Empathy Map

Dive into the mind of the user for focused product development

- Build empathy and keep your focus on the user by putting yourself in their shoes.

Crop Yield Prediction using Machine Learning Algorithms

Agriculture is first and foremost factor which is important for survival. Machine learning (ML) could be a crucial perspective for acquiring real-world and operative solution for crop yield issue. Considering the present system including manual counting, climate smart pest management and satellite imagery, the result obtained arent really accurate. This paper focuses mainly on predicting the yield of the crop by applying various machine learning techniques. The classifier models used here include Logistic Regression, NaÃ¯ve Bayes and Random Forest, out of which the Random Forest provides maximum accuracy. The prediction made by machine learning algorithms will help the farmers to come to a decision which crop to grow to induce the most yield by considering factors like temperature, rainfall, area, etc. This bridges the gap between technology and agriculture sector.

EOSDA Crop Monitoring provides farmers with weather analytics that include current and historical weather data, as well as forecasts up to two weeks ahead. Also, this software allows agrarians to detect the extreme weather states that can affect crop yields

Hardcastle GIS offers a unique and efficient way to accurately and reliably forecast biomass and yield throughout the full growing season. It rapidly equips sugar mills with essential information to make key decisions about sugarcane harvesting and crushing. Hardcastle solution helps mill operators manage their logistics (opening dates, inputs, distribution of harvesting machines, etc.) and allocate resources (labor, machinery, etc.) according to the yield forecasts. Specific use cases of Hardcastle solution include optimization of harvesting based on maturity; growth monitoring throughout the season to better plan on-field operations; and biomass prediction to maximize yield output.

Accurate Weather Prediction

The average crop yield per acre on a given field is very much conditioned by weather factors. With the same quality of soil and the same species of seeds planted, the climate conditions have a predominant influence on the development of plants and, consequently, on yields. It is especially true when considering how climate change affects agriculture in separate regions and on Earth in general. To work efficiently and cooperatively with such an important but uncontrollable factor as weather, farmers have an opportunity to refer to the newest technological solutions that help them obtain accurate weather prediction.

Forecasting Crop Yield

Crop yield prediction is very important for global production of food. Governments all over the world use analytical data concerning crop yields forecasting to take grounded decisions as to their national import/export operations. Companies specialized in seed breeding need to foresee how new hybrids will perform in different climate and soil conditions to plan on further improvement of new variations of seeds. Farmers, in their turn, take advantage of crop yield prediction to make well-weighted agribusiness decisions.

Says

Thinks

Does

Feels

Select an area that is representative of the paddock. Using some type of measuring rod or tape, measure out an area of 1m2 and count the number of heads or pods.
Do this 5 times to get an average of the crop (A)

Using Table 1 determine the grain weight for the crop concerned (C)

Yield in t/ha = (A × B × C) / 10,000

crop insurance purposes

forward marketing and delivery planning

planning harvest and storage requirements

cash-flow budgeting

Identifying Whether Providing Information Improves Self-Reported Accuracy

we first georeferenced each of the 115 fields using the GPS data that we collected for each plot (detailed in section social survey data). Georeferencing was done by overlaying all GPS points on the March 11 SkySat image in ArcGIS. We then examined GPS points collected for each individual field one at a time, and drew a polygon around the visible field boundaries of the field that overlapped most of the GPS points. If the GPS points did not clearly overlap with one field, we did not draw a field polygon for this field. In total, we were able to create polygons for 101 fields out of the 115 fields originally surveyed (50 fields were for group 1, and 51 fields were for group 2). For each of these polygons, we extracted the mean yield estimated by satellite data using the raster package in R project software. Before doing any additional analyses, we also removed any self-reported yield estimates that were unrealistic. Specifically, we removed any self-reported yield values that were <1,000 kg/ha and >6,000 kg/ha, since these were the minimum and maximum yield values that we observed in our crop cut dataset for the region, which is considered the gold standard of yield estimation. This reduced our sample size to 74 fields (33 fields were in group 1, and 41 fields were in group 2. We conducted the power analysis to check the accuracy of our sample size using the pwr package in R project software. When using a “medium” effect sizes (0.5) as defined in previous study (Cohen, 1992), we found that the power of our experiment is 99% after removing extreme self-reported yield values (33 fields in group 1, and 41 fields in group 2). However, with a “small” effect size (0.2), we found the power our experiment is 41%. These 74 data points were used for all subsequent analyses in the paper.

Share your feedback

we summarized overall self-reported accuracy across all farmers using our metric of self-reported accuracy described in section Identifying whether providing information improves self-reported accuracy. We also assessed the accuracy of self-reported yield estimates by identifying whether these estimates could capture the known relationship between sowing date and wheat yields. Specifically, we were interested in identifying whether there was a significant and negative relationship between sowing date and self-reported yield. To quantify whether this relationship exists, we used a linear regression model (Equation 3) and assessed model fit using R2 and whether the beta coefficient on sowing date (β1) was significant and negative.

Assessing Self-Reported Accuracy and Its Drivers

This is a textbox...

Self-reported accuracy (kg/ha) ~ β0+β1Irrigation+β2Age+β3Education+β4Plot Area+β5Plot Yield+β6Fertilizer+ β7Wealth Index+ε (4)

Self-reported yield (kg/ha) ~ β0+β1sowing date+ε (3)
As a comparison, we also assessed whether this known relationship between sowing date and wheat yield could be detected using crop cut estimates of yield for the 64 fields for which we had crop cut data. To do this, we also used Equation 3, but replaced self-reported yield with as crop cut as the dependent variable.

This is a textbox...

Finally, to understand which factors may be significantly associated with self-reported accuracy, we ran a multiple linear regression. We were interested in identifying which socio-economic, management, and yield variables may be associated with whether a farmer is more likely to under or over-report yields on his/her field. For this analysis, we used Equation 4.