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# PREDICTION OF LAND USE/LAND COVER CHANGE IN INDONESIA USING THE OPEN SOURCE LAND COVER DATASET: A REVIEW

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**Abstract.** Indonesia, as a promising developing country, faced with the fact that the development is not evenly distributed. Moreover, the number of people living in urban area is more and increasing at least 2.1% per year according to Central Statistics Agency (BPS). Hence, urban area has better transportation access and public facilites. However, high number of people living in urban area leads to spatial confilcts if spatial planning is not carried out based on sustainable development. For this reason, it is necessary to carry out long-term spatial planning using predictions of changes in land use/land cover in Indonesia. The purpose of this literature review is to get an overview of research development trends related to predictions of land use/land cover in Indonesia. Based on bibliometric analysis, the research trend related to this topic is that most research locations are in urban areas using satellite imagery input data and the Cellular Automata-Marcov Chain (CA-MC) method for making predictive models. Meanwhile, open source land cover datasets have not been widely used in land use/land cover prediction research in Indonesia. This can be used as input for updating further research.

**Keywords:** prediction, land use/land cover change, spatial planning, open source dataset.

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## 1. Introduction

Indonesia is the biggest archipelago country in the world. The number of islands in Indonesia is 16,772 islands with a land area of Indonesia 1,892,555.47 km$^2$ based on Keputusan Menteri Dalam Negeri Nomor 050-145 Tahun 2022 Tentang Pemberian Dan Pemutakhiran Kode, Data Wilayah Administrasi Pemerintahan, Dan Pulau Tahun 2021. Meanwhile, the population of Indonesia is increasing every year. Based on data from the Central Statistics Agency (BPS) the population in Indonesia is increasing every year. In 1960 the population of Indonesia ranged from 93,928,500 people and increased by 188% in 2020 to 270,203,900 people. In 2022 the population will increase by 2.1% from 2020 around 5,569,900 people. If calculated mathematically, the population density in 2022 in Indonesia will be 145 people/km$^2$. This means that in every 1 km$^2$ there are 145 people living in it. This is still classified as a low level of population density. Unfortunately, population growth in Indonesia has not been evenly distributed and has resulted in differences in the development of regions in Indonesia.

Prayitno et al. (2020) said that there is a correlation between regional development activities and an increase in population with changes in land use. Changes in land use are closely related to the quality of human life (Hakim et al., 2021). A sign of regional development is the development of infrastructure, as well as infrastructure and economic activities are aspects that can improve the quality of life. An increase in the quality of life can be a factor in increasing the population in developing areas which are often concentrated in big cities. This increase in population is an indication of urbanization. Urbanization can lead to changes in land use in urban areas, both land use and land cover (Mosammam et al., 2017, as cited in Helena Agustina et al., 2022). DKI Jakarta, for example, population density from 2011–2021 increased by 8.8%, of course the demand for built-up areas for settlements causes changes in land cover land from non-built-up land to built-up land. Changes in land cover can cause flood intensity because it disrupts the hydrological properties of an area, causing a decrease in infiltration rate and an increase in surface runoff (Farid et al., 2022). Santosa et al. (2022) predicted flood susceptibility in Ledug River, Tangerang City in the range of 10, 50 and 100 years from 2020 and the result is that changes in land use/land cover are one of the factors in flood vulnerability apart from elevation, rainfall, soil type, slope distance to the river and distance to the estuary. Antomi et al. (2019) predicts the quality of the environment in the city of Padang based on the effects of changes in land use and hydrological balance for 2030 and the conclusion from his research is that changes in land use in the city of Padang can cause an increase in surface water surplus. Yulianto et al. (2019) conducted research in the Citarum watershed and the results of his research said that land use change is the main problem that causes flooding. Changes from non-built-up land to built-up land are also related to a decrease in the region's ability to fulfill food stability, so that the region depends on food supplies from other regions (Suriadikusumah et al., 2022). Another impact of land use change in big cities is the decline in the quality of human life along with the decline in the quality of the urban environment.

Regional development can also occur not in big cities, but in an area that has natural resource potential. Miettinen et al. (2016), as cited in Umarhadi et al. (2022) saying that there was a change in land from peat forests to plantations (deforestation) in the Southeast Asian Islands (including Indonesia) by 71% from 1990 to 2015. Agroforestry activities such as plantations that are carried out intensely can result in land degradation with significant impacts from ecological aspect (Hasannudin et al., 2022). Global climate change is also the impact of deforestation (changes in land cover from forest to non-forest) (Guan et al., 2011; Li et al., 2020; McCarl et al., 2014; Sterling et al., 2013; Zhang et al., 2016; Supriatna et al., 2022). In fact, in 2021 there will be flooding in South Kalimantan, even though Kalimantan is an island with extensive forests when compared to other large islands in Indonesia (Supriatna et al., 2022). Putra et al. (2021)predict the potential for landslides in Pacitan Regency in 2030 and changes in land use are the main factors that have an influence on landslides. Struebig et al., (2015) conducted research on the correlation of changes in land use/land cover for orangutan habitat on the island of Borneo and the result is that orangutan habitat will decrease by 74% in 2080 if changes in land use from forest to non-forest are increasingly massive. This means that spatial problems due to changes in land cover and land use can arise in all regions in Indonesia if the spatial regulations are not effective.

In order to minimize spatial conflicts that have social, economic and environmental impacts, Indonesia implements sustainable development-based spatial management planning (Hsu & Perry, 2015, as cited in Hakim et al., 2020). Regulations related to spatial planning made by policy makers should use a geographical approach. This approach can be carried out by predicting changes in land cover/land use. This prediction can provide information related to problem identification and the impact of changes in land cover and/or land use in an area (Saputra & Lee, 2019). Land use prediction can be done using various modeling methods and using land use or land cover data multiyears. Modeling methods include Cellular Automata (CA) (Clarke & Gaydos, 1998, as cited in Artikanur et al., 2022), the Conversion of Land Use/Land Cover and Its Effect (CLUE) (Veldkamp & Fresco, 1996, as cited in Artikanur et al., 2022), Logit Model (LM)) (Wear & Flamm, 1993, as cited in Artikanur et al., 2022), and Spatial Markov (SM) (Wood et al., 1997, as cited in Artikanur et al., 2022). Meanwhile, in this era of globalization, the development of mapping technology and data sharing related to changes in land cover is very rapid. Land cover datasets, which are generally carried out using image interpretation methods, can now be obtained easily through a variety of open source data, both globally and locally. Examples of land cover datasets are GlobeLand30, Environmental Systems Research Institute (ESRI) Land Cover, The European Space Agency (ESA) World Cover, and The European Space Agency Climate Change Initiative (ESA-CCI) Land Cover on a global scale, as well as MapBiomas Indonesia on a local scale. This land cover dataset is very profitable to use as input data in making land use or land cover predictions.

To see research development trends related to land use/land cover 2014–2023, a literature review is needed to obtain information regarding updates that can be carried out for further research. It is hoped that this literature review can provide information regarding the development of methods, data (especially the use of open source datasets) and the use of land use/land cover predictions in Indonesia.

## 2. Method

The method used in this literature review is a bibliometric analysis related to predictions of land cover/land use in Indonesia which is associated with the use of open source land cover data. Bibliometric analysis is a technical analysis carried out by mapping the development of science and technology from various studies in order to evaluate and find updates for further research in a scientific field (Tupan et al., 2018). Database used in this literature review is Scopus. This database was chosen because it is a database comprehensive literature globally accompanied by comprehensive peer-reviewed quality literature (Tupan et al., 2018). The applications used for bibliometric analysis are VOSviewer and Scopus itself. The first step taken to carry out a bibliometric analysis is to enter keywords into the Scopus database. The keys used in this study can be seen in Table 1.

**Table 1.** Keyword Search in the Scopus database regarding LU/LC Prediction (source: Scopus search results processed by the author, 2023)

| Step | Keywords | Number of Articles |
|---|---|---|
| 1 | TITLE-ABS-KEY("Land Cover Change" OR "Land Use Change" AND "prediction") | 3,042 |
| 2 | PUBYEAR > 2013 | 2063 |
| 3 | DOCTYPE("ar") | 1,776 |
| 4 | AFFILCOUNTRY("Indonesia") | 34 |

The keywords of the first step are entering a title and abstract. From the results of this study there were 3,042 literature. Next, the keyword is added the year of publication. In this study, the documents sought will be limited from 2014 to 2023 (10 year period). Then added keywords for the article document type which resulted in 1,776 articles in the Scopus database. Another filter was carried out by adding Country Affiliation Indonesia and 34 articles were produced. This data is then mapped/selected relevant articles which are presented in the form of a Literature Review Flowchart.

**Table 2.** Keyword Search in the Scopus database regarding the Use of Opensource LC (source: Scopus search results processed by the author, 2023)

| Step | Keywords | Number of Articles |
|---|---|---|
| 1 | TITLE-ABS-KEY("Land Cover Change" OR "Land Use Change" AND "prediction" AND "GlobeLand30") PUBYEAR > 2013 | 6 |
| 2 | TITLE-ABS-KEY("Land Cover Change" OR "Land Use Change" AND "prediction" AND "ESRI Land Cover") PUBYEAR > 2013 | 0 |
| 3 | TITLE-ABS-KEY("Land Cover Change" OR "Land Use Change" AND "prediction" AND "ESA World Cover") PUBYEAR > 2013 | 0 |
| 4 | TITLE-ABS-KEY("Land Cover Change" OR "Land Use Change" AND "prediction" AND "MapBiomass Indonesia") PUBYEAR > 2013 | 0 |

Table 2 shows the search results for keywords from titles and abstracts related to predictions of land use change or land cover change using the GlobeLand30 land cover dataset which produced 6 articles in the Scopus database. Meanwhile, for the land cover datasets of ESRI Land Cover, ESA World Cover and MapBiomass Indonesia, there has been no research published on the Scopus database.

## 3. Discussion

This section will explain in 4 parts starting from the search results on Scopus, bibliometric analysis, discussion of the literature on Land Use/Land Cover change prediction and analysis of research gaps.

### 3.1. Scopus Analyze search result

Analysis based on the Scopus database using keywords in Table 1 point 2 produces a graphic analysis of the number of documents per year (Figure 1) and analysis of document types (Figure 2). Figure 1 shows that the number of research documents per year related to predictions of land use/land cover has increased significantly from 2020 to 2022.

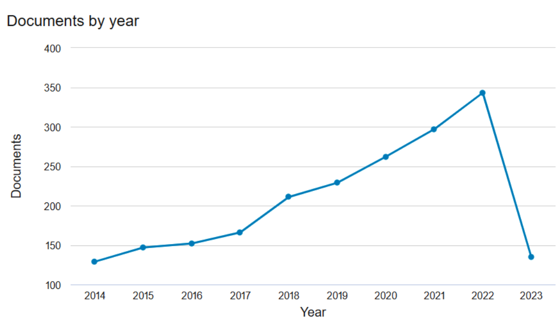


**Figure 1.** Analysis of the number of documents per year (source: Scopus Analyze search result, 2023)

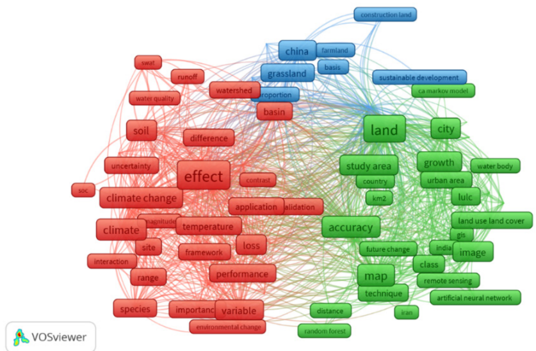


**Figure 2.** Bibliometric analysis based on words that appear frequently in the title and article abstract

Meanwhile, Table 3 shows that most of the research related to land use/land cover prediction is in the form of articles followed by conference paper types, reviews, book chapters and conference reviews. With the large number of studies with article types, the bibliometric analysis in this literature review uses document type limitations in the form of articles.

**Table 3.** Analysis of the number of documents based on document type (source: Scopus Analyze search results processed by the author, 2023)

| Document Type | Amount |
|---|---|
| Articles | 1784 |
| Conference Papers | 153 |
| Reviews | 66 |
| Book Chapter | 35 |
| Conference Reviews | 19 |
| Erratum | 4 |
| Editorial | 3 |
| Note | 3 |
| Data Paper | 2 |
| letters | 2 |

### 3.2. Bibliometric analysis

Bibliometric analysis using VOSviewer software uses keywords in Table 1 point 3. This analysis can be in the form of words that appear frequently in titles and abstracts and can also be based on keywords. VOSviewer can provide an overview regarding this analysis to make it easier to review research developments.

Figure 2 shows the words that appear frequently in titles and abstracts related to predictions of land use/land cover from 2014–2023. The analysis is divided into 3 clusters. For each word it appears. The first cluster is red where the words that often appear are effects and climate change. This means that there are many studies linking predictions of changes in land use/land cover and their impacts on climate change. The second cluster is green in which the words that often appear in the title and abstract are land, accuracy, map and city. This cluster shows more of the process/method of modeling land use/land cover change, it can also be seen that there is an Artificial Neural Network (ANN), CA Markov Model (CA-MC) and Random Forest (RF). The third cluster is blue, the word that often appears is China, grassland and sustainable development.

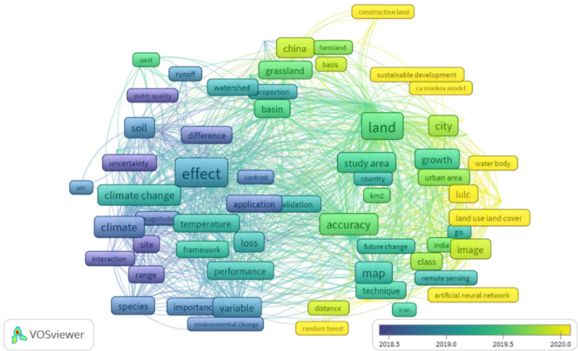


**Figure 3.** Bibliometric analysis based on words that appear frequently in the title and abstract and the year of publication of the article

Figure 3 shows the words that appear in the title and abstract accompanied by the year of publication. Words that pop up frequently with recent years are LULC, Artificial Neural Network (ANN), CA Markov Model (CA-MC) and Random Forest (RF), and sustainable development. Followed by the words city and urban area which indicate that most of the recent research research locations are urban areas. Meanwhile, the words that appear in the title and abstract from quite a long time ago are land use/land cover related to water quality, environmental change and climate.

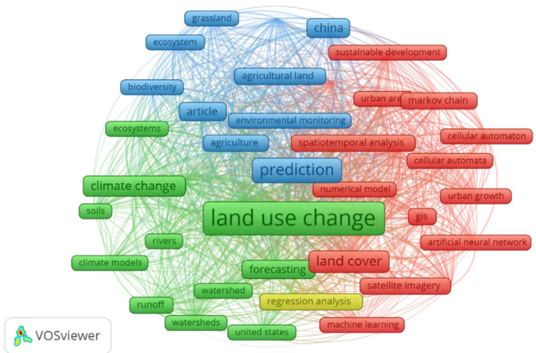


**Figure 4.** Bibliometric analysis based on keywords that frequently appear in articles

Figure 4 shows the keywords that often appear for the theme of predicting land use/land cover change. The visualization of VOSviewer is divided into 4 clusters. The first cluster is colored red and the words that appear are more indicative of the process of obtaining predictions, namely Cellular Automata, Artificial Neural Networks, machine learning, spatiotemporal analysis, and satellite imagery. The second cluster is green, which shows environmental interrelationships such as climate change, soil, watershed, runoff. The third cluster (in blue) shows predictions of land use/land cover often associated with the classification of grassland, agricultural land for environmental monitoring. The 4th cluster in yellow that is visible is the regression analysis related to the variable linkage process used to build the land use/land cover model.

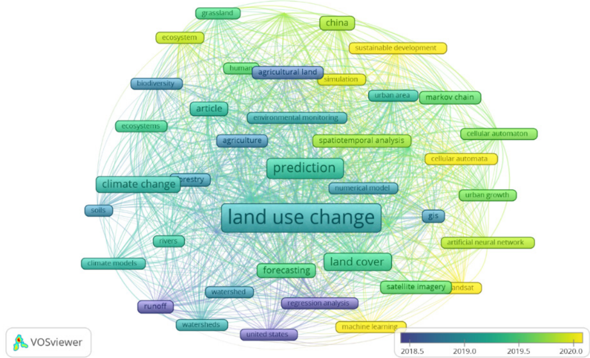


**Figure 5.** Bibliometric analysis based on keywords that frequently appear in articles

Figure 5 shows the frequently appearing keywords for the theme of predicting land use/land cover change accompanied by the year of publication. Cellular Automata and machine learning are the most recent methods that are often used as a method of modeling land use/land cover predictions. The data used for the latest research is in the form of multi-temporal satellite images. Research on land use/land cover prediction models associated with flooding and the use of regression analysis is a fairly old research from the last 10 years.

The trend of the modeling method for predicting changes in land use/land cover based on the results of bibliographical analysis is Cellular Automata (CA). Cellular Automata-Marcov Chain (CA-MC) is a combined method that can predict changes in land use and its spatial distribution (Lihawa et al., 2022) predict Sejati et al. (2019) land use/land cover using CA-MC with a kappa index of 0.5217. The kappa index is included in quite good category (Feizizadeh et al., 2022). Apart from Markov Chain, Cellular Automata can also be combined with Artificial Neural Network (CA-ANN). Ramadan and Hidayati (2022) never conducted research on land use/land cover change using the CA-ANN method in Purwokerto and the prediction has a kappa index of 0.634. Kappa index of 0.634 is included in the category of fairly good accuracy (Feizizadeh et al., 2022). Avtar et al. (2022) also predicts land use/land cover using 2020 on Viti Levu Island with a kappa index of 0.755. Kappa index category 0.755 is good accuracy (Feizizadeh et al., 2022). CA-ANN and the CA-MC and CA-ANN kappa index can be used for modeling predictions of land use/land cover, the difference is that CA-ANN is more suitable for research using transition probability model development (Wayan Gede Krisna Arimjaya & Dimyati, 2022).

## 3.3. Discussion of LAND USE/LAND COVER PREDICTION LITERATURE

Literature Review Flowchart is made to make it easier to map the literature. The input that is included in the flowchart is the result of keyword searches in the Scopus database, totaling 34. The data is then screened based on relevant titles, relevant abstracts and full papers that are relevant to the theme so that there are 20 potentials to be studied. Out of 20 In these articles, 12 of them used the Cellular Automata (CA) method to build land use/land cover prediction models. In order to map the literature more objectively, 5 articles were selected based on document citations (minimum number of citations 3) and the latest year to be studied in more detail. The Literature Review Flowchart can be seen in Figure 6.

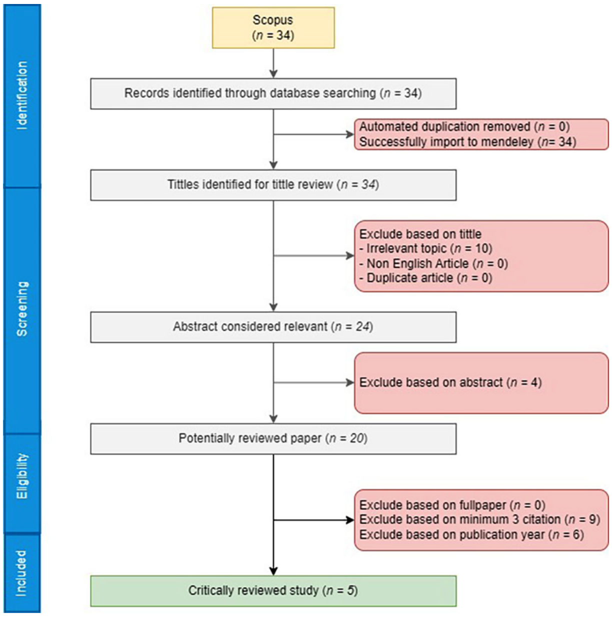


**Figure 6.** Bibliometric analysis based on keywords that frequently appear in articles

The five research articles were then compared in terms of methods, data, objectives, locations and classification of land use, etc. The comparison of the 5 articles can be seen in Tables 4–6.

Based on Table 4, most of the research on predicting changes in land use/land cover is published by journals related to the environment. The topics related to the prediction of land use/land change are tropical peat degradation, sugar balance, agroforestry, landslides and the use of (MLPNN) method.

From Table 5 it can be concluded that the trend of research is to use more satellite imagery as data in making a prediction model for changes in land use/land cover. Most of the satellite images used are Landsat and SPOT. The research area is sufficient to represent various administrative areas such as villages, cities, districts and islands. Three of the five studies use slope as a research variable. The number of classification classes of land use/land cover is more than 5 classes.

Based on Table 6, most research on land use/land cover prediction in Indonesia uses ArcGIS software for data processing and spatial analysis and modeling software such as TerrSet, PCI Geomatica, QGIS, and R studio. The five studies also used different methods so that they could represent the diversity of methods in making land use/land cover prediction models. From the results of the study, most of the land use/land cover classes that experienced an increase were built-up land which was a conversion of the vegetation class. This is the result of an increase in population in an area. The role of predicting changes in land use/land cover is very important for regional spatial planning based on sustainable development.

## 3.4. Research gaps

Based on bibliographic analysis and discussion of 5 literature related to land use/land cover prediction, the input data used is mostly satellite imagery. In fact, in this

**Table 4.** List of reviewed references

| No. | Title | Publications | Year | Keywords | Reference |
|---|---|---|---|---|---|
| 1 | Tropical peat subsidence rates are related to decadal LULC changes: Insights from InSAR analysis | Science of the Total Environment 816 (2022) 151561 | 2022 | peat subsidence, SBAS InSAR, LULC change, Tropical peatlands | Umarhadi et al. (2022) |
| 2 | Predicting Sugar Balance as the Impact of Land-Use/Land-Cover Change Dynamics in a Sugarcane Producing Regency in East Java, Indonesia | Frontiers in Environmental Science February 2022 Volume 10 Article 787207 | 2022 | Prediction, Modeling, LULCC, Driving factor, Land competition | Artikanur et al. (2022) |
| 3 | Agroforestry management systems through landscape-life scape integration: A case study in Gowa, Indonesia | BIODIVERSITY Volume 23, Number 4, April 2022 Volume 23, Number 4, April 2022 | 2022 | Agroforestry pattern, Business feasibility, Gowa District, Landscape, Life scape | Hasannudin et al. (2022) |
| 4 | Landslide Risk Analysis on Agriculture Area in Pacitan Regency in East Java Indonesia Using Geospatial Techniques | Environment and Natural Resources Journal 2021; 19(2): 141–152 | 2021 | Landslides, Land use, Agriculture, Geographic information system, Remote sensing | Putra et al. (2021) |
| 5 | Modeling land use/land cover changes prediction using multi-layer perceptron neural network (MLPNN): a case study in Makassar City, Indonesia | International Journal of Environmental Studies 2021, VOL. 78, NO. 2, 301–318 | 2021 | remote sensing; land cover changes; MLPNN | Hakim et al. (2021) |

**Table 5.** Data sources, objectives, locations and research variables

| No. | Objective | Variables | Data | Location | Reference |
|---|---|---|---|---|---|
| 1 | Analyze the subsidence rate using decadas LULC changes (8 classes: water, mangrove, rubber/mixed plantations, oil palm plantations, forest, shrub, cleared/burned land, built-up areas) and drainage period;<br>Estimate peat subsidence rate in Bengkalis Island by using time series SBAS InSAR on ALOS PALSAR-2;<br>Assess potentials enlarging coverage of SBAS InSAR results with LULC maps, elevation data, and distance from the edge of peatlands. | vertical velocity modeling: elevation data, distance from peat edge, LULC Change (1972, 1988, 1998, 2010, 2015 and 2019), vertical velocity produced by SBAS InSAR | PALSAR-2 (2016–2019) from Japan Aerospace Exploration Agency (JAXA), Landsat 1 MSS (1972) from USGS Earth Explorer, Landsat 5 TM (1988, 1998, 2010) and Landsat 8 OLI (2015 and 2019) from Google Earth Engine (GEE), Ground Water Level (GWL) from field survey and daily GWL from Peatland Water Monitoring System (SIPALAGA), DEM from SRTM, Topographic map of 1977, SPOT images from the Indonesian Geospatial Agency (BIG). | Bengkalis Island | Umarhadi et al. (2022) |
| 2 | Analyze LULC change (9 classes: forest, field/moor, built-up area, open land, sugarcane plantation, rice field, shrubs, fishpond, water body) in 2007, 2013 and 2019;<br>Predict LULC in 2031;<br>Examining the sugar sufficiency balance in Lamongan Regency 2031. | 4 driving factors: slope, distance from the road, rainfall, temperature | SPOT 4 (2007), SPOT 5 (2013 and 2019) from the National Institute of Aeronautics and Space (LAPAN); slope from NASA's DEM; road data from the Indonesian Geospatial Information Agency (BIG); climate data from the Meteorology, Climatology, Geophysics Agency (BMKG); population data and sugarcane productivity from Indonesian Statistics. | Lamongan Regency, East Java | Artikanur et al. (2022) |
| 3 | Assess LULC change (8 classes: water bodies, shrub, bare ground, paddy field, mixed dry agriculture, primary dryland forest, secondary dryland forest, settlement areas) in 2010, 2015 and 2020 and predicting 2030;<br>Analyze the ecological feasibility of plant species. | 3 driving factors: river network, road network, definite administrative boundaries | Identity of the respondents, type of species and preferences, land management patterns, cost and revenue agroforestry system, Landsat 7 ETM+ and Landsat 8 TIRS (2010, 2015 and 2020), river network, road network, administrative boundaries from the Ministry of Home Affairs of the Republic Indonesia, village monograph, and invasive series. | Bontolerung Village, Tinggimoncong Sub-district, Gowa District, South Sulawesi | Hasannudin et al. (2022) |
| 4 | Analyze LU change (7 classes: agroforestry, bush settlement, coastal, dryland, forest and paddy field) in 1998, 2008, 2018;<br>Predicting LU in 2030;<br>Analyze and predict landslide potentials in Pacitan regency in 2030. | parameters: topography, land use, soil, geology, slope and rainfall | Landsat 5 TM (1998), Landsat 7 ETM (2008), Landsat OLI (2018), Indonesian Topography maps, DEM, landform data, climate data, geological data, watershed maps, and water management data. | Pacitan Regency, East Java | Putra et al. (2021) |
| 5 | Analyze LU change (5 classes: built-up area, vegetation, barren area, waterbody, agriculture area) in 2006, 2011 and 2016;<br>Predict LU/LC changes in Makassar City in 2031. | 10 driving factors: slope, distance from downtown, distance from downtown, distance from education facility, distance from river, distance from health facility, distance from sea, distance from road, population density/ pixel, and elevation. | SPOT 4 (2006) from the Center for Regional Development and Spatial Information/ WITaRIS of Hasanuddin University, Spot 4 (2011) and SPOT 6/7 (2016) from National Institute of Aeronautics and Space/LAPAN, LU/ LC of Makassar from Geospatial Information Agency (BIG) | Makassar City | Hakim et al. (2021) |

**Table 6.** Method, software and research results

| No. | Method | Software | Results | Reference |
|---|---|---|---|---|
| 1 | Machine learning algorithm-based Support Vector Machine (SVM), Random Forest regression | MintPy (Miami InSAR Time series Software in Python); EnMAP-Box in QGIS; Dzetsaka plugin in QGIS | Machine learning methods can be regarded as one of useful methodologies to show the correlation of spatial coverage within vegetated areas in the tropical peatlands. It is shown that peat dominated areas in the Bengkalis island were subsiding in a range of long-term peat subsidence. Moreover, areas that had longer drainage, approximately more than 9 years, contributed to decelerate the subsidence rates. This occurs mainly within the vegetation types of oil palm and mixed/rubber plantations. Approximately, the rate of subsidence around the LULC vegetation is around 0.594 cm/year. | Umarhadi et al. (2022) |
| 2 | Conversion of Land Use and its Effect at Small Regional Extent (CLUE-s model) | Arc GIS, R studio | Comparing to other land use/land cover, the built-up area will be a significant competitor for sugarcane plantation areas between the year of 2025 and 2031. This may happen because it was predicted that the number of population will have a significant growth in 2031. The elasticity value of LULC conversion rate between built up areas and sugarcane plantation areas are one and 0.7. This means, the built up areas will continue to grow while sugarcane plantations will decrease. Therefore, a strategy needs to be established to secure the sugar cane production in the Lamongan Regency. | Artikanur et al. (2022) |
| 3 | Field observation, semi-structured-interviews, open questionaires, Cellular Automata-Artificial Neural Network (CA-ANN) | ArcGIS; QGIS | It is estimated that around 19% of the forest area will continue to decrease by 2030 in the Gowa Regency. However, the land use/land cover of settlement and agriculture areas are predicted to be increasing. Therefore, the agroforestry scheme is a viable option which brings benefits to farmers and the environment. By using the agroforestry system, farmers may cultivate commodities that have an economic impact on them while at the same time still preserving the nature. This concept could also reduce the potential issue of land-use conflict within the local community. | Hasannudin et al. (2022) |
| 4 | Unsupervised classification, weighted by paimin method, regression formula | ArcGIS, PCI Geomatica | Without the intervention of proper regional spatial planning, the risk value of landslides in the Pacitan Regency is 65.51%. Moreover, by considering the land capability classification during the creation of regional spatial planning, the risk value of landslides is reduced to 12%. This means, land capability classification plays a significant role as a factor that influences the risk value of landslides. This factor can reduce the risk value from high to medium, medium to low and low to very low. Moreover, this study also shows that the paimin modification method has an accuracy rate of 82%. | Putra et al. (2021) |
| 5 | Supervised classification, Multi-Layer Perceptron Neural Network (MLP NN), Marcov Chain | ArcGIS, TerrSet | The Kappa index of the prediction model is more than 0.8 which is in the category of good accuracy. Built-up land in Makassar City in 2031 is predicted to increase by 21.8% from 2016. This means that Makassar City will be dominated by built-up land of 80.37%. The increase in built-up area was accompanied by a decrease in water bodies, agricultural land vegetation and barren areas. Spatial-based spatial planning for the distribution of the population is urgently needed as a control over changes in land use in order to improve the quality of life of residents in Makassar City. | Hakim et al. (2021) |

era of globalization, mapping technology is increasingly advanced and global and local land cover data can be obtained easily. GlobeLand30 is a global land cover dataset (2000, 2010 and 2020) with a spatial resolution of 30 meters which is processed based on Landsat imagery and the Chinese Environmental Disaster Alleviation Satellite (HJ-1) by the Ministry of Science and Technology of China (Supriatna et al., 2022). ESRI Land Cover (2017–2022) and ESA World Cover (2020 and 2021) are processed based on sentinel satellite imagery (spatial resolution of 10–20 meters) but different in terms of Minimum Mapping Unit (MMU), ESA World Cover is digitized with MMU 100 m$^2$ while MMU ESRI Land Cover 250 m$^2$ (Venter et al., 2022). MapBiomas Indonesia Land Cover (2000–2019) is a local land cover dataset that is integrated into the MapBiomas Global Network created by MapBiomas Indonesia based on landsat imagery with a spatial resolution of 30 meters (https://mapbiomas.nusantara.earth/selayang).

Based on Table 2 in the methods chapter, the search results for research using the Scopus database related to the use of open source land cover are 6 studies using GlobeLand30. Meanwhile, the ESRI Land Cover, ESA World Cover and MapBiomas Indonesia Land Cover datasets do not yet exist. Of the 6 studies using GlobeLand30, 1 of them is research from Indonesia with a research location in the city of Banjarmasin. The conclusion is that the research gap for predicting land use/land cover change exists in the use of global and local open source land cover datasets. This prediction modeling research can use GlobeLand30 data for other regions in Indonesia, or it can also use the ESRI Land Cover, ESA World Cover and MapBiomas Indonesia Land Cover datasets which have not yet been researched in the Scopus database. Using this land cover data can cut some of the steps to get predictions of land use/land cover. Thus, the use of open source land cover datasets is felt to be more effective and efficient and can be used as an update from research on land use/land cover prediction models.

## 4. Conclusions

From several bibliometric analyzes using the Scopus database and visualization from VOSviewer, the research trend in 2014–2023 is that the research location is in urban areas, using the Cellular Automata-Marcov Chain (CA-MC) method and satellite imagery data to predict changes in land use/cover. land and linked to sustainable development. The use of open source land cover datasets for predicting land use/cover is still not widely used in Indonesia. From several available open source land cover datasets, research in Indonesia has only used the GlobeLand30 dataser. For further research developments related to changes in land use/land cover in Indonesia, it is necessary to update research related to the use of other open source land cover datasets such as ESRI Land Cover, ESA World Cover and local datasets, namely MapBiomass Indonesia Land Cover.

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## Author contributions

YIA is responsible for searching literature related to research themes, data processing, discussion and wrote the article. Meanwhile the MD is responsible for providing advice and reviewing the research draft.

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