

Doctoral Dissertation

**Mapping Rice Cropping Systems in Data-Scarce Regions Using
NDVI Time-Series and Dynamic Time Warping Clustering: A Case
Study of Maliana, Timor-Leste**

(東ティモールのデータ不足地域を対象とした時系列 NDVI と動的
時間伸縮法クラスタリングによる稲作体系マッピング)

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Abstract

Mapping rice cropping regimes at operational spatial scales is critical for effective irrigation planning and agricultural monitoring, particularly in regions with limited data availability and scarce field records. This research presents a remote-sensing workflow for delineating rice cropping regimes in the Maliana region of Timor-Leste, using high-resolution PlanetScope imagery and time-series clustering that accounts for spatial variation in crop phenology. Monthly NDVI was calculated from PlanetScope surface reflectance and compiled into a 48-month time series spanning December 2018 to November 2022. NDVI values were aggregated onto a hexagonal grid with a 25-meter edge length to minimize pixel-scale noise while preserving spatial detail. In total, 14,101 cultivated grid cells, covering approximately 2,289.7 hectares, were analyzed. To identify similar seasonal patterns despite temporal misalignment, Dynamic Time Warping (DTW) and k-means clustering were applied to normalized NDVI sequences. The optimal number of clusters was determined using DTW inertia and internal validity indices (silhouette, Davies-Bouldin, and Calinski-Harabasz), yielding a two-regime solution for interpretation. The resulting partition exhibits spatial imbalance: Cluster 1 comprises 3,684 cells (26.13%; approximately 598.2 ha), whereas Cluster 2 comprises 10,417 cells (73.87%; approximately 1,691.5 ha). Cluster-average phenology metrics indicate that Cluster 1 demonstrates a higher mean NDVI (0.5420 compared to 0.4693), fewer low-canopy months (6 versus 25 months below NDVI 0.45), more high-vigor months (11 versus 7 months above NDVI 0.60), and a greater frequency of peaks (8 versus 6 peaks above NDVI 0.55). These findings indicate more persistent and intensive cropping in Cluster 1. Rainfall-NDVI lag correlations further distinguish the clusters: Cluster 1 peaks at a shorter positive lag (+1 month; $r = 0.358$), while Cluster 2 peaks at a longer lag (+3 months; $r = 0.595$). These correlations reflect timing consistency rather than causality, as both clusters are influenced by shared seasonality and autocorrelation. Off-season NDVI mosaics (June–November) and overlays of digitized irrigation canals reinforce the spatial plausibility of differential irrigation access; however, formal proximity analysis and field validation remain necessary. In summary, this dissertation presents a contemporary framework for high-resolution rice regime mapping to inform irrigation management and seasonal monitoring in Timor-Leste and other data-limited regions.

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List of Abbreviations

API	— Application Programming Interface
CCF	— Cross-Correlation Function
CHI	— Calinski–Harabasz Index
CRS	— Coordinate Reference System
CVI	— Cluster Validity Indices
DBA	— DTW Barycenter Averaging
DBI	— Davies–Bouldin Index
DTW	— Dynamic Time Warping
EPSG	— European Petroleum Survey Group (coordinate reference system identifier)
FAO	— Food and Agriculture Organization (of the United Nations)
FAO GIEWS	— Global Information and Early Warning System (of FAO)
GIS	— Geographic Information System
ID / IDs	— Identifier(s)
JICA	— Japan International Cooperation Agency
MAF	— Ministry of Agriculture and Fisheries (Timor-Leste)
MAUP	— Modifiable Areal Unit Problem
NDVI	— Normalized Difference Vegetation Index
NIR	— Near-Infrared
OLS	— Ordinary Least Squares
PBC	— Public Benefit Corporation
PCA	— Principal Component Analysis
PSScene	— PlanetScope Scene
QGIS	— QGIS (Geographic Information System software)
ROI	— Region of Interest
SAR	— Synthetic Aperture Radar
SR	— Surface Reflectance
UTM	— Universal Transverse Mercator
WCSS	— Within-Cluster Sum of Squares
WGS84	— World Geodetic System 1984

Chapter 1. Introduction

1.1 Background and Context

Rice is a cornerstone of food security and rural livelihoods across Asia, where the majority of global production and consumption occurs (Khush, 2005; Sasaki, 2019). In Timor-Leste, however, domestic rice production often fails to meet national demand, and the country remains vulnerable to climate variability and external market fluctuations. A recurring barrier is not only biophysical constraints, but also limited, inconsistent, and slow-to-update agricultural information, which restricts timely, evidence-based planning in irrigation maintenance, input allocation, and climate-risk response (FAO, 2019; World Bank, 2023; FAO GIEWS, n.d.).

This problem is fundamentally spatial and temporal. Decision makers need to know where rice is cultivated, how cropping patterns vary across the landscape, and when key growth cycles occur. In data-limited environments, conventional monitoring based on field surveys and administrative statistics is typically sparse, fragmented, and difficult to update at seasonal time scales. As a result, strategic actions—such as prioritizing canal maintenance, planning irrigation scheduling support, or targeting risk-reduction services—can be mistimed or misallocated because the spatial distribution of cropping regimes is unclear or outdated (JICA & Sanyu Consultants Inc., 2007; National Directorate for Agriculture and Horticulture, 2015).

Satellite Earth observation provides a practical alternative because it enables repeated monitoring of vegetation dynamics at consistent spatial coverage across administrative boundaries (Huuborg & McCabe, 2016; Xue & Su, 2017). Vegetation indices such as NDVI—derived from red and near-infrared reflectance—are widely used as indicators of canopy vigor and seasonal change and have been successfully applied to crop phenology characterization across diverse environments (Tucker, 1979; Reed et al., 1994; Zhang et al., 2003; Zhang et al., 2006; Essaadia et al., 2022). To translate dense imagery into interpretable and comparable units, spatial aggregation frameworks such as a hexagonal lattice can reduce edge effects and support neighborhood reasoning while remaining independent of cadastral boundaries, which are often incomplete or unavailable (Birch et al., 2007; Esri, n.d.).

However, a central methodological challenge remains: temporal misalignment. Rice planting and growth stages do not occur at the same calendar time everywhere; even within a single basin, planting dates can shift due to water availability, management decisions, and rainfall timing. Naïve time-series comparisons (e.g., month-to-month

matching without alignment) risk grouping fields incorrectly because similar growth trajectories may be phase-shifted in time. Dynamic Time Warping (DTW) addresses this problem by elastically aligning time series and comparing trajectories based on their shape rather than strict calendar synchronization (Sakoe & Chiba, 1978). When applied to NDVI trajectories, DTW-based clustering provides a defensible way to detect recurring cropping-regime patterns under flexible agricultural calendars, particularly in rice systems where planting dates may vary across space (Guan et al., 2016).

Because clustering in data-scarce contexts can easily become arbitrary or over-interpreted, internal validation is non-negotiable. Robust workflow design requires explicit evaluation of clustering structure using multiple internal indices (e.g., silhouette, Davies–Bouldin, Calinski–Harabasz) and clear criteria for selecting the number of clusters (Rousseeuw, 1987; Davies & Bouldin, 1979; Calinski & Harabasz, 1974). In addition, interpretation should not rely on cluster shape alone; it should be corroborated using independent contextual evidence such as rainfall timing, off-season greenness patterns, and proximity to irrigation infrastructure.

This dissertation operationalizes a PlanetScope NDVI time-series + DTW clustering workflow to map rice cropping regimes and interpret them using rainfall timing and irrigation infrastructure. Research Aim, Objectives, and Guiding Questions.

1.2 Research Aim, Objectives, and Guiding Questions

1.2.1 Aim: This dissertation aims to develop and implement a transparent, update-ready remote sensing workflow for characterizing and mapping probable rice cropping regimes in a priority rice basin in Timor-Leste. The approach is explicitly descriptive and indicative, focusing on identifying consistent spatial patterns in seasonal vegetation dynamics and interpreting these patterns in relation to rainfall timing and irrigation context. Definitive causal attribution is not asserted without supporting external agronomic and water-delivery records.

1.2.2 Objectives

Objective 1 — Time-series construction and spatial aggregation: A multi-year, high-resolution NDVI time series will be constructed from PlanetScope imagery, with NDVI values aggregated into uniform spatial units using a hexagonal grid appropriate for phenological analysis (Huuborg & McCabe, 2016; Birch et al., 2007).

Objective 2 — DTW-based clustering and k-selection with internal validation: DTW-based k-means clustering will be applied to NDVI trajectories to identify dominant temporal regimes. The final cluster structure will be justified using multiple internal

validation criteria, including DTW inertia (elbow) and indices such as silhouette, Davies–Bouldin, and Calinski–Harabasz (Sakoe & Chiba, 1978; Rousseeuw, 1987; Davies & Bouldin, 1979; Calinski & Harabasz, 1974; Guan et al., 2016).

Objective 3 — Interpretable phenology metrics using explicit thresholds: Concise, interpretable phenology descriptors will be computed from each cluster’s NDVI behavior using threshold-based metrics that summarize canopy vigor and seasonal dynamics, such as the proportion of months with low NDVI, months above vigor thresholds, and peak characteristics (Reed et al., 1994; Zhang et al., 2003; Xue & Su, 2017).

Objective 4 — Rainfall–NDVI coupling through lag correlation: The relationship between rainfall timing and NDVI dynamics will be quantified using lagged correlations across a defined temporal window (–6 to +6 months), supporting interpretation of delayed or buffered vegetation responses under varying management contexts (Chatfield, 2003; Xue & Su, 2017).

Objective 5 — Regime interpretation and contextual validation: Descriptive cropping-regime labels (such as probable irrigation-buffered multi-season or rainfall-dependent single-season patterns) will be assigned using convergent evidence from phenology metrics, rainfall–NDVI lag response, off-season greenness checks, and spatial association with irrigation infrastructure layers (JICA & Sanyu Consultants Inc., 2007; National Directorate for Agriculture and Horticulture et al., 2015).

1.2.3 Guiding Questions

- a. Where do rice areas exhibit NDVI trajectories consistent with single-season patterns compared to those consistent with more intensive multi-season patterns?
- b. How do the identified temporal regimes correspond to rainfall timing, including lagged vegetation response across months?
- c. How do regime patterns vary with proximity to irrigation infrastructure, and how does this support the interpretation of probable water-control conditions?
- d. Which regime indicators and summary products most effectively support operational planning, such as irrigation maintenance prioritization and climate-risk targeting?

1.3 Significance of the Study

This dissertation presents a defensible, reproducible workflow for mapping rice cropping patterns in data-scarce environments. Its significance is established through

concrete outputs and methodological rigor, with contributions traceable to specific chapters and results.

Contribution 1: High-resolution, multi-year regime mapping in a data-scarce basin: High-resolution NDVI time series and hexagonal aggregation are used to generate spatially explicit regime maps suitable for operational interpretation in the Maliana basin context (Huuborg & McCabe, 2016; Birch et al., 2007).

Contribution 2: DTW clustering designed for temporal misalignment: The application of DTW-based clustering enables the workflow to account for phase shifts in crop calendars and prevents calendar-locked comparisons that may misclassify similar growth trajectories occurring at different times (Sakoe & Chiba, 1978; Guan et al., 2016).

Contribution 3: Internal validation for defensible unsupervised results: The workflow explicitly evaluates clustering structure using multiple internal indices and a DTW inertia elbow, thereby reducing arbitrariness in k-selection and enhancing interpretability (Rousseeuw, 1987; Davies & Bouldin, 1979; Calinski & Harabasz, 1974).

Contribution 4: Multi-evidence interpretation linking phenology, rainfall response, and infrastructure context: The dissertation integrates Threshold-based phenology metrics, rainfall–NDVI lag diagnostics, off-season greenness checks, and irrigation-network context to support regime interpretation using convergent evidence rather than relying on single-source inference (Xue & Su, 2017; JICA & Sanyu Consultants Inc., 2007).

Contribution 5: Replicable and update-ready mapping pipeline for other data-limited regions: As the pipeline does not require cadastral parcels or intensive field records as mandatory inputs, it is, in principle, transferable to other regions where consistent seasonal monitoring is needed, provided that local calibration and contextual datasets are available (FAO, 2011; FAO, 2021).

1.4 Scope and Limitations

The present study examines the Maliana basin in Bobonaro municipality, a region of policy significance for rice production that features gravity-fed irrigation schemes and adjacent areas reliant on rainfall (JICA & Sanyu Consultants Inc., 2007; National Directorate for Agriculture and Horticulture et al., 2015). The analysis uses satellite-derived NDVI time series and supplementary contextual layers, such as rainfall and irrigation infrastructure, that are either nationally available or compiled using transparent geospatial methods.

The interpretation of management regimes is intentionally indicative rather than definitive. The absence of plot-level agronomic data, such as field calendars, plot-specific planting and harvest dates, and yield measurements, as well as detailed records of water delivery or irrigation scheduling, limits the precision of the analysis. Consequently, the mapped regimes should be regarded as probable management patterns consistent with irrigation buffering or rainfall dependence, rather than as verified categorical ground truth.

The credibility of the workflow is supported by rigorous methodological practices and convergent lines of evidence: (i) explicit temporal alignment using dynamic time warping (DTW), (ii) evaluation of clustering through multiple internal indices, (iii) application of interpretable phenology thresholds, and (iv) contextual interpretation based on rainfall timing, off-season greenness, and association with irrigation networks. Nevertheless, internal methodological consistency does not replace the need for external validation. Additionally, NDVI is subject to limitations, including saturation at high biomass levels and sensitivity to atmospheric effects such as cloud and haze contamination. These issues are addressed through conservative interpretation and meticulous data handling, but cannot be fully eliminated (Xue & Su, 2017).

The methodological framework is designed for transferability beyond the Maliana basin. However, successful application in other regions necessitates local calibration, including knowledge of cropping calendars, rainfall seasonality, and irrigation system structure, as well as access to consistent satellite observations and essential contextual data layers.

1.5 Structural Outline

This dissertation is structured to present a coherent research program that aligns with the organization of the published paper. It progresses from contextual motivation and data constraints to a reproducible methodology, followed by regime-mapping results, and concludes with interpretation, limitations, and transferability.

Chapter 1 (Introduction) defines the food security and monitoring challenges in Timor-Leste, justifies the use of time-series remote sensing under conditions of temporal misalignment, and articulates the descriptive research aims and contributions.

Chapter 2 (Literature Review) synthesizes research on NDVI-based phenology monitoring, spatial aggregation methods, dynamic time warping (DTW)-based time-series clustering, internal validation metrics, and the interpretation of rainfall-vegetation lag relationships.

Chapter 3 (Study Area and Datasets) describes the Maliana basin and provides detailed information on the datasets utilized, including NDVI time series derived from PlanetScope imagery, rainfall data, and irrigation infrastructure layers, along with quality-control procedures.

Chapter 4 (Methodology) presents the complete workflow, including hexagonal aggregation, NDVI time-series construction, DTW-based clustering and selection of the number of clusters, calculation of phenology metrics, analysis of rainfall–NDVI lag correlations, and contextual validation using off-season greenness and irrigation network overlays.

Chapter 5 (Results) reports the outcomes of clustering and associated validity indicators, summarizes phenology metrics by regime, presents findings on rainfall–NDVI lag, and provides regime maps alongside contextual validation results.

Chapter 6 (Discussion) interprets the two-regime structure based on convergent evidence, evaluates the operational implications and limitations of the results, and discusses the potential for transferability to other data-limited regions.

Chapter 7 (Conclusion) summarizes the key findings and contributions, clearly restates the scope and limitations, and outlines steps for enhanced external validation and routine operational updates.

Chapter 2. Literature Review

This chapter reviews the literature necessary to justify the dissertation's workflow and delineate its interpretive boundaries. The structure follows the components presented in the published paper: (1) NDVI time-series phenology, (2) spatial aggregation using a hexagonal lattice, (3) time-series clustering under temporal misalignment with dynamic time warping (DTW), (4) cluster validation and model selection, and (5) rainfall-vegetation lag analysis as contextual evidence.

2.1 NDVI time-series for crop phenology

NDVI remains a widely used proxy for vegetation greenness because it exploits the contrast between red absorption and near-infrared reflectance from plant canopies (Tucker, 1979). In the context of crop monitoring, single-date NDVI measurements are generally inadequate; accurate phenological interpretation requires temporal trajectories that capture the timing and intensity of canopy development, peak biomass, and senescence (Reed et al., 1994; Zhang et al., 2003; Zhang et al., 2006). Time-series approaches are especially important in rice systems, where the cropping calendar often varies spatially and temporally due to differences in rainfall timing, water availability, and management practices.

Extensive phenology research demonstrates that the shape of the vegetation curve, rather than its magnitude alone, provides critical information for distinguishing seasonal regimes (Reed et al., 1994; Zhang et al., 2003). Consequently, summary descriptors of seasonal behavior, such as periods of sustained low NDVI, peak frequency, and duration above vigor thresholds, are commonly used. These descriptors are not absolute; rather, they serve as transparent operational metrics designed to facilitate interpretation, enable comparison across clusters, and support communication with non-technical stakeholders (Xue & Su, 2017).

High-resolution optical imagery enhances the utility of time-series phenology analysis in fragmented agricultural landscapes by minimizing mixed-pixel contamination, enabling signal stabilization through aggregation, and preserving field-scale variability (Huuborg & McCabe, 2016). Nevertheless, NDVI-based phenology is subject to recognized limitations, including saturation in dense biomass, sensitivity to atmospheric conditions, and contamination from clouds and haze (Xue & Su, 2017). As a result, NDVI trajectories can inform indicative regime characterization but do not provide definitive agronomic labels without validation against field calendars, yield data, or irrigation operation records.

In summary, NDVI time series are suitable for mapping and comparing rice canopy dynamics; however, existing literature indicates that NDVI alone cannot conclusively determine management regimes. The appropriate scientific approach is to employ NDVI in a descriptive or indicative capacity, with explicit assumptions and careful interpretation (Xue & Su, 2017; Huuborg & McCabe, 2016).

2.2 Spatial units for aggregation and neighborhood analysis: why hexagons

Time-series analysis requires a stable spatial unit to facilitate repeated measurements across multiple dates. In data-scarce environments, parcel boundaries are often missing, inconsistent, or unavailable, rendering parcel-based phenology mapping fragile and frequently irreproducible. Uniform grids provide a viable alternative by enabling consistent zonal statistics, supporting spatial comparability, and eliminating reliance on administrative or cadastral boundaries.

A hexagonal lattice is often preferred over square grids for neighborhood-based analysis because hexagons offer more uniform adjacency and reduce directional bias, resulting in a more stable representation of spatial gradients and neighborhood connectivity (Birch et al., 2007). This consideration is particularly relevant in agricultural basins, where gradients in irrigation influence, moisture availability, and management intensity typically follow curved, branching patterns, such as canal networks, which are not well represented by square-grid artifacts. In practice, hexagon aggregation supports the following:

1. the generation of stable zonal statistics from high-resolution imagery,
2. reduced edge effects compared to equivalent square partitions, and
3. improved representation of curved spatial gradients (Birch et al., 2007; Esri, n.d.).

2.3 Time-series clustering under temporal misalignment: DTW-based k-means

Unsupervised clustering provides an effective approach for identifying recurring phenological regimes across landscapes when labeled ground-truth data are scarce. A primary methodological challenge is the lack of synchronization in agricultural time series, as planting and harvest dates vary spatially due to factors such as rainfall timing, irrigation availability, and farmer management decisions. Conventional similarity metrics, such as Euclidean distance, interpret phase shifts as dissimilarity, which can artificially divide a single agronomic regime into multiple clusters based solely on temporal differences in occurrence across locations.

Dynamic Time Warping (DTW) addresses this issue by elastically aligning time series to minimize mismatches caused by temporal shifts, while preserving the similarity of trajectory shapes (Sakoe & Chiba, 1978). As a result, DTW serves as a robust similarity measure for phenological analyses in which phase misalignment is anticipated. In the remote sensing literature, DTW has been applied to vegetation time series to more effectively group trajectories that share similar seasonal patterns but differ in timing, particularly within cropping systems (Guan et al., 2016; Zhang & Hepner, 2017).

DTW is frequently combined with k-means-like clustering algorithms, in which cluster prototypes represent typical trajectory patterns. Research on DTW averaging, including global averaging and barycenter methods, facilitates more stable centroid estimation in DTW-based clustering (Petitjean et al., 2011). Differentiable variants, such as soft-DTW, offer a smooth, optimization-friendly formulation that enhances the theoretical foundation for trajectory comparison and averaging (Cuturi & Blondel, 2017). In applied settings, modern software implementations, such as tslearn, support reproducible DTW-based clustering workflows when parameters and preprocessing steps are clearly documented (Tavenard et al., 2020; tslearn developers, 2025).

2.4 Model selection and dimensionality aids

2.4.1 Elbow Method

In cluster analysis, the Elbow method formalizes the principle of parsimony by evaluating improvements in model fit as the number of clusters increases. Substantial initial reductions in within-cluster dispersion are typically followed by diminishing returns beyond a characteristic bend, which is interpreted as the optimal value of (k) (GeeksforGeeks, n.d.; Shi et al., 2021; Umaragono, Suseno, & Gunawan, 2019). To minimize subjectivity, recent recommendations include averaging results across multiple random initializations, smoothing noisy curves when necessary, and employing quantitative knee detectors such as two-segment piecewise fits, curvature or second-derivative tests, and change-point rules to programmatically identify the most pronounced change in slope on the inertia curve (Shi et al., 2021; Umaragono et al., 2019). These procedures are particularly relevant for seasonal remote-sensing series, where minor gaps or plateaus may obscure the visual identification of the bend. Formally, for Euclidean **k means** the inertia—within-cluster sum of squares (WCSS)—at a given **k** is:

$$WCSS(k) = \sum_{i=1}^k \sum_{j=1}^{n_i} (\mathbf{x}_j^{(i)}, \mathbf{c}_i)^2 \quad (1)$$

Thus, the elbow is defined as the smallest value of k beyond which additional clusters yield only minimal reductions in the total squared deviation of members from their respective centroids (GeeksforGeeks, n.d.; Shi et al., 2021). In this context, $\mathbf{x}_j^{(i)}$ represents the j -th data vector assigned to cluster i , n_i is the Euclidean centroid of cluster i .

Phenological cycles often display spatial asynchrony, which can cause Euclidean dispersion to conflate differences in timing with differences in shape. To address this, the literature augments elbow analysis with an alignment-aware metric, DTW inertia, calculated using Dynamic Time Warping (DTW) to ensure that improvements reflect shape similarity following elastic temporal alignment (Guan et al., 2016; Sakoe & Chiba, 1978; Petitjean, Ketterlin, & Gancarski, 2011). DTW inertia is defined as:

$$WCSS_{DTW}(k) = \sum_{i=1}^k \sum_{\mathbf{x} \in C_i}^{n_i} DTW(\mathbf{x}, \mathbf{c}_i) \quad (2)$$

In this context, $\mathbf{x}$ represents a univariate or multivariate time series assigned to cluster i ; C_i is the set of members in cluster i ; $\mathbf{c}_i$ denotes the DTW barycenter (DBA prototype) obtained by aligning members and averaging along their warping paths, and $DTW(\dots)$ indicates the alignment-based distance, which can be constrained by a global band such as Sakoe–Chiba to prevent unrealistic warps (Sakoe & Chiba, 1978). Under this definition, a reduction in $WCSS_{DTW}(k)$ signifies that clusters are becoming more phenologically coherent in shape rather than merely more synchronized in calendar time (Guan et al., 2016; Petitjean et al., 2011).

2.4.2 Silhouette score and Principal Component Analysis (PCA)

Principal Component Analysis (PCA) is frequently implemented prior to clustering to reduce dimensionality, concentrate variance, and mitigate noise, thereby improving separability for k-means in high-dimensional time-series contexts (Tajunisha & Saravanan, 2011; Marín-Celestino et al., 2018). After centering and scaling, observations are projected onto the principal components, and clustering is conducted in this reduced space to promote cluster cohesion and separation. The quality of the resulting partitions is evaluated using the Silhouette coefficient (Rousseeuw, 1987), which quantifies the balance between within-cluster cohesion and nearest-cluster separation. The same distance metric applied during clustering (Euclidean or DTW-based summaries) is used to compute the coefficient for each observation i as follows:

$$s(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}} \quad (3)$$

Here, $a(i)$ represents the mean dissimilarity between observation i and all other points within its assigned cluster, while $b(i)$ denotes the lowest mean dissimilarity between i and any other cluster. Values close to (+1) reflect confident cluster assignment, values near (0) indicate ambiguous or boundary cases, and negative values suggest potential misclassification (Rousseeuw, 1987).

Consistent with previous studies, average Silhouette widths were calculated for candidate values of (k) (e.g., 2–5) and compared across multiple initializations. Silhouette profiles were examined in conjunction with low-dimensional PCA scatterplots to confirm cluster compactness and separation prior to evaluating additional indices (Tajunisha & Saravanan, 2011; Marín-Celestino et al., 2018; Rousseeuw, 1987).

2.4.3 Cluster Validity Index: Davies–Bouldin Index (DBI) and Calinski–Harabasz Index (CHI)

In addition to the Elbow and Silhouette methods, the literature emphasizes internal cluster validity indices (CVIs), such as the Davies–Bouldin Index (DBI) and the Calinski–Harabasz Index (CHI), as important tools for evaluating partition compactness and separation from multiple perspectives. These indices are recognized for their label independence and applicability to any number of clusters. However, comparative studies demonstrate that each index relies on specific assumptions about cluster geometry. Therefore, it is recommended to interpret these indices collectively, with careful attention to data preprocessing procedures and the selection of distance metric (Awong & Zielińska, 2023; Wang & Xu, 2019).

According to Davies and Bouldin (1979), the DBI quantifies, for each cluster, the maximum ratio of within-cluster scatter to between-centroid separation. Lower DBI values indicate more compact and better-separated clusters:

$$DBI = \frac{1}{N} \sum_{i=1}^N \max_{i \neq j} \left(\frac{s_i + s_j}{d_{ij}} \right) \quad (4)$$

Here, N denotes the number of clusters; s_i represents the average distance of members in cluster i to its centroid; and d_{ij} is the distance between the centroids of clusters i and j . Typically, s_i and d_{ij} are calculated using the same dissimilarity measure as the clustering algorithm, most often Euclidean distance, although DTW-based measures may be applied in time-series contexts (Davies & Bouldin, 1979).

The Calinski–Harabasz Index (CHI) is a criterion that evaluates the ratio of between-cluster dispersion to within-cluster dispersion (Calinski & Harabasz, 1974). Higher CHI

values indicate that clusters are both well separated and internally compact. In comparison to the Davies-Bouldin Index (DBI), the Calinski-Harabasz Index (CHI) tends to favor partitions characterized by widely separated centroids and clusters exhibiting low, uniform scatter. This property renders CHI particularly effective for detecting global structure, even when no specific cluster pair presents significant issues (Wang & Xu, 2019) [53]. Nevertheless, the literature identifies two recurring limitations: first, CHI may increase with the number of clusters in small samples or when minor splits reduce within-cluster variance without meaningfully enhancing separation; second, CHI may prefer spherical or balanced clusters when computed in the raw feature space (Awong & Zielińska, 2023; Wang & Xu, 2019). A common mathematical form is:

$$CHI = \frac{B(K) \cdot (N - K)}{W(K) \cdot (K - 1)} \quad (5)$$

In this formula, N is the number of samples, K is the number of clusters, $B(K)$ denotes the between-cluster dispersion, and $W(K)$ represents the within-cluster dispersion. The equivalent variance-ratio form CHI is frequently reported in clustering studies (Calinski & Harabasz, 1974).

2.5 Rainfall-vegetation coupling and lag interpretation

In geophysical time-series analysis, the timing of vegetation response to precipitation is typically summarized using monthly Pearson cross-correlations. This approach shifts rainfall by an integer lag and compares it to contemporaneous greenness (Chatfield, 2003; Box et al., 2015). Following this convention, the correlation at lag (k) months is defined as:

$$r_k = \text{corr}(\text{Rain}_t, \text{NDVI}_{t+k}) \quad (6)$$

In this context, t indexes months in the overlapping period following the lag shift, using pairwise complete alignment. Rain_t represents monthly precipitation at month t . NDVI_{t+k} denotes monthly greenness measured k months after t .

In this formula, positive lags $k \geq 0$ indicate that greenness follows rainfall by k months. This pattern is consistent with soil-moisture recharge and management delays documented in hydro-ecological studies (Vicente-Serrano et al., 2012; Wu et al., 2015). To ensure comparability across stations and pixels, the series are aligned on common months using pairwise-complete matching and evaluated over a symmetric lag window $k \in [-6, +6]$, which encompasses typical response times for monthly NDVI in monsoonal and semi-arid environments (J & Peters, 2003; Chen et al., 2020).

Consistent with previous studies, the interpretable delay is defined as the best positive lag, specifically the value of $k \geq 0$ that maximizes rk . This provides a concise indicator of how rapidly vegetation responds to precipitation inputs (Kamthonkiat et al., 2005; Herrmann, Anyamba, & Tucker, 2005). To validate this timing signal and minimize the risk of spurious associations, the literature recommends lagged scatter diagnostics. This involves plotting $Rain_t$ against $NDVI_{t+k}$ at the selected k , overlaying ordinary least squares fits, and visually assessing the slope sign, potential leverage points, and seasonal clustering patterns (Weiss et al., 2004; Meyer & Millar, 1999). Because both rainfall and NDVI often exhibit seasonality and autocorrelation, peak cross-correlations may reflect phase alignment rather than a strictly causal relationship (Chatfield, 2003; Box et al., 2015). As a result, recent studies emphasize interpretation on the positive-lag side, where vegetation follows climate.

2.6 Where this dissertation fits in the literature

The literature provides foundational elements: NDVI time-series phenology is effective for monitoring seasonal dynamics (Reed et al., 1994; Zhang et al., 2003), dynamic time warping (DTW) addresses temporal misalignment in trajectory comparisons (Sakoe & Chiba, 1978; Guan et al., 2016), and internal indices can justify clustering structure when external labels are limited (Rousseeuw, 1987; Davies & Bouldin, 1979; Calinski & Harabasz, 1974). However, there remains a lack of end-to-end, high-resolution, and interpretable regime mapping pipelines that are both methodologically rigorous and operationally interpretable, particularly in data-scarce, fragmented rice landscapes.

The gaps:

- Many phenology mapping studies assume stable calendars or use similarity metrics that penalize phase shifts, which is a poor fit for rice systems with variable planting dates (Guan et al., 2016).
- Unsupervised regime maps are frequently published with minimal internal validation and insufficient justification for selecting k , which undermines their defensibility (Rousseeuw, 1987; Davies & Bouldin, 1979; Calinski & Harabasz, 1974).
- Interpretations are often based solely on NDVI data, lacking triangulation with rainfall timing and infrastructure context, or they overstate causality in the absence of external records (Chatfield, 2003; Xue & Su, 2017).
- In data-scarce contexts, parcel boundaries are often unreliable, yet many workflows continue to rely on them instead of adopting reproducible spatial units (Birch et al., 2007).

This research addresses these gaps through the following contributions:

- DTW-based clustering is applied explicitly to address temporal misalignment in rice phenology trajectories (Sakoe & Chiba, 1978; Guan et al., 2016).
- Internal validation and transparent k-selection are enforced using multiple indices rather than relying on a single metric (Rousseeuw, 1987; Davies & Bouldin, 1979; Calinski & Harabasz, 1974).
- Hexagon-based aggregation is employed as a reproducible spatial sampling framework independent of parcel datasets, enabling stable zonal statistics and coherent spatial interpretation (Birch et al., 2007; Esri, n.d.).
- Regimes are interpreted using convergent evidence, including phenology metrics, rainfall lag response, off-season greenness, and irrigation proximity, while maintaining an appropriately cautious 'indicative, not definitive' stance consistent with the limitations of NDVI and time-series analysis (Xue & Su, 2017; Chatfield, 2003).

Chapter 3. Study Area and Datasets

3.1 Study Area: Maliana Basin, Bobonaro

Maliana is located on the central floor of Bobonaro's west–east oriented alluvial plain, predominantly below 100 meters above sea level. The basin receives inflow from the Bulobu, Nunura, and Malibaka rivers, and is situated approximately 149 kilometers southwest of Dili and a few kilometers from the Indonesian border ($8^{\circ} 52' -9^{\circ} 20' \text{ S}$; $124^{\circ} 12' -125^{\circ} 26' \text{ E}$). The regional gradient channels runoff and fine sediments onto clay-rich lowlands, creating conditions favorable for ponded rice cultivation (JICA & Sanyu Consultants Inc., 2015).

The region has a monsoonal climate with distinct wet and dry seasons, during which irrigation demand peaks. Hydromorphic clays are widespread across the plain, while levee and backswamp facies generate micro-relief that can delay field access and transplanting by several weeks. Settlements, along with a network of roads and tracks, connect villages to mills and the municipal center, reinforcing Maliana's role as a distribution hub. Two gravity irrigation schemes, Maliana-I and Maliana-II, as shown in Figure 1, divert river flows to the command area through main and secondary canals. Although earlier flood events reduced the original command area, perennial irrigation service remains substantial following rehabilitation efforts. A 2008 upgrade nearly doubled the irrigable area of Maliana-I. Together, these schemes support cropping intensities exceeding 1.3 in well-served laterals (JICA & Sanyu Consultants Inc., 2015).

Maliana is a significant contributor to Timor-Leste's rice production. The planted area expanded from approximately 866 hectares to 3,503 hectares between 2016 and 2019, while average yields of about 3.6 tons per hectare exceeded the national average of approximately 2.5 tons per hectare (FAO, 2021). Recent municipal records report an output of roughly 7,173 tons of unmilled rice in 2024 (Autoridade Munisípiu Bobonaro, 2025), and national assessments identify the basin as one of the few high-potential paddy districts (JICA & Sanyu Consultants Inc., 2015).

Maliana was selected as the study site due to its strategic significance as an irrigated rice basin in Timor-Leste, providing a representative case for regime mapping to inform irrigation planning and production monitoring. The basin encompasses both irrigation-supported paddy fields and rainfall-dependent areas, resulting in anticipated spatial gradients in crop phenology and off-season canopy persistence. These characteristics render Maliana an appropriate context for assessing the internal consistency and spatial coherence of time-series-derived regimes relative to irrigation infrastructure.

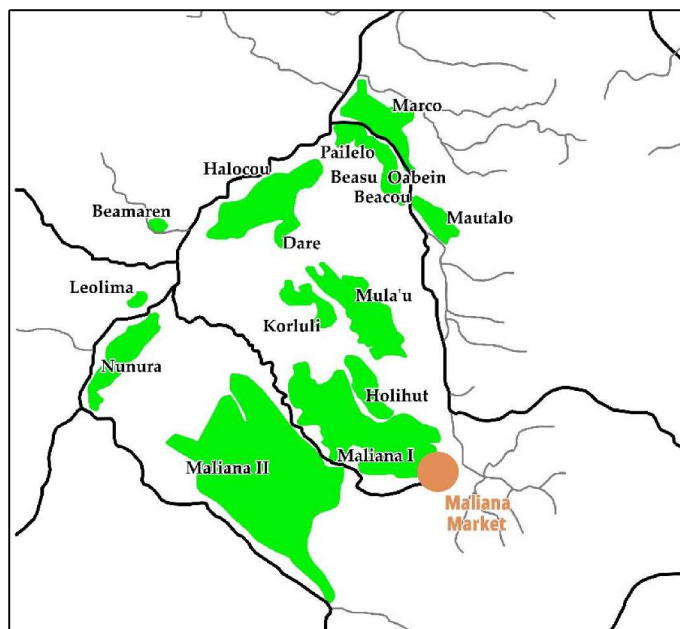
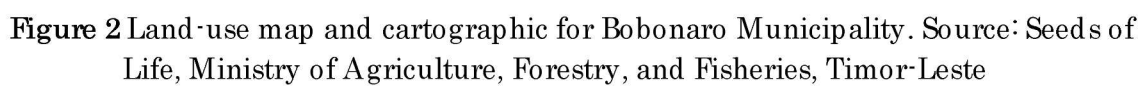


Figure 1 Regional irrigation schemes (Maliana-I and Maliana-II).

Analysis of the Bobonaro Land Use Map, produced with Seeds of Life (2005) and shown in Figure 2, shows that cropland is concentrated on the low-lying floodplain. Rice fields are clustered along flood-recession pockets, while broader agricultural areas occupy nearby terraces and levees. Hydrologic layers, such as rivers, streams, braided beds, and areas marked as “land subject to inundation,” outline seasonal water pathways. These pathways support double-cropping near head and mid-laterals and restrict cultivation on rain-dependent margins. Administrative and settlement layers link production zones to service centers and road corridors, reinforcing Maliana’s role in regional distribution.

Figure 3 defines the final study area as a hexagonized extent that overlays land-use and hydrologic patterns with the Maliana-I/II context. This approach ensures the analysis focuses on the core irrigated plain, where phenological variability and irrigation effects are most significant.



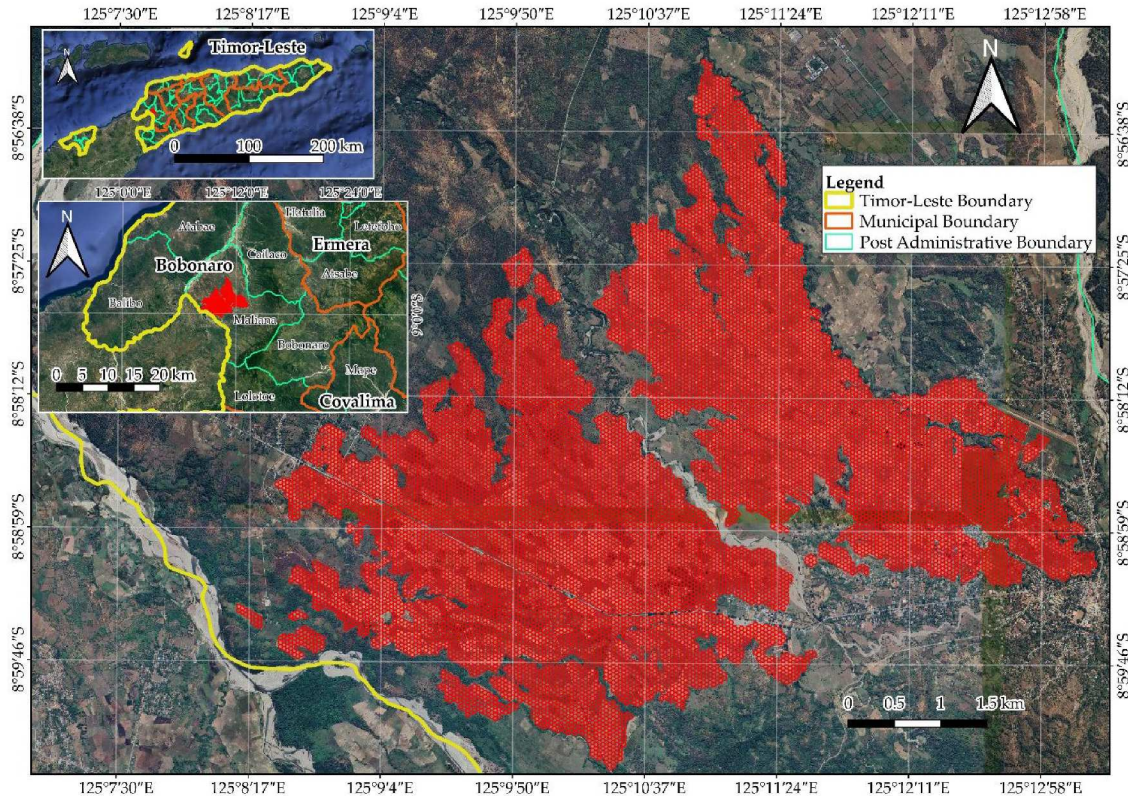


Figure 3 Study area in Bobonaro Municipality, Timor-Leste, showing the area of interest within national, municipal, and post-administrative boundaries.

3.2 PlanetScope NDVI Time Series

PlanetScope multispectral imagery (PSScene–Surface Reflectance) from Planet Labs was utilized to generate a high-resolution NDVI time series tailored for smallholder paddy systems. The Surface Reflectance product is both orthorectified and atmospherically corrected, facilitating consistent multi-temporal analyses. Each selected scene is accompanied by quality metadata, including acquisition time, solar and view geometry, and cloud indicators, which enable systematic pre-analysis screening.

To reduce contamination from cloud cover and geometric distortions, scenes were systematically screened using metadata and excluded if cloud coverage exceeded 20 percent or if severe off-nadir viewing was present. Only scenes meeting these quality criteria were retained for NDVI calculation and monthly compositing. Excluded scenes were omitted from clustering, phenological metric derivation, and rainfall coupling analyses to prevent the introduction of spurious temporal variability unrelated to crop processes.

For each retained scene, the Normalized Difference Vegetation Index (NDVI) was computed as:

$$NDVI_{planetScope} = \frac{\rho NIR_{planetScope} - \rho Red_{planetScope}}{\rho NIR_{planetScope} + \rho Red_{planetScope}} \quad (7)$$

where ρNIR and ρRed represent surface reflectance values from the near-infrared and red spectral bands, respectively. Some of the results are shown in Figure 4, the NDVI Time-Series Map for the Main-season period.

The analysis window extends from December 2018 to November 2022, encompassing 48 monthly observations. The Normalized Difference Vegetation Index (NDVI) was aggregated to a monthly resolution to align with rainfall data and reduce noise associated with irregular acquisition frequency and variable scene counts per month. All subsequent analyses, including Dynamic Time Warping (DTW) clustering, phenology metrics, and rainfall lag correlation, employ this consistent monthly window. Any alternative date ranges mentioned in earlier drafts are now outdated and should be replaced to maintain internal consistency.

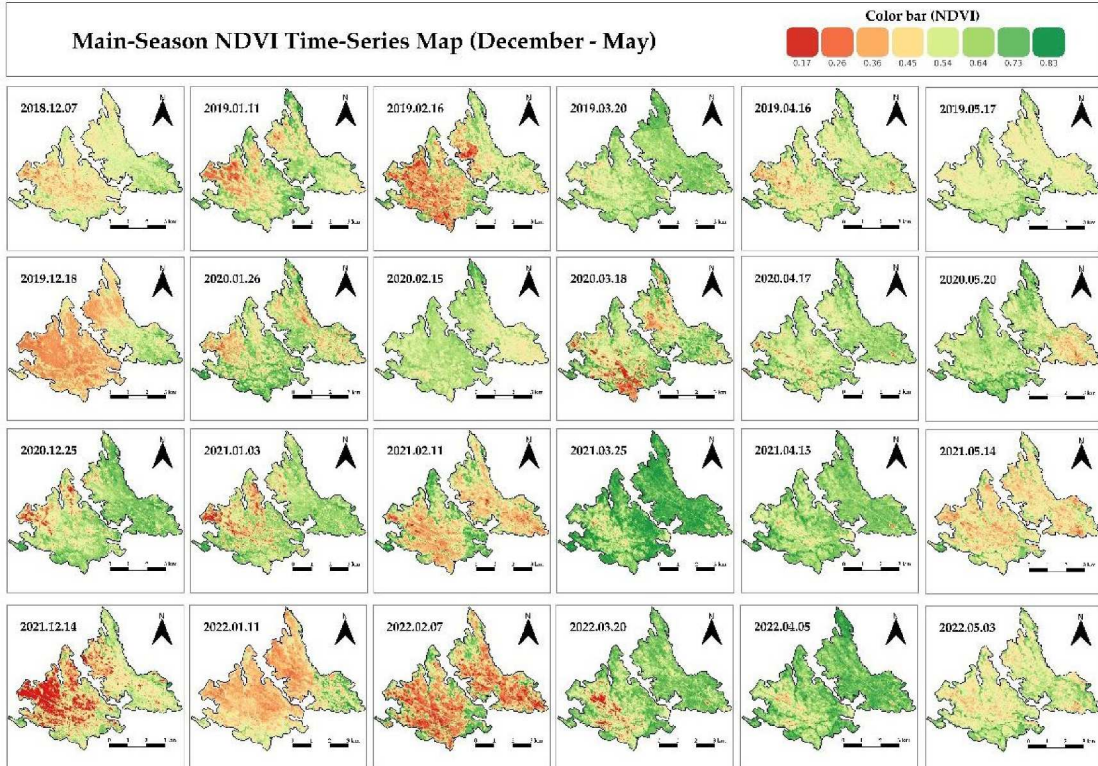


Figure 4 Main-season NDVI Time-Series Map (December - May)

In rice systems, dense NDVI time series effectively track short-lived phenological events such as flooding, transplanting, panicle initiation, heading, and senescence, as well as episodic stress from drought or excess water (Xiao et al., 2010; Zhang et al., 2003, 2006). Recent field validations confirm NDVI's ability to capture crop phenological signatures (Bhatti et al., 2024). Combining NDVI with complementary indices in high-resolution PlanetScope imagery also enhances sub-field detection of rice diseases and management effects, supporting precision agriculture applications (Shi et al., 2018).

Accordingly, NDVI rasters derived from PlanetScope constitute the primary inputs to the phenology time-series analysis and clustering workflow used in this study (Xue & Su, 2017; Huuborg & McCabe, 2016).

3.3 Rainfall Data (Monthly Aggregation)

Monthly average rainfall data were acquired from the Agro-Meteorology Section of the Ministry of Agriculture and Fisheries (MAF), Timor-Leste, and processed at a monthly temporal resolution to ensure consistency with the NDVI time series. Rainfall was measured at 0.2 mm increments and subsequently aggregated to monthly means for analytical purposes. The rainfall dataset was temporally aligned with the NDVI dataset (December 2018 to November 2022) to avoid spurious lag correlations arising from non-concurrent time windows. These rainfall data were used for monthly lag correlation analysis and for diagnostic scatterplot interpretation, as detailed in Chapter 4.

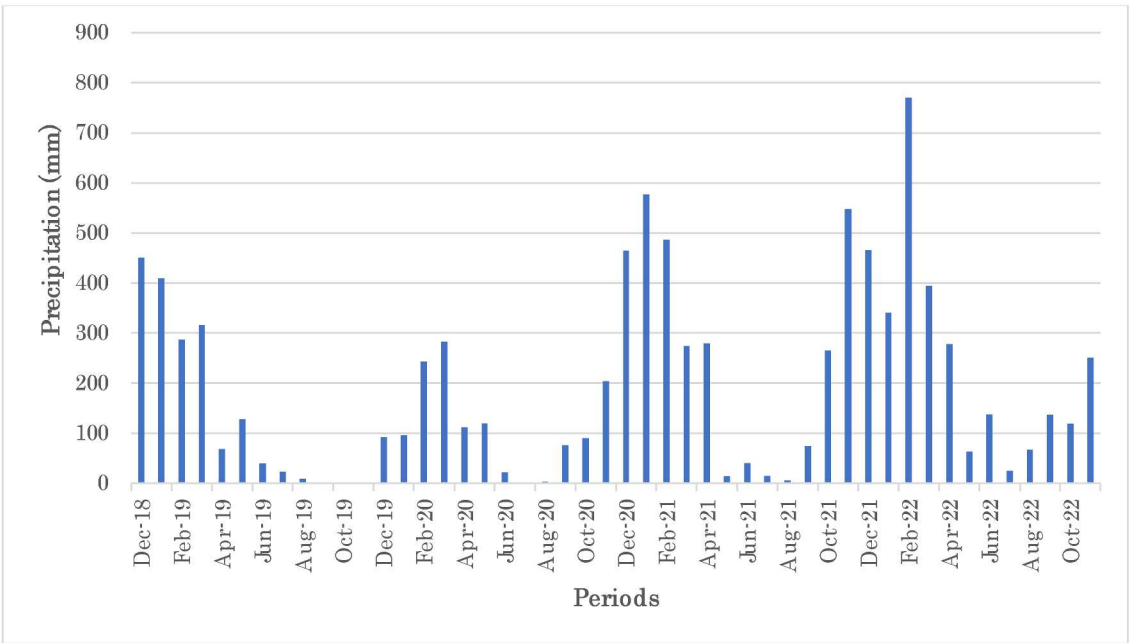


Figure 5 Monthly precipitation (mm) for the Maliana area, December 2018–November 2022. *Source:* Ministry of Agriculture and Fisheries (MAF), Agro-Meteorology

3.4 Irrigation and Orthophoto Layers

Reference irrigation vector data layers for the Maliana-I scheme were obtained from the Japan International Cooperation Agency (JICA, Timor-Leste). High-resolution orthophotos were sourced from the Centro Nacional de Dados Geoespaciais under the Ministry of Planning and Strategic Investment. All datasets were standardized to UTM WGS84 Zone 51S (EPSG: 32751) and visually checked against commercial satellite base maps for positional accuracy. In QGIS 3.40.3-Bratislava, we digitized main, secondary, and tertiary canals and key control structures as GeoPackage layers (Figure 6), applied topology rules to ensure no gaps or overlaps and consistent connectivity, and recorded class, status, source, and observable dimensions or lining for each feature. The resulting canal vectors and structures were overlaid on DTW-derived NDVI clusters to analyze spatial patterns of hydraulic reach and off-season greenness, supporting the distinction between irrigated double-cropping and rain-dependent regimes.

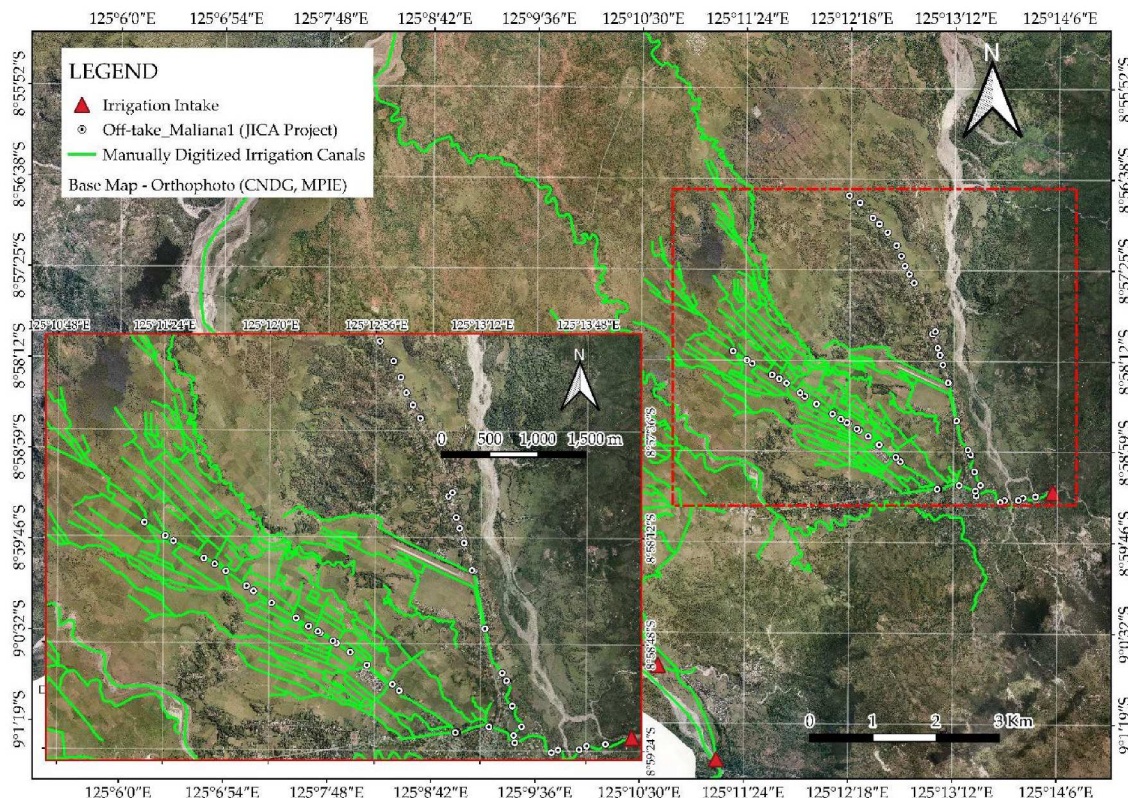


Figure 6 Maliana-I irrigation network over orthophoto—digitized canals

Chapter 4. Methodology

This chapter implements the NDVI–DTW time-series workflow to characterize rice cropping regimes in the Maliana basin. The structure adheres to the research flow chart (Figure 6) and comprises four interrelated components: (i) data inputs, (ii) preprocessing and spatial framework, (iii) time-series clustering and metrics, and (iv) interpretation, validation, and outputs. This workflow is tailored for data-scarce environments, where plot-level crop calendars, yield measurements, and irrigation delivery records are not available at the spatial and temporal resolutions necessary for external validation.

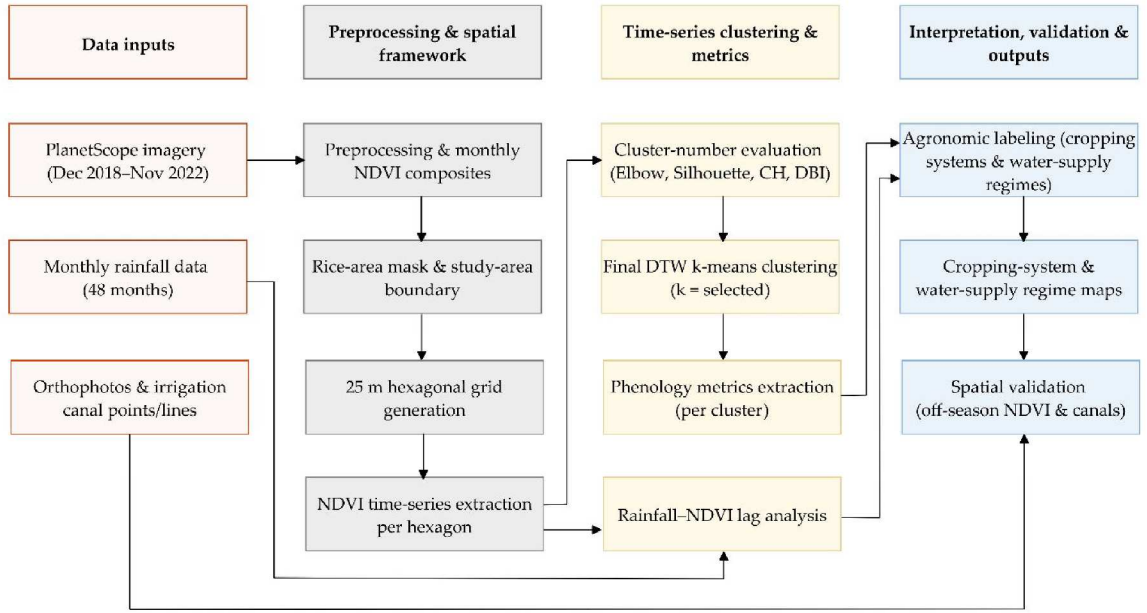


Figure 7 Research Flow chart

Overview of flowchart dependencies:

- PlanetScope imagery is processed to generate monthly NDVI composites, which are then masked and overlaid with a 25-meter hexagonal grid. NDVI time-series are then extracted for each hexagon. Subsequent steps include (a) cluster-number evaluation, DTW k-means clustering, and derivation of phenology metrics, and (b) rainfall–NDVI lag analysis.
- Monthly rainfall data spanning 48 months is used exclusively for the rainfall–NDVI lag analysis, which subsequently informs agronomic labeling.
- Orthophotos and irrigation canal data are incorporated into the spatial validation step, which combines off-season NDVI with canal locations and further supports the interpretation of labeled regimes.

4.1 Data Inputs

Three datasets are integrated within the workflow: (1) PlanetScope imagery, which is used to construct monthly NDVI time series at field-relevant resolution; (2) monthly rainfall data, which enables diagnosis of timing and moisture dependence through lag correlation; and (3) orthophotos and irrigation infrastructure layers, which are employed to assess the spatial plausibility of the derived regimes. The workflow uses a fixed temporal window from December 2018 to November 2022 to ensure a consistent time extent. This period provides 48 monthly observations, which are used uniformly for clustering, phenology metrics, and rainfall coupling.

- **PlanetScope imagery (December 2018–November 2022):** PSScene–Surface Reflectance, orthorectified and atmospherically corrected to surface reflectance, is used to compute NDVI and generate monthly composites.
- **Monthly rainfall data (48 months):** Monthly average rainfall values are aligned with the NDVI series and are used exclusively for lag analysis.
- **Orthophotos and irrigation canals/control structures:** Canal lines and key points, such as intakes and junctions, are used for overlay-based consistency checking and for optional distance-to-canal diagnostics.

All spatial datasets were standardized to WGS 84 / UTM Zone 51S (EPSG:32751) to ensure accurate metric distances and areas during grid generation, overlay, and distance calculations. Geospatial data preparation was conducted in QGIS 3.40.3. Time-series clustering and statistical diagnostics were conducted in Python 3.13.5, utilizing tslearn for DTW k-means and standard scientific libraries for validation metrics and regression analyses.

4.2 Preprocessing and spatial framework

This component transforms raw PlanetScope scenes into a harmonized monthly NDVI cube and establishes the spatial sampling unit for the analysis. The processing sequence is critical: quality screening and monthly compositing are conducted prior to time-series extraction to prevent the introduction of cloud or geometric artifacts into the data trajectories. The rice or cultivated mask and study boundary are applied before finalizing grid retention counts. The hexagonal grid is generated using a metric coordinate reference system to ensure that subsequent distance-to-canal and spatial summaries are accurate. The final output is a single analysis-ready dataset consisting of an $N \times T$ matrix of monthly NDVI values (N cultivated hexagons, $T = 48$ months), along with aligned rainfall months and reference canal layers for subsequent analyses.

4.2.1 Preprocessing and monthly NDVI composites

PlanetScope scenes were filtered using metadata to minimize contamination from cloud cover and view-geometry artifacts, both of which can reduce NDVI and introduce artificial temporal variation. Scenes with more than 20% cloud coverage or severe off-nadir viewing were excluded. The remaining scenes were used to calculate NDVI from surface reflectance, and these NDVI values were aggregated to a monthly resolution to align with the monthly rainfall series. Monthly compositing further reduces residual noise and establishes a consistent temporal grid (T=48) appropriate for time-series clustering.

- Apply a scene retention rule by excluding scenes with cloud cover greater than 20 percent and those exhibiting severe off-nadir geometry indicators.
- Calculate the Normalized Difference Vegetation Index (NDVI) for each retained scene using surface reflectance data (Tucker, 1979).

$$NDVI_{PlanetScope} = \frac{\rho NIR_{PlanetScope} - \rho Red_{PlanetScope}}{\rho NIR_{PlanetScope} + \rho Red_{PlanetScope}} \quad (7)$$

where ρNIR and ρRed represent surface reflectance values from the near-infrared and red spectral bands, respectively.

4.2.2 Rice-area mask and study-area boundary

Clustering and phenology metrics are restricted to cultivated rice areas by applying a rice or cultivated-area mask to the study domain. The mask is implemented before finalizing the analysis lattice, and only hexagons that overlap cultivated parcels are retained. This approach prevents the clustering algorithm from generating spurious regimes that merely distinguish forest, water, urban, or mangrove NDVI patterns from crop NDVI patterns. Visual inspection with orthophotos or base maps confirms that retained hexagons do not systematically overlap non-cultivated classes. This restriction serves as a core defensibility constraint: regime labels are assigned exclusively to cultivated areas, and all mapped outputs should be interpreted as conditional on this domain restriction.

4.2.3 Hexagonal grid generation

A continuous hexagonal lattice served as the spatial sampling framework to ensure stable zonal statistics and a uniform neighborhood structure. Hexagons offer six equidistant neighbors and minimize directional bias compared to square grids, thereby enhancing spatial aggregation and neighborhood-consistency reasoning (Birch et al.,

2007). Grid generation and all distance-based operations were conducted in WGS 84 / UTM Zone 51S (EPSG:32751) to maintain metric units. Each hexagon received a unique identifier that served as the primary key for joining time-series tables across dates and for mapping cluster labels. Following application of the cultivated mask, the analysis domain comprised $N = 14,101$ cultivated hexagons, consistent with the published paper.

4.2.4 NDVI time-series extraction per hexagon

For each selected PlanetScope NDVI acquisition date, zonal statistics were calculated to obtain the mean NDVI for each retained hexagon.

Scene-level mean NDVI values for each hexagon were aggregated into date-stamped tables and then consolidated across all acquisition dates. Because the canonical workflow operates at a monthly temporal resolution, scene-level values within the same month were averaged to produce monthly NDVI estimates. The resulting dataset is organized as an $N \times T$ matrix X , where each row represents a cultivated hexagon and each column corresponds to a monthly interval from December 2018 to November 2022.

For subsequent time-series analysis using `tslearn`, the matrix was reshaped to $N \times T \times 1$, ensuring that each sample is represented as a univariate time series indexed by time along the second axis.

4.3 Time-series clustering and metrics

The selection of the number of clusters (k) in this study followed a systematic and reproducible procedure, rather than an arbitrary assignment. Multiple internal validation indices were computed across a range of candidate k values to guide this process. For each candidate k , the DTW-based k -means algorithm was applied using the standardized model parameters established previously in this chapter, including normalization, DTW constraints, and reproducibility settings. Following model fitting, cluster compactness and separation were evaluated using the indices described in subsequent sections. The optimal k was identified through a two-step decision rule: first, by locating the point at which further increases in k produced minimal gains in within-cluster compactness (the elbow criterion), and second, by verifying that the selected k was supported by separation and dispersion metrics, indicating higher inter-cluster separation and reduced overlap.

This approach mitigates the risk of selecting cluster solutions that appear visually appealing but lack stability or are prone to over-segmentation.

4.3.1 Cluster-number evaluation

4.3.1.1 Elbow Method

Candidate cluster numbers (k) were evaluated using the dynamic time warping (DTW)-based elbow criterion, implemented with `tslearn`'s `TimeSeriesKMean`. The gridded NDVI table was imported from a CSV file and reshaped into a three-dimensional time-series array of dimensions ($N \text{ series} \times T \text{ months} \times 1 \text{ variable}$). The time series was scaled using `TimeSeriesScalerMinMax()` with default pipeline settings. For each candidate k in the range 2 to 8, a `TimeSeriesKMeans` model was fitted to the scaled series using the "dtw" metric, or "softdtw" if specified. DTW alignment was constrained by a Sakoe–Chiba global constraint with a radius of 3 months. Model stability and reproducibility were ensured by setting `n_init = 3`, `max_iter_barycenter = 30`, and `random_state = 0`. The DTW inertia value was extracted from `km.inertia_` for each k and plotted to generate an elbow curve. The optimal number of clusters was identified as the smallest k for which additional clusters yielded only marginal decreases in inertia.

4.3.1.2 Silhouette score and Principal Component Analysis (PCA)

The number of candidate clusters (k) was evaluated using the silhouette criterion as an internal consistency measure, implemented with `scikit-learn` (`silhouette_score` and `silhouette_samples`). Since silhouette computation is most stable and efficient with Euclidean distances, the scaled NDVI time series were transformed into a lower-dimensional Euclidean feature space using Principal Component Analysis (PCA) (`sklearn.decomposition.PCA`) with `n_components` set to 2. For each candidate k in the range of 2 to 5, cluster labels were generated using `KMeans` (`sklearn.cluster.KMeans`) fitted in the PCA-transformed space with `n_init` set to 3, `max_iter` set to 300, and `random_state` set to 0. The mean silhouette score (`silhouette_score`) was recorded for each k , and per-sample silhouette values (`silhouette_samples`) were used to assess within-cluster cohesion and between-cluster separation. Higher, more stable silhouette profiles were considered evidence supporting the selection of an appropriate k .

4.3.1.3 Davies–Bouldin Index (DBI) and Calinski–Harabasz Index (CHI)

Cluster solutions were evaluated using the Davies–Bouldin Index (DBI), calculated with `scikit-learn` (`davies_bouldin_score`). For each candidate value of k from 2 to 5, cluster labels generated by `KMeans` in the principal component analysis (PCA) space (PCA `n_components = 2`, `KMeans n_init = 3`, `max_iter = 300`, `random_state = 0`) were used to assess DBI based on a Euclidean feature representation of the scaled normalized

difference vegetation index (NDVI) time series. DBI values were summarized for each k . Lower DBI values indicated more compact clusters with greater separation from their nearest neighboring clusters. The DBI trend was used to support the selection of k in conjunction with elbow and silhouette analysis results.

The Calinski–Harabasz Index (CHI) was computed as an additional internal validation criterion using `scikit-learn` (`calinski_harabasz_score`). For each candidate value of k from 2 to 5, CHI was calculated based on the candidate partitions generated by KMeans in principal component analysis (PCA) space (PCA `n_components` = 2, KMeans `n_init` = 3, `max_iter` = 300, `random_state` = 0) using a Euclidean feature representation of the scaled normalized difference vegetation index (NDVI) time series. Higher CHI values indicated stronger between-cluster separation relative to within-cluster dispersion. CHI was employed to confirm that the selected k was consistently supported by multiple internal validity measures.

4.3.1.4 Selecting the number of clusters (k)

We adopt a two-track, complementary approach:

- **Shape-aware elbow (primary):** Run DTW k -means for $k = 2$ to 8 and plot DTW inertia (within-cluster DTW distance to the barycenter) versus k . The elbow, where marginal gains diminish, indicates plausible values of k using the same distance metric as the clustering method.
- **Shape-informed diagnostics (secondary):** For $k = 2$ to 5, project the scaled series into two dimensions using PCA (for visualization only), cluster with Euclidean k -means in this reduced space, and compute internal validity indices on the original scaled series: (i) Silhouette (higher is better), (ii) Davies–Bouldin (DBI) (lower is better), and (iii) Calinski–Harabasz (CHI) (higher is better). We generate (i) silhouette panels to assess per-cluster cohesion and overlap, and (ii) PCA scatterplots to visually evaluate separability.
- **Decision rule:** We select k by consensus, prioritizing a strong elbow and favorable internal indices. Preference is given to the most parsimonious k that maintains clear separation, avoiding over-partitioning unless justified by indices and visualizations.

4.3.2 Final model fitting and labeling

After selecting k , the final clustering model is implemented using DTW-based k -means, with DTW barycenter averaging (DBA) used to estimate cluster prototypes. Each hexagon time series is treated as a univariate sequence and normalized individually to the $[0,1]$ range via per-series Min–Max scaling, which emphasizes trajectory shape over

absolute magnitude. Time-series clustering was conducted using DTW-based k-means (`TimeSeriesKMeans`) with a Sakoe–Chiba band radius of 3 (`metric_params = {sakoe_chiba_radius: 3}`). Cluster prototypes were updated using DTW Barycenter Averaging (DBA). To ensure solution stability, the model was executed with `n_init = 3`, prototype optimization set to `max_iter_barycenter = 30`, and a fixed seed (`random_state = 0`) to guarantee reproducibility of the final clustering assignments and centroids. The workflow yields (i) cluster assignments for each hexagon, (ii) barycenter prototype curves for each cluster, and (iii) prototype envelopes or variability summaries. These cluster labels are subsequently used in phenology metric extraction, rainfall-lag analysis, spatial mapping, and agronomic interpretation.

4.4 Phenology Metrics

Phenology metrics are derived from monthly NDVI time-series to facilitate the interpretation of cluster morphologies as quantitative descriptors of canopy dynamics. These metrics are calculated at the hexagon scale and subsequently aggregated by cluster using measures of central tendency and distributional summaries. Consistent with established rice phenology literature and the referenced workflow, three threshold-based indicators are employed: low canopy months, vigorous, and vigorous months. These thresholds are intended to characterize periods of sustained canopy density during peak growth phases and serve as descriptive metrics rather than direct yield proxies.

The operational definitions for these thresholds are as follows, in alignment with the published methodology:

- A low-canopy month is defined as any month with an NDVI below 0.45.
- A vigorous peak corresponds to a local maximum in the NDVI series with a value of at least 0.55.
- A vigorous month is any month in which NDVI is greater than or equal to 0.60.
- The core metrics computed for each hexagon include the mean, minimum, and maximum NDVI; amplitude; counts of low-canopy months; counts of vigorous months; counts of vigorous peaks; and the number of phenological cycles per year.

4.5 Rainfall–NDVI lag analysis

Rainfall–NDVI lag relationships were quantified using Pearson lag cross-correlation to evaluate how rainfall variability precedes or follows vegetation response at the cluster level. Analyses were performed in Python, employing `pandas` and `numpy` for time-series processing and `matplotlib` for visualization.

Monthly rainfall and cluster-level NDVI series were imported from tabular files (CSV), and the Period field was converted to a monthly datetime index to ensure accurate temporal alignment. For each cluster time series (identified by columns labeled “Cluster”), Pearson correlations were calculated across symmetric lags of ± 6 months ($\text{max_lag} = 6$). Lagged correlation was defined as $\text{corr}(\text{Rain}_t, \text{NDVI}_{\{t+k\}})$ for each integer lag k , following the removal of missing values and consistent pairing of observations. Correlation values were recorded for all lags and summarized per cluster by identifying the optimal positive lag ($k \geq 0$) with the maximum correlation, which served as an indicator of the most probable rainfall lead time associated with the NDVI response.

Outputs were generated to support both reporting and interpretation. A multi-cluster lag cross-correlation curve (Pearson correlation versus lag) was produced, and the complete lag–correlation results were exported to CSV for traceable downstream analysis. When enabled, additional lagged scatter plots were generated for non-negative lags (0-6 months) to visualize the rainfall–NDVI relationship at each assumed lead time, with a fitted trend line and the corresponding Pearson r displayed in each panel.

4.6 Interpretation, validation, and outputs

This component converts numeric cluster outputs into interpretable regime maps and evaluates the spatial plausibility of these interpretations using irrigation infrastructure and off-season canopy behavior. The processes clearly delineate dependencies: phenology metrics and rainfall–NDVI lag behavior guide agronomic labeling, while orthophotos and canal layers support spatial validation. Importantly, spatial validation is framed as consistency checking rather than ground-truth accuracy assessment, given the lack of external field validation datasets at the required scale.

4.6.1 Agronomic labeling (cropping systems and water-supply regimes)

Clusters are assigned descriptive agronomic regimes using convergent evidence rather than a single indicator. The labeling process integrates DTW barycenter prototype shapes, including the number and timing of peaks as well as green-up and senescence structure; cluster distributions of phenology metrics, such as amplitude, number of vigorous months, and peak counts; and rainfall–NDVI lag profiles, specifically the timing and strength of moisture coupling. Labels are deliberately framed as probable regimes, such as comparatively irrigated or irrigation-buffered versus rainfall-dependent, rather than

as definitive irrigation status. This strategy maintains defensible claims in data-scarce contexts.

Label assignment is informed by the following lines of evidence:

- Prototype curve characteristics (barycenter): peak count, temporal spacing, and seasonal timing.
- Phenological metrics: duration of vigorous canopy, duration of low canopy, amplitude, and annual cycle frequency.
- Rainfall–NDVI lag behavior: timing of peak positive lag and strength of correlation.
- Spatial plausibility: proximity to and spatial alignment with irrigation infrastructure.

4.6.2 Canal network digitization and quality control

The irrigation canal network was digitized in QGIS as a vector layer stored in a GeoPackage to facilitate spatial analysis of cropping system clusters. Manual digitization was conducted using high-resolution reference imagery and orthophotos by tracing visible canal alignments and organizing features within a standardized layer schema. Topology rules were enforced during editing to minimize digitizing artifacts, such as self-intersections, unintended overlaps, or duplicates, and to ensure snapping of adjacent line endpoints when canal continuity was visually apparent.

Attribute fields were assigned to each canal segment to enable interpretation and filtering, including canal type or class, notes or source tags, and editing status. Following digitization, the canal layer was cross-checked against the NDVI-cluster map through overlay inspection to verify that canal-dense areas corresponded to clusters exhibiting sustained greenness and multi-cropping signatures. Additional spot checks were conducted throughout the study area to confirm geometric alignment and attribute consistency before using the canal layer as contextual evidence in spatial validation.

4.6.3 Cropping-system and water-supply regime maps

Following the labeling process, regime maps are generated by assigning each cultivated hexagon its respective cluster label and rendering the resulting categorical layer in the study coordinate reference system (CRS; EPSG:32751). The map products comprise: (i) raw cluster maps, (ii) labeled regime maps, and (iii) supporting overlays depicting irrigation canals and key structures. These maps serve as the primary outputs for the Results chapter and facilitate the interpretation of spatial patterns, including

regime concentration within irrigation command areas and transitions toward rainfall-responsive patterns in regions distant from infrastructure. Export parameters, including CRS, resolution, and symbology, are standardized to ensure reproducibility of figures.

4.6.4 Spatial validation (off-season NDVI and canals)

Spatial validation is conducted according to the established flowchart, integrating off-season NDVI mosaics with irrigation infrastructure overlays. Off-season greenness is defined as NDVI values greater than 0.50 during June to November. Monthly NDVI mosaics for each month within this period are evaluated against this threshold to identify areas that maintain a persistent vegetation signal throughout the off-season. These spatial patterns are then compared with the mapped cluster outputs to determine whether clusters interpreted as irrigated regimes exhibit sustained greenness relative to rain-fed regimes.

4.7 Software and computational environment

Geospatial processing, including grid generation, masking, zonal statistics, digitizing and cross-checking irrigation layers, and map production, was conducted using QGIS 3.40.3. Time-series clustering and statistical analyses were performed in Python 3.13.5, utilizing tslearn for dynamic time warping (DTW) k-means clustering and standard scientific libraries for validity metrics and regression analyses. All processing and clustering experiments were conducted on an Ubuntu workstation equipped with an Intel Core i9-10980XE CPU, 252 GB of RAM, and an NVIDIA Quadro RTX 6000 GPU. This computational environment was consistently employed throughout the workflow, encompassing NDVI time-series preparation, DTW-based clustering, and validation index computation.

Chapter 5. Results

This chapter presents the results of dynamic time warping (DTW)-based k-means clustering applied to monthly normalized difference vegetation index (NDVI) time series, evaluating whether the resulting classes are internally coherent and agronomically meaningful. The analysis proceeds in five steps: (i) selection of the number of clusters (k), (ii) internal validation using multiple cluster-quality indices, (iii) phenological characterization of each cluster, (iv) rainfall–NDVI lag diagnostics as an independent check of temporal consistency, and (v) spatial plausibility assessment using off-season PlanetScope mosaics and irrigation canal overlays. The final partition comprises 14,101 cultivated grid cells, with 3,684 cells (26.13%) assigned to Cluster 1 and 10,417 cells (73.87%) to Cluster 2.

5.1 Optimal Number of Clusters

The DTW-inertia curve exhibits diminishing returns as k increases. Inertia decreases sharply at lower k values and then plateaus, indicating that additional clusters provide only marginal improvements in within-cluster compactness. In this analysis, the elbow pattern suggests that a solution near $k \approx 4$ is justified solely on the basis of inertia reduction. However, inertia alone does not guarantee meaningful separation or interpretability of temporal signatures. Consequently, the final value of k was selected by jointly considering the elbow pattern, silhouette behavior, and cluster separation in the projected space, as well as complementary validity indices such as the Davies-Bouldin Index (DBI) and the Calinski-Harabasz Index (CHI). Based on this combined evidence and with an emphasis on extracting agronomically interpretable regimes rather than over-segmenting noise, the analysis proceeds with $k = 2$ as the primary partition for subsequent interpretation of the monthly NDVI time series.

The average silhouette width reaches its maximum at $k = 2$ (0.517) and is generally lower for larger k values (0.472 for $k = 3$, 0.477 for $k = 4$, and 0.447 for $k = 5$), indicating weaker average separation as additional partitions are introduced.

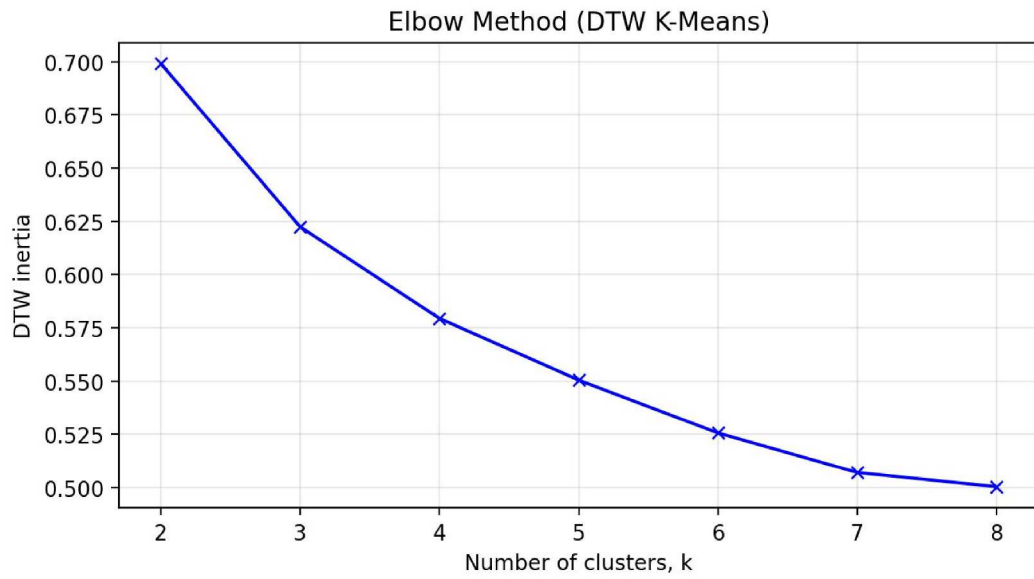
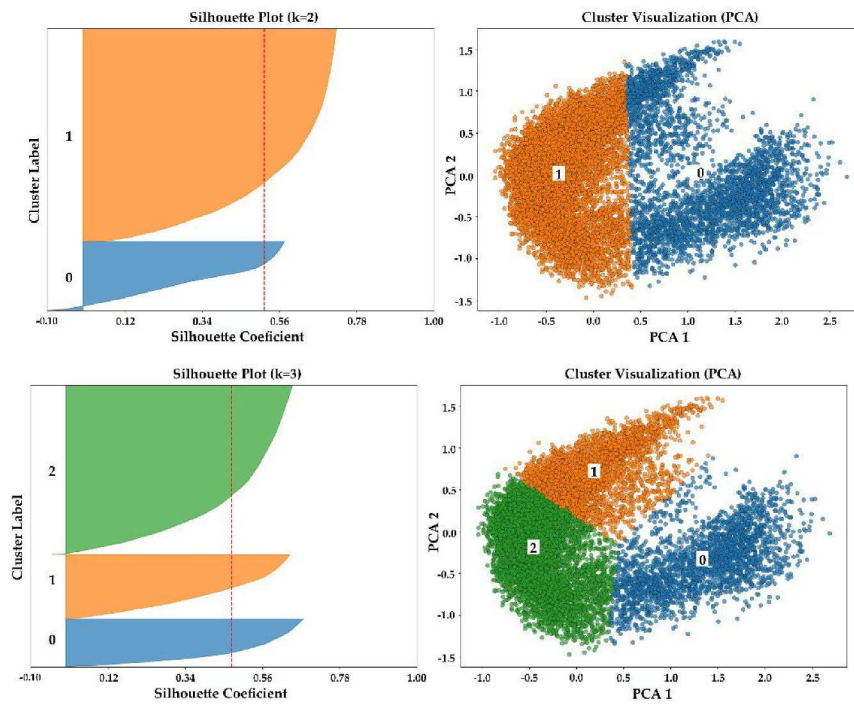


Figure 8 DTW inertia by k shows diminishing returns with increasing k; elbow behavior suggests candidate solutions rather than a single definitive k.



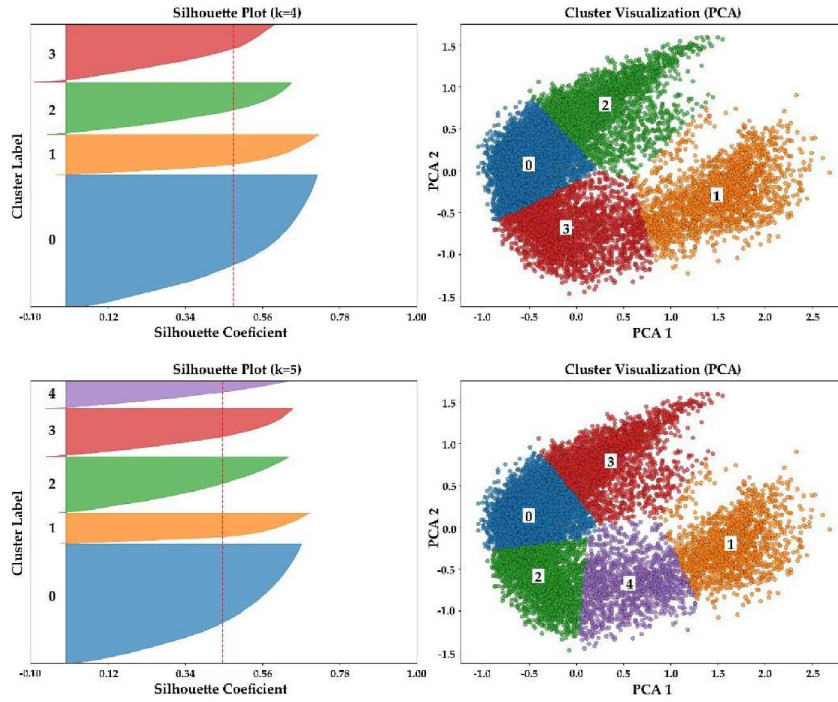


Figure 9 Silhouette analysis and PCA visualizations for $k = 2, 3, 4$, and 5 clusters, illustrating cluster separation and changes in partitioning with increasing k .

Table 1 Silhouettes scores for $k=2-5$.

k	Silhouette
2	0.517
3	0.472
4	0.477
5	0.447

5.2 Additional Validity Metrics

Additional internal validity metrics support the two-cluster solution. The Davies–Bouldin Index (DBI), where lower values indicate better partition quality, is minimized at $k = 2$, and increases for higher k values, suggesting that adding clusters reduces overall compactness-to-separation performance. The Calinski–Harabasz Index (CHI), where higher values indicate stronger between-cluster separation relative to within-cluster dispersion, is also maximized at $k = 2$ and decreases thereafter. Taken together with the silhouette results and the objective of extracting stable, interpretable temporal regimes,

these indices justify selecting $k = 2$ as the final working partition even though inertia alone could motivate a larger k .

Table 2 Cluster Validity Indices for $k = 2-5$.

k	Davies-Bouldin	Calinski-Harabasz
2	1.632	4231.683
3	1.721	3544.408
4	1.779	3135.728
5	2.010	2561.544

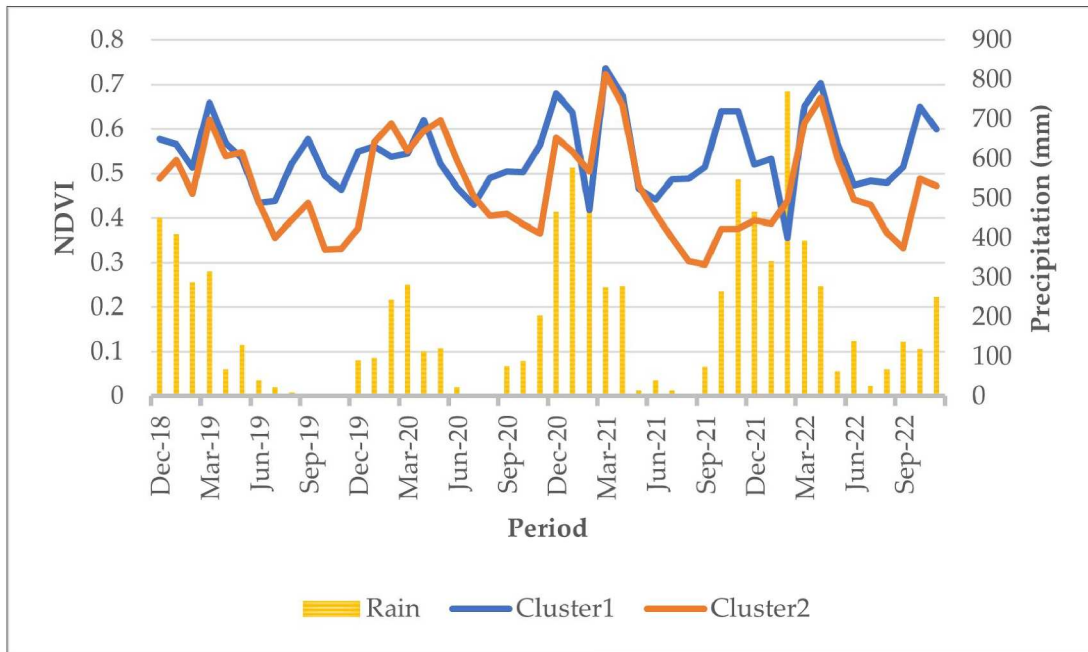


Figure 10 Mean monthly NDVI trajectories for the two clusters overlaid with monthly precipitation totals (Dec 2018–Nov 2022), illustrating differences in vegetation dynamics and rainfall alignment.

5.3 Crop Phenology Metrics

The 48-month NDVI record reveals two distinct canopy regimes (Table 3). Cluster 1 maintains a higher baseline greenness and experiences more frequent high-vigor months

compared to Cluster 2. The mean NDVI for Cluster 1 is greater (0.5420 versus 0.4693), and low-canopy conditions are infrequent (6 months below 0.45 across the entire record, compared to 25 in Cluster 2). High-vigor conditions are also more prevalent in Cluster 1 (11 months above 0.60 versus 7 in Cluster 2). While both clusters reach similar maximum NDVI values (0.7375 versus 0.7244), Cluster 2 remains at low NDVI for longer periods (minimum 0.2962 versus 0.3555) and demonstrates a larger seasonal amplitude (0.4283 versus 0.3819), which suggests deeper dry-season troughs and extended off-season intervals.

Annual tallies further emphasize these differences. For months with NDVI below 0.45, Cluster 1 records 2, 1, 2, and 1 occurrence in the four December–November periods, whereas Cluster 2 records 6, 6, 6, and 7. For months exceeding 0.60, Cluster 1 registers 1, 1, 6, and 3, compared to 1, 2, 2, and 2 in Cluster 2. The number of peaks above 0.55 is higher in Cluster 1 (8 total; 2 per year) than in Cluster 2 (6 total; 1, 2, 2, and 1 by year), corresponding to cycle frequencies of 2.0 cycles/year and 1.5 cycles/year, respectively. Collectively, these findings indicate that Cluster 1 supports longer and more frequently renewed growing periods with sustained canopy during peak phases. In contrast, Cluster 2 exhibits extended intervals of low greenness and fewer, more widely spaced peaks. These patterns are consistent with established interpretations of NDVI plateaus (approximately 0.50–0.60) as indicators of dense, actively growing rice canopy (Bhatti et al., 2024; Xiao et al., 2010).

Table 3 Phenology-based NDVI metrics by cluster (Dec 2018–Nov 2022).

Metric	Cluster 1	Cluster 2
Average NDVI	0.5420	0.4693
max	0.7375	0.7244
min	0.3555	0.2962
Amplitude (max - min)	0.3819	0.4283
No. of months < 0.45 (Dec18 - Nov22)	6	25
No. of months < 0.45 (Dec18 - Nov19)	2	6
No. of months < 0.45 (Dec19 - Nov20)	1	6
No. of months < 0.45 (Dec20 - Nov21)	2	6
No. of months < 0.45 (Dec21 - Nov22)	1	7
No. of months > 0.60 (Dec18 - Nov22)	11	7
No. of months > 0.60 (Dec18 - Nov19)	1	1
No. of months > 0.60 (Dec19 - Nov20)	1	2
No. of months > 0.60 (Dec20 - Nov21)	6	2
No. of months > 0.60 (Dec21 - Nov22)	3	2

Peaks > 0.55 NDVI (Dec18 · Nov22)	8	6
Peaks > 0.55 NDVI (Dec18 · Nov19)	2	1
Peaks > 0.55 NDVI (Dec19 · Nov20)	2	2
Peaks > 0.55 NDVI (Dec20 · Nov21)	2	2
Peaks > 0.55 NDVI (Dec21 · Nov22)	2	1
Cycles / year	2	1.5

5.4 Rainfall–NDVI Lag Correlation

Rainfall–NDVI lag correlations provide an independent means of assessing the temporal coherence between climatic drivers and vegetation responses. Cluster 1 exhibits its peak positive correlation at a one-month lag ($r = 0.358$), indicating a relatively rapid canopy vigor response following rainfall events. In contrast, Cluster 2 shows stronger positive correlations at extended lags, with a maximum at 3 months ($r = 0.595$) and comparably high values at 2 months ($r = 0.525$). Given the pronounced seasonality and autocorrelation inherent in both rainfall and NDVI time series, these correlations are interpreted as measures of temporal association and alignment, rather than as evidence of direct causality. The contrasting lag profiles observed between clusters further substantiate their characterization as distinct water-availability regimes. The full set of lag profiles is provided in Table 4 and visualized in Figure 11.

Table 4 Pearson rainfall–NDVI cross-correlation by lag (–6 to +6 months).

Cluster 1		Cluster 2	
Lag (k)	Pearson r	Lag (k)	Pearson r
-6	-0.332	-6	-0.268
-5	-0.269	-5	-0.348
-4	-0.116	-4	-0.593
-3	0.076	-3	-0.600
-2	0.109	-2	-0.548
-1	0.324	-1	-0.325
0	0.296	0	0.005

+1	0.358	+1	0.314
+2	0.259	+2	0.525
+3	0.063	+3	0.595
+4	-0.118	+4	0.483
+5	-0.262	+5	0.230
+6	-0.332	+6	-0.097

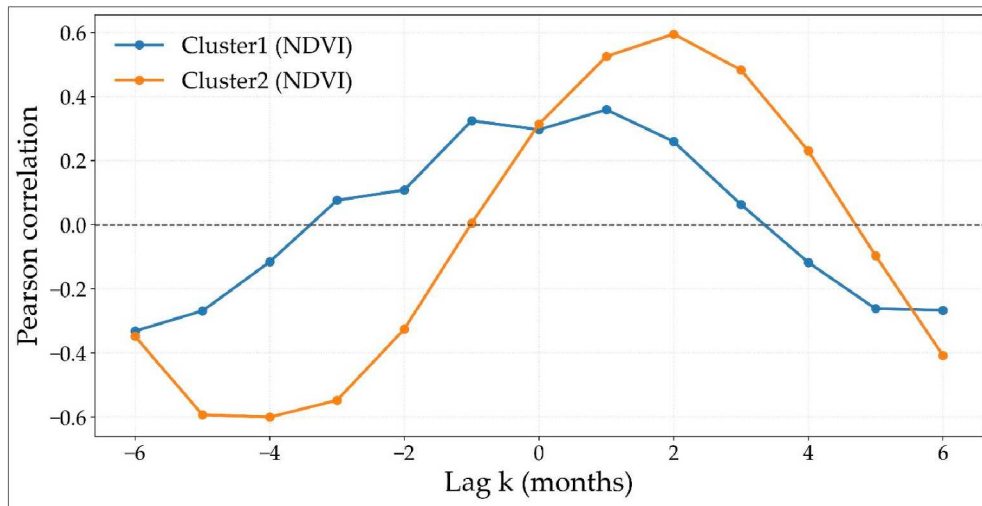


Figure 11 Rain–NDVI Lag Cross-Correlation (Pearson) showing the relationship between rainfall and NDVI for Cluster 1, Cluster 2, respectively, across different time lags (-6, +6 months).

5.5 Cropping System Assignment

The two clusters were classified into agronomic cropping-system categories by integrating their phenological profiles and the temporal relationships between rainfall and NDVI. Cluster 1 is characterized by elevated baseline greenness, reduced frequency of low-NDVI intervals, increased occurrence of NDVI peaks, and a shorter lag between rainfall events and NDVI response, all of which align with irrigated double-cropping systems and extended periods of canopy vigor. In contrast, Cluster 2 exhibits more sustained low-NDVI phases and greater sensitivity to the timing of seasonal rainfall, consistent with single-rainfed cropping regimes. These classifications reflect an

interpretation grounded in temporal signature analysis, rather than a direct attribution of irrigation management.

Table 5 Cropping-system class assignments for DTW-derived clusters.

Cluster	Crop system
Cluster 1	Irrigated double crop
Cluster 2	Single rain-fed crop

A regular hexagonal grid with a 25 m edge length results in an area of 1,623.80 m² (0.16238 ha) per grid. Under the full-hexagon assumption, the 14,101 cultivated cells correspond to approximately 2,289.7 ha in total. Cluster 1 comprises approximately 598.2 ha (26.13%), while Cluster 2 comprises 1,691.5 ha (73.87%). If grid polygons are clipped to field boundaries, area calculations should be based on the actual polygon geometries rather than the full-hexagon approximation.

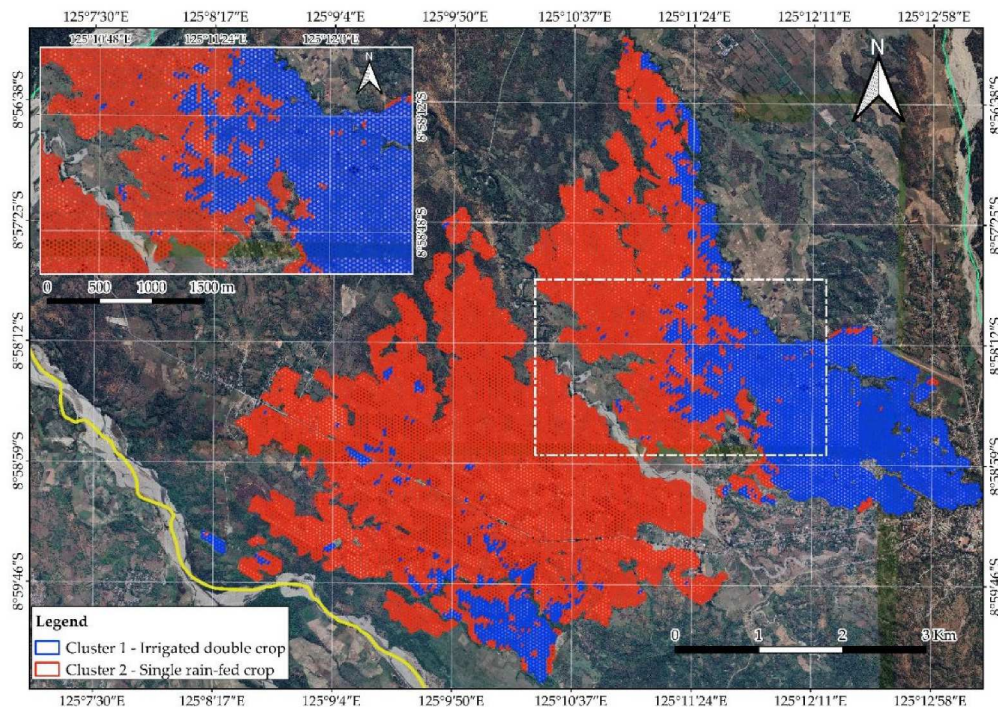


Figure 12 Map of Spatial distribution of rice cropping systems within the study area, showing single rain-fed crop, and irrigated double crop.

5.6 Visual Validation with Off-season NDVI and Irrigation Infrastructure

Off-season PlanetScope mosaics (June–November; Figure 13) serve as a spatial plausibility check for the temporal classes. Areas identified as Cluster 1 remain greener further into the dry season, while Cluster 2 areas display earlier or more extensive senescence, which aligns with reduced dry-season water availability. The irrigation canal overlay (Figure 14) reinforces this interpretation: Cluster 1 is concentrated along the canal network and irrigation-served zones, whereas Cluster 2 predominates in regions more distant from canal infrastructure. the spatial assessment is treated as a qualitative plausibility check, as formal proximity statistics, such as distance-to-canal distributions or buffer-based summaries, were not calculated. Nevertheless, the combined temporal and spatial patterns offer coherent evidence that the two DTW-derived classes correspond to distinct cropping regimes.

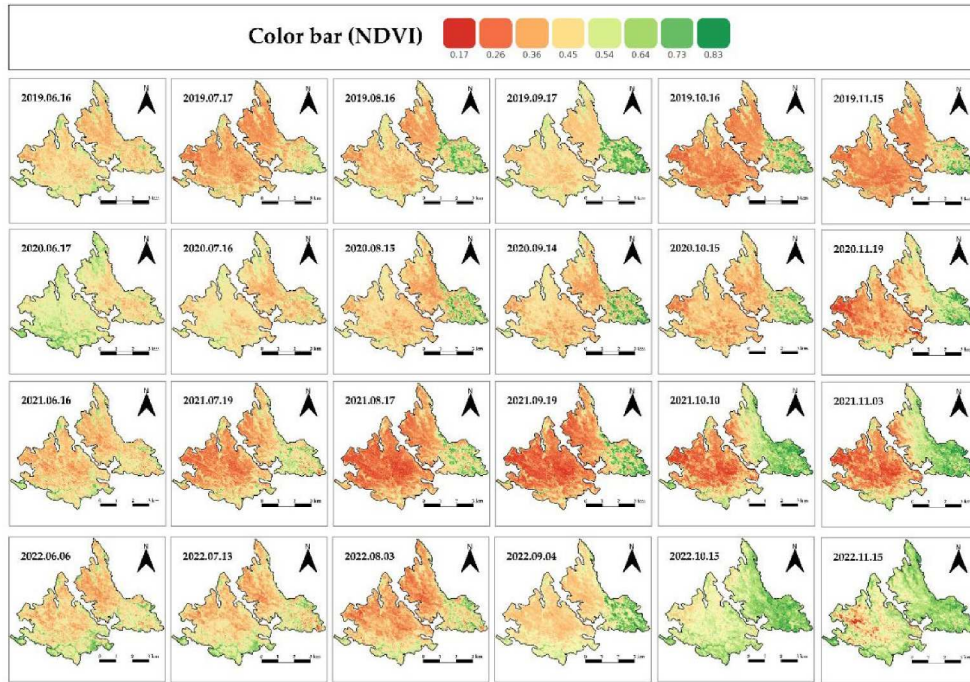


Figure 13 Off-season NDVI mosaic (June–November) used for qualitative plausibility checking of dry-season greenness patterns.

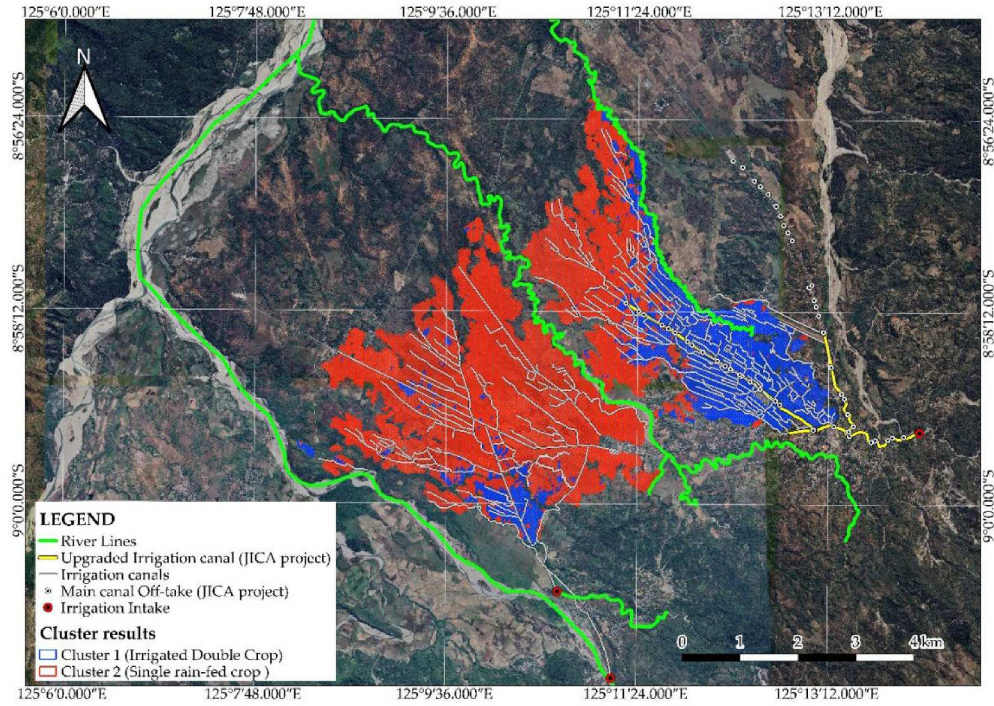


Figure 14 Irrigation canals Overlay with the Clusters results

DTW k-means clustering produces a robust two-regime classification of rice cropping dynamics across 14,101 cultivated grids. Cluster 2 represents the dominant pattern (73.87 percent), while Cluster 1 captures a smaller but distinct temporal regime (26.13 percent). Internal validity indices, including silhouette, DBI, and CHI, consistently indicate that $k = 2$ is the most interpretable solution. Phenology metrics and rainfall–NDVI lag behavior further distinguish the clusters, supporting the interpretation of an irrigated, multi-peak regime compared to a more rainfall-dependent, single-peak regime. Spatial plausibility assessments that incorporate off-season mosaics and canal network overlays reveal spatial patterns aligned with differential irrigation access. These findings enhance the interpretability of the two regimes, but do not constitute direct evidence of causality.

Chapter 6. Discussion

6.1 Interpreting the two-regime structure

Analysis of four years of 3 m PlanetScope NDVI time series, clustered using Dynamic Time Warping (DTW), delineates the cultivated area into two dominant phenological regimes. Multiple internal validity indices, including Silhouette, Calinski-Harabasz, and Davies-Bouldin, consistently favor $k = 2$, indicating a stable two-mode structure rather than over-partitioning of noise.

While both regimes can attain similar peak NDVI values during the main wet-season growth phase, their distinction is most pronounced in dry-season behavior and baseline greenness. Regime 1 maintains a higher NDVI baseline, more months above high-vigor thresholds ($\text{NDVI} \geq 0.60$), and more frequent seasonal peaks, consistent with sustained canopy cover and approximately 2 growth cycles per year. In contrast, Regime 2 exhibits deeper troughs and prolonged low-NDVI periods, indicating a predominantly single-season system with occasional second cycles in certain parcels or years.

Rainfall-NDVI lag profiles serve as an independent check of timing consistency. Regime 1 demonstrates a shorter positive-lag peak of approximately one month, whereas Regime 2 exhibits a stronger but delayed peak of approximately two to three months. Given the strong seasonality and autocorrelation shared by rainfall and NDVI, these lags are interpreted as indicative of association and relative buffering, rather than as evidence of causality.

6.2 Water control as a plausible organizing mechanism

Qualitative plausibility checks using off-season mosaics and irrigation canal overlays indicate that persistent dry-season greenness is concentrated in areas with greater visual proximity to the canal network, whereas earlier senescence is more prevalent in zones farther from the canal network. This spatial pattern is consistent with the influence of irrigation scheme design and operational factors, which can generate heterogeneous water availability across the hydraulic reach (JICA & Sanyu Consultants Inc., 2015). When considered alongside temporal evidence, such as higher baseline NDVI, more frequent peaks, and shorter rainfall response lag, the observed two-regime structure is most plausibly interpreted as an irrigation-buffered regime rather than a more rainfall-dependent one. This interpretation is consistent with previous remote-sensing studies that differentiate irrigated and rain-fed rice systems in tropical environments (e.g., Kamthonkiat et al., 2005), although it remains an association-based inference rather than definitive causal evidence.

6.3 Rationale for key methodological choices

Key design decisions were implemented to balance field-scale representation, interpretability, and computational feasibility. The following sections explicitly outline these choices.

- a) **Index choice (NDVI):** NDVI offers physical interpretability and is directly supported by PlanetScope four-band imagery (R, G, B, NIR). However, NDVI may saturate at high biomass and remains sensitive to residual atmospheric effects and soil background. To enhance robustness, key diagnostics can be repeated using band-compatible indices such as EVI2, SAVI, and GNDVI. Indices requiring SWIR, such as NDMI or LSWI, cannot be derived from PlanetScope alone and necessitate integration with sensors like Sentinel-2.
- b) **Spatial unit (25 m hexagons):** A 25 m hexagonal lattice closely matches parcel dimensions in Maliana and reduces mixed land cover relative to coarser grids. Hexagons also provide a more uniform neighborhood structure than squares, supporting spatially consistent sampling. However, edge contamination may still occur near trees, canals, settlements, or bare soil. This consideration motivates the use of a mixed-pixel risk score, such as the fraction of non-crop pixels within each cell, and the down-weighting or exclusion of high-risk cells in future analyses.
- c) **Temporal scope (full 48 months):** Clustering the entire four-year time series captures both seasonal patterns and interannual variability, resulting in regime centroids that summarize persistent behaviors. Year-by-year clustering remains useful as a stability test to determine whether cells systematically switch regimes during droughts, flood seasons, or infrastructure changes.
- d) **DTW configuration (warping window):** A three-month Sakoe-Chiba radius was chosen to accommodate realistic planting-date shifts resulting from rainfall variability and management delays, while preventing implausible alignments.

6.4 Robustness of the regime interpretation

Unsupervised clustering does not yield conventional classification accuracy metrics in the absence of external reference labels. In this study, robustness is demonstrated through three approaches: (i) convergence of internal indices on a two-regime structure, (ii) consistent contrasts in interpretable phenology metrics, and (iii) independent spatial plausibility assessments using dry-season greenness patterns and the context of irrigation infrastructure. A drone RGB survey facilitated canal digitization and visual interpretation,

although it was not collected as systematic in situ ground truth for regime labels. Regime labels are therefore considered indicative.

6.5 Hydroclimatic Context and Interannual Variability

Rainfall forcing was represented using a single local rain gauge, with daily measurements aggregated to monthly values. This approach is sufficient for basin-scale timing diagnostics but does not capture micro-climatic gradients within Maliana. The study period encompasses significant hydroclimatic anomalies in Timor-Leste, including the 2018-2019 El Niño, the extended La Niña period from 2020 to 2022, and major flood events such as the 2021 Tropical Cyclone Flood. Incorporating climate-mode indices and event-based rainfall anomalies would facilitate distinguishing between structural regime differences and year-specific climate shocks and clarify whether regime membership remains stable or shifts during extreme events.

6.6 Implications for Management and Policy

The mapped regimes provide practical decision-support outputs when applied as a monitoring layer instead of serving as definitive ground-truth labels.

- a) **Targeted irrigation investment:** Areas identified as more rainfall-dependent should be prioritized for maintenance, conveyance improvements, and outlet rehabilitation, particularly where dry-season greenness declines consistently across multiple years.
- b) **Dry-season planning:** Zones exhibiting persistent off-season greenness indicate locations where dry-season planting is most feasible, thereby informing seasonal scheduling and input allocation under water-limited conditions.
- c) **Annual monitoring metric:** Agencies may monitor year-to-year changes in the proportion of area assigned to each regime and in key phenology metrics, such as months below 0.45, months above 0.60, and peak counts, to create a straightforward performance scorecard.
- d) **Risk and equity screening:** Spatial contrasts between regimes provide an initial map of areas with less reliable water service, facilitating transparent prioritization of interventions and farmer support programs.

6.7 Limitations and Validity Considerations

The primary limitations can be categorized as measurement, inference, and contextual constraints. These factors restrict interpretation and inform subsequent steps required for operational implementation.

- a. Index and sensor constraints include NDVI saturation at high canopy density, residual atmospheric artifacts, and the absence of shortwave infrared (SWIR) bands in PlanetScope, which collectively reduce sensitivity to moisture and flooding signals.
- b. Temporal aggregation through monthly compositing obscures short-duration events such as transplanting, brief flooding, or rapid harvest, potentially leading to underestimation of peak timing or amplitude.
- c. Unsupervised labeling involves inferring regime names from time-series behavior, thresholds, and lag structure, rather than from plot-level calendars, irrigation records, or yield data.
- d. Rainfall representativeness is limited by reliance on a single gauge, which cannot capture spatial rainfall gradients within the basin. Additionally, lag correlations may partially reflect shared seasonal patterns.
- e. Infrastructure interpretation is constrained because canal vectors represent intended infrastructure, while actual water delivery is influenced by maintenance, gate operation, sedimentation, and water withdrawals. As a result, canal overlays support plausibility rather than establish causality.
- f. Mixed pixels and adjacency effects persist despite masking and visual screening, as cells near field boundaries may be affected by adjacent trees, settlements, bare soil, or canals, potentially biasing NDVI trajectories.
- g. Varietal and management heterogeneity, including differences in crop varieties (such as maturity length) and agricultural practices (such as fertilizer application, transplanting date, and fallow cover), can alter NDVI curves independently of water management.

6.8 Future Research Directions

The following priorities are proposed to advance results from indicative regime mapping toward calibrated monitoring and enhanced attribution, while also supporting scalability.

- a) Enhance robustness by repeating clustering and key phenology metric calculations using EVI2, SAVI, and GNDVI, and compare regime stability to results based on NDVI.
- b) Augment analysis by integrating Sentinel-2 for SWIR-based moisture indices and Sentinel-1 SAR for cloud-resilient flood and transplanting signals, thereby reducing cloud and saturation limitations.

- c) Conduct external validation by collecting plot-level crop calendars, irrigation schedules, and yield samples. Employ targeted drone surveys to verify dry-season cropping and boundary conditions.
- d) Calculate quantitative irrigation-context metrics, including distance-to-canal and upstream/downstream segmentation statistics. Where rehabilitation records are available, apply before-and-after or quasi-experimental comparisons to strengthen attribution.
- e) Improve spatial rainfall representation by combining gauge data with gridded rainfall products or reanalysis. Test whether rainfall gradients account for within-regime variability.
- f) Explicitly model ENSO phase, cyclone and flood periods, and rainfall anomalies to assess whether regime membership shifts during extreme climate events.
 - g) **DTW configuration (warping window):** A three-month Sakoe-Chiba radius was chosen to accommodate realistic planting-date shifts resulting from rainfall variability and management delays, while preventing implausible alignments.
- h) Detailed records of crop planting and harvesting dates, delivery documentation, and crop samples should be collected to verify label accuracy and to quantify yield increases attributable to irrigation compared to rainfed agriculture.

Chapter 7. Conclusion

An update-ready remote sensing workflow was developed and implemented to characterize and map probable rice cropping regimes in the Maliana basin, Timor-Leste, under limited data availability, including scarce field calendars, yield records, and irrigation delivery logs. The analysis utilized 48 monthly observations (December 2018 to November 2022) from 3 m PlanetScope NDVI, aggregated to a 25 m hexagonal grid, and employed a shape-based time-series clustering approach to address phenological misalignment across spatial domains. The primary objective was to extract consistent spatial patterns in NDVI seasonality and interpret these patterns using convergent evidence from rainfall timing and irrigation context, while avoiding assertions of causality.

Dynamic time warping (DTW)-based k-means clustering analysis identified a two-regime partition as the most interpretable and internally supported solution. Although DTW inertia suggested that a higher number of clusters could be plausible, the selection of $k = 2$ was substantiated by multiple internal indices (silhouette, Davies-Bouldin Index, and Calinski-Harabasz Index), supporting a parsimonious structure that minimizes over-partitioning of noise. The final partition comprised 14,101 cultivated grid cells (approximately 2,289.7 ha), distributed as Cluster 1: 3,684 cells (26.13%; approximately 598.2 ha) and Cluster 2: 10,417 cells (73.87%; approximately 1,691.5 ha), based on the full-hexagon area assumption (regular hexagon, 25 m edge length).

Phenology metrics derived from cluster-average NDVI trajectories indicate two distinct canopy regimes. Cluster 1 demonstrates a higher mean NDVI (0.5420 compared to 0.4693), significantly fewer low-canopy months (6 versus 25 months below NDVI 0.45), more high-vigor months (11 versus 7 months above NDVI 0.60), and more frequent peak events (8 versus 6 peaks above NDVI 0.55), corresponding to approximately 2.0 cycles per year. In contrast, Cluster 2 exhibits deeper troughs (lower minimum NDVI), extended low-greenness intervals, and fewer peaks, corresponding to approximately 1.5 cycles per year. Based on these temporal signatures, Cluster 1 is interpreted as an irrigation-buffered, more intensive double-cropping regime, while Cluster 2 is interpreted as a rainfall-dependent, single-season regime. These classifications are interpretations of temporal behavior and do not represent confirmed management categories.

Rainfall-NDVI lag diagnostics further distinguish the regimes and provide an independent assessment of timing consistency. Cluster 1 shows its strongest positive correlation at a one-month lag ($r = 0.358$), indicating a more rapid greenness response to rainfall, consistent with irrigation or stored soil moisture buffering. Cluster 2 exhibits

peak correlations at longer lags (three months, $r = 0.595$; two months, $r = 0.525$), reflecting a greater reliance on cumulative rainfall and a delayed canopy response. Given the seasonal and autocorrelated nature of both rainfall and NDVI time series, these lag results are interpreted as indicative of association and timing consistency rather than causality.

Spatial plausibility was assessed using off-season (June to November) NDVI mosaics and canal overlays. Areas assigned to Cluster 1 generally exhibit more persistent dry-season greenness, and the spatial distribution of this cluster visually corresponds with the irrigation network, suggesting differential access to water delivery. This evidence serves as a qualitative plausibility check, as formal distance-to-canal or hydraulic-reach statistics and operational delivery records were not calculated. Consequently, the findings support the interpretation that the two regimes are organized by water availability in a manner consistent with irrigation infrastructure, while explicitly refraining from causal claims.

This research makes methodological contributions by (i) presenting a robust high-resolution regime mapping pipeline utilizing DTW clustering to address temporal misalignment, (ii) implementing explicit internal validation to minimize arbitrariness in cluster selection, (iii) converting complex NDVI trajectories into interpretable phenology metrics through transparent thresholds, and (iv) integrating rainfall timing and infrastructure context to facilitate convergent interpretation. In practical terms, the outputs provide an operational monitoring layer to support irrigation maintenance prioritization, dry-season planning, and year-to-year tracking of regime shifts, contingent upon users treating labels as indicative and periodically recalibrating thresholds and interpretations as infrastructure and climate conditions evolve.

Several key limitations remain: NDVI saturation and atmospheric artifacts limit precision; monthly compositing may overlook short-duration events such as transplanting or flooding phases; and the absence of field calendars, yield observations, and water delivery logs precludes direct external validation and causal attribution. Future research should prioritize targeted ground truth collection, integration of soil, topography, and groundwater context, and the development of quantitative proximity and hydraulic metrics (such as distance-to-canal distributions, upstream and downstream segmentation, and before-and-after rehabilitation comparisons) to assess whether regime membership systematically shifts with changes in infrastructure condition or drought events. Incorporating these elements would enable the workflow to progress from indicative regime mapping toward stronger attribution and routine operational monitoring at municipal and national levels.

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