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Original research

Spectral features fusion of effective criteria on wheat yield prediction

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ABSTRACT

The yield of the wheat crop is affected by the climate and soil parameters such as moisture and nutrients, plant pests and diseases. The main objective of this research is the feature level fusion of multiple effective criteria on the wheat yields using linear and machine learning regression models. The effects of vegetation condition, moisture, nutrients and pests on wheat yield are represented by spectral indices those are extracted from remotely sensed data. Optimum spectral indices are selected as the input features to each of the multiple linear and machine learning regression models such as decision tree, support vector regression and generalized regression neural network. The evaluation of the experimental results in eight wheat fields indicates that the wheat yield prediction based on spectral features fusion show the mean improvement of 0.81 in RMSE comparing with considering only one vegetation index in all regression models.

Moreover, all investigated machine learning regression models have about 0.03 more performance than the multiple linear regression model as indicated by R^2 coefficient. The generalized regression neural network model with the least RMSE error 0.0063 has the best results compared with other machine learning regression models and MLR.

Keywords: Feature fusion; Machine learning; Regression analysis; Spectral indices; Wheat; Yield prediction

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1. Introduction

Wheat, as one of the most productive cereals in the 21st century, has a high area under cultivation all around the world. As wheat provides the global main food supply, yield prediction is essential for decision making about rapid responses to the increase in wheat demand. In this regard, the use of remote sensing technology for wheat yield prediction can control food supply and demand. Statistical-experimental relationships between crop and spectral indices extracted from remotely sensed data are used to estimate the yield of agricultural products such as wheat (Nagy et al., 2021; Han et al., 2020; Vannoppen et al., 2020; Haung et al., 2018; Pinter et al., 2003; Pena et al., 2019; Atzberger 2013).

Many researches have been performed on investigating the relationship between vegetation indices and crop yields (Nagy et al., 2021; Vannoppen et al., 2020; Atzberger 2013; Kastens et al., 2005; Palanisamy et al., 2019; Miranda et al., 2020). A linear regression model is used for wheat yield prediction using the Normalized Difference Vegetation Index (NDVI) and Soil Adjusted Vegetation Index (SAVI) derived from Landsat-8 satellite images. The Nash-Sutcliffe efficiency index was 0.716 for the NDVI prediction model and 0.909 for SAVI model, which means that the yield prediction performed with good results (Nagy et al., 2021). Vannoppen et al. evaluate the possibility of using NDVI spectral index to estimate wheat yield in Latvia. The multi-temporal NDVI products for spring and winter wheat fields are used as a predictor to model wheat yield from 2014 to 2018. Their results indicate that high temperatures had a negative correlation with wheat yield. They concluded that NDVI and regional climate models output enabled wheat yield prediction better than regional statistics (Vannoppen et al., 2020). A new technique called yield-correlation masking to predict the yield of corn, soybeans, winter wheat, spring wheat, and barley is developed using AVHRR images in six time intervals from 1989 to 2000. The main objective of this methodology was to determine the correlation between the NDVI at the pixel level and the final yield of the region (Kastens et al., 2005). Palanisamy et al. found it appropriate to use the Leaf Area Index (LAI) to estimate vegetation cover and predict growth and fertility (Palanisamy et al., 2019).

The Landsat-5 TM, Landsat-7 ETM+ and Landsat-7 OLI sensors are used to calculate the LAI, which is an improved NDVI index, in which the blue band reflectance is used to correct for

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background soil signals and reduce atmospheric effects. Therefore, it works well in places where the vegetation is low and scattered, and the closer its values are to one, the higher the density of vegetation and the growth and fertility of the plant (Miranda et al., 2020).

Soil is one of the most effective factors in the growth of agricultural crops such as wheat. The soil's moisture and nutrients increase the crop yields and quality. Another effective factor in increasing the crop yield is water. Assessing water content is important to monitor crop conditions, detect water stress, and assess fire risk and water status for irrigation. Water spectral indices have been used in research on more than 40 different types of agricultural crops based on NIR, SWIR and thermal infrared remote sensing data (Pinter et al., 2003; Lakhankar et al., 2009; Cosh et al., 2019; Zhang et al., 2013).

The Vegetation Water Content (VWC) index is used to assess plant water status. This index is measured by calculating the weight of moisture to dryness ratio. Multiple statistical methods are available to estimate it from hyperspectral data (Lakhankar et al., 2009). The VWC index is also used in another research for investigating the various crop water status using Normalized Difference Water Index (NDWI) and Landsat-8 images (Cosh et al., 2019). Zhang et al. investigated the crop water content in China based on the six spectral indices. In this study, the Land Surface Water Index (LSWI), Moisture Stress Index (MSI), Shortwave Infrared Soil Moisture Index (SISMI), Surface Water Capacity Index (SWCI), Visible and Shortwave Infrared Drought Index (VSDI) and NDVI from MODIS satellite data are measured with and without removing the cloud cover (Zhang et al., 2013).

Nitrogen is described as the most important nutrient for plants and its sufficient resources in the soil are essential for agricultural production. One of the most important methods for assessing nitrogen concentration is the use of vegetation indices that have been used by many researchers (Haung et al., 2014; Oliveira et al., 2017; Chen, 2015; Li et al., 2010). The multi-temporal spectroscopic data and the nitrogen reflectance index are used to investigate the nitrogen concentration in China (Haung et al., 2014). OSAVI and RVI indices and IKONOS satellite imagery are used to estimate the nitrogen status of the winter wheat crop (Chen, 2015). In another study, the OSAVI and RVI indices and spectrometer ground data are utilized to estimate winter wheat nitrogen status (Li et al., 2010). In general, nitrogen deficiency reduces leaf chlorophyll concentration and leads to increased leaf reflectance in the visible spectrum (400-700 nm). However, pests and diseases also increase plant reflectance due to reduced chlorophyll content. Early detection of crop and plant diseases is very important for farmers and agricultural managers who want to reduce economic losses due to these threats. Therefore, some researches have been conducted on using vegetation spectral indices for crop disease detection based on remote sensing data (Zhao et al., 2020; Mahlein et al., 2013; Shanmugam et al., 2017).

According to the research background, performing regression analysis for crop yield prediction based on spectral indices extracted from remote sensing data has high research concentration (Gonzales-Sanchez et al., 2014; Sellam & Poovammal, 2016; Roell et al., 2020; Sharifi, 2021). Regression analysis techniques such as linear regression and machine learning models are proper tools for simultaneous analysis of multiple dependent variables (crop spectral indices) for efficient decision making about complicated problems such as yield prediction (Sellam & Poovammal, 2016; Sharifi, 2021). The yield of the wheat crop is affected by the climate and soil parameters such as moisture and nutrients, and plant pests and diseases. The main objective of this research is the fusion of multiple effective criteria on the wheat yields using linear and machine learning regression models. The optimum selected spectral indices from the groups of vegetation condition, moisture, nutrients, and pests are considered as the input features to the regression models. Linear and machine learning regression models are used for feature level fusion of the effective criteria on wheat yield prediction.

2. Material and Methods

2.1. Study area and data sets

The study area includes eight wheat fields with dry farming located around Qorveh city and its villages in Kurdistan province, Iran. The medium spatial resolution images captured by the Landsat-8 satellite are used for spectral index measurement.

Due to the fact that wheat is cultivated in this study area every two years, four Landsat-8 satellite images related to the years 2013, 2015, 2017 and 2019 were taken for this research. Table 1 shows each of the under consideration fields including the area and the amount of harvest in the years 2013 to 2019.

Table 1. Wheat fields characteristics in the study area.

Field No.	Area (ha)	Year	Yield (Ton)	Field No.	Area (ha)	Year	Yield (Ton)
1	4.2	2013	6.500	5	2.60	2013	3.900
		2015	6.000			2015	4.100
		2017	6.300			2017	3.700
		2019	7.000			2019	4.400
2	6.71	2013	8.000	6	6.00	2013	7.000
		2015	8.500			2015	8.000
		2017	8.200			2017	9.500
		2019	11.000			2019	10.000
3	4.50	2013	7.000	7	8.90	2013	11.000
		2015	7.200			2015	13.500
		2017	6.700			2017	12.000
		2019	7.500			2019	14.000
4	4.30	2013	6.800	8	6.10	2013	9.000
		2015	7.000			2015	9.000
		2017	6.500			2017	9.000
		2019	7.200			2019	9.000

Table 2. Mathematical basis of the spectral indices in four groups.

Index Group	Index Name	Mathematical Formula	Simple Linear Regression Error
Vegetation index	NDVI	(NIR – Red) / (NIR + Red)	**0.9065**
	LAI	0.332915 × SR - 0.00212	0.9752
	EVI	2.5 * [(NIR – Red) / (NIR + 6*Red - 7.5*Blue + 1)]	1.1908
Moisture Index	NDWI1	(NIR – SWIR) / (NIR + SWIR)	1.0458
	VWC	4.1110 * NDWI + 0.46821	1.0546
	NDWI	(Green – NIR) / (Green + NIR)	**0.9330**
	SWCI	(SWIR6 – SWIR7) / (SWIR6 + SWIR7)	1.2198
Nutrient Index	NRI	(Green – Red) / (Green + Red)	**0.9954**
	OSAVI	(NIR – Red) / (NIR +Red +0.16)	1.2419
	RVI	NIR / Red	1.0028
Pest and disease Index	PSRI	(Red - Blue) / NIR	1.0092
	SAVI	(NIR – Red / NIR + Red + 0.5)×1.5	**1.0063**
	LAI2	-3.45 ln(1 - SAVI) - 0.58	1.2020

Table 3. The values of the representative spectral indices in four years.

Field No.	Index Name	Mean Values Year 2013	Year 2015	Year 2017	Year 2019	Field No.	Index Name	Mean Values Year 2013	Year 2015	Year 2017	Year 2019
1	NDVI	0.4231	0.3824	0.4381	0.4707	5	NDVI	0.6321	0.6366	0.4400	0.6733
	NDWI	-0.5266	-0.4907	-0.5257	-0.5798		NDWI	-0.6886	-0.7178	-0.5337	0.7248
	NRI	-0.1332	-0.1334	-0.1139	-0.1500		NRI	-0.1016	-0.1545	-0.1226	-0.1063
	SAVI	0.2458	0.1619	0.2529	0.1933		SAVI	0.0080	0.0043	0.0064	0.0054
2	NDVI	0.5334	0.3543	0.4822	0.5451	6	NDVI	0.5205	0.5671	0.5302	0.5000
	NDWI	-0.6014	-0.4514	-0.5574	-0.6215		NDWI	-0.5792	-0.6472	-0.5675	-0.5851
	NRI	-0.1003	-0.1155	-0.1032	-0.1160		NRI	-0.0842	-0.1268	-0.0538	-0.1206
	SAVI	0.2732	0.1290	0.2413	0.1934		SAVI	0.3342	0.2421	0.3333	0.2365
3	NDVI	0.6087	0.6798	0.4298	0.7056	7	NDVI	0.3016	0.4317	0.4570	0.4843
	NDWI	-0.6659	-0.7421	-0.5229	0.7447		NDWI	-0.4323	-0.5697	-0.6038	-0.5542
	NRI	-0.0983	-0.1307	-0.1201	-0.0844		NRI	-0.1503	-0.1830	-0.2027	-0.0957
	SAVI	0.2617	0.1681	0.2038	0.2030		SAVI	0.1363	0.0959	0.0916	0.2403
4	NDVI	0.6308	0.6665	0.4352	0.6593	8	NDVI	0.4552	0.4222	0.3841	0.4652
	NDWI	-0.6886	-0.7360	-0.5291	-0.7183		NDWI	-0.5369	-0.5243	-0.4558	-0.5667
	NRI	-0.1039	-0.1406	-0.1220	-0.1164		NRI	-0.1083	-0.1310	-0.0871	-0.1383
	SAVI	0.0300	0.0163	0.0242	0.0192		SAVI	0.1782	0.0736	0.1615	0.1285

Table 4. Actual and Predicted yields of regression models in investigated fields.

Field No.	Predicted Yields MLR	DT	SVR	GRNN	Actual Yields
1	6.7725	6.6799	7.1579	7.0069	7.000
2	10.5035	10.7894	11.3004	11.0128	11.000
3	7.3044	7.6390	7.7565	7.5110	7.5000
4	7.0112	7.3328	7.3547	7.2067	7.2000
5	4.3894	4.4803	4.5105	4.4049	4.4000
6	9.1171	9.7898	9.9940	10.0005	10.000
7	12.9261	14.3127	14.0015	13.9989	14.000
8	9.0046	9.0676	9.1540	9.0068	9.000

2.2. *Spectral indices measurement*

The main objective of this research is to predict the yield of the wheat crop based on the fusion of multiple indices those are representative of effective criteria on the wheat crop. The linear and machine learning regression models are used for spectral features fusion and yield prediction. In the first step, widely used spectral indices from remotely sensed data were selected in each group of vegetation, moisture, nutrients, and pests based on previous research and considering the spectral capabilities of Landsat-8 satellite images (Nagy et al., 2021; Vannoppen et al., 2020; Palanisamy et al., 2019; Miranda et al., 2020; Cosh et al., 2019). Then, by applying simple linear regression to each of these indices, an optimal representative index with the minimum error was selected in each group. Table 2 shows the mathematical basis of the investigated spectral indices and the selected representative in each group of vegetation, moisture, nutrients, and pest indices.

By combining the representative indices as independent variables, the yield of wheat crop is predicted based on multiple linear regression and machine learning regression models, including decision tree, support vector machine, and neural network. In the following sub-sections, the basis of each regression model used in this research is explained and the results of applying them to the study areas are compared with each other.

2.3. Multiple linear regression model

Multiple Linear Regression (MLR) model can be applied to a set of independent variables Xij to predict a dependent variable Yi (Eq. 1) (Gonzales-Sanchez et al., 2014).

$$Y_i = \sum_{j=1}^{k} B_j X_{ij} + \varepsilon_i \tag{1}$$

where k is the number of independent variables, B_j is a regression coefficient, X_{ij} is the value j for the observation i of the independent variable X, and ε_i is the mean of residual errors which is obtained by the difference between the actual yields and the predicted values. In the utilized multiple linear regression model in this research, the NDVI vegetation index, NDWI moisture index, NIR nutrient index, and SAVI in the group of pest indices are used as independent variables.

2.4. Decision tree regression

The Decision Tree (DT), which belongs to the group of supervised machine learning algorithms, is a decision support tool for solving regression and classification problems and has been widely used in remotely sensed data processing applications (Han et al., 2020; Gonzales-Sanchez et al., 2014). The tree consists of a root node (containing all the data), internal nodes, and several leaves (end nodes defining the class names). One of the major advantages of the decision tree algorithm is its easy comprehensibility and interpretation, which has increased the popularity of this algorithm.

2.5. Support vector regression

The Support vector machine is also a supervised machine learning algorithm that is used for both classification and regression. Support Vector Regression (SVR) works like a SVM classifier, but instead of deciding to classify the data, it fits a function that can generate a prediction number as an output for each input data set. During SVR, the input data is mapped into a higher dimensional feature space using a kernel, and a linear regression model is applied in the new feature space to balance between maximizing and minimizing errors (Han et al., 2020). Kernel functions (linear, Gaussian, polynomial, etc.) are one of the important hyper parameters in SVR that help to find a hyperplane in higher space without increasing the computational cost.

2.6. Generalized regression neural network

Artificial neural networks are nonlinear statistical models that show a complex relationship between inputs and outputs to discover a new pattern (Han et al., 2020). The Generalized Regression Neural Network (GRNN) is a network for solving statistical regression problems. This type of neural network is based on radial basis functions and consists of three layers, including the input, hidden, and output layers, in which the Gaussian transfer function is used in the hidden layer and in the output layer, the transfer function is linear. GRNN is based on the nonlinear regression theory for yield prediction. The training set consists of input values X, each of which corresponds to an output Y. This regression method produces an estimated value of Y that minimizes the square error (Eq. 2).

$$Yr = \frac{\sum_{b=1}^{n} T_b \times f(X_r, b)}{\sum_{b=1}^{n} f(X_r, b)} \tag{2}$$

where X_r is independent variable, Y_r is dependent variable, T is the Activation weight for neurons at point b and $f(X_r,b)$ is the Gaussian kernel.

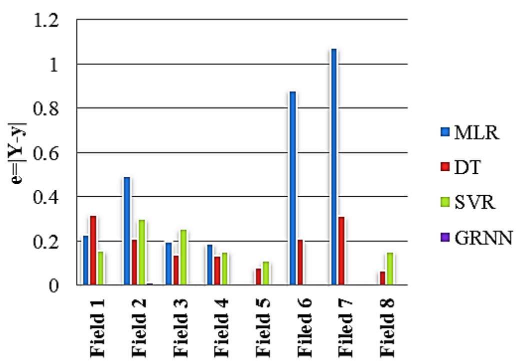

Fig. 1. Difference errors of MLR and machine learning regression models.

3. Results and Discussion

The capabilities of multiple linear regression and machine learning models (DT, GRNN, and SVR) in yield prediction based on spectral features fusion were evaluated in the eight wheat fields in the study area. As it is depicted in Table 3, the mean values of four selected representative spectral indices of each group of vegetation, moisture, nutrients, and pests were yearly measured for each of the eight wheat fields.

All regression models have been implemented in MATLAB programming software. The values of the representative spectral indices and the actual wheat yield of the first three years (2013, 2015 & 2017) were defined as training samples and those of the last year (2019) as test samples into the regression process. The training samples are entered in the regression model and the model coefficients are obtained. Then, the crop yield in 2019 is predicted by the model and the difference between the actual (Y) and the predicted (y) yield is calculated as the model error (e=|Y-y|) for each of the eight wheat fields. Table 4 compares the predicted yields for the year 2019 based on multiple linear regression and machine learning models with the actual crop yield.

Fig. 1 shows the calculated errors for each of the machine learning and multiple linear regression models. As it can be seen, MLR has the most difference errors and GRNN has the least difference errors in the study area.

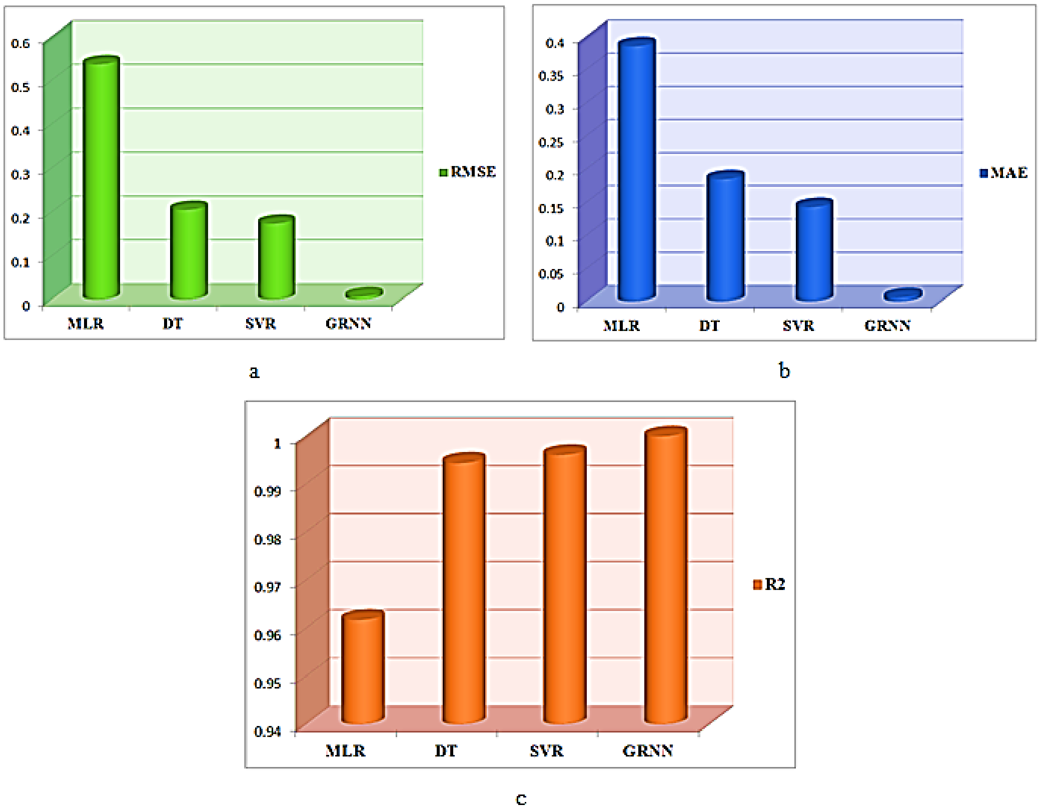

Fig. 2. Evaluation of the regression models based on a) RMSE, b) MAE and c) R^2.

For evaluating the performance of the multiple linear regression and machine learning regression models in this research, the Root Mean Square Error (RMSE), the Mean Absolute Error (MAE) and the coefficient of determination (R^2) are used, which can be calculated as follows (Eq.3, Eq. 4 & Eq.5):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - f_i)^2} \quad (3)$$

$$R^2 = \frac{(\sum_{i=1}^{n}(y_i - \overline{y_i})(P_i - \overline{P_i})^2)}{\sum_{i=1}^{n}(y_i - \overline{y_i})^2 \sum_{i=1}^{n}(P_i - \overline{P_i})^2} \quad (4)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - P_i| \quad (5)$$

where n is the number of wheat fields, y_i is the actual (observed) wheat yield of the field i, $\overline{y_i}$ is the corresponding mean value, P_i is the predicted wheat yield of the field i, $\overline{P_i}$ is the corresponding mean value.

Small RMSE and MAE values indicate more similarities between the actual and predicted yields. Moreover, the closer R^2 value to 1, the higher the prediction performance of the model is. Fig. 2 shows the evaluation results of multiple linear regression and machine learning models based on the RMSE, MAE and R^2.

One of the objectives of this research is to compare the capabilities of MLR, DT, SVR, and GRNN regression models for fusing multiple effective criteria on wheat yield prediction. The obtained differences between actual and predicted wheat yields show the capabilities of the GRNN machine learning regression model with a mean difference of 0.0063. The mean differences between actual and predicted yields are 0.1427, 0.1842 and 0.3850 for the SVR, DT and MLR regression models, respectively.

Moreover, using RMSE and MAE for evaluating the regression models indicates that the GRNN machine learning regression model has the best prediction results with RMSE=0.0075 and MAE=0.0063 compared to the DT, SVR, and MLR models. After GRNN, SVR has the best prediction results with RMSE=0.1735 and MAE=0.1427. The Decision tree regression model has the third grade with RMSE=0.2052 and MAE=0.1842 among the investigated machine learning models in this research. The Multiple linear regression model has the most errors with RMSE=0.5368 and MAE=0.3850. The closer to one value of the R^2 coefficient depicts the higher performance of the regression model. The R^2 value of all investigated machine learning regression models is 0.03 more than the multiple linear regression model.

The other main objective of this research is to investigate the impact of integrating the multiple spectral indices as representative of vegetation condition, moisture, nutrients, and pest criteria affected on the wheat yield, to improve the yield prediction results. The obtained yield prediction results based on spectral features fusion are compared with using only the NDVI vegetation index in all regression models. The RMSE evaluation values for the linear regression, decision tree, support vector regression, and generalized regression neural network with NDVI index are 0.9065, 1.4649, 0.7217, and 1.0805, respectively. This comparison shows a mean improvement of 0.81 for the predicted yields from spectral features fusion in regression models.

4. Conclusion

The NDVI, NDWI, NRI, and SAVI, as the selected representatives of vegetation, moisture, nutrients, and pest groups of spectral indices, are used for feature fusion in multiple linear and machine learning regression models (decision tree, support vector regression, and generalized regression neural network) for wheat yield prediction in eight fields in Kurdistan, Iran. The values of indices and actual wheat yields of the fields in the years 2013, 2015, and 2017 are entered into the regression models as training sets due to predict yields for 2019. The predicted yields in all eight wheat fields are evaluated based on the RMSE, MAE and R^2 factors. The evaluation results confirm that all machine learning regression models have better performance than linear regression models. Among the investigated machine learning regression models in this research, GRNN has the best prediction results. Moreover, using multi-indices in all investigated regression models can improve the prediction results compared with using only one vegetation index.

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Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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