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RESEARCH ARTICLE

Field-level rice yield estimations under different farm practices using the crop simulation model for better yield

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Abstract

Crop yield estimation is essential for decision-making systems and insurance policy makers. Numerous methodologies for yield estimation have been developed, encompassing crop models, remote sensing techniques, and empirical equations. Each approach holds unique limitations and advantages. The primary aim of this study was to assess the accuracy of the DSSAT (Decision Support System for Agro Technology Transfer) model in predicting rice yields and LAI (Leaf Area Index) across various management methods. Additionally, the study sought to identify the optimal management practice for attaining higher yields. Crop models facilitate the expeditious evaluation of management strategies aimed at improving crop yield and analyzing the balance between production, resource efficiency, and environmental impacts. The study region selected for analysis is Karimnagar district of Telangana state. DSSAT has been chosen as the preferred tool due to its high efficiency in evaluating crop yield. The model's simulated yield was compared to the observed yield obtained from crop-cutting experiments. The results indicate a correlation of 0.81 and 0.85 between observed and simulated yields, as well as between model LAI and yield. An observation was made regarding a discrepancy between predicted and actual yields, which can be attributed to biotic stress. However, it should be noted that the current model does not account for this factor. The observed average yield was 5200 kg ha^{-1}, whereas the projected yield was 5400 kg ha^{-1}. The findings indicate that the model's performance is influenced by both the timing of sowing and the amount of nitrogen applied. The findings indicate that the DSSAT model has demonstrated a high level of accuracy in predicting both yields and leaf area index (LAI) across various management strategies. This study showcases the potential use of crop simulation models as a technology-driven tool to identify the most effective management strategies for rice production.

Keywords

Crop model; DSSAT; rice; sowing; LAI

Introduction

Rice is the staple food for millions of rural households and the phrase "rice is life" is appropriate in the Indian context. By 2050, the world's population is expected to reach 9.8 billion (1), demanding enhanced food production. Global food security is threatened due to an upsurge in food demand and a diminution in the water supply (2). In India, rice cultivated area, production, and productivity in 2020-21 were approximately 44 million ha, 12.1 million tonnes, and 4.1 metric tons per hectare, respectively (1). In the Telangana state of India, rice is one of the major crops cultivated, contributing to the national area and production of 4.49 % (1.9 million ha) and 5.54 % (6.25 million tons), with a productivity of 3176 kg/ha (3). Karimnagar district in Telangana is the major rice-growing district with high yield potential and is considered the “rice bowl of Telangana”.

Providing timely and precise crop yield estimation has become crucial for the government in decision-making, overcoming national food security, and regulating import and export activities (4, 5). The conventional crop acreage and yield estimation method is time-consuming, inaccurate, requires a considerable labour force, and is nearly difficult to deploy on a large scale. Thus, agricultural policy programs rely solely on timely field and aerial assessments. In this aspect, the use of crop growth model-based yield predictions are both realistic and desirable for quick and accurate yield prediction (6).

By integrating data from agricultural meteorology, soil, plant physiology, and management, crop simulation models have been developed to predict growth, development, and yield. Crop growth models effectively predict the potential growth of plants and plant traits and can provide real-time vegetation cover status (7). The development of computational models for crops and soils began about 60 years ago (8). Yield gaps and biophysical system performance factors can be addressed with proven cropping system simulation models. These models have been shown to improve farmer practices (9, 10), breeding techniques (11), and government policies (12) and help address challenges such as food security, climate change mitigation, and adaptation. The simulation approach will be beneficial by improving crop productivity and understanding and assessing yield gaps through optimizing management practices (13, 14). Crop simulation models such as APSIM, DSSAT, WOFOST, STICS, EPIC, and AquaCrop were developed based on numerous principles and has been used by the researchers extensively (4, 15-18). Crop biophysical information is very important for environmental analysis. Crop leaf area index (LAI) is one among the important parameter reflecting crop growth stages of crop vegetation and important input for most of the crop models (19, 20). Leaf area index (LAI), which measures leaf area per unit horizontal ground surface area, is a fundamental plant metric for modelling biosphere-atmosphere and is considered as the key parameter for biophysical modeling (20-23). Several studies have extracted various biophysical parameters like LAI, Crop canopy cover, FAPAR, GFAPAR, etc., from satellite imagery (24, 25).

Decision Support System for Agro-technology Transfer (DSSAT) is a widely used tool which comprises of dynamic crop growth simulation models for over 42 crops (8, 26). The CSM-CERES-Rice model can simulate the physiological responses of rice to specific climatic and soil conditions from sowing or transplanting to maturity. The modules included in CERES-Rice replicate the primary crop growth and development processes, such as phenological development, leaf area increase, dry matter accumulation, and grain production. Many studies have evaluated the CERES-Rice model at various locations, finding high agreement between predicted and observed results (17, 27-30). Models can be used to identify the suitable package of practices under the changing climatic conditions. Using CERES-Rice results reveal that yields of aerobic rice can be improved with proper management of irrigation and nitrogen inputs by changing the irrigation threshold and by increasing number of split applications (18). The most effective nitrogen application rate for drip-irrigated winter wheat was determined using DSSAT CERES-Wheat, and it was found that 180 kg ha^{-1} of nitrogen resulted in good grain yields, net margins, WUE, and nitrogen usage efficiency. These findings are useful in establishing a scientific nitrogen management strategy with high yield and minimal pollution for winter wheat in the North China Plain (31). Hence the calibrated and evaluated CERES model can be effectively used for estimating rice yields by incorporating various management practices at the individual farmer level, such as sowing date, cultivar details, and fertilizer dosage in the selected study areas to understand its predictability. Therefore, this study was planned with an overall objective of estimating rice yield under different management practices at the farmer level in a village with the below mentioned objectives:

1. Evaluate the performance of the rice model CSM-CERES under different management practices at the field level under semi-arid conditions.
2. Identify the best management practices to maintain yields with optimal use of inputs.

Materials and Methods

Study area

In Karimnagar district, Gangipalle village was selected as the study area. Rice is the main crop in this village and is grown under both the kharif and rabi seasons. This village lies under latitude 18^{0}37'13" N, longitude 79^{0}27'27" E, and an altitude of 261 m above mean sea level. This area has dry summers and cool winters. Southwest monsoon rains are dominant. Summer average temperature ranges between 27–39°C in this district, while winter temperatures are 20–35°C. Black and red sandy loam soils are predominant. The annual average rainfall is 898.3 mm. Fifteen locations were selected in this village which covers all the parts of the village (Fig. 1).

CERES-Rice model

DSSAT CERES-Rice (4.7.5) was used to predict rice yield in this study. The platform DSSAT-CSM (cropping system model) uses modules for meteorology, soil, soil-plant-atmosphere (SPAM), and management to simulate crop development, yield, carbon, and water balance. A detailed flowchart representing input and output parameters were mentioned (Fig. 2).

Weather data

Weather inputs such as daily maximum and minimum temperatures, rainfall, and solar radiation were consid-

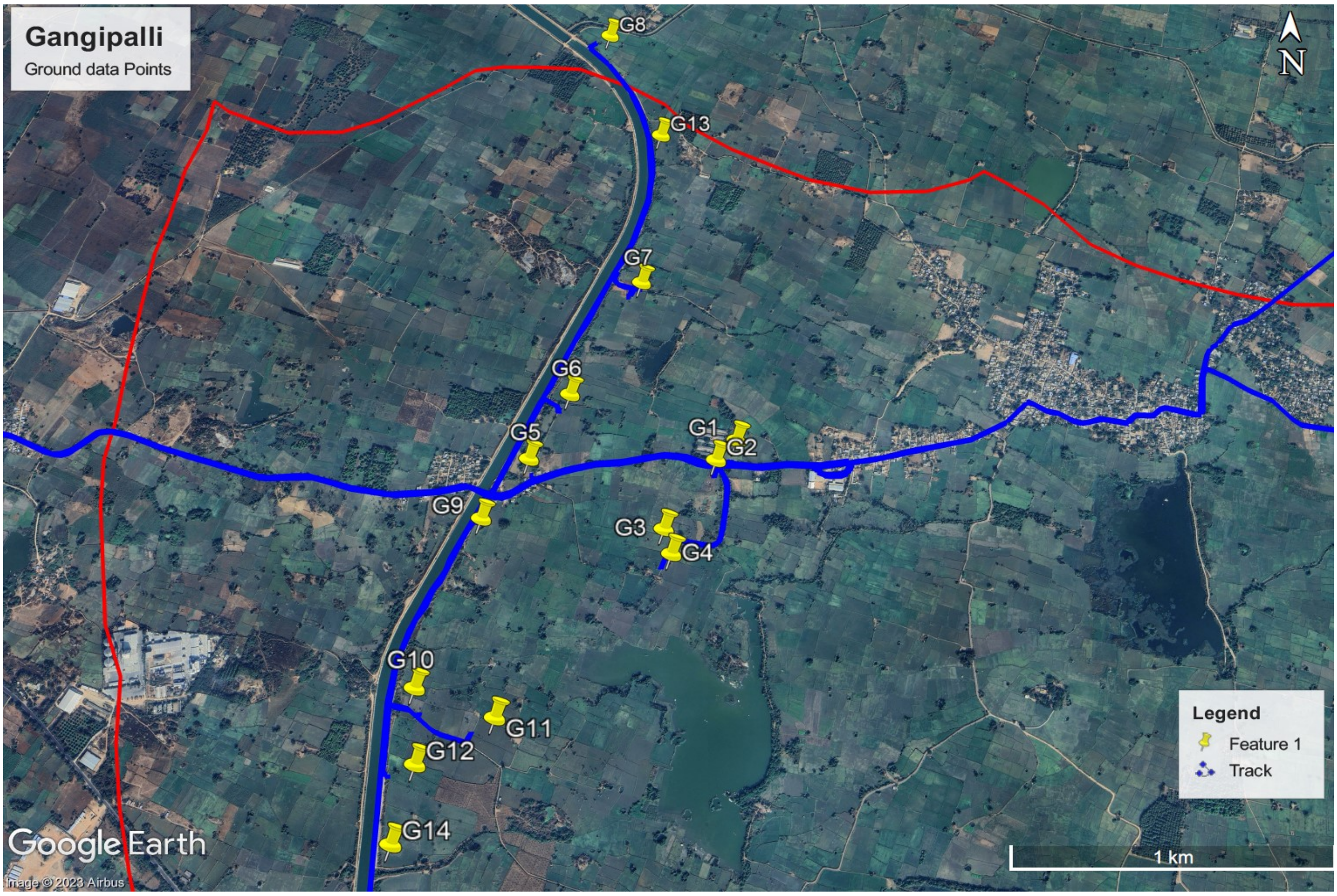

Fig. 1. Collected ground data points of Gangipalli village.

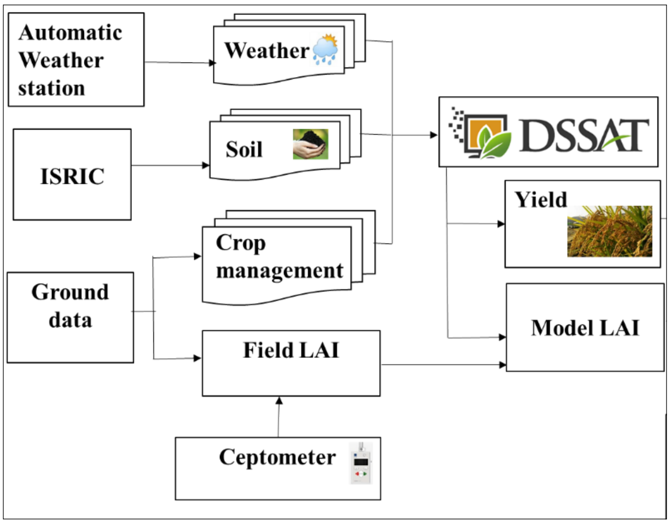

Fig. 2. Flowchart for DSSAT crop model representing input and output parameters.

ered as the minimum data set for the DSSAT model to simulate which were collected from automatic weather stations located near the village. Dew point temperature, wind speed, photosynthetically active radiation, minimum relative humidity, and vapour pressure are all optional daily inputs. The solar radiation required for the model was calculated using the Hargreaves equation with the maximum and minimum temperatures (32, 33). Once the data is available weather file can be prepared with the help of the weatherman tool present in the DSSAT. After entering the data, file should be saved with WTH extension with formatted text (space delimited) *i.e.,* CSV.

Soil data

DSSAT requires certain soil parameters for its simulation. Measured soil properties like soil texture (sand, silt, and clay percent), pH, EC, cation exchange capacity, nitrogen content, organic carbon percent, and bulk density were used as inputs, collected from ISRIC 2.0, which has a spatial resolution of 250 m (33) . Google Earth points were used to collect data for each field at depth, *i.e.* 0–200 cm.

A questionnaire was developed to record cropping practices such as variety, planting date, number of hills/ plants, sowing depth, time and amount of irrigation and fertilizer applied, which were collected from farmers during field visits. The most commonly grown varieties were MTU1010 and BPT5204, which were selected for sampling. Each individual field was selected on the basis of the variety grown, sowing date, fertilizer dosage, etc. to avoid duplication of data and to cover the entire village.

Management practices

Sowing was done in the selected fields in July 2021. Transplanting was done within 25–30 days after sowing. A high amount of nitrogenous fertilizers were used *i.e.,* 150 –220 kg ha^{-1}. Phosphorus and potash fertilizers were applied in the range of 60–115 kg ha^{-1} and 20–40 kg ha^{-1}, respectively. Fertilizer was applied through broadcast method. P and K were applied as basal and nitrogen has been applied in 3 splits. Irrigation was planned depending on the climate and crop requirements. Flooding method was followed and irrigation was applied through borewell. Data collected from farmers during field visits were given as input to the crop model (Table 1).

Table 1. Details of management practices followed in the Gangipalli village.

S.no	Date of Transplanting	Quantity of Nitrogen Applied (kg ha^{-1})	Observed Yield (kg ha^{-1})	Simulated Yield (kg ha^{-1})	LAI
1	20/07/2021	200	5450	5326	4.2
2	02/08/2021	180	4100	4400	3.0
3	20/07/2021	140	4800	4986	3.8
4	19/07/2021	180	5000	5437	4.3
5	22/07/2021	150	4800	4597	3.4
6	19/07/2021	220	5600	5549	4.5
7	20/07/2021	160	5300	5184	4.0
8	20/07/2021	180	5600	5359	4.1
9	28/07/2021	180	5300	5361	4.1
10	28/07/2021	200	5100	5190	3.9
11	02/08/2021	180	4800	4964	3.8
12	20/07/2021	210	5700	5668	4.6
13	25/07/2021	180	5100	5081	3.8
14	20/07/2021	210	5700	5668	4.6

Statistical analysis

The performance of the model was evaluated using the coefficient of determination (R^2), absolute and normalized root mean square error (RMSE) and Wilmot d-index (34) and modeling efficiency (ME). The equations for measuring model performance are as follows:

$$R^2 = \left[\frac{\left[\sum_{i=1}^{n}(O_i-\bar{O}) \times (S_i-\bar{S})\right]^2}{\sum_{i=1}^{n}[O_i-\bar{O}]^2 \times \sum_{i=1}^{n}[S_i-\bar{S}]^2}\right] \quad \text{.................. (Eqn. 1)}$$

Where S_i and O_i are the predicted and observed values, n is the number of observations, and the mean of the observed and simulated values. An R^2 value of 1 indicates a good relationship between the simulated and observed values.

$$RMSE = \left[n-1 \sum_{i=1}^{n}(\mathrm{Pi}-\mathrm{Oi})^2\right]^{0.5} \quad \text{...........(Eqn. 2)}$$

Where P_i and O_i are the predicted and observed values, n is the number of observations

$$\text{D Index} = 1 - \left[\frac{\sum_{i=1}^{n}(P_i-O_i)^2}{\sum_{i=1}^{n}[|P_i{'}|+|O_i{'}|]^2}\right] \quad \text{.................(Eqn. 3)}$$

Where n is the number of observations, Pi is the predicted observation, Oi is the measured observation, P_i = P_i - M, and O_i = O_i - M (M is the mean of the observed variable) (35). The value of D-index 1 indicates that the observed and simulated data are fully consistent.

$$ME = \left[\frac{\left[\sum_{i=1}^{n}(O_i-\bar{O}) - \sum_{i=1}^{n}(P_i-O_i)^2\right]}{\sum_{i=1}^{n}[O_i-\bar{O}]^2}\right] \quad \text{................(Eqn. 4)}$$

Where, P_i, O_i is the predicted and observed values, n is the number of observations, and $\bar{O}$ is the mean of the observed variable.

Table 2. Simulated and observed physiological maturity and grain yield for rice under kharif.

Variable (Average)	Simulated	Observed
Physiological maturity	128	125
Grain yield	5200 kg ha^{-1}	5400 kg ha^{-1}

Results and discussion

Yield estimation

After preparation of all the input files and incorporating them into the model, the model is now ready to commence the simulation of results. By selecting the required experiments file in crop system model proceed to click on the run option. Based on the aforementioned weather data, soil data, and climate data, as well as the management practices such as variety selection, sowing time, and applied fertilizer quantity, the model will simulate the results. Once running the model is completed, from the analysis tab of the run dialogue box, the output file of the interest can be selected. For this study purpose, Plant gro. Out and Summary. Out were selected where the required parameters were like grain and straw yield and leaf area index etc. were present.

The current study employed DSSAT version 4.7.5 to assess rice yields through the utilization of specific weather and soil data. The grain yields in the selected fields in Gangipalli were obtained through ground visits and were found to vary between 4200 kg ha^{-1} to 5700 kg ha^{-1}. On the other hand, the model-simulated yields ranged from 4400 kg ha^{-1} to 5800 kg ha^{-1} under diverse management practices, as presented in Table 1 and 2. Diverse yield fluctuations have been observed, potentially attributable to varying agricultural management practices implementted at the individual farm level.

The CERES model has been employed to predict rice yields under varying nitrogen application levels, that extend from 0 to 200 kg ha^{-1}. According to the analysis conducted using DSSAT CERES-Rice, it has been observed that the application of 150 kg N ha^{-1} results in a decrease in yields when compared to the application of higher nitrogen rates (200 kg ha^{-1}). According to prior studies, utilizing higher N rates to boost rice yield is a feasible management alternative for increasing revenue in low-income farmers. Threshold level varies with the variety and region and this enhancement in yield due to nitrogen application is up to a certain threshold level. However, beyond this threshold level *i.e.,* 200 kg ha^{-1}, further increases in nitrogen rates have been reported to decline crop yield (36, 37).

The results indicate that the maximum leaf area index (LAI) simulated by the model exhibited a range of 3.0 to 4.6. The high-yield scenarios exhibited the highest leaf area index (LAI) among the samples. The application of nitrogen fertilizers is observed to result in a detectable augmentation of vegetative cover, thereby contributing to the attainment of the maximal leaf area index. The present study results were consistent with those of past investigations (38, 39). An increased leaf area index (LAI) has been found to be significantly associated with both biological and grain yield, thereby leading to increased yields (40).

The sensitivity of the model in assessing crop yields across varying sowing dates has been evaluated. The study reveals that the sowing window significantly impacts the crop's growth, development, and productivity. Transplanting prior to July 20th resulted in optimal yield production without any reduction in yield. Planting after July 25th caused a decline in yield due to temperature fluctuations. According to previous research, it has been observed that delaying the sowing process results in yield declination. This is attributed to the plants being subjected to unfavourable low temperatures during the reproductive stage (35). The sensitivity of the model in yield estimation is evident with respect to the sowing dates. While the application of an optimal quantity of nitrogen is essential, the time of sowing also plays a crucial role in maximizing production. The reduction in crop yield in certain fields may be attributed to factors such as delayed sowing, overuse of fertilizers, and other external variables that contribute to the lower yields. The model yields were then compared with the actual yields and the results were analysed, an accuracy of 82% was observed.

Upon comparing the model-simulated yields with the observed yields, variations in the yields were observed. The causes of deviation could result from the model's failure to incorporate real-time factors that exist in the field, leading to the model's inability to account for yield losses caused by biotic factors such as pests and diseases, weeds, and abiotic factors like lodging. Similar constraints with the DSSAT model were reported (41).

Statistical analysis

The assessment of the CSM CERES model involved comparing field data with the model's simulated results obtained during the 2021 kharif season. A statistical analysis was performed to assess the agreement between observed and simulated yields within the study area. Based on the analysis executed, outcomes indicate that the R2 value was determined to be 0.81 (Fig. 3). Additionally, the root mean square error (RMSE) was calculated to be 238 Kg ha^{-1}, the D-index was found to be 0.83, and the model efficiency was determined to be 0.76%. These values were obtained by comparing the observed yields with the yields simulated by the model. In order to establish the relationship between yields and leaf area index (LAI), it has been observed that there is a correlation of 0.85 between the LAI simulated by the model and the resulting yield. The observed data suggests a positive correlation between leaf area index (LAI) and crop yield. Based on the results of the statistical analysis, it can be concluded that the model illustrates adequate reliability in predicting rice yield at the village level, even when considering different management practices.

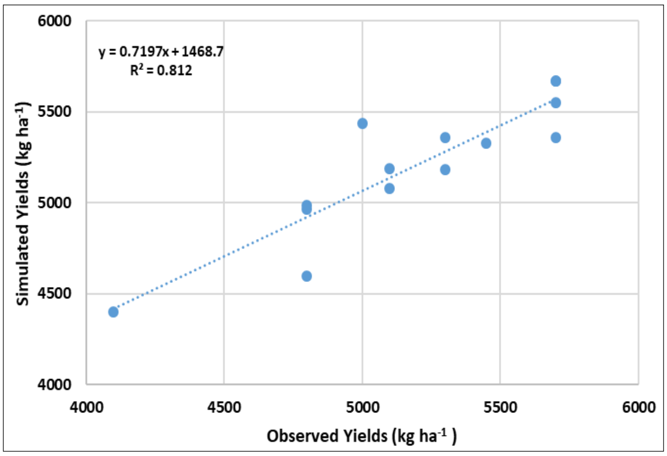

Fig. 3. Comparing observed and model simulated rice yields**.**

Identifying best management practices

In Karimnagar district sowing window range in kharif was for one month, *i.e.,* from July 1–30. Sowing at the proper time is vital for getting maximum yield. From the above-mentioned result, it can be depicted that sowing time plays an essential role on yield. Optimal timing for sowing plays a crucial role in maximizing production. The application of nitrogen in varying quantities has been observed to have a significant impact on the growth and development of crops, ultimately affecting their yield and leaf area index (LAI). The utilization of excessive fertilizer results in a decrease in crop yields once an appropriate threshold is reached. Based on the findings of this study, it has been determined that the optimal management practice for achieving high productivity is to transplant crops prior to July 20th and apply the recommended fertilizer dosage of 150 kg N ha^{-1}.

Conclusion

The present study utilized DSSAT version 4.7.5 to estimate rice yield. This was achieved by using location-specific weather and soil files that were generated for the purpose of this study. The analysis revealed a correlation coefficient of 0.81 and a D-index of 0.83 between the observed and simulated yields. Additionally, a correlation coefficient of 0.85 was observed between LAI and yield. Based on the obtained results, it has been determined that the DSSAT model demonstrates an acceptable level of accuracy in simulating rice yields across diverse management practices at the field level. The observed yields ranged from 4300 kg ha^{-1} to 5800 kg ha^{-1} across various management practices. On the other hand, the model-simulated grain yields ranged from 4200 kg ha^{-1} to 5900 kg ha^{-1}. The observed and simulated data exhibited a slight deviation, which can be attributed to the model's omission of stress caused by biotic factors such as pests, weeds, diseases, and other similar factors. Additionally, it has been discovered that the model exhibits sensitivity to both the timing of sowing and the quantity of fertilizer that is applied. The recommended management practice for the chosen study area entails conducting sowing activities prior to the 20th of July and optimizing the application of nitrogen fertilizers. This approach aims to enhance crop yields and promote sustainable production. To ensure high accuracy in yield estimation, it is essential to calibrate models appropriately for specific local cultivars. The utilization of Leaf Area Index (LAI) in yield estimation can be enhanced by integrating crop models with remote sensing data. This integration enables the prediction of yields with a high level of accuracy.

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Authors contributions

RM carried out the studies, conducted analysis and drafted the manuscript. MK planned the experiment, supervised the analysis results and corrected the manuscript. MD and SM participated in supervision and correcting the manuscript. All authors read and approved the final manuscript.

Compliance with ethical standards

Conflict of interest: Authors do not have any conflict of interests to declare.

Ethical issues: None.

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