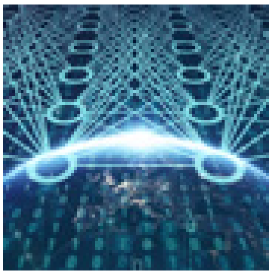

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Integrating Field Observations and Machine Learning for National-Scale Agricultural Yield Classification from Sentinel-2

Content

Accurate and timely crop mapping is essential for agricultural monitoring, climate-risk assessment, forecasting, and evaluating hazard-related damage. However, understanding agricultural yield on ground remains a major challenge in many parts of the world, especially when cloud cover and limited cost- and time-intensive field surveys restrict timely assessments. In this study, we develop a national-scale crop classification framework that combines field-verified observations with machine-learning models applied to Sentinel-2 multispectral imagery. Ground-reference data were collected using stratified random sampling during 'Rabi' (15 February–25 March 2021) and 'Kharif' (09 August–21 September 2021) winter and summer crop cycles, resulting in 600 georeferenced ground truth samples across 12 crop and land-cover classes.

The dataset was split into training (80%) and independent validation (20%) subsets. During the analysis, it became clear no single vegetation index could capture all crop conditions, so we generated a suite of features including four key indices—NDVI, GNDVI, EVI, and SAVI, alongside multispectral bands. These complementary indices improved separability among crop types. Our pipeline, implemented in Google Earth Engine, consisted of (1) image pre-processing using cloud removal and median composposititing, (2) feature generation using multispectral bands and key indices, (3) NDVI-based masking to retain only vegetated pixels, and (4) classification. A Random Forest classifier, benchmarked against alternative ML algorithms, was trained on these features and deployed to produce spatially consistent crop maps at national scale.

To contextualize performance, we compared our results with the IBM–NASA Prithvi crop classification model. We found that combining field information with machine-learning models can offer tailored and therefore more reliable results compared to relying solely on large pretrained systems. This workflow was also applied to assess flood-related crop damage, demonstrating its practical utility for rapid decision-making during extreme climate-exacerbated events. Overall, our study shows that tailored ML pipelines can make a meaningful contribution to national-scale agricultural monitoring.

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