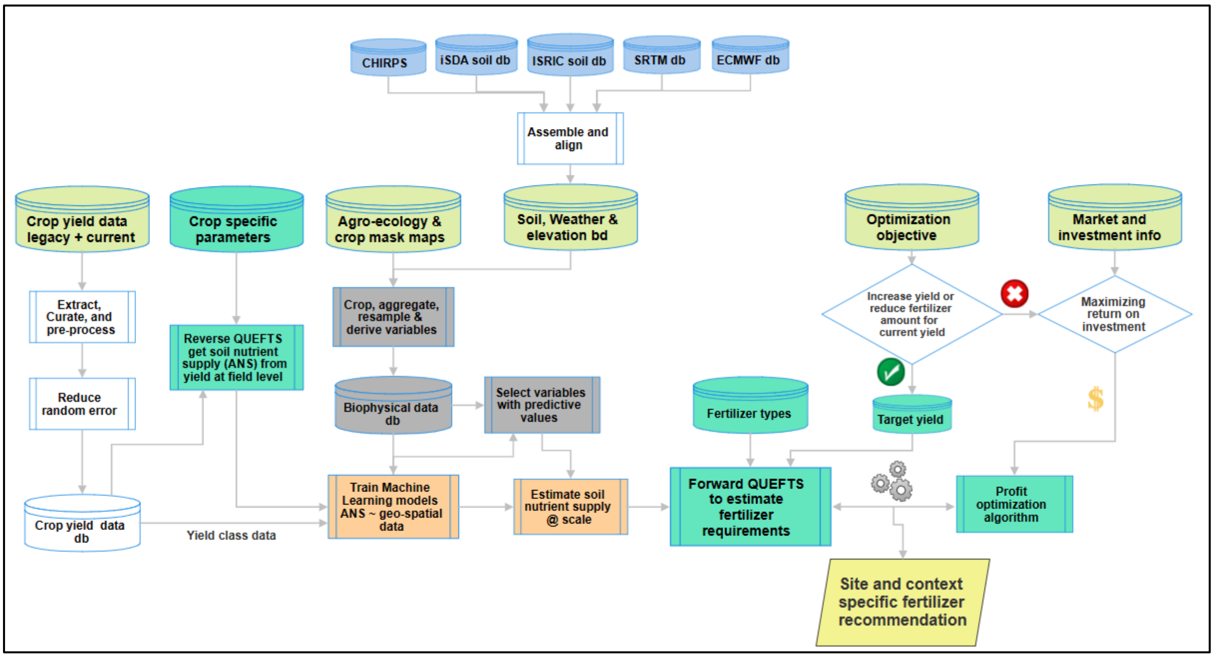
Tailored fertilizer advice analytical methods

QUEFTS- based and Machine Learning approach



Advancing upon the methodologies of the previous approaches, this integrated approach combines QUEFTS principles with machine learning techniques to extrapolate the estimation of apparent soil nutrient supply (ANS) to a more variable environment by accounting the variation in the geo-spatial factors into account. Machine learning models are trained to establish intricate relationships between ANS derived from reverse QUEFTS and geo-spatial variables at experimental sites. This trained model is then used to estimate ANS at scale, at desired resolutions, across various locations. While it is naturally logical to attribute soil nutrient supply bio-physical factors such as sol properties, elevation, and weather variables, the current geo-spatial data available at scale, can account for approximately 30% - 40% of the structured spatial variation of soil nutrient supply. To enhance the model's predictive capabilities substantially, the inclusion of local soil fertility indicators, particularly current yield class information, has been proven instrumental. The current yield class can be established from survey or field trials data and curated by agronomists working in the target area.

Data Needs: This approach requires field trials data to estimate the current yield class and the ANS using reverse QUEFTS. The field trials data should meet the quality standards outlined in the QUEFTS-alone approach, with the addition of data or indications of current yield class being essential. Extensive geo-spatial data is also needed to apply the machine learning models.

Complexity: Of higher complexity, this approach integrates QUEFTS and machine learning techniques, requiring extensive data assessment to establish current yield levels. Ideally deployed within a system enabling users to input historical yield data from their fields and facilitating real-time computation for customized advice adjustments based on user-specific parameters such as farm size, fertilizer types and prices, and investment capacity. In such setup, it is possible to deliver hyper-contextualized advisory based on user input data on farm size, fertilizer types and prices, investments capacity, etc.

Application: This integrated approach is successfully deployed in developing tailored fertilizer advice for maize in Kenya and potato for Rwanda.