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SPATIAL MODELS OF LANDSCAPE RESPONSES TO CLIMATE CHANGE

Doctoral thesis

Mr Elvis TANGWA

Supervisor: **assoc. prof. Vilém PECHANEC**

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Author's statement

I declare that this PhD thesis of P1031 Geography study program has been completed independently and under the supervision of doc. RNDr. Vilem PECHANEC, PhD. All the materials and resources are cited with regard to scientific ethics, copyrights and laws protecting intellectual property. All provided and created digital data will not be published without the consent of the Department of Geoinformatics, Faculty of Science, Palacky University Olomouc.

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ABSTRACT

Landscapes are constantly being modified by changing climate and human-induced processes. The interaction of both processes has given rise to landscapes different in composition and structure, affecting species and the quality of life for communities and services to humanity. Spatial processes, by nature, are very complex. Hence a range of tools or models may be tested to understand them. Part of the complexity has to do with the fact that spatial processes operate at different scales. Therefore the scale is crucial to understanding ecological processes.

This thesis aimed to explore a range of spatial modelling approaches to improve understanding of landscape development, mainly due to climate change but also due to topography and land use or cover change across multiple scales. The spatial models tested included: EcoCrop, EUROMOVE, a spatial custom model to map land cover change and geostatistical models, which were studied at regional, national and field-scale.

The main results are that the current climate has a milder impact on species, which are already shifting to higher altitudes. Highland habitats are the most stable and are slowly expanding; however, they will shrink with rising temperatures. The current trajectory of land use/cover change is an overall expansion of vegetation which has increased the potential for regulating ecosystem services. However, the potential for provisioning services is declining due to urban expansion. The main contribution of the research is the assessment and quantification of change in the stability of landscapes in the Czech Republic and its implications for biodiversity loss and ecosystem services. The thesis has also shown that topographic heterogeneity is an important feature of complex terrains which, if adequately captured, can greatly improve species mapping. Further research is needed to understand these changes in detail or at the ecosystem level.

Keywords. Climate change, land cover change, topographic heterogeneity, species diversity, ecosystem services

ABSTRACT (in Czech)

Krajina se neustále mění vlivem klimatu a antropogenních procesů. Vzájemné působení obou hybných sil vede ke vzniku krajiny s odlišným složením a strukturou, což ovlivňuje druhovou rozmanitost a kvalitu života a míru plnění ekosystémových služeb. Krajinné procesy jsou ze své podstaty velmi složité. Proto je třeba k jejich pochopení hledat a vyvíjen řadu nástrojů a modelů. Složitosti poznání jednotlivých procesů souvisí s jejich víceměřítkovým charakterem. Procesy popsané v určitém měřítku z určitého modelu nemusí být v jiném měřítku srovnatelně identifikovány. Proto je měřítko dat a prováděných analýz klíčové pro pochopení ekosystémovýchprocesů.

Cílem této práce bylo prozkoumat několik přístupů prostorového modelování pro lepší pochopení vývoje krajiny především v důsledku klimatických změn, ale též zohlednit vliv topografie a změny landuse na různých měřítkových úrovních. Mezi testované modely patří EcoCrop, EUROMOVE, vlastní prostorový model pro mapování trajektorií změn půdního pokryvu a geostatistický model, které byly aplikovány na lokálním, regionálním i národním měřítku.

Mezi hlavní poznatky této práce patří: současné klima má mírnější dopad na rozšíření druhů, které se již přesouvají do vyšších nadmořských výšek. Nejstabilnější a pomalu se rozšiřující jsou vysokohorské biotopy, které se však s rostoucí teplotou budou zmenšovat. Současná trajektorie změny využití půdy (vegetačního krytu) představuje celkové rozšíření vegetace, která má zvýšený potenciál pro regulaci ekosystémových služeb. Potenciál pro zásobovací služby však klesá v důsledku rozšiřování měst. Hlavním přínosem výzkumu je hodnocení a kvantifikace změny stability krajiny v ČR, její důsledky pro úbytek biodiverzity a ekosystémové služby. Práce rovněž ukázala, že topografická heterogenita je důležitým rysem složitých terénů, který při vhodném zachycení může výrazně zlepšit mapování druhů.

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1. INTRODUCTION

1.1. Background.

The extent and quality of natural landscapes worldwide and their potential to support humanity through the goods and services they provide are declining. The decline is directly or indirectly related to climate change and human activities, including deforestation, intensive agriculture, and infrastructural development(Cardinale et al., 2012; Ramankuttyet al., 2008). These human-related processes have degraded landscapes much faster than climate change, increasing the volume of greenhouse gases in the atmosphere. Thus, the strong and positive relationship between land use and climate change has given rise to landscapes different in composition and structure, affecting species abundance and the quality of life for communities (Alkemade et al., 2009; Arets et al., 2014; ten Brink, 2007). Depending on the rate of change, species that cannot survive within a specific climate range migrate or disappear with time (Bakkenes et al., 2002; 2006; Thomas et al., 2004). Likewise, potential cropland has reduced in some regions, followed by changes in planting dates, flowering dates, and other phonological adjustments (Beebe et al., 2011; Ramirez-Villegas et al., 2013; Egbebiyi et al., 2019)

Climate change, globally recognised as a major driver of biodiversity and habitat loss in this research, mostly refers to long-term changes in average temperature and total precipitation patterns. Its impact has been felt and seen in almost every location. However, the scale of devastation from such changes varies with region and is often mediated by vegetation cover and the local topography (De Frenne et al., 2021; De Lombaerde et al., 2022). In water-deficient regions, rising temperatures above the global average have increased the frequency of heat spells and droughts. While in cold and mountainous regions, conditions have become favourable for most species as the length of the growing season has increased (Lindner et al., 2010). The broad question is, to what extent or how long will these "buffer zones" and their species persist, given the current pace of climate change?

Scientists and ecologists try to answer this and related questions by incorporating climate scenarios and their greenhouse emission pathways (Riahi et al., 2017; van Vuuren et al., 2011) into spatial models (Alkemade et al., 2009; Michel Bakkenes et al., 2006; Schipper et al., 2020). Climate scenarios and emission pathways are respectively the different narratives and model-based quantification of the anticipated impact of population growth, human activity on resource availability, and land use that may add to or deplete the atmosphere of greenhouse gases. They have allowed possible changes in climatic conditions, including extreme events, and possible mitigation strategies to be proposed (Alkemade et al., 2009). Scenarios and their emission pathways are used to drive global climate models, which can subsequently be used to drive regional and local climate models providing more insights into climate patterns at the local scale. In short, climate scenarios and emission pathways are crucial for impact studies and biodiversity models at all scales.

While scenarios are important, the processes shaping landscapes are very complex to be sufficiently captured by a single model or at a single scale (Anderson, 2018; Leempoel et al., 2015; Noss, 1990; Wiens, 1989), hence the need to test existing models or develop new once. Fortunately, spatial model development continues to improve with technological advances, data quality and statistical computing (Heywood et al., 2016). The spatial dimension of ecological models heavily depends on the possibility of capturing or proving change by integrating data from diverse sources in a geographical information system (GIS). However, not all GIS models can represent complex or dynamic phenomena. Not all can deal with multiple variables and data-related issues, including data types and scarcity. For example, geostatistical models are limited when a phenomenon is not sufficiently sampled but ideal when a predictor is available and more densely sampled than the investigated phenomenon. Conversely, the widely used maximum entropy model, Maxent (Phillips, 2010), can only be driven by predictors, which can be categorical or continuous data, unlike geostatistical models that run with or without predictors. Spatial models may differ in scope or may be too generic to quantify change on the local scale. For example, the expert base and climate-driven model, EcoCrop (Ramirez-Villegas et al., 2013), with its default parameter commonly applied to assess landscape suitability, may be incorrect for some crops. Lastly, not all spatial ecological models comprehensively quantified or measured change on a comparative scale. Exemplary models in this category include species-dependent models such as EUROMOVE (European vegetation model) and the habitat-dependent global biodiversity model (GLOBIO). EUROMOVE is based on relative changes in species richness and potential habitat extent compared to the situation in natural or near-natural conditions (Bakennes et al., 2002; 2006). The more robust GLOBIO model is also based on changes in species abundance from a reference number for different biomes. However, it is a cause-effect model with established relationships between human-induced pressures of changes and species occurrence captured from the extensive study of species distribution models (Alkemade et al., 2009, Schipper et al., 2020). GLOBIO summarises the impact of individual and aggregated pressures on ecosystems and biodiversity into an indicator of biodiversity intactness. Thus GLOBIO has become the standard tool for assessing and comparing biodiversity loss.

This thesis is motivated by a need to improve our understanding of landscape evolution and plant species' response to climate and environmental change on different spatial and temporal scales and possible impact on selected ecosystem services. The scale of the study varies from regional to national and field-scale. It expands on the generic species distribution model to adapt regional and global biodiversity models and their indicators of change at the local scale. The spatial models mentioned above were tested or fine-tuned for two categories of species: those grown in agricultural fields and species naturally growing in the wild. The former is expected to improve our understanding of changes in landscapes' potential for closely related crops. The latter category is expected to improve our understanding of the evolution of landscapes from their near-natural states and the long-term implications for biodiversity monitoring and selected ecosystem services. This thesis has three main objectives presented in four papers. They each address specific research questions that build up and strengthen the overall hypothesis of the thesis.

This thesis is divided into eight chapters. The context of the research has already been introduced in Chapter 1. Chapter 2 focuses on the aim and objective. Chapter 3 looks at the role and benefits of geographical information systems, especially in ecological studies. Chapter 4 discusses the literature review on different themes ranging from climate change, its impact on biodiversity and approaches to understanding and quantifying change. It also expands on the key research gaps highlighted in the introduction. Chapter 5 discusses the methods section, describing case studies, data sources and the spatial models tested. Chapter 6 summarises research results in the same chronological order in which the research objectives have been as presented in chapter 2. In chapter 7, a general discussion of these results is presented. Chapter 8, the last chapter, connects and discusses each chapter's main results. The main conclusions, including the research's significance, are discussed here. At the same time, answers to the proposed research questions and future research directions are proposed.

2. AIM AND OBJECTIVES

This thesis aims to test suitable spatial models explaining the evolution of landscapes leading to biodiversity loss and a decline in the agricultural potential of selected legume crops. Existing spatial models capturing these changes differ in their scope of application, algorithms and the level of details. Moreover, biodiversity is a broad concept often studied at different levels using different models to be understood. Based on this hypothesis, this thesis seeks to understand the specific response of different landscapes, mainly to climate change and change mediated by the local topography. The selected landscapes are in central Europe and East Africa and differ in complexity, number, and type of species to be modelled. The objectives leading to the fulfilment of this aim include.

OBJECTIVE 1: Modelling landscape potential for selected legume crops in East Africa

The East African region is one of the most vulnerable on the African continents to climate change, with a high frequency of droughts, torrential rains, and floods (Nicholson, 2017). Agriculture in the region is dominantly rain-fed across diverse agro-ecological zones (Fischer et al., 2008) with varying sensitivity to climate change and soil degradation.

The first objective of this research was to understand how the agricultural landscapes of East Africa will evolve with changing climatic conditions. Five legume crops, including common bean, pea, lentils, chickpea, and pigeon pea, were tested using the EcoCrop model implemented in DivaGIS and in TerrSet-CCAM software. The default temperature and precipitation ranges for the key climate indices used in the model are too generic and may not accurately reflect the spatial pattern of these crops under current and changing climatic conditions. Hence, there was a need to fine-tune the model parameter and compare regional input with the generic input parameter. There was also a need to assess the vulnerability of the different agro-ecological zones of the region to climate change. Thus, the question is:

- What will be the spatial response of agro-ecological zones in the East African region to climate change, and how will it affect the agricultural potential of the selected legumes?

OBJECTIVE 2: Modelling changes in species richness in response to climate and environmental change

Habitats are shifting to higher altitudes and mountains in response to climate change (Michel Bakkenes et al., 2006; Thomas et al., 2004). However, in mountainous and heterogeneous terrains, species distribution is dominantly controlled by environmental conditions and the local topography (Geertsema & Pojar, 2007; Pang, Ma, Lo, Hung, & Hau, 2018; Seiwa et al., 2013; Tracz et al., 2019; Guisan & Zimmermann, 2000).

Objective -2 was to characterise topographic heterogeneity as convergence points density from a 1m digital elevation model (DEM) within the Outer (Flysch), Upper Carpathian forested landslide region, south Poland, and assess its usefulness as a surrogate of species richness. Slope exposition (aspect) and slope inclination (slope) are important factors in the species distribution models with overlapping roles. However, we still do not adequately understand how they supplement each other or how they can be integrated into a surrogate of species distribution. Mapping species richness from a surrogate of topographic variation, in this case, was based on the fact that field sampling in such terrains is challenging. Second, there is evidence that locations with strong topographic heterogeneity are potential sites for the evolution and succession of new species (Geertsema & Pojar, 2007; Pang et al., 2018; Seiwa et al., 2013; Tracz et al., 2019). Therefore, it was argued that if a strong positive correlation exists between species richness and an indicator of topographic heterogeneity, the indicator should be a useful predictor of species richness. Thus, the question raised in this sub-objective needing research is:

- Can we use an indicator of topographic heterogeneity to improve species mapping in such complex terrains?
- Which spatial models will be most appropriate?

OBJECTIVE 3: Modelling the loss of habitat naturalness and changes in providing ecosystem function in the Czech Republic

There are diverse landscapes and ecosystems in the Czech Republic, which also vary considerably in extent (Pechanec et al., 2021; 2019). However, how her different classes of land use or land cover in will evolve, changing landscape potential for ecosystem services is not well known. Likewise, the evolution of landscapes in the Czech Republic from their near-natural states under the influence of climate change, leading to the loss of species and their habitats, is not well known. Available results are mostly regional and often based on global datasets, which may not reflect the actual situation (Bakkenes et al.,2006; Alkemade et al., 2009; Lindner et al., 2010; Verboom et al., 2007).

The third objective has two parts. The first part is to understand trends in the evolution of landscapes in terms of change in land use categories as a base for assessing landscape capacity for provisioning and regulating ecosystem services over the last 28 years (1990, 2000, 2006, 2012, 2018) based on the Corine landcover datasets. To that end, an expert-based ecosystem services matrix developed by Burkard et al. (2009) was used as the standard for assessing landscape potential. For the selected category of ecosystem services, the focus was not on individual services but all possible services associated with each.

The second part was to model the loss of habitat naturalness in the Czech Republic from changes in the current and future trends in species richness. To that end, the EUROMOVE modelling approach and its indicator of change, the mean stable area index (MSAi), was adapted as the first attempt to quantify the vulnerability of landscapes to species loss. Vulnerability is also assessed for the most common species under the current climatic conditions; however, mediated by the local topography and hydrogeological conditions. A more detailed assessment of the vulnerability of the main ecosystem of the Czech Republic to climate based on the GLOBIO modelling framework was also envisaged depending on the research progress and time constraints. Thus the questions raised in the third objective are:

- How vulnerable are landscapes or ecosystems in the Czech republic to climate change and biodiversity loss?
- How has climate and or land use/cover change affected provisioning and regulating ecosystem services in the Czech Republic

The relationship between the research aim and objectives, including the specific issues to be investigated, is summarized in Fig 1.

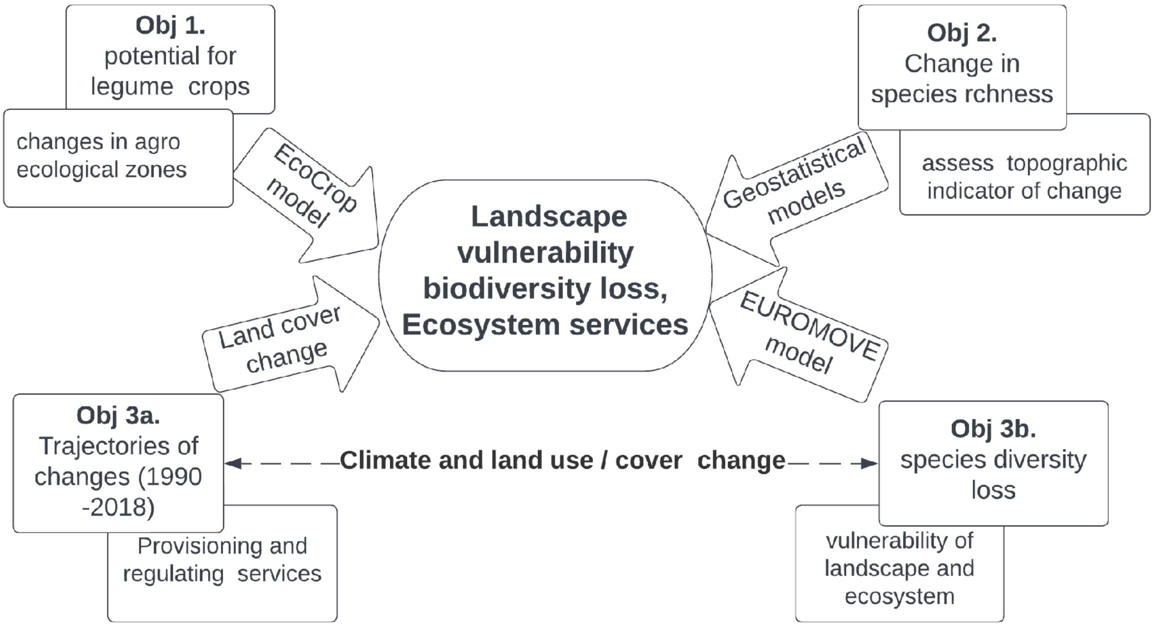

Figure 1. Summary of research objective and relationship to the aim of the research

3. GEOGRAPHICAL INFORMATION SYSTEMS.

Geographical information systems (GIS), the science of where things are and how they change with time (Heywood et al., 2011; Longley et al., 2011), is becoming an important consideration in every discipline. It focuses on the roles of space and time and allows processes and events to be studied locally and globally. GIS science integrates knowledge from statistics, computer science, programming, databases and web technology to solve location-based problems. Its broad scale of application and link to technology has increased access to GIS data and new tools to support GIS workflows.

3.1. GIS softwares

GIS software typically consists of a range of tools for data collection, management, storage, processing, analysis and visualisation of georeferenced data (Longley et al., 2011). GIS software may be distributed as free and open-source soft (FOSS) or proprietary software. They are commonly implemented across multiple operating systems. On desktop, workflow is interactive via a graphical user interphase (GUI) on private computers or servers. They are also implemented through the command line interphase (CLI), where every step in a workflow has to be programmed. Both situations depend on extensions, plugins or external libraries commonly written in Python, C++ or the R programming languages to unlock their full functionality. With the increasing availability of source codes, especially from FOSS, the possibility to customize and extend GIS functionality by scripting the GUI for specific tasks is an important feature in their development (Steiniger & Bocher, 2009; Steiniger & Hay, 2009). Freely available plugins and packages in the case of a desktop program like Quantum GIS (QGIS) and the command line software, R (R core team) largely depend on contributions from volunteers. On the contrary, extensions from proprietary software need to be paid. However, they have been developed to accommodate open-source extensions, as is the case with the Vlate (Lang and Tiede, 2003) and FRAGSTAT (McGarigal and Marks, 1995) extensions for landscape analysis in ArcGIS.

GIS software also differs in its scope of implementation and functionality. For example, QGIS is a versatile software that integrates graphical elements or algorithms from other GIS softwares, including SAGA GIS, and GRASS GIS, allowing even more options and possibilities for GIS workflows. Even with that, QGIS and related desktop programs still depend on R for advanced statistical calculation and temporal analysis. However, this is changing as more statistical and machine learning tools are progressively integrated into desktop GIS. The R software, on the contrary, it is rarely used as GIS, partly due to its limited digitization capacity. However, like other CLI, it remains a valuable tool in ecological studies for workflow automation and reproducibility, a growing concern in GIS studies (Hampton et al., 2017; Naimi & Araújo, 2016; Rocchini et al., 2017). In short, advanced GIS workflows tend to rely on desktop and command-line operations to complement each other. In addition, some GIS softwares have been developed for specific discipline and problems. Such domain-specific tools may exist as stand-alone software or as a collection of softwares dealing with related problems. For example, FRAGSTATS (McGarigal and Barbara, 1995) for landscape analysis and Maxent (Phillips et al., 2006) for species distribution modelling can run as stand-alone tools but are also part of the Habitat and biodiversity modeller (HBM) in TerrSet software (Clark Labs, 2022). The HBM, together with additional modules for ecosystem service modelling (ESM), Earth Trend modelling (ETM), land change modeling and the climate change adaptation modeling (CCAM), TerrSet is one of the leading proprietary softwares for monitoring and modelling earth systems to address sustainability issues (Eastman, 2016). Each of these modellers in TerrSet are associated with tools or softwares that may also be available as FOSS. For example, the crop suitability tool, EcoCrop in CCAM is also available in DivaGIS (Hijmans et al.,2001) and the dismo package in R (Hijmans & Elith, 2017). Hence, the integration of command line interphase in GIS software and vice versa, coupled with technical support from a growing community of users, has significantly contributed to the development of GIS science. Technology has been the major force behind all advances in GIS, including data capture, processing, visualization and distribution. With improvements in sensor technology, data storage and the deployment of GIS applications on smartphones and handheld devices, GIS data has increased in volume and format. However, these improvements have also led to data interoperability and management issues in GIS workflows (Pinos & Dobesova, 2019).

3.2. GIS data and integration

Entities (objects, features, phenomena) are represented in GIS software using either the vector or raster data models (Longley et al., 2011) that may be stored in different formats or file extensions. Each model holds (x, y) coordinate location and corresponding attribute information. Vectors are commonly available as shapefile (.shp). They are simply georeferenced data frames, with points as their basic building unit. Rasters, on the contrary, are georeferenced rectangular matrices commonly distributed as Tag Image File Format (TIFF) (Dorman, 2014; Heywood et al., 2011; Longley et al., 2011). They are pixilated and most appropriate for representing continuous phenomena (temperature, soil pH, etc.) or discrete entities (land use/cover types, biomes, ecosystem etc.). Thus, the vector data models tend to be better representations of reality due to the accuracy and precision of points, lines, and polygons over the regularly spaced grid cells of the raster model (Longley et al., 2016; Heywood et al., 2011). However, rasters are better for quantitative and environmental analysis than vectors.

With increasing availability from remote or crowd-based sources, also known as volunteer geographical information (Goodchild, 2007), GIS data is distributed through diverse portals and databases. These include but not limited to Worldclim and CORDEX for global and regional climate data, GBIF for species locations, and EarthExplorer for satellite imagery and open street maps. Data from such portals may be available in different formats based on the need for efficient storage and management. For example, the Network Common Data Form (NetCDF) is becoming popular for storing and distributing voluminous and multi-dimensional climate data, often requiring additional extensions for processing in most GIS. In addition, simple GIS data may be stored in a software-specific format requiring conversion to a more appropriate format for advanced GIS operations. Fortunately, the Geospatial Data Abstraction Library - GDAL (Warmerdam, 2008) is an important infrastructure in GIS softwares for dealing with such issues in addition to those related to geo-referencing and data resampling. GDAL is a translation library with different drivers for reading and writing raster and vector data. It is also important interphase in the cloud, allowing access to remotely sensed data or online data conversion tools from commercial providers (https://gdal.org/, accessed June 15, 2022). Its accessibility via the command line has allowed popular GIS softwares to develop data conversion tools usually to meet specific needs, as is the case with the "conversion tool" in the arc Toolbox in ArcGIS. However, such conversion tools may be lacking for some data formats. It may happen that conversion may only be possible in one direction or through an intermediate software that may not be available to the user. For example, "Idris Raster File to ASCII" conversion between TerrSet and ArcMap softwares is possible but not the other way around, without the loss of spatial information. However, data interoperability is becoming less an issue with the rapid development and frequent updates of GIS softwares, which may allow direct or indirect conversion to an appropriate format. For example, QGIS can read and deal with diverse file formats that can be exported to other formats. However, advanced users may choose to script their conversion tool to achieve similar or better results. For example, the ATTA (ArcGIS-TerrSet, TerrSet-ArcGIS) tool developed by Pinos and Dobesova (2019) accurately converts between ESRI and TerrSet vectors and raster layers without losing spatial information.

Spatial databases or geo-databases are tools for managing GIS data. They link the spatial data represented by rasters or vectors and their non-spatial attribute data. The standard for designing and querying spatial databases has been defined by the Open Geospatial Consortium (OGC). Generally, rasters are expected to have to look up attribute data (description) in a database table that should correspond with the characteristic value of each raster cell. Vector data, on the contrary, automatically get a unique identifier for each record. As such, they allow location queries for the selective display of information. They vary from personal and file geodatabases to enterprise geodatabases (ESRI access June 10, 2022). The former offers storage and is held and managed in a file system or Microsoft Access. In contrast, the latter with limited storage with unlimited storage, and the number of users is managed in a relational database including PostgreSQL/PostGIS, Microsoft SQL Server, Oracle, SpatiaLite or SQLite databases. The essential components of a GIS are summarised in Fig. 2

3.3. Analyses, visualisation and dissemination

Queried data are often analysed to identify trends or view relationships between variables. Depending on the data models, it may involve operations like (i) map algebra, combining pixel values using arithmetic or Boolean operators, (ii) buffer analysis, showing proximity between features, (iii) reclassification to generalize and reduce the number of category in a data layer (iv) data mining to discover statistical patterns in data and (v) overlay operations to integrate multiple layers representing different themes (Heywood et al., 2011; Longley et al., 2011).

Thematic maps are generally the main output of GIS analysis. Depending on the types of analysis, graphs and charts may also be presented or integrated with maps to make comparisons and show relationships and trends. Effective communication with maps is generally based on cartographic principles, including data types, symbology rules, colour, context, information hierarchy etc. (Ormeling et al., 2010). Maps may be static or dynamic, visualisable in the second (2D) or third dimension (3D) and, more importantly, on the cloud with the deployment of GIS on the internet

(Web GIS). With the advent of Web GIS, access to a wide range of background maps and web mapping services (WMS) has increased. Likewise, access to cloud-based platforms like ArcGIS online has facilitated the development of Living Atlas layers - a collection of base maps on different themes, contributed by individuals but curated and maintained by ESRI to support decision making (ESRI 2017). Similar services are becoming available in QGIS through its plugins. However, ESRI online is the platform for telling stories with maps, allowing users to combine interactive maps with texts, photos, illustrations and videos. With a wide range of visualization options, especially on dashboards, real-time events, including weather conditions, disasters, traffic information etc., can be easily monitored and understood. Advanced platforms like Google Maps allow advanced users skilled in JavaScript programming to develop web mapping applications for specific tasks. Similarly, Google Earth Engine allows developers more flexibility to mine, analyse and visualise big data (satellite imagery).

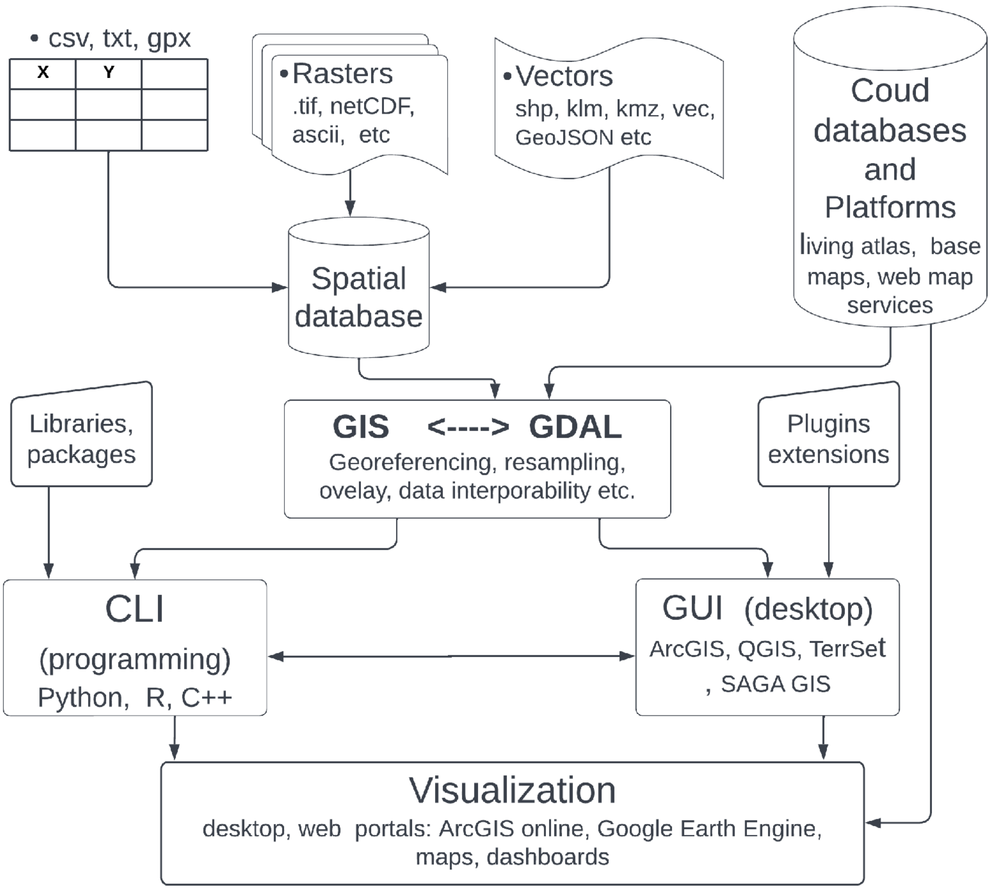

Figure 2:Summary description of Geographical Information Systems and its components.
CLI = command line interphase, GUI = graphical user interphase

4. LITERATURE REVIEW

Habitat potential for diverse species and ecological functions is controlled by abiotic and biotic processes operating on landscapes (Turner et al. 2001). Abiotic processes include topography and climate, which regulate geological processes, moisture availability, soil formation and vegetation types (Bailey 1996; 2009). Abiotic processes also include natural disturbances such as windstorms, landslides, wildfires and hurricanes, which are important drivers of ecological succession (Turner et al., 2013, Alexandrowicz and Margielewski, 2010, Turner et al., 2001). Landscapes have also been fragmented by human-induced processes, including land transformation for agriculture, road construction and infrastructure (Forman 1995b; Fahrig et al. 2003, Collinge and Forman 1998). Biotic processes, in contrast, are internal and include competition between or within species and insect outbreaks which may produce landscapes dominated by the same or diverse species even under stable conditions (Turner et al. 2001). Hence, the interaction among these complex processes is the cause of landscape heterogeneity (Turner et al. 2013; Kienast et al. 2007, pp 177 - 192; Forman 1995b; Oliver et al. 2010); a well-recognised principle explaining biodiversity patterns and ecosystem functions (Burkard et al. 2009; Schroter et al. 2005). Because landscape heterogeneity is expected to be stronger with changes in topographic and climatic conditions (Fig. 3); the spatial scale at which heterogeneity can be best captured continues to be a challenge in ecological studies (Turner et al. 2001, Bailey et al. 2007, Jung et al., 2017, Pearson et al. 2004, Trivedi et al. 2008). Scale is particularly important because it is the basis for accurate prediction, sound policies and best practices on landscape adaptation to optimise the goods and services they can provide (Opdam et al., 2009; Wiens, 1989).

Among these processes shaping landscapes and impacting biodiversity, land use and climate change have been recognised as major drivers of change because they are global (the intergovernmental panel on climate change - IPPC). The impact of unstainable land use, especially in agriculture, is also well recognised by the IPPC (2019) as a major contributor to greenhouse gases ($CO2$, $CH4$ and $N2O$). Every change from one land use/cover type to another changes the potential for particular ecosystem services (Foley et al., 2005; Burkard et al., 2009; Pechanec et al.,2019). However, our understanding of how both drivers synergistically impact biodiversity and ecosystem function, especially at the local scale, which could lead to better adaptation measures, is not well known (Schroter et al., 2005, Newbold et al., 2018; Opdam et al. 2009; Opdam and Washer 2004).

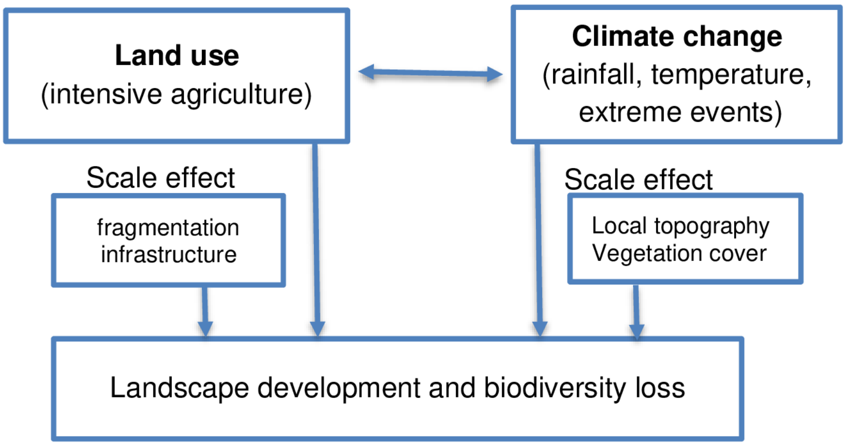

Figure 3. Relationship between land use, climate change scale effect and biodiversity.

4.1. Spatial Models

Spatial models are GIS-based descriptions of simulated processes from a set of spatially related features (Reddy 2018). Spatial models are simplified representations of reality, usually to improve understanding and decision support (Longley et al., 2011). Their building blocks are raster or vector data models (chapter 3). They may be deductive or inductive (Overmars et al., 2007). The former follows a "bottom-up" approach, integrating components of individual data models through overlay operations and some form of weightings based on expert opinion to develop habitat suitability models. The latter follows a "top-down" approach and depends on empirical data and statistical methods (Johnson & Gillingham, 2004). Deductive models have low precision with limited validation options, unlike inductive models. Hence, they are less common in biodiversity and ecological studies. However, they are still useful where data is scarce, and baseline information is needed to guide empirical studies (Overmars et al., 2007). Spatial models may be static, dealing with the state of spatial data or phenomena at a given time or may be dynamic, emphasizing time-dependent changes (Wainright and Mulligan, 2004). Both allow predictions that may be deterministic (empirical) or stochastic, applying statistics, probability and machine learning algorithms. Deterministic models are mainly correlative or descriptive to the specific conditions. They say little about underlying processes. Stochastic models attempt to explain random processes, allowing predictions beyond environmental conditions and observation scales (Wainright and Mulligan, 2004). However, stochastic models are highly uncertain as they may not adequately capture all causal factors for a particular phenomenon. This limitation points to our limited understanding of environmental systems and explains why models are often calibrated or evaluated with independent observations of the current situation before future predictions can be made (Guisan and Zimmerman 2000; Verboom and Warmelink 2005).

Spatial ecological models may also be mechanistic. In which case, they are based on prior knowledge and actual cause-effect relationship of processes determining the establishment and survival of species in a given environment. In other words, they incorporate physiological, behavioural, biotic and abiotic interactions and are thus the closest to reality (Dormann et al., 2012; Kearney and Porter, 2009). However, mechanistic models can be extrapolated to other scales with a loss in precision (Kearney and Porter, 2009; Cuddington et al., 2013). They are also data-intensive, requiring time and effort to construct. Hence they are less common in ecology studies. In summary, while spatial models are expected to reflect reality and be consistent with theory, there is always a tradeoff between precision and generality which justifies the need for diverse models. The relationship between these three important elements of spatial models is shown in Fig 4 (Levins 1966; Guisan and Zimmermann 2000).

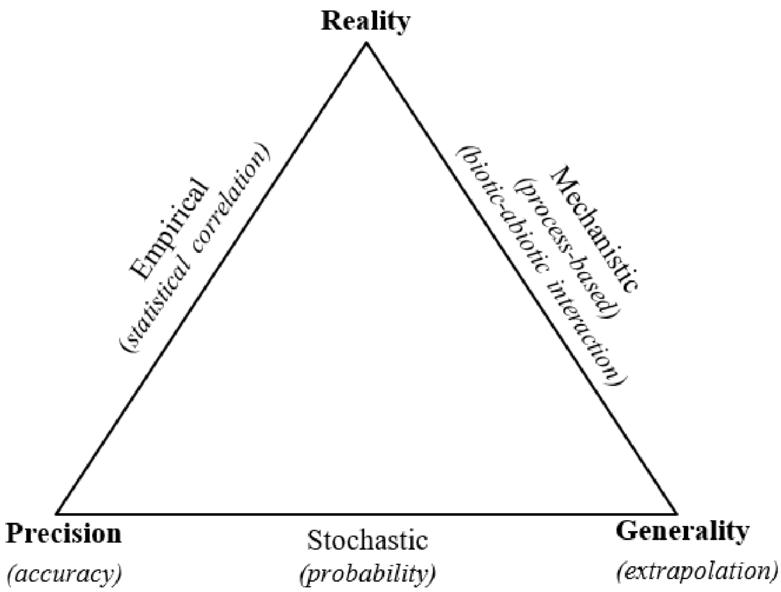

Figure 4. Classification of spatial models and their distinctive features
Adapted from (Levins, 1966; Sharp,1990)

An important feature of spatial models which sets them apart from other models is the spatial dependency of data locations (Tobler, 1970). Modelling methods attempt to correct or account for spatial dependency to improve accuracy (Wagner et al., 2003; Olthof et al., 2016). However, accuracy may also decrease if neglected in some models (Dormann et al., 2007; Legendre, 1993). The need for improved understanding, accuracy and practicality, especially for impact assessment, has led to the development of the so-called "hybrid models" (Guisan and Thuiller, 2005; Gallien et al., 2010) or "aggregate models" (Longley et al., 2011), integrating different modelling approaches or their outputs. For example, the GLOBIO model is an aggregation of 5 models based on expert knowledge and empirical and or stochastic modelling approaches to quantify habitat and biodiversity loss (Alkemade et al., 2009; Arets et al., 2011). Likewise, geostatistical models have been integrated with multivariate algorithms (ordination techniques) (Olthoff et al., 2018) to improve our understanding of spatially structured ecological communities. Similarly, hybrid geostatistical models may also be integrated with machine learning and regression model to deal with multiple variables and non-linear relations (Hengl, 2007; Miller, 2005; Bishop and McBratney, 2001).

Uncertainty and error in models may be inherent in data or due to missing predictors representing a phenomenon (Barry and Elith 2006). A common approach to minimize data error is to bootstrap samples (Guisan and Zimmermann 2000) or partition data for model training and testing (Fielding and Bell 1997), followed by evaluating accuracy metrics. The choice of evaluation metrics depends on whether the predicted phenomenon is continuous or categorical. In the former, a comparison is made between the observed and predicted value and quantified as mean error (ME) or root mean square error (RMSE). In the latter, cross-tabulations of the percentage of correct and false predictions are determined and used to calculate evaluation metrics that may either be threshold dependent or independent. Threshold-dependent matrices include Cohen's kappa (hereafter, kappa) and true skill statistics (TSS), which compares the level of similarity between observed and predicted values not happening by chance. However, kappa has been criticized for being dependent on the prevalence of sample location (Allouche et al., 2006). Threshold-independent matrices, for example, the area under the receiver operating characteristic curve (AUC). The AUC gives an overall assessment of model performance) for which models with AUC ≤ 0.5 are random or poor while those close to 1.0 are perfect (Freeman and Moisen, 2008; Fielding and Bell, 1997). While accuracy measures are well developed for empirical and stochastic models, expert-based models rely more on sensitivity and uncertainty analysis to calibrate model inputs and define their confidence intervals (Verboom et al., 2005).

4.2. Climate variation and change

Natural climatic conditions vary with latitude and thus explain regional differences in temperature and precipitation patterns and the distribution of major ecosystems and climate zones (Olson et al. 2001; Baan et al. 2012; Conradi et al. 2020). It is also an important consideration in classifying potential crop production zones known as agro-ecological zones -AEZ (Fischer et al. 2008). Change under such natural conditions is often too slow to impact species and ecosystems. However, since the last quarter of the 20th century, there has been growing evidence of accelerated change from long-term temperature changes, also known as global warming (IPCC, Hansen et al., 2006; 2010).

Long-term mean changes in the prevailing weather of a locality or region are a common justification for climate change (Intergovernmental Panel on Climate Change -IPCC; Bailey 1996). Ideally, the IPCC and the World Meteorological Organisation (WMO) recommend a baseline of at least 30 years for impact studies as it reliably reflects global trends. According to IPCC reports, global temperatures have risen by 1.5^{o}C, approximately 0.1 degrees per decade (IPPC) since the pre-industrial period (1850 - 1990). Rising temperatures are affecting agricultural landscapes and ecosystems worldwide (Leeman and Eickhout 2004, Bakkenes et al. 2006). These authors showed that above 2 degrees rise in global mean temperature, only about 84% of the world ecosystem would remain stable through considerable differences will still exist among ecosystems. Although change is gradual, it may occasionally be associated with short-lived extreme events, indirectly driving most natural disturbances (Turner et al., 2013). Hence, climate indices for ecology studies are often selected to reflect average, seasonal, and extreme (minimum-maximum) patterns in temperature and precipitation. Those tailored for agricultural studies may include additional parameters related to growth conditions specific to a given region or crops and may include growing degrees days above 5 ^{o}C, heating degrees days above 18 ^{o}C, moisture index, etc. (Ramirez et al. 2011; Qian et al. 2010, Egbebiyi et al. 2019).

The impact of climate change varies across regions and mainly involves range shifts in species' habitat, biodiversity loss, and a decline in ecosystem resilience (Leemans and Eickhout, 2004; Alkemade et al., 2009; Arets et al., 2014; Schipper et al., 2020). In arid, semi-arid and

Mediterranean regions, landscape and biological processes are already limited by heat spells and drought, which will become frequent or persistent (Coppola et al., 2021; Leemans & Eickhout, 2004; Schipper et al., 2020; Schröter et al., 2005). Climate impact will be particularly severe in sub-Saharan Africa for two reasons. First, over 90 per cent of agriculture in the region is rain-fed (UN Food and Agricultural organisation - FAO, 2019). Second, her ecosystems are currently the most vulnerable to climate change (Schipper et al. 2020, Newbold 2018, Alkemade 2009). There is also evidence of temporal (phonological) shifts, although such studies are uncommon (Bellard et al., 2012). For example, planting dates and seasons of some crops will shift with rising temperatures and droughts (Egbebiyi et al., 2019). Notwithstanding the negative impact, climate change will increase the potential for some crops and expand vegetation cover in some regions. For example, the cassava crop will be one of the most adapted crops in Africa to climate change, possibly expanding production by ~ 8% (Jarvis et al. 2012). Projected changes in Europe based on EURO-Cordex climate data showed higher warming and increased precipitation over mountain regions (Coppola et al., 2021) which will expand vegetation cover (Leemans & Eickhout, 2004; Schipper et al., 2020; Schröter et al., 2005; Bakkenes et al., 2006; Alkemade et al., 2011). While temperate and mountainous regions will more tolerant to global warming, they are equally at risk of losing their climate space without concerted efforts to curb global warming (Araujo et al., 2011; Barry et al., 2003; Leemans and Eickhout, 2004).

Researchers and policymakers have made global calls in regional and international conventions to halt biodiversity loss by preventing average global temperatures from rising above 2 ^{o}C from the pre-industrial level (for example, The European Union 2007, Warren et al. 2011, Bakkenes et al., 2006; Leemans and Eickhout 2004). However, much effort is still needed, given that this target has not been reached in most regions (Bakkened et al. 2006, Verboom et al. 2007). There have also been recommendations to expand the network of protected areas, establish plantation forests in degraded areas, and scale-up bioenergy production (Alkemade et al., 2009, Leclere et al., 2020). However, Araujo et al. (2011) argued that the effectiveness of some of these measures might be undermined if global warming continues unabated. Nevertheless, climate scenarios and possible warming levels have improved our understanding of what to do or expect in the distant future

4.2.1. Climate scenarios and models

According to the fifth assessment report of the intergovernmental panel on climate change (IPCC-AR5), climatic conditions have not been stable. Still, they have been changing with demography, socio-economic development, resource availability, energy consumption and trends in technology. The different narratives associated with these factors and translated to reflect future land use/cover, energy demands and changes in greenhouse emissions are known as shared socio-economic pathways –SSPs (Riahi et al., 2017). The SSPs vary from SSP1 with low mitigation and adaptation challenges to SPP5 with high mitigation and low adaptation challenges due to the over-exploitation of fossil fuels (Riahi et al., 2017). The quantitative reflection of how these factors will interact, adding greenhouse gases to the environment, is known as representative concentration pathways- RCPs (van Vuuren et al., 2011). Current RCPs range from RCP2.6, with the least climate forcing to RCP8.5, with the most forcing. Thus the different combinations of SSPs and RCPs define future trajectories for climate impact studies. They are also associated with different policy options, whose soundness must be tested in models (Trisurat et al., 2010).

These current climate scenarios are particularly attractive for ecological studies because they now allow a wide range of land use and climate change relevant for ecological studies to be combined (Kim et al., 2018; Schipper et al., 2020). Thanks to integrated assessment models, for example, the IMAGE model (Stehfest et al., 2014), the interaction between these major drivers under scenarios relevant to ecology and biodiversity studies is improving our understanding of how human activities will contribute to climate change and global biodiversity loss (Schipper et al. 2020). However, the IMAGE model, like other integrated model outputs, is still too coarse with different uncertainties to understand scenario changes in a local context, given that it is driven by global or regional climate models and other global datasets (Veerkamp et al., 2020).

Projected changes in climate by global climate models (GCM) are based on different RCP pathways (Fick and Hijmans 2017). The GMCs depict different levels of interaction between atmospheric, land and oceanic processes (Wilby et al., 2009). Hence, impact studies recommend model averaging to reduce bias associated with individual GCM. Selected variables from global or regional climate models output across multiple scenarios have been used to drive species and ecological models. However, such variables from extreme scenarios are increasingly being questioned for being unrealistic considering the current efforts to curb global emissions through alternative and renewable energy in the CMIP6 model framework (Riahi et al., 2011). These authors recommend the less extreme RCP6.0 or SSP3-7.0 scenarios as alternatives to RCP8.5

4.2.2. Local and microclimatic conditions

Temperatures anomalies may be lower in some locations than the global average due to vegetation cover and local topographic variations (Franklin, 1995; Moore et al., 1991; Bailey, 1996, 2009, De Frenne et al., 2021; De Lombaerde et al., 2022). Local climatic conditions become even more important in such situations than global change (Guisan and Zimmermann 2000). Local variation in climatic conditions is the basis for recognising distinct forest vegetation zones (FVZ) conservation management on the national scale (Lenihan 1993, Hlasny et al. 2011).

Primary topography variables have varying and sometimes overlapping roles in ecological studies. Slope angle (slope), slope exposition (aspect) and elevation (altitude) are also crucial in regulating the flow of energy and moisture balance in complex terrains (Walz, 2011; Burnett et al., 2008; Franklin, 1995; Moore et al. 1991). Most studies have either reported a species-dependent relationship with primary terrain attributes or a weak and sometimes no relationship with closely related terrain attributes. (Gracia et al. 2007; Bolstad et al. 1998; Burnet et al. 1997). However, multi-scale investigations have also shown that a weak relationship between terrain attributes and plant species may be due to the difference between the spatial resolution of derived terrain attributes and the scale of field sampling (Leempoel et al., 2015; Lassueur et al., 2006; Bolstad et al.,1998). Moreover, it has been shown that biological activity is high at the interphase between interacting terrain attributes based on landscape heterogeneity (Forman and Godron, 1986; Metzger and Muller, 1996, Tracz et al., 2019). This evidence suggests that the role of topographic heterogeneity is still not well understood and may be underestimated in some species distribution models

4.3. Quantifying spatial patterns

Two main approaches have been proposed to quantify spatial patterns on landscapes: the patch matrix approach and the gradient approach (Cushman and Huettmann, 2010; Lausch et al., 2015; Turner et al., 2001). The former qualitatively describe landscape elements as discrete entities. It is commonly applied to understand the relationship between landscape indices and species diversity (McGarigal & Marks, 1995). It relies on earth observation data –EOD including satellite imagery, LiDAR data and digital elevation models, from which key landscape matrices and vegetation indices can be derived (Wegmann et al. 2016; Gillespie et al. 2008; Cohen and Goward 2004, Reidler et al. 2015, Cohen and Goward 2004). The gradient approach, on the contrary, is quantitative and suitable for understanding continuous phenomena. It includes species distribution models (SDMs), biodiversity models, ecosystem functions and services models

4.3.1. Species Distribution Models (SDM)

Species distribution models are the most widely used tools to understand how landscape species respond to environmental change. They are diverse in appellation but are generally based on statistical correlation (Guisan et al., 2002; Guisan and Zimmermann, 2000). They aim to correlate the geolocations of species to the most significant environmental factors, which theoretically reflect the ecological requirements of species (Guisan and Thuiller, 2005; Guisan & Zimmermann, 2000, Elith and Graham, 2009). Hence, they provide spatial information for reserve selection conservation planning, ecological restoration (Rodriques et al., 2004), and understanding species invasion risk (Ibanez et al., 2009). Species distribution models assume species are in equilibrium with their environment without dispersal or migration (Dormann, 2007; Thuiller et al., 2006; Araujo et al., 2006). The most common SDMs have been classified into statistical and machine learning methods with different algorithms to handle presence-absence or presence-only species data.

Statistical approaches are extensions of generalised linear models with the possibility to fit different family functions depending on the data distribution. Statistical methods emphasise estimating model parameters and fitting functions that best describe the relationship between species occurrence and environmental predictors (Guisand et al., 2002). Algorithms in this category are regression-based, including geostatistical methods (Goovaerts, 2000; Miller et al., 2007). Geostatistical methods (tested in this thesis) are less commonly applied in species mapping because they are not robust enough to handle multivariate datasets and non-linear variations (Kienel and Kumke, 2002). Studies in which they have performed well depend on the observational scale or in combination with hybrid methods and techniques capable of dealing with multiple variables (Olthoff et al., 2018; Maestre et al., 2005; Meng et al., 2013., Hengl, 2007)
In contrast, machine learning methods use different algorithms to learn classification rules, especially in the case of complex and no linear phenomena. (Olden et al. 2008). The maximum

entropy model - Maxent (Phillips et al., 2006; Phillips, 2010) is one of the most popular algorithms in ecological studies. Random forests (RF) and boosted regression trees (BRT) are increasingly becoming popular, owing to their high accuracy (Cutler et al., 2007; Elith et al., 2006). They are based on the averaging of several models. Although these algorithms have evolved with technology and statistical computing, they tend to produce slightly different spatial patterns on the same ecological processes operating in a given landscape (Elith and Graham, 2009; Araújo & New, 2007). These authors attributed variability to the difference in their ability to accurately capture species-environmental relationships associated with different data properties, data sparsity and their interaction effects. Thus, averaging the results from at least three comparable algorithms is recommended to minimise uncertainties in predictions (Araújo & New, 2007). While single-species models are the most widely used, the accuracy of range shift associated with them may be questioned because coexistence and the buffering effect of other species limiting such shifts are commonly ignored (Pretzesch et al., 2013; Kearney and Porter, 2009).

Species distribution models have also been extended to cases involving multiple species, also known as community models, multispecies models, or stacked models (S-SDM) (Ferrier and Guisan, 2006; Guisan and Rahbek, 2011). They describe biodiversity in terms of species richness or abundance based on different approaches, including the predict and then assemble approaches, the assemble and then predict approach or simultaneously combining the two (assemble and predict) (Baker et al. 2014). In the first approach, individual species maps are additively aggregated (Guisand and Rahbek, 2011; Ferrier and Guisan, 2006; Bakkenes et al., 2006). The second approach estimates species richness from rarefaction curves before prediction. This approach applies distance-based matrices to summarise and estimate the similarity between communities. It has been applied to capture climate-dependent changes in ecologically structured communities (Caddy-Retalic et al., 2019, Sera-Diaz and Franklin, 2019). Statistical and machine learning models are commonly evaluated based on the AUC, TSS and kappa metrics for binary phenomena or ME and RMSE for continuous phenomena.

A variant of SDM developed specifically to assess landscape potential for field-grown crops is the EcoCrop model (Hijmans et al., 2001; Ramirez-Villegas et al., 2013). It does not simulate complex processes such as growth development and yield typical of sophisticated crop models (Jones et al. 2003). Unlike SDMs, EcoCrop is an expert model, driven exclusively by temperature and precipitation ranges that define each crop's optimal and marginal growth conditions. These limitations imply additional effort is needed to adapt or calibrate the model input to reflect reality, especially for local studies. There are no standard calibration or evaluation procedures for the model, which is a possible reason why some studies have tested the model with its default inputs.

Nonetheless, efforts have been made to understand the model and improve its accuracy. For example, Manners and van Etten (2018) showed in a sensitivity analysis that temperature and precipitation ranges were more crucial than the length of the growing season. Manner et al. (2021) further adapted the model by adding temperature and precipitation requirements during critical growth periods for long-duration crops (cassava and banana) and achieved more reliable results than the default parameter. Likewise, Piikki et al. (2017) integrated soil organic matter into the model framework to accurately capture the suitability of common beans in Tanzania. Similarly, Ramirez-Villegas et al. (2013); Rippe et al. (2016) showed that the model input could be improved and its classification ability assessed using basic descriptive statistics of a crop's distribution. Alternatively, some researchers have compared crop suitability simulation against the MapSpam crop distribution dataset (You et al., 2009; Manner et al., 2021, Rippke et al., 2016) or against local landcover data (Rhiney et al., 2018). Although EcoCrop is not as robust as process-based crop models, which unfortunately are limited to a few crops, researchers have found map output from models to be comparable. Ramirez et al. (2012) also notes that with the most appropriate climate datasets, the accuracy of EcoCrop can be greatly improved.

4.3.2. Biodiversity indicators and models

Biodiversity is a broad term involving many structural, functional and compositional organisation levels of ecosystems that need to be captured and quantified to be adequately understood (Noss 1990; Dale and Beyeler. 2001; Magurran 2004). Hence, biodiversity indicators are tools intended to capture and quantify the complexity of ecosystems and ecological processes in ways that are easy to communicate and monitor (Dale and Beyer, 2001; Opdam et al., 2009). Many indicators have been developed over the years to quantify specific aspects of biodiversity. They also vary in scope, complexity and scale of application. For example, the Shannon and Simpsons indices based on species richness and evenness are the most common on a plot or field scale. Site-specific indices tend to be based on biophysical properties specific to a given ecosystem. For example, Riedler et al. (2015) computed a composite indicator to capture biodiversity in riparian ecosystems on a patch scale based on vegetation structure, water regime and species composition. Likewise, Burnette et al. (1998) and Tracz et al. (2019) developed indices of topographic heterogeneity from the interaction of different classes of primary terrain attributes to map species richness in complex landscapes. However, these indicators are limited because they are not based on a reference period/ state. Hence the context on which change is based is unknown (Lamb et al., 2009)(Lamb et al., 2009)

Broad-based (global and regional) indicators have attempted to fill this gap based on different criteria, including the number of species on their way to extinction (Thomas et al. 2004) and change in species abundance and richness (Alkemade et al. 2009, 2011; Arets et al. 2011; Scholes and Biggs 2005). A criticism of the former is that extinction is the last step in species decline and, therefore, not a reliable indicator of change (Bellard et al., 2012). Indices based on changes in species richness or abundance quantify changes relative to a predefined reference state or period applicable to different taxonomy groups (Buckland et al., 2005; Nielsen et al., 2007), which is very similar to the natural capital index approach (ten Blink et al. 2002). They reflect changes in habitat intactness on a scale from 0 for completely degraded habitats to 1 for habitats in their natural states. In the case of climate impact studies, 1990 is a common reference period (Bakennes et al., 2006, 2002, Alkemade et al., 2006), assumed to be the time when human impact on the environment became apparent on a global scale. Alternatively, protected areas have been considered the reference state for studies in which land-use intensity is the major driver of change (Scholes and Biggs 2005). Nonetheless, Nielsen et al. (2007) argued that reference periods or states should vary with individual species based on empirical relationships with human footprints to avoid bias.

Broad-based indicators also differ in their robustness and scope of application. For example, the mean stable area indicator (MSAi) from the EUROMOVE model is exclusively based on climate change for plant species distribution (Bakennes et al., 2006, Alkemade et al., 2011). In contrast, the mean species abundance indicator (MSA) in the GLOBIO model is an indicator for biodiversity (for different taxonomy) based on climate changes, land use, infrastructure, nitrogen deposition, fragmentation and hunting pressure (Alkemade et al., 2009, Schipper et al., 2016, 2020). Hence, MSA may be aggregated or disaggregated to quantify a taxonomy's biodiversity loss. Another indicator sharing some features of GLOBIO MSA is the biodiversity intactness index -BII (Scholes and Biggs 2005), a regional biodiversity indicator for southern Africa. However, BII is based exclusively on expert opinion regarding trends in species populations and bias toward species-poor areas, which are less rated than species-rich areas. The relation between these models and their indicators of change is summarized in Fig 5.

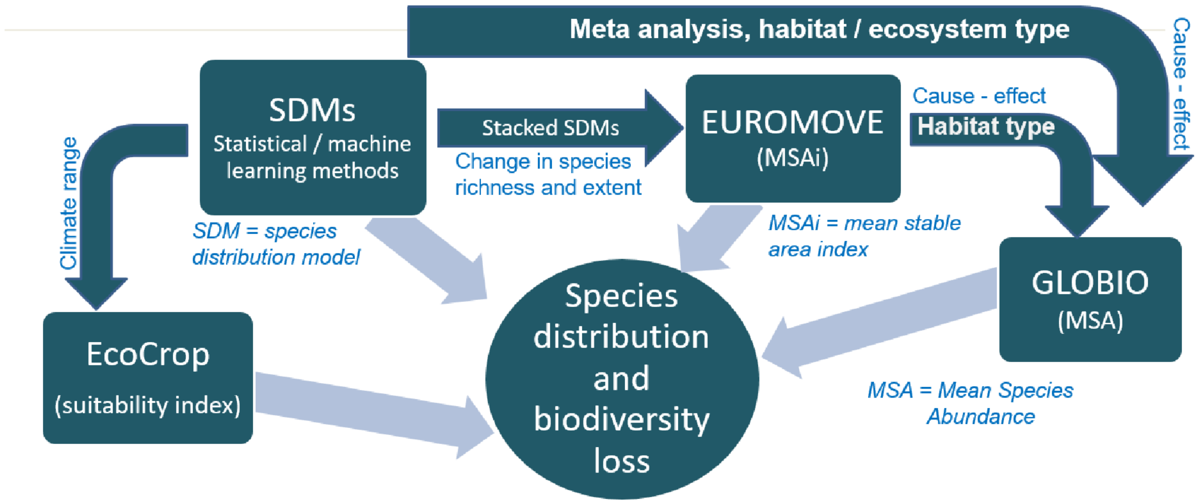

Figure 5. Relationship between spatial models for species distribution and biodiversity loss

4.3.3. Ecosystem functions and services models

Ecosystem service models are tools that attempt to quantify the impact of human activities on the goods and services provided by nature for the well-being of humanity (Burkhard et al., 2009; Nelson et al., 2009). The wide range of existing models uses different criteria, including monetary consideration (Costanza et al., 1997; Frélichová et al., 2014) or biophysical terms (Naidoo et al., 2008) or both. Some methods are based on specific functional properties in the ecosystem, including, for example, plant height or leaf area size (Lavorel and Grigulis, 2012). More robust models like the Integrated Valuation of Ecosystem Services and Tradeoffs tool – INVEST (Tallis & Polasky, 2009) can dynamically estimate ecological production functions like the amount of carbon sequested. INVEST can also perform future predictions based on projected scenarios of land use/cover change (Tallis and Polasky, 2009; Nelson et al., 2009; Krkoska et al., 2016). However, a simpler and very popular approach is to apply a point-based expert rating on typologically processed background maps, usually for individual land cover types or land use (Burkhard et al., 2009). The approach is advantageous because it can be applied at different scales (Frélichová et al., 2014; Jacobs et al., 2015). Common to all these approaches is that services and functions are optimal for the ecosystem when the state of the ecosystem is favourable or closest to nature.

In summary, spatial processes changing landscape and impacting biodiversity and ecosystem services are very complex to capture in a single. Different ecological models attempt to address these issues in one way or the other. In addition, Ecological models have evolved from species distribution models that only prove change to biodiversity models that prove and quantify change by integrating expert knowledge results from empirical to derive indicators of change for different drivers of biodiversity loss. The former has been tested at all scales; however, it is still limited because habitat and phonological shifts have been rarely assessed. On the contrary, biodiversity models depend on habitat rather than species information to quantify change and thus provide a better description of changes in biodiversity and a standard for comparing biodiversity changes across scales. Biodiversity models and their indicators should be tested to understand local change in a global context.

5. METHODS AND DATA

This section summarises the data types, methods and models tested to meet the aim and objectives of this thesis. Details have been described in related publications. The section begins with case studies in east Africa, south-east Poland and the Czech Republic. Followed by a brief description of the geography and environmental conditions for each case study. Lastly, summaries of spatial models and workflows in each case study are presented

5.1. Study area

5.1.1. Cast study 1: Legume crops in east Africa

Five east African countries, namely Ethiopia, Tanzania, Kenya, Uganda, Rwanda and Burundi, covering ~2.93M km^2, were considered. The region's landscape is heterogeneous and characterised by rifts, valleys, lakes and highlands reaching 5895 meters above sea level. Annual precipitation in most locations varies from 700 to 1200 mm, with more precipitation in mountainous and lake regions (Ndomeni et al., 2018; Nicholson, 2017). The rainy season varies from March to May (MAM) for long rains, June to August (JAS) and October to November (ON) for short rains. However, most tropical parts experience both the MAM and the ON rainy seasons per year. Mean Temperatures of the warmest months range from 24 to 34^{o}C in most locations (Waithaka et al., 2013)

Common legume crops in the region include chickpea *(Cicer arietinum)*, lentils *(Lens culinaris)*, beans (*Phaseolus vulgaris*), dry pea *(Pisum sativum*) and pigeon pea (*Cajanus cajan)*. They thrive in cool environments and are commonly grown with maize, millet, sorghum cassava and groundnuts by smallholder farmers (van Loon et al., 2018; Thornton et al., 2010). These crops grow in distinct agro-ecological zones (AEZs) - homogeneous areas with similar temperatures, water and resource availability, elevation, soil types and growing seasons (Fischer et al. 2008, FAO/IIASA, 2012), (Fig 6). For example, common beans and pigeon pea are grown twice a year in regions with two planting seasons (van Loon et al., 2018, Thornton et al., 2010). Chickpea is generally restricted to highlands (~2300 to 3200 metres a.s.l.), has much lower water requirements than the common bean, and can survive on residual moisture to complete its growth cycle. Temperatures during its growing season range from 16 to 21 ^{o}C, while precipitation varies from 78 to 350 mm (Singh et al., 2014, van Loon et al., 2014; Hurni, 1998). Lentils are equally grown on highlands between late June and mid-July, during which temperature varies from 18 to 21°C and precipitation from 350 -550mm. However, unlike chickpeas, they are severely affected at temperatures above 27°C (Andrew and McKenzie, 2007, Yadav, 2007; Mitiku, 2016; Telaye et al., 1994; Bejiga, 1991).

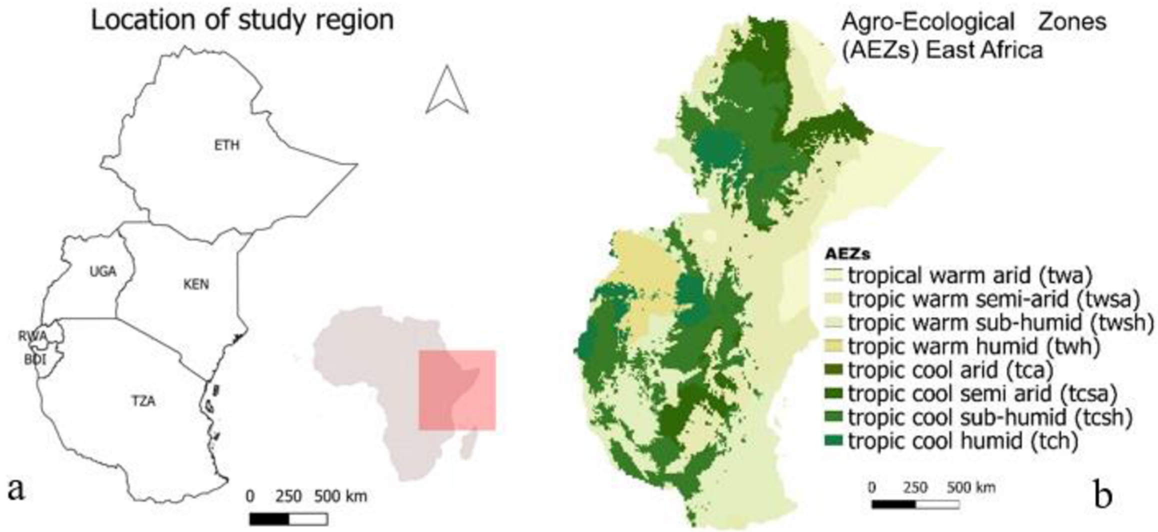

Figure 6: (a) Location of the study region and (b) Agro-ecological zone in the study region
(data source: HarvestChoice, 2009)

Dry pea is grown at 1800 to 3000 a.s.l, mainly from July to December. Annual precipitation at this altitude varies from 800 to 1000mm, and growth is optimal at temperatures between 10 to 20 °C, with 27 °C as the max (Telaye et al. 1994). Pigeon pea is the most resistant to drought and is grown year-round in top-producing localities. Precipitation and temperature during its growing season vary from 600 to 800mm and 17 to 26 degrees, respectively, while its growth cycle varies from 90 to 280 days, depending on the cultivar (van Loon et al., 2014; Snapp et al., 2018; 2003, Omanga, et al. 1996; Slim and Omanga 200). Hence the agro-ecological conditions of these crops provided a base for assessing the model inputs calibrated from climate data.

5.1.2. Case study 2: Species richness in forested landslide zone, south Poland

The study area is in Pogórze Dynowskie, which is part of the Outer (Flysch) Carpathians, south Poland (Fig. 7) and is among the chain of biodiversity hotspots associated with the Carpathians mountains (Hurdu et al. 2016, Mraz and Ronikier 2016). Landslide zones are of different ages and are among the largest in Poland (Zabuski et al., 1999; Polish Geological Institute, 2018). The landslides are situated in the watershed area along Bonarówka Creek (Podkarpackie Province, Poland). Elevation varies from 243 to 412 m a.s.l, while slope angle varies from 0° to 57°. Slope exposition is very diverse but generally facing the east and, to a lesser extent, the SW direction. Landslides and species distribution are tied to the geomorphology and the complex geology of the study region (Alexandrowicz and Margielewski, 2010). The main rock types are metamorphosed sandstones, conglomerates, mudstones, and clay stones, often associated with folds and faults, scarps, rock trenches, colluvium, tongues/ramparts, block fields, and debris (Ślączka et al. 2007). These structures have favoured weathering processes and the formation of diverse habitats, including meadows, peat bogs, and bog springs which are generally associated with a high composition of plant species. Plant species consist of diverse multispeciess of spruce, fir, pine, beech, and lichens (Alexandrowicz and Margielewski, 2010; Grodzińska and Szarek-Łukaszewska 1997).

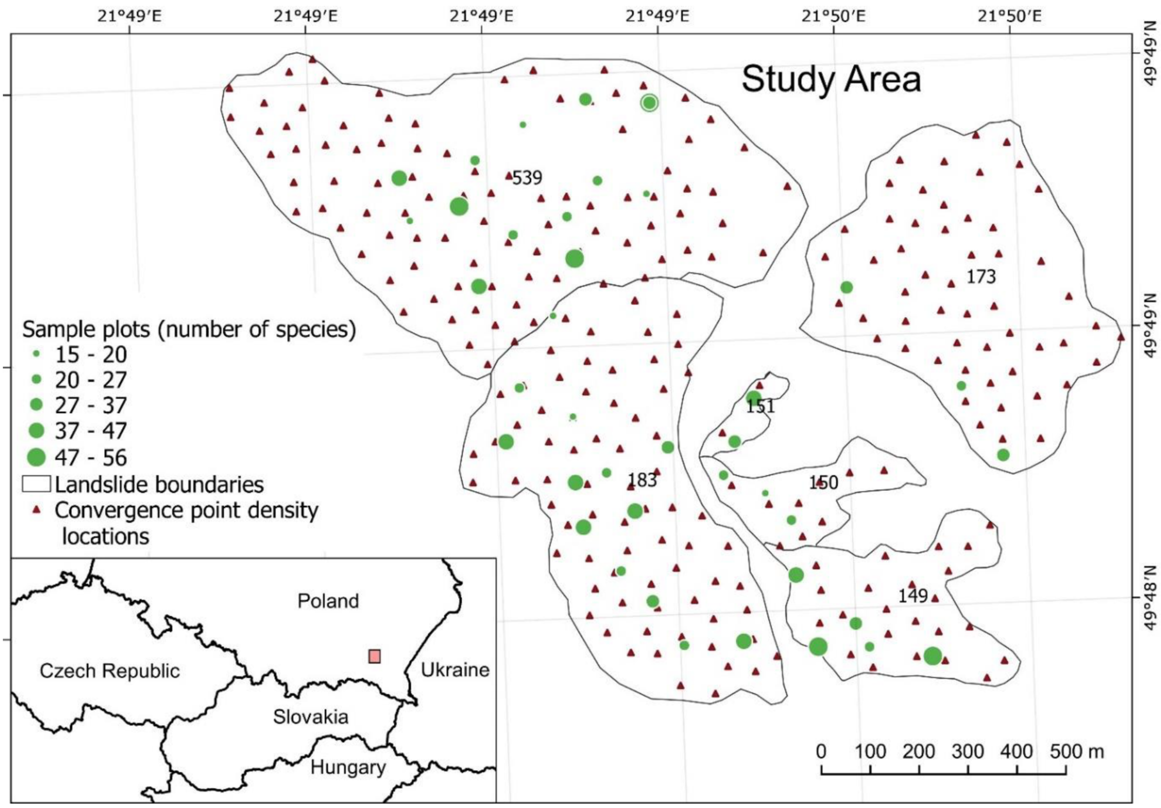

Figure 7: Location of the study area and sample plots (circle symbols) and randomly determined convergence point density locations (triangles).

The number labels are the SOPO catalogue numbers used to distinguish the six landslides in the study area.

5.1.3. Case studies 3 and 4: Loss of Plant species and biodiversity in the Czech Republic.

Located in central Europe, the Czech Republic covers about 78,866 km^2, of which ~2% is water. The Czech landscape is very diverse, with basins and rivers surrounded by low mountains in the west to more hilly areas in the east. Climatic conditions are dominantly temperate, with warm summers and cold winters. Average annual temperatures generally decrease with altitude and vary from - 4.0 ^{o}C at the highest spot, ~ 1.6 km asl, to about 10 ^{o}C in lowlands (Vondrakova et al. 2013). About 70 per cent of the annual total precipitation is received between April–September. The mean annual total precipitation varies from ~ 400 mm in the west to 1400 mm in the mountains up north (Tolasz et al., 2007, Hanel et al., 2016). The World Wide Fund for Nature (WWF) identifies four terrestrial ecoregions in the Czech Republic, including Western European Broadleaf Forests, Central European Mixed Forests, Pannonian Mixed Forests, and Carpathian Mountain Conifer Forests. These ecoregions constitute the nine vegetation belts of the Czech Republic, also known as forest vegetation zones (FVZ). The FVZs reflect altitudinal variations and different indicator species. Generally, species of oaks are common at < 350 m; beech dominates at 350 -600m, beech-fir is common at 600 - 900m, while spruce -pine species dominate above (Hlasny et al. 2011, Machar et al. 2017). Diverse natural and near-natural ecosystems, mainly of type grassland, forest, wetlands and rocks, are associated with these vegetation zones (Pechanec et al., 2021, Chytry et al., 2010, p.447). As of 2018, there are over 3000 plant species in the Czech Republic (Agency for Nature Conservation and Landscape Protection - AOPK)

5.2. Data and Software

Data from diverse sources was used to drive spatial models to meet the aim and objectives of the research. Data types included climate, species, land cover/biotope, topographic, cropland, agro-ecological zone, and environmental data (geology, soil, hydrology). A summary description of these data types, including scale, spatiotemporal resolution and source, is presented in (Table 1)

5.2.1. Climate data.

Historical and projected climate data were obtained at different spatial and temporal resolutions. For case study 1, long-term averages from 1970 to 2000 at roughly 1km x 1km were sourced from the Worldclim database. Projected data at the same resolution was the mean ensemble of four global climate models: ACCESS 1-0, CCSM4, HadGEM-ES and NorESM1-M. The data was based on the representative concentration pathways (RCP) 4.5 of the (CMIP5) Coupled Model Intercomparison Project) experiment up to the year 2070. These datasets were processed to derive the required indices for crop suitability models.

Climate data for the third and fourth case study was obtained from the Czech Globe at ~ 500 m x 500 m resolution were long-term averages for the periods 1961 - 2018 (historical data) and 2040 - 2100 (projected data). The climate variables associated with both datasets included: the mean annual temperature *(antemp),* the mean annual sum of rainfall *(anrain)*, mean annual temperature of the coldest month *(tcold)*, mean temperature of the growing season above 5 °C *(tempgs)*, the effective sum of temperature above 5 °C *(efstemp)* and the length of the vegetation season *(lenvegt)* as they reflect varying conditions of energy and moisture availability. The projected dataset, dynamically downscaled from the HadGEM 2-ES global model, is considered the most accurate model, capturing changes in precipitation patterns in the Czech Republic

5.2.2. Species data

Species location datasets include field plots and aggregated datasets over different periods. All species data were acquired as presence-only data. The data can be grouped under two broad categories: species grown in the field and those growing in the wild. The former was used in the first case study. It was obtained from the Genesys - a platform for plant genetic resources for food and agriculture- and the GBIF (global biodiversity information facility) portals from 1960 to 2017 to ensure a sufficient number of observations. After checking and removing duplicate points, missing or completely absent coordinates, and misrepresented coordinates, the sample size for valid occurrences for bean was 685, chickpea = 694, lentil= 249, pea=394 and pigeon pea =315 (Fig. 8). These crops were chosen because some are still under-researched (Manner et al. 2018), in addition to the fact that they are related.

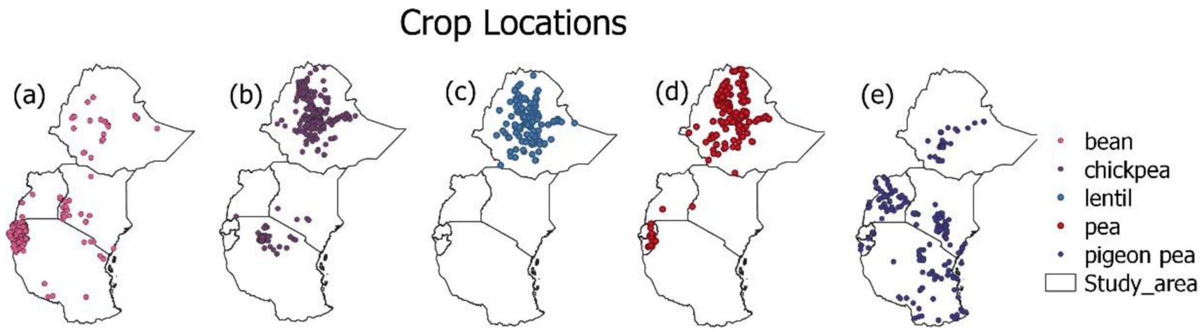

Figure 8 . Crop locations (a) common bean, (b) chickpea, (c) lentil, (d) pea (e) pigeon pea.
Species Data was obtained from the Genesys (https://www.genesys-pgr.org/) and GBIF (https://www.gbif.org/) portals from 1960 – 2017.

Species data for the second case study was obtained during the fieldwork in 2015 as above and below surface vegetation from 40 sample plots. Species richness (counted species) in the sampled plots varied from 15 to 56 species (Fig. 7), of which about 124 were vascular plants and 23 were bryophytes. Thirty-two of the 40 samples consisted of 16 potential locations of high and 16 potential locations of low species divers predetermined from a DEM analysis, while the remaining eight locations were randomly chosen during fieldwork to minimize sample bias. All sample plot locations (predetermined and randomly chosen) recorded were determined using the Trimble Pathfinder ProXH and measured about 100 m^2 each. Thus the hypothesized variability in species richness was verified and confirmed during fieldwork. The details of the sampling and DEM processing procedures have been published by Tracz et al. (2019).

For the 3rd case study, national survey records from 1960 to 1991 and 1991 to 2017 were obtained from the Czech Agency for Nature Conservation and Landscape Protection (OAPK). Each data consisted of ~ 3000 species and ~ 2 million records excluding alien species. The 1960 -1990 dataset was used to model the baseline species distribution using a representative sample of 686 species. First, aggregating species records selected them on 500m by 500m grids for the entire country. Next, species abundance on each grid was further reduced to presence-absence records, which were further reduced during the modelling process by selecting only models for species with TSS values ≥ 0.4 considered moderately correlated with their actual distribution.

5.2.3. Topographic data

The influence of topography, mainly slope exposition (aspect) and slope angle (slope), on species distribution was tested in case studies 2 and 3. In the second case study, a 1m digital elevation model (DEM) covering five distinct landslide zones was obtained from the Polish Geological Institute and the Polish Protection Agency Against Extreme Hazards – ISOK (National Water Management Authority 2013). A detailed vector layer indicator of topographic heterogeneity - convergence point computed in a series of geoprocessing steps, including the overlay of areas with slope values ≥ 25° and aspect into ecoslopes, followed by the identification locations with three or more ecoslopes vertices (Fig 9) were obtained (Tracz et al. 2019). Subsequently, convergence points were converted to a convergence point density (CPD) surface to assess its effectiveness as a predictor of species diversity.

In the third case study, slope and aspect were derived from a 5m DEM for the Czech Republic to understand topographic-mediated changes in climate on species diversity. The DEM was obtained from the Czech Office for Surveying, Mapping, and Cadastre

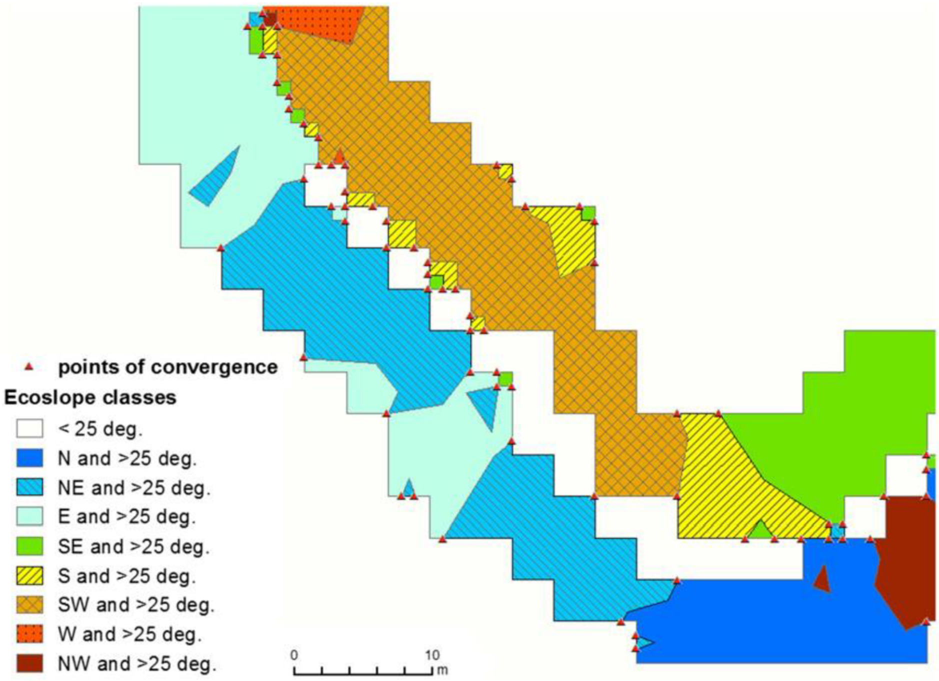

Figure 9. A sample of ecoslopes polygons shows terrain classes and convergence points
Adapted from Tracz et al. (2019).

5.2.4. Cropland dataset

Gridded datasets on croplands at 5 min arc (app 10km at the equator) for the year 2000 were obtained from Socioeconomic Data and Applications Center (SEDAC). The data was needed in caste study 1 to assess cropland availability in each country of the study region. The data was produced by Ramankutty et al. (2008) by integrating field-based agricultural inventory datasets and two global land cover classes derived from the sensors: The Moderate-resolution Imaging Spectrometer (MODIS) and Satellite Pour l'Observation de la Terre (SPOT). The dataset is scaled from 0 for pixels not under cropland to 100 for pixels completely under cropland and pasture. More details of the methodology leading to the data from Ramankutty et al. (2008)

5.2.5. Land cover and habitat data

CORINE Land Cover (CLC) from the years 1990 (reference year), 2000, 2006, 2012, and 2018 were sourced from the Corpernicus Land monitoring service in vector format (ESRI shapefiles). The data was needed in case study 3 as it was hypothesised that land use/cover evolution is changing landscape potential for ecosystem services. It was also thought that biodiversity loss should vary with ecosystems. The data consists of an inventory of land cover in 44 classes, each tagged with a unique three digits identifiable code. The Minimum Mapping Unit (MMU) of each landcover class is ~ 25 hectares (ha) for areal phenomena and minimum width of 100 m for linear phenomena. The Eionet National Reference Centres Land Cover (NRC/LC) network is producing the national CLC databases, which are coordinated and integrated by EEA. Most countries produce CLC by visual interpretation of high-resolution satellite imagery. In some countries, semi-automatic solutions are applied, using national in-situ data, satellite image processing, GIS integration and generalization. CLC has a wide variety of applications, underpinning various community policies in the environment, but also agriculture, transport, and spatial planning (Pechanec et al., 2018)

5.2.6. Environmental data: Geology, soil and hydrology

Other environmental data included soil texture, depth, geology, distance to water bodies, soil drainage, slope and aspect were also considered important for species distribution. Soil depth and texture were scaled from 1 to 2, where 1 represented shallow and coarse soils, respectively, while 2 represented deep and fine soils. Soil drainage varied from 1 for poorly drained to 5 for well-drained soil. Geology considered different rock fragments and varied from 1 for coarser and heterogeneous rocks to 1.9 for finer and homogeneous rocks. Distance to water body varied from 15 to 3539 m.

Table 1. Summary of research data

	Data type	Description	Resolution /scale	source
Case study 1	Climate	Historical and projected RCP4.5 upto 2070	30-sec arc, ~ 1km 2	WorldClim (accessed November 2019) https://www.worldclim.org
	Crop locations	Data from 1960 -2017		Genesys, (accessed, December 2019) https://www.genesys-pgr.org/ GBIF, (accessed November 2019) https://www.gbif.org/
	Agro-ecological zones	Homogenous crop zones at different altitude	5 min arc	HarvestChoice/International Food Policy Research Institute (IFPRI) (accessed November 2019) https://harvestchoice.org/data/aez8_clas
	Cropland	Cropland and pasture land	5 min arc	SEDAC (accessed November 2019), http://sedac.ciesin.columbia.edu/es/aglands.html
Case study 2	Digital elevation model (DEM)	Topographic data	1 meter	Polish Geological Institute https://www.pgi.gov.pl/en/services/landslides.html
	Species locations	Plant Species richness		Field survey
	Convergence point	Detail analysis of slope–aspect overlay		
Case study 3	Regional Climate data	Historical data from 1961 to 2018, Projected data for RCP 8.5 up to 2100	500m2	Climate change in the Czech Republic (http://www.klimatickazmena.cz accessed through Czechglobe (http://www.czechglobe.cz) on 1 May 2020
	Species	Higher vascular plants surveyed between 1961-1991, excluding alien species	500m2	Agency for Nature Conservation and Landscape Protection (OAPK) (http://www.ochranaprirody.cz/en/, accessed on (26 September 2019)
	topography	Slope and aspect	5m2	The Czech Office for Surveying, Mapping, and Cadastre
	geology	Geological material	1:100,000	Czech Geological Survey
	Soil		1:100,000	Research Institute for Soil and Water Conservation + Forest Management Institute (2018)
	Drainage	Infiltration ability	1:100,000	Research Institute for Soil and Water Conservation + Forest Management Institute (2018)
	Distance to waterbody	10 or 100 m distance from the river		Open street map (OSM)
Case study 4	Climate data	Historical data from 1961 to 2018, Projected data for RCP 8.5 up to 2100	500m2	Climate change in the Czech Republic (http://www.klimatickazmena.cz accessed through Czechglobe (http://www.czechglobe.cz), on 1 May 2020

	Climate data	Historical data from 1901 to 2020,Projected data for RCP 4.5 and 8.5 up to 2100	1000m2	Marchi et al 2020 https://sites.ualberta.ca/~ahamann/data/climateeu.html
	Biotope data	Detail vector layers of ecosystems in Czechia		
	Land cover	Land cover of Czechia based on EU regional land cover classification	100m2	https://land,copernicus.eu (accessed January 10, 2019)

5.3. Summary of methods and spatial models

Five spatial models were tested, including the maximum entropy algorithm –Maxent, EcoCrop, Geostatistical models, EUROMOVE and GLOBIO, and a custom land use/cover change model. Non-spatial models like random forest and logistic regression were equally tested mainly to compare and gauge the performance of Maxent. A brief description of the spatial models, their implementation and workflow are presented in the subsection below

5.3.1. Maxent.

Maxent was tested in case studies 1 and 3. The model optimises prediction by comparing the probability density of environmental conditions where a species is observed to the probability density of background environmental conditions in an area based on minimum distance (Philip et al., 2006, Elith et al., 2010). Maxent was chosen for its robustness and popularity in species distribution modelling. Given that the first objective was to fine-tune the EcoCrop model (Fig 10), modelling in Maxent allowed optimum temperature and precipitation values for each crop to be derived from response curves and compared with statistically computed values. Maxent was implemented in R through the dismo package (Hijman and Elith 2017). The model was tested on 10,000 background points, and the environmental attributes of species for the case studies were sampled. Presence only and background points were partitioned in the ratio of 70:30 for model testing and validation. The models were validated in both cases based on the area under the receiver operating characteristic curve (AUC) and the true skill statistics (TSS).

5.3.2. EcoCrop

EcoCrop, a mechanistic model for predicting crop suitability based on climate indices (Hijmans et al., 2001; Ramirez-Villegas et al., 2013), was tested in case study 1. The model predicts suitability on a pixel basis by comparing crops' specific temperatures and precipitation ranges with the prevailing conditions elsewhere. EcoCrop also determines the optimum climate range and the marginal range, usually the minimum and maximum climatic conditions for growth. The model then scores suitability on a scale of '0' for unsuitable areas or areas outside the crop climate range to '1' for excellently or optimally suitable areas. Behind the model is the EcoCrop database documenting the base biophysical parameter of more than 2500 plant species. Despite the limitation of not considering biotic factors and extreme climatic conditions during a crop's life cycle (Manner et al., 2021), EcoCrop was chosen because of its simplicity and broad scope of application. Unlike robust process-based crop models available only for a few crops, the EcoCrop database has been growing with experts understanding the climate range of undocumented crops. Second, the model input has been successfully validated for sorghum, bean, millet, maize, banana, cassava and yam using the empirical method (Ramirez Villegas et al., 2013, Manner et al., 2018, 2021, Rippke et al., 2016), but not for most legume crops. Third, climate information about these legume crops in East Africa is scanty or poorly documented. Lastly, there is evidence that the model distribution corresponds with actual geographical distribution (Manner et al., 2020, 2021; Ripkki et al., 2016). The model implemented in DivaGiS and TerrSet-CCAM software was tested for historical climate data (1970 -2000) and the projected data (2000 – 2070) under the RCP 4.5 scenario.

The model input was calibrated using basic descriptive statistics of historical climatic conditions in the region compared with field values and values from response curves derived from the spatial model - Maxent. The entire workflow is summarized in Fig 10. First, the geometric mean of the growing season was used to create two fictitious growing seasons for mean temperature and total precipitation (Equations 1 & 2), respectively. Each growing season had 12 consecutive sequences of four months for chickpea, lentil, common beans and six months for pigeon pea. The sequence with the lowest, highest and mean temperatures was used to calibrate temperature inputs. The sequence with the highest sum of rainfall to ensure enough moisture during the growing season was chosen for precipitation.

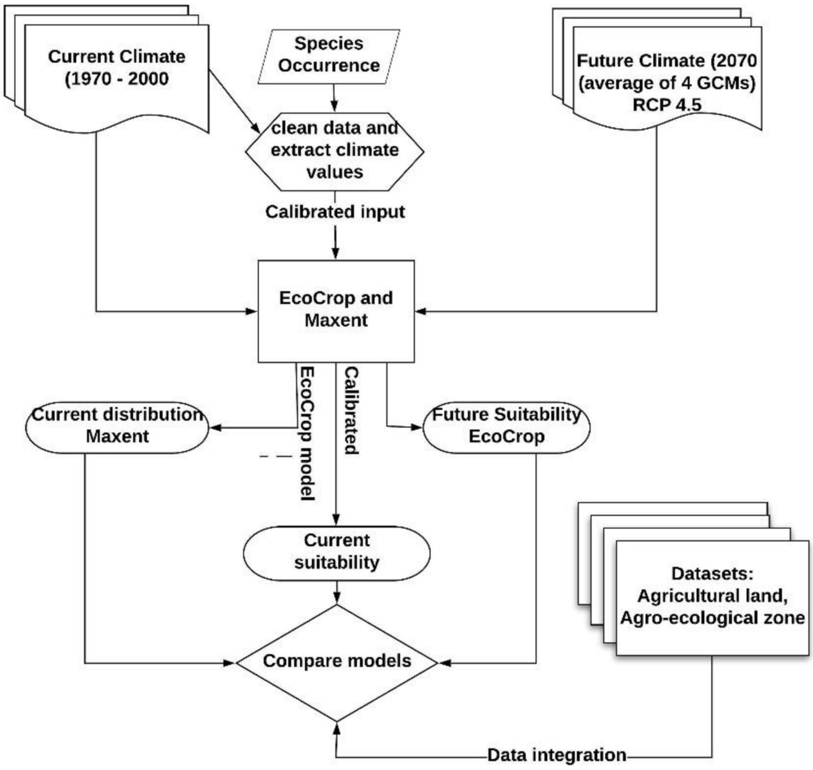

Figure 10. Workflow and methodology to calibrate climate inputs for EcoCrop

$$T_{GS} = \frac{1}{4}\left(\sum_{i=1}^{i=4} t_{\mathrm{avg}_i}, \sum_{i=2}^{i=5} t_{\mathrm{avg}_i}, \ \ldots, \sum_{i=12}^{i=3} t_{\mathrm{avg}_i}\right) \qquad (1)$$

$$R_{GS} = \left(\sum_{i=1}^{i=4} r_{\mathrm{sum}_i}, \sum_{i=2}^{i=5} r_{\mathrm{sum}_i}, \ \ldots, \sum_{i=12}^{i=3} r_{\mathrm{sum}_i}\right) \qquad (2)$$

Where i represents the month(s), the mean temperature(t_{avg_i}) for 12 consecutive growing seasons (T_{GS}), has four consecutive months per season. The total rainfall (r_{sum_i}) for 12 consecutive growing seasons (R_{GS}) has four consecutive months per growing season

Because the growing season for field pea is three months, values of the historical quarterly bioclimatic variables (BIO10 -Mean Temperature of Warmest Quarter, BIO11-Mean Temperature of Coldest Quarter, BIO16-Precipitation of Wettest Quarter and BIO12-Annual Precipitation) were extracted from each location. Extracted temperature and precipitation values for each crop location for the chosen sequences and variables were used to plot frequency curves and determine the model inputs (Ramirez-Villegas et al., 2013). The chosen sequences and climate variables were tested in Maxent and optimum values from their response curves compared with calibrated values. Table 1 summarises the input parameters used to drive EcoCrop. Hence, projected land suitability or availability changes were based on the calibrated inputs. Suitability maps were aggregated by a factor of 10 and overlaid with the global cropland dataset (Rammankutty et al., 2008) and agro-ecological zone dataset (IFPRI, 2015) to estimate the share of land that might be lost. Thus the estimated share of agricultural land that could be lost is the difference between total lost minus total gained for each country.

5.3.3. Geostatistical models

Three geostatistical models: Ordinary kriging (OK), Ordinary cokriging (OCK), and Regression kriging (RK), were tested in the second case study to address the research questions raised in the second objective. The models generally assume that the spatial variability in an observed phenomenon is due to random and stationary processes that can be modelled using probability principles (Krivoruchko, 2011; Goovaerts, 2000), expressed in Equation 3.

$$Z(x_i) = \mu + e(x_i) \qquad (3)$$

Where the observed number of species richness, Z at a given location, x_i represented by x, y coordinates are the sum of the mean (μ) of a process plus the spatially correlated random error $e(x_i)$.

All three models are also based on spatial auto- or cross-correlation that can be quantified with a variogram (Rossiter, 2012; Wu et al., 2006; Goovaerts, 1999; Oliver and Webster, 1990, 2014; Webster and Oliver, 1992). Variograms describe distance and directional variation and quantify the average weighted influence of nearby observations based on the type of mathematical model fitted to the data, the configuration of observation points, and variogram parameters (Oliver and Webster 2014; Krivoruchko 2011; Johnston et al. 2001; Goovaerts 1997). The sample variogram $\gamma(h)$ estimating spatial variability is commonly expressed using Equation 4 and become more complex for cokriging as the number of variables increase. While the computation of weights between sample points is generally estimated from Equation 5.

$$\gamma(h) = \frac{1}{2n}\sum_{i=1}^{n}[Z(x_i) - Z(x_{i-h})]^2 \qquad (4)$$

$$Z(x_o) = \sum_{n=1}^{n} \lambda_i \, Z(x_i) \qquad (5)$$

Where x_i is the data location, n represents the number of paired points for a given lag (h), and *i-h*; is a unit distance between two sample locations. $Z(x_o)$ is the estimated value at an unvisited location(x_o). $Z(x_i)$ is the observed sample value, λ_i is the kriging weight, which minimises the variance in prediction error, and n is the number of sampled points used in the estimation.

However, these models differ in their flexibility or ability to deal with two or more variables. For example, regression kriging deals with multiple variables by performing ordinary kriging on regression residuals (), avoiding the need to fit multiple variograms. Cokriging, on the other hand, is ideal when the surrogate of sparsely sampled phenomena can be more densely sampled. However, it requires that multiple variograms be fitted simultaneously. In contrast, ordinary kriging is a univariate method for a sufficiently sampled variable. Thus it was possible to compare their ability to capture the spatial pattern of species richness with or without considering topographic heterogeneity quantified as convergence point density. It was possible to verify if there was an added benefit when the surrogate was densely sampled. Before variogram modelling, the assumption of normality of distribution in the dataset was checked. All direct and cross-variogram were omnidirectional and fitted with spherical mathematical models. Ordinary and cokriging were done using the Geostatistical Analyst extension in ArcGIS 10.6 (ESRI), while regression kriging was done using the gsat package in R (R Development Core Team 2021). Model evaluation statistics included the mean error (ME) and the root means square error (RMSE)

5.3.4. Modelling landscape development and ecosystem services

Modelling landscape development is mostly based on the publication of Pechanec et al. (2018), for which I am the second co-author. The first step was to estimate changes in area (km^2) and share of land use/cover category for the selected modelling periods. Next persistent areas, defined as areas same land use category in all five modelling periods and main trajectories of change, were calculated. Next, the percentages of persistent areas of each land use/cover class from the reference period (1990) were calculated. The workflow involved multiple overlay spatial operations (Identify, Update, Intersect) and basic statistical calculations (Frequency, Summarize by) performed in ArcGIS PRO 2.3. Subsequently, the two categories of ecosystem services: Provisioning and Regulating for each of the five analysed years, were separately determined by categorizing or scoring the capacity of these services based on the expert-based ecosystem service (ES) matrix score (capacity values) developed for Germany (Burkard et al. 2009). The ES matrix score varies from 0 to 5 where 0 = no relevant capacity, 1 = low relevant capacity, 2 = relevant capacity, 3 = medium relevant capacity, 4 = high relevant capacity and 5 = very high relevant capacity.it was directly applied to the situation in the Czech Republic because both countries' physical-geographical and data sources are the same. Each group of ecosystem services was rated as the sum of the capacities of all sub-services in that group.

Changes in individual areas were compared to the reference period to identify development trajectories. That is, by comparing the switch to another land use category than the one in the baseline (1990). The main trajectories of landscape development (the same development trend) were selected for further analysis. Each trajectory is identified by the TAG code of the landscape cover according to the Corine LC nomenclature (Table 12, Appendix) and in the individual monitored years. Thus for the selected trajectories, only areas with at least 100 hectares were included in the main axes of the ES matrix as they were considered the main trends of landscape development in the Czech Republic. At the same time, the number of facets showing this trend was calculated. An ES matrix was attached to the analyzed plots, and the evolution of land use and ecosystem services' capacity was analysed. The workflow is summarized in Fig11

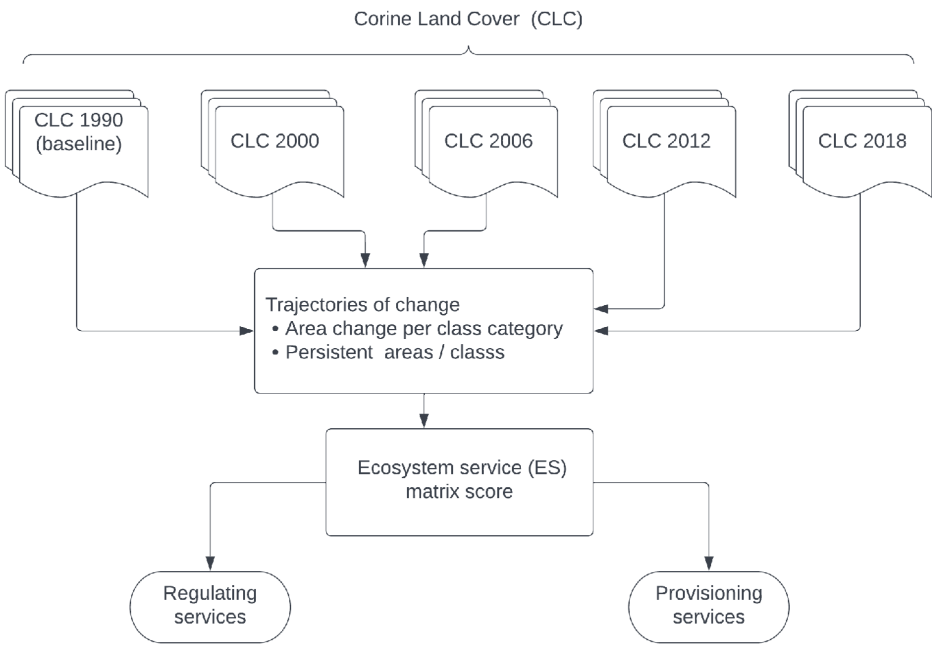

Figure 11. Workflow to assess the development of land use/cover for Ecosystem Services

5.3.5. EUROMOVE

The EUROMOVE modelling approach was tested in the 3rd case study. EUROMOVE is a multi-logistic regression-based species distribution model for the European region originally developed and tested at a scale of 50 km x 50 km for ~1400 or ~ 900 species (Bakkenes et al. 2002; 2006). The indicator of change in the model, the mean stable area index (MSAi), is an aggregation of change in species richness and habitat extent compared to a reference situation (Equation 6).

$$\mathrm{MSAi} = \frac{\sum_{i=1}^{n} {}^{A_{i1,y2}}\!/_{A_{i1,y1}}}{N} \qquad (6)$$

Where $A_{i1,y1}$ is the area of species i for the baseline period and $A_{i1,y2}$ is the area of species i for a later modelling period. N is the total number of species that should be the same for the two modelling periods, irrespective of whether some species have disappeared in the future

Conceptually, the model was selected because of its flexibility, offering the possibility to replace logistic regression with more robust SDM modelling approaches. Lastly, the modelling approach offers a comprehensive way to summarize multi-species data. The model was adapted to the conditions in the Czech Republic by integrating very high-resolution climate data (500 m x 500 m) with geology, hydrology, and topography with a representative sample of 687 species. The 687 species are the baseline species (1961 -1990) selected based on the following criteria: (i) species could be observed in at least 50 locations considering a sample grid of 500m x 500m for the entire Czech Republic. TSS value between observed and model species was ≥ 0.4. Thus Logistic regression was replaced with Maxent, accepting all default settings. For the representative species, changes under the current (1991 - 2018) and the projected RCP 8.5 scenario up to 2100 were compared to the baseline situation (1960 -1990). In addition, changes in the distribution of eight indicator species sampled under the current and baseline climatic condition were also compared to further assess their vulnerability to climate change.

6. RESULTS

Model results included changes in species richness or biodiversity loss under static and dynamic conditions. Dynamic changes were assessed from 1990 to 2100 under the moderate (RCP 4.5) to the extreme (RCP 8.5) climate change scenarios. It involved quantifying the impact of climate on the integrity of key habitats, landscapes and their potential for specific species or crops. Detail results can be found in the cited publications.

6.1. Modelling landscape potential for selected legume crops (paper 1)

Climate Change and the Agricultural Potential of Selected Legume Crops in East Africa. Tangwa, E., Voženílek, V., Brus, J., & Pechanec, V. Saima Consult Ltd. https://doi.org/10.32008/geolinks2020/b1/v2/02

The results of paper one are based on the calibrated temperature and precipitation inputs for the EcoCrop model. The paper highlights the vulnerability of legume crops and their production zones in east Africa. First, estimating the crop niche from the region's annual variations in temperature and precipitation was necessary to get an overview of the crops' ecology. As shown in Figure 12, most pea, bean and lentil-growing areas received almost the same amount of precipitation per year. However, the mean annual temperature for lentil and pea production sites ranged from 13 ^{o}C to about 20 ^{o}C compared to 16 ^{o}C - 22 ^{o}C in bean-growing areas

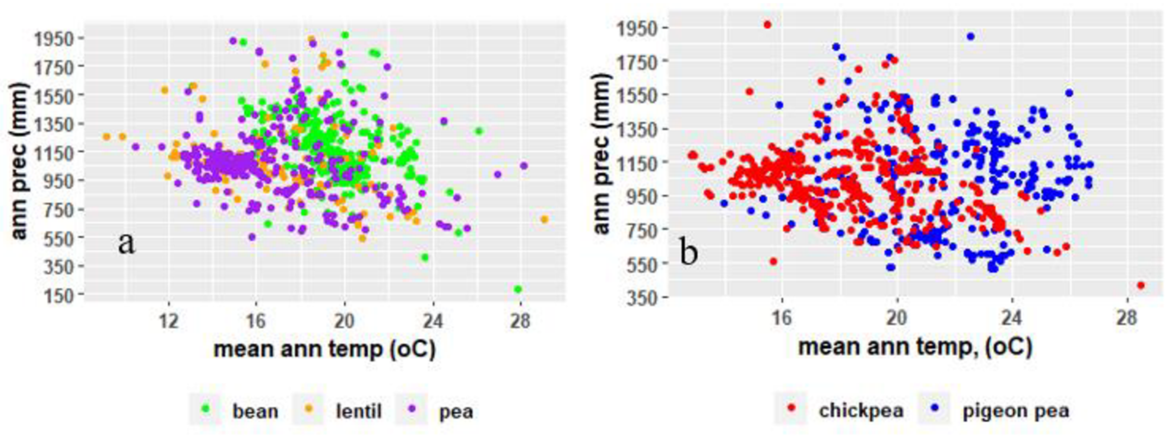

Figure 12: Annual temperature and precipitation range of the chosen crops (a) bean, lentil and pea (b) chickpea and pigeon pea

Likewise, the mean annual precipitation range for chickpea and pigeon pea locations was almost the same. However, the temperature range for most chickpea locations varies from 12 °C to 24°C compared to 20 °C to 27 °C for pigeon pea.

In Table 2, the calibrated inputs based on computed growing seasons and selected climate indices were compared with the FAO base parameters. The table shows that the calibrated optimum temperature and precipitation were 6 to 27% consistent with the FAO base parameter except for the maximum optimum rainfall for common beans. The base marginal precipitation ranges were generally not comparable and differed considerably from the calibrated range by ~ 9 to 68%. Field pea had the lowest moisture requirement, while pigeon pea and chickpea were the most tolerant to high temperatures and precipitation.

Table 2. Comparison of calibrated and FAO base inputs

	LGS (days)	Tkill (°C)	Tmn (°C)	TopMn (°C)	TopMx (°C)	Tmx (°C)	Rmn (mm)	RopMn (mm)	RopMx (mm)	Rmx (mm)
Bean	90	0	10	15	20	27	151	452	1054	1355
FAO base	160	0	7	16	25	32	300	500	2000	4300
Chickpea	120	0.85	3.4	10.2	24	31	182	547	1274	1638
FAO base	135	-9	7	15	29	35	300	600	1000	1800
Lentil	120	0.75	3	9	21	27	167	506	1180	1517
FAO base	155	0	5	15	29	32	250	600	1000	2500
Pea	90	0.82	3.3	9.9	23.1	29.7	151	452	1054	1355
FAO base	100	-2	4	10	24	30	350	800	1200	2500
Pigeon pea	180	1.1	5	14.1	33	42.3	220	658	1537	1976
FAO base	228	0	10	18	38	45	400	600	1500	4000

Where: Rmx= maximum rainfall, RopMx= optimum maximum rainfall, RopMn= optimum minimum rainfall, Rmn= minimum rainfall, Tmx= maximum temperature, TopMx=maximum optimum temperature, TopMn= optimum minimum temperature, Tmn= minimum temperature, Tkill= temperature that will kill the crop and LGS = length of the growing season

The spatial distribution of the selected legume crops from 2000 to 2070 is shown in Fig 13. Potential areas for pigeon pea, chickpea and pea were the most extensive under the current climatic conditions. Future patterns showed shifts in landscape suitability to cold and cool zones. There will also be a significant contraction in the share of suitable areas for common bean and lentils compared to chickpea and pigeon pea, which will remain unchanged by 2070. In general, common bean and lentil were the most vulnerable crops having about 60% suitability in the south-west and south-east of Tanzania and the Northeast of Uganda (Fig 13a and 13c).

Across AEZs, Fig 14 shows that under future climatic conditions, suitability either increased or nearly remained constant in the cool agro-ecological zones as opposed to the warm AEZs. The most optimal zones for legume cultivation will be the cool humid (tch), the cool semi-arid (tcsa), and the cool sub-humid (tcsh) zones. Suitability within these zones will increase by 10% and 15%, respectively and will be most favourable for field pea cultivation..

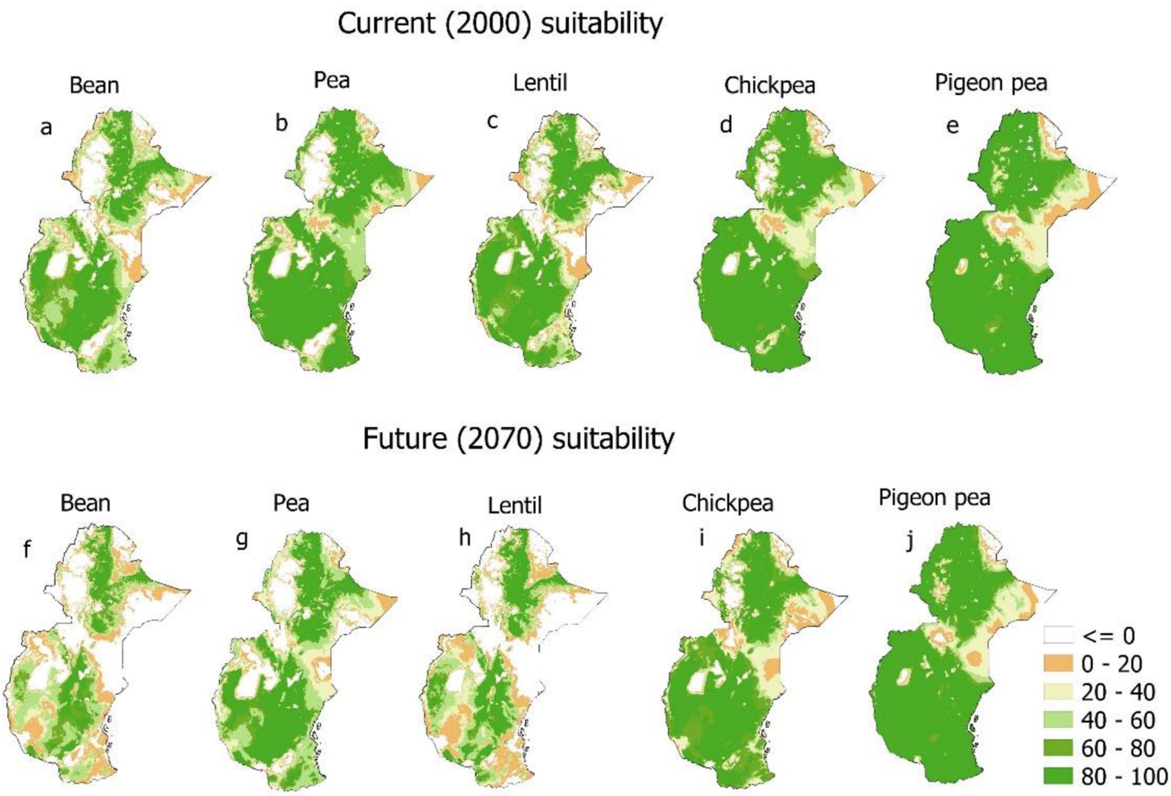

Figure 13. current (a - e) and future (f – j) suitability of legume crops.

Within the warm AEZs, the warm sub-humid (twsh) and the warm semi-arid (twsa) zones will be the most impacted, decreasing suitability at all production sites. Generally, landscape potential for, pea will be most reduced in the warm semi-arid (twsa) and the warm (twa) arid zone compared to other crops. The suitability of lentil, chickpea and pigeon pea will be more reduced in the warm humid (twh) zone compared to common bean and pea. The cool humid (tch) zones and cool arid (tca) zones will be negligibly affected. Fig 15 shows the estimated share of suitable agricultural land that could be lost at the country level based on the total lost minus total gained crop land for each country.

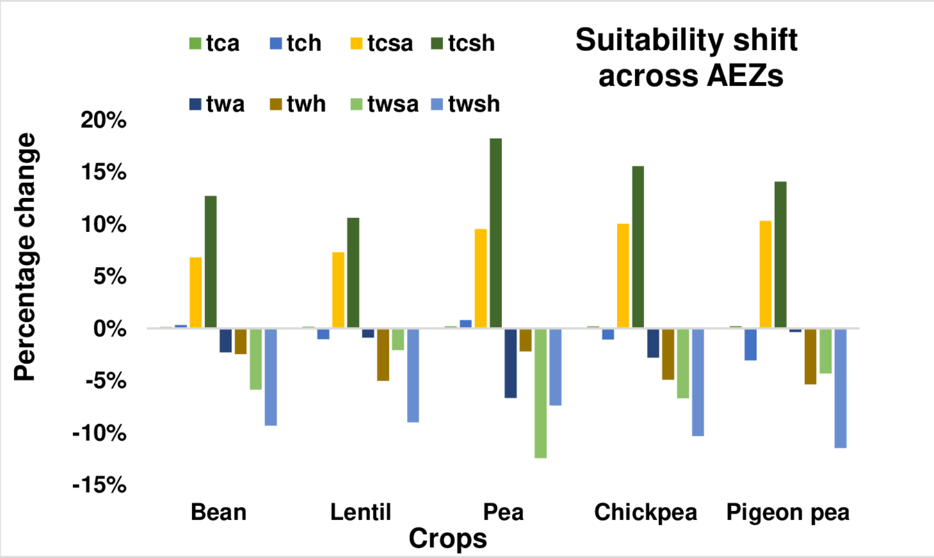

Figure 14. Suitability shift across agro-ecological zones (AEZs).
tca = tropic cool arid, tch= tropic cool humid, tcsa= tropical cool semi-arid, tcsh=tropic cool sub-humid, twa= tropic warm arid, twh= tropic warm humid, twsa= tropic warm semi-arid, twsh=tropic warm sub-humid.

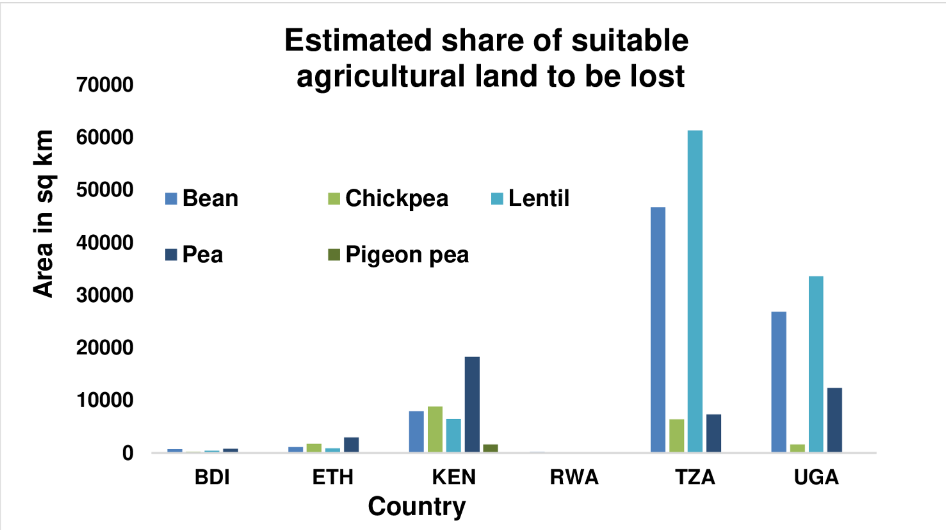

Figure 15. Estimated share of suitable arable land that could be lost
The share of suitable land in each country is based on an overlay with agricultural land, which is cropland + pastureland (Ramankutty et al., 2008).

The figure shows that common beans will be the most vulnerable to climate change, losing approximately 61,000 and 33,000 km2 share of suitable arable land in Tanzania and Uganda, respectively. Approximately 18,200, 12,000 and 7300 km^2 of suitable land for field pea cultivation will be lost in Kenya, Uganda and Tanzania, respectively. Most of the suitable agricultural land in Ethiopia will remain suitable, although the share of suitable land for pea will reduce. In contrast, Rwanda will have little or no cropland loss.

6.2. Quantifying topographic heterogeneity and modelling variability in species richness (Paper 2).

Predicting Plant Species Richness in Forested Landslide Zones Using Geostatistical Methods. Tangwa, E., Tracz, W., Pechanec, V., and Yuh, Y. Ecological Indicators132 (July 2020):108297.doi:10.1016/j.ecolind.2021.108297.

The results from three geostatistical models, namely ordinary kriging (OK), ordinary cokriging (OCK) and regression kriging (RK), were presented in paper 2. The paper compares the extent and accuracy of spatial dependency captured by these models and their accuracy. The models were tested based on a moderate to relatively strong positive correlation (r= 0.65, Table 3) between species richness and the topographic indicator of change, convergence point density (CPD). It is worth noting the correlation between species richness and convergence point density was higher than that for the interaction between slope and aspect via ordinary least square regression. Hence it was necessary to investigate the effectiveness of CPD as a surrogate of species diversity.

Table 3. Correlation between terrain attributes and species richness

Topographic attribute	NoS	Elevation	Aspect	Slope	CPD
Species richness (NoS)	1				
Elevation (m)	- 0.13 (-0.06)	1			
Aspect(degree)	- 0.26 (0.07)	-0.68 (-0.57)	1		
Slope(degree)	0.53 (0.30)	0.24 (0.03)	-0.26 (-0.31)	1	
Convergence point density (CPD)	0.65	-0.16 (-0.06)	0.01 (-0.17)	0.48 (0.56)	1

Values in the bracket are Pearson's correlation coefficients when DEM attributes are resampled from 1 m to 5 m

More importantly, it was necessary to check if there was any benefit when CPD was densely sampled compared to species richness. The geostatistical models tested showed spatial dependency, which generally decreased with distance as expected. However, the cross-correlation between CPD and species richness was captured at a much shorter distance ~ 118 m compared to 170 m and 270 m for direct variograms of species richness and CPD (Fig 16).

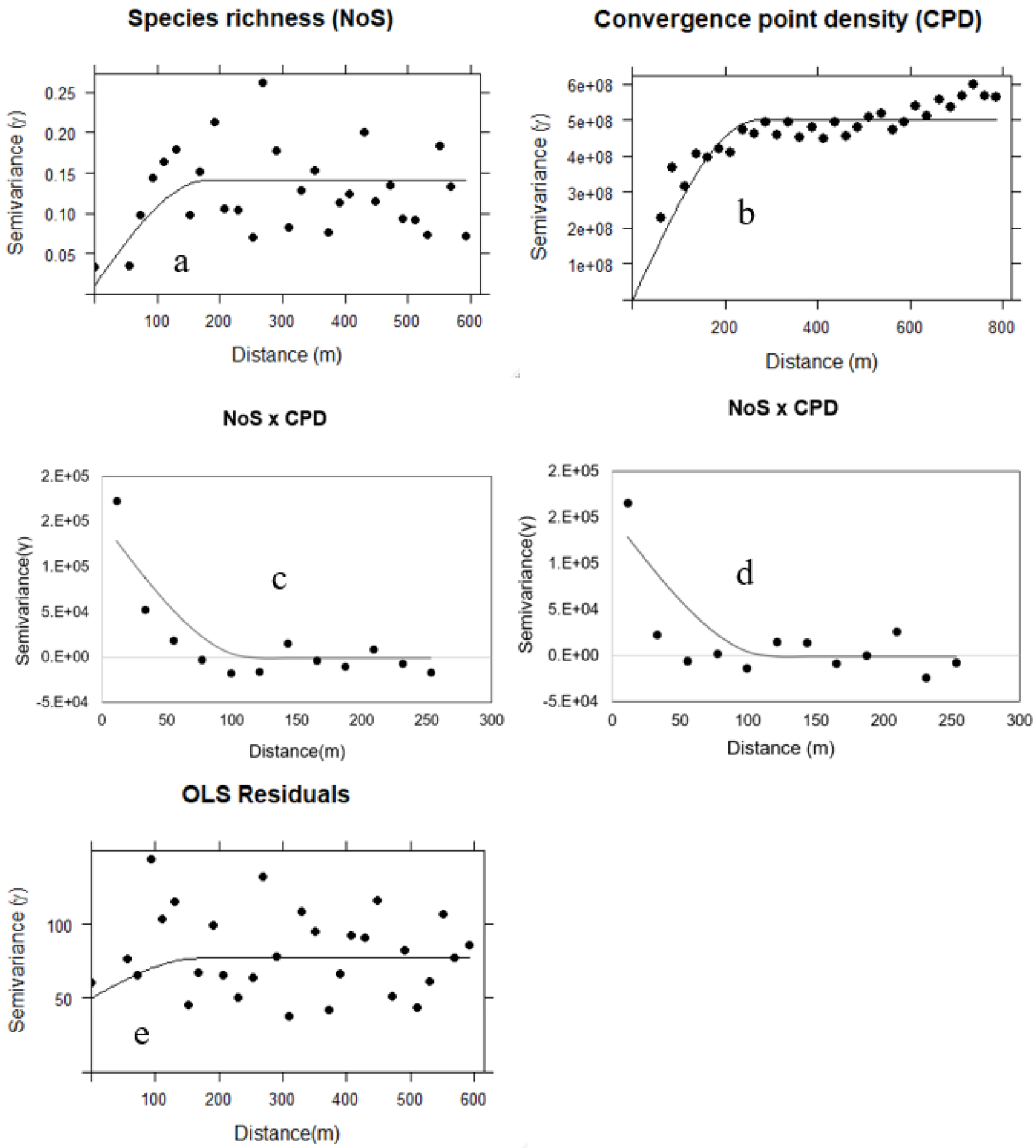

Figure 16. Variogram models.

(a) Species richness, (b) convergence point density, (c) cross variogram for identical variable locations (d) cross variogram for unidentical variable locations (e) OLS residuals

The minimum species richness was generally overpredicted, while the maximum was overpredicted as expected. However, RK was the most accurate with the least RMSE (9.3), followed by OCK (10.54) and then OK (13.6) (Table 4), whose predictions were not so different from the mean species richness (~ 32 species) of the study area.

Table 4. Summary of cross-validation statistics of geostatistical models

	Species richness (NoS)	Ordinary least squares (OLS)	Regression kriging (RK)	Ordinary kriging (OK)	Cokriging(OCK1)	Cokriging (OCK2)
Min	15	21	19	25	22	19
Max	56	46	47	46	50	51
ME	-	8.04	0.09	0.16	1.39	-0.05
RMSE	-	9.57	9.23	13.60	11.27	10.54

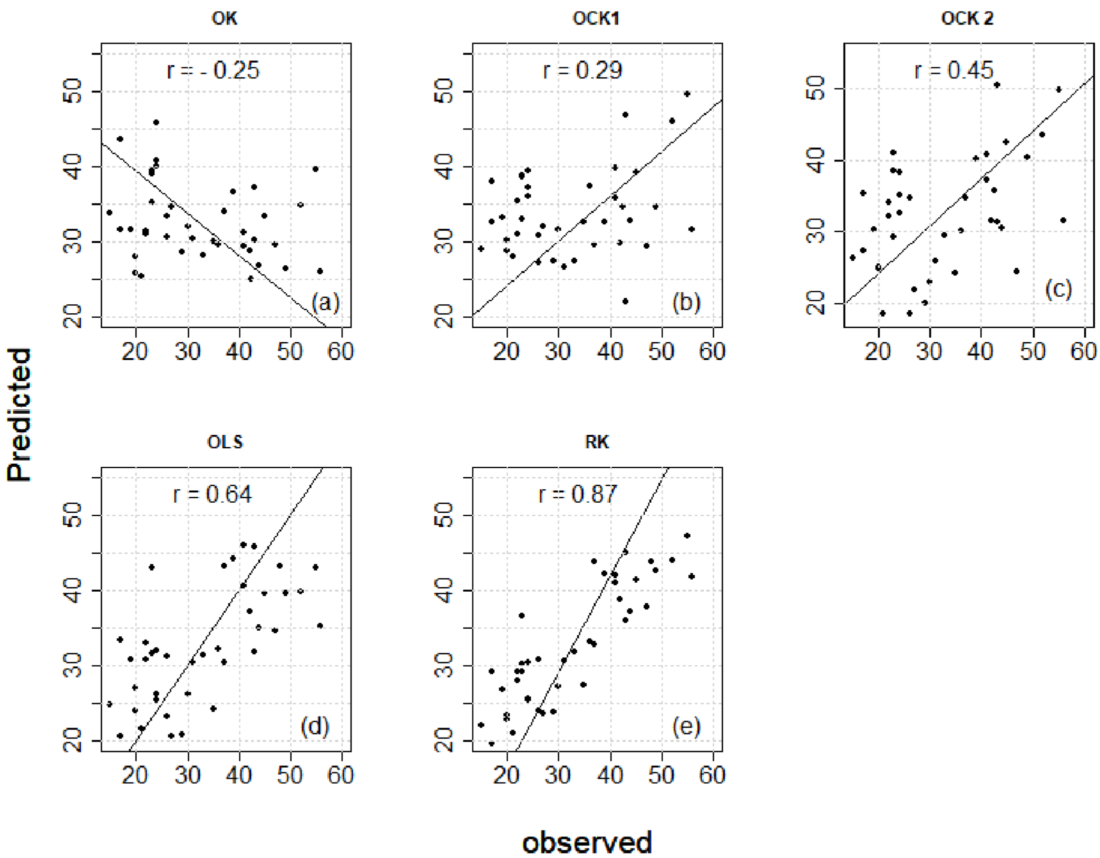

Figure 17.Comparison between observed and predicted species richness.
(a) OK (ordinary kriging), (b) OCK1 (cokriging with unidentical variable locations), (c) OCK2 (cokriging with identical variable locations), (d) OLS regression and (e) regression kriging

The difference in model accuracy can be seen in predicted maps. Generally, species richness predictions based on ordinary kriging were too general and showed less variability in species composition at unsampled locations than OCK and RK (Fig 22, Appendix). Thus, the correlation coefficient, r, between observed and predicted species richness was much higher for the case of regression kriging compared to OCK or OK (Fig. 17).

6.3. Landscape development and potential for provisioning and regulating services (Paper 3)

Pechanec, V.; Kilianová, H.; Tangwa, E.; Vondráková, A.; Machar, I. What is the development capacity for provision of ecosystem services in the Czech Republic? Sustain. 2019, 11, 1–17, doi:10.3390/su11164273.

During the study period, the area covered by artificial surfaces (settlements), forests and semi-natural wetlands and water bodies increased, whereas agricultural cropland areas decreased. (Appendix, Table 12). This change translates to ~ 79.48 % of total persistent areas in the Czech Republic (Table 5). The highest persistence is associated with Water bodies, representing the most stable class for the monitored period. Other stable categories include Road and rail networks, Discontinuous urban fabric (93.27%), Industrial or commercial units (92.3%) and Broad-leaved forest ~92.98%. Conversely, the least persistent were open or low vegetation categories: Transitional woodland shrubs (22.09%) and Bare rocks (24.74%). Dump sites (26.26%) continue to show low persistence, a logical consequence of a significant decline in this category to around one-third of its initial area.

Based on the assessment for Provisioning services, only three capacity levels were identified for the Czech Republic: no relevant well capacity, low capacity and relevant capacity (Table 6). The area with no relevant capacity gradually decreased by 708.7 km^2, ~9.1% of the original area. Then it started to rise (by 2.17 km^2 and 539.88 km^2). The final area is 166.65 km^2, i.e. 2.14% lower than the baseline. The area of the relevant capacity gradually decreased by 5417.9 km^2, i.e. 2.06%. The area of the territory with low relevant capacity increased all the time to more than twice its original area. The increase was 5583.87 km^2. Area persistence with No Relevant capacity and Low Relevant Capacity represents about 13.05% of the Czech Republic area.

Table 5. The persistence of individual land cover classes

Land cover category	Area (km²)	Percentage of persistence (%)
111 Continuous urban fabric	13.01	88.88
112 Discontinuous urban fabric	3337.49	93.27
121 Industrial or commercial units	481.06	92.3
122 Road and rail networks and associated land	45.07	93.75
123 Port areas	0.76	50.87
124 Airports	49.22	87.75
131 Mineral extraction s ites	86.05	47.64
132 Dump sites	40.6	26.26
141 Green urban areas	57.09	87.49
142 Sport and leisure facilities	88.55	75.22
211 Non-irrigated arable land	27335.16	76.91
221 Vineyards	77.76	70.2
222 Fruit trees and berry plantations	159.79	48.69
231 Pastures	2086.58	82.55
242 Complex cultivation patterns	316.21	76.13
243 Land principally occupied by agriculture ….	5440.98	80.77
311 Broad-leaved forest	2320.08	92.98
312 Coniferous forest	14368.4	86.81
313 Mixed forest	5034.2	85.98
321 Natural grasslands	209.84	51.86
322 Moors and heathland	12.3	46.36
324 Transitional woodland-shrub	549.21	22.09
332 Bare rocks	0.52	24.74
411 Inland mars hes	38.57	72.04
412 Peat bogs	31.68	84.49
511 Water courses	39.46	92.18
512 Water bodies	462.98	93.93
Total	62682.62	79.48

Table 6 Development of the area (km^2) of classes of ES capacity for Provisioning services

Capacity	1990	2000	2006	2012	2018	Persistent
No relevant capacity	7802.37	7230.42	7093.67	7095.84	7635.72	5067.91
Low relevant capacity	3886.92	6706.45	8619.92	9365.11	9470.79	3115.89
Relevant capacity	67179.49	64931.92	63155.21	62407.85	61762.3	54498.82

Table 7 Development of the area (km^2) of classes of ES capacity for Regulating services

Capacity	1990	2000	2006	2012	2018	Persistent
No relevant capacity	7177.26	6608.39	6560.1	6553.77	7085.11	4680.75
Low relevant capacity	45938.83	45861.5	45423.08	45337.75	45210.95	35827.01
Relevant capacity	812.91	799.23	654.86	629.68	598.29	420.5
Medium relevant capacity	37.5	37.11	46.72	45.52	45.68	31.68
High relevant capacity	24902.28	25562.56	26184.04	26302.08	25928.78	21722.68

Five levels, excluding the very high relevant capacity level, were identified for Regulating services (Table. 7). The area with no relevant capacity gradually decreased until 2012 by 623.5 km^2, and then there was a significant increase in the area by 531.34 km^2. The area of the territory with low relevant capacity gradually decreased by up to 942.5 km^2 in total. Areas with high relevant capacity gradually increased by 1026.5 km^2, representing an increase of 4.12% of the original area of this level. Areas with a low relevant capacity (57.16%, i.e. 35827.01 km^2) and high relevant capacity (34.66%, i.e. 21722.68 km^2) show the highest persistence.

Table 7 shows the evolution of the capacity level potential for providing ecosystem services at five-time horizons. A total of 22 main trajectories of land cover development in the Czech Republic were identified. Each represents the transition between land cover classes based on their code tags.

Table 8. Main trajectories of land cover development in the Czech Republic

No.	Development trajectory (1990-2000-2006-2012-2018)	Number of patches this trajectory	Area of patches this trajectory (ha)
1	211-211-112-112-112	18894	174.79
2	211-211-211-211-112	6315	111.09
3	211-211-211-211-231	6450	253.91
4	211-211-211-231-231	1511	707.68
5	211-211-231-231-231	9566	1856.04
6	211-211-243-243-243	29578	878.037
7	211-211-312-312-312	31691	158.79
8	211-231-211-211-211	2360	209.79
9	211-231-231-231-231	3601	2269.18
10	243-243-211-211-211	24065	226.13
11	243-243-231-231-231	11624	350.50
12	243-243-312-312-312	14355	108.42
13	312-312-312-312-324	2222	473.53
14	312-312-312-324-324	254	172.40
15	312-312-313-313-313	10962	374.95
16	312-324-312-312-312	3218	124.82
17	312-324-324-324-324	729	171.94
18	313-313-311-311-311	4266	230.60
19	313-313-312-312-312	9649	265.86
20	324-312-312-312-312	3212	807.92
21	324-313-313-313-313	683	189.24
22	324-324-312-312-312	5132	227.73

The 211-231-231-231-231 trajectories with an area of 2,269 hectares are the most extensive. It is followed by 211-211-231-231-231 with an area of 1856 hectares and 211-211-243-243-243 with 878 hectares. The most frequent trajectory is 211-211-312-312-312 with 31691 patches, followed by 211-211-243-243-243 (29578 patches) and 243-243-211-211-211 (24065 patches)

In verbal terms, the largest change in area is the transition from Non-irrigated arable land to Pastures with 3,601 patches with a total area of 2269.18 ha. Regarding capacity for providing Ecological Integrity, both categories are rated as level 3 - relevant capacity, so there is no change in capacity level over time. In terms of capacity level for Provisioning services, after a category change, the level decreases from 2 - relevant capacity to 1 - low relevant capacity, remains at level 1 - low relevant capacity for Regulating services.

Table 9. Trend of development capacity for Regulating and Provisioning services for 22 main trajectories

No.	Regulating services						Provisioning services					
	1990	2000	2006	2012	2018	Trend	1990	2000	2006	2012	2018	Trend
1	1	1	0	0	0	negative	2	2	0	0	0	negative
2	1	1	1	1	0	negative	2	2	2	2	0	negative
3	1	1	1	1	1	unchanged	2	2	2	2	1	negative
4	1	1	1	1	1	unchanged	2	2	2	1	1	negative
5	1	1	1	1	1	unchanged	2	2	1	1	1	negative
6	1	1	1	1	1	unchanged	2	2	2	2	2	unchanged
7	1	1	4	4	4	positive	2	2	2	2	2	unchanged
8	1	1	1	1	1	unchanged	2	1	2	2	2	negative
9	1	1	1	1	1	unchanged	2	1	1	1	1	negative
10	1	1	1	1	1	unchanged	2	2	0	0	0	negative
11	1	1	1	1	1	unchanged	2	2	1	1	1	negative
12	1	1	4	4	4	positive	2	2	2	2	2	unchanged
13	4	4	4	4	0	negative	2	2	2	2	0	negative
14	4	4	4	0	0	negative	2	2	2	0	0	negative
15	4	4	4	4	4	unchanged	2	2	2	2	2	unchanged
16	4	0	4	4	4	negative	2	0	2	2	2	negative
17	4	0	0	0	0	negative	2	0	0	0	0	negative
18	4	4	4	4	4	unchanged	2	2	2	2	2	unchanged
19	4	4	4	4	4	unchanged	2	2	2	2	2	unchanged
20	0	4	4	4	4	positive	0	2	2	2	2	positive
21	0	4	4	4	4	positive	0	2	2	2	2	positive
22	0	0	4	4	4	positive	0	0	2	2	2	positive

Examples of a downward trend in capacity levels for all ecosystem services under review are the transitions from the Non-irrigated arable land category to the Discontinuous urban fabric or

Coniferous forest transitioning to Transitional woodland-shrub. The opposite is the upward trend in capacity levels for all monitored ecosystem services at all-time horizons in the Transitional woodland-shrub category, transitioning to Coniferous or Mixed forest.

6.3. Species diversity loss and the vulnerability of natural landscapes and habitats in the Czech Republic (Paper 4)

Spatial Shifts in Species Richness in Response to Climate and Environmental Change: An Adaption of the EUROMOVE Model in the Czech Republic: Tangwa, E.; Pechanec, V.; Brus, J.; Vyclecka, P https://doi.org/10.3390/d14040235

Detail variations in the stability of landscapes in the Czech Republic from the integration of two main indicators of change, species richness and habitat extent, into the mean stable area indicator (MSAi) according to the EUROMOVE model were presented in paper 3. Comparing change between each modelling period (2018, 2060 and 2100) and the baseline (1990) was the basis for assessing both species and habitat vulnerability. Vulnerability was therefore understood to mean a decline in the MSAi value. For individual species, it meant a contraction of habitat over time. The main climatic factor controlling species distribution included annual rainfall, minimum temperature and temperature of the growing season above 5 ^{o}C, which are highly mediated by the local topography, mainly slope and the drainage system (Fig 23 and 24 Appendix). From the modelled pool of ~687 representative baseline species, species richness varies from 1 to 576, with about 80% of the landscape having 1 to 200 species (Fig 18a). About 2% (~ 11 species) were lost between 1991 and 2018 (Table 10). More than 20% of the baseline species may be at risk of becoming extinct at the end of the 21st century (Table 10). As of 2018, species richness has increased on highlands but will sharply decline under the RCP 8.5 climate scenario (Fig 18b, 18c and 18d).

Table 10. Change in habitat extent, species richness and MSAi with time

Modelling period	Mean area (km2)	Species number	Species lost	Estimated MSAi
1990	22194	686	-	-
2018	23746	675	11	0.99
2060	11544	661	26	0.50
2100	12021	548	140	0.43

At baseline, species were more heterogeneously distributed, becoming more restricted and homogeneous with time (Fig 18a). The simultaneous change in species richness and habitat extent summarized as MSAi is close to 1 for near-natural to natural areas, which are currently confined to highlands around the borders and a few patches of flat areas inland. The average MSAi under the current climatic conditions varied from ~ 0.85 in highlands to ~ 0.3 in lowlands (Fig 19a). The stability of highland habitats is also projected to decline to ~ 0.65 by the end of the century. It is worth noting that the loss of species from 1991 to 2018 was not proportional to the loss of potential habitat extent, which increased by ~ 7 % compared to the baseline.

In general, species habitats have expanded on highlands and declined in low lowlands. The shift in habitat shows that currently, indicator species of Alnus (alder) and Festuca (fescue), typical of lowland habitats, are among the most vulnerable, already showing a net loss of their current habitat extent (Table 11). In contrast, six of the eight tested species have expanded their climate space. The most remarkable expansion was observed for Picea abie and species of salix.

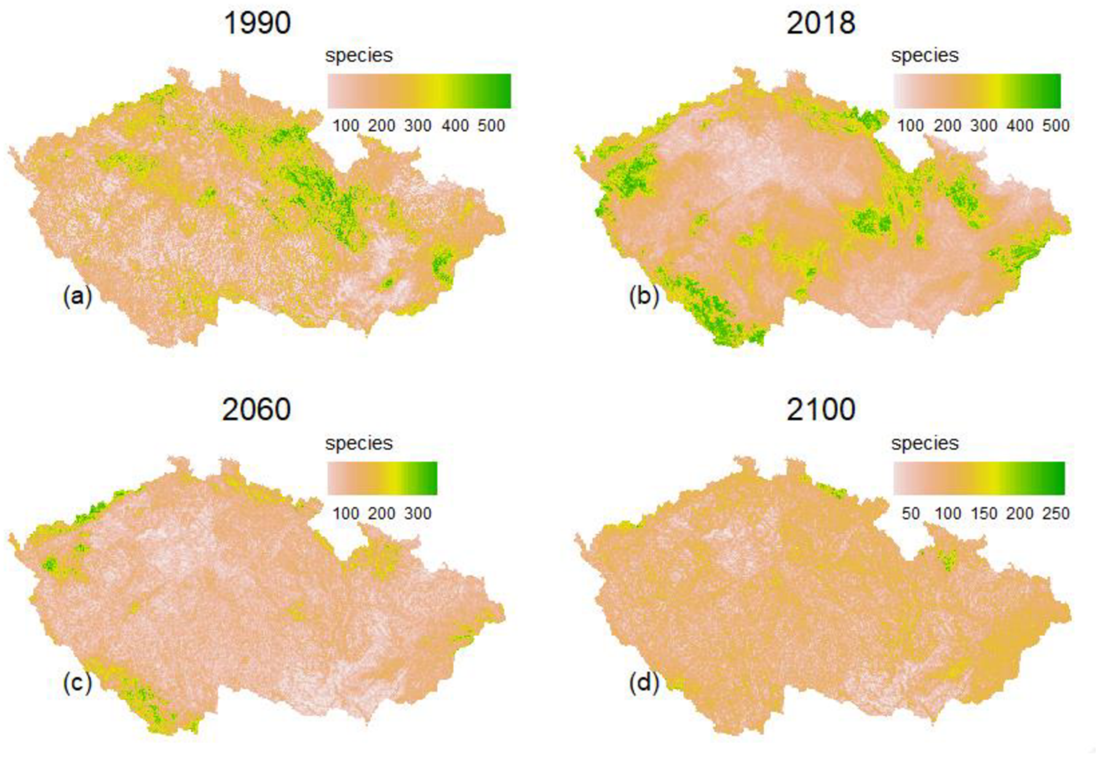

Figure 18: Change in species richness from 1990 to 2100
Future changes are based on the climate scenario(RCP 8.5)

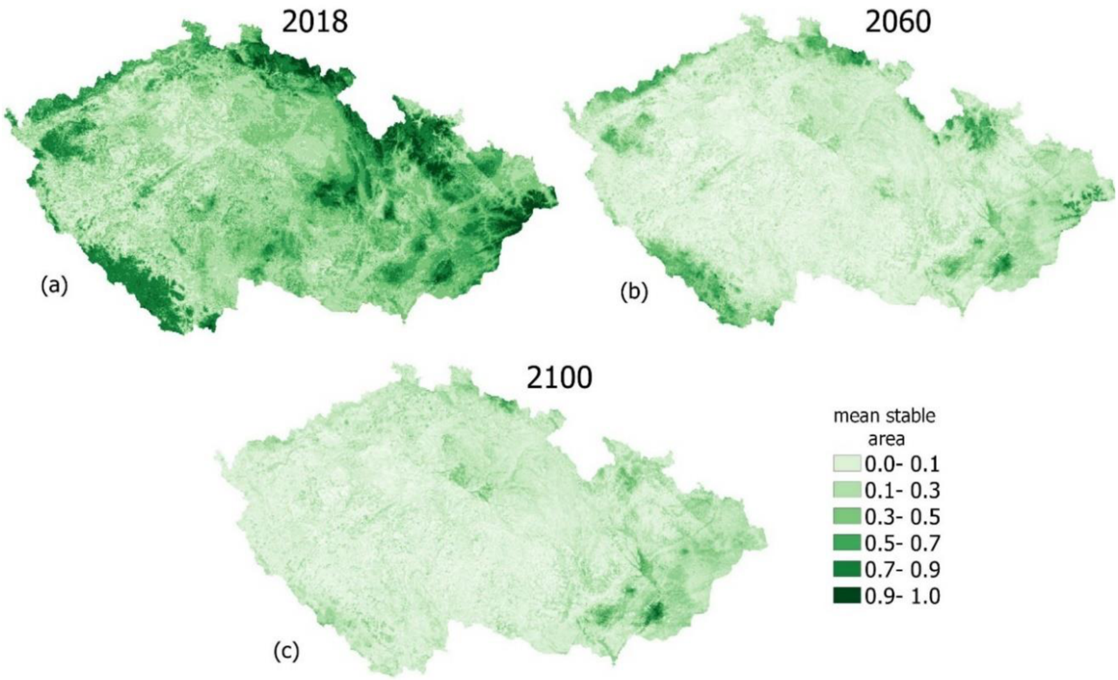

Figure 19. Variability in the mean stable area index (MSAi)

Table 11. Net change in habitat suitability based on Random Forest classification

Species	Net Change (%) 2018[a] −1990
Alnus sp.	−2
Fagus syvestica L.	+10
Festuca. sp.	−1
Picea abie	+42
Poa sp.	+6
Quercus sp.	+5
Rubus sp.	+9
Salix sp.	+26

The presence-only species records in 2018 were modelled before calculating the net change in species loss between 1990 and 2018.

7. DISCUSSION

The response of the selected landscapes in this study was assessed under static and dynamic conditions to improve understanding of their potential for diverse species and ecosystem function. The tested models address these issues differently. In general, the results of this thesis have shown that the development of the selected landscapes is dominantly controlled by climate and topographic variations. While these factors are positively correlated, their influence depends on the scale at which they were studied. At the national and regional scale, the climate is more important. Generally, the current climatic conditions have a milder impact on most species, given that, ~ 2% of the representative species sample tested with the finest climate data for the Czech Republic (paper 4) have been lost since 1990. Similarly, the potential for legume crops based on available suitable land is still high (paper 1). In other words, many species are coping with changes in climatic conditions. However, while climatic conditions are still favourable, the climate range of the species assessed differs. Those with a narrow climate range are the most vulnerable.

Highland habitats are the most stable to climate change and are currently expanding. However, they are expected to shrink with rising temperatures. Under the two scenarios of climate change considered, RCP 4.5 and RCP 8.5, global mean temperatures are projected to rise in the range 1.4 - 1.8^{o}C and 2.0 - 3.7^{o}C, respectively (Knutti et al., 2013). These scenarios are possible global trajectories and were tested to understand local change in a global context. Both scenarios show a shift in species diversity to higher altitudes due to drought and heat stress (Hlásny et al., 2011) (papers 1 and 2). It must remember that while these are the general trend, the response of species growing in the wild is expected to differ from crops grown in the field because the impact of climate in the former situation is further mediated by local the topography and vegetation cover (De Frenne et al., 2021; De Lombaerder et al.,2022).

This research has also shown that micro-climatic conditions created by topographic variation are particularly important at the local scale. The improvement in species mapping from the indicator of topographic heterogeneity, convergence point density (CPD), (paper 2), suggests that its role should not be overlooked in species distribution models, particularly in complex terrains (Guisan and Zimmermann, 2000). Though not explicitly assessed, the interaction between topography variation and climate change suggests that some species are currently restricted to a specific altitude range.

The current trend of landscape development from land use/cover analysis is toward expanding vegetation class (Paper 3). The results are consistent with the current expansion of plant species' habitats (paper 4) and reflect an improvement in regulating services. These trends are discussed in addition to limitations and future research direction in the proceeding sections.

7.1. Landscape evolution and potential for Legume crops.

The purpose of assessing the evolution of the East African landscape and its potential for legume crops was to understand their vulnerability to climate change. It was, therefore, important to calibrate the EcoCrop model for the selected legume crops (paper 1) as the basis for prediction. The calibrated optimum temperature and precipitation range for the selected legume compared reasonably with the FAO base input (Table 2), although deviating by ±5oC and ±200mm, respectively. The high uncertainty with precipitation calibration, especially maximum rainfall, may be traced to the high uncertainty inherent in the precipitation pattern for some locations in East Africa from global circulation models (Ndomeni et al., 2018; Nicholson, 2017). However, the precipitation difference for common beans is so much to be solely attributed to being attributed to calibration error. The deviation may also be because field studies tend to be very localized and not representative of the entire region. However, the fact that optimum conditions are comparable reflects the soundness of expert knowledge with regard to the base input. It further suggests that the approach could be promising for other crops.

Based on calibrated model inputs, our results further show that there is currently a high potential for lentil and field pea production (Ghanem et al., 2015), (Fig 13a and 13b), which appear to be neglected or undocumented. The overlap in the climate ranges of selected legumes (Fig 12 and Table 2) reflects how these legumes can be grown together or substituted for each other. However, their adaptation to extreme conditions is different. For example, the climate range of lentils, pea and beans is very narrow compared to pigeon pea and chickpea (Fig 13i and 13j), which aligns with the studies which show that they can survive on residual moisture to complete their growth (van Loon et al., 2014, Singh et al. 2014).

The integration agro-ecological zone and potential cropland dataset to the output from the EcoCrop model allowed us to understand possible shifts between AEZ and the dominant stress factor limiting crop suitability in each zone. Generally, heat stress will be the dominant factor reducing crop suitability in the future, as Thornton et al. (2009) reported. In addition to heat stress, drought will equally be a limiting factor, especially in the warm semi-arid zones (twsa) and will significantly reduce the agricultural potential of field pea.

The impact of climatic change on landscape suitability and legume production for each selected country will also largely depend on which AZE dominates. The potential for common bean and lentil cultivation in Uganda, Kenya and Tanzania with a large share of suitable arable land is currently within the warm sub-humid (twsh) and the warm semi-arid (twsa) zones. They will shrink considerably. On the contrary, most of the agricultural land in Burundi, Rwanda and Ethiopia with a more stable cool sub-humid and cool semi-arid conditions will continue to be suitable. Although suitability will generally decrease for crops in each country, chickpea and pigeon pea are the most resistant to drought (Singh et al., 2014; van Loon et al., 2018). The decreasing suitability of the warm AEZs is consistent with the findings of Manner et al. (2020), who showed that in the future, most regions with low temperatures will be favourable for legume production in Europe. Therefore different adaptation measures will be needed to optimize legume production in the East African region. For example, shortening crop cycles by delaying planting dates or months (Egbebiyi et al., 2019, Manner et al., 2022) will be ideal for the warm sub-humid zones. Alternatively, switching to drought-tolerant legume variety could be a workable solution for the warm semi-arid zones (Singh et al., 2014; Manner et al., 2022). Generally, chickpea and pigeon pea will be the future legumes for the region. Although these analyses were done on a very coarse scale, the results have highlighted the vulnerability of legumes crops and their production zones in East Africa, which could be the first step in formulating adaptation strategies for the study region.

7.2. Variability in species richness

Mapping variations in species richness in paper 2 was important to understand how local conditions (topography) considered dominant in the forested landslide region have shaped and maintained the current landscape structure and species composition. Therefore, the indicator of such variation, convergence point density (CPD), solely reflects topographic heterogeneity. The results of paper 2 showed that it was a better predictor than primary terrain attributes (Table 1). Slope angle at the original DEM scale moderately correlated with species richness, in agreement with (Pang et al., 2018; Seiwa et al., 2013; Geertsema and Pojar, 2007) but was not sufficient compared to CPD. The improvement in correlation could be explained by the fact the processing of the DEM into convergence points and eventually to convergence point density was more appropriate to capture the heterogeneity of the terrain and varied abiotic conditions at a scale comparable to the scale of field sampling (Leempoel et al. 2015; Lassueur et al. 2006). In other words, the convergence point density raster with a 5 m resolution was closer to the 10 m by 10 m scale of the sample plots than the original DEM with a 1m resolution. The advantage of using convergence points was that it reduced the difficulty of finding the most appropriate scale for independent terrain attributes. This difficulty could be even more challenging when multiple species are involved. We also found that resampling the original DEM attributes to the scale of the convergence point density raster did not improve or significantly explain the variability in species richness (Table 3).

Prior knowledge of the terrain was the basis for selecting and processing slope exposition and inclination into convergence points. Slope exposition was considered in the different typologies of terrain classes (Fig 9) to identify convergence points because it regulates solar radiation and soil moisture, especially in the northern hemisphere (Moore et al., 1991; Franklin, 1995). The improved and significant correlation between species richness and convergence point density agrees with the results of Burnet et al. (1997). While the work of these authors did not focus on convergence points, they equally reported a strong correlation between vegetation type and an indicator of topographic heterogeneity computed from different classes of soil properties, topographic aspect, and slope angle.

The difference in the decrease in spatial dependency implied a weak autocorrelation between species richness sample plots beyond a lag distance of ~170 m (Fig. 16a). Likewise, the two long lag distances, from 0 to 270 m and from 450 to 750m of autocorrelation for convergence point density(Fig. 16b), suggested two possible scales of spatial dependency regarding variability in abiotic conditions (Olthoff et al. 2018; Bolstad et al. 1998). The cross-correlation between NoS and CPD was observed at a much shorter distance lag of ~118 m (Fig. 16c). It may imply an increased likelihood of finding homogenous topographic conditions beyond this distance (Bolstad et al. 1998).

Because ordinary kriging was the only method in which the effect of topographic heterogeneity was not considered, it was the basis for assessing the role of convergence point density. Our results show that the ordinary kriging was the least accurate, having the highest RMSE (Table 4). The predicted species richness based on OK was not so different from the mean species richness of ~32 (Fig. 17a) and reflected the poor fit of its semivariogram. We attributed its poor performance to a weak spatial autocorrelation (Fig. 16a) and the limited sample size of species richness. A sample size of 40 in this study was insufficient to guarantee a stable and accurate variogram considering the complexity of the terrain (Johnston et al., 2001; Webster and Oliver, 1992). Cokriging generally outperformed OK (Goovaerts, 2000; Wu et al., 2006; Han et al., 2003), decreasing the RMSE from 13.71 to 10.54 and predicting much more variability in species richness than OK (Fig 17 and 22 appendix). In agreement with (Goovaerts, 2000), we also observed a better fit of the cross variogram within this lag distance and a significant improvement in prediction when convergence point density and species richness had identical locations (Fig. 16c). The improvement highlights the benefit of detailly accounting for topographic heterogeneity in the study area. However, it is worth noting that the performance of cokriging was still below expectation as we expected the more densely sampled CPD to be fully exploited. We attributed this to the weak spatial cross-correlation between NoS, and CPD (Fig. 16c), explained by the differences in their spatial structure (Rossiter, 2012). Cross-correlation is known to increase as more observations overlap between variables (Rossiter, 2012; Hengl et al., 2004; Wackenagel, 1998; Han et al., 2003)

The overlap is largely a function of the sampling density of the target variable (Han et al. 2003), which further suggests that NoS was not sufficiently sampled to improve its spatial dependency on CPD. Regression kriging performed better than OK and OCK because there was evidence of spatial autocorrelation in the regression residuals (Fig. 6e), in addition to the fact that the residuals were almost normally distributed (Hengl et al. 2007, 2004), (Appendix…). Hence, modelling the spatial structure of OLS residuals decreased the RMSE and significantly increased the correlation between the observed and the predicted species richness (Fig.17e). The effect of modelling without considering the spatial structure of the residual could be seen in the OLS model, which performed relatively well but was the most biased with the highest ME (Table 4).

Due to limited performance, the predicted maps of species composition from ordinary and cokriging methods were too general (Appendix, Fig 22). They showed less variability in species composition at unsampled locations than regression kriging. Hence, regression kriging was more robust to the limited number of observation plots and more stable to topographic variations than OCK (Meng et al., 2013). Therefore, the results have highlighted that the species distribution model for complex terrain can be improved if topographic heterogeneity is adequately captured.

In addition, results can be used as the first step to support short-term conservation efforts, especially when time-dependent changes in species composition are unimportant.

7.3. Land use/cover change and impact on ecosystem services.

The 28-year time series analysis of LULC data has given a general overview of the influence of the past and present natural and human-driven processes on the development of landscapes in the Czech Republic. In general, there is an overall increase in Artificial Surfaces, Forest and semi-natural areas and Inland waters, and a decrease in Agricultural areas (cropland) which is consistent with established trends in the Central European cultural landscape (Machar 2008; Kilianova 2012). The decline in Agricultural areas by 852 km^2 was the largest change, compared to Wetlands with the lowest. The sum of persistent areas from, Coniferous forest, Land principally occupied by agriculture, Mixed forest, Discontinuous urban fabric, Broad-leaved forest and Pastures was over 2000 km^2. The vastness of these cover classes, in addition to Non-irrigated arable land, are major contributors to the prevalence of persistent areas for the entire territory. The sum of highly persistent areas was ~ 33767.3 km^2, compared to ~ 28915.32 km^2 for low-persistence classes. If non-irrigated arable land belonging to this group and occupying almost half of the monitored area is not included, the category area will be only 1580.16 km^2.

The observed transitions in land cover /use classes reflect changes in landscape potential for ecosystem services. In general, transition to a more favourable ecosystem means preserving or restoring ecological integrity and all the processes necessary to optimize its function (Müller and Burkhard, 2007). In this regard, a significant decrease in the capacity level is apparent, for example, in the change from Coniferous forest category to Transitional woodland-shrub. On the contrary, the transition from Woodland to the coniferous or mixed forest is associated with an increase in regulating services, consistent with the findings of (Frélichová et al., 2014). Based on persistent classes, the high persistence of non-irrigated arable land, with ~5968 patches and an area of ~27335.15 ha in all five monitored periods, suggested the capacity level for Provisioning services is at level 2 - relevant capacity, and level 1 for Regulating services. Generally, the capacity for Provisioning services in the Czech Republic is at a lower level of relevant capacity (0 -2) mainly because of the urban development.

On the contrary, the potential for Regulating services has increased over time mainly because of the expansion of areas of higher relevant capacity. While these results are yet to be validated, changes in selected services from the trajectories of land use/cover development for the Czech Republic have shown that landscape conservation needs to be intensified. At the same time, the expansion of urban areas should be restricted.

7.4. Landscape vulnerability and loss of species diversity due to climate change

The impact of climate and environmental change on individual species distribution is very diverse but varies with the local topography. Species richness has slightly declined under the current climate as more than 97 per cent of the representative baseline species are currently preserved in most areas (Table 5). The change is due to the near stable climate between the two modelling periods, which shows that the average minimum temperature was nearly the same between these two periods. The mean temperature of the growing season increased by 0.85 °C, while the mean length of the vegetation period increased by three days (Appendix, Table 13). Although species richness is nearly the same, species habitat expanded remarkably between the two modelling periods as growth conditions have become more favourable for most species. While these conditions have extended highland habitats where low temperature is a limiting factor for growth (Lindner et al., 2010). The results of paper 4 suggest that a further rise in temperature will be devastating, resulting in a decline in species composition and contraction of habitat extent as the average minimum temperature and the growing season temperature rise by +5 °C and +3 °C, respectively (Supplementary material). These results are comparable to those of Hlásny et al., (2011); Machar et al., (2017). They showed heat spells might become frequent in lowland habitats under a moderately mitigated climate scenario. As growth conditions under the baseline climate scenario may become too extreme for most species, these results should be interpreted with caution because they are only a simulation of what may be possible(Raskin, 2005; Riahi et al., 2011; van Vuuren et al., 2011).

The spatial pattern of MSAi values has reaffirmed that the most stable areas of the Czech Republic are currently restricted to protected and mountainous areas (Figure 18b). Their MSAi values range from 0.7 to 0.94 but may drop from 0.5 to 0.8 by 2100 without intervention or mitigation efforts. Lowlands with the least species variety are the least stable and the most vulnerable. Our results show more variability in the MSAi ratio for the Czech Republic than the regional EUROMOVE model for Europe (M. Bakkenes et al., 2002; Michel Bakkenes et al., 2006). A possible reason for the difference could be that we modelled change based on 686 species for the Czech Republic compared to 430 species for the entire Czech Republic, Slovakia, and Hungary in the regional EUROMOVE model (MBakkenes et al., 2006). The extra details also highlight the benefits of using high-resolution climate and environmental data to account for local variations (Pearson et al., 2004).

The advantage of quantifying change as MSAi is that additional information about the state of the landscape, which is more related to ecosystem functions than species richness alone, is known (Burkhard et al., 2009; Pechanec et al., 2019). Experimental studies have generally associated a decline in species richness with a decline in biomass production, leading to a 20 per cent loss in species as a proposed threshold for stable ecosystems (Hooper et al., 2012). The application of such species-based thresholds in nature has been questioned due to inconsistencies in the underlying processes that affect species richness (Vellend et al., 2013). Our results also show that species loss may not be proportionate to potential habitat loss. (Table 5). Second, losing a few dominant species may drastically shrink or expand habitats, impacting selected ecosystem functions and services. Thus, integrating both parameters to obtain information about the state of landscapes, we expect vulnerability thresholds established from MSAi to be more reliable and applicable than those based solely on species richness. While MSAi does not explicitly quantify ecosystem function, our result also shows that it may be used as a validation tool or dataset to supplement such studies because changes in stable areas are based on surveyed records. Stable areas can be compared to favourable or persistent areas of land use /cover classes preserved or appearing over time as the basis for assessing ecosystem function and services in paper 2 (Krkoška et a.,2016; Pechanec et al., 2019). Therefore, the detailed spatial variation in MSAi has highlighted highly vulnerable areas where a decline in species richness relative to habitat extent should be accompanied by a loss of key ecosystem functions and services.

The response of the eight selected species justifies grouping species with nearly the same ecological requirements into distinctive FVZs as an effective management option for biodiversity in the Czech Republic. Generally, species most tolerant of high precipitation, including alder, beech and spruce, become more adaptable as minimum temperature decreases (Hlásny et al., 2011; Machar et al., 2017). These species typically prefer well-drained soils and are expected to thrive on moderate to steep slopes. In contrast, species tolerant of low and moderate precipitation, including fescue, poa, oak, blackberry, and willow, prefer gentle slopes where soil moisture is high, and drainage is low to moderate. Because some of these major species impact the distribution of understory species, current efforts should focus on their preservation. Appropriate species mixing in the different FVZs could be adapted as a long-term strategy to buffer the most vulnerable species and minimise further species loss (Pretzsch, Schütze, & Uhl, 2013). The selected species' response also reflects how habitats have shifted within the main forest vegetation zones of the Czech Republic from 1990 to 2018. The results in Table 6 show that habitat contraction has occurred primarily in the first, second and third FVZs, typical of lowlands and dominated by alder, oak, and fescue species. Habitat contraction has been accompanied by a wider expansion in the higher (sixth to eighth) FVZ, where spruce and willow species dominate. These trends are consistent with the works of (Čermák et al., 2018; Hlásny et al., 2011), who attributed the shift to rising temperatures and decreasing precipitation in the lower FVZs.

7.5. Limitations and future research

The limitations of this research are linked to data quality, modelling approach and study design. The main data quality issues in assessing landscape potential for legume crops (paper 1) included the fact that crop location data was sourced regardless of the legume variety. Applying the same modelling approach to different varieties can be problematic as they tend to adapt differently to change (Manner et al., 2022). Second, while input parameters for the EcoCrop model were relatively comparable to the base parameter, the accuracy could best be assessed with local climate data (Ramirez-Villegas and Challinor, 2012), which was not available for this research. Therefore, the predicted shift in AEZ or the contraction of cropland, though consistent with existing studies, could be ascertained given that it was based on a much coarser dataset at 5 minutes degree. Hence, we may have missed spatial variability at the country level. The main data quality issue in paper 2 was the insufficient sampling of species richness. Secondly, although the indicator of topographic heterogeneity was densely sampled for geostatistical methods, it was not robust enough because it could not completely capture the spatial pattern of abiotic conditions in the study area. Hence the need for a more robust indicator. The limitation of the Chorine Land Cover (CLC) data is that it was too coarse to capture change at the national level. However, this should not be a problem in future studies as work is in progress to improve land use and land cover for Europe with the availability of high-resolution sentinel 1 and 2 datasets. In paper 4 (EUROMOVE model), climate impact was assessed on RCP 8.5, which is currently considered unrealistic even though it is still very popular in the Czech Republic. The RCP 8.5 of the CMIP 5 experiment have been criticized because it does not consider current global or country-specific efforts such as substituting coal with clean and renewable energies to reduce greenhouse gas emissions (Riahi et al., 2011). Hence an objective assessment based on a mild or moderate climate scenario is highly recommended for future studies.

Model limitations, for example, EcoCrop, are linked to the exclusion of biophysical factors like soil factors or critical climatic conditions (Manners et al., 2021; Piikki et al., 2017). The inclusion of these variables in future studies will not only make the model comparable to process-based crop models but will also increase its practical application. Hence a more accurate way to assess the vulnerability of AEZ from the model may include using a local AEZ map of the region. Alternatively, parameters critical to sustaining growth in the respective climate zone may be integrated into the model.

The limitation of the geostatistical method, especially ordinary and cokriging, is that these models are very sensitive to limited samples and could not accurately capture changes in species richness. This limitation makes conventional geostatistical methods less attractive than non-linear or hybrid methods. However, a possibility to further test the model in future studies is to summarise the entire plant community using ordination techniques and predict the ordination scores (Olthoff et al., 2018; Maestre et al., 2005; Kienel and Kumke, 2002). These authors found this approach successful in identifying and predicting spatially structured communities.

A drawback with the MSAi indicator in paper 4 is that it is limited in understanding biodiversity loss at the habitat or ecosystem level. It should be noted that this limitation was considered in the study design with the possibility of addressing it by equally adapting the GLOBIO model for climate change. Unfortunately, it was impossible because some of the existing cause-effect coefficients for ecosystems and biotopes in the Czech Republic are yet to be validated. The GLOBIO modelling approach is particularly promising given that it is based on habitat data rather than species data, implying a better understanding of biodiversity change. It is worth noting that the major drivers of biodiversity loss in the Czech Republic, excluding climate change, have been tested and adapted as GLOBIO-CZ (Pechanec et al., 2021). Therefore it was hoped that once assessed for climate change and integrated into GLOBIO-CZ will improve understanding of the current state of biodiversity in the Czech Republic. Moreover, given that MSA in GLOBIO also assesses the stability of the ecosystem, the result will also be useful to assess the potential for the selected ecosystem category and whether they are comparable with those captured from the trajectory of land use and cover change in paper 3.

8. CONCLUSIONS

Spatial processes are very complex. Hence a range of tools or models may be tested to understand them. Part of the complexity has to do with the fact that spatial processes operate at different scales. As such, processes captured at a particular scale by a given model may not be the case on another scale. Therefore scale is crucial to understanding ecological processes. This thesis explored a range of spatial modelling approaches to improve understanding of landscape development, mainly due to climate change but also due to topography and land use and cover change across multiple scales. Therefore the issues investigated are the spatial patterns of species and changes in vulnerability of habitats, the role of topographic heterogeneity in the evolution of plant species, especially in complex terrain and the trajectories of land use and land cover change and its impact on Provisioning and Regulating ecosystems services in the Czech Republic. Hence, the modelling approach tested (EcoCrop, Geostatistical model, EUROMOVE and a custom land cover change model) adapted to specific scales. Hence, each tested model captured specific aspects of the landscape development.

The detailed model results are presented in chapter five and related publications. The main findings were.

- The current climate has a milder impact on species which are already shifting to higher altitudes (papers 1 and 4)
- Highland habitats are the most stable and slowly expanding but will shrink with rising temperatures. (papers 1 and 4)
- The current trajectory of land use/cover change is an overall expansion of vegetation which has increased the potential for regulating ecosystem services. However, the potential for provisioning services is declining due to urban expansion (paper 3)
- Micro-climatic conditions created by topographic heterogeneity are particularly important at the local scale and can improve species mapping if adequately captured
- Landscape development is dominantly controlled by climate change and topographic variation. The former dominate at the national to regional scale while the latter dominates at the local scale

Theoretically, this thesis has reaffirmed the growing evidence of climate change on the development of landscape and range shift in species distribution. The main output is the assessment and quantification of changes in the stability of landscapes. For the Czech Republic, such changes are associated with a loss of species diversity and selected ecosystem services. For the East African region, change implies the production zones for legumes with narrow climate ranges will shrink drastically even under a moderate climate scenario.

There is a need for a detailed assessment of individual habitats, Ecosystems or crop production zones to further our understanding of landscape vulnerability and their potential for ecosystem services (paper 3). For the Czech Republic, GLOBIO is a promising model to address these issues because it has already been tested and locally adapted as GLOBIO-CZ (Pechanec et al., 2021) for other drivers excluding climate change. Hence once tested for climate change and integrated into GLOBIO-CZ should better describe both biodiversity and habitat situation in the Czech Republic. It will also be possible to validate the GLOBIO model results with results from EUROMOVE, which is based on field observations. Therefore the model results of landscape development in the Czech Republic complement each other in one way or the other. In summary, spatial models are powerful tools for studying ecological processes. This study has shown that their power lies in the possibility of integrating expert knowledge with empirical approaches.

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APPENDIX

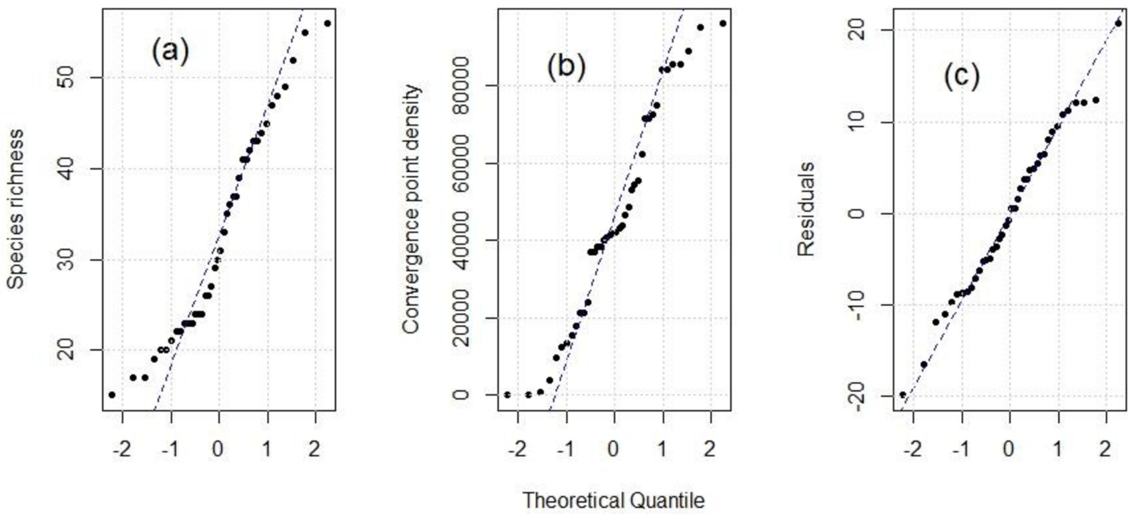

Figure 20. Quantile-Quantile plot of target and covariable.
(a)species richness, (b) convergence point density, (c) residuals of OLS between species richness and convergence point density. Supplementary figure paper 2

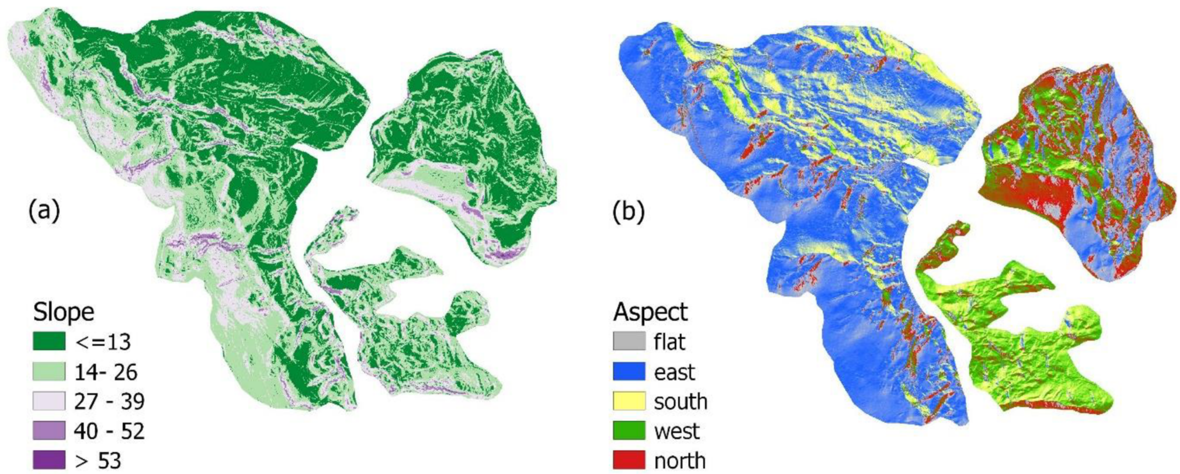

Figure 21: Topographic variation. (a) slope angle, (b) slope exposition (aspect),

derived from a 1 m DEM. Supplementary figure paper 2

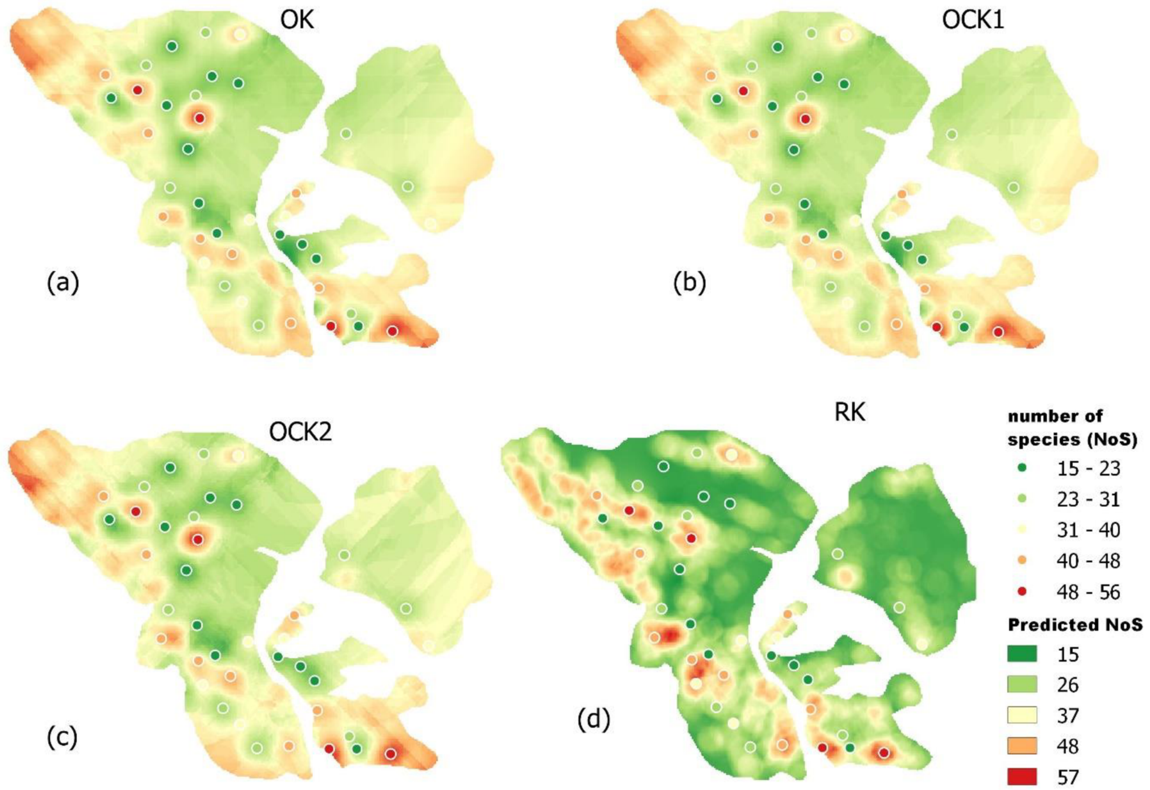

Figure 22. Predicted variability in species diversity

(a) Ordinary kriging (OK), (b) Ordinary cokriging (OCK), (c) Regression kriging (RK) and (d) Ordinary least squares regression (OLS). Supplementary figure for paper 2

Table 12. Land cover devlopment in the Czech Republic in five periods from 1990 to 2018 *(supplementary table for paper 3)*

TAG	Land Cover category	1990	2000	2006	2012	2018[1]
111	Continuous urban fabric	14.64	14.64	15.67	15.67	15.7
112	Discontinuous urban fabric	3578.5	3625.85	3783.53	3825.26	3947.14
121	Industrial or commercial units	521.2	547.73	602.11	631.01	656.45
122	Road and rail networks and associated land	48.07	52.73	62.6	72.09	71.88
123	Port areas	1.5	1.5	0.79	0.79	0.79
124	Airports	56.09	56.27	53.31	53.01	54.69
131	Mineral extraction s ites	180.63	171.02	165.56	169.35	179.59
132	Dump sites	154.61	138.86	94.55	79.4	59.94
133	Construction sites	21.24	8.57	23.44	10.9	15.12
141	Green urban areas	65.26	65.55	66.88	66.58	67.15
142	Sport and leisure facilities	117.71	127.33	158	173.34	185.86
211	Non-irrigated arable land	35541.03	32621.67	29891.77	28991.31	28705.47
221	Vineyards	110.77	119.42	156.92	164.66	169.04
222	Fruit trees and berry plantations	328.21	326.44	313.9	294.06	262.8

231	Pastures	2527.62	5317.05	7185.62	7943.93	8067.84
242	Complex cultivation patterns	415.34	429.53	476.2	472.53	473.94
243	Land principally occupied by agriculture, with significant areas of natural vegetation	6736.18	6747.69	7079.4	7114.46	7128.05
311	Broad-leaved forest	2495.24	2527.4	2783.22	2838.85	2833.73
312	Coniferous forest	16552.1	16992.92	17226.97	17126.26	16658.11
313	Mixed forest	5854.94	6042.24	6173.85	6336.97	6436.94
321	Natural grasslands	404.64	392.04	261.97	256.63	251.92
322	Moors and heathland	26.52	27.39	18.15	18.15	22.58
324	Transitional woodland-shrub	2486.74	1869.7	1598.99	1528.7	1909.01
332	Bare rocks	2.1	2.1	1.48	1.48	1.97
333	Sparsely vegetated areas	0	0	1.15	1.45	3.79
334	Burnt areas	1.17	0	0	0	0
411	Inland mars hes	53.54	53.36	60.84	60.84	60.99
412	Peat bogs	37.5	37.11	46.72	45.52	45.68
511	Water courses	42.8	43.01	44.78	45.16	46.56
512	Water bodies	492.89	509.67	520.43	530.44	536.08
	Total	78868.8	78868.8	78868.8	78868.8	78868.8

[1] The area of each year is in km^2

Table 13. Summary statistics of the main climate indices for 1990 and 2018.
(supplementary table, paper 4)

	Anrain		Tcold		Tempgs		Lenvegt	
	Min	**Max**	**Min**	**Max**	**Min**	**Max**	**Min**	**Max**
1990	445	1345	−8.0	−2.9	9.1	13.8	151	240
2018	352	1713	−8.3	−3.3	9.6	15.0	116	281
2060	457	1541	−6.8	0.7	10.4	15.0	154	283
2100	480	1617	−4.1	3.6	12	15.8	173	324

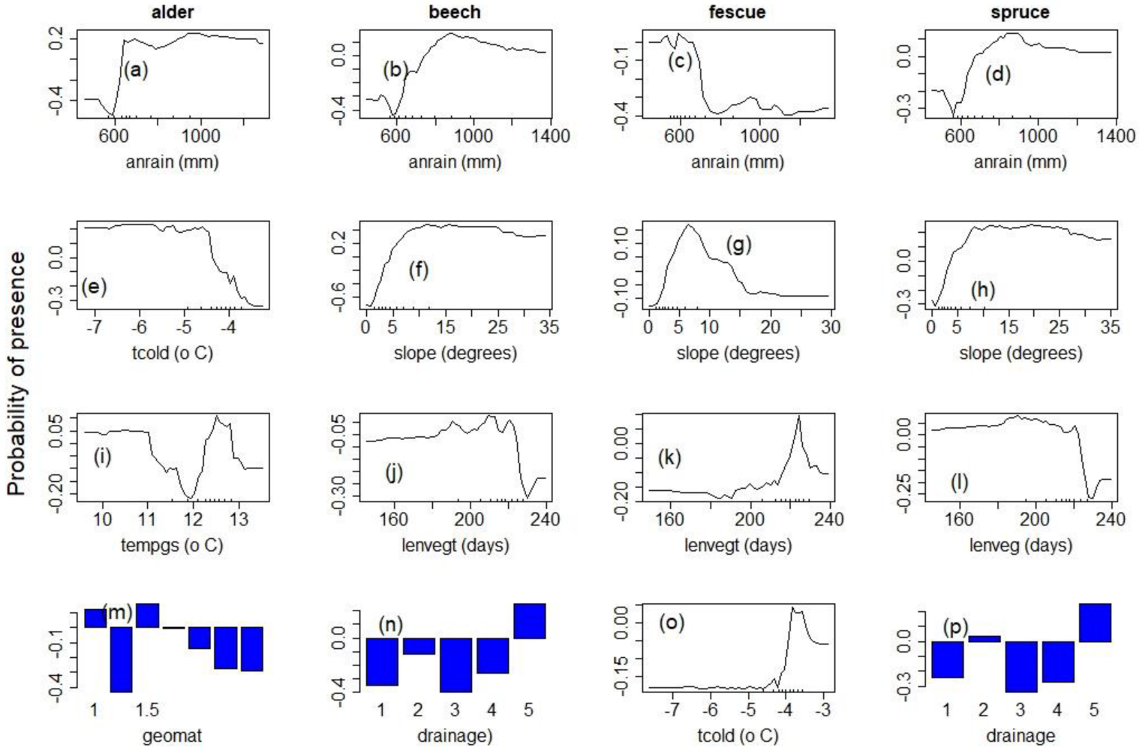

Figure 23. Species response to climate and environmental conditions.

Panel 1: alder, panel 2: beech, panel 3: fuscue , panel 4: spruce. Supplementary figure (paper 4) "anrain" = annual rainfall; "tcold" = average minimum temperature; "tempgs" + temperature of the growing season; "lenvgt" = length of the vegetation period and "geomat" = geological material.

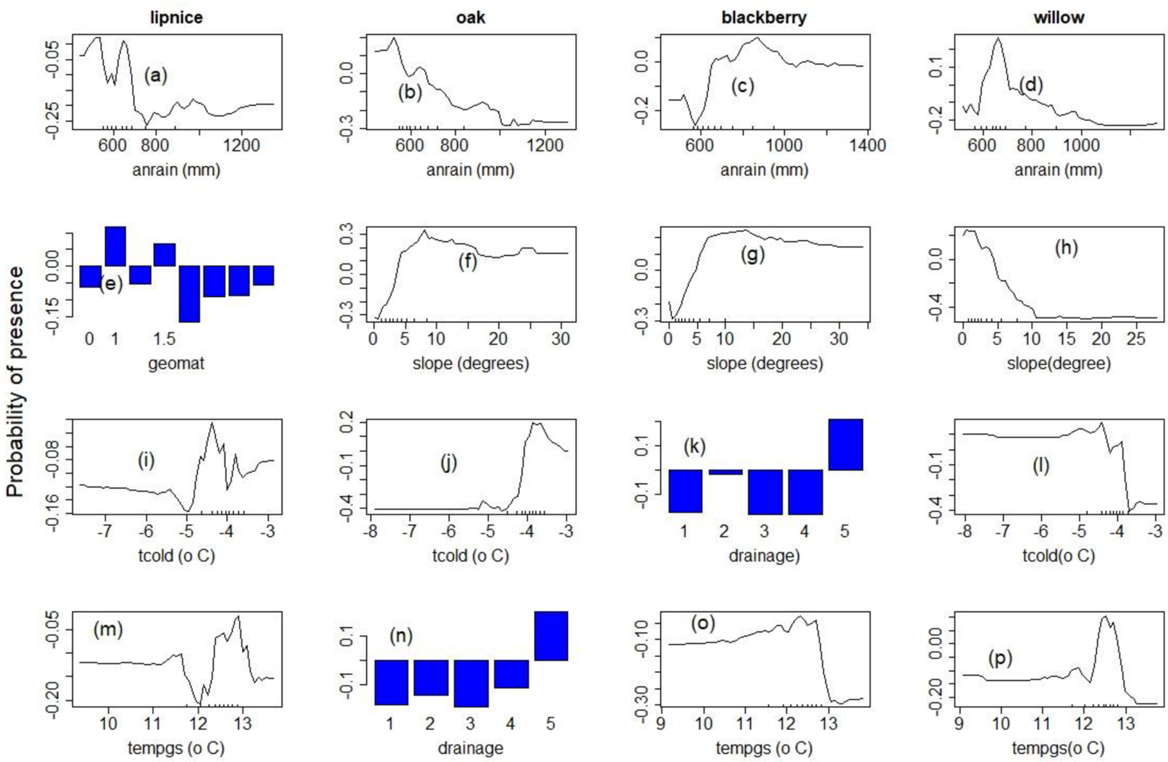

Figure 24 Species response to climate and environmental conditions.

Panel 1: lipnice, panel 2: oak, panel 3: blackberry , panel 4: willow. Supplementary figure (paper 4) "anrain" = annual rainfall; "tcold" = average minimum temperature; "tempgs" + temperature of the growing season; "lenvgt" = length of the vegetation period; and "geomat" = geological material.

Table 14 Comparison model evaluation result for selected species.

Supplementary table (paper 4)

		Classification Methods		
Evaluation Metrics	**Species**	**Maxent**	**Random Forest**	**GLM (Logistic)**
	Alnus sp., n = 544 sites, subspecies = 2			
AUC		0.80	0.79	0.70
TSS		0.54	0.46	0.34
	Fagus syvestica L., n = 884 sites, subspecies = 1			
AUC		0.79	0.82	0.80
TSS		0.52	0.50	0.44
	Festuca sp., n = 9031 sites, subspecies = 11			
AUC		0.64	0.78	0.62
TSS		0.62	0.41	0.17
	Picea abie, n = 16,301 sites, subspecies = 1			
AUC		0.73	0.75	0.73
TSS		0.58	0.39	0.34

Poa sp., n = 6215 sites, subspecies = 6			
AUC	0.66	0.80	0.58
TSS	0.59	0.44	0.13
Quercus sp., n = 4939 sites, subspecies = 3			
AUC	0.76	0.82	0.75
TSS	0.57	0.50	0.38
Rubus sp., n = 16,899 sites, subspecies = 4			
AUC	0.69	0.80	0.69
TSS	0.58	0.47	0.28
Salix sp., n = 617 sites, subspecies = 2			
AUC	0.76	0.79	0.71
TSS	0.50	0.47	0.29

Palacký University
Olomouc

Faculty of Science

Department of Geoinformatics

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Field of study: **Geoinformatics and Cartography**

SPATIAL MODELS OF LANDSCAPE RESPONSES TO CLIMATE CHANGE

DOCTORAL THESIS SUMMARY

Mr Elvis TANGWA

Supervisor: **assoc. prof. Vilém PECHANEC**

Olomouc 2022

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1. Introduction

The extent and quality of natural landscapes worldwide and their potential to support humanity through the goods and services they provide are declining. The decline is directly or indirectly related to climate change and human activities, including deforestation, intensive agriculture, and infrastructural development(Cardinale et al., 2012; Ramankuttyet al., 2008). These human-related processes have degraded landscapes much faster than climate change, increasing the volume of greenhouse gases in the atmosphere. Thus, the strong and positive relationship between land use and climate change has given rise to landscapes different in composition and structure, affecting species abundance and the quality of life for communities (Alkemade et al., 2009; Arets et al., 2014; ten Brink, 2007). Depending on the rate of change, species that cannot survive within a specific climate range migrate or disappear with time (Bakkenes et al., 2002; 2006; Thomas et al., 2004). Likewise, potential cropland has reduced in some regions, followed by changes in planting dates, flowering dates, and other phonological adjustments (Beebe et al., 2011; Ramirez-Villegas et al., 2013; Egbebiyi et al., 2019)

Climate impact has been felt and seen in almost every location. However, the scale of devastation from such changes varies with region and is often mediated by vegetation cover and the local topography (De Frenne et al., 2021; De Lombaerde et al., 2022). In water-deficient regions, rising temperatures above the global average have increased the frequency of heat spells and droughts. While in cold and mountainous regions, conditions have become favourable for most species as the length of the growing season has increased (Lindner et al., 2010). The broad question is, to what extent or how long will these "buffer zones" and their species persist, given the current pace of climate change?

Scientists and ecologists try to answer this and related questions by incorporating climate scenarios and their greenhouse emission pathways (Riahi et al., 2017; van Vuuren et al., 2011) into spatial models (Alkemade et al., 2009; Bakkenes et al., 2006; Schipper et al., 2020) which are often studied at different spatial scales. They vary from expert-based to empirical models or a combination of the two, also known as hybrid models. Those tested in this thesis included the **EcoCrop, EUROMOVE, Maxent, geostatistical models, and a custom mode**l to assess land cover change. These models differ in how they capture and quantify change. They also differ in their scope and scale of application.

Therefore, **the motivation for this thesis was to test these models to improve our understanding of landscape evolution at different spatial scales which should be important to understand the change in species diversity and the potential for ecosystem services**. The scale of the study varies from regional to national and field-scale. This thesis has three main objectives presented in four papers. They each address specific research questions that build up and strengthen the overall hypothesis of the thesis.

2. Aim and Objectives

This thesis aims to test suitable **spatial models explaining the evolution of landscapes leading to biodiversity loss and a decline in the agricultural potential of selected legume crops**. Existing spatial models capturing these changes differ in their scope of application, algorithms and the level of details. Moreover, biodiversity is a broad concept often studied at different levels using different models to be understood. Based on this hypothesis, this thesis **seeks to understand the specific response of different landscapes, mainly to climate change and change mediated by the local topography.** The selected landscapes are in central Europe and East Africa and differ in complexity, number, and type of species to be modelled. The objectives leading to the fulfilment of this aim include.

OBJECTIVE 1: Modelling landscape potential for selected legume crops in East Africa

The East African region is one of the most vulnerable on the African continents to climate change, with a high frequency of droughts, torrential rains, and floods (Nicholson, 2017). Agriculture in the region is dominantly rain-fed across diverse agro-ecological zones (Fischer et al., 2008) with varying sensitivity to climate change and soil degradation.

The first objective of this research was to understand how the agricultural landscapes of East Africa will evolve with changing climatic conditions. Five legume crops, including **common bean, pea, lentils, chickpea, and pigeon pea**, were tested using the EcoCrop model implemented in DivaGIS and in TerrSet-CCAM software. **The default temperature and precipitation ranges for the key climate indices used in the model are too generic**. They may not accurately reflect the spatial pattern of these crops under current and changing climatic conditions. Hence, there was a need to fine-tune the model parameter and compare regional input with the generic input parameter. There was also a need to assess the vulnerability of the different agro-ecological zones of the region to climate change. Thus, the question is:

- What will be the spatial response of agro-ecological zones in the East African region to climate change, and how will it affect the agricultural potential of the selected legumes?

OBJECTIVE 2: Modelling changes in species richness in response to climate and environmental change

Habitats are shifting to higher altitudes and mountains in response to climate change (Michel Bakkenes et al., 2006; Thomas et al., 2004). However, in mountainous and heterogeneous terrains, species distribution is dominantly controlled by environmental conditions and the local topography (Geertsema & Pojar, 2007; Pang, Ma, Lo, Hung, & Hau, 2018; Seiwa et al., 2013; Tracz et al., 2019; Guisan & Zimmermann, 2000).

Objective -2 was to **characterise topographic heterogeneity as convergence points density from a 1m digital elevation model (DEM)** within the Outer (Flysch), Upper Carpathian forested landslide region, south Poland, and assess its usefulness as a surrogate of species richness. Slope exposition (aspect) and slope inclination (slope) are important factors in the species distribution models with overlapping roles. However, **we still do not adequately understand how they supplement each other or how they can be integrated into a surrogate of species distribution**. Mapping species richness from a surrogate of topographic variation, in this case, was based on the fact that field sampling in such terrains is challenging. Second, there is evidence that locations with strong topographic heterogeneity are potential sites for the evolution and succession of new species (Geertsema & Pojar, 2007; Pang et al., 2018; Seiwa et al., 2013; Tracz et al., 2019). Therefore, it was argued that if a strong positive correlation exists between species richness and an indicator of topographic heterogeneity, the indicator should be a useful predictor of species richness. Thus, the question raised in this sub-objective needing research is:

- Can we use an indicator of topographic heterogeneity to improve species mapping in such complex terrains?
- Which spatial models will be most appropriate?

OBJECTIVE 3: Modelling the loss of habitat naturalness and changes in providing ecosystem function in the Czech Republic

There are diverse landscapes and ecosystems in the Czech Republic, which also vary considerably in extent (Pechanec et al., 2021; 2019). However, **how different classes of land use or land cover will evolve and change landscape potential for ecosystem services is not well known**. Likewise, the evolution of landscapes in the Czech Republic from their near-natural states under the influence of climate change, leading to the loss of species and their habitats, is not well known. Available results are mostly regional and often based on global datasets, which may not reflect the actual situation (Bakkenes et al.,2006; Alkemade et al., 2009; Lindner et al., 2010; Verboom et al., 2007).

The third objective has two parts. The first part is to understand trends **in the evolution of landscapes in terms of change in land use categories as a base for assessing landscape capacity for provisioning and regulating ecosystem services over the last 28 years** (1990, 2000, 2006, 2012, 2018) based on the Corine landcover datasets. To that end, an expert-based ecosystem services matrix developed by Burkard et al. (2009) was used as the standard for assessing landscape potential. For the selected category of ecosystem services, the focus was not on individual services but all possible services associated with each.

The second part was to **model the loss of habitat naturalness in the Czech Republic from changes in the current and future trends in species richness**. To that end, the EUROMOVE modelling approach and its indicator of change, the mean stable area index (MSAi), was adapted as the first attempt to quantify the vulnerability of landscapes to species loss. Vulnerability is also assessed for the most common species under the current climatic conditions; however, mediated by the local topography and hydrogeological conditions. A more detailed assessment of the vulnerability of the main ecosystem of the Czech Republic to climate based on the GLOBIO modelling framework was also envisaged depending on the research progress and time constraints. Thus the questions raised in the third objective are:

- How vulnerable are landscapes or ecosystems in the Czech republic to climate change and biodiversity loss?
- How has climate and or land use/cover change affected provisioning and regulating ecosystem services in the Czech Republic

The relationship between the research aim and objectives, including the specific issues to be investigated, is summarized in Fig 1.

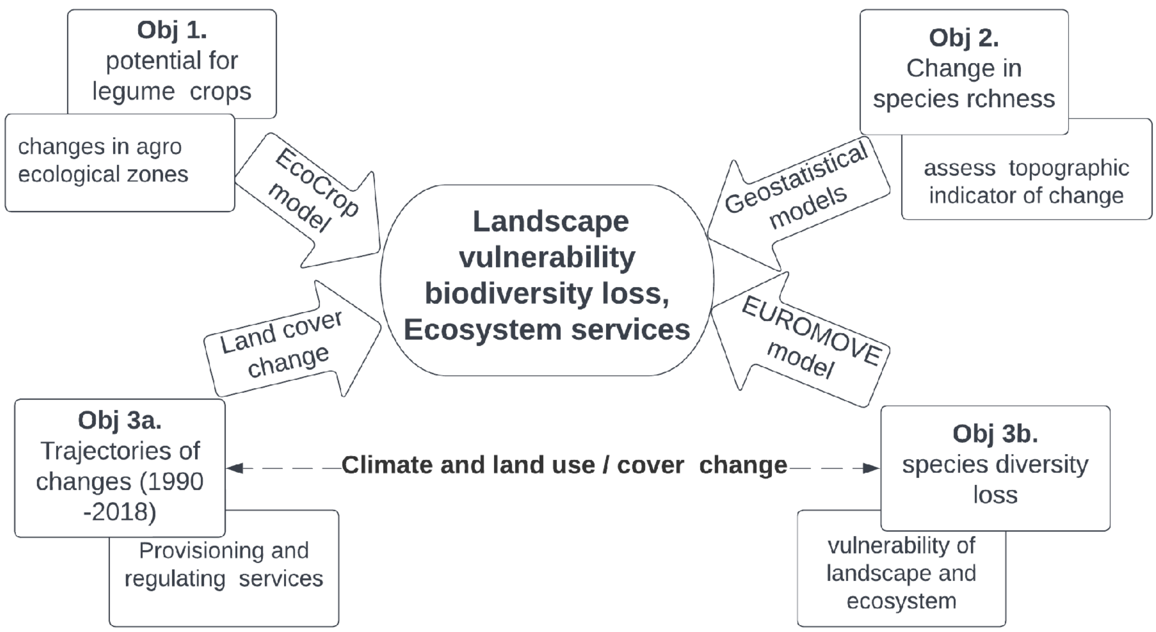

Figure 1. Summary of research objective and relationship to the aim of the research

3. Literature Review

Habitat potential for diverse species and ecological functions is controlled by abiotic and biotic processes operating on landscapes (Turner et al. 2001). Together with human-induced processes such as land transformation for agriculture, road construction and infrastructure is the cause of landscape heterogeneity (Turner et al. 2013; Kienast et al. 2007, pp 177 -192; Forman 1995b; Oliver et al. 2010); a well-recognised principle explaining biodiversity patterns and ecosystem functions (Burkard et al. 2009; Schroter et al. 2005). Because landscape heterogeneity is expected to be stronger with changes in topographic and climatic conditions; the spatial scale at which heterogeneity can be best captured continues to be a challenge in ecological studies (Turner et al. 2001, Bailey et al. 2007, Jung et al., 2017, Pearson et al. 2004, Trivedi et al. 2008). Scale is particularly important because it is the basis for accurate prediction, sound policies and best practices on landscape adaptation to optimise the goods and services they can provide (Opdam et al., 2009; Wiens, 1989).

Among these processes shaping landscapes and impacting biodiversity, land use and climate change have been recognised as major drivers of change because they are global (the intergovernmental panel on climate change - IPPC). The impact of unstainable land use, especially in agriculture, is also well recognised by the IPPC (2019) as a major contributor to greenhouse gases (CO_2, CH_4 and N_2O). Every change from one land use/cover type to another changes the potential for particular ecosystem services (Foley et al., 2005; Burkard et al., 2009; Pechanec et al.,2019). However, **our understanding of how both drivers synergistically impact biodiversity and ecosystem function, especially at the local scale, which could lead to better adaptation measures, is not well known** (Schroter et al., 2005, Newbold et al., 2018; Opdam et al. 2009; Opdam and Washer 2004). The relation between land use/cover climate change and scale effect is shown in Fig. 2.

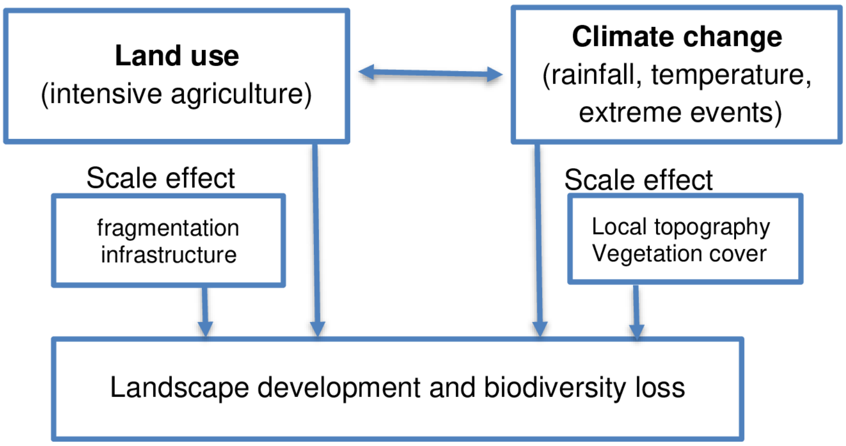

Figure 2. Relationship between land use, climate change scale effect and biodiversity.

Spatial Models

Spatial models are simplified representations of reality based on Geographical Information Systems to improve understanding and decision support (Longley et al., 2011). Their building blocks are raster or vector data models (chapter 3). They may be deductive or inductive (Overmars et al., 2007). The former follows a "bottom-up" approach, integrating components of individual data models through overlay operations and some form of weightings based on expert opinion to develop habitat suitability models. The latter follows a "top-down" approach and depends on empirical data and statistical methods (Johnson & Gillingham, 2004). Deductive models have low precision with limited validation options, unlike inductive models. Hence, they are less common in biodiversity and ecological studies. However, they are still useful where data is scarce, and baseline information is needed to guide empirical studies (Overmars et al., 2007). Spatial models may be static, dealing with the state of spatial data or phenomena at a given time or may be dynamic, emphasizing time-dependent changes (Wainright and Mulligan, 2004). Both allow predictions that may be deterministic (empirical) or stochastic, applying statistics, probability and machine learning algorithms. Deterministic models are mainly correlative or descriptive to the specific conditions. They say little about underlying processes. Stochastic models attempt to explain random processes, allowing predictions beyond environmental conditions and observation scales (Wainright and Mulligan, 2004). However, stochastic models are highly uncertain as they may not adequately capture all causal factors for a particular phenomenon. This limitation points to our limited understanding of environmental systems and explains why models are often calibrated or evaluated with independent observations of the current situation before future predictions can be made (Guisan and Zimmerman 2000; Verboom and Warmelink 2005).

Spatial ecological models may also be mechanistic. In which case, they are based on prior knowledge and actual cause-effect relationship of processes determining the establishment and survival of species in a given environment. In other words, they incorporate physiological, behavioural, biotic and abiotic interactions and are thus the closest to reality (Dormann et al., 2012; Kearney and Porter, 2009). However, mechanistic models can be extrapolated to other scales with a loss in precision (Kearney and Porter, 2009; Cuddington et al., 2013). They are also data-intensive, requiring time and effort to construct. Hence they are less common in ecology studies. In summary, while spatial models are expected to reflect reality and be consistent with theory, there is always a tradeoff between precision and generality (Levins, 1966; Sharp,1990), which justifies the need for diverse models. Generally, accuracy measures are well developed for empirical and stochastic models compared to expert-based models that rely more on sensitivity and uncertainty analysis to calibrate model inputs and define their confidence intervals (Verboom et al., 2005).

Climate change

Long-term mean changes in the prevailing weather of a locality or region are a common justification for climate change (Intergovernmental Panel on Climate Change -IPCC; Bailey 1996). Ideally, the IPCC and the World Meteorological Organisation (WMO) recommend a baseline of at least 30 years for impact studies as it reliably reflects global trends. According to IPCC reports, global temperatures have risen by 1.5^{o}C, approximately 0.1 degrees per decade (IPPC) since the pre-industrial period (1850 - 1990). According to the fifth assessment report of the intergovernmental panel on climate change (IPCC- AR5), climatic conditions have not been stable. Still, they have been changing with demography, socio-economic development, resource availability, energy consumption and trends in technology. The different narratives associated with these factors and translated to reflect future land use/cover, energy demands and changes in greenhouse emissions are known as shared socio-economic pathways –SSPs (Riahi et al., 2017). The SSPs vary from SSP1 with low mitigation and adaptation challenges to SPP5 with high mitigation and low adaptation challenges due to the over-exploitation of fossil fuels (Riahi et al., 2017). The quantitative reflection of how these factors will interact, adding greenhouse gases to the environment, is known as representative concentration pathways- RCPs (van Vuuren et al., 2011). Current RCPs range from RCP2.6, with the least climate forcing to RCP8.5, with the most forcing. Thus the different combinations of SSPs and RCPs define future trajectories for climate impact studies. They are also associated with different policy options, whose soundness must be tested in models (Trisurat et al., 2010).

Rising temperatures are affecting agricultural landscapes and ecosystems worldwide (Leeman and Eickhout 2004, Bakkenes et al. 2006). These authors showed that above 2 degrees rise in global mean temperature, only about 84% of the world ecosystem would remain stable through considerable differences will still exist among ecosystems. The impact of climate change varies across regions and mainly involves range shifts in species' habitat, biodiversity loss, and a decline in ecosystem resilience (Leemans and Eickhout, 2004; Alkemade et al., 2009; Arets et al., 2014; Schipper et al., 2020). There is also evidence of temporal (phonological) shifts, although such studies are uncommon. For example, planting dates and seasons of some crops will shift with rising temperatures and droughts (Egbebiyi et al., 2019). Notwithstanding the negative impact, climate change will increase the potential for some crops and expand vegetation cover in some regions. For example, the cassava crop will be one of the most adapted crops in Africa to climate change, possibly expanding production by ~ 8% (Jarvis et al. 2012). Projected changes in Europe based on EURO-Cordex climate data showed higher warming and increased precipitation over mountain regions (Coppola et al., 2021) which will expand vegetation cover (Leemans & Eickhout, 2004; Schipper et al., 2020; Schröter et al., 2005; Bakkenes et al., 2006; Alkemade et al., 2011). While temperate and mountainous regions will more tolerant to global warming, they are equally at risk of losing their climate space without concerted efforts to curb global warming (Araujo et al., 2011; Barry et al., 2003; Leemans and Eickhout, 2004).

Researchers and policymakers have made global calls in regional and international conventions to halt biodiversity loss by preventing average global temperatures from rising above 2 ^{o}C from the pre-industrial level (for example, The European Union 2007, Warren et al. 2011, Bakkenes et al., 2006; Leemans and Eickhout 2004). However, much effort is still needed, given that this target has not been reached in most regions (Bakkened et al. 2006, Verboom et al. 2007). There have also been recommendations to expand the network of protected areas, establish plantation forests in degraded areas, and scale-up bioenergy production (Alkemade et al., 2009, Leclere et al., 2020). However, Araujo et al. (2011) argued that the effectiveness of some of these measures might be undermined if global warming continues unabated. Nevertheless, climate scenarios and possible warming levels have improved our understanding of what to do or expect in the distant future

Local and microclimatic conditions

Temperatures anomalies may be lower in some locations than the global average due to vegetation cover and local topographic variations (Franklin, 1995; Moore et al., 1991; Bailey, 1996, 2009, De Frenne et al., 2021; De Lombaerde et al., 2022). Local climatic conditions become even more important in such situations than global change (Guisan and Zimmermann 2000). Primary topography variables have varying and sometimes overlapping roles in ecological studies. Slope angle (slope), slope exposition (aspect) and elevation (altitude) are also crucial in regulating the flow of energy and moisture balance in complex terrains (Walz, 2011; Burnett et al., 2008; Franklin, 1995; Moore et al. 1991). Most studies have either reported a species-dependent relationship with primary terrain attributes or a weak and sometimes no relationship with closely related terrain attributes. (Gracia et al. 2007; Bolstad et al. 1998; Burnet et al. 1997). However, multi-scale investigations have also shown that a weak relationship between terrain attributes and plant species may be due to the difference between the spatial resolution of derived terrain attributes and the scale of field sampling (Leempoel et al., 2015; Lassueur et al., 2006; Bolstad et al.,1998). Moreover, it has been shown that biological activity is high at the interphase between interacting terrain attributes based on landscape heterogeneity (Forman and Godron, 1986; Metzger and Muller, 1996, Tracz et al., 2019). **This evidence suggests that the role of topographic heterogeneity is still not well understood and may be underestimated in some species distribution models**

Species Distribution Models (SDM)

Species distribution models are the most widely used tools to understand how landscape species respond to environmental change. They are diverse in appellation but are generally based on statistical correlation (Guisan et al., 2002; Guisan and Zimmermann, 2000). They aim to correlate the geolocations of species to the most significant environmental factors, which theoretically reflect the ecological requirements of species (Guisan and Thuiller, 2005; Guisan & Zimmermann, 2000, Elith and Graham, 2009). The most common SDMs have been classified into statistical and machine learning methods with different algorithms to handle presence-absence or presence-only species data. Statistical approaches are extensions of generalised linear models with the possibility to fit different family functions depending on the data distribution. Statistical methods emphasize estimating model parameters and fitting functions that best describe the relationship between species occurrence and environmental predictors (Guisand et al., 2002). Algorithms in this category are regression-based, including geostatistical methods (Goovaerts, 2000; Miller et al., 2007). Geostatistical methods (tested in this thesis) are less commonly applied in species mapping because they are not robust enough to handle multivariate datasets and non-linear variations (Kienel and Kumke, 2002). Studies in which they have performed well depend on the observational scale or in combination with hybrid methods and techniques capable of dealing with multiple variables (Olthoff et al., 2018; Maestre et al., 2005; Meng et al., 2013., Hengl, 2007)

In contrast, machine learning methods use different algorithms to learn classification rules, especially in the case of complex and no linear phenomena. (Olden et al. 2008). The maximum entropy model - Maxent (Phillips et al., 2006; Phillips, 2010) is one of the most popular algorithms in ecological studies. Random forests (RF) and boosted regression trees (BRT) are increasingly becoming popular, owing to their high accuracy (Cutler et al., 2007; Elith et al., 2006). They are based on the averaging of several models.

Species distribution models have also been extended to cases involving multiple species, also known as community models, multispecies models, or stacked models (S-SDM) (Ferrier and

Guisan, 2006; Guisan and Rahbek, 2011). They describe biodiversity in terms of species richness or abundance based on different approaches. A variant of SDM developed specifically to assess landscape potential for field-grown crops is the EcoCrop model (Hijmans et al., 2001; Ramirez-Villegas et al., 2013). Unlike SDMs, EcoCrop is an expert model, driven exclusively by temperature and precipitation ranges that define each crop's optimal and marginal growth conditions. **These limitations imply more studies are needed to adapt or calibrate the model input to reflect reality, especially for local studies**. Efforts have been made to understand the model and improve its accuracy. For example, Manners and van Etten (2018) showed in a sensitivity analysis that temperature and precipitation ranges were more crucial than the length of the growing season. Manner et al. (2021) further adapted the model by adding temperature and precipitation requirements during critical growth periods for long-duration crops (cassava and banana) and achieved more reliable results than the default parameter. Likewise, Piikki et al. (2017) integrated soil organic matter into the model framework to accurately capture the suitability of common beans in Tanzania. Similarly, Ramirez-Villegas et al. (2013); Rippe et al. (2016) showed that the model input could be improved and its classification ability assessed using basic descriptive statistics of a crop's distribution. Alternatively, some researchers have compared crop suitability simulation against the MapSpam crop distribution dataset (You et al., 2009; Manner et al., 2021, Rippke et al., 2016) or against local landcover data (Rhiney et al., 2018).

Biodiversity indicators and models

Many indicators have been developed over the years to quantify and describe biodiversity at different functional levels in the simplest way possible. Scale and context of application are what are what distinguishes them. For example, those developed to capture topographic heterogeneity (Burnett, 1998; Tracz et al., 2019) or change in a specific ecosystem(Riedler et al., 2015) are limited to a small area and may not be transferable. They are limited because they are not based on a reference period/ state. Hence the context on which change is based is unknown (Lamb et al., 2009). **Broad-based (global and regional) indicators have attempted to fill this gap by quantifying changes in species abundance and richness** (Alkemade et al., 2009, 2011; Arets et al. 2011; Scholes and Biggs 2005) **relative to a predefined reference state or period applicable to different taxonomy groups** (Buckland et al., 2005; Nielsen et al., 2007). The approach is very similar to the natural capital index approach (ten Blink et al. 2002). They reflect changes in habitat intactness on a scale from 0 for completely degraded habitats to 1 for habitats in their natural states. In the case of climate impact studies, 1990 is a common reference period (Bakennes et al., 2006, 2002, Alkemade et al., 2006), assumed to be the time when human impact on the environment became apparent on a global scale. Broad-based indicators also differ in their robustness and scope of application. **For example, the mean stable area indicator (MSAi) from the EUROMOVE model is exclusively based on climate** change for plant species distribution (Bakennes et al., 2006, Alkemade et al., 2011). **In contrast, the mean species abundance indicator (MSA) in the GLOBIO model is an indicator for biodiversity** (for different taxonomy) **based on climate changes, land use, infrastructure, nitrogen deposition, fragmentation and hunting**

pressure (Alkemade et al., 2009, Schipper et al., 2016, 2020). Hence, MSA may be aggregated or disaggregated to quantify a taxonomy's biodiversity loss. The relation between these models and their indicators of change is summarized in Fig 3.

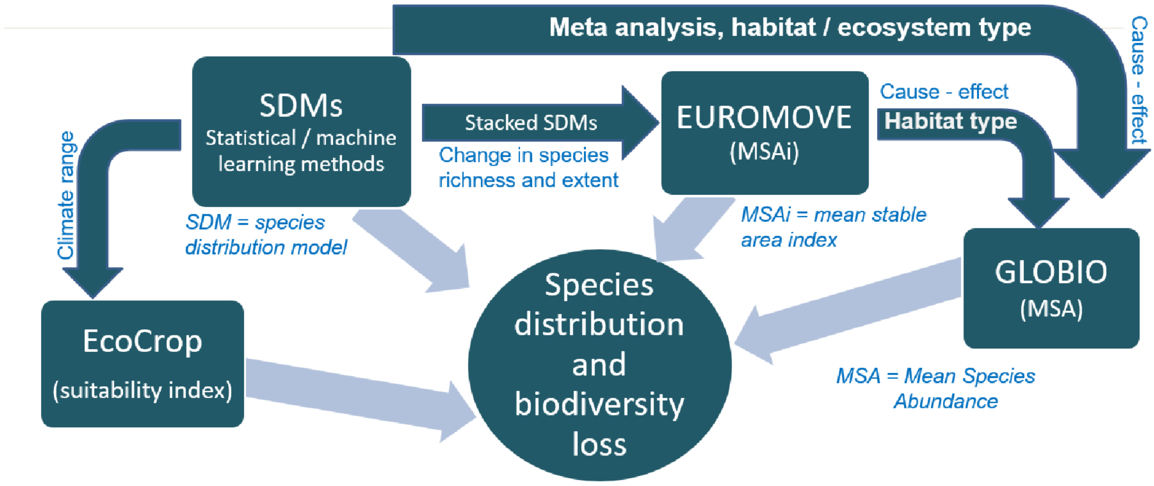

Figure 3. Relationship between spatial models for species distribution and biodiversity loss

Ecosystem functions and services models

Ecosystem service models are tools that attempt to quantify the impact of human activities on the goods and services provided by nature for the well-being of humanity (Burkhard et al., 2009; Nelson et al., 2009). The wide range of existing models uses different criteria, including monetary consideration (Costanza et al., 1997; Frélichová et al., 2014) or biophysical terms (Naidoo et al., 2008) or both. Some methods are based on specific functional properties in the ecosystem, including, for example, plant height or leaf area size (Lavorel and Grigulis, 2012). More robust models like the Integrated Valuation of Ecosystem Services and Tradeoffs tool – INVEST (Tallis & Polasky, 2009) can dynamically estimate ecological production functions like the amount of carbon sequested. INVEST can also perform future predictions based on projected scenarios of land use/cover change (Tallis and Polasky, 2009; Nelson et al., 2009; Krkoska et al., 2016). **However, a simpler and very popular approach is to apply a point-based expert rating on typologically processed background maps, usually for individual land cover types or land use** (Burkhard et al., 2009). The approach is advantageous because it can be applied at different scales (Frélichová et al., 2014; Jacobs et al., 2015). Common to all these approaches is that services and functions are optimal for the ecosystem when the state of the ecosystem is favourable or closest to nature.

In summary, spatial processes changing landscape and impacting biodiversity and ecosystem services are very complex to capture in a single. Different ecological models attempt to address these issues in one way or the other. In addition, Ecological models have evolved from species distribution models that only prove change to biodiversity models that prove and quantify change by integrating expert knowledge results from empirical to derive indicators of change for different drivers of biodiversity loss. The former has been tested at all scales; however, it is still limited because habitat and phonological shifts have been rarely assessed. On the contrary, biodiversity models depend on habitat rather than species information to quantify change and thus provide a better description of changes in biodiversity and a standard for comparing biodiversity changes across scales. Biodiversity models and their indicators should be tested to understand local change in a global context.

4. Methods and Data

Study area

The first study area was East Africa (Ethiopia, Tanzania, Kenya, Uganda, Rwanda and Burundi, covering ~2.93M km^2). The region's landscape is heterogeneous and characterised by rifts, valleys, lakes and highlands reaching 5895 meters above sea level. Annual precipitation in most locations varies from 700 to 1200 mm, with more precipitation in mountainous and lake regions (Ndomeni et al., 2018; Nicholson, 2017). The rainy season varies from March to May (MAM) for long rains, June to August (JAS) and October to November (ON) for short rains. However, most tropical parts experience both the MAM and the ON rainy seasons per year. Mean Temperatures of the warmest months range from 24 to 34^{o}C in most locations (Waithaka et al., 2013). Common legume crops in the region include chickpea *(Cicer arietinum)*, lentils *(Lens culinaris)*, beans (*Phaseolus vulgaris*), dry pea *(Pisum sativum*) and pigeon pea (*Cajanus cajan).* They thrive in cool environments and are commonly grown with maise, millet, sorghum cassava and groundnuts by smallholder farmers (van Loon et al., 2018; Thornton et al., 2010). These crops grow in distinct agro-ecological zones (AEZs) - homogeneous areas with similar temperatures, water and resource availability, elevation, soil types and growing seasons (Fischer et al. 2008, FAO/IIASA, 2012),

The second case study was in Pogórze Dynowskie, which is part of the Outer (Flysch) Carpathians, south Poland (Fig. 4) and is among the chain of biodiversity hotspots associated with the Carpathians mountains (Hurdu et al. 2016, Mraz and Ronikier 2016). Landslide zones are of different ages and are among the largest in Poland (Zabuski et al., 1999; Polish Geological Institute, 2018). Elevation varies from 243 to 412 m a.s.l, while slope angle varies from 0^o to 57^o. Slope exposition is very diverse but generally facing the east and, to a lesser extent, the SW direction. Landslides and species distribution are tied to the geomorphology and the complex geology of the study region (Alexandrowicz and Margielewski, 2010), which has led to the creation of diverse habitats and species. Plant species consist of diverse multispeciess of spruce, fir, pine, beech, and lichens (Alexandrowicz and Margielewski, 2010; Grodzińska and Szarek-Łukaszewska 1997).

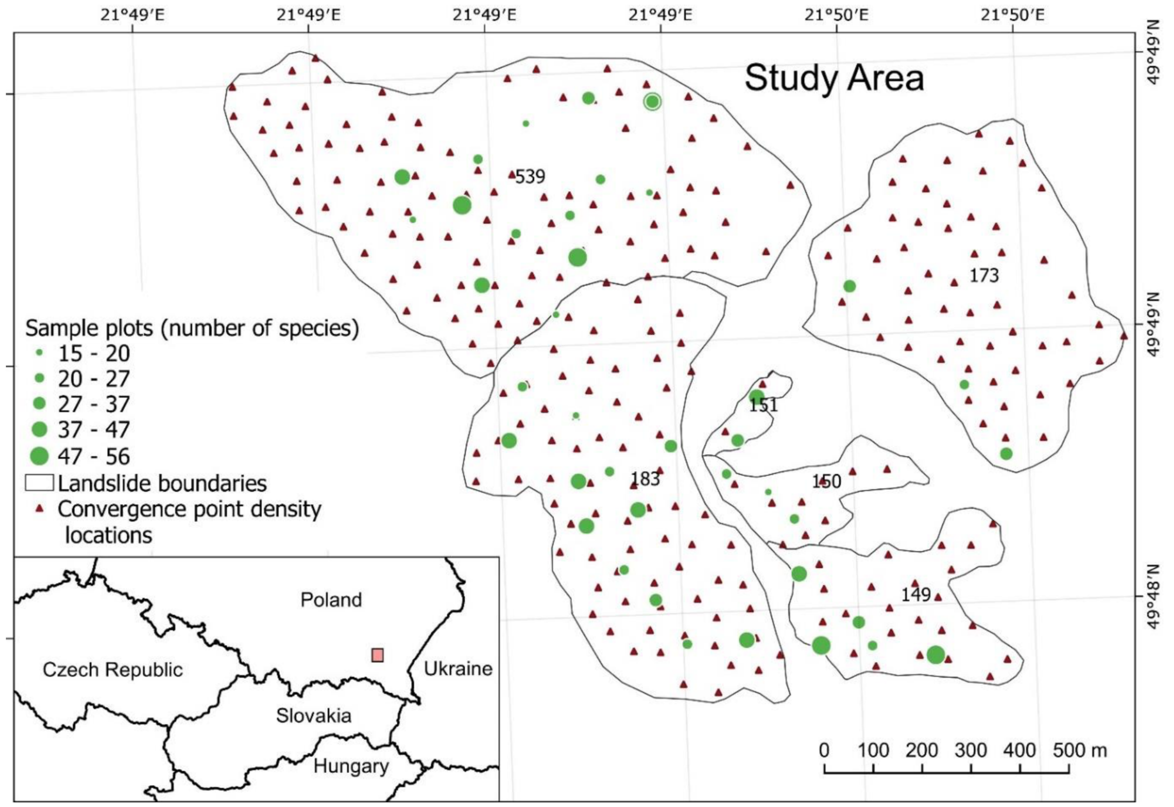

Figure 4: Location of the study area and sample plots (circle symbols) and randomly determined convergence point density locations (triangles).

The number labels are the SOPO catalogue numbers used to distinguish the six landslides in the study area.

The study area is the Czech Republic. Its landscape is very diverse, with basins and rivers surrounded by low mountains in the west to more hilly areas in the east. Climatic conditions are dominantly temperate, with warm summers and cold winters. Average annual temperatures generally decrease with altitude and vary from - 4.0 ^{o}C at the highest spot, ~ 1.6 km asl, to about 10 ^{o}C in lowlands (Vondrakova et al. 2013). About 70 per cent of the annual total precipitation is received between April–September. The mean annual total precipitation varies from ~ 400 mm in the west to 1400 mm in the mountains up north (Tolasz et al., 2007, Hanel et al., 2016). The World Wide Fund for Nature (WWF) identifies four terrestrial ecoregions in the Czech Republic, including Western European Broadleaf Forests, Central European Mixed Forests, Pannonian Mixed Forests, and Carpathian Mountain Conifer Forests. These ecoregions constitute the nine vegetation belts of the Czech Republic, also known as forest vegetation zones (FVZ). Hlasny et al. 2011, Machar et al. 2017). Diverse natural and near-natural ecosystems, mainly of type grassland, forest, wetlands and rocks, are associated with the FVZ (Pechanec et al., 2021, Chytry et al., 2010, p.447). As of 2018, there are over 3000 plant species in the Czech Republic (Agency for Nature Conservation and Landscape Protection - AOPK)

Data and software

Data from diverse sources was used to drive spatial models to meet the aim and objectives of the research. Data types included climate, species, land cover/biotope, topographic, cropland, agro-ecological zone, and environmental data (geology, soil, hydrology). The data were sourced from different portals and institutions and are of different results. The current climate data included long-term average from 1960 – 1990, 1970- 2000 and 1991 to 2018. Projected climate data up to 2100 are those for the RCP 4.5 and 8.5 scenarios. Species data for the Czech Republic spaned from 1960 to 2018, while the case study in East Africa stretched from 1965 to 2017 and was from very diverse sources. Topographic data were acquired at 1m and 5 m resolution. A summary description of these data types, including scale, spatiotemporal resolution and source, is presented in (Table 1)

Table 1. Summary of research data

	Data type	Description	Resolution /scale	source
Case study 1	Climate	Historical and projected RCP4.5 upto 2070	30-sec arc, ~ 1km 2	WorldClim (accessed November 2019) https://www.worldclim.org
	Crop locations	Data from 1960 -2017		Genesys, (accessed, December 2019) https://www.genesys-pgr.org/ GBIF, (accessed November 2019) https://www.gbif.org/
	Agro-ecological zones	Homogenous crop zones at different altitude	5 min arc	HarvestChoice/International Food Policy Research Institute (IFPRI) (accessed November 2019) https://harvestchoice.org/data/aez8_clas
	Cropland	Cropland and pasture land	5 min arc	SEDAC (accessed November 2019), http://sedac.ciesin.columbia.edu/es/aglands.html
Case study 2	Digital elevation model (DEM)	Topographic data	1 meter	Polish Geological Institute https://www.pgi.gov.pl/en/services/landslides.html
	Species locations	Plant Species richness		Field survey
	Convergence point	Detail analysis of slope–aspect overlay		
Case study 3	Regional Climate data	Historical data from 1961 to 2018, Projected data for RCP 8.5 up to 2100	500m2	Climate change in the Czech Republic (http://www.klimatickazmena.cz accessed through Czechglobe (http://www.czechglobe.cz) on 1 May 2020
	Species	Higher vascular plants surveyed between 1961-1991, excluding alien species	500m2	Agency for Nature Conservation and Landscape Protection (OAPK) (http://www.ochranaprirody.cz/en/, accessed on (26 September 2019)

	topography	Slope and aspect	5m2	The Czech Office for Surveying, Mapping, and Cadastre
	geology	Geological material	1:100,000	Czech Geological Survey
	Soil		1:100,000	Research Institute for Soil and Water Conservation + Forest Management Institute (2018)
	Drainage	Infiltration ability	1:100,000	Research Institute for Soil and Water Conservation + Forest Management Institute (2018)
	Distance to waterbody	10 or 100 m distance from the river		Open street map (OSM)
Case study 4	Climate data	Historical data from 1961 to 2018, Projected data for RCP 8.5 up to 2100	500m2	Climate change in the Czech Republic (http://www.klimatickazmena.cz accessed through Czechglobe (http://www.czechglobe.cz), on 1 May 2020
	Climate data	Historical data from 1901 to 2020,Projected data for RCP 4.5 and 8.5 up to 2100	1000m2	Marchi et al 2020 https://sites.ualberta.ca/~ahamann/data/climateeu.html
	Biotope data	Detail vector layers of ecosystems in Czechia		
	Land cover	Land cover of Czechia based on EU regional land cover classification	100m2	https://land,copernicus.eu (accessed January 10, 2019)

Summary description of the tested model

Maxent

Maxent was tested in case studies 1 and 3. The model optimises prediction by comparing the probability density of environmental conditions where a species is observed to the probability density of background environmental conditions in an area based on minimum distance (Philip et al., 2006, Elith et al., 2010). **Maxent was chosen for its robustness and popularity in species distribution modelling**. Given that the first objective was to fine-tune the EcoCrop model (Fig 10), modelling in maxent allowed optimum temperature and precipitation values for each crop to be derived from response curves and compared with statistically computed values. Maxent was implemented in R through the dismo package (Hijman and Elith 2017). The model was tested on 10,000 background points, and the environmental attributes of species for the case studies were sampled. Presence only and background points were partitioned in the ratio of 70:30 for model testing and validation. The models were validated in both cases based on the area under the receiver operating characteristic curve (AUC) and the true skill statistics (TSS).

EcoCrop

EcoCrop, a mechanistic model for predicting crop suitability based on climate indices (Hijmans et al., 2001; Ramirez-Villegas et al., 2013), was tested in case study 1. The model predicts suitability on a pixel basis by comparing crops' specific temperatures and precipitation ranges with the prevailing conditions elsewhere. EcoCrop also determines the optimum climate range and the marginal range, usually the minimum and maximum climatic conditions for growth. The model then scores suitability on a scale of '0' for unsuitable areas or areas outside the crop climate range to '1' for excellently or optimally suitable areas. Behind the model is the EcoCrop database documenting the base biophysical parameter of more than 2500 plant species. Despite the limitation of not considering biotic factors and extreme climatic conditions during a crop's life cycle (Manner et al., 2021), **EcoCrop was chosen because of its simplicity and broad scope of application**. Unlike robust process-based crop models available only for a few crops, the EcoCrop database has been growing with experts understanding the climate range of undocumented crops. Second, the model input has been successfully validated for sorghum, bean, millet, maize, banana, cassava and yam using the empirical method (Ramirez Villegas et al., 2013, Manner et al., 2018, 2021, Rippke et al., 2016), but not for most legume crops. Third, climate information about these legume crops in East Africa is scanty or poorly documented. Lastly, there is evidence that the model distribution corresponds with actual geographical (Manner et al., 2020, 2021; Ripkki et al., 2016). The model implemented in DivaGiS and TerrSet-CCAM software was tested for historical climate data (1970 -2000) and the projected data (2000 – 2070) under the RCP 4.5 scenario.

The model input was calibrated using basic descriptive statistics of historical climatic conditions in the region compared with field values and values from response curves derived from the spatial model - Maxent. The entire workflow is summarized in Fig 5. First, the geometric mean of the growing season was used to create two fictitious growing seasons for mean temperature and total precipitation (Equations 1 & 2), respectively. Each growing season had 12 consecutive sequences of four months for chickpea, lentil, common beans and six months for pigeon pea. The sequence with the lowest, highest and mean temperatures was used to calibrate temperature inputs. The sequence with the highest sum of rainfall to ensure enough moisture during the growing season was chosen for precipitation.

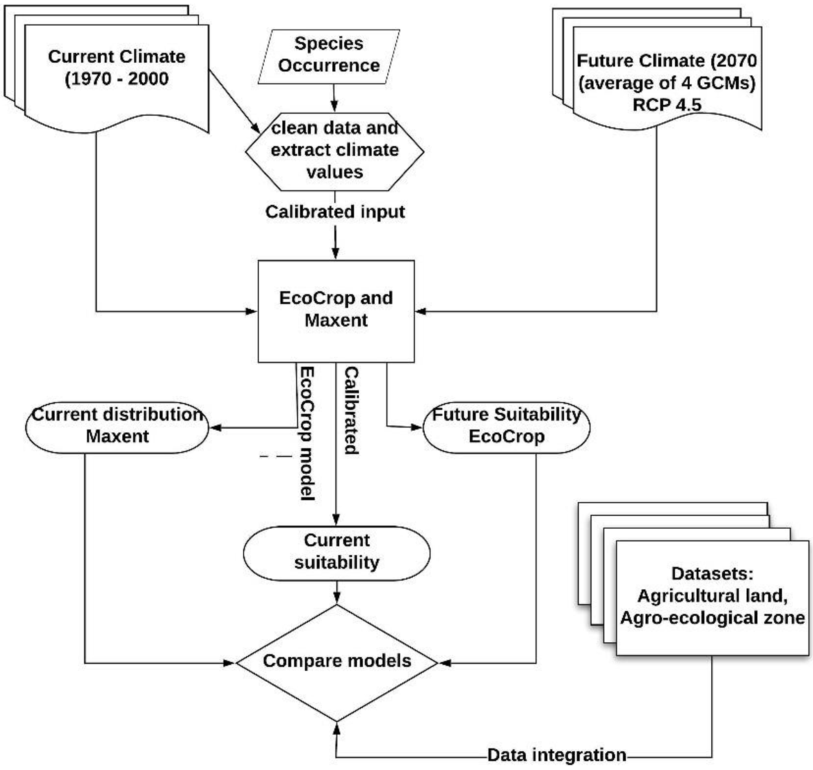

Figure 2. Workflow and methodology to calibrate climate inputs for EcoCrop

$$T_{GS} = \frac{1}{4}\left(\sum_{i=1}^{i=4} t_{\text{avg}_i}, \sum_{i=2}^{i=5} t_{\text{avg}_i}, \dots, \sum_{i=12}^{i=3} t_{\text{avg}_i}\right) \quad (1)$$

$$R_{GS} = \left(\sum_{i=1}^{i=4} r_{\text{sum}_i}, \sum_{i=2}^{i=5} r_{\text{sum}_i}, \dots, \sum_{i=12}^{i=3} r_{\text{sum}_i}\right) \quad (2)$$

Where i represents the month(s), the mean temperature(t_{avg_i}) for 12 consecutive growing seasons (T_{GS}), has four consecutive months per season. The total rainfall (r_{sum_i}) for 12 consecutive growing seasons (R_{GS}) has four consecutive months per growing season

Because the growing season for field pea is three months, values of the historical quarterly bioclimatic variables (BIO10 -Mean Temperature of Warmest Quarter, BIO11-Mean Temperature of Coldest Quarter, BIO16-Precipitation of Wettest Quarter and BIO12-Annual Precipitation) were extracted from each location. Extracted temperature and precipitation values for each crop location for the chosen sequences and variables were used to plot frequency curves and determine the model inputs (Ramirez-Villegas et al., 2013). The chosen sequences and climate variables were tested in Maxent and optimum values from their response curves compared with calibrated values. Table 1 summarises the input parameters used to drive EcoCrop. Hence, projected land suitability or availability changes were based on the calibrated inputs. Suitability maps were aggregated by a factor of 10 and overlayed with the global cropland dataset (Rammankutty et al., 2008) and agro-ecological zone dataset (IFPRI, 2015) to estimate the share of land that might be lost. Thus the estimated share of agricultural land that could be lost is the difference between total lost minus total gained for each country.

Geostatistical models

Three geostatistical models: Ordinary kriging (OK), Ordinary cokriging (OCK), and Regression kriging (RK), were tested in the second case study to address the research questions raised in the second objective. The models generally assume that the spatial variability in an observed phenomenon is due to random and stationary processes that can be modelled using probability principles (Krivoruchko, 2011; Goovaerts, 2000). All three models are also based on spatial auto- or cross-correlation that can be quantified with a variogram (Rossiter, 2012; Wu et al., 2006; Goovaerts, 1999; Oliver and Webster, 1990, 2014; Webster and Oliver, 1992). Variograms describe distance and directional variation and quantify the average weighted influence of nearby observations based on the type of mathematical model fitted to the data, the configuration of observation points, and variogram parameters (Oliver and Webster 2014; Krivoruchko 2011; Johnston et al. 2001; Goovaerts 1997). However, these models differ in their flexibility or ability to deal with two or more variables. For example, regression kriging deals with multiple variables by performing ordinary kriging on regression residuals (), avoiding the need to fit multiple variograms. Cokriging, on the other hand, is ideal when the surrogate of sparsely sampled phenomena can be more densely sampled. However, it requires that multiple variograms be fitted simultaneously. In contrast, ordinary kriging is a univariate method for a sufficiently sampled variable. Thus it was possible to compare their ability to capture the spatial pattern of species richness with or without considering topographic heterogeneity quantified as convergence point density. It was possible to verify if there was an added benefit when the surrogate was densely sampled. Before variogram modelling, the assumption of normality of distribution in the dataset was checked. All direct and cross-variogram were omnidirectional and fitted with spherical mathematical models. Ordinary and cokriging were done using the Geostatistical Analyst extension in ArcGIS 10.6 (ESRI), while regression kriging was done using the gsat package in R (R Development Core Team 2021). Model evaluation statistics included the mean error (ME) and the root means square error (RMSE)

Land cover change and potential for ecosystem services

Modelling landscape development is mostly based on the publication of Pechanec et al. (2018), for which I am the second co-author. The first step was to estimate changes in area (km^2) and share of land use/cover category for the selected modelling periods. Next persistent areas, defined as areas same land use category in all five modelling periods and main trajectories of change, were calculated. Next, the percentages of persistent areas of each land use/cover class from the reference period (1990) were calculated. The workflow involved multiple overlay spatial operations (Identify, Update, Intersect) and basic statistical calculations (Frequency, Summarize by) performed in ArcGIS PRO 2.3. Subsequently, the two categories of ecosystem services: **Provisioning and Regulating for each of the five analysed years, were separately determined by categorizing or scoring the capacity of these services based on the expert-based ecosystem service (ES) matrix score (capacity values) developed for Germany** (Burkard et al. 2009). The ES matrix score varies from 0 to 5 where 0 = no relevant capacity, 1 = low relevant capacity, 2 = relevant capacity, 3 = medium relevant capacity, 4 = high relevant capacity and 5 = very high relevant capacity.it was directly applied to the situation in the Czech Republic because both countries' physical-geographical and data sources are the same. Each group of ecosystem services was rated as the sum of the capacities of all sub-services in that group.

Changes in individual areas were compared to the reference period to identify development trajectories. That is, by comparing the switch to another land use category than the one in the baseline (1990). The main trajectories of landscape development (the same development trend) were selected for further analysis. Each trajectory is identified by the TAG code of the landscape cover according to the Corine LC nomenclature (Table 12, Appendix) and in the individual monitored years. Thus for the selected trajectories, only areas with at least 100 hectares were included in the main axes of the ES matrix as they were considered the main trends of landscape development in the Czech Republic. At the same time, the number of facets showing this trend was calculated. An ES matrix was attached to the analyzed plots, and the evolution of land use and ecosystem services' capacity was analyzed. The workflow is summarized in Fig11

EUROMOVE

The EUROMOVE modelling approach was tested in the 3rd case study. EUROMOVE is a multi-logistic regression-based species distribution model for the European region originally developed and tested at a scale of 50 km x 50 km for ~1400 or ~ 900 species (Bakkenes et al. 2002; 2006). The indicator of change in the model, the mean stable area index (MSAi), is an aggregation of change in species richness and habitat extent compared to a reference situation (Equation 3).

$$\mathrm{MSAi} = \frac{\sum_{i=1}^{n} A_{i1,y2} / A_{i1,y1}}{N} \qquad (3)$$

Where $A_{i1,y1}$ is the area of species i for the baseline period and $A_{i1,y2}$ is the area of species i for a later modelling period. N is the total number of species that should be the same for the two modelling periods, irrespective of whether some species have disappeared in the future

Conceptually, the model was selected because of its flexibility, offering the possibility to replace logistic regression with more robust SDM modelling approaches. Lastly, the modelling approach offers a comprehensive way to summarize multi-species data. The model was adapted to the conditions in the Czech Republic by integrating very high-resolution climate data (500 m x 500

m) with geology, hydrology, and topography with a representative sample of 687 species. The 687 species are the baseline species (1961 -1990) selected based on the following criteria: (i) species could be observed in at least 50 locations considering a sample grid of 500m x 500m for the entire Czech Republic. (ii) TSS value between observed and model species was ≥ 0.4. Thus Logistic regression was replaced with maxent, accepting all default settings. For the representative species, changes under the current (1991 - 2018) and the projected RCP 8.5 scenario up to 2010 were compared to the baseline situation (1960 -1990). In addition, changes in the distribution of eight indicator species sampled under the current and baseline climatic condition were also compared to further assess their vulnerability to climate change.

5. Results

Modelling landscape potential for selected legume crops

The results of calibrated temperature and precipitation inputs for the EcoCrop model is shown in Table 2. The calibrated inputs based on computed growing seasons and selected climate indices were compared with the FAO base parameters. The table shows that the calibrated optimum temperature and precipitation were 6 to 27% consistent with the FAO base parameter except for the maximum optimum rainfall for common beans. The base marginal precipitation ranges were generally not comparable and differed considerably from the calibrated range by ~ 9 to 68%.

Table 2. Comparison of calibrated and FAO base inputs

	LGS (days)	Tkill (°C)	Tmn (°C)	TopMn (°C)	TopMx (°C)	Tmx (°C)	Rmn (mm)	RopMn (mm)	RopMx (mm)	Rmx (mm)
Bean	90	0	10	15	20	27	151	452	1054	1355
FAO base	160	0	7	16	25	32	300	500	2000	4300
Chickpea	120	0.85	3.4	10.2	24	31	182	547	1274	1638
FAO base	135	-9	7	15	29	35	300	600	1000	1800
Lentil	120	0.75	3	9	21	27	167	506	1180	1517
FAO base	155	0	5	15	29	32	250	600	1000	2500
Pea	90	0.82	3.3	9.9	23.1	29.7	151	452	1054	1355
FAO base	100	-2	4	10	24	30	350	800	1200	2500
Pigeon pea	180	1.1	5	14.1	33	42.3	220	658	1537	1976
FAO base	228	0	10	18	38	45	400	600	1500	4000

Where: Rmx= maximum rainfall, RopMx= optimum maximum rainfall, RopMn= optimum minimum rainfall, Rmn= minimum rainfall, Tmx= maximum temperature, TopMx=maximum optimum temperature, TopMn= optimum minimum temperature, Tmn= minimum temperature, Tkill= temperature that will kill the crop and LGS = length of the growing season

The spatial distribution of the selected legume crops from 2000 to 2070 is shown in Fig 6. Potential areas for Pigeon pea, chickpea and pea were the most extensive under the current climatic conditions. **Future patterns showed shifts in landscape suitability to cold and cool zones**. There will also be a significant contraction in the share of suitable areas for common bean and lentils compared to chickpea and pigeon pea, which will remain unchanged by 2070. Across AEZs, Fig 7 shows that under future climatic conditions, suitability either increased or nearly remained constant in the cool agro-ecological zones as opposed to the warm AEZs. The most optimal zones for legume cultivation will be the cool humid (tch) the cool semi-arid (tcsa), and the cool sub-humid (tcsh) zones. Suitability within these zones will increase by 10% and 15%, respectively and will be most favourable for field pea cultivation..

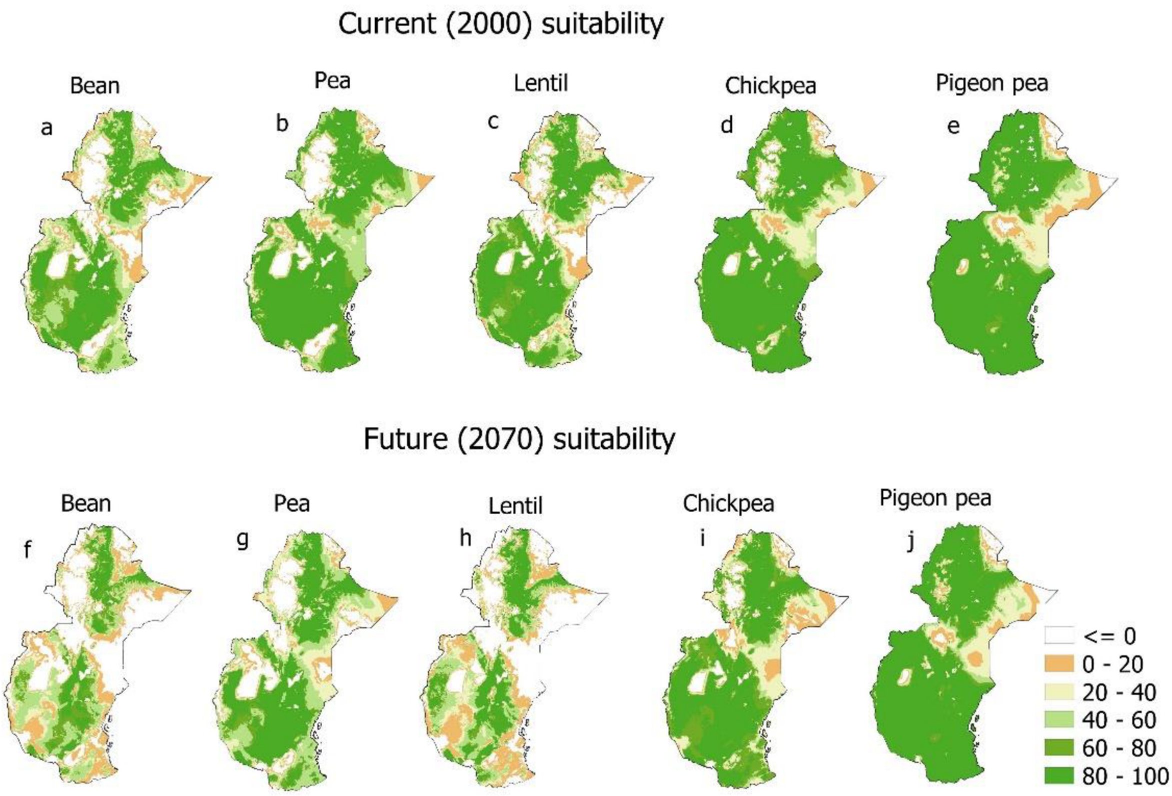

Figure 6. current (a - e) and future (f – j) suitability of legume crops.

Within the warm AEZs, **the warm sub-humid (twsh) and the warm semi-arid (twsa) zones will be the most impacted, decreasing suitability at all production sites**. Generally, landscape potential for, pea will be most reduced in the warm semi-arid (twsa) and the warm (twa) arid zone compared to other crops. The suitability of lentil, chickpea and pigeon pea will be more reduced in the warm humid (twh) zone compared to common bean and pea. The cool humid (tch) zones and cool arid (tca) zones will be negligibly affected.

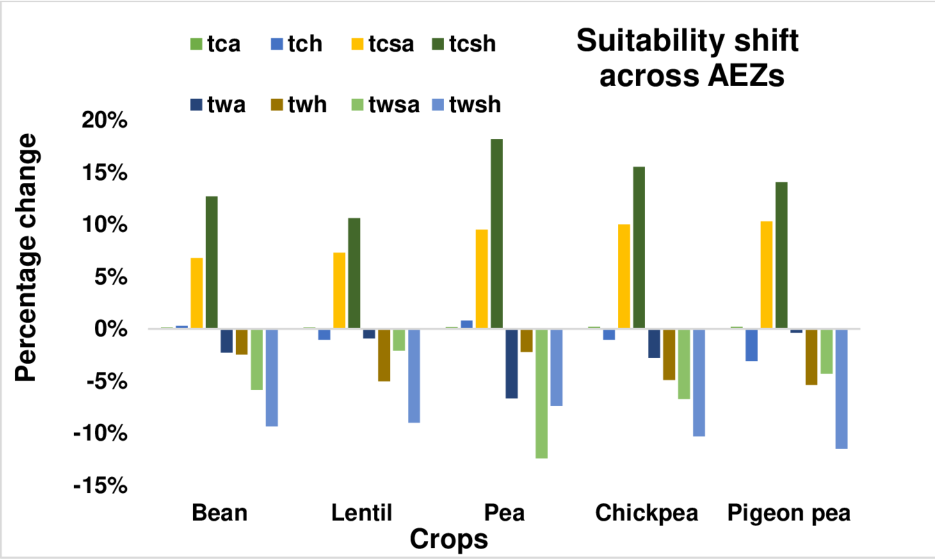

Figure 7. Suitability shift across agro-ecological zones (AEZs).
tca = tropic cool arid, tch= tropic cool humid, tcsa= tropical cool semi-arid, tcsh=tropic cool sub-humid, twa= tropic warm arid, twh= tropic warm humid, twsa= tropic warm semi-arid, twsh=tropic warm sub-humid.

Modelling variability in species richness from topographic data

The geostatistical models ordinary kriging (OK), ordinary cokriging (OCK) and regression kriging (RK) showed spatial dependency, which generally decreased with distance as expected. However, the cross-correlation between CPD and species richness was captured at a much shorter distance ~ 118 m compared to 170 m and 270 m for direct variograms of species richness and CPD (Fig 8). The minimum species richness was generally overpredicted, while the maximum was overpredicted as expected. **However, RK was the most accurate with the least RMSE** (9.3), followed by OCK (10.54) and then OK (13.6) (Table 3), whose predictions were not so different from the mean species richness (~ 32 species) of the study area. Low accuracy led to predictions that were and showed less variability in species composition at unsampled locations.

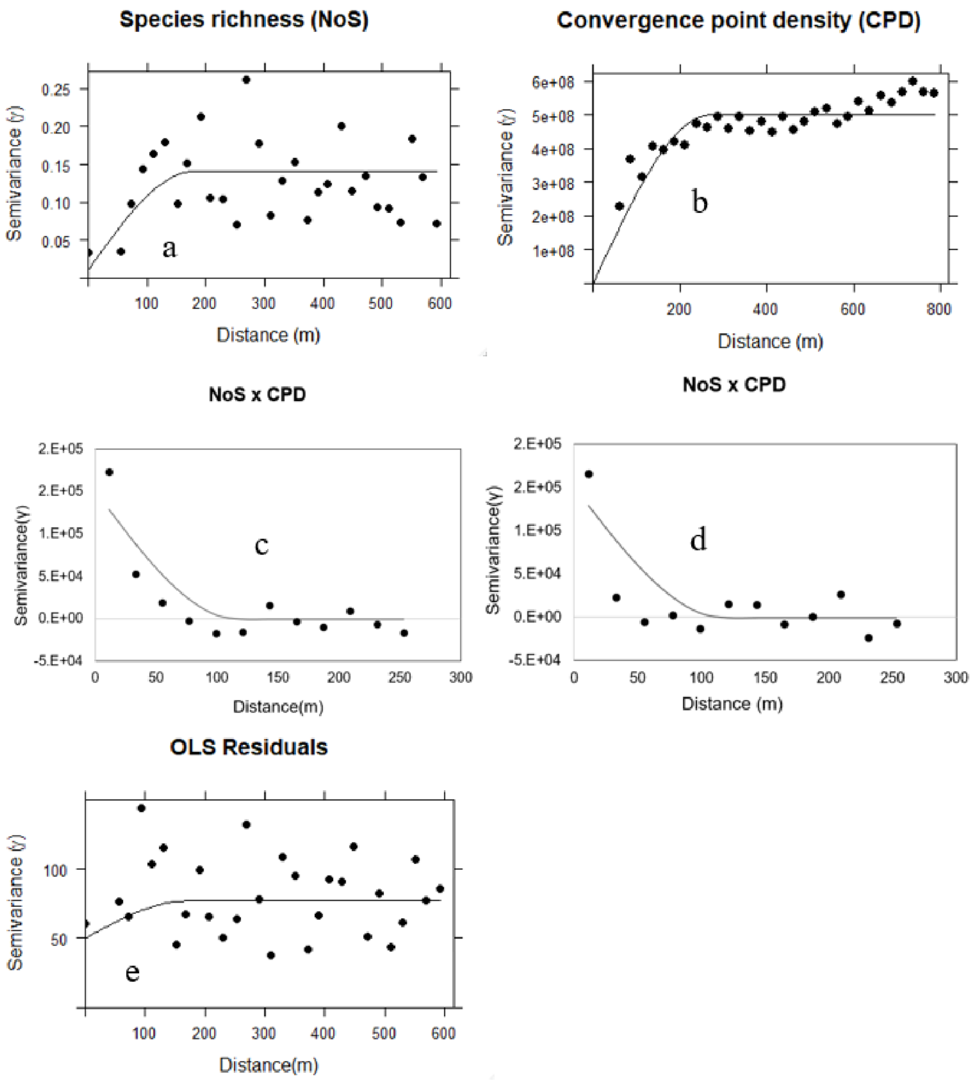

Figure 8. Variogram models.
(a) Species richness, (b) convergence point density, (c) cross variogram for identical variable locations (d) cross variogram for unidentical variable locations (e) OLS residuals

Table 3. Summary of cross-validation statistics

	Species richness (NoS)	Ordinary least squares (OLS)	Regression kriging (RK)	Ordinary kriging (OK)	Cokriging(OCK1)	Cokriging (OCK2)
Min	15	21	19	25	22	19
Max	56	46	47	46	50	51
ME	-	8.04	0.09	0.16	1.39	-0.05
RMSE	-	9.57	9.23	13.60	11.27	10.54

Landscape development and potential for provisioning and regulating services

Over the study period, the area covered by artificial surfaces (settlements), forests and semi-natural wetlands and water bodies increased, whereas agricultural cropland areas decreased. This change translates to ~ 79.48 % of total persistent areas in the Czech Republic (Table 5). The highest persistence is associated with Water bodies, representing the most stable class for the monitored period. Other stable categories include Road and rail networks, Discontinuous urban fabric (93.27%), Industrial or commercial units (92.3%) and Broad-leaved forest ~92.98%. Conversely, the least persistent were open or low vegetation categories: Transitional woodland shrubs (22.09%) and Bare rocks (24.74%). Dump sites (26.26%) continue to show low persistence, a logical consequence of a significant decline in this category to around one-third of its initial area. **Based on this, only three capacity levels were identified for Provisioning services in the Czech Republic: no relevant well capacity, low capacity and relevant capacity** (Table 4). **Five levels, excluding the very high relevant capacity level, were identified for Regulating services** (Table. 5). A total of 22 main trajectories of land cover development in the Czech Republic were identified. Each represents the transition between land cover classes based on their code tags. The 211-231-231-231-231 trajectories with an area of 2,269 hectares are the most extensive(Table 6). It is followed by 211-211-231-231-231 with an area of 1856 hectares and 211-211-243-243-243 with 878 hectares. The most frequent trajectory is 211-211-312-312-312 with 31691 patches, followed by 211-211-243-243-243 (29578 patches) and 243-243-211-211-211 (24065 patches).

In verbal terms, the largest change in area is the transition from Non-irrigated arable land to Pastures with 3,601 patches with a total area of 2269.18 ha. Regarding capacity for providing Ecological Integrity, both categories are rated as level 3 - relevant capacity, so there is no change in capacity level over time. In terms of capacity level for Provisioning services, after a category change, the level decreases from 2 - relevant capacity to 1 - low relevant capacity, remains at level 1 - low relevant capacity for Regulating services.

Examples of a downward trend in capacity levels for all ecosystem services under review are the transitions from the Non-irrigated arable land category to the Discontinuous urban fabric or Coniferous forest transitioning to Transitional woodland-shrub. The opposite is the upward trend in capacity levels for all monitored ecosystem services at all-time horizons in the Transitional woodland-shrub category, transitioning to Coniferous or Mixed forest.

Table 4 Development of the area (km^2) of classes of ES capacity for Provisioning services

Capacity	1990	2000	2006	2012	2018	Persistent
No relevant capacity	7802.37	7230.42	7093.67	7095.84	7635.72	5067.91
Low relevant capacity	3886.92	6706.45	8619.92	9365.11	9470.79	3115.89
Relevant capacity	67179.49	64931.92	63155.21	62407.85	61762.3	54498.82

Table 5 Development of the area (km^2) of classes of ES capacity for Regulating services

Capacity	1990	2000	2006	2012	2018	Persistent
No relevant capacity	7177.26	6608.39	6560.1	6553.77	7085.11	4680.75
Low relevant capacity	45938.83	45861.5	45423.08	45337.75	45210.95	35827.01
Relevant capacity	812.91	799.23	654.86	629.68	598.29	420.5
Medium relevant capacity	37.5	37.11	46.72	45.52	45.68	31.68
High relevant capacity	24902.28	25562.56	26184.04	26302.08	25928.78	21722.68

Table 6. Main trajectories of land cover development in the Czech Republic

No.	Development trajectory (1990-2000-2006-2012-2018)	Number of patches this trajectory	Area of patches this trajectory (ha)
1	211-211-112-112-112	18894	174.79
2	211-211-211-211-112	6315	111.09
3	211-211-211-211-231	6450	253.91
4	211-211-211-231-231	1511	707.68
5	211-211-231-231-231	9566	1856.04
6	211-211-243-243-243	29578	878.037
7	211-211-312-312-312	31691	158.79
8	211-231-211-211-211	2360	209.79
9	211-231-231-231-231	3601	2269.18
10	243-243-211-211-211	24065	226.13
11	243-243-231-231-231	11624	350.50
12	243-243-312-312-312	14355	108.42
13	312-312-312-312-324	2222	473.53
14	312-312-312-324-324	254	172.40
15	312-312-313-313-313	10962	374.95
16	312-324-312-312-312	3218	124.82
17	312-324-324-324-324	729	171.94
18	313-313-311-311-311	4266	230.60
19	313-313-312-312-312	9649	265.86
20	324-312-312-312-312	3212	807.92
21	324-313-313-313-313	683	189.24
22	324-324-312-312-312	5132	227.73

Species diversity loss and the vulnerability of natural landscapes and habitats in the Czech Republic

Detail variations in the stability of landscapes in the Czech Republic from the integration of two main indicators of change, species richness and habitat extent, into the mean stable area indicator (MSAi) according to the EUROMOVE model were presented in paper 3. Comparing change between each modelling period (2018, 2060 and 2100) and the baseline (1990) was the basis for assessing both species and habitat vulnerability. Vulnerability was therefore understood to mean a decline in the MSAi value. For individual species, it meant a contraction of habitat over time.

About 2% (~ 11 species) were lost between 1991 and 2018 (Table 7). More than 20% of the baseline species may be at risk of becoming extinct at the end of the 21st century. As of 2018, species richness has increased on highlands but will sharply decline under the RCP 8.5 climate scenario

Table 7. Change in habitat extent, species richness and MSAi with time

Modelling period	Mean area (km2)	Species number	Species lost	Estimated MSAi
1990	22194	686	-	-
2018	23746	675	11	0.99
2060	11544	661	26	0.50
2100	12021	548	140	0.43

The average MSAi under the current climatic conditions varied from ~ 0.85 in highlands to ~ 0.3 in lowlands (Fig 9). The stability of highland habitats is also projected to decline to ~ 0.65 by the end of the century. It is worth noting that the loss of species from 1991 to 2018 was not proportional to the loss of potential habitat extent, which increased by ~ 7 % compared to the baseline. In general, species habitats have expanded on highlands and declined in low lowlands. The shift in habitat shows that currently, **indicator species of Alnus (alder) and Festuca (fescue), typical of lowland habitats, are among the most vulnerable, already showing a net loss of their current habitat extent** (Table 8). In contrast, six of the eight tested species have expanded their climate space. The most remarkable expansion was observed for Picea abie and species of salix.

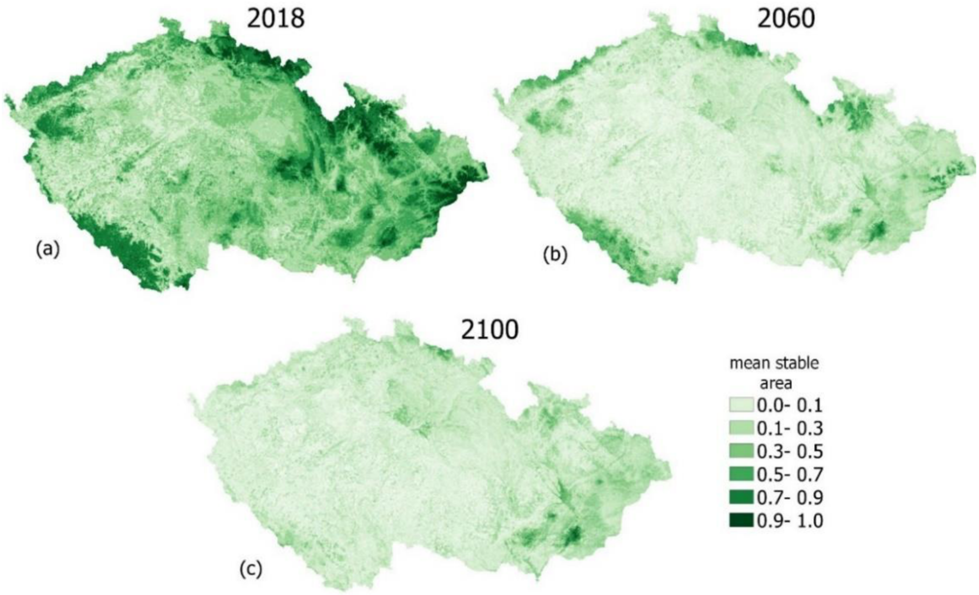

Figure 9. Variability in the mean stable area index (MSAi)

Table 8. Net change in habitat suitability based on Random Forest classification

Species	Net Change (%) 2018[a] −1990
Alnus sp.	−2
Fagus syvestica L.	+10
Festuca. sp.	−1
Picea abie	+42
Poa sp.	+6
Quercus sp.	+5
Rubus sp.	+9
Salix sp.	+26

The presence-only species records in 2018 were modelled before calculating the net change in species loss between 1990 and 2018.

6. Discussion

The response of the selected landscapes in this study was assessed under static and dynamic conditions to improve understanding their potential for diverse species and ecosystem function. The tested models address these issues differently. In general, the results of this thesis have shown that **the development of the selected landscapes is dominantly controlled by climate and topographic variatio**ns. The **current climatic conditions have a milder impact on most species**, given that ~ 2% of the representative species sample tested with the finest climate data for the Czech Republic (paper 4) have been lost since 1990. Similarly, the potential for legume crops based on available suitable land is still high (paper 1). In other words, many species are coping with changes in climatic conditions. However, while climatic conditions are still favourable, the climate range of the species assessed differs. Those with a narrow climate range are the most vulnerable.

Highland habitats are the most stable to climate change and are currently expanding. However, they are expected to shrink with rising temperatures. Under the two scenarios of climate change considered, RCP 4.5 and RCP 8.5, global mean temperatures are projected to rise in the range of 1.4 - 1.8^{o}C and 2.0 - 3.7^{o}C, respectively (Knutti et al., 2013). Both scenarios show a shift in species diversity to higher altitudes due to drought and heat stress (Hlásny et al., 2011) (papers 1 and 2). It must remember that while these are the general trend, the response of species growing in the wild is expected to differ from crops grown in the field because the impact of climate in the former situation is further mediated by local the topography and vegetation cover (De Frenne et al., 2021; De Lombaerder et al.,2022).

This research has also shown that micro-climatic conditions created by topographic variation are particularly important at the local scale. The improvement in species mapping from the indicator of topographic heterogeneity, **convergence point density** (CPD), (paper 2), **suggests that its role should not be overlooked in species distribution models, particularly in complex terrains** (Guisan and Zimmermann, 2000). Though not explicitly assessed, the interaction between topography variation and climate change suggests that some species are currently restricted to a specific altitude range. The current trend of landscape development from land use/cover analysis is toward expanding vegetation class (Paper 3). The results are consistent with the current expansion of plant species' habitats (paper 4) and reflect an improvement in regulating services. These trends are discussed in addition to limitations and future research direction in the proceeding sections.

The purpose of assessing the evolution of the East African landscape and its potential for legume crops was to understand their vulnerability to climate change. It was, therefore, important to calibrate the EcoCrop model for the selected legume crops (paper 1) as the basis for prediction. The observation between calibrated optimum climate range for the selected and the FAO base input, especially maximum rainfall, may be traced to the high uncertainty inherent in the precipitation pattern for some locations in East Africa from global circulation models (Ndomeni et al., 2018; Nicholson, 2017). However, the precipitation difference for common beans is so much to be solely attributed to being attributed to calibration error. The deviation may also be because field studies tend to be very localized and not representative of the entire region. **However, the fact that optimum conditions are comparable reflects the soundness of expert knowledg**e with regard to the base input. It further suggests that the approach could be promising for other crops.

The integration agro-ecological zone and potential cropland dataset to the output from the **EcoCrop model allowed us to understand possible shifts between AEZ and the dominant stress factor limiting crop suitability in each zone**. Generally, heat stress will be the dominant factor reducing crop suitability in the future, as Thornton et al. (2009) reported. In addition to heat stress, drought will equally be a limiting factor, especially in the warm semi-arid zones (twsa) and will significantly reduce the agricultural potential of field pea.

The impact of climatic change on landscape suitability and legume production for each selected country will also largely depend on which AZE dominates. They will shrink considerably in zones dominated by warm AEZ in favour of chickpea and pigeon pea, which will be the future legumes for the region. Therefore different adaptation measures will be needed to optimize legume production in the East African region. For example, shortening crop cycles by delaying planting dates or months (Egbebiyi et al., 2019, Manner et al., 2022) will be ideal for the warm sub-humid zones. Alternatively, switching to drought-tolerant legume variety could be a workable solution for the warm semi-arid zones (Singh et al., 2014; Manner et al., 2022). Although these analyses were done on a very coarse scale, the results have highlighted the vulnerability of legumes crops and their production zones in East Africa, which could be the first step in formulating adaptation strategies for the study region.

Mapping variations in species richness in objective 2 was important to understand how local conditions (topography) considered dominant in the forested landslide region have shaped and maintained the current landscape structure and species composition. Therefore, the indicator of such variation, convergence point density (CPD), solely reflects topographic heterogeneity. **The improvement in correlation could be explained by the fact the processing of the DEM into convergence points and eventually to convergence point density was able to capture the heterogeneity of the terrain and varied abiotic conditions at a scale comparable** to the scale of field sampling (Leempoel et al. 2015; Lassueur et al. 2006). In other words, the convergence point density raster with a 5 m resolution was closer to the 10 m by 10 m scale of the sample plots than the original DEM with a 1m resolution. The improved and significant correlation between species richness and convergence point density agrees with the results of Burnet et al. (1997). While the work of these authors did not focus on convergence points, they equally reported a strong correlation between vegetation type and an indicator of topographic heterogeneity computed from different classes of soil properties, topographic aspect, and slope angle.

The advantage of using convergence points was that it reduced the difficulty of finding the most appropriate scale for independent terrain attributes. This difficulty could be even more challenging when multiple species are involved. We also found that resampling the original DEM attributes to the scale of the convergence point density raster did not improve or significantly explain the variability in species richness (Table 3). The cross-correlation between NoS and CPD was observed at a much shorter distance lag of ~118 m (Fig. 16c). It may imply an increased likelihood of finding homogenous topographic conditions beyond this distance (Bolstad et al. 1998). Because ordinary kriging was the only method in which the effect of topographic heterogeneity was not considered, it was the basis for assessing the role of convergence point density. Cokriging generally outperformed OK (Goovaerts, 2000; Wu et al., 2006; Han et al., 2003), decreasing the RMSE from 13.71 to 10.54 and predicting much more variability in species richness than OK (Fig 17 and 22 appendix). In agreement with (Goovaerts, 2000), we also observed a better fit of the cross variogram within this lag distance and a significant improvement in prediction when convergence point density and species richness had identical locations (Fig. 16c). The improvement highlights the benefit of detailly accounting for topographic heterogeneity in the study area. However, it is worth noting that the performance of cokriging was still below expectation as we expected the more densely sampled CPD to be fully exploited. We attributed this to the weak spatial cross-correlation between NoS, and CPD (Fig. 16c), explained by the differences in their spatial structure (Rossiter, 2012).

The overlap is largely a function of the sampling density of the target variable (Han et al. 2003), which further suggests that NoS was not sufficiently sampled to improve its spatial dependency on CPD. Regression kriging performed better than OK and OCK because there was evidence of spatial autocorrelation in the regression residuals (Fig. 6e), in addition to the fact that the residuals were almost normally distributed (Hengl et al. 2007, 2004), (Appendix…). Hence, modelling the spatial structure of OLS residuals decreased the RMSE and significantly increased the correlation between the observed and the predicted species richness (Fig.17e). The effect of modelling without considering the spatial structure of the residual could be seen in the OLS model, which performed relatively well but was the most biased with the highest ME (Table 4).

They showed less variability in species composition at unsampled locations than regression kriging. Hence, regression kriging was more robust to the limited number of observation plots and more stable to topographic variations than OCK (Meng et al., 2013). Therefore, the results have highlighted that the species distribution model for complex terrain can be improved if topographic heterogeneity is adequately captured. In addition, results can be used as the first step to support short-term conservation efforts, especially when time-dependent changes in species composition are unimportant.

The 28-year time series analysis of LULC data has given a general overview of the influence of the past and present natural and human-driven processes on the development of landscapes in the Czech Republic. In general, there is an **overall increase in Artificial Surfaces, Forest and semi-natural areas and Inland waters, and a decrease in Agricultural areas** (cropland) which is consistent with established trends in the Central European cultural landscape (Machar 2008; Kilianova 2012). The sum of persistent areas from, Coniferous forest, Land principally occupied by agriculture, Mixed forest, Discontinuous urban fabric, Broad-leaved forest and Pastures was over 2000 km^2. The vastness of these cover classes, in addition to Non-irrigated arable land, are major contributors to the prevalence of persistent areas for the entire territory. The sum of highly persistent areas was ~ 33767.3 km^2, compared to ~ 28915.32 km^2 for low-persistence classes. If non-irrigated arable land belonging to this group and occupying almost half of the monitored area is not included, the category area will be only 1580.16 km^2.

The observed transitions in land cover /use classes reflect changes in landscape potential for ecosystem services. In general, transition to a more favourable ecosystem means preserving or restoring ecological integrity and all the processes necessary to optimize its function (Müller and Burkhard, 2007). In this regard, a significant decrease in the capacity level is apparent, for example, in the change from Coniferous forest category to Transitional woodland-shrub. On the contrary, the transition from Woodland to the coniferous or mixed forest is associated with an increase in regulating services, consistent with the findings of (Frélichová et al., 2014). Based on persistent classes, the high persistence of non-irrigated arable land, with ~5968 patches and an area of ~27335.15 ha in all five monitored periods, suggested the capacity level for Provisioning services is at level 2 - relevant capacity, and level 1 for Regulating services. **Generally, the capacity for Provisioning services in the Czech Republic is at a lower level of relevant capacity (0 -2) mainly because of the urban development. On the contrary, the potential for Regulating services has increased over time mainly because of the expansion of areas of higher relevant capacity**. While these results are yet to be validated, changes in selected services from the trajectories of land use/cover **development for the Czech Republic have shown that landscape conservation needs to be intensified. At the same time, the expansion of urban areas should be restricted**.

The impact of climate and environmental change on individual species distribution is very diverse but varies with the local topography. **Species richness has slightly declined under the current climate as more than 97 per cent of the representative baseline species are currently preserved in most areas.** The change is due to the near stable climate between the two modelling periods, which shows that the average minimum temperature was nearly the same between these two periods. The mean temperature of the growing season increased by 0.85 °C, while the mean length of the vegetation period increased by three days. Although species richness is nearly the same, species habitat expanded remarkably between the two modelling periods as growth conditions have become more favourable for most species. While these conditions have extended highland habitats where low temperature is a limiting factor for growth (Lindner et al., 2010). The results from the EUROMOVE model suggest that a further rise in temperature will be devastating, resulting in a decline in species composition and contraction of habitat extent as the average minimum temperature and the growing season temperature rise by +5 °C and +3 °C, respectively. These results are comparable to those of Hlásny et al., (2011); Machar et al., (2017). They showed heat spells might become frequent in lowland habitats under a moderately mitigated climate scenario. As growth conditions under the baseline climate scenario may become too extreme for most species, these results should be interpreted with caution because they are only a simulation of what may be possible (Raskin, 2005; Riahi et al., 2011; van Vuuren et al., 2011).

The spatial pattern of MSAi values has reaffirmed that the most stable areas of the Czech Republic are currently restricted to protected and mountainous areas (Figure 18b). **Their MSAi values range from 0.7 to 0.94 but may drop from 0.5 to 0.8 by 2100 without intervention or mitigation efforts**. Lowlands with the least species variety are the least stable and the most vulnerable. Our results show more variability in the MSAi ratio for the Czech Republic than the regional EUROMOVE model for Europe (Bakkenes et al., 2002; Michel Bakkenes et al., 2006). A possible reason for the difference could be that we modelled change based on 686 species for the Czech Republic compared to 430 species for the entire Czech Republic, Slovakia, and Hungary in the regional EUROMOVE model (MBakkenes et al., 2006). The extra details also highlight the benefits of using high-resolution climate and environmental data to account for local variations (Pearson et al., 2004).

The **advantage of quantifying change as MSAi is that additional information about the state of the landscape, which is more related to ecosystem functions than species richness alone, is known** (Burkhard et al., 2009; Pechanec et al., 2019). Experimental studies have generally associated a decline in species richness with a decline in biomass production, leading to a 20 per cent loss in species as a proposed threshold for stable ecosystems (Hooper et al., 2012). The application of such species-based thresholds in nature has been questioned due to inconsistencies in the underlying processes that affect species richness (Vellend et al., 2013). **The EUROMOVE model results also show that species loss may not be proportionate to potential habitat loss.** (Table 5). Second, losing a few dominant species may drastically shrink or expand habitats, impacting selected ecosystem functions and services. Thus, **integrating both parameters to obtain information about the state of landscapes, we expect vulnerability thresholds established from MSAi to be more reliable and applicable than those based solely on species richness**. While MSAi does not explicitly quantify ecosystem function, our result also shows that it may be used as a validation tool or dataset to supplement such studies because changes in stable areas are based on surveyed records. **Stable areas can be compared to favourable or persistent areas of land use /cover classes preserved or appearing over time as the basis for assessing ecosystem function and services in paper 3** (Krkoška et a.,2016; Pechanec et al., 2019). Therefore, the detailed spatial variation in MSAi has highlighted highly vulnerable areas where a decline in species richness relative to habitat extent should be accompanied by a loss of key ecosystem functions and services.

The limitations of this research are linked to data quality, modelling approach and study design. The main data quality issues in assessing landscape potential for legume crops (EcoCrop Model) included the fact that crop location data was sourced regardless of the legume variety. Applying the same modelling approach to different varieties can be problematic as they tend to adapt differently to change (Manner et al., 2022). Second, while input parameters for the EcoCrop model were relatively comparable to the base parameter, the accuracy could best be assessed with local climate data (Ramirez-Villegas and Challinor, 2012), which was not available for this research. Therefore, the predicted shift in AEZ or the contraction of cropland, though consistent with existing studies, could be ascertained given that it was based on a much coarser dataset at 5 minutes degree. Subsequent studies should address these issues and explore possibilities to include biophysical factors like soil factors or critical climatic conditions (Manners et al., 2021; Piikki et al., 2017). These considerations not only make the model comparable to process-based crop models but will also increase its practical application. The main limitation of the geostatistical model was the insufficient sampling of species richness. This limitation makes conventional geostatistical methods less attractive than non-linear or hybrid methods. However, a possibility to further test the model in future studies is to summarise the entire plant community using ordination techniques and predict the ordination scores (Olthoff et al., 2018; Maestre et al., 2005; Kienel and Kumke, 2002). These authors found this approach successful in identifying and predicting spatially structured communities. The limitation of the Chorine Land Cover (CLC) data is that it was too coarse to capture change at the national level. However, this should not be a problem in future studies as work is in progress to improve land use and land cover for Europe with the availability of high-resolution sentinel 1 and 2 datasets. In the EUROMOVE model, climate impact was assessed on RCP 8.5, which is currently considered unrealistic even though it is still very popular in the Czech Republic. Hence an objective assessment based on a mild or moderate climate scenario is highly recommended for future studies. In addition, the MSAi indicator applied in this research does not capture biodiversity loss at the habitat or ecosystem level. Alternative and more robust like GLOBIO can be tested to address this limitation as it is based on habitat rather than species data. The GLOBIO modelling approach is particularly promising given that it is based on habitat data rather than species data, implying a better understanding of biodiversity change. It is worth noting that the major drivers of biodiversity loss in the Czech Republic, excluding climate change, have been tested and adapted as GLOBIO-CZ (Pechanec et al., 2021). Therefore it was hoped that once assessed for climate change and integrated into GLOBIO-CZ will improve understanding of the current state of biodiversity in the Czech Republic. Moreover, given that MSA in GLOBIO also assesses the stability of the ecosystem, the result will also be useful to assess the potential for the selected ecosystem category and whether they are comparable with those captured from the trajectory of land use and cover change.

8. Conclusions

Spatial processes are very complex. Hence a range of tools or models may be tested to understand them. Part of the complexity has to do with the fact that spatial processes operate at different scales. As such, processes captured at a particular scale by a given model may not be the case on another scale. Therefore scale is crucial to understanding ecological processes. This thesis explored a range of spatial modelling approaches to improve understanding of landscape development, mainly due to climate change but also due to topography and land use and cover change across multiple scales. **Therefore the issues investigated are the spatial patterns of species and changes in vulnerability of habitats, the role of topographic heterogeneity in the evolution of plant species, especially in complex terrain and the trajectories of land use and land cover change and its impact on Provisioning and Regulating ecosystems services in the Czech Republic**. Hence, the modelling approach tested (EcoCrop, Geostatistical model, EUROMOVE and a custom land cover change model) adapted to specific scales. Hence, each tested model captured specific aspects of the landscape development.

The detailed model results are presented in chapter five and related publications. The main findings were.

- The current climate has a milder impact on species which are already shifting to higher altitudes (papers 1 and 4)

- Highland habitats are the most stable and slowly expanding but will shrink with rising temperatures. (papers 1 and 4)
- The current trajectory of land use/cover change is an overall expansion of vegetation which has increased the potential for regulating ecosystem services. However, the potential for provisioning services is declining due to urban expansion (paper 3)
- Micro-climatic conditions created by topographic heterogeneity are particularly important at the local scale and can improve species mapping if adequately captured
- Landscape development is dominantly controlled by climate change and topographic variation. The former dominate at the national to regional scale while the latter dominates at the local scale

Theoretically, this thesis has reaffirmed the growing evidence of climate change on the development of landscape and range shift in species distribution. **The main output is the assessment and quantification of changes in the stability of landscapes. For the Czech Republic, such changes are associated with a loss of species diversity and selected ecosystem services**. For the East African region, change implies the production zones for legumes with narrow climate ranges will shrink drastically even under a moderate climate scenario.

There is a need for a detailed assessment of individual habitats, Ecosystems or crop production zones to further our understanding of landscape vulnerability and their potential for ecosystem services (paper 3). **GLOBIO is a promising model for the Czech Republic to address these issues because it has already been tested for other driver**s (Pechanec et al., 2021). It will also be possible to validate the GLOBIO model results with results from EUROMOVE, which is based on field observations. Therefore the model results of landscape development in the Czech Republic complement each other in one way or the other. In summary, spatial models are powerful tools for studying ecological processes. This study has shown that their power lies in the possibility of integrating expert knowledge with empirical approaches.

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PERSONAL INFORMATION

Name: Elvis TANGWA
Nationality: Cameroonian
Address: Druzebni 719/19,
77 900 Olomouc, Czech Republic
Email: elvis.k.tangwa@gmail.com

EDUCATION

10.2018 – present)	**PhD student** Department of Geoinformatics, Palacky University, Olomouc, Czech Republic**.**
10.2015 - 06-2017	**MSc. Forest information Technology:** Eberswalde University of Applied Sciences (HNEE), Germany
09.2007 - 09.2009	**MS.c. Exploration and Environmental Geosciences**: Luleå University of Technology, Sweden
10.2001 – 07.2005	**BSc. Geology.** University of Buea, Cameroon.

TRAINING AND EXPERIENCE

09.2021 - 11.2021	Research Stay Warsaw University of Life Sciences (2 months) Assessing changes in landscape fragmentation, python scripting
0.3.2020 - 03.2020	Copernicus Climate data service (3 days) Training on climate data acquisition and sectorial application
01.2020 – 02.2020	CEEPUS Research stay, Universität Salzburg, Austria (1 month). Climate science and climate change research
04.2019 - 04.2019	Institute of Geography, Bratislava, Slovakia (2 days). Remote sensing, land use and land cover application in Ecology

05.2017 – 06.2017	GEOS4S Summer school, AIT, Bangkok, Thailand (3 weeks) Intelligent transport systems and Geo application and development

RELEVANT WORK E XPERIENCE

10.2017 -12.2017	**Intern** Amazon Berlin Germany: data entry and packaging
01.2010 – 08.2011	**Laboratory assistant** Kjeoy Research and Education Centre Norway: laboratory routines, sample preparation and analysis

LANGUAGES

English	First Language, proficient user
French	Second Language, proficient user
German, Norwegian	Level A2

OVERVIEW STUDIES AND RESEARCH ACTIVITIES

Activities undertaken so far in include mandatory course exams, writing a research articles, mandator research stay and some teaching. These activities are summarised below.

Courses

Ac. year	Subject	Date	Status
2018/2019	VCJ/PGSAJ English for PhD students	21.01.2019	passed
2018/2019	KGI / PGSKP Mapping of landscape cover and their changes	04.05.2019	passed
2018/2019	KGI / PGSMK GIT in landscape management	29.08.2019	passed
2018/2019	KGI / PGS2S Co-authorship in a magazine with IF	02.09.2029	passed
2019/2020	PRF/PGS00 Scientific and research management	01.03.2020	passed
2019/2020	KGI / PGS3K Conference presentation (poster)	06.01.2020	passed
2019/2020	KGI / PGS3V Teaching a professional subject at UP	06.01.2020	passed
2020/2021	KGI/PGSMS Modeling and simulation of spatial phenomena	06.01.2021	passed

2020/2021	KGI / PGS3U Oral presentation at the international. conference	25.05.2021	passed
2020/2021	KGI / PGS2S Co-authorship in a magazine with IF	25.05.2021	passed
2020/2021	KGI / PGS3P Project activity	25.05.2021	passed
2020/2021	KGI / PGS3K Conference presentation (poster)	25.05.2021	passed
2020/2021	KGI / PGSVS Software development. prostr. for open-source GIS	26.04.2021	passed
2021/2022	KGI/PGSC6 Cartographic visualisation		passed

Research stays at foreign institutions

Ac. year	Institution	Date (duration)
2019/2020	Z_GIS, University in Salzburg, Austria	04.01 – 31.01.2020 (4 weeks)
2021/2022	Warsaw University of life Science, Poland	13.9.-13.11.2020 (2 months)

Teaching duties

Code	Subject	Teaching years	Total hours
KGI/GEOIN	Geoinformatics	2019 -2020	24
KGI/GINEW	New issues in geosciences	2019	8

Publications (ORCID: https://orcid.org/0000-0002-0430-1105)

TANGWA, ELVIS.; PECHANEC, VILEM.; BRUS, JAN.; VYCLECKA, PAVEL: Spatial Shifts in Species Richnessin Response to Climate and Environmental Change: An Adaption of the EUROMOVE Model in the Czech Republic https://doi.org/10.3390/d14040235 (**IF 3.01**)

TANGWA, ELVIS, WIKTOR TRACZ, VILÉM PECHANEC, and YISA GINATH YUH. 2021.

"Predicting Plant Species Richness in Forested Landslide Zones Using Geostatistical Methods." *Ecological Indicators* 132(July 2020):108297. doi: 10.1016/j.ecolind.2021.108297. (**IF = 4.9**)

PECHANEC, VILÉM, ONDŘEJ CUDLÍN, MILOŠ ZAPLETAL, JAN PURKYT, LENKA ŠTĚRBOVÁ, KAREL CHOBOT, **ELVIS TANGWA**, RENATA VČELÁKOVÁ, MARCELA PROKOPOVÁ, and PAVEL CUDLÍN. 2021. "Assessing Habitat Vulnerability and Loss of Naturalness: Applying the GLOBIO3 Model in the Czech Republic." *Sustainability* 13(10):5355. doi: 10.3390/su13105355. (**IF = 2.57**)

PECHANEC, VILÉM, HELENA KILIANOVÁ, **ELVIS TANGWA**, ALENA VONDRÁKOVÁ, and IVO MACHAR. 2019. "What Is the Development Capacity for Provision of Ecosystem Services in the Czech Republic?" *Sustainability (Switzerland)* 11(16):1–17. doi: 10.3390/su11164273. (**IF =2.87**)

Conference Proceedings

ELVIS TANGWA ,VIT VOŽENÍLEK, JAN BRUS, VILEM PECHANEC: Climate Change and the Agricultural Potential of Selected Legume Crops in East Africa (2020) GEOLINKS Conference proceedings, 2020 DOI: 10.32008/geolinks2020/b1/v2/02

Conference presentations

Land suitability and the agricultural potential of selected pulses in East Africa in response to climate change GEOLINKS Conference (2020), Plovdiv, Bulgaria (poster presentation)

Predicting plant species diversity in forested landslide zones using geostatistical methods: International conference on landscape Science and Landscape Ecology (IAEL2020) Russia: (online presentation)

Publications unrelated to doctoral studies

GINATH YUH, YISA, PAUL K. N'GORAN, ZACHARIE N. DONGMO, WIKTOR TRACZ, **ELVIS TANGWA**, MICHAEL AGUNBIADE, HJALMAR S. KÜHL, TENEKWETCHE SOP, and CHEFOR FOTANG. 2020. "Mapping Suitable Great Ape Habitat in and around the Lobéké National Park, South-East Cameroon." *Ecology and Evolution* 10(24):14282–99. doi: 10.1002/ece3.7027.

YUH, YISA GINATH, ZACHARIE N. DONGMO, PAUL K. N'GORAN, HERBERT EKODECK, ACHILE MENGAMENYA, HJALMAR KUEHL, TENEKWETCHE SOP, WIKTOR TRACZ, MICHAEL AGUNBIADE, and **TANGWA ELVIS**. 2019. "Effects of Land Cover Change on Great Apes Distribution at the Lobéké National Park and Its Surrounding Forest Management Units, South-East Cameroon. A 13 Year Time Series Analysis." *Scientific Reports* 9(1):1–19. doi: 10.1038/s41598-018-36225-2.

Involvement in departmental Projects

I have been a member of the following projects at the Department of Geoinformatics:

- IGA (2020), "Innovation and application of geoinformatics methods for solving spatial challenges in the real world." (IGA_PrF_2020_027)
- IGA (2021), Advanced application of geospatial technologies for spatial analysis, modelling, and visualisation of the phenomena of the real world