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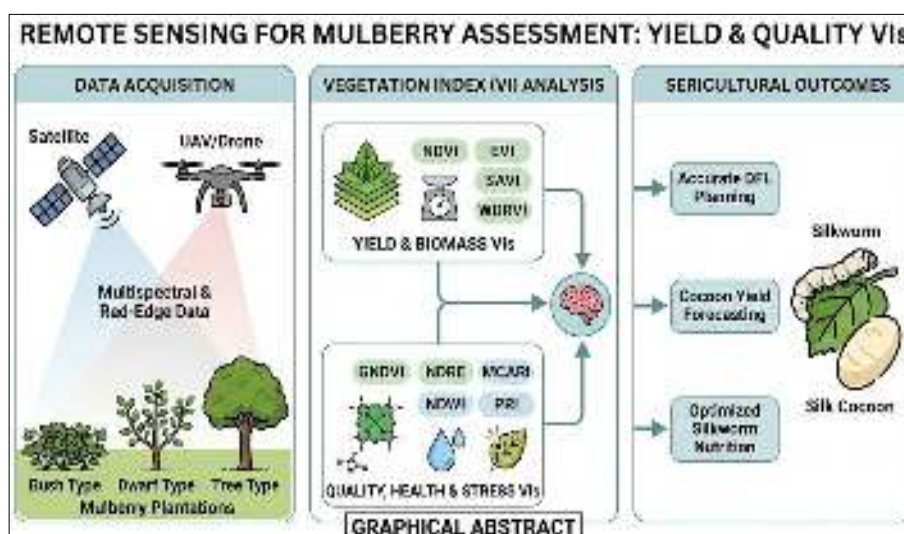
Vegetation Index-Based Remote Sensing Approaches for Evaluating Mulberry (*Morus* Spp.) Leaf Yield

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Abstract

Mulberry (*Morus* spp.) is the sole host plant of the silkworm (*Bombyx mori* L.), and its leaf yield and biochemical quality directly govern silkworm growth, cocoon yield and overall sericultural productivity. Conventional methods of mulberry leaf yield estimation rely heavily on field-based measurements and visual assessments, which are labour-intensive, subjective and inadequate for large-scale planning and forecasting. In this context, satellite-based remote sensing, particularly vegetation index (VI)-based approaches, has emerged as a robust, non-destructive and spatially explicit tool for evaluating mulberry canopy condition, biomass and leaf quality. This review critically synthesizes existing research on vegetation index-based remote sensing techniques for the assessment of mulberry leaf yield and canopy biochemical attributes. Core yield-sensitive indices such as NDVI, EVI, SAVI and OSAVI, along with ratio- and difference-based indices (RVI, DVI, IPVI), soil and atmosphere-adjusted indices (ARVI, MSAVI) and high-biomass indices (WDRVI) are examined for their utility in estimating mulberry leaf biomass. In addition, chlorophyll, nitrogen, water and pigment-sensitive indices, including GNDVI, NDRE, chlorophyll indices, MCARI, TCARI, MTCI, PRI, NDWI, MSI and senescence-related indices, are reviewed for their potential in assessing leaf nutritional quality and physiological status. The synthesis highlights the growing relevance of multispectral and red-edge based indices from sensors such as Sentinel-2, MODIS and UAV platforms in capturing mulberry canopy dynamics. Overall, vegetation index-based remote sensing offers a powerful framework for timely estimation of mulberry leaf yield and quality, enabling improved DFL planning, cocoon production forecasting and sustainable intensification of sericulture.



Keywords: Mulberry, leaf yield, leaf quality, vegetation indices, remote sensing, UAV, Remote sensing

Introduction

Mulberry (*Morus* spp.) is cultivated primarily for its foliage, which constitutes the sole food source for the silkworm (*Bombyx mori* L.). The quantity and nutritional quality of mulberry leaves play a decisive role in silkworm growth, cocoon development and overall sericultural

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productivity. Owing to the monophagous nature of silkworms, exclusive dependence on mulberry leaves makes leaf quality a critical determinant in the selection of superior silkworm races and in achieving optimal cocoon yield (Bongale *et al.* 1997) ^[51]. It is estimated that over 60% of the total cost of cocoon production is invested in mulberry cultivation. Consequently, improving mulberry leaf yield and nutritional composition has remained a major focus of sericultural research, as silkworm growth, development and cocoon production are closely linked to leaf biomass and nutrient status (Yokoyama, 1963) ^[52]. Although mulberry is a fast-growing, deciduous, perennial woody plant capable of adapting to diverse agro-climatic conditions, its leaf yield and quality are influenced by several interacting factors, including varietal traits, soil fertility, agronomic management practices, pest and disease pressure and climatic variability. In sericulture, productivity and profitability are largely governed by the availability of high-quality mulberry foliage per unit area. Since cocoon yield is generally proportional to the quantity of leaf biomass available, accurate estimation of mulberry leaf yield is essential for effective planning of silkworm rearing operations, including the determination of disease-free laying (DFL) requirements and reliable forecasting of cocoon production (Jyothi and Manjunatha, 2024) ^[32].

Traditionally, mulberry leaf yield assessment has relied on visual observations and field-based methods, which are subjective, labour-intensive, time-consuming and prone to considerable error. Such limitations often result in inaccurate predictions of leaf availability, DFL demand and silk output, thereby constraining large-scale planning, infrastructure development, and sustainable growth of the sericulture sector. In this context, satellite-based remote sensing technologies have emerged as robust and efficient tools for acquiring large-scale, repetitive and objective information on crop condition and productivity (Anonymous, 1994) ^[2]. When integrated with Geographic Information System (GIS) and Global Positioning System (GPS) technologies, remote sensing offers a powerful framework for mapping, monitoring and assessing silkworm host plants. Crop production forecasting using remote sensing typically involves crop identification, acreage estimation, yield prediction and quality assessment by exploiting the unique spectral signatures of vegetation. Such integration enables precise estimation of mulberry acreage and leaf yield potential, thereby enhancing decision-making and strategic planning in sericulture (Knippling, 1970) ^[34]. Remote sensing observations of crop canopies are commonly acquired using sensors mounted on satellites, aircraft, or unmanned aerial vehicles (UAVs). Recent advances in high-resolution satellite constellations, such as Planet Scope equipped with multispectral sensors (RGB and near-infrared), have significantly improved the detection of plant vigour and temporal variability, even in small and fragmented mulberry plantations (Sozzi *et al.* 2021) ^[46].

Vegetation indices (VIs) represent one of the most widely used remote sensing approaches for quantifying vegetation cover, vigour and biomass at the pixel level (Ouyang *et al.* 2010) ^[39]. These indices are derived from spectral bands that are highly sensitive to vegetation characteristics, particularly the red and near-infrared regions of the electromagnetic spectrum. By mathematically combining these spectral bands through ratios, differences, or normalized formulations, vegetation indices provide single-value

metrics that effectively capture plant physiological and structural conditions (Matricardi *et al.* 2010) ^[36]. Vegetation indices derived from remotely sensed data have been extensively applied as quantitative proxies for plant health and have demonstrated strong potential in estimating biomass, water stress, yield and product quality in both annual and perennial cropping systems. However, despite these advancements, the application of remote sensing and vegetation index-based approaches for mulberry cultivation and monitoring remains relatively limited (Bannari *et al.* 2009) ^[4].

Satellite-derived vegetation indices offer considerable potential for monitoring mulberry leaf biomass and quality and for establishing relationships with key cocoon production parameters. Such approaches enable timely, accurate and spatially explicit estimation of mulberry leaf yield and nutritional status, which are crucial for optimizing DFL planning, forecasting silk production and promoting sustainable and economically viable sericulture practices (Giora *et al.* 2022) ^[16]. Therefore, the primary objective of this review is to critically synthesize and evaluate existing research on vegetation index-based remote sensing techniques for the assessment and estimation of mulberry leaf yield and quality.

A. Vegetation index-based canopy yield estimation

Mulberry (*Morus* spp.) is a globally important crop grown primarily for foliage to sustain sericulture. Since crop productivity is closely linked to plant architecture and spatial arrangement, optimized planting geometry is essential for achieving higher leaf yield and improved leaf quality (Vinodkumar Yadav *et al.* 2020) ^[51]. Mulberry leaf yield is governed by interactions between environmental conditions and cultivar-specific genetic potential. Key yield-contributing traits include branch number, leaf number, total leaf area, and leaf yield per plant (Susheelamma *et al.* 2005) ^[47]. However, accurate yield estimation remains challenging due to the complex, nonlinear relationships among plant physiological status, climate, and management practices. Vegetation indices derived from multispectral and hyperspectral remote sensing data provide quantitative information on canopy structure and vigour, offering an efficient means for indirect estimation of mulberry leaf yield (Vina *et al.* 2011) ^[50].

In this context, multiple vegetation indices have emerged as reliable tools for evaluating mulberry leaf yield, as discussed in the following sections.

A1. Core Yield Indices

Normalized Difference Vegetation Index (NDVI)

The Normalized Difference Vegetation Index (NDVI) was introduced by Rouse *et al.* (1974) as a modification of the simple ratio (SR) index, which was originally developed for estimating above-ground biomass. Kriegler *et al.* (1969) ^[35] proposed a simple spectral band transformation using near-infrared (NIR) and red reflectance, calculated as the difference between the two bands normalized by their sum. This formulation formed the basis for the development of NDVI. NDVI is widely used for identifying vegetated areas and is commonly applied in agricultural and land-use studies. It is defined as the normalized ratio of the difference and sum of reflectance in the NIR and red spectral regions and is sensitive to chlorophyll and green vegetation. NDVI can be used to examine spatial and temporal variations in

crop canopy development and to monitor crop growth conditions over time (Trout *et al.* 2008) ^[48].

NDVI is mathematically expressed as:

$$NDVI = \frac{\rho_{NIR} - \rho_R}{\rho_{NIR} + \rho_R}$$

NDVI values range from -1 to +1 and are interpreted as follows:

- Values close to +1 (typically 0.6–0.9) represent dense, healthy vegetation.
- Values between approximately 0 and 0.2 correspond to bare soil, rocks, or senescent vegetation.
- Negative values generally indicate non-vegetated surfaces such as water bodies, snow, or clouds.

Enhanced Vegetation Index (EVI)

The Enhanced Vegetation Index (EVI) was developed by Liu and Huete to overcome some limitations of NDVI, particularly atmospheric and soil background effects, and to reduce saturation in dense vegetation conditions. EVI values range from -1 to +1, with healthy vegetation typically falling between 0.2 and 0.8. Compared with NDVI, EVI is more sensitive in high-biomass regions where NDVI commonly saturates, making it more suitable for monitoring dense vegetation (Huete *et al.* 2002) ^[29].

EVI is calculated as:

$$2.5 \times \frac{\rho_{NIR} - \rho_R}{\rho_{NIR} + C1 \times \rho_R - C2 \times \rho_{Blue} + L}$$

where C1 and C2 correct for atmospheric aerosol scattering and L adjusts for soil and canopy background. For the MODIS sensor, for which EVI was originally developed, standard coefficient values of C1=6, C2=7.5 and L=1 are commonly used.

Soil-Adjusted Vegetation Index (SAVI)

The Soil-Adjusted Vegetation Index (SAVI) was proposed by Huete (1988) ^[30] to reduce the influence of soil background reflectance on vegetation measurements, particularly in areas with low or moderate vegetation cover. SAVI modifies the Normalized Difference Vegetation Index (NDVI) by incorporating a soil adjustment factor, thereby improving vegetation assessment under varying soil and canopy conditions.

SAVI is calculated using the following equation:

$$SAVI = \frac{\rho_{NIR} - \rho_R}{\rho_{NIR} + \rho_R + L} \times 1 + L$$

where ρ_{NIR} denotes the reflectance of the near-infrared band (760–900 nm), ρ_R represents the reflectance of the red band (630–690 nm) and L is a soil adjustment constant. The value of L depends on vegetation density and ranges from 0 for dense canopy cover to 1 for sparse vegetation or exposed soil. SAVI can be generated using different L values (e.g., 0.25, 0.5, and 0.75) to account for varying vegetation conditions. Commonly, an L value of 0.5 is used to represent intermediate vegetation cover and is recommended when vegetation cover is unknown. (Fadhil Al-Quraishi *et al.* 2021) ^[13].

Optimized Soil-Adjusted Vegetation Index (OSAVI) ed Soil Adjusted

The Optimized Soil-Adjusted Vegetation Index (OSAVI) is a modified form of SAVI and is also based on reflectance from the near-infrared (NIR) and red bands. The key difference between SAVI and OSAVI is the use of a fixed canopy background adjustment factor. In OSAVI, this factor (L) is set to a constant value of 0.16, which allows for soil background correction without the need to vary L according to vegetation density.

OSAVI is calculated as:

$$OSAVI = \frac{\rho_{NIR} - \rho_R}{\rho_{NIR} + \rho_R + L} \times 1 + L$$

where ρ_{NIR} is the reflectance of the near-infrared band (760–900 nm), ρ_R is the reflectance of the red band (630–690 nm) and L is the adjustment factor with a fixed value of 0.16 (Fadhil Al-Quraishi *et al.* 2021) ^[13].

A2. Ratio/Difference Indices

Ratio Vegetation Index (RVI)

The Ratio Vegetation Index (RVI) is among the earliest vegetation indices used in remote sensing analysis. It is derived from the simple ratio of near-infrared (NIR) to red band reflectance and has been applied since the late 1960s for assessing vegetation properties such as biomass and leaf area index (LAI). Initially, this index was referred to as the Vegetation Index Number (VIN) (Pearson and Miller, 1972) ^[40].

The ratio between NIR and red reflectance provides a basic indication of vegetation presence and condition. One of the main advantages of RVI is its ability to enhance the contrast between vegetated surfaces and bare ground, while also reducing the influence of varying illumination conditions.

RVI is expressed as:

$$RVI = \frac{\rho_{NIR}}{\rho_R}$$

where ρ_{NIR} represents the reflectance in the near-infrared band and ρ_R denotes the reflectance in the red band.

Difference Vegetation Index (DVI)

The Difference Vegetation Index (DVI) is one of the earliest vegetation indices used in remote sensing, particularly with early satellite data such as Landsat MSS in the 1970s. It is a simple index that emphasizes the contrast between near-infrared and red reflectance (Silleos *et al.* 2006) ^[45].

DVI is calculated as:

$$DVI = \rho_{NIR} - \rho_R$$

where ρ_{NIR} is the reflectance in the near-infrared band and ρ_R is the reflectance in the red band. Unlike normalized indices such as NDVI, DVI is sensitive to illumination, atmospheric effects, and scene brightness. Values near zero indicate bare soil, positive values represent vegetation, and negative values correspond to water bodies. Due to these characteristics, DVI is more suitable for areas

with low to moderate vegetation cover and is less effective in densely vegetated regions (Gowri and Manjula, 2019) [25].

Infrared Percentage Vegetation Index (IPVI)

Unlike NDVI, the Infrared Percentage Vegetation Index (IPVI), proposed by Crippen (1990) [10] is scaled between 0 and 1, thereby eliminating negative values. Although the numerical range differs, IPVI is functionally equivalent to NDVI and provides similar information on vegetation condition.

IPVI is calculated as:

$$IPVI = \frac{\rho_{NIR}}{\rho_{NIR} + \rho_R}$$

A3. Soil & Atmosphere Adjusted:

Atmospherically Resistant Vegetation Index (ARVI)

To minimize the effects of atmospheric interference, particularly aerosol scattering that alters reflectance in the visible bands, the Atmospherically Resistant Vegetation Index (ARVI) was developed. This index modifies the NDVI formulation by incorporating the blue band to correct red band distortions caused by atmospheric scattering.

ARVI is calculated as:

$$ARVI = \frac{\rho_{NIR} - [\rho_R - \gamma(\rho_B - \rho_R)]}{\rho_{NIR} + [\rho_R - \gamma(\rho_B - \rho_R)]}$$

where ρ_{NIR} is the reflectance in the near-infrared band, ρ_R represents the reflectance in the red band, ρ_B denotes the reflectance in the blue band and γ is a weighting factor with a value of 1.7. By replacing the red band in NDVI with a corrected red term, ARVI provides improved performance under conditions such as haze or smoke (Kaufman and Tanre, 1992) [33].

MSAVI-1 (modified soil adjusted vegetation index - 1)

The Modified Soil-Adjusted Vegetation Index (MSAVI) is an extension of SAVI in which the soil adjustment factor (L) is allowed to vary with vegetation cover rather than remaining constant. This variable adjustment improves the separation of vegetation from soil background, particularly in areas with sparse or discontinuous canopy cover (Chehbouni *et al.* 1994) [8].

MSAVI is computed as

$$MSAVI = \frac{(1+L)(\rho_{NIR} - \rho_R)}{\rho_{NIR} + \rho_R + L}$$

where ρ_{NIR} and ρ_R represent reflectance in the near-infrared and red spectral regions, respectively. The adjustment factor L ranges between 0 and 1, with lower values corresponding to dense vegetation and higher values indicating sparse vegetation or bare soil. When L approaches zero, MSAVI converges to NDVI. MSAVI values range from -1 to 1, where negative values indicate bare or sparsely vegetated surfaces and positive values represent active vegetation, with higher values reflecting greater vegetation vigour.

MSAVI-2 (modified soil adjusted vegetation index - 2)

MSAVI-2 is a further modification of the Soil-Adjusted Vegetation Index designed to reduce soil background

effects, particularly under sparse vegetation conditions. Unlike earlier forms, MSAVI-2 computes the soil adjustment internally, eliminating the need to specify an external correction factor (Chehbouni *et al.* 1994) [8].

MSAVI-2 is calculated as:

$$MSAVI-2 = \frac{2\rho_{NIR} + 1 - \sqrt{(2\rho_{NIR} + 1)^2 - 8(\rho_{NIR} - \rho_R)}}{2}$$

where ρ_{NIR} represents reflectance in the near-infrared band and ρ_R denotes reflectance in the red band. MSAVI-2 values are generally negative in areas with very low vegetation cover and positive in areas with active vegetation, with higher values indicating greater vegetation vigour.

A4. High-Biomass Sensitivity

Wide Dynamic Range Vegetation Index (WDRVI)

The Wide Dynamic Range Vegetation Index (WDRVI) was proposed to overcome the saturation limitations of NDVI under moderate to high biomass conditions. It is calculated as:

$$WDRVI = \frac{a \times \rho_{NIR} - \rho_{Red}}{a \times \rho_{NIR} + \rho_{Red}}$$

where ρ_{NIR} and ρ_R denote reflectance in the near-infrared and red spectral bands, respectively. Vegetation exhibits high reflectance in the NIR region due to internal leaf structure, whereas red reflectance is strongly absorbed by chlorophyll. The parameter a is a weighting coefficient applied to the NIR band, typically set to 0.1 (and occasionally 0.2), which reduces NIR dominance, expands the dynamic range of the index, and limits saturation effects. WDRVI has been widely applied in agricultural crop monitoring, phenological analysis, and biomass estimation, and is compatible with both satellite-based sensors such as MODIS and UAV-derived multispectral imagery (Gitelson, 2003) [17, 19].

A5. Visible- Band Greenness

Visible Atmospherically Resistant Index (VARI)

Gitelson *et al.* (2002) [21, 23] introduced visible-band vegetation indices, such as the Visible Atmospherically Resistant Index (VARI), for estimating vegetation fraction and greenness using only red, green, and blue bands. VARI is especially useful when near-infrared data are unavailable and is calculated as:

$$VARI = \frac{\rho_{Green} - \rho_{Red}}{\rho_{Green} + \rho_{Red} - \rho_{Blue}}$$

where Green, Red and Blue represent reflectance values in the respective visible bands. The index was developed to reduce atmospheric effects, particularly blue-band scattering, and shows good correlation with vegetation fraction and canopy greenness, performing best under open or moderately dense vegetation conditions.

B. Vegetation index-based assessment of canopy biochemical quality

In sericulture, mulberry leaf quality is a critical determinant of silkworm growth, cocoon yield and silk filament

characteristics (Nguyen *et al.* 2024) [38]. Owing to the monophagous feeding habit of *Bombyx mori*, the nutritional and biochemical composition of mulberry foliage is directly converted into silk proteins, making leaf physiological status a central driver of sericultural productivity (Chundang *et al.* 2020) [9]. Mulberry leaf quality is governed by a range of physiological and biochemical traits that vary markedly across genotypes, environmental conditions and agronomic management practices (Tunc *et al.* 2025) [49]. Key physiological attributes, including leaf area, chlorophyll concentration, photosynthetic efficiency and stomatal regulation, strongly influence leaf biomass accumulation and nutrient availability (Al-Gaadi *et al.* 2024) [1]. Enhanced photosynthetic activity and stable chlorophyll pigments promote carbohydrate synthesis, thereby supporting larval energy metabolism and cocoon formation (Wu *et al.* 2024) [53]. In addition, leaf water status and turgor maintenance are essential for preserving succulence and palatability, which ultimately enhances larval feeding efficiency and overall silkworm performance (Nguyen *et al.* 2024). Within this framework, several vegetation indices have proven effective for the assessment of mulberry leaf quality and are discussed in detail in the subsequent sections.

B1. Chlorophyll and nitrogen content-sensitive vegetation indices:

Green Normalized Difference Vegetation Index (GNDVI)

Gitelson *et al.* (1996) [20] proposed the Normalized Difference Vegetation Index based on the green band (GNDVI) after demonstrating that reflectance in the green spectral region (520–630 nm) is sensitive across the full range of leaf chlorophyll concentrations (0.3–45 $\mu\text{g cm}^{-2}$). In contrast, the red band shows limited sensitivity, particularly within chlorophyll concentrations of 3–5 $\mu\text{g cm}^{-2}$, and responds poorly to variations in yellow-green to fully green leaves.

GNDVI is calculated as:

$$\text{GNDVI} = \frac{\rho_{\text{NIR}} - \rho_{\text{Green}}}{\rho_{\text{NIR}} + \rho_{\text{Green}}}$$

This index was developed as a complement to NDVI, which uses the red band that is strongly absorbed by chlorophyll. By replacing the red band with the green band, which is more strongly reflected by healthy vegetation, GNDVI exhibits greater sensitivity to chlorophyll content and reduced influence of soil background compared to NDVI.

Normalized Difference Red Edge (NDRE)

The Normalized Difference Red Edge (NDRE) is a vegetation index used to assess plant physiological condition by capturing variations in chlorophyll content from multispectral imagery. Owing to its sensitivity to chlorophyll and nitrogen status, NDRE has gained increasing relevance in agricultural applications, particularly for monitoring crop nutrient conditions. The index utilizes reflectance information from the near-infrared (NIR) and red-edge spectral regions, both of which are available in Sentinel-2 imagery.

NDRE is calculated as:

$$\text{NDRE} = \frac{\rho_{\text{NIR}} - \rho_{\text{Red-edge}}}{\rho_{\text{NIR}} + \rho_{\text{Red-edge}}}$$

where ρ_{NIR} represents reflectance in the near-infrared band and ρ_{RedEdge} denotes reflectance in the red-edge spectral band.

B2. Chlorophyll concentration-based vegetation indices: Chlorophyll index green (CIgreen) and chlorophyll index red edge (CIred-edge)

Chlorophyll Index Green (CI_{green}) and Chlorophyll Index Red-Edge (CI_{red-edge}) were developed to estimate canopy chlorophyll concentration using remote sensing techniques (Gitelson *et al.* 2005) [24]. At elevated chlorophyll levels, simple reflectance measurements tend to saturate, resulting in minimal response to further increases in chlorophyll content. This limitation can be addressed by combining reflectance from chlorophyll-sensitive wavelengths, such as the green and red-edge regions, with the more stable near-infrared (NIR) band (Gitelson *et al.* 2003) [17, 19].

Both CI_{green} and CI_{red-edge} are based on this principle and are specifically designed to enhance sensitivity to chlorophyll variations.

The Chlorophyll Index Green is expressed as:

$$\text{CI}_{\text{green}} = \frac{\rho_{\text{NIR}}}{\rho_{\text{Green}}} - 1$$

where ρ_{NIR} and ρ_{Green} represent reflectance in the near-infrared and green spectral bands, respectively. This index exploits the contrast between high NIR reflectance and chlorophyll-responsive green reflectance to estimate chlorophyll content.

Similarly, the Chlorophyll Index Red-Edge is calculated as:

$$\text{CI}_{\text{red-edge}} = \frac{\rho_{\text{NIR}}}{\rho_{\text{Red-edge}}} - 1$$

where $\rho_{\text{Red-edge}}$ denotes reflectance in the red-edge region, which is highly sensitive to changes in leaf chlorophyll concentration. Both indices effectively leverage the strong spectral contrast between NIR reflectance and pigment-sensitive green or red-edge wavelengths for improved chlorophyll assessment.

B3. Chlorophyll Absorption-Based Vegetation Indices:

1.1.1. Modified Chlorophyll Absorption Ratio Index (MCARI)

Daughtry *et al.* (2000) [12] proposed the Chlorophyll Absorption Ratio Index modification to enhance sensitivity to canopy chlorophyll content while minimizing the influence of background reflectance. The approach combines reflectance information from the red, red-edge and green spectral regions to strengthen the chlorophyll absorption signal. Compared with earlier chlorophyll indices, this formulation provides improved resistance to background interference, although some sensitivity to soil reflectance may persist under sparse canopy conditions.

MCARI is expressed as:

$$\text{MCARI} = \left[(\rho_{710} - \rho_{670}) - 1.2(\rho_{710} - \rho_{550}) \right] \times \frac{670}{670}$$

where ρ_{550} , ρ_{670} and ρ_{710} denote reflectance in the green (550 nm), red (670 nm; chlorophyll absorption peak) and red-edge (710 nm) spectral regions, respectively. This

formulation enhances sensitivity to chlorophyll absorption while partially compensating for non-photosynthetic background components.

Transformed Chlorophyll Absorption in Reflectance Index (TCARI)

To further suppress soil background and canopy structural effects, Haboudane *et al.* (2002) ^[27] introduced the Transformed Chlorophyll Absorption in Reflectance Index (TCARI) as a scaled transformation of MCARI. By applying a multiplication factor of three, TCARI amplifies the chlorophyll absorption signal and improves responsiveness across a wider range of chlorophyll concentrations.

TCARI is defined as:

$$TCARI = 3 \times [(p_{700} - p_{670}) - 0.2(p_{700} - p_{550})] \times \frac{p_{700}}{p_{670}}$$

where p_{550} , p_{670} and p_{700} again represent reflectance in the green, red and red-edge spectral regions, respectively. The scaling factor enhances the stability and strength of the chlorophyll signal without altering the spectral structure of the index. Consequently, TCARI provides a more robust estimate of chlorophyll content than MCARI and is frequently combined with soil-adjusted vegetation indices such as OSAVI to further reduce soil background influence.

B4. Advanced Chlorophyll Absorption-Based Indices MERIS Terrestrial Chlorophyll Index (MTCI)

The MERIS Terrestrial Chlorophyll Index (MTCI) was introduced by Dash and Curran (2004) ^[11] as a red-edge-based vegetation index for estimating canopy chlorophyll content. The index is designed to capture shifts in the red-edge position associated with changes in chlorophyll concentration and has been evaluated and validated using both satellite observations and ground-based measurements. MTCI utilizes reflectance from the red, red-edge and near-infrared spectral regions, making it sensitive to variations in canopy chlorophyll levels.

MTCI is computed using discrete spectral bands centered at approximately 681.25 nm, 708.75 nm and 753.75 nm, allowing effective estimation of canopy chlorophyll concentration without requiring continuous spectral sampling, as is necessary for traditional red-edge position methods (Guyot *et al.* 1992) ^[26]. Due to its sensitivity across a wide range of chlorophyll concentrations and compatibility with Earth observation sensors, MTCI was adopted by the European Space Agency (ESA) in 2004 as an operational land product for space-based estimation of canopy chlorophyll content.

The index is expressed as:

$$MTCI = \frac{p_{NIR} - p_{Red-edge}}{p_{Red-edge} - p_{Red}}$$

where p_{Red} , $p_{Red-edge}$ and p_{NIR} denote reflectance in the red, red-edge and near-infrared spectral bands, respectively (approximately 681, 709, and 754 nm for the MERIS sensor).

B5. Indices for Photosynthetic Performance and Stress Detection

Photochemical Reflectance Index (PRI)

The Photochemical Reflectance Index (PRI), developed by Gamon *et al.* (1992) ^[14] is a narrowband spectral index used

to assess photosynthetic efficiency in vegetation. It is particularly sensitive to changes in carotenoid pigments, especially xanthophylls, which are closely associated with light-use efficiency and carbon dioxide uptake per unit of absorbed radiation. Consequently, PRI has been widely applied in studies of vegetation productivity, physiological stress and ecosystem carbon balance.

PRI captures rapid plant physiological responses to environmental stress and is therefore useful for evaluating vegetation condition and ecosystem health using satellite or proximal remote sensing data. Its applications span forests, evergreen shrublands and agricultural crops, especially during active growth stages prior to senescence.

The index is calculated using reflectance at 531 nm and a reference wavelength near 570 nm, which helps reduce spectral artefacts caused by broad-band reflectance variations such as chloroplast movement. Analogous in formulation to the Normalized Difference Vegetation Index (NDVI), PRI is expressed as:

$$PRI = \frac{p_{531} - p_{570}}{p_{531} + p_{570}}$$

where p_{531} and p_{570} represent reflectance at approximately 531 nm and 570 nm, respectively. These wavelengths may vary slightly depending on sensor characteristics and vegetation type. PRI values range from -1 to +1, with higher values indicating greater photosynthetic efficiency (Brugnoli & Bjorkman, 1992) ^[6].

Structure Insensitive Pigment Index (SIPI) Intensive Pigment V

Penuelas *et al.* (1995) ^[41] proposed the Structure Insensitive Pigment Index as a means to minimize the influence of canopy structure while enhancing sensitivity to variations in the carotenoid-to-chlorophyll ratio, making it a robust indicator of vegetation stress and pigment composition. By combining reflectance information from the near-infrared, blue and red spectral regions, the index emphasizes physiological pigment changes rather than effects caused by canopy geometry or leaf area differences.

Higher index values indicate increased carotenoid content relative to chlorophyll, a condition commonly associated with plant stress, chlorophyll degradation, or the onset of crop diseases. Owing to its reduced sensitivity to structural variability, the index is particularly suitable for monitoring plant health in areas with heterogeneous canopy structure or LAI and for detecting early stress signals using remote sensing data.

The index is expressed as:

$$SIPI = \frac{p_{NIR} - p_{Red}}{p_{NIR} - p_{BLUE}}$$

and is commonly written in wavelength-specific form as:

$$SIPI = \frac{p_{800} - p_{680}}{p_{800} - p_{445}}$$

where p_{800} denotes near-infrared reflectance, p_{445} represents reflectance in the blue (carotenoid absorption)

region and ρ_{680} corresponds to the red band dominated by chlorophyll absorption.

B6. Indices for plant Water Status and Moisture Assessment

Normalized Difference Water Index (NDWI)

Gao (1996) ^[15] introduced the Normalized Difference Water Index (NDWI) to estimate vegetation liquid water content using remote sensing. NDWI has been widely validated as a reliable indicator of leaf and canopy water status, including equivalent water thickness (Wu *et al.* 2009) ^[52]. The index combines reflectance from the near-infrared (NIR) and short-wave infrared (SWIR) spectral regions to capture variations in plant water content.

$$NDWI = \frac{\rho_{NIR} - \rho_{SWIR}}{\rho_{NIR} + \rho_{SWIR}}$$

where:

- ρ_{NIR} is reflectance in the near-infrared region (0.86 μm), characterized by high reflectance from healthy vegetation.
- ρ_{SWIR} is reflectance in the short-wave infrared region (1.24–2.13 μm), where liquid water strongly absorbs radiation.

NIR reflectance provides information on dry matter content and internal leaf structure, while SWIR reflectance is sensitive to leaf water content and mesophyll structure. By combining these bands, NDWI effectively captures the influence of water in leaf tissues on spectral reflectance, providing a robust measure of vegetation water status (Ceccato *et al.* 2001) ^[7].

Moisture Stress Index (MSI)

The Moisture Stress Index (MSI), introduced by Hunt and Rock (1989) ^[31], is a spectral index that reflects variations in vegetation water content and is widely used to assess leaf and canopy water status as well as water stress in plants. MSI is calculated as the ratio of short-wave infrared (SWIR) reflectance to near-infrared (NIR) reflectance, exploiting the strong water absorption in the SWIR region.

$$MSI = \frac{\rho_{SWIR}}{\rho_{NIR}}$$

where:

- ρ_{SWIR} represents reflectance in the short-wave infrared (1.6 μm), which is strongly influenced by leaf water content.
- ρ_{NIR} denotes reflectance in the near-infrared (0.86 μm), sensitive to leaf and canopy structure.

MSI values generally range from 0 to over 3, with typical values for healthy green vegetation between 0.4 and 2. Unlike some other water indices, higher MSI values indicate greater water stress and reduced water content, making it a direct indicator of vegetation moisture limitations (Anonymous, 2022) ^[3].

Water Index (WI)

Penuelas *et al.* (1993) ^[42] introduced the Water Index (WI) as a simple ratio of reflectance in the water absorption

region (970 nm) to a reference band (900 nm). This index has been demonstrated to be effective for evaluating leaf water content and detecting plant water stress (Zhang *et al.* 2021) ^[55].

$$WI = \frac{\rho_{970}}{\rho_{900}}$$

Where:

- ρ_{900} → reflectance at 900 nm (reference wavelength, weak water absorption)
- ρ_{970} → reflectance at 970 nm (strong water absorption band, sensitive to leaf water content and plant water status).

B7. Indices for Vegetation Senescence and Pigment Loss

Plant Senescence Reflectance Index (PSRI)

The Plant Senescence Reflectance Index (PSRI) is designed to assess leaf senescence and fruit ripening with high precision. The index is particularly sensitive to the relative accumulation or retention of carotenoids in senescing leaves and ripening fruits. Over the growing season, PSRI values typically decrease during leaf development after spring green-up, reach a minimum in mid-summer and then increase during autumn as senescence advances. This increase reflects a rising carotenoid-to-chlorophyll ratio associated with chlorophyll degradation in aging foliage (Merzlyak *et al.* 1999) ^[37].

$$PSRI = \frac{\rho_{680} - \rho_{500}}{\rho_{750}}$$

Where:

- ρ_{680} → reflectance in the red band associated with chlorophyll absorption
- ρ_{500} → reflectance in the blue-green region sensitive to carotenoids
- ρ_{750} → reflectance in the near-infrared used as a reference

By capturing changes in chlorophyll loss and carotenoid accumulation, PSRI serves as a reliable indicator for monitoring vegetation senescence, physiological stress, and fruit ripening processes (Gitelson and Merzlyak, 1994) ^[18].

Anthocyanin Reflectance Index (ARI)

Gitelson *et al.* (2001) ^[22] introduced the Anthocyanin Reflectance Index as a non-destructive spectral indicator for estimating anthocyanin content in plant leaves. This index has been widely applied in remote sensing studies to monitor pigment dynamics and evaluate vegetation physiological condition. Anthocyanins typically accumulate in foliage in response to environmental stresses such as drought, nutrient imbalance and during leaf senescence, making the index particularly useful for stress detection. By using reciprocal reflectance values, the formulation enhances sensitivity to subtle spectral variations associated with anthocyanin absorption. To further minimize the influence of leaf internal structure and background effects, modified versions of the index (mARI or ARI2) incorporate additional spectral bands, often including near-infrared

wavelengths, thereby improving its robustness across varying canopy conditions.

The commonly used formulation is expressed as:

$$ARI = \frac{1}{\rho_{550}} - \frac{1}{\rho_{700}}$$

where ρ_{550} represents reflectance in the green region associated with anthocyanin absorption and ρ_{700} corresponds to reflectance near the red-edge region, primarily influenced by chlorophyll and used to isolate anthocyanin effects.

Carotenoid Reflectance Index (CRI)

The CRI (Carotenoid Reflectance Index), proposed by Gitelson *et al.* (2002) [21, 23], along with its commonly used variants CRI1 and CRI2, was developed to estimate carotenoid pigment content in vegetation using spectral reflectance data. These indices show strong relationships with leaf carotenoid concentration and are particularly responsive to physiological changes associated with environmental stress and leaf aging. Since carotenoids tend to accumulate under stress conditions and during senescence, CRI-based metrics are widely applied for vegetation health assessment, stress detection and analysis of pigment composition.

The CRI formulations are expressed as:

$$CRI1 = \frac{1}{\rho_{510}} - \frac{1}{\rho_{550}}$$

$$CRI2 = \frac{1}{\rho_{510}} - \frac{1}{\rho_{700}}$$

Where

- ρ_{510} denotes reflectance at approximately 510 nm, corresponding to a strong carotenoid absorption region
- ρ_{550} represents reflectance near 550 nm and serves as a green reference band
- ρ_{700} indicates reflectance around 700 nm, associated with chlorophyll absorption and the red-edge region

By exploiting the contrasting absorption features of carotenoids and chlorophyll, the CRI provides a reliable means of tracking pigment dynamics and stress-induced changes in vegetation (Penuelas *et al.* 1995) [41].

Conclusion

Accurate assessment of mulberry leaf yield and quality is fundamental to improving silkworm performance, cocoon productivity and the economic sustainability of sericulture. This review demonstrates that vegetation index-based remote sensing approaches provide an efficient, objective and scalable alternative to conventional field-based yield estimation methods. A wide range of vegetation indices, derived from visible, near-infrared, red-edge and short-wave infrared spectral regions, have shown strong potential for characterizing mulberry canopy structure, biomass accumulation, chlorophyll concentration, water status,

pigment dynamics and physiological stress. Core indices such as NDVI, EVI, SAVI and OSAVI remain widely applicable for canopy vigour and yield estimation, while advanced indices including NDRE, chlorophyll indices, MTCI and MCARI offer enhanced sensitivity to leaf biochemical quality and nutrient status. Water and stress sensitive indices such as NDWI, MSI, PRI and SIPI further enable early detection of moisture stress, photosynthetic inefficiency and senescence which are critical determinants of leaf palatability and nutritional value for silkworms.

Despite these advancements, the application of vegetation index-based remote sensing in mulberry cultivation remains relatively underexplored compared to major food crops. Future research should focus on integrating multi-temporal and multi-sensor datasets, combining satellite and UAV observations and coupling vegetation indices with ground-based physiological and yield measurements to develop robust, region-specific predictive models. The integration of remote sensing with GIS and sericulture management systems holds significant promise for precision mulberry farming, optimized DFL planning and reliable cocoon yield forecasting. Overall, vegetation index-based remote sensing represents a transformative tool for advancing data-driven, sustainable and climate-resilient sericulture practices.

References

1. Al-Gaadi KA, Tola E, Madugundu R, Zeyada AM, Alameen AA, Edris MK, et al. Response of leaf photosynthesis, chlorophyll content and yield of hydroponic tomatoes to different water salinity levels. *PLoS One*. 2024;19(2):e0293098.
2. Anonymous. Manual of satellite remote sensing applications for sericulture development. Bangalore: Central Silk Board; 1994. p. 1-64.
3. Anonymous. Moisture Stress Index (MSI) dataset. Yareta institutional repository. 2022. Available from: <https://yareta.unige.ch/archives/2d95788d-b400-4ed7-9ca0-67b8320da5f6>
4. Bannari A, Morin D, Bonn F, Huete AR. A review of vegetation indices. *Remote Sens Rev*. 2009;13:95-120.
5. Bongale UD, Chaluvachari, Mallikarjunappa RS, Narahari Rao BV, Anantharaman MN, Dandin SB. Leaf nutritive quality associated with maturity levels in fourteen important varieties of mulberry (*Morus* spp.). *Sericologia*. 1997;37(1):71-81.
6. Brugnoli E, Björkman O. Chloroplast movements in leaves: Influence on chlorophyll fluorescence and measurements of light-induced absorbance changes related to pH and zeaxanthin formation. *Photosynth Res*. 1992;32:23-35.
7. Ceccato P, Flasse S, Tarantola S, Jacquemoud S, Gregoire JM. Detecting vegetation leaf water content using reflectance in the optical domain. *Remote Sens Environ*. 2001;77:22-33.
8. Chehbouni, Qi J, Huete A, Kerr AR, Sorooshian YH. A modified soil adjusted vegetation index. *Remote Sens Environ*. 1994;48:119-126.
9. Chundang P, Thongprajukaew K, Kovitvadhi U, Chotimanonthum B, Kovitvadhi A, Pakkong P. Improving the nutritive value of mulberry leaves, *Morus* spp. (Rosales: Moraceae) for silkworm larvae, *Bombyx mori* (Lepidoptera: Bombycidae) using gamma irradiation. *J Radiat Res Appl Sci*. 2020;13(1):629-641.
10. Crippen RE. Calculating the vegetation index faster. *Remote Sens Environ*. 1990;34(1):71-73.

11. Dash J, Curran PJ. The MERIS Terrestrial Chlorophyll Index. *Int J Remote Sens*. 2004;25(23):5403-5413.
12. Daughtry CST, Walthall CL, Kim MS, Colstoun EBD, McMurtrey JEI. Estimating corn leaf chlorophyll concentration from leaf and canopy reflectance. *Remote Sens Environ*. 2000;74:229-239.
13. Fadhil Al-Quraishi AM, Razvanchy HAS, Gaznayee HAA. A comparative study for performance of five landsat-based vegetation indices: Their relations to some ecological and terrain variables. *J Appl Sci Technol Trends*. 2021;2(1):58-67.
14. Gamon J, Penuelas J, Field C. A narrow-waveband spectral index that tracks diurnal changes in photosynthetic efficiency. *Remote Sens Environ*. 1992;41:35-44.
15. Gao BC. NDWI—A normalized difference water index for remote sensing of vegetation liquid water from space. *Remote Sens Environ*. 1996;58(3):257-266.
16. Giora D, Assirelli A, Cappelozza S, Sartori L, Saviane A, Marinello F, et al. Remote sensing imaging as a tool to support mulberry cultivation for silk production. *Remote Sens*. 2022;14:5450.
17. Gitelson AA. Wide Dynamic Range Vegetation Index for remote quantification of biophysical characteristics of vegetation. *J Plant Physiol*. 2003;161(2):165-173.
18. Gitelson AA, Merzlyak MN. Quantitative estimation of chlorophyll-a using reflectance spectra: Experiments with autumn chestnut and maple leaves. *J Photochem Photobiol B Biol*. 1994;22(3):247-252.
19. Gitelson AA, Gritz Y, Merzlyak MN. Relationships between leaf chlorophyll content and spectral reflectance and algorithms for non-destructive chlorophyll assessment in higher plant leaves. *J Plant Physiol*. 2003;160(3):271-282.
20. Gitelson AA, Kaufman YJ, Merzlyak MN. Use of a green channel in remote sensing of global vegetation from EOS-MODIS. *Remote Sens Environ*. 1996;58(3):289-298.
21. Gitelson AA, Kaufman YJ, Stark R, Rundquist D. Novel algorithms for remote estimation of vegetation fraction. *Remote Sens Environ*. 2002;80(1):76-87.
22. Gitelson AA, Merzlyak MN, Chivkunova OB. Optical properties and non-destructive estimation of anthocyanin content in plant leaves. *Photochem Photobiol*. 2001;74(1):38-45.
23. Gitelson AA, Zur Y, Chivkunova OB, Merzlyak MN. Assessing carotenoid content in plant leaves with reflectance spectroscopy. *Photochem Photobiol*. 2002;75(3):272-281.
24. Gitelson A, Vina A, Ciganda V, Rundquist D, Arkebauer T. Remote estimation of canopy chlorophyll content in crops. *Geophys Res Lett*. 2005;32(8):L08403.
25. Gowri L, Manjula KR. Evaluation of Various Vegetation Indices for Multispectral Satellite Images. *Int J Innov Technol Explor Eng*. 2019;8(10):3494-3500.
26. Guyot G, Baret F, Jacquemoud S. Imaging spectroscopy for vegetation studies. *Imaging Spectroscopy: Fundamentals and Prospective Applications*. 1992;2:145-165.
27. Haboudane D, Millera JR, Tremblay N, Zarco-Tejadad PJ, Dextraze L. Integrated narrow-band vegetation indices for prediction of crop chlorophyll content for application to precision agriculture. *Remote Sens Environ*. 2002;81:416-426.
28. Hariadi B, Sastrohartono H, Krisdiarto AW, Sukarman S, Sagoro TH, Pramananda S, et al. The use of the Normalized Difference Red Edge (NDRE) vegetation index from multispectral cameras mounted on unmanned aerial vehicle to estimate the nutrient content in oil palm leaves. *J Tek Pertan Lampung*. 2024;13(4):1051-1063.
29. Huete A, Didan K, Miura T, Rodriguez EP, Gao X, Ferreira LG. Overview of the radiometric and biophysical performance of the MODIS vegetation indices. *Remote Sens Environ*. 2002;83:195-213.
30. Huete AR. A soil-adjusted vegetation index (SAVI). *Remote Sens Environ*. 1988;25(3):295-309.
31. Hunt ER, Rock BN. Detection of changes in leaf water content using Near- and Middle-Infrared reflectances. *Remote Sens Environ*. 1989;30(1):43-54.
32. Jyothi BL, Manjunatha HB. Tree mulberry crop acreage and leaf yield estimation using remote sensing and geographical information system. *Int J Res Anal Rev*. 2024;11(2):2349-5138.
33. Kaufman YJ, Tanre D. Atmospherically resistant vegetation index (ARVI) for EOS-MODIS. *IEEE Trans Geosci Remote Sens*. 1992;30(2):261-270.
34. Knipling EB. Physical and physiological basis for the reflectance of visible and near infrared radiation from vegetation. *Remote Sens Environ*. 1970;1:155-159.
35. Kriegler FJ, Malila WA, Nalepka RF, Richardson W. Preprocessing transformations and their effect on multispectral recognition. *Remote Sens Environ*. 1969;6:7-132.
36. Matricardi EAT, Skole DL, Pedlowski MA, Chomentowski W, Fernandes LC. Assessment of tropical forest degradation by selective logging and fire using Land sat imagery. *Remote Sens Environ*. 2010;114:1117-1129.
37. Merzlyak MN, Gitelson AA, Chivkunova OB, Rakitin VY. Non-destructive optical detection of pigment changes during leaf senescence and fruit ripening. *Physiol Plant*. 1999;106(1):135-141.
38. Nguyen H, Nguyen T, Pham T, Le T, Bui T, Jang D, et al. Leaf position of mulberry (*Morus alba* L.) affects silkworm growth, silk cocoon yield and quality. *Vegetos*. 2024;38(4):1681-1688.
39. Ouyang W, Hao FH, Zhao C, Lin C. Vegetation response to 30 years hydropower cascade exploitation in up- per stream of Yellow River. *Commun Nonlinear Sci Numer Simul*. 2010;15:1928-194.
40. Pearson RL, Miller LD. Remote mapping of standing crop biomass for estimation of the productivity of the shortgrass prairie, Pawnee National Grasslands, Colorado. *Proc 8th Int Symp Remote Sens Environ*. 1972:1355-1381.
41. Penuelas J, Baret F, Filella I. Semi-empirical indices to assess carotenoids/chlorophyll a ratio from leaf spectral reflectance. *Photosynthetica*. 1995;31(2):221-230.
42. Penuelas J, Filella I, Biel C, Serrano L, Save R. The reflectance at the 950–970 nm region as an indicator of plant water status. *Int J Remote Sens*. 1993;14(10):1887-1905.
43. Silleos NG, Alexandridis TK, Gitas IZ, Perakis K. Vegetation indices: advances made in biomass

- estimation and vegetation monitoring in the last 30 years. *Geocarto Int.* 2006;21(4):21-28.
44. Sozzi M, Kayad A, Gobbo S, Cogato A, Sartori L, Marinello F, et al. Economic comparison of satellite, plane and UAV-acquired NDVI images for site-specific nitrogen application: Observations from Italy. *Agronomy*. 2021;11:2098.
 45. Susheelamma BN, Dandin SB, Bongale UD. Genetic improvement of mulberry. *Indian J Sericult.* 2005;44(1):1-15.
 46. Trout TJ, Johnson LF, Gartung J. Remote sensing of canopy cover in horticultural crops. *HortSci.* 2008;43(2):333-337.
 47. Tunc Y, Khadivi A, Yaman M, Yilmaz KU, Yildiz E, Gunes A, et al. Characterization of Turkish mulberry genetic resources based on antioxidant capacity, biochemical composition, nutrient content and morphological traits of leaves. *Sci Rep.* 2025;15(1).
 48. Vina A, Gitelson AA, Nguy-Robertson AL, Peng Y. Comparison of different vegetation indices for the remote assessment of green leaf area index of crops. *Remote Sens Environ.* 2011;115(12):3468-3478.
 49. Vinodkumar Yadav K, Sivaprasad V, Dandin SB, Qadri SMH. Effect of planting geometry on growth, leaf yield, and quality of mulberry (*Morus* spp.). *Indian J Sericult.* 2020;59(1):1-7.
 50. Wu C, Niu Z, Tang Q, Huang W. Predicting vegetation water content in wheat using normalized difference water indices derived from ground measurements. *J Plant Res.* 2009;122(3):317-326.
 51. Wu J, Li L, Qin D, Chen H, Liu Y, Shen G, et al. Silkworm haemolymph and cocoon metabolomics reveals valine improves feed efficiency of silkworm artificial diet. *Insects.* 2024;15(4):291.
 52. Yokoyama T. Sericulture. *Annu Rev Entomol.* 1963;8:287-298.
 53. Zhang HY, Liu MR, Feng ZH, Song L, Li X, Liu WD, et al. Estimations of water use efficiency in winter wheat based on multi-angle remote sensing. *Front Plant Sci.* 2021;12:614417.