

## RECONSTRUCTING WINTER WHEAT NDVI TIME SERIES USING SENTINEL-1 RADAR DATA

**KOSHKIN D.L.** – PhD, Associate Professor

*orcid.org/0000-0002-6927-8487*

Mykolaiv National Agrarian University

**PANFILOVA A.V.** – Doctor of Sciences, Professor

*orcid.org/0000-0003-0006-4090*

Mykolaiv National Agrarian University

**Problem Statement.** Satellite crop monitoring enables the assessment of vegetation condition and the tracking of seasonal changes. One of the most widely used indicators is the normalized difference vegetation index (NDVI), calculated from red and near-infrared reflectance. NDVI time series are widely used to characterize crop development and identify deviations from expected vegetation dynamics [1]. Sentinel-2 multispectral data provide the spatial and spectral information required for such analyses [2].

However, cloud cover and atmospheric effects frequently limit the availability of optical observations, while the removal of low-quality observations can disrupt the continuity of NDVI time series [2]. For winter wheat, maintaining information on the sequence of autumn development, winter dormancy, spring regrowth, and ripening is particularly important. Therefore, gap filling should not only replace missing observations at individual dates but also preserve the phenological structure of the seasonal NDVI trajectory.

Sentinel-1 SAR observations provide complementary information that is largely unaffected by cloud cover and solar illumination [3]. However, SAR predictors are not direct equivalents of NDVI, as their dynamics depend on canopy structure, soil conditions, and crop phenological stage [4-6]. Consequently, the integration of radar and optical observations requires a temporal alignment that accounts for differences in the timing of phenological development between growing seasons.

This study addresses this problem using observations from three experimental winter wheat plots at Mykolaiv National Agrarian University in the Southern Steppe of Ukraine. The working hypothesis is that phenologically normalized time provides a common temporal framework for comparing growing seasons, while SAR predictors can improve the reconstruction of the seasonal NDVI trajectory. The ability of the proposed approach to reconstruct NDVI under different gap configurations, including a continuous block gap, and its robustness across growing seasons require quantitative evaluation.

**Review of Recent Research.** Vidican et al. [1] reviewed the use of vegetation indices for crop identification and monitoring. The authors emphasise the importance of temporal analysis and validation against ground-based observations when interpreting satellite-derived vegetation

indices. Hird and McDermid [9] compared approaches for reducing noise in NDVI time series and showed that smoothing performance depends on noise characteristics and the objectives of phenological analysis. Nevertheless, noise reduction in an optical time series and the reconstruction of long gaps using information from another sensor represent distinct tasks.

Veloso et al. [4] investigated the joint use of optical and radar observations by comparing seasonal backscatter and NDVI dynamics across different crops. Nasrallah et al. [5] demonstrated the applicability of Sentinel-1 observations for identifying winter wheat phenological stages. Mercier et al. [6] demonstrated the benefits of combining Sentinel-1 and Sentinel-2 observations for identifying phenological stages of wheat and rapeseed. These studies support the use of phenological information in multi-sensor crop monitoring, but they do not directly address the accuracy of NDVI reconstruction across missing observation periods.

Pipia et al. [10] specifically investigated multi-sensor data fusion for gap filling. The authors combined a Sentinel-1 radar vegetation index with a Sentinel-2 leaf area index in a multioutput Gaussian process model. These results demonstrate the potential of SAR as an auxiliary information source for reconstructing vegetation-related time series, particularly across long gaps. However, the approach was developed for LAI rather than NDVI, and its performance cannot therefore be assumed to transfer directly to NDVI reconstruction.

Thus, for the MNAU experimental plots, the accuracy of NDVI reconstruction using phenologically normalized time and SAR predictors, as well as the robustness of the approach across growing seasons, requires evaluation.

**Aim.** The aim of this study is to assess the accuracy of winter wheat NDVI time series reconstruction using phenologically normalized time and Sentinel-1 SAR predictors under incomplete Sentinel-2 optical coverage, and to evaluate the robustness of the proposed approach across growing seasons within the MNAU experimental plots.

**Materials and methods.** The study was conducted on three experimental winter wheat plots at the Educational, Scientific and Practical Center of Mykolaiv National Agrarian University in the Southern Steppe of Ukraine during four growing seasons (2021–2025). The dataset combined



Sentinel-2 optical observations with Sentinel-1 SAR observations acquired from both ascending and descending orbits. Before spatial aggregation, each satellite acquisition was treated as a separate observation. Therefore, the initial counts represented the number of available satellite scenes across the three experimental plots. The observations were then spatially averaged, and the resulting mean values were treated as unique acquisition dates separately for Sentinel-2 and Sentinel-1. The sequential stages of data aggregation and multisensor dataset construction are summarized in Table 1, while the phenological matching procedure is described below.

The optical dataset consisted of the NDVI values derived from Sentinel-2 data after cloud masking. The radar dataset comprised Sentinel-1 backscatter coefficients in VV and VH polarizations, the polarization ratio Q, and the Radar Vegetation Index (RVI). Sentinel-1 data were processed in Google Earth Engine. The backscatter coefficients in VV and VH polarizations, originally expressed in decibels (dB), were converted to a linear units, according to

$$\sigma_{VV}^0 = 10^{VV_{dB}/10}, \quad \sigma_{VH}^0 = 10^{VH_{dB}/10}, \quad (1)$$

where  $\sigma_{VV}^0$  and  $\sigma_{VH}^0$  are the Sentinel-1 backscatter coefficients in VV and VH polarizations, expressed on a linear scale;  $VV_{dB}$  and  $VH_{dB}$  are the corresponding backscatter coefficients in decibels.

The polarization ratio Q and RVI were calculated according to

$$Q = \frac{\sigma_{VH}^0}{\sigma_{VV}^0}, \quad RVI = \frac{4\sigma_{VH}^0}{\sigma_{VV}^0 + \sigma_{VH}^0}. \quad (2)$$

No additional normalization or clipping to the 0–1 range was applied. RVI was used as an indicator of crop condition because it is sensitive to changes in vegetation density

and canopy structure [7]. For each Sentinel-1 acquisition date, SAR predictor values from the three experimental plots were spatially averaged. The resulting mean values were subsequently used for time-series construction and phenological matching.

To compare growing seasons, phenologically normalized time ( $t_{norm}$ ) was used instead of the calendar day of year. The normalized  $t_{norm}$  scale ranged from 0 to 6, where integer values corresponded to the boundaries of the major phenological stages of winter wheat listed in Table 2.

This scale preserves the natural sequence of phenological development and enables data from seasons with different dates of phase onset to be analyzed within a common temporal framework. In general, normalization within the interval between two consecutive phenological phases was defined as

$$t_{norm} = k + \frac{t - t_k}{t_{k+1} - t_k}, \quad (3)$$

where  $t$  is the calendar date of observation;  $t_k$ ,  $t_{k+1}$  are the start dates of two consecutive phenological phases, and  $k$  is the integer value of the normalized phenological scale corresponding to the beginning of the respective phenological interval.

Phenological boundaries for each growing season (Table 2) were established from field observations conducted at the Educational, Scientific and Practical Center of Mykolaiv National Agrarian University and used as agronomic reference dates. A formal sensitivity analysis of shifts in phenological boundaries was not performed and remains a topic for future research.

After phenological normalization, the optical and radar time series were converted into matched observation pairs for subsequent modelling. Matching was performed

Table 1

#### Formation of a multisensory dataset by growing season

| Growing season | Number of observations before aggregation |            | Number of observations after aggregation |            | Number of matched SAR–NDVI pairs |
|----------------|-------------------------------------------|------------|------------------------------------------|------------|----------------------------------|
|                | Sentinel-1                                | Sentinel-2 | Sentinel-1                               | Sentinel-2 |                                  |
| 2021-2022      | 234                                       | 282        | 78                                       | 60         | 52                               |
| 2022-2023      | 183                                       | 219        | 61                                       | 49         | 40                               |
| 2023-2024      | 180                                       | 318        | 60                                       | 67         | 39                               |
| 2024-2025      | 255                                       | 399        | 85                                       | 71         | 52                               |
| Total          | 852                                       | 1218       | 284                                      | 247        | 183                              |

Table 2

#### Sowing date and major phenological stages of winter wheat used for time normalization

| Stage                                  | $t_{norm}$ | 2021-2022  | 2022-2023  | 2023-2024  | 2024-2025  |
|----------------------------------------|------------|------------|------------|------------|------------|
| Sowing                                 | 0          | 30.09.2021 | 30.09.2022 | 30.09.2023 | 30.09.2024 |
| Emergence (beginning of autumn growth) | 1          | 13.10.2021 | 12.10.2022 | 05.10.2023 | 11.10.2024 |
| End of autumn growth                   | 2          | 20.12.2021 | 21.12.2022 | 09.12.2023 | 29.11.2024 |
| Spring regrowth                        | 3          | 24.03.2022 | 04.03.2023 | 08.02.2024 | 03.03.2025 |
| Heading                                | 4          | 17.05.2022 | 13.05.2023 | 16.05.2024 | 07.05.2025 |
| Beginning of grain ripening            | 5          | 28.06.2022 | 25.06.2023 | 14.06.2024 | 18.06.2025 |
| Physiological maturity                 | 6          | 14.07.2022 | 03.07.2023 | 02.07.2024 | 09.07.2025 |

in normalized phenological time rather than by calendar acquisition dates. For each Sentinel-1 observation, the nearest Sentinel-2 NDVI observation was identified based on the phenological distance

$$\Delta t_i = |t_{norm,i}^{SAR} - t_{norm,j}^{NDVI}|. \quad (4)$$

where  $t_{norm,i}^{SAR}$  is the normalized phenological time of the  $i$ -th Sentinel-1 observation,  $t_{norm,j}^{NDVI}$  is the normalized phenological time of the  $j$ -th Sentinel-2 observation, and  $\Delta t_i$  is the phenological distance between them.

Observation pairs were generated using the nearest-neighbor approach and retained only when  $\Delta t_i \leq 0.20$ . Sentinel-1 observations served as the reference, while the nearest Sentinel-2 observations provided the target NDVI values. When multiple Sentinel-1 observations matched the same Sentinel-2 observation, all corresponding pairs were retained, resulting in a many-to-one matching scheme. In cases where two optical observations had the same phenological distance, the first nearest neighbor was selected. No additional constraints on calendar acquisition dates were applied.

Before matching, Sentinel-1 and Sentinel-2 observations were spatially averaged across the three experimental plots. Consequently, Table 1 reports the numbers of observations before spatial averaging (at the acquisition date–plot level) and after averaging, when each acquisition date was represented by a single mean value.

This procedure produced 183 matched SAR–NDVI pairs, with 39 to 52 pairs obtained in each growing season (Table 1). The predictors originated from 183 unique Sentinel-1 observations, whereas the target values were derived from 112 unique Sentinel-2 observations. Consequently, each Sentinel-2 observation was matched to an average of 1.63 Sentinel-1 observations, with a maximum of six Sentinel-1 observations associated with a single Sentinel-2 observation. All retained pairs satisfied the matching criterion, with a phenological distance not exceeding 0.20 units of  $t_{norm}$ .

To model the seasonal dynamics of NDVI, a Generalized Additive Model (GAM) was fitted using the *mgcv* package in R [8]. The model describes the nonlinear seasonal trajectory of NDVI as a function of phenologically normalized time and its interaction with the SAR predictors RVI and Q, defined in Eq. (2). Smoothing parameters were estimated automatically using the Restricted Maximum Likelihood (REML) criterion, providing an appropriate balance between model flexibility and overfitting.

The final model was defined as

$$NDVI = \beta_0 + s(t_{norm}) + te(t_{norm}, RVI) + te(t_{norm}, Q) + \varepsilon_i, \quad (5)$$

where  $s(t_{norm})$  is the smooth function of phenologically normalized time,  $te(\cdot)$  denotes tensor-product smooths describing the interaction of phenologically normalized time and the SAR predictors, and  $\varepsilon_i$  is the residual error. Because RVI and Q are correlated SAR predictors, the model was intended primarily for NDVI prediction and reconstruction rather than for interpreting the individual effects of these variables. Model performance was evaluated under two validation scenarios using the coefficient of determination

(R<sup>2</sup>), root mean square error (RMSE), and mean absolute error (MAE).

The first validation scenario used a random split of the data into training (75%) and test (25%) sets. The dataset contained 183 matched SAR–NDVI observation pairs (Table 1), of which 137 were used for model training and 46 were reserved for testing. This scenario evaluates the model's ability to reconstruct NDVI for held-out observations that were not used during model fitting.

The second validation scenario simulated a continuous block gap in the optical time series. All SAR–NDVI pairs within the spring regrowth interval ( $3.0 \leq t_{norm} \leq 4.0$ ) were removed from the training data. The test set contained 48 observations, while the remaining 135 observations were used for model training. This scenario evaluates the model's ability to reconstruct NDVI when an entire period of optical observations is unavailable, for example because of persistent cloud cover.

The same model specification was used in both validation scenarios. For each validation run, the test set was excluded before model fitting, and the model was refitted using only the corresponding training set. The fitted model was then used to predict NDVI for the held-out observations. Consequently, no information from the test set was used during model fitting or smoothing parameter estimation.

**Results.** The overall correlations between NDVI and the individual SAR predictors were weak to moderate. Their phase-dependent variation throughout the winter wheat growing season is presented in Fig. 1. The VV backscatter coefficient showed the weakest relationship with NDVI ( $r = -0.04$ ), whereas both the polarization ratio Q and RVI exhibited the highest overall positive correlations ( $r = 0.35$ ). These results indicate that Q and RVI better capture seasonal changes in crop condition than the VV backscatter coefficient alone.

Phase-specific analysis of Pearson correlation coefficients (Fig. 1) revealed that the relationship between NDVI and the SAR predictors varied substantially during the growing season. The strongest associations were observed during the spring regrowth period ( $3.0 \leq t_{norm} \leq 4.0$ ), when the correlation reached 0.567 for RVI and 0.537 for Q. During winter dormancy, correlations were considerably weaker. At the beginning of the growing season, only 15 matched observations were available; therefore, the correlation obtained for the VV backscatter coefficient ( $r = -0.439$ ) should be interpreted with caution.

The results of NDVI reconstruction under the two validation scenarios are presented in Fig. 2. Panel (a) shows reconstruction from randomly withheld observations distributed throughout the growing season. Panel (b) shows reconstruction after withholding the gray-shaded interval corresponding to the spring regrowth period, simulating an extended gap in optical observations caused, for example, by persistent cloud cover.

In both validation scenarios, the model successfully reproduced the overall seasonal trajectory of NDVI (Fig. 2). The solid black curve represents the characteristic development pattern of winter wheat, including the autumn increase in NDVI, its decline during winter dormancy, and the rapid increase during spring regrowth, reaching a maximum near the heading stage.

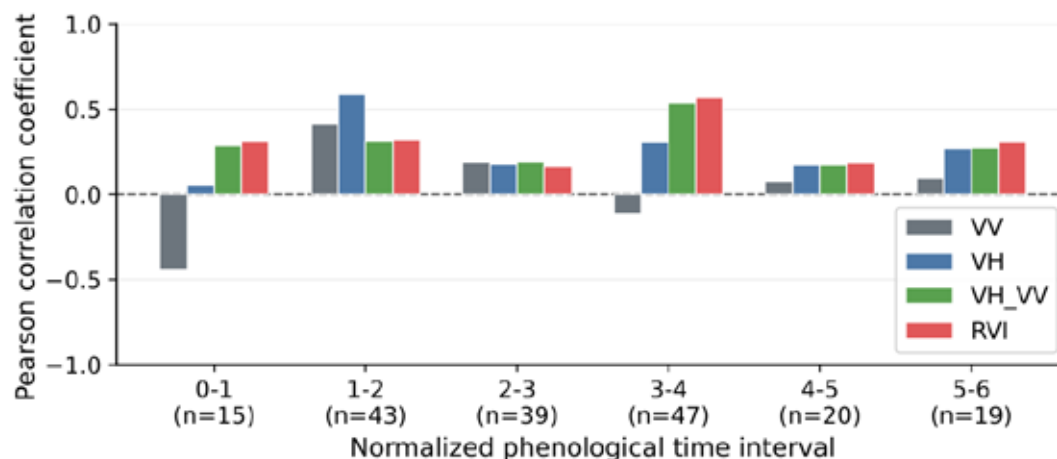


**Fig. 1. Phase-dependent Pearson correlation coefficients between NDVI and Sentinel-1 SAR predictors. Numbers in parentheses denote the number of matched observation pairs within each  $t_{norm}$  interval**

This demonstrates that phenologically normalized time ( $t_{norm}$ ) provides an appropriate temporal framework for describing crop development across the growing season. The largest discrepancies between reconstructed and observed NDVI values occurred only for a few individual observations that deviated markedly from the overall seasonal pattern. Overall, the model accurately reconstructed the seasonal trajectory of NDVI, although short-term local fluctuations were reproduced less precise.

In the random withholding scenario, the model reconstructed NDVI with high accuracy (Fig. 2a). This performance is expected because the withheld observations originated from the same growing seasons and phenological stages represented in the training set. Consequently, the model reconstructed isolated missing observations within the range of conditions represented during model fitting.

The block-gap scenario was substantially more challenging because the model had to reconstruct NDVI across an entire missing interval of optical observations. Nevertheless, the model preserved the overall seasonal trajectory of NDVI and reproduced crop development throughout the missing interval (Fig. 2b), although with larger reconstruction errors than in the random withholding scenario.

The results highlight the importance of phenological normalization and the phase-dependent informativeness of SAR predictors. Replacing calendar time (day of year, DOY) with phenologically normalized time ( $t_{norm}$ ) aligned growing seasons with different dates of phenological stage transitions, allowing the common seasonal trajectory of NDVI to be separated from local variations explained by the SAR predictors.

At the same time, the overall relationships between NDVI and the SAR predictors remained weak because radar backscatter is influenced by different physical mechanisms throughout the growing season. During winter dormancy, the radar signal is largely controlled by soil moisture, surface roughness, and freezing conditions, whereas during spring regrowth the depolarization-related predictors Q and RVI better reflect changes in canopy structure. Consequently,

these predictors provided the greatest predictive value during the spring regrowth period, whereas their performance was lower during the remaining phenological stages. The observed relationships are consistent with previous studies reporting the complementary use of Sentinel-1 and Sentinel-2 observations for crop monitoring [4–6].

The practical value of the proposed approach lies in reconstructing continuous NDVI time series during periods when Sentinel-2 optical observations are unavailable because of cloud cover or other acquisition constraints. Unlike approaches based solely on temporal interpolation or smoothing of NDVI time series [9], the proposed model incorporates complementary information from Sentinel-1 SAR observations. This is consistent with recent studies demonstrating the benefits of combining SAR and optical data for gap filling in vegetation and biophysical time series [10].

Although the proposed approach showed promising results, further validation using larger datasets is needed. Future studies should include additional growing seasons and agroclimatic regions, as well as evaluate hierarchical GAMM formulations with season-specific smooth components [11]. Further improvements may also be achieved by incorporating meteorological predictors, applying grouped validation based on unique Sentinel-2 acquisition dates, and performing spatially independent validation.

**Conclusions.** This study proposed a phenology-based approach for reconstructing winter wheat NDVI by combining phenologically normalized time ( $t_{norm}$ ) with Sentinel-1 SAR predictors. The normalized phenological scale aligned data from different growing seasons and provided a consistent representation of seasonal crop dynamics.

The predictive value of the SAR predictors was strongly phase dependent. The highest correlations between NDVI and the polarization-based predictors RVI and Q were observed during the spring regrowth period, whereas the VV backscatter coefficient showed the weakest relationship with NDVI. These results support the use of polarization-based SAR predictors for NDVI reconstruction.

The generalized additive model (GAM) successfully reconstructed seasonal NDVI dynamics under both validation

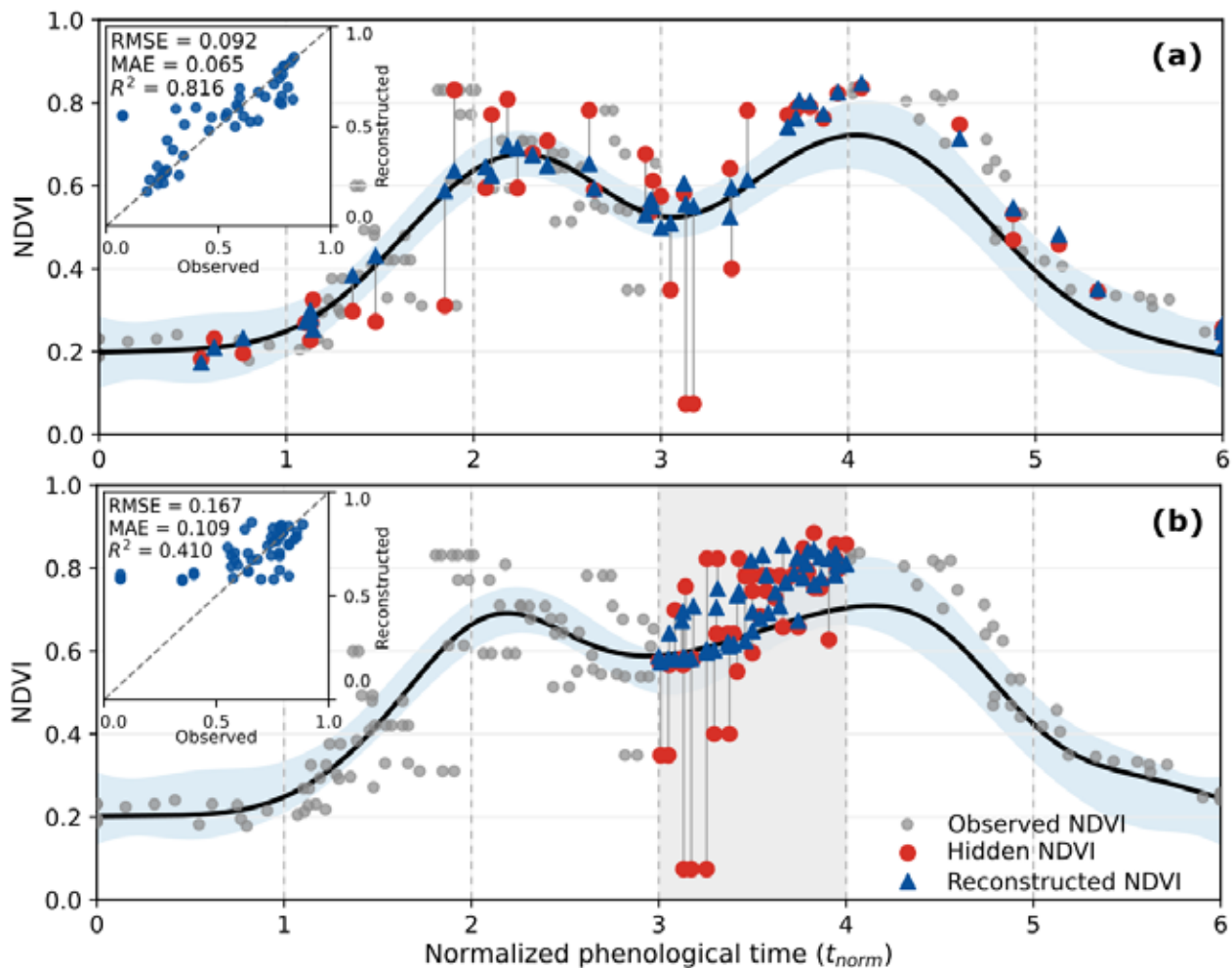


**Fig. 2. Reconstruction of seasonal NDVI dynamics under two validation scenarios:**  
**(a) random withholding of individual observations throughout the growing season;**  
**(b) withholding of the gray-shaded spring regrowth interval**

scenarios. The highest accuracy was achieved for randomly withheld observations, while the block-gap experiment demonstrated that the model preserved the overall seasonal trajectory and satisfactorily reconstructed NDVI across an extended interval without optical observations.

The proposed approach demonstrates the potential of combining Sentinel-1 and Sentinel-2 observations to reduce gaps in optical NDVI time series caused by persistent cloud cover. Future work should evaluate the method using additional growing seasons and agroclimatic regions, incorporate meteorological predictors, and assess its performance using grouped and spatially independent validation.

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#### Кошкін Д.Л., Панфілова А.В. Використання радарних даних Sentinel-1 для реконструкції часового ряду NDVI пшениці озимої

**Мета.** Метою дослідження було оцінити точність реконструкції часових рядів нормалізованого різницевого вегетаційного індексу (NDVI) пшениці озимої за використанням радіолокаційних даних Sentinel-1 та фенологічно нормалізованого часу в умовах неповного оптичного покриття Sentinel-2, а також оцінити стійкість підходу в різні вегетаційні періоди. **Методи.** Дослідження проведено за даними трьох дослідних ділянок Навчально-науково-практичного центру Миколаївського національного аграрного університету протягом чотирьох вегетаційних сезонів (2021–2025). Для формування єдиного часового масштабу між вегетаційними періодами використано фенологічно нормалізований час. Як предиктори використано коефіцієнти зворотного розсіювання Sentinel-1 VV і VH, коефіцієнт поляризації Q та індекс радіолокаційної рослинності RVI. Спостереження Sentinel-1 і Sentinel-2 узгоджували за найближчим фенологічним часом. Реконструкцію сезонної динаміки NDVI виконано за допомогою узагальненої адитивної моделі (GAM) та оцінено за двома сценаріями: випадковим утриманням окремих спостережень і блоковою валідацією, що моделювала тривалу відсутність оптичних спостережень через хмарність. **Результати.** Взаємозв'язок NDVI із SAR-предикторами мав виражений фазозалежний характер. Найвищі кореляції з NDVI спостерігалися для RVI та Q у період весняного відновлення вегетації, тоді як VV характеризувався найслабшим зв'язком. В обох сценаріях модель відтворила основну сезонну траєкторію NDVI, включаючи осінній розвиток вегетаційного покриву, зимове зниження, весняне відновлення та максимальні значення індексів поблизу фази колосіння. Точність реконструкції була вищою при випадковому утриманні спостережень, тоді як блокова валідація була складнішою, але також забезпечила відтворення сезонної динаміки в межах безперервного оптичного пропуску. **Висновки.** Поєднання фенологічно нормалізованого часу та SAR-предикторів Sentinel-1 у складі GAM є придатним підходом для реконструкції NDVI пшениці озимої за неповного покриття Sentinel-2. Інтеграція даних Sentinel-1 і Sentinel-2 має потенціал для підвищення часової безперервності NDVI-спостережень

під час моніторингу посівів пшениці озимої. Подальші дослідження доцільно проводити із залученням додаткових вегетаційних періодів та агрокліматичних регіонів і застосуванням просторово незалежної валідації.

**Ключові слова:** пшениця озима, Sentinel-1, Sentinel-2, NDVI, SAR, фенологічно нормалізований час, GAM, реконструкція часових рядів.

**Koshkin D.L., Panfilova A.V. Reconstructing winter wheat NDVI time series using Sentinel-1 radar data**

**Purpose.** This study aimed to assess the accuracy of reconstructing winter wheat normalized difference vegetation index (NDVI) time series using Sentinel-1 radar data and phenologically normalized time under incomplete Sentinel-2 optical coverage, and to evaluate the robustness of the approach across growing seasons. **Methods.** The study used data from three experimental plots at the Educational, Scientific and Practical Center of Mykolaiv National Agrarian University over four growing seasons (2021–2025). Phenologically normalized time was used to establish a common temporal scale across seasons. Sentinel-1 VV and VH backscatter coefficients, the polarization ratio Q, and the Radar Vegetation Index (RVI) were used as predictors. Sentinel-1 and Sentinel-2 observations were matched according to their closest phenological timing. Seasonal NDVI dynamics were reconstructed using a Generalized Additive Model (GAM)

and evaluated under two scenarios: random withholding of individual observations and block-gap validation simulating a prolonged absence of optical observations caused by persistent cloud cover. **Results.** The relationship between NDVI and SAR predictors was strongly phase dependent. RVI and Q showed the highest correlations with NDVI during spring regrowth, whereas VV showed the weakest relationship. In both validation scenarios, the model reproduced the main seasonal NDVI trajectory, including autumn canopy development, winter decline, spring regrowth, and maximum values around heading. Reconstruction was more accurate under random withholding, while block-gap validation remained more challenging but preserved the seasonal NDVI dynamics across the continuous optical gap. **Findings.** Combining phenologically normalized time with Sentinel-1 SAR predictors within a GAM provides a suitable basis for reconstructing winter wheat NDVI under incomplete Sentinel-2 coverage. The results demonstrate the potential of Sentinel-1 and Sentinel-2 integration to improve the temporal continuity of NDVI time series for winter wheat monitoring. Further research should include additional growing seasons and agroclimatic regions and apply spatially independent validation.

**Key words:** winter wheat, Sentinel-1, Sentinel-2, NDVI, SAR, phenologically normalized time, GAM, time series reconstruction

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