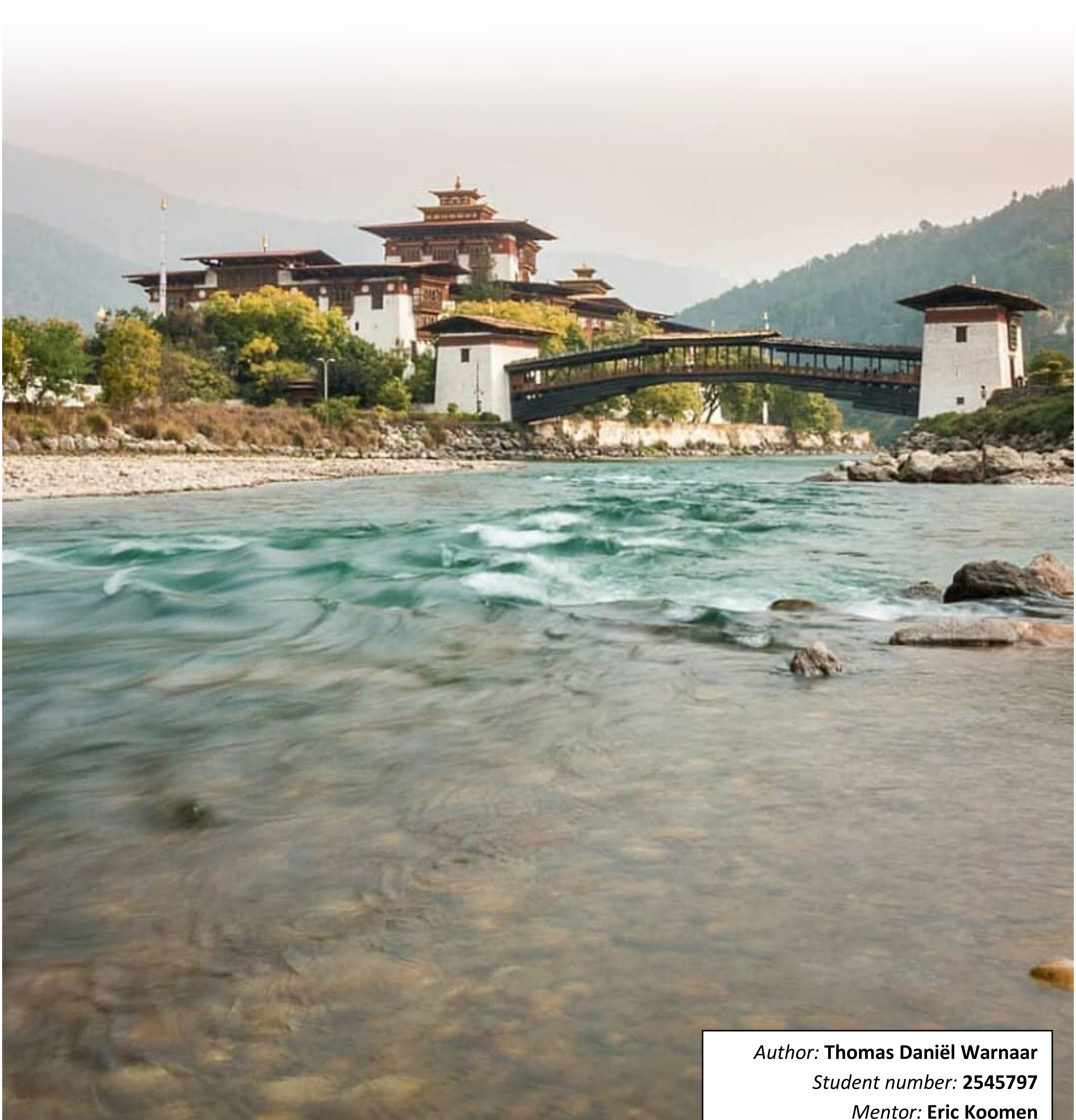
Landscapes of the Thunder Dragon

Creating a Typology of Bhutanese Landscapes as a tool for Policy-makers and Researchers



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Abstract

Bhutan is undergoing rapid changes after lifting a self-imposed isolation which exposed a development lag with the rest of the world. The nation is developing from a traditional into a modern society in rapid pace. This development is putting a pressure on Bhutan's landscapes because of large-scale infrastructure projects and diminishment in perceived importance of cultural landscapes. The Bhutanese government puts great effort in developing the nation in an ecologically and culturally sustainable manner. A landscape typology and map is created to aid these efforts. A literature review of existing typologies shows a lack of standardised methods aimed at (sub-)national scale. Proposed standards for supra-national landscape typologies are found to be inadequate for this goal. Previous methodologies are examined and discovery of general patterns has led to a methodology flowchart which is used to develop a robust but simple method that is suitable for Bhutan.

The typology for Bhutan is based on altitude, slope and landcover, with class boundaries determined using landcover and settlement patterns. In an attempt to include a larger scale landscape attribute as source data for the landscape typology commonly used relief roughness indicators were found to be unsatisfactory in discriminatorily indicating different types and measures of relief roughness. An improved indicator was therefore developed called the Comprehensive Roughness Indicator (CRI). In a technical comparison CRI outperformed four commonly used indicators in accuracy, scalability and flexibility. Noise in the Digital Elevation Model prevented the use of CRI in the final typology creation. The final landscape map uses a minimum mapping unit of 230 ha for a general overview and 15 ha for research and guidance for policy-makers.

The landscape map resulting from this typology is found to be accurate with a minimum accuracy of over 72 % and a realistic accuracy of over 86.6 %. Based on the validation results it is recommended to include an additional heterogeneity landscape attribute. The developed landscape typology is used in two case-studies concerning real world issues. The first case study addresses vulnerability of cultural heritage and difficulties for archaeological research. Two types of archaeological heritage prediction models are calculated, where the landscapes generated by the developed methodology perform optimal in delineating high potential archaeological sites and the typology adds considerable discerning capability. The second case-study addresses landscape change. The landscape typology is found to help explain and increase understanding of processes related to landscape change. Based on the literature review and building upon the developed method a proposal is made for a standard framework which can be used to create coherent super-national scale landscape typologies in greater detail than currently feasible.

Bhutan's national flag.

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1. Introduction

1.1 Background

Bhutan, known by locals as Druk yul which is Dzongkha for 'the Land of the Thunder Dragon', is a country undergoing rapid transformations. Throughout history the Himalayan kingdom has never been conquered or ruled over by other nations or any other form of outside power (Aris, 2005; Rose, 1977). This fact, together with its difficult traversable mountainous terrain and in part naturally impenetrable border consisting of some of the world's highest mountain peaks has ensured Bhutan has been relatively free from foreign cultural influences (Mathou, 2000; Silva & Sinha, 2017). Consequently the Bhutanese people have adhered strongly to their cultural identity and practices imparting Bhutan's traditional society with an almost time-capsule like quality which much of the modern world has passed by for a long time (Mathou, 2000). Relatively recent changes in the political structure have paved the way for a more open stance towards the outside world. More modern forms of government introduced throughout the 20th century together with the China-Tibet conflict and fear for similar encroachment efforts on Bhutan led the Bhutanese to seek out a stronger relationship with India, its neighbour to the south (Savada, 1993; Ueda, 2003). Supported and partly funded by India a program of modernisation was implemented which included the construction of roads throughout Bhutan and connecting this network to India. The end of Sikkim's 300 year old monarchy in 1975 through Nepalese actions may have further encouraged the Bhutanese to solidify Bhutan's independence and international position by establishing diplomatic relations with other nations and joining international organizations, resulting in even more contact with the more modern outside world (Savada, 1993).

Now modernisation has finally achieved a solid foothold it is increasingly influencing and quickly altering all aspects of the nation's society including culture, environment, landscape, economy and much more (Asian Development Bank: Bhutan Country Team, 2005; Palden, 2016; Topping, 2014; Ueda, 2003). The country is being pulled from a traditional society and technology level into the modern world at an unprecedented pace. Modernisation is having both desirable and detrimental effects on many of the nation's cultural and ecological attributes (Palden, 2016; Topping, 2014). The stronger ties with the rest of the world have improved healthcare and education and ensured better infrastructure, the abolishment of slavery and so on (BBC, 2018; Topping, 2014). Small villages that had been isolated for centuries are now connected to the electricity grid and can receive television and internet. Also they are physically becoming connected to the outside world by newly built roads where previously its inhabitants had to hike for up to a week to reach the next township (Y. Samdrup, personal communication, March 29, 2017; Topping, 2014). The lifting of the ban on television and the internet in 1999 has especially lead to many societal and cultural changes, not all of them beneficial (McDonald, 2004). Global cultural influences and modern knowledge could now easily spread to the least developed regions (Knaster, 2008; Silva & Sinha, 2017). Information about stronger building techniques and materials have caused the prevalence of typical ancient architecture used for centuries to decline, altering the look of traditional houses (Fig. 1).

Fig. 1) Modern influences on Bhutanese society can also be found in its architecture. For example typical wood shingle roofs weighed down with rocks (left) are replaced with low maintenance corrugated sheet roofs (right). Image credit: Bhutan Nuns Foundation; Living Travel.

Children are being schooled via telepresence solutions and gain aspirations outreaching their traditional environment, driving them to the nation's cities. This results in traditional villages becoming increasingly abandoned as has been happening in other modern nations for decades (Asian Development Bank: Bhutan Country Team, 2005; CNN, 2007; Knaster, 2008; Topping, 2014; Ueda, 2003). Traditional villages play an important role in the perpetuation of Bhutanese culture and traditional landscapes. The villages act as a repository for local legends through village elders (Chand, Nel & Pelc, 2017). Surrounding landscapes are shaped by the local customs but also by local legends and beliefs (Allison, 2015; Nassauer, 1995). The decline of their population is thus expected to have a large influence on the landscape and Bhutanese heritage (Nassauer, 1995). The influx of globalised culture through television and the internet has resulted in a decrease of experience with, and perceived importance of, Bhutanese culture. These processes resonate throughout the entire social, economical and ecological structure of Bhutan. Because of the pressure on traditional practices Bhutanese culture itself is increasingly under pressure. The decline of traditional practices and cultural awareness are particularly visible in the traditional Bhutanese landscapes (Allison, 2015; Palden, 2016). Their appearance is more often than not strongly tied to legends, beliefs and cultural features like temples and stupas. The landscapes, cultural practices and cultural features have evolved around each other and the value of both is derived from this reciprocal relationship (Allison, 2015; *Cultural Heritage Act of Bhutan*, 2016; Nassauer, 1995). The decrease in importance and value associated with cultural features and practices thus also has a large influence on the perceived importance and value of traditional cultural landscapes. Adding a sense of urgency to the pressure on Bhutan's landscapes and heritage is that analysis shows that even though in the course of a country's economic development the nation becomes less dependent on provisioning and regulating ecosystem services it becomes more dependent on cultural services of landscapes (Guo, Zhang, & Li, 2010 in Plieninger, Dijks, Oteros-Rozas, & Bieling, 2013, p. 119). This highlights the importance of understanding cultural landscapes in developing countries. There are additional factors that exacerbate these negative consequences of Bhutans modernisation.

One significant pressure on Bhutanese landscapes is Bhutan’s enormous potential for generating hydropower due to its geography and climate (Tshering & Tamang, 2004). High-level governmental cooperation with India has led to the (future) construction of multiple hydroelectric plants and is now shaping Bhutan's hydropower export into its most important economic input, thereby skyrocketing the tiny economy to the second fastest growing economy worldwide in 2007 (The World Bank Group, 2014; The World Bank Group, 2017). Since the valleys are where most of Bhutanese life takes place flooding of parts of the valleys combined with large scale scarring of the mountain side has a big impact on the landscape. In addition to the direct influences of large-scale construction projects there are many indirect effects associated with them as well. For example relocation of people living in to-be-flooded regions which may involve them leaving traditional villages and moving into more modern apartment blocks. Workers of these projects (often Indians with no local homes) have to be housed in semi-temporary buildings and additional roads are constructed for transport of workers, materials and machines. Because of the indirect effects of the large scale construction projects their effect on the Bhutanese landscape reaches farther than solely the construction site. The scale of these and other large scale infrastructure projects are affecting all aspects of Bhutan's society and ecology, including its cultural landscapes (Dharmadhikary, 2015; Rinzin, 2017). For these reasons the more open attitude of Bhutan to the rest of the world appears to have set in motion an unstoppable cascade of processes that may diminish the impact, presence and importance of the Bhutanese heritage, including cultural landscapes.

The interplay between landscapes and local legends and traditions is exemplified by the Bhutanese religion which is a combination of Buddhism and a pre-Buddhistic animistic belief system called Bon. As such the Bhutanese assign great importance to many natural features like rocks, trees, cliffs, rivers, mountains and even small features like specific indents in rock faces. These features are believed to be inhabited by deities or incorporate the spirit of important historic persons (which are often shrouded in mythology) who have visited those locations. Such features are called Nye's and are absolutely everywhere in the Bhutanese landscape where they influence every aspect of day to day life. As such they are vulnerable to many changes in Bhutan's environment and culture. The box on the next page has an example of a Nye and the effects large infrastructure has had on this Nye.

The influence of Bhutans modernisation on a Nye near Thimphu

An example of the effect of infrastructure growth is found in a little known Nye very close to the capital of Thimphu where one of Bhutan's two important historical influencers, Guru Rinpoche, is believed to have meditated together with many deities. The Guru, his horse and the deities have left imprints of various body parts in the cliff face which are closely guarded by the villagers to this day. They are believed to house religious insights known as treasures which can be unlocked by a Tertön (treasure seeker). When looking at the cliff face from across the valley one should also see the face of the Guru in the shape of the rocks. During a field visit this very holy and otherwise tranquil location was found to suffer from its proximity to the capital as city noise was very clearly audible, diminishing –according to the caretaker of the Nye- the suitability of the location for meditation and religious festivities.

Fig. 2) View of Thimphu from Tandin Nye in 2018. Image source: Google Earth Pro

Fig. 2 contains a view from Tandin Nye towards the capital of Thimphu in 2018. Fig. 3 features a top down aerial image of the urban area seen in the view from Tandin Nye. The increased urban density is clear.

Fig. 3) Aerial view of the area seen from Tandin Nye. 2003 on the left, 2018 on the right. Image source: Google Earth Pro

Fig. 3 clearly shows the increase in urban density but maybe even more importantly in this case the new highway that has been built. The highway has replaced a dirt road and when seen in high resolution clearly is home to a much higher traffic density which is responsible for the noise pollution mentioned earlier.

The example in the box reveals the pressures on Bhutanese culture and cultural landscapes due to modernisation which are in this case two-fold. Important locations are suffering from the modern world finding its way into Bhutan altering the properties of the landscape (in this case noise pollution and the view from the Nye, which has rapidly changed from a forested valley to a highway and apartment blocks). The other factor in this example is that the population of the neighbouring capital mostly does not know of this location as especially the younger generation is losing touch with the importance and significance of these places and rituals. The professional guide employed during the field study had, to his own surprise, never before heard of this location, same as anyone who was asked about it in the capital even though it is one of four locations where Guru Rinpoche, unanimously regarded as one of the two most important individuals in Bhutanese history, has spent a significant amount of time. Both pressures enforce each other as well, because when people are less aware of the presence of such locations they are unable to protect them during planning phases of (urban or infrastructural) development projects. Encroaching development further diminishes the sanctity of these places which ensures that less people will regard them as important and so they slide into obscurity. Various departments within the Bhutanese government are working on projects to map and spread knowledge of these locations. The projects have just begun in recent years and there is a lot of work to do before such an overview is complete.

The Bhutanese government has expressed a great desire to protect the cultural heritage and traditions of Bhutan, including cultural landscapes as was laid down in the 1990 Paro Resolution, the 11th and 12th Five Year Plan and the Economic Development Policy. Bhutan is famous for being the only nation to adopt Gross National Happiness as its guiding philosophy where other nations around the world measure their success through the Gross National Product. The pursuit of Gross National Happiness (GNH) is even dictated by the 2008 Bhutan constitution and is taken very seriously. The GNH commission is one of the most important governmental bodies of Bhutan influencing just about every other regulatory body. The GNH philosophy is supported by the four main pillars of GNH: 1) Good Governance, 2) Sustainable Socio-economic Development, 3) Preservation and Promotion of Culture and 4) Environmental Conservation. Especially pillar 3 and 4 are vulnerable to the influences of modernization. The GNH centre of Bhutan describes the importance of the pillars as such (Gross National Happiness Centre [GNHC], n.d.; Silva & Sinha, 2017):

Preservation and Promotion of Culture. *Happiness is believed to be contributed to by preserving the Bhutanese culture. Developing cultural resilience, which can be understood as the culture's capacity to maintain and develop cultural identity, knowledge and practices, and able to overcome challenges and difficulties from other norms and ideals.*

Environmental Conservation. *Environmental Conservation is considered a key contribution to GNH because in addition to providing critical services such as water and energy, the environment is believed to contribute to aesthetic and other stimulus that can be directly healing to people who enjoy vivid colours and light, untainted breeze and silence in nature's sound.*

In these two pillars an acute awareness of the development pitfalls described by Guo et al. (2010) is clearly visible. The concept of cultural landscapes is relevant for both pillars and they are thus a large contributor to GNH in the view of the Bhutanese government. The fourth pillar is often closely tied to the third pillar as their subjects are influenced by each other. Especially due to large infrastructure projects, like the enormous hydropower installations being constructed at multiple locations and the earlier mentioned urban developments, many parts of the Bhutanese landscape are being affected.

In order to aid the Bhutanese with their goal of sustainable development (pillar 2) the World Bank is offering technology, materials and knowledge. This report is a continuation of these efforts aimed at helping the Bhutanese transition to the modern age in a sustainable fashion, in particular the '*Bhutan cultural mapping for large infrastructure planning and development*' project (contract number 7182038) which is undertaken by the World Bank Group and Spinlab of the Vrije Universiteit Amsterdam.

The aim of this research is to create a nationwide landscape typology and create the first ever landscape map of Bhutan. A landscape typology has many possible uses. Use cases for Bhutan include, but are not limited to, aiding with environmental protection, finding or designating cultural landscapes, aid in protection of sensitive areas, track landscape changes over time and find unknown cultural heritage. A landscape map will help quantify the influence of several processes associated with large scale construction and the modernization of the Bhutanese civilization like urban development, decline of traditional village populations etc. In order to quantify the changes the Bhutanese landscape is undergoing data from earlier years will be used in a case study as input for creating the landscape map, after which differences in locations and coverage of landscape types can create insight into landscape dynamics and vulnerable landscapes or areas.

Additionally there may be a possible use for locating unknown cultural heritage sites, which will also be examined in a case study. Bhutan's library and historical records containing most knowledge of the nation's history was situated in the old capital of Punakha. When Punakha was destroyed by fire in 1827 this repository, which was the only one of its kind, was lost. Because of this event very little is known about the nation's history before the 19th century (*Arches: Protecting the World's Irreplaceable Cultural Sites*, 2016; Gupta, 2007; Mason, 2014). As a consequence many historic cultural sites have also been lost or forgotten and archaeological research proves to be difficult because of it. With the inundation of large sections of valley there is a possibility that important cultural heritage may be destroyed and/or lost forever. So there is a need to develop a method for predicting possible locations where the likelihood of finding previously unknown archaeological sites or cultural heritage is high. It stands to reason that requirements of locations for building different types of cultural heritage will have been similar for both known and, as of yet, unknown heritage sites. If a pattern can be found between the locations of known heritage and associated landscape types the typology can aid in predicting sites with greater archaeological potential which in turn will reduce cultural losses sustained through for example large scale infrastructure construction.

The importance of creating GIS based tools and their ability to help with emerging challenges of socio-economic development and environmental conservation is well understood as can be read in the foreword to the Atlas of Land Cover and Institutional Facilities (2016) written by the National Land Commission Secretary, Mr. Pema Chewang. The landscape typology and the mentioned use cases fall within this goal. Additionally this study is an interesting exercise in landscape studies in Asian countries. Attribute based automated landscape typology designation through GIS is commonly used in the West but is not yet common for Asian nations. If this study and the developed methodology prove to be useful they can be applied to many more nations where it may help achieve similar goals.

1.2 What is a Landscape?

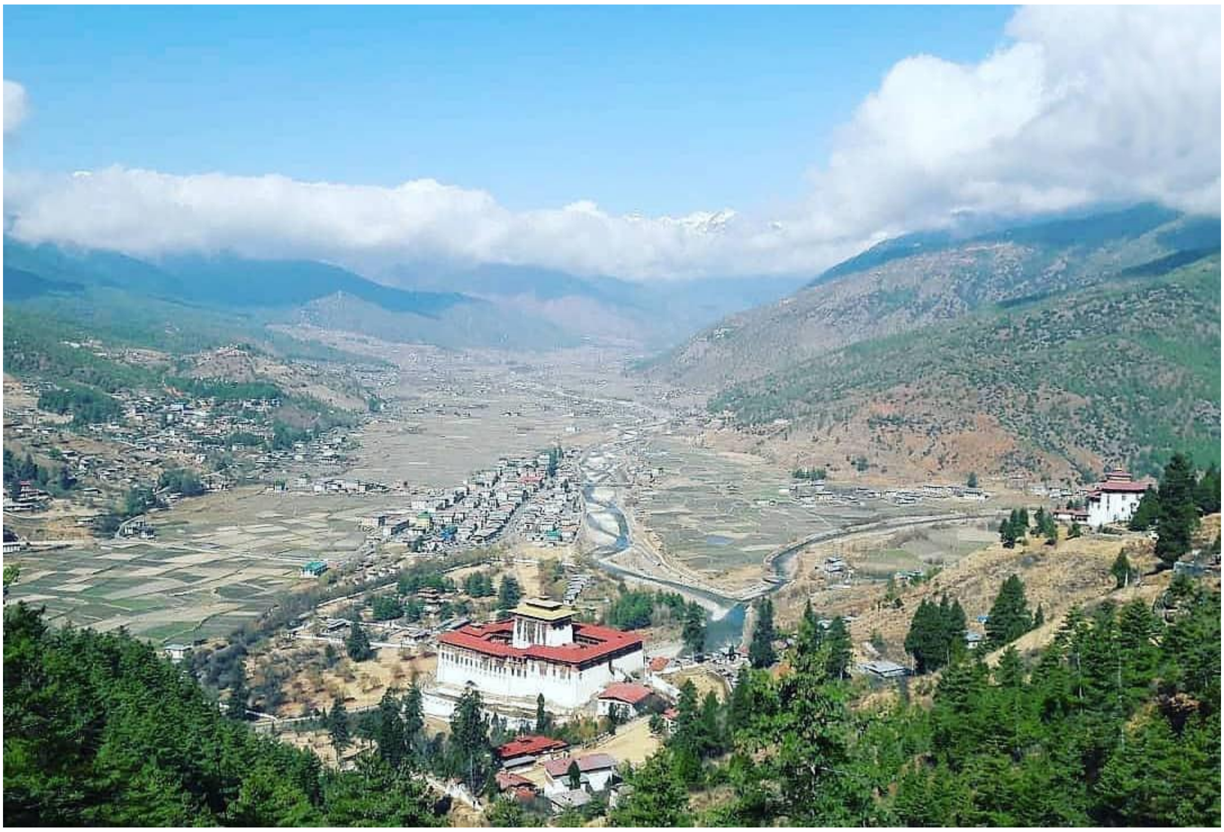


Fig. 4) A cultural landscape. The Paro river valley. This relationship of humans and the landscape is typical for Bhutan. The Paro Dzong is overlooking the valley from a strategic location. The flat area of the floodplain is where most of the human activity is found. Agricultural activity is dominant in the floodplain and the historical city of Paro is located next to the river. Photo credit: IG_Bhutan, 22-03-2018.

There are many definitions of the term landscape. Mücher, Klijn, Wascher and Schaminée (2009) define landscapes as "recognizable, although often heterogeneous, parts of the earth's surface, which show a characteristic ordering of elements" (p. 87). Wascher (2005) uses the Countryside Agency and Scottish Natural Heritage (2001) definition of landscape character: "a distinct, recognisable and consistent pattern of elements in the landscape that makes one landscape different from another, rather than better or worse" (p. 1) where landscape character is described as what the average traveller would designate as a landscape. In order to further muddle the concept of landscape there is another type of landscape concept, the cultural landscape. This is a landscape that is influenced by humankind, or in the official terminology agreed upon in Article 1 of the World Heritage Convention (1992) landscapes that represent the "combined works of nature and of man". In Article 1 the term cultural landscapes is further subdivided into three categories: 1) Clearly defined landscape designed and created intentionally by man, 2) Organically evolved landscape and 3) Associative cultural landscape. Associative cultural landscapes are landscapes that carry "powerful religious, artistic or cultural associations of the natural element rather than material cultural evidence, which may be insignificant or even absent" ("*Operational Guidelines,"* 2008). Especially the last definition of a cultural landscape basically designates the entirety of Bhutan as a cultural landscape, which is how the Bhutanese people actually treat their land. This concept is known as

'Beyul', a term encompassing the spiritual and historic value of an area and widely regarded to be applicable to the whole nation by the Bhutanese (Silva & Sinha, 2017). The preamble of the Heritage Sites Bill illustrates this school of thought (UNESCO, 2015):

> *Bhutan's uniqueness lies in its cultural landscape where heritage sites coexist harmoniously with nature bearing witness to the distinctive history, wisdom and custom of the people of Bhutan. (…) thus heritage sites should be protected with the understanding of its association with natural settings and living traditions in such a manner as to respect the cultural landscape.*

As all of Bhutan is regarded as cultural landscape this paper from here on out will adhere to the less holistic definition by Mücher et al. (2009).

1.3 Project Area

Bhutan is located between India and Tibet and has an area of approximately 38.400 km^2. It stretches from the flat planes of India to the apex of the eastern Himalayan mountain range. Bhutan encompasses a huge range of elevation, in the south the elevation is ±28 m above sea level whereas in the north the highest peaks are over 7500 m above sea level. This also means that there is a rough North-South gradient in climate leading to a couple of climatic "bands". The Köppen-Geiger climate zones can be found in fig. 5. The northern "band" is primarily Polar Tundra (ET) with some areas of boreal Cold continental climate with dry winters and cold summers (Dwc). Towards the north-east it is primarily warm Temperate climate with dry winters and warm summers (Cwb). The middle "band" is predominantly Cwb and the southern "band" is primarily Cwa (Temperate with dry winters and hot summers). The middle band also features a couple of polar ET zones in local high elevation areas (Kottek, Grieser, Beck, Rudolf, & Rubel, 2006).

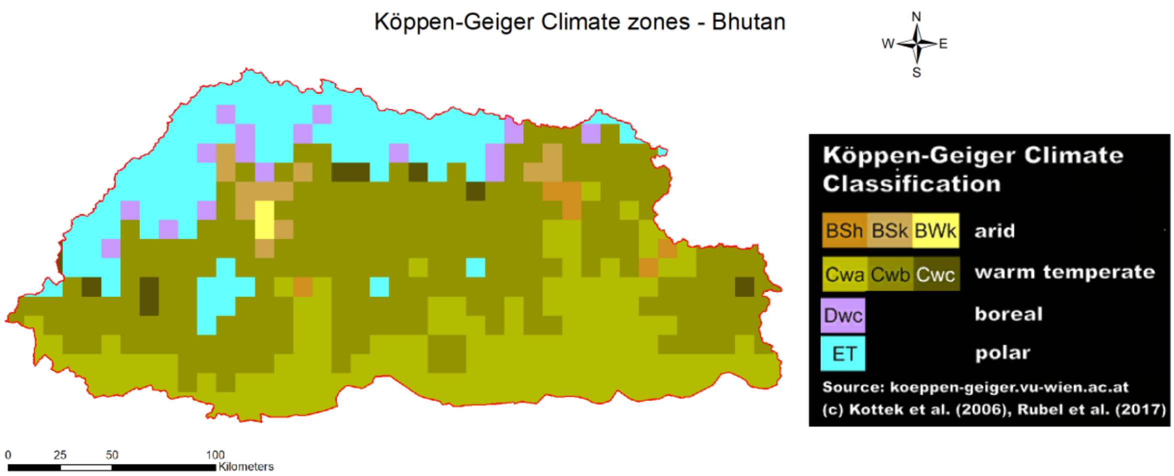


Fig. 5) Bhutan's climate zones according to the Köppen-Geiger classification. Data source: (Kottek et al., 2006)

The country features multiple river systems in the north-south direction that have created a series of river valleys. Some areas in the middle and lower climate bands feature flood plains, which is where most of the population of Bhutan is concentrated. Between the river valleys the Himalayan mountains extend towards the south in multiple smaller ranges. The alternating mountain range-valley-mountain range system has led to slightly different cultural properties between the people of the valleys, which in turn may have an influence on the landscapes found there.

Bhutan is mainly covered by natural forests. Broadleaved forest in the southern region and coniferous forest in the middle region. 72% of Bhutan is covered by forest according to Gilmour, Chhetri, Temphel, and Schmidt (2009). In 1969 all forests were nationalised and in 1974 the National Forest Policy was approved which set a goal to maintain 60% of Bhutan as forest coverage. The nationalisation resulted in reduced engagement of local populations with their forests and this had an adverse effect on forests as a sense of responsibility diminished (Wangdi, Lhendup & Wangdi, 2013). In part to counter this effect in 1995 the National Forest Policy was amended with the Forest and Nature Conservation Act which restored communities' traditional rights with regards to use of local forests thereby reinstating their responsibility. As a result forest vitality was restored and preservation of local cultural and environmental heritage was enhanced (Wangdi, Lhendup & Wangdi, 2013).

2. Review of Existing Typologies

A literature review was carried out to understand which methods and data types are commonly used for the creation of landscape typologies. The initial focus was on typologies of similar landscapes, i.e. rice cultivation type landscapes, Asian landscapes and Himalayan mountain landscapes. The literature review, however, showed there are hardly any landscape typologies for these categories and areas. Therefore it was only possible to review landscape typologies created for western countries where they are much more common. In the European Union member states are strongly encouraged to create landscape typologies under Article 6 of the European Landscape Convention (CoE, 2000 in Mücher et al., 2009, p. 88). At the Sofia Conference in 1995 eleven action themes were defined, the fourth of which detailing the objective to create a Pan-European Landscape Map (CoE, UNEP & ECNC, 1996; Vervloet, Spek, & Unwin, 2003 in Mücher et al., 2009, p. 88). Most European countries have a national landscape typology as a result. This has caused confusion however as no standard method was used and the large variety of developed methodologies resulted in very different typologies even between neighbouring areas. To achieve the goals set by the Sofia Conference an overarching typology for the European continent has been created called LANMAP (Mücher et al., 2009). Examples of comprehensive landscape classifications are also available for non-European western countries like New Zealand (Brabyn, 1996; Brabyn, 2009), the United States and Canada (Moss, 1985; Moss, 1989 in Lipský & Romportl, 2015, p. 4; Nair, Preston, King, & Mei, 2016). This chapter first outlines the types of methods used in the creation of the typologies after which the source data used for these typologies is discussed.

2.1 Previous Methodologies

A total of 22 articles were reviewed of which seventeen directly treat the creation of a landscape typology. Additionally the European Landscape Character Assessment Initiative or ELCAI report has reviewed 49 national typologies and five international ones in light of the Pan-European efforts (Wascher, 2005). A surprising find of this review of earlier work, which is corroborated in the ELCAI report, is that there is no standardised method to create landscape typologies and as a result typologies and their creation methods can differ substantially between two neighbouring areas. Wascher (2005) describes the phenomenon as follows: *"The different regional and national landscape typologies form a patchwork of classification models, which are conceptually rather incompatible at the international level. This is one of the reasons that classification models also started to evolve at the international level"* (p. 8). This problem is in part addressed in Europe by the establishment of the LANMAP project, one of the goals of which is to create a unified landscape typology throughout Europe. The LANMAP project methodology is influenced by standards set by ELCAI (Wascher, 2005). Regardless of best efforts a comprehensive typology of such a large and diverse area will suffer from one of two issues. The first possible issue is that detail is lost through generalisation of landscape categories and thus a typology for such a large area may not be useful on a national or smaller scale. The second possible issue is that the typology can become unwieldy and difficult to interpret when there are too many landscape categories, which are needed to accurately display actual landscapes on a smaller than (supra)national scale (Mücher et al., 2009).

The ELCAI and LANMAP projects and other international typologies like the World Map of Present-day Landscapes by Milanova, Kushlin, and Middleton (1993), the EEA Dominant Landscape Types (EEA-ETC, 2002 in Wascher, 2005, p. 12) or the Dobříš Landscape Map by Meeus (1995) unavoidably suffer from those problems. Because of the scale issues they are often not very useful on a national or smaller level for any kind of policy-making or research and this maintained the necessity for typologies being created by and for individual nations. The literature reveals that those typologies more often than not use a different individually created method which explains in part the different typology sets often found to exist between neighbouring administrative regions (there are differences in typology between nations, but also depending on the administrative system and regulations between intranational regions). This practice results in incompatibility between typologies causing edge problems and difficulties for projects requiring the use of multiple typologies together, a problem also identified by ELCAI. Between all the typologies some similarities have been found and approaches used in literature can be generalised into types, which is discussed in this section.

According to Lipský & Romportl (2015) there are two major distinctions in the basic approach to the creation of a landscape typology, the geochemical and the physicogeographical approach. The latter is used most often as the former, based on sometimes labour intensive or difficult to measure (physio)chemical properties of the study area, presents all kinds of difficulties in creating complex landscape units because of for example low spatial and temporal data resolution. The physicogeographical approach is more representative of what people intuitively think of when discussing landscapes (the 'average traveller experience' discussed earlier) and can often be created using more accessible (remote sensing) data. The approaches can be further subdivided in two methods. The method used most often is the establishment of landscapes led by a hierarchical classification through multiple GIS data layers, which will henceforth be called the parametric method. There are variations in every instance where the parametric method is used but the overall process is aimed at assigning relevant attribute values retrieved from source data layers (like thematic maps) to a standardized grid cell layer, after which the result is used to delineate landscape units. The less used method is the holistic method, where landscape types are assigned intuitively by an operator through the use of for example aerial photography or landscape picture slides. The parametric method uses clearly defined source data and source data classes, the holistic method is based on the subjective interpretation by each individual typology developer. Often a combination of the parametric and holistic method is used with the parametric method primarily driving the definition of the typology and the holistic method being used for validation, further refinement etc.

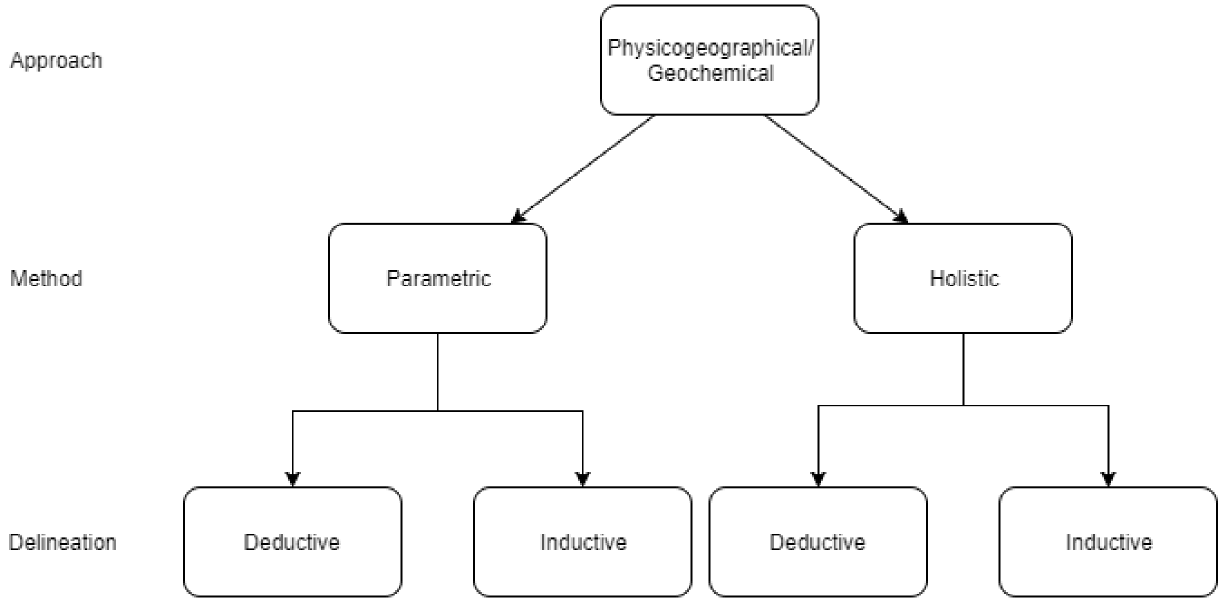


Fig. 6) The methodology flowchart.

Finally for all approaches and methods there is the possibility to delineate the landscape types in an inductive or deductive manner. Inductive delineation entails the gridcell by gridcell combination of all source data and subsequent automated and sensible grouping of small and unique landscape units (or patches) into larger ones. Deductive delineation entails the division of large units, like climate or altitude, in smaller landscape units through smaller scale data like land cover. A typology establishment thus always roughly follows a path on the methodology flowchart (Fig. 6).

An example of a hierarchical divisionary system is shown in fig. 7. These systems are almost always based on increasing dependency of the attribute. In the example in fig. 7 climate and geology are not influenced by geomorphology, hydrology etc. Geomorphology is influenced by climate and geology but not by hydrology, soils etc. Therefore the deductive physicogeographical approaches divide landscape types by increasing dependency of attributes.

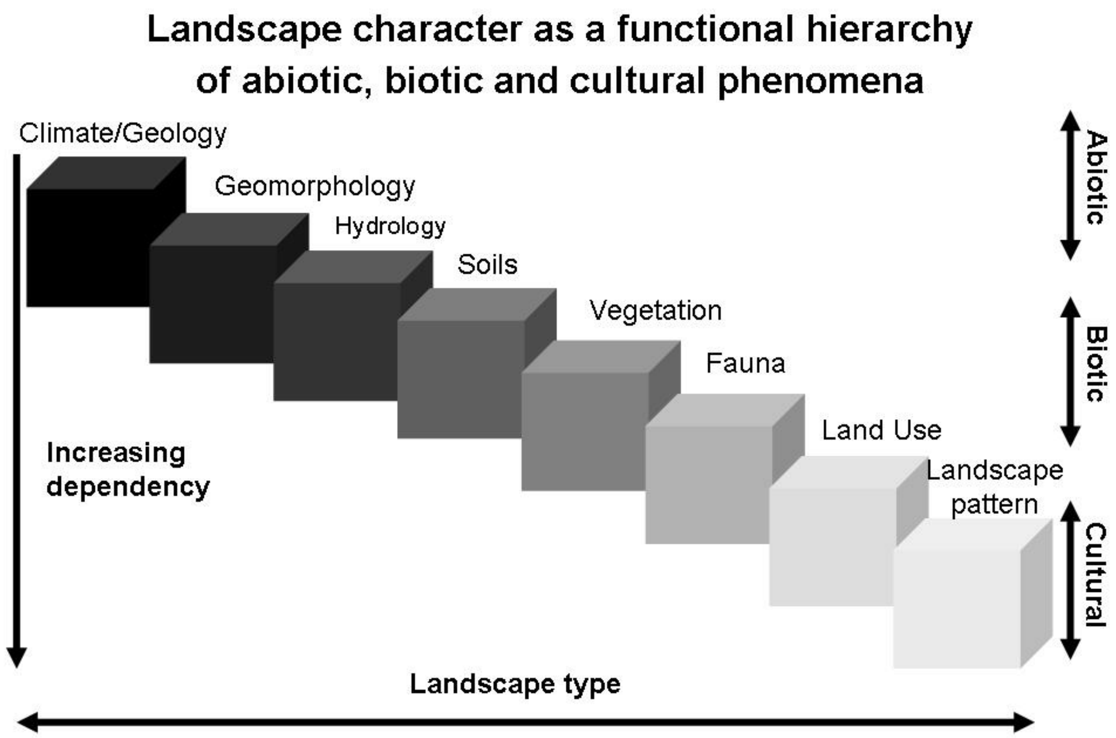


Fig. 7) Example of a hierarchical system. Based on the work of Jenny (1941) and Vos & Stortelder (1992). The phenomena mentioned in this image are also the most used landscape variables according to a study of 49 existing typologies by Groom (2005) and have been found to be the most prevalent in this literature review as well. Image Source: Mücher et al., (2003) in Lipský & Romportl, (2015)

2.1.1 Parametric method

The parametric method was used for example by Mücher et al., (2009), Vogiatzakis, Griffiths, Melis, Marini and Careddu (2006), van Eetvelde and Antrop (2009), Bastian (2000), Blankson and Green, (1991), Odeh et al., (2017) and Nair et al., (2016) as well as most of the studies reviewed by Groom (2005) in Wascher (2005, p. 32). The abundance of studies that use this method reveals the widespread support for and confidence in this method. The specific implementation differs for each study however. A generalised roadmap for the parametric method incorporates at least the following steps. First of all data will be gathered on the area of interest. This can be GIS data but also paper maps, tables, census data or anything that contains useful information on the study area. This data then has to be readied to be used in a GIS environment, i.e. digitizing and georeferencing of paper maps, tables etc. Next the project is shaped by creating a tessellated grid cell layer by which maximum resolution and extent of the final result is determined. The next step is to use the GIS environment to assign attributes extracted from the source data layers to the grid cells. This can be done in multiple ways depending on the data type. For example land cover is generally represented on a per grid cell basis by relative values of each land cover type found in the extent of a particular standardized grid cell, rather than assigning the entire grid cell the most prominent land cover type. During this step the developer of the typology has to make choices in how to best represent the original data, which often follows different formats than the standardized grid layer. The choices made will have a big influence on the typology so they should be made with care. The choices made earlier and in this step determine the main divisionary landscape attributes -and boundary conditions for each attribute- and consequently the amount of landscape units. Often these choices will be represented in the naming of categories in the final typology. In many reviewed typologies however the choices, as well as the process of selecting relevant data, are not explicitly substantiated leaving some uncertainty into the process and rationale driving the decisions.

During the next step the typology starts to take shape as the attributes assigned to the grid cells are now used to design landscape units or types. This is generally done by using a variety of similarity based, size based or statistics based methods or a combination thereof to automatically cluster (groups of) grid cells with similar attributes. Using the result sometimes a validation step follows, which is often borrowed from the holistic method, where the developer uses previous knowledge, aerial imagery, maps or any other type of useful resource to determine whether the created typology is accurate, whether the distribution pattern of the landscape units are sensible and if needed manually guide the clustering process. After this step each reviewed method may even diverge more if edits are needed. Some switch to manually refining the typology (van Eetvelde & Antrop, 2009), others use landscape metrics to further group the landscape units (Mücher et al., 2009). The final step however is always the creation of a clear visual representation of the end product, the landscape map.

2.1.2 Holistic method

This method was used for example by Zoderer, Tasser, Erb, Stanghellini and Tappeiner (2016), Plieninger et al., (2013) and Marusic (1999). The holistic method is a more hands-on approach to landscape typology creation. In the studies found for this review the focus was often on peoples' perception of the landscapes. This more subjective quality of a landscape is hard to capture in GIS data and is often the reason for choosing the holistic method. The processes used are very different for this method. Generally it depends on the manual division or grouping of perceived landscape units. Often much less data types are used to create this kind of typology. Sometimes data is in the shape of mapped questionnaire answers (for example Plieninger et al., 2013) and a typology is first created for the area relevant to the questionnaire after which it may be used throughout a larger area, other times typologies are created using photographs of perceived significant and hopefully comprehensively selected landscapes. This was used for example by Marusic (1999) to create a landscape typology for Slovenia. This study used photographs of Slovenian landscapes, collected over many years, to manually define landscape types by grouping them according to similar morphological features. These were then linked to GIS data layers to find what attributes and values were found to be present in the landscapes, and then extrapolate the findings over the entire research area in order to map landscape type distribution. This method however requires a lot more time and knowledge of the area as it depends on (on-site) collection of subjectively perceived distinct landscapes, and then grouping by an operator, again by perceived similarities and differences. The drawbacks in terms of objective evaluation, workload and automation possibilities are the reason the holistic method is less used. The Marusic (1999) example shows how also within the holistic method there can be a symbiosis with the parametric method as the extrapolation phase uses distinctly parametric methods. Purely holistic approaches were not found.

The most detailed description of a used methodology found in this review is by van Eetvelde and Antrop (2009). Their methodology creates two scale levels of landscape typology using the physicogeographical parametric approach. The first scale level contains the standardized tessellated grid with landscape units derived from a combination of the source layers using the parametric method. This is then used to create the second scale level where the grid cells are aggregated, for which the holistic method is also used. The combination of parametric and holistic method represents the human factor in landscape evaluation as landscapes cannot always be distinguished purely by parametric values because of intrinsic or spiritual values sometimes associated with them. This also addresses the fact that not all required landscape attributes are available as GIS data, or can even be expressed in such a way.

The resulting process consists of five steps:

1. Selection of data sources, defining variables, geocoding of grid cells, building the database.
2. Defining landscape types at grid cell (first scale) level (parametric).
3. Delineation of landscape units at the second scale level (holistic).
4. Defining landscape types at the second level.
5. Visualisation of landscape character areas.

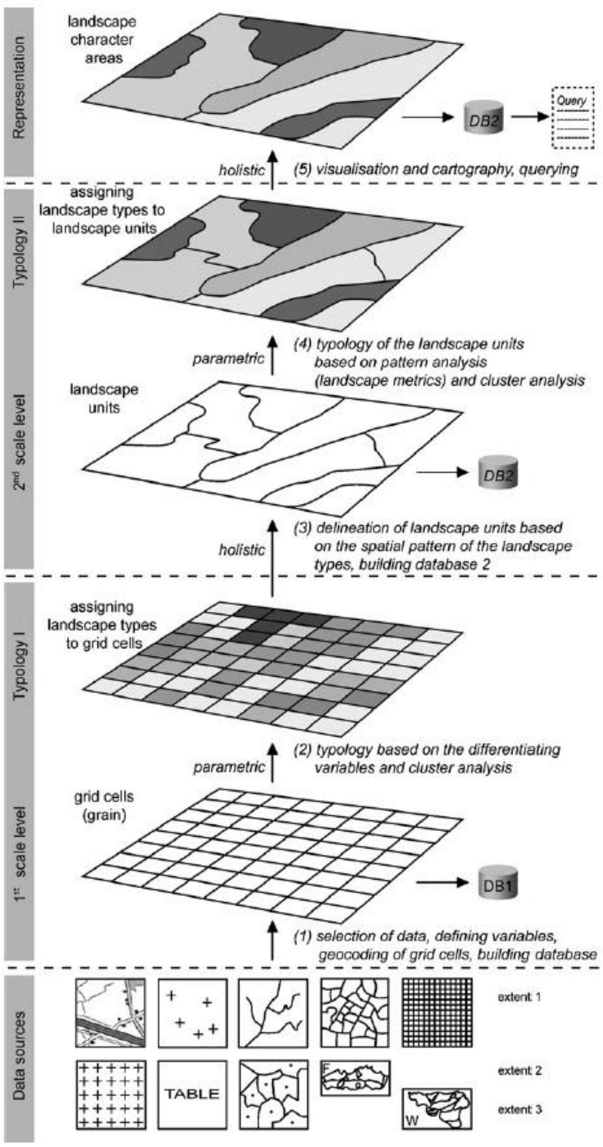


Fig. 8) The process of hierarchical landscape typology creation. Source: van Eetvelde and Antrop (2009).

The steps are also visualised in fig. 8. One starts by selecting and then collecting data that is relevant to the study area, which is then attributed to a standard grid cell layer. Then using cluster analysis landscape types were defined and assigned to the grid cells by grouping cells with similar properties into a pre defined maximum amount of possible types. This is the first scale. Next using a slightly holistic approach a landscape unit delineation was created where aerial photography, maps, local knowledge etc. were used to further refine the delineation. Landscape metrics of the first level grid landscape types are used to assign the second level landscape units to their definitive landscape type. Finally the data is visualised in a landscape map.

In general a similar process was used by most of the landscape typology projects, combining the source data and grouping the result (creating the typology), and from this creating a final landscape map. However as there is no established process no two projects really used the same methodology. Many studies did not explain their parameter and method choices in any detail, making their efficacy and rationale hard to check. Boundary conditions and divisionary values for the parametric approach as well as how they were chosen are never fully given. This was even true for studies trying to standardize typologies for continents like LANMAP in which no explanation was given as to what particular available source data was omitted and for what reason. Their choices with regard to the definition of data class boundaries and grouping of nominal source data classes to reduce class count also are not discussed. Finally the method they used appears to be restricted by the use of image recognition software for delineating landscape units for which an RGB image was needed limiting the possible source layers for a typology created using this method to three, with a fourth edited in afterwards by the developers.

Consensus on the best approach for creating typologies aimed at a sub-continental or national scale is lacking and discussion about the creation of a standard method is non-existent. Between the (European) national typologies analysed by Groom (2005) in Wascher (2005, p.32) huge differences are found. The German landscape typology (Gharadjedaghi et al., 2004) for example is based on a national standardised parametric physicogeographical approach whereas the Spanish national typology is based on a more holistic approach using extensive field work and partly also personal judgement (Mata Olmo & Sanz Herraiz, 2003). Nations sometimes even submitted multiple typologies, aimed at the same mapping goals, covering that nation. For example 'Taxonomic distribution of natural landscapes' and 'Landscape types' both submitted by and covering the entirety of Hungary with a 3-level hierarchical typology, which shows that even within countries consensus on methodology is lacking (Wascher, 2005). With this in mind the method for this study could not follow an established standard method but at best be modelled after one of the approach types mentioned earlier and shown in the methodology flowchart (Fig. 6).

Parametric typologies are easiest to recreate and standardise, and can be automatically applied to a large area because of their methodical and numerical approach to landscape type designation. Parametric methods often could be applied to other areas, and source data or source data classes can be changed to better suit the new target area whilst still applying the exact same method. This possibility for general use in multiple areas makes this approach very powerful and an attractive option for a possible standardised method. The automated nature of the parametric method allowing large areas to be designated automatically makes it quick and effective which is the reason it is the most used method in the literature. The method used in this study will be modelled after the parametric approach

The lack of a standard method and sometimes the use of statistical methods without explicitly naming the choices and settings used in them can make typologies difficult to understand for the lay-person and impractical to adapt for use in other areas. Also comparing regions that use two different typologies is impossible. The insights gained from this literature review suggest that pan-continental typologies suffer from a significant lack in detail, in the case of LANMAP using a landscape minimum mapping unit ~68 times larger than the average MMU used by European nations. This scale is too large to reflect locally valued and important landscapes in sufficient detail for policy-making or scientific research as many significant landscape changes or effects on landscapes would be missed. A more advisable and refined approach for establishing a continuous and corresponding landscape coverage over multiple individual regions would be to create a standard framework containing guidelines for initial source data selection, source data class boundary definition and a robust method for creation of the typology using this data instead of 'brute forcing' a large area scale typology. This framework could then be implemented by nations or regions on scales that are sufficiently small to be useful and accurate but because of the standardised and predictable method could easily be used and compared on pan-continental scale.

2.2 Data Requirements

The reviewed typologies were all created using some form of GIS data. The data types used were tallied for this review in order to find which are most common. As with the methods there was no prescribed or standardized set of required data agreed upon to create a typology, and similar to the methods typology developers appear to use what they think is sensible and distinctive, without always providing an underlying rationale behind their choice. This again led to differing aggregations of data being used for the typology creation. According to work by Jenny (1941) adapted by Vos and Stortelder (1992) landscape is primarily determined in order of increasing dependency by climate, geology and geomorphology, hydrology, soils, vegetation, fauna, land use and landscape structure. In the typologies analysed by Groom (2005) in the ELCAI report (Wascher, 2005) these factors also played an important role. In part this is also seen in the data of the studies analysed for this review although fauna and landscape structure were not used at all.

A count of data sets used in the reviewed literature is shown in fig. 9. The most important result is the "Typologies" selection which only shows figures for landscape typology creation projects (17 in total). Also shown is the "All" selection which also incorporates studies into landscape evaluation, character and ecosystem services that share some similarities with typologies (an additional 5 studies). Some trends were clearly visible in the data selection. The use of a DEM was almost ubiquitous, used in 15 of 17 typology studies when including altitude in this category. Generally a product derived from the DEM served as data layer, like a slope-, relief- or altitude map. Altitude is seen by many as a higher order determining factor than slope and relief (see fig. 7) as it determines the local climate which is deemed the most important and independent determining factor for landscapes. Also parent material/soil type were used in most of the studies (14 of 17). Land use/Land cover is used in 13 of the studies making it another important data source, with finally climate being important as it is used in 10 of the studies. Geology and vegetation are both used in 7 of the studies. It is worth noting that land use/land cover was often seen as a cultural data layer indicating that many landscape typologies already use a hybrid approach with regards to natural and cultural landscapes.

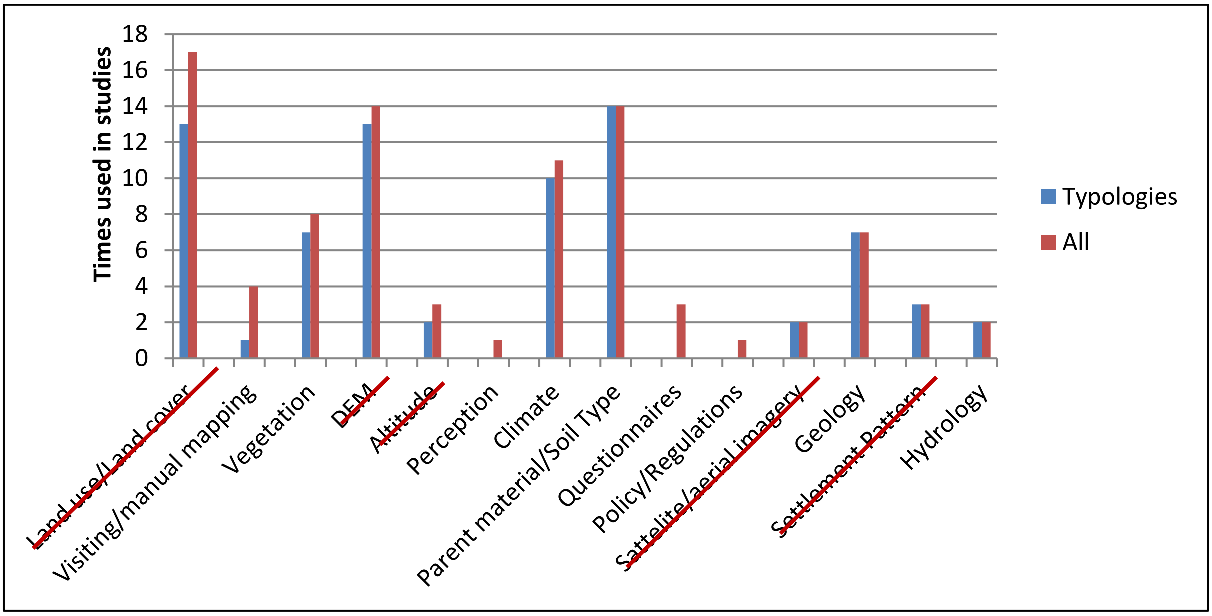


Fig. 9) Data sets used in reviewed literature on creating a landscape typology.

With regard to this study a lot of GIS data on the study area was already gathered through the '*Bhutan Cultural Mapping for Large Infrastructure Planning and Development'* project to which this work is related. Of the categories used in the reviewed studies land use/land cover, DEM/altitude, Satellite/aerial imagery and settlement pattern are already available (underlined in red in fig. 9).

3. Developing a landscape typology for Bhutan

The goal for this study is to create a nationwide landscape typology, which dictates a couple of restrictions in choosing the method. First the approach needs to be decided. As observed in Bhutan the landscape is directly dictated by geomorphological attributes, especially on the proposed scale of individual landscape units for which the landscape typology will be created. This can be described best by using the physicogeographical approach whereas the geochemical approach would be much less descriptive. Additionally the landscape is very much dictated by the DEM of Bhutan because of the large altitude range and accompanying climatic properties, which lends itself best for the physicogeographical approach. The nationwide aspect of the to be created landscape typology calls for the use of the parametric approach. The holistic method would require extensive and labour intensive on-site collection of subjectively distinguished landscapes. This would need to be done throughout the nation in order to acquire a comprehensive collection of landscapes. Within the possibilities of this study such an effort is not possible. The parametric method in contrast can be applied through the use of relevant data which is already available for the entire country. This method allows for automatic allocation of areas to a particular landscape type. An important side note is that there is no widely accepted standard method for creating landscape typologies. The review of approaches and methods indicated that none of the considered studies employed one path from the methodology flowchart exclusively but rather used a combination of most or all techniques for their typology creation with only a focus on a specific direction of the flowchart. The same holds true for this study. So the applied methodology primarily suits the physicogeographical parametric inductive path but holistic and deductive elements will be used as well in order to finalise and validate the typology.

The landscape typology was created using the ArcMAP software by ESRI. A custom method was created using previous methods discussed in the literature review as a source of inspiration. The method follows a couple of steps:

1. Collect and create datasets.
2. Determine and create source data categories by enforcing relevant boundary conditions.
3. Combine datasets into a first order landscape map.
4. Refine first order landscape typology into final landscape map.
5. Validate results using aerial photography.

The individual source datasets (Step 1) will be subdivided into relevant classes resulting in classified rasterised source datasets (Step 2). These are then combined into a first order typology containing many small individual landscape units. These units are clusters of cells with the same attribute combination (Step 3). The raster of the first order typology is then converted into a shapefile containing polygons representing the individual landscape units. These are finally combined into the final typology using a minimum mapping unit size to determine which units are combined to create features that can be counted as landscapes (Step 4). The final typology will be validated using a holistic method making use of satellite imagery (Step 5).

Throughout every step a border shapefile was used. This was created using a Dzonkhag (province) border shapefile (National Land Commission Secretariat [NLCS], 2013) and then compiling all Dzonkhag polygons so only the national border remains. The visual representation of the border is instrumental in assessing the results of many of the intermediate steps, as well as preserving oversight of the study area for data that does not cover the entire nation continuously.

3.1 Collect and create datasets

The first step of any typology creation is the acquisition of data. In this case a lot of data was already collected for the *'Bhutan Cultural Mapping for Large Infrastructure Planning and Development'* project led by the World Bank Group. This data was collected through a multitude of different resources. Important datasets for the landscape typology were the Digital Elevation Model (DEM), the slope map (derived from the DEM) and the landcover dataset. For the creation of relevant class breaks a couple of additional data sources were used: Settlement locations derived from NCRP (National Cadastral Resurvey Project) data and National Statistics Bureau (NSB) statistics data.

A geological map of Bhutan was not available during this study. Because of the extreme elevation (and therefore climatic) and geomorphologic differences of Bhutan the geology might actually not be as important as it is in many other regions. The large differences in elevation and geomorphology within fairly small areas may have a larger effect on the landscape than geology would.

For the assessment of a possible link between landscape type and cultural heritage also data from the NLCS (Nye Atlas project) was used, as well as data supplied by the World Bank and data retrieved from OpenStreetMaps.

3.1.1 The DEM

For the DEM, ASTER elevation data was used (Fig. 10). ASTER (Advanced Spaceborn Thermal Emission and Reflection Radiometer) is a remote sensing tool developed by JPL, NASA, the Japanese Ministry of Economy, Trade and Industry and Japan Space Systems incorporated and is deployed on the Terra satellite. It captures high resolution images in 14 bands through three telescopes: Visible and Near infrared or VNIR, Shortwave Infrared or SWIR and Thermal Infrared or TIR. Elevation data is constructed through stereoscopy in which the difference between two viewpoints of the same location is used to extract distance to that location (National Aeronautics and Space Administration [NASA], n.d.; Jet Propulsion Laboratory [JPL], n.d.). The resultant elevation data is divided into standard sized tiles. The ASTER data was retrieved from the NASA Worldview data portal. This data portal allows easy selection of relevant tile files through a map based selection tool. For Bhutan a total of 15 ASTER tiles were needed to cover the entire nation: N26-28, E88-92. The tiles were loaded into ArcMAP and combined into a single layer file for ease of use after which the extent was clipped to the Bhutanese border to reduce computer memory requirements and operation runtime.

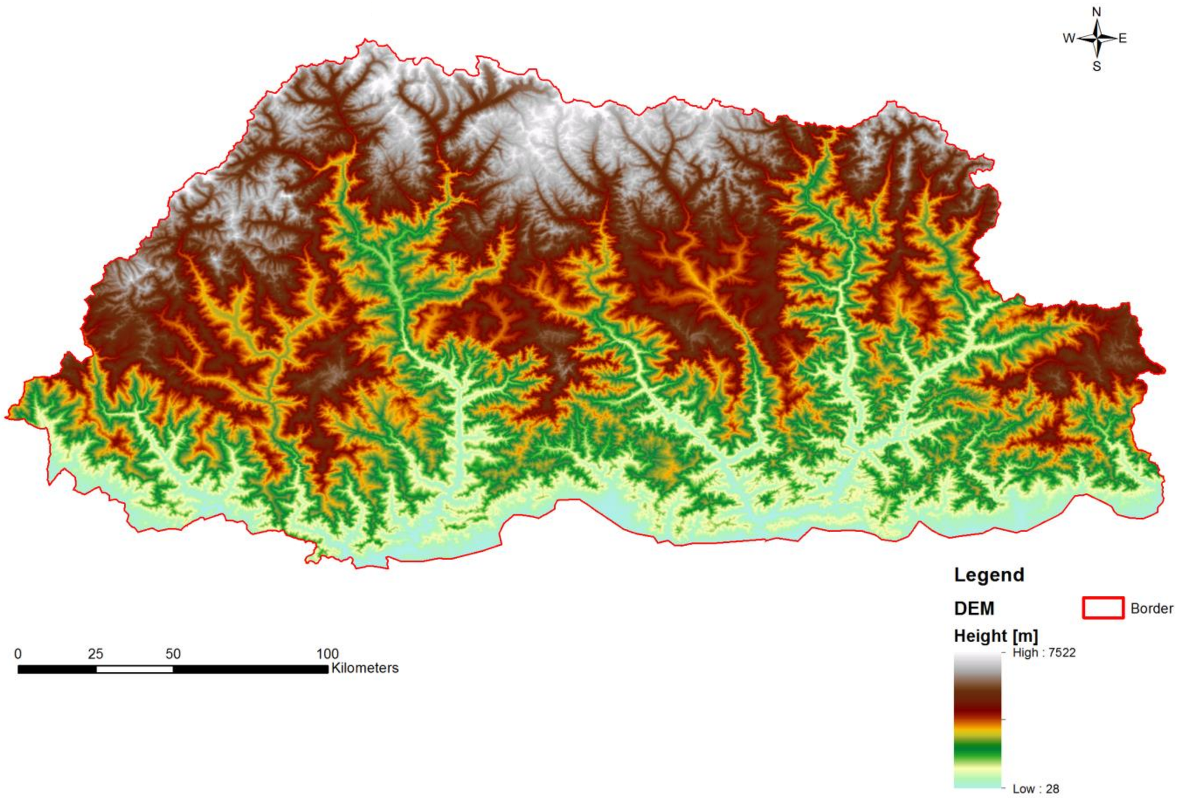


Fig. 10) Digital elevation model of Bhutan (ASTER).

3.1.2 Landcover

For landcover two different datasets were used. For the typology creation a vector based landcover was used, generously provided for this study by the NLCS of Bhutan (Fig. 12). For the landscape change analysis a raster based landcover dataset made by ICIMOD (the International Centre for Integrated Mountain Development, fig. 11) was used. The NLCS vector file is made manually through field observations whereas the ICIMOD data is generated automatically. The NLCS file is more precise and more accurate in terms of spatial and thematic resolution as can be seen in fig. 13 and fig. 14. However the NLCS file only exists for 2010 with no earlier versions having ever been made. Therefore this data cannot be used for the landscape change analysis whereas the ICIMOD data exists for every 10 years since 1990.

The ICIMOD landcover data was retrieved from the Bhutan geospatial data portal (NLCS). It was created for use by the Ministry of Agriculture and Forests (MoAF) by ICIMOD using LandSat 30m resolution imagery 'for general purpose and Assessment and Monitoring of land cover dynamics in Bhutan' (ICIMOD, 1990/2000/2010). An algorithm is applied to the LandSat imagery to build the landcover dataset (ICIMOD, 2018; Di Gregorio & Jansen, 2005). The NLCS landcover data was compiled by the NLCS using data from the National Cadastral Re-survey database and data from the MoAF (NLCS, 2016).

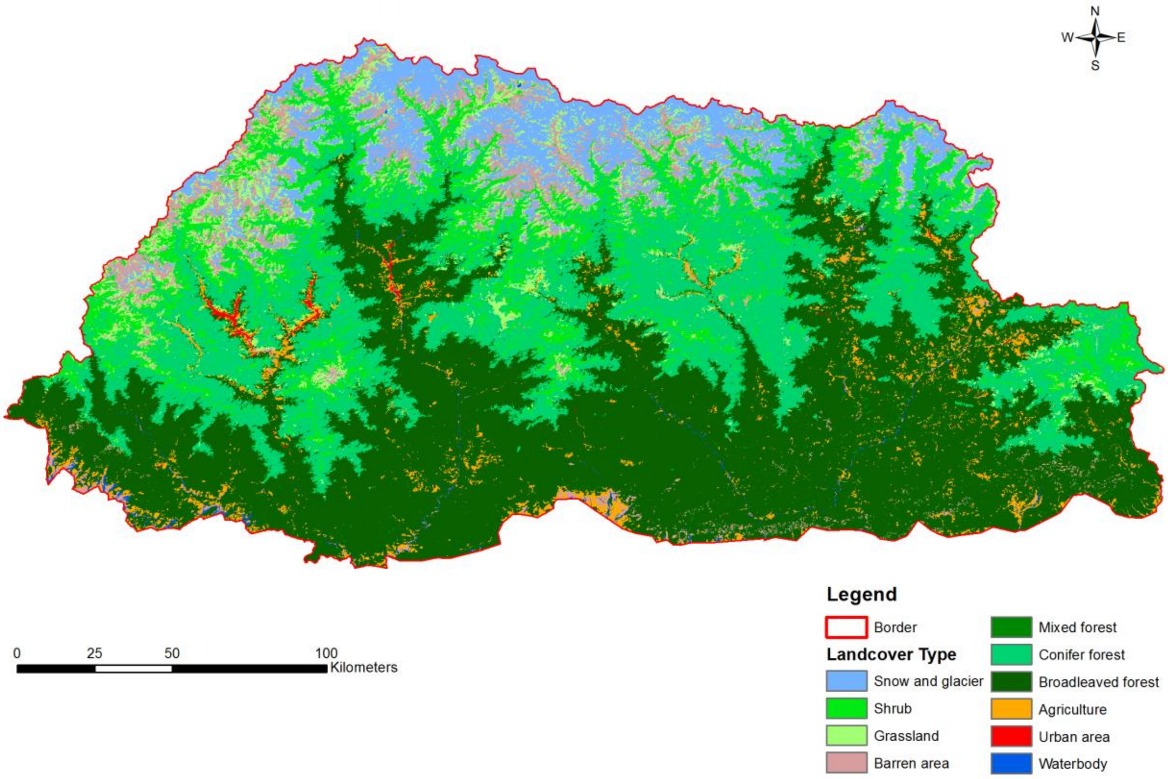


Fig. 11) Original ICIMOD landcover map of Bhutan in 2010 (Source: ICIMOD).

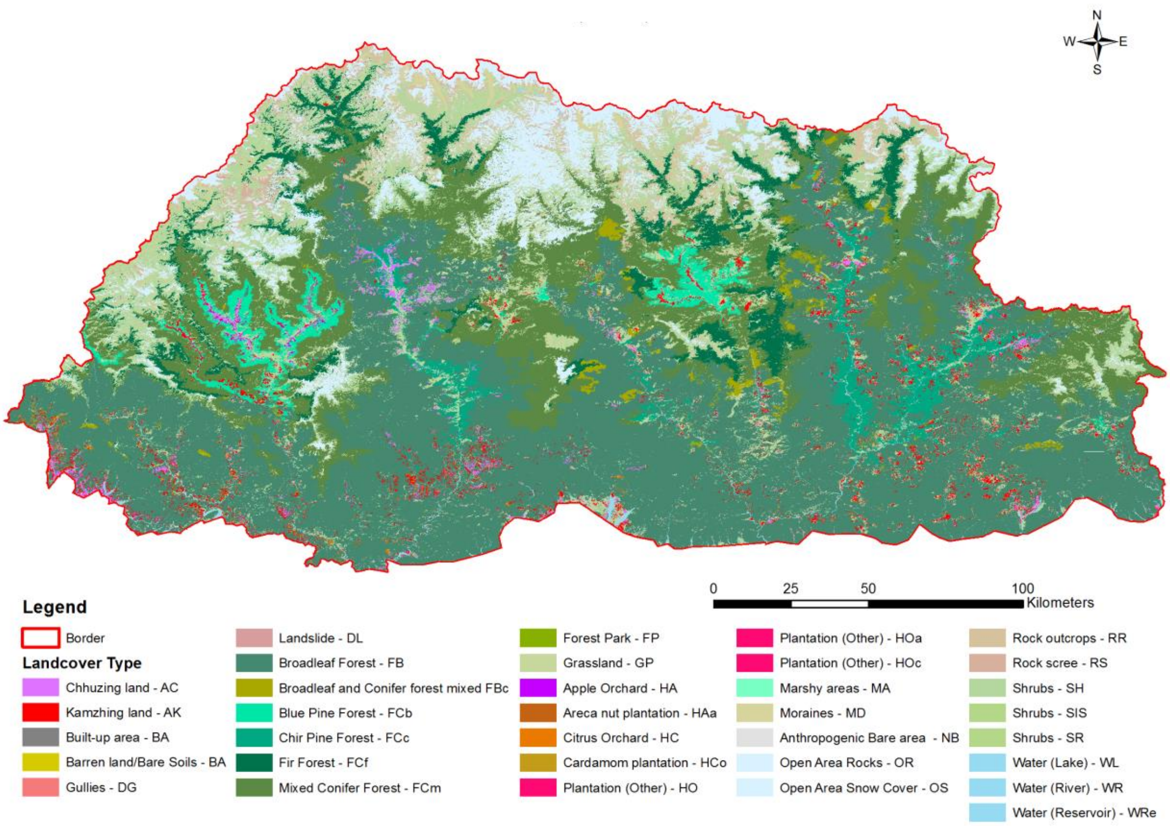


Fig. 12) Original NLCS landcover map of Bhutan in 2010 (Source: NLCS).

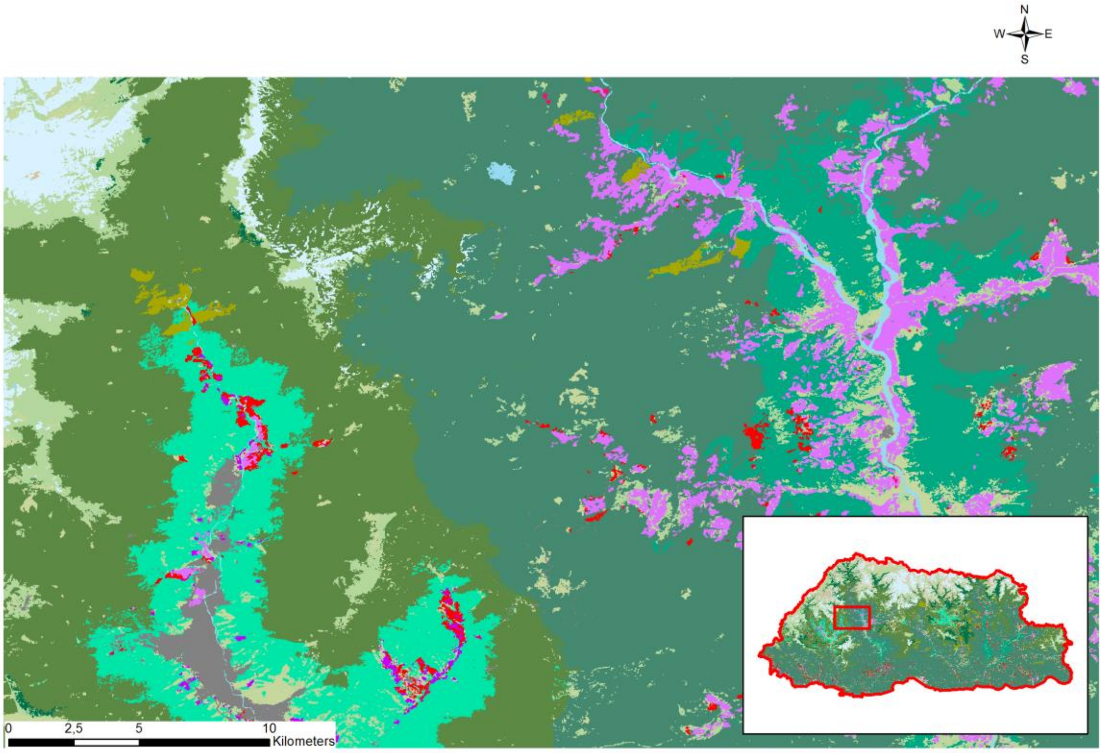


Fig. 13) Section of the NLCS landcover map. Paro/Thimphu area.

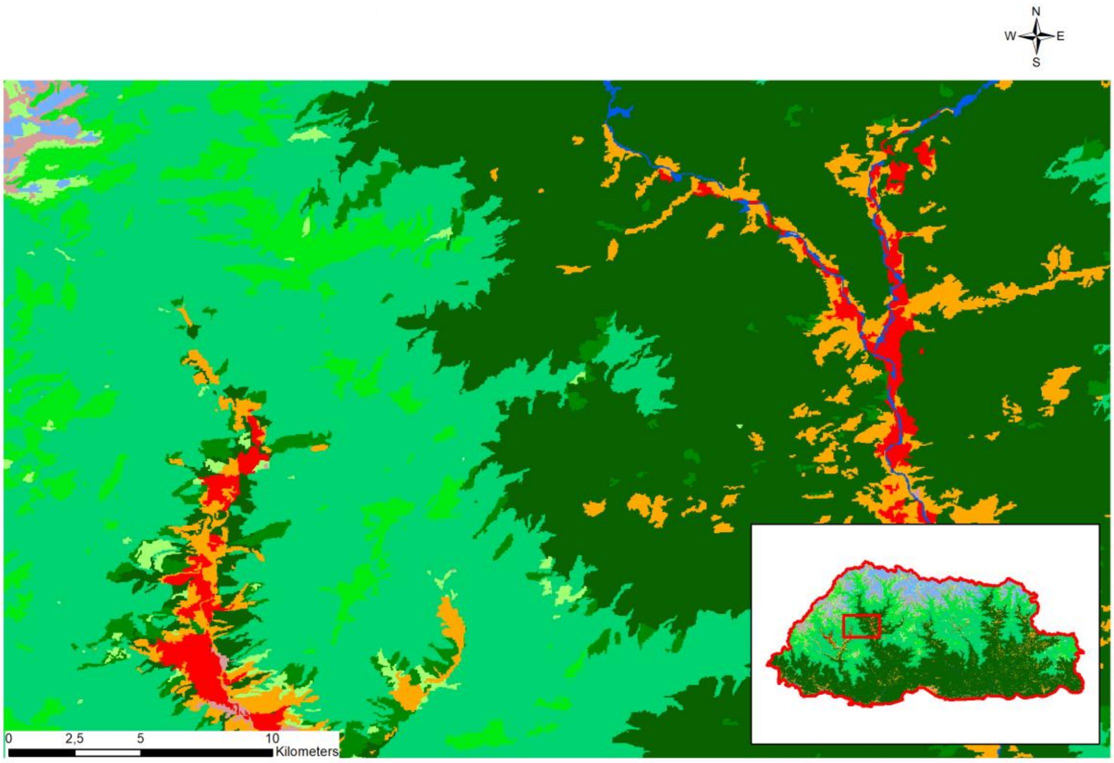


Fig. 14) Section of the ICIMOD 2010 landcover map. Paro/Thimphu area.

3.1.3 Slope map

On location in Bhutan it quickly became apparent that slope plays an important part in determining both landcover and land use. To be able to incorporate this a slope map was derived from the ASTER DEM using the Slope tool in ArcMAP. The Slope tool calculates the maximum rate of change in elevation by checking for each cell which neighbour features the largest elevation difference. The location specific ratio between the height unit [m] and the ground unit [degrees] (Z-factor) was set as $9 \cdot 10^{-6}$. The result is the map below.

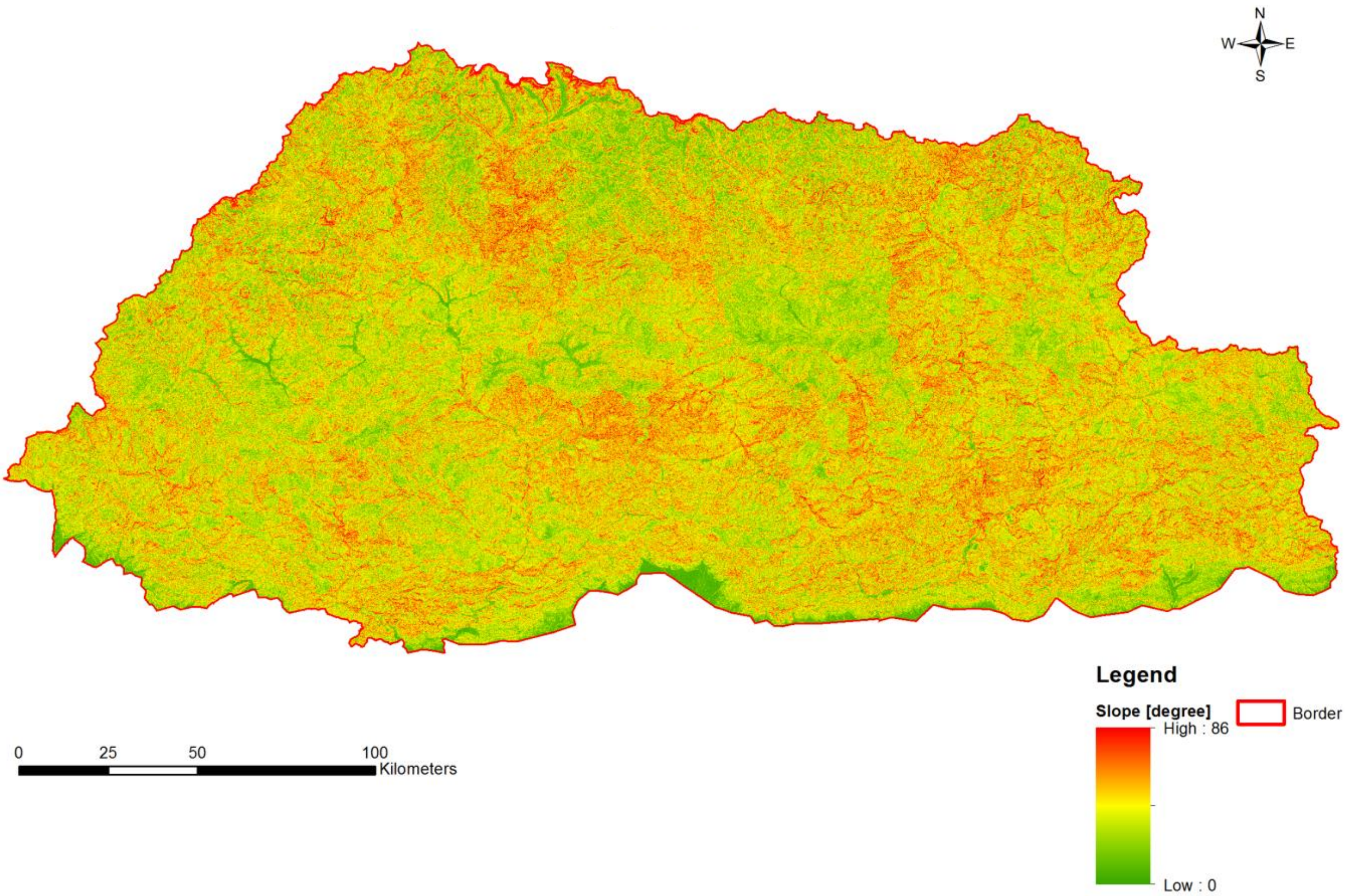


Fig. 15) Slope map of Bhutan derived from ASTER DEM data.

3.1.4 Settlement data

Settlement data was created by the National Statistics Bureau, it includes all individual structures (Fig. 16). This data can be used to analyse population distribution patterns.

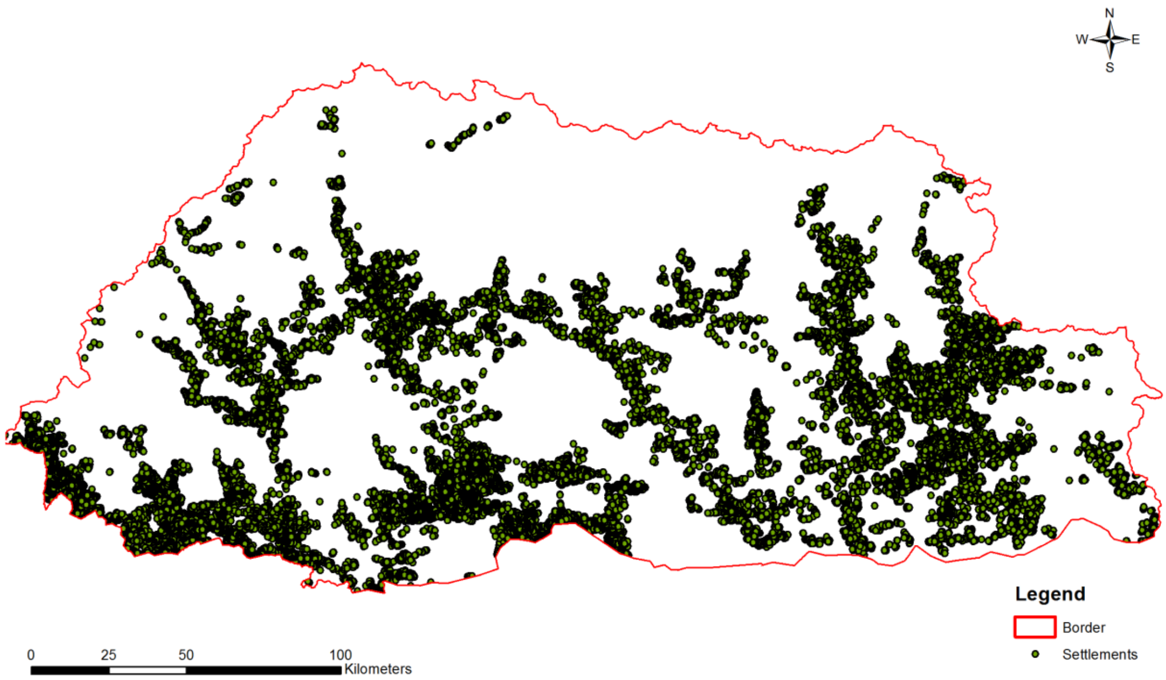


Fig. 16) Settlement locations (Source: National Statistics Bureau of Bhutan).

3.1.5 Cultural heritage data

To investigate a possible correlation between landscape type and cultural heritage, location data of heritage features was retrieved from multiple sources. At the start of this study Bhutan did not have an established comprehensive official database of cultural heritage features. Towards the end of this study a project was finished in which national cultural heritage was surveyed and inventoried. This data was incorporated in the analysis shortly before this thesis was finished. Because of this initial lack of data other sources for heritage location data were considered in order to achieve a more thorough and nationwide coverage. One interesting possible source is crowd sourced location data, the most notable example of which is Open Street Map (openstreetmap.org).

OpenStreetMap (OSM) is an online geospatial data service similar to Google Maps but its data is added to the database by volunteers (registered users). This often results in more detailed data with a stronger focus on locally valued features, which presents a significant opportunity for this project. Data quality is dependent on the user that created it and verification of data depends primarily on the OSM community. The World Bank has used OSM data created by the Humanitarian OpenStreetMap Team together with other NGO's in their relief aid projects after the 2010 Haiti earthquake. Data acquisition is also encouraged through events organized by the OpenStreetMap team, organizations and governments. Humanitarian NGO's also work on encouraging the growth of local OSM communities and build improved risk models. The OSM data is or has also been used by high profile commercial companies and services like Apple, Flickr, Craigslist, Foursquare and many others, indicating a current general high confidence level of the provided data (Barth, 2012; Humanitarian OpenStreetMap Team, n.d.; Wikipedia, 2018; World Bank Group, & Vrije Universiteit Amsterdam, 2018)

Data in OSM is structured in tags containing in their most basic form a key and a value in the format key=value. The key indicates a category, feature type, classification scheme etc. The value further specifies what sub-category, feature class etc. a data entry is. A feature can have multiple tags attached to it, for example a historic Buddhist temple might have the tags religion=Buddhist, building=temple and historic=monument. The tag system was used to extract relevant data from the OpenStreetMap database via the online tool Overpass Turbo (https://overpass-turbo.eu/). Bhutan data was acquired from OSM using the tags relevant to cultural, religious and heritage features. This method resulted in 250 heritage locations (Fig. 17). They are mainly concentrated in the most densely inhabited medium elevation region. This concentration may be either explained by the population density of this area, or by the fact that tourists and representatives of international NGO's (often adept in OSM) primarily visit this area, adding features.

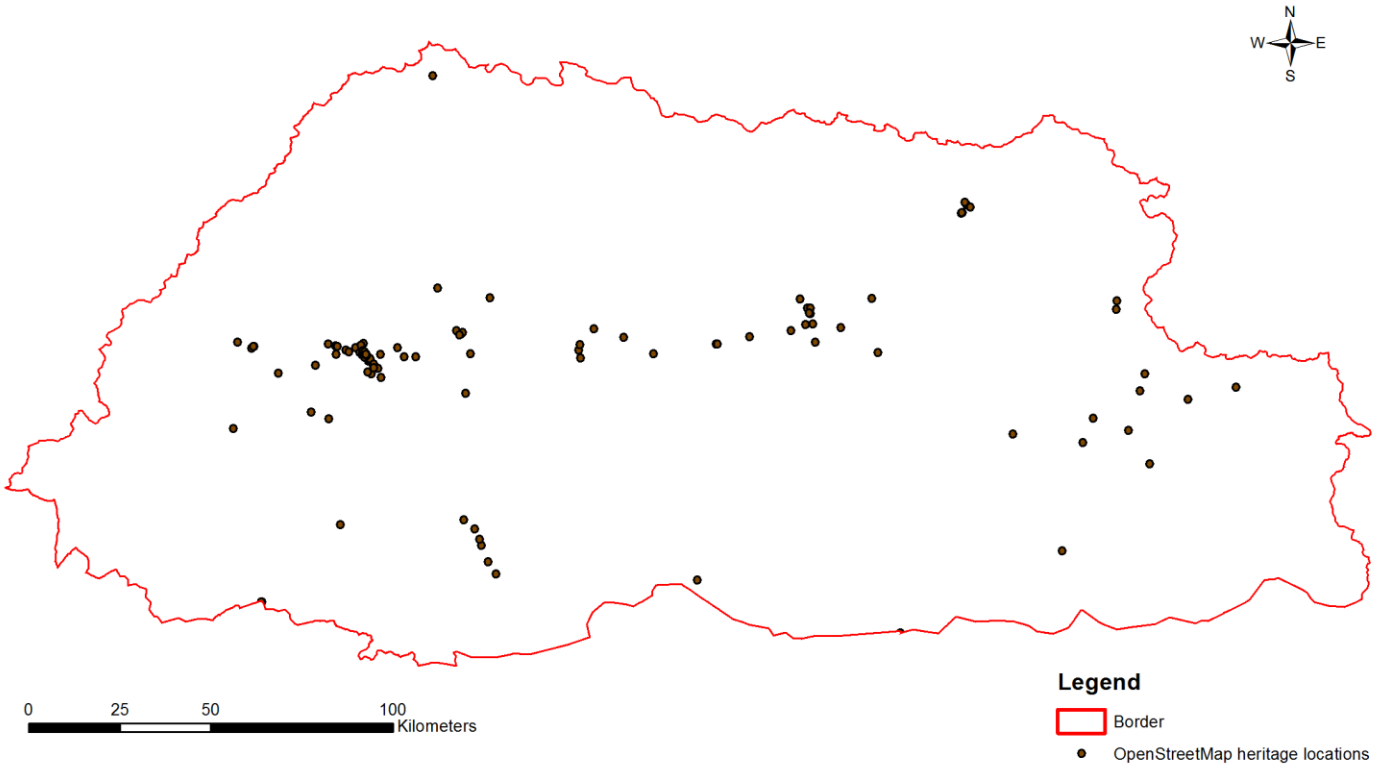


Fig. 17) Heritage locations extracted from OpenStreetMap.

Another source of cultural heritage location data was supplied by the World Bank for the '*Bhutan cultural mapping for large infrastructure planning and development*' project. The data was supplied by their local contact Karma Athang. The dataset appears to be a compilation of data accessible through the geospatial data portal. A dataset focussing on historical locations, buildings and features was used for the analysis. The data contains 1776 data points (Fig. 18). There is an area without features in the middle northern region of Bhutan. This is in part expected as this region is a very rough and highly elevated mountainous area with little human inhabitation. Combined with the holiness associated with high mountains in Bhutan that restricts access to these areas this explains the absence of features.

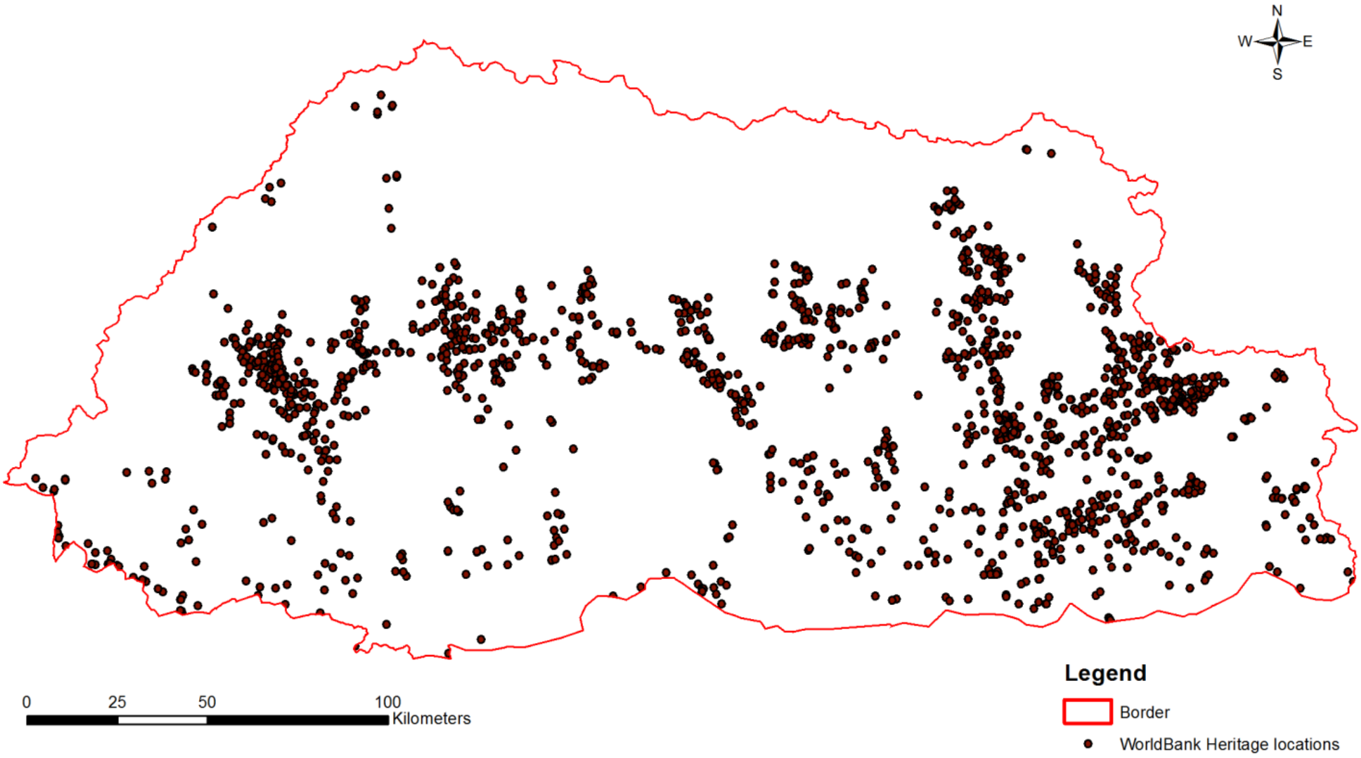


Fig. 18) Heritage location map supplied by the World Bank.

A final cultural heritage dataset became available just before this thesis was finished. This official centralised comprehensive database of cultural heritage features dataset is called the Nye Atlas of Bhutan. This data originates from a project started by the NLCS in July 2016 and was carried out in cooperation with the Department of Culture (DoC). Survey teams have visited Dzonkhags (provinces) and Gewogs (villages) to find and record cultural heritage sites together with Dzonkhag cultural officers. A pilot was done for the Chhukha region and the experience from the pilot has been applied in cataloguing the rest of the nation's cultural features. The project was completed near the end of 2017. The NLCS has graciously provided the finished dataset for analysis purposes on the condition that individual locations are not shown and the data is not disseminated further. A total of 10154 heritage features have been recorded in this project. The exact data is still classified at the moment of writing this report and only a density map of the data can be shared here (Fig. 19).

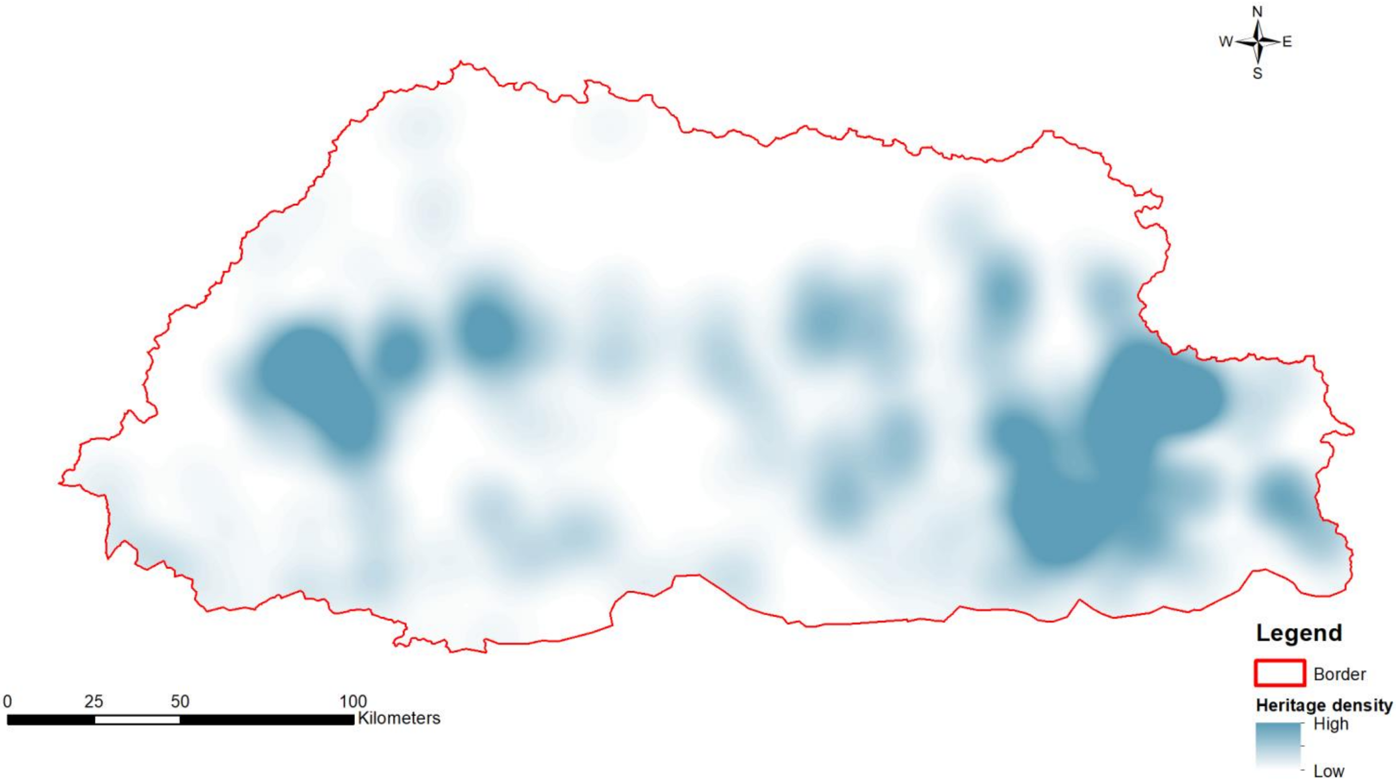


Fig. 19) Nye Atlas based heritage feature density. Source: NLCS Nye Atlas database.

The Nye Atlas data is the most comprehensive dataset of cultural heritage. The project aim was to include all heritage features. These features are built-up structures but also includes natural features associated with cultural heritage, for example rocks and streams that are important in (local) legends.

In contrast to the data in the Nye atlas the OSM data is added voluntarily and for the most part not systematically. The exact origin and methodology behind the collection of the data supplied by the World Bank is unclear. A quick comparison between the population of features in three Dzonkhags surveyed in the Nye Atlas pilot study for all three data sources reveals the difference in density between the datasets. The Nye atlas data shows a total of 1203 features, the World Bank data shows 169 features, and the OSM data has only 4 features in these three Dzonkhags.

3.1.6 Relief Ruggedness

The literature review revealed multiple methods used to create landscape typologies and landscape maps. All of those used data pertaining to the study area, but relief ruggedness was not found in any of the studies even though for some regions it seems like an important addition in order to represent a larger scale connection of a landscape to the surrounding area. This can be especially important for the visual quality of the landscape. For topologically heterogeneous study areas relief ruggedness seems a compelling extra feature that will reflect the great impact topology can have on the experience of the individual with the landscape. Gently sloping hills stretching into the distance create a different landscape character than steep and deep valleys, see fig. 20.

Fig. 20) Two viewpoints revealing the large scale impact of relief on the experience of landscape. Both were taken almost at the bottom of the valley. The image on top shows the gentle valley of Punakha, the one on the bottom was taken in the valley between Paro and Thimphu. For an honest comparison two panoramic photo's where chosen of roughly similar locations (in a valley, just above the valley floor). Both photo's are taken using the same device and have not been cropped or stretched. Bigger differences are possible in reality and do exist in Bhutan. Image source: Author.

Adding a measure for relief ruggedness can reflect this landscape quality that because of its visual nature can extend beyond the borders of a landscape unit. For this study the matter has been looked into and a total of 13 different relief ruggedness indicators have been evaluated with four of those methods evaluated more thoroughly. This is described below. The evaluation revealed that none of the methods return a comprehensive indication of ruggedness as envisioned for this study and thus a new method has been developed which is also described in the following paragraph.

The examined indicators of landscape relief or relief ruggedness generally followed one of two approaches. One common approach was examining the rate of elevation change in a neighbourhood around each cell, which is similar to calculating slope. The other common approach is based on a comparison of 3D area vs. 2D area, or planimetric vs. surface area. However the evaluated methods were all found to represent a very basic and singular dimension or approximation of relief ruggedness, meaning that they could not exhaustively differentiate particular different features of ruggedness. Different landforms that intuitively should represent different ruggedness values can return the same ruggedness value using these methods. An indicator looking at height difference within a neighbourhood for example will not differentiate between a smooth slope running between the maximum and minimum heights found in the neighbourhood and a strongly undulating relief. Similarly, a method based on the difference between surface area and planimetric area cannot tell the difference between one large peak or many small peaks which would result in the same surface area. This problem has been noted by others as well (Grohmann, Smith, & Riccomini, 2011) especially in mountainous areas (Hoechstetter, Walz, Dang, & Thinh, 2008). A mention was found of an interpretation of a combination of many statistical parameters of multiple morphometric factors (Klinkenberg, 1992). However apart from not having been fully proven, applying this is a whole study in and of itself.

One common indicator, the Topographic Position Index (TPI) (also known as Relative Topographic Position) uses the following formula (Cooley, 2016; Jennes, 2006):

$$TPI = \frac{Elevation_{Max} - Elevation_{Min}}{0{,}5 \cdot Cell\ length}$$

Another common indicator is the Standard Deviation of Elevation (SDE) (Ascione, Cinque, Miccadei, Villani, & Berti, 2008; Cooley, 2016):

$$SDE_{Cell} = \frac{Elevation_{Mean} - Elevation_{Cell}}{Elevation_{Max} - Elevation_{Min}}$$

The SDE uses a mean value in the formula. Multiple observations are needed to find this mean value. In table 1 the function of SDE has therefore been approximated by dividing the examples in 25 m horizontal increments and calculating the SDE first for every 25m increment and its two neighbours (three point approximation) and then the same for every increment and its four neighbours (five point approximation). Different ranges will return different results.

The next common indicator in the comparison is basin-scale ruggedness. This indicator is designed to compare the relief of drainage areas. The method can easily be adapted to find the relief ruggedness of a target cell by substituting the area of a watershed with the area around the cell:

$$Ruggedness = \frac{Watershed\ Area}{Stream\ Density}$$

Finally the comparison includes the 2D area : 3D area ratio method. This method calculates the ratio between the planimetric cell area (the cell size on the flat horizontal plain) and the DEM derived surface area of that cell. This ratio is then an index for the roughness because as surface area within a specific size of planimetric area increases then increasingly steep slopes must be present in that area.

Based on the experience with the existing methods it was found that a good ruggedness indicator should take into account the undulation of the landscape together with elevation ranges. Very simply put: it should be able to indicate variations between all possible combinations of amplitudes and undulations of relief found in the study area. The existing methods were lacking this possibility and a new method was created based on hypothetical stream density and surface area.

The newly developed method combines stream density of a hypothetical flow pattern (so not based on real world surveyed streams but based on a DEM derived stream network in order to get flexibility and full coverage) of a particular neighbourhood with surface area of that same neighbourhood. The drainage system reveals the ratio of undulation in the landscape by revealing local lows (where water converges into a stream) indicating where the borders of relatively high areas are located, thereby segmenting the relief into individual higher elevation "islands". This is combined with the surface area (revealing the amount of land between each stream, larger surface area thus means larger elevation differences within each “island’) which then accurately indicates the actual roughness of the area. The formula for this method is very simple:

$$Comprehensive\ Ruggedness\ Indicator\ (CRI) = Stream\ Density\ (SD) \cdot Surface\ Area\ (SA)$$

In which *SD* is hypothetical stream density in [length/planimetric roving window area] and *SA* is roving window surface area in [km^2]. In addition to the simplicity of the method and comprehensiveness as an indicator it can also easily be scaled to all possible desired DEM resolutions, neighbourhood sizes (by choosing different sizes of roving window for SD and SA) and sensitivities (by changing the amount of water needed to hypothetically constitute a stream, i.e. choosing stream formation threshold values).

This method is further exemplified and compared to the others using the following two dimensional schematic representation of possible differences in landscape relief (Fig. 21):

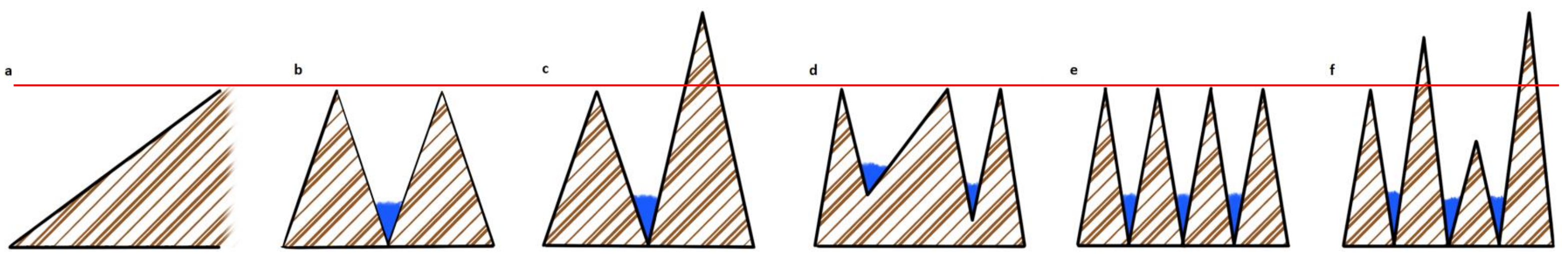


Fig. 21) Examples of different relief types shown in order of increasing designed relief roughness. All reliefs are to scale with a horizontal size of 200 m. The red line indicates a height of 150 m. Blue areas indicate streams.

In table 1 the developed method CRI is compared to other accepted methods. For each example in fig. 21 the ruggedness value returned by each method is calculated.

Example relief	Range [m]	TPI	SDE (3 point approximation)	SDE (5 point approximation)	Basin-Scale Ruggedness	2D Area:3D Area ratio	CRI (developed method)
a	150	1.5	0	0	-	1.3	250
b	150	1.5	-0.095	-0.12	200	3.2	633
c	225	2.3	-0.1111	-0.137	200	3.9	778
d	150	1.5	-0.0682	0.055	100	3.9	1575
e	150	1.5	-0.095	0.08	$66\frac{2}{3}$	6.1	3650
f	225	2.3	-0.157	0.082	$66\frac{2}{3}$	6.8	4099

Table 1) Relief ruggedness results for multiple accepted indicators calculated for the hypothetical set of relief examples of fig. 21.

There is a clear difference in effectiveness of the different accepted methods. The developed method CRI returns results that conform well with expectations (returning the correct order of increasing relief roughness as they were designed). For TPI table 1 shows how the method performs at indicating relief roughness. Only two unique values are found. As the results are only influenced by the range of elevation the method fails to take into account the undulation of the landscape and does not reflect the order of landscape complexity of the examples.

Next on the list is the Standard Deviation of Elevation (SDE). Both approximations return an unrealistic estimation of roughness with notable differences between the three and five point approximations. There appears to be no useful relief ruggedness information contained within the results. In part this is related to the theoretical nature of the examples, relief 'e' especially returns unexpected results in the three point approximation because of its regularity which either cancels out or strengthens the influence of each increment's value through destructive and constructive interference, resulting in the same SDE roughness value for relief e as for relief b for the three point approximation. However comparing the five point approximation to the three point approximation also reveals the method is very dependent on scale as well, both returning a different order of complexity for the examples. Other strange results were observed during the SDE calculations as well, for example local SDE values of 0 in case of uniform slopes meaning a cell within a uniform steep slope would receive the same SDE value as a cell within a horizontal plain, or seemingly arbitrary positive/negative SDE values. These examples show that the SDE method is unsuitable for the analysis of relief roughness.

Basin-scale ruggedness also performs unsatisfactory. In the examples the calculation was 200[m]/[amount of streams]. The results show that the method does return the correct order of roughness due to its incorporation of the undulation of the landscape. However the method cannot distinguish between large and small elevation ranges meaning a hypothetical landscape with 3 streams in a flat plain would receive the same value as a hypothetical landscape with three streams with high peaks between them. This is evident in the results which for a collection of cells with identical sizes are dependent purely on stream density. Therefore example reliefs with the same amount of streams get the same basin-scale ruggedness value and this method is therefore not suitable to indicate cell by cell relief ruggedness in a raster. When surface area is used instead of planimetric area the method performs worse, returning the wrong order of complexity: c-b-f-e-d-a. This is because increasing surface area, which is correlated in part with stream density, is cancelled out by that same increasing stream density. In other words, if the roughness of an area increases both surface area and stream density increase, and thus cancel each other out. Additionally (but less importantly as the area can be adapted to suit the needs of the research) as basin-scale ruggedness is based on watershed area it is hard to standardize and compare in a standardized grid.

Finally 2D area : 3D area ratio is examined. The method returns the most useful results by almost completely succeeding to find the correct order of roughness for the provided examples. Only example c and example d return the same value which reveals the weak point of this method: it has no sensitivity to the undulation of the landscape. A single high peak within a specified planimetric area may have the same surface area as multiple lower peaks within that same planimetric area and would thus return the same value.

From the comparison made in table 1 it can only be concluded that none of the established methods succeeds in combining both landscape undulation and landscape elevation, which are both needed for an accurate representation of landscape relief ruggedness. The newly developed method CRI uses the potential stream network in conjunction with surface area in order to combine both the undulation and amplitude of the land. Together these provide an accurate and robust indicator for the relief ruggedness. This method can be applied on both large and small scales in both mountainous and flatter terrain. When the same size of roving window is applied it can also be used to directly compare relief ruggedness between completely separate areas. CRI is also easily adjusted to suit different goals and reliefs. By adjusting the threshold value for the hypothetical stream pattern, which controls how much 'runoff' is needed in order to create a hypothetical stream, the sensitivity can be adjusted. A low threshold value will reveal smaller undulations because a low threshold value can create a stream underneath a small hill whereas a large threshold value needs more runoff to create a stream and thus a larger hinterland which smoothes out small scale undulations. Furthermore CRI can be used over all sizes of neighbourhoods and is therefore suitable for ruggedness analyses in all conceivable scales. Finally the method is simple and easy to intuitively understand making it easy to use and adapt to individual project needs.

After these hypothetical explorations the CRI for Bhutan was created. A drainage system shapefile was already supplied by the World Bank Group as part of the '*Bhutan Cultural Mapping for Large Infrastructure Planning and Development'* project, however the coverage of this data was incomplete. Therefore a complete drainage system was calculated following a standardised method (ESRI, 2017). The first step in this method is to apply hydrologic conditioning to the DEM. In order to allow the hypothetical flow of a unit of water to continue to its end (the edge of the area of interest) cells which are local low points, or sinks, have to be removed. In order to find these sinks first the flow direction is calculated with the Flow Direction tool. This tool calculates to which neighbouring cell flow would take place, by retrieving the cell pair with the steepest slope between them. The output of the tool is a raster where each cell has one of eight possible values indicating the neighbouring cell into which water would flow. This is the most conventional method, called D8 for the eight directional possibilities of waterflow out of each cell (Turcotte et al., 2001). The result is used to determine the sinks (Sink tool). If a cell of the Flow Direction output has received a value indicating it does not flow towards a lower cell (undefined drainage direction) the tool marks this cell in the output as a sink. The next step incorporates the Fill tool which heightens the DEM height value of the cells marked as sinks to the height of their "pour point", i.e. the neighbouring cell from which water flows into the sink cell. The result is a hydrologically conditioned DEM. Without this conditioning step a flow into a sink would end in that sink as the function is not engineered to calculate filling of a basin.

The hydrologically conditioned DEM is used as a valid input product to determine the drainage system. Again flow direction of the conditioned DEM is calculated using the Flow Direction tool. With the result flow accumulation can be calculated for each cell (Flow Accumulation tool).

The Flow Accumulation tool follows the flow paths ending up in each cell and adds up how many cells "drain" into the examined cell. Finally the normal procedure is to determine streams by applying a boundary condition using for example a "Con" tool or a raster calculator operation to find cells that exceed the threshold value and would thus be considered a stream. The threshold value should be based on field observations on how much drainage flow is needed to form the predetermined definition of a stream. In reality this would be dependent on local conditions like soil properties, geomorphology, precipitation etc (Pilotti, Gandolfi, & Bischetti, 1996). However in this case the goal is to find the potential stream system (every instance where in the given DEM surface runoff could potentially converge in a local low into a contained structured water flow in ideal circumstances) in order to calculate relief ruggedness which means the real world stream dynamics are not very important. To find a suitable stream network a couple of threshold values were tried: 80, 100, 150, 200, 250, 300, 400 and 500. A smaller value means that the resulting stream network has a lower threshold for the formation of a stream and would therefore be more densely populated. This can be explained as representing a higher resolution of or sensitivity for relief roughness. Smaller landscape undulations (which would only form a stream when applying a lower threshold value as their potential to collect water is smaller) are visible in the resulting stream network, whereas a larger threshold value will ensure that small scale relief features are not taken into account. The choice of threshold value is important for CRI as it determines sensitivity. A low threshold value will, depending on the accuracy of the DEM, produce a very large stream density which would then overpower the influence of surface area and smooth out the end product so much that little information could be gathered from it. On the other end of the scale a very high threshold value will create such a sparse stream density that the end result would be dominated by surface area where the remaining streams would clearly stand out in the relief roughness pattern.

This means that a trade-off exists between having the final product represent relief features and fulfilling a distinguishing function. To find the ideal threshold value the line density was calculated for the threshold values mentioned earlier. To reduce computing time needed for this validation process it was only performed for the Punakha Dzonkhag. For each threshold value two sizes of roving window were used to find which would return the most distinguishing result. The size of roving window (the area around the cell that is seen as functional area for the determination of landscape relevant relief ruggedness) was decided to be around 4 km in diameter, or 0,036 degrees which should be a good measure to represent local landscape ruggedness conditions. The roving window diameter sizes tested were ±4 km (0,036 degrees; 12,56 km^2) and ±5,56 km (0,05 degrees; 24,27 km^2). Results in fig. 22.

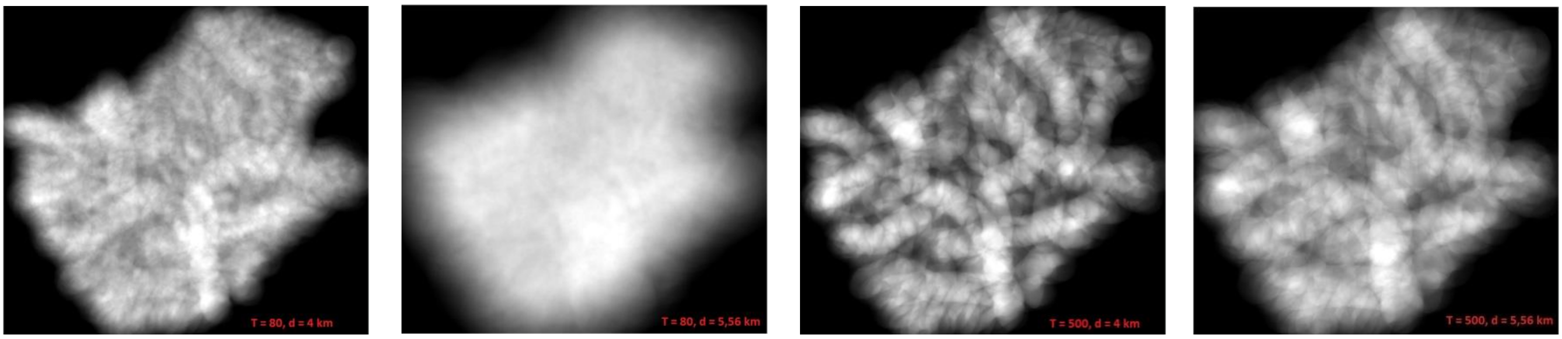


Fig. 22) Punakha stream density maps for different stream threshold values (T_{stream}) and roving window diameter sizes (d). Whiter areas have higher stream densities. From left to right: T_{stream} = 80, d = 4 km - T_{stream} = 80, d = 5,56 km - T_{stream} = 500, d = 4 km - T_{stream} = 500, d = 5,56 km.

A threshold value of 150 with a roving window of 4 km was found to be the most distinguishing combination whilst still providing a continuous image.

When compared to the results of the supplied official stream data however the result is very different. Not only the visual appearance is very different (more patchy), but also the pattern of areas where the highest stream densities are found is different, as can be seen in the comparison in fig. 23.

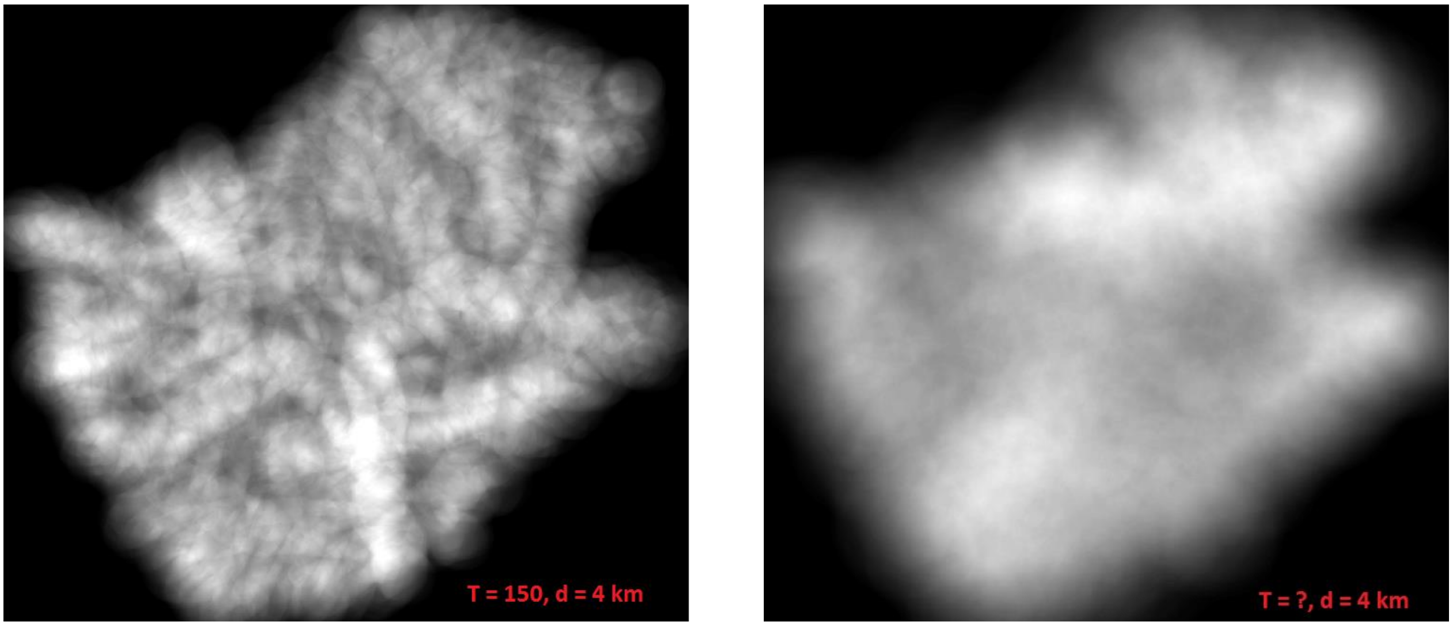


Fig. 23) Punakha stream density maps based on the calculated stream network data (left) vs. the official stream network data (right).

The threshold value applied to the supplied stream file appears to be smaller than the 150 used for the self-made stream network but that should not have any effect on the distribution of maximum and minimum density, this does seem to be the case for the comparison in fig. 23. The high values (white spots) show a different distribution. Some areas have a high stream density in both results, other areas have high density in one and low density in the other. The only structural difference that was found between the official and calculated stream network sets that might explain the difference was the delineation of the calculated streams in the flatter parts of the valleys (Fig. 24).

The difference between the two stream networks is clear in this image. The calculated stream network in red has multiple parallel streams in the valley. This is especially noticeable in valleys with floodplains. The correct natural behaviour is clear in the official stream network (blue), where streams from the valley slopes flow straight into the river. Additionally the official stream network appears more organized, in general featuring less small tributary streams than the calculated network and the tributary streams of the official network are often longer, reaching farther from the main river.

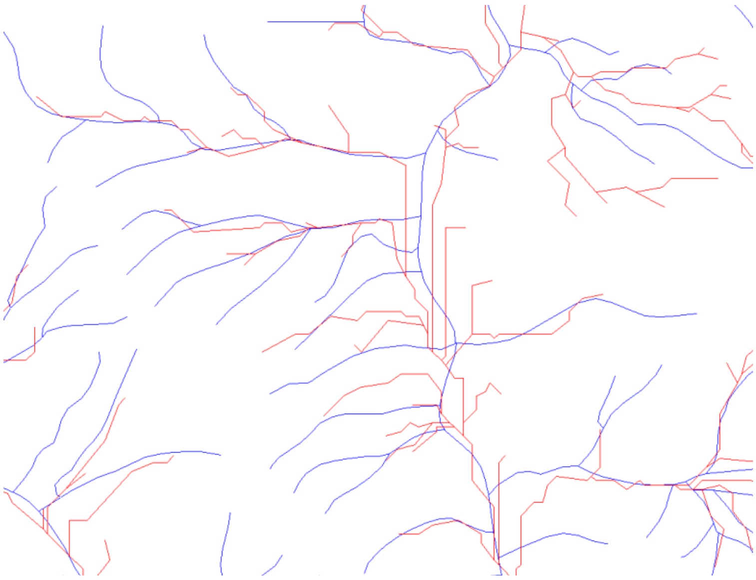


Fig. 24) Example of the difference between the two stream networks. Blue: the official dataset. Red: the calculated dataset.

The unnatural parallel streams in the valley appear to be caused by very small height differences in the DEM which enforce a 'boundary' between two streams that should actually converge into one stream. This could explain the irregular difference between stream density maps based on the official and calculated stream networks, where in floodplain valleys where density in reality is low, the calculated version returns very high density and in steep valleys both versions show low density. The same may happen on steeper slopes but no good example or explanation was found.

Looking into the problem on GIS forums and Google apparently this happens often in the DEM-based calculation of stream networks. According to McMaster (2002) the resolution of a DEM must be greater than the average hillslope length to be used for hydrologic modelling. This is of course not achievable for the small height differences causing the problem observed in this chapter. Apparently there is no good solution for the problem. The search for a solution or a better method led to a referral by the Dutch national water management authority (Rijkswaterstaat) to Deltares, a Dutch independent knowledge institute specializing in water and subsurface with great global expertise in the modelling and calculation of these kinds of networks. They offered to help in person with the problem. After explaining the applied method and the exact problems by e-mail and telephone however it became clear that they follow the exact same procedure and suffer from the same problems. The Deltares expert stated upon reviewing the calculated stream network that it was already as accurate as it can get. They solve these problems by outsourcing to foreign companies to manually rectify those areas (E. Van Meerendonk at Rijkswaterstaat, personal communication, October 31, 2017; H. Venema at Deltares, personal communication, November 7, 2017). The official stream network also appears hand-made given the smoothness of the stream delineation vs. the mechanical shapes of the calculated streams and the lack of parallel streams in the valleys.

The solution of manually correcting the stream network was unfortunately outside the scope of this study. Since the calculated stream network was considered to be too inaccurate and the official dataset featured large gaps, the decision was made to not include relief roughness in the typology. The developed method CRI is nonetheless a promising option for more accurately calculating a relief roughness indicator, and it would be interesting to include if at some point a complete dataset of the official stream network could be acquired.

3.2 Create dataset categories by enforcing relevant boundary conditions

After having selected the most important datasets that characterise the landscape variation it may be necessary to classify each dataset into a limited number of distinct classes that each bare relevance to specific landscape characteristics. This increases the discerning value of the datasets as well as reduce final category count resulting in a more powerful final landscape map. One must choose categories so that they add discriminatory value, an elevation class containing only one landcover type for example does not add any value to the final product.

3.2.1 Elevation classes (DEM)

In order to define elevation classes a couple of options were evaluated. The customary method is to divide elevation classes based on climatic properties, the boundaries of which are often determined through observations of dominating vegetation or biomes. A widely used classification based on climatic properties is the Holdridge life zones system (Holdridge, 1947). This classification uses annual precipitation, potential evapotranspiration and biotemperature to determine possible climax vegetation in a location. The most suitable factor for division of elevation classes within the Holdridge life zones system is biotemperature (the mean annual temperature between 0 and 30˚C). As seen in fig. 25 the system divides altitudinal belts according to their biotemperature.

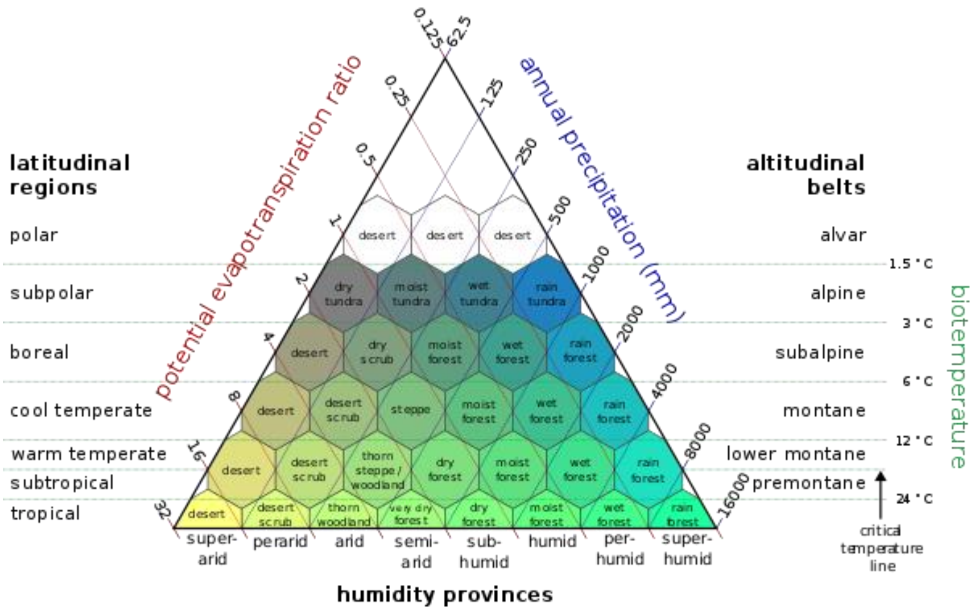


Fig. 25) Holdridge life zones system. Image credit: Peter Halasz.

For Bhutan however annual climate data was not available in sufficient temporal and spatial resolution to be able to create the altitudinal belts according to Holdridge. This means that many other classification schemes cannot be used in order to determine elevation classes either as they too are based on climatic data and/or potential vegetation or biomes. This applies to biome based classification systems like ecoregions (Bailey, 1989), zonobiomes (Walter, 1976) and biome-types (Whittaker, 1962; Whittaker, 1975).

Existing climate based division systems thus cannot reasonably be used to find boundary conditions for elevation in the case of Bhutan. The grand principle behind all these systems however is something that can be applied to the available data. The systems are all designed to indicate where a specific biome or vegetation type can be expected. As land cover data is available for Bhutan the distribution of certain types of vegetation is known. This distribution can therefore be used to find boundary conditions for the elevation classes.

To find sensible boundaries for the elevation classes the distribution of land cover over elevation ranges was used (Table 2).

Landcover category	min	max	mean	St. dev.
Snow&Glacier	2851	7522	4984	468
Shrub	2504	5187	3940	399
Grassland	2155	6534	4227	757
Barren Area	44	5717	4127	1385
Mixed Forest	102	3828	2482	655
Conifer Forest	1573	6395	3262	439
Broadleaved Forest	43	3270	1575	654
Agriculture	44	3188	1330	828
Urban Area	871	2650	2006	477
Waterbody	28	5459	496	582

Table 2) Landcover/elevation distribution statistics in meters.

NOTE: For the determination of these boundaries the ICIMOD landcover data was used. Ideally one would use the more accurate NLCS landcover data however this dataset was only made available later on in the study. As a consequence a lot of work had already been done using the boundaries derived from the ICIMOD data. Additionally for the landscape change analysis ICIMOD data must be used as the NLCS data only exists for one year. For those reasons the boundary conditions for the elevation ranges were not changed after receiving the NLCS dataset. When more years of accurate NLCS landcover data are created one may want to adapt the boundary conditions to suit these datasets. The elevation boundary values were however found to be extremely similar to the ICIMOD based boundaries, especially those of the categories used for determining the boundary values. A detailed comparison between both datasets can be found in the landscape change analysis chapter.

The data in table 2 is represented visually in fig. 26. Fig. 26-A shows the mean elevation value for each landcover class with the accompanying standard deviation indicated. Fig. 26-B shows the means with two times the standard deviation indicated.

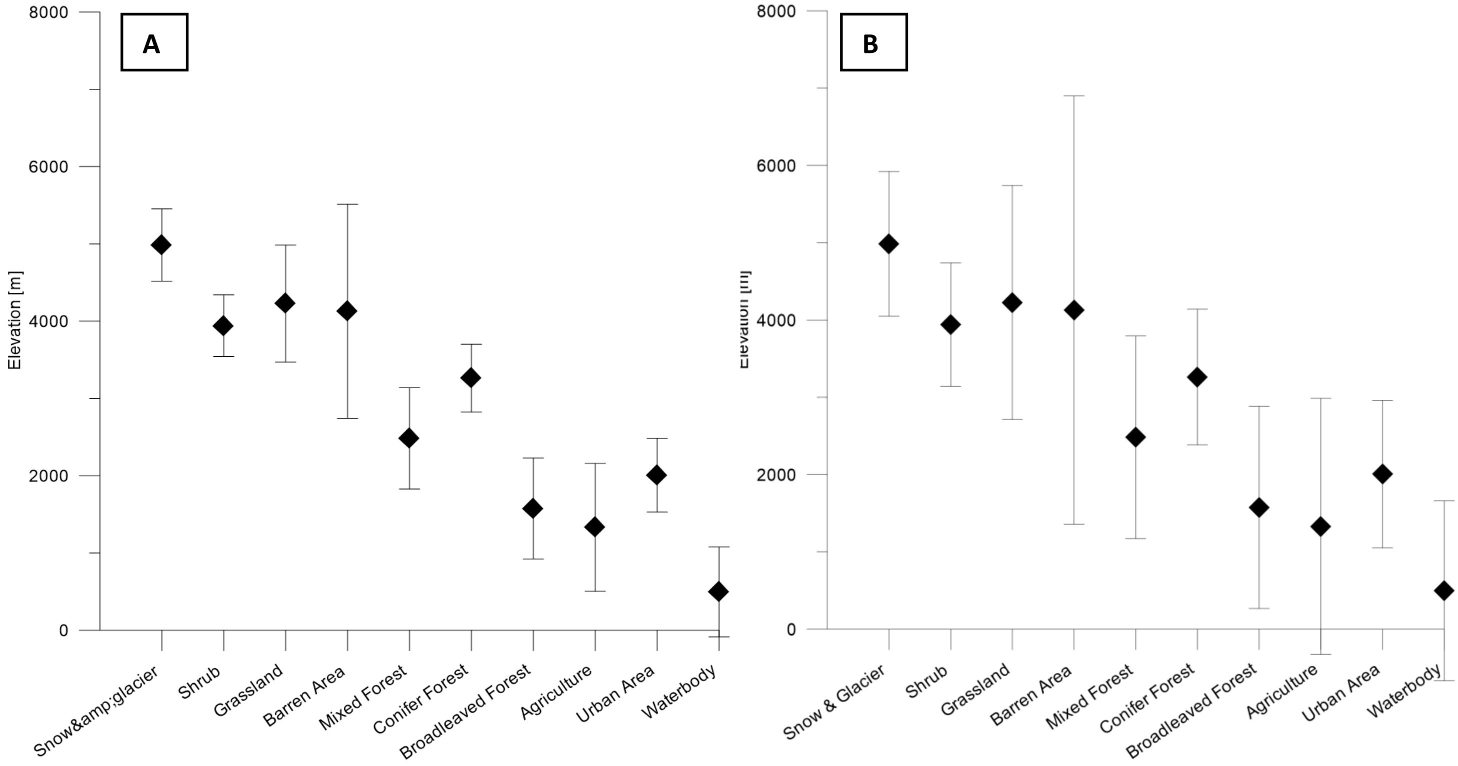


Fig. 26) Landcover elevation means with 1x St.Dev. (left) and 2x St.Dev. (right).

Of the landcover types included in the landcover data a couple of types lend themselves best for determining elevation classes based on vegetation type. The first logical class break is the lowest elevation where the Snow & Glacier landcover type is found or the highest elevation where vegetation is found. This class break would denote the barrier where vegetation is at all possible and is thus an important indicator of local climate, as well as an important factor for determining the (visual) attributes of the landscape. It is also clearly a class break that determines what types of land use are possible in the area. Another logical elevation class break may be found in the maximum elevation where trees are found indicating the tree line. Again this is a major change in type of vegetation and is important for landscape. A final interesting class break is the upper elevation value where agriculture is practiced. The prevalence of agriculture is indicative of human influence in the landscape. Agriculture is also confined to specific geomorphological areas. In Bhutan most agriculture is focused in the relatively flat areas of the country.

Preferably the 2x standard deviation data would be used to determine elevation class breaks. The 2x standard deviation reflects the elevation where the majority (>95 %) of the area containing a specific land cover type would be included in a specific elevation class, and would thus be the most discerning indicator for climatic elevation bands. The class breaks for the 2x standard deviation would be 3000 m and 4000 m elevation. The 3000 m class break is found in the maximum height of agriculture. The 4000 m class break falls in the tree to snow&glacier transition. The grass and shrub landcover classes are invisible in this scheme as the tree and snow&glacier classes completely overlap the grass and shrub classes and demarcate a more important transition. The resulting elevation classes are mapped in fig. 27.

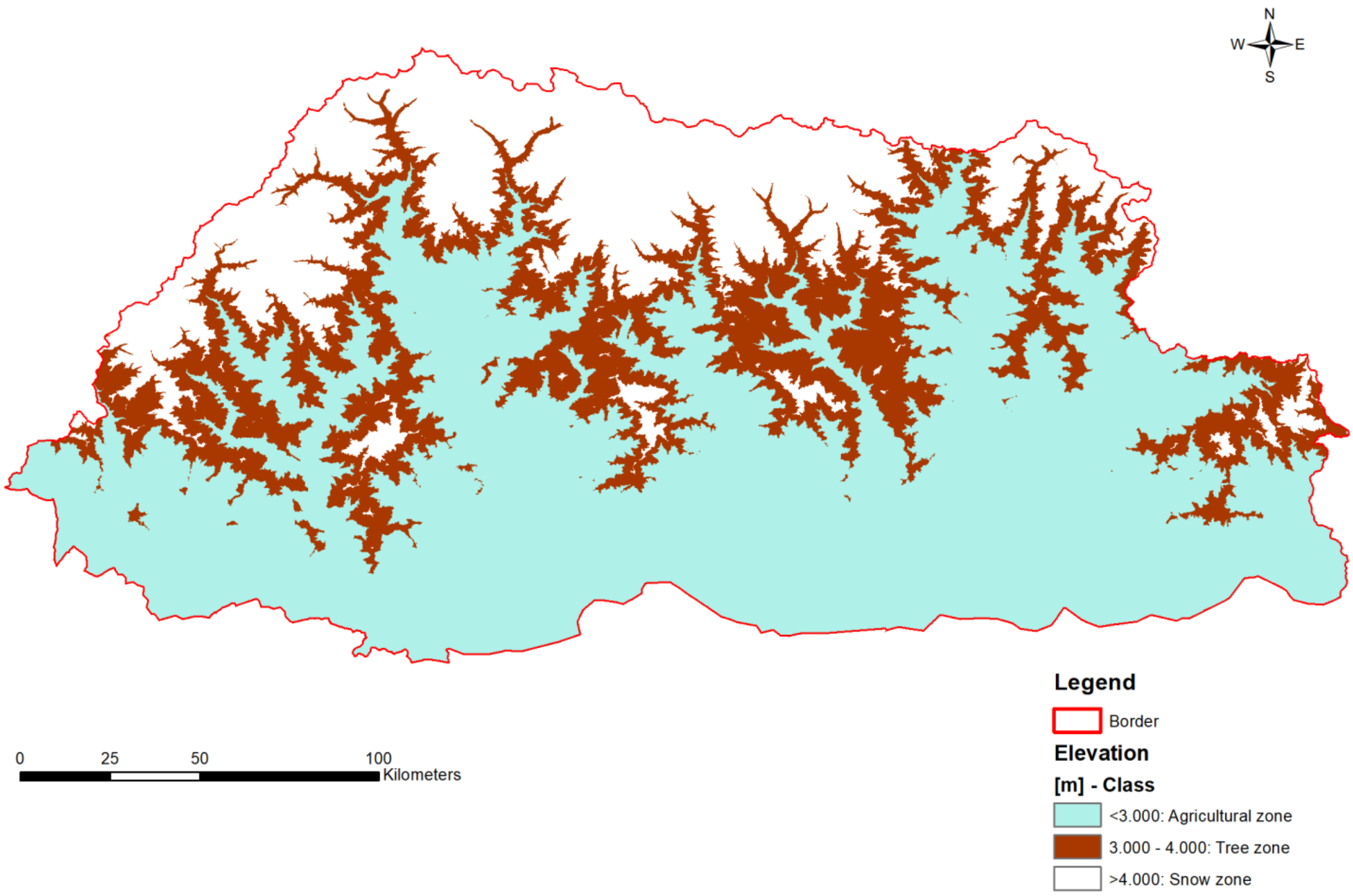


Fig. 27) Elevation class boundaries using 2x St.Dev. resulting in three elevation classes.

The elevation classes based on the 2x standard deviation class breaks visually divide the map in two main altitude bands with a relatively thin line of the middle altitude class. The area represented by the <3000 m class is 57 % of total area, 3000-4000m represents 21 % and >4000m represents 22 %. This division is not very discerning due to its topography and could lead to an overrepresentation of 'low altitude' landscapes in the final product.

The 1x standard deviation altitude class division divides the area a lot more evenly. This is not necessary in and of itself as long as the map accurately represents the real situation. But there is another relevant landcover class break that can be applied when using the 1x standard deviation as a guideline which would divide the elevation classes in such a way it becomes much more discerning. The 1x standard deviation leaves room to represent an area dominated by grassland and shrubs. The classes are now <2200 m, representing the occurrence of agriculture, 2200-3700 m representing the zone where tree growth is possible and is more important than agriculture, 3700-4500m where only low vegetation is possible and >4500 m where no vegetation at all is possible. Note that these class breaks are based on the upper limit of the mean plus 1 standard deviation (or the lower limit in case of the snow & glacier class), meaning that above the class breaks still over 15 % of the total area corresponding to the agriculture or tree landcover can be found. In the case of the 4500 m class break this is based on the mean minus 1 standard deviation of the snow & glacier land cover class as there is some overlap of the grassland/shrub and the snow & glacier landcover classes. This is unavoidable as the transition between classes is not a hard boundary and is influenced as well by seasonal and local influences (especially for the snow & glacier class). The resulting altitude bands can be seen in fig. 28.

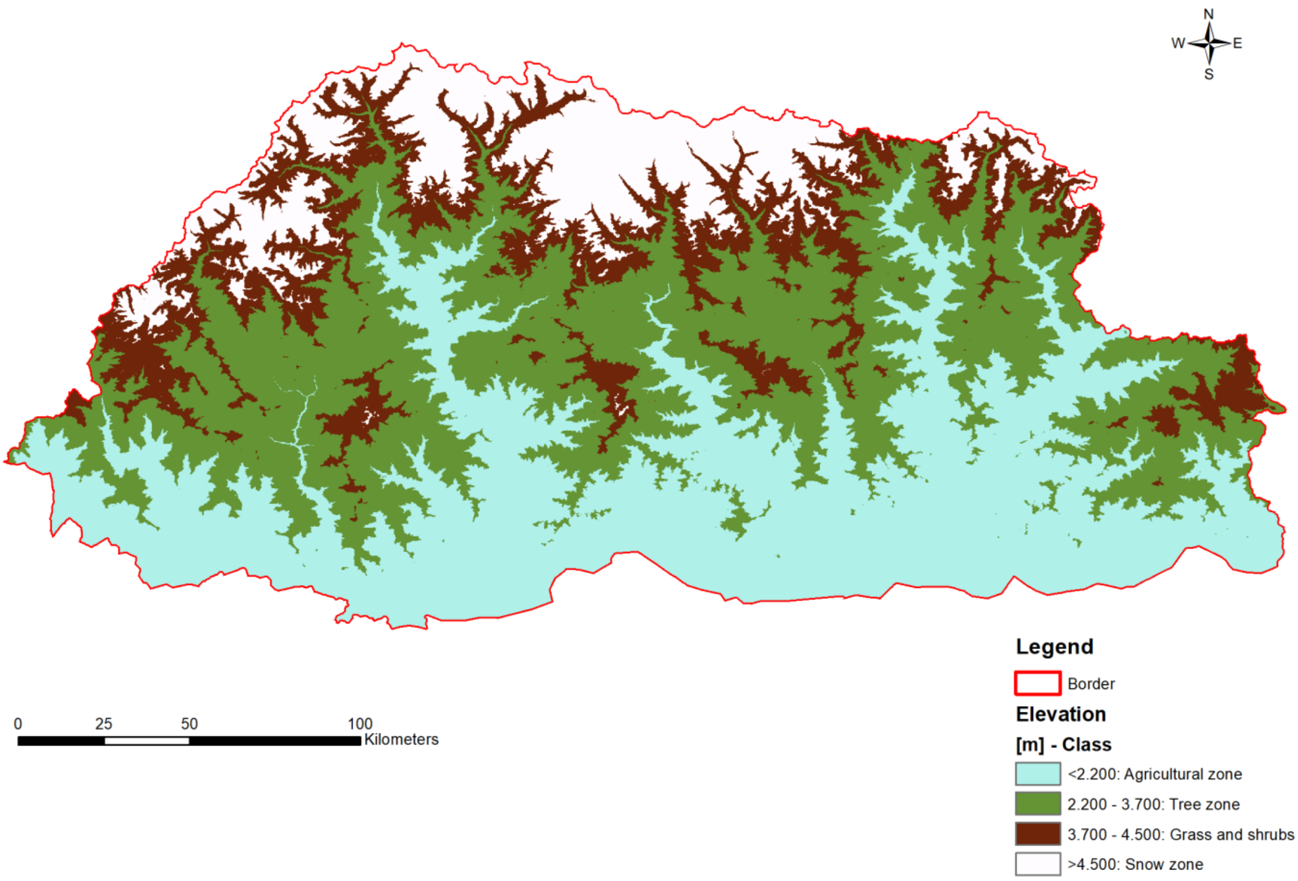


Fig. 28) Elevation class boundaries using 1x St.Dev. resulting in four elevation classes.

For these elevation classes the total area is made up of <2200 m (37 %), 2200-3700 m (36 %), 3700-4500 m (15 %) and >4500 m (12 %). As these divisions result in a more balanced division of the area while still being based on relevant land cover categories the 1x standard deviation based altitude classes will be used for the final landscape typology.

3.2.2 Slope

Slope has a clear influence on landcover in Bhutan. The nation's most populous middle elevation band (from west to east) is characterised by relatively low mountain ranges with mild to steep slopes with a relatively flat valley floor in between where most of the human activity is found. In fact the nation's urban areas are closely tied to the valleys. A couple of options were looked at in order to determine relevant slope categories. Among these were human and animal gait analyses with regard to slope, slope related vegetation patterns, slope related erosion patterns and influence of slope on agriculture (United States Department of Agriculture [USDA], 2016; Whittaker, 1967). In the end none of these options resulted in relevant figures for determining slope classes in this study. Class breaks were therefore found through settlement locations which is deemed a relevant discerning factor. Slope values where human activity is statistically most prevalent can be expected to stand a higher chance of being influenced by human activity or else possibly be influenced by human activity in the future. Slope classes are based primarily on the slope distribution of the nation's settlements. A shapefile containing every individual settlement of Bhutan was linked to the slope map resulting in a dataset containing the slope value for every settlement which was analyzed with the following results (Fig. 29):

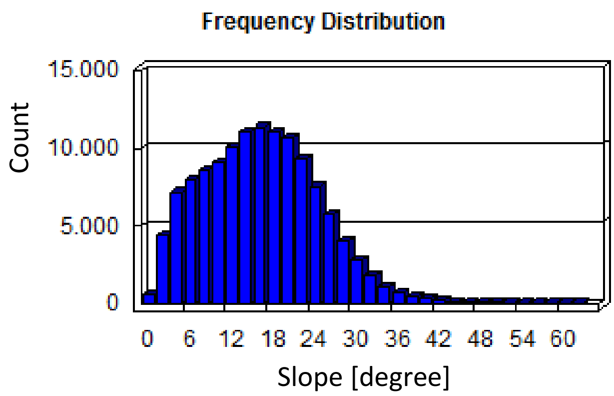


Fig. 29) Settlement/slope distribution.

The mean slope value of all settlements is 16.5 degrees with a standard deviation of 8.2 degrees. Next two different options for determining the class breaks were discussed. The first option was to divide the slope map in four classes based on the settlement slope values.

The first class break was set on the mean + one standard deviation: 24.7. This was rounded to 25 degrees. For the next class break another standard deviation was added to reach 32.9 which was rounded to 33 degrees. These two classes include almost 98 % of all settlements in Bhutan. The last class break was chosen to represent extreme values, i.e. cliffs. This break was somewhat arbitrarily chosen after looking at options like maximum angle of repose of materials, which idea was disregarded seeing as this isn't really applicable to for example rock. The chosen class break was 50 degrees. The resulting slope map with these classes is shown in fig. 30.

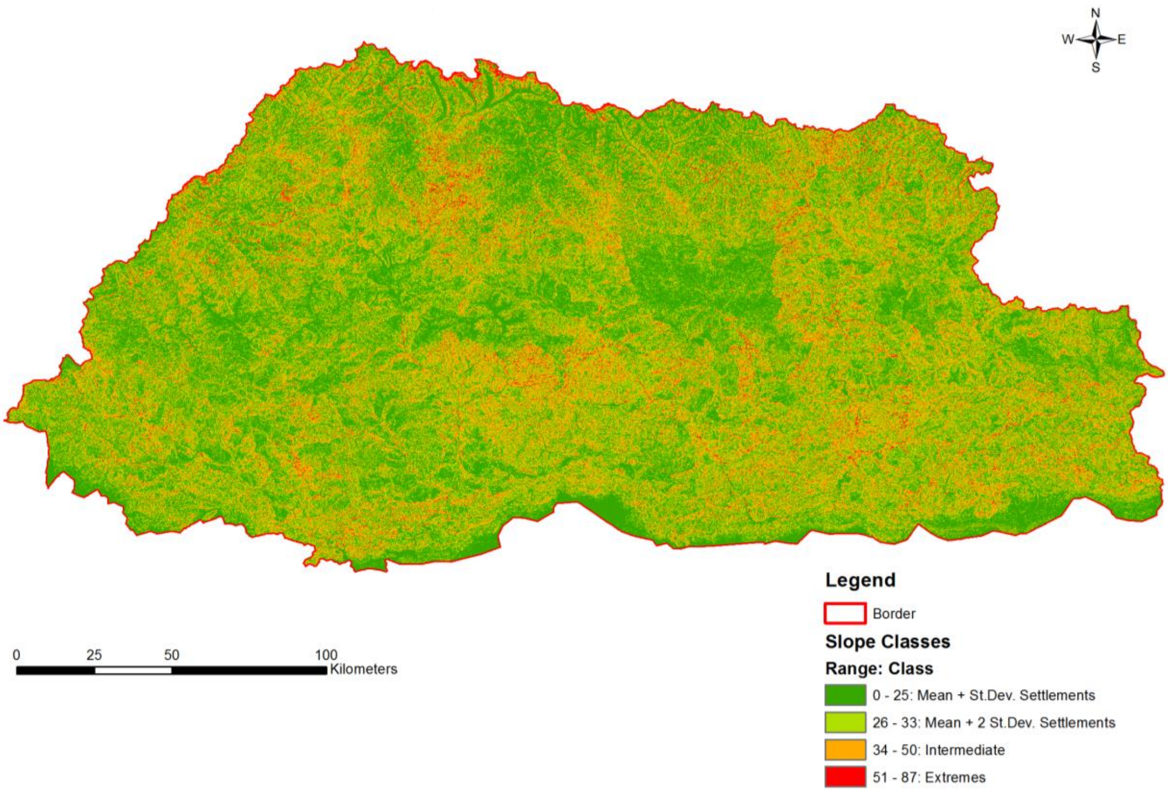


Fig. 30) Slope map (4 classes).

The first two classes are indicative of possible human influence on the local landscape, whereas the last two classes are more discerning of natural/geomorphological properties of the landscape. The extremes are representative of cliffs and extreme landscapes where vegetation coverage may be affected.

Another approach was to more generally divide the slope map into two classes based on the settlement values. Here the division would be telling of the possibility of human influence found in the landscape versus a much lower possibility, i.e. primarily natural attributes influencing the local landscape. For this the class break was set on the mean settlement slope + 2 times standard deviation. The first class is now 0 - 33 degrees, the second class 33 - 90 degrees. The first class includes 97.8 % of all settlements and therefore a large majority of human activity. The resulting map is seen in fig. 31.

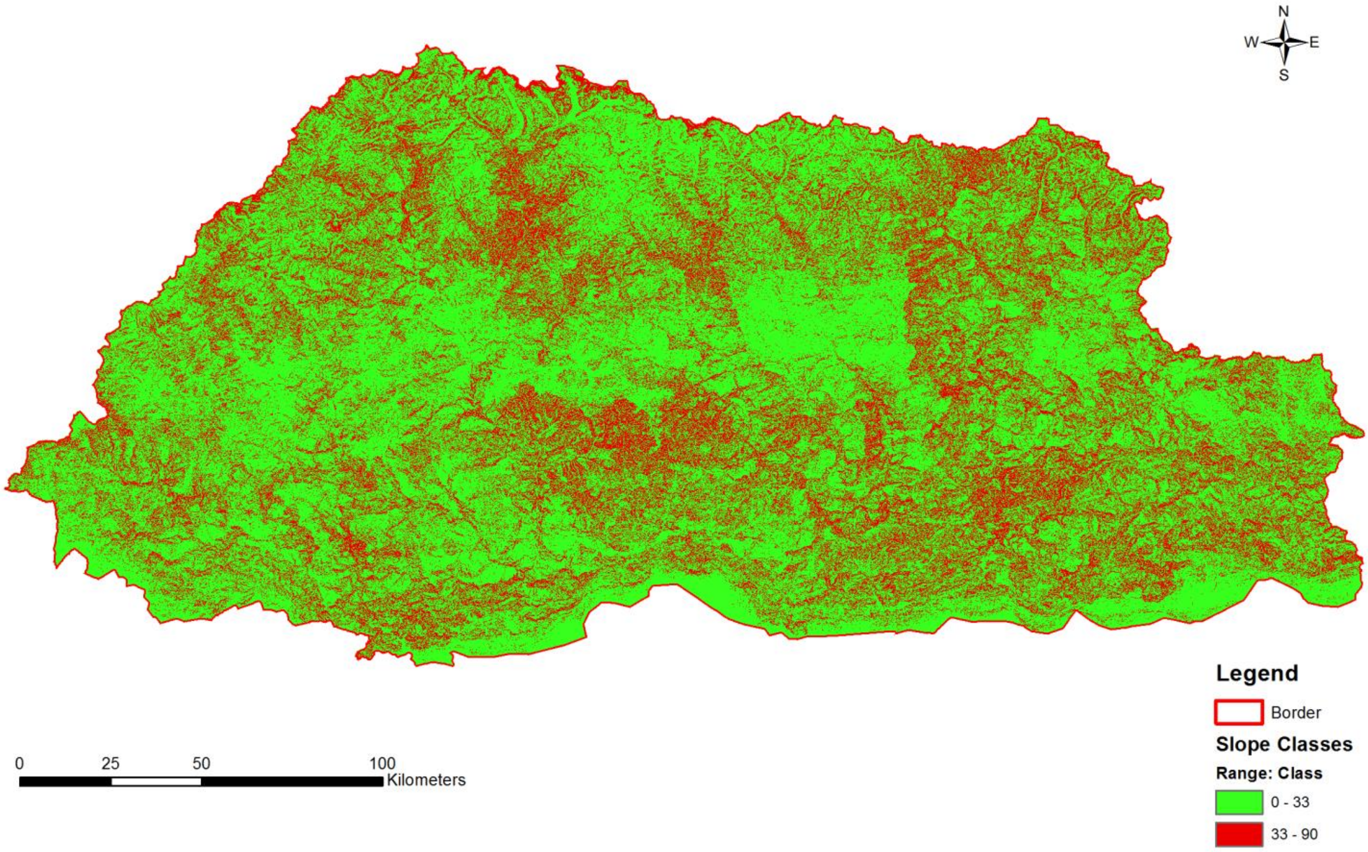


Fig. 31) Slope map (2 classes).

The 0 - 33 degree class represents 70.7 % of total area, the 33 - 90 class represents 29.3 %.

For the final map the two class slope map will be used. This binary classification limits the resulting number of classes by 50 % compared to including four slope classes. The two class slope map has the advantages of offering a simple distinction into relatively mild slopes where human activity is concentrated and steep slopes where natural processes will dominate.

3.2.3 Landcover

Landcover categories have been based on the original categories used in the ICIMOD landcover data. The original dataset uses ten categories: Snow and Glacier, Shrub, Grassland, Barren area, Mixed forest, Conifer forest, Broadleaved forest, Agriculture, Urban area and Waterbody. Operational constraints required the amount of categories to be reduced to nine total classes due to the three-digit structure of the landscape codes. For this reduction there were three possible options. The first was to combine the grassland and shrub landcovers, the second possibility was combining broadleaved forest and mixed forest and the third option was to combine conifer forest and mixed forest. These options combine classes that are already somewhat similar in character and spatial distribution whereas the remaining classes have a more unique character. Based on the total areas of the mentioned class pairs the choice was made to combine the broadleaved forest and mixed forest classes. In the case of grassland and shrub the area ratio is 1:1.9. For conifer forest and mixed forest the ratio is 1:13.1 and for broadleaved forest and mixed forest the ratio is 1:23. So the impact of combining mixed forest with broadleaved forest is relatively small compared to the impact of combining any of the other landcover class pairs. The shared border length between mixed forest and either conifer forest or broadleaved forest is similar at 9707 km and 9344 km respectively. The slightly shorter border length of broadleaved and mixed forest (96.3 % of conifer and mixed forest) is insignificant compared to the relative area differences.

The resultant ICIMOD landcover map is shown in fig. 32 below.

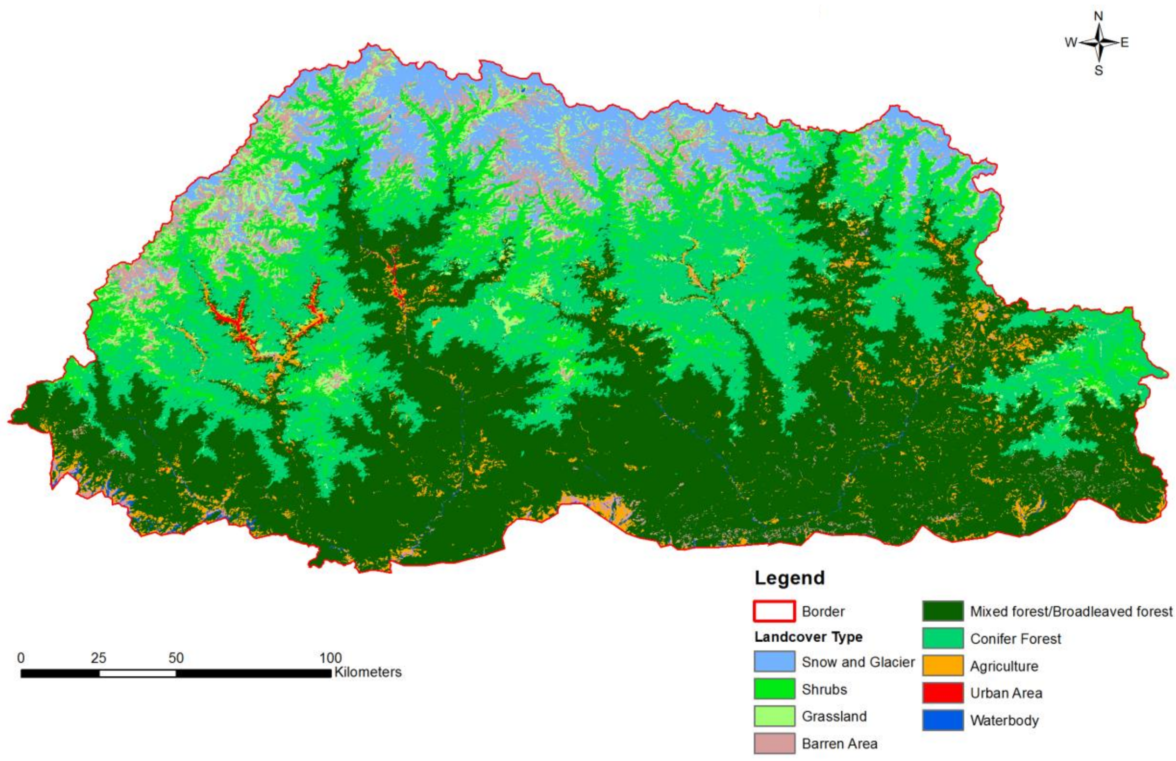


Fig. 32) ICIMOD 2010 reclassified landcover map.

The NLCS landcover was adapted to follow the same nine categories. To this end the original classes were reassigned to one of the nine landcover ICIMOD based classes. The decisions were based on the closest relationship of the original classes with one of the ICIMOD based nine classes, for example all types of orchards, plantations as well as Chhuzhing land (which translates to paddy fields) are grouped into Agriculture. The complete conversion scheme can be found in appendix A. Fig. 33 shows the resultant NLCS based landcover map.

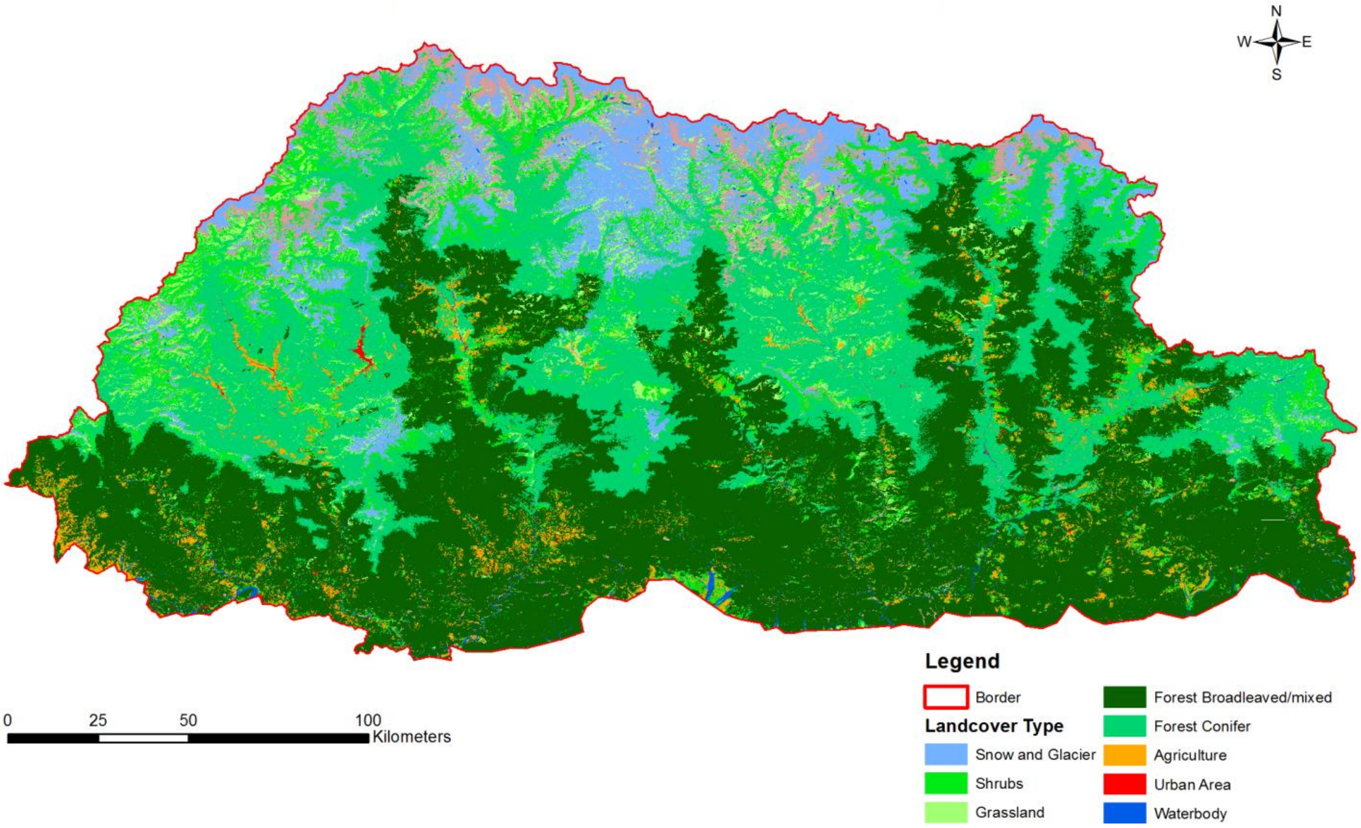


Fig. 33) NLCS reclassified landcover map.

A comparison of the total relative area of each of the nine classes of both the ICIMOD and the NLCS based landcover maps shows that they are very similar (Table 3). A more detailed comparison of the NLCS and ICIMOD landcover datasets and the landscape maps based thereon can be found in the landscape change chapter.

Landcover class	NLCS Area [%]	ICIMOD Area [%]
Waterbody	0.8	0.4
Urban Area	0.2	0.2
Snow and Glacier	8.7	7.7
Shrub	12.2	9.9
Mixed/Broadleaved Forest	49.9	44.5
Grassland	4.6	5.1
Conifer Forest	16.0	24.3
Barren Area	4.4	4.8
Agriculture	3.3	3.1

Table 3) NLCS vs ICIMOD landcover class area comparison.

3.3 Combine datasets into a preliminary/first order landscape map

The first step in creating the final product is combining the prepared (i.e. classified) datasets. In this step a map is created where each cell represents the values of all three datasets and no further manipulation is applied. This will yield a preliminary first order landscape map where all existing combinations of the dataset classes will be shown no matter how small their unit area.

The combination of the data will be done using a raster operation. As the NLCS landcover file is a vector file this was first converted into a raster. The operational parameters were set so that the cells of the resultant raster file exactly match size and position of the elevation and slope rasters.

In order to be able to combine the source datasets they are reclassified again according to hierarchical importance of the data. The cells in the first order landscape map will have a 3-digit value with the first digit representing the class of the hierarchically most important dataset (Elevation), the second digit the hierarchically second most important dataset (Landcover) and the final digit the least important dataset (Slope). In preparation the datasets were reclassified so that the elevation classes got a value between 100 and 400, the landcover classes a value between 10 and 90 and finally the slope classes a value of 1 or 2 (Table 4). Now the datasets can be combined by simply adding the values of each cell within each dataset.

Altitude

1xx:	< 2200 m,	Agricultural zone, name: Low Land (L)
2xx:	2200 - 3700 m,	Tree zone, name: Montane (M)
3xx:	3700 - 4500 m,	Grass and Shrubs, name: Alpine (A)
4xx:	> 4500 m,	Unvegetated zone, name: Nival (N)

Landcover

x1x:	Snow and Glacier
x2x:	Shrubs
x3x:	Grassland
x4x:	Barren Area
x5x:	Broadleaved forest/Mixed forest
x6x:	Conifer forest
x7x:	Agriculture
x8x:	Urban Area
x9x:	Waterbody

Slope [Degree]

xx1:	0 - 33
xx2:	33 - 90

Table 4) Landscape variable reclassification scheme.

The combined map features 67 unique values from a total of 72 possible values, where each unique value represents a unique combination of elevation, landcover and slope. Some of the found combinations feature landcover types where elevation and slope are irrelevant. These are Urban Area and Waterbody. All cells with value 'x9x' (Waterbody) are, therefore, reclassified into value '1' and all cells with value 'x8x' reclassified into value '2'. Also cells with Snow and Glacier as landcover are reclassified, however the influence of slope is retained as slope does influence the visual and practical quality of a snow landscape. Consequently cells with value 'x11' are reclassified to value '3' (Snow and Glacier mild slope) and cells with value 'x12' are reclassified to value '4' (Snow and Glacier steep slope). The result is the first order typology map shown in fig. 34.

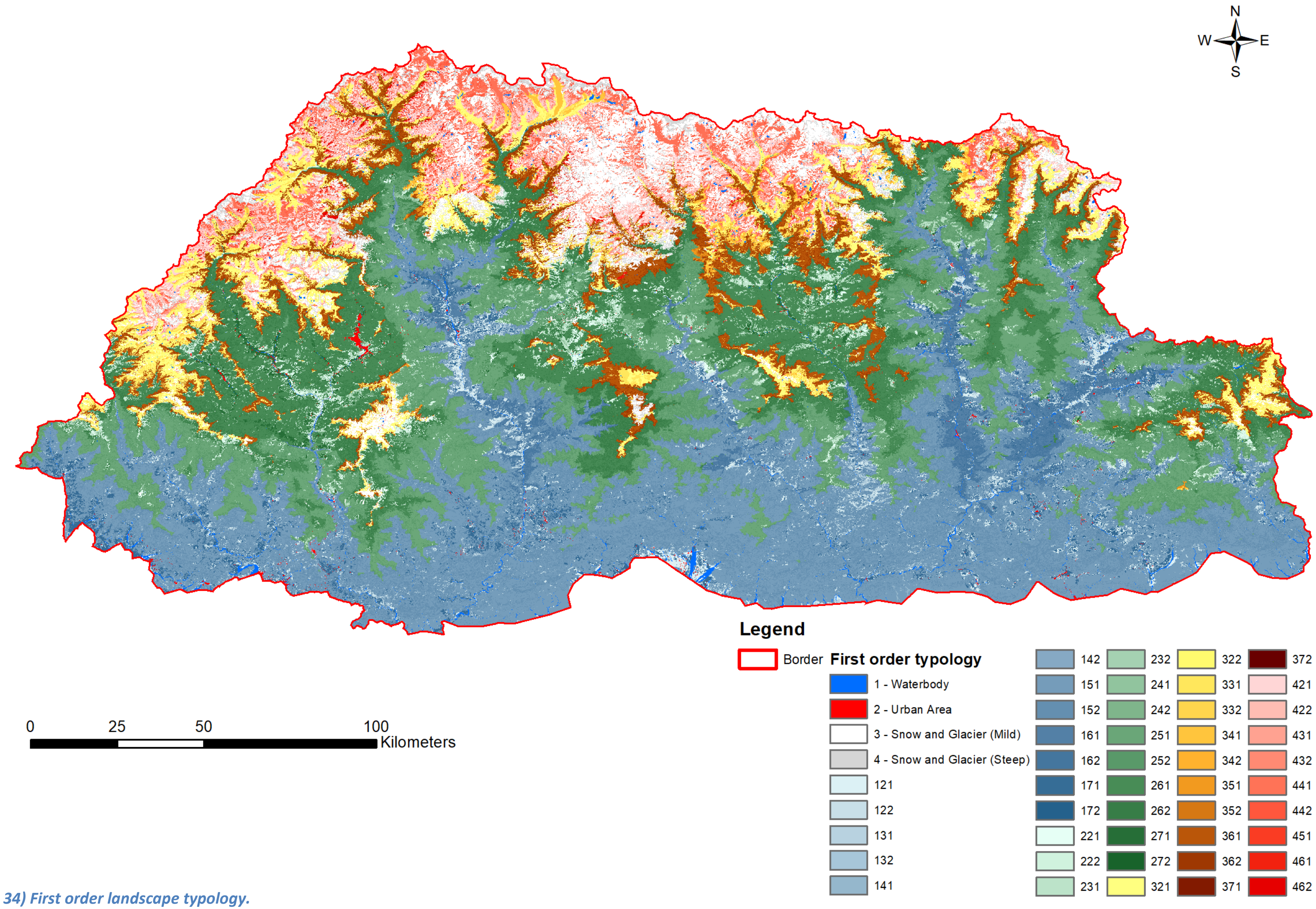


Fig. 34) First order landscape typology.

3.4 Refine first order landscape typology into final landscape map

At this point the definitive landscape map can be created using the first order landscape map. The first order map is a patchwork of landscape units of all sizes starting at only one cell (30x30 m). A landscape unit of a single cell does not count as a coherent landscape. The small primary landscape units must thus be combined which is done through the application of a minimum mapping unit (MMU) that enforces a minimum size for each individual landscape unit.

For the best result landscape units should be combined with preservation of the original borders of the landscape units. Preserving unit borders is not possible using raster data so the first order landscape map was converted into vector format. The vector data was constructed using non-simplified polygons such that polygon borders exactly followed the original raster cell borders in order to minimize inaccuracies (Fig. 35).

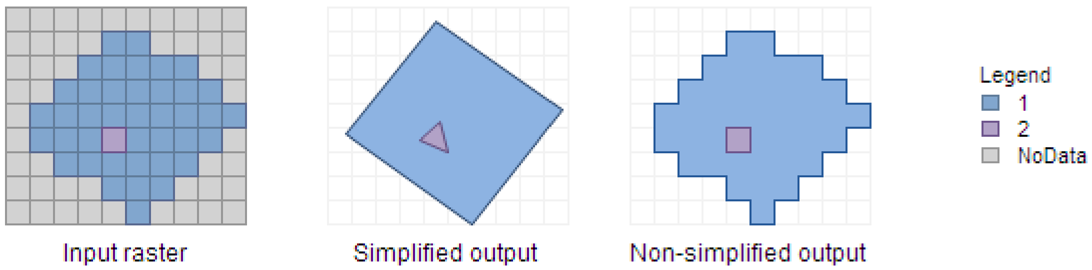


Fig. 35) Raster data was converted into polygons using the non-simplified output method in order to maximize preservation of original borders. Image source: ArcMAP raster to vector tool help.

With this operation a vector file is created based on the values of the first order typology raster cells. In the resulting file groups of adjacent cells with the same value are converted to a single polygon (see fig. 35) representing that particular landscape unit. The first order units are then clustered using the eliminate tool. Here the minimum mapping unit is needed.

The minimum mapping unit is determined by examining typical landscape areas through a combination of explorative site visits, examination of aerial photography and viewshed analysis. The site visits have already helped determine what data is important for creating a Bhutanese landscape typology. During the visit however also typical landscapes were found which have guided the viewshed analysis. Viewshed analysis was done using Google Earth Pro. Locations for viewsheds were chosen in such a manner that no extremes were included, for example viewshed analysis was not performed from a mountain top which would result in an exorbitantly large area. The analysis was performed using locations that represent the everyday experience one would have of the Bhutanese landscape, think of viewsheds found while driving, when hiking to important landmarks or from typical inhabited areas. The calculated viewshed was then used as a guide together with photographs, aerial imagery and experience from the specific location to delineate multiple areas that qualify as a coherent and relevant landscape. As a result of this work a couple of sizes were tested to use as MMU for the final landscape map, shown in table 5.

Size	Source
2.3 km^2 or 230 hectare	Viewshed analysis (Average viewshed size)
1 km^2 or 100 hectare	Viewshed analysis (Typical small viewshed size)
0.15 km^2 or 15 hectare	Optimum landscape size found through analysis of aerial imagery of visited locations. This turned out to be very similar to European average national typology MMU sizes of 16 ha (Mücher et al., 2009)

Table 5) Possible landscape sizes.

Using the MMU's from table 5 the first order map was clustered with the elimination tool. Through the clustering process landscape unit polygons with areas smaller than the MMU are added to adjacent larger landscape units. The eliminate tool used for clustering adds selected polygons (i.e. landscape units in this case) to unselected polygons. This allows for precise control over which landscape units are to be added to larger landscape units. Landscape unit polygons to be assimilated are selected based on their area. The file was found to have erroneous polygon areas which was solved by reprojecting the file to a projection that allows polygon areas to be recalculated. Then polygon attributes are used to select polygons which are smaller than the MMU and that are not of the "Waterbody" or "Urban Area" type. The initial selection typically includes between 300.000 and 700.000 landscape units that meet these requirements.

The landscape types "Waterbody" and "Urban Area" have to be excluded from the clustering process as they are sharply defined landscape types and completely different in nature from the other landscape types. Clearly the borders of waterbodies are sharply defined, the borders of urban areas which are based on census and cadastre data should not be subject to change because these are not only clearly very distinct from other landscape types but also offer a reference with which to more easily interpret the final map. If included in the clustering this would result in land being added to rivers and lakes or vice versa, or urban areas being added to natural areas or vice versa.

The eliminate tool is then programmed to add landscape units smaller than the MMU to landscape units larger than the MMU based on the longest shared border whilst again excluding landscape units of the type Waterbody or Urban Area. This means

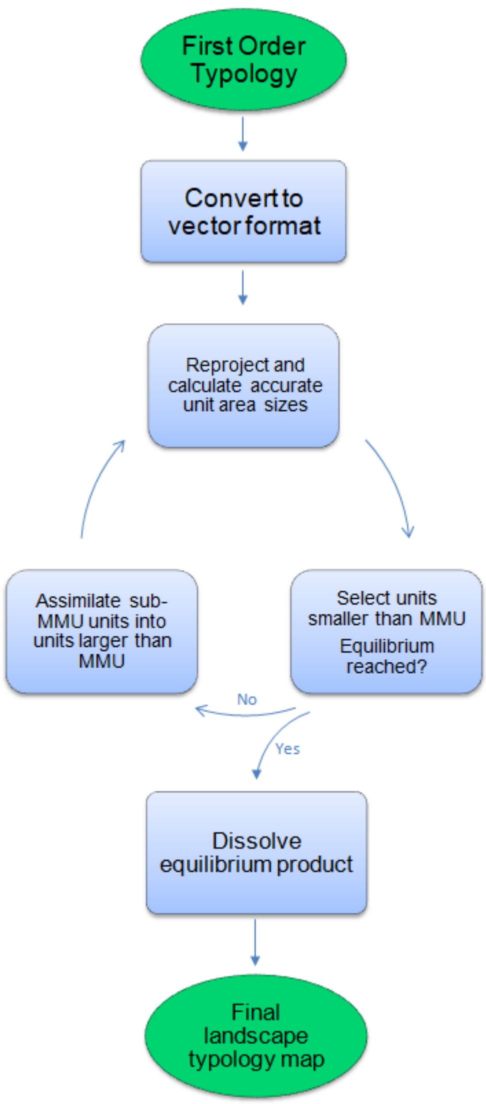


Fig. 36) Schematic view of step 4.

that if a landscape unit smaller than the MMU is adjacent to more than one landscape unit larger than the MMU the smaller landscape unit is added to the landscape unit with whom it shares the longest border. Also the selected landscape units cannot be added to landscape units larger than the MMU but of the Waterbody or Urban Area type (the previous selection by attributes only excluded Waterbody and Urban Area units smaller than the MMU from clustering, this step ensures units of these types larger than the MMU are excluded as well).

The result of this first cluster step still features many landscape units smaller than the MMU. This can, for example, be caused by sub-MMU sized landscape units being completely surrounded by other sub-MMU sized landscape units. That means the clustering process must be repeated after the recalculation of polygon size in order to ensure correct landscape unit areas. After a couple of clustering steps (typically between 5 and 8 repeats) an equilibrium is reached where the amount of landscape units that are smaller than the MMU remain constant. Not all of the landscape units smaller than the MMU can be added to larger than MMU units, for example because they are surrounded completely by Waterbody (islands) or Urban Area. on average around 650 individual units smaller than the MMU remain (Table 6).

	NLCS 15 ha	**NLCS 230 ha**	**ICIMOD 2010 15 ha**	**ICIMOD 2010 230 ha**
Individual units before clustering	1790010	1790010	851707	851707
Individual units after clustering	45885	25001	25917	2303
Cluster steps	7	8	5	7
Remaining sub-MMU	1271	1282	82	88
Avg. Size before clustering [ha]	2.2	2.2	4.5	4.5
Avg. Size after clustering [ha]	84.4	154.8	149.4	1681

Table 6) The clustering step drastically reduces the amount of landscape units. The NLCS based map retains more sub-MMU units in the final product than the ICIMOD based maps.

The final step in the cluster process is dissolving the equilibrium result. After the elimination steps there is a possibility of landscape units of the same type to have grown adjacent to one another by repopulating the sub-MMU sized units that previously divided them. Dissolving the map connects those units together creating a single landscape unit of that type. At this point the final landscape map is completed. The entire process is shown schematically in fig. 36.

For the landscape change study the exact same process is repeated using ICIMOD landcover data made in 1990 and 2000. By using the same parameters and methods the landscape maps of the different years should be directly comparable.

At this point there is an option to enforce additional restraints, for example landscape types with a total area smaller than 1 % of Bhutan could be discarded. This would decrease the amount of landscape types in the final typology. However there was no indication for what percentage would be sensible. Additionally it was reasoned that some uses of the typology, like landscape change, would need these rarer landscapes. For this study therefore such a boundary was not used.

The final step is creating a visual language that can convey the map data in a structured manner.

3.5 Validate results using aerial photography

The final landscape map can now be validated. In the literature validation was only done in four of the articles, 3 of which used a validation method that could be applicable to this study. Mücher et al. (2009) compare their result to national landscape maps (the precise method is not discussed), which is impossible for Bhutan as no such map exists. Lioubimtseva and Defourney (1999) mention the traditional field survey of random sample points method (used by Odeh et al. (2017)) before proposing substitution of the field survey with a comparison of aerial photography which is better suited for landscape maps with a large extent. They compare multiple sample points with aerial photographs that have been classified automatically into land cover. Their precise method of comparing the landscape and automatically generated landcover maps remains unknown.

Validation will be done in two different ways, similar to the method of Lioubimtseva and Defourney (1999). 5 points will be randomly generated within the border polygon and a buffer with a 1 km radius is applied to them. For these 5 areas landscapes will be delineated manually using aerial photography after which the manual typology will be compared with the created typology. In this way bias is eliminated and a measure of difference between perceived landscape units and landscape map units can be quantified by comparing the zonal geometry of the landscape units made manually and automatically. As this is very labour intensive the amount of area that can be used for validation is limited. For this reason also a visual comparison will be done. 10 additional points will be randomly generated within the border polygon and a buffer with a 2 km radius will be applied. These areas will be compared to the created typology visually. Using the combination of these two approaches a much larger area can be used for verification.

The landscape map is extracted for the sample areas and projected over a background map showing aerial photography. This will be done using Google Earth Pro because it offers a choice of which year of satellite imagery you want to see. That control allows for the best fit between aerial photography and the year of the landcover data used for the landscape typology thereby excluding as many temporal changes in aerial imagery compared to the map as possible. The map is loaded into Google Earth Pro by converting the file into KML which can be opened in Google Earth Pro.

4. Results

4.1 Landscape map

Whilst creating the final landscape map it quickly became clear that two maps of different scale would be required in order to be clear at different zoom levels. For the national level a map with 230 hectare (average viewshed size) set as the MMU showed the best results, creating a clearer map suitable for rough or low detail analysis (Fig. 37). However for closer zoom levels and more in depth analyses this MMU can be too large and an additional landscape map with a 15 hectare MMU (similar to average national typology MMU's) was created (Fig. 40). The larger scale map will also be more accurate for the landscape change analysis as it will be more sensitive to landscapes that are being 'nibbled', i.e. incrementally changed.

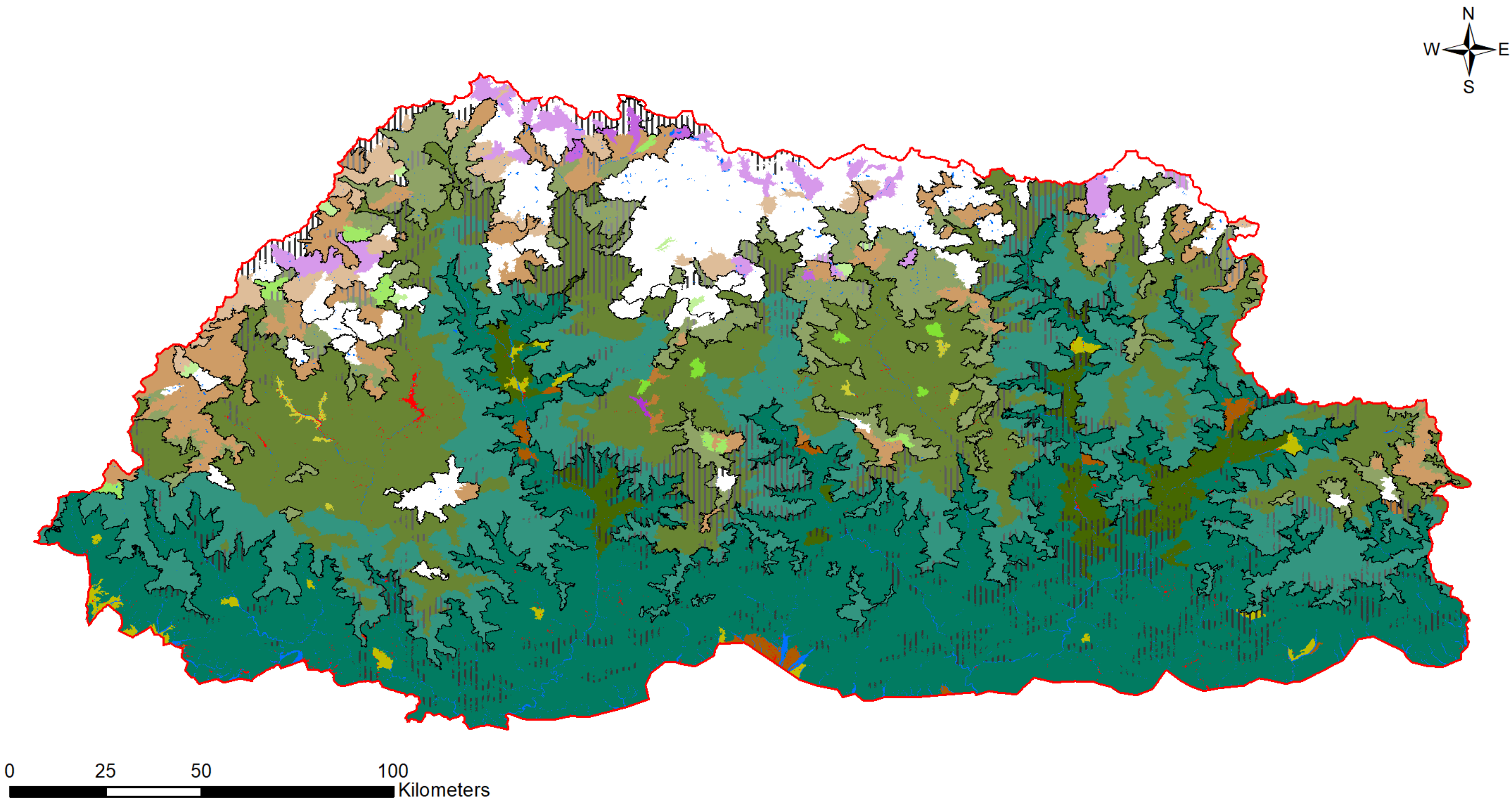


Fig. 37) Final landscape typology map using a 230 ha MMU. Legend in fig. 38.

In the 230 hectare map some relation between landscape type distribution and topography is clear. Lower elevation landscapes penetrate northwards via long valleys and conversely higher elevation landscapes extend into the lower lying southern regions of Bhutan through the mountain ranges intersecting the valleys. Landscape types with exceptionally large individual units are Snow and Glacier (mild slope) and M_CoF1 (Tree Zone Conifer forest mild slope). Landscape L_BMF1 also features a large semi-continuous landscape unit, spanning from the easternmost part to the westernmost part of the country, containing pockets of other landscape types.

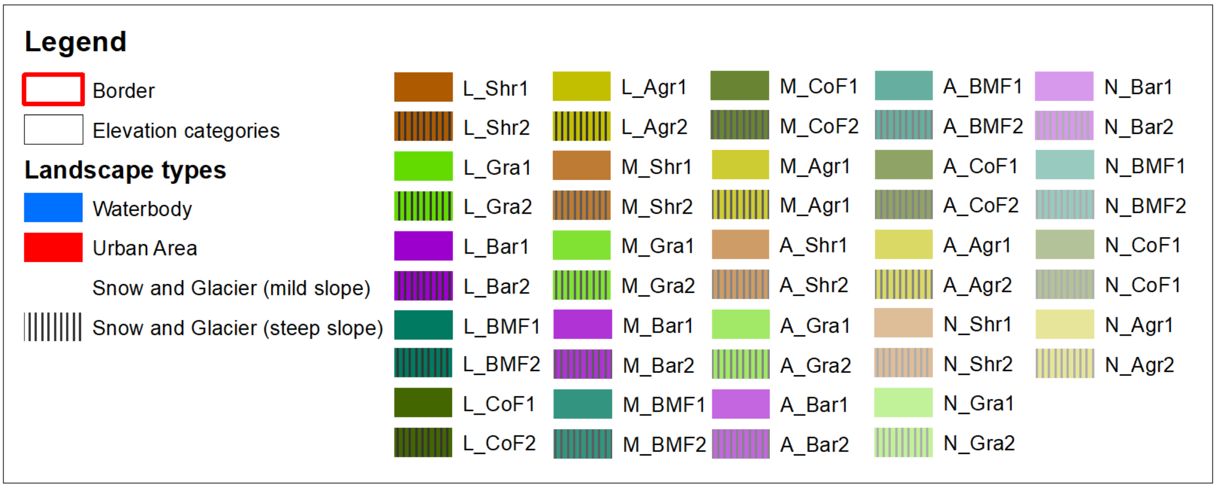


Fig. 38) Legend suitable for all typology maps.

Because of the mountain range/valley configuration of Bhutan's topology L_BMF1 is the only landscape type capable of developing such a large continuous east to west unit as landscape types on higher elevations will be divided by other landscape units in the valleys or on the mountain ridges. M_BMF1 visually appears to be present in a similar extent but upon closer observation is also divided into multiple individual units by incursions of other landscape types. Due to the mountain ranges extending into the south the Snow and Glacier landscape type can be found relatively far to the south on higher elevated peaks contained within these ranges.

In more detail the individual landscape units are clearly visible (Fig. 39). Because urban areas and waterbodies have retained their original shape and size locating areas of interest is simple. Roughly a pattern appears to be present where the succession of landscape types moving away from the river/valley floor is similar on both sides of the river.

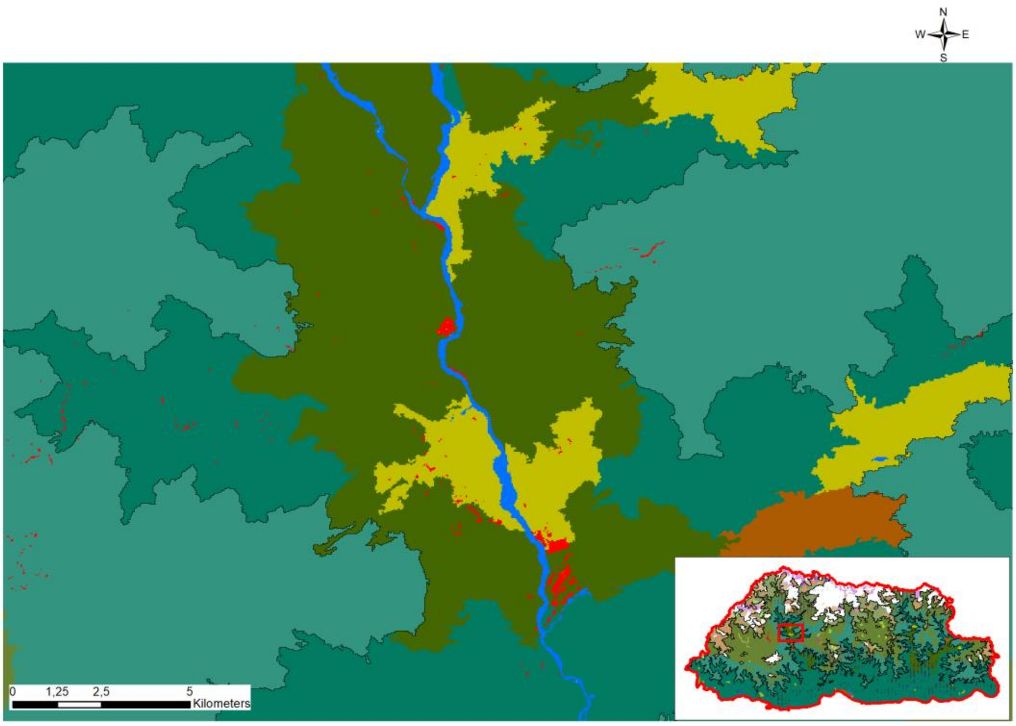


Fig. 39) Detail of the 230 ha MMU typology map at the location of Chimi Lhakhang temple.

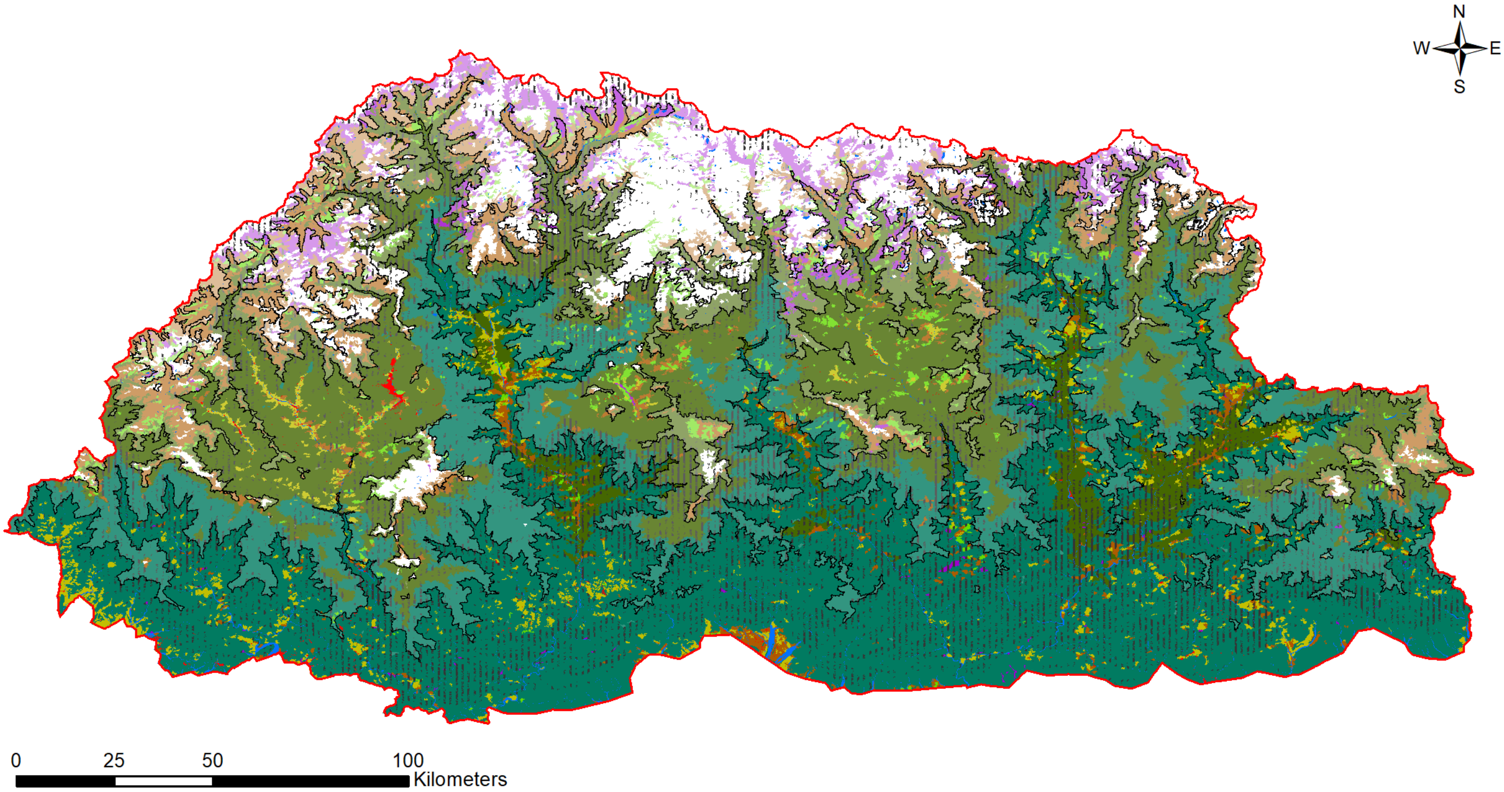


Fig. 40) Final landscape typology map using a 15 ha MMU. Legend in fig. 38.

In the 15 hectare MMU landscape map it is more difficult to see overarching landscape patterns as the resolution of individual units becomes quite small. The same larger patterns as in the 230 hectare small scale map can be found but what happens in between is less clear. This map however is better suited when looking in detail at smaller areas. In the zoomed map of fig. 41 the difference with the 230 MMU map of fig. 39 is immediately obvious from the smaller landscape units. An important distinction however between the two maps on this zoom level is that landscape types that do not appear on the small scale map are suddenly visible. This is an expected consequence of choosing a larger MMU. When using the landscape map for research on an area of this more detailed size, or where small scale dynamics are important the 15 ha map will be preferable.

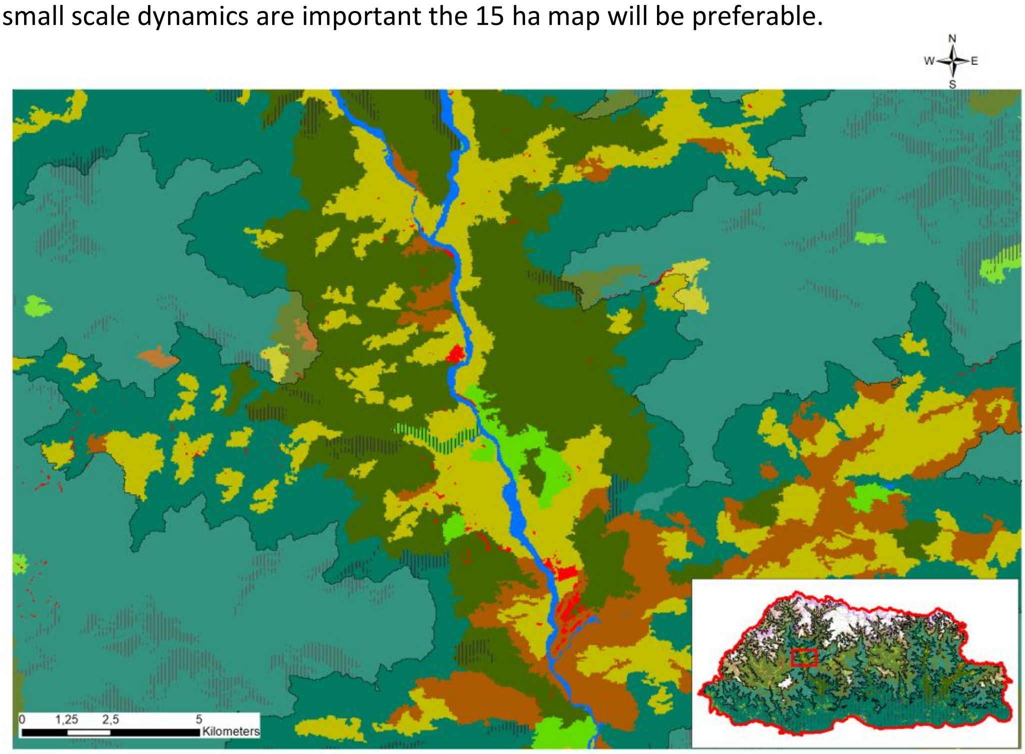


Fig. 41) Detail of the 15 ha typology map at the location of Chimi Lhakhang temple.

There are large differences in total areas of landscape types between the 15 ha en 230 ha map (Appendix C). Again the influence of MMU is clear in the pattern. Almost every landscape type has a bigger area in the 15 ha map than in the 230 ha map except for eight types that had exceptionally large individual units in the first order typology: Snow and Glacier (mild slope), all mild slope forest landscapes except for A_BMF1 and N_CoF1, L_Agr2 and A_Shr1. A_BMF1 and N_CoF1 are larger in the 15 ha map because they represent small patches of Broadleaved and Mixed forest and Conifer Forest that are found above their main elevation range. The smaller patches are retained in the 15 ha MMU assimilation steps. A big surprise was the larger area of L_Agr2 (Steep agriculture in the lowest elevation zone) in the 230 ha MMU map. Agricultural fields on steeper slopes were expected to be divided in small patches because of the unfavourable angle. All other landscape types with a steep slope are larger in total area in the 15 ha map. The total amount of L_Agr2 units is 2 for the 230 ha map and 9 for the 15 ha map. This appears to be a rare instance where there were some patches of steep agriculture that were larger than 230 ha that were surrounded by smaller than 230 ha but bigger than 15 ha units. In the 230 ha map they could therefore assimilate other smaller units whereas in the 15 ha map their growth was stopped by the surrounding units that were then classified as legitimate landscapes. This is the only example were that happened in the final typologies.

For most other landscapes the 15 ha map has 3 to 8 times more area. The agricultural elevation zone is an exception to this rule. Five landscape types have an extreme difference in area between the 230 and 15 ha map: L_Shr2 (5905 times larger in the 15 ha map), L_Gra1 (280 times larger), L_Gra2 (20616 times larger), L_Bar1 (54 times larger) and L_Bar2 (30096 times larger). The other elevation zones have a total of nine landscape types in the map that do not exist in the 230 ha map, which one might argue is the same phenomenon. Often these landscape types are less frequently found on those specific elevation zones meaning their patches are smaller. Therefore they can be assimilated in the 230 ha map. These findings indicate that it is a small minority of large area landscape types, namely forest landscapes, that assimilate large amounts of smaller landscape units in the 230 ha map and therefore that the chosen MMU highly influences the end result. All landscape type sizes and individual unit counts can be found in appendix C.

By excluding waterbodies and urban areas from the aggregation process between the first order typology and the final map these features act as a guide for interpreting the found landscape distribution as well as anchor points for finding exact locations.

4.2 Validation of the landscape map

The final 15 ha landscape map is validated by comparing it to satellite imagery as proposed by Lioubimtseva and Defourney (1999). The traditional method of random sample locations will still be used but performing a field survey is not possible. As the precise method used by Lioubimtseva and Defourney (1999) to compare the satellite images and landscape map is not described two different approaches are used. The first approach is a comparison of the created landscape boundaries with manually delineated landscape boundaries, the second a purely visual comparison done for a larger area. The validation focuses primarily on whether landscape unit distribution follows holistically interpreted unit distribution rather than designation of landscape type. Typologies are normally not validated, probably because they are a product of a pre-determined definition and validation would be nonsensical. In this study landscape units are distributed using a newly created method. The question of whether this method delineates sensible areas is found in this section.

For the manual delineation five randomly generated points within the national border were used (Fig. 42). No points within 1 km of the border were allowed so as to be able to create a sample area. The sample areas (circular polygons with a radius of 1 km, 314 ha per location) around each random point (1571 ha total) were imported into Google Earth Pro so that satellite imagery from 2010 could be used for the manual delineation. This in order to more closely reflect the data used for the NLCS landcover based landscape map. Within each polygon visually perceived landscapes were delineated manually with an attempt made to meet the 15 ha MMU requirement. A manually delineated landscape could be smaller than the 15 ha MMU if it continued outside the sample area to achieve sufficient size. The manually delineated landscapes were then imported into the GIS environment to analyze the similarities and differences with the landscape map.

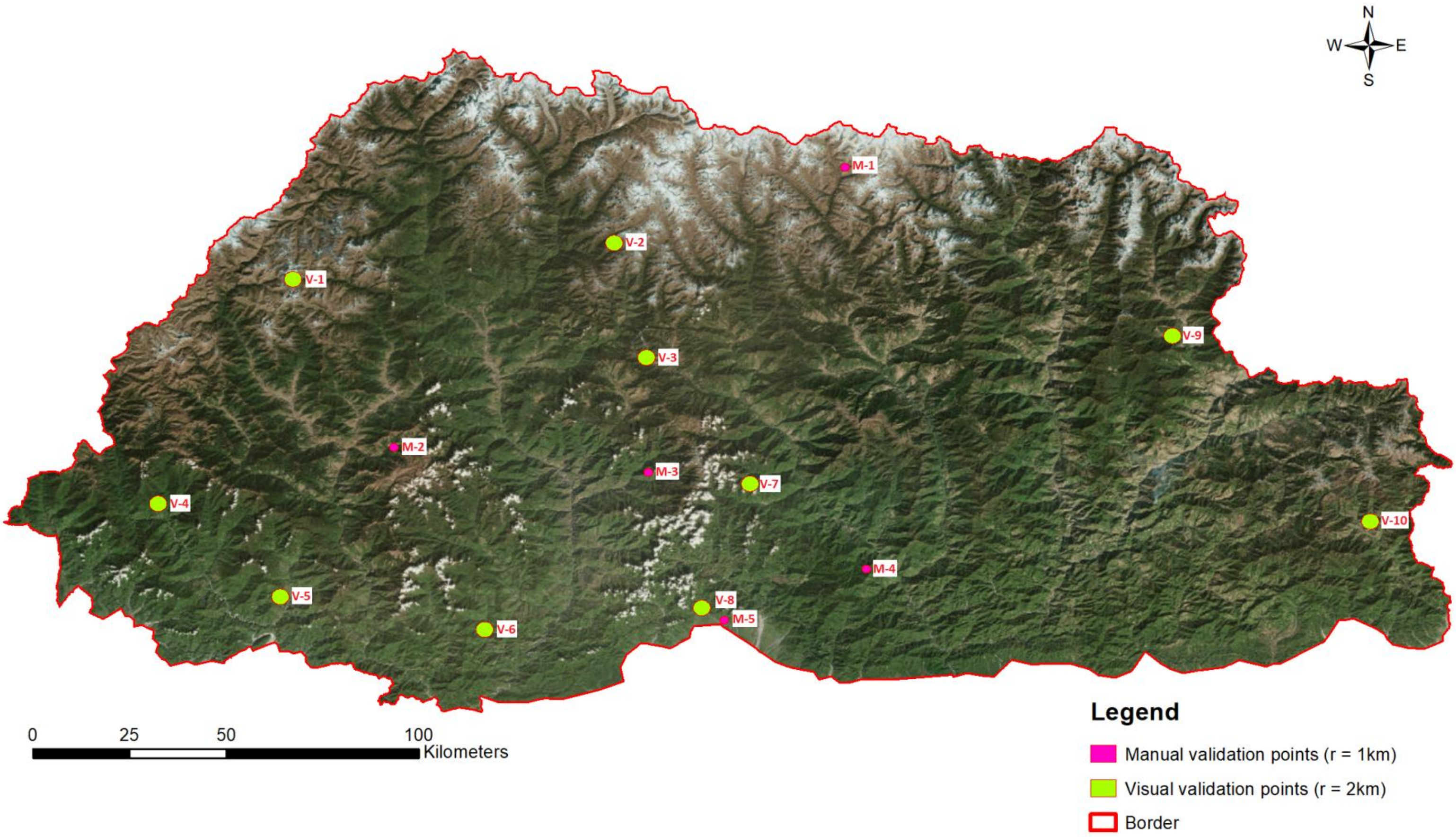


Fig. 42) Randomly generated sample areas used for typology performance validation.

For the visual comparison a larger area could be analyzed. Ten points were randomly generated (Fig. 42) within the national border (minimum distance of 2km) and a sample area (radius of 2 km, 1257 ha per location, 12566 ha total) was used to extract the associated typology. The ten typology circles were then also imported into Google Earth Pro for a visual comparison. A listing of the sample area coordinates can be found in appendix E.

4.2.1 Manual validation

For the manual validation the typology had to be somewhat simplified as precision estimates of slope and height are not feasible by eye. The manual delineations were however not based solely on landcover. The 15 ha MMU was adhered to and landscapes were delineated by what would holistically count as a single landscape for an average human observer. These manual landscapes were then labelled by their most dominant characteristic with the label names mostly based on landcover. For comparison with the typology the landscape types present in the sample areas were given an additional attribute with one of the labels of the manually delineated landscapes most representative of the landscape type. Broadleaved and Mixed Forest types and Conifer forest types were grouped under “forest” as the difference cannot reliably be seen from satellite imagery. Snow and Glacier mild slope and steep slope were grouped under Snow and Glacier. In total six different landscapes were present in the manual sample areas: Agricultural, Barren Area, Forest, Snow and Glacier, Waterbody and Shrub landscapes. Three of the samples are shown below in fig. 43. The M-3 and M-4 sample plots are not shown as these were purely forest and their similarity score was 100 %.

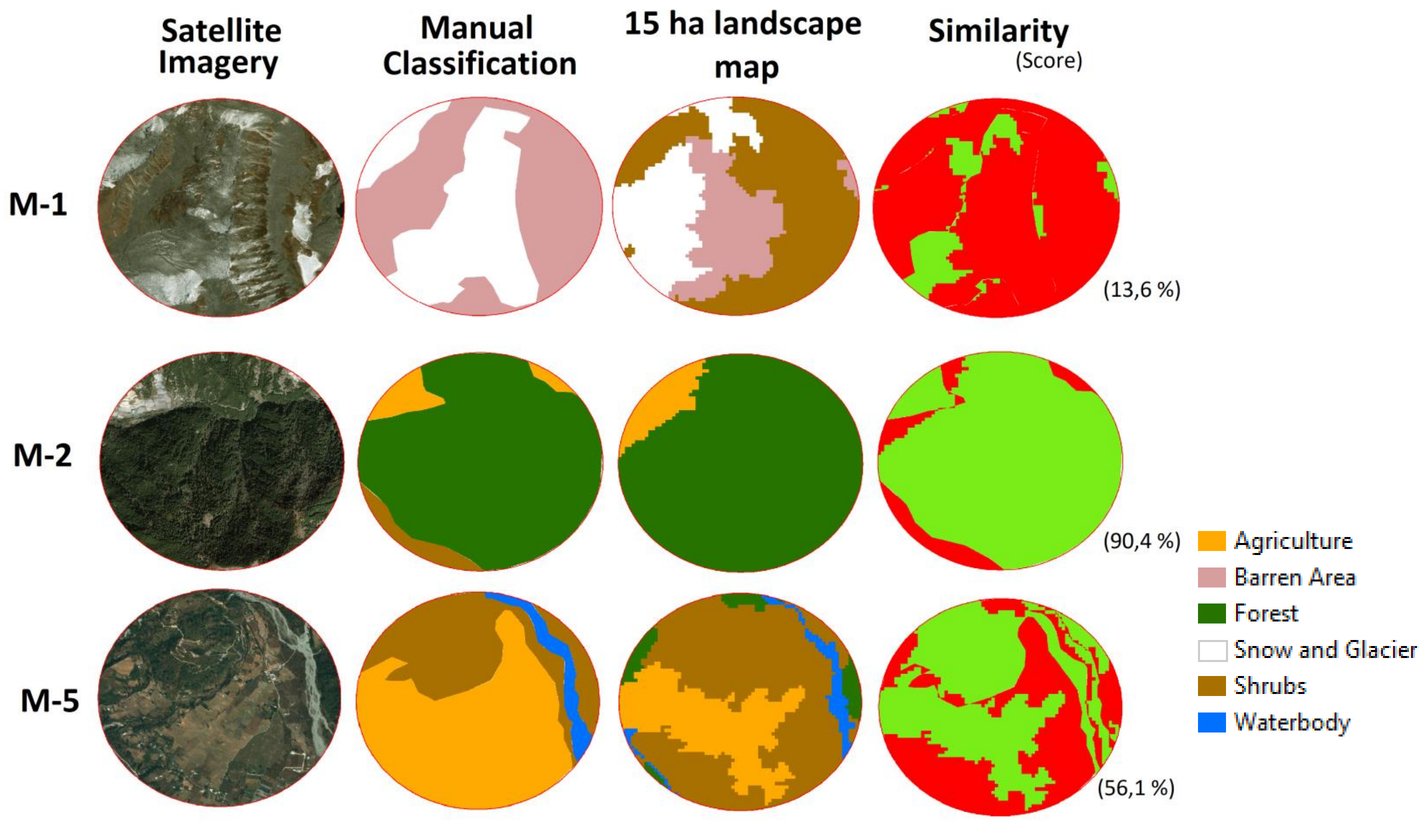


Fig. 43) The three most telling samples used for manual validation (coded as M-1, M-2 and M-5). The similarity column shows where the manual and automated landscape maps agree (green) or disagree (red) and their similarity score (area percentage that agrees).

Some interesting observations can be made in relation to these samples. M-1 is located in the high Himalayan region in a location with little vegetation and a lot of snow fields, glaciers and barren area. The similarity between the manual designation and the automated typology is only 13.6 %. Within the manually designated landscape distribution no shrubs were present even though these cover a large part of the automated map. With this in mind the M-1 satellite imagery was examined more closely and shrubs were indeed found to be present, indicating the automated typology can help improve understanding of landscapes even when similarity is low.

Precise designation was open to interpretation for M-1 as there was light intermittent snow coverage present in the satellite photos and a choice had to be made between designation as Barren Area or Snow and Glacier. Also the area containing shrubs was not a continuous area larger than the MMU, but interspersed by barren parts or snow cover. It was however also noted that the automated typology was not very accurate in specific areas. For example the large area of Shrub landscapes dominating the right part of the sample area is in reality primarily Barren Area, possibly a boulder field deposited by a glacier. To investigate the performance of the automated typology further the original NLCS landcover for the sample area was compared to the satellite image and typology (Fig. 44).

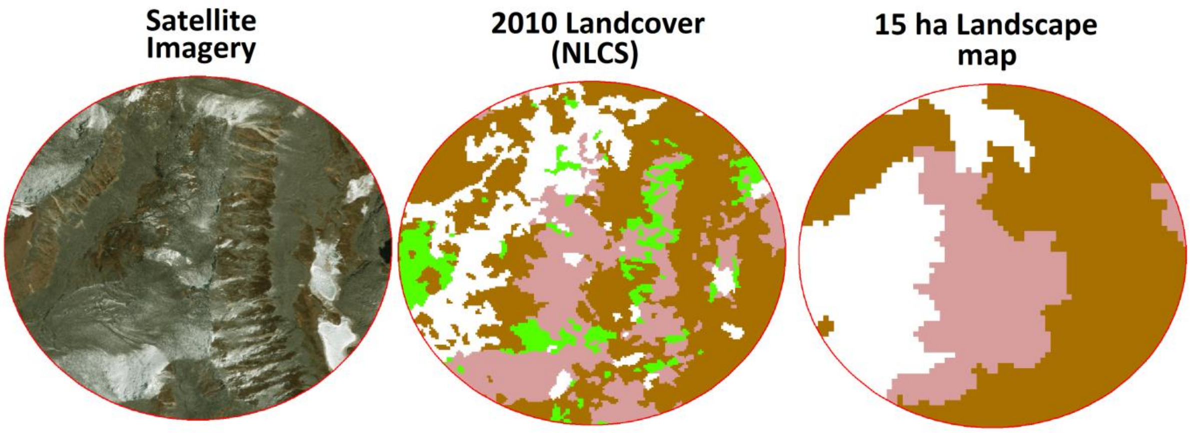


Fig. 44) M-1 sample area compared to original landcover data. The green areas in the 2010 Landcover indicate grass.

Fig. 44 suggests that the automated typology has performed as expected in delineating landscapes according to the MMU used in the method. Even when taking into account the additional influence of slope and elevation (which can further subdivide landscape units and weren't used for manual validation) the typology represents the overarching 2010 landcover patterns with a large area of Shrubs on the right, Barren Area in the middle part and Snow and Glacier on the left. As it turns out the 2010 landcover data did not accurately represent the landcover seen on the Google Earth satellite images, explaining part of the large difference between the automated and manual landscape designation. The large presence of Shrubs on the right for example is probably due to the boulder field being classified as shrubs, as the visual properties of both can be very similar. Adding to the dissimilarities between the manual and automated designation introduced by the unsharp real world boundaries between different landcover types and inaccurate landcover data is the large difference in landcover that can exist between even two consecutive days. One day of snowfall for example can completely change the landcover perceived on satellite imagery. More than most other areas of Bhutan the designation of landscape type distribution in this high mountainous area is uncertain because of the possibility for large day-to-day and season-to-season variations in landcover/visual appearance. The day-to-day variances in this region could be circumvented in part by separating the highly variable snow cover from the more stable glacier cover. In doing this higher accuracy can be achieved in the highest elevation zone.

The M-2 sample point has a similarity of 90.4 %. There are three important differences. The agricultural landscape on the top left of the sample area has a different distribution compared to the manual designation. This difference is small and can be explained through the original landcover data which has a collection of small landcover units there that happen to have been assimilated into the larger agricultural landscape just outside the sample area. The manual designation does have another agricultural landscape in the top right, which in reality extends outside the sample area. In the automated typology this agricultural landscape has been assimilated completely into a Broadleaved and Mixed Forest landscape unit. In the original landcover data the associated agricultural unit is 12 ha (smaller than the MMU) with another agricultural unit smaller than the MMU next to it and a corridor of Shrubs in between. From the Google Earth imagery this seems a coherent agricultural landscape, but strictly using the MMU the unit has correctly been assimilated into the larger forest landscapes surrounding it. The manually designated shrub landscape on the bottom left could also be forest, visual differences with the forested areas surrounding it led to the decision to manually label it as shrubs. It is possible however that the automated typology is correct in this case. Everything considered the model has performed well, returning a very useable approximation of landscape types in the sample area. Only the agricultural area on the top right would be interpreted differently by a human observer but the model did perform well complying to the pre-set landscape parameters.

The similarity of the M-5 sample plot in the very south of Bhutan is 56.1 %. The dissimilarity of the elongated area from north to south just right of the middle is because of inaccurate designation of agricultural area as shrubs in the original landcover data. Satellite imagery very clearly shows this area is used for agriculture. Just next to the river there is a small band of shrubs and in the landcover data this extends too far to the west. Satellite images of the area in 2001 show a broader band of shrub area. Probably the landcover data was based on an older situation. The area on the bottom left is an extended area of evenly mixed shrubs and agricultural fields. The designation by the model as shrub area is therefore understandable. A human observer would probably classify this area as agricultural as it is clearly shaped by humans and the shrub covered parts are only found on the disused pieces of land between the agricultural fields. The designation of this area is open to interpretation, but agricultural landscape seems the most appropriate label for this area. The dissimilarly classified region on the far right of the sample area is manually designated as shrub landscape, but automatically designated as forest landscape. The satellite imagery is inconclusive to the best description of this area’s landcover so it is possible that the manual designation is incorrect in this case. If the automated landscape designation of the ambiguous areas at the bottom left and far right area is assumed to be correct the similarity of M-5 would increase to 71.6 %. When only reclassifying the far right area, which is probably justified as the landcover data probably correctly shows forested area here, similarity would increase to 58.2 %.

The total similarity of all 5 sample areas is 72 % (using 56.1 % similarity for M-5). Because of the extreme variability and uncertainty of M-1 for the reasons discussed earlier an argument could be made that this sample area is not representative of the performance of the typology. If excluded the similarity of the remaining 4 sample areas rises to 86.6 % (using the worst case 56.1 % similarity rating for M-5). This figure better represents the performance of the model for the largest part of

Bhutan, which is less prone to very short term landcover changes and interpretation differences of vague coverage boundaries.

With regard to all the manual sample areas there are some additional remarks that influence the similarity between the manual and automated landscape designation. If a sample area has more than one landscape type a 100 % similarity between the manual and automated typology is impossible. The automated typology is based on raster data with a resolution of about 30x30m resulting in stepped border lines whereas the manual landscapes feature straight vector borders. Even in the case of perfect agreement between the manually and automatically designated landscape maps the vector borders will bisect the cell based stepped borders resulting in an inherent dissimilarity (Fig. 45). The quantity of this dissimilarity is difficult to estimate but increases with total border length within any given sample area and can add up to multiple percentages.

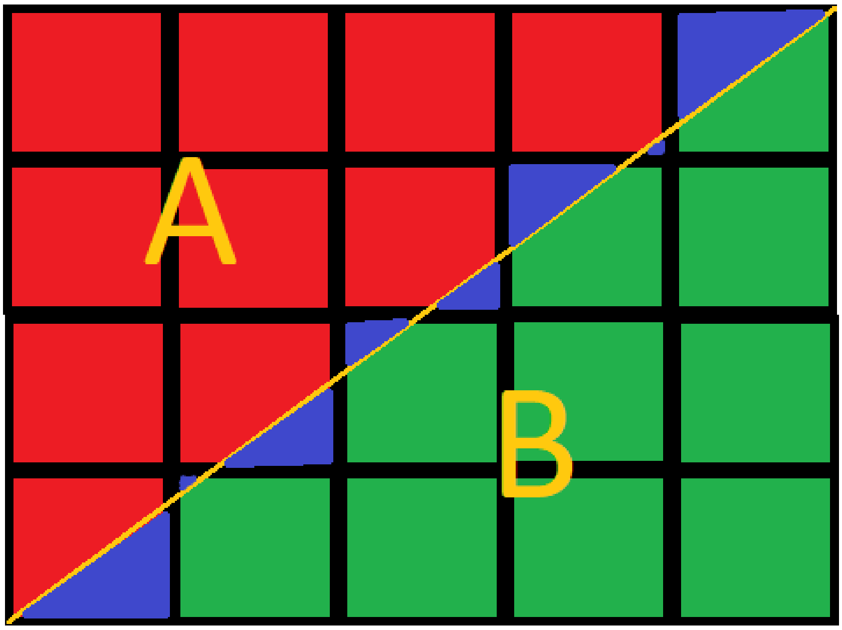


Fig. 45) Example of the inherent dissimilarity caused by the different border properties of raster and vector data. The red landscape 'A' and green landscape 'B' are separated by a stepped border because of their raster based origin. A manual designation using vector format produces a straight border (the yellow line) which bisects individual gridcells. The similarity check will treat these overlapping areas as erroneously designated landscapes (the purple regions).

Additional dissimilarities are introduced through unclear landscape boundaries where even when there is agreement in principle between the manual and automated typologies the boundaries may not be in exactly the same location (this is visible for example in M-5 where the waterbody has a much smaller footprint in the automated typology than in the manual typology). The accuracy of the automated typology might therefore actually be higher than the similarity figures mentioned before. This effect is, however, difficult to quantify.

In conclusion the manual validation returns at least a 72 % accuracy compared to a human interpretation of the landscapes. A more realistic figure (without M-1 and 58.2 % for M-5) is at least 86.6 %. The high mountainous areas can change quickly and significantly in landcover -and therefore visual appearance on satellite imagery- meaning landcover data in these regions will never be very precise, also the types of landcover here often do not feature sharp boundaries introducing more uncertainty. The validation revealed that a lot of accuracy could possibly be gained by separating snow cover from glaciers as glaciers are more stable landcover over time. Snow cover could then be classified as barren area, which is closely related. The available satellite images did not always agree with the landcover data, especially in the higher regions. Taking all these uncertainties into account the performance of the typology is good, especially for the relatively few landscape variables (Elevation, Landcover and Slope) included in the typology.

4.2.2 Visual Validation

In order to validate the model using a larger sample area a simpler visual comparison was done as well. For the visual comparison the generated landscape distribution was extracted for ten randomly generated sample areas and imported into Google Earth Pro. They were then compared to satellite imagery as close as possible to 2010. For the visual validation the complete typology definition could be used. The visual comparison is a quick visual estimation of performance that particularly focuses on spatial landscape distribution. Sample areas were checked for similarity of perceived landscape boundaries. Using the complete typology definition and larger sample areas possible negative trends can also be spotted more easily. The sample area satellite imagery and typologies can be found in fig. 46 and fig. 47 on the next two pages. These figures also include the NLCS landcover to help analyse perceived trends and find explanations for them.

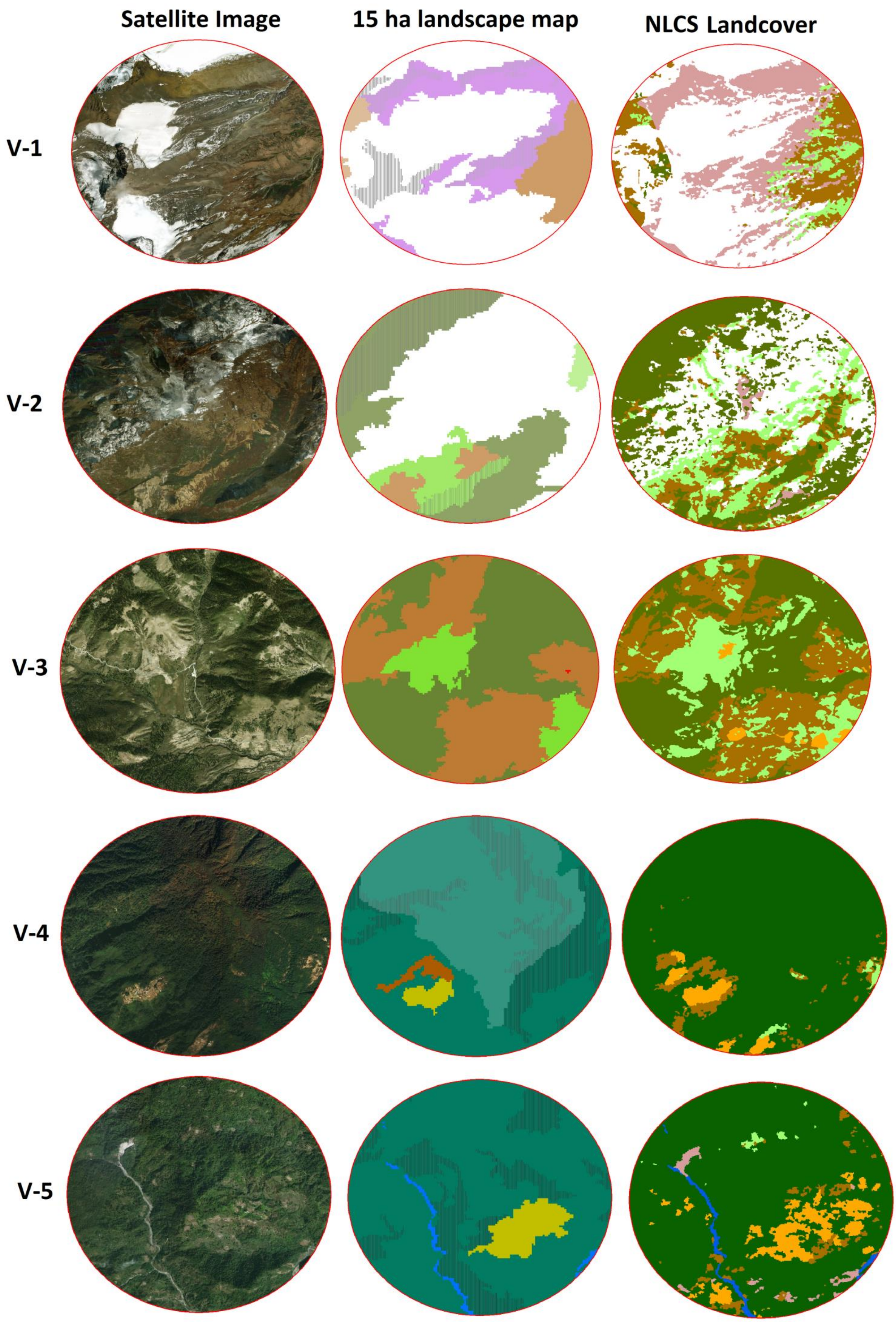


Fig. 46) The first five visual comparison samples.

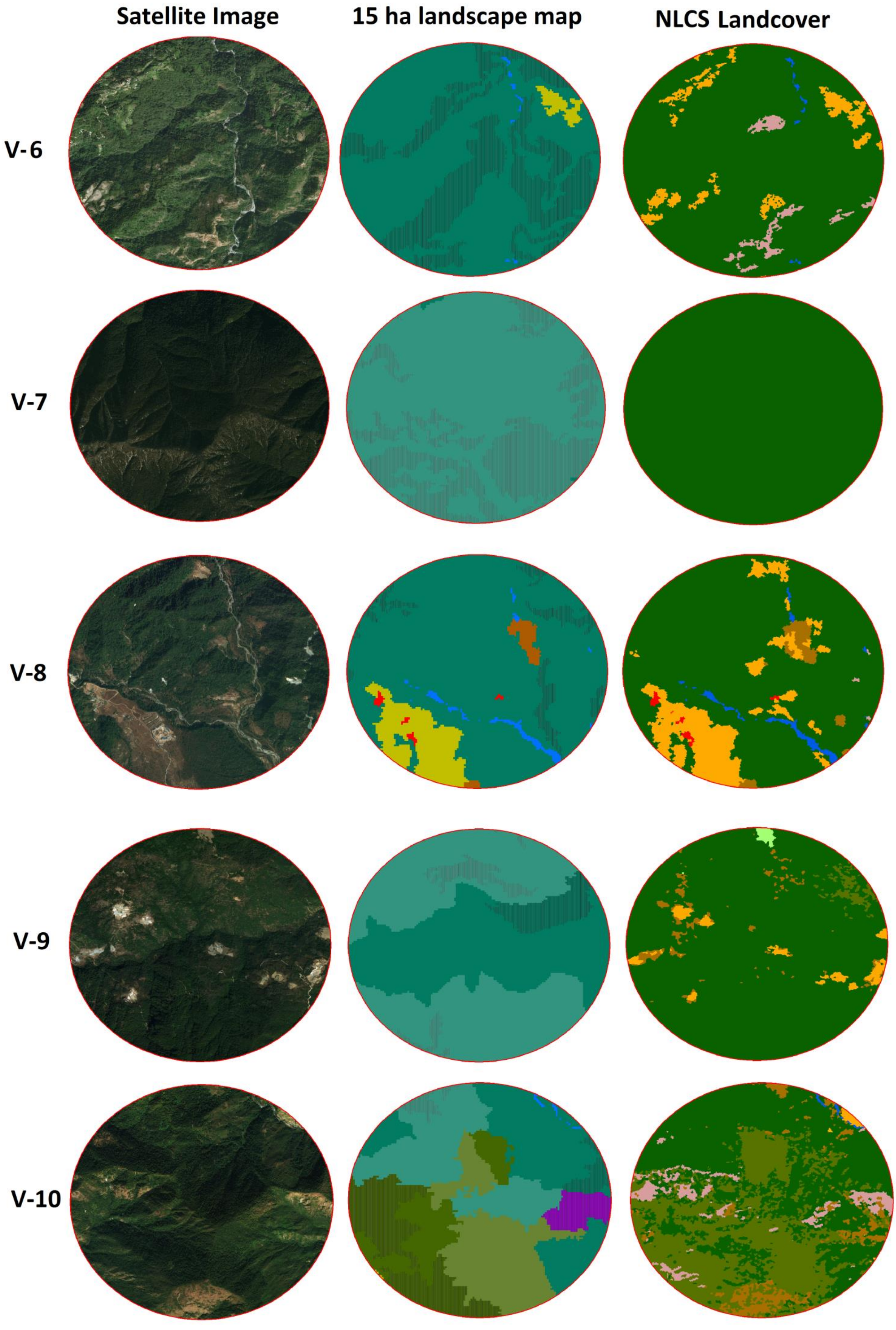


Fig. 47) The second five visual comparison samples.

Analysis of the visual samples again shows good performance. The generated landscape map is capable of showing the type of landscape that can be expected. Even the two samples in the higher mountainous regions (V-1 and V-2) perform well. The designation of V-3 was not very accurate, this could be traced back to the original landcover data which showed a different interpretation of a particular region in the centre of the sample (forest instead of grassland) which had a large effect on the rest of the sample area typology designation. This cannot be attributed to bad typology performance, the typology accurately used landcover data to determine landscape type distribution. One weak point of the typology method is detected however. The landscape map performs well at designating landscape boundaries and is useful as an aid in getting a feel for a particular region. Where the typology is lacking, however, is with landscapes that include multiple patchy, sub-MMU sized areas of a different type of landcover. In the visual samples it was found that the designed landscape type labels, based on the combination of the three base variables, were not always satisfactory for these regions. This effect was found in V-6 and V-9. The samples featured a dominant forest landcover but with significant areas of mostly agricultural landcover patches within the forested areas. An observer would not classify this type of landscape as purely forest landscape and the experience of such a landscape is significantly different from a purely forest landscape. V-8 features the same landcover types in similar concentrations (mostly forest, a little agriculture) but here they are not mixed and consequently the performance of the model is good. This is a scale issue that is hard to avoid when combining small scale and large scale data. It would be desirable therefore to include some extra layer to the typology.

This layer should use some form of landscape metrics to indicate the “patchiness” of a landscape unit and could then be queried and/or activated at will depending on the user’s need. Often this effect is found in areas where there is a certain human presence, large enough to influence the landscape in multiple close by locations, but small enough not to grow together into one larger agricultural or urban area. The effect can also be observed with patches of barren area or shrubs. For a small part the unaltered Urban Area landscape type was expected to circumvent this effect for patches of human activity by indicating the presence of a population, it is now found in this visual validation that concentrations of human activity can be too small to register as Urban Area but still significantly influence the landscape.

In earlier studies multiple different approaches have been used, van Eetvelde and Antrop (2009) used landscape metrics to define patchiness which was used in the grouping process. De Agar, Ortega and de Pablo (2016) applied landscape mosaics in order to emphasise the interaction between different landscape patches and Jellema, Stobbelaar, Groot and Rossing (2009) used correlation of shape and size variables to group landscape patches that were indicative of past landuse practices. For Bhutan landscape metrics would be the preferred option as the trend observed in the visual validation appears to be independent of other patches (ruling out the use of landscape mosaics) and are not created through a coherent (past) landscape use or landscape shaping process, ruling out the method employed by Jellema et al. (2009).

If the extra “patchiness” metrics data layer is included in the digital landscape map data improved representation of landscape type is possible. The data, gathered using landscape metrics, could even be appended as an attribute to the current map.

4.3 Landscape Typology and Heritage Richness (Case Study)

Archaeological research is normally based on combining experience, knowledge of many sources and intensive on-site field inspection which is a costly and labour intensive process. Modelling the potential for archaeological features of a study area using GIS can greatly improve the speed and accuracy of this process while decreasing the cost of research (Groenewoudt & Kvamme, 1992). Investigating the relationship between heritage feature location and landscape type may help to find vulnerable heritage locations as well as designate areas with an increased probability of containing unknown cultural heritage, which is of great interest for archaeological research as little is known about pre-19th century Bhutan. The importance of such analyses for protection against disappearance by development projects is also recognized in the archaeological community (Espa, Benedetti, De Meo, Ricci, & Espa, 2006; Kamermans & Wansleeben, 1999; Williams, 2016). To analyse the potential of the proposed landscape typology for predicting heritage richness a spatial analysis was set up. The analysis is performed by overlaying known heritage feature locations on the landscape map so the associated landscape type can be extracted per heritage feature. Using the landscape map combined with known heritage feature locations a chart of heritage distribution per landscape type was created (Fig. 48). A full overview of results can be found in appendix B. The heritage locations were retrieved from the NLCS Nye Atlas and World Bank databases with double entries between both datasets removed.

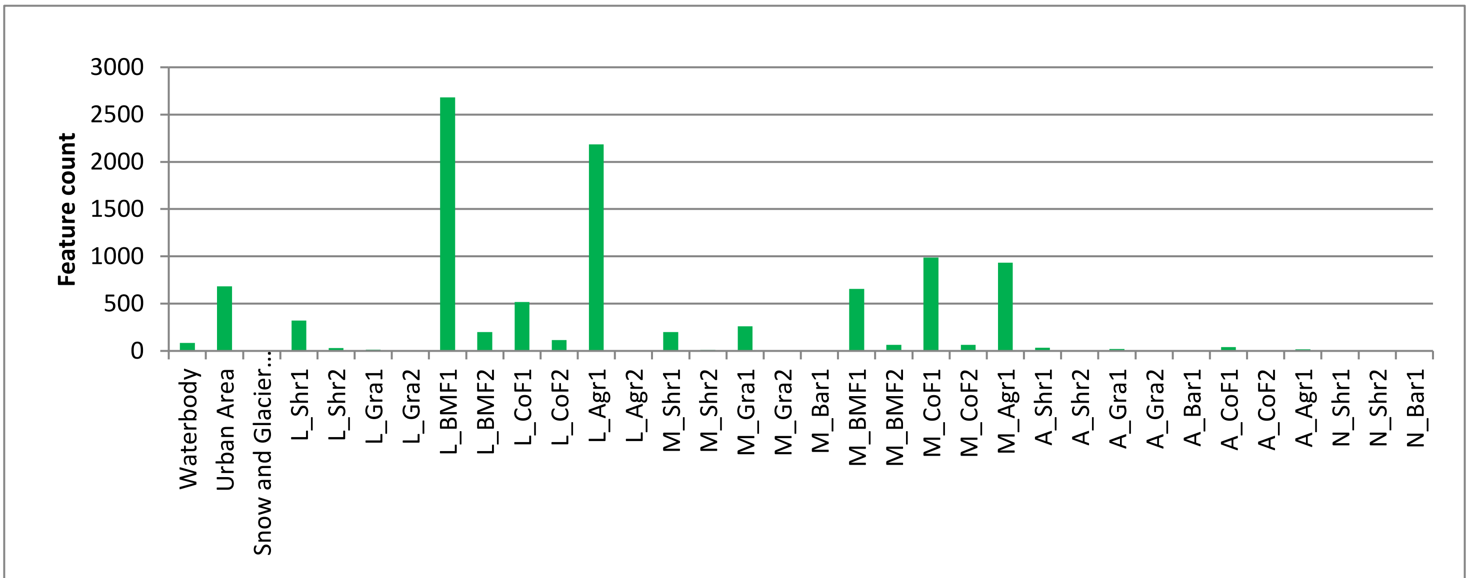


Fig. 48) Heritage feature count per landscape type.

Surprisingly Waterbody also features 85 heritage features (0.8 % of the total amount). This may seem remarkable but there are a couple of heritage feature types that can be expected to be centred in a body of water.

Examination of the 85 features located in a waterbody reveals that 20 of the features are bridges and 16 are prayer wheels. Bridges are logically located over a body of water and water powered prayer wheels can also be expected in a waterbody. Other features are harder to explain logically. There are five Lhakhangs (temples) located in a waterbody. As far as they are traceable in the data they appear to be normal temples which therefore should not be in a waterbody. These locations are probably due to inaccuracies in either the feature location or the landcover data. 24 other features are chortens which are not expected to be in waterbodies, so these locations are probably based on inaccuracy as well. Finally there are nine Nye's: one cave, six boulders and two unspecified Nye's. It is possible that these are found in water or along the water's edge. This cannot be verified however with the available data and no assessment as to possible inaccuracy of their placement can be made. Further examination of these heritage locations superimposed over satellite imagery and the landscape type map shows that their Waterbody landscape designation is largely caused by the coarse resolution of the original source data (Fig. 49). The Waterbody landscape type was excluded from the landscape aggregation process and this inaccuracy is therefore inherent in the coarseness of the data.

Fig. 49) A relatively course resolution introduced by the original landcover data can misrepresent the landscape type in which a feature is placed. The feature in these images is clearly located on land in the Urban Area, because of the course resolution however the typology places it in a Waterbody.

However the amount of heritage features per landscape type is only half the story. It stands to reason that more prominent landscape types with a larger total area will contain a larger amount of heritage features. A more telling property of the landscape types with regard to the probability of containing archaeologically interesting sites therefore would be feature density per landscape type. The feature density per landscape type is shown in fig. 50 below.

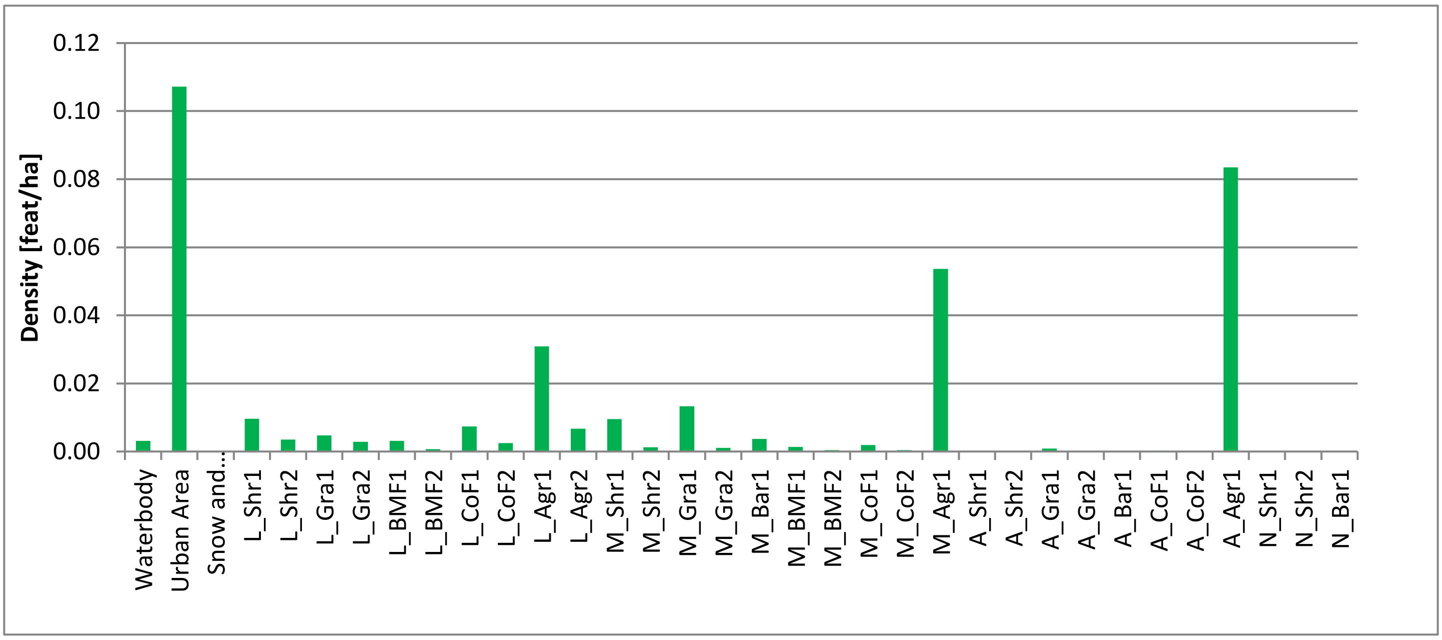


Fig. 50) Feature density per landscape type in features/hectare.

The conclusions drawn from the feature density figures are very different from those one would get from the heritage count per type. Urban Area is now the most important landscape type. This is not very remarkable as one would expect a concentration of heritage features in population centres. Some of the most prominent landscape types for heritage feature count have become quite unimportant when using feature density. L_BMF1 is one of the least significant landscape types now whereas it was the most significant type in total feature count. L_Agr1 has also become much less important while overall remaining one of the most significant types. M_BMF1 and M_CoF1 are completely insignificant in the density chart as opposed to the total feature count where they were among the most significant types. A_Agr1 has become extremely important.

For designating archaeologically interesting locations a deductive and an inductive approach have been used (Stančič & Kvamme, 1999; Kamermans & Wansleeben, 1999). Both approaches attempt to model archaeological potential of a specific location. The approaches both have pro's and con's but when applied with complete information both should result in the same outcome. In reality this is impossible and therefore both methods complement each other. Both approaches have previously been used in archaeological site modelling.

4.3.1 *Deductive Approach*

The deductive approach followed here, makes use of an analysis of the attributes of known cultural sites. This method is based on the continuity principle, where requirements for selection of a build site are supposed to be similar between known and unknown heritage features. In other words by analysing the properties of known heritage sites other locations that feature the same attributes and thus have a greater chance of finding archaeological features can be highlighted. This type of modelling is especially useful when the heritage feature attributes are categorical, as is the case with the landscape typology (Groenewoudt & Kvamme, 1992; Stančič & Kvamme, 1999).

The approach suggests that landscape types with the highest densities can be seen as the most promising for discovering archaeological heritage, both man-made and natural, that have been missed in current surveys or were lost in time. Urban Area can be disregarded in that view. Population centres may contain interesting archaeological opportunities but their locations are clearly well known and the presence of cultural heritage there will not be a surprise to anyone researching (archaeological) heritage. One could argue that landscape types with high feature densities have little left to discover and that therefore landscape types with low densities are the most interesting. This may be partly true but the continuity principle suggests that high density landscapes are the types forgotten or lost heritage features will have been built on as well. One explanation for the absence of existing/known features in other landscape types can be that they have been destroyed through events that are more likely to occur in those landscapes, for example destruction through fires may be more likely in forested landscape types (which are some of the least densely populated landscape types). In the scope of this research however there is no data available on such processes and it is most logical to use the relative densities of landscape types.

The threshold for designation of a landscape type as promising for heritage sites is set at a feature density of at least 0.005 features/ha. This threshold returns around one quarter of heritage containing landscape types for consideration and appears to be broad enough to also include more than just the most feature rich landscape types. The most promising landscape types are following this selection: A_Agr1, M_Agr1, L_Agr1, M_Gra1, L_Shr1, M_Shr1, L_CoF1 and L_Agr2.

The selected areas are shown in fig. 51. The map returns a total of 232546 ha for the selected landscape types, still a large area to study.

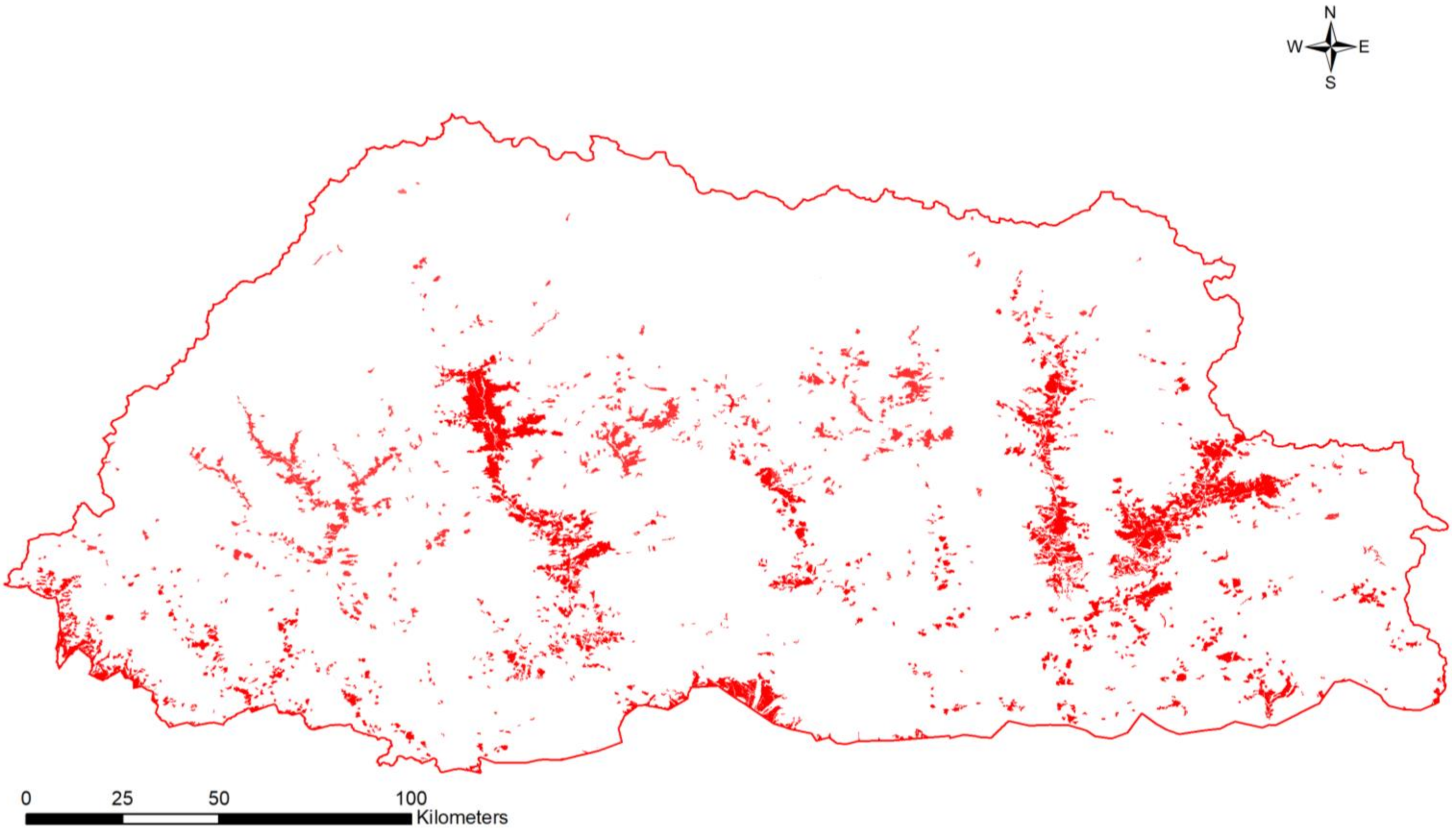


Fig. 51) The most heritage dense landscape types (more than 0,005 features/hectare) highlighted.

To further narrow down the search area two location specific attributes are also included in the spatial analysis: Distance to the nearest river and distance to the nearest urban area. These attributes were analysed because they are traditionally linked to human activity. Rivers are logical locations for human settlements, and in Bhutan where the rivers are often responsible for the only somewhat flat areas by creating flood plains where settlements grow to any significant size this is especially true. The overlay of heritage features on the DEM in fig. 52 shows a pattern where heritage features are located for a large part along the valley walls lending credibility to this assumption. The distance to the nearest urban area follows a similar reasoning. There is a larger possibility for cultural heritage in locations near to human population centres (Espa et al., 2006). These assumptions appear to be corroborated when examining the distribution of known heritage locations over these distances.

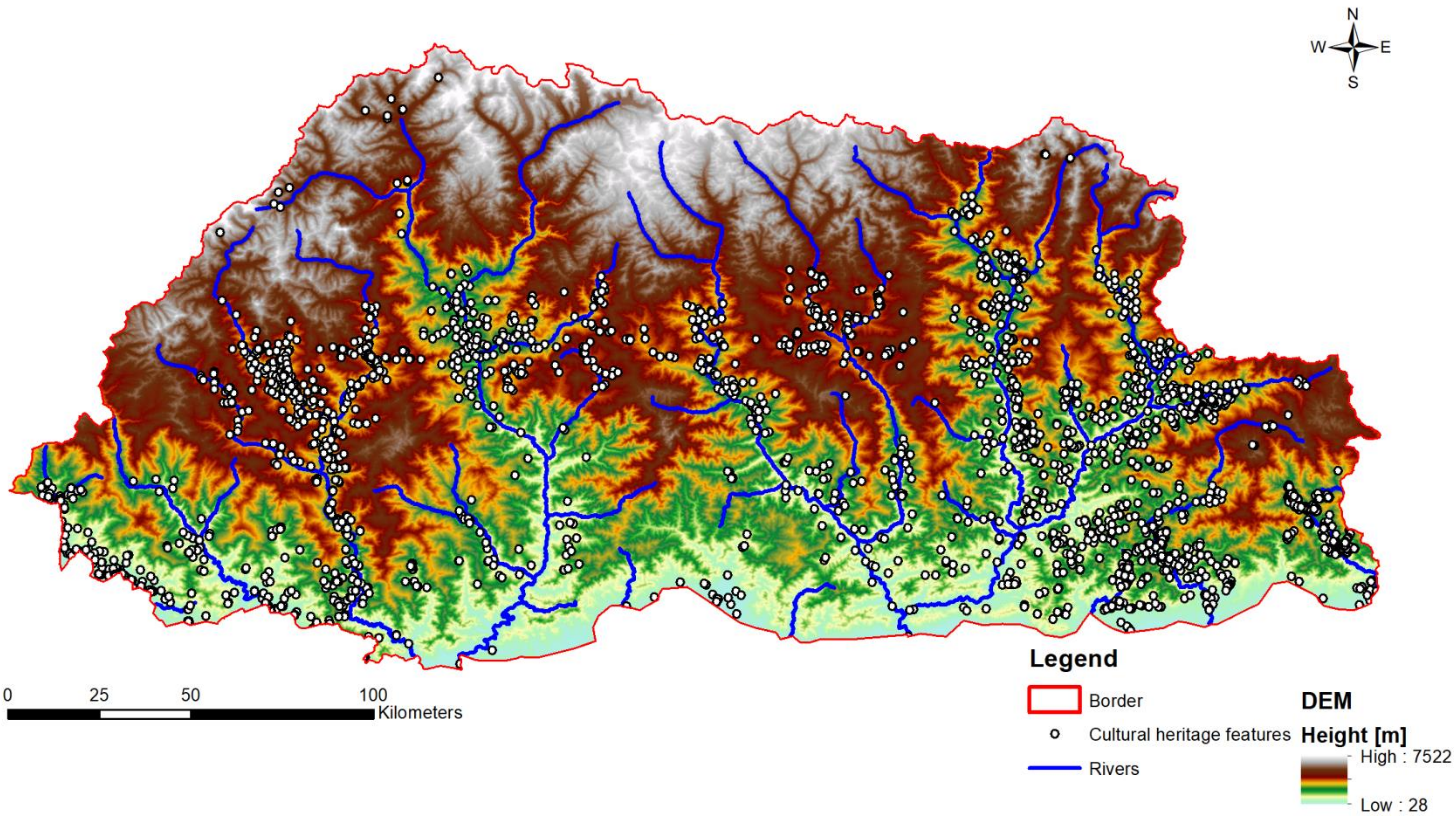


Fig. 52) Locations of cultural heritage features supplied by the World Bank overlain on the Digital Elevation Model show a correlation between valleys, rivers and heritage feature locations.

The histogram of fig. 53 shows the distance to the nearest river up to 30 km. Beyond 30 km the occurrence of features is negligible (± 0 %). The distance to the nearest Urban Area is shown in fig. 54. Here the amount of heritage features occurring beyond 15 km is negligible.

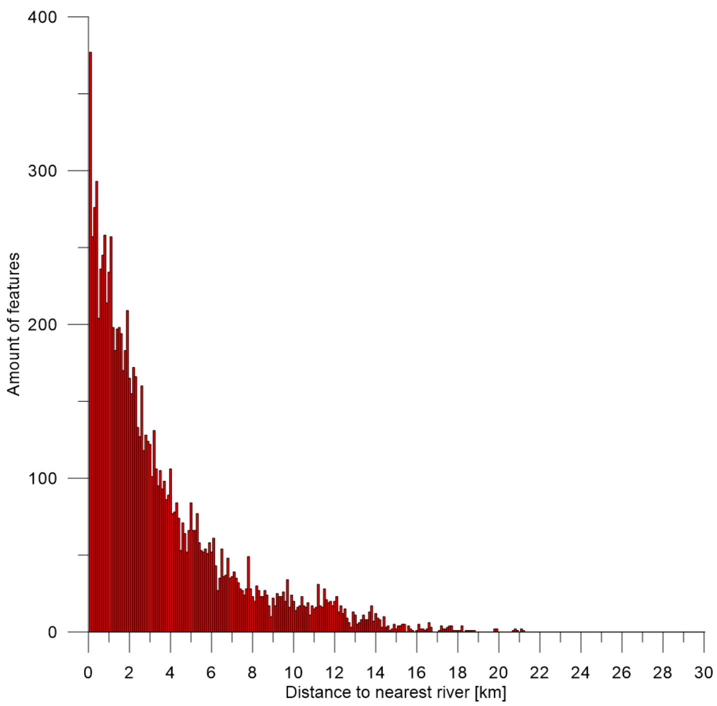


Fig. 53) The histogram of heritage feature distance to the nearest river confirms a negative correlation of heritage feature occurrence to river distance.

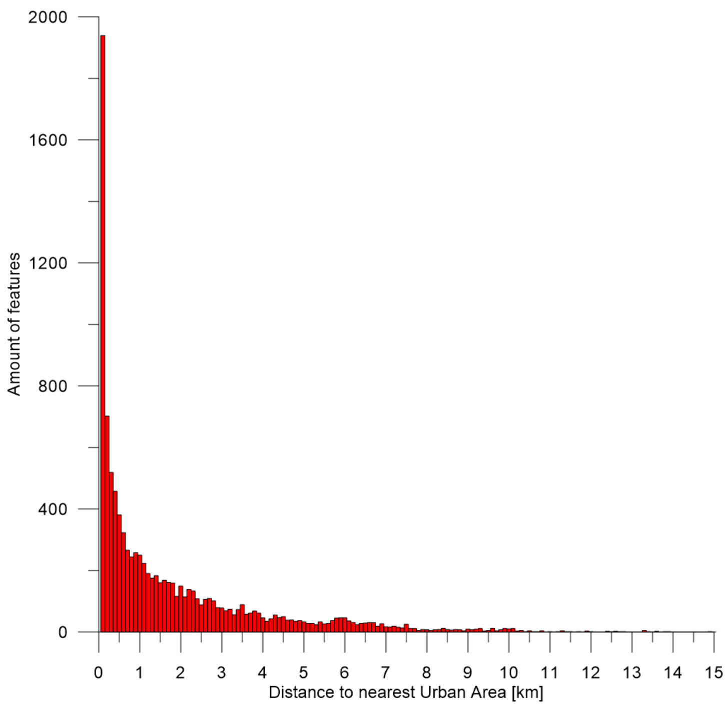


Fig. 54) The histogram of heritage feature distance to the nearest Urban Area confirms a negative correlation of heritage feature occurrence to Urban Area distance.

The distributions were then plotted to their corresponding distances using Euclidian distances from each river and reclassifying the distance values with the percentage of total heritage features found at that distance which resulted in maps where the cell values represents the relative amount of features progressing in distance from rivers and the relative amount of features progressing in distance from Urban Areas. These values were then added to each other and a mask of the pre-selected heritage dense landscapes applied resulting in the prediction model seen in fig. 55.

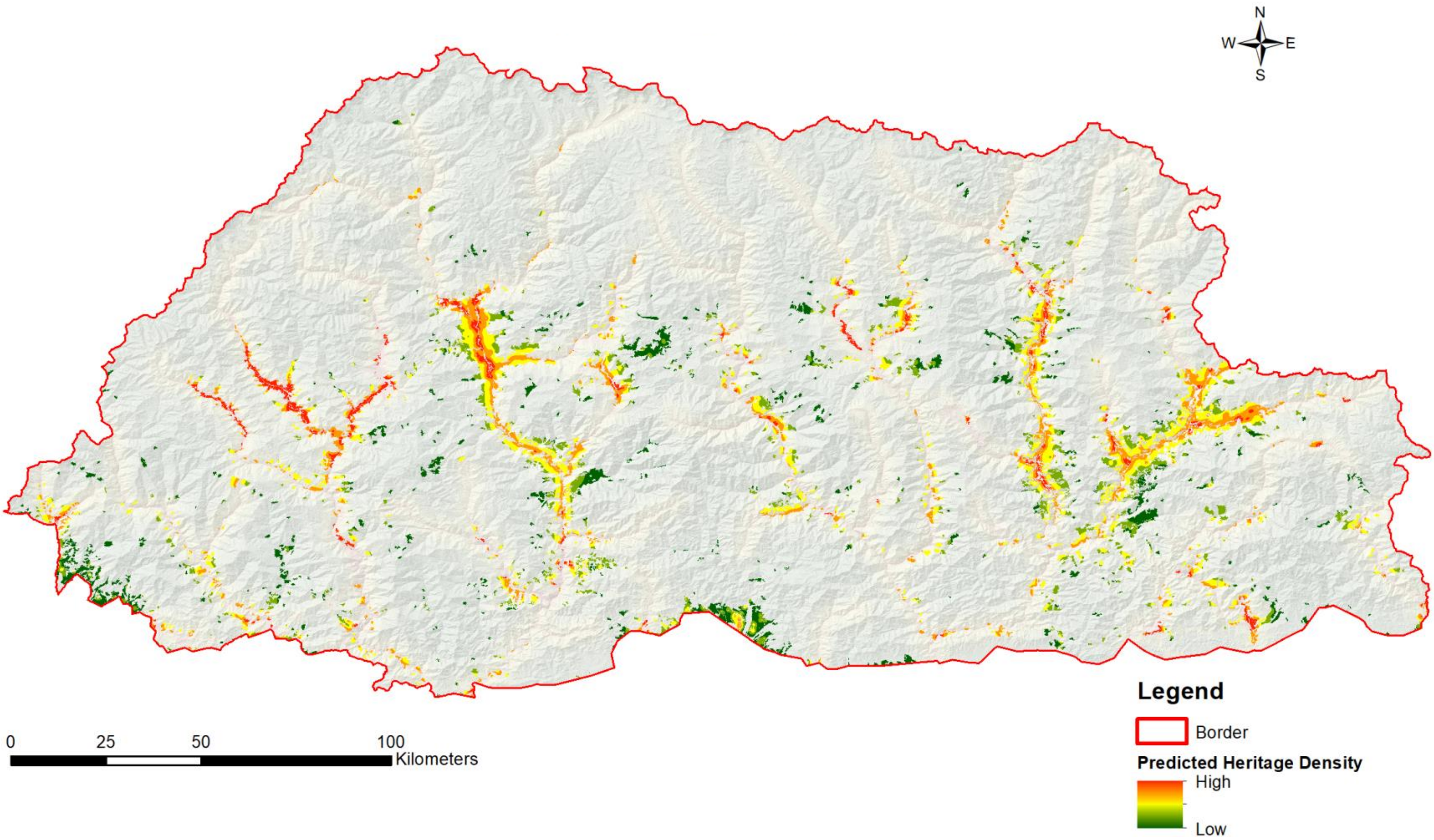


Fig. 55) Heritage feature prediction model found using the deductive approach.

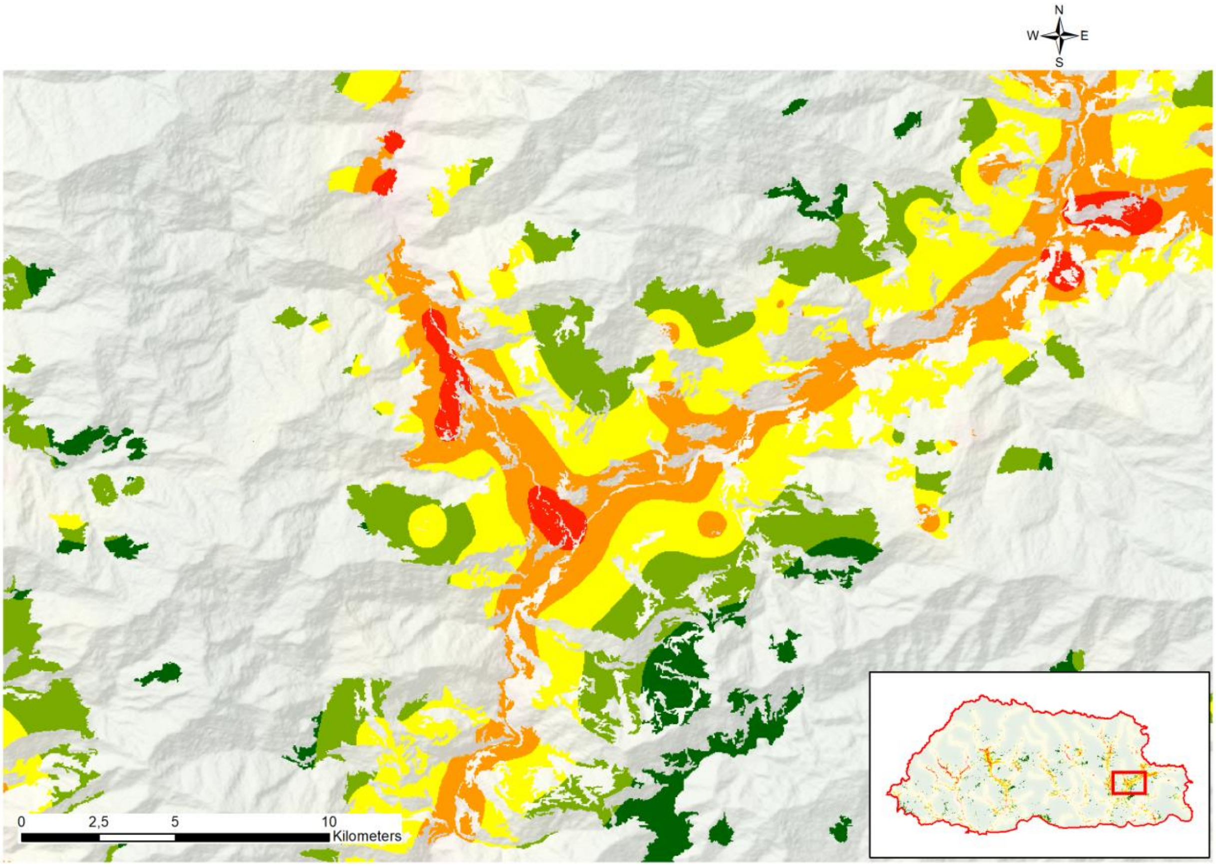


Fig. 57) Detailed view of the deductive heritage prediction model.

This model's prediction gradient is intentionally unitless as it is a basic extrapolation of known attributes. It provides a relative indication of potential heritage density.

By combining the prediction model with a density plot of known heritage features (Fig. 57) the designation of locations of exceptional archaeological opportunity can be specified even further. Areas with a high known heritage feature density are less likely to yield unknown heritage features because these locations are often still actively used and/or relatively densely populated. Also areas with a higher known heritage density are logical candidates for archaeological research if little other data is available and for this reason are no surprise to archaeologists. Therefore the locations with the highest potential for finding unknown/archaeological heritage sites are generally those with a high predicted heritage density and a low known heritage density.

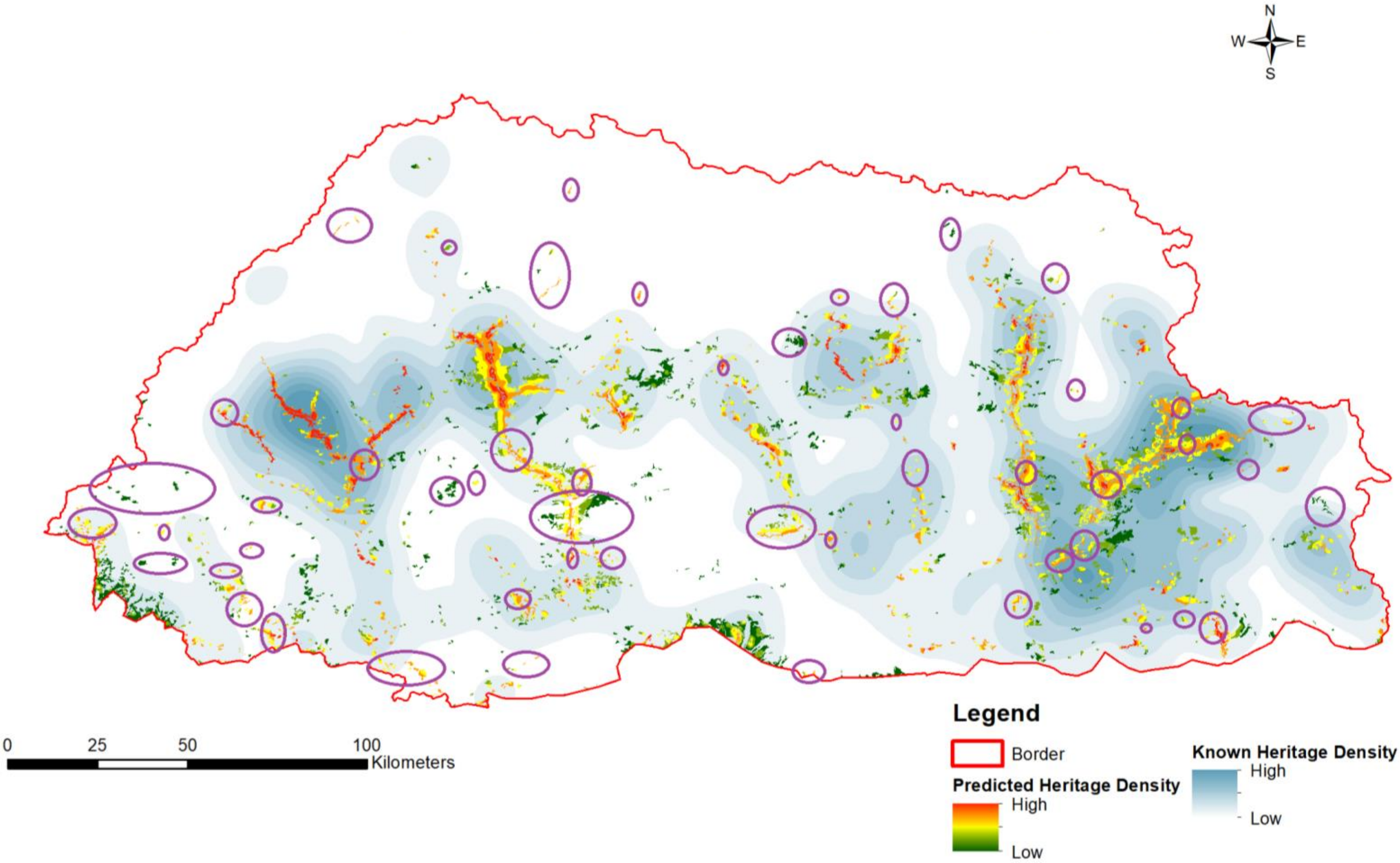


Fig. 57) The deductive prediction model superimposed over a density map of known heritage features. With this information locations with high potential for unknown heritage features can be found. Examples of such locations are encircled.

When reviewing the exact locations of the heritage features also within heritage dense areas there are opportunities for locating archaeologically interesting sites. An example of such a site is shown in fig. 58. Here an area with high potential but also a high density is found, however this particular high potential region does not have any actual heritage sites in the direct vicinity.

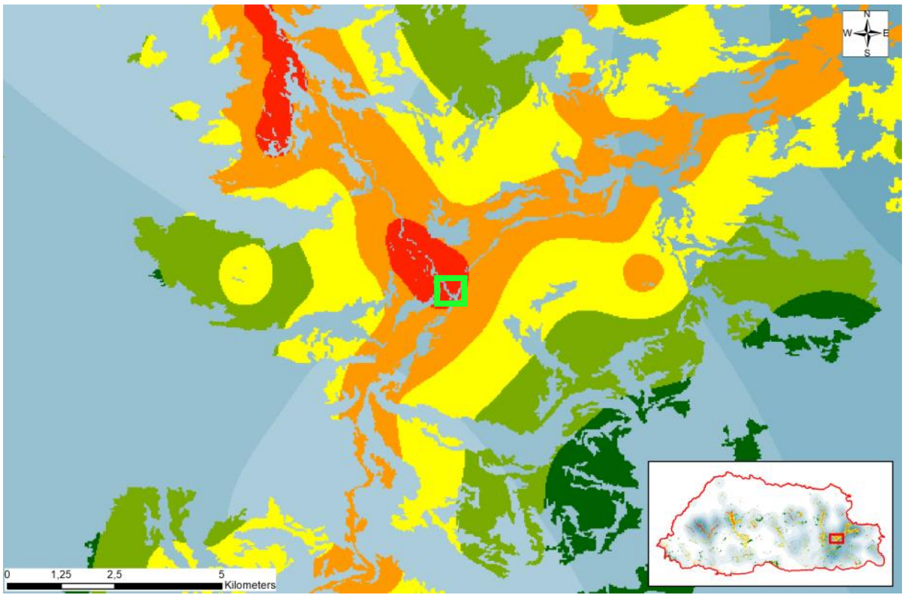


Fig. 58) A location with a high heritage prediction in a heritage dense location that nonetheless contained no heritage in the Nye Atlas and World Bank heritage databases.

Upon closer inspection using aerial imagery a possible unknown heritage site (possibly a temple or chorten) was found (Fig. 59).

Fig. 59) The possible cultural heritage feature shown with the prediction model (left) and without (right).

Next to the possible feature there was an apparent footbridge which also wasn't found in any of the databases. However wether this bridge is actually historical is unkown. Additionally the model was found to be capable of locating areas with human activity even though they were not designated as urban area in the NLCS landcover data. These two finds suggest that the model performs well at it's task of finding areas of interest for archaeological research.

The six selected landscape types contain 43.8 % of all heritage features (4451 of 10154) in just 6 % of total area, the percentage of heritage features is thus over seven times as large as the represented area with an effectiveness (measured through $\frac{\text{Heritage Coverage [\%]}}{\text{Area of Interest [\% of total Bhutan area]}}$) of 7.3. A high as possible percentage of heritage in a low as possible percentage of area (and thus high effectiveness score) is indicative of good performance. The chosen landscape type density cut-off value is therefore quite effective in selecting relevant areas, indicating that selection by landscape type may be a useful aid for researching possible heritage locations. It was noted that many heritage features not covered by the selected landscapes were located right next to them. A possibility to further improve the effectiveness of the method therefore might be to apply a buffer to the selected landscapes. When buffering the areas by 1 km the coverage of heritage features increased to 82.3 % (8354 of 10154 features) but the total area of interest increased to 27.5 % of the nation resulting in an effectiveness of just 3 reducing the effectiveness by a factor of 2.4. A buffer of 500 m covers 73.2 % of heritage features with a total area covering 18 % of the nation resulting in an effectiveness of 4.1 and thus also performing worse than the unbuffered areas. A 250 m buffer returns an effectiveness of 5.1 and a 100 m buffer an effectiveness of 6.2. Fitting a trendline through these results ($f = -1.39 \cdot LN(x) + 12.68$; $r^2 = 0.995$) and solving for 7.3 it would appear possible to increase efficiency with a buffer smaller than 48 meters, a test with a buffer of 20 meters however returned an efficiency of just under 7.1 (Fig. 60). This suggests the model is optimised as good as possible.

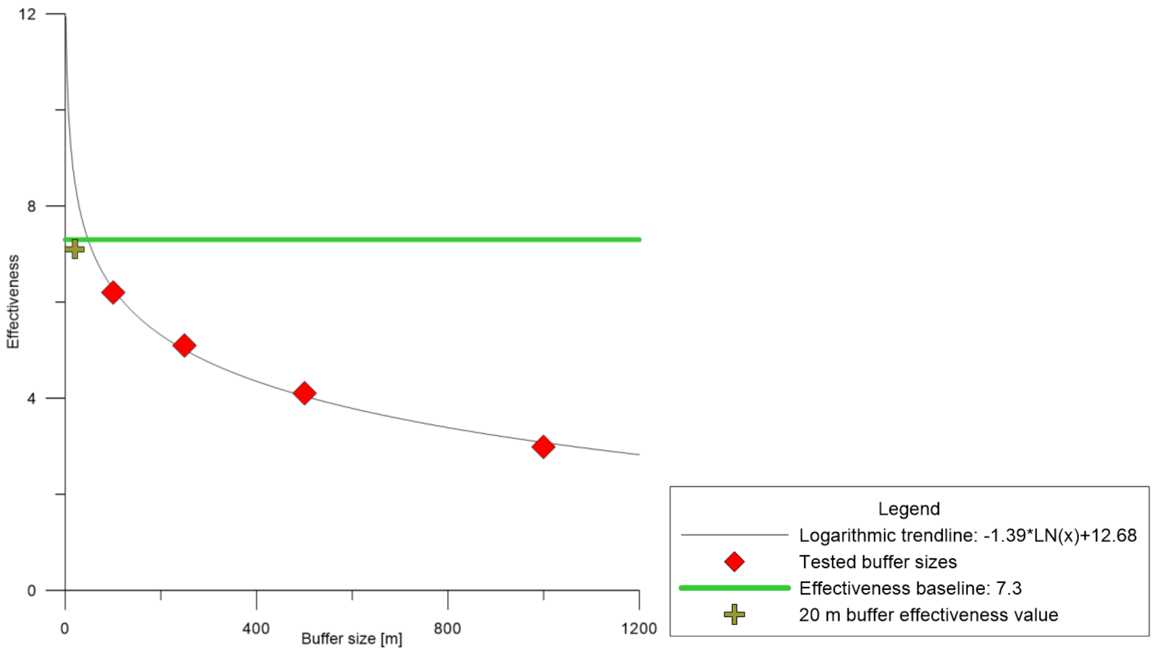


Fig. 60) Graph with the tested buffers and their resulting effectiveness (red). Also showing the original effectiveness of 7,3 (green line), the trendline (black line) and the 20 m additional test buffer (dark green cross).

4.3.2 *Inductive Approach*

The inductive approach employs a statistics centred method. Where the deductive approach uses data of heritage features and extrapolates these to the entire study area the inductive method analyses the properties of every gridcell after which predictive weights of each attribute are returned. The weights of each attribute are telling of the attributes' relation to cultural heritage features. These weights are used to create a formula which when incorporated into the GIS builds the heritage prediction model (Espa et al., 2006). The main benefit of the inductive approach is that the prediction model not only reveals which areas have a high potential for containing cultural heritage, but also quantifies the likelihood. Additionally a statistical model can be calculated that predicts the amount of heritage features that can be found in each gridcell. As the model returns a prediction of the chances of finding cultural heritage a better informed decision can be made on where to conduct archaeological research and there is less uncertainty about a chosen study site as the contrast is higher compared to the deductive method. One must keep in mind though that these figures are still an estimation and a large area with a fairly high chance can still contain no heritage due to the probabilistic character of the approach and the limited explanatory power (and thus remaining error) of such models. Drawbacks of the inductive method are the fact that it is less flexible because of the dependence on the functional form of the logistic regression, and requires a certain amount of understanding on the topic of statistics and analysis (Espa et al., 2006). This makes it more difficult to spot errors or quickly introduce changes in the model (and compare the results).

For the inductive model the same attributes were used as for the deductive method. The first step in creating the model is preparing the attribute data. In GIS a database is created of every individual gridcell's attributes. They may be the same as for the deductive method but they are used in a different way because every cell is used in the analysis. Therefore in addition to the previously mentioned attributes a binary attribute indicating the presence of heritage in a cell and an attribute indicating the amount of individual heritage sites in each cell was created. Also landscape types were classified according to their typical heritage density. M_Gr1, L_Shr1, M_Shr1, L_CoF1 and L_Agr2, the landscape types that had the lowest heritage densities of the included types, became one class. Ag_Agr1, M_Agr1 and Gs_Agr1 (the landscapes with the highest densities in ascending order) each got their own class.

For the presence of heritage prediction model these variables were analysed through logistic regression with the binary presence of heritage data as dependent variable. The results are found in table 7 below.

	B	Standard Error	Sig.
Distance to River [LN(m)]	-0.112	0.008	0.000
Distance to Urban Area [LN(m)]	-0.617	0.006	0.000
M_Gra1/L_Shr1/M_Shr1/L_CoF1/L_Agr2	0.988	0.035	0.000
L_Agr1	2.061	0.029	0.000
M_Agr1	1.970	0.043	0.000
A_Agr1	5.462	0.245	0.000
Constant	4.743	0.141	0.000

Table 7) Results of the statistic analysis explaining presence of heritage features. The Nagelkerke R^2 = 0.185.

The B values (coefficients for the constant) confirm the assumptions made for the location variables. The negative B value for Distance to River indicates that the chance of presence of cultural heritage declines with distance from the river, as was expected. The same goes for Distance to Urban Area with an even stronger negative correlation. These results are in line with the distance decay plots in fig. 53/54. The landscape type classes also reflect their increasing heritage density in the ascending B values. The exception to this is the B value for M_Agr1 which is smaller than the B value of the less heritage dense landscape L_Agr1. This is probably caused by the fact that this analysis uses a binary factor to indicate the presence of heritage. This would suggest that within M_Agr1 clusters of cultural heritage are more prevalent than in the other landscape categories. The reasoning behind this will become clear when the linear regression is discussed in the subsequent section.

Table 7 also shows the correlation coefficient of the different landscape types. The difference in explanatory value between A_Agr1 and the category with the closest B value L_Agr1 is 3.401. Compared to the coefficient of Distance to Urban Area (which at -0.617 is much larger than Distance to River) the difference in coefficient between A_Agr1 and L_Agr1 is 5.5 times larger than the entire coefficient of distance to urban area. This suggests that the explanatory value of Distance to Urban Area/River pales in comparison to the explanatory value of the difference between the landscape classes. This is because Distance to Urban Area/River is measured on a different scale. The B value for Distance to Urban Area is per 100 meter distance, so in order to reach the same difference in heritage potential as is present between the two landscape types a distance of 550 meters is required. For an oversimplified comparison in area size one can take an area of 550 x 550 meters which is 302.5 ha. As the MMU is 15 ha in this simplified comparison the difference in landscape type has over 20 times more explanatory value when seen by area unit (302.5 vs 15 ha to reach the same difference in heritage potential). The landscape types are thus very discerning in explaining presence of heritage.

To create the presence of heritage prediction model the B values can be used to create a formula with which the relative importance’s of the attributes will be combined. The base formula is:

$$Chance\ of\ heritage = \frac{e^{(Constant\ + B_1 \cdot Variable_1 + \cdots + B_i \cdot Variable_i)}}{1 + e^{(Constant\ + B_1 \cdot Variable_1 + \ldots + B_i \cdot Variable_i)}}$$

Applying the formula in the GIS using the B values found in the logistic regression results in the prediction model for presence of heritage sites. This model is shown in fig. 61.

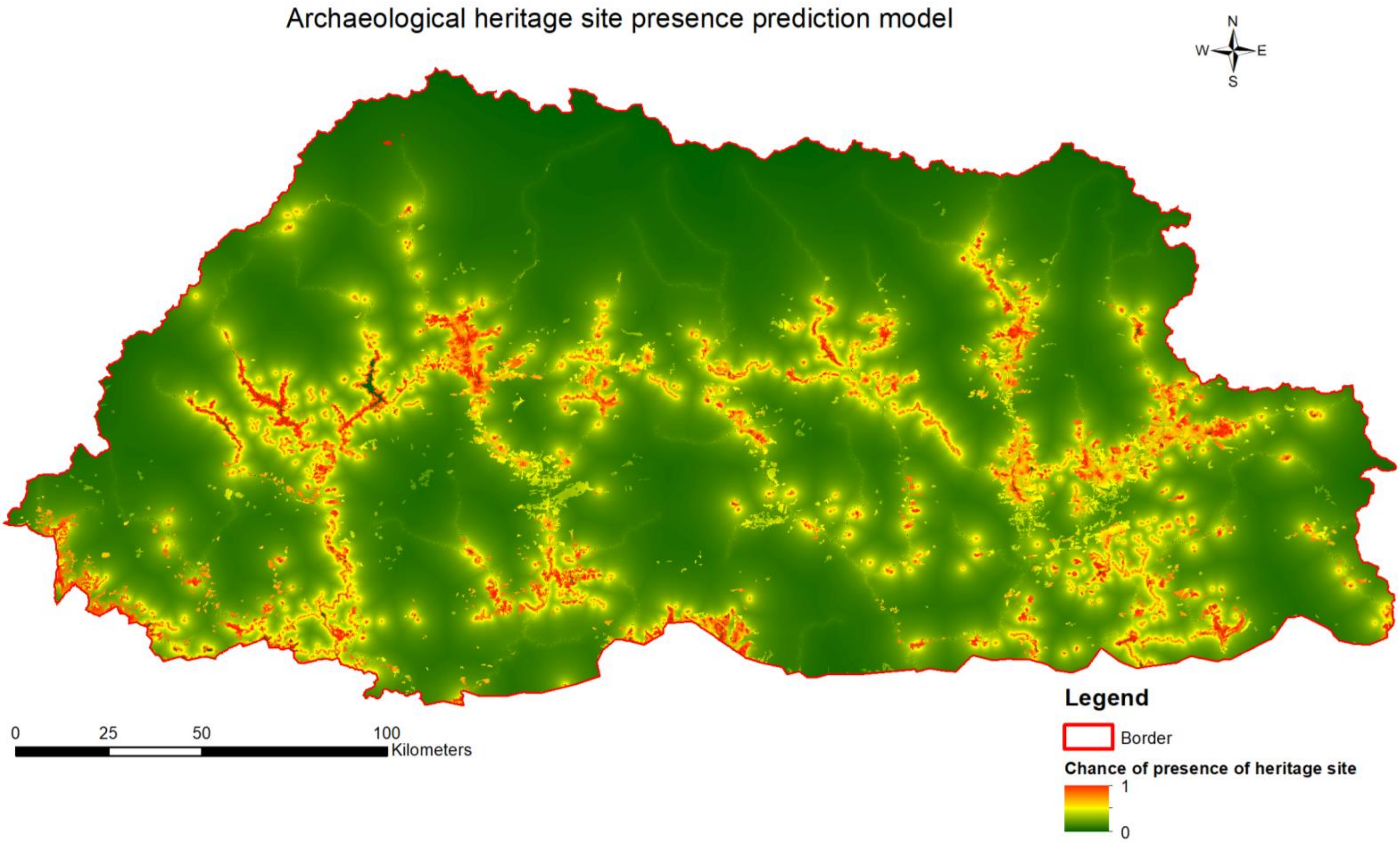


Fig. 61) Results of the statistic analysis explaining presence of heritage features mapped onto Bhutan.

Additionally the inductive statistical approach allows for quantifying the expected amount of heritage features in a location. This model is made using linear regression. For the linear regression the same attributes are used as for the logistic regression except that the binary 'presence of heritage' dependent variable is replaced with a variable containing the amount of known heritage features in any given cell. The results are found in table 8.

	B	Standard Error	Sig.
Distance to River	0.000	0.000	0.000
Distance to Urban Area	-0.004	0.000	0.000
M_Gra1/L_Shr1/M_Shr1/L_CoF1/L_Agr2	0.005	0.000	0.000
L_Agr1	0.034	0.000	0.000
M_Agr1	0.064	0.001	0.000
A_Agr1	0.126	0.006	0.000
Constant	0.038	0.000	0.000

Table 8) Results of the statistic analysis explaining amount of heritage features. R^2 = 0.015.

The results show that distance to the nearest river has no influence on the heritage feature count within a grid cell. Distance to Urban Area explains a small part of the heritage count. The increasingly heritage dense landscape types provide the strongest contribution to explaining the amount of heritage features.

In the linear regression results the heritage density of the landscape types is mirrored in the B values of each landscape class. This goes back to the earlier observation made using the results of the logistic regression where the B value of M_Agr1 was unexpectedly smaller than that of the less heritage dense landscape classes. Because the B values of the linear regression do reflect the order of heritage density of these landscapes this means that heritage features within M_Agr1 landscapes tend to be more clustered than those in the other landscapes as their amount is not accurately reflected in the relative B values of the binary value used for logistic regression. The binary value makes no distinction between different amounts of heritage features within one grid cell and a relatively high tendency of heritage to cluster together can be the only explanation for the difference in B value order between the logistic and linear regression.

The B values from the linear regression are then used to create a predictive model of the amount of expected heritage features. This is again done using the GIS to apply a standard formula with the B values used to represent the importance of each variable. The formula is:

$$Amount\ of\ heritage = \ Constant + B_1 \cdot Variable_1 + \cdots + B_i \cdot Variable_i$$

Applying this formula in the GIS using the B values found in the linear regression results in a model predicting the amount of features per gridcell. For easier interpretation and comparison the per gridcell amount is adjusted to represent the amount of features per hectare, producing the map in fig. 62.

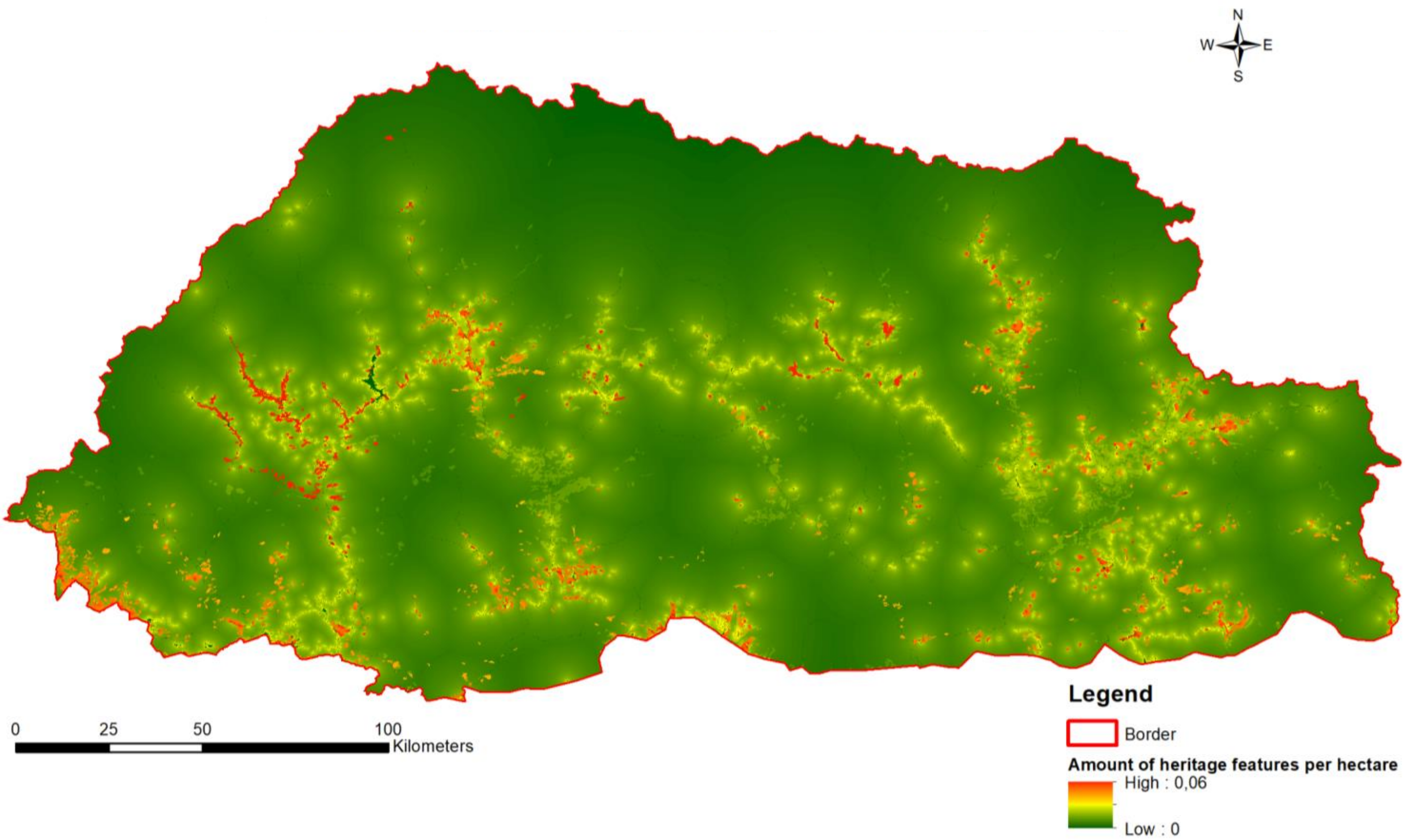


Fig. 62) Results of the statistic analysis explaining amount of heritage features mapped onto Bhutan.

The deductive model and the inductive presence of heritage models are very similar in the areas designated as high potential for heritage sites. The inductive model puts a greater emphasis on river valleys than the deductive model. The inductive heritage feature count model is also very similar to the inductive presence of heritage model. Without the point cloud of known heritage locations it is difficult to assess which areas predicted by the models are promising for archaeological research. Access to the known heritage locations dataset would therefore be highly recommended for anyone involved in archaeological research in Bhutan. For an initial indication of areas of high potential for this case study the known features database was used to indicate some areas that are particularly promising (Fig. 63).

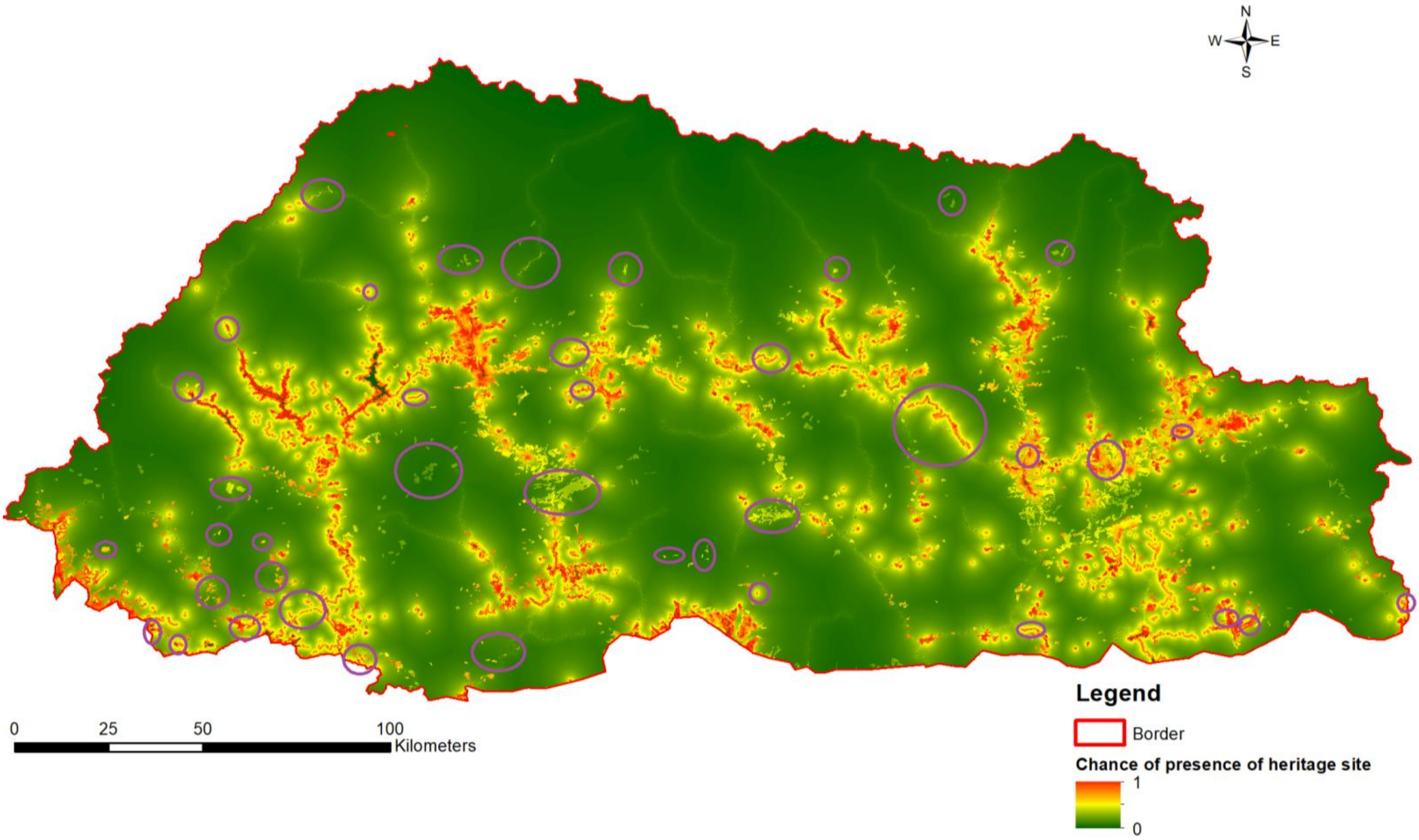


Fig. 63) Promising areas for archaeological research are encircled.

Again the database with exact locations of known heritage features cannot be displayed in this paper but was used in the GIS in order to designate areas of high potential for archaeological research. The most promising areas for archaeological research found through both the deductive and inductive method show similarities and indeed some areas are designated using both approaches. There are however multiple areas of high potential that only show up in one of the two results. This indicates that both methods have value and complement each other.

4.3.3 Application of Results in Development Planning

Apart from archaeological research this method can be helpful for development planning. When selecting locations for new development projects the maps in this chapter can be used to roughly dismiss certain areas and put emphasis on others, based on their (predicted) heritage density and location. One example could be the roads being built throughout Bhutan at this moment in order to connect remote villages. The information contained within these maps can help determine the routes of new roads in order to avoid a heritage rich landscape, or even to reduce noise pollution in important locations and determine impact on sightlines from heritage rich landscapes. Additionally with regard to the planning and construction of hydropower projects the models created in this chapter can be valuable. Hydropower construction has a large influence on vast areas both through the construction process and the upriver flooding associated with hydropower generation. The mandatory environmental impact assessments can benefit from this data by helping to focus research on the presence of (archaeological) cultural heritage to more specific high potential locations. Also when deciding on locations for new hydropower projects the data presented in this chapter can inform initial inventories of possible construction locations to help avoid locations with a high chance of cultural heritage. An example of the impact of hydropower construction is given below in fig. 64 and in fig. 65 on the next page.

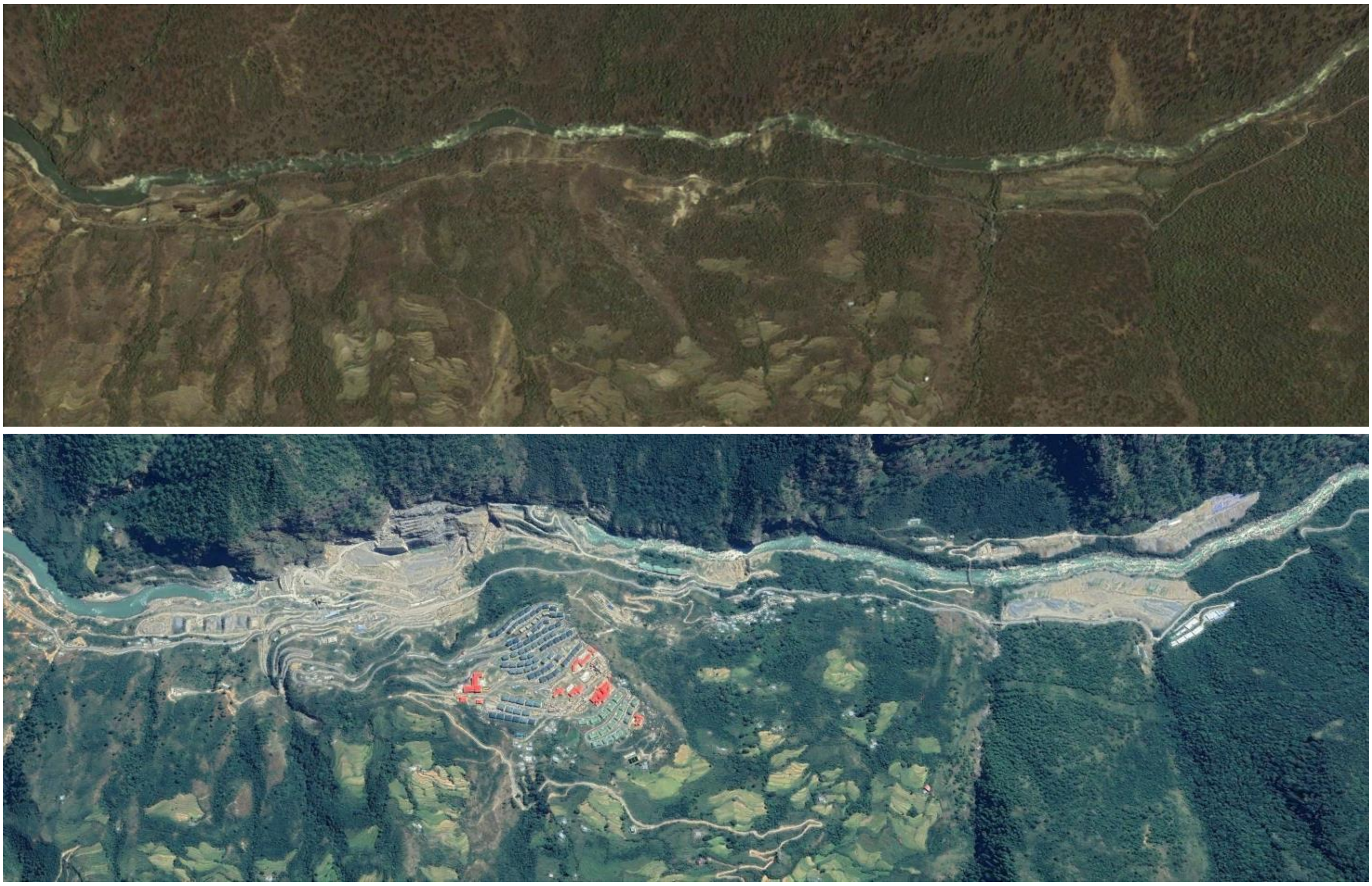


Fig. 64) The top panel shows the location of the Punatsangchhu-1 Hydroelectric Project near Wangdue Phodrang on 23-05-2002, before construction began. The bottom panel shows the exact same location during construction (18-10-2017). The large impact on the area is very clearly visible. The construction site has an enormous impact in and of itself, the blue, orange and green coloured structures in the middle underneath the path of the river is a village build for the workforce, showing how these large scale construction projects have an impact surpassing that of only the construction site. Image source: Google Earth Pro.

Fig. 65) A panoramic view of the Punatsangchhu-1 Hydroelectric plant construction site as seen during a visit on 29-03-2017. The scale is hard to convey in this image, the holes in the mountain can comfortably fit two cement trucks side by side. Image source: Author.

The natural location for hydropower projects is in river valleys which were found to be the most heritage dense locations and therefore can be expected to contain (archaeological) heritage that is exceptionally vulnerable to these projects. The effect of these construction projects is not limited to the actual construction site. Additional support infrastructure is needed in the form of bigger roads and temporary housing for construction workers (Fig. 64). Also because of the associated water level rise upstream an additional area is affected.

In addition to direct changes affecting cultural heritage there is also an indirect effect in some cases. As was mentioned in the introduction noise pollution and affected vistas are also a consequence of the developments in Bhutan. The example in fig. 66 below shows the view from historic Trongsa Dzong in 2004 (left) and in 2017 (right) after downriver construction of the Manghdechhu hydropower plant had begun. In addition to the visual impact in this example a construction worker village has been build just over the ridge on the left and it can be reasonably expected that the sudden increase in local population will add to the impact of the hydropower plant. While some impact may be temporary as they relate to the period of construction, others like dams and roads may remain visible in the landscape for longer periods.

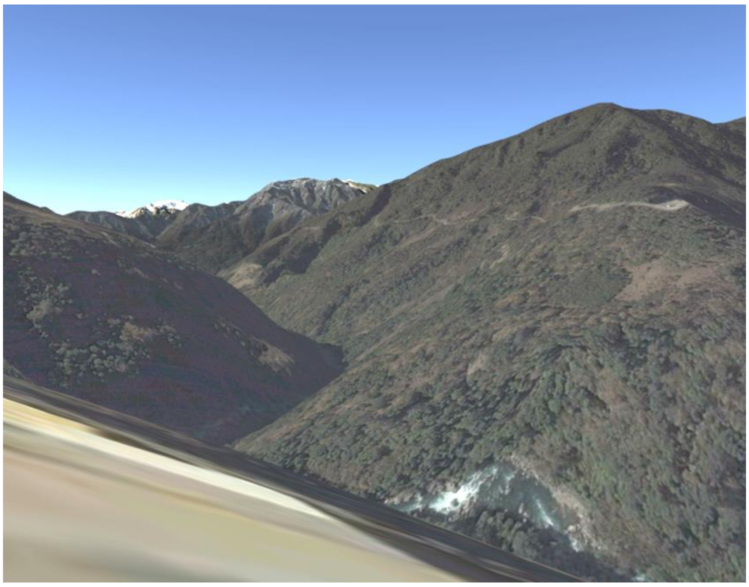


Fig. 66) The view from Trongsa Dzong in 2004 (left) and 2017 (right). It has clearly been impacted by the Manghdechhu hydropower plant construction. Made with Google Earth Pro.

Dzongs are ancient centres of power as well as the seat of the monastic body and are some of the most impressive historic features of Bhutan. Realizing the impact of large scale construction on the historic environment and tranquillity associated with dzongs and other similarly important features is essential for achieving Bhutan's goal of sustainable development.

Fig. 67) Trongsa Dzong. To the left the impacted mountainside from fig. 68 before construction began. Image credit: Lonely Planet.

Changes in hydrodynamics as a consequence of (hydropower) construction have been reported to have an even less directly visible consequence as this can propagate through invisible (underground) routes leading to instances of important (sacred) wells drying up (Dharmadhikary, 2015).

The data presented in this chapter offers exciting possibilities for cultural heritage related work. It can also act as an aid for planning and assessing development projects and governmental entities like zoning commissions. Furthermore the outstanding effectiveness of the selected landscapes in the deductive approach lends credibility to the method used in this project to create the landscape typology. If the typology would have been based on wrong assumptions, data and/or methods one might expect that the predictive models would not be optimized and effectiveness could easily be increased by applying a buffer. The models created in this chapter should be seen as a preliminary result as even though they are based on assumptions which have proven to be valid the models can possibly be improved further by archaeologists or heritage specialists using additional data and/or applying different classification schemes that more accurately indicate archaeological heritage properties.

4.4 Landscape change analysis 1990-2010 (Case Study)

Bhutan is undergoing rapid societal changes that affect the landscape. During the field visit a World Bank employee noted how much changes between each of her visits (1-2 year increments). The landscape typology can be used to investigate vulnerability of specific landscape types. As the Bhutanese culture is strongly tied to and derived from the landscape it is very important to understand which landscapes are changing (Palden, 2016; Topping, 2014). An example of an important cultural location undergoing changes is Chimi Lhakhang and its surrounding area. Chimi Lhakhang is an ancient temple built on top of a hill where according to legend the “Divine Madman” Drukpa Kunley subdued a demon and trapped it in a rock (Wangdi & Chema, 2008). One side of the hill is flanked by a river, the other side features three small villages and rice paddies. Because of the striking lifestyle and practices of Drukpa Kunley the area is turning into one of the most visited tourist locations of Bhutan, as shown by the top attractions lists of lonely planet and tripadvisor, which has had a significant effect on the landscape. Roads have been widened, extra paths and hotels built, the villages have grown and densified and completely new buildings have been built in locations that used to be agricultural land or have natural landcover. All these changes are very recent as is clearly visible in satellite images of just under 15 years apart shown in fig. 68.

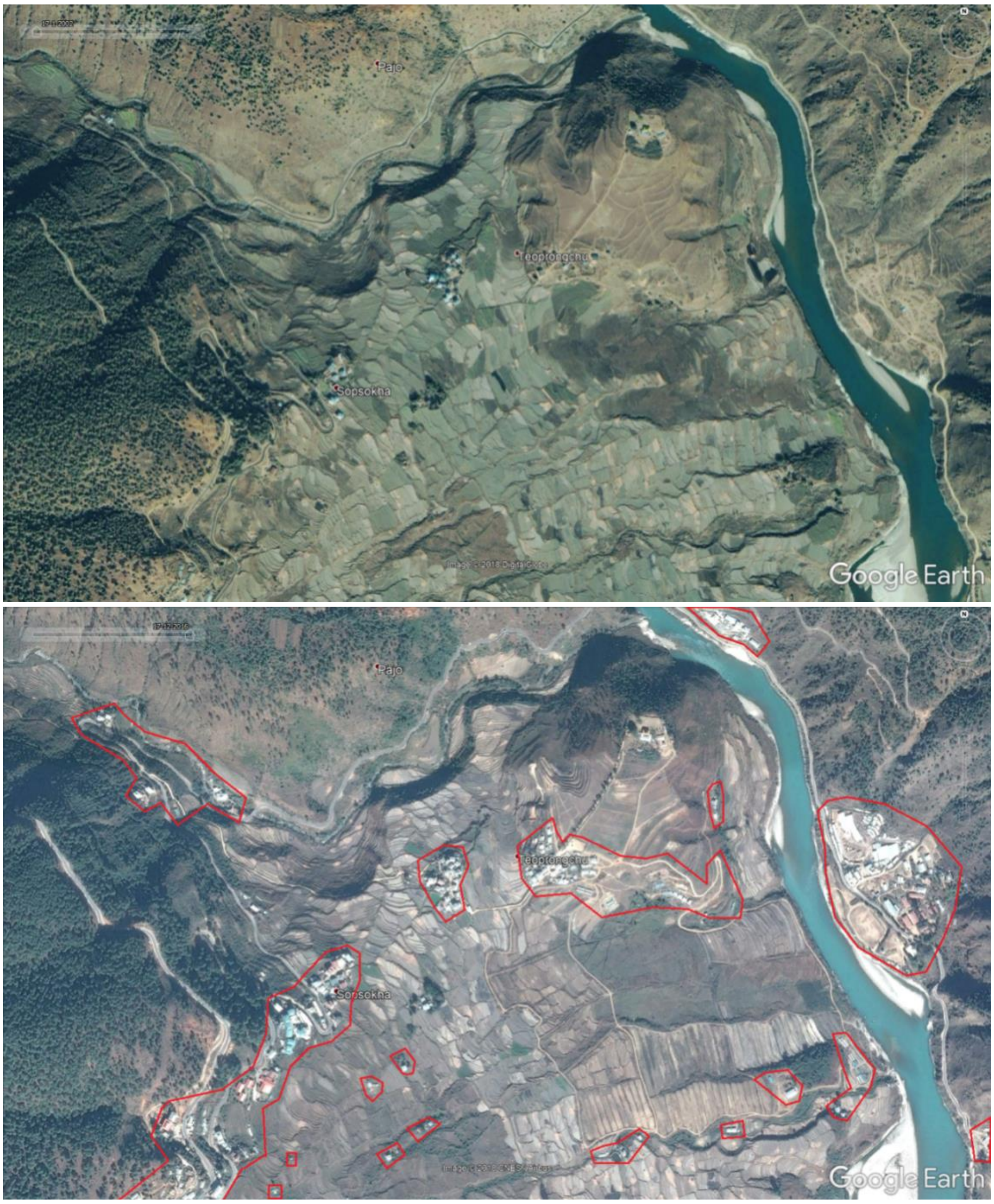


Fig. 68) The changes of the Chimi Lhakhang area. The top image is from 17-01-2002 and the bottom image from 17-12-2016. Significant changes (new Urban Area and higher urban density) are marked. Image source: Google Earth and Author

Fig. 68 shows aerial views of Chimi Lhakhang on 17-1-2002 in the upper pane and on 17-12-2016 with most notable changes highlighted in the bottom pane. Not highlighted are the widened and blacktopped roads and newly created paths through the rice paddies. The photo of fig. 69, which was taken on location, shows the view from the viewpoint in fig. 70. As can be concluded from the comparison of fig. 68 on the previous page most of the buildings seen in this photo are less than 15 years old, the large blue-roofed constructions are hidden from view by the trees on the left of the photo.

Fig. 69) A view on recently developed buildings as seen from Yuwakha village (Viewpoint in fig. 70). Image source: Author.

The small village of Yuwakha from where the previous photo has been taken is dominated by construction projects as is shown in the photo in fig. 71 on the next page. This was an omnipresent process in this village and most of it was aimed at tourism (guest houses, artisan shops etc.).

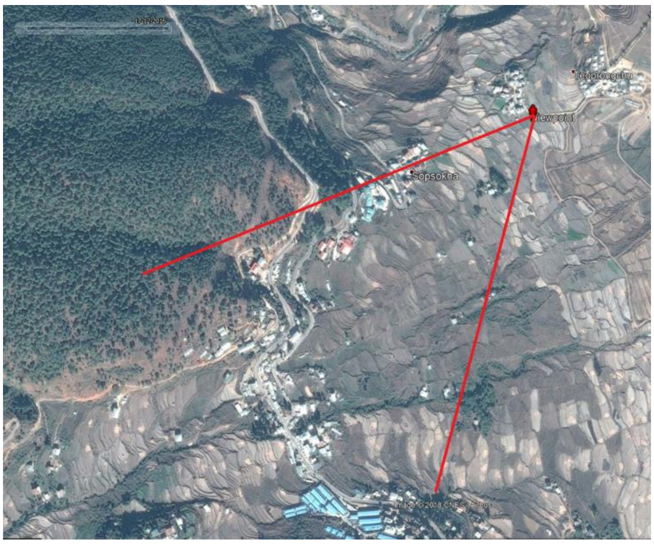


Fig. 70) Location and direction of the view in fig. 69. Image source: Google Earth Pro and Author.

Fig. 71) Construction in the centre of Yuwakha. The villages surrounding Chimi Lhakhang are rife with new construction due to the touristic appeal of the site. Image source: Author.

The changes in landscape are found throughout Bhutan, often showing increased urban density and the spreading and settlement in new locations of Urban Areas combined with newly built or widened roads. A sample of locations showed significant changes over a period of 10-15 years from the most western point of Bhutan to the most eastern point. As can be expected the changes are most visible near human population centres (and were often visible in areas where the heritage prediction model showed a high potential).

One other example is given in fig. 72 on the next page. These two images show the Jakar valley in Bumthang, a dzonkhag that is often named as the most historically important area of Bhutan containing many sacred sites and temples. The construction of an airport runway has had a big influence on this area with a new road, an increase in built up area, removal of a small foot bridge, new industrial area, decrease in grassland and most notably fixing the course of the river by constructing an embankment. The influence on the quality of landscape here is clear and there are numerous such examples of landscape changes due to large scale construction projects. With the endless supply of similar examples in mind the importance of increasing knowledge with regard to landscape change is obvious. This importance should not be lost on the Bhutanese people because of their aim for ecologically and culturally sustainable development of the nation, as was laid down in the 1990 Paro Resolution, the 11th and 12th Five Year Plan and the Economic Development Policy.

Fig. 72) Jakar valley in Bumthang. The top pane is from 24-11-2003 and the bottom pane from 31-12-2017. The changes mentioned in the text have had a visible impact on the valley landscape. Image source: Google Earth Pro.

For the landscape change analysis the ICIMOD landuse datasets were used. These datasets are less precise and accurate compared to the NLCS landuse data, but contrary to the NLCS data they are available for years prior to 2010. The total areas of the landcover classes are very similar to that of the NLCS based landcover distribution which gives some confidence that even though distributions and sizes of individual landscape units may be inaccurate in the ICIMOD based maps, the trends in total area coverage over the years should be representative of the actual dynamics. An analysis was made using data from 1990, 2000 and 2010 which was the latest edition of the ICIMOD data. All landscape maps were made using the same methodology used to create the NLCS based landscape map described in earlier chapters, only landuse data was substituted. A detailed comparison between the NLCS based and the ICIMOD based landscape maps can be found next in the "Comparison NLCS vs. ICIMOD" sub-chapter.

4.4.1 Comparison NLCS vs. ICIMOD

The landscape change analysis can only be done using ICIMOD landcover data. This introduces some uncertainties as both landcover datasets may differ from each other and conclusions drawn from one may not apply to the other. This chapter investigates the differences of each dataset so these can be accounted for when discussing change analysis results. As the NLCS landcover map is from 2010 the ICIMOD 2010 landcover will be used for the comparison.

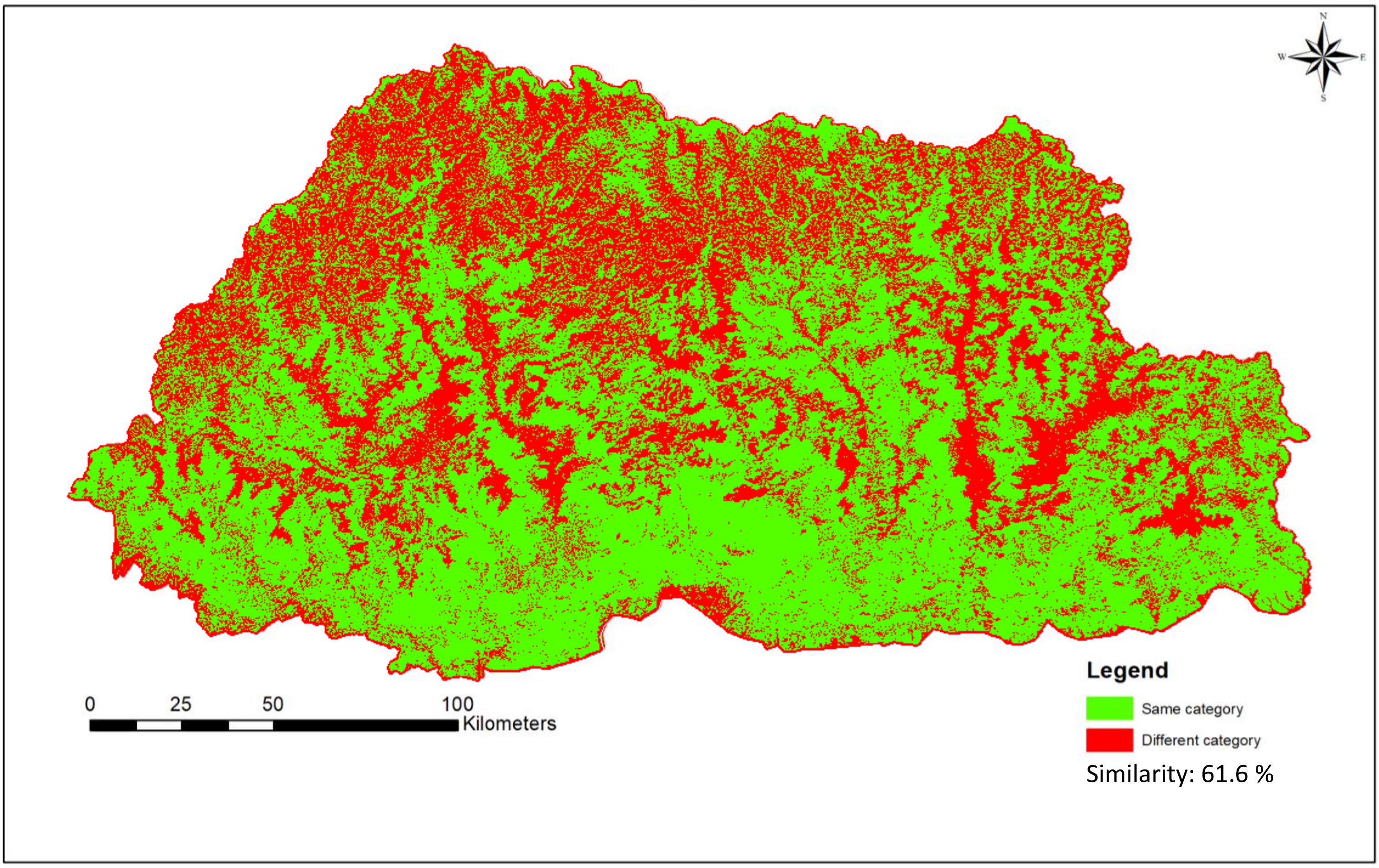


Fig. 73) Spatial landcover category comparison showing similarity between NLCS and ICIMOD landcover data.

Fig. 73 is a comparison between the two landcover datasets. 61.6 % of the total area is classified as the same category in both datasets with the rest classified as different categories. The discrepancy between the two datasets is primarily present in the northern regions. Also the valleys are often qualified differently. The NLCS dataset contains more Conifer forest in the valleys where the ICIMOD features primarily Broadleaved and mixed forest. Only the Paro and Thimphu valleys are primarily different because of the large amount of Urban Area described in the ICIMOD map. The differences can be explained by the different methods used to create these maps. The NLCS landcover map is based on physical surveys whereas the ICIMOD landcover map is created using image classification through the Land Cover Classification System (LCCS) developed by FAO/UNEP (ICIMOD, 2018). The ICIMOD landcover map uses assumptions to help with landcover classification through aerial images which are responsible for the overestimated urban sizes.

The most obvious variables that can be compared between the two landcover datasets are the total areas (Appendix F) and elevation distributions of the nine landcover categories. This basic analysis shows that the areas of each landcover class are very similar both in total area (Fig. 74) and distribution of the classes over elevation ranges (Fig. 75).

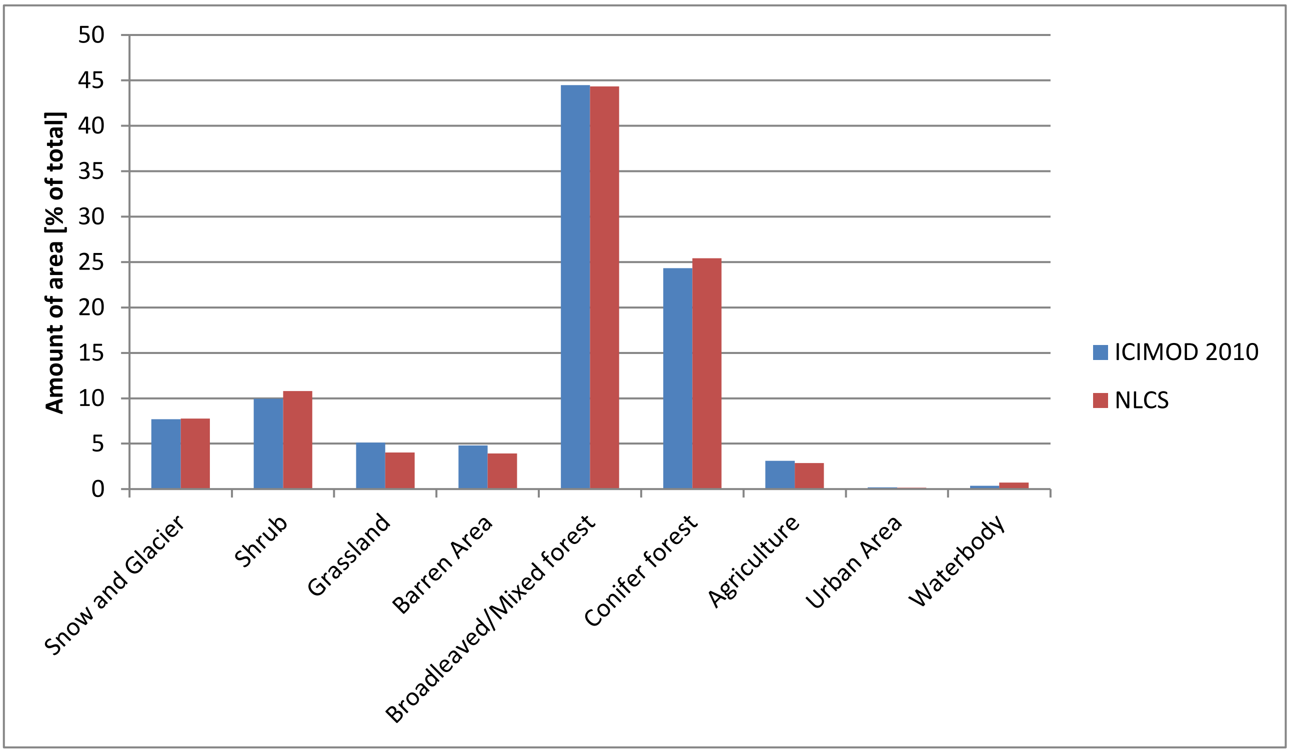


Fig. 74) Portions of each landcover category in the ICIMOD 2010 and NLCS datasets.

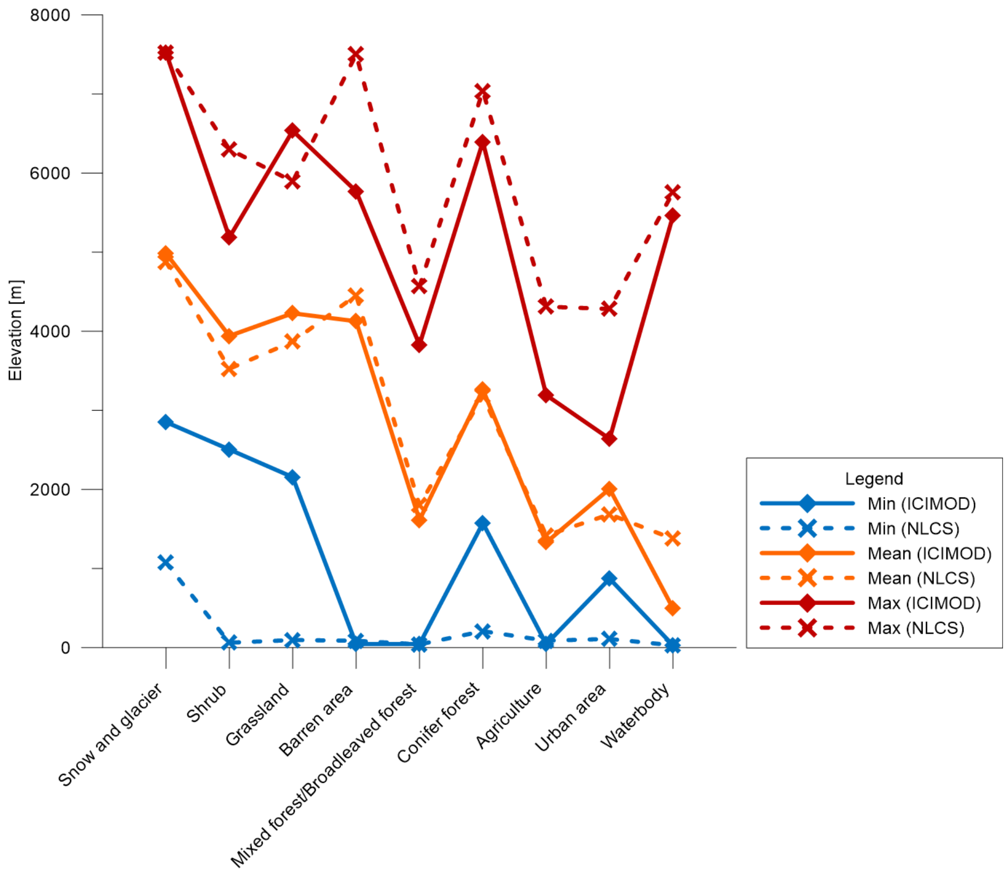


Fig. 75) Landcover distribution comparison: Landcover class elevation ranges for the ICIMOD 2010 and NLCS datasets.

The elevation distributions of the landcover types, presented in fig. 75, are also generally similar. The mean values of the ICIMOD categories are extremely close to the mean values of the NLCS categories. The maximum elevation of the classes follow a similar trend between the ICIMOD and NLCS datasets although the differences between the maximum values of some categories are somewhat larger. Especially the maximum values for barren area, shrubs, agriculture and urban area differ by a fairly large amount with the NLCS dataset indicating a higher maximum elevation for every class except grassland. The trends in minimum values are less similar between the NLCS and the ICIMOD dataset. Except for snow and glacier the NLCS dataset features every landcover class at almost the lowest possible elevation in Bhutan. The ICIMOD landcover data returns significantly higher minimum values for five of the nine landcover classes. The differences in the extreme values can be expected as the NLCS dataset is based on surveys which returns high resolution data and is more likely to find occurrences in all possible locations. The less precise ICIMOD data by comparison is created using an automated satellite imagery interpretation approach which focuses on general patterns and may discard some of the more extreme (low elevation) areas. Also the ICIMOD algorithm is originally bound to fewer categories (ten originally) than the creators of the NLCS dataset (44 originally) which creates a need to combine more different landuses in one category and therefore requires averaging their properties, like elevation range, and in this way introduces additional dampening to the elevation range amplitudes.

The similarities in relative areas of every category in both the NLCS and ICIMOD landcovers (Fig. 74) combined with the very similar category mean elevation values between the two datasets and the similar behaviour of the maximum elevation values (Fig. 75) would suggest that the trends in the ICIMOD landcover are comparable with the NLCS landcover data. These large scale trends are most important for the evaluation of landscape change as the data can thus be expected to reflect actual nationwide landcover change trends even when smaller scale dynamics may still be misrepresented in the ICIMOD data.

4.4.1.1 Influence of landcover patch size difference on clustering

Small scale dynamics are expected to have some influence however because of the aggregation used in the landscape typology creation. If landcover of a particular category in a particular area is for example less scattered in the ICIMOD data compared to the NLCS data it may be less likely to assimilate, or be assimilated into, surrounding landscapes. This could introduce an error in the typology and consequently misrepresent actual landscape change trends. Also the on average larger ICIMOD units may underestimate small scale dynamics. To analyse this difference landscape metrics may be helpful. By comparing average sizes of individual landcover patches the possible misrepresentation of landscape change may be better understood. The NLCS landcover has 601087 individual landcover patches vs 33219 individual patches in the 2010 ICIMOD landcover, so the NLCS data has over 18 times more individual landcover patches meaning every individual patch will be smaller in size. In table 9 below is some data of the individual landcover patches for both datasets.

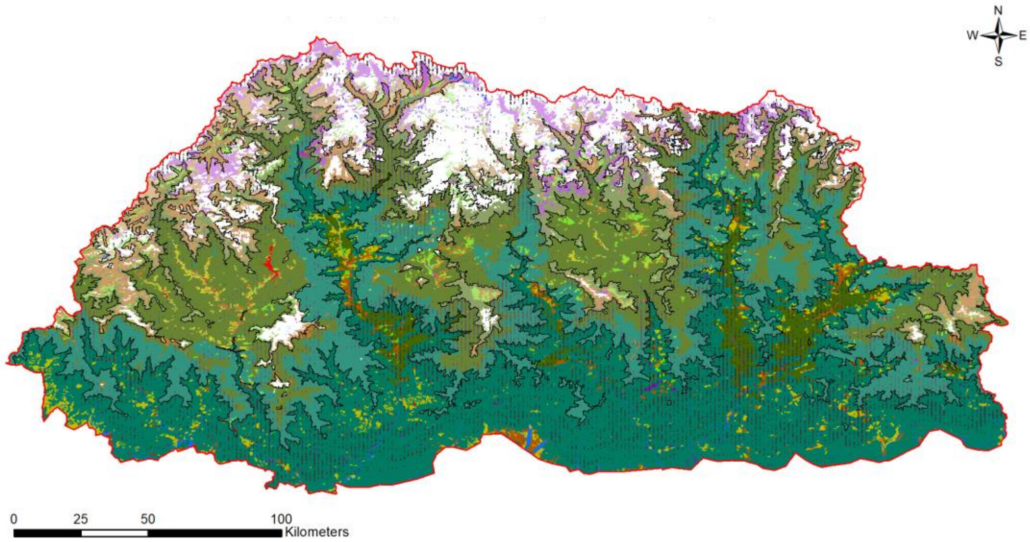
Table 9 confirms that the total size of each category is very similar (as was shown in fig. 74). The only category where both datasets have a relatively large discrepancy is Waterbody of which the NLCS landcover data features almost twice as much area as the ICIMOD landcover data. The patch count per category, average patch size and standard deviation all reveal that the ICIMOD data is less detailed. The ICIMOD data is divided in less individual landcover patches which has consequences for average patch size and their standard deviation. The per category patch count is an order of magnitude smaller than that of the NLCS which means the average patch size per category is much larger. Standard deviation for the individual landcover patches is also much larger. The much larger average landcover patch size in the ICIMOD data may have consequences for the landscape map if the increase in average patch size over NLCS patch size differs a lot between categories.

Category	**Total Size [ha] NLCS (ICIMOD)**	**Patch Count NLCS (ICIMOD)**	**Average Patch Size [ha] NLCS (ICIMOD)**	**NLCS:ICIMOD Avg. patch size ratio**	**St.Dev NLCS (ICIMOD)**
Urban Area	6464 (6834)	6243 (228)	1.0 (29.9)	0.03	13.96 (179.71)
Waterbody	27445 (14421)	9924 (476)	2.8 (30.3)	0.09	25.72 (57.59)
Snow and Glacier	299339 (299119)	54686 (4049)	5.5 (73.9)	0.07	431.96 (2648.38)
Shrubs	419154 (386168)	203537 (4826)	2.1 (80.0)	0.03	66.03 (453.34)
Grassland	157238 (199405)	108566 (8290)	1.4 (24.1)	0.06	11.75 (85.80)
Barren Area	151749 (186397)	64597 (6178)	2.3 (30.2)	0.08	47.76 (183.50)
Broadleaved and Mixed Forest	1720310 (1726653)	50255 (2311)	34.2 (747.1)	0.05	3806.44 (34995.71)
Conifer Forest	983240 (944249)	71655 (2076)	13.72 (454.8)	0.03	1162.09 (8763.00)
Agriculture	112156 (120595)	31624 (4785)	3.5 (25.2)	0.14	20.43 (72.42)

Table 9) Landcover patch statistics. As there were single cell patches it is unlikely the NLCS and ICIMOD landcover data used an MMU.

If one landcover category features a much larger average patch size ratio (NLCS:ICIMOD) compared to another landcover category patch ratio increase this will result in a disproportionate assimilation of low NLCS:ICIMOD ratio categories by larger ratio categories in the clustering phase. If all categories have a similar patch size ratio the effects will cancel each other out. Table 9 reveals that the ratios between NLCS and ICIMOD individual landcover unit sizes can in fact differ greatly. This is not an ideal situation but it is still possible that the landcover unit size is of relatively little influence on the final landscape map. This is possible because the landscape map is dependent on many other variables (slope and elevation and their respective individual unit sizes) as well as many possible unseen factors that may be at play like dynamics between and properties of typically neighbouring landcover types and the variables that are not explicitly used in the typology creation but are still influencing it. The complex interplay between all those factors can have a bigger impact on the final map than the ratio of average landcover unit size diminishing the impact of that ratio.

With this in mind comparing the final landscape maps based on both datasets will help assess the total effect of differences in the landcover datasets. For comparison fig. 76 shows the results for the NLCS based landscape map (using 2010 NLCS data) and the 2010 ICIMOD based map.



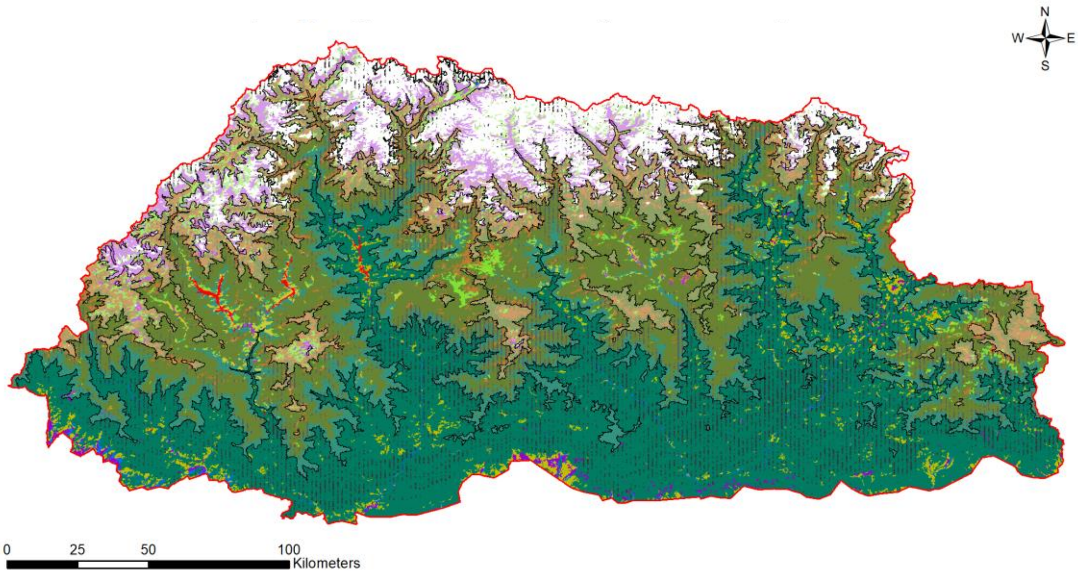


Fig. 76) Final landscape typologies (MMU=15 ha) based on NLCS data (top) and ICIMOD 2010 data (bottom).

On a cursory glance one can see both 2010 maps by and large follow similar trends. The north is dominated by Snow and Glacier landscapes as well as Barren Area landscapes. The middle part is for a significant part covered by Conifer Forest landscapes and the southern part by Mixed and Broadleaved Forest landscapes. The Mixed and Broadleaved forest landscapes penetrate towards the north through the valleys. The ICIMOD based map has 10 fewer landscape categories than the NLCS map (8 fewer categories for the 230 ha map, all type area sizes and individual unit counts can be found in appendix C).

Most noticeable differences in fig. 76 are the absence of the most southern Snow and Glacier landscapes in the ICIMOD based map and the difference in coverage of Urban Area. The NLCS based map has one relatively large Urban Area at the location of Thimphu, while many smaller Urban Areas can be seen at the location of Paro and Ha with very small Urban Areas dotted throughout Bhutan. In the ICIMOD based map three major Urban Area landscape units are visible at the locations of Paro, Thimphu and Punakha and very few other instances of Urban Area are present. This pattern is consistent with the trends shown in table 9 where total areas of landcover categories are similar but they are grouped together more in larger patches in the ICIMOD data. The NLCS based map does show a lot of Agriculture landscape near the Paro area, which appears to be interpreted as Urban Area in this case by the ICIMOD algorithm. Another noticeable difference is the presence of a significant area of L_CoF1 and L_CoF2 in the NLCS based map when there is none found in the ICIMOD map. Also there is a much larger presence of M_BMF1 and M_BMF2 in the NLCS based map. In the ICIMOD map the different forest types are almost perfectly split between the first elevation zone boundary.

Earlier this section the range of ratios between the landcover categories' individual patch sizes was hypothesised to possibly influence the final typology result. If that is the case one would expect to see the range of NLCS:ICIMOD ratios of the individual patch sizes of landcover categories reflected in the ratios of total coverage change of those landcover categories in the final maps. For example, if all categories were to have the same average patch size ratio (NLCS compared to ICIMOD) of 1 except the ratio of landscape X which would be 2, one would expect for the ICIMOD based landscape map to feature a relatively larger area increase of X landcover based landscapes compared to the area increase of X landcover based landscape in the NLCS based landscape map. This is because the ICIMOD based typology would favour the assimilation of non landcover X areas into the initially larger landcover X areas. In short, the ratio of landcover X based landscape area change between the NLCS and ICIMOD based landscape maps should be positively correlated to the ratios of the average landcover patch sizes of the original NLCS and ICIMOD landcover data. However possibly the individual patch size is of little influence in the final typology result due to many other (sometimes unseen) variables at play. In that case the ratio of landcover X based landscape coverage change should not be reflected in the landscape map.

The data is inconclusive about the influence of average landcover patch size on the final landscape map through the spatial aggregation process. What is immediately clear is that the larger average landcover patch sizes of the ICIMOD data dampen the total coverage change of each landcover category (when calculated by the sum of the area of landscapes based on each landcover category) as can be found in table 10. The reason for this dampening effect is that the average patch size for each landcover category is already greater than the MMU of 15 ha. Therefore a lot more of the first order landscape units are classified as valid landscapes and there is less opportunity to be assimilated by other first order landscape units and the equilibrium state within the aggregation phase is reached sooner thereby altering the original landcover distribution less. The NLCS landcovers' smaller average landcover patch size means there is more potential to be assimilated by other patches and therefore the landcover category areas are able to change more significantly.

Category	NLCS landcover [ha]	NLCS based landscape map [ha]	NLCS area change [%]	ICIMOD landcover [ha]	ICIMOD landscape map [ha]	ICIMOD area change [%]	Change ratio NLCS/ICIMOD
Snow and Glacier	299339	336698	12.5	299119	318000	6.3	1.98
Shrubs	419154	342400	-18.3	386168	384482	-0.4	41.95
Grassland	157238	84691	-46.1	199405	152109	-23.7	1.95
Barren Area	151749	124599	-17.9	186397	173240	-7.1	2.53
Broadleaved and mixed forest	1720310	1818847	5.7	1726653	1743824	1.0	5.76
Conifer forest	983240	1049959	6.8	944249	976997	3.5	1.96
Agriculture	112156	88742	-20.9	120595	101628	-15.7	1.33

Table 10) Comparison of the original landcover areas vs area of landscape types based on those landcover categories in the final landscape maps of NLCS and ICIMOD 2010.

The dampening effect is clear from table 10 (Urban Area and Waterbody are not included because they were excluded from the aggregation phase) as the ICIMOD area change is always smaller than the NLCS area change. A correlation between average NLCS:ICIMOD landcover patch ratio and change ratio is less obvious from this data. The R^2 value of the best fitting trendline through these points is 0.458 ($y = 0.062x^{-1.39}$) (Fig. 77). The Shrubs category could possibly be classified as an outlier because of its enormous NLCS:ICIMOD change ratio of 41.95 (significant in Dean and Dixon outlier test) in which case however there would be even less correlation (R^2 = 0.305. $y = 3.832e^{-7.27x}$). In contrast when disregarding Conifer forest the R^2 value becomes 0.81 ($y = 0.012x^{-2.04}$), providing a much better fit. The amount of datapoints is too small to confidently qualify either Conifer forest or Shrubs as an outlier, hence the existence of a correlation between patch size and area change from landcover to landscape is unclear and the most logical conclusion is that there is little correlation between initial landcover patch size ratio and landscape change ratio between the NLCS based typology and the ICIMOD based typology.

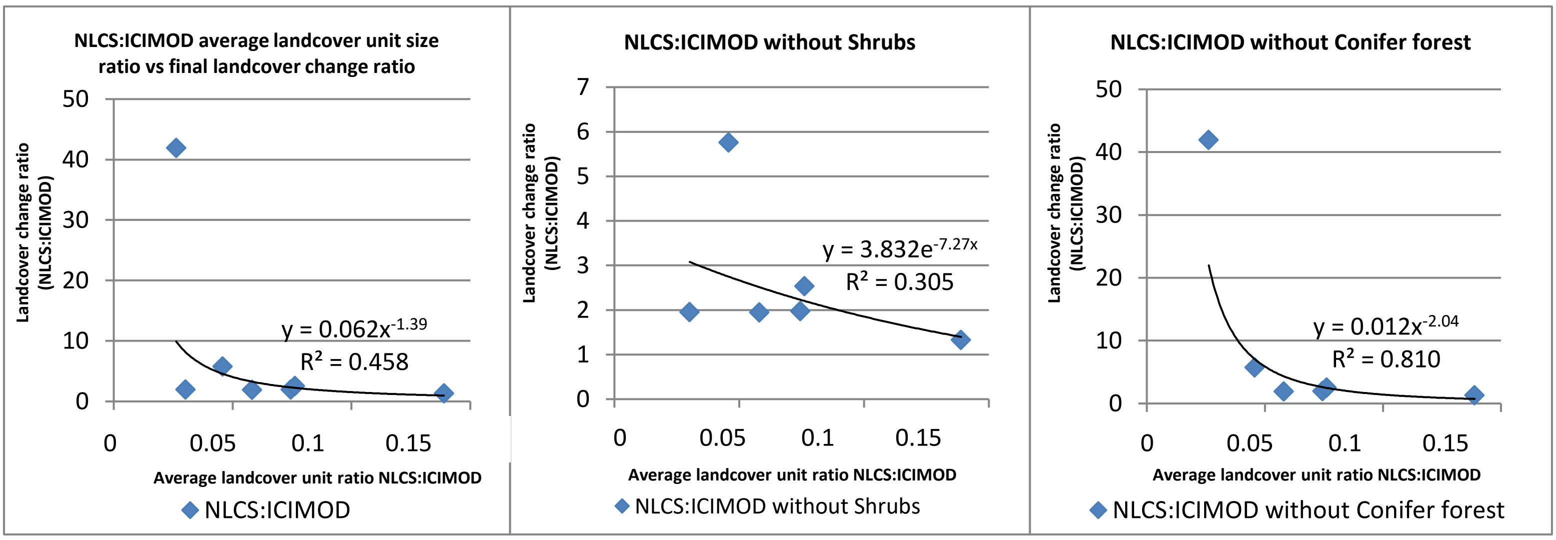


Fig. 77) Plots of average landcover unit size ratios and their best fit trendlines. Left: all categories, middle: possible outlier shrubs omitted, right: possible outlier Conifer forest omitted. On the X-axis the ratios from table 9, on the Y-axis the ratios of table 10 after clustering of the first order map.

In conclusion the ICIMOD dataset has proven to resemble the total areas of the NLCS landcover categories closely making it applicable for the landscape change analysis. The dampening effect of the coarser data through the bigger initial landcover patch sizes should not be forgotten when discussing the results of the change analysis however. With regard to small scale effects of the discrepancy in original relative landcover patch sizes of the ICIMOD data categories compared to the original relative landcover patch sizes of the NLCS data categories it is difficult to predict their influence. There does appear to be some effect on the final representation of each landscape category in the landscape map thanks to this discrepancy but a definitive correlation can't be found. Compared to the dampening effect any influence of the discrepancy seems minor.

4.4.2 Change Analysis

For the change analysis a couple of different sets of landscape types are compared. This is for the sake of clarity as a simultaneous analysis of all 33 occurring types (for the ICIMOD based typology) would be impractical to comprehend. The different sets are:

- The 10 largest total area types
- The 8 smallest total area types
- The pre-selected heritage rich landscape types

All data on landscape type area and individual unit count can be found in appendix C. The low spatial and temporal accuracy of the ICIMOD data limits the analytical possibilities through more extensive statistical analyses like patch- and class-level landscape metrics (Zomeni, Tzanopoulos, & Pantis, 2008) or (stochastic) Markov chain modelling (Weng, 2002). The applied analysis is a simplified version of the post-classification change detection analysis applied by Dewan and Yamaguchi (2009) and the similar diachronic approach of Bender et al. (2005). This is the most that can be done with the available data without hampering the reliability of the results because of the low accuracy of the ICIMOD data. The 1990 coverage area was used as the baseline level for the analysis. A graph visualises the dynamics of the landscape sets. In order to further investigate the dynamics of the landscapes the three landscape maps have been cross tabulated against each. In this way data is created on what portion of each landscape type is converted in what type of new landscape. These tables can be found in appendix D.

4.4.2.1 Change of the 10 largest landscape types

Fig. 78 shows total landscape type areas for the largest 10 landscape types. Many of the landscape type coverages appear to stay relatively constant between 1990 and 2010. Visually many of the largest landscape types are somewhat stable in their total coverage. M_CoF1 shows a small increase in coverage between 1990 and 2000 and A_Shr1 exhibits a small decrease in 2000 returning to almost it's original value in 2010. More significant coverage changes are seen in Snow and Glacier (mild slope), A_CoF1 and N_Gra1. A_CoF1 increases between 1990-2000 and then stabilizes, Snow and Glacier (mild slope) is stable between 1990-2000 but increases greatly between 2000-2010.

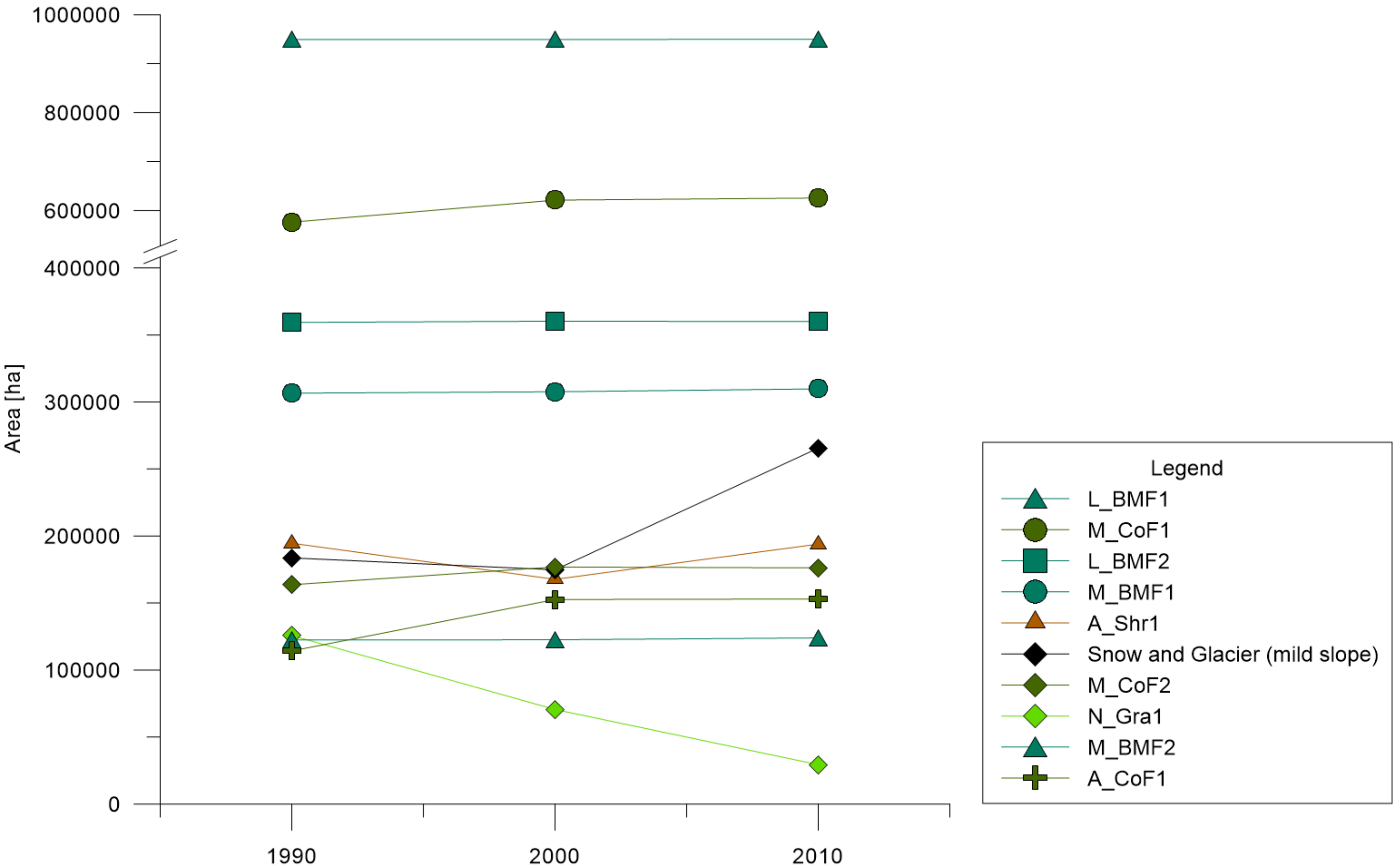


Fig. 78) Total area of the ten largest landscape types from 1990-2010.

Most notably N_Gra1 is the only landscape type that shows a large and steady decline in the entire time frame and might therefore possibly be seen as pressured. The decrease in N_Gra1 between 1990-2000 is primarily explained by losses in area to N_Bar1 (data in appendix D). The net loss of area to N_Bar1 is responsible for 75 % of its decrease. Within this period there is one landscape type that N_Gra1 recovers a significant amount of area from, Snow and Glacier (mild slope) which contributes 12% of the overall coverage change but in the positive. In contrast in the 2000-2010 time frame the coverage change of N_Gra1 is for 82 % explained through coverage loss to Snow and Glacier (mild slope) and only 7 % loss to N_Bar1. When considering the complete time frame between 1990-2010 the contributions of N_Bar1 and Snow and Glacier (mild slope) to the decrease in area coverage of N_Gra1 are very similar at 48 % and 44 % respectively. These are landscape types that are closely related to each other and as such it is highly probable that differing conditions throughout the years can easily lead to Grassland landscapes, Snow and Glacier landscapes and Barren Area landscapes interchanging area. The small impact of other types of landscapes on the N_Gra1 coverage corroborates this theory. As it is quite possible that after a period of climate favourable for grass growth the balance switches to more grassland. Similar changes in this elevation range with little human activity are thus most likely due to natural causes and N_Gra1 should not be classified as an endangered landscape.

For many of the other landscapes the changes are relatively small, and a specific amount of increase or decrease has a larger impact on a landscape type with a smaller total area. It may be more informative to visualise the change in coverage as a percentage of original coverage. This is shown in fig. 79.

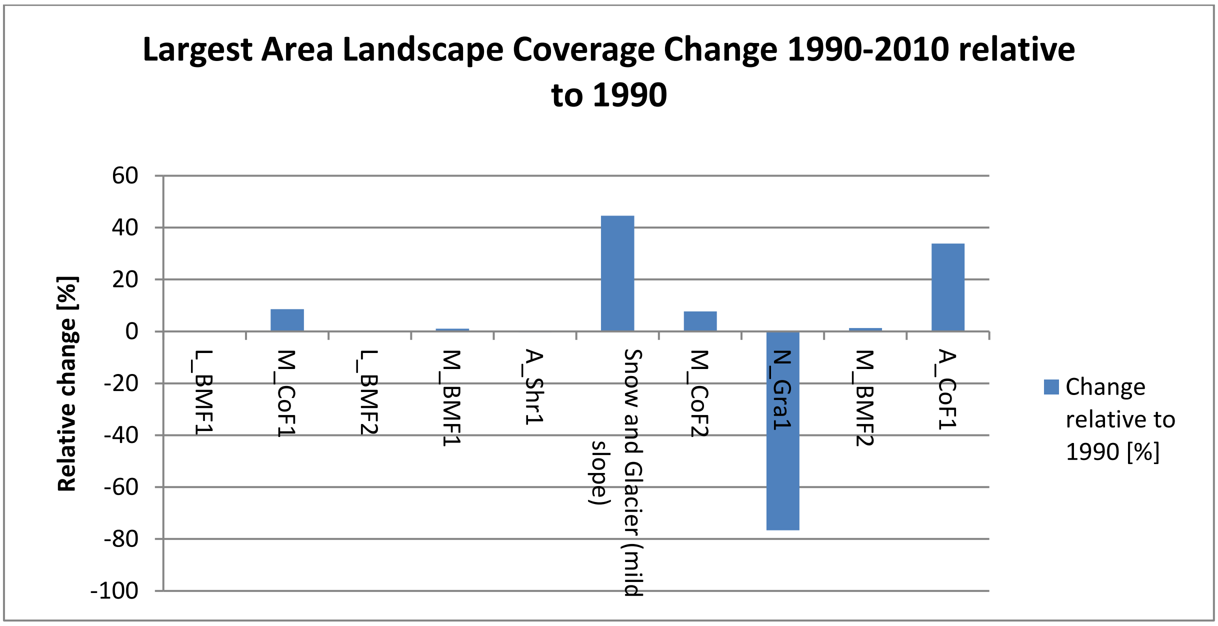


Fig. 79) Total area change relative to 1990 total area.

A_CoF1 shows a large increase of coverage (34 %). The increase occurs primarily between 1990-2000 with the new coverage primarily occupying space that was previously A_Shr1 (85 % of the increase) and A_Shr2 (8 %). The transition into A_CoF1 is also the most important factor for the decrease of A_Shr1 in that period (39 % of decrease) together with A_Shr1 lost to A_Gra1 (30 % of decrease). The A_Shr1 area lost to A_Gra1 is almost completely recovered between 2000-2010 along with a significant portion of the area initially lost to A_CoF1. These interactions appear to be due to fluctuating landscape borders, and the overall landscape coverage sizes of these types don't warrant any concern for these landscapes. The last most notable change is the large increase of Snow and Glacier (mild slope) coverage between 2000-2010, 81 % of this increased coverage area is taken from N_Gra1 and N_Bar1 as discussed earlier.

With regard to the large forested landscape areas more general analysis suffices. Within the Grass and Shrubs elevation range all landscape types show decrease in coverage except A_CoF1, A_CoF2 and A_Shr2. In fact all conifer forest based landscape types are increasing in size in all elevation ranges except the Agricultural zone, where no conifer forest landscape types are found at all. The Broadleaved and Mixed forest landscape types are very constant in coverage even though these represent the largest total coverage in the entire nation (All 4 occurring Broadleaved and Mixed forest based landscape types are found in the top 10). The most significant coverage increase of these landscape types is found in M_BMF2 with a 1.3 % increase in coverage throughout the investigated time frame. These figures mean that Bhutan is very successful in protecting it’s forested landscapes. The National Forest Policy and the Forest and Nature Conservation Act can be seen as a great success according to these numbers.

4.4.2.2 The 8 smallest area landscape types

Total area for the eight landscapes with the smallest coverages are shown in fig. 80. The smallest area landscapes are more dynamic than the largest area landscapes since a small amount of landscape coverage change already has a relatively large impact on these landscapes. They may therefore be more vulnerable to pressure caused by Bhutan’s societal changes.

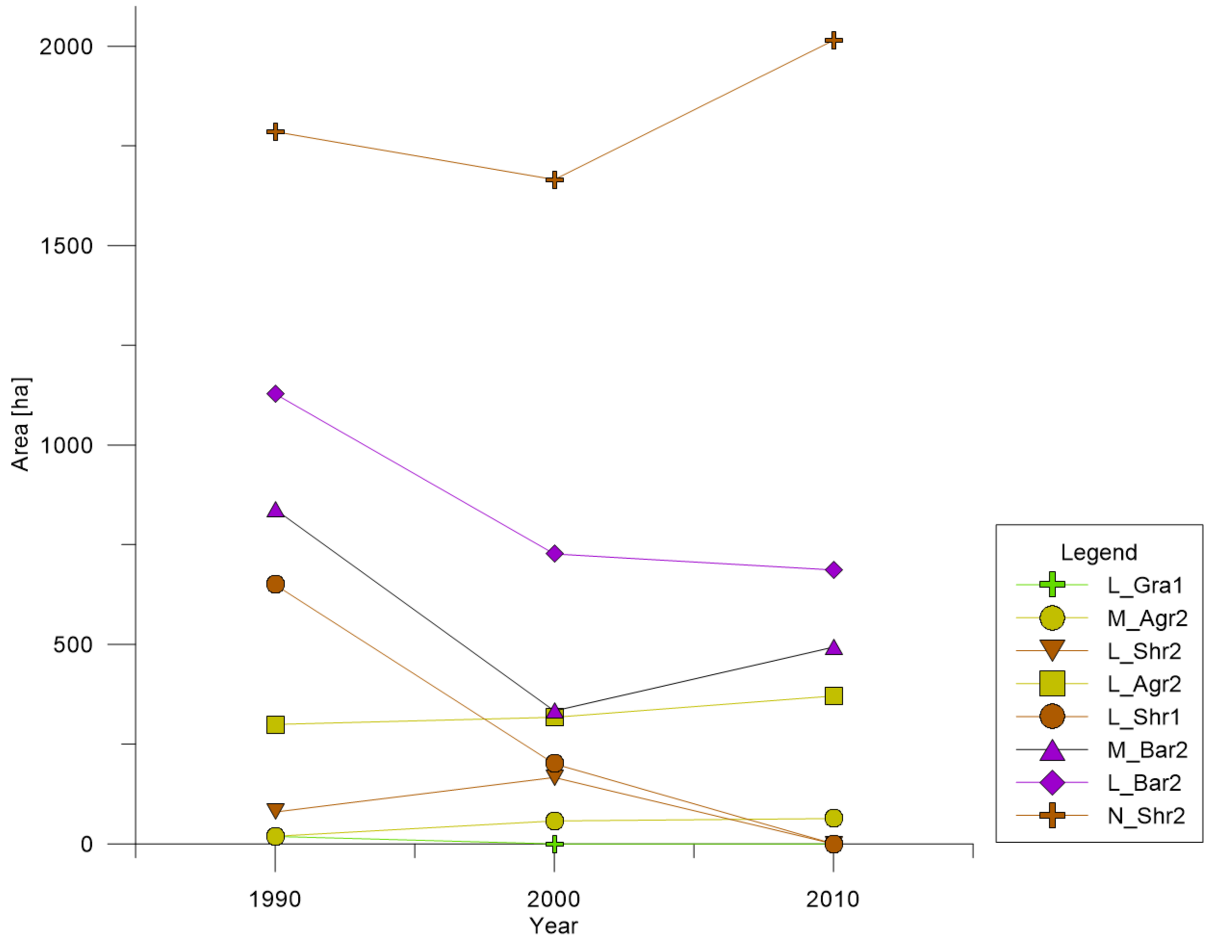


Fig. 80) Total area of the eight smallest landscape types from 1990-2010.

The smallest landscapes are primarily Barren Area, Shrubs and Agricultural landscapes. Five of the landscapes show a continuous downward or upward trend: M_Agr2, L_Agr2 (upwards trend), L_Gra1, L_Shr1 and L_Bar2 (downwards trend). The remaining three have a minimum (N_Shr2, M_Bar2) or maximum (L_Shr2) in 2000. N_Shr2 loses and gains area from other landscape types associated with the higher elevation dynamics discussed in the 10 largest area section (Grassland, Barren Area, Snow and Glacier). The dynamics can be expected to be very similar to those of the large areas.

The Agricultural elevation zone is well represented in this set with five landscape types, indicating that landscape units in this low elevation zone are small or fragmented. There is a steady increase in landscapes associated with agriculture in both elevation zones where agricultural activity is found (Agricultural zone and Tree zone). Throughout the entire time frame L_Agr2 increases by 23.9 %. M_Agr2 increases in total area by an enormous 233.5 %. Compared to the agriculture found on mild slopes the increases in steep slope agriculture are very interesting. In the Agricultural elevation zone the increase of L_Agr1 is a mere 2 % from 1990 to 2010. In the next elevation zone M_Agr1 increases by 24 %. The relative increase in steep slope agricultural landscapes is around ten times that of agricultural landscapes on mild slopes. Along with the larger relative growth of agricultural landscapes in the Tree zone (which is less associated with agricultural activity) this may be indicative of an increased need for agricultural land such that less desirable locations are now also being used for agriculture. M_Agr2 encroaches in only two other landscape types, Grassland landscapes and Broadleaved and Mixed Forest landscapes. L_Agr2 increases area at the expense of Broadleaved and Mixed Forest and Shrub landscapes (see appendix D). Within the Agricultural elevation zone except for Agricultural and Broadleaved and Mixed Forest landscape types all other types (Shrub and Grassland landscapes) decrease in area. Shrub and Grassland landscapes may thus be under pressure from human activities through the increased need for agriculture.

The total area covered by L_Bar2 and M_Bar2 both decrease in total coverage. L_Bar2 decreases both between 1990-2000 and 2000-2010 with the decrease in the later decade smaller than in the former and a total decrease of 39.1 % compared to 1990. It loses coverage only to Broadleaved and Mixed Forest landscapes. M_Bar2 decreases from 1990 to 2000 but increases in the next decade, with a decrease over the entire time frame of 41.2 %. M_Bar2 loses area to many landscape types, but the most important ones are again Broadleaved and Mixed Forest types and Agricultural types.

L_Shr1 and L_Shr2 both decrease in area over the entire time frame. L_Shr1 however decreases over both decades whereas L_Shr2 only decreases between 2000 and 2010. Over the entire time frame L_Shr1 loses almost all of its area to increased agriculture (89 % of the change in total area is explained by loss to agriculture). L_Shr2 can ascribe almost 100 % of its area loss to Broadleaved and Mixed Forest landscapes. This is probably due to natural encroachment of the forests on these otherwise undisturbed locations.

As noted earlier this may be an indication of the pressure to increase the amount of agricultural area. First the Bhutanese may have used more easily farmable flatter areas for creating additional agricultural land and later on they start using the less easily farmable steep areas.

4.4.2.3 The pre-selected heritage rich landscape types

The change in landscape types associated with heritage can shed light on the vulnerability of heritage features under the dynamics of modernizing Bhutan. However of the eight pre-selected heritage dense landscapes (>0.005 features per ha, urban area neglected) two of them are not present in the ICIMOD based landscape maps. These two are L_CoF1 and A_Agr1. This discrepancy can probably be ascribed to the algorithm used by ICIMOD as from the data it appears that Conifer forest and Agriculture designation of areas has a cut-off value at specific elevations. The change analysis for heritage dense landscapes can only be done for the remaining six landscape types. Their data is displayed in fig. 81.

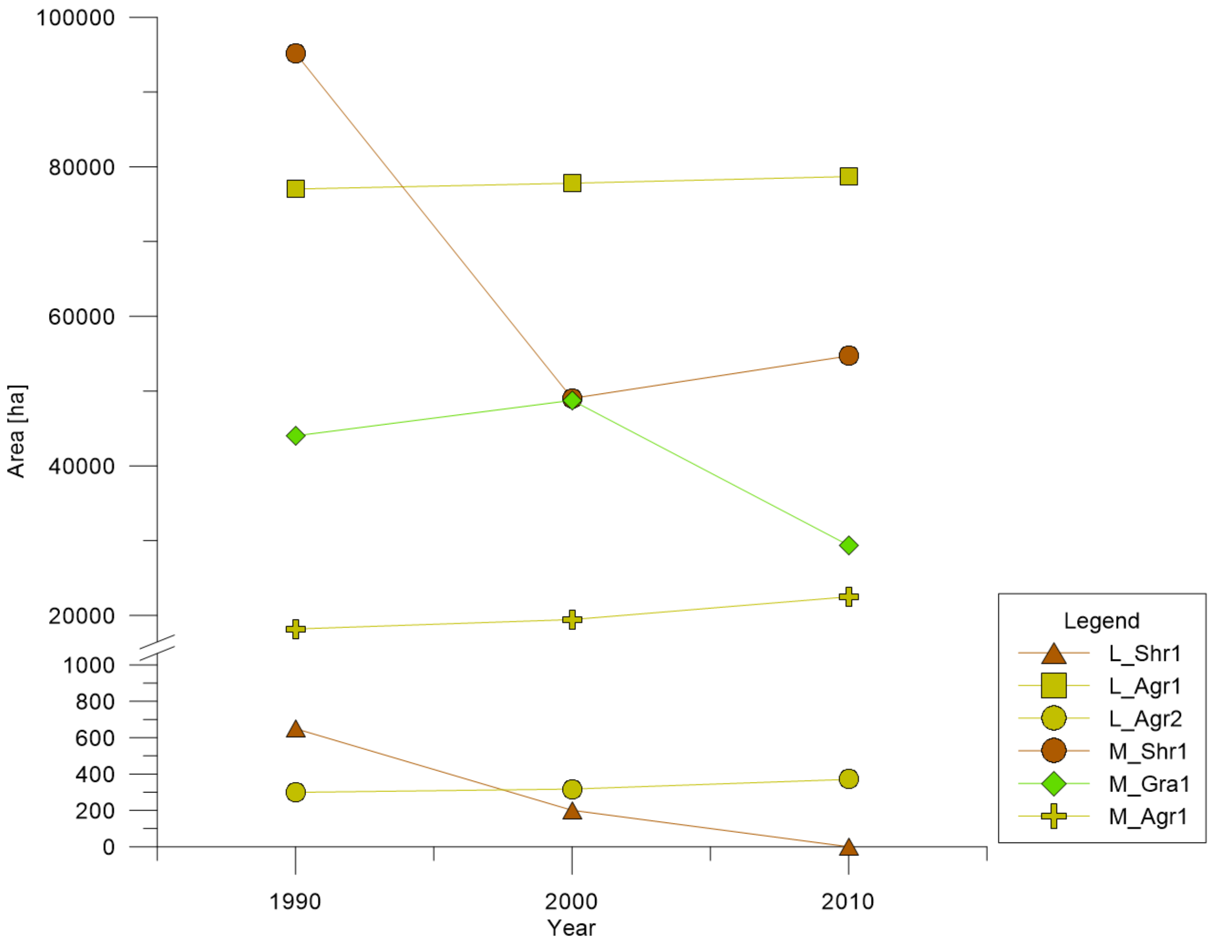


Fig. 81) Total area of the pre selected heritage rich landscape types from 1990-2010.

The total amount of pre-selected heritage dense landscape types have decreased in coverage by 49727 ha between 1990 and 2010 (-21 % of the 1990 original combined total coverage area). Out of the six analysed landscape types three have declined in total area and three have increased. Two of the heritage rich landscape types also belong to the landscape types with the smallest total coverage (L_Shr1 and L_Agr2). L_Shr1 disappears completely and as mentioned before this appears to be caused by the pressure exerted from the increased demand for agricultural land leading to an increase in Agricultural landscape, in particular in this case L_Agr1 which is responsible for 89 % of the lost area of L_Shr1. All heritage rich landscapes that increase in area are agricultural landscape types. These landscape types have a steady upward trend. M_Gra1 increases slightly between 1990 and 2000 but then decreases sharply between 2000 and 2010. This fits with the change analysis for the eight smallest landscape areas that showed grassland area is under pressure. In the case of M_Gra1 only a part of the lost area can be ascribed to increased agricultural area (15 % of M_Gra1 decrease). As might be expected in this elevation zone area loss to forested landscape types have a larger influence as 62 % of decrease is lost to M_Cof1 and 20 % to M_BMF1. As a side note the data fits with the supposed properties of the elevation zones, indicating the parameters for dividing the zones have been chosen correctly. M_Shr1 increases in area after a large decrease between 1990 and 2000. The total coverage has decreased significantly over the entire time frame (Fig. 82). 94 % of M_Shr1 area is lost to Conifer Forest landscapes between 1990 and 2010. Fig. 82 also clearly shows how the most heritage dense landscape types show large relative decreases in total coverage (L_Shr1 -100 %, M_Shr1 -43 % and M_Gra1 -33 %) versus smaller relative increases in total coverage for L_Agr1 (2 %), L_Agr2 (24 %) and M_Agr1 (24 %).

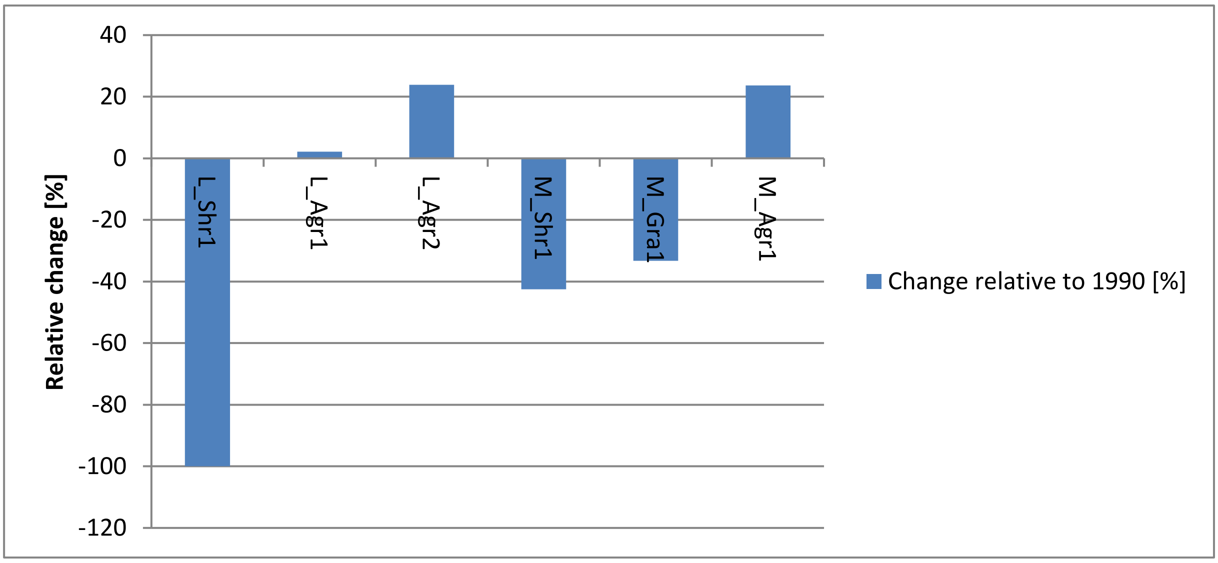


Fig. 82) Total area change of the heratige dense landscapes relative to 1990 total area.

The increased area of L_Agr1 is taken in roughly equal amounts from L_Shr1, L_Bar1 en L_BMF1. M_Agr1 receives it's additional area primarily from M_Gra1 and M_Bar1. L_Agr2 shows a large relative change but is so small in total coverage that it's dynamics are of no real influence on any of the other landscape types.

The shift in landscape type in which the heritage features may be found should perhaps be interpreted as more important than their absolute coverage areas. As landscape type changes heritage features are not necessarily destroyed. Their historical function in the landscape however can be lost as well as their perceived ties to their particular location leading to a diminished importance and a larger probability of degrading (due to lack of maintenance or later destruction). Many of the historical heritage features have (origin) stories attached to them that relates to the landscape in which they are found. The features and the landscapes have historically evolved around -and co-existed with- each other, a symbiotic balance that may very well be disturbed by the processes associated with modernisation of the nation and accompanying landscape change. This analysis shows heritage dense agricultural landscape types increase in coverage whereas all other heritage rich landscape types decrease. Therefore it is a very real possibility that historical cultural landscapes are threatened by, amongst other possibilities, agricultural needs creating pressure on the historical landscapes. This is a finding where further study is advisable in order for Bhutan to comply with its aim to develop in a culturally sustainable fashion.

A couple of other sets were considered for analysis, namely largest absolute changes, largest relative changes, and landscape types with the smallest average individual units. Many of the landscapes that would be in those sets were already represented in the other analyses in this chapter, and otherwise many of them have already been discussed when trying to explain the behaviour of landscape types in the discussed sets.

5. Discussion

The landscape map created in this study is found to be fairly precise. For the final accuracy figures of the automated landscape map it is stated that the figure that best reflects the real life accuracy of the method is 86.6 %. Low accuracy was found in high mountainous regions with high day-to-day variability. Separating snow cover from glaciers could improve the results. Without such a distinction the landscape map may not be suitable for end-users with a focus on those regions. The inaccuracy in these regions is further ascribed to vague landscape boundaries. Even in areas with low accuracy the landscape map helped improve understanding of the landscape.

Validation has returned one important weak point of the method. It was found that landscape units of the same type can in some cases differ in character, here the area is not as homogenous as the typology might suggest. In these cases the landscape unit includes significant amounts of patches of a different landcover, often of the same kind. A suggestion for the typology would be to include a patchiness factor in the landscape designation. The data can for example be appended to the typology by using landscape metrics to calculate a parameter indicating the patchiness of the landscape unit. The usefulness of such a parameter and difficulties with their implementation have been discussed by Lausch and Herzog (2002). Otherwise a more general 'patchiness' layer could be created beforehand and included as source data when creating the first order typology. It is recommended to include what type of patches are dominant in a landscape unit in this attribute. The inclusion of this data might also be able to further enhance the predictive power of the heritage prediction models or the informative possibilities of the landscape change analysis.

What is important to remember is that some dissimilarity is not a major problem. The landscape map is a semi-schematic approximation by definition, and like all maps inaccuracy compared to the real world situation is unavoidable, whether it is because of simplification of data for practical purposes (which is the case here), translation of a three dimensional object to a 2D surface or any other reason. What the validation of the method relying on NLCS landcover data shows is that the landscape map is able to aid in finding trends in landscape distribution or pinpoint where a certain landscape can be found.

An interesting result from the landscape change analysis is the large increase in Snow and Glacier (mild slope). After the small dip in 2000 there is an enormous increase in total area of 44.6 % compared to 1990. Satellite imagery of those years found in Google Earth does show this decrease-increase pattern when comparing areas in detail, however a 44.6 % increase seems unlikely based on visual interpretation. The most plausible explanation would be that the Google Earth images and the images used by ICIMOD are of different dates as snow cover is highly variable from day-to-day. This could also be improved by separating snow cover from the more stable glaciers.

Another recommendation for this typology or possible future typologies using this method would be to devise a way to guide the assimilation process between the first order and final typologies. In this paper sub MMU landscape units were assimilated by the landscape units with the longest shared border. To more accurately portray the real situation some preference should be included to have similar landscape units assimilate each other. One idea is to include a weight for each landscape type pair indicating their similarity. This weight should be used together with shared border lengths to determine what unit a sub MMU unit will assimilate into. So a shorter border with a neighbouring unit of a similar landscape type should take precedence over a longer border with a less similar landscape type up to a certain limit. Implementing such a system would require knowledge on smaller scale or more subtle landscape dynamics and properties. The weights would be representative of a particular region, so such a system would diminish the flexibility, robustness, objective nature and reproducibility of the methodology.

This study limited the amount of possible landscape types by limiting the amount of classes represented in the thematic base data. There are other viable options to limit the final total amount which were rejected for this study but might be interesting for future versions. One option is to disregard landscape types smaller than a certain percentage of Bhutan's total area, adding these to another type. Another option is to disregard types that have a small amount of individual units. The addition to another (larger) landscape type could then be based on most similar hierarchical type, i.e. the most dependent attributes would first be grouped. For this study there were no relevant figures to base the cut-off values on. For a first landscape map it might even be undesirable as types with a small total area or amount of units might prove to be important for particular types of users. Future experience with the use of the map could guide such decisions if a newer version is made.

A final recommendation would be to refrain from using the raster format as an intermediate step. The conversion between raster and vector formats may introduce errors. Also converting vector data into raster data will normally decrease its resolution and accuracy. The NLCS vector based landcover data in this study was already based on a raster file as was evident when zooming in close enough which reveals stepped borders. Vector data does require more computing power and memory space and the gain in accuracy can be limited so this is not the most important improvement. In reality it would be a decision made based on available computing power, study area size and original source data formats.

This study resulted in a number of general findings. First of all it was found in the course of this study that it is customary practice for landscape typology and map creators to develop a customised method. This has led to a patchwork of incompatible typologies, instigating efforts to standardise landscape typologies for supranational areas like LANMAP. These efforts aim at "brute-forcing" a landscape typology covering areas the size of continents, or even the entire globe. Inevitably such typologies will suffer from destructive generalisation by using source data that is too general to do justice to the diversity in actual landscapes. This approach also necessitates the use of multiple sources for the same thematic source layer as coverage of such data often does not extend across the entire area of interest, forcing the developers to edit the original datasets to comply with each other. Also too large MMU sizes are used. Typologies created in this way will be too general to use for research or policy-making and may cause discontent in regions when policy based on these general landscape maps affects their inhabitants in a negative way. According to Zoderer et al. (2016) traditional landscapes are extremely important and highly valued but often small and scattered. This is exactly the type of landscape important for policy-makers and locals as well as the type that will be missed by such landscape maps.

This paper puts forward another approach to international or continent-wide landscape typology creation and mapping that will return more useable results and involve regions in the creation of the typology. A preferable approach to large scale typology creation would be to create a standard framework using a version of this method and guidelines for choosing source data, determining class boundaries and for documenting and visualising the final typology. In this way regions can incorporate local knowledge and values in the landscape map, but the results of all regions will be easily comparable combining into a supranational landscape map. In this study an attempt has been made to rationalise the choices made with regard to source data and source data class boundaries which was absent in the landscape typology papers reviewed for this study. Documenting the rationalisation behind choices should be an integral part of the standard framework as it is imperative to end-users when trying to understand, verify or adapt a typology. The methodology of this paper fulfils all requirements set by Mücher et al. (2009) for a standard typology. The flexibility in a well structured GIS and methodological transparency requirements may even be fulfilled to a higher degree. The work described in this paper may help with the creation of comprehensive typologies spanning across nations as the method developed for the Bhutan typology has proven to be simple, flexible, robust and accurate. The possibility to implement as many source data layers as needed (by applying the reclassification scheme with as many digits as needed in the source data combination phase) and create an accurate landscape typology and map in a straightforward manner without the use of specialist software apart from a GIS program is not found in earlier typology methods.

A second finding of this paper was the absence of a relief roughness indicator capable of accurately discerning relief variability. Many commonly used indicators are based on some ratio of cell size and elevation range that disregards undulation and amplitude of the relief within the cell. The Comprehensive Ruggedness Indicator (CRI), developed in this study, is capable of distinguishing different types and extents of relief roughness. Additionally sensitivity and resolution can be scaled. In the reviewed indicators this accuracy combined with flexibility was not possible. A drawback of CRI is the need for a realistic yet DEM-based stream network. If available an official stream network can be used, however sensitivity is not scalable in that case. Because the supplied official stream network did not cover the entire nation and the accepted method for calculating a stream network based on the DEM returns a model with too many errors and artefacts it was not possible to include this landscape attribute. In order for CRI to be used to its full potential a new, more accurate method for calculating DEM based stream networks is needed. This would be an interesting opportunity for new research. Improvements might for example be found in the emerging field of machine learning.

The heritage prediction model presented in this thesis is primarily intended to show the power and usefulness of the landscape typology. Factors for predicting heritage locations were based on field visits and data already available within the project. Better results can be achieved by archaeologists and other heritage experts by adding additional data of determining factors together with the landscape map. This model must thus be seen as a tentative case study and not be used as a comprehensive guideline for directing future archaeological research. Thorough investigation and implementation of spatial and temporal patterns of Bhutanese customs and practices and extensive selection of factors dictating heritage locations was outside the scope of this case study.

The landscape map has been received positively by the World Bank where it is being used to help with their development and research for projects in Bhutan. In this light it has been passed along to the team working on the *Cumulative Impacts of Hydropower in the Kuri-Gongri River in Bhutan* project. Positive reactions have also been received from an archaeologist specialising in Bhutan and the NLCS who will add the landscape map to their published paper atlas. This means that the potential and usefulness of the typology and associated landscape map is recognized by both governmental and non-governmental organizations. The landscape map as a tool has many more possibilities than the two use-cases examined in this paper. Among many options one could think of aiding with zonal planning, environmental protection and use by the tourism industry. This versatility combined with the mapping accuracy and enthusiasm expressed by policy-makers and researchers leads to the final conclusion that the landscape typology is successful.

6. Conclusion

The primary goal of this study was to create a nationwide landscape typology and map for Bhutan to be used as an aid for ensuring ecologically and culturally sustainable development. The incredible rate at which Bhutan is changing because of the recent end to their self-imposed isolation has had an enormous influence on the nation both ecologically and culturally. The Bhutanese government is acutely aware of the possible detrimental effects this can have on, amongst many other issues, their (cultural) landscapes. A landscape typology and map may be an important tool for protection and conservation of Bhutanese nature and culture which are closely entwined.

A review of existing methods was done to find an optimal method to design a landscape typology. The literature review revealed that most existing typologies are created using an individually customised method. The patchwork of different typologies that policy-makers and researchers have to deal with have given rise to a need for a standardised typology and led to efforts to create a pan-continental/supranational landscape typology. In this study it was found that a standardised framework used by individual regions is preferable over the normally used approach of a centrally created generalised landscape typology and map.

The method designed for this study is similar to the method used by van Eetvelde and Antrop (2009) in that initially a first order landscape map was created by combining all the landscape attributes in a tessellated grid cell layer which was then refined into a final product. The method used in this study was simpler in its execution by relying less on multiple calculated landscape metric properties for clustering and relying more on automated designation in the final product. The method conforms to the requirements set by Mücher et al. (2009). The study proves that a simple highly automated method can produce accurate landscape designation which is easy to understand because of its simplicity and the provided rationalisation behind choices that were made.

Another find of this literature review was that hardly any typologies, if any at all, exist for Asian regions. This fact combined with the lack of a standardised typology creation method meant that a new method had to be devised for the Bhutanese landscape typology. The knowledge of existing methods and the possible future need for a coherent pan-Asia landscape typology steered the methodology to a robust but simple and flexible design. A physicogeographical parametric method was designed which is capable of automated landscape designation over any area size using as many source datasets as desired. For the typology altitude, landcover and slope were used. Classes for altitude were determined using landcover distribution statistics, slope classes were determined using settlement data. These classified datasets were combined into a first order typology which was then shaped into the final landscape typology by enforcing a minimum mapping unit. For a general overview a 230 ha MMU was used while for research and policy-making purposes a more detailed 15 ha MMU was used. The 15 ha MMU is representative of average national landscape sizes and should result in a representative landscape delineation. The resulting landscape map was verified using satellite imagery and knowledge of the area acquired through a field visit. Both a comparison between manually designated landscapes in five sample areas and a visual comparison of ten additional sample areas returned a good performance of the automatically generated landscape map.

The visual validation showed accurate landscape delineation using the automated typology. Most inaccuracies were traced back to landcover data not matching with satellite imagery, which analysis shows may be based on pre-2010 data in some cases. One performance issue of the typology is when multiple substantial but sub-MMU sized areas are assimilated into a single landscape. This can result in two landscapes to be designated with the same landscape type even if a human observer would consider them to be different in character. This effect is not always as important and was only found in two of the sample areas so does not necessarily render the map useless.

Having validated the landscape map and found it to be accurate the power of the landscape map and associated typology as a tool for aiding with policy-making and research were demonstrated by two use-cases. First the landscape map was used to create a heritage occurrence prediction model. Because of the limited knowledge about pre 19th century Bhutan difficulties have been experienced in performing archaeological research. Designation of possible archaeological sites is very difficult as there is little information on which to base decisions of which sites to allocate research time and funds to. Archaeologists have previously used GIS to extrapolate heritage feature location attribute patterns to large areas. Landscape is a very important factor and can now be applied to create a Bhutanese archaeological prediction model. Two models were created using both an inductive and deductive approach. The statistical inductive model showed that landscape type can be a more determining factor than distance to Urban Area and distance to River with higher correlation coefficients for heritage dense landscape types indicating a larger explanatory value. Compared by influence per area unit the landscape types can be many times more discerning than the classically significant distance to Urban Area or distance to River attributes. The different landscape categories also have a large difference in explanatory value between them again indicating the excellent explanatory value added to the model by using the distinction between landscapes.

Both models were able to designate sites with high heritage potential. Using the deductive model a possible undocumented temple was found. Both models were successful at designating areas with human activity even when the source data used for either the landscape map or the archaeological model had no record of human activity in these locations. This suggests that the models perform well as heritage features are most prevalent near locations with human activity. Using the landscape map in this way can help both researchers and policy-makers. Researchers can make better informed decisions where to conduct research with maximum efficiency. Policy-makers can use this information to guide zoning planning, construction projects and generally improve preservation of heritage.

The second case study examined landscape change. This is important for Bhutan as landscape and culture are closely intertwined. Landscapes are under pressure because of the modernisation of Bhutan. An accurate landscape map is instrumental in analysing the status of these landscapes. The additional value of a landscape map over merely landcover data for the change analysis is found in a better representation of different factors that also have an influence on the pressures relevant to a particular landscape. A specific type of landcover might be under pressure in a certain area but still show a stable net area size, or even an increasing net area size. The landscape map incorporates more factors and can therefore be able to spot landscapes under pressure where a purely landcover based analysis would miss them. In other words a landscape map has the added value of more precisely describing an area and the changes that occur there, revealing more information about the processes taking place. Change analysis of the largest landscape types show that coverage of grassland, barren area and snow and glacier landscapes appear to be closely related within the Nival elevation zone. This appears to be an interaction based primarily on natural (climate) factors and therefore not require intervention by the Bhutanese government. The numbers indicate that the

National Forest Policy and the Forest and Nature Conservation Act are working very well. Forests across Bhutan are stable or increasing in size, Broadleaved and Mixed forest landscapes have increased in coverage between 0.06 and 1.28 %. Conifer Forest landscape types have increased more significantly with a maximum coverage increases of 36.5 %. There is some doubt about the reliability of the snow coverage (mild slope) and N_Gra1 figures because of the use of different dates and/or image quality issues.

The landscape types with the smallest coverages appear to be under pressure from forested landscapes and agricultural landscapes. The landscape types with smallest total areas are primarily in the elevation zones with the largest human populations. This fact combined with the increased total area of agricultural landscapes creates the idea that human activity creates a significant pressure on these small coverage landscape types. The larger increase of agricultural landscape on less desirable steep slopes suggests the need for agricultural area is growing rapidly. This is a factor that Bhutanese policy-makers should take note of. There is a marked decrease in coverage of heritage dense landscapes other than agricultural landscape types. As seen when evaluating the other landscape sets agricultural landscapes are gaining area at the cost of other landscape types. This can act as a threat to historical cultural features as their perceived function and importance is often derived in a large part from the landscape in which they are found. If the type of landscape changes the role of the historical feature can be lost, thereby diminishing its importance in the eyes of the local people and increasing the risk of the feature disappearing.

The method devised to create the typology and landscape map is robust and flexible, as shown by the possibility to easily substitute source data for the landscape change analysis. The demonstrated accuracy of the landscape map shows that a simple methodology can be very powerful with the right source data. For Bhutan elevation, land cover and slope were selected, for other regions other landscape attributes will be more important. Elevation and slope for example will be substituted in regions without much topology, for example by hydrology and/or soils. Therefore this methodology could also be used to build a standardised framework with which coherent supranational typologies can be created, building upon and adding to the work done by Wascher (2005) and Mücher (2009).

The case studies show the potential of the landscape map as a tool for researchers and policy-makers, in the case of Bhutan providing a great tool to help the Bhutanese achieve their goal of ecologically and culturally sustainable development. The need for such a tool and confidence in the product from this study is already evident from the quick adoption by policy-makers and researchers alike. This quick adoption combined with demonstrated high accuracy makes the typology and landscape map based thereon a success.

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References

Allison, E. (2015). Religion Inscribed in the Landscape: Sacred Sites, Local Deities and Natural Resource Use in the Himalayas. In S. Brunn, *The Changing World Religion Map.* Dordrecht: Springer.

Arches Project. (2016). *Arches: Protecting the world's irreplaceable cultural sites.* Retrieved from: http://archesproject.org/wp-content/uploads/2016/09/Arches_GettyMag_Sum2016.pdf

Aris, M. (2005). *The Raven Crown: The Origins of Buddhist Monarchy in Bhutan*. Chicago: Serinda Publications.

Ascione, A., Cinque, A., Miccadei, E., Villani, F., & Berti, C. (2008). The Plio-Quaternary uplift of the Apennine chain: new data from the analysis of topography and river valleys in Central Italy. *Geomorphology, 102*(1), 105-118.

Asian Development Bank. (2005). *Country Strategy and Program 2006-2010: Bhutan.* Mandaluyong: Bhutan Country Team

Bailey, R. (1989). Explanatory supplement to ecoregions map of the continents. *Environmental Conservation, 16*, 307-309.

Barth, A. (2012, March 19). *World Bank Commits to Open Geo Data - OpenStreetMap's Hour?* Retrieved from: https://developmentseed.org/blog/2012/mar/19/world-bank-open-geo-data/

Bastian, O. (2000). Landscape classification in Saxony (Germany) - a tool for holistic regional planning. *Landscape and Urban Planning, 50*, 145-155.

BBC. (2018). *Bhutan profile – Timeline.* Retrieved from http://www.bbc.com/news/world-south-asia-12641778

Bender, O., Boehmer, H. J., Jens, D., & Schumacher, K. P. (2005). Using GIS to analyse long-term cultural landscape change in Southern Germany. *Landscape and Urban Planning, 70*, 111-125.

Blankson, E. J., & Green, B. H. (1991). Use of landscape classification as an essential prerequisite to landscape evaluation. *Landscape and Urban Planning, 21*, 149-162.

Brabyn, L. K. (2009). Classifying Landscape Character. *Landscape Research, 34*(3), 299-321.

Brabyn, L. K. (1996). Landscape Classification Using GIS and National Digital Databases (Dissertation). Department of Geography, University of Canterbury.

Brown, G. (2004). Mapping Spatial Attributes in Survey Research for Natural Resource Management: Methods and Applications. *Society & Natural Resources, 18*(1), 17-39.

Brown, G., & Brabyn, L. (2012). An analysis of the relationships between multiple values and physical landscapes at a regional scale using public participation GIS and landscape character classification. *Landscape and Urban Planning, 107*, 317-331.

Brown, G., & Raymond, C. M. (2007). The Relationship between Place Attachment and Landscape Values: Toward Mapping Place Attachment. *Applied Geography, 27*, 89-111.

Brown, L., & Mayhew, B. (2014). *Lonely Planet Bhutan.* Lonely Planet.

Centre for Bhutan Studies & GNH. (2018). *Centre for Bhutan Studies & GNH*. Retrieved from: http://www.bhutanstudies.org.bt/

Chand, R., Nel, E., & Pelc, S. (2017). *Societies, Social Inequalities and Marginalization. Marginal Regions in the 21st Century.* Cham: Springer International Publishing.

Cooley, S. (2016). *Terrain Roughness - 13 ways*. Retrieved from: http://gis4geomorphology.com/roughness-topographic-position/

CoE. (2000). European Landscape Convention, Florence, October 20, 2000. *European Treaty Series No.176*, Florence.

CoE, UNEP, ECNC. (1996). *The Pan-European Biological and Landscape Diversity Strategy: A Vision for Europe's Natural Heritage.* Strasbourg: Council of Europe Publishing.

De Agar, P.M., Ortega, M., & de Pablo, C.L. (2016). A procedure of landscape services assessment based on mosaics of patches and boundaries. *Journal of Environmental Management, 180,* 214-227.

Department of Culture - Ministry of Home and Cultural Affairs. (sd). *Department of Culture - Ministry of Home and Cultural Affairs*. Retrieved from: http://www.departmentofculture.gov.bt/en/

Department of Culture. (2016). *Cultural Heritage Act of Bhutan 2016.* Thimphu.

Department of Culture. (n.d.). *Cultural Heritage Regulation 20… (draft for submission).* Thimphu.

Dewan, A. M., & Yamaguchi, Y. (2009). Land use and land cover change in Greater Dhaka, Bangladesh: Using remote sensing to promote sustainable urbanization. *Applied Geography, 29*, 390-401.

Dharmadhikary, S. (2015, 08 01). *Hydropower in Bhutan - Time for a Rethink?* Retrieved from: https://www.internationalrivers.org/blogs/328-5

Food and Agriculture Organization of the United Nations. (2005). *Land Cover Classification System Classification concepts and user manual Software version (2).* Rome: Di Gregorio, A., & Jansen, L. J.

Espa, G., Benedetti, R., De Meo, A., Ricci, U., & Espa, S. (2006). GIS based models and estimation methods for the probability of archaeological site location. *Journal of Cultural Heritage, 7*, 147-155.

ESRI. (2017). *Deriving runoff characteristics.* Retrieved from: http://pro.arcgis.com/en/pro-app/tool-reference/spatial-analyst/deriving-runoff-characteristics.htm

Gharadjedaghi, B., Helmann, R., Lenz, K., Martin, C., Pieper, V., Schulz, A., et al. (2004). Verbreitung und Gefährdung schutzwürdiger Landschaften in Deutschland. *Natur und Landschaft, 79*, 71-81.

Ministry of Agriculture and Forests. (2009). *Community Forestry in Bhutan: Directions for the future. Proceedings of a National Workshop Thimphu, Bhutan, 16-17 April, 2009.* Thimphu; Gilmour, D., Chhetri, B. B., Temphel, K. J., & Schmidt, K.

Global Land Cover Facility. (sd). *Data & Products*. Retrieved from: http://glcf.umd.edu/data/

GNH Centre. (sd). *The 4 Pillars of GNH*. Retrieved from: http://www.gnhcentrebhutan.org/what-is-gnh/the-4-pillars-of-gnh/

Google. (2013, June 26). *Only clear skies on Google Maps and Earth*. Retrieved from: https://maps.googleblog.com/2013/06/only-clear-skies-on-google-maps-and.html

Google. (2016, June 27). *Timelapse*. Retrieved from: https://techcrunch.com/2016/06/27/google-earth-and-maps-get-sharper-satellite-imagery-with-new-update/

Groenewoudt, B. J., & Kvamme, K. L. (1992). An Experiment in Archaeological Site Location: Modeling in the Netherlands using GIS Techniques. *World Archaeology, 24*(2), 268-282.

Grohmann, C. H., Smith, M. J., & Riccomini, C. (2011). Multiscale Analysis of Topographic Surface Roughness in the Midland Valley, Scotland. *IEEE Transactions on Geoscience and Remote Sensing, 49*(4), 1200-1213.

Groom, G. (2005). *Methodological review of existing classifications.*

Guo, Z., Zhang, L., & Li, Y. (2010). Increased dependance of humans on ecosystem services and biodiversity. *Plos ONE, 5*.

Gupta, A. (2007). *Going to school in South Asia.* Westport: Greenwood Publishing Group.

Hoechstetter, S., Walz, U., Dang, L. H., & Thinh, N. X. (2008). Effects of topography and surface roughness in analyses of landscape structure – A proposal to modify the existing set of landscape metrics. *Landscape Online, 1*, 1-14.

Holdridge, L. (1947). Determination of World Plant Formations From Simple Climatic Data. *Science, 105*(2727), 367-368.

Humanitarian OpenStreetMap Team. (sd). *The World Bank*. Retrieved from: https://hotosm.org/partner/the_world_bank

ICIMOD. (1990/2000/2010). *Land Cover of Bhutan 1990/2000/2010* [Data file]. Retrieved from: http://rds.icimod.org/Home/DataDetail?metadataId=8880&searchlist=True

ICIMOD. (2018). *Mountain Geoportal*. Retrieved from: http://www.icimod.org/?q=20438

International Rivers. (2015, April 14). *Status of hydropower dams in Bhutan*. Retrieved from: https://www.internationalrivers.org/resources/8703

Janík, T., & Romportl, D. (2016). Comparative Landscape Typology of the Bohemian and Bavarian Forest National Parks. *European Journal of Environmental Science, 6*(2), 114-118.

Jellema, A., Stobbelaar, D., Groot, J.C.J., & Rossing, W.A.H. (2009). Landscape character assessment using region growing techniques in geographical information systems. *Journal of Environmental Management, 90,* 161-174.

Jennes, J. (2006). *Topograpic Position Index (TPI) v.1.2.* Flagstaff: Jennes Enterprises.

Jenny, H. (1941). *Factors of soil formation.* New York/London: Mac Graw-Hill.

Jet Propulsion Laboratory (JPL). (sd). *ASTER Mission*. Retrieved from: https://asterweb.jpl.nasa.gov/mission.asp

Kamermans, H., & Wansleeben, M. (1999). Predictive Modelling in Dutch Archaeology, Joining Forces. *New Techniques for Old Times. CAA98. Computer Applications and Quantitative Methods in Archaeology. Proceedings of the 26th conference, Barcelona, March 1998 (BAR International Series 757).* Oxford: Archaeopress.

Klijn, F., & de Haes, A. U. (1994). A hierarchical approach to ecosystems and its implications for ecological land classification. *Landscape Ecology, 9*(2), 89-104.

Klinkenberg, B. (1992). Fractals and morphometric measures: is there a relationship? *Geomorphology, 5*, 5-20.

Knaster, M. (2008). *Bhutan at a Crossroads.* Retrieved from https://greatergood.berkeley.edu/article/item/bhutan_crossroads

Kottek, M., Grieser, J., Beck, C., Rudolf, B., & Rubel, F. (2006). World Map of the Föppen-Geiger climate classification updated. *Meteorologische Zeitschrift, 3*(15), 259-263.

Lausch, A., & Herzog, F. (2002). Applicability of landscape metrics for the monitoring of landscape change: issues of scale, resolution and interpretability. *Ecological Indicators, 2*, 3-15.

Lioubimtseva, E., & Defourney, P. (1999). GIS-based landscape classification and mapping of European Russia. *Landscape and Urban Planning, 44*, 63-75.

Lipský, Z., & Romportl, D. (2015). *Classification and typology of cultural landscapes: methods and applications.* Prague: Charles University Prague, Faculty of Science.

Marusic, J. (1999). Landscape Typology as the Basis for Landscape Protection and Development. *Agriculturae Conspectus Scientificus, 64*(4), 269-274.

Mason, C. (2014). *A Short History of Asia.* Basingstoke: Palgrave Macmillan Ltd.

Mata Olmo, R., & Sanz Herraiz, C. (2003). *Atlas de los Paisajes de España.* Madrid: Ministero de Medio Ambiente de España.

Mathou, T. (2000). The politics of Bhutan: Change in continuity. *Journal of Bhutan Studies, 2*(2), 228-262.

McDonald, Ross. (2004). *Television, Materialism and Culture: An exploration of imported media and its implications for GNH.* Thimphu: The Centre for Bhutan Studies.

McMaster, K. J. (2002). Effects of digital elevation model resolution on derived stream network positions. *Water Resources Management, 38*(4), 1-8.

Meeus, J. H. (1995). Pan-European landscapes. *Landscape and Urban Planning, 31*, 57-79.

Milanova, E. V., Kushlin, A. V., & Middleton, N. J. (1993). *World Map of Present-Day Landscapes. An explanatory guide.* Moscow: UNEP.

Millennium Ecosystem Assessment Board. (2003). *Ecosystems and Human Well-being: A Framework for Assessment.* Washington - Covelo - London: Island Press.

UNESCO. (2009). *World Heritage Cultural Landscapes: A Handbook for Conservation and Management.* Paris: Mitchell, N., Rössler, M., & Tricaud, P.-M.

Moss, M. R. (1985). Land Processes and land classification. *Journal of Environmental Management, 20*(4), 295-319.

Mücher, C. A., Bunce, R. G., Jongman, R. H., Klijn, J. A., Koomen, A. J., Metzger, M. J., & Wascher, D.M. (2003). *Identification and Characterisation of environments and landscapes in Europe.* Wageningen: Alterra.

Mücher, C. A., Klijn, J. A., Wascher, D. M., & Schaminée, J. H. (2009). A new European Landscape Classification (LANMAP): A transparent, flexible and user-oriented methodology to distinguish landscapes. *Ecological Indicators, 10*, 87-103.

Nair, S. S., Preston, B. L., King, A. W., & Mei, R. (2016). Using landscape typologies to model socioecological systems: Application to agriculture of the United States Gulf Coast. *Environmental Modelling & Software, 79*, 85-95.

NASA. (sd). *ASTER - Advanced Spaceborne Thermal Emission and Reflection Radiometer*. Retrieved from: https://terra.nasa.gov/about/terra-instruments/aster

NASA. (sd). *Worldview – Earthdata* [Data file]. Retrieved from: https://worldview.earthdata.nasa.gov

Nassauer, J. I. (1995). Culture and changing landscape structure. *Landscape Ecology, 10*(4), 229-237.

National Land Commission Secretariat. (2016). *National Land Commission Secretariat*. Retrieved from: http://www.nlcs.gov.bt/

National Library and Archives. (2015). *Research and Documentation of Cultural Heritage of Bhutan*. Retrieved from: http://www.bhutanculture.bt/index.php

National Statistics Bureau. (sd). *Settlement data* [Data file]. Retrieved from: geo.gov.bt.

National Land Commission Secretariat. (sd). Retrieved from: geo.gov.bt

National Land Commission Secretariat. (2016). *Atlas of Land Cover and Institutional Facilities.* Thimphu: National Land Commission, Bhutan.

National Land Commission Secretariat. (2013, April 06). *Dzonkhag Boundary of Bhutan* [Data file]. Retrieved from: geo.gov.bt.

National Land Commission Secretariat. (sd). *Nye Atlas location survey* [Data file]. Bhutan.

Odeh, T., Boulad, N., Abed, O., Yahya, A. A., Khries, N., & Abu-Jaber, N. (2017). The Influence of Geology on Landscape Typology in Jordan: Theoretical Understanding and Planning Implications. *Land, 6*(51), 1-14.

Palden, T. (2016, August 05). Saving cultural landscape; a race against time. *Kuensel*.

Pilotti, M., Gandolfi, C., & Bischetti, G. B. (1996). Identification and Analysis of Natural Channel Networks from Digital Elevation Models. *Earth Surface Processes and Landforms, 21*, 1007-1020.

Plieninger, T., Dijks, S., Oteros-Rozas, E., & Bieling, C. (2013). Assessing, mapping and quantifying cultural ecosystem services at community level. *Land Use Policy, 33*, 118-129.

Richling, A. (1984). Typology of Natural Landcapes in Poland on the scale of 1:500.000. *Miscellanea Geographica*.

Rinzin, C. (2017, January 05). The future of Bhutan's hydropower. (D. Gyelmo, Interviewer)

Romportl, D., & Chuman, T. (2018). *Proposal Method of Landscape Typology in the Czech Republic.* Prague: Charles University.

Rose, L.E. (1977). *The Politics of Bhutan.* Ithaca: Cornell University Press.

Savada, A. M. (1993). Bhutan: A Country Study. In A. M. Savada, *Nepal and Bhutan: country studies* (263-266). Washington: Library of Congress.

Silva, K. D., & Sinha, A. (2017). *Cultural Landscapes of South Asia: Studies in Heritage Conservation and Management.* Routledge: Taylor & Francis Group.

Stančič, Z., & Kvamme, K. L. (1999). Settlement patterns modelling through Boolean overlays of social and environmental variables. *New Techniques for Old Times. CAA98. Computer Applications and Quantitative Methods in Archaeology. Proceedings of the 26th conference, Barcelona, March 1998 (BAR International Series 757)* (pp. 231-238). Oxford: Archaeopress.

The Centre for Bhutan Studies. (2003). *Culture and Modernisation: From the Perspectives of Young people in Bhutan.* Thimphu: Ueda, A.

The World Bank Group. (2017). *Bhutan Cultural Heritage Bill Action Planning and Support to Cultural Landscape Mapping for Infrastructure Planning. Support Mission Draft Aide Mémoire March 26 – April 7, 2017.* Washington, DC: The World Bank Group.

The World Bank Group. (2014). *Bhutan Development Update-Poverty Reduction and Economic Management, South Asia Region.* The World Bank Group.

The World Bank Group. (2017). *World Bank Data Catalog*. Retrieved from: https://datacatalog-worldbank-org.vu-nl.idm.oclc.org/dataset/world-development-indicators

The World Bank Group. (2018). *Integrating Cultural Landscape Considerations in Large Infrastructure Planning in Bhutan. Internal report.* Washington, DC: The World Bank Group, Vrije Universiteit Amsterdam.

Topping, A. (2014, August 26). Bhutan battles to preserve its culture as development accelerates. *The Guardian*.

Tshering, S., & Tamang, B. (2004). Hydropower-Key to sustainable, socio-economic development of Bhutan. *United Nations Symposium on Hydropower and Sustainable Development*.

Turcotte, R., Fortin, J.-P., Rousseau, A.N., Massicotte, S., & Villeneuve, J.-P. (2001). Determination of the drainage structure of a watershed using a digital elevation model and a digital river and lake network. *Journal of Hydrology, 240,* 225-242.

UNESCO. (1992). *World Heritage Convention (Art. 1)*. Paris.

UNESCO. (2008). *Operational Guidelines for the implementation of the World Heritage Convention - Annex 3.* Paris

UNESCO. (2015, September 07). *Bhutan 2015: Workshop and Forum on the Cultural Landscape and Sustaining its Significance*. Retrieved from: http://whc.unesco.org/en/news/1342

UNESCO. (2016, April 26). *Cultural Atlas Workshop in Thimphu and the release of the Bhutan Cultural Atlas Brochure*. Retrieved from: http://whc.unesco.org/en/events/1302/

UNESCO. (2016, July 12). *Cultural Landscape Workshop to be held in Paro and Thimphu, Bhutan*. Retrieved from: http://whc.unesco.org/en/events/1324/

UNESCO World Heritage Convention. (2016). *Support to the South Asian Cultural Landscape Initiatives: A UNESCO/Japanese Funds-in-Trust Project, 2016 - 2018*. Retrieved from: http://whc.unesco.org/en/activities/889/

UNESCO World Heritage Convention. (2016, August 03). *UNESCO and Bhutan launch two-year project for South Asian Cultural Landscape Initiatives*. Retrieved from: http://whc.unesco.org/en/news/1541/

UNESCO (2016). *Support for the Preparation for the World Heritage Serial Nomination of the Silk Roads in South Asia: Final Report.* Paris: UNESCO Cultural Heritage Administration.

UNESCO (1992-2018). *Bhutan*. Retrieved from: http://whc.unesco.org/en/statesparties/BT/

University of Washington. (2009). *DrukDIF Druk Dynamic Information Framework*. Retrieved from: http://www.drukdif.ocean.washington.edu/

United States Department of Agriculture. (2016, October 07). *Watershed Physical Processes Research: Oxford, MS*. Retrieved from: https://www.ars.usda.gov/southeast-area/oxford-ms/national-sedimentation-laboratory/watershed-physical-processes-research/docs/revised-universal-soil-loss-equation-rusle-welcome-to-rusle-1-and-rusle-2/

van Eetvelde, V., & Antrop, M. (2009). A stepwise multi-scaled landscape typology and characterisation for trans-regional integration, applied on the federal state of Belgium. *Landscape and Urban Planning, 91*, 160-170.

OpenStreetMap (2018, April 04). Retrieved from: https://en.wikipedia.org/wiki/OpenStreetMap

Vervloet, J. A., Spek, T., & Unwin, T. (2003). Towards a Pan-European Landscape Map - a Mid-Term Review. *European Landscapes: From Mountain to Sea*. Tallinn: Huma.

Vogiatzakis, I. N., Griffiths, G. H., Melis, M. T., Marini, A., & Careddu, M. B. (2006). Landscape Typology in the Mediterranean context: A tool for habitat restoration. *Journal of Mediterranean Ecology, 7*(4), 23-30.

Vos, W., & Stortelder, A. H. (1992). *Vanishing Tuscan Landscapes: Landscape Ecology of a Submediterranean-Montane Area (Solano Basin, Tuscany, Italy).* Wageningen: Pudoc Scientific Publishers.

Walter, H. (1976). *Die ökologischen Systeme der Kontinente (Biogeosphäre). Prinzipien ihrer Gliederung mit Beispielen.* Stuttgart: Ulmer.

Wangdi, P., & Chema, R. (2008). *Seeds of Faith: A Comprehensive Guide to the Sacred Places of Bhutan volume 1.* Thimphu: KMT Printers & Publishers.

Wangdi, T., Lhendup, P., & Wangdi, N. (2013). *An Analysis of Forestry Policy, Acts and Rules of Bhutan to Mainstream Climate Change Adaptation.* Regional Climate Change Adaptation Knowledge Platform for Asia. Bangkok: Stockholm Environment Institute.

Wascher, D.M. (ed). 2005. European Landscape Character Areas – Typologies, Cartography and Indicators for the Assessment of Sustainable Landscapes. Final Project Report as deliverable from the EU's Accompanying Measure project *European Landscape Character Assessment Initiative* (ELCAI), funded under the 5th Framework Programme on Energy, Environment and Sustainable Development (4.2.2), x + 150 pp.

Weng, Q. (2002). Land use change analysis in the Zhujiang Delta of Cchina using satellite remote sensing, GIS and stochastic modelling. *Journal of Environmental Management, 64*, 273-284.

Whittaker, R. H. (1962). Classification of Natural Communities. *Botanical Review, 28*(1), 1-239.

Whittaker, R. H. (1975). *Communities and Ecosystems.* New York: MacMillan Publishing Company.

Whittaker, R. H. (1967). Gradient Analysis of Vegetation. *Biological Reviews, 42*(2), 207-264.

Willemen, L., Verburg, P. H., Hein, L., & van Mensvoort, M. E. (2008). Spatial characterization of landscape functions. *Landscape and Urban Planning, 88*, 34-43.

Williams, T. (2016). Silk Roads in the Kingdom of Bhutan and the Development of a National Heritage Inventory. *Archaeology International, 19*, 122-133.

Zoderer, B. M., Tasser, E., Erb, K.-H., Stanghellini, P. S., & Tappeiner, U. (2016). Identifying and mapping the tourists' perception of culturalecosystem services: A case study from an Alpine region. *Land Use Policy , 56*, 251-261.

Zomeni, M., Tzanopoulos, J., & Pantis, J. D. (2008). Historical analysis of landscape change using remote sensing techniques: An explanatory tool for agricultural transformation in Greek rural areas. *Landscap and Urban Planning , 86*, 38-46.

Further Reading

Amundsen, I. B. (1997). On Bhutanese and Tibetan Dzongs. *The Lhasa valley: History, conservation and modernisation of tibetan architecture*. Paris: Journal of Bhutan Studies.

Arches Project. (2018). *Arches: An Open Source Data Management Platform for the Heritage Field*. Retrieved from: https://www.archesproject.org/

Bhutan Broadcasting Service. (2014, August 20). *International Competition on Cultural Landscape in Bhutan 2014*. Retrieved from: http://www.bbs.bt/news/?p=43162

Bhutan Virtual Museum. (sd). *Bhutan - Mountain Fortress of the Gods*. Retrieved from: http://bhutan.ims.tuwien.ac.at/ahtcde00/b-home/b-home/start.html

Central Intelligence Agency. (sd). *The World Factbook: Bhutan*. Retrieved from: https://www.cia.gov/library/publications/the-world-factbook/geos/bt.html

Coeterier, J. F. (1996). Dominant attributes in the perception and evaluation of the Dutch landscape. *Landscape and Urban Planning, 34*, 27-44.

College of Language and Culture Studies, UNESCO, Centre de recherche sur les civilisations de l'Asie orientale - CRCAO, . (sd). *Introduction to sites and structures in Bhutan*. Retrieved from: http://www.bhutanculturalatlas.org/371/culture/sites-structures/introduction-to-sites-and-structures-in-bhutan/)

De Jesus, R. P. (2018). *Bhutan*. Retrieved from: http://www.who.int/countries/btn/en/

Division for Conservation of Architectural Heritage, DoC, MoHCA, RGoB. (2006). *Survey on Historical Monuments in Wangduephodrang Dzongkhag.* Thimphu.

Dorji, D. (2015). *Intangible Cultural Heritage of Bhutan.* Thimphu: Yoez Graphics.

Eiumnoh, A., & Shrestha, R. (2000). Application of DEM Data to Landsat Image Classification: Evaluation in a Tropical Wet-Dry Landscape of Thailand. *Photogrammetric Engineering & Remote Sensing, 66*(3), 297-304.

European Union. (2013). *Mapping and Assessment of Ecosystems and their Services.* Brussels.

Geertman, S., & Stillwell, J. (2004). Planning support systems: An inventory of current practice. *Computers Environment and Urban Systems, 28*(4).

Yungaburra: Center for Biodiversity Management. (2009). *Developing a Functional Landscape-Scale Land Cover, Biodiversity, Hydrology Modeling Framework (DrukDIF) for the SLMP areas of Bhutan. Phase I: Rapid Natural Resource Assessment Along Land Cover and Land Use Gradients.* Yungaburra: Gillison, A. N.

Goldstein, J. H., Caldarone, G., Duarte, T. K., Ennaanay, D., Hannahs, N., Mendoza, G., et al. (2012). Integrating ecosystem-service tradeoffs into land-use decisions. *Proceedings of the National Academy of Sciences of the United States of America (PNAS), 109*(19), 7565-7570.

Intangible Cultural Heritage Courier of Asia and the Pacific. (sd). *ICH Courier online*. Retrieved from: http://ichcourier.ichcap.org/en/the-national-heritage-board-launches-an-ich-survey-2/

Kaida, Y. (1991). Irrigation Landscapes and Waterscapes in the Rice Land of Tropical Asia. *Southeast Asian Studies, 28*(4), 124-135.

Luc, M., & Szmańda, J. (2014). Should Renaturalised and Recultivated Landscapes Appear in Landscape Typology? *Quaestiones Geographicae, 33*(3), 65-75.

Meybeck, M., Green, P., & Vörösmarty, C. (2001). A New Typology for Mountains and Other Relief Classes. *Mountain Research and Development, 21*(1), 34-45.

Ministry of Home and Cultural Affairs - DoC. (2015). *Workshop on Cultural Landscape and Sustaining its Significance – Bhutan 2015*. Retrieved from: http://www.departmentofculture.gov.bt/en/workshop-on-cultural-landscape-and-sustaining-its-significance-bhutan-2015/

Phillips, A. (1998). The nature of cultural landscapes — a nature conservation perspective. *Landscape Research, 23*(1), 21-38.

Rennie, F., & Mason, R. (2008). *Bhutan: Ways of Knowing.* Charlotte: Information Age Publishing.

Schmitz, M. F., De Aranzabal, I., Aguilera, P., Rescia, A., & Pineda, F. (2003). Relationship between landscape typology and socioeconomic structure Scenarios of change in Spanish cultural landscapes. *Ecological Modelling, 168*, 343-356.

Shejun Agency for Bhutan's Cultural Documentation and Research. (2013). *Shejun Agency for Bhutan's Cultural Documentation and Research*. Retrieved from: http://www.shejun.org/main/main.php#&slider1=1

Slaymaker, O. (2010). Drivers of mountain landscape change during the twenty-first century. *Journal of Soil Sediments, 10*, 597-610.

Tourism Council of Bhutan. (2018). *About Bhutan*. Retrieved from: http://www.tourism.gov.bt/about-bhutan/culture

University of Virginia. (2015). *Bhutan Cultural Library*. Retrieved from: http://bhutan.virginia.edu/places/427/overview/nojs

van Berkel, D. B., & Verburg, P. H. (2012). Spatial quantification and valuation of cultural ecosystem services in an agricultural landscape. *Ecological Indicators*, 1-12.

Vizzari, M., & Sigura, M. (2015). Landscape sequences along the urban–rural–natural gradient: A novel geospatial approach for identification and analysis. *Landscape and Urban Planning, 140*, 42-55.

Vlčková, V., Buček, A., Machar, I., Daněk, T., Pechanec, V., Brus, J., et al. (2015). The Application of Geobiocoenological Landscape Typology in the Modelling of Climate Change Implications. *Journal of Landscape Ecology, 8*(2), 69-81.

Wood, C. (2014). *Bhutan's Cultural Landscape.* Retrieved from: http://www.asatours.com.au/bhutans-cultural-landscape/

Appendices

A. Reassigning NLCS landcover classes

Original main code	Original sub code	Original landcover class	Reassigned landcover class (colours match those used in maps)
A		*Cultivated Agricultural Land*	
	AC	Chhuzhing Land	Agriculture
	AK	Kamzhing Land	Agriculture
B		*Not Related*	
	BA	Built Up Areas	Urban Area
	BS	Bare Soils	Barren Area
D		*Degraded Areas*	
	DG	Gullies	Barren Area
	DL	Landslides	Barren Area
F		*Forests*	
	FB	Broadleaf Forest	Broadleaved/Mixed Forest
	FBc	Broadleaf mixed with Conifer	Broadleaved/Mixed Forest
	FCb	Blue Pine Forest	Conifer Forest
	FCc	Chir Pine Forest	Conifer Forest
	FCf	Fir Forest	Conifer Forest
	FCm	Mixed Conifer Forest	Conifer Forest
	FP	Forest Park	Broadleaved/Mixed Forest
G		*Grassland*	
	GP	Grassland	Grassland
H		*Horticulture Land*	
	HA	Apple Orchard	Agriculture
	HAa	Areca Nut Plantation	Agriculture
	HC	Citrus Orchard	Agriculture
	HCo	Cardamom Plantation	Agriculture
	HO	Others	Agriculture
	HOa	Others	Agriculture
	HOc	Others	Agriculture
M		*Meadows*	
	MA	Marshy Areas	Barren Area
	MD	Moraines	Barren Area
	NB	Anthropogenic Non-Built up Area (Quarries, waste dump, etc.)	Urban Area
O		*Open Area*	
	OR	Open area	Barren Area
	OS	Snow Cover	Snow and Glacier
R		*Bare Areas*	
	RR	Rock Outcrops	Barren Area
	RS	Scree	Barren Area
S		*Shrubs*	
	SH	Shrubs	Shrubs
	SIS	Shrubs	Shrubs
	SR	Shrubs	Shrubs
W		*Waterbodies*	
	WL	Lake	Waterbody
	WR	River	Waterbody
	WRe	Reservoir	Waterbody

B. Heritage feature counts per landscape type and densities in [features/ha]

Landscape type	230 ha count	15 ha count	230 ha Density	15 ha Density
Waterbody	31	31	0.001135	0.001135
Urban Area	265	265	0.04166	0.04166
Snow and Glacier (mild slope)	0	3	0	1.03E-05
Snow and Glacier (steep slope)	1	0	2.81E-05	0
L_Shr1	36	92	0.002408	0.002778
L_Shr2	0	11	0	0.001218
L_Gra1	0	5	0	0.001968
L_BMF1	1300	773	0.001185	0.00089
L_BMF2	72	55	0.00048	0.000188
L_CoF1	93	84	0.001313	0.0012
L_CoF2	12	17	0.000491	0.000363
L_Agr1	133	771	0.007939	0.010886
L_Agr2	19	0	0.021153	0
M_Shr1	9	70	0.002685	0.003323
M_Gra1	7	62	0.001659	0.003162
M_Gra2	0	4	0	0.001075
M_Bar1	2	1	0.002469	0.001225
M_BMF1	433	213	0.000677	0.000434
M_BMF2	16	9	0.000183	5.45E-05
M_CoF1	499	288	0.000776	0.00057
M_CoF2	3	11	2.05E-05	6.65E-05
M_Agr1	40	199	0.00808	0.011447
A_Shr1	11	12	6.53E-05	8.05E-05
A_Shr2	0	2	0	6.76E-05
A_Gra2	0	1	0	0.000128
A_CoF1	10	9	4.65E-05	4.63E-05
A_CoF2	0	1	0	1.57E-05
A_Agr1	0	3	0	0.013911

C. Landscape type total area and unit count.

		NLCS				ICIMOD 2010				ICIMOD 2000				ICIMOD 1990			
		230 ha MMU		15 ha MMU		230 ha MMU		15 ha MMU		230 ha MMU		15 ha MMU		230 ha MMU		15 ha MMU	
GRIDCODE	**Type**	**Area [ha]**	**Unit Count**	**Area [ha]**	**Unit Count**	**Area [ha]**	**Unit Count**	**Area [ha]**	**Unit Count**	**Area [ha]**	**Unit Count**	**Area [ha]**	**Unit Count**	**Area [ha]**	**Unit Count**	**Area [ha]**	**Unit Count**
1	Waterbody	273201	14771	27321	14771	14318	471	14318	471	12218	1516	12218	1516	13487	801	13487	801
2	Urban Area	63601	7522	6361	7522	6832	224	6832	224	6654	299	6654	299	6701	274	6701	274
3	Snow and Glacier (mild slope)	344110	175	291314	1331	401466	101	265594	986	222872	96	174785	1163	257617	94	183683	923
4	Snow and Glacier (steep slope)	35528	16	45383	494	49424	32	52406	604	44822	28	28357	266	41912	23	41792	438
121	L_Shr1	14952	344	33122	741	0	0	0	0	0	0	201	2	496	1	650	3
122	L_Shr2	2	8	9034	145	0	0	0	0	0	0	166	2	0	0	80	1
131	L_Gra1	9	44	2541	89	0	0	0	0	0	0	0	0	0	0	19	1
132	L_Gra2	0	1	1747	27	0	0	0	0	0	0	0	0	0	0	0	0
141	L_Bar1	12	20	657	35	6615	47	15990	266	8223	47	18999	307	7366	44	18456	309
142	L_Bar2	0	1	2552	49	98	1	687	19	0	0	727	19	0	0	1128	28
151	L_BMF1	1097288	549	868074	1917	1206131	152	950052	1250	1208827	146	949314	1258	1215188	151	949531	1247
152	L_BMF2	150111	191	292933	3340	243042	278	360000	3367	246565	279	360306	3378	243944	280	359394	3395
161	L_CoF1	70817	78	70029	526	0	0	0	0	0	0	0	0	0	0	0	0
162	L_CoF2	24430	32	46843	456	0	0	0	0	0	0	0	0	0	0	0	0
171	L_Agr1	16753	154	70822	1122	29376	62	78699	1150	28633	60	77810	1139	27241	58	77032	1136
172	L_Agr2	898	2	300	9	0	0	371	11	0	0	317	11	0	0	299	10
221	M_Shr1	3352	80	21066	388	17508	15	54711	856	12413	11	49037	785	45765	35	95196	1241
222	M_Shr2	1099	4	8171	116	4245	4	44128	704	4919	4	41147	652	11509	5	56180	808
231	M_Gra1	4220	33	19608	338	13411	13	29380	394	30789	26	48770	615	25901	20	44021	594
232	M_Gra2	0	0	3723	54	0	0	3867	72	0	0	7448	117	0	0	4753	89
241	M_Bar1	810	9	816	17	381	2	3031	63	52	7	2110	55	1328	8	7060	130
242	M_Bar2	0	0	843	10	0	0	493	10	0	0	333	6	0	0	839	12
251	M_BMF1	639787	183	490264	1108	320606	240	309798	1596	323158	237	307649	1592	325646	235	306567	1570
252	M_BMF2	87522	87	165004	1837	31266	31	123973	1794	32083	30	122625	1757	32920	30	122402	1754

		NLCS				ICIMOD 2010				ICIMOD 2000				ICIMOD 1990			
		230 ha MMU		15 ha MMU		230 ha MMU		15 ha MMU		230 ha MMU		15 ha MMU		230 ha MMU		15 ha MMU	
GRIDCODE	**Type**	**Area [ha]**	**Unit Count**	**Area [ha]**	**Unit Count**	**Area [ha]**	**Unit Count**	**Area [ha]**	**Unit Count**	**Area [ha]**	**Unit Count**	**Area [ha]**	**Unit Count**	**Area [ha]**	**Unit Count**	**Area [ha]**	**Unit Count**
261	M_CoF1	643285	193	504968	1338	856850	206	625548	1625	866640	211	621272	1678	838092	233	576363	1767
262	M_CoF2	146239	85	165385	1468	108281	73	176214	2172	119791	76	176890	2161	102072	64	163631	2044
271	M_Agr1	4950	57	17384	263	7730	19	22494	329	5332	10	19453	312	4253	8	18186	304
272	M_Agr2	0	0	21	1	0	0	631	2	0	0	57	2	0	0	19	1
321	A_Shr1	168413	88	149155	1030	219289	111	193938	1544	135888	69	167681	1594	205009	111	194624	1713
322	A_Shr2	11633	10	29579	420	17391	17	70872	1064	27244	26	56683	871	22359	24	59761	926
331	A_Gra1	12027	14	24667	328	20966	16	49210	716	40748	27	86105	1181	58847	41	78306	1111
332	A_Gra2	803	3	7818	126	1910	3	22362	373	6477	6	36076	563	6615	10	31898	505
341	A_Bar1	6620	38	20014	230	7914	9	20275	293	8113	11	20178	317	41725	22	53274	715
342	A_Bar2	0	0	8074	112	0	0	2260	47	376	1	965	23	2313	4	15516	255
351	A_BMF1	0	0	1824	21	0	0	0	0	0	0	0	0	0	0	0	0
352	A_BMF2	0	0	747	12	0	0	0	0	0	0	0	0	0	0	0	0
361	A_CoF1	215137	112	194261	1134	162819	91	152973	986	184867	88	152628	960	121439	62	114292	873
362	A_CoF2	26344	19	63578	804	4550	6	22204	470	9919	9	19894	399	11106	11	14110	285
371	A_Agr1	0	0	216	2	0	0	0	0	0	0	0	0	0	0	0	0
421	N_Shr1	59815	27	79874	632	2761	2	18818	294	6504	5	17986	267	1455	2	12875	200
422	N_Shr2	935	3	12400	187	699	1	2015	46	463	1	1666	39	1208	1	1785	28
431	N_Gra1	5814	8	20893	273	5933	7	29381	535	40368	34	70564	937	127475	66	125761	1048
432	N_Gra2	1079	2	3694	52	0	0	17909	335	3478	3	37481	618	6536	7	33882	573
441	N_Bar1	48501	36	69376	636	105868	64	112658	922	229692	84	162301	927	62483	39	79530	903
442	N_Bar2	2642	2	22266	304	3748	5	17846	326	3238	4	14440	271	1362	2	8287	171
461	N_CoF1	0	0	1944	32	0	0	58	1	0	0	59	1	0	0	0	0
462	N_CoF2	0	0	2951	38	0	0	0	0	0	0	21	1	0	0	0	0

D. Landscape change analysis cross tabulated area dynamics (in Ha).

Red boxes are pairs used in the landscape change analysis

1990-2000

	Wat.b	Urb. Ar.	Sn.& Gl. mild sl.	Sn.& Gl. St.sl.	L_Shr1	L_Shr2	L_Bar1	L_Bar2	L_BMF 1	L_BMF 2	L_Agr1	L_Agr2	M_Shr 1	M_Shr 2	M_Gra 1	M_Gra 2	M_Bar 1	M_Bar 2	M_BM F1	M_BM F2	M_Co F1	M_Co F2	M_Agr 1	M_Agr 2	A_Shr 1	A_Shr 2	A_Gra 1	A_Gra 2	A_Bar 1	A_Bar 2	A_CoF 1	A_CoF 2	N_Shr 1	N_Shr 2	N_Gra 1	N_Gra 2	N_Bar 1	N_Bar 2	N_CoF 1	N_CoF 2
Water body		0,1	0	0	0	0	1.357.752,0	0	4.998.135,0	2.358.323,0	2.152.356,0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,1	0	0	0	0	0	0	0	0	0,3	0	0	0	0
Urban Area	0,1		0	0	0	0	0,3	0	0,7	0,1	0,5	0	0	0	0,3	0,0	0,7	0,0	0,4	0,0	0,0	0	0,7	0,0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Sn.& Gl. mild sl.	0	0		1.679.404,0	0	0	0	0	0	0	0	0	0,1	0,1	0	0	0,0	0	0	0	0	0	0	0	3.836.137,0	1.810.794,0	1.142.517,0	7.153.065,0	4.206.019,0	0,0	0,3	0,2	2.656.117,0	0,3	2.163.916,0	4.319.816,0	2.705.506,0	8.604.275,0	0	0
Sn.& Gl. St.sl.	0	0	5.298.332,0		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1.304.458,0	0,2	3.199.355,0	1.081.327,0	0,4	0	0,1	0	0,0	0	2.064.906,0	7.988.691,0	1.892.837,0	725.519,0	0	0
L_Shr1	0,0	0	0	0		0	0,2	0	0,2	0	6.063.156,0	0,1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L_Shr2	0	0	0	0	0		0	0	0	0,8	0	0	0	0	0	0	0	0	0,0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L_Gra 1	0	0	0	0	0	0	0	0	0,2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L_Bar1	3.757.183,0	0,1	0	0	0	0		0,1	1.288.238,0	1.716.392,0	6.397.852,0	0,0	0	0	0	0	0,0	0	0,4	0,0	0	0	0,0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L_Bar2	0,0	0	0	0	0	0	0,1		0,8	3.461.963,0	0,0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L_BMF 1	3.677.371,0	0,5	0	0	188.889,0	0,1	9.597.208,0	0,1		1.274.945,0	1.951.452,0	0,1	0	0	0	0	0,0	0	8.223.236,0	2.963.351,0	0,0	0,0	0,2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L_BMF 2	1.255.541,0	0,2	0	0	0,1	1.525.873,0	0,7	0,1	1.187.014,0		1.316.473,0	0,0	0	0	0	0	0,0	0,0	3.191.632,0	5.331.973,0	0	0,0	0,0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L_Agr1	107.532,0	0,4	0	0	0	0	6.174.721,0	0,0	1.888.632,0	2.705.893,0		0,3	0	0	0	0	0,0	0	0,2	0,0	0	0	0,2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L_Agr2	0	0	0	0	0	0	0	0	0,0	0,1	0,1		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M_Shr 1	0	0	1.906.054,0	0,9	0	0	0	0	0	0	0	0		2.281.858,0	726.403,0	300.197,0	1.099.349,0	0	0,7	0,9	3.641.987,0	3.236.086,0	0	0	56.332,0	3.504.873,0	0,2	0,8	0	0	8.720.131,0	1.810.794,0	0	0	0	0	0	0	0	0
M_Shr 2	0	0	1.614.267,0	4.244.638,0	0	0	0	0	0	0	0	0	199.359,0		3.677.371,0	1.463.825,0	0,3	0	0,6	2.375.487,0	4.884.595,0	859.063,0	0	0	2.668.132,0	8.505.582,0	0,6	150.356,0	0,2	0,0	3.801.809,0	3.255.138,0	0	0	0	0	0	0	0	0
M_Gra 1	0	0,1	0	0	0	0	0	0	0	0	0,0	0	7.007.172,0	0,2		4.256.653,0	0,5	0,0	2.055.037,0	1.397.143,0	8.090.044,0	2.832.906,0	153.188,0	0,0	0,2	0,1	0	0,0	0,0	0	0	0	0	0	0	0	0	0	0	0
M_Gra 2	0	0,0	0	0	0	0	0	0	0	0	0	0	0,1	0,5	2.323.995,0		0	0	0,4	1.647.737,0	2.676.714,0	4.623.961,0	0,4	0	0,0	0	0	0	0	0	0,0	0,0	0	0	0	0	0	0	0	0
M_Bar 1	0	1.107.931,0	0,1	0	0	0	0	0	0,0	0,2	0	0	2.100.006,0	0	2.635.263,0	0,6		0,5	3.518.604,0	1.683.781,0	3.916.807,0	0,2	1.443.229,0	0	0	0,1	0	0	0	0	0,1	0,1	0	0	0	0	0	0	0	0
M_Bar 2	0	0,0	0	0	0	0	0	0	0	0,0	0	0	0,3	0,1	0,8	1.859.7110	0,2		0,4	1,0	0,2	0	0,7	0	0,0	0,1	0	0,2	0	0	0	0	0	0	0	0	0	0	0	0
M_BM F1	0	0,5	0	0	0	0	0,0	0	9.513.105,0	2.252.765,0	0,3	0	0,0	0,1	1.150.669,0	2.136.908,0	0,3	0,1		298.515,0	230.666,0	3.309.204,0	6.112.931,0	0,2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M_BM F2	0	0,0	0	0	0	0	0,0	0,1	1.826.241,0	294.018,0	0,1	0	0,0	0,2	1.203.191,0	4.380.233,0	0	0,0	3.057.324,0		769.802,0	7.143.625,0	0,3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

M_CoF1	0	0,0	0,3	0,3	0	0	0	0	0,0	0,0	0	0	6.619.267,0	264.067,0	4.136.935,0	4.065.275,0	1,0	0	2.122.147,0	7.596.753,0		9.338.376,0	2.570.298,0	0	2.842.346,0	1.466.657,0	0,4	0,3	0,0	0	1.474.982,0	1.626.282,0	0	0	0	0	0	0	0	0
M_CoF2	0	0	0,4	0,4	0	0	0	0	0,0	0,0	0	0	2.140.341,0	3.748.601,0	3.029.432,0	3.540.917,0	0,0	0	227.422,0	4.212.885,0	8.544.716,0		0,1	0	1.833.965,0	2.357.465,0	0,7	0,6	0	0	7.482.612,0	6.015.097,0	0	0	0	0	0	0	0	0
M_Agr1	0	0,3	0	0	0	0	0,0	0	0,1	0,0	0,2	0	0	0	1.706.008,0	0,4	0,5	0	6.090.618,0	0,3	2.617.498,0	0,1		0,2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M_Agr2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,0	0	0	0	0,0	0	0	0	0		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A_Shr1	0,0	0	7.766.246,0	7.265.489,0	0	0	0	0	0	0	0	0	605.629,0	6.425.315,0	0,8	0,2	0,0	0	0	0	1.489.399,0	8.009.545,0	0	0		7.382.633,0	2.720.542,0	2.796.604,0	2.271.216,0	0,8	3.586.951,0	2.075.204,0	5.713.012,0	0,9	277.369,0	1.501.843,0	7.500.635,0	163.658,0	0,2	0,0
A_Shr2	0,0	0	1.505.362,0	769.287,0	0	0	0	0	0	0	0	0	5.776.518,0	1.233.314,0	0,1	0,7	0	0	0	0	8.234.392,0	1.521.925,0	0	0	6.589.917,0		2.998.452,0	5.814.365,0	0,6	1,0	3.719.422,0	2.785.962,0	0,7	0,1	0,8	0,2	2.749.661,0	0,4	0	0
A_Gra1	0,3	0	4.940.635,0	3.443.941,0	0	0	0	0	0	0	0	0	0,3	0,1	0	0	0	0	0	0	0,4	0,3	0	0	2.888.397,0	2.535.884,0		238.836,0	7.094.622,0	1.226.362,0	1.605.685,0	1.491.545,0	3.715.989,0	0,1	3.346.107,0	4.114.192,0	1.149.725,0	1.732.698,0	0	0
A_Gra2	0,2	0	1.094.887,0	5.691.557,0	0	0	0	0	0	0	0	0	0,7	0,4	0,0	0	0	0	0	0	0,1	0,2	0	0	3.860.338,0	79.033,0	2.387.673,0		5.204.102,0	1.621.991,0	731.269,0	1.301.884,0	0,7	0,2	1.209.198,0	4.292.697,0	5.291.638,0	1,0	0	0
A_Bar1	0,0	0	4.221.553,0	2.184.109,0	0	0	0	0	0	0	0	0	0,2	0,0	0,1	0	0	0	0	0	0,1	0,0	0	0	1.582.994,0	129.519,0	1.860.595,0	1.400.319,0		0,6	8.400.882,0	1.515.574,0	3.812.966,0	0,7	2.299.108,0	2.466.456,0	1.231.254,0	3.510.022,0	0	0
A_Bar2	0	0	66.227,0	1.815.085,0	0	0	0	0	0	0	0	0	0,1	0,0	0	0	0,1	0	0	0	0,2	0,3	0	0	199.934,0	3.144.517,0	1.465.713,0	6.151.464,0	2.038.216,0		2.333.435,0	1.018.679,0	1.512.142,0	0,4	0,9	1.395.427,0	4.758.698,0	2.831.189,0	0	0
A_CoF1	0	0	1.267.556,0	0,0	0	0	0	0	0	0	0	0	1.092.484,0	0,4	0,4	0,1	0	0	0	0,0	1.321.193,0	2.932.456,0	0	0	2.621.703,0	6.939.374,0	1.740.937,0	2.191.833,0	0,3	0,0		2.043.193,0	0,5	0,0	0,3	0,0	0,3	0,0	0	0
A_CoF2	0	0	0,4	0,0	0	0	0	0	0	0	0	0	0,3	0,4	0,1	0,0	0	0	0	0	1.455.501,0	224.075,0	0	0	2.723.056,0	1.823.667,0	1.229.795,0	2.287.951,0	0,0	0	1.554.451,0		0,0	0	0	0	0,1	0	0	0
N_Shr1	0	0	1.134.879,0	0,0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1.955.829,0	0,8	111.308,0	0,3	1.002.373,0	0	0,1	0		0,4	8.953.561,0	2.278.511,0	5.897.181,0	2.690.445,0	0	0
N_Shr2	0	0	0,3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,1	0,5	0,3	0,2	0,2	0	0	0	0,2		0,6	4.213.743,0	3.573.529,0	7.564.999,0	0	0
N_Gra1	0	0	1.179.256,0	2.266.496,0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6.257.966,0	1.571.357,0	6.801.205,0	386.789,0	341.133,0	0,2	0,3	0,1	2.065.163,0	1.637.438,0		3.907.796,0	6.763.804,0	1.997.795,0	0,2	0,2
N_Gra2	0	0	9.844.368,0	3.067.193,0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2.995.963,0	1.712.101,0	4.127.065,0	7.440.561,0	1.307.033,0	0,4	0,1	0,0	1.172.296,0	0,3	2.670.792,0		5.911.513,0	499.762,0	0	0
N_Bar1	0	0	9.367.812,0	2.161.796,0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1.161.225,0	3.421.628,0	1.016.791,0	4.607.655,0	2.634.662,0	0,2	1.841.689,0	0,2	9.676.076,0	2.681.863,0	4.937.117,0	1.241.552,0		1.263.694,0	0,2	0
N_Bar2	0	0	4.650.565,0	1.200.616,0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2.688.729,0	1.815.085,0	155.076,0	2.579.738,0	0,5	0,2	0,2	0,0	3.863.599,0	871.584,0	3.554.649,0	9.877.838,0	1.577.879,0		0	0

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	Wat.b	Urb. Ar.	Sn.& Gl. mild sl.	Sn.& Gl. St.sl.	L_Bar1	L_Bar2	L_BMF1	L_BMF2	L_Agr1	L_Agr2	M_Shr1	M_Shr2	M_Gra1	M_Gra2	M_Bar1	M_Bar2	M_BMF1	M_BMF2	M_CoF1	M_CoF2	M_Agr1	M_Agr2	A_Shr1	A_Shr2	A_Gra1	A_Gra2	A_Bar1	A_Bar2	A_CoF1	A_CoF2	N_Shr1	N_Shr2	N_Gra1	N_Gra2	N_Bar1	N_Bar2	N_CoF1
Water body		0.3	0	0	1638296.0	0.0	6855271.0	2377203.0	2336868.0	0.0	0	0	0	0	0	0	0	0	0	0	0	0	0.0	0.0	0.0	0.0	0.0	0	0	0	0	0	0	0	0	0	0
Urban Area	0.3		0	0	0.0	0	1210915.0	0.1	1.0	0	0	0	0.0	0.0	0.1	0.0	1147408.0	0.0	0.1	0.0	1166289.0	0.0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Sn.& Gl. mild sl.	0.0	0		7965004.0	0	0	0	0	0	0	0.5	0.9	0	0	0.0	0	0	0	0.1	0.4	0	0	1047343.0	6834674.0	429613.0	1295876.0	3981172.0	1319048.0	2232168.0	0.7	1147408.0	0.2	6594379.0	2370338.0	2103267.0	4291839.0	0.0
Sn.& Gl. St.sl.	0	0	2196725.0		0	0	0	0	0	0	0.2	0.5	0	0	0	0	0	0.0	0.1	0.1	0	0	1.0	0.8	0.3	0.1	0.1	0.5	0.3	0.1	0	0.0	0.7	1181736.0	0.2	0.6	0
L_Shr1	0	0	0	0	0	0	1876017.0	0.1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L_Shr2	0.0	0	0	0	0	0	0.2	1429755.0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L_Bar1	1590752.0	0.3	0	0		0.4	1701975.0	0.9	9763698.0	0	0	0	0	0	0.0	0	0.0	0	0	0	0.0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L_Bar2	0.0	0	0	0	0.5		0.4	0.6	0.0	0	0	0	0	0	0	0	0	0.0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L_BMF1	9120909.0	1337928.0	0	0	68321.0	0.3		2139698.0	5156128.0	0.2	0	0	0	0	0.0	0	1211172.0	3690244.0	0.0	0.0	0.3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L_BMF2	4353629.0	0.2	0	0	1120804.0	0.4	2201908.0		4884853.0	0.3	0	0	0	0	0	0.1	3746026.0	5140595.0	0.0	0.0	0.0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L_Agr1	4212027.0	1150841.0	0	0	392968.0	0.0	4737415.0	3569238.0		0.6	0	0	0	0	0	0	0.9	0.1	0	0	0.1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L_Agr2	0.0	0	0	0	0	0	0.2	0.2	0.2		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M_Shr1	0	0	0.5	0.4	0	0	0	0	0	0		186898.0	1140543.0	0.0	0.2	0	0.0	0.2	2679288.0	7213997.0	0	0	5821145.0	4097887.0	0.1	0.1	0.0	0.0	2310264.0	1199758.0	0	0	0	0	0	0	0
M_Shr2	0	0	0.2	0.2	0	0	0	0	0	0	1529906.0		0.1	0.1	0	0	0.1	0.7	9963658.0	9161244.0	0	0	3918524.0	107695.0	0.0	0.0	0	0	2046798.0	1119088.0	0	0	0	0	0	0	0
M_Gra1	0	0.3	0	0	0	0	0	0	0	0	459976.0	3348681.0		3541776.0	1198042.0	0.1	2571327.0	2590036.0	9284653.0	4030089.0	2943956.0	0.0	0.2	0.1	0	0.0	0	0	0.5	0.1	0	0	0	0	0	0	0
M_Gra2	0	0.0	0.1	0.2	0	0	0	0	0	0	2162654.0	135226.0	4455755.0		0.5	1111364.0	3343532.0	4867689.0	5364584.0	5062499.0	0.7	0.3	0.1	0.5	0.0	0.2	0	0	0.1	0.1	0	0	0	0	0	0	0
M_Bar1	0	0.8	0.0	0	0.0	0	0.1	0.0	0.0	0	0.2	0.0	0.4	0		0.3	1643446.0	0.0	1107073.0	0.1	1339644.0	0	0.0	0.1	0	0	0	0	0.0	0	0	0	0	0	0	0	0
M_Bar2	0	0.0	0	0	0	0.0	0	0.0	0	0	0	0	0	0.0	0.1		0.1	0.0	0.1	0	0.0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M_BMF1	0	1.0	0	0	0.1	0	106957.0	4518403.0	0.7	0	0.1	0.4	3162453.0	0.4	0.6	0.2		7037466.0	4736642.0	8461814.0	1184311.0	0.0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M_BMF2	0	0.0	0	0.0	0.1	0	4417994.0	6933367.0	0.1	0	0.2	1192034.0	0.7	0.3	0.0	0.2	6024022.0		1973851.0	1340417.0	0.7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M_CoF1	0	0.1	0.0	0.2	0	0	0.0	0.0	0	0	4313551.0	1401349.0	1173583.0	0.9	0.7	0.1	5553817.0	1653487.0		1151442.0	5519918.0	0.0	6984859.0	5144886.0	0.0	0.0	0	0	1440139.0	3413904.0	0	0	0	0	0	0	0
M_CoF2	0	0.0	0.3	0.5	0	0	0.0	0.1	0	0	7728915.0	1932829.0	1156848.0	0.4	0.0	0	83451.0	1606286.0	1090862.0		0.2	0	3206221.0	7839622.0	0.0	0.1	0.0	0.0	538089.0	802156.0	0	0	0	0	0	0	0
M_Agr1	0	1616842.0	0	0	0.0	0	0.7	0.2	0.4	0	0.0	0	0.9	0.7	1276996.0	0.0	1094887.0	0.4	3588118.0	0.2		0.0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M_Agr2	0	0.0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.0	0	0	0	0.2		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A_Shr1	0.0	0	1140285.0	3276593.0	0	0	0	0	0	0	4307287.0	2411531.0	0.0	0	0.0	0	0	0	5116566.0	2454441.0	0	0		7226355.0	2319189.0	6028828.0	7206273.0	0.9	4906908.0	7177095.0	4248929.0	0.3	1.0	0.5	5258168.0	1333637.0	0

A_Shr2	0	0	497153.0	2639811.0	0	0	0	0	0	0	2443285.0	4555305.0	0.1	0	0.0	0	0	0	1666617.0	365849.0	0	0	4825208.0		2808876.0	4025798.0	0.8	0.4	9403255.0	5484732.0	0.9	0.6	0.1	0.3	1339644.0	0.8	0
A_Gra1	0.1	0	5134674.0	9496799.0	0	0	0	0	0	0	0.3	0.3	0	0	0	0	0	0	0.7	0.5	0	0	2407781.0	3245355.0		1406498.0	3681404.0	2042507.0	412698.0	57851.0	2054522.0	0.1	2428695.0	243127.0	9503664.0	2279369.0	0
A_Gra2	0.0	0	1925878.0	21182.0	0	0	0	0	0	0	0.3	1916352.0	0	0.0	0	0	0	0	0.5	0.7	0	0	3206736.0	5376685.0	1216236.0		5581708.0	6838965.0	6758295.0	6862137.0	0.5	0.1	1583372.0	3728862.0	3909942.0	285436.0	0
A_Bar1	0.0	0	1245414.0	0.7	0	0	0	0	0	0	0.0	0.2	0	0	0	0	0	0	0.0	0	0	0	1412333.0	2223586.0	2061473.0	2587461.0		3594126.0	1122521.0	0.1	0.6	0	0.8	0.9	4156244.0	1516433.0	0
A_Bar2	0	0	0.3	0.1	0	0	0	0	0	0	0.0	0.1	0	0	0	0	0	0	0	0.0	0	0	0.6	0.5	0.2	1186885.0	0.4		0.1	0.0	0.0	0	0.1	0.0	0.2	0.1	0
A_CoF1	0	0	1714676.0	0.3	0	0	0	0	0	0	2547126.0	1212631.0	0.0	0	0	0.0	0	0	111248.0	5943008.0	0	0	7547235.0	20716.0	2402949.0	1262407.0	0.7	0.1		2573387.0	0.3	0	0.2	0.1	0.7	0.2	0
A_CoF2	0	0	0.8	0.1	0	0	0	0	0	0	0.7	1311324.0	0.1	0	0	0	0	0.0	1829674.0	3779496.0	0	0	720284.0	8895203.0	0.4	0.3	0.0	0.0	1698971.0		0	0.0	0	0.0	0.2	0	0
N_Shr1	0	0	5095969.0	0.1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6758295.0	2050231.0	1333637.0	0.3	0.8	0.0	0.3	0.1		1.0	2053663.0	0.3	1002888.0	0.8	0
N_Shr2	0	0	0.8	0.2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.6	0.5	0.1	0.2	0.0	0	0.0	0.1	0.7		0.2	0.0	1321622.0	0.5	0
N_Gra1	0.3	0	3555472.0	2441482.0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3092081.0	2696452.0	1119946.0	1106215.0	0.8	0.0	0.6	0.0	5595439.0	1149125.0		1228765.0	1473351.0	1354234.0	0
N_Gra2	0.3	0	6203128.0	8999989.0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3612148.0	198415.0	2862084.0	3064619.0	0.5	0.2	0.3	0.0	1873442.0	3341816.0	1275709.0		3251534.0	4603364.0	0
N_Bar1	0	0	5108267.0	2595614.0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8389726.0	5126864.0	6748855.0	3872181.0	7076686.0	0.7	0.8	0.1	205229.0	14083.0	1170614.0	2350857.0		284904.0	0.0
N_Bar2	0	0	1304029.0	1274679.0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1234944.0	0.5	1276996.0	1352517.0	1482963.0	0.4	0.1	0	0.9	0.2	4425718.0	1438766.0	1636666.0		0
N_CoF1	0	0	0.0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.0	0	0	0	0	0	0	0	0	0	0	0	0.0	0	
N_CoF2	0	0	0.2	0.0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.0	0	0	0	0.0	0	0	0	0	0	0	0	0	0	0

1990-2010

	Wat.b	Urb. Ar.	Sn.& Gl. mild sl.	Sn.& Gl. St.sl.	L_Bar1	L_Bar2	L_BMF1	L_BMF2	L_Agr1	L_Agr2	M_Shr1	M_Shr2	M_Gra1	M_Gra2	M_Bar1	M_Bar2	M_BMF1	M_BMF2	M_CoF1	M_CoF2
Waterbody		0.4	0	0	1723258.0	0.0	6554902.0	2387502.0	2579738.0	0.0	0	0	0	0	0	0	0	0	0	0
Urban Area	0.4		0	0	0.0	0	1070171.0	0.1	0.9	0	0	0	0.0	0.0	0.1	0.0	0.9	0.0	0.0	0.0
Sn.& Gl. mild sl.	0.0	0		3937833.0	0	0	0	0	0	0	0.0	0.0	0	0	0.0	0	0	0	0.0	0.0
Sn.& Gl. St.sl.	0	0	282913.0		0	0	0	0	0	0	0.0	0	0	0	0	0	0	0	0.0	0.0
L_Shr1	0.0	0	0	0	0.2	0	0.4	0	5858047.0	0.1	0	0	0	0	0	0	0	0	0	0
L_Shr2	0	0	0	0	0	0	0	0.8	0.0	0	0	0	0	0	0	0	0.0	0	0	0
L_Gra1	0	0	0	0	0	0	0.2	0	0	0	0	0	0	0	0	0	0	0	0	0
L_Bar1	6.454.493.0	0.1	0	0		0.2	1998825.0	1703519.0	9102887.0	0	0	0	0	0	0.0	0	0.4	0.0	0	0
L_Bar2	0.0	0	0	0	0.5		1169721.0	3758041.0	0.0	0	0	0	0	0	0	0	0	0.0	0	0
L_BMF1	7.226.012.0	1.0	0	0	6.257.108.0	0.3		1458470.0	4901502.0	0.2	0	0	0	0	0.0	0	657035.0	3047455.0	0.0	0.0
L_BMF2	3.163.311.0	0.2	0	0	1.0	0.3	1.428.922.0		3721997.0	0.4	0	0	0	0	0	0.1	2843204.0	4000052.0	0.0	0.1
L_Agr1	3.460.247.0	0.9	0	0	3.541.776.0	0.0	4.390.446.0	3.576.962.0		0.5	0	0	0	0	0	0	0.8	0.0	0	0
L_Agr2	0.0	0	0	0	0	0	0.1	0.3	0.1		0	0	0	0	0	0	0	0	0	0
M_Shr1	0	0	1.785.906.0	1.055.581.0	0	0	0	0	0	0		2699284.0	1812339.0	0.8	1751578.0	0.0	0.9	1044425.0	3739907.0	3491571.0
M_Shr2	0	0	1.161.998.0	4.135.647.0	0	0	0	0	0	0	2.110.133.0		111308.0	174128.0	0	0.4	0.7	255485.0	456466.0	8168912.0
M_Gra1	0	0.1	0	0	0	0	0	0	0.0	0	1.414.479.0	1.006.664.0		2451008.0	3438792.0	0.1	3537914.0	280716.0	1115964.0	3535768.0
M_Gra2	0	0.0	0	0	0	0	0	0	0	0	0.5	1.684.639.0	2.123.177.0		0.0	0.7	1309607.0	2827756.0	3050887.0	6043417.0
M_Bar1	0	1.219.497.0	0.1	0	0	0	0.1	0.2	0.0	0	4.180.274.0	0.0	1.207.225.0	0.5		0.4	5215258.0	1523298.0	593271.0	0.3
M_Bar2	0	0.1	0	0	0.0	0.0	0	0.0	0.0	0	0.5	0.3	0.4	0.7	0.7		0.6	0.7	0.2	0
M_BMF1	0	0.7	0	0	0.1	0	6.295.727.0	2.767.683.0	0.9	0	0.1	0.4	2.733.355.0	0.4	0.4	0.3		5654912.0	4525097.0	83923.0
M_BMF2	0	0.0	0	0.0	0.1	0	2.781.414.0	3.249.989.0	0.1	0	0.2	0.7	1.143.975.0	0.6	0.0	0.1	4.609.457.0		1879793.0	1468374.0
M_CoF1	0	0.0	0.3	0.2	0	0	0.0	0.0	0	0	13.617.0	6.668.184.0	1.177.445.0	1.458.075.0	0.3	0.0	5.088.073.0	1.528.018.0		1151145.0
M_CoF2	0	0.0	0.5	0.4	0	0	0.0	0.1	0	0	436.736.0	7.781.265.0	0.9	1.037.559.0	0.0	0	7.379.629.0	1.365.133.0	1.026.016.0	
M_Agr1	0	1.107.073.0	0	0	0.0	0	0.6	0.1	0.3	0	0	0	2.106.013.0	0.4	0.5	0	9.752.541.0	0.4	3.361.554.0	0.1

	M_Agr1	M_Agr2	A_Shr1	A_Shr2	A_Gra1	A_Gra2	A_Bar1	A_Bar2	A_CoF1	A_CoF2	N_Shr1	N_Shr2	N_Gra1	N_Gra2	N_Bar1	N_Bar2	N_CoF1
Waterbody	0	0	0	0	0.0	0	0	0	0	0	0	0	0	0.0	0	0	0
Urban Area	1074462.0	0.0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Sn.& Gl. mild sl.	0	0	3926247.0	1422889.0	2342876.0	1026403.0	1020395.0	0.6	0.3	0.2	1435762.0	0.4	8232676.0	3027716.0	3521351.0	7114446.0	0
Sn.& Gl. St.sl.	0	0	0.5	0.3	0.1	0.2	0.2	0.2	0.1	0	0.1	0.0	1122521.0	2658692.0	2500784.0	1667475.0	0
L_Shr1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L_Shr2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L_Gra1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L_Bar1	0.0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L_Bar2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L_BMF1	0.3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L_BMF2	0.0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L_Agr1	0.1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L_Agr2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M_Shr1	0	0	5643498.0	3456814.0	0.0	0.2	0	0.0	8575954.0	1929225.0	0	0	0	0	0	0	0
M_Shr2	0.0	0	3500582.0	1075062.0	0.1	0.2	0.0	0.0	408673.0	3622446.0	0	0	0	0	0	0	0
M_Gra1	2618871.0	0.0	0.3	0.1	0	0	0	0	0	0	0	0	0	0	0	0	0
M_Gra2	0.6	0.3	0.0	0	0	0	0	0	0	0.1	0	0	0	0	0	0	0
M_Bar1	1634435.0	0	0.0	0.1	0	0	0	0	0.0	0.0	0	0	0	0	0	0	0
M_Bar2	1.0	0	0.0	0.3	0	0.1	0	0	0	0	0	0	0	0	0	0	0
M_BMF1	1073689.0	0.2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M_BMF2	0.6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M_CoF1	5684691.0	0.0	2575447.0	1749862.0	0.0	0.0	0	0.0	1509825.0	2505075.0	0	0	0	0	0	0	0
M_CoF2	0.2	0	1917210.0	4184565.0	0	0.1	0	0	7522089.0	9208445.0	0	0	0	0	0	0	0
M_Agr1		0.0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

M_Agr2	0	0.0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.0	0	0	0	0		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A_Shr1	0.0	0	9.089.413.0	124.919.0	0	0	0	0	0	0	5.273.615.0	4.532.992.0	0.0	0	0.0	0.0	0	0	1.248.332.0	7.485.187.0	0	0		8814705.0	9409091.0	1019108.0	2204706.0	1718967.0	3636057.0	242346.0	427725.0	0.5	0.9	0.8	5268466.0	1431471.0	0.2
A_Shr2	0.0	0	1.537.115.0	1.245.758.0	0	0	0	0	0	0	3.032.007.0	9.233.333.0	0.0	0.0	0	0	0	0.0	5.332.831.0	1.023.399.0	0	0	6.277.705.0		81357.0	2152785.0	0.6	0.9	3209654.0	3375543.0	0.2	0.1	0.2	0.1	0.7	0.2	0
A_Gra1	0.3	0	6.865.827.0	7.861.077.0	0	0	0	0	0	0	0.1	0.1	0	0	0	0	0	0	0.5	0.4	0	0	339.517.0	3.144.002.0		2035126.0	6689639.0	227422.0	188108.0	1768742.0	3108387.0	0.1	3229392.0	1506992.0	8438643.0	2057096.0	0
A_Gra2	0.2	0	1.528.791.0	1.597.017.0	0	0	0	0	0	0	0.6	0.4	0	0	0	0	0	0	0.1	0.2	0	0	4.175.468.0	9.203.982.0	1.487.511.0		3012269.0	3755466.0	7113588.0	3121259.0	1243526.0	0.1	1125953.0	1753295.0	3055178.0	1654602.0	0
A_Bar1	0.0	0	5.223.497.0	4.800.749.0	0	0	0	0	0	0	0.2	0.1	0	0	0	0	0	0	0.3	0.0	0	0	1.877.931.0	2.054.178.0	1.348.921.0	814.514.0		3302339.0	7733206.0	1342219.0	3907367.0	0.7	0.7	0.8	1196154.0	3965725.0	0
A_Bar2	0	0	8.242.974.0	4.975.821.0	0	0	0	0	0	0	0.1	0.1	0	0	0.0	0	0	0	0.3	0.1	0	0	2.376.431.0	4.823.062.0	9.985.971.0	3.451.837.0	4.345.905.0		2891263.0	1176587.0	0.7	0.3	0.1	0.3	536201.0	363017.0	0
A_CoF1	0	0	1.0	0.3	0	0	0	0	0	0	1.415.165.0	0.3	0	0	0	0.0	0	0	1.135.222.0	3.600.133.0	0	0	3.581.682.0	9.447.023.0	1.729.265.0	0.8	0.2	0.1		2816257.0	0.2	0	0.0	0.1	0.3	0.0	0
A_CoF2	0	0	0.3	0.0	0	0	0	0	0	0	0.6	0.2	0.0	0	0	0	0	0	1.720.683.0	2.196.982.0	0	0	3.365.845.0	2.743.653.0	0.2	0.5	0.0	0	1.716.221.0		0.0	0	0	0	0.0	0.0	0
N_Shr1	0	0	2.499.668.0	1.186.885.0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2.941.038.0	0.5	0.9	0.3	0.6	0.1	0.2	0		0.2	8885763.0	1506134.0	4347622.0	3234541.0	0
N_Shr2	0	0	1.353.375.0	0.6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.2	0.2	0.2	0.2	0.2	0.0	0	0	0.2		0.9	326372.0	1695796.0	8850577.0	0
N_Gra1	0.3	0	4.378.191.0	1.411.389.0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6.258.825.0	366.793.0	4.672.878.0	2.390.076.0	4.474.635.0	0.4	0.5	0.1	2.320.305.0	2.965.926.0		2145576.0	4904651.0	2425348.0	0.2
N_Gra2	0.0	0	3.451.922.0	166.533.0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	426.781.0	2.576.305.0	3.113.536.0	5.170.632.0	0.9	0.6	0.0	0	2.254.481.0	2.383.211.0	1.318.018.0		4581394.0	7143797.0	0
N_Bar1	0	0	1.497.921.0	5.600.588.0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1.354.834.0	6.253.676.0	5.816.854.0	2.658.692.0	2.873.241.0	0.5	1.281.287.0	0.1	103.901.0	2.864.659.0	1.503.131.0	1.770.459.0		1818518.0	0.2
N_Bar2	0	0	8.709.833.0	3.128.125.0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2.864.659.0	2.154.931.0	0.7	1.992.732.0	0.5	0.1	0.3	0.1	4.656.572.0	9.497.657.0	0.7	1.686.355.0	1.309.436.0		0

E. Typology validation locations.

	Latitude	Longitude
M-1	27.970452	90.707973
M-2	27.319321	89.656428
M-3	27.260855	90.249317
M-4	27.036061	90.757405
M-5	26.917049	90.426233
V-1	27.710202	89.4214
V-2	27.794645	90.169813
V-3	27.527978	90.244941
V-4	27.188096	89.107159
V-5	26.971341	89.391986
V-6	26.895111	89.868125
V-7	27.234337	90.4863
V-8	26.945568	90.373923
V-9	27.578565	91.470476
V-10	27.146646	91.931307

F. Total Landcover Area

	NLCS Area [ha]	ICIMOD Area [ha]
Snow and Glacier	299339	298845
Shrubs	419154	385734
Grassland	157238	199170
Forest Broadleaved/Mixed	1720310	1725619
Forest Conifer	983240	943577
Agriculture	112156	120565
Urban Area	6464	6835
Waterbody	27445	14409
Barren Area	151749	186200