weather + DEM$$









The trained model will be used to develop the yield response to NPK curves from which a tailored fertilizer rates optimized for target or maximum profit will be identified.

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Tailored agronomic advice

Maize	Potato	Rice	Teff	Wheat	Soybean	Cassava	Sorghum

Maize	Potato	Rice	Teff	Wheat	Soybean	Cassava	Sorghum
Ethiopia, Rwanda, Kenya, Ghana	Rwanda, Nigeria	Rwanda, Cambodia	Ethiopia	Ethiopia, Rwanda	Malawi, Zambia, Mozambique, Ghana	Rwanda, Nigeria, Tanzania, Ghana, Burundi	Ethiopia

Validated
Under validation
To be validated
Being developed

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