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# Research Progress in Monitoring Arbor Moisture Content via Image Processing Technology: A Case Study of Typical Trees in Central Yunnan

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## Abstract

**The moisture content of arbor trees is a core indicator that reflects the dryness of forest combustibles and evaluates forest fire risk levels. Traditional methods for measuring moisture content have limitations such as time consumption, strong destructiveness, and difficulty in large-scale popularization. In contrast, image processing technology has gradually become an important method for rapid vegetation moisture monitoring due to its advantages of non-contact, low cost, high efficiency, and easy automated monitoring. This paper systematically reviews the research progress on the inversion of plant moisture content using image processing technology at home and abroad, summarizes the application rules of image features including color, texture and morphology, and reviews the research status of image monitoring for the moisture content of arbor trees and forest combustibles in forestry. The aim is to provide a reference for dynamic forest fire risk monitoring, rapid assessment of combustible moisture content and related academic research in central Yunnan.**

## Keywords

**Image Processing; Arbor Moisture Content; Forest Combustibles.**

## 1. Introduction

Fuel moisture content (FMC) is a critical factor influencing the occurrence and development of forest fires, affecting fire probability, spread rate, and combustion intensity. It is one of the most fundamental and sensitive indicators in forest fire early warning systems [1] . Central Yunnan, as a core distribution area of forest resources in Yunnan Province, features typical tree species such as Pinus yunnanensis, *Pinus armandii, Alnus nepalensis*, and *Cyclobalanopsis glaucoides* as its main forest components, giving it a prominent ecological status. However, this region experiences significant dry-wet seasonal differences, with continuous drought and low rainfall during winter and spring, resulting in persistently high forest fire risk levels and a heavy burden of fire prevention and control [2] . Rapid, accurate, and large-scale acquisition of tree moisture content information is of great practical significance for improving the precision of regional forest fire warnings and optimizing fire prevention layouts.

The traditional method for determining FMC is the oven-drying method, which yields accurate and reliable results. However, it requires field sampling and laboratory processing, leading to long turnaround times, heavy workloads, destructive effects on vegetation, and difficulty in achieving continuous dynamic monitoring over large areas. Although modern techniques such as near-infrared spectroscopy, hyperspectral remote sensing, and LiDAR enable large-scale inversion, they involve expensive equipment, complex data interpretation, and high maintenance costs, making them difficult to popularize in grassroots forest fire prevention departments. In contrast, image processing technology relies on standard digital cameras, surveillance cameras, smartphones, or drones for image acquisition. By extracting visual features using computer algorithms and establishing predictive models, it enables rapid, non-destructive, and batch estimation of moisture content. This approach offers significant advantages, including low cost, ease of operation, and high efficiency, making it highly suitable for forest field monitoring scenarios [3] .

In recent years, image processing has been widely applied in agricultural crop moisture monitoring, and its use in tree moisture content monitoring is also gradually being explored. Nevertheless, comprehensive systematic reviews focusing on forest trees-especially typical native species in central Yunnan-remain scarce. Existing research findings are relatively fragmented, and a unified technical framework and application system have yet to be established. Therefore, this paper reviews the research progress on image processing technology for tree moisture content monitoring from the perspectives of technical principles, feature extraction, modeling methods, application status, existing problems, and development trends. Considering the regional characteristics, future development directions are proposed, aiming to provide a reference for related research and engineering applications.

## 2. Theoretical Basis

### 2.1 Response Mechanism of Plant Moisture Content Variation

The inversion of plant moisture content using image processing technology is based on the physiological foundation that changes in plant water status exhibit regular responses in external visual characteristics. When plant tissues contain high moisture levels, cells are turgid, leaves are expanded, colors are bright, and surface textures are uniform. As water is lost, cells shrink due to dehydration, leaves gradually wilt and curl, and colors shift from bright green to dark green, grayish-green, or even yellow and brown. Meanwhile, surface gloss decreases, textural roughness increases, and wrinkles become more pronounced [4]. These visible changes are reflected in digital images as quantifiable variations in color components, grayscale values, textural entropy, contrast, leaf contours, and other indicators [5]. By converting leaf visual information into digital signals through camera imaging, and after preprocessing steps such as denoising, segmentation, and enhancement, feature parameters highly correlated with moisture content are extracted. Mathematical models or machine learning algorithms are then used to establish a mapping relationship between these features and moisture content, enabling quantitative estimation of moisture content. The entire process requires no sample contact or plant destruction, allows continuous acquisition and batch processing, and is easily adaptable to automation and long-term online monitoring. These advantages underpin the technology's potential for widespread application in the field of forest fire prevention [6].

### 2.2 Common Image Features and Extraction Methods

In image-based moisture content inversion research, feature extraction is a critical step that determines model accuracy. Existing studies generally construct feature systems from three dimensions: color, texture, and morphology.

Color features are the most sensitive and widely applied indicators. Moisture content affects the light reflectance and absorption characteristics of leaves. As moisture content decreases, leaf water content reduces while the relative concentration of chlorophyll increases, leading to regular changes in RGB channel values, grayscale values, saturation, brightness, and other parameters [7]. The mean value of the G channel, grayscale mean, and saturation exhibit significant correlations with moisture content and are among the most stable input variables in prediction models. Compared with other features, color features are less affected by leaf posture and shooting angle, are computationally simple, and are suitable for rapid field monitoring.

Texture features mainly reflect the subtle structural changes on leaf surfaces. During continuous water loss, the contraction of epidermal cells and changes in cuticle texture become evident, with metrics such as texture entropy, contrast, and correlation changing accordingly. The gray-level co-occurrence matrix (GLCM) is the most commonly used texture analysis method, effectively capturing

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changes in leaf surface roughness, directionality, and uniformity. Compared with color features, texture features are more sensitive at lower moisture content levels, making them suitable for fine-scale identification of dry fuel under high fire risk conditions.

Morphological features primarily describe changes such as wilting, curling, and shrinkage caused by leaf water loss. These include leaf area, perimeter, aspect ratio, solidity, circularity, and others. Morphological features do not change significantly at higher moisture content levels but become prominent under severe water loss when leaves are visibly wilted. They can serve as auxiliary features to improve model stability in the low moisture content range.

**Table 1.** Comparison of commonly used image features for plant moisture content monitoring

| Feature Type | Sensitive Range of Moisture Content | Main Advantages | Main Limitations | Common Extraction Methods |
|---|---|---|---|---|
| Color features | Full range (most sensitive at medium to high moisture content stages) | Simple computation; less affected by shooting posture; strong field applicability | Easily disturbed by illumination, leaf age, and disease | RGB/HSV color space conversion; grayscale processing |
| Texture features | Low moisture content stage (< fiber saturation point) | Captures microstructural changes of leaf surface; suitable for high fire risk identification | High computational complexity; requires high image resolution | Gray-level co-occurrence matrix (GLCM); wavelet transform |
| Morphological features | Severe water loss stage (obvious leaf wilting and curling) | Intuitively reflects leaf water loss and wilting degree | No significant changes at high moisture content stages; easily affected by natural leaf morphology | Image segmentation; contour extraction; geometric parameter calculation |

### 2.3 Theories and Methods of Image-Based Moisture Content Modeling

After the extraction of image features, establishing a quantitative relationship between these features and tree moisture content becomes the core component of the entire monitoring technical system. The modeling methods commonly used in current research can be categorized into three main types: traditional regression models, machine learning models, and deep learning models.

Traditional regression models, represented by multiple linear regression, stepwise regression, and partial least squares regression, offer the advantages of simple model structures and strong interpretability. Researchers typically use selected color, texture, or morphological features as independent variables and measured moisture content as the dependent variable to establish linear or nonlinear regression equations. These methods exhibit good stability in scenarios with small sample sizes and low feature dimensions, but they struggle to capture the complex nonlinear relationships between features and moisture content.

**Table 2.** Comparison of mainstream modeling methods for tree moisture content inversion

| Modeling Method | Representative Algorithms | Advantages | Limitations |
|---|---|---|---|
| Traditional regression models | Multiple linear regression, stepwise regression, partial least squares regression | Simple structure; strong interpretability; low computational cost | Difficulty in capturing complex nonlinear relationships; sensitive to noise |
| Traditional machine learning models | Support vector regression, random forest, gradient boosting tree | Capable of handling nonlinear relationships; strong robustness; automatic feature selection | Generalizability depends on training samples; prone to overfitting |
| Deep learning models | Convolutional neural network (CNN), lightweight CNN | Automatic deep feature extraction; strong resistance to illumination/background interference | Require large sample sizes; high computational resource demands; poor interpretability |
| Hybrid modeling strategies | Deep learning for feature extraction + traditional machine learning for regression | Balances feature extraction capability with model interpretability; reduces sample requirements | Relatively high model complexity |

The emergence of machine learning models has, to some extent, addressed this limitation. Methods such as support vector regression, random forest, and gradient boosting trees have been successively introduced into the field of plant moisture content prediction [8]. These models can automatically learn interactions and nonlinear patterns among features and demonstrate good robustness to noisy data. Particularly in multi-feature fusion scenarios, random forest can automatically screen effective variables through feature importance evaluation, reducing manual intervention. However, the performance of machine learning models is highly dependent on the quantity and quality of training samples, and their generalizability across different tree species and environmental conditions still requires further validation.

Deep learning models, particularly convolutional neural networks (CNNs), have demonstrated powerful capabilities in plant image analysis in recent years [9]. Unlike handcrafted color, texture, and morphological features, CNNs can automatically learn hierarchical feature representations from raw images-from edges and corners to more complex leaf structural information-thereby avoiding information loss that may result from manual feature extraction. In tree moisture content monitoring, researchers have begun attempting to use pre-trained CNN models for end-to-end regression prediction on leaf images, or combining them with transfer learning to achieve good results under small-sample conditions.

The advantages of deep learning models lie in their certain adaptability to factors such as image background and illumination changes, as well as their ability to fuse local details and global structural information of leaves. However, they require substantial computational resources and need large amounts of labeled data for model training, which is often difficult to satisfy in forestry research. Moreover, the "black box" nature of deep models makes the decision-making process difficult to interpret, hindering the establishment of trust in prediction results for practical forestry applications. Therefore, a more common approach in current research is to use deep learning for deep feature

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extraction, followed by regression prediction using traditional machine learning, forming a hybrid modeling strategy.

# 3. Current Application Status, Existing Problems, and Development Trends

## 3.1 Current Status of Technical Application Research

Research on image-based monitoring of individual trees and forest fuels started relatively late but has achieved initial progress. Some researchers have used unmanned aerial vehicles (UAVs) equipped with standard cameras to obtain forest canopy images and invert live fuel moisture content by extracting canopy color indices [10]. The study found that canopy greenness and the red/green ratio index are significantly correlated with tree water status and can be used for preliminary discrimination of high fire risk levels. At the individual tree scale, image acquisition and analysis of needle or leaf samples from species such as *Pinus yunnanensis, Platycladus orientalis*, and *Pinus tabuliformis* indicate that the G value and R/G ratio among color features are most sensitive to changes in moisture content, while texture features exhibit clear variation patterns when moisture content falls below the fiber saturation point.

Image processing technology also shows application potential for monitoring moisture content of dead fuels such as surface litter [11]. Some scholars have established a color feature-based classification model for dead fuel moisture content by photographing the surface litter layer and extracting the RGB variation patterns during the color transition from yellowish-brown to dark brown. Although such studies are still in the exploratory stage, they offer a new technical pathway for rapid assessment of fine understory fuels.

## 3.2 Main Problems in Current Research

Although image processing technology has shown promising prospects for tree moisture content monitoring, existing research still faces several common problems that constrain its transition from laboratory settings to practical forest fire warning applications.

The lighting conditions during image acquisition are the primary factor affecting feature stability. Variations in natural light intensity, color temperature, and directionality can cause significant shifts in the color features extracted from the same leaf at different times, thereby reducing model prediction accuracy. Currently, most studies are conducted under fixed indoor lighting conditions or employ standard whiteboard calibration during field collection. However, these methods incur high operational costs for large-scale, long-term monitoring. Background interference is another issue that cannot be ignored. Leaf images often contain background pixels such as soil, dead branches, and shadows, which can directly contaminate feature extraction results if precise segmentation is not performed.

Most existing studies build models for a single tree species within a specific growth period, and the transferability of these models across different species, site conditions, and seasons has not been systematically validated [12]. The image features of tree moisture content are influenced not only by water status but also by factors such as leaf age, disease, and nutrient conditions, introducing theoretical uncertainty when relying solely on visual features for moisture content prediction. In central Yunnan, the dominant tree species include *Pinus yunnanensis, Pinus armandii, Alnus nepalensis*, and *Cyclobalanopsis glaucoides*, which exhibit considerable differences in leaf morphology and anatomical structure, making the development of a unified model challenging.

Currently, most studies still adopt a mode of "image acquisition first, laboratory analysis second," and have yet to achieve truly in-situ, real-time, online moisture content monitoring in forests [13]. The level of automation and intelligence in image acquisition, transmission, processing, and prediction remains low, making it difficult to provide dynamic, continuous early warning information for forest fire prevention departments. Furthermore, existing studies generally suffer from insufficient prediction accuracy in the low moisture content range (i.e., high fire risk conditions), which is precisely the value range of greatest concern for forest fire warnings.

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### 3.3 Development Trends and Research Countermeasures

In response to the above problems, future development of image processing technology for tree moisture content monitoring will exhibit several trends, forming regionally distinctive technical pathways that address the actual needs of central Yunnan.

Single color or texture features are insufficient to cover the sensitive range of moisture content variation throughout the entire process. Future research will place greater emphasis on the deep fusion of color, texture, and morphological features, while introducing preprocessing methods such as illumination correction algorithms and background segmentation algorithms to enhance feature robustness against environmental variations. In terms of modeling, dynamic modeling approaches such as adaptive learning and online learning will gradually replace static models, enabling models to continuously update based on newly acquired samples and adapt to the dynamic moisture content patterns across different seasons and tree species.

The development of deep learning models toward lightweight architectures provides technical feasibility for field real-time monitoring. Lightweight convolutional neural networks can be deployed on low-power devices such as smartphones and Raspberry Pi, enabling localized processing of image acquisition and moisture content prediction without the need to upload images to the cloud. Combined with edge computing technology, forest fire patrol personnel can capture leaf images in real time within forests and obtain immediate moisture content estimates, greatly enhancing the timeliness of fire risk assessment [14]. This technical pathway is particularly suitable for the actual conditions of grassroots fire prevention stations in central Yunnan, where equipment resources are limited and network coverage is often incomplete.

For the typical tree species in central Yunnan, including *Pinus yunnanensis, Pinus armandii, Alnus nepalensis,* and *Cyclobalanopsis glaucoides*, future efforts should systematically establish leaf image sample libraries across different seasons, forest ages, and terrain conditions. Concurrent acquisition of image features and oven-drying measured moisture content data should be performed to construct regionally targeted monitoring models. Special attention should be given to the rapid moisture content changes during the dry-wet seasonal transition period, identifying key image feature indicators most sensitive to fire risk responses. Furthermore, integrating the grid-based forest fire prevention management system in central Yunnan, image processing technology should be embedded into existing patrol and early warning workflows to form a closed-loop application model.

**Table 3.** Key priorities for localized monitoring of typical tree species in central Yunnan

| Typical Tree Species in Central Yunnan | Main Leaf Characteristics | Priority Image Features | Key Monitoring Period |
|---|---|---|---|
| *Pinus yunnanensis* | Needle leaf; thick cuticle; strong drought tolerance | R/G ratio; texture entropy; grayscale mean | Dry winter-spring season (November to May) |
| *Pinus armandii* | Needle leaf in clusters; dense canopy | Canopy greenness; texture contrast | Dry-wet seasonal transition period (March to April) |
| *Alnus nepalensis* | Broad leaf; deciduous; fast water loss rate | Saturation; leaf area; solidity | Pre-deciduous period (October to November) |
| *Cyclobalanopsis glaucoides* | Evergreen broad leaf; leathery texture | Mean value of G channel; texture correlation | Year-round (with emphasis on dry season) |

## 4. Conclusion

Image processing technology offers a new technical approach for rapid, non-destructive, and low-cost monitoring of tree moisture content, holding broad application prospects in the field of forest fire risk warning. This paper systematically reviews research progress in this area from the perspectives of theoretical basis, feature extraction, modeling methods, application status, existing problems, and development trends. Among color features, RGB components, grayscale values, and saturation are the most widely used and consistently responsive indicators in current research. Texture features provide supplementary value in the low moisture content range, while morphological features can serve as auxiliary variables to improve model stability. Traditional regression and machine learning models each have their own advantages, and deep learning models represent the future direction of development, although their current promotion in forestry applications remains constrained by sample size and computational resources.

Current research still faces significant bottlenecks in terms of environmental illumination interference, model generalizability, and real-time monitoring implementation. Future efforts should focus on multi-source feature fusion, lightweight deep learning deployment, and localized modeling research targeting typical tree species in central Yunnan, advancing image processing technology from the laboratory toward operational forest fire warning applications, thereby providing technical support for enhancing regional forest fire prevention capabilities.

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