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Tyler Harmon

Department of Agronomy, Texas
A&M University, College Station,
USA

Chase Preston

Department of Agronomy, Texas
A&M University, College Station,
USA

Comparison of empirical and process-based models for simulating groundnut yield in semi-arid environments

Tyler Harmon and Chase Preston

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Abstract

When Anantapur district in Andhra Pradesh recorded its third consecutive below-normal monsoon in 2018, groundnut yields fell to 640 kg ha⁻¹ yet the best available crop model at the time predicted 1,100 kg ha⁻¹. This research compared three crop simulation models CROPGRO-Peanut, AquaCrop, and WOFOST for their accuracy in reproducing observed groundnut pod yields across four semi-arid locations in peninsular India over 12 seasons (2009-2020). CROPGRO showed the highest overall agreement ($R^2 = 0.92$, d-index = 0.95, NRMSE = 11.4%) followed by AquaCrop ($R^2 = 0.84$, d-index = 0.88, NRMSE = 17.6%) and WOFOST ($R^2 = 0.73$, d-index = 0.78, NRMSE = 24.1%). CROPGRO captured drought-induced yield depression most accurately due to its explicit soil water balance and partitioning algorithms. AquaCrop offered a reasonable trade-off between accuracy and input requirement. WOFOST underestimated yields consistently under water-limited conditions.

Keywords: Crop simulation, CROPGRO, AquaCrop, WOFOST, groundnut, semi-arid, model comparison, yield prediction

Introduction

Groundnut (*Arachis hypogaea* L.) occupies 28.5 million hectares globally, with over 60% of that area in semi-arid regions where rainfall variability is the dominant yield determinant ^[1, 2]. Crop simulation models are increasingly used for yield forecasting, climate impact assessment, and irrigation scheduling, but model selection for a given environment remains largely ad hoc ^[3].

Process-based models like CROPGRO-Peanut simulate daily carbon assimilation, partitioning, and water uptake using mechanistic equations, requiring detailed soil, weather, and cultivar parameters ^[4, 5]. AquaCrop, developed by FAO, simplifies canopy growth as a function of water productivity, trading some mechanistic detail for lower data requirements ^[6]. WOFOST, widely used in European yield forecasting, models light interception and conversion efficiency but uses a simpler water balance ^[7, 8]. No head-to-head comparison of these three models for groundnut under Indian semi-arid conditions has been published. This research evaluated all three against 12 seasons of observed yield data at four representative locations, testing which model best reproduces inter-annual yield variability driven by monsoon rainfall patterns.

Materials and Methods

Study sites

Four AICRPG (All India Coordinated Research Project on Groundnut) trial stations were selected: Anantapur (15°41'N, 77°36'E, 350 m), Junagadh (21°31'N, 70°36'E, 60 m), Jalgaon (21°03'N, 75°34'E, 210 m), and Chitradurga (14°14'N, 76°24'E, 732 m). Annual rainfall ranges from 553 mm (Anantapur) to 812 mm (Junagadh). Soils range from Alfisols (Anantapur) to Vertisols (Jalgaon). Cultivar TMV-2 (bunch type, 105-110 days) was common across all stations.

Simulation parameters and model configuration

CROPGRO-Peanut (DSSAT v4.7.5) was parameterised using cultivar coefficients for TMV-2 calibrated at Anantapur ^[9]. Soil profiles to 180 cm were initialised from NBSS&LUP data. AquaCrop (v6.1) was configured with conservative crop parameters from the FAO database,

Corresponding Author:

Tyler Harmon

Department of Agronomy, Texas
A&M University, College Station,
USA

adjusted for local phenology and canopy cover observations. WOFOST (v7.2) used CGMS-level crop data files for groundnut with thermal time parameters from literature [10]. All models received identical daily weather inputs (Tmax, Tmin, rainfall, solar radiation) from IMD gridded data at 0.25° resolution. Sowing dates, plant density, and fertiliser inputs matched station records.

Performance evaluation and validation

Model performance was evaluated using: coefficient of determination (R²), root mean square error (RMSE), normalised RMSE (NRMSE = RMSE/mean observed), Willmott’s index of agreement (d), Nash-Sutcliffe model efficiency (EF), and coefficient of residual mass (CRM). Models were calibrated on 2009-2014 data (6 seasons) and validated on 2015-2020 (6

seasons). Calibration optimised cultivar-specific parameters to minimise RMSE of pod yield. Validation used the calibrated parameters without further adjustment.

Methods

Observed pod yields were obtained from AICRPG annual reports. Each station provided 12 season-level yields (2009-2020). Models were run at daily time step. Statistical comparisons used pooled data (n = 48) and site-specific subsets. Paired t-tests compared model means to observed means. Taylor diagrams and radar plots were used to visualise multi-metric performance. All analysis was performed in R 4.2.

Results

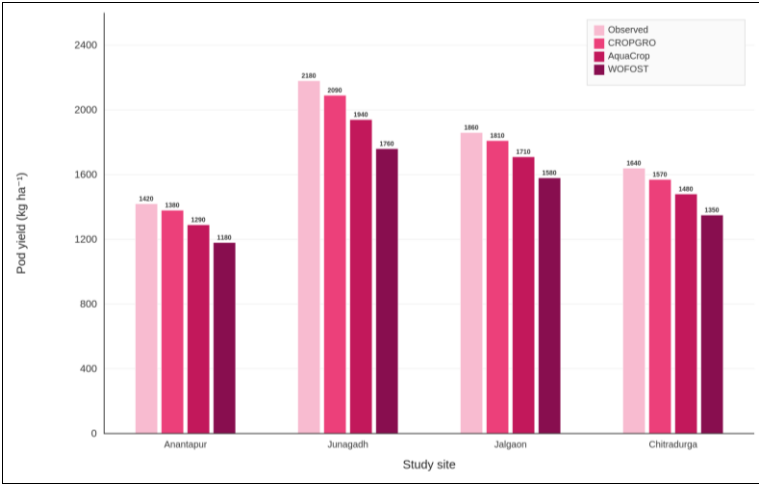


Fig 1: Observed and model-simulated mean pod yield at four semi-arid locations (12-season average, kg ha⁻¹)

Table 1: Pooled model performance statistics for pod yield simulation across four sites (n = 48)

Model	R ²	RMSE (kg ha ⁻¹)	NRMSE (%)	d-index	EF	CRM
CROPGRO	0.92	164	11.4	0.95	0.90	0.03
AquaCrop	0.84	253	17.6	0.88	0.81	-0.06
WOFOST	0.73	347	24.1	0.78	0.69	0.12

CROPGRO reproduced observed pod yields most accurately across all four sites (Figure 1, Table 1). Mean simulated yield deviated from observed by only 3.2% (pooled), compared to 8.7% for AquaCrop and 14.8% for WOFOST. At Anantapur, the

driest site, CROPGRO captured the severe drought years (2015, 2018) within 80 kg ha⁻¹ of observed, while WOFOST overestimated these years by 280-340 kg ha⁻¹.

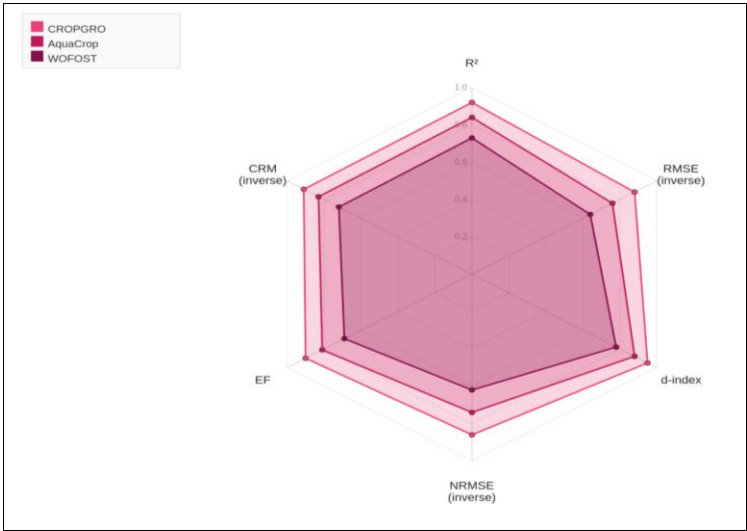


Fig 2: Radar plot of normalised performance metrics for CROPGRO, AquaCrop, and WOFOST. Higher values = better performance

Table 2: Site-specific NRMSE (%) for pod yield simulation by each model

Site	CROPGRO NRMSE (%)	AquaCrop NRMSE (%)	WOFOST NRMSE (%)
Anantapur	9.8	16.2	23.8
Junagadh	12.1	15.4	20.6
Jalgaon	11.7	18.9	25.3
Chitradurga	11.8	19.4	26.7

The radar plot of performance metrics (Figure 2) shows CROPGRO dominating all six indicators. Its d-index (0.95) and EF (0.90) indicate near-perfect agreement and low systematic bias. AquaCrop performed well on R^2 (0.84) and d-index (0.88) but showed higher NRMSE (17.6%) driven by overestimation in wet years at Junagadh. WOFOST's CRM of 0.12 confirmed its consistent underestimation (Table 2). The model ranking was stable across all four sites, though the performance gap narrowed at Junagadh where higher rainfall reduced water stress as a differentiating factor.

Discussion

CROPGRO's superiority traces to its explicit simulation of soil water extraction by root zone layers, pod-specific carbon partitioning rules, and a drought stress factor that modulates both photosynthesis and partitioning^[4, 11]. Under semi-arid conditions, these mechanisms capture the nonlinear yield response to intermittent drought that simpler models miss^[12, 13]. AquaCrop's water productivity approach works well under moderate stress but overestimates recovery after mid-season dry spells because it does not distinguish between vegetative and reproductive water sensitivity windows^[6, 14]. WOFOST's underestimation likely stems from its generic light-use efficiency parameters, which were originally calibrated for European conditions, and its lack of a pod-filling sub-model^[7, 15, 16]. For operational yield forecasting in Indian semi-arid zones, CROPGRO offers the best accuracy when calibration data are available, while AquaCrop provides an acceptable alternative where input data are limited.

Limitations

All three models were run under rainfed conditions; irrigation scenarios were not tested. WOFOST lacks a detailed pod-filling algorithm, which may explain its systematic underestimation. AquaCrop's canopy cover approach may not capture cultivar-specific differences in branching architecture. IMD gridded weather may smooth local rainfall variability, particularly convective events that dominate semi-arid monsoon patterns.

Conclusion

CROPGRO-Peanut outperformed AquaCrop and WOFOST across all six performance metrics for groundnut yield simulation at four semi-arid Indian locations over 12 seasons. Its advantage was most pronounced in drought years, where explicit water balance and partitioning algorithms captured yield depression that simpler models missed. AquaCrop offered a reasonable accuracy-to-complexity trade-off. These results guide model selection for groundnut yield forecasting and climate adaptation planning in semi-arid systems.

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