Climate risks, exposure, vulnerability and resilience in Nepal[1]

Authors: Mattia Amadio, Patrick Behrer, Lander Bosch, Heidi Kaila, Nandini Krishnan and Giuseppe Molinario

Abstract

We investigate key climate change hazards affecting Nepali households and livelihoods: river flooding, heat exposure, drought, landslides, and air pollution. We analyse the distributional impacts of these hazards by combining spatial distributions of exposure with measures of socio-economic vulnerability and coping ability. While landslides are more likely to occur in the northern mountainous areas of Nepal, the southern parts of Nepal are at higher exposure to river flooding, heat, and drought hazards. Coping ability is highest in the southern lowlands (Terai) and urban settlements, which leaves northern, mountainous areas more vulnerable, despite being less affected. New human settlements in mountainous areas are built on steeper slopes as flat land in valleys has become scarce, which increases their vulnerability to floods and landslides. Forward modelling (2041-2060) shows increasing severity of heat and intensifying extreme rainfall. The increase in extreme precipitation events affects particularly the historically less-affected western provinces with relatively low economic development. Overall, the northern parts of the country will require concerted support to withstand shocks, and in the south, investments in agricultural livelihoods will be needed to support adaptation to climate risk. Proactive, spatially targeted investments are needed by all levels of government to mitigate the welfare impacts of these diverse climate change hazards. National investments in human capital are required to transform Nepali livelihoods in line with a green transition.

1. Introduction

With a geography spanning from the plains of the Terai to Mount Everest, the agroecological zones and the variability of natural hazards varies tremendously within Nepal. Nepal is also one of the most vulnerable countries to climate change in the world. Nepal ranks 139th out of 182 countries in terms of its exposure, sensitivity, and ability to adapt to the negative impact of climate change (ND-GAIN, 2022). Yet, like in many countries in the developing world, Nepal ranks in the bottom 20 percent in terms of greenhouse gas (GHG) emissions per capita (164th among 190 countries), and 87th in total emissions (out of 194 countries).[2] Despite the low carbon footprint, GHG emissions are rising and also contribute to air pollution, which is extremely high in Nepal, and affects the health of nearly the entire population (Nepal CCDR, 2022).

With rising temperatures across South Asia, Nepal is facing increased climate and disaster risks. The country's temperature is projected to increase by about 1 degree Celsius between 2016-45 (Nepal CCDR,

[1] This background paper was prepared as part of the Nepal Climate Change and Development Report (CCDR) and is a joint output of the Nepal Poverty and Equity GP and the South Asia Climate Adaptation and Resilience Partnership (SCARP). It was also supported by the Climate Support Fund. This work draws on a regional effort on natural hazard risk and forecasting. We gratefully acknowledge inputs from Nethra Palaniswamy and the regional team including Maham Faisal Khan, Henrik Fisser, Walker Kosmidou-Bradley, Vincent Mariathasan, and Moritz Meyer.

[2] Nepal's per capita GHG emissions were 1.94 tonnes of CO_2 equivalent (tCO_2e) per capita in 2018. Nepal is polluting less per capita than India (2.47 tCO_2e), but more than Sri Lanka (1.71 tCO_2e) and Bangladesh (1.37 tCO_2e).

2022). Nepal is part of Himalaya, Karakoram and Hindu Kush Mountain region of South Asia, which stores more ice than any part of the world outside the poles. Rising temperatures pose additional risks through accelerated glacier melting, which can exacerbate flooding risks above and beyond those caused by variations in precipitation.

Nepal's livelihoods profile is also highly exposed to climate risk, and the economy is particularly vulnerable to shocks affecting the agricultural sector. Of the labour force, 62 percent work in agriculture alone. The nature of agrarian livelihoods, with a high degree of subsistence, small holder farming, reliant on rainfed crop production and livestock, in the low-lying terai areas and floodplains in river valleys, is highly exposed to flooding and associated losses in incomes and capital (land and assets). Outside of agriculture, most of the jobs in services and manufacturing are small-scale and informal, with high exposure to heat stress and air pollution. Finally, in a context where topography poses an inherent challenge to inclusion and service delivery to remote, rural, hard to reach communities, very limited coverage of public social protection as well as limited instruments to scale up relief in times of need, imply that most households have very limited coping strategies in the face of a shock. As a result, adapting to climate change and strengthening household and community resilience is an important priority, while maintaining a low emission footprint.

We analyse the distributional impacts of climate change in Nepal by combining spatial distributions of exposure to a range of climate hazards with measures of socio-economic vulnerability and coping ability. We investigate these against the background of the evolution of the human footprint, namely human settlements and changes in land use and land cover. These three elements – the exposure to physical risk, socio-economic vulnerability, and changing patterns in the human footprint jointly (i) determine the potential for welfare losses from climate change; and (ii) identify the areas and sub-groups who may need tailored support to navigate climate related shocks. Finally, we examine the potential for green livelihoods in Nepal, with a particular focus on livelihoods in agriculture, which are important in terms of both employment, and exposure to climate risk.

We investigate the geographical expansion of population settlements by using satellite remote-sensing observations of built-up area (BUA), an indicator of whether a given area of land, represented by a pixel in a satellite image, is covered by human settlements. Population settlements in Nepal are heavily determined by geographic endowments: elevation and slope of land, and proximity to river valleys and trade routes. Growth in BUA during 2000-2019 has been concentrated in areas that have population growth, and places where there has been an expansion of transport infrastructure and improvements in accessibility. The areas of BUA growth are also clustered around pre-existing pockets of high population density and economic activity. The expansion in BUA has come with a loss of area covered by vegetation, crowding out mainly cropland, grassland, and forest: 17.5% of all municipalities lost 20% or more of their cropland between the years 2000-2019.

The key climate change hazards affecting Nepali livelihoods are river flooding, heat exposure, drought, and landslides. While river floods and landslides were the most frequent hazards over the last 40 years, the incidence of drought and heat exposure are increasing (Nepal CCDR, 2022). Landslides are more likely to occur in the northern mountainous areas of Nepal, the southern parts of Nepal are more exposed to river flooding, heat, and drought hazards. Densely populated urban settlements and river valleys, including the Kathmandu valley, are also pockets at high risk of river flooding, heat extremes, and drought. Potential damages to built-up assets are more prevalent in the southern part of the country, whereas potential mortality risks are more spatially dispersed, and extend to central, primarily urban municipalities.

Given the co-incidence of GHG and air pollution emissions and the co-benefits of addressing them together, this paper adopts a similar approach to the Nepal CCDR (2022) and includes air pollution in the analysis, as an environmental hazard that should be addressed with climate hazards. Outdoor air pollution in Nepal is associated with over 2.5 times more deaths per capita than in low-income countries on average in 2019 (Health Effects Institute, 2020). Nepal ranks 3rd out of 240 countries in the severity of the reductions to the life span by air pollution, which in Nepal is 4 years on average, with a distribution of up to 7 years in the Terai and just 1 year in the most remote mountainous areas (AQLI, 2022)[3]. We also examine the spatial dispersion of air pollution finding that higher pollution, and also higher risk of mortality and morbidity are concentrated in the southern Terai.

We investigate socio-economic vulnerability to climate shocks at the household level, finding significant geographical variation in household resilience to shocks despite the preponderance of agriculture as a source of livelihood throughout the country. Our assessment of socio-economic vulnerability or resilience goes beyond asset losses and incorporates household and individual ability to cope in the face of an adverse shock. The ability of a household to maintain their incomes in the face of an asset loss is also shaped by the availability of government relief, access to private support networks, access to savings, and access to formal or informal credit markets. In our analysis combining household survey data with geographical hazard measures, we find that the northern parts of Nepal are least resilient to climate-related disasters, while Kathmandu valley and the southern parts of the country are somewhat less vulnerable. This is somewhat opposite to the findings on the hazard exposure itself and suggests the need for a mitigation strategy for disaster impacts, that considers both vulnerability and hazard exposure.

In addition to contemporaneous hazard and vulnerability analysis, we also conduct forward-looking modelling of temperature and precipitation for the period 2041-2060[4]. We investigate high, intermediate, and low-emission climate change scenarios, which all paint a worrisome picture for Nepal. Current heat stress patterns are set to increase in severity, and, while the overall precipitation patterns are unlikely to considerably alter, extreme rainfall events are likely to increase in magnitude. The stark projected increase in extreme events in the historically less-affected western provinces of Karnali and Sudurpaschim, provinces with relatively low economic development, calls for particular attention to adaptative measures and preparedness efforts. Simultaneously, the forecasted deepening of historical spatial patterns of agricultural drought and wetness demonstrates that structural measures need to be implemented to overcome the disparities currently seen across Nepal, to ensure the lives and livelihoods of all Nepalis.

Overall, notwithstanding the trend of increasing risk and hazard exposure due to climate change, different geographical regions face different types of challenges, which calls for policy action that acknowledges the heterogeneity in hazard exposure and resilience within the country. In the southern parts of Nepal, crop production and livestock herding are pervasive, which face high risks of both droughts and heat stress, and a high risk of physical asset damage resulting from river flooding. Yet at the same time, these areas also have the highest resilience ratio, that is, in southern parts of the country asset losses translate to the lowest level of consumption losses. At the same time, northern parts of the country have a high degree of vulnerability due to more limited access to coping, even though exposure to most hazards is lower.

[3] India and Bangladesh rank higher and are estimated to be able to increase life expectancy by 5 years and 6.9 years on average, respectively, if WHO guidelines of air quality are met.

[4] We choose this time period, i.e., from 20 years from now, as the minimum amount of time needed to detect a significant climate change trend.

Landslides are an exception as they occur more often in the northern mountainous areas and can also cause significant damage, particularly on steep terrain.

The overall potential for transforming Nepal's livelihoods profile for a green transition is limited: under one percent of the labour force in 2017 was engaged with new occupations closely associated with those brought by the new green economy, occupations such as chemical and mechanical engineers. These occupations are almost entirely male-dominated in Nepal and require tertiary education. While the capacity to transform the economy into a sustainable one can benefit from innovations and activity coming from a wide range of occupations, the lack of new green jobs can decelerate green growth. Our analysis shows that the northern parts of the country will require concerted support to withstand shocks, and in the south, investments in agricultural livelihoods will be needed to support adaptation to climate risk.

2. Data and Methods

The analysis in this paper was developed using several different data sources. In all cases the team aimed to use the most recent data with the highest spatial resolution and accuracy. As such the analyses presented in the following sections represent the state of the art of climate induced hazard exposure mapping and vulnerability analysis. This approach yields a replicable and standardised methodology that uses readily available global datasets. A broader in-depth initiative by the Ministry of Forests and Environment of Nepal (MoFE) produced the Vulnerability and Risk Assessment (VRA) for Nepal, published in 2021. The VRA was a critical step in producing a National Action Plan (NAP)[5] ; an integral step of the roadmap and membership of Nepal to the UNFCCC (MoFe 2021). The analysis presented here and the MoFE VRA differ in their scope in several ways, yet the most relevant is the use in this study of regional and global datasets and standardised methods that are currently applied by the World Bank to other SAR countries.

Data

In general, there are three main sources of data employed in this analytical work:

- **Socio-economic data from the ground**: This includes, for example, population data from the Census (2010) that was modelled spatially and temporally from teams such as CIESIN and WorldPop, in order to be made adequate for grid-level spatial analysis, and socio-economic survey data used for analysing vulnerability and green jobs.
- **Infrastructure and administrative unit data**: This includes data such as the road network and the administrative units (admin 3 – Municipality (palika) level, in most cases). The road network and some other infrastructural elements are digitized using a variety of different sources from the ground and are then made available through open source and freely available projects such as OpenStreetMap. Administrative boundaries and designations have changed as a result of the move to federalism in 2015. The latest administrative boundaries used for this analysis were obtained from the Nepal Survey Department. [6]
- **Satellite Remote Sensing Data:** Data from satellite observations is used for several components of the analysis as it provides high spatial resolution observations suitable for modelling at the local scale, with national extent. It is used, first and foremost, for the geographical contextualization of the country, using topography from Digital Elevation Model and Land Cover data from ICIMOD.

[5] https://unfccc.int/sites/default/files/resource/NAP_Nepal.pdf
[6] https://www.dos.gov.np/

Specific land cover-derived masks are used throughout, specifically built-up area observed and classified using Landsat and Sentinel satellite data and cropland, derived from the ICIMOD land cover map and European Space Agency. Hazard data is also derived in large part from satellite observations, including river flood Return Period (RP), droughts (drought indices), landslide (precipitation) heat and air quality.

Table 1 provides a reference for the data sources used in the analyses in all sections of this report. For more information regarding data sources please refer to the specific sections, annexes, and references.

TABLE 1: DATA SOURCES

Section	**Analysis theme**	**Data sources**
3.	**An evolving human footprint**	
	Topography	NASA Shuttle radar Topography Mission (SRTM) Digital Elevation Model (DEM)
	Land cover	International Centre for Integrated Mountain Development (ICIMOD) 2019 and Regional Land Cover Monitoring System (RLCMS) 2000-2020
	Built-up area (BUA)*	BUA 2000-2005-2010-2015-2019 Binary map (either 1 – BUA is present or 0 – BUA is not present) prepared by New Light Technology for World Bank in 2020-2021, modelled on World Settlement Footprint (WSF) 2019 “ground truth”.
	Population*	WorldPop constrained 2020 based on Central Bureau of Statistics (CBS) 2010 census data.
4.	**Present-day risk profile**	
	Population & BUA	*See above – BUA is WSF 2019
	River floods	1) FATHOM model
		2) European Space Agency (ESA) WorldCover 2020
	Heat	Extreme Heat Hazard layer - VITO/GFDRR (2017) (EH-GLOBAL-VITO-5). Wet Bulb Global Temperature (WBGT)
	Drought	UN Food and Agriculture Organization (FAO) Agricultural Stress Index (ASI) 1984-2022
	Landslides	World Bank-ARUP Landslide Susceptibility Index at 1km resolution
	Air Pollution	PM2.5 concentrations 1998 to 2020 @ 1.1km resolution (van Donkelaar et al., 2021) combining Aerosol Optical Depth retrievals from NASA MODIS, MISR, and SeaWIFS instruments together with the GEOS-Chem chemical transport model.
5.	**An example of increasing granularity in hazard exposure**	
	Population & BUA	*Same as above
	Slope	Derived from the NASA SRTM DEM
6.	**Sensitivity analysis of population data**	
	Population	WorldPop 2000-2021; Meta (Facebook) 2019; World Settlement Footprint 3D 2021
7.	**Socio-economic Vulnerability**	
	Socio-economic variables	Nepal Household Risk and Vulnerability survey (HRVS); Nepal Central Bureau of Statistics (CBS)
8.	**Estimating future climate risks**	

	Shared Socioeconomic Pathways	Coupled Model Intercomparison Projects (CMIP6) from IPCC
	Hazard data	Same as section 4.
9.	**Green Jobs**	
	Employment data from Nepal	Nepal Labour Force Survey (LFS) 2017
	Green jobs classifications	Montoya, Olivieri, Sanchez, Vazquez and Winkler (2022)

Note: Data source details covered in the Annexes and in References.

Methods

Standard Geospatial Information System (GIS) and data analysis methods were used to turn the input data sources into the analytical comparisons, correlations and future estimates provided in the following sections. In the table below we have summarized the main methods used for each analysis. For all specific methods, each section provides more in-depth information.

There are 4 main groups of methods used in this paper, divided into the following categories:

- Sections 3, 5 and 6 rely on standard GIS methodologies applied to satellite remote sensing products that are freely and openly available to the public.
- Sections 4 and 8:
    - Both sections draw on ongoing work on hazard exposure mapping which follows a standardised approach based on the use of replicable and open-source GIS-based codebooks scripted using the python programming language and QGIS geospatial software[7]. A detailed technical note, World Bank (2022) documents the data and analyses. The note is currently a work in progress and available upon request. See also Annex 5.
    - In section 8 the forward-looking estimates of climate hazards use the methods above in conjunction with IPCC CMIP6 Shared Socioeconomic Pathways for the period 2041-2060
- Section 7: The Socio-economic vulnerability section follows closely the methods laid out by the *Unbreakable* methodology pioneered by Hallegatte, Vogt-Schilb & Rozenberg (2017)
- Section 9: This section uses data analysis methods to correlate data from the Nepal labour survey, green jobs classification, and land cover data.

3. An evolving human footprint

In Nepal, BUA, which is a rough proxy for population settlements, density, and agglomeration, is heavily predetermined by the geographic endowment of the country, particularly elevation and slope. BUA is therefore observed in areas with population settlements and areas with more economic activity and better connectivity.

[7] This hazard mapping is a joint effort by the Pakistan and Nepal Poverty and Equity GP teams in collaboration with DEC and GFDRR.

This section leverages multiple data sources on BUA, as outlined in Annex 1. The main data source used is an ad-hoc built-up area mask in 5-year increments for the period 2000-2019, developed by New Light Technologies (NLT) for the World Bank which uses input Landsat data (hereafter, WB BUA). The product, developed in 2020, was created using a classification algorithm that was trained on the best available data at the time, the World Settlement Footprint (WSF) 2019 product. As such, for 2019 the WSF and the WB BUA are very similar, but not identical. The WB BUA has a spatial resolution of 30 meters. Since 2019 the WSF team has produced more advanced and updated built-up area masks (binary maps that contain only two values [0-BUA not present and 1-BUA is present], which at 10m resolution provide improved granularity in identifying individual settlements. This product also employs Synthetic Aperture Radar (SAR) data in addition to Sentinel optical imagery. In Annex 1 is a full discussion on the pros and cons of different BUA products.

Overall, BUA in Nepal accounts for less than 1% of total land cover, as the largest land cover type in the country is forest, followed by cropland and grassland (see Table 2). Bagmati province, where Kathmandu valley is situated, has the highest share of BUA of all land area, 1.4%. Moreover, built up area is heterogenous, as the patterns of human settlements vary across the country. For instance, more than a quarter of palikas (municipalities) have negligible built-up area (Figure 4). These municipalities are heavily concentrated in the mountainous provinces of Karnali (mean elevation 3,387 meters above sea level), and the northern parts of Sudurpaschim, and Koshi province (mean elevation ~1,900 meters above sea level).

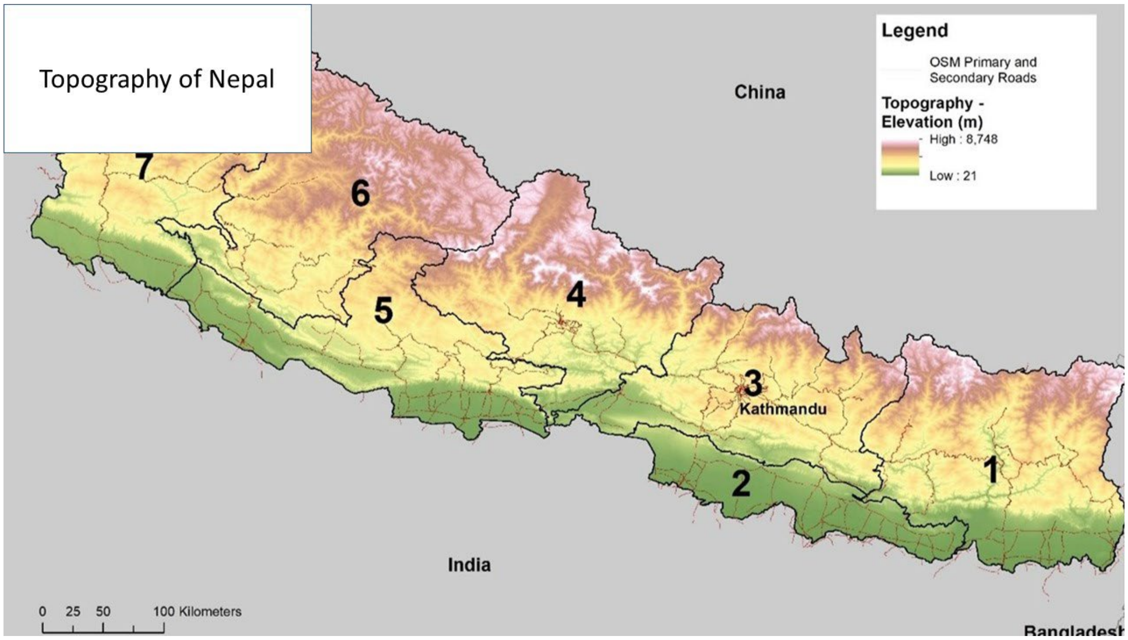
There aren't many settlements at high altitudes as measured by remotely sensed BUA. Furthermore, slope (i.e., steepness) in mountainous areas is a more binding determinant of the ability to build than elevation itself – while the average elevation of a province in Nepal is 1,857 meters above sea level, the mean elevation of built-up areas is only 454 meters. This means that while the variations in altitude in Nepal are enormous, the variance in the altitude of settlements is much smaller. Only in the Terai regions in the south of the country the topography flattens out and allows for dispersed, but pervasive human settlements. In mountainous areas, slopes are the flattest in valleys, where settlements can be large despite high elevations. Indeed, built up area in Nepal is currently heavily concentrated in the Kathmandu and Pokhara valleys, as well as southern municipalities in the Terai, closely following population density (Figure 5, Figure 6).

Individual built-up area pixels are not easily visible in a national scale map such as the Figure 1. The two zoomed-in details at the local scale allow built-up area (and its change through space and time) to be seen in both urban settings, where they are densely clustered (map in Figure 2 showing Kathmandu) as much as more rural ones in the Terai, where BUA is more pervasively distributed in space (map in Figure 3 showing Madhesh). At the national level, over the last two decades, a net increase in snow and glacier, forest and built-up area has come at the expense of cropland, bare rock and grassland land cover types.[8]

In 2019, forest cover was the single largest land use class in provinces 1, 3, 5 and 7, while cropland was the highest land use classification in the remaining provinces (Table 2). Province 2 in the south was the only province with more cropland than forest cover, while Gandaki and Karnali have a relatively large percentage of grasslands.

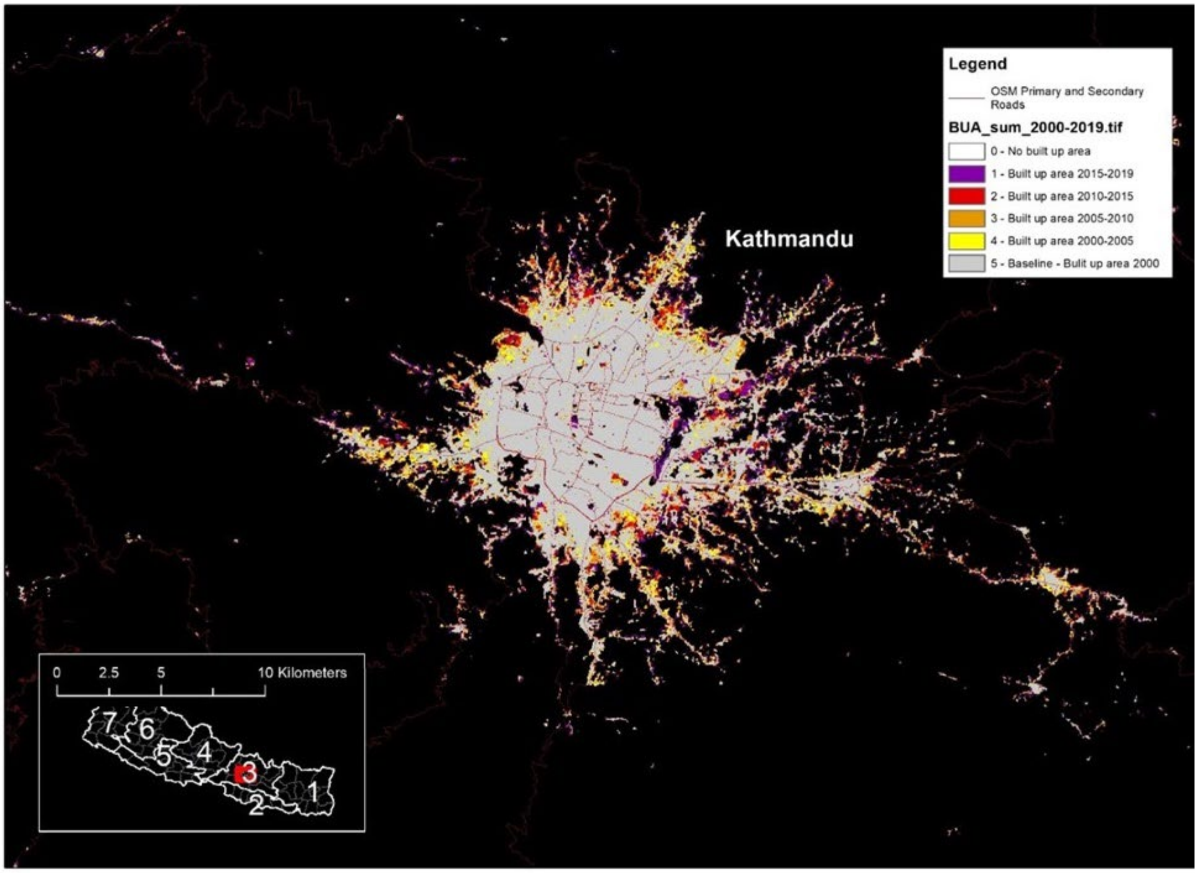
[8] Future work will analyse in more detail, at the pixel/local level, land cover and land use transitions over time to understand in order to tabulate what land cover has been replaced by what other land cover type to understand changes in land use patterns.

FIGURE 1: TOPOGRAPHY- ELEVATION IN NEPAL



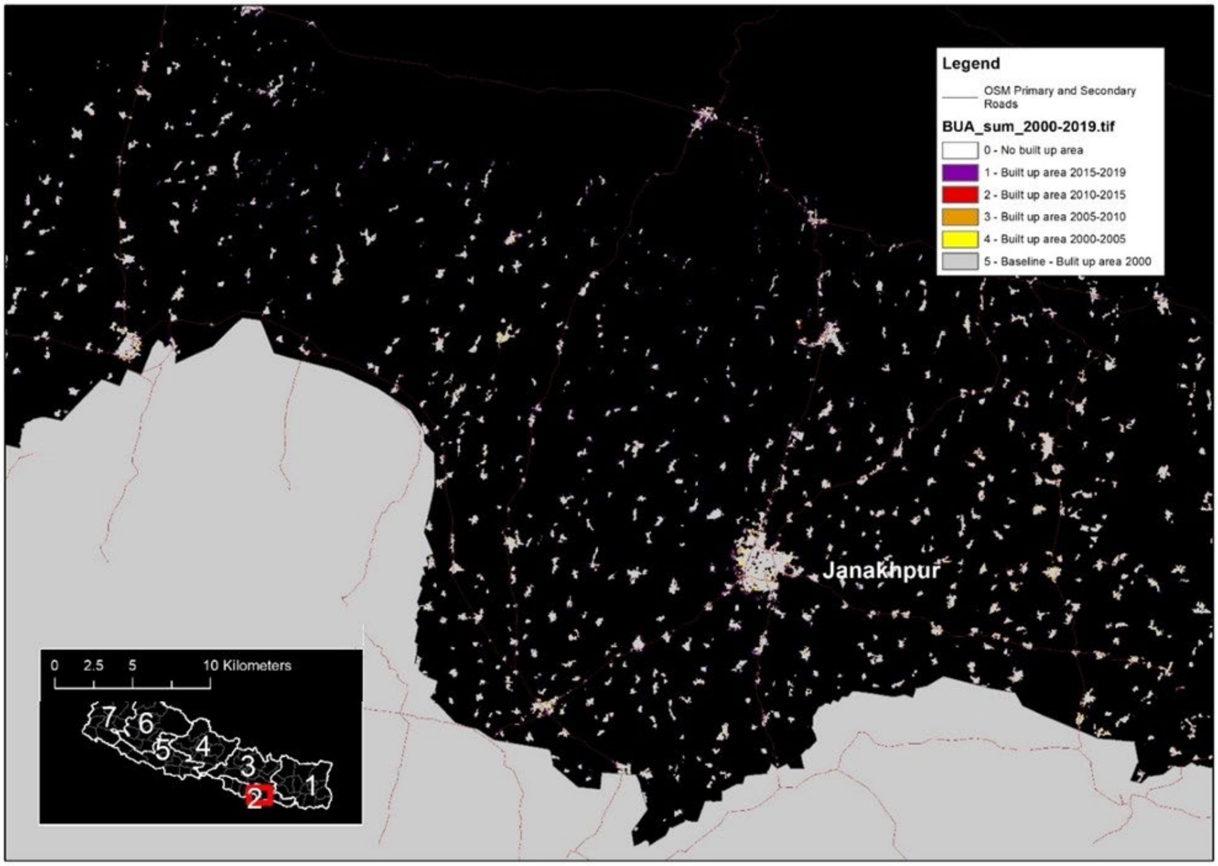
Notes: Data source is NASA Digital Elevation Model (DEM) from Shuttle Radar Topography Mission (SRTM). Province numbers correspond to province names as follows: Province 1 Koshi, Province 2 Madhesh, Province 3 Bagmati, Province 4 Gandaki, Province 5 Lumbini, Province 6 Karnali, and Province 7 Sudurpaschim.

FIGURE 2: BUILT-UP AREA KATHMANDU



Notes: Based on World Bank analysis using WB Built up area footprint 2000-2019.

FIGURE 3: BUILT-UP AREA MADHESH



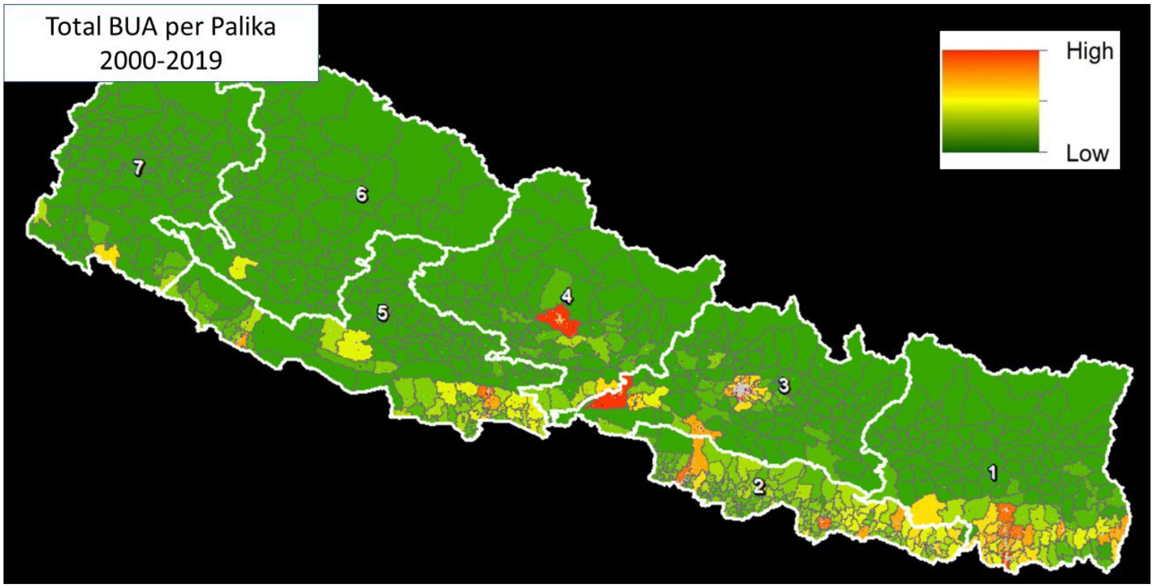
Notes: Based on World Bank analysis using NASA Landsat and the World Settlement Footprint 2019 product.

TABLE 2: COMPOSITION OF LAND USE, BY PROVINCE, 2019

Land Cover	Province 1	Province 2	Province 3	Province 4	Province 5	Province 6	Province 7	Total
No Data	0.18%	0.70%	0.21%	0.00%	0.49%	0.00%	0.12%	0.19%
Water Body	0.56%	0.87%	0.44%	0.44%	0.55%	0.37%	0.45%	0.49%
Snow and Glacier	8.11%	0.00%	4.64%	15.65%	0.38%	18.11%	7.86%	9.30%
Forest	49.19%	25.41%	60.21%	41.40%	54.92%	30.80%	53.04%	45.42%
River Bed	1.14%	4.89%	1.22%	0.42%	1.52%	0.16%	0.97%	1.11%
Built-up Area	0.49%	0.84%	1.38%	0.39%	0.72%	0.37%	0.24%	0.59%
Cropland	27.79%	61.63%	21.76%	12.18%	34.76%	12.35%	23.13%	23.85%
Bare Soil	0.01%	0.01%	0.00%	0.17%	0.00%	0.03%	0.00%	0.03%
Bare Rock	2.99%	0.00%	2.20%	8.95%	0.62%	14.39%	2.87%	5.65%
Grassland	9.54%	5.65%	7.93%	20.39%	6.03%	23.43%	11.30%	13.38%
Total	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%

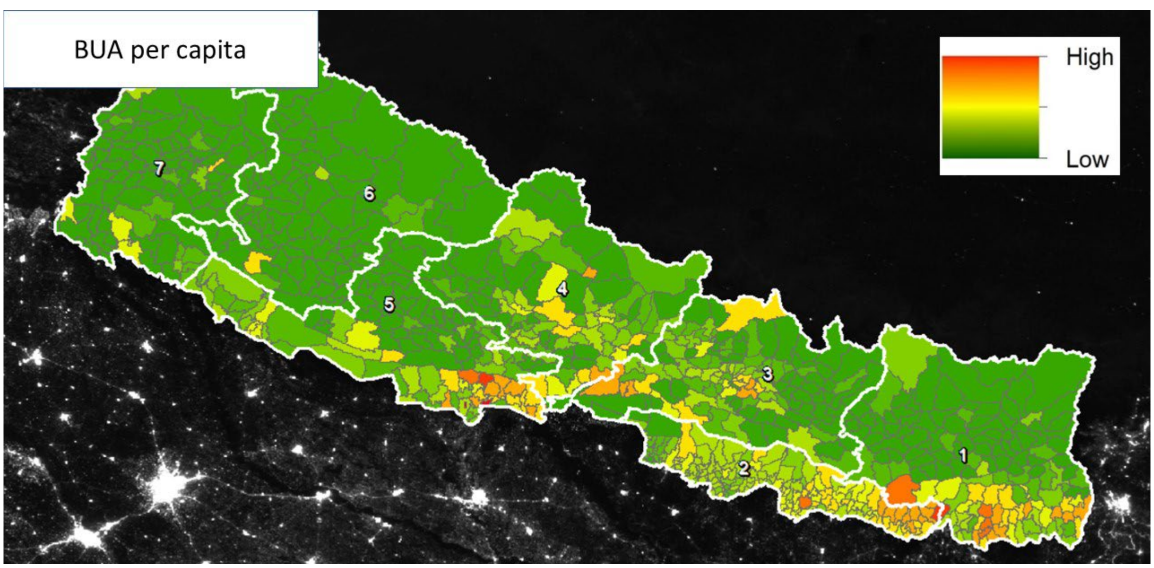
Notes: Province numbers correspond to province names as follows: Province 1 Koshi,, Province 2 Madhesh, Province 3 Bagmati, Province 4 Gandaki, Province 5 Lumbini, Province 6 Karnali, and Province 7 Sudurpaschim. Data source ICIMOD 2019. For a table of areas in Hectares see Annex 1.

FIGURE 4: TOTAL BUA PER PALIKA, 2019



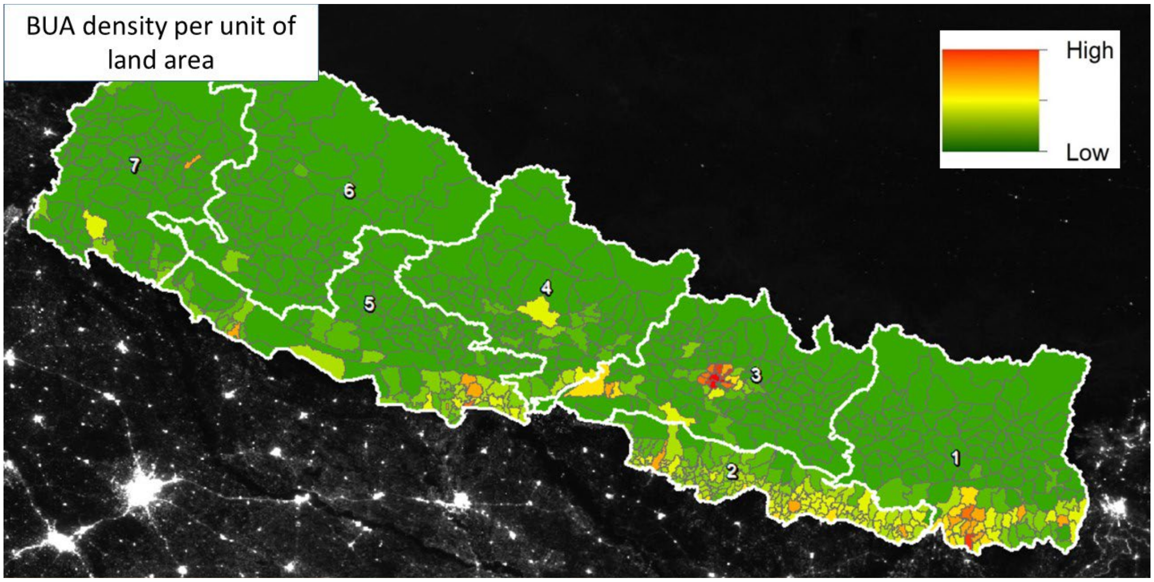
Notes: Low to High values refer to the presence in the Palika of BUA Hectares from low to high. Data source: WB BUA 2000-2019. Province numbers correspond to province names as follows: Province 1 Koshi, Province 2 Madhesh, Province 3 Bagmati, Province 4 Gandaki, Province 5 Lumbini, Province 6 Karnali, and Province 7 Sudurpaschim.

FIGURE 5: BUA PER CAPITA



Notes: Data source WB BUA 2000-2019. Province numbers correspond to province names as follows: Province 1 Koshi, Province 2 Madhesh, Province 3 Bagmati, Province 4 Gandaki, Province 5 Lumbini, Province 6 Karnali, and Province 7 Sudurpaschim.

FIGURE 6: BUA PER AREA

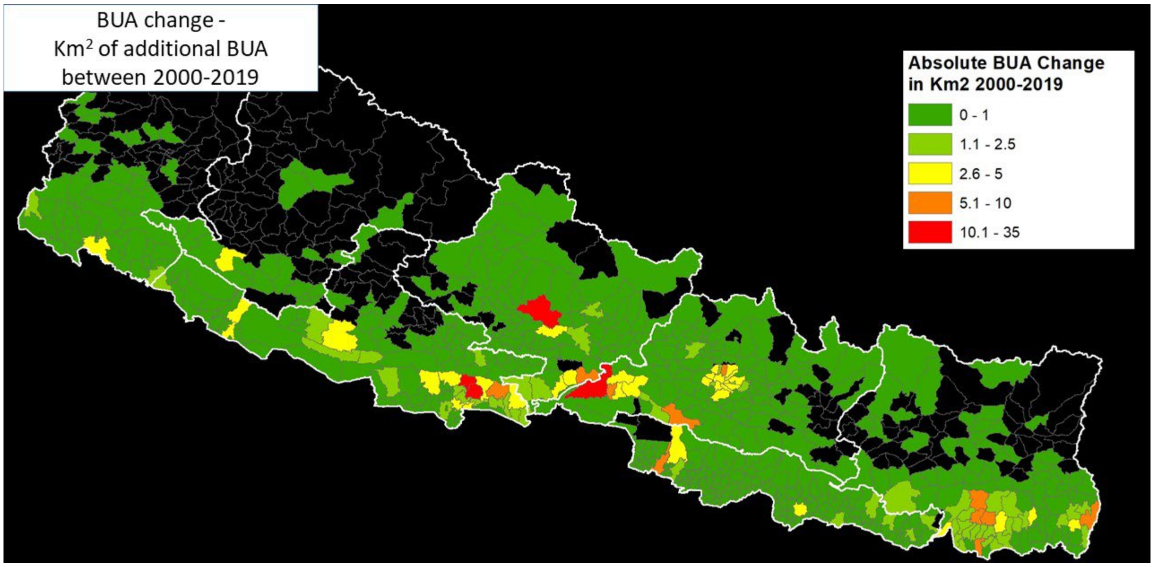


Notes: Data source WB BUA 2000-2019. Province numbers correspond to province names as follows: Province 1 Koshi, Province 2 Madhesh, Province 3 Bagmati, Province 4 Gandaki, Province 5 Lumbini, Province 6 Karnali, and Province 7 Sudurpaschim.

Even though BUA as a fraction of land cover is very small even in 2019, this level is still a result of rapid increases in human settlements in the 2000's, as there was a 62% increase in built-up area relative to 2000 at the national level. This growth is correlated with population growth and facilitated by expansion in transport infrastructure and accessibility. The largest absolute increase in built up area is in the south-central parts of the country (map in Figure 7). A slightly different view of the same data, showing the growth in built-up area (2001-2019) as a percentage of the baseline built-up area (2000) is shown in the map in Figure 8. While there is some overlap in where the absolute BUA growth (map in Figure 7) and relative BUA growth (map in Figure 8) are, the northern palikas are seeing only large changes in relative terms, given that these areas had very small concentrations of BUA in 2000.

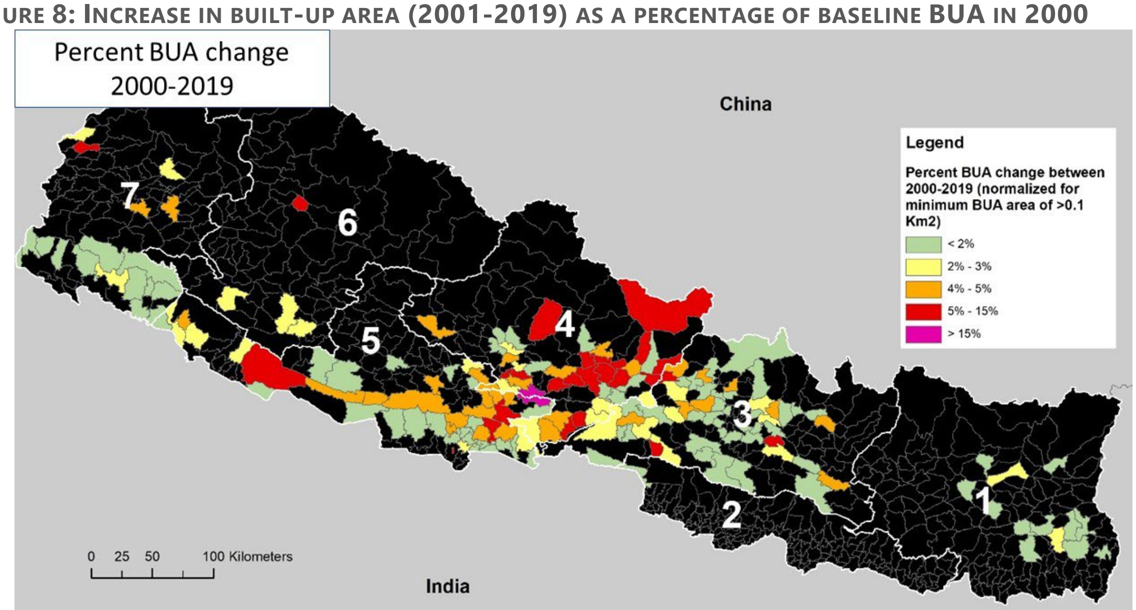
At the provincial level, built-up area has doubled since 2000 in Gandaki, Lumbini, Karnali and Sudurpaschim. However, despite this increase, Karnali and Sudurpaschim contributed less than 4% of national change in built up area, with province 1, Bagmati and Lumbini each accounting for at least a fifth of the total change in built up area at the national level.

FIGURE 7: INCREASE IN BUILT-UP AREA IN SQUARE KM IN 2000-2019



Notes: Data source WB BUA 2000-2019

FIGURE 8: INCREASE IN BUILT-UP AREA (2001-2019) AS A PERCENTAGE OF BASELINE BUA IN 2000



Note: The above map is normalized by removing all palikas that have < 0.1Km2 of BUA in 2000. Province numbers correspond to province names as follows: Province 1 Koshi, Province 2 Madhesh, Province 3 Bagmati, Province 4 Gandaki, Province 5 Lumbini, Province 6 Karnali, and Province 7 Sudurpaschim.

Increasing built-up area has replaced existing areas of land cover types such as cropland, grassland, and forest (see Annex 3). The changes have environmental and socio-economic impacts, including those discussed in the next section that relate to changing hazard exposure and vulnerability. About 135 palikas (17.5% of all municipalities) have lost at least 20% of their 2000 cropland by the year 2019.

TABLE 3: CHANGES IN BUILT-UP AREA BY PROVINCE 2000-2019

		Province							National
Variable	**Unit**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	
BUA growth over period 2000-2019	km^2	91.4	69.8	130.5	52	103.6	4.6	11.9	*463.8*
BUA growth as % of land area	%	0.35%	0.73%	0.64%	0.24%	0.54%	0.01%	0.07%	*0.32%*
BUA growth as % of baseline 2000 BUA	%	43.20%	26.39%	80.80%	196.45%	151.41%	255.40%	115.03%	*62.29%*
BUA 2000 area	km^2	211.6	264.4	161.5	26.5	68.4	1.8	10.3	*745*
BUA 2019 area	km^2	303.0	334.2	292.0	78.5	172.0	6.4	22.2	*1,208*
Share of national change in BUA	%	19.7%	15.0%	28.1%	11.2%	22.3%	1.0%	2.6%	*100.0%*
Province land area	km^2	26,125	9,597	20,305	21,974	19,269	30,737	17,692	*145,699*
% change in BUA per capita	%	110.4%	88.6%	117.9%	488.4%	254.9%	751.2%	114.4%	*136.1%*
BUA per capita change 2000 - 2019	m^2	5.06	-7.55	6.06	35.76	27.08	5.00	0.89	*11.24*
BUA per capita 2000	m^2	48.79	66.10	33.96	9.21	17.48	0.77	6.17	*31.15*
BUA per capita 2019	m^2	53.85	58.55	40.02	44.96	44.56	5.77	7.06	*42.39*
Population 2000 (WP adjusted CBS)		4,335,850	4,000,761	4,756,381	2,875,206	3,914,882	2,343,778	1,677,361	*23,904,219*
Population 2019 (WP adjusted CBS)		5,626,406	5,708,616	7,296,097	1,744,954	3,860,854	1,116,873	3,150,550	*28,504,350*
Share of national population 2019	%	19.7%	20.0%	25.6%	6.1%	13.5%	3.9%	11.1%	

Data sources: WB BUA 2000-2019, WorldPop 2000 – 2019. Province numbers correspond to province names as follows: Province 1 Koshi, Province 2 Madhesh, Province 3 Bagmati, Province 4 Gandaki, Province 5 Lumbini, Province 6 Karnali, and Province 7 Sudurpaschim.

4. Present-Day Risk Profile

This section uses a standardised, replicable analytical approach to describe the current physical exposure and risk of the Nepali population, and their built-up and agricultural assets, to distinct climate hazards. In the analysis that follows, assessment of present-day risk, determined based on historical data, relies on the high-resolution location of hazards, the population exposed, and a measure of impact (in this case, potential mortality and loss of physical assets and built-up area)[9]. The analysis focuses on five key hazards which are particularly relevant for Nepal – river flooding, heat exposure, droughts, landslides, and air pollution. While river flooding hazard is high in Nepal, heatwave hazards and drought hazards are also significant in the country. Furthermore, the nature of these hazards is unique in Nepal as they all contribute and aggravate the highly prevalent earthquake hazard. While in this section we describe the risk profiles separately for each hazard, it is important to note that each of the described hazards also can aggravate and contribute to the risk of disaster events related to the high prevalence of earthquakes (European Commission 2019; World Bank and Asian Development Bank, 2021).

River flooding

We analyse river flood hazard, exposure, and impact at the grid and small administrative unit level. Table 4 shows the range of population exposed to a 1 in 100-year river flood, or 100-year return period (RP), per category of flood depth to which they are exposed in such extreme river flooding event. The maps below show the physical hazard posed by a 1 in 100-year flood in Nepal at the 90m grid level using data from the FATHOM flood model (Figure 9), the exposure of population using WorldPop 2020 data (Figure 10), built-up area (using 2019 World Settlement Footprint data, as in Section 2) (Figure 11), and agricultural land using 2020 ESA WorldCover data (Figure 12). A clear spatial pattern emerges showing that river flood hazard is highest along the southern border areas of Nepal, as well as in and around the densely populated urban settlements in the Kathmandu valley, and to a lesser extent, Pokhara, with population groups, built-up assets and agricultural land in these areas exposed to flooding events.

Using these measures of physical hazard and exposure, the impact of these river floods is calculated by intersecting population data and land cover data to compute the risk of population mortality for a given flooding depth and the damage that a flood of that depth would cause to physical assets and structures[10].

The resulting risk profiles, incorporating the impact on mortality or damage to built-up assets of river floods with a 10, 100, and 1,000-year return period (RP), are aggregated to the municipality or palika level. Around 2.5 million Nepalis are likely to be exposed to a 1 in 100-year flood with a flood depth of at least 0.5 metres. Interestingly, the resulting risk picture differs between population risk and risk to built-up assets. Whereas the risk of population mortality is more dispersed across municipalities of Nepal, the built-up assets at risk

---

[9] This section draws on a joint effort by the Pakistan and Nepal Poverty GP teams in collaboration with DEC and GFDRR to produce hazard exposure maps & tabular results following a standardised approach based on the use of replicable and open-source GIS-based codebooks scripted using the python programming language and QGIS geospatial software. A detailed technical note, World Bank (2022) documents the data and analyses. The note is currently work in progress and available upon request. Also see Annex 4.

[10] It is important to note that the flood min threshold is set at 0.5 m, assuming lower water depths to be mitigated by basic response measures. Also, it is important to note that population uses a mortality function (Jonkman et al 2008), that uses the maximum risk estimate, which likely surpasses real impact, while built-up uses damage functions (Huizinga et al 2017).

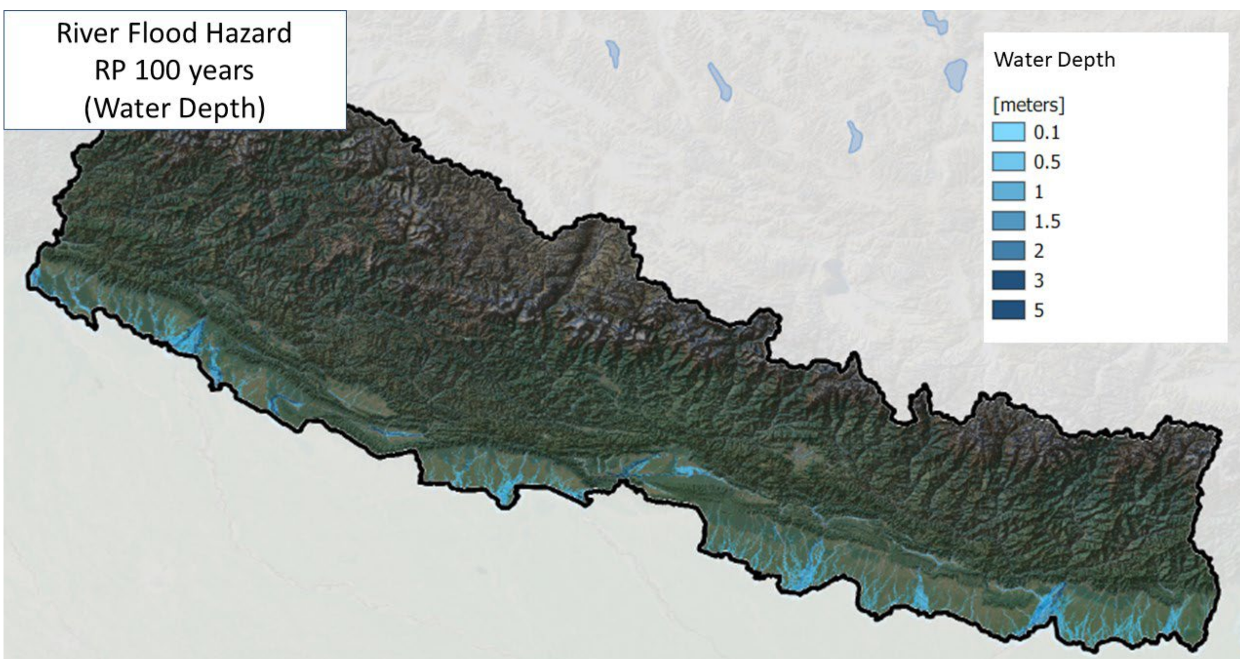
of being damaged by river flooding is far higher in the southern administrative units. These are also the areas where cropland is most frequently exposed to severe flooding.

TABLE 4: POPULATION EXPOSED TO FLOOD DEPTHS FOR A 1-IN-100-YEAR FLOOD

Province	*0.01-0.15m*	*0.15-0.50m*	*0.50-1m*	*1-1.50m*	*1.50-2m*	*>2m*	*Total*
1	837,329	719,708	486,207	200,315	63,195	35,406	2,342,159
2	1,139,725	769,188	334,918	99,054	22,673	8,881	2,374,440
3	126,354	158,448	140,916	96,547	64,640	155,101	742,006
4	34,459	10,144	10,668	7,143	5,968	53,593	121,976
5	326,008	237,143	182,638	69,556	33,700	62,783	911,828
6	9,831	3,210	3,790	3,332	1,914	19,074	41,152
7	340,689	172,110	122,504	130,218	65,141	67,156	897,818
Grand Total	**2,814,396**	**2,069,952**	**1,281,641**	**606,165**	**257,231**	**401,995**	**7,431,380**

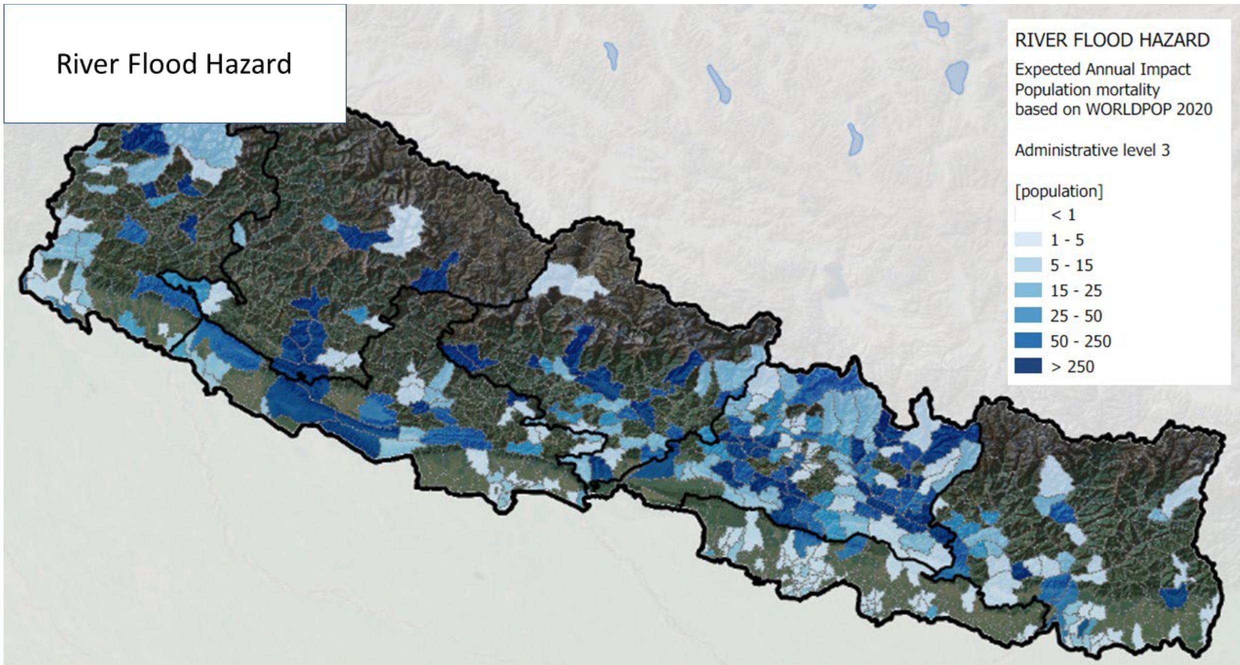
Notes: Data sources FATHOM flood model and WorldPop 2020. Province numbers correspond to province names as follows: Province 1 Koshi, Province 2 Madhesh, Province 3 Bagmati, Province 4 Gandaki, Province 5 Lumbini, Province 6 Karnali, and Province 7 Sudurpaschim.

FIGURE 9: FLOOD HAZARD RP 100 YEARS FOR NEPAL



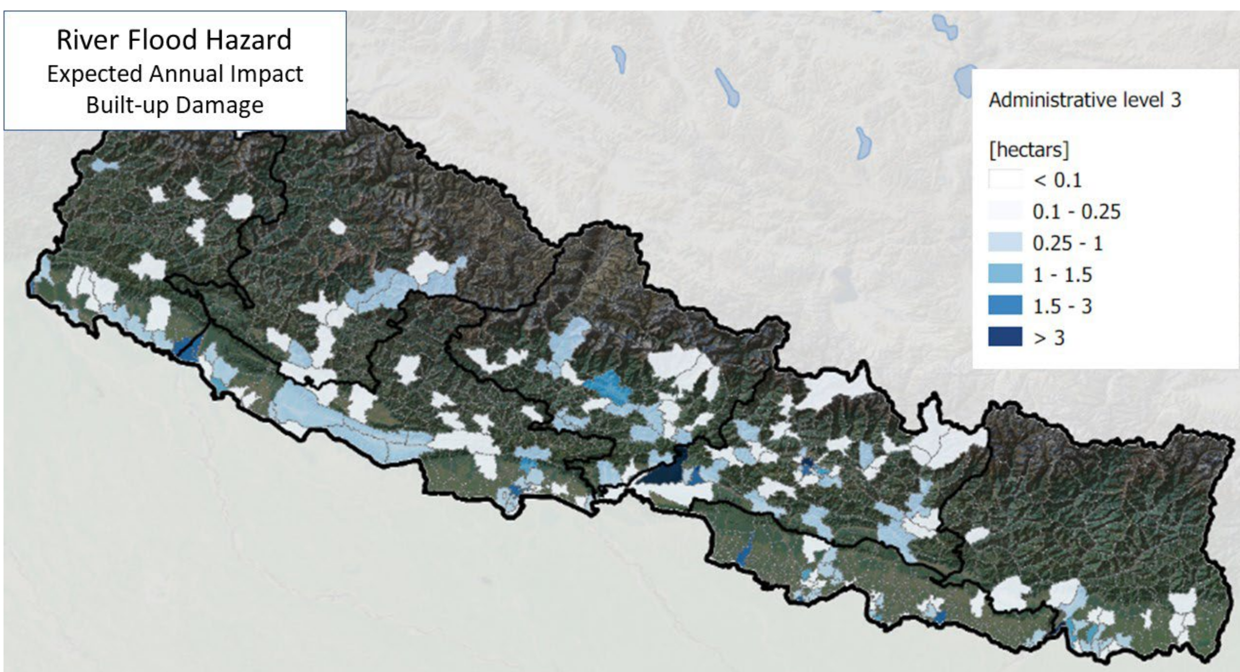
Notes: Data from FATHOM flood model

FIGURE 10: EXPECTED ANNUAL IMPACT ON POPULATION (POTENTIAL MORTALITY) AT PALIKA LEVEL



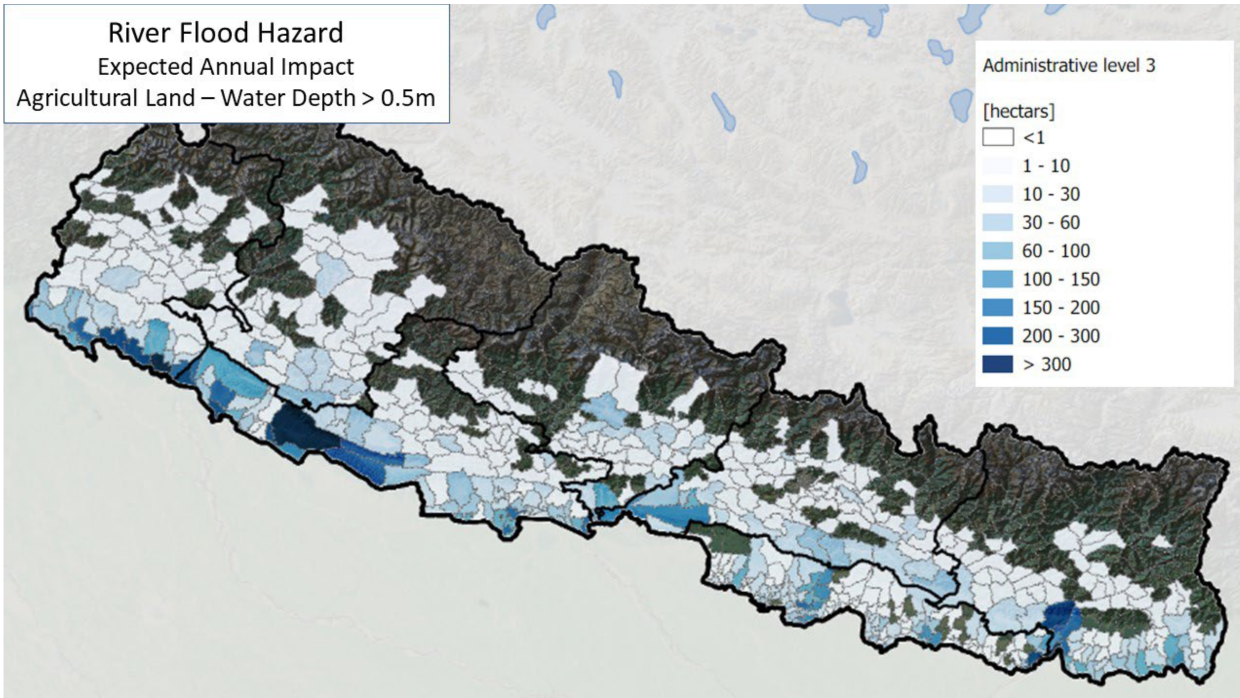
Notes: Data from FATHOM flood model and WorldPop 2020.

FIGURE 11: EXPECTED ANNUAL IMPACT ON PHYSICAL ASSETS (HA OF BUILT-UP AREA/SETTLEMENTS AT THE RISK OF DAMAGE) AT THE PALIKA LEVEL



Notes: Data source FATHOM flood model and 2019 World Settlement Footprint.

FIGURE 12: EXPECTED ANNUAL IMPACT ON AGRICULTURAL LAND (HA OF CROPLAND EXPOSED TO FLOODING) AT THE PALIKA LEVEL



Notes: Data source FATHOM flood model and 2020 ESA WorldCover data.

Heat exposure

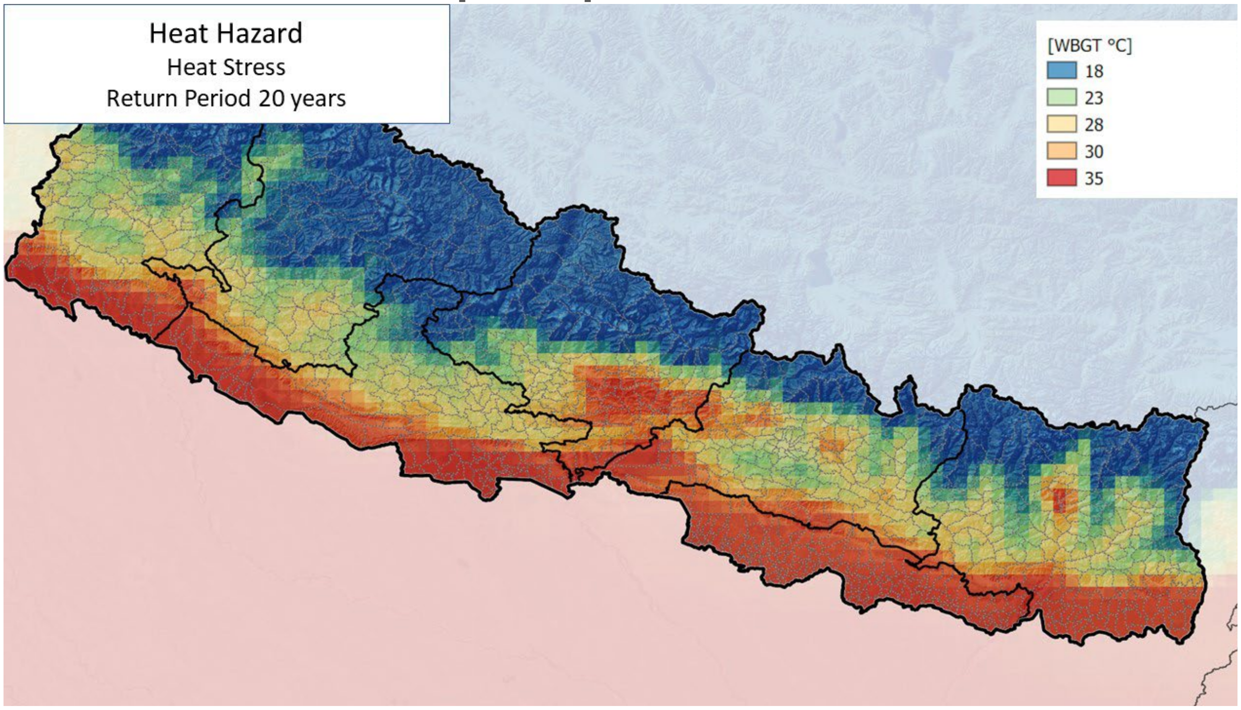
Heat stress affects large swathes of Nepal. The maps below show the hazard and population exposure to extreme heat events with a return period of 20 years. In such extreme conditions, the southern Nepalese municipalities experience significant thermal stress (Figure 13). The expected annual impact was calculated by combining the population risk for extreme heat events with a return period of 5, 20, and 100 years. Over four million Nepalese citizens face the health impacts of extreme heat (Figure 14 and Table 5).

TABLE 5: HEAT STRESS RP 20 EXPOSED POPULATION

WBGT (°C)	Heat stress category	Exposed Population
> 30	Extreme	4,325,304
28 to 30	Very strong	264,070
23 to 28	Strong	1,860,180
18 to 23	Moderate	81,942
<18	None	

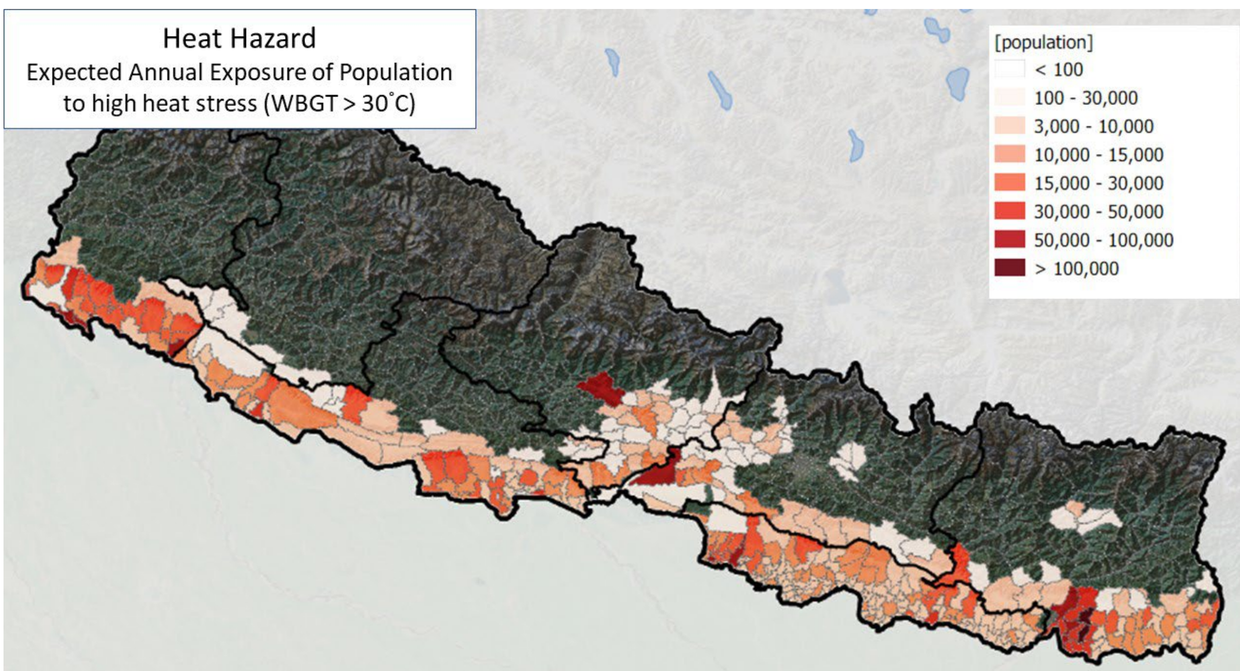
Data source: Wet Bulb Global Temperature (WBGT) *Extreme Heat Hazard layer - VITO/GFDRR (2017) (EH-GLOBAL-VITO)*

Figure 13: Heat Stress RP 20 Years [WBGT °C]



Notes: Data source: Extreme Heat Hazard layer - VITO/GFDRR (2017) (EH-GLOBAL-VITO)

Figure 14: Heat Stress Annual Exposure

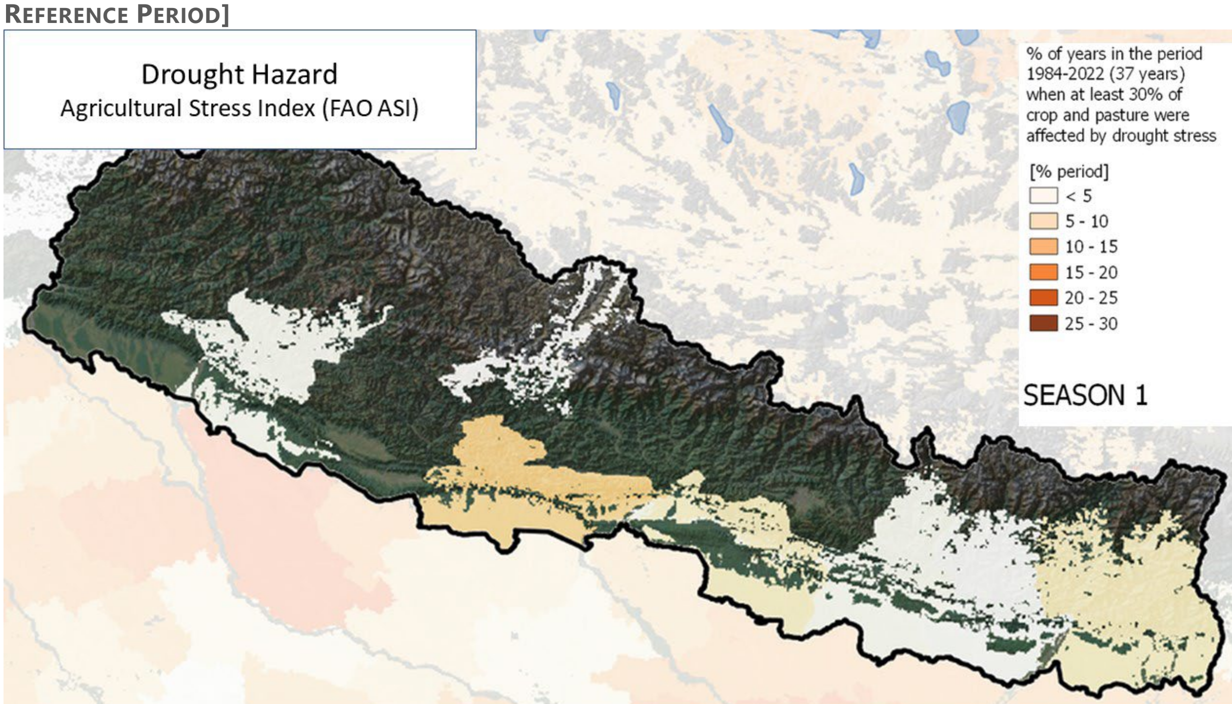


Notes: World Bank analysis using Extreme Heat Hazard layer - VITO/GFDRR (2017) (EH-GLOBAL-VITO) and World Pop 2021.

Drought

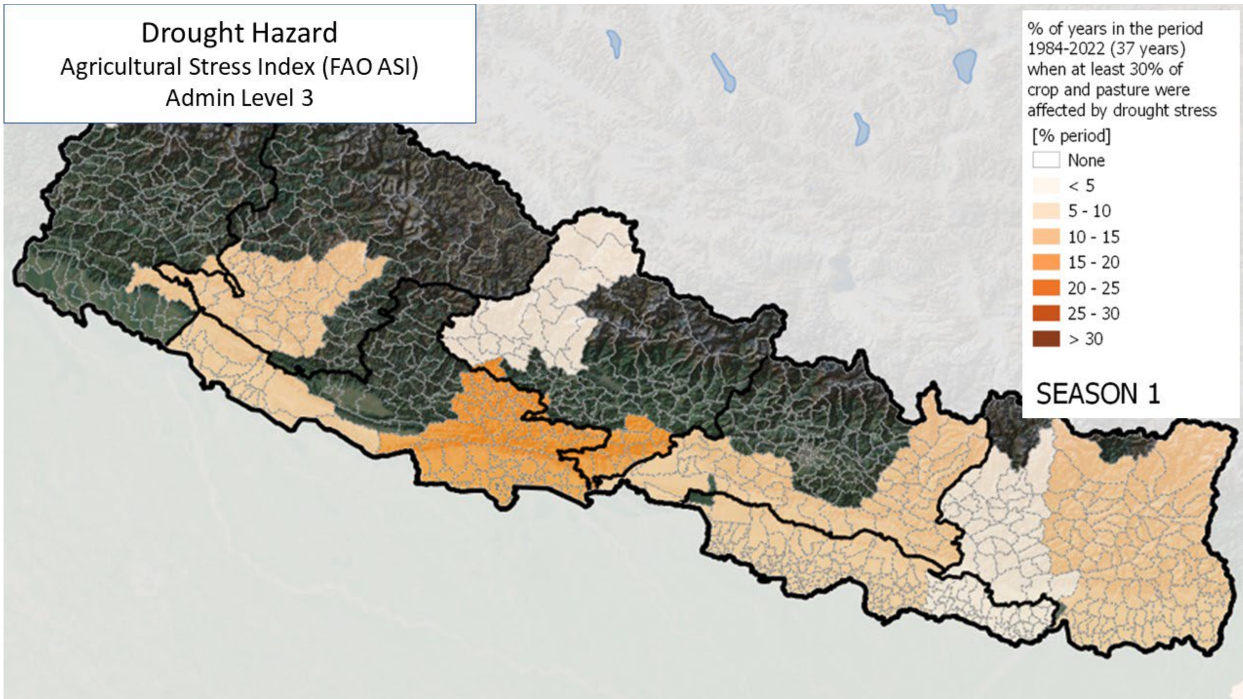
Using FAO's Agricultural Stress Index (FAO, 2022), the effect of droughts on cropland and pasture are studied, again at the municipal level. Fertile lands in the south faced the largest drought peaks in the 1984-2022 reference period (Figure 15). In southern and western municipalities, over 30% of fertile land was affected by drought stress once every four to ten years (Figure 16), which is associated with reduced crop harvests, increasing food costs, and negative impacts on the livelihoods of primarily rural communities reliant on the agricultural sector. The Drought Hazard is based on the evolution of Normalized Difference Vegetation Index (NDVI) detected from satellite imagery and not related to crop-specific harvest times. The data displayed relates to the main growing season ranging from March-April to December-January, as detected by the NDVI (labelled as "season 1"). This thus includes all crops and pastureland outside of the winter months.

Figure 15: Drought Hazard and exposure of Agricultural Land [Maximum Exposure Based on Reference Period]



Data source FAO's Agricultural Stress Index.

FIGURE 16: DROUGHT RISK AT MUNICIPAL LEVEL FOR REFERENCE PERIOD



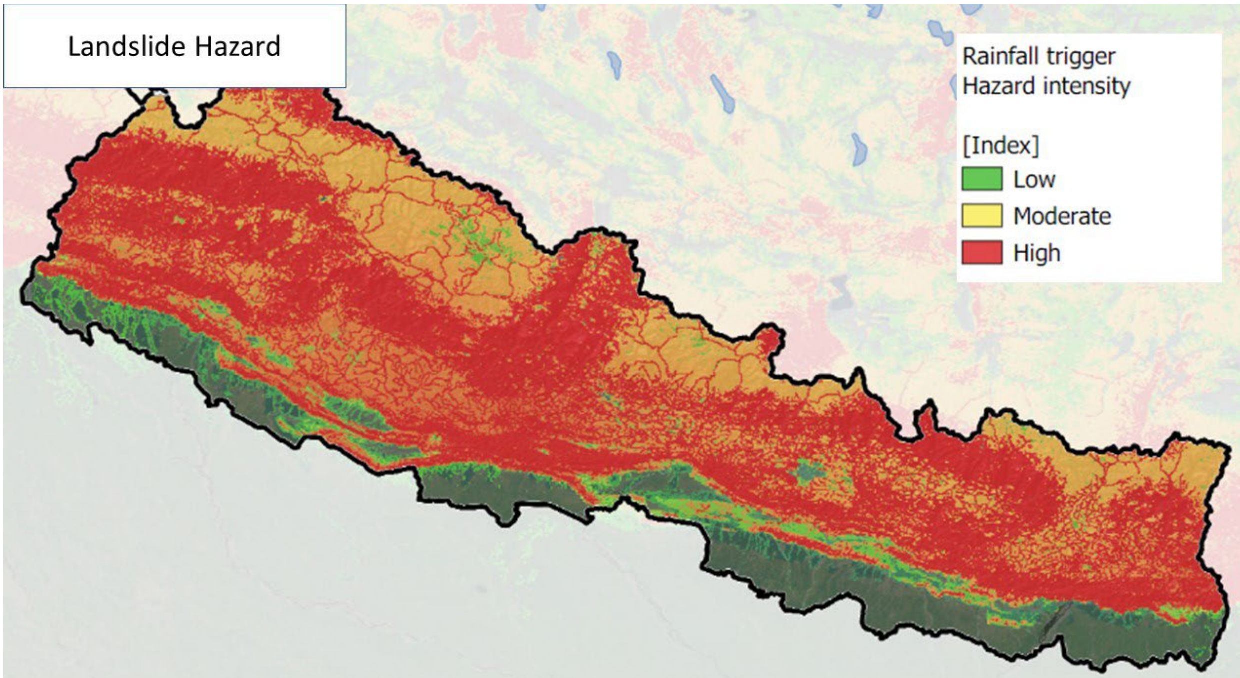
Data source FAO's Agricultural Stress Index.

Climate-Induced Landslides

During earthquakes, landslide hazard is considerable and forms a compounding disaster event. However, outside of an earthquake, landslides are primarily triggered by heavy rainfall during the monsoon season in mountainous and steep hilly terrain. Combined with urbanization in mountainous environments, this poses a considerable risk of loss of life and damage to critical infrastructure and ecosystems. The World Bank-ARUP Landslide Susceptibility Index at 1km resolution was used to map this hazard. Given the topography of Nepal, nearly the entire country is exposed to moderate to high landslide hazard, with exception of the southernmost municipalities (Figure 17).

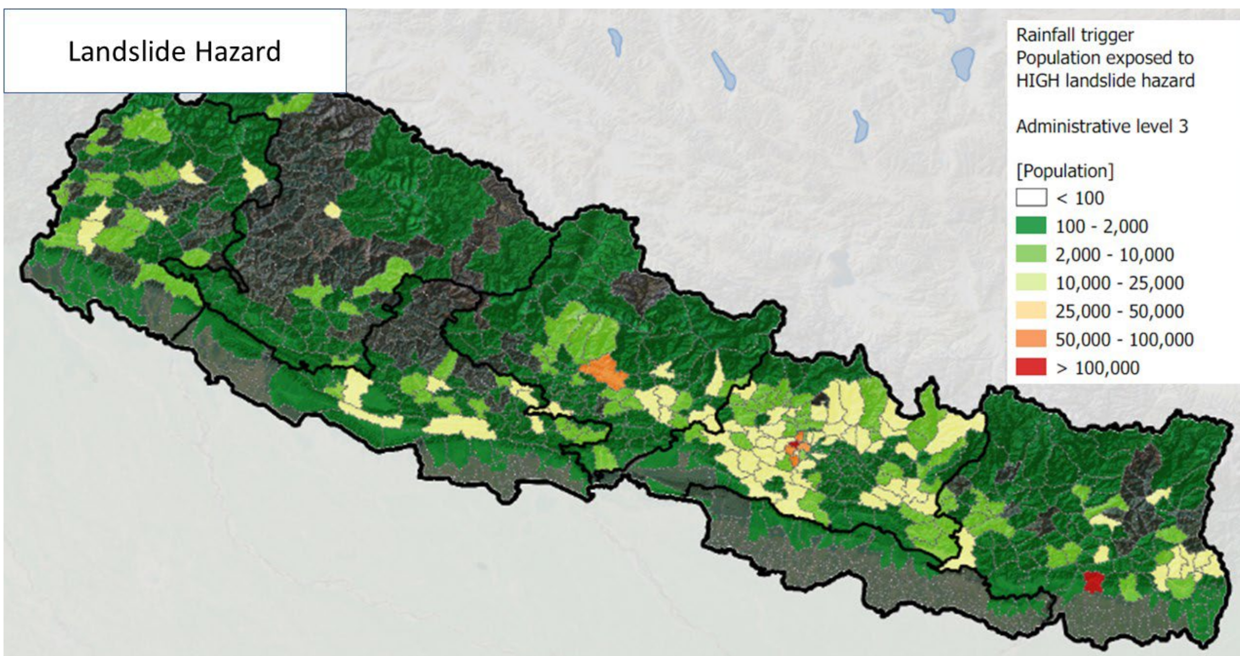
Urban environments in these landslide-prone areas are then most exposed to these extreme events. Municipalities in provinces 1, 3, and 4, and particularly those in and around Kathmandu, face the highest population exposure to high landslide hazard (Figure 18), with over 100,000 people exposed in specific urban municipalities. There are municipalities with over 50 hectares of built-up assets exposed to high landslide hazard in provinces 1, 3, and 4, particularly in the densely populated valleys of Kathmandu and Pokhara (Figure 19).

Figure 17: Landslide Hazard and Intensity Across Nepal at 1KM Resolution



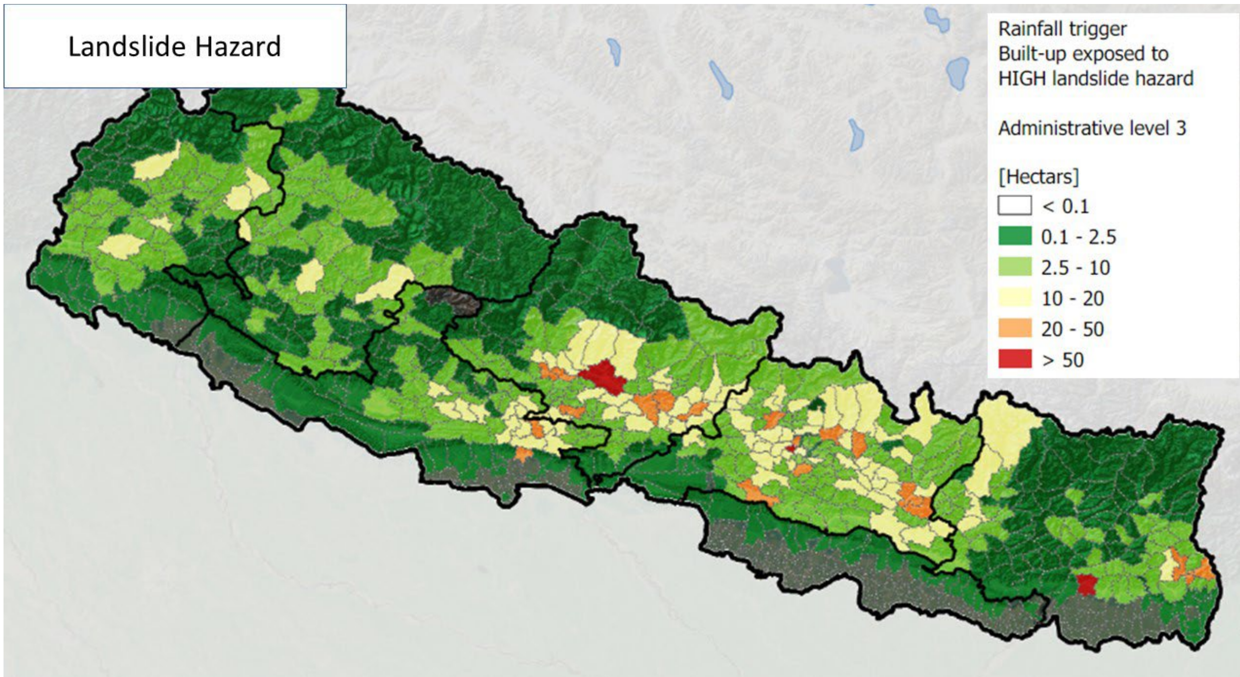
Notes: Data source The World Bank-ARUP Landslide Susceptibility Index

Figure 18: Population Exposed to High Landslide Risk for Nepali Palikas



Notes: Data source The World Bank-ARUP Landslide Susceptibility Index and WorldPop 2020

FIGURE 19: BUILT-UP ASSETS EXPOSED TO HIGH LANDSLIDE RISK FOR NEPALI PALIKAS



Notes: Data source The World Bank-ARUP Landslide Susceptibility Index and 2019 World Settlement Footprint data

Air Pollution

While not a climate hazard in and of itself, outdoor air pollution is adversely affected by climate change. There are meteorological feedback cycles that affect the biochemistry of air pollutants, the circulation of pollutants in the atmosphere, but also, importantly, the modulation of certain air pollutants by drought conditions, such as for example the air pollution from wildland fires. Therefore, air pollution hazards are compounded by other hydrometeorological hazards that will increase in frequency and intensity due to changing climatic conditions, such as droughts and heatwaves.

Using surface-level $PM_{2.5}$ concentrations[11] between 1998 and 2020 with a 1.1km resolution, drawn from the research by van Donkelaar et al. (2021) combining Aerosol Optical Depth retrievals from the NASA MODIS, MISR, and SeaWIFS instruments with the GEOS-Chem chemical transport model, the high-resolution spatial patterning of outdoor air pollution can be mapped for Nepal (Figure 20).[12] It is important to note that this combines both human-induced and natural sources of $PM_{2.5}$.

The highest concentrations of air pollution are seen along Nepal's southern border, where $PM_{2.5}$ concentrations of up to 60 μg/m^3 almost double the World Health Organization (WHO) norm of 37.5 μg/m^3. Over 15,000 citizens in each of these southern municipalities are at risk of premature morbidity and mortality through their exposure to these high concentrations of airborne pollutants (Figure 21). It is also important

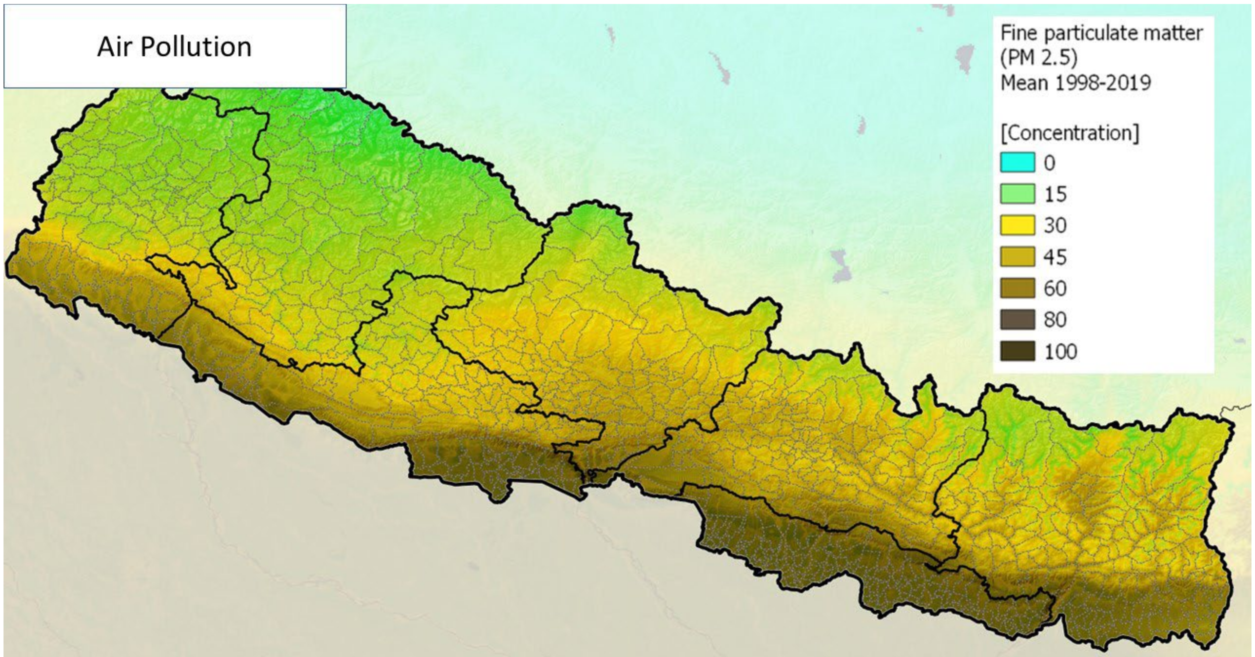
---

[11] PM2.5 refers to fine particulate matter, tiny particles or droplets in the air that are two and one half microns or less in width. Particles of this size can travel to the lungs.

[12] The data underlying the van Donkelaar et al. (2021) analysis can be accessed at https://sites.wustl.edu/acag/datasets/surface-pm2-5/

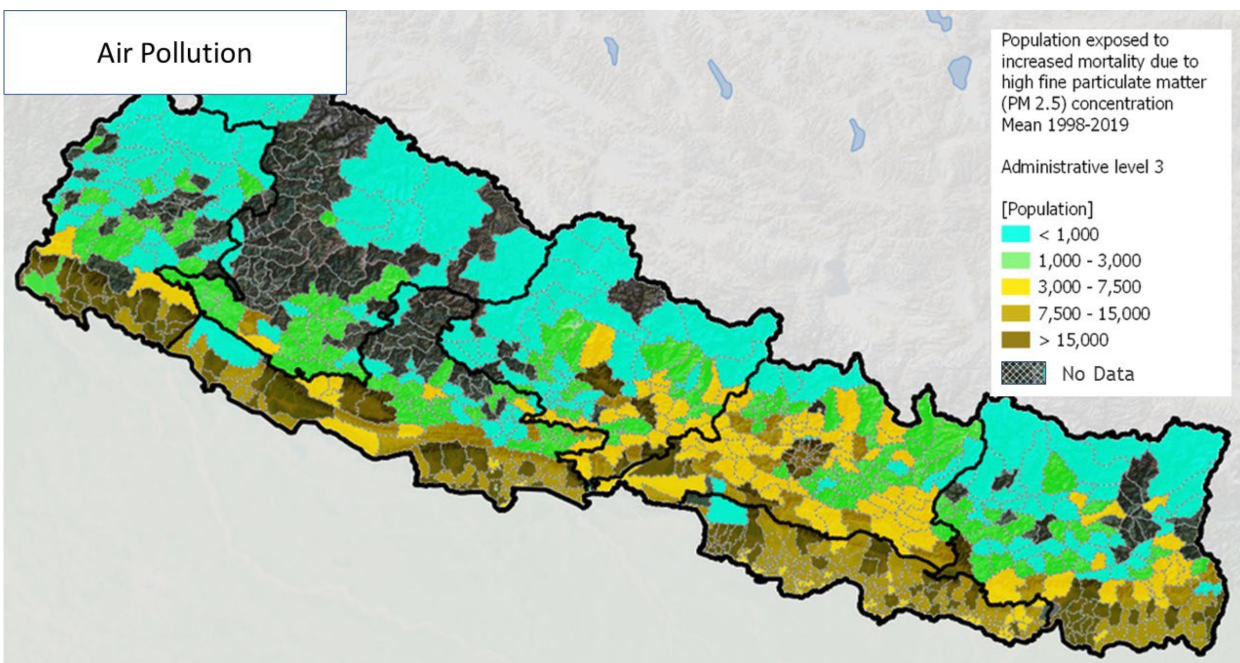
to note that we do not investigate indoor air pollution that often results from air-polluting cooking methods. Exposure to air pollution both outdoors and indoors increases mortality risk.

FIGURE 20: PM 2.5 AIR POLLUTION CONCENTRATIONS (IN MICROGRAM PER CUBIC METER) ACROSS NEPAL AT 1.1. KM RESOLUTION



Notes: Data source Van Donkelaar et al. (2021)

FIGURE 21: POPULATION EXPOSED TO HIGH PM2.5 AIR POLLUTION CONCENTRATIONS ACROSS NEPALI PALIKAS



Notes: Data source Van Donkelaar et al. (2021) and WorldPop 2020

5. Improving damage estimates: an example of flood risk in new built-up areas developed on steep slopes

In the previous sections we have illustrated how the distribution of built-up area and population affect the distributions of severity of natural hazards. But not all built-up areas are the same in either their building characteristics or the characteristics of the land area they occupy. While building characteristics are more readily (and accurately) assessed from the ground, much can be said about the physical characteristics of the building locations by using satellite remote sensing data. For example, we can look at how changing building slope can inform the analysis of hazard, risk. In this section we conduct this analysis by intersecting the built-up area maps with elevation and slope values derived from Digital Elevation Models (DEM) provided by the 30m grid-level data from the Shuttle Radar Topography Mission (SRTM).

We find that a large percentage of palikas that have had any built-up area change over the period 2000-2019 have seen the mean slope (in degrees) become steeper (Figure 23). The most preferable land for settlements is flatter and in time it becomes unavailable for development for one reason or another (be it economic, socio-cultural, legal, or other). These palikas where there have been BUA developments in steeper ground are highlighted in orange-red hues in Figure 23. New developments in those palikas must find less-desirable, steeper ground on which to build. In the palikas marked in red this has meant more than a doubling of the steepness of ground on which built-up area is developed, since 2000 (Figure 23). While we focus here on the heightened risk caused by development in steeper terrain where there are hazards, the same can be said about developing in *flatter* terrain, which can correspond to river beds and flood plains. This latter risk factor is not evaluated here.

Slope therefore has repercussions not only on landslide hazard but also flooding hazard: both flash floods that are caused by precipitation but also river flooding. Flash flood hazards are more ephemeral hazards that are harder to model, and as such they are not part of the analysis developed in this report.

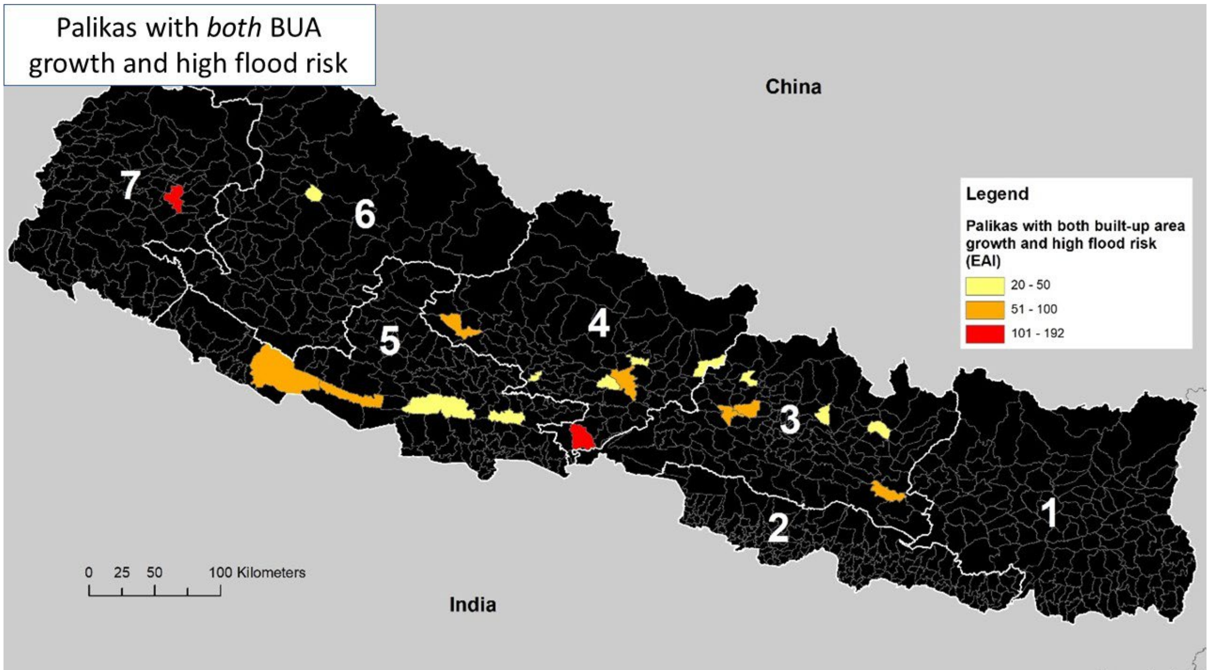
An initial, simple overlay analysis of physical susceptibility due to BUA can indicate which areas might be at higher risk across the board. In Figure 22, for example, is a map of palikas that have the compounded risk of river flood risk estimates (EAI mortality) and BUA growth. To create the map in Figure 22 we exclude palikas when:

i. there is very little built-up area: those with less than 0.1 Km2 of total built-up area in 2019
ii. there is low BUA growth: that is less than 3% increase in BUA between 2000 and 2019.

We then intersected these remaining palikas with flooding hazard risk of value EAI 20 or more, that is, a high risk on mortality, to get an intersection of areas that have new BUA and an elevated flooding risk. This risk profile results in the selection of 19 palikas, where population and built-up area are potentially at higher susceptibility to flooding.

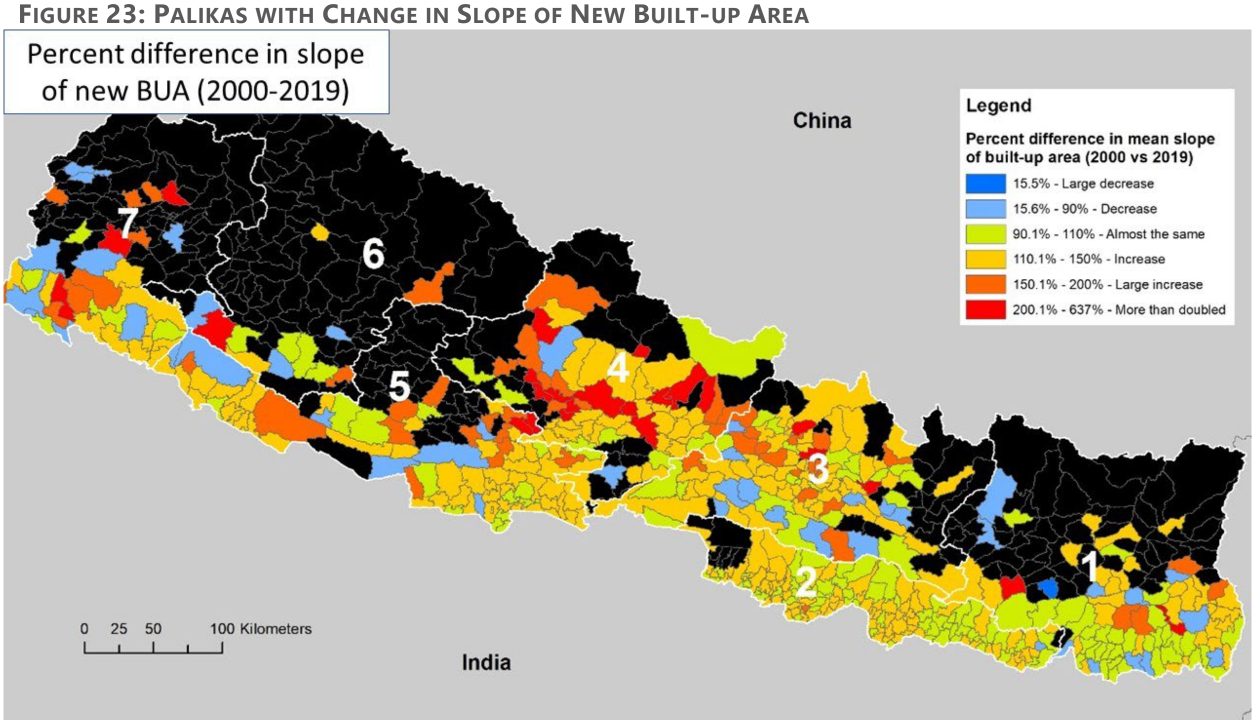
Furthermore, if we put together the maps in Figure 22 and Figure 23 we can then further subset the data and obtain a map Figure 24 of the palikas that have *high-slope change* BUA growth and also high flood risk. In this map 11 palikas are highlighted in red. These are the municipalities in which the BUA slope change has been at least 150% (1.5 times steeper terrain in 2019 than in 2000) and the Flood risk estimated annual impact (EAI) on BUA is at least 50.

FIGURE 22: PALIKAS WITH HIGH FLOOD RISK AND GROWING BUILT-UP AREA



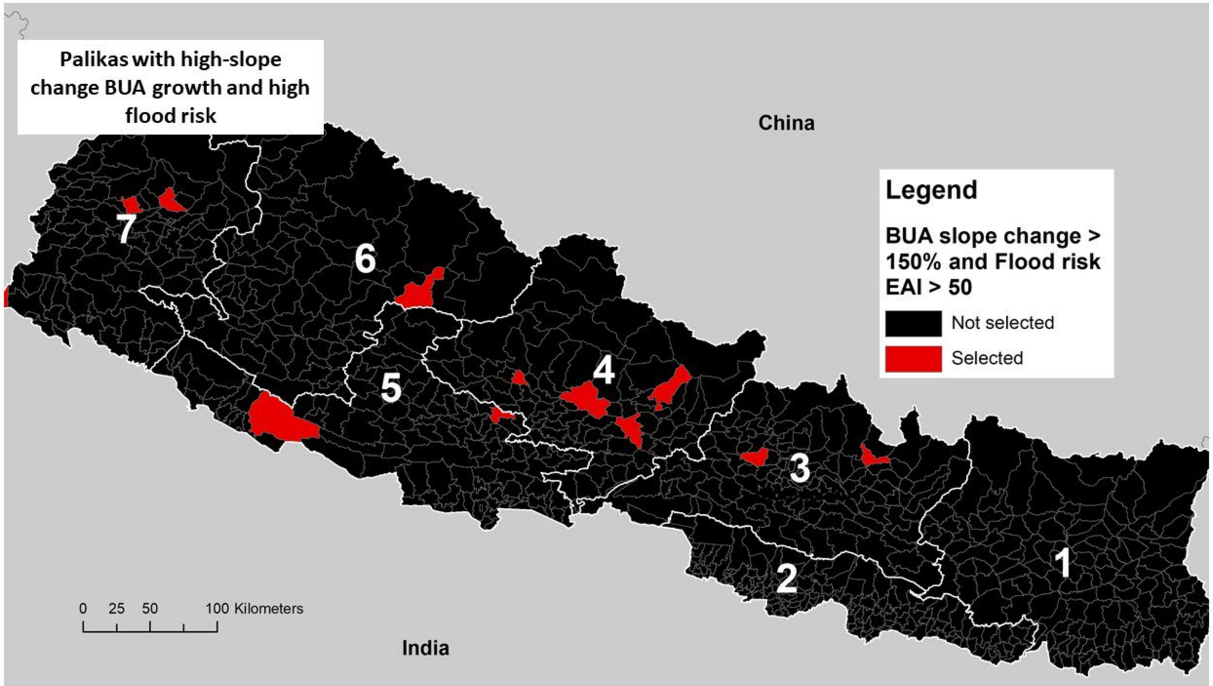
Notes: Data sources are the flood risk models in section 4. and the WB BUA.

FIGURE 23: PALIKAS WITH CHANGE IN SLOPE OF NEW BUILT-UP AREA



Notes: The map shows the average Palika-level change in BUA Slope between 2000-2019; or in other words, the areas in which BUA slope (steepness in degrees) has changed the most and the least between 2000 and 2019. In the first class, are Palikas where the average BUA slope has decreased significantly – BUA was bult on much flatter ground in 2019 compared to 2000 and the opposite is ture for the last class, showing the Palikas where BUA was built on twice-steeper ground in 2019 vs 2000. Data sources are the NASA SRTM DEM and the WB BUA.

FIGURE 24: SELECTION OF PALIKAS WITH HIGH-SLOPE CHANGE BUA AND FLOOD RISK



Notes: The map shows the palikas selected by having very high slope change in the BUA growth and also very high Flood risk. Data sources are the NASA SRTM DEM and the WB BUA.

6. Sensitivity Analysis to the Use of Different Population Products for Hazard Exposure Mapping

The hazard exposure models presented in Section 4 rely on grid-level, high spatial resolution built-up area footprints together with the associated grid-level population estimates to quantify the estimated annual impact (EAI) of hazards on built-up assets and mortality, respectively. The accuracy of these estimates depends on 1) the accuracy of the input data on the location of the hazard, and 2) the population and built-up area within that location. For this reason, we investigate the sensitivity of the estimated hazard-related mortality and damage to assets to the choice of the population dataset.

Several built-up area maps are available for Nepal. These multiple products are discussed in Section 3 and further results from this sensitivity analysis are presented in Annex 1. These BUA maps from satellite observations differ not only in their spatial and temporal resolution, but also in their definitions of BUA: for example, some products include roads while others do not, some products target informal, sparse buildings (such as in the high mountains) and others do not. The spatial resolution is the minimum area unit that has data, which in many of the gridded products available varies between 10m-100m. Spatial resolution of the input satellite observations has a lot to do with the granularity of the built-up objects identified, so in general[13], the more fine-grained the spatial resolution is, and the more built-up area objects on the ground will be observed. The temporal resolution is defined as the quantity of time-steps for which the data is available, some are single date (i.e., WSF for 2019) and some are multi-date (WB BUA for 2000,2005,2010,2015,2019). Only with the multi-date products is it possible to quantify change.

In addition to the target definition of the BUA itself, datasets also differ in their performance accuracy, or how well they perform at mapping their targets. The accuracy with which the classification algorithms pick up the target BUA differs in many dimensions: geographically by region, topography, land cover, but also by other characteristics that might be building materials, density (or clustering) of the built-up assets, etc., These differences make it difficult to compare the accuracy between datasets. In Nepal, this means that a certain product might be more accurate in the low-altitude Terai region, while another product may be more accurate in the mountains, and less accurate in the Terai. However, without a systematic ground truthing exercise of these data, it is impossible to know in more detail why a certain product performs better than another in a certain geographical landscape.[14]

In this section we investigate the sensitivity of the mortality estimates of river floods (Section 4) to using different input population products. Throughout the analysis, all the population products use a standard population data from the Columbia Climate School, Center for International Earth Science Information Network (CIESIN), which collects population data from official sources across the globe (for Nepal, the latest in the CIESIN database is the 2011 census) and then applies demographic modelling techniques to update the estimates in time.[15] This allows us to use WorldPop with the 2020 population estimates derived from CIESIN data. The other population products used in this sensitivity analysis, Meta and WSF, either use these CIESIN-modelled 2011 Census population estimates, or in one case, presented in annex 3, the preliminary census 2021 estimates.

We compare two ways in which the population measures are distributed spatially: *constrained* population estimates constrain the population to a specific footprint where residential household settlements are observed. The map of constrained estimates is derived using the *dasymetric* approach (Stevens et al. 2015) that forces (constraints) all the population values to the pixels of a given land cover class, in our case, the BUA class which includes all settlements. The result is a gridded-level map where only the grid cells of the BUAs have a population value. The constrained method does not allocate any population to other land cover types other than the specific one it uses for the constraining (for example BUA), meaning that it does not allocate population to, for example, cropland, water, or forest.

By doing this constraining, the *dasymetric* method allows data that is at coarser aggregation unit (for example a census block or an administrative unit) to be distributed onto finer resolution units. In our case this unit is a BUA pixel, but it could also be some other type of land cover pixel. This implies that, for example, if in the original data the population count is at the admin level, which includes both forest and BUA, the constrained population map will only allow for population to be allocated to the BUA portions of that area.

---

[13] This general rule of thumb contains many assumptions, but other characteristics of the satellite data products are key: sensor characteristics (which make it suited to picking up BUA) and the performance of the classification algorithm used to pick up the BUA from the satellite imagery.
[14] In the absence of a ground truthing exercise, we compared the available BUA products with each other to determine which one gives us the most unbiased indicator (relative to other products).
[15] http://www.ciesin.org/

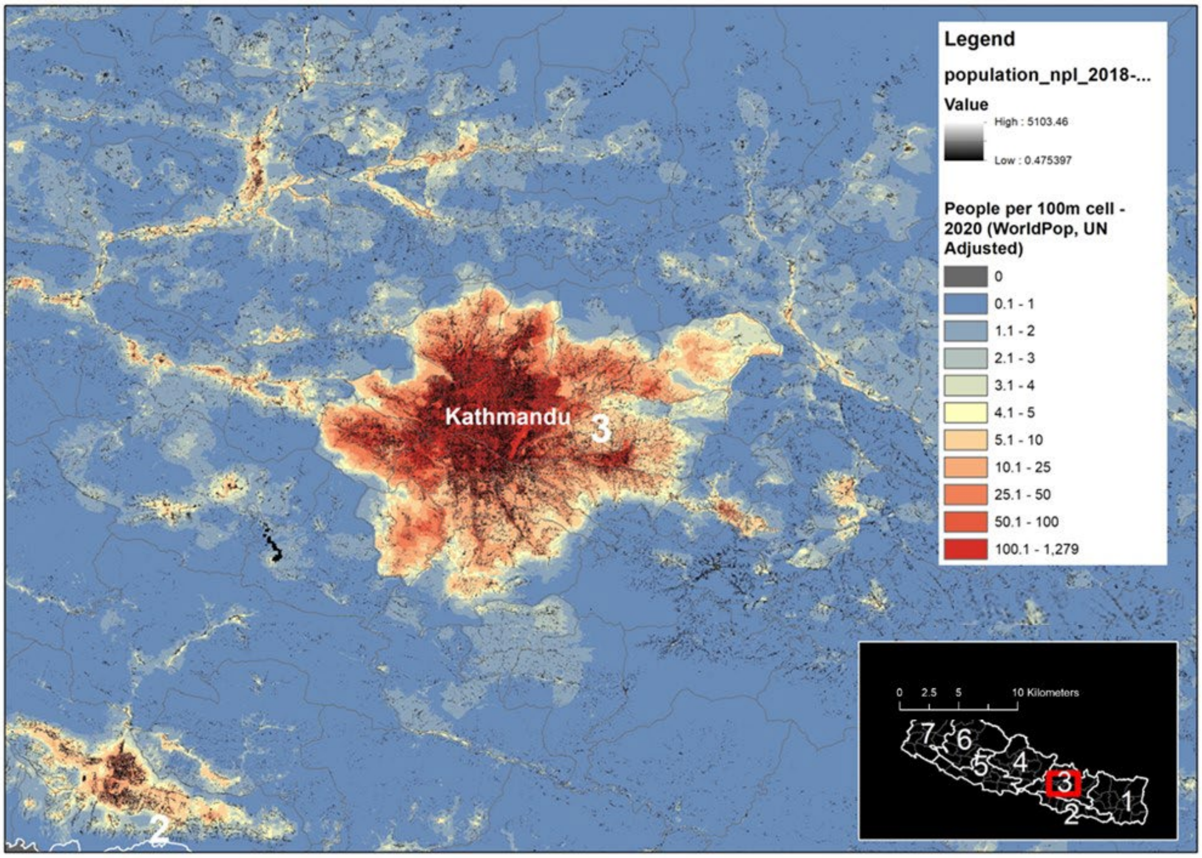
The *unconstrained* method, on the other hand, assumes that the population is distributed across the census block or administrative unit defined by the original population data source. Some unconstrained products follow loosely top-level land-cover classes, for example assuming that population is never located in water or forests, thus allocating it over large land-cover based areas, for example on cropland and on settlements.[16]

How many people are estimated to live in a certain pixel of BUA affects the mortality estimated for that area. There are large variations in the size of the Nepalese population estimated from different grid-level population products for 2020. For example, the WorldPop constrained 2020 product used throughout this study estimates 3.9 million fewer people compared to the 2021 preliminary census at the national level.[17] The Meta constrained (formerly known as Facebook) national estimates show 600,000 people less compared to the 2021 preliminary census, while the World Settlement Footprint constrained CIESIN 2020 product estimates some 950,000 people more compared to the 2021 population census. The map in Figure 25 illustrates the difference between constrained and unconstrained population datasets.

Having ascertained that there are major differences between the grid-level population products for Nepal; as well as with the 2021 preliminary Census estimates from CBS, we investigated the impacts that these differing population estimates have on the estimates of mortality due to river flood hazard.

[16] Across the products used in our analysis, WorldPop has both constrained and unconstrained versions. WSF and Meta have only constrained versions.
[17] This data was used in this analysis in order to be consistent with other regional CCDRs.

FIGURE 25: CONSTRAINED VS UNCONSTRAINED POPULATION DATA



Notes: This example over Kathmandu illustrates the difference between constrained and unconstrained datasets. In the blue-to-red colour palette is the unconstrained World Pop population estimates, whereas in the white-to-black palette is the finer resolution dataset that uses the CBS census 2021 preliminary data and constrains it to the World Settlement Footprint 3D 2020 built-up area.

We calculated the Expected Annual Impact (EAI) mortality of river floods using both the WorldPop input population estimates and the Meta population estimates and found that the WorldPop-based analysis resulted in ca. 5,500 deaths more at the national level. About two thirds of that difference is in the Kathmandu urban area, which is also where the biggest population discrepancies between the two population datasets are. The full results are shown in Table 7 in and relative maps in Annex 3.

The implication of the findings is that both hazard-related mortality and damage impact estimates are highly sensitive to the input population estimates and the location and spatial resolution of the BUA maps. Therefore, while the results presented in the hazard analysis are derived from the best available input datasets, they should be interpreted as indicative of estimated risk, with the knowledge that they are subject to change depending on the input population data used. In the future, as population and BUA datasets become more accurate, these results will undoubtedly change quantitatively, although it is likely that they will not change drastically in their overall depiction of hazard risk in the country.

7. Socio-economic vulnerability and resilience

Socio-economic vulnerability to disasters reflects the reality that the ability to respond to a given hazard exposure will vary across a society. In other contexts, this is referred to as resilience. Previous sections illustrate how hazards are mapped, how populations and assets are exposed, and how geospatial analysis can be used to fine-tune hazard exposure models to include further physical susceptibility parameters, such as slope, elevation or others. Here we lean on survey data from Nepal and the *Unbreakable* methodology pioneered by Hallegatte, Vogt-Schilb & Rozenberg (2017) which recognizes that disasters cause both asset losses and well-being losses, which are different and cause variations in resilience.

Specifically, a disaster might destroy part of a farmer's field. That is an asset loss. But it also represents a well-being loss to the extent that it reduces the farmer's ability to earn income and therefore spend on consumption. The specific size of the well-being loss depends on the ability of the farmer to maintain their income in the face of the asset loss. This may depend on the availability of government relief, access to private support networks, access to savings, and access to formal or informal credit markets. Because the wealthy tend to have better access to these various support networks the impacts of a given asset loss on well-being tends to be smaller for the wealthy. This is true despite the fact that the absolute magnitude of asset losses tends to scale with wealth.

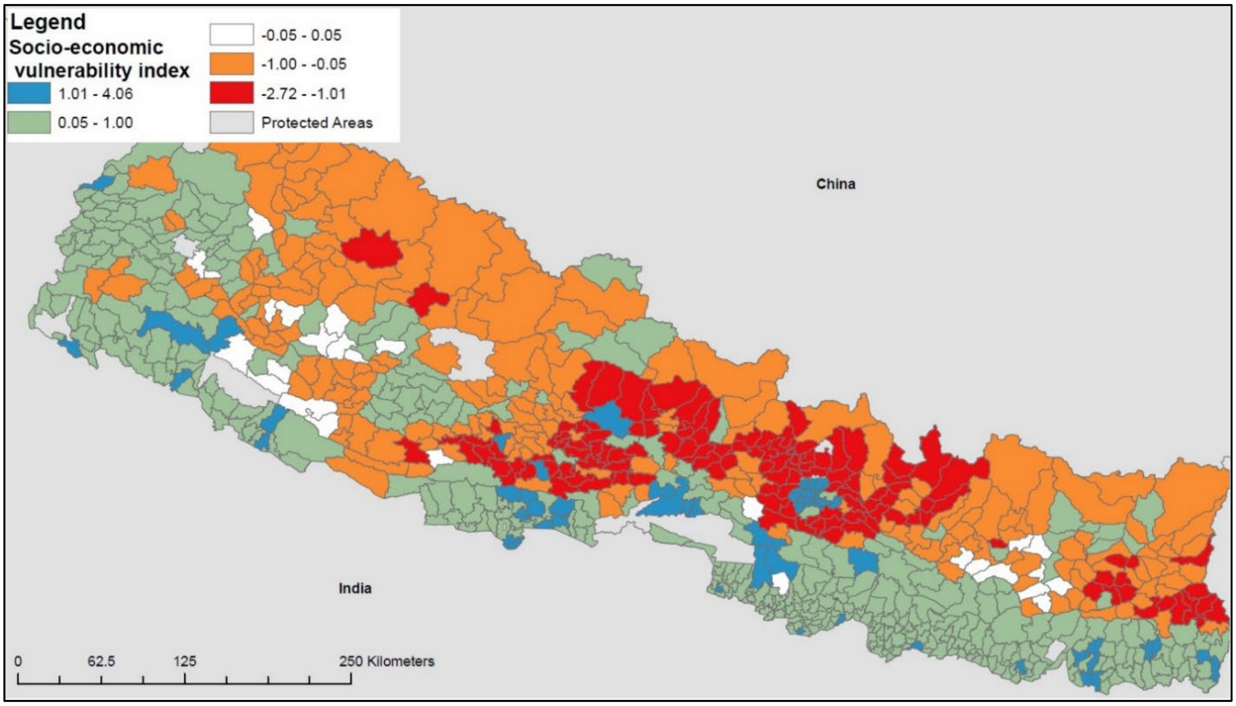
The methodology outlined in Hallegatte, Vogt-Schilb & Rozenberg (2017) is intended to capture the differences that asset losses can have on well-being across the wealth distribution and account for the fact that the poor are often less resilient to asset losses than the wealthy. The *Unbreakable* methodology defines socio-economic resilience as the ratio of asset losses to well-being losses. In their terms, "If socio-economic resilience is 50 percent, then well-being losses are twice as large as asset losses—that is, $1 in asset losses from a disaster is equivalent to $2 in consumption losses, perfectly shared across the population."

We cannot directly measure well-being losses to disasters in Nepal given current data limitations. Instead, we use the Nepal Household Risk and Vulnerability survey to measure household consumption and use this as a proxy for well-being. We bin households into five groups based on their total consumption and combine this with data from the same survey on asset and income losses following the occurrence of disasters to calculate a socio-economic resilience ratio for every bin in the survey data. We then use Census data and a random forest algorithm to calculate the same consumption bins for households across Nepal. This provides the number of households in each consumption bin in various administrative units across Nepal. Using these shares, we calculate the weighted average resilience ratio within administrative units across Nepal. We weight by the share of households in each consumption bin when calculating the overall average resilience ratio. Lower resilience ratios indicate that the well-being losses associated with a given asset loss are larger. In other words, areas with lower resilience ratios are more vulnerable to disasters.

In Figure 26 we show how these ratios vary across the country. We report here only an index showing the relative position of an administrative unit in the distribution of the resilience ratio. This provides a relative sense of which locations are more or less vulnerable based on their resilience ratio. More negative index values indicate higher vulnerability. The most vulnerable places have a resilience ratio that is nearly three standard deviations below the average in Nepal. We do not report the combination of hazard risk, exposure, and vulnerability that would reflect a comprehensive measure of the threat from climate driven increases in disasters.

Based on this metric the areas around Kathmandu are some of the least vulnerable. Broadly speaking the southern portion of the country is less vulnerable than the northern portion. Across the whole country asset losses exceed well-being losses on average. Unlike the approach taken in *Unbreakable* our approach does not place more weight on losses suffered by the least wealthy individuals in society. Doing so would likely increase the relative well-being losses but is unlikely to change the geographic pattern of vulnerability.

FIGURE 26: RESILIENCE RATIO BY PALIKA



Notes: Data sources used are the Nepal Household Risk and Vulnerability survey round 3 (2018), Nepal census 2011.

There are many margins of vulnerability and adaptation that are not currently captured in any available survey data. For example, information about migration is only available at very limited temporal scales and does not include many forms of migration (short-term migration to India for example). Understanding how individuals and households use migration as a strategy to deal with the negative shocks of climate change is an important policy question. For example, which is more prevalent, short-term labour driven migration to supplement incomes in response to drought or permanent relocation? These dimensions of adaptation to shocks, and the implications they have for vulnerability, are not fully captured in our approach.

We examine how vulnerability varies across two sub-groups: households that receive at least 90% of their income from agriculture and households that are in the top 25th percentile of remittance recipients. In both cases we do not find significant differences in vulnerability in these sub-groups compared to the overall average. Households that receive substantial remittance income appear slightly more vulnerable, but the difference is insignificant. This analysis is limited by the small size of the sub-groups in our data – for this analysis we are unable to use the census data because of limits in what data is recorded by the census. Future work examining vulnerability across individual households will be aided by the ongoing National Living Standard Survey (NLSS-IV). This will allow us to look at climate risk, livelihoods, and consumption patterns at a more granular level of disaggregation.

8. Estimating future climate risks (2041-2060)

We have established the present-day risks of a wide variety of natural hazards on people, built-up assets, and agricultural land. Next, we turn to a forward-looking perspective to explore how climate risks are set to develop within Nepal in the decades ahead. The screening and assessment of future impacts of natural hazards due to climate change typically involves the comparison of baseline conditions (observed or simulated) against future scenarios of climate variability. These baseline conditions are determined by computing the long-term average of a climate variable. Projections of this climate variable in the future will show anomalies, or variation, of this variable relative to the historical baseline. The magnitude of these anomalies depends strongly on the future time horizon studied, and the climate change scenario that is adhered to.

To set this baseline and model projected anomalies for the future, we obtained data from climate models released under the IPCC Sixth Assessment Report (AR) framework (IPCC, 2021). ARs are supported by coordinated climate modelling efforts referred to as Coupled Model Intercomparison Projects (CMIP).

We draw on CMIP6 data for our future modelling, and consider three climate change scenarios, which are called Representative Concentration Pathways (RCPs) in CMIP5, or Shared Socioeconomic Pathways (SSPs) in CMIP6. These pathways cover the range of possible future scenarios of anthropogenic drivers of climate change by accounting for various future greenhouse gas emission trajectories, as well as a specific focus on carbon dioxide (CO2) concentration trajectories (IPCC, 2021). First, we include SSP1/RCP2.6, a scenario with low greenhouse gas emissions and CO2 emissions declining to net zero after 2050, followed by net negative CO_2 emissions. Next, we look at SSP2/RCP4.5, with intermediate greenhouse gas emissions and CO_2 emissions remaining around current levels until the middle of the century before dropping off. As a final scenario, we incorporate SSP5/RCP8.5, a very high greenhouse gas emission scenario with CO_2 emissions that roughly double from current levels by 2050. As a time-horizon, the period 2041-2060 is selected, allowing us to assess climate risks around the middle of the century.

Modelled variables: projecting changes in precipitation and temperatures

The three included climate scenarios each will predict different spatial patterns, intensities, and frequencies of future natural hazards. This will provide crucial information on which geographic areas are at the highest risk of climate-related disasters under a specific climate pathway. With a grid resolution of around 100 kilometres, we can aggregate this information at the province level, and pinpoint which provinces are likely to face an increase or reduction in the frequency and intensity of a specific natural hazard. Underlying these projections are several key climate variables, connected to the changing patterns of precipitation and temperature, summarized in Table 6. The number of consecutive wet days, days with rainfall over 10mm, precipitation volume on extremely wet days, and maximum five-day precipitation allow to forecast the trend in the risk of floods and rainfall-induced landslides across Nepal. The Wet Bulb Globe Temperature Index predicts spatial changes in heat stress for the three climate scenarios. Finally, the number of consecutive dry days and the Standardised Precipitation-Evapotranspiration Index (SPEI) allows to assess the projected changes in drought patterns for the country. No projections for air pollution can be made.

TABLE 6: CLIMATE VARIABLES UNDERLYING CLIMATE PROJECTIONS

Hazard	Associated climate indices	Unit of measurement
Floods and Landslides	Consecutive wet days	Days per year
	Rainfall > 10 mm	Days per year
	Maximum 5-day precipitation	mm
	Extremely wet days	mm
Drought	Annual SPEI	Dimensionless
	Consecutive dry days	Days per year
Heat stress	WBGT Heat index (mean)	°C
	Days with WBGT Heat index > 23°C	Days
	Days with WBGT Heat index > 30°C	Days

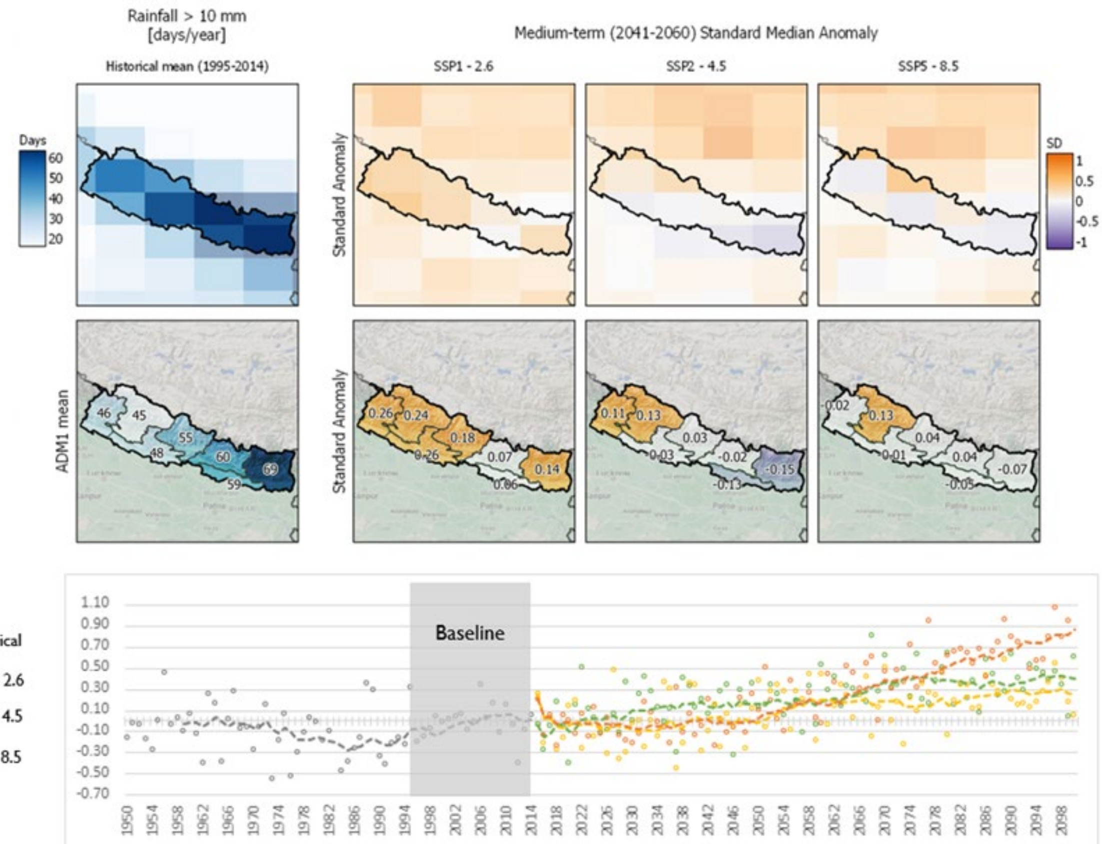
Flooding and landslide projections

Four variables underly the projection of changes in floods and rainfall-induced landslides: the modelled annual days of rainfall with over 10mm of precipitation (Figure 27), the annual number of consecutive wet days (Figure 28), the maximum precipitation over five days (in mm, Figure 29), and the precipitation during extremely wet days (in mm, Figure 30).

Each of these mapping ensembles has a similar structure. The historical mean over the baseline period 1995-2014 is shown in the top left, with the historical provincial average over this period shown on the map at the bottom left. The second, third and fourth columns then represent the projected anomalies for the climate variables under SSP1 – 2.6 (second column), SSP2 – 4.5 (third column), and SSP5 – 8.5 (fourth column). The top row shows the gridded standardised anomalies derived from CMIP6 for our time horizon 2041-2060, while the bottom row shows the average standardised anomaly for each province in Nepal. Below the maps, for each climate variable, the historical variation during the baseline period is shown, together with the projected future anomalies for the three SSPs.

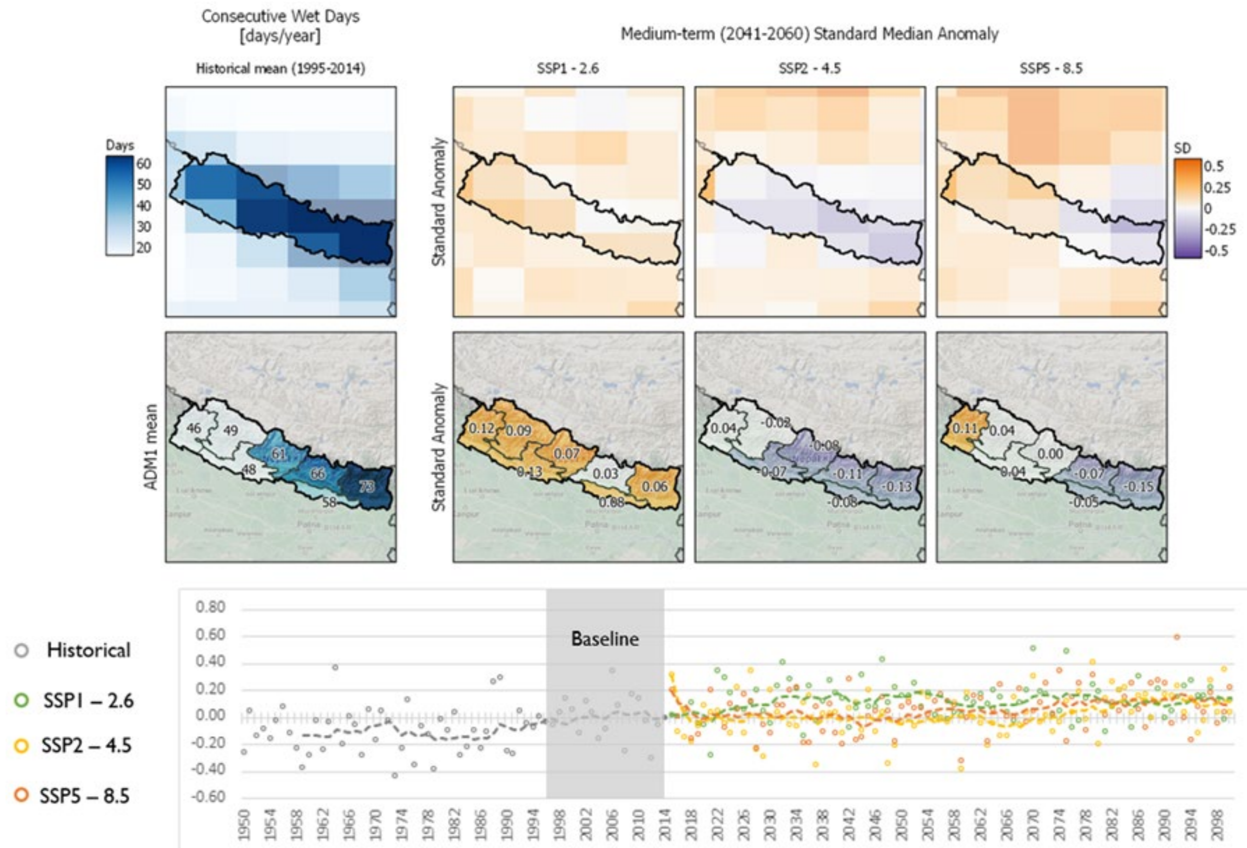
The historical baseline shows a clear pattern of wetter conditions in eastern Nepal consistent across the four precipitation-related variables, with gradually decreasing extreme precipitation conditions towards the east of the country in Koshi, Madhesh, Bagmati and Gandaki, and overall drier conditions with fewer and shorter extreme events in the western provinces of Lumbini, Karnali, and Sudurpaschim.

FIGURE 27: CLIMATE CHANGE PROJECTIONS -- RAINFALL OVER 10MM (DAYS/YEAR) FOR NEPAL



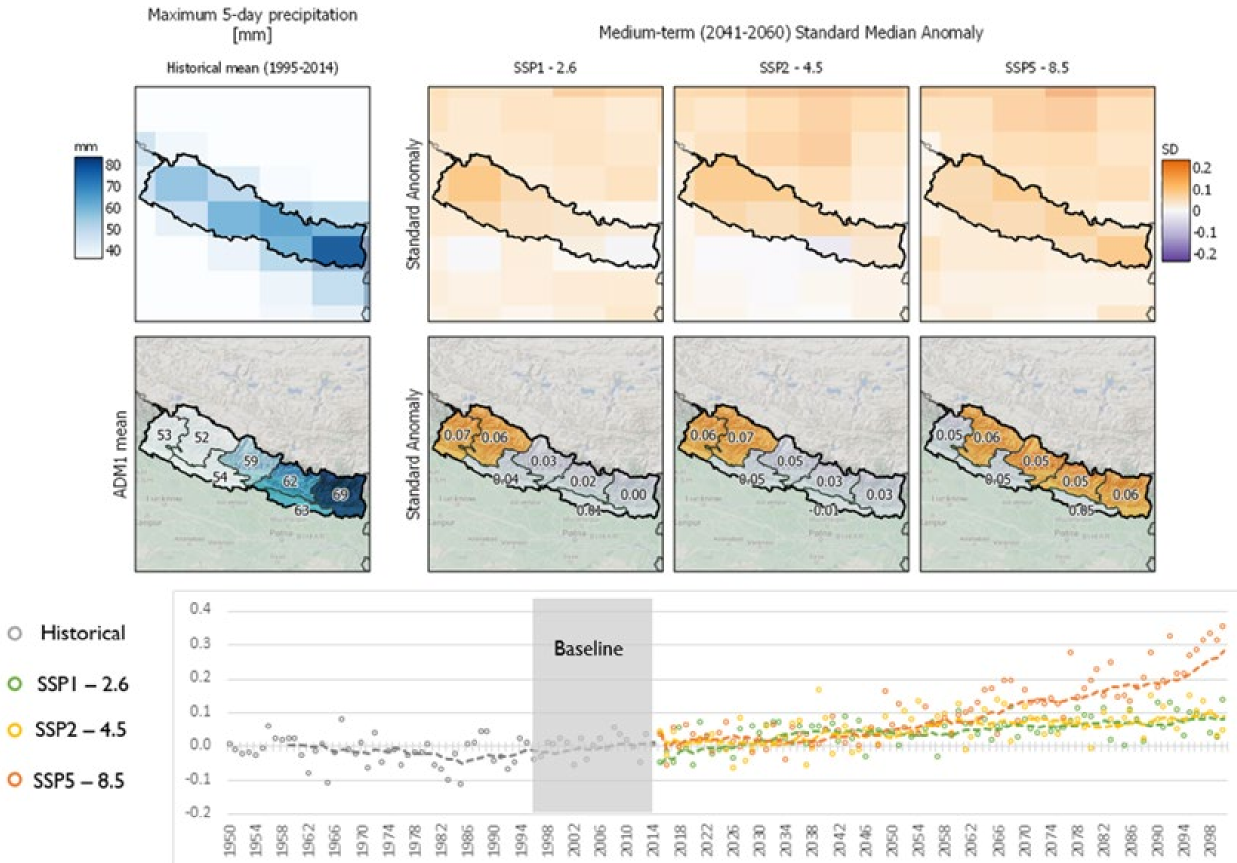
Notes: Data Source - Copernicus Climate extreme indices and heat stress indicators derived from CMIP6 global climate projections

FIGURE 28: CLIMATE CHANGE PROJECTIONS -- CONSECUTIVE WET DAYS (DAYS/YEAR) FOR NEPAL



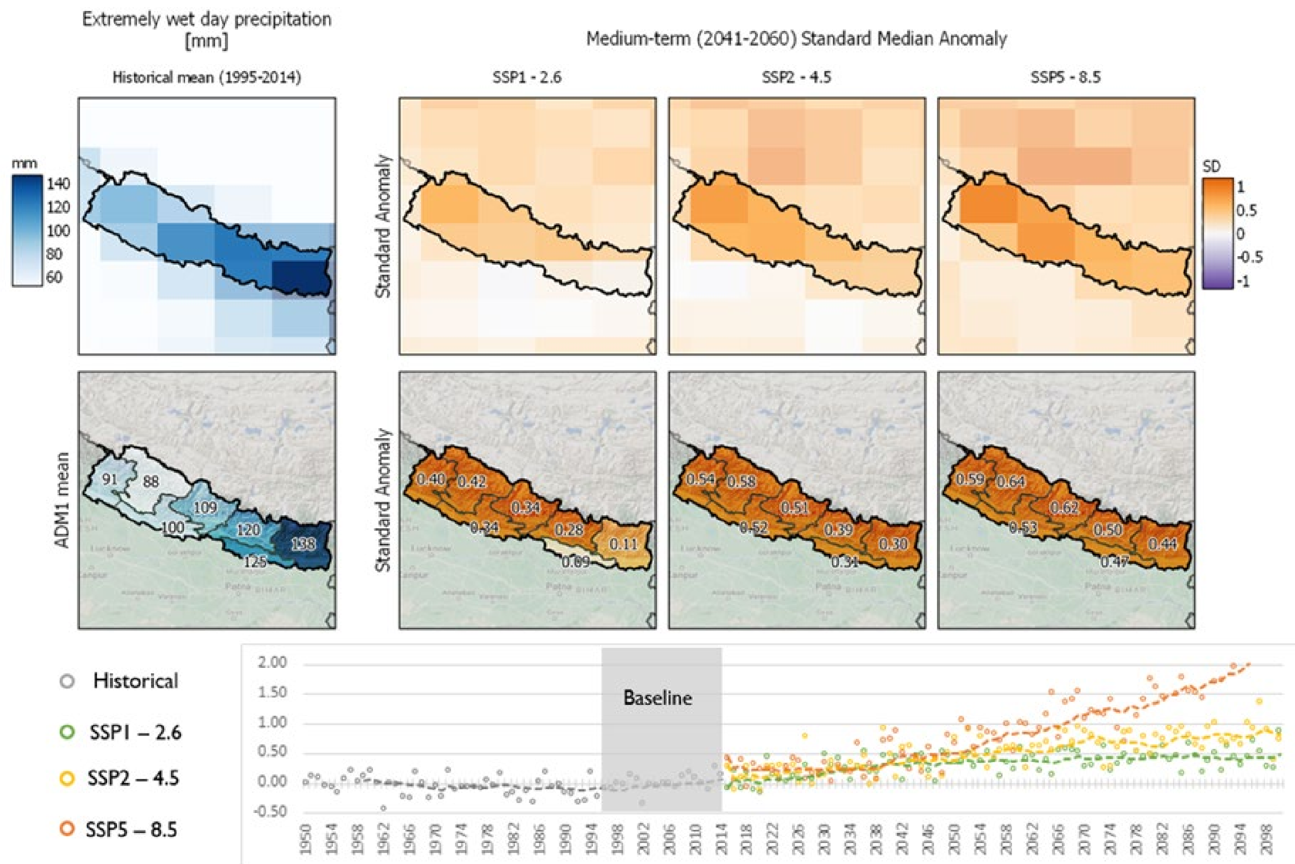
Notes: Data Source - Copernicus Climate extreme indices and heat stress indicators derived from CMIP6 global climate projections

FIGURE 29: CLIMATE CHANGE PROJECTIONS -- MAXIMUM 5-DAY PRECIPITATION (MM) FOR NEPAL



Notes: Data Source - Copernicus Climate extreme indices and heat stress indicators derived from CMIP6 global climate projections

FIGURE 30: CLIMATE CHANGE PROJECTIONS -- EXTREMELY WET DAY PRECIPITATION (MM) FOR NEPAL



Notes: Data Source - Copernicus Climate extreme indices and heat stress indicators derived from CMIP6 global climate projections

According to the standardised anomalies for the number of consecutive wet days and annual days with rainfall over 10mm, as well as the cumulative rainfall over a period of five days, only modest changes are expected compared to the baseline period. Under all three climate scenarios, a slight increase in the anomalies for these variables is seen in the western provinces, with a lower increase, or even a decrease, in the eastern provinces. This points to a low likelihood of structurally wetter conditions in Nepal in the period 2041-2060. In contrast, the rainfall volumes during extremely wet days are expected to increase significantly, particularly in western Nepal, with standardised anomalies sharply increasing under higher-emission climate change scenarios. Under all three scenarios, Lumbini, Karnali, and Sudurpaschim are likely to be most strongly affected by an increase in these short, extreme precipitation events.

While the overall trend thus does not show a significant alteration in spatial precipitation trends for Nepal, the projected increase in extreme rainfall events, particularly in the western provinces, is concerning, particularly as this can go hand in hand with flooding and rainfall-induced landslides. Adaptative measures (including those highlighted in the 2022 Nepal CCDR) to prevent an increase in mortality and damage to built-up and agricultural assets thus will need to be taken, with particular attention to the west of the country.

Drought projections

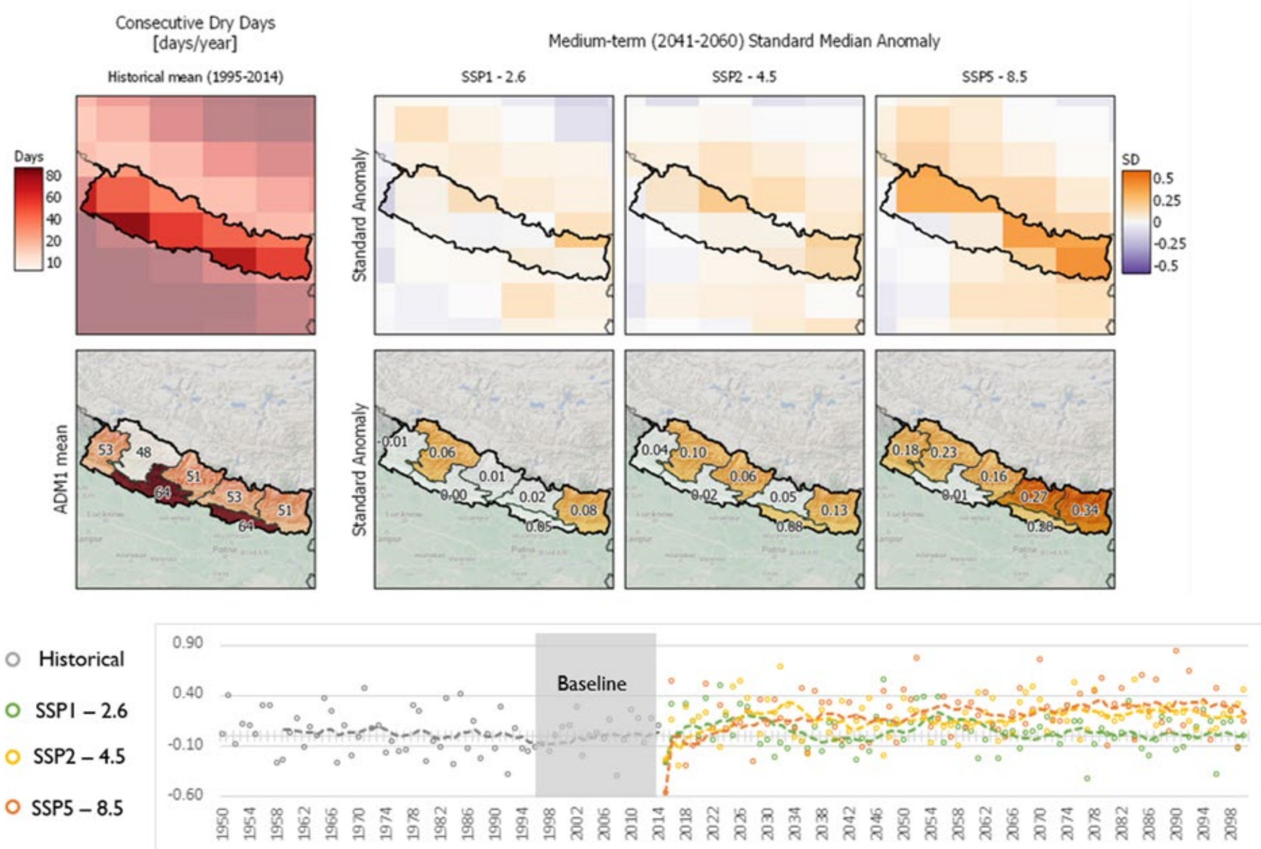
Two variables underpin the projection of changes in drought patterns across Nepal: the number of consecutive wet days per year (Figure 31), and the 12-month Standardised Precipitation-Evapotranspiration Index (SPEI, Figure 32). The SPEI has been found to be closely related to drought impacts on ecosystems, crop, and water resources, and has been designed to take into account both precipitation and potential evapotranspiration in determining drought (Vicente-Serrano and Beguería, 2022). It is important to note that negative SPEI values indicate drier conditions. The mapping ensembles for these drought-related variables follow a similar design to the precipitation-related variables, again with the 1995-2014 period as a historical baseline.

Both variables offer a complementary, yet slightly different, spatial picture. The SPEI shows little change in standardised anomaly under any of the SSPs compared to the baseline. This suggests that little change is expected in agricultural drought patters during the period 2041-2060 compared to the 1995-2014 reference period, implying the historically drier western provinces (Lumbini, Karnali, and Sudurpaschim) will remain confronted with more frequent drought episodes. However, the climate projections do not foresee a significant worsening – or improvement – of this spatial pattern of agricultural drought in the decades ahead.

Under the low-emission and moderate-emission SSPs (SSP1 – 2.6 and SSP2 – 4.5), the number of annual consecutive dry days is forecasted to increase, as the standardised anomalies would increase above the historical baseline. This increase is, however, limited, and uniform across Nepal. In contrast, under a high-emission SSP (SSP5 – 8.5), the anomaly increases sharply, in particular in Koshi, Madhesh and Bagmati. These areas are thus set for an increase in short-term dry episodes mid-century, in the event of sharply rising greenhouse gas emissions. In the western provinces, standardised anomalies rise as well, yet this increase is comparatively smaller, suggesting the historical patterns are unlikely to shift significantly.

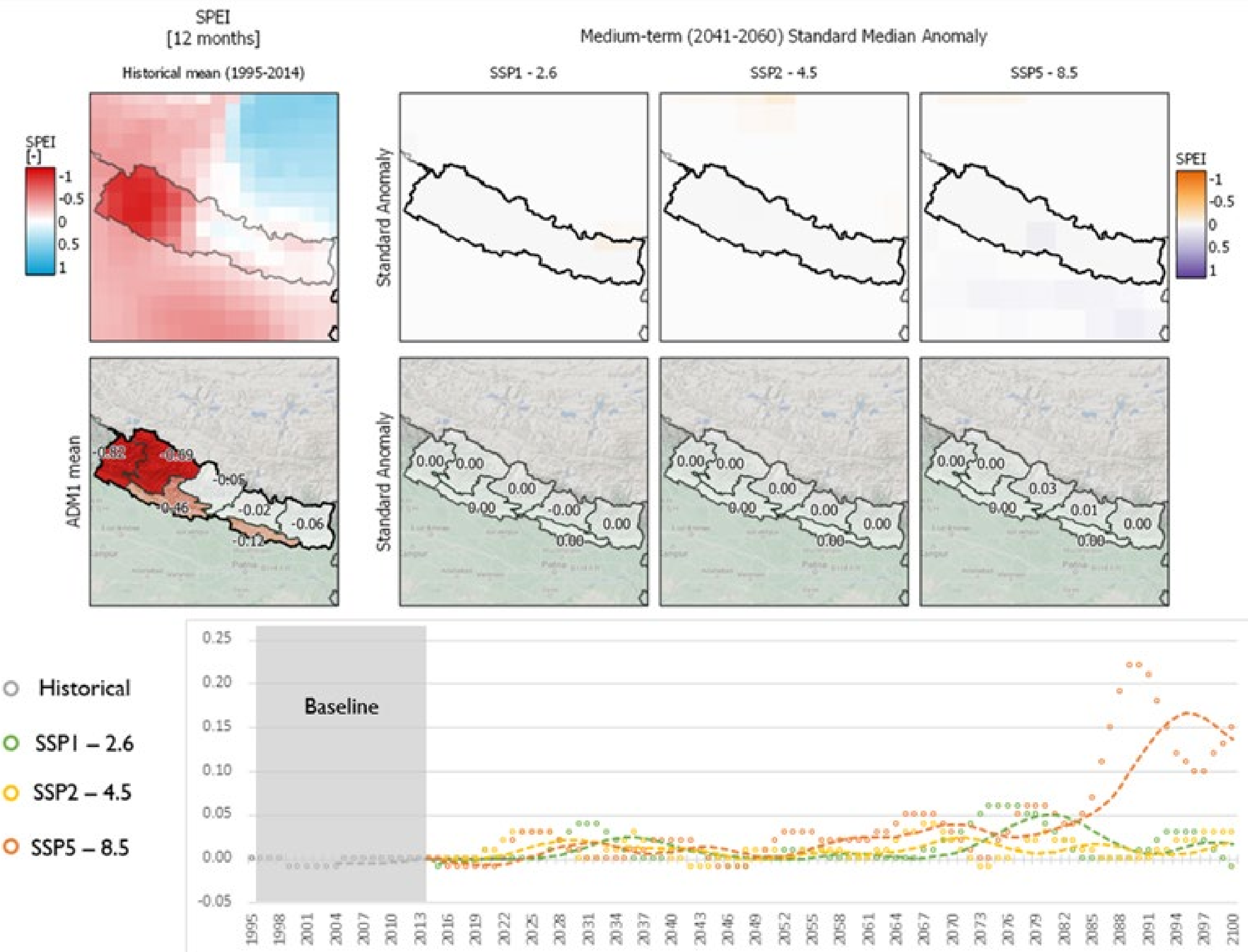
This limited shift in projected drought patterns suggests that current agricultural drought concerns – closely related to food prices and food security – will remain valid in the decades ahead.

FIGURE 31: CLIMATE CHANGE PROJECTIONS -- CONSECUTIVE WET DAYS (DAYS/YEAR) FOR NEPAL



Notes: Data Source - Copernicus Climate extreme indices and heat stress indicators derived from CMIP6 global climate projections

FIGURE 32: CLIMATE CHANGE PROJECTIONS -- SPEI (-) FOR NEPAL



Notes: Data Source - CSIC (SPEI historical records); World Bank CCKP (SPEI projections)

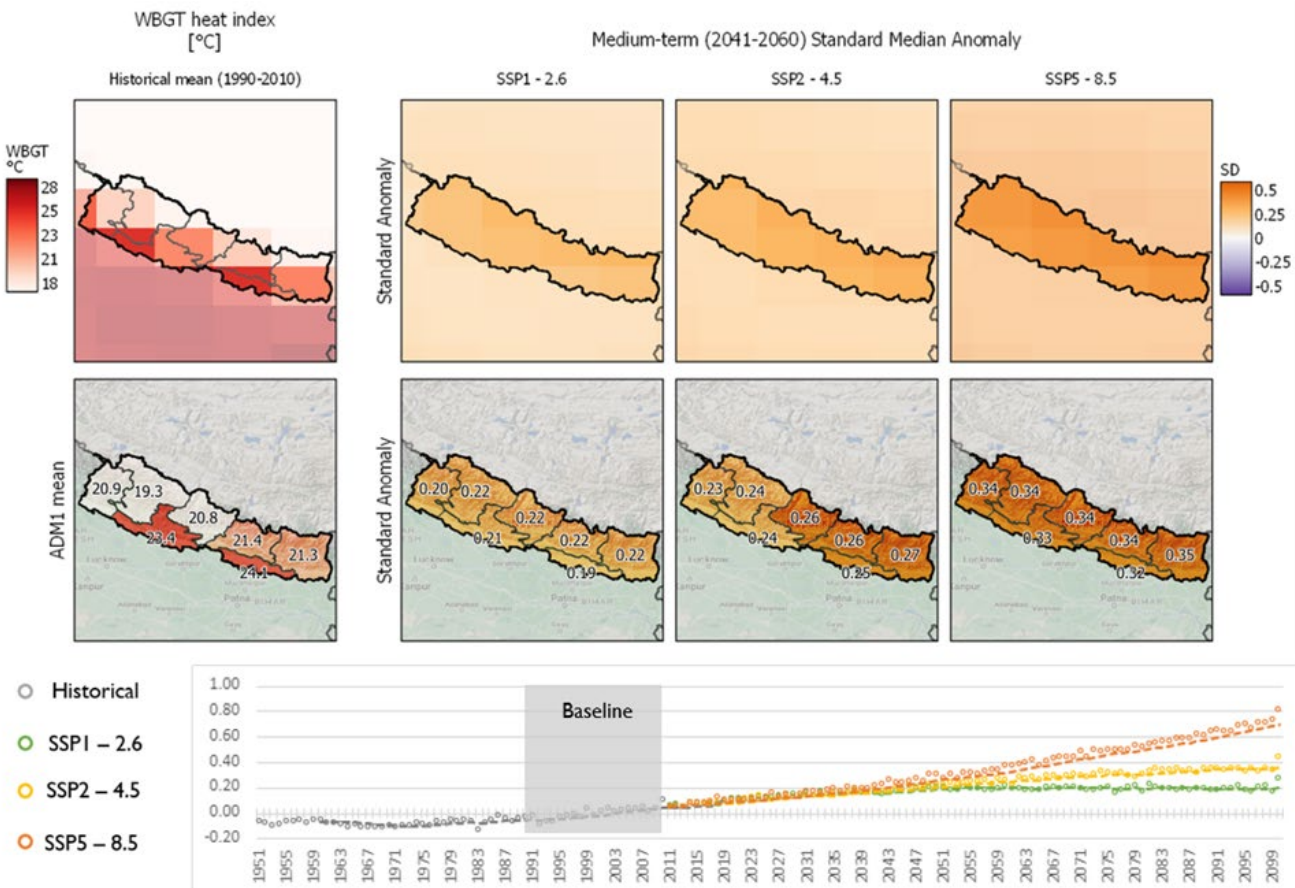
Heat projections

The change in heat patterns under the three climate change scenarios is performed by modelling the WBGT heat index, combining the effects of temperature, humidity, and prolonged workload on the heat stress experienced (Figure 33). Under all three SSPs, and relatively uniformly across Nepal, the standardised anomalies of heat are forecasted to increase relative to 1990-2010. This increase is considerably stronger under higher-emission future scenarios.

The projected rise in temperatures is concerning, as it indicates increased heat stress across Nepal by 2041-2060, potentially putting even more lives at risk. The fact that this increase is fairly homogenous across the country raises particular questions on adaptation and prevention for the urban environments in southern and eastern Provinces (Koshi, Madhesh, Bagamati and Lumbini), where heat has historically been a cause of significant climate risk. Moreover, increasing temperatures are likely to accelerate snow and glacier melting, and therefore further contribute to higher risk of flooding.

The increase in heat, while uniform, is expected to have differential impacts on health and productivity of agricultural workers in the terai, who often spend considerable amounts of time in physically demanding tasks. The effects may be different from the wage workers and self-employed in elementary occupations in the terai and major urban settlements. Furthermore, the compounded risk of landslides and floods due to melting glaciers will affect the population in the mountainous areas. The NLSS data can be used to investigate these impacts and to draw firmer policy conclusions, given that it will provide extensive information on livelihood profiles across the country.

Figure 33: Climate Change Projections – WBGT Heat Index (°C) for Nepal



Notes: Data source - Copernicus Climate extreme indices and heat stress indicators derived from CMIP6 global climate projections

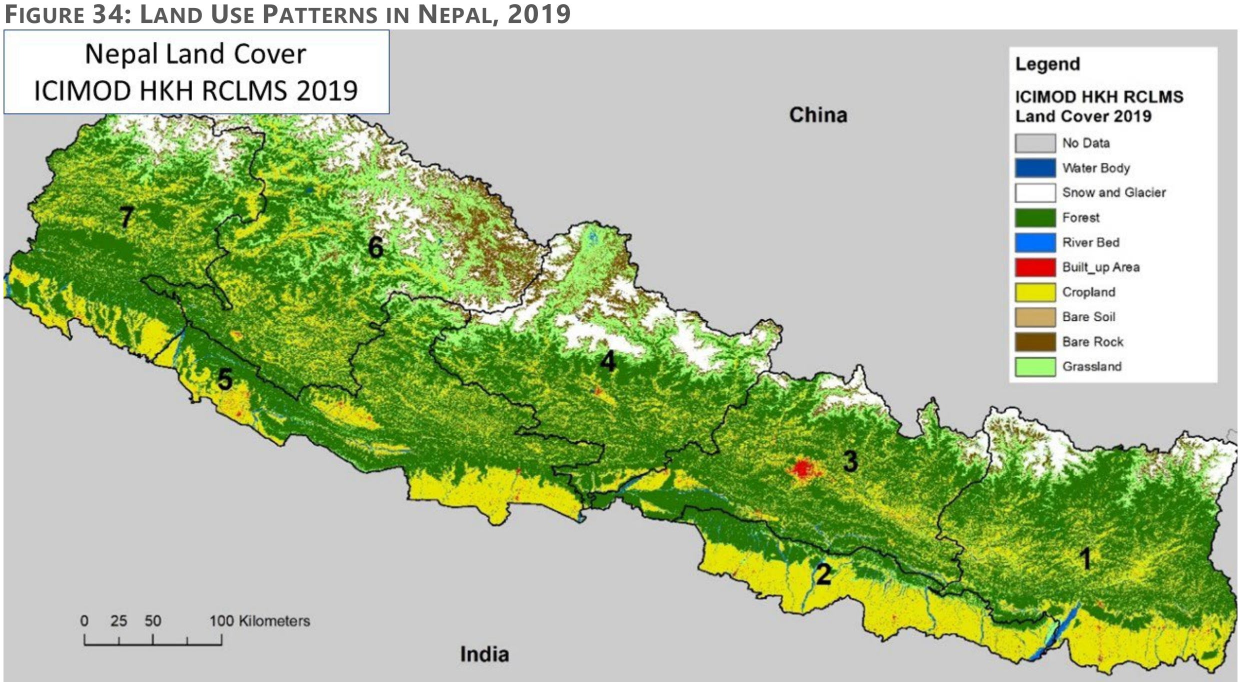
9. Green jobs in the context of at-risk livelihoods

The results of this analytical work show that risk profiles will likely change over time in different parts of the country. At present, the southern parts of Nepal, along with several central areas (including Kathmandu valley) are more prone to be affected by climate hazards, and experience asset losses. In addition, however, the populations in northern areas are more vulnerable in terms of welfare losses from climate hazards. By mid-century, increase in intensity of extreme events will disproportionately affect the western provinces, which are currently ranking low in several measures of living standards relative to other provinces. We examine whether areas that are more highly exposed to hazard risk (and are relatively more resilient) are also characterized by a particular livelihood profile, specifically, if they are more reliant on agricultural livelihoods.

In addition, we undertake a profiling of occupations in Nepal to identify the potential for green jobs. While livelihoods in the agricultural sector, particularly in farming, are especially vulnerable to various forms of natural hazards, the agricultural sector is also important as the largest employer in the country, as well as an important contributor to GHG emissions (namely methane), albeit with low levels in international standards both in per capital and as a country.

The agricultural sector employs the largest share of the workforce in Nepal, 63%, followed by 21% in services and 16% in industry, in various occupations around farming, livestock, forestry, and fishery across the value chain. Yet, in terms of occupations, the most prevalent occupations are found in the retail sector –the largest occupation (using the International Standard Classification of Occupations (ISCO) 4-digit categorization) are shopkeepers making up almost 12% of the workforce, and together with shop sales assistants the group makes up over 17% of the workforce. Other most prevalent occupations are in the construction industry and in education.

FIGURE 34: LAND USE PATTERNS IN NEPAL, 2019



Notes: Data source is ICIMOD HKH RCLMS 2019 data on types of land cover.

Cropland and agricultural labour (both crop farming and livestock production) are concentrated to the south of the country, provinces 1, 2 and 5 having the largest shares of labour in the agricultural sector (Figure 34). These areas comprise of a large share of southern Nepal, that have high risks of both droughts and heat stress, and a high risk of physical asset damage resulting from river flooding. Yet at the same time, these areas have also the highest resilience ratio, that is, in southern parts of the country asset losses translate to the lowest level of consumption losses. Taken together, although agricultural livelihoods face heightened environmental risks in the south, risks to the welfare of agricultural households may be more detrimental in in areas where these hazards are less likely to occur given that the agricultural share of the labour force is significant in every province.

GHG emissions in Nepal result largely from agriculture and energy. These two sources made up over 90% of greenhouse gas emissions in 2018. In Land-Use Change and Forestry there has also been a shift to net emissions and away from sequestration in the 2000's. The most common greenhouse gas from agriculture is methane, to which the livestock production sector is an important source.

While Nepal ranks low in GHG emissions in global comparisons, it also simultaneously lacks 'green jobs', that is, occupations that have the specific sets of skills required for the green transition. For classifying green jobs in Nepal, we use data from ongoing work by Montoya et al. (2022) for the classification, which we merge with the 2017 Nepal Labour Force Survey's information of the respondent's main occupation.[18] Green job classifications used in Montoya et al. (2022) are i) New and emerging green occupations (e.g., solar panel, wind turbine technicians) ii) Green enhanced skills occupations (occupations subject to substantial greening effects due to changes in technology or legislation, e.g., architects) iii) Green increased demand occupations, that are not subject to major changes, but are in increased demand due to greening (e.g., electrical power line installers). We also include two categories for jobs that cannot be considered green, as done in Montoya et al. (2022). These are 'green rival' jobs that may have some potential to be green such that they have at least one green job among their registered "similar" jobs. Finally, non-green jobs are jobs that do not satisfy any of these requirements. 'Non-green' does however not imply that the jobs are high in GHG emissions.

We find that the average job in Nepal has a less than 1% probability of being a new and emerging green occupation, such as a solar panel technician. Individuals with post-secondary education have by far the highest probability of being employed in these new and emerging occupations. Green enhanced skills, and green increased demand occupations are more common with the average job having a 19% and 11% probability of being classified as one, respectively. Men are more likely to be employed in any of the green occupations, while women are more likely to be employed in non-green occupations.

The agricultural sector is less green than the average job in Nepal – an average job in the agricultural sector has a 79% probability of being in either one of the non-green categories, and a 21% probability of being in green increased demand occupations. None of the occupations in the agricultural sector can be considered new and emerging green. Women make up 66% of the workforce in the agricultural sector, and these occupations are spread quite evenly across all the 7 provinces.

It is important to acknowledge that this is the first attempt to capture the greenness of occupations in South Asia, using existing data and methodologies. Therefore, the analysis suffers from limitations of the data and methodology used. Specifically, a limitation to the greenness measure is that it is adapted from studies focused on developed and higher middle-income countries (specifically, following Montoya et al. 2022), developed based on tasks specific to the occupational code, and the extent to which the Nepal Labor force data can accommodate this methodology.

In order to follow the greening of Nepal's agricultural sector over time, one would need i) collect information on the use of agricultural practices specific to the smallholder farming in South Asia and incorporating the use of climate-smart inputs and technologies. This can be done in both household and labour force surveys,

[18] This data includes information on 52,559 individuals 15 years or older of whom 34% (16,792 individuals) had been employed in the last 7 days preceding the survey.

and ii) develop a measure of greenness better adapted to the South Asian context, developed using South Asian data. The GRID agenda needs to improve data collection and methodology to better capture the transition to green jobs, and more broadly, green livelihoods.

This suggests while the overall potential for transforming Nepal's livelihoods profile for a green transition is limited based on this classification, investments in agricultural livelihoods will be needed to support adaptation to climate risk. At the same time, northern parts of the country have a high degree of vulnerability due to more limited access to coping and will also need concerted support to weather shocks. This is also the case with western provinces that are projected to see an increasing intensity of extreme weather events.

10. Conclusions and policy implications

After a decade of consistent gross domestic product (GDP) growth (averaging 4.9 percent), Nepal obtained lower middle-income status in 2020. By 2050, just three climate hazards, flooded infrastructure, heat stress on labour productivity and health, and heat stress on crops and livestock, are estimated to drag growth 0.27 percent lower each year in the most pessimistic warming scenario (Nepal CCDR, 2022). Our findings highlight the elevated risks to human life, physical investments, and assets. These are both wide-ranging, and likely to occur in a context with limited coping and resilience. Our findings suggest considerable spatial heterogeneities in these climate risks, both at present and decades ahead, as well as spatial heterogeneities in the ability to cope with these climate shocks.

Our contemporaneous and backward-looking analysis finds large spatial heterogeneities in climate hazards and air pollution, with southern areas being more affected by various hazards. Yet, these areas also appear to be somewhat more resilient based on their relative vulnerability score. Much of the south of the country appears to suffer lower welfare losses for a given disaster as compared to more northern areas. Furthermore, our analysis on the built-up area development shows that there are specific geographic areas where populations are growing, but new built-up area is concentrated on increasingly steep ground, given the scarcity of flat ground in mountainous areas. Palikas with such growth where flooding risk is also high constitute a set of very vulnerable communities, where extreme weather events or disasters may have very severe consequences.

Combining this diverse set of climate change variables presents a worrisome picture for Nepal, especially with respect to heat stress, flooding, and landslides for the period 2041-2060. Current heat stress patterns are set to increase in severity and while the overall precipitation patterns are unlikely to alter considerably, extreme rainfall events are likely to increase in magnitude. This increase in intensity of extreme events – heat stress and days with extreme rainfall – is a concern for the whole of Nepal, yet the stark increase in the historically less-affected western provinces calls for particular attention to adaptative measures and preparedness efforts there, as communities may have lower adaptative capacity and resilience due to historically low exposure. The projected continuation, and possible deepening, of historical spatial patterns demonstrates that structural measures need to be taken to overcome the disparities seen across Nepal, to ensure the lives and livelihoods of all citizens of Nepal are safeguarded. Particular attention should therefore be given to the western provinces of Karnali and Sudurpaschim in terms of the risks for agricultural drought, southern provinces Madhesh and Lumbini, which have the highest historical and continued heat index values and risks of intermediate agricultural drought, and the eastern Koshi and Bagmati, which face the highest likelihood of extreme precipitation events.

A spatially disaggregated approach, going beyond the national average and zooming in to the highest possible geographic detail, thus allows to disentangle climate hazards, and pinpoint policy-relevant focus areas by studying the co-occurrence, frequency, and intensity of these hazards. A forward look then sends a stark warning signal for how these trends are set to develop for Nepal. The fact that we are only two decades away from these worrying scenarios calls for prompt and decisive adaptation and prevention measures, tailored to the specific hazards identified for each area.

At the same time, mitigation of GHG emissions remains important, as the adverse effects of climate change will deepen under worse emission conditions. Yet, at present, less than one percent of the labour force is employed in occupations that have emerged as new occupations in the green economy, and this part of the workforce is predominantly male and tertiary educated, such as in occupations involving technical expertise in solar power. While these jobs are just a part of the greening of the economy, it is important that women are not excluded from these opportunities. Furthermore, skills in greening the agricultural and energy sector are particularly needed to transform the sectors that emit the most, and this development needs to be monitored with labour force data that includes task-specific information on green practices and use of green technology, in order to monitor the development. In this regard, Nepal also requires skills and investments in climate adaptation. Given the large share of agriculture in the livelihood portfolio of the population, it is important to build skills, agricultural practices, and safety nets that can not only cushion the agricultural sector against losses caused by extreme events, but also to build longer-term resilience. Urban areas on the other hand, and the Terai, where population density is higher, need local solutions specifically to target outdoor air pollution, which is already at globally high levels.

References

AQLI, Air Quality Life Index (2022) Energy Policy Institute at the University of Chicago https://aqli.epic.uchicago.edu/the-index/ Accessed August 10, 2022

Bluhm, R., & McCord, G. C. (2022). What Can We Learn from Night-time Lights for Small Geographies? Measurement Errors and Heterogeneous Elasticities. *Remote Sensing*, *14*(5), 1190. https://doi.org/10.3390/rs14051190

CAIT Database (2022) Historical GHG emissions data https://www.climatewatchdata.org/. Accessed February 16, 2022

Esch, T., Brzoska, E., Dech, S., Leutner, B., Palacios-Lopez, D., Metz-Marconcini, A., Marconcini, M., Roth, A., & Zeidler, J. (2022). World Settlement Footprint 3D - A first three-dimensional survey of the global building stock. *Remote Sensing of Environment*, *270*, 112877. https://doi.org/10.1016/j.rse.2021.112877

European Commission (2019). INFORM Index for Risk Management. Nepal Country Profile. URL:https://drmkc.jrc.ec.europa.eu/inform-index/Countries/Country-Profile-Map

FAO, Food and Agriculture Organization of the United Nations (2022) Earth Observation, Seasonal Global Indicators https://www.fao.org/giews/earthobservation/asis/index_1.jsp?lang=en Accessed August 9, 2022

Farr, T. G. et al., 2007, The Shuttle Radar Topography Mission, Rev. Geophys., 45, RG2004, doi:10.1029/2005RG000183. (Also available online at http://www2.jpl.nasa.gov/srtm/SRTM_paper.pdf)

Hallegatte, Stephane; Vogt-Schilb, Adrien; Bangalore, Mook; Rozenberg, Julie. (2017). Unbreakable : Building the Resilience of the Poor in the Face of Natural Disasters. Climate Change and Development; Washington, DC: World Bank. © World Bank. https://openknowledge.worldbank.org/handle/10986/25335 License: CC BY 3.0 IGO.

Health Effects Institute (2020). State of Global Air 2020. Data source: Global Burden of Disease Study 2019. IHME, 2020. https://www.stateofglobalair.org/data/

Huizinga, J., De Moel, H., & Szewczyk, W. (2017). *Global flood depth-damage functions: Methodology and the database with guidelines* (No. JRC105688). Joint Research Centre (Seville site).

AR6 Climate Change 2021: The Physical Science Basis (WG1) https://www.ipcc.ch/report/ar6/wg1/

Jonkman, S. N., & Vrijling, J. K. (2008). Loss of life due to floods. *Journal of Flood Risk Management*, *1*(1), 43-56.

Marconcini, M., Metz-Marconcini, A., Üreyen, S., Palacios-Lopez, D., Hanke, W., Bachofer, F., Zeidler, J., Esch, T., Gorelick, N., Kakarla, A., Paganini, M., & Strano, E. (2020). Outlining where humans live, the World Settlement Footprint 2015. *Scientific Data*, *7*(1), 242. https://doi.org/10.1038/s41597-020-00580-5

Montoya, Olivieri, Sanchez, Vazquez and Winkler (2022): *Green Jobs, Dirty Sectors and Economic Development. Evidence across countries*- LAC Stats, work-in-progress

Ministry of Forests and Environment of Nepal, (MoFE). (2021). Vulnerability and Risk Assessment and Identifying Adaptation Options: Summary for Policy Makers. Ministry of Forests and Environment, Government of Nepal. Kathmandu, Nepal

NASA Shuttle Radar Topography Mission (SRTM)(2013). Shuttle Radar Topography Mission (SRTM) Global. Distributed by OpenTopography. https://doi.org/10.5069/G9445JDF. Accessed: 2022-09-16

ND-GAIN (2022) Notre Dame Global Adaptation Initiative. URL: https://gain.nd.edu/our-work/country-index/ Accessed August 8, 2022

OpenStreetMap. OSM History Dump © OpenStreetMap Contributors. Available online: https://planet.openstreetmap.org/planet/full-history/ (accessed on 14 December 2020).

Stevens F R, Gaughan A E, Linard C and Tatem A J (2015) Disaggregating Census Data for Population Mapping Using Random Forests with Remotely-Sensed and Ancillary Data PLOS ONE 10 e0107042

Tiecke, T. G., Liu, X., Zhang, A., Gros, A., Li, N., Yetman, G., Kilic, T., Murray, S., Blankespoor, B., Prydz, E. B., & Dang, H.-A. H. (2017). *Mapping the world population one building at a time* (arXiv:1712.05839). arXiv. https://doi.org/10.48550/arXiv.1712.05839

Uddin, K., Matin, M. A., Khanal, N., Maharjan, S., Bajracharya, B., Tenneson, K., Poortinga, A., Quyen, N. H., Aryal, R. R., Saah, D., Lee Ellenburg, W., Potapov, P., Flores-Anderson, A., Chishtie, F., Aung, K. S., Mayer, T., Pradhan, S., & Markert, A. (2021). Regional Land Cover Monitoring System for Hindu Kush Himalaya. In B. Bajracharya, R. B. Thapa, & M. A. Matin (Eds.), *Earth Observation Science and Applications for Risk Reduction* *and Enhanced Resilience in Hindu Kush Himalaya Region: A Decade of Experience from SERVIR* (pp. 103–125). Springer International Publishing. https://doi.org/10.1007/978-3-030-73569-2_6

Aaron van Donkelaar, Melanie S. Hammer, Liam Bindle, Michael Brauer, Jeffery R. Brook, Michael J. Garay, N. Christina Hsu, Olga V. Kalashnikova, Ralph A. Kahn, Colin Lee, Robert C. Levy, Alexei Lyapustin, Andrew M. Sayer and Randall V. Martin (2021). Monthly Global Estimates of Fine Particulate Matter and Their Uncertainty Environmental Science & Technology, 2021, doi:10.1021/acs.est.1c05309

Vicente-Serrano, Sergio M. and Beguería, Santiago (2022): The Standardised Precipitation-Evapotranspiration Index https://spei.csic.es/index.html Accessed September 14, 2022

VITO/GFDRR (2017) (EH-GLOBAL-VITO-5), Extreme Heat Hazard layer 1981-2010, https://datacatalog.worldbank.org/int/search/dataset/0040194/global-extreme-heat-hazard

World Bank and Asian Development Bank (2021) Climate Risk Country Profile: Nepal. Report.

World Bank Group, Nepal Country Climate and Development Report (CCDR) September 2022

World Bank (2022) The Geospatial Analysis of Current and Future Climate Risks informing Country Climate & Development Reports (CCDRs). Technical Note (unpublished) by Mattia Amadio and Lander Bosch

Zanaga, D., Van De Kerchove, R., De Keersmaecker, W., Souverijns, N., Brockmann, C., Quast, R., Wevers, J., Grosu, A., Paccini, A., Vergnaud, S., Cartus, O., Santoro, M., Fritz, S., Georgieva, I., Lesiv, M., Carter, S., Herold, M., Li, Linlin, Tsendbazar, N.E., Ramoino, F., Arino, O., 2021. ESA WorldCover 10 m 2020 v100.

Annexes

Annex 1: Data availability on land use and built-up area

There are several products available for the observation of land cover and built-up area in Nepal, however these differ in some major ways:

a. Map products with land-cover based classification of "built-up area": In these products the built-up area class is understood as "anything anthropogenic" and includes anything that is not natural in appearance or material, as observed via satellite remote sensing using passive optical imaging sensors. For example, these products will include in the built-up area category roads, paths, parking lots, etc. Especially urban environments, buildings and paved roads all have a similar spectral "signature" that allows their classification as being anthropogenic. These signals are often confused also for bare ground natural signals.

   The products that have this information for Nepal are:

   i. ICIMOD Hindu Kush Himalaya Regional Land Cover Monitoring System (HKH RCLMS). These maps are annual for the period 2000-2019 at 30m resolution.
   ii. European Space Agency (ESA) World Cover, a 10m resolution land cover map for 2020.
   iii. University of Maryland Global Land and Discovery Global Land Cover map for 2019 at 30m resolution.

b. Map products from earth observation (EO) that specifically target built-up area understood as settlements, but not roads or other anthropogenic common areas in urban settings:

   i. Built-up area maps by NLT technology developed for WB Nepal in FY21 (BUA WB), at 30 m resolution available in 5-year intervals for the time-period 2000-2019
   ii. World Settlement Footprint (WSF) at 20m for 2019.

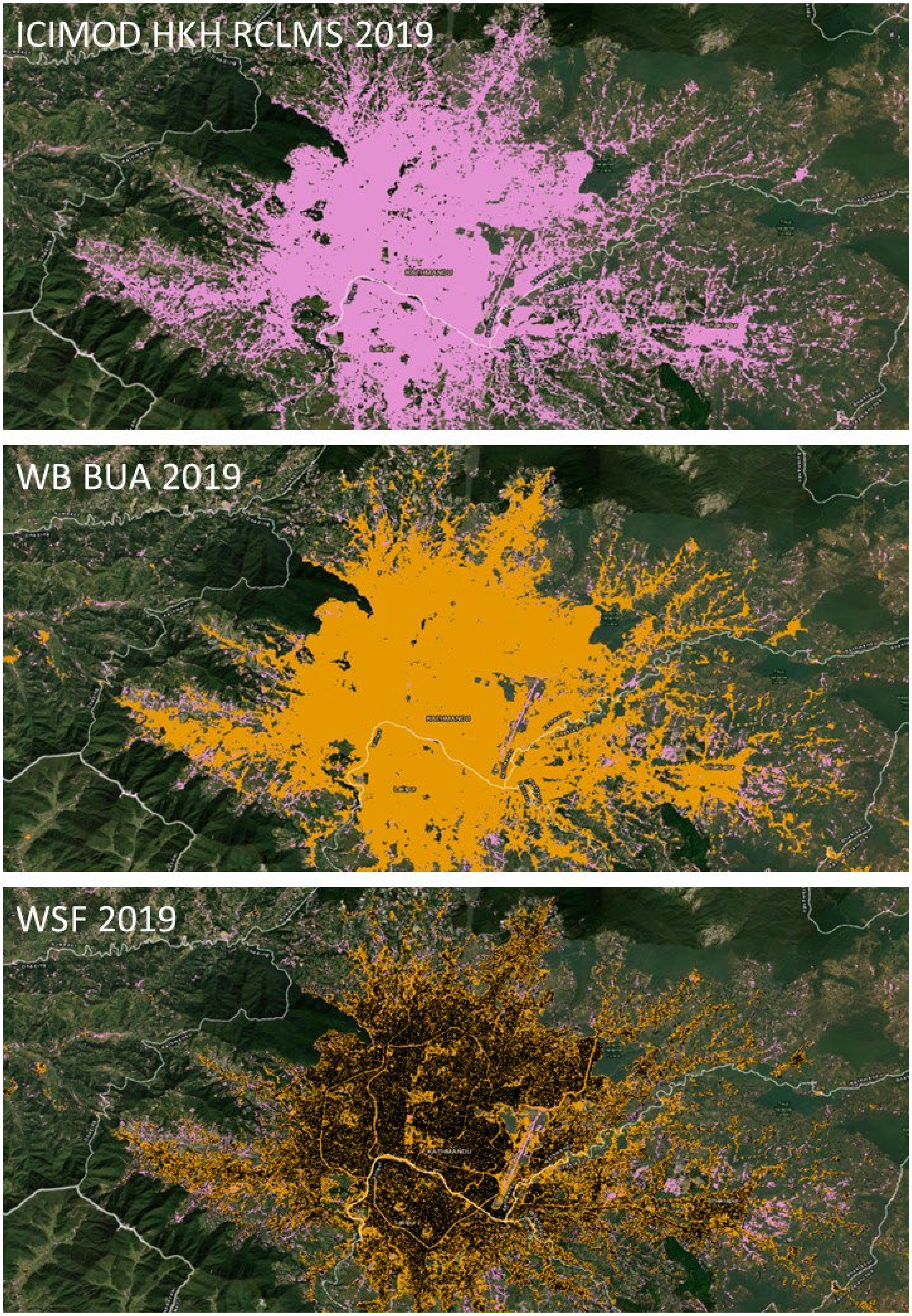
c. Map products that allow for analysis of change, as they map multiple temporal periods:

   i. Built-up area WB (as above) – 2000-2005-2010-2015-2019 (5 time periods)
   ii. ICIMOD HKH RCLMS – 2000-2019 (annual – 19 time periods)

*caveat – as discussed above these use different definitions of "built-up area" which results in different tabulated results.

Because of the above the WSF 2019 product is selected for the CCDR analysis as it has better granularity in picking out individual settlements as opposed to just anthropogenic infrastructure, as show in the figure below, where the WSF product in black, overlaid on the others:

FIGURE 35: COMPARISON OF DIFFERENT BUILT-UP AREA DATA IN KATHMANDU



Notes: The difference in the resolution is most striking between WSF (Black) and the other products, but there are significant differences between the ICIMOD (Purple) product and the WB BUA (orange) as well.

TABLE 2B: COMPOSITION OF LAND USE, BY PROVINCE, 2019 – IN KM2

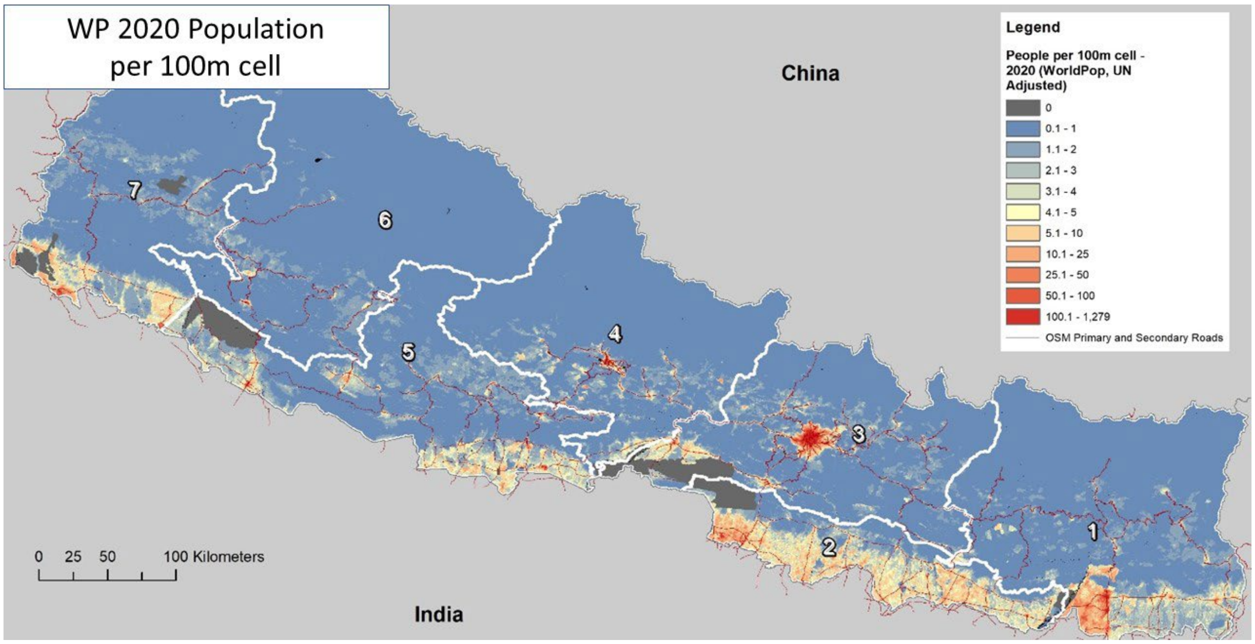
Land Cover	Prov 1	Prov 2	Prov 3	Prov 4	Prov 5	Prov 6	Prov 7	Total
No Data	48	68	42	0	94	0	22	273
Water Body	147	83	90	98	107	113	80	717
Snow and Glacier	2,119	0	942	3,439	73	5,565	1,390	13,528
Forest	12,850	2,439	12,226	9,098	10,582	9,468	9,385	66,047
Riverbed	298	469	248	92	294	50	171	1,622
Built-up Area	128	81	281	86	139	114	42	872
Cropland	7,261	5,914	4,419	2,676	6,699	3,796	4,093	34,859
Bare Soil	1	1	1	38	0	9	1	51
Bare Rock	782	0	446	1,966	119	4,423	509	8,244
Grassland	2,491	542	1,610	4,480	1,162	7,200	2,000	19,485
Totals	26,125	9,597	20,305	21,974	19,269	30,737	17,692	145,699

Notes: Province numbers correspond to province names as follows: Province 1 Koshi, Province 2 Madhesh, Province 3 Bagmati, Province 4 Gandaki, Province 5 Lumbini, Province 6 Karnali, and Province 7 Sudurpaschim. Data source ICIMOD 2019.

Annex 2: Population distribution and Settlements Pattern in Nepal

The map below shows how most of the land area in Nepal is rural with a population density below 3 people per 100m^2 . Population has historically settled along valleys and trade routes, with a lot of the steeper terrain in the Himalayas remaining predominantly rural.

FIGURE 36: POPULATION DISTRIBUTION



Notes: Data source WorldPop 2020

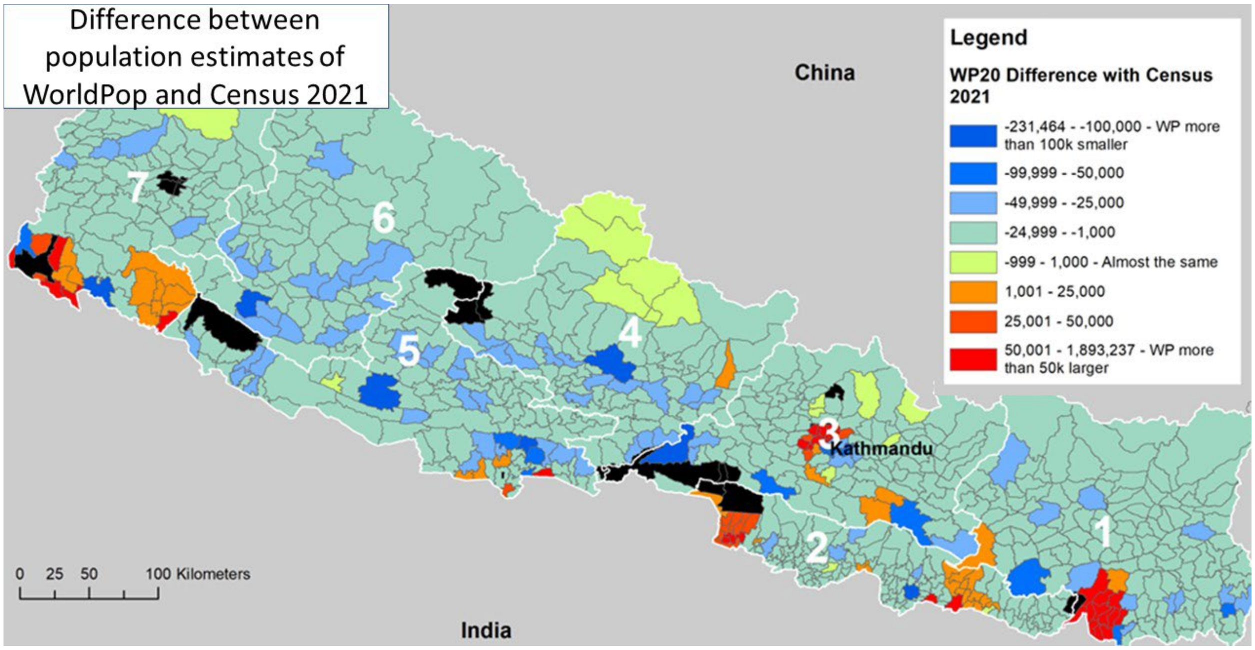
Annex 3: Sensitivity analysis of population data to hazard exposure maps

TABLE 7: COMPARISON OF POPULATION DATA BY PROVINCE

	Province level population							
Dataset	1	2	3	4	5	6	7	Grand Total
WP Unconstrained 2000	4,335,775	3,998,918	4,737,107	2,870,000	3,909,695	2,343,778	1,673,818	23,869,093
Census 2011	4,492,053	5,373,348	5,413,188	2,389,352	4,438,723	1,569,166	2,504,770	26,180,600
Census 2021	4,963,474	6,115,562	6,030,444	2,466,871	5,106,200	1,688,346	2,704,093	29,074,990
WP Unconstrained 2020	5,934,483	5,732,343	7,656,998	1,659,801	3,743,969	1,064,025	3,238,414	29,030,033
WP Constrained 2020	5,217,772	5,696,220	7,485,251	1,078,491	3,031,625	264,036	2,390,418	25,163,812
Meta 2019	5,083,612	5,870,807	6,487,206	2,190,136	4,464,398	1,393,391	2,983,057	28,472,607
WSF3D Constrained CIESIN 2020	6,135,697	5,958,347	7,935,881	1,719,184	3,873,453	1,066,249	3,333,598	30,022,407
WSF3d Constrained Census 2021	4,966,107	6,115,165	6,031,463	2,465,973	5,106,359	1,690,525	2,702,052	29,077,644
Mortality estimates								
WP Constrained Flood Expected Annual Mortality	624	173	3,382	1,291	926	823	767	7,986
Meta Constrained Flood Expected Annual Mortality	231	175	477	526	324	510	313	2,556
Difference in mortality (*Positive numbers = WP-based mortality estimates are bigger)	393	-1	2,905	765	602	313	454	**5,430**

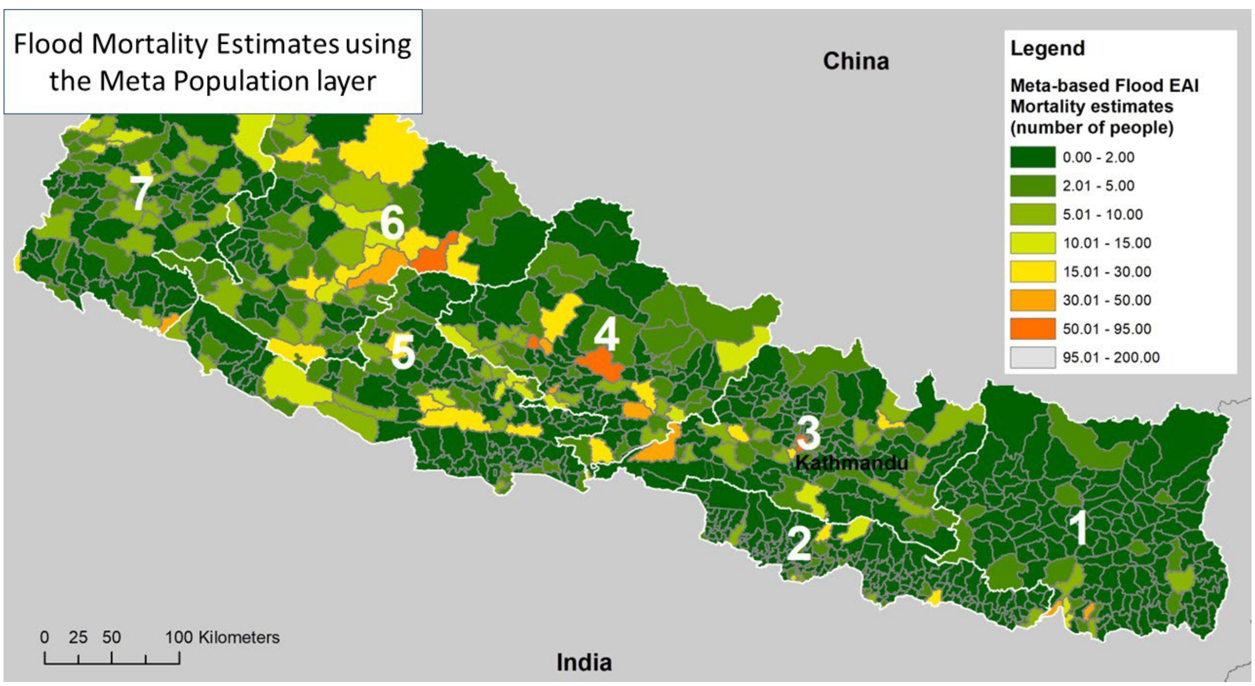
Notes: Province numbers correspond to province names as follows: Province 1 Koshi, Province 2 Madhesh, Province 3 Bagmati, Province 4 Gandaki, Province 5 Lumbini, Province 6 Karnali, and Province 7 Sudurpaschim.

FIGURE 37: COMPARISON OF FLOOD MORTALITY USING WORLDPOP 2020 VS META POPULATION ESTIMATES



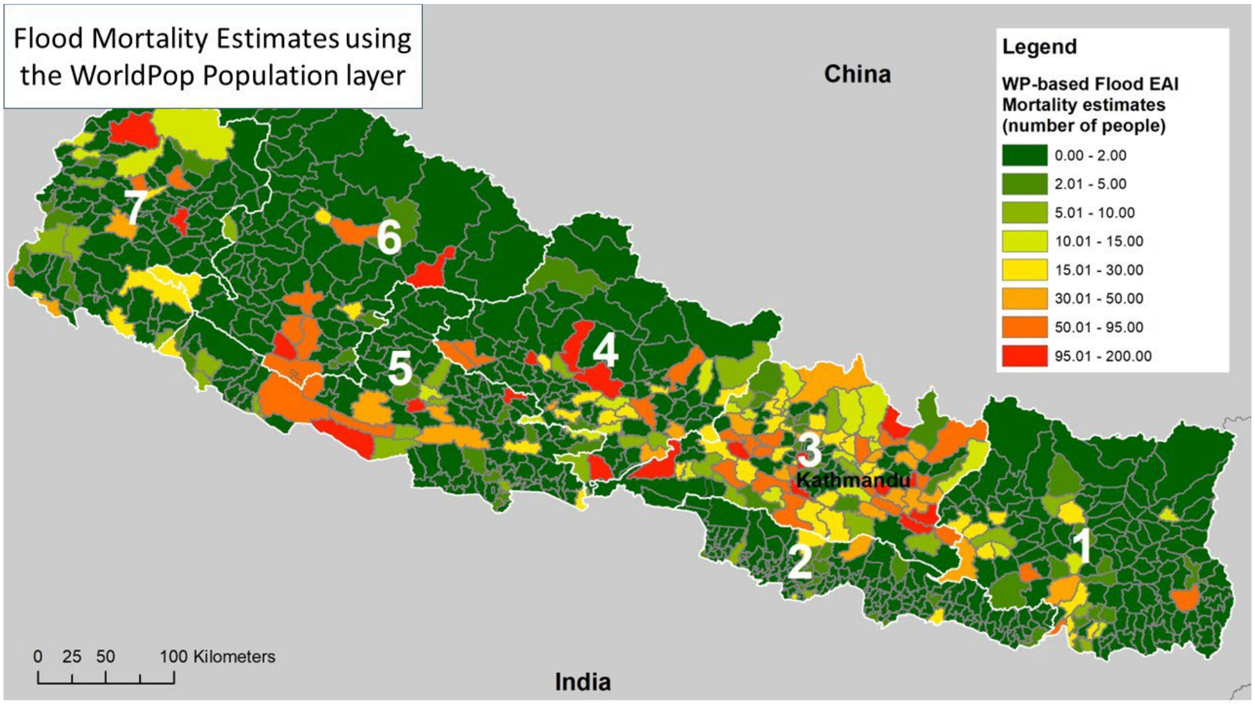
Notes: Data source WorldPop 2020 and Preliminary Census 2021

FIGURE 38: FLOOD MORTALITY USING META POPULATION LAYER



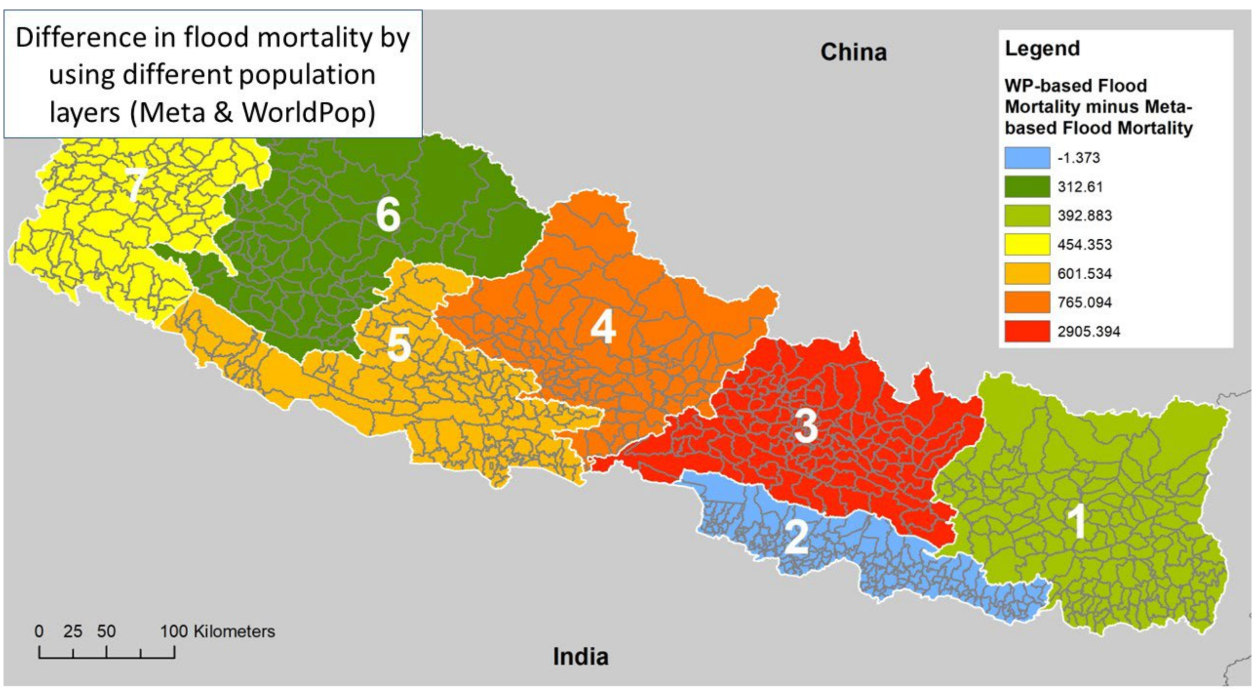
Notes: Data source is Meta (formerly Facebook 2019) and Flood models from Section 4.

FIGURE 39: FLOOD MORTALITY USING WORLDPOP 2020 POPULATION LAYER



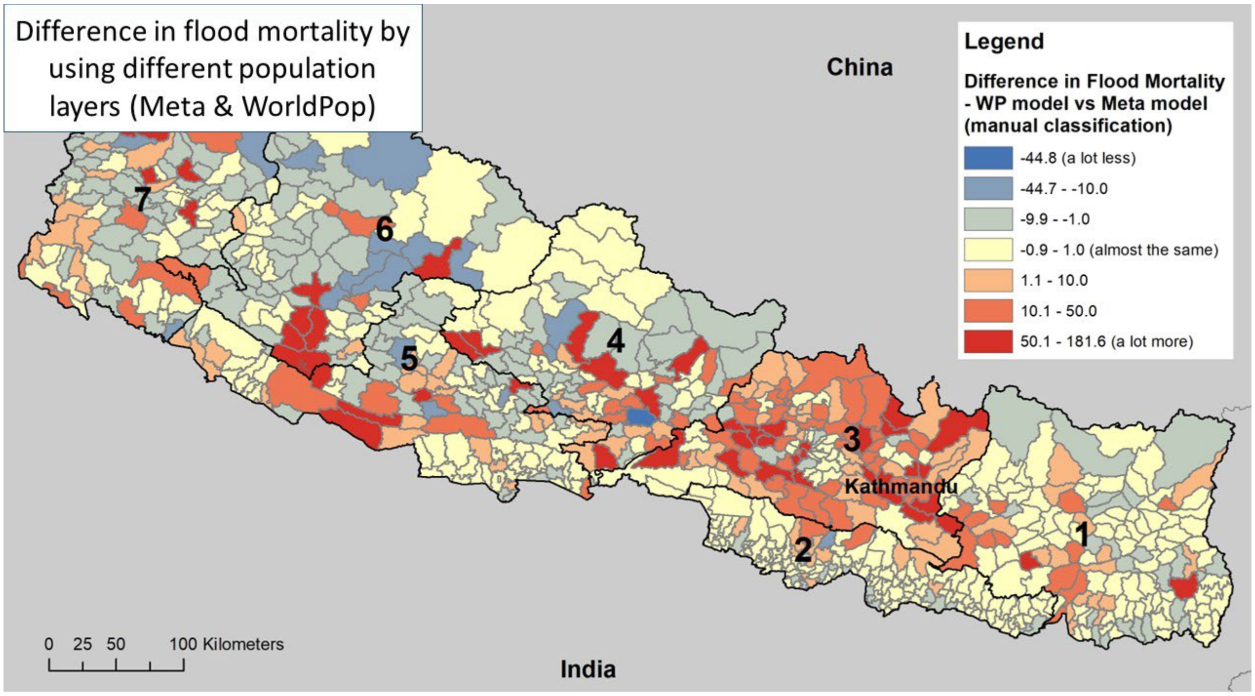
Notes: Data source is WorldPop 2020 and Flood Models from Section 4.

FIGURE 40: DIFFERENCE IN MORTALITY BETWEEN META MODEL AND WORLDPOP MODEL - PROVINCE LEVEL



Notes: Positive numbers mean the WP-based product indicates more casualties than the Meta-based product.

FIGURE 41: DIFFERENCE IN MORTALITY BETWEEN META-BASED MODEL AND WORLDPOP 2020-BASED MODEL

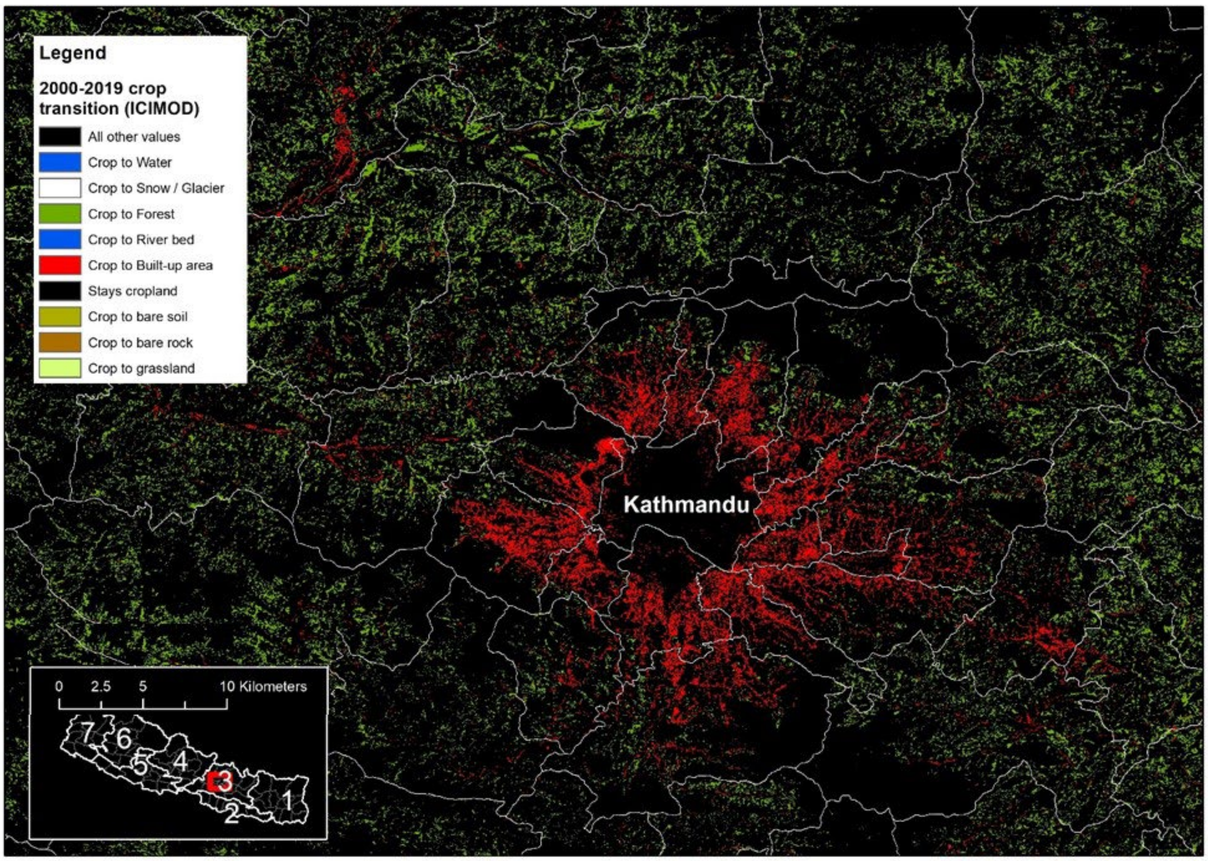


Notes: Data source is WorldPop 2020, Meta 2019 and Flood model from section 4. Positive numbers mean the WP-based product indicates more casualties than the Meta-based product.

Annex 4: Land cover transition maps for 2000-2019

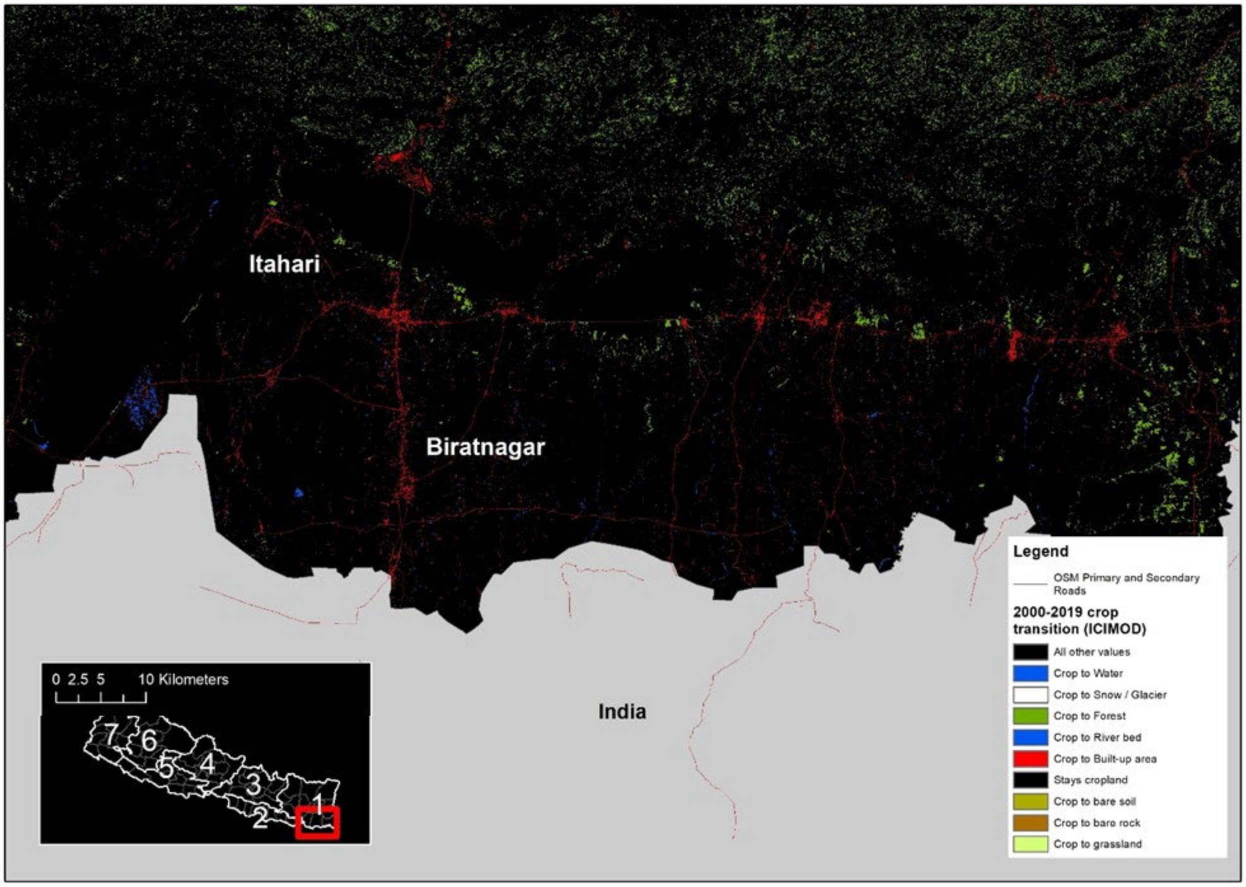
The availability of novel Land Cover and Land Use Change (LCLUC) data that was published in November 2021 (ICIMOD) allows us to map and tabulate all land cover transitions pertaining to the below visualized 9 classes over individual years of the period 2000-2019. The figures below illustrate examples of these transitions, such as the expansion of Built-up area around Kathmandu, that has come at the expense of cropland. The same map of crop transition tells also the story of land abandonment / afforestation, which according to the data has been occurring throughout the country but particularly in the hilly and mountainous regions.

FIGURE 42: LAND COVER CROP TRANSITIONS IN KATHMANDU (ICIMOD)



Notes: Data source is ICIMOD 2000-2020

FIGURE 43: LAND COVER CROPLAND TRANSITIONS (ICIMOD)



Notes: Data source is ICIMOD 2000-2020

Annex 5: Data sources for the risk profile

The goal of the risk profile is to identify the areas of Nepal that will be most impacted by climate change. Climate change will increase the frequency and intensity of a variety of natural hazards that occur in Nepal today. The impacts of the increase in these hazards will be determined by changes in the hydrometeorological system, where individuals live and work, and the likely loss of life or built-up assets in the face of these hazards. In addition, vulnerability to climate change is also shaped by the capacity of these individuals to respond to negative shocks caused by these hazards – this socio-economic vulnerability is assessed in the next section.

Calculation of hazards is be based on globally available data sets and climate modelling aggregated to relevant Nepalese administrative units. Data on hazard incidence will come from global remotely sensed data provided on a grid that can be aggregated to Nepal administrative units. Data sets to be used include the FATHOM global flood data, ARUP global landslide hazards, ASI and WSI drought hazard layers, PDSI drought severity, and CORDEX South Asia 22 heatwave data. These data may be supplemented by additional data sets as they become available.

Exposure to hazard is based global population assessments supplemented by data on built-up area in Nepal. Data from WorldPop and the Global Human Settlement Population grid provides gridded estimates of population at between 100m and 250m resolution. These data provide information at the sub-municipality level on where individuals live in Nepal. The Nepal GeoNode also includes information on built up area at 30m resolution. This data will be combined with the Hazard maps to provide estimates of how many individuals, and buildings, will be impacted by changes in the hazard risks through Nepal.

Annex 6: Details on vulnerability profile

Vulnerability assessment will be based on data from the Nepalese Census, the Nepalese economic census, the Nepal HRVS, the Nepal LFS, and the NLSS. Vulnerability measures how a given shock impacts and given individual's economic well-being. It accounts for both the direct impact of the shock as well as the ability of individuals to adapt or respond to a shock and the fact that this capacity varies across the population. Vulnerability is determined by an individual's source(s) of income, the physical structures in which they reside, their access to formal credit markets and insurance schemes, and their ability to self-insure. Data from the HRVS provides information on these factors for rural and peri-urban households.

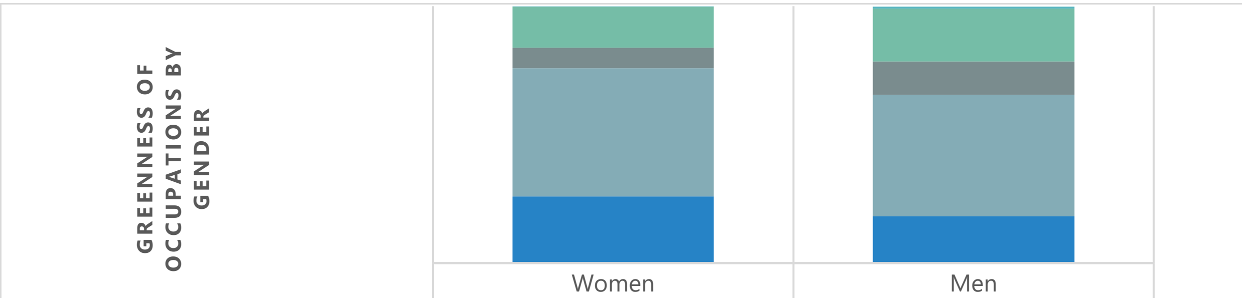
We measure vulnerability based on the strategy employed by the Unbreakable report with a probabilistic assessment of how different subgroups of the population respond to shocks of various sizes. Climate shocks and natural disasters have differential impacts on different streams of incomes and assets. Floods, for example, may be less damaging to agricultural workers than droughts if their fields survive the flood but crops die due to the drought. Our probabilistic approach examines how consumption and poverty of various subgroups responds to shocks of different sizes to each of n different income streams. We define n based on income streams described in the Nepal HRVS data. We define subgroups based on total consumption reported in the HRVS. We then conduct a Monte Carlo analysis that examines how consumption for each subgroup changes when incomes streams experience shocks of various sizes. Subgroups are then ranked based on the sensitivity of their consumption to shocks of various sizes with those with the highest sensitivity considered the most vulnerable.

Data on the consequences of specific disaster occurrences and their impact on household incomes and assets are used to validate the results of the probabilistic analysis. Household responses to specific questions in the HRVS contain information about income and asset losses after disasters. They also include information about how the household responded to those loses (e.g., by access to formal or informal insurance markets). These data will be used to validate the rankings of vulnerability produced by the Monte Carlo analysis by comparing predicted levels of vulnerability for a household based on the Monte Carlo analysis with their actual responses as recorded in the HRVS.

We map household vulnerability across Nepal based on the distribution of households within each subgroup as described by the census. The HRVS provides information for a subset of households that is not geographically explicit. To produce a vulnerability layer that is geographically comprehensive and includes all households we use information from the census about the distribution of household types across the country to predict vulnerability at a sub-municipality level. This is then combined with hazard and exposure layers to estimate the overall impact of climate change driven shocks with results aggregated to appropriate admin levels.

Annex 7: Figures illustrating the green jobs profile

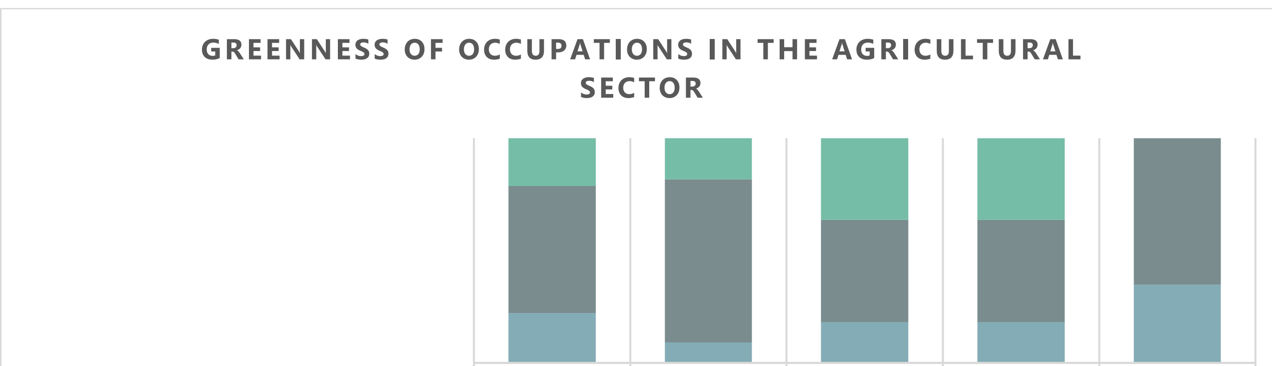
Figure 44: Greenness of Occupations by Gender



	Women	Men
Green new and emerging occupation 4d	0.09%	0.77%
Green enhanced skills occupation 4d	16.04%	20.55%
Green increased demand occupation 4d	8.02%	13.04%
Green rival occupation 4d	49.91%	47.31%
Other non-green occupation 4d	25.91%	18.17%

Notes: Data source is Nepal Labour Force Survey 2017 using green jobs classification from Montoya, Olivieri, Sanchez, Vazquez and Winkler (2022).

Figure 45: Greenness of occupations in the Agricultural Sector



	All occupations in agriculture	Field crop and vegetable growers	Livestock and dairy producers	Poultry producers	Crop farm labourers
Green new and emerging occupation 4d	0.00%	0.00%	0.00%	0.00%	0.00%
Green enhanced skills occupation 4d	0.00%	0.00%	0.00%	0.00%	0.00%
Green increased demand occupation 4d	21.27%	18.22%	36.39%	36.39%	0.00%
Green rival occupation 4d	56.57%	72.67%	45.41%	45.41%	65.17%
Other non-green occupation 4d	22.17%	9.11%	18.20%	18.20%	34.83%

Notes: Data source is Nepal Labour Force Survey 2017 using green jobs classification from Montoya, Olivieri, Sanchez, Vazquez and Winkler (2022).