Europa-Universität Flensburg

Department of Ecology

Biodiversity and Land Use Change

Part 1

Scientific thesis for the attainment of the PhD-Degree (Dr. Phil.) at the University of Flensburg

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1. Introduction

“Biodiversity means the variability among living organisms from all sources including, inter alia, terrestrial, marine, and other aquatic ecosystems and the complexes of which they are part; this includes diversity within species, between species, and of ecosystems” (Butchart, et al., 2010). The primary objective of the Convention on Biological Diversity (1992) is to safeguard species from extinction, curtail the rate of biodiversity loss, and protect ecosystems around the globe. The convention highlights that "biological diversity is being significantly reduced by certain human activities" and "the fundamental requirement for the conservation of biological diversity is the in-situ conservation of ecosystems and natural habitats and the maintenance and recovery of viable populations of species in their natural surroundings" (United Nations , 1992; Rodríguez-Echeverry, et al., 2018; Hobohm, et al., 2021).

Biodiversity plays a pivotal role in providing ecosystem goods and services that are essential for humanity's well-being and survival. It is an essential component of human development and security, although it is susceptible to both human activities and natural phenomena. Global biodiversity change stands as one of the most crucial environmental concerns, as the challenges associated with it have escalated in recent decades. Numerous species across the world currently face the threat of extinction (Trisurat, et al., 2011; Pereira, et al., 2012; Hobohm, et al., 2021; Akbar & Saritha, 2021; Imran, 2022).

Currently, 902 species (135 plant and 767 animal species) have gone extinct globally, while 9,065 species (including 6,206 plant and 2,859 animal species) remain endangered, and this trend persists (Chemini & Rizzoli, 2003; Salem, 2003; Singh, 2010; Meshesha, et al., 2013; Kumari, et al., 2021; Pimm, 2021; Prakash & Verma, 2022; Penjor, et al., 2022; IUCN, 2023).

Environmental disasters, natural causes, and human activities can destroy or alter the structure of ecosystems and reduce biodiversity. The reduction or loss of biodiversity affects ecosystem function, making biodiversity conservation essential for ecosystem maintenance. Some factors such as land use change, migration, population growth, and increasing food production have led to massive changes in ecosystems in recent centuries. Among these factors, human influence appears to pose the most formidable threat to biodiversity, contributing significantly to habitat loss (Chemini & Rizzoli, 2003; Salem, 2003; Meine, 2018; Nelder, 2018; Hobohm, et al., 2021; Prakash & Verma, 2022).

According to Singh's 2010 definition, the conservation of biodiversity is “the planning and management of biological resources in a way to secure their wide use and continuous supply, maintaining their quality, value and diversity”. Biodiversity conservation involves determining which species should be protected and employing suitable approaches. Neglecting biodiversity preservation leads to the development of poverty, diseases, and inequitable development (Salem, 2003; Singh, 2010; Trisurat, et al., 2011; Meine, 2018).

Human activities such as intensified land use, have resulted in the depletion of ecosystem services, disruptions in ecosystem balance, and consequently, the extinction of numerous species on Earth. Land use is a complex process that involves various variables and factors at different social and spatial scales (Trisurat, et al., 2011; Katalin, 2014; Kakati & Borah, 2021).

Land use is a complex process influenced by various economic, social, and cultural environments, as well as management practices and human activities. Land use change arises from the intricate interplay of these factors, posing a significant threat to biodiversity. The principal drivers of land use change are economics and population dynamics, with income generation standing as the primary economic objective of land use (Chemini & Rizzoli, 2003; Haines-Young, 2009; Hansen, et al., 2012; Petz, 2014; Rodríguez-Echeverry, et al., 2018; Hobohm, et al., 2021; Prakash & Verma, 2022).

In the past half-century, there has been a substantial transformation in land use systems, and human activities have reshaped the Earth's natural systems into human-dominated land uses. This includes the conversion of forests into agricultural land, the transformation of one type of forest into another, and the conversion of agricultural land into residential land (Persson, 2010; Loh, et al., 2016; Williams & Newbold, 2019; Mosisa & Asefa, 2022).

Ecosystems are being destroyed by human actions to accommodate settlements, infrastructure development, farmland expansion, forestry practices, and mining activities. Consequently, forests, grasslands, and shrublands are being converted into agricultural lands, artificial surfaces, and pastures, all in an effort to meet the demands for energy, food, water, fuelwood, and building materials for the world's ever-growing population. Presently, agriculture occupies half of all habitable land, while forests, shrubs, and grasslands cover

48%, with freshwater and built-up areas each accounting for 1%. The widespread alterations in water, air, and soil utilization, coupled with rapid industrial expansion in sectors like agriculture, aquaculture, forestry, urban development, transportation, and mining, present substantial challenges to the survival of numerous endangered species (Chemini & Rizzoli, 2003; Verburg, et al., 2009; Kaul & Sopan, 2012; Petz, 2014; Our World in Data, 2019; Hobohm, et al., 2021).

Different types of land use have varying impacts on ecosystem biodiversity depending on the intensity of land use. This results in the destruction and loss of natural habitats, ultimately leading to a decline in biodiversity. The consequences of these activities are far-reaching, affecting the delicate balance of ecosystems and endangering numerous species. It is imperative to recognize the interdependence between land use decisions and the preservation of biodiversity to ensure the long-term health and stability of our natural environment (Hansen, et al., 2012; Verburg, et al., 2009; Kaul & Sopan, 2012; Petz, 2014; Hobohm, et al., 2021).

Land use change stands as a primary driver of biodiversity decline, impacting a broad spectrum of ecosystem functions and services. The concept of land use change encompasses various issues, spanning ecological, socioeconomic, cultural, and political dimensions. Understanding land use change is crucial for analyzing environmental concerns. The examination of patterns in land use and land cover change aids in identifying the mechanisms behind human-land interactions, mitigating conflicts in human-land relationships, and fostering sustainable development (Anderson, et al., 1976; Mwewr & Turner, 1992; Trisurat, et al., 2011; Braun, et al., 2021).

The effects of land use change on biodiversity exhibit variations, as multiple processes can generate both positive and negative impacts on species richness. Consequently, ecological conditions can undergo changes that either enhance or diminish regional or local biodiversity. Certain species may thrive under new environmental circumstances, emerging as winners, while others may suffer adverse consequences or remain unaffected. To facilitate effective land use planning and management, it is imperative to promote awareness, disseminate information about natural resources, and expand scientific research on land cover change (Pereira, et al., 2012; Hobohm, et al., 2021; Menbere, 2021).

Despite the well-known and significant consequences of land use change and the recognized need to address associated problems, there is still a lack of systematic evaluation of research findings in this field. This study aims to address this gap by analyzing the conservation of biodiversity as a critical attribute of ecosystems, with a specific focus on land use change and its impacts on biodiversity. To achieve the objectives of this study, the initial step involves analyzing various variables related to land use change in relation to biodiversity. The severity of these changes and their effects on habitat quality will be assessed. Multiple Linear Regression (MLR) models and Quantum Geographic System (QGIS) will be employed to quantify the impacts of land use change on biodiversity. The use of QGIS will aid in exploring land use change and identifying factors that influence biodiversity over time. The findings will be presented and visualized through a series of maps and data visualizations. To conduct the regression analyses, a comprehensive database will be required, encompassing information on biodiversity richness, endangered species and their threats, geographical indicators, economic indicators, and demographic indicators. The ultimate goal is to analyse the interconnections among environmental, social, and economic indicators.

This research aims to address the concept of planning for a more effective response to the environmental and security challenges posed by land use change on biodiversity in the 21st century. The primary purpose is to safeguard biodiversity and mitigate species loss by enhancing assessments of the impacts of land use changes on the environment and biodiversity. The ultimate objective is to protect species before they become extinct. In particular, this study seeks to investigate the following questions:

- What is the relationship between biodiversity, land use and land cover change?
- Which factors have a strong impact on the composition of the biodiversity of countries?
- Which habitat types harbor the most threatened species?
- Do threats differ from one habitat to another habitat type?
- How important are threats caused by economic processes?
- How important are threats caused by climate change and severe weather?
- How important is the number of species for the number of threatened species?
- How important are side effects, such as threats caused by alien species (neobiota)?
- Which factors of land use and land use change are the most important threats to biodiversity?
- What are the important effects of land use change on biodiversity?

- Are there any positive examples of land use change and biodiversity?
- How strong is the relationship between land use change and threats to biodiversity?
- What are the main drivers and patterns of land use change that significantly affect biodiversity?

By investigating these questions, the research aims to provide valuable insights and recommendations for more effective and sustainable approaches to address the challenges of land use change and protect biodiversity. Based on the research questions, the following hypotheses can be derived:

Hypothesis 1: Land use change and land cover change are the most important factors threatening the biodiversity at global scale.

Hypothesis 2: Climate change, severe weather, and natural processes pose threats to biodiversity, albeit of lower priority.

This research aims to provide comprehensive answers to its questions by conducting a thorough examination of biodiversity. Through detailed case studies and systematic comparisons, it enables a deeper analysis of biodiversity vulnerability. The findings will be presented through a series of maps and data visualizations using the Quantum Geographic Information System (QGIS) and Multiple Linear Regression (MLR) analysis models. The study employs a systematic approach to data collection, which involves gathering locational information, land use maps, and various layers of information within a geographic information system. Furthermore, the research incorporates the study of contemporary global experiences, conducts in-depth case study analyses, and utilizes statistical modeling techniques to address different factors effectively.

2. Material and Methods

2.1. Material

2.1.1. Abbreviations

Abbreviations used in this research are:

Ag	Agricultural land
ANOVA	Analysis of Variance. It is a statistical tool used to detect differences between experimental group means.
Ar	Arable land
As	Artificial surface
Ba	Bare area
Bu	Build up area
Ca	Caves and subterranean
CBD	Convention on Biological Diversity
CIA	Central Intelligence Agency
CR	Critically Endangered Species. It is a category used in the IUCN Red List of threatened species.
Cr	Crop land
DD	Data Deficient. It is a category used in the IUCN Red List of threatened species.
De	Desert
EN	Endangered Species. It is a category used in the IUCN Red List of threatened species.
EPSG	European Petroleum Survey Group Geodesy
EW	Extinct in the Wild Species. It is a category used in the IUCN Red List of threatened species.

EX	Extinct Species. It is a category used in the IUCN Red List of threatened species.
FAO	Food and Agriculture Organization of the United Nations
Fr	Forest
GDP	Gross Domestic Product. It is a measure of the total value of goods and services produced within a country's borders in a specific period.
GLC	Global Land Cover
Gr	Grassland
Hc	Herbaceous Crops
IPCC	The Intergovernmental Panel on Climate Change
IUCN	International Union for Conservation of Nature
Iv	Introduced vegetation
Iw	Inland water
LC	Least Concern. It is a category used in the IUCN Red List of threatened species.
LR/cd	Lower Risk. It is a category used in the IUCN Red List of threatened species.
LRA	Linear Regression Analysis
LULC	Land Use Land Cover
Ma	Marine
MLR	Multiple Linear Regression. It is a statistical method used to analyse the relationship between a dependent variable and multiple independent variables.
Mz	Maize production
NT	Near Threatened. It is a category used in the IUCN Red List of threatened species.

OECD	Organization for Economic Co-operation and Development
Ou	Other units
Pc	Permanent crop
Pp	Permanent pasture
QGIS	Quantum Geographic Information System. It is a free and open-source geographic information system (GIS) software that allows for spatial data analysis, mapping, and visualization. Uses for land use classification.
Ro	Rocky areas
RS	Remote Sensing. Collection of information about objects or areas from a distance, using satellites or aircraft.
Sa	Savana
Sh	Shrubland
Sv	Sparse vegetation
Svasc.	Number of native vascular plant species
Tc	Tree cover
UN	United Nations
Un	Unknown
UNO	United Nations Organization
USGS	United States Geological Survey
VU	Vulnerable species. It is a category used in the IUCN Red List of threatened species.
Wc	Woody crops
We	Wetland
Wb	Water body

2.1.2. Databases and Definitions

In this research, the impact of land use change on biodiversity is evaluated on a global scale. The main objective was to determine the relationship between biodiversity and land use change. However, this relationship is complex, and it is challenging to establish a simple cause-and-effect connection (Haines-Young, 2009). The evaluation employed Quantum Geographical Information System (QGIS) and SPSS for quantitative analysis of the interrelationships between variables. The utilization of QGIS facilitates the understanding of land cover change over time through the preparation of land cover maps, considering both the initial and current conditions. The variables used include parameters of physical geography, land cover, land use, economy, demographics, and natural biological richness.

To record the diversity of species on a global scale, an Excel spreadsheet database was created which includes the following variables: physical geography, demographics, urban and rural population, mainland or oceanic islands, land cover, urbanization, built-up area, protected marine area, protected terrestrial area, maize production, nitrogen fertilization, phosphate fertilization, pesticide use, economy, critically endangered species, and native vascular plant species, number of species in the IUCN Red List categories, number of CR species related to threat categories, number of VU species related to threat categories, number of CR and VU species in different habitats, number of CR species threatened in different habitats, number of VU species threatened in different habitats (Tables 55 to 66, appendix).

The database was employed to explore the relationship between land use and land cover change, biodiversity, and threatened species. The study area, as depicted in Figure 1, encompasses a global scale with a specific emphasis on 166 selected countries worldwide. Various indicators associated with natural richness, including endemic vascular plant species, critically endangered (CR) species, endangered (EN) species, and vulnerable (VU) species present within these 166 selected countries, were incorporated into the database. Subsequently, the data obtained from the database were subjected to statistical analysis using SPS.

The analysis focused on examining the indicators of land use and their impacts on biodiversity. Land use change plays a crucial role in economic development, as it influences economic, social, and cultural values that are reliant on environmental conditions, natural processes, ecosystems, and natural resources. These values contribute to the allocation of land for various purposes. Therefore, this research incorporated the Gross Domestic Product (GDP) as an indicator to provide a comprehensive understanding of ecosystem valuation. Additionally, economic conditions were assessed by utilizing indicators such as GDP per sector (agriculture, industry, and services), as well as inequality indices like Gini and Palma. Geography-related indicators included the country's area in square kilometers (both land and water) and the elevation of countries, including their highest and lowest points in meters (Hobohm, et al., 2021; Dale, et al., 2010; FAO, 2022).

The study also took into account several other parameters. For instance, the percentage of mainland or oceanic islands (estimated based on (CIA, 2021; UNEP, 2022)) was estimated based on specific criteria. Demographic parameters included the urban and rural populations, their changes between 1960 and 2017, the rate of urbanization, and the extent of built-up areas measured in square kilometers and as a percentage. Land cover indicators considered in the analysis encompassed the area of forest, arable land, permanent crop, permanent pasture, cropland, sparse vegetation, tree cover, grassland, wetland, shrubland, artificial surfaces, bare areas, and inland water for the years 1992 and 2018.

Furthermore, a crucial indicator that was considered was the threats faced by critically endangered (CR) species. These threats encompassed categories such as residential and commercial development, agriculture and aquaculture, energy production and mining, transportation and service corridors, biological resource use, human intrusions and disturbance, natural system modification, invasive and other problematic diseases, pollution, geological events, climate change, and severe weather. The information regarding these threats was obtained from the IUCN Red List (2021).

The analysis also involved numerical data related to natural richness and endangerment of biodiversity. The number of critically endangered (CR) species and the number of chordate species (including CR, EN, and VU species) for each country were extracted from the global IUCN Red List (2021, assessed in 05/2021)) as the response variable. Various combinations of predictor variables were selected for statistical analysis. Most of the data are available online, and all the data are organized in tables provided in the appendix. However, it is important to note that the number of databases available on the internet is continuously expanding and updating at a rapid pace. Therefore, the databases used in this research may indicate the state of the field a few years before the publication of the thesis (WIID, 2019; CIA, 2021; OECD, 2021; Our World in Data, 2021). Table 1 provides a summary of the different variables used in this research. All of the variables with their values can be found in the appendix (part 2).

In the other part of the research, land use change over time is analysed within the study area, utilizing the Quantum Geographic Information System (QGIS). QGIS software serves as a valuable tool for surveying, mapping, monitoring, and quantifying natural habitats. It plays a crucial role in environmental analysis and management. This software, available as a free desktop application, supports various platforms and accommodates a wide range of spatial and attribute data. It offers features for viewing, editing, and analyzing geospatial data, along with quality measures. QGIS also aids in analyzing, measuring, locating, and planning for monitoring and assessment purposes (Salem, 2003; Meedeniya, et al., 2020). In this study, the city of Mölln in northern Germany was chosen as the focal area for analysis and examination.

Table 1: Categories of variables used in this study

Effect variables (IUCN Red List, May 2021)	All critically endangered species (CR) Threatened chordate species (CR, EN, VU)
Economy (World Bank, 2018; CIA, 2020; WIID, 2019)	Total GDP (PPP) GDP per Area GDP in agriculture (absolute, PPP) GDP in the industry (absolute, PPP) GDP in service (absolute, PPP) Inequality
Physical Geography (cf. Gaens et al., 2021; CIA, 2021)	Number of Native Vascular Plant Species Elevation Space (km^3) (area*elevation)
Land Cover (OECD, 2021; CIA, 2020)	Tree Cover (in 1000 sq. km) Grassland (in 1000 sq. km)

	Wetland (in 1000 sq. km) Shrubland (in 1000 sq. km) Sparse Vegetation (in 1000 sq. km) Cropland (in 1000 sq. km) Artificial Surface (in 1000 sq. km) Bare Land (in 1000 sq. km) Inland water (in 1000 sq. km) Agricultural Land (arable land+ permanent crop+ permanent pasture), (sq. km) Arable Land (sq. km) Permanent Crop (sq. km) Permanent Pasture (sq. km) Forest (sq. km) Area (sq. km)
Land Use (OECD, 2021; Our World in Data, 2021)	Build-up Area (sq. km) Maize Production (t/country) Fertilization of Nitrogen (kg/ha) Fertilization of Phosphate (kg/ha) Pesticide (use per area of cropland) (kg/ha) Pesticides (Agricultural Use) t
Demographic (Our World in Data, 2021)	Urban Population Rate of urbanization Growth of Urban Population Rural Population Growth of Rural Population The population of the Country World
Threats for CR species (according to the (IUCN, 2022))	Residential and Commercial development Agriculture and Aquaculture

	Energy production and mining
	Transportation and service corridors
	Biological resource use
	Human intrusions and disturbance
	Natural system modification
	Invasive and other problematic diseases
	Pollution
	Geological events
	Climate change and severe weather

2.1.2.1. Selection of Countries

Due to the insufficient data availability for all countries worldwide pertaining to the variables of this research, a representative approach was adopted. Countries were selected based on their extensive and accessible databases related to the variables under investigation. A total of 166 countries were ultimately included in the study. It is important to acknowledge that even among these selected countries, certain data gaps existed in some sections of their databases. To address this issue, missing data points were estimated using information from neighbouring countries or countries with similar parameters. When data from neighbouring countries was unavailable, missing values were approximated using data from other years within the same country. This approach aimed to ensure a more accurate analysis by incorporating diverse conditions such as economic, climate, environmental factors, and biological richness from various regions worldwide. Moreover, the selected countries maintained consistent borders throughout the studied years to preserve the integrity of the analysis. Each selected country has been assigned letter abbreviations, as specified in Table 2. The primary criterion for country selection was the availability of data required for analysis, with an attempt made to include countries with the highest number of endangered species. The necessary information for analysis was extracted from reliable references, including The IUCN Red List of Threatened Species (2022), The World Fact Book (2021), Our World in Data (2019), FAO, and other credible scientific sources.

Table 2: Abbreviation of the name of 166 selected countries

Abbreviation, Country			
(Af) Afghanistan	(Al) Albania	(Aj) Algeria	(Ao) Angola
(Ar) Argentina	(Am) Armenia	(As) Australia	(Au) Austria
(Aj) Azerbaijan	(Bs) Bahamas	(Bg) Bangladesh	(Bb) Barbados
(Bo) Belarus	(Be) Belgium	(Bh) Belize	(Bn) Benin
(Bt) Bhutan	(Bl) Bolivia	(Bc) Botswana	(Bk)Bosnia & Herzegovina
(Br) Brazil	(Bu) Bulgaria	(Uv) Burkina Faso	(By) Burundi
(Ca) Canada	(Cv) Cape Verde	(Cd) Chad	(Ct)CentralAfrican Republic
(Ci) Chile	(Ch) China	(Co) Colombia	(Cn) Comoros
(Cg) Congo, DRC	(Cs) Costa Rica	(Hr) Croatia	(Cu) Cuba
(Cy) Cyprus	(Da) Denmark	(Dj) Djibouti	(Do) Dominica
(Es) El Salvador	(Ec) Ecuador	(Eg) Egypt	(Dr) Dominican Republic
(Er) Eritrea	(En) Estonia	(Et) Ethiopia	(Fj) Fiji
(Fi) Finland	(Fr) France	(Gb) Gabon	(Gg) Georgia
(Ge) Germany	(Gh) Ghana	(Gr) Greece	(Gl) Greenland
(Gj) Grenada	(Gt) Guatemala	(Pu) Guinea-Bissau	(Gy) Guyana
(Ha) Haiti	(Ho) Honduras	(Hu) Hungary	(Ic) Iceland
(In) India	(Id) Indonesia	(Ir) Iran	(Iz) Iraq
(Ei) Ireland	(Is) Israel	(It) Italy	(Jm) Jamaica
(Ja) Japan	(Jo) Jordan	(Kz) Kazakhstan	(Ke) Kenya
(Ku) Kuwait	(Kg) Kyrgyzstan	(La) Laos	(Lg) Latvia
(Le) Lebanon	(Lt) Lesotho	(Li) Liberia	(Ly) Libya
(Lh) Lithuania	(Lu) Luxembourg	(Ma) Madagascar	(Mi) Malawi
(My) Malaysia	(Mv) Maldives	(Ml) Mali	(Mt) Malta
(Mr) Mauritania	(Mp) Mauritius	(Mx) Mexico	(Md) Moldova
(Mg) Mongolia	(Me) Montenegro	(Mo) Morocco	(Mz) Mozambique
(Wa) Namibia	(Np) Nepal	(Ni) Netherlands	(Nc) New Caledonia
(Nz) New Zealand	(Nu) Nicaragua	(Ng) Niger	(Ni) Nigeria

Abbreviation, Country			
(Ne) Niue	(Cq) Northern Mariana Is.	(No) Norway	(Mu) Oman
(Pk) Pakistan	(Pp) Papua New Guinea	(Pm) Panama	(Pa) Paraguay
(Pe) Peru	(Rp) Philippines	(Pl) Poland	(Po) Portugal
(Rq) Puerto Rico	(Qa) Qatar	(Ro) Romania	(Ru) Russia
(Sa) Saudi Arabia	(Tp) Sao Tome and Principe	(Sg) Senegal	(Rs) Serbia
(Sl) Sierra Leone	(Sn) Singapore	(Lo) Slovakia	(Si) Slovenia
(So) Somalia	(Sf) South Africa	(Ks) South Korea	(Sp) Spain
(Ce) Sri Lanka	(Wz) Swaziland	(Sw) Sweden	(Sz) Switzerland
(Sy) Syria	(Ti) Tajikistan	(Tz) Tanzania	(Th) Thailand
(Ga) The Gambia	(Td) Trinidad and Tobago	(To) Togo	(Tz) Tunisia
(Tu) Turkey	(Tx) Turkmenistan	(Tk) Turks and Caicos Is.	(Ug) Uganda
(Up) Ukraine	(Tc) United Arab Emirates	(Uk) United Kingdom	(Us) United States
(Uy) Uruguay	(Uz) Uzbekistan	(Nh) Vanuatu	(Ve) Venezuela
(Vm) Vietnam	(Ye) Yemen	(Za) Zambia	(Zi) Zimbabwe

Figure 1 displays the geographical representation of the 166 selected countries worldwide, along with the distribution of Critically Endangered (CR) species within these countries. The darker shade of red represents a higher number of CR species, while the lighter shade of red indicates a lower number of CR species within each country.

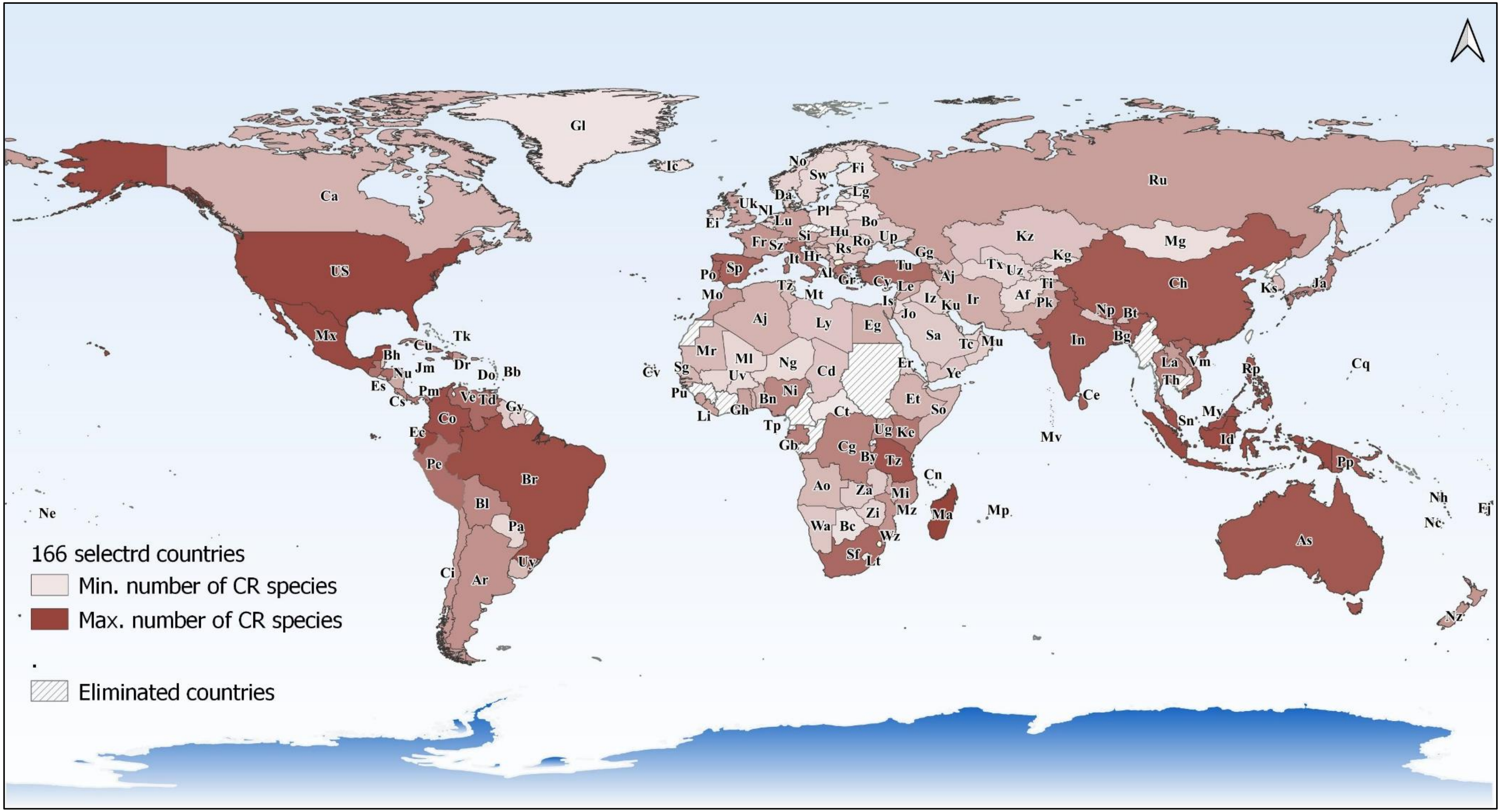


Figure 1: Study area (166 selected countries) and the distribution of CR species in these countries

2.1.2.2. Physical Geography

The variety and spatial arrangement of habitats affect the connectivity and viability of species populations, and mediate competition, making it essential to consider habitat heterogeneity when identifying threats to biodiversity. Environmental heterogeneity refers to the spatial or temporal variability in resources and factors that forms a region's biodiversity. It is a complex phenomenon that encompasses the size, shape, and composition of different landscape units as well as the spatial relationships between them. This includes variations in topography, slope, aspect, daily temperature, and precipitation. Taking into account these factors is essential for understanding the ecological dynamics and conservation needs of diverse ecosystems.

The physical-geographical characteristics of the countries vary significantly, it is not easy to quantify the influence of landscape heterogeneity on species richness, due to the multitude of environmental variables involved. However, one commonly used physical geography variable is elevation, which was employed in this study as a measure of landscape heterogeneity's impact on species richness.

Additionally, it is generally expected that species richness will increase with landscape heterogeneity. As landscape heterogeneity typically increases with area, the number of species within a given spatial region tends to correlate with the area of that region. Consequently, if a country harbors a high number of species, the probability of species being at risk of extinction also increases. Hence, the area of countries was another geographic parameter utilized in this study. Furthermore, the number of inhabitants and the density of the human population were incorporated as geographical parameters. These factors can have significant implications for biodiversity conservation, as human activities and population density can exert pressure on ecosystems, leading to habitat degradation and species decline (Cale & Hobbs, 1994; Wilson, 2000; Stein, et al., 2014; Tuanmu & Jetz, 2015; Ben-Hur & Kadmon, 2020; Hobohm, et al., 2021; Udy, et al., 2021).

2.1.2.3. Land Cover/ Land Use and Land Cover/ Land Use Change

To investigate the impact of land cover and land use change on biodiversity, the study classified relevant variables and analysed their changes over time. The city of Mölln in Germany was selected as a case study to examine land cover change from 1879 to 2020.

Land cover maps were prepared, and calculations were performed to analyse the changes over time. Data on land cover types from historical and recent years were collected to understand the spatial changes that occurred over time. The objective was to visualize these changes on maps and conduct statistical analyses. In land use and land cover change analysis, remote sensing (RS) methods and satellite images are commonly used. However, due to the study's focus on monitoring changes over an extended period, the use of high-resolution satellite images was limited. Instead, old scanned maps obtained from the State Surveying Office were utilized to create a classified land cover map. These maps dated back to 1879. For the current analysis, a new classified land use map for 2020 was developed. The analysis was conducted using QGIS software, which facilitated the necessary spatial analysis and mapping. While high-resolution satellite images were not extensively used, the available data from scanned maps and the classified land use map provided valuable insights into the land cover changes over time in the study area (Guliyeva, 2020; Ahmad, et al., 2022).

The city of Mölln in Germany was selected as the study area to investigate changes in land cover over time. Mölln was chosen due to its diverse range of land cover types and the presence of diverse plant and animal species within the area. In addition, there was a possibility to access to Geo TIFF Image files of this area from the State Office for Surveying and Geoinformation Schleswig-Holstein. Furthermore, there was the possibility of multiple personal field observations for this area. The purpose of the case study approach in this research was to illustrate the changes in land cover over time for a region (Mölln) and generalize the findings to the state of Schleswig-Holstein, Germany, or even worldwide. Figure 2 shows the location of the study area within Schleswig-Holstein, Germany.

To explore the relationship between land use change variables and the number of Critically Endangered (CR) species in each country, a database consisting of various variables related to land use change was consulted. These variables included build-up area, maize cultivation, nitrogen fertilization, phosphate fertilization, pesticide use on cropland, pesticides in agriculture, and demographic variables. The data for these variables were obtained from sources such as OECD.Stat (2021) and Our World in Data (2021), and they were the most recent and freely available information.

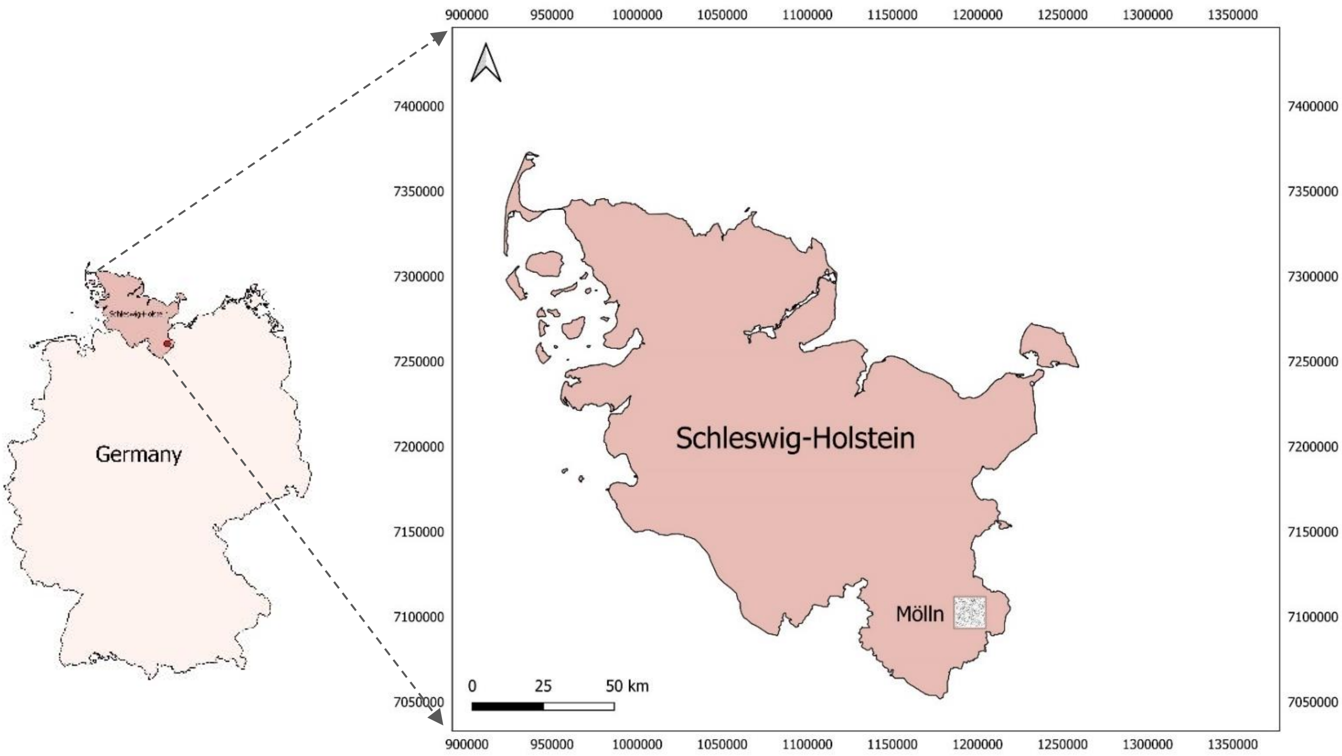


Figure 2: Location of the study area (Mölln, Schleswig-Holstein, Germany)

2.1.2.4. Biodiversity

To investigate the impacts of land use change on biodiversity, some influential variables related to biodiversity were considered in order to analyse their relationship with land use and land cover. The number of "critically endangered (CR) species" and the number of "chordate species" related to 166 selected countries were extracted as as indicators of endangerment and analysed. In this way, the relationship between the number of threatened species and factors such as different threats and habitat types were analysed. Chordate species include the total number of Critically Endangered (CR) species, Endangered (EN) species, and Vulnerable (VU) species altogether. In this study, a total of 8478 critically endangered (CR) species were analysed, consisting of 3467 animal species and 4973 plant species.

The data were obtained from the World Conservation Union (IUCN) Red Lists of Threatened Species, assessed in May 2021. These data can be accessed online on the IUCN Red List website (https://www.iucnredlist.org/). The IUCN regularly publishes lists of organisms and classifies them based on their conservation status. In this classification, a population of fewer than 50 individuals have been classified as an Endangered (EN) species. Other species categorised as Extinct (EX), Extinct in the Wild (EW), Critically Endangered (CR), Vulnerable (VU), Lower Risk (LR), Near Threatened (NT), Least Concern (LC), and Data Deficient (DD) (Kumari, et al., 2021; Hobohm, et al., 2021; Nelder, 2018; IUCN, 2023). The number of species falling under each category worldwide can be found in Table 3. Detailed information regarding the species classification can be found in Tables 55 to 66, which are located in the appendix section.

Table 3: Red List category and the number of species in each category in the world (IUCN, 2023)

Red List category	**Number of species**	**(%)**
Extinct (EX)	902	0,6%
Extinct in The Wild (EW)	84	0,06%
Critically Endangered (CR)	9251	6,15%
Endangered (EN)	16364	10,88%
Vulnerable (VU)	16493	10,97%
Lower Risk: Conservation Dependent (LR/cd)	152	0,1%
Near Threatened (NT or LR/nt)	8816	5,86%
Least Concern (LC or LR/lc)	77491	51,53%
Data Deficient (DD)	20835	13,85%

In this study, the main variable used to assess biodiversity richness is the number of native vascular plant species (Svasc.) in each country. This variable serves as an indicator of the diversity and richness of plant species within a given country. The citation for this information is provided as Gaens et al., 2021.

2.2. Methods

2.2.1. Quantum Geographical Information System

2.2.1.1. Classification of Land Cover Units

The classification and definition of land cover units used in this research for the case study area of Mölln (MTB 2330) are essential for establishing a standardized framework and facilitating a comprehensive understanding of the different land cover types. These defined units allow for a systematic categorization of the various land cover types present in the area, enabling a quantitative assessment of their significance and relationship to the overall landscape. Overall, the classification and definition of land cover units in this research offer a basic framework that facilitates a comprehensive analysis and evaluation of the land cover patterns and dynamics in Mölln, providing valuable insights into the composition and importance of each land cover unit within the study area.

For this purpose, the Earth's surface was classified into two main units: "sea" and "land". The sea unit was categorized into "deep sea" and "shelf sea", and the land unit was divided into "forest" and "non-forest" categories. The non-forest unit was further subdivided into two parts: "artificialsurface" and "open land". The open land unit was classified as several subcategories such as "arable land", "freshwater", "grassland", "bare land", and "shrubland". Additionally, there is another category labeled as "other", which encompasses land cover units that do not fall into the previously mentioned classifications. It should be noted that this specific category was not identified in the land cover classification of the Mölln area.

Due to the difficulty in precisely delineating the boundaries between grassland, bare land, sparsely vegetated areas, and shrubland on the scanned maps, a simplification approach was employed. All these land cover units were collectively classified under the category of "other". As a result, a total of five land cover units were considered for the classification of the case study area: "forest", "artificial", "arable land", "freshwater", and "other" (as depicted in Figure 3).

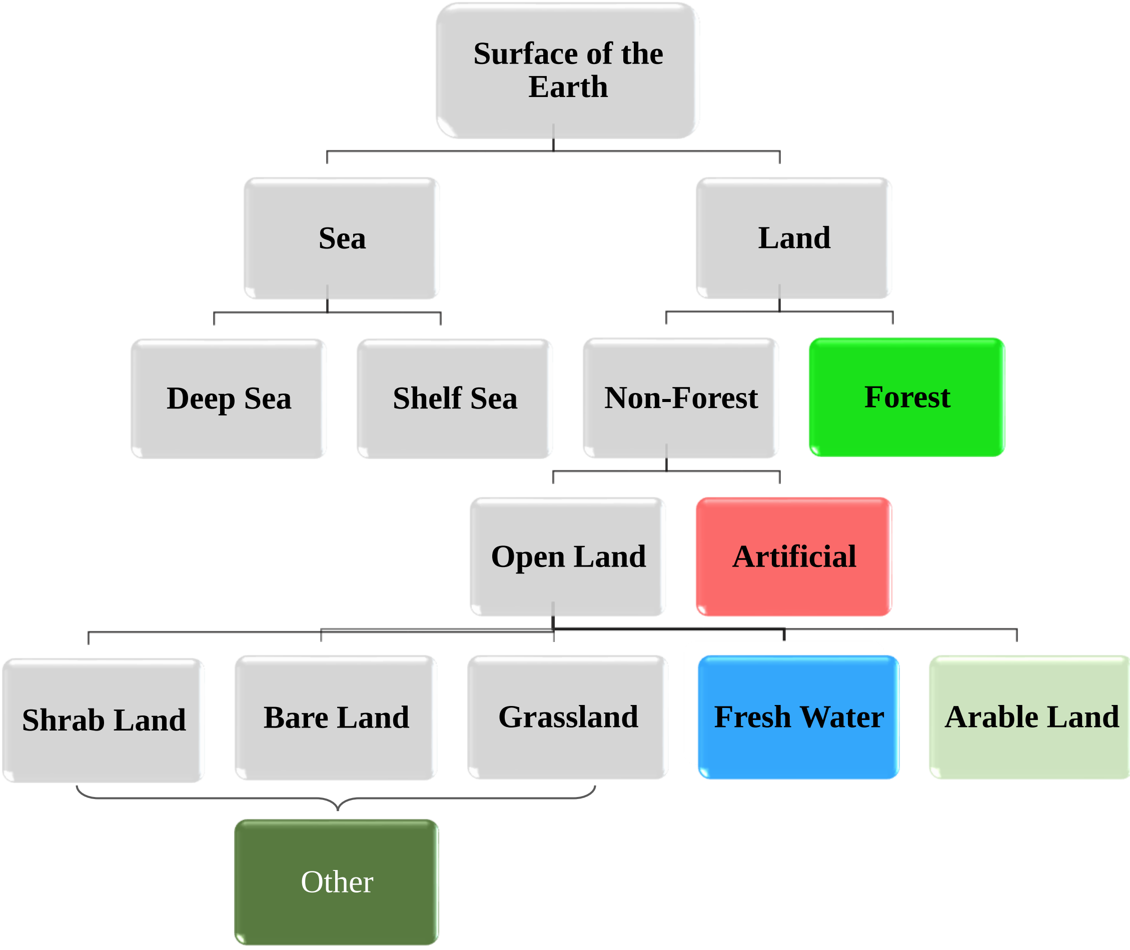


Figure 3: Land cover units (colors in this chart used in the analysis of QGIS software).

The descriptions of each unit for the analysis with the Quantum Geographic Information System (QGIS) are listed in Table 4, providing valuable insights into the characteristics and attributes of every unit.

Table 4: Description of land cover units used in this research

Land Cover Unit	**Description**
Forest	This unit encompasses terrestrial ecosystems predominantly characterized by the presence of trees, including dense forests, open forests, and woodlands. It also includes specific

	types of forests such as riverine forests and swamp forests, which are typically found in wetland areas (Matthews, et al., 2000).
Artificial	This unit includes urban areas and their associated features, including buildings, roads, pavements, urban green spaces such as parks and gardens, commercial and industrial sites (such as ports, landfills, quarries, and runways), infrastructures, mining areas, cemeteries, and waste dump sites. It also includes areas where extraction activities take place (Hobohm, et al., 2021).
Fresh Water	This unit includes areas that are predominantly covered by inland water bodies such as lakes and rivers, as well as ponds, river banks, lake margins, reeds, and coastal dunes.
Arable Land	This unit encompasses agricultural land, including areas used for temporary agricultural crops, land under temporary cultivation, land with temporary fallow, and cropland. It also includes specific types of agricultural fields such as cornfields, rice fields, and plantations of apple trees, olive groves, and other tree plantations. These areas are dedicated to agricultural practices and cultivation of various crops.
Other	This unit encompasses areas dominated by grasses and herbaceous plants, including natural grasslands, pastures, meadows, wetlands, heathlands, moors, marshy areas, bogs, swamps, fens. It also includes bare land or sparsely vegetated ground, such as stony areas or areas with very low vegetation cover (between 2 percent and 10 percent). Additionally, shrubland ecosystems dominated by woody and/or stem-succulent plants are considered part of this unit (Kim, 2016).

Photo 1: Landscape dominated by arable land (cereals), near Mölln, Schleswig-Holstein, Germany (Mahsa Tafaghodakbarpour, 2022)

Photo 2: Field with potatoes near Husum, Schleswig-Holstein, Germany (Mahsa Tafaghodakbarpour, 2022)

Photo 3: River Seege near Restorf, Niedersachsen, Germany (Mahsa Tafaghodakbarpour, 2021)

Photo 4: Grazed saltmarsh on Sylt, Schleswig-Holstein, Germany (Mahsa Tafaghodakbarpour, 2022)

2.2.1.2. Land Cover Classification of Mölln Area Using QGIS

The past few decades have witnessed significant advancements in land use information systems, driven by the need for more efficient land management practices (Matuk, 2021). In this research, the primary software used for processing land cover maps is QGIS 3.16.7. This software enabled the creation of a classification map of land cover in Mölln, serving as the study area, and facilitated the analysis of land cover changes over time. The objective was to assess and quantify the changes in land cover units, thereby understanding the extent and impacts of both human-induced and natural changes on biodiversity (Potapov, et al., 2008; Kouassi, et al., 2020; Meedeniya, et al., 2020). To generate the land cover classification maps, old scanned maps provided by the State Office for Surveying and Geoinformation Schleswig-Holstein were utilized. The available maps span multiple years, including 1879, 1924, 1955, 1984, and 2020. These maps were employed to create land use change maps for four distinct periods: 1879-1924, 1924-1955, 1955-1984, and 1984-2020. The percentage of land use change within each period was subsequently calculated to quantify the observed changes in land cover.

For this purpose, the following steps were implemented in QGIS:

1. Georeferencing the old maps
2. Digitizing the georeferenced maps and creating land cover units
3. Quantifying and calculating the properties of created land use units

The first step was georeferencing the old scanned maps. Georeferencing involves aligning the scanned maps with real-world coordinates. In this process, the Universal Transverse Mercator Coordinate System (UTM) and the WGS84 Datum were used to ensure accurate spatial referencing. Once the maps were georeferenced, the next step was to digitize them. Digitization involves manually tracing the land cover classes on the georeferenced maps to create vector layers representing different land cover units. This process improves the readability and interpretability of the maps. Whenever land cover units of satellite images and geographical maps are analysed, it is neccessory to train and identify the unite ba field work. Because of logistic reasons and because of the existence of accurate and old maps since 1879, we used the Mölln region as training area for field work.

Before starting the digitization process, the land cover classes used in this research were identified in the fields and defined. These classes were categorized into five main categories, as described in section 2.2.1.1 of the study. The digitization process resulted in several vector layers representing the study area, with each layer corresponding to a specific land cover unit. These vector layers maintained the information from the original raster data without altering the map content. Finally, various calculations were performed to analyse the land cover changes. The area and coverage percentage of each land cover unit were calculated for each year. Additionally, the growth percentage of each unit compared to the previous year was determined, providing insights into the rate of change for each land cover unit over time. By following these steps, the old scanned maps were georeferenced and digitized and land cover units were created for analysis of land cover changes over time (Fisher & Unwin, 2005; Kim, 2016; Ringim, et al., 2019; Duarte, et al., 2021; Congedo, 2021).

The primary data for analysing land cover change over time in this research consisted of Geo TIFF Image files provided by the State Office for Surveying and Geoinformation Schleswig-Holstein. The study area encompassed the city of Mölln and a portion of the city of Ratzeburg, located in the south-east of Schleswig-Holstein in northern Germany. The geographical coordinates of the study area were approximately 53º 35′ - 53º 41′ N and 10º 39′ - 10º 48′ E, covering an area of approximately 98,000 km2. The elevation of the area was reported to be around 19 ± 1 meters above sea level. The maps used for the analysis were part of the national map series on a scale of 1/25000. The coordinate system used for these maps was EPSG 3857. The study focused on five land cover categories: arable land, forest, artificial areas, fresh water bodies, and other. To study land cover and land cover change over time, data from five different years were used, with a time interval of 48, 31, 29, and 36 years between each period. The selected years were 1879, 1924, 1955, 1984, and 2020, providing a span of 141 years to investigate land cover change. The city of Mölln was chosen as a case study due to the availability of old maps through the land surveying office of Schleswig-Holstein. Additionally, the region offered a diverse range of land cover classes, including cities, arable lands, forests, and water bodies, which contributed to increasing the accuracy of the study. Access to the study area for field observations was also easy, which was crucial for measuring and monitoring land use and land cover (Hansen, et al., 2004). By utilizing these data sources and conducting field observations, land cover change over a significant time period in the Mölln region was studied, and old maps and contemporary data were analysed to gain insights into the dynamics of land cover and its changes.

2.2.2. Analysis of the IUCN Red List

In this section, was relied on the data provided by the Species Survival Commission of the IUCN, which maintains a comprehensive list of globally threatened species known as the IUCN Red List. The analyses specifically focused on the 8321 species classified as critically endangered (CR). The IUCN Red List incorporates a robust classification scheme for assessing the threats faced by species. It consists of 99 specific threat types, which are further grouped into 12 broader classifications. These classifications help in understanding and categorizing the various types of threats that impact species. Additionally, the IUCN Red List also includes a comprehensive habitat classification scheme. This scheme comprises 103 specific habitat types, which are further grouped into 18 broader classifications. By utilizing the data from the IUCN Red List, the habitats, threats, and conservation status of critically endangered species were analysed (Burke, et al., 2000; Trull, et al., 2017).

In this section, an in-depth analysis of critically endangered (CR) species was conducted using data from the IUCN Red List. The primary focus was on several key aspects related to CR species, including their numbers, distribution across different habitats, threats they face, and the intersection of threats and habitats. To begin with, available filters on the IUCN Red List website was utilized to select a subset of 166 study countries. This allowed to narrow down the analysis to specific regions of interest. Then the number of CR species within each of the 18 main classes of habitats present in the selected countries were examined. This provided insights into the distribution and abundance of CR species across various ecological settings. Furthermore, the number of CR species that are threatened by different categories of threats was investigated. The IUCN Red List employs a comprehensive threat classification scheme consisting of 12 main threat categories. By applying the appropriate filters, the number of CR species affected by each threat category was determined.

Within the realm of threats, a special attention was paid to the "climate change and severe weather" factor. The importance of this specific threat category was ranking by analyzing the number of species that are threatened by climate change and severe weather events. Finally, the intersection of threats and habitats was examined by applying filters to assess the number of CR species threatened by different factors across all habitats. This analysis helped to identify the specific threats that pose the greatest risks to CR species in different ecological contexts.

2.2.3. Statistics

2.2.3.1. Univariate Statistics

In this section, quantitative data analysis techniques were employed for data evaluation and analysis, including the use of measures such as mode, median, mean, and graphical representations. Univariate descriptive statistical methods were applied to provide numerical summaries of the data. A comprehensive dataset consisting of 35 variables related to land use was collected for all 166 selected countries. These variables encompassed various aspects such as the physical geographical features of countries, urban and rural populations, urbanization levels, built-up areas, land cover characteristics, and economic parameters (Ali, 2021; Venables & Ripley, 1999).

To analyse the dataset, structural techniques were employed, and the results were presented in the form of analysis tables and graphs. These techniques facilitated a deeper understanding of the relationships and patterns within the data. By utilizing both numerical and visual representations, a comprehensive picture of the land use-related factors and their interconnections was established (Burhan, et al., 2021).

In order to assess the relationship between land use change and environmental biodiversity, we conducted an analysis to examine the associations between various indicators. These indicators included economic factors such as GDP in agriculture, GDP in service, GDP in industry, and inequality, as well as demographic factors such as urban population and artificial surface. Additionally, we considered the presence of vascular plants, the extent of arable land and permanent crops, and the pressure on biological diversity.

Data for these indicators were collected from multiple sources, including the IUCN Red List dataset, Our World in Data, OECD, and CIA World Factbook. The data covered the years 2017 to 2020. To conduct the analysis, we utilized the raw data extracted from these sources. The detailed data used for the analyses can be found in the appendix, ensuring transparency and providing a reference for further examination (Chan, 2004; Kalemis, 2022).

2.2.3.2. Bivariate Statistics

This section commenced with the application of regression correlation techniques on the dataset. For measuring the correlation between pairs of variables Spearman's correlation coefficient was employed. Indeed, Spearman rank correlation was utilised to statistically identify the linear relationship between variables and uncover patterns of land use and land cover change, along with their correlation with biodiversity (Zhang, 2015; Zhang & Li, 2015; Field, 2016; Zheng, et al., 2022).

The data used in the analysis were sourced from various online databases, including the IUCN Red List, CIA World Factbook, OECD, and Our World in Data. To assess the normality of variable distributions, the Kolmogorov-Smirnov statistical test was conducted. The results of this test can be found in the appendix section (Table 69). Subsequently, the data were normalized by calculating the logarithm of all variables using SPSS (Dytham, 2003). After confirming the normality assumptions for all variables, a bivariate correlation analysis was performed. Spearman's rank correlation was employed to determine the relationship between the variables related to land use and land cover change and factors affecting threatened species. The use of the Spearman correlation coefficient is advantageous in mitigating the effects of extreme values or the effects of violations of assumptions (Field, 2016). The statistical software SPSS was utilized to examine the associations among quantitative variables using Spearman's rank correlation. The objective was to characterize and analyse the relationship between two variables. Spearman's correlation coefficient was chosen due to its insensitivity to outliers, which is an important consideration in this research. By calculating the dependence of data in terms of rank, Spearman's correlation coefficient provides a reliable estimation of the relationship between two variables, even in the presence of outliers (Wiśniewski, 2022; Pirie, 2006; Kalemis, 2022). While correlation coefficients provide insights into the relationship between two continuous variables, they do not account for the effects of other covariates in the analysis. In situations where the influence of other factors needs to be considered and controlled for, a Regression Model becomes necessary. Regression analysis allows for the examination of the relationship between a dependent variable and one or more independent variables, taking into account the potential effects of other covariates. This helps to better understand the specific contributions of different variables and their impact on the outcome of interest (Chan, 2004).

2.2.3.3. Multivariate Statistics

In order to test the hypotheses of this research, the statistical method of Multiple Linear Regression (MLR) analysis was employed. Multivariate statistics holds significance in the field of biological sciences, offering valuable insights into relationships between variables (Boyce, 2002). The proposed model in this research includes two response variables and 35 predictor variables. Statistical evaluation of the data aims to describe the relationships between these variables (Schneider, et al., 2010). Regression analysis, being one of the most commonly used tools, enables the analysis of relationships between variables and facilitates the comparison of effects among variables with different scales (Sarstedt & Mooi, 2014). The linear regression model is used as a helpful tool for prediction and optimisation in the field of environmental protection (Załuska & Gładyszewska-Fiedoruk, 2020).

The objective of this study was to conduct a comprehensive statistical evaluation of the relationships between different variables, quantifying the functional relationship between them, and identifying the significance of each variable in influencing the final outcome while examining their interdependencies.

To facilitate this complex analysis, SPSS software which is a statistical program was employed. This software enables the examination and quantification of relationships between variables through Linear Regression analysis. Additionally, SPSS automatically generates the analysis of variance (ANOVA) output, providing further insights into the relationships being investigated.

In this study, the relationships between various variables such as land use and land cover, geographic factors, economic variables, and physical geography were analysed as predictor variables, while endangered species data from 166 countries were used as response variables. Through the statistical analysis, the aim was to uncover patterns and associations that contribute to a better understanding of these relationships (Pandit, 2019).

The study incorporated various factors to assess their impact on biodiversity. Arable land and permanent crops were considered as land use factors, while indicators such as GDP in agriculture, inequality, GDP in service, and GDP in industry were used to measure the economic aspects of each country. The number of endemic vascular plants was employed as an indicator of natural richness, while area and elevation served as physical geography factors. Geographical factors were represented by urban and rural population as well as the extent of artificial surface. The response variables in this analysis were the number of critically endangered (CR) species and the number of Chordate Species (including critically endangered, endangered, and vulnerable species) based on the IUCN Red List. These variables were used to assess the pressure on nature and biodiversity.

It is important to acknowledge that there may be additional local and regional factors that can influence the results. However, by utilizing this methodology, the study aimed to identify the specific impact of various parameters related to land use on biodiversity.

Statistics provide a quantitative approach to analyzing the relationship between natural species richness, physical geography, land use and land cover, economic, and demographic factors. In this study, Spearman correlation analyses and multiple linear regression (MLR) analyses were employed to untangle the complexity of the data and understand the relationships between variables. To ensure the validity of the analyses, all variables underwent a log-transformation (ln) to address skewed distributions and normalize the data. This transformation helps in achieving more accurate and reliable results. In the interpretation of the findings, only consistent and congruent results were considered to ensure robust conclusions. By applying statistical techniques, the study aimed to provide meaningful insights into the connections between different factors and their impact on biodiversity and natural species richness.

Our primary objective was to identify the best combination of variables that would yield a high adjusted R2 value while keeping the number of variables as low as possible. To achieve this, we conducted multiple linear regression (MLR) analyses for 166 countries. However, it is important to acknowledge that interpreting the results of multivariate analyses can sometimes be challenging, as they rely on certain assumptions that may be difficult to assess (Anderson, et al., 1976; Shiker, 2012; Kumari & Yadav, 2018; Hariaji, et al., 2020; Kalemis, 2022). By calculating numerous MLRs, we aimed to find the most optimal models with high adjusted R2 and low numbers of variables (Hobohm, et al., 2021). These models can offer valuable numerical summaries of the relationships between land use, land cover, and biodiversity parameters.

3. Results

3.1 . Land Cover and Land Cover Change

3.1.1. Global Land Cover and Land Cover Change

The results of the analysis on land cover change in the 166 countries studied are presented in Figure 4. The dominant land cover on terrestrial land in both 1992 and 2019 is tree cover. It is followed by cropland, bare area, grassland, shrubland, sparse vegetation, inland water, wetland, and artificial surface, in that order (Figure 4).

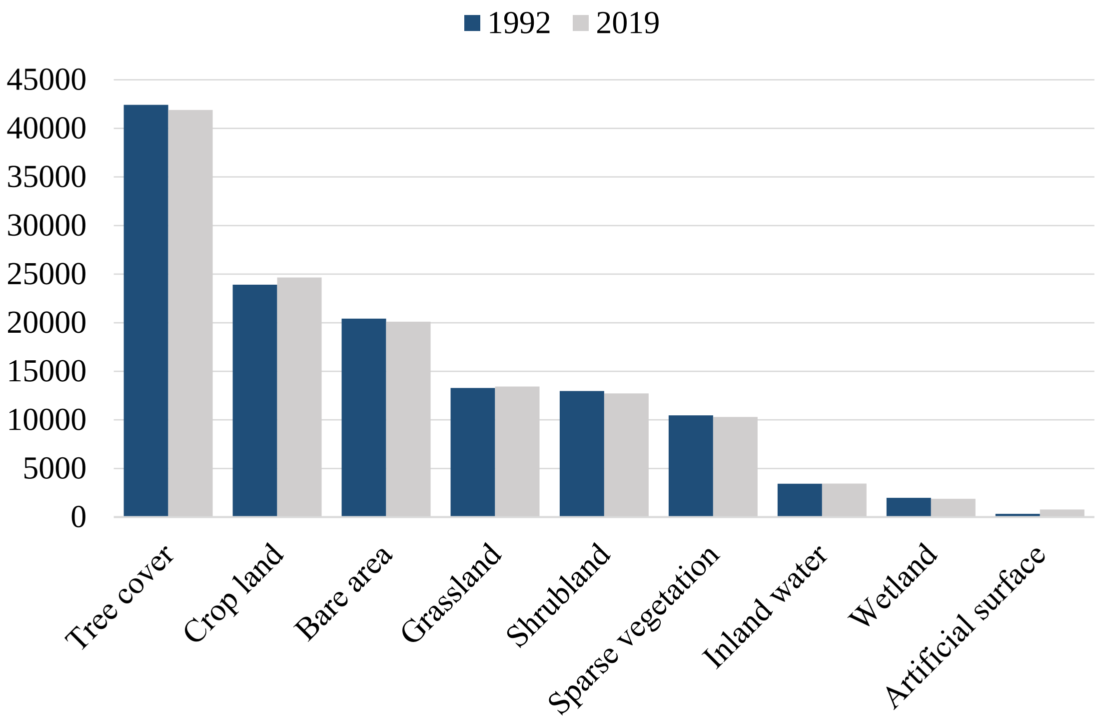


Figure 4: The area of land cover units in 1992 and 2019 in 166 selected countries, Square kilometers (000's) (OECD, 2021)

The results of land cover change analysis indicate that over a span of 27 years, from 1990 to 2019, certain land cover categories experienced changes. In 2019, compared to 1992, there was an increase in the area covered by artificial surface, cropland, grasslands, and inland water. On the other hand, the total area of tree cover, bare area, sparse vegetation, shrubland, and wetland decreased in 2019 compared to 1992 (Table 5).

Table 5: Percentage of land cover classes in 1992 and 2019, and the growth rate of land cover during this period (OECD, 2021)

Land cover unit	1992 (%)	2019 (%)	Growth rate of land cover (%) (2019-1992)
Tree cover	32.83	32.42	-1.25
Crop land	18.5	19.08	3.14
Bare area	15.81	15.56	-1.58
Grassland	10.28	10.4	1.17
Shrubland	10.04	9.85	-1.9
Sparse vegetation	8.10	7.97	-1.6
Inland water	2.65	2.67	0.75
Wetland	1.53	1.45	-5.22
Artificial surface	0.26	0.61	134.6

During the specified period, there has been a notable increase in the area covered by artificial surfaces worldwide, with an approximate growth rate of 134.6%. Cropland also experienced a significant growth rate of 3.14%. Conversely, the most substantial decrease in land cover area was observed in wetlands, with a decrease rate of -5.22%. It is worth noting that tree cover remains the dominant land cover throughout the entire period analysed, as depicted in Figure 5.

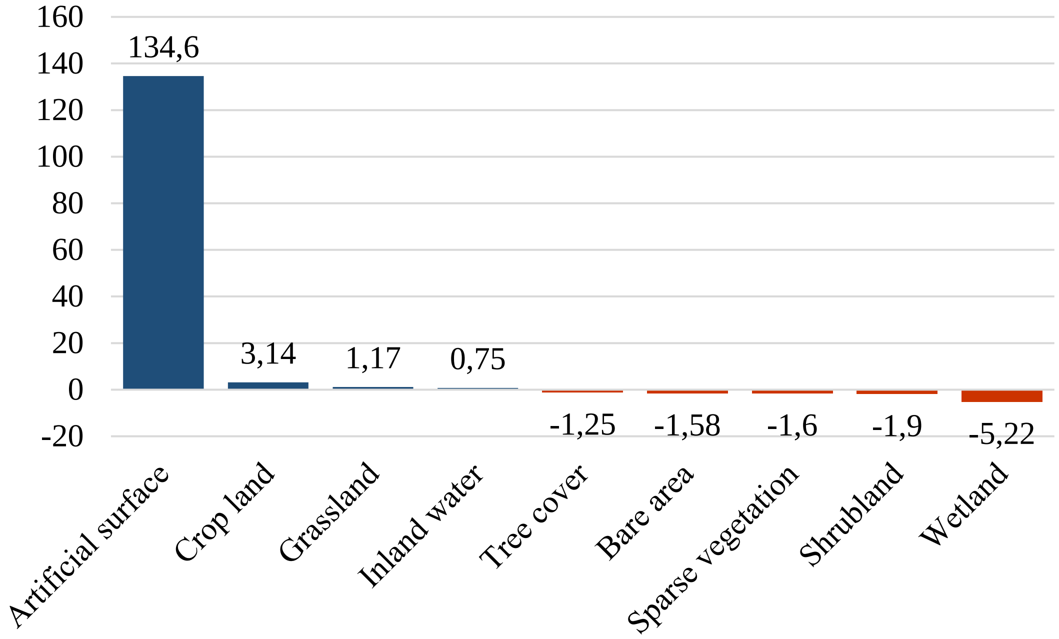


Figure 5: Land cover change between 1992 and 2019, in 166 selected countries (%) (OECD, 2021)

Among all countries studied, Ethiopia exhibited the largest increase in tree cover, with a growth rate of +17.2%, while Brazil experienced the largest decrease in tree cover, with a decline of -6.5% between 1992 and 2019. Brazil also recorded the largest increase in cropland area, with a growth rate of +14.9%, whereas Ukraine had the largest decrease in cropland area, with a decline of -5.7%. Regarding shrubland, Russia witnessed the largest increase in area, with a growth rate of +9.7%, while Nigeria had the largest decrease, with a decline rate of -42.3%. China recorded the largest increase in artificial surfaces, with a remarkable growth rate of +313.8%. Conversely, certain countries like Niue and the Northern Mariana Islands did not exhibit significant growth in artificial surfaces, as indicated in Table 6.

Table 6: Countries with the highest positive and negative growth rates in the area of land cover classes between 1992 and 2019 (OECD, 2021)

Land cover class	**Country** (The largest positive growth)	**Country** (The largest negative growth)
Tree cover	Et (+17.2%)	Br (-6.596%)
Crop land	Br (+14.95%)	Up (-5.72)
Wetland	Br (+9.64%)	Us (-37.86%)
Inland water	Br (+27.69%)	Kz (-7.55%)
Grassland	As (+8.65%)	Kz (-4.14%)
Bare area	Ir (+2.05%)	Ch (-3.99%)
Artificial surface	Ch (+313.84%)	Niue (0%)
Sparse vegetation	Cha (+10.97%)	Ru (-5.56%)
Shrubland	Ru (+9.74%)	Ni (-42.36%)

Table 7 displays the calculated Spearman's Rank Correlation coefficients between different land use variables. The table reveals a significant positive correlation of +0.474 between the area of artificial surface and cropland. Furthermore, the area of artificial surface exhibits the largest negative correlation of -0.462 with permanent pasture.

Table 7: Correlation coefficients between land use variables

	Tc (2018)	Gr (2018)	We (2018)	Sh (2018)	Sv (2018)	Cr (2018)	As (2018)	Ba (2018)	Iw (2018)	Ag	Ar	Pc	Pp	Fr	Bu (before 2014)	Mz (2018)
Tc (2018)	1															
Gr (2018)	-0.242	1														
We (2018)	0.050	0.269	1													
Sh (2018)	-0.077	0.173	0.037	1												
Sv (2018)	-0.472	0.005	0.049	0.055	1											
Cr (2018)	-0.139	-0.182	-0.333	0.066	-0.319	1										
As (2018)	-0.087	-0.032	-0.209	-0.310	-0.254	0.474	1									
Ba (2018)	-0.683	0.156	0.028	-0.240	0.531	-0.581	-0.235	1								
Iw (2018)	0.113	-0.123	0.485	-0.065	-0.117	0.153	0.141	-0.318	1							
Ag	-0.302	0.229	0.001	0.380	0.260	-0.024	-0.386	0.128	-0.165	1						
Ar	-0.247	0.087	0.019	0.318	0.124	0.265	-0.153	-0.085	-0.011	0.867	1					
Pc	-0.071	-0.101	-0.006	0.161	0.039	0.139	-0.218	0.001	-0.004	0.749	0.757	1				
Pp	-0.332	0.332	0.033	0.392	0.317	-0.160	-0.462	0.274	-0.222	0.945	0.721	0.622	1			
Fr	0.235	-0.018	0.067	0.339	0.004	-0.061	-0.352	-0.252	-0.044	0.703	0.674	0.641	0.608	1		
Bu (before 2014)	-0.095	-0.044	-0.111	-0.029	0.102	-0.074	0.003	0.072	-0.024	-0.021	-0.131	-0.145	0.013	-0.182	1	
Mz (2018)	-0.083	0.160	-0.023	0.357	-0.123	0.382	-0.034	-0.223	0.066	0.653	0.789	0.677	0.537	0.578	-0.113	1

In Table 8, the highest positive and negative correlation between land cover classes and other predictor variables is presented.

The results of the correlation analyses indicate a strong and highly significant relationship between the area of artificial surface and GDP per area, with a correlation coefficient of 0.871. On the other hand, the highest negative correlation is observed between the area of tree cover and bare land, with a correlation coefficient of -0.683.

Table 8: Highest positive and negative correlation coefficients between land cover classes and other predictor variables

Land Cover Units	Highest Positive Correlation	Highest Negative Correlation
Tree cover (2018)	Inequality (0.272)	Ba (2018) (-0.683)
Grassland (2018)	Pp (0.332)	Tc (2018) (-0.242)
Wetland (2018)	Iw (2018) (0.485)	Cr (2018) (-0.333)
Shrubland (2018)	Pp (0.392)	GDP per Area (-0.259)
Sparse vegetation (2018)	Ba (2018) (0.531)	Tc (2018) (-0.472)
Cropland (2018)	Mz (2018) (0.382)	Ba (2018) (-0.581)
Artificial surface (2018)	GDP per Area (0.871)	Area (-0.490)
Bare area (2018)	Sv (2018) (0.531)	Tc (2018) (-0.683)
Inland water (2018)	We (2018) (0.485)	Ba (2018) (-0.318)

3.1.2. Land Cover and Land Cover Change in the Mölln Area

Over the last 141 years, the land cover in Mölln has undergone significant changes. Initially, arable land was the dominant land cover type. However, the arable land gradually decreased by 28%, while both forest cover and artificial surface have experienced notable increases of 28% and 63%, respectively. Consequently, the land cover pattern in Mölln has changed from predominantly arable land to predominantly forest cover between 1879 and 2020. The range of open waters in the area has remained relatively stable without significant changes over this period. Additionally, the "other" land cover category has nearly halved in area compared to its extent in 1879. Figures 6 to 15 display land cover classification maps for five different years between 1879 and 2020, showcasing the evolving land cover patterns over time. These maps were created by georeferencing and digitizing the original map provided by the Surveying and Geoinformation Schleswig-Holstein to accurately represent the study region.

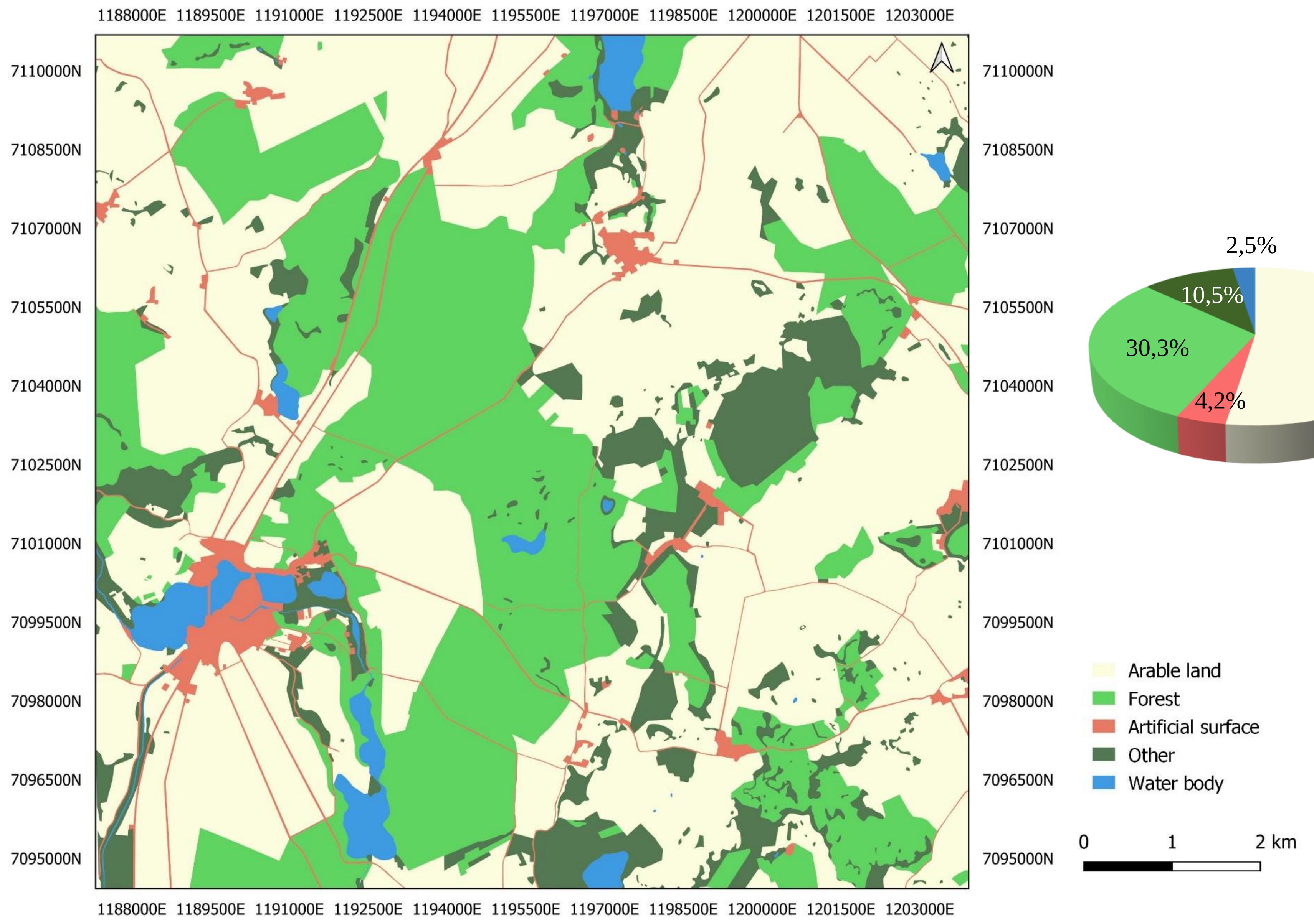


Figure 6: Land cover classification map of Mölln (1879).

In 1879, the dominant land cover in Mölln was arable land (including agricultural land, temporary agricultural crops, land under temporary crops, land with temporary fallow, and cropland), which covered approximately 51389.43 square kilometers or 52.5% of the total area (approximately 98000 square kilometers). The second largest land cover was forest, covering 29694.37 square kilometers or 30.3% of the total area. Other unit accounted for 10.5% of the land cover, representing the third largest land cover category. Due to the difficulty in distinguishing between grassland, bare land, and sparsely vegetated areas on old maps, all these land cover types were classified under the category of other unit. Artificial land accounted for approximately 4.2% of the region, while freshwater covered 2.5% representing the smallest land cover categories in the area.

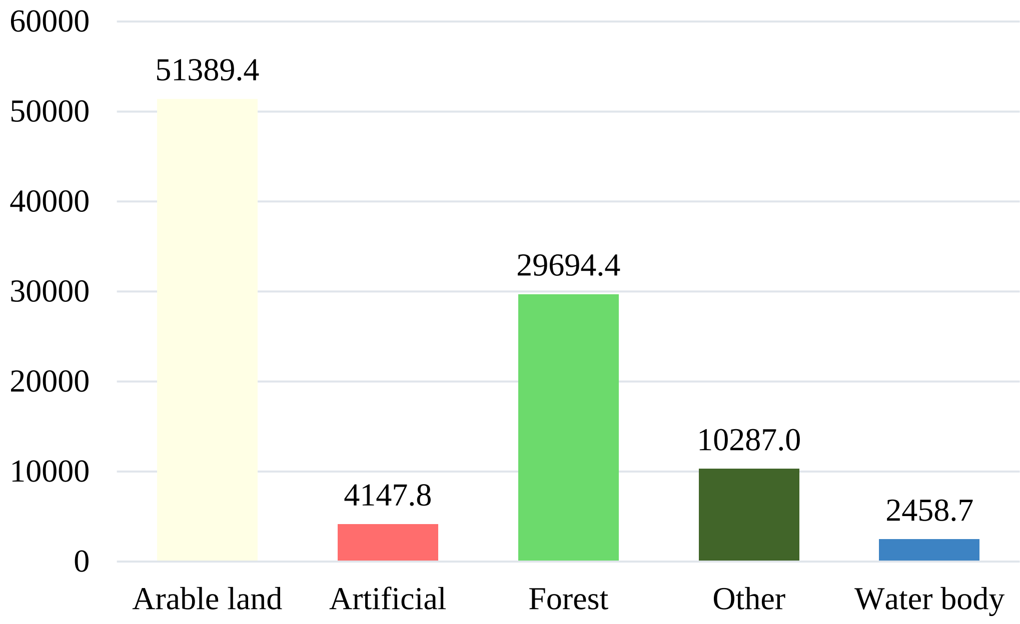


Figure 7: The area of land cover units in Mölln (km^2), (1879)

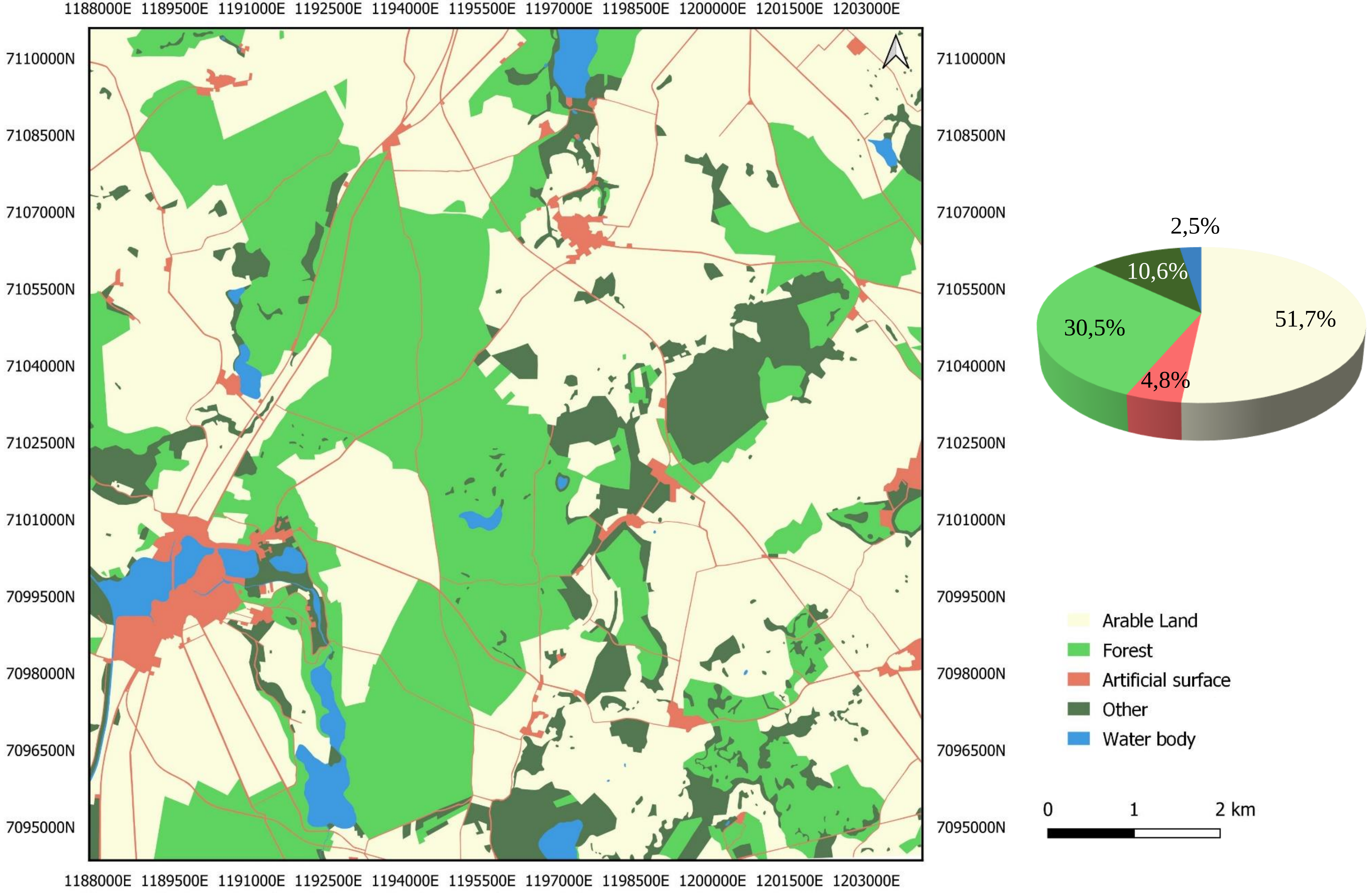


Figure 8: Land use classification map of Mölln, (1924).

By 1924, arable land remained the dominant land cover in Mölln, comprising approximately 51.7% of the region, which is a slight decrease of about 0.2% compared to the year 1879. Forests maintained their position as the second dominant land cover, covering 30.5% of the area, representing a slight increase of about 0.2% compared to 1879. Grassland emerged as the next dominant land cover, with a coverage of 10.6%, experiencing a slight increase of about 0.1% compared to 1879. The most significant increase was observed in artificial surfaces, which experienced a growth rate of approximately 0.6%. However, there was a slight decrease in the area covered by water bodies, with the coverage declining from about 2458743 square kilometers in 1879 to approximately 2405602 square kilometers in 1924.

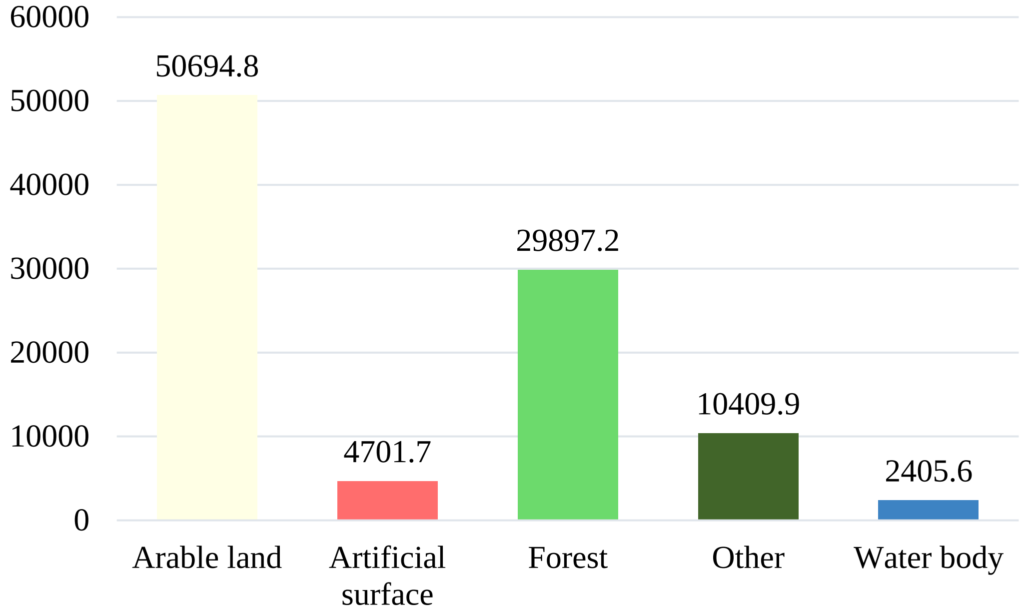


Figure 9: The area of land cover units in Mölln (km^2), (1924)

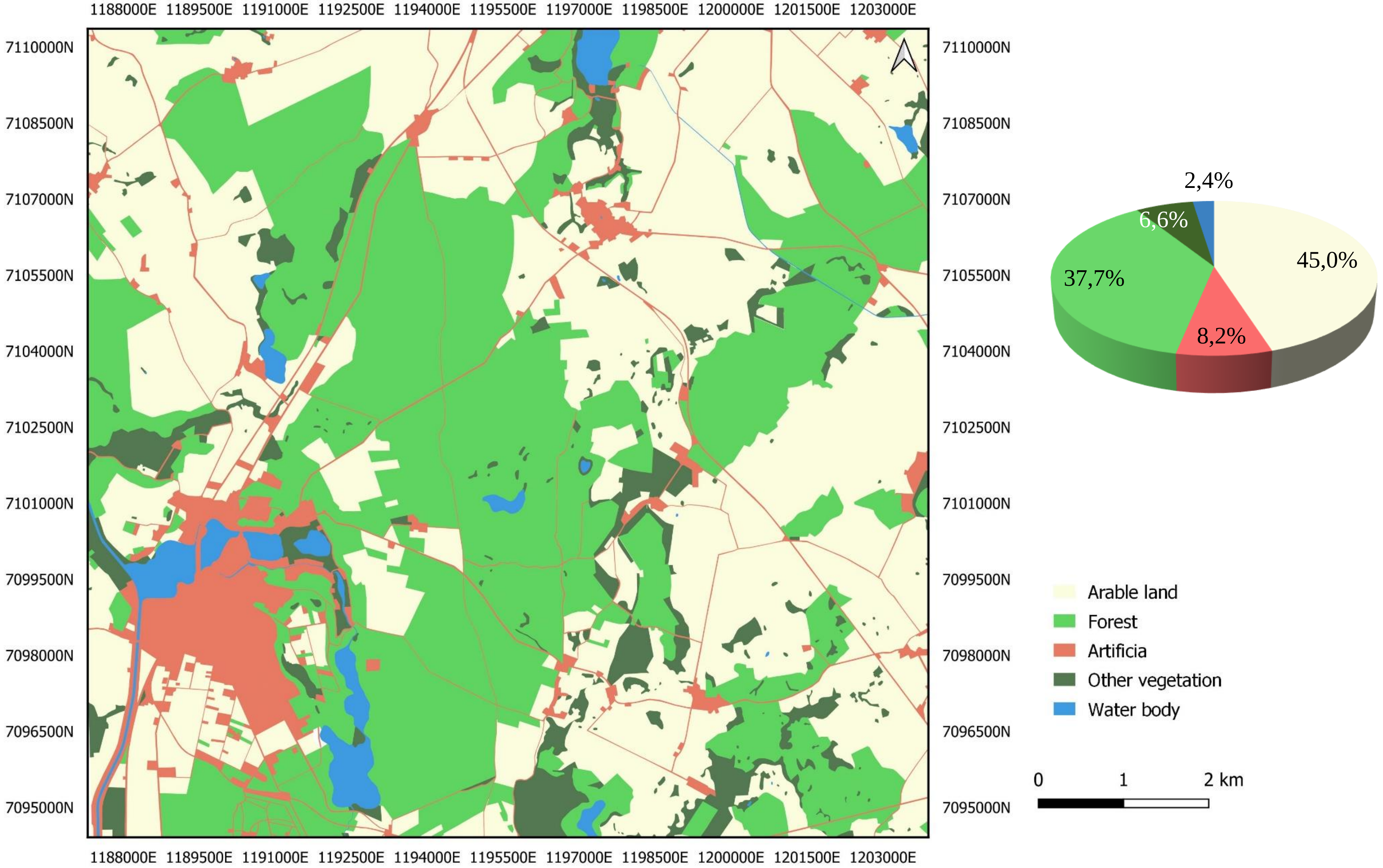


Figure 10: Land use classification map of Mölln (1955)

As of 1955, there was a low decrease in the area of arable land, amounting to approximately 7%. However, arable land still remained the dominant land cover, covering around 44112673 km2 or 45% of the total area. Forests experienced an increase in coverage, occupying approximately 36958407 km2, which represents a 7% increase compared to 1924. The maps prepared for this period indicate a conversion of other unit types into forests. The area of artificial surfaces showed significant growth, nearly doubling from 4.8% in 1924 to 8.2% in 1955. Most arable lands have been replaced with artificial surfaces. The area covered by other units decreased significantly from 10.6% in 1924 to 6.6% in 1955. There was a slight decrease in the area of freshwater bodies from around 2405602 km2 in 1924 to approximately 2385638 km2 in 1955.

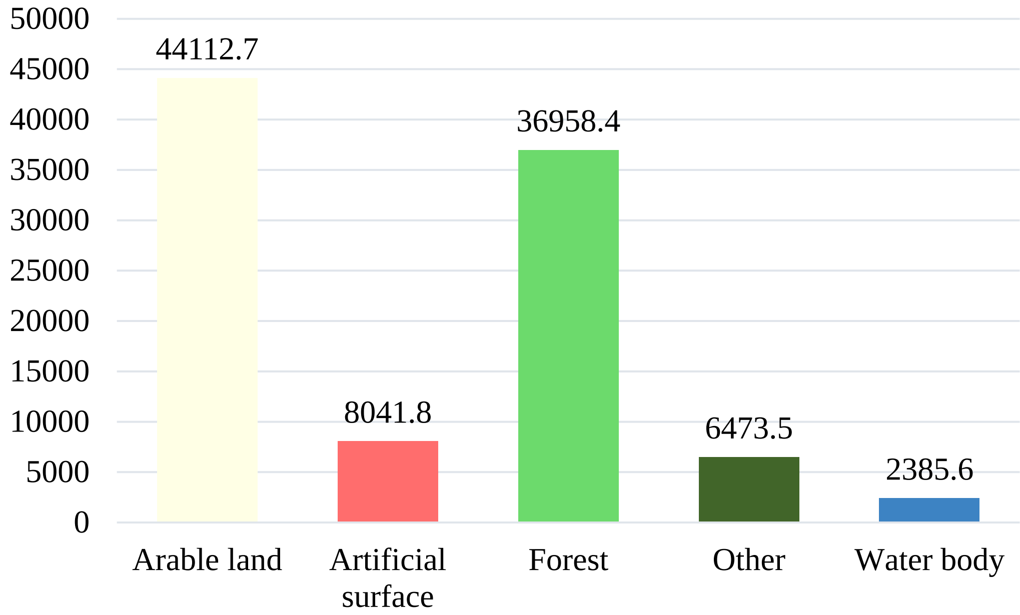


Figure 11: The area of land cover units in Mölln (km^2), (1955)

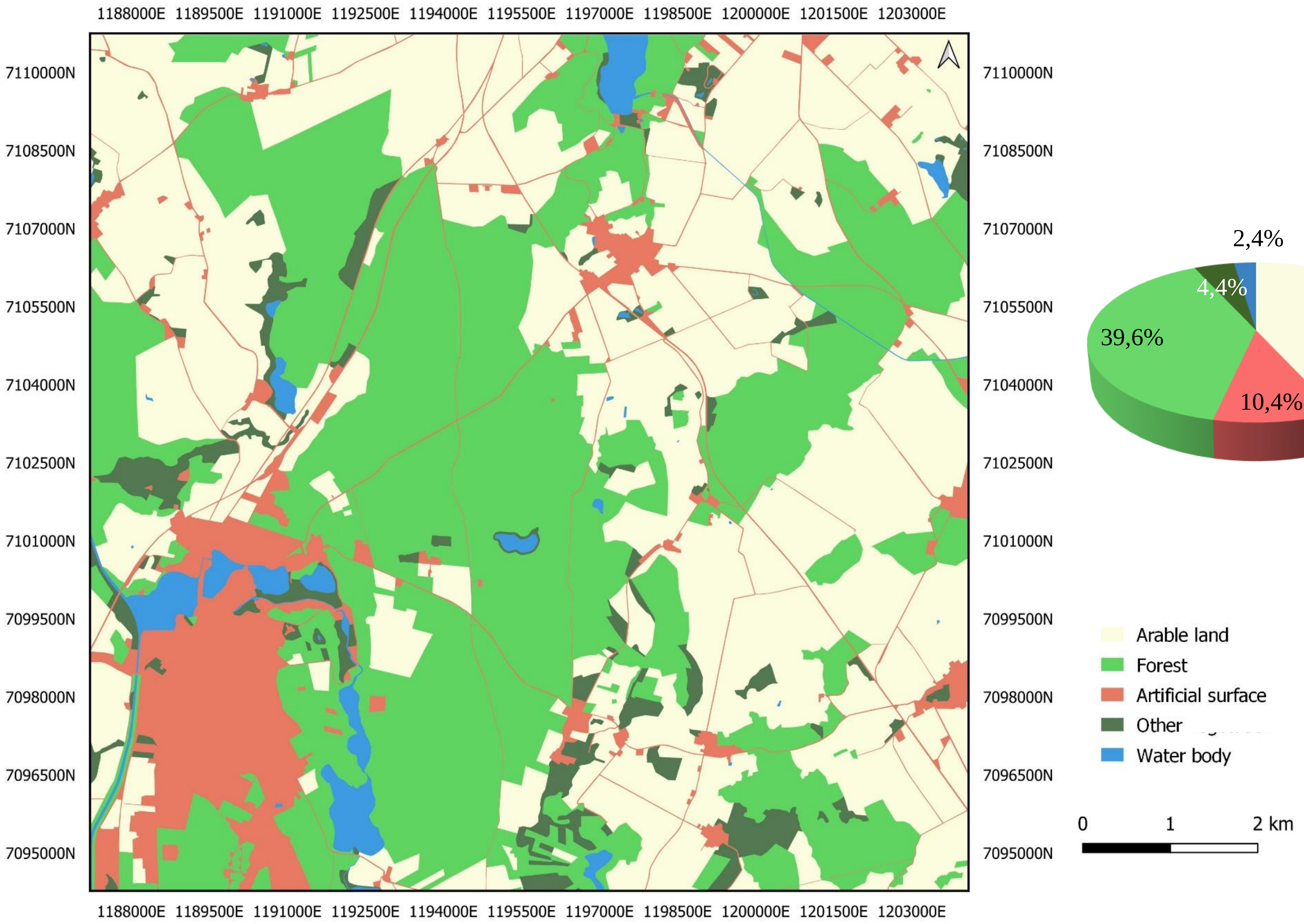


Figure 12: Land use classification map of Mölln (1984)

By 1984, there was a slight decrease in the area of arable land, amounting to approximately 2%. Nonetheless, arable land remained the dominant land cover in the region, covering about 42295402 km2 or 43% of the total area. Forests experienced a 2% increase compared to 1955, making it the second dominant land cover, occupying approximately 38827928 km2 or around 39% of the land. Other unit underwent a reduction of about 2% from 1955 to 1984, covering only 4.4% of the land area, equivalent to approximately 4350865 km2. Freshwater bodies, with an area of approximately 2394103 km2 or 2.4%, showed no significant change and remained at the lowest level among the land cover types in the region.

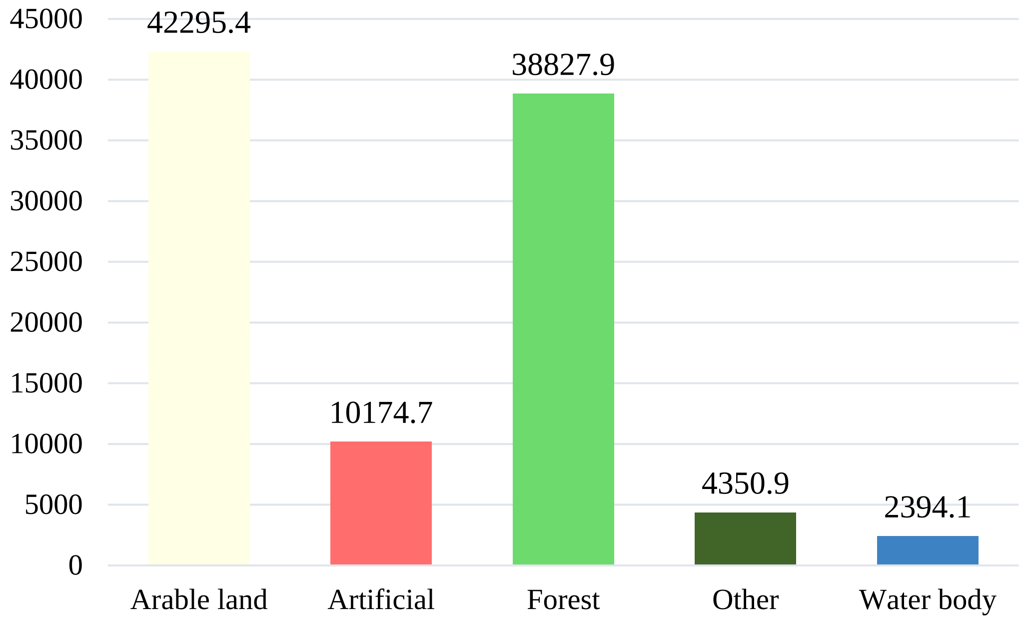


Figure 13: The area of land cover units in Mölln (km^2), (1984)

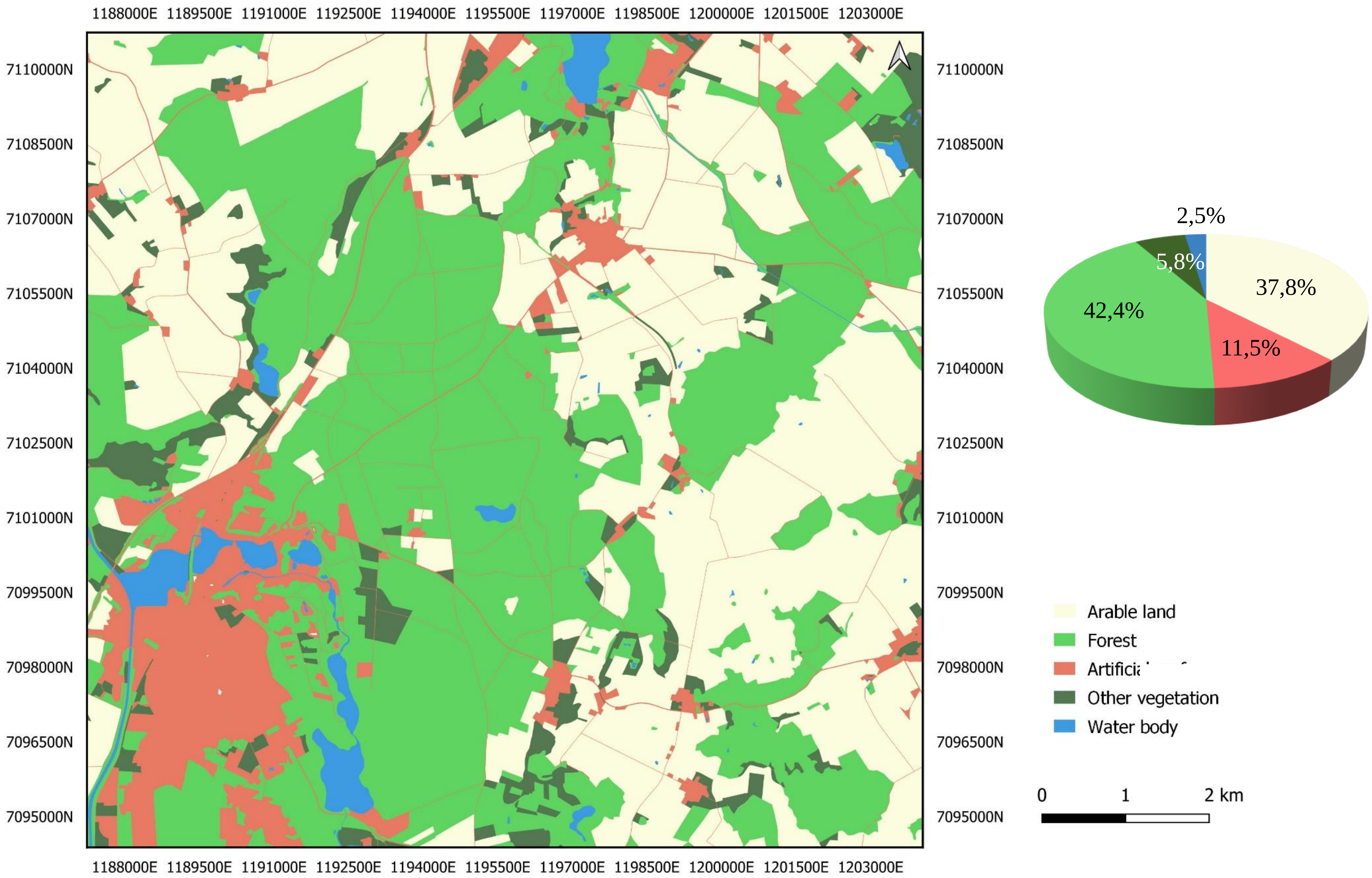


Figure 14: Land use classification map of Mölln, 2020

In 2020, there was a notable shift in land cover patterns in the region. Forest area expanded to approximately 41601531 km^2, becoming the dominant land cover and covering around 42% of the total area. Arable land, which was the dominant land cover in the past, became the second dominant land cover, encompassing approximately 37049039 km^2 or 38% of the region. Artificial lands experienced a slight increase of 1.1% compared to 1955, covering an area of 11314167 km^2. Other unit occupied 5.8% or 5727914 km^2 of the land area, exhibiting a decrease of about 1.4% compared to 1984. Freshwater bodies maintained their position as the lowest level land cover, with an area of approximately 2400113 km^2 or 2.5%, and no significant changes were observed in their coverage during the study period. Overall, the most significant change was the replacement of arable land by artificial surface and forests as the dominant land cover in the region.

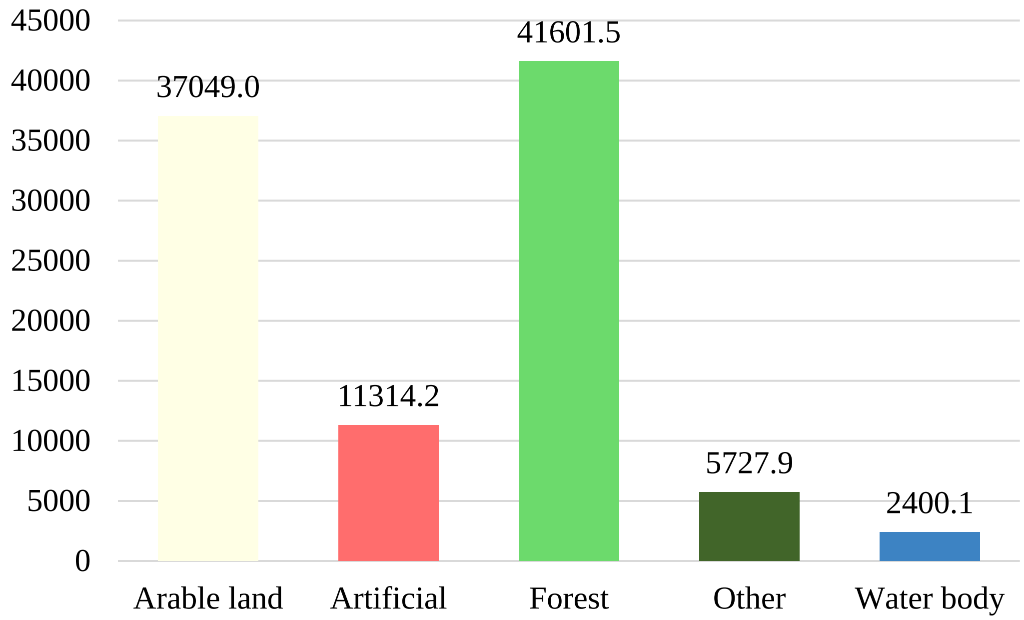
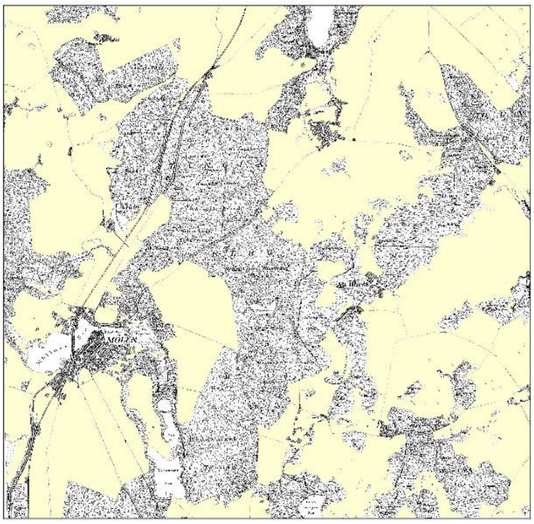
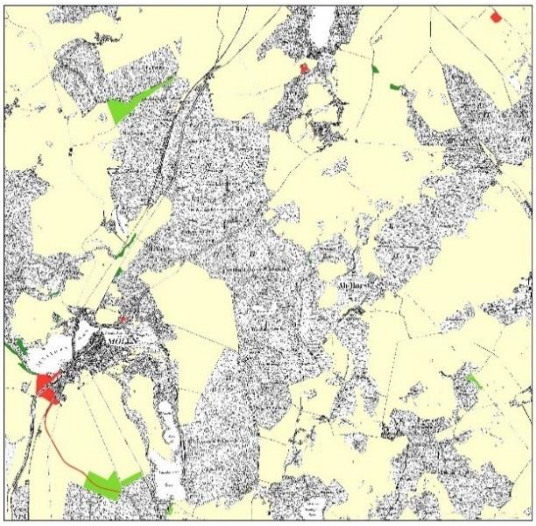


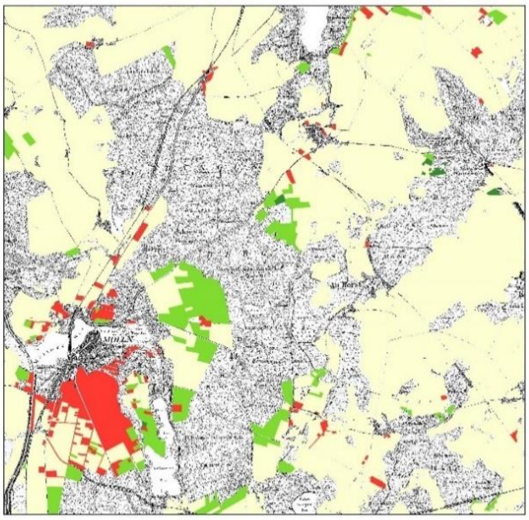
Figure 15: The area of land cover units in Mölln (km^2), (2020)



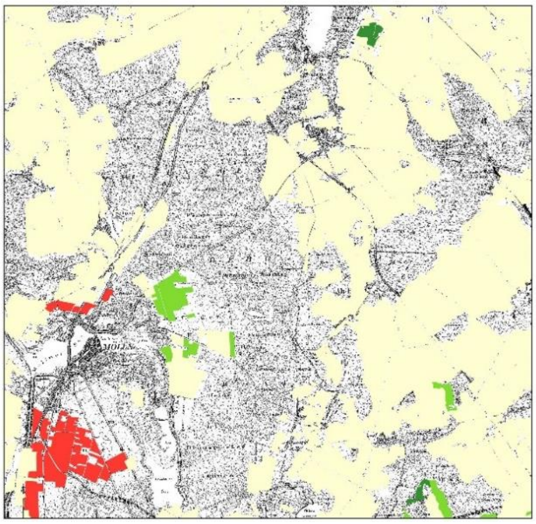
1879



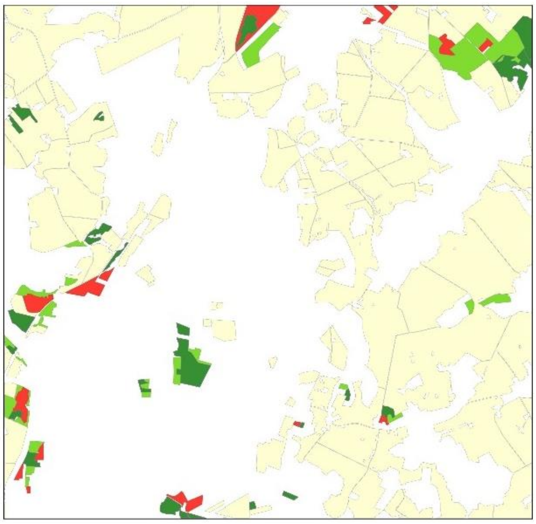
1924



1955



1984



2020

Figure 9: Changes in the area of arable land in Mölln (1879-2020)

The data presented in Table 10 highlight a decreasing trend in the area of arable land from 52.5% in 1879 to 37.8% in 2020. The most significant decrease in arable land occurred between 1924 and 1955, with a clearing of 12.8%. The cleared arable land underwent transitions to artificial surfaces (40%), forest (58%), and other units (1.5%).

Between 1879 and 1924, the reduction of arable land accounted for 1,5% and experienced transitions to artificial surfaces (25%), forest (58%), and other units (16%). From 1955 to 1984, 4,2% of arable land was converted to artificial surfaces (57%), forests (35%), and other units (7%). Between 1984 and 2020, 12,5% of arable land was converted to artificial surface (24%), forest (41%), and other units (35%). These land use transitions indicate a shift from arable land to other land cover types, particularly artificial surfaces and forests, with smaller contributions from other unit types.

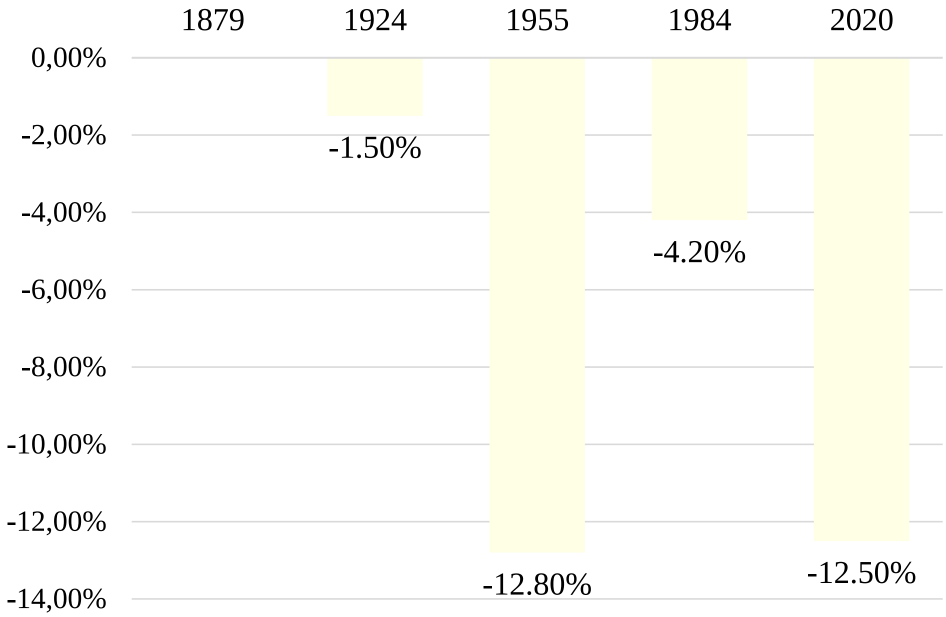
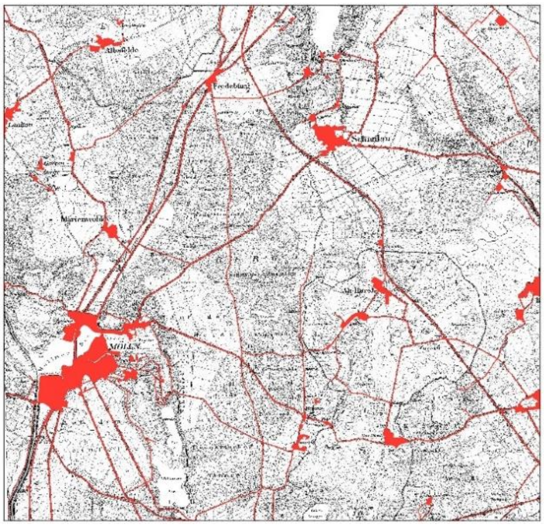
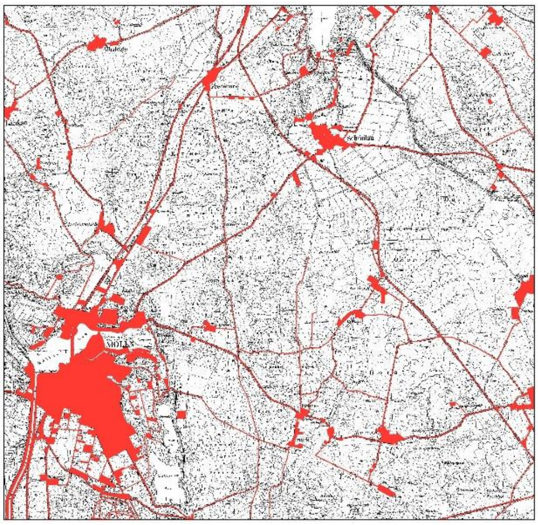


Figure 16: Percentage of changes in the area of arable land in the study area, compared to the time before, (1879- 2020)

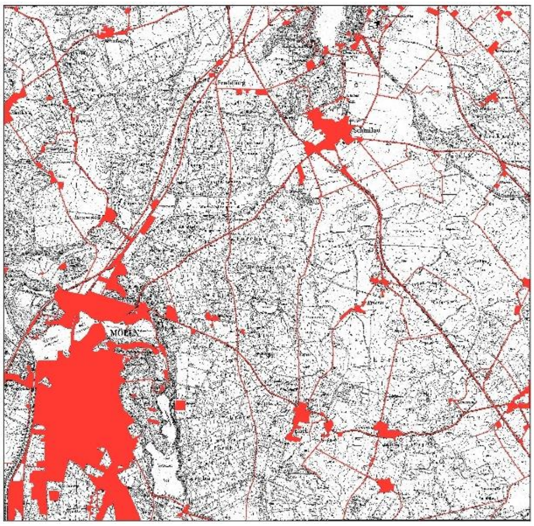
1879



1924



1955



1984

Figure 10: Changes in the artificial surface area in Mölln (1879-2020)

2020

The data presented in Table 10 demonstrate an increasing trend in the area of artificial surface in Mölln between 1879 and 2020. In 1879, the artificial surface covered 4.2% of the study area, which then increased to approximately 11.5% in 2020. The growth of the artificial surface area can be observed throughout the study period. From 1879 to 1924, there was a modest increase of 14.3%, reaching 4.8%. Between 1924 and 1955, the area covered by artificial surface experienced the highest growth rate of 70.8%, reaching 8.2%. Subsequently, between 1955 and 1984, there was a further increase to 10.4%. Finally, in 2020, the artificial surface area reached 11.5%.

The highest growth in the artificial surface area occurred between 1924 and 1955, as indicated in Figure 17. This period witnessed a significant expansion of artificial surfaces in Mölln, reflecting changes in land use and urbanization processes.

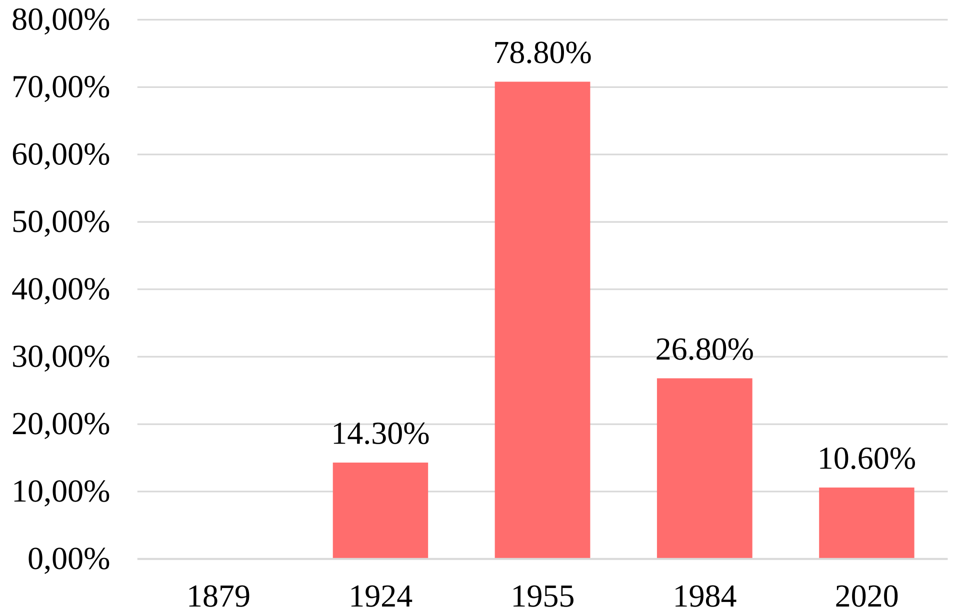
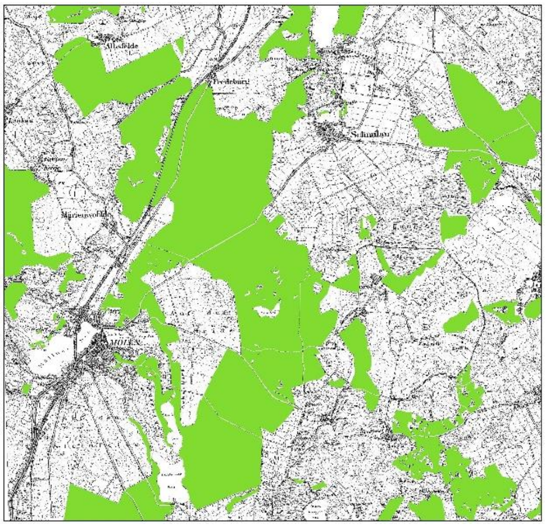
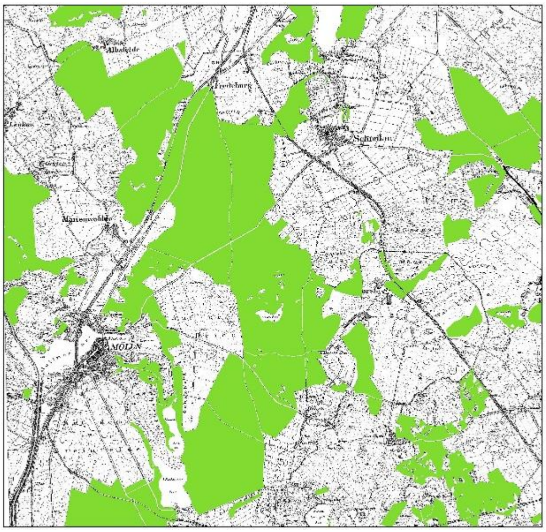


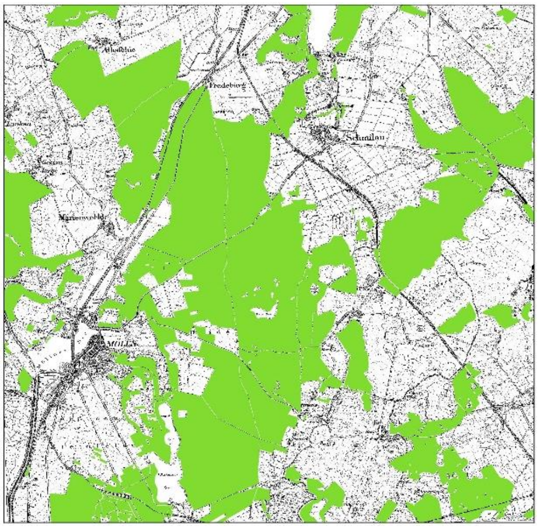
Figure 17: Percentage of changes in the area of the artificial surface in the study area, compared to the time before, (1879-2020)



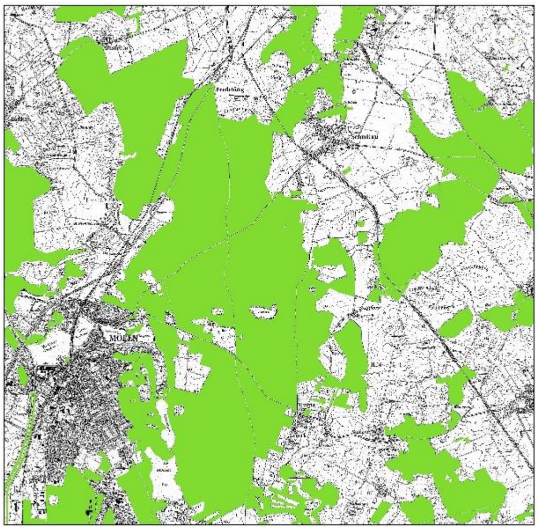
1879



1924



1955



1984

2020

Figure 11: Changes in the area of forest in Mölln (1879-2020)

There has been an increasing trend in the area of forest in Mölln between 1879 and 2020. The land covered by forests has expanded from 30.3% in 1879 to 42.4% in 2020 (Table 10). The most significant increase occurred between 1924 and 1955, with a growth of 23.8% (Figure 18).

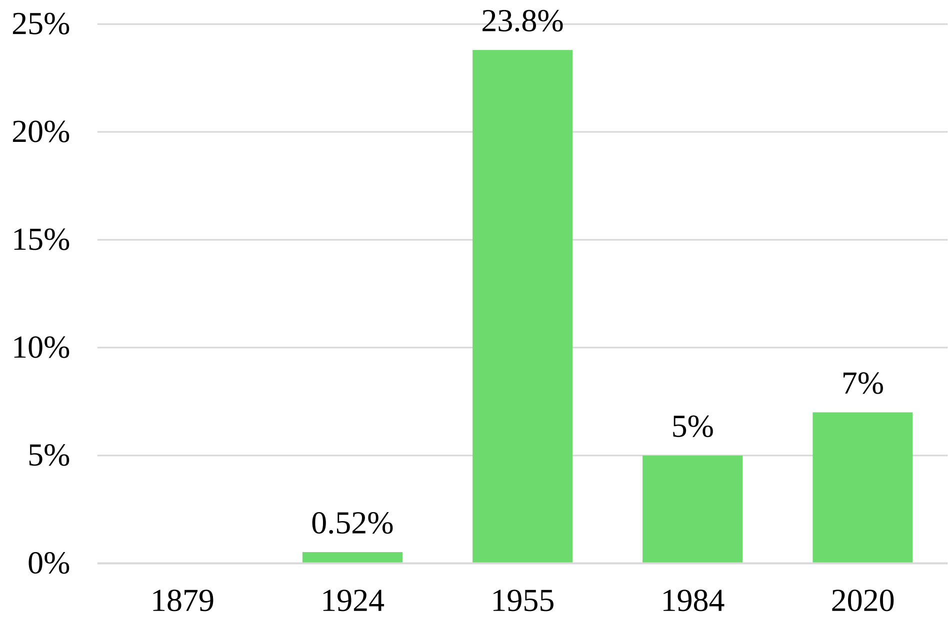
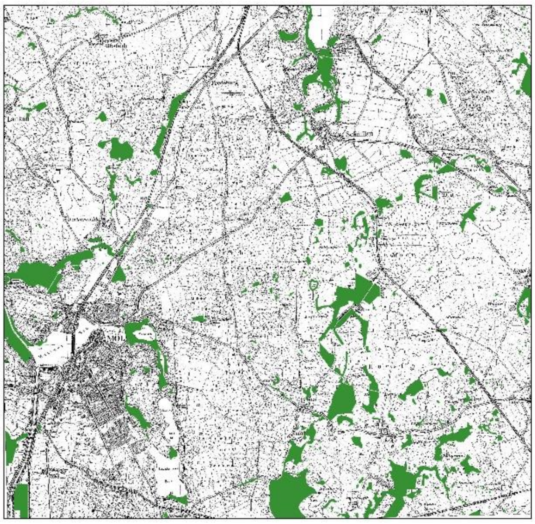


Figure 18: Percentage of changes in the area of forest in in the study area, compared to the time before, (1879- 2020)

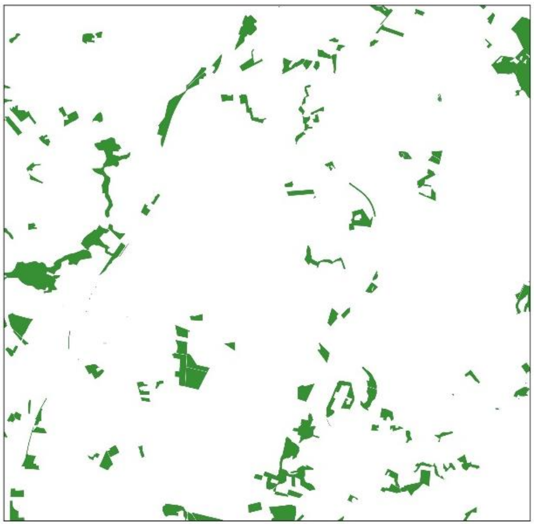
1879

1924



1955

1984



2020

Figure 12: Changes in the area of other unit in Mölln (1879-2020)

Regarding other unit in Mölln, there has been a fluctuating pattern in the area over the period from 1879 to 2020 (Table 10).

Initially, there was a slight increase of 1% between 1879 and 1924. However, a significant decrease of 37.7% occurred between 1924 and 1955. Another decrease of 32.8% was observed between 1955 and 1984. Subsequently, there was an increase of 31.5% between 1984 and 2020 (Figure 19).

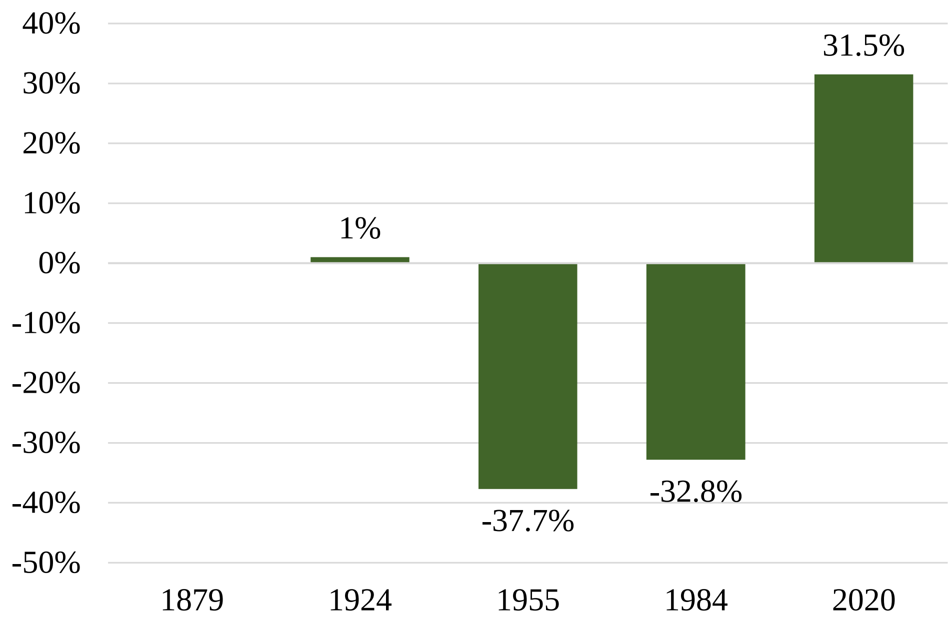
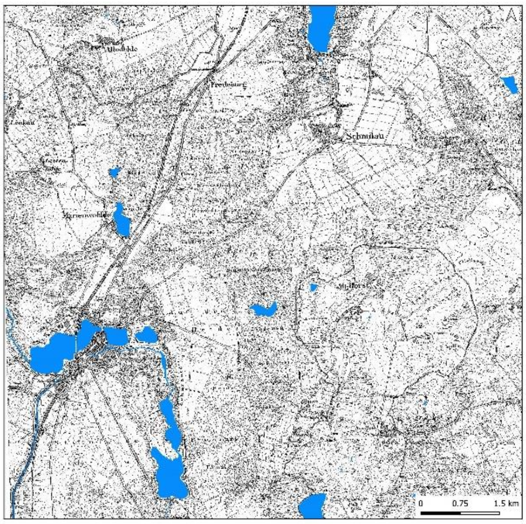
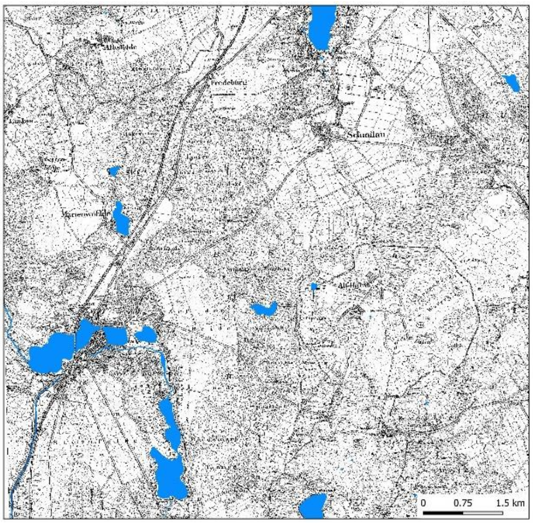


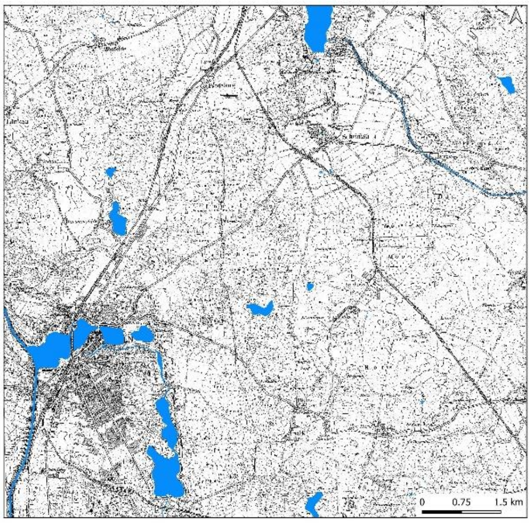
Figure 19: Percentage of changes in the area of other units in the study area, compared to the time before, (1879- 2020)



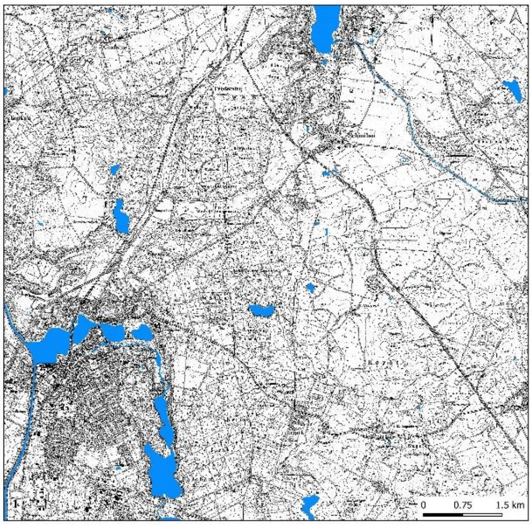
1879



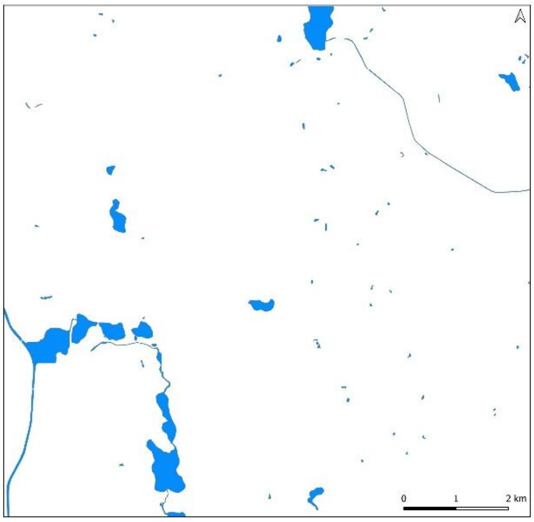
1924



1955



1984



2020

Figure 20: Changes in the area of water bodies in Mölln (1879-2020)

In Mölln, there has been a slight decrease in the area of water bodies between 1879 and 2020, with the coverage decreasing from 2.51% to 2.45% (Figure 21). This reduction in water body area is relatively small and indicates a negligible change over the studied period.

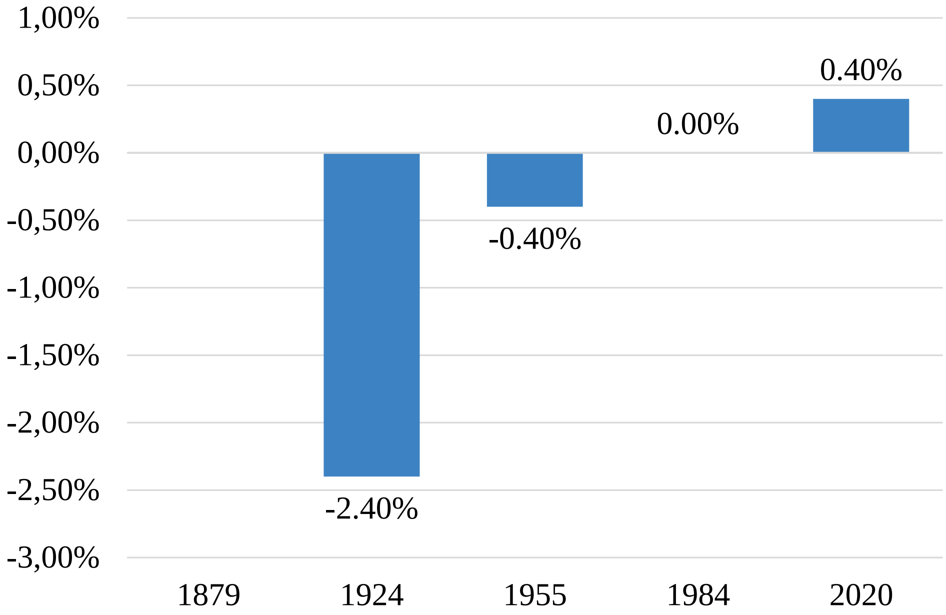
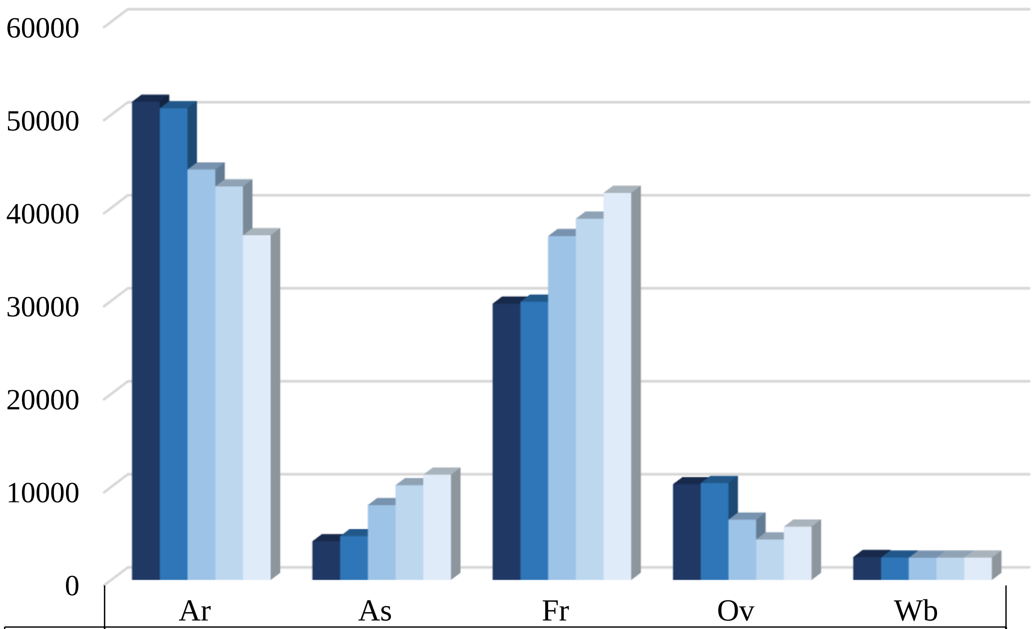


Figure 21: Percentage of annual changes in the area of water body in the study area, compared to the time before, (1879- 2020)

The results of the analysis on land cover change in Mölln between 1879 and 2020 are summarized in Table 10. The study shows a decrease in the area of arable land and other unit, indicating a shift in land use. On the other hand, there is an increase in the area covered by artificial surfaces and forests, suggesting changes in land cover patterns over the studied period. These findings provide insights into the dynamics of land use in Mölln and its impact on the landscape.

Table 9: Area of land cover units in Mölln (1879-2020), (km^2)



	Ar	As	Fr	Ov	Wb
1879	51389,43	4147,75	29694,37	10286,96	2458,74
1924	50694,84	4701,71	29897,23	10409,91	2405,60
1955	44112,67	8041,78	36958,41	6473,52	2385,64
1984	42295,40	10174,66	38827,93	4350,87	2394,10
2020	37049,04	11314,17	41601,53	5727,91	2400,11

Table 10: Area of land cover units in Mölln (1987-2020), (%) (numbers are rounded)

Land cover	Area of the land cover units (%)				
	1879	1924	1955	1984	2020
Arable land	52.5%	51.7%	45%	43.1%	37.8%
Artificial surface	4.2%	4.8%	8.2%	10.4%	11.5%
Forest	30.3%	30.5%	37.7%	39.6%	42.4%
Other	10.5%	10.6%	6.6%	4.4%	5.8%
Water body	2.5%	2.5%	2.4%	2.4%	2.5%

Table 10 illustrates the changes in land cover in Mölln between 1879 and 2020. It indicates an increase in the area covered by artificial surfaces, which grew from 4.2% in 1879 to 4.8% in 1924, 8.2% in 1955, 10.4% in 1984, and 11.5% in 2020. Similarly, the forest area experienced growth, expanding from 30.3% in 1879 to 30.5% in 1924, 37.7% in 1955, 39.6% in 1984, and 42.4% in 2020. These findings suggest a trend of increasing artificial surfaces and forest cover in Mölln over the studied period. Nonetheless, a decrease in arable land from 52.5% in 1879 to 51.7% in 1924 and further decreased to 45% in 1955, 43.1% in 1984, and 37.8% in 2020. Also, the other unit decrese from 10.5% in 1879 to 10.6% in 1924, 6.6% in 1955, 4.4% in 1984, and 5.8% in 2020.

Most of the land cover changes observed in Mölln occurred in close proximity to the artificial areas, which could be attributed to the expanding population. As the population grows, there is often a demand for infrastructure development, housing, and other human activities, resulting in the conversion of natural land covers. The increase in artificial surfaces could reflect urbanisation and the need for built-up areas to accommodate the growing population. This urban expansion may have led to changes in the surrounding land cover, including the conversion of arable land and other unit to artificial surfaces. Notable ecological shifts encompass the decline of indigenous and rare species and the proliferation of non-native species, are other effects of urbanisation (Kühn & Klotz, 2006).

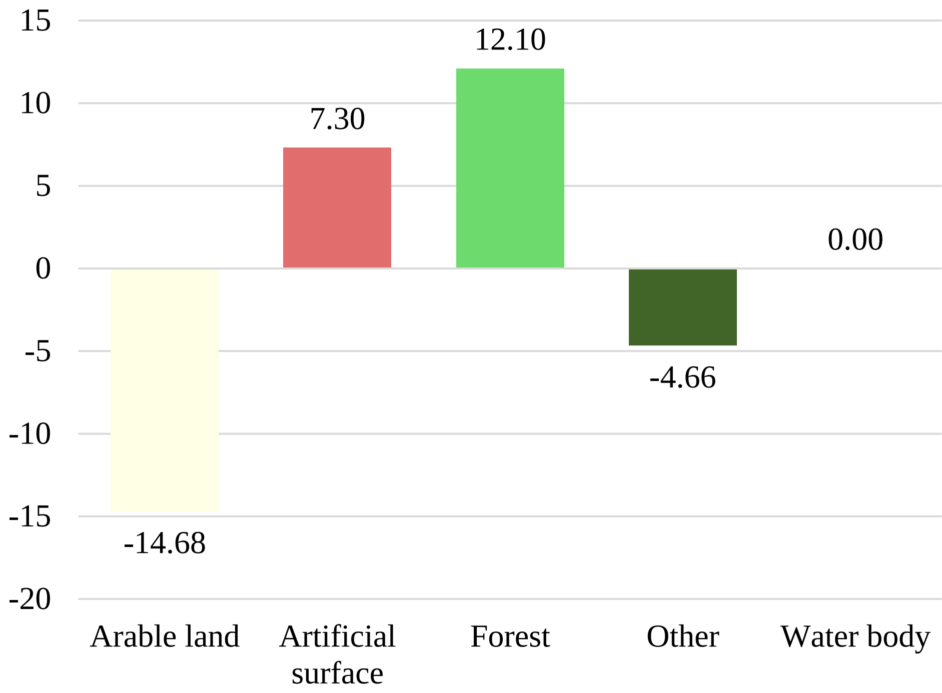


Figure 22: Land cover change in Mölln between 1879 and 2020 (%)

The major land cover changes in Mölln between 1879 and 2020 were the reduction of arable land and the expansion of forest areas. Arable land, which was always the dominant land cover in this area, decreased slightly between 1879 and 2020. In 1879, 52.5% of the total land area was under arable land; this had shrunk to 51.7% in 1924, 45% in 1955, 43.1% in 1984, and 37.8% in 2020. During the period studied, the other unit cover in the area progressively declined (Figure 22).

3.2. Land Use and Land Use Change

3.2.1. Build-up Area

The global area of built-up regions has exhibited an increasing trend from 1975 to 2014. In 1975, the area was approximately 226,000 square kilometers, and by 2014, it had increased to around 494,000 square kilometers. Figure 23 visually represents this trend, depicting the expansion of the built-up regions in 1975, 1990, 2000, and 2014.

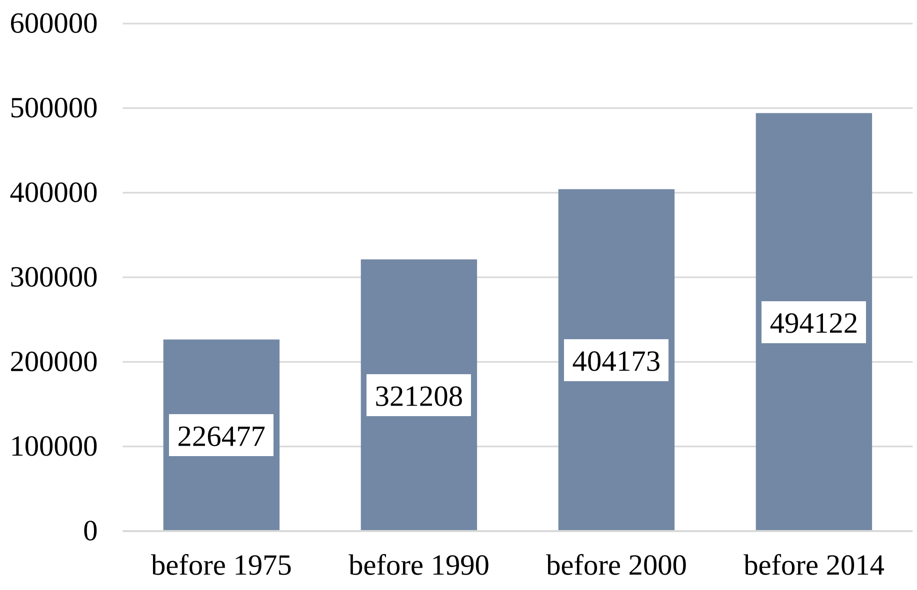


Figure 23: Build-up areas (sq. km) (OECD, 2021)

During the period of 1975-1990, the built-up area experienced the highest annual percent growth rate, which was equal to 2.78%. Between 1990 and 2000, the annual percent growth rate slightly decreased to 2.58%. A further decline in the growth rate was observed between 2000 and 2014, with a rate of 1.58%.

Table 11 provides information on the area of built-up regions during these periods, as well as the corresponding annual growth rates:

Table 11: Build-up areas (sq. km) and annual percent growth rate (OECD, 2021)

Period	Bu (sq. km)	Annual percent growth rate
Before1975	226477	-
Before1990	321208	2.78%
Before 2000	404173	2.58%
Before 2014	494122	1.58%

3.2.2. Maize Production

The amount of maize production has experienced a significant increase of 508.23% from 1961 to 2018. The production has risen from 186,710,167 tonnes in 1961 to 1,135,626,694 tonnes in 2018. The countries with the highest maize production in 2018 were the United States, China, and Brazil, with production amounts of 392,450,000 tonnes, 257,350,000 tonnes, and 82,290,000 tonnes, respectively.

Table 12 provides information on the total maize production in the study area for the years 1961, 1993, and 2018, as well as the percentage increase during these periods. As shown, the increase in maize production from 1961 to 1993 is higher than the increase from 1993 to 2018.

Table 12: Maize Production (t/country) (Our World in Data, 2021)

Year	Mz	Percentage Increase
1961	186710167	-
1992/1993	490017773	162.45%
2018	1135626694	131.75%

3.2.3. Fertilization of Nitrogen and Phosphate

Figure 24 visually compares the usage of nitrogen and phosphate fertilizers in the years 2002 and 2017. It shows a substantial increase in the use of chemical fertilizers during this period. Specifically, the use of nitrogen fertilizers has increased by 24%, while the use of phosphate fertilizers has increased by 8%.

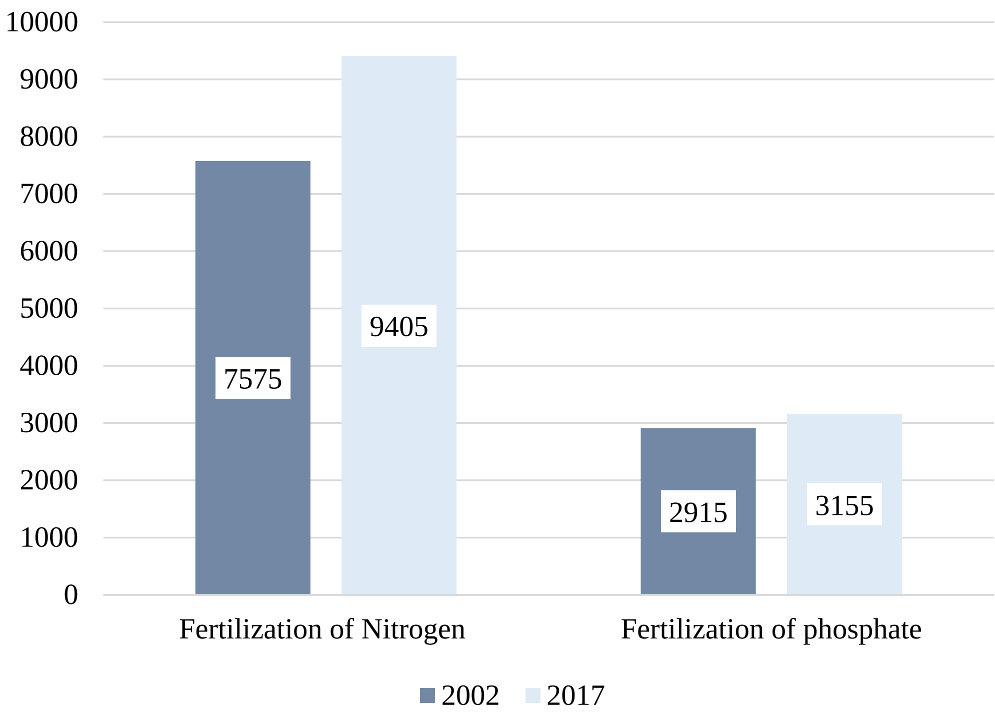


Figure 24: Fertilization of nitrogen and phosphate (kg/ha) (Our World in Data, 2021)

Table 13 shows the correlation coefficient between CR species and the Fertilization of Nitrogen and Phosphate in 2017. It is known that there is no high correlation between the number of CR species and chemical fertilizers. However, the correlation between phosphate fertilizers and the number of endangered species is higher.

Table 13: Correlation coefficients between CR species and fertilization of nitrogen and phosphate (2017)

		Fertilization of nitrogen (2017)	Fertilization of phosphate (2017)
All CR species	Correlation Coefficient	0.062	0.240**
	Sig. (2-tailed)	0.426	0.002

** Correlation is significant at the 0.01 level (2-tailed)

3.2.4. Pesticides in Agricultural Land

Pesticides used in agricultural lands increased by 33% (kg/ha) and 68% (t) from 2017 compared to 1990.

Table 14: Use of pesticides (kg/ha and t) (Our World in Data, 2021)

	kg/ha	t
1990	298.6	2693991.5
2017	397.21	4544880.5
Percentage Increase (1990-2017)	33.02%	68.70%

About 83.56% of pesticides used in agriculture are consumed in only 15 countries and the rest (16.43%) in 151 other countries. Regarding the use of pesticides in croplands, 42.07% of it is used in only 15 countries and the rest (57.92%) is used in other 151 countries.

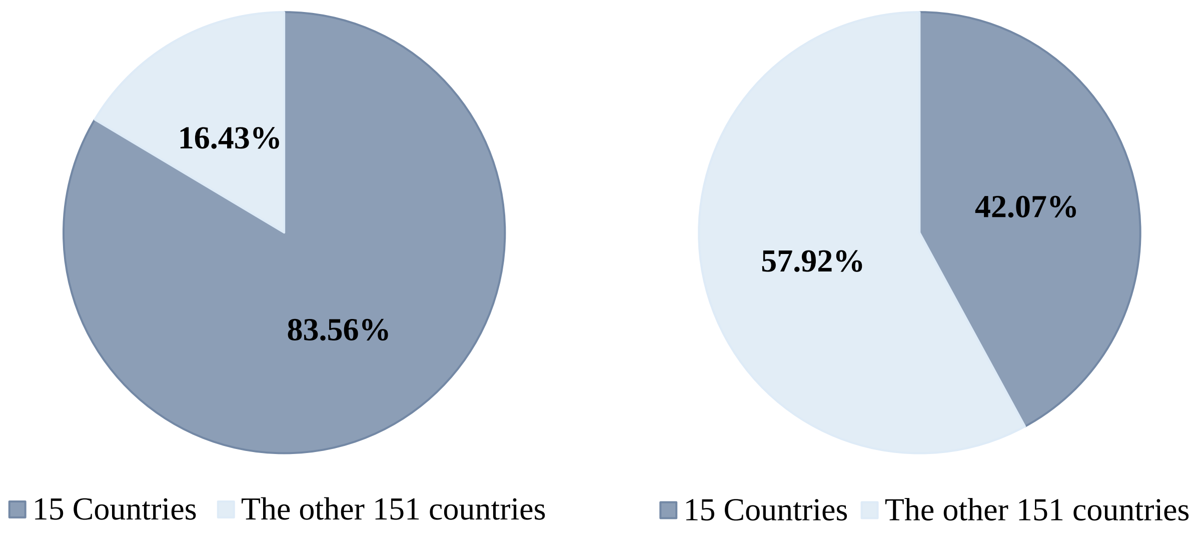


Figure 25: Pesticide used in agriculture (left) and pesticide used in cropland (right) in 15 countries with the highest consumption compared to other countries

Table 14 shows the 15 countries with the highest consumption of pesticides in agriculture and cropland.

Table 15: 15 Countries with the highest use of the pesticides in agriculture (2017) (Our World in Data, 2021)

Country	**Agricultural Use (t)**	**Country**	**Cropland Use (kg/ha)**
China	1770000	Trinidad and Tobago	24.96
United States	407779	Ecuador	13.9
United Arab Emirates	400000	China	13.07
Brazil	377176	Israel	12.61
Argentina	196009	Korea South	12.37
Canada	90839	Japan	11.76
Ukraine	78201	Guatemala	10.02
France	70589	Mauritius	9.75
Malaysia	67288	Belize	9.65
Australia	63416	Suriname	9.17
Spain	60896	Cyprus	8.21
Italy	56641	Malaysia	8.1
Turkey	54098	Netherlands	7.9
India	52750	New Zealand	7.89
Japan	52249	Dominican Republic	7.78

3.2.5. Demographic Parameters

The urban and rural populations showed a sharp increase from 1960 to 2017 in the world (Figure 26). The urban population growth rate during this period is equal to 302.22%, and the rural population growth rate is 66.71%.

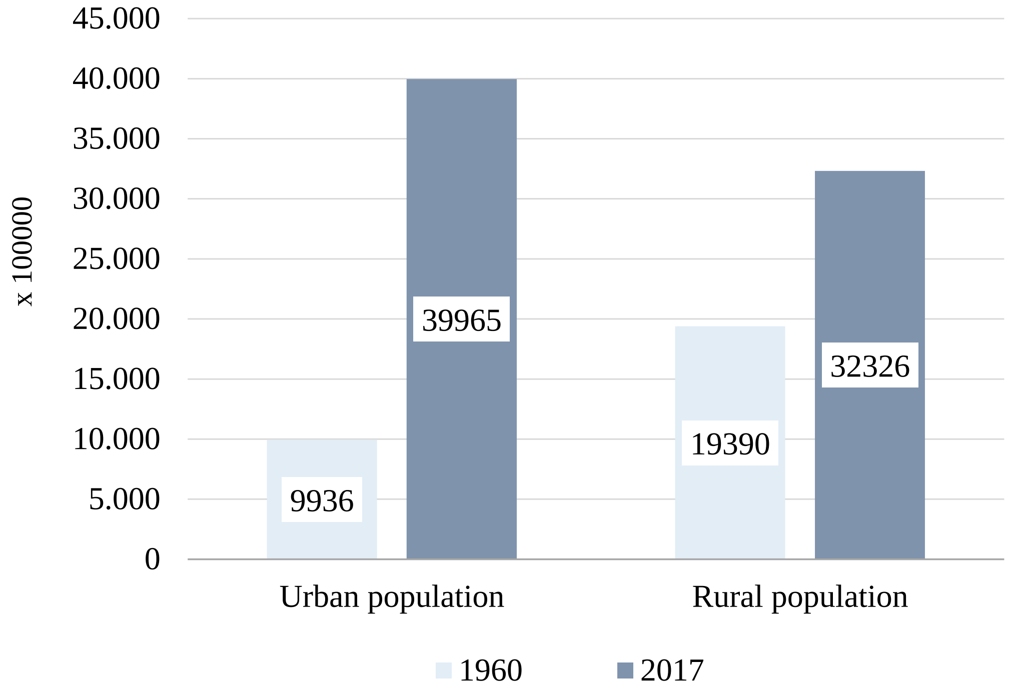


Figure 26: Rural and urban population in 1960 and 2017 (Our World in Data, 2021)

Based on the results of this study, the correlation coefficient between the number of CR species and the growth of the urban population between 1960 and 2017 is 0.544, which indicates an almost high positive correlation. The correlation coefficient between the number of CR species and the growth of the rural population between 1960 and 2017 is 0.360 which is not very high.

The median number of CR species in 33 countries with an urban population growth of less than 600000, is 12. While the average number of CR species in 33 countries with an urban population growth of more than 18 million is 73 (Figure 27). As a result, with an increase in the urban population growth, the average number of CR species also increases.

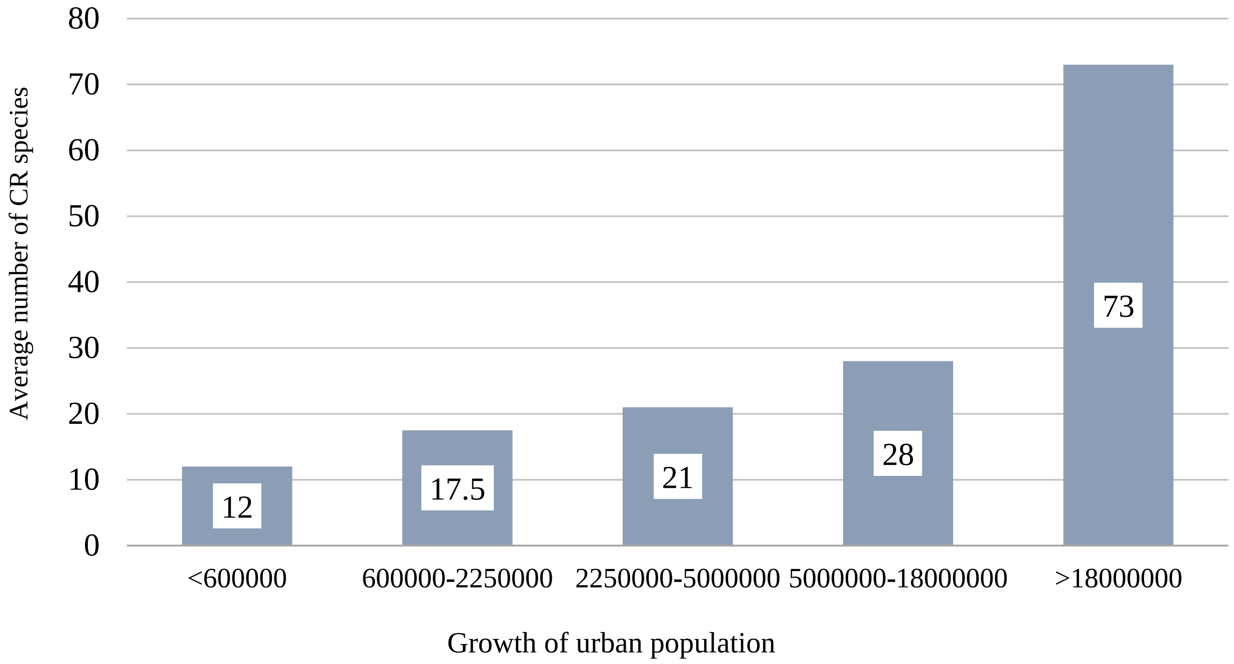


Figure 27: The median number of CR species in countries with different growth of urban populations (number of people) (Our World in Data, 2021)

3.3. Threatened Biodiversity

The average number of Critically Endangered (CR) species in these 166 selected countries is 60 species. Madagascar has the highest number of CR species among all the countries, with 856 species. On the other hand, Central African Republic, Lesotho, Lithuania, and Niue have the lowest number of CR species, each with only two species.

The average number of Chordate species, including Critically Endangered (CR), Endangered (EN), and Vulnerable (VU) species, is 151 species. Indonesia has the highest number of Chordate species with 856 species, while Luxembourg has the lowest number with only 13 species.

The number of Critically Endangered (CR) species shows the strongest positive correlations with Native Vascular Plants (0.695), followed by permanent crops (0.649), and elevation (0.464). As these variables increase, the number of CR species is expected to increase as well. Conversely, the largest negative correlation is observed between the number of CR species and the area of bare land (-0.235), sparse vegetation (-0.159), and build-up region (-0.128) (Table 16).

Table 16: Spearman's Rank Correlation coefficients of CR species and other variables

	CR species	Svasc.	Permanent crops	Elevation	Build-up area (before 2014)	Sparse vegetation (2018)	Bare land (2018)
CR species	1						
Svasc.	0.695**	1					
Permanent crops	0.649**	0.512**	1				
Elevation	0.464*	0.671**	0.602**	1			
Build-up area (before 2014)	-0.128	-0.164*	-0.145	0.021	1		
Sparse vegetation (2018)	-0.159	0.090	0.722**	0.228*	0.102	1	
Bare land (2018)	-0.235*	-0.227*	0.001	0.163	0.072	0.531**	1

** Correlation is significant at the 0.01 level (2-tailed)

* Correlation is significant at the 0.05 level (2-tailed)

The number of Chordate species exhibits the strongest positive correlations with Native Vascular Plants (0.664), permanent crops (0.662), and the Growth of the Urban Population (0.600). On the other hand, the lowest correlations were observed between Chordate species and Artificial Surface (-0.212), Build-up area (-0.158), and Grassland (-0.132) (Table 17).

Table 17: Spearman's Rank Correlation coefficients of Chordate species and other variables

	Chordate species	Svasc.	Permanent crops	Growth of urban population (1960-2017)	Artificial surface (2018)	Build-up area (before2014)	Grassland (2018)
Chordate species	1						
Svasc.	0.664**	1					
Permanent crops	0.662**	0.722**	1				
Growth of urban population (1960-2017)	0.600**	0.644**	0.782**	1			
Artificial surface (2018)	-0.212**	-0.262**	-0.218**	-0.128	1		
Build-up area (before2014)	-0.158*	-0.164*	-0.145	-0.100	0.003	1	
Grassland (2018)	-0.132	-0.006	-0.101	0.038	-0.032	-0.044	1

** Correlation is significant at the 0.01 level (2-tailed)
* Correlation is significant at the 0.05 level (2-tailed)

The results obtained from the Multiple Linear Regression (MLR) analysis model provide valuable insights into the relationship between various variables and the number of Chordate species (including CR, EN, and VU species) per country in the study area.

The model demonstrates a relatively high adjusted R-squared value of 0.684, indicating that the predictor variables included in the model can explain approximately 68.4% of the variation in the number of Chordate species. This suggests a robust relationship between the predictor variables and the response variable. Among the predictor variables, the regression analyses reveal a significant association between the number of Chordate species and the following variables: native vascular plant species, urban population, and permanent crops. These variables exert a statistically significant influence on the number of Chordate species in the study area. Furthermore, the appendix (Table 68) contains MLR models for other predictor variables and their relationships with the number of Chordate species. These models offer additional insights into the interplay between different variables and their impact on biodiversity. Overall, these regression analyses highlight the importance of factors such as native vascular plant species, urban population, and permanent crops in determining the number of Chordate species.

Table 18**:** Results of Multiple Linear Regression Model 1

Model Summary

Model	R	R square	Adjusted R Square	Std. Error of the Estimate
1	0.884[a]	0.712	0.684	0.47985

a. Predictors: (Constant), Artificial Surface 2018, Urban Population 2017, Wetland 2018, Inequality, Vascular plant species, Permanent Crop, Arable Land, GDP in Agriculture

ANOVA[a]

Model		Sum of Square	df	Mean Square	F	Sig.
1	Regression	47.777	8	5.972	25.38	<0.001[b]
	Residual	19.341	84	0.230		
	Total	67.119	92			

a. Response variable: Chordate Species (CR species+ EN species +VU species)

Predictors: (Constant), Artificial Surface 2018, Urban Population 2017, Wetland 2018, Inequality, Vascular plant species, Permanent Crop, Arable Land, GDP in Agriculture

Coefficients[a]

Model 1	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sign.
(Constant)	-2.520	1.317		-1.913	0.059
Ln Native vascular plant	0.340	0.090	0.381	3.754	<0.001
Ln GDP in agriculture	0.124	0.102	0.261	1.220	0.226
Ln Wetland 2018	0.050	0.042	0.078	1.172	0.245
Ln Inequality	0.571	0.357	0.138	1.602	0.113
Ln Arable land	-0305	0.057	-0.732	-5.358	<0.001
Ln Permanent crop	0.126	0.054	0.288	2.328	0.022
Ln Urban population	0.217	0.082	0.445	2.638	0.010
Ln Artificial Surface (2018)	-0.122	0.048	-0.195	-2.546	0.013

a. Response Variable: Chordate Species (CR species+ EN species +VU species)

The calculated regression is highly significant with a p-value of less than 0.001 (Table 18). Therefore, it can be concluded with a high level of confidence that there is a connection between the number of native vascular plants, GDP in agriculture, wetland, inequality, arable land, permanent crop, urban population, artificial surface, and the number of chordate species.

The coefficient of determination (R-squared) obtained from the linear regression is 0.684 (Table 18). This value represents the proportion of the variation in the number of Chordate species that can be explained by the predictor variables. A relatively high R-squared value of 0.684 indicates that the model can account for 68.4% of the variability in the number of Chordate species, suggesting a good fit of the model.

Furthermore, the results of the linear regression confirm the presence of positive relationships between economic factors such as GDP in agriculture and inequality, population, land use factors including wetland, arable land, permanent crop, and artificial surface, and threats to biodiversity.

The model indicates that higher GDP in agriculture, permanent crop, and urban population, as well as a smaller range of arable land, are associated with increased pressure on Chordate Species in a country. Additionally, artificial surface poses a threat to biodiversity, albeit to a lesser extent.

The model indicates that higher GDP in agriculture, permanent crop, and urban population, as well as a smaller range of arable land, are associated with increased pressure on Chordate Species in a country. Additionally, artificial surface poses a threat to biodiversity, albeit to a lesser extent.

On the other hand, the number of chordate species shows negative correlations with arable land and artificial surface. This indicates that smaller arable land areas and reduced artificial surfaces are associated with a higher presence of critically endangered species.

The available results of the linear regression support the confirmation of Hypothesis 1, which states that "Natural richness and economic processes are the most important determinants explaining the number of threatened species." The positive correlations observed between various natural richness indicators (such as native vascular plants and wetland) and economic factors (such as GDP in agriculture) with the number of threatened species suggest that both natural richness and economic processes play significant roles in explaining the variation in the number of threatened species.

In most of the models, the variable "permanent crop" exhibited the highest contribution, indicating its strong relationship with the pressure on biodiversity. Additionally, the variables "native vascular plants" and economic indicators such as "GDP in agriculture" and "inequality" demonstrated significant relationships with biodiversity pressure, suggesting their importance as key factors in understanding this pressure. On the other hand, several other relationships between variables showed weak associations.

In Model 2, as presented in Table 19, the relationships between land cover indicators and the number of Chordate species in a country are found to be highly significant. Notably, this model excludes other indicators such as human population, economy, and physical geography, focusing specifically on the impact of land cover on Chordate species.

Table 19: Results of Multiple Linear Regression Model 2

Model Summary

Model	R	R square	Adjusted R Square	Std. The error of the Estimate
2	0.914[a]	0.835	0.719	0.40951

a. Predictors: (Constant), Tree Cover 2018, Artificial Surface 2018, Permanent Crop, Sparse Vegetation 2018, Inland Water 2018, Shrubland 2018, Grassland 2018, Cropland 2018, Wetland 2018, Bare Land 2018, Vascular plant species, Forest, Permanent Pasture, Arable Land

ANOVA[a]

Model		Sum of Square	df	Mean Square	F	Sig.
2	Regression	16.963	14	1.212	7.225	<0.001[b]
	Residual	3.354	20	0.168		
	Total	20.316	34			

a. Response Variable: Chordate Species (Cr+En+Vu)

b. Predictors: (Constant), Tree Cover 2018, Artificial Surface 2018, Permanent Crop, Sparse Vegetation 2018, land Water 2018, Shrubland 2018, Grassland 2018, Cropland 2018, Wetland 2018, Bare Land 2018, Vascular plant species, Forest, Permanent Pasture, Arable Land

Coefficients[a]

Model 2	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sign.
(Constant)	3.004	1.298		2.315	0.031
Ln Svasc.	0.437	0.154	0.511	2.843	0.010
Ln Tree Cover (2018)	0.003	0.101	0.007	0.034	0.973
Ln Grassland (2018)	0.089	0.093	0.136	0.960	0.348
Ln Wetland (2018)	0.257	0.122	0.414	2.109	0.048
Ln Shrubland (2018)	-0.034	0.052	-0.072	-0.664	0.515
Ln Sparse Vegetation (2018)	-0.088	0.065	-0.196	-1.349	0.193
Ln Cropland (2018)	-0.599	0.185	-0.646	-3.236	0.004
Ln Artificial Surface (2018)	0.089	0.091	0.144	0.986	0.336
Ln Bare Land (2018)	-0.111	0.081	-0.230	-1.383	0.182
Ln Inland Water (2018)	-0.196	0.167	-0.192	-1.176	0.253
Ln Arable Land	0.211	0.134	0.523	1.573	0.131
Ln Permanent Crop	0.301	0.127	0.620	2.371	0.028
Ln Permanent Pasture	-0.148	0.098	-0.461	-1.500	0.149
Ln Forest	-0.235	0.135	-0.592	-1.742	0.097

a. Response Variable: Chordate Species (CR species+ EN species +VU species)

In Model 2, the number of native vascular plants was utilized as a measure of natural wealth, while all land cover factors were considered as predictor variables. This model demonstrated that the Permanent Crop factor had the most significant impact on species, while Cropland exhibited the largest negative effect in this model.

Many other relationships were weak or not statistically significant. However, several regression analysis models revealed a significant relationship between the number of critically endangered (CR) species and the variables related to land cover and land use.

3.3.1. The IUCN Red List Categories

The data set utilized in this research was obtained from the IUCN Red List, encompassing a total of 142,941 species from various categories within the study area. Table 20 presents the species categories utilized in this research, as listed in the IUCN Red List, along with the corresponding number of species within each category.

Table 20: Number of species in the IUCN Red List categories

IUCN Red List category	**Number of species**	**(%)**
Least Concern (LC)	74861	52.37%
Data Deficient (DD)	19301	13.50%
Vulnerable (VU)	15728	11%
Endangered (EN)	15328	10.73%
Near Threatened (NT)	8499	5.95%
Critically Endangered (CR)	8321	5.82%
Extinct (EX)	684	0.48%
Lower Risk (LR)	158	0.11%
Extinct in the Wild (EW)	61	0.04%

The largest category among the species in the dataset is the "Least Concerned" category, which comprises 74,861 species, accounting for 52.37% of the total. The "Vulnerable" category includes 11% of the species, the "Endangered" category comprises 10.72% of the species, and the "Critically Endangered" category represents 5.82% of the species. Consequently, chordate species including CR species, EN species, and VU species encompass a total of 27.57% of the species in the dataset.

3.3.2. Threats and CR species

According to the IUCN Red List, agriculture and aquaculture are identified as the primary threats to Critically Endangered (CR) species. They are followed by biological resource use and natural system modifications. Figure 28 provides a visual representation of the various threat categories as per the IUCN Red List, indicating the number of CR species threatened by each category (Access date February 2023).

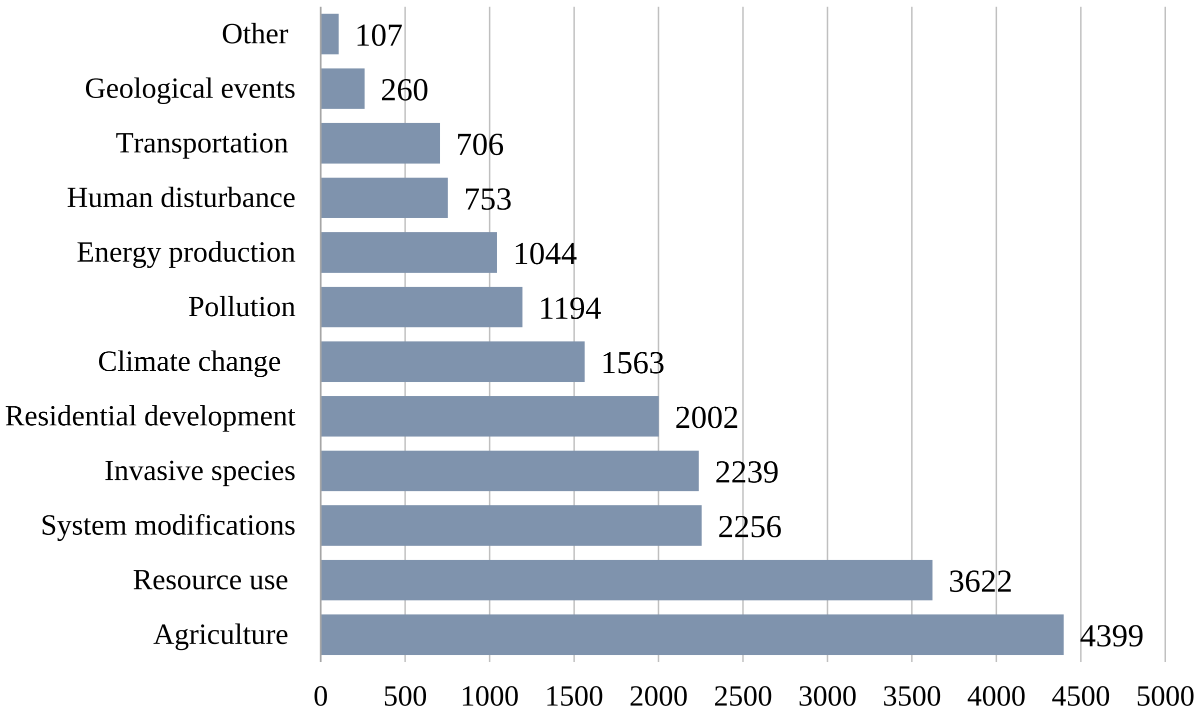


Figure 28: Number of CR species threatened by various threats

Out of the threat categories mentioned, "agriculture and aquaculture" affects 4,399 species, while "biological resource use" threatens 3,622 species. Climate change is identified as the sixth most significant threat among all categories, impacting a total of 1,563 species.

3.3.3. Habitats and CR species

Based on the information obtained from the IUCN Red List, out of the total number of Critically Endangered (CR) species (8,492) across 166 selected countries, the majority of CR species are found in forest habitats, with a count of 4,903 species. Wetlands support the next highest number of CR species, with 1,832 species, followed by shrublands with 982 species. In contrast, desert habitats have relatively few CR species, with only 62 species recorded. Artificial surfaces, such as human-made structures, are home to 325 CR species. This data is presented in Table 21 (access date February 2023).

Table 21: Number of CR, EN, and VU species in different habitats

Habitat type	No. CR (%)	No. EN (%)	No. VU (%)
Forest	4903 (48.87%)	10070 (50.59%)	8203 (43.58%)
Wetland	1832 (18.26%)	2828 (14.20%)	2924 (15.53%)
Shrubland	982 (9.78%)	2114 (10.62%)	2215 (11.77%)
Rocky area	600 (5.98%)	1069 (5.37%)	1056 (5.61%)
Grassland	495 (4.93%)	1299 (6.52%)	1178 (6.25%)
Marine	447 (4.45%)	814 (4.08%)	1394 (7.40%)
Artificial surface	325 (3.23%)	871 (4.37%)	924 (4.90%)
Savana	165 (1.64%)	488 (2.45%)	518 (2.75%)
Caves	79 (0.78%)	105 (0.52%)	177 (0.94%)
Unknown	82 (0.81%)	54 (0.27%)	34 (0.18%)
Desert	62 (0.61%)	106 (0.53%)	125 (0.66%)
Other	44 (0.43%)	53 (0.26%)	50 (0.26%)
Introduced vegetation	15 (0.14%)	33 (0.16%)	21 (0.11%)

Figure 29 shows the number of CR species in different habitats according to the IUCN Red List (February 2023).

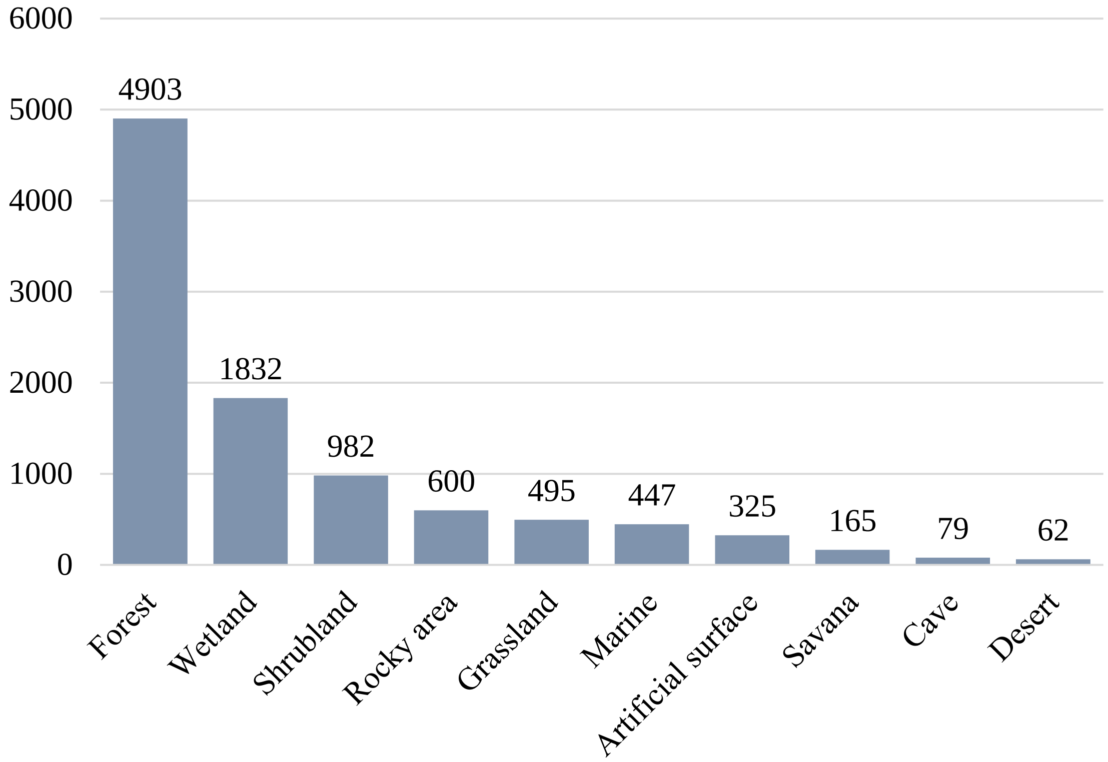


Figure 29: Number of CR species in different habitats (February 2023)

According to Table 22, which presents the information regarding threats to Critically Endangered (CR) species in different habitats, agriculture and aquaculture are identified as the most significant threats to CR species in the forest, shrubland, grassland, and artificial surface habitats. In wetlands, the most important threat to CR species is natural system modifications. Additionally, biological resource use and natural system modifications are also considered significant threats to CR species across these habitats. On the other hand, geological events are reported as the least impactful threat to CR species in all of these habitats.

Table 22: Number of CR species threatened in different habitats (IUCN, 2023)

Threats	Fr	We	Sh	Gr	As
Agriculture and aquaculture	3217	749	467	351	223
Biological resource use	2600	755	320	153	190
Invasive and other problematic species, genes and diseases	1257	746	392	157	131
Residential and commercial development	1223	431	254	129	136
Natural system modifications	1149	833	346	161	96
Climate change and severe weather	915	411	264	129	86
Energy production and mining	609	262	159	69	53
Transportation and service corridors	401	141	150	64	50
Human intrusions and disturbance	378	194	143	58	59
Pollution	341	907	86	66	104
Geological events	175	27	56	10	12
Other options	75	11	22	17	8

Figure 30 shows the number of CR species in different habitats and the main threats to CR species in each habitat (cf. IUCN Red List, 2021).

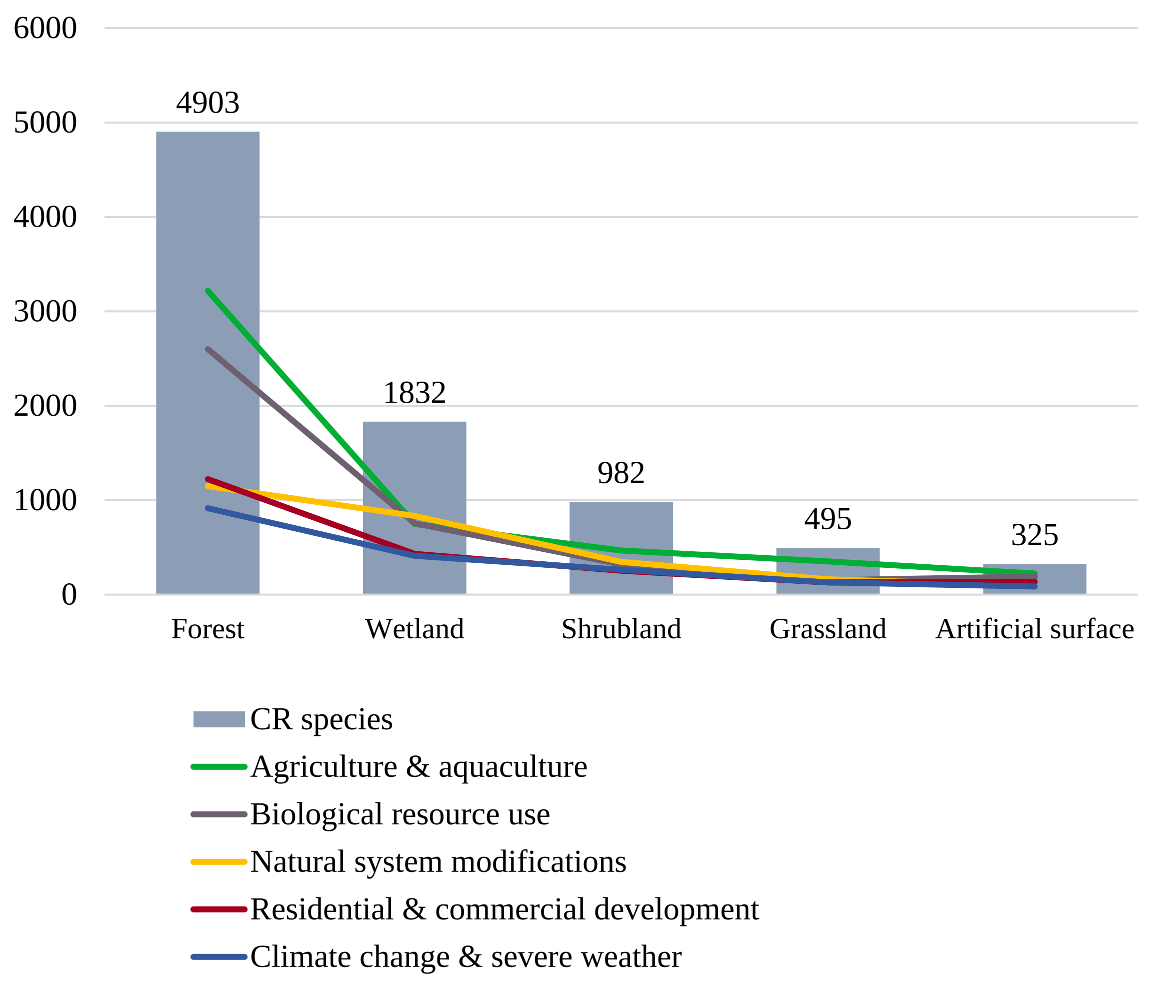


Figure 30: Number of CR species related to different threats in different habitats

3.4. Relationship between Land Use and Land Cover Change and Threats to Biodiversity

3.4.1. Climate Change and Threats to Biodiversity

Table 23 showcases the categorization of climate change and severe weather impacts on Critically Endangered (CR) species. The categories include: habitat shifting and alteration, droughts, temperature extremes, storms and flooding, and other impacts.

Table 23: Number of CR species threatened by climate change and severe weather (IUCN, 2023)

Climate change and severe weather	**No. of CR species**
Habitat shifting and alteration	774
Droughts	798
Storms and flooding	420
Temperature extremes	267
Other impacts	140

According to the information provided, climate change and severe weather are identified as less effective threats to Critically Endangered (CR) species compared to other threats such as agriculture and aquaculture, as well as biological resource use. Figure 28 indicates that only 1,563 CR species are threatened by climate change and severe weather, while larger numbers of CR species are affected by other threats, such as agriculture and aquaculture (4399) and biological resource use (3622).

The largest number of CR species threatened by climate change and severe weather is found in the Hawaiian Islands, where 190 species occur. This number represents only 22.04% of all threatened species in this country while the remaining 77.95% of species face other threats. The greatest threat to CR species in the Hawaiian Islands is "invasive and other problematic species, gens and diseases" which threaten 339 CR species, as per Table 24, climate change and severe weather are recognized as the second most important threat to CR species in the Hawaiian Islands.

Table 24: CR species in the Hawaiian Islands in relation to different threats (IUCN, 2023)

Threats	**CR species (No./ %)**	
Invasive and other problematic species	339	39.33%
Climate change and severe weather	190	22.04%
Natural System modification	112	12.99%
Geological events	78	9.05%
Agriculture and aquaculture	51	5.92%
Residential and commercial	22	2.55%
Biological resource use	21	2.44%
Human intrusions and disturbance	19	2.20%
Other Options	19	2.20%
Transportation and Service Corridors	5	0.58%
Pollution	4	0.46%
Energy Production and mining	2	0.23%

Based on the provided information, Haiti and Australia are two countries where a significant number of Critically Endangered (CR) species are threatened by climate change and severe weather. Haiti has 129 CR species threatened by this category, while Australia has 112 CR species affected. In Haiti, the primary threats to CR species are identified as "biological resource use" with 147 species impacted and "agriculture and aquaculture" with 136 species affected. "Climate change and severe weather" is ranked as the third most important threat for CR species in the country.

In Australia, the primary threat to Critically Endangered (CR) species is indeed attributed to "invasive and other problematic species, genes, and diseases," which affect 174 species. Following this, "natural system modification" poses a significant threat, encompassing subcategories such as "fire and fire suppression," "dams and water management," and "other ecosystem modification." Finally, "climate change" is recognized as the third most significant threat to CR species in Australia.

Based on the provided information, it is evident that "climate change and severe weather" is not the primary threat to Critically Endangered (CR) species, even in countries where a substantial number of CR species are impacted by it. Instead, factors such as biological resource use, agriculture and aquaculture, invasive species, and natural system modifications emerge as more immediate and prominent threats to CR species in these regions. This conclusion highlights the complexity and multi-faceted nature of threats faced by CR species.

3.4.2. Mega-Diverse Countries and Threats to Biodiversity

Among the world's ten megadiverse countries, which include Madagascar, Mexico, Ecuador, Indonesia, Brazil, Colombia, Malaysia, the Philippines, and Tunisia, collectively hosting over 32% of all Critically Endangered (CR) species, nine countries face significant biodiversity threats. These threats primarily arise from two categories: 'agriculture and aquaculture' (2230) and 'biological resource use' (1919). Table 25 displays the number of CR species in these nine megadiverse countries, along with the number of CR species threatened by these two significant threat categories, as well as other threats.

Table 25: Number of CR species threatened by two effective threat categories, and other threats together in 9 mega-diverse countries (IUCN, 2023)

Country	No. of CR species	Agriculture and aquaculture threat	Biological resource use threat	All other threats
Madagascar	682	463	550	418
Mexico	401	267	275	342
Ecuador	389	171	114	175
Indonesia	348	223	224	241
Brazil	320	253	203	330
Colombia	301	305	138	232
Malaysia	285	163	156	176
Philippines	277	291	260	249
Tanzania	240	150	164	135

In the Hawaiian Islands, which is the country with the second-highest number of Critically Endangered (CR) species totaling 433, the primary threats to CR species differ from those in other megadiverse countries. In this region, the most significant threats to CR species are attributed to "invasive and other problematic species, genes, and diseases" as well as "climate change and severe weather." Unlike the other megadiverse countries, these two factors are identified as the most important threats impacting CR species in the Hawaiian Islands.

According to Figure 31, it is illustrated that 52.60% of Critically Endangered (CR) species in the nine megadiverse countries are threatened by the impact of two categories: "agriculture and aquaculture" and "biological resource use." These categories pose significant threats to more than half of the CR species in these countries. On the other hand, the remaining 47.40% of CR species are threatened by other categories.

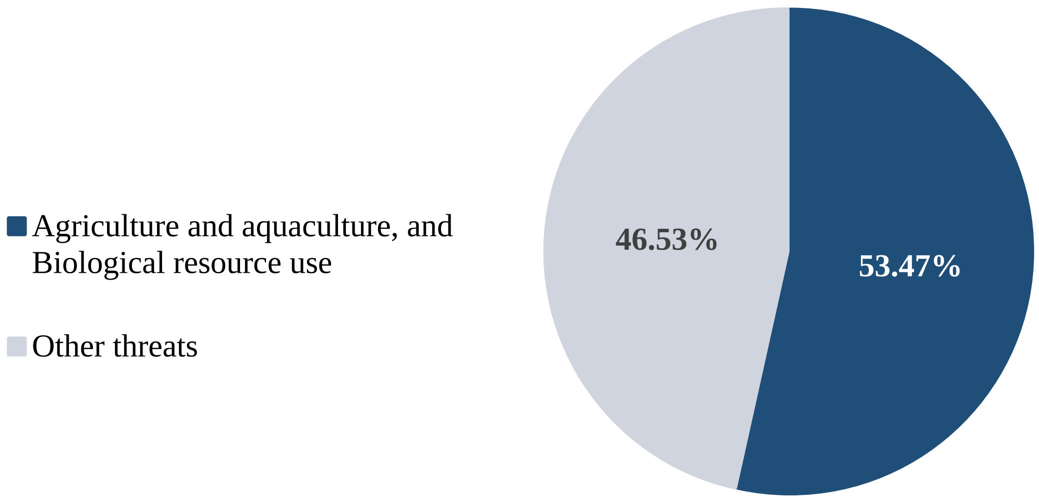


Figure 31: Percentage of CR species threatened by agriculture, aquaculture, biological resource use and other threats in megadiverse countries

According to Table 26, the threats in various categories and the number of Critically Endangered (CR) species threatened by each category in the nine megadiverse countries are presented. It is evident from the table that climate change and severe weather pose a threat to only 298 CR species across these countries.

Table 26: Number of CR species threatened by different categories in 9 megadiverse countries (IUCN, 2023)

Categories of Threats	No. of CR species
Agriculture and aquaculture	2230
Biological resource use	1919
Residential and commercial development	864
Energy production and mining	465
Natural system modifications	780
Invasive and other problematic species, genes and diseases	555
Pollution	373
Climate change and severe weather	298
Human intrusions and disturbance	221
Transportation and service corridors	211
Geological events	41
Other options	24

3.4.3. Land Cover Change in Countries with the Highest Number of CR Species

Madagascar, Mexico, and Ecuador are indeed countries that boast the largest number of Critically Endangered (CR) species worldwide. Madagascar is home to 688 CR species, followed by Mexico with 443 species, and Ecuador with 396 species.

In terms of land cover change, it is noteworthy that Madagascar has experienced a significant decrease in shrubland area between 1992 and 2019. This suggests that the shrubland habitat in Madagascar has undergone substantial alterations and reductions over the course of nearly three decades. The specific factors contributing to this land cover change in Madagascar's shrubland area would require further investigation and analysis.

In Mexico, it is observed that there has been a considerable increase in artificial surfaces. Additionally, there has been a significant decrease in wetland areas in Mexico over the specified period. Similarly, in Ecuador, there has been a substantial increase in artificial surfaces, exceeding the average increase in artificial surfaces worldwide during the same period. As per Figure 32, the rate of increase in artificial surfaces in Ecuador is higher than the global average. However, the other land cover units in these countries, as detailed in Table 27, do not demonstrate significant changes during the specified period. This implies that apart from the notable changes in artificial surfaces and wetlands, the overall land cover in Mexico and Ecuador has remained relatively stable for the selected land cover units.

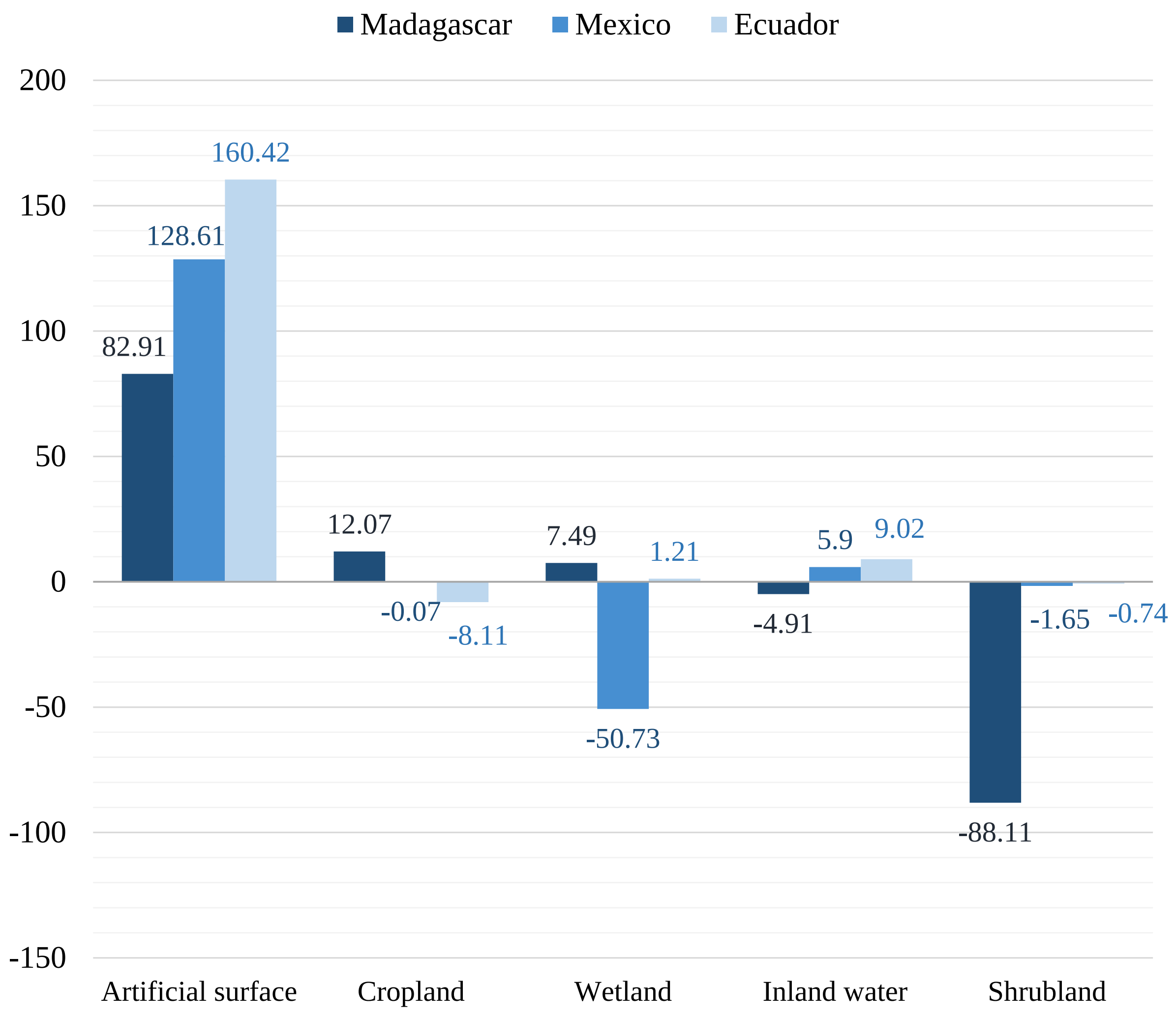


Figure 32: Land cover change in Madagascar, Mexico, and Ecuador between 1992 and 2019 (%) (OECD, 2021)

Table 27: Land cover change (%) in three countries with the highest number of CR species and land cover change in the world between 1992 and 2019

Land cover units	Madagascar	Mexico	Ecuador	World
Artificial surface	82.91%	128.61%	160.42%	129.87%
Crop land	12.07%	-0.07%	-8.11%	3.14%
Wetland	7.49%	-50.73%	1.21%	-4.84%
Bare area	3.88%	-0.24%	1.53%	-1.58%
Sparse vegetation	3.69%	4.60%	-2.21%	-1.60%
Tree cover	1.49%	-0.77%	1.40%	-1.27%
Grassland	-2.80%	4.99%	-2.76%	1.18%
Inland water	-4.91%	5.90%	9.02%	0.49%
Shrubland	-88.11%	-1.65%	-0.74%	-1.85%

In Mexico, "agriculture and aquaculture" have been identified as the primary threats to Critically Endangered (CR) species. It is noteworthy that between 1992 and 2019, a significant decline in the area of wetlands has been observed in the country. This decline in wetland areas is concerning as wetlands play a crucial role in supporting biodiversity and providing habitat for numerous species. Wetlands in Mexico continue to host 95 CR species, making them the second most common habitat for CR species in the country after forests. Forests, with 288 CR species, remain the most significant habitat for CR species in Mexico.

In Madagascar, the most significant threat to Critically Endangered (CR) species is identified as biological resource use, encompassing activities such as hunting and trapping terrestrial animals, gathering terrestrial plants, logging and wood harvesting, and fishing and harvesting aquatic resources. This highlights the unsustainable utilization of natural resources as a major concern for the conservation of CR species in Madagascar.

Shrubland, hosting 42 CR species, is the fourth most important habitat for CR species in Madagascar, following forests (563), wetlands (81), and rocky areas (50). Even in the shrubland habitat, the main threat to CR species remains biological resource use, specifically logging and wood harvesting. In Ecuador, the majority of CR species (244) are found in forests. The most significant threat to CR species in Ecuador is "agriculture and aquaculture." Only 10 CR species are known to inhabit artificial surfaces in Ecuador.

Furthermore, Spearman correlation analyses reveal the strongest correlation coefficient between CR species and Chordate species in relation to permanent crops. This suggests a notable association between the presence of CR species and the cultivation of permanent crops.

Table 28: Correlation coefficients between land cover units and CR species, and land cover units and chordate species

Land cover units	Chordate species (CR+EN+VU)	All CR species
Permanent crop (2020)	0.662**	0.649**
Forest (2020)	0.440**	0.441**
Aggricultural land (Arableland+ Permanent Crop+ Permanent Pasture) (2020)	0.370**	0.368**
Permanent pasture (2020)	0.322**	0.305**
Arable land (2020)	0.319**	0.366**
Tree cover (2018)	0.178*	0.171*
Shrubland (2018)	0.127	0.154
Wetland (2018)	0.022	-0.029
Inland water (2018)	-0.016	0.045
Crop land (2018)	-0.037	0.148
Bare area (2018)	-0.114	-0.235**
Sparse vegetation (2018)	-0.122	-0.159
Grassland (2018)	-0.132	-0.081
Artificial surface (2018)	-0.212**	-0.043

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

3.4.4. Mainland and Islands and Threats to Biodiversity

According to Table 29, out of the selected countries, 142 countries are categorized as Mainland, 15 countries are classified as Oceanic Islands, and 9 countries are a combination of Mainland and Oceanic Islands.

Regarding the distribution of Critically Endangered (CR) species, it is observed that the majority, approximately 86.22%, occur on the mainland. In contrast, only a small percentage, 2.83%, are found on oceanic islands.

This information highlights the disparity in CR species distribution between mainland areas and oceanic islands. It suggests that the mainland regions tend to have a higher concentration of CR species compared to the relatively lower representation on oceanic islands. The reasons for this disparity could be attributed to various ecological factors, habitat availability, and anthropogenic influences on each respective habitat type.

Table 29: Number of CR species in mainland and oceanic islands (IUCN, 2021; cf. Tab. 5 appendix)

Mainland or islands	**No. of countries (%)**	**No. of CR species (%)**
Mainland	142 (85.54%)	8686 (86.22%)
Oceanic islands	15 (9.04%)	285 (2.83%)
Mainland and oceanic islands	9 (5.42%)	1103 (10.95%)

According to Table 30, the main threats to Critically Endangered (CR) species differ between Oceanic Islands and the mainland. In Oceanic Islands, the primary threats to CR species are identified as "invasive and other problematic species, genes, and diseases." This indicates that the introduction and establishment of non-native species, genetic issues, and diseases pose significant risks to the conservation of CR species in Oceanic Islands.

On the mainland, the main threats to CR species are attributed to "agriculture and aquaculture." This highlights the adverse impacts of agricultural practices and aquaculture activities on the conservation status of CR species in mainland areas.

Table 30: Number of CR species in relation to threats in Mainland and Oceanic Islands (IUCN, 2023)

Number of CR species in relation to threats	Mainland	Oceanic islands
Agriculture and aquaculture	3674	88
Biological resource use	3130	128
Natural system modifications	2097	18
Invasive and other problematic species, gens and diseases	1872	157
Residential and commercial development	1624	70
Climate change and severe weather	1350	68
Pollution	1109	35
Energy production and mining	939	10
Human intrusions and disturbance	651	30
Transportation and service corridors	623	30
Geological events	187	5
Other options	92	3

3.4.5. Economy and Threats to Biodiversity

According to Table 31, the results of Spearman correlation analyses indicate a positive correlation between the number of Critically Endangered (CR) species and certain economic variables. The economic indicators used in the analysis include GDP (Gross Domestic Product), GDP per area, GDP per sector, and inequality.

Among these indicators, the most significant correlation is observed between GDP in agriculture and the number of CR species, with a correlation coefficient of 0.521. This suggests that there is a positive relationship between agricultural GDP and the number of CR species. Furthermore, a positive correlation is also observed between GDP in agriculture and the number of chordate species, with a correlation coefficient of 0.493. This indicates that higher agricultural GDP is associated with a higher number of chordate species. Inequality also shows a significant relationship with the number of chordate species, with a correlation coefficient of 0.398. This suggests that higher levels of inequality are associated with a higher number of chordate species. On the other hand, the correlation between GDP per area and the number of CR species (0.095) as well as chordate species (-0.018) is not found to be significant.

These results highlight the potential influence of economic variables, particularly GDP in agriculture and inequality, on the number of CR and chordate species.

Table 31: Spearman's Rank Correlation coefficients of CR species and economic variables

	All CR species	Chordate species	Total GDP	GDP per area	GDP in agriculture	GDP in industry	GDP in service	Inequality
All CR species	1.000	0.886	0.400	0.095	0.521	0.392	0.392	0.317
Chordate species		1.000	0.350	-0.018	0.493	0.346	0.338	0.398
Total GDP			1.000	0.502	0.836	0.984	0.995	-0.211
GDP per area				1.000	0.141	0.463	0.543	-0.258
GDP in agriculture					1.000	0.814	0.806	-0.102
GDP in industry						1.000	0.971	-0.193
GDP in service							1.000	-0.213
Inequality								1.000

Chordate species include: CR species +EN species +VU species

Based on Figure 33, it can be observed that the median number of Critically Endangered (CR) species in countries with a GDP in agriculture below 600 (absolute, PPP) is 12. As the GDP in agriculture increases, the median number of CR species also increases. In countries with a GDP in agriculture exceeding 15,000 (absolute, PPP), the median number of CR species reaches 66.

This suggests a positive relationship between the GDP in agriculture and the median number of CR species in a country. As the agricultural GDP grows, it is likely that there is an increase in the pressures and impacts on biodiversity, leading to a higher number of CR species. Additionally, the linear model results showed an interaction between biodiversity and land use changes. Overall, these findings emphasize the importance of considering the relationship between economic factors, land use changes, and biodiversity conservation to effectively address the threats faced by CR species.

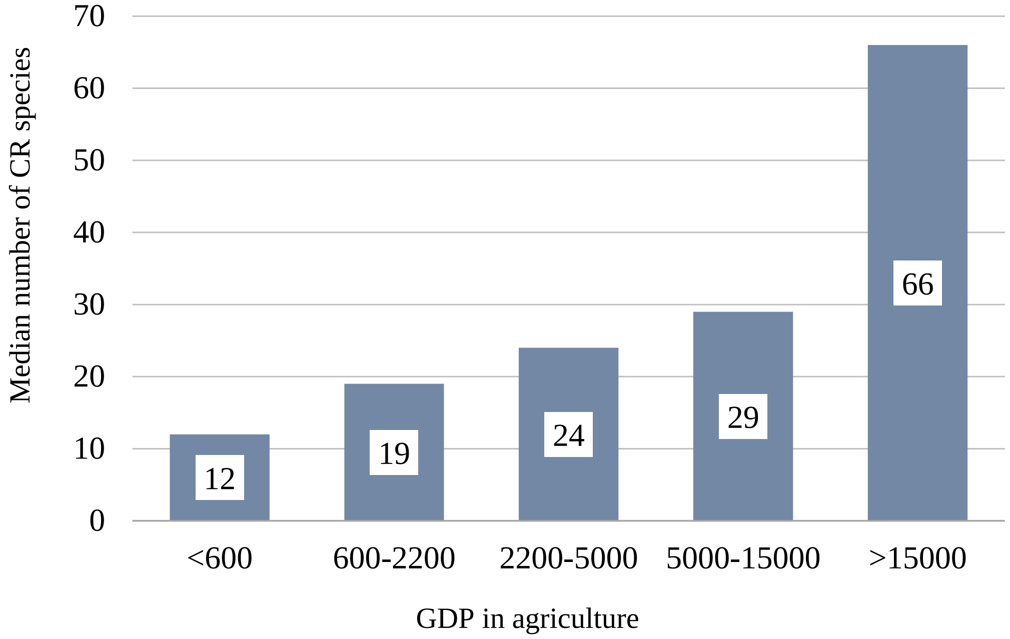


Figure 33: The median number of CR species in countries with different classes of GDP in agriculture (absolute, PPP) (Million US$) (CIA, 2021)

4. Discussion

4.1. Data Quality and Methods Used

The creation of a comprehensive database incorporating variables related to land use and land cover, as well as data from the IUCN Red List, was a crucial step in this research. This database allowed for the quantitative analysis of various aspects of threatened biodiversity, including threats and habitats.

It is important to acknowledge that the IUCN Red List data, although a valuable resource, may have inherent biases. The data input into the IUCN Red List is based on expert knowledge and assessment, which can introduce biases in terms of species representation. Some taxonomic groups may be underrepresented, while others may be overrepresented in the list. It is important to consider these biases when interpreting the results related to threatened biodiversity (Trull, et al., 2017). To estimate the relationships between variables, data from multiple sources were collected, including the IUCN Red List, the CIA World Factbook, the OECD, FAO, and Our World in Data. The selection of the most accurate and reliable data sources was a priority, and in the case of land use variables, the FAO database was considered the most accurate and used for the analysis. SPSS, a statistical software package, was utilized to perform Spearman's correlation analysis and Multiple Linear Regression Analysis (LRA). Spearman's correlation analysis allowed for the assessment of the strength and direction of the relationships between variables. LRA, on the other hand, provided a more comprehensive understanding of the relationships, quantifying the functional relationships and identifying the importance of each variable in contributing to the final results. It also helped in identifying dependencies between variables (Schneider, et al., 2010).

The utilization of statistical methods, such as LRA, enabled the researchers to statistically evaluate the relationships between different variables and quantify their impact on the outcomes of interest. This approach provided valuable insights into the complex relationships between land use, biodiversity, and other factors, shedding light on the importance of each variable and their interdependencies (Shiker, 2012).

The IUCN Red List of Threatened Species indeed plays a crucial role in guiding conservation efforts. It serves as a valuable resource by providing comprehensive assessments of the extinction risk for various species, encompassing fungi, plants, animals, and chromista. These assessments are conducted using rigorous scientific criteria and expert knowledge, making the IUCN Red List a trusted reference for conservation purposes. However, it is important to acknowledge that the IUCN Red List assessments do not cover all species present on Earth. The list represents only a fraction of the world's biodiversity, and this limited coverage can introduce bias and impact conservation priorities. It is crucial to recognize that there are numerous species that are not yet assessed or included in the Red List due to various factors, such as limited available data or resource constraints (Betts, et al., 2020; Rønsted, et al., 2022; IUCN, 2023).

Betts et al. (2020) argue that the IUCN Red List is comprehensive, complex, and long-term in nature. However, they acknowledge that the assessments of species on the list may be influenced by biases. Expert input and published data are used to determine the factors that contribute to the extinction risk of each species. For example, out of the 6.495 known mammal species worldwide, 5.973 are listed on the IUCN Red List. In contrast, only 12.441 out of more than 1.5 million insect species have been assessed (Trull, et al., 2017; Burgin, et al., 2018; Betts, et al., 2020; Belluco, et al., 2023).

Using QGIS in this research for land use change analysis and mapping was a suitable choice. QGIS provides a robust platform for handling spatial data, enabling the integration and analysis of various types of data, including vector, raster, and database formats. Its capabilities in managing geographic information and conducting spatial analysis make it a valuable tool for studying land use change (Haines-Young, 2009; Lu & Xiao, 2020).

One of the key features of QGIS is its capability to work with GeoTIFF images, which were utilized in this research to quantify land cover changes over time in the Mölln area. QGIS's raster analysis tools, coupled with on-screen digitizing and editing capabilities, allowed for the extraction of valuable information from the GeoTIFF images and the creation of accurate land cover maps. Moreover, the open-source nature of QGIS offers researchers a cost-effective and flexible solution for their spatial analysis requirements. The combination of SPSS and QGIS in this research facilitated a comprehensive analysis of the relationship between variables and land use change. SPSS, as a statistical software, provided the means for quantitative analysis and statistical evaluation of the data, while QGIS complemented this analysis by offering spatial visualization and geospatial analysis capabilities.

Overall, the use of QGIS in this research greatly aided the examination of land use patterns and changes in the Mölln area over time, leading to a more detailed understanding of land use dynamics and their relationship with biodiversity (Anderson, et al., 1976; Fisher & Unwin, 2005; Potapov, et al., 2008; Kim, 2016; Kouassi, et al., 2020; Meedeniya, et al., 2020; Duarte, et al., 2021; Congedo, 2021).

In this research, all variables were subjected to normalization in order to reduce deviations. Normalizing the data helps meet the assumption of normality, which is important for many statistical significance tests. It is common for empirical data to exhibit substantial deviations from normality, which can potentially affect the results of significance tests. Therefore, removing outliers from the data can enhance the accuracy of estimates and improve the reliability of the analysis. By addressing these issues, the research aimed to ensure that the statistical tests performed were valid and provided reliable insights into the relationships between variables (Osborne & Waters, 2002; Knief & Forstmeier, 2021).

The SPSS software, known for its capabilities in statistical data analysis, was utilized for the analysis in this study. However, it is important to exercise caution when interpreting the results of multivariate analysis, as they can be complex and reliant on certain assumptions that may be challenging to evaluate. Therefore, it is crucial to approach the interpretation of these results with care and consider the limitations associated with them.

Furthermore, it is important to acknowledge that the variables used in this research exhibit different characteristics. For instance, the areas of countries and elevation remain constant over time. In contarary, economic variables, the number of CR species, and population variables undergo significant changes over time. These inherent differences and variations pose challenges in the analysis process, requiring careful consideration and appropriate analytical approaches to account for these complexities and accurately interpret the results.

The spatial analyses in this study were performed using QGIS 3.16.7 software. QGIS, being an open-source geographic information system, offers robust support for multiple spatial data formats, including vector, raster, and database formats. It provides an extensive set of functionalities and tools specifically designed for spatial analysis tasks. This makes QGIS an invaluable tool in conducting land use change analysis, as it enables researchers to effectively manipulate, analyse, and visualize spatial data (Potapov, et al., 2008; Kouassi, et al., 2020; Meedeniya, et al., 2020).

Due to the advancement of satellite technologies, QGIS has become an important and practical tool for land use change analysis. While satellite technologies have advanced significantly, allowing for comprehensive land cover assessments and change detection in recent decades, the availability of historical data is limited, this feature is only possible for the last 3 decades. If we want to go further back in time, we need old maps for analyses. To overcome this limitation and visualize land use and land cover changes over time, the study utilized old maps for analysis (Eder, et al., 2018; Lu & Xiao, 2020).

The focus of the research was to examine land use and land cover changes within a specific area rather than attempting to depict global changes. Schleswig-Holstein was chosen as the study area due to the availability of high-quality and long-term map series. By utilizing these old maps, the research was able to analyse land use changes over an extended period. Similar approaches have been employed in other studies. For instance, Hansen et al. (2004) used land cover maps produced by the United States Geological Survey's Gap Analysis Program (USGS) to investigate the impacts of land use change on biodiversity. Guliyeva (2020) also employed satellite images and ArcGIS for land use classification and crop monitoring. By leveraging the strengths of historical maps and spatial analysis tools like QGIS, the study aimed to provide insights into land use and land cover changes over time in the selected area, contributing to the understanding of these dynamics and their implications (Guliyeva, 2020).

Despite efforts to collect reliable and authentic information, it is important to acknowledge several limitations in conducting this research. One significant limitation is the presence of biases in the IUCN Red List data. The Red List primarily focuses on vascular plants and larger animals, which could result in the potential omission of other important plant and animal species. It is crucial to consider this bias when interpreting the research findings. Another limitation arises from the lack of access to comprehensive data for all countries worldwide. As a result, the study was constrained to analyzing data from 166 countries that had the most complete information available. Even within these selected countries, certain variables had missing values, which were addressed through the use of estimation techniques. However, it is important to note that these data gaps may introduce a degree of uncertainty into the analysis. These limitations should be acknowledged and considered when interpreting the results of the research, as they may impact the generalizability and accuracy of the findings. Future research efforts should aim to address these limitations by expanding data collection and incorporating a broader range of species and countries to achieve a more comprehensive understanding of land use change and its impacts on biodiversity.

Additionally, the study was constrained by the unavailability of old land use maps for regions outside of Germany. The intention was to analyse land use changes in other countries such as Iran and Australia to provide a broader understanding and facilitate comparisons. Unfortunately, due to the absence of access to relevant old maps, the investigation was limited to a specific region in Germany. The selection of a case study approach allowed for a detailed examination of land cover changes in that particular area, with the aim of generalising the findings to Germany and potentially extrapolating them to the wider global context. It is important to acknowledge these limitations when interpreting the research outcomes and consider their potential impact on the overall conclusions.

The selection of Mölln as the study area was based on several factors that made it a suitable choice for conducting the research. Firstly, Mölln's location in the state of Schleswig-Holstein provided easy access for frequent field observations, allowing for on-the-ground assessments and monitoring. The area's diverse land uses, including forests, agricultural lands, urban areas, and rural areas, offered a variety of land cover types to study and analyse.

A crucial aspect for selecting this region as a case study was the availability of very old Geo TIFF Image files specifically prepared by the State Office for Surveying and Geoinformation Schleswig-Holstein. These images provided a unique opportunity to examine land use changes over a long period of 140 years, allowing for a comprehensive analysis of historical trends. However, it should be noted that the old maps presented challenges in accurately identifying the boundaries between grassland, bushes, and bare land. As a result, a simplified classification was employed, categorising these areas as "other". While this approach may introduce some limitations, it was a pragmatic solution given the constraints of the available data. One limitation of the research was the restricted time period available for analysing the relationship between land use change and biodiversity parameters. The study focused on a specific time frame, and therefore, the findings may not capture long-term trends or provide a comprehensive understanding of the relationship between land use change and biodiversity over extended periods.

In general, the definition and identification of land cover units via satellite image interpretation and related field work is in progress (Hansen, et al., 2004; Kaul & Sopan, 2012). In the case of old maps in the Mölln area, the borders between the units could easily identified. However, the information about the structure and species composition within the units is limited. Thus, we can only speculate on the plants cultivated in arable land and forest of the old maps.

Overall, despite these limitations, the chosen study area offered valuable insights into land use changes and their potential implications for biodiversity.

4.2. Land Use and Land Cover Change

Land use and land cover change can have both positive and negative impacts on biodiversity. Changes in land use results in habitat loss, fragmentation, and degradation, which are the main causes of biodiversity decrease. In addition, land use changes can change environmental conditions, which in turn can affect biodiversity. Land cover change analysis is a valuable method for studying ecosystems and their dynamics, and it plays a crucial role in understanding biodiversity patterns, assessing environmental impacts, and guiding environmental planning and resource management. By studying changes in land cover over time, researchers can gain understanding of the transformation of natural habitats, the expansion or shrinkage of ecosystems, and the impact of human activities on the environment (Anderson, et al., 1976; Liang & Liu, 2017; Al-Taei, et al., 2023).

Creating land cover and land use map is a valuable tool for effective land management, monitoringland cover change and understanding its impacts over time. These maps provide a context based on which land use change can be evaluated and analysed in detail. Land cover information can also be used to facilitate development activities (Potapov, et al., 2008; Nelder, 2018; Meedeniya, et al., 2020).

Indeed, conducting a comprehensive land cover analysis for the entire world can be a challenging task due to data availability and accessibility limitations. In this research, the city of Mölln in Germany was chosen as a case study to explore land cover changes over time, mainly because of the availability of historical land cover maps for that specific region. While it would have been desirable to include additional case studies in different regions such as Iran and Australia, the lack of access to old land cover maps for these areas posed a limitation. The unavailability of such historical maps restricts the ability to analyse and compare land cover changes in these regions over a long period. While it would have been ideal to have multiple case studies from different regions, the limitations on data availability are a common challenge in research. It is important to acknowledge such limitations and work with the available data to draw meaningful conclusions and insights within the scope of the study. The findings of this study reveal distinct patterns of land cover change in different regions across the world. Generally, there has been a decline in the extent of tree cover, bare areas, shrubland, sparse vegetation, and wetlands over the past three decades. On the other hand, croplands, grasslands, inland water, and artificial surfaces have experienced an expansion during the same period. These changes in land cover have had significant implications for biodiversity, contributing to the global decline in biodiversity. The observed trends in land cover change and their consequences for biodiversity highlight the need for effective land management and conservation strategies (Hobohm, et al., 2021; Menbere, 2021).

The findings from the land cover change analysis in Mölln over a span of 141 years reveal several notable trends. First, there has been an increase in the area of forest and artificial surfaces. The forest area experienced the most substantial increase, primarily at the expense of the other unit. This suggests a possible expansion of forested areas and a shift in land use dynamics over time. Conversely, the area of arable land, which historically constituted the largest portion of the region, has shown a decrease. This decline in agricultural land indicates a transformation in land use patterns. One of the main factors contributing to this change is the conversion of agricultural land into artificial surfaces, which may include urban development, infrastructure, and other human-made structures. The loss of agricultural land can be attributed to several factors, including the increasing human population and the need for housing, industrial areas, and infrastructure to support urbanization. Additionally, modern sustainable agricultural practices may have led to the consolidation of agricultural lands and increased efficiency, resulting in a reduced overall land area dedicated to farming (Wiyono, et al., 2023).

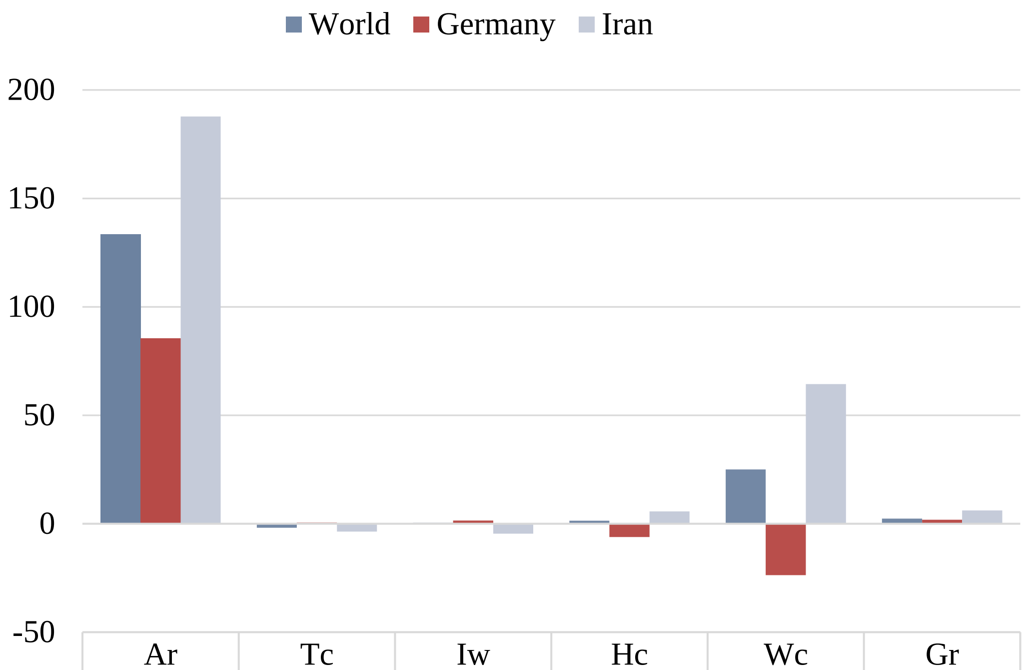
The trend of changes in the other unit in Mölln exhibited a decreasing pattern until 1984, followed by an increasing trend. This fluctuation can be attributed to various factors influencing land cover dynamics. Some possible reasons for the initial decrease in “other” may include land conversion for agricultural purposes, urbanization, or changes in land management practices. However, it is important to note that after 1984, the other unit began to increase, suggesting a potential recovery or changes in land use practices. This increase could be attributed to reforestation efforts, afforestation initiatives, ecological restoration projects, or changes in land management practices that prioritize the conservation of natural vegetation.

The area of water bodies, on the other hand, did not show significant changes during the study period. This suggests that the water bodies in Mölln have remained relatively stable in terms of their extent and are less influenced by land cover changes compared to other land cover types. Overall, the main land cover changes observed in Mölln have been the increase in artificial surfaces and forest areas, as is commonly observed in many developed countries. The expansion of forest and other natural cover observed in the study can be attributed to various factors, including afforestation efforts, environmental policies, and increased recognition of the importance of preserving natural ecosystems. These efforts have contributed to the restoration and protection of forested areas. Conversely, the decrease in the area of arable land, particularly between 1924 and 1955, signifies a significant conversion of arable land to forested areas and artificial surfaces. This conversion is influenced by factors such as urbanization, infrastructure development, and changes in agricultural practices. The conversion of arable land to other land uses reduces the available land for food production, which can have implications for food security and agricultural sustainability. However, it is important to note that despite the decrease in arable land, advancements in agricultural technology, methods, and techniques have resulted in improved efficiency of agricultural land use over time. These advancements have increased productivity and allowed for greater yields per unit of land. This highlights the importance of agricultural innovation in maximizing the potential of limited arable land resources to meet food demand (Wu, 2008; Hansen, et al., 2012; OECD, 2021).

In Table 32, land cover change in the whole world, Germany and Iran are compared.

Table 32: Land cover change in the whole World, Germany, and Iran (1992-2020) (%) (according to (FAO, 2022))

Land cover units	World	Germany	Iran
Artificial surface	133.45	85.56	187.77
Tree Cover	-1.84	0.5	-3.62
Inland Water	0.46	1.5	-4.6
Herbaceous Crops	1.42	-6.1	5.66
Woody crops	25.03	-23.7	64.41
Grassland	2.38	1.82	6.13



	Ar	Tc	Iw	Hc	Wc	Gr
World	133,45	-1,84	0,46	1,42	25,03	2,38
Germany	85,56	0,5	1,5	-6,1	-23,7	1,82
Iran	187,77	-3,62	-4,6	5,66	64,41	6,13

Figure 34: Land cover change in the whole world, Germany, and Iran (1992-2020) (%) (according to (FAO, 2022))

Figure 34 illustrates the land cover changes in three different cases: Germany, Iran, and the whole world. It indicates that the artificial surface has experienced the most significant growth across all three cases. This expansion of artificial surfaces reflects urbanisation, infrastructure development, and the conversion of natural land into built-up areas (Dissanayake, et al., 2020; Hobohm & Jansen, 2021).

While an increase in the area of the surface of the wter is being experienced globally, including in Germany, a sharp decrease can be observed in Iran. In general, human activities, particularly in agriculture, play a significant role in impacting water bodies, ultimately affecting biodiversity and the survival of living organisms (Revenga, et al., 2000).

In terms of tree cover, Germany shows an increase in tree cover while Iran and the whole world show a decrease. The increase in tree cover in Germany may be attributed to reforestation efforts, afforestation initiatives, and environmental policies aimed at preserving and expanding forested areas. Conversely, the decrease in tree cover in Iran and the world highlights the loss of forests due to deforestation, land conversion, and human activities.

The area of cropland has decreased in Germany. This trend may be influenced by factors such as urbanisation, land use policies, and changes in agricultural practices. In contrast, both Iran and the whole world show an increase in cropland area. This expansion of cropland globally can be attributed to the growing demand for food and the need to increase agricultural production. However, this expansion of agriculture can have negative impacts on biodiversity as natural habitats are converted into agricultural land. Grassland shows a similar increasing trend in all three cases, indicating a potential expansion or preservation of grassland areas. This increase may be driven by factors such as land management practices, agricultural policies, or the recognition of the importance of maintaining grassland ecosystems. The pattern of land cover change in Germany aligns with the findings observed in Mölln, indicating similar trends in land use and cover changes at a broader scale. This consistency suggests that the results from the case study can be generalized to some extent to reflect the broader land cover dynamics in Germany (Wood, et al., 2000; Petit, et al., 2001).

More than half of land cover changes in the world have occurred in countries with the highest number of critically endangered (CR) species such as Brazil, China, the USA, and Indonesia which shows a direct relationship between land cover change and the increase in the number of CR species (Reid, et al., 2000; Meshesha, et al., 2013; Balasubramanian, 2015; OECD, 2021; FAO, 2022). Land use change has the complicated direct and indirect impacts on biodiversity. Each type of land use while providing human needs, must also support native species (Mckinney, 2002; Nelder, 2018).

The findings of Hobohm et al. (2021) and the FAO study (2022) align with the results of this research, confirming a global trend of increasing artificial surfaces and croplands, as well as a decrease in tree cover and other. These patterns of land use change reflect the ongoing processes of agricultural expansion, industrialization, and urbanization that have shaped landscapes worldwide (Hobohm, et al., 2021; FAO, 2022).

Phases of land use over time in the world, associated with land use change, include nature, agricultural expansion, industrial expansion, and urbanization. A review of the conducted studies highlights the importance of land cover change in a wide range of key issues, including sustainable development, livelihood systems, and the Earth's biogeochemical cycles (Turner, et al., 1995; Hansen, et al., 2012).

During the last few decades, there has been a significant transformation in land cover worldwide, particularly with the expansion of artificial surfaces and croplands (Hansen, et al., 2012). The predominant land use changes have occurred within the past three decades on a global scale (FAO, 2022). Analysing these changes over time is crucial for making informed decisions regarding biodiversity conservation. So important is land use change that Sala et al. 2000 have argued that by 2100, the impact of land use change on biodiversity is likely to be more significant than other variables at global scales (Sala, et al., 2000).

While there has been considerable research on the impact of climate change on biodiversity, the influence of land use change on biodiversity has not received as much attention in the scientific literature. To address this gap, more comprehensive studies are needed to investigate the mechanisms through which global land use change influences biodiversity (Titeux, et al., 2016).

Davison et al. have highlighted that land use change poses the most significant threat to the natural environment, leading to substantial impacts on ecosystems (Davison, et al., 2021). However, it's important to note that the effects of land use change can vary considerably by region. For example, an evaluation of land use change and its impact on forest cover in Nigeria between 1980 and 2020 reveals a reduction in forest area, in contrast to the findings in Mölln. Instead, there has been an increase in other land use classes such as built-up areas, grasslands, agricultural land, and water bodies. Several factors contribute to these changes in Nigeria's land use patterns. Population growth, urbanisation, and the expansion of social and economic activities are identified as the main drivers (Rosemary Egodi, et al., 2021).

Between 1986 and 2011, Chile experienced a significant decline in native forest habitat areas, which has had adverse effects on biodiversity within these habitats. The reduction in forest cover has coincided with the expansion of agricultural land, indicating a shift in land use practices. This land use change has contributed to the loss of important habitat for numerous plant and animal species.

Between 1986 and 2011, Chile experienced a significant decline in native forest habitat areas, which has had adverse effects on biodiversity within these habitats. The reduction in forest cover has coincided with the expansion of agricultural land, indicating a shift in land use practices. This land use change has contributed to the loss of important habitat for

numerous plant and animal species. The highest rates of deforestation are observed in Southeast Asia and the Amazon region. These areas are home to a vast array of plant and animal species, with approximately two-thirds of global biodiversity residing in these regions. The deforestation occurring in these areas poses a substantial threat to the rich biodiversity they harbour (Hansen, et al., 2012; Haines-Young, 2009; Rodríguez-Echeverry, et al., 2018).

In 2019, Alam et al. conducted a study utilizing Landsat satellite data to investigate land use and land cover change in the Kashmir Valley, India. Their findings revealed changes in various land cover categories between the years 1992 and 2015. Specifically, they observed a decline in the areas occupied by agriculture, forests, pastures, and water bodies during this period. On the other hand, there was an increase in the areas covered by swamp, cultivated land, bare land, plantations, and shrubland. These results align, to some extent, with the findings of the present study. Both studies highlight the dynamic nature of land use and land cover change, with shifts occurring in different categories over time. While the specific changes observed in each study may differ, the overall patterns of transformation indicate the evolving nature of landscapes and the influence of various factors, such as human activities, climate, and natural processes (Alam, et al., 2020).

India, situated in Southeast Asia, has experienced notable urban growth and a decrease in other land cover types, particularly agricultural land, between 1985 and 2005 (Thanekar, 2021). This trend is consistent with the expansion of urban areas observed in many tropical regions. Additionally, regions like eastern China and the southeastern United States have witnessed significant declines in arable land (Haines-Young, 2009).

An evaluation of landscape changes along the east coast of China highlights the rapid pace of urbanization as a key driver of landscape transformation. In this region, agricultural land, pastures, and water bodies have been converted into urban areas to accommodate urban growth and development (Deng, et al., 2009).

Land use change varies across different regions of the world. Arid regions in Asia experience rapid rates of change, while land cover in Europe tends to be relatively stable. However, this stability in Europe should not be mistaken for the absence of pressures on ecological systems (Haines-Young, 2009).

In Ethiopia, a significant land use change observed over a 40-year period includes deforestation, expansion of grazing areas, a decrease in bare land, and a slight increase in cropland. These changes are attributed to shifts in social-economic policies and increased agricultural activities. The factors driving these changes are multifaceted. Changes in policies related to land management, agriculture, and economic development can influence land use patterns (Amsalu Taye, 2006). Countries experiencing higher rates of economic growth are likely to worsen the biodiversity crisis. These changes can escalate the ongoing biodiversity crisis. Although It can be argued that economic growth, coupled with increased funding for conservation, has the potential to lead to a relative decrease in the rate of biodiversity loss (Dietz & Neil Adger, 2003; Clausen & York, 2008).

The study conducted by You et al. (2023) in the Huaihe River region of China highlighted the dominant pattern of land use change in the area, which is characterized by extensive construction activities driven by economic development. Additionally, certain policies, such as returning farmlands to forests, have contributed to a significant decline in arable land. This suggests that urbanization and reforestation efforts have had substantial impacts on land use dynamics in the region (You, et al., 2023).

In another study by Li et al., the researchers simulated the projected impact of land use change on habitat quality in 2030. The findings indicated an increase in urban surface area and a corresponding decrease in forest and water body areas by that time. Moreover, the study revealed that habitats in urban construction lands exhibited lower quality compared to habitats in water bodies and mountains. These results underscore the influential role of land use change in shaping habitat quality and highlight the potential challenges associated with urban expansion and its impact on ecosystems (Li, et al., 2022).

The study conducted by Thanekar (2021) aimed to assess the impacts of land use and land cover change (LULC) on species distribution on a global scale using QGIS. The research considered several variables, including altitude, slope, direction, distance from the road, and soil type, to analyse the relationship between LULC change and species distribution patterns. The findings of the study revealed that altitude and distance from the road were the most influential factors impacting species distribution in the context of LULC change. The research demonstrated a significant increase in urban areas and a corresponding decrease in agricultural land and other land cover types during the studied period (1985-2005). Industrial growth and urban development were identified as the primary drivers of this land use change. The results of Thanekar's research align with the findings of the present study, which also highlighted the growth of urban areas and the decline of agricultural land as prominent land cover change patterns (Thanekar, 2021).

The study conducted by Haladova in Slovakia focused on the classification of land use and the examination of its changes over a 10-year period. The research aimed to understand the dynamics of land use patterns in Slovakia and identify any significant shifts or transformations. The findings of the study revealed a notable decline in agricultural land during the studied period, accompanied by its conversion into residential and industrial areas. This suggests a shift in land use priorities and an increasing demand for land for urban development and industrial purposes (Haladova & Petrovic, 2015).

While there has been considerable research on the impact of climate change on biodiversity, the influence of land use change on biodiversity has not received as much attention in the scientific literature. To address this gap, more comprehensive studies are needed to investigate the mechanisms through which global land use change influences biodiversity. By utilizing satellite remote sensing data, the researchers were able to gather valuable information on the characteristics and extent of wetlands across the United States. They integrated this data with GIS analysis to identify areas that were particularly vulnerable to both natural stressors and human stressors. This information can be crucial for long-term wetland planning and management, as it enables decision-makers to prioritize conservation efforts and implement effective strategies to mitigate the impacts of stressors on wetland ecosystems (Akumu, et al., 2018).

Land use change plays a significant role in economic development (FAO, 2022). Various economic, social, and cultural activities rely on the availability and quality of environmental conditions, natural processes, ecosystems, and natural resources.

These factors influence the allocation of land for different uses based on their economic value and potential benefits (Dale, et al., 2010). Economic efficiency is often a driving force behind land use change. While the economic benefits of land use change are often prioritized, the public benefits derived from biodiversity services and the costs associated with the loss of these services are frequently overlooked or undervalued (Nelder, 2018).

Large countries with a high GDP, such as China, Brazil, and Australia, contain almost the highest number of CR species too (IUCN, 2023; CIA, 2021). Residential and commercial development followed by agriculture and aquaculture is the most important threat to CR species in the 20 richest countries by GDP in the world (IUCN, 2023).

Land use change is predicted to have a significant impact on biodiversity in the coming decades, and it is crucial to pay special attention to managing land use in order to mitigate its negative effects on ecosystems and protect biodiversity. As human populations continue to grow and economic activities expand, the demand for land for agriculture, infrastructure development, and urbanisation is expected to increase (García-Vega & Newbold, 2020). The most obvious consequences of land use change are loss, fragmentation, and degradation of habitat, which makes these areas uninhabitable for many native species, and also increases the number of species threatened with extinction. So, it is necessary to have special attention to land use to control its impacts and protect biodiversity in areas affected by land use change (Hansen, et al., 2012).

Agricultural expansion is indeed a major driver of land use change and is a significant contributor to biodiversity decline worldwide. The impact of agricultural expansion on biodiversity is particularly concerning for critically endangered (CR) species. This expansion is to the extent that today more than 25% of Earth's terrestrial surface has been converted to agricultural lands. According to the IUCN Red List, a significant number of highly threatened species (4630 species of 9065 critically endangered (CR) are directly affected by agricultural activities. The loss of their habitats, the introduction of agrochemicals, and other associated factors pose severe threats to their survival (Hassan, et al., 2005; Our World in Data, 2019; IUCN, 2023).

4.3. Threatened Biodiversity

Understanding the threats that affect biodiversity is crucial for effective habitat and biodiversity management. The IUCN Red List provides valuable information about the status and trends of species worldwide, including those that are critically endangered (CR). The IUCN Red List has documented a significant number of critically endangered species, including plants, animals, fungi, and Chromista. As of the 2022 assessment, there are 9,065 species listed as critically endangered. Among them, 5,332 are plants, 3,797 are animals, 32 are fungi, and 4 belong to the Chromista group. The decline in the population of vertebrate species by 60% since 1970 is a staggering statistic. This decline is indicative of the immense pressures that biodiversity faces due to various factors. Currently, approximately 25% of species globally are threatened with extinction. Understanding the specific threats affecting different species and ecosystems is crucial for developing targeted conservation measures (Oliver & Morecroft, 2014; Bjelle, et al., 2021; IUCN, 2023).

Digital data has provided new opportunities for quantifying public awareness of important societal issues, including conservation issues such as endangered species. Measuring public awareness is indeed valuable for evaluating the effectiveness of conservation efforts and understanding the level of engagement and support from the public (Rodriguez, et al., 2015).

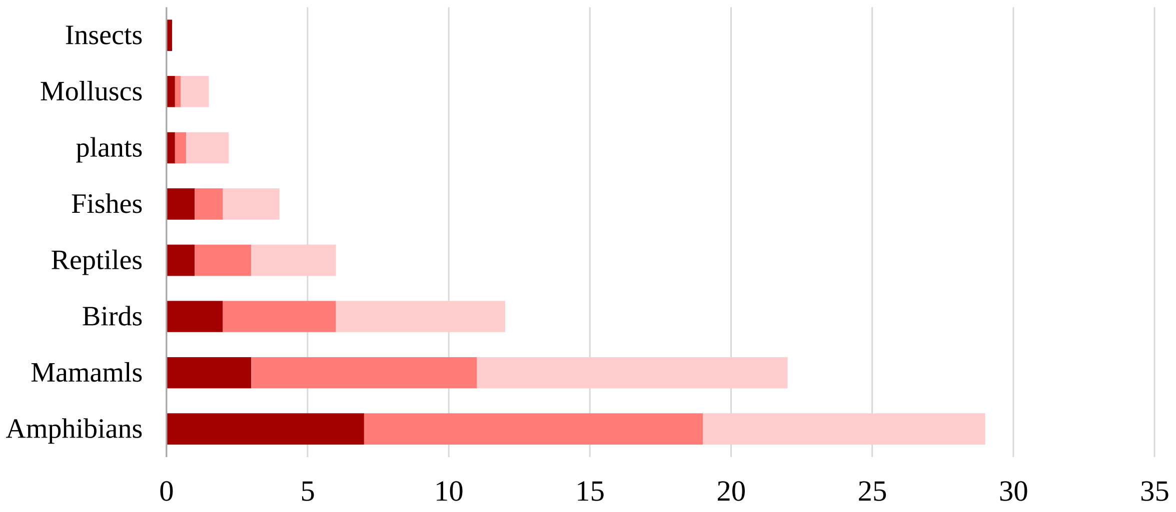
Tropical rainforests, coral reefs, wetlands, mangroves, and scrublands are highly diverse and ecologically important ecosystems that support a wide range of species. Unfortunately, these habitats are particularly vulnerable to threats and are often hotspots for endangered and threatened species (Chapin, et al., 2000; Hobohm, et al., 2021). Biodiversity is threatened by human activities in the last century at an alarming rate following the increase in population. While it is the basis of ecosystem services and human survival and welfare are dependent on benefits provided by it (Pereira, et al., 2012; García-Vega & Newbold, 2020; Prakash & Verma, 2022).

The extinction of species with a specific role in nature could seriously affect ecosystem processes (Penjor, et al., 2022). Extinction of a species means the loss of interactions and ecological functions that are critical to the survival of other species or the ecosystem (Prakash & Verma, 2022), and can have a significant impact on ecosystem services, for example, the extinction of birds, which play an important role in the dispersal and pollination of plant seeds (Pereira, et al., 2012). Penjor et al. (2022) found that the extinction rate of larger species has been higher than smaller species and species with larger body mass are much more vulnerable than smaller ones (Penjor, et al., 2022).

The IUCN Red List (2022), recorded 902 extinctions including 778 animal species and 124 plant species around the world. Meanwhile, 27 species have become extinct in the last 20 years alone. While the majority of extinctions documented by the IUCN Red List represent the loss of animal and plant species, it's important to note that not all extinctions are negative from a human perspective. The extinction of certain disease-causing organisms, like the Variola major and minor viruses responsible for smallpox, can indeed be seen as positive events (Pereira, et al., 2012; Kumar & Verma, 2017; IUCN, 2023).

The major drivers of these extinctions were invasive and other problematic species, genes, and diseases which were responsible for the extinction of 306 species (273 animal species and 33 plant species), followed by biological resource use (responsible for the extinction of 185 species) and agriculture and aquaculture (responsible for the extinction of 114 species). Threats for endangered species are different with respect to habitats (Hobohm, et al., 2021), about half of these extinctions (48%) have occurred in the forest (252 species) and wetland (186 species) habitats (IUCN, 2023). In forests, hunting is the main threat specially for large birds and mammals (Pereira, et al., 2012).

Figure 35 shows the percentage of CR, EN, and VU species in various biological groups based on the IUCN Red List 2023 statistics. It is obvious that amphibians and mammals are more threatened with extinction than other biological groups, and the least threatened are insects (IUCN, 2023).



	Amphibians	Mamamls	Birds	Reptiles	Fishes	plants	Molluscs	Insects
CR (%)	7	3	2	1	1	0,3	0,3	0,2
En (%)	12	8	4	2	1	0,4	0,2	0
Vu (%)	10	11	6	3	2	1,5	1	0

Figure 35: Percentage of CR, EN, and VU species in various biological groups (IUCN, 2023)

Human activities such as hunting, recreation, and walking in nature or road accidents have had significant impacts on species diversity and have led to the reduction of natural habitats and a decline in global species richness (Hansen, et al., 2012). The effects of these activities on species vary, and certain groups may be more vulnerable to extinction than others. Amphibians and mammals are indeed among the biological groups that are more threatened with extinction. Insects, on the other hand, are generally considered to be less threatened compared to other groups (Hansen, et al., 2012; Newbold, et al., 2020; IUCN, 2023).

Humans and other species often occupy overlapping areas across different spatial scales. Consequently, the transformation of natural habitats by human activities and its impact on native species occur more rapidly in these shared areas (Hansen, et al., 2004). Native species, which are less tolerant of human activities, experience population declines due to habitat loss and disturbances caused by human presence. On the other hand, certain human-dominated areas exhibit high habitat heterogeneity and a diverse range of habitat types. These areas can support populations of species that are more adaptable to human activities, often including non-native species. As a result, these human-dominant areas can harbor rich biodiversity. For instance, species like raccoons tend to thrive in environments influenced by human activities, benefiting from the resources and habitats provided. The prevalence of non-native species varies across different regions, with their presence ranging from a small percentage in rural areas to over 50% in urban areas (Mckinney, 2002). Consequently, cities and urban areas can exhibit surprisingly high levels of biodiversity compared to surrounding rural areas.

While urban areas are typically associated with human development and habitat alteration, they can still provide habitats for certain rare and endangered species. Urbanized habitats such as parks, green spaces, and even gardens can serve as refuges for these species, offering pockets of suitable habitat and resources in otherwise transformed landscapes (Mckinney, 2002; Hansen, et al., 2004; Hobohm, et al., 2021).

According to the IUCN Red List 2022, there are 10 megadiverse countries that stand out for their exceptional levels of biodiversity. These countries not only host a significant number of species but also face a high number of Critically Endangered species (CR) within their borders. Collectively, these 10 countries are home to more than 32% of all CR species worldwide. These megadiverse countries are particularly vulnerable to threats related to land use change, with the two main categories of concern being "agriculture and aquaculture" and "biological resource use" (IUCN, 2023).

Previous research conducted by Hobohm et al. (2021) has identified several factors as major threats to biodiversity on a global scale. These include agriculture, land use change, forestry, and biological resource use. Additionally, Steffan-Dewenter et al. (2007) highlight the main causes of biodiversity loss as agricultural intensification and the decline of tropical forests (Steffan-Dewenter, et al., 2007).

The current global situation indicates an increased risk of species extinction due to factors such as human consumption patterns and environmental degradation. However, it is important to acknowledge that our understanding of many species is still limited (Nelder, 2018; Padhy, et al., 2022).

The research findings highlight a significant positive correlation between the number of Critically Endangered (CR) species and the area of permanent crops. This suggests that permanent crop cultivation has a substantial impact on CR species compared to other land uses. As the area dedicated to permanent crops expands, the number of CR species also increases. These results reinforce the understanding that land use change plays a major role in biodiversity loss.

4.4. Land Use and Other Factors that Threaten Biodiversity

Habitat loss and degradation, pollution, climate change, invasive species, overexploitation of resources, agricultural production, and changes in land use patterns are significant factors that pose substantial threats to biodiversity. These factors can directly and indirectly impact biodiversity, occurring at different spatial and temporal scales (Foley, et al., 2005; Reid, et al., 2005; Uribe, et al., 2021). Human activities play a major role in driving these threats, particularly in relation to land use changes for urbanisation and other human needs (Marland, et al., 2003; Prakash & Verma, 2022).

The study highlights that agriculture and aquaculture are the main threats to biodiversity, affecting 21% of all CR species, followed by the use of biological resources, which is responsible for threatening 17.9% of CR species. Climate change and severe weather threaten only 7.7% of CR species. Therefore, the second hypothesis of this study is confirmed by these results.

Numerous studies in the field of land use change and biodiversity have consistently highlighted the significant role of land use change as a major threat to biodiversity, particularly for Critically Endangered species. The IUCN Red List 2022 also provides evidence of the impact of land use change on biodiversity, with numerous species listed as Critically Endangered due to the loss and degradation of their habitats (Hansen, et al., 2012; Prakash & Verma, 2022; IUCN, 2023).

Human activities have historically been linked to changes in habitats, land structure, land use change, and habitat loss, which are significant factors contributing to biodiversity decline. Forest habitats, in particular, are known to harbor a high number of critically endangered (CR) species, accounting for approximately 48% of such species. Wetlands are the second most important habitat, hosting around 18% of CR species. It is important to note that the threatening factors to CR species can vary depending on the specific habitat. In forest habitats, agriculture and aquaculture are identified as the most significant threats to CR species, while in wetland habitats, pollution emerges as the primary threat to CR species (Oliver & Morecroft, 2014; Khaleghi, 2017; Newbold, et al., 2020; Hobohm & Jansen, 2021).

In addition to the direct impacts of land use and land cover change (LULC) on biodiversity, there are several indirect effects that can significantly affect ecosystems and species populations. One of these effects is the alteration and fragmentation of remaining habitats that can vary across different regions and over time (Oliver & Morecroft, 2014; Titeux, et al., 2016; Ayeni, et al., 2023).

Agricultural expansion, excessive use of water, the release of pollutants into the environment, the use of pesticides and chemicals in agricultural practices, overexploitation of natural resources, unsustainable harvesting of plants and animals, overexploitation of economic activities, and global trade are some anthropogenic activities that cause biodiversity extinction (Kumari, et al., 2021). While agricultural land can provide valuable habitat for many wildlife species, intensive agriculture has severe ecosystem consequences and is one of the greatest impacts on the environment and biodiversity (Marland, et al., 2003). The dynamics in agriculture and habitat transformation can lead to shifts in species composition and distribution across the landscape (Baessler & Klotz, 2006).

With the global population steadily increasing over the past decades and the expansion of human activities to meet the growing needs of people, we have witnessed the significant loss of natural habitats. Cities and croplands have expanded to accommodate the demands of human settlements and agricultural production across various regions of the world. While cities currently cover less than 3% of the Earth's surface, they are home to more than half of the world's population. Unfortunately, in these urban areas, native species face numerous threats as a result of human factors (Nelson, et al., 2010; Aronson, et al., 2014; Prakash & Verma, 2022).

The impact of land use change varies across different habitats, and threats to biodiversity are influenced by the specific characteristics of each habitat type. In forest ecosystems, deforestation and habitat fragmentation are major threats to biodiversity. Aquatic habitats, face different challenges. Pollution, including the release of chemicals, toxins, and excess nutrients, poses a significant threat to aquatic biodiversity. One of the most notable impacts of land use change has been observed in tropical forests. These biodiverse regions have experienced extensive deforestation and habitat loss (Butchart, et al., 2010; Sharma, et al., 2018; García-Vega & Newbold, 2020; Prakash & Verma, 2022).

Between 2000 and 2012, the average annual decrease in the area of tropical forests was estimated to be 2,101 km^2 (Loh, et al., 2016). This alarming rate of deforestation is concerning, especially considering that approximately half of the critically endangered species, totaling 5,244 species or 49.22%, reside in forest habitats, and many ecosystem services are provided by forests. These ecosystem services are reduced or destroyed by the conversion of forests to other land uses (IUCN, 2023; Marland, et al., 2003).

Forest habitats have experienced a significant number of species extinctions thus far, with the highest annual losses occurring in America and Africa (Trisurat, et al., 2011; IUCN, 2023).

Annually, a staggering 5.8 million hectares of trees are lost in tropical forests due to deforestation and over-exploitation. In Africa, human pressures have led to the extinction of 75% of large mammal populations in recent decades, highlighting the detrimental impact of human activities on wildlife (Ayeni, et al., 2023). Deforestation results in a range of negative effects on both the biological and physical environment. Habitat loss, fragmentation, and species extinction are among the most significant consequences. Additionally, deforestation can lead to soil degradation, drought, and flooding (Trisurat, et al., 2011). The Mediterranean environment is particularly sensitive to land use change, with high biodiversity at risk. Degradation of Mediterranean habitats due to land-use change has a profound impact on biodiversity, even if habitat recovery measures are implemented. So, preserving primary habitats becomes crucial in maintaining the natural species composition and protecting the delicate balance of the ecosystem (García-Vega & Newbold, 2020).

While the process of evolution leads to the emergence of new species, various filters can influence the population dynamics and distribution of species. Dispersal filters, such as migration, play a significant role in determining the success and survival of species in different ecosystems. Species that possess the ability to migrate can adapt to new environments and establish viable populations in other regions. On the other hand, ecological filters, like volcanoes, can have a detrimental impact on species populations. Volcanic eruptions, can lead to the loss of many species, although, human activities in the past centuries have aided species in overcoming these natural barriers (Kühn & Klotz, 2007; Hobohm, et al., 2021).

According to Rawat and Agarwal, habitat change, climate change, overexploitation of invasive species, and pollution are identified as the most significant direct factors that impact biodiversity. These factors can have substantial and often detrimental effects on species populations and ecosystem functioning.

Climate change is another important factor affecting biodiversity. While climate change receives significant attention in discussions on biodiversity loss, researchers should also consider the interactive effects of other factors. Indeed, it is important to consider that climate change interacts with other factors, such as habitat change and pollution, leading to complex and cumulative effects on biodiversity (Rawat & Agarwal, 2015; Sirami, et al., 2016). According to Musisa and Asfa, several factors contribute to land use and land cover change in rangelands, resulting in negative impacts on plant and animal diversity, ecosystem services, and soil fertility. The main drivers identified include agricultural activities, increasing population pressure, illegal fires, and deforestation. These factors interact and exacerbate the transformation of rangeland ecosystems (Mosisa & Asefa, 2022).

Another factor affecting biodiversity is increasing urbanization, which is unavoidable, and the consequent economic development can have significant negative impacts. Factors such as industrial fishing, harvesting wild plants and animals, extracting resources, and excessive logging are some other important activities that may lead to the extinction of species (Ayeni, et al., 2023). In addition, increases in the population of some species in urban areas, such as domestic cats and dogs, can have negative impacts on wildlife populations (Maestas, et al., 2001). Climate change is indeed a global phenomenon that is affecting climates and ecosystems worldwide. Its impacts are diverse and can have significant consequences for biodiversity. Some of these impacts, such as the retreat of glaciers and changes in Arctic ecosystems, are irreversible and have already been observed (IPCC, 2023). Climate change has important impacts on biodiversity, which can have far-reaching consequences for the structure of ecosystems.While climate change poses a significant threat, the majority of these species, more than 85%, are impacted by a range of human activities, and only less than 20% are affected by climate change (Titeux, et al., 2016), and so far less than 4% of species have become extinct under the influence of climate change (IUCN, 2023).

Human activities are the main reason of global warming and changes in climate patterns (Prakash & Verma, 2022). The study conducted by Ameztegui et al. (2016) in the Catalan Pyrenees highlights the importance of land use change as a significant driver of impacts on treelines. The findings suggest that land use change has a more substantial influence on treeline dynamics compared to the impact of climate change (Ameztegui, et al., 2016). In addition to human activities the increase in the human population, urban development, and invasive species are also the other main factors affecting biodiversity. This urban expansion can lead to edge effects, where human activities, hunting, settlement, recreation, and the introduction of exotic organisms and diseases have a greater impact on natural areas (Marland, et al., 2003; Pereira, et al., 2012; Hansen, et al., 2012; Kumari, et al., 2021).

The results of this study indicate a correlation between the level of GDP in the agricultural sector and the number of critically endangered (CR) species. It suggests that as the GDP in agriculture increases, there is also an increase in the number of CR species. This finding highlights the potential negative impacts of economic activities in the agricultural sector on biodiversity. The other important threat to biodiversity and ecosystems is economic growth. Threats from economic processes such as urbanisation, industrial activities, agriculture, and infrastructure development can have significant impacts on biodiversity. These activities often lead to habitat loss, fragmentation, and pollution, which can have detrimental effects on species populations. The study conducted by Hobhom et al. (2021) further supports the notion of a positive relationship between the number of critically endangered species and economic growth, as measured by GDP. Also, Mikkelson et al. analysed how economic inequality is related to biodiversity loss. They found that the number of endangered species increases with the Gini ratio of income inequality (Mikkelson, et al., 2007).

The results of this study also highlight a strong correlation between the number of critically endangered (CR) species and total GDP. It means that the number of CR species increases with an increase in total GDP. In addition, all regression analysis models presented in this study emphasize the role of economic factors as major drivers of biodiversity loss.

5. Summary and Conclusion

This study aimed to analyse the impacts of land use/land cover change on biodiversity change at a global scale. This study analysed the relationship between variables related to land use and land cover and biodiversity and the impact of land use change on biodiversity. The scale of the study was global, and the study was limited to 166 countries with the largest amount of data. In the first section, two variables related to threatened species, including the number of CR species and Chordate species, were determined for selected countries as response variables. Then, the relationship between these variables and the parameters affecting them was analysed. For this purpose, 35 variables related to land use, land cover, physical geography, demographic and economic variables were determined as predictor variables to analyse the relationship between them. Spearman Correlation coefficient and Multiple Linear Regression were used for the analysis using SPSS software. Numerous regression analysis models were calculated to find the best result. The second part deals with land cover and its changes in the world. In this section, land use changes in a region were studied as a case study using QGIS 3.16.7 software to perform spatial analyses and calculating land use change by reference maps. In geographical terms, a local dataset was tested. However, these observations could be generalized to other cases (Escribano, et al., 2016). Results demonstrated an increase in the area of artificial surfaces and forests and a decrease in the area of arable lands. The study emphasizes the important relationship between land cover change and impacts on biodiversity. The study also shows that geographic information system (GIS) technology is a powerful tool for mapping and identifying land cover change.

Various methods are used to protect biodiversity, such as restoring degraded ecosystems, creating more and better protected areas, biosphere reserves, national parks, and wildlife sanctuaries, to protect species and ecosystems from harmful human activities, that protect biodiversity in its natural habitat. Or special care of threatened species outside their natural habitat such as zoological parks, botanical gardens, and aquariums which play a vital role in the survival and propagation of rare species. And accommodating endemic species in parks and botanical gardens from the region. Other advanced methods are the fertilization of eggs in laboratory conditions or storing plant seeds in the seed bank (Kumar & Verma, 2017; Singh, 2010; Salem, 2003; Kleijn, et al., 2008; Hobohm & Jansen, 2021). At the moment there are more than 100 seed banks in the world to store approximately 3 million samples at low temperatures (Kumari, et al., 2021).

Some methods can be important and effective to reduce land use change problems such as ecological forestry, sustainable agriculture, and nature-friendly cities, and restoring some of the farmlands back to forests and natural habitats (Rosemary Egodi, et al., 2021; Our world in data, 2019). However, land cover change does not always reduce species diversity. For instance, the conversion of agricultural land to forest can lead to an increase in the population of forest species. Expanding the urban ecosystems is the other example. Although many species do not have the ability to adapt to the urban ecosystem, the richness of some species may increase due to the ability to use human food resources, the use of artificial structures as habitats, adapt to exotic plants, and also to reduce the risk of hunting in these areas (Hobohm & Jansen, 2021; Pereira, et al., 2012; Ringim, et al., 2019).

A combination of theory, recognising the areas with the highest amount of biodiversity, having tools to monitor these areas over time, and political and administrative structures are the most important factors for managing and protecting biodiversity against land use change. It can also be useful to consider environmental fines at different local, regional, and global scales. And ultimately the support of citizens for policies of biodiversity management and protection is necessary. Protection and maintenance efforts should be customized to the needs of each site (White, et al., 2000; Hansen, et al., 2012; Ubaekwe, et al., 2021; Hobohm, et al., 2021).

The conservation of biological diversity requires the development and implementation of national strategies and action plans. There is not one simple solution or any globally effective package of measures to solve these issues and protect the environment. Therefore, various concepts, decisions, and measures should be discussed and implemented at all scales among researchers, practitioners, and politicians. We must encourage a diversity of solutions and more collaboration between the natural sciences, social sciences, and humanities. Conservation must be done in a fair way that does not play off people's basic needs against nature. The yield of agricultural products has increased significantly in recent decades, and it is now possible to convert some of this agricultural land back into forests and natural habitats (Salem, 2003; Hassan, et al., 2005; Our World in Data, 2019; Hobohm, et al., 2021; Pimm, 2021).

Support of citizens of policies of biodiversity management for stopping the decline of biodiversity, especially in the countryside. Parks and botanical gardens in cities could focus on accommodating endemic species from the region (Hobohm, et al., 2021).

Some of the world conservation strategies to protect biodiversity include: efforts to conserve endangered species, proper planning and management to prevent extinction, protecting habitats, reforestation and social forestry, zoological gardwns, and regulating international trade in wild plants and animal. Also, some land-use laws include mitigation and adaptation strategies that protect and restore the natural systems that buffer communities from the impacts of natural hazards such as floods (Rawat & Agarwal, 2015; Kumar & Verma, 2017; Adams-Schoen & Smith, 2023).

However, even if all societies agree to conserve Earth's biodiversity, it is very difficult to translate this issue into effective global action. One of the other aspects of biodiversity conservation is sustainable development through a balance between environment, development and society, for which implementation policies are required (Rawat & Agarwal, 2015; Bebbington, et al., 2021).

The results of this research indicate that 7,7% of CR species are threatened by climate change. Overall, the IUCN Red List identifies climate change as a threat for 11% of the species listed as threatened. Trull et al. believe that often, the threat of climate change on the IUCN Red List occurs in combination with other threats, however, the IUCN Red List underestimates climate change as a threat to species. They explain that the reason for this could be the IUCN's evaluations in relatively short periods of time, and the other is that it is difficult to distinguish the effects of climate change from other threats which may be easier observed and quantified that leads to underestimations of the importance of climate change on the IUCN Red List. Climate change and severe weather threatened only 1.2% of the 79,837 species assessed by 2016. This threat is often relevant in combination with other threats. Finally, it must be said that it is practically impossible to estimate the extinction risk of all species, but it may be possible to prevent species extinction. However, the most important question is how we can prevent species extinction? (Pereira, et al., 2012; Rodriguez, et al., 2015; Trull, et al., 2017; Hobohm, et al., 2021).

Photo 5 and 6: River bank and part of the river Elbe, Pevestorf, Niedersachsen, Germany. Dry dune grassland, Pevestorf, Niedersachsen, Germany (Mahsa Tafaghodakbarpour, 2021)

Photo 7 and 8: Pasture grazed by cows near Husum, Schleswig-Holstein, Germany. Arable land, near Husum, Schleswig-Holstein, Germany (Mahsa Tafaghodakbarpour, 2022)

Photo 9: Fresh water in Nature Reserve, Stockholm, Sweden (Mahsa Tafaghodakbarpour, 2023)

Photo 10: Pasture grazed by ships, Kollund, Denmark (Mahsa Tafaghod akbarpour, 2022)

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Statutory declaration

“I hereby affirm that the present work was written by me alone, using no sources or aids other than those referenced in it. All of the materials taken directly or indirectly from external sources (including electronic sources, the Internet and oral communication) are marked as such, without exception and with a precise indication of the source. Core dissertation content has not been used previously for another thesis or work submitted in order to obtain an academic qualification. In particular, I have not received the help of a so-called “doctoral consultant” (“Promotionsberaterinnen/Promotionsberater”). Third parties have neither directly nor indirectly received money or goods with a monetary value from me in exchange for work related to the content of the herewith submitted dissertation. The work has not been submitted, in its present form or a similar form, to any other examination authority, either in Germany or abroad. I have been informed of what it means to submit an affidavit in lieu of an oath, of the penal consequences of a submitting negligent, false or incomplete affidavit, and of the provisions of §§ 156,161 StGB [German Criminal Code]."

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