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Land Use Land Cover Change Detection and Future Forecasting in Ningxia, China: A Random Forest and ANN-Based Approach for Sustainable Development

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Abstract
The accurate tracking and prediction of Land Use Land Change monitoring and prediction precision or accuracy are urgent for technological development and practical ecology management. This objective is pursued by understanding of the changing patterns of LULC temporally and spatially in Ningxia, China, a semi-arid region experiencing desertification and over-rapid urbanization. Therefore, one of the main objectives of this work is prediction for the future trends within this field of research. This research utilized the MODIS data taken from the satellite Moderate Resolution Imaging Spectroradiometer through remote sensing and advanced machine learning algorithms. During 2003 to 2023, the random forest classifier was used to monitor the LULC change in Ningxia, passing to different stage and increasingly affluent cities. These surveys predict the possible scenarios, including the rapid increase in desertification, urbanization side and erosion of the areas for agriculture, forestry and water-covered. A merging approach based on cellular automata and artificial neural network employed with the purpose of typing the future condition of land use and land cover. This approach relies on calibration to study future operations that remain unaffected by peoples' choice. The calibrated version could be done to become tightly related to the spatial variables that heavily shift in time. The altered model achieved a great accuracy of 85% similarly the maximum value of 0.96 for the Kappa coefficient, which indicates the discovery of the ANN. Deserts and town are a few of the surfaces that have grown under science. As a result, wild animals' facilities and natural flora have deteriorated, lowering agricultural output. (1) According to the transition probability matrix, this could be as high as 28% from agricultural land to desert. (2) One of the findings from spatial analytical trend analysis that I mentioned above, is also detected in terms of a distinct rise accumulation just for the desert category with respect to all other LULC types combined. (3) Thus, further increases in desert and artificial land might be coupled with urbanization (e. g.) to climate change.

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Keywords: Land Cover Change, random forest modeller, sensors; transition, CA-ANN

1. Introduction

Land use and land cover (LULC) are basic features of the Earth's surface necessary for ascertaining their impacts on environment. Changes in LULCs can lead to significant impacts on biodiversity, as well as climate and water resources (representing environmental aspects) or human health/well-being (economic aspects). LULC changes monitoring and forecasting in the region is necessary for sustainable development as well as land management practices (Jin *et al*., 2020) [14]. The development of novel methodologies for efficient and accurate detection or mapping LULCC is critical to environmental science, as changing land use can have profound ecological consequences (such as effects on biodiversity) and also play a significant role in the global carbon cycle that drives climate change with impacts reverberating through human societies worldwide [1];. Knowledge on the spatiotemporal dynamics of LULCC is crucial to understand, manage, and plan sustainable land use changes in order to support decision-making on land-use policy.

The complexity of LULCC is discussed in this review and presents trends on past changes along with advanced modelling forecasting future scenarios (Aguilar *et al*., 2018) [2]. Land use and cover transformation are driven by many factors including urbanization, agricultural expansion, deforestation and climate change. These changes have implications that extend beyond the immediate environment and wildlife, with further consequences related to habitat loss, potential alterations of ecosystem service delivery systems including carbon emissions; all ultimately affecting local communities. LULCC studies are critical for understanding these processes, identifying major drivers and taking actions to avoid the negative impacts of land use practices (J. Yang *et al*., 2021) [32]. These figures highlight dramatic changes in land use from historical data on LULCC over the decades. A high rate of urbanization, agricultural intensification and deforestation have considerably modified land cover types with consequences on biodiversity, water resource or even climate change mitigation. These trends serve as the basis for deciphering processes of land use /cover change (LULCC) and their consequent environmental impacts (Ersi *et al*., 2022) [11]. The human-environmental dynamics of LULCC is highly complex and uncertain [2-6], therefore, there are several challenges in modeling future patterns proliferated by all these aspects. Moreover, due to the uncertainties associated with climate projections, socio-economic trends and land management practices accurate predictions are challenging. Nonetheless, progress in remote sensing/GIS-based analyses and modelling provides new avenues for refining confidence intervals around future forecasted changes (Cui *et al*., 2022) [9]. Objectives of this research paper 1) Analyze historical trends in LULCC using remote sensing data and GIS techniques. 2) Identify key drivers of LULCC at local, regional, and global scales. 3) Develop predictive models to forecast future scenarios of LULCC under different socio-economic and climate change scenarios. 4) Assess the potential impacts of future LULCC on ecosystems, biodiversity, and human well-being. 5) Recommend sustainable land management practices and policy interventions based on research findings. In conclusion, understanding the dynamics of LULCC and predicting future changes are crucial for informed decision-making and sustainable land use planning. By addressing these challenges and objectives, this research paper aims to contribute to the growing knowledge of LULCC and its implications for the environment and society.

2. Materials and Methods

2.1 Study Area

Ningxia Hui Autonomous Region Located in northwest China as an autonomous region neighboring Shaanxi, Gansu and Inner Mongolia. Covering 66,400 square kilometers in area the park has a variety of landscapes from large deserts to rugged mountains and fertile river valleys. Most of what is now the western third of Ningxia looks over the Tengger Desert, one China's four major deserts. The Yellow River, which is called the "Mother of Rivers" in China, plays an important role for local economy and eco-environment with its resources serving agriculture and urban populations. Ningxia has a continental climate and experiences hot summers, cold winters and low annual precipitation levels due to which the effective management of water resources in Ningxa is extremely crucial for sustainable development. Akto county, located in the northern mountainous region of Xinjiang Uygur autonomous regions (XUAR), is a typical area for land use/cover changes and human-animal-vegetation relations studies in northwestern China with its rich multi-flanked cultural ethos; one being predominant Hui Muslim population and ensuing prevalent culture. Random forest and artificial neural network models can be used to identify patterns, drivers and future trends beneficial for the process of decision support in sustainable development.

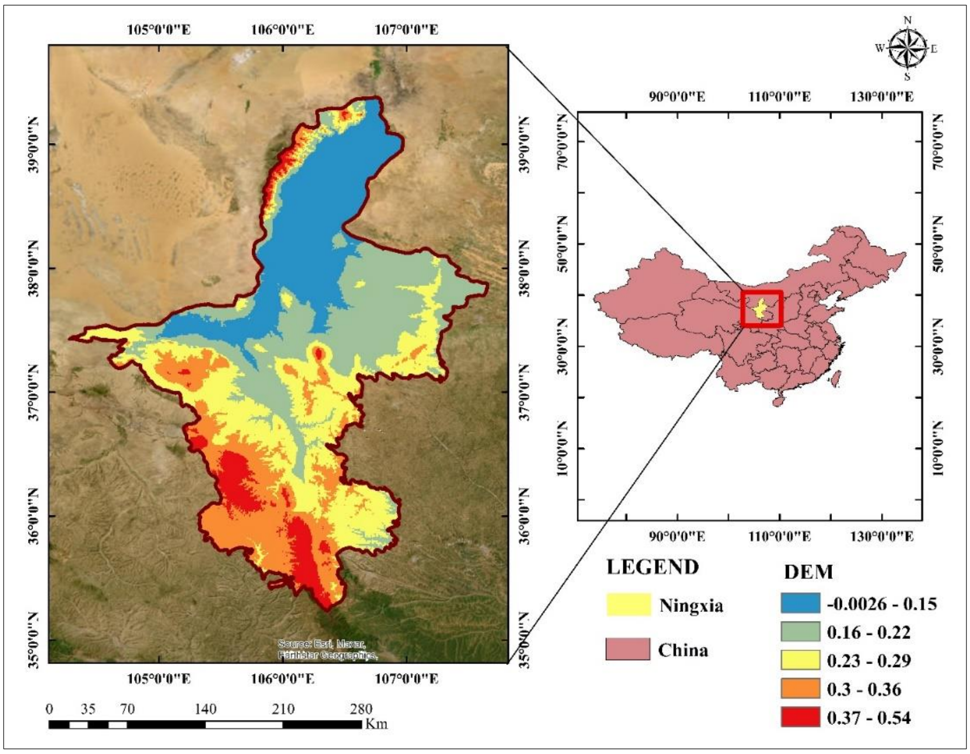


Fig 1: Study Area Map

2.2. Datasets

In this study the data set used was MODIS (Moderate Resolution Imaging Spectroradiometer). MODIS belongs to the series of instruments aboard both Terra and Aqua satellites, which is critical in delivering low latitude global coverage at both fine spatial resolution level and temporal (Wen *et al*., 2020) [29]. One of the most widespread uses are in remote sensing, as it applies to random forest classification. The data sources and satellite imagery used in this study have a coverage of 20 years, starting from mid-2003 to March/April 2023. We obtained satellite data from different sensors including Earth Explorer, Earth Engine and DIVA-GIS. The MODIS data products, which provide weekly temporal resolution and spatial resolutions from 500m to 1200km were used here including the MOD09GA (nearest collocation within acceptable cloud cover) as well as MCD43A4. We have defined the boundary data from DIVA-GIS to limit specific focus of study area. 2017 (2003 and 2023), respectively, allowing examination of change over these ~20 years. A multi-source-mutitemporal satellitedata set and detailed boundary information are to the best of our knowledge an excellent basis for a comprehensive analysis within the study area, in order that significant changes can be identified over 2 decades (Borisova *et al*., 2018) [5].

Table 1. Datasets used in the study

Satellite	Sensor	Year	Spatial Resolution	Source
MODIS	MOD09GA, MCD43A4	2003-2023	500m, 1200*1200km	https://earthengine.google.com/
Boundary	-	2023	-	https://www.diva-gis.org/gdata

2.3 Processing and Methods

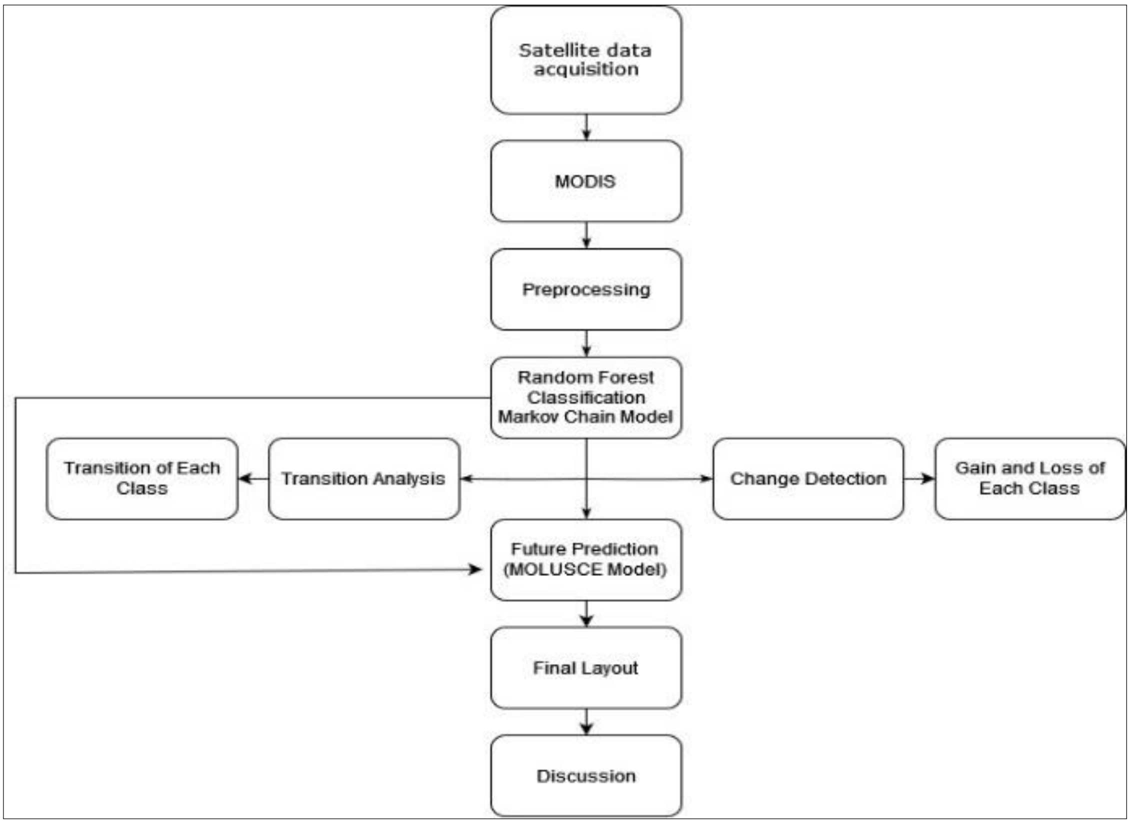


Fig 2: Methodology Flowchart

This research article is focused on random forest classification, which is a popular machine learning algorithm based upon multiple decision trees for performing the task of categorization (Cheng *et al*., 2021) [7]. This general indicative method can deal with multi-dimensional information, i.e., multispectral bands that MODIS offers and is proper for remote detecting applications. While applying random forest classification with the MODIS dataset, researchers generally combine spectral bands and vegetation indices as input features in addition to ancillary data (i.e., elevation, slope or aspect). This model then further embraces the features to develop a random forest, which with passes over these characteristics and through multiple decision trees leads to learning associations and patterns between the input data verses among classes of output (land use/cover types or vegetation species etc) For classification tasks. One important strength of the MODIS dataset in random forest classification is a global daily or near-daily revisit time which can provide information for monitoring phenomena acting on dynamic processes and changes covering large extension (Zhu & Ren, 2000) [36].

The MODIS provides a wide range of data products such as surface reflectance, land-surface temperature and vegetation indices that when combined can improve the accuracy in classification (QUAN *et al*., 2007) [26]. A popular machine learning algorithm Random forest classification has been used for several applications like land cover mapping, vegetation mapping urban area delineation among others. For remote sensing applications and the MODIS dataset in general, it is of important that this algorithm (an) work on high-dimensional data; (b) be insensitive to noise and outliers; (c)have a variable importance ranking/partial dependence scores. Land cover in the study area was classified using Landsat imagery on Google Earth Engine for this research. A nonparameteric machine learning algorithm based on Random Forest Classification was trained by using training data generated from the study area. Different land cover types including forest, grasslands and urban areas can be classified with the received classification (Matson *et al*., 1997) [21]. Remote sensing is rapidly becoming one of the most efficient ways for researchers to analyze data, and so naturally algorithms like Random Forest Classification are growing in importance perpendicular to that. Refines the response by assigning a numerical value (for regression trees) or class (classification tree-wise).

RF classification, a popular method to deal with remote sensing data contains multiple features should use ensemble models than single model because they have more capability of eliminating the conflict between feature subsets (Quan *et al*., 2011) [25]. The model uses 100 trees and the square root of total features as maximum number fo feature. The model internally implement on the basis of attribute selection using out-of-bag (OOB) sample statistics. Abstract Machine learning algorithms have become crucial for effective data analysis in remote sensing, with Random Forest Classification being one of the most widely used. This method mainly uses or integrates remote sensing data, random classification, gains-losses-transitions as well as Markov chain model and machine learning to predict land conditions at the site of a study area.

2.4. Cellular Automata-Artificial Neural Network Simulation

Within the field of land use and land cover change (LULCC) research, hybridization between Cellular Automata (CA) and Artificial Neural Networks (ANNs), has arisen as a promising novel approach that combines both techniques in an integrated manner to exploit their best properties while circumventing or reducing their downside. The integrated CA-ANN formulation make this simulation framework an exciting tool to study the dynamics and complexity of land usage transformation which would provide useful insights for sustainable development initiatives. For this example, the CA-ANN simulation takes advantage of a cellular automata capacity to do spatial and temporal modelling that can represent land use changes as complex interactions (i.e. transitions) between different categories in time. CA is able to assess the changing patterns of land use change over both space and time, taking account of neighbouring cells interactions based on some specific transition rules. However, the traditional CA methodology has limited capability of representing complex and nonlinear driving relations between determinants and land use dynamics in certain circumstances. This is where the magic of ANN begins. ANN (Artificial Neural Network): it is a machine learning method modelled after the human brain neural network that can detect and simulate non-linear complex relationships throughout knowledge. For example, by embedding ANN within the CA framework, researchers are enabled to exploit its capacity to be fed historical records on observed land use transitions and analyze detailed patterns of interrelations guiding these processes. The strength of CA is a weakness in ANN and vice versa that allows them to be used together for outstanding performance.

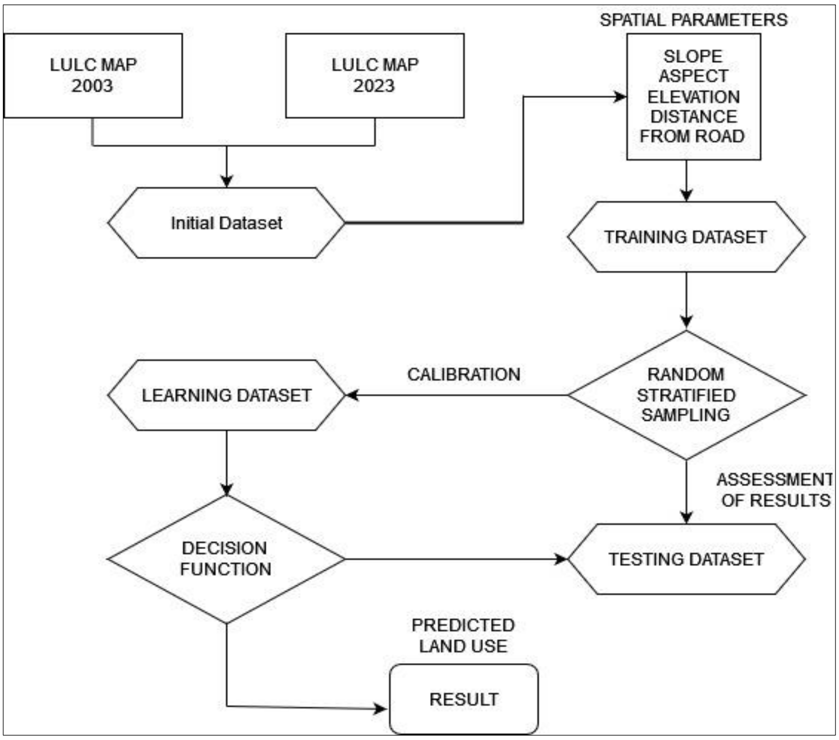


Fig 3: Flow chart illustrating the steps of CA-ANN simulation to predict LULC maps

The CA-ANN simulation framework is a land use changes simulation tool that can simulate the spatial and temporal population dynamics of ANN to offer geo-simulation modeling, which may achieve better transition potential modelling performance. CA simulates the dynamic process of changing land use patterns over time and serves as a framework with ANN taking advantage of historical data, spatial variables, enhancing intelligence by predicting probabilities for changes between different land uses (J. Liu *et al*., 2008) [19]. With this integration, researchers are able to proactively investigate "What-if" scenarios; evaluate the policy impacts on land use and predict future patterns of changing at a greater precision level. Overall, by integrating various spatial variables to better represent the local context clearly, this CA-ANN approach provides flexibility and adaptability for fully informed decisions about sustainable land use planning. It has been extensively applied globally by researchers motivated to decode the intricacies of LULCC in pursuit of sustainable development processes (Atkinson *et al*., 2013) [4]. Provide valuable insights for policy makers, urban planners and environmental conservationists in understanding the adverse impacts of unsustainable land use practices.

3. Results

3.1. Spatial and Temporal Patterns of Change

Desertification and urban sprawl in Ningxia have both expanded dramatically over the past two decades, some of it as a result not only of factors caused by human activities but also due to natural or climatic conditions. Global warming has also contributed to climate change, which in turn disturbs the ecological balance of this region resulting in prolonged drought periods with rise evapotranspiration rates as a consequence. Overgrazing and misuse of irrigation additionally degrade the soil resulting in quicker desertification. Similarly, the rapid pace of urbanization and economic development has deeply embedded rural-to-urban migration and driven up expected population growth within cities (Pleydell *et al*., 2008) [24]. Such growth, however is usually associated with the loss of agricultural lands and furthur coverting of encroached areas into urban developments at the expense on farmland previously under productive use. The unchecked spread of deserts and that human pressure in Ningxia is far from being only an environmental issue but rather a long-term societal task. Desertification creeping onto agricultural lands threatens food security and rural livelihoods, as once-fertile land is turned to desert; this further decreases productivity due to nutrient unavailability and renders the challenge of ever increasing human population feeding an already acute predicament. As seen in the random forest classification map illustrated in Figure 3, Ningxia's desert area and built-up have effectively expanded from 2003 to over and beyond time of only two decades.

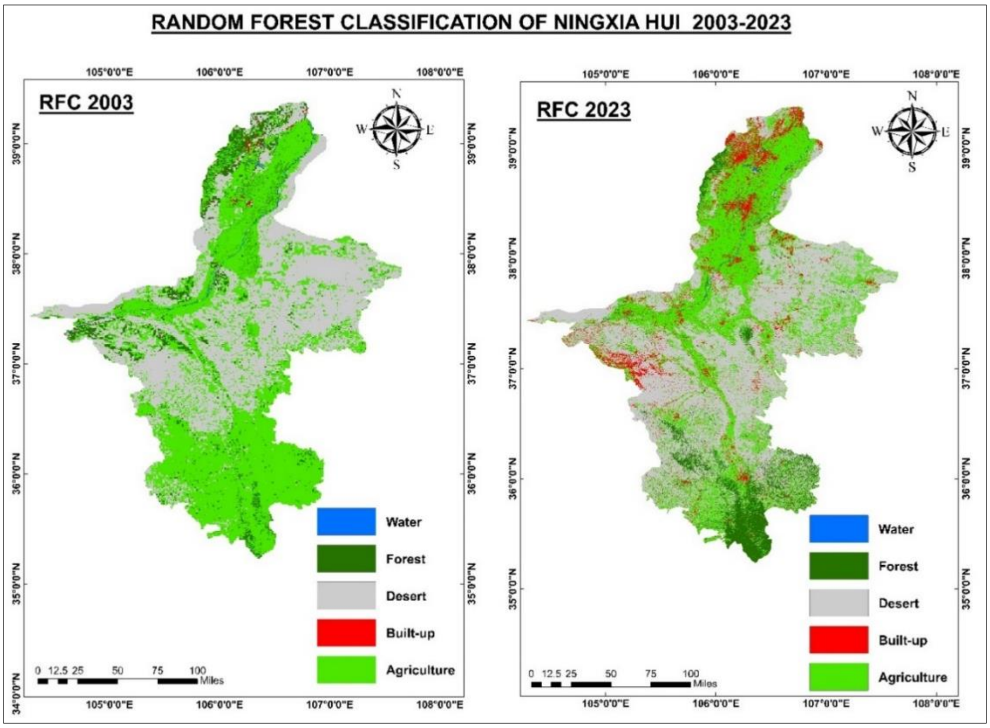


Fig 4: Random Forest Classification 2003-2023

Desertification is the increase of dryland that can further cause soil erosion, dust storms and other related environmental hazards. Exposed soil is fragile and easily blown away by the wind, this striking poses risks blowing dirt that will degrade air quality as well complicate respiratory health constraints. Carbon sinks are habitats that keep carbon out of the atmosphere, and reducing any forest or other land used for agriculture reduces our capacity to address climate change. This means the food security and also urban water supply systems will be jeopardised due to lack of resources whereas other source conflicts are waiting increased with that diminishing availability for some part. The interaction between land cover, water resources and human activities necessitates sustainable land management practices and environmental policies to tackle these urgent matters. This is only adding to the woes of Ningxia as shown by reduced levels in Figure 4.

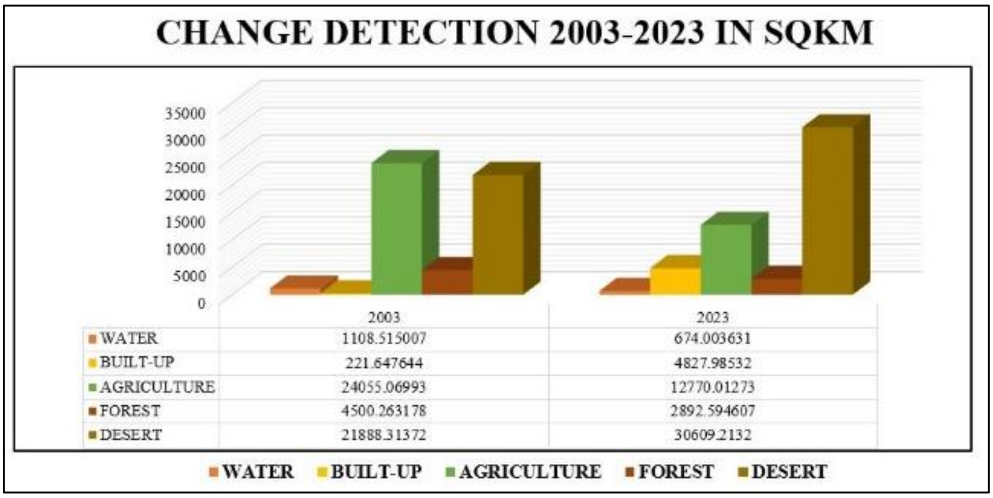


Fig 5: Change Detection Graph 2003-2023

3.2. Transition Dynamics

The machine learning model transition analysis on TerrSet2020 indicated that forest converting to desert, agriculture areas altering into a smaller zone as built-up and the largest decline of agricultural landcover meanwhile rapidly shifting to desert. The disappearance of rational forest is a consequence mainly by the deforestation for urban expansion, incorrect logging activities and influence of climate change which has imposed region more arid due to drought (Owada *et al*., 2017) [23]. The transition from cultivated to desert land is unsettling because it means the soil on an acre of farmland that previously grew crops has been degraded and dried up by water shortages or desiccation processes out there in the sands. It was found that the desert area in Ningxia has almost doubled, while a half of its forest areas were lost. This creeping desertification reflects North Africa's larger environmental issues, which include climate change as well as overuse of resources and unsustainable soil management practices. The shrinking forests (biodiversity and ecological balance) directly affects millions of communities living in the region, as it is a significant resource base for multitude ecosystems services. Results of the change trend analysis on land cover types in Ningxia According to Figure 5, it can be seen that there are significant changes in recent years. The main negative consequences of these changes are the depletion and extinction (biodiversity loss) due to increased use of land resources, desertification. Given constrained resources and competing stakeholders, increased land use conflicts are a socioeconomic issue. In addition, the loss of biological diversity could perturb the functional stability in ecosytems and cause a province-scale cascading impact to environmental health.

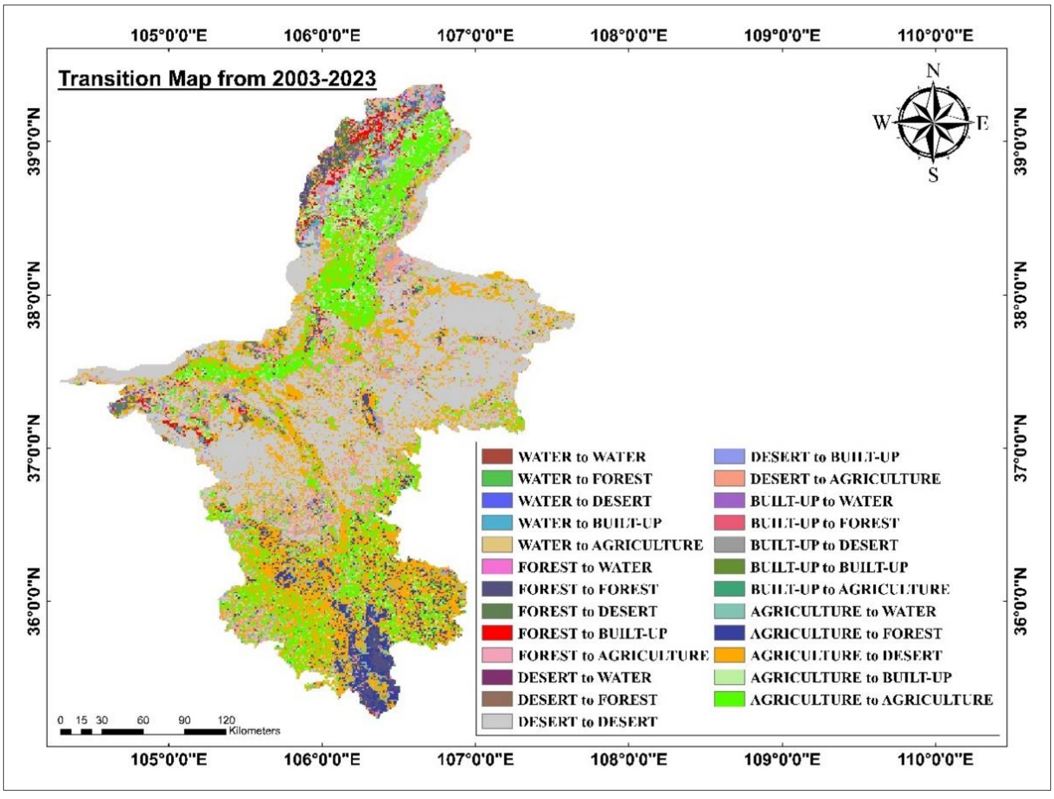


Fig 6: Land use land cover Transition Map of Ningxia from 2003-2023

3.3. Gains and Losses

This map shows the change trajectory of land use andcover (LULC) classes in Ningxia Hui Autonomous Region, China from 2003 to2023. It has focused on these changes-the spread of desert and built-up land in central China, particularly the west while there are less agricultural use forests water side. The combination of rapid urbanization and economic development when combined with the arid climate in Ningxia may have caused the loss of natural habitats, reducing agricultural land into Urban extensions or other Infrastructure. There might have been some desert loss in the northern part of Ningxia, either due to regional measures against desertification (Wei *et al*., 2021) [28] or changes in precipitation patterns. Still the increase has been bigger in desert areas than this loss, so there are more deserts across the whole region. Climate Change and Overgrazing, unsuitable land management practices, unsustainable irrigation practices can also lead to desertification processes allowing for more soil erosion and degradation. A similar map demonstrates how land cover (red gains and green losses depicting progression of surface water into new fields) persisted over time together with the hatched contours.

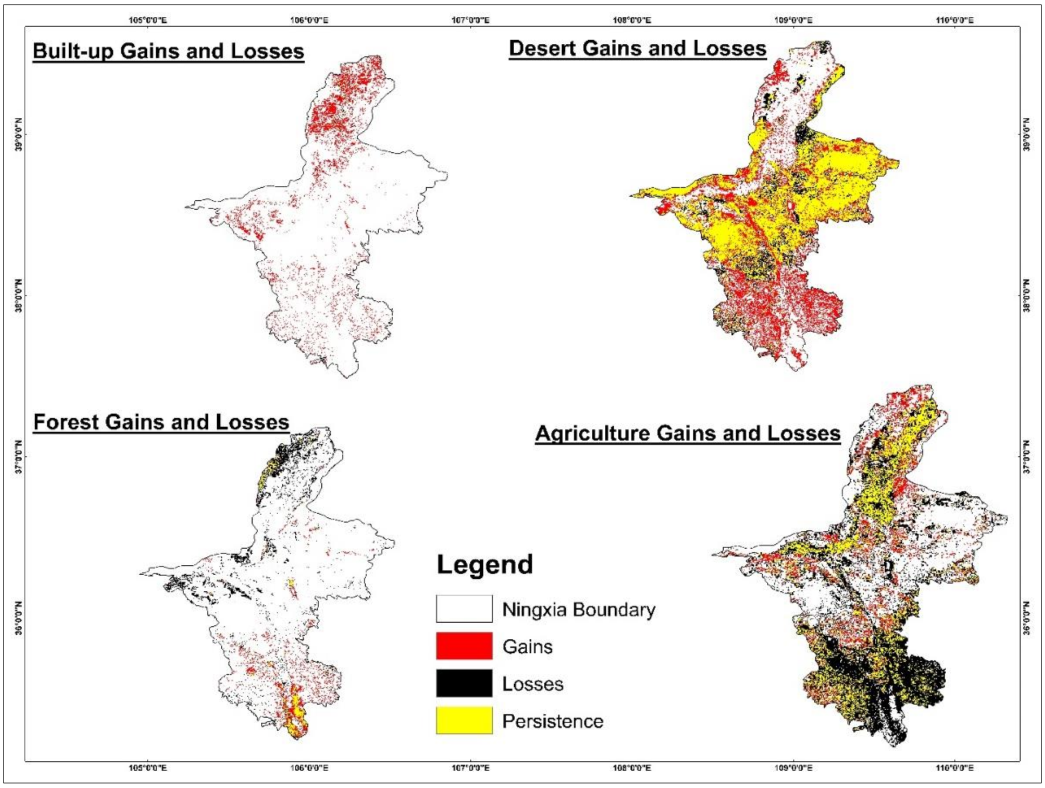
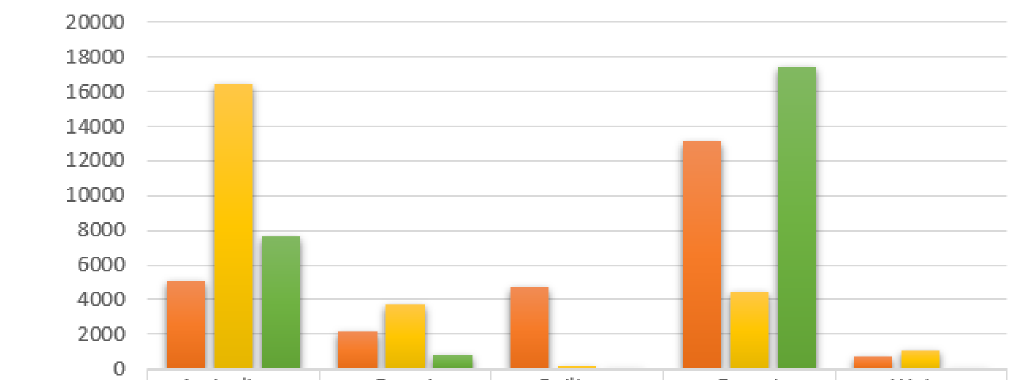


Fig 7: Gain and Loss Map of the Desert 2003-2023

Tables 2 and Fig. 7 depict the quantitative estimation of land cover losses and gains in km^2 from year 2003 to hypothesised at end-decade (year) period i.e., by year-2023 for each LULC type-Saharan Africa Cross hatching (L & G = Losses + Expansions; White Within within class changes; Black generated Random input cells). Such information allows for an in-depth assessment of the size and extent, as well as potential drivers and implications associated with land cover change in different fronts that modify this environment affecting ecosystem services delivery under various socio-economic conditions facing the region (Cadavid Restrepo *et al*., 2017) [6]. For instance, data may be significant for agriculture areas but also to observe the loss of agricultural land (and thus food supply) and increasing built-up areas that would signal population increase as well urban growth. The results of this study highlight the needs for effective land use management, grassland and farmland policies, combined with ecological conservation efforts in Ningxia to mitigate desertification alongside urban sprawl and habitat fragmentation impacts. Yonglong Lu explained: These results could serve as a reference for policy makers and stakeholders to make planning, such as sustainable agriculture or targeted restoration of ecosystems conservation on the grassland region/ its major gradients development under formulating mode on economic- environmental aspect.

Table 2: Gains and Losses of each class in km^2

	Gains	Losses	Persistence
Agriculture	5122.271	16407.33	7647.741
Forest	2126.802	3734.471	765.7922
Built-up	4721.578	115.2401	106.4076
Desert	13169.57	4448.673	17439.64
Water	659.2343	1093.746	14.76934



	Agriculture	Forest	Built-up	Desert	Water
Gains	5122.271349	2126.802366	4721.577744	13169.57275	659.234289
Losses	16407.32856	3734.470936	115.240068	4448.673269	1093.745665
Persistence	7647.741376	765.792242	106.407576	17439.64046	14.769342

Gains Losses Persistence

Fig 8: Gains and Losses graph 2003-2023

3.4 Spatial Trend of Change

Spatial perspectives of Land Use and Cover Changes (LULC) change analysis is a technique that perceptible information for region level development in patterns. The interplay between natural processes and human activities that forms the Mediterranean landscape is laid bare in two LULC maps. A tool producing maps on transformed desert areas to all LULC classes for some period was employed (Ding *et al*., 2005) [10]. To more faithfully represent nature and narratives of planetary transformations its patterns generally capture, the tool employs a third-order polynomial parameter to properly describe complex spatial structures. The maps quantify the change and directionality of transitions giving researchers, policy makers empirical evidence on which to base decisions. This spatial trend of the desert to all LULC classes is given in Fig. 8. The findings indicating the marked increases in desert areas of Ningxia should serve as a strong indication that more vigilance and action, such as those promoting sustainable land management strategies to combat against desertification are imperative. This serves as an important reminder on the necessity of maintaining balance with fragile ecosystems and surrounding community welfare.

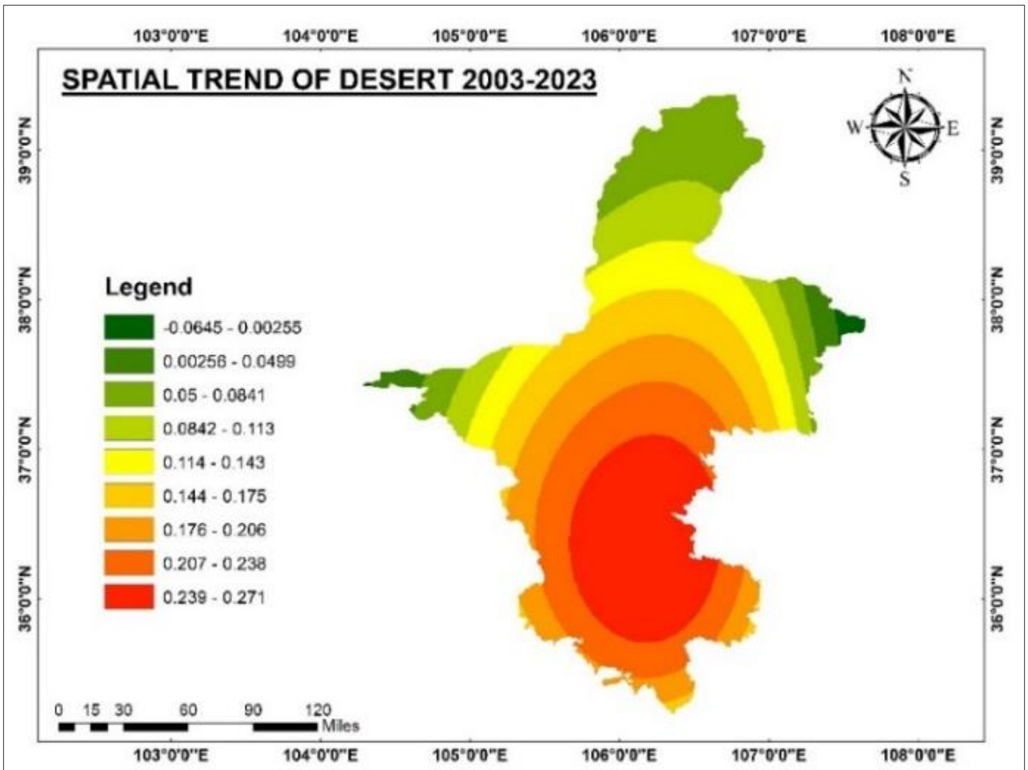


Fig 9: Spatial Trend of Desert from 2003-2023

3.5 Markov-Chain Model

For analyzing Land Use and Land Cover (LULC) dynamics of a particular region Markov chain models have been used extensively in recent days. Generating different-period maps (alternatively reclassification into sub-categories) and the calculation of transition probability matrix using the Markov transition estimator, was another step within this process (Yu *et al*., 2014). The integrated matrix was employed to gain a quantitative understanding of the temporal sequence, process dynamics and area extent of LULC changes. This means, for example in 2033, the state transition probability matrix suggests that built-up areas have a 9% chance of becoming deserts states (i.e. pluvial environments), forests an18%, and agricultural land28%, while water bodies at5%. Markov chain analysis indicates that 6% of agricultural land transitions to built-up, only 2% of deserts give way and become built-up, a quarter (25%) of water bodies move towards its counterpart state and one-eighth forest area changes it status to that are under occupation. Such an analysis could be used to aid situational land use management decision-making and policy design (Huang *et al*., 2021) [13]. Being aware of the enablers and barriers - transformations leading to a change in land use, policymakers are better equipped locate suitable interventions (actions capable to avoid unwanted changes of classes like urban sprawl or deforestation or degradation towards desertification) The analysis can also help pinpoint where more stringent regulations or rewards need to be in place to encourage sustainable land use practices. The analysis could also aid in comprehension of the factors and mechanisms determining urban development, whose information might contribute to future land use policies. Nevertheless, the analysis should be supplemented by other analytical tools and expert knowledge for a complete comprehension of LULC change dynamics. This type of analysis, if combined with other complementary data sets can increase the success rate in land use management.

Table 3: Markov transition probability matrix for 2033

	Water	Built-up	Agriculture	Forest	Desert
Water	0.3825	0.2508	0.3087	0.0038	0.0542
Built-UP	0.0186	0.7002	0.1742	0.0088	0.0982
Agriculture	0.0126	0.0643	0.5852	0.0525	0.2854
Forest	0.0272	0.1237	0.1734	0.4937	0.182
Desert	0	0.0216	0.0907	0.0049	0.8828

3.6. Future Prediction of Land Use Land cover

MOLUSCE is a QGIS plugin also for transition potential modelling, based on the ANN and using weights of evidence method combined with multicriteria evaluation (CA algorithm) or logistic regression approach. This model was used to simulate the land use changes in 2033 and paired with LULC data from 2003 to 2023 as well as some spatial variables affecting land-use dynamics. Transition potential modeling & forecasting was conducted using the CA-ANN approach (Feng *et al*., 2023) [12]. These spatial variables for model calibration were selected there association with land use and coverage as produced by Cramer's coefficient is found to be high. The agreement of ANN evaluated by the Kappa value was 0.96 and thus yielded an accuracy up to 85 per cent in average for calibrated model This plugin uses an integrated concept and has a friendly user interface permetting to ease the detection of changes in land cover as well future perspectives regarding patterns of change in long term analysis. The 2033 predicted map has desert and built up areas on the rise, These projections correlate with what is happening in Zona Metropolitana de Guadalajara where urbanization and climate change are making great changes. The MOLUSCE plugin within QGIS offers a viable tool for exploring and identifying land use dynamics, to support the interpretation of future trends as well as decision-making in planning efforts and sustainable territorial management.

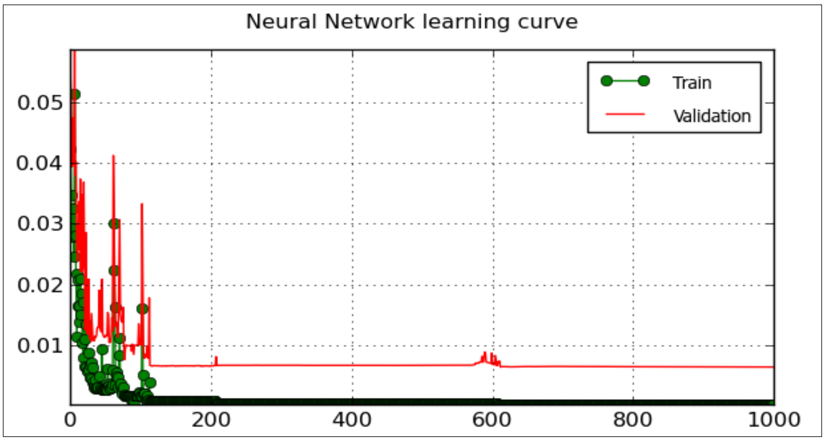


Fig 10: CA-ANN Model validation

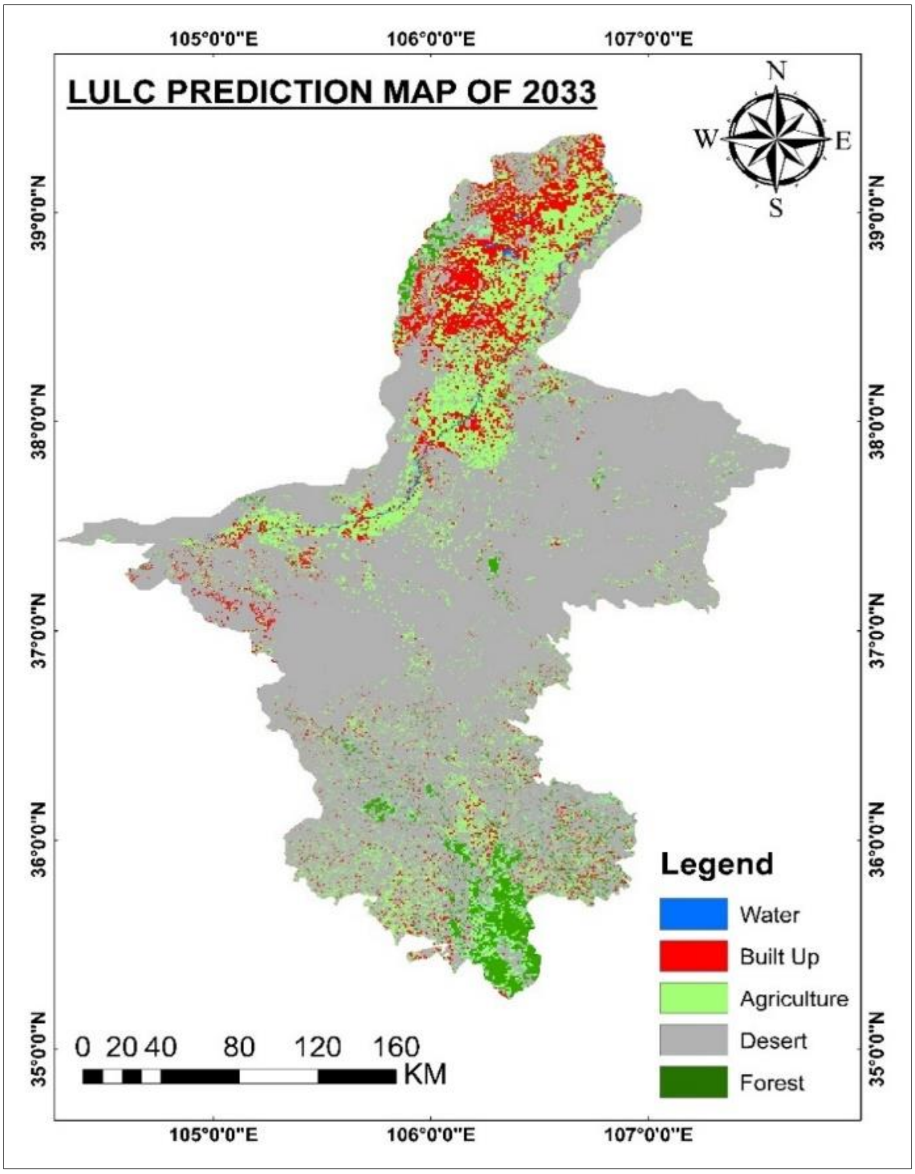


Fig 11: Future prediction 2033

4. Discussion

This study makes plain the desperate need for a sustainable land-use policy in conjunction with full environmental stewardship across areas of Ningxia, China. The relentless spread of desertification and urban growth, tracking across the globe with more frequency as disclosed by state-of-the-art remote sensing methods powered by machine learning algorithms offers a grim glimpse into how human actions need to correspond directly or indirectly with ecological sustainability. The effects of these land use and land cover (LULC) shifts also cascade through complex societa l, ec onomic, and environmental spheres well beyond the physical reach of this region (H. Liu *et al*., 2022) [9].

Desertification expansion to formerly fertile agricultural lands is first of all a problem for food security and rural life unprecedented. Arable lands are being turned into deserts, and the result is reduced productivity which empowers problems such as providing food for a growing population. This may increase the risk of regional food self-sufficiency and have significant implications for social stability, economic development, and human welfare. At the same time, it is essential to improve sustainable land management through desertification control and recovery strategies (e.g., climate-smart agriculture promotion, soil conservation practices adoption and community-based land use practices) to protect the agricultural heritage of this region as well as long-term food security.

Urban sprawl, a sign of economic growth and development, has to be kept in check lest its environmental cost exceeds established social costs. Uncontrolled urban expansion may result in fragmented habitat, biodiversity decline and also exacerbate the existing pressure on limited natural resources (B. Yang *et al*., 2022) [31]. In this regard, it is essential that the development aspirations of the region are balanced with environmental stewardship by including concepts from sustainable urban planning while incorporating green infrastructure principles and building energy efficient & effective waste management systems (Abd El-Hamid *et al*., 2020) [1].

The probability matrix of transition and resultant spatial patterns projected in this study provide crucial insights for prediction applications by policymakers, end users to efficiently plan strategies (Zhao *et al*., 2022) [35]. The Cellular Automata-Artificial Neural Network (CA-ANN) model can explain the predicting capacity of concerning land use changes, which opens to possibilities for decision-makers in investigating different "what if" scenarios or examining possible impacts on policy responses and further targeting strategies are developed as valuable policies-making support tool towards counteracting such undesired consequences from this study (Z. Liu *et al*., 2022) [9]. This approach helps policy more informed better supporting a have the impact on economic development, environmental protection but sustainability (Ahmad *et al*., 2022) [3].

These should be taken as a wake-up call to promote regulation and sustainable land use in Ningxia, China. Through the adoption of innovative technologies, informed decision-making based on reliable data and a more holistic environmental stewardship concept we can start figuring out how to journey safely through all the complexity that LULC transformations entail into an sustainable future. Humanity's destiny - as a creative culture that honors and protects the intricate relationships among all species who collectively maintain life on earth, or otherwise implodes into catastrophic mass destruction of our own home world- is being decided in action every day (C. Liu *et al*., 2021) [7].

5. Conclusion

Ningxia, located in the arid region of China (average annual precipitation,200 mm), is experiencing dramatic trends on land use and land cover (LULC) over recent two decades. The research involved high-level machine learning algorithms coupled with remote sensing platforms, and showed that deserts are swallowing farmlands as well as built-up areas increasing at alarming rates thereby reducing the available forest cover strengthens on already existing dwindling water resources. According to the transition probability matrix, in 2033, it is expected to have a 28% chance of converting from agricultural land use types and built-up area reaching deserification (around9%). The standing desert eats ever possible inch, threatening food security and biodiversity while amplifying a whole host of environmental challenges: soil erosion, dust storms; impacts from climate change. The model of Cellular Automata-Artificial Neural Network (CA-ANN) is an explorative tool to understand the future planning and soil management strategies. The 2033 predicted map can act as a wake-up call to redress desertification, sprawl and habitat fragmentation. By incorporating these observations into policy formation and decision mechanisms, policymakers could design interventions specifically geared towards alleviating the negative repercussions of LULC changes while still promoting sustainable urban development trajectories along with reinforcing environmental conservation actions. This point is reinforced in the research with a call for stakeholder engagement, community participation and interdisciplinary collaboration to maximise attaining SDGs. Through the engagement of local communities, researchers and decision-makers Ningxia would be able to institute a balanced model based on 3E - economic growth (prosperity), environment (stability) and social well-being (fairness). Through the effective incorporation of cutting edge technologies, data-driven decision-making and an integrated land management approach to LULC transformations Ningxia will be able to navigate a complex path into sustainability.

6. References

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