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Review

Machine learning in modelling land-use and land cover-change (LULCC): Current status, challenges and prospects

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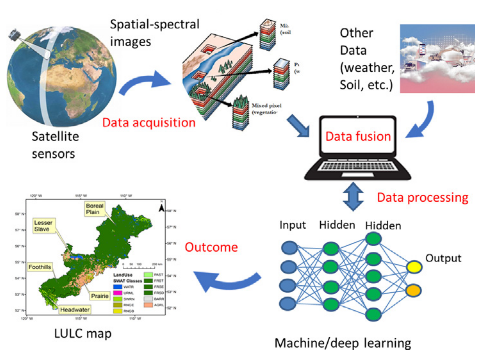
HIGHLIGHTS

- A cross-disciplinary review of machine learning in modelling land use and land cover change (LULCC)
- Identifying gaps and challenges of machine learning in modelling LULCC
- Examining integrated model of machine learning and cellular automata
- Exploring potentials of machine learning in modelling LULCC

GRAPHICAL ABSTRACT



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ABSTRACT

Land-use and land-cover change (LULCC) are of importance in natural resource management, environmental modelling and assessment, and agricultural production management. However, LULCC detection and modelling is a complex, data-driven process in the remote sensing field due to the processing of massive historical and current data, real-time interaction of scenario data, and spatial environmental data. In this paper, we review principles and methods of LULCC modelling, using machine learning and beyond, such as traditional cellular automata (CA). Then, we examine the characteristics, capabilities, limitations, and perspectives of machine learning. Machine learning has not yet been dramatic in modelling LULCC, such as urbanization prediction and crop yield prediction because competition and transition between land cover types are dynamic at a local scale under varying natural drivers and human activities. Upcoming challenges of machine learning in modelling LULCC remain in the detection and prediction of LULC evolutionary processes if considering their applicability and feasibility, such as the spatio-temporal transition mechanisms to describe occurrence, transition, spreading, and spatial patterns of changes, availability of training data of all the change drivers, particularly sequence data, and identification and inclusion of local ecological, hydrological, and social-economic drivers in addressing the spectral feature change. This review points out the need for multidisciplinary research beyond image processing and pattern recognition of machine learning in accelerating and advancing studies of LULCC modelling. Despite this, we believe that machine learning has strong potentials to incorporate new exploratory variables in modelling LULCC through expanding remote sensing big data and advancing transient algorithms.

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Contents

1. Introduction

Land-use and land-cover (LULC) is an indicator to represent natural and economic processes. Detection and modelling of land-use and land-cover change (LULCC) facilitate interpreting the causes and consequences of land-use dynamics and support policy-makers decisions. Therefore, detection and modelling of LULCC are of importance in natural resource management, environmental assessment, territorial and urban planning, and agricultural production management (Metzger et al., 2006; Sohl and Claggett, 2013; Li et al., 2018; Song et al., 2018; Bhanja et al., 2018; Bhanja and Wang, 2021; Longato et al., 2019; Sasmito et al., 2019; Zhang et al., 2019a; Jiang et al., 2020). Estimating regional agricultural production can provide information for food supply and security (Gebbers and Adamchuk, 2010; Li et al., 2018; Khanal et al., 2020; Sishodia et al., 2020; Weiss et al., 2020). Planning land resource for urbanization requires timely detection and prediction of accurate LULCC to evaluate the impact of land cover transformation on natural environments. Therefore, it is a prerequisite of agricultural production management and urbanization planning to assess real LULC information over time (Neinavaz et al., 2021; Zhang et al., 2021).

In the past decades, satellite or airborne spatial images and data have increased exponentially with the recent years with the advent of remote sensing technology and the launch of a number of satellites (Yu et al., 2014; Ju and Masek, 2016). Fig. 1 shows a schematic of remote sensing sensor and spectral waveband images (Shaw and Burke, 2003). These images provide valuable spatially explicit patterns of LULC and multiple spectral wavebands in a region. Each pixel in the image includes a sampled spectral measurement of reflectance and associated spectral variation for assessments of environmental impact and ecosystem services. However, LULCC is particularly temporally and spatially dynamic. Satellite images provide a single snapshot of land cover at one point in time without any spatiotemporal pattern linkage of resource development and environmental change (Mertens et al., 2000; Giri et al., 2012). Despite the time series images, the frequency of imaging may be not sufficient for LULCC modelling in many regions (Parker et al., 2002; Tayebi et al., 2008; Roy et al., 2010). This means they are lost historical information, but LULCC requires to account for the old information. Furthermore, the mixed-pixel composition in the sub-pixel is not resolved in a remotely sensed image.

Considerable efforts have been made to modelling of LULCC. Because LULCC modelling is data intensive, requiring both current and historical land cover maps combined with data depicting the drivers of land change, artificial intelligence and machine learning (ML) have advantages to provide analytical methods to spatial image analysis that fosters this task. LULCC modelling are complicated processes to extract remotely sensed imagery into meaningful information in an efficient way without compromising accuracy. There are two approaches in modelling LULCC using remote sensing images. First, LULCC models have been developed to analyze the classification and change of LULC, such as, Cellular Automata (CA) (Clarke and Gaydos, 1998; Clarke, 2007), CLUE (Verburg et al., 2002), and Stochastic Element Augmentation (Qiang and Lam, 2015). Second, with advent of machine-learning techniques, Artificial Neural Networks (ANNs) have proven to be a breakthrough and an extremely powerful tool to tackle unprecedented, large-scale, influential challenges in remote-sensing data analysis (Zhu et al., 2017; Talukdar et al., 2020). Therefore, a variety of LULC models using machine learning (ML) have been developed to analyze the LULCC, such as, Deep Neural Networks (DNNs) (Zhu et al., 2017; Zhang et al., 2019a; Maimaitijiang et al., 2020), Convolutional Neural Networks (CNNs) (Zhang et al., 2018), and self-organizing maps (SOMs) (Du and Swamy, 2014; Panda, 2017), and models of integrated ANNs with CA. However, while ML is useful for analysis of data classifications, the drivers of LULCC modelling require to take into account environmental and socio-economic factors, such as agriculture, hydrology, geography and ecology. This requires linking spatial pattern to land use process to derive either potential-transition and occurrence maps. The likelihood or probability of a land transition or occurrence maps requires to account for socio-economic, landscape ecological and remote sensing techniques for the spatial suitability and spatially-allocate the demand of land-cover types (Verburg et al., 2002). In the past years, many reviews of ML or deep learning (DL) in remote sensing field have been performed (Gomez et al., 2016; Zhu et al., 2017; Ma et al., 2019; Heydari and Mountrakis, 2019; Chaves et al., 2020). However, most of these existing reviews focus on image processing and partition recognition techniques of DL with applications to analysis of remote sensing images. It is unclear how we best use ML or DL for the ever-expanding range of increasingly accessible satellite data for LULCC research, particularly under environmental and social-economic drivers. The current studies of complex LULCC modelling are still in infancy to explore dynamic processes of mixed pixelation in classifying per-pixel scenarios and its drivers which are segregated within different disciplines. It is critical how LULCC modelling using ML advances to a "next generation" model with strengthened

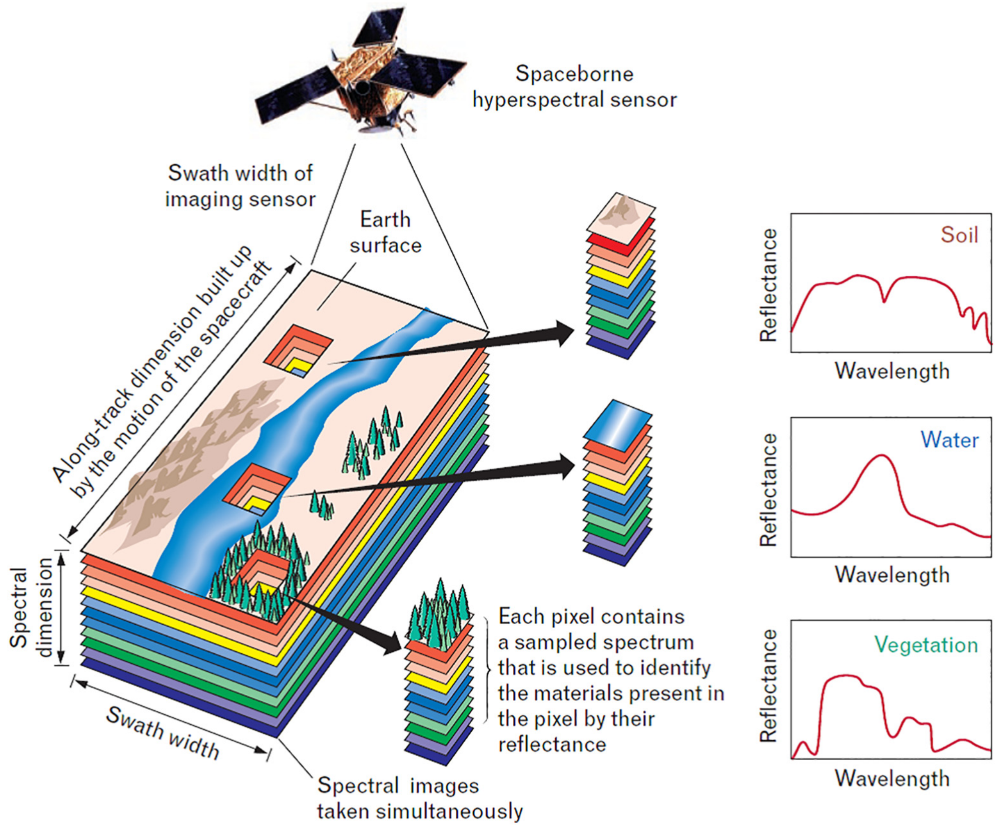

Fig. 1. Schematics of the airborne or spaceborne imaging sensor and multiple spectral wavebands in a region. Each pixel in the image includes a sampled spectral measurement of reflectance and associated spectral variation (Shaw and Burke, 2003).

functionality and capabilities that allow their applications to LULCC in various scenarios.

The objectives of this paper are to synthesize our understanding in modelling LULCC using ML and beyond. While considering the applicability and feasibility of LULCC modelling in a wide range of agricultural, environmental, and ecological problems, this review is going beyond image processing and partition recognition of ML in modelling LULCC to include the traditional LULCC modelling, such as CA. This review is organized as follows. In Section 2, we examine the fundamental processes of LULCC from satellite remote sensing images and identify the main indicators. In Section 3, we review modelling techniques of several MLs, including ANNs and CA, DL, SOMs, in modelling LULCC and examine their capabilities. In Section 4, we identify the knowledge gaps and upcoming challenges in modelling LULCC. In Section 5, we explore the potential ways to bridge the knowledge gaps and foster a path forward using ML to facilitate data integration and point out research priorities for the integration of such data models into both other models and their incorporation into larger processes or cycles of upgrading data models and mixed-pixel classification problems. Finally, we discuss perspectives and conclude this paper.

2. Principles of LULCC modelling

2.1. Land-use and land-cover change (LULCC)

LULC classification is to categorize land covers into different types according to their use and cover, such as crop, forest, road, residential or industrial areas. LULCC is a spatiotemporal pattern change of their uses over time, such as urbanization and crop growth (Simoes et al., 2021). Therefore, LULCC is a dynamic process, and therefore, the land transition requires to follow up some rules or relationships. LULCC modelling is quantifying the combined effects of anthropogenic and environmental drivers on landscape patterns using information derivation of shapes, fringe, textures, and characteristics. Principles of LULCC modelling are to represent remotely-sensed time series data and images with ground-based social science data into spatiotemporal pattern change, land transitions, and the processes underlying them to improve our comprehension of the causal relationships regarding LULCC (Chen and Cihlar, 1996; Rindfuss and Stern, 1998; Parazoo et al., 2014; Cleveland et al., 2015; Maus et al., 2016; Yang et al., 2018a, 2018b). In most raster-based LULCC models, the demand-allocation relationship could represent a potential transition. The demand is a quantity of change at a time step. Thus, this relationship can select the cells to be transformed to the target land-cover class and to allocate model land transitions from one land-cover class to another at a given spatial pixel (Aquilué et al., 2017). LULCC modelling is comprised of several foundational elements: 1) the drivers of land change, 2) pattern recognition of land cover on a regional scale, 3) the local history of land use, and 4) the geographical context and characteristics of the region (Heisterman et al., 2006; Sohl et al., 2010). Thus, it is key in LULCC modelling using remote-sensing to “socialize the pixel”, which is the melding of social science observations with data taken from remote-sensing images (Geohegan et al., 1998; Jacobs-Crisioni et al., 2014).

2.2. Transitional methods in modelling LULCC

Traditionally, Cellular Automata (CA) is used for LULCC modelling, such as SLEUTH (Clarke and Gaydos, 1998; Clarke, 2007) and CLUE (Verburg et al., 2002). CA is a spatially and temporally discrete model on a grid at discrete time steps and evolves according to a set of rules of neighboring cells or dynamical transition rules (Clarke and Gaydos, 1998). The rules are then applied iteratively up to desired time. The value of individual cells in next time only depends on the total value of a group of neighboring cells and generates emergent spatial patterns from simple rules, in discrete time steps. The likelihood or probabilities of a grid cell to change type is calculated according to a set of transition rules or system's expert knowledge with the type of neighboring cells (Verburg et al., 2002). Therefore, CA has been used for simulating a variety of real-world systems, including urban development (Clarke and Gaydos, 1998; Verburg et al., 2002) and biological systems (Delavar and Wang, 2020a, 2020b, 2021).

The CA-based SLEUTH model incorporates four rules, namely land cover, slope, transportation network, and protected areas to calculate the transition of cells (Clarke and Gaydos, 1998; Clarke, 2007). Recently SLEUTH has been extended to incorporate the simulation skills of CA with the ML approach called support vector machines and a probability map of other biophysical and socio-economic parameters (Rienow and Goetzke, 2015). Another widely used CA based model is CLUE (Verburg et al., 2002). A transition rule can be designed using a set of factors driving urban expansion, such as distance to the coast, road, local economy, natural protection region, water, or the recreation park. Then, competition to change at a grid cell is calculated iteratively according to the defined sequential hierarchy transition rule. These CA-based models have been widely used for simulating urban growth patterns, such as urban sprawl (Clarke and Gaydos, 1998). However, the hierarchy transition rules are still a priori. This limits its generality to other regions which may follow other rules or factors (Clarke, 2007). Furthermore, CA has been reported to predict rural futures while a set of LULCC transition rules was defined to consider all the potential drivers of LULCC for each location (Verburg et al., 2010). However, LULCC can be driven by natural processes, such as flooding, wildfire, ecology, agriculture, and plant phenology in time and space (Gomez et al., 2016). These rules in rural regions require to further account for natural factors.

2.3. Search and selection methods

LULCC modelling is a fast-moving area and is one of the hottest topics in the geoscience and RS community. About 233,000 results are searched using key word: “remote sensing AND land use change AND machine learning OR deep learning” from Google Scholar about 16,400 results even since 2021. Unlike reviews with meta-analysis, a multi-disciplinary review cannot focus on only a narrow topic in a subfield to perform a meta-analysis. Therefore, this review is structured to state the main topics and problems related to the research in a cross-disciplinary overview. Main delivered results are knowledge gaps, challenges, and research priorities. We focus on some general and fundamental challenges that never solved due to some inherent weakness of the existing methods. Naturally, we explore other disciplines that are potential to address these LULCC problems beyond the image processing and remote sensing. Therefore, it is better to keep some old references for readers to refer to its origin of a problem, such as SOM (Kohonen, 1995), ANN-CA (Li and Yeh, 2002) and CA (Clarke and Gaydos, 1998; Verburg et al., 2002), while recent references allow the readers for recent progresses of the models. We selected the papers to keep a balance among different disciplines, such as DL, SOM, ANN-CA, according to their scope and objectives, methods and characteristics. We especially selected papers of clearer method descriptions to illustrate some fundamental problems and challenges, favoring innovative and reproducible methods that permit the reasoning about LULCC dynamics, considering the capability to distinguish different classes because of their dynamics and heterogeneity. Although we keep a basic balance between old and recent references as well as among different disciplines, the cited references are not exhausted and may somehow be unfair. The construction of such a multidisciplinary review is a great effort that should be given more emphasis in the description of methods and in the discussion of challenges why they have weaknesses and need to be overcome using other approaches. We believe that this structure makes the readers easier to catch the knowledge gaps, problems, and challenges and understand what they should make efforts, potential ways, and trends.

3. Machine learning in modelling LULCC

The ML is central in modelling LULCC since LULCC is often taken as to be one specific image processing and pattern recognition. Because there are many different architectures, such as ANN, DNN, SOM, recurrent neural network (RNN), multi-layer perceptron (MLP), and deep belief network (DBN) (Li et al., 2019), we select several widely used MLs in modelling LULCC, including the DNN, RNN, SOM, and ANN-CA.

3.1. Deep learning

ML uses algorithms to parse data, learn from that data, and make informed decisions based on what it has learned, such as support vector machine (SVM), random forest (RF) method, and K-nearest neighborhood (KNN) (Garg et al., 2021). DL is a type of ML as a subset of artificial intelligence. DL structures algorithms in layers to create an “ANN” which can learn and make intelligent decisions on its own (Gunen, 2021). Therefore, DL is an extension of ANNs which use multiple layers in the network and may be one of the most active topics right now in the world. The larger the number of layers, the deeper the network is, and therefore, the term “deep learning”. The DL has been used for LULCC of remotely sensed imageries (Maxwell et al., 2018; Adam et al., 2014). A DL for remote sensing image classification consists of three main steps: 1) input data processing, 2) hierarchical DL model training, and 3) classification.

CNNs are one of the deep learning networks and are originally designed for image processing (Valueva et al., 2020; Vali et al., 2020). CNNs are one of the most popular neural network architectures because they can extract low-level features with a high frequency spectrum, such as edges, angles, and outlines of objects, whatever the shape, size, or color of the objects. Therefore, the DNNs are well suited for LULC classification. Fig. 2 shows a deep CNN architecture that consists of interconnected multiple layers (Liu et al., 2018). The input layer collects input patterns. Convolutional layers filter the input through weightings when extracting features from the input image until the neural network's margin of residual error is minimal. Thus, the convolutional layers extrapolate salient features in the input data regarding the output classifiers. The pooling layers are to lower the dimensionality of feature maps from the convolution layers. Within a CNN, a backpropagation is commonly used for the training to adjust internal parameters to transfer gradient. The output layer has target classifications or output class labels of different LULC patterns. Successive convolution and pooling adaptations of the probability-weighted associations train the neural network to increase similarity to fine-structured objects target output with the class features and contexts. Finally, input remote sensing images or data are categorized to the label of the pixels that contain characteristics, such as buildings, trees, and grasslands. For example, the patterns may comprise a list of quantities for technical indicators about agricultural productions or major building blocks (Ghamisi et al., 2017a).

An advantage of CNNs is the capacity to automatically learn a hierarchy of numerous filters through training data under the constraints of classification of spatial-spectral images (Li et al., 2019; Ma et al., 2019; Zhang et al., 2016a). Wan et al. (2020) developed a graph convolutional network to classify the hyperspectral image. They used an arbitrarily constructed non-Euclidean of convolution layers to account for the irregular image zones. Maimaitijiang et al. (2015) studied spatial and temporal dynamics of urban growth in the St. Louis metropolitan region using remote sensing derived LULC changes and socio-economic factors. They also analyzed RGB, multispectral, and thermal images collected by Unmanned Aerial Vehicle (UAV) and sensor technology to evaluate soybean production in Columbia, Missouri, USA (Maimaitijiang et al., 2020). They used a DNN to analyze multimodal information, such as canopy spectral, structure, thermal, and texture features. Their results showed that DNN improves the yield prediction accuracy and more adaptive performance in predicting grain yields. Zhang et al. (2019a) used a Joint Deep Learning (JDL) model of a multilayer perceptron within CNNs to simulate LULC classifications and change at two sites in Southampton and Manchester, the UK. They used a Markov process for iterative updating. The CNN was used for land use classifications under conditional probabilities. Their results greatly increased the accuracies of classification with increasing iteration. He et al. (2018a) developed an integrated model of CNN with CA to simulate urban

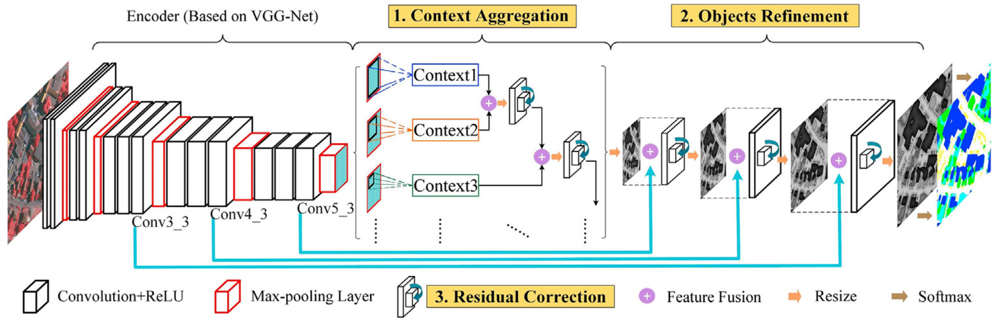

Fig. 2. A schematic of spectral classifier for LULC based on a deep CNN (Liu et al., 2018).

development in the Pearl River Delta of China. They explored the drivers and the transition rules revealed by the urban land-use patterns in 2000, 2005, and 2010 and predict the urban expansion status in 2020 and 2030. Their results showed that the CNN-CA model could be used for urban planning and policy-making.

Wang and Maduako (2018) used a coupled Multi-Layer Perceptron and Markov Chain analysis of remote-sensing data to simulate sustainable-urban planning in Lagos Metropolitan Region, the Nigerian Federation. They found that LULC distribution in this region expanded about 50% during the period of 2000–2015. Nasiri et al. (2019) performed a similar MLP and MC analysis to simulate LULC change in Kalibar Township, Eastern Azerbaijan Province, Iran. They analyzed images of three years (1990, 2002, and 2014) from satellite images of Landsat 7 and 8. The demand pixels to change LULC class was simulated using the Markov Chain algorithm between the years 1990 and 2002. Independent driving factors were used as explanatory variables. The results generated in the previous steps were applied to update transitional potential layers. Then historical LULC changes were calculated. Those changed pixels during 2002–2014 were inputted into the model as training data in their MLP model.

An RNN is one direction of the DL family, which is mainly designed to process time series data. The past, present, and future data can be correlated by using statistical regression. In an RNN, a recurrent hidden state is used for recognizing patterns in a sequence of data and characteristics. Activation at each step relies on that of the previous steps. Thus, RNNs are well-suited for change detections of LULC in sequences of data since each pixel vector in hyperspectral data can be taken as a set of orderly and continual spectra sequences in the spectral space. Lyu et al. (2016) used RNN to detect land cover change. Mu et al. (2019) developed an RNN for pixelwise hyperspectral classification in sequential data. They improved Long Short-Term Memory (LSTM) model to acquire and record the change information of long-term sequence remote sensing data and used three thresholds to optimize the input, output, and update data of the LSTM model. The transition rule can be used for change detection, which transfers from one image at the previous steps to the next target multiple time sequent image. They found that the RNN can learn effectively transition rules to detect multi-class change. Chen et al. (2020) proposed a deep Siamese convolutional multiple-layers RNN for change detection of sequent high-resolution images. The LSTM units were applied to extract the spatial–spectral features and detect the change through change probability. Their results showed the proposed RNN was superior to several state-of-the-art approaches.

3.2. Self-organizing maps (SOMs)

A self-organizing map (SOM) is a branch of ANNs which is trained using machine learning to reduce high-dimensional data, such as a map with features, to a low-dimensional one (Kohonen, 1995). Unlike other ANNs, the SOM uses competitive learning for unsupervised clustering and visualization through error-correction learning (such as backpropagation with gradient descent) (Kalteh et al., 2008). This makes SOMs useful for visualization by creating low-dimensional views of high-dimensional data, akin to multidimensional scaling. As such, SOMs are mostly utilized for unsupervised clustering and visualization for the purpose of sorting or classification tasks involving the visualization of low dimensional depictions of high dimensional data (Panda, 2017; Riese et al., 2020). In competitive learning, the individual nature of the data is seldom lost; rather, it is maintained utilizing the neurons with the winning output from the clusters. This approach to ML means that SOMs are at least comparable, if not actually better than other unsupervised classification methods, that are utilized for image categorization, such as data dimensionality reduction and clustering methods (Panda, 2017). The SOMs are an effective means for LULC classification of satellite observations in terms of dimensionality reduction.

Wang et al. (2018) studied the spatiotemporal patterns of surface urban heat islands to represent urban thermal environments caused by global climatic changes and urbanization. They used SOMs to simulate the surface urban heat islands across 32 cities in China. Li et al. (2021) developed several landscape indexes: aggregation index, largest patch index, patch density, and shape index using annual forest distribution maps (1987–2018). Then they used SOMs to determine three spatially heterogeneous pattern types: severely fragmentised pattern, incompletely fragmentised pattern, and relatively intact pattern. Post-classification change detection was conducted to analyze the change process of the forest spatial patterns. Hu and Weng (2009) evaluated impervious surfaces from medium spatial resolution imagery using the SOM with multi-layer perceptron in Marion County, Indiana, U.S.A. Their results showed that the SOM model has better results than MLP neural network for image classification at both per-pixel and sub-pixel levels. Riese et al. (2020) proposed a Supervised Self-organizing Maps (SuSi) framework for regression and classification of Hyperspectral Data. They found that SuSi has a better performance than random forest in the regression of soil moisture. Neumann et al. (2017) used a SOM analysis as an amalgamation algorithm to characterize dominant patterns of data by integrating multidimensional socio-environmental variables in the Lake Simcoe watershed, Canada. Their results showed that there is a closed relationship between demographics, tributary nutrient export, and environmental degradation in the watershed. Yuan et al. (2009) used a SOM and simulated annealing (SA) algorithm to enhance the degree of precision for LULC classification. The SA within SOM was utilized to determine or approximate the nearest global or global optimal found in a hybrid optimization problem. Their results showed that the training algorithm of SOM-SA has the better classification capabilities of the automated SOM_SA over the single SOM system. Goncalves et al. (2012) indicated that SOMs are particularly important in cases where there is a substantial lack of prior information about image data available. Such techniques analyze the unknown pixels in an image and classify them according to a set of categories. These categories are derived via the natural clusters of the grey levels of the pixels. Cluster analysis is a technique that organizes a large set of data so that information retrieval will be more efficient (Goncalves et al., 2012). However, SOM applications are generally dependent on ad-hoc approaches characterized by guesswork and/or trial-and-error approaches and require sufficient data of weight vectors to successfully cluster meaningful objects and distinguish inputs. A good data set is a key factor in determining whether a SOM can be used.

3.3. Artificial neural networks with cellular automata

An ANN is a mathematical framework to be analog to the human brain's neural system, which consists of layers of interconnected neurons. ANNs are the backbone of DL algorithms. Therefore, ANNs are essentially a part of Deep Learning, which in turn is a subset of ML. The neurons are used for the connection between the outputs and inputs with weights (Paoletti et al., 2019). Each neuron is a perceptron to decide and classify data using statistical regression. The perceptron serves the signal created by a multiple statistical regression as a predictor function which might be non-linear. Each of the inputs is then combined by its corresponding weights (Bendiktsson and Sveinsson, 1997; Foody and Arora, 1997; Bischof et al., 1997). These weights account for the strength of the interconnection among neurons within the ANN. All the weighted inputs are summed up for outputs. Thus, ANN can build correlations among images, pixels, and locations for classification.

ANNs have been used to classify multi-hyperspectral data and forecast hydrological phenomena very accurately according to features and contexts (Du and Swamy, 2014; Talukdar and Pal, 2020) because ANNs have the advantage of self-organizing, self-adaptation, and self-learning techniques. ANN's can be designed for emulating the transition and change of LULC, such as urbanization, rural abandonment, and agriculture conversion. However, ANNs in modelling LULCC are difficult to detect change between time series images. There are the two phases inherent on land transitions: (1) land change occurrence (i.e., the origination of a new patch-of-change) and (2) change spreading (or the spatial contagion of the land transition) that will generate the final spatial extent and configuration of that patch-of-change. LULC change occurrence and spreading have been identified as critical phases to explain observed patterns of land change. The derivation of transition functions is a very non-linear task, and therefore it is challenging to determine a relevant and logical transition function. For example, those generated by deforestation in the Amazon (Rosa et al., 2013). The LULC change is determined through a comparison of the values of the probabilities of conversion. Therefore, the relation between both rates of change occurrence and change spreading allows determining patches-of-change before other patches arise or vice versa. This is commonly to use a probability or gradient based protocol to implement the allocation procedure as the core of a spatial explicit LULC change model. The LULC category is then converted from its current category to the category having the greatest values of conversion probabilities (Deng et al., 2015). However, LULC change is a dynamic process of the spatial complex system. The construction development of urban and agricultural crop production can be readily affected by many factors, such as environment, society, economy, culture, politics, and geology. The real LULC is affected by biophysical and socio-economic drivers that are specific in the studied region, such as weather, soil, and vegetation. Spatial land-cover type suitability or change requires to account for competition for the most productive locations among land-cover types, in which transition rule is calculated iteratively through the spatialization of the demand-allocation. Based on the mathematical inference and the statistical method, empirical classification models are built to simulate the LULC change (Choodarathnakara et al., 2012). ANNs learn about past functional relationships using empirical data to identify a change likelihood, such as urban development or deforestation (Pijanowski et al., 2002). However, there are some drawbacks of data statistical regression approaches: (i) lack of the spatio-temporal mechanisms that account for occurrence, transition, and spatial configuration of changes (Rosa et al., 2013), (ii) limitation due to data unavailability of all the parameters to change (Sohl et al., 2007), (iii) the static relations (Poelmans and Van Rompaey, 2010), and (iv) lack of the explicit description and validation of the spatial pattern change. This limits the applicability of ANNs to predict the LULC change.

CA is spatially and temporally discrete and evolves on a grid system at discrete time steps according to a set of rules of neighboring cells or dynamical transition rules. In Mahiny and Clarke (2012), an alternative to hybrid CA modelling, is presented in the form of multi-criteria evaluation (MCE) to calibrate SLEUTH simulations. Using SLEUTH simulations guided by MCE calibration, the MCE accounts for key socioeconomic and ecological factors. SLEUTH can be used to develop uncertainty maps, which involves predicting the quantity of times land-use is forecasted for a selected location using Monte Carlo simulations. Thus, some integrated algorithms of ANNs with CA have been developed in modelling LULCC. Therefore, in a hybrid model of ANN and CA, an ANN model can be used to quantify LULC classification based on the conditional probability of LULC in the environmental space and, a CA model can impose spatial constraints on the transition to obtain the best-suited classifier (Zhan and Yu, 2020).

Gashaw et al. (2018) simulated the hydrological impacts on LULCC using a CA Markov chain in the Andassa watershed, Blue Nile Basin, Ethiopia. The changes of each LULC class were inputted into the SWAT model to examine the effects of LULCC on stream flow and runoff. They found that the increasing vegetation covers could decrease the stream flow and runoff in the wet seasons and increase stream, lateral and groundwater flows in the dry season. Feng and Liu (2016) studied the effects of ecological and environmental conditions on urban development using CA in Lingang New City, southeast of Shanghai, China. They indicated that CA could predict urban development under a different scenario. Guan et al. (2011) simulated urban land use change using an integrated model of CA and Markov model. They predicted future land use changes during the period of 2015–2042. Qian et al. (2020) proposed a hybrid algorithm of CA and spatiotemporal neighborhood features learning (Fig. 3). A SOM divided the entire domain into several homogeneous sub-domain. Then, a three-dimensional CNN was applied to extract the spatiotemporal neighborhood features. An ANN used these extracted features to establish a transition probability map. Finally, with constraint factors that CA drive the land change, the dynamic results of the whole simulated area were outputted by aggregating these probability maps, constraints, and stochastic factors.

Mu et al. (2019) used the LSTM RNN to simulate the urban LULCC and evaluate change trends that consider the weather and economic effects. In their model, spatial-spectral, climate, and economic data can be normalized by the self-adaptive CA-based data. They found a continuing downward trend in agricultural land and forestland areas while an upward trend in built-up areas. They indicated that building land would increase in suburban regions. In the meantime, RNNs have a strong ability in solving time series data prediction problems that could be utilized to dynamically simulate the urban LULCC. Qiang and Lam (2015) developed a hybrid algorithm of ANN and CA to analyze the LULCC of the region between 1996 and 2006. The LULC change rules were derived from 15 human and natural variables from time-series remote sensing images. Then they used the rules to explain future LULCC using CA. However, they do not show which variable has the strongest impact on output, nor does it show the way that one variable has an impact on other variables that affected the output. Lam et al. (2018) used a spatial dynamic model to analyze population changes as well as the heavily linked LULCC resulting from such changes in the Mississippi River Basin. Deng et al. (2015) developed a coupled ANN-CA watershed land use and land cover change simulation model to simulate land use or cover type in the upper reaches of the Hanjiang Basin. Li and Yeh (2002, 2004) used CA with a data-mining technique to describe the transition of LULCC as a single LULC category. The explicit transition rules of CA can be updated through the induction of data mining parameters and processes, such as demand-allocation relation (Aquilué et al., 2017). ANNs are very effective at modelling complex non-linear mapping relations involving many factors while their transition function is calculated by the CA model. Their results showed that CA is capable of simulation of complex geographical transition phenomena. In their approach the systems of equations influencing the target variables were tightly coupled and simulated, thereby clearly quantifying the variables in explicit terms. This approach is referred to by the authors as a "white box approach" and is suitable for the LULCC at a regional scale (Almeida et al., 2008; Deng et al., 2015). These CA models do not account well for the role of climate change in long-term land use pattern changes (Saputra and Lee, 2019).

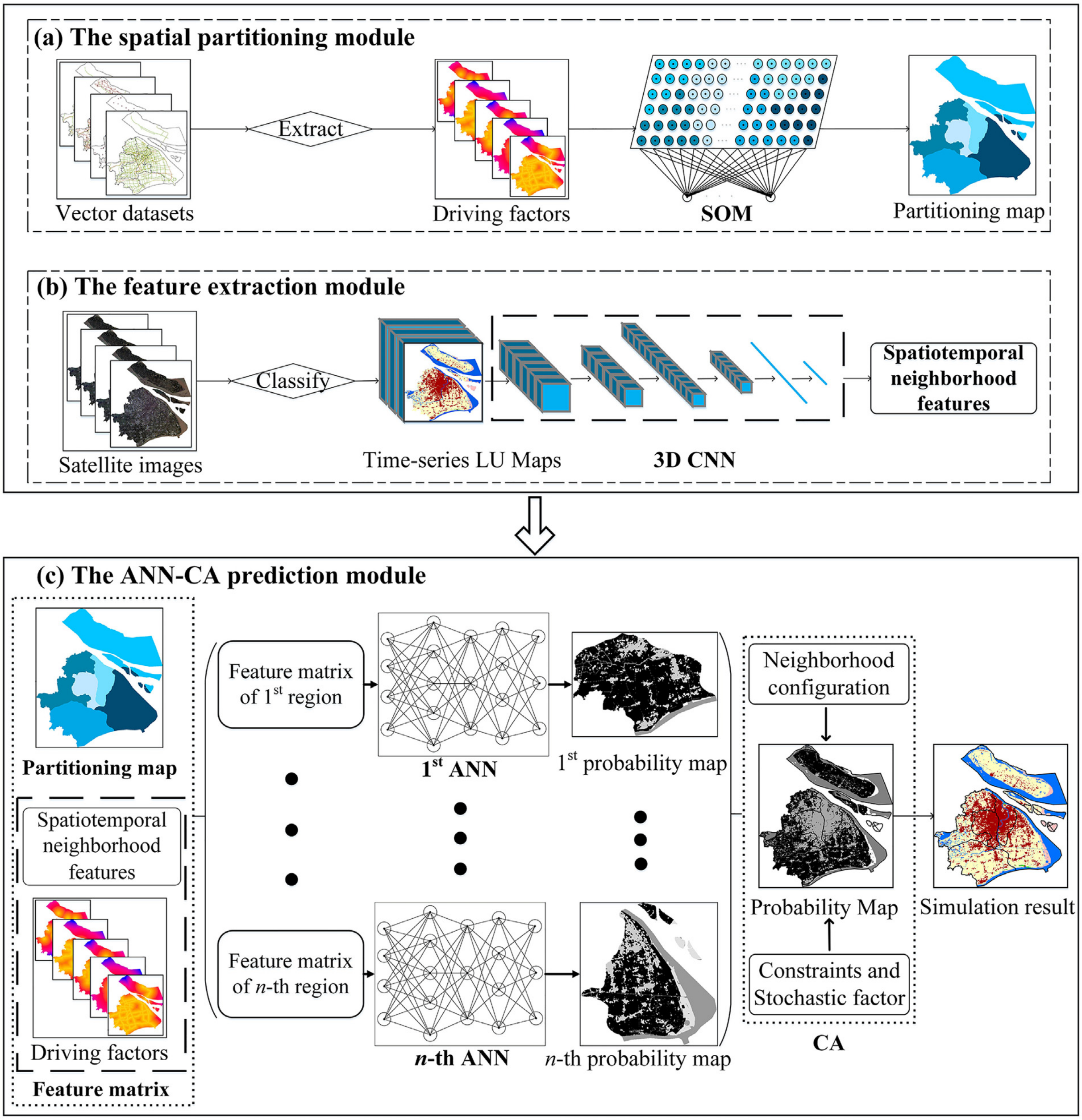

Fig. 3. Framework of a hybrid model of CNN, SOM, and ANN-CA (Qian et al., 2020).

4. LULC classification

LULCC is a dynamic process. LULC of each image in time series images needs to be classified before detection and modelling of LULCC (Gomez et al., 2016; Simoes et al., 2021). Therefore, classification plays an important role in modelling the LULCC of remote sensing images and is one of the hottest topics in the geoscience and RS community. A hyperspectral image is commonly three-dimensional: two dimensions to represent spatial locations of each object and another to the electromagnetic spectrum of each material in different bands (Fig. 4) (Zhong et al., 2016b). The image can include the pixels, pixel density, distributions, features, histograms, color distribution etc. The LULC classification is to categorize land covers into different classes by using the spatial spectral band features of the image, such as shape, texture, color, and land cover discrimination. As shown in Fig. 5, a satellite image is categorized into different classes through a hierarchical object-based classification in three levels (Kindu et al., 2013). Clustering and segmentation are parts of classification and object detection. These labeled data sets can be applied to train the DL model. Depending on its application, the classification of data is implemented through thresholds of mean and/or standard deviation of spectral features, color bands, digital elevation model (DEM), texture, or normalized difference vegetation index (NDVI) (Duro et al., 2012). Different LULC classes can be distinguished using classifying algorithms, such as decision trees (Delalieux et al., 2012), random forests (Ham et al., 2005), and support vector machines (Melgani and Bruzzone, 2004; Ghosh and Das, 2020). While these classification algorithms can be independently used for image analysis, they can be incorporated into different MLs or DLs for analysis of spatial-spectral imagery to extract a richer set of features (Heydari and Mountrakis, 2019).

The LULC classification algorithms can be categorized into different groups of classifiers in terms of different criteria Ghamisi et al. (2017a, 2017b). For example, classification algorithms can be divided into parametric and non-parametric classifiers (Seto and Kaufmann, 2005). Parametric classification is based on the assumption that the data of input data for

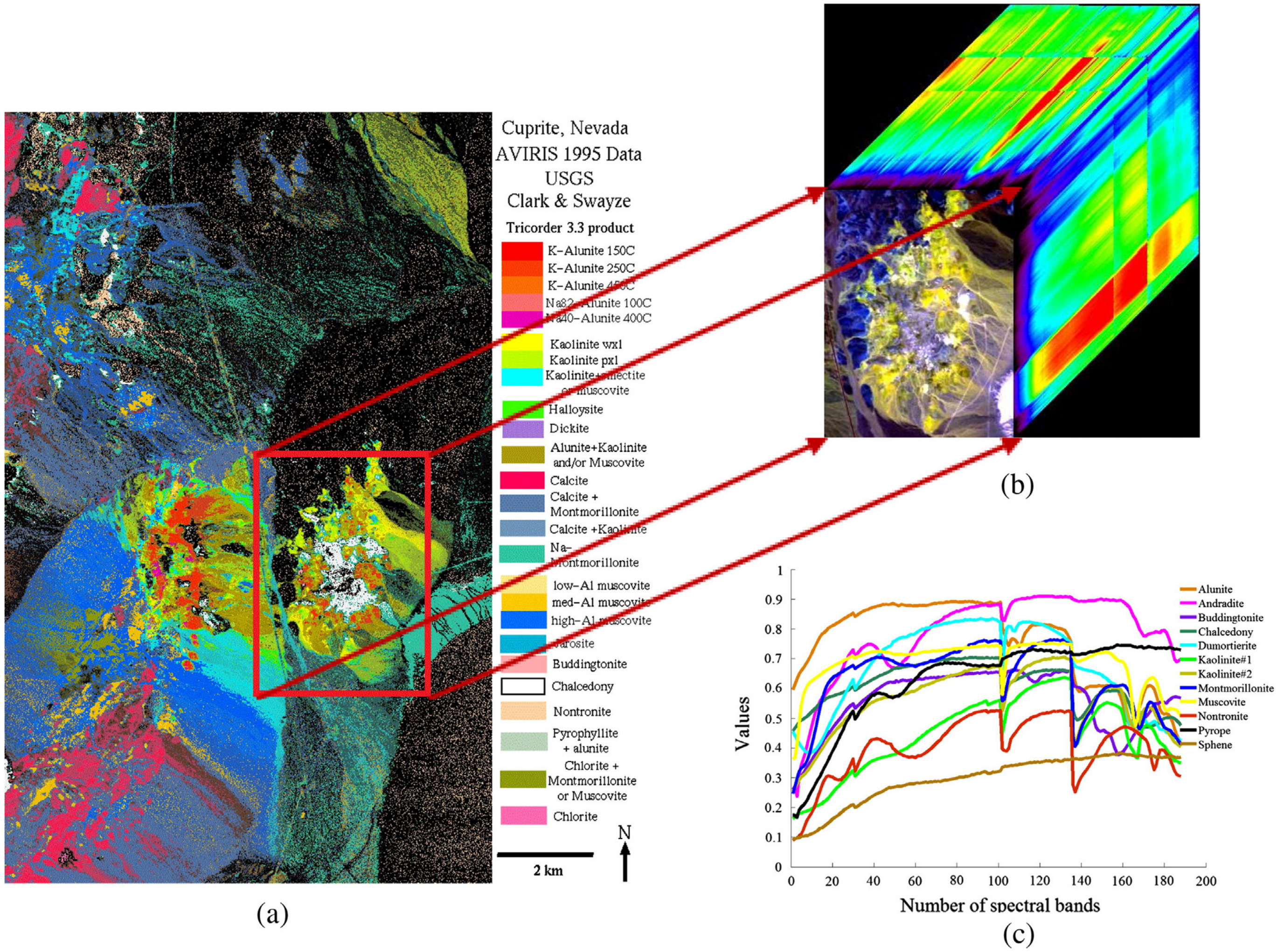

Fig. 4. AVIRIS hyperspectral data from Cuprite, Nevada, U.S.: (a) USGS map showing the location of the different minerals in the Cuprite mining district, (b) 3D cube form of the experiment area, and (c) USGS library mineral spectral signatures (Zhong et al., 2016b).

each class are distributed normally while non-parametric classification is not constrained by any statistical distribution. LULC classification algorithms can also be divided into supervised, unsupervised, and semi-supervised (Halder et al., 2011; Akerkar and Sajja, 2016; Ma et al., 2019). Supervised classification uses a set of representative samples to segment the input data into each class as training samples. In contrast, unsupervised classification as a clustering algorithm, does not account for the labels of training samples to segment the input data. Classification algorithms can also be categorized into pixel-based and object-based (Whiteside et al., 2011). In pixel-based classification, a segmentation technique allocates a label-oriented classifier for each pixel in the image in such a way that pixels with the same label share certain visual characteristics. In contrast, object-based classification divides an image into segments and assigns a specific class of interest to each of the segments. Thus, objects are known as underlying units after applying segmentation. Classification is conducted based on the objects instead of a single pixel. Since classification is a wide field of research, we focus our description on pixel-based and object-based classifications. Chaves et al. (2021a) applied the Time-Weighted Dynamic Time Warping method to recognize patterns in MODIS time series for LULCC detection, identifying crop successions and rotations at crop field level in Brazilian Cerrado. They detected temporal cropping patterns and distinguished seasonal variations caused by interannual succession and rotation. Chaves et al. (2021b) applied CBERS-4/WFI data cubes from the Brazil Data Cube project to generate LULC classifications for the Extremo Oeste Baiano agricultural belt, incorporating ground truth samples, crop calendar knowledge, and spectral indices to a dense time series analysis approach. The results indicate CBERS-4/WFI data cubes as a useful tool for improving crop monitoring in the Cerrado biome based on machine learning. He et al. (2021) optimized sensors and features for identifying early, middle, and late rice, generating a 10 m cropping intensity map by integrating Sentinel-1 and Sentinel-2 images. They investigated the performances of different features (i.e., spectral, seasonal, polarization backscatter) by comparing five scenarios with different combinations of sensors and features, and identified the most suitable features for certain rice types (early, middle, and late rice), revealing that single rice cropping dominates the cropping system in the study area in 2017. Aduvukha et al. (2021) investigated the synergetic advantage of integrating multi-date freely available medium spatial resolution Sentinel-2 data of vegetation indices and Vegetation Phenological (VP) Variables, and Sentinel-1 backscatter data for mapping cropping patterns using the guided regularized random forest (GRRF) for variable selection and the random forest (RF) algorithms for cropping pattern classification. They mapped cropping patterns of a typical African smallholder heterogeneous farming area within three sub-counties in Muranga County, Kenya. Liu et al. (2020a, 2020b) proposed an integrated framework of multi-source satellite data, including Landsat, Sentinel-2, and resampled MODIS, for cropping intensity mapping at fine resolution. Cropping intensity is determined by a binary phenophase profile for each cropland pixel. Their results show a great potential of revealing cropping practices in the detection of multiple cropping systems with high spatial (30 m) and temporal (16 days) resolutions.

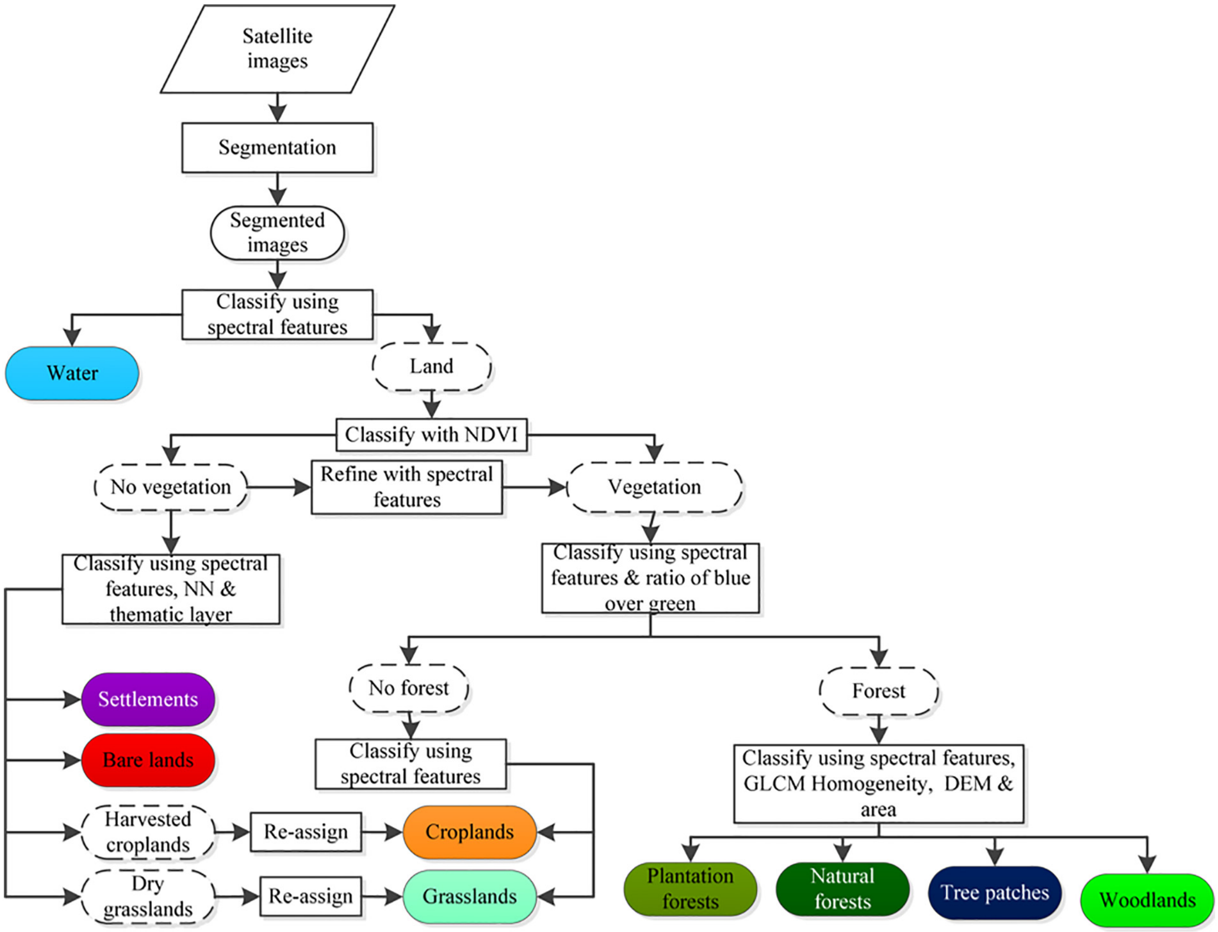

Fig. 5. Flow chart of LULC classification. Dash line boxes are intermediate classes and colored boxes are final LULC classes (Kindu et al., 2013).

4.1. Pixel-based classifications

Pixel-based classification is one of the most popular algorithms in the remote sensing field. In the pixel-based classification, an image is understood at a pixel level, and clustered individual homogeneous pixels into classes, such as, road, grass, forest, and water. Classifying each pixel of a satellite image is one of the most popular ways in LULC classification. Traditional segmentation algorithms are not robust enough for the classification task. DL-based pixel classification for remote sensing images is based on a DL network for the pixel-based data representation (Alhassan et al., 2020; Ozdemir and Polat, 2020). DL-based pixel classification is more robust to extract and abstract feature representations and thus improves the classification accuracy due to successive training and learning.

He et al. (2018b) proposed a pixel-based approach to correlate spatial dependency among pixels spatially related based on Tobler's first law of geography. Relationships among spatially related independent pixels can be built on the same geography surface since land structures are typically bigger than the pixel size. The spatial and label similarity between two objects has an inverse relationship with their distance and the material at one pixel influences the likelihood of the same material in its neighboring pixels. Pixel-based analyses generally exhibit effective classification at a relatively coarse spatial resolution. However, the pixel-based approach assumes that individual pixels are independent, leading to a 'salt-and-pepper' effect for high- or very high-resolution images (Yan et al., 2015; Kemker et al., 2018). Sardooi et al. (2019) used a pixel-based algorithm to analyze the remotely sensed data of the Karkheh watershed in the west of Iran. They derived remotely sensed indices, such as NDVI, leaf area index (LAI), soil-adjusted vegetation index (SAVI), normalized difference moisture index (NDMI), and information on land use, elevation, slope, aspect, relative slope position (RSP), and topographic wetness index (TWI), from MODIS, Landsat, and Terra/ASTER. These indices were used for classifying homogeneous areas in the watershed. Their results show that the pixel-based approach can be used for land cover classification. Bey et al. (2020) used Collect Earth and Google Earth to efficiently generate training and validation data. They examined five pixel-based algorithms to analyze LULC dynamics of continually cloudy, mosaic landscapes using a more limited Landsat dataset in the Gurué district of Mozambique. They categorized land covers for three time periods, 2006, 2012, and 2016, and detected land use change among small-scale cropland, large-scale mechanized cropland, and other land uses. Their results showed that the pixel-based algorithms are effective to classify cloud-, haze- and shadow-free images in a continually cloudy region of Africa, even with a less complete Landsat dataset. Franklin (2018) compared pixel- and object-based algorithms to classify forest tree species of UAV-based multispectral imagery into nine boreal tree species in Ontario, Canada. Their results showed that the object-based classifications with machine learning obtained a maximum overall classification accuracy of approximately 80%, while the pixel-based unsupervised and supervised maximum likelihood classifications did 50% and 60%, respectively. Pixel-based classification might cause unknown information or loss in representing hyperspectral pixels because the number of sequence-based bands is limited (Liu et al., 2020a, 2020b).

4.2. Object-based classification

Object-based classification is to split pixels of a digital image into different subgroups called Image Objects (Whiteside et al., 2011). An object feature can be defined as the spectral value, texture, size, shape, and context. These parameters, such as scale, shape, and compactness, are applied to successfully segment objects in an image through trial and error. Each of the objects represents the homogeneous regions of an image as objects of classification (Shiraishi et al., 2014). The same common feature pixels are labeled and clustered under an object category. Thus, the most desired objects in an image can be distinguished from the rest ones, such as a tree, road, and buildings. Object-based classification has three benefits: (i) the salt and pepper effect associated with per-pixel classification can be overcome from a spectrally variable loss at the pixel level, (ii) real features can be represented better than that of pixel-based because of non-arbitrary units for analysis, and (iii) the rule sets to construct objects can be designed for various scenes as a repeatable approach.

Whiteside et al. (2011) compared object-based hybrid nearest-neighbor/rule-based and pixel-based maximum likelihood classifications in mapping land cover from tropical savanna using ASTER data. They found a significant difference existed. The object-based was superior to pixel-based classification. Zhong et al. (2016a) developed a multiscale and multi-featured normalized threshold related to a super pixel-based graph to segment high spatial resolution images. The normalized threshold considered diverse connections of multi-featured information through the integration of superpixel, smoothness, and multiscale cues to provide a powerful rule to cluster the segments. Their results showed the proposed algorithm enhances the expression ability of the grouping for a more efficient segmentation.

Object-based classification uses the whole image as a sample map to directly be segmented. This approach needs a higher-level understanding of the data to identify the desired objects and those pixels related to the objects. Moreover, if the LULC classification requires very fine-grained objects or the remote sensing data are very complex, this approach needs a large set of fully annotated images or training samples, which may not be available. The segmentation process and subsequent calculation of the topological relationships among objects could require a large amount of computer memory and computing time for large-scale training. Further, there is no definitive algorithm or parameters for the creation of image objects. Thus, this approach may not be practical for detailed LULC classification, because it makes it difficult to reuse previous data sets. Consequently, pixel-based classification is more popular for LULC classification.

5. Upcoming challenges and current trends

An important feature of LULCC is multi-scale, multi-process interactions during LULCC. There are three interacting scales: subpixel, pixel, neighbor pixels, and regions. Furthermore, the land use changes are driven by both natural and man-made environments over time. Practical LULCC can be driven by many factors, such as weather, biological, social, and hydrological (Lam et al., 2018; Verburg et al., 2019; Feng et al., 2020; Xu et al., 2020; Wang et al., 2020, 2021) (Fig. 6). Grove and Burch (1997) indicated that there is a clear connection among the ecological, physical, and social realms in both agroecosystem and urban science.

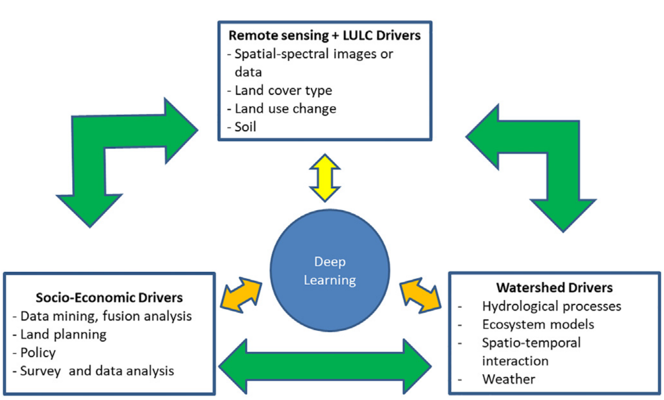

Fig. 6. Drivers of LULCC in the machine learning system.

5.1. Upcoming challenges

A society and ecosystem require dynamically cooperation to maintain its function despite competing for ecological, political, economic, and cultural factors in the Earth's environment. Therefore, LULCC requires exploring the physical–ecological–social drivers and dynamics of land use. For example, how can vegetation under conflicting stresses and motivations maintain a stable psychological condition? How can ecosystem processes respond to LULCC and climate change? How the interaction of supply and demand keeps market prices reasonably stable under LULCC? How will the ecosystem maintain steady levels of temperature and other vital conditions such as the water, climate, nutrient, and soil under LULCC?

MLs-based techniques originate from computer areas, such as computer vision, face recognition, pattern recognition, and natural language processing (Mu et al., 2019). Most MLs-based LULCC are based on spatial-spectral analysis of remote sensing images (Yuan et al., 2005; Ridd, 1995; Phinn et al., 2002). Although hyperspectral images include abundant spatial-spectral information of classes, they cannot account for other key drivers of LULCC, such as weather, hydrology, and social and economic activities. These limits modelling and prediction of ML-based LULCC. Furthermore, besides remote sensing spatial-spectral sensors, there are many data available from various sources, such as monitoring networks, watershed modelling, and national statistics and survey (Fig. 7). MLs could be a linker among remote sensing data, and other data (Deng et al., 2015; Gashaw et al., 2018), such as phenology for agricultural production (Maimaitijiang et al., 2020; Rosa et al., 2013), gravity for groundwater resources (Bhanja et al., 2018; Bhanja and Wang, 2021), soil respiration for greenhouse gas emission (Zhao and Running, 2010) and urbanization (Herold et al., 2002; Chen et al., 2006; Dewan and Yamaguchi, 2009; Mu et al., 2019). However, it is a big challenge how to integrate effectively these big data into DL models. Table 1 shows characteristics of different methods in modelling LULCC.

Despite many successes, MLs in modelling LULCC of spatio-spectral images still faces several significant challenges in all the four main processing: data preprocessing and assimilation, pixel-based classification or object feature extraction, and scene understanding for land transition. Particularly, LULCC, such as crop growth, and urban growth, is a dynamic process. Hence, much effort remains to be done in adapting the existing neural network architectures and semantic segmentation to solve problems in LULCC (Ghamisi et al., 2017b; Wang et al., 2021).

5.1.1. Data transfer and integration

Because of the rapid development of remote sensing techniques and monitoring networks, remote sensing data, monitoring, and geographic information systems (GIS), movements of open access and open data lead to the unprecedented growth of data in LULCC (Ma et al., 2015; Chi et al., 2016; Li et al., 2016; Miu et al., 2018). However, these data are usually represented with different formats and many scenes, such as depth images, point clouds, meshes, volumetric grids, human activities, scenes, weather, hydrology, and ecology (Miu et al., 2018; Guo et al., 2020; Li et al., 2020). Due to different collecting technologies in different disciplines, the massive samples in Big Data require to be assimilated from multiple sources at different time points using different technologies. This creates issues of heterogeneity, experimental variations, and statistical biases, and requires us to develop more adaptive and robust procedures (Wang et al., 2008; Batty, 2010). It is extremely difficult to integrate these drivers for the high-level representation in modelling LULCC. Therefore, data transfer and synthesis can play key roles in driving, redirecting, or resolving core questions and exhibited much greater cross-theme connectivity in accelerating and advancing LULC issues.

In recent years, some efforts have been made to consider other data sources. For example, Mu et al. (2019) used a self-adaptive cellular-based DL algorithm in urban land change trend prediction to analyze the multi-source data, including weather related data, economy related data, construction related data, and remote sensing data. Then they used a RNN to

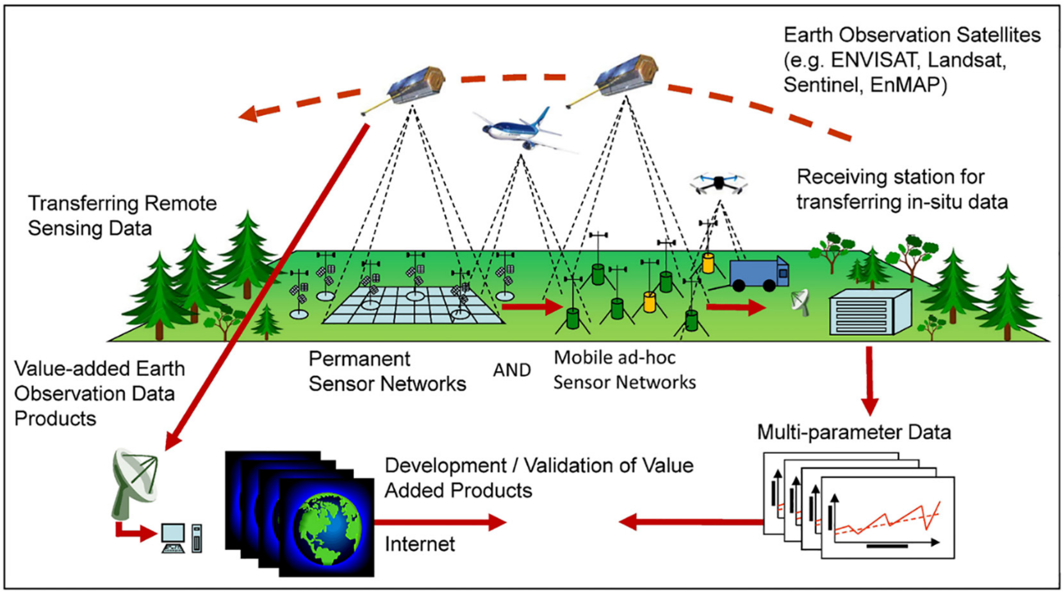

Fig. 7. Schematic of monitoring networks with satellite and airborne remote sensing image of the spectral variation in reflectance for soil, water, and vegetation, and imaging spectroscopy at varying wavelengths (Lausch et al., 2018).

analyze remote sensing images captured from 1984 to 2016 for urban LULCC prediction. Their results showed that LULC change could be predicted efficiently with an accuracy of 93%. Fernandes et al. (2017) evaluated the use of metrics derived from MODIS/NDVI time series to predict sugarcane yield. They incorporated the phenological cycle of sugarcane related both to the cloud occurrence and to variations of atmospheric quality to perform temporal image analysis to characterize the spectral variation of pixels along with a time series. Their results showed that the neural network wrapper can remove irrelevant and/or redundant features from the initial data set, reducing over-fitting and improving the prediction performance.

Training and testing data are crucial in DL classification since the detection change and recognition accuracy depend upon numerous training samples (Zhou et al., 2015; Ghamisi et al., 2017b). The more a DL can train on training data, the more accurate it will be. Fig. 8 showed a false color composite image of Indian Pines and its associated training and test samples (Rasti et al., 2018). While massive data has been generated from various technologies, DL training and testing data is still inadequate for classifying the image in many regions. This causes often DLs unsuccessful. Training and test data should represent the realities of the land cover types. Collecting samples is time-consuming and costly when most statistical data were collected manually (Miu et al., 2017; Guo et al., 2020). Under these situations, how to keep good learning performance of the DL approaches using less training data remains a big challenge. On the other hand, a large amount of data can lead to low efficiency of the CNN training, which is the main barrier for practical applications. To solve this dilemma, many studies have explored the approximation capability of feed forward neural networks, particularly in a limited training dataset (Long et al., 2015; Shelhamer et al., 2017). On the other hand, some efforts have been made to combine image time series analysis with machine learning methods to improve land use and cover change mapping has been explored by organizing multidimensional data cubes (Ferreira et al., 2020). A SOM can be used to cluster the available data and to allocate data samples from each cluster to the training, testing, and validation subset (Maier et al., 2010). As a result, patterns from different zones of the multivariate input-output space can be represented in each subset. The data are classified into their respective subsets on a random basis according to the random unsupervised approach. In the physics-based approach, the data are classified into various classes based on knowledge about the underlying physical processes or domain knowledge.

5.1.2. Spatial-spectral feature analytics and extraction

Despite many progresses on automatic segmentation of hyperspectral image classification, developing efficient algorithms and robust classifiers for spatial-spectral feature extraction and recognition remains to be problems in: (1) recognition and extraction of multi-scale manmade objects, (2) scene understanding and parameterization, (3) neighbor pixel relationship, and (4) representation of mixed pixels.

Many manmade objects, such as ships, aircraft, buildings, and vehicles, have various structures and shapes, and each type could be made up of different materials (Li et al., 2015; Cheng et al., 2017). Such a manmade object classification is less efficient and difficult to be accurate labelling due to sematic gaps in different features and fine-structured confusions (Liu et al., 2018). Cai et al. (2018) indicated difficulty to classify aircraft from the background. Furthermore, some small size objects and their complex neighbor environments may require hundreds of bands along the spectral dimension of a hyperspectral image. The classifier needs to elucidate a set of features using original bands or customized bands, and a set of samples to describe different segmented objects, leading to too large input dimensions. The volume of the feature space increases quickly as the number of spectral bands increase. On the other hand, fewer channels can make the recognition of target objects irrelevant to ground objects. Therefore, spatial information should be widely explored to optimize problem dimensionality. Effective feature dimension reduction is key for accurate classification (Zhou et al., 2015).

Many land cover types (e.g., grasslands and forests) can be continuous in the spatial domain, and neighboring pixels in image data are highly correlated. Therefore, the spatial feature of a specific pixel in the original image can be extracted from the assistance of its neighbor pixels since their properties are constrained with one another (Fauvel et al., 2013; He et al., 2018b). Thus, the use of the spatial feature of neighboring pixels can greatly increase classification accuracy. However, image classifications may be very heterogeneous areas. They do not always accurately reflect ground information of spatial structures. This can lead to noticeable uncertainty in algorithms of neighboring pixels (Husak et al., 2008). For example, the nearest pixels do not represent accurate spatial information at the border of classes (Ghamisi et al., 2017b). Inadequate samples can also degrade the effectiveness of the classifier. Furthermore, a larger neighborhood system may substantially increase computational complexity.

Selecting object features in object-based classification is a parametrization process to identify the morphological index and pixel shape index of

Table 1
Strengths and weaknesses of machine learning algorithms used for land-use and land-cover change.

Types	Strengths	Weakness
Artificial neural networks	• Storing information on the entire network. • Ability to work with incomplete knowledge. • Having fault tolerance. • Having a distributed memory.	• Hardware dependence. • Unexplained behavior of the network. • Determination of proper network structure. • Unclear optimal structure for the number of layers and neurons in a specific application.
Convolutional neural networks	• Very High accuracy in image recognition problems. • Automatic detection of the important features without any human supervision. • Little dependence on pre-processing • Easy to understand and fast to implement • Efficient dense network and weight sharing. • Ability to learn highly abstract features	• No encoding the position and orientation of object. • Lack of ability to be spatially invariant to the input data. • Requires lots of training data and a long time to be trained when multilayers are applied. • Overfitting, exploding gradient, and class imbalance
Recurrent neural network	• Capturing the time series information in the input data i.e. dependency between the words in the text while making predictions and Long Short Term Memory. • Sharing the parameters across different time steps to train • Fewer parameters and lower computational cost. • Ability to use convolutional layers to extend the effective pixel neighborhood	• Gradient vanishing and exploding problems with many time steps. • A difficult task for training • Difficult to process very long sequences if using tanh or Rectified Linear Unit (relu) as an activation function.
Self-organizing map	• Without the requirement of any kind of supervising or pre-training • The data and the algorithm are easily interpreted and understood • The ability for reduction of dimensionality and grid clustering • The ability for handling several types of classification problems while providing a useful, interactive, and intelligible summary of the data • The ability for clustering large, complex data sets.	• Requiring the computational time cost and the input space normalization • Requiring necessary and sufficient data in order to develop meaningful clusters • The weight vectors must be based on data that can successfully group and distinguish inputs. • Requiring extraneous data in the weight vectors to add randomness to the groupings. • Difficult to obtain a perfect mapping where groupings are unique within the map. • Requiring a good, correct data set in determining whether a SOM is used or not. • Requiring similar behavior in nearby data points
Artificial neural network with cellular automata	• The ability to model non-linear features and handle well the uncertainties of spatial data. • Simple algorithm and moderate simulation time. • Transition rules of CA simulation represented by ANN. • This means that users can overcome the problem of providing detailed transition rules that are often difficult to define • Ability to represent various conversion probabilities and detect potential interdependencies through the implied driving forces • An open structure to easily integrate knowledge-driven models.	• Black-box devises • The user's intervention for the quality of the result needed • No explicit knowledge about the process of land use conversion. • Problems in capturing the changing features, such as the type, structure, and internal parameters of the network competing land-use conversion between multiple land uses.

objects or scenes. Unlike natural scene images, remote sensing images include various types of objects with different sizes, colors, rotations, materials, and locations in a single scene, while distinct scenes belonging to different classes seem to be similar to one another in many respects. For example, bare lands could be street, snow cover, deserts, beaches, mining sites, exposed rock, quarries, and gravel pits. The arable class could be grasses, vegetables, wheat, corn, potato, and so on. These classes require to be defined in terms of some criteria (Di Gregorio and Jansen, 2000). Understanding scenes is a subjective process, depending on past experience and user knowledge (Laliberte et al., 2010). Selection of the most informative samples requires to be parameterized in their inner principle and can reduce the number of training samples while retaining discrimination capabilities as much as possible (Wan et al., 2015; Zhang et al., 2016a, 2016b).

Most LULC data are some discrete classes assigned to each pixel and disregard within-pixel heterogeneity. Because of the imaging spectrometer's insufficient spatial resolution, these mixed classes cannot be resolved. However, classes in a pixel are probably a mixture of different types in the ground truth. For example, the spatial resolution of remote sensing images is at 10 ∼ 30 m, depending on remote sensing sensors (Giri et al., 2013; Huang et al., 2020; Roy et al., 2020). A pixel may include different classes in such a pixel of 10 m × 10 m, particularly in transition zones. This means that image classification does not account for variability inside a pixel since each pixel is taken as a pure class pixel. Increasing the spatial resolution is useful but limited by techniques and cost. The complexity leads to a difficulty of learning robust and discriminative representations of objects, such as spurious correlations and incidental homogeneity, where a pixel response happens to have more than a single pure attribute of the classes within the image in question when classifying a hyperspectral remotely sensed image in scenarios (Zhao et al., 2018). Pixels that yield response to more than just one class are referred to as mixed pixels. If a pixel response to each class's spectral qualities occurs, the pixel is deemed a mixed-pixel and does not fit into a specified class (Kaur and Bansal, 2014). Thus, categorical classification could partition a pixel into sub-pixel percentages of different homogenous classes (Hansen et al., 2011; Zhang et al., 2019b).

5.1.3. Change detection and prediction limitation

Change detection is the process of identifying and examining spectral–temporal changes in signals. Generally, the periodic capturing of multispectral and multitemporal data in a long period can be used for change detection (Lu et al., 2014). However, there are two challenges: difficulty to reuse previous data sets, such as lack of historical data, different resolution and formats between historical data, and effects of humans and environments. Similar historic images may be unavailable (Fritz et al., 2010; Bey et al., 2020). Economic contexts may be in great differences between small-towns and large-scale cities while exploring land use change. Therefore, it can be problematic when modelling urban land change phenomena such as urban decay and renewal because there may be different types of urban decay and renewal (Du et al., 2018). Such issues need multiple land change modelling, which enables the use of transitions between varying types of natural and built-up lands.

A land change modelling strategy is necessary to provide realistic and accurate predictions, such as crop yield prediction, and urban planning. In practical applications, LULCC is seasonal and climate variations (Liu et al., 2015a, 2015b). Some recent research on crop-type classification is based on not only spectral features of single static images but also combining spectral and time-series data (Zaman-Allah et al., 2015). Preharvest crop yield prediction is critical for agricultural management and food security. Due to seasonal and regional variation in plant growth, the phenotyping of different crops is different. Vintrou et al. (2012) analyzed agricultural areas under high spatial variation in the Sahel belt, Africa. They indicated

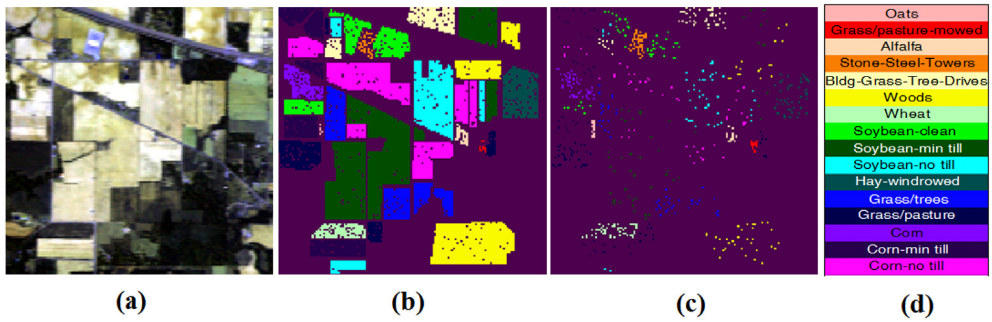

Fig. 8. LULC classification of Indian Pines: (a) a color composite, (b) test samples, (c) training samples, and (d) the corresponding color bar (Rasti et al., 2018).

the difficulty in mapping the transitional region between the arid Sahara in the north and the semi-arid savannas in the south. Mi and Chen (2020) indicated the difficulty to satisfactorily distinguish plant types only using spectrum information. The conflict between capturing contextual data and maintaining detailed features can cause prediction noise and edge blur.

Unmanned Aerial Vehicle (UAV) can provide hyperspectral images with a high spatial resolution in n recent years. Some classification algorithms can deal with the problem of high dimensionality and limited training sets but result in a salt-and-pepper classification appearance in hyperspectral image classification (Zhao et al., 2018). Fig. 9 shows an example of hyperspectral image classification where different spectral signals were classified into different classes using DL (Zhao et al., 2018). In Fig. 9, high resolution images of at 303 × 1217 pixels and 274 spectral bands from the 400–1000 nm spectral range were categorized into different crops of 16 semantic types of land covers on field scale. Maimaitijiang et al. (2020) estimated soybean yield prediction from UAV using multimodal data fusion and DL in Columbia, Missouri, USA. Their results showed that DNN-based model exhibited strong adaptability to different varieties and improved prediction accuracy, compared to PLSR, SVR, and RFR methods. Wen et al. (2017) categorize urban trees as parks, roadsides, and residential-institutional trees performed in two typical Chinese megacities, in Shenzhen and Wuhan. Cai et al. (2018) used a DNN to classify crop types through the aggregation of spectral information for each field based on a time-series Landsat image data image. Bolton and Friedl (2013) developed linear models to predict maize and soybean yield in the Central United States using spectral indices derived from MODIS data. The shortwave infrared bands can improve performance in classifying corn and soybean, compared to the widely used visible and near-infrared bands. All results showed the inclusion of temporal phenology information did improve classification performance in the study regions. Chen et al. (2020) proposed a new, general deep Siamese convolutional multiple-layers RNN for change detection of multitemporal high-resolution images. The LSTM units were applied to change detection of mining areas through change probability. Their results showed that the proposed RNN is better than other several advanced approaches. Generally, the provision of transition matrices in current ML and DL brings up a sequence of additional challenges. The decision of which land-cover type should be replaced upon cropland or pasture expansion (or introduced in case of abandonment) is in fact only based on the statistical regression and the accuracy of the transitions are heavily dependent on the sophistication (i.e., knowledge about

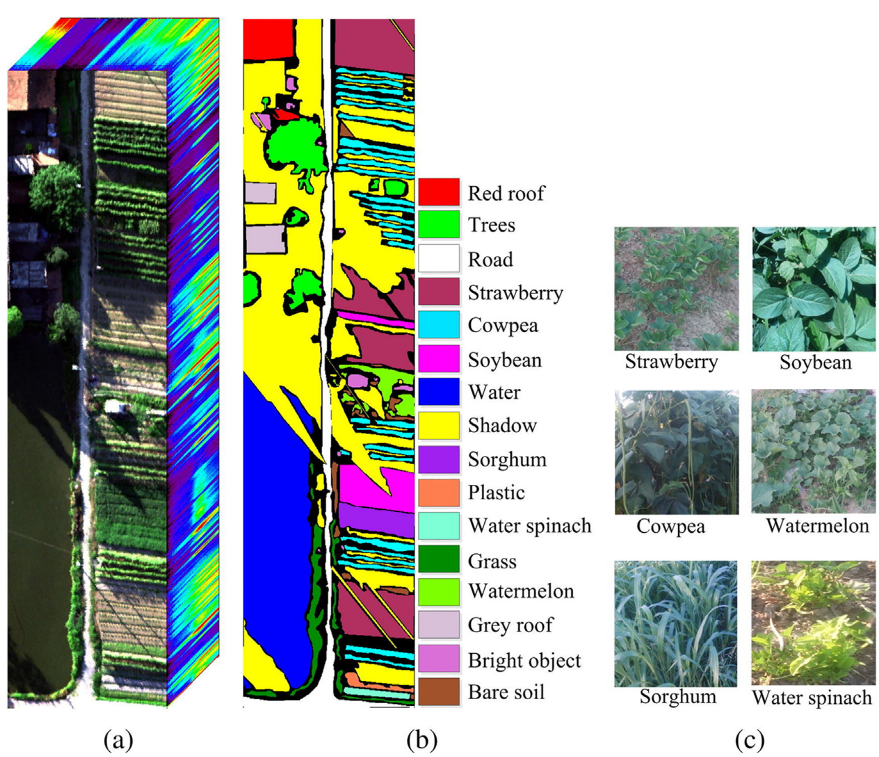

Fig. 9. WHU-Hanahan UAV dataset: (a) Image cube. (b) Ground-truth image. (c) Typical crop photos in the study area (Zhao et al., 2018).

and depiction of land-use change drivers and processes on the grid scale) of the land-use allocation algorithm in the original model providing the land-use data. This complexity is poorly represented by ML/DL algorithms.

5.2. Current trends

Despite progresses, most DLs for modelling LULCC are based on analysis of hyperspectral images due to the fact the DL originated from pattern recognition and image processing. These studies have not considered the main drivers of LULC change, such as weather and hydrology. This has a limited ability of predictions of DL modelling. If a LULCC and its driver is assumed as a unified, complex, homeostatic, or "goal-seeking" ecosystem in which it seeks to keep the system function, the ecosystem requires an automatic response to disturbance, any change or departure from equilibrium to seek the stable positions back. It is difficult to establish generalized supervised rules or conditions for machine learning to be suitable for different LULCC scenarios. Such a learning process requires to be performed under unsupervised conditions with some self-adaptive processes in land transition. Some studies have considered other drivers of land change, such as weather (Mu et al., 2019) and phonology (Maimaitijiang et al., 2020), and gravity for groundwater resources (Bhanja et al., 2018). Multi-source satellite data, such as Sentinel-1, Sentinel-2, and MODIS, have been integrated for cropping intensity mapping and cropping pattern classification at higher resolution (Ferreira et al., 2020; Liu et al., 2020a, 2020b; Aduvukha et al., 2021; He et al., 2021). These studies provide a tool to synthesize vegetation indices, vegetation phenophase variables, and mapping cropping patterns. However, most LULCC modellings are based on supervised methods, but learning transition or change is a complex, self-adaptive process. At each time step, the exact fraction of a grid cell that has changed from one land-use category to another should be determined, thus providing the option to replace the simple allocation options with detailed information about land-use transitions within each pixel (Verburg et al., 2019). On the other hand, CA is powerful in formalizing knowledge regarding the boundaries and change of land use systems (Basse et al., 2014). The basic principle of CA is that the state of a given pixel is determined by taking into account its previous state, the spatial interactions with the surroundings in a given neighborhood, and a set of defined transition rules. These elements dictate the possible change of a cell and can be expert-based or calculated from statistical analysis of historical LULC changes (Gounaridis et al., 2019). CA models, although very simple, have the strong ability to represent rich LULC patterns and handle nonlinear, stochastic, and spatially explicit LULC processes (Sante et al., 2010; Zeshan et al., 2021). Therefore, an integrated model of ML or DL with CA or SOMs could be potential for LULCC modelling as unsupervised methods but only a few studies of integrated models have been performed up to now (He et al., 2018a; Roy et al., 2020; Qian et al., 2020). However, much work remains to be done to develop more adaptive and robust procedures as the future direction.

6. Concluded remark

LULCC modelling is of importance in natural resource management, environmental assessment, territorial planning, urban change detection, and agricultural management. However, our scientific understanding of the distribution and dynamics of LULC change is limited by many factors, such as data availability, big data, data resolution, and understanding of scene and phenology, because of complex interaction among the biophysics, biogeochemistry, and biogeography of the Earth's surface and the atmosphere that drive land changes. With the advent of remote sensing technologies, massive data has been generated by satellite and airborne sensors.

ML and DL have been used for LULCC modelling of remote sensing data but have not been as dramatic in modelling LULC changes, such as urbanization prediction and crop yield prediction. While considering competition and transition between land-cover types are dynamic in nature at the local scale, the detection and prediction of LULC evolutionary processes rely on an understanding of drivers, phenology, and scene. Therefore, the MLs/DLs may be limited due to (i) lack of the spatio-temporal transition mechanisms to describe occurrence, transition, and spatial patterns of changes, (ii) unavailability of training data of all the change drivers, particularly sequence data, and (iii) lack of inclusion of local ecological, hydrological, and social-economic drivers when addressing the spectral feature change. Predicting LULCC in remote sensing images is relatively in infancy for most scenarios. It requires lateral considerations and building connections in conceptual and methodological development if we require to combine knowledge, ideas, and methods from different disciplines within the MLs or beyond image processing and pattern recognition of remote sensing images using MLs and DLs.

CA is powerful in formalizing knowledge regarding the transition and change of land use systems. Therefore, an integrated model of ML/DL and CA could be potential for LULCC modelling as an unsupervised method, but new algorithms require to account for ecological and environmental drivers. Although both ANN + CA and SOMs are a promising technique suitable to investigate, model, and control many types of water resources processes and systems, these unsupervised learning approaches have not yet been examined fully in a comprehensive way within, for example, LULCC modelling. This is a deep and common challenge in interdisciplinary research. Much work remains to be done in data integration, mechanism understanding of LULCC, index identification, and preprocessing training data while incorporating new exploratory variables for LULCC models and allowing the integration of empirical data to learn about past functional relationships, such as in urbanization or crop yields. Despite this, we believe that ML techniques have strong potentials in modelling LULCC, through expanding remote sensing big data and advancing transition algorithms. This review points out the need for multidisciplinary research beyond image processing and pattern recognition of ML in accelerating and advancing studies of LULCC modelling.

CRediT authorship contribution statement

J.W., M.B, and M.A.A.D. conceived the review. M.B. and M.M.A.D. helped with the collections, classification and interpretation of the references. J.W. wrote the manuscript. All authors reviewed and edited the manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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