ADAPTATION FUTURES 2025
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Africa Rice Center
Centre du riz pour l'Afrique

SIMULATING RICE YIELD USING ENSEMBLE MACHINE LEARNING MODELS AND PREDICTING CLIMATE CHANGE IMPACTS IN WEST AFRICA

by :
Your paragraph text
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SHORT BIOGRAPHY – CEDARTA DONOU

- Cedarta Donou is a Senior Data Scientist, AI Researcher, and Crop Modeler passionate about leveraging digital technologies to strengthen climate resilience and sustainable agriculture in Africa.
- He is currently pursuing a PhD focused on modelling land suitability and rice yield for sustainable multiple-harvest systems in Sub-Saharan Africa.
- His research integrates niche ecology, agricultural modelling, artificial intelligence, and agro-economics to support climate adaptation and food security strategies.
- Cedarta has presented his work at major international conferences, including Adaptation Futures 2023 (Canada), and in 2025 (New Zealand), he will present innovative approaches to simulating rice yields and predicting climate change impacts in West Africa.

PRESENTATION OUTLINE

1. Introduction & Motivation
2. Research Objectives
3. Study Area & Data
4. Method
5. Results
6. Discussion
7. Conclusion
8. Acknowledgments

INTRODUCTION & MOTIVATION 1/2

- On average, rice yield in sub-Saharan Africa is 2.8 t/ha, and much lower than world average yield of 4.8 t/ha (FAOSTAT, 2023).
- Rice is mainly produced in irrigated lowlands, rainfed lowlands and rainfed uplands.
- Large variation in yield: 0.03 to 4.0 t/ha in rainfed uplands, 0.1 to 6.0 t/ha in rainfed lowlands and 0.3 to 8.0 t/ha in irrigated lowlands (Niang et al., 2017).
- Major determinants of rice yield variations include varieties, soils, climates and management practices (Niang et al., 2017).
- Several approaches including statistical analysis, remote sensing and crop models were used for quantifying yield variation.

INTRODUCTION & MOTIVATION 2/2

- Crop models rely on high resolution input data, which are difficult to obtain in SSA.
- The quantity and quality of input data limit statistical methods. They also assume linear correlations with variables and report generating large uncertainties.
- Machine learning can be used to address these challenges. However, reports from machine learning were shown to largely vary based on models/algorithms used.
- Ensemble modeling approach combining several algorithms may provide better predictive performance. Also, little is known about the magnitude of rice yield changes due to changes in climate conditions.

RESEARCH OBJECTIVE

The objectives were to :

- i) Evaluate performance of ensemble machine learning approach in simulating rice yield,
- ii) identify most important determinants of rice yield and
- iii) Simulate climate change impacts on rice yield in growing environments in WA.

RESEARCH INSTITUTE

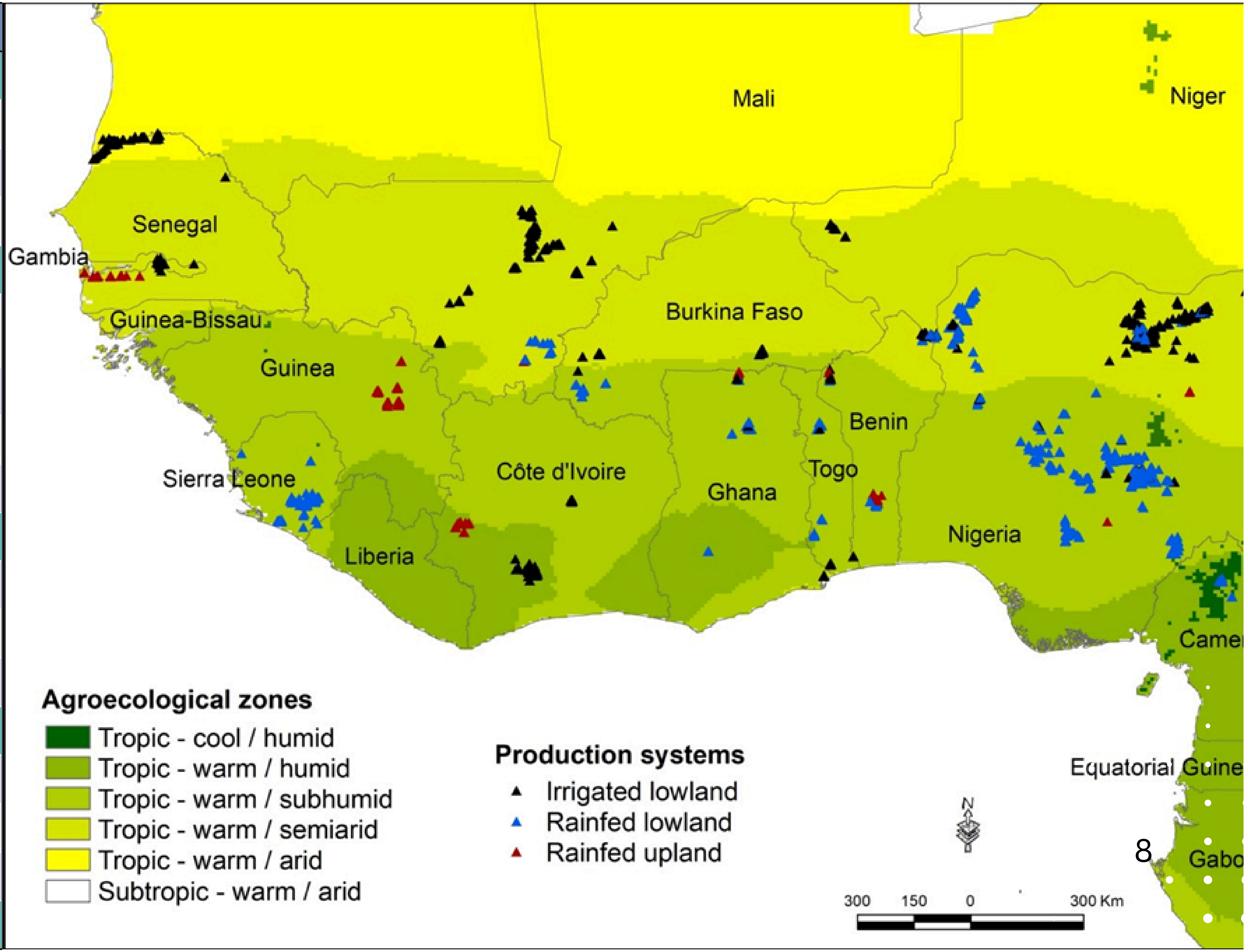
🌾 About AfricaRice

- AfricaRice (Africa Rice Center) is a pan-African research organization and one of the CGIAR centers.
- Headquartered in Abidjan, Côte d'Ivoire, with regional research stations across Africa.
- Mission: "To contribute to poverty alleviation and food security in Africa through research, development, and partnerships to improve rice-based systems."
- Works with national research institutions, universities, and farmers in more than 30 African countries.
- Plays a key role in developing improved rice varieties, sustainable farming practices, and policy support.

STUDY AREA & DATA 1/3 : MATERIAL AND METHODS

Data collected on 17,647 rice fields distributed in three growing environments. Irrigated lowlands include both wet and dry seasons.

Production system	Agro-ecological	Number of fields
Dry Irrigated		4027
	Tropic warm arid	210
	Tropic warm	3267
	Tropic warm	550
Wet Irrigated		7635
	Tropic warm arid	42
	Tropic warm humid	27
	Tropic warm	7443
	Tropic warm	123
Rainfed lowland		5759
	Tropic warm humid	10
	Tropic warm	1149
	Tropic warm	4600
Rainfed upland		226
	Tropic warm humid	17
	Tropic warm	99
	Tropic warm	110
	Grand Total	17647



STUDY AREA & DATA 2/3: MEAN AND VARIATIONS OF DATA AND DATA SOURCES

Variables	Mean	Standard deviation	CV (%)	Source
Agro-ecological zone (AEZ)				http://www.harvestchoice.org/
Growing environment				Field Surveys
Season (wet/dry)				Field Surveys
Rice yield (t/ha)	4.5	1.6	36	Field Surveys
Management practices				
N input (kg/ha)	104	37	35	Field Surveys
P input (kg/ha)	31	25	79	Field Surveys
K input (kg/ha)	31	24	76	Field Surveys
Soil properties				
Sand (%)	56	9	16	https://zenodo.org/record/4085160#.YXA_Dhy2xaQ
Clay (%)	21	6	28	https://zenodo.org/record/4085160#.YXA_Dhy2xaQ
Soil organic carbon (%)	1.8	1	13	https://zenodo.org/record/4085160#.YXA_Dhy2xaQ
Total nitrogen (%)	0.5	0.1	26	https://zenodo.org/record/4085160#.YXA_Dhy2xaQ
Soil pH	6	0.4	7	https://zenodo.org/record/4085160#.YXA_Dhy2xaQ
Available soil water holding capacity (%) (ASWC)	17	3	17	https://zenodo.org/record/4085160#.YXA_Dhy2xaQ
Weather variables of growing season				
Rainfall (mm)	915	261	29	ftp.cpc.ncep.noaa.gov/fews/fewsdata/africa/arc2
Maximum temperature (oC)	33.8	1.2	4	https://data.ceda.ac.uk/badc/cru/data/cru_ts/cru_ts_4.05/data
Minimum temperature (oC)	21.2	1	5	
Relative humidity (%)	31	20	65	https://www.metoffice.gov.uk/hadobs/hadisdh/anomalymapmaterial_RHLAND.h
Solar radiation (MJ/m2/day)	24	1	6	https://solargis.com/maps-and-gis-data/download/sub-saharan-africa
Topography				
Elevation (m)	310	152	49	https://earthexplorer.usgs.gov/

STUDY AREA & DATA 3/3: FUTURE CLIMATE SCENARIOS

- Future climate data (precipitation, and minimum and maximum temperatures, and solar radiation) from GCM were used under the RCPs emission scenarios (RCP 8.5).

- The future scenarios were divided into four-time frames which include the horizons 2030s, 2050s, 2070s and 2100s.

- The baseline period of 2012 – 2014 depending on the year the data were collected and considering the season of cultivation.

METHOD

Existing Approaches

- Crop Models → Good but less accurate on large scales
- Statistical Models → Limited, miss non-linearities
- Machine Learning (ML) → Captures complexity, but depends on algorithm choice

Why Ensemble ML?

- Combines strengths of multiple ML models
- More robust, less bias
- Gap: No regional-scale study for West Africa rice yields using ensemble ML

METHOD

Models :

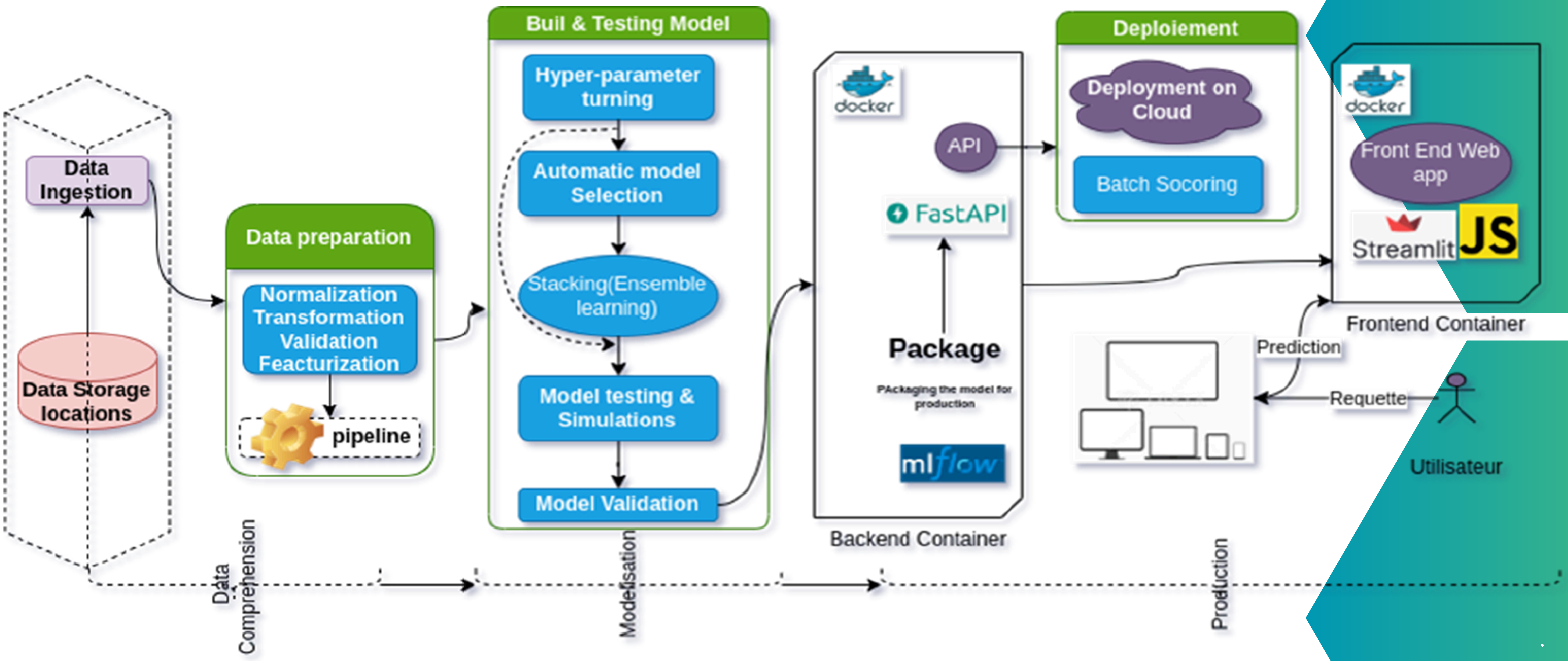
- AdaBoostRegressor (ABR)
- DecisionTreeRegressor (CART)
- RandomForestRegressor (RFR)
- ExtraTreesRegressor (ETR)
- GradientBoostingRegressor (GBR)
- HistGradientBoostingRegressor (HR)
- KNeighborsRegressor (KNN)
- Lasso (LASSO)
- ElasticNet (EN)
- LinearRegression (LR)
- Multilayer Perceptron (MLP)
- Support Vector Regression (SVR)
- XGBoostRegressor (XGBOOST)

To

Stacking Approach :

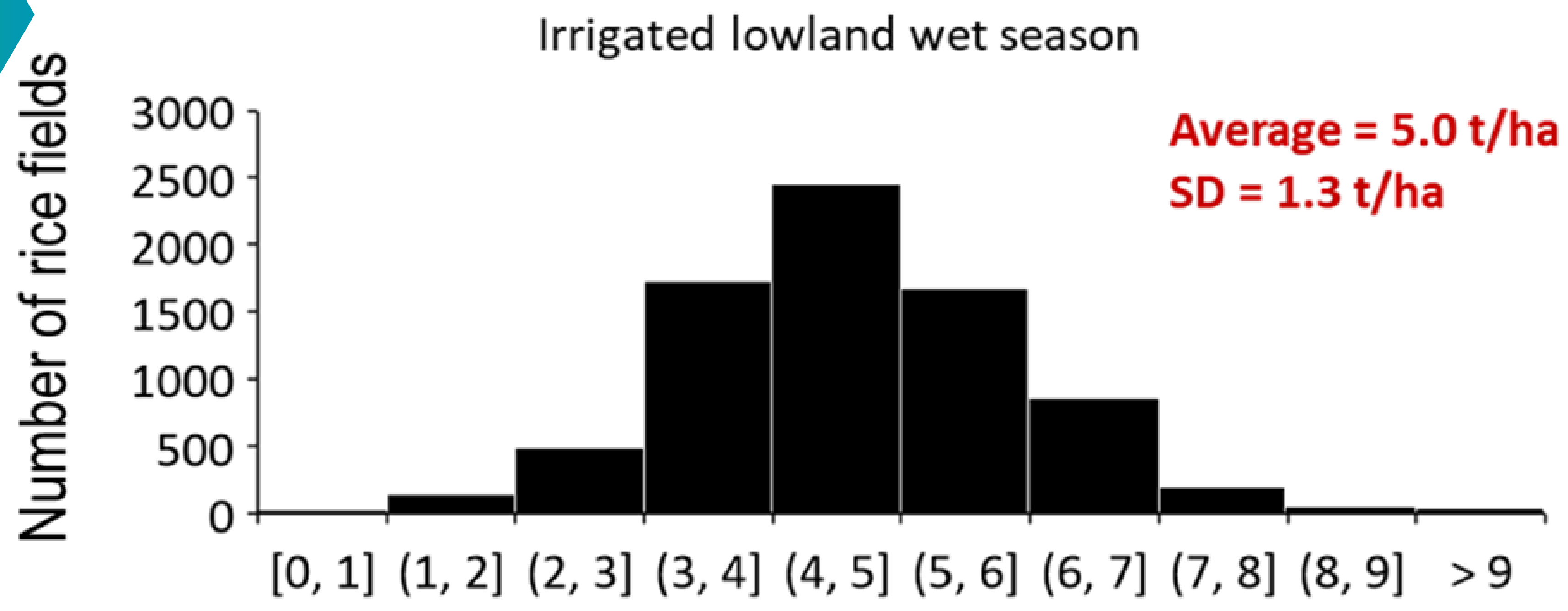
- Data were analyzed per growing environment and season.
- The dataset was randomly split into training (2/3 of dataset) and testing (1/3 of dataset)
- Automatic hyperparameters tuning was performed for optimizing number of trees and number of splitting variables
- R2, root mean squared error (RMSE), mean squared error (MSE) were used for selecting the four best models.
- Ensemble model was developed based on the four best performing models.

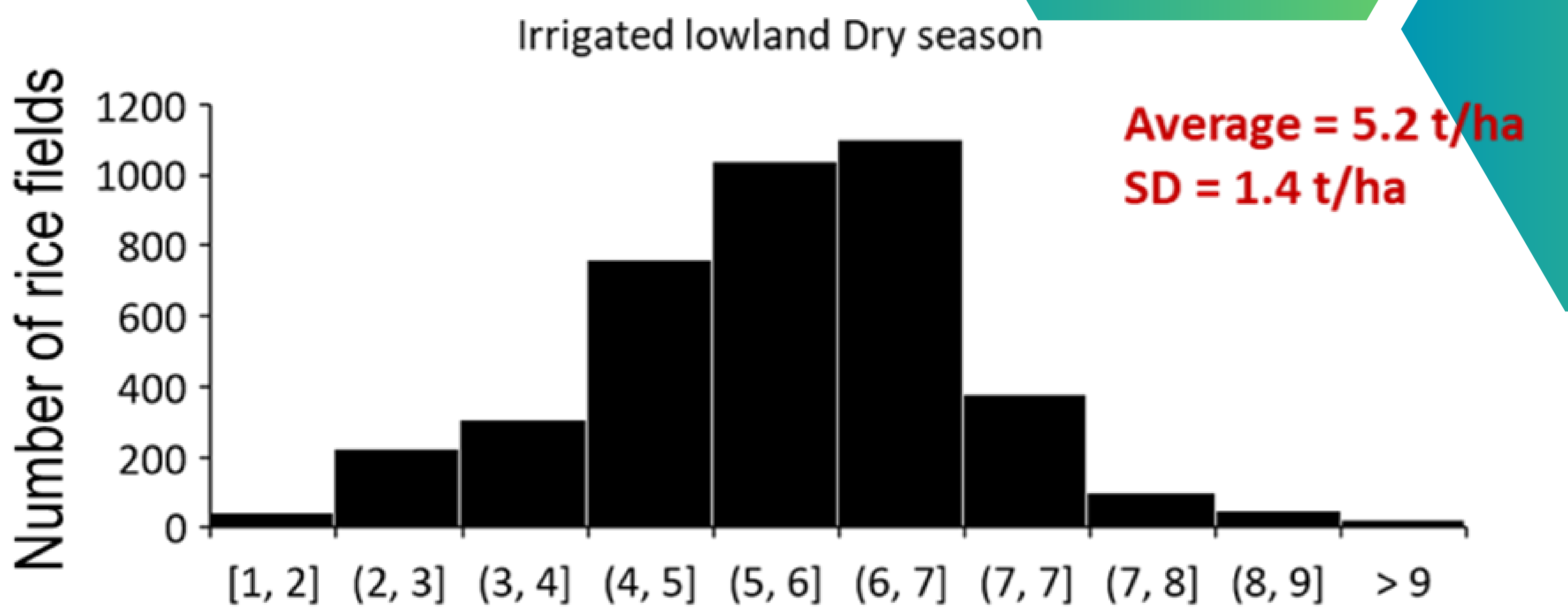
SYSTEM ARCHITECTURE

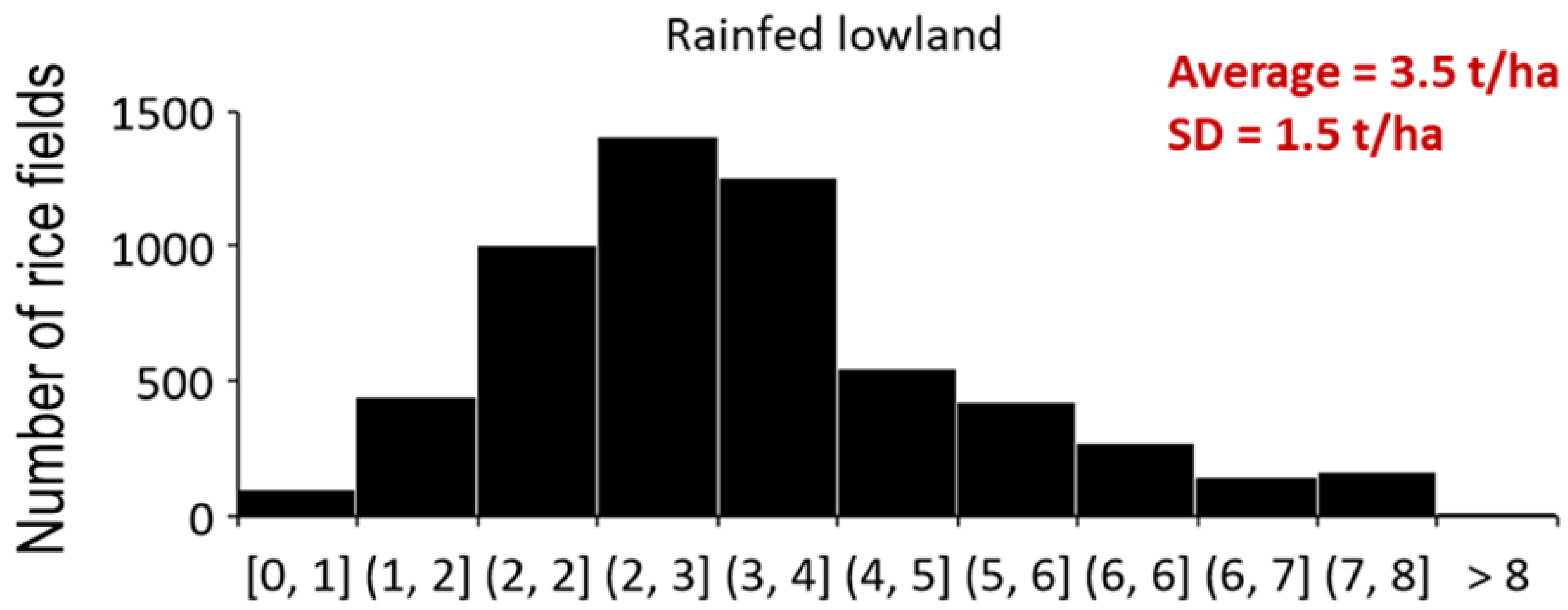


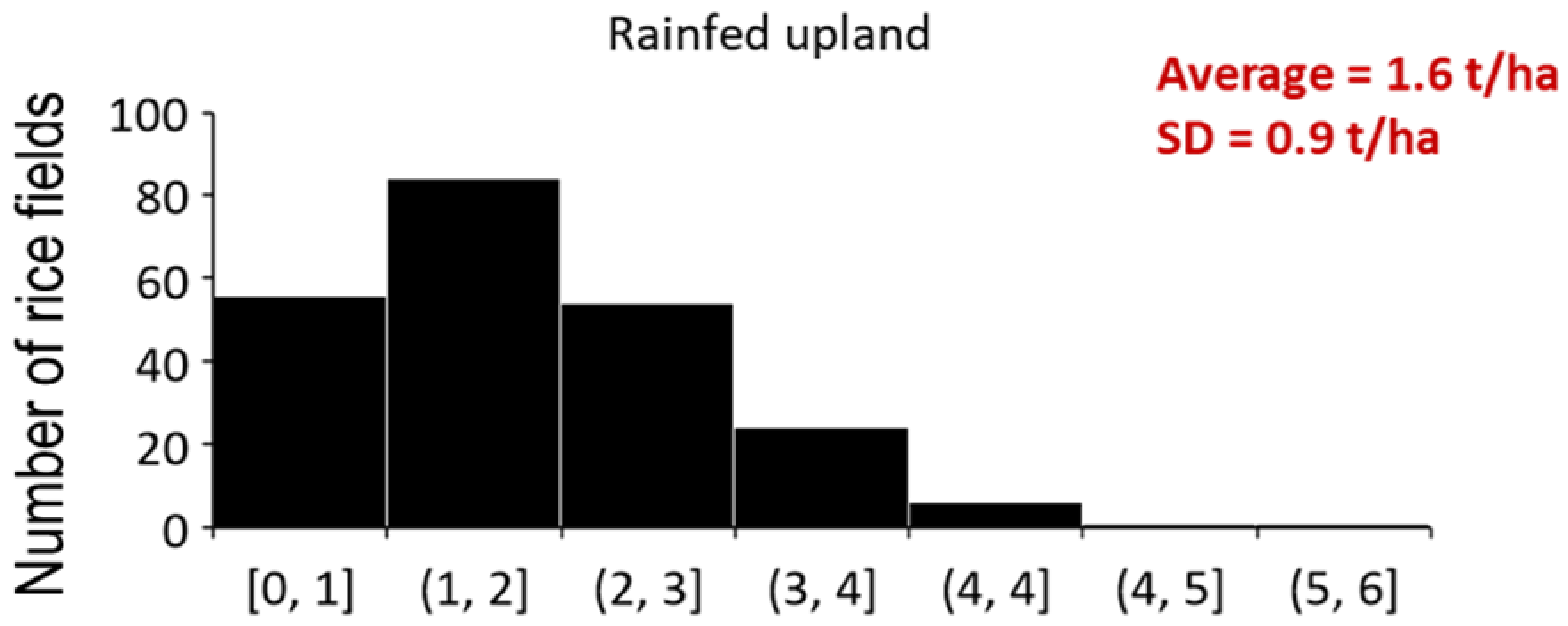
RESULTS 1/10

Overview of variation in rice yield per rice growing environment



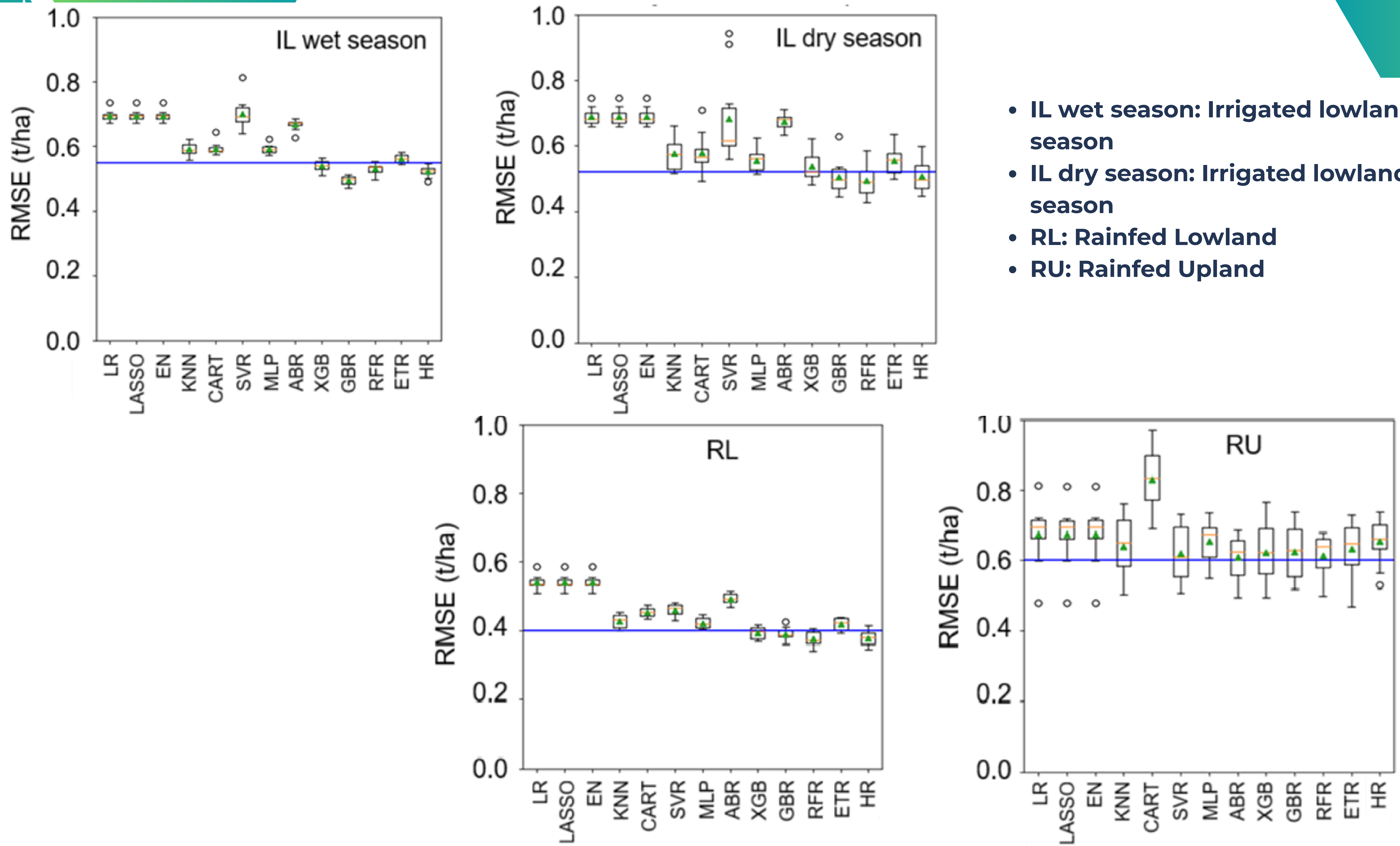






RESULTS 2/10

ROOT MEAN SQUARE ERROR (RMSE) OF 13 MODELS

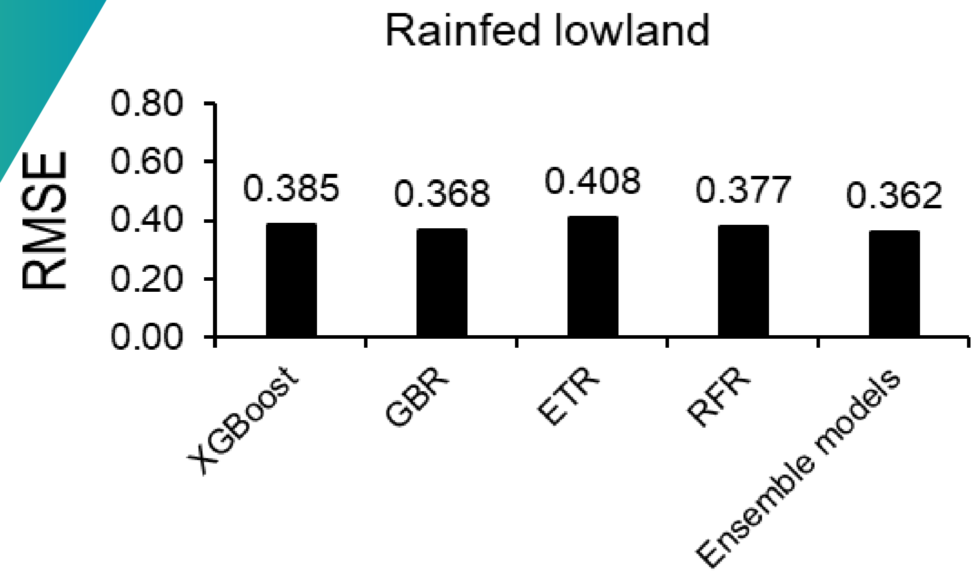


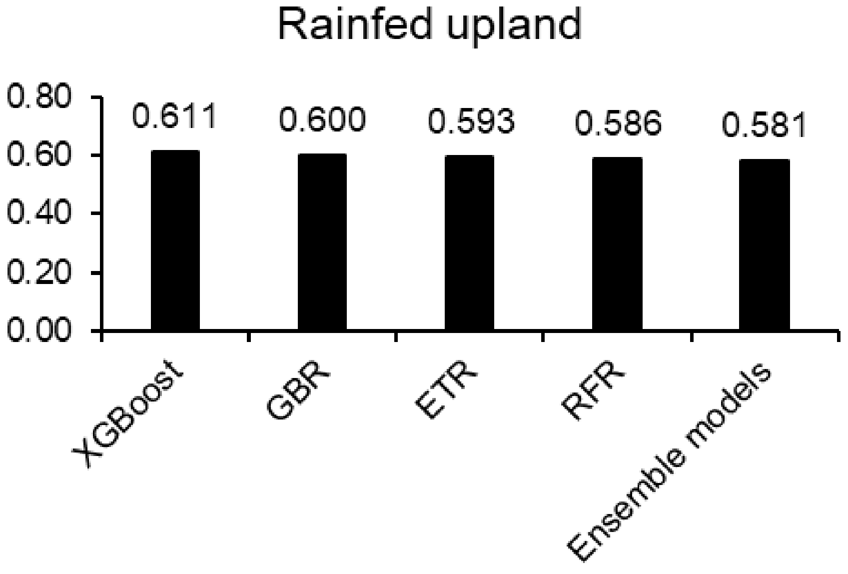
- **IL wet season: Irrigated lowland wet season**
- **IL dry season: Irrigated lowland dry season**
- **RL: Rainfed Lowland**
- **RU: Rainfed Upland**

RESULTS 3/10

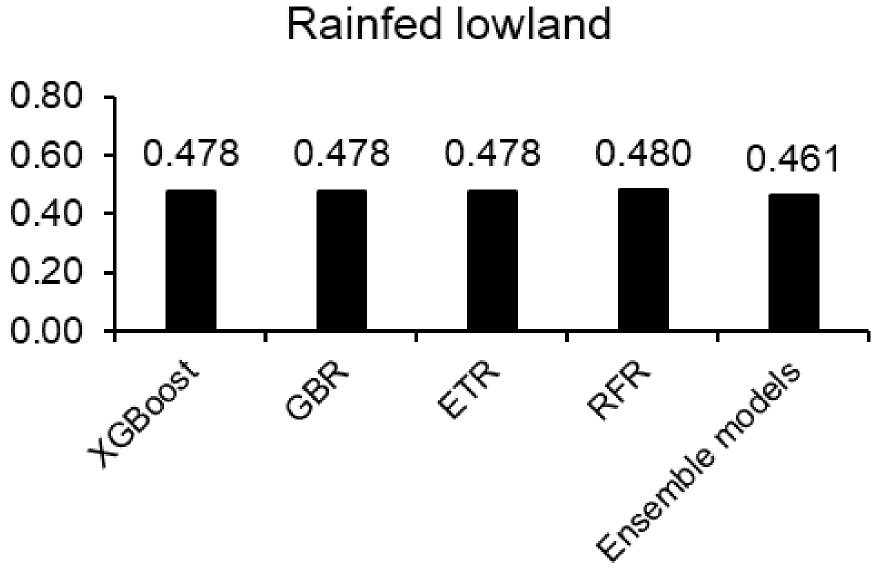
ROOT MEAN SQUARE ERROR (RMSE) OF THE ENSEMBLE MODELS

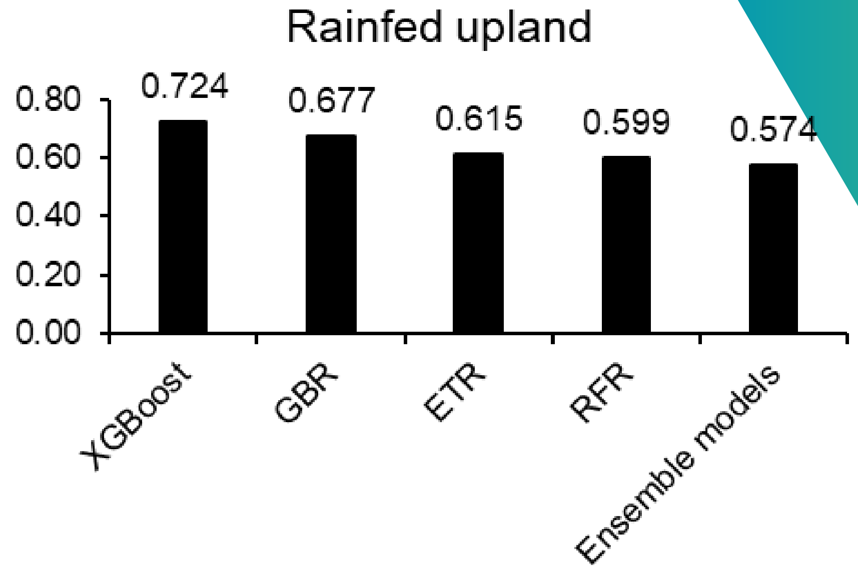
Training



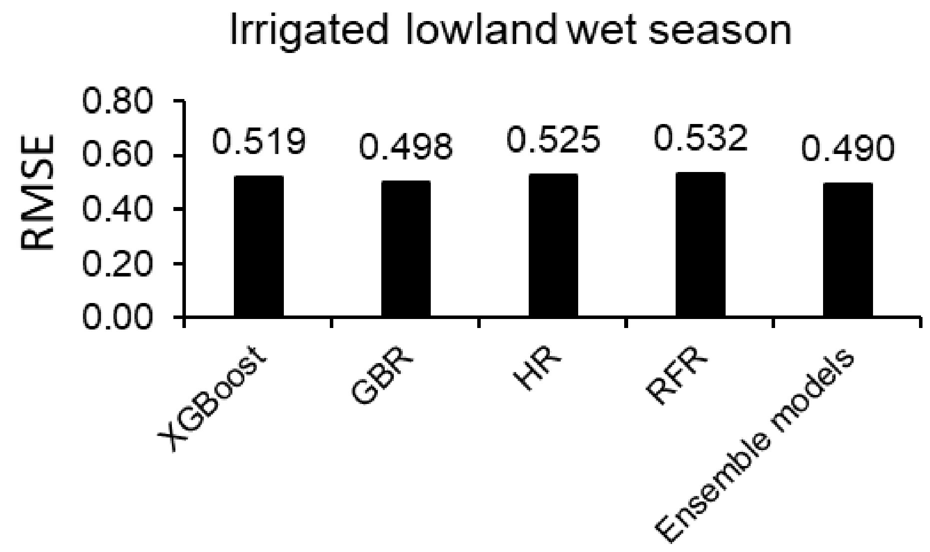


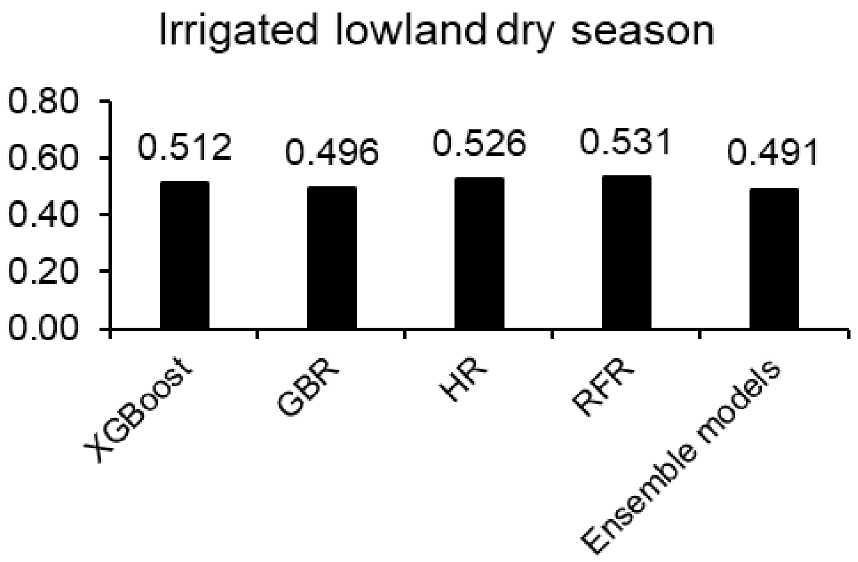
Testing



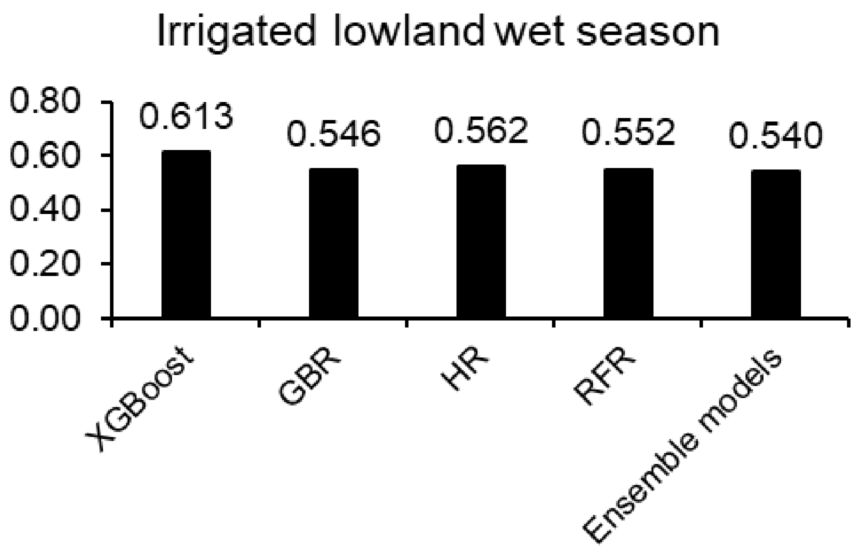


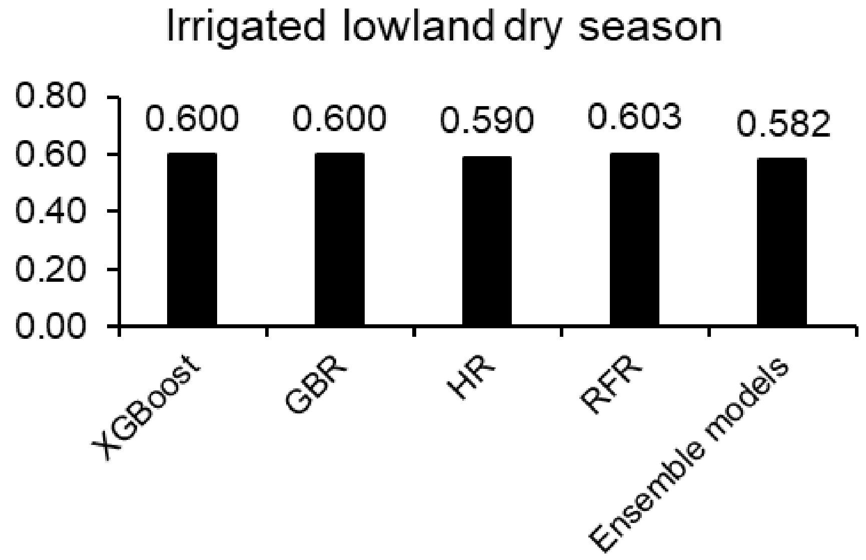
Training





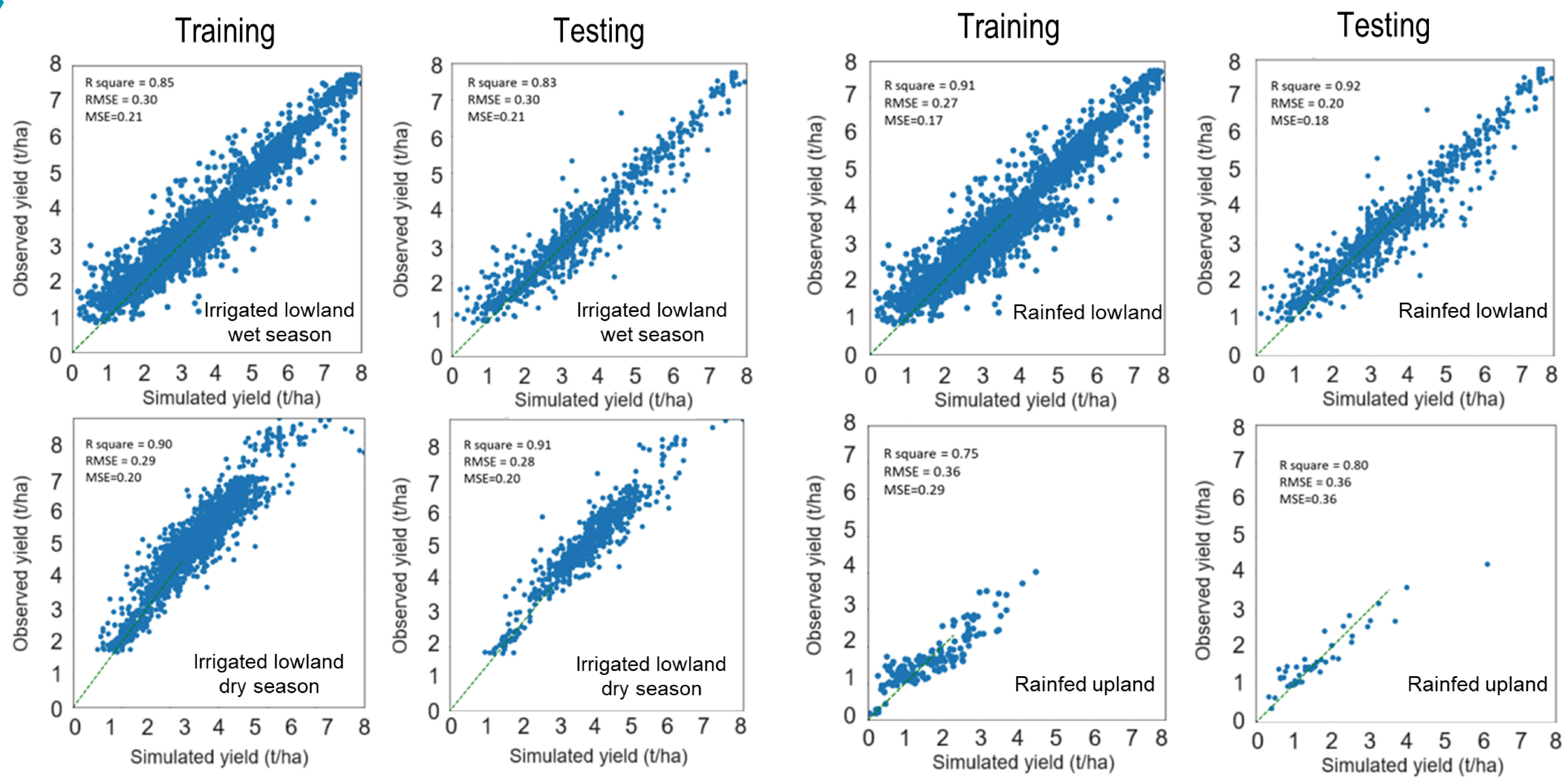
Testing





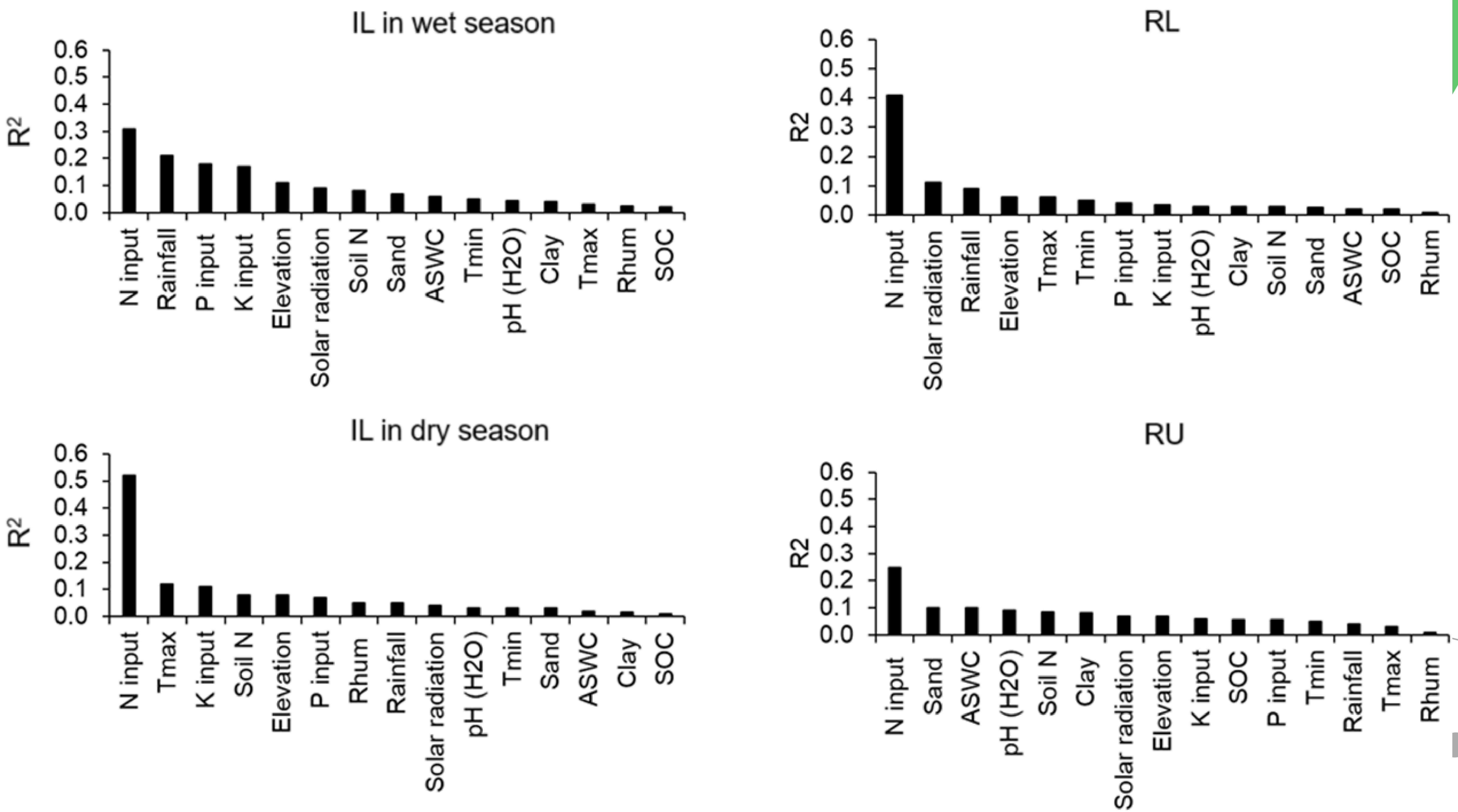
RESULTS 4/10

PERFORMANCE OF ENSEMBLE MODELS



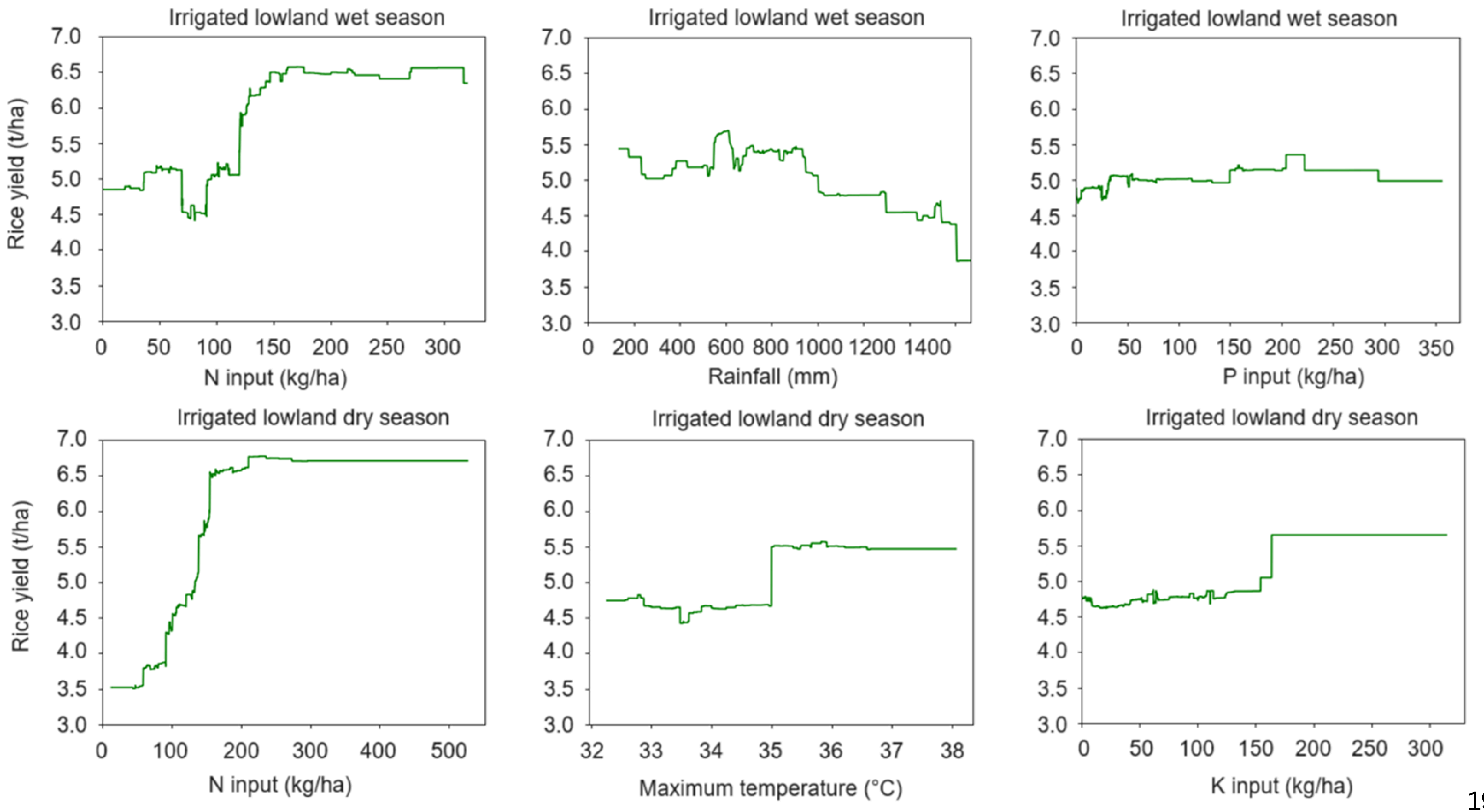
RESULTS 5/10

VARIABLES IMPORTANCE



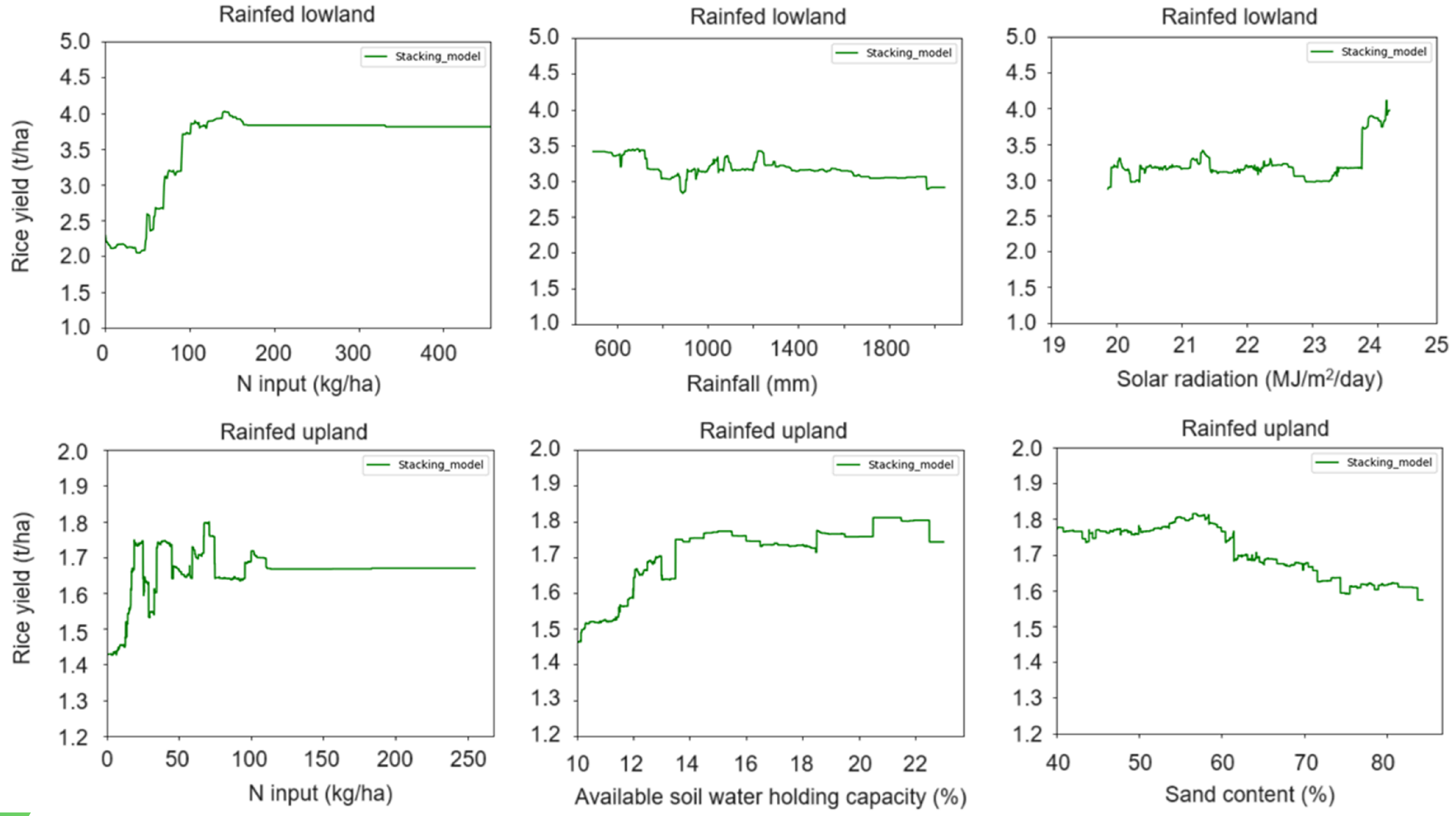
RESULTS 6/10

PARTIAL RESPONSE CURVES OF RICE YIELD IN IRRIGATED LOWLANDS



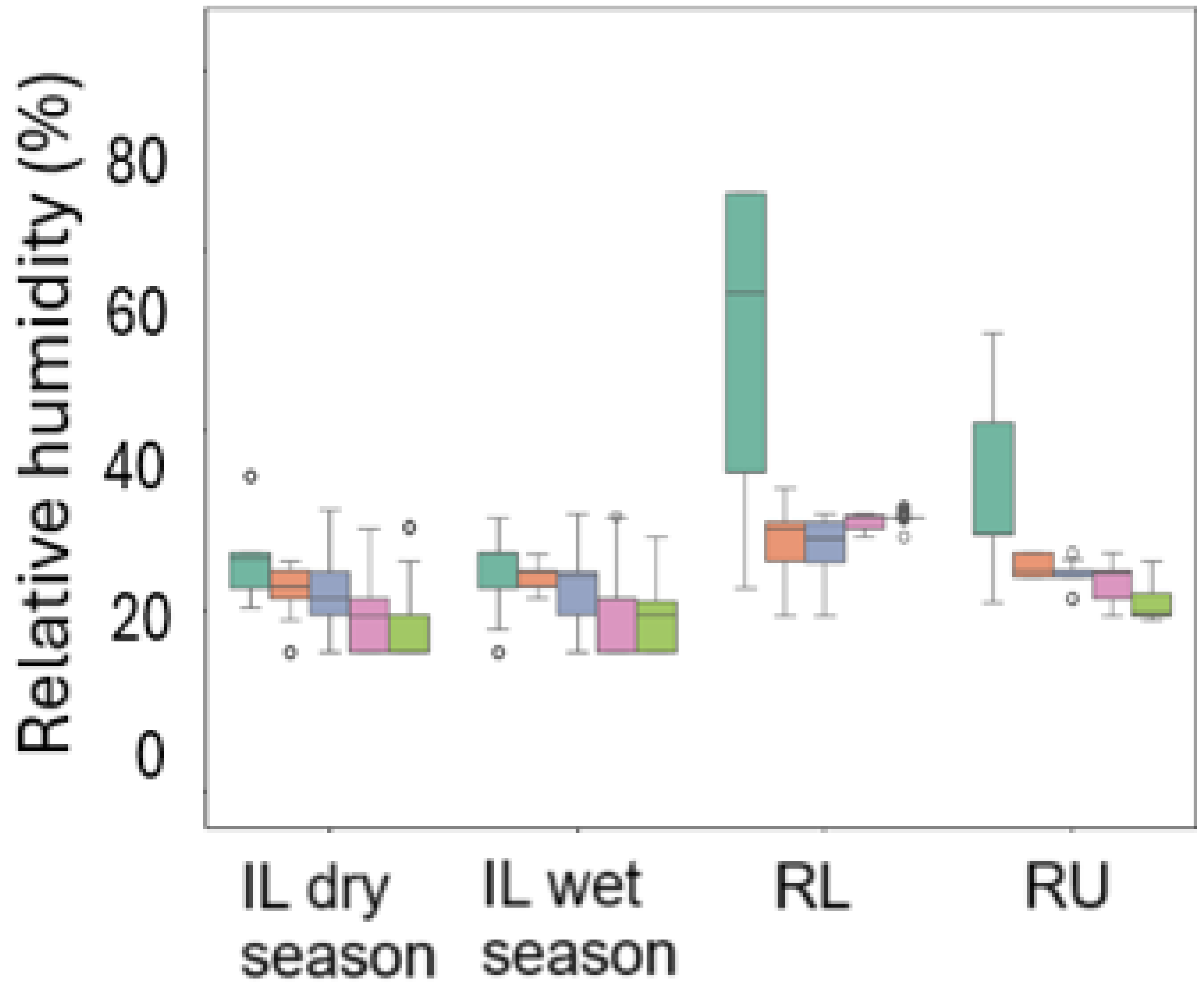
RESULTS 7/10

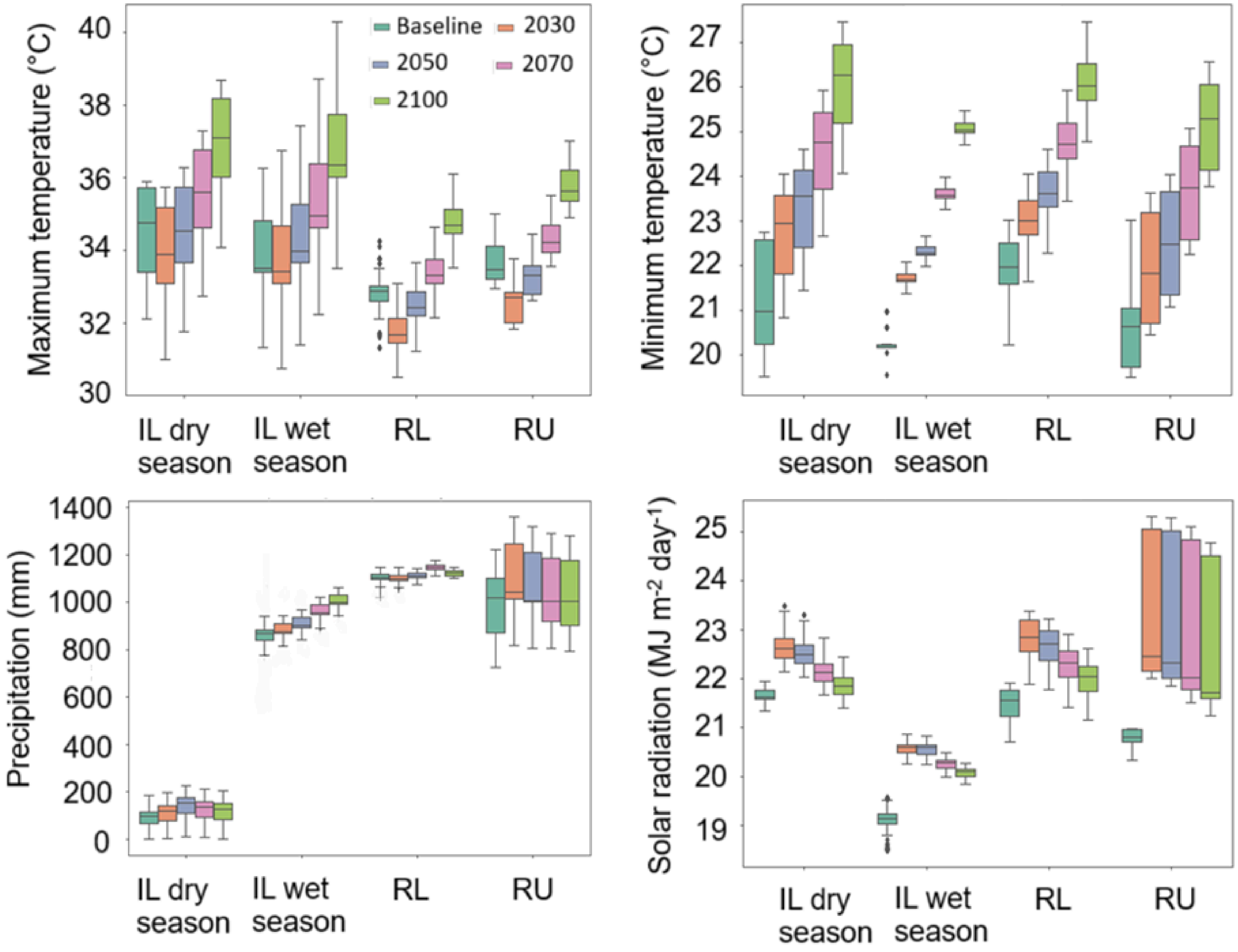
PARTIAL RESPONSE CURVES OF RICE YIELD IN RAINFED LOWLANDS AND UPLANDS



RESULTS 8/10

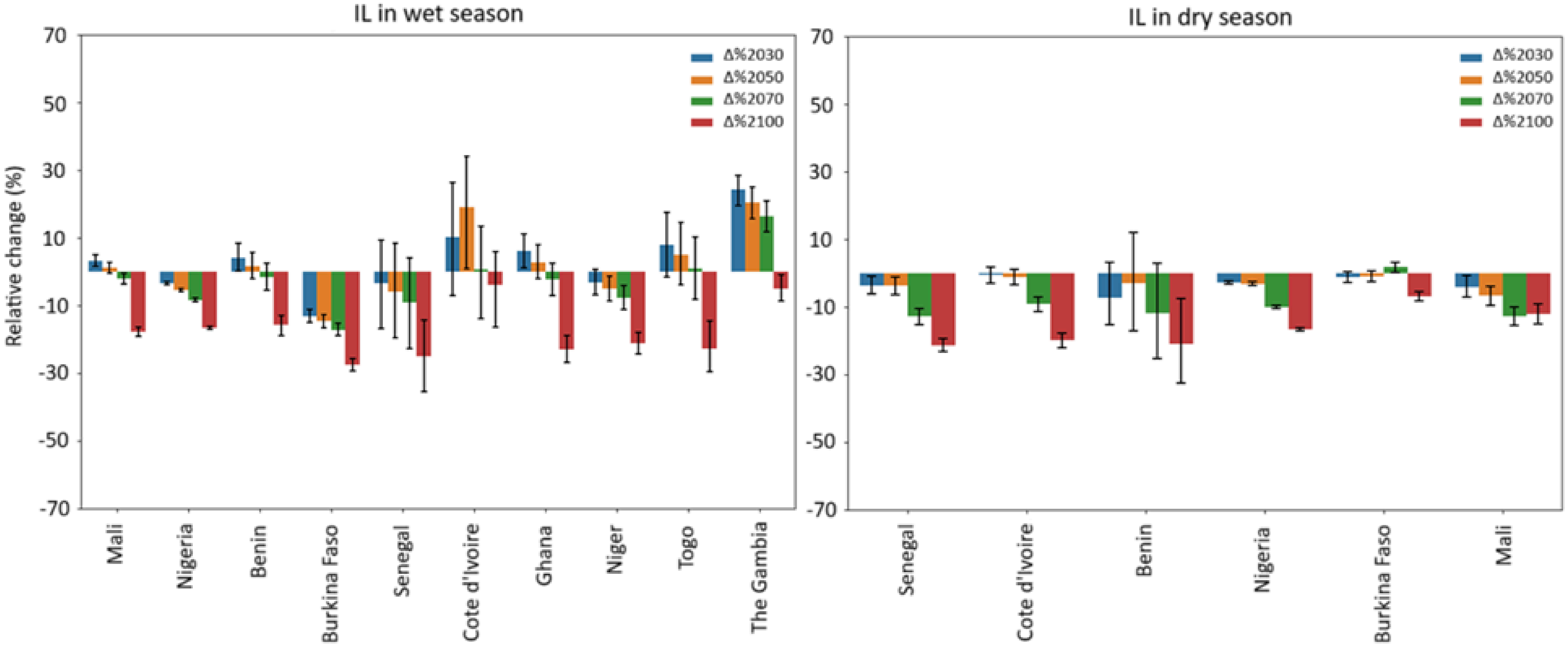
CLIMATE DATA FOM BASELINE TO FUTURE VALUES





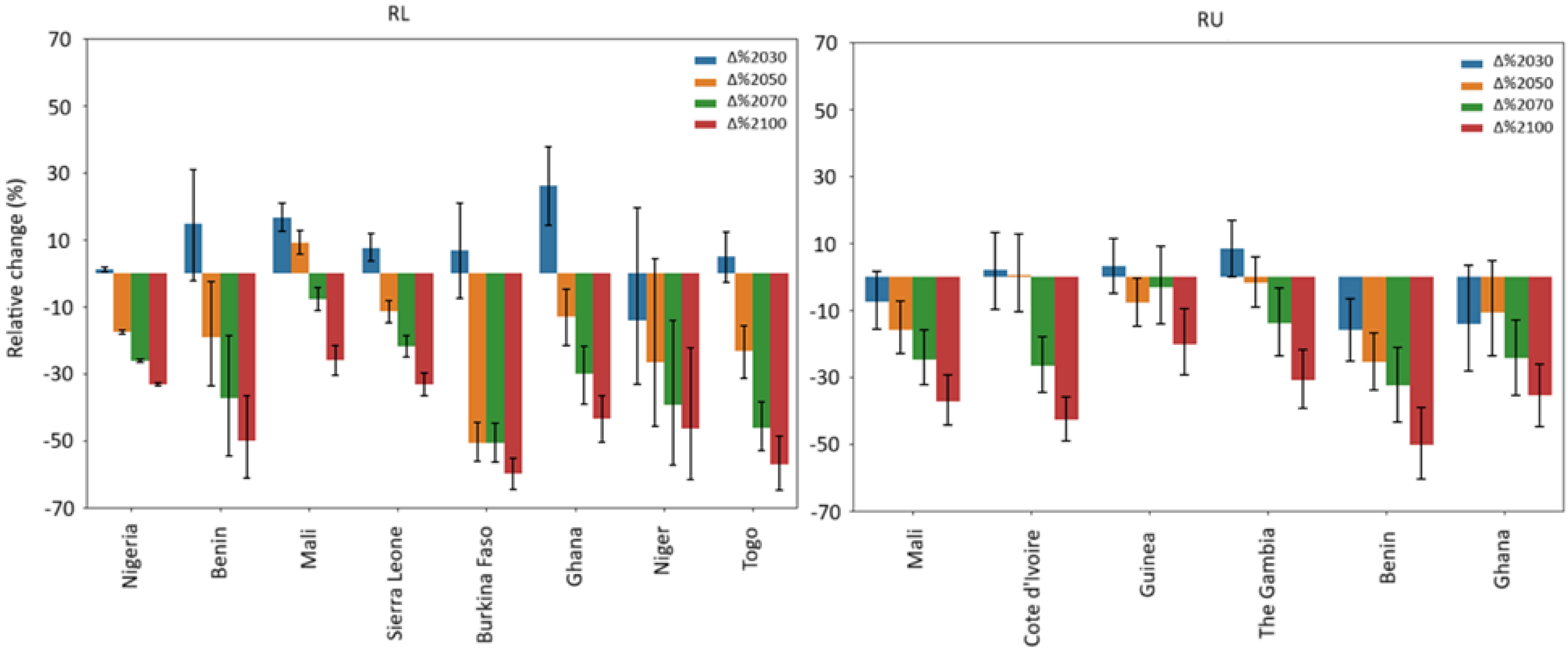
RESULTS 9/10

SIMULATED CHANGES IN RICE YIELD



RESULTS 10/10

SIMULATED CHANGES IN RICE YIELD



KEY CONCLUSIONS & DISCUSSION

ENSEMBLE ML WINS

Ensemble machine learning outperformed the best individual models in simulating rice yields.

ENVIRONMENT MATTERS

Stronger performance in irrigated and rainfed lowlands; weaker in uplands due to factors like weeds, pests, and crop rotations not captured by models.

NITROGEN IS KING

Nitrogen input was consistently one of the top three drivers of rice yield across all environments.

CLIMATE CHANGE HURTS

Projected climate change will reduce rice yields overall, though impacts vary by country.

FROM INSIGHT TO ACTION

Need to better link climate conditions with yield outcomes to design targeted adaptation strategies.

ACKNOWLEDGMENTS

AfricaRice Scientific Team

for continuous guidance.

mentorship, and collaboration

Adaptation Futures 2025 Scientific Committee

for the opportunity to present and share this work.

Accountability for the impact of AI

Farmers across 12 West African countries

whose real-world experiences made this research possible

TOGETHER, WE CAN BUILD RESILIENT AND SUSTAINABLE FOOD SYSTEMS FOR WEST AFRICA.

THANK YOU

Cedarta donou