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Machine learning approaches to Landsat change detection analysis

Galen Richardson[a], Anders Knudby[a], Morgan A. Crowley[b], Michael Sawada[a], and Wenjun Chen[c]

[a]Department of Geography, Environment and Geomatics, University of Ottawa, Ottawa, Canada; [b]Canadian Forest Service (Great Lakes Forestry Centre), Natural Resources Canada, Sault Ste. Marie, Canada; [c]Canada Centre for Mapping and Earth Observation, Natural Resources Canada, Ottawa, Canada

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ABSTRACT

The Landsat mission has captured images of the Earth's surface for over 50 years, and the data have enabled researchers to investigate a vast array of different change phenomena using machine learning models. Landsat-based monitoring research has been influential in geography, forestry, hydrology, ecology, agriculture, geology, and public health. When monitoring Earth's surface change using Landsat data and machine learning, it is essential to consider the implications of the size of the study area, specifics of the machine learning model, and image temporal density. We found that there are two general approaches to Landsat change detection analysis with machine learning: post-classification comparison and sequential imagery stack approaches. The two approaches have different advantages, and the design of an appropriate type of Landsat change detection analysis depends on the task at hand and the available computing resources. This review provides an overview of different Landsat change detection approaches using machine learning, outlines a framework for understanding the relevant considerations, and discusses recent developments such as generative artificial intelligence, explainable machine learning, and ethical analysis considerations.

HIGHLIGHTS

- Landsat-based change detection with machine learning can be used to track environmental phenomena.
- There are two general approaches to Landsat change detection with machine learning: post-classification comparison and sequential imagery stack approaches.
- Study area size, model computational requirements, and image temporal density are essential considerations for Landsat change detection analysis.
- Generative AI, explainable machine learning, sensor harmonization, change attribution, and ethical analysis should be further developed in Landsat change detection analysis.

RÉSUMÉ

La mission Landsat a capturé des images de la surface de la Terre pendant plus de 50 ans, et les données ont permis aux chercheurs d'étudier une vaste gamme de phénomènes de changement différents à l'aide de modèles d'apprentissage automatique. La recherche sur la surveillance basée sur Landsat a eu une influence sur la géographie, la sylviculture, l'hydrologie, l'écologie, l'agriculture, la géologie et la santé publique. Lors de la surveillance des changements à la surface de la Terre à l'aide des données Landsat et de l'apprentissage automatique, il est essentiel de prendre en compte les implications de la taille de la région d'intérêt, les spécificités du modèle d'apprentissage automatique et la densité temporelle de l'image. Nous avons constaté qu'il existe deux approches générales de l'analyze de la détection des changements Landsat à l'aide de l'apprentissage automatique: la comparaison post-classification et l'empilement séquentiel d'images. Ces deux approches présentent des avantages différents, et la conception d'un type approprié d'analyze de détection des changements Landsat dépend de la tâche à accomplir et des ressources informatiques disponibles. Cette étude donne un aperçu des différentes approches de détection des changements Landsat à l'aide de l'apprentissage automatique, présente un cadre pour comprendre les considérations pertinentes et discute des développements récents tels que l'intelligence artificielle générative, l'apprentissage automatique explicable et les considérations relatives à l'analyze éthique.

CONTACT Galen Richardson galen.richardson@uottawa.ca.

1. Introduction

Landsat satellites have been consistently observing the Earth since 1972, creating the longest continuous satellite-derived terrestrial record that is available from regularly updated open-access online databases (Wulder et al. 2012; White et al. 2014; Crawford et al. 2023). Substantial development has gone into value-added products that improve image processing, such as cloud masking algorithms (Foga et al. 2017; Zhu and Woodcock 2012), atmospheric correction algorithms (Masek et al. 2006; Vermote et al. 2016), analysis-ready data (Dwyer et al. 2018; Potapov et al. 2020), and the production of coefficients for harmonizing imagery captured from different Landsat sensors and/or other satellites (Claverie et al. 2018; Roy et al. 2016). These products facilitate the use of Landsat data to detect environmental change on the Earth's surface.

Landsat change detection analyses have been fundamental to advancing our understanding of environmental processes and how they are changing the surface of the Earth (Crowley and Cardille 2020; Kennedy et al. 2014; Hemati et al. 2021). Historically, change detection studies compared Landsat images of different dates and used the differences in pixel spectral response to quantify change (Rogan et al. 2002; Singh 1989). While this approach is simple to implement, it can be challenging to find images collected at desired time intervals and to appropriately control for ecosystem dynamics (Zhu and Woodcock 2014). With advancements in computational power, the shift to open access Landsat data, increased accessibility through cloud platforms such as Google Earth Engine (GEE), Microsoft Planetary Computer, and Open Data Cube (ODC), there has been a paradigm shift away from change detection based on a few images at a time and toward tracking changes using datasets containing hundreds or thousands of Landsat images (Crowley et al. 2023; Kennedy et al. 2014; White et al. 2014; Woodcock et al. 2020).

At the same time, there has been a recent proliferation of high-performance machine learning models used in remote sensing applications (Maxwell et al. 2018; Tulbure et al. 2022). Recent studies favor machine learning approaches over traditional parametric models because of their ability to model complex patterns and their tendency for higher performance (Maxwell et al. 2018). Machine learning models such as Random Forest (RF), neural networks, Support Vector Machines (SVM), and boosted decision trees are commonly used for classification and regression tasks with Landsat data (Baumann et al. 2012; Gómez et al. 2016; Guo et al. 2022; Junaid et al. 2023). These models can use Landsat images, image composites, harmonic regression coefficients of pixel values, and stacks of observations as model inputs to predict different phenomena (Phan et al. 2020; Zhang et al. 2024; Zhu and Woodcock 2014).

Machine learning approaches for Landsat change detection analysis can generate products that track environmental changes on regional and global scales with varying temporal resolutions (Gómez et al. 2016; Kennedy et al. 2014; Tulbure et al. 2022; Zhu and Woodcock 2014). Many studies have used these approaches to track changes in land use and land cover (LULC), monitor agriculture, map the spread of urbanization, and map changes in glacier extent (Ambinakudige & Intsiful 2022; Czekajlo et al. 2021; Luciano et al. 2022; Potapov et al. 2022). These approaches can also be used to calculate changes in forest biomass, track disturbances to forests, monitor water quality, and map changes in wetland and water extents (Crowley et al. 2019; Guo et al. 2022; Pelletier et al. 2024; Tulbure et al. 2016; White et al. 2022; Wulder et al. 2018).

Given the diverse set of Landsat change detection methodologies and the broad application of machine learning models, the annual number of primary research publications on "Landsat Change Detection", "Landsat Machine Learning", and "Landsat Change Detection Machine Learning" continues to increase (Figure 1). The quantity and distribution of earth observations, long record of imagery (> 50 years), and spatial resolution that is appropriate for monitoring and detecting land transformations, are substantial benefits that make the Landsat archive so commonly used with machine learning to detect change (Townshend and Justice 1988; Wulder et al. 2016). While each study presents a unique set of objectives and challenges, two general approaches to Landsat change detection can be discerned: post-classification comparison and sequential imagery stack approaches. Post-classification comparison involves using machine learning models to make mapped predictions of an environmental variable of interest from individual images, and then compare those mapped predictions throughout time to detect changes (e.g. Luciano et al. 2022; Hermosilla et al. 2019). Sequential imagery stack approaches use collections of sequentially captured overlapping imagery to train models to detect environmental change directly from the observed changes in the radiometric variables (top of atmosphere or surface reflectance) (e.g. Zhu and Woodcock 2014; Zhou et al., 2020). This paper provides an overview

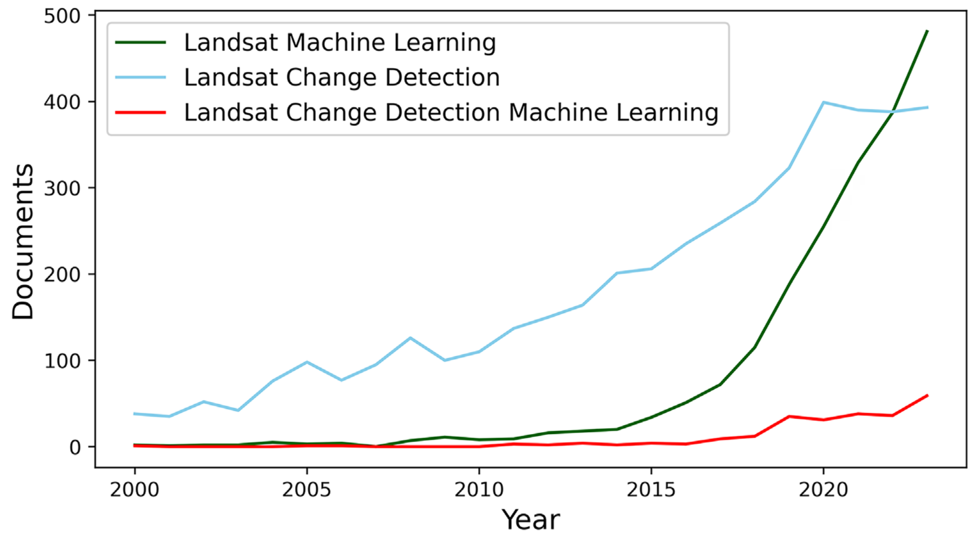

Figure 1. Yearly number of publications including the relevant terms within article titles, abstracts, and keywords from 2000 to 2023 indexed by Scopus. Data was downloaded on October 17th, 2024.

of machine learning methodologies used in Landsat change detection analysis by (1) examining approaches to data pre-processing and considerations, (2) introducing commonly used machine learning models, (3) outlining the different research themes of Landsat change detection analysis using machine learning, and (4) reviewing the current state of change detection analysis, and possibilities for future development in virtual constellations, change attribution, explainable machine learning, generative artificial intelligence, and ethical analysis.

2. Methodology

This review examined published manuscripts on machine learning approaches to Landsat change detection analysis by searching the keywords "Landsat Change Detection", "Landsat Machine Learning", "Landsat Change Detection Machine Learning", "Landsat Time Series", and "Landsat Time Series Machine Learning" in Google Scholar. The results were sorted by recency of publication to find recent work relevant to our study. Additionally, an identical query was completed and sorted by "relevance" to find the most prominent contributions. Manuscripts that did not use machine learning or multi-temporal imagery were excluded from the selection process. After an initial search, selected manuscripts were sorted into the topics "post-classification comparisons" and "sequential imagery stack approaches". Each topic was further investigated in Google Scholar using relevant keywords to their topics. For example, "recurrent neural network Landsat" and "long short-term memory models" were terms used to query literature on types of sequential imagery stack approaches, which typically do not have the keywords "Landsat change detection machine learning" even when they are used for such analysis. Many publications that conduct Landsat change detection analysis with machine learning did not include all the keywords, such as publications focused on LULC, deforestation, and water quality change. Such papers were sorted by "relevance" in Google Scholar, and manuscripts that used machine learning approaches to analyze Landsat time series were purposively included in this review. Selected publications from Google Scholar on topics such as different machine learning models, generative artificial intelligence, image composition techniques, change detection algorithms, and sensor harmonization methodologies were also included due to their relevance to topics in this paper.

3. Fundamental considerations for Landsat change detection analysis

3.1. Landsat data inputs for change detection analysis

Landsat imagery is distributed in different processing levels (1, 2, 3) with progressively greater amounts of pre-processing (top of atmosphere, surface reflectance, and analysis-ready respectively) (Young et al. 2017; Crawford et al. 2023). Additionally, Landsat imagery is released in different tiers corresponding to their geolocation accuracy, with Tier 1 images having geolocation RMSE ≤ 12m, and Tier 2 images RMSE > 12m (Crawford et al. 2023). Finally, there are different collections (1 and 2), with Collection 2 being the most recent reprocessing effort of the Landsat archive (Crawford et al. 2023). Selecting the right type of Landsat imagery is imperative for conducting Landsat change detection analysis. Collection 2 Tier 1 surface reflectance imagery is often used in Landsat change detection analysis since it has high geolocation accuracy and has been corrected for atmospheric conditions, sun geometry, and terrain (Young et al. 2017).

There are three commonly used data structure approaches when using Landsat data as inputs for change detection analysis: (1) individual images are used in direct comparison to determine changes; (2) images are composited for different time periods, and the composites are then used to determine changes; (3) stacks of sequentially captured overlapping images are used to determine changes (Figure 2). Methods 1 and 2 can be used in post-classification comparison where changes are based on comparing prediction maps representing different periods in time (Rogan et al. 2002; Singh 1989). Method 3 is primarily used for sequential imagery stack approaches, but can also be used in post-classification comparison.

The direct comparison of two or more images is challenging due to variable cloud coverage and the 16-day revisit time of Landsat sensors, which often results in inconsistent temporal gaps between successive cloud-free observations (Gondore and Hunduma 2023; Rogan et al. 2002; Z. Zhu and Woodcock 2014). A common method to address such concerns is to use image compositing, where users mask unwanted pixels and merge overlapping images to create a composite image (Gómez et al. 2016; Phan et al. 2020; Qiu et al. 2023). This approach allows researchers to make Landsat image composites for change detection that represent an area over a sequence of periods, each period often representing one or several years (Gómez et al. 2016; Junaid et al. 2023; Piao et al. 2021). Image composition can also provide seasonality information that can benefit machine learning model performance (Phan et al. 2020).

Landsat image composition techniques often use cloud detection algorithms such as CFmask to remove cloudy pixels before fuzing the Landsat images (Foga et al. 2017; White et al. 2014). Selecting an appropriate image composition strategy requires knowledge of the study objective, composition methods, data availability over the study region, and considerations of temporal aggregation (Phan et al. 2020). For example, studies focused on changes in vegetation of northern latitudes tend to consider vegetation phenology and composite imagery acquired within a 60-day window (e.g. White et al. 2014; Zhou et al. 2001), while studies focused on LULC or mid-latitude vegetation studies tend to use longer windows (e.g. Chen et al., 2020; Phan et al., 2020; Pouliot et al., 2021). After considering data availability, the rationale behind the image composition method based on the project objective, and image compositing period, the next step is to choose a strategy that selects the highest-quality pixel, such as the most recent cloud-free observation, maximum NDVI, median pixel values, minimum, and maximum pixel values (Phan et al. 2020; Pu et al. 2020; Qiu et al. 2023; Roy et al. 2010; Yong Du et al. 2001). Highest-quality pixel strategies can involve a series of variables including pixel proximity to clouds, image quality metrics, date of year, and sensor name to create optimal image composites (Griffiths et al. 2013; White et al. 2014). Aside from studies that compare

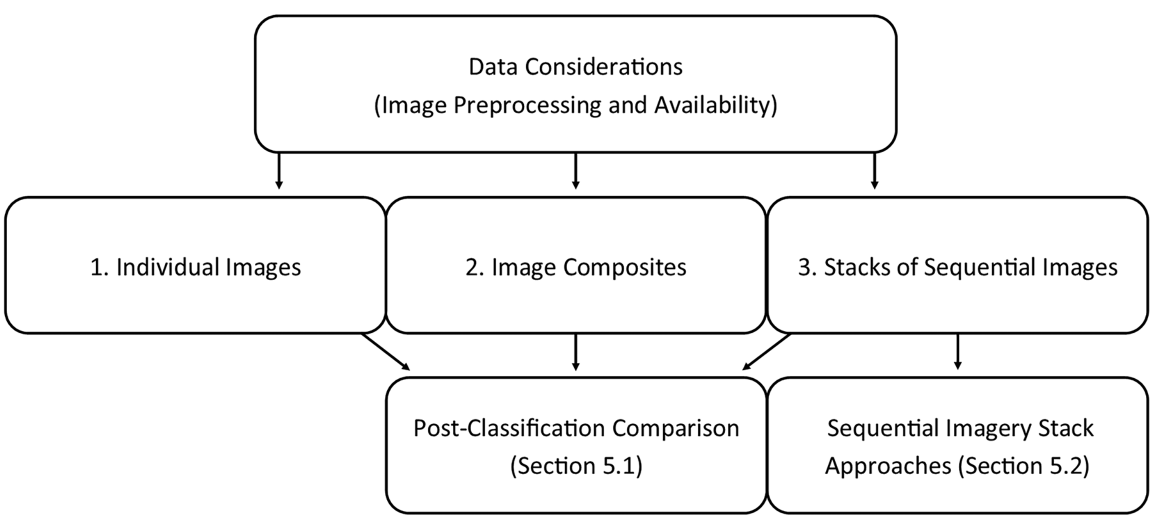

Figure 2. Overview of different image input data for post-classification comparison and sequential imagery stack approaches.

highest-quality pixel strategies to determine which one performs best for a given purpose (e.g. Phan et al. 2020), most composites are evaluated based on visual checks, since there are often no reference images to compare with (Qiu et al. 2023; Zhu 2017).

Another approach to composition is post-classification composition, where individual images are passed through models that generate predictions, and the result from the combination of the individual prediction maps is the final output (e.g. Guindon and Edmonds 2002; He et al. 2024; Souza et al. 2013; Wijedasa et al. 2012; Knudby et al. 2014). These final output predictions are composited using a function such as median or majority value (He et al. 2024; Wijedasa et al. 2012; Knudby et al. 2014). To date, this approach has only been applied in regional studies, potentially due to the additional computing power required to produce overlapping Landsat prediction maps.

In addition to using single images or image composites for change detection, sequential imagery stacks can be used as input to change detection algorithms and machine learning models. Accessible Landsat imagery has given rise to algorithms that can be used to detect changes, using large quantities of overlapping Landsat imagery, with higher temporal accuracy than post-classification approaches (Huang et al. 2010; Kennedy et al. 2010; Zhao et al. 2019; Zhu et al. 2020; Zhu and Woodcock 2014). Landsat time series algorithms such as Continuous Change Detection and Classification (CCDC) (Zhu and Woodcock 2014) use harmonic regression to determine where and when a change event occurred and leverage machine learning models to classify pixels according to their temporal spectral patterns (Deng and Zhu 2020; Zhu and Woodcock 2014). Machine learning models such as recurrent neural networks (RNN) can be designed to process sequentially captured Landsat images for change detection analysis (Lyu et al. 2016; Sun et al. 2019; Zhang et al. 2024). Another approach proposed by Phan et al. (2020) stacked the bands of selected imagery over a period into one multiband image and used an RF model to predict land cover. While the approach by Phan et al. (2020) provided a slightly higher accuracy than the image composition methods evaluated in their study, the RF model was not designed to consider the sequential nature of how the images were captured.

3.2. Sensor harmonization

The Landsat mission has collected imagery using the Multi-Spectral Scanner (MSS), Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+), Operational Land Imager (OLI), and OLI-2 sensors, each of which provides slightly different relative spectral responses. Most Landsat time series models using machine learning use the TM, ETM+, and OLI/OLI-2 sensors, avoiding the MSS sensor found on Landsat 1-5 because the 60 m MSS imagery can be challenging to integrate with the other Landsat data due to its lower spatial resolution, fewer bands, poorer atmospheric correction and cloud masking algorithms, lower radiometric resolution, and less reliable georeferencing (Braaten et al. 2015; Markham and Helder 2012; Yan and Roy 2021). The TM and ETM+ sensors used on Landsat 4, 5, and 7 are typically considered equivalent despite having subtle differences in relative response functions (Baumann et al. 2012; Flood 2014; Maciel et al. 2023; Vogeler et al. 2018). Similarly, the OLI and OLI-2 sensors found on Landsat 8 and 9 are typically considered equivalent and have more consistent spectral responses than previous Landsat sensors (Gross et al. 2022; Holden and Woodcock 2016; Trevisiol et al. 2024). However, studies that combine imagery from MSS, TM/ETM+ and OLI/OLI-2 sensors need to consider the differences between these sensors, especially their different spectral response functions.

The TM/ETM+ sensors capture images with an 8-bit radiometric resolution using a whiskbroom sensor, while the OLI/OLI-2 sensors capture images with a 12-bit resolution using a pushbroom sensor (Irons et al. 2012). The OLI/OLI-2 sensors have a substantially higher signal-to-noise ratio than the TM/ETM+ sensors, and the difference in radiometric resolution can make topographic correction less effective in TM/ETM+ imagery. The OLI/OLI-2 sensors also have different spectral responses across all bands compared to the TM/ETM+ sensors (Mishra et al. 2014; Roy et al. 2016; Vermote et al. 2016). A comparison of near-coincident overpasses between ETM+ and OLI sensors at the Libya 4 site revealed a ~2% difference in TOA reflectance values for all bands, except for the near-infrared (NIR) band which had a ~4% difference (Mishra et al. 2014). Roy et al. (2016) sampled pixels across the contiguous USA and calculated that the top of atmosphere normalized difference vegetation index (NDVI) values from the OLI sensor can be approximately 9% different from coincident NDVI values calculated from ETM+ data. In addition to differences in relative spectral response, TM and ETM+ surface reflectance products are based on the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) atmospheric correction algorithm, while surface reflectance produced from the OLI and OLI-2 sensors are based on the Landsat Surface Reflectance Code (LaSRC) (Masek et al. 2006; Vermote et al. 2016). These atmospheric correction algorithms are fundamentally different in their radiative transfer models and have different radiometric calibration uncertainties: 5-10% and 4% for LEDAPS and LaSRC respectively (Masek et al. 2006; Vermote et al. 2016). Consequently, surface reflectance products from different Landsat sensors can be substantially different even for coincident observations (Wulder et al. 2019; Yusuf et al. 2018).

Common TM/ETM+ and OLI/OLI-2 harmonization methodologies rely on linear models trained on overlapping images sampled within a short period (typically one day) between sensor overpasses (Perez & Vitale, 2023; Roy et al., 2016; Trevisiol et al., 2024). While there are substantial differences between the sensors, specifically for the NIR band that is important for vegetation studies, many Landsat time series approaches do not harmonize TM/ETM+ and OLI/OLI-2 sensors (e.g. Ambinakudige & Intsiful 2022; Amini et al. 2022; Ashok et al. 2021; Brovelli et al. 2020; Cai et al. 2018; Chen et al. 2021; Chen et al. 2020; He et al. 2024; Junaid et al. 2023). Some of these studies mention advancements in surface reflectance products and subtle differences in the spectral ranges as reasons that not harmonizing data from the different sensors will have only a minor impact on change detection analysis (Cai et al. 2018; He et al. 2024). Such perspectives can lead to uncertainty about a model's prediction of change over time when there has been a substantial amount of literature advocating for the need to harmonize data between sensors even when using surface reflectance products (Cao et al. 2022; Claverie et al. 2018; Flood 2014; Holden and Woodcock 2016; Luciano et al. 2022; Markham and Helder 2012; Olthof and Fraser 2024; Perez and Vitale 2023; Potapov et al. 2020; Roy et al. 2016; Trevisiol et al. 2024; Vogeler et al. 2018).

While less common, there are approaches to Landsat change detection analysis which use TM/ETM+ and OLI/OLI-2 data separately to train different machine learning models. For example, Venter et al. (2018) used separately trained RF models for Landsat 5, 7, and 8 imagery to predict woody plant cover dynamics over sub-Saharan Africa. While this approach avoided the need for sensor harmonization, different machine learning models can have substantially different predictive performances and biases, leading to uncertainty about conclusions reached from the analysis.

3.3. Model validation

All types of measurements in remote sensing change detection analysis are subject to uncertainty. Substantial contributions to model uncertainty include retrieval error (e.g. clouds, sensor degradation, bi-directional reflectance distribution function, geolocation), sampling limitations (e.g. spatial, temporal, and spectral), and inadequate training and validation data (Olofsson et al. 2014; Mayr et al. 2019; Tulbure et al. 2022). Most retrieval errors for Landsat studies have reliable models, tools, or techniques that can be implemented for correction. Temporal sampling limitations caused by the 16-day orbit of a Landsat sensor can be overcome by using data from multiple Landsat sensors or the implementation of harmonized datasets such as the Harmonized Landsat Sentinel-2 (HLS) 30-m dataset which has a median revisit period of 3 days (Claverie et al. 2018; Berra et al. 2024). In Landsat time series studies that use both TM/ETM+ and OLI/OLI-2 imagery, there are specific uncertainties such as differences between the sensors (e.g. radiometric resolution, type of sensor, and spectral response functions), differences in atmospheric correction algorithms (LEDAPS and LaSRC), and differences in geolocation accuracy, all of which need to be accounted for.

To minimize machine learning model uncertainties, appropriate sample design (e.g. stratified random sampling), address spatial autocorrelation between the training and validation data (e.g. through blocked data splitting), and taking preventative steps to avoid machine learning overfitting, should be considered (Dietterich 1995; Ploton et al. 2020; Olofsson et al. 2014; Knudby and Richardson 2023). Independent validation data that adequately captures the variable of interest is essential for quantifying the model's uncertainties (Mayr et al. 2019; Olofsson et al. 2014; Tulbure et al. 2022). Determining the locations of erroneous model predictions, the specific type of error (e.g. by calculating producer and user accuracies), and error magnitude, can improve the understanding of model uncertainty (Foody 2002; Olofsson et al. 2014).

Across studies that conduct Landsat change detection analysis with machine learning, training and validation data are created in different ways. Appropriate training/validation data should be of higher accuracy than the model output, and can be obtained from sources such as field plots, drone imagery, forest inventory data, and classification maps from higher resolution satellites (Olofsson et al. 2014; He et al. 2024; Lovitt et al. 2022; Hermosilla et al. 2022). The ideal training/validation data are georeferenced field measurements that span the entire period of the analysis (Olofsson et al. 2014). While that is not feasible for most studies, many studies use field observations from multiple sources as base data (Cao et al. 2022; Gumma et al. 2020; Macander et al. 2022). A substantial limitation to field measurements is that they are often temporally limited and might not be able to validate a model across the entire time or geographic space of a study. Especially for many Landsat change detection studies that span long periods of time, it can be difficult to acquire accurate data from the beginning of the period in question (Alawamy et al. 2020; Gondore and Hunduma 2023; Guo et al. 2022; Junaid et al. 2023; Li et al. 2022).

Other studies use visual interpretation of higher-resolution imagery to assign classes to Landsat pixels (e.g. Luciano et al. 2022; Potapov et al. 2022; Tulbure et al. 2016) or use down-sampled outputs from machine learning models trained on higher-resolution data (e.g. He et al. 2024; Olthof and Fraser 2024; Pickens et al. 2020). These validation data are generally less costly than field measurements to create and can cover larger spatial extents. However, validation data generated from estimates of other remote sensing products are not always field-validated, which can be a cause of uncertainty. Additionally, with the 30 m resolution of most Landsat data, there are often instances where mixed pixels contain multiple class values of higher resolution validation data (Pi-Fuei Hsieh et al. 2001; Shafique et al. 2022).

Finally, many Landsat time series studies use reference datasets from operational products such as national forest or land cover inventories (e.g. Cai et al. 2020; Somching et al. 2020; White et al. 2022; P. Zhang et al. 2024). Operational products occasionally have annual releases which can be used to validate time series models across different periods (Maxwell et al. 2018; Hemati et al. 2021; Tulbure et al. 2022). However, many operational products designed for larger regions of the world might perform poorly in unique environments of interest, and additional forms of validation data might thus be required (Tulbure et al. 2022; Wang et al. 2024). Many studies use a combination of field measurements, visual interpretation, and operational products to quantify model uncertainty (Giannetti et al. 2020; Wang et al. 2024; White et al. 2022).

For Landsat change detection analysis, it is ideal to have multi-temporal training/validation data that also capture the spatial variability of the study variable of interest (Tulbure et al. 2022). This can especially be challenging and expensive for global or large regional studies (Miller et al. 2024; Tulbure et al. 2022). To understand the uncertainty of a Landsat change detection model, the acquisition of appropriate validation data must be considered.

4. Machine learning models used in Landsat change detection analysis

Machine learning models are algorithms that use input data to produce a prediction while automatically altering their structure (e.g. internal parameters) by evaluating each new data item (El Naqa et al. 2015). Using a machine learning model for change detection analysis involves collecting data that can be used for training and validation (e.g. Landsat pixel values, and known instances of change or no change), dividing the data into training and validation datasets, calibrating the model using the training dataset, evaluating the model performance using the validation dataset, and deploying the model to make predictions and detect changes. Compared to programmed algorithms such as LandTrendr or Multivariate Alteration Detection (MAD), machine learning models iteratively re-structure themselves to improve their predictive performance, rather than being hardcoded to perform in a certain way (Nielsen et al. 1998; Kennedy et al. 2010; El Naqa et al. 2015; Souza et al. 2013). Considerations when using machine learning models include the type of input data, target accuracy, scalability, supervised or unsupervised learning, interpretability of the model, and ease of use (Gómez et al. 2016; Rolf et al. 2024). In Landsat change detection analysis, these models are used for classification tasks such as mapping changes in land covers (e.g. Zalles et al. 2021) or regression tasks such as predicting above ground biomass (e.g. Arévalo et al. 2023). This section outlines commonly used machine learning models that have been used in Landsat change detection analysis.

4.1. Likelihood approaches

Models that evaluate the likelihood between variables, such as Maximum Likelihood Estimator (MLE) or Bayesian models, are used in remote sensing-based models for change detection, classification, and regression tasks (El Naqa et al. 2015; Strahler 1980; Zhao et al. 2019). In these models, the likelihood of the dependent variable is set to be conditional on the independent variable(s), typically per-pixel spectral band values (El Naqa et al. 2015). One of the most commonly used likelihood approaches is MLE, which uses a log-likelihood function to create predictions (Strahler 1980).

4.2. Support Vector Machines

SVM models use kernel functions to transform the input data into feature space and determine the optimal boundary in this space to maximize separation between classes (Baumann et al. 2012; Cortes and Vapnik 1995; Maxwell et al. 2018). SVM models were developed for binary classification but have been adapted to handle multi-class cases (Baumann et al. 2012; Huang et al. 2002; Maxwell et al. 2018). Users can define how complex the separation boundary is through the C parameter, where higher C values tend to result in lower generalizability but potentially a better model fit (Cortes and Vapnik 1995; Maxwell et al. 2018).

4.3. Decision tree models

Decision tree (DT) models are designed to break a complex classification problem into multiple stages using Boolean conditions (Huang et al. 2002; Maxwell et al. 2018). The model logic can be visualized as a set of rules and requires little computational effort to make a prediction (Beaubien et al. 1999; Maxwell et al. 2018). However, individual DT models often generate a non-optimal decision tree, a problem that can be overcome by RF models that use a large number of DTs in an ensemble (Breiman 2001). In RF models, each DT is optimized using a bootstrap sample of input data and a random subsample of predictors, and the models then use the average prediction from all DTs as the ensemble prediction (Breiman 2001).

4.4. Boosted DT models

Boosting models are adapted ensemble DT models that attempt to minimize errors through iterative model training (Chen and Guestrin 2016; Maxwell et al. 2018). A loss function applies penalties to poor predictions, and model performance is optimized over epochs of training (Cao et al. 2022; Chen and Guestrin 2016; Maxwell et al. 2018). Commonly used Boosted DT models are XGBoost and AdaBoost due to their proven performance on a wide range of datasets (Chen and Guestrin 2016; Pedregosa et al. 2011).

4.5. Neural network approaches

Neural networks are a broad type of model that is becoming more prevalent in Landsat time series studies due to their customizability and proven performance. Neural networks consist of self-optimizing neurons that are trained by randomly searching for weight values, and iteratively optimizing the weights using backpropagation, in which the model computes how slightly altering every weight would modify model predictive performance (Lillicrap et al. 2020; Maxwell et al. 2018; Svozil et al. 1997). Dense neural networks, often called multilayer perceptrons (MLP), consist of fully connected layers of neurons (Nazari and Yan 2021). Convolutional neural networks (CNN) consist of convolutional layers which iterate over the data to activate the neurons (Nazari and Yan 2021). Two-dimensional convolutional neural networks (Conv2D) are primarily used for image analysis since they can leverage spectral, textural, and spatial patterns to inform predictions (Nazari and Yan 2021; Richardson et al. 2023). One of the most used Conv2D models for pixel segmentation is the U-Net model, which leverages the spatial domain for pixel segmentation results and has been adapted for remote sensing applications (De Bem et al. 2020; Lovitt et al. 2022; Ronneberger et al. 2015). RNN models use recurrent connections between the neurons to capture temporal patterns in the input data (Lyu et al. 2016; Miller et al. 2024; Zhong et al. 2019). Long short-term memory (LSTM) models are a commonly used type of RNN with a unique "gates" structure that enables the model to determine information used to update a memory "cell" during training (Lyu et al. 2016; Yang et al. 2024). While typically used as a standalone model, LSTM units, the primary component of LSTM models, can be used within complex neural network architecture to improve model predictive performance (Yin et al. 2023).

5. Common approaches to Landsat change detection using machine learning

There is substantial diversity in Landsat change detection studies resulting from differences in study objective, region, proposed model, and temporal characteristics. Machine learning models for Landsat change detection analysis have been used for research in a variety of different scientific topics such as geography, forestry, hydrology, ecology, agriculture, geology, and public health (Ayinde et al. 2024; Hermosilla et al. 2016; Olthof and Fraser 2024; Luciano et al. 2018; Zhao et al. 2018; Zalles et al. 2021; Hemati et al. 2021). Consequently, model comparison studies have produced different results concerning which type of machine learning model performs best for Landsat change detection analysis, with RF being the most popular but not always the highest performing model. No single model or data structure is optimal for all research objectives, rather, conducting a Landsat change detection study with machine learning often requires a nuanced approach. As mentioned above, Landsat change detection analysis with machine learning tends to fall into two methodologies, post-classification comparison and sequential image stack approaches. This section provides an overview of both approaches and discusses general themes that past studies have investigated.

5.1. Post-classification comparison

In post-classification comparison, model-generated prediction maps representing different times are compared to detect changes in the variable of interest (Figure 3) (Zhu and Woodcock 2014; Goswami et al. 2022). Many studies that use post-classification comparison train different machine learning models on the same dataset and select the model with the best performance on the validation dataset (Luciano et al. 2018; Pouliot et al. 2021; Zhong et al. 2019). This method can be applied over large study regions due to the simple design and typically small computational demands. However, post-classification comparison is often less than optimal to monitor changes over short time periods, because an ideal pair of before-after images (or image composites) that are cloud-free with minimal phenological and sun angle difference can be difficult to find (Knudby et al. 2010; Cai et al. 2020; Zhu and Woodcock 2014). The low temporal resolution of post-classification comparison using only Landsat data can make it harder to isolate a response to a change event because such events can mix with other ecosystem processes (Kennedy et al. 2014). While post-classification comparison has temporal drawbacks, many machine learning Landsat time series studies use this approach since it is more computationally efficient than sequential imagery stacks and meaningful conclusions can still be derived from observations.

Mapping LULC change is essential to understanding climate change, anthropogenic processes, urban development, ecosystem functions, biodiversity, and carbon stocks (Brown et al. 2020; Czekajlo et al. 2021; Effat and Hassan 2014; Ganjirad and Bagheri 2024; Hansen et al. 2000; Potapov et al. 2022). LULC mapping can have classes specific to a research objective (e.g. classifying urban land uses or crop types) or contain classes that are generally used in operational landcover products (e.g. Dynamic World) (Brown et al. 2022). For example, Potapov et al. (2022) created a 2000-2020 annual global LULC dataset using multiple harmonized Landsat sensors and a series of regionally calibrated machine learning models. This dataset was then used to track net changes in the extent of surface water, built-up lands, perennial snow and ice,

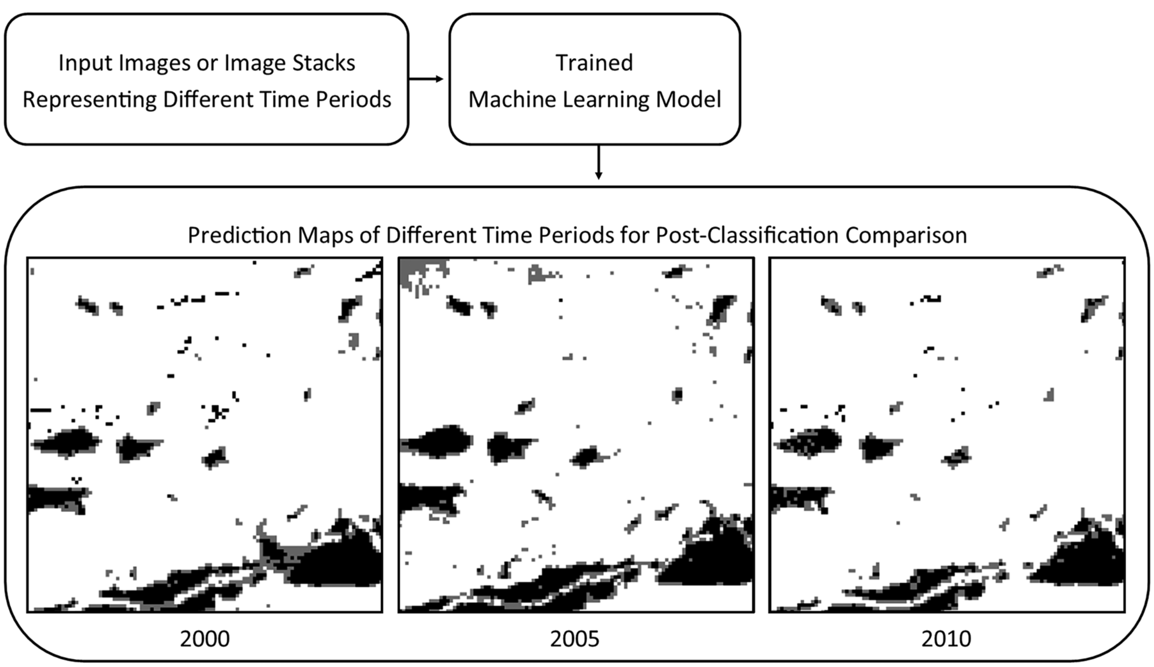

Figure 3. A diagram depicting a post-classification comparison, where input images or image stacks representing different time periods are passed through a trained machine learning model to create prediction maps of different time periods (e.g. 2000, 2005, 2010), and these maps are used for change detection.

croplands, and forests (Potapov et al. 2022). Landsat data analyzed with machine learning can also be used for regional change detection, such as Zalles et al. (2021) who used a DT model to create annual LULC maps of South America from 1985 to 2018 to track land use conversion and modifications. Singh et al. (2021) created LULC maps of India using the first and second principal components from annual TM and OLI composites. These components explained 98% of the spectral variability and were used to train an MLE classifier (Singh et al. 2021). Piao et al. (2021) used Landsat 7 data in GEE to train an RF classifier to track LULC changes in North Korea between 2001 and 2018. Other similar studies have used GEE and RF models for LULC regional mapping efforts in Iran, Mongolia, and the São Paulo State of Brazil (Amini et al. 2022; Luciano et al. 2022; Phan et al. 2020).

While single-pixel models are efficient and can perform well for GEE applications, models that consider surrounding pixels tend to perform better and achieve higher accuracies for LULC classification (Chen et al. 2020; Keshtkar et al. 2017; Pouliot et al. 2021). Keshtkar et al. (2017) compared single-pixel and object-based machine learning model performances for predicting LULC in Thuringia Germany using Landsat TM and ETM+ images. In this comparison, object-based SVM that leveraged neighboring pixel values outperformed single-pixel RF, DT, and SVM models (Keshtkar et al. 2017). In addition to object-based SVM models, Conv2D models have been used for LULC change mapping for agricultural (e.g. Li et al. 2022; Pouliot et al. 2021) and built-up areas (e.g. Bao and Lehnert 2024; Chen et al. 2020, 2023). Chen et al. (2020) used annual TM, ETM+, and OLI image composites and LiDAR scans to create a Conv2D model for a retrospective prediction of urban densities in Denmark. The Conv2D model had substantially higher overall accuracy than single-pixel RF models for predicting different classes of urban vertical and horizontal density respectively (Chen et al. 2020). Pouliot et al. (2021) used annual composited Landsat 5 and 8 imagery and a Cov2d model to detect changes in crop cover over the Prairie region of Canada. When compared to an RF model that had additional neighboring pixel statistics as inputs, the Conv2D model had a 4% higher overall accuracy (Pouliot et al. 2021). Li et al. (2022) used a CNN to delineate the extent of farming fields, and then an RF model to classify whether it was a tree crop or non-tree crop plantation to create accurate LULC change maps over plantations in Saudi Arabia. This study demonstrates that using multiple types of machine learning models in sequence for segmentation and classification can be used to create finely tuned map products based on Landsat time series data.

Regional LULC models can also focus on unique research questions that involve changes in land cover specific to local phenomena. For example, Ramadhani et al. (2020) and Somching et al. (2020) used machine learning models to track the changes in rubber and rice plantations, respectively, in Southeast Asia. Zhao et al. (2018) mapped changes in quarry land cover using an RF model and found there was a positive relationship between quarry area and regional economic development. Effat and Hassan (2014) used Landsat 5 images to map LULC changes in Cairo and extracted land surface temperature to determine shifts in urban heat islands. Yin et al. (2018) used an RF model to predict agricultural land probability in a stack of Landsat imagery and used the LandTrendr change detection algorithm to determine the timing of agricultural land abandonment in Russia and Georgia. This study demonstrates that classified maps from machine learning models can be used by change detection models to answer complex research questions. Landsat post-classification comparison studies have also focused on detecting land cover changes in shrubs and lichens using RF, SVM, and boosted DT models (He et al. 2024; Macander et al. 2022; Suess et al. 2018). Farda (2017) used a combination of MSS, TM, ETM+, and OLI data to track changes in coastal LULC in Indonesia using DT models in GEE from 1978 to 2014. Ambinakudige & Intsiful (2022) compared SVM, RF, and MLE models for predicting ice cover in the Columbia Icefield using TM and OLI images. The authors stated that all models showed a high accuracy of ~99% for distinguishing ice coverage from other land covers, and they were able to determine how much the studied glaciers were shrinking (Ambinakudige & Intsiful 2022).

While machine learning models can detect ice cover with high accuracy, not all land covers can be mapped with such high performance. For example, Landsat-based coastal wetland and blue carbon mapping efforts tend to be less accurate due to the high spatial and temporal resolution required to monitor this dynamic environment (Malerba et al. 2023). Ashok et al. (2021) and Zhu et al. (2019) both used RF models and band indices to determine changes in wetland extents in regions of India and China respectively. Wulder et al. (2018) used an RF classifier and annual Landsat image stacks to create yearly class probability classes for interior wetlands in Canada, and used the prediction outputs to explore the temporal consistencies and changes in Canadian wetlands.

Many aquatic remote sensing methodologies use satellites that are optimized for monitoring aquatic environments, and the primary focus of the Landsat mission is terrestrial. However, researchers have used machine learning-based Landsat change detection models for water occurrence (Olthof and Fraser 2024), bathymetry (Sagawa et al. 2019), and Chl-a mapping (Cao et al. 2020). Pickens et al. (2020) mapped the stable and dynamic surface global inland surface water extents from 1999 to 2018 using harmonized Landsat imagery and an RF model. Tulbure et al. (2016) used an RF model and seasonally continuous Landsat imagery to map the extent of flooding over the Murray-Darling Basin between 1986 and 2011. Other aquatic research has focused on mapping changes in water Chl-a concentration using machine learning for Landsat change detection analysis (Cao et al. 2020, 2022; Guo et al. 2022). In these studies, Chl-a estimates from machine learning models are aggregated to create maps of hotspot locations over specified periods (Cao et al. 2020, 2022; Guo et al. 2022). These studies showed that machine learning approaches to Landsat change detection analysis can effectively monitor various aspects of aquatic environments, despite its original terrestrial focus.

Monitoring the age, extent, tree type, and disturbance-driven changes in forest environments has also been a common objective for researchers using Landsat change detection analysis (Brovelli et al. 2020; Maltman et al. 2023; Li et al. 2013; White et al. 2017). Rogan et al. (2002) proposed one of the first change detection methods using machine learning, discovering that a DT classification outperformed other available models in identifying classes of vegetation cover change in Southern California between 1990 and 1996 in near-anniversary Landsat 5 images. Most studies of forest environments focus on longer time periods, such as Junaid et al. (2023) who used Landsat MSS, TM, ETM+, and OLI satellite images to train an RF model to classify vegetation coverage in Pakistan. Images with the least cloud coverage were selected from 1980 to 2020 at 5-year intervals to look at the trends of forest land cover over a study region located within a single Landsat scene (Junaid et al. 2023). Baumann et al. (2012) used stratified random samples of Landsat summer and winter images to train an SVM to classify changes in Russian forest coverage after the collapse of the Soviet Union. Chen et al. (2024) used a U-Net-based Conv2D model to track the cumulative effect of landslides on forests in Nepal over 30 years of Landsat imagery. Their approach involved mapping landslide occurrence in annual image composites and investigating the impact on vegetation loss and regrowth.

One region of the world that has been extensively studied using Landsat time series models is the Amazonian rainforest. Due to the relatively low temporal resolution of Landsat sensors (16 days) and frequent cloud cover, it is difficult to acquire cloud-free imagery to use in change detection applications in this region (Asner 2001; Skole and Tucker 1993; Souza et al. 2013; Wulder et al. 2015). Brovelli et al. (2020) used GEE and RF models to create binary forest/non-forest maps for 2000, 2005, 2010, 2015, and 2022 over the Para region of the Amazon. De Bem et al. (2020) used a selection of study sites to produce deforestation change maps between 2017 and 2019 using common machine learning algorithms (RF and MLP), and found a considerable improvement in F1 scores when instead using a modified U-Net model (De Bem et al. 2020). While the study regions for Brovelli et al. (2020) and De Bem et al. (2020) did not encompass the entire Amazonian rainforest, both studies show that Landsat change detection analysis can be conducted in frequently cloudy regions of the world.

Given the vast forest extent in Canada, many studies of Canadian forests have created large-scale forest mapping products (Hermosilla et al. 2016, 2019, 2022; Maltman et al. 2023, 2024; Mulverhill et al. 2024; Pelletier et al. 2024; White et al. 2014, 2017, 2022; Wulder et al. 2018, 2024). These studies often use a set of pixel-scoring criteria proposed by White et al. (2014) and large quantities of downloaded Landsat data to make annual image composites for model training and predictions. Maltman et al. (2024) mapped the different types of forest changes (harvests, fires, and non-stand replacing) occurring within caribou habitats between 1985 and 2019 to inform conservation efforts. Hermosilla et al. (2016) used the analysis of spectral trends to determine when and where a change occurred in a series of national Landsat composites. Spectral values from before and after the change occurrence were used to train an RF classifier to predict forest change attributions, such as fire, road construction, harvesting, and non-stand replacing change (Hermosilla et al. 2016). This example illustrates that simple machine learning architectures can be used to answer complex research questions over large study regions.

5.2. Sequential imagery stack approaches

Sequential imagery stack approaches use sequentially captured images to train models for change detection (Zhu and Woodcock 2014). The high temporal accuracy, limited by the availability of cloud-free pixel observations, makes these approaches optimal for monitoring dynamic environments with low latency (Brown et al. 2020). Many studies that use sequential imagery stacks implement change detection algorithms, such as LandTrendr, COntinuous monitoring of Land Disturbance (COLD), Vegetation Change Tracker (VCT), Breaks For Additive Seasonal and Trend (BFAST), and Bayesian Estimator of Abrupt change, Seasonality, and Trend (BEAST) methods (Cai et al. 2020; Huang et al. 2010; Pasquarella et al. 2022; Zhu et al. 2020; Verbesselt et al. 2010). There are two primary approaches for using sequential imagery stacks with machine learning models; (1) leveraging the coefficients (e.g. sin, cos, slope, and intercept) from change detection algorithms (e.g. CCDC) to train machine learning models and (2) using specialized neural network models designed for using sequential pixel value data to make predictions (Figure 4) (Zhu and Woodcock 2014). To date, both approaches have only been applied to regional studies, primarily due to the high data storage and computational power required to process large quantities of imagery.

5.2.1. Change detection algorithm coefficients

Coefficients from change detection algorithms (e.g. CCDC, BFAST, LandTrendr, or VCT) can be used to train machine learning models. For example, De Marzo et al. (2021) used LandTrendr coefficients to train a random forest classifier to generate annual estimates of forest disturbances in Argentina. The integration of machine learning in studies that use change detection algorithms can enable a more detailed understanding of environmental changes.

One of the most prominent change detection algorithms which have been integrated with machine learning models is CCDC (Zhu and Woodcock 2014). Zhu and Woodcock (2014) proposed an RF model that was trained on harmonic regression values to classify LULC with high classification and change detection accuracy (Zhu and Woodcock 2014). Many published studies have followed the general approach outlined in Zhu & Woodcock (2014) to detect changes in forests (e.g. Chen et al. 2021; Fu et al. 2024; Jiang et al. 2022; Tang et al. 2021; Zhou et al. 2023), monitor wetlands (e.g. Peng et al. 2021; Wang et al. 2024), create national LULC maps (e.g. Brown et al. 2020; Du et al. 2023), and detect changes in surface water (e.g. Berhane et al. 2020). Zhou et al. (2023) used CCDC to track the expansion of plantations in Guangxi, China in a study area with high precipitation and cloud coverage. Another study on forest environments (Chen et al. 2021) used CCDC and spectral mixture analysis to track forest degradation and deforestation in Georgia. In aquatic environments, Wang et al. (2024) used CCDC to monitor changes in water bodies and vegetated wetland extents near major cities in China using Landsat imagery from between 1985 and 2022, a task that global LULC maps are often unable to accomplish.

CCDC coefficients can be used to train different machine learning models, including XGBoost and 2dCNN models (e.g. Arévalo et al. 2023; Chen et al. 2023; Sun et al. 2023), and train regression models to predict biomass (e.g. Arévalo et al. 2023; Liao et al. 2022; Obata et al. 2021), and impervious surface percentage cover (e.g. Chen et al. 2023; Deng and Zhu 2020). Arévalo et al. (2023) used CCDC coefficients to train machine learning models to predict changes in biomass in the Amazonian rainforest. Liao et al. (2022) compared different approaches to predicting

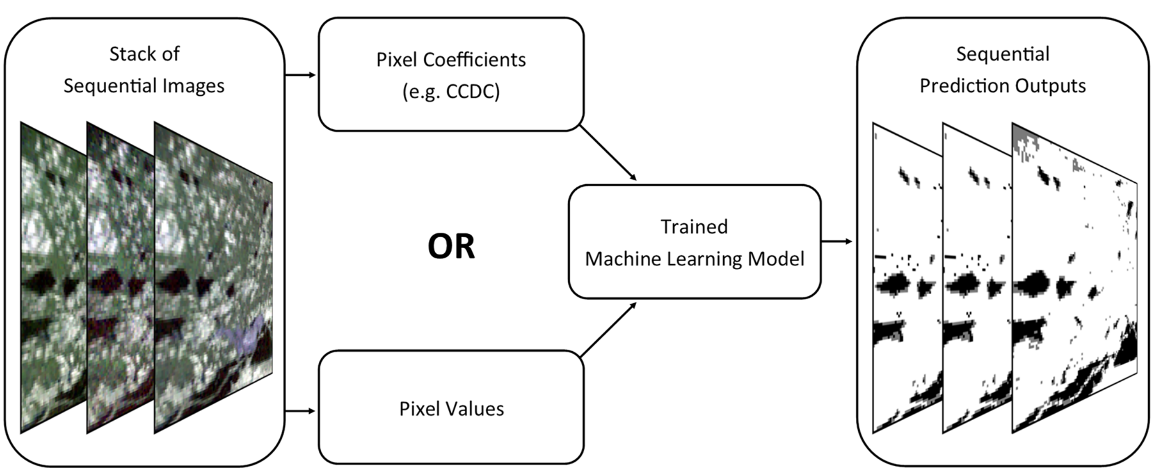

Figure 4. A diagram depicting sequential imagery stack approaches for change detection, where data is extracted from stacks of sequential images as either the pixel values over time or coefficients from change detection algorithms, then passed through a machine learning model to create sequential prediction maps for change detection.

above-ground biomass with an RF and determined that models trained on CCDC coefficients outperformed those trained on mean image composites. Chen et al. (2023) evaluated whether harmonic temporal features generated from CCDC and a U-Net model would improve the classification of settlements in Nepal over sequential Landsat image stacks. The U-Net trained on spectral features generated higher quality maps and had a higher producer's accuracy than a U-Net model trained on CCDC features, illustrating that some applications might not benefit from CCDC coefficients (Chen et al., 2023).

5.2.2. Recurrent neural network models

RNN models use patterns detected in sequences of data (e.g. pixel values in stacks of sequential images) and use recurrent connections between neurons to retain temporal information that informs the model predictions. The two types of RNN models that have been used for Landsat change detection analysis are LSTM models and Conv2D models with LSTM units. LSTM units have been implemented in models for LULC (e.g. Lyu et al. 2016; Sun et al. 2019; Zhong et al. 2019), detection of landslides (e.g. Zhou et al. 2020), and water body boundary delineation (e.g. Yin et al. 2023). Lyu et al. (2016) developed an LSTM model for detecting cropland changes in ETM+ imagery that could be used for binary and multi-class changes. Zhou et al. (2020) used ETM+ and OLI time series NDVI images to train an LSTM model to predict what future NDVI images should look like in the absence of change. The estimated NDVI images were compared to more recent NDVI images, and an SVM model was used to detect where landslides occurred (Zhou et al., 2020). This study highlights the potential of using RNNs for complex change detection contexts. LSTM units have also been implemented within Conv2D models to leverage spatial and temporal features. Yin et al. (2023) proposed a Conv2D model based on the U-Net architecture that incorporated LSTM units for predicting changes in the edge of Lake Umir. While the model was computationally intensive, this study illustrates that well-known Conv2D architectures can be used with LSTM units for Landsat change detection analysis.

6. Current state of knowledge and recommendations

This study has provided a comprehensive review of machine learning approaches to Landsat change detection analysis, including important considerations, commonly used models, and different approaches for analysis. New studies that apply machine learning for Landsat change detection analysis need to consider the period of interest, the temporal frequency of observation required to detect changes, the size of the region of interest, the necessary data for model calibration and validation, and the complexity of the machine learning model required to create accurate predictions.

The appropriate temporal frequency for a new change detection study depends on the period of interest, acceptable temporal resolution, the number of observations required to model the relevant change, and the nature of the change (sudden or gradual). Sequential imagery stack approaches, although more computationally expensive, tend to provide a more comprehensive understanding of environmental changes due to their higher temporal resolution (Brown et al. 2020; Kennedy et al. 2014; Zhu 2017). Such approaches are best suited for changes over shorter periods (< 5 years) because they can produce high temporal accuracy in their description of when a change occurred (Brown et al. 2020). Post-classification comparison approaches tend to be lower in temporal resolution and require extra care to manage cloud coverage, seasonality, and environmental considerations such as phenology (Zhu and Woodcock 2014). These approaches are best suited for change detection over longer temporal scales (e.g. >40 years), with annual or biannual estimates of when a change occurred. Many change detection models developed to analyze long term (e.g. >40 years) changes avoid using imagery collected from the MSS sensor found on Landsat 1-5. Despite the reasons for this mentioned in section 3.2, MSS data have been used effectively in Landsat time series models using machine learning for tracking changes in LULC (Farda 2017; Junaid et al. 2023; Vogeler et al. 2018). Future studies should consider incorporating MSS data since it can be harmonized with other Landsat sensors for change detection studies across the entire Landsat archive (Vogeler et al. 2018).

Presently, sequential imagery stack approaches with machine learning are confined to regional studies, largely due to the computational and image storage requirements. On the other hand, post-classification approaches have been used on global scales to determine LULC changes, since they are relatively more computationally efficient (Potapov et al. 2022).

While substantial efforts have been made to increase the accessibility of Landsat data through computing platforms such as GEE, Microsoft Planetary Computer, and ODC, a limiting factor for machine learning is the computational cost of running intensive machine learning models over large amounts of data (Crowley et al. 2023; Junaid et al. 2023; Miller et al. 2024). Most studies rely on less intensive machine learning models like RF that are more feasible to implement across larger study areas. Computationally intensive models such as complex CNNs and RNNs are often limited to smaller regions of interest. While relatively less common, machine learning models that consider multiple domains (temporal, spatial, spectral), tend to perform better than those that rely on a single domain (De Bem et al. 2020; Zhong et al. 2019). There is a multiplicative relationship in the computational cost associated with temporal density, the size of the region of interest, and the complexity of the machine learning model used in the study (Figure 5). These components of change detection analysis must be considered to determine the optimal methodology for a given study.

6.1. Harmonization and virtual constellations

A fundamental issue with many recent studies on Landsat change detection analysis is the lack of harmonization between MSS, TM/ETM+, and OLI/OLI-2 sensors, despite their different relative spectral responses. Studies such as that by Olthof and Fraser (2024) created their own harmonization coefficients between ETM+ and OLI sensors over their study region before predicting changes in fractional water coverage. This approach is sensible and created harmonization coefficients derived from pixels located within the study region, ensuring that the ETM+ and OLI data were the most similar for change detection analysis.

Sensor harmonization does not need to be limited to imagery collected within the Landsat program but can also be used to integrate data from other multispectral satellite sensors such as Sentinel-2 MSI (Claverie et al. 2018). Virtual constellation (VC) approaches integrate data from different sensors with similar spatial, spectral, radiometric, and temporal characteristics. VCs can be used to enhance the temporal density of observations, and have been used in studies monitoring the spread of wildfires (e.g. Cardille et al. 2022; Crowley et al. 2019; Zhang et al. 2024), wetlands (e.g. Mu et al. 2020; Tahsin et al. 2021), water quality (e.g. Peterson, Sagan, and Sloan 2020), and farmland changes (e.g. Lobert et al. 2021). Most change detection studies that use VCs combine Landsat with Sentinel-2 data (e.g. Peterson, Sagan, and Sloan 2020) or MODIS data (e.g. Lu et al. 2016), but many other satellites such as ASTER, AVHRR, and PlanetScope can be used in VCs (Tahsin et al. 2021; Berra et al. 2024). However, VC data are not available for the entire Landsat archive and are therefore of limited use in long term (e.g. >40 year) change detection studies. Nevertheless, VCs should be considered when available across the entire time frame of a study, especially when high temporal resolution is required.

6.2. Change attribution

An aspect of Landsat change detection analysis which needs further development is change attribution (Zhu

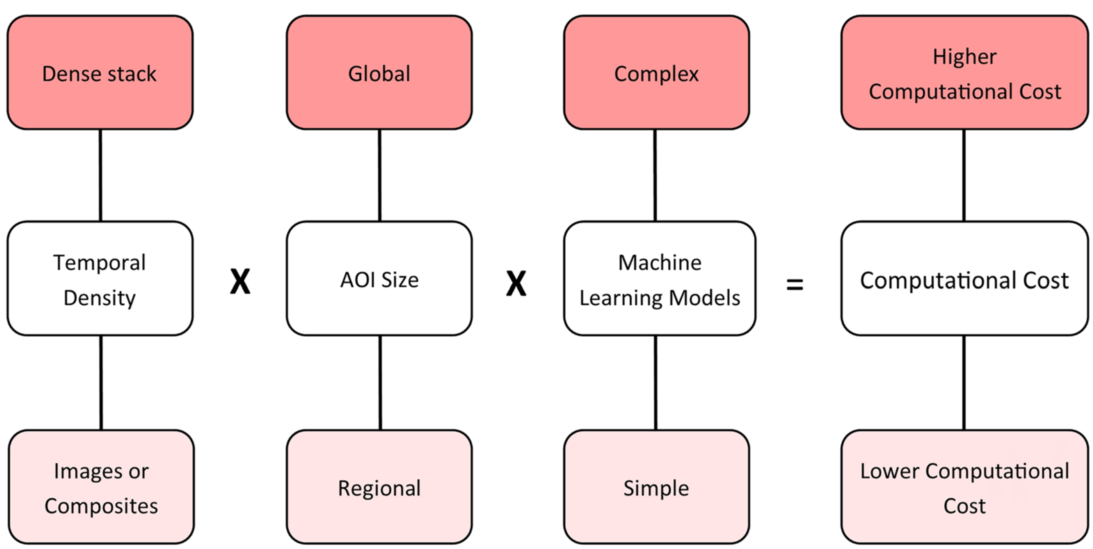

Figure 5. The multiplicative relationship of how temporal density, area of interest (AOI) size, and machine learning model selection, typically affect the computational cost for Landsat change detection analysis. Darker colors refer to having a higher computational cost.

et al. 2022). Only a few studies (e.g. Hermosilla et al. 2016) that classified forest change based on annual image composites have been able to identify the causes of observed changes using Landsat change detection analysis. Attributing change requires substantial knowledge of environmental phenomena and conditions, and thus is domain-specific and could be limited to specific change processes in particular environments (Kennedy et al. 2014). However, change attribution is essential to move from the detection of changes to the management of such changes and should be a focus of future research efforts (Kennedy et al. 2014; Zhu et al. 2022). Further understanding of how the Earth is changing from an ecological perspective could aid in the development of change attribution models (Kennedy et al. 2014; Zhu et al. 2022).

6.3. Explainable machine learning

There has been substantial development in furthering the understanding of how machine learning models make their decisions (Merchant and Edwards 2024; Richardson et al. 2024; Aksoy et al. 2024). Explainable machine learning through investigating variable importance, Shapley additive explanations (SHAP), and partial dependency plots, can provide insight into which domains (spectral, spatial, and temporal) or variables contribute the greatest to the model performance (Merchant and Edwards 2024; Richardson et al. 2024; Aksoy et al. 2024). An example of this is Aksoy et al. (2024) who used SHAP values to investigate which Landsat bands and indices carry information on soil salinity in Iran, concluding that higher blue and green pixel values often corresponded to greater levels of salinity. Explainable machine learning should be further integrated into Landsat change detection studies since they can provide researchers with a greater understanding of how input variables are contributing to their model predictions.

6.4. Generative artificial intelligence

Generative artificial intelligence (genAI) is a broad term that refers to artificial intelligence (AI) models that can produce new, previously unseen outputs, dependent on statistical connections and patterns derived from the data they were trained on (Spennemann 2024; García-Peñalvo and Vázquez-Ingelmo 2023). In the AI research community, "generative" refers to advanced models that create high-quality, human-like content, unlike other models (e.g. RF) which focus on predicting label probabilities from given observations (García-Peñalvo and Vázquez-Ingelmo 2023). Currently, in the field of remote sensing, generative adversarial networks (GANs) and visual language models (VLMs) have been used for creating new earth observation products.

The objective of a GAN is to learn the probability distribution underlying a set of training samples and generate new examples from these distributions that mimic the training data (Goodfellow et al. 2020; Oluwadare et al. 2024). GANs have been used to create artificial RGB images from base maps (Xu and Zhao 2018), fill in gaps caused by the Landsat 7 scan line error (Adıyaman et al. 2024), mask clouds or snow pixels and generate new values (Xu et al. 2022; Ghildiyal et al. 2024; Oluwadare et al. 2024), and generate false Landsat imagery from MODIS (Bouabid et al. 2020). The potential for using data generated from GANs has yet to be fully realized in Landsat change detection studies since the recent rise in popularity of genAI.

VLMs have also been developed that synthesize text-based prompts and return image responses (Osco et al. 2023; Wu et al. 2023; Wagner et al. 2024). Wagner et al. (2024) developed a tool where users type in a simple remote sensing request and the tool loads relevant imagery from ODC and creates an output product which can be used for analysis. Visual ChatGPT is a visual language model developed by Wu et al. (2023) which can be used to perform different remote sensing tasks (e.g. image classification, image segmentation, straight line detection, and edge detection) provided that the user submits the imagery to the model (Osco et al. 2023). While the initial results for Visual ChatGPT have poor results, this area of research is relatively new and there is substantial potential for future development with change detection models (Osco et al. 2023).

6.5. Ethical analysis considerations

There is often a division in remote sensing studies between those who are using satellite data for analysis and the communities that are being observed in the satellite data (Bennett et al. 2022). To "ground the satellite gaze", it is essential to involve local communities, environmental scientists, and geographers in remote sensing practices (Bennett et al. 2022). The emerging field of critical remote sensing encourages remote sensing scientists to engage with local communities, support remote sensing capacity building in marginalized groups, and examine environmental and socioeconomic issues relevant to critical scholarship (Bennett et al. 2022, 2024; Crowley et al. 2023). One way that marginalized communities have been left behind in remote sensing science is that many LULC studies overlook the importance of connecting with local environments and communities. In a participatory remote sensing effort in Rajasthan India, Robbins and Maddock (2000) showed multispectral SPOT images to local professionals and asked them to identify the land covers. Their local-knowledge-driven land cover classifications diverged substantially from the state-centric framework, which labeled many cultivation lands as "barren" and viewed the forest as a homogenous source of productivity (Robbins and Maddock 2000; Bennett et al. 2022). Disconnections between local observations and generalized state-centric frameworks can negatively affect the perspectives and policies of the communities present in the study area (Bennett et al. 2022). In change detection studies, projects lacking community engagement could result in not focusing on changes meaningful to local communities or misrepresenting terrestrial changes.

The challenges presented in critical remote sensing are compounded by growing concerns about data-intensive technologies like machine learning and AI. Machine learning models in remote sensing could risk strengthening oppressive power structures due to their ever-growing ease of implementation, performance, and accessibility to training data (Spennemann 2024; Bennett et al. 2024). These concerns have reinforced discussions on data sovereignty, meaningful control, ownership, and claims to the data or models (Carroll et al. 2020; Hummel et al. 2021). Data governance principles such as Findable, Accessible, Interoperability, and Reusability (FAIR) for scientific management and Collective benefit, Authority to control, Responsibility, and Ethics (CARE) for Indigenous data governance should be considered in Landsat change detection analysis, to ensure the research is developed effectively and ethically (Wilkinson et al. 2016; Carroll et al. 2020).

7. Conclusion

Approaches to change detection with Landsat time series data have changed over time alongside increases in computational performance, data accessibility, and the ambition of researchers. Cloud platforms such as GEE, Microsoft Planetary Computer, and ODC have made it easier than ever to sort through the Landsat archive to find relevant imagery, and to analyze vast amounts of data. Landsat time series studies tend to either use post-classification or sequential imagery stack approaches; both have advantages and disadvantages that need to be considered. Understanding previous approaches to Landsat change detection analysis is essential to better assessing how new methodologies fit into this field of research. Future work on Landsat change detection analysis should consider the balance between the temporal frequency of image acquisition, study area size, and machine learning model complexity. Additionally, researchers should focus on the emerging fields of explainable machine learning and genAI, while ensuring their analysis follows best practices in ethical analysis and data management. These considerations are essential to answering research questions with products that can track surface changes of our dynamic planet.

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ORCID

Galen Richardson http://orcid.org/0000-0002-4348-4119
Anders Knudby http://orcid.org/0000-0001-8970-8504
Morgan A. Crowley http://orcid.org/0000-0001-5946-529X
Michael Sawada http://orcid.org/0000-0001-5180-5325
Wenjun Chen http://orcid.org/0000-0002-5858-8578

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