Supplementary Material

of

Estimating Irrigation Water Consumption Using Machine Learning and Remote Sensing Data in Kansas High Plains

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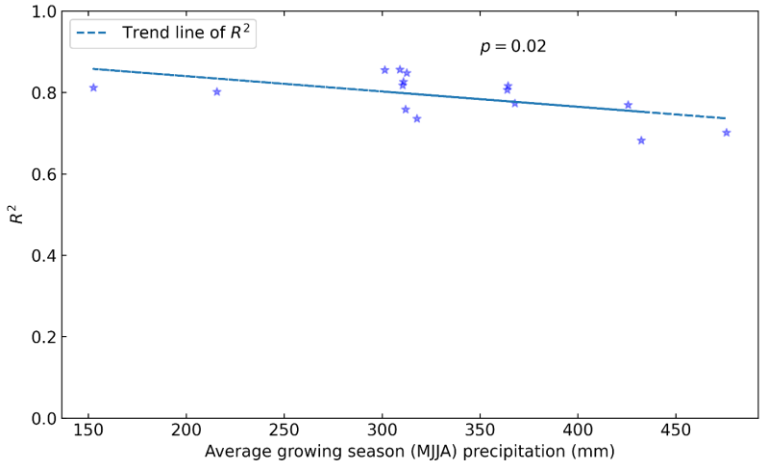


Figure S1. Experiment A (random split) test R^2 varies with the growing season (MJJA) precipitation amount for 2006-2020. A statistically significant ($p = 0.02$) linear declining trend is also shown.

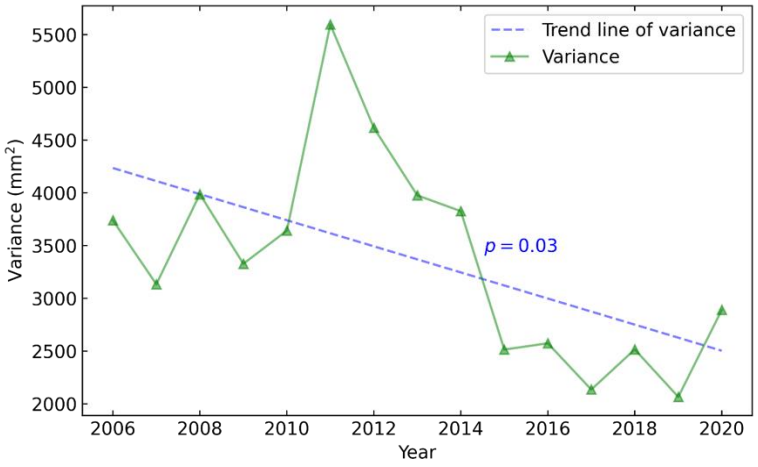


Figure S2. Annual variance of *in situ* irrigation depth (mm^2) of the test data in Experiment A (random split). Also shown is a statistically significant declining trend ($p = 0.03$).

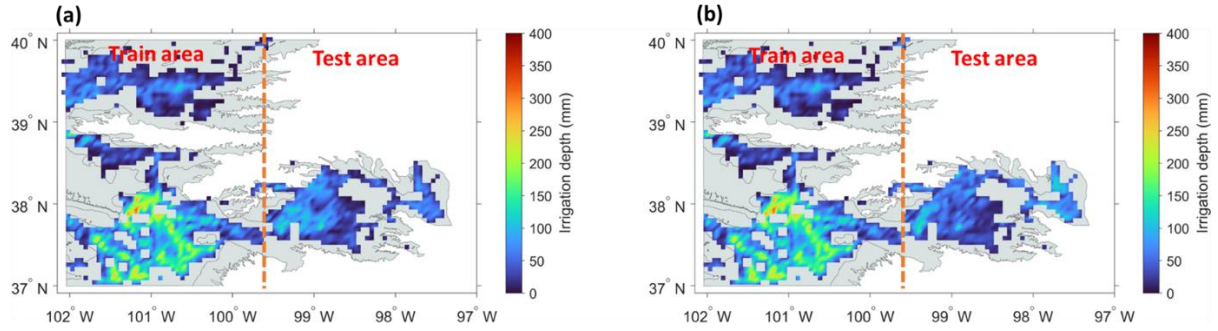


Figure S3. (a) *In situ* and (b) RFR estimated irrigation amount in Experiment B (regional split) for a poor performance year 2020 with $R^2 = 0.37$. The red dash line divides the training (western) and test (eastern) regions.

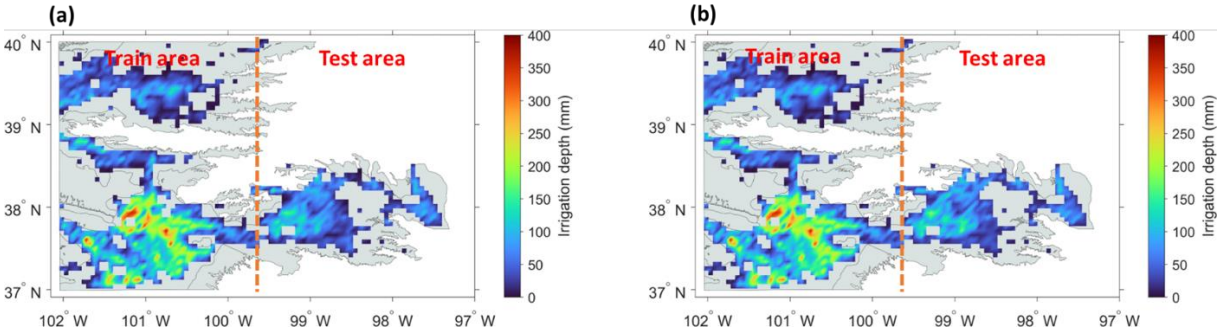


Figure S4. (a) *In situ* and (b) RFR estimated irrigation amount in Experiment B (regional split) for a good performance year 2006 with R2 = 0.77. The red dash line divides the training (western) and test (eastern) regions.

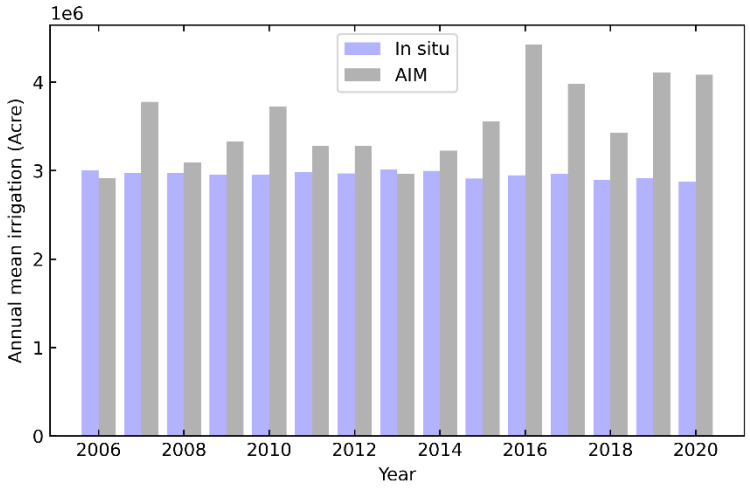


Figure S5. Annual total irrigation acreage within the study area from *in situ* records (WIMAS, purple) and remote sensing derived irrigation map (AIM-HPA, grey).

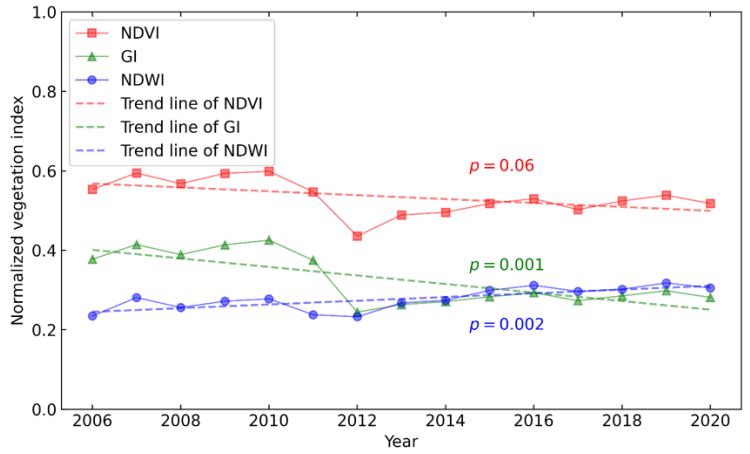


Figure S6. Normalized annual GI (green, triangles), NDVI (red, squares), and annual NDWI (blue, circle) averaged across the study area during 2006-2020. Linear regression lines of GI, NDVI and NDWI are also shown with *p*-values.