Combining Sentinel-1 and -3 Imagery for Retrievals of Regional Multitemporal Biophysical Parameters Under a Deep Learning Framework

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Abstract—Regions with excessive cloud cover lead to limited feasibility of applying optical images to monitor crop growth. In this article, we built an upsampling moving window network for regional crop growth monitoring (UMRCGM) model to estimate the two key biophysical parameters (BPs), leaf area index (LAI), and canopy chlorophyll content (CCC) during the main growth period of winter wheat by using Sentinel-1 Synthetic Aperture Radar (SAR) and Sentinel-3 optical images. Sentinel-1 imagery is unaffected by cloudy weather and Sentinel-3 imagery has a wide width and short revisit period, the organic combination of the two will greatly improve the ability to monitor crop growth at a regional scale. The impact of two different types of SAR information (intensity and polarization) on the estimation of the two BPs was further analyzed. The UMRCGM model optimized the correspondence between inputs and outputs, it had more accurate LAI and CCC estimates compared with the three classical machine learning models, and had the highest accuracy at the green-up stage of winter wheat, followed by the jointing stage and the heading-filling stage, and the lowest accuracy was found at the milk maturity stage. The estimation accuracies of CCC were slightly higher than that of LAI for the first three growth stages of winter wheat, while lower than that of LAI for the milk maturity stage. This article proposes a new method for regional BPs (especially for CCC) estimation by combining SAR and optical imagery with large differences in spatial resolution under a deep learning framework.

Index Terms—Canopy chlorophyll content, deep learning, leaf area index, multitemporal monitoring, sentinel-1 and -3.

I. INTRODUCTION

Wheat (HEAT) is one of the important food crops. Timely and effective acquisition of wheat growth information is important for its yield prediction. With the rapid development of remote sensing technology, research on crop growth monitoring at the regional and field scales based on satellite remote sensing data has received a lot of attention.

Optical satellite sensors are developing rapidly and have the advantages of low cost and high accuracy, so optical remotely sensed images are widely used for crop growth monitoring and yield estimation [1]. However, optical images have a higher probability of being affected by cloudy weather, which leads to lower feasibility of using optical images to monitor crop growth changes. Compared with optical satellite sensors, Synthetic Aperture Radar (SAR) satellite sensors emit long wavelength electromagnetic radiation and can obtain backscattered information from inside the vegetation layer and soil layer under all-weather conditions [2], [3]. In this regard, SAR remote sensing technology has a unique advantage in monitoring crop growth.

SAR data include not only intensity information but also phase and polarization information. In recent years, an increasing number of studies have been conducted on the application of satellite-based SAR data for crop monitoring, and the polarization characteristics of SAR data have been widely used in monitoring studies such as classification and mapping of vegetation [4], [5]. In a vegetation growth monitoring study, Voormansik et al. [6] applied an entropy/alpha decomposition approach to the TerraSAR-X dual-polarization and Radarsat-2 full-polarization data, and the results indicated $HV/VV$ polarimetric coherence and the scattering entropy provide the most reliable indication about a mowing activity based on the polarimetric SAR time series. Yang et al. [7] used the polarimetric characteristics of the full-polarization Radarsat-2 data to estimate the biomass of rapeseed and compared it with the biomass estimation results based on single-polarization and dual-polarization SAR data. The results showed that the rape biomass estimation model constructed based on full-polarization SAR data is simple, with a high saturation point and high accuracy, which indicated that polarization information had important value in crop quantitative monitoring. The abovementioned studies showed that the polarization information of full-polarization SAR data has great advantages in monitoring vegetation growth and crop growth. During the growing season of crops, the influence of soil background information on SAR echo signals varies at different times, which requires consideration of the extent to which polarization information affects crop growth monitoring.
at different growth stages. However, there is currently little research in this area.

Compared with the full-polarization mode SAR sensors, which are still very much experimental missions, the dual-polarization mode SAR sensors can obtain satellite images with a wider swath width and higher spatial resolution. The dual-polarization satellite, Sentinel-1, provides data are freely available worldwide and, thus, is increasingly used for monitoring the crop growth information within the growing season [8], [9]. The polarimetric information from full-polarization SAR data plays an important role in monitoring crop growth. This is mainly because the crop canopy structure changes as the crop grows and the sensitivity to the intensity from different polarizations varies. The same reason applies to the dual-polarization SAR data. At present, there are few studies on the application of polarization information from dual-polarization SAR data for crop growth monitoring. Mercier et al. [10] estimated crop physiological parameters using polarimetric decomposition information from time series of Sentinel-1 data based on the Gaussian processes regression approach and the results showed that the ratio of backscattering coefficient VH to VV was most correlated with the leaf area index (LAI) of wheat, and the Shannon entropy polarization contribution has the best performance on wheat vegetation water content estimation. Mandal et al. [11] combined backscattering information in terms of the degree of polarization and the eigenvalue spectrum to derive a new vegetation index (DpRVI) from Sentinel-1 SAR data, and the results showed that DpRVI had a higher correlation with crop physiological variables compared with the traditional radar vegetation index. All of these studies indicate that the polarization information from dual-polarized SAR data has great potential for the monitoring of crop growth parameters.

In recent years, there has been an increasing amount of studies on integrating optical and SAR remote sensing data and combining the advantages of both for crop growth monitoring [12], [13]. Pipia et al. [14] proposed a method of multioutput Gaussian processes (MOGPs) for filling the missing Sentinel-2 LAI caused by clouds by using Sentinel-1 time series radar vegetation index (RVI), which can be applied to multiple types of crops and had different LAI prediction capabilities at different growth stages of the crops. These methods mostly perform data-based fusion for different types of remote sensing images, which yield good results but ignore the temporal and spatial correlation of remote sensing images. In real situations, the spatial structure of surface parameters may affect crop growth through factors such as soil moisture. Therefore, the spatial structure of remotely sensed variables plays an important role in building a crop growth estimation model [15]. Most of the existing studies exploring the relationship between image parameters and crop physiological variables are based on simple statistical analysis methods, which may have limitations in fully exploring the relationships between those temporal and spatial features, in which the introduction of machine learning (ML) methods may yield more desirable results than previous studies.

Deep learning (DL) is a major ML method and can fully exploit the high-dimensional features contained in massive remote sensing data, and thus, can effectively extract the temporal and spatial information of the remotely sensed imagery. In recent years, studies have reported on the introduction of DL methods into the field of remote sensing image processing [16], [17]. In the field of agricultural remote sensing, DL methods are also being used more and more widely [18], and are mainly applied to crop classification [19], crop growth dynamic monitoring [20], [21], and crop disease monitoring [22], [23]. Crop dynamics monitoring requires high timeliness of remote sensing data. The susceptibility of optical images to cloudy weather makes its application to regional-scale crop growth monitoring limited. Therefore, the integration of multisource remote sensing data, especially the integration of optical data and SAR data based on DL methods for crop growth monitoring is getting more and more attention.

The convolutional neural network (CNN), as a classical DL method, is one of the core algorithms in the field of image recognition and has a stable performance when the amount of data is sufficient [24]. He and Yokoya [25] utilized a combined CNN and conditional generative adversarial network (cGAN) approach for multitemporal Sentinel-1 (SAR satellite) and -2 (optical satellite) data fusion. CNNs are also used in agriculture for quantitative crop yield estimation. Barbosa et al. [26] applied a CNN to learn the relationship between the field environmental and management variables and crop yield, in which both the input features and output features are images. However, there are still relatively few studies that integrate SAR and optical remotely sensed images based on CNNs to simulate crop biophysical parameters (BPs). In addition, most of the existing studies have been conducted on the integration of Sentinel-1 and -2 images, which have an approximate spatial resolution. The width of Sentinel-2 satellite imagery (about 100 km) is relatively small, with a revisit period of 5-6 days. Considering the effects of cloudy weather, the availability of Sentinel-2 satellite imagery is further reduced [27]. Therefore, integration of SAR images with optical remotely sensed images of greater width and higher temporal resolution (e.g., Sentinel-3 image has an approximate width of 1270 km, which is approximately 12 times the width of the Sentinel-2 image, and the revisit period of Sentinel-3 in a relatively large area, such as the Guanzhong Plain, is approximately 1 day.) maximizes the benefits of SAR data and needs to be considered.

This article presents a novel deep learning architecture, named upsampling moving window network for regional crop growth monitoring (UMRCGM) model, to simulate the BPs of winter wheat, by using the backscattering coefficient, local incidence angle, and polarimetric decomposition information contained in the Sentinel-1 images as the input data and the LAI and canopy chlorophyll content (CCC) retrieved from Sentinel-3 images as the labels. The reason for choosing Sentinel-1 and Sentinel-3 images is that Sentinel-1 can provide stable and high-quality time-series SAR observation images, Sentinel-3 can provide high temporal resolution and wide width multispectral images, the two can complement each other’s strengths in the temporal and spatial dimensions, and will improve the ability to estimate crop BPs at the regional scale. Due to the large differences in spatial resolution between the Sentinel-1 and Sentinel-3 images, in the UMRCGM model, a moving window module is introduced.
for determining the optimal way to combine the inputs and outputs. The reason for choosing local incidence angle information as input is that SAR sensors get different information about the characteristics of the scatterer from different angles. The study analyzes the performance of the UMRCGM model with different input schemes, and the optimal model for simulating the LAI and CCC of the main growth period of winter wheat is determined. And the simulated results of LAI and CCC are also compared with those based on classic ML methods, such as partial least squares regression (PLSR), random forest (RF), and XGBoost. Finally, regional-scale LAI and CCC are simulated. The rest of this article is organized as follows. Section II details the overview of the study area, the remote sensing data and its preprocessing methods, and proposes the UMRCGM model. Section III shows and analysis the experiments and results. Section IV compares this article with the studies of others and discusses the potential research directions and future perspectives. Finally, Section V concludes this article.

II. MATERIALS AND METHODS

A. Study Area

The study area is located in the Guanzhong Plain in northwestern China. The plain has a typical continental monsoonal semihumid climate with an average annual temperature of 10 °C, average annual precipitation of about 600 mm, and the area is approximately 3.6 × 10^4 km^2. Two rivers running through the plain, the Jing River, and the Wei River, converge in the abdomen of the Guanzhong Plain. The soil along the Wei River is soft and fertile and has good cultivation conditions. The crop planting area is mainly concentrated in the west of the Guanzhong Plain, which is mainly located on the northern bank of the Wei River and has good farming conditions. The middle of Guanzhong Plain has the second largest crop planting area, and the area of crop planting area in the east of Guanzhong Plain is the smallest. The crops grown in this area are mainly winter wheat and summer maize in rotations. Winter wheat is sown around early October each year, with the green-up stage from early to mid-March, the jointing stage from late March to mid-April, the heading-filling stage from late April to early May, the milk maturity stage from mid-May to late May, and the harvest time is early June. In this article, crop lands in the study area were extracted by using the Global Land Cover with Fine Classification System at 30 m in 2020 products, which was validated in the Guanzhong Plain region [28]. The type of irrigated cropland in this product is closest to the actual distribution of winter wheat cultivation in the study area, thus, it was used to extract the actual growing areas of winter wheat. The products were first resampled to the same spatial resolution as Sentinel-3 image, and then the LAI and CCC estimation results of the study area were masked, and finally, the masked results were analyzed further.

B. Remote Sensing Data

1) Optical Remote Sensing Images: The optical remote sensing images collected in the study area were taken by ESA’s Sentinel-3 satellite (see Table I). The Sentinel-3 Level-2 Synergy products were collected, which provided atmospherically corrected surface directional reflectance with their associated error estimates for the sun-reflective sea and land surface temperature radiometer channels and Ocean and land color instrument channels, and have a spatial resolution of 300 m. The Sentinel-3 LAI and CCC were calculated using the S2 Toolbox Level 2 Product algorithm [29]. The algorithm uses the neural network to estimate the LAI and CCC from the top of canopy (TOC) reflectances along with a set of corresponding angles defining the observational configuration. The selected bands for Sentinel-3 data include Oa06, Oa08, Oa11, Oa12, Oa16, Oa17, S5, and S6. The three angle parameters were obtained from Sentinel-3 Level-2 Land Full Resolution products and were the viewing zenith angle, solar zenith angle, and relative azimuth angle [30].

2) SAR Remote Sensing Images: The SAR remote sensing images collected in this study were taken by ESA’s Sentinel-1 satellite (see Table I). Sentinel-1 is a C-band synthetic aperture radar satellite with a SAR sensor centered at 5.405 GHz, containing two polarization information (VV and VH). Single look complex data of Sentinel-1 interferometric wide swath mode were downloaded at the four growth stages of winter wheat and were preprocessed using ESA SNAP software. The SAR polarimetric characteristics provide information on the shape and structure of the target that is not available from other SAR parameters [31]. The processes of extracting the polarimetric decomposition information of Sentinel-1 data were as follows: S1 terrain observation with progressive scans split, apply orbit file, complex calibration, deburst, polarimetric matrices extraction, and multilook (number of range looks is 4 and azimuth looks is 1). The shuttle radar topography mission was selected as digital elevation model to geocode the obtained covariance matrix and which was reprojected to UTM reference. The Refined Lee filter [32], which has advantage of retaining the polarization information better while eliminating the effect of coherent spots, thus, was used to perform polarimetric speckle filter on the covariance matrix in this article.

C. SAR Polarization Information Extraction

The extracted polarimetric matrix from Sentinel-1 data is the covariance matrix C2, which contains all polarization information of scatterers and is used to analyze the crop state in this article [33]. It can be derived from

\[
C_2 = \begin{bmatrix}
S_{VV}S_{VV}^* & S_{VV}S_{VH}^* \\
S_{VH}S_{VV}^* & S_{VH}S_{VH}^*
\end{bmatrix} = \begin{bmatrix}
C_{11} & C_{12} \\
C_{21} & C_{22}
\end{bmatrix} \tag{1}
\]

where * denotes complex conjugate, VV represents the electromagnetic waves that are transmitted vertically and received vertically, VH represents the electromagnetic waves that are transmitted vertically and received horizontally, and \(S_{VV}\) and \(S_{VH}\) are scattering vectors in VV and VH polarization mode, respectively. It is worth noting that C12 is a complex number and C21 is the conjugate of C12. We convert the real part and imaginary part of the off-diagonal complex value of the C2 matrix to C2_re and C2_imag, respectively. Although the C2 matrix was polarimetrically filtered when it was calculated, the
TABLE I

| Growth stage | Sentinel-1 (Orbit 1, 2 and 3) | Sentinel-3 | Date difference between SAR and optical images | Major date differences |
|--------------|-----------------------------|------------|-----------------------------------------------|------------------------|
| Green-up     | 30, 25 and 20 March         | 20 March   | 0-10 days                                     | 5 days                 |
| Jointing     | 11, 18 and 13 April         | 12 April   | 1-6 days                                      | 6 days                 |
| Heading-filling | 23, 30 and 25 April      | 27 April   | 2-4 days                                      | 3 days                 |
| Milk maturity | 17 and 12 May               | 15 May     | 2-3 days                                      | 3 days                 |

Notes: Complete coverage of the entire study area requires three Sentinel-1 images from three adjacent orbits (Fig. 1) and only one Sentinel-3 image from one orbit. Since the Sentinel-1 satellite’s Orbit 2 covers most of the Guanzhong Plain, we used the difference between the date of the image acquired by the Sentinel-1 satellite in orbit 2 and the date of the Sentinel-3 image to calculate the major date differences between the two data sources.

resulting C2 matrix still contained outliers. If these outliers are ignored, the input data distribution of the model will be unbalanced, thus affecting the estimation results of the model. Therefore, this article adopts a 2% linear stretching treatment for the computed C2 matrix.

D. UMRCGM Model

In this article, the UMRCGM model was proposed and used to extract features of Sentinel-1 images separately (see Fig. 2). The backscattering coefficients ($\sigma_{VV}$ and $\sigma_{VH}$), local incidence angle (LIA), and covariance matrix C2 of Sentinel-1 images are used as the inputs of UMRCGM model, respectively, and LAI and CCC retrieved from Sentinel-3 images are used as models’ labels, respectively. The preprocessed Sentinel-1 images have a spatial resolution of about 15 m $\times$ 15 m and Sentinel-3 images have a spatial resolution of about 300 m $\times$ 300 m. When Sentinel-1 images are used as input features of a model, considering that there is a certain degree of geographical intercorrelation between two real targets that are close together in space, there can be several different mapping relationships between features (Sentinel-1 images) and targets (Sentinel-3 images). Thus, we adopted a moving window module to select the optimal image information extraction strategy, which contains optimal window size and optimal step size. On this basis, 16 convolutional kernels of size $3 \times 3$ are used to extract image features and pass through a $2 \times 2$ pooling layer, and then 32 convolutional kernels of size $3 \times 3$, which are used to extract features and pass through a $2 \times 2$ pooling layer. Finally, a fully connected layer and two dense layers are used to output the results. The model 1 is called UMRCGM-S3 model, in which the input has three parameters ($\sigma_{VV}$, $\sigma_{VH}$, and LIA), contains intensity characteristics of the target and angle characteristics of radar echo. The model 2 is called UMRCGM-S4 model, in which the input has four parameters (C11, $C_{rel}$, $C_{img}$, and C22), contains all the polarimetric characteristics of the target. The model 3 is called UMRCGM-S7 model, in which the input has all the seven parameters ($\sigma_{VV}$, $\sigma_{VH}$, LIA, C11, $C_{rel}$, $C_{img}$, and C22). All input parameters were normalized to ensure uniformity of magnitude in the three models. Mean squared error (MSE)
TABLE II
HYPERPARAMETERS USED IN THE UMRCGM MODEL

| Hyperparameters     | LAI  | CCC  |
|---------------------|------|------|
| Batch size          | 128  | 128  |
| Dropout rate        | 0.2  | 0.8  |
| Regularization      | 0.01 | 0.01 |
| Learning rate       | 0.001| 0.01 |
| Learning rate decay | 0.001| 0.01 |

and L2 norm regularization were used for these three models to minimize the squared sum loss of the objective function and prevent overfitting. The leaky rectified linear function was chosen as the activation function for the convolutional layers and dense layers in the models [34]. The batch normalization was used after the dense layer to speed up the training process and improve accuracy [35]. The Adam optimizer was used to find a local minimum of the objective function and an early stopping strategy was used to avoid overfitting [36]. The optimal hyperparameters for the UMRCGM models are shown in Table II. The optimal image information extraction strategy was determined to be 30 × 30 × 10, which means we correspond a pixel matrix (feature matrix) of size 30 pixels × 30 pixels in the Sentinel-1 image to one pixel in Sentinel-3, a step size of 20 pixels between two adjacent pixel matrices, which means an overlap between these two adjacent pixel matrices are 10 pixels × 30 pixels. Considering the overwhelming size of the model input data, this article sampled the entire Sentinel-3 LAI and CCC images of the study area at intervals of 3, i.e., one pixel every four pixels. In this way, a one-to-one correspondence between the feature quantity and the target quantity can be guaranteed.

E. Three Classic ML Methods and Feature Importance Analysis

Since Sentinel-1 and Sentinel-3 data have different spatial resolutions when Sentinel-1 data is used as model input to simulate Sentinel-3 data, it is often necessary to first resample the Sentinel-1 data to the same spatial resolution as the Sentinel-3 data, and then some end-to-end machine learning models are used to output the estimation results. To better illustrate the advantages of the method proposed in this article on simulating winter wheat growth, three classical ML methods (PLSR, RF, and XGBoost) are used to simulate winter wheat growth and their results are compared with the proposed UMRCGM model. Unlike UMRCGM model, the mapping relationship between the input and output of these methods is unique, and there is only a one-to-one correspondence between input features and labels. For remote sensing images, with different spatial resolutions of input and output images, it is not possible to have one input pixel corresponding to one output pixel (as represented in Fig. 2). Therefore, the study resamples each input Sentinel-1 parameter image to the same spatial resolution of Sentinel-3 data using the nearest neighbor method, and the LAI and CCC of winter wheat at four growth stages were simulated based on each regression prediction method with Sentinel-1 SAR data as independent variables.

Both RF and XGBoost are algorithms that evolve based on decision trees. For both algorithms, Gini importance is used to evaluate feature importance [37]. The Gini index indicates the purity of the node, a lower Gini index means that the probability of a selected sample in the set being misrepresented is lower, i.e., the lower the Gini index the higher the purity, which can be expressed as (2). Thus, the Gini index is used to determine the optimal node for a feature. The importance of a feature at node m is expressed as the change in the Gini index before and after the branching of that node, which can be expressed as (3). If the node where the feature appears in the decision tree is in the set M, then the importance of the feature in the i'th tree can be expressed as (4). The mean value of the change in the Gini index is used as a measure of the importance of the feature, can be expressed as (5)

\[
Gini(P) = \sum_{k=1}^{k} p_k (1 - p_k) = 1 - \sum_{k=1}^{k} p_k^2 \tag{2}
\]

\[
FPM_{jm} = GI_m - GI_u - GI_v \tag{3}
\]

\[
FPM_{ij} = \sum_{m \in M} FPM_{jm} \tag{4}
\]

\[
FPM_{ij} = \frac{FPM_{ij}}{\sum_{i=1}^{n} FPM_{i}^{\text{Gini}}} \tag{5}
\]

where \( k \) is the number of categories, \( p_k \) is the weight for category \( k \). \( Gini(P) \) is the Gini index of the probability distribution. \( GI_m \) is the Gini index of node \( m \). \( GI_u \) and \( GI_v \) are the Gini index of the two new nodes before and after node \( m \), respectively. \( FPM_{jm} \) is the feature importance at node \( m \). \( FPM_{ij} \) is the importance of the feature in the \( i \)th tree. \( FPM_{ij} \) is the Gini importance of the feature. \( n \) is the number of trees.

The variable importance in projection (VIP) score [38] is used to evaluate the feature importance of the PLSR algorithm, which is defined as

\[
VIP_j = \sqrt{\frac{J \sum_{k=1}^{F} (c_k^{2} t_k^{j} t_k^{j}) (w_{jk})^2}{\sum_{k=1}^{F} c_k^{2} t_k^{j} t_k^{j}}} \tag{6}
\]

where \( VIP_j \) is the feature importance of variable \( j \). \( J \) is the number of variables. \( F \) is the number of latent variables of the PLSR model. \( w_{jk} \) is the weight used in the mapping of variable \( j \) at the \( k \)th iteration. \( c_k \) is the PLSR inner relation coefficients. \( t_k \) is the independent variables scores matrix. \( t_k' \) is the transpose matrix of \( t_k \).

III. RESULTS AND ANALYSIS

The proposed UMRCGM models for the LAI and CCC estimation at four growth stages of winter wheat (green-up stage, jointing stage, heading-filling stage, and milk maturity stage), respectively. The Sentinel-1 and Sentinel-3 images collected
at each growth stage were randomly divided into three parts, namely the training set, validation set and test set, with the number of samples in each part accounting for 70%, 20%, and 10% of the total number of samples in the whole study area, respectively. The Sentinel-3 retrieved LAIs and CCCs at the four growth stages of winter wheat were used to evaluate the accuracy of the proposed UMRCGM models. R² and RMSE were used as indicators to assess the model’s accuracy on those three datasets. The LAI and CCC estimations of the UMRCGM models were compared with three classic ML methods (PLSR, RF, and XGBoost), respectively, and the feature importance of those three methods was analyzed. Finally, the UMRCGM model based on the optimal input scheme was applied to simulate the regional LAI and CCC of the Guanzhong Plain at four growth stages of winter wheat.

A. Results of LAI Estimation by UMRCGM Models

For LAI estimation, Fig. 3 shows the accuracy results of the models on the validation set. During the winter wheat growing season, all three UMRCGM models have the highest LAI estimation accuracy at the green-up stage of winter wheat, followed by the second highest at the jointing stage of winter wheat, then the heading-filling stage of winter wheat, and the lowest LAI estimation accuracy at the milk maturity stage of winter wheat. This may be due to the fact that at the green-up stage of winter wheat, the wheat canopy has not been completely closed and does not yet have a dense canopy structure, which makes the C-band radar signals more effectively describe the state of the vegetation layer. During the winter wheat jointing stage and heading-filling stage, the vegetation cover is high and the radar signal is less likely to penetrate the vegetation layer, making it difficult to obtain information about the interior of the vegetation canopy by means of radar signals, and this becomes more apparent as the vegetation cover increases. At the milk maturity stage of winter wheat, grains filling, which leads to disturbances in the wheat ears and, thus, to large errors. In addition, the decreases in LAI during the milk maturity stage also cause the radar signal to receive more interference from the soil layer, which reduces the accuracy of the LAI estimation.

As can be seen in Fig. 3, among the three models, the UMRCGM-S7 model, which utilized seven features as inputs, has the highest LAI estimation accuracy at four growth stages of winter wheat. This is mainly because the input features of the UMRCGM-S7 model combine radar backscatter information, incidence angle and polarimetric decomposition information, allowing the model to extract different types of features more adequately, which in turn improves the accuracy of the model’s estimation of LAI. The UMRCGM-S3 model has higher LAI estimation accuracy than the UMRCGM-S4 model during the first three growth stages of winter wheat. However, at the milk maturity stage, the LAI estimation accuracy of the UMRCGM-S4 model is slightly higher than that of the UMRCGM-S3 model. The optimal input feature combinations corresponding to the accurate estimation of LAI were listed in Table III.

The accuracy of the UMRCGM-S7 model in simulating LAI at different growth stages of winter wheat was further explored. Fig. 4 shows the scatter plots and kernel density estimations (KDEs) of LAI predicted on test sets by the UMRCGM-S7 model. It can be seen that LAI at the green-up stage of winter wheat has the highest estimation accuracy (R² = 0.72 and RMSE = 0.36 m² m⁻²), followed by the jointing stage (R² = 0.69 and RMSE = 0.48 m² m⁻²) and the heading-filling stage (R² = 0.65 and RMSE = 0.44 m² m⁻²), with the lowest correlations at the milk maturity stage (R² = 0.23 and RMSE = 0.49 m² m⁻²). At the jointing stage of winter wheat, there is a large RMSE of LAI estimation. This may be because, among these four growth stages, the longest acquisition time difference (6 days) was observed for Sentinel-1 and Sentinel-3 images at the jointing stage. The rapid growth of winter wheat at the jointing stage and the fast growth of LAI increase the estimation error of the model.

B. Results of CCC Estimation by UMRCGM Models

As can be seen in Fig. 5, compared with the UMRCGM-S4 model, the UMRCGM-S3 and UMRCGM-S7 models have higher and closer CCC estimation accuracy at the four growth stages of winter wheat. All three models have high CCC estimation accuracy for the first three growth stages and the lowest CCC...
Fig. 4. Results of LAI estimation based on UMRCGM-S7 model at winter wheat (a) green-up stage, (b) jointing stage, (c) heading-filling stage, and (d) milk maturity stage, respectively.

Fig. 5. R2 and RMSE results of CCC on the validation set by three UMRCGM models.

The chlorophyll content of winter wheat leaves increases rapidly from the green-up stage to the jointing stage and decreases from the heading-filling stage to the milk maturity stage [39]. It is important to effectively estimate the chlorophyll content at the jointing stage and heading-filling stage to monitor the growth status of winter wheat. At the green-up stage, the UMRCGM-S3 model uses SAR backscatter information and incidence information as input features to obtain better estimation results of chlorophyll content. After adding the SAR polarimetric decomposition information, the accuracy of the chlorophyll content estimation is slightly reduced instead. This is probably because the SAR polarimetric decomposition information contains more soil background information during this period.
which makes the input features of the UMRCGM-S7 model contain more noise information, and therefore, the accuracy of the chlorophyll content estimation is lower. When the winter wheat canopy is closed, UMRCGM-S7 has a higher accuracy of chlorophyll content estimation compared to UMRCGM-S3. During the heading-filling stage of winter wheat, the wheat starts to grow ears. The SAR signal contains both leaf information and ear information, which makes the estimation accuracy of canopy chlorophyll content with SAR information as input features to the UMRCGM model decrease during this period. At the milk maturity stage of winter wheat, the leaves of the wheat begin to turn yellow, the leaves start to shrivel, and the ears mature further and become larger. At this time, the accuracy of the SAR signal estimation of canopy chlorophyll content is the lowest of the four growth stages. The optimal input feature combinations corresponding to the accurate estimation of CCC were listed in Table III. In general, the UMRCGM-S7 model, which utilized seven features as model inputs has slightly higher CCC estimation accuracy and can consistently simulate winter wheat chlorophyll content based on Sentinel-1 data.

Fig. 6 shows the scatter plots and KDEs of CCC predicted on test sets by the UMRCGM-S7 model. And it can be seen that CCC simulated by Sentinel-1 images have the highest accuracy with CCC retrieved by Sentinel-3 images at the green-up stage of winter wheat ($R^2 = 0.72$ and RMSE = 18.79 $\mu$g cm$^{-2}$), followed by the jointing stage ($R^2 = 0.70$ and RMSE = 24.92 $\mu$g cm$^{-2}$), and the heading-filling stage ($R^2 = 0.66$ and RMSE = 25.11 $\mu$g cm$^{-2}$), with the lowest accuracy at the milk maturity stage ($R^2 = 0.13$ and RMSE = 26.77 $\mu$g cm$^{-2}$).

### C. Results of LAI and CCC Estimation by Three Classical ML Methods

LAI and CCC were simulated at the four growth stages of winter wheat based on three classic ML methods (PLSR, RF, and XGBoost). For the test set, the three models’ accuracies and UMRCGM-S7 model’s accuracies are presented in Table IV. The results showed that the LAI and CCC estimation accuracies of the UMRCGM-S7 model were higher than those of the three classic ML models. Of the three methods, XGBoost had the highest accuracy in simulating LAI and CCC at all four growth stages, with RF having the next highest accuracy and PLSR having the lowest accuracy. Of the four growth stages, all three methods had the highest LAI and CCC estimation accuracies at the green-up stage, followed by the jointing and heading-filling stages, with the lowest accuracy at the milk maturity stage.

The article further analyzed the feature importance for the three models, as shown in Fig 7. For each method, the importance of the features is relatively similar in the first three growth stages of winter wheat but different at the last growth stage of winter.
TABLE IV
ACCURACY OF SIMULATED LAI AND CCC AT THE FOUR GROWTH STAGES OF WINTER WHEAT BY THREE CLASSIC ML METHODS AND UMRCGM-S7 MODEL

| Models         | Parameters | Green-up   | Jointing   | Heading-filling | Milk maturity |
|----------------|------------|------------|------------|-----------------|---------------|
|                |            | $R^2$ / RMSE |            |                 |               |
| PLSR           | LAI        | 0.25/0.81  | 0.23/0.95  | 0.24/0.80       | 0.10/0.55     |
|                | CCC        | 0.25/40.75 | 0.24/51.43 | 0.25/48.09      | 0.09/31.42    |
| RF             | LAI        | 0.36/0.74  | 0.32/0.90  | 0.35/0.74       | 0.15/0.54     |
|                | CCC        | 0.36/37.56 | 0.33/48.42 | 0.36/44.22      | 0.12/30.87    |
| XGBoost        | LAI        | 0.37/0.74  | 0.33/0.89  | 0.36/0.73       | 0.16/0.53     |
|                | CCC        | 0.37/37.32 | 0.33/48.37 | 0.37/43.87      | 0.12/30.28    |
| UMRCGM-S7      | LAI        | 0.72/0.36  | 0.69/0.48  | 0.65/0.44       | 0.23/0.49     |
|                | CCC        | 0.72/18.79 | 0.70/24.92 | 0.66/25.11      | 0.13/26.77    |

Fig. 7. Feature importance for classic ML models (PLSR, RF, and XGBoost). (a) Mean values of the normalized feature importance for the first three growth stages of winter wheat. (b) Mean values of the normalized feature importance for the last growth stage of winter wheat. Note: There are two bars for each feature, the left bar represents the feature importance for the three methods of simulating LAI and the right bar represents the feature importance for the three methods of simulating CCC.

wheat. Fig. 7 shows the averages of the normalized feature importance of SAR input parameters of the three methods (see Fig. 7(a) for the first three growth stages and Fig. 7(b) for the last growth stage). For the first three growth stages, the feature importance of $C1_{img}$ and $C1_{rel}$ is less in all three models, the feature importance of $C11$, $C22$, $\sigma_{VV}$, and $\sigma_{VH}$ is greater in the XGBoost and RF methods, and the feature importance of all input parameters is greater in the PLSR method except for $C1_{img}$ and $C1_{rel}$, which are both less important. The abovementioned results indicate that the backscatter coefficient of SAR data and SAR polarimetric decomposition information ($C11$ and $C22$) have relatively larger influence on the LAI and CCC estimation results when using the classic ML modeling approach, while the influence of incidence and partial
SAR polarimetric decomposition information (C12img and C12rel) is relatively smaller. For the last growth stage, the feature importance of C12img and C12rel is still less in all three models. In both the XGBoost and PLSR methods, the feature importance is higher and closer, except for C12img and C12rel. However, in the RF method, only the C11 and $\sigma_{VV}$ features are of higher importance, while all other features are of lower importance. In contrast to the first three growth stages, the feature importance of the LIA increased significantly at the last growth stage of winter wheat. This may be because the wheat ears of winter wheat tend to mature during the milk maturity stage when the radar incidence information has a greater influence on the radar echo signal, which makes the feature importance of the radar incidence information greater.

D. Results of Regional Estimations of Biophysical Parameters

Given that the UMRCGM-S7 model can better simulate LAI and CCC during the four growth stages of winter wheat, we simulated the spatial distribution maps of LAI and CCC for the entire Guanzhong Plain based on this model. Figs. 8 and 9 showed the simulated LAI and CCC images at four growth stages of winter wheat in the study area. The white pixels in the original Sentinel-3 image are not the winter wheat growing areas. Due to cloudy weather, the Sentinel-3 retrieved LAI and CCC images have more nonvalued pixels at the milk maturity stage and fewer nonvalued pixels at the other three growth stages. SAR images of the eastern region of the Guanzhong Plain collected from Alaska Satellite Facility are partially missing on May 7, 2020. Therefore, the spatial distribution of LAI and CCC in winter wheat at the milk maturity stage, for the estimation, is partly missing. In terms of spatial distribution, the higher estimated LAI and CCC are mainly in the western and central areas of the Guanzhong Plain, which is close to the actual spatial distribution of LAI and CCC (Sentinel-3 retrieved). In addition, the values of estimated LAI and CCC simulated are smaller at the the green-up and milk maturity stages and larger at the jointing and heading-filling stages, which are also consistent with the actual winter wheat phenological stages in the region. It can be seen that the differences between the simulated LAI and the Sentinel-3 retrieved LAI for all four growth stages obey a normal distribution (see Figs. 8 and 9). Compared to LAI, the regional estimations of CCC are closer to those of Sentinel-3 retrievals of CCC for the four growth stages of winter wheat. For LAI, the estimated LAI are mostly lower than the Sentinel-3 retrieval at the jointing stage, and slightly lower than the Sentinel-3 retrievals at the green-up stage and heading-filling stage, while higher than the Sentinel-3 retrievals at the milk maturity stage. For CCC, in the latter two growth stages of winter wheat, the estimated CCC are lower than that of the Sentinel-3 retrievals. Overall, the proposed UMRCGM model for regional biophysical parameter estimation in this article has good spatial applicability.

IV. DISCUSSION

This article explores the possibilities and accuracy performance of using SAR data to simulate two BPs (LAI and CCC) at different growth stages of winter wheat. Few previous studies have explored the estimation of CCC from SAR data, and this article provides a preliminary attempt to address this issue.
effectively simulate the spatial distribution of LAI and CCC at the regional scale, this article is also the first attempt to simulate these two BPs based on a deep learning framework and combining two remote sensing data sets with different spatial resolutions, Sentinel-1 and Sentinel-3 data. Most of the previous related studies have focused on the estimation of optical vegetation indices, for example, Chen et al. [40] used optical remote sensing image parameters as inputs, considering optical images are susceptible to cloudy weather, they utilized the cropland change detection GAN and CNN-based models for time series enhanced vegetation index (EVI) estimation, for cropland, the $R^2$ of result is 0.692. EVI has a high sensitivity to dense vegetation. For winter wheat, the density of the vegetation canopy varies at different growth stages. Zhang et al. [41] concluded that the LAI of remotely sensed observations augmented with a data augmentation technique (GAN) showed different accuracy performances at different growth stages of winter wheat. Therefore, large errors may arise when the data-augmented time series LAIs are used as a state variable in the crop growth model for growth or yield simulation. Previous studies have also shown that different types of SAR image parameters respond differently to crop growth parameters and, in particular, the response curves for different parameters differ at different stages of crop growth [7], [42]. In contrast to the idea of data augmentation, in this article, we used SAR data as input and the LAI of the original remote sensing observation is used as a label. Although the estimations of the two BPs (LAI and CCC) were not explored in time series, we tested the difference in accuracy between different classes of SAR input information or their combinations when they are used to simulate the LAI and CCC for winter wheat during the four growth stages through a control variable approach, and the results indicated that the accuracies of LAI and CCC estimations at the first three growth stages were satisfactory. This showed that SAR data has practical use and generates accurate results in simulating crop growth parameters. The selection of the size of the SAR feature matrix is key to the quantitative monitoring of land surface parameters by using SAR images. Han et al. [43] compared the difference in the accuracy of SAR images for estimating wheat biomass in the North China Plain (small fragmented plots) and Inner Mongolia farms (large uniform plots) by artificial setting an appropriate region of interest window size for extracting SAR image matrix. In our proposed BPs estimation framework, we collect SAR image matrices autonomously by a moving window module, which makes our method more stable and effective compared to the abovementioned study. Theoretically, deep learning methods have better modelling accuracy when the vegetation cover is more uniform and the plots are more neatly distributed. This is because the data obtained in this case is more evenly distributed, the sample set is more balanced, and, therefore, the model is trained with better accuracy [44]. For example, in the Southern California region of the USA, Hosseini et al. [20] used the backscatter information ($VV$ and $VH$) from time-series Sentinel-1 images as input features for a 1-dimensional CNN model and then combined it with a long short-term memory model for simulating the time-series Sentinel-2 retrieved NDVI, with an accuracy of $R^2 = 0.941$ and RMSE = 0.043 for winter wheat crops. In this article, the selected study area, the Guanzhong Plain, has a fragmented distribution of farmland and mostly small plots, and the UMRCGM model built using two-dimensional (2-D) convolutional kernels is proposed to extract features from the input SAR information for Sentinel-3 LAI and CCC simulation. The main reason why
our study was able to achieve relatively satisfactory accuracy in estimating the winter wheat BPs compared to Zhao’s study is that the 2-D convolutional kernel can effectively extract spatial distribution features of ground targets, and the actual ground targets follow certain spatial distribution patterns, this allows the 2-D UMRCGM model to accurately capture such information and, thus, obtain more accurate estimation results.

Based on traditional time series regression method, Gaussian Process (MOGP) regression for estimating LAI, the results showed that the R^2 of LAI estimation accuracy for wheat crops under synergistic LAI-RVI conditions was between 0.4 and 0.6 by using SAR data and optical data [14]. In this article, the LAI of winter wheat was simulated based on UMRCGM model, and the R^2 of LAI estimation results in the first three growth stages of winter wheat were all greater than 0.6. This indicated that the deep learning method may have an advantage over traditional statistical method in the synergistic use of SAR and optical images to estimate winter wheat growth parameters. For crop growth monitoring, the time series analysis method can obtain a more outstanding performance compared to the mono-temporal analysis method in both the traditional statistical and deep learning methods [45]. Since the remote sensing data covering the study area were heavily influenced by clouds during most of the winter wheat main growth period [46], this article was not able to make full use of the time series remote sensing images to simulate the two BPs of winter wheat but used mono-temporal remote sensing images to simulate these two parameters in each of the four growth stages. In the future, we will acquire available time-series remote sensing images of winter wheat during the main growth period of multiple years, and introduce the gated recurrent units (GRU) model based on the UMRCGM model proposed in this article to further improve the accuracy of the estimation of BPs of winter wheat. GRU is chosen because it is a variant of the traditional recurrent neural network (RNN), which can effectively capture the association information between long sequences, mitigate gradient disappearance or explosion, while its structure and computation are simpler than traditional RNN [47]. Besides, the coherence performance of the SAR effectively monitors the changing conditions of the feature pattern between the two time phases. For winter wheat, the degree and speed of change in vegetation canopy structure between two adjacent SAR image time phases during the main growth period vary from one time period to another, so using coherence information as model input information can be an effective way to improve the accuracy of BPs estimation of winter wheat when data sources are not very adequate.

V. CONCLUSION

In this article, two different types of data sources, highly reliable Sentinel-1 SAR images and wide width, high temporal resolution Sentinel-3 optical images, were organically combined the first time to complement each other’s strengths for estimating the regional BPs under a deep learning framework. For the large difference in spatial resolution between Sentinel-1 and Sentinel-3 images, the UMRCGM model was proposed and it can effectively optimize the correspondence between the input SAR parameters and the output BPs. The UMRCGM model was used for estimating regional multi-temporal LAI and CCC during the main growth stages of winter wheat, and the accuracy of LAI and CCC estimates was validated and analyzed at different growth stages of winter wheat. The results showed that the SAR backscatter coefficients, local incidence, and polarimetric decomposition information of Sentinel-1 data as the model inputs, can effectively simulate the LAI and CCC of the four growth stages of winter wheat. The article compared the proposed approaches with three classical ML methods (PLSR, RF, and XGBoost regression model). It showed that the UMRCGM models have higher accuracy than those classic ML methods at all four growth stages of winter wheat on LAI and CCC estimation. The results showed that the LAI and CCC simulated by Sentinel-1 images had the highest accuracy at the green-up stage of winter wheat, followed by the jointing stage and heading-filling stage, the lowest accuracy was at the milk maturity stage. Compared with LAI, CCC from Sentinel-1 images estimation had higher accuracy at the first three growth stages of winter wheat, whereas the estimation accuracy of CCC was lower than that of LAI for the last growth stage of winter wheat. The estimation accuracy of CCC was slightly higher than that of LAI for the first three growth stages of winter wheat but lower than that of LAI for the last growth stage of winter wheat. This article is the first to combine Sentinel-1 SAR and Sentinel-3 optical data to simulate two BPs during the main growth period of winter wheat, and is also the first attempt to use SAR data to simulate CCC, which provides a new approach for accurate growth monitoring of winter wheat during the growing season.

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