# DECOMPOSING TREE AND GRASS PHENOLOGY IN DRYLANDS: ANALYZING THE MIXED PIXEL EFFECT WITH NEAR-SURFACE AND SATELLITE OBSERVATIONS

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***ABSTRACT***

*This study investigates the phenological dynamics of a heterogeneous dryland ecosystem in Alice Springs, Australia, through the integration of high-resolution phenocam observations and multi-sensor satellite data. By decomposing the phenological responses of grasses and tree canopies, we found that grass phenology, despite covering less than 30% of the satellite-pixel footprint, exerts a dominant influence on the overall land surface phenology (LSP) at the landscape scale, with stronger correlations evident in coarser-resolution satellite data. The analysis further shows that while lower spatial resolution sensors capture broad-scale phenological patterns effectively, they often mask finer-scale variations critical for accurate ecosystem assessments in drylands. These findings highlight the need for techniques to mitigate the mixed-pixel effect in LSP studies, enhancing the precision of remote sensing applications.*

***Key words*** *— Phenocam, Mixed pixel effect, Remote Sensing, Phenology.*

## 1. INTRODUCTION

The seasonality and temporal dynamics observed in vegetated land surfaces based on remote sensing images is commonly known as land surface phenology (LSP). By providing continuous, long-term perspective and global coverage, LSP is particularly valuable in regions lacking ground-based monitoring, enabling large-scale assessment of ecosystem responses to environmental changes. However, discrepancies often emerge between satellite-derived metrics and near-surface observations (e.g., phenocams) due to temporal mismatches and the coarser spatial resolution of satellite products. A significant source of this uncertainty is the mixed pixel effect, where a single pixel contains a mosaic of vegetation species or land cover types, each with distinct phenological patterns [1, 2]. The resulting signal does not fully capture the behaviour of individual species or vegetation types, complicating the attribution of observed phenological shifts.

This issue is particularly relevant in ecosystems where the signals of understory vegetation, such as grasses and shrubs, interact with or mask the overstory signals from tree canopies [3]. These interactions introduce ambiguity, as the aggregated signal may not accurately represent the distinct responses of each vegetation layer. In drylands, which cover approximately 41% of Earth's terrestrial surface and play a critical role in regulating global carbon and water cycles [4, 5], this issue is particularly pronounced. For example, drylands exhibit contrasting phenological patterns between herbaceous and woody species, with herbaceous and deciduous species generally showing faster responses to seasonal climate variability compared to the slower, more stable patterns of evergreen woody species [6]. The spatial heterogeneity and species diversity within these regions further complicate the interpretation of satellite data, as the aggregated nature of pixels may obscure the individual contributions of different vegetation types to overall landscape phenology.

This challenge is even more pronounced in the Southern Hemisphere's drylands, where phenological monitoring is limited, and the variability of vegetation patterns is high. The absence of long-term ground-based data, coupled with the lack of a distinct dormant season and diverse species compositions, hinders accurate tracking and understanding of phenological shifts in response to climate variability [7, 8]. Addressing these complexities requires a refined understanding of how mixed pixel composition influences LSP, enabling the validation of satellite-derived metrics and enhancing ecosystem response models to historical and projected climate changes.

This study addresses these challenges with three key objectives: 1) to decompose the phenological responses of grasses and trees within a heterogeneous dryland landscape by integrating near-surface and satellite remote sensing data; 2) to identify the primary driver that shape landscape-level LSP; and 3) to quantify the impact of varying spatial and

temporal resolutions on the detection and accuracy of LSP signals across multiple orbital sensors.

## 2. MATERIALS AND METHODS

### *2.1 Study area*

This study focuses on Alice Springs site (AS: 22.28°S, 133.24°E), situated within a representative arid biome in central Australia and monitored by the Terrestrial Ecosystem Research Network (TERN) [9] (Figure 1). The AS site is characterized by a heterogeneous landscape comprising a mosaic of tree and grassland communities, which presents unique challenges and opportunities for studying vegetation dynamics through remote sensing.

The AS site exhibits pronounced seasonal variations, with monthly temperatures ranging from 24°C to 38°C during the summer/wet season (December–February) and from 5°C to 20°C in the winter/dry season (June–August). The mean annual precipitation is 285 mm [9], with approximately 20% of this precipitation distributed sporadically throughout the dry season, contributing to substantial variability in vegetation phenology, particularly in grass-dominated areas.

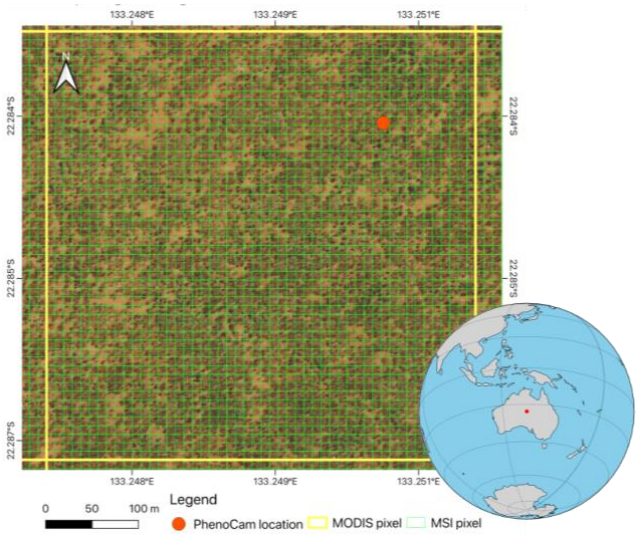


**Figure 1. Study area location in Alice Springs, Australia. The colored squares denote the orbital sensor pixel footprints, while the red dot indicates the position of the phenocam tower. The AHI pixel footprint is omitted for clarity.**

### *2.2 Datasets and methods*

Phenocam imagery was collected at the AS site from 2021 to 2023, using Campbell Scientific CCFC cameras configured to capture half-hourly RGB images, available by the TERN platform (https://ecoimages.tern.org.au). To analyse vegetation dynamics, we processed the phenocam data using Python-based functions, extracting the daily 90th percentile of the Green Chromatic Coordinate (GCC) as a proxy of greenness, following the methodology outlined by [3, 10]. Regions-of-Interest (ROIs) in the phenocam images were delineated specifically to capture the landscape and the dominant vegetation types – grasses and tree canopies – enabling a precise evaluation of how each vegetation type contributes to the overall greenness signal in the heterogeneous landscape of the AS site.

Satellite data were selected to coincide temporally with the phenocam observations. Surface reflectance data from the Sentinel-2 Multispectral Instrument (MSI, 5-day, 10-m resolution) were utilized, in addition to daily 500-m MODIS product (MCD43A4 Collection 6) and 10-minute Himawari-9 Advanced Himawari Imager (AHI, 2-km and 10-km) data. The daily 90th percentile GCC values derived from the phenocam imagery were compared to vegetation indices (VIs) from the satellite datasets, including the GCC, Enhanced Vegetation Index 2 (EVI2), Normalized Difference Vegetation Index (NDVI), Soil-Adjusted Vegetation Index (SAVI), and Visible Atmospherically Resistant Index (VARI). These comparisons were conducted using statistical metrics including Pearson's correlation coefficient (r), slope, root-mean-square deviation (RMSE), and coefficient of determination ($R^2$) to assess the vegetation response signals across different temporal and spatial scales at the AS site. Additionally, land cover classification was performed using a supervised Random Forest algorithm applied to high-resolution images from Google Earth Pro (acquisition date: May 10, 2020). This classification identified, for each satellite pixel footprint, distinct vegetation types within the AS site, including trees, grasses, and bare soil, achieving an accuracy above 98%.

## 3. RESULTS AND DISCUSSION

The multiple linear regression analysis revealed distinct phenological dynamics influenced by grass and tree components within the landscape based on the phenocam signals (Figure 2). The grass component exhibited a higher coefficient of determination ($R^2 = 0.81$) compared to the tree component ($R^2 = 0.63$), indicating that variations in grass phenology exerted a greater influence on the overall phenological patterns observed across the entire landscape. These findings underscore the critical role of grasses in driving seasonal changes within the AS savanna, suggesting that the temporal dynamics of grasslands are more influential in shaping ecosystem responses and phenological signals than evergreen tree canopies, which may exhibit less pronounced variability. Such dominance of grass-driven phenology is crucial for interpreting the LSP captured by satellite data in savanna environments, where mixed vegetation types coexist.

The comparison between phenocam-derived GCC values and satellite-based VIs at the AS savanna site further demonstrate the differential contributions of the components in the overall signal detected by satellite-derived LSP. Figure 3 (A – B) illustrates the $R^2$ between VIs derived from the orbital sensors and GCC values obtained from phenocam

ROIs, categorized by grass, tree canopy, and landscape. The results reveal distinct patterns in the relation strength across different vegetation components and sensor resolutions. For the landscape, AHI at 10 km resolution exhibits the highest $R^2$ value but a wide range of variability between the VIs, while MODIS shows a more consistent and higher correlation on average. When focusing on the background component, the $R^2$ values reached the highest values across all orbital sensors analysed, indicating that these sensors are particularly more sensitive to the phenology of grass, dominating the $R^2$ values observed in the landscape. In contrast, the tree canopy relations are notably lower, highlighting the challenges in capturing the phenological dynamics of evergreen tree species. The spatial analysis of land cover proportions shown that trees were the predominant vegetation type (> 70%) within the footprints of all orbital sensors analysed (Figure 3D). This finding underscores the critical influence of seasonal grass phenology in driving overall phenological signals detected by remote sensing, even when grasses constitute a smaller proportion of the landscape (< 30%).

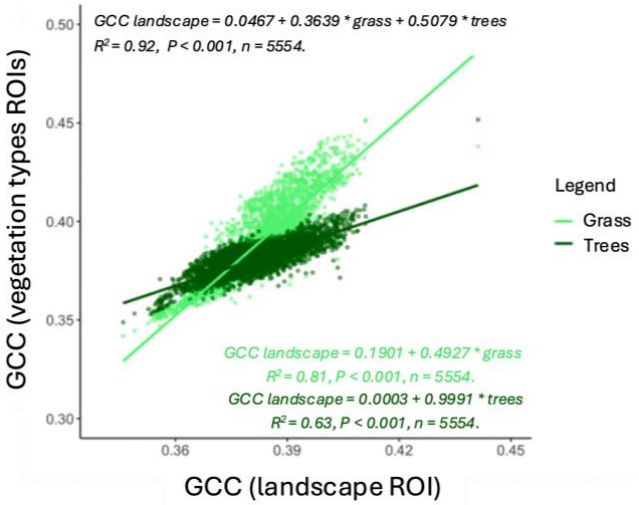


**Figure 2. Multiple linear regression plot comparing the phenology of GCC for grass components and tree canopy ROIs (y-axis) against the GCC for the overall landscape (x-axis), derived from phenocam time series.**

Figure 4 illustrates the relationships between the landscape GCC values derived from phenocam data and NDVI values derived from orbital sensors, presented through linear regression analyses. For the MSI sensor, the relationship shows an R value of 0.81 and an $R^2$ of 0.65 ($p < 0.001$, $n = 100$), indicating a strong and significant correlation between the NDVI and GCC. The slope of 0.132, combined with a low RMSE of 0.006, suggests that MSI effectively captures the fine-scale variations in phenological patterns observed in the GCC data. MODIS, similarly, demonstrates a strong correlation ($R = 0.79$, $R^2 = 0.62$, $p < 0.001$, $n = 614$). The higher slope value of 0.189 and RMSE of 0.006 reflect MODIS's capacity to capture landscape-level phenology, although its coarser resolution may limit its sensitivity to small-scale variations. The AHI sensors at 2 km and 10 km resolutions exhibit progressively higher R values (0.85 and 0.87, respectively) and $R^2$ values (0.72 and 0.75, respectively, $p < 0.001$), indicating that these coarser-resolution sensors are capturing general phenological trends effectively. However, the slopes (0.201 for AHI 2 km and 0.17 for AHI 10 km) suggest that while these sensors can detect broader patterns, their ability to capture finer-scale dynamics diminishes as the resolution coarsens. Additionally, the lower RMSE values for AHI (0.005 and 0.004) indicate that, despite their coarser resolution, these sensors still maintain consistency in the relationship between the phenocam data.

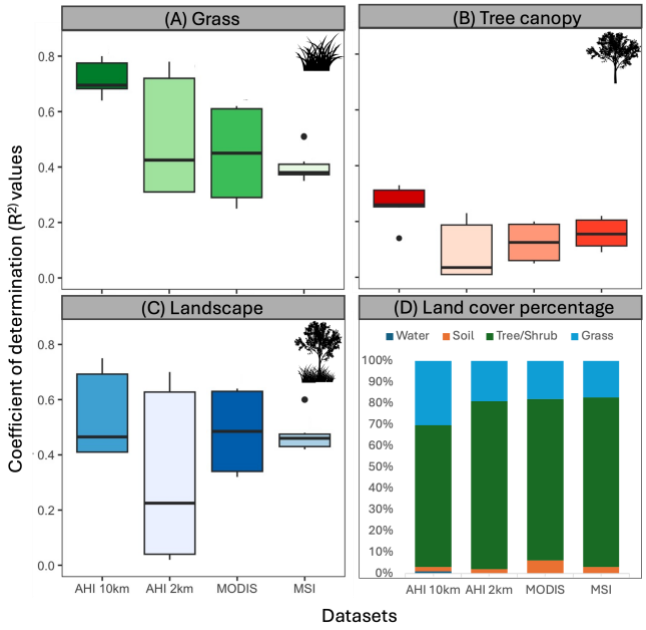


**Figure 3. (A–C) Boxplots displaying the determination coefficient ($R^2$) based on vegetation indices calculated from each orbital sensor and GCC values from phenocam ROIs for grass, tree canopy, and landscape. (D) Land cover proportions of each pixel footprint showing the percentage of soil (orange), grass (light blue), trees/shrubs (green), and water (dark blue) as determined by land cover classification.**

Overall, these results suggests that while as the spatial resolution of the sensor becomes coarser and the temporal resolution become higher, the strength of the relationship between satellite and phenocam (quantified by R and $R^2$ values) generally increases. This counterintuitive trend suggests that coarser-resolution sensors (e.g., AHI at 10 km) are more effective in capturing broad, landscape-level phenological trends, likely because they average out small-scale variability, resulting in a more stable and generalizable signal [11]. Additionally, the AHI 10-km pixel footprint presented the highest grass land cover proportion (Figure 3D). However, while these coarser sensors capture broader trends effectively, they may lose the ability to detect local or small-scale variations that higher-resolution sensors, like MSI, can capture.

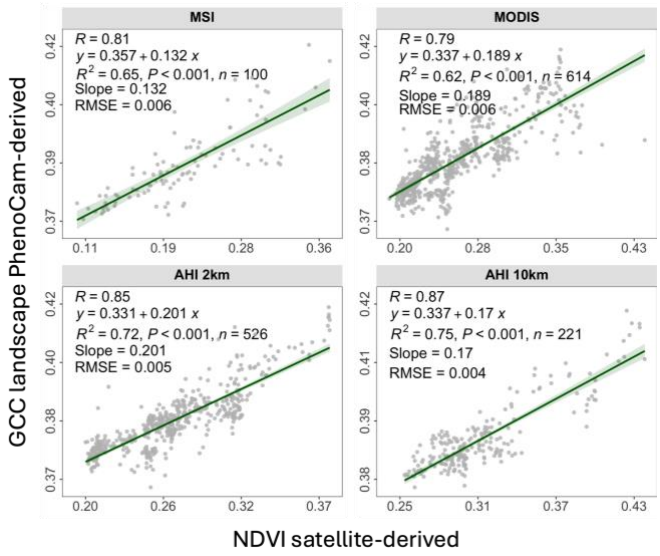


**Figure 4. Linear regressions depicting the GCC-NDVI relationship across varying temporal and spatial scales (MSI, MODIS, AHI). The x-axis shows GCC values derived from phenocam (landscape ROI), while the y-axis displays NDVI values derived from satellite data. Note y-axis exhibits different scales.**

## 4. CONCLUSION

This study underscores the dominant role of grass phenology in shaping LSP signals within heterogeneous dryland landscapes. While coarse-resolution satellite sensors capture broad trends effectively, high-resolution near-surface data reveal significant vegetation-specific dynamics, especially for grasses. Our findings emphasize the necessity of understanding mixed-pixel effects in LSP studies to enhance the accuracy of remote sensing applications in ecosystem monitoring, particularly in complex landscapes like savannas. Accurate differentiation of vegetation responses in LSP is not only essential for refining phenological metrics but also crucial for more realistic assessments of ecosystem functioning, particularly in the context of climate change and its impact on vegetation dynamics.

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