

# Detecting land use changes using hybrid machine learning methods in the Australian tropical regions

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Abstract The present study evaluates the application of the hybrid machine learning methods to detect changes of land use with a focus on agricultural lands through remote sensing data processing. Two spectral images by Landsat 8 were applied to train and test the machine learning model. Feed forward neural network classifier was utilized as the machine learning model in which two evolutionary algorithms including particle swarm optimization and invasive weed optimization were applied for the training process. Moreover, three conventional training methods including Levenberg-Marquardt back propagation (LM), Scaled conjugate gradient backpropagation (SCG) and BFGS quasi-Newton backpropagation (BFG) were used for comparing the robustness and reliability of the evolutionary algorithms. Based on the results in the case study, evolutionary algorithms are not a reliable method for detecting changes through the remote sensing analysis in terms of accuracy and computational complexities. Either BFG or LM is the best method to detect the agricultural lands in the present study. BFG is slightly more robust than the LM method. However, LM might be preferred for applying in the projects due to low computational complexities.

M. Sedighkia (🖂) · B. Datta College of Science and Engineering, James Cook University, Townsville, Australia e-mail: Mahdi.sedighkia@my.jcu.edu.au **Keywords** Particle swarm optimization · Invasive weed optimization · Back propagation · Neural network classifier · Remote sensing

### Introduction

Land use/ Land cover (LULC) maps are highly applicable for economic evaluation of land resources and hydrological studies (Spruce et al., 2018). Hence, generating land use maps have been highlighted in the literature from many years ago (Fallati et al., 2017). Increasing population in recent decades affect the land use in different countries. In fact, quick change of the land use might be a challenge in the projects that means updating the LULC map is essential Traditional methods for surveying LULC might be expensive and arduous that means they are not utilizable for quick update of the land use maps (Cienciała et al., 2021). Hence, novel methods have been highlighted in recent decades. One of the applicable and efficient methods to update the land use map for different urban and non-urban areas is remote sensing data processing. Many previous studies corroborated the applicability of the remote sensing analysis to detect the LULC (Liping et al., 2018).

Due to focus of the present study on using remote sensing for monitoring LULC, it is necessary to have review on the remote sensing analysis and related methods. Several satellites with different sensors have been launched in recent decades for remote sensing purposes reviewed by (Zhu et al., 2018). In fact, these satellites are able to capture the spectral images from the lands and oceans that could be utilized in a wide range of projects and studies. Different methods have been proposed for change detection including Image Differencing, Image Ratioing, Change Vector Analysis, Principal Component Analysis, Chi-Square Transformation, Post-Classification Comparison, Artificial Neural Networks (ANNs) and Hybrid Change Detection (Full review on methods by Algurashi & Kumar, 2013). Change detection techniques for remote sensing applications are categorized to five classes including algebra based change detection, transform based change detection, classification based change detection, Geographical information system based methods and advanced methods (Asokan & Anitha, 2019). Three popular algebra based models include image differencing (Ke et al., 2018), image rationing and Change Vector Analysis(CVA) (Liu et al., 2015). Principal Component Analysis (PCA) are the most known transform based method (Sadeghi et al., 2018). Unsupervised change detection methods and Artificial Neural Network based methods are popular classification based methods (Radhika & Varadarajan, 2018). Hopfield Neural Network(HNN) are one of the advanced models that has been proposed in the literature (Wang et al., 2014). It should be noted that using GIS based methods might make it easier to extract and evaluate the change detection information (Gandhi et al., 2015).

As reviewed, one of the classification methods that has successfully been applied in the change detection is ANN (Ge et al., 2020). It should be noted that neural networks are one of the efficient machine learning models that have extensively been applied in different branches of engineering. Different types of neural networks could be utilized in the engineering applications (reviewed by Cao et al., 2018).

Feed forward neural networks are one of the widely used methods in the engineering problems (A basic review on the structure of FNNs by Bebis & Georgiopoulos, 1994). The previous studies corroborated that feed forward neural networks are simple, efficient, and reliable for many engineering simulations. Hence, using FNN has broadly been recommended in the literature. The objective of the FNN is to generate a computational map that is able to simulate the output(s) for unseen combination of the inputs (More details reviewed by Huang et al., 2019).

Training method are highly important for developing a robust machine learning model (Ahmad et al., 2020). Back propagation is a known method to train the feed forward neural network. It should be noted that training process of a machine-learning model is inherently an optimization problem that means the aim of the training process is to find the optimal weights for generating a reliable computational map. Hence, the robust optimization methods might be applicable as well. Metaheuristic optimization has been introduced as one of the reliable methods for optimization processes which has extensively been applied in previous studies. Metaheuristic algorithms have generally been classified as the classic and new generation algorithms (Dokeroglu et al., 2019). The classic algorithms such as the genetic algorithm and particle swarm optimization have broadly been applied in many previous optimization problems. The robust response of the classic algorithms convinced the researchers to recommend the application of these algorithms in many new forms of the optimization problems. Moreover, new generation algorithms such as invasive weed optimization has been developed to improve the optimal solutions. The metaheuristic algorithms are classified in terms of methodology as well. Animal inspired algorithms are known algorithms in which the social behaviour of the animals might be imitated. In contrast, some algorithms might follow the physical laws (Geem et al., 2009). Some recent studies applied the metaheuristic optimization in the training process of machine learning models. However, the outputs of these studies demonstrated that nature of the problem for modelling by machine learning method might be effective on the efficiency and applicability of the training methods. Hence, application of hybrid machine learning should be investigated in different problems.

Due to focus of the present study on the change detection models of LULC, it is necessary to review some significant recent studies in this regard. Different types of data driven models have been applied for detecting land use changes. Comparing four machine learning methods including k-nearest neighbor (KNN), random forest (RF), support vector machine (SVM) and artificial neural network (ANN) for the LUCC classification of the Dengkou Oasis, China indicated that ANNs are slightly more robust (Ge et al., 2020). Another study however indicated that Support Vector Machine (SVM) is more reliable than ANNs (Shih et al., 2019). Furthermore, SVM was recognized as the best method for detecting changes of land use in the wetland ecosystems (Kesikoglu et al., 2019). It seems that geographical characteristics could affect the accuracy of the machine learning methods. Moreover, land use change models by applying random forest method are utilized to assess the environmental sustainability that might be helpful for selecting future directions in the development (Nguyen et al., 2021). Furthermore, separating forests, land, and the vegetation utilizing principal component analysis (PCA) and morphological operations has been studied that provided superior results compared with the standard methods (Dharani & Sreenivasulu, 2021).

The advanced data driven models have been proposed in recent studies. For example, the supervised image classification method combined with the remote sensing analysis has been applied to detect changes of land use. However, a robust accuracy assessment has not been carried out for evaluating the performance of the model (Shawul & Chakma, 2019). Furthermore, applying faster region-based convolutional neural networks (Faster R-CNN) is another advancement to detect changes by high-resolution images. It is claimed that higher overall accuracy is the main advantage of this method (Wang et al., 2018).

Recent studies in the Nile Delta of Egypt demonstrated that using remote sensing and GIS techniques is highly effective for detecting changes in LULC (Elagouz et al., 2020). One of the recent studies highlighted that shifting change detection to monitoring with remote sensing should be noticed in the future studies (Woodcock et al., 2020). Using eco-environment evaluation index associated with land use changes has been recommended for advanced land use studies in the literature (Zhu et al., 2021).

Assessing LULC through the remote sensing data processing is a critical issue for quick update of the LULC maps that are a vital requirement for many civil engineering projects. It seems that robustness of the hybrid machine learning methods such as linked evolutionary algorithms–FNNs are not highlighted in the literature. In other words, their applicability and efficiency are not clear for the engineers. Due to this research need, the novelties of the present study are as follows.

- 1. Evaluating the applicability of the hybrid machine learning methods to detect the changes in land use studies
- 2. Comparing the outputs of the hybrid algorithms with conventional training methods
- 3. Recognizing the most effective methods for training the machine learning models in the remote sensing data processing and opening new windows for applying novel hybrid machine learning models in the remote sensing science.

## Study area

The present study was carried out in Cairns, Queensland, Australia. This region is located in the northern QLD, Australia (Lat: -16.95°, Lon: 145.75°). Figure 1 displays the location of the study area. The applicability of metaheuristic optimization for detecting LULC was tested in part of agricultural lands. The study area is one of the important regions in terms of economic activities in the state in which agriculture and food production is highly important in the current condition. Hence, assessing quick change of the LULC might need to apply reliable and inexpensive methods. Two regions are mainly recognizable in the study area including agricultural lands and natural lands, which are classified as the tropical region. This area is located on the east coast of Cape York Peninsula on a long, narrow coastal strip edged between the Coral Sea and the Great Dividing Range. Mountains, beaches, tidal wetlands, freshwater lakes, mudflats, mangrove swamps, bays, rivers, estuaries and rich coastal plains are all features of this diverse tropical region. Sugar cane is the main crop in this region.

### Material and methods

It might be helpful for the readers to have an overview on the workflow of the present study. Figure 2 displays the workflow of the present study. More details regarding each part will be presented in the following sections.

Data acquisition and architecture of the model

The present study evaluates how the metaheuristic optimizations associated with FNN are able to



Fig. 1 Location of the study area

detect the agricultural lands correctly. Two available land use maps surveyed by city council in previous years were applied for implementing the proposed framework (Fig. 3). The area of agricultural lands has slightly been changed in two available maps. One map is utilized for the training process and another one was applied for the testing process. Data acquisition is one of the important steps to develop a robust model through the remote sensing data processing. Many satellites are launched in recent decades to capture the spectral images from the earth that could be applied in the remote sensing analysis. Landsat 8 was launched on an Atlas-V rocket from Vandenberg Air Force Base, California on 2013 which carries the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS) instruments. This satellite is able to capture the spectral images from each point of the earth at 16 days intervals (Roy et al., 2014). In **Fig. 2** Workflow of the present study



the present study, two spectral images were applied for training and testing the machine learning method. The LULC map was available for two years. Hence, two spectral images were downloaded from the USGS data bank in these two years. Figure 4 shows Band 1 of the testing spectral images as a sample of acquired data. The information of the driven Landsat data for the present study is displayed in the Table 1.

We applied an ANN classifier as the machinelearning model to detect the changes through the remote sensing data processing. Figure 5 displays the general architecture of the feedforward neural networks (FNNs) in which three main parts are identifiable. Input layer contains the effective input of the model. Table 2 shows more details regarding the developed model. Hidden layers are responsible to connect the input layer to the output layer that might have the significant impact in the accuracy of the data driven model. In the present study, we considered 8 hidden layers in the network based on the initial assessments for developing the machine learning model. As presented, ANN classifier was used to detect the agricultural lands in the case study. Hence, the output of the model consists of two classes including the natural areas and agricultural lands.

### Training methods and accuracy assessment

The main purpose of the present study is to evaluate the abilities of the metaheuristic optimization to train the machine learning model to classify the land use. Thus, we selected one classic and one new generation algorithm to optimize the weights of the neural network in the present study including particle swarm optimization (PSO) and invasive weed optimization (IWO). These algorithms were selected due to some reasons. First, the previous studies corroborated that these two algorithms might be more robust compared with the other algorithms (Sedighkia & Datta, 2021). Moreover, different origins of these algorithms might be helpful to evaluate the impact of the methodology of each algorithm on the results. Thirdly, PSO is a known classic algorithm that means its application could demonstrate the efficiency of the classic algorithms to train the machine learning classifier to detect the agricultural lands in the spatial analysis studies. Conversely, IWO is one of the robust new generation optimization algorithms that indicated the reliable results in the previous studies. Hence, using IWO might show how the new generation algorithms might be able to improve the performance of the machine learning models.

It is necessary to present more details regarding the methodology of these algorithms. PSO is able to find the best solution in the optimization problem by moving the particles or candidates around the searchspace considering a mathematical formula for changing particle's position and velocity. This algorithm is the first algorithm in which social behaviour of the animals such as movement of organisms in a bird flock or fish school is imitated. Many previous studies describe philosophical aspects of swarm intelligence e.g. (Jain et al., 2018; Janga et al., 2021); This algorithm can search the large space of possible solutions that might be an advantage for its application in the practical optimization problems. Figure 6 shows the





Fig. 3 LULC maps used in the training and testing process of the machine learning model (Yellow area: simulated natural lands, red area: simulated agricultural lands)

flowchart of this algorithm to find the best solution. Furthermore, IWO was applied in the present study as well. This method is one of the unique algorithms which is able to imitate compatibility of the weed's colony for survival and reproduction. In fact, colonies of invasive weeds in agriculture might be highly detrimental for the crop production. These colonies apply a complex strategy for survival and reproduction in the farms. The behaviour of the invasive weeds was smartly applied to develop an evolutionary algorithm that is able to follows the features of a weed colony such as seeding, growth, and competition to find the best solution for the optimization problem. More details regarding the steps of this algorithm to find the solution have extensively been addressed in the literature. However, Fig. 7 displays the flowchart of this algorithms to find the optimal solution.

It was required to utilize the conventional training methods for comparing the abilities of the evolutionary algorithms to train the machine learning classifier to detect the agricultural lands through the remote sensing data processing. The back propagation is a general method to train the FNNs where might be reliable for some problems. Different types of back propagation methods have been cited in the literature. In the present study, we applied different types of back propagation methods as displayed in the Table 3. It should be noted that these training methods have broadly been addressed in the previous studies.

Assessing the accuracy of detecting land use changes is one of the needs to measure the robustness of the methods. Based on the recommendations by the previous studies four indices were used in the present study including overall accuracy index (OAI), user's accuracy (UA), producer's accuracy (PA), and Kappa coefficient was used to assess the accuracy of detecting land use change. In the present study, OAI means the total number of correct cells divided by the total number of cells which could be converted to a percentage. We used all the points as the sample of the assessment due to availability of real data in the selected area. More details regarding accuracy indices have been addressed in the literature (Foody 2002).

#### **Results and discussion**

In this section, results of testing process of the developed machine learning model are presented. Then a full discussion on the results is provided. Figures 8 and 9 displays the results of detecting agricultural lands in the simulated area. Real land use in the simulated area is displayed as well. It seems that the performance of used algorithms is totally different. Hence, utilizing the optimal training method might be essential. It is necessary to present the performance of different methods regarding detection of agricultural lands through the remote sensing data processing. Three conventional methods were applied in the present study including SCG, BFG and LM method. **Fig. 4** Band 1 of the testing spectral images as a sample of data acquisition from the database of Landsat 8



Table 1 Details of the driven Landsat data

Image code	Application	Num- ber of tiles	Acquisition date	Path	Row
1	Training	1	2013/07/02	096	072
2	Testing	1	2017/08/14	096	072



Fig. 5 general architecture of ANNs

It seems that the performance of SCG method is not as appropriate as two other methods. In fact, many agricultural lands have been detected as the natural lands by this method that means utilizing this method might cause considerable underestimation on the available agricultural lands in the study area. In contrast, the performance of the LM and BFG might be more robust compared with the SCG method.

The main purpose of the present study is to evaluate the robustness of the metaheuristic optimization to train the machine learning model for detecting the agricultural lands. As could be observed, the performance of two evolutionary algorithms (EAs) including IWO and PSO is not the same. In other words, different algorithms might not have the similar performance in the optimization process of the machine learning models. At the first glance, it sounds that the performance of EAs to train the machine learning method is not robust and reliable. In other words, the conventional methods have the better performance compared with the new generation training methods such as metaheuristic optimization. However, the accurate evaluation of the methods might need to generate the error map to detect and classify the LULC in the study area.

Table 4 shows the indices of the accuracy assessment in the present study. Based on this table, no method is perfect to detect the agricultural lands in the study area. BFG, LM and IWO have the better performance compared with the other training methods. However, IWO is not as robust as two other conventional training methods. Moreover, the performance of PSO as another used EA method in

Table 2 Main features of data driven model for detecting changes

Inputs	Output	Number of hid- den layers	Training methods
Band 1 Visible (0.43–0.45 μm) 30 m	Land use classes including natu- ral and agricultural lands	8	Three conventional meth- ods and two evolutionary algorithms
Band 2 Visible (0.450–0.51 µm) 30 m	_	-	-
Band 3 Visible (0.53–0.59 µm) 30 m			
Band 4 Red (0.64–0.67 µm) 30 m			
Band 5 Near-Infrared (0.85–0.88 µm) 30 m			
Band 6 SWIR 1(1.57–1.65 µm) 30 m			
Band 7 SWIR 2 (2.11–2.29 µm) 30 m			



Fig. 6 Particle swarm optimization (PSO) flowchart (Eberhart & Kennedy, 1995)

the present study is not defensible. Hence, it is recommendable to apply BFG and LM method to train the ANN classifier to detect the agricultural lands in the future studies. In other words, metaheuristic optimization might not provide the acceptable performance for detecting the agricultural lands through remote sensing data processing. However, the outputs of the present study demonstrated that all conventional methods might not be suitable for training the machine learning models in the remote sensing analysis for detecting the agricultural. BFG and LM methods indicated the acceptable performance. However, the performance of SCG is poor. It should be noted that BFG method is slightly better than LM method in the case study.

A full discussion on the results of the present study is essential. It should be noted that we only applied



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Fig. 7 Flowchart of IWO

 Table 3 More details regarding the conventional training algorithms for FNN

Name of algo- rithm	Short description on the methodology	References
LM	The Levenberg–Marquardt algorithm is proposed to approach second-order training speed without computing the Hessian matrix	Mardquardt (1963)
SCG	This algorithm is based on conjugate directions; however, it does not perform a line search at each iteration	Møller (1993)
BFG	Newton's method is an alternative to the conjugate gradient methods for fast optimization. The quasi-Newton methods does not however require calculation of second derivatives. The best form of these methods that has been published is the Broyden, Fletcher, Goldfarb, and Shanno (BFGS) update	Gill (1981)

two metaheuristic optimization methods including PSO and IWO. However, other methods could be applied as well. The outputs of the present study demonstrated that the performance of the new generation algorithms is more robust compared with classic algorithms in the remote sensing data processing. However, both algorithms were not adequately reliable to detect the agricultural lands. The previous studies corroborated the robust performance of the evolutionary algorithms to train the machine learning model (e.g. Sedighkia & Datta 2021). However, the present study indicated that a general recommendation to apply the metaheuristic optimization for training the machine learning model is not correct. In fact, changing the nature of problem and effective inputs might alter the performance of the training methods. Hence, it is needed to apply a group of the training methods in each problem. In the present study, a machine learning classifier was utilized to detect the agricultural lands. The metaheuristic optimization might not be a good option to train this type of machine learning model for detecting agricultural lands. The generated land use map by the BFG and LM method could be convincible for applying these methods in the future studies. However, the limitations of the training methods should be noticed as well.

The main limitation for applying the training algorithms in the development of machine learning model is computational complexities. According to the official definition, the computational complexities include the given time and memory to an optimization algorithm to find the best solution. In fact, computational complexities might be very important in the application of the machine learning methods in the engineering projects. It should be noted that high computational complexities might be a serious hindrance for using the optimization algorithms in practice. In fact, it might be needed to numerously carry out the training process for updating the model. Moreover, using the data driven model for a big data bank might need more time for training process. Hence, engineers are not willing to utilize the complex algorithms in which much time and memory might be needed to find the best solution. In the training of the machine learning models, the purpose is to find the optimal weights of the neural network that is able to generate the best outputs for unseen scenarios of the inputs. Hence, it is essential to discuss on the computational complexities for selected training methods. As discussed, two types of training methods were applied including conventional training methods (i.e. SCG, BFG and LM) and metaheuristic optimizations (i.e. IWO and PSO). Based on the analysis of the required time and memory for each algorithm, metaheuristic optimization might need much more time and memory to find the best solution. Conversely, some conventional methods such as LM need less time and memory for finding the optimal weights of the network. In fact, LM was the best method in terms of computational complexities. However, other conventional methods such as BFG and SCG are more complex compared with LM method. Results demonstrated that BFG is the most complex method among the conventional training algorithms. It sounds that using metaheuristic optimization for detecting the agriculture lands through the remote sensing analysis is not logical in terms of either accuracy or computational complexities.



Fig. 9 Results of training by evolutionary algorithms (Green area: correct assessment, red area: Incorrect assessment)

One of the important issues in the application of the metaheuristic optimization is termination criterion. In the present study, we considered the number of iterations as the termination criterion to find the best solution. In fact, several initial tests were carried out to find an appropriate number of iterations for applying the evolutionary algorithms. We considered 10,000 iterations as the final termination criterion in which the algorithms could be converged. Our experiments demonstrated that more than 5000 iterations provide the same optimal values for the weights of the neural network. It is recommendable to apply the number of iterations as the termination criterion in



Fig. 8 Results of conventional training methods (Green area: correct assessment, red area: Incorrect assessment)

Land use class	BFG		SCG		LM		IWO		PSO	
	PA (%)	UA (%)								
Agricultural lands	79.7	76.3	57.2	55.4	76.4	74.3	68.8	66.1	62	59
Natural lands	83.2	87.7	64.3	66.9	80.2	83.4	74.1	76.3	67.1	69.5
Overall accuracy	81.5		61.2		78.4		72.8		64.4	
Kappa coefficient	0.80		0.57		0.77		0.69		0.62	

Table 4 Accuracy assessment in the study area

the future studies to train the machine learning models. It should be noted that the proposed recommendations on the training methods are cautiously useable in the future studies for detecting the agriculture lands through the remote sensing data processing. In other words, the best solution is to apply all possible algorithms for training process and selecting the best algorithm based on the results. However, it might not be applicable in the project to use all methods due to practical limitations such as time and computational costs. Hence, the outputs of the present study might be an applicable guideline to select the best training algorithms for developing machine learning models regarding detecting agricultural lands through the remote sensing data processing. Another alternative machine learning model that could be applied is neuro fuzzy inference systems. Hence, it is recommendable to use this type of machine learning models in the future studies. In fact, this model applies a fuzzy inference system in the structure of the neural network reviewed by (Salleh et al., 2017). Another advanced option that could be applied is convolutional neural networks that have been used in the simplest form in the previous studies e.g. (Li et al., 2020). More details regarding the deep learning methods are reviewed in the literature (Sharma & Singh, 2017). Moreover, it should be noted that we applied the metaheuristic optimization for detecting the agricultural lands. However, the efficiency of these methods might be the same for detecting the urban areas.

### Conclusions

The present study evaluates the application of the metaheuristic optimizations for detecting the agricultural lands through coupling remote sensing data processing and machine learning model. FNN classifier was applied as the machine learning model. Two metaheuristic optimizations including PSO, and IWO were applied to train the machine learning model. Furthermore, three conventional training methods including SCG, LM and BFG back propagation algorithms were utilized to compare the results of the metaheuristic optimization with the conventional methods. Based on the results in the case study, the metaheuristic optimization is not adequately efficient to develop the machine learning models for detecting the agricultural lands through the remote sensing data processing. The results corroborated that the conventional methods might be more appropriate to develop a robust machine learning model in terms of accuracy and the computational complexities. Either BFG or LM is efficient to train the machine learning model. However, the BFG method is slightly more robust compared with the LM method.

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**Data availability** Some or all data and materials that support the findings of this study are available from the corresponding author upon reasonable request.

#### Declarations

**Conflicts of interest** The authors decalared that they have no conflict of interest.

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