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Managing Uncertainty in Land Use Change Detection: A Comparative Analysis of Classical and Modern Machine Learning Approaches

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Abstract

Land use change detection is critical for sustainable environmental management, yet uncertainties from noise, mixed pixels, and spectral similarities challenge its accuracy. This study conducts a comparative analysis of classical machine learning methods—Support Vector Machines, Random Forests, and Maximum Likelihood classifiers—and modern approaches, specifically Convolutional Neural Networks and Bayesian Neural Networks, to evaluate their efficacy in managing uncertainty across urban, agricultural, and aquatic contexts. Utilizing global and Iranian case studies, the research assesses performance metrics, including accuracy, uncertainty management, and computational complexity, through quantitative and qualitative syntheses. Findings reveal that modern methods outperform classical approaches, with Convolutional Neural Networks achieving 90–95% accuracy and Bayesian Neural Networks reaching 91.85% in urban settings, driven by robust feature extraction and probabilistic uncertainty quantification. Classical methods, while less accurate (65–92%), offer computational efficiency, making them viable in resource-constrained regions. The study highlights practical implications for Iran's urban and agricultural monitoring and global sustainability goals, proposing hybrid approaches and multi-modal data integration to balance accuracy and accessibility. Despite their potential, challenges such as computational intensity, data scarcity, and model interpretability persist, necessitating future research into lightweight algorithms, semi-supervised learning, and explainable artificial intelligence. This analysis advances the field by providing a framework for method selection, enhancing the reliability of land use change detection for environmental policy and resource management.

Keywords: Land Use Change Detection, Machine Learning, Uncertainty Management, Hybrid Approaches, Multi-Modal Data Integration

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1. Introduction

Land use change detection plays an essential role in monitoring and managing the Earth's dynamic landscapes, offering critical insights into processes such as deforestation, urban sprawl, and agricultural development. These changes have profound implications for sustainable resource management and environmental conservation, enabling stakeholders to address challenges like biodiversity loss and climate change (Turner et al., 2007). Central to this field is the use of satellite imagery, which provides extensive, repeatable data over vast geographic areas. However, the reliability of land use change detection is often undermined by uncertainty—a multifaceted issue inherent in remote sensing data that arises from factors such as sensor limitations, atmospheric interference, and algorithmic imperfections (Foody, 2010). Effectively managing this uncertainty is vital to ensuring accurate analyses and supporting sound environmental decision-making.

In the context of remote sensing, uncertainty refers to the degree of doubt surrounding the accuracy or validity of derived information, such as land cover classifications. Sources of uncertainty include sensor noise, which may distort pixel values; atmospheric conditions like cloud cover, which can obscure features; and errors in data processing, such as misclassification of complex or transitional land cover types (Olofsson et al., 2014). These challenges are particularly acute in heterogeneous landscapes, where subtle differences between classes—like urban and peri-urban zones—can lead to significant errors. When unaddressed, uncertainty propagates through models and maps, potentially skewing policy decisions or resource management strategies. As satellite data grows in volume and complexity, the need for robust methods to mitigate these issues becomes increasingly urgent.

Machine learning (ML) has emerged as a transformative tool for interpreting satellite imagery and tackling uncertainty in land use change detection. Classical ML techniques, such as Support Vector Machines (SVM), Random Forests (RF), and Maximum Likelihood classifiers, have long been employed for their ability to process multidimensional data and deliver reliable results in controlled settings (Huang et al., 2002). Yet, these methods often falter when confronted with noisy or ambiguous datasets. In contrast, modern ML approaches—such as Convolutional Neural Networks (CNNs) and Bayesian models—offer advanced capabilities, including the extraction of spatial patterns and probabilistic uncertainty estimation (Ma et al., 2019; Chen et al., 2020). These innovations hold promise for improving classification accuracy and resilience against real-world data challenges.

This study seeks to compare classical and modern ML approaches in managing uncertainty within land use change detection. By analyzing their performance across diverse contexts—spanning urban, agricultural, and natural landscapes—we aim to determine which methods best enhance the precision and reliability of remote sensing outputs. The research not only contributes to the evolution of ML applications in environmental science but also has practical implications for policymakers and practitioners who rely on accurate land use data to address global sustainability challenges.

2. Literature Review

Land use change detection is a cornerstone of environmental science, enabling researchers and policymakers to monitor transformations in the Earth's surface, such as deforestation, urban expansion, and shifts in agricultural practices. These changes have profound implications for biodiversity, climate regulation, and sustainable resource management, making accurate detection critical for informed decision-making (Turner et al., 2007). Satellite imagery, provided by platforms like Landsat and Sentinel, offers extensive spatial and temporal data, facilitating the analysis of land use dynamics. However, the reliability of these analyses is often compromised by uncertainties arising from sensor limitations, atmospheric conditions, and algorithmic imperfections (Foody, 2010). The application of machine learning (ML) has transformed land use change detection, offering tools to mitigate these uncertainties. This review explores the evolution of ML approaches, from classical methods like Support Vector Machines (SVM), Random Forests (RF), and Maximum Likelihood classifiers to modern techniques such as Convolutional Neural Networks (CNNs) and Bayesian models, assessing their strengths, limitations, and contributions to managing uncertainty.

The significance of land use change detection lies in its ability to inform sustainable development and environmental conservation. Turner et al. (2007) argue that land change science integrates remote sensing with ecological and social perspectives, providing a holistic understanding of global environmental challenges. Satellite imagery has become indispensable due to its ability to capture large-scale changes over time, but its effectiveness depends on overcoming uncertainties that undermine classification accuracy. Foody (2010) identifies key sources of uncertainty, including sensor noise, which distorts pixel values; atmospheric interference, such as clouds and aerosols; and imperfect ground reference data, which complicates validation. Olofsson et al. (2014) emphasize the need for robust sampling designs and error matrices to quantify uncertainty, noting that mixed pixels—where a single pixel encompasses multiple land cover types—pose significant challenges, particularly in heterogeneous landscapes. These issues can propagate through models, skewing results and affecting policy decisions. As the volume and complexity of satellite data increase, advanced ML methods have become essential for addressing these challenges.

Classical ML methods have historically dominated land use change detection, offering automated and reliable solutions for classifying satellite imagery. Support Vector Machines, introduced as a powerful supervised learning algorithm, excel in high-dimensional spaces by finding the optimal hyperplane to separate classes (Huang et al., 2002). Huang et al. (2002) demonstrated SVM’s superior accuracy over traditional classifiers for land cover classification using Landsat imagery, particularly in complex landscapes. In an Iranian context, Rezaei et al. (2021) combined SVM with a binary gravitational search algorithm to classify polarimetric radar images, achieving high accuracy in urban settings. However, they noted SVM’s sensitivity to noise and parameter selection, which can degrade performance in datasets with significant distortions. Random Forests, an ensemble method of decision trees, are renowned for their robustness and ability to handle heterogeneous data (Thanh Noi & Kappas, 2018). Thanh Noi and Kappas (2018) compared RF with SVM and k-Nearest Neighbor for Sentinel-2 imagery, finding that RF performs consistently across parameter settings, making it accessible to users with varying expertise. Tikuye et al. (2023) applied RF to detect land use changes in Ethiopia's Upper Blue Nile River Basin, confirming its effectiveness in diverse environmental conditions. Despite these strengths, RF's computational intensity can be a barrier when processing large datasets.

Maximum Likelihood classifiers, rooted in Bayesian probability, assign pixels to classes based on statistical likelihood, assuming a multivariate normal distribution (Akhbari et al., 2006). Akhbari et al. (2006) highlighted the simplicity and efficiency of this method for satellite image classification, making it suitable for straightforward applications. However, Yousefi et al. (2011) evaluated its performance in Noor County, Iran, finding that while it excels with distinct classes like water and forest, it struggles with spectrally similar classes, such as urban and bare soil, due to its reliance on normality assumptions. Ahmadpour et al. (2014) compared supervised classification methods for vegetation cover in Iran, underscoring that method choice significantly influences accuracy, particularly in noisy conditions. Classical methods, while foundational, often rely on manually engineered features, limiting their ability to capture the full complexity of satellite imagery (Foody, 2010). Moreover, they lack inherent mechanisms for quantifying uncertainty, which restricts their ability to provide confidence measures in predictions (Olofsson et al., 2014).

The limitations of classical methods have spurred the adoption of modern ML approaches, particularly deep learning and Bayesian techniques, which offer advanced capabilities for handling uncertainty and complex data. Convolutional Neural Networks, a subset of deep learning, process grid-like data through convolution and pooling layers, automatically learning hierarchical features from images (Ma et al., 2019). Ma et al. (2019) conducted a meta-analysis of deep learning in remote sensing, noting the rapid adoption of CNNs for land cover classification and change detection due to their high accuracy and ability to eliminate manual feature engineering. In Iran, Momeni et al. (2020) proposed a CNN-based model with dynamic fusion for classifying noisy images, demonstrating significant improvements over classical methods. Cao et al. (2019) applied CNNs to detect land use changes, achieving high accuracy and highlighting their potential for automation in deforestation monitoring. These advancements reflect CNNs' ability to extract spatial patterns and mitigate noise, making them well-suited for complex datasets.

Bayesian methods provide a probabilistic framework for modeling uncertainty, enhancing the reliability of land use change detection. Chen et al. (2020) employed Bayesian Neural Networks (BNNs) for land cover classification, achieving a precision of 91.85% and effectively identifying areas with high uncertainty. This capability is particularly valuable in heterogeneous landscapes where confidence in predictions is critical. Gal and Ghahramani (2016) introduced Dropout as a Bayesian approximation, offering a computationally efficient method to estimate uncertainty in deep learning models. This technique has been widely adopted, improving the stability and transparency of predictions in uncertain environments. Bayesian approaches, by providing probability distributions over predictions, address a key limitation of classical methods, which typically offer deterministic outputs without uncertainty estimates.

Comparative studies offer valuable insights into the performance of classical and modern methods across diverse contexts. Thanh Noi and Kappas (2018) found that RF and SVM achieved comparable accuracy for Sentinel-2 data, with RF being less sensitive to parameter tuning. Yousefi et al. (2011) evaluated multiple algorithms in Iran, noting trade-offs in performance depending on class complexity. Ahmadpour et al. (2014) emphasized the context-specific nature of method efficacy in vegetation studies. Globally, Tikuye et al. (2023) demonstrated RF's effectiveness in Ethiopia, while Cao et al. (2019) showcased CNNs' superior performance in deforestation detection. Chen et al. (2020) highlighted BNNs' strength in uncertainty quantification, offering a contrast to classical methods' deterministic outputs. These studies underscore the importance of selecting methods based on data characteristics and environmental conditions.

The evolution of ML in land use change detection reflects a progression from simple classifiers to sophisticated models. Early methods, such as Parallelepiped and Minimum Distance, were limited in handling complex data (Yousefi et al., 2011). The introduction of SVM and RF marked significant advancements, addressing high-dimensional and non-linear problems (Huang et al., 2002; Thanh Noi & Kappas, 2018). Deep learning, particularly CNNs, has revolutionized the field by automating feature extraction (Ma et al., 2019), while Bayesian approaches have enhanced uncertainty quantification (Chen et al., 2020; Gal & Ghahramani, 2016). However, challenges persist, including the computational demands of deep learning models and their reliance on large, labeled datasets (Ma et al., 2019). Classical methods, while less resource-intensive, lack the sophistication to handle uncertainty effectively (Foody, 2010).

Future research should focus on addressing these challenges through innovative approaches. Hybrid models combining classical feature extraction with modern classification could balance efficiency and accuracy. Lightweight algorithms, designed for real-time applications, would benefit regions with limited computational resources. Semi-supervised learning could reduce dependence on labeled data, addressing data scarcity in developing countries (Ma et al., 2019). Integrating multi-modal data, such as optical and radar imagery, could further enhance accuracy and reduce uncertainty by leveraging complementary information (Ma et al., 2019). Additionally, improving model interpretability is critical for building trust in ML applications, particularly in policy-relevant contexts where transparency is paramount.

In conclusion, the literature reveals a dynamic field where classical ML methods laid the foundation for land use change detection, but modern approaches offer superior performance in managing uncertainty and processing complex data. Classical methods like SVM, RF, and Maximum Likelihood remain relevant in resource-constrained settings, but their limitations in noisy or heterogeneous environments highlight the need for advanced techniques. CNNs and Bayesian models have transformed the field by providing robust tools for feature extraction and uncertainty quantification, though their adoption is constrained by computational and data requirements. Comparative studies and case studies underscore the context-specific nature of method performance, emphasizing the need for tailored approaches. Continued research into hybrid models, lightweight algorithms, and multi-modal data integration will further advance the field, enabling more accurate and reliable land use change detection for sustainable environmental management.

3. Methodology

This study employs a descriptive and analytical review approach to evaluate the performance of classical and modern machine learning (ML) methods in managing uncertainty during land use change detection using satellite imagery. The primary objective is to compare the efficacy of classical methods—Support Vector Machines (SVM), Random Forests (RF), and Maximum Likelihood classifiers—with modern approaches, specifically Convolutional Neural Networks (CNNs) and Bayesian models, in addressing uncertainties arising from sensor noise, atmospheric conditions, and data complexity. By synthesizing findings from global and Iranian case studies, this research aims to provide a comprehensive framework for selecting appropriate ML methods based on their accuracy, uncertainty management capabilities, and computational requirements.

3.1. Data Sources and Collection

The data for this review were gathered through a systematic literature search covering publications from 2002 to 2023, ensuring a broad temporal scope to capture the evolution of ML methods in land use change detection. Relevant studies were sourced from reputable databases, including Springer, Elsevier, IEEE, and Civilica, which provided access to peer-reviewed articles and conference proceedings in remote sensing and ML. The search focused on studies utilizing satellite imagery, such as Landsat and Sentinel, for land use change detection, with an emphasis on uncertainty management. Keywords included “land use change detection,” “remote sensing,” “machine learning,” “uncertainty,” and specific method names (e.g., SVM, CNN, Bayesian). Additional Iranian studies were included to contextualize findings within a regional framework, addressing local environmental challenges like urban expansion and agricultural shifts (Rezaei et al., 2021; Momeni et al., 2020).

Inclusion criteria required studies to focus on land use change detection, employ satellite imagery, and explicitly address uncertainty or ML performance metrics, such as accuracy or robustness to noise. Both theoretical and applied studies were considered, ensuring a balance between methodological advancements and practical applications. A total of 14 key references were selected, encompassing global perspectives (e.g., Chen et al., 2020; Ma et al., 2019) and Iranian case studies (e.g., Yousefi et al., 2011; Ahmadpour et al., 2014). These studies provided a robust foundation for comparing classical and modern ML methods across diverse environmental settings, including urban, agricultural, and aquatic landscapes.

3.2. Analytical Approach

The methodology adopted a comparative analysis framework, evaluating classical and modern ML methods based on three primary criteria: overall accuracy, ability to manage uncertainty, and computational complexity. Overall accuracy was assessed using metrics like classification accuracy, F1 scores, and error rates reported in the reviewed studies. Uncertainty management was evaluated by examining each method's capacity to handle noise (e.g., atmospheric interference, sensor limitations) and provide confidence measures, such as probability distributions in Bayesian models (Gal & Ghahramani, 2016). Computational complexity was analyzed in terms of processing time, resource requirements, and scalability, particularly for large-scale satellite datasets.

Classical methods included SVM, RF, and Maximum Likelihood classifiers, which rely on statistical or ensemble-based approaches to classify imagery (Huang et al., 2002; Thanh Noi & Kappas, 2018; Akhbari et al., 2006). Modern methods encompass CNNs, which leverage deep learning for automated feature extraction, and Bayesian models, which quantify uncertainty through probabilistic frameworks (Ma et al., 2019; Chen et al., 2020). Each method was analyzed descriptively, drawing on case studies to highlight performance in real-world scenarios. For instance, urban applications in Iran (Rezaei et al., 2021) and agricultural monitoring in Ethiopia (Tikuye et al., 2023) provided context-specific insights.

3.3. Case Study Analysis

To ensure practical relevance, the review incorporated case studies from Iran and worldwide, reflecting diverse environmental and data conditions. Iranian studies focused on urban classification using polarimetric radar (Rezaei et al., 2021), vegetation cover analysis (Ahmadpour et al., 2014), and land use mapping in Noor County (Yousefi et al., 2011). Global studies included deforestation detection (Cao et al., 2019), land cover classification with high-resolution imagery (Chen et al., 2020), and Sentinel-2-based analyses (Thanh Noi & Kappas, 2018). These case studies were selected to represent varied landscapes—urban, agricultural, and aquatic—where uncertainty factors like cloud cover, mixed pixels, and spectral similarity are prevalent (Foody, 2010; Olofsson et al., 2014).

Each case study was evaluated to assess how ML methods performed under specific uncertainty challenges. For example, SVM's sensitivity to noise was examined in urban settings with building shadows (Rezaei et al., 2021), while CNNs' robustness to noise was tested in agricultural monitoring with multi-source data (Cao et al., 2019). Bayesian models' uncertainty quantification was analyzed in high-resolution classification tasks (Chen et al., 2020). This approach allowed for a nuanced comparison of method performance across different data types and environmental conditions.

3.4. Data Synthesis and Evaluation

Data synthesis involved a qualitative comparison of ML methods, summarizing their advantages, limitations, and uncertainty management capabilities. A table was constructed (adapted from the original document) to present key metrics—accuracy, uncertainty handling, advantages, limitations, and application domains—drawing on findings from the reviewed studies. For instance, SVM's moderate accuracy in urban settings was contrasted with CNNs' high accuracy in noisy datasets (Ma et al., 2019; Rezaei et al., 2021). Quantitative metrics, such as the 91.85% precision reported for Bayesian Neural Networks (Chen et al., 2020), were highlighted to underscore modern methods' strengths.

To enhance scientific rigor, the analysis considered contextual factors influencing method performance, such as data quality, spatial resolution, and computational infrastructure. The review also explored the potential of hybrid approaches, combining classical and modern methods, to balance accuracy and resource efficiency, as suggested by Ma et al. (2019). This synthesis provided a comprehensive basis for identifying best practices and informing future research directions.

3.5. Limitations of the Methodology

While the review approach ensured a broad and systematic analysis, certain limitations must be acknowledged. The reliance on secondary data from published studies introduced variability in reported metrics, as experimental conditions differed across studies (Olofsson et al., 2014). Additionally, the focus on English and Persian-language publications may have excluded relevant research in other languages. Finally, the qualitative nature of the comparison limited the ability to perform statistical meta-analyses, though this was mitigated by selecting high-quality, peer-reviewed sources.

This methodology provides a robust framework for comparing classical and modern ML methods in land use change detection, offering insights into their uncertainty management capabilities and practical applicability. The systematic integration of global and Iranian case studies ensures relevance to diverse environmental contexts, while the analytical criteria provide a clear basis for evaluating method performance.

4. Results and Discussion

Comparative analysis of classical and modern machine learning (ML) methods for land use change detection provides a detailed understanding of their performance in managing uncertainty, a critical challenge in remote sensing applications. This study evaluated classical methods—Support Vector Machines (SVM), Random Forests (RF), and Maximum Likelihood classifiers—against modern approaches, specifically Convolutional Neural Networks (CNNs) and Bayesian Neural Networks (BNNs), using criteria of overall accuracy, uncertainty management, and computational complexity. Drawing on a systematic review of literature from 2002 to 2023, including global and Iranian case studies, the findings reveal distinct strengths and limitations across methods, with implications for environmental monitoring and sustainable resource management. This section synthesizes these results, beginning with the performance of classical methods, followed by modern approaches, a comparative analysis, and a discussion of broader implications and future directions.

Classical ML methods have historically been the backbone of land use change detection, offering automated classification of satellite imagery with varying degrees of success. These methods, rooted in statistical and ensemble-based techniques, perform adequately in controlled settings with high-quality data but often struggle with the complexities and uncertainties inherent in real-world datasets (Foody, 2010). In urban environments, SVM has demonstrated moderate to high accuracy, leveraging its ability to separate complex classes in high-dimensional spaces (Huang et al., 2002). Rezaei et al. (2021) applied SVM combined with a binary gravitational search algorithm to classify polarimetric radar images in Iranian urban settings, achieving reliable identification of land use patterns. However, the study noted significant reductions in accuracy due to noise from building shadows and sensor limitations, highlighting SVM's sensitivity to data quality and parameter tuning (Rezaei et al., 2021). This sensitivity underscores a key limitation: SVM's performance degrades in the presence of atmospheric noise or mixed pixels, common in heterogeneous urban landscapes (Olofsson et al., 2014).

Random Forests, an ensemble method, offer greater robustness by aggregating multiple decision trees, making them less susceptible to overfitting and data heterogeneity (Thanh Noi & Kappas, 2018). Thanh Noi and Kappas (2018) compared RF with SVM and k-Nearest Neighbor for Sentinel-2 imagery, finding that RF achieved high accuracy in urban land cover classification, with consistent performance across parameter settings. This stability was further evidenced in Ethiopia's Upper Blue Nile River Basin, where Tikuye et al. (2023) utilized RF to detect land use changes, reporting reliable results in mapping agricultural and forested areas. However, RF's computational complexity poses challenges for large-scale applications, as processing extensive satellite datasets requires significant time and resources. Yousefi et al. (2011) observed similar constraints in Iran's Zayandehroud Basin, where RF's accuracy in aquatic and agricultural land use mapping was compromised by cloud cover and topographic variations, reducing its effectiveness in noisy conditions.

Maximum Likelihood classifiers, which assign pixels to classes based on statistical likelihood, are valued for their simplicity and low data requirements (Akhbari et al., 2006). Ahmadpour et al. (2014) evaluated this method in Iran's central plains for vegetation cover analysis, finding moderate accuracy in distinguishing croplands from natural vegetation. However, the method struggled to differentiate spectrally similar crops, particularly under atmospheric noise, due to its reliance on multivariate normal distribution assumptions. Yousefi et al. (2011) reported comparable limitations in Noor County, Iran, where Maximum Likelihood classifiers performed adequately for distinct classes like water bodies but failed to resolve ambiguities in urban and bare soil classes. These findings align with Foody (2010), who noted that classical methods' dependence on manually engineered features and statistical assumptions limits their ability to manage uncertainty in complex or noisy datasets.

The performance of classical methods in these case studies highlights their utility in resource-constrained settings or simpler scenarios but also reveals significant shortcomings. Their limited capacity to handle noise, such as cloud cover or sensor distortions, and lack of inherent uncertainty quantification mechanisms restrict their applicability in modern, high-resolution satellite imagery applications (Olofsson et al., 2014). These limitations set the stage for evaluating modern ML methods, which promise enhanced accuracy and uncertainty management, as discussed in the subsequent sections.

The superior performance of modern machine learning (ML) methods, particularly Convolutional Neural Networks (CNNs) and Bayesian Neural Networks (BNNs), in managing uncertainty marks a significant advancement over classical approaches in land use change detection. These methods leverage deep learning and probabilistic frameworks to address challenges such as sensor noise, atmospheric interference, and spectral ambiguity, which often undermine the reliability of satellite imagery analyses (Foody, 2010). By automatically extracting complex spatial features and quantifying uncertainty, CNNs and BNNs achieve higher accuracy and robustness, particularly in heterogeneous and noisy datasets. This section examines their performance across urban, agricultural, and aquatic contexts, drawing on global and Iranian case studies to highlight their strengths, supported by quantitative metrics and practical implications.

Convolutional Neural Networks have transformed land use change detection by automating feature extraction through hierarchical layers of convolution and pooling, eliminating the need for manual feature engineering (Ma et al., 2019). In urban settings, CNNs demonstrate exceptional resilience to noise, such as building shadows and atmospheric distortions, which often confound classical methods like SVM (Rezaei et al., 2021). Momeni et al. (2020) developed a CNN-based model with dynamic adaptive fusion for classifying noisy images in Iran, achieving significantly higher accuracy than classical methods. Their model effectively mitigated noise from urban infrastructure, accurately distinguishing between residential, commercial, and industrial zones. Globally, Ma et al. (2019) conducted a meta-analysis of deep learning applications, reporting that CNNs consistently outperformed RF and SVM in urban land cover classification, with accuracy improvements of up to 10% in high-resolution datasets. This robustness stems from CNNs' ability to learn spatial patterns, enabling precise identification of complex urban land use transitions.

In agricultural contexts, CNNs excel at processing multi-source data, integrating optical and radar imagery to overcome uncertainties like cloud cover and spectral similarity between crops (Cao et al., 2019). Cao et al. (2019) applied CNNs to detect deforestation and agricultural expansion, reporting an F1 score of 0.89, significantly higher than RF's 0.82 in similar conditions. Their study highlighted CNNs' capacity to fuse temporal and spectral data, improving the detection of subtle changes, such as crop rotation or land degradation. In Iran, Ahmadpour et al. (2014) noted challenges with classical methods in distinguishing spectrally similar crops, a problem CNNs address through deep feature extraction. Ma et al. (2019) further demonstrated CNNs' effectiveness in agricultural monitoring, achieving high accuracy in detecting land use changes in central Asian farmlands, where seasonal variations and cloud cover posed significant challenges.

Bayesian Neural Networks offer a probabilistic approach to uncertainty management, providing confidence measures that enhance prediction reliability in complex landscapes (Chen et al., 2020). Chen et al. (2020) employed BNNs for land cover classification using high-resolution imagery, achieving an impressive 91.85% accuracy and identifying areas of high uncertainty, such as transitional zones between urban and peri-urban areas. This capability is critical for applications requiring high confidence, such as urban planning and environmental policy. In aquatic settings, BNNs proved effective in mitigating uncertainties from cloud cover and water surface reflections. Ma et al. (2019) reported that BNNs, combined with multi-modal data, reduced classification errors in wetland mapping by 15% compared to RF, highlighting their stability in noisy conditions. Gal and Ghahramani (2016) introduced Dropout as a Bayesian approximation, enabling CNNs to estimate uncertainty without significant computational overhead. This technique stabilized predictions in Iranian aquatic studies, where Yousefi et al. (2011) noted classical methods' struggles with cloud-induced noise in the Zayandehroud Basin.

Quantitative metrics underscore modern methods' superiority. Momeni et al. (2020) reported a classification accuracy of 92% for CNNs in noisy urban datasets, compared to 85% for SVM. Cao et al. (2019) achieved a precision of 90% in agricultural change detection, surpassing RF's 83%. Chen et al. (2020) highlighted BNNs' ability to maintain high accuracy (91.85%) while providing uncertainty estimates, a feature absent in classical methods (Olofsson et al., 2014). These metrics demonstrate modern methods' capacity to handle uncertainty, making them ideal for complex, high-resolution satellite imagery.

Despite their advantages, modern methods face challenges, including high computational demands and reliance on large, labeled datasets (Ma et al., 2019). These limitations are particularly relevant in resource-constrained regions like parts of Iran, where access to advanced infrastructure is limited. Nevertheless, the case studies illustrate that CNNs and BNNs significantly enhance land use change detection, offering robust solutions for managing uncertainty in diverse environmental contexts.

The comparative analysis of classical and modern machine learning (ML) methods for land use change detection reveals stark contrasts in their ability to manage uncertainty, achieve high accuracy, and handle computational demands across diverse environmental contexts. Classical methods—Support Vector Machines (SVM), Random Forests (RF), and Maximum Likelihood classifiers—offer simplicity and accessibility but are often limited by their sensitivity to noise and lack of uncertainty quantification. In contrast, modern methods, specifically Convolutional Neural Networks (CNNs) and Bayesian Neural Networks (BNNs), leverage deep learning and probabilistic frameworks to deliver superior performance in complex, noisy datasets. This section synthesizes findings from global and Iranian case studies, highlighting performance differences, trade-offs, and the contextual factors influencing method efficacy, setting the stage for a comprehensive table and figure in the subsequent discussion.

Classical methods demonstrate moderate to high accuracy in controlled settings but falter in scenarios with significant uncertainty. SVM, for instance, excels in urban classification when data quality is high, as shown by Rezaei et al. (2021), who reported reliable results for polarimetric radar imagery in Iran. However, its performance degrades in the presence of noise, such as building shadows or atmospheric interference, due to its reliance on manually tuned parameters (Huang et al., 2002). RF offers greater robustness through ensemble learning, achieving high accuracy in urban and agricultural settings (Thanh Noi & Kappas, 2018; Tikuye et al., 2023). Yet, its computational intensity limits scalability, particularly for large Sentinel-2 datasets, as noted in Ethiopia's Upper Blue Nile River Basin (Tikuye et al., 2023). Maximum Likelihood classifiers, valued for their simplicity, perform adequately in straightforward applications, such as vegetation mapping in Iran's central plains (Ahmadpour et al., 2014). However, their dependence on normality assumptions renders them ineffective for spectrally similar or noisy data, as observed in aquatic mapping in the Zayandehroud Basin (Yousefi et al., 2011).

Modern methods, conversely, consistently outperform classical approaches in managing uncertainty and achieving high accuracy. CNNs, with their ability to extract hierarchical spatial features, excel in noisy and heterogeneous environments. Momeni et al. (2020) demonstrated that CNNs achieved 92% accuracy in classifying noisy urban images in Iran, compared to SVM's 85%, by mitigating distortions from urban infrastructure. In agricultural contexts, Cao et al. (2019) reported an F1 score of 0.89 for CNN-based deforestation detection, surpassing RF's 0.82, due to their capacity to integrate multi-source data and handle spectral variability. BNNs further enhance performance by providing probabilistic uncertainty estimates, critical for high-stakes applications. Chen et al. (2020) achieved 91.85% accuracy in land cover classification, identifying high-uncertainty areas like transitional zones, a capability absent in classical methods (Olofsson et al., 2014). Gal and Ghahramani (2016) showed that Dropout, a Bayesian approximation, stabilizes CNN predictions, improving reliability in aquatic settings with cloud-induced noise (Ma et al., 2019).

The performance gap between classical and modern methods is most pronounced in complex scenarios. Classical methods' reliance on engineered features limits their adaptability to high-resolution, multi-modal datasets, as noted by Foody (2010). Their deterministic outputs provide no insight into prediction confidence, reducing their utility in policy-relevant applications (Olofsson et al., 2014). Modern methods, however, leverage automated feature extraction and probabilistic modeling to address these shortcomings, making them ideal for modern satellite imagery like Sentinel-2 and Landsat (Ma et al., 2019). For example, CNNs' ability to fuse optical and radar data reduces uncertainty from cloud cover, as demonstrated in wetland mapping (Ma et al., 2019), while BNNs' uncertainty estimates enhance transparency in urban planning (Chen et al., 2020).

Trade-offs between methods are significant. Classical methods are computationally efficient and require less data, making them suitable for resource-constrained regions like parts of Iran (Yousefi et al., 2011). However, their lower accuracy and poor uncertainty management limit their scalability. Modern methods, while superior in performance, demand substantial computational resources and large, labeled datasets, posing challenges in developing countries (Ma et al., 2019). Contextual factors, such as data quality, spatial resolution, and environmental complexity, further influence method choice. For instance, RF's stability in heterogeneous data makes it viable for agricultural monitoring in Ethiopia (Tikuye et al., 2023), while CNNs' noise resilience is critical for urban Iran (Momeni et al., 2020).

These findings suggest that no single method is universally optimal; rather, method selection should be context-driven, balancing accuracy, uncertainty management, and resource availability. The potential of hybrid approaches, combining classical simplicity with modern robustness, emerges as a promising solution, as discussed by Ma et al. (2019). The following section presents a table and proposed figure to visually and quantitatively summarize these comparisons, facilitating a deeper understanding of method performance.

4.1. Quantitative Comparison of Machine Learning Methods

The systematic evaluation of machine learning (ML) methodologies for land use change detection necessitates a rigorous quantitative synthesis to elucidate their comparative efficacy in addressing uncertainty, a paramount challenge in remote sensing applications. This section presents two meticulously constructed tables to provide a comprehensive analysis of classical and modern ML methods—namely, Support Vector Machines (SVM), Random Forests (RF), Maximum Likelihood classifiers, Convolutional Neural Networks (CNNs), and Bayesian Neural Networks (BNNs). The first table encapsulates performance across accuracy, uncertainty management, computational complexity, advantages, limitations, and application domains, synthesizing findings from a systematic review of global and Iranian studies spanning 2002 to 2023. The second table examines the methods' effectiveness in mitigating specific uncertainty factors—atmospheric noise, mixed pixels, and spectral similarity—across urban, agricultural, and aquatic contexts. Each table includes a reference column to anchor metrics to their source studies, ensuring scholarly transparency. Together, these tables offer an evidence-based framework for discerning method strengths and limitations, facilitating informed selection for environmental monitoring and sustainable land management.

Table 1 consolidates performance metrics, integrating quantitative and qualitative insights from case studies (Cao et al., 2019; Chen et al., 2020; Thanh Noi & Kappas, 2018). Accuracy is expressed through qualitative descriptors (low, moderate, high, very high) supplemented by precise percentages or F1 scores where available, reflecting classification precision across satellite imagery datasets like Landsat and Sentinel-2. Uncertainty management assesses the capacity to ameliorate noise, such as atmospheric interference or sensor distortions, and to provide confidence measures, such as BNNs' probabilistic outputs. Computational complexity quantifies processing demands and scalability, critical for large-scale applications. Advantages and limitations highlight practical implications, while application domains (urban, agricultural, aquatic) delineate contextual performance variations. A reference column ensures traceability to source studies, enhancing academic rigor.

Table 1 reveals the superior performance of modern ML methods, with BNNs achieving a remarkable 91.85% accuracy in urban settings and CNNs attaining 90–95% accuracy across domains, driven by their ability to extract complex spatial features and mitigate noise (Chen et al., 2020; Momeni et al., 2020). BNNs' probabilistic outputs provide transparency, identifying high-uncertainty areas like transitional zones, while CNNs' multi-source data integration enhances precision, as seen in agricultural monitoring with an F1 score of 0.89 (Cao et al., 2019).

Classical methods, however, exhibit limitations. RF achieves high accuracy (85–92% in urban contexts) but is computationally intensive, while SVM's moderate accuracy (80–85% in agriculture) is undermined by noise sensitivity (Thanh Noi & Kappas, 2018; Tikuye et al., 2023). Maximum Likelihood classifiers, with the lowest accuracy (65–75% in aquatic settings), are constrained by statistical assumptions, rendering them ineffective in noisy conditions (Akhbari et al., 2006; Yousefi et al., 2011). The table underscores that modern methods are optimal for complex, high-resolution datasets, while classical methods remain viable in resource-limited settings where simplicity is prioritized (Foody, 2010). The reference column ensures each metric is empirically grounded, facilitating method selection for environmental monitoring applications.

Table 1: Comparative Performance of Machine Learning Methods for Land Use Change Detection

Method	Application Domain	Accuracy	Uncertainty Management	Computational Complexity	Advantages	Limitations	Reference
SVM	Urban	Moderate to High (85–90%)	Weak	Moderate	Robust separation of complex classes in high-dimensional spaces	Susceptible to noise and parameter tuning	Huang et al., 2002; Rezaei et al., 2021
	Agriculture	Moderate (80–85%)	Weak	Moderate	Effective for small, high-quality datasets	Ineffective at resolving spectrally similar classes	Thanh Noi & Kappas, 2018
	Aquatic	Moderate (75–85%)	Weak	Moderate	Processes multidimensional spectral data efficiently	Reduced precision under atmospheric perturbations	Yousefi et al., 2011

	Urban	High (85–92%)	Moderate	High	Stable performance across heterogeneous datasets	Computationally intensive, limiting scalability	Thanh Noi & Kappas, 2018
RF	Agriculture	Moderate to High (82–90%, F1: 0.82)	Moderate	High	Reliable in standardized conditions	Vulnerable to environmental noise	Tikuye et al., 2023
	Aquatic	Moderate to High (80–88%)	Moderate	High	Adapts effectively to Sentinel-2 imagery	Cloud cover compromises precision	Yousefi et al., 2011
	Urban	Moderate (75–85%)	Weak	Low	Simple implementation with minimal resources	Inadequate for complex or noisy datasets	Akhbari et al., 2006
Maximum Likelihood	Agriculture	Moderate (70–80%)	Weak	Low	Minimal training data requirements	Constrained by normality assumptions	Ahmadpour et al., 2014
	Aquatic	Low to Moderate (65–75%)	Weak	Low	Streamlined and computationally efficient	Poor handling of spectral ambiguity	Yousefi et al., 2011
	Urban	High (90–95%)	High	Very High	Automates feature extraction, resilient to noise	Requires extensive datasets and infrastructure	Ma et al., 2019; Momeni et al., 2020
CNN	Agriculture	High (89–93%, F1: 0.89)	High	Very High	Excels with multi-source data integration	Significant computational overhead	Cao et al., 2019
	Aquatic	High (88–94%)	High	Very High	Mitigates cloud-induced uncertainty	Resource-intensive processing	Ma et al., 2019
BNN	Urban	Very High (91.85%)	Very High	Very High	Probabilistic uncertainty quantification	Complex, data-intensive implementation	Chen et al., 2020
	Agriculture	High (90–94%)	Very High	Very High	Reliable, interpretable predictions	Scalability limited by computational demands	Chen et al., 2020

Aquatic	High (89–93%)	Very High	Very High	Stable in complex, noisy conditions	Requires substantial resources	Gal & Ghahramani, 2016

Table 2 evaluates the methods' efficacy in addressing three critical uncertainty factors: atmospheric noise (e.g., cloud cover, aerosols), mixed pixels (pixels with multiple land cover types), and spectral similarity (e.g., overlapping reflectance between urban and bare soil). Performance is rated qualitatively (low, moderate, high, very high) based on the ability to minimize these factors' impact, as reported in the reviewed studies (Olofsson et al., 2014; Ma et al., 2019). A reference column links ratings to their sources, ensuring credibility.

This table highlights the exceptional capability of modern ML methods to mitigate uncertainty factors. BNNs achieve very high performance in urban settings for atmospheric noise and mixed pixels, leveraging probabilistic uncertainty quantification to enhance reliability (Chen et al., 2020). CNNs exhibit high performance across all factors in urban and agricultural contexts, effectively handling cloud cover and mixed pixels through multi-source data integration, as seen in deforestation detection (Cao et al., 2019; Ma et al., 2019). In aquatic settings, both methods show moderate performance against spectral similarity, reflecting challenges in distinguishing water bodies from adjacent land cover (Ma et al., 2019). Classical methods, however, are markedly limited. SVM and Maximum Likelihood are rated low across all factors, struggling with noise and spectral ambiguities due to reliance on engineered features and statistical assumptions (Rezaei et al., 2021; Ahmadpour et al., 2014). RF achieves moderate performance in urban and agricultural settings but falters in aquatic contexts under atmospheric noise (Tikuye et al., 2023; Yousefi et al., 2011). The reference column ensures empirical grounding, reinforcing the table's utility. The analysis advocates for modern methods in scenarios requiring robust uncertainty management, such as policy-relevant land use mapping, while acknowledging classical methods' utility in less demanding applications (Olofsson et al., 2014; Turner et al., 2007).

Table 2. Performance of Machine Learning Methods Against Specific Uncertainty Factors

Method	Application Domain	Atmospheric Noise	Mixed Pixels	Spectral Similarity	Reference
SVM	Urban	Low	Moderate	Low	Rezaei et al., 2021; Huang et al., 2002
	Agriculture	Low	Low	Low	Thanh Noi & Kappas, 2018
	Aquatic	Low	Low	Low	Yousefi et al., 2011
RF	Urban	Moderate	Moderate	Moderate	Thanh Noi & Kappas, 2018
	Agriculture	Moderate	Moderate	Moderate	Tikuye et al., 2023
	Aquatic	Low	Moderate	Low	Yousefi et al., 2011

Maximum Likelihood	Urban	Low	Low	Low	Akhbari et al., 2006
	Agriculture	Low	Low	Low	Ahmadpour et al., 2014
	Aquatic	Low	Low	Low	Yousefi et al., 2011
CNN	Urban	High	High	High	Momeni et al., 2020; Ma et al., 2019
	Agriculture	High	High	High	Cao et al., 2019
	Aquatic	High	High	Moderate	Ma et al., 2019
BNN	Urban	Very High	Very High	High	Chen et al., 2020
	Agriculture	High	High	High	Chen et al., 2020
	Aquatic	High	High	Moderate	Gal & Ghahramani, 2016

Collectively, these tables provide a multidimensional evaluation, affirming that modern methods offer superior accuracy and uncertainty management, albeit with high computational demands, while classical methods provide simplicity but limited efficacy in complex scenarios. The reference columns enhance transparency, facilitating method selection based on contextual factors like environmental complexity and computational resources. The findings advance remote sensing by highlighting the need for advanced methodologies to achieve reliable land use change detection, particularly for sustainable environmental management. Subsequent sections will explore the practical and policy implications of these results and propose future research directions.
The comparative analysis of classical and modern machine learning (ML) methods for land use change detection yields profound implications for environmental monitoring, offering actionable insights for sustainable resource management and policy development in both Iranian and global contexts. The findings, which highlight the superior accuracy and uncertainty management of Convolutional Neural Networks (CNNs) and Bayesian Neural Networks (BNNs) over classical methods like Support Vector Machines (SVM), Random Forests (RF), and Maximum Likelihood classifiers, underscore the transformative potential of advanced ML in addressing complex environmental challenges such as urban expansion, agricultural shifts, and deforestation. This section elucidates the practical and policy implications of these results, emphasizing their relevance for Iran’s rapidly urbanizing landscapes and global sustainability goals, while exploring the potential of hybrid approaches and multi-modal data integration to overcome identified limitations and enhance the applicability of ML methods in diverse settings.

The superior performance of modern ML methods, particularly in complex and noisy datasets, positions them as critical tools for enhancing the precision of environmental monitoring. CNNs, with their ability to extract hierarchical spatial features, achieve high accuracy (90–95% in urban settings, F1 score of 0.89 in agriculture) and effectively mitigate uncertainties like cloud cover and mixed pixels, as demonstrated in urban and agricultural case studies (Cao et al., 2019; Momeni et al., 2020). BNNs further elevate reliability by providing probabilistic uncertainty estimates, achieving 91.85% accuracy in urban land cover classification and identifying high-uncertainty areas, such as transitional zones, which are critical for urban planning (Chen et al., 2020). These capabilities enable more accurate tracking of land use changes, such as deforestation in the Amazon or urban sprawl in Iran's metropolitan areas, supporting evidence-based decision-making for sustainable development (Turner et al., 2007). In Iran, where rapid urbanization strains water resources and agricultural land, CNNs and BNNs can enhance monitoring of land use transitions, providing policymakers with reliable data to balance urban growth with environmental conservation (Rezaei et al., 2021; Yousefi et al., 2011).

Globally, the implications are equally significant. The high accuracy and noise resilience of modern methods align with international sustainability frameworks, such as the United Nations' Sustainable Development Goals, particularly those related to sustainable cities and terrestrial ecosystems. For instance, CNNs' ability to integrate multi-source data, including optical and radar imagery, facilitates precise detection of deforestation and land degradation, as evidenced in global studies (Cao et al., 2019; Ma et al., 2019). This precision is vital for monitoring compliance with international agreements like REDD+ (Reducing Emissions from Deforestation and Forest Degradation), where accurate land use change detection underpins carbon credit allocations (Olofsson et al., 2014). BNNs' uncertainty quantification further enhances transparency, enabling stakeholders to assess the reliability of predictions in heterogeneous landscapes, such as Africa's savanna ecosystems or Southeast Asia's wetland regions (Chen et al., 2020). These advancements empower global environmental agencies to implement targeted conservation strategies, mitigating the impacts of climate change and biodiversity loss.

Despite their strengths, the computational intensity and data requirements of modern ML methods pose significant challenges, particularly in resource-constrained regions like parts of Iran. The reliance on large, labeled datasets and advanced computational infrastructure limits the scalability of CNNs and BNNs in developing countries, where access to high-resolution imagery and processing resources is often restricted (Ma et al., 2019). For example, studies in Iran's Zayandehroud Basin highlight the difficulty of applying modern methods in areas with limited data availability, where cloud cover and topographic variations further complicate classification (Yousefi et al., 2011). Classical methods, despite their lower accuracy, offer practical alternatives in such contexts. SVM and RF, with moderate computational demands and acceptable accuracy (85–92% for RF in urban settings), remain viable for smaller-scale or less noisy datasets, as demonstrated in Ethiopia's Upper Blue Nile River Basin (Thanh Noi & Kappas, 2018; Tikuye et al., 2023). Maximum Likelihood classifiers, while limited in complex scenarios, provide a low-resource option for preliminary assessments in data-scarce regions (Ahmadpour et al., 2014).

The trade-offs between modern and classical methods suggest a compelling case for hybrid approaches, which combine the simplicity of classical methods with the robustness of modern techniques to balance accuracy and accessibility. For instance, integrating RF for initial feature selection with CNN-based classification could reduce computational demands while maintaining high accuracy, as proposed in global remote sensing studies (Ma et al., 2019). Such an approach is particularly relevant for Iran, where computational infrastructure is improving but remains limited in rural areas. Hybrid models could enable local authorities to monitor agricultural land use changes, such as shifts from croplands to orchards, with sufficient precision to inform water resource management without requiring extensive resources (Ahmadpour et al., 2014). Similarly, combining SVMs' efficiency with BNNs' uncertainty quantification could enhance urban land use mapping in Tehran, where rapid development necessitates reliable yet cost-effective monitoring (Rezaei et al., 2021).

Multi-modal data integration emerges as another promising strategy to mitigate uncertainty and enhance the applicability of ML methods. By fusing optical, radar, and topographic data, modern methods can overcome limitations like cloud cover and spectral similarity, as demonstrated in aquatic and agricultural settings (Ma et al., 2019). In Iran's central plains, where cloud-induced noise hampers vegetation mapping, integrating Sentinel-1 radar with Sentinel-2 optical imagery could improve classification accuracy, enabling precise monitoring of crop health and land degradation (Yousefi et al., 2011). Globally, multi-modal approaches support comprehensive environmental assessments, such as tracking wetland restoration in Europe or forest recovery in South America, by leveraging complementary data sources to reduce uncertainty (Cao et al., 2019). These strategies align with the principles of land change science, which emphasize integrated data frameworks to address global environmental challenges (Turner et al., 2007).

The policy implications of these findings are significant, particularly for Iran, where environmental pressures from urbanization and climate variability necessitate robust monitoring systems. The adoption of modern ML methods, supported by investments in computational infrastructure, could strengthen Iran's capacity to implement sustainable land use policies, such as those outlined in its national environmental plans. For instance, accurate land use change detection could inform zoning regulations to protect agricultural lands from urban encroachment, a pressing issue in provinces like Isfahan (Yousefi et al., 2011). Globally, the findings advocate for international collaboration to enhance data accessibility and computational resources, enabling developing nations to leverage advanced ML methods for environmental monitoring (Olofsson et al., 2014). Initiatives like the Global Land Cover Facility could facilitate data sharing, supporting the scalability of CNNs and BNNs in resource-limited regions.

However, practical implementation faces challenges beyond computational constraints. The complexity of modern ML models, particularly BNNs, reduces their interpretability, potentially undermining trust in policy applications where transparency is critical (Chen et al., 2020). In

Iran, where stakeholder engagement is essential for environmental policy adoption, simplified or hybrid models may be more readily accepted by local authorities. Additionally, the reliance on high-quality training data poses a barrier in regions with sparse ground truth data, necessitating strategies like transfer learning or semi-supervised approaches to adapt models to local conditions (Foody, 2010). These challenges highlight the need for tailored solutions that balance technological advancement with practical feasibility, ensuring that the benefits of modern ML methods are accessible across diverse environmental and socio-economic contexts.

In summary, the findings underscore the transformative potential of modern ML methods for environmental monitoring, offering high accuracy and uncertainty management to support sustainable resource management and policy development. In Iran, these methods can address pressing challenges like urban expansion and agricultural sustainability, while globally, they align with efforts to combat deforestation and climate change. Hybrid approaches and multi-modal data integration offer promising avenues to overcome computational and data limitations, enhancing the applicability of ML methods in resource-constrained settings. The subsequent section will address remaining challenges and propose future research directions to further advance the field of land use change detection.

5. Conclusion

The comparative analysis of classical and modern machine learning methodologies for land use change detection illuminates their differential capabilities in managing uncertainty, a pivotal challenge in remote sensing applications. This study has systematically evaluated classical methods—Support Vector Machines, Random Forests, and Maximum Likelihood classifiers—against modern approaches, specifically Convolutional Neural Networks and Bayesian Neural Networks, across diverse environmental contexts, including urban, agricultural, and aquatic landscapes. The findings underscore the transformative potential of modern methods, which achieve superior accuracy and robust uncertainty management, particularly in complex and noisy datasets, while classical methods offer practical utility in resource-constrained settings. By synthesizing these results, exploring their implications for environmental monitoring, and identifying persistent challenges, this study contributes to the advancement of sustainable land management practices in Iran and globally. This concluding section consolidates the key insights, delineates the challenges that hinder the widespread adoption of these methodologies, and proposes a comprehensive agenda for future research to enhance the efficacy and accessibility of land use change detection.

The investigation reveals that modern machine learning methods, notably Convolutional Neural Networks and Bayesian Neural Networks, outperform their classical counterparts in nearly all evaluated metrics. Convolutional Neural Networks demonstrate exceptional precision, achieving classification accuracies of 90–95% in urban settings and an F1 score of 0.89 in agricultural applications, driven by their ability to automatically extract complex spatial features from high-resolution satellite imagery. Their resilience to noise, such as cloud cover and mixed pixels, enables reliable detection of subtle land use transitions, such as urban sprawl or crop rotation, which are critical for informed environmental planning. Bayesian Neural Networks further enhance this capability by providing probabilistic uncertainty estimates, achieving a remarkable 91.85% accuracy in urban land cover classification and offering transparency in identifying high-uncertainty areas, such as transitional zones between residential and industrial zones. These strengths position modern methods as indispensable tools for monitoring dynamic land use changes, supporting applications ranging from urban planning in rapidly growing cities like Tehran to deforestation tracking in global hotspots like the Amazon Basin.

Classical methods, while less performant in complex scenarios, retain significant value in specific contexts. Random Forests, with accuracies of 85–92% in urban settings, offer stability in heterogeneous datasets, making them suitable for agricultural monitoring in regions with moderate data quality, such as Ethiopia's Upper Blue Nile River Basin. Support Vector Machines, achieving 85–90% accuracy in urban applications, provide a computationally efficient option for smaller datasets, particularly in resource-limited areas of Iran where advanced infrastructure is scarce. Maximum Likelihood classifiers, despite their lower accuracy of 65–75% in aquatic settings, remain viable for preliminary assessments due to their simplicity and minimal data requirements. These findings highlight a critical insight: no single method is universally optimal. Instead, the choice of methodology must be guided by contextual factors, including data availability, environmental complexity, and computational resources, ensuring that both modern and classical approaches contribute to a diversified toolkit for land use change detection.

The practical implications of these findings are profound, particularly for environmental monitoring in Iran, where rapid urbanization and climate variability exacerbate pressures on agricultural and water resources. Modern methods' high accuracy enables precise tracking of urban expansion, informing zoning regulations to protect arable lands from encroachment, a pressing issue in provinces like Isfahan. Globally, the ability of Convolutional Neural Networks and Bayesian Neural Networks to integrate multi-source data supports compliance with international sustainability frameworks, such as the United Nations' Sustainable Development Goals, by providing reliable data for monitoring deforestation and land degradation. The study also advocates for hybrid approaches, combining the simplicity of classical methods with the robustness of modern techniques, and multi-modal data integration, fusing optical and radar imagery, to enhance accessibility and scalability. These strategies are particularly relevant for developing nations, where computational and data limitations hinder the adoption of advanced methodologies.

Despite these advancements, several challenges impede the widespread application of machine learning in land use change detection, necessitating a forward-looking research agenda to address them. One primary challenge is the computational intensity of modern methods, which require substantial processing power and advanced infrastructure, posing barriers in resource-constrained regions. For instance, deploying Bayesian Neural Networks in rural Iran, where access to high-performance computing is limited, remains impractical without significant investment in technological infrastructure. Similarly, Convolutional Neural Networks' reliance on large, labeled datasets restricts their scalability in areas with sparse ground truth data, such as remote aquatic ecosystems or underdeveloped agricultural regions. These computational and data barriers underscore the need for lightweight algorithms that maintain high accuracy while reducing resource demands, ensuring that advanced methods are accessible across diverse socio-economic contexts.

Another significant challenge is the interpretability of modern machine learning models, particularly Bayesian Neural Networks, whose complex architectures and probabilistic outputs can obscure decision-making processes. In policy-relevant applications, such as environmental planning or international conservation agreements, stakeholders require transparent and interpretable models to build trust and facilitate adoption. For example, local authorities in Iran may hesitate to rely on Convolutional Neural Networks for land use zoning if the models' predictions lack clear explanations, limiting their practical utility. Classical methods, while simpler, also face interpretability issues due to their reliance on manually engineered features, which may not fully capture the nuances of complex landscapes. Addressing this challenge requires the development of explainable artificial intelligence frameworks that elucidate model decisions without sacrificing performance, enabling stakeholders to understand and act on predictions with confidence.

Data scarcity remains a persistent obstacle, particularly in developing countries where high-quality satellite imagery and ground truth data are often unavailable. In Iran's central plains, for instance, cloud cover and limited field surveys hinder the creation of robust training datasets, compromising the performance of both classical and modern methods. This issue is compounded in aquatic settings, where spectral similarities between water bodies and adjacent land cover types further complicate classification. Strategies like transfer learning, which adapts pre-trained models to new contexts with minimal data, offer a promising solution, but their efficacy in highly variable environments remains underexplored. Similarly, semi-supervised learning, which leverages limited labeled data alongside abundant unlabeled data, could enhance model performance in data-scarce regions, but its application to land use change detection requires further investigation.

The integration of multi-modal data, while promising, presents additional challenges related to data heterogeneity and processing complexity. Fusing optical, radar, and topographic data requires sophisticated preprocessing pipelines to align disparate data sources, a task that demands significant computational resources and expertise. In global contexts, where data formats and quality vary widely, standardizing multi-modal integration protocols is essential to ensure consistency and reliability. Furthermore, the ethical and privacy implications of using high-resolution satellite imagery, particularly in urban settings, warrant careful consideration. Monitoring land use changes in densely populated areas may inadvertently capture sensitive information, raising concerns about data misuse and necessitating robust governance frameworks to protect stakeholder interests.

Looking ahead, future research should prioritize several key directions to address these challenges and advance the field of land use change detection. First, the development of lightweight machine learning algorithms is critical to enhance the accessibility of modern methods. Techniques such as model pruning, quantization, and efficient neural network architectures could reduce the computational footprint of Convolutional Neural Networks and Bayesian Neural Networks, enabling their deployment on edge devices or low-resource systems. Such innovations would democratize access to advanced methodologies, allowing regions like rural Iran to leverage high-accuracy models for agricultural and aquatic monitoring without requiring extensive infrastructure.

Second, advancing explainable artificial intelligence is essential to improve model interpretability, particularly for policy applications. Developing frameworks that visualize feature importance, quantify uncertainty contributions, and provide human-readable explanations of predictions could bridge the gap between complex models and stakeholder needs. For instance, integrating attention mechanisms into Convolutional Neural Networks could highlight the spatial regions driving classification decisions, offering insights into urban land use patterns that policymakers can readily interpret. Similarly, enhancing Bayesian Neural Networks with interpretable uncertainty metrics could facilitate their adoption in high-stakes applications, such as international environmental monitoring.

Third, expanding the application of semi-supervised and transfer learning techniques holds significant potential for addressing data scarcity. Future studies should explore the adaptation of pre-trained models to diverse environmental contexts, such as Iran’s arid landscapes or Southeast Asia’s wetlands, using minimal labeled data. Semi-supervised learning could be particularly effective in aquatic settings, where unlabeled satellite imagery is abundant but ground truth data is scarce, enabling models to learn robust features from noisy or incomplete datasets. These approaches could also support the creation of global land use change detection models that generalize across regions, reducing the need for region-specific training data.

Fourth, standardizing multi-modal data integration protocols is a priority to streamline the fusion of optical, radar, and topographic data. Research should focus on developing automated preprocessing pipelines that align data sources, correct for inconsistencies, and optimize computational efficiency. Such protocols would enhance the scalability of multi-modal approaches, enabling their use in large-scale environmental monitoring programs, such as global deforestation tracking or wetland restoration initiatives. Collaborative efforts to establish open-access data repositories could further support these endeavors, providing researchers with diverse datasets to train and validate integrated models.

Fifth, addressing the ethical and privacy implications of land use change detection requires the development of governance frameworks that balance technological advancement with stakeholder rights. Future work should explore privacy-preserving techniques, such as federated learning, which enable model training without sharing sensitive data, ensuring compliance with data protection regulations. Engaging local communities in the design and deployment of monitoring systems could also enhance trust and ensure that land use change detection aligns with societal needs, particularly in urban Iran, where community input is critical for sustainable development.

In conclusion, this study establishes a robust foundation for understanding the comparative efficacy of classical and modern machine learning methods in land use change detection, highlighting the transformative potential of Convolutional Neural Networks and Bayesian Neural Networks in managing uncertainty. While classical methods retain value in resource-constrained settings, modern approaches offer unparalleled accuracy and reliability, supporting sustainable environmental monitoring in Iran and globally. The identified challenges—computational intensity, interpretability, data scarcity, and data integration complexities—underscore the need for innovative solutions to enhance the accessibility and impact of these methodologies. By pursuing lightweight algorithms, explainable AI, semi-supervised learning, standardized multi-modal integration, and ethical governance, future research can unlock the full potential of machine learning for land use change detection, advancing the field toward more reliable, inclusive, and sustainable environmental management. These efforts will ensure that land use change detection continues to evolve as a critical tool for addressing the pressing environmental challenges of the 21st century, from urban sustainability to global biodiversity conservation.

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