ASEAN Project on Disaster Risk Reduction by Integrating Climate Change Projection into Flood and Landslide Risk Assessment

Technical Report on Integrating Climate Change Projection into Landslide Risk Assessment

Case Study: Phoukhoun River Basin Pilot, Lao PDR

Japan-ASEAN Integration Fund (JAIF)
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ABSTRACT

Disaster Risk Reduction by Integrating Climate Scenarios into Landslide Risk Assessment (ASEAN DRR-CCA). The main purpose of this case study is to illustrate application of the methodologies described in the landslide guidelines developed for this project. The study area is the Phoukhoun River Basin, located in Luang Prabang Province of Lao PDR. A similar study under ASEAN DRR-CCA was conducted in Taunggyi, Myanmar.

The hazard, exposure, vulnerability and capacity assessment approach adopted in this case study is based on UNDRR definitions (formerly known as UNISDR). It should be noted that the landslide hazard used in this case study refers to landslide susceptibility, which is defined as the spatial likelihood or probability for a landslide to occur in the future, and no information on magnitude (size/volume and velocity) was available due to lack of data needed to perform the hazard assessment covering the study area.

A bivariate statistics analysis incorporating weight of evidence (WOE) was used for the landslide susceptibility mapping. The methodology relies on an inventory of landslide locations that were obtained from satellite images covering the study area, combined with controlling factors such as slope, distance to road and river network, land use, land cover and geological features. The majority of the data used for this study is freely available from the public domain. Based on the weight of evidence, GIS datasets were combined by weighted overlay techniques and to create the area landslide susceptibility map. The study used two Representative Concentration Pathway (RCP) scenarios in three time periods: the 2030s, 2050s, and 2080s. Results show an increase in susceptibility areas in the RCP 4.5 from 2050 to 2080. The high and very high zone areas increased from 1,070.13 to 1,325.52 km2 and 567.04 to 861.23 km2 respectively. In the RCP 8.5 scenario, the total zone areas fall into high and very high categories increasing from 1,011.44 km2 to 1,639.46 km2 and from 507.43 to 1091.01 km2 respectively.

Landslide vulnerability assessment is a complex process that should consider multiple dimensions and aspects, including both physical and socioeconomic factors. The vulnerability assessment for this study was completed with a sampling of surveyed households mostly located in high and very high susceptible zones.

The spatial distribution of susceptibility and vulnerability were integrated to obtain the spatial distribution of risk. Analyses indicate that highly susceptible and vulnerable households are not demonstrated to have a high level of risk individually. However, a combination of susceptibility and vulnerability creates a high level of risk. Landslide risk was classified into five categories: very high, high, moderate, low and very low. Out of 204 surveyed households, 45 and 43 households were identified as very high-risk and high-risk respectively. The three-upper classes of moderate, high, and very high-risk households made-up 64.21 percent of total households samples.

This risk assessment provides essential information for a better understanding of the potential impact caused by landslides, leading to development, initiation and enhancement of better disaster risk reduction strategies and prioritization of future landslide hazard reduction and mitigation efforts. This study also shows that the developed approach and methodology is applicable to a vulnerability assessment and can be updated when new data becomes available in future.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

1. LANDSLIDE HAZARD RISK MANAGEMENT INTRODUCTION

It is generally agreed on a global level that disaster risk management should be based on an understanding of disaster risk in all its dimensions, including vulnerability, capacity, exposure of persons and assets, and hazard characteristics. **Figure 1.1** below illustrates the basic concept of landslide hazard and risk assessment and its application in disaster risk reduction and management.

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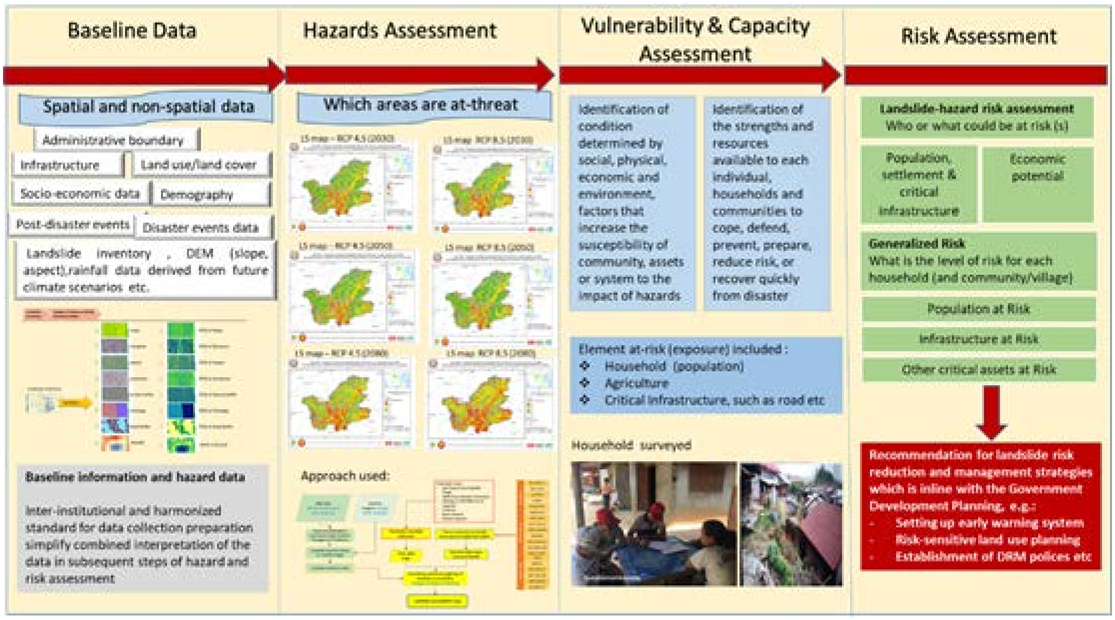


Figure 1.1 Flowchart showing the basic concept of landslide hazard & risk assessment and its application in disaster risk reduction and management

This risk assessment uses the UNISDR definition sating that disaster risk is the potential loss of life, injury, or destroyed or damaged assets which could occur to a system, society, or a community in a specific period of time and determined probability as a function of hazard, exposure, vulnerability and capacity.

From disaster risk reduction lens, risk is defined as:

Risk = Hazard x Vulnerability/Capacity.

Based on the above concept, the disaster risk assessment for this case study has been prepared based on the following basic formula.

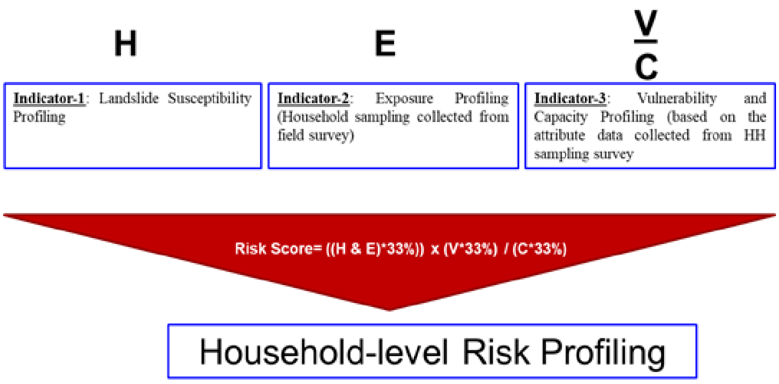


Figure 1.2 Basic formula used for calculating household risk profile in this case study

1.1 Study Area Background

The Phoukhoun watershed pilot site is located in the Central-Northern part of Lao PDR in Luang Prabang Province that has two main national roads (Road N13 and N7). Phoukhoun has a mountainous topography (~90%) with a total land area of 1,707 km2, with the highest point reaching 1600 meters. Geologically, the area is covered mainly with metamorphic and sedimentary rock formations that include a wide variety of rock types, especially slate, schist, metamorphosed claystone and sandstone, and spotted tuffaceous sandstone. Many rock masses exposed in the natural slopes are laminated and slaked, and are therefore vulnerable to frequent slope failures due to being prone to crumble. In addition, the weathering process is intensified in the relatively humid climate conditions, largely contributing to the rock mass weakening process. This has resulted in a thin soil layer with deep weathered rock layers, combined with colluvium deposits over the slopes, making this area subject to erosion and slope failures.

Phoukhoun District weather is humid and windy year-round. Minimum and maximum temperatures are 0°C and 29°C respectively. Rainfall patterns in these Northern Lao districts are dominated by the Southwest monsoon. According to historical data, the area receives annual rainfalls of around 3,000 mm, and in some cases can reach above 4,000 mm, such as in 2011. Several days during the rainy season can have rainfalls as high as 100 mm. This rainfall can lead to the development of high groundwater in slopes as well as saturation of the upper part of the soil mass that gives rise to landslides and the formation of erosion gullies.

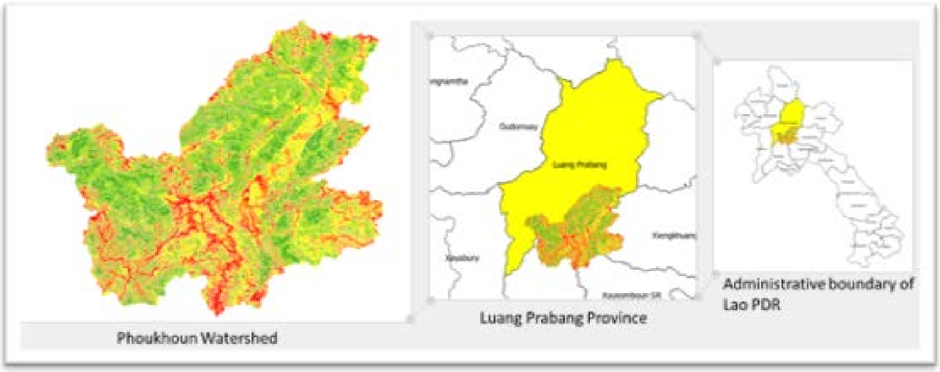


Figure 1.3 The Phoukhoun Watershed area in Lao PDR

The Phoukhoun Watershed study area can be seen in **Figure 1.4**.

Figure 1.4 shows the main road that includes more than a hundred landslides. Landslide density is higher in the urban area that includes the road from Phoukhoun to Luang Prabang, as well as at National Road Number 7 to Xieng Kuang District.

Figure 1.4 Field photos from Phoukhoun RBP, Lao PDR

In the recent past, many of these steep slopes have been disturbed due to intense development and human activities such as road expansion, building construction, etc. The intense precipitation events, the mountainous relief and geological formations combined with human activities are seen to be the key factors in triggering slope failures within many parts of Phoukhoun.

2. LANDSLIDE HAZARD AND RISK ASSESSMENT USED IN THIS CASE STUDY

2.1 Landslide susceptibility mapping

The main conditional factors (static maps) considered for susceptibility mapping were:

- Lithology
- Land use and land cover
- Slope
- Aspect
- Landslide inventory

The causative factor (dynamic maps) considered was rainfall derived from climate projection scenarios. The methodology adopted in this study is shown in **Figure 2.1**.

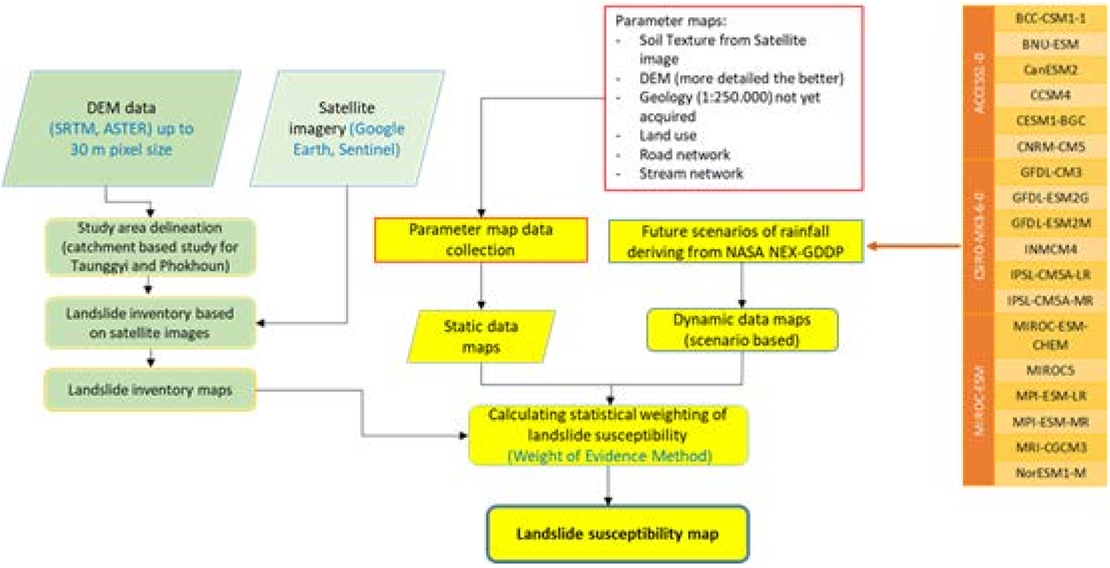


Figure 2.1 Landslide susceptibility analysis flowchart using Weight of Evidence

2.1.1 Conditional factors and parameters for data preparation

Data and information are fundamental for a reliable landslide susceptibility mapping as the assessment process is data intensive. Data gathering requires a great deal of effort. Alternative approaches to treat gaps must be found if data and information is unavailable.

Geo-spatial data mainly covers lithology, topography (elevation, slope and aspect), stream networks, land use and land cover maps, road networks, etc. The preparation and analyses have been done in a GIS environment, and the results are presented as maps. Conditional factors and parameter spatial data were built in the GIS environment using QGIS as discussed in the following section.

(1) Slope gradient

Slope is a measure of steepness using a degree of inclination relative to the horizontal plane. It is typically expressed as a percentage, an angle, or a ratio. Slope gradient can be generated from the DEM of a 30-meter pixel SRTM. Before generating a slope gradient, the map projection needs to be translated into a specific geographical area UTM (meter units), for example UTM zone 48N (for Lao PDR).

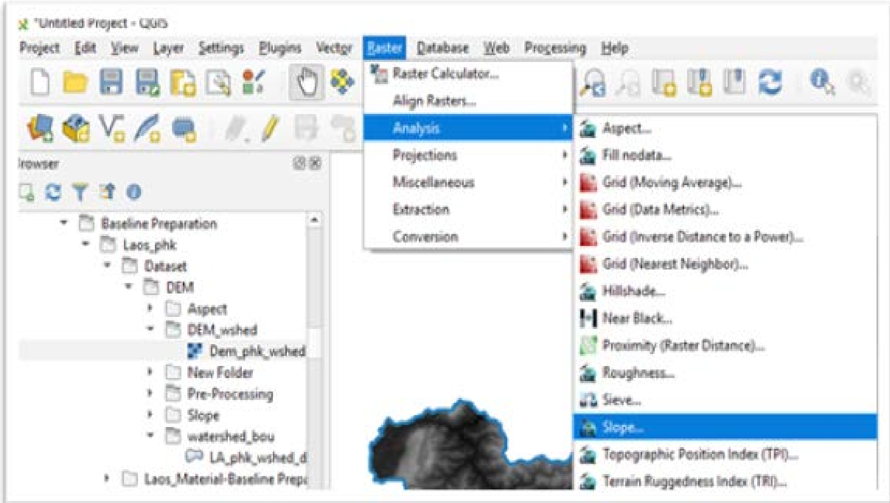


Figure 2.2 Slope gradient process

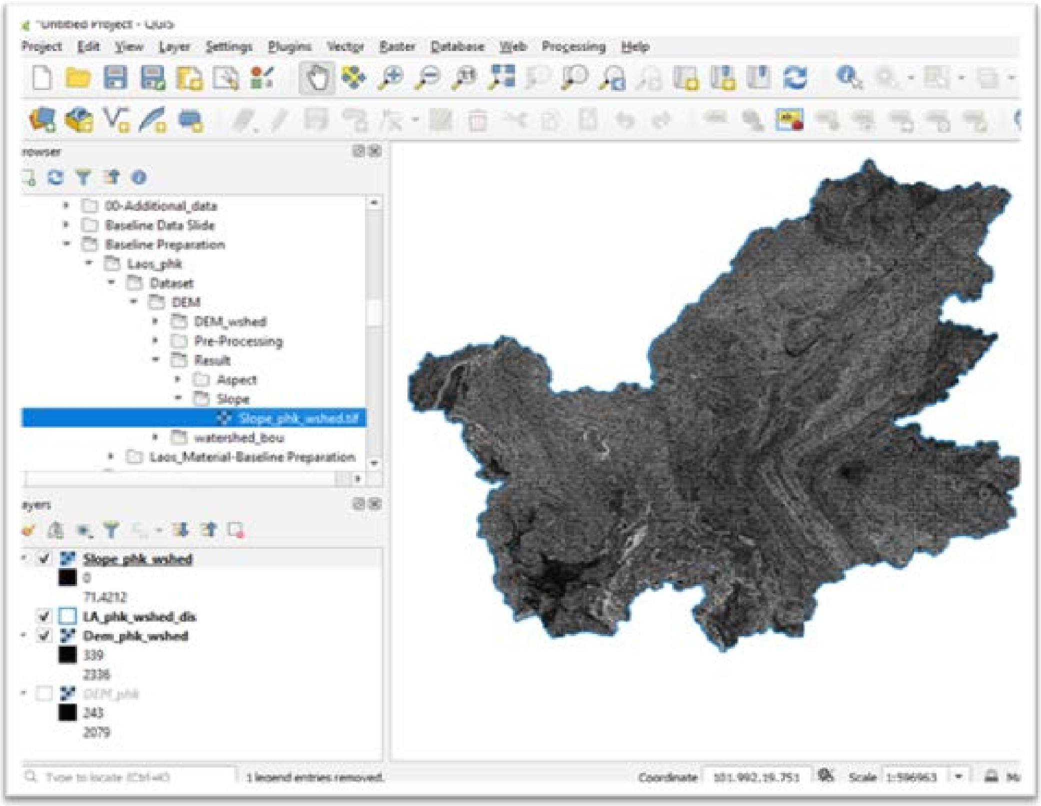


Figure 2.3 Slope in QGIS

Slope gradient is generated from a Digital Elevation Model (DEM) of SRTM 30 meterpixels. The slope gradient varies from 0° to approximately 71.42° within the watershed area as seen in the picture above. The mean value of slope is 20.71°, with a standard deviation of approximately 8.99.

Slope Classification

1. Slope gradient is reclassified into 15 classes for the landslide susceptibility analysis.
2. Right click the slope layer from the table of contents and select layer properties.
3. Change the render type to “single band pseudo color”.
4. Change the classification mode to “equal interval” and type “15” classes.
5. Select the color ramp.

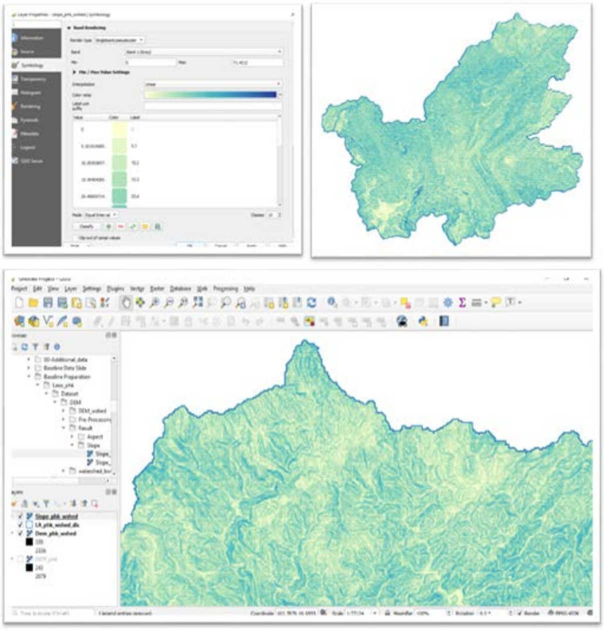
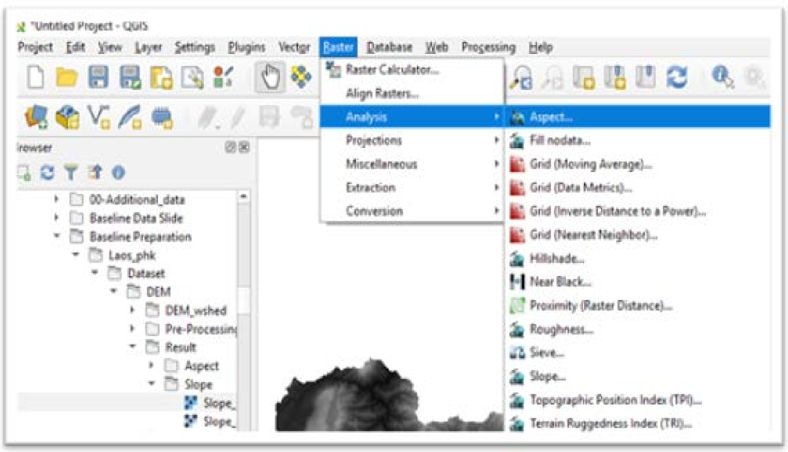


Figure 2.4 Slope classification

(2) Slope aspect

Slope aspect is also known as slope orientation or slope azimuth. It represents the direction of a slope. Aspect can be classified according to the slope angle with a descriptive direction. An output aspect raster (horizontal lines composed of individual pixels) will typically result in several slope direction classes. Aspect is measured clockwise starting north at 0° and returning back to 360° north. After running the aspect tool, the output raster symbolizes aspect direction based on slope angle. Each slope direction will represent a slope angle range. Reclassifying the aspect map can be done through changing the symbols and setting the number of classes.



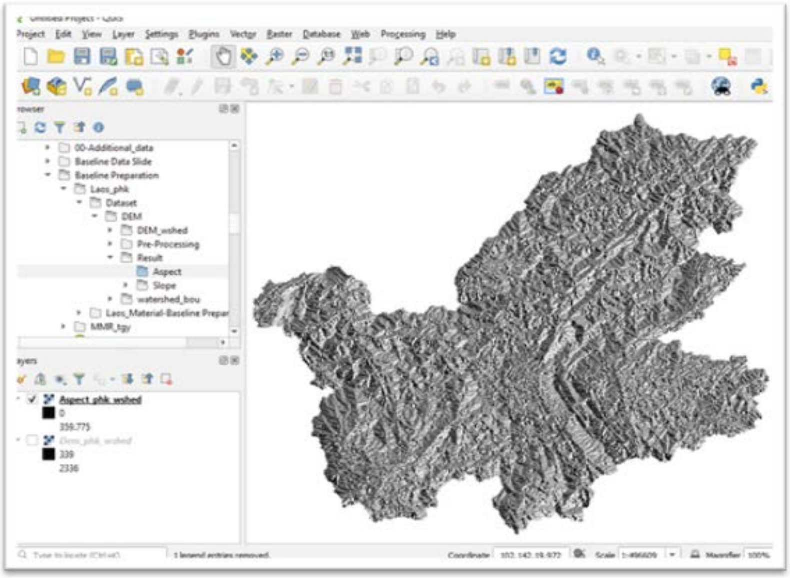


Figure 2.5 Slope aspect

Aspect Classification

1. Aspect is reclassified into 9 classes for the landslide analysis.
2. Right click the slope layer from the table of contents and select layer properties.
3. Change the render type to “singleband pseudocolor”.
4. Change the classification mode to “equal interval” and type “9” classes.
5. Select the color ramp.

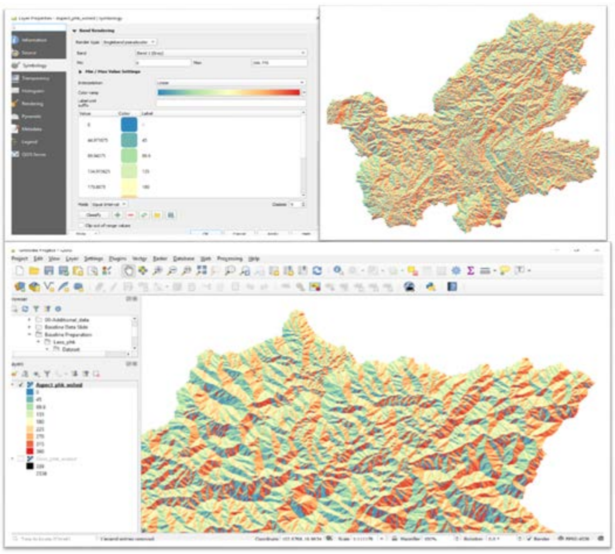


Figure 2.6 Aspect Classification

(3) Distance from road

Proximity to roads is also considered a potentially important factor because road construction usually includes land or material excavation in some slope areas and the addition of land or materials to the slope in other areas. This might result in slope line changes, artificial slope creation or road cuts that might be affected by landslide activities (Che et al., 2011). Proximity to road was regrouped into four classes (25m,50m,100m, and 150m) using *multiple ring buffer* tool in GIS environment.

(4) Distance from river

Proximity to a river may adversely affect slope stability due to slope toe undercutting, or saturation in the lower part of the slope, resulting in a water level increase.

(5) Land use and land cover

A land use and land cover map can be derived from processing satellite imagery, such as Landsat, or can be obtained from existing maps kept by relevant agencies. In this study, the land use and land cover map were derived from the regional land cover monitoring system developed by the SERVIR-Mekong program. SERVIR has produced a series of annual land cover maps with multi-purpose typologies using Landsat images from 2000-2017 at a 30-meter resolution.

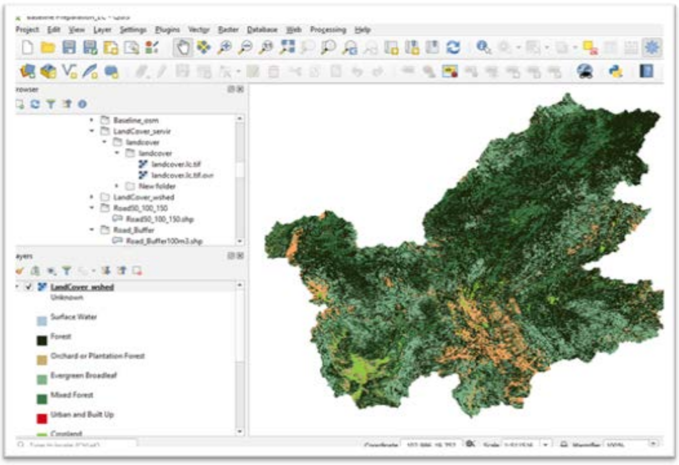


Figure 2.7 Land use and land cover of Phoukhoun RBP

(6) Hydro-meteorological datasets

Hydro-meteorological data consists of a precipitation (mainly rainfall) time-series. Additionally, temperature and humidity can often be collected from ground observation stations, as well as remote sensing sources. In this study, rainfall datasets that were used for the RBPs were derived from historical climate data and future climate projections discussed in sub-chapter 2.1.2.

(7) Landslide inventory

A landslide inventory is a detailed register of the distribution and characteristics of past landslides. Historical disaster data (location, type, damage scale, response, etc.) and the subsequent landslide inventory preparation are important for generating the landslide hazard/susceptibility map. This map exercise and the subsequent risk assessment process is based on statistical methods. A landslide inventory can be built using past records and high-resolution satellite imagery, such as Google Earth or Sentinel.

Currently there are no comprehensive landslide inventory databases covering the case study area. In the absence of these detailed inventories, an inventory covering the study areas was created using free access satellite images, such as those from Google Earth. This additional landslide inventory data helps generate better landslide susceptibility prediction accuracy.

2.1.2 Rainfall data derived from climate projection scenarios

Hydro-meteorological data consists of precipitation (mainly rainfall) time-series data derived from historical climate data and future climate projection scenarios as discussed in this section.

A changing climate may lead to changes in the frequency, intensity, spatial extent, duration, and timing of weather and climate impacts, and can result in unprecedented extremes (Seneviratne et al., 2012). Weather or climate events, though not extreme in a strict statistical sense, can cause extreme conditions or impacts either by crossing a critical threshold in a social, ecological, or physical system, or by occurring simultaneously with other events. Some climate extremes may not be the result of one event but the accumulation of multiple single events (Seneviratne et al., 2012). Under the changing climate, it is indispensable to attribute whether a rise in extreme events is a normal recurrence or it indicates a changing profile of weather-related events. There are three types of challenges. First, to understand and attribute the relative contribution of global warming for triggering extreme hydrological events in a given scale, intensity and frequency. Second, to predict by how much the global warming induced climate change is going to escalate extreme hydrological events in future. Third, and most importantly, how to correctly predict the abnormal changes in hydrological events at a given spatial scale and use it for decision making by minimizing the uncertainty.

This section introduces the development of climate scenarios and explains its application for landslide risk assessment and mapping. One of the critical challenges for scenario development is to downscale global and regional scale projections into a watershed scale. This process is fraught with high uncertainty. As a result, utilization of downscaled results at the local or watershed level is far from straightforward. It needs to adopt a cautious approach and filter the results by contrasting them with the local context. A good understanding of observed data, climate simulations and projections mechanisms and uncertainties is essential to develop realistic scenarios and properly assess the risks in each local context. The whole process should be designed such that decision makers will be able to understand, interpret and use the results from climate simulation and projections and then develop realistic scenarios for mitigation measures planning, design and implementation.

Climate projections are widely used to understand climate extremes and probability of future occurrence. Knowledge on the construction, assessment, and communication of climate change projections, including regional projections for extremes, can be drawn from four sources (Seneviratne et al., 2012; Christensen et al., 2007; Knutti et al., 2010) that include: global climate models (GCMs), downscaling of GCM simulations, physical understanding of the processes governing regional responses, and recent historical climate change.

The climate impact modeling process for identification of extreme events at the watershed or local scale consists of six methodological steps as shown in Figure **2.8.**

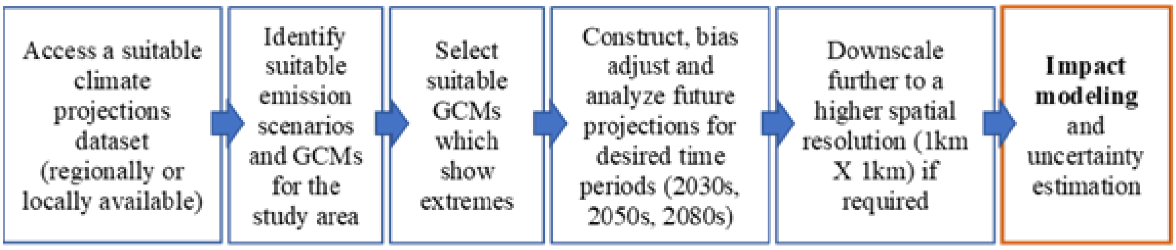


Figure 2.8 Impact modeling steps for assessing risk from extreme landslides at the

2.1.2.1 Available global/regional circulation models and their selection for developing realistic scenarios

Global circulation models (GCMs) were the main source of globally available regional information on the range of possible future climates including extremes (Christensen et al., 2007) during the Fourth Assessment Report (AR4) of Intergovernmental Panel on Climate Change (IPCC). The IPCC AR4 concluded that statistics of extreme events for the present-day climate, especially temperature, could be well simulated by current GCMs at the global scale. Simulating precipitation extremes, however, are less robust (Randall et al., 2007). With improvement of spatial resolution, as well as its complexity, GCMs could be useful for investigating smaller-scale features, including changes in extreme weather events. However, while projecting climate and weather extremes, not all atmospheric phenomena potentially of relevance can be realistically or explicitly simulated (Seneviratne et al., 2012). Nevertheless, the requirement for extreme event projections has provided motivation for the development of regionalization or downscaling techniques (Carter et al., 2007). These have been specifically developed for the study of regional and local-scale climate change to simulate weather and climate at finer spatial resolutions than is possible with GCMs – a step that is particularly relevant for many extremes given their spatial scale. Studies have indicated that climate models are fundamental tools for simulating and understanding regional and local-scale climate, as well as understanding impacts on environmental systems (Wang et al., 2013; Ahmadalipour et al., 2015). These models exercise quantitative methods to simulate the interactions of atmosphere, oceans, land surface, and ice and provide plausible estimates of future climate change.

The Coupled Model Inter-comparison Project Phase 5 (CMIP5) is the latest dataset available with simulation from the new generation of GCMs (Rupp et al., 2013). There are more than 40 GCMs in the CMIP5 archive developed by various meteorological organizations and agencies that include different spatial resolutions. In the Fifth Assessment Report (AR5) of the IPCC, climate simulations have been carried out for the 21st century according to representative concentration pathways (RCPs) based on four greenhouse gas (GHG) concentration trajectories (Demirel and Moradkhani, 2016).

RCPs are the latest generation of scenarios that provide input to climate models. These pathways describe different climate futures, all of which are considered possible depending on the volume of greenhouse gases emitted in future years. There are four pathways: RCP8.5 (high emissions), RCP6.0 (intermediate emissions), RCP4.5 (intermediate emissions) and RCP2.6 (low emissions). The goal of working with scenarios is not to predict the future but to better understand uncertainties and alternative futures, in order to consider how robust different decisions or options may be under a wide range of possible futures.

Numerous research groups around the globe are engaged in evolving models to simulate the current climate and its future progression under several GHG and aerosol scenarios (Buser et al., 2009) by means of downscaling the GCMs. The NASA Earth Exchange (NEX) Downscaled Climate Projections (NEX-DCP30) dataset is the only globally available set of downscaled climate scenarios that is derived from the GCM runs conducted under CMIP5 (Taylor et al. 2012) and across the four GHG emission scenarios known as RCPs (Meinshausen et al. 2011) developed for IPCC AR5. The dataset includes downscaled projections from 21 models, as well as ensemble of statistics calculated for each RCP from all available model runs. The purpose of these datasets is to provide a set of high resolution, bias-corrected climate change projections that can be used to evaluate climate change impacts on processes that are sensitive to finer-scale climate gradients and the effects of local topography on climate conditions. Each of the climate projections includes monthly averaged maximum temperature, minimum temperature, and precipitation for the periods from 1950 through 2005 (retrospective run) and from 2006 to 2099 (prospective run).

The bias correction and spatial disaggregation (BCSD) approach used in downscaling the dataset inherently assumes that the relative spatial patterns in temperature and precipitation observed from 1950 through 2005 will remain constant under future climate change. Other than the higher spatial resolution and bias correction, this dataset does not add information beyond what is contained in the original CMIP5 scenarios and preserves the frequency of periods of anomalously high and low temperature or precipitation (i.e., extreme events) within each individual CMIP5 scenario. The purpose of these datasets is to provide a set of global, high resolution, bias-corrected climate change projections that can be used to evaluate climate change impacts on processes that are sensitive to finer-scale climate gradients, as well as evaluate the effects of local topography on climate conditions. The sets also assist the science community for understanding climate change impacts at local, national and regional levels and to enhance public understanding of these impacts' possible consequences. **Table 2.1** summarizes the data field description for the NASA Earth Exchange-Global Daily Downscaled Projections (NEX-GDDP).

2.1.2.2 Datasets for predicting future climate scenarios

Historical as well as the future climate projections data is needed for the analysis of future climate scenarios. There are several sources of globally and regionally available historical meteorological datasets. CHIRPS precipitation data from Climate Hazard Group (CHG), with 5x5 km2 resolution, is available from 1981 to date. APHRODITE project precipitation data from Research Institute for Humanity and Nature(RIHN) and the Meteorological Research Institute of Japan Meteorological Agency (MRI)/JMA), with 25x25km2 resolution, is available from 1951 to 2007. For temperature, ERA5 reanalysis temperature data (https://cds.climate.copernicus.eu), is available starting from 1950. In addition, in-situ observed meteorological data (rain gauge, temperature data) over a longer period is also needed for result verifications and GCM bias corrections.

Climate projection data selection needs a thorough review to access and acquire future climate change data with acceptable horizontal resolution to assess impacts of future climate relevant sectors in target countries. The NEX models (CMIP5 models), which has future climate change scenarios from 21 GMCs under two emission scenarios (RCP 4.5 and 8.5) with 25x25 km2 resolution provides a good database for starting analyses, in particular for a regional analysis.

Table 2.1 Field description for NEX-GDDP

CMIP5 models included	21 GCMs ACCESS1-0, CSIRO-MK3-6-0, MIROC-ESM, BCC-CSM1-1, GFDL-CM3, MIROC-ESM-CHEM, BNU-ESM, GFDL-ESM2G, MIROC5, CanESM2, GFDL-ESM2M, MPI-ESM-LR, CCSM4, INMCM4, MPI-ESM-MR, CESM1-BGC, IPSL-CM5A-LR, MRI-CGCM3, CNRM-CM5, IPSL-CM5A-MR, NorESM1-M
RCP scenarios	RCP 4.5 and RCP 8.5
Temporal resolution	Daily from 1950-01-01 to 2100-12-31 from 1950 through 2005 (“Retrospective Run”) and from 2006 to 2100 (“Prospective Run”)
Spatial Resolution	0.25 degrees x 0.25 degrees
Climate Variables	Precipitation, maximum and minimum temperature
Dataset projection and datum	Geographic, WGS84
Data access	https://www.nccs.nasa.gov/services/data-collections/land-based-products/nex-gddp

All CMIP5 GCMs are not applicable for all regions of the globe. Based on the region of interest, GCMs should be selected from those available under CMIP5. For example, in the case of the RPB in Phoukhoun, Lao PDR, a selection of suitable GCMs for the target areas was carried out based on published reports and journal papers such as *Evaluating the performance of the latest climate models over Southeast Asia* published by CSIRO, Australia for the Asian Development Bank (ADB)

(Hernaman et al., 2017). The report was used to identify and select suitable models for the Southeast region, including Lao PDR. This literature identified a subset of CMIP5 models based on a set of metrics that avoided least realistic models but included models to capture the maximum possible range of change with satisfactory performance across all the metrics. On the basis of these studies, target area GCMs were selected as shown in **Table 2.2**.

Table 2.2 Target area GCMS selected for this study

Target Area	**Selected GCMs**
Lao PDR	bcc-csm1-1, BNU-ESM, CanESM2, CESM1-BGC, CSIRO-Mk3-6-0, GFDL-CM3, GFDL-ESM2G, GFDL-ESM2M, IPSL-CM5A-MR, MPI-ESM-LR, MPI-ESM-MR

This study focuses on identifying extreme events in the future with an aim to understand the maximum hazardous level possible for the target areas. It is therefore pertinent to identify which of the 10 models represent future extreme events in the target areas. In the Phoukhoun RBP, the future scenarios for 2030 (taking an average from 2016-2045), 2050 (taking an average from 2036-2065) and 2080 (taking an average from 2066-2095) are generated based on current climate (rainfall and mean temperature from 1976-2005) at the same study area during the wet season. Since landslides are more prominent during the wet (monsoon) season in the May – September period, that season is considered the most suitable time period for selecting GCMs.

A scatter plot is suggested for model identification. The scatter plot involves calculating annual mean temperature change (ΔT) and percentage change in annual precipitation (ΔP%) in each of the NEX models (CMIP5 models) from RCP4.5 and RCP8.5 emission scenarios. Results are built into scatter plots for Southeast Asia and South Asia that give possible extreme conditions in the region during the 2030s, 2050s and 2080s. The models that are closest to the 5th and 95th percentile of annual mean temperature (ΔT) change and percentage of change of annual precipitation (ΔP%) during the 2030s, 2050s and 2080s in the two RCPs can be selected. To depict this methodology, **Figure 2.9** shows the scatter plots for identifying suitable GCMs for predicting extreme conditions over the Phoukhoun watershed during the 2080s.

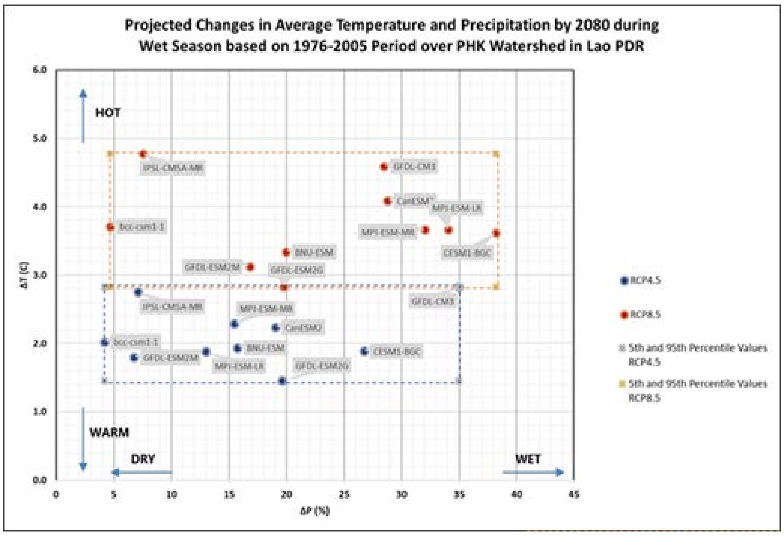


Figure 2.9 Scatter plot showing possible extreme conditions over Phoukhoun

In **Figure 2.9** the CESM1-BGC (wettest) and bcc-csm1-1 (driest) models show extreme conditions (temperature and precipitation) in Phoukhoun Watershed during all time horizons with RCP 4.5 and RCP 8.5 scenarios out of the 10 GCMs.

Table 2.3 provides a summary of selected suitable GCMs that represent possible extreme conditions for target areas.

Table 2.3 GCMs showing highest (wettest) and lowest (driest) extremes in the Phoukhoun study

Target area	Highest extreme (wettest)	Lowest extreme (driest)
Phoukhoun Watershed	CESM1-BGC	bcc-csm1-1

Temperature was shown to have little effect on rainfall triggering landslides in each watershed size such as RBPs. Therefore, rainfall was considered as the only climatological variable.

Advantages of using this approach to identify extreme GCMs include:

- Different climate variables from different models (or sets of models) are not mixed as this may lead to values having internal inconsistency and may not be physically possible.
- It ensures all information and data is placed in the context of the emissions scenarios used (RCP 4.5 is a medium emission scenario, whereas RCP8.5 represents a high emission scenario).
- Baseline periods are of sufficient duration to include a range of climate variations and encompass the same number of years as the future periods.
- The GCM biases were handled by converting results to changes relative to a baseline period or by using a bias correction method such as BCSD (ADB, 2017)
- It seeks the optimal balance between ensuring that the selected GCMs well represent changes in averages and extreme climatic conditions and simulating the past climate, with a focus on the monsoon dynamics.

There are also some disadvantages of this approach of GCM selection:

- Scale of the application: during the first selection step, projected changes are averaged over the entire area, and this may dilute the spatial variation in these changes (A potential solution is to divide the study area into multiple parts and apply the selection approach to each part independently).
- It causes changes in means during the selection approach. This may result in a reduction in the range of change projections in climatic extremes in the ensemble.

2.1.2.3 Downscaling to construct a higher resolution (1km x 1km) climate surface

Since the resolution of NEX dataset is coarse (i.e. 25x25km2), it might prevent detailed climate change analyses at national, and especially local, scales such as in RBP sites. A comprehensive analysis of the local impacts of climate change for future planning requires local, high-resolution climate variables that cannot be obtained directly from coarse resolution projections (Komurcu et al., 2018). Therefore, it is extremely important to include a downscaling methodology for generating high resolution (1kmx1km) datasets for further impact studies in the target areas.

Since it is difficult to find a strong relationship between precipitation and elevation to build a nonlinear or circular function, a straight univariate bilinear resampling method is proposed for resampling of 25kmx25km resolution precipitation data into a 1kmx1km resolution grid. The APHRODITE dataset can be used as the reference surface to resample precipitation surface. This resampling process can generate approximate patterns as per the reference data surface and it doesn't disturb the pattern of the original GCM. Downscaling to 1kmx1km resolution in RBPs that represent possible extreme conditions was completed for selected GCMs using the above process. The downscaled 1kmx1km resolution datasets were then used for developing future climate projections and analysis of rainfall hotspots for target areas.

2.1.2.4 Impact modelling methodology

Identification of hotspots and intensity of associated hazards results from impact modeling that is carried out after selection of suitable GCMs and construction of the current climate using historical data from satellite-derived and in-situ datasets. **Figures 2.10** and **2.11** below show two results of climate analysis in the Phoukhoun Watershed with and without climate impacts.

2.1.2.4.1 Developing climate change projections with rainfall intensity

Analyses of wet season total rainfall changes in Phoukhoun Watershed in the 2030s, 2050s and 2080s with respect to the baseline (1976-2005) under RCP 4.5 and and 8.5 emission scenarios were derived for CESM1-BGC (Wettest-Highest Extreme) and bcc-csm1-1 (Driest-Lowest Extreme) GCMs. The following figures show the wet season average precipitation changes for RCP 4.5 and RCP 8.5 respectively.

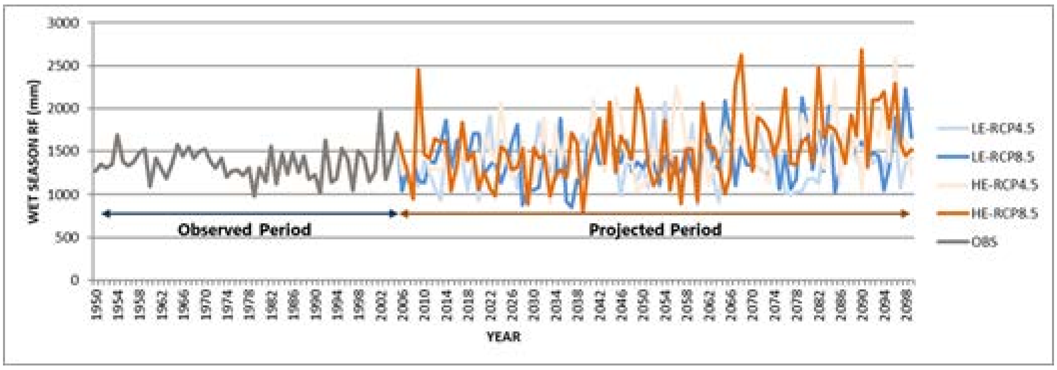


Figure 2.10 Wet season rainfall historical and projected variability in Phoukhoun Watershed

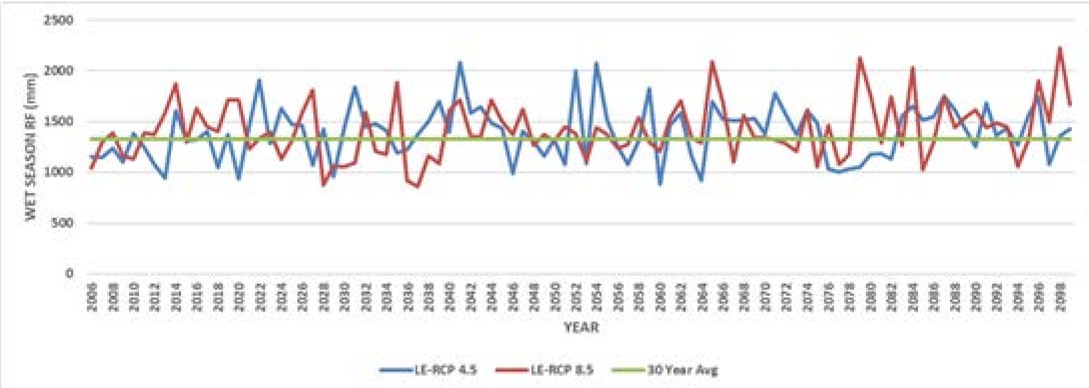


Figure 2.11 Wet season rainfall projected variability with regards to climatology for

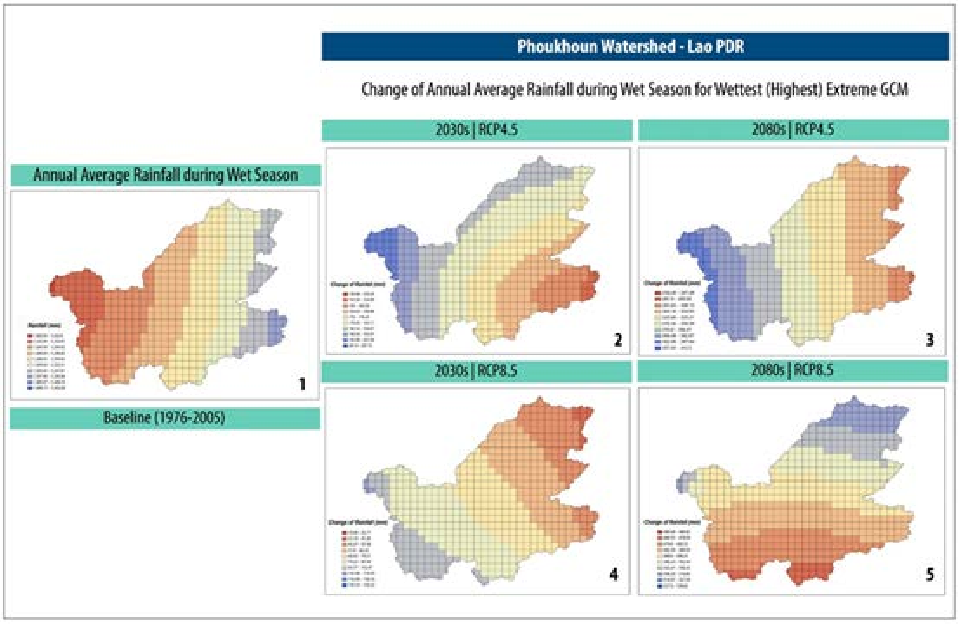


Figure 2.12 Average rainfall during wet season extreme GCM, RCP4.5. (3) Change of Annual Average Rainfall during Wet Season by 2080, Wettest-Highest extreme GCM, RCP4.5. (4) Change of annual average rainfall during wet Season by 2030, wettest-highest extreme GCM, RCP 8.5

The below table depicts the likely amount of rainfall change in ‘mm’ with respect to the baseline period for each time horizon and emission scenario for wettest-highest extreme GCM.

Table 2.4 Likely amount of rainfall change for each time horizon

Time Horizon	RCP 4.5	RCP 8.5	Remarks
2030s	*203*	*131*	Rainfall increase of 73% and 75% is likely for RCP 4.5 and RCP 8.5 in the future
2050s	*192*	*350*	
2080s	*339*	*493*	

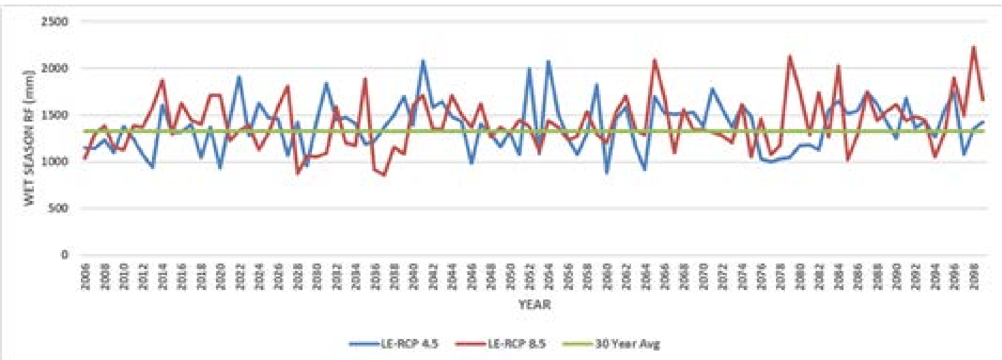


Figure 2.13 Projected variability of wet season rainfall with regards to climatology for

The below table depicts the likely amount of rainfall change in mm with respect to the baseline period for each time horizon and emission scenarios for lowest extreme GCM.

Table 2.5 Likely amount of rainfall change (in mm) for each time horizon

Time Horizon	*RCP 4.5*	*RCP 8.5*	*Remarks*
2030s	*20*	*64*	Rainfall increase of 67% and 69% is likely for RCP 4.5 and RCP 8.5 in the future
2050s	*87*	*121*	
2080s	*145*	*203*	

Study results indicate the wettest GCM in medium and high emission scenarios shows a considerable spatial variability with a projected gradual increase in wet season rainfall for the three-time horizons. In the wet season, average rainfall is also projected to increase by 73% and 75% for both emission scenarios respectively towards the future. These increases are gradual over all future time horizons. The driest GCM also shows a similar trend in gradual increase in wet season rainfall by the 2080s for both emission scenarios. These results likely indicate that landslide hazards may be common in the future in the hilly areas in Phoukhoun watershed.

2.1.2.5 Conclusion

- The wettest (highest extreme) GCM for each target area clearly shows a trend of increasing rainfall during the wet season in the future for Phoukhoun watershed.
- The driest (lowest extreme) GCM also shows an increasing trend for Phoukhoun watershed during the wet season.
- Both intermediate (RCP 4.5) and high (RCP 8.5) emission scenarios have a similar pattern of rainfall change into the future.
- It is recommended to run an impact model for both the highest and lowest extreme GCMs as well as both medium and high emission scenarios to understand the full range of variability into the future. Climate projections are not predictions of the future, but instead provide a range of possible future climate. As such, projection values should be used to guide thinking in impact assessments and planning, and users should include flexibility in their planning and adopt an adaptive management approach to allow for change as more information becomes available through appropriate observational-based monitoring, scientific research, and evaluation.

2.1.2.6 Understanding the uncertainty

There are two factors to consider when dealing with the uncertainties in climate modeling. One is uncertainty of the GCM, for example, uncertainty in climate system response and uncertainty in natural variability. The other is uncertainty in future emissions and future concentration of greenhouse gases (GHGs). The uncertainty of the GCM can be addressed using projections from a range of GCMs and an ensemble of GCM projections with different initial conditions. The uncertainty in future emissions and future concentration can be addressed using a number of carbon cycle and atmospheric chemistry models, in addition to climate models with a range of emission scenarios such as RCP 4.5 and 8.5.

Even after the selection of best available approaches or strategies for climate modelling and projections, they are not necessarily complete or meant to be adopted directly for decision making. As such, climate projections are not predictions of the future. Instead, the projections provide a range of possible future climate. The projection values should be used to guide thinking in impact assessments and planning, and users should include flexibility in their planning and adopt an adaptive management approach to allow for change as more information becomes available through appropriate observational-based monitoring, scientific research, and evaluation.

2.1.3 Landslide Susceptibility Map Zoning using Weight of Evidence

Calculation of each particular predictive hazard variable involves assigning a positive weight (W+), when the event occurs and a negative weight (W-), when the event does not occur. The weights are measures of correlation between evidence (predictive variable) and event, making them easy to interpret in relation to empirical observation. Formulation is based on density functions. Weights (Wi) of each cell (ith pixel) are determined by the equation:

$$W_i = \sum_{j=1}^{n} W_j^k$$

Where Wj is a parameter of the jth class and Wk signifies positive and negative weight values. Controlling landslide factors can be mapped with this method. The weights can be used to produce a contrast value (C) for the specific susceptibility variable.

$$C = W^+ - W^-$$

The difference between weights (C) provides a measure of strength of correlation between the analyzed variable and the landslide.

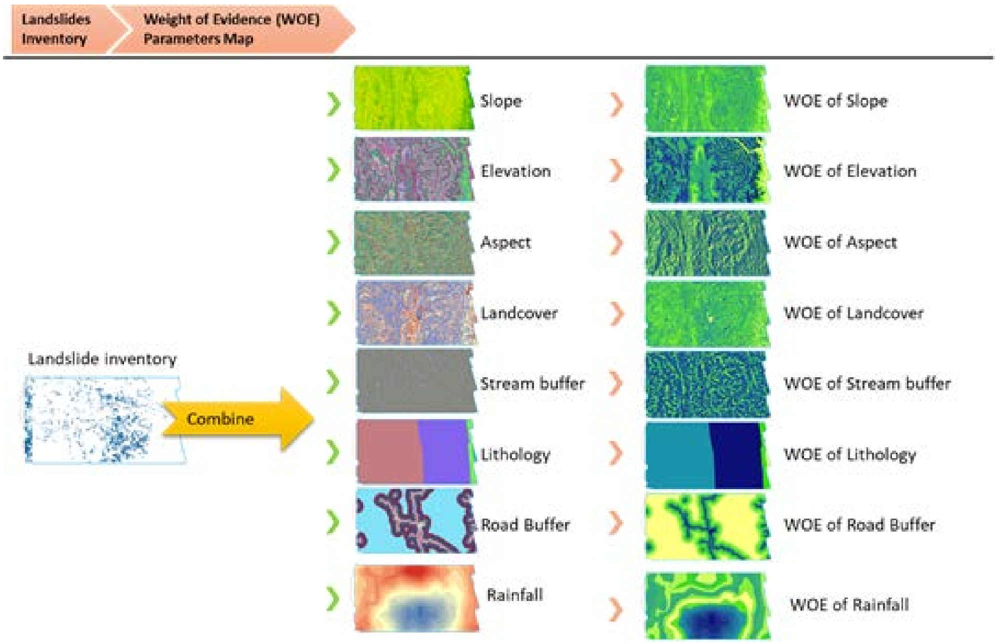


Figure 2.14 Landslide susceptibility assessment using WOE (where rainfall data was derived from future climate scenarios)

Susceptibility zoning uses GIS to overlay the WOE (weight of evidence) parameter maps. The overlaid map is first divided into approximately 255 classes (the more classes the better) at equal intervals from high to low WOE. These classes are then analyzed with a landslide occurrence using the raster analysis.

Based on the sorted classes, susceptibility zones are defined as follows:

50% of landslide occurrence is classified as very high zone

20% of landslide occurrence is classified as high zone

15% of landslide occurrence is classified as medium/moderate zone

10% of landslide occurrence is classified as low zone

5% of landslide occurrence is classified as very low zone

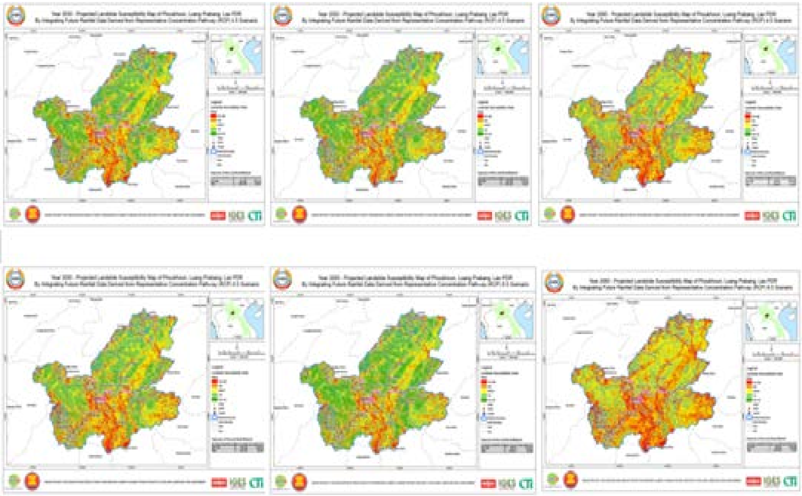


Figure 2.15 Landslide susceptibility map results of Phoukhoun Watershed from two different future climate scenarios at RCP 4.5 and RCP 8.5

Figure 2.16 Total area of landslide susceptibility in Phoukhoun Watershed from two different future climate scenarios at RCP 4.5 and RCP 8.5

Table 2.6 Total area of landslide susceptibility in Phoukhoun Watershed, RCP 4.5 and RCP 8.5

	RCP 4.5 (Unit in Km^2)		
Susceptibility Area	2030	2050	2080
Very Low	748,99	748,99	185,00
Low	1717,84	1717,84	1385,16
Moderate	1169,76	1169,76	1514,30
High	1070,13	1070,13	1325,52
Very High	567,04	567,04	861,23
Total	5273,76	5273,76	5271,21

	RCP 8.5 (Unit in Km^2)		
Susceptibility Area	2030	2050	2080
Very Low	445,38	921,19	48,54
Low	1656,15	1743,92	867,25
Moderate	1312,12	1087,22	1624,95
High	1164,00	1011,44	1639,46
Very High	696,11	507,43	1091,01
Total	5273,76	5271,20	5271,21

The increase in area susceptibility can be seen in the RCP 4.5 from 2050 to 2080. Both areas of high and very high zones increase from 1070.13 to 1325.52 and 567.04 to 861.23 km2 respectively. A similar trend was also found in the 2050 to 2080 for RCP 8.5 scenario. The total areas fall into high and very high categories, increasing from 1011.44 km2 to 1639.46 km2 and from 507.43 to 1091.01 km2 respectively. This trend can be seen in **Figure 2.16**.

2.2 Exposure Assessment

One of the main steps in risk assessment is to evaluate the element at-risk exposed to different hazards, which is called an exposure assessment. As defined by UNISDR (2004), exposure indicates the degree to which the elements at risk are exposed to a particular hazard. Exposure can also be defined as the total number or value of the element at risk. Exposure is the total value of elements at risk. It is expressed as the number of human lives and the number/value of the properties or assets that can potentially be affected by hazards. An exposure assessment comes at the intermediate stage of risk assessment.

The exposure assessment in this case study includes a quantification of the number of households (sampling) located in landslide-prone areas. The analysis was carried out for the households located in high and very high landslide prone areas. Household sample data was collected from field surveys completed by the project team in 2019 within the Phoukhoun case study area. The spatial household information and attributes were then overlaid with landslide susceptibility maps using GIS tools.

The following flowchart depicts the process of spatial overlay between landslide susceptibility maps and surveyed household data.

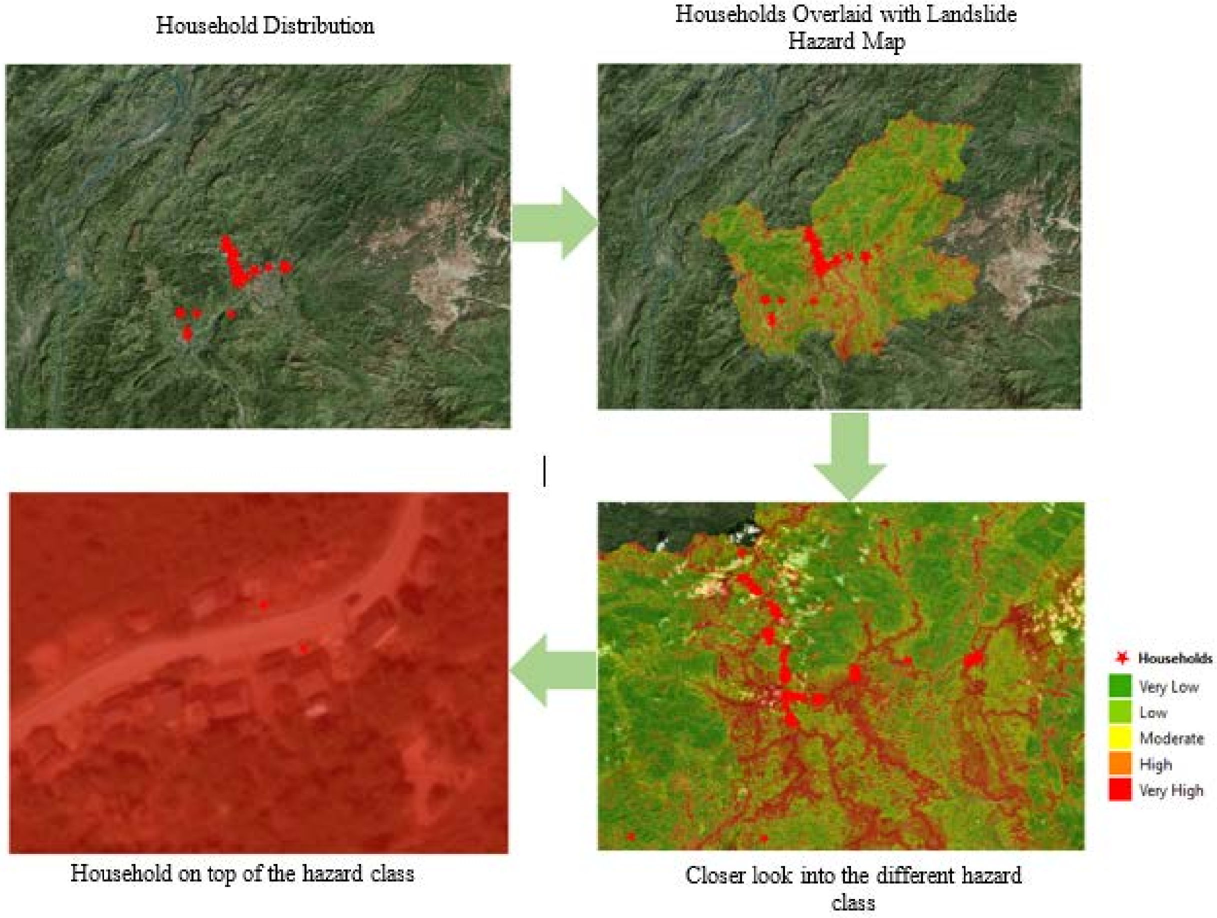


Figure 2.17 Illustration of exposure (spatially overlaid between landslide susceptibility maps and household)

The element at-risk signifies assets that might be exposed to hazards. The element at-risk considered in this case study is represented by households that are exposed to landslide hazard. In total, there were

207 households surveyed, but the analysis focused on the 204 households that are located within the watershed. The households exposed to hazard analysis were applied to 6 different scenarios. The applied projected scenarios are Year 2030 RCP 4.5, Year 2030 RCP 8.5, Year 2050 RCP 4.5, Year 2050 RCP 8.5, Year 2080 RCP 4.5 and Year 2080 RCP 8.5.

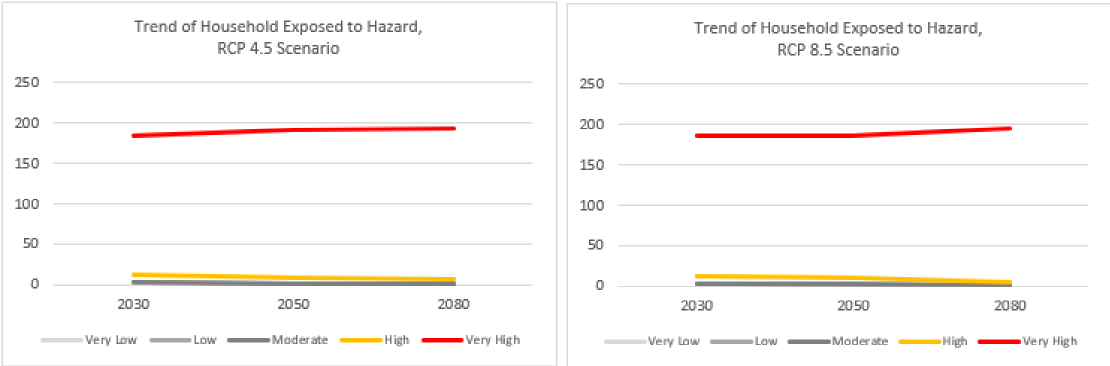


Figure 2.18 Households exposed to hazard trends in Phoukhoun for three projected times

Table 2.7 Households (surveyed sampling) exposed to hazard, scenario RCP 4.5 and RCP 8.5

Hazard Class	RCP 4.5			RCP 8.5		
	2030	2050	2080	2030	2050	2080
Very Low	0	0	0	0	2	0
Low	4	3	3	3	2	2
Moderate	3	1	1	3	3	2
High	12	9	7	12	10	5
Very High	185	191	193	186	187	195
Grand Total	204	204	204	204	204	204

The exposed households in Phoukhoun are dominated by the very high hazard class. The increased number of households that fall under very high class can be seen in **Table 2.7**. It should be noted that the number presented in this case study only represents the surveyed households. The spatial distribution of the surveyed households exposed to different classes of landslide susceptibility zones can be seen in **Figure 2.19**.

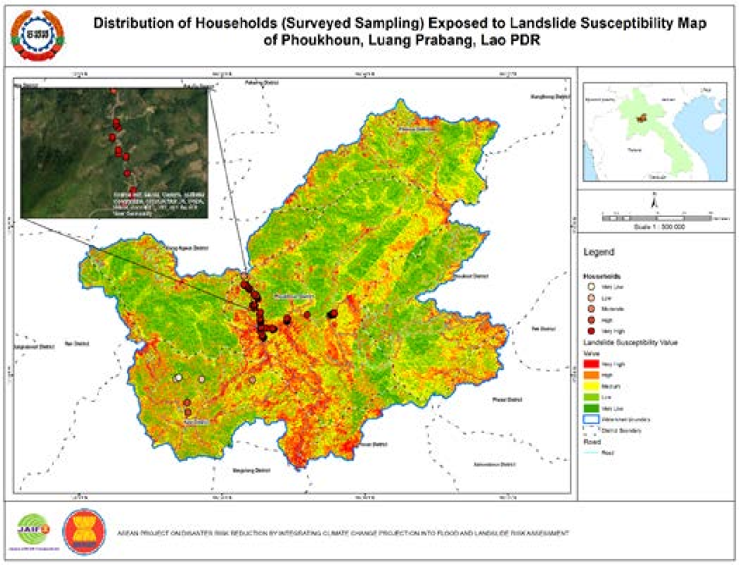


Figure 2.19 Distribution of households exposed to landslide hazard

Limitation of Exposure Assessment

The household data collected was limited. The data was analyzed in Geographic Information System (GIS) format and is presented at the household level (as point). It is recommended that more details and comprehensive household data covering the study area is collected and included in future analyses.

2.3 Vulnerability and Capacity Assessment

2.3.1 Vulnerability Assessment

The vulnerability assessment results presented here are derived from the methodology outlined in the Guidelines text.

Landslide vulnerably scoring (LVS) is used for assessing household landslide vulnerability. It is a qualitative method of assessing landslide vulnerability of individual households wherein the scores are assigned to individual indicators based on the value an indicator takes and how those values correspond to the overall vulnerability that is constructed as a range (i.e. 0 means no vulnerability and 1 means high vulnerability).

Assigning scores: The basis for LVS is the published literature (e.g. for below poverty line, etc.), wherever possible and expert judgements. For assigning the ratings, a structural elements resistance factor is used. However, due to lack of resistance factors for the location-specific conditions, literature available elsewhere was used to decide the gradient of ratings allocated to different structural elements (for example, n reinforced concrete (RC) building is considered to have a high resistance factor compared to stone masonry structures, framed structures higher resistance over load bearing structures, etc.). Similarly, recent construction (less than 10 years old) can be considered to have higher resistance than older construction. Scoring mostly follows a binary classification wherever possible to simplify the vulnerability assessments and for ease in understanding the results. Wherever more resolution is necessary for scoring, ternary and quaternary scores are also assigned.

Data normalization: Since various indicators can have different ratings that are based on different units of measurement (such as km, years etc.), a linear normalization method has been employed to bring all indicators in a 0-1 scale so that the values can be combined within a category.

The formula for normalizing the indicator values is given as:

Normalized value $$z_i = \frac{x_i - T_{\min}(x)}{T_{\max}(x) - T_{\min}(x)}$$

Where: x_i is the value of the indicator

T_{min} is the minimum threshold value of the indicator xi
T_{max} is the maximum threshold value of the indicator xi.

Mutual dependencies and hierarchy of indicators: There is a mutual dependency/hierarchy among the indicators. For example, RC constructions that are recent but have a shallow foundation, or those that do not satisfy the basic conditions of anchoring to bedrock, could be more vulnerable to damage than other types of framed structures, such as bamboo, that are anchored to the bedrock. However, such interdependencies were not considered for this preliminary analysis. These results will therefore have to be updated at the next stage to show these mutual dependencies.

Weightages: Indicators could take on relative weightings depending on the importance they play in the final vulnerability. For example, if structural vulnerability plays a larger role, due to its physical location or the type of structure, than social vulnerability, structural vulnerability can be given higher weightage in the overall vulnerability. However, such weightages need careful consideration based on evidence (i.e. empirical studies). Since no such studies were available for the study location, all vulnerabilities in this study were considered equal in the final vulnerability determination.

Proxy indicators were derived for more relevance to the vulnerability assessment. For example, the distance to the health care center is converted into minimum response time (MRT) equivalent distance (MED) to imply that the difference between the actual distance and the MRD results in higher vulnerability. Similarly, the number of people at home is converted into a household residence time (HRT) to imply the higher the HRT, the higher the vulnerability.

Table 2.8 Priority Socio-Economic sensitivity indicators

Indicator	Description
Family without educated members	Counts all households without an educated person. This household type has a landslide vulnerably scores (LVS) rating (landslide risk sensitivity).
Vulnerable population	Counts all households with a woman, child, and/or an elder older than 60 years. A household that satisfies at least one of these conditions is given an LVS rating of 1, two conditions LVS 2, and 3 conditions LVS 3. This data is then normalized to a 0-1 scale to combine with other indicators.
Female headed household	Counts households that do not have a living male elder. Given an LVS of 1.
Differently abled	Counts households with a physically disabled family member. Given an LVS of 1. This is in addition to gender and age considerations (for example a household with a disabled female will get two LVS values).
Poverty	Counts the monthly poverty income line. Households below the income poverty line are given an LVS of 1.
Access to Health	Counts the household's distance to a health center. Households beyond a 4.5 km radius from the health center are treated as sensitive, with an LVS of 1.
Home vacant time (HVT)	Counts amount of time during the day a household is vacant. Those with less vacant time are considered the most sensitive. Vacant hour values are linear and are given to fall within the LVS range of 0-1.
Rate of service interruption	Counts the average rate of service (such as water, electricity etc.) interruption (in percentage) with linear values and is given an LVS range of 0-1.
Interruption duration	Counts number of days of interruption (of water, electricity etc.) with linear values, and is given an LVS range of 0-1.

Table 2.9 Priority Physical Sensitivity Indicators

Indicator	Description
Slope of the land	Counts households located on a slope of greater than 15%. These are considered sensitive and are given an LVS of 1.
Living floor	Counts household living on the ground floor. This household type is considered sensitive (in accordance with earthquake literature), and given an LVS of 1.
Building age	Counts buildings more than 10 years old, given an LVS of 1.
Architectural Approval	Counts buildings without architectural/formal approval, given an LVS of 1.
Foundation type	Counts buildings that used clay aggregates or rubble in construction, given an LVS of 1.
Bedrock anchoring	Counts buildings with foundations reaching or anchored in bedrock and are given an LVS of 0 (not sensitive).
Nature of walls	Counts load bearing wall structures, and given an LVS of 1.
Damage susceptibility rating	Self-assessed damage susceptibility ratings ranging between 1-10 are linear, normalized to LVS values.

2.3.2 Capacity Assessment

Capacity is a combination of all the resources that exist within a household, community, group, or organization that can reduce the level of risk or disaster impact. A capacity assessment identifies the strengths and resources available to each individual, household and community to cope, defend, prevent, prepare, reduce risk, or recover quickly from disaster. Six capacity assessment indicators were used, with data collection, as shown in **Table 2.10**.

Table 2.10 Capacity indicators

Indicator	Description
Disaster risk management participation	Counts households that have reported DRM participation, and given an LVS of 0.
Microfinance	Counts households that participate in microfinance programs, and given an LVS of 0.
Landslide discussions	Counts households that discuss landslides, and given an LVS of 0.
Migration readiness	Counts households that report having landslide preparedness measures in place, and given an LVS of 0.
Disaster risk management awareness	Counts households that expressed having disaster risk management awareness measures in place, and given an LVS of 0.
Alternative roads	Counts households that have more than one access road, and given an LVS of 0.

As a part of the risk assessment methodology, the collection of vulnerability and capacity components are essential. For these purposes, this study used a household survey to collect individual perception and experience on landslide disaster, and socio-economic data to assess landslide disaster vulnerability and capacity.

As discussed in the Guidelines, the primary data on the socio-economic and demographic details of the households was collected through structured questionnaires. A total of 9 villages were selected for household surveys as shown in **Table 2.11**. The villages were identified based on the susceptibility map, consultation with officials from the National Disaster Management Agency, and ease of access to the villages. All of the surveyed villages were located along the two main national roads (Road N13 and N7). From each village, 22-24 households were surveyed depending on the availability of suitable houses (in particular those affected by landslides in the recent past). A total of 207 households were surveyed.

Figure 2.20 Sample survey conducted by the survey team

For the household survey, the study collaborated with National University of Laos (NUL) faculty and students. The involvement of the university and its students in the survey ensured methodology and knowledge transfer. The project team, members of river basin pilots and faculty from NUL supervised the students before embarking on the survey. At the end of each day, the project team and students reviewed the survey progress, ensuring interaction with the students in regards to their understanding. **Tables 2.8 – 2.10**. Note that a similar study was conducted in Taunggyi RBP, Myanmar, thus several comparisons are made between these two cases.

In Lao PDR, family income influenced the type of house in which the family lives (**Figure 2.21**). The difference in income between households living in a framed structure as opposed to a load-bearing structure is significant, i.e. more than one million Lao Kip. However, the average income of a family that obtained official approval compared to those that didn't receive official approval for constructing the house didn't differ, indicating that the income level does not influence the ability or willingness to obtain official approval for building.

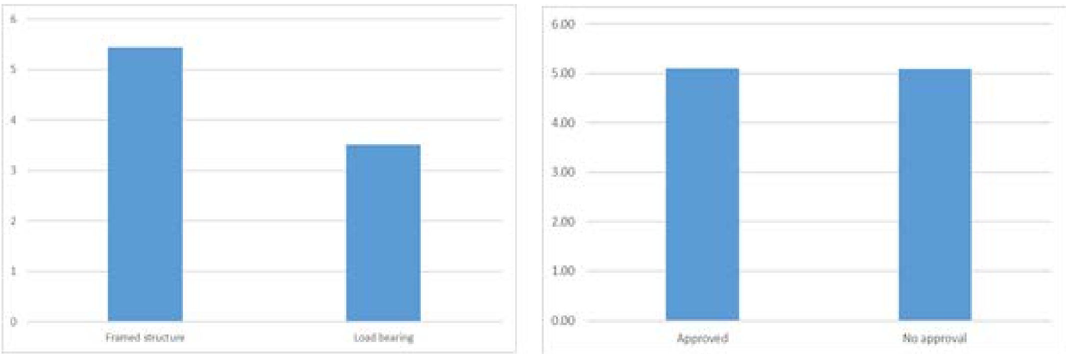


Figure 2.21 Left: Income difference between households living in framed structure and load bearing structure. Right: official approval for house building and no approval

No significant difference in income was observed among households living on slopes greater than 15 percent and those less than 15 percent. Though the number of households on slopes greater than 15 percent did not differ significantly in Lao and Myanmar, the income of households living on steeper slopes was marginally higher in Myanmar compared to Lao, where families living on steeper slopes earned marginally less income than those living on lower slopes. In both countries, male-headed households earned a marginally higher income than female-headed households and the difference in income between male and female-headed households was similar. However, in terms of poverty incidence among female-headed families, the difference in poverty is higher in Myanmar (two percentage points) compared to Lao PDR (one percentage point). A marginally lower number of households reported being prepared for landslides in Lao PDR compared to Myanmar. However, 92 percent of Lao households that discuss landslides find themselves prepared while in Myanmar, only 43 percent of families that discuss landslides tend to be prepared. The willingness to migrate is significantly less among the Lao households, although for the poor, the desire to migrate is higher in Lao than observed in Myanmar. Fewer families living on higher slopes showed a willingness to relocate in Lao PDR compared to Myanmar.

In terms of population exposure, unlike in Myanmar (Taunggyi RBP), the percentage of the sampled population living in very high landslide susceptible zones (exposure) is already high at present, and hence the shift in the population from very low to very high landslide susceptibility zones is negligible in all future climate change scenarios (**Figure 2.22**).

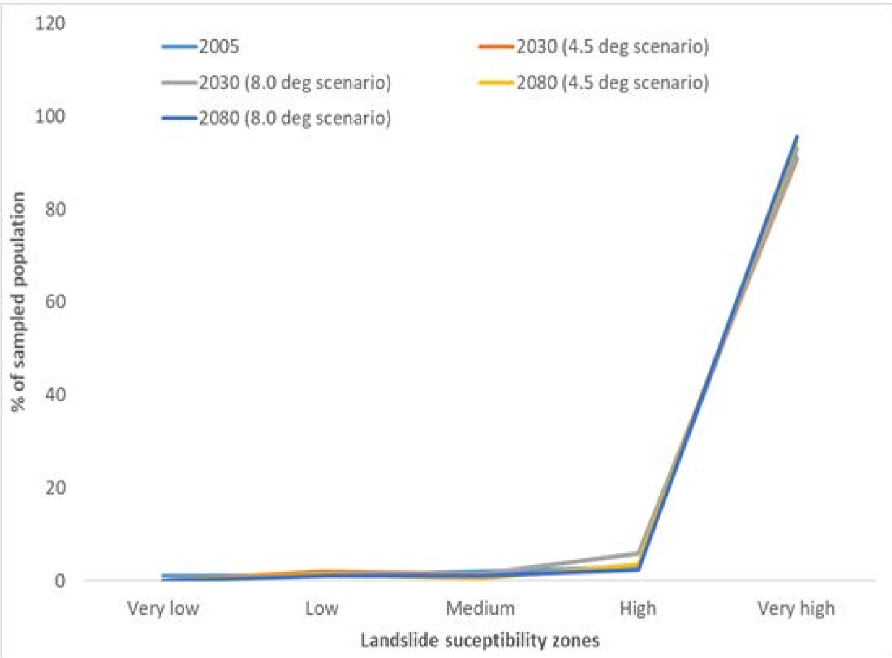


Figure 2.22 Trend in percentage of households living in various landslide

In terms of vulnerability spatial distribution, households in Phoukhoun RBP exhibited considerable capacity when compared to sensitivity (**Figure 2.23**). Also, there are no families in the sampled population living in low and very low landslide sensitivity zones. The landslide sensitivity of families did not change considerably across various landslide susceptibility zones. However, capacity showed considerable variation across these zones. The capacity of households was high in low and medium landslide susceptibility zones. In comparison, households exhibited a marginally lower capacity in high and very high landslide susceptibility zones. These zones should receive priority to strengthen family capacity in any future interventions.

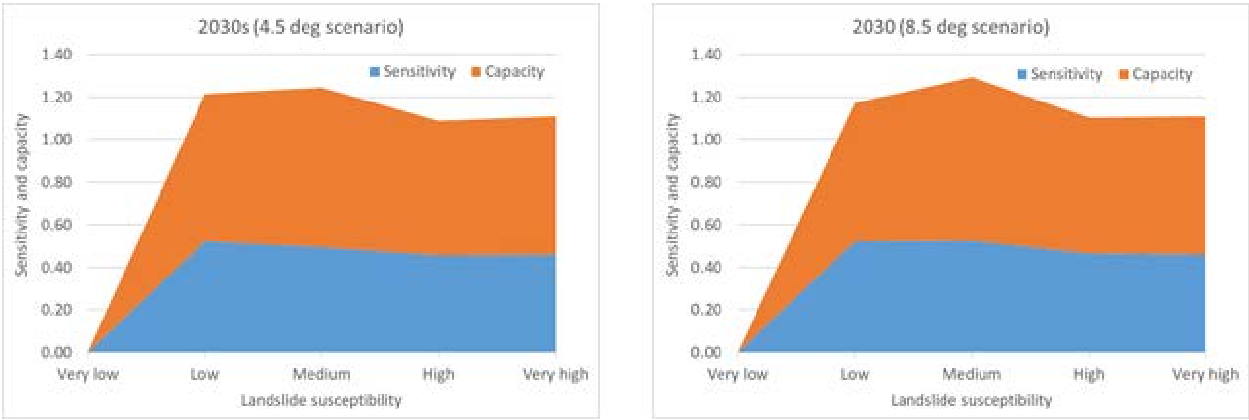


Figure 2.23 Spatial distribution of vulnerability in various landslide susceptibility zones

The surveyed household's vulnerability analysis can be presented in a map as shown in **Figure 2.24**.

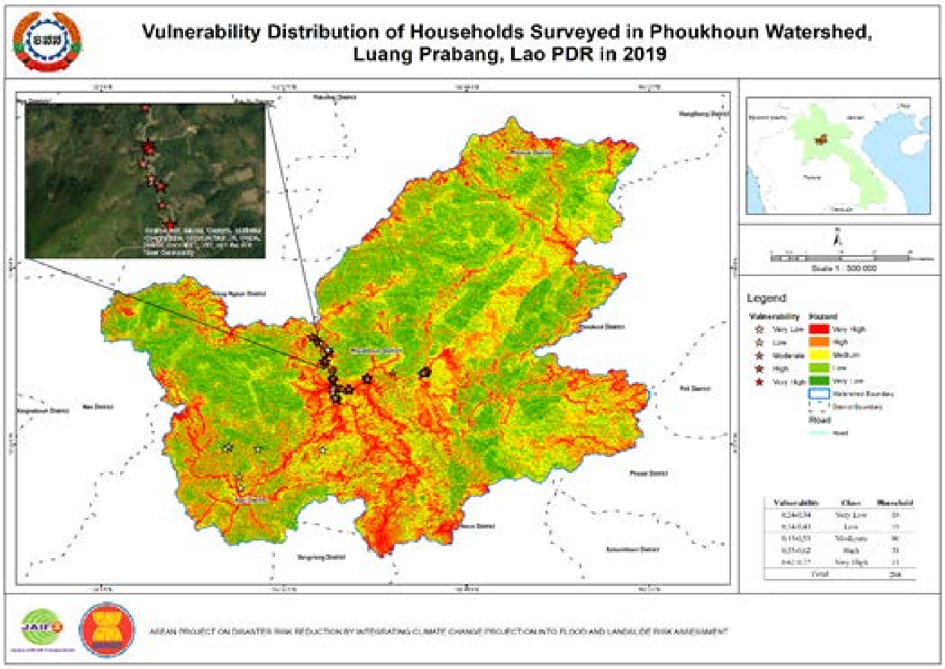


Figure 2.24 Vulnerability distribution of households surveyed in

3. HOUSEHOLD LANDSLIDE RISK PROFILE

3.1 Landslide risk profile development using future climate scenarios of RCP 4.5

The landslide hazard and risk assessment were based on the concept introduced by UNDRR (formerly known as UNISDR) described in the *ASEAN Project for Disaster Risk Reduction by Integrating Future Climate Scenarios into Landslide Risk Assessment* guidelines. Risk assessment was conducted for two different scenarios, RCP 4.5 and RCP 8.5, and three different projected years: 2030, 2050 and 2080.

Risk assessment results were categorized into five different classes of risk: very high, high, moderate, low and very low. Results show that the moderate, high and very high classes increase in the projected years (2030, 2050, and 2080). The number of households at high risk increased from 41 to 43, with very high increasing from 43 to 44. It should be noted that the exposure data used in this case study is based on sample data of the surveyed households only. For future studies, it is recommended to use projected population and household data.

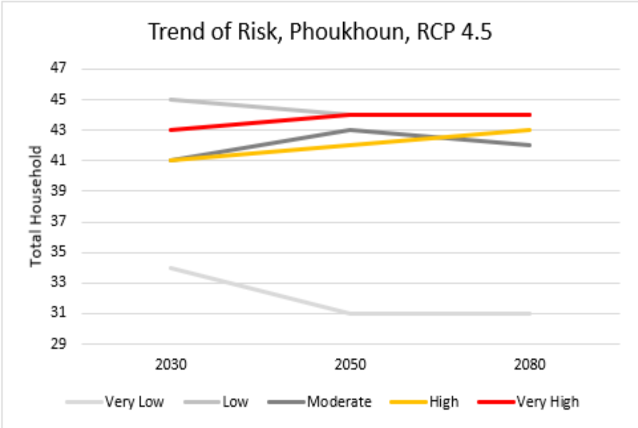


Figure 3.1 Risk trend for Phoukhoun at RCP 4.5

Table 3.1 Risk table for surveyed households at RCP 4.5

Risk	RCP 4.5		
	2030	2050	2080
Very Low	34	31	31
Low	45	44	44
Moderate	41	43	42
High	41	42	43
Very High	43	44	44
Grand Total	204	204	204

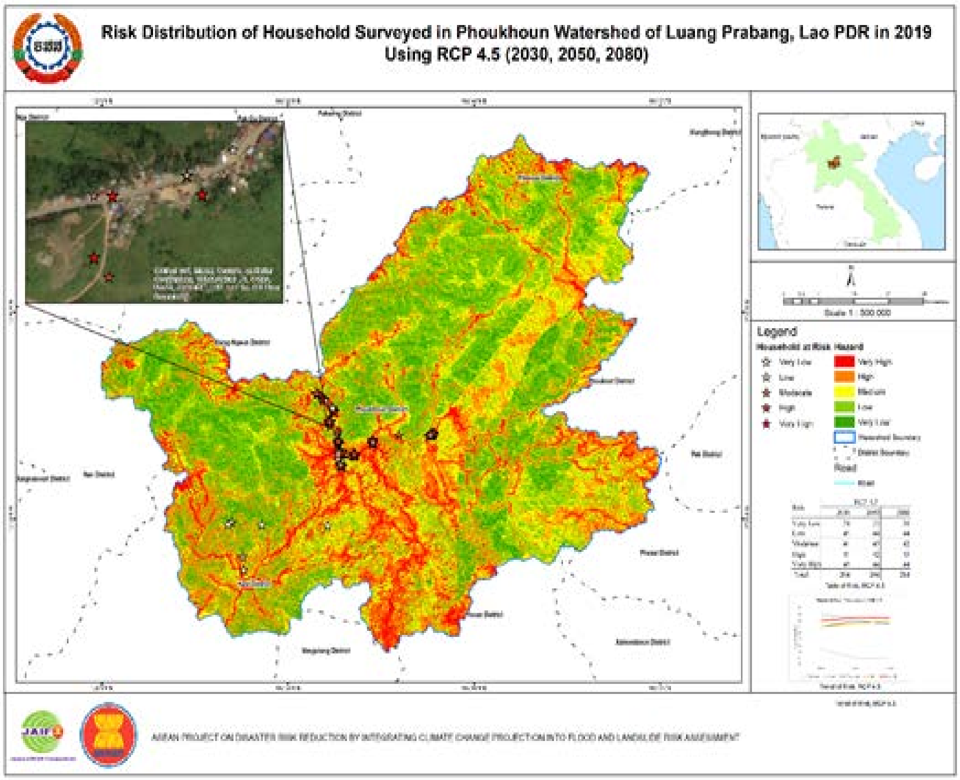


Figure 3.2 Risk distribution of households surveyed in the Phoukhoun Watershed, Lao PDR in 2019 using RCP 4.5 (2030, 2050 and 2080)

Table 3.2 depicts the cross tabulation between the risk and the slope for RCP 4.5. The original slope is classified into 15 classes using the equal interval of the Geographic Information System to see the distribution of the slope. The class is then reclassified into 5 classes to detail the majority of the slope classes. The classes are ranging from 0-15, 15-30, 30-45,45-60, and 60-75. The class is then aggregated into two major classes of less than 15 and greater than 15 degrees.

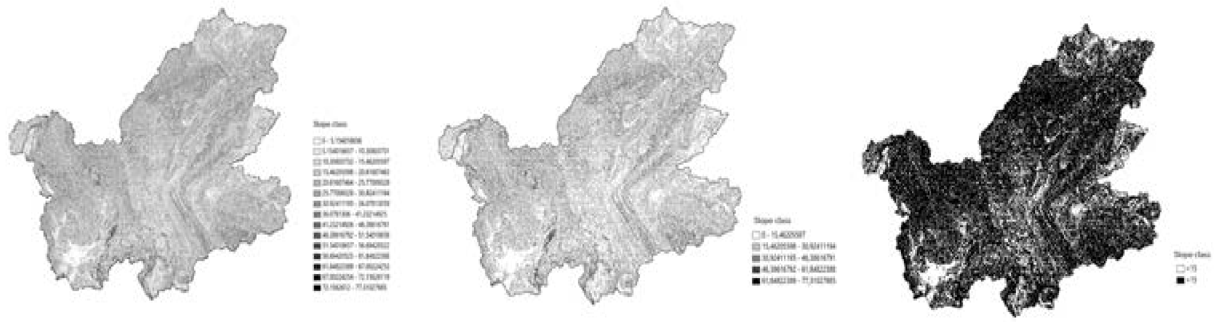


Figure 3.3 Slope classification process

Table 3.2 Cross tabulation of risk and slope in RCP 4.5

Slope Class	Risk Scenario RCP 4.5, Year 2030					Total Household
	Very Low	Low	Moderate	High	Very High	
<15%	18	8	9	11	9	55
>15%	16	37	32	30	34	149
Total	34	45	41	41	43	204
Slope Class	Risk Scenario RCP 4.5, Year 2050					Total Household
	Very Low	Low	Moderate	High	Very High	
<15%	18	8	9	11	9	55
>15%	16	37	32	30	34	149
Total	34	45	41	41	43	204
Slope Class	Risk Scenario RCP 4.5, Year 2080					Total Household
	Very Low	Low	Moderate	High	Very High	
<15%	18	8	9	11	9	55
>15%	16	37	32	30	34	149
Total	34	45	41	41	43	204

3.2 Landslide risk profile developed using future climate scenarios of RCP 8.5

Using RCP 8.5 in the risk assessment also shows a similar result to 4.5. The high risk and very high-risk classes in terms of households increase throughout the projected years. The study result shows that the risk in the very high class increased from 43 households to 45 households in 2080. It should be noted that this number only represents surveyed households. An assumption is being made that the trend will increase when samples are increased. A greater number of households potentially increases the number of houses that are at-risk.

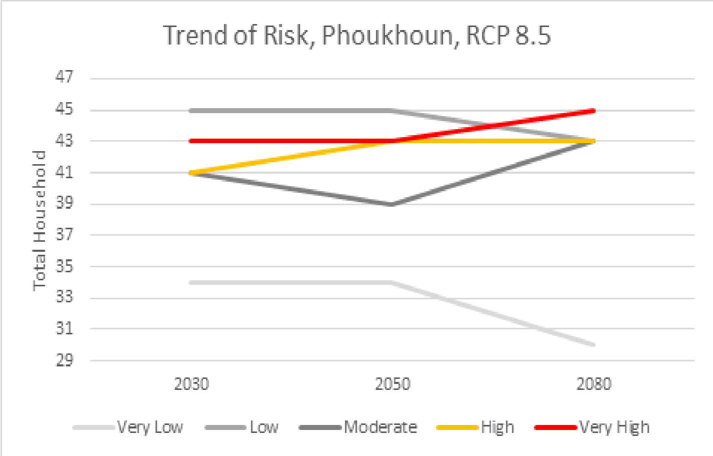


Figure 3.4 Risk trend for Phoukhoun at RCP 8.5

Table 3.3 Risk table for surveyed households at RCP 8.5

Risk	RCP 8.5		
	2030	2050	2080
Very Low	34	34	30
Low	45	45	43
Moderate	41	39	43
High	41	43	43
Very High	43	43	45
Grand Total	204	204	204

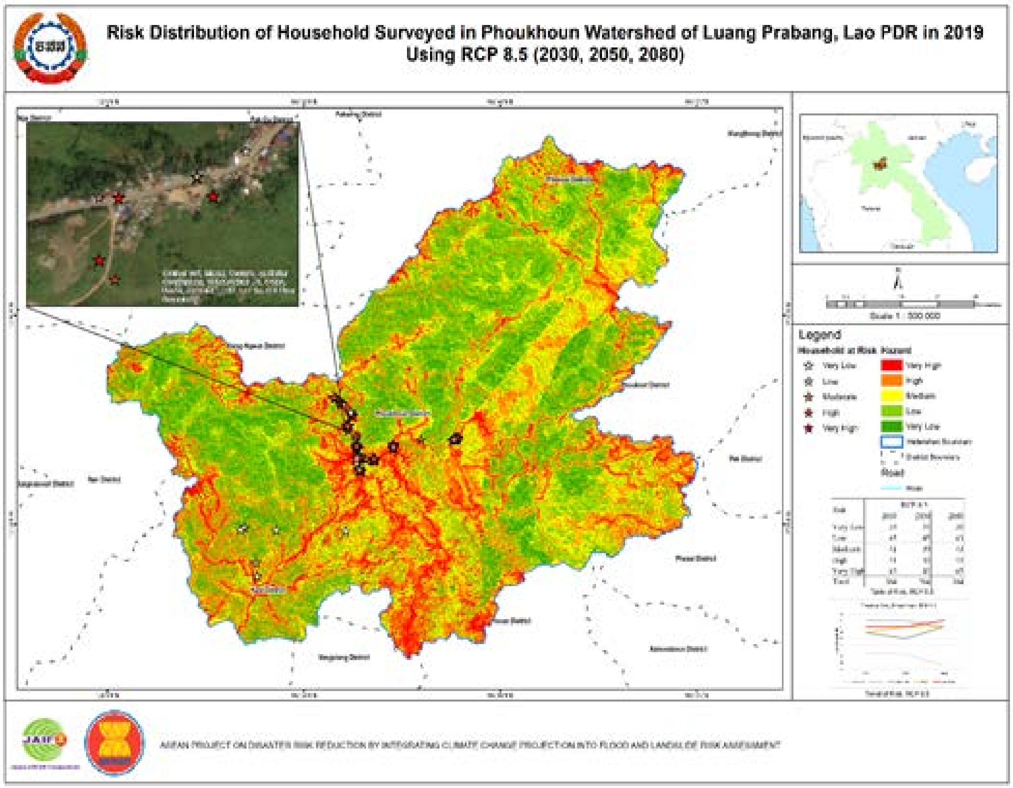


Figure 3.5 Risk distribution of households surveyed in the Phoukhoun Watershed of Luang Prabang, Lao PDR in 2019 using RCP 8.5 (2030, 2050 and 2080)

Slope Class	Risk Scenario RCP 8.5, Year 2030					Total Household
	Very Low	Low	Moderate	High	Very High	
<15%	18	8	9	11	9	55
>15%	16	37	32	30	34	149
Total	34	45	41	41	43	204
Slope Class	Risk Scenario RCP 8.5, Year 2050					Total Household
	Very Low	Low	Moderate	High	Very High	
<15%	18	8	9	11	9	55
>15%	16	37	32	30	34	149
Total	34	45	41	41	43	204
Slope Class	Risk Scenario RCP 8.5, Year 2080					Total Household
	Very Low	Low	Moderate	High	Very High	
<15%	18	8	9	11	9	55
>15%	16	37	32	30	34	149
Total	34	45	41	41	43	204

Table 3.4 Cross tabulation of risk and slope in RCP 8.5

3.2.1 Potential Applications

This case study illustrates potential applications of a landslide risk assessment that integrates future climate change scenarios. Results can be used as a reference to design landslide risk reduction and management strategies and programs, as well as to prioritize high and very high-risk areas and households that have been identified through the case study. **Table 3.5** presents samples of the suggested action level based on the identified risk condition.

Table 3.5 Suggested risk level and DRR related action level

Risk Level	Color Code	Action level
Very high	**Red**	**Urgent action** - Very high -risk condition with highest priority for risk reduction & contingency planning.
High	**Orange**	**Immediate action** - High risk condition with high priority for risk reduction & contingency planning.
Moderate	**Yellow**	**Prompt action** – Moderate to high-risk condition with risk addressed by reduction & contingency planning.
Low	**Light Green**	**Planned action** – Risk condition sufficiently high to give consideration for further reduction & contingency planning.
Very low	**Green**	**Advisory in nature** – Low risk condition with additional reduction and contingency planning.

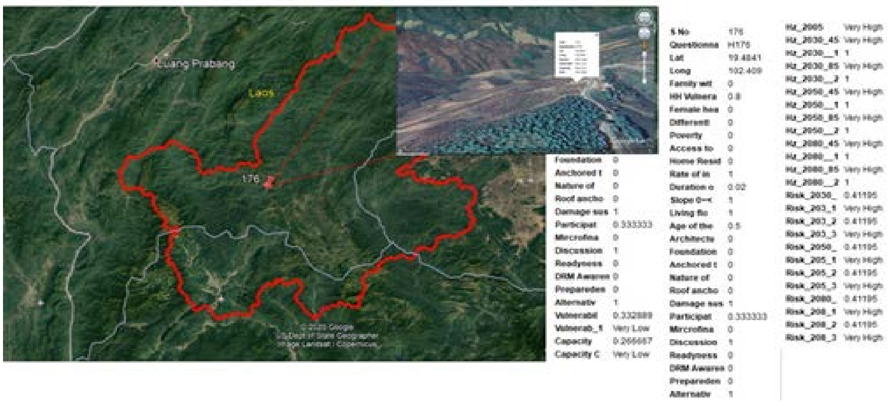


Figure 3.6 Google Earth screenshot displaying the household sample and attributes

The surveyed household's data can also provide important information on vulnerability and capacity, especially for households located in high and very high landslide prone areas. Using GIS technology where open-source options such as QGIS and Google Earth are also available, household surveys can be presented as easy and user-friendly tools to help in the decision-making process. **Figure 3.6** shows a household sample located in a high landslide prone area, with detailed information and attributes collected and mapped in Google Earth, making landslide hazard level, vulnerability, capacity and risk easily readable.

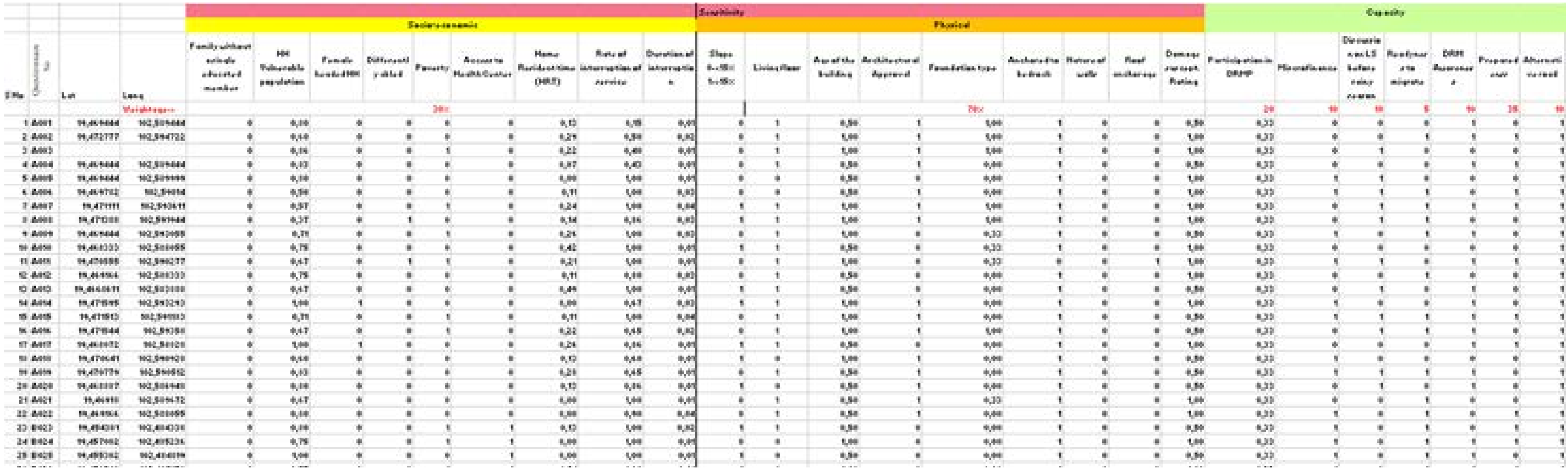
4. CONCLUSION AND RECOMMENDATIONS

This case study on landslide risk assessment by integrating future climate scenarios that has been piloted in Phoukhoun River Basin in Luang Prabang Province in Lao PDR has identified landslide-prone areas in the Phoukhoun River Basin. This study can be replicated in other river basins in Lao PDR in order to get a comprehensive picture of landslide risk in the country that can be used to identify programming gaps and opportunities that will enable government and other relevant agencies to formulate landslide risk reduction plans and strategies. The hazard maps and surveyed household and statistical data that were generated as a result of this study can be used as a model (to be adapted and replicated in other river basins, especially those prone to landslides) and integrated into the local and national disaster risk management framework in Lao PDR in the following ways.

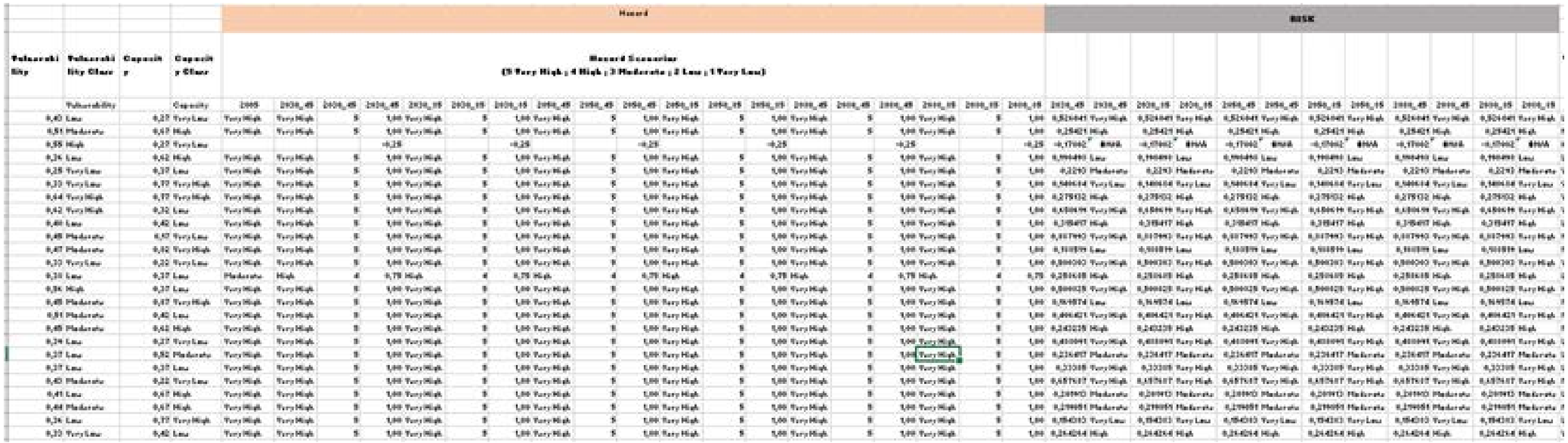
- The hazard maps can be used by policy makers, decision makers and planners as a basis for future master plans and sustainable development. Authorities can take necessary actions to reduce the potential impacts of landslides on various economic sectors such as transport, housing, etc.
- The hazard maps and statistical data can help policy makers, decision makers, planners and other parties to plan and implement effective landslide risk management strategies in Lao PDR, particularly at the river basin scale.
- Prevention and response related agencies can use the hazard maps to coordinate prevention and response strategies and identify sites for structural and non-structural mitigation programs and initiatives.
- The hazard maps can assist local governments in introducing and enforcing building codes and permitting regulations to protect homes and infrastructure.
- The case study report, e.g., the hazard, vulnerability and risk maps, can be used as a tool to educate and create public awareness on landslide hazard and risk.
- Development of community-based landslide risk reduction and management can be initiated, especially for those communities located in high and very high landslide prone areas.

The landslide hazard and risk assessment in this case study was carried out using scientific tools and relevant methods with the outputs generated to the appropriate scale. For this extensive hazard assessment and mapping, several datasets were required, including geological, hydro-meteorological, geo-morphological and other related data. Though information was widely available, a large quantity of data also was missing. When better resources, such as higher resolution datasets, become available in future, it is recommended that more detailed landslide analyses be conducted in zones with high and very high susceptibility

Annex 1. Surveyed household database (2019)

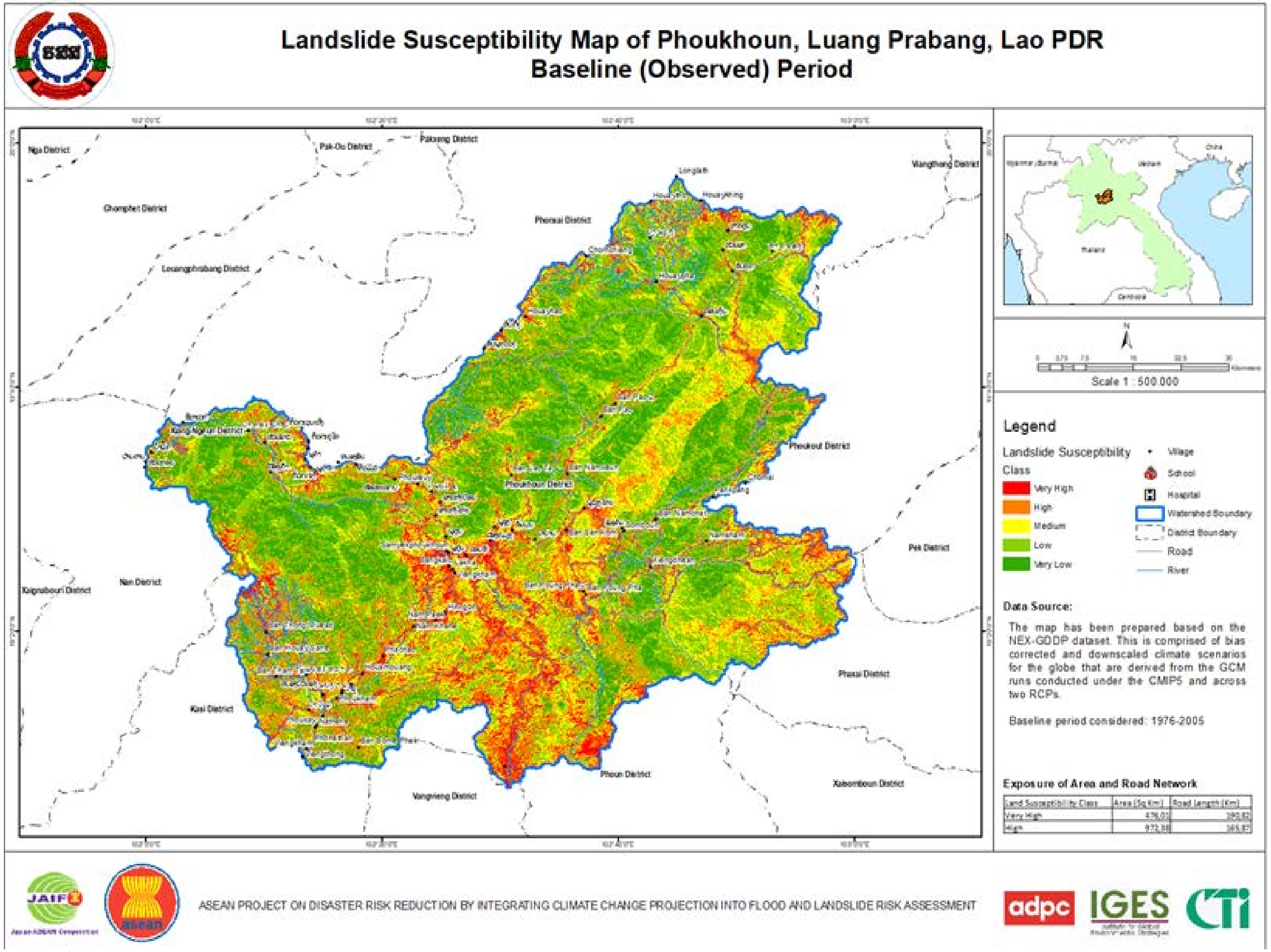


				Sensitivity																		Capacity						
				Socio-economic									Physical															
S No	Questionnaire No	Lat	Long	Family without schooled educated member	HH Vulnerable population	Female headed HH	Differently abled	Poverty	Access to Health Center	Remote Residential time (HRS)	Rate of interruption of service	Duration of interruptio n	Slope 0-<35% 5-<35%	Living floor	Age of the building	Architectural Approval	Foundation type	Anchored to bedrock	Retained walls	Roof anchorage	Damage assessment Rating	Participation in DRMP	Microfinances	Domestic ...LS before rainy season	Readiness to migrate	DRM Awareness	Prepared ness	Alternative ...
			Weightages					30%									70%					20	10	10	5	10	35	10

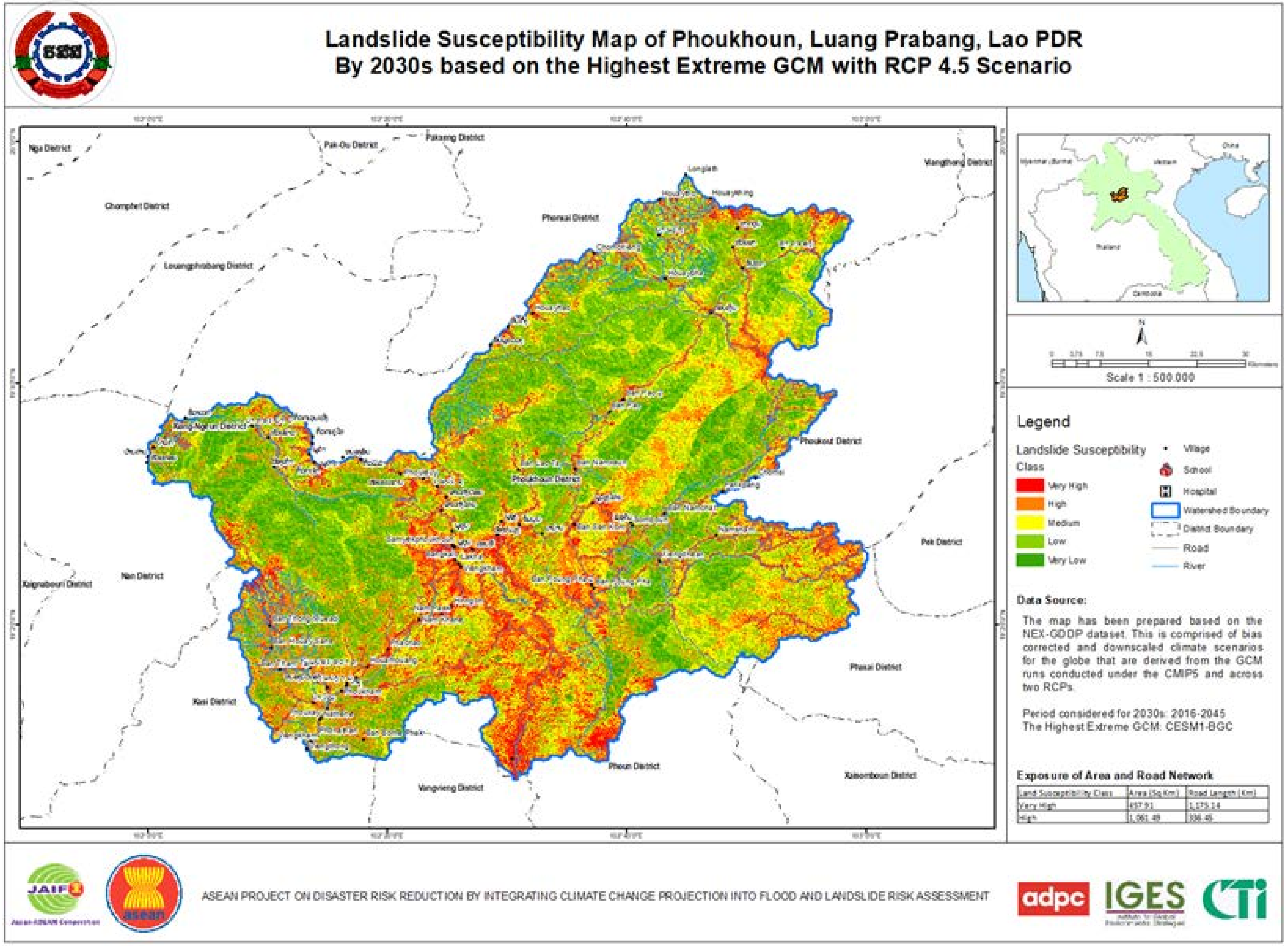


Vulnerability	Vulnerability Class	Capacity	Capacity Class	Hazard: Hazard Scenarios (5 Very High ; 4 High ; 3 Moderate ; 2 Low ; 1 Very Low)	RISK
	Vulnerability		Capacity	2005, 2030_45, 2030_45, 2030_45, 2030_85, 2030_85, 2030_85, 2050_45, 2050_45, 2050_45, 2050_85, 2050_85, 2050_85 …	

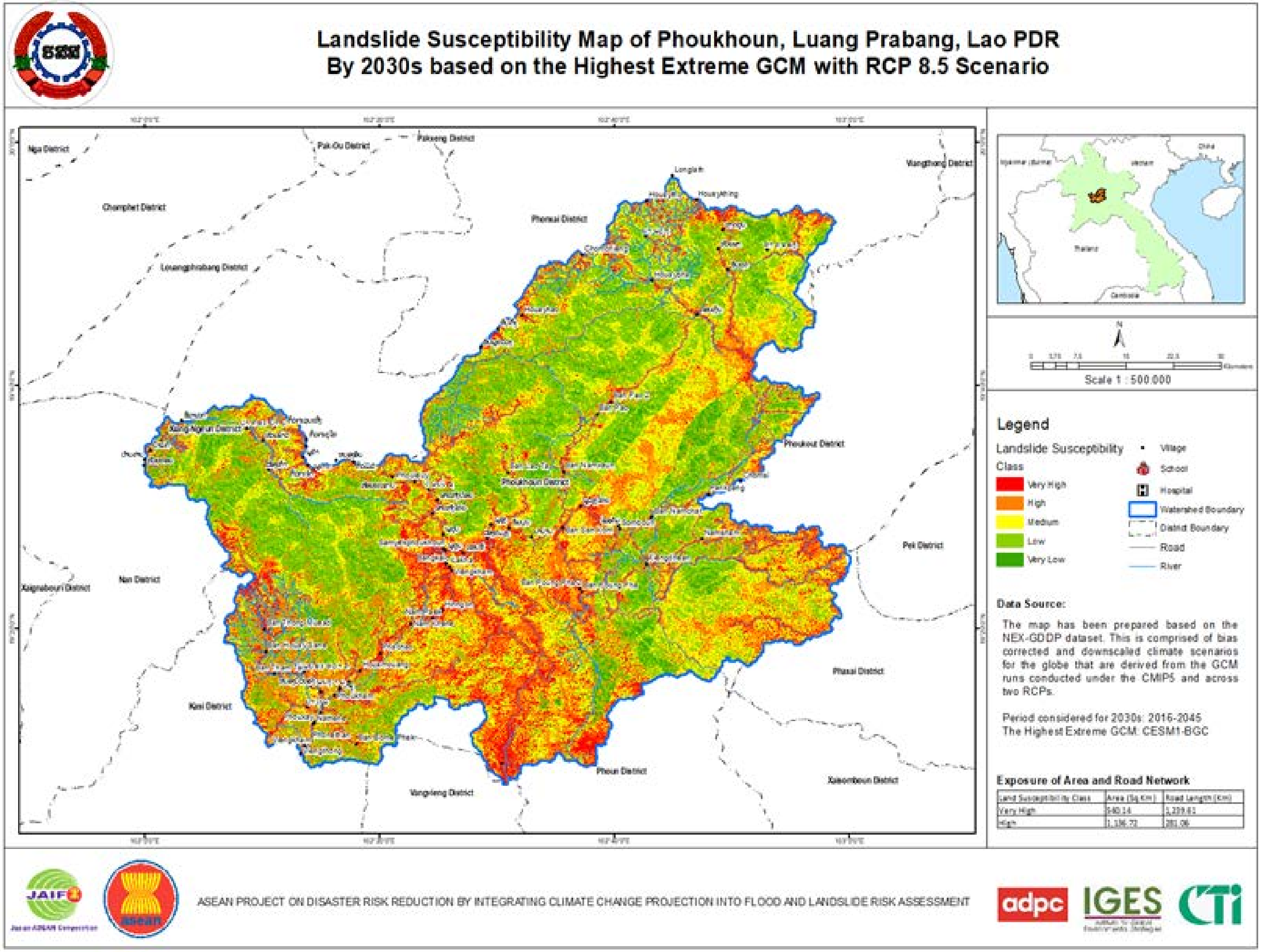
Map 1. Landslide susceptibility map of Phoukhoun, Luang Prabang, Lao PDR. Baseline (observed) period



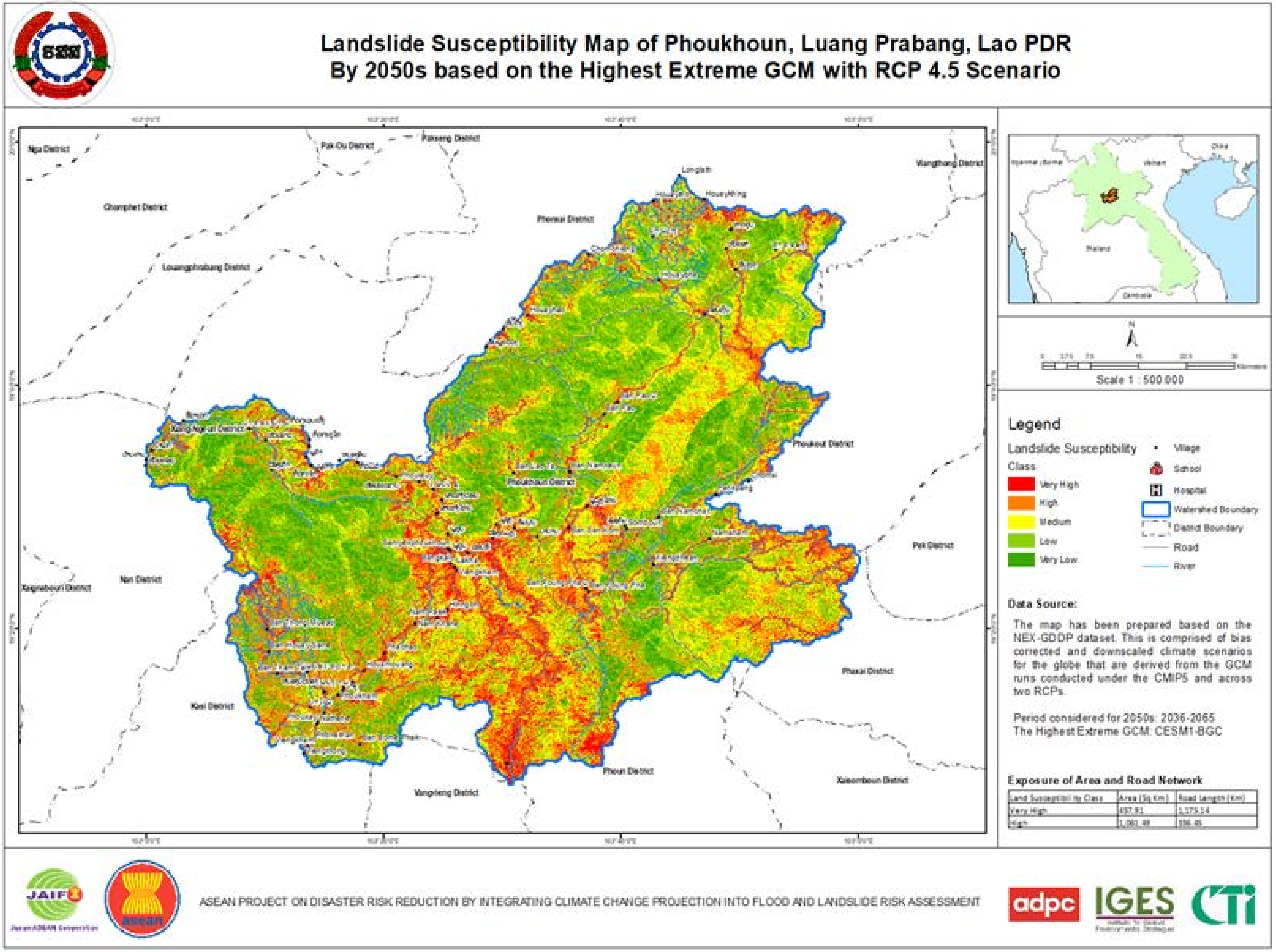
Map 2. Landslide susceptibility map of Phoukhoun, Luang Prabang, Lao PDR by 2030s based on the highest extreme GCM with RCP 4.5 scenario



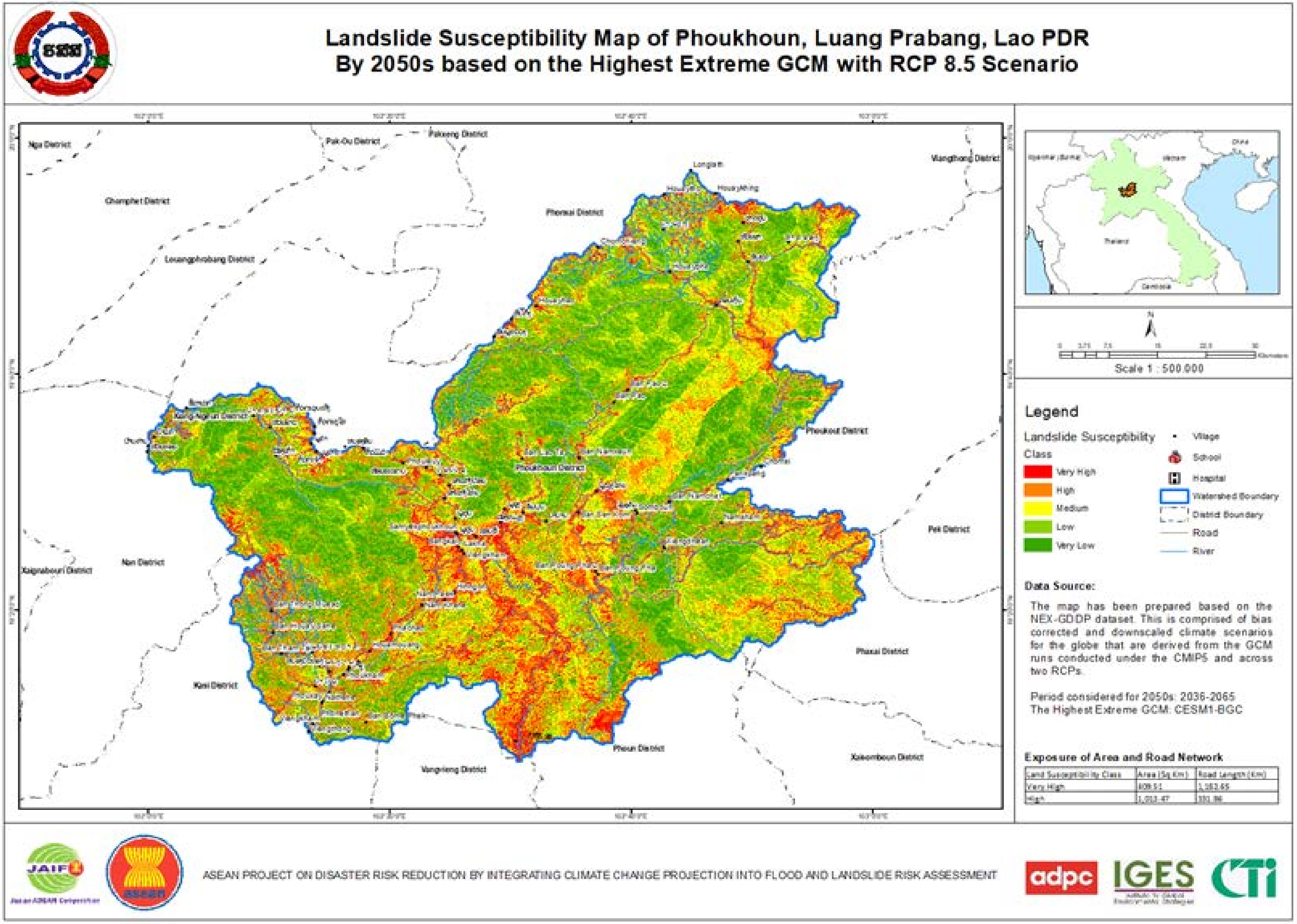
Map 3. Landslide susceptibility map of Phoukhoun, Luang Prabang, Lao PDR by 2030s based on the highest extreme GCM using RCP 8.5 scenario



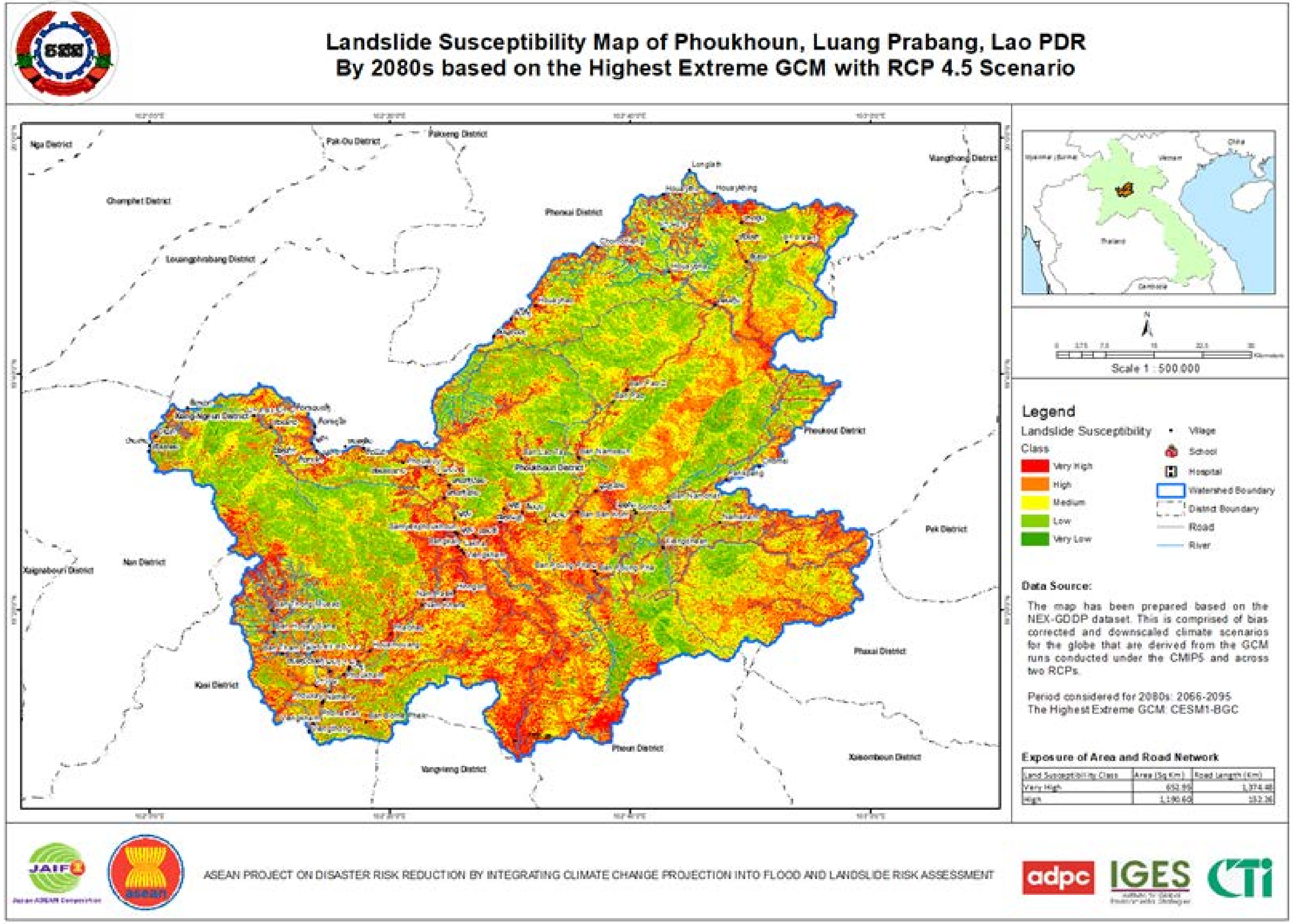
Map 4. Landslide susceptibility map of Phoukhoun, Luang Prabang, Lao PDR by 2050s based on the highest extreme GCM using RCP 4.5 scenario



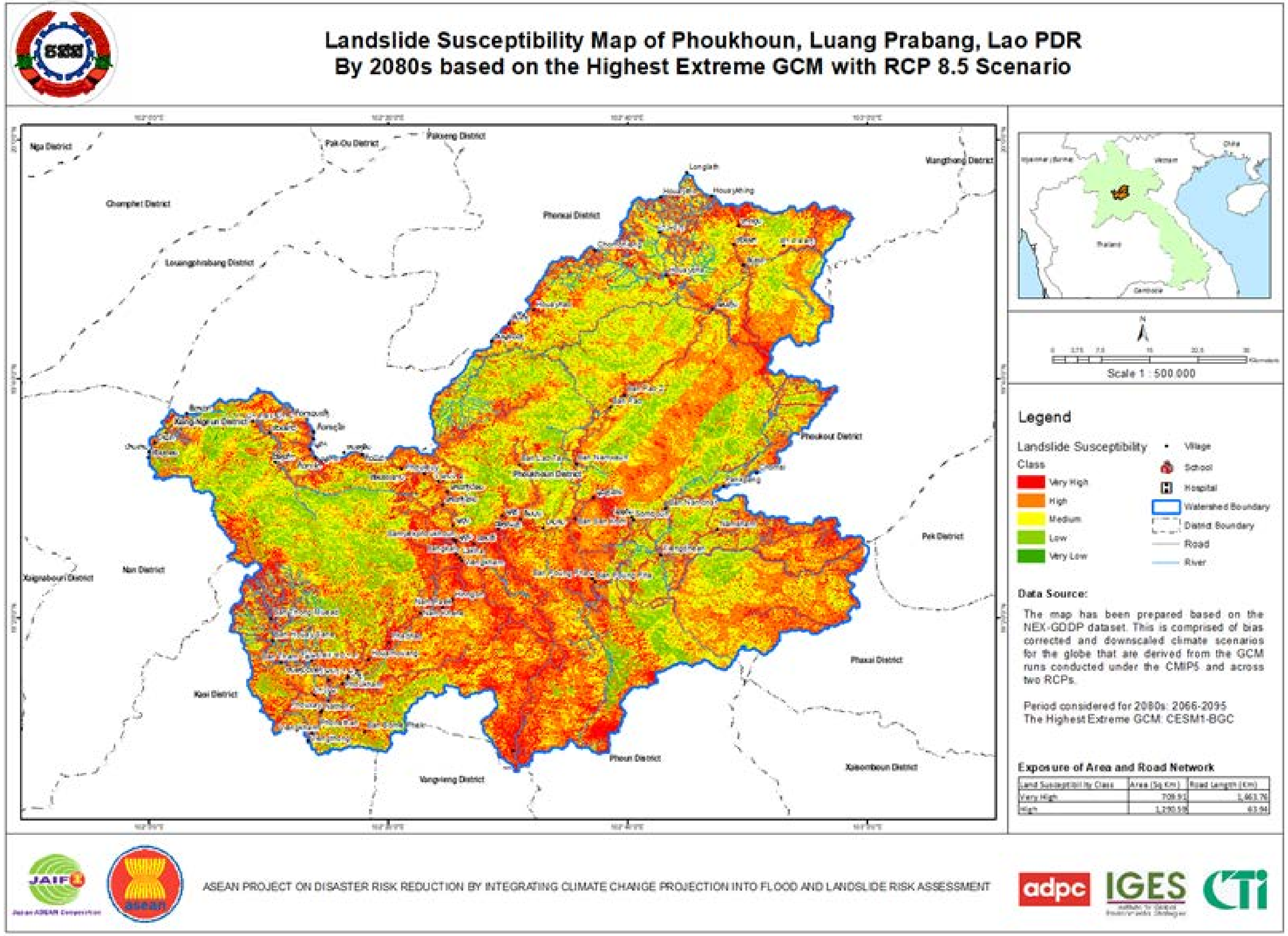
Map 5. Landslide susceptibility map of Phoukhoun, Luang Prabang, Lao PDR by 2050s based on the highest extreme GCM with RCP 8.5 scenario



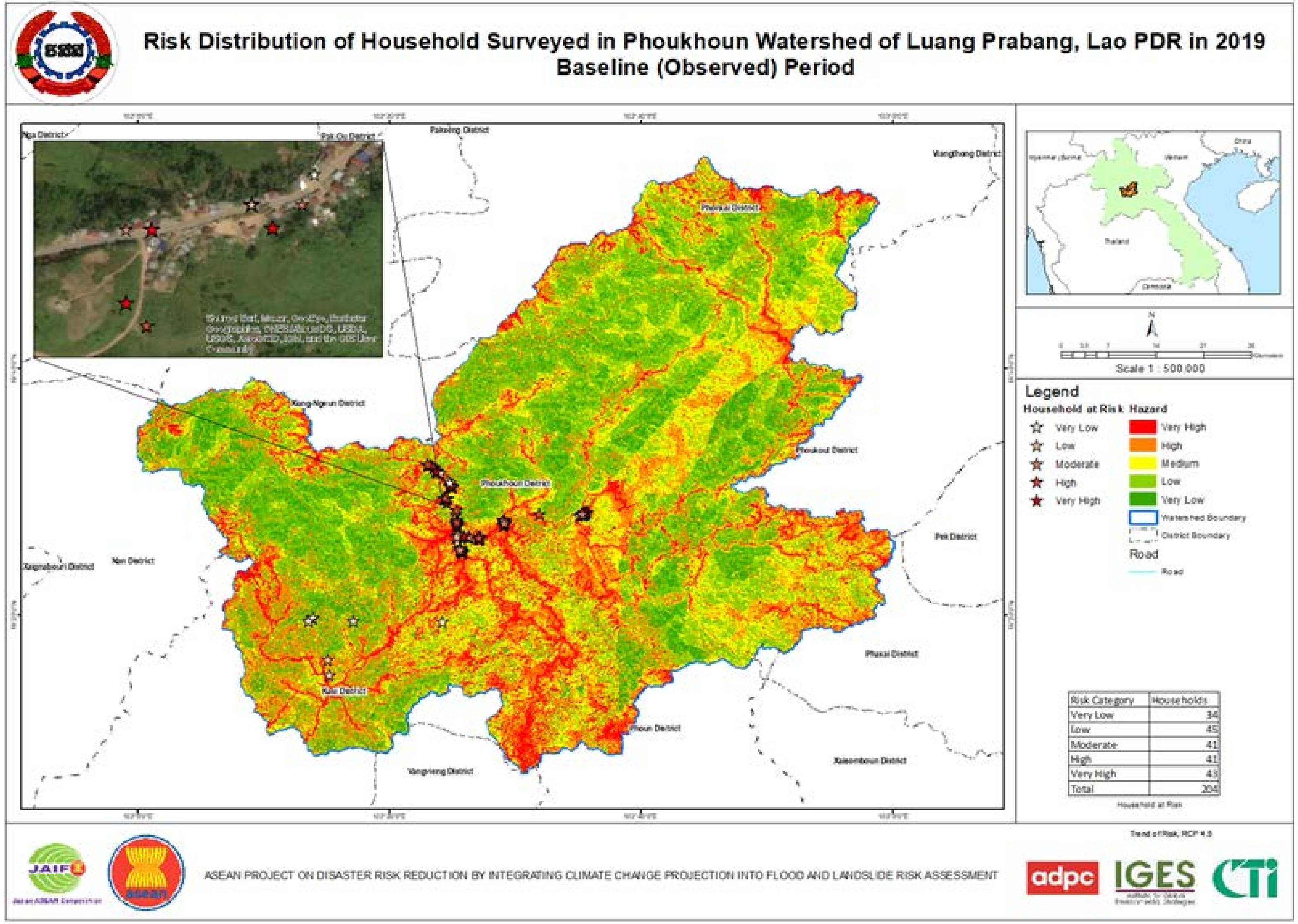
Map 6. Landslide susceptibility map of Phoukhoun, Luang Prabang, Lao PDR by 2080s based on the highest extreme GCM with RCP 4.5 scenario



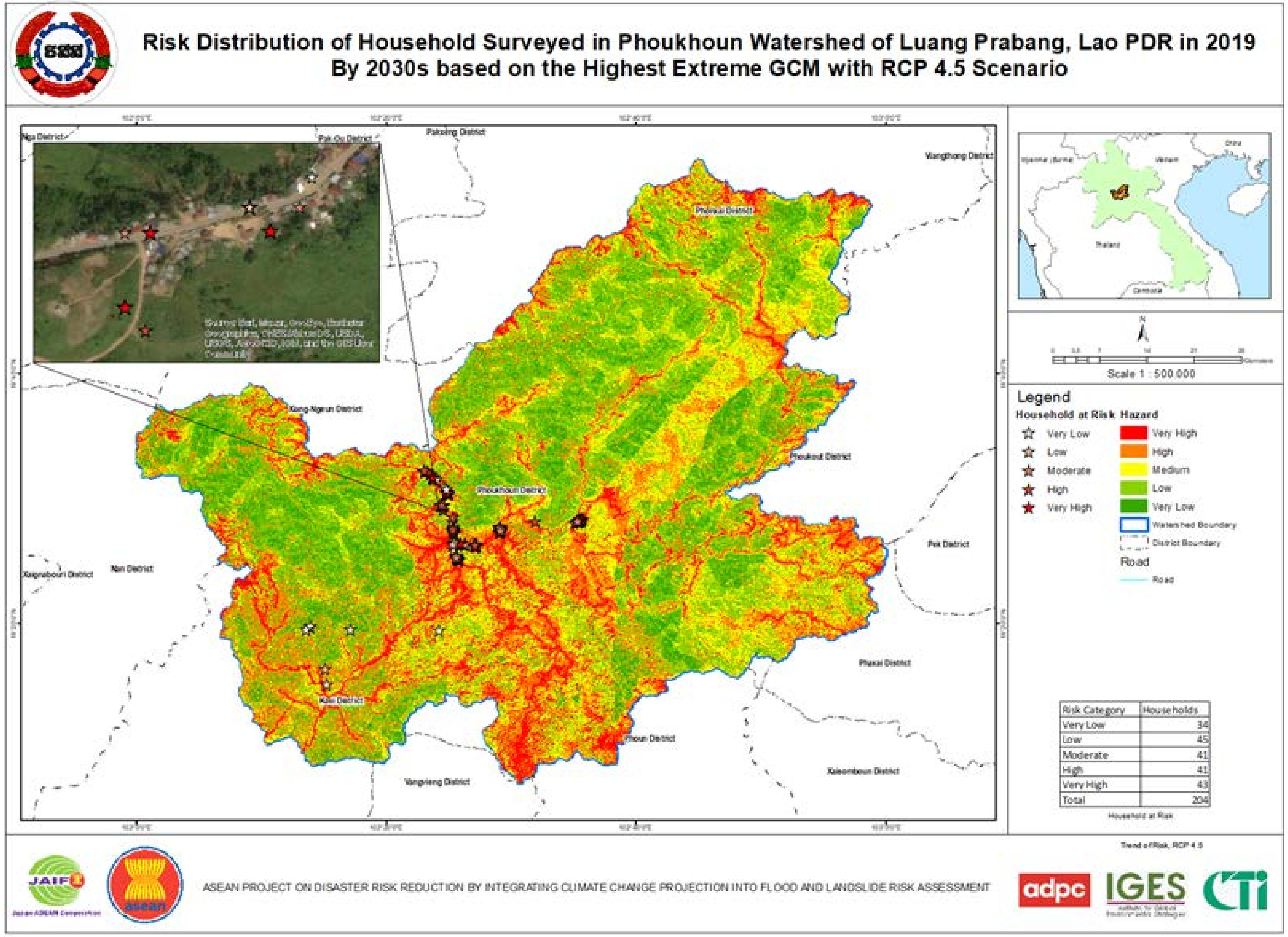
Map 7. Landslide susceptibility map of Phoukhoun, Luang Prabang, Lao PDR by 2080s based on the highest extreme GCM with RCP 8.5 scenario



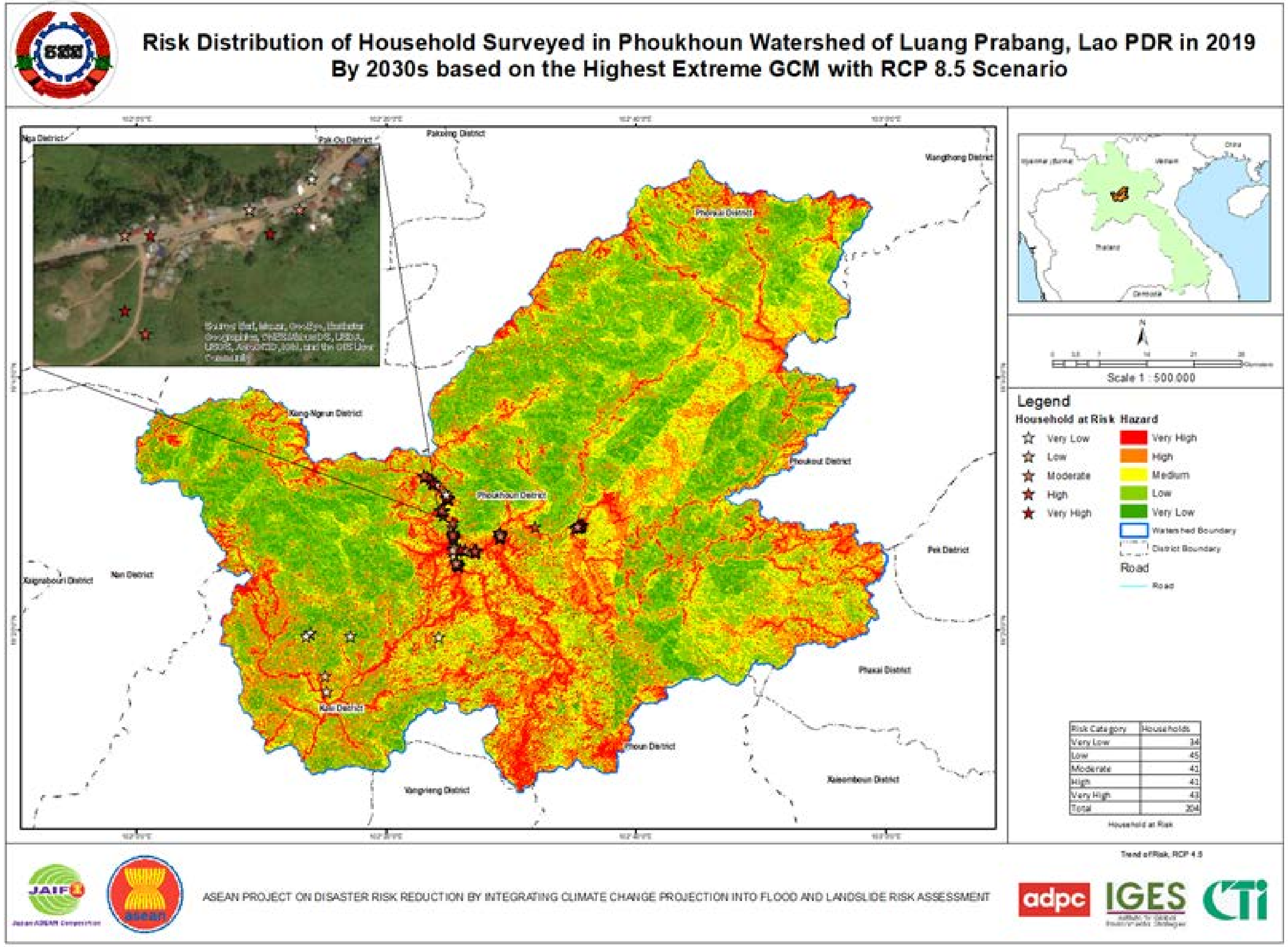
Map 8. Risk distribution of surveyed households in the Phoukhoun Watershed of Luang Prabang, Lao PDR in 2019. Baseline (observed) period



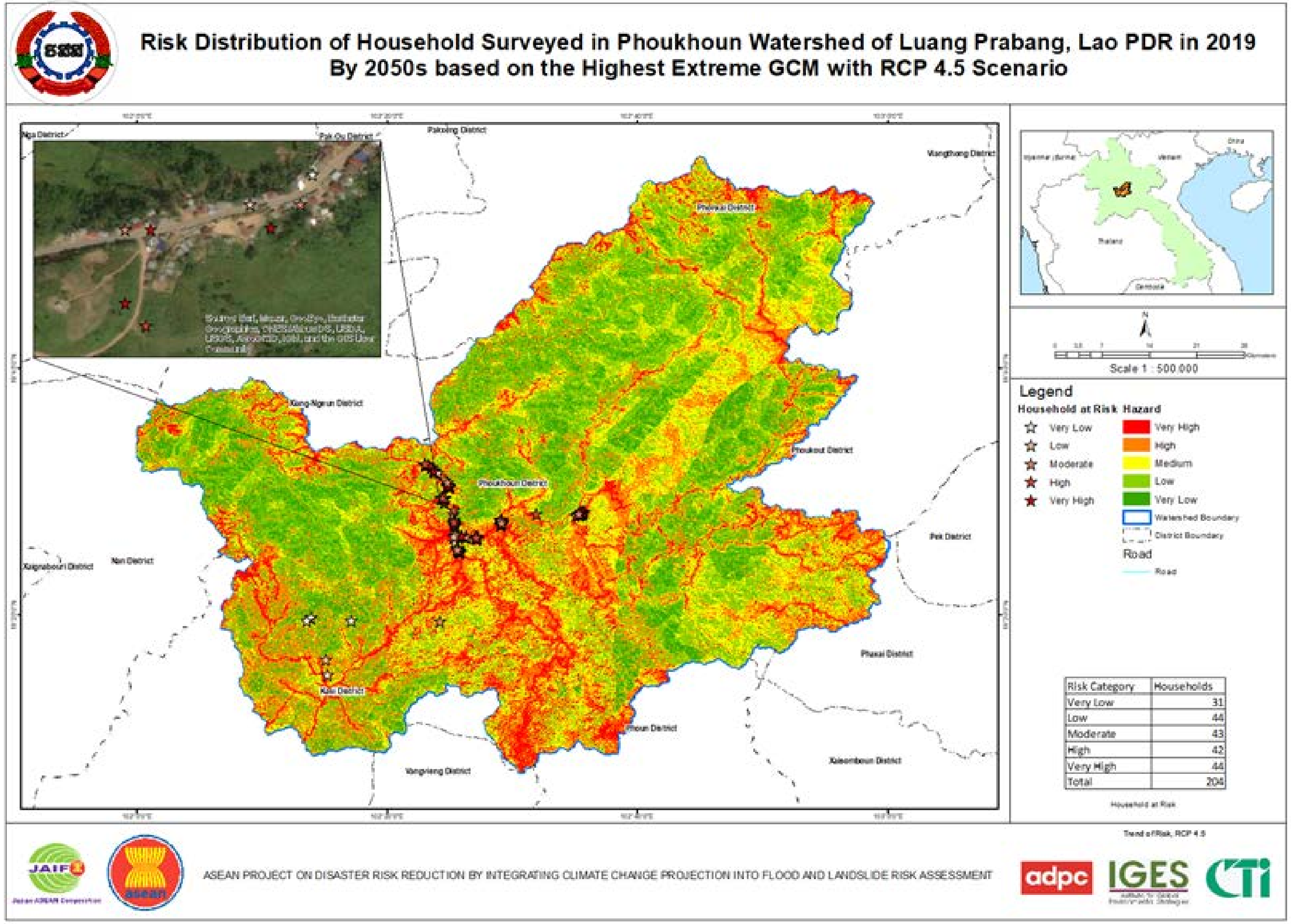
Map 9. Risk Distribution of surveyed households in the Phoukhoun Watershed of Luang Prabang, Lao PDR in 2019 by 2030s based on the highest extreme GCM with RCP 4.5 scenario



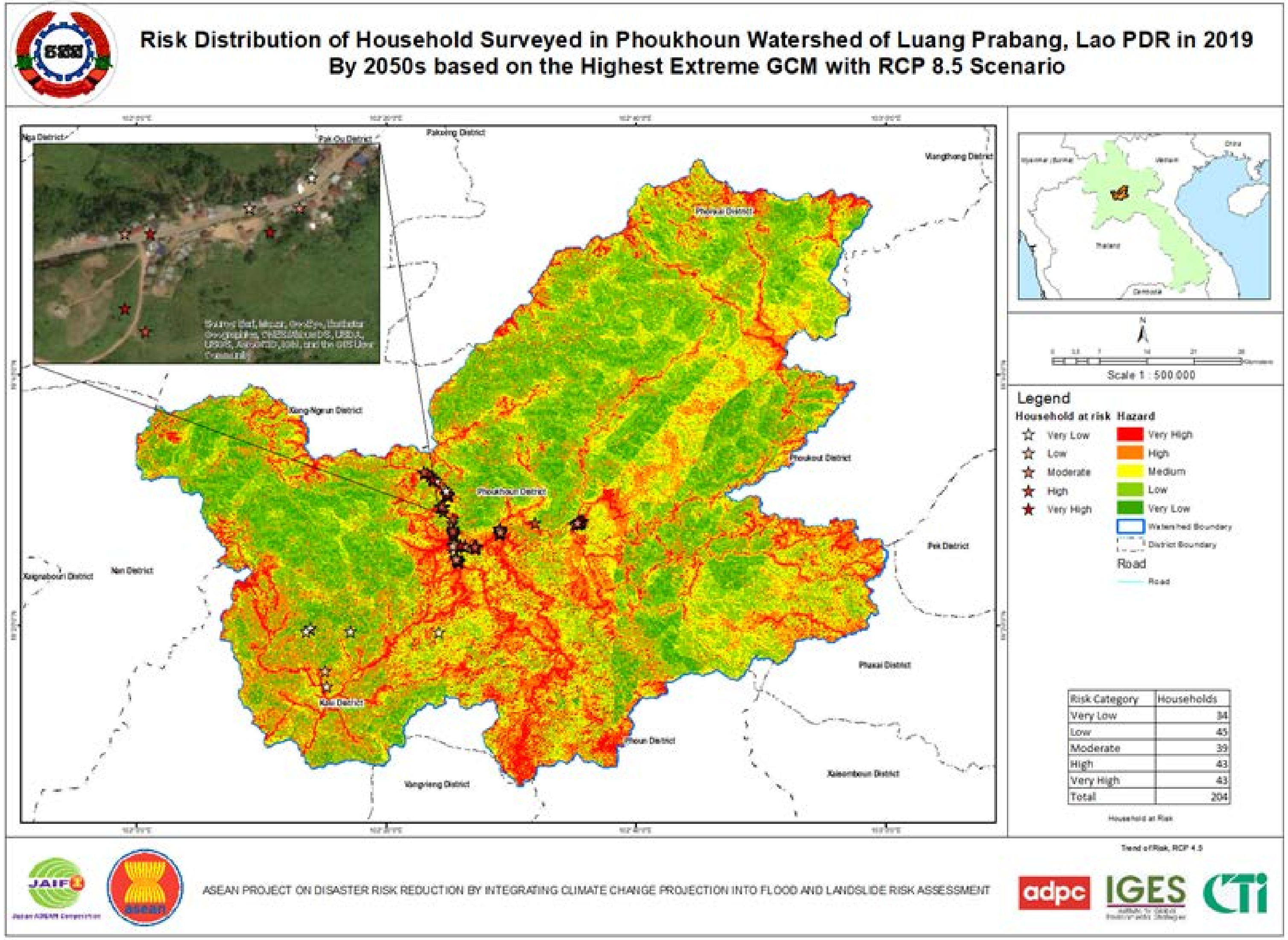
Map 10: Risk distribution of surveyed households in the Phoukhoun Watershed of Luang Prabang, Lao PDR in 2019 by 2030s based on the highest extreme GCM with RCP 8.5 scenario



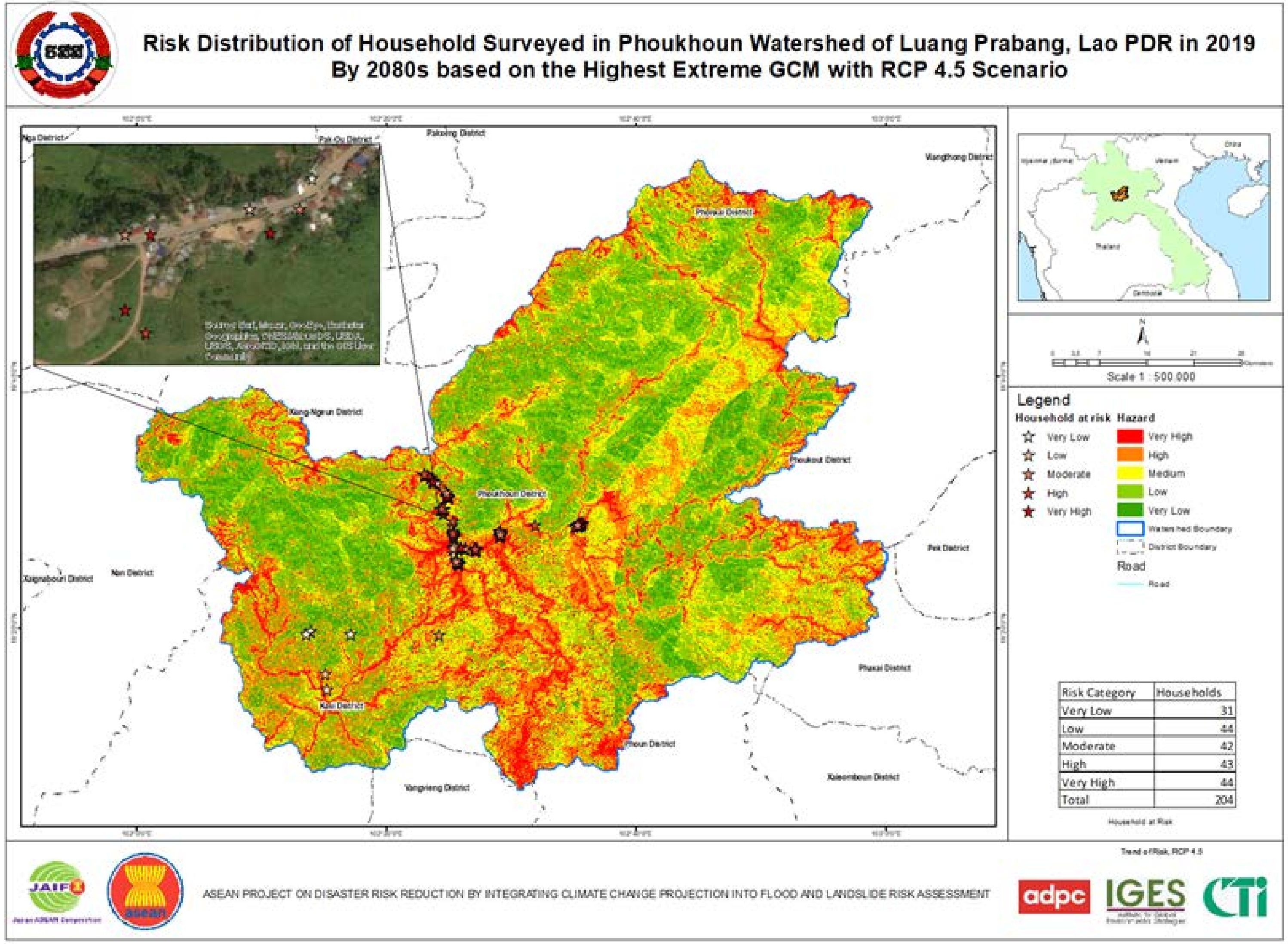
Map 11. Risk distribution of surveyed households in the Phoukhoun Watershed of Luang Prabang, Lao PDR n 2019 by 2050s based on the highest extreme GCM with RCP 4.5 scenario



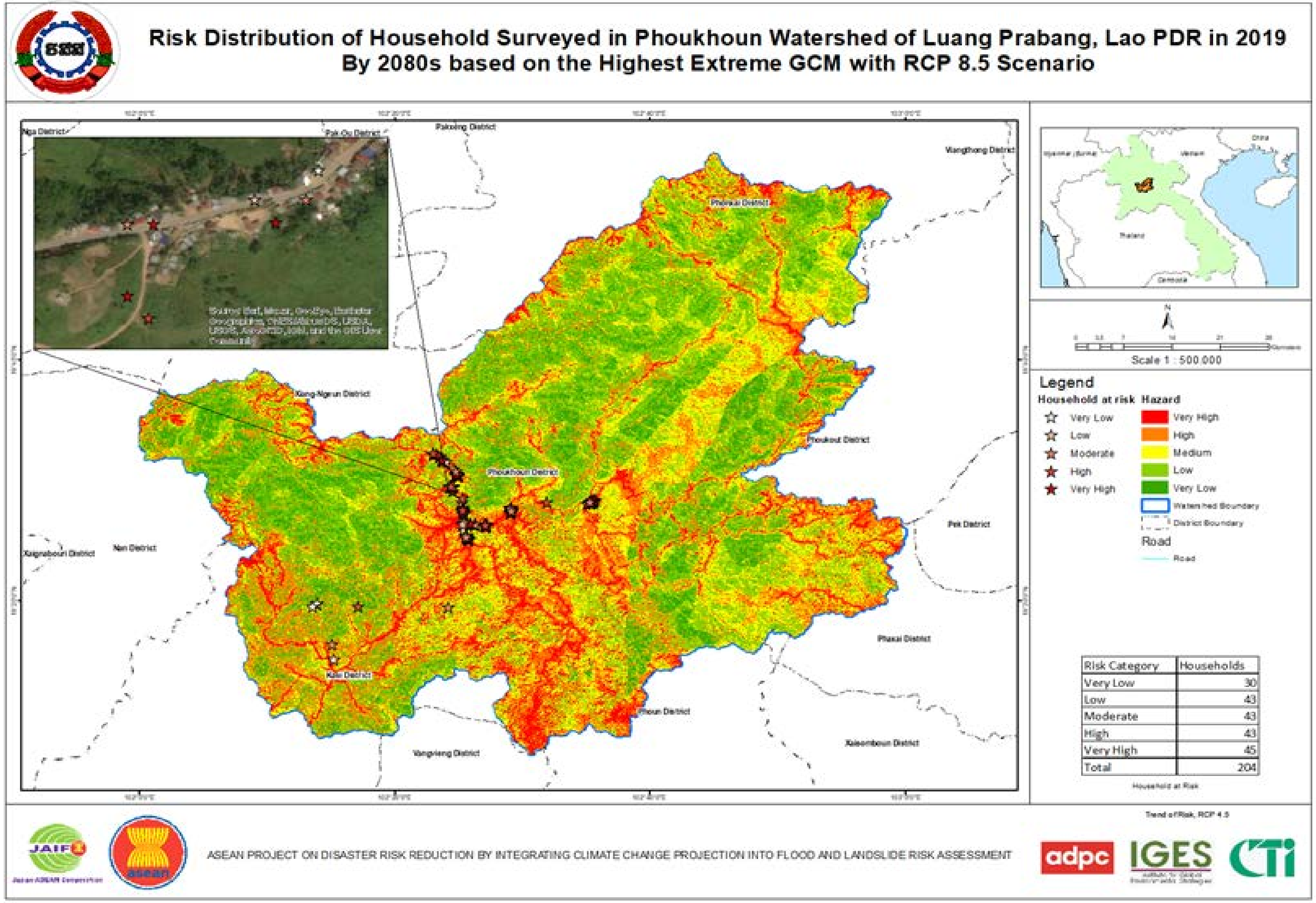
Map 12. Risk distribution of surveyed households in the Phoukhoun Watershed of Luang Prabang, Lao PDR in 2019 by 2050s based on the highest extreme GCM with RCP 8.5 scenario



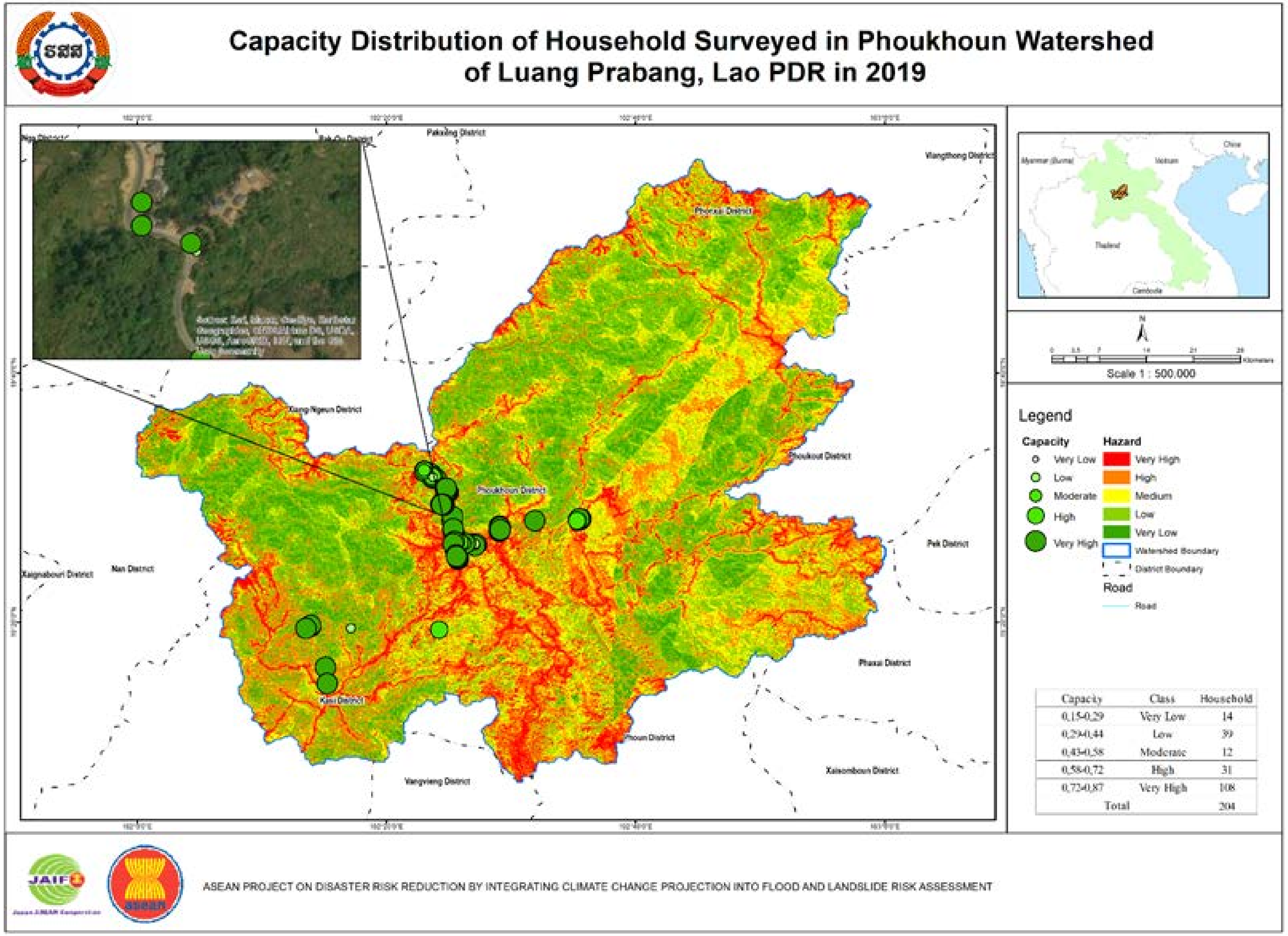
Map 13. Risk Distribution of surveyed households in the Phoukhoun Watershed of Luang Prabang, Lao PDR in 2019 by 2080s based on the highest extreme GCM with RCP 4.5 scenario



Map14. Risk distribution of surveyed households in the Phoukhoun Watershed of Luang Prabang, Lao PDR in 2019 by 2080s based on the highest extreme GCM with RCP 8.5 scenario



Map 15. Capacity distribution of surveyed households in the Phoukhoun Watershed of Luang Prabang, Lao PDR in 2019



Map 16. Vulnerability distribution of households surveyed in the Phoukhoun Watershed of Luang Prabang, Lao PDR in 2019