Academic Journal of Science and Technology
ISSN: 2771-3032 | Vol. 15, No. 2, 2025

Research Progress on Remote Sensing Inversion of Forest Fuel Moisture Content

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Abstract: As the material basis and primary carrier for the occurrence and spread of forest fires, the moisture content of forest fuels is one of the critical factors influencing fire ignition and development. Efficient and accurate simulation of the dynamic changes in forest fuel moisture content is crucial for predicting fire occurrence and behavior. This paper introduces the influencing factors of fuel moisture content, reviews major research methods for forest fuel moisture content domestically and internationally, analyzes existing challenges, and proposes future research directions.

Keywords: Forest fuels, Moisture content, Remote sensing inversion, Influencing factors.

1. Introduction

As a natural disaster characterized by suddenness, high destructiveness, and difficulty in containment and rescue, forest fires pose a severe threat to the stability of forest ecosystems and human life and property. Forest fuels, serving as the material basis and primary carrier for fire ignition and spread, have moisture content that is a key factor influencing fire occurrence and behavior. Variations in forest fuel moisture content directly affect ignition likelihood, combustion rate, and fire intensity. When fuel moisture content is low, fuels ignite more easily, burn rapidly, and exhibit intense flames, complicating fire suppression efforts. Conversely, higher moisture content reduces ignition probability and fire severity. Traditional methods for measuring forest fuel moisture content—including oven-drying, electrical resistance, and capacitance techniques—are precise but suffer from limited spatial representativeness, inefficiency, and challenges in large-scale rapid monitoring, failing to meet modern forest fire prevention demands for real-time and comprehensive data (Jurdao,2013). In recent years, satellite remote sensing technology has emerged as a novel solution for retrieving forest fuel moisture content. Remote sensing offers advantages such as large-scale coverage, rapidity, and dynamic monitoring, enabling real-time observation of forest regions and acquisition of moisture content data across spatiotemporal scales. Analyzing this information helps track moisture distribution and trends, providing scientific support for fire prevention and suppression while enhancing operational efficiency. Thus, research on remote sensing inversion of forest fuel moisture content holds significant practical and applicative value.

2. Influencing Factors of Remote Sensing Inversion for Fuel Moisture Content

Forest fuel moisture content (FMC), defined as the ratio of canopy water content to dry biomass, serves as a core indicator for assessing wildfire risk and fire spread rates (Chuvieco,2004a,2004b,2009a,2002;Danson and Bowyer, 2004; Hu Haiqing et al., 2016; Yebra and Chuvieco, 2009a, 2009b; Yebra et al., 2008, 2013; Yu Hongzhou et al., 2013). Accurate retrieval of FMC is critical for wildfire prevention and control. Remote sensing technology, with its strengths in large-scale and real-time dynamic monitoring, has become a vital tool for estimating forest FMC (Quan Xingwen,2017). However, the inversion process using remote sensing data is influenced by multiple factors, including sensor performance (wavelength range, spatial resolution, radiometric resolution), fuel properties (type, structure, moisture distribution), environmental conditions (topography, climate, atmospheric state), and data processing algorithms.

2.1. Sensor Factors

2.1.1. Wavelength Selection

The interaction mechanisms between electromagnetic waves and forest fuels vary across wavelengths, making wavelength selection a critical factor in FMC inversion. In the near-infrared (NIR) band (0.76–1.3 μm), water in vegetation weakly absorbs electromagnetic waves, while structural features and chlorophyll content predominantly influence reflectance. Reflectance in this band correlates with vegetation growth status, indirectly providing information on vegetation coverage and biomass to support FMC estimation. The shortwave infrared (SWIR) band (1.3–3 μm) exhibits higher sensitivity to water absorption, where moisture changes in fuels significantly alter SWIR reflectance. Studies demonstrate that spectral indices like the Normalized Difference Water Index (NDWI) and Moisture Stress Index (MSI), derived from SWIR bands, effectively capture FMC variations (Gao et al., 1996; Zhao Jianhui, 2021; Verbeke et al., 2012; Wilson, 2015). The mid-infrared band (3–5 μm) also responds to fuel moisture but is strongly influenced by vegetation temperature. When using mid-infrared bands for FMC inversion, temperature-induced reflectance interference must be addressed through calibration to improve accuracy.

2.1.2. Spatial Resolution

Spatial resolution determines the smallest distinguishable ground objects in remote sensing imagery. High-resolution data enable precise identification of vegetation types, topography, and forest structural features, reducing mixed-pixel effects. In low-resolution images, a single pixel may encompass diverse elements (e.g., canopy, trunk, understory vegetation, soil), each with distinct moisture levels,leading to significant inversion errors. High-resolution data allow clearer separation of ground objects, facilitating FMC inversion for individual features and improving accuracy.

2.1.3. Radiometric Resolution

Radiometric resolution refers to a sensor's ability to detect minimal differences in radiation intensity. Subtle changes in fuel moisture content alter electromagnetic wave absorption and reflection, manifesting as slight variations in radiation intensity. Sensors with high radiometric resolution capture these nuances, enriching data for accurate FMC inversion. When using thermal infrared bands, fuel temperature—closely linked to moisture content—affects radiation intensity. High-resolution thermal sensors precisely measure these changes, enhancing moisture estimation. Conversely, low radiometric resolution may fail to detect moisture-induced radiation differences, reducing inversion accuracy. Thus, sensors with higher radiometric resolution should be prioritized for FMC inversion.

2.2. Fuel Characteristics

2.2.1. Fuel Type

Variations in chemical composition, physical structure, and physiological traits among fuel types lead to distinct moisture behaviors and electromagnetic responses, significantly impacting FMC inversion. For example, coniferous forests exhibit dense cellular structures, high NIR reflectance, and weak SWIR water absorption due to resin content. Broadleaf forests, with large thin leaves and high water content, show strong NIR reflectance and low SWIR reflectance due to pronounced water absorption. Understory vegetation and surface litter also differ: understory moisture is highly sensitive to environmental changes, while litter moisture and electromagnetic responses vary with decomposition stages. Fresh litter has high moisture, which decreases over time as structure loosens, altering scattering and absorption properties. Thus, inversion models tailored to specific vegetation types are essential for improving accuracy.

2.2.2. Fuel Structure

Fuel structure—including canopy shape, foliage density, trunk size, and understory distribution—plays a critical role in FMC inversion. Diverse canopy shapes (e.g., conical, spherical, umbrella-like) alter sunlight interception and reflection patterns, influencing temperature, humidity, and moisture distribution within the canopy.

2.2.3. Moisture Distribution

Spatial heterogeneity in fuel moisture poses challenges for remote sensing inversion. Vertically, upper canopy foliage exposed to direct sunlight experiences higher temperatures and faster evaporation, resulting in lower moisture content. Lower canopy foliage, shaded and cooler, retains higher moisture. Trunk moisture typically decreases from base to apex due to water transport gradients. Horizontally, moisture varies with proximity to water sources (e.g., streams, lakes) and microclimatic conditions (e.g., light and ventilation in forest gaps). Addressing spatial heterogeneity requires correction methods or zonal inversion to enhance reliability.

2.3. Environmental Factors

2.3.1. Topography

Topography alters solar radiation, heat, and moisture distribution, affecting FMC and inversion accuracy. Sunny slopes receive more radiation, leading to higher temperatures, faster evaporation, and lower moisture, while shaded slopes retain higher moisture. Steep slopes promote water runoff and drier fuels, whereas gentle slopes favor moisture retention. Terrain-induced wind patterns (e.g., valley breezes) also create microclimates. Integrating DEM data to correct for topographic effects improves inversion precision.

2.3.2. Climatic Conditions

Temperature, humidity, precipitation, and wind speed directly influence FMC and inversion accuracy. Rising temperatures accelerate evaporation, reducing moisture content (negative correlation beyond thresholds). Relative humidity governs moisture exchange between fuels and the environment. Precipitation replenishes moisture, with effects depending on intensity, duration, and frequency. Wind speed enhances evaporation and airflow, further modulating FMC.

3. Research Methods for Forest Fuel Moisture Content

Current techniques for direct measurement of surface fuel moisture content in forests remain insufficient both domestically and internationally, leaving ample room for research. Existing methods include meteorological regression (Luo Yongzhong, 2005), equilibrium moisture content modeling (Zhang Yunlin, 2022), process-based models (Yang Changbao, 2017; Man Ziyuan, 2020), and remote sensing estimation (Viney NR, 1991; Chuvieco E, 2004). Among these, meteorological regression is the primary method in China for predicting dead surface fuel moisture. However, sparse weather station distribution limits its accuracy in complex terrains with spatially variable microclimates, and model reliability depends heavily on data quality and sample representativeness. Equilibrium moisture models are physically sound for small-scale predictions but less effective at larger scales. In contrast, remote sensing satellites provide wide-coverage, multi-band, near-real-time imagery. Vegetation canopy moisture sensitivity in near-infrared (NIR) and shortwave infrared (SWIR) bands enables FMC estimation via remote sensing.

Remote sensing applications in forest fire management began in the 1920s, initially focusing on fire monitoring, forest mapping, and fuel type classification (Qi Huaiqin et al., 2013). With advancements in satellite and computing technologies, remote sensing matured in the 1970s for soil and vegetation moisture monitoring. The 1990s saw hyperspectral technology enabling fuel moisture inversion. Current methods include spectral reflectance inversion, spectral water indices, and radiative transfer models.

3.1. Spectral Reflectance Inversion Method

Li Yuxia et al. (2009) analyzed correlations between spectral features and vegetation moisture, using the ratio of spectral reflectance at 1600 nm and 820 nm (SR) as a key parameter for FMC modeling. By linking measured spectral reflectance with FMC, their model captured spatiotemporal moisture patterns. Deng Bing et al. (2016) identified strong correlations between FMC and reflectance in visible red (620–700 nm) and NIR bands (800–1350, 1600–1950, 2200–2400 nm). They proposed the Near-infrared Angle Normalized Index (NANI) and Near-infrared Angle Slope Index (NASI), constructing linear regression models to enhance inversion accuracy.

3.2. Spectral Water Index Method

Studies indicate that leaf water and dry matter content—critical for FMC calculation—significantly influence SWIR and NIR reflectance. Leveraging satellite remote sensing, scholars have developed empirical models linking spectral indices (derived from field spectra and FMC measurements) to achieve high-precision FMC inversion (Tang Yuan, 2023). Villacrés et al. (2019) examined spectral responses of two dominant plant species across five dehydration stages, identifying 18 moisture-related spectral indices and establishing a linear regression model for local FMC estimation.

3.3. Radiative Transfer Model Method

Riaño et al. (2005) found that equivalent water thickness (EWT) and dry matter content (DMC) in the PROSPECT leaf reflectance model (Jacquemoud & Baret, 1990) closely relate to FMC, enabling its approximation. This discovery allowed forward simulation of spectral reflectance via radiative transfer models for FMC estimation. Researchers now use these models to identify FMC-sensitive bands, build lookup tables, and develop inversion indices. Portable spectroradiometers enable small-scale field or lab measurements, while multispectral satellites support large-scale vegetation moisture detection.

4. Conclusions and Discussion

Research on forest FMC has evolved from single-factor to multi-factor integrated studies, yet challenges persist:

(1) Spatial Resolution Trade-offs: Most satellite data struggle to balance large-scale monitoring with high-detail capture. Medium-low resolution data cover vast forests but fail to resolve fuel distribution in complex terrains (e.g., valleys, steep slopes). High-resolution data, while precise, lack sufficient coverage for large-area FMC inversion.

(2) Overemphasis on Live Fuels: While most studies focus on live vegetation moisture, dead fuels (e.g., litter, branches) significantly influence small fires. Hidden under canopies, their moisture is difficult to quantify via satellites, hindering research progress.

To build a comprehensive FMC prediction system in China, future efforts should prioritize:

(1) Radar/Microwave Inversion for Dead Fuels: Leveraging radar and microwave remote sensing to retrieve dead fuel moisture, improving physical parameter reconstruction and wildfire risk assessment.

(2) Spatiotemporal Heterogeneity Analysis: Investigating daily, seasonal, and interannual FMC variations under interacting factors to enhance fire prediction accuracy.

(3) Multi-Ecosystem Fuel Studies: Optimizing measurement methods, enriching datasets, and employing big data/machine learning to model complex factor-FMC relationships. Multi-scale studies will address model adaptability across regions and scales.

Acknowledgements

This work is supported by the National Nature Science Foundation of China(32360396, 31860214),the Joint Agric ultural Project of Yunnan Province (202101BD070001-09 4),the Science and Technology Innovation Project for Uni versity Students of Yunnan Education Department(s20231 0677053, s202310677051,202310677020).

References

[1] Jurdao S, Yebra M, Guerschman J. P, Chuvieco E. 2013.Regional estimation of woodland moisture content by inverting Radiative Transfer Models [J].Remote Sensing of Environment, 132,59-70.

[2] Chuvieco E, Aguado I and Dimitrakopoulos A. P.2004a.Conversion of fuel moisture content values to ignition potential for integrated fire Danger assessment[J].Canadian Journal of Forest Research,34(11):2284–2293.

[3] Chuvieco E,Cocero D,Riaño D,Martin P,Martínez-Vega J,de la Riva J and Pérez F.2004b.Combining NDVI and surface temperature for the estimation of live fuel moisture content in forest fire dangerrating[J].Remote Sensing of Environment, 92(3): 322–331.

[4] Chuvieco E,González I,Verdú F,Aguado I and Yebra M.2009a.Prediction of fire occurrence from live fuel moisture content measurements in a Mediterranean ecosystem [J]. International Journal of Wildland Fire,18(4): 430–441.

[5] Chuvieco E,Riaño D,Aguado I and Cocero D.2002.Estimation of fuel moisture content from multitemporal analysis of Landsat Thematic Mapperreflectance data: applications in fire danger assessment[J].International Journal of Remote Sensing, 23(11): 2145–2162.

[6] Danson F M and Bowyer P.2004.Estimating live fuel moisture content from remotely sensed reflectance[J].Remote Sensing of Environment, 92(3): 309–321 .

[7] Hu Haiqing, Lu Xin,Sun Long, Guan Dao. 2016.Dynamic changes and prediction models of surface dead fuel moisture content in typical forests of the Greater Khingan Mountains [J].Chinese Journal of Applied Ecology, 27(7): 2212–2224.

[8] Chuvieco E,González I,Verdú F,Aguado I and Yebra M.2009a.Prediction of fire occurrence from live fuel moisture content measurements in a Mediterranean ecosystem [J]. International Journal of Wildland Fire,18(4): 430–441 .

[9] Chuvieco E, Wagtendonk J, Riaño D, Yebra M and Ustin S L.2009b.Estimation of fuel conditions for fire danger assessment. Earth Observation of Wildland Fires in Mediterranean Ecosystems[J]. Berlin Heidelberg: Springer, 83–96.

[10] Quan Xingwen, He Binbin, Liu Xiangzhuo,Liao Zhanmang, Qiu Shi,and Yin Changming.2019.Remote sensing inversion of vegetation canopy fuel moisture content under multi-model coupling[J].Journal of Remote Sensing, 23(1), 62–77.

[11] Gao, B. C.1996.NDWI—A Normalized Difference Water Index for Remote Sensing of Vegetation Liquid Water from Space[J].Remote Sensing of Environment, 58(3), 257-266.

[12] Zhao Jianhui, Zhang Chenyang, Min Lin, et al.2021.Multi-source remote sensing inversion of farmland soil moisture based on feature selection and GA-BP neural network [J]. Transactions of the Chinese Society of Agricultural Engineering, 37(11), 112–120.

[13] Verbeke S, Hook S,and HulleyG.2012.An Alternative Spectral Index for Rapid Fire Severity Assessments[J].Remote Sensing of Environment,123, 72-80.

[14] Wilson, R. H, Nadeau, K. P, Jaworski, F. B, Tromberg, B. J, and Durkin, A. J. 2015. Review of Short-Wave Infrared Spectroscopy and Imaging Methods for Biological Tissue Characterization[J]. Journal of Biomedical Optics, 20(3), 030901.

[15] Luo Yongzhong, Che Kejun, Jiang Zhirong, et al.2005.Study on the variation of forest fuel moisture content in Qilian

Mountain forest area[J].Journal of Gansu Agricultural University, 40(02), 239–244.

[16] Zhang Yunlin, Lan Shixia, Hu Zhaoliu, et al.2022. Effects of bed compactness on moisture dynamics in Pinus massoniana litter beds[J].Journal of Northeast Forestry University, 50(12), 46–50.

[17] Yang Changbao, Zhou Zhenchao, Liu Na, et al.2017.Research on a time-series-based fuel moisture content index model[J].Journal of Jilin University, 35(04), 419–423.

[18] Man Ziyuan. 2020. Dynamic changes of forest fuel moisture content and applicability of humidity codes in Nanchang, Jiangxi[D]. Northeast Forestry University, Harbin, China.

[19] Viney N R. A review of fine fuel moisture modelling [J]. International Journal of Wildland Fire, 1991, 1(4): 215-234.

[20] Chuvieco E, Cocero D, Riano D, et al. Combining NDVI and surface temperature for the estimation of live fuel moisture content in forest fire danger rating[J]. Remote Sensing of Environment, 2004, 92(3): 322-331.

[21] Qi Huaiqin, Zhang Song, Wang Han, et al.2013. Design of an ultra-low-power forest fire warning system based on MSP430F5438 [J]. Measurement & Control Technology, 32(01), 28–32.

[22] Li Yuxia, Yang Wunian, Tong Ling, et al. 2009. Remote sensing quantitative monitoring and analysis of vegetation water content based on spectral index method[J]. Acta Optica Sinica,29(05), 1403–1407.

[23] Deng Bing, Yang Wunian, Mu Nan, et al.2016. Study on vegetation water content based on spectral analysis and angular slope index[J]. Spectroscopy and Spectral Analysis, 36(08), 2546–2552.

[24] Tang Yuan, Wang Xiaoping, Lu Congcong, et al.2023. Estimation of alfalfa canopy water content based on PROSAIL model and spectral indices[J].Journal of Lanzhou University (Natural Sciences), 59(01), 55–62.

[25] Villacrés J, Arevalo-Ramirez T, Fuentes A, et al. Foliar Moisture Content from the Spectral Signature.for Wildfire Risk Assessments in Valparaiso-Chile[J]. Sensors, 2019, 19 (24): 1-19.

[26] Jacquemoud S and Baret F.1990.PROSPECT:a model of leaf optical properties spectra[J]. Remote Sensing of Environment, 34(2): 75–91.