INDICATORS AND ASSESSMENT PROTOCOL FOR THE VULNERABILITY ASSESSMENT

FOR THE PANJ-AMU RIVER BASIN AFGHANISTAN

Funded by the European Union

Wildlife Conservation Society

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Disclaimers:

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DOI: https://doi.org/10.19121/2023.Report.49928

Design and layout: Ahmad Reza Amiri

Supporting organizations:

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FOR THE PANJ-AMU RIVER BASIN
AFGHANISTAN

OVERVIEW

This document presents the methodologies employed in a climate vulnerability assessment for the Panj-Amu River Basin in Afghanistan. The assessment covers six broad categories for which ecosystems, wildlife, and local communities can be considered vulnerable from climate change. *Vulnerability* has been described as the 'state of susceptibility to harm from exposure to stresses associated with environmental and social change and from the absence of capacity to adapt' (Adger 2006). In the context of climate change, vulnerability is the extent to which an ecosystem, species, or community is threatened with decline, reduced fitness, genetic loss, or extinction owing to climate change. Vulnerability is typically composed of three components. Exposure refers to the extent of climate change likely to be experienced in a particular location and depends on the rate and magnitude of climate change. Sensitivity refers to the degree to which the survival, persistence, fitness, performance, or regeneration of an ecosystem, species, or community is dependent on prevailing climate conditions. Adaptive capacity refers to the capacity of an ecosystem, species, or community to cope with climate change through persistence, by shifting location, attitudes, or behaviours, or by moving to new regions (Dawson et al. 2011).

Several indicators are presented within each category that together provide an assessment of vulnerability along the dimensions of exposure, sensitivity, and/or adaptive capacity. This document serves as technical guidance to stakeholders and those collecting primary field data for climate vulnerability analyses and describes the analytical tools and approaches to enable others to perform a climate vulnerability assessment. While this document was developed in the context of a climate vulnerability assessment for the Panj-Amu River Basin, the underlying principles and methodological and analytical frameworks were developed to apply to a wide range of geographic, ecological, and socioeconomic contexts. Furthermore, several data resources are outlined in tables in this document that contain links to global datasets and datasets for other geographic contexts – these should facilitate wider application.

For each broad category within the climate vulnerability assessment, this document provides a description of:

1. The background and scientific justification for its inclusion
2. The indicators determining vulnerability
3. The category of the indicator (1. Essential; 2. Desirable to improve understanding of vulnerability, but not essential; or 3. Desirable to improve understanding of vulnerability, but requires specific collection)
4. The necessary data sources to perform the vulnerability assessment
5. The specific methodologies for field data collection, modelling, and data analysis

Each section is supported by scientific literature, reports, and other authoritative citations. The content and protocols included in this document have been reviewed and endorsed by WCS, AKF/UCA, and government partners.

GEOGRAPHIC AND SOCIO-ECOLOGICAL CONTEXT FOR THE CLIMATE VULNERABILITY ASSESSMENT

The methodologies described in this document were designed in the context of the Panj-Amu River Basin of Afghanistan (Figure 1). The Panj-Amu River Basin ecosystem largely consists of rangeland interspersed with patches of woodland. The region is generally characterised by protracted insecurity and high levels of poverty. Over 80% of local communities living in this landscape depend on natural resources for their livelihoods. Livestock grazing is common throughout the landscape, while two forms of agriculture (rainfed and irrigated) is also used. Rapid growth in livestock numbers together with unsustainable grazing practices hinders the regeneration of harvested biomass and degrades vegetation cover, compacts the soil, reduces groundwater replenishment, and increases erosion, including and stream incision.

Woody vegetation from these ecosystems is the main source of energy for heating and cooking in rural households. Cutting of trees and collection of dwarf shrubs has led to dramatic shrinkage in woodland areas and removal of rangeland vegetation cover. Together, these practices have contributed to rangeland degradation and forest depletion.

The region also contains a variety of wildlife, including top predators (e.g., snow leopards, brown bear), mesopredators (e.g., Pallas's cat, Eurasian lynx), and herbivores (e.g., Marco Polo sheep, urial). These species both rely on the landscape, compete with livestock for resources, and sometimes directly consume livestock.

Extreme weather events such as heatwaves, floods and droughts, reduced snow cover, and subsequent glacial lake outflows are expected to increase in frequency and intensity under climate change. As the majority of people rely directly or indirectly on natural resources for their livelihoods, these hazards pose a serious threat to the local economy, stability, and food security. Degraded ecosystems and impoverished biodiversity resulting from unsustainable grazing, harvesting, and management are less resilient and offer less potential for adaptation under changing climate conditions. Thus, the future health of ecosystems, wildlife, and people are intricately linked in this landscape (Figure 2), such that the vulnerability of the ecosystem will influence the vulnerability of the people and vice versa. Because of this, it is essential to include components of ecosystems, wildlife, and communities in vulnerability assessments to gain a holistic understanding of overall vulnerability.

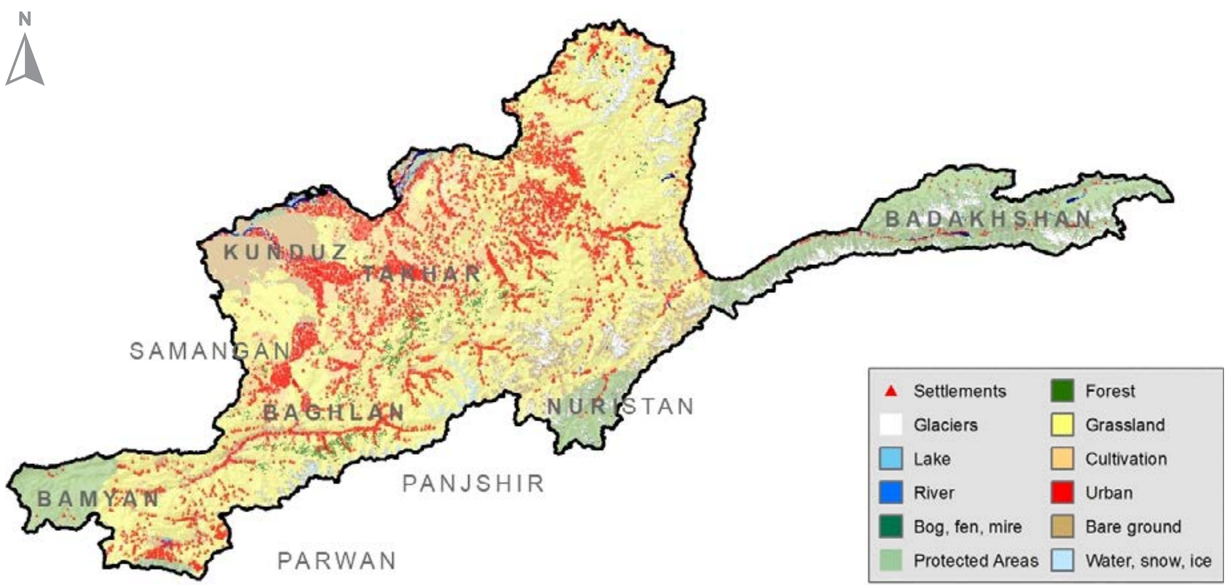

Figure 1. Map of the Panj-Amu River Basin (PARB) ecosystem depicting major habitat types, hydrological features, protected areas, settlements, and topography. Inset shows the position of the PARB within Afghanistan.

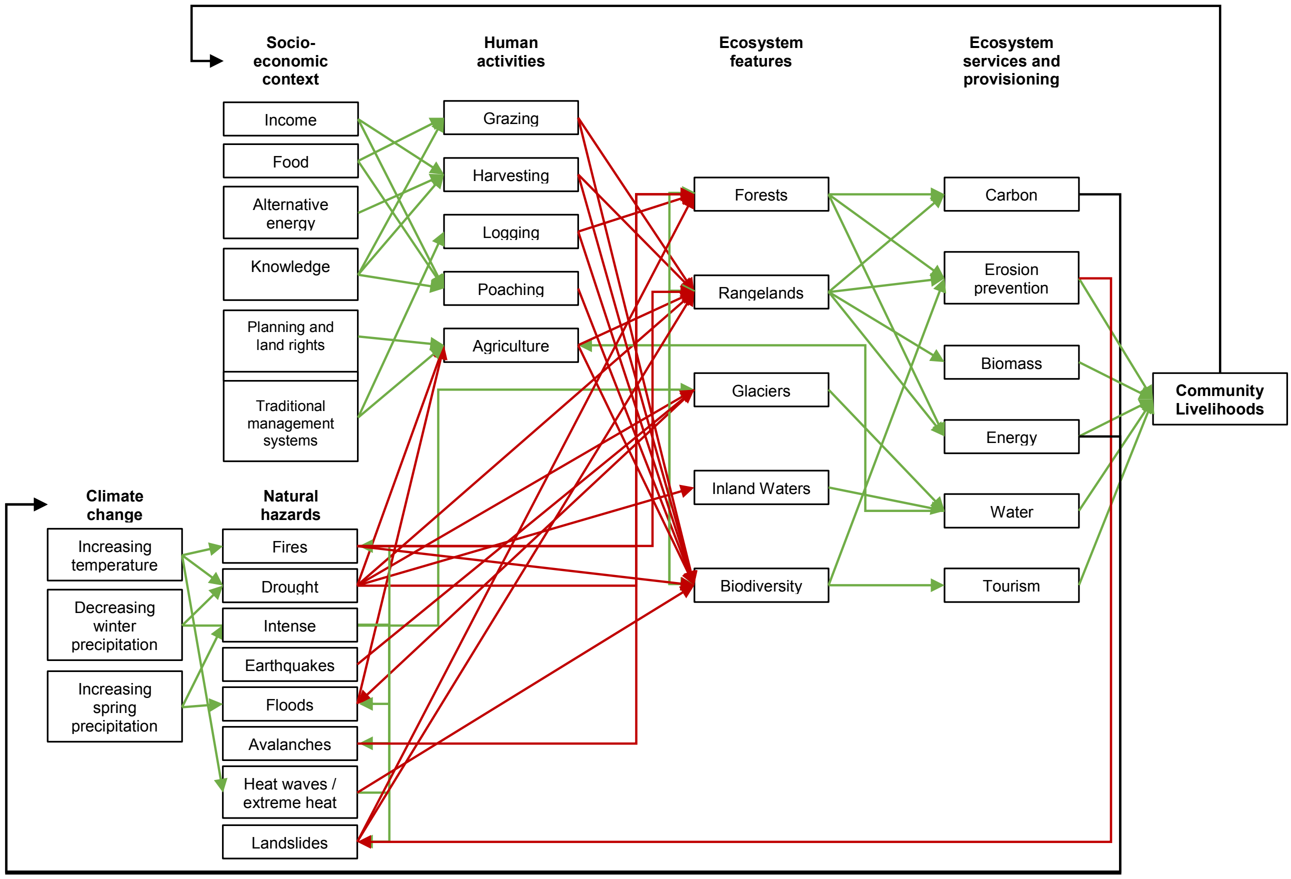

Figure 2. Conceptual diagram depicting how climate change influences select relationships between ecosystems, wildlife, and communities (green arrows reflect positive relationships, red arrows reflect negative relationships).

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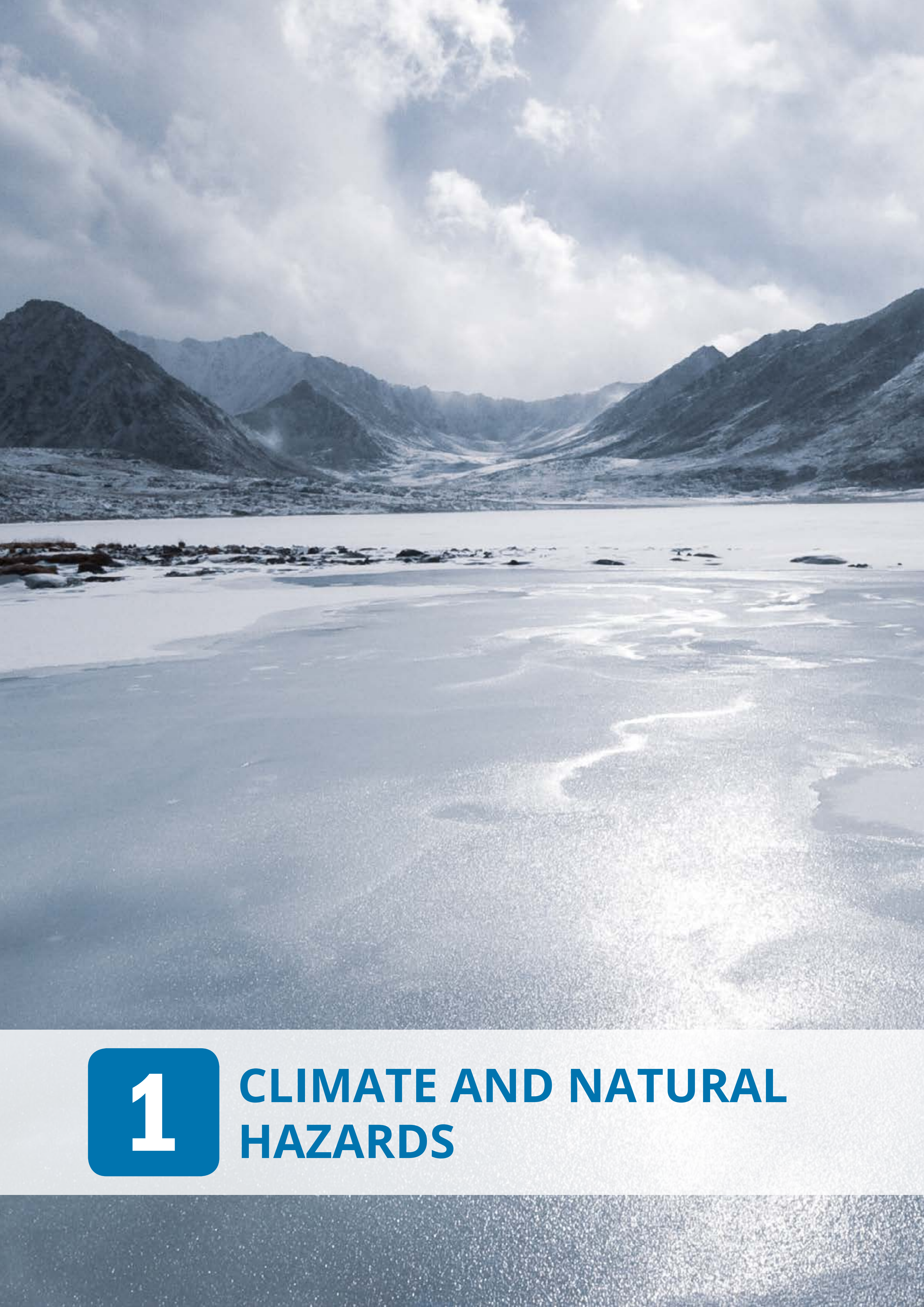

1 CLIMATE AND NATURAL HAZARDS

Background and scientific justification

Climatic factors determine vegetation extents (Woodward et al. 2004), species distributions (Chen et al. 2011), and suitable growing conditions for crops (Rosenzweig & Parry 1994), and thus changes in climate are expected to drive changes in patterns of ecosystems, biodiversity, and human communities (Scheffers et al. 2016) over large scales. Furthermore, climate change is associated with increasing risk of many natural hazards, such as extreme heatwaves, flooding, and drought (Van Aalst 2006). The foundation of a climate vulnerability assessment is the determination of the level of exposure of variables related to temperature and precipitation. These two primary climate variables drive ecosystem and wildlife distributions and are associated with the numerous threats from natural hazards listed (Woodward et al. 2004; Van Aalst 2006). Four characteristics of these variables are important to holistically represent these conditions: means, extremes, variability, and seasonality. For example, mean and maximum temperatures provide an evaluation of average temperatures and temperature extremes, respectively. Similarly, the magnitude and timing of summer versus winter precipitation provides distinct information related to the availability of water for flora and fauna. A total of nineteen commonly used climatic variables, known as bioclimatic variables, can be derived from monthly measurements of temperature and precipitation and represent annual trends, seasonality, and extreme or limiting climatic factors. As such, these variables are highly relevant to ecosystem and species distribution modelling and assessments of vulnerability (Hijmans et al. 2005).

Spatially-explicit projections of climate change can determine the magnitude of changes in these climate conditions as well as their geographic location (Fick & Hijmans 2017). Such models contain three essential components: (1) a particular general circulation model (GCM), which describes the climate-ecosystem modelling process and equations determining atmospheric circulation; (2) a representative concentration pathway (RCP), which describes the level of global CO_2 emissions (i.e., emissions scenario); and (3) a time horizon for the prediction. Incorporating multiple GCMs, RCPs, and time horizons into an assessment is a common practice as it incorporates and acknowledges the variability in climate projections, leading to stronger inference (Harris et al. 2014).

Description of indicators

The climate vulnerability analysis contains two major indicators (Table 1). The first is an assessment of the degree of exposure of 25 key climatic variables relevant to ecosystem processes, species distributions, and human livelihoods, which are captured by the bioclimatic variables described above. The general expectation is that greater deviations in any bioclimatic variable from the current climate represents an increased risk because ecosystems, species, and communities are adapted to prevailing current climatic conditions.

The second is an assessment of how these variables drive expected exposure to natural disasters, including floods and drought. Here, the general expectation is that areas experiencing increased floods (both duration and magnitude) and more severe or prolonged drought, as well as areas expected to experience higher probabilities of floods and droughts, will be at greater risk because of their influence on resources, physiology, and mobility.

Table 1. Climate hazards, key impacts, and risks.

No.	Climate Attribute	Indicator	Rationale	Category[1]
1.1.1	Mean annual temperature	Change in average temperate	Greater risks associated with warming events	1
1.1.2	Mean diurnal range (max temp – min temp)	Change in temperature range	Greater risks associated with unstable climates	1
1.1.3	Isothermality	Change in isothermality	Greater risks associated with unstable climates	1
1.1.4	Temperature seasonality	Change in temperature seasonality	Greater risks associated with unstable climates	1
1.1.5	Max temperature (of the warmest month)	Change in max temperature	Greater risks associated with extreme heat events	1
1.1.6	Min temperature (of the coldest month)	Change in min temperature	Greater risks associated with extreme cold events	1
1.1.7	Temperature annual range	Change in annual temperature range	Greater risks associated with unstable climates	1
1.1.8	Mean temperature (of the wettest quarter)	Change in mean temperature (of the wettest quarter)	Greater risks associated with warming events	1
1.1.9	Mean temperature (of the driest quarter)	Change in mean temperature (of the driest quarter)	Greater risks associated with warming events	1
1.1.10	Mean temperature (of the warmest quarter)	Change in mean temperature (of the warmest quarter)	Greater risks associated with warming events	1
1.1.11	Mean temperature (of the coldest quarter)	Change in mean temperature (of the coldest quarter)	Greater risks associated with warming events	1
1.1.12	Heat index	Change in heat index	Greater risks associated with increasing heat index	2
1.1.13	Total annual rainfall	Change in total precipitation	Greater risks associated with increased drought or flooding	1
1.1.14	Rainfall (of the wettest month)	Change in rainfall (of the wettest month)	Greater risks associated with increased drought or flooding	1
1.1.15	Rainfall (of the driest month)	Change in rainfall (of the driest month)	Greater risks associated with increased drought or flooding	1
1.1.16	Rainfall seasonality	Change in rainfall seasonality	Greater risks associated with unstable climates	1
1.1.17	Rainfall (of the wettest quarter)	Change in rainfall (of the wettest quarter)	Greater risks associated with increased drought or flooding	1
1.1.18	Rainfall (of the driest quarter)	Change in rainfall (of the driest quarter)	Greater risks associated with increased drought or flooding	1
1.1.19	Rainfall (of the warmest quarter)	Change in rainfall (of the warmest quarter)	Greater risks associated with increased drought or flooding	1
1.1.20	Rainfall (of the coldest quarter)	Change in rainfall (of the coldest quarter)	Greater risks associated with increased drought or flooding	1

No.	Climate Attribute	Indicator	Rationale	Category[1]
1.1.21	Total annual snowfall	Change in total annual rainfall	Greater risks associated with increased drought and flooding	1
1.1.22	Snowfall (of the wettest month)	Change in snowfall (of the wettest month)	Greater risks associated with increased drought or flooding	2
1.1.23	Snowfall seasonality	Change in snowfall seasonality	Greater risks associated with unstable climates	2
1.1.24	Snowfall (of the wettest quarter)	Change in snowfall (of the wettest quarter)	Greater risks associated with increased drought or flooding	2
1.1.25	Snowfall (of the coldest quarter)	Change in snowfall (of the coldest quarter)	Greater risks associated with increased drought or flooding	2
1.2.1	Flooding duration	Duration of flooding (number of days per year)	Greater risks associated with increased duration of flooding	2
1.2.2	Flooding magnitude	Amount of area flooded	Greater risks associated with more area flooded	1
1.2.3	Flooding frequency	Number of floods per year	Greater risks associated with more frequent floods	1
1.2.4	Flooding probability	Probability of flooding occurrence	Greater risks associated with higher flooding probabilities	2
1.2.5	Drought duration	Duration of drought (number of days per year)	Greater risks associated with increased duration of drought	1
1.2.6	Drought probability	Probability of drought occurrence	Greater risks associated with higher drought probabilities	2
1.2.7	Avalanche frequency	Number of avalanches per year	Greater risks associated with more frequent avalanches	1
1.2.8	Avalanche probability	Probability of avalanche occurrence	Greater risks associated with higher avalanche probabilities	2
1.2.9	Landslide frequency	Number of landslides per year	Greater risks associated with more frequent landslides	1
1.2.10	Landslide probability	Probability of avalanche occurrence	Greater risks associated with higher landslide probabilities	2

1. Category 1 = Essential; Category 2 = Desirable to improve understanding of vulnerability, but not essential; Category 3 = Desirable to improve understanding of vulnerability, but requires specific collection

Necessary data

The first and second assessments concerning analyzing the degree of exposure for 25 bioclimatic variables and the expected changes in magnitude, frequency and duration of natural hazard events both require downscaled, spatially-explicit current and future climate datasets. Some freely available data sources are described in Table 2.

Table 2. A selection of freely available global and regional climate models for conducting climate vulnerability assessments, with their spatial and temporal resolutions and extents and model parameters.

Dataset	Spatial resolution	Temporal resolution	Spatial extent	Temporal extent	GCMs/ RCMs	RCPs
CORDEX[1]	0.5º (~55 km)	Monthly	Global (by region)	Historic (1980-2005) and future (2040-2099)	Multiple	2.6, 4.5, 8.5
NASA-NEX-DCP30[2]	30 arc-seconds (~1 km)	Monthly	CONUS	Historic and future (1950-2100)	33 models	2.6, 4.5, 6.0, 8.5
NASA-NEX-GDDP3	0.25º (~27.5 km)	Daily	Global	Historic and future (1950-2100)	21 models	4.5, 8.5
ClimateNA (Adaptwest)[4]	1 km	Monthly, annual, decadal, and 30-year time steps	North America	Paleo (Last Glacial Maximum, Mid Holocene, and Last Millennium), historic (1901-2014), future (the 2020s, 2050s, 2080s), and annual time-series for 2011-2100	Multiple	4.5, 8.5
Basin Characterization Model[5]	270 m	30-year time steps	CA and parts of OR and NV	1921-1950, 1951-1980, 1981-2010, 2010-2039, 2040-2069, 2070-2099	Multiple	Multiple
WorldClim[6]	1 km	Monthly and 30-year time steps	Global	Paleo (Mid Holocene, Last Glacial Maximum, Last inter-glacial), historic (1960-1990 for v1 and 1970-2000 for v2), future (2041-2060, 2061-2080)	Multiple	2.6, 4.5, 6.0, 8.5
CHELSA[7]	30 arc-seconds (~1 km)	Monthly	Global	Paleo (Last Glacial Maximum), historic (1901-2016), future (2041-2060 and 2061-2080)	Multiple	2.6, 4.5, 6.0, 8.5
LOCA[8]	0.0625º (~7 km)	Daily	North America (central Mexico to South Canada)	Historic (1950-2005) and future (2006-2100)	Multiple	4.5, 8.5
MACA[9]	0.0625º (~7 km) and 0.0416º (~4 km)	Daily, Monthly	CONUS	Historic (1950-2005) and future (2006-2099)	Multiple	4.5, 8.5

Dataset	Spatial resolution	Temporal resolution	Spatial extent	Temporal extent	GCMs/ RCMs	RCPs
gridMET[10]	0.0416º (~4 km)	Daily	CONUS	Historic (1979-current)	NA	NA
BCSD[11]	0.125º (~14 km), 0.5º (~55 km), 1º (~110 km), 2º (~220 km)	Monthly	CONUS, Global (only at 0.5º and 1º)	Historic and future (1950-2099)	Multiple	2º warming
BCCA[11]	0.125º (~14 km), 1º (~110 km), 2º (~220 km)	Daily	CONUS	Future (2046-2100)	Multiple	2º warming
Daymet[12]	1 km	Daily, Monthly, annual	North America, Puerto Rico, Hawaii	Historic (1980-current)	NA	NA
PRISM[13]	800 m and 4 km	Monthly, 30-year normals	USA	Historic (1895-2010) for 4 km; Historic (1971-2010) for 800 m	NA	NA

1. https://www.cordex.org/
2. https://cds.nccs.nasa.gov/nex/
3. https://cds.nccs.nasa.gov/nex-gddp/
4. https://adaptwest.databasin.org/pages/adaptwest-climatena
5. http://climate.calcommons.org/bcm
6. https://worldclim.org
7. http://chelsa-climate.org/
8. http://loca.ucsd.edu/
9. http://www.climatologylab.org/maca.html
10. http://www.climatologylab.org/gridmet.html
11. https://gdo-dcp.ucllnl.org/downscaled_cmip_projections/dcpInterface.html#Projections:%20Complete%20Archives
12. https://daac.ornl.gov/cgi-bin/dataset_lister.pl?p=32
13. http://www.prism.oregonstate.edu/

Methods

Indicator 1.1 – Degree of exposure of 25 bioclimatic variables

Field data collection protocol

The required data for this component are publicly available spatial data. Therefore, no fieldwork is required. Downscaled climate models are developed by professional organizations specializing in calculating continuous climate data surfaces from weather station data. Such organizations can benefit from freely available remotely-sensed data and also the deployment of additional weather stations in the field, but this process is beyond the scope of the current assessment.

Analysis & modelling

When utilizing any of the available general or regional climate circulation models that do not contain the full suite of bioclimatic variables, the first step in the climate vulnerability assessment is to calculate each of the bioclimatic variables from temperature (monthly mean, min, and max) and monthly precipitation data. This process can be performed using the biovars function in the dismo package in R statistical software (Hijmans et al. 2017). However, several sources (e.g., WorldClim, CHELSA) include these variables as downloads for both current and future layers.

The second step is to use each of the current bioclimatic variables and associated future bioclimatic variables using several (minimum 5, up to all) GCMS, at least two RCPs, and for at least one time horizon (some models only have one future horizon). Typically, it is best practice to choose a range of GCMs that capture distinct future climatic scenarios, such as dry/hot, wet/hot, dry/warm, and wet/warm scenarios, in addition to an intermediate scenario, though all GCMs can be used and evaluated. The two most commonly used RCPs are RCP 4.5 and RCP 8.5, which reflect reasonable bounds for expected and heightened emissions scenarios (RCPs 2.6 and 6.0 are sometimes also available, though not for all GCMs). The choice of time horizon should reflect the objectives of the project. For example, a choice of 2050 might be appropriate for near-term forecasts suitable for making management decisions, while a choice of 2070 or 2100 would be more important for understanding long-term effects and sustainability. It often makes sense to analyze multiple time horizons, as climate changes are not always linear over time.

For each GCM/RCP/horizon, exposure can simply be calculated as the future projections minus the long-term historical mean for each bioclimatic variable. Because these are spatially-explicit projections, the results depict maps of areas showing the highest deviations from the long-term averages. Based on the rationale that greater deviations in climatic conditions are associated with greater levels of risk, these areas represent those of greater vulnerability. It should be noted that changes in climatic parameters can also influence adjacent regions. For example, extreme rain in one area may cause high flood for another area downstream of the river. These dynamics can be more adequately captured when modelling natural hazards (see Indicator 1.2).

A final step in the analysis is summarizing the data into spatial units appropriate for the analysis. This could be within administrative units, such as districts, provinces, or community associations, within hydrological catchments, and/or within ecological units, such as ecoregions or land cover types. Summaries should include the mean and standard deviation values within the spatial unit chosen to assess the average condition and variability within the spatial unit.

The main outputs from this component of the climate vulnerability assessment is maps of current and future climate conditions across 25 bioclimatic variables, highlighting regions of more pronounced exposure and variability of the included bioclimatic variables for each GCM/RCP/horizon considered.

Indicator 1.2 – Change in duration, magnitude, frequency and probability of natural hazards

Field data collection protocol

For modelling natural hazards, data from weather and hydrological stations is necessary. These data are often collected by local authorities and government departments; consultations and data-sharing agreements with these entities are required to access these data. It is not practical for individuals or institutions to collect these data independently.

Analysis & modelling

The modelling procedure for this component follows a similar protocol as Indicator 1.1. All natural hazards will be derived from the fundamental climate model components of temperature and precipitation. For example, flooding events will be determined using thresholds of total precipitation accumulation within a certain time period. Because this uses spatially-explicit data, these flooding events can then be used to define durations (i.e., end time minus start time of flood events) and extents (i.e., the number of pixels represented by floods multiplied by the pixel area).

1. For each GCM/RCP/horizon, the change in duration, magnitude, frequency, and the probability of natural hazards can simply be calculated as the difference in future projections minus the long-term historical averages of these variables, separately for each hazard (e.g., flooding, drought, avalanches, and landslides). Because the hazard maps are spatially-explicit projections, the results depict maps of areas showing the highest deviations from long-term historical averages. Based on the rationale that increases in the duration, magnitude, frequency, and probability of natural hazards are threatening to ecosystems, biodiversity, and people, areas with the greatest increases in these variables represent those of greatest vulnerability for each hazard.

Data can then be summarized by appropriate spatial units as above and should include the mean and standard deviation values within the spatial unit chosen to assess the average condition and variability within the spatial unit.

The main outputs from this component of the climate vulnerability assessment are spatial maps representing characteristics of historical and future natural hazards, highlighting regions of more pronounced exposure of the included bioclimatic variables for each GCM/RCP/horizon considered.

2 VEGETATION

Background and scientific justification

Vegetation and land cover broadly constitute habitat for wildlife (Thuiller et al. 2004) and influence landscape suitability for agriculture (Kraemer et al. 2015) and livestock grazing (Landsberg et al. 2003). Vegetation characteristics are strongly driven by climatic factors at scales from individuals to entire plant and ecological communities (Woodward et al. 2004). Thus, climate change has the potential to shift vegetation community boundaries and alter land cover condition and suitability (Hansen et al. 2001). In the context of climate change, wildlife species and human communities are more vulnerable in ecosystems that are currently degraded or are expected to become degraded in the future, which can arise directly through changing climate, such as desertification (LeHouerou 1996), or indirectly through vegetation shifts (Gonzalez et al. 2010).

Field measurements can provide direct evidence of vegetation and ecosystem characteristics and human activities from the area. These datasets, when measured over time, can provide detailed assessments of changing biophysical conditions that can be used to determine vulnerability. While such data are rich in detail, they can only provide a relatively small spatial and temporal sample due to the practical and often financial constraints of data collection. As a complement to field-based measurements, satellite imagery can be used to map land cover (Friedl et al. 2002) and proxies for rangeland condition (Vanderpost et al. 2011), such as biomass and productivity (Garroutte et al. 2016) continuously at multiple spatial and temporal scales across vast landscapes. Rangeland condition is likely related to the resilience of the ecosystem to climate change, and understanding the localities and drivers of healthy rangelands is important for sustaining the benefits they provide to local communities.

Time series analysis can be used to detect trends in these variables over time using either repeatedly-collected field data or remotely sensed satellite imagery, which gives insight into historical baselines and trajectories (Chen et al. 2004). Regions experiencing declining trajectories of biomass and productivity represent vulnerable regions, especially when changes in climatic factors are expected to hinder growth potential or cause damage to human livelihoods (Rosenzweig et al. 2002). In the case of using remote sensing, combining vegetation models with climate models can enable forecasting of how land cover, biomass, and productivity are expected to change in the future (Polley et al. 2013), which provides insights into the ecosystem, wildlife, and human community vulnerability. Direct measurements and satellite-derived maps of productivity and biomass can also be useful in determining important landscapes for mitigation of climate change (Lu 2007), because biomass can be linked to carbon storage potential (Fan et al. 2007).

The above approaches serve to inform about the level of exposure expected to affect vegetation. Plant species with higher sensitivities to this exposure will be most negatively impacted by climate change. Databases of ecological traits of plant species containing information on movement, specialization, reproduction, and geographic extent can provide useful information as they are proxies for vulnerability that can also inform appropriate management actions under climate change (Butt & Gallagher 2018). In this way, ecological trait analysis of dominant plant species in each major vegetation type can add information about sensitivity, providing a useful complement to the exposure analysis previously described to enable a more holistic view of each vegetation type's vulnerability to climate change.

Description of indicators

The vegetation vulnerability analysis contains four major indicators (Table 3). The first is an assessment of the changes in the extent of broad vegetation types. The general expectation is that greater reductions in rangeland and forest vegetation types represent increased vulnerability, because these systems support wildlife populations and human livelihoods, and are also responsible for capturing most of the carbon in the ecosystem.

The second is an assessment of the changes in the condition or quality of rangelands. The general expectation is that greater reductions in rangeland condition represent increased vulnerability because rangelands provide primary foraging grounds for wildlife and livestock and habitat for biodiversity.

The third is an assessment of changes in biomass and carbon storage within major vegetation types. The general expectation is that greater reductions in biomass represent increased vulnerability, because biomass provides fodder for wildlife and livestock, habitat for biodiversity, fuelwood for local communities, and can infiltrate rainwater, reduce runoff, limit soil erosion, and regulate water supplies. Similarly, greater reductions in carbon are expected to represent increased vulnerability, because carbon supports plant life and ecosystem processes and can be used for monitoring of climate mitigation benefits.

The fourth is an assessment of the sensitivities of dominant plant species of major vegetation types to climate change. The general expectation is that traits indicative of limited movement potential, greater ecological specialization, shorter reproduction cycles, and limited geographic ranges and ecological niches represent species with lower adaptive capacity. Major vegetation types that are dominated by species with these characteristics thus are expected to be more vulnerable to climate change.

Table 3. Description of vegetation indicators.

No.	Vegetation Attribute	Indicator	Rationale	Category[1]
2.1	Vegetation extent	Change in area of each vegetation type over time	Loss of native vegetation (e.g., grassland, forests) limits wildlife habitat and wildlife and livestock foraging potential	1
2.2	Rangeland condition	Overall and change in rangeland condition over time	Reduction in rangeland condition limits foraging potential for wildlife and livestock	1
2.3	Biomass	Overall and change in biomass over time	Biomass is an important component of rangeland condition and carbon storage potential; reductions in biomass limits fodder for wildlife and livestock and fuelwood for local communities	1
2.4	Carbon storage	Overall and change in carbon (aboveground vegetation and soil) of each vegetation type	Lower carbon limits ecosystem functioning and represents lower mitigation benefits and opportunities	1
2.5	Ecological traits of dominant plant species	Plant species sensitivity based on ecological traits	Species exhibiting limited movement potential, greater ecological specialization, shorter reproduction cycles, and limited geographic ranges and ecological niches are associated with lower adaptive capacity, thus greater vulnerability to climate change	3

Necessary data

The first assessment concerning vegetation extent requires ground-truthed GPS points of all land cover classes to be mapped. This requires a land cover classification system or scheme to be established (for an example land cover classification system for the Panj-Amu River Basin, see Table 4 below). It also requires satellite imagery covering the study area. Some examples of available satellite imagery are shown in Figure 3.

The second assessment concerning rangeland condition also requires satellite imagery of the Earth's surface as well as climate models containing information on precipitation. Rangeland condition models can be enhanced by local information on biomass collected in the field.

The third assessment concerning biomass requires field-collected data on the mass of either aboveground or belowground vegetation, or both.

1. Category 1 = Essential; Category 2 = Desirable to improve understanding of vulnerability, but not essential; Category 3 = Desirable to improve understanding of vulnerability, but requires specific collection

The fourth assessment concerning carbon storage requires field-collected data on the mass of vegetation (wet and dry samples, for carbon in vegetation) and/or soil samples (for soil organic content).

The fifth assessment concerning ecological traits of dominant plant species requires data on the longevity, flowering duration, maximum height, dispersal model, number of ecoregions occupied, thermal niche breadth, rainfall niche breadth, clay content breadth, soil total P breadth, and range size for each focal plant species. This information can be collected in the field, obtained through primary literature, or accessed through online databases, such as the TRY Plant Trait Database https://www.try-db.org/TryWeb/Home.php.

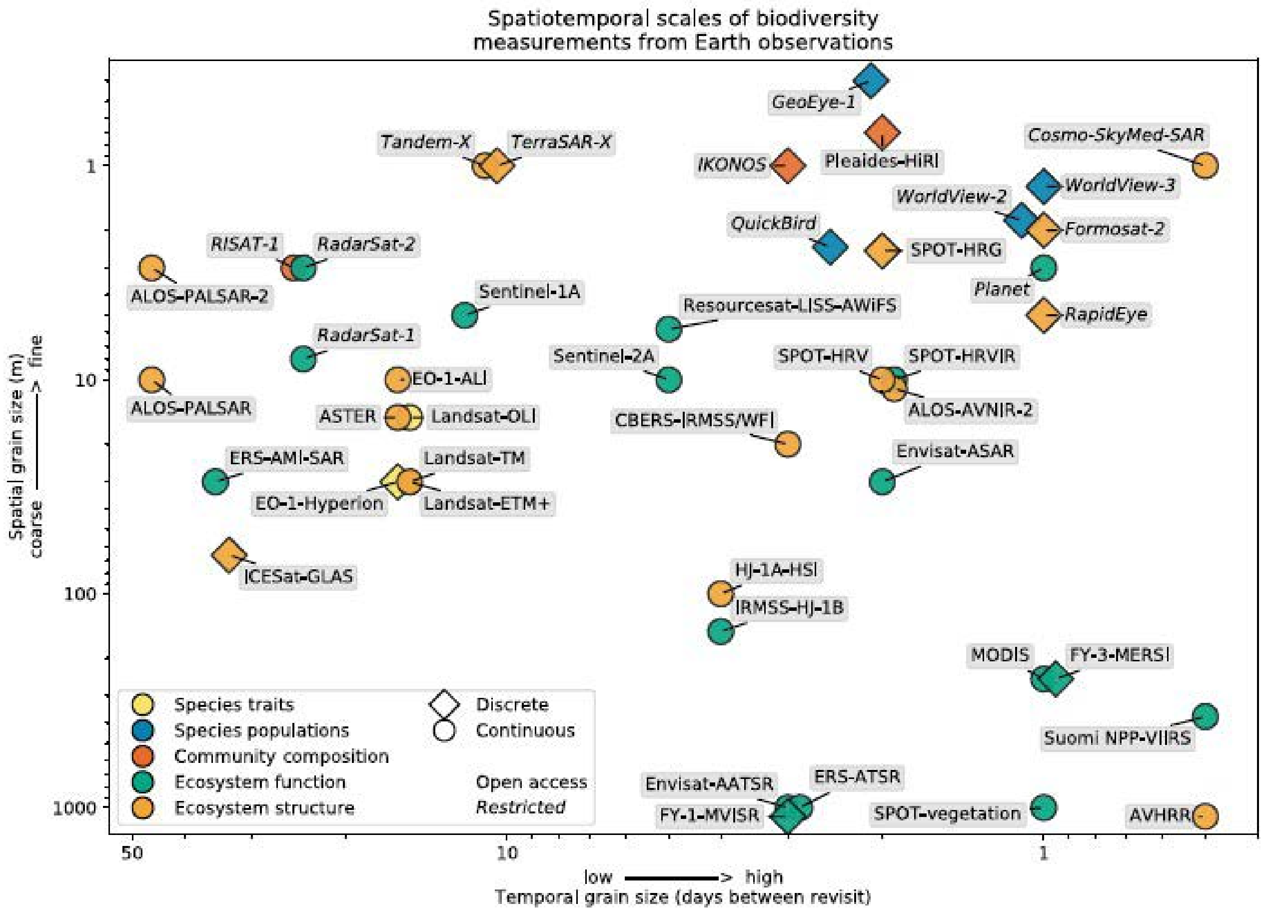

Figure 3. A selection of satellite imagery datasets suitable for land cover classification (orange circles), with their spatial and temporal resolutions. Note those not in italics are freely available—image is taken from Anderson (2018).

Methods

Indicator 2.1 – Change in vegetation extent

Field data collection protocol

GPS points must be collected in the field to train and validate land cover classifications depicting vegetation extent. Field teams should collect 100-200 GPS points of each land cover class to produce reasonably accurate models, but this number should not be considered a maximum: more collected points typically produce more accurate models. Each sampling point should contain a description of the land cover class, photos, physical characteristics, and percentage of green and non-green vegetation alongside the coordinates. Additional training points can be created virtually in geospatial software through visual inspection, but such points cannot be used to assess model accuracy.

Collected GPS points should cover the natural variation of conditions within each land cover class to best ensure that this variability is captured by the classification. This means that, to the degree possible, points should not be heavily clustered, but should be randomly positioned to cover and span the latitudinal, longitudinal, and elevational range of the study region, though in practice this can be difficult.

Analysis & modelling

The supervised land cover classification approach is used to map land cover across the study region. Image classification is the process of assigning land cover classes to pixels of remotely-sensed satellite imagery. Supervised classification is a type of image classification where representative samples of each land cover class are initially selected by the user. Computer software then uses 'training data'—typically derived from field observations of known land cover classes, but also derived from virtual observations created by the user through visual inspection in the software—and applies them to the entire satellite image. A computer algorithm then uses the spectral information from the training data to determine the class best represented by a given pixel. To be able to create accurate land cover classes, satellite datasets must be pre-processed to eliminate the effects of variable atmospheric and light conditions during the image acquisition. Moreover, satellite images should be selected from similar time windows (for example, all from summer or spring) to eliminate seasonal change effect on results.

To perform the classification, the user must follow an established or pre-defined land cover classification system based on natural vegetation communities that occur in the study region, based on information gathered through published flora guides and local knowledge. Several existing land cover classifications exist regionally and globally. For example, see Table 4 for an example classification system for the Panj-Amu River Basin, which is a hierarchical land cover classification system where land cover classes can be 'nested', thereby enabling more fine-scale (i.e., more land cover classes) or coarse-scale (fewer land cover classes) maps by merging land cover classes together that can be nested together. This approach is desirable when comparing with existing maps produced by organizations such as FAO, SERVIR, and IUCN is an objective.

Supervised land cover classification follows six major steps:

1. Collect training and validation data (see field data collection protocol above), noting known (pre-defined) land cover class for each point along with relevant values for predictor variables (e.g., elevation, soil, temperature, spectral information from satellite bands, etc.);
2. Compile pre-processed/corrected satellite imagery for the time period of interest;
3. Select an algorithm for classification (e.g., random forests, classification and regression trees, etc.);
4. Train the algorithm using training points (a subset of the field-collected points, reserving others to be used in the validation step below);
5. Classify the image based on the trained algorithm; and
6. Estimate classification error using independent validation data (using a different subset of field-collected data not used in the training step above).

These steps can be repeated for a given time period of interest (e.g., for each decade) to enable trend analysis.

By including climatic covariate information in the land cover classification in addition to spectral-based information from satellite imagery (i.e., including climate information in step two of the process above), the classification can determine statistical relationships between each vegetation type and the climatic variables used as inputs. Then, the user can create projected vegetation extents by swapping the current climate variables for future forecasts from various GCMs/RCPs/horizons. This enables change detection in vegetation extent through a comparison with the current vegetation extent produced during the original classification. Regions that have undergone reductions in vegetation extents of natural vegetation, such as rangeland or forest, represent regions of greater vulnerability.

Table 4. Example land cover classification system for the Panj-Amu River Basin that is hierarchical and based on pre-existing classification schemes developed by FAO, SERVIR, and IUCN.

FAO AC ID	FAO Aggregated class	FAO Map code	FAO Land cover class	Equivalent SERVIR class	Equivalent IUCN biome	IUCN functional group (ecotype)
URB	Built-up	1A	Urban	Urban and built up	T7 Intensive land-use systems	T7.4 Urban and Infrastructure lands
		1B	Non-urban	Mining		
AGT	Fruit trees	2A	Fruit trees	Orchard or plantation forest	T7 Intensive land-use systems	T7.3 Plantations
AGV	Vineyards	2B	Vineyards	Orchard or plantation forest	T7 Intensive land-use systems	T7.3 Plantations
AGI	Irrigated agricultural land	3A	Intensively cultivated area	Cropland	T7 Intensive land-use systems	T7.1 Croplands
		3A1	Irrigated herbaceous crop(s)			
		3B	Marginal irrigated crop			
		3C	Karez system			
AGR	Rainfed agricultural land	4A	Flat lying areas		T7 Intensive land-use systems	T7.2 Sown pastures and old fields
		4B	Sloping areas			
NFS	Forest and shrubs	6A	Closed needle-leaved trees	Evergreen Broadleaf	T2 Temperate-boreal forests & woodlands	T2.1 Boreal and montane needle-leaved forest and woodland
		6B	Open needle-leaved trees			
		6B1	Closed to open undifferentiated trees			
		6C	High shrubs	Shrubland	T3 Shrublands & shrub-dominated woodlands	T3.2 Seasonally dry temperate heaths and shrublands
		[6A]	*Salix riparian*		T6 Polar/alpine	T6.4 Temperate alpine meadows and shrublands
		[6B]	Riparian meadow		T6 Polar/alpine	T6.4 Temperate alpine meadows and shrublands
		[6B]	*Juniperus excelsa/ semiglobosa* woodland		T2 Temperate-boreal forests & woodlands	T2.1 Boreal and montane needle-leaved forest and woodland

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NFS		[6C]	Subalpine Juniperus and Rhododendron scrub		T2 Temperate-boreal forests & woodlands	T2.1 Boreal and montane needle-leaved forest and woodland
		[6C]	Subalpine thorn-cushion shrublands		T5 Deserts and semi-deserts	T5.2 Thorny deserts and semi-deserts
		[6C]	Semidesert shrub		T5 Deserts and semi-deserts	T5.1 Semi-desert steppes
		[6C]	Canyon bottom shrub		T3 Shrublands & shrub-dominated woodlands	T3.2 Seasonally dry temperate heaths and scrublands
NHS	Rangeland	7	Rangeland	Grassland	T4 Savannas and grasslands	T4.4 Temperate grasslands
		[7]	*Artemesia-Acantholimon* dwarf shrub cushion steppe			
		[7]	*Artemesia-Onobrychis-Acantholimon* dwarf shrub cushion steppe			
		[7]	*Artemesia-Astragalus-Acantholimon* dwarf shrub cushion steppe			
		[7]	*Krascheninnikovia* dwarf shrub cushion steppe			
		[7]	Cold desert scrub	T5 Deserts and semi-deserts	T5.4 Cool temperate deserts	
BRS	Barren land	8A	Bare soil/rock outcrops	Barren	T3 Shrublands and shrub-dominated woodlands	T3.4 Rocky pavements, screes, and lava flows
BSD	Sand cover	8B	Sand covered areas	Barren	T5 Deserts and semi-deserts	T5.4 Cool temperate deserts
		[8B]	Alpine semi-deserts and meadows		T6 Polar/alpine	T6.4 Temperate alpine meadows and shrublands
		[8B]	Other semi-deserts rich in chenopods		T5 Deserts and semi-deserts	T5.1 Semi-desert steppes
		8C	Sand dunes			T5.5 Hyper-arid deserts
WAT	Waterbody and marshland	9A	Permanent marsh	Wetlands	TF1 Palustrine wetlands	TF1.3 Subtropical/temperate forested wetlands
		[9A]	*Leymus* salt grass			
		9B	Seasonally inundated vegetation	Flooded forest	TF1 Palustrine wetlands	TF1.2 Seasonal floodplain marshes
		10A	Permanent lake	Surface water	F2 Lakes	F2.1 or F2.2 Large/small permanent freshwater lakes
			Seasonal lake		F2 Lakes	F2.3 Seasonal freshwater lakes
			River		F1 Rivers and streams	F1.2 Permanent lowland rivers
			Riverbank			
SNW	Permanent snow		Snow-covered area	Snow and ice	T6 Polar/alpine	T6.1 Ice sheets, glaciers, and perennial snowfields

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Indicator 2.2 – Overall and change in rangeland condition

Field data collection protocols

Change in rangeland condition can be measured at two spatial scales: plot scale and landscape scale (i.e., continuously across the entire study region). Field data collection is essential for assessing changes in rangeland condition at the plot scale, but is not necessary for assessing changes in rangeland condition at the landscape scale. However, field data can help validate models developed at the landscape scale, giving increased confidence in predictions.

Field data should be collected at survey sites in pre-selected for where documenting change in rangeland condition is desired. Ideally, these sites would span the range of degrees of intactness and usage by local communities. The exact locations of survey sites can also be chosen using stratified random sampling, where the stratification is based on vegetation communities, elevation, slope, and aspect.

At each survey site, a transect should be established in a random direction that covers 50 m in length within one vegetation community type. There should be multiple line transects established within each vegetation community type that together act as a representative sample. Five variables that can be collected in the field are recorded that indicate different components of rangeland condition:

1. Vegetation, litter, and ground cover characteristics

Vegetation and ground cover are measured by the foliar cover, which is the measurement of the ground covered by the vertical projection of plant parts, excluding the gaps and overlaps within species, along a line transect. The ground cover is measured using the line and point intercept method along each transect: for the point intercept method, the foliar cover is noted every 1 m of the transect excluding the zero-meter mark; for the line intercept method, the covers are measured in every centimetre from the zero-meter mark to the end of the transect. The cover values of plants are separately recorded in groups according to the life form or growth habit as follows:

- Graminoids: grass-like plants, separated into grasses and sedges
- Forbs/herbs: herbal plants without significant aboveground woody material, separated into legumes (Fabaceae) and others
- Subshrubs: low-growing shrubs at ground level usually under 0.5 m
- Shrubs: multi-stemmed woody plants growing up to a height of 5 m

The mean height of graminoids is measured at 5 equally spaced points along the transect (if the grass is present) and averaged.

2. The degree of erosion

Several signs related to erosion are recorded by direct visual observation from the transect lines and rated according to explanations in Table 5. Respective ratings are summed to provide an overall score of the degree of erosion (i.e., erosive intensity) and divided into four classes for interpretation: 0 – 6 low erosion; 7 – 12 moderate erosion; 13 – 18 high erosion; and 19 – 24 very high erosion.

Table 5. Classification and description of erosion variables.

Variable	Rating			
	0	1	2	3
Rills	None	Single rills	5 % cover or more	10 % cover or more
Water flow patterns	None	Single patterns	Affecting 5 % of the area or more	Affecting 10 % of the area or more
Pedestals/terracettes	None	Single	Several, 10 % cover or more	Large areas, parallel terracettes, 50 % cover or more
Bare ground class (line intercept measurements from transects)	Nearly no bare ground (0 - ≤25 %)	>25 – ≤50 % bare ground	>50 – ≤75 % bare ground	>75 % bare ground
Gullies	None	One small (width < 50 cm), single gully with depth >50 cm	Two gullies with depth >50 cm or single gully with width >50 cm	Several gullies with depth >50 cm or single gully with width > 1m
Slope (cf. Montgomery and Brandon 2002)	Flat	1° to < 15°	15° to < 25°	More than 25°
Soil organic matter (from soil color assessment)	h5 – h7	h3 to h4	h1 to h2	h0
Solifluction	None	Single patterns	Affecting 10 % of the area or more	Affecting 50 % of the area or more

3. Signs of grazing activities by livestock

Grazing activity on field plots is assessed using several descriptive classes related to grazing activity and rated on an ordinal scale (Table 6). Grazing classes are summed to provide an overall score for the degree of grazing and divided into four classes for interpretation: 0 – 2.25 low; 2.26 – 4.5 moderate; 4.6 – 6.75 high; and 6.76 – 9 very high grazing.

Table 6. Classification and description of grazing variables.

Variable	Rating			
	0	1	2	3
Trampling	No hoof tracks visible	Single hoof prints visible	Visibility of one to a number of terracettes resulting from trailing. Significant gaps of several meters between the terracettes or more than 10 % of the area affected by hoof prints	Intensive trailing resulting in parallel terracettes with only small gaps in between or more than 50 % of the area visibly trampled
Grazing and browsing damage	No visible signs of grazing on plants	Single plants show signs of grazing or browsing	Grazing or browsing damage on a large number of plants (> 50 %) or whole groups of preferred plants	Nearly all species show grazing or browsing damage. Palatable plant parts are grazed/browsed to the ground (or woody parts). Root damage or dead plants are visible (digging of goats)
Dung	No dung visible	Small or single dung amounts visible	Several accumulations of dung at different locations visible	10 or more larger accumulations of dung visible

4. Direct signs of human utilization

Direct signs of human utilization are qualitatively described and documented. Examples of signs of human utilization include shrub harvesting, excavations, and car tracks (agricultural activities, such as dryland farming, are not considered in the assessment). Based on the magnitude of the impact, human utilization intensity is then rated as none, low, moderate, or high.

5. Productivity

Aboveground net primary productivity can be measured by taking biomass clippings from plots of a standard size. It is important that these plots be constructed so as to prevent grazing by animals. Productivity, determined through the collection of green vegetation from within the exclosure plot, can then be measured without the influence of grazing activities.

At each survey plot used to determine land cover (see the previous section), data will also be collected on vegetation communities related to rangeland condition:

1. Grazing intensity: presence/degree of grazing will be recorded, following a scoring system of 0 – no grazing, 1 – minimal grazing (single plant show signs of grazing or browsing), 2 – grazing (grazing or browsing damage on a large number (>50%) or whole groups of preferred plants), and 3 – heavy grazing (nearly all species show grazing or browsing damage. Palatable plant parts are grazed/browsed to the ground or woody parts. Root damage or dead plants are visible. See also Zandler (2018) for descriptions. Definitions for each grazing category will follow established rangeland quality assessment protocols;
2. Presence of shrub collection: signs of shrub collection, such as digging or remnant holes, will be noted;
3. Foliar height and vegetative ground cover: a 50 m transect will be laid in a random direction (determined by tossing a spinning a pen in the air) at the GPS location. Along the 50 m transects, the foliar cover will be estimated by calculating the coverage of all vegetation versus bare ground/rock at the height of 1 m. An average foliar height measurement will be taken for the entire transect;
4. Aboveground biomass: a 4 m x 4 m quadrat will be placed 4 m from the right of the start location. Within this quadrat, all aboveground vegetation will be clipped, placed in a paper bag, and weighed. The biomass sample will also be dried and weighed when returning from the field.

Analysis & modelling

For assessing changes in rangeland condition at the plot scale, time series analysis can be used to fit trend lines of each sub-indicator listed above and calculate slopes of the trends. Plots with decreasing trend trajectories represent plots with reductions in rangeland condition. It is generally expected that such plots represent greater vulnerability, as ecosystem quality is diminishing. Data can then be summarized by the spatial unit chosen and should include the mean and standard deviation values within the spatial unit to assess the average condition and variability within the spatial unit. The main outputs from this component of the vegetation vulnerability assessment are maps of the trends in the change in rangeland condition for each variable described at the plot scale and at the scale of the spatial unit chosen for summarization.

For assessing changes in rangeland condition at the landscape scale, satellite imagery can be used to produced maps of productivity—based on the normalized difference vegetation index (NDVI) and/or net primary productivity—of natural vegetation over time. It is important for these maps to control for natural factors known to influence productivity, such as rainfall, such that the metric depicts how rangeland condition has changed due to human activities. The approach can depict areas of enhanced vegetation and net primary productivity (e.g., due to natural regeneration, growth, or irrigation) versus degradation (e.g., due to drought or overgrazing).

The calculation of commonly used metrics of vegetation, such as NDVI and EVI, is now straightforward in remote sensing software. For example, using freely available Landsat 8 imagery, the process follows four major steps:

1. Obtain Landsat 8 satellite imagery covering the spatial and temporal extent of the survey region;
2. Mask clouds from each image using QA bands;
3. Calculate NDVI for each image using the equation (B5 – B4) / (B5 + B4), where B5 equals Band 5 of the image, and B4 equals Band 4 of the image;
4. Create a maximum NDVI composite by stacking all images over the time interval and taking the maximum NDVI value.

This process can be repeated for different time windows (e.g., years or decades, depending on the availability of images) to enable time series analysis and change detection of productivity over time. It is important to incorporate data on rainfall from historical or projected climate models and perform detrending as a final step to control for the effects of precipitation in the analysis. Data can then be summarized by the spatial unit chosen and should include the mean and standard deviation values within the spatial unit to assess average and variability in productivity change within the spatial unit. The main outputs from this component of the vegetation vulnerability assessment are high-resolution maps of NDVI and its change over time, as well as trends in the change in NDVI at the scale of the spatial unit chosen for summarization.

Indicator 2.3 – Overall and change in biomass

Field data collection protocol

Change in biomass can also be measured at two spatial scales: plot scale and landscape scale. Field data collection is necessary for assessing changes in biomass at the plot scale, but is not necessary for assessing changes in biomass at the landscape scale. However, field data can help validate models developed at the landscape scale, giving increased confidence in predictions.

Field data should be collected alongside the data collected for the assessment of rangeland condition, using the same pre-selected survey sites. At each survey site, adjacent to one end of the line transect used for the vegetation sampling described in the previous section, a 4x4 m plot should be established. Within this plot, all standing green vegetation should be clipped and collected in paper bags of known weight. After all green vegetation is removed, bags should be weighed with the biomass samples inside to measure wet biomass. Afterwards, samples in bags should be taken to air-dry until all moisture is removed from the vegetation and then re-weighed to measure dry biomass.

Analysis & modelling

For assessing changes in biomass at the plot scale, time series analysis can be used to fit trend lines and calculate slopes of the trends. Plots with decreasing trend trajectories represent plots with reductions in biomass. It is generally expected that such plots represent greater vulnerability, as the amount of biomass for food, fuel, and habitat is diminishing. Data can then be summarized by the spatial unit chosen and should include the mean and standard deviation values within the spatial unit to assess the average biomass and variability within the spatial unit. The main outputs from this component of the vegetation vulnerability assessment are maps of the trends in the change in biomass at the plot scale and at the scale of the spatial unit chosen for summarization.

For assessing changes in biomass at the landscape scale, satellite imagery can be used to produced maps of biomass based on available products of net primary productivity (NPP). As with rangeland condition, it is important for these maps to control for natural factors known to influence biomass, such as rainfall, such that the metric depicts how biomass has changed due to human activities. The approach can depict areas of enhanced net primary productivity and biomass (e.g., due to natural regeneration, growth, or irrigation) versus degradation (e.g., due to drought or overgrazing).

Biomass can be calculated from NPP using satellite imagery from MODIS as:

$$\text{Biomass} = \text{NPP} \times (30 / 12)$$

Therefore, using freely available MODIS imagery, the process follows the same general steps as above for modelling rangeland condition:

1. Obtain MODIS satellite imagery covering the spatial extent of the survey region processed to NPP at the temporal extent desired (note: masking clouds is not necessary since using preprocessed MODIS data)
2. Calculate biomass for each image using the above equation
3. Create a mean biomass composite by stacking all images over the time interval and taking he mean biomass value.

Again, this process can be repeated for different time windows to enable time series analysis and change detection of biomass over time. Also, as above, to control for the effects of precipitation in the analysis, rainfall must be incorporated and detrended in the time series analysis. We will repeat these steps for distinct time periods to produce biomass maps that enable change detection. Modelled decreases in biomass over time when accounting for potential long-term and seasonal changes in climatic factors such as rainfall reveal the degree of biomass loss due to human activities. Data can then be summarized by the spatial unit chosen and should include the mean and standard deviation values within the spatial unit to assess average and variability in biomass change within the spatial unit. The main outputs from this component of the vegetation vulnerability assessment are high-resolution maps of biomass and its change over time, as well as trends in the change in biomass at the scale of the spatial unit chosen for summarization. Field data on aboveground biomass can then be used to validate models, making sure that the temporal scales of comparison are aligned.

Indicator 2.4 – Overall and change in the carbon of aboveground vegetation and soil

Field data collection protocol

Change in the carbon of aboveground vegetation and soil can also be measured at two spatial scales: plot scale and landscape scale. Field data collection is necessary for assessing changes in carbon at the plot scale, but is not necessary for assessing changes in carbon at the landscape scale. However, field data can help validate models developed at the landscape scale, giving increased confidence in predictions.

Field data should be collected alongside the data collected for the assessment of rangeland condition and biomass, using the same pre-selected survey sites. At each survey site, within the 4x4 m plot that is established to collect biomass, a minimum of 100 g of soil at a depth of 5-15 cm should be collected, put in a brown paper bag of known weight, and weighed. The soil sample should then be analyzed by a professional in a laboratory for soil organic content.

Analysis & modelling

For assessing changes in soil carbon at the plot scale, time series analysis can be used to fit trend lines and calculate slopes of the trends. Plots with decreasing trend trajectories represent plots with reductions in soil carbon. It is generally expected that such plots represent greater vulnerability, as the amount of carbon is diminishing, which is usually associated with a reduction in or removal of vegetation. Data can then be summarized by the spatial unit chosen and should include the mean and standard deviation values within the spatial unit to assess the average soil carbon and variability within the spatial unit. The main outputs from this component of the vegetation vulnerability assessment are maps of the trends in the change in biomass at the plot scale and at the scale of the spatial unit chosen for summarization.

For assessing changes in carbon storage at the landscape scale, satellite imagery can be used to produced maps of carbon in aboveground vegetation based on land cover maps and known values of carbon per land cover class. The methodology for producing the land cover classification is outlined in section 1.1 above. The default values for land cover classes are available in the Intergovernmental Panel on Climate Change Guidelines for National Greenhouse Gas Inventories, Volume 4: Agriculture, Forestry, and Other Land Use (IPCC, 2006). Land cover classes can then be assigned their appropriate default aboveground carbon value for visualization and analysis. For example, this process can be repeated for different time windows to enable time series analysis and change detection of aboveground carbon over time.

Data can be summarized by the spatial unit chosen and should include the mean and standard deviation values within the spatial unit to assess average and variability in carbon change within the spatial unit. The main outputs from this component of the vegetation vulnerability assessment are high-resolution maps of aboveground carbon and its change over time, as well as trends in the change in soil carbon at the scale of the spatial unit chosen for summarization. Field data on soil carbon can then be used as an indirect measure to validate models, making sure that the temporal scales of comparison are aligned.

Indicator 2.5 – Plant species sensitivity based on traits

Field data collection protocols

Data for the assessment of plant species sensitivity based on traits largely originates from published sources, including published literature, field guides, and online databases. If data are lacking for desired species from these sources, primary data would need to be collected in the field and should be done so alongside data collection for the other components of the vegetation vulnerability assessment. To fill in any data gaps, expert opinion on plant species sensitivity scoring should be sought. In such cases, the scoring sheet and a detailed description of the methodology should be given to the expert to fill in any gaps (see below).

Analysis & modelling

Data related to movement, specialization, geographic range size, and reproduction of focal plant species should be recorded from published literature, field guides, and online databases, with source information noted. Focal species should represent dominant species within land cover classes, so that sensitivity of individual species can reasonably provide insight into the sensitivity of broad vegetation types, consistent with the spatial scale of the other components the vegetation vulnerability assessment. Some example focal species characteristic of land cover types found in the Panj-Amu River Basin are presented in Table 7.

Table 7. Characteristic plant species of land cover classes.

FAO Land cover class	Characteristic plant species
Artemesia-Acantholimon dwarf shrub cushion steppe	Species from the genera *Artemesia, Astragalus, Stipa*, and *Polygonum*
Artemesia-Onobrychis-Acantholimon dwarf shrub cushion steppe	*Artemisia* spp. and *Onobrychis* spp.
Artemesia-Astragalus-Acantholimon dwarf shrub cushion steppe	*Astragalus cuneifolius* and *Onobrychis afghanica*
Canyon bottom shrub	Distinct communities found in canyons with high water availability
Semidesert shrub	*Krascheninnikovia ceratoides, Haloxylon griffithi, Hymenocrater sessilifolius,* and *species in the genera Stipa, Zygophyllum,* and *Artemesia*
Salix riparian	*Salix pycnostacya, Myricaria germanica, Caragana aurantiaca, Hippophae rhamnoides, Populus* spp.
Riparian meadow	*Species in the genera Carex, Juncus, Scirpus, and Triglochin,* as well as *Eleocharis palustris, Dactylorhiza umbrosa, and Typha beome*
Juniperus excelsa/globose woodland	*Juniperus excelsa and semiglobosa, Locinera nummularifolia, Ephedra equisetina, species in the genera Rosa, Berberis, Prunus, and Cotoneaster, annuals including Impatiens parviflora, Lepyrodiclis holosteoides, Geranium rotundifolium, and Parietaria lusitanica, geophytes such as Eremurus furseorum, E. spectabilis, and Allium rosenbachianum, hemi-cryptophytic plants such as Prangos pabularia and Codonocephalum grande,* and sometimes trees including *Celtis caucasica, Fraxinus xanthoxyloides, Acer turkestanicum, and Amygdalus kuramica* and herbaceous plants include *Rheum ribes and Ferula spp.* In East Afghanistan common shrubs can include *Ephedra major, E. gerardiana, and Ribes orientale, herbaceous layer of Stipa turkestanica, Piptatherum baluchistanicum, Psathyrostachys caduca, Poa* spp., *Cousinia* spp., *Ferula* spp., *and Artemesia* spp.

FAO Land cover class	Characteristic plant species
Subalpine Juniperus and Rhododendron scrub	*Abies spectablis, Picea, and Quercus semecarpifolia* and thickets of *Rosa macrophylla, Ribes alpestre, R. villosum, Lonicera webbiana,* and *Rhododendron collettianum*
Subalpine thorn-cushion shrublands	Species are in the genera *Cousinia, Astragalus, Onobrychis, Acantholimon, Acanthophyllum, and Cicer. Other common dwarf shrubs are Artemesia spp., Ephedra gerardiana, Rhamnus prostrata, Koeleria spp., and Festuca spp.* Grazing pressure may have led to an increase in *Leucopoa karatavica*
Alpine semi-deserts and meadows	Similar species as in subalpine thorn-cushion shrublands
Other deserts and semi-deserts rich in chenopods	*Halothamnus subaphyllus, Salsola arbuscular, S. montana, S. gemmascens, Seiditzia Rosmarinus, Artemsia spp., Zygophyllum atriplicoides, Z. eurypterum, Ephedra strobilacea, E. sarcocarpa,* and *Cousinia deserti*
Snow-covered area (nival belt, glaciers)	*Juniperus semiglobosa, Lonicera microphylla, Cystopteris dickieana*
Krascheninnikovia dwarf shrub cushion steppe	*Krascheninnikovia ceratoides, Artemisia* spp., *Potentilla spp., Oxytropis* spp., *Stipa* spp.
Cold desert shrub	*Artemisia* spp., *Krascheninnikovia ceratoides, Stipa* spp.
Leymus salt grass	*Leymus* spp., *Hordeum spp. Puccinellia* spp.

A total of 10 species traits provide metrics for species sensitivity along several different ecological dimensions(Butt & Gallagher 2018). These traits include longevity, flowering duration, maximum height, dispersal mode, range size, niche breadths for rainfall, temperature, and soil fertility, and the number of ecoregions occupied. It is necessary to obtain trait information and compile a database covering all focal species included in the analysis. Each trait is then converted from a numeric or categorical value to a sensitivity score following the descriptions outlined in Table 8. Higher scores represent greater sensitivity because they signify more specialized ecologies and lower adaptive capacity. For instance, plant species with very narrow ranges have a lower adaptive capacity than species with very large ranges. Thus, they receive a higher score in the geographic range size category.

Table 8. Ten ecological traits determining plant species sensitivity to climate change adapted from Butt & Gallagher (2018).

Trait	Value	Score
Longevity	Annual, biennial, annual/biennial	1
	Annual/perennial, biennial/perennial	2
	Perennial	3
Flowering duration (months)	11-2	1
	9-10	2
	7-8	3
	5-6	4
	3-4	5
	<1-2 or ephemeral	6
Maximum height (m)	0-0.1	1
	0.1-1	2
	1-10	3
	10-100	4
Dispersal mode	Wind	1
	Vertebrate	2
	Invertebrate	3
	Localized (gravity)	4

Trait	Value	Score
Number of ecoregions occupied	7	1
	6	2
	5	3
	4	4
	3	5
	2	6
	1	7
Thermal niche breadth (ºC)	>20	1
	15-20	2
	10-15	3
	5-10	4
	0-5	5
Rainfall niche breadth (mm)	>2000	1
	1000-2000	2
	600-1000	3
	300-600	4
	100-300	5
	0-100	6
Clay content breadth (%)	>40	1
	30-40	2
	20-30	3
	10-20	4
	0-10	5
Soil total P breadth (mg/kg)	0.2	1
	0.1	2
	0	3
Range size (km^2)	>70000	1
	20000-70000	2
	<20000	3

Scores for each category for each species are then converted to a sensitivity class, where the top 33% of values per category are assigned 'high sensitivity', the middle 33% of values per category are assigned 'medium sensitivity', and the bottom 33% of values per category are assigned 'low sensitivity'. Species thus then receive a final sensitivity score by looking for consensus, equality, or mixed combinations across all scores.

The main output from this component of the vegetation vulnerability assessment is a compiled database of plant species traits and a ranked list of relative species sensitivity to climate change. Because the species chosen should represent the dominant species of a land cover class mapped in section 1.1, the sensitivity scores can then be assigned to land cover classes and mapped to depict a spatial representation of sensitivity. If desired, multiple species from a given land cover class could be analyzed, and a composite averaged sensitivity score can be mapped that would enhance confidence in results.

3 HYDROLOGY

Background and scientific justification

Watersheds provide important resources for communities, including water for irrigated agriculture and domestic use. The Amu Darya river, which feeds the Panj-Amu River Basin, is one of the largest and most heavily irrigated rivers in the world (Immerzeel et al. 2019). Projected temperature increases are expected to significantly influence water availability and water quality, through the melting of glaciers and snowpack and drying of wetlands (Zemp et al. 2019). Increased spatiotemporal variability in snowfall can greatly affect water availability for agriculture in the region, as water for agriculture is mostly fed by snowmelt (Pervez et al. 2014). Glacier degradation affects regional runoff, initially increasing runoff until an inflexion point where runoff steadily declines (Huss & Hock 2018). Currently, observed changes in glaciers threaten the area in the short term with floods, snow avalanches and mudflow and with reduced water resources in the long term. The seasonal timing of peak runoff is also impacted and is expected to enhance water flow earlier in the spring, but reduce water flow in late summer (Huss & Hock 2018). This will, in turn, put pressure on communities depending on regional runoff for irrigation, and can also increase the risk of flooding (Milly et al. 2002). Due to inefficient irrigation technology (around 50%), there is great concern that water shortages will likely put additional pressure on both food and energy supplies, and could aggravate tensions between neighbouring countries.

At the same time, climate change is anticipated to result in declining precipitation that is most pronounced in spring (Aich et al. 2017). In addition to increasing the likelihood of general drought conditions (LeHouerou 1996), any reductions in spring rainfall could affect natural plant and crop growth, reducing the overall growing season length. Together with the increase in temperature and resultant evapotranspiration, a reduction in rainfall can negatively impact the entire hydrological cycle from snow coverage and availability of irrigation water to moisture stored in the soil, leading to reduced agricultural productivity and ecosystem deterioration (Lipper et al. 2014; Scheffers et al. 2016). Consequently, ongoing and predicted climate change will likely worsen existing land-use and natural resources management issues. Moreover, increasing glacier degradation will be accompanied by increasing debris flow and the formation of glacial lakes that have the potential for outburst floods for downstream communities.

Of particular importance for sustainable development, energy, and food security in Central Asia is water resources availability. Therefore, measuring and quantifying variables related to water availability, extent and stability of snowpacks and glaciers, is vital for the area. Spatially-explicit hydrological models combined with downscaled climate models can forecast how hydrological characteristics are expected to change in the future (Block et al. 2009) and can, in turn, be used for risk assessments from natural hazards, such as flooding (Bartholmes & Todini 2005). Glaciers and inland waters, including lakes, have recently been mapped globally using high-resolution satellite imagery (Pekel et al. 2016; Pfeffer et al. 2017), which enables assessment of their extent and trajectories over time, thereby providing insights into rates of change and vulnerability. Ground-based hydrological monitoring, snow measuring, and glacier monitoring networks can provide accurate datasets for evaluation of remotely-sensed products as well as hydrological model calibration and validation to increase confidence trajectories. Forecasted glacier models, such as the Global Glacier Evolution Model (Huss & Hock 2015), can also determine anticipated glacier mass changes, where reductions in glacier and snowpack mass—as well as changes to temporal patterns of snow cover—are expected to increase vulnerability.

Climate change impacts on water availability and hydrological risks have been widely studied. However, the consequences on water quality is just beginning to be studied as the impacts of climate change on the quality of freshwater systems are likely to be significant (Delpla et al. 2009). Global warming and the consequences of extreme events can affect drinking water production and quality as well as environmental water quality in rivers and lakes. For example, climate change can lead to variation in physiochemical parameters, micropollutants and biological parameters. Moreover, the degradation trend of drinking water quality due to climate change leads to an increase of at-risk situations related to potential health impact (Delpla et al. 2009).

Description of indicators

The hydrology-related vulnerability analysis contains several major indicators (Table 9). The first is an assessment of the changes in the magnitude and frequency of runoff and discharge from waterways. Increased frequency of extreme events as a result of temperature rise has made Central Asia one of the world's most vulnerable regions to climate change. The general expectation is that greater reductions in magnitude and frequency of waterways discharge represent an increased vulnerability. This reduces water availability that supports natural plant and crop growth and thus negatively impacts wildlife populations and human livelihoods. However, seasonal variability in runoff and discharge would affect agricultural practices and food security, resulting in increased vulnerability.

The second is an assessment of the changes in the glacier, ice, and snow extents (see Indicator 1.2 for assessments related to spatiotemporal variation in snowfall). The general expectation is that greater reductions in glacier extent represent increased vulnerability because intact glaciers can continue to provide seasonal water resources sustaining plant growth and providing energy and food security and human livelihoods.

The third is an assessment of changes in inland water resources, including lakes and rivers. The general expectation is that greater reductions in volume and extent of inland waters represent increased vulnerability, because these freshwater resources provide habitat for wildlife, contribute to flood prevention, and can support livestock and hydropower energy production.

Table 9. Description of hydrology indicators.

No.	Hydrology Attribute	Indicator	Rationale	Category[1]
3.1	Runoff and discharge related parameters including magnitude and frequency of extreme events, and long term monthly, seasonal and annual discharge	Change in rates of runoff and discharge from rivers and waterways	Reduction of runoff and discharge limits plant and crop growth and overall water availability and quality	1
3.2	Glacier, ice, and snow extent	Change in glacier extent over time	Reduction in glacier extent limits the sustainability of water resources and increases seasonal flood risk	1
3.3	Inland waters parameters including seasonal and annual variability of extent, height, and volume of water	Change in inland waters extent over time	Reduction in inland waters extent limits habitat for wildlife, contributes to soil erosion, and diminishes water availability	1
3.4	Water quality	Changes in water physical and chemical quality over time	Degradation in water quality limits freshwater availability for wildlife, agriculture and also reduces hydropower production due to reservoir sedimentations	3

Necessary data

The first assessment concerning runoff and discharge requires the availability of long term data records from hydrological networks. The Global Runoff Data Base (GRDB) archives and provides hydrological data and information on a global scale at different temporal scales. The GRDB database comprises discharge data of more than 9,900 gauging stations from all over the world, which can be downloaded and used for runoff variability assessment as well as calibrating hydrological models. In addition to ground-based hydrological data, remotely-sensed data are commonly used for regional and global monitoring of hydrological variables, including soil moisture, rainfall, water level, flood extent, evapotranspiration, and land water storage. These freely available data have extensively been used for the forcing, calibration, or assimilation into hydrodynamics

1. Category 1 = Essential; Category 2 = Desirable to improve understanding of vulnerability, but not essential; Category 3 = Desirable to improve understanding of vulnerability, but requires specific collection

and hydrological or hydrometeorological models. Spatially-explicit hydrological models and downscaled future climate data can be used to predict runoff and discharge variability in future due to different climate change scenarios. Some available hydrological models are described in Table 10 (see also Table 2 for a list of freely available data sources for downscaled climate models). Earth observation satellites provide a large diversity of remote sensing data that can be accessed through multiple data providers webpages. Table 11 summarises the list of remotely-sensed hydrological data.

The second assessment concerning glacier, ice, and snow extent requires mapped extents of these variables over time. For example, in the context of the Panj-Amu River Basin, the International Centre for Integrated Mountain Development (ICIMOD) has used satellite imagery to produce glacier extent maps for Afghanistan for 1990, 2000, 2010, and 2015 (available at http://geoapps.icimod.org/glacier/afglacier/). More localized assessments require field-collected GPS data on terminus positions of glaciers, monitored and recorded over time. Snow and ice extent can be mapped using remotely-sensed imagery, and several pre-processed data layers on snow and ice already exist (see Table 11).

The third assessment concerning inland waters extent requires mapped inland waters extents over time. For example, a global database on inland surface water occurrence, change intensity, recurrence, seasonality, and transitions from 1984-2015 is available as a supplement in (Pekel et al. 2016).

Table 10. A selection of available global and regional hydrological models for conducting hydrology vulnerability assessments, with their spatial and temporal resolutions and extents and model parameters (adapted from Terink et al. 2015).

	Hydrological model										
	SPHY	TOPKAPI-ETH	SWAT	VIC	LIS-FLOOD	SWIM	HYPE	mHM	MIKE-SHE	PCRGLOB-WB	GEO-top
Process integrated											
Rainfall-runoff	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Evapotranspiration	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Dynamic vegetation growth	Y	N	Y	Y	Y	Y	N	N	Y	Y	N
Unsaturated zone	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Groundwater	Y	N	Y	Y	Y	Y	Y	Y	Y	Y	Y
Glaciers	Y	Y	N	N	N	Y	Y	N	N	N	Y
Snow	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Routing	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Lakes incorporated into routing	Y	N	Y	Y	Y	Y	Y	N	Y	Y	N
Reservoir management	N	N	Y	N	N	Y	Y	N	N	Y	N
Field of application											
Climate change impacts	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Land-use change impacts	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Irrigation planning	Y	N	Y	Y	N	Y	Y	N	Y	N	Y
Floods	N	N	N	N	N	N	Y	N	Y	Y	Y
Droughts	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Water supply and demand	N	N	Y	N	N	N	Y	N	N	N	N
Scale of application											
Catchment scale	Y	Y	Y	Y	N	N	Y	N	Y	N	Y
River basin scale	Y	Y	Y	Y	Y	Y	Y	Y	Y	N	N
Mesoscale river basins	Y	N	Y	Y	Y	Y	Y	Y	Y	Y	N
Global scale	N	N	N	Y	Y	N	N	N	N	Y	N
Farm level	Y	N	N	N	N	N	Y	N	N	N	N
Country level	Y	N	N	N	N	N	Y	N	N	N	N

Fully distributed	Y	Y	N	Y	Y	N	N	Y	Y	Y	Y
Sub-grid variability	Y	N	N	Y	N	N	N	Y	N	Y	Y
Flexible spatial resolution	Y	Y	N	Y	Y	N	N	Y	Y	Y	Y
Hourly resolution	N	Y	Y	N	Y	N	Y	Y	Y	N	Y
Sub-daily resolution	N	N	N	Y	Y	N	Y	N	Y	N	N
Daily resolution	Y	Y	Y	Y	Y	Y	Y	N	Y	Y	N
Implementation											
Open-source	Y	N	Y	Y	N	N	Y	N	N	N	Y
Forcing with remote sensing	Y	Y	N	Y	Y	N	Y	N	N	N	Y
GIS compatibility	Y	Y	Y	N	Y	Y	Y	Y	Y	Y	Y
Modular setup	Y	N	N	Y	Y	Y	Y	Y	Y	N	N
Computationally efficient	Y	Y	Y	N	Y	Y	Y	Y	N	Y	Y
Climate forcing requirements	Y	Y	N	N	N	N	Y	Y	N	N	N
Flexible output reporting options	Y	Y	N	Y	Y	Y	Y	N	Y	N	Y
Graphical user-interface in GIS	N	N	Y	N	N	Y	N	N	Y	N	N

Table 11. Remotely-sensed hydrological datasets.

Data type	Datasets	Spatio-temporal resolution and extent	Link to dataset and comments
Topography	Digital Elevation - Shuttle Radar Topography Mission (SRTM)	1 arc-second (~30m) spatial resolution; 54 °S to 60 °N; Acquisition: February 11-22, 2000	https://gdemdl.aster.jspacesystems.or.jp/ The Shuttle Radar Topography Mission (SRTM) was flown aboard the space shuttle Endeavour February 11-22, 2000. The National Aeronautics and Space Administration (NASA) and the National Geospatial-Intelligence Agency (NGA) participated in an international project to acquire radar data which were used to create the first near-global set of land elevations
	ASTER Global Digital Elevation Model (GDEM)	1 arc-second (~30 m) spatial resolution; 83 °S to 83 °N; the first version of the ASTER GDEM, released in June 2009, with V3 on August 2019	https://asterweb.jpl.nasa.gov/gdem.asp The Ministry of Economy, Trade, and Industry (METI) of Japan and the United States National Aeronautics and Space Administration (NASA) jointly announced the release of the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Global Digital Elevation Model. The first version of the ASTER GDEM, released in June 2009, was generated using stereo-pair images collected by the ASTER instrument onboard Terra. A total of 1,880306 scenes (Level-1A products) that were acquired from March 1, 2000, to November 30, 2013, were used to generate ASTER Global Digital Elevation Model (ASTER GDEM) version 3
	ALOS Global Digital Surface Model "ALOS World 3D - 30m (AW3D30)"	Horizontal resolution of 1 arc-second (~30 m)	This data set is a global digital surface model (DSM) by the Panchromatic Remote-sensing Instrument for Stereo Mapping (PRISM), which was an optical sensor onboard the Advanced Land Observing Satellite "ALOS". The latest version is 3.1 https://www.eorc.jaxa.jp/ALOS/en/aw3d30/data/index.htm
Rainfall	TRMM & GPM	Temporal resolution: 3-hour, daily, monthly and annual Spatial resolution: 0.25°-1°; 50 °S to 50 °N; January 1998 to present	The Tropical Rainfall Measuring Mission (TRMM) is a joint space mission between NASA and Japan's National Space Development Agency designed to monitor and study tropical and subtropical precipitation and the associated release of energy https://gpm.nasa.gov

Data type	Datasets	Spatio-temporal resolution and extent	Link to dataset and comments
Water level	Altimetry satellites	Multiple altimetry satellites and products at variable spatial and temporal resolution.	Aviso have been distributing altimetric data worldwide since 1992 https://www.aviso.altimetry.fr/en/techniques/altimetry.html
	Hydrology From Space at CTOH (hydroweb)	At present, water level time series of about 100 lakes (in Europe, Asia, Africa, North and South America) including Aral & Caspian seas are available. About 250 sites (called virtual stations) on large rivers are also available.	database contains time series over water levels of large rivers, lakes and wetlands around the world. These time series are mainly based on altimetry data from Topex/Poseidon for rivers, but ERS-1 & 2, Envisat, Jason-1 and GFO data are also used for lakes. Users of the database can visualize the water level time series as well as Landsat images showing the geographic location of the site. Users can download the numerical values of the time series as well as associated errors http://hydroweb.theia-land.fr/?lang=en
	Copernicus Global Land Service Water Level	Lakes: Sept 1992 – present Rivers: May 2002 - present	observed by space radar altimeters that measure the time it takes for radar pulses to reach the ground targets, directly below the spacecraft (nadir position), and return. Hence, only water bodies located along the satellite's ground tracks can be monitored, with a quality of measurement that not only depends on the size of the water body, but also on the reflecting targets in its surroundings such as topography or vegetation https://land.copernicus.eu/global/products/wl
	USDA Global Reservoirs and Lakes Monitor (G-REALM)	Temporal resolution: 10-day, 27-day and 35-day From 1992-present	The U.S. Department of Agriculture's Foreign Agricultural Service (USDA-FAS), in co-operation with the National Aeronautics and Space Administration, and the University of Maryland, are routinely monitoring lake and reservoir height variations for many large lakes around the world. The program utilizes NASA/CNES/ESA/ISRO radar altimeter data over inland water bodies in an operational manner https://ipad.fas.usda.gov/cropexplorer/global_reservoir/
	HydroSat	Variable spatial and temporal coverage	from the Institute of Geodesy (GIS), within the Faculty of Aerospace Engineering and Geodesy at University of Stuttgart presented HydroSat which provides the results of the studies and projects, in which spaceborne geodetic sensors are used to estimate: Surface water extent from satellite imagery Water level from satellite altimetry Water storage change from satellite gravimetry River discharge from satellite altimetry, imagery or gravimetry http://hydrosat.gis.uni-stuttgart.de/php/index.php
Water extent/floods	Global Surface Water GIEMS (Global Inundation Extent from Multi-Satellites)	The satellite data are used to calculate monthly-mean inundated fractions of equal-area grid cells (0.25° resolution at the equator). The resulting GIEMS data set covers 1993 to 2007	Global wetland extent and dynamics are estimated from a remote-sensing technique employing a suite of complementary satellite observations: it uses both passive and active microwave measurements, along with visible and near-infrared reflectances https://global-surface-water.appspot.com/download https://lerma.obspm.fr/spip.php?article91&lang=fr
	SRTM Water Body Dataset (SWBD)	1 arc-second (~30 m) spatial resolution The SRTM WBD (SWBD) covers the Earth's surface from 54 °S to 60 °N Temporal extent: 2000-02-11 to 2000-02-21	SRTM Water Bodies (South East, one of six data sets) represents the lakes, rivers, and ocean areas within the SRTM coverage area (between 60 degrees North and 56 degrees South latitude) of the world. All SRTM elevation values within lakes and ocean areas were set to be a constant elevation for that feature. Elevation values within river areas were set to ensure the proper flow direction https://lpdaac.usgs.gov/products/srtmswbdv003/

Data type	Datasets	Spatio-temporal resolution and extent	Link to dataset and comments
Water extent/floods	ASTER Water Body Dataset (ASTWBD)	1 arc-second (~30 m) spatial resolution; 83 °S to 83 °N	The ASTWBD is the only near-global raster data set; it delineates water bodies smaller than 0.2 km². ASTWBD generation consisted of two parts: separation of waterbodies from land areas; and classification of detected waterbodies into three categories: ocean, river, and lake. DOI: 10.5067/ASTER/ASTWBD.001
	The Landsat Global Surface Water Explorer (GSWE)	1 arc-second (~30 m) spatial resolution; 60 °S to 80 °N	The Landsat GSWE, developed by the European Commission, is based on 32 years of Landsat data, resolution and is available at https://global-surface-water.appspot.com/
	Copernicus Global Land Service Water Bodies	300 m spatial resolution; global extent; Jan 2014 - Present	The Water Bodies product detects the areas covered by inland water along the year, providing the maximum and the minimum extent of the water surface as well as the seasonal dynamics. The area of water bodies is identified as an Essential Climate Variable (ECV) by the Global Climate Observing System (GCOS) https://land.copernicus.eu/global/products/wb
River and Basin Information	WWF HydroSHEDS	3 to 30 arc-seconds	Hydrological data and maps based on SHuttle Elevation Derivatives at multiple Scales (HydroSHEDS) is a mapping product that provides hydrographic information for regional and global-scale applications in a consistent format. It offers a suite of geo-referenced data sets (vector & raster) at various scales, including river networks, watershed boundaries, drainage directions, and flow accumulations. HydroSHEDS is based on high-resolution elevation data obtained during a Space Shuttle flight for NASA's Shuttle Radar Topography Mission (SRTM) https://www.hydrosheds.org/
	HydroBASINS	Using the HydroSHEDS database at 15 arc-second resolution, watersheds were delineated in a consistent manner at different scales	HydroBASINS is a series of polygon layers that depict watershed boundaries and sub-basin delineations at a global scale. The goal of this product is to provide a seamless global coverage of consistently sized and hierarchically nested sub-basins at different scales
	HydroRIVERS	The global coverage of HydroRIVERS encompasses a total of 8.5 million individual river reaches with an average length of 4.2 km, representing a total of 35.9 million km of rivers globally	HydroRIVERS is a database aiming to provide the vectorized line network of all global rivers that have a catchment area of at least 10 km² or an average river flow of 0.1 cubic meters per second, or both
	HydroLAKES	Additional attributes for each of the 1.4 million lakes include estimates of the shoreline length, average depth, water volume and residence time	HydroLAKES is a database aiming to provide the shoreline polygons of all global lakes with a surface area of at least 10 ha

Data type	Datasets	Spatio-temporal resolution and extent	Link to dataset and comments
River and Basin Information	HydroATLAS	HydroATLAS offers a global compendium of hydro-environmental sub-basin and river reach characteristics at 15 arc-second resolution	HydroATLAS is a comprehensive database gathering and presenting a wide range of hydro-environmental attributes from existing global datasets in a consistent and organized manner. HydroATLAS is divided into two datasets, BasinATLAS and RiverATLAS, which represent sub-basin delineations (polygons) and the river network (lines), respectively. HydroATLAS offers attributes grouped in seven categories: hydrology; physiography; climate; land cover & use; soils & geology; and anthropogenic influences. In its first version, HydroATLAS contains 56 hydro-environmental variables, partitioned into 281 individual attributes
	GloRiC	The Global River Classification GloRiC provides a database of river types and sub-classifications for all river reaches globally	The Global River Classification GloRiC provides a database of river types and sub-classifications for all river reaches globally. Version 1.0 of GloRiC provides a hydrologic, physio-climatic, and geomorphic sub-classification, as well as a combined type for every river reach, resulting in a total of 127 river reach types. It also offers a k-means statistical clustering of the reaches into 30 groups. The dataset comprises 8.5 million river reaches with a total length of 35.9 million km
	MERIT Hydro	Global flow direction map at 3 arc-second resolution (~90 m at the equator)	MERIT Hydro is a global hydrography dataset, developed based on the MERIT DEM and multiple inland water maps. It contains flow direction, flow accumulation, hydrologically adjusted elevations, and river channel width http://hydro.iis.u-tokyo.ac.jp/~yamadai/MERIT_Hydro/index.html
Glaciers, snow, and ice	National Snow & Ice Data Center (NSIDC)	Provides data on snow, glaciers, ice sheets, sea ice, ice shelves, soil moisture and frozen ground at several spatial and temporal resolutions	The National Snow and Ice Data Center (NSIDC) supports research into our world's frozen realms: the snow, ice, glaciers, frozen ground, and climate interactions that makeup Earth's cryosphere. NSIDC manages and distributes scientific data, creates tools for data access, supports data users, performs scientific research, and educates the public about the cryosphere https://nsidc.org/
Soil moisture	Soil Moisture Active Passive (SMAP)	SMAP is designed to measure soil moisture, at a spatial resolution of 36 km every 2-3 days	The Soil Moisture Active Passive mission, or SMAP, launched in 2015 and has helped map the amount of water in soils worldwide https://smap.jpl.nasa.gov/
Water Quality	Copernicus Global Land Service Lake Surface Water Temperature	From Sentinel3/SLSTR satellite: Global 1 km from Nov 2016-present From ENVISAT-AATSR satellite: Global 1 km from May 2002-March 2012	Lake surface water temperature (LSWT) describes the temperature of the lake surface, one important indicator of lake hydrology and biogeochemistry. Temperature trends observed over many years can be an indicator of how climate change affects the lake. LSWT is recognized internationally as an Essential Climate Variable (ECV) and complements the water quality information, in environmental monitoring of a large number of lakes globally https://land.copernicus.eu/global/products/lswt
	Copernicus Global Land Service Lake Water Quality	100m, 300m and 1 km spatial resolutions Temporal: depending on the satellite used from May 2002 - present	The Lake Water Products (lake water quality, lake surface water temperature) provide a semi-continuous observation record for a large number (nominally 1,000) of medium and large-sized lakes, according to the Global Lakes and Wetlands Database (GLWD) https://land.copernicus.eu/global/products/lwq

Data type	Datasets	Spatio-temporal resolution and extent	Link to dataset and comments
Groundwater	Gravity Recovery and Climate Experiment (GRACE) satellite mission and its successor, GRACE Follow-On.	The two GRACE satellites have completed more than 13 years of continuous measurements in spatial resolution of 1 degree	The Gravity Recovery and Climate Experiment (GRACE) refers to a pair of NASA satellites that has flown in low-Earth orbit since 2002. GRACE measures changes in Earth's gravity field, which are directly related to changes in surface mass. The surface mass signal largely reflects total water storage (TWS); over the ocean, TWS is interpreted as ocean bottom pressure and on land, it is the sum of groundwater, soil moisture, surface water, snow and ice https://grace.jpl.nasa.gov/data/get-data/
A planetary-scale platform for Earth science data and analysis	Google Earth Engine	Multiple products with variable spatial and temporal scales	Google Earth Engine combines a multi-petabyte catalogue of satellite imagery and geospatial datasets with planetary-scale analysis capabilities and makes it available for scientists, researchers, and developers to detect changes, map trends, and quantify differences on the Earth's surface https://earthengine.google.com/

Methods

Indicator 3.1 – Change in rates of runoff and discharge from rivers and waterways

Field data collection protocols

For each country, the National Hydrological and Hydro-Meteorological Services are the primary providers of river discharge data. The responsibility for hydrometric and hydrologic data varies from country to country. Depending on geographic conditions and political priorities, operational hydrology is the responsibility of the energy, agriculture, transport or environment ministries. Most often, real-time data and historical data are managed by different institutions. The required data for this component are publicly available data from government departments; therefore, no fieldwork is required. Hydrological models are developed by professional organizations specializing in calculating runoff, discharge, and other hydrological variables from hydrological stations. Moreover, the Global Runoff Data Base (GRDB; https://www.bafg.de/GRDC/EN/01_GRDC/13_dtbse/database_node.html) archives and provides hydrological data and information on a global scale at different temporal scales. The GRDB database comprises discharge data of more than 9,900 gauging stations from all over the world, which can be downloaded and used for runoff variability assessment as well as calibrating hydrological models.

Analysis & modelling

Hydrological models have been applied at a variety of scales to simulate precipitation driven runoff and river discharge (Abbaspour et al. 2015; Hazenberg et al. 2015). A limitation of most catchment hydrology models is that they are tested based on runoff responses at the catchment outlet. While this may seem reasonable, and is appropriate for applications like downstream flood assessment, it does not ensure that internal catchment processes are captured. Thus, it may be difficult to quantify the effects of spatially distributed land management on runoff, in particular, the advantages and disadvantages of satisfactorily capturing flow regime, peak flows, low flows, and seasonality of runoff (Sidle et al. 2017). Empirical models based on statistical relationships between stream discharge and precipitation drivers may simulate hydrologic regime, but do not reflect the internal hydrological processes or the spatial effects of land use and thus cannot be transferred to other catchments. Examples of such empirical models include the SCS-Curve Number approach, regression models, and neural network models (Sitterson et al. 2017). In contrast, complex, physically-based hydrological models often require prohibitive amounts of soil and vegetation data, particularly if they are fully, spatially distributed (Zehe et al. 2006). However, more parsimonious models require parameter calibration by using local data that makes them non-transferable to other ungauged basins. Rapidly increasing computational power and availability of spatially-explicit remote sensing data have improved the predictive power of hydrological models (Jarihani et al. 2015). Thus, the most promising approach incorporates remotely-sensed environmental data, together with limited field data, in a fully- or semi-distributed hydrological model to assess climate change scenarios and coupled land cover changes on the hydrological regime at various scales.

Indicator 3.2 – Change in glacier, ice, and snow extents

Field data collection protocols

Glacier changes are key indicators of climate change. Changes in glacier extent can be measured using two approaches: field visits and remotely-sensed change detection. For analyses of localized change in glacier extent, GPS points must be collected in the field of the glacier's terminus. Glaciers are first identified by satellite imagery and subsequently visited and recorded at approximately the same time of year each year. Field teams should use a laser telemeter to measure the distance from the terminus point to the sides of the glaciers, mark the distances in black paint on a well visible, permanent rock located at the terminus point (noting the date) as a reference point for subsequent monitoring. On return visits, field teams can use a tape meter to measure and record the difference in terminus position. Multiple glaciers (10-12) should be visited and recorded each year, and trips should prioritize revisiting glaciers that have been measured previously to facilitate analysis of change in glacier extent over time.

Remotely-sensed change detection analyses do not require field data collection, but field observations from the first approach can be used to validate remotely-based assessments.

Analysis & modelling

For assessing changes in glacier extent from field visits, time series analysis can be used to fit trend lines of detected terminus position change and calculate slopes of the trends. Glaciers with increasing trend trajectories represent plots with reduced glacier extents. It is generally expected that regions proximate to such glaciers represent greater vulnerability, as reductions in glacier extents can initially lead to seasonal increases in runoff that increase flood risk and over time reduce water availability for local communities. Data can then be summarized by the spatial unit chosen, though regions where glacier information was not collected should be noted and removed from analyses. The main outputs from this component of the hydrology vulnerability assessment are maps of trends in the change in glacier extent of distinct glaciers and at the scale of the spatial unit chosen for summarization.

For assessing changes in glacier extent using remote sensing, satellite-based classifications of glaciers taken at distinct time periods enable time series analysis and change detection of glaciers over time. Data can be summarized by the spatial unit chosen and should include the mean and standard deviation values within the spatial unit to assess average and variability in glacier change within the spatial unit. The main outputs from this component of the hydrology vulnerability assessment are high-resolution maps of glacier extents over time, as well as trends in glacier extents at the scale of the spatial unit chosen for summarization.

Indicator 3.3 – Change terrestrial water and wetland extents

Field data collection protocols

Changes in terrestrial water and wetland extents are calculated from existing remote-sensing based classifications of inland waters and therefore require no field data collection.

Analysis & modelling

For assessing changes in wetland extent using remote sensing, satellite-based classifications of wetlands taken annually enable time series analysis and change detection of wetlands over time. Data can be summarized by the spatial unit chosen and should include the mean and standard deviation values within the spatial unit to assess average and variability in wetland change within the spatial unit. The main outputs from this component of the hydrology vulnerability assessment are high-resolution maps of wetland extents over time, as well as trends in wetland extents at the scale of the spatial unit chosen for summarization.

Indicator 3.4 – Change in water quality

Field data collection protocols

Changes in water quality is beyond the scope of the current assessment, but if required, qualitative and quantitative measurements can be performed from time to time to constantly monitor the quality of water from the various sources of supply. Water quality indicators, including physical, chemical, and biological properties, are traditionally determined by collecting samples from the field and then analysing the samples in the laboratory. As a comprehensive guideline, U.S. Geological Survey National Field Manual (NFM) for the collection of water quality data can be used (Delpla et al. 2009). The NFM provides detailed, comprehensive, and citable procedures for sampling water resources, processing samples for analysis of water quality, measuring field parameters, and specialized procedures.

Analysis & modelling

Over the past decades, increasing effort has been devoted to the development of suitable techniques and models for water quality assessment. Water quality modelling involves the prediction of water pollution using statistical and mathematical simulation techniques. Several water quality models have been developed and implemented to answer different scientific questions. These models can be classified based on water body types, model-establishing methods, water quality coefficient, water quality components, model property, and spatial dimensions (Cao & Zhang 2006). Based on the objectives and availability of historical datasets, appropriate water quality models can be selected and used in selected catchments of this project.

Remote sensing tools also provide spatial and temporal views of surface water quality parameters. A list of commonly-used satellites and airborne systems is available and can be used as a guideline for the assessment of water quality by remote sensing (Gholizadeh et al. 2016).

4 BIODIVERSITY

Background and scientific justification

Biodiversity plays a critical role in ecosystem functioning (Maestre et al. 2012) and is, therefore, an essential component of ecosystem stability and sustainability (Tilman et al. 2006). For example, ecosystems with greater plant diversity have higher productivity and cycle and store more carbon, nitrogen, and phosphorus, which regulates ecosystem health and slows the onset of desertification in dryland ecosystems (Tilman et al. 1996; Maestre et al. 2012). Similarly, ecosystems containing full and intact assemblages of mammals across trophic levels are more stabilized through proper nutrient transfer, maintenance of biomass, reductions in invasive species and disease, and regulation of other ecosystem processes (Estes et al. 2011).

Climate change threatens biodiversity by altering the climatic conditions under which species have evolved, forcing species to adapt, shift their ranges, or face local extinction (Araujo & Science 2006). Over recent decades, climate change has already resulted in widespread range shifts (Chen et al. 2011), reduced the species' abundances(Root et al. 2003), and led to full species-level extinctions (Pounds et al. 1999). Approximately 35% of species may face extinction by 2050 under certain change scenarios (Thomas et al. 2004). Loss of biodiversity has profound impacts on ecosystem structure, processes, and services, as well as multiple aspects of human well-being, including health and security, particularly if the plant communities provide vital resources to human communities (Díaz et al. 2006). Understanding and meeting the future needs of biodiversity is thus an essential component of limiting environmental, economic, and social vulnerability to climate change.

Direct monitoring of biodiversity can provide evidence of where species occur within a landscape. These direct observations can then be linked to environmental variables thought to drive species occurrences, such as climate, habitat, and the presence of competing or facilitating organisms through a process called species distribution modelling (Phillips et al. 2006). By creating separate species distribution models (SDMs) using current and future projections of climate, it is possible to determine how a species is expected to shift its distribution in the future, which can be used as a proxy measure for local extinction risk and overall vulnerability (Kearney et al. 2010).

Wildlife species with ranges tightly linked to climate variables (e.g., those with narrow thermal tolerances, adapted to narrow bands of elevation), will be most impacted by climate change. Information from published literature on traits such as dispersal, phenotypic adaptability, migratory status, habitat specialization, and physiological tolerance can provide useful information as they are proxies for the vulnerability that can also inform conservation interventions and strategies (Pacifici et al. 2015). Ecological trait analysis of important or 'keystone' mammal species (i.e., those with a disproportionate impact on ecosystem structure, function, and maintenance) can add information about sensitivity that complements vulnerability arising from high exposure as determined through species distribution modelling.

Finally, information on broad biodiversity patterns can be combined with other environmental, economic, and social variables to optimize conservation planning while considering and incorporating practical constraints to conservation. For example, spatial prioritization can determine optimal locations for establishing protected areas or restoration opportunities in a landscape (Watson et al. 2010). Vulnerable regions are then determined where priority regions for conservation are currently unprotected.

Description of indicators

The biodiversity vulnerability analysis contains three major indicators (Table 12). The first is an assessment of the changes in the distribution of focal mammal, bird, and reptile species. The general expectation is that greater shifts in species ranges represent increased vulnerability because ecosystem function is likely to be negatively impacted through their displacement.

The second is an assessment of the sensitivities of focal mammal, bird, and reptile species to climate change. The general expectation is that traits indicative of limited movement potential, greater ecological specialization, shorter reproduction cycles, and limited geographic ranges and ecological niches represent species with lower adaptive capacity.

The third is an assessment of the alignment between current protected lands and priority regions for protection. The general expectation is that vulnerability is greatest where identified priority regions are not protected, because the loss of biodiversity in such regions will likely have disproportionate consequences for ecosystems and local communities.

Table 12. Description of biodiversity indicators.

No.	Biodiversity Attribute	Indicator	Rationale	Category[1]
4.1	Species distributions	Difference in current and projected species distributions	Larger necessary range shifts are more likely to negatively impact species and affect ecosystem functioning	1
4.2	Ecological traits of focal wildlife species	Wildlife species sensitivity based on ecological traits	Species exhibiting limited movement potential, greater ecological specialization, shorter reproduction cycles, and limited geographic ranges and ecological niches are associated with lower adaptive capacity, thus greater vulnerability to climate change	2
4.3	Protection status	Unprotected land in biodiversity conservation priority region	Unprotected lands face ongoing threats to species, and loss of biodiversity in priority regions would have disproportionately negative consequences on ecosystems and local communities	1

Necessary data

The first assessment concerning species distributions requires georeferenced coordinates of species occurrences. These can be collected in the field through standardized or ad-hoc wildlife surveys (see field data collection protocol in Indicator 4.1 below for examples), from online databases (see Table 13 for examples), or from published and grey literature (Fletcher et al. 2019). To fit species distribution models, ancillary environmental data is also required. Such data typically consists of land cover, elevation, and climate models (see Table 14, for example, land cover and elevation data sources and Table 2 for example climate data sources).

The second assessment concerning ecological traits of focal wildlife species requires data on the trophic level, diet breadth, dispersal distance, number of ecoregions occupied, thermal and rainfall niche breadths, median elevation, elevational range size, and geographic range size. This information can be collected in the field, obtained through primary literature, or accessed through online databases, such as the EltonTraits Database (Wilman et al. 2014).

The third assessment concerning the protection status of priority regions for biodiversity conservation requires data on current and future species distributions and overall biodiversity patterns as well as constraints or cost layers that typically hinder biodiversity conservation actions. Such data typically consists of land value models or related surrogates, such as agricultural suitability, population density, and variables related to human pressure.

1. Category 1 = Essential; Category 2 = Desirable to improve understanding of vulnerability, but not essential; Category 3 = Desirable to improve understanding of vulnerability, but requires specific collection

Table 13. A selection of available online databases for species occurrence points used in SDMs.

Dataset	Taxa covered	No. of occurrences	Temporal Extent	Spatial extent
GBIF[1]	Multiple (>6 million species)	>1 billion	1600-2019	Global
NatureServe[2]	Multiple	~1 million	1970-2019	North America
BISON[3]	Multiple	~0.5 million	1601-2019	North America
iNaturalist[4]	Multple	~150,000	1919-2019	Global
VertNet[5]	Vertebrates	>80 million	1800s-2019	Global
eBird[6]	Birds	>500 million	1810-2019	Global
Map of Life[7]	Multiple	>1 billion	1600-2019	Global

Table 14. A selection of available global and regional land cover and elevation datasets typically used as predictor variables in species distribution modelling. See also Table 2 for climate models used in SDMs.

Data type	Dataset	Spatial resolution	Temporal Period(s)	Spatial extent
Land cover	Globeland30[8]	30 arc-seconds (~1 km)	2010	Global
Land cover	NLCD[9]	30 m	1992, 2001, 2004, 2006, 2008, 2011, 2013, 2016	CONUS
Land cover	GLC-Share[10]	30 arc-seconds (~1 km)	2013	Global
Land cover	GlobCover[11]	10 arc-secons (~300 m)	2009	Global
Land cover	MODIS VCF[12]	250 m	2000-2018 (annual)	Global
Land cover	ESA-CCI[13]	10 arc-seconds (~300 m)	1992-2015 (annual)	Global
Elevation	SRTM[14]	1 arc-second (~30 m)	Static	Near global
Elevation	ASTER GDEM[15]	1 arc-second (~30 m)	Static	Global
Elevation	NED[16]	1/3 and 1 arc-second	Static	CONUS

Methods

Indicator 4.1 – Difference in current and projected species distributions

Field data collection protocols

The difference in current and projected species distribution relies on creating SDMs for focal species under current and future climate conditions and assessing alignment between the two distributions. While online databases and published literature can be used to compile species occurrence points to use in species distribution modelling, field data collection is often necessary to obtain occurrences local to the region of interest. Primary field data can also be useful in validating fitted models of current distributions.

Wildlife species differ markedly in their ecologies, and so there is an array of methodologies used to adequately survey different species. These range from passive methodologies, such as camera trapping, to active methodologies, such as line transect surveys. Each methodology is described in full below, and a general overview is provided in Table 15:

1. http://gbif.org
2. http://services.natureserve.org/ipt/resource?r=occurrences
3. https://bison.usgs.gov/#home
4. https://www.inaturalist.org/projects/io-database
5. http://vertnet.org/index.html
6. https://ebird.org/science/download-ebird-data-products
7. https://mol.org
8. www.globallandcover.com
9. https://www.mrlc.gov/
10. http://www.fao.org/geonetwork/srv/en/main.home?uuid=ba4526fd-cdbf-4028-a1bd-5a559c4bff38
11. http://due.esrin.esa.int/page_globcover.php
12. https://lpdaac.usgs.gov/products/mod44bv006/
13. http://maps.elie.ucl.ac.be/CCI/viewer/
14. https://www2.jpl.nasa.gov/srtm/
15. https://asterweb.jpl.nasa.gov/gdem.asp
16. https://ned.usgs.gov

1. Camera trapping

Camera trapping is a passive survey method that automatically takes pictures of species that move in front of stationary cameras. Cameras are typically set out in a grid or are placed along trails or paths thought to be used for species movement and dispersal in order to maximize detection for the target species, though the placement of cameras should also consider human activities and potential for theft or vandalism to avoid conflicts. There is no standard number of cameras to be placed in a given region, but detections generally increase with camera density. Camera traps run continuously, and data should be downloaded from cameras as often as is feasible to the potential for lost data due to stolen or damaged equipment.

2. Line transects

Line transects are an active survey method whereby one or more observers walk along a line or trail for a fixed length of time or for a fixed distance. Observers identify and count all individuals seen or heard from the line and can use binoculars or a spotting scope to aid observations. When individuals are seen, the perpendicular distance to the organism from the line is recorded (which can be aided by using a rangefinder), as is the location of the observation using a GPS unit. Signs of wildlife species, such as tracks or scat, can also be recorded as indirect observations of occurrence. The total amount of time spent surveying should be recorded as a measure of survey effort. Observations of individuals detected behind observers should not be counted to minimize double-counting.

The general line transect methodology is suitable for a wide range of species that are observable by sight or sound, but can be modified and tailored for particular species of interest to maximize detectability. For example, when surveying ungulate species, the double-observer variant is typically used, whereby two survey teams of two people each walk to a series of pre-determined vantage points that are selected based on their visibility. Observers spend an average of 10 minutes scanning for ungulates with binoculars and a spotting scope at each vantage point. Approximately 45 minutes to one hour after the first team has surveyed a particular vantage point, the second team follows a parallel route with vantage points slightly displaced, such that the range of observations of the first and second teams just overlap. Observers can also record sightings between vantage points. Teams should keep in constant communication by walkie talkie to report their observations to minimize double-counting. Observers record the GPS location and bearing of any observation, along with the aspect, location, number of individuals, age and sex composition, behaviour, prominent morphological features, escape behaviour (if the second team notices anything), and a second GPS point and bearing from the next vantage point.

Another variant of the general line transect method is suitable for ground-dwelling organisms like marmots. For these surveys, randomly selected 200-500m line transects should be walked and burrows counted within a perpendicular distance of 20 m on either side of the transect. A survey team of two individuals should record direct sightings and indirect evidence, such as scats and tracks. In addition, the observers should investigate the status of burrows to determine whether they are active or inactive, the number of burrows in a cluster, aspects of the burrow openings, the topographic features of the burrow cluster, and the ground cover. Observers should record the burrow clusters in three categories: 1) active colony (consecutive sightings of individuals of different age and sex); 2) potential colony (single animal observed with no sign of reproduction); and 3) inactive colonies (unused burrows with no animals observed). Observers should also record the number and status of burrows excavated by predators. When direct sightings are made, observers should record the number of sighted animals and each animal's sex and age category: 1) Adult males + unproductive females, 2) productive females that are seen with young, and 3) juveniles. Observers should also record the connection of individuals with different families when possible. Family members will be determined by the observed animal location.

3. Fixed radius search

The fixed radius search is used to survey territorial organisms that are cryptic and have small home ranges. In these surveys, the radius is defined usually to approximately match the home range size of the individual. For example, in the case of surveying for certain pika species, a 12 m radius (equivalent to a searchable area of 452 m^2) can be used. The search is typically for a fixed time (e.g., 10 minutes), which should scale with the size of the search area to enable the entire area to be adequately searched. During the search, direct evidence (e.g., sightings, calls) or indirect evidence (e.g., scat, tracks, markings) should be recorded. Typically searching is done with two observers to ensure quality search and that all observations are recorded during the time limit. Following the search period, observers should record data on ground cover, topography, weather, and the overall status of the survey plot. Survey sites should be repeated, with at least 24 hours between surveys to enable the calculation of detection probabilities (i.e., increase the chance that any apparent absences are real).

4. Point counts

Point counts are commonly used to survey birds, which can be detected at a distance because of their frequent vocalizations. Points should be spaced at least 200 m apart to ensure they are independent of one another (i.e., that birds or other organisms are not likely to move between points), and can be arranged in a grid, along line transects, or at random locations. The placement of points should be informed by the goal of the survey and the target species. Surveys at points are conducted within a fixed radius (typically 100 m). At each point, a skilled observer identifies all birds by sight and sound within the established radius for a duration of 10 minutes; a secondary observer should note the species, count, distance to observer, and cardinal direction to the bird. Each point should be revisited a minimum of two times (>2 preferable) on different days (i.e., no count should be done >1 time in a single day). Counts should begin at dawn and end by 10 am. Observers should also note the weather (sunny, partly cloudy, mostly cloudy, cloudy) and wind (no wind, light wind, moderate wind) and should not conduct counts in heavy wind or during rain. When surveying for birds, detectability is usually maximized if conducted in spring and summer when birds are breeding, holding territories, and vocalizing most frequently.

5. Mist netting

Mist netting is a survey methodology appropriate for surveying understory birds, particularly cryptic species that are difficult to detect using line transects or point counts. Mist nets are nets made of fine mesh (typically between 30 and 40 mm mesh) typically around 2.4 m tall and between 3-4 m in length. Mist netting can either be passive or active. In passive mist-netting, a series of nets is erected in a rough line in a place where birds are thought to be active. Passive mist-netting aims to survey any bird in the community. Approximately every 15 minutes, a minimum of two observers should walk alongside the nets and retrieve any birds that have flown into them and return to a centralized bird banding station for data processing. Nets are typically opened at dawn and remain open until around 10 am or when activity begins to subside. Nets should be closed and wound after surveys are complete. Surveys are usually conducted for three consecutive days in a given survey location.

In active mist-netting, a series of nets is erected in place thought to be suitable habitat for one or a few target species. Near the net locations, a speaker playing the target species' call can be played to try to lure the target species to flying into the net, at which time it can be retrieved for data processing. Nets used in active mist-netting are typically opened at day, but usually remain open all day to maximize the chances of capture. Surveys are usually conducted for multiple consecutive days in a given survey location, with the number depending on recapture rates and whether species begin to avoid nets.

For both forms of mist netting, captured birds should be banded with metal and plastic coloured rings using special pliers specifically designed for bird banding. The metal rings are necessary to note whether the individual has been captured previously, whereas the coloured rings can help visually identifying unique individuals in the field. Alongside banding, observers should record the sex, body mass (using a Pesola spring scale), and the length of the wing, tail, tarsus, and bill (using a calliper). As with point counts, observers should also note the weather (sunny, partly cloudy, mostly cloudy, cloudy) and wind (no wind, light wind, moderate wind) and should not conduct surveys in heavy wind or during rain.

Table 15. Overview of biodiversity survey methodologies with example taxonomic groups and species targeted and specialized equipment needed.

Methodology	Best used for	Example species/groups	Specialized equipment needed
Camera trapping	Cryptic and nocturnal species	Most large mammals, some ground-dwelling birds, some human activities	Camera trap unit, GPS
Line transects	Species that can be observed from a distance	Ungulates, marmots, some pikas, some primates, some birds, reptiles	Binoculars, spotting scope, GPS, rangefinder, compass
Fixed radius search	Territorial and/or denning species	Some pikas, small rodents, some bird nests	GPS
Point counts	Species with high diversity that vocalize	Birds (particularly canopy-dwelling), possibly some primates	Binoculars, GPS, rangefinder, compass
Mist netting	Arial species that are cryptic or do not regularly vocalize	Understory birds, most bats	Mist nets, poles, bags, pliers, rings, callipers, Pesola scale, GPS (passive and active); speaker, phone/mp3 player (active only)

Analysis & modelling

Species distribution modelling is used to determine current and future habitat suitability for target species across a landscape. SDMs are correlative models that relate the occurrence of species to environmental predictors (including, for example, topography, climate, and landcover; see Table 2 and Table 14), then project those relationships across geographic space. In addition to projecting these relationships onto current environmental predictors, they can be projected onto future conditions by using future climate models. Species occurrence point used to train the models can be derived from field-collected data containing georeferenced occurrence points, published literature, or from online databases (see Table 13).

Species distribution modelling follows six major steps:

1. Collect and compile training and validation data (i.e., georeferenced occurrence points) for focal species (see field data collection protocol above)
2. Compile environmental predictors thought to influence habitat suitability for the focal species
3. Select an algorithm for modelling (e.g., Maxent, random forests, bioclim envelope models; see (Elith et al. 2006) for a review and comparison of approaches)
4. Train the algorithm using training points (a subset of occurrences, reserving others to be used in the validation step below)
5. Predict habitat suitability based on the trained algorithm
6. Estimate suitability performance using independent validation data (using a different subset of occurrence points data not used in the training step above).

Model predictions using this approach have the potential to go beyond the boundaries of the focal region of interest because they project across the full extent of the input layers. Thus, resulting distribution models should be clipped to the region of interest after fitting for further analysis.

These steps should be performed once using current climate information as a predictor, and again using projected future climate information from downscaled climate models. The two models of habitat suitability can then be compared to evaluate expected suitability change, where greater regions of change represent regions of greater vulnerability. Data can then be summarized by the spatial unit chosen and should include the mean and standard deviation values within the spatial unit to assess average and variability in species distribution (habitat suitability) change within the spatial unit. The main outputs from this component of the biodiversity vulnerability assessment are high-resolution maps of current and future habitat suitability and expected spatial mismatches in suitability, with the maps also summarized at the scale of the spatial unit chosen.

Indicator 4.2 – Wildlife species sensitivity based on traits

Field data collection protocols

Data for the assessment of wildlife species sensitivity based on traits largely originates from published sources, including published literature, field guides, and online databases. For example, much of this data can be obtained from the online database EltonTraits (Wilman et al. 2014), which contains data on diet, foraging strata, foraging time, and body size for nearly 10,000 bird species and 5,400 mammal species. Information on geographic range size, threatened status, and habitat affinities can be obtained from IUCN Red List of species (https://www.iucnredlist.org/).

If data are lacking for focal species from these sources, primary data would need to be collected in the field and should be done so alongside data collection for the other components of the biodiversity vulnerability assessment. To fill in any data gaps, expert opinion on wildlife species sensitivity scoring should be sought. In such cases, the scoring sheet and a detailed description of the methodology should be given to the expert to fill in any gaps (see below).

Analysis & modelling

Ecological trait data for focal wildlife species should be recorded from published literature, field guides, and online databases, with source information noted. Focal species should represent keystone or ecologically, economically, and culturally important species, so that sensitivity of individual species can reasonably provide insight into the sensitivity of entire ecosystems and for local communities. Some example focal species characteristic of the Panj-Amu River Basin are presented in Table 16 along with a justification for inclusion.

Table 16. Example focal wildlife species for assessing species sensitivity based on traits.

Common name	Scientific name	Rationale for inclusion
Snow Leopard	*Panthera uncia uncia*	Charismatic and well-recognized apex predator; occurs at high elevations; potential conflict with local communities
Brown Bear	*Ursus arctos isabellinus*	Large-bodied predator with key behaviours (e.g., hibernation) dependent on climate; potential conflict with local communities
Asiatic Black Bear	*Ursus thibetanus*	Large-bodied predator with key behaviours as above
Asiatic Ibex	*Capra sibirica sakeen*	Major prey species of Snow Leopard; occurs at high elevations
Afghan Urial	*Ovis orientalis cycloceros*	Major prey species of Snow Leopard
Macro Polo Sheep (Argali)	*Ovis ammon polii*	Major prey species of Snow Leopard; occurs at high elevations; of economic importance to local communities
Markhor	*Capra falconeri*	Major prey species of Snow Leopard; occurs at high elevations
Persian Leopard	*Panthera pardus tuliana*	Charismatic, apex predator
Pallas's Cat	*Otocolobus manul manul*	Occurs at high elevations; potential conflict with local communities
Leopard Cat	*Prionailurus bengalensis*	Meso-carnivore and possible predator of pika
Jungle Cat	*Felis chaus*	Meso-carnivore and lower elevation species (to contrast with high elevation species)
Wild Cat	*Felis silvestris*	Meso-carnivore and lower elevation species (to contrast with high elevation species)
Turkestan Lynx	*Lynx lynx isabellinus*	Meso-carnivore and predator of pika
Striped Hyena	*Hyaena hyaena*	Large carnivore with limited range

Common name	Scientific name	Rationale for inclusion
Long-tailed Marmot	*Marmota caudata*	Occurs at high elevations; of economic importance to local communities
Afghan Pika	*Ochotona rufescens rufescens*	Occurs at mid to high elevations
Large-eared Pika	*Ochotona macrotis macrotis*	Occurs at mid to high elevations
Afghan Snowfinch	*Pyrgilauda theresae*	Range-restricted species; occurs at high elevations
Large-billed Reed Warbler	*Acrocephalus orinus*	Range-restricted species; occurs at mid to high elevations
Himalayan Agama	*Paralaudakia himalayana*	Occurs at high elevations
Badakhshana Rock Agama	*Paralaudakia badakhshana*	Range-restricted species; occurs at high elevations

A total of nine species traits provide metrics of wildlife species sensitivity along several different ecological dimensions (Pacifici et al. 2015) . These traits include trophic level, diet breadth, dispersal distance, number of ecoregions occupied, thermal and rainfall niche breadths, median elevation, elevational range size, and geographic range size. Trait information for each focal species should be collected and compiled in a trait database. Each trait is then converted from a numeric or categorical value to a sensitivity score following the description outlined in Table 17. Higher scores represent greater sensitivity because they signify more specialized ecologies and lower adaptive capacity. For instance, wildlife species with very narrow ranges have a lower adaptive capacity than species with very large ranges. Thus, they receive a higher score in the geographic range size category.

Table 17. Nine ecological traits determining wildlife species sensitivity to climate change.

Trait	Value	Score
Trophic level	1	1
	2	2
	3	3
Diet breadth (# of food types consumed)	>2	1
	2	2
	1	3
Dispersal distance (km)	>100	1
	10-100	2
	1-10	3
	<1	4
Number of ecoregions occupied	7	1
	6	2
	5	3
	4	4
	3	5
	2	6
	1	7
Thermal niche breadth (°C)	>20	1
	15-20	2
	10-15	3
	5-10	4
	0-5	5

Trait	Value	Score
Rainfall niche breadth (mm)	>2000	1
	1000-2000	2
	600-1000	3
	300-600	4
	100-300	5
	0-100	6
Median elevation (km)	<1.5	1
	1.5-2.5	2
	2.5-3.5	3
	>3.5	4
Elevational range size (km^2)	>3	1
	2-3	2
	1-2	3
	<1	4
Geographic range size (km^2)	>70000	1
	20000-70000	2
	<20000	3

Scores for each category for each species are then converted to a sensitivity class, where the top 33% of values per category are assigned 'high sensitivity', the middle 33% of values per category are assigned 'medium sensitivity', and the bottom 33% of values per category are assigned 'low sensitivity'. Species thus then receive a final sensitivity score by looking for consensus, equality, or mixed combinations across all scores.

The main output from this component of the biodiversity vulnerability assessment is a compiled database of wildlife species traits and a ranked list of relative species sensitivity to climate change. Because the species chosen should represent species of particularly high ecological, economic, or cultural significance, the sensitivity scores can be assigned to species range maps and overlay maps can be generated to depict a spatial representation of sensitivity.

Indicator 4.3 – Unprotected land in biodiversity conservation priority regions

Field data collection protocols

Spatial prioritization for conservation relies on several different ecological, social, and economic data sources, such as species distribution models and maps of land use/land cover, and land values. Many of these data sources are available in online repositories, but field data would be required for any layers that need to be developed. See the relevant sections above for field data collection and data analysis and modelling protocols associated with generating the underlying layers necessary for spatial prioritization analysis, in particular those sections related to species distribution modelling (Indicator 4.1) and modelling vegetation extent and related parameters (Indicators 2.1-2.4).

Analysis & modelling

Spatial prioritization in the context of conservation is identifying the most important areas for conservation interventions (e.g., establishing protected areas, designing management actions, initiating restoration activities) while minimizing user-defined tradeoffs (e.g., limiting access to resources, reducing economic costs). There are several statistical approaches and associated software packages that implement such optimization, including Marxan and Zonation (Ball et al. 2009). Typically, the optimization is usually seeking to achieve full representation of biodiversity with minimum economic costs. Representation of biodiversity can be defined in different ways, such as protecting a percentage of each species' range, or a percentage of key habitat types or environmental facets (oftentimes 'ecoregions'). At the initial stages, the user defines the target, the cost layers, and the number of planning units allowed, and the software develops a number of optimal solutions for achieving the target while minimizing the costs.

In the case of vulnerability assessments, the target to be optimized should consider not only representation of current biodiversity patterns or habitat types, but the expected future distributions as well (Game et al. 2011). This ensures that conservation interventions work towards sustaining biodiversity (or the processes maintaining biodiversity) over time. The use of current and future species distributions and overall biodiversity patterns as the representation target enables the software to develop a reserve network that accommodates the dynamic nature of species ranges under climate change.

As inputs to the prioritization, current and future species distributions and overall biodiversity patterns (overlaid distributions of all focal species) can be generated following the methodology outlined in Indicator 4.1. Cost layers can be consist of direct variables where available (e.g., economic values of land parcels); otherwise, indirect variables can be used, such as agricultural suitability, population density, or other surrogates of human activities and pressure. Many of these variables have been mapped at global scales (Naidoo & Iwamura 2007; Venter et al. 2016).

The output of the prioritization is an idealized reserve network that would best meet the representation targets, which in this case facilitates species adaptation to climate change. This reserve network can be compared to the existing reserve network to evaluate areas where conservation priorities are not covered by existing protected lands, which are determined to be areas of greatest vulnerability. The main outputs from this component of the biodiversity vulnerability assessment are example reserve networks optimized for biodiversity conservation given constraints that explicitly incorporate risks associated with climate change and maps depicting discrepancies in priority conservation regions and existing protected lands.

5 LOCAL COMMUNITIES AND NATURAL RESOURCES

Background and scientific justification

The socioeconomic status of a person, family, or community can significantly influence overall vulnerability to climate change. This is because several socioeconomic variables relate directly to adaptive capacity—adaptive capacity is typically associated with governance, civil and political rights, and literacy, which suggests that the negative consequences of climate change are expected to be greater for countries with civil and social conflict, high levels of poverty, and low levels of education (Brooks et al. 2005). Similarly, adaptive capacity is generally lower for communities that rely directly or indirectly on natural resources for their livelihoods, because they have fewer options if such resources are negatively impacted by climate change (Tompkins & Adger 2004). For example, lack of access to renewable energy resources could significantly impact communities that currently depend on fuelwood for cooking and heating with few alternatives, as drought conditions may limit regrowth potential (Akther et al. 2011). Communities dependent on water for irrigation may face similar challenges with climate change-induced shortages in seasonal water availability (Elliott et al. 2014). Overall, communities with limited options and opportunities face greater vulnerability under climate change, because their ability to cope with more frequent or more extreme stressors is lower (Smit & Wandel 2006).

There are also interactions and feedbacks between socio-economic circumstances and use of natural resources. For example, increasing pressure on natural resources following climate change can lead to economic instability and can be a source of violent conflict, which reduces adaptive capacity (Barnett & Adger 2007). There are also environmental feedbacks. For instance, unsustainable grazing and harvesting practices can lead to land degradation that in turn can affect soil quality, runoff, and erosion, and thus suitability for alternate land uses, such as agriculture (Oztas et al. 2003). Overgrazing also reduces biomass and carbon storage, increasing carbon dioxide emissions that contribute to climate change (Conant & Paustian 2002). Under changing climate conditions, degraded ecosystems with impoverished biodiversity are less resilient and offer less potential for adaptation.

The distribution and availability of natural resources for communities, along with the underlying socioeconomic status of local communities, interact to influence overall vulnerability. Of particular importance are the natural resources that provide food, shelter, and energy for communities, such as livestock, timber, and fuelwood. From the perspective of local communities, socioeconomic variables related to age, gender, income, education, occupation, and access to resources have the largest influence on their sensitivity to and ability to cope with climate change.

A wide range of interview and survey techniques exist to document and quantify human demographic and natural resource use parameters. Questionnaires can be given to local community members, and focus groups can be interviewed in Basic Necessities Surveys to get data on personal information, education, family status, livestock, land ownership, socioeconomic status, and use of natural resources. The interactive method of participatory mapping can be used to have local communities depict a spatial representation of resources and perceived threats and natural hazards to resources.

Description of indicators

The local communities and natural resources vulnerability analysis contains three major groups of indicators (Table 18). The first is an assessment of biophysical resources in terms of their use of and access to fuelwood; the types and numbers of livestock owned; the number of agroforestry trees grown and owned; the area of rainfed/dryland, irrigated, and high-yielding crops; the number of agricultural landholdings; the total net sown area; the amount of fertilizers consumed and manure used; mean rainfed crop yields; biological richness; and the area of high-quality grazing land. The general expectation is that communities with greater dependencies on and lower access to biophysical resources are more vulnerable because they have fewer options for adaptation (lower adaptive capacity) to cope with potential reductions in these resources under climate change.

The second is an assessment of the demographic status of communities in terms of their age, gender, and family membership make-up. The general expectation is that families and communities that are older, more dominated by women, and are smaller in size are represent those with greater vulnerability because they have less income potential, have fewer opportunities for education and employment, and (in the case of women) tend to bear most of the child-rearing responsibilities in many cultures; all of these factors reduce adaptive capacity and thus increase overall vulnerability. There are also a number of related, sub-indicators in this portion of the assessment, outlined in more detail below.

The third is an assessment of the socioeconomic status of communities in terms of their wealth, income, education, occupation, diversification of income sources, livelihood support institutions, the human and social capital of families and communities, and rural population density and distributions with respect to landscape features. The general expectation is that families and communities that are poorer, have a lower income, are uneducated, have no occupation, and have more limited access to alternative livelihoods represent those with greater vulnerability, because they have lower financial security and have a lower potential for more advanced occupations requiring education, which tend to reduce their adaptive capacity and thus increase overall vulnerability.

Table 18. Description of the local community and natural resources indicators.

No.	Local Community and Natural Resource Attribute	Indicator	Rationale	Category[1]
5.1	Biophysical resources	Community use of and access to fuelwood, pastures, and medicinal plants; types and numbers of livestock owned; number of agro-forestry trees grown and owned; area of rainfed/dryland, irrigated, and high-yielding crops; number of agricultural landholdings; net sown area; amount of fertilizers consumed and manure used; mean rainfed crop yields; biological richness; area of high-quality grazing land	Communities with greater dependence on and lower access to biophysical resources have lower adaptive capacity with reductions in resource availability under climate change	1
5.2	Demographic status	Age of household members, sex of household members, household size	Households that are older, smaller, and more dominated by women have fewer income and employment opportunities that reduces their adaptive capacity	1
5.3	Socioeconomic status	Wealth, income, education, occupation, diversification of income sources, livelihood support institutions, human and social capital of households, rural population density	Families and communities that are poorer, have lower income, are uneducated, have no occupation, and have more limited access to alternative livelihoods have fewer opportunities and resources are more insecure, which reduces adaptive capacity	1

Necessary data

The first assessment concerning a suite of biophysical indicators requires data on the distribution and utilization of natural resources. Much of this information can be collected using household or community interviews using questionnaires, basic necessities surveys, and participatory mapping tools. Other components require spatially-explicit models (e.g., of livestock grazing patterns, rangeland condition, land cover) that are described in other sections of this document (e.g., Indicators 2.1, 2.2) and also below.

The second assessment concerning a suite of demographic indicators requires data on age and sex of members of households and the size structure of households and families for each community. These data can be collected directly by conducting household or community interviews using questionnaires.

1. Category 1 = Essential; Category 2 = Desirable to improve understanding of vulnerability, but not essential; Category 3 = Desirable to improve understanding of vulnerability, but requires specific collection

The third assessment concerning a suite of socioeconomic indicators requires data on wealth, income, education, and occupation of members of households within families for each community, as well as information on rural population density, human and social capital, diversification of income sources, and livelihood support institutions. Most of these data can be collected directly by conducting household or community interviews using questionnaires, while others (e.g., rural population density) can be obtained from online databases such as standardized censuses.

Methods

General methodological overview

Many of the local communities and natural resources indicators utilize data originating from field-conducted household and community surveys using questionnaires, semi-structured interviews, basic necessities surveys (BNS), and by conducting participatory mapping. The main purpose of BNS is to document, through interviews conducted with local communities, perceptions of poverty and assets and services deemed to be basic necessities—things that all households have and none should be without. The BNS consists of a questionnaire delivered by an interviewer to a set of participants (referred to as focus groups), following the approaches outlined in Table 19.

Table 19. Components of Basic Necessities Surveys.

Component	Description
Focus groups	Focus groups are used to allow participants to self-identify their basic necessities. Neither the interviewer nor others from outside the landscape offer suggestions. The participants in the focus group should cover a range of ages and levels of education and should be composed of both men and women to constitute a representative sample of the population. The focus group produces a final list of goods they consider to be basic necessities. Multiple focus groups (>2) should be approached to limit bias
Questionnaire	Questionnaires are designed with input from local expert staff and are given to a representative sample of community members. Questions included pertain to personal information about the participant (e.g., name, sex, occupation, education, family members, etc.), utilized resources such as fuel, livestock, and wildlife (e.g., how many owned, of what type, what type of fuel to heat home, plant collection habits, observation of wildlife, hunting practices employed, etc.), sources of food (e.g., agriculture, how much land owned, types of crops grown, market access, etc.), and socioeconomics (e.g., income, ownership of goods, etc.). The end of the questionnaire requires participants to acknowledge whether they own any of the assets from a provided list of assets, or use any services from a provided list of services as identified from the focus groups

Table 20. Overview of the four methods in participatory mapping.

Method	Objective	Time	Supplies
Hazard ranking	To identify the natural hazards that exist in the community and rank them according to the levels of disruptive impact they have on community life	1 hour	Flipchart paper, coloured markers, place markers
Community social mapping	To take a snapshot of the community and better understand its geographic layout, provision, and the existence of basic services, access to infrastructure, and the dynamics of inclusion/exclusion from development planning and decision-making	2-3 hours	Flipchart paper, coloured markers
Hazard and vulnerability mapping	To identify the natural hazards that exist in the community, the people they impact, and the places and assets that are affected, in order to identify the underlying drivers of exposure and vulnerability	1 hour	Large sheets of paper, preferably translucent or tracing paper, coloured markers

Method	Objective	Time	Supplies
Natural resource and livelihood mapping	To identify the natural resources and modes of production utilized by a community in order to identify the ecosystem services that are relied upon before and after a natural hazard strikes	1 hour	Flipchart paper, large sheets of paper, preferably translucent or tracing paper, coloured markers

Each of the four participatory mapping tools are appropriate for assessing different aspects of biophysical, demographic, and socioeconomic variables that make up the local community and natural resource vulnerability, as outlined in Table 21.

Table 21. Descriptions of local community variables and the participatory mapping tools used to assess them.

Community variable	Description	Hazard ranking	Community social mapping	Hazard and vulnerability mapping	Natural resource and livelihood mapping
Livelihoods and income generation	A greater diversity of livelihoods increases sources of income generation and resilience to a larger number of natural hazards and climate change		✓		✓
Human capital	Low levels of education, literacy, and skills impact income-earning opportunities and employability		✓	✓	✓
Social capital	The socio-cultural networks and resources that people draw upon in daily life and for livelihoods		✓		
Poverty	Lower household income and less financial assets limits the opportunities to respond and adapt when hazards strike		✓	✓	✓
Food security and nutrition	Access to a sufficient quantity of food and a nutritionally valuable diet are essential to good health				✓
Natural resources	Healthy ecosystems and abundance natural resources help absorb the shocks of natural hazards and provide the foundation for rural livelihood resilience to climate change				✓
Infrastructure	The absence and poor quality of transportation, water, and sanitation infrastructure undermine community and household resilience to natural hazards		✓	✓	
Preparedness and response	If households and communities are unprepared for natural hazards and climate change, they fail to take preventative measures that could reduce their impacts	✓		✓	

Community variable	Description	Hazard ranking	Community social mapping	Hazard and vulnerability mapping	Natural resource and livelihood mapping
Conflict and displacement	Conflict and insecurity are the largest drivers of displacement, which contributes to vulnerability by uprooting households and communities, undermining their sources of income, and reducing their access to resources and services		✓	✓	✓
Gender equity	Women in Afghanistan have less access to livelihoods and income generation, lower mobility, are less educated and more illiterate, have less access to resources and services, are considerably food insecure, and face severe maternal health issues		✓	✓	✓

Each of the four participatory mapping tools follow a specific set of steps when conducted in the field, as outlined in Table 22.

Table 22. Detailed methodological guidelines for the four components of participatory mapping.

Step	Procedure
	Hazard ranking
1	Explain objective and set up materials for ranking the natural hazards
2	Ask participants to list all hazards that occur in their community
3	Facilitator draws a spider chart on flipchart paper, with four concentric circles and the names of each hazard spaced evenly along the outside circle
4	Lay the chart on the ground. Give participants one place marker for each natural hazard they identified and ask them to rank the hazards on a scale of 1-5 according to the degree to which they are disruptive to the community (1 = not disruptive, 5 = extremely disruptive)
5	Once all hazards have been ranked, ask participants to reflect on any changes in frequency, severity, and impact of hazards today as compared to the past 20, 30, or 40 years
6	Thank all participants for their time and contributions
Output	**Hazard ranking diagram**
	Community social mapping
1	Explain the objective of this exercise and select an appropriate location for putting the map together. Make sure that the space is large enough and accessible to everyone that wants to participate. If the exercise is organized outside, ensure that there is sufficient shade and seating areas
2	Ask participants to start drawing prominent places and key landmarks of their community, such as mosques, roads, schools, clinics, etc. Allow the participants to be creative and choose their own symbols and designs for these landmarks to start giving the map the unique flavour of the community
3	Ask participants to identify the common areas in their community, like bazaars, social areas, cemeteries, etc.

4	Ask participants to identify where there are households and other shelter structures in their community. Next, ask participants to identify where marginalized or disadvantaged households live, in order to begin gauging the social dynamics and distribution of land and other resources in the community
5	Ask participants to identify the existence of basic services, their locations, as well as the status of their provision—for example, clinics, government offices, community centres, etc.
6	Once all major features of the community are mapped, and participants are satisfied with their map, engage with the group with some probing questions about changes and developments in the community over recent years. For example, inquire about the origin of communal spaces and how they're managed today as compared to in years past, etc.
7	Thank all participants for their time and contributions
Output	**Detailed mapping of the community's structure, assets, resources, and livelihood patterns**
	Hazard and vulnerability mapping
1	Explain the objectives of the exercise and set up the materials for drawing the map
2	Using the list of natural hazards produced in the Hazard Ranking exercise, the facilitator goes one-by-one through each natural hazard and asks participants to identify and draw on the map: 1) where they take place, 2) which areas are impacted, 3) which households are impacted, 4) which assets are impacted, and 5) any changes that have occurred in the past 20-30 years in terms of frequency or severity of the hazard
3	The facilitator continues asking these five questions for each natural hazard until participants complete mapping for all hazards on top of the community social map (see above). Make sure that there is a thorough discussion on infrastructure and resources, such as roads, houses, bridges, schools, clinics, micro-hydropower, mosques, flour mills, markets, irrigation canals, agriculture land, forest land, rangeland, soil, etc., and stress how some of these anthropogenic activities may exacerbate various hazards
4	Ask participants to brainstorm on the similarities and differences between the impacts of different hazards
5	Ask participants to mark on the map areas where the most vulnerable households, assets, and natural resources are located, to help identify those areas of the community that are most exposed to the natural hazards
6	At this point, basic facts about exposure and vulnerability to natural hazards should be identified in the community, namely which persons, assets, and resources are most or least in harm's way. In order to bring in a climatological angle, engage the participants in a probing discussion on observed changes in the frequency, severity, and impacts of the relevant natural hazards over recent decades, e.g. 20, 30 or 40 years. These observations should be documented in a narrative format which can then be compared to climate change models and projections to ground-truth the potential future impacts of climate change on the community
7	Thank all participants for their time and contributions
Output	**Detailed mapping of the community's natural hazards and potential vulnerabilities**
	Natural resource and livelihood mapping
1	Explain the objectives of the exercise and set up the materials for drawing the map
2	Ask participants to brainstorm all the different livelihoods that exist in their community. Once these livelihoods are identified, continue by probing questions on which natural resources are used to support these livelihoods, e.g., rangelands for animal grazing, wood forests for furniture production, etc.

3	List all these livelihoods and natural resources on a flipchart paper and ask the participants to draw a symbol or index for each one
4	Working off the Community Social Map, ask participants to identify the locations of these natural resourc-es, marking with the symbols they previously selected for each one
5	With all mapping completed, the Facilitator now asks the participants questions about the distribution and use of these natural resources by "interviewing the map" and asking open-ended questions about which natural resources are most impacted by natural hazards, which are most relied upon in the aftermath of a natural hazard, etc.
6	Ask the participants to describe any changes in the existence, access or management of natural resourc-es over recent decades, e.g. 20, 30 or 40 years, in order to understand the potential impacts of climate change on the ecosystem and livelihoods, as well as anthropogenic impacts on ecosystem services and the community's overall resilience. Ask how management changes have affected the occurrence of certain hazards (e.g., landslides)
7	Ensure that the Note Taker captures the subtleties of the discussion during the exercise and that the Facil-itator takes proactive steps to ensure everyone's participation in the exercise
8	Thank all participants for their time and contributions
Output	**Detailed mapping of the community's natural resources and livelihoods**

In the context of assessing local community and natural resources vulnerability, different field methodologies should be employed, as outlined in Table 23.

Table 23. Field methods for assessing local community and natural resources vulnerability indicators.

No.	Sub-indicator	Field data collection method	Secondary data sources	Component of vulnerability assessed
Biophysical resources indicators				
5.1.1	Community use of and access to fuelwood	BNS; participatory mapping; vegetation surveys	None	Adaptive capacity
5.1.2	Types and numbers of livestock owned	BNS, livestock count surveys	None	Adaptive capacity
5.1.3	Number of agroforestry trees grown and owned	BNS; participatory mapping	None	Adaptive capacity
5.1.4	Area of rainfed/dryland, irrigated, and high-yielding crops	BNS; participatory mapping; vegetation surveys	None	Sensitivity
5.1.5	Number of agricultural landholdings, including orchards	BNS; participatory mapping	None	Adaptive capacity
5.1.6	Net sown area	BNS; participatory mapping	None	Sensitivity
5.1.7	Amount of fertilizers consumed and manure used	BNS	None	Sensitivity

No.	Sub-indicator	Field data collection method	Secondary data sources	Component of vulnerability assessed
5.1.8	Mean rainfed crop yields	BNS	None	Sensitivity
5.1.9	Biological richness	Biodiversity surveys	None	Sensitivity; adaptive capacity
5.1.10	Area of high-quality grazing land	BNS; participatory mapping; vegetation surveys; livestock grazing pattern surveys	None	Sensitivity; adaptive capacity
Demographic status indicators				
5.2.1	Age of household members	BNS	NSIA, FNS, CCAP, DHS, QoL	Adaptive capacity
5.2.2	Sex of household members	BNS	NSIA, FNS, CCAP, DHS, QoL	Adaptive capacity
5.2.3	Household size	BNS	NSIA, FNS, CCAP, DHS, QoL	Adaptive capacity
Socioeconomic status indicators				
5.3.1	Household wealth	BNS; participatory mapping	NSIA, FNS, CCAP, DHS, QoL	Adaptive capacity
5.3.2	Household income	BNS; participatory mapping	NSIA, FNS, CCAP, DHS, QoL	Adaptive capacity
5.3.3	Education of household members	BNS; participatory mapping	NSIA, FNS, CCAP, DHS, QoL	Adaptive capacity
5.3.4	Occupation of household members	BNS; participatory mapping	NSIA, FNS, CCAP, DHS, QoL	Adaptive capacity
5.3.5	Household diversification of income sources	BNS; participatory mapping	NSIA, FNS, CCAP, DHS, QoL	Sensitivity
5.3.6	Community livelihood support institutions	BNS; participatory mapping	NSIA, FNS, CCAP, DHS, QoL	Adaptive capacity
5.3.7	Human and social capital	BNS; participatory mapping	NSIA, FNS, CCAP, DHS, QoL	Sensitivity; adaptive capacity
5.3.8	Rural population density and distribution	BNS; participatory mapping	NSIA, FNS, CCAP, DHS, QoL	Sensitivity

Secondary data sources

The National Statistics and Information Authority (NSIA), also previously known as the Central Statistics Organization (CSO), publishes periodic papers, using a large number of demographic indicators to serve as reliable and high-quality data at the country level. The NSIA, 2018 reports on some important demographic indicators in the form of 'Afghanistan's Provincial Profile'. In addition, "to respond to the need for the quality and reliable data of provinces of Afghanistan, National Statistics and Information Authority (NSIA) initiated friendly use of the data and developed 2018 provincial profile which is the latest provincial profile based on four comprehensive surveys of National Risk and Vulnerability Assessment (NRVA). This series of surveys is the largest national surveys in Afghanistan. The survey was conducted every two years during 2007-2017 and provides important socio-economic and demographic information about Afghanistan population at the provincial level", (NSIA, 2018). Moreover, "for the development of Afghanistan provincial profile, microdata from the NRVA 2007-08, ALCS 2011-12, ALCS 2013-14, and ALCS 2016-2017 is used. The key indicators are mostly focused on population density, health, education, gender equity, economy, and services and infrastructure. This provincial profile compares selected indicators between the four rounds of the surveys and provides a clear numeric profile of the country, which allows data users to quickly catch up what they are interested in" (NSIA, 2018).

The Food and Nutrition Security (FNS) is part of the AKF-A's internal level studies used to report on food security and nutrition status in a few districts of Badakhshan province as part of some core program areas of AKF-A. In addition to food security, consumption, and nutrition, the report further highlights household wealth, characteristics of the study population, household socio-demographic characteristics, and occupation, based on three selected districts (Wakhan, Zebak, and Ishkashim) of Badakhshan province. The study used "a non-experimental design, using quantitative methods to collect household-level food security data, and nutrition data about women of childbearing age and under five children" (FNS, 2018).

The Citizen Charter Afghanistan Project, (CCAP) is a national/country level program/project implemented across Afghanistan by some development agencies. The program focuses on the development priorities at the community level through the leadership of Community Development Councils (CDCs). AKF-A, as one of the international development agencies, also facilitates the implementation of CCAP around its target regions: Badakhshan, Baghlan/Samangan, Bamyan/Parwan, and Takhar/Kunduz as a facilitating partner. As part of the facilitation processes and related data management aspects, AKF-A also manages the relevant demographic data at the CDC level that mainly highlights some demographic figures at the community level, including family and household. These data are collected at different stages and are a type of progressive activity.

The Demographic and Health Survey (DHS), Afghanistan, is implemented by the Central Statistics Organization (CSO) now also known as National Statistics and Information Authority (NSIA) and the Ministry of Public Health (MoPH) around Afghanistan. The overall objective is to provide reliable, accurate, and up-to-date data for the country, while it specifically "is a national sample survey that provides up to date information on fertility levels; marriage, fertility preferences, awareness and use of family planning methods, child feeding practices, nutrition, adult, and childhood mortality, awareness and attitudes regarding HIV/AIDS, women's empowerment, and domestic violence." (CSO, MoPH, and ICF, 2017). The study has been conducted and analyzed at the household level and contains relevant information, such as household characteristics, household possessions, wealth quintiles, household population by age, sex, and residence, household composition, school attendance by survivorship of parents, educational attainment of the female household population, educational attainment of the male household population, school attendance ratios, reasons for children never attending school, reasons for children dropping out of school, background characteristics of respondents, educational attainment of women, educational attainment of men, literacy of women, literacy of men, employment status of women, employment status of men, occupation of women, occupation of men, types of employment of women, types of employment of men, and other necessary health-related information. The study is mostly based on quantitative research methodologies and used the stratified two-stage sample design based on households listing.

The Aga Khan Development Network (AKDN)'s Quality of Life (QoL) Assessments are periodic assessments that are conducted every three to five years to understand the overall quality of life of people living in AKDN program areas in relation to various socio-economic domains. These assessments are periodically conducted in all AKDN's coverage areas, including overall countries where AKDN operates. "The main objective of the quality of life assessment programme is to create an understanding about the quality of life of people living in Aga Khan Development Network's programme area and assess changes over time. The body of knowledge helps guide AKDN in strategic decision making and programme development toward a multi-input area-based development approach, and contributes to the general debate on impact assessment of development interventions" (USAID, AKF, 2015). These assessments cover a broad range of life domains: the household economy, social and cultural life, the natural and built environment, health and education, and issues of voice and representation. A mixed research methodology is used to conduct such assessments. First, a household survey using a structured questionnaire is used to collect representative quantitative information for a core set of indicators at household and individual levels (household head and spouse). The domains covered in the survey include the household economy, health, education, the natural and built environment, some aspects of associational life, voice and representation as well as overall QoL. Second, a qualitative study of 'sentinel sites' is conducted. Sentinel sites are a limited number of villages or urban sites that are chosen to reflect variations in key characteristics which affect the quality of life. The sentinel sites study does not yield representative data, as the survey does, but instead aims to capture diversity in the geographical area. In these sites, group discussions and individual interviews are used to explore a range of topics: changes in livelihoods, access to and quality of health and education services, aspects of social relations and associational life, issues of voice an representation, as well as concerns and aspirations among different population groups such as youth. The QoL quantitative assessments obtain a large sample using proportionate to population size (PPS) and stratified random sampling methodologies. While purposive sampling methods are applied in terms of the qualitative part.

It is important to mention that the availability of QoL assessment reports and data are strictly subjected to the prior permission and consent of the director of QoL based at Geneva's main headquarters office, while in AKF-A it is subjected to the consent of the Chief Executive Officer (CEO).

Indicator 5.1 – Biophysical resources indicators

5.1.1. Community use of and access to fuelwood

Field data collection protocol

Within the BNS administered, a subset of questions should ask participants about their use of and access to fuelwood, the plant species that typically constitute fuelwood, and where they typically collect fuelwood. These questions can also be used in participatory mapping, using the natural resource and livelihood mapping tool (see Table 22). Community use of and access to fuelwood can also be directly assessed in field plots by recording direct signs of human utilization following the approaches outlined in Indicator 2.2, section 4.

Analysis & modelling

For assessing community use of and access to fuelwood at the plot scale, analysis of variance can be used between plots to determine spatial differences in human utilization (shrub collection) and within plots over time to determine temporal differences in the use of and access to fuelwood. For assessments at the community scale, BNS results can be tabulated directly at the spatial unit conducted (e.g., household, community) and can be mapped using administrative layers (e.g., village points, community polygons) in GIS. Participatory mapping outputs (e.g., a detailed map of areas with fuelwood) can be georeferenced and mapped in GIS indicating areas of actual or perceived vulnerability. Communities that have a high use of and low access to fuelwood likely have a lower adaptive capacity and thus are likely more vulnerable.

The main output from this component of the local communities and natural resources vulnerability assessment are vectorized maps of fuelwood areas, as well as spatial and temporal trends in community use of fuelwood at the scale of individual survey plots.

5.1.2. Types and numbers of livestock owned

Field data collection protocol

Within the BNS administered, a subset of questions should ask participants about the types and numbers of livestock owned and their age/sex distribution. However, because the answers to these questions can sometimes be unreliable, it is often necessary to also conduct livestock counts in the field. Livestock counts can be performed to directly observe livestock and quantify their densities. First, livestock herds must be located in the field. Speaking with villagers about where shepherds have gone to graze animals is one way to locate individual herds. Another approach is to select herds to sample that are close to villages. The third approach is to hire a local guide to assist with finding a given herd in the field.

Once the livestock have been located, all individuals should be counted using binoculars and/or a spotting scope by species (e.g., sheep, goat) and the sex and age should be noted. Two observers should be used to ensure the accuracy of the count, and a GPS point should be taken from the point where the count was conducted.

Analysis & modelling

For assessments at the community scale, BNS results can be tabulated directly at the spatial unit conducted (e.g., household, community) and can be mapped using administrative layers (e.g., village points, community polygons) in GIS. Livestock densities obtained through livestock counts can be calculated through simple summation of observed animals through counts divided by the area of the survey. Densities can be checked against the reported values in the BNS. Households or communities that own fewer livestock likely have less income and lower income diversification, which equates to lower adaptive capacity. Thus they are likely to be more vulnerable.

The main output from this component of the local communities and natural resources vulnerability assessment is a map of livestock densities by type, summarized at the spatial unit chosen for analysis.

5.1.3. Number of agroforestry trees grown and owned

Field data collection protocol

Within the BNS administered, a subset of questions should ask participants about the number of agroforestry trees grown and owned. These questions can also be used in participatory mapping, using the natural resource and livelihood mapping tool (see Table 22).

Analysis & modelling

For assessments at the community scale, BNS results can be tabulated directly at the spatial unit conducted (e.g., household, community) and can be mapped using administrative layers (e.g., village points, community polygons) in GIS. Participatory mapping outputs (e.g., a detailed map of agroforestry plantations by type and owner) can be georeferenced and mapped in GIS. Households or communities that own fewer agroforestry trees likely have less income and lower income diversification, which equates to lower adaptive capacity. Thus they are likely to be more vulnerable.

The main output from this component of the local communities and natural resources vulnerability assessment are vectorized maps of agroforestry plots (plantations) by type and owner.

5.1.4. Area of rainfed/dryland, irrigated, and high-yielding crops

Field data collection protocol

Within the BNS administered, a subset of questions should ask participants about the amount of rainfed/dryland, irrigated, and high-yielding crops owned. These questions can also be used in participatory mapping, using the natural resource and livelihood mapping tool (see Table 22). Areas of each agriculture type can also be mapped using the supervised land cover classification approach outlined in Indicator 2.1, which requires GPS points of different agricultural types collected in the field. However, it is difficult to differentiate similar agricultural types using that approach, so this should be combined with the BNS and participatory mapping methodologies.

Analysis & modelling

BNS results can be tabulated directly at the spatial unit conducted (e.g., household, community) and can be mapped using administrative layers (e.g., village points, community polygons) in GIS. Participatory mapping outputs (e.g., a detailed map of agricultural areas by type) can be georeferenced and mapped in GIS. Following the land cover classification approach outlined in Indicator 2.1, areas of irrigated and rainfed agricultural can be calculated by summing pixels of each and multiplying by the spatial resolution of the classified dataset. Households or communities that own less area of agricultural lands of various types are likely more sensitive to climate change-related reductions in agricultural potential (particularly rainfed agriculture). Thus they are likely to be more vulnerable.

The main outputs from this component of the local communities and natural resources vulnerability assessment are vectorized and high-resolution maps of agricultural areas by type.

5.1.5. Number of agricultural landholdings

Field data collection protocol

Within the BNS administered, a subset of questions should ask participants about their number of agricultural landholdings. This question can also be used in participatory mapping, using the natural resource and livelihood mapping tool (see Table 22).

Analysis & modelling

BNS results can be tabulated directly at the spatial unit conducted (e.g., household, community) and can be mapped using administrative layers (e.g., village points, community polygons) in GIS. Participatory mapping outputs (e.g., a detailed map of agricultural landholdings by owner) can be georeferenced and mapped in GIS. Households or communities that own fewer agricultural landholdings likely have less income and lower income diversification, which equates to lower adaptive capacity. Thus they are likely to be more vulnerable.

The main outputs from this component of the local communities and natural resources vulnerability assessment are vectorized maps of the number of agricultural landholdings area within the spatial unit of analysis considered.

5.1.6. Net sown aread

Field data collection protocol

Within the BNS administered, a subset of questions should ask participants about their net sown area. This question can also be used in participatory mapping, using the natural resource and livelihood mapping tool (see Table 22).

Analysis & modelling

BNS results can be tabulated directly at the spatial unit conducted (e.g., household, community) and can be mapped using administrative layers (e.g., village points, community polygons) in GIS. Participatory mapping outputs (e.g., a detailed map of sown areas) can be georeferenced and mapped in GIS. Households or communities have less net sown area are likely more sensitive to climate change-related reductions in agricultural suitability. Thus they are likely to be more vulnerable.

The main outputs from this component of the local communities and natural resources vulnerability assessment are vectorized maps of net sown area within the spatial unit of analysis considered.

5.1.7. Amount of fertilizers consumed and manure used

Field data collection protocol

Within the BNS administered, a subset of questions should ask participants about the amount of fertilizers consumed and manure used.

Analysis & modelling

BNS results can be tabulated directly at the spatial unit conducted (e.g., household, community) and can be mapped using administrative layers (e.g., village points, community polygons) in GIS. Households or communities that use less fertilizer and manure are likely more sensitive to climate change-related reductions in agricultural suitability. Thus they are likely to be more vulnerable.

The main outputs from this component of the local communities and natural resources vulnerability assessment are vectorized maps of the amount of fertilizers consumed and manure used within the spatial unit of analysis considered.

5.1.8. Mean rainfed crop yields

Field data collection protocol

Within the BNS administered, a subset of questions should ask participants about their mean rainfed crop yields.

Analysis & modelling

BNS results can be tabulated directly at the spatial unit conducted (e.g., household, community) and can be mapped using administrative layers (e.g., village points, community polygons) in GIS. Households or communities have lower rainfed crop yields are likely more sensitive to climate change-related reductions in agricultural suitability. Thus they are likely to be more vulnerable.

The main outputs from this component of the local communities and natural resources vulnerability assessment are vectorized maps of mean rainfed crop yields within the spatial unit of analysis considered.

5.1.9. Biological richness

Field data collection protocol

The number of wildlife species can be calculated within a given spatial unit by conducting wildlife surveys (see Indicator 4.1).

Analysis & modelling

Richness results from wildlife surveys can be tabulated directly at the spatial unit conducted (e.g., household, community) and can be mapped using administrative layers (e.g., village points, community polygons) in GIS. However, because exhaustive surveys are often infeasible, for this indicator, it is also possible to utilize published databases on species range maps, such as those from the International Union for the Conservation of Nature Red List of Threatened Species (available at https://www.iucnredlist.org/resources/spatial-data-download). Range maps can be overlaid in GIS and richness can be calculated as a simple sum, at the spatial resolution desired. The values can then further be summarized within the spatial unit desired. Regions that have less biological richness typically represent unproductive or degraded landscapes, which are characterized as having a lower adaptive capacity and greater sensitivity. Such regions are thus likely to be more vulnerable.

The main outputs from this component of the local communities and natural resources vulnerability assessment are vectorized maps of species richness within the spatial unit of analysis considered.

5.1.10. Area of high-quality grazing land

Field data collection protocol

Within the BNS administered, a subset of questions should ask participants about the area of high-quality grazing land accessible. This question can also be used in participatory mapping, using the natural resource and livelihood mapping tool (see Table 22).

Livestock grazing intensity can also be measured as a proxy for high-quality grazing land using field vegetation surveys at two spatial scales: plot scale and landscape scale. At the plot scale, field methods for quantifying overall rangeland condition can be followed as described in Indicator 2.2, section 3. At the landscape scale, if GPS units are available to deploy on livestock (the preferred method), then GPS collars should be attached to two animals per herd for the duration of the grazing period (e.g., summer). The GPS units should continuously record data every 20-30 minutes and should be collected from the animals at the end of the survey period. The type of livestock (e.g., cattle, goat) should be noted along with the approximate herd size.

If GPS units are unavailable to deploy, then a questionnaire should be given to each household or community (it can be as part of the BNS). The following questions should be asked during each questionnaire:

1. Where did you take your livestock for grazing this season (names of places or points on a map)?
2. How did you decide where to take your livestock?
3. How much time did you spend at each possible grazing location?
4. Why didn't you spend more time at each location? Why didn't you spend less time?
5. Describe the preferred grazing areas for livestock. Rank the following attributes from most to least important: slope, aspect, elevation, land cover, distance from water, distance from the road, distance from the village.
6. Describe undesirable grazing areas for livestock. Rank the following attributes from worst to best in terms of grazing potential: slope, aspect, elevation, land cover, distance from water, distance from the road, distance from the village.
7. Do you always follow the same grazing routes each year? If no, where do you go during "bad" years?

In addition to the questionnaire, it is necessary to conduct direct counts of the livestock herds because the information from the questionnaires can be inaccurate. See Indicator 5.2 for the field data collection protocol for livestock counts.

Analysis & modelling

BNS results can be tabulated directly at the spatial unit conducted (e.g., household, community) and can be mapped using administrative layers (e.g., village points, community polygons) in GIS. Participatory mapping outputs (e.g., a detailed map of high-quality grazing lands) can be georeferenced and mapped in GIS.

For assessing high-quality grazing areas at the plot and landscape scales, the analytical methods outlined in Indicator 2.2 can be followed. In addition, for assessing livestock grazing intensity at the landscape scale—an inverse proxy for high-quality grazing areas—cost-weighted distance surfaces can be modelled that serve as direct and indirect measures of grazing. Direct measures include point locations from GPS collars. Using all existing point records from GPS collars (standardized by operating time across herds), a heat map can be created by converting point locations into frequencies along a gridded surface (raster) using GIS, which can then further be scaled by livestock densities. The spatial resolution of the gridded surface should be set to the maximum resolution of any environmental layers (e.g., elevation, land cover) that will also be considered in the analysis. Other environmental layers will be used to define "cost surfaces" and will be informed by the data collected during household interviews. For example, if respondents indicate that animals do not graze in steep areas, a slope layer can be calculated from a digital elevation model and can be used as an inverse proxy for grazing suitability. Similarly, if shepherds tend to graze near roads and water sources, then distance layers can be created in a GIS from these variables that act as proxies as well.

The resolution of all cost layers should be standardized to the layer with the maximum resolution, and layers should be resampled to this resolution if necessary. Then, using the information on ranked importance from the surveys, each cost layer can be weighted to the appropriate level of significance to produce a final model that represents grazing intensity. Regions that have less high-quality grazing land and higher livestock grazing intensities are likely more degraded and less suitable for alternative land uses, which limits adaptive capacity and represents regions of greater vulnerability.

The main outputs from this component of the local community and natural resources vulnerability assessment are vectorized and moderate to high-resolution resolution maps of rangeland condition and livestock grazing intensity, as well as spatial and temporal trends in rangeland condition and livestock grazing intensity at the scale of individual survey plots.

Indicator 5.2 – Demographic status indicators

5.2.1. Age of household members

Field data collection protocol

Within the BNS administered, a subset of questions should ask participants about the age of each household member. Because primary data is limited in its geographic coverage, secondary data from the NSIA, FNS, CCAP, DHS, and QoL surveys can best be used for this indicator.

Analysis & modelling

BNS results can be tabulated directly at the spatial unit conducted (e.g., household, community) and can be mapped using administrative layers (e.g., village points, community polygons) in GIS. Households with higher mean ages likely have fewer income and employment opportunities, which reduces their adaptive capacity. Thus they are likely to be more vulnerable. Results from the NSIA, FNS, CCAP, DHS, and QoL surveys are already tabulated in their nominal spatial scales; these results can be aggregated if desired to match coarser spatial resolutions.

The main outputs from this component of the local communities and natural resources vulnerability assessment are vectorized maps of mean age of household members within the spatial unit of analysis considered.

5.2.2. Sex of household members

Field data collection protocol

Within the BNS administered, a subset of questions should ask participants about the sex of each household member. Because primary data is limited in its geographic coverage, secondary data from the NSIA, FNS, CCAP, DHS, and QoL surveys can best be used for this indicator.

Analysis & modelling

BNS results can be tabulated directly at the spatial unit conducted (e.g., household, community) and can be mapped using administrative layers (e.g., village points, community polygons) in GIS. Households with greater proportions of women likely have fewer income, education, and employment opportunities, which reduces their adaptive capacity. Thus they are likely to be more vulnerable. Results from the NSIA, FNS, CCAP, DHS, and QoL surveys are already tabulated in their nominal spatial scales; these results can be aggregated if desired to match coarser spatial resolutions.

The main outputs from this component of the local communities and natural resources vulnerability assessment are vectorized maps of the mean sex ratio of household members within the spatial unit of analysis considered.

5.2.3.Household size

Field data collection protocol

Within the BNS administered, a subset of questions should ask participants about the number of household members. Because primary data is limited in its geographic coverage, secondary data from the NSIA, FNS, CCAP, DHS, and QoL surveys can best be used for this indicator.

Analysis & modelling

BNS results can be tabulated directly at the spatial unit conducted (e.g., household, community) and can be mapped using administrative layers (e.g., village points, community polygons) in GIS. Households with fewer members likely have fewer income and employment opportunities, which reduces their adaptive capacity. Thus they are likely to be more vulnerable. Results from the NSIA, FNS, CCAP, DHS, and QoL surveys are already tabulated in their nominal spatial scales; these results can be aggregated if desired to match coarser spatial resolutions.

The main outputs from this component of the local communities and natural resources vulnerability assessment are vectorized maps of mean household size within the spatial unit of analysis considered.

Indicator 5.3 – Socioeconomic status indicators

5.3.1. Household wealth

Field data collection protocol

Within the BNS administered, a subset of questions should ask participants to list all of their assets that determine wealth. An exhaustive, predefined list of assets can also be provided to household members in the survey for participants to fill out. Because primary data is limited in its geographic coverage, secondary data from the NSIA, FNS, CCAP, DHS, and QoL surveys can best be used for this indicator.

Analysis & modelling

BNS results can be tabulated directly at the spatial unit conducted (e.g., household, community) and can be mapped using administrative layers (e.g., village points, community polygons) in GIS. Households with lower wealth likely have fewer opportunities to obtain necessary livelihoods, which reduces their adaptive capacity. Thus they are likely to be more vulnerable. Results from the NSIA, FNS, CCAP, DHS, and QoL surveys are already tabulated in their nominal spatial scales; these results can be aggregated if desired to match coarser spatial resolutions.

The main outputs from this component of the local communities and natural resources vulnerability assessment are vectorized maps of mean household wealth within the spatial unit of analysis considered.

5.3.2. Household income

Field data collection protocol

Within the BNS administered, a subset of questions should ask participants about their total income within a specified time period (e.g., week or month). Because primary data is limited in its geographic coverage, secondary data from the NSIA, FNS, CCAP, DHS, and QoL surveys can best be used for this indicator.

Analysis & modelling

BNS results can be tabulated directly at the spatial unit conducted (e.g., household, community) and can be mapped using administrative layers (e.g., village points, community polygons) in GIS. Households with lower income likely have fewer opportunities to obtain necessary livelihoods, which reduces their adaptive capacity. Thus they are likely to be more vulnerable. Results from the NSIA, FNS, CCAP, DHS, and QoL surveys are already tabulated in their nominal spatial scales; these results can be aggregated if desired to match coarser spatial resolutions.

The main outputs from this component of the local communities and natural resources vulnerability assessment are vectorized maps of mean household income within the spatial unit of analysis considered.

5.3.3. Education of household members

Field data collection protocol

Within the BNS administered, a subset of questions should ask participants about the highest level of education obtained by each household member. Because primary data is limited in its geographic coverage, secondary data from the NSIA, FNS, CCAP, DHS, and QoL surveys can best be used for this indicator.

Analysis & modelling

BNS results can be tabulated directly at the spatial unit conducted (e.g., household, community) and can be mapped using administrative layers (e.g., village points, community polygons) in GIS. Households with lower education levels likely have fewer opportunities for employment and lower income, which reduces their adaptive capacity. Thus they are likely to be more vulnerable. Results from the NSIA, FNS, CCAP, DHS, and QoL surveys are already tabulated in their nominal spatial scales; these results can be aggregated if desired to match coarser spatial resolutions.

The main outputs from this component of the local communities and natural resources vulnerability assessment are vectorized maps of mean and maximum household education level within the spatial unit of analysis considered.

5.3.4. Occupation of household members

Field data collection protocol

Within the BNS administered, a subset of questions should ask participants about the occupation of each household member. Because primary data is limited in its geographic coverage, secondary data from the NSIA, FNS, CCAP, DHS, and QoL surveys can best be used for this indicator.

Analysis & modelling

BNS results can be tabulated directly at the spatial unit conducted (e.g., household, community) and can be mapped using administrative layers (e.g., village points, community polygons) in GIS. Households with fewer occupations, unstable occupations, and occupations associated with little income generation likely have fewer opportunities to obtain necessary livelihoods, which reduces their adaptive capacity. Thus they are likely to be more vulnerable. Results from the NSIA, FNS, CCAP, DHS, and QoL surveys are already tabulated in their nominal spatial scales; these results can be aggregated if desired to match coarser spatial resolutions.

The main outputs from this component of the local communities and natural resources vulnerability assessment are vectorized maps of occupation distributions within the spatial unit of analysis considered.

5.3.5. Household diversification of income sources

Field data collection protocol

Within the BNS administered, a subset of questions should ask participants about the number of sources from which they derive income. An exhaustive, predefined list of income sources can also be provided to household members in the survey for participants to fill out. Because primary data is limited in its geographic coverage, secondary data from the NSIA, FNS, CCAP, DHS, and QoL surveys can best be used for this indicator.

Analysis & modelling

BNS results can be tabulated directly at the spatial unit conducted (e.g., household, community) and can be mapped using administrative layers (e.g., village points, community polygons) in GIS. Households with fewer income sources have fewer options and likely have fewer opportunities to obtain necessary livelihoods, which reduces their adaptive capacity and increases their sensitivity to climate change-related natural hazards. Thus they are likely to be more vulnerable. Results from the NSIA, FNS, CCAP, DHS, and QoL surveys are already tabulated in their nominal spatial scales; these results can be aggregated if desired to match coarser spatial resolutions.

The main outputs from this component of the local communities and natural resources vulnerability assessment are vectorized maps of mean number of income sources within the spatial unit of analysis considered.

5.3.6. Community livelihood support institutions

Field data collection protocol

Within the BNS administered, a subset of questions should ask participants about the number of livelihood support institutions they have access to in the community. An exhaustive, predefined list of livelihood support institutions can also be provided to household members in the survey for participants to fill out. Because primary data is limited in its geographic coverage, secondary data from the NSIA, FNS, CCAP, DHS, and QoL surveys can best be used for this indicator.

Analysis & modelling

BNS results can be tabulated directly at the spatial unit conducted (e.g., household, community) and can be mapped using administrative layers (e.g., village points, community polygons) in GIS. Households with fewer community livelihood support institutions have fewer benefits and opportunities to obtain necessary livelihoods, which reduces their adaptive capacity and increases their sensitivity to climate change-related natural hazards. Thus they are likely to be more vulnerable. Results from the NSIA, FNS, CCAP, DHS, and QoL surveys are already tabulated in their nominal spatial scales; these results can be aggregated if desired to match coarser spatial resolutions.

The main outputs from this component of the local communities and natural resources vulnerability assessment are vectorized maps of mean number of community livelihood support institutions within the spatial unit of analysis considered.

5.3.7. Human and social capital

Field data collection protocol

Within the BNS administered, a subset of questions should ask participants about their literacy rates (related to human capital) and their opinion on the degree of gender equality in their district (related to social capital). Participants should provide examples of actions or institutions that support their statement related to gender equality. Because primary data is limited in its geographic coverage, secondary data from the NSIA, FNS, CCAP, DHS, and QoL surveys can best be used for this indicator.

Analysis & modelling

BNS results can be tabulated directly at the spatial unit conducted (e.g., household, community) and can be mapped using administrative layers (e.g., village points, community polygons) in GIS. Households with lower literacy rates likely have fewer employment and income opportunities. Households with lower gender equality likely have greater imbalances in resource and income distribution. Both of these factors likely reduce adaptive capacity and increase sensitivity to climate change-related natural hazards. Thus such households are likely to be more vulnerable. Results from the NSIA, FNS, CCAP, DHS, and QoL surveys are already tabulated in their nominal spatial scales; these results can be aggregated if desired to match coarser spatial resolutions.

The main outputs from this component of the local communities and natural resources vulnerability assessment are vectorized maps of mean literacy rates and gender equality within the spatial unit of analysis considered.

5.3.8. Rural population density and distribution

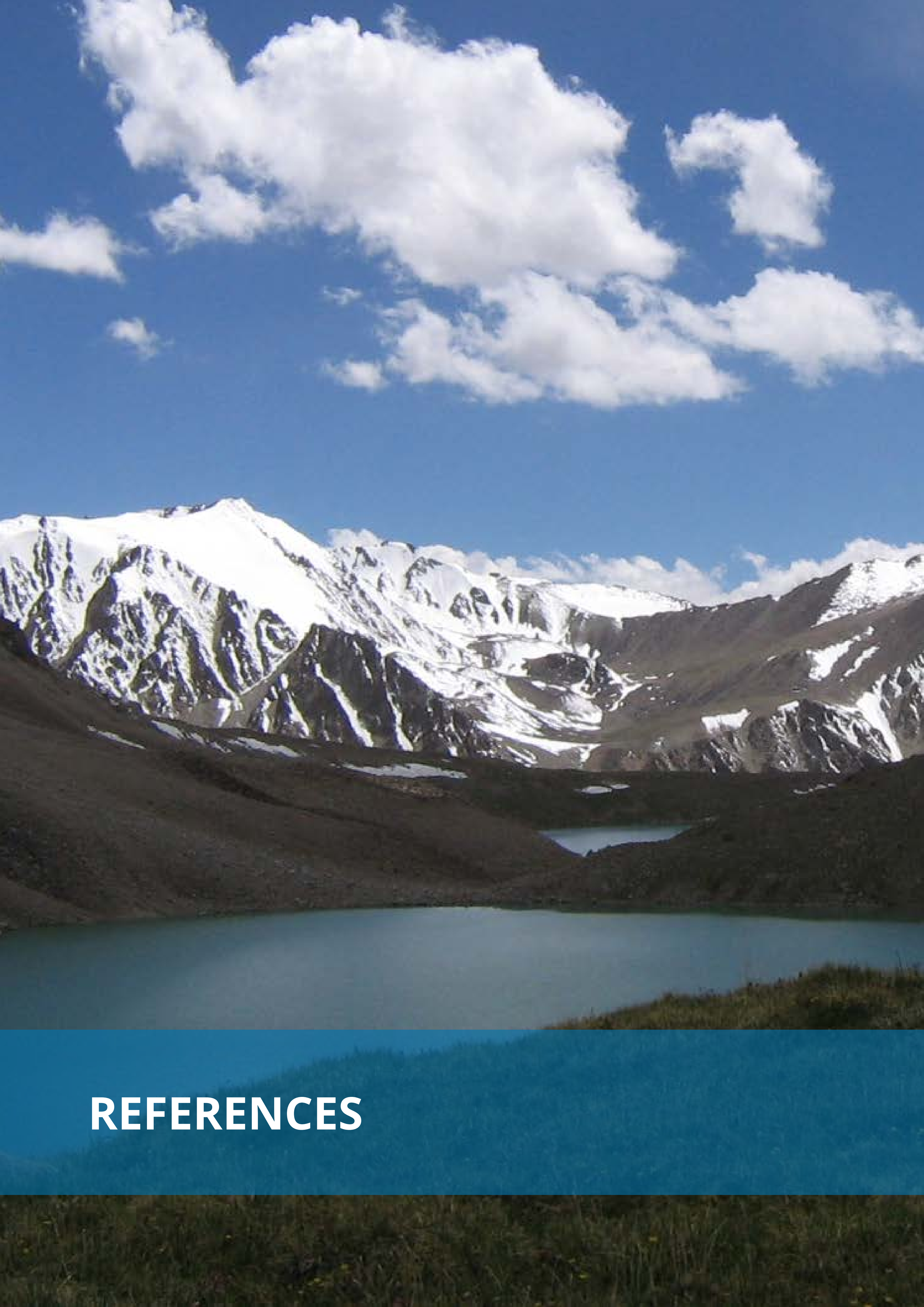
Field data collection protocol

The number of individuals per household is collected when conducting the BNS and asking questions on household size (see 5.2.3 above). Because primary data is limited in its geographic coverage, secondary data from the NSIA, FNS, CCAP, DHS, and QoL surveys can best be used for this indicator.

Analysis & modelling

BNS results can be tabulated directly at the spatial unit conducted (e.g., household, community) and can be mapped using administrative layers (e.g., village points, community polygons) in GIS. Densities can then be calculated by dividing the total number of individuals by the area considered. Rural population density can also be mapped using existing online GIS databases that have compiled census records. Regions with greater rural population density have more competition for resources, which reduces their adaptive capacity and increases their sensitivity to climate change-related natural hazards. Thus they are likely to be more vulnerable. Spatial patterns and distribution of population density can be assessed by combining population density information with results from vegetation and hydrology sections. Results from the NSIA, FNS, CCAP, DHS, and QoL surveys are already tabulated in their nominal spatial scales; these results can be aggregated if desired to match coarser spatial resolutions.

The main outputs from this component of the local communities and natural resources vulnerability assessment are vectorized and moderate resolution maps of rural population density within the spatial unit of analysis considered.



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