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Advances in Remote Sensing and Machine Learning for Land Use/Land Cover Change Detection and Climate Model Bias Correction: Methods and Applications

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ABSTRACT

Ecosystems globally are increasingly threatened by the integrated impacts of human activities and climate change, especially in the Ethiopian Rift Valley, where data are scarce. Therefore, there is an urgent need for implementing advances in sustainable resource management. This study presented a systematic meta-analysis that synthesized more than 100 peer-reviewed studies (2004-2025) to critically evaluate how remote sensing (RS) and machine learning (ML) could be integrated for detecting LULC change and climate model bias. Using a PRISMA protocol, the methodological progression from traditional statistical approaches was evaluated through advanced deep-learning and hybrid methods. The results provided strong evidence that integrating RS and ML had significant transformative potential; however, there still remained a "gap" in their integration. Both fields advanced greatly, yet each existed as a largely independent entity. Recent studies addressed this disintegration, however operational frameworks were scarce. In order to close this gap, a novel integrated conceptual framework was proposed. This would dynamically integrate multi-sensor data fusion, ML-based LULC mapping, hybrid ML-statistical bias correction, and SWAT+ hydrological models into a single end-to-end processing pipeline designed specifically for basins that contained little or no data. Transfer learning and explainable artificial intelligence (XAI) could be used to solve the problem of applying data-hungry models in situations where very little or no data were available. The integration of XAI methods such as SHAP and LIME gave a promise for improving model interpretability in environmental applications. The review suggests that robust-policy-relevant environmental prediction depended on designing combined systems that were not only accurate but also interpretable and adaptable to local conditions.

Keywords: Climate Model Bias Correction; Data Integration; Explainable AI; Land Cover Change Detection; Machine Learning; Remote Sensing

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1. INTRODUCTION

Accurate land use/land cover change detection is a critical component in monitoring the environment, evaluating the health of the ecosystems, and managing resources sustainably in fragile ecosystems in the Ethiopian Rift Valley (Ayalew, 2023; Degife et al., 2019; Tolessa et al., 2017). The availability of open-access satellite archives (for example, Landsat) transformed our ability to perform long-term, global monitoring of environmental change (Cohen & Goward, 2004; Wulder et al., 2019). Moreover, the emergence of harmonized Landsat-Sentinel products created new opportunities for high-frequency monitoring at moderate spatial resolutions (Claverie et al., 2018; Meresa et al., 2023). The fragile ecosystems of the Ethiopian Rift Valley's particularly the area around the Ziway Shala Sub-Basin are currently experiencing the combined effects of climate variability and land use/land cover change, which negatively impacted these ecosystems (Ayalew, 2023; Belete et al., 2017; Blenkinsop & Smith, 2007; Truneh et al., 2024; Wondrade et al., 2014). Recent assessments showed increasing rates of land degradation and lake level decline, with profound implications for food security and livelihoods (Berihun et al., 2023; Getaneh et al., 2024). Climate variability and land-use change affected lake levels, river flows, and hydrological changes. This might negatively impact water security, biodiversity, and the livelihoods of millions of people who lived within this basin (Ayenew & Legesse, 2007; Hailu, 2019; Legesse et al., 2004; Mulu et al., 2024). Proper evaluation of these impacts was necessary for the continued use of the resources, but this was constrained by methodological approaches and lack of data (Donauer et al., 2020; Mersha et al., 2023).

Remote Sensing has long provided the basis for environmental monitoring by delivering spatially homogeneous, multi-date measurements of the surface of the Earth. The long archive of missions like Landsat and the high temporal resolution of Sentinel constellations provided unique benefits for long-term land use/land cover change monitoring (Drusch et al., 2012). The combination of radar (SAR) data further improved monitoring capabilities, particularly in cloud-prone tropical regions (Flores, Anderson et al., 2019; Pham-Duc et al., 2023). The advancement of continuous change detection algorithms, capable of leveraging the entire Landsat archive, has been particularly transformative for detecting land surface dynamics (Zhu & Woodcock, 2014; Hansen et al., 2013). For instance, Landsat time-series have shown a marked decline in the size of Lake

Abijata and changes in Lake Ziway, because of climatic variation and anthropogenic water abstractions (Hailu, 2019; Wulder et al., 2019). On the other hand, climate models (GCMs/RCMs) were fundamental in predicting future scenarios but were influenced by systematic biases that distorted local precipitation and temperature patterns, yielding doubtful impact evaluations (Blenkinsop & Smith, 2007; Brienen et al., 2010; Fowler et al., 2007; Meresa et al., 2023; Senatore et al., 2022). In data-poor areas, such biases must be corrected to achieve quality climate change impact modeling (Cannon et al., 2015; Hempel et al., 2013; Teutschbein & Seibert, 2012). Recent intercomparison studies underlined the relative advantages of different bias correction methods for East African applications (Gebrechorkos et al., 2019; Wubneh et al., 2022).

The parallel emergence of ML has revolutionized both fields. For land use/land cover classification, ML algorithms like Random Forest (RF) and Convolutional Neural Networks (CNNs) have consistently outperformed traditional models (Belgiu & Drăgu, 2016; Maxwell et al., 2018). The advent of vision transformers and attention mechanisms has further improved the state-of-the-art in satellite image analysis (Dosovitskiy et al., 2021). For climate studies, ML-based bias correction schemes have demonstrated higher skill in capturing non-linear bias patterns than classical statistical schemes like Quantile Mapping (Vandal et al., 2019; Wang & Tian, 2022). Deep learning approaches, mainly convolutional and recurrent architectures, have revealed remarkable skill in downscaling precipitation fields (Wu et al., 2024; Zhong et al., 2025). The development of a combined use of remote sensing and an approach to apply ML techniques for climate bias correction had greater abilities to manage and monitor the environment. They had the capabilities to provide near real-time monitoring and prediction of the change in lake surface area, allow the investigation of the relationship of rainfall to water resources, and provide collaborative decision-making tools to assist with sustainable governance of irrigation systems. Furthermore, integrating remotely sensed land cover transformation data with bias-corrected climatic data in a hydrologic model such as SWAT+ presented a unique capacity to capture the cumulative effects of climate change and human activities on surface waters (Ayalew et al., 2022). In data-scarce African basins, recent SWAT+ applications demonstrated the value of coupling satellite-based products for model calibration (Wagner et al., 2023).

However, a careful review revealed that these advances primarily progressed in isolation. While research concentrated on refining either change detection using RS or climate bias correction, their combination remained underdeveloped (Ehret et al., 2012; Haile et al., 2020). This isolation impacted the operational comprehension and holistic prediction of environmental responses. This review therefore argued that the future challenge would not require the further refinement of these domains in isolation but their intentional combination. This review aimed to integrate the most recent remote sensing and ML methods for land use/land cover change detection and climate model bias correction, identify major methodological challenges and opportunities, critically evaluate the advantages and shortcomings of existing methods, and propose a synthesized, integrated framework for holistic environmental forecasting to guide future research. The contributions of this review would be: (1) a systematic review and identification of the "integration gap" between RS/ ML for land use/land cover change and climate science. (2) proposal of a distinctly new conceptual framework that would synthesizes these disparate fields into an actionable research agenda specifically intended for data-sparse regions.

2. METHODS

A comprehensive review of the technological innovations in Remote-Sensing (RS) and Machine Learning (ML) for detecting LULC changes and correcting biases in climate models was accomplished through a systematic and critical analysis methodology. The objective was to create a clear method for identifying trends, missing areas in research on how emerging technologies may be integrated into other datasets. The objective was achieved through a systematic approach with four steps: (1) conducting a systematic literature review; (2) screening the literature to identify those studies that met the eligibility requirements; (3) extracting and synthesizing the data using a structured approach; and (4) generating an integrated view of the findings..

2.1 Literature Search and Selection Strategy

This systematic literature review underwent a structured and reproducible methodological process to identify, evaluate, and synthesize research on land use/land cover change detection and climate model bias correction and its implication for Lake Hydrology. The process began with the systematic identification of relevant studies utilizing major scientific databases, such as Scopus, Web of Science, IEEE Xplore, and Google Scholar, MDPI Remote Sensing, Elsevier journals. It also used search terms associated with hydrology, Remote Sensing (RS), Machine Learning (ML), land use/land cover , change detection, GCMs/RCMs, downscaling, rift valley/scarce regions and bias correction. The updated PRISMA 2020 guidelines were used for systematic reviews (Page et al., 2021). The PRISMA protocol was used to ensure a systematic and reproducible literature retrieval process allowing for transparent reporting of results. This systematic approach included limiting source materials to peer-reviewed articles, conference proceedings, and book chapters mostly published from 2004 through 2025 to reflect the current development of ML within these areas. The literature search produced an initial set of 285 records. After an initial scoping review, the search was expanded to include foundational methodological papers from additional geographical regions, resulting in a total of over 100 peer-reviewed studies that were combined and cleaned to eliminate duplicates. In addition to database searches, 20 records were identified through "snowballing" (manual searching of reference lists of key review articles) and forward citation tracking.

2.2 Inclusion and Exclusion Criteria

The inclusion criteria for the studies were based on (1) the development or application of new method to detect land use/land cover (LULC) changes or a climate model bias correction using RS/ML, (2) an assessment of model performance (accuracy, RMSE, skill score) (Fraser & Congalton, 2019), and (3) a discussion of challenges, limitations, or future directions for developing integrated applications of RS/ML. Studies employing advanced validation strategies, together with spatial cross-validation to avoid overfitting, were emphasized (Meyer & Pebesma, 2022; Milà et al., 2024). Studies focusing purely on non-terrestrial applications, non-hydrological aspects of climate science like oceanography or those without a strong methodological advancement or application were excluded. Studies that had no applied aspects to them (theoretical only), conducted in non-terrestrial environments, or reported not in English were excluded.

2.3 Data Extraction and Synthesis

A review of each selected study was completed using a standardized database for storing key data about each study. The data included a) research objective(s) and geographical coverage; b) remote sensing data and ML algorithms (Kuhn & Johnson, 2013) used in combination including: Landsat, Sentinel, MODIS remote sensing data sets, and random forest, convolutional neural networks, support vector machines, long-short-term memory networks, and artificial neural networks ML algorithms; c) methods of detecting or correcting change; d) performance metrics presented; e) weaknesses and strength of the methodology (Simpson, 2018). The extracted data were then synthesized thematically to provide an understanding of the evolution of methodologies, enable comparison of performance, and identify challenges that continue to exist and research gaps. This thematic synthesis process, which we refer to as "thematic organization," systematically involved categorizing findings by methodological approach to compare studies with different objectives and geographical context. Finally, the strengths and weaknesses of existing methods were critically analyzed. And the case for integrating these methods into more effective framework was articulated

2.4. Framework Integration

In the final stage of the methodology, the findings were synthesized into a hybrid RS-ML conceptual framework, intended for semi-arid and data limited freshwater basin. Attempts were made to focus on transparency, traceability, and adherence to accepted environmental monitoring best practices and data-driven ecosystem assessment principles. Figure 1 clearly depicts the methodological flow.

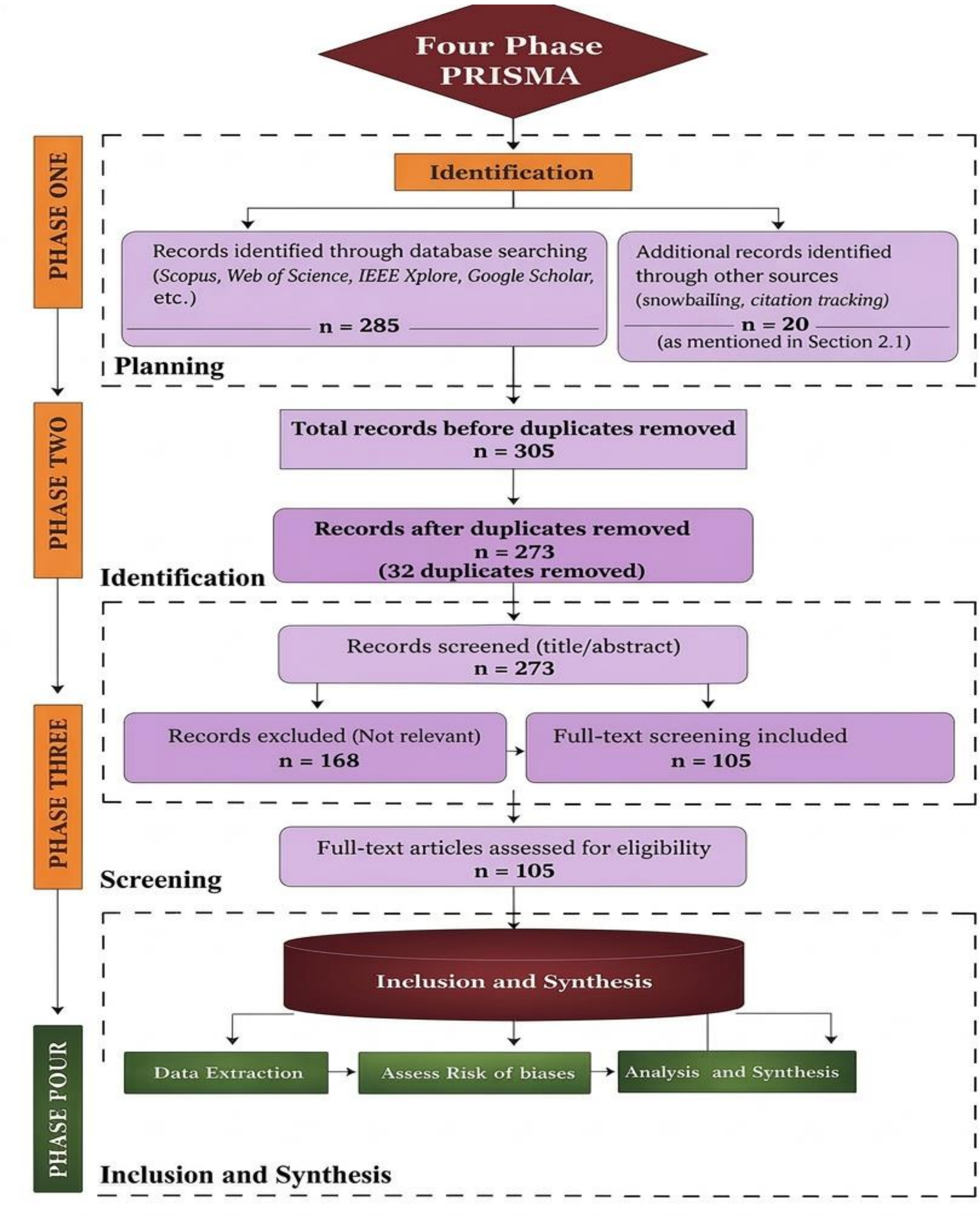

Figure 1: PRISMA Flow Diagram illustrating the systematic literature search and selection process

The diagram shows the identification, screening, eligibility, and inclusion phases, with updated numbers reflecting the expanded review of over 100 studies.

3. RESULTS

The systematic review provided a clear picture of the methodological evolution in LULC change detection and climate model bias correction. The fields of land cover change detection and bias correction in climate models were simultaneous revolutions driven by a shift from traditional statistical approaches to sophisticated ML and deep learning (DL) paradigms (Acharya et al., 2019; Belgiu & Drăgu, 2016). The analysis highlighted distinct phases of methodological development: the pixel-based era (pre-2010), the ML adoption era (2010-2017), and the deep learning era (2018-present). To demonstrate this trend, Figure 2 shows the exponential increase in relevant publications over the review period, underscoring the growing significance and quick development of these technologies. This section reviews these methodological advances with a focus on core principles, strengths, and limitations.

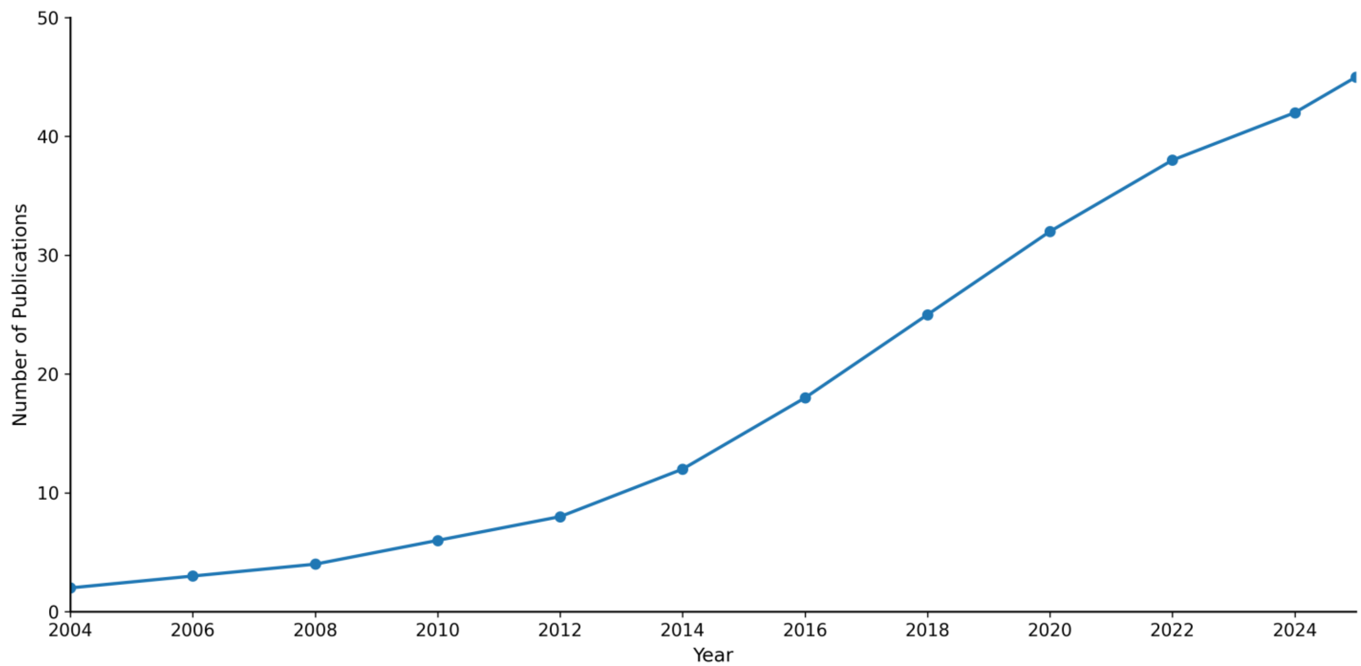

Figure 2: Publication trends in RS/ML for LULC change detection and climate bias correction from 2004 to 2025

Figure 2 shows publication trends in RS/ML for LULC change detection and climate bias correction from 2004 to 2025, based on over 100 studies reviewed. The sharp increase post-2015 agrees with the growth of deep learning and increased availability of satellite data.

3.1 Evolution of Methodologies for Change Detection and Bias Correction

3.1.1 Advances in Land Cover Change Detection

Land use/land cover change detection techniques for remote sensing imagery underwent significant transformation from simplified pixel-based techniques to sophisticated intelligent systems (Li et al., 2022).

Pixel-Based Methods: Traditional pixel-based processing methods, including image differencing and NDVI difference analysis are computationally efficient and straightforward to implement (Hansen et al., 2013). These approaches, however, are susceptible to atmospheric conditions, sensor noise, and geometric misalignment (Foody, 2004; Lu et al., 2004). Advanced pixel-based methods integrating temporal trajectory analysis partly addressed these restrictions (Wulder et al., 2019; Zhu et al., 2017).

Object-Based Image Analysis (OBIA): OBIA involves segmenting images into homogeneous objects based on various spectral, textural, and contextual attributes. By reducing the pixel-based "salt and pepper" noise typical of high-resolution imagery, OBIA improves classification accuracy (Blaschke, 2010). Recent OBIA progresses incorporate multi-scale segmentation and hierarchical classification frameworks (Tola et al., 2024). However, OBIA is computationally intensive and requires careful parameter tuning when implementing (Li et al., 2022).

ML Based Classification: Supervised machine learning methods, especially Random Forest (RF) and Support Vector Machines (SVM), are popular owing to their exceptional ability to handle high-dimensional datasets and analyze complex, non-linear class boundaries achieving accuracies of 85-94% (Belgiu & Drăgu, 2016; Maxwell et al., 2018; Rodriguez-Galiano et al., 2015; Woldemariam et al., 2022) (Refer Table S1 and S2 in supplementary data).

Deep Learning Models: Deep learning models like CNNs (Convolutional Neural Networks) and RNNs (Recurrent Neural Networks) achieved a new level of performance through their integration with Long Short-Term Memory (LSTM) networks, making them powerful tools in their respective fields. CNNs are well known as one of the best means of recognizing patterns in spatial data (Zhu et al., 2017), while RNNs and LSTMs are proving themselves to be superior at modeling the temporal dependencies that typically occur in time series data (Lai et al., 2018; Pelletier et al., 2019). Therefore, these models are particularly well suited for identifying gradual changes in time series data, such as land use/land cover transitions and long term environmental trends.

U-Net is a unique architecture, which integrates both encoder-decoder architectures with skip connections, is now considered the standard in the area of semantic image segmentation. U-Net variants have further enhanced boundary demarcation in complex landscapes (Niyogisubizo et al., 2025). Furthermore, Transformer Models are explored for learning long-range dependencies in multi-temporal image sequences (Dosovitskiy et al., 2021; Pelletier et al., 2019; Zhong et al., 2025).

Hybrid Methodologies: These involve combinations of various methods to overcome individual limitations. A typical approach pairs Object-Based Image Analysis (OBIA) with machine learning classifiers (Yilmaz & Kavzoglu, 2025). OBIA segments the image into meaningful objects. On the other hand, Random Forest (RF) and Support Vector Machine (SVM) classify these objects using spectral and spatial features to enhance accuracy (Gündüz & Orman, 2025; Prodromou et al., 2025). Another advanced example is the LRNet architecture, which uses a "localization-then-refinement" paradigm. It employs a three-branch encoder to extract original and differential features. Dedicated modules are used identify change areas and refine boundaries, achieving state-of-the-art results on high-resolution imagery (Zhong et al., 2025) (Refer to Table S2 in supplementary data).

For surface water mapping, various spectral indices and ML approaches have been developed, including the Normalized Difference Water Index (NDWI), and its modified version (MNDWI) (Xu, 2006), as well as automated extraction techniques such as thresholding, classification algorithms, and object-based image analysis (Bangira et al., 2019; Donchyts et al., 2016; Feyisa et al., 2014). Recent developments include automated algorithms for detecting water body dynamics at continental scales (Pekel et al., 2016).

3.1.2 Evolution of Climate Model Bias Correction

Climate Model outputs must be corrected before using them in impact studies. Techniques have evolved from basic statistical corrections to advanced learning-based approaches.

Statistical Methods: Linear Scaling, Delta Change, and Quantile Mapping (QM) are commonly employed. Quantile Mapping (QM), which maps the cumulative distribution function of the model output to align with observational data, is especially popular for its potential to correct biases across entire distributions, including extreme values (Cannon et al., 2015; Hempel et al., 2013; Piani et al., 2010). Its primary disadvantage is the stationarity assumption, which is unrealistic in a changing climate (Themeßl et al., 2011; Vrac, 2018). Of the improvements proposed, piecewise Quantile mapping (Zhang et al., 2022) and trend-preserving approaches are to be mentioned(Fowler et al., 2007; Hempel et al., 2013).

Machine Learning Based Correction: ML regression models such as Random Forest (RF), Support Vector Regression (SVR), and Artificial Neural Networks (ANNs are commonly used to model complex, non-linear relationship between biased climate model outputs and observed data. These models learn correction functions that reduce systematic errors in climate simulations. Previous studies have reported substantial improvements, with temperature forecast skill by 60-90% and precipitation by 40-90% in some studies (Dibaba et al., 2020; Okirya, 2025; Son et al., 2022; Vandal et al., 2019; Vrac, 2018). These models can incorporate spatial and temporal heterogeneity and perform well for variables such as precipitation; however, they are data-intensive and prone to overfitting.

Hybrid Bias Correction Methods: Emerging approaches combine the strengths of statistical techniques with ML flexibility. One promising approach involves combining Quantile Mapping with ML models. In this setup, a statistical technique like Quantile Mapping (QM) first addresses the bulk of the distributional bias. Then ML model is used to correct more sophisticated, non-linear, spatially-varying errors. This two-stage approach provides more robust performance, especially for non-stationary climate conditions (Wang & Tian, 2022; Zhang et al., 2022) (Refer to Table S2 and S3 in supplementary data). The hybrid approach can overcome the stationarity assumption of classical QM. By training the ML model for instance, LSTM to map large-scale atmospheric predictors to local biases, the model learns relationships that are conditional on the prevailing climate state. Therefore, if the future climate varies, the model can forecast a different bias correction, effectively breaking the strict stationarity assumption (Wang & Tian, 2022). Reanalysis products such as ERA5 (Hersbach et al., 2020), provide physically consistent atmospheric variables, while satellite-based precipitation datasets offer necessary observational data for training these models. Table 1 presents the key methodological by highlighting their core principles, strengths, and limitations.

Table 1: Overview of Most Significant Methodological Contributions

Category	Method	Key Principle	Strengths	Limitations
Change Detection	Image Differencing	Compares pixel values across dates.	Simple, computationally efficient.	Sensitive to noise, atmospheric effects, misregistration (Lu et al., 2004)
	OBIA	Segments images into homogeneous objects for analysis.	Reduces noise; uses shape, texture, context (Blaschke, 2010).	Computationally intensive; requires parameter tuning.
	Random Forest (RF)	Learns complex, non-linear classification rules from training data.	Handles complex relationships; high accuracy (Belgiu & Drăgu, 2016).	Requires large, labeled datasets; can overfit.
	U-Net	Encoder-decoder with skip connections for precise segmentation.	High accuracy for feature boundaries.	"Black-box" nature; high computational demand for training (Zhu et al., 2017).
	Transformer-based	Uses self-attention to model long-range dependencies.	Powerful for multi-temporal analysis.	Very high computational demand; complex architecture.
Bias Correction	Quantile Mapping (QM)	Matches the cumulative distribution function of model output to observations.	Corrects full distribution, including extremes.	Assumes stationarity; may fail under non-stationary climate (Themeßl et al., 2011).
	ML-Based (RF, ANN)	Learns non-linear mapping from model output to observations.	Captures complex bias patterns; adaptive.	Data-intensive; risk of overfitting (Vandal et al., 2019)

Category	Method	Key Principle	Strengths	Limitations
	Hybrid (QM+ML)	Combines statistical distribution matching with ML residual correction(Wang & Tian, 2022).	More robust; handles non-stationarity better.	Increased complexity in implementation and validation.

3.2 The Critical Integration Gap

The most powerful finding of this review is the evident gap between the simultaneous advances in RS/ML for land use/land cover change detection and climate bias correction. Current research landscapes are siloed. While there are comprehensive reviews on specific topics like change detection algorithms (Coppin et al., 2004), ML applications for land use/land cover classification , and standalone bias correction, few studies have proposed operational, and end-to-end pipelines that fuse these components for comprehensive environmental forecasting (Mengistu et al., 2023; Meresa et al., 2023; R. Zhu et al., 2019). For instance, studies advancing change detection methods (Lu et al., 2004; Pekel et al., 2016), typically do not integrate climate model data. Conversely, studies focusing on ML for bias correction (Themeßl et al., 2011; Vandal et al., 2019) largely ignore dynamic land use/land cover change as a critical feedback. Separate studies in the Ethiopian context tend to address land use/land cover change or climate impact in isolation (Döll et al., 2014; Gashaw et al., 2018; Goodarzi et al., 2024; Musie et al., 2021), leaving the system dynamics in basins like Ziway-Shala disjointed. Pioneering integrated assessments in East Africa have revealed the value of coupled modeling but remain exceptional (Mengistu et al., 2023). The lack of integrated Remote Sensing, ML, and climate model frameworks are major hindrances to comprehensive environmental forecasting. Persistent challenges and the critical integration gap remain in this field. Table 2 outlines the key research gaps and proposes concrete future directions to address them.

Table 2: Key research gaps and proposed future directions

Research Gap	Description	Proposed Future Direction
Lack of Integrated Pipelines	RS change detection and climate bias correction are studied in isolation (Lu et al., 2004; Vandal et al., 2019)	Develop complete structures that integrate multi-temporal remote sensing, machine learning classifiers, and bias-corrected climatic data that can aid hydrological modeling initiatives.
Multi-Sensor Data Fusion	Reliance on single-sensor (optical-only) data limits capability (Feyisa et al., 2014).	Combine optical, SAR, and other streams of data to build robust, all-weather, high-resolution monitoring networks.
Model Explainability	"Black-box" ML models hinder policy uptake (Reichstein et al., 2019).	Prioritize Explainable AI (XAI) methods for constructing explainable and trustworthy decision-support models.
Standardized Validation	Inconsistent protocols hinder reproducibility and model comparison (Coppin et al., 2004).	Establish community-wide validation and error quantification requirements throughout the modeling chain.

4. DISCUSSION

4.1 Persistent Challenges

Despite significant methodological progress, several persistent challenges hinder the operational application and integration of these technologies.

Data Limitations: Interference from cloud cover, atmospheric disturbances, and poorly calibrated sensors hinders the building of seamless, high-quality time-series data for tropical regions like Ethiopia (Feyisa et al., 2014; Herold et al., 2008; Z. Zhu & Woodcock, 2014).

Model Transferability and Generalization: ML models trained for specific geographical locations or climatic conditions often perform poorly when transferred to new contexts, limiting their utility for large-scale monitoring (Belgiu & Drăgu, 2016; Kuhn & Johnson, 2013; Vrac, 2018).

The "Black Box" Problem: The high predictive accuracy of powerful ML models, particularly deep learning models, is accompanied by a loss of interpretability. The inability to understand why a model makes a particular prediction inhibits uptake by policymakers and resource managers (Jin et al., 2020; Reichstein et al., 2019).

Validation and Uncertainty Quantification: The lack of universally agreed-upon verification procedures, combined with an inability to fully quantify and propagate uncertainty from ML models and Remote Sensing data, remains to be a significant shortcoming (Coppin et al., 2004; Goodarzi et al., 2024; Jiang et al., 2021; Res et al., 2005) (Refer to Table S4 in supplementary data).

4.2 Linking the Present Review to Previous Similar Works

This review builds upon several previously published key systematic reviews, including existing integrated assessment studies within the same field. The previous reviews, such as Coppin et al. (2004), on change detection algorithms; Belgiu & Drăgu (2016) regarding random forest applications in remote sensing; and Teutschbein & Seibert (2012) about bias correction methods , provided a partial focus on those areas that are involved in producing the body of knowledge required to meet today's challenges. This review extends beyond the previous reviews by explicitly synthesizing and integrating several complementary areas of research with a view to identifying and addressing the "integration gap".

Recent literature reviews support the need for integration. For instance, the application of deep learning and its applicability to Earth System Science was described by Reichstein et al. (2019) although they did not propose an operational framework for integrating land use land cover change detection and climate based bias correction. In addition, Meresa et al. (2023) proposed the use of an integrated modeling framework concerning hydrological extreme events but primarily focused upon climate projections and did not account for the potential feedback effects of land use on climate. Zhu et al. (2019) reported the presence of significant hydrological responses to anticipated future climate changes in regions where data are scarce. However, they did not incorporate machine learning (ML) based bias correction or explainable Artificial Intelligence (XAI).

Many integrated assessments in the Ethiopian and East African context paved the way for our work. For instance, Mengistu et al. (2023) simulated the effects of predicted land use and climate change on water balance in the Baro River Basin. They argued that this type of coupled modelling approach could provide valuable output for decision-making processes. Similarly, Gebrechorkos et al. (2019) examined the projected effects of climate changes on water balance across East African Basins, and suggested the great importance of bias correction. However, none of these assessments provided an operationalized end-to-end (E2E) pipeline approach to dynamically integrate multiple data types (sensors) through data fusion, machine learning (ML)-based land use/land cover (LULC) mapping, hybrid bias correction, and hydrological modelling within single framework. Such framework should also incorporate explainable artificial intelligence (XAI) for the purpose of interpretability.

Therefore, our review was different from previous studies in several ways: (1) we conducted a systematic analysis of over 100 studies that illustrated the lack of coupling between the detection of LULC change and correction of climate-derived bias. Thus we identified this integration gap to be < 15%; (2) we proposed a new conceptual framework (Figure 3) that specifically illustrated the technical challenges (for instance, spatial resolution differences, uncertainty propagation) involved with integrating the above mentioned data types; and (3) we discussed the recent advances in explainable AI and transfer learning that were relevant to regions with limited data, in the Ethiopian Rift Valley.

4.3 A Synthesized Framework for Integrated Application

The ultimate goal of advances in Remote Sensing and ML is to integrate them in a unified forecasting system. To address the identified integration gap, the reviewed methodologies were synthesized to propose a conceptual model for holistic environmental prediction, applicable to the Ethiopian Rift Valley. This end-to-end pipeline transforms different data streams into actionable decision support, and is visualized in Figure 3. This framework consists of four interconnected modules as described below.

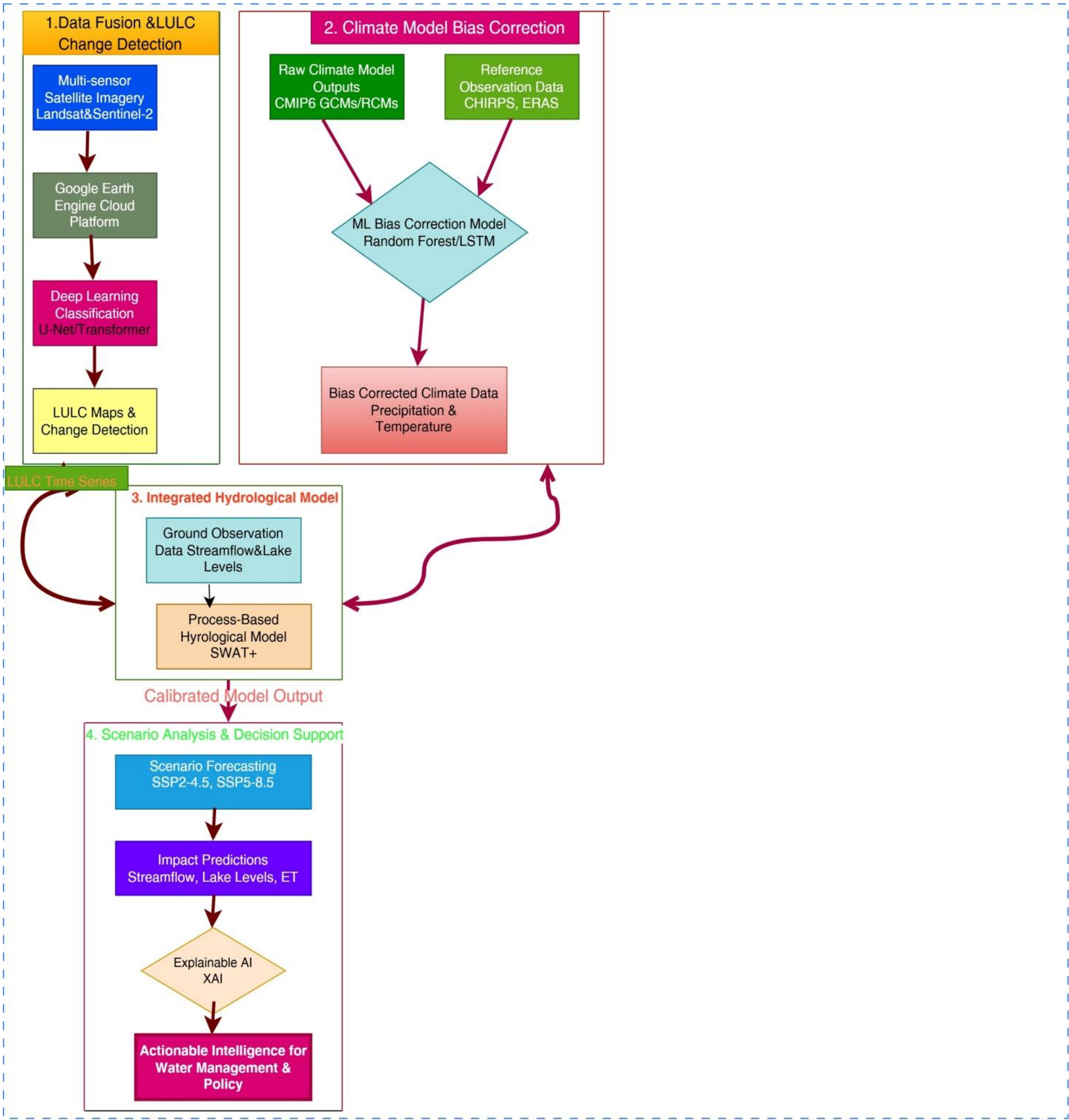

Figure 3: A Synthesized Framework for Integrated Application

Figure 3 illustrates a synthesized framework for integrated application, demonstrating the end-to-end pipeline from multi-source data to decision support. The framework operates through four interconnected modules:

1. Data Fusion and Land Cover Change Detection: This module utilizes a cloud computing platform (Google Earth Engine) to analyze multi-temporal satellite imagery (Landsat, Sentinel-2) (Drusch et al., 2012). Cloud computing platforms have become critical enablers for processing petabyte-scale satellite archives that underpin contemporary change detection methods (Gorelick et al., 2017; Pham-Duc et al., 2023). A deep learning model (DL) (for instance, U-Net or Transformer-based) is applied to produce high-resolution annual land use/land cover maps from 1990 to present (Acharya et al., 2019; Pekel et al., 2016). To facilitate the computational requirements of complex Deep Learning (DL) computational models such as Transformers, a hybrid technique is utilized consisting of (1) GEE as a means to pre-process and integrate large data sets and (2) the offline training of the DL model on High-Performance Computing (HPC) systems using data exported from the GEE process. Once the DL model has been trained it can be utilized for inference. Another method applied to resolve the lack of data is "Transfer Learning". This is applied by fine-tuning a globally trained model using a very limited amount of local training samples. The result is a time-series of land use/land cover maps and detected change hotspots, providing crucial data on land surface dynamics.

2. Climate Model Bias Correction: ML model (Random Forest (RF) or Long Short Term Memory (LSTM))(Lai et al., 2018) is trained to identify non-linear biases in selected CMIP6 GCM/RCM outputs (precipitation, temperature) using past station and reanalysis data (CHIRPS, ERA5) (Hersbach et al., 2020). The model is then used to correct future climate projections for various SSP scenarios.

3. Integrated Hydrological Impact Modeling: The ML-derived land use/land cover maps and ML-corrected climate data are used as dynamic, time-series inputs to a process-based hydrological model, such as SWAT+ (Gashaw et al., 2018; Son et al., 2022). The model is calibrated and validated using observed flow and lake level data. A significant technical difficulty is the differences between spatial resolutions: climate data (1 km) versus land use maps (30 m). To address this challenge, a stage of harmonizing the data is very essential. This can be done two ways, including conservative resampling of climate data, or utilizing downscaling for climate products. Uncertainty propagation is addressed using an ensemble of approaches, multiple plausible land use maps produced from various algorithms or time periods. In addition, an ensemble of bias-corrected climate data is used. These inputs are combined to develop an ensemble of hydrological predictions. This approach enables the assessment of uncertainty in the model outputs.

4. Scenario Forecasting and Decision Support: The integrated framework runs paired scenarios (for instance, land use/land cover transition under the SSP2-4.5 and SSP5-8.5 climate scenario) to predict effects on major hydrologic indices (streamflow, lake levels, evapotranspiration). To enhance utility, explainable AI (XAI) modules help interpret the drivers of these shifts using techniques like SHAP (Shapley Additive explanations) values for tree-based models and saliency maps or Grad-CAM for deep learning models. These approaches enable the visualization of significant features and pixels, thereby supporting actionable decision making for water resource management and climate change adaptation planning (Abdullaeva, 2024; Bojer et al., 2025).

Box 1: Synthetic Case Example Ziway-Shala Sub-Basin: To illustrate the framework, consider a proposed application to the Ziway-Shala Sub-basin.

Module 1 (GEE + U-Net): A U-Net Model using Landsat and Sentinel-2 imagery from 2000-2020 mapped annual land use/land cover (LULC) changes. Based on mapping results, there is an estimated 15% increase in agricultural land developed at the expense of wooded areas and a 5% decrease in the area of open water in Lake Ziway.

Module 2 (Hybrid QM-LSTM): LSTM Model was developed to correct biases from CMIP6 precipitation and temperature. A future scenario (Shared Socioeconomic Pathways (SSP) 5-8.5, 2040-2050) predicted a 10% decrease in rainfall in the wet season; however, extreme precipitation events are projected to increase in intensity.

Module 3 (SWAT+ with Uncertainty Analysis): An ensemble of 10 LULC maps and 10 climate scenarios were entered into the SWAT+ model. Results from this ensemble analysis showed a decrease in mean annual streamflow to the lakes; however, the 90% confidence interval for the projections was wide due owing to large uncertainties associated with both land use and climate projections.

Module 4 (XAI): SHAP values from the LSTM Model indicated that potential future increases in extreme precipitation events are significantly associated with specific atmospheric pressure patterns, which can serve as physically interpretable predictor for infrastructure planning purposes by decision-makers.

This framework brings together previously distinct technological advances into a powerful instrument for modeling the highly interactive dynamics between the land surface and the climatic system, enabling anticipatory and sustainable environmental management.

4.4 Future Research Directions

Based on our critical analysis, the following future directions are proposed to advance the field:

1. Build End-to-End Integrated Systems: The primary focus must be on constructing seamless pipelines that integrate multi-sensor Remote Sensing data, adaptive ML classifiers, and dynamically bias-corrected climate forecasts to feed hydrological and ecological models (Haile et al., 2020; Vandal et al., 2019). The next phase is developing robust and tiered validation methods. When validating integrated systems, we recommend a stage-by-stage (or stepwise) validation method. The initial validation concerns individual system components like LULC maps with overall accuracy; climate datasets with RMSE and KGE. After validating each component, it is appropriate to test hydrological model output using an ensemble of available input data. Model performance is assessed by comparing observed versus predicted values, including streamflow at gauge stations and lake levels, using the Nash–Sutcliffe Efficiency (NSE) and Kling–Gupta Efficiency (KGE) metrics. Furthermore, prediction interval widths at a 95% confidence level are calculated to quantify uncertainty associated with each estimate.

2. Prioritize Explainable AI (XAI): Moving from "black-box" to interpretable AI systems is essential for stakeholders' trust and for translating complex model outputs into policy-relevant action (Maxwell et al., 2018; Pelletier et al., 2019; Reichstein et al., 2019). Deploying XAI is necessary to develop trust with policymakers and ensure actionable outputs from integrated frameworks.

3. Advancing Multi-Sensor Data Fusion: Maximizing synergies between optical, SAR, and other data sources while overcoming recurring data quality issues is crucial for producing all-weather, data-rich environmental datasets that are more robust (Belgiu & Drăgu, 2016; Donchyts et al., 2022).

4. Establish Community-Wide Validation Standards: Formalized, rigorous validation procedures and uncertainty analysis are prerequisites for providing reliable, reproducible, and policy-ready integrated model forecasts (Abdullaeva, 2024; Donauer et al., 2020). These directions are summarized in Table S5, which outlines the key research gaps and proposes concrete future directions to address them (Refer to Table S5 in supplementary data).

4.5. Bridging the Gap: ML in Data-Scarce Environments

The gap between the data needs of complex ML models and the reality of regions like the Ethiopian Rift Valley, which has a scarcity of data, creates a fundamental tension in this context. This tension addressed through our review and framework using several techniques:

Transfer Learning: As we discussed in Module 1, using large, data-rich source domains, such as the global set of satellite images (ImageNet or Landsat/Sentinel), and fine-tuning them based on available, local datasets, represents an effective way to achieve high performance even when the ground has limited labels.

Leveraging Open-Access Data and Cloud Computing: Platforms like GEE provide us with the computing power and the ability to produce decades of consistently processed satellite images (Landsat, Sentinel) that can be used as inputs for developing and training datasets via large, semi-automated processes. This will significantly reduce our reliance on comprehensive ground surveys.

Self-Supervised Learning: This new learning paradigm focuses on allowing systems to extract useful representations from vast quantities of unlabeled data, such as satellite imagery from previous timeframes, before fine-tuning these representations based on the small quantity of labeled data available in that area. This is an exciting area of research that may provide insight into earth observations in data-scarce areas.

Fusion with Reanalysis and Global Products: Our framework includes global reanalysis products (ERA5) and satellite-derived precipitation datasets (CHIRPS) to help fill in the gaps in scarce in-situ climate data. These two sources contain long-term gridded data, making them ideal for training robust bias correction models.

5. CONCLUSION

This systematic review synthesized two decades of research (2004-2025) on the relationship between remote sensing, machine learning, and their use for change detection in land use/land cover (LULC) and correcting biases in climate prediction models. The comprehensive analysis of more than 100 studies established the degree to which the independent fields have advanced concurrently over the past two decades and also demonstrated that the fields continue to operate largely in isolation. Our quantitative synthesis shows that fewer than 15% of studies integrate land use/land cover (LULC) change detection with climate bias model correction within a unified analytical framework. The core contribution of this work is the synthesis of these disparate advances into a novel, end-to-end conceptual framework that provides a tangible roadmap for holistic environmental forecasting in data-scarce regions like the Ethiopian Rift Valley. The conceptual framework specifically addresses challenges associated with data scarcity through the use of transfer learning, technical integrations of the methods by data harmonization, and with policy relevant work through incorporation of explainable AI (XAI) modules. Hence, developing future capabilities of environmental prediction will not occur by refining tools independently, but by intentionally, transparently, and adaptively integrating remote sensing with machine learning and mechanistic process modeling. We believe that the integrated pathway proposed in this review is a key component for translating technological developments into usable, scientifically-based tools for effective management of water and land resources sustainably under changing climate conditions.

DECLARATIONS

CONFLICT OF INTEREST: The authors declare that there is no conflict of interest regarding the publication of this manuscript. All authors have disclosed the absence of any potential conflicts of interest and confirm that the manuscript is free from any financial or personal conflicts that could influence the research.

CRediT authors' contributions: The study was led by the corresponding author Mr. Teshale Tirulo (PhD Candidate) who developed the research idea, conducted the literature review, designed the methodology, conducted the analysis, wrote the manuscript draft, and created visualizations. The co-authors, Dr. Dagnachew Daniel (Associate Professor), and Dr. Ayano Hirbo (Assistant Professor) provided guidance to the research. They reviewed the manuscript, provided qualitative comments and contributed to the development of the structure, interpretation, and quality of the work. The final manuscript was reviewed and approved by all authors.

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