solar radiation drives the crop photosynthesis and a higher Leaf Area Index (LAI) in July ensures better light interception and photosynthetic efficiency, crucial for the plant's vegetative growth phase. Enhanced Vegetation Index (EVI) in July indicates healthier, more vigorous plant growth, and contribute to higher biomass and yield potential.

IV. Discussion

This study employs a random forest model designed with changes in only one standard deviation to simulate impacts on predicted corn yield. Research indicates that extreme weather events, although infrequent, can have significant effects on crop production, and often more severe than average weather conditions [22]. We have excluded all outliers for each input. However, the sensitivity test (one standard deviation) primarily assesses how sensitive the model's predictions are to errors in the input variables. All observations and measurements contain errors. Small errors in very sensitive input variables can cause significant errors in predicted yield. While we cannot control the weather, but we use weather model and sensitivity analysis on over one million input combinations, we identified the key environmental factors impacting yield. From the results, we found that higher solar radiation and vegetation indices (VIs) often correlate with higher yields. Also, errors in solar radiation and vegetation indices can lead to significant inaccuracies and biases in yield predictions.. These findings emphasize the importance of solar radiation and vegetation indices during critical growth periods to corn yield, and accurate measurement of the two types of inputs in the yield prediction. This study faces limitations include using changes in only one standard deviation and excluding outliers, which may restrict our understanding of the full impact range. Future research should incorporate multiple standard deviations and outliers to better capture weather variability and extreme impacts on crop yields. High-resolution weather datasets are essential for providing accurate input data, and their integration could enhance model performance. This study provides a framework for forecasting corn yield, and potential for improving crop yield predictions amid climate challenges. More importantly,

when certain other inputs are missing, we can use the relationship between solar radiation, LAI, and EVI to reasonably predict corn yield.

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