UNIVERSIDAD SAN FRANCISCO DE QUITO

Colegio de Posgrados

Impact Analysis of Climate Change on Andean Crops

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Tesis de grado presentada como requisito
para la obtención del título de Magister en Sistemas de Información Geográfica

Quito, enero de 2014

Universidad San Francisco de Quito

Colegio de Posgrados

HOJA DE APROBACIÓN DE TESIS

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ACKNOWLEDGMENTS

I thank Julian Ramirez-Villegas and Andy Jarvis—the latter leader of the Decision and Policy Analysis (DAPA – http://dapa.ciat.cgiar.org/) Research Area in the International Center for Tropical Agriculture (CIAT – http://dapa.ciat.cgiar.org/)—for their invaluable help regarding research guidance, inputs for this analysis and support with data and software access for the development of this analysis. I also thank the Project Panorama Andino, led by CONDESAN (http://www.condesan.org/portal/programas/que-es-panorama-andino), in which this analysis was framed.

RESUMEN

A continuación se presenta un análisis del impacto que tendrá el cambio climático durante los periodos 2020 y 2050, sobre cinco de los cultivos más importantes para la seguridad alimentaria de las comunidades andinas que ocupan la región tropical (desde Venezuela hasta Bolivia). A saber; fríjol, café, tomate, trigo y papa. Se concluyó que el área potencial impactada negativamente en toda la región será significativamente mayor a la impactada positivamente.

Los casos más extremos, según el escenario A1B para 2020, se observan en café, frijol y trigo, cultivos cuya disminución en aptitud climática es de 79.7% (30 millones de hectáreas, de un total de 37.7 millones con aptitud climática para crecer el cultivo), 76.3% (193 millones de hectáreas de un total de 253.8 millones) y 96.9% (24.5 millones de hectáreas de una de 25.4 millones), respectivamente. Las proyecciones estiman que dicha tendencia continuará hacia el año 2050, según el mismo escenario climático.

Por lo tanto, y para hacer frente a tan desalentador panorama, será necesario tomar medidas que disminuyan los niveles de vulnerabilidad de los agricultores a pequeña escala. Algunas ideas sobre estrategias de corto (gestión del riesgo) y largo plazo (adaptación), así como de mitigación, son presentadas hacia el final del documento.

ABSTRACT

This document will present an analysis of the impact that climate change will have during the 2020 and 2050 periods on five of the most important food security crops of the tropical Andean communities (from Venezuela to Bolivia). Namely: bean, coffee, tomato, wheat and potato. It was concluded that the potential area impacted negatively across the region will be significantly larger than the area impacted positively.

Most extreme cases, according to the A1B scenario for 2020, are observed in coffee, bean and wheat, crops whose climatic suitability will decrease by 79.7% (30 million hectares out of a total 37.7 million with climatic suitability), 76.3% (193 million hectares out of a total of 253.8 million) and 96.9% (24.5 million hectares out of 25.4 million), respectively. Projections estimate that this trend will continue until 2050, according to the same climatic scenario.

Therefore, and in order to deal with such a disheartening panorama, it is necessary to take measures to reduce the levels of vulnerability of small-scale farmers. Some ideas on short- (risk management) and long-term strategies (adaptation), as well as mitigation, are presented towards the end of the document.

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CHAPTER 1

1. INTRODUCTION

Our environment is a precious gift of immense value. For some people it is not clear where such a gift came from, while for others it is obvious that it originates beyond the material plane. However, whatever its origin is the sacred duty of mankind to appreciate it, use it and enjoy it—while it is preserved and protected. It is worthwhile, then, to think about the following questions: How many times in a lifetime have we compared our environment with a gift? How many times in a lifetime have we assessed whether our actions are impacting our gift positively or negatively?

Most likely, the answer to the first question will be: “No, I have never done this type of comparison before”, a situation that is completely normal as we seldom dare to see our reality through the lens of the abstract. On the other hand, the answer to the second question may lead us to think that, daily, we carry out actions that directly or indirectly impact our environment (e.g. by using aerosols, smoking or, from a more general point of view, applying fertilizers to crops or burning forests indiscriminately). All these actions, surely, are affecting our environment, our livelihoods. It is in this point where the problem becomes visible; man is somehow influencing negatively or positively his environment, his gift. We, as the human race, are accelerating changes that have a direct impact on ourselves and on future generations.

In these terms, one of the sectors that is significantly impacted by human activity is agriculture; in this case, such impact comes from the anthropogenic climate change (CC). This means that, as a consequence of huge amounts of greenhouse gases released every year into the atmosphere, climate is becoming threatening to the agricultural sector (IPCC, 2001, 2007). Indeed, agricultural activities carried out to produce food also produce greenhouse gases (those most known are carbon dioxide (CO_2), methane (CH_4) and nitrous oxide (N_2O) (Quintanilla, 2004). In general terms, the accumulation of gases in the atmosphere prevents the movement of the sun's rays back into space in the proportion required, and generates abnormal conditions in the biosphere, causing climate anomalies for which we are not prepared (IPCC, 2007; Quintanilla, 2004). In that sense, changes in climate patterns generate uncomfortable conditions for crops to grow, directly impacting all producers, small and large, in the agricultural chain. That is our problem, and the tropical Andes will not be exempt from the implications of CC.

Overall, according to the Intergovernmental Panel on Climate Change (IPCC, 2007), the agricultural sector will be substantially affected at the global level by increases in temperature (which could reach up to 3–5 °C by 2050 depending on the greenhouse gas emission pathway) and variability in precipitation patterns (rain) (Ramirez-Villegas, Jarvis, & Läderach, 2011). Such changes will affect both production systems and specific crops that, in some instances, are the basis of the economy in some sub-regions of our tropical Andes (potatoes, beans, coffee, tomatoes, and wheat, among others). The implementation of appropriate actions will be useful to face the impacts of these phenomena, as well as to help to visualize some future opportunities for the sector.

It is also important to understand that climate challenges will need to be faced not only by decision makers but by each one of the actors involved (i.e. governments, research centers, academic institutions, and grassroots communities). It is through the creation of common vision and goals that feasible solutions can be found.

2. BACKGROUND

The world has been surprised by strong changes in climate since the mid-20th century. Those changes are mainly related to a significant increase in temperature and variations in precipitation according the different characteristics (e.g. topography) of each place in the world (IPCC, 2007). Up to now, recent findings indicate that causes of such anomalies have a solid relationship with CO_2 accumulation in the atmosphere, which is greater each time (IPCC, 2007; R. Jones et al., 2004; Quintanilla, 2004). Such situation has put humanity in a dilemma for which it was not prepared or, rather, of which it was not aware. Hence, the issue of CC has become in one of great relevance today. According to climate projections (IPCC, 2007), the agricultural sector in the Andes would not be exempt from those changes in climate and it is likely that the economy linked to it would be hit in the future.

Therefore, it is necessary to generate adaptation paths for the agricultural sector. Some of the tools widely used currently are climate projections and ecological niche modeling (ENM) manipulated in Geographic Information Systems (GIS). These tools have demonstrated good performance to identify the likely impact of climate on crops and, in general, to analyze the distribution of species. With its use it is possible to generate alternatives that promote the welfare of communities for which agriculture is the main activity. In addition, these tools help assess both the negative effects and potential opportunities in relation to crop climatic suitability. For that reason, this analysis aims to assess the likely impact on the potential distribution and climatic suitability (current and future) of five main crops in terms of production and consumption for communities in the tropical Andes by using ENM and GIS.

More specifically, what is intended in this study is to use two emission scenarios (SRES), A1B and A2, for the periods 2010–2039 (2020) and 2040–2069 (2050). The Global Circulations Models (GCMs) for those periods will be taken from the IPCC; in this case ten for SRES-A1B and eight for A2 SRES (due to the availability of all required variables in a scale of 30 Arc-Seconds in the Equator). The modeling process for current and future conditions will be done by using EcoCrop (Hijmans, Guarino, et al., 2005)—a model oriented to identify an index of climatic suitability based on basic growth parameters of the species in question (temperature and optimal and absolute precipitation).

Moreover, by using the models mentioned above and GIS tools contained in ArcGIS 10.1, this study will help in the quantification of percentage of crop area involved in different climatic suitability categories as well as percentage and number of hectares impacted by positive and negative changes. The process will face different constraints—for instance lack of information about the presence of crops and uncertainty in model projections. It is hoped that this study will be useful to help in the decision-making process by generating recommendations focused on progressive adaptation of farmers in the tropical Andes over the next 40 years.

3. PROBLEM

A significant portion of agricultural producers in the world is small and poor. They have no economic resources to face CC impacts. Farmers and grassroots communities in the tropical Andes are not exempt from this phenomenon and need help from governments, research centers and academic institutions to continue carrying out their agricultural activity. Thus, the major concern for farmers in remote areas, such as the tropical Andes,

is how to face the impacts that CC will bring on staple crops that are consumed by them on a daily basis. In this sense, it is worth thinking about the generation of alternatives through the use of crop modeling and GIS tools.

4. HYPOTHESIS

- **Hypothesis:** climate change will have a significant impact on staple crops (i.e. bean, coffee, tomato, wheat and potato) produced and consumed in tropical Andean communities.
- **Null hypothesis:** climate change will not have any implications on staple crops (i.e. bean, coffee, tomato, wheat and potato) produced and consumed in tropical Andean communities.

5. RESEARCH QUESTION

What are the potential implications in terms of decrease and increase of climatic suitability (%) that CC will have on areas where bean (legume), coffee (high value), tomato (vegetable), wheat (cereal) and potato (tubercle) are produced and consumed by tropical Andean communities?

6. DISCUSSION

It is predicted that the agricultural sector in the Andean region will be substantially affected by increases in temperature (which can reach up to 3–5 ºC by 2050) and variability in precipitation (IPCC, 2007). Such changes will affect production systems, as well as those staple crops that support the income and food necessities in some sub-regions over the Andes (beans, coffee, tomatoes, and wheat and potatoes, among others).

The implementation of appropriate actions could be useful to face the impacts and simultaneously visualize opportunities for agriculture in the future. In this case, this investigation will be useful to propose mechanisms for adaptation to and mitigation of likely impacts on agriculture. It is necessary that small Andean farmers take ownership of the issue, but it is also required to capture the interest of institutions and individuals that are involved in the social and scientific fields to obtain greater impact. On the one hand, there are research centers (e.g. CIAT, CIP, EMBRAPA) and international institutions (e.g. Andean Community), which have the scientific and technological potential to help identify impacts on a larger scale. Furthermore, academia (public and private universities) could open research areas related to CC modeling in specific countries and regions, so as to expand the knowledge and techniques to assess the impact and, ultimately, contribute to finding solutions.

Lastly and most importantly, are individuals and communities in the region—people who are part of the agrarian life of the region and whose livelihood depends on the environment. In their hands it is the implementation of the proposed changes in agricultural practice, as well as water and soil resources. Through the combination of traditional knowledge and suggestions from experts and technicians, would arise simple but effective practices that would enable farming communities in the region to be less vulnerable to CC impacts, while finding opportunities in the different scenarios that this process will bring.

To do carry out complex analysis the use an ENM (i.e. EcoCrop) is proposed to identify potential current and future distribution of crops as mentioned above. At the end of this study, there will be a Geodatabase composed for climate data from the IPCC and crop climatic suitability outputs.

7. REVIEW OF TARGETS

- **General:** to assess the potential impact of climate change, in terms of affected area, on five (5) staple crops in the tropical Andes.
- **Specifics:** 1) identify and quantify potential areas where climatic suitability decreases and increases given future climate conditions for five staple crops: bean, coffee, tomato, wheat and potato. And 2) identify adaptation and mitigation measures to be taken by governments, research centers and academic institutions in countries of the tropical Andes in order to mitigate the impacts on crops.

8. DEFINITIONS OF TERMS

- Climate change (CC): it is understood as strong variations in climatic patterns across time. These variations are related with anthropic actions.
- General Circulation Models (GCMs): future climatic information useful to generate projections on the behavior of climate in different scenarios and periods of time (e.g. 2020, 2050, etc.)
- Intergovernmental Panel on Climate Change (IPCC): Institution in charge of the generation and distribution of climate information worldwide.

- International Center for Tropical Agriculture (CIAT, by its acronym in Spanish): agricultural research center based in Colombia.
- International Potato Center (CIP, by its acronym in Spanish): agricultural research center based in Peru.
- Brazilian Enterprise for Agricultural Research (EMBRAPA, by its acronym in Portuguese): agricultural research center based in Brazil.
- Ecological niche modeling (ENM): methodology used for species distribution analysis.
- Climatic suitability: level of fitness of a crop currently or in future climatic conditions.
- EcoCrop: ecological niche model based on crop and climate (current and future) information to generate projections of potential distribution and climatic suitability for crops.

9. PRESUMPTION OF THE AUTHOR

This study will contribute to a better understanding of CC impacts in the tropical Andes and will be an opportunity for different stakeholders (e.g. grassroots communities, research centers, academic institutions, etc.) involved in the agricultural and social development of the region, to work together and collaboratively around the climate phenomenon and its implications on agriculture.

10. ASSUMPTIONS OF THE STUDY

First, this study aims to demonstrate that climate change has the potential to impact important crops consumed in Andean communities—in this case, beans, coffee, tomatoes, wheat and potatoes. It will assess climatic suitability increases or decreases for these crops in the future. This will be done by taking as baseline the current-potential distribution of the crops, for which it is necessary to use current climate information—i.e. WorldClim, (Hijmans, Cameron, Parra, Jones, & Jarvis, 2005). Then a comparison will be done with results of projections for the years 2020 and 2050 (e.g. GCMs), and finally the difference between the baseline and future projections will be assessed. It is assumed that assessed crops will have negative changes in areas where they are currently being cultivated, but that new niches, especially in zones located in high altitude levels, will appear.

Second, Tropical Andean communities will need to find alternative crops that are resistant to CC.

Third, the agricultural sector of tropical Andean communities will adapt gradually to CC if analysis tools work in their benefit. If so, decisions such as migrating to other crops or planting improved resistant varieties will be done at the right time, thus avoiding significant negative impacts.

CHAPTER 2

1. PROCESS OF LITERATURE REVISION

The literature review was entirely based on scientific documents (i.e. peer-reviewed journals, conference papers, scientific books, reports, etc.). Effort was made to find current publications that were directly related to the subjects of the research (i.e. ENM, Andean crops, CC). Among the sources of information consulted for the theoretical support of this investigation, it is worth mentioning IPCC, CIAT, Australian biological Resources Study, International Journal of Climatology, Ecological Economics, Ecography, and Ecological Modelling, among varied important research institutions and peer-reviewed journals.

It is worth noting that, although a significant number of publications related to CC and crops for the tropical Andes region was found, the number of articles that address the issue of ENM (e.g. EcoCrop), is significantly smaller. With this argument in mind, this document becomes a reference for future researches whose aim is to use EcoCrop or other ENM as an evaluation tool.

The process of literature review was done by using different methods. The first was based on Google Scholar (http://scholar.google.com/). It was performed using key words (e.g. ecological niche modeling + Andean crops, impact of climate change in Andean crops, Andean crops and climate, etc.). The second method consisted in looking up documents such as reports, papers and a thesis that I had already collected over the last three years, when I worked at CIAT in topics mainly related with CC, ENM, and biodiversity.

Among the topics found in the literature review there are some interesting themes that shed light on the logic of the modeling and the importance of using it as a means to preserve and even potentiate (in specific cases) the agricultural sector in tropical Andes. Some of the relevant documents touched on topics such as understanding fundamental ecological niches and species distribution areas; indigenous peoples and climate change; and the adaptation of Andean crops (e.g. potato) to changing climates, among others.

In general terms and in relation to the steps that were performed during the literature review; it was ensured that searches were made among experiences whose aim was similar to this study. In this way and, as mentioned above, it was found that this study is unique in its class and will serve as parameter for future research in the field.

2. DESCRIPTION OF THE STUDY AREA

The tropical Andes region is quite diverse in terms of cultures, landscapes, and economies. Colombia and Venezuela share the traits of the Caribbean countries, while Ecuador, Peru and Bolivia are known as Andean countries. According to U.S. Census Bureau (2013), total population of this region in 2012 was 128,350,000, which means 37% of South America total population of (398,091,000).

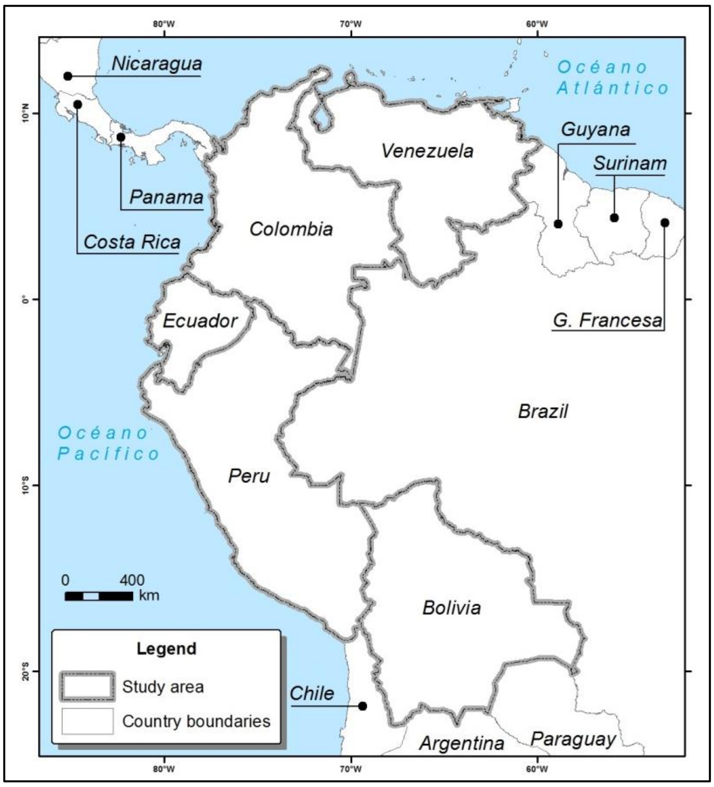

Figure 1. Study area

Below a brief description of each country will be given based on country studies of the Library of the Congress[1] and World Fact Book[2]:

Bolivia: it is located central South America, surrounded by Brazil to the north and east, Argentina and Paraguay to the south, and Peru and Chile to the west. Its total area is total: 1,285,216 km$^{2.}$ In terms of agriculture, its main products are soybeans, coffee, cotton, sugarcane, rice, potatoes; Brazil nuts; timber. The contribution of this sector to the Gross Domestic Product (GDP) in 2012 was 9.6%.

Colombia: it is located the northwestern part of South America, bordered by the Caribbean Sea to the north; the North Pacific Ocean and Panama to the west; Ecuador and

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[1] Accessed on October, 2013: http://lcweb2.loc.gov/frd/cs/

[2] Accessed on October, 2013: https://www.cia.gov/library/publications/the-world-factbook/docs/guidetowfbook.html

Peru to the south; and Brazil and Venezuela to the east. It is estimated that only less than 3 percent of Colombia's total land area, such as the fertile Andean mountainsides and valleys, is cultivated for crops. Regarding agriculture, the country is within the top ten of the coffee producers in the worlds, locating at the fourth place. Furthermore, others agricultural products as cut flowers, bananas, rice, tobacco, maize, sugarcane, cocoa beans, oilseed, vegetables; shrimp; forest products, are also important for the country economy. The contribution of this sector to the Gross Domestic Product (GDP) in 2012 was 6.5%.

Ecuador: it is located to the west South America, bordering the Pacific Ocean at the Equator, between Colombia and Peru. Its total area is about 283,561 km^2 and it has an estimate population of 15,439,429 (July 2013.). Amongst its main agricultural products are bananas, coffee, cocoa, rice, potatoes, manioc (tapioca), plantains, sugarcane; cattle, sheep, pigs, beef, pork, dairy products; fish, shrimp; balsa wood. The contribution of this sector to the Gross Domestic Product (GDP) in 2012 was 5.9%.

Peru: it is located in the western South America, bordering the South Pacific Ocean, and between Chile and Ecuador. Its elevations are between 0 and 6,768 m. Peru is one of the most diverse countries in terms of agricultural products. Many of these products are exclusively Andeans, amongst them are asparagus, coffee, cocoa, cotton, sugarcane, rice, potatoes, corn, plantains, grapes, oranges, pineapples, guavas, bananas, apples, lemons, pears, coca, tomatoes, mangoes, barley, medicinal plants, palm oil, marigold, onion, wheat, dry beans; poultry, beef, pork, dairy products; guinea pigs; fish. The contribution of this sector to the Gross Domestic Product (GDP) in 2012 was 6.4%.

Venezuela: this country is located in northern South America. Its borders are Caribbean Sea and the North Atlantic Ocean to the north, to the east by Guyana, to the south by Brazil, and to the west by Colombia. Its total area is 912,050 km^2. Venezuela is a country located entirely within the tropics thus it has a climate that is tropical, hot, and humid. Regarding agriculture, its main crops are corn, sorghum, sugarcane, rice, bananas, vegetables, coffee; beef, pork, milk, eggs; fish. The contribution of this sector to the Gross Domestic Product (GDP) in 2012 was 3.7%.

CHAPTER 3

1. METHODOLOGY

When studying the issue of crop modeling and its relation to CC, it is clear that ENM are practical tools that should be taken into account. In recent years these models have begun to play an important role in this research field. This argument is reflected in the large and growing number of publications that are regularly reported, and give value to the use of such tools to find real solutions (Guisan & Zimmermann, 2000; S. Phillips, 2008; Ramirez-Villegas et al., 2011; Vieglais, 2001). What is interesting is that using ENM opens the possibility of combining climate data with crop parameters and, in turn, includes expert knowledge for more accurate modeling.

For this reason, the possibility of working with several ENM (e.g. Bioclim, Domain, Canasta, MaxEnt, EcoCrop, Homologue, GARP) was considered, but eventually EcoCrop was selected for its suitability in terms of the scale of work and the resolution of the climate data to be used in the study.

EcoCrop (Hijmans, Guarino, et al., 2005) is a useful model for situations in which there is no available evidence data for a particular crop and a researcher is therefore forced to use environmental ranges instead of evidence points. Outcomes, however, are very general and can only be used to describe general trends in time and space. At this point it is important to mention that among all models assessed, EcoCrop is the one able to work based on climate ranges (e.g. temperature between 18–22°C and rainfall between 100–250mm during growing season for a specific crop). Homologue also allows the user to work based on evidence data, but just with one point. This is a constraint, as the user will not be able to assess the existing relationship into a set of points (evidence data). Moreover, the pixel resolution is too high, approximately 18x18km. On the other hand, MaxEnt, Bioclim, Domain, Canasta and GARP work based on evidence data (and some of them, such as MaxEnt, with absence data). These are some of the reasons why EcoCrop was selected for the modeling process in this study. A detailed description of each one of the above-mentioned models will be provided, which will further clarify the selection of EcoCrop.

But before, let's take a moment to think about the following question: What does an ENM do? Basically an ENM characterizes the distribution of a species in a space defined by environmental parameters that are determining the geographical distribution of the species. The geographical distribution refers to the set of locations in which a species or taxon defines an area that is occupied by its members (Herrera Campo, 2010).

In other words, ENM represent an approach to the ecological niche of the species in one or more specific environmental dimensions, and are used to predict the distribution of a species or to determine their ideal habitat (S. J. Phillips, Anderson, & Schapire, 2006).

The variables used for the prediction depend on both the available information and working scale (Guisan & Zimmermann, 2000). At a continental scale (large scale) global climate is considered a factor, while locally (small scale) topography, soil type and biotic interactions play an important role (Pearson & Dawson, 2003).

Below is a description of the different models assessed, through which the reasons for selecting EcoCrop will become clear. These descriptions will also explain the possibilities of working with other models when research has a smaller scale and the input data are of another type (i.e. there are no growth parameters but occurrences are available).

Bioclim (Busby, 1991): it is an algorithm that uses a “wrapper” of environmental points. (i.e. cutoff values above a certain user-defined percentile, are mapped as ‘true’ [1], and all other areas are mapped as ‘false’ [0]). Thus, the study areas with environmental conditions within the environmental envelope edges are predicted as potential sites of occurrence. The predicted probability is calculated by breaking up the 5% of the low and high values of each environmental predictor and is often called ‘core bioclimatic’.

Domain (Carpenter, Gillison, & Winter, 1993; Hijmans, Guarino, et al., 2005): the model calculates the distance between point A and the grid cell of point B. Similarity between pixels or dots is then mapped. The maps show the areas with higher similarities in terms of climate. Predictions are measured as a measure of confidence rating.

Canasta (O’Brien, 2004): this algorithm creates conditional probability tables of all variable predictors vs. response variable categories. The first model output is a discrete probability distribution at each location. One certainty of value is also associated with each location, derived from the number of occurrences in the test data of a particular combination of predictors and responses. The probability distribution is the probability that this response variable is in a state potential. This information can be used to create maps showing the most probable value of response. The values of the probability distribution may also be pondered to produce an appropriate value (score). Finally, the certainty of value can be displayed as a map (certainty), and may assist in the interpretation of results.

MaxEnt (Elith et al., 2010; S. J. Phillips et al., 2006; S. Phillips, 2008): the maximum entropy is a general methodology for making predictions or inferences from incomplete information. The idea is to estimate the probability of a target distribution to find the probability distribution of maximum entropy, subject to a set of constraints that represent incomplete information about the target distribution. The information available on the target distribution is often presented as a set of real-valued variables, called 'characteristics or properties', and the limitations are that the expected value of each element must match its empirical average. Similar to logistic regression, weighted MaxEnt weights each environmental variable by a constant. The probability distribution is the sum of each variable weight divided by a constant reduction to ensure that the probability of values ranges from 0 to 1. The model begins with a uniform probability distribution and iteratively alters weight while maximizing the probability of reaching the optimal distribution probability.

Homologue: it is a model developed by the CIAT after working with FloraMap (P. G. Jones, Guarino, & Jarvis, 2002), to identify only one point or other sites with similar or homologous conditions. The concept has been developed in the Homologue software that is available, but requires refinement to reduce the pixel size to be effective in extremely heterogeneous areas such as the Andean region. Homologue has the great advantage of requiring only a point to run while others require several models available to find benchmarks homologues.

GARP (Stockwell, 2010): it is a genetic algorithm that creates ecological niche models for species. The models describe environmental conditions under which the species should be able to maintain populations. For input, GARP uses a set of point localities where the species is known to occur and a set of geographic layers representing the environmental parameters that might limit the species' capabilities to survive.

2. JUSTIFICATION OF THE SELECTED METHODOLOGY

The methodology is based on the use of an ENM to generate projections of current and future potential distribution (years 2020 and 2050) of selected crops. The selected model for the analysis is EcoCrop (Hijmans, Guarino, et al., 2005), which involves the possibility of crop growth parameters.

Input data for the ENM will be climatic variables known as bioclimatic index (Busby, 1991), extracted from WorldClim database (Hijmans, Cameron, et al., 2005) for the study area (Table 1). Resolution of the information will be 30 arc-seconds (~1 km^2 in the Equator).

Table 1. Bioclimatic indexes

ID	Variable
Bio 1	Annual Mean Temperature
Bio 2	Mean Diurnal Range (Mean of monthly (max temp - min temp))
Bio 3	Isothermality (BIO2/BIO7) (* 100)
Bio 4	Temperature Seasonality (standard deviation *100)
Bio 5	Max Temperature of Warmest Month
Bio 6	Min Temperature of Coldest Month
Bio 7	Temperature Annual Range (BIO5-BIO6)
Bio 8	Mean Temperature of Wettest Quarter
Bio 9	Mean Temperature of Driest Quarter
Bio 10	Mean Temperature of Warmest Quarter
Bio 11	Mean Temperature of Coldest Quarter

Bio 12	Annual Precipitation
Bio 13	Precipitation of Wettest Month
Bio 14	Precipitation of Driest Month
Bio 15	Precipitation Seasonality (Coefficient of Variation)
Bio 16	Precipitation of Wettest Quarter
Bio 17	Precipitation of Driest Quarter
Bio 18	Precipitation of Warmest Quarter
Bio 19	Precipitation of Coldest Quarter

There will be two premises for crop selection: first, crops must grow above 500m and, second, they must be important for the region in terms of harvested area, production and yield. Likewise, crops must be important for Andean minority communities (e.g. indigenous). From the information available for area harvested (ha), production (ton) and yield (hg/ha) located on FAOSTAT (2008)[3], the 21 most important crops will be selected with the condition of being present in at least four of the countries that are part of the tropical Andes (Bolivia, Colombia, Ecuador Peru, and Venezuela). The four remaining crops will be selected for their importance in their consumption for Andean indigenous communities.

3. THE ECOLOGICAL NICHE MODEL SELECTED – ECOCROP

The selected ENM for this study is EcoCrop (Hijmans, Guarino, et al., 2005) is a mechanistic model implemented in DIVA-GIS software. As mention before, the main reason for selecting EcoCrop as the model to be used was its usefulness for situations in which there is no available evidence data for a particular crop and the researcher, therefore, is forced to use environmental ranges instead of evidence points. Even though parameters of growth for the five crops assessed here (bean, coffee, tomato, wheat and potato) were the output of evidence data from different sources (e.g. CIAT's database, Genetic

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[3] Available here: http://faostat.fao.org/site/567/default.aspx#ancor.

Resources System–Phase 2 [GPG2]), the decision was made based on the premise that EcoCrop will not be biased for the specific locations where evidence data was collected but, instead, will cover the whole climatic range of the crops. This argument is supported by the fact that, generally, species distribution models such as MaxEnt, deal with spatial autocorrelation constraints (S. J. Phillips et al., 2006).

So, talking about some specifics of the model, below are the eleven parameters of growth that the model uses to calculate the climatic suitability for a crop (Table 2):

Table 2. Eleven EcoCrop parameters

Parameter	Description
Gmin	Minimum length of the growing season (days)
Gmax	Maximum length of the growing season (days)
Tkill	Temperature at which the stops crop development (°C)
Tmin	Minimum absolute temperatures at which the crop can grow (ºC)
Topmin	Minimum crop optimum temperature at which the crop can grow (°C)
Topmax	Maximum crop optimum temperature at which the crop can grow (°C)
Tmax	Maximum absolute temperatures at which the crop can grow (°C)
Rmin	Minimum absolute rainfall at which the crop grows (mm)
Ropmin	Minimum optimum rainfall at which the crop grows (mm)
Ropmax	Maximum optimum rainfall at which the crop grows (mm)
Rmax	Maximum absolute rainfall at which the crop grows (mm)

Among the absolute thresholds and optimal conditions there is a range of climatic “fitness” (1 to 100). The model evaluates precipitation and temperature separately, and then multiplies the combined results (Figure 2). The model is conceptually useful to detect changes in major crop niches and for decision making at the regional level.

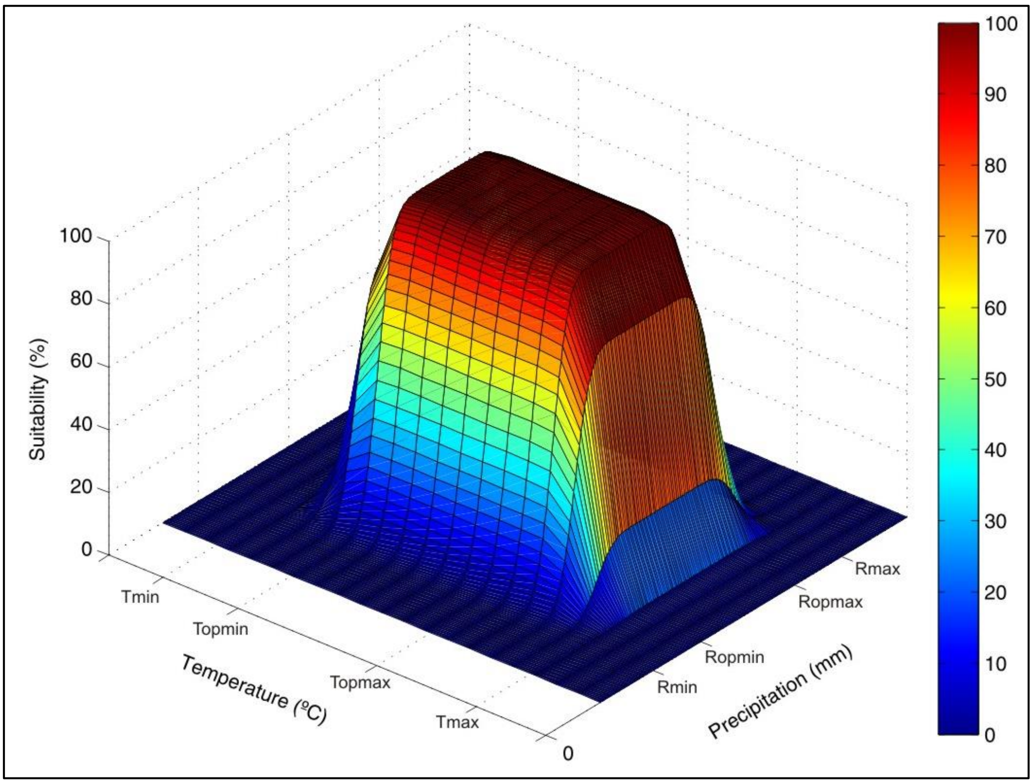

Figure 2. EcoCrop model (Ramirez-Villegas et al., 2011)

EcoCrop parameters calculation can be done by using frequency analysis (Figure 3). In this light, and in order to obtain the growth parameters for crops under analysis (i.e. bean, potato, tomato, wheat and coffee), the following procedure was implemented:

1. Bioclimatic index creation: climate information was extracted for each growing season—three months for bean, four for potato and tomato, six for wheat and twelve for coffee. The detailed explanation of the process is as follows: 1) average temperature of the three hottest and coldest months, and precipitation of the three wettest and driest months—for beans. 2) Average temperature of the four hottest and coldest months, and precipitation of the three wettest and driest months—for tomato. 3) Average temperature of the six hottest and coldest months, and precipitation of the three wettest and driest months—for wheat. 4) For coffee, variables bio1 and bio12

from WorldClim were used (annual mean temperature and annual precipitation, respectively).

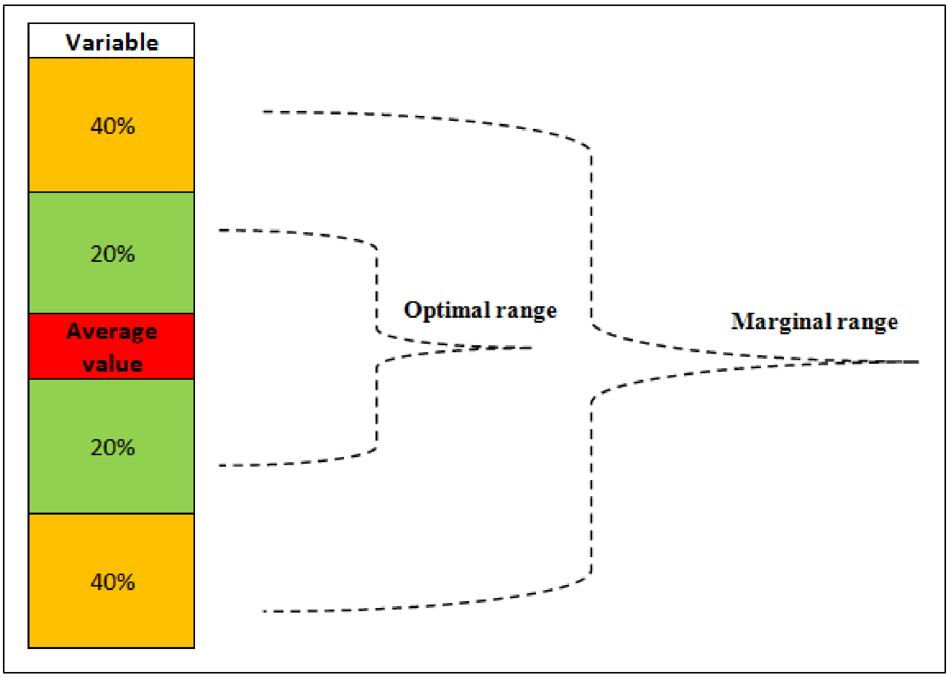

Figure 3. Example of parameters calculation

In other words, these new bioclimatic indices were calculated from monthly averages of minimum, mean and maximum temperatures, and precipitation by using a script developed by Robert Hijmans[4] in Arc Macro Language (AML)—Annex 1.

2. Data Extraction: temperature and precipitation values were extracted (from new bioclimatic indexes mentioned above) for each point where crop sample data was available (Figure 4). Afterwards, frequency analysis was done in order to get the optimal niche range, which was defined for the values located at 40th and 60th percentiles (i.e. 20% to each side of the average). In the same way, marginal range was

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[4] January, 2006. rhijmans@ucdavis.edu.

defined for the values located in 20th and 80th percentiles (i.e. 40% to each side of the average).

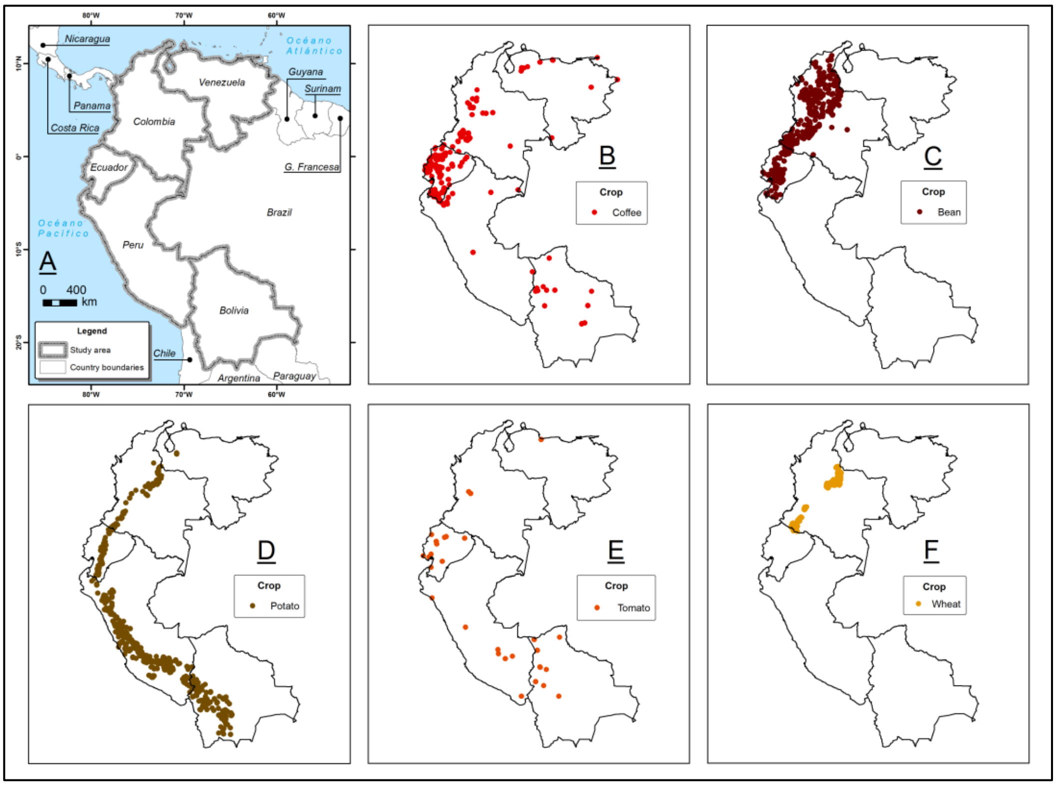


Figure 4. Study area and evidence points

3. Parameters calibration: the parameters extracted from the new bioclimatic indexes were adjusted, initially, for the current climate (WorldClim). The procedure consisted in making some initial runs and using visual inspection to correct the distributions that do not fit well with the evidence points. Then, corrections were made in the parameters to be adjusted to the prediction (Table 3).

4. Subsequently, these parameters (Figure 3) were used in EcoCrop but with the GCM data as input to get the potentially future distributions (future projections).

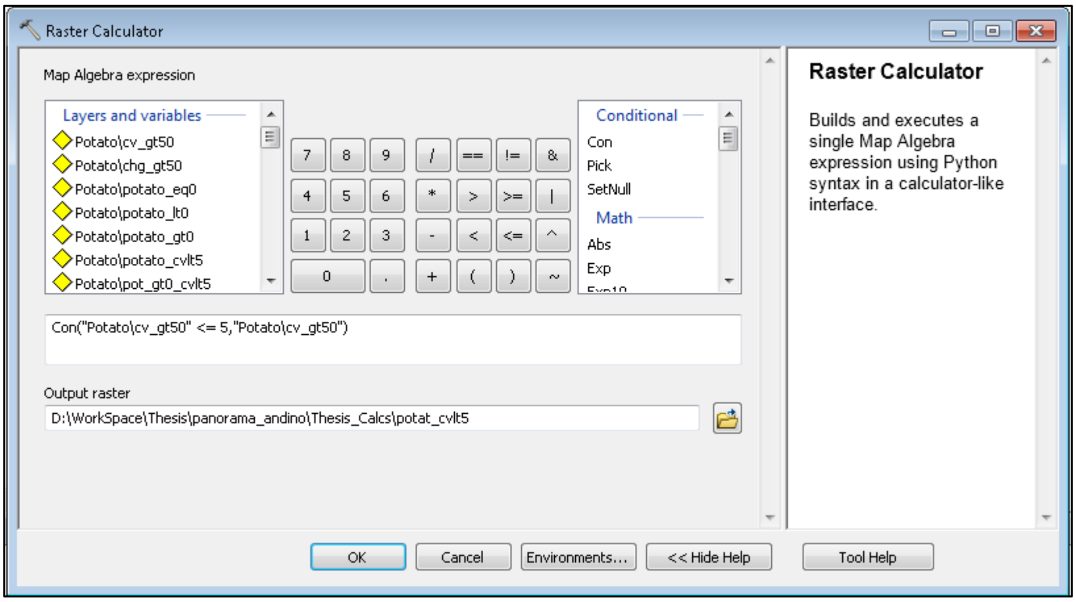
Table 3. Growth parameters by crop (temperature [°C] and rainfall [mm])

Parameter/Crop	Coffee	Bean	Potato	Tomato	Wheat
Gmin	365	90	120	120	180
Gmax	365	90	120	120	180
Tkill	0	0	-8	0	0
Tmin	11.0	13.6	3.8	15.7	3.4
TOPmin	15.6	17.5	12.4	21.3	8.0
TOPmax	24.8	23.1	17.8	24.8	17.2
Tmax	26.4	25.7	24.0	27.0	21.7
Rmin	294	200	150	54	383
ROPmin	991	362	251	277	449
ROPmax	2,540	450	327	1,242	1,231
Rmax	3,315	710	786	1,540	1,666

As and additional analysis, and an exercise of validation, it was made and analysis to compare uncertainties (coefficient of variation) with changes in climatic suitability of the five crops. This process included further processing of the data. For instance, it was necessary to define a mask of uncertainty, which for the sake of this study was defined as all areas lower or equal than 5%. Below are the name of the layers and their definitions:

- cvlt5: coefficient of variation lower than 5%.
- crop_eq0_cvlt5: mask of the crop when change is equals to zero and after being overlaid with mask of uncertainty lower than 5%.
- crop_lt0_cvlt5: mask of the crop when change is lower than zero and after being overlaid with mask of uncertainty lower than 5%.
- crop_gt0_cvlt5: mask of the crop when change is greater than zero and after being overlaid with mask of uncertainty lower than 5%.
- cv_gt50: coefficient of variation in areas with climatic suitability above 50%.
- chg_gt50: change in areas with climatic suitability above 50%.

Once uncertainty mask was created, a selection of areas where crop changes presented negative, positive, or will not change was made. To better understand the selection process below are presented the conditionals used in ArcMap tool, "Raster Calculator" of ArcToolbox (Figure 5):



Con("Potato\cv_gt50" <= 5,"Potato\cv_gt50")

Output raster: D:\WorkSpace\Thesis\panorama_andino\Thesis_Calcs\potat_cvlt5

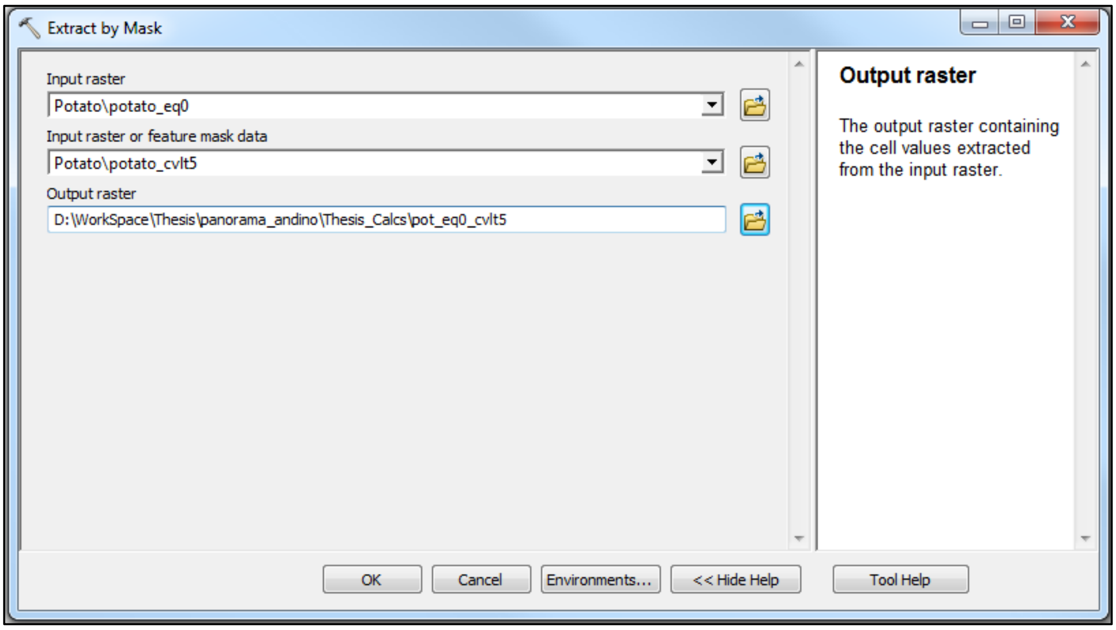
Raster Calculator

Builds and executes a single Map Algebra expression using Python syntax in a calculator-like interface.

Figure 5. Raster calculator tool

- Con("crop\cv_gt50" <= 5," crop\cv_gt50"): if crop coefficient of variation is lower or equal to 5% then create a mask selection that area.
- Con("crop\chg_gt50" > 0," crop\chg_gt50"): if crop change is greater than 5% then create a mask selection that area (positive change).
- Con("crop\chg_gt50" < 0," crop\chg_gt50") : if crop change is greater than 5% then create a mask selection that area (negative change).
- Con("crop\chg_gt50" == 0," crop\chg_gt50") : if crop change is equals to 0% then create a mask selection that area (no change).

The final raster was the result of combining uncertainties mask with the different selections (explained before). Figure 6 shows the tool used for this calculation. This time the estimate is made with potatoes. Potato_eq0 means areas where potato did not presented change at 2050.



Input raster: Potato\potato_eq0

Input raster or feature mask data: Potato\potato_cvlt5

Output raster: D:\WorkSpace\Thesis\panorama_andino\Thesis_Calcs\pot_eq0_cvlt5

Output raster

The output raster containing the cell values extracted from the input raster.

Figure 6. Final raster

4. CLIMATE DATA AND SOURCE OF INFORMATION

Baseline or current data: the historical weather data were obtained from the database WorldClim (Hijmans, Cameron, et al., 2005), available at www.worldclim.org. These data represent long-term averages (1950–2000) of precipitation, and maximum temperature, monthly minimum and mean, with a native resolution of 30 arc-seconds (approximately 1 km^2 in the Equator) and then were added to 5 arc-minutes (approximately 10km^2 in the Equator) using bilinear interpolation.

Future climate: according to IPCC (2007), a Global Circulation Model (GCM) is a computational model that projects weather patterns in a number of years in the future. It uses equations of motion as the basis for a weather prediction model (Numerical Weather Prediction model [NWP]), in order to model the changes in climate as a result of slow changes in some boundary (such as the solar constant) or physical (as the concentration of greenhouse gases) conditions. The model is based on a cell in three dimensions and in the transfer of matter and energy between cells. Once the simulation is running, it is possible to determine a number of weather patterns, from patterns in precipitation to evaporation rates. In the present study, outputs of future climate realizations corresponding to different GCMs for two emission scenarios were used: SRES-A2 (8 GCMs) and SRES-A1B (10 GCMs), representing the fourth assessment report of the Intergovernmental Panel Climate Change (IPCC, 2001, 2007).

The IPCC (2000) explained that the A1B (business as usual) emissions scenario has the special feature of taking into account technological change on the energy system. It is balanced in the use of different energy sources. In this scenario, there is no excessive use of fossil fuels. On the other hand, the A2 emissions scenario describes a very heterogeneous world. The underlying theme is self-reliance and preservation of local identities. Fertility patterns across regions converge very slowly, resulting in a continuously increasing global population. Economic development is primarily regionally oriented and per capita economic growth and technological change are more fragmented and slower than in other scenarios (IPCC, 2000).

Climate data used for the calculation of climatic suitability and climate impact assessment on the five crops came from the IPCC data portal. Data was obtained for

SRES-A1B and SRES-A2 for the periods 2010–2039 (“2020s”) and 2040–2069 (“2050s”) using climate data from a representative group of GCMs, ten for SRES-A1B, and eight for SRES-A2. It is worth to bear in mind, as mentioned before, that in this study pixel resolution for the current and future climate data is 5 arc-minutes (approximately 10km^2 in the Equator). To reach this pixel resolution, bilinear interpolation was used[5]. Table 4 illustrates the group that developed the model, the country they came from, the model ID and the original size of climate simulation grid:

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[5] For the purpose of this study, processed climate data was taken from the CIAT-CCAFS data base, available here: http://www.ccafs-climate.org/statistical_downscaling_delta/. None process of downscale was done for the author of this study.

Table 4. GCMs used for climate projection with EcoCrop for periods 2020s and 2050s of the SRES A1B and A2 (IPCC, 2007)

No.	***Group that developed the model***	***Country***	***Model-ID***	***Atmosphere***[a]	***Ocean***[b]
1	Bjerknes Centre for Climate Research	Norway	BCCR-BCM2.0	T63 (1.9° x 1.9°) L31 (Déqué, Dreveton, Braun, & Cariolle, 1994)	0.5°–1.5° x 1.5° L35 (Bleck, Rooth, Hu, & Smith, 1992)
2	CSIRO Atmospheric Research	Australia	CSIRO-Mk3.0	T63 (~1.9° x 1.9°) L18 (Gordon, Waterman, Hirst, Wilson, & Collier, 2002)	0.8° x 1.9° L31 (Gordon et al., 2002)
3		Australia	CSIRO-Mk3.5	T63 (~1.9° x 1.9°) L18	0.8° x 1.9° L31
4	US Dept. of Commerce, NOAA Geophysical Fluid Dynamics Laboratory	USA	GFDL-CM2.0	2.0° x 2.5° L24 (GFDL GAMDT, 2004)	0.3°–1.0° x 1.0° (Gnanadesikan et al., 2006)
5		USA	GFDL-CM2.1	2.0° x 2.5° L24 (GFDL GAMDT, 2004)	0.3°–1.0° x 1.0° (Gnanadesikan et al., 2006)
6	NASA / Goddard Institute for Space Studies	USA	GISS-AOM	3° x 4° L12 (Russell, Miller, & Rind, 1995)	3° x 4° L16 (Russell et al., 1995)
7	Institute of Numerical Mathematics, Russian Academy of Science	Russia	INM-CM3.0	4° x 5° L21 (Galin, Volodin, & Smyshlyaev, 2003)	2° x 2.5° L33 (Volodin, Dianskii, & Gusev, 2010)
8	Center for Climate System Research National Institute for Environmental Studies Frontier Research Center for Global Change	Japan	MIROC3.2(hires)	T106 (~1.1° x 1.1°) L56	0.2° x 0.3° L47
9		Japan	MIROC3.2(medres)	T42 (~2.8° x 2.8°) L20	0.5°–1.4° x 1.4° L43
10	National Center for Atmospheric Research	USA	NCAR-CCSM3.0	T42 (~2.8° x 2.8°) L20	1° x (0.27-1) L40

[a] Horizontal resolution is expressed either as degrees latitude by longitude or as a triangular (T) spectral truncation with a rough translation to degrees latitude and longitude. Vertical resolution (L) is the number of vertical levels.

[b] Horizontal resolution is expressed as degrees latitude by longitude, while vertical resolution (L) is the number of vertical levels.

CHAPTER 4

1. DATA ANALYSIS

This section will describe EcoCrop outputs and specific analysis for the five crops assessed. Results will be shown from worst to best case, meaning, the first crop is the one whose climatic suitability will decrease by a higher percentage and the last is the one whose climatic suitability will decrease by a lower percentage. The order will be tomato, wheat, bean, coffee and potato. As the distribution of the both SRES (A1B and A2) demonstrated to be highly similar[6], the following descriptions will cover the general tendencies that both scenarios will have in the study area.

Parameters described in each figure are:

- Current climatic suitability: current potential distribution as well as current climatic suitability of the crop. It is the outcome of the EcoCrop modeling using current data (WorldClim) and parameters of growth. It is given in percentage (%).
- Future climatic suitability: future (i.e. 2020 or 2050) potential distribution as well as future climatic suitability of the crop. It is the outcome of the EcoCrop modeling using future data (GCMs for periods 2020 and 2050 and for the both SRES [A1B and A2]) and parameters of growth. It is given in percentage (%).

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[6] This could be related to the ampleness of the analysis scale, 10x10km pixels.

- Change in climatic suitability: future (i.e. 2020 or 2050) potential change suitability of the crop. It is the outcome of the subtraction of two EcoCrop outputs; future climatic suitability and current climatic suitability (future – current). Both SRES were analyzed (A1B and A2). It is given in percentage (%).
- Uncertainty: it is expressed as the coefficient of variation of the future modeling (i.e. of the GCMs for each period [2020 and 2050] and for each SRES [A1B and A2]). It is given in percentage (%).

Furthermore, as a validation, the results of uncertainties (coefficient of variation) and changes during the period A1B-2050 were compared. In order to restrict the analysis to areas with less uncertainty, those that were within the 0–5% range were selected. This range was chosen empirically based on the logic that there is more certainty around values close to 0%.

For this reason, subsequently will be presented, along with the results of climatic suitability of the five crops in question, an analysis that shows the amount of area per country with different kind of changes (i.e. negative, positive and none change), that falls in zones with low uncertainty. Comparisons will be done based on three parameters: First, those departments that will have suitable climatic conditions for growing the five crops analyzed; second, those that will not have suitable climatic conditions to grow the five crops; and third, those where future climatic conditions will not change for the five crops (i.e. change equals 0). The entire analysis will be focused in zones where the uncertainty range (coefficient of variation) is below 5%.

Looking ahead, further analysis should include the identification of departments where these crops are currently grown and, according to changes in climatic suitability, an evaluation of the extent to which their production will be affected, and even an estimate of the economic losses that such changes will entail.

1.1. TOMATO (Detailed maps in Annex 2)

According to Figure 7, areas that are currently suitable for growing tomatoes are distributed primarily through the highlands of the tropical Andes mountain range (Figure 7, A), showing a significant proportion of areas where climatic suitability would be in the range from 91% to 100%. Figure 7, B and E describe a scenario in 2020 that does not change the current distribution, but in which some areas in which current climatic suitability (CS) is between 50% and 60%, experience a losses. Figures showing change (Figure 7, C and F), indicate significant losses over southern Bolivia and an overall decrease in the lower areas of the mountain range (-4% - 0%).

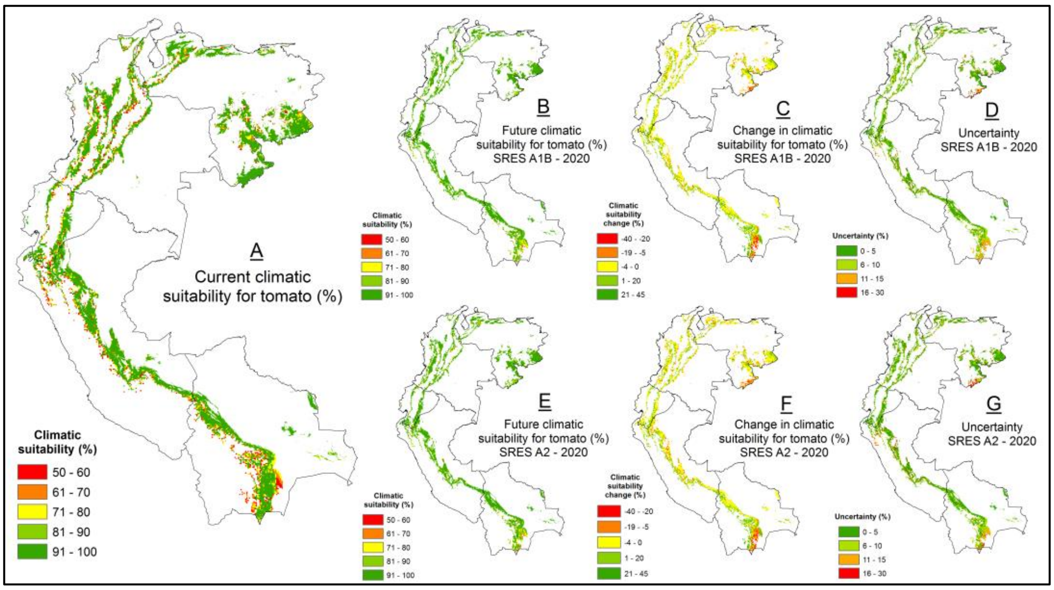

Figure 7. Climatic suitability for tomato 2020: (A) Current climatic suitability, (B) climatic suitability 2020-A1B, (C) climatic suitability change 2020-A1B, (D) uncertainty 2020-A1B, (E) climatic suitability 2020-A2, (F) climatic suitability change 2020-A2, (G) uncertainty 2020-A2

The uncertainty maps (Figure 7, D and G) allow having confidence in the projections, although not much in areas that lose CS, observed mainly over southern Bolivia. On the other hand, Figure 8, climatic suitability versus altitude, shows that the losses will be significant regarding SRES-A1B in 2050. The optimal niche under the current conditions is found between 500 and 1,200 meters, where the CS varies between 78% and 90%. Losses in the future will involve approximately 128 million hectares while CS will vary between 36% and 80%.

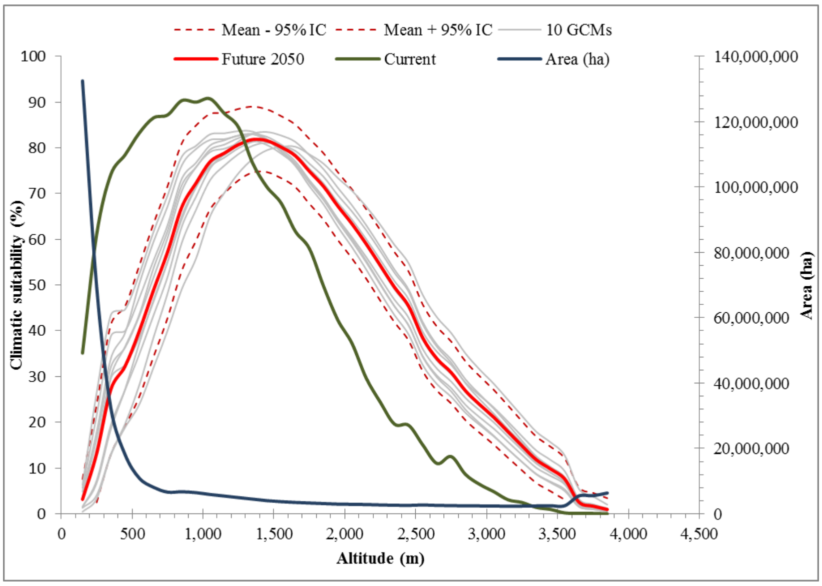

Figure 8. SRES-A1B: current and future (2050) climatic suitability for tomato

In 2050 (Figure 9) CS losses will be slightly higher than 2020, mainly over southern Bolivia (Figure 9, C and F). Meanwhile, toward the center of the country, there are some places where the change will be positive. In terms of uncertainty, this will remain low in the entire region, except for the south of Bolivia, which will present slightly higher values (16%–30%).

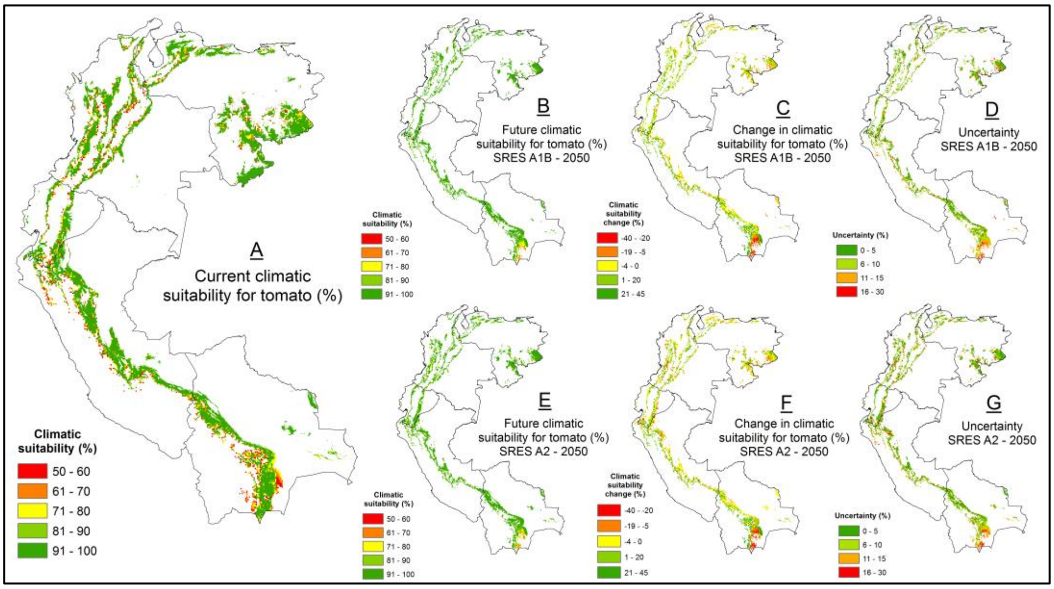

Figure 9. Climatic suitability for tomato 2050: (A) Current climatic suitability, (B) climatic suitability 2050-A1B, (C) climatic suitability change 2050-A1B, (D) uncertainty 2050-A1B, (E) climatic suitability 2050-A2, (F) climatic suitability change 2050-A2, (G) uncertainty 2050-A2

1.2. WHEAT (Detailed maps in Annex 2)

According to the current distribution (Figure 10, A), the wheat crop fits climatically well between 2,100 and 3,200 meters. For that reason, the tropical Andes present suitable conditions for the crop to grow. Some areas scattered over central-eastern Venezuela and southern Bolivia demonstrate CS in ranges from 50% to 80%—the same areas that in the future (Figure 10, B and E) will disappear as the model projections. According to Figure **10** (C and F) most of the area involved will be in CS range between -14 and 0%, mainly on the central-eastern part of Venezuela.

Also, in terms of uncertainty (Figure 10, D and G), there is confidence that models have low uncertainty, since they are pointing in the same direction of the average. Most of the areas projected as suitable for crop growing in current and future conditions have low uncertainty (0 to 5%).

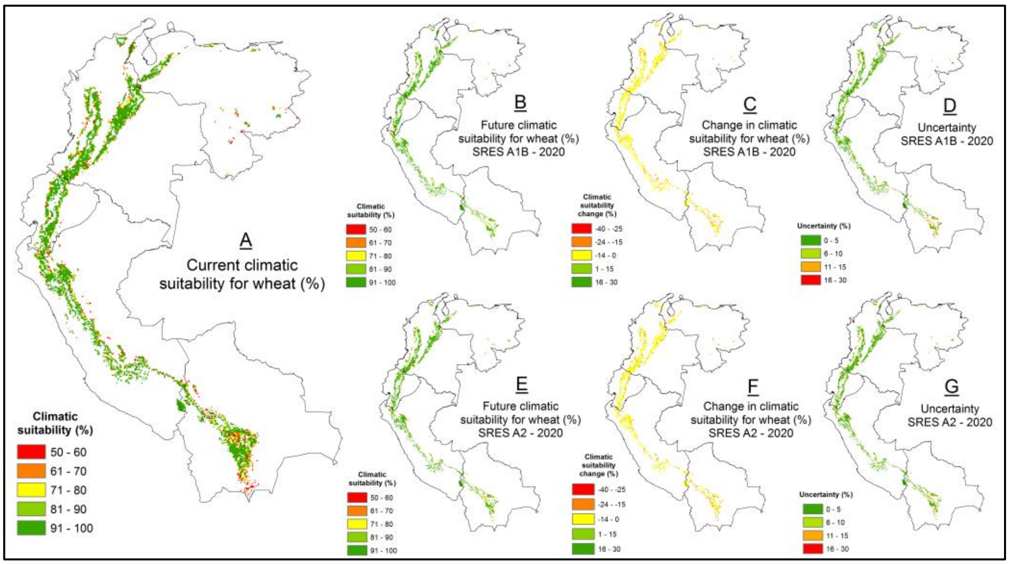

Figure 10. Climatic suitability for wheat 2020: (A) Current climatic suitability, (B) climatic suitability 2020-A1B, (C) climatic suitability change 2020-A1B, (D) uncertainty 2020-A1B, (E) climatic suitability 2020-A2, (F) climatic suitability change 2020-A2, (G) uncertainty 2020-A2

In 2050, changes in CS will be a little more dramatic, especially on the south-central region of Bolivia and the eastern part of Venezuela (Figure 11, C and F). Uncertainty (Figure 11, D and G) will continue being low according to the projection.

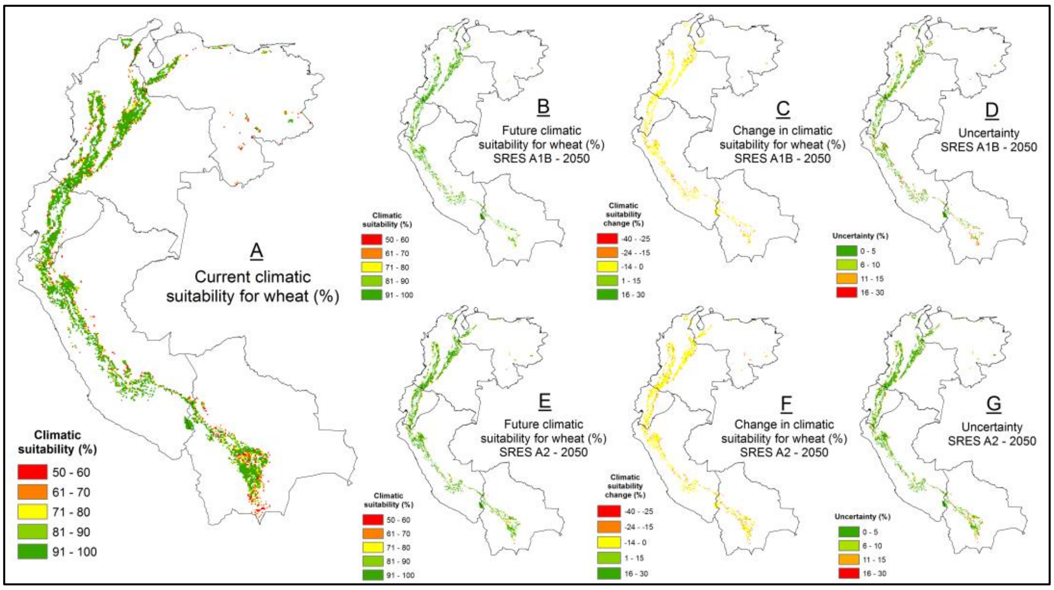

Figure 11. Climatic suitability for wheat 2050: (A) Current climatic suitability, (B) climatic suitability 2050-A1B, (C) climatic suitability change 2050-A1B, (D) uncertainty 2050-A1B, (E) climatic suitability 2050-A2, (F) climatic suitability change 2050-A2, (G) uncertainty 2050-A2

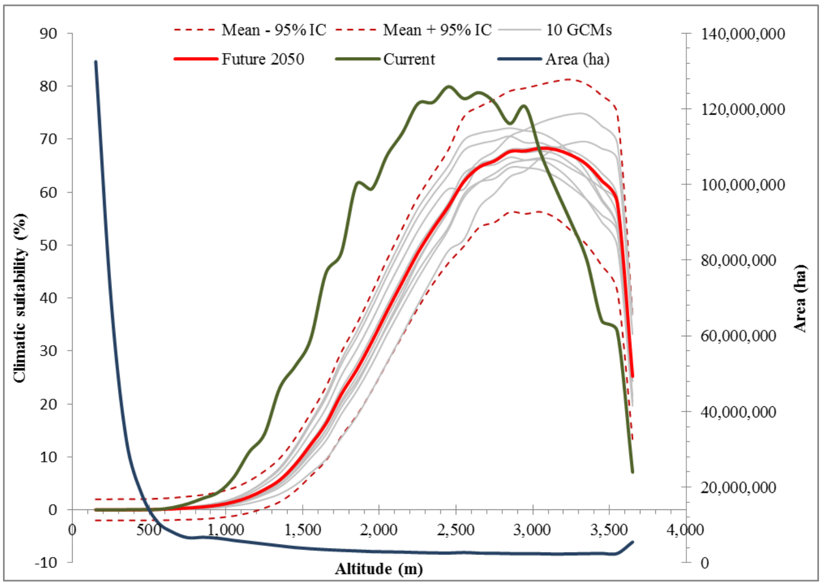

Figure 12. SRES-A1B: current and future (2050) climatic suitability for wheat

Figure 12 helps to understand the losses in CS, illustrating that between 2,300 and 3,000 meters, CS for the crop will vary between 67% and 77% and, in 2050 will range between 49% and 67%, involving approximately 124 million hectares.

1.3. BEAN (Detailed maps in Annex 2)

Currently, the crop is well adapted between 1,100 and 1,800 meters, hence why the tropical Andes have proper conditions for the crop to grow (Figure 13). Some scattered areas over southern Venezuela, northwestern Peru and Southern Bolivia present CS between 50% and 80%. These correspond to the same areas that will disappear in the future according to model projections (Figure 13, B and E). Figure 13 (C and F) is a clear example of the losses in CS described so far. According to these figures most of the area involved will be in the range of CS between -14% and 0%.

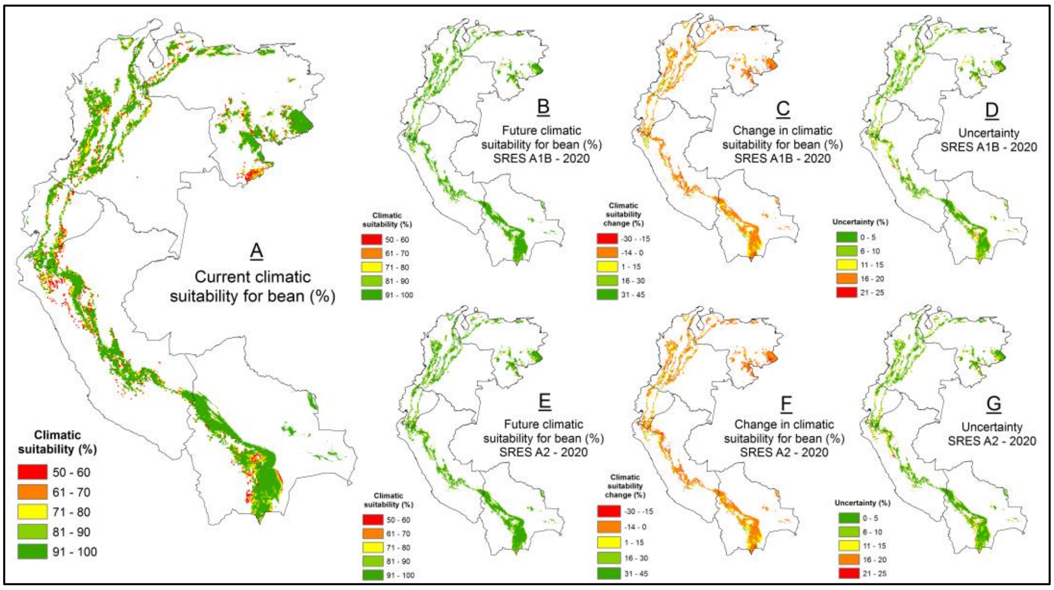

Figure 13. Climatic suitability for bean 2020: (A) Current climatic suitability, (B) climatic suitability 2020-A1B, (C) climatic suitability change 2020-A1B, (D) uncertainty 2020-A1B, (E) climatic suitability 2020-A2, (F) climatic suitability change 2020-A2, (G) uncertainty 2020-A2

In terms of uncertainty (Figure 13, D and G), there is confidence in the models, since they agree in the direction of the average. Most of the projected area as suitable for crop growth at present and future has low uncertainty (0–5%).

On the other hand, Figure 14 helps to understand the decline in crop CS, illustrating that between 1,100 and 1,800 meters bean CS is approximately between 83% and 78%. In 2050, CS will drop from about 1,800 meters, involving approximately 118 million hectares with negative changes.

Also, in 2050 (Figure 15) changes in CS will be much more dramatic, especially on the south-central region of Bolivia and the eastern part of Venezuela (Figure 15, C and F), where the change will reach even -30% in the SRES-A2.

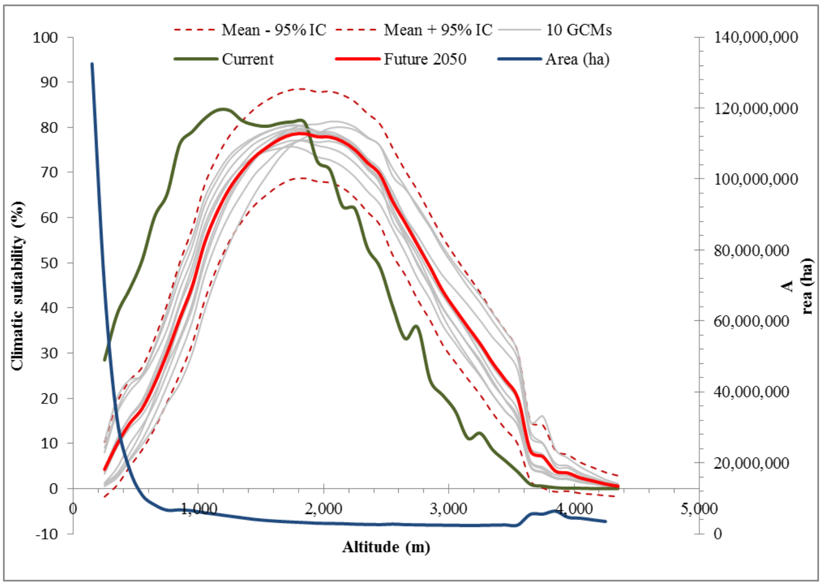

Figure 14. SRES-A1B: current and future (2050) climatic suitability for bean

Uncertainty (Figure 15, D and G) will continue being low in the projections, suggesting that there may be confidence in the results of the models.

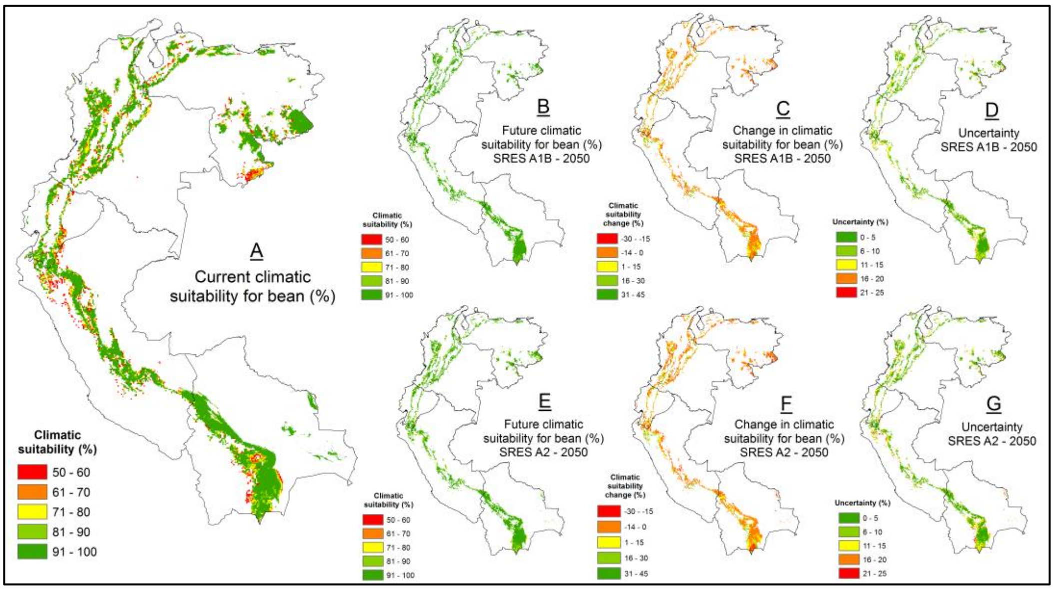

Figure 15. Climatic suitability for bean 2050: (A) Current climatic suitability, (B) climatic suitability 2050-A1B, (C) climatic suitability change 2050-A1B, (D) uncertainty 2050-A1B, (E) climatic suitability 2050-A2, (F) climatic suitability change 2050-A2, (G) uncertainty 2050-A2

1.4. COFFEE (Detailed maps in Annex 2)

The tropical Andes generally have optimum conditions for coffee growth (Figure 16, A). These conditions are present in areas where heights do not exceed 2,000 meters. However, in central Ecuador and southern Peru, CS for the crop is medium. The same situation is observable in southern Bolivia, where conditions for crop growth are good but do not reach the highest category of CS (i.e. 80%–100%)—they only reach the range of 50% to 80%.

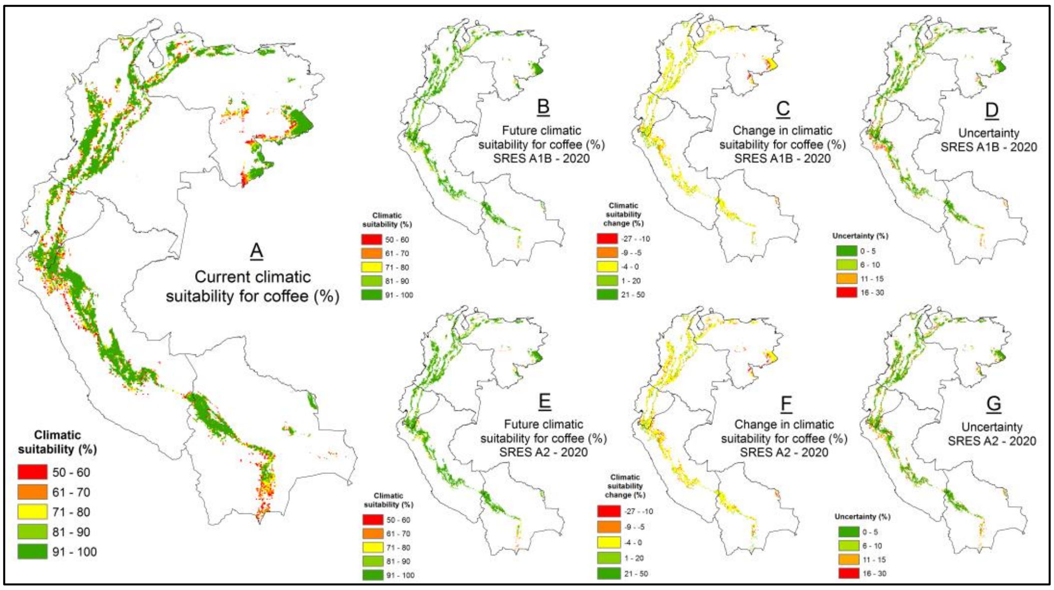

Figure 16. Climatic suitability for coffee 2020: (A) Current climatic suitability, (B) climatic suitability 2020-A1B, (C) climatic suitability change 2020-A1B, (D) uncertainty 2020-A1B, (E) climatic suitability 2020-A2, (F) climatic suitability change 2020-A2, (G) uncertainty 2020-A2

Figure 17 shows the losses in CS for the crop in the current optimal niche, which is located between 1,000 and 1,850 meters (areas with 70% of CS) where, in addition, about 64 million hectares will be affected by changes. While there is a clear downward trend in CS, between 2,000 and 2,200 meters appears a new niche for the crop to grow; about 60 million hectares will be suitable for growing coffee.

In the future (Figure 18, B and E), over central Venezuela, southern Bolivia and northwestern Peru there will be a significant losses of CS, ranging between 50% and 80%.

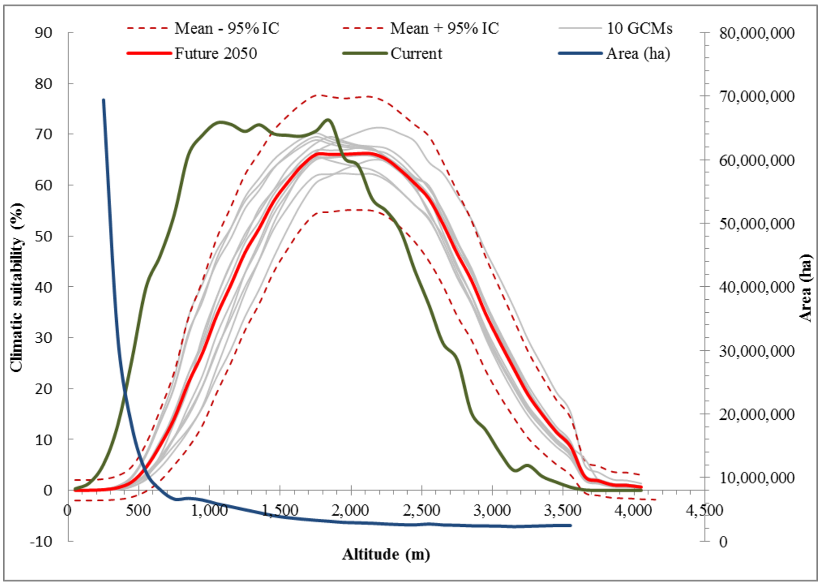

Figure 17. SRES-A1B: current and future (2050) climatic suitability for coffee

Figure 18 (C and F) presents changes in CS and validates the above–mentioned statements, showing that virtually all presently suitable areas will lose about 4% of their capacity. Confidence in projections is high because uncertainty values are low in most of the areas. These uncertainty values range between 0% and 5%.

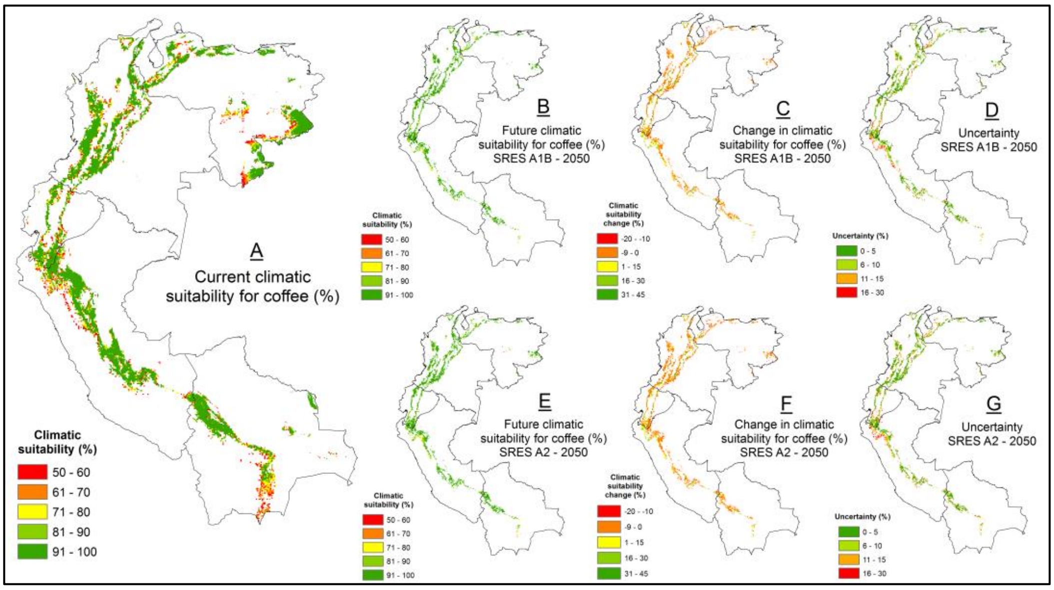

Figure 18. Climatic suitability for coffee 2050: (A) Current climatic suitability, (B) climatic suitability 2050-A1B, (C) climatic suitability change 2050-A1B, (D) uncertainty 2050-A1B, (E) climatic suitability 2050-A2, (F) climatic suitability change 2050-A2, (G) uncertainty 2050-A2

1.5. POTATO (Detailed maps in Annex 2)

The potato crop grows very well through the tropical Andes (Figure 19, A). Countries with higher CS for cultivation will be Colombia, Ecuador, Peru and Bolivia, with a significantly large number of areas where the CS range will be between 91% and 100%. However, there are also significant extensions with less suitable areas for growing the crop (60-80%). This is mainly observable in western Bolivia and southwestern Colombia. Going forward (Figure 19, B and E), most areas within the CS lower ranges will disappear in Bolivia and Colombia, but will remain optimal niches, indicating that crops will disappear in small areas. On the other hand, the CS change (Figure 19, C and F) will be largely negative (-4%–0%), but areas will still exist where crop suitability will tend to increase, such as the boundary between Peru and Bolivia, where conditions improve (1% - 15%). In terms of uncertainty, most of the area involved will present an uncertainty of 0% to 5%.

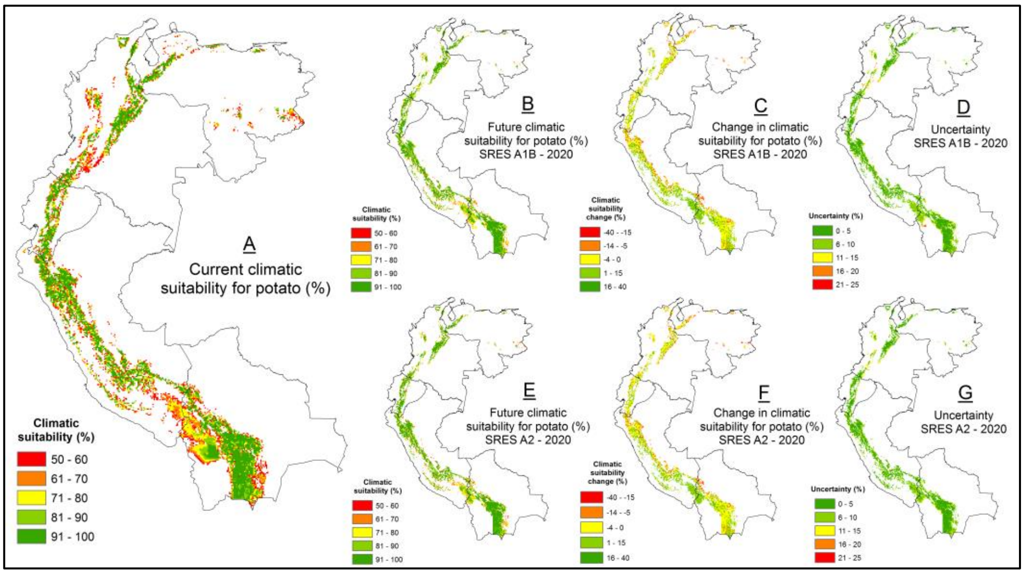

Figure 19. Climatic suitability for potato 2020: (A) Current climatic suitability, (B) climatic suitability 2020-A1B, (C) climatic suitability change 2020-A1B, (D) uncertainty 2020-A1B, (E) climatic suitability 2020-A2, (F) climatic suitability change 2020-A2, (G) uncertainty 2020-A2

On the other hand, Figure 20 (B and E) describes a similar situation in 2050 to that presented in 2020, but indicates that climate CS change will present losses in Bolivia, Peru and Colombia, but also a significant increase on the border between Peru and Bolivia, where the benefits are in the order of 16% to 40%. Uncertainty remains low for the study area (0 to 10%).

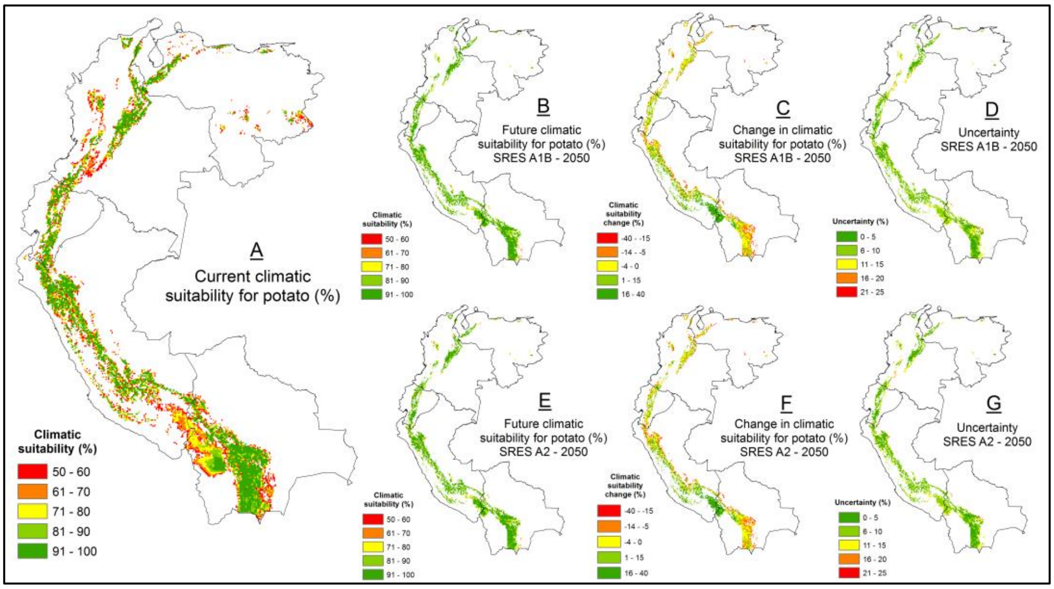

Figure 20. Climatic suitability for potato 2050: (A) Current climatic suitability, (B) climatic suitability 2050-A1B, (C) climatic suitability change 2050-A1B, (D) uncertainty 2050-A1B, (E) climatic suitability 2050-A2, (F) climatic suitability change 2050-A2, (G) uncertainty 2050-A2

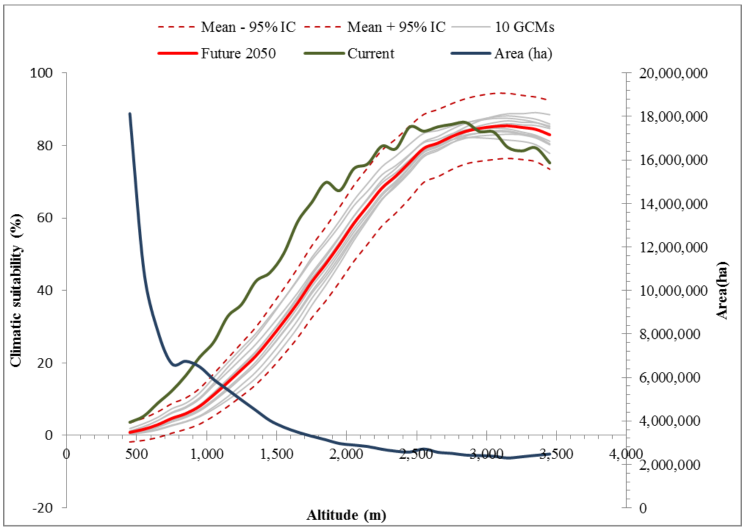

Figure 21. SRES-A1B: current and future (2050) climatic suitability for potato

Figure 21 provides an optimal range (80%–86%) for crop growth between 2,200 and 3,400 meters where the area involved is about 16 million hectares. In general, the area reported CS, but in 2050 will appear a new niche for growing between 3,000 and 3,600 meters with CS between 82% and 84%.

2. IMPACT ANALYSIS

Below are the outcomes of the uncertainty analysis based on SRES A1B-2050. As mentioned before, this was a validation exercise carried out to compare areas below 5% uncertainty (coefficient of variation) with changes in climatic suitability of the five crops. Further analysis can be done in the future to really understand the implications of these numbers. At this point, the purpose is to show how much area will be impacted in each country in relation to each one of the five countries assessed.

Table 5. Tomato: negative changes in climatic suitability

Country	**Sum of Area (km2)**
Bolivia	14,117
Colombia	7,329
Ecuador	3,950
Peru	9,093
Venezuela	9,032
Total	**43,522**

Table 8. Potato: negative changes climatic suitability

Country	**Sum of Area (km2)**
Bolivia	39,272
Peru	30,677
Colombia	12,134
Ecuador	10,153
Venezuela	3,449
Total	**95,685**

Table 6. Tomato: positive changes in climatic suitability

Country	**Sum of Area (km2)**
Peru	21,255
Venezuela	19,511
Colombia	18,800
Bolivia	16,614
Ecuador	8,529
Total	**84,709**

Table 9. Potato: positive changes in climatic suitability

Country	**Sum of Area (km2)**
Peru	28,093
Bolivia	16,621
Colombia	6,944
Ecuador	6,510
Venezuela	1,603
Total	**59,772**

Table 7. Tomato: no changes in climatic suitability

Country	**Sum of Area (km2)**
Peru	18,078
Colombia	17,888
Venezuela	17,537
Bolivia	13,230
Ecuador	6,730
Total	**73,463**

Table 10. Potato: no changes in climatic suitability

Country	**Sum of Area (km2)**
Peru	12,093
Bolivia	5,918
Colombia	5,729
Venezuela	3,865
Ecuador	3,428
Total	**31,032**

Table 11. Coffee: negative changes in climatic suitability

Country	Sum of Area (km2)
Colombia	9,792
Peru	9,193
Ecuador	5,194
Venezuela	4,461
Bolivia	3,257
Total	**31,896**

Table 12. Coffee: positive changes in climatic suitability

Country	Sum of Area (km2)
Colombia	5,995
Peru	3,215
Bolivia	2,401
Ecuador	2,249
Venezuela	1,663
Total	**15,523**

Table 13. Coffee: no changes climatic suitability

Country	Sum of Area (km2)
Colombia	34,978
Peru	15,820
Ecuador	10,826
Venezuela	9,130
Bolivia	6,806
Total	**77,561**

Table 14. Bean: negative changes in climatic suitability

Country	Sum of Area (km2)
Colombia	20,912
Peru	16,075
Ecuador	8,987
Bolivia	7,576
Venezuela	5,153
Total	**58,702**

Table 15. Bean: positive changes in climatic suitability

Country	Sum of Area (km2)
Colombia	16,564
Ecuador	6,997
Peru	5,925
Bolivia	3,945
Venezuela	2,270
Total	**35,701**

Table 16. Bean: no changes in climatic suitability

Country	Sum of Area (km2)
Colombia	13,007
Venezuela	7,831
Peru	6,229
Ecuador	1,280
Bolivia	943
Total	**29,290**

Furthermore, it is important to note that the figures and tables that accompany this section of the analysis help to describe the situation projected for the five crops under analysis. The aim is to show the results of both emission scenarios (A1B and A2) in the two periods (2020 and 2050). It is also worth noting that important similarities were found in the process of comparing the modeling outputs for both scenarios, mainly due to the pixel resolution, which does not allow identifying the possible differences in detail. If that were the purpose of this analysis, pixel resolution would need to be much smaller (i.e. $1km^2$). As it is known, rather than identifying small changes in specifics areas, the purpose of this study is to detect tendencies and estimate implications regarding decrease and increase in climatic suitability (%) that CC will have on areas where bean, coffee, tomato, wheat and potato are produced and consumed by tropical Andean communities.

This section will show the estimate percentage of hectares affected by CC. However, it must be clarified that the below figures are related to the total number of hectares that would be potentially affected, either negatively or positively. In terms of area potentially negatively and positively affected by climate change, Figure 22 is an example of the trend toward losing CS of the five crops, since in all cases it is greater than the area with benefits for changes.

Most extreme cases in SRES-A1B for 2020 are observed in coffee, beans and wheat, where areas with CS decreasing is 79.7% (30 million hectares out of a total of 37.7 million), 76.3% (193 million hectares of a total of 253.8 million) and 96.9% (24.5 million hectares of one of 25.4 million), respectively. The trend continued in 2050 where the area with CS decreasing for coffee, beans and wheat is 70.6% (16.9 million hectares out of 24 million), 70.9% (27.8 million hectares out of a total of 39.3 million) and 98.8% (18.3

million hectares out of a total of 18.6 million), respectively, indicating that some of the areas that CS decreasing in 2020 will disappear by 2050 (Figure 22).

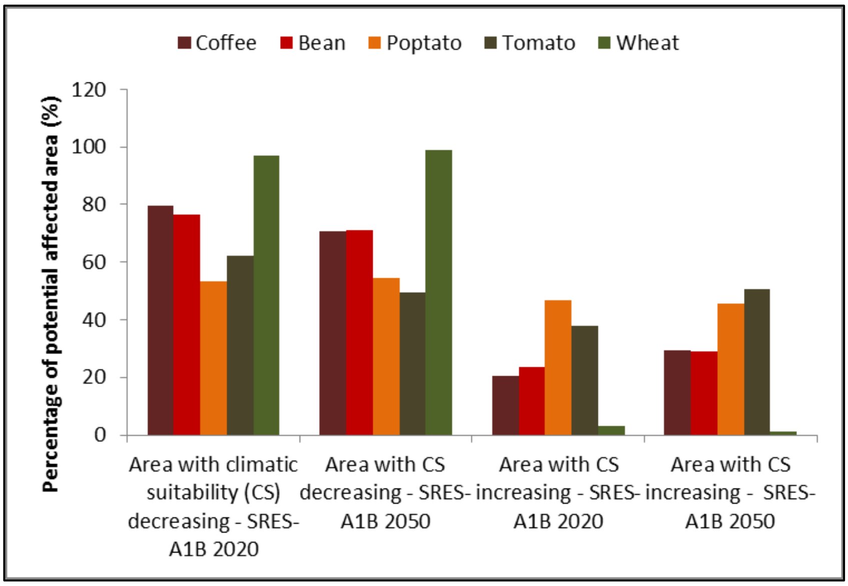

Figure 22. Percentage of area with climatic suitability decreasing and increasing per crop - SRES-A1B

Figure 23 describes the situation for the SRES-A2. In this case, the impact tends to be stronger, and it is reflected in the rates of CS decreasing and increasing by 2020: coffee (81.7% of a total of 38.8 million hectares), beans (76% a total of 55.7 million hectares) and wheat (97.2% of a total of 25.6 million hectares) are the most affected crops. In 2050 the situation maintains a negative trend—in coffee, beans and wheat 74.4%, 71.2% and 98.8% of the suitable area, respectively, area will be affected negatively. In hectares, these percentages are part of a total of 27, 43.5 and 20.2 million, respectively.

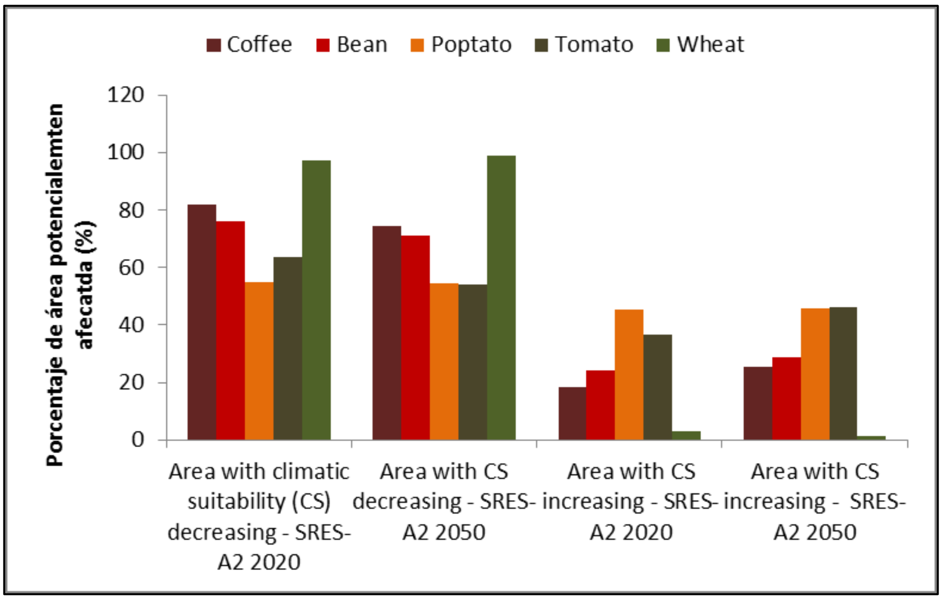

Figure 23. Percentage of area with climatic suitability decreasing and increasing per crop - SRES-A2

CHAPTER 5

1. CONCLUSIONS

Undoubtedly, CC will have implications for agriculture in the tropical Andes. According to this study, those staple crops consumed by Andean communities will suffer significant effects. This analysis has presented the situation of five crops, from the worst to the best case (i.e. tomato, wheat, bean, coffee and potato). However, even in the best case crop, losses are visible in some specific zones of the study area (i.e. potato). Nevertheless, countries such as Ecuador and Peru will have good opportunities to continue planting the crop, especially in areas over 2,000 meters.

In the case of coffee (a high value crop), it is clear that, overall, the south of Ecuador will be one of the areas with optimal conditions for crop in the future (2020 and 2050). Nonetheless, it is in the same area where also some spots (lower areas) will experience significantly negative changes. Furthermore, possible losses for the crop optimal niche are inevitable, as it is located between 1,200 and 1,850 meters above sea level, and such an environment will have progressive losses in CS for the 2020 and 2050 periods according the projections. It will be wise to think about some mitigation measures (such as shade or migration).

On the other hand, results for bean modeling show a clear trend of decreasing its CS throughout the study area. The projections suggest that areas with better CS are more than 1,100 meters above sea level. It is also evident that the crop is restricted to areas between 1,100 and 1,800 meters above sea level.

In relation to potato, EcoCrop describes good conditions for the future. The model shows that areas above 3,000 meters above sea level are suitable for crop growth.

Regarding tomato, the model shows that the crop can be grown with probabilities of good CS in places located between 500 and 1,200 meters.

Finally, the decline in CS for wheat is clearly observable, especially regarding projections of CC until 2050. Uncertainty of the projections is below 40% for most of the study area.

2. STUDY LIMITATIONS

Elements such as the uncertainty of climate data, lack of data on crop occurrence, probable inconsistency in crop data sources, among others, were some of the restrictions on this analysis.

In relation to climate data, the fourth IPCC report was based on results from 21 GCMs (IPCC, 2007), whose data are available on the IPCC website (www.ipcc-data.org), or directly on the web pages of the different institutions where each one of the models were developed (Web page of World Climate Research Programme (WCRP) CMIP3 multi-model database also provides information). Nevertheless, the original spatial resolution of each GCM was inappropriate to analyze CC impacts on agriculture and, in almost all cases; the cells are larger than $100km^2$. This becomes a problem, especially in heterogeneous landscapes such as those presented in the tropical Andes, where in some places one GCM cell can cover the full range of variability of a crop. To solve this problem and use the models from the IPCC, an interpolation process is usually performed. However, the problem continues in other ways, as this new process (interpolation) adds even more uncertainty to the modeling projections.

On the other hand, and related to the limitations from evidence points of the crops, it is worth mentioning that the number of points recorded was different for the five crops: coffee 14,141, bean 16,883, potato 2,838, tomato 1,964 and wheat 13,080. It is further noted that some evidence points are very focused on one or two countries and do not have much representation over the rest of countries in the region. It is the case of tomato, indicating some level of geographical bias. This situation could lead to a significant spatial autocorrelation, affecting the performance of the models. The results, therefore, may be underestimating both the current presence of crops and the impact of CC on such evidence points.

3. RECOMMENDATIONS

The process to face CC impacts can be divided into three major segments or paths: 1) risk management (short term), 2) the gradual adaptation to CC (long term) and 3) mitigation of greenhouse gases (GHG). The main work of researchers should be to examine and improve the knowledge about the potential synergies between the three segments and the offsets between them. It is worth mentioning that the following statements are based on a paper by Jarvis et al. (2011) entitled “An Integrated Adaptation and Mitigation Framework for Developing Agricultural Research: Synergies and Trade-Offs”.

Risk management (short term): most agricultural producers are small, poor and vulnerable to the climate variability. Despite measures that small producers can take now in order to counter the risk, they continue being vulnerable to climate impacts that can result in bad health conditions, attacks on productive assets, and even damage on infrastructure. The uncertainty surrounding climate variability and debilitating fear of these events hinders investment in agricultural technologies and market opportunities, which are usually profitable. Therefore, climate can limit revenue even in years when no adverse effects will occur. Innovations such as microcredit and subsidies for inputs such as fertilizers, pesticides and improved seeds, are some of the tools that can help address the old barriers of implementation and overcome constraints related to the risk, food security and rural poverty reduction. In some cases, when there are no incentives to the private sector, the government should spearhead these efforts. In addition to financial support, the producers need a better flow of information to anticipate climate impacts for incoming agricultural seasons. In particular, forecasting systems and early warning will teach farmers about the best options to pursue (e.g. invests when conditions are favorable and protect themselves when the risk is high). These systems will not only help farmers themselves, but also vendors and intermediaries, as they could use climate forecasts to better manage production and storage, interchange and distribution of food, and will also help governments to better target food assistance in emergency times.

Producers may also initiate changes in their farming practices about how to manage soil and water in order to minimize risk. In addition, producers could take advantage of new varieties or crops that are more resistant or appropriate in different contexts, and stagger the timing of planting and harvesting to reduce the risk. Similarly, diversification into other types of agriculture (e.g. to livestock or aquaculture) or other sources of income not related to agriculture (e.g. ecotourism) could provide insurance.

These measures reflect mostly possible solutions that would help small farmers to cope with the risks of climate variability. Surely, it will be necessary to implement these win-win solutions with the adoption of techniques required to face the anthropogenic CC.

Adaptation (long term): The CC challenge is driven by anthropogenic causes, an accelerated version of a more or less familiar challenge. For centuries, farmers and production systems have faced the problem and have found a climate dynamic response. However, never before in history had climate changed with today’s speed and magnitude. Moreover, parallel to CC, the world is experiencing a large increase in population and power demands. So most than risk mitigation, the CC requires accelerated adaptation. Certainly, achieving this goal will involve the development of technologies to improve crops and increase resistance to climate-related stresses (e.g. flood, drought and heat). In recent decades, breeding and development of genetically modified (GM) crops have proved to be effective means to address abiotic stress and increase food production. In this sense, another challenge and opportunity is also apparent, agro-biodiversity. In the past, while breeding programs multiplied harvests in some crops, they also reduced genetic diversity, with the consequence of making crops more vulnerable to the climate change process. Therefore, toward the future, agricultural diversity should be preserved both in gene-banks and fields. Agro-biodiversity plays a crucial role in adapting to face CC.

In addition, “analogs” are presented when the conditions of climate, soil and other variables in a specific place, after suffering effects of climate in a given year (e.g. 2000), are similar to the climatic conditions elsewhere today. This means that analogues point out how climate will “migrate” and can therefore be used to create a chain of knowledge across producers, and later, share coping strategies and information on specific crops.

Mitigation of greenhouse gases: in some cases, it is possible to exploit the synergies between GHG mitigation and risk management or increasing adaptive capacity, for instance through: A) enhanced systems: producing more crops on the same land unit will achieve both goals, but the environmental costs of some methods of intensification (e.g. the use of fertilizers, pesticides and insecticides) would have to be reviewed. Usually, GM crops and other farming strategies that minimize costs are preferred. In all cases, both the poor and small farmers have less access to such technologies or lack knowledge of how to enhance their systems. Policies that support low-income farmers would be key to help them. B) Payments for ecosystem services: paying farmers to grow sustainably or implement agroforestry systems will be an ideal solution to take advantage of synergies between adaptation and mitigation. This measure will work because it will be based on economic incentives. However, there are several factors that currently limit its scope, including the lack of improvements in measurement and monitoring tools, more specific definitions of how to measure ecosystem services (i.e. per hectare, carbon sequestration, taking into account the species of plants or not, etc.) and, of course, reliable sources of funding.

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5. ANNEXES

ANNEX 1:

```
/* MkBCvars.AML
/* /*
/* Author Robert Hijmans
/* January 2006
/* rhijmans@uclink.berkeley.edu
/*
/* Version 2.3
/*
/* This AML creates the 19 BIOCLIM variables from
/* monthly Tmin, Tmax, and Precipitation grids
/* The results are rounded where integers would become reals
/* (I assume that input values were multiplied by 10
/* and stored as Integers to begin with)
/* P2 is first multiplied by 10
/* CVs are first multiplied by 100.
/*
/* rounding of "x" is done with "int(floor(x + 0.5))"
/* because "int(x+0.5)" as suggested by ESRI (see INT in Arc Help), does not
/* round negative numbers correctly (-2.6 -> -2 intstead of -3)
/*
/* You must change the first four lines (input files and output directory)
/* If you do not have average temperature, create it with the lines that follow
/*
/* Also note that the AML removes some temporary grids if they exist
/* (the first "&do i = 0 &to 15" bit)
/* Please make sure that you do not have files
/* with those names that you want to keep.
/*
/* BIO1 = Annual Mean Temperature
/* BIO2 = Mean Diurnal Range (Mean of monthly (max temp - min temp))
/* BIO3 = Isothermality (P2/P7) (* 100)
/* BIO4 = Temperature Seasonality (standard deviation *100)
/* BIO5 = Max Temperature of Warmest Month
/* BIO6 = Min Temperature of Coldest Month
/* BIO7 = Temperature Annual Range (P5-P6)
/* BIO8 = Mean Temperature of Wettest Quarter
/* BIO9 = Mean Temperature of Driest Quarter
/* BIO10 = Mean Temperature of Warmest Quarter
/* BIO11 = Mean Temperature of Coldest Quarter
/* BIO12 = Annual Precipitation
/* BIO13 = Precipitation of Wettest Month
/* BIO14 = Precipitation of Driest Month
```

```
/* BIO15 = Precipitation Seasonality (Coefficient of Variation)
/* BIO16 = Precipitation of Wettest Quarter
/* BIO17 = Precipitation of Driest Quarter
/* BIO18 = Precipitation of Warmest Quarter
/* BIO19 = Precipitation of Coldest Quarter
/*
/* These summary Bioclimatic variables are after:
/*   Nix, 1986. A biogeographic analysis of Australian elapid snakes. In: R. Longmore
(ed.).
/*      Atlas of elapid snakes of Australia. Australian Flora and Fauna Series 7.
/*      Australian Government Publishing Service, Canberra.
/*
/* and Expanded following the ANUCLIM manual
/*
/*
/* Temperature data is in units of  °C * 10 because that allows me to store the data as
Integer values,
/* (with 0.1 °C precision) which is more efficient than storing the data as Real values.
/* However, you will want to report the data in °C. Precipitation data is in mm.
/*
/*
&args inmonthly outselected gslength

&if [null %inmonthly%] OR [null %outselected%] OR [NULL %gslength%] &then
        &do
                &ty
                &ty INCORRECT SYNTAX
                &ty Run the aml as: '&r mkSelBCvars.aml INPUT_FOLDER
OUTPUT_FOLDER GS_LENGTH'
                &ty
                &return
        &end
&else w %inmonthly%

&TERMINAL 9999

&s program [locase [show program]]
&if %program% ^= grid &then grid

&sv tn = tmin_
&sv tx = tmax_
&sv ta = tmean_
&sv pt = prec_

/* if TAVG does not exist.....
&do j = 1 &to 12
  &if [EXISTS %ta%%j% -grid] &then &type %ta%%j%
  &else %ta%%j% = (%tn%%j% + %tx%%j%) / 2
&end
```

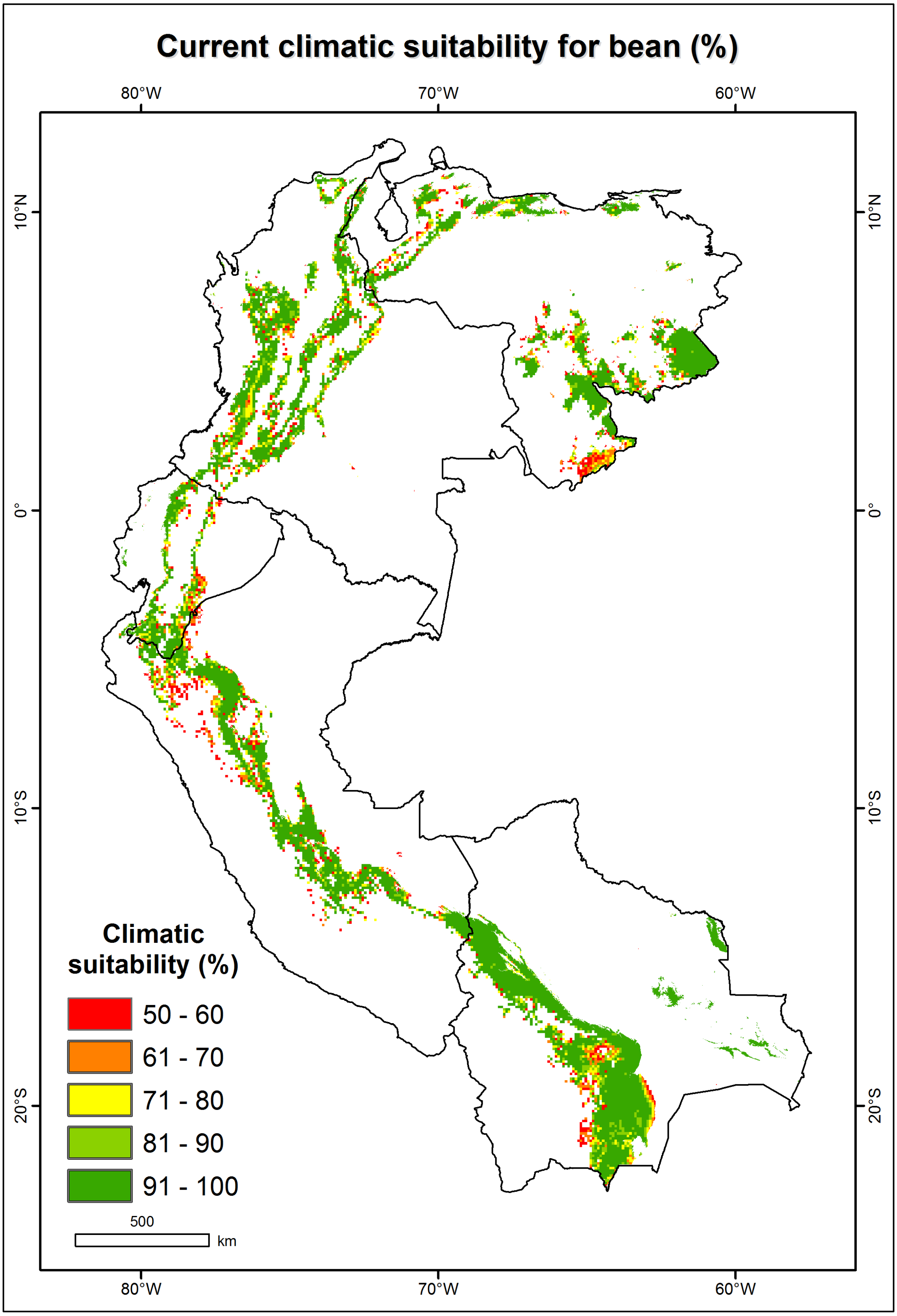
```
&if [exists drym -grid] &then kill drym
&if [exists wetm -grid] &then kill wetm

&sv TAvar = %ta%1
&sv TXvar = %tx%1
&sv TNvar = %tn%1
&sv PTvar = %pt%1

&do j = 2 &to 12
  &sv tavar = %tavar%,%ta%%j%
  &sv txvar = %txvar%,%tx%%j%
  &sv tnvar = %tnvar%,%tn%%j%
  &sv ptvar = %ptvar%,%pt%%j%
&end

/* Wettest and driest (this is the only part to be modified)

&do i = 1 &to 12
  &sv gsstart = %i%
  &sv gsend = %i% + %gslength% - 1

  &ty Month %i% (GS %gsstart% to %gsend%)

  &do k = %gsstart% &to %gsend%
          &sv j = %k%
          &if %j% > 12 &then &sv j [calc %j% - 12]

          &if %k% EQ %gsstart% &then
                  &do
                          &sv listpgrids %pt%%j%
                          &sv listtgrids %ta%%j%
                  &end
          &else
                  &do
                          &sv listpgrids %listpgrids%,%pt%%j%
                          &sv listtgrids %listtgrids%,%ta%%j%
                  &end

  &end

  q%i% = SUM(%listpgrids%)
  t%i% = SUM(%listtgrids%)
&end

mnt0 = con(isnull(q1),0,100)
mnt1 = setnull(mnt0 < 1, 1)
wet1 = q1

&do i = 1 &to 11
```

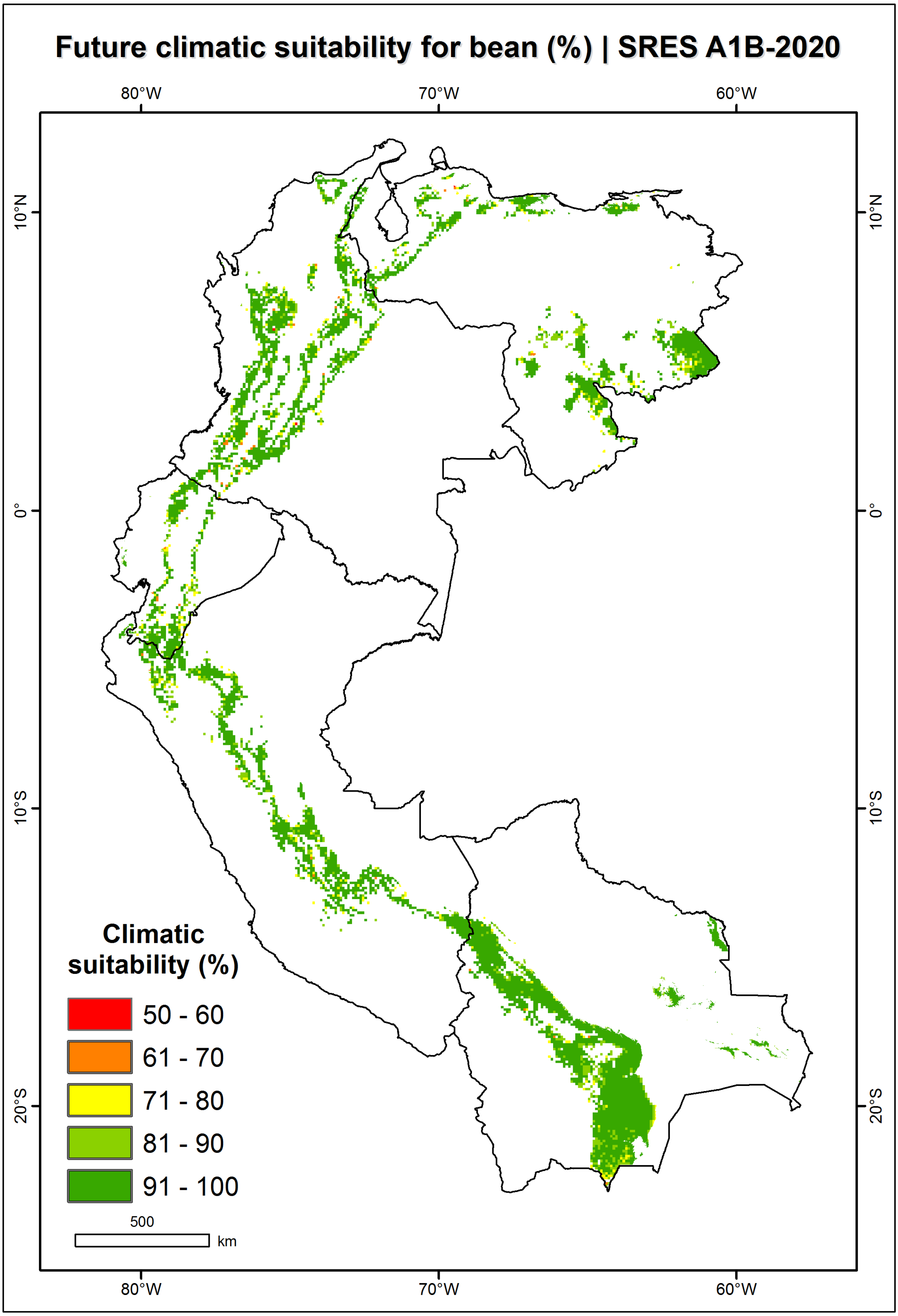
```
  &sv j = [calc %i% + 1]

  mnt%j% = con(q%j% > wet%i%, [calc %j%], mnt%i%)
  wet%j% = con(q%j% > wet%i%, q%j%, wet%i%)
&end
wetm = mnt12

/* P16. Precipitation of Wettest X-month period
&if [exists %outselected%\wettest -grid] &then &type Wettest exists
&else
&do
  %outselected%\wettest = wet12
  &type Wettest done
&end

&do i = 1 &to 12
  kill mnt%i%
  kill wet%i%
&end

mnt1 = setnull(mnt0 < 1, 1)
dry1 = q1

&do i = 1 &to 11
  &sv j = [calc %i% + 1]
  mnt%j% = con(q%j% < dry%i%, [calc %j%], mnt%i%)
  dry%j% = con(q%j% < dry%i%, q%j%, dry%i%)
&end
drym = mnt12

/* P17. Precipitation of Driest X-month period
&if [exists %outselected%\driest -grid] &then &type Driest exists
&else
&do
  %outselected%\driest = dry12
  &type Driest done
&end

&do i = 1 &to 12
  kill mnt%i%
  kill dry%i%
&end
kill mnt0

/* Warmest and coldest

mnt0 = con(isnull(t1),0,100)
mnt1 = setnull(mnt0 < 1, 1)
hot1 = t1
```

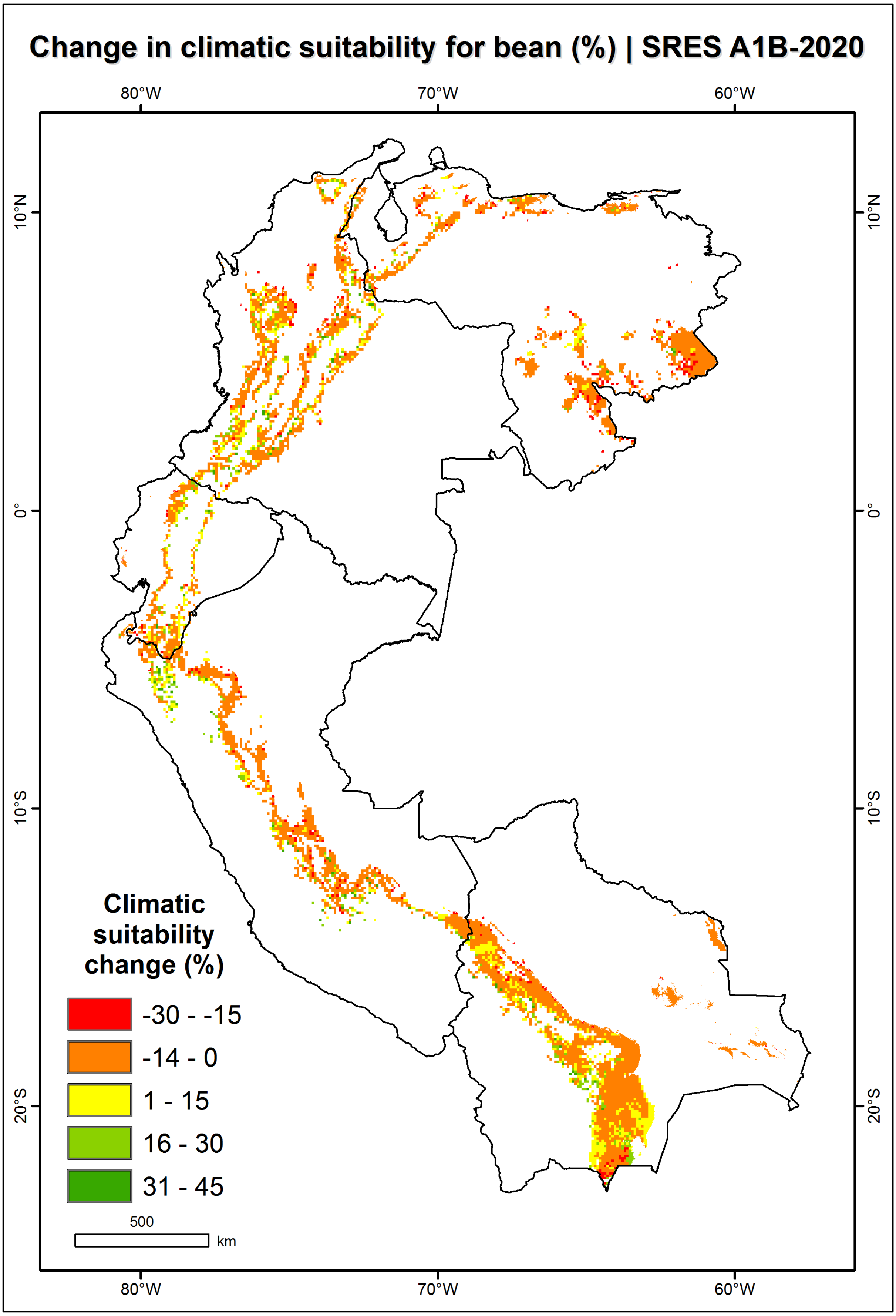
```
&do i = 1 &to 11
  &sv j = [calc %i% + 1]
  mnt%j% = con(t%j% > hot%i%, [calc %j%], mnt%i%)
  hot%j% = con(t%j% > hot%i%, t%j%, hot%i%)
&end
hotm = mnt12

/* P10 Mean Temperature of Warmest X-month period
&if [exists %outselected%\warmest -grid] &then &type Warmest exists
&else
&do
  %outselected%\warmest = int(floor(hot12 / %gslength% + 0.5))
  &type Warmest done
&end

&do i = 1 &to 12
  kill mnt%i%
  kill hot%i%
&end


mnt1 = setnull(mnt0 < 1, 1)
cld1 = t1

&do i = 1 &to 11
  &sv j = [calc %i% + 1]
  mnt%j% = con(t%j% < cld%i%, [calc %j%], mnt%i%)
  cld%j% = con(t%j% < cld%i%, t%j%, cld%i%)
&end
cldm = mnt12

/* P11 Mean Temperature of Coldest X-month period
&if [exists %outselected%\coldest -grid] &then &type Coldest exists
&else
&do
  %outselected%\coldest = int(floor(cld12 / %gslength% + 0.5))
  &type Warmest done
&end

&do i = 1 &to 12
  kill mnt%i%
  kill cld%i%
&end
kill mnt0

kill hotm
kill cldm
kill drym
kill wetm
```

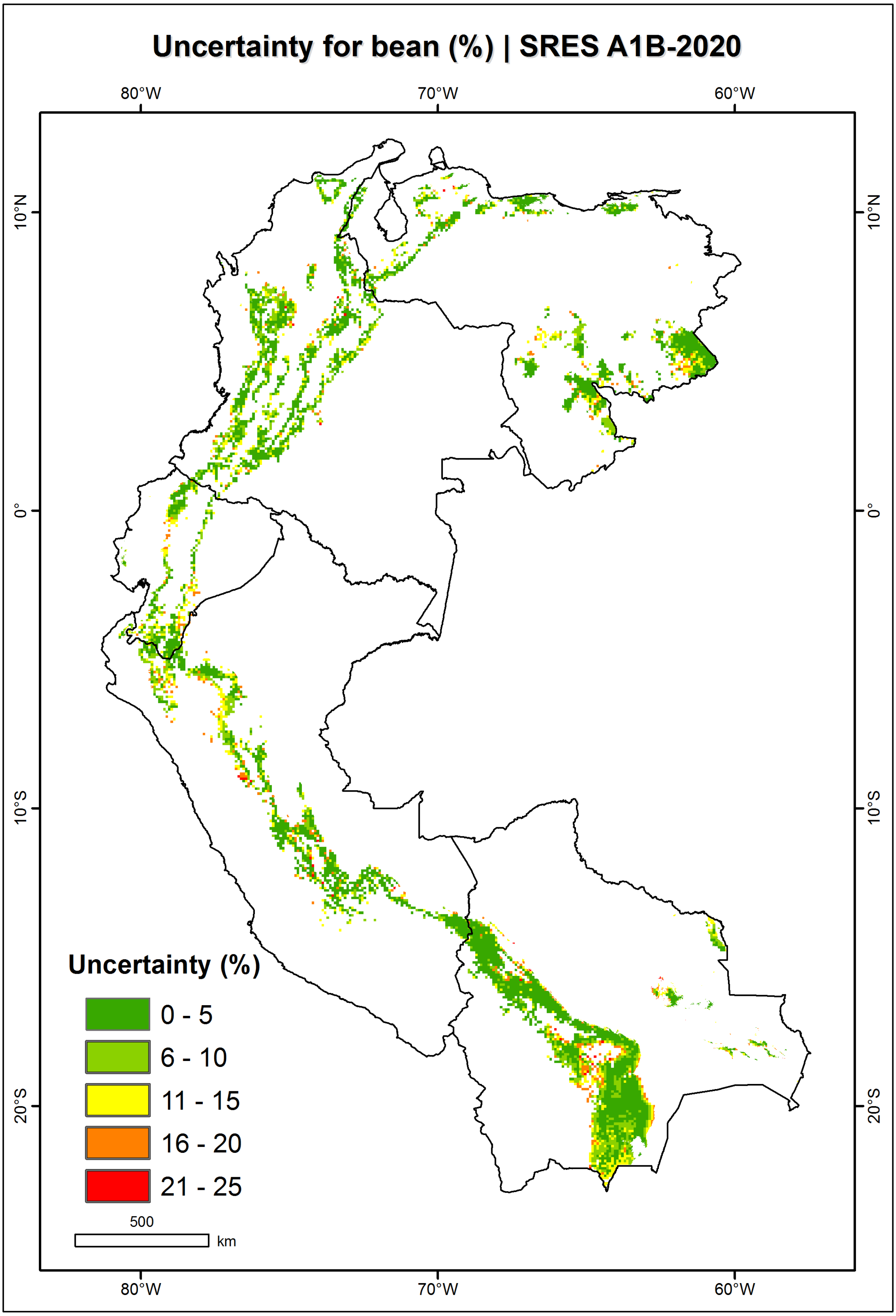
```
&do i = 1 &to 12
  kill q%i%
  kill t%i%
&end

&type Done!
&return
```

ANNEX 2:

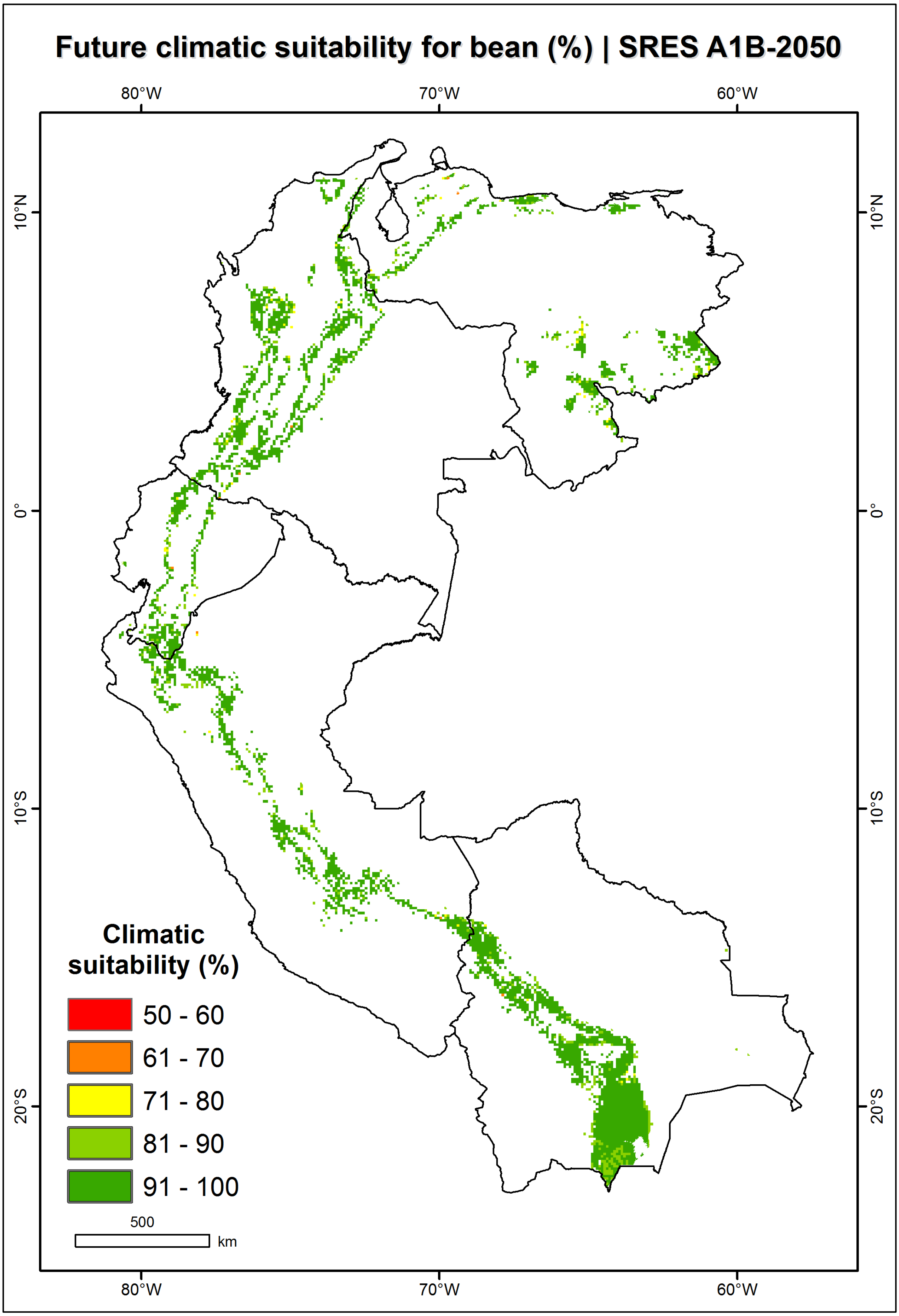

Current climatic suitability for bean (%)
80°W
70°W
60°W
10°N
0°
10°S
20°S
Climatic suitability (%)
🟥 50 - 60
🟧 61 - 70
🟨 71 - 80
🟩 81 - 90
🟩 91 - 100
500
km


Future climatic suitability for bean (%) | SRES A1B-2020
80°W
70°W
60°W
10°N
0°
10°S
20°S
Climatic suitability (%)
50 - 60
61 - 70
71 - 80
81 - 90
91 - 100
500
km

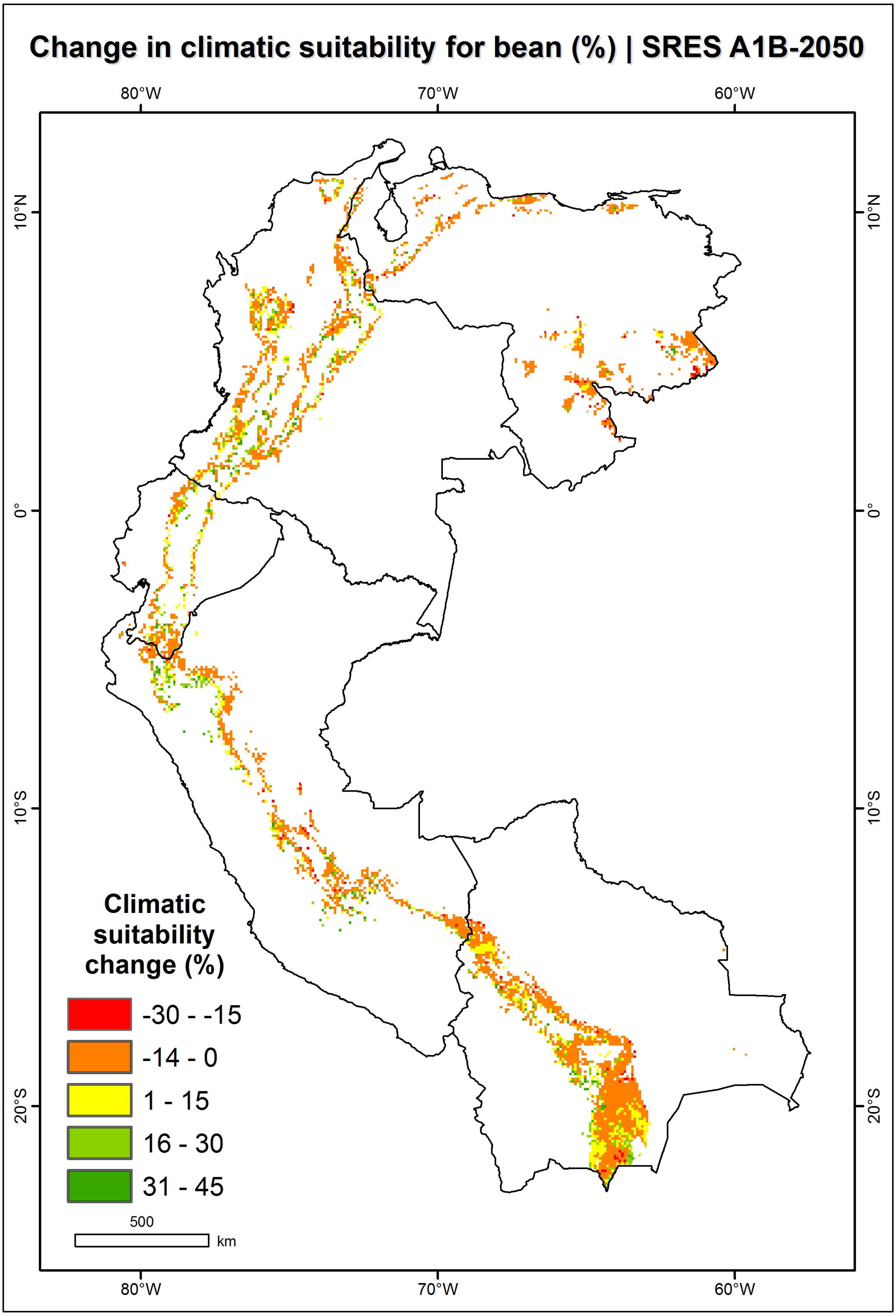

Change in climatic suitability for bean (%) | SRES A1B-2020
80°W
70°W
60°W
10°N
0°
10°S
20°S
Climatic suitability change (%)
-30 - -15
-14 - 0
1 - 15
16 - 30
31 - 45
500
km

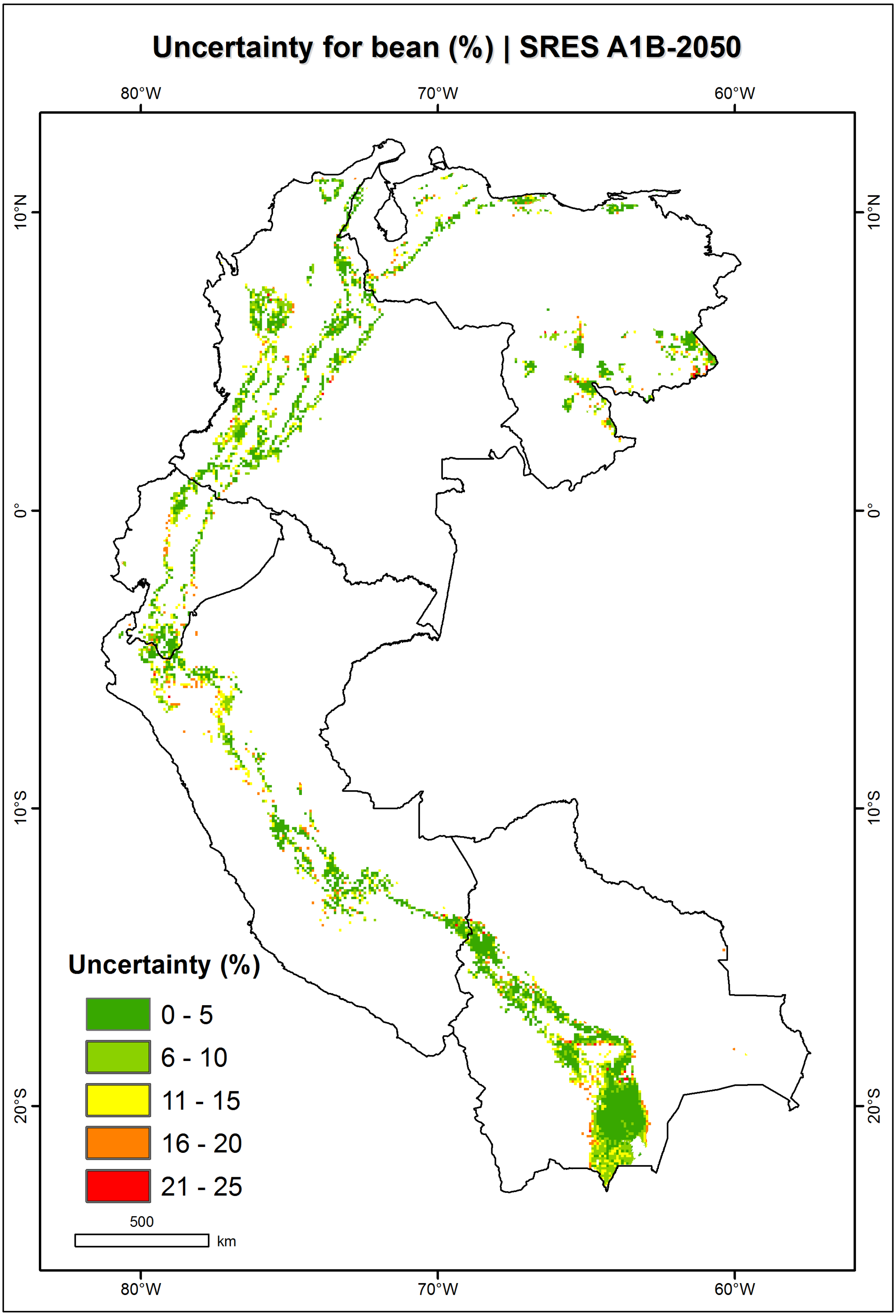


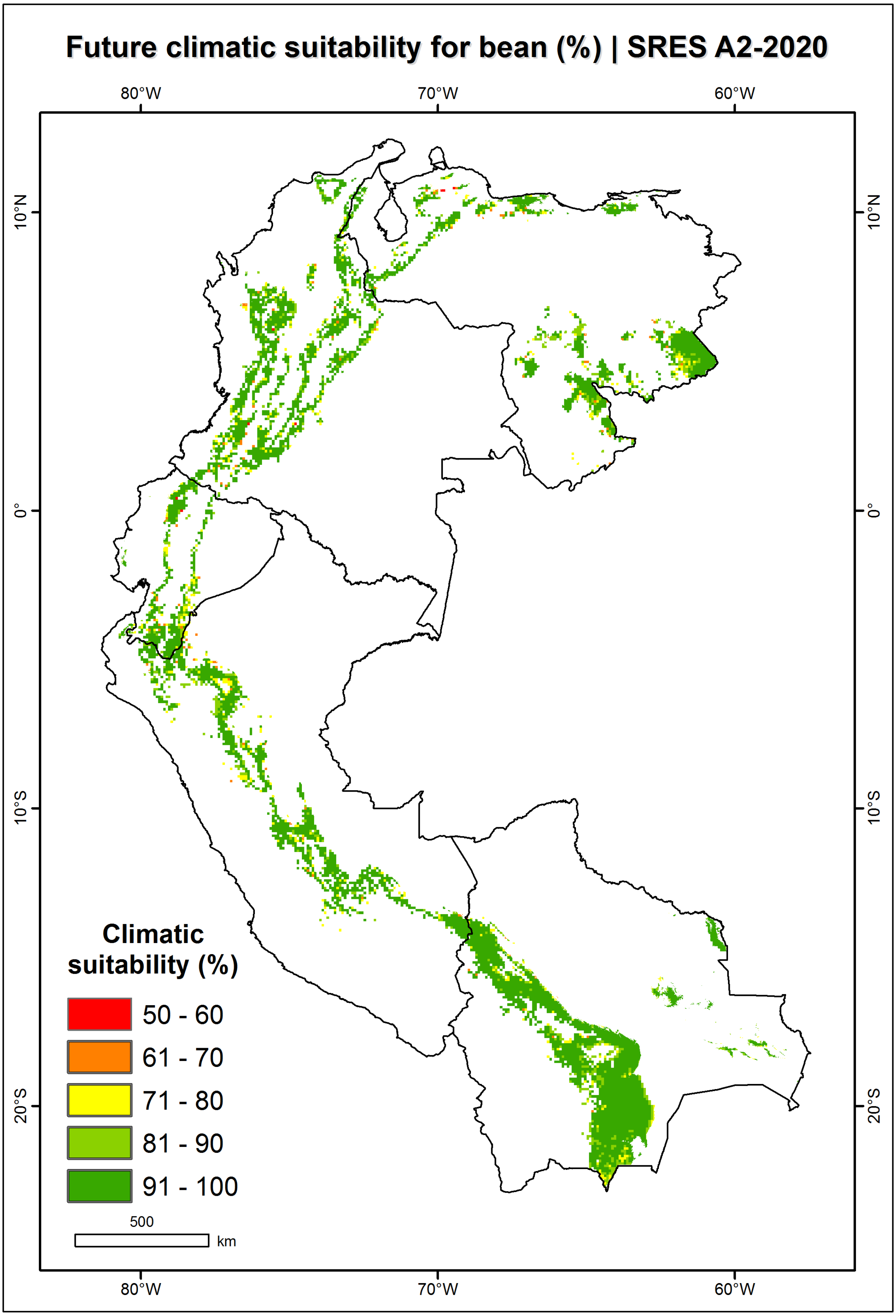
Uncertainty for bean (%) | SRES A1B-2020



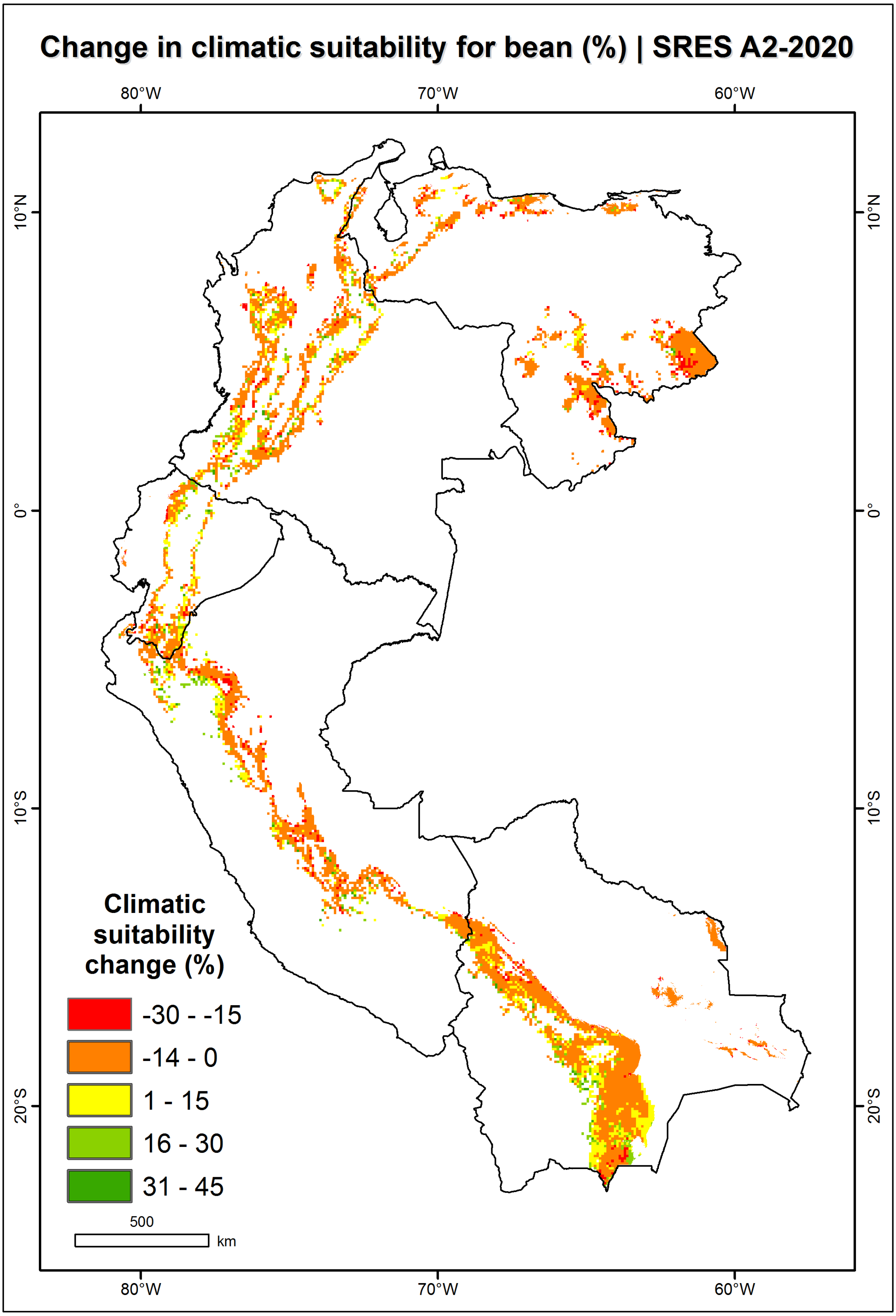
Future climatic suitability for bean (%) | SRES A1B-2050

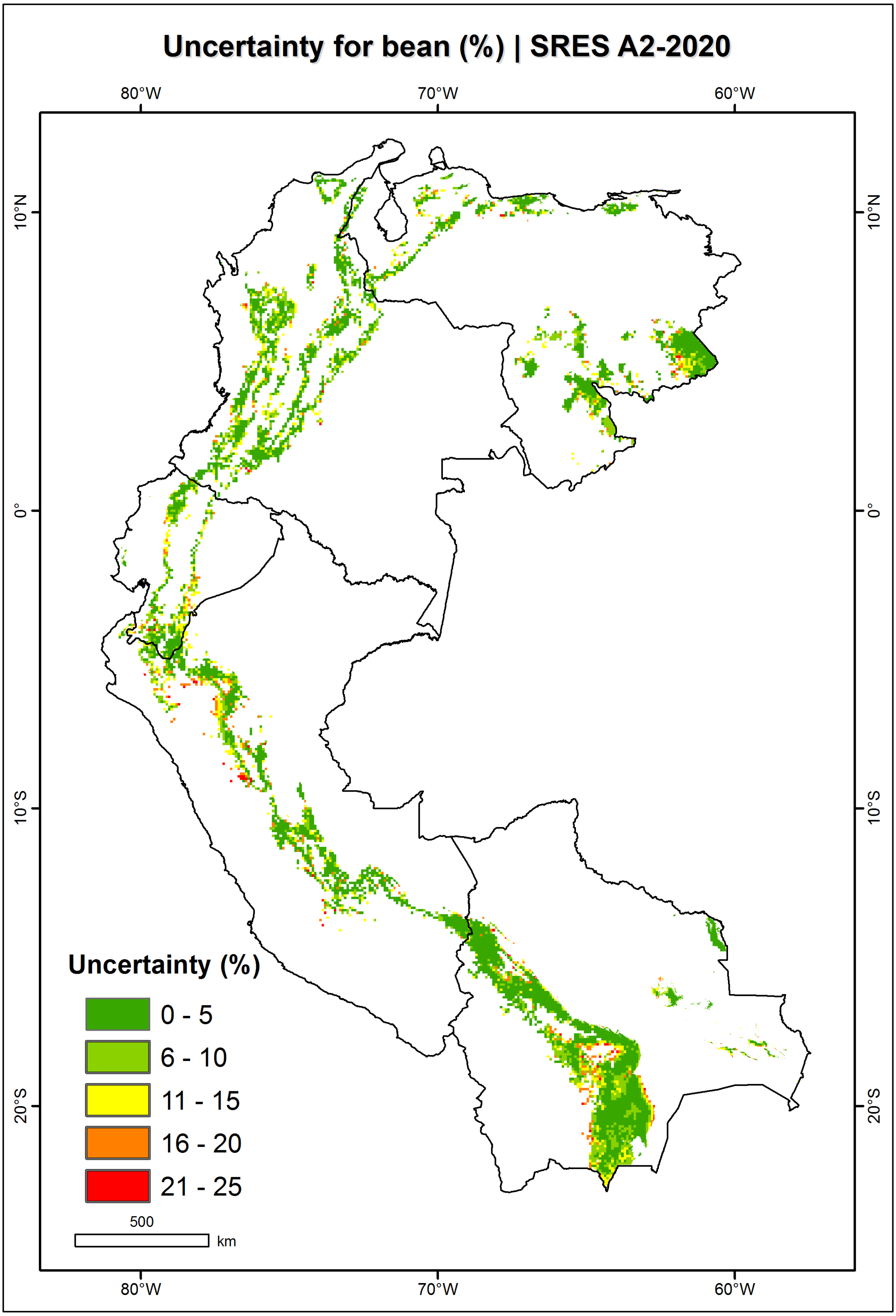

Change in climatic suitability for bean (%) | SRES A1B-2050
80°W
70°W
60°W
10°N
0°
10°S
20°S
Climatic suitability change (%)
-30 - -15
-14 - 0
1 - 15
16 - 30
31 - 45
500
km

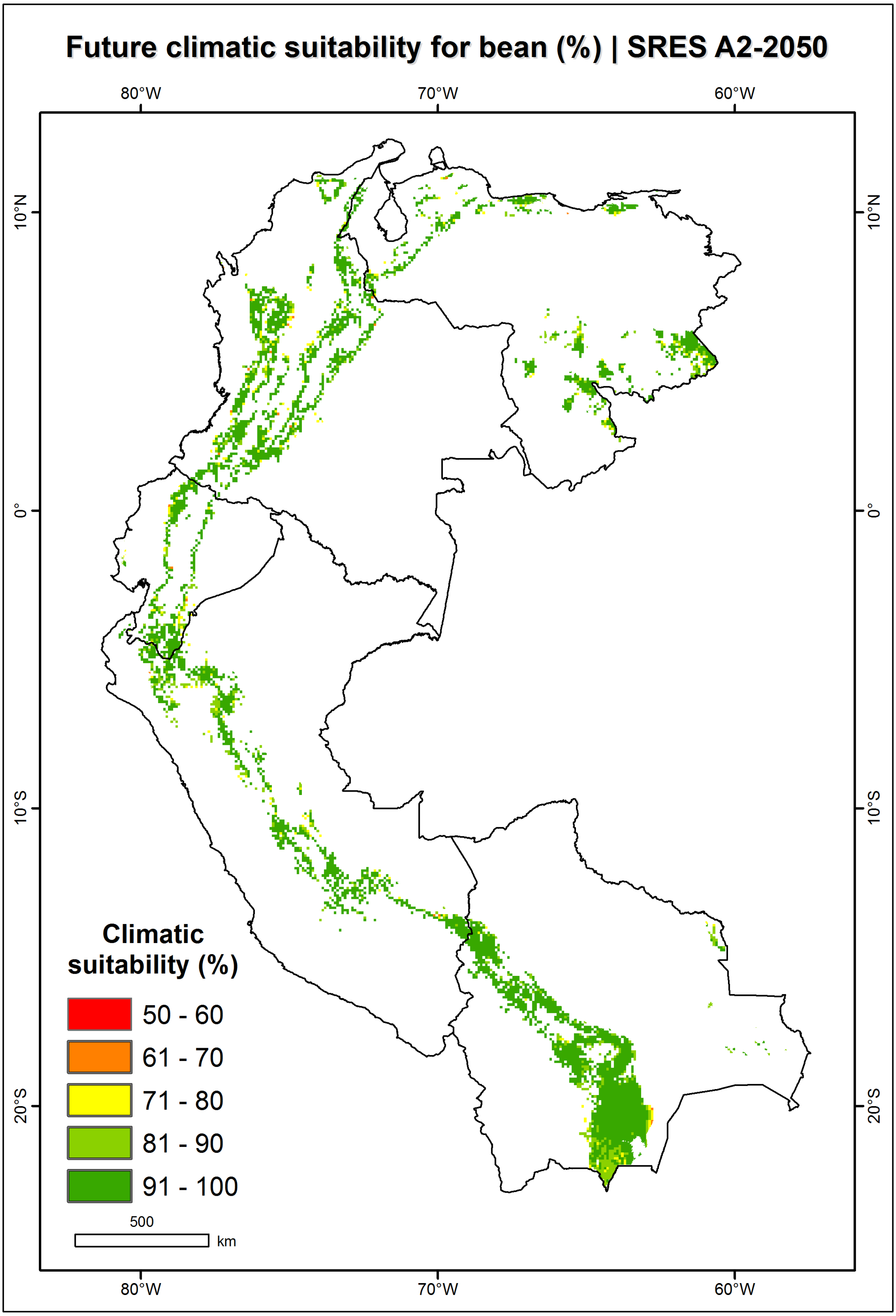

Uncertainty for bean (%) | SRES A1B-2050
80°W
70°W
60°W
10°N
0°
10°S
20°S
Uncertainty (%)
0 - 5
6 - 10
11 - 15
16 - 20
21 - 25
500
km



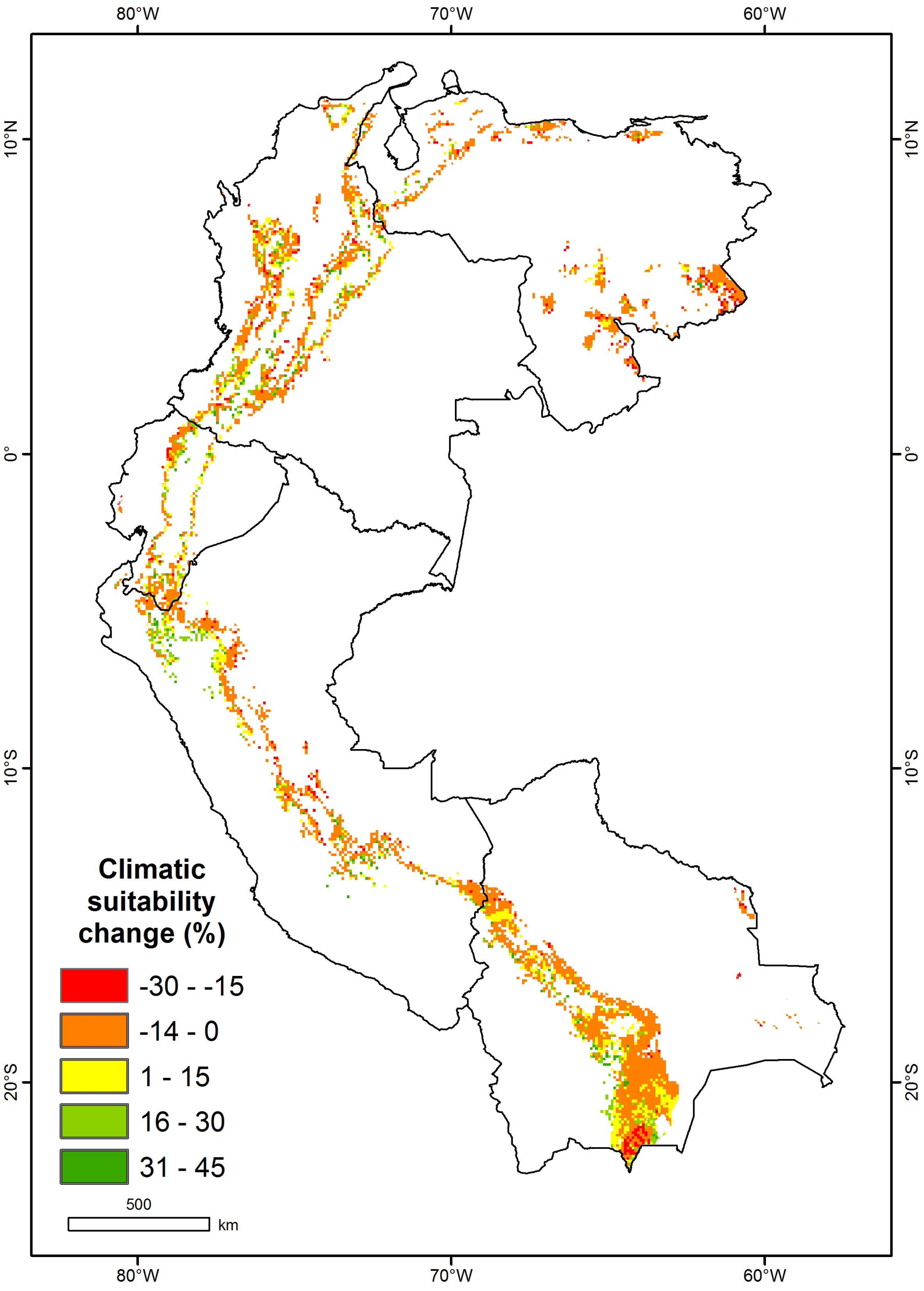
Future climatic suitability for bean (%) | SRES A2-2020


Change in climatic suitability for bean (%) | SRES A2-2020
80°W
70°W
60°W
10°N
0°
10°S
20°S
Climatic suitability change (%)
🟥 -30 - -15
🟧 -14 - 0
🟨 1 - 15
🟩 16 - 30
🟩 31 - 45
500
km

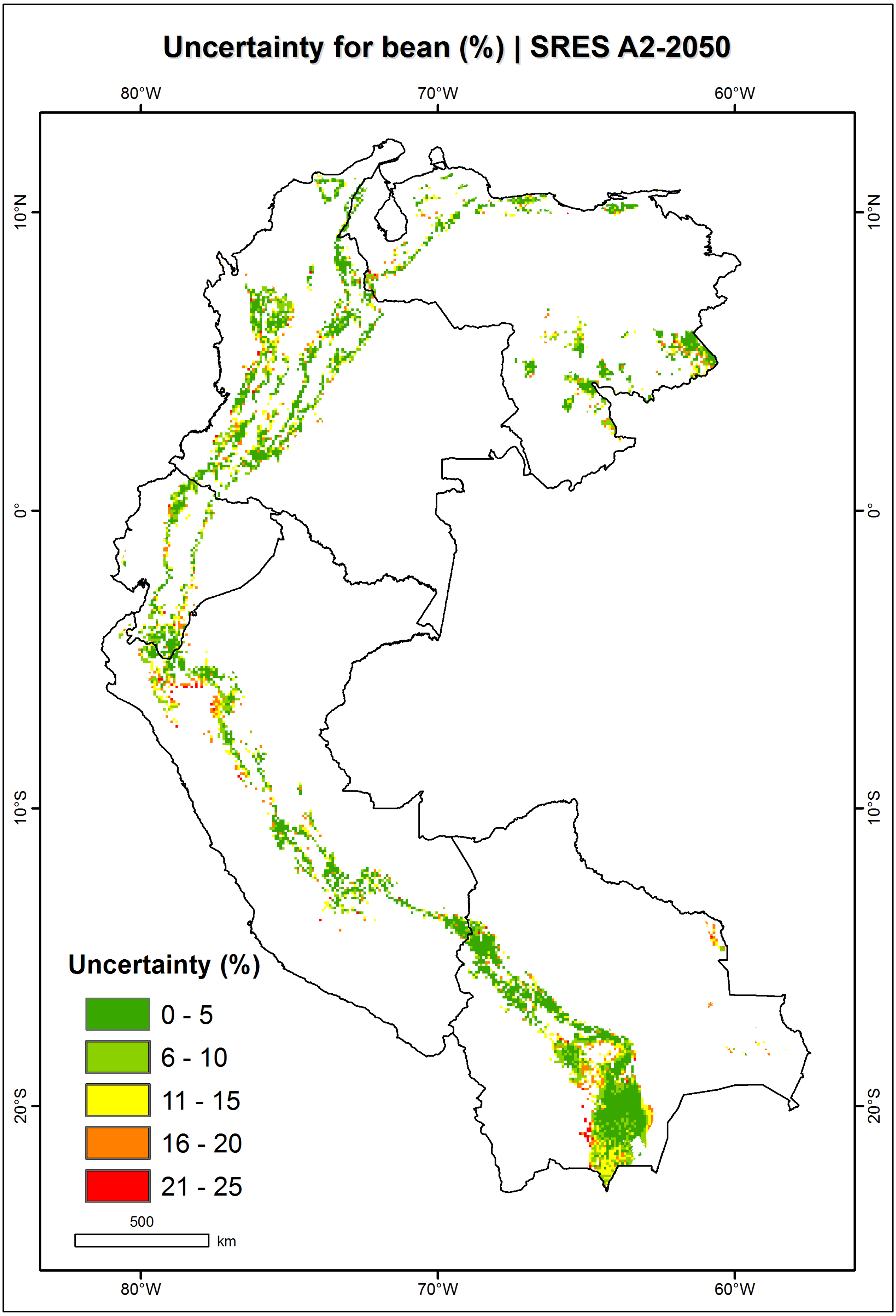

Uncertainty for bean (%) | SRES A2-2020
80°W
70°W
60°W
10°N
0°
10°S
20°S
Uncertainty (%)
0 - 5
6 - 10
11 - 15
16 - 20
21 - 25
500
km

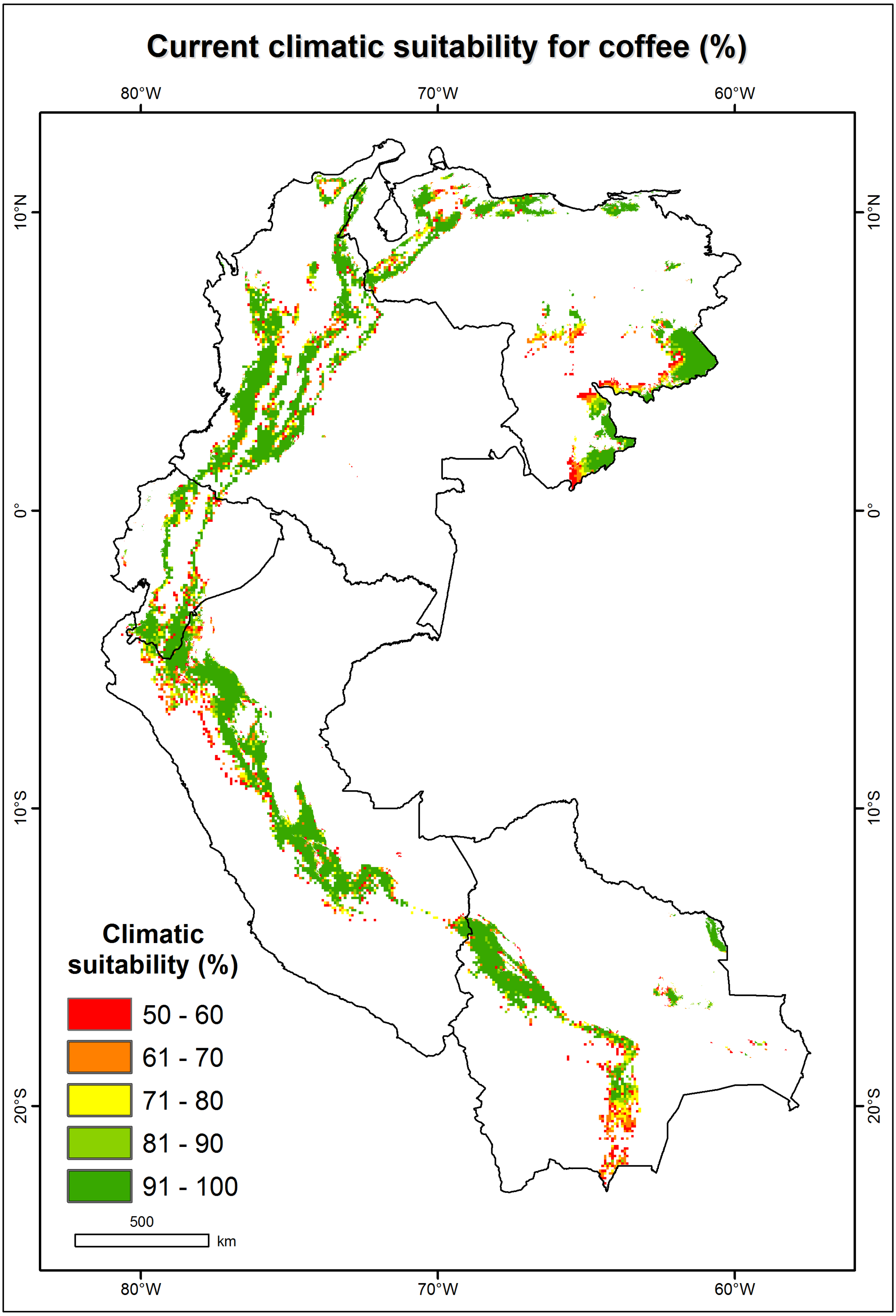


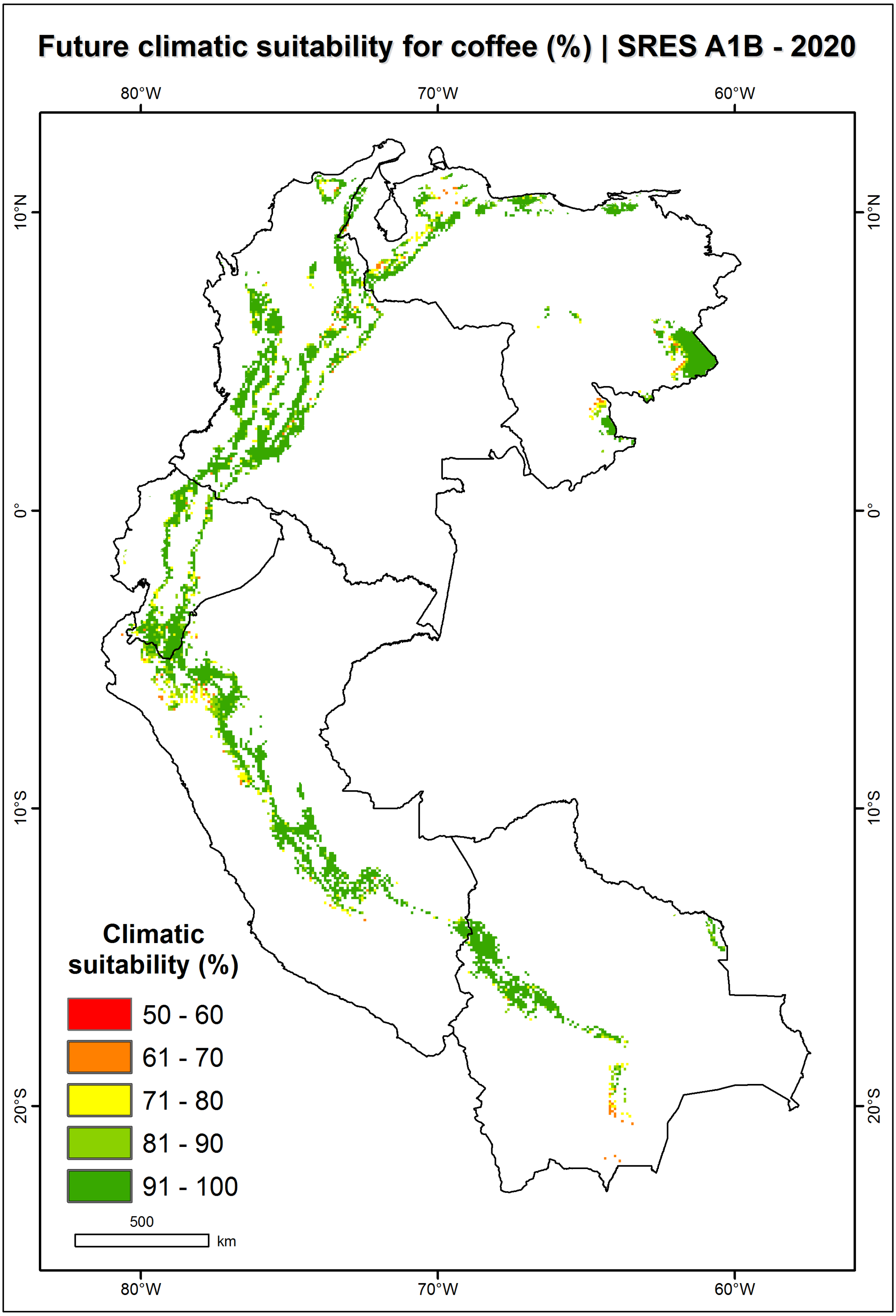
Future climatic suitability for bean (%) | SRES A2-2050

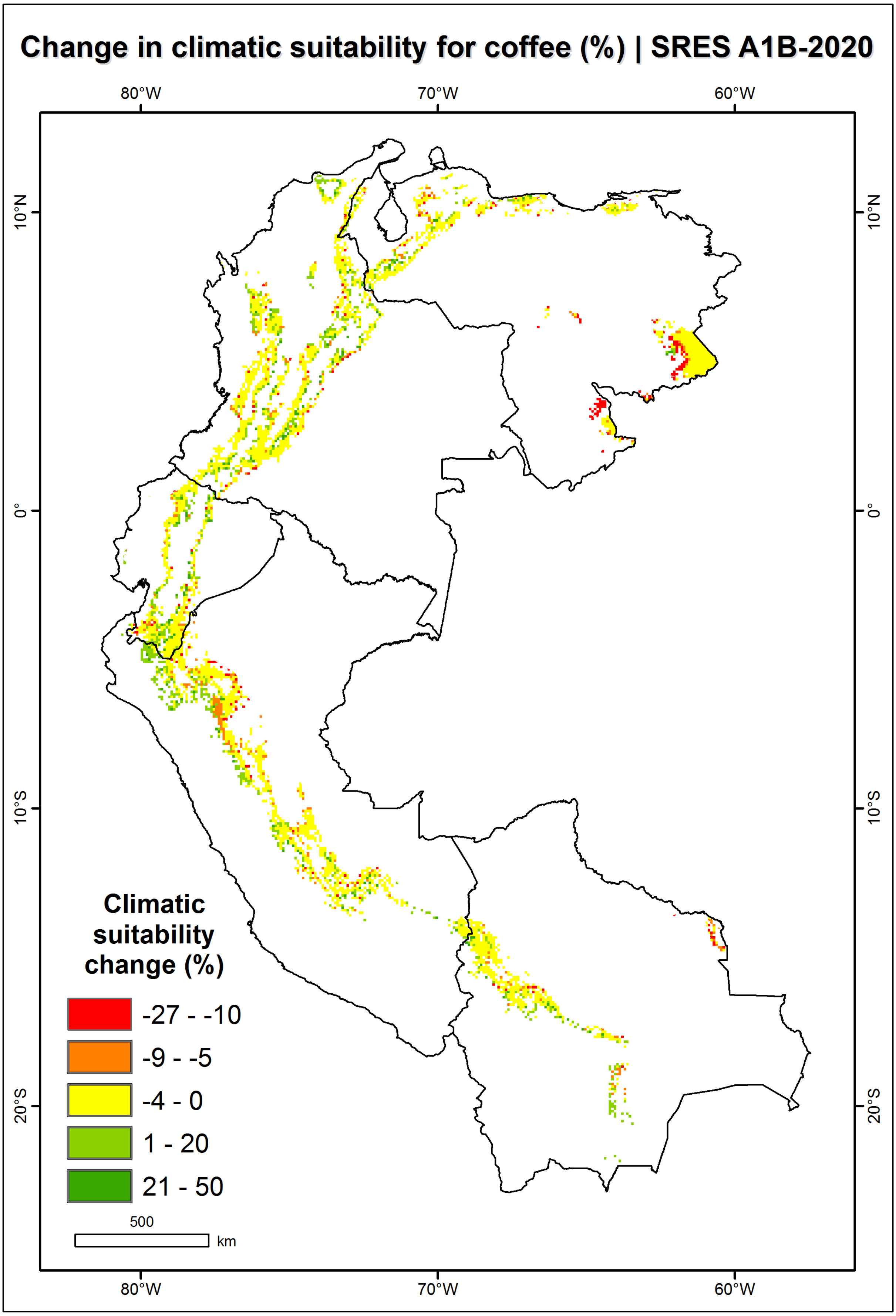


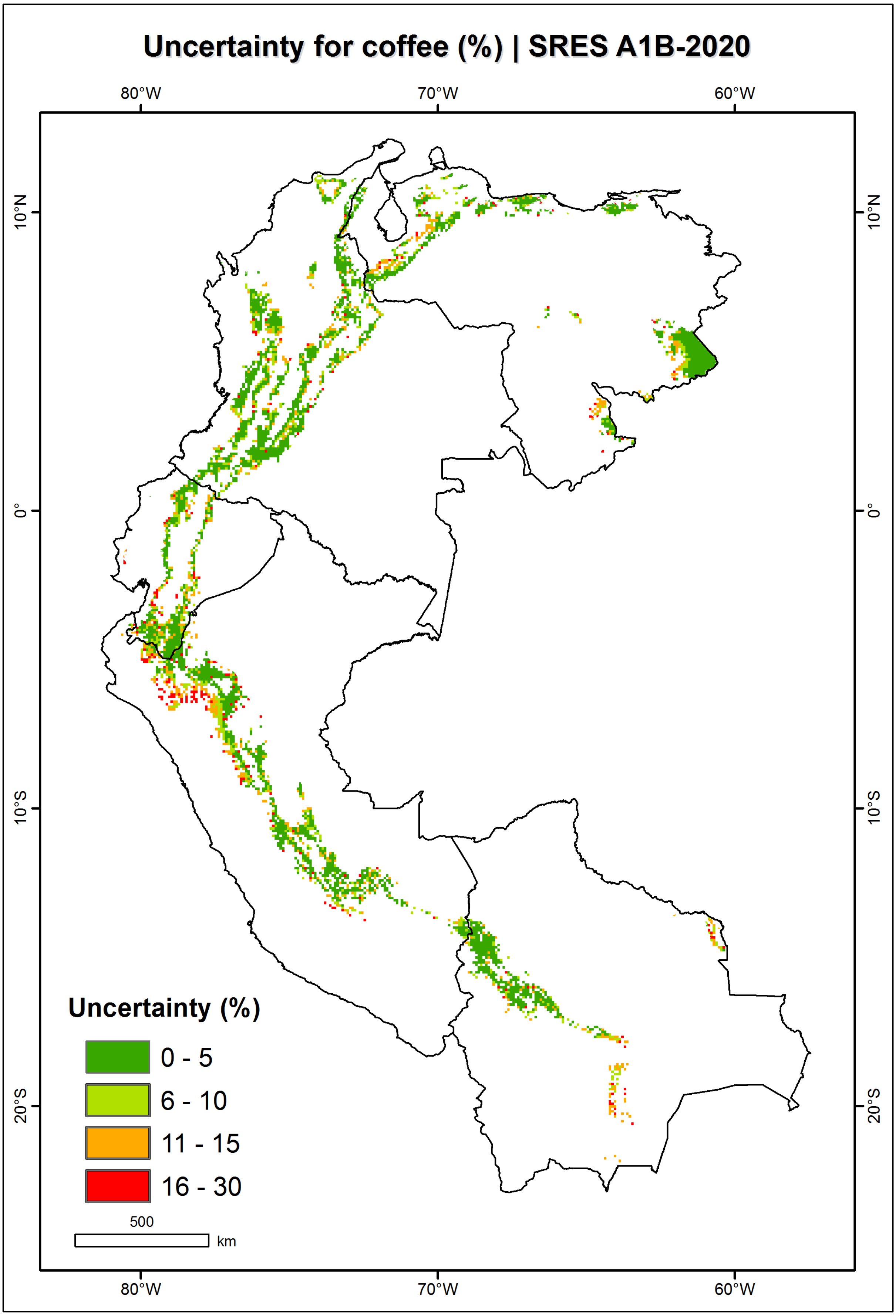
Change in climatic suitability for bean (%) | SRES A2-2050

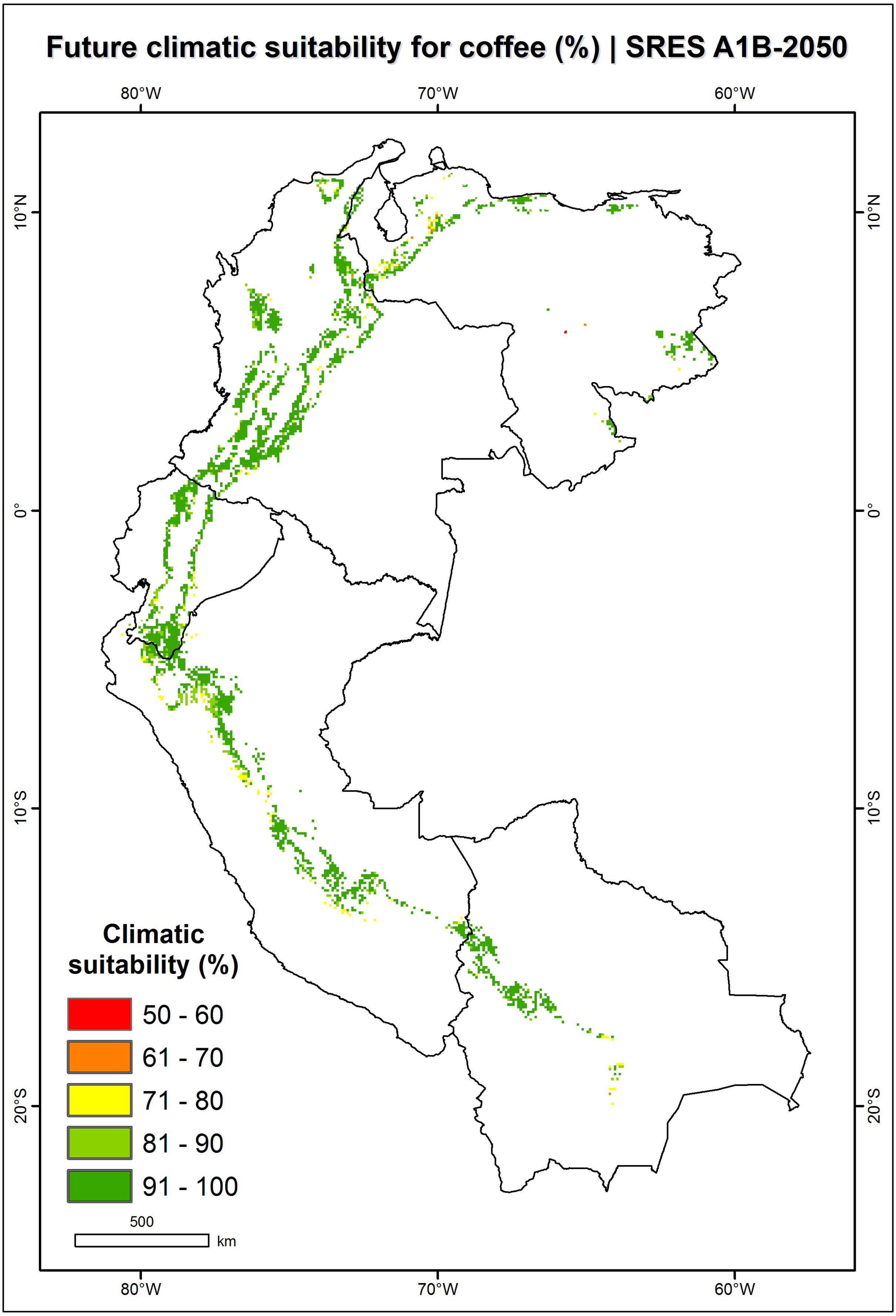

Uncertainty for bean (%) | SRES A2-2050
80°W
70°W
60°W
10°N
0°
10°S
20°S
Uncertainty (%)
0 - 5
6 - 10
11 - 15
16 - 20
21 - 25
500
km

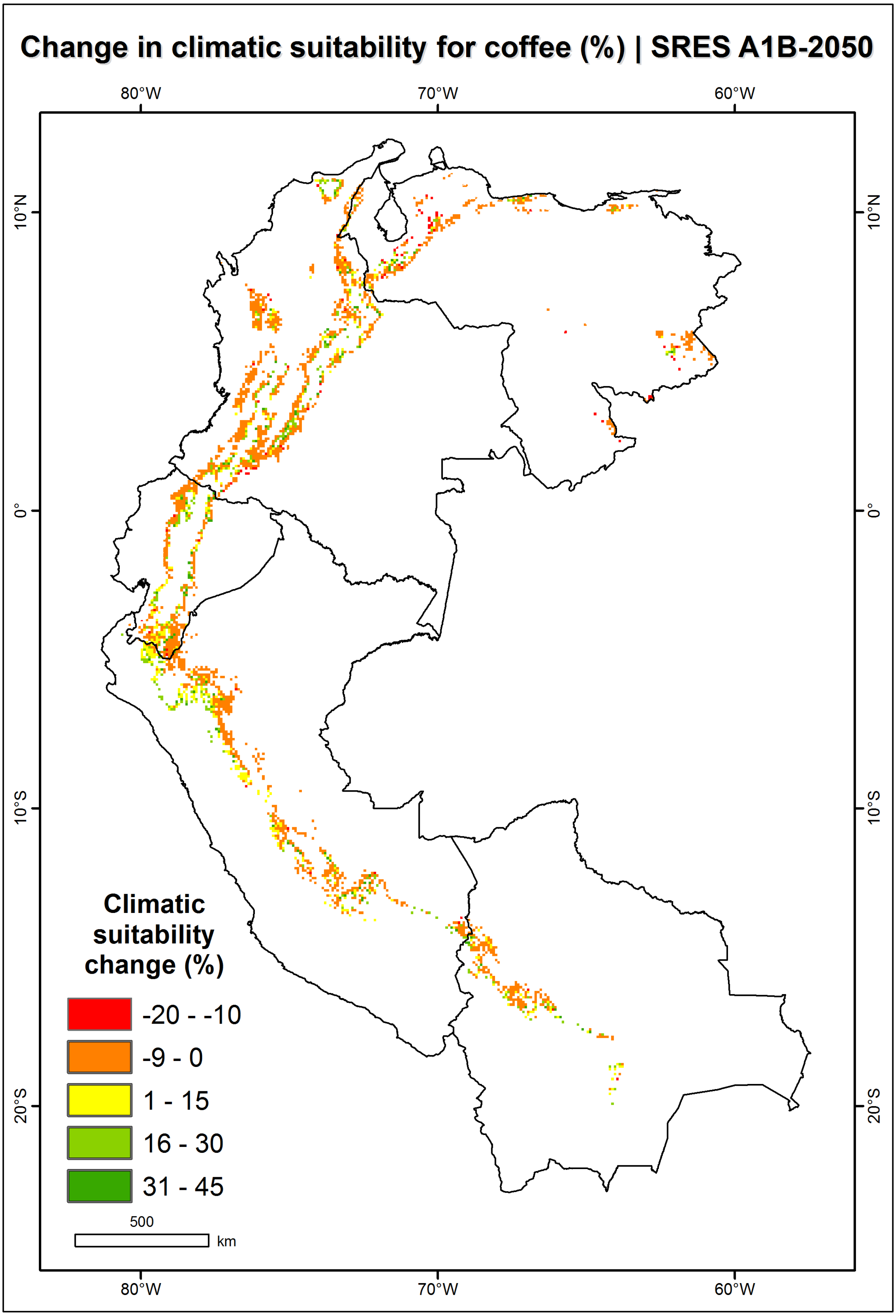

Current climatic suitability for coffee (%)
80°W
70°W
60°W
10°N
0°
10°S
20°S
Climatic suitability (%)
🟥 50 - 60
🟧 61 - 70
🟨 71 - 80
🟩 81 - 90
🟩 91 - 100
500
km

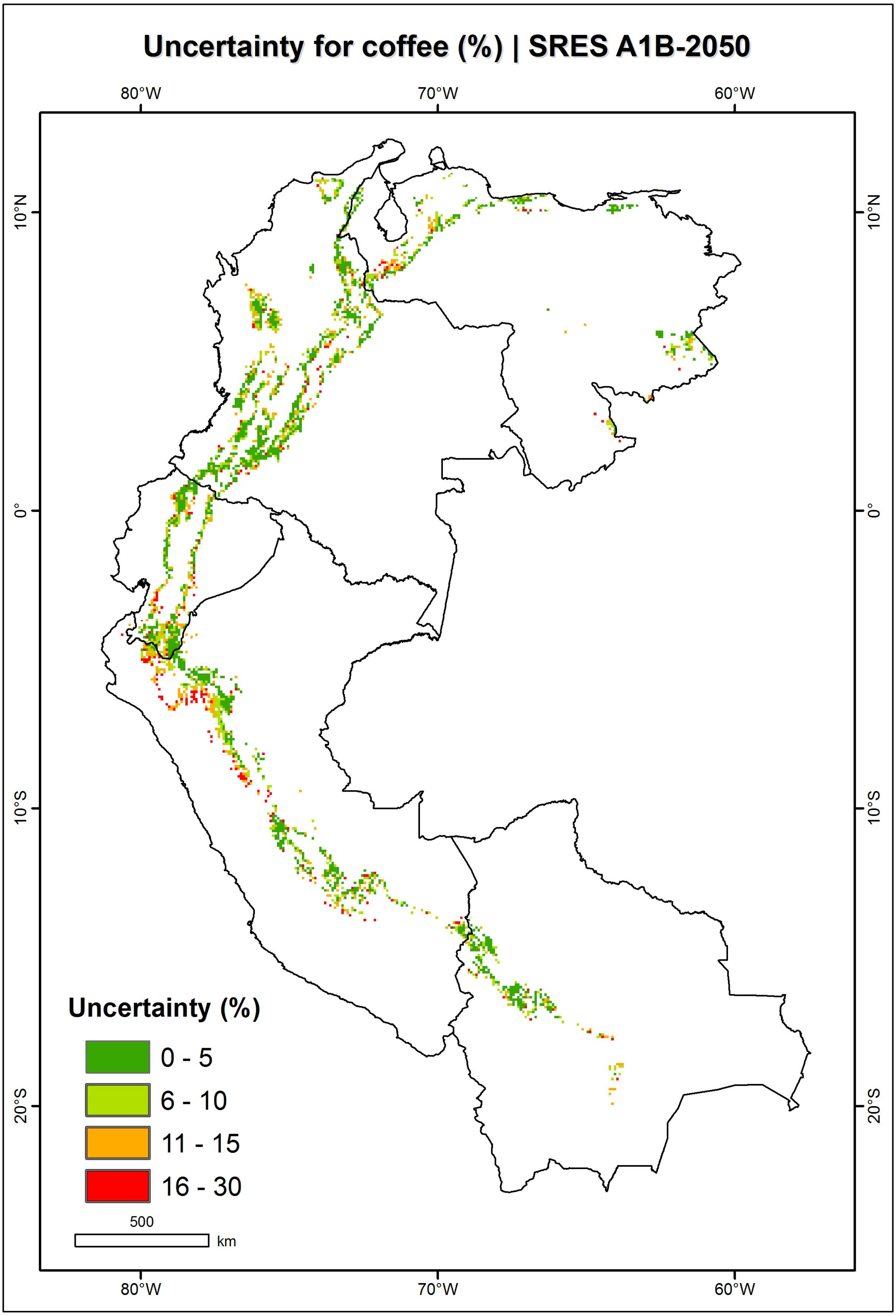

Future climatic suitability for coffee (%) | SRES A1B - 2020
80°W
70°W
60°W
10°N
0°
10°S
20°S
Climatic suitability (%)
50 - 60
61 - 70
71 - 80
81 - 90
91 - 100
500
km

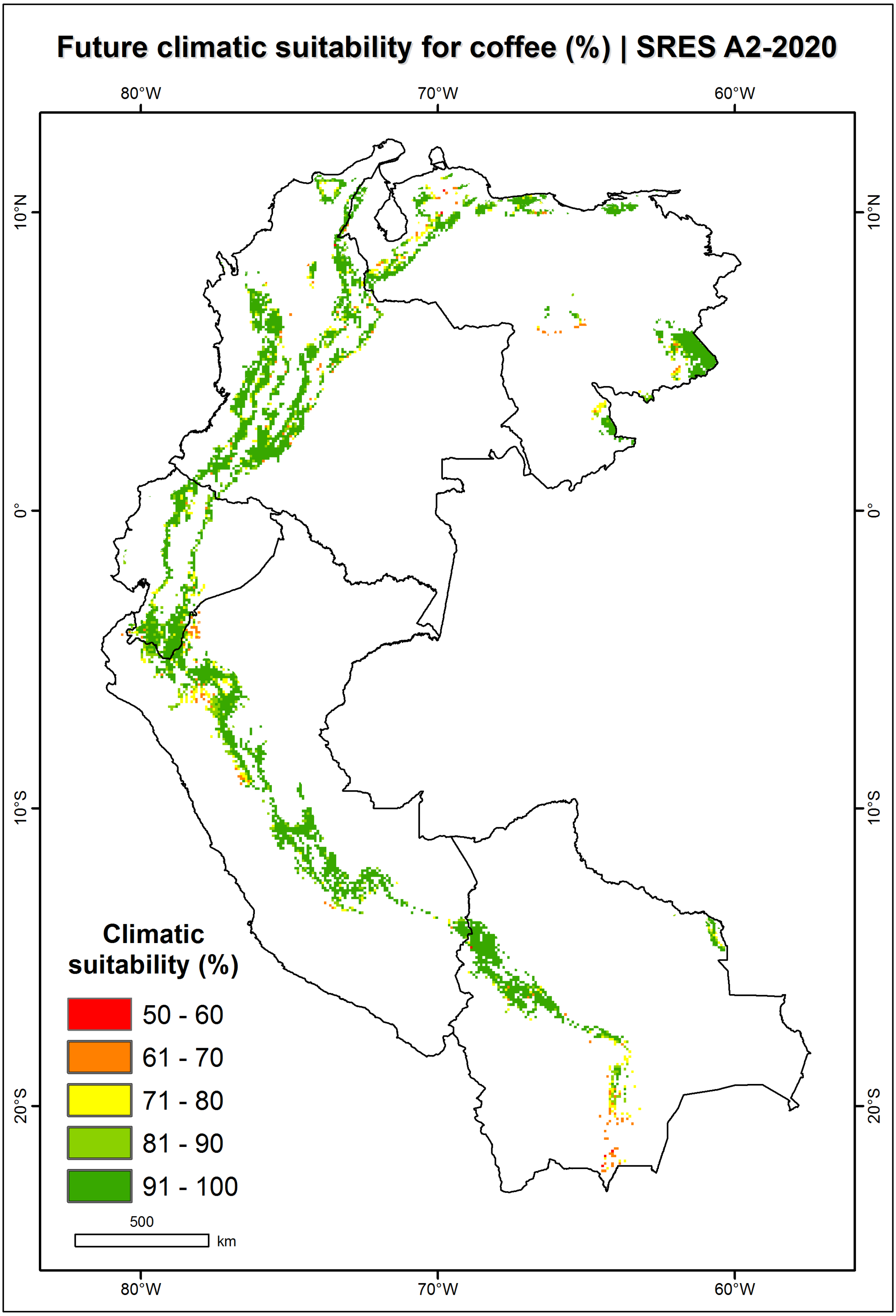

Change in climatic suitability for coffee (%) | SRES A1B-2020
80°W
70°W
60°W
10°N
0°
10°S
20°S
Climatic suitability change (%)
-27 - -10
-9 - -5
-4 - 0
1 - 20
21 - 50
500
km

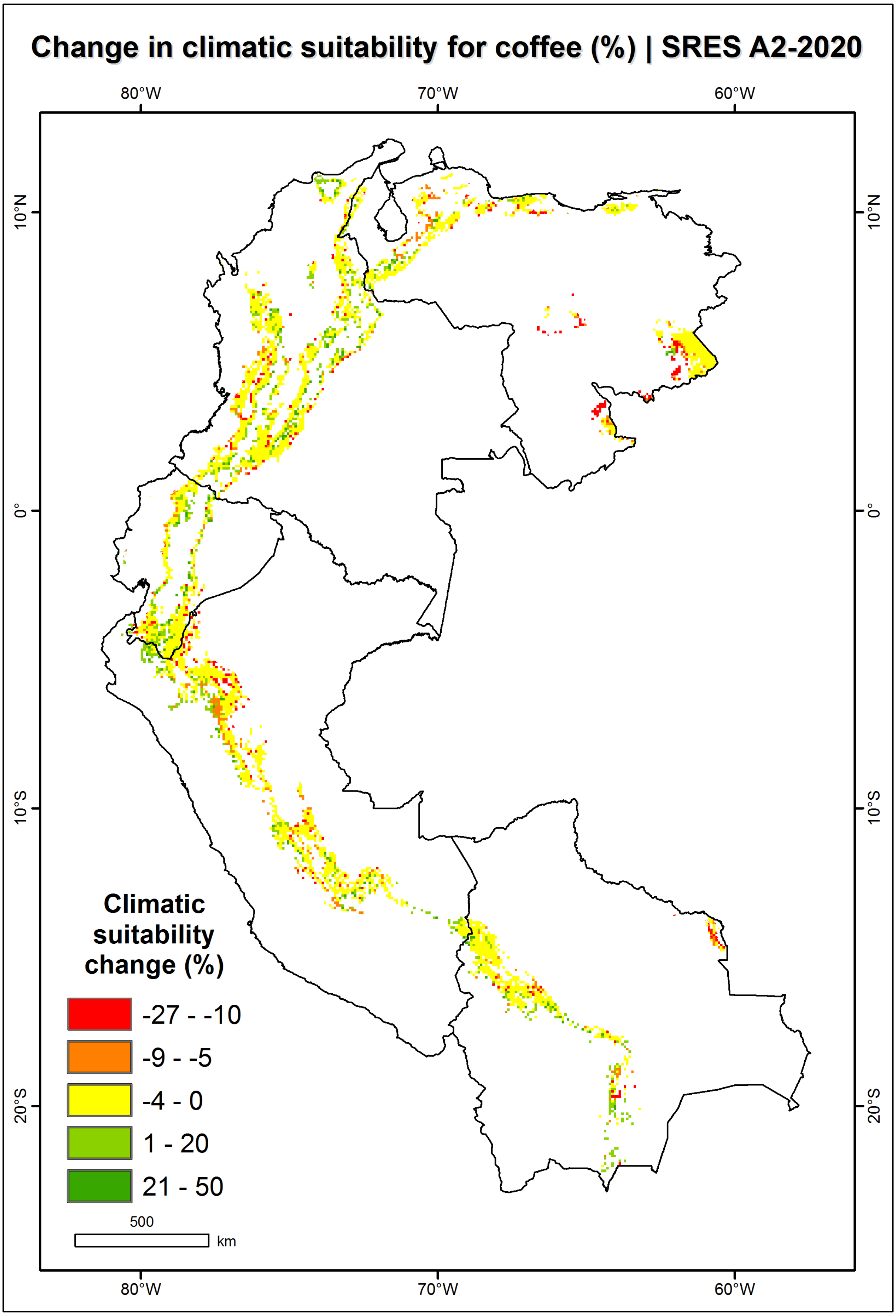

Uncertainty for coffee (%) | SRES A1B-2020
80°W
70°W
60°W
10°N
0°
10°S
20°S
Uncertainty (%)
0 - 5
6 - 10
11 - 15
16 - 30
500
km

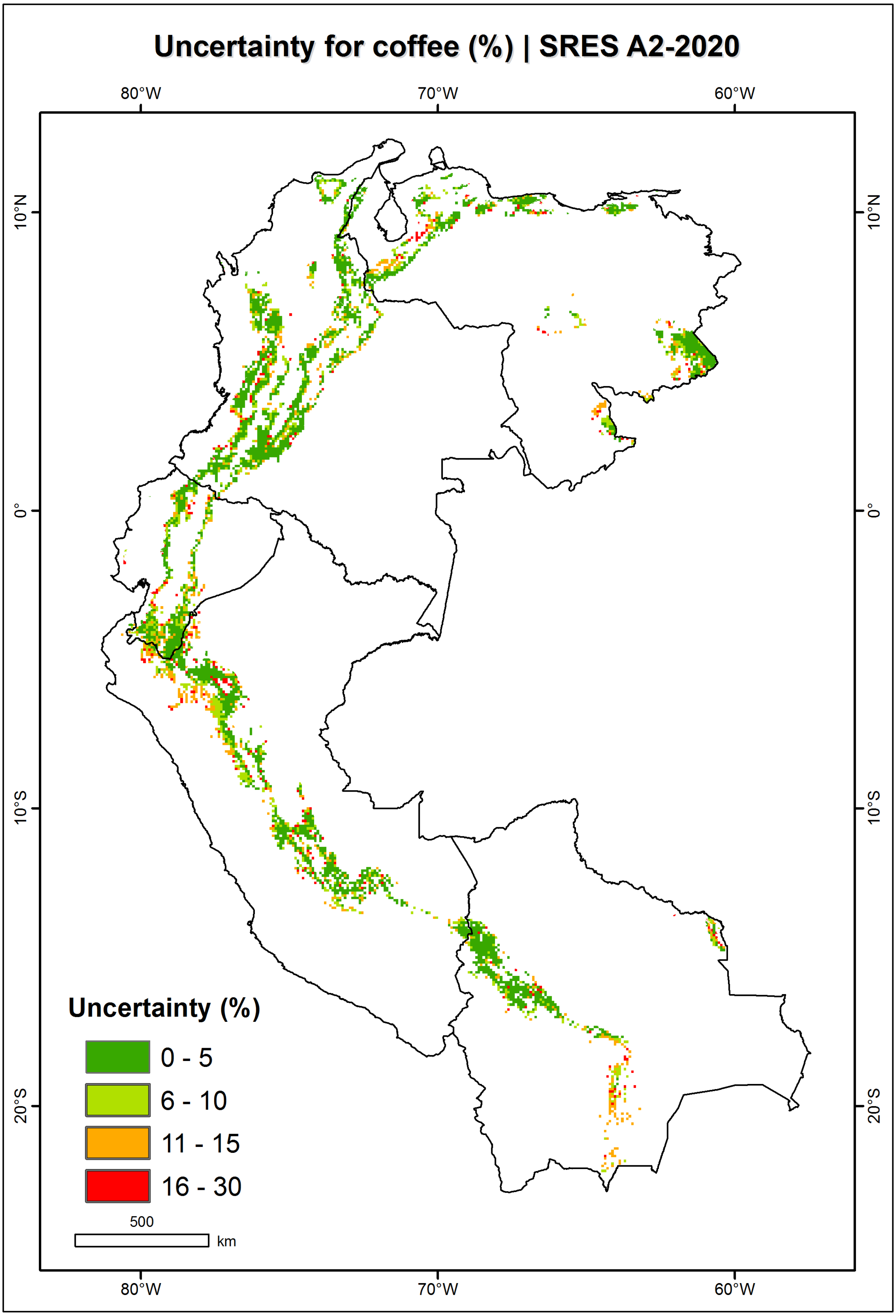

Future climatic suitability for coffee (%) | SRES A1B-2050
80°W
70°W
60°W
10°N
0°
10°S
20°S
Climatic suitability (%)
50 - 60
61 - 70
71 - 80
81 - 90
91 - 100
500
km

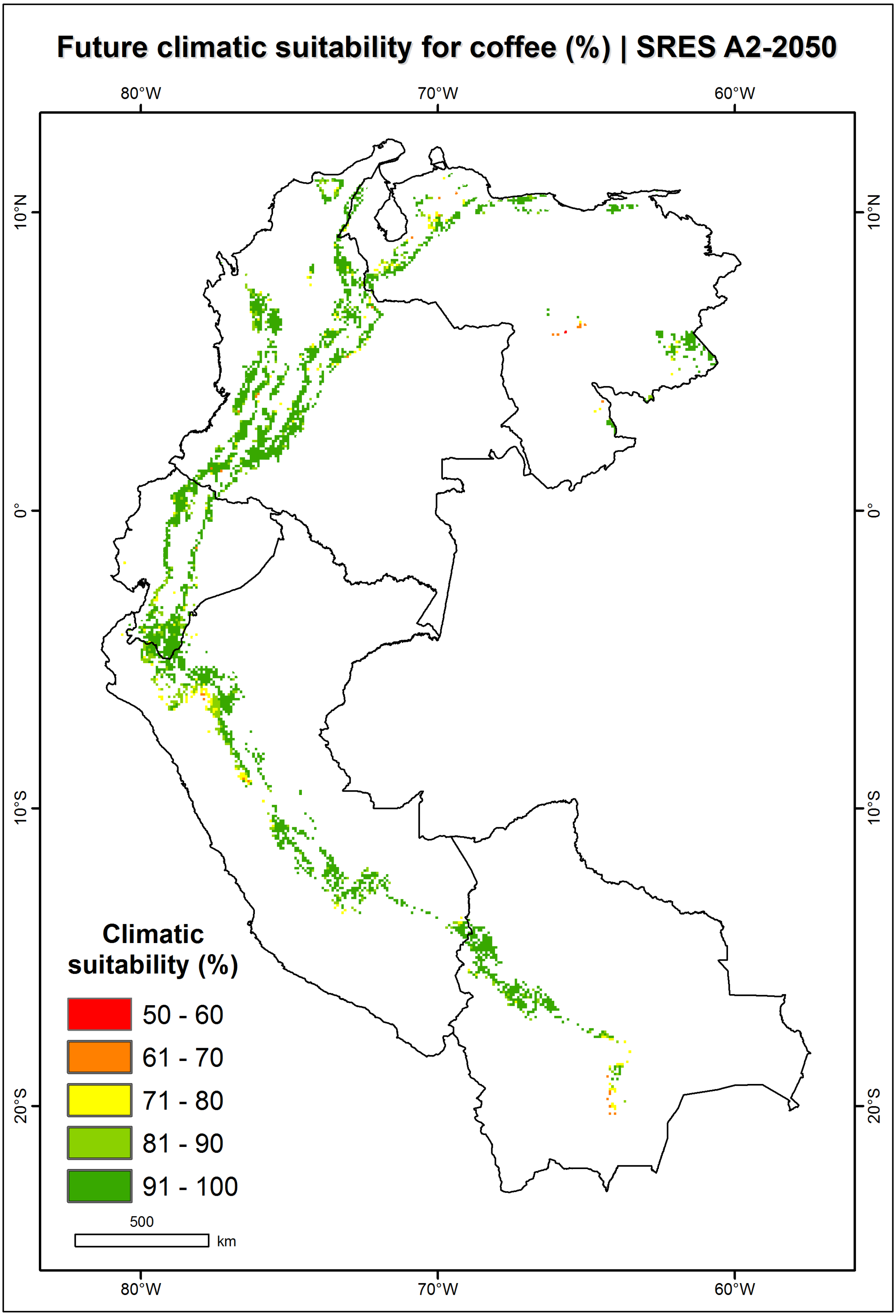

Change in climatic suitability for coffee (%) | SRES A1B-2050
80°W
70°W
60°W
10°N
0°
10°S
20°S
Climatic suitability change (%)
🟥 -20 - -10
🟧 -9 - 0
🟨 1 - 15
🟩 16 - 30
🟩 31 - 45
500
km

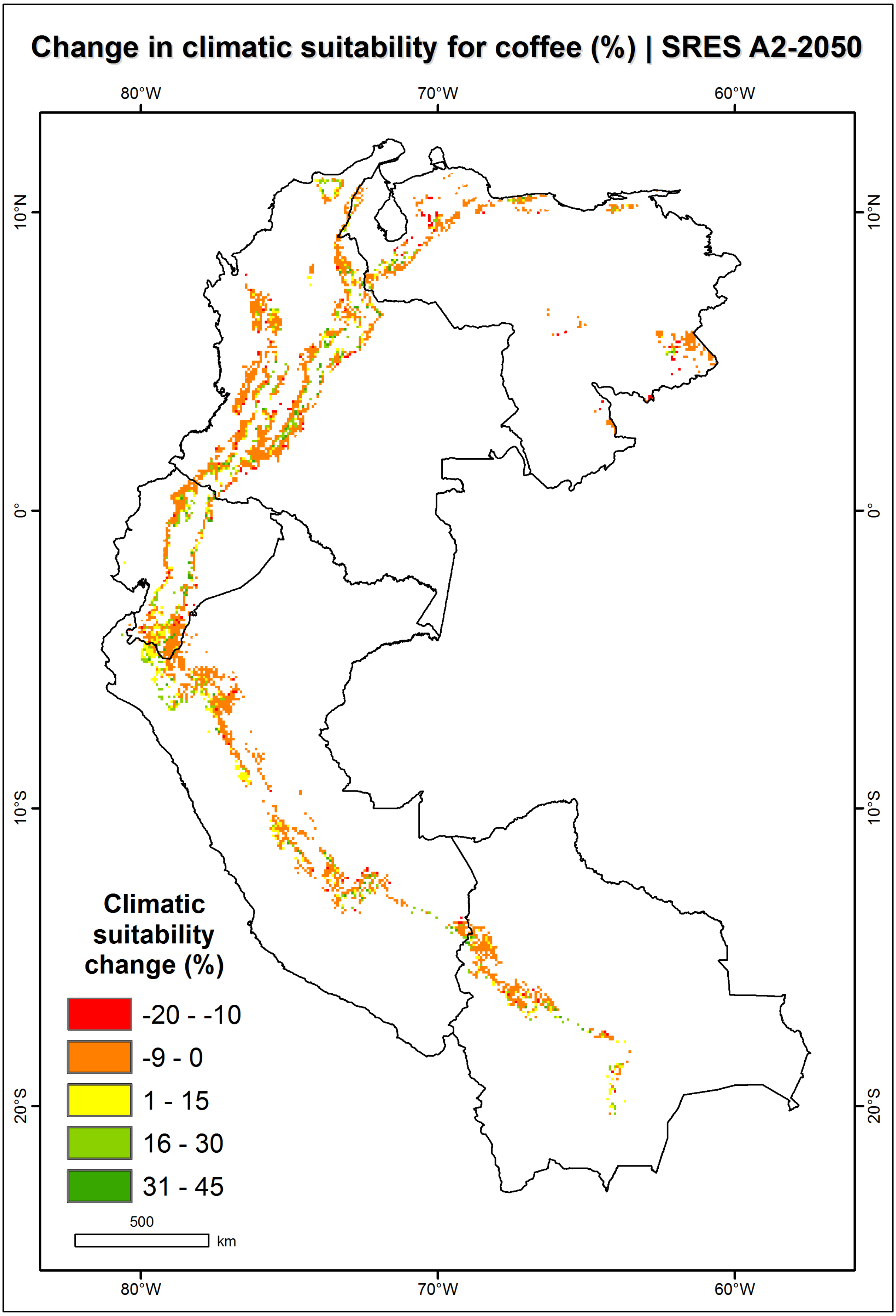

Uncertainty for coffee (%) | SRES A1B-2050
80°W
70°W
60°W
10°N
0°
10°S
20°S
Uncertainty (%)
0 - 5
6 - 10
11 - 15
16 - 30
500
km

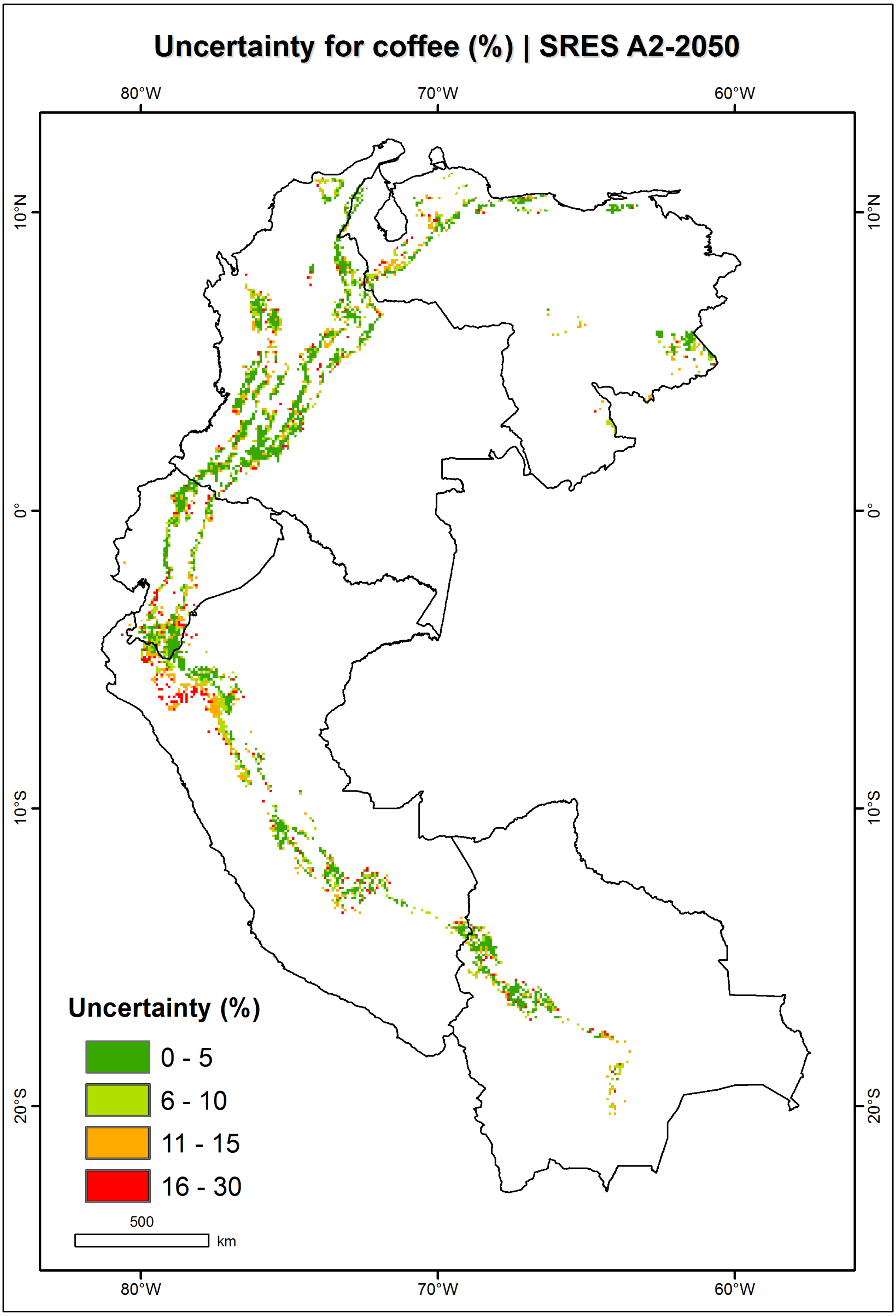

Future climatic suitability for coffee (%) | SRES A2-2020


Change in climatic suitability for coffee (%) | SRES A2-2020
80°W
70°W
60°W
10°N
0°
10°S
20°S
Climatic suitability change (%)
-27 - -10
-9 - -5
-4 - 0
1 - 20
21 - 50
500
km

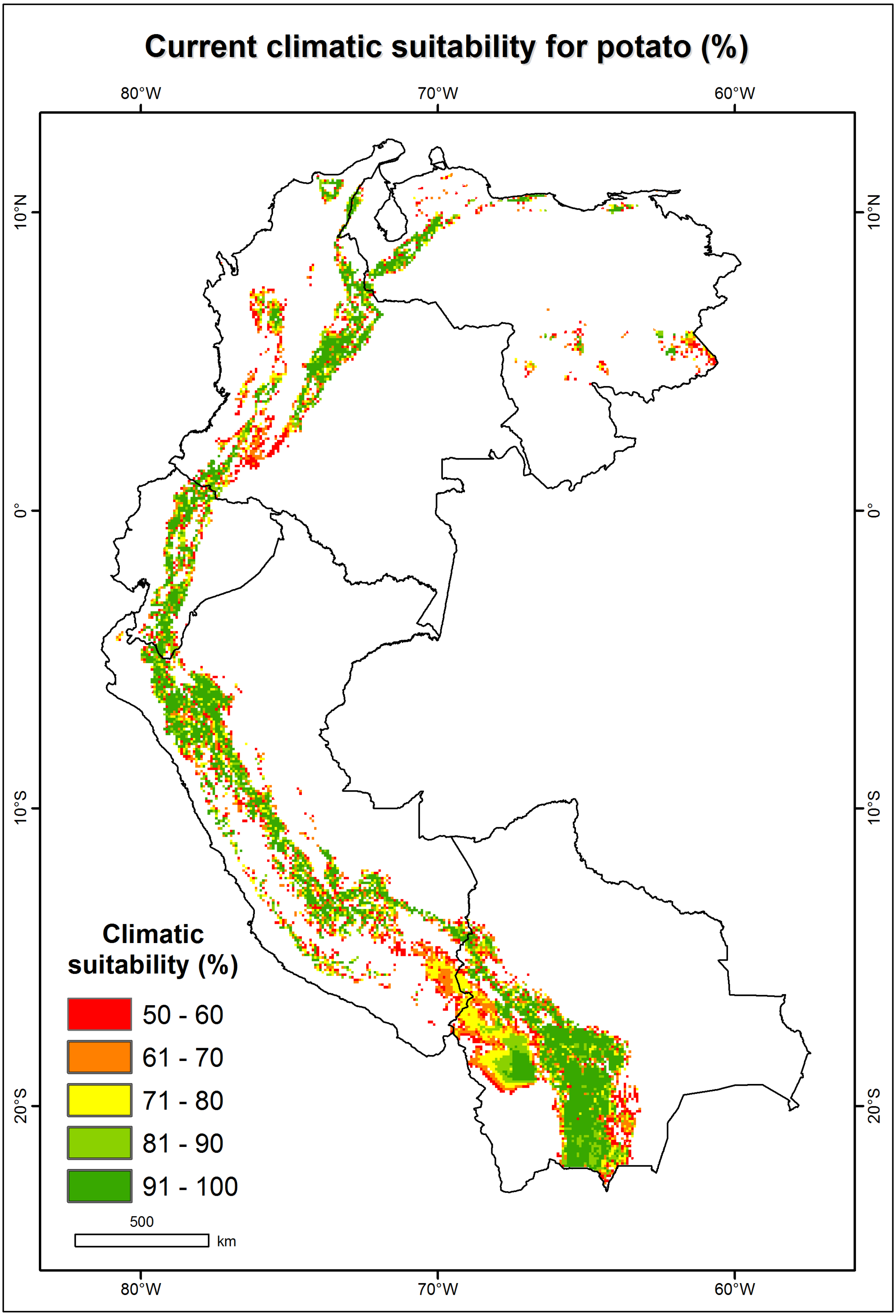

Uncertainty for coffee (%) | SRES A2-2020
80°W
70°W
60°W
10°N
0°
10°S
20°S
Uncertainty (%)
🟩 0 - 5
🟩 6 - 10
🟧 11 - 15
🟥 16 - 30
500
km


Future climatic suitability for coffee (%) | SRES A2-2050
80°W
70°W
60°W
10°N
0°
10°S
20°S
Climatic suitability (%)
🟥 50 - 60
🟧 61 - 70
🟨 71 - 80
🟩 81 - 90
🟩 91 - 100
500
km

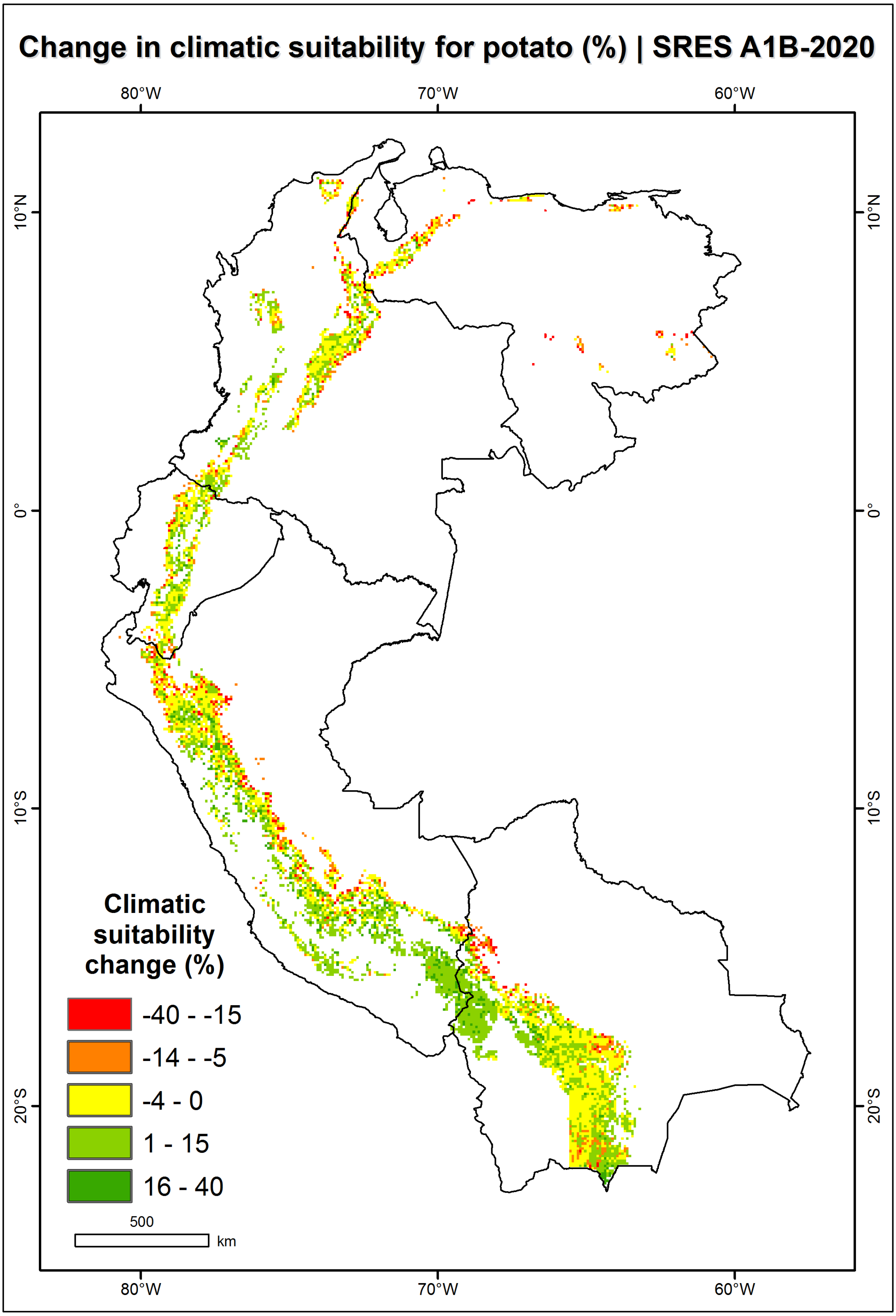

Change in climatic suitability for coffee (%) | SRES A2-2050
80°W
70°W
60°W
10°N
0°
10°S
20°S
Climatic suitability change (%)
-20 - -10
-9 - 0
1 - 15
16 - 30
31 - 45
500
km

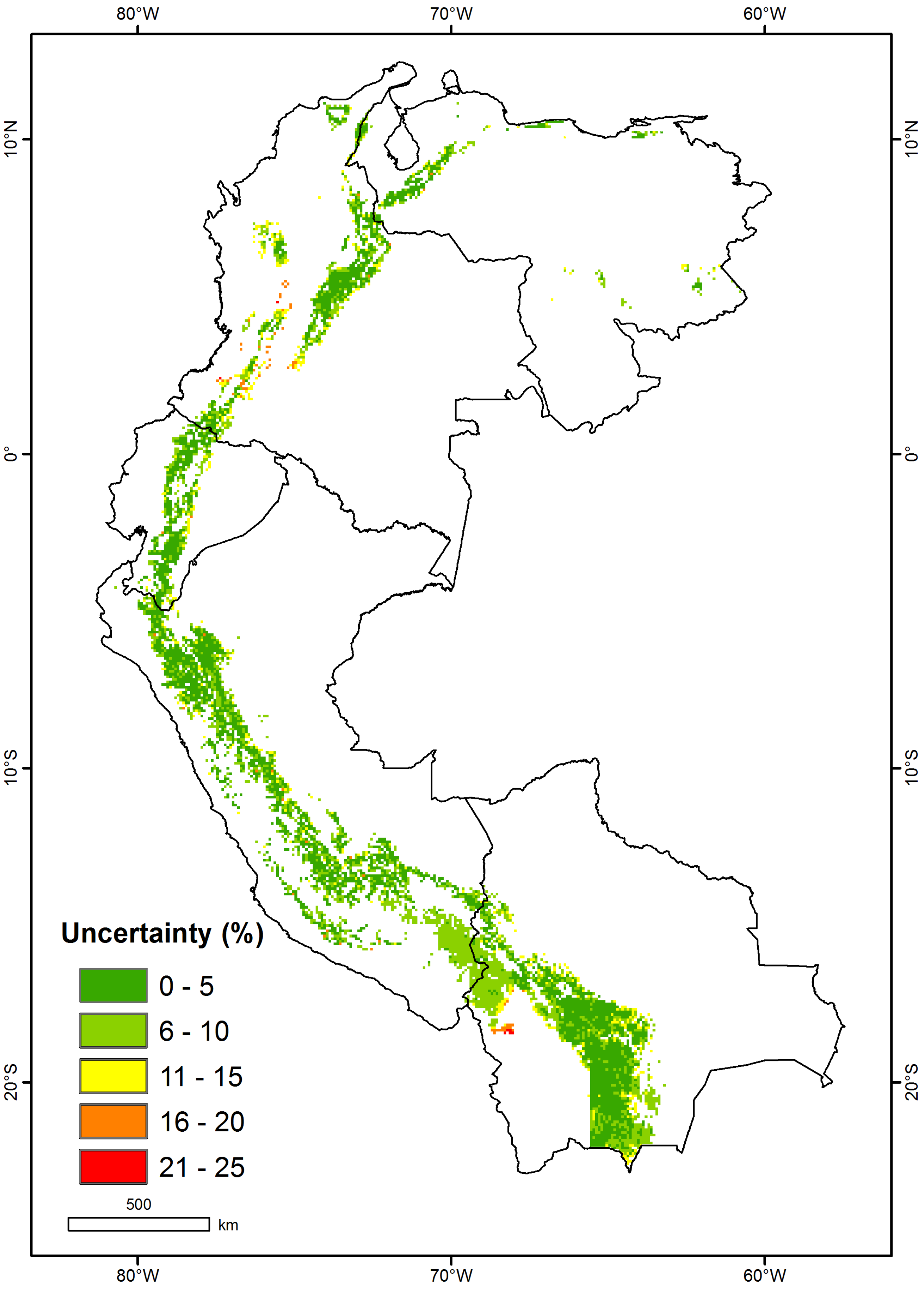


Uncertainty for coffee (%) | SRES A2-2050

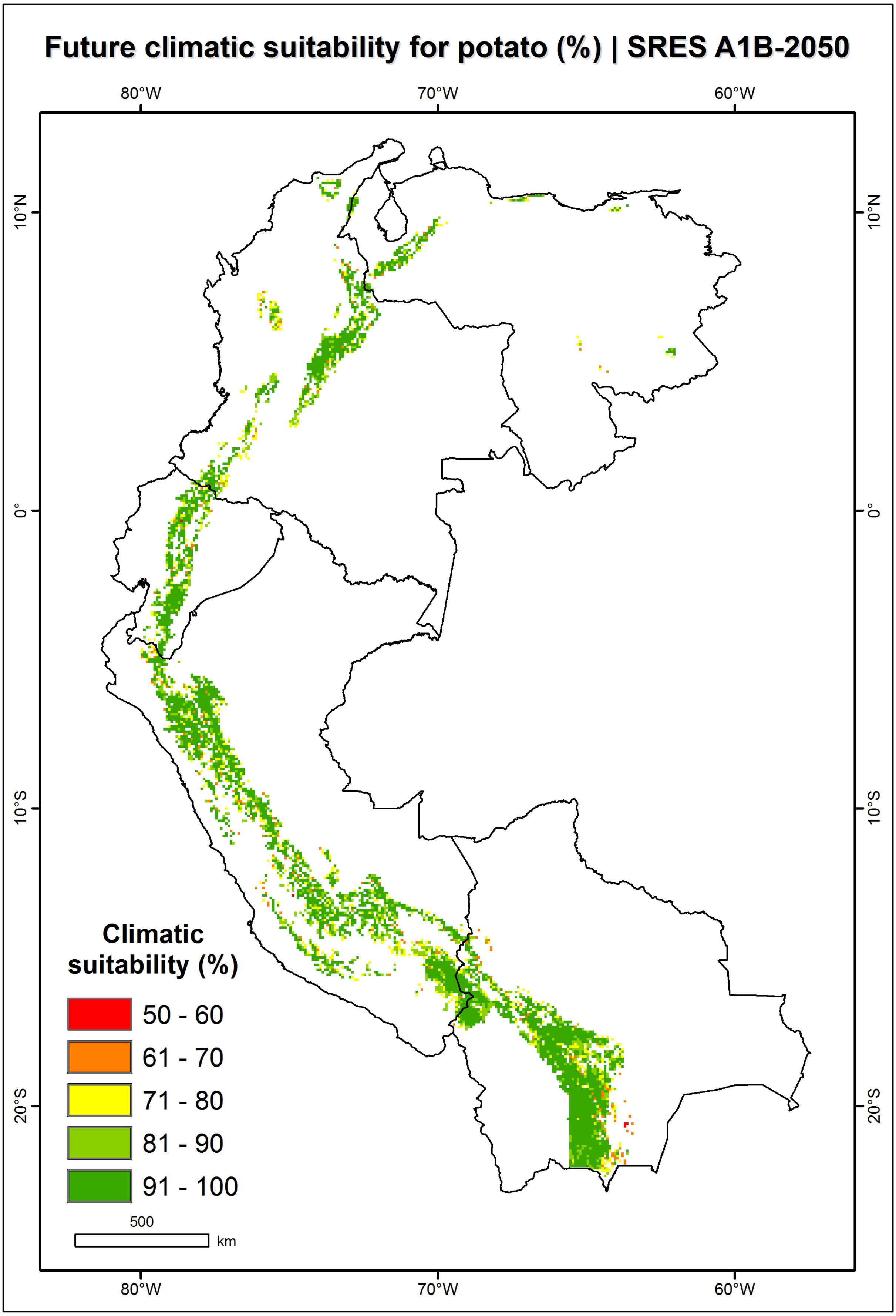


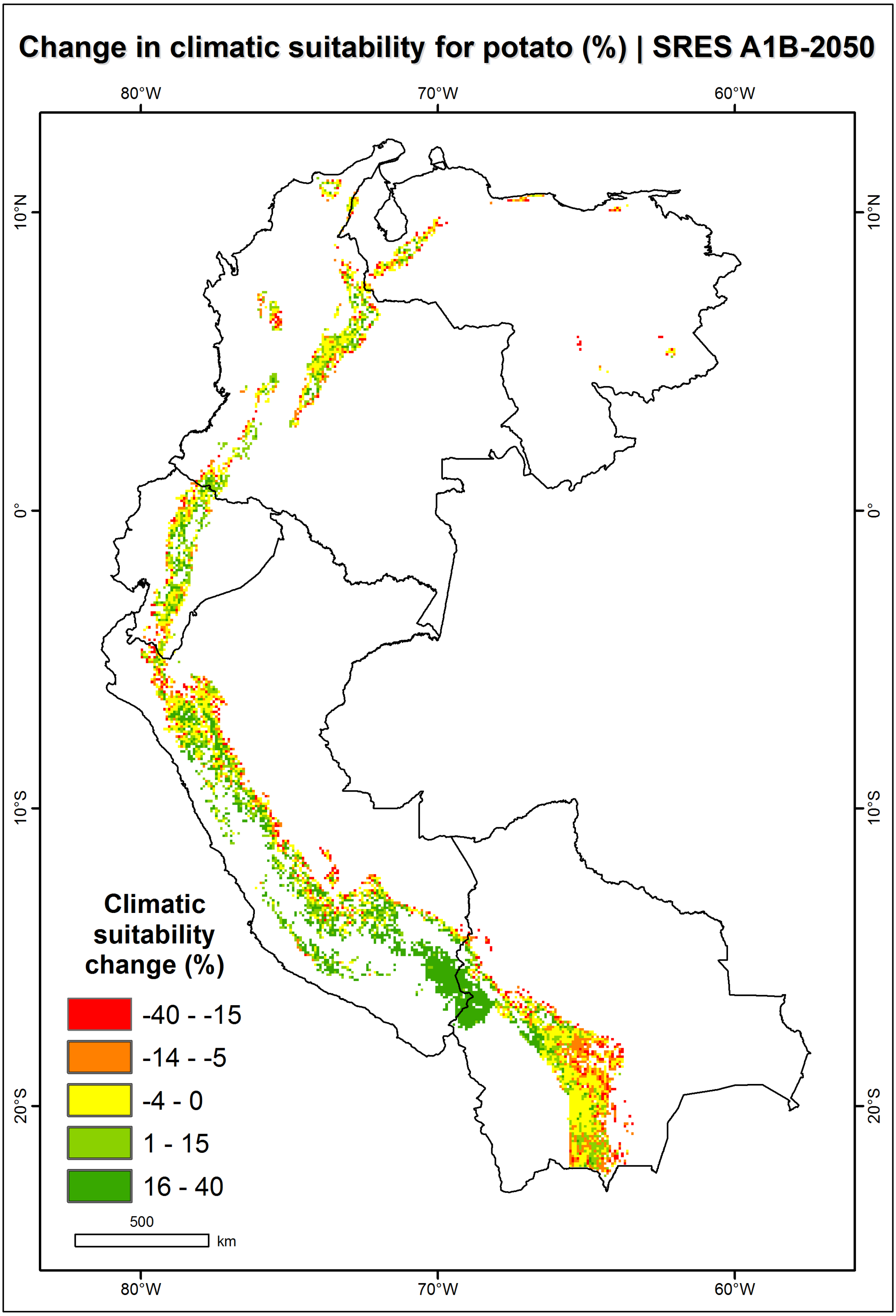
Current climatic suitability for potato (%)

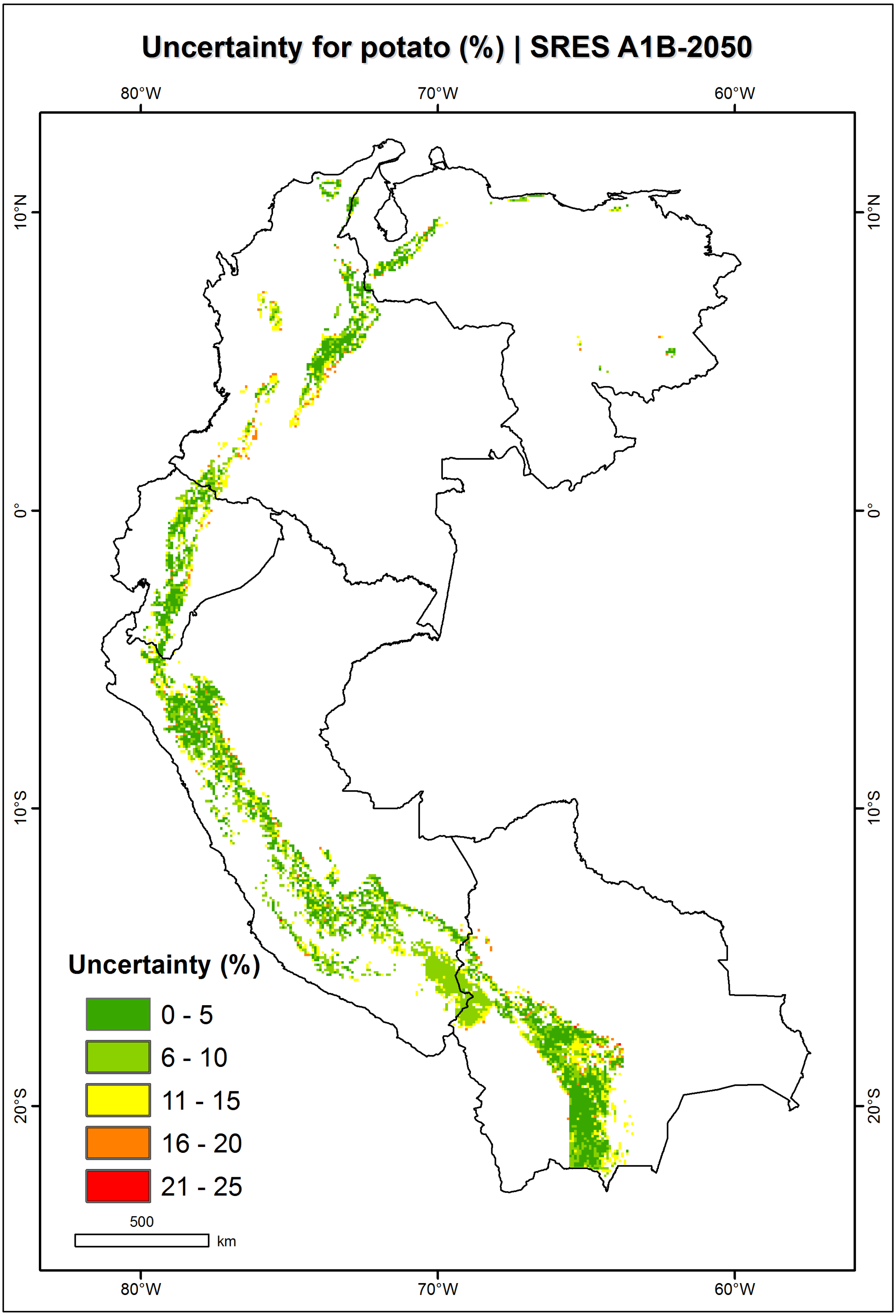

Change in climatic suitability for potato (%) | SRES A1B-2020
80°W
70°W
60°W
10°N
0°
10°S
20°S
Climatic suitability change (%)
-40 - -15
-14 - -5
-4 - 0
1 - 15
16 - 40
500
km

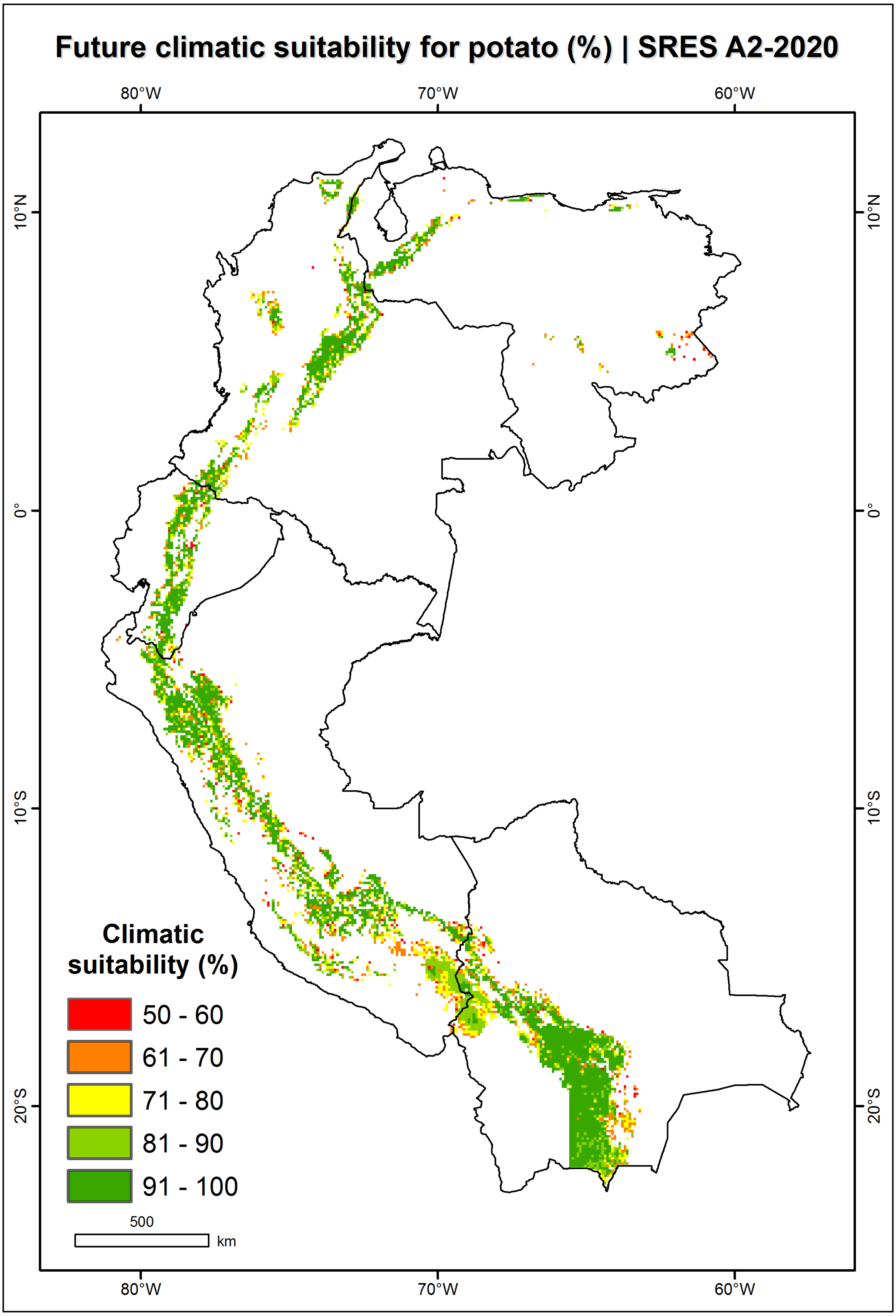


Uncertainty for potato (%) | SRES A1B-2020

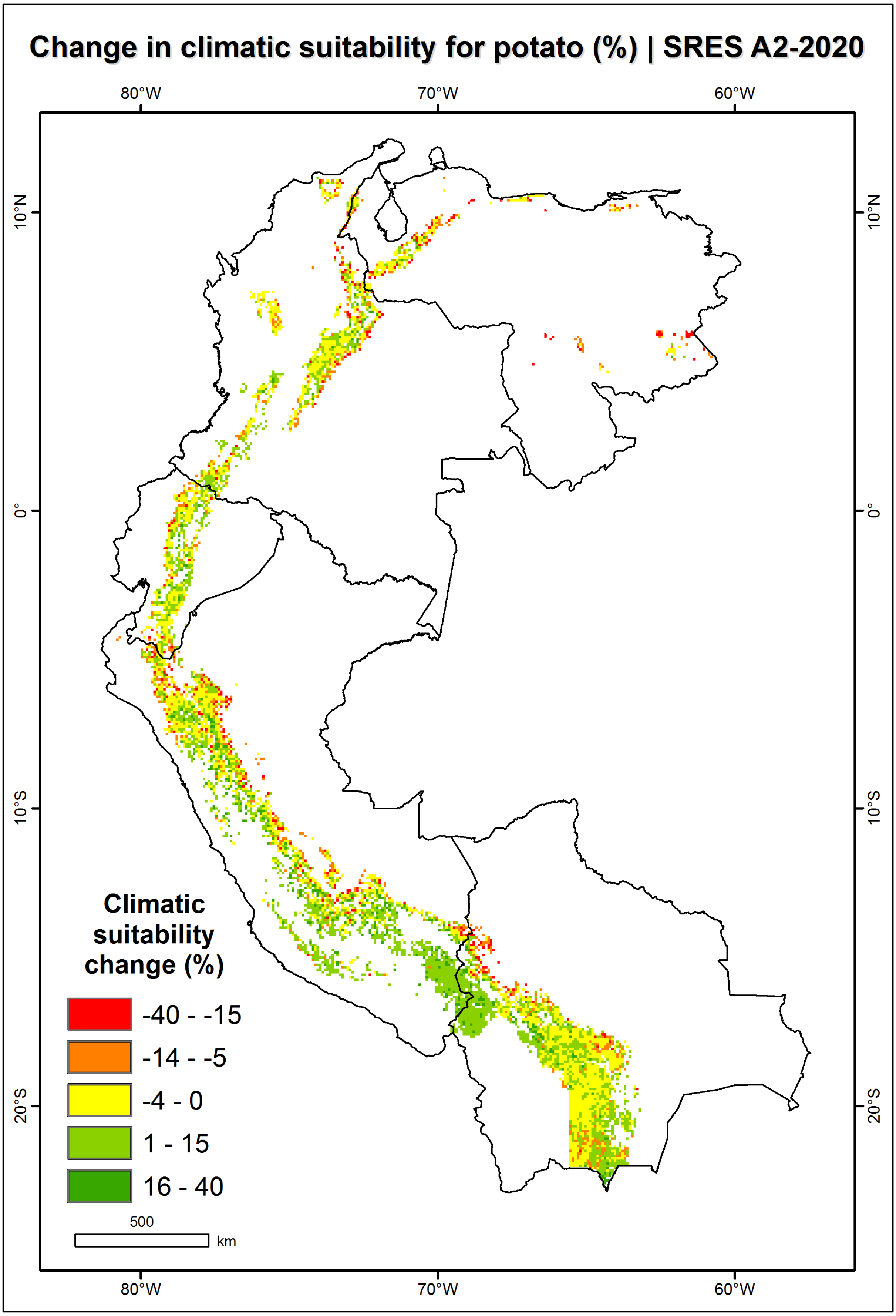

Future climatic suitability for potato (%) | SRES A1B-2050
80°W
70°W
60°W
10°N
0°
10°S
20°S
Climatic suitability (%)
🟥 50 - 60
🟧 61 - 70
🟨 71 - 80
🟩 81 - 90
🟩 91 - 100
500
km

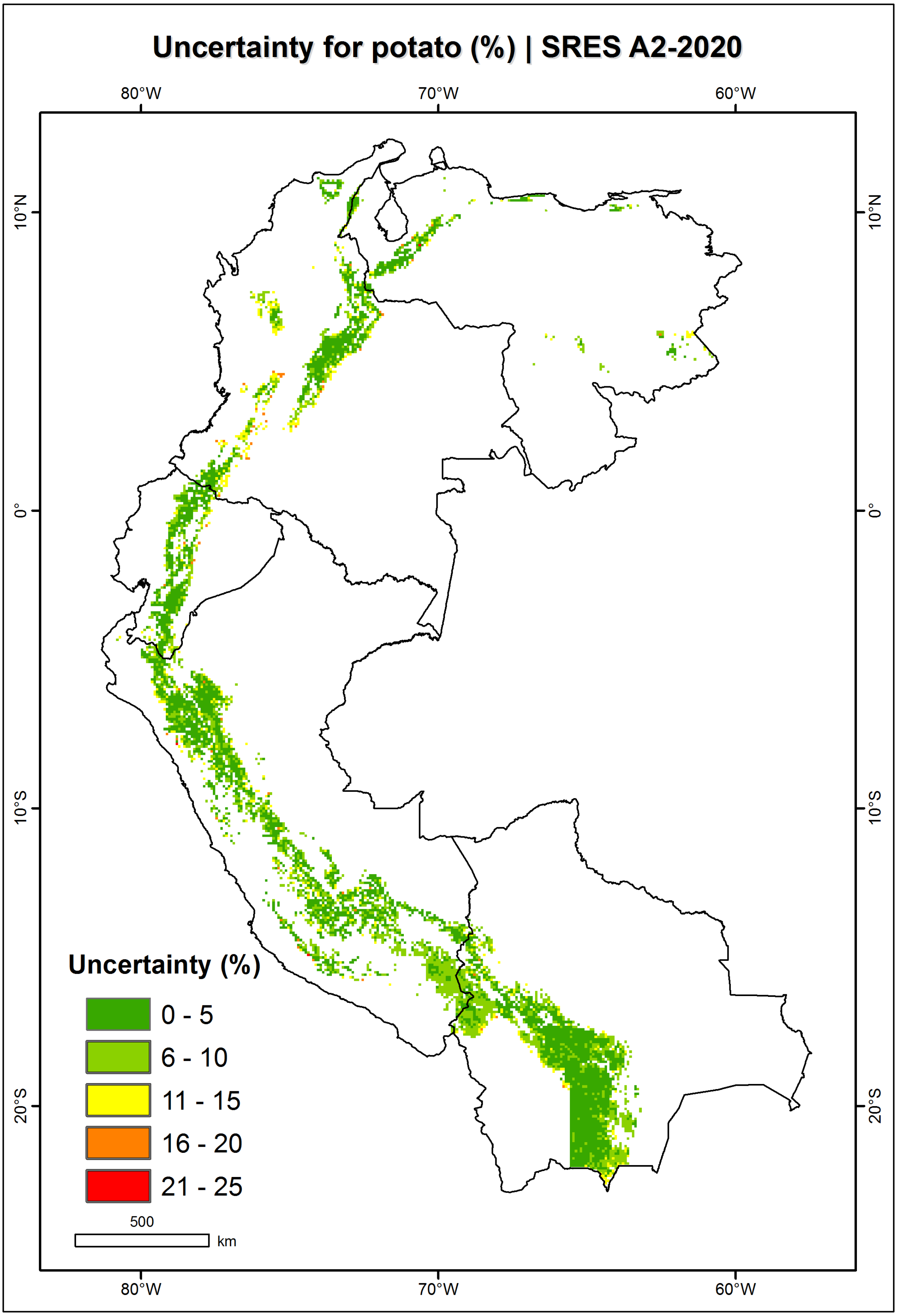

Change in climatic suitability for potato (%) | SRES A1B-2050
80°W
70°W
60°W
10°N
0°
10°S
20°S
Climatic suitability change (%)
🟥 -40 - -15
🟧 -14 - -5
🟨 -4 - 0
🟩 1 - 15
🟩 16 - 40
500
km

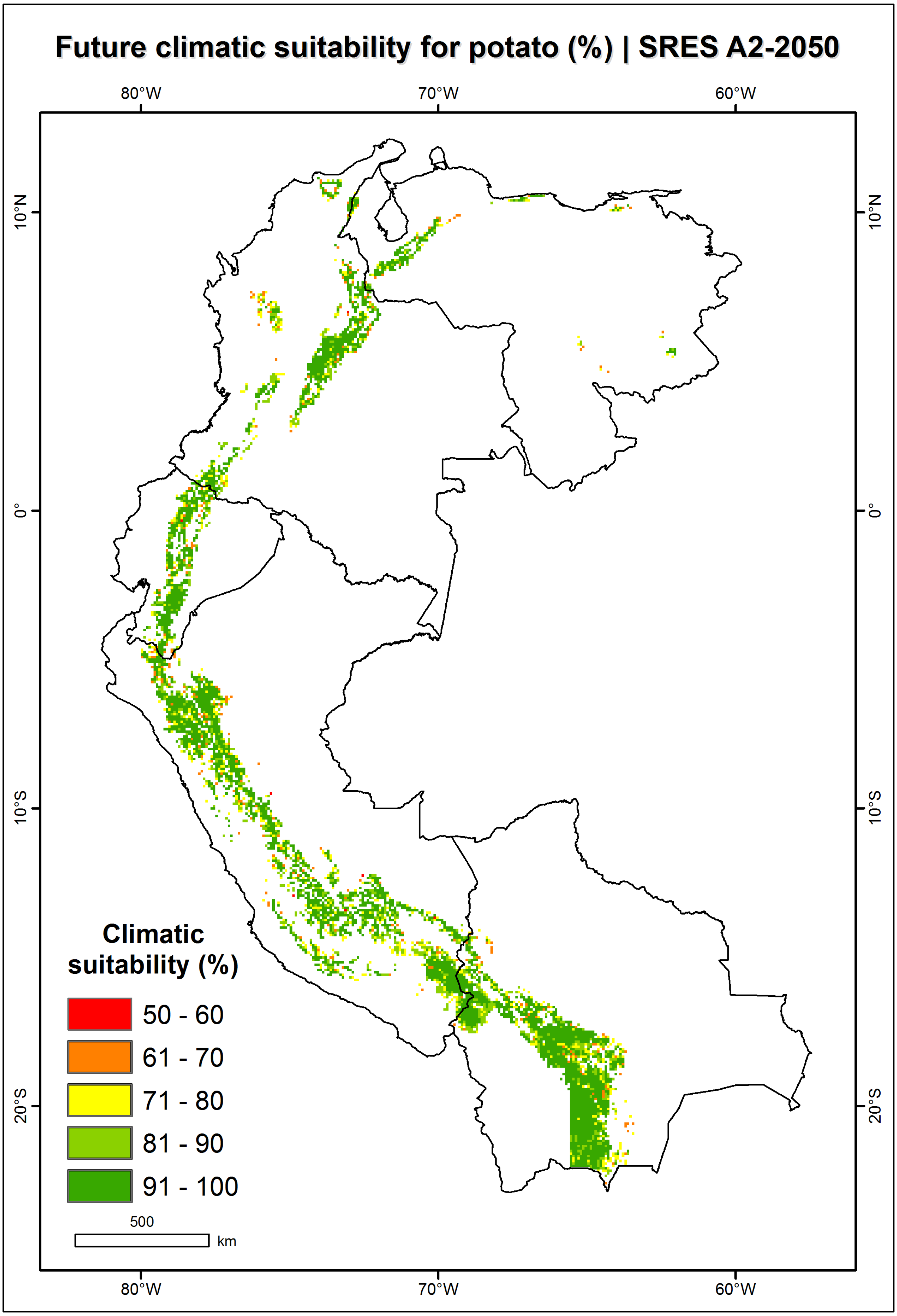

Uncertainty for potato (%) | SRES A1B-2050
80°W
70°W
60°W
10°N
0°
10°S
20°S
Uncertainty (%)
0 - 5
6 - 10
11 - 15
16 - 20
21 - 25
500
km

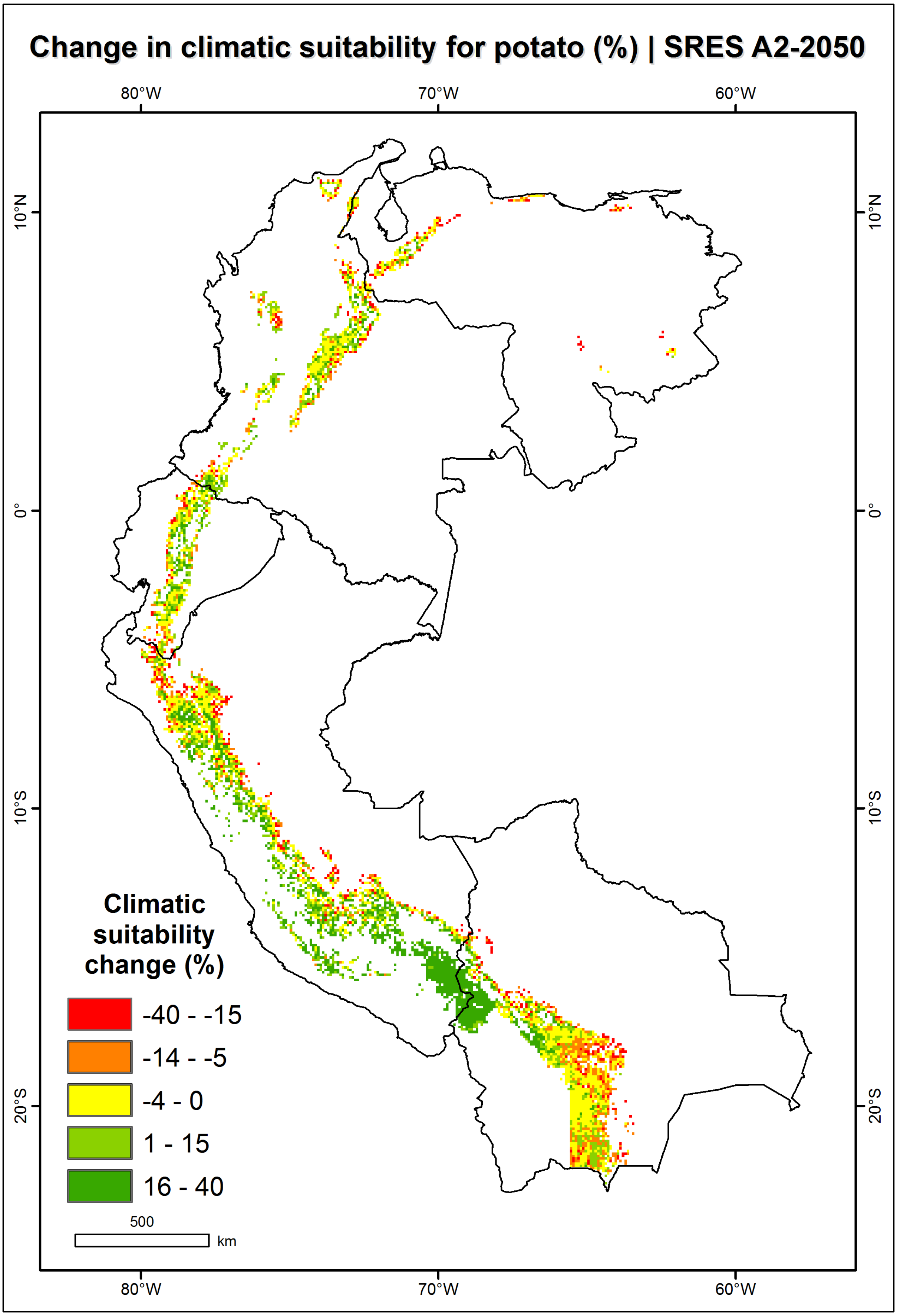


Future climatic suitability for potato (%) | SRES A2-2020

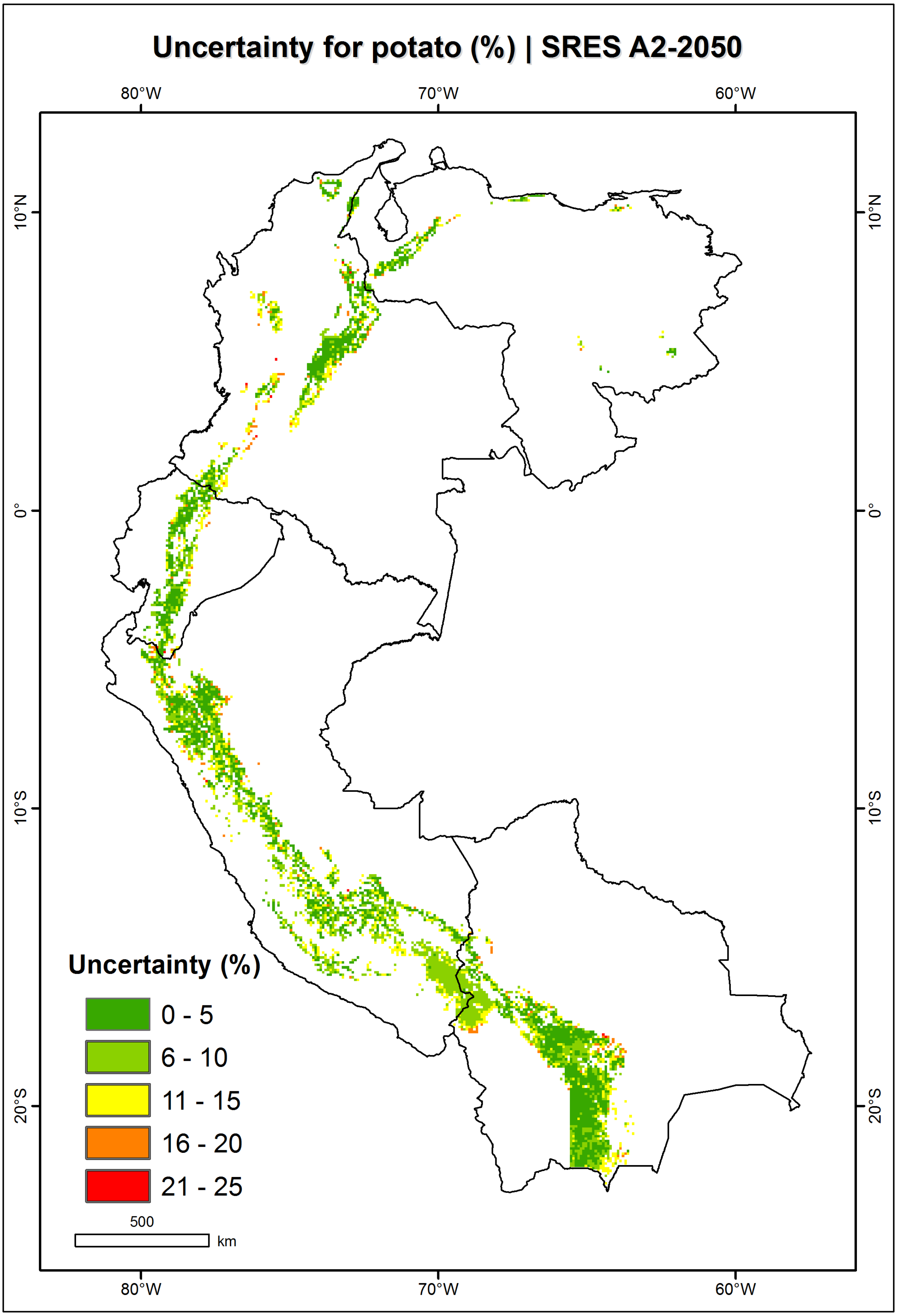

Change in climatic suitability for potato (%) | SRES A2-2020
80°W
70°W
60°W
10°N
0°
10°S
20°S
Climatic suitability change (%)
🟥 -40 - -15
🟧 -14 - -5
🟨 -4 - 0
🟩 1 - 15
🟩 16 - 40
500
km

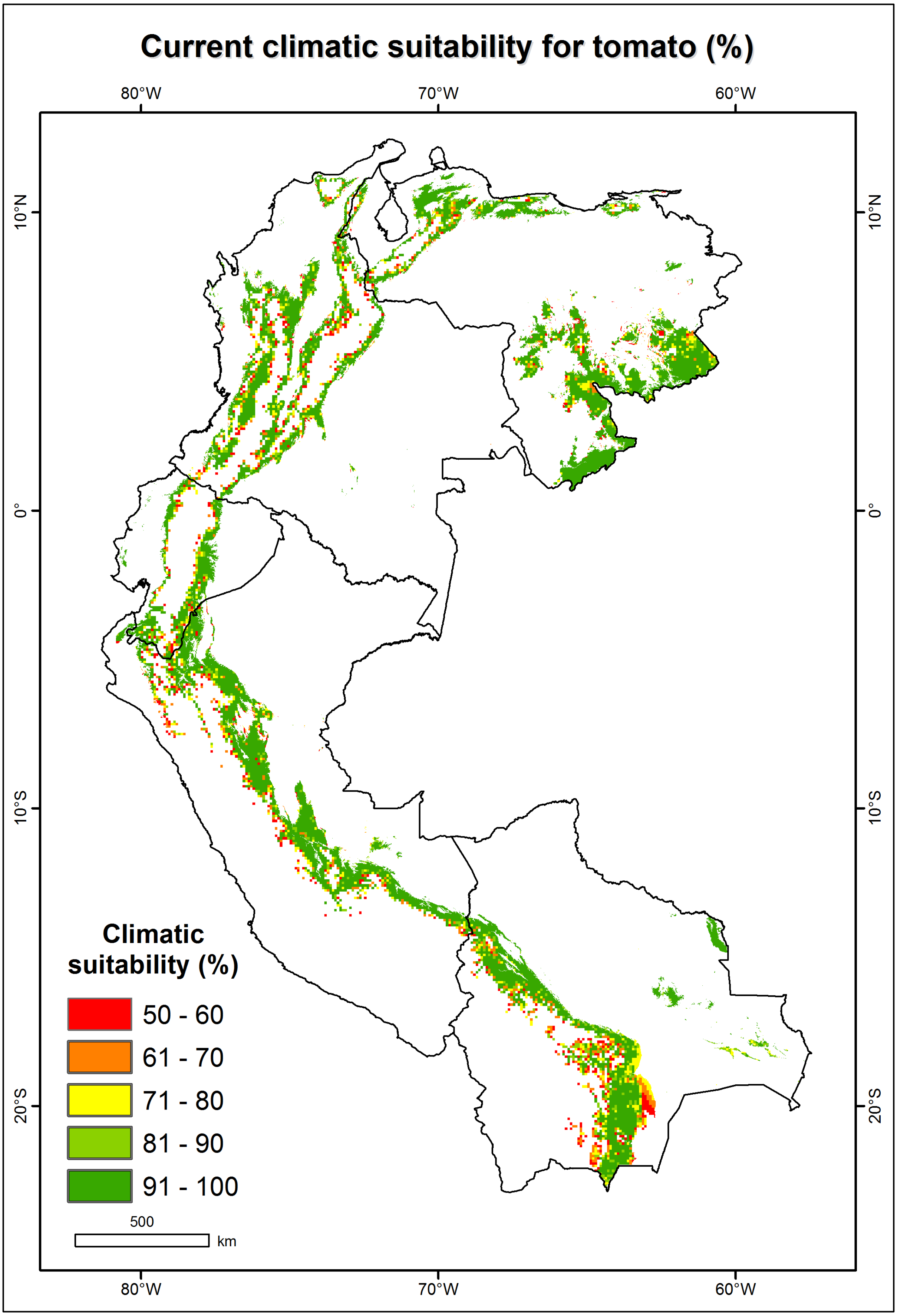

Uncertainty for potato (%) | SRES A2-2020
80°W
70°W
60°W
10°N
0°
10°S
20°S
Uncertainty (%)
0 - 5
6 - 10
11 - 15
16 - 20
21 - 25
500
km


Future climatic suitability for potato (%) | SRES A2-2050
80°W
70°W
60°W
10°N
0°
10°S
20°S
Climatic suitability (%)
50 - 60
61 - 70
71 - 80
81 - 90
91 - 100
500
km

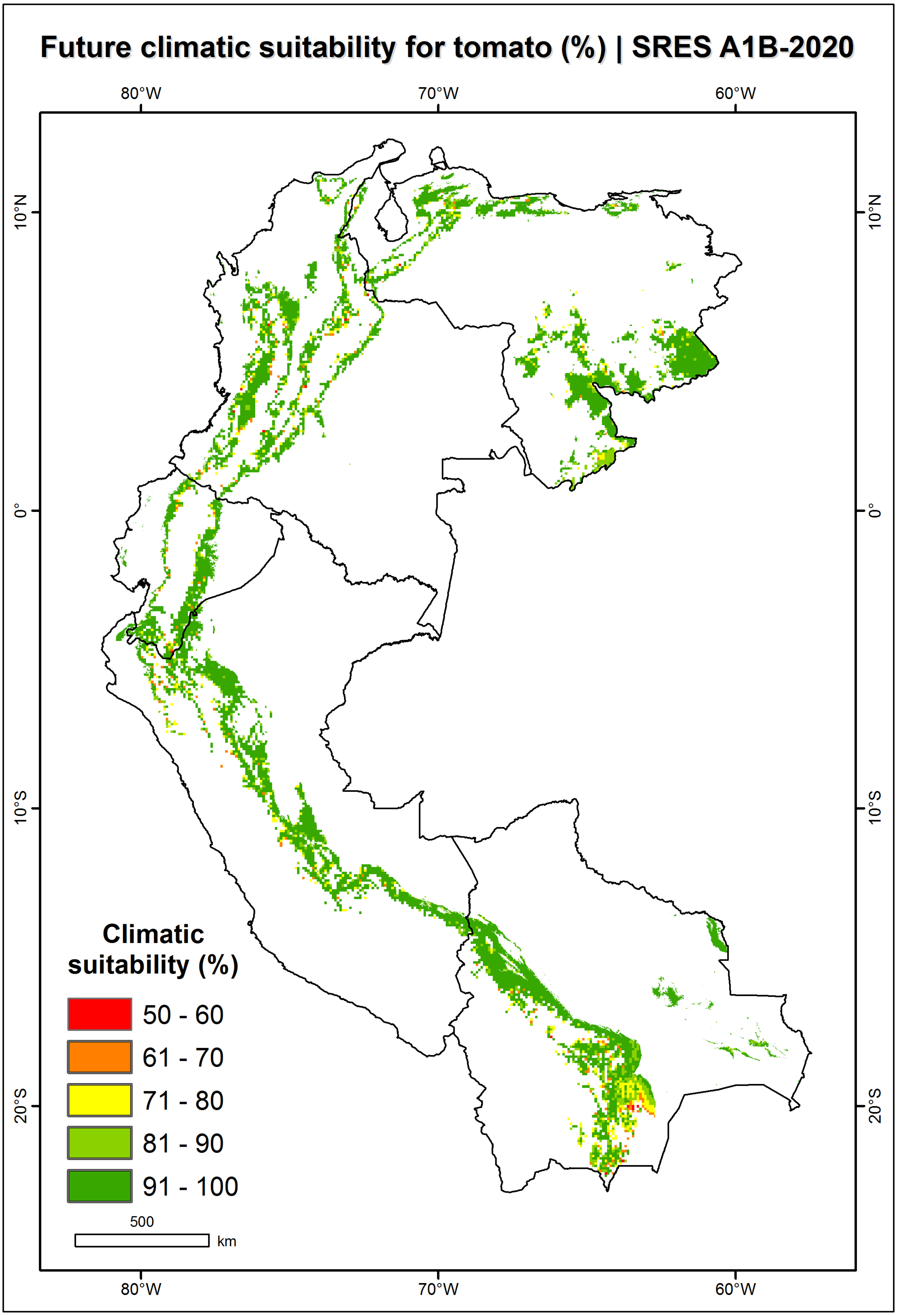


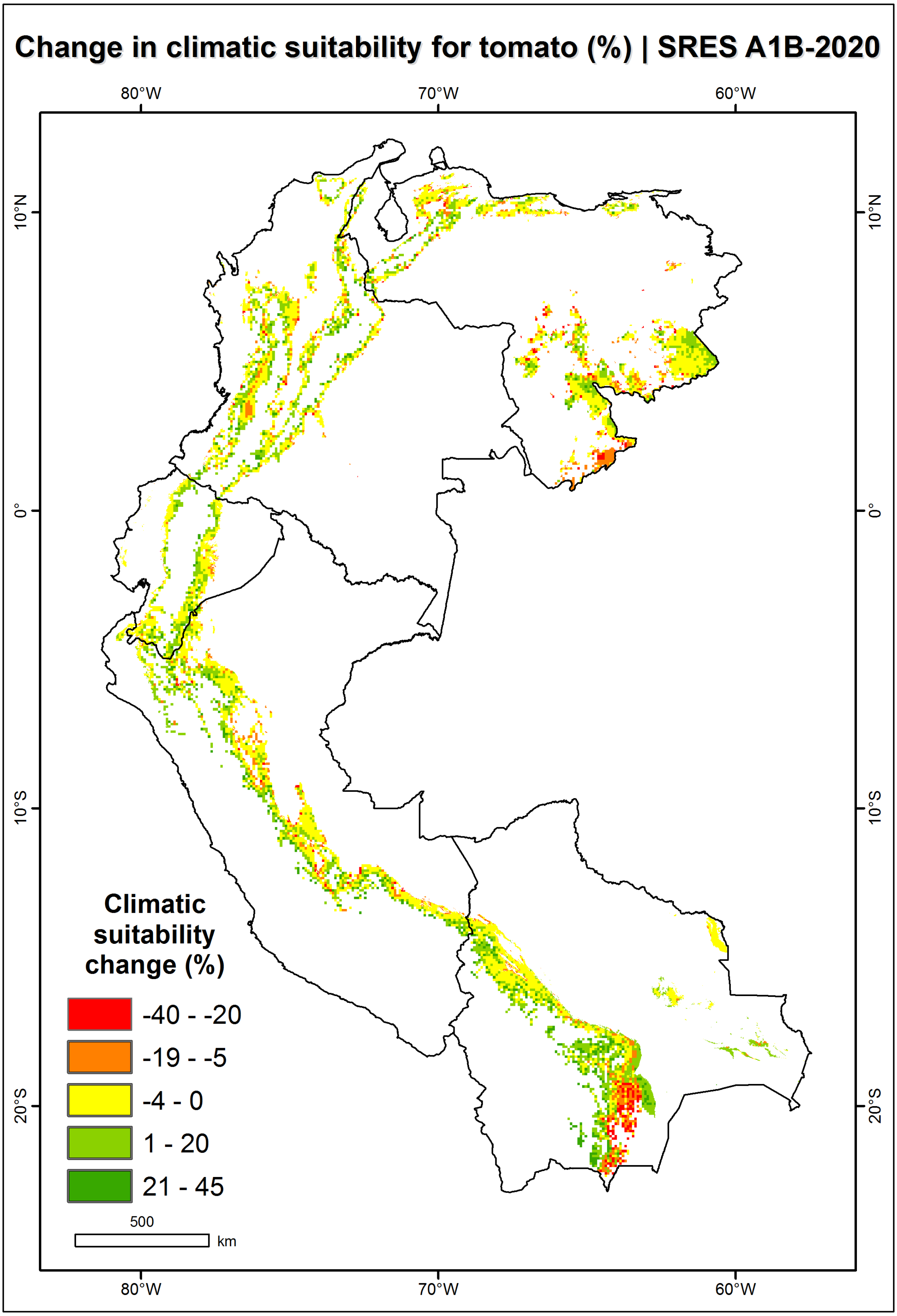
Change in climatic suitability for potato (%) | SRES A2-2050


Uncertainty for potato (%) | SRES A2-2050
80°W
70°W
60°W
10°N
0°
10°S
20°S
Uncertainty (%)
0 - 5
6 - 10
11 - 15
16 - 20
21 - 25
500
km

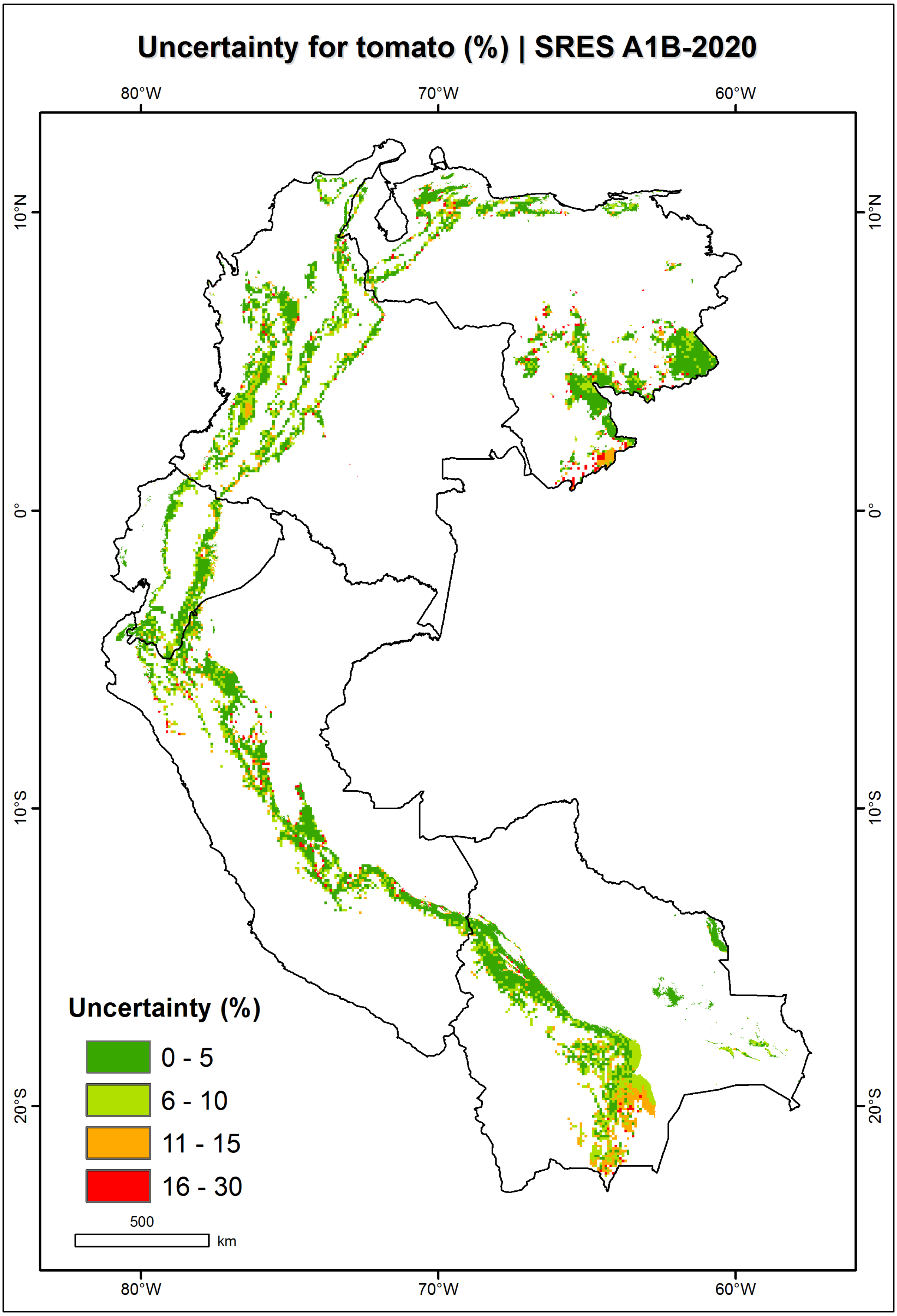


Current climatic suitability for tomato (%)

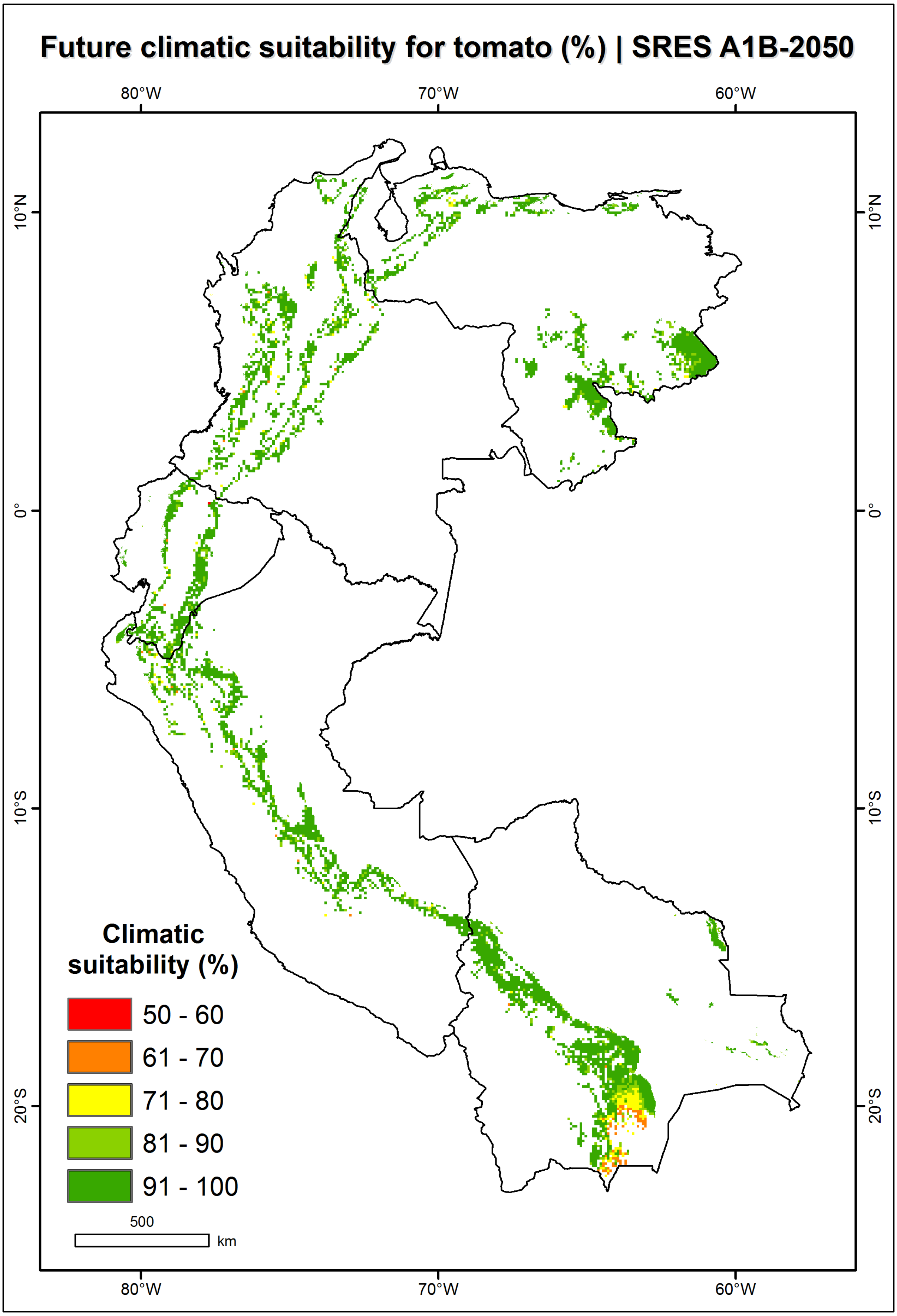

Future climatic suitability for tomato (%) | SRES A1B-2020
80°W
70°W
60°W
10°N
0°
10°S
20°S
Climatic suitability (%)
50 - 60
61 - 70
71 - 80
81 - 90
91 - 100
500
km



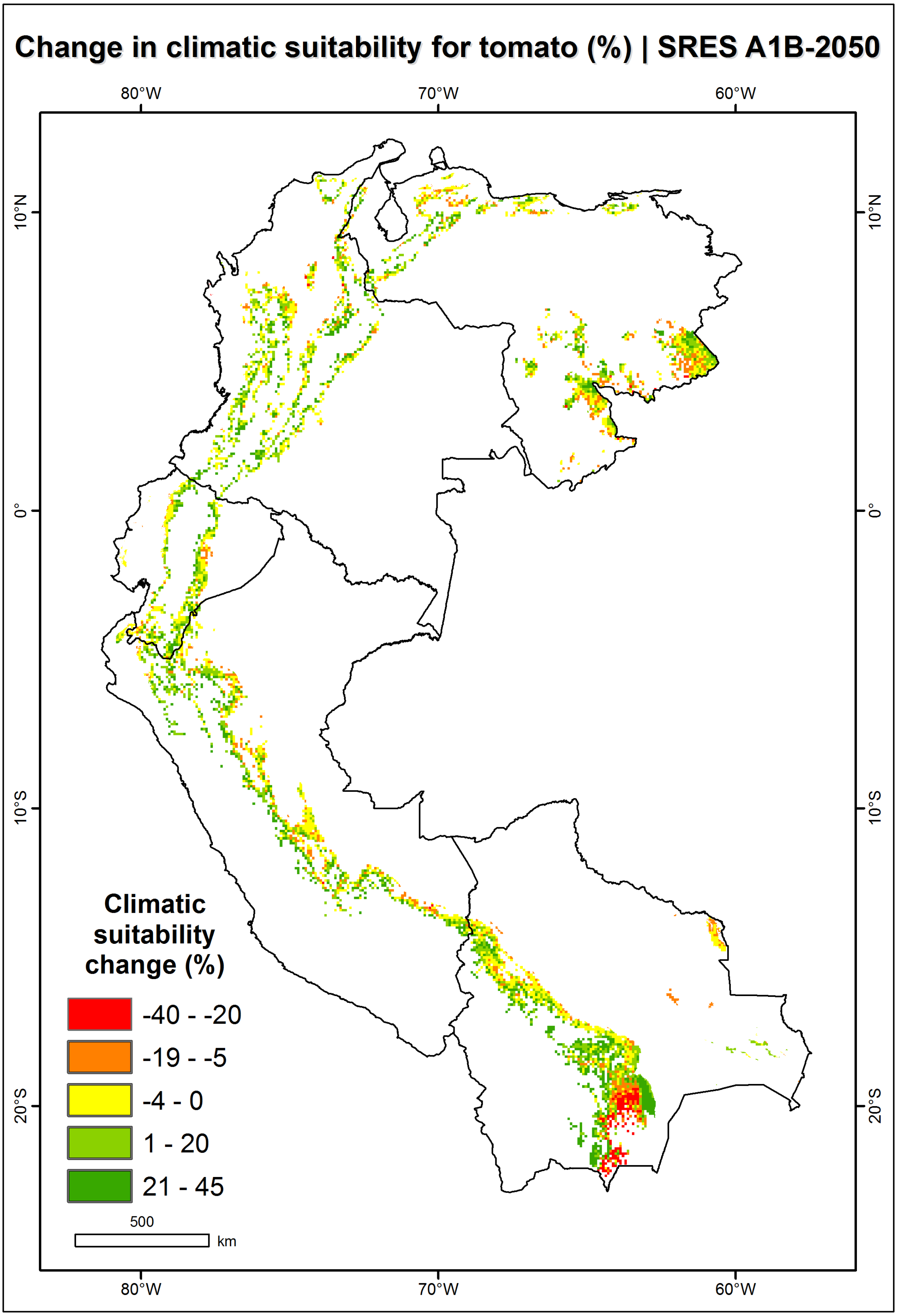
Change in climatic suitability for tomato (%) | SRES A1B-2020

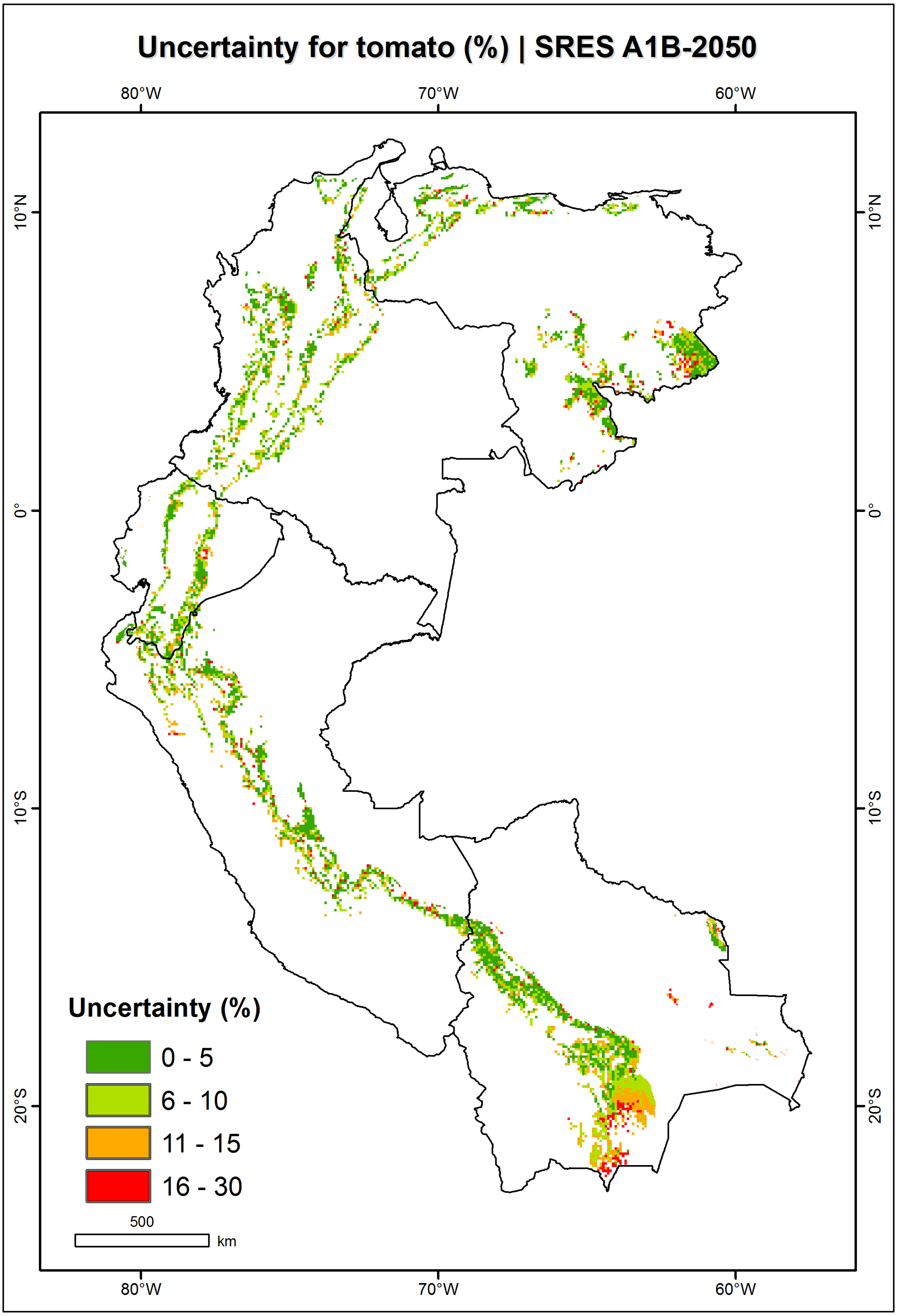


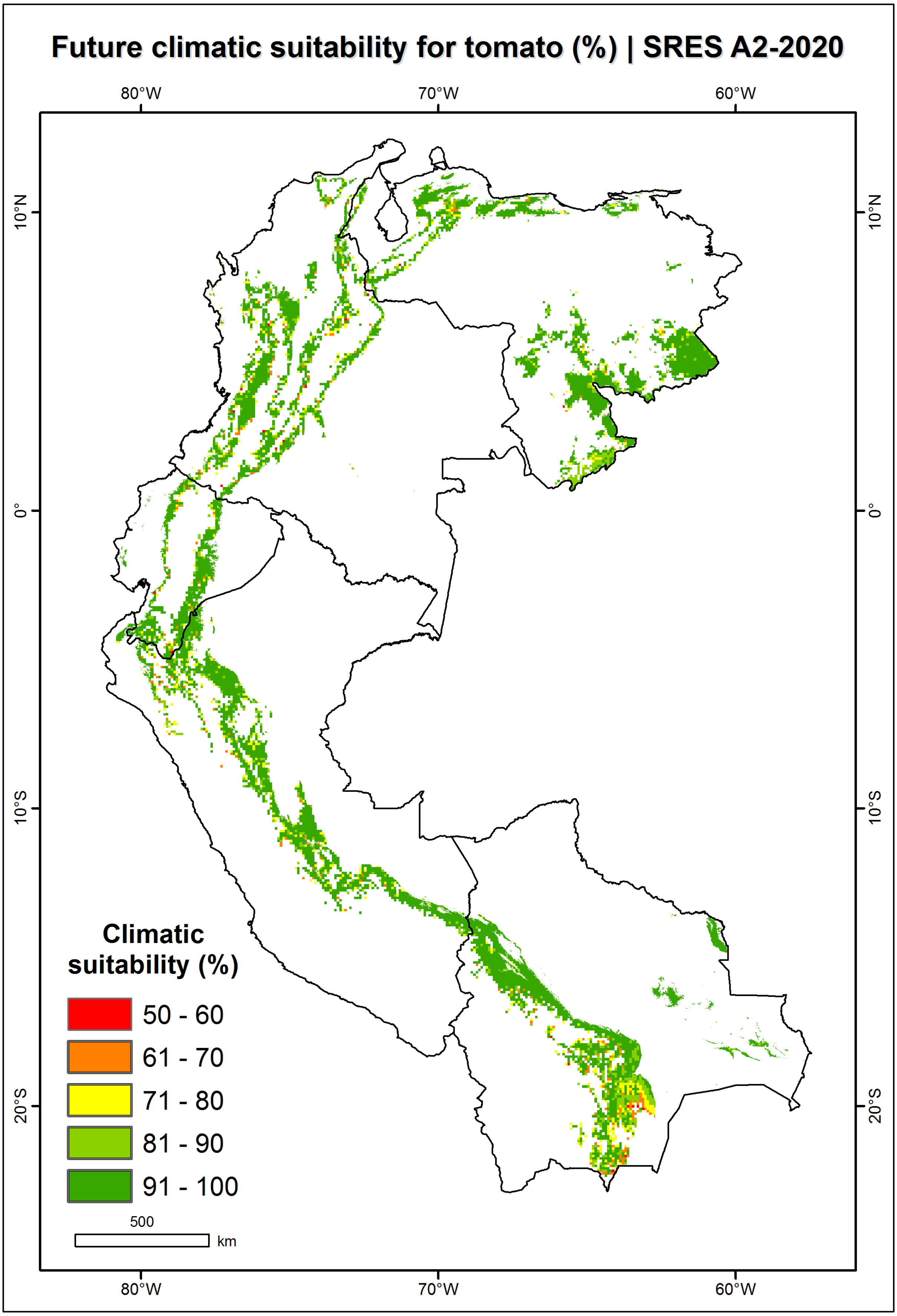
Uncertainty for tomato (%) | SRES A1B-2020

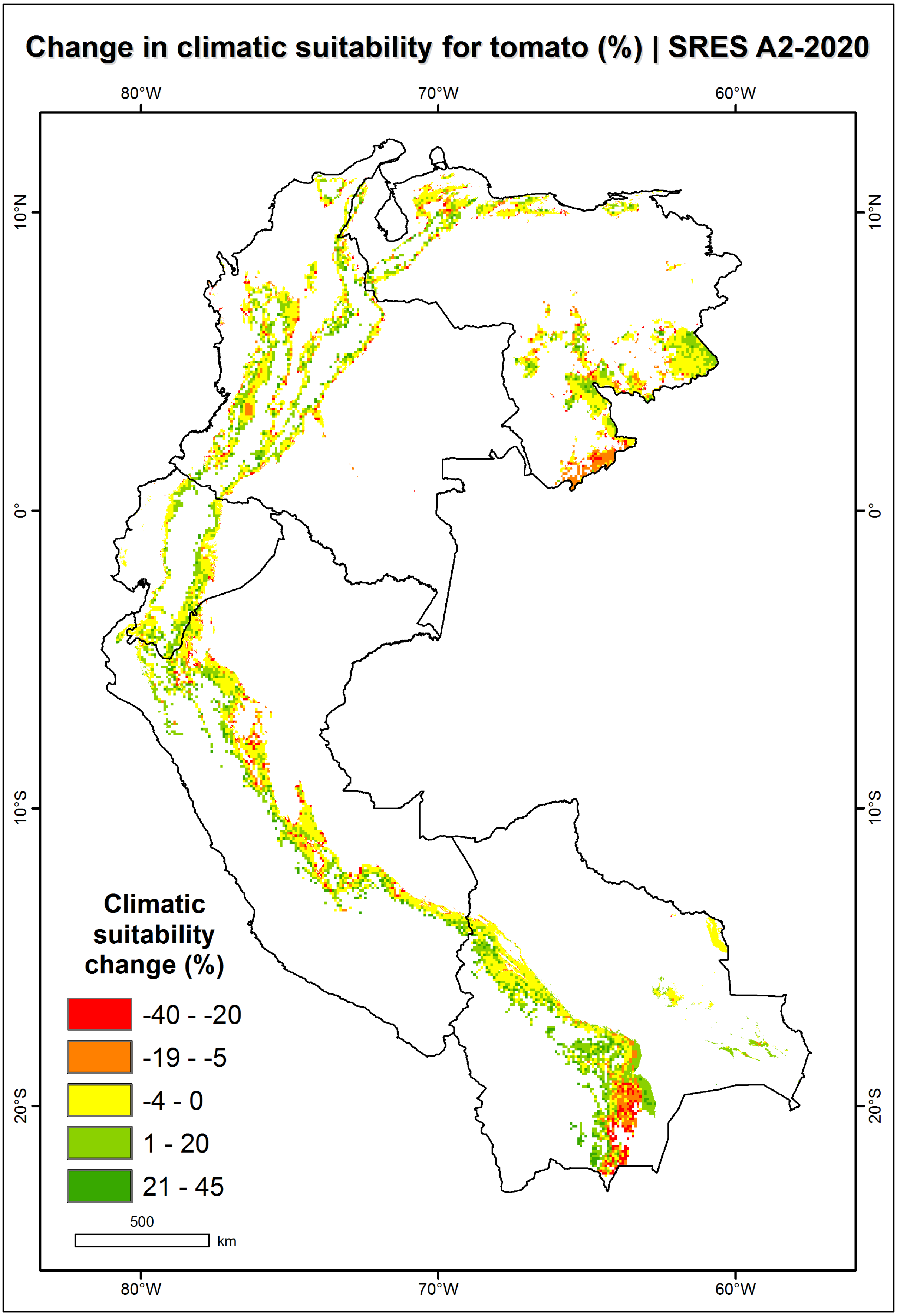


Future climatic suitability for tomato (%) | SRES A1B-2050


Change in climatic suitability for tomato (%) | SRES A1B-2050
80°W
70°W
60°W
10°N
0°
10°S
20°S
Climatic suitability change (%)
-40 - -20
-19 - -5
-4 - 0
1 - 20
21 - 45
500
km

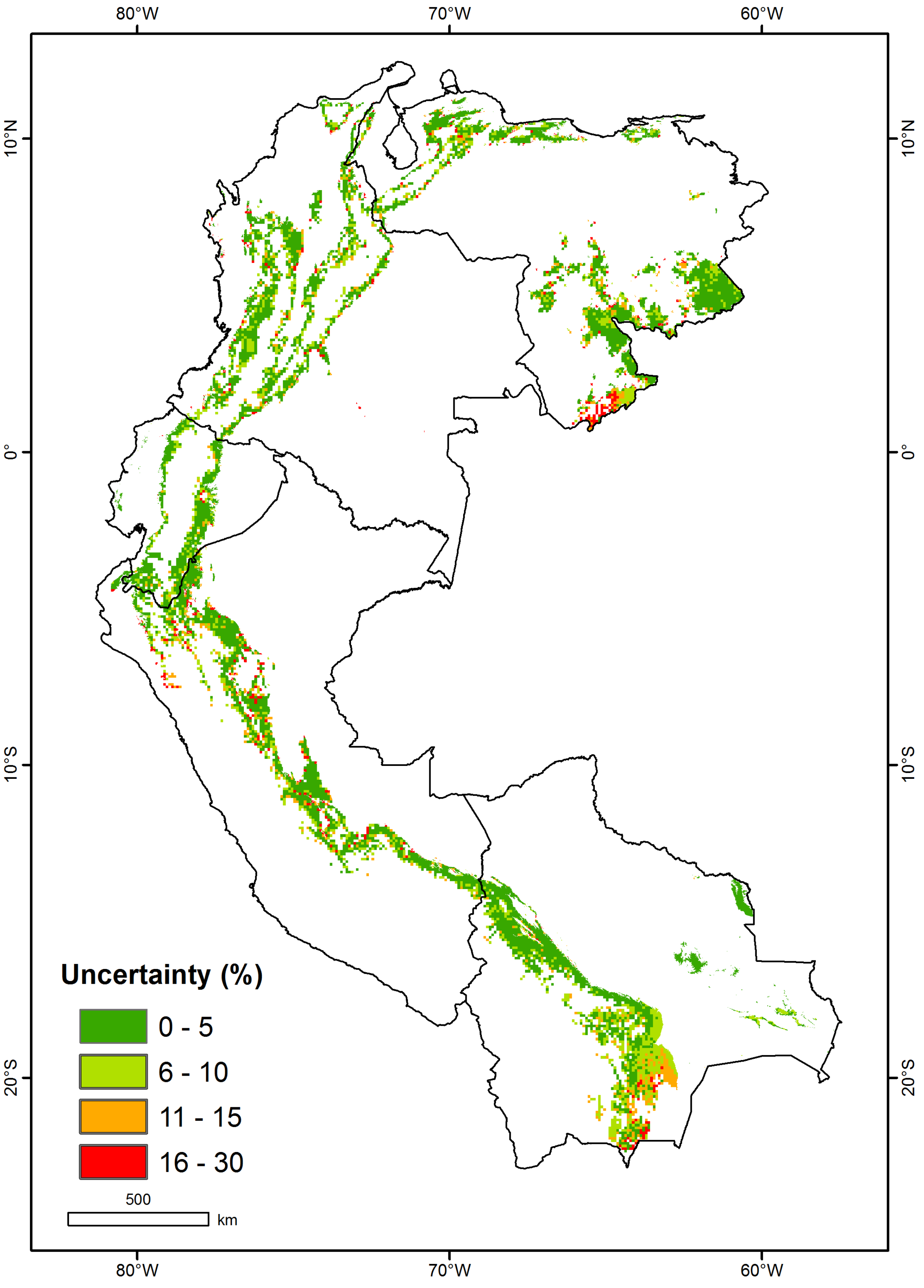

Uncertainty for tomato (%) | SRES A1B-2050
80°W
70°W
60°W
10°N
0°
10°S
20°S
Uncertainty (%)
🟩 0 - 5
🟩 6 - 10
🟧 11 - 15
🟥 16 - 30
500
km

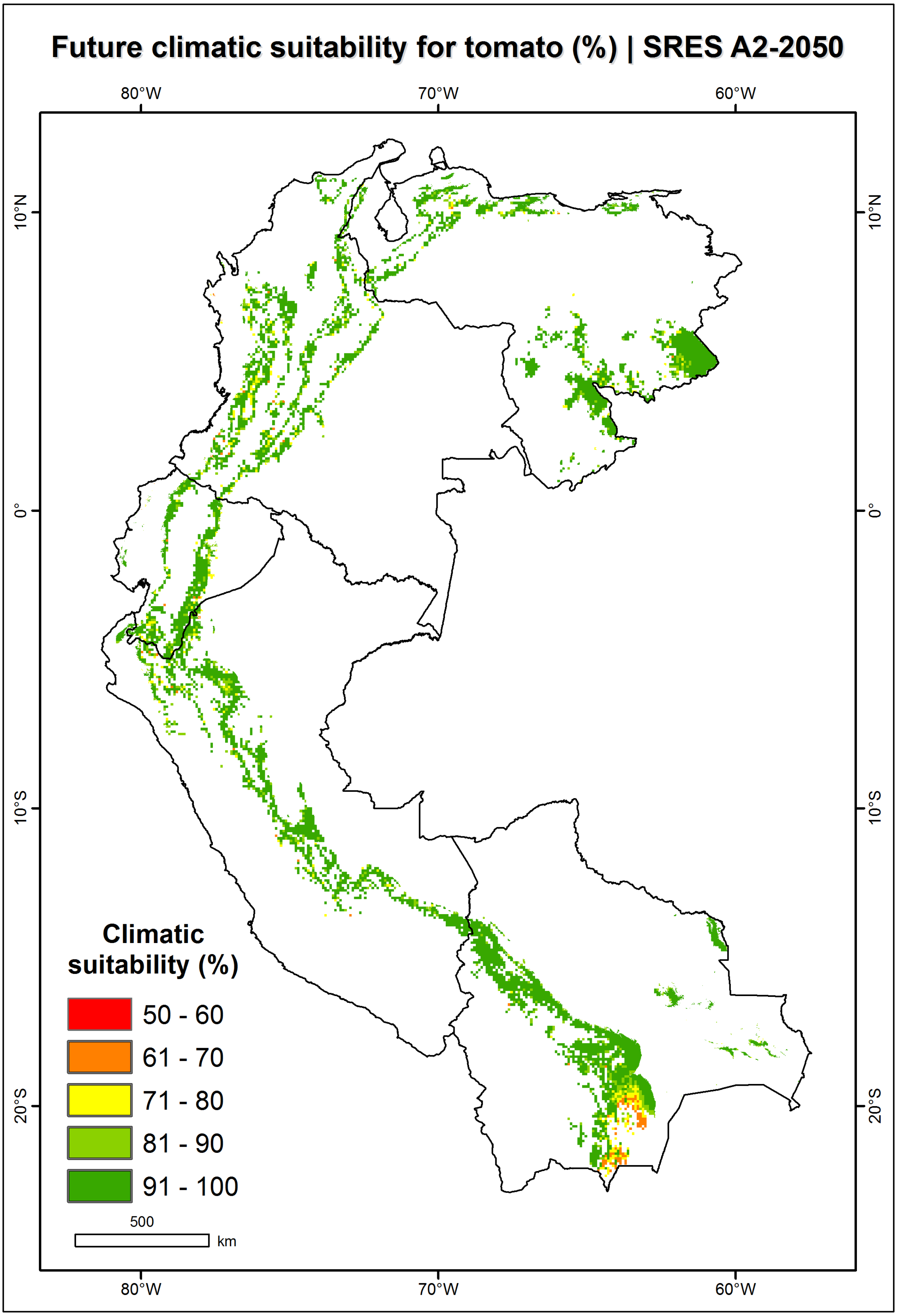

Future climatic suitability for tomato (%) | SRES A2-2020
80°W
70°W
60°W
10°N
0°
10°S
20°S
Climatic suitability (%)
50 - 60
61 - 70
71 - 80
81 - 90
91 - 100
500
km

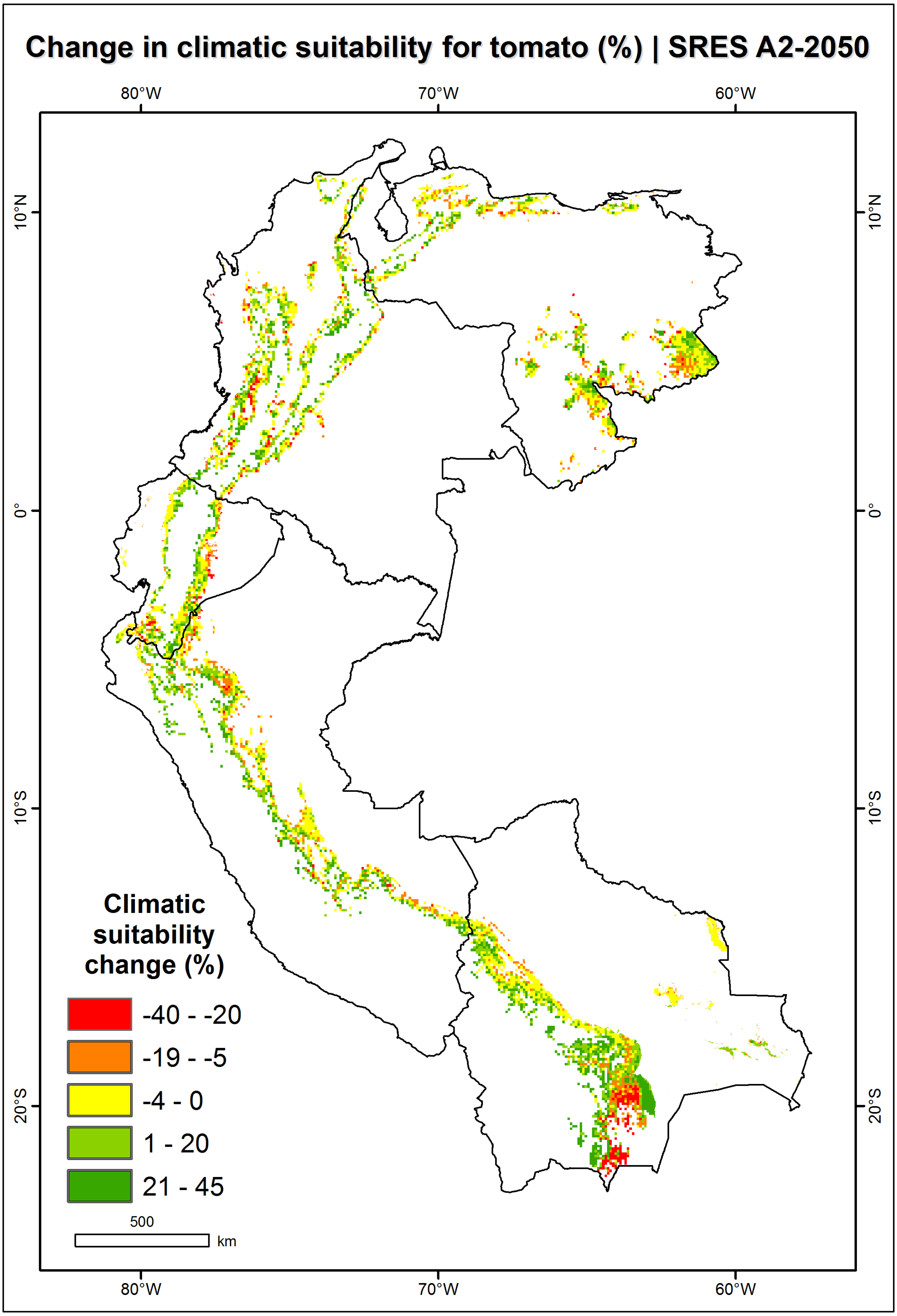


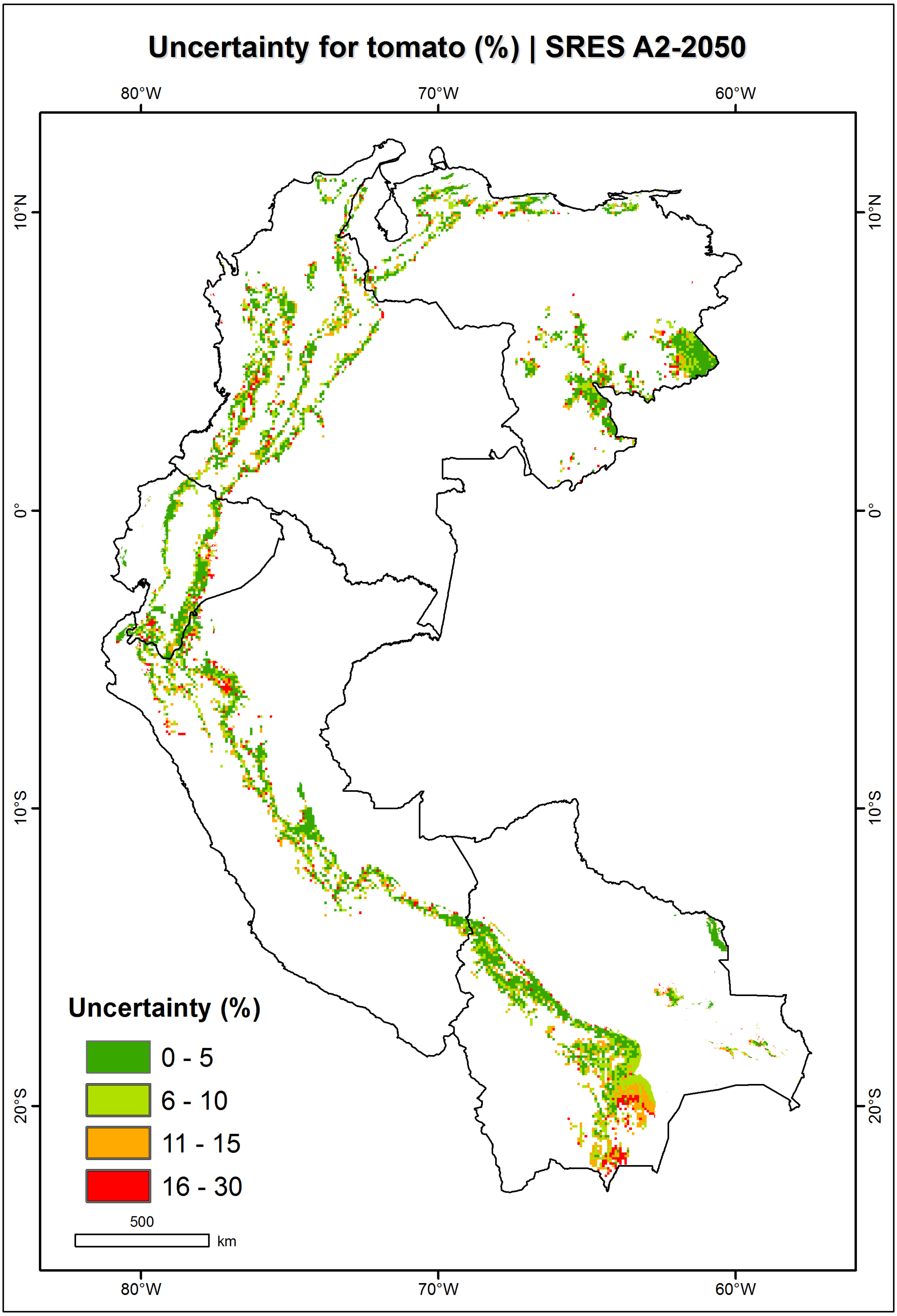
Change in climatic suitability for tomato (%) | SRES A2-2020

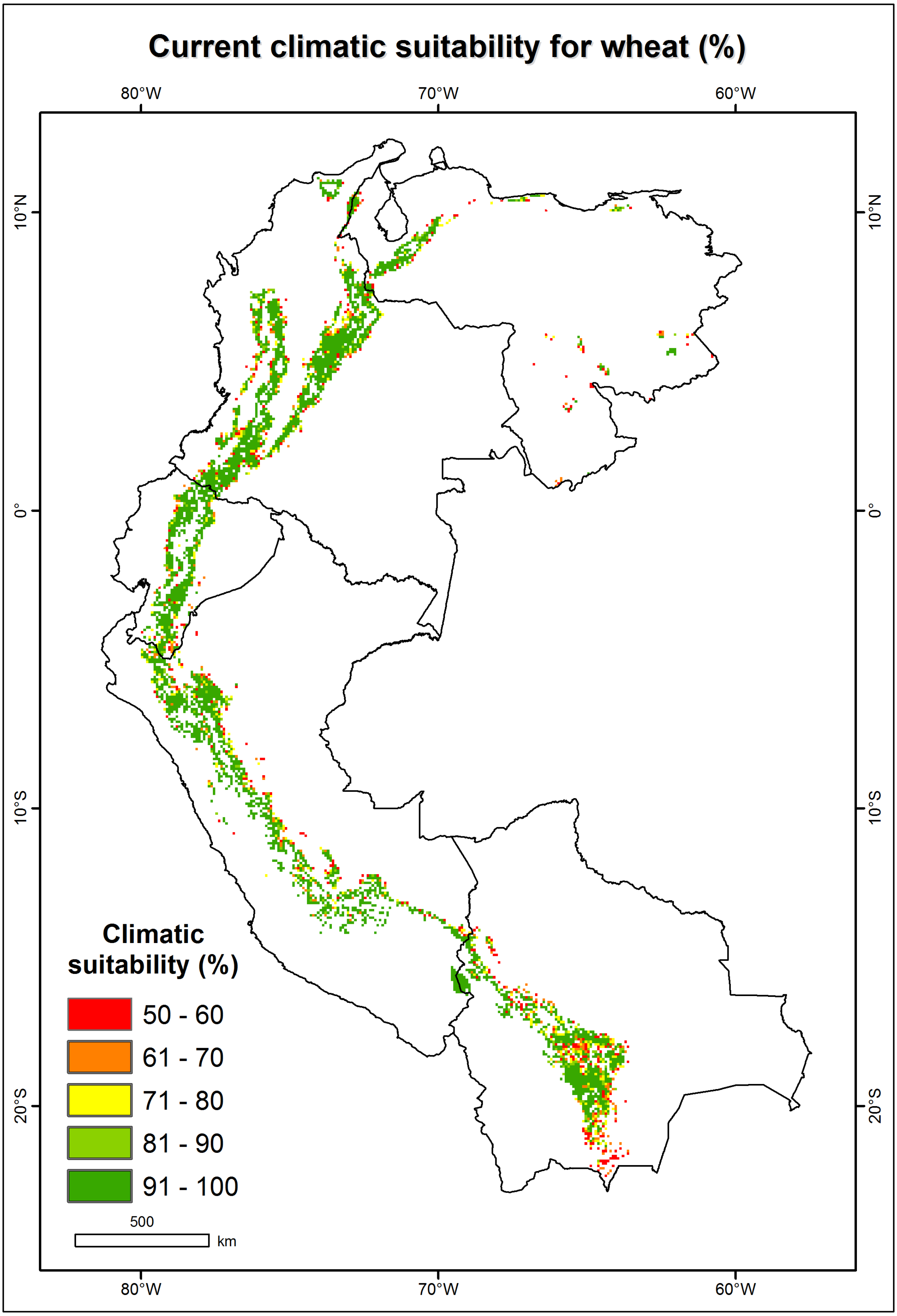
Uncertainty for tomato (%) | SRES A2-2020

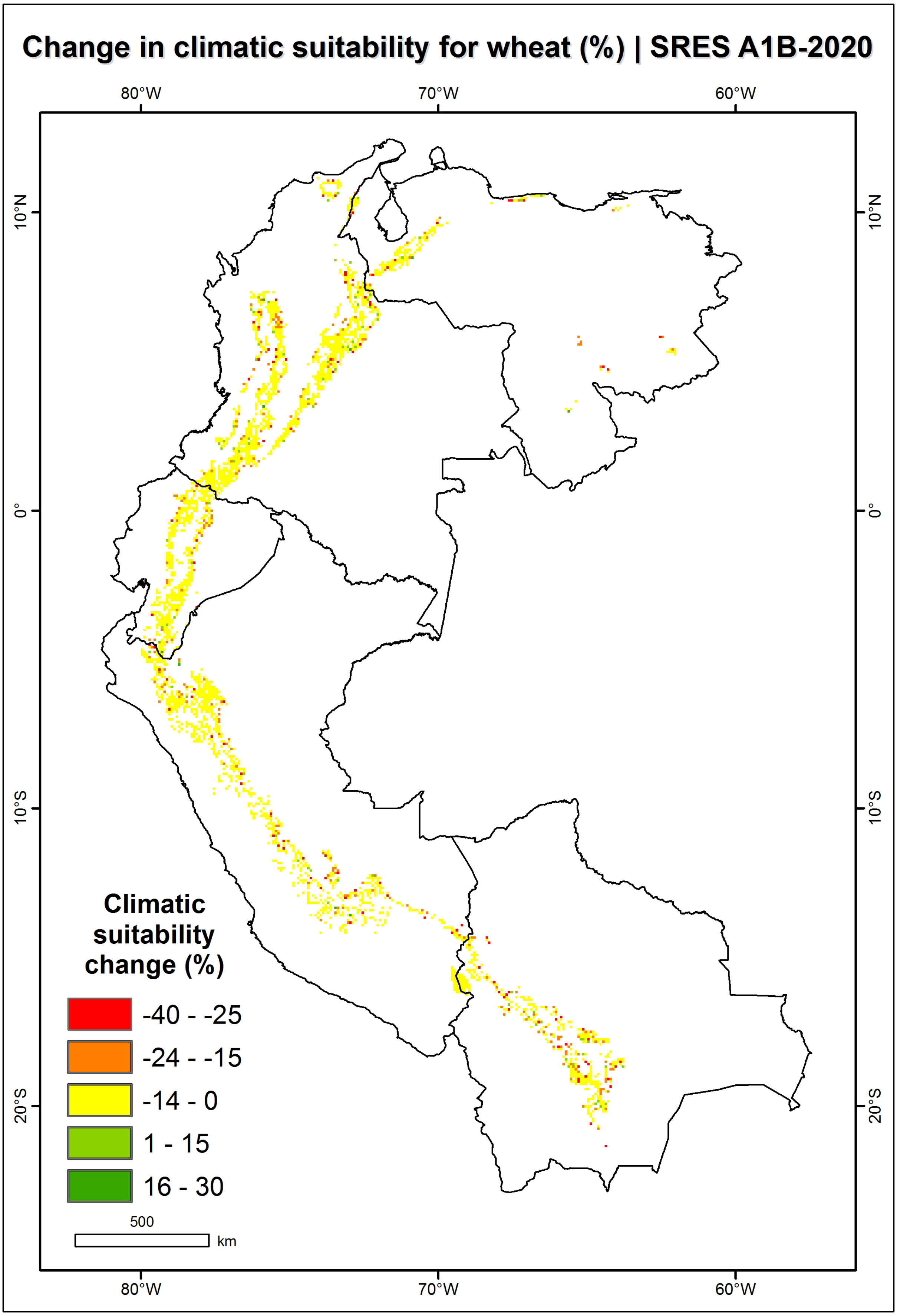



Future climatic suitability for tomato (%) | SRES A2-2050
80°W
70°W
60°W
10°N
0°
10°S
20°S
Climatic suitability (%)
50 - 60
61 - 70
71 - 80
81 - 90
91 - 100
500
km

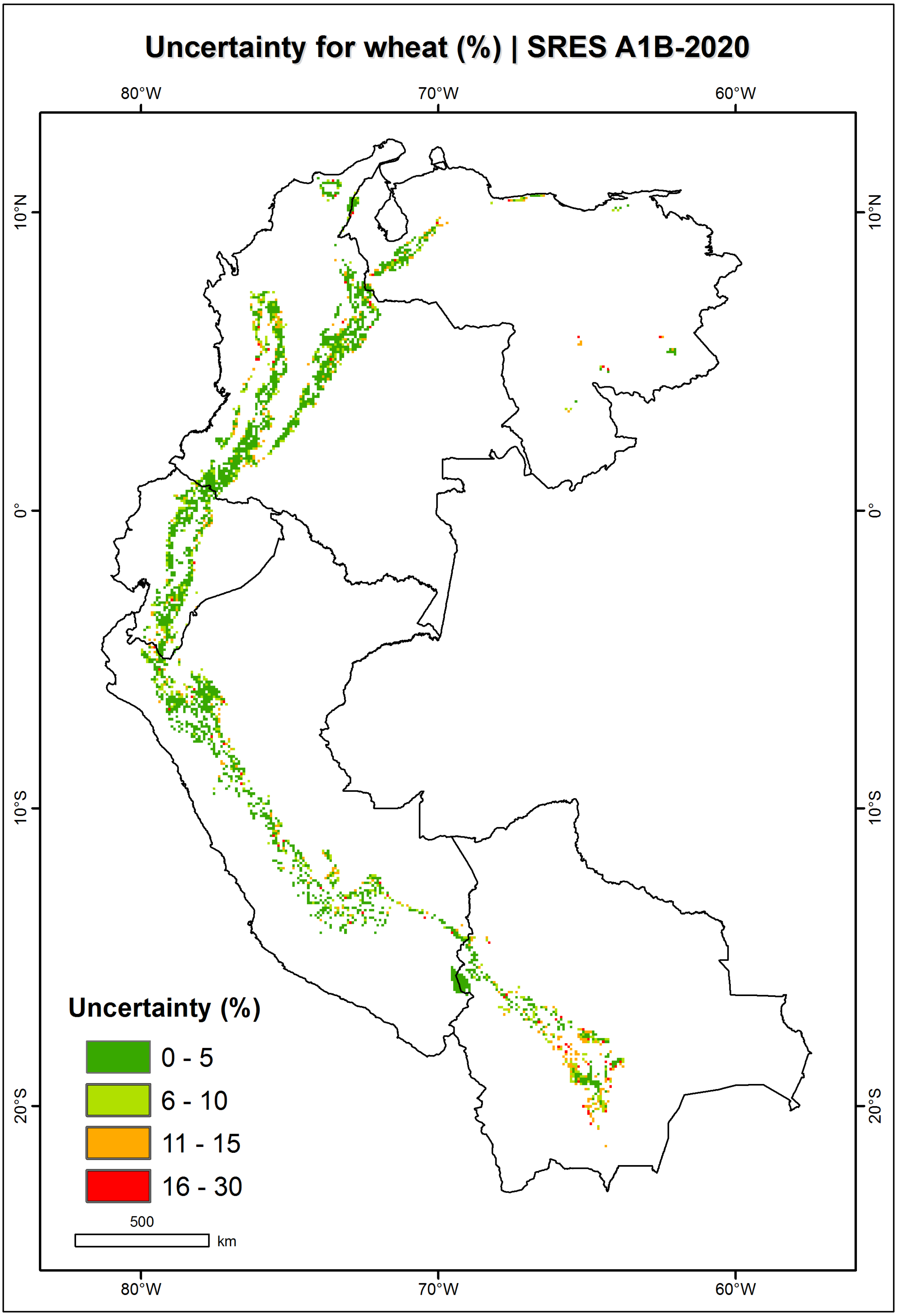

Change in climatic suitability for tomato (%) | SRES A2-2050
80°W
70°W
60°W
10°N
0°
10°S
20°S
Climatic suitability change (%)
-40 - -20
-19 - -5
-4 - 0
1 - 20
21 - 45
500
km


Uncertainty for tomato (%) | SRES A2-2050
80°W
70°W
60°W
10°N
0°
10°S
20°S
Uncertainty (%)
0 - 5
6 - 10
11 - 15
16 - 30
500
km

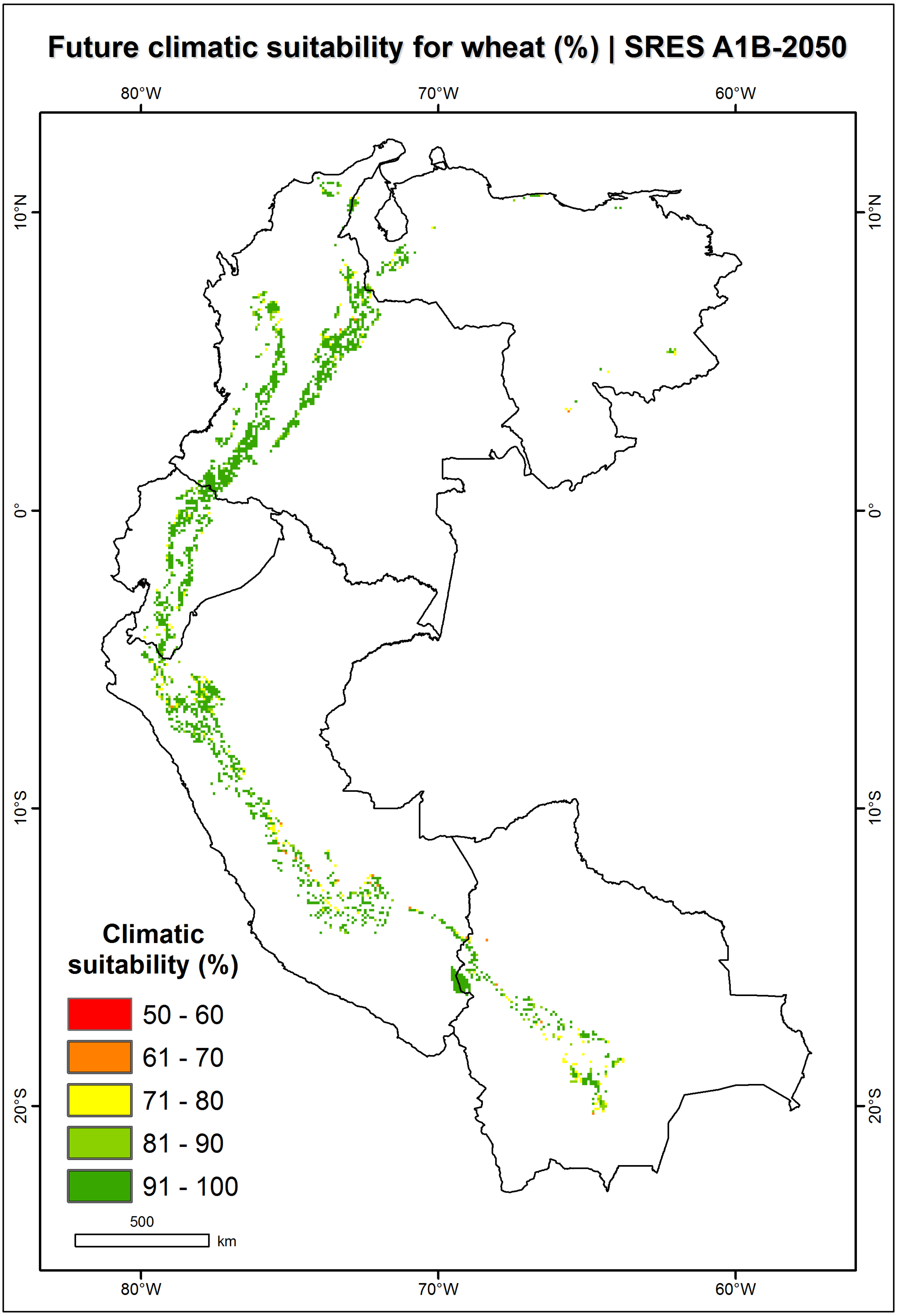

Current climatic suitability for wheat (%)
80°W
70°W
60°W
10°N
0°
10°S
20°S
Climatic suitability (%)
50 - 60
61 - 70
71 - 80
81 - 90
91 - 100
500
km

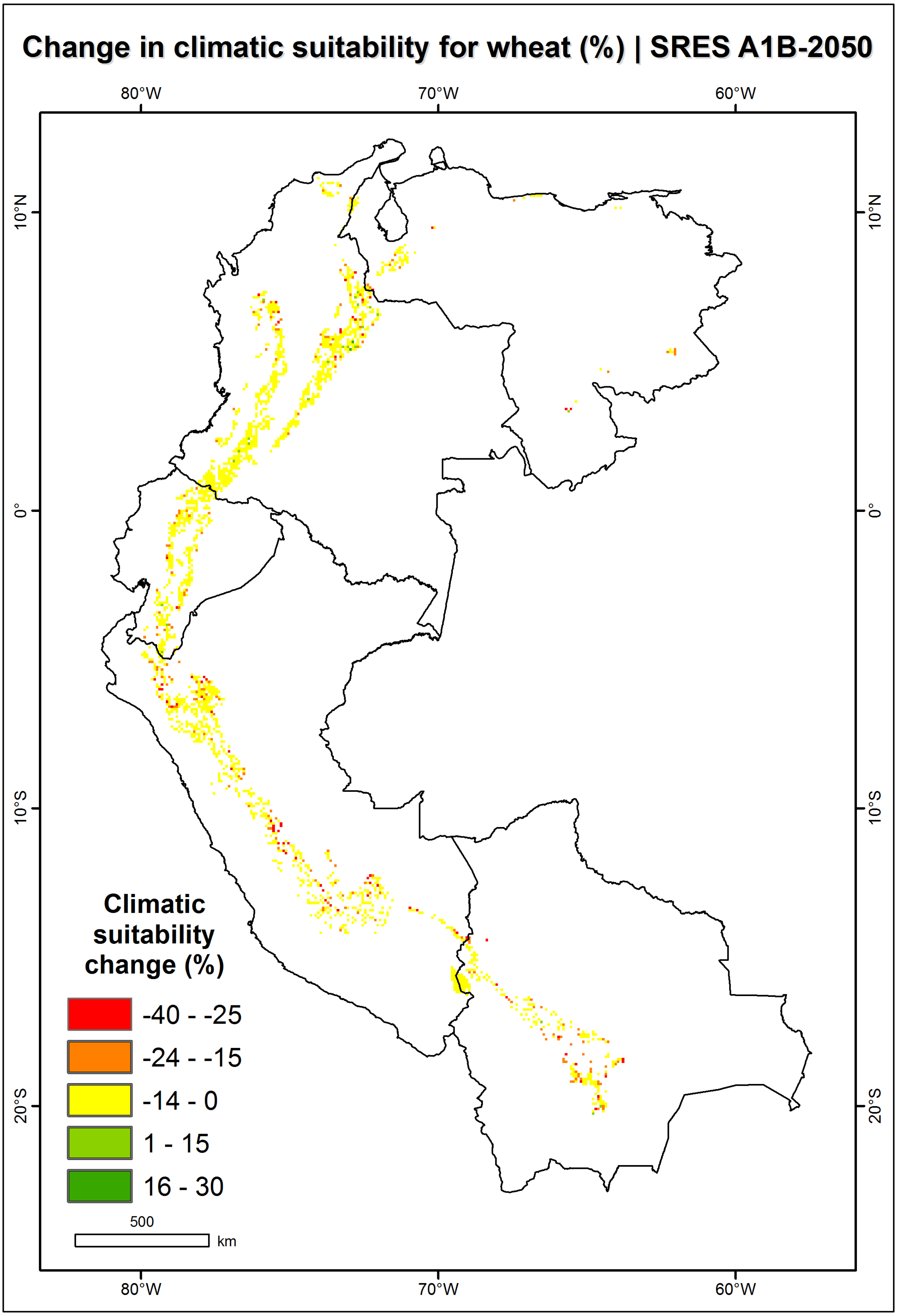


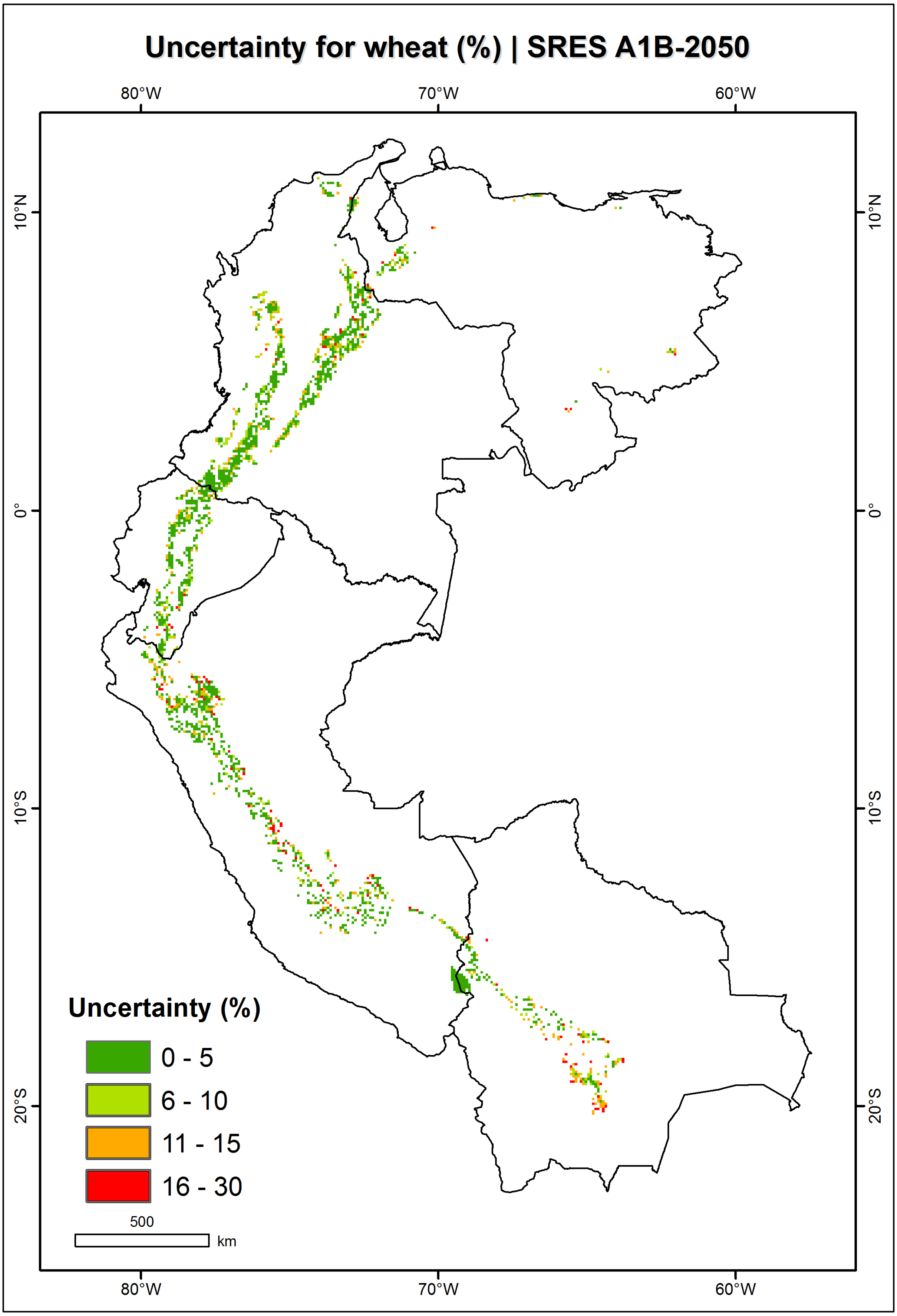
Change in climatic suitability for wheat (%) | SRES A1B-2020

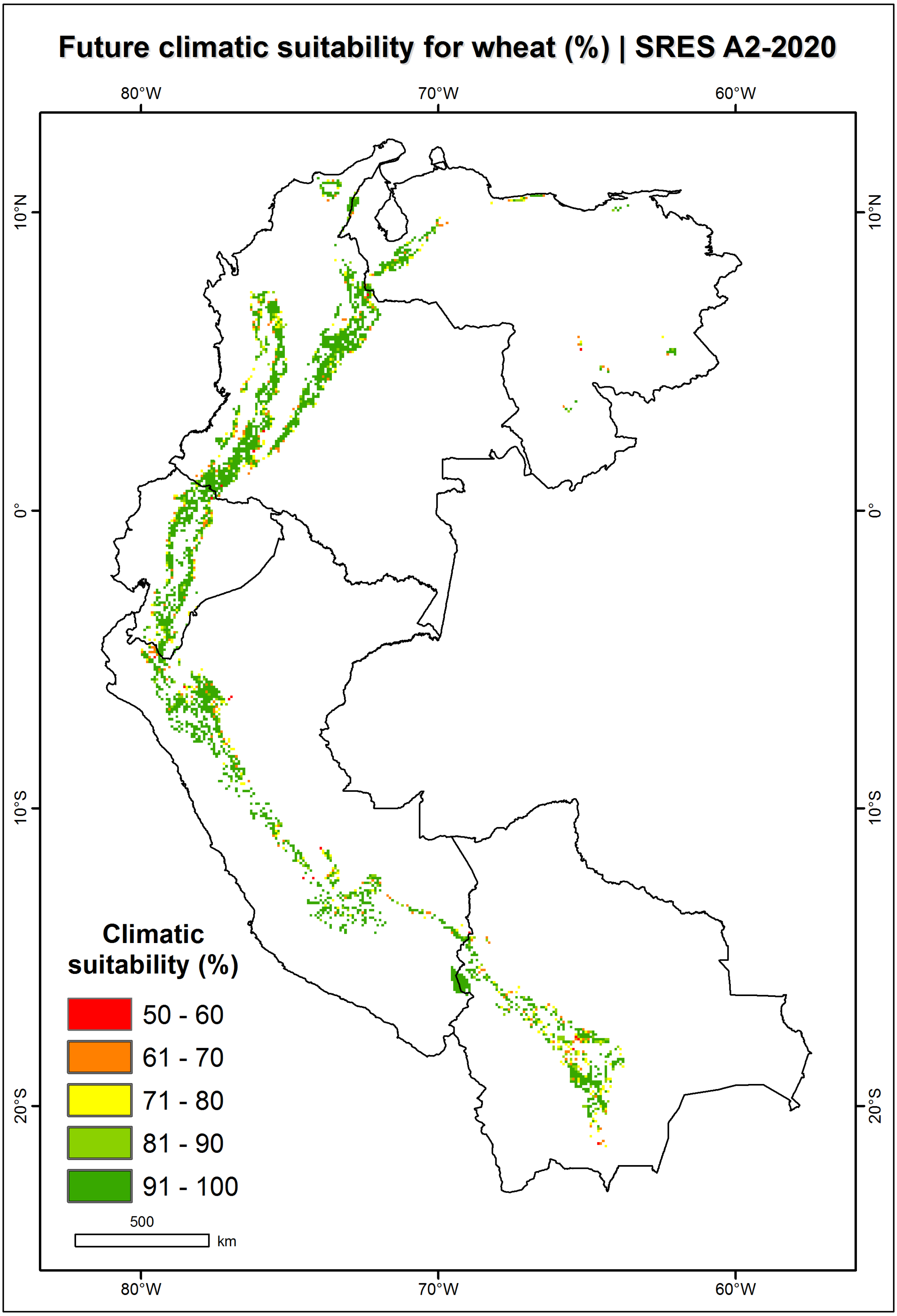


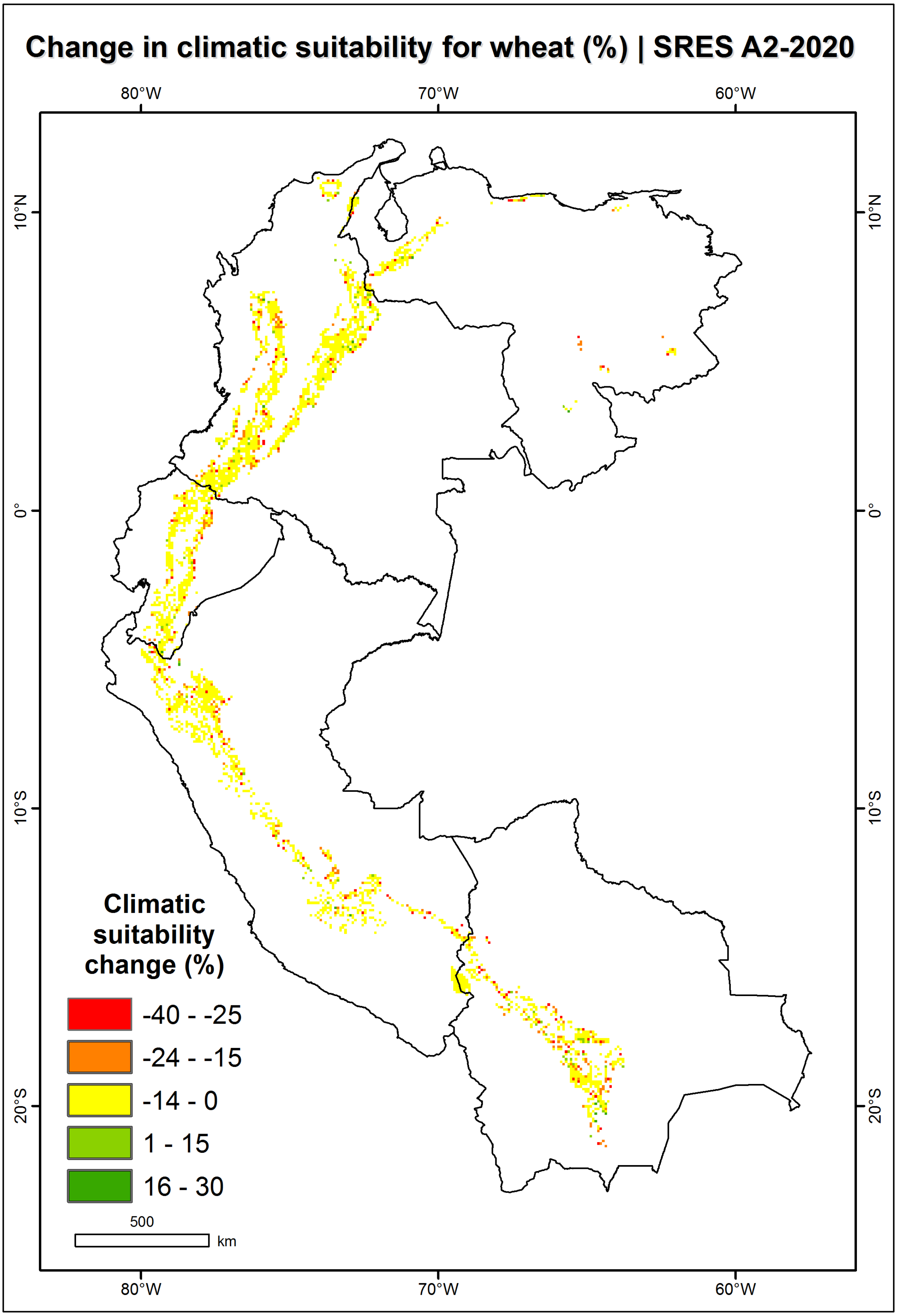
Uncertainty for wheat (%) | SRES A1B-2020

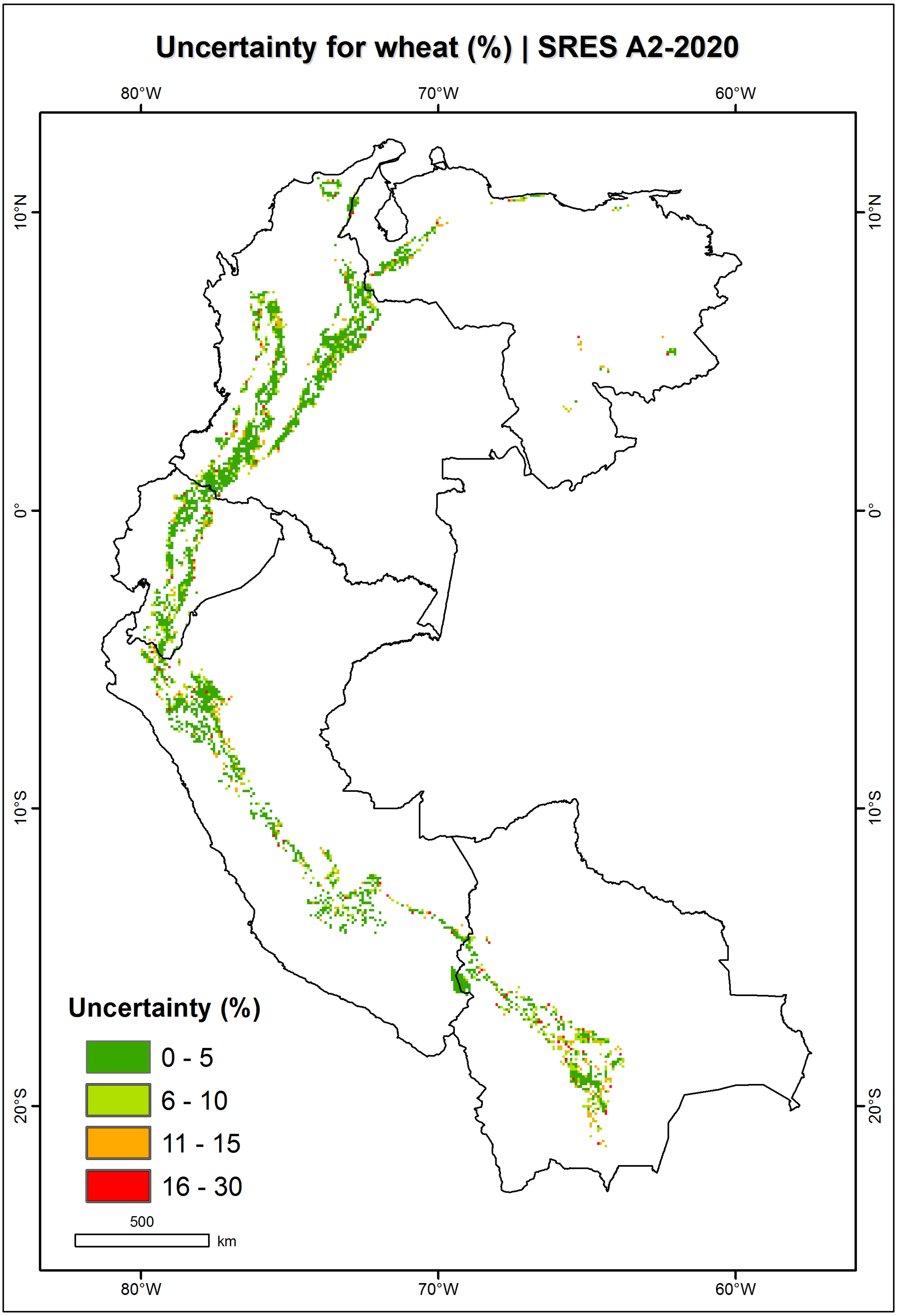

Future climatic suitability for wheat (%) | SRES A1B-2050
80°W
70°W
60°W
10°N
0°
10°S
20°S
Climatic suitability (%)
50 - 60
61 - 70
71 - 80
81 - 90
91 - 100
500
km

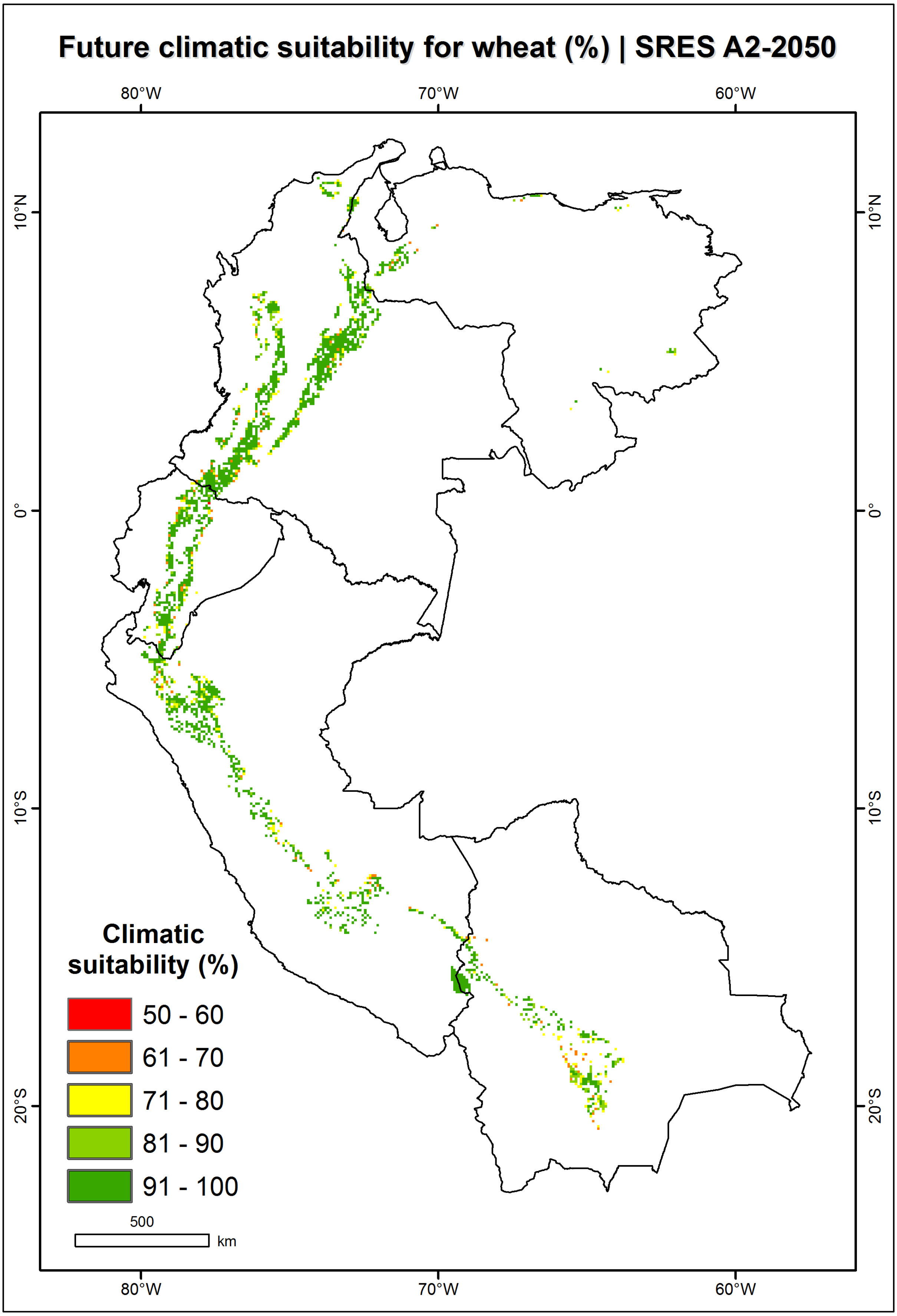

Change in climatic suitability for wheat (%) | SRES A1B-2050
80°W
70°W
60°W
10°N
0°
10°S
20°S
Climatic suitability change (%)
🟥 -40 - -25
🟧 -24 - -15
🟨 -14 - 0
🟩 1 - 15
🟩 16 - 30
500
km

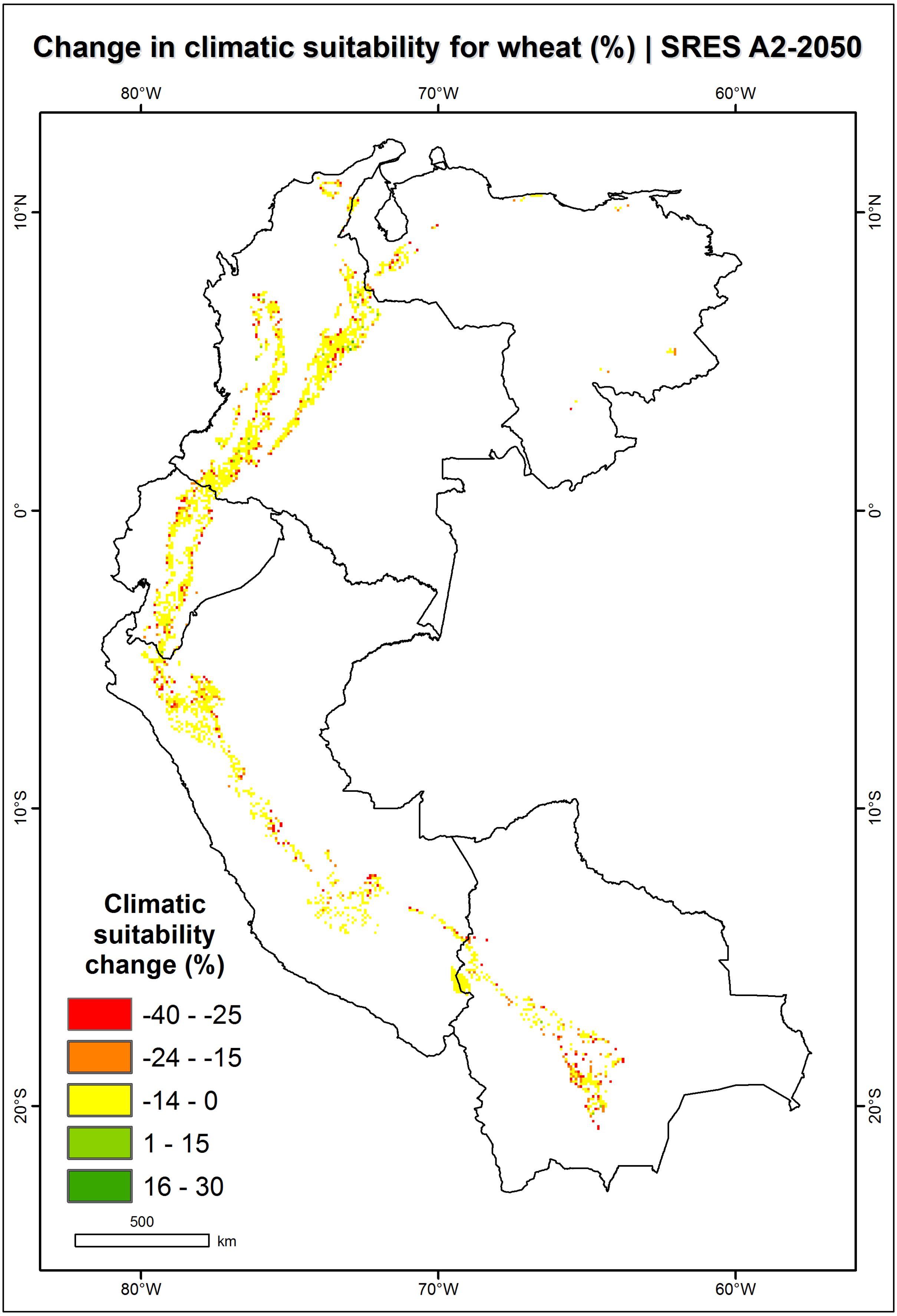

Uncertainty for wheat (%) | SRES A1B-2050
80°W
70°W
60°W
10°N
0°
10°S
20°S
Uncertainty (%)
0 - 5
6 - 10
11 - 15
16 - 30
500
km


Future climatic suitability for wheat (%) | SRES A2-2020
80°W
70°W
60°W
10°N
0°
10°S
20°S
Climatic suitability (%)
🟥 50 - 60
🟧 61 - 70
🟨 71 - 80
🟩 81 - 90
🟩 91 - 100
500
km

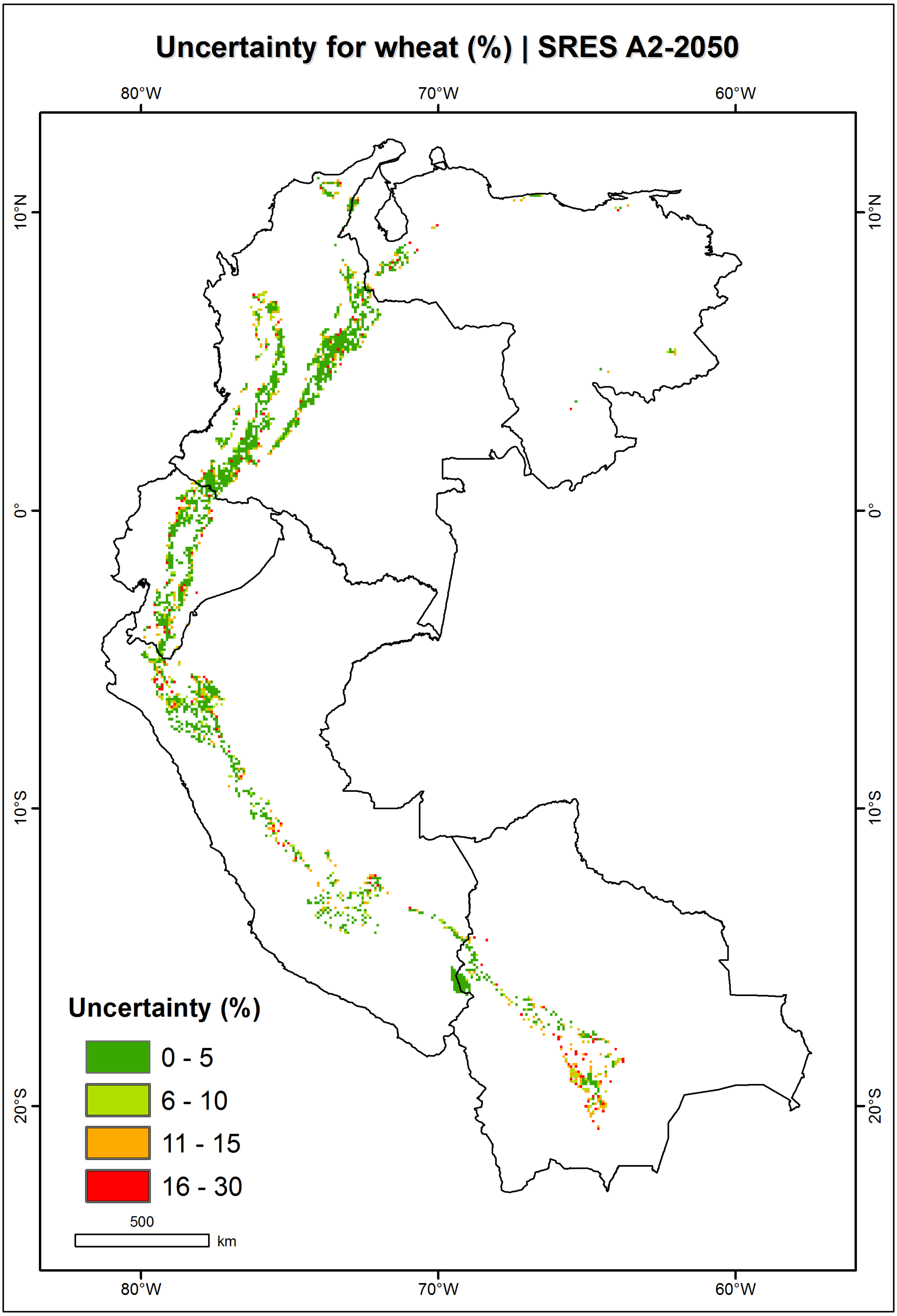

Change in climatic suitability for wheat (%) | SRES A2-2020
80°W
70°W
60°W
10°N
0°
10°S
20°S
Climatic suitability change (%)
🟥 -40 - -25
🟧 -24 - -15
🟨 -14 - 0
🟩 1 - 15
🟩 16 - 30
500
km


Uncertainty for wheat (%) | SRES A2-2020
80°W
70°W
60°W
10°N
0°
10°S
20°S
Uncertainty (%)
0 - 5
6 - 10
11 - 15
16 - 30
500
km


Future climatic suitability for wheat (%) | SRES A2-2050
80°W
70°W
60°W
10°N
0°
10°S
20°S
Climatic suitability (%)
50 - 60
61 - 70
71 - 80
81 - 90
91 - 100
500
km



Change in climatic suitability for wheat (%) | SRES A2-2050


Uncertainty for wheat (%) | SRES A2-2050
80°W
70°W
60°W
10°N
0°
10°S
20°S
Uncertainty (%)
0 - 5
6 - 10
11 - 15
16 - 30
500
km