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Monitoring the Onset of Phenological Phases "Stem Elongation" and "Heading" of Winter Wheat in the Republic of Armenia Using Remote Sensing Methods

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ABSTRACT

Winter wheat constitutes a significant share of Armenia's grain production, but can be severely affected by the spread of fungal diseases. According to recent scientific studies, methods based on the dynamics of spectral signatures of crops allow for the timely detection of early signs of crop diseases, prevention of epidemiological threats, and minimization of economic losses. The paper addresses the problem of determining optimal monitoring periods for phytopathogens across the republic of Armenia using these methods. The study covers various regions of Armenia, taking into account their climatic and agronomic characteristics, as the Normalized Difference Vegetation Index (NDVI), weather conditions and digital elevation model. The data show potential for determining the timing of key phenological stages in winter wheat development, which is essential for this type of monitoring. Cartographic materials have been created to indicate recommended start dates for monitoring, based on average data from 2018-2024. The paper also outlines necessary steps to improve the outcomes of the proposed methodology, as well as key actions for implementing this approach in practice.

Introduction

Despite the high significance of orchards, vineyards, and forage crops (approximately 18 % and 24 % of agricultural land, respectively), winter wheat remains one of the leading agricultural crops in Armenia, representing a significant part of grain production. In 2022, statistical data show that grain crops covered more than 44 % of Armenia's sown areas, with over half dedicated to winter wheat (Statistical Committee of the Republic of Armenia).

This study aims to determine the phenological stages of crop development using remote sensing methods and to map these timings for the territory of Armenia. The core idea is that the phenological stages of crop development can be determined based on the seasonal trends in NDVI, temperature, and precipitation (Longchamps & Philpot, 2023; Li, et al., 2023; Bhatti, et al., 2024).

One of the most striking examples may be the early diagnosis of cereal crop diseases. Armenia's climate promotes the development of certain phytopathogens affecting grain crops, such as yellow and brown rusts, powdery mildew, smut diseases, and root rot. Each of these diseases has its own set of risk factors and requires integrated plant protection approaches, including the use of resistant crop varieties and fungicide treatments.

Recent scientific studies have consistently shown a stable correlation between pathogen infections in cultivated plants and changes in their spectral signature dynamics, confirmed through extensive field and laboratory research (Lin-Sheng, et al., 2015; Wang, et al., 2015; Wang, et al., 2016; Jung, et al., 2021). These approaches describe that the most significant period for the early detection of winter wheat diseases is the stage between stem elongation and heading, when fungal plant diseases actively develop (Kremneva, et al., 2022; Sereda, et al., 2023; Danilov, et al., 2024). Therefore, this study focuses on determining the timing of these phenological development stages.

To implement this technology effectively, sensing of agricultural fields is necessary during the significant phenological stages of pathogen development on regular, ideally daily basis (Zhang, et al., 2012; Mahlein, et al., 2019; Bohnenkamp, et al., 2019; Rieker, et al., 2023), especially when plant diseases are in the incubation phase. During this period, visual symptoms are not yet visible to the naked eye but can already be detected through spectral analysis. For wheat, this corresponds to the stem elongation to heading stages. Relying solely on satellite data for this imaging frequency is challenging, mainly due to potential cloud cover. Unmanned aerial vehicles (UAVs) equipped with multi- and hyperspectral cameras offer a viable solution to this limitation.

The hypothesis of this study is that this approach will facilitate the scheduling and organization of phytopathological monitoring using multi-temporal spectral measurements of crops.

Through disease monitoring of crops using remote sensing data, it is possible to localize pathogen hotspots at both the regional (field group) and local (individual plot) levels. This technology shows promise in precision agriculture, as timely disease management can reduce economic losses, enhance product quality, lower the risk of large-scale epidemics, and contribute to efficient resource use and ecosystem sustainability.

The complexity of this work for the territory of Armenia is associated with additional challenges, as the country has diverse climatic zones and significant altitude variation. Different regions have varying soil types and microclimatic characteristics. Further complexity is added by the heterogeneity of agrotechnical practices and the limited availability of data.

Materials and methods

As the initiation of phytopathological monitoring for winter wheat using the dynamics of crop spectral imagery dynamics aligns with the onset of the BBCH-40 phenological stage (Stem Elongation), it was essential to determine the multi-year average date for this stage across regions of Armenia.

According to the methodology presented in the reference literature "Agroclimatic Resources of the Armenian SSR" (Kalantarova, et al., 1976), in order to determine the phenological stages of winter wheat while adhering to the sowing recommendations for the crop, information on the growing elevations, as well as the temperature and precipitation during the season, is required. The methodology includes a series of reference tables that outline the following necessary steps:

1. Determine the elevation at which the crop is grown separately for the Northeastern regions (Lori, Tavush) and the internal regions. For each elevation, the multi-year average date of the onset of each phenophase is provided in the case of 100% provision of heat and moisture for the crops.
2. Determine the percentage of moisture provision for the crops. If the moisture provision was below the required level, adjust the dates of phenophase onset for this period according to the tables.
3. Determine the percentage of active temperature provision for the crops. If the heat provision was below the required level, adjust the dates of phenophase onset for this period according to the tables.

Since the sowing and resumption of vegetation dates for all winter wheat crops across Armenia are unknown, applying this methodology sequentially to each phenophase is not feasible for this study. However, we hypothesize that the heading stage corresponds to the peak NDVI value, as confirmed by numerous studies (Dížková, et al., 2022; Zhao, et al., 2021; Zhao, et al., 2022). In the current study, we further validate this hypothesis.

Furthermore, since "stem elongation" and "heading" are consecutive phenophases, validating the methodology requires only one reverse calculation: determining the duration of the "stem elongation" phase by counting backward from the heading stage. This will provide the recommended start date for monitoring to assess the pathogenic background of the crops.

Study Area

The current administrative division of Armenia into 10 marzes was considered too broad for this study's purposes. Therefore, Armenia was divided into 39 parts corresponding to the 39 districts (hamaynks) that existed in Armenia prior to the 1995 administrative reform. This division was chosen for several reasons: the datasets used in the research offer sufficient detail for this level of subdivision, and it aligns conveniently with historical maps and reference data from 40–50 years ago.

Figure 3 illustrates the contribution of administrative districts to grain production, based on the "Atlas of Agriculture of the Armenian SSR" (Bogatova, 1984) and on modern statistical data (Statistical Committee of the Republic of Armenia). Modern statistics are collected at the marz level (10 regions), so a full comparison of this indicator is difficult.

In 2024, for the plots near the village of Nerkin Sasnashen (Talin municipality of the Aragatsotn region), the author conducted field studies on spring wheat from April 26 (BBCH 29, maximum tillering) to June 18 (BBCH 68, beginning of wax ripeness) (Fig. 1). These studies included multispectral and thermal imaging using UAVs and ground observations.

It was initially assumed that this site would allow for the testing of an early disease detection method based on remote sensing data. However, due to significant contamination of the crops by weeds, this was challenging. Nevertheless, actual field data were collected, data on the timing of key phenological stages of development according to the BBCH scale (Meier, 2001) for spectral pathogen monitoring (Table 1).

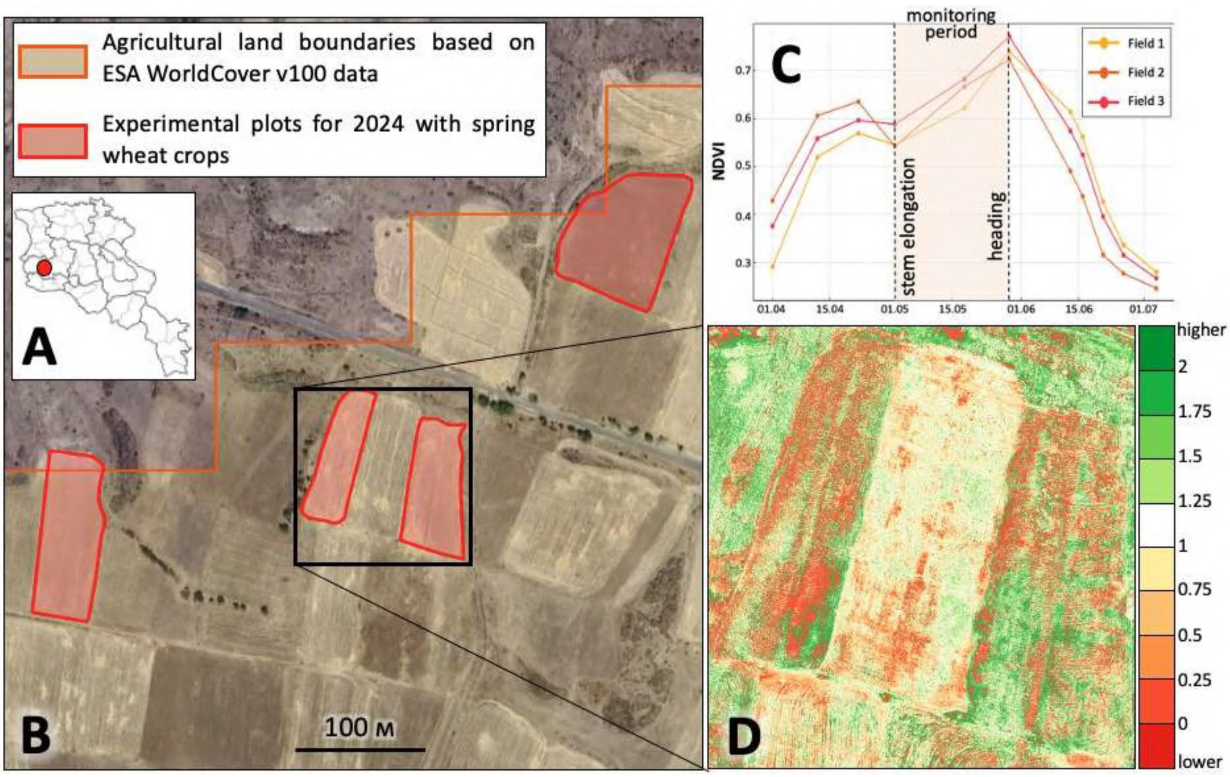

Figure 1. Research on spring wheat plots near Nerkin Sasnashen: A – Location of the plots within Armenia; B – Local positioning of the plots; C – Seasonal NDVI trend for 2024 based on Planet Scope data; D – NDVI ratio on 05.20 compared to 04.26.2024 derived from multispectral UAV imaging *(composed by the author).*

Table 1. Dates of phenological stages of spring wheat development for the fields near Nerkin Sasnashen in 2024*

Date	Phenophase	BBCH Code
04.26	Maximum tillering, stem elongation	29-31
05.16	Stem elongation, flag leaf	35-39
05.20	Heading, beginning of spike emergence from the sheath	41-44
05.23	Heading, full spike emergence	45-49
05.27	Flowering	51-59
06.03	Grain filling, beginning of milk ripeness	61-63
06.10	End of milk ripeness	64-68
06.18	Beginning of wax ripeness	69-73

*Composed by the author.

Data Sources

Various sources of information were used in this study. Some of the data were obtained using the Google Earth Engine (GEE) platform, a cloud-based tool for analyzing geospatial data with capabilities for accessing and processing remote sensing data and their products (Google Earth Engine, n.d.).

Agricultural lands of the Republic of Armenia: This represents a vector layer of areas where agricultural activities are conducted. It was obtained from the ESA WorldCover 10m v100 dataset, provided by the European Space Agency (ESA) (Zanaga, et al., 2021). The dataset classifies the Earth's surface into 11 categories at a 10-meter spatial resolution, including a "cropland" class. Using the GEE platform, the dataset was clipped to Armenia's borders, and the "cropland" class was extracted as a binary mask and then vectorized (Fig. 2).

Seasonal NDVI Dynamics: NDVI (Normalized Difference Vegetation Index) data (Rouse, et al., 1974) for plots near the village of Nerkin Sasnashen were derived from PlanetScope data (SuperDOVEs satellites, PSB.SD imaging system). Surface Reflectance level images were acquired for the plot areas on the following dates: 01.04.2024, 12.04.2024, 22.04.2024, 01.05.2024, 18.05.2024, 29.05.2024, 13.06.2024, 16.06.2024, 21.06.2024, 26.06.2024, and 04.07.2024. For the entire territory of Armenia, NDVI data were sourced from Sentinel-2 (MSI) satellites via the GEE platform, covering the period from 01.09.2017 to 31.12.2023. This period was selected due to the availability of images with the necessary sensing frequency.

Weather Data: This dataset includes historical daily average air temperatures and daily precipitation totals from 01.09.2017 to 31.12.2023 (consistent with the NDVI data). These data were obtained using the GEE platform based on the ERA-5 atmospheric and surface reanalysis developed by the European Centre for Medium-Range Weather Forecasts (ECMWF), combining meteorological observations, satellite data, and numerical modeling methods. The data were obtained separately for each district (Herbach, et al., 2020) (Figure 2).

Relief Data: This dataset includes absolute elevation values and slope angles, sourced from the GEE platform using ALOS World 3D (AW3D30) data, a global elevation dataset provided by the Japan Aerospace Exploration Agency (JAXA, 2019). For each district, statistical values of elevation and slope angles were calculated for agricultural land polygons.

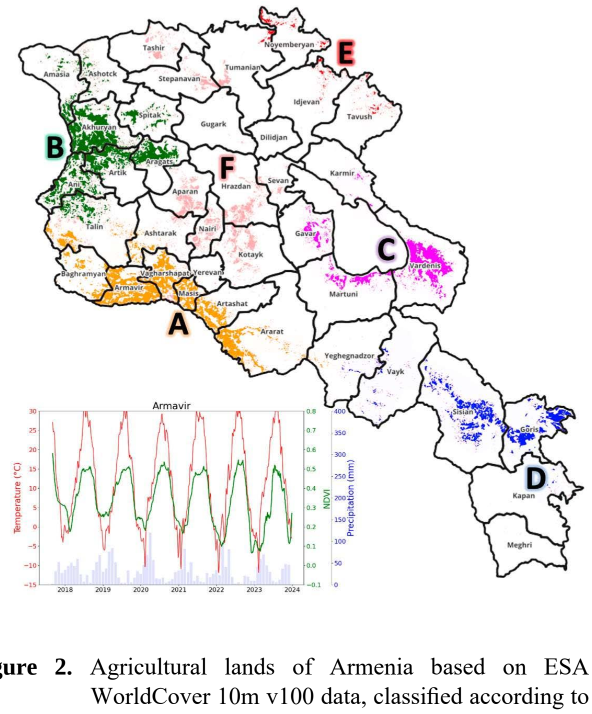

Figure 2. Agricultural lands of Armenia based on ESA WorldCover 10m v100 data, classified according to the seasonal dynamics of temperature, precipitation, and NDVI (classes A, B, C, D, E, F). Seasonal trends of these indicators from 2017 to 2023 are shown for several regions *(composed by the author)*.

Historical data: These data are represented by the following maps: "Average Dates of Termination and Resumption of Vegetation in Winter Wheat," "Average Data on Heading and Wax Ripeness of Winter Wheat," "Average Dates of Heading and Wax Ripeness of Spring Wheat" from the "Atlas of Agriculture of the Armenian SSR" (Bogatova, 1984). Additionally, reference information was drawn from the book "Agroclimatic Resources of the Armenian SSR" (Kalantarova, et al., 1976).

Data Processing

For the plots near the village of Nerkin Sasnashen, UAV imaging data were processed, although the results are used indirectly in this study. From these data NDVI and simple ratio images for different dates, were obtained (Fig. 1D), to evaluate the potential for early detection of pathogenic contamination using spectral data. Zonal statistics for these plots were calculated from PlanetScope data using a Python script and the GDAL library (Open Source Geospatial Foundation). Based on these data, a seasonal NDVI trend graph was created for each plot (Fig. 1C).

Data collection for the Republic of Armenia was conducted using the agricultural land layer derived from ESA WorldCover 10m v100 data. For each dataset, including terrain, meteorological data, and NDVI, information was collected within this vector layer for each of the 39 studied regions. This ensured that the necessary data were collected exclusively within agricultural areas. For instance, in mountainous regions, only data from valleys where agricultural land is located were included.

NDVI values were calculated from Sentinel-2 satellite images. To ensure a complete data series, the resulting values were processed using the Savitzky-Golay filter (Savitzky and Golay, 1964) and recalculated for each date within the specified time period, even on days without available images. Daily available meteorological data, required no additional recalculation. Elevation data are static, so statistical values were calculated for each region, with arithmetic mean values.

All collected data were aggregated within the studied regions. The timing of the heading phenophase for winter wheat was identified by the peak NDVI value, while the onset of the stem elongation phenophase was established using reference data, following the previously described methodology (Kalantarova, et al., 1976).

Results and discussions

In the current work on the spring wheat plots near Nerkin Sasnashen, an attempt was made to apply an early disease diagnosis method for winter wheat based on the dynamics of remote sensing spectral data. However, data processing revealed a high degree of field heterogeneity, largely due to extensive weed growth and soil variability. These factors had a significantly stronger impact on the spectral level of the crops, making it difficult to identify zones with increased pathogenic contamination (Fig. 1D).

Despite these challenges, phenological field observations (Table 1) and the seasonal NDVI trend (Fig. 1C) enabled the establishment of a correlation between these indicators. For spring wheat, maximum NDVI values were found to correspond to the end of heading and the beginning of flowering (BBCH 58-60). The observed time interval between stem elongation and the vegetation peak was approximately 30 days (27 days based on observations). According to reference data (Kalantarova, et al., 1976), this corresponds to the average duration of the phenophases from stem elongation to heading for both spring and winter wheat (24-40 days).

Although spring and winter wheat are different crops, they share similar plant architecture, phenophase timing after tillering, and spectral image dynamics. However, winter wheat reaches its NDVI peak several weeks earlier (typically around 3 weeks) than spring wheat, and the NDVI peak in most of the studied regions corresponds to winter crops.

To determine the timing of phenological development phases, the previously mentioned cartographic, meteorological, reference materials, and remote sensing data were utilized. Historical data facilitated the creation of maps showing the onset of phenological stages for winter wheat based on multi-year averages from 1976–1980. The vector layer boundaries of agricultural lands of the Republic of Armenia were used as areas of interest for data extraction. NDVI data enabled the determination of the estimated phenological phase "heading" for winter cereal crops. Data on topography, temperature, and precipitation were used to calculate the duration of the phenological stage "stem elongation" for various regions. Together, these datasets provided insights into how the territory of Armenia can be zoned according to the seasonal dynamics of these indicators.

Among the regions with the highest share of winter wheat crops, three main groups can be identified: the Western districts (Akhuryan, Artik, Ani, Talin), the Vardenis district, and the Goris and Sisian districts. In terms of elevation, four main regions stand out: the Ararat Valley (Ararat and Armavir), Tavush, the Southeastern regions (Gegharkunik, Vayots Dzor, Syunik), and the Northwestern regions (Shirak, Lori, Kotayk, Aragatsotn). Based on climate and NDVI, 5-6 regions can be identified: the Ararat Valley (Ararat, Artashat, Masis, Vagharshapat, Armavir), the Western regions (Akhuryan, Spitak, Aragats, Artik, Ani, Talin), the southern shore of Lake Sevan (Vardenis, Martuni, Gavar), Syunik (Sisian, Goris), Tavush (Noyemberyan, Shdjev, Tavush), and a number of central and northwestern districts, where climate and NDVI indicators are intermediate (Aparan, Hrazdan, Sevan, Nairi, Kotayk, Tashir, Stepanavan, Tumanyan). This zoning can be considered the main one, as it is more detailed and also includes larger zoning categories based on elevation and the main zones of winter wheat cultivation (Fig. 2).

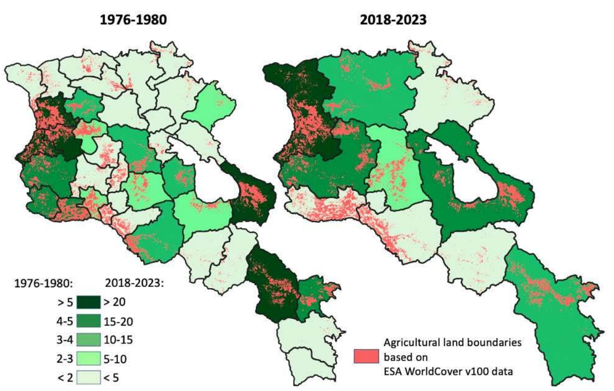

Figure 3. Share of administrative districts in grain production (in percentages) *(composed by the author).*

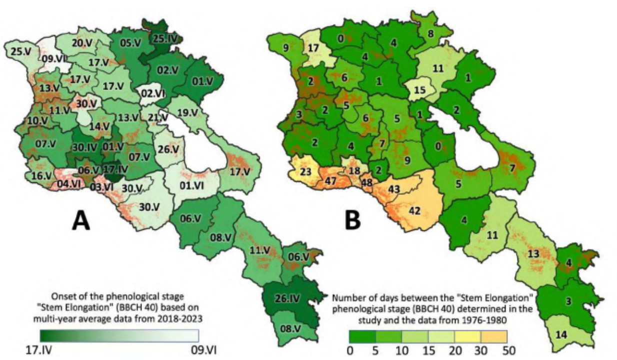

Figure 4. Results of determining the dates of the phenological stage "Stem Elongation" (BBCH 40) for the regions of Armenia: A – Start dates of the phenophase based on data from 2018-2023; B – Difference in days between the start dates of the phenophase based on data from 2018-2023 and the reference data from 1976-1980. *(composed by the author).*

The results of the assessment for the start date of monitoring to identify an increased pathogenic contamination in winter wheat are presented in maps (Fig. 4). The map showing the timing of the "stem elongation" phenological stage (Fig. 4A) displays the estimated start dates of monitoring calculated in this study. The map showing the number of days between the start dates of "stem elongation" based on data from 2018-2023 and 1976-1980 (Fig. 4B) is also presented.

It can be observed that the discrepancies between the calculations and the historical data (Bogatova, 1984) in most regions of Armenia do not exceed 10 days. The model takes into account the specific features of the territory. For instance, in the mountainous Aragats region, the onset of the targeted phenophase occurs significantly later than in the surrounding regions but no significant discrepancies with historical data are observed.

The largest discrepancies with historical data are found in the Ararat Valley (regions of Baghramyan, Armavir, Vagharshapat, Masis, Artashat, Ararat). Noticeable differences are also present in certain individual regions (Ashotsk, Dilijan, Ijevan, Vayq, Sisian, Meghri).

The NDVI dynamics show that in the Ararat Valley, the seasonal maximum of this index occurs in July-August. It can be concluded that grain crops are not sufficiently represented in these regions. This can be confirmed by looking at the maps of the share of administrative districts in grain production (Fig. 3). Similar factors likely account for the discrepancies observed in Ashotsk, Dilijan, Ijevan, Vayq, and Meghri. We do not have statistical data on the areas of winter wheat cultivation in Sisian, but it can be assumed that the crop rotation structure in this region may have significantly changed over the 40 years since the release of the historical map.

It is important to note that this study used generalized and aggregated data on agricultural lands. Consequently, the spectral signatures of the vegetation were influenced not only by winter cereals but also by row crops, orchards, vineyards, forage grasses, and other types of vegetation.

Even with these factors considered, the method for calculating the "stem elongation" phenological stage (BBCH-40) for winter wheat proves effective and correlates well with the characteristics of Armenia's environmental territorial systems. The presence of regions where this method shows poor results only confirms its reliability, as it assumes that certain conditions must be met for its proper operation (a high proportion of plots with winter crops). Nonetheless, it is clear that this method can and should be improved.

To implement this approach in practice, it is essential to account for the specifics of the current season, which often differ from multi-year averages. Additionally, the method for accurately determining the NDVI peak date may need adjustments. Possible solutions include calculating phenophase timings sequentially from the time of crop emergence, using multi-year climate data that are continuously refined based on current weather conditions, or dynamically updating the NDVI peak date in response to real-time weather conditions. Several studies address this issue (Dížková, et al., 2022; Zhao, et al., 2021; Zhao, et al., 2022).

It is also necessary to consider the NDVI of winter crops separately from all other crops. For the method of early disease detection based on spectral image dynamics to be applied effectively to spring cereals, it is equally important to differentiate between spring cereals and other crop types. Numerous scientific advancements in this area have already been successfully implemented in practice (Bartalev, et al., 2011; Vorobyeva, et al., 2016).

However, determining the specific composition of crops on agricultural lands through remote sensing methods is not always feasible in real time, particularly for distinguishing spring crops. Therefore, crop rotation characteristics can be more accurately tracked by using a geoinformation system (GIS) for agricultural land monitoring, where details about cultivated crops are entered in advance, taking into account annual changes in cultivated areas. Even without such a system, similar monitoring can still be conducted on a case-by-case basis for interested organizations and entrepreneurs, provided they supply data on field locations, crop types, and sowing dates for the current season.

As possible recommendations for conducting phytosanitary monitoring to detect winter wheat diseases early using remote sensing methods, the following sequence of actions can be proposed. This can be schematically represented as a data flow diagram (Fig. 5). The main analytical operations in this diagram are:

Establishing whether the weather conditions of the current season are favourable for the emergence of certain pathogens. This is done based on phytopathological reference materials using weather data.

Determining the timing of the monitoring

Identifying zones with an increased pathogenic contamination. During active spectrometry, it is recommended to use imaging systems with the necessary spectral resolution, placed on UAVs, as this provides the most comprehensive coverage of the area without the problems associated with satellite imaging (low frequency, cloud cover).

The spectrometry results are expected to yield maps highlighting zones of increased pathogenic contamination, which will require additional field validation studies. It's also important to emphasize that implementing this approach necessitates the involvement of both remote sensing specialists and agronomists.

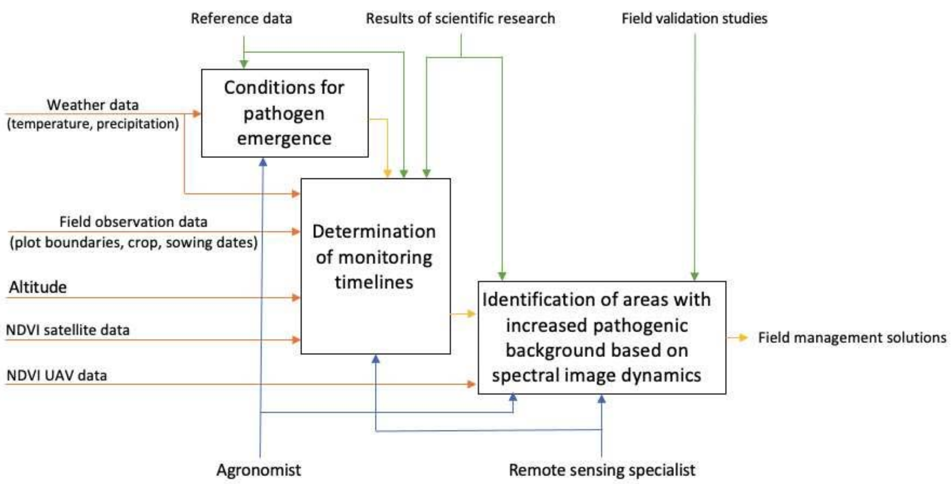

Figure 5. Proposed data flow diagram for monitoring cereal crop diseases *(composed by the author).*

Agronomists' expertise is crucial at each stage, as they play an integral role in interpreting data and ensuring the practical application of findings. Their expertise is essential at each stage, and the outcome of the work is the creation of field management solutions for which they are responsible.

Conclusion

This study has demonstrated the possibility of indicating the phenological stages for winter wheat in the various regions of the Republic of Armenia using remote sensing methods and, thus, it can be implemented as a model for the phytopathological monitoring.

This was demonstrated using a set of multi-temporal data from 2018 to 2024. Regional variations in the monitoring timeline results underscored the need for local adaptation of the methods, taking into account each region's specific climatic and agronomic characteristics. Recommendations for refining the proposed methodology were provided, along with a suggested implementation procedure.

The proposed approach has the potential to become a valuable tool in precision agriculture, enabling reduced crop losses and enhancing the resilience of Armenia's agricultural systems to phytopathogens. However, further efforts are needed to optimize the methodology and integrate remote sensing data with agricultural land monitoring geoinformation systems for its successful application.

References

1. Bartalev, S. A., Egorov, V. A., Lupyan, E. A., Plotnikov, D. E., & Uvarov, I. A. (2011). Recognition of arable lands based on long-term satellite data from MODIS spectroradiometer and locally adaptive classification. Computer Optics, 35(1), -pp. 103–116.
2. Bhatti, M.T., Gilani, H., Ashraf, M., Iqbal, M. S., & Munir, S. (2024). Field validation of NDVI to identify crop phenological signatures. Precision Agriculture, 24(7), - pp. 892–903. https://doi.org/10.1007/s11119-024-10165-6.
3. Bohnenkamp, D., Kuska, M.T., Mahlein, A.K., & Behmann, J. (2019). Hyperspectral signal decomposition and symptom detection of wheat rust disease at the leaf scale using pure fungal spore spectra as reference. Plant Pathology, 68, - pp. 1188-1195. https://doi.org/10.1111/ppa.13020.
4. Bogatova, G.A. (Ed.). (1984). Atlas sel'skogo khozyaistva Armyanskoy SSR [Atlas of Agriculture of the Armenian SSR]. Moscow-Yerevan: GUGK.
5. Danilov, R., Kremneva, O., Sereda, I., Gasiyan, K., Zimin, M., Istomin, D., & Pachkin, A. (2024). Study of the spectral characteristics of crops of winter wheat varieties infected with pathogens of leaf diseases. Plants, 13(14), 1892 p. https://doi.org/10.3390/plants13141892.
6. Dížková, P., Bartošová, L., Bláhová, M., Balek, J., Hájková, L., Semerádová, D., Bohuslav, J., Pohanková, E., Žalud, Z., & Trnka, M. (2022). Modeling phenological phases of winter wheat based on temperature and the start of the growing season. Atmosphere, 13(11), 1854. p. https://doi.org/10.3390/atmos13111854.
7. Google Earth Engine. (n.d.). Google Earth Engine: A planetary-scale platform for Earth science data & analysis. Retrieved from https://earthengine.google.com/ (accessed on 2 October 2024).
8. Hersbach, H., Bell, B., Berrisford, P., et al. (2020). The ERA5 global reanalysis. Quarterly Journal of the Royal Meteorological Society, 146, - pp. 1999-2049. https://doi.org/10.1002/qj.3803.
9. JAXA. (2019). ALOS Global Digital Surface Model "ALOS World 3D - 30m" (AW3D30) dataset. Japan Aerospace Exploration Agency (JAXA). Retrieved from https://www.eorc.jaxa.jp/ALOS/en/aw3d30/ (accessed on 2 October 2024).
10. Jung, J.G., Song, K.E., Hong, S.H., & Shim, S.I. (2021). Hyperspectral characteristics of an individual leaf of wheat grown under nitrogen gradient. Plants, 10(11), - 2291 p. https://doi.org/10.3390/plants10112291.
11. Kalantarova, M.G., Kotikovskaya, A.B., Rogovskaya, E.G., Braykina, M.I., Timchenko, Z.T., & Chernenko, T.N. (1976). Agroklimaticheskie resursy Armyanskoy SSR [Agroclimatic resources of the Armenian SSR]. Vologda: Vologodskaya Pravda.
12. Kremneva, O.Y., Danilov, R.Y., Sereda, I.I., Tutubalina, O.V., Pachkin, A.A., & Zimin, M.V. (2022). Spectral characteristics of winter wheat varieties depending on the development degree of Pyrenophora tritici-repentis. Precision Agriculture, 24(3), - pp. 1-23. https://doi.org/10.1007/s11119-022-09976-2.
13. Li, C., Jia, X., Zhu, R., Mei, X., Wang, D., & Zhang, X. (2023). Seasonal spatiotemporal changes in the NDVI and its driving forces in Wuliangsu Lake Basin, Northern China from 1990 to 2020. Remote Sensing, 15(12), 2965. https://doi.org/10.3390/rs15122965.

14. Lin-Sheng, H., Ju, S.C., Jin-Ling, Z., Dong-Yan, Z., Teng, L., & Yang, F. (2015). Hyperspectral measurements for estimating vertical infection of yellow rust on winter wheat plant. International Journal of Agriculture and Biology, 17(6). https://doi.org/10.17957/IJAB/15.0034.

15. Longchamps, L., & Philpot, W. (2023). Full-season crop phenology monitoring using two-dimensional normalized difference pairs. Remote Sensing, 15(23). 5565 https://doi.org/10.3390/rs15235565.

16. Mahlein, A.K., Alisaac, E., Masri, A.A., Behmann, J., Dehne, H.-W., & Oerke, E.-C. (2019). Comparison and combination of thermal, fluorescence, and hyperspectral imaging for monitoring Fusarium head blight of wheat on spikelet scale. Sensors, 19, 2281. https://doi.org/10.3390/s19102281.

17. Meier, U. (Ed.). (2001). Growth stages of mono- and dicotyledonous plants. BBCH Monograph. Federal Biological Research Centre for Agriculture and Forestry.

18. Open Source Geospatial Foundation. (2024). GDAL/OGR contributors. Retrieved from https://gdal.org (accessed on 2 October 2024).

19. Rieker, M.E.G., Lutz, M.A., El-Hasan, A., Thomas, S., & Voegele, R.T. (2023). Hyperspectral imaging and selected biological control agents for the management of Fusarium head blight in spring wheat. Plants, 12(20), 3534. https://doi.org/10.3390/plants12203534.

20. Rouse, J.W., Haas, R.H., Schell, J.A., & Deering, D.W. (1974). Monitoring vegetation systems in the Great Plains with ERTS. Third Earth Resources Technology Satellite-1 Symposium, NASA SP-351, 1, - pp. 309-317.

21. Savitzky, A., & Golay, M.J.E. (1964). Smoothing and differentiation of data by simplified least squares procedures. Analytical Chemistry, 36(8), - pp. 1627-1639. https://doi.org/10.1021/ac60214a047.

22. Sereda, I., Danilov, R., Kremneva, O., Zimin, M., & Podushin, Y. (2023). Development of methods for remote monitoring of leaf diseases in wheat agrocenoses. Plants, 12(18), 3223 p. https://doi.org/10.3390/plants12183223.

23. Statistical Committee of the Republic of Armenia. (n.d.). Retrieved October 1, 2024, from https://www.armstat.am/en/ (accessed on 20 July 2024).

24. Vorobyeva, N.S., Sergeev, V.V., & Chernov, A.V. (2016). Information technology for early recognition of crop types from satellite images. Computer Optics, 40(6), - pp. 929–938. https://doi.org/10.18287/2412-6179-2016-40-6-929-938.

25. Wang, H., Qin, F., Liu, Q., Ruan, L., Wang, R., & Ma, Z. (2015). Identification and disease index inversion of wheat stripe rust and wheat leaf rust based on hyperspectral data at canopy level. Journal of Spectroscopy. https://doi.org/10.1155/2015/651810.

26. Wang, H., Qin, F., Ruan, L., Wang, R., Liu, Q., Ma, Z., & Li, X. (2016). Identification and severity determination of wheat stripe rust and wheat leaf rust based on hyperspectral data acquired using a black-paper-based measuring method. PLOS ONE, 11(4). https://doi.org/10.1371/journal.pone.0152064.

27. Zanaga, D., Van De Kerchove, R., De Keersmaecker, W., Souverijns, N., Brockmann, C., Quast, R., Wevers, J., Grosu, A., Paccini, A., Vergnaud, S., Cartus, O., Santoro, M., Fritz, S., Georgieva, I., Lesiv, M., Carter, S., Herold, M., Li, L., Tsendbazar, N. E., Ramoino, F., & Arino, O. (2021). ESA WorldCover 10 m 2020 v100. https://doi.org/10.5281/zenodo.5571936.

28. Zhang, J., Pu, R., Wang, J., Huang, W., Yuan, L., & Luo, J. (2012). Detecting powdery mildew of winter wheat using leaf level hyperspectral measurements. Computers and Electronics in Agriculture, 85, - pp. 13-23. https://doi.org/10.1016/j.compag.2012.03.006.

29. Zhao, F., Yang, G., Yang, X., Cen, H., Zhu, Y., Han, S., Yang, H., He, Y., & Zhao, C. (2021). Determination of key phenological phases of winter wheat based on the time-weighted dynamic time warping algorithm and MODIS time-series data. Remote Sensing, 13(9), 1836 p. https://doi.org/10.3390/rs13091836.

30. Zhao, Y., Wang, X., Guo, Y., Hou, X., & Dong, L. (2022). Winter wheat phenology variation and its response to climate change in Shandong Province, China. Remote Sensing, 14(18), - 4482 p. https://doi.org/10.3390/rs14184482.

Declarations of interest

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