

A REVIEW OF EXISTING ARTIFICIAL INTELLIGENCE MODELS AND SPECTRAL INDICES FOR CLIMATE CHANGE MITIGATION AND ADAPTATION

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ABSTRACT The earth and humanity are in serious trouble because of climate change. Recently, more than 11,000 scientists around the world released and signed a statement that the Earth is facing a climate emergency. Several works have been published on how to proffer immediate and long term solutions to this global issue, and one nexus from all the research works carried out point to the fact that the use of Artificial Intelligence (AI) can help in climate change mitigation and adaptation. This is because it has been noticed that the rebounding effects of the use of AI are directly and indirectly exacerbating climate change and there is need to focus more attention on AI for solution. However, there are ethical issues that need to be resolved about the reduction of the use of AI towards mitigation and adaptation to accommodate all the stakeholders. Other works dealt with the use of satellite spectral indices to determine how human activities have affected various climatic variables such as rainfall, land-use/land-cover, flood, air quality, heat waves among others. Hence, this paper presents the review of previous research on AI models, satellite spectral indices, opportunities, ethical issues, solutions and policy levers for climate change mitigation and adaptation.

KEYWORDS: Artificial Intelligence (AI), Machine Learning, Climate Change, Mitigation, Adaptation, Ethical Issues

I. INTRODUCTION

Man and climate are two allies over many centuries. All human activities were planned according to the climatic pattern of his environment. However, uncontrolled and insensitive human activities about the immediate surrounding and its implications, man went on deforestation, urban sprawling, transportation, oil exploration and fossil fuel burning among others. For every action there is a reaction. Hence, in response to these age long activities, the climate is readjusting its pattern - climate change, which has become a big issue and an “emergency” to humanity because the weather is now unpredictable for him to also matchup. There are only two options, either we quickly matchup and adjust to this change –adaptation, or we look for means to reverse the change – mitigation, both humanity and the earth are on disaster pathway. Artificial intelligence, if properly managed and utilized can help in both adaptation and mitigation by providing methods that are useful for education, research, engineering, and decision making policies. Also, with the help of electromagnetic wave bands from satellite captured images it is easier to determine the extend to how man has really affected the environment using climate features such as land-use/land-cover, air quality, rainfall, heat waves, flood among others. Hence, this paper presents a review of various literatures on artificial intelligence algorithms and satellite spectral indices for climate change mitigation and adaptation.

II. METHODOLOGY

The PRISMA guidelines which lays out the globally approved approaches for the conducting systematic reviews was adopted for this study. This process started with the conduct of a systematic search of databases and search engines using predefined keywords to get abstracts from related published articles. These abstracts were screened based on a set of inclusion criteria by considering research papers, journals and scholarly articles obtained from some bibliographic databases such as (i) Research Gate; (ii) ScienceDirect; (iii) IEEE Transactions on Geoscience and Remote Sensing; (iv) Elsevier; (v) ResearchGate; (vi) MDPI; (viii) The World Bank (IBRD-IDA) and (viii) arXiv, among other scientific databases. This search was conducted primarily with the intention of finding related research papers on the subject matter of discuss. To select the appropriate articles from digital libraries, an attempt was made to conduct an initial search process using pre-selected search terms or strings with Boolean search query terms such as “climate change” AND “machine learning”, “climate change” AND “artificial intelligence”, “spectral indices” OR “machine learning”, “spectral indices” AND “land use land cover” and so on. These search phrases, which are based on artificial intelligence models and spectral indices for climate change mitigation and adaptation terms and their derivatives, acronyms, and often searched synonyms, have to be determined in order to prevent results from unrelated research publications. Terms and phrases such as application of artificial intelligence of air pollutants in cities, using deep learning models to detect air pollution from satellite imagery, ensemble machine learning models’ strengths and weaknesses in predicting air quality, machine learning and rainfall estimation, AI for climate change adaptation, ethical issues of AI in climate change, satellite spectral indices and land-use/land-cover, index-based extraction of built-up areas. These search strings were used in order to avoid searches from research papers that are not related and for selecting papers that were published in reputable conferences and journals.

However, the bibliography of the articles and other relevant papers cited can help in obtaining more insights into the remaining content of the topic under study. To add to this, the areas where the most recent contributions are related were covered. The main aim of this review is to propose across-the-board literature investigations on artificial intelligence models and spectral indices for climate change mitigation and adaptation. A time-restricted filtering of published papers between 2019 and 2024 was further applied as the main focus for the selection of the articles. This was done to ensure that the review is based on recent and up to date knowledge on the topic. However, older articles with relevant knowledge on the subject matter were also included, especially where the recent ones made reference and information found were highly relevant. Papers mainly published in English language were only considered for this study, while adopting Mendeley style of referencing. Following the completion of the search procedures, the researchers went through a screening procedure to locate pertinent papers by first analyzing the paper title, content of the abstract, methodology used, results and the conclusion from the screened papers were taken note. Multiple exclusion criteria were established, such as (i) duplicate papers, (ii) full-text availability, and (iii) papers that are not related to artificial intelligence models and spectral indices for climate change mitigation and adaptation. The objectives of this study are to:

- a) Review related papers that focused on application of AI-based model in addressing climate change challenges,
- b) satellite spectral indices used in analyzing various environmental variables,
- c) ethical issues posed by the application of AI on the environment and
- d) socio-economic divide between developed and developing nations in climate resilience efforts

A. AI AND AIR QUALITY MONITORING IN CITIES

Table 1 shows work done on monitoring air quality in cities using AI. [21] carried out a general review of application of geospatial artificial intelligence in mapping of air pollutants in urban cities. It also discussed deep learning architectures in developing models from air pollution obtained from satellite sensors, and the adoption of AI and machine learning in dealing with hazards of air pollution from works of many researchers. The paper affirmed that deep learning has shown to have promising models with the potential

to increase the resolution in data-poor scenarios with accurate forecasting results. And that according to literatures, it has been argued that low- and middle-income countries with minimal monitoring and surveillance infrastructure may depend on image-based convolutional neural networks (CNN) as a cost-effective method of estimating local environmental exposures, as supported by [17]. In its proposal the paper advocated that many researchers have deployed successfully geospatial artificial intelligence (a combination of Geospatial Technology and Artificial Intelligence) in many disaster related problems and agricultural studies, which are now being used in air quality mapping and air pollutants modeling. The methodology used geospatial technology for spatio-temporal mapping of air pollutants and prioritization of locations while the AI techniques (Deep Learning techniques, ANN, CNN etc.) are applied to forecast the concentration of the pollutants in order to install air purifiers in the prioritized locations. They however proposed their own model based on this methodology and hoped to deploy it on android and web application. However, their proposal is not clear enough on how they intend to achieve their aim. [5] explored the potential of AI in transforming ambient air quality control. They conducted an in-depth review of current machine learning, deep learning, and other AI applications, focusing on their strengths and weaknesses in predicting and controlling air quality. The paper reviewed research works conducted on two great cities, Beijing, China and California, USA. The paper cited the research conducted in Beijing using Gradient Boosting Regression Tree (GBRT) model to predict PM_{2.5} with the result outperforming linear regression model, demonstrating a higher degree of accuracy and precision, while Convolutional Neural Network (CNN) model was used in forecasting Air Quality Index (AQI) in California. They concluded by recommending that AI could be integrated with Internet of Things (IoT) devices for real-time air quality monitoring and control for automated and timely interventions that will enhance responsiveness of air quality management systems. Also, that AI could provide personalized advice to individuals about when to avoid outdoor activities or when to wear pollution masks and by identifying air pollution 'hot spots'. It can also enable policy makers to target affected and marginalized communities [2].

[14] proposed an end-to-end air quality predictive model for smart city applications, utilizing four machine learning techniques and two deep learning techniques - Ada Boost (AB), support vector regressor (SVR), Random Forest (RF), K-nearest neighbor (KNN), multi-layer perceptron (MLP) regressor and long short-term memory (LSTM). The study was conducted in four different urban cities in Malaysia. The air pollutant concentrations considered were PM_{2.5}, PM₁₀, O₃, and CO. Other meteorological data such as wind speed and wind direction and their interaction with the pollutants were also considered. Results obtained showed that LSTM performed best among all the models with overall high coefficient of determination (R^2) values in the four study areas, with the R^2 values of 0.998, 0.995, 0.918, and 0.993. And that among the studied pollutants, PM_{2.5}, PM₁₀, NO₂, wind speed and humidity are the most important elements to monitor. It also concluded that the results can aid policymakers in understanding the underlying causes of air pollution and develop more effective smart strategies for reducing city pollution levels. They also suggested remedies for implementing several technologies such as IoT, integrated health impact assessment and drone technology to improve air quality prediction accuracy that will eventually notify the public on the air quality depending on the health condition of each individual. Their conclusion also corroborated statement made by other authors that AI can help in integrating governmental policies to promote a more sustainable and healthier environment regarding greenhouse gas emissions and air quality. However, the study needs to improve the work by including more states for more data generalization. The work also needs to include natural phenomenon and extreme weather for similar reason. Table 1 shows similar works done on monitoring air quality in cities using AI.

Table 1: AI and Air Quality Monitoring in Cities

S/N	Objectives	AI model	Authors	Year
1.	general review of application of geospatial artificial intelligence in mapping of air pollutants in urban cities	A survey (CNN and ANN)	Mishra et al.	2021
2.	review of strengths and weaknesses of current AI models in predicting and controlling air quality	A survey (GBRT and CNN)	Kulikova et al	2023
3.	end-to-end air quality predictive model for smart city	AB, SVR, RF, KNN, MLP and LSTM	Neo et al.	2023

B. MACHINE LEARNING-BASED MODEL AND RAINFALL ESTIMATE

Authors in [13] designed a machine learning approach for rainfall estimation by integrating heterogeneous data sources such as Rain Gauges Sensors (RGs), radars, and satellites. This methodology permits estimation of the rainfall where RGs are not present, while exploiting the spatial pattern recognition ensured by radars and satellites. The paper is of the opinion that providing an accurate rainfall estimate at individual points is a challenging problem in mitigating risks (floods and landslides) as a result of severe rainfall events. They cited previous works that implemented dense networks of RGs sensors, used to obtain direct measurements of precipitation intensity, where the results are usually interpolated over the entire studied area by employing spatial interpolation methods for estimating the precipitation field. However, these methods are computationally expensive, and that it is necessary to integrate further information to be able to improve the estimation of the variable of interest in unknown locations. To overcome these issues, the paper proposed a machine learning-based methodology that exploits a classifier based on ensemble methods (combination of many machine learning models) for rainfall estimation, which is able to integrate information from different remote sensing measurements. The ensemble is based on a set of trained Random Forest (RF) classifiers and a probabilistic meta-learner, used to combine the estimated probabilities provided by the base classifiers according to a stacking schema. Their proposal supplies an accurate estimate of the rainfall where RGs are not available, permits the integration of heterogeneous data sources exploiting both the high quantitative precision of RGs and the spatial pattern recognition ensured by radars and satellites, and is computationally less expensive than the interpolation methods. Experimental results, conducted on real data from an Italian region, Calabria, showed a significant improvement with probability of detection of 0.58 and mean-square error of 0.11, as against the Kriging with external drift (KED), a well-recognized method in the field of rainfall estimation, with probability of detection of 0.48 and mean-square error of 0.15. However, the performance of the algorithm worsens the sensibly for all the measures when the RG information is removed. The lowest MSE value (0.11) was obtained when all the data are used, which confirms that it is necessary to use all the sources of data to obtain better results. There is also a need to validate this method on a larger time interval, so as to consider the effects of seasonal and yearly variability of the model.

Authors in [15] reviewed some published articles on rainfall measurements using state-of-the-art artificial intelligent techniques while presenting some open research issues from the review papers such as (1) Data validation not being from real measurement (2) Rainfall events being limited to only 6 cases for model verification (3) More experiments are required on satellite link and (4) Limitations to detect events with rain rates < 0.3 mm owing to small attenuation inducement. It stated further that lack of datasets is a major issue in machine learning modeling. Long term rainfall validation data from calibrated measuring instruments is very necessary to obtain adequate variations in rainfall intensity throughout the year on a country such as Indonesia with various topographical conditions ranging from low-lying urban areas, highlands, and mountainous valleys making the country prone to hydrometeorological disasters like flash floods and landslides. Also, its geographical position between the Pacific and Indian oceans and vast

surrounding oceans makes high-density rainfall observations indispensable for both disaster mitigation and climate monitoring. This makes the amount of rainfall data captured all over the country to be very adequate to be used as training, testing and validation data in deep learning. That for a country like Indonesia, rainfall estimation methods should be done in line with its peculiarity as stated below:

- a. using combination of terrestrial/satellite link and meteorological surface data for mainland area;
- b. The coastal area should combine weather radar and meteorological satellite, an
- c. The offshore or open sea area should combine meteorological satellite and maritime satellite link.

The authors however failed to conduct any empirical research on how to achieve all their proposals.

For authors in [8] to generate improved precipitation estimates over the Upper Blue Nile Basin presented artificial intelligence-based techniques for rainfall estimation, integrating multisource precipitation datasets using ensemble machine learning models such as decision tree (DT), random forest (RF), gradient boosting (GB), and neural network (NN). The ensemble models merged multiple satellite and atmospheric rainfall datasets to generate error-corrected precipitation estimates. It was discovered that the training time of the decision trees was the shortest, followed by gradient boosting and random forest while neural networks took the longest training time and the most resource intensive. The model predictions accuracy was evaluated using ground-based precipitation data derived from local rain gauge networks between 2000 and 2012. The ML models outperformed the input models, especially in cases above the 25th percentile and between 75th to 100th percentile range that often indicates the flooding of the area. They hoped that this information will be helpful for the authorities to take necessary action to minimize loss in the future. However, they failed to extract numerical values from the satellite images that should have been used to complement they work as against using just 13 years dataset for a climate related feature like rainfall.

Authors in [9] proposed deployment of artificial intelligence for climate change adaptation. They based their case study on three continents namely: North America, South America and Africa. Findings revealed that 80% of respondents from North America and 75% from South America are already utilizing Digital Technologies (DTs) and AI as tools to increase climate change adaptation. The authors were of the opinion that these high percentages of positive responses can be attributed to the availability of appropriate infrastructural facilitates that are available to them. The opposite was confirmed from respondents in Africa who indicated that they seldom use DTs or AI as part of their climate adaptation tools box. Other issues raised by the respondents from all the continents include fear: that AI is an existential threat to humanity which will lead to robots taking their jobs; potential privacy intrusion of unregulated and unchecked AI, and lack of legal-ethical frameworks for the regulation of AI use in the context of climate change. However, 44 % among the respondents believed that AI is a vital tool for enhancing climate resilience and supporting the post-COVID-19 recovery process. Also, that DTs are valuable tools for enhancing governance and policy coherence on issues related to climate change adaptation, towards the implementation of SDG13. However, the paper failed to accommodate more than 104 people from 51 countries, which might not be a true representation of the happenings, especially across African countries. Presented in table 2 are similar works on machine learning-based model and rainfall estimate.

Table 2: Machine Learning-Based Model and Rainfall Estimate

S/N	Authors, (year)	Objectives	AI model
1.	Guarascio et al., (2020)	Using radars and satellites images to estimate rainfall where rain gauges sensors are not present	Random Forest (RF) classifiers and a probabilistic meta-learner
2.	Mardyansyah et al., (2024)	reviewed of published articles on rainfall measurements using state-of-the-art artificial intelligent techniques	A Survey
3.	Khan et al., (2021)	to generate improved precipitation estimates over Upper Blue Nile Basin	decision tree, random forest, gradient boosting and neural network

4.	Walter et al., (2022)	AI adoption for climate change adaptation in 3 continents	carried out a survey
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C. OPPORTUNITIES, ETHICAL ISSUES, SOLUTIONS AND POLICY LEVERS

Authors in [11] presented a comprehensive overview of multi-faceted relationship of AI with climate change, and recommend policy levers for mitigation and adaptation pathways. The paper submitted that with the increasing deployment of Artificial Intelligence (AI) technologies across various fields, it is important to understand the duo nature of AI, which may accelerate or impede climate progress, and how various stakeholders can guide those developments. It also emphasized two important scenarios where: (1) AI can facilitate climate change mitigation and adaptation strategies in sectors such as forestry, manufacturing, energy, agriculture, and disaster management; and (2) AI contributes to rising greenhouse gas emissions by high-emitting sectors that benefit from the applications of AI or increase in consumer demand, and via energy use associated with the applications of AI itself. The paper further cited various examples of the application of AI in oil and gas exploration and extraction, transportation sector via autonomous vehicles that may result in increased emissions depending on the conditions of deployment, marketing or manufacturing leading to increased consumption of goods and services thereby raising associated emissions. The authors particularly cited [17] saying that advancement in digital technologies through AI in the oil and gas sector by 2025 could generate as much as USD 425 billion in value that may slow the transition to low-carbon technologies. Although the paper was of the opinion that some autonomous vehicles such as platooning, 11 eco-driving, and integrating autonomous vehicles (AVs) with low-carbon transportation could reduce the energy consumed, however it is also of the view that AVs could actually lead to higher energy consumption, where individualized transportation will become easier thereby increasing the number of miles traveled, and shifting passengers and freight away from low-carbon options such as rail [25]. Also, [20] observed that most widely used AI systems run on very little power on standard laptops and smartphones while most research dedicated systems use larger amounts of energy with estimated carbon impacts much more than the lifetime emissions of a car. As supported by the reports of International Energy Agency [7] that currently data centers consume around 1 percent of global electricity with its impact on the global GHG emissions.

Conclusively, for the present and future well-being of the society, the paper highlighted three main potential areas that policy makers could align the use of AI with climate change mitigation and adaptation, which include (a) fostering the research, development, and deployment of AI in applications explicitly aimed at addressing climate change, (b) regulating the impacts of AI-driven technologies that are emerging or already in use across many sectors of the economy, and (c) increasing public sector capacity for regulation and innovation at the intersection of AI and climate change. However, the authors failed to carry out any empirical study on the use of AI in climate change mitigation or adaptation. On artificial intelligence and climate change: ethical issues, [2] cited a statement released and signed by more than 11,000 scientists around the world who concluded that planet Earth is facing a climate emergency [16] And one of the moral obligations of scientists is to “tell it like it is” sending clear warning to humanity of any catastrophic threats. This statement was also supported by the Intergovernmental Panel on Climate Change [6] who described climate change as an “emergency” because its adverse effects, such as extreme weather events, drought, wildfires, flooding and sea-level rise are already present at 1.1°C above preindustrial levels. It further cited big tech companies like Apple, Microsoft and Google who always see themselves as “clean tech” due to the purchase of emission credits. Whereas, it is unclear how large their emissions actually are [4]. Another typical example is the research conducted by [3] on GHGs emissions from computing devices (tablets, desktops, smartphones and laptops), data centers and communication networks. They discovered that data centers had the largest emission of 45% followed by communication networks with 24%. Another research conducted by [20] focusing explicitly on AI as a contributor to climate change concluded that training of an AI model for natural language processing (NLP) emitted approximately 300,000 kg CO₂e. This is huge value that can be likened to emissions from multiple vehicular activities, which calls for a serious concern

about the negative contribution of AI to climate change. The paper went further to explain rebound effects such that trying to improve energy efficiency of cars may lead to increased use of cars, increase in the demand (production) for tires, batteries (such as lithium and cobalt and other materials) for electric vehicles, including transportation of these materials to factories for production and eventual increase use of energy in restaurants and hotels visited when travelling around. Simply put, AI has both direct and indirect link to the increase use of fossil fuels with direct link to change in climate. As part of options for fighting climate change, the paper emphasized that AI companies need to reduce their own emissions that will in return lead to mitigation of climate change through the following: reduction in the energy needed for cooling in data centres and reduction in the amount of data used in training AI models, that is, avoid using more data than necessary - Bigger is not always better. Generating larger models to achieve smaller improvements might be questionable from a climate change perspective [22]. However, these options also raise ethical concerns about what should be done:

- a) How should emissions from training and use of AI be reduced?
- b) How should AI be used for mitigation?
- c) How should AI be used for adaptation?

These three climate-related ethical issues were addressed with the following four key aspects: usefulness, freedom, justice and responsibility.

- a) **Usefulness** - assessing the usefulness of AI for mitigation and adaptation should account for the expected costs in terms of emissions due to the use of fossil fuel energy and not just the benefits of using the AI.
- b) **Freedom**. That freedom could either be negative or positive. And in the context of climate mitigation and adaptation, negative freedom is always more or less constrained by laws or social norms, while positive freedom is the opportunity to live in a good environment with a reasonable standard of living and making reasonable choices for both future generations and low-income countries. That it should not only be for the present generations and high-income countries, as it is being done presently. However, limiting AI use in the society to reduce emissions may be problematic from a freedom perspective, as some market liberals may oppose such political steering, while eco-socialists will find it acceptable. Therefore, issue arises in determining acceptable AI applications in the society, such as combating climate change or improving healthcare, and regulating and enforcing restrictions. There need to be mutual agreement between negative and positive freedom in the context of climate change mitigation and adaptation. To this end, two key ethical issues arise that require balancing of present-day negative freedom and future positive freedom with the following questions:
 - i. To what extent should the negative freedom of companies and individuals be restricted to reduce emissions from the use of AI?
 - ii. To what extent should the negative freedom of present generation be restricted for the sake of ensuring the positive freedom of future generation companies and individuals?
- c) **Justice** - According to UNFCCC [24] justice requires high income countries assume stronger responsibilities than low-income countries in undertaking mitigation and adaptation measures, because high-income countries caused most of the greenhouse gas emissions while the low-income countries suffer the consequences. Hence, high-income countries should pay more for fighting climate change based on three options (1) the polluter-pays principle – based on their percentage of contribution (2) the ability-to-pay principle – because they are richer than low-income countries and (3) the principle of equal per capita shares – individuals in high-income countries should pay more because they emit more than their counterparts in low-income countries [18]. However, there are two key ethical issues to contest with: (1) how should low-income countries get equal access to AI? and (2) how should AI be used to assist low-income countries in mitigation and adaptation context? The paper is of the belief that however difficult it is to proffer answers to these questions, it is clear that many low-income countries find adaptation more urgent than mitigation because of their vulnerability and willingness to become more resilient to the adverse effects of climate change [4]. Again, there exist other issues because

mitigation is a global issue whereas adaptation is mainly a local or regional issue that could easily be tackled.

- d) **Responsibility** -This ethical aspect is all about (1) Who should take responsibility for the use of AI in relation to climate change? (2) How should they do it? According to the authors, the answer may be all who are connected in the production or consumption of AI services, such as AI developers, tech workers, AI companies, governments and individuals as consumers. This is because companies develop and sell AI services for profit while governments regulate the activities of these companies nationally and by means of international agreements. The answer to second question was that, audit and certification mechanisms are relevant options. It also argued the EU agenda for AI to support environmental sustainability should be spread globally and make the environmental potential of AI available to low-income and middle-income countries.

Authors in [10] reviewed recent research works on the applications of artificial intelligence in mitigating the adverse effects of climate change, with a focus on energy efficiency, carbon sequestration and storage, weather and renewable energy forecasting, grid management, building design, transportation, precision agriculture, industrial processes, reducing deforestation, and resilient cities. The paper affirmed that climate change is a major threat already causing system damage, inducing global economic losses of over \$500 billion. They are of the view that artificial intelligence can be applied to solve these issues because of its ability to integrate internet resources to make prompt suggestions based on accurate climate change predictions. Findings from their reviewed literatures revealed that enhancing energy efficiency can significantly contribute to reducing the impact of climate change, especially by using AI to predict energy demand and enhance energy efficiency to reduce environmental pollution. According to the paper, numerous nations are already going this direction to improve their energy efficiency and reduce energy waste. And that AI has also been used to improve accurate weather forecast for renewable energy production that guaranteed a continuous electricity supply and in transportation, by optimizing bus routes and passenger traffic. So also its ability to help in reducing environmental impact of agrochemical use by collecting and analyzing environmental data related to crop growth, enabling farmers to reduce chemical use with maximum yield. The paper further stated, that AI assisted smart manufacturing will promote sustainability by reducing energy consumption, waste, carbon emissions and energy consumption in buildings between 30% to 50%. It will also reduce electricity bills by 10–20% and carbon dioxide emissions due to transportation systems by approximately 60%. However, the authors also failed to conduct empirical research. Table 3 presents issues and opportunities of integrating AI into climate change.

Table 3: Issues and Opportunities of Integrating AI into Climate Change

Authors, Year	Objectives	AI model
Kaack et al., (2020)	overview of multi-faceted relationship of AI with climate change, and policy levers for mitigation and adaptation	A review of journals
Nordgren, (2022)	ethical issues arising from the use of AI in climate change adaptation and mitigation	AI ethical issues
Chen et al., (2023)	reviewed of recent works in using AI to predict energy demand and enhance energy efficiency to reduce environmental pollution	A review of journals

D. SATELLITE SPECTRAL INDICES AND LAND-USE/LAND-COVER

Table 4 shows authors who carried out work on satellite spectral indices and land-use/land-cover. [12] proposed Monitoring built-up area transformation using urban index and normalized difference built-up index analysis on Makassar city, Indonesia. The city is one of the metropolitan cities that are experiencing massive increased construction because of population growth. The purpose of the study was to identify changes in land use and density (built areas) in the Makassar City between 2013 and 2017. Multi-temporal Landsat OLI 8 was the dataset used to analyze the study area. Several spectral indices were used to reveal

changes in land use and land cover were considered. Such as Normalized Difference Built-Up Index (NDBI), Urban Index (UI) and Normalized Difference Vegetation Index (NDVI). These indices rely on combination of different bands of the electromagnetic wavelength for computation, such as Short Wave Infrared (SWIR), visible Red (Red) and Near Infrared (NIR) bands. Results show that over a period of four years both NDBI and UI spectral indices indicated that built-up areas in the city increased by approximately 18 and 6%, respectively. And that some areas in the city witnessed more increase in built-up areas than others. However, the numerical values were not extracted from the satellite images for further analysis.

Authors in [1] proposed development of new index-based methodology for extraction of built-up area using landsat7 imagery: a comparison of performance with SVM, ANN, and existing indices. The authors introduced a new built-up index named powered B1 built-up index (PB1BI). They claimed that their proposed index is conceptually simple and computationally inexpensive for extracting built-up areas from Landsat7 satellite images. It adopted bootstrapping method for threshold estimation, which improved the classification performance of the built-up indices by 17.75% overall accuracy and 40.49% kappa (κ) coefficient. They also claimed that their proposed index has similar performance when compared with the machine learning models, which are considered to be computationally expensive. The PB1BI achieved 97.45% average overall accuracy and 0.907 kappa (κ) coefficient, while the SVM achieved 99.10% and 0.942 and ANN with 87.24% and 0.450, respectively. The index classification performance was also verified for built-up classification using satellite product, Landsat8, showing similar improvement with 95.7151% average accuracy and 0.8843 κ , respectively. However, there is need to compare their results with other robust machine learning models such as Random Forest etc to concretize their claims.

Authors in [23] evaluated spectral built-up indices for impervious surface extraction using Sentinel-2A MSI imageries: A case of Addis Ababa city, Ethiopia. The study compared the performance of seven spectral built-up indices used in land-use and land-cover classification, such as Built-up Area Extraction Index (BAEI), Band Ratio for Built-up Area (BRBA), Modified Built-up Index (MBI), Normalized Built-up Area Index (NBAI), New Built-up Index (NBI), Normalized Difference Built-up Index (NDBI), and Urban Index (UI). All the indices were evaluated based on histogram overlap and spectral discrimination index (SDI). Findings revealed that NBAI has the highest SDI values of 1.24, 1.23 and 1.54, followed by NBI with 1.06, 1.08, and 1.23 and NDBI having 1.16, 1.1 and 1.26. The classification overall accuracy for these three indices were 81%, 86%, and 82% respectively. The paper concluded that index-based methods are fast and easy to implement with superior performance because of the higher surface reflectance of built-up in the Short Wave Infra-Red (SWIR 1/SWIR 2) bands that permits them to be clearly distinguished from other land surfaces.

Table 4: Satellite Spectral Indices and Land-Use/Land-Cover

Authors, (Year)	Objectives	Spectral Index
Ichsan et al, (2019)	identify changes in land use and density in Indonesia	NDBI, UI and NDVI
Mukherjee et al., (2021)	Comparison of ML models with new spectral index-based methodology	PB1BI, SVM and ANN
Kebede et al., (2022)	compared the performance of seven spectral built-up indices	BAEI, BRBA, MBI, NBAI, NBI, NDBI and UI

III. CONCLUSION

It is evident that climate change is a global “emergency issue” that needs all hand on deck towards a common and lasting solution, not only for the developed nations that have all it takes for mitigation and adaptation but also for developing countries who are struggling with their immediate needs – adaptation. Among the ethical issues raised on the use of AI towards climate change mitigation, there must be concerted effort by the developed countries on proper disposal of waste products from AI and other technological devices from data centers, autonomous vehicles, batteries and so on. They should not see the developing countries as their dumping ground because of the rebounding effects which will further exacerbate climate

change globally. Future work should focus on how to accurately forecast climate change features using AI, to ensure citizens and governments make informed decision about their health, lives and properties.

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