



Seasonal agricultural vulnerability in semi-arid Morocco: combining remote sensing and farmer knowledge to inform climate adaptation

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Abstract

Agricultural systems in semi-arid regions are increasingly exposed to climate variability, yet the drivers of seasonal vulnerability remain insufficiently understood. This study examines whether perceived vulnerability during winter and summer cropping seasons is shaped by distinct mechanisms—climatic exposure during the wet season and adaptive capacity during the dry season. Using Morocco as a representative case for North African agriculture, we integrate long-term Earth observation indicators of environmental variability (precipitation, temperature, and NDVI) with survey data from 3,591 smallholder farmers and apply machine learning classification models evaluated under spatially explicit cross-validation. Model performance was benchmarked against multinomial logistic regression and majority-class baselines. While standard cross-validation yielded optimistic estimates, spatial cross-validation produced more conservative and policy-relevant results. Under spatial validation, Random Forest and XGBoost consistently outperformed simpler models, with macro F1 scores ranging from approximately 0.53 for overall vulnerability to over 0.70 for seasonal outcomes. Comparative experiments showed that survey-based predictors explain a larger share of perceived vulnerability than Earth observation indicators alone, while their combination provides complementary gains, particularly for winter vulnerability. Explainable model analysis revealed clear seasonal contrasts: winter vulnerability was dominated by hydroclimatic variability and soil moisture conditions, whereas summer vulnerability was more strongly shaped by adaptive capacity, including ground-water access, irrigation practices, and climate information use. The proposed framework offers a transferable approach for assessing climate vulnerability and informing targeted adaptation strategies in semi-arid farming systems.

Keywords Morocco · Climate vulnerability · Semi-arid agriculture · Earth observation · Farmer perceptions

1 Introduction

Agriculture plays a fundamental role in rural livelihoods and national economies in many developing countries, particularly in areas where climate variability intersects with limited adaptive capacity. In Morocco, the agricultural sector contributes approximately 15% of the gross domestic product and provides employment for more than 40% of the population (African Development Bank Group, 2024). However, agricultural systems across the country face increasing vulnerability due to climate-related stressors, including rising temperatures, erratic precipitation, and intensifying droughts (Mushagalusa et al. 2023; Aniyi et al. 2024). These climatic shifts pose mounting risks to food production and security, farmer income, and long-term rural development.

In recent years, smallholder farmers have experienced increasingly unpredictable growing seasons, disrupted planting cycles, and extreme weather events. These challenges are further compounded by socioeconomic constraints, such as inadequate access to irrigation infrastructure, limited formal education, and insufficient climate information services (Asrat and Simane 2018). Most rural households depend on small-scale farming for their livelihoods (World Bank Group 2023), and the combined effect of environmental and structural limitations has made it difficult for many to respond to and recover from climatic shocks.

Traditional assessments of agricultural vulnerability in Morocco have often focused on climatic or economic exposure indicators. While useful, these approaches tend to overlook equally critical dimensions of sensitivity and adaptive capacity—factors shaped by farmers' lived experiences, access to resources, and capacity to adjust practices under changing conditions (IPCC 2022). There is a growing need for integrative frameworks that combine environmental monitoring with local knowledge to provide a more comprehensive understanding of vulnerability.

To better capture vulnerability in real agricultural contexts, this work focuses on Morocco's most agriculturally active regions, where seasonal climate variability significantly affects smallholder livelihoods. Previous studies have documented how Moroccan farmers perceive climatic change and apply adaptation strategies in areas such as Khemisset and the arid rangelands of the east (Chaachouay and Zidane 2024; Chaachouay 2025; Snaibi et al. 2021). However, these efforts highlight the importance of continual monitoring and data integration to fully understand and support adaptive capacity on the ground.

Remote sensing offers powerful tools for observing key environmental indicators—such as precipitation, temperature, vegetation health, vegetation indexes, and land cover—across broad spatial and temporal scales (Tucker 1979; Gao 1996; Wan 1996). Yet satellite data alone are not sufficient to understand how climate risks are experienced, interpreted, and managed by farmers. A more holistic approach combines satellite-derived environmental data with farmer surveys capturing perceptions, adaptation practices, and access to resources. Recent research in Morocco has shown that this integrated method can reveal nuanced patterns of vulnerability that conventional models often miss (Alvarez and Govind 2025a).

Analysing such complex, multidimensional datasets require advanced computational techniques. Machine learning algorithms such as Random Forest and XGBoost are particularly effective in capturing non-linear interactions among social and environmental variables. These models can integrate diverse data sources—including climatic records, land surface indicators, and survey-based variables—thus enhancing the robustness of agri-

cultural vulnerability modelling (Balasubramaniam et al. 2025). However, their predictive strength comes at the cost of transparency, often functioning as “black boxes” that hinder interpretability.

Explainable artificial intelligence (XAI) methods, such as SHAP (SHapley Additive Explanations), help address this issue by revealing the contribution of each input variable to model predictions. This approach not only improves interpretability but also supports future monitoring, better variable selection, and policy relevance (Li et al. 2025). Making model outputs understandable is essential for translating scientific evidence into meaningful strategies for resilience and adaptation.

This research aims to enhance understanding of seasonal agricultural vulnerability to climate variability in Morocco by integrating satellite-based environmental monitoring with farmer perceptions. Focusing on the country’s most productive and climate-sensitive agricultural regions, the study analyses survey data from 3,591 smallholder farmers using explainable machine learning models. By examining interactions between environmental and social factors across winter, summer, and annual periods, the findings are intended to inform more targeted, locally grounded adaptation strategies. Ultimately, effective climate resilience cannot rely solely on technological innovation; it must also center the experiences, knowledge, and participation of those most affected.

2 Materials and methods

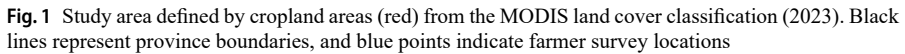
2.1 Study area

Morocco’s geography creates distinct regional disparities in climate and agricultural potential. The northern and central regions—home to the Rif Mountains, Atlantic coastal plains, the Saïs Plain, and the foothills of the Middle Atlas—receive most of the country’s rainfall, typically ranging from 400 to over 1,200 mm annually, depending on elevation and proximity to the coast (World Bank, 2021).

In contrast, the southern and southeastern parts of Morocco are arid to semi-arid, receiving as little as 100 mm of rainfall per year, with temperatures regularly exceeding 35 °C in the summer and dropping below 0 °C in winter in the mountainous interior (World Bank, 2025). Rainfall is highly seasonal, with most precipitation occurring between October and May, influenced by Atlantic and Mediterranean weather systems and modulated by the Atlas Mountains.

Given the predominance of rainfed agriculture and the uneven distribution of rainfall, the northern and central agricultural zones are especially critical for national food security and rural livelihoods but are also highly sensitive to seasonal climatic variability (Verner et al. 2018). For this study, we focused on these agriculturally productive areas.

Cropland regions were identified using the MODIS Land Cover Type product (MCD12Q1) for 2023. We selected pixels classified as croplands and cropland-natural vegetation mosaics to ensure that both environmental and farmer survey data were drawn from zones under active agricultural use. The final dataset includes 3,591 smallholder farmer locations (blue points), primarily located within these key regions (Fig. 1).



Spatial support and extraction The EO predictors used in this study have different native spatial supports. MODIS NDVI (MOD13Q1) is provided at 250 m spatial resolution, whereas ERA5-Land monthly aggregates are provided on a regular grid of approximately 0.1° (≈ 11 km; 11,132 m in GEE). CV for NDVI, precipitation, and 2 m temperature were computed on the native grids for the period 2010–2023. Survey locations were linked to EO predictors by extracting raster values at the survey coordinates in GEE using a nearest-neighbour operator, without statistical downscaling or interpolation, to preserve the original measurement support of each product.

Because ERA5-Land represents regional-scale climatic conditions, multiple households located within the same reanalysis grid cell may share identical precipitation and temperature CV values. Accordingly, ERA5-based indicators are interpreted as contextual exposure descriptors reflecting broader agro-climatic variability rather than plot-level conditions. In contrast, the finer-resolution MODIS NDVI CV captures more localized vegetation dynamics that may vary between neighbouring farms. This multi-scale structure is consistent with the objective of relating perceived vulnerability to both farm-level characteristics and regional climatic context. A limitation is that reanalysis-based EO predictors cannot resolve within-pixel heterogeneity and should not be interpreted as field-scale climatic measurements.

2.2.2 Survey data

The survey was conducted in October 2024 with 3,591 smallholder farmers across Morocco, with support from the International Center for Agricultural Research in the Dry Areas (ICARDA). A random sampling approach was applied, facilitated by local farmer collaborators, and covered the country's main agricultural regions to ensure representativeness of dominant cropping systems (Fig. 1).

The questionnaire consisted of 44 items (Supplementary Table S1), including two questions capturing geographic coordinates and a broader set addressing climate perceptions, farm management practices, access to resources, and perceived climate vulnerability. No personal identifiers were collected to protect respondent privacy.

Perceived vulnerability was directly reported by farmers for winter, summer, and overall conditions. Prior to these questions, enumerators provided a standardized explanation of climate vulnerability, emphasizing exposure to climate stress, crop sensitivity, and adaptive capacity. Farmers then classified their vulnerability as low, medium, high, or “not aware” if they felt unable to assess it. These perception-based responses form the dependent variables used in the modeling framework.

2.3 Preprocessing

Survey and geospatial data were integrated into a unified analytical dataset. Survey responses were first standardized through variable coding, with full definitions and original question wording provided in Supplementary Table S1. Each farmer record was georeferenced using the reported latitude and longitude coordinates, enabling spatial linkage with the CV layers of NDVI, precipitation, and temperature.

For each survey location, CV values were extracted from the corresponding raster layers and appended as additional attributes, creating a dataset in which each row represents an individual farmer's perceptions alongside long-term environmental variability. Data cleaning was performed to address missing values and inconsistencies prior to modeling.

To reflect seasonal dynamics, three modeling datasets were prepared: one containing summer-related variables, one containing winter-related variables, and a combined dataset representing overall vulnerability. The complete survey instrument and coding scheme are publicly available for transparency and reproducibility at <https://github.com/osoivan/datasciencemscthesis>.

2.4 Modeling approach

To explore the relationships between farmer perceptions of climate vulnerability and environmental variability, we implemented a supervised multi-class machine learning classification framework. The primary objective was to predict perceived vulnerability levels for three outcomes—summer, winter, and overall vulnerability—by integrating Earth observation indicators with survey-derived socioeconomic and management variables.

We employed two widely adopted ensemble learning algorithms (IEEE Computer Society, 2023): Random Forest (RF) (Lundberg et al. 2020) and Extreme Gradient Boosting (XGBoost). These models were selected due to their capacity to handle high-dimensional data, capture nonlinear interactions, and perform robustly on tabular datasets that combine numerical and categorical predictors in environmental and agricultural applications (Fukš et al. 2024). To contextualize the performance of these ensemble models, we additionally implemented two baseline approaches: a majority-class classifier and a multinomial logistic regression model, representing simpler alternatives against which model gains could be assessed.

Environmental predictors were derived from the coefficient of variation (CV) of MODIS NDVI, ERA5-Land precipitation, and ERA5-Land 2-m air temperature, computed over the period 2010–2023 and spatially extracted at georeferenced survey locations. These EO indicators were merged with survey responses after data cleaning and categorical encoding.

To avoid tautological prediction and information leakage, all vulnerability perception variables (CA_CC_VUL, WT_VL_CC, SM_VL_CC) were strictly excluded from the predictor set, irrespective of the modeled outcome. In addition, spatial identifiers and coordinates (LAT, LONG, spatial block indices) were never used as predictors. Seasonal information leakage was further mitigated by excluding summer-related survey variables (prefix “SM”) when modeling winter vulnerability, and winter-related variables (prefix “WT”) when modeling summer vulnerability.

Before model training, class balance across vulnerability levels (low, moderate, high, and “not aware”) was assessed. To address imbalanced class distributions, we applied Synthetic Minority Over-sampling Technique (SMOTE) within each training fold for the overall and winter models, generating synthetic observations for underrepresented classes through interpolation between minority samples (Pradipta et al. 2021). For the summer models, where some classes were extremely sparse, Random Over-Sampling (ROS) was used instead to ensure numerical stability (Miftahushudur et al. 2025). Importantly, resampling was applied only within training folds, preventing information leakage and preserving valid performance estimates (Wang et al. 2021).

Because the dataset is cross-sectional and spatially clustered, standard random cross-validation may yield overly optimistic estimates of predictive performance. To obtain a more conservative and policy-relevant assessment of generalization, we implemented a spatial block cross-validation strategy (Tziachris et al. 2023). Farms were assigned to spatial blocks using a regular grid with resolutions of approximately 25 km, 50 km, and 100 km, and model evaluation was conducted using GroupKFold cross-validation with five folds, ensuring that entire spatial blocks were held out during validation (Koldasbayeva et al. 2024).

Model performance was evaluated using accuracy and macro-averaged F1 score, allowing balanced assessment across vulnerability classes. Confusion matrices were computed using out-of-fold predictions, such that each observation contributed exactly once to model evaluation. Separate models were trained for each seasonal outcome, and performance was compared across RF, XGB, and baseline models, as well as across different predictor configurations (survey-only, EO-only, and combined).

2.5 Explainability with SHAP

To interpret the machine learning models and identify the most influential predictors of seasonal vulnerability, we applied the SHAP (SHapley Additive exPlanations) method (Poncela-Bobadilla et al. 2024). SHAP is a model-agnostic explainability framework grounded in cooperative game theory, which quantifies the marginal contribution of each feature to the model's prediction. This approach allowed us to evaluate not only which variables were most important globally across the dataset, but also how each individual feature influenced specific predictions.

SHAP analyses were conducted separately for the Random Forest (RF) and XGBoost (XGB) models and for each vulnerability outcome (summer, winter, and overall). SHAP values were computed after fitting the final models using the same leakage-controlled predictor sets employed in the spatial cross-validation framework. To ensure interpretability aligned with model evaluation, SHAP values were calculated on the imputed feature space used internally by each model.

Feature importance was summarized using global SHAP bar plots, in which predictors were ranked according to the mean absolute SHAP value across the sample population. This representation highlights the variables that contribute most strongly to model predictions on average, without focusing on individual observations. The resulting rankings provided a clear and interpretable hierarchy of predictors influencing perceived vulnerability, allowing comparison between environmental indicators—such as variability in precipitation and NDVI—and socioeconomic or management-related factors, including access to irrigation, climate information services, and education level. The complete methodological workflow is summarized in Fig. 2.

3 Results

3.1 Spatial patterns of environmental variability

To assess environmental variability across Morocco, we computed the coefficient of variation (CV) for precipitation, temperature, and NDVI over the period 2010 to 2023. As shown

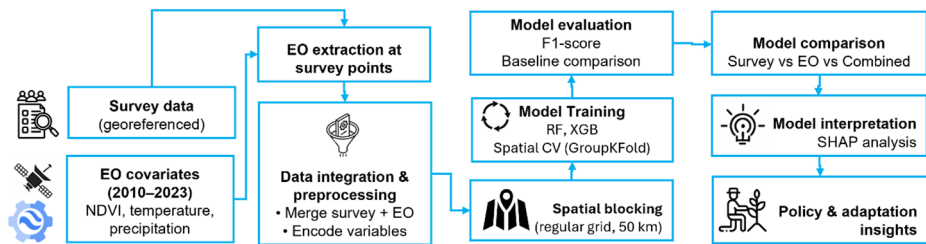


Fig. 2 Overview of the methodological workflow integrating georeferenced farmer surveys and Earth observation covariates, followed by spatially explicit model training, evaluation, and interpretation

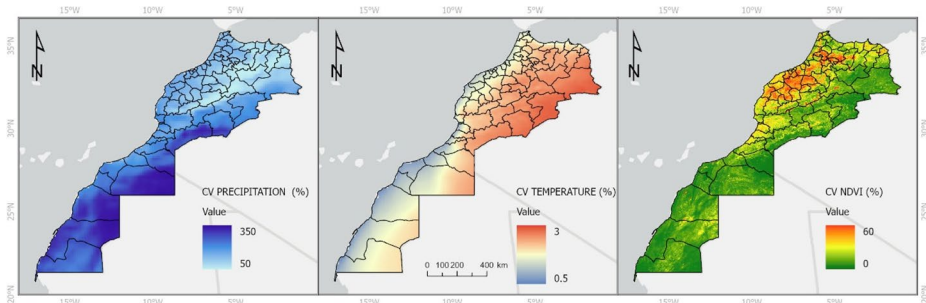


Fig. 3 Spatial distribution of the coefficient of variation (CV) for precipitation (left), temperature (center), and NDVI (right) across Morocco from 2010 to 2023. Higher CV values indicate greater environmental variability, with notable spatial contrasts across regions

in Fig. 3, precipitation variability exhibits a clear spatial gradient, with the highest values—exceeding 300%—found in the arid southern regions, particularly near the Anti-Atlas and Saharan zones. In contrast, the more agriculturally productive northern and central areas experienced lower variability, generally below 100%, indicating more stable rainfall patterns. Temperature variability was relatively uniform across the country, with CV values mostly under 2%, although slightly higher fluctuations were observed in elevated interior zones. NDVI variability revealed more localized patterns, with higher CV values (over 40%) concentrated in the northern agricultural zones where cropping cycles, drought, and land cover changes are more dynamic. In contrast, NDVI values remained more stable in central plateaus and were very low in the sparsely vegetated southern deserts. These spatial patterns highlight the uneven distribution of climatic and ecological variability across Morocco, and they provide a strong basis for understanding regional differences in perceived vulnerability. The CV layers were used as key predictors in the subsequent machine learning models.

3.2 Model performance

Model performance was evaluated using both standard cross-validation and a spatially explicit cross-validation framework to assess predictive accuracy and generalization under realistic geographic conditions. While standard cross-validation yielded higher performance estimates, spatial cross-validation produced more conservative results by explicitly accounting for spatial clustering among surveyed farmers.

Under spatial cross-validation, both Random Forest (RF) and XGBoost (XGB) consistently outperformed the multinomial logistic regression and majority-class baseline models across all vulnerability outcomes (Table 1). For overall vulnerability, RF and XGB achieved comparable macro-averaged F1 scores (≈ 0.53), substantially exceeding the performance of the logit model (0.36) and the majority-class classifier (0.22). A complete comparison of performance metrics across models and validation strategies is provided in Supplementary Table S2. Similar performance patterns were observed for winter and summer vulnerability, with ensemble models maintaining clear advantages over simpler baselines, despite reduced accuracy relative to standard cross-validation.

Figure 4 presents confusion matrices based on spatial out-of-fold predictions, providing a class-wise view of model performance under spatial cross-validation. Across all vulnerability outcomes, misclassifications occur predominantly between adjacent vulnerability categories, rather than between extreme classes. This pattern is particularly evident for the low- and medium-vulnerability classes, which exhibit lower recall due to their limited representation.

The summer vulnerability models exhibited the strongest predictive performance, with spatial F1 scores exceeding 0.70 for both RF and XGB, suggesting more consistent seasonal patterns in farmer perceptions during summer. In contrast, winter vulnerability showed lower—but still meaningful—predictive performance, likely reflecting greater heterogeneity in climatic exposure, adaptive practices, and management strategies during the winter season.

To assess the robustness of these results to the choice of spatial block size, we repeated the spatial cross-validation using alternative grid resolutions of approximately 25 km, 50 km, and 100 km. Performance remained stable across block sizes, indicating that the results reported using the 50 km grid, adopted as a representative intermediate scale, are not sensitive to the specific spatial partitioning choice (Supplementary Table S3).

Class distributions for overall, winter, and summer vulnerability outcomes are reported in Supplementary Table S4, showing a pronounced imbalance across vulnerability levels, particularly for the low-vulnerability class. Class-wise precision, recall, and F1 scores based on spatial out-of-fold predictions are provided in Supplementary Table S5, while confusion matrices with absolute counts are reported in Supplementary Figure S1. Together with the

Table 1 Performance metrics of Random Forest (RF), XGBoost (XGB), Logit and Majority-class models through a Random or Standard CV and Spatial CV. Standard CV results are reported for comparison; spatial CV results are used for interpretation

Model	Target	F1 - Standard CV	F1 - Spatial CV
RF	Overall	0.60	0.53
XGB		0.60	0.53
Logit model		0.49	0.36
Majority-class classifier		0.25	0.22
RF	Winter	0.64	0.69
XGB		0.63	0.68
Logit model		0.56	0.5
Majority-class classifier		0.33	0.39
RF	Summer	0.76	0.72
XGB		0.71	0.71
Logit model		0.68	0.57
Majority-class classifier		0.32	0.28

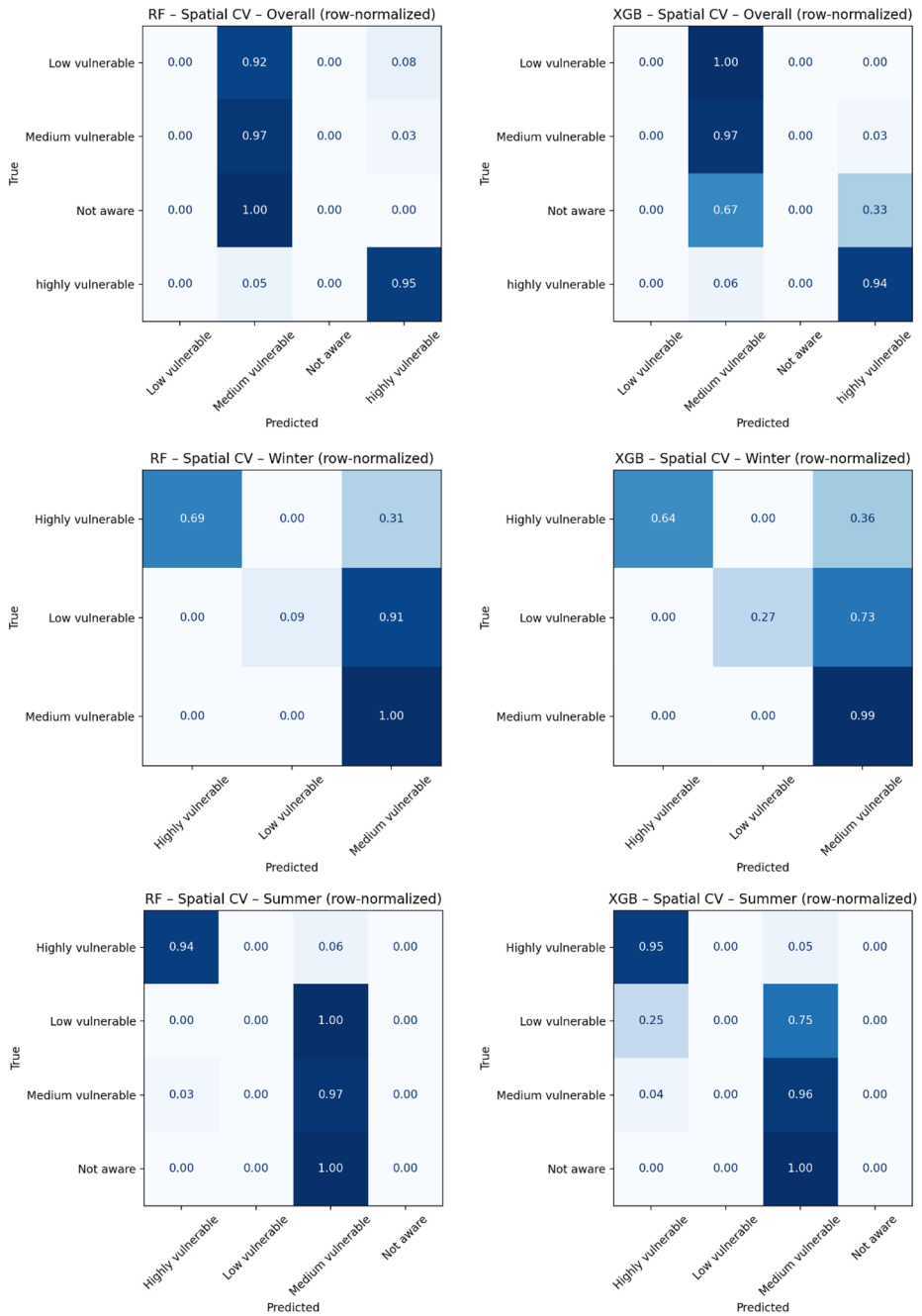


Fig. 4 Confusion matrices based on spatial out-of-fold predictions under GroupKFold cross-validation

row-normalized confusion matrices shown in Fig. 4, these results explain why overall accuracy remains high while macro-F1 scores are lower, reflecting reduced recall for minority classes rather than model instability.

3.3 SHAP-based interpretation of key drivers

For overall vulnerability, both Random Forest (RF) and XGBoost (XGB) models identified summer soil moisture status (SM_SM_ST), soil problems (SOIL_PROB), and climatic variability indicators, particularly precipitation (PRECIPITAT) and temperature (TEMPERATUR) coefficients of variation, as the most influential predictors (Fig. 5). These variables capture the combined effects of hydroclimatic stress and local biophysical constraints that shape farmers' long-term vulnerability perceptions. Management and adaptation-related variables, including groundwater depth (SM_GW), crop yield (SM_CR_YL_KG), and irrigation practices (SM_IR_WA_Y), also contributed substantially, indicating that vulnerability is mediated by farmers' capacity to manage water resources and sustain production under variable climatic conditions. The consistency of variable rankings between RF and XGB models reinforces the robustness of these findings.

Winter vulnerability models exhibited a stronger concentration of importance among environmental and biophysical variables (Fig. 6). Winter soil moisture status (WT_SM_ST), precipitation variability (PRECIPITAT), temperature variability (TEMPERATUR), and soil problems (SOIL_PROB) dominated SHAP rankings in both RF and XGB models. This suggests that winter vulnerability perceptions are more directly linked to environmental exposure and soil–water conditions, with less influence from management heterogeneity. Nevertheless, variables related to adaptive capacity—such as crop yield (WT_CR_YL_KG), pest pressure (WT_PS), and access to extension services (WT_SY_YN)—also contributed meaningfully, particularly in the XGB model, highlighting the role of institutional support in moderating winter vulnerability.

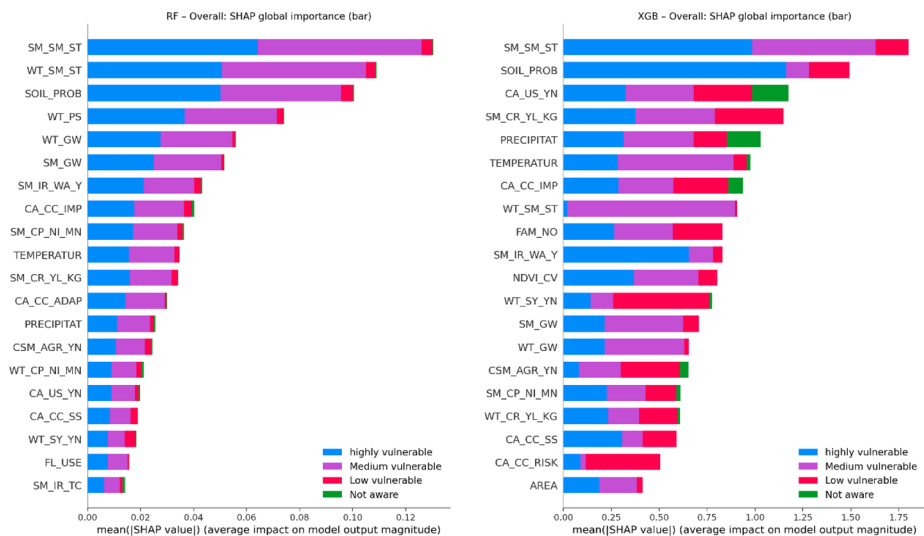


Fig. 5 SHAP summary plots of the top predictors for overall climatic vulnerability using the RF (left) and XGB (right) models for overall vulnerability

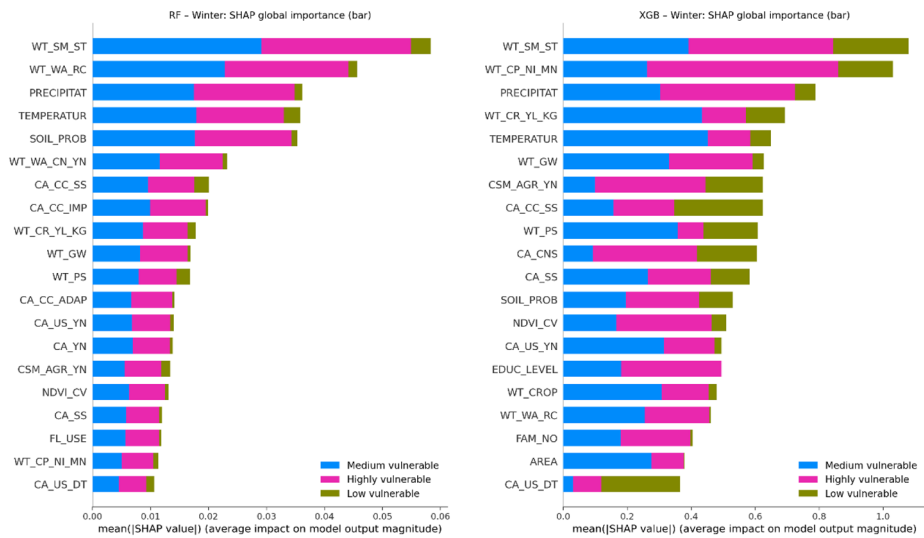


Fig. 6 SHAP summary plots of the top predictors for winter climatic vulnerability using the RF (left) and XGB (right) models for winter vulnerability

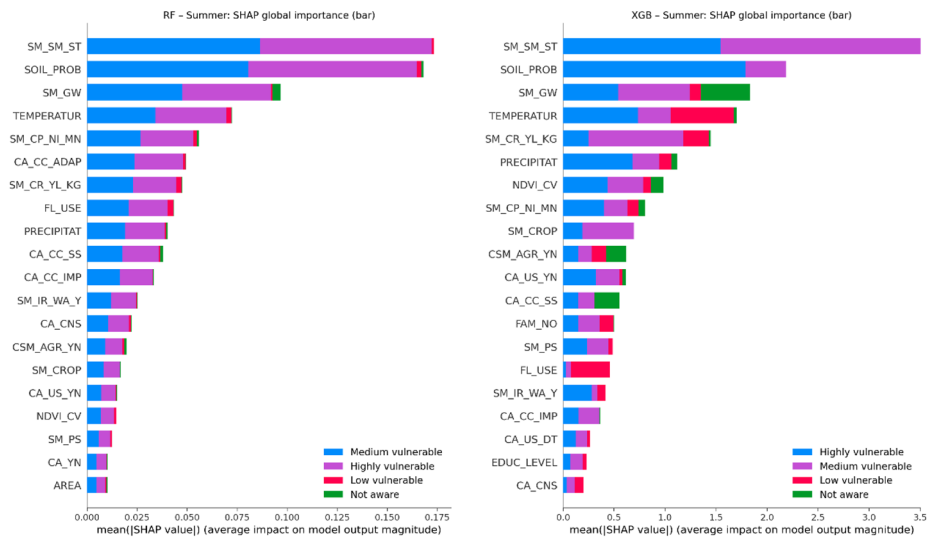


Fig. 7 SHAP summary plots of the top predictors for winter climatic vulnerability using the RF (left) and XGB (right) models for summer vulnerability

Summer vulnerability showed the greatest diversity of influential predictors (Fig. 7). Soil moisture status during summer harvest (SM_SM_ST) emerged as the dominant driver across both models, followed by soil problems (SOIL_PROB), groundwater depth (SM_GW), and climatic variability indicators (PRECIPITAT, TEMPERATUR). These results reflect the heightened sensitivity of summer cropping systems to water availability and

thermal stress. In contrast to winter, management and adaptive capacity variables—including irrigation practices (SM_IR_WA_Y), crop yields (SM_CR_YL_KG), knowledge of climate-smart agriculture (CSM_AGR_YN), and use of climate information services (CA_CC_SS)—played a more prominent role. This indicates that summer vulnerability perceptions are strongly shaped by farmers' ability to actively respond to climatic stress through management decisions.

3.4 Contribution of survey-based and earth observation predictors

To assess the relative explanatory power of subjective survey-based variables and objective Earth observation (EO) indicators, we trained and evaluated three model configurations for each vulnerability outcome: (i) models using only EO-derived predictors (NDVI, precipitation variability, and temperature variability), (ii) models using only survey-based predictors, and (iii) models combining both predictor sets. All models were evaluated using spatially explicit cross-validation (GroupKFold, $n = 5$) to ensure realistic generalization across agro-climatic zones.

The results (Table 2) indicate that survey-only models consistently outperformed EO-only models across all vulnerability outcomes, confirming that farmer perceptions, management practices, and institutional factors play a dominant role in explaining perceived climatic vulnerability. For overall vulnerability, the EO-only model achieved a macro F1 score of 0.35, compared to 0.53 for the survey-only model. Similar patterns were observed for winter (0.47 vs. 0.67) and summer vulnerability (0.51 vs. 0.72).

Importantly, integrating EO and survey predictors yielded clear improvements over EO-only models and, in some cases, modest gains relative to survey-only models. For winter vulnerability, the combined model achieved the highest performance ($F1 = 0.69$), exceeding both EO-only and survey-only configurations. For overall and summer vulnerability, combined models matched the performance of survey-only models, indicating that EO indicators provide complementary contextual information but do not replace perception-based data. Detailed performance metrics for all model configurations are reported in Supplementary Table S5.

Interpretation of EO contributions should consider the spatial support of the underlying datasets. In particular, ERA5-Land predictors operate at a regional scale and therefore capture shared climatic exposure rather than plot-level variability. This scale characteristic explains why EO-only models exhibit lower predictive power than survey-based models, while still providing meaningful contextual information when combined with farmer-reported variables. EO indicators thus complement perception-based data by situating local vulnerability assessments within broader patterns of climatic variability, rather than acting as primary determinants on their own.

Table 2 F1 scores from spatial cross-validation (GroupKFold, $n = 5$) comparing model performance using remote sensing-only, survey-only, and combined predictor sets for overall, winter, and summer vulnerability

Target	Remote sensing-only	Survey + Remote sensing	Survey-only
Overall	0.35	0.53	0.53
Winter	0.47	0.69	0.67
Summer	0.51	0.72	0.72

4 Discussion

This study contributes to the growing body of research emphasizing the need for integrative approaches to climate vulnerability assessment in agriculture, particularly in semi-arid regions such as Morocco where seasonal climatic stressors intersect with structural constraints on water and land management. By combining Earth observation indicators, farmer perception surveys, and machine learning models with explicit spatial validation, this work provides a nuanced understanding of how climatic exposure and adaptive capacity jointly shape perceived vulnerability across seasons (Alvarez and Govind 2025b).

Our results reveal clear seasonal contrasts in the drivers of perceived vulnerability. Winter vulnerability was more strongly associated with environmental and biophysical factors, including precipitation variability, temperature variability, soil moisture status, and soil-related constraints. This pattern reflects Morocco's climatic regime, where winter rainfall underpins rainfed agriculture and largely determines crop establishment and yield stability. The prominence of these variables in both RF and XGB models suggests that farmers' perceptions of winter vulnerability are closely aligned with observable hydroclimatic conditions, reinforcing earlier findings that local knowledge systems can accurately reflect environmental signals (Asrat and Simane 2018; Mushagalusa et al. 2023; Ayinde et al. 2024). The importance of soil moisture and precipitation variability further highlights the sensitivity of winter crops to interannual rainfall fluctuations, which remain a central challenge under projected climate change scenarios for North Africa.

In contrast, summer vulnerability was shaped more strongly by factors related to adaptive capacity and management. Variables such as summer soil moisture status, groundwater depth, irrigation practices, crop yields, and knowledge of climate-smart agriculture consistently ranked among the most influential predictors. This indicates that, during the dry season, vulnerability is less a function of direct climatic exposure alone and more dependent on farmers' ability to actively manage water scarcity and thermal stress. Access to groundwater, irrigation decision-making, and institutional support thus play a critical role in mediating summer vulnerability, consistent with studies highlighting the growing importance of adaptive capacity in dry-season agriculture (Fildes et al. 2023; Kertolli et al. 2024). These findings underscore that vulnerability is not static across the agricultural calendar but dynamically shaped by seasonal constraints and available response options.

Across all seasons, precipitation variability emerged as a consistently important predictor, confirming its central role in structuring agricultural risk in semi-arid systems. Soil moisture status during harvest was likewise influential in both winter and summer models, emphasizing the need for improved soil and water management practices that enhance moisture retention and reduce yield instability (Wang et al. 2025). The practical relevance of these findings becomes clearer when considered alongside prevailing cropping patterns. As shown in Fig. 8, winter agriculture in the study area is dominated by wheat and barley, while summer cultivation is highly concentrated in maize, with limited crop diversification in both seasons. This strong seasonal specialization constrains farmers' adaptive options and amplifies sensitivity to climatic variability, particularly during summer when water scarcity is most acute. From a policy perspective, this highlights the importance of promoting crop diversification strategies aligned with seasonal water availability, drought-tolerant varieties, and improved rotation schemes that can buffer climate shocks and reduce vulnerability in smallholder systems.

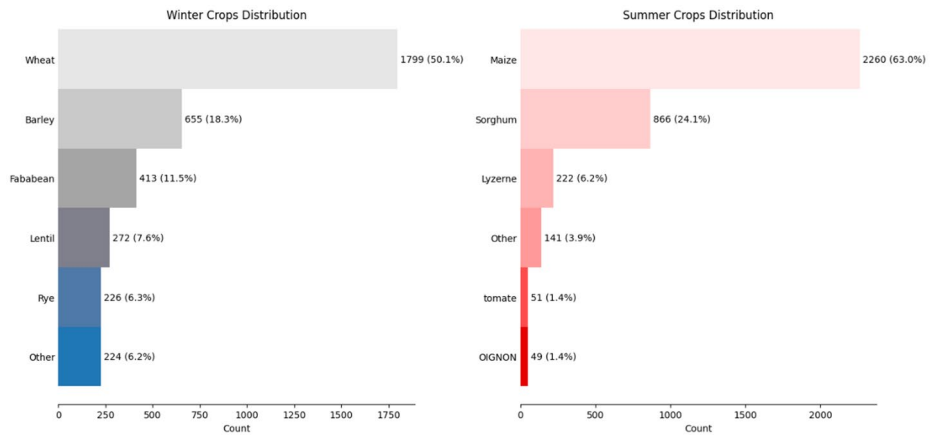


Fig. 8 Summer and winter crops reported for the farmers in the survey

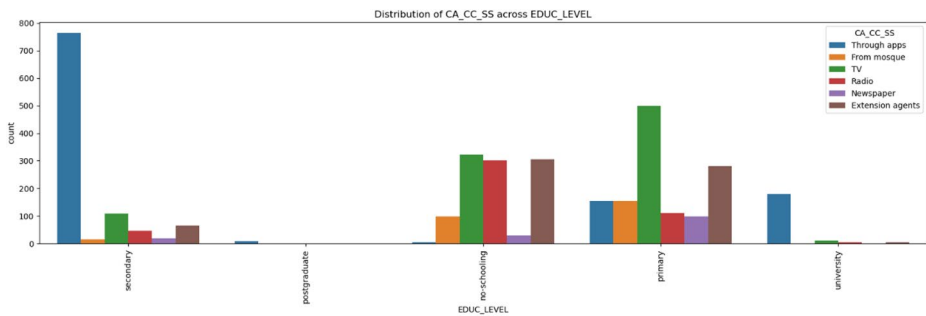


Fig. 9 Preferred channels for receiving climate information (CA_CC_SS) by education level, showing that app-based delivery is most favored among secondary and university-educated farmers, while primary and non-schooled groups rely more on mosques, radio, and extension agents

The use of SHAP-based model interpretation allowed us to transparently quantify the contribution of individual predictors, addressing a common limitation of machine learning approaches in climate risk research (Gholami et al. 2024). By identifying consistent patterns across two different ensemble algorithms, our results demonstrate that vulnerability is shaped by an interplay between climatic exposure, biophysical constraints, and socio-institutional factors. Importantly, variables related to climate information services (CA_CC_SS) emerged as influential across models, reflecting growing demand for timely and actionable climate information. Younger and more educated farmers expressed preferences for mobile- and app-based delivery channels, especially for drought warnings, irrigation scheduling, and crop planning. This finding suggests a clear opportunity to strengthen digital advisory systems as part of national adaptation strategies, while ensuring inclusivity for farmers with lower educational attainment who may rely more on traditional communication channels (Fig. 9).

The explicit comparison between survey-only, EO-only, and combined predictor models further clarifies the relative contribution of different data sources. Survey-based variables

consistently outperformed EO-only models across all vulnerability outcomes, indicating that farmer perceptions, management practices, and institutional contexts capture dimensions of vulnerability that are not fully observable from satellite data alone. However, the integration of EO indicators improved performance relative to EO-only models and, in the case of winter vulnerability, modestly enhanced predictive accuracy beyond survey-only configurations. This suggests that EO data provide valuable contextual information on environmental stressors, even if they do not replace perception-based insights. These results align with previous work emphasizing that remote sensing is most effective when embedded within socio-environmental frameworks rather than used in isolation (Osman et al. 2025; San et al. 2024; Elagib et al. 2025).

Some limitations should be acknowledged. First, the survey data focus on actively cultivated plots and may underrepresent marginal or abandoned lands, which also contribute to rural vulnerability dynamics (Balasha et al. 2023). Second, while SHAP improves interpretability, it does not establish causal relationships between predictors and outcomes. In addition, EO predictors—particularly reanalysis-based climate variables—operate at a coarser spatial resolution than individual farm plots and therefore capture regional climatic exposure rather than field-scale variability, which limits their ability to explain fine-grained differences in perceived vulnerability. Future research should integrate longitudinal data, panel surveys, or experimental designs to better capture dynamic adaptation processes and causal pathways (Lambarraa-Lehnhardt et al. 2024). Additionally, while this study employs established machine learning methods, exploring deep learning approaches in future work could help assess whether more complex representations yield additional insights, particularly when larger or multi-temporal datasets become available.

Taken together, these findings reinforce the view that climatic vulnerability in semi-arid agricultural systems is inherently multidimensional and seasonally differentiated. The results illustrate how environmental exposure, as captured by Earth observation indicators, interacts with management practices, institutional access, and farmer knowledge to shape vulnerability perceptions in distinct ways across winter and summer seasons. While satellite-derived metrics provide essential context on spatial and temporal climate variability, the stronger explanatory power of survey-based variables highlights the central role of human decision-making and adaptive capacity in mediating climate risk (Epule et al. 2022). Situating Earth observation data within a broader socio-environmental framework therefore allows vulnerability assessments to move beyond biophysical exposure alone and better reflect the lived realities of smallholder farmers, supporting more context-sensitive interpretations of climate risk in semi-arid regions.

5 Conclusion

This study shows the value of integrating Earth observation data, farmer perception surveys, and machine learning to assess climatic vulnerability in smallholder agricultural systems in Morocco. By explicitly accounting for spatial structure and seasonal differentiation, the results show that vulnerability drivers vary markedly between winter and summer, reflecting shifts from climate exposure-dominated processes to management- and adaptation-driven responses. While remote sensing indicators provide essential spatial context on environmental variability, farmer-reported information related to soil moisture, water access, cropping

practices, and institutional support emerged as the strongest predictors of perceived vulnerability. The comparison of survey-only, EO-only, and combined models further indicates that Earth observation data complement—but do not substitute—local knowledge, particularly by enhancing interpretation of seasonal climate stress rather than directly predicting vulnerability perceptions. Together, these findings highlight the importance of coupling biophysical monitoring with participatory data to produce vulnerability assessments that are both scientifically robust and relevant for adaptation planning. The framework presented here offers a transferable approach for semi-arid regions where climate variability, water scarcity, and limited adaptive capacity continue to challenge agricultural resilience.

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Author contributions Cesar Ivan Alvarez designed the study, extracted, processed, and analyzed the data, and wrote the original draft. Katharina Waha and Adnane Labbaci contributed to the interpretation and contextual discussion regarding vulnerability in Morocco and the lived realities of farmers in the Global South. Ajit Govind and Anna Muñoz Bollas provided supervision and guidance throughout the development of the project.

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Data availability The remotely sensed and field sampling data used in this study is available from the corresponding author upon reasonable request.

Declarations

Declarations of generative AI and AI-assisted technologies in the writing process During the preparation of this work the author(s) used Grammarly and ChatGPT to improve the grammar quality. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Competing interests The authors declare that they have no competing interests.

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