A HIGH-RESOLUTION DATA-DRIVEN MONTHLY AQUACULTURE AND IRRIGATION WATER USE MODEL IN THE MISSISSIPPI ALLUVIAL PLAIN

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INTRODUCTION

Background

- ➢ Groundwater is a vital resource for global agriculture, supplying over 20% of the world's irrigation water. However, increasing demand from population growth and climate variability is placing these resources under severe stress, leading to aquifer depletion, land subsidence, and streamflow reduction in many regions (Hasan et al., 2023; Ott et al., 2024; Ketchum et al., 2023).
- ➢ A critical gap in sustainable water management is the lack of adequate monitoring of groundwater withdrawals at high spatiotemporal resolutions (Majumdar et al., 2024).
- ➢ This research addresses this challenge by developing a high-resolution (1 km), data-driven model to estimate monthly groundwater use (2014-2021) for aquaculture and irrigation in the Mississippi Alluvial Plain (MAP), a major agricultural hub in the United States.

Key Challenges & Objectives

- ➢ **Inadequate Monitoring:** Groundwater pumping, a critical part of the water budget, is not sufficiently monitored for effective water management (Majumdar et al., 2020, 2022, 2024).
- ➢ **Modeling Complexity:** Traditional physical models are often computationally intensive and difficult to calibrate for large-scale applications. Direct water balance estimates are hampered by a lack of data on key variables.
- ➢ **Data Scarcity:** Supervised machine learning models require extensive, high-quality, in-situ pumping records, which are often unavailable.

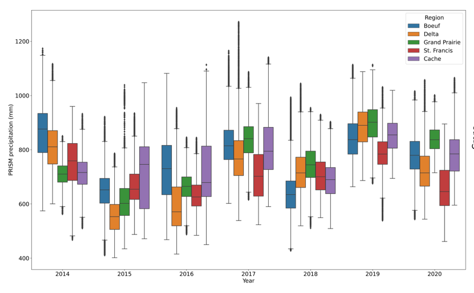
Our Approach

- ➢ We enhance the existing Aquaculture and Irrigation Water Use Model (AIWUM 2.0; Majumdar et al., 2024; Wilson, 2021) by developing a machine learning-driven framework to estimate monthly, crop-specific groundwater withdrawals at a 100m to 1km resolution.
- ➢ Our model integrates diverse datasets, including remote sensing products (MODIS, Landsat), gridded hydrometeorological data (PRISM, TerraClimate), and a combination of observed and synthetically generated monthly groundwater use records.
- ➢ By improving the temporal resolution from annual to monthly, this work offers a more dynamic and accurate tool for the U.S. Geological Survey (USGS) to assess water use and availability, advancing hydrologic decision-support systems in the MAP.

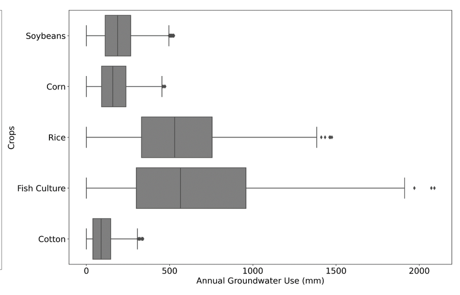
STUDY AREA, DATA, AND METHODS

Study Area

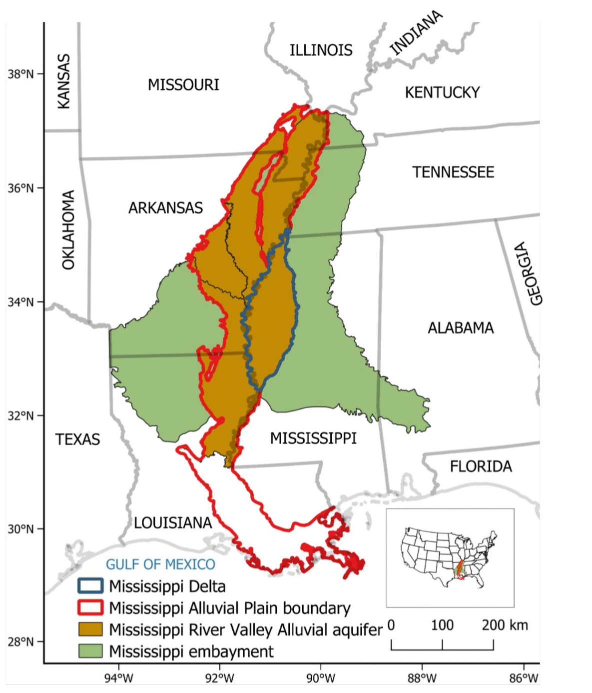
- ➢ The **Mississippi Alluvial Plain (MAP)** is a major U.S. agricultural region characterized by heavy groundwater use (averaging nearly 11 km³/year).
- ➢ **Primary Uses:** Irrigation for rice, soybeans, corn, and cotton, as well as aquaculture (fishponds).
- ➢ **Timeline:** The primary growing season for crops is April to September, while groundwater pumping for aquaculture occurs year-round.
- ➢ **Aquifers:** Our model's domain covers the full extent of the Mississippi Embayment (MISE) and the Mississippi River Valley alluvial aquifer (MRVA).



Annual precipitation over the generalized regions of the MAP from 2014-2020 (Majumdar et al., 2024)

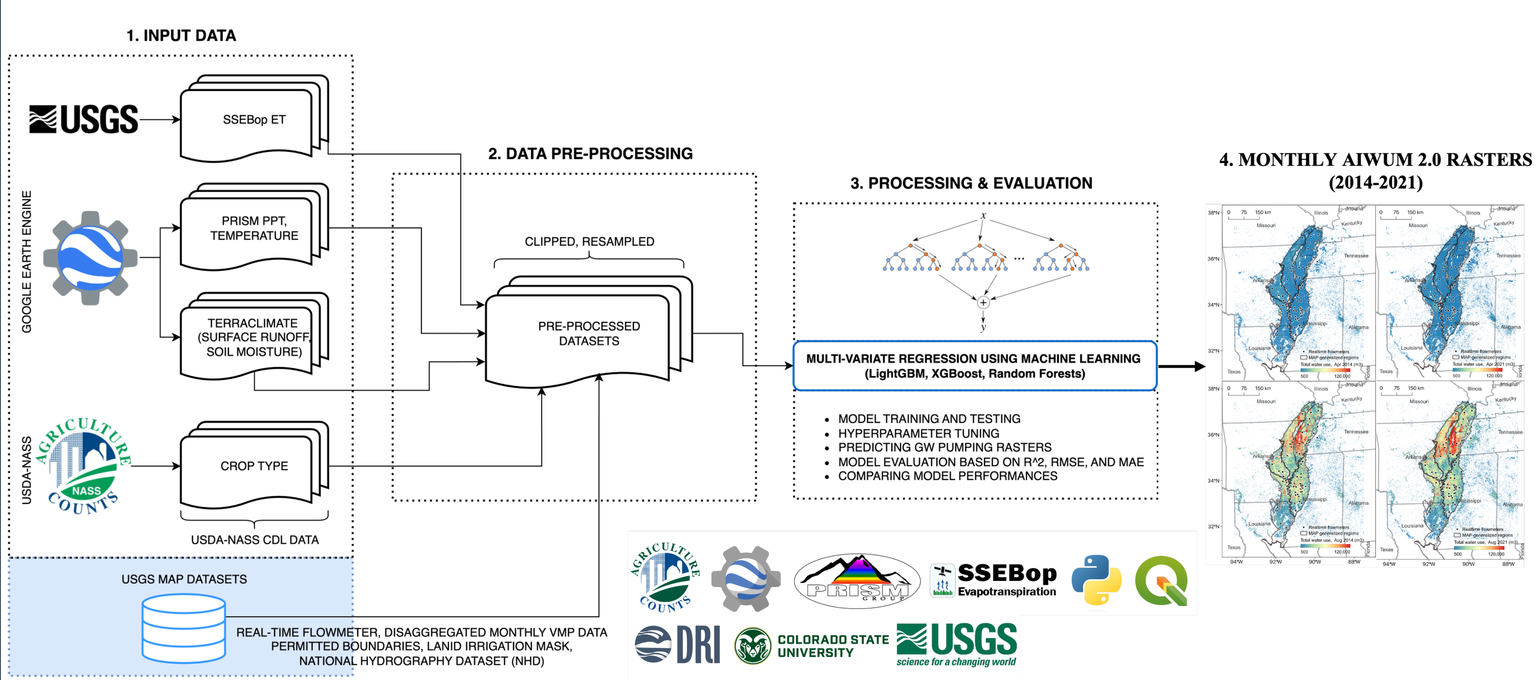


Annual groundwater pumping/use data from the DVMP dataset (Majumdar et al., 2024)



Data

- ➢ Our model integrates multiple data sources to serve as predictor variables and ground truth for training and validation.
- ➢ **Remote Sensing Products:**
  - a) Monthly 1-km MODIS SSEBop Evapotranspiration (ET).
  - b) Annual 30-m USDA Cropland Data Layer (CDL).
  - c) Annual 30-m Landsat-based Irrigation Dataset (LANID).
- ➢ **Gridded Hydrometeorological Data:**
  - a) Monthly 800-m PRISM data for precipitation and maximum air temperature.
  - b) Monthly ~4-km TerraClimate data for surface runoff and soil moisture.
- ➢ **Flowmeter Records:**
  - a) Annual data (2014-2020) from the Mississippi Department of Environmental Quality (MDEQ) Delta Voluntary Metering Program (DVMP).
  - b) Daily real-time measurements (2018-2021) from 93 USGS sites across the MAP.
- ➢ **GIS & Irrigation Masks:**
  - a) Vector layers for the MAP boundary, field boundaries, and well locations.
  - b) Annual irrigation masks were created by combining LANID, CDL, and the National Hydrography Dataset (NHD) to constrain model predictions to actively irrigated areas.



Methods

- ➢ This research updates the AIWUM 2.0 framework to predict groundwater withdrawals at a monthly, rather than annual, timestep.
- ➢ **Creating a Monthly Training Dataset:**
  - a) We developed a "synthetic" monthly groundwater use dataset by disaggregating the annual DVMP records.
  - b) This was achieved by creating normalized, crop-specific monthly weights from the daily USGS real-time flowmeter data and applying them to the annual DVMP totals.
  - c) This synthetic dataset was then combined with the observed USGS real-time measurements to form a comprehensive monthly training dataset.
- ➢ **Machine Learning Model:**
  - a) We employed the **Light Gradient Boosting Machine (LGBM)** algorithm and compared it with XGBoost and Random Forests.
  - b) The model was trained on 24 predictor variables, including field location (latitude, longitude), crop type, month, and the various remote sensing and hydrometeorological data products.
- ➢ **Training and Prediction:**
  - a) The dataset was split into 80% for training and 20% for testing.
  - b) The model was optimized using 5-fold cross-validation with Root Mean Square Error (RMSE) as the loss function.
  - c) The final trained model generates gridded monthly predictions of crop-specific (100 m) and total (1 km) groundwater use across the MAP from 2014-2021.

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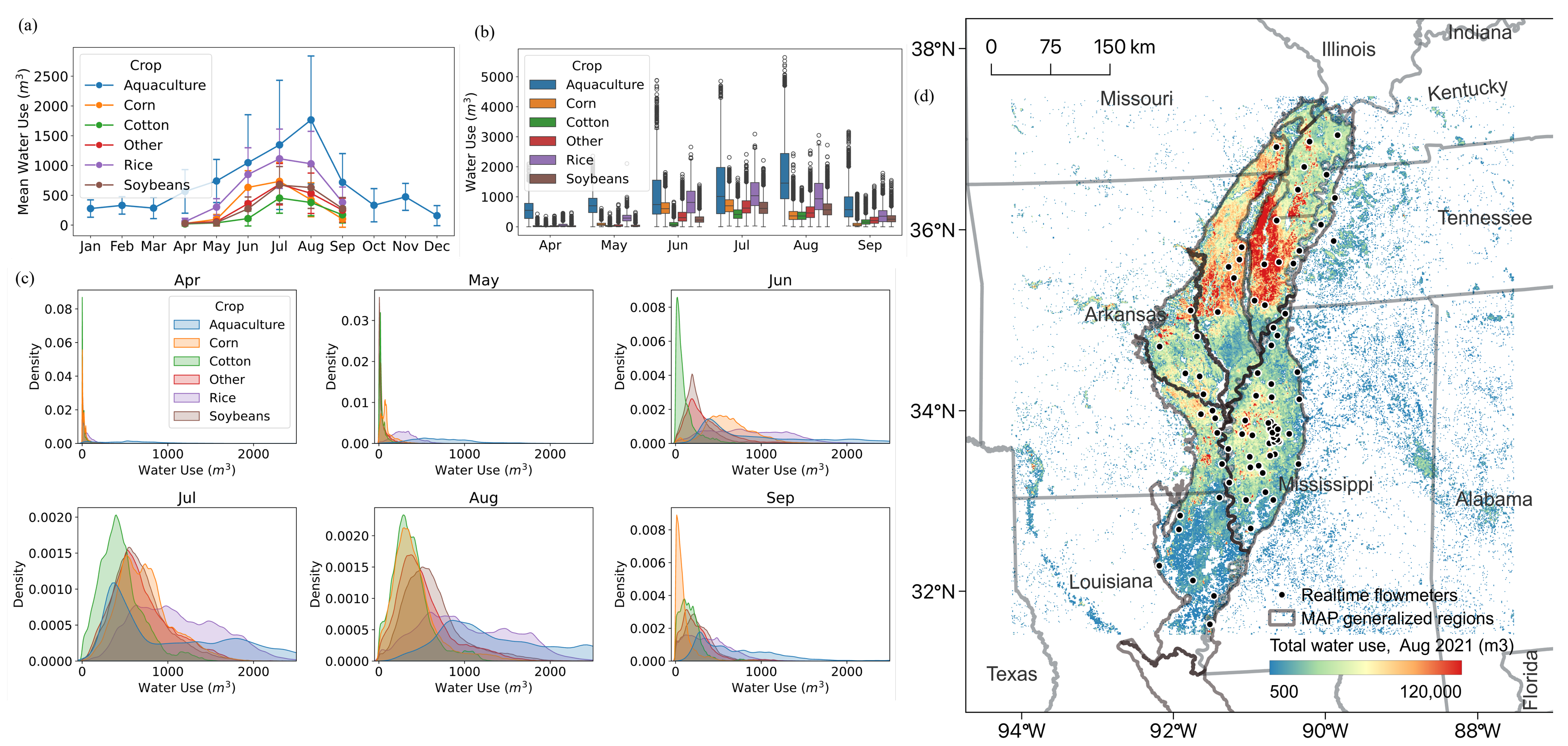
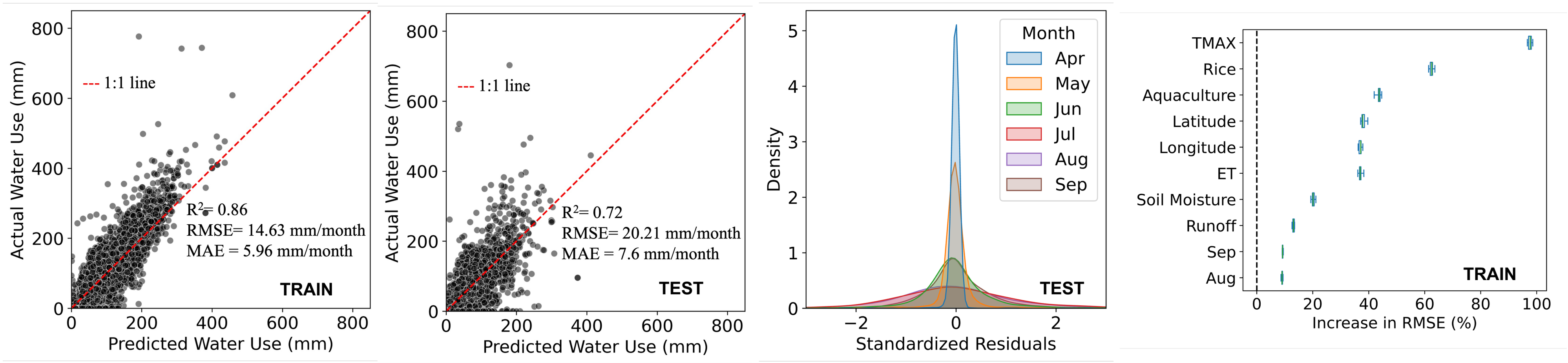
RESULTS

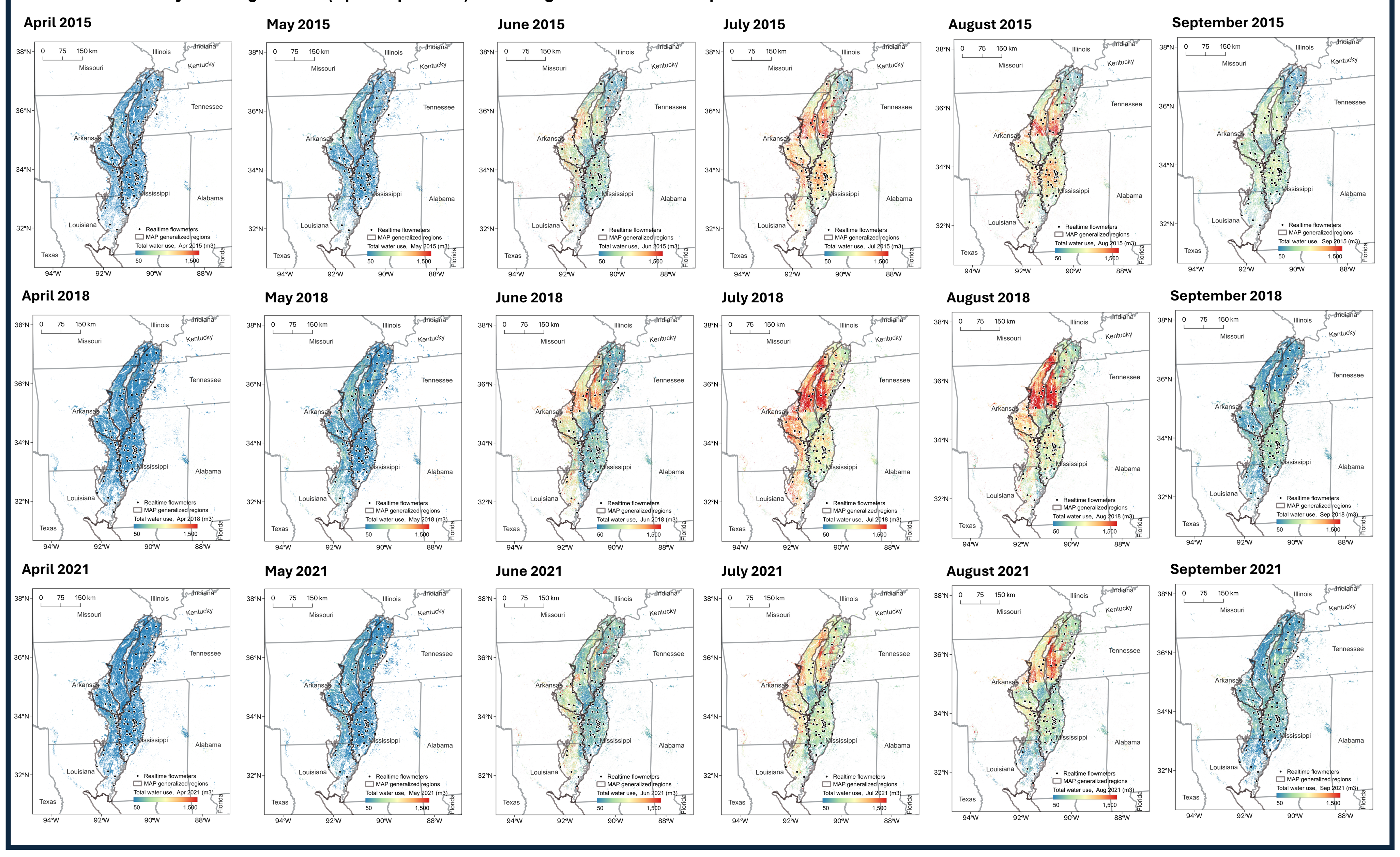


(a) shows the monthly mean crop-specific water use for all the years (2014-2021). (b) and (c) represent the boxplot and kernel density plots that show the growing season (April-September) water use distributions for each crop across all these years. (d) shows the predicted total water use map across the full MISE and MRVA extent for August 2021 at 1 km spatial resolution along with the USGS real-time flowmeter locations and the generalized MAP regions (Majumdar et al., 2024).



The training, validation, and test RMSEs are 15 mm/month, 21 mm/month, and 20 mm/month, respectively, with the corresponding mean absolute errors (MAEs) being 6 mm/month (R^2=0.85), and 8 mm/month (R^2=0.72) each for the validation and test data. The overall training and validation R^2, RMSE, and MAE are 0.86, 14.63 mm/month, and 5.96 mm/month, respectively,

AIWUM 2.0 Monthly Growing Season (April-September) 100m Irrigation Water Use Maps



CONCLUSIONS

- ➢ **This research presents the first high-resolution (100 m to 1 km), machine learning-driven monthly estimates of total and crop-specific irrigation water use for the entire Mississippi Alluvial Plain from 2014-2021.**
- ➢ **The updated AIWUM 2.0 demonstrates strong predictive skill (Test RMSE: 20 mm/month), effectively learning the non-linear relationships between groundwater pumping and its climatic and land use drivers.**
- ➢ Our model improves upon the existing AIWUM 1.1 framework (Wilson, 2021) by providing more refined and realistic monthly water use estimates, particularly correcting for underestimation at the beginning (April) and end (September) of the growing season.
- ➢ Future work will focus on intercomparisons with other national-scale water use datasets (Martin et al., 2025) and incorporating field-scale ET data (e.g., from OpenET; Melton et al., 2022; Volk et al., 2024; Ott et al., 2024) to further enhance model accuracy and applicability.

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