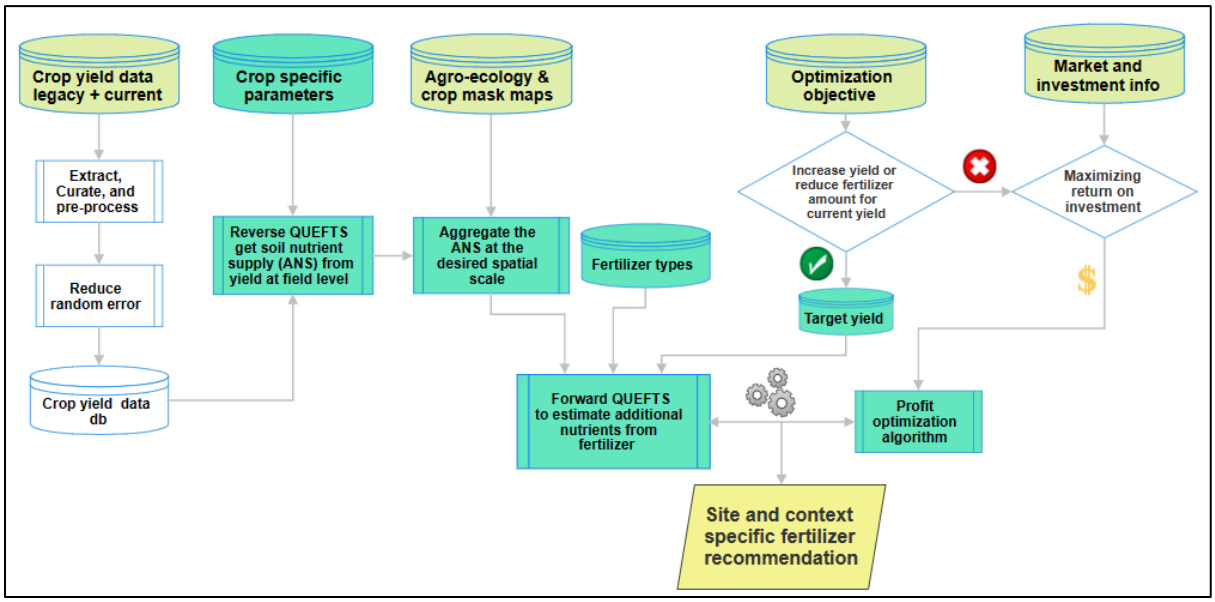
Tailored fertilizer advice analytical methods

QUEFTS-based approach



As an alternative to the machine learning approach, this approach leverages the QUEFTS (Quantitative Evaluation of Fertility of Tropical Soils) crop model to produce tailored fertilizer advice. QUEFTS's strength lies in its ability to model the dynamic relationship between soil nutrients supply and yield, accounting for crop specific nutrient uptake capacity and the maximum attainable yield at a given location. The estimation of apparent soil nutrient supply (ANS), representing the soil's NPK available to a crop considering indigenous soil nutrients, water availability, and field management effects, is central to this method. Achieving this estimation relies on an optimization algorithm rooted in reverse QUEFTS methodology, iteratively adjusting ANS values to best fit observed yield responses while minimizing the residual sum of squared errors of the estimation. This iterative and location-specific approach ensured that ANS estimations are tailored to the unique conditions present at each trial location. Subsequently, ANS values can be aggregated based on similar recommendation domains, such as agroecological zones, to define the NPK availability for crops in specific areas. Forward QUEFTS is then employed with large sets of combinations of NPK to predict yields based on ANS. Like the machine learning approach, the results can be further refined to provide fertilizer advice aimed at meeting yield or profit increases.

Data Needs: The QUEFTS approach requires quality field trials data with at least three treatments being tested at a location with yields, along with information on NPK combinations. While data from nutrient omission trials, including full NPK, a control with zero fertilizer input and the three omission treatments, are ideal, they are not mandatory.

Complexity: Moderate in complexity, this approach necessitates meticulous data curation and error reduction, coupled with QUEFTS methodology application. It is less data intensive than the machine learning approach as it can account for crop specific parameters to model biologically realistic yield response curves from fewer nutrient rate levels. As a result, it can predict yields for NPK levels that are not available in training dataset safeguarding users in high yield potential areas from conservative fertilizer advice. This approach however has limited application when there is limited field trials data in a highly variable environment basically because of the inability to explain the soil nutrient supply of the target area using few ANS obtained from the experimental sites. This limitation lays the groundwork for the subsequent approach integrating QUEFTS and the ML methods to estimate ANS at scale.

Application: The QUEFTS approach is successfully deployed in developing tailored fertilizer for maize and rice in Rwanda.