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CLIMATE CHANGE DRIVES DIVERGENT OUTCOMES FOR STREAM FISHES IN THE RED RIVER

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Table of Contents

List of Tables and Figures

Abstract

Climate change is expected to alter the distributions of stream fishes in ecosystems around the world, but climate projections vary widely among competing climate models. Conservation practitioners face the challenge of designing conservation strategies that are robust to the uncertainty surrounding future climatic conditions. Here, we use species distribution models (SDMs) for 31 fish species in the Red River basin to quantify the variation in potential species distributions across 9 different climate scenarios. We created SDMs by pairing historical fish occurrence records with a set of temporally dynamic South-Central Climate Adaptation Science Center (SC-CASC) built climate covariates and temporally static lithospheric and anthropogenic covariates that are known to drive species' distributions. We find that the range width of most fish species in the Red River Basin will contract by 2050 and 2070; this was true for both MAXENT and BRT models and across all climate scenarios. However, species also varied dramatically in the uncertainty associated with their future distributions, with the range in outcomes across climate scenarios being more than 10 times higher for some species than for others. Our analysis also revealed that the greatest absolute changes in range width are projected to occur for those species which have historically been the most widespread. This comprehensive assessment on Red River stream fishes suggests a general decline in range width across the basin due to climate change and anthropogenic stressors.

Chapter 1: Introduction and Literature Review on Species Distribution Modeling

Overview

Climate change is expected to drive large shifts in the distributions of stream fishes in ecosystems around the world (Buisson et al. 2008). To conserve and enhance freshwater biodiversity, practitioners are increasingly interested in developing conservation strategies based on predicted future fish distributions in the face of climate change. However, global climate models show a range of possible future environmental conditions depending on climate model choice, greenhouse gas emission scenarios and mathematical downscaling techniques (Hawkins and Sutton 2009). Given this uncertainty in future environmental conditions, conservation practitioners have a need for understanding how variability in future climate conditions may drive uncertainty in future species' distributions, and a need for conservation strategies that are robust to these uncertainties.

In this thesis, I explore how variability and uncertainty across future climate scenarios may drive uncertainty in projected stream fish distributions in the Red River of the south-central United States. I draw on recent high-resolution models of climate and hydrology (Xue et al. 2016; Gaitan et al. 2016) constructed for the Red River basin. The species distribution models produced incorporate these recent high-resolution models, as well as a broader suite of landscape covariates, to project stream fish distributions across a range of future climate scenarios. Here, I begin with a literature review to summarize existing work on species distribution models and their potential for characterizing fish under climate scenarios.

Literature review

The purpose of this literature review is to establish which species distribution modeling techniques may be the most predictive for stream fish species within the Red River basin temporally with respect to climate change. Currently, there is little to no literature on the Red River basin for fish species distribution modeling; however, species distribution models have been constructed for other river basins that are climatically, hydrologically, and biologically similar. Thus, this literature review analyzes species distribution modeling efforts in similar semi-arid river basins across the globe during the past two decades. Additionally, this Red River project spans a large future temporal scale and discusses how fish distributions are projected to alter with respect to climate change.

Environmental planners seek to incorporate as much data into their decision-making process. It is the responsibility of researchers and conservation practitioners to produce the most effective and accurate data to decision makers so that their choices are accurate and informed. In the case of species distribution modeling of stream fish, biodiversity information is extremely impactful. Vertebrate stream fish are keystone species in most aquatic environments which provide countless ecosystem services contributing both to overall water quality and the biodiversity of its respective ecosystem (Vorosmarty 2000). Many stream fish species, particularly in the Red River basin, are either endangered or endemic to a region which is experiencing heavy urbanization (Perkin and Gido 2012). Anthropogenic threats from warming temperatures, dam construction and water scarcity pose an existential threat to stream ecosystems and water quality. As such, the decision-making processes behind water resource allocation is vital both to fish populations and water quality for human consumption.

Species distribution models (SDMs) are a regression based approaches to interpolating historical species occurrence data against a set of environmental covariates to construct a spatially projected probability of occurrence map (Merow et al. 2013). Utilization of projected occurrence maps are to inform conservation and biodiversity planners about the most probable locations in which a species may occur. In turn, conservation planners use the projected range of occurrence maps to decide which areas are targets for conservation and conversely which areas are suitable for resource extraction and urban development.

Species distribution models present the middle ground between the actual distribution of a species and the projected range of suitability for the species. Conflicting research has been produced asserting that SDMs are only suitable for determining a possible range of suitability (Gomes et al. 2018) rather than producing a map of the actual distribution of a species (VanDerWal et al. 2009). As no models are perfect, researchers aim to model suitable range and realized occurrence based on model selection, model calibration and the empirical suitability of environmental covariates used. As such, SDMs are used with the risk of over/under prediction of probability of occurrence based off of species presence records (Fitzpatrick et al. 2013). There are a number of competing methods of species distribution modeling that have gradually become more effective and accurate as the field has progressed.

Species distribution modeling for freshwater stream fish is a particularly difficult task; fish are mobile and have a wide set of variables that drive their distribution, dispersal and lifespan (Labay and Hendrickson 2014). Due to the complexity of both the physical habitat structure of fish –dendritic ecological networks – and their complex life cycles, there is a broad range of species distribution modeling techniques used in modern literature (Bond et al. 2011). In addition to selecting the most appropriate SDM for current climate conditions, SDM literature has shifted to modeling climate change on a multi-temporal platform, adding in another dimension of complexity in narrowing down the most appropriate SDM technique (Bond et al. 2011).

In the case of species distribution models for stream fish, there is a fair amount of conflicting literature on which models are most effective. This issue is apparent for three reasons: (1) unique spatial configuration of hierarchical structure of catchments and dendritic streams, (2) the high level of difficulty in obtaining spatially continuous bioclimatic covariates and (3) species detectability issues when collecting historic species collection data along a stream network (Domisch et al. 2015).

I reviewed 12 papers which examine a large range of species distribution modeling projects. In scale, some of the larger projects mapped projected fish occurrence for the better part of a continent (Annis et al. 2012; Labay and Hendrickson 2014; Domisch et al. 2015) down to sub-basins of dendritic ecological networks (Hernandez 2015). Each paper reviewed utilized a different number of fish species, differing species distribution models and a wide array of bioclimatic covariates.

Table 1*: Results from Stream Fish SDM Literature Review. The first column gives the title of the study followed by a set of key statistics gathered from each paper. The scale, SDM used and number of covariates used are highlighted.*

Study	Source	Region	Fish Surveyed	SDM	Total Covariates	Climate Covariates	Lithospheric Covariates	Hydrologic Covariates	Other Covariates
Modeling fish species distributions throughout the Arkansas, Red and White River basins	(Annis et al. 2012)	Arkansas/ White/ Red basins	220	BRT	55	1	46	8	0
Using species distribution models to infer potential climate change-induced range shifts of freshwater fish in south-eastern Australia	(Bond et al. 2011a)	South Eastern Australia	43	BRT	42	16	24	2	0

Climate-change winners and losers: stream macroinvertebrates of a submontane region in Central Europe	(Domisch, Jähnig, and Haase 2011)	Central Europe	38	GLM/GAM/GBM/ANN	10	5	2	3	0
Final report: conservation assessment and mapping products for GPLCC priority fish taxa	(Labay and Hendrickson 2014)	US Great Plains	28	MAXENT	24	15	4	3	2
Relative effects of temperature vs. physical factors	(Buisson L., Blanc L., and Grenouillet G. 2007)	SW France	28	GLM	8	2	2	4	0
A comparison of statistical approaches for modelling fish species distributions	(Olden Julian D. and Jackson Donald A. 2002)	South Central Ontario	27	LRA/LDA/CFT/ANN	11	0	3	4	4
Low mountain ranges: summit traps for montane freshwater species under climate change	(Sauer et al. 2011)	Central Europe	23	GLM/GAM/GBM/CTA/ANN/MARS	12	8	3	1	0
Comparative performance of generalized additive models and multivariate adaptive regression splines for statistical modelling of species distributions	(Leathwick et al. 2005)	New Zealand	15	GAM/MARS	17	3	5	1	8
Development and evaluation of species distribution models for fourteen native central U.S. fish species	(Bouska, Whitledge, and Lant 2015)	Central U.S.	14	GLM/GBM/CTA/RF/MARS	28	6	19	3	0
Use of ecological niche modelling to predict distributions of freshwater fish species in Kansas	(McNyset K. M. 2005)	Eastern Kansas	12	GARP	12	3	7	2	0
Species distributions represent intraspecific genetic diversity of freshwater fish in conservation assessments	(Hermoso Virgilio et al. 2016)	Daly River Basin, Australia	4	MARS	10	0	8	2	0
Ecological niche modeling of *Pteronotropis hubbsj*, the Bluehead Shiner: Evaluating the effects of spatial filtering and Maxent features across various spatial extents	(Hernandez 2015)	SE Texas/ NW Louisiana	1	MAXENT	14	6	3	4	1

The history of species distribution modeling can be classified into 3 main developmental stages. The first stage of SDM development, envelope regression techniques (such as BIOCLIM and DOMAIN) were the most popular methods (Leathwick et al. 2006). These models' results were overly reliant on the spatial locality and species analyzed. In many cases these SDMs would over-predict species occurrence in the bottom 5th and top 5th percentile of range (Carpenter et al. 1993). These original models "elucidate spatial and temporal patterns" of species occurrence records and identify the corresponding variables correlated to that specific site (Carpenter et al. 1993; Leathwick et al. 2006). In this sense, these models were not as statistically robust as they exclusively analyzed environmental covariates independently rather than taking the cumulative effect of the covariates between each occurrence record. Modern methods of species distribution models are proven to outperform these classical models (Stockman et al. 2006; Khatchikian et al. 2011). The latter is supported by the fact that none of the reviewed studies utilized these methodologies.

Computing power and storage limitations restricted the mathematical development of SDMs for some time but the research gradually shifted away from the classical models – also known as climate envelope models – and moved towards the utilization of linear additive models and multivariate linear regression models (Guthery et al. 2003). These multivariate and additive models took shape in the early 21st century as computing power exploded. Some of the most common techniques produced during this time period were the General Additive Model (GAM), General Linear Model (GLM) and the Multivariate Adaptive Regression Splines (MARS) techniques (Bouska et al. 2015). Each of these techniques produced superior area under the curve (AUC) scores than their predecessors (Khatchikian et al. 2011). AUC serves as the main metric for model evaluation – ranging in value from 0 to 1 representing the statistical randomness of the results. In essence, the closer that a model's output is to 1 the better the model does at isolating areas where presences are likely to occur (Elith et al. 2006).

The third stage can be interpreted as a slight deviation from multivariate regression modeling of machine learning methods and quadratic methods were added (Leathwick et al. 2006). As time progressed, more sophisticated computational techniques like Maxent (Phillips, 2006) and Boosted Regression Trees (BRT; Elith et al. 2008) became more widely used. Maxent and BRT are two of the more commonly used species distribution modeling techniques in geography. Based on the literature review (Table 1), Maxent and Boosted Regression Trees (BRT) are often used as stand-alone methods in their respective studies.

Presently, the four most commonly used species distribution modeling techniques stratified against the results of the literature review – this table was derived from a recent study evaluation model performance for "range-shifting" species (Table 2; Elith et al. 2010).

Table 2*: Top SDM occurrence in literature review for "range-shifting" species. This table summarizes the types of SDMs used from Table 1. BRT and Maxent are the two models used most often in the Great Plains/ Red River Basin.*

Species Distribution Modeling Method	**Occurrence in Stream Fish Literature Review**
Boosted Regression Trees (BRT)	(Annis et al. 2012; Bond et al. 2011a)
Maximum Entropy Modeling (MAXENT)	(Labay and Hendrickson 2014; Hernandez 2015)
Generalized Additive Model (GAM)	(Domisch, Jähnig, and Haase 2011; Sauer et al. 2011; Leathwick et al. 2005)
Generalized Linear Model (GLM)	(Domisch, Jähnig, and Haase 2011; Buisson L., Blanc L., and Grenouillet G. 2007; Sauer et al. 2011; Bouska, Whitledge, and Lant 2015)

These studies focus on factors surrounding dendritic ecological networks (DENs) and incorporated climatic, lithospheric and hydrologic variables in one facet or another. Additionally, some research included other covariates ranging from a spatial ranking of habitat suitability – such as the National Fish Habitat Assessment Project (NFHAP) – to weighted measures of distance to coastlines (Leathwick et al. 2005; Labay and Hendrickson 2014). In most cases, the past and projected climate data were derived from WorldClim, which produced 19 global bioenvironmental covariates and can be downscaled to most projects (Fick and Hijmans 2017). WorldClim's datasets utilize a number of global climate models to spatially interpolate both past and future datasets. In the cases where WorldClim was not used in SDM studies, studies typically incorporated a downscaled global climate model similar to the methodology used to create the rasters by WorldClim.org (Domisch et al. 2011). Dendritic ecological networks heavily rely on elevation, slope and aspect in order to create comprehensive networks outlining areas likely to be stream beds. Every study included slope into their model in order to help isolate the DEN. On a relative scale, stream fish theoretically would be found in the lower points of the slope layers in the channels; this seemingly auto-correlated feature is crucial to stream fish species distribution models as it delineates stream channels from land. Additionally, geological/ soil type layers were heavily utilized in these models as they serve as a proxy for conductivity – one of the most influential factors which drives fish assemblage in stream fish populations (Taylor et al. 1993).

The most predictive covariates in these studies are stream flow, stream direction and Strahler stream order. Each of these variables provided inputs to the models to isolate which streams were larger (depth and width) versus smaller. The categorical stream order classification also assisted in the development of cascading input where the higher stream order channels were more likely to contain larger fish.

Empirically, the larger a project (spatially or fish surveyed) the larger the number of bioclimatic covariates used. Published projects sought to include justification and reasoning for the quantity of covariates selected while larger watershed assessment projects incorporated a “black box” method of covariate inclusion (Annis et al. 2012). The proverbial “sweet spot” in the number of covariates used rests at the point where each covariate has a significant contribution to the production of the model. The “black box” approach is used over large swaths of land because each covariate is likely to have a broader range of values as the area of study increases. Regardless of the scale of the project, the general consensus seems to be that each covariate selected for an SDM should have a hypothesized reason for inclusion either to isolate the species’ habitat or assist in driving the projected distribution.

Overall, Maxent and BRT both produce high AUC scores while being relatively parsimonious, making them prime candidates for my application of projecting fish species distributions across climate scenarios in the Red River. Maxent’s strengths are that it has been used in studies that are biogeographically similar to the Red River basin (Labay and Hendrickson 2014; Hernandez 2015) and is an extremely highly accredited model across the broad spectrum of biogeography (Fitzpatrick et al. 2013). Boosted Regression Trees (BRT), like Maxent, is a SDM that has been used on stream fish within the Red River basin in the past (Annis et al. 2012) and has been used on a dynamic temporal scale for modeling climate change effects (Bond et al. 2011).

Summary and Introduction to Chapter 2

This literature review illustrates that species distribution models are powerful quantitative tools for understanding the environmental covariates that drives species’ distributions, and for estimating the future distributions of species across climate scenarios. Based on the literature review, I conclude that Maxent and BRT models are the most appropriate SDMs for stream fishes. In Chapter 2, I use both of these models to characterize future distributions of stream fishes in the Red River, and their variability across climate scenarios. Throughout the analysis, my aim is to inform conservation science in the basin by quantifying the uncertainty and variability in future stream fish distributions across a range of future climate conditions.

Chapter 2: Species Distribution Modeling

Introduction

Climate change and resource uncertainty are widely expected to impact societies and ecosystems throughout the 21st century (Adger et al. 2003). These existential threats to societies and ecosystems around the world are exemplified by global mean temperature rise, climate variability and increased agricultural mechanization (Hansen et al. 2006). Specifically, freshwater aquatic ecosystems face the added pressures of agricultural water extraction, anthropogenic barrier fragmentation and pollution (Strayer and Dudgeon 2010). Riverine ecosystems will be exacerbated by climate change and development as direct human response to mitigate these issues loses pace (Vorosmarty et al. 2000).

Arid and semi-arid river basins in particular may be strongly impacted by climate change because of limited freshwater availability (Zamani Sabzi et al. 2018) and are susceptible to a greater frequency and severity of droughts (Altieri and Nicholls 2017). Drought and decreasing availability of freshwater threaten the diversity, distribution and habitat suitability of stream fish in Great Plains of central North America (Labay and Hendrickson 2014, Perkin and Gido 2011). As resource managers work to allocate water supply, the Red River basin in the south-central plains of the United States exhibits the hallmarks of a drought-prone river basin facing considerable water resource uncertainty. As water demand from agricultural and municipal users continues to increase, less and less water remains available for stream fish habitat (Labay and Hendrickson 2014).

Overuse of water resources paired with anthropogenic barrier construction, increased urbanization and drought lead to stream habitat fragmentation (Perkin and Gido 2011).

Continued human interference within the Red River basin could prove to be detrimental to some vulnerable stream fish in the basin. Stream fish provide essential ecosystem services to humans – for water quality – and each fishes' respective food chains as keystone species contributing to biodiversity. Endangered species like the Leopard Darter (*P. pantherina*) continue to lose habitat from anthropogenic barriers (Bouska and Paukert 2009) while sportfish like the Black Bullhead (*A. melas*) and Blue Catfish (*I. furcatus*) are heavily impacted by shifts in distributional range (Rypel 2009). Based on surrounding research, Red River stream fish are in need of conservation strategies that provide resource managers and environmental planners with vital information to enhance outcomes for these species (Annis et al. 2012).

To understand how changing climate and reduced water availability may alter the distributions of stream fishes, researchers employ mathematical species distribution models. Species distribution models take into account bioclimatic covariates and interpolate them against historic distributions of species in order to produce a probability of occurrence suitability map (Elith et al. 2006). There are a number of different SDM methodologies used which can produce distributional projections for static species and "range-shifting" species alike (Elith et al. 2010). The data input into SDMs involves a level of uncertainty requiring empirical vetting of both covariates and occurrence records to ensure model validity.

In addition to the options of SDMs available for research, climate change modeling incorporates a degree of uncertainty with general circulation model (GCM) and representative concentration pathway (RCP) selection. Over the past few decades, the quantity of GCMs available have drastically increased to incorporate more variables at work in the climate system (Hayhoe et al. 2017). The selection of GCM and RCP scenarios is defined by the geographic and temporal scale of the research.

In this paper, we use two SDMs (Maxent and BRT) to project stream fish distributions across the Red River basin across nine climate scenarios. First, we used a number of spatial variables describing the recent historical environment to fit a SDM for each species. We then projected the distribution of each species under three GCMs (CCSM4, MIROC5 and MPI_ESM_LR) regionally downscaled for the Red River Basin over three RCP (26, 45 and 85) greenhouse gas emission scenarios (Gaitan et al. 2016). These future climate scenarios incorporate our fitted species distribution models and projected values for climatic and hydrologic variables under future climate scenarios. The projections are aimed to provide the most accurate futures for our study region and temporal scale (2050 average and 2070 average). Using these projected future distributions, we summarized inter- and intra-species variability in future stream fish distributions across climate scenarios. The outputs of the species distribution models is intended to assist decision makers in risk assessment of biodiversity in the Red River Basin. The results from this project will serve as a framework of reference for other environmental planners as they seek to assess the impacts of climate change and urbanization within their own localities.

Methods

Selection of fish species and historical data

There are over 150 species of fish in the Red River Basin (Annis et al. 2012). For our analysis, we selected a subset of 31 of these species that collectively span a range of spawning modalities, range width, conservation status and societal value (e.g., sportfish; Table 3). Furthermore, the species selected for this study were chosen to be representative of the basin or are target species for conservation efforts. Final selection of the 31 species was based on consultation with Dr. Bill Matthews and Dr. Edie Marsh Matthews, University of Oklahoma, and members of the Oklahoma Department of Wildlife Conservation (Kurt Kuklinksi and Trevor

Starks). Thus, our species list is generally representative of the management priorities of the Oklahoma Department of Wildlife Conservation and the Texas Parks and Wildlife Department.

Table 3*: The 31 stream fish species used in this analysis. For each species, column headings give common and scientific name; spawning guild based on its method of reproduction; and conservation status according to the USGS species of Greatest Conservation Need (SGCN); IUCN Red List, and NatureServe conservation status assessment*

Common Name	Scientific Name	Spawning Mode	SGCN Tier	IUCN Red List	NatureServe
Pelagic Broadcast Spawners					
Plains Minnow	*Hybognathus placitus*	Pelagic Broadcast (Hoagstrom and Turner 2015)	Species of Concern	Least Concern	Apparently Secure
Prairie chub	*Macrhybopsis australis*	Pelagic Broadcast (Hoagstrom and Turner 2015; Perkin and Gido 2011)	Under Review in the Candidate or Petition Process	Vulnerable	Vulnerable
Red River Shiner	*Notropis bairdi*	Pelagic Broadcast (Hoagstrom and Turner 2015)	N/A	Least Concern	Apparently Secure
Shoal Chub	*Macrhybopsis hyostoma*	Pelagic Broadcast (Perkin and Gido 2011)	N/A	Least Concern	Secure
Silver Chub	*Macrhybopsis storeriana*	Pelagic Broadcast (Perkin and Gido 2011)	N/A	Least Concern	Secure
Riverine Spawners					
Bigeye Shiner	*Notropis boops*	Riverine Species (Hoagstrom, Brooks, and Davenport 2011)	N/A	Least Concern	Secure
Blackspot Shiner	*Notropis atrocaudalis*	Riverine Species (Hoagstrom, Brooks, and Davenport 2011)	N/A	Least Concern	Apparently Secure
Bluehead Shiner	*Pteronotropis hubbsi*	Riverine Species	Under Review in the Candidate or Petition Process	Near Threatened	Vulnerable
Chub Shiner	*Notropis potteri*	Riverine Species (Hoagstrom, Brooks, and Davenport 2011)	N/A	Least Concern	Apparently Secure
Emerald Shiner	*Notropis atherinoides*	Riverine Species (Taylor 2010)	N/A	Least Concern	Secure

Kiamichi Shiner	*Notropis ortenburgeri*	Riverine Species (Hoagstrom, Brooks, and Davenport 2011)	N/A	N/A	Vulnerable
Ouachita Shiner	*Lythrurus snelsoni*	Riverine Species	Species of Concern	Least Concern	Vulnerable
Peppered Shiner	*Notropis perpallidus*	Riverine Species (Hoagstrom, Brooks, and Davenport 2011)	Under Review in the Candidate or Petition Process	Vulnerable	Vulnerable
Plains Killifish	*Fundulus zebrinus*	Broadcast Demersal (Hoagstrom, Brooks, and Davenport 2011)	N/A	Least Concern	Secure
Red Shiner	*Cyprinella lutrensis*	Crev. Spawning Ad. Eggs (Hoagstrom, Brooks, and Davenport 2011)	N/A	Least Concern	Secure
Rocky Shiner	*Notropis suttkusi*	Riverine Species (Hoagstrom, Brooks, and Davenport 2011)	Under Review in the Candidate or Petition Process	N/A	Vulnerable
Sand Shiner	*Notropis stramineus*	Riverine Species (Taylor 2010)	N/A	Least Concern	Secure
Suckermouth Minnow	*Phenacobius mirabilis*	Riverine Species	N/A	Least Concern	Secure
Egg Burriers/ Attachers					
Channel Darter	*Percina copelandi*	Egg Burrier (Hoagstrom, Brooks, and Davenport 2011)	N/A	Least Concern	Apparently Secure
Creole Darter	*Etheostoma collettei*	Egg Burrier/Attacher (Hoagstrom, Brooks, and Davenport 2011)	N/A	Least Concern	Apparently Secure
Leopard Darter	*Percina pantherina*	Egg Burrier (Hoagstrom, Brooks, and Davenport 2011)	Threatened	Endangered	Imperiled
Orangebelly Darter	*Etheostoma radiosum*	Egg Burrier/Attacher (Hoagstrom, Brooks, and Davenport 2011)	N/A	Least Concern	Secure
Red River Pupfish	*Cyprinodon rubrofluviatilis*	Egg Attacher (Hoagstrom, Brooks, and Davenport 2011)	N/A	Least Concern	Secure
Generalist Species					
Blue Catfish	*Ictalurus furcatus*	Nesting	N/A	Least Concern	Secure

Black Bullhead	*Ameiurus melas*	Nesting	N/A	Least Concern	Secure
Green Sunfish	*Lepomis cyanellus*	Nesting	N/A	Least Concern	Secure
Largemouth Bass	*Micropterus salmoides*	Nesting (Hoagstrom, Brooks, and Davenport 2011)	N/A	Least Concern	Secure
Smallmouth Bass	*Micropterus dolomieu*	Nesting (Hoagstrom, Brooks, and Davenport 2011)	N/A	Least Concern	Secure
Spotted Bass	*Micropterus punctulatus*	Nesting (Hoagstrom, Brooks, and Davenport 2011)	N/A	Least Concern	Secure
Striped Bass	*Morone saxatilis*	Nesting	N/A	Least Concern	Secure
Western Mosquitofish	*Gambusia affinis*	Livebearer (Hoagstrom, Brooks, and Davenport 2011)	N/A	Least Concern	Secure

We then grouped the 31 fish species into four spawning guilds: pelagic broadcast spawners, riverine spawners, those that bury or attach their eggs, and generalist species (Table 3). Our intent behind the creation of different guilds was to identify groups of species that might be expected to respond to environmental covariates in a similar way. For example, pelagic broadcast spawners require long stretches of free-flowing river for successful recruitment (Perkin and Gido 2011); thus, we hypothesize that all species in this spawning guild should respond to fragmentation in a similar manner. A number of the fish selected are listed as a “Species of Concern” or “Threatened” by the USGG’s Species of Greatest Conservation Need (SGCN) list or are listed as a priority species by the states of Texas, Oklahoma, Louisiana or Arkansas. Ancillary to these region-specific classifications, a number of species are listed by the International Union for Conservation Nature (IUCN) as “Nearly Threatened,” “Vulnerable,” or “Endangered.” Overall, the above list is a tabulation to best reflect how Red River fish will be affected by both anthropogenic induced fragmentation and climate change.

For each of the 31 species, we gathered historical occurrence records from the Global Biodiversity Information Facility (GBIF, www.gbif.org). GBIF serves as one of the most extensive biogeographical resources in the world (Beck et al. 2014), collecting species occurrence data from peer reviewed research articles' collections and museum collections. We automated the collection of our species occurrence records from GBIF using the R package "dismo" (Hijmans and Elith 2017). This method of collection included removal of duplicate records and eliminated abundance records. The historical occurrence records have a statistically random relative occurrence rate (ROR) as observed within the GBIF relative observation trends function ranging from 30 to 1576 historical records per fish. Verifying that each species' occurrence points are statistically random (ROR) is a necessary step in production of unbiased Maxent and BRT models (Merow et al. 2013).

Overview of modelling approach

Our modeling approach proceeded in three steps. First, we used a suite of spatial variables describing the recent historical environment to fit a species distribution model (SDM) for each species. The variables selected (Table 2) for our SDM analysis are environmental factors within the Red River Basin which are known to drive the distribution of the 31 fish species selected for modeling and are commonly used for modeling stream fish distributions (Annis et al. 2012; Bond et al. 2011; Labay and Hendrickson 2014; Hernandez 2015). As a second step, we projected the distribution of each species under future climate scenarios using our fitted species distribution models and projected values for climatic and hydrologic variables under future climate scenarios. Third, we summarized inter- and intra-species variability in future stream fish distributions across climate scenarios.

Table 4: *Bioclimatic covariates selected to predict distribution. Each covariate is accompanied by its data source and data source for inclusion. Variables are indicated as either continuous or categorical and whether or not they remain static across the future climate scenarios*

Name	**Source**	**Type**	**Change to 2050/2070**
Climatic Covariates			
Annual Mean Temperature	CASC Data	Continuous	Dynamic
Annual Mean Rainfall	CASC Data	Continuous	Dynamic
Mean Temperature of Wettest Quarter	CASC Data	Continuous	Dynamic
Mean Temperature of Driest Quarter	CASC Data	Continuous	Dynamic
Hydrologic Covariates			
Mean Annual Flow	CASC Data	Continuous	Dynamic
Mean Flow of Wettest Quarter	CASC Data	Continuous	Dynamic
Mean Flow of Driest Quarter	CASC Data	Continuous	Dynamic
Strahler Stream Order	NHD	Continuous	Static
Lithospheric Covariates			
National Anthropogenic Barrier Density	NABD	Continuous	Static
Topography	USGS	Continuous	Static
Lithology Type	USGS	Categorical	Static
Land Cover	NLCD	Categorical	Static
National Fish Habitat Action Plan Disturbance Index	NFHAP	Categorical	Static

For both historical and future species distribution models, we used a set of climatic and hydrologic variables derived from recent high-resolution studies of climate and hydrology for the basin (Xue et al. 2016; Gaitan et al. 2016). Climate variables are used in almost every species distribution modeling project, regardless of temporal dimension or type of species modeled (Fick and Hijmans 2017). For stream fish species, climatic variables that indirectly contribute to stream flow are used most often and are often the most predictive variables (Labay and

Hendrickson 2014). We included “Mean Temperature of Driest Quarter” and “Mean Temperature of Wettest Quarter” as duplicate proxies for stream flow for this reason.

We used climatic and hydrologic variables which delineate the ecosystem for conditions of specific locality. Table 4 encapsulates an appropriate list of variables which drive fish occurrence within the Red River Basin (Annis et al. 2012; Labay and Hendrickson 2014, 2014; Perkin and Gido 2012). The climatic and hydrologic variables in our model were produced by McPherson et al. fitted to the dimensions of our historical variables gathered from WorldClim.org (Fick and Hijmans 2017).

We also used lithospheric and anthropogenic covariates that were static across historical and future climate scenarios. Lithospheric (and anthropogenic) datasets are also included in the models to delineate dendritic ecological networks which actualize the locations of streams (i.e. low points). The lithology type (soil type) layer is included to serve as a proxy for conductivity – one of the most important variables driving fish assemblages in the Red River basin (Taylor, et al. 1993). Barrier density is calculated using the National Anthropogenic Barrier database and modeling tool RivEX which created a dataset indicative of the level of fragmentation in the basin. Fragmentation is one of the most detrimental anthropogenic factors driving unnatural stream fish distribution change (Perkin and Gido 2012). The National Fish Habitat Action Plan Index is also used for categorical analysis on anthropogenic effect in the basin as it characterizes stream reach length and human disturbance (Tingley III et. al 2013). Land use is also interpolated to meet the raster grain requirements and used in the model. Land use is utilized as a general way to define areas with heavy urbanization versus areas less developed. Each of the rasters produced are reclassified in order to standardize the resolution among all 13 covariates.

Species Distribution Models

For each of the 31 species in our data set, we fit both a Maxent and BRT model to fit historical distributions as a function of all landscape covariates (Table 2). We chose to use both Maxent and BRT models because they are the most frequently used and most appropriate choices for modeling fish distributions (Hernandez 2015; Labay and Hendrickson 2014; Annis et al. 2012; Bond et al. 2011b), and frequently give complementary projections (Olden and Jackson 2002). An analysis isolating the Bluehead Shiner (*Pteronotropis hubbsi)* in the Red River Basin found that optimizing the regularization multiplier between 1.5x – 2.0x is necessary to prevent over-prediction while staying under the target training omission rate of 30% (Hernandez 2015). Thus, we optimized the regularization multiplier within Maxent and BRT to give more predictive power to the covariates that have the most influence and to penalize the variables which do not influence the model outputs. Additionally, we used a jackknife approach in our Maxent and BRT models for a qualitative analysis on the most influential covariates. By increasing the regularization multiplier, our model generally produced a broader range of projected occurrence probabilities and is better fitted with respect to model area under the curve (AUC) values (Hernandez 2015; Radosavljevic and Anderson 2014).

To project fish distributions under future climate scenarios, we coupled our fitted Maxent and BRT models for each species with projected climatic and hydrologic variables from all combinations of three global climate models (GCMs) and three representative concentration pathways (RCPs) downscaled from South Central Climate Adaptation Science Center, (SC-CASC; Xue et al. 2016; McPherson et al. 2015). Thus, we explored a total of nine future climate scenarios. For each of the 31 fish species tested, one Maxent and one BRT model was produced across each GCM/RCP scenario. The objective of running multiple models per fish for each technique is to best tabulate the projected distribution for each fish based off of a range of future climate scenarios. Each SDM incorporated trained results from historical model runs and parameterized for use in the model runs for future climate scenarios (2050 and 2070). The GCM/RCP scenarios we used selected are the same used in other ongoing Red River Basin projects (Gaitan et al. 2016). Each fish has 9 SDMs modeled (per technique) with respect to each time period. The historical SDMs serve purely as a baseline for each model but are also a useful representation of the current distribution of each species. Each SDM output is analyzed mutually exclusive from one another but the synthesis of the outputs' range delivers the best- and worst-case scenario for each fish. The 9 SDM outputs from each respective modeling technique are identical one another in terms of parameter set-up.

Results

Overall, we found that historical distributions of stream fishes were well explained by both Maxent and BRT models. The majority of model outputs produced an area under the curve (AUC) value of 0.85 or greater; on average 22 of 31 species for Maxent and 31 of 31 species for BRT. Values between 0.7 and 0.9 are considered 'usable' while values above 0.9 are considered excellent (Swets 1988). Additionally, the variable which contributed most to the generation of each model varied among species. In the Maxent models, the lithology type contributed most with an average of 29.14% across models. In BRT, topography was on average the most predictive with an influence of 25.82% (Table 5). Despite the fact that the lithology and topography layers contributed greatly to model generation, the mean temperature of the driest quarter averaged a relative influence of 21.37% in Maxent and 17.20% in BRT. Each of the species distribution raw output maps were produced through R-code and represent the projected distribution of each species (to 2050 or 2070) with respect to its SDM modeling technique, GCM and RCP scenario (Fig. 1, Appendix 1).

We found that species differed markedly in projected changes to their distributional range under future climate scenarios, and also in the variability of these projected outcomes across climate scenarios (Figs. 2-5). For example, both the Maxent model and BRT model suggest that the distributional range of *N. atrocaudalis* or *P. hubbsi* should increase or remain similar in the future. Conversely, both SDMs suggest that *M. punctulatus*, *L. cyanellus*, and *M. salmoides* will be more narrowly distributed in the future. For some species, like *M. saxatilis*, projected changes to their distribution are similar across all nine climate scenarios; ranging from a maximum of -0.52% delta in proportion of cells with a >50% occurrence (under GCM MPI_ESM_LR and RCP 85) to a minimum of -1.59% delta in proportion of cells with a >50% occurrence (under GCM MIROC5and RCP 45) in 2050 under BRT. For other species, like *G. affinis*, changes to their projected range width vary widely across the nine climate scenarios. For this species, its distribution is projected to increase to encompass an additional 7.5% of the basin under the most optimistic climate scenario (under GCM MIROC5 and RCP 45) in 2050 under Maxent. However, the most pessimistic climate scenario is dramatically different, and suggests that its future distribution will contract and fail to include 32% of the basin where it historically occurred (under GCM MPI_ESM_LR and RCP 45). With regard to future time period overall, we found that projected fish distributions in 2070 (Figs. 3, 5) represent an extension of the trends in distributional change observed in 2050 (Figs. 2, 4).

We also found that the greatest absolute changes in distributional range under future climate scenarios occurred for the most widely distributed species (Figs. 6-9). For example, *G. affinis*, *L. cyanellus* and *C. lutrensis* are all widely distributed species within the basin but are projected to drastically decrease in distribution. Conversely, absolute changes to the distributional range of several species that were historically narrowly distributed (e.g., *P.*

pantherina, *N. ortenburgeri*, and *M. australis*) were small because those species were rare to begin with. Each GCM and RCP scenario within both Maxent and BRT produced similar futures for all 31 fish species; the majority of fish in each model run are projected to decrease in occurrence. For example, in the RCP26-MPI_ESM_LR models for both Maxent and BRT the majority of fish show a loss in distribution regardless of the magnitude of their historical range. Model outputs like RCP45-CCSM4 and RCP85-CCSM4 for both Maxent and BRT show similar trends to the latter. Despite the swooping downward trend in future distribution, some models produced more favorable results across the board; RCP45-MIROC5 predicts that a number of stream fishes will increase in projected occurrence (Fig. 3).

Despite differences in how individual species fared among climate scenarios, the average change in range width across the entire fish community was similar across climate scenarios (Figs. 10-13). Each of the 9 methods showed similar results among all 31 fish species regardless of temporal scale, dynamic covariate variability and greenhouse gas emission scenario. Overall, Maxent models produced a larger range of projected occurrence while BRT models range in outputs is smaller. Note that RCP26-MIROC shows that model outputs for all 31 species are extremely similar despite change in temporal scale and modeling method (BRT v.s. Maxent). The majority of other GCM and RCP scenarios follow this trend as well.

Table 5*: Average relative influence of each covariate within both Maxent and BRT models. These values are based solely off of the historical Maxent and BRT models and were then projected into the 2050 and 2070 models.*

Name	**Change to 2050/2070**	**Maxent Avg. Relative Influence**	**BRT Avg. Relative Influence**
Climatic Covariates			
Annual Mean Temperature	Dynamic	4.74%	6.77%
Annual Mean Rainfall	Dynamic	8.03%	5.48%
Mean Temperature of Wettest Quarter	Dynamic	4.64%	11.69%
Mean Temperature of Driest Quarter	Dynamic	21.37%	17.20%
Hydrologic Covariates			
Mean Annual Flow	Dynamic	2.63%	5.10%
Mean Flow of Wettest Quarter	Dynamic	1.09%	2.45%
Mean Flow of Driest Quarter	Dynamic	12.00%	11.41%
Strahler Stream Order	Static	0.66%	2.48%
Lithospheric Covariates			
National Anthropogenic Barrier Density	Static	1.87%	0.96%
Topography	Static	9.46%	25.82%
Lithology Type	Static	29.14%	8.75%
Land Cover	Static	2.35%	0.73%
National Fish Habitat Action Plan Disturbance Index	Static	1.93%	1.08%

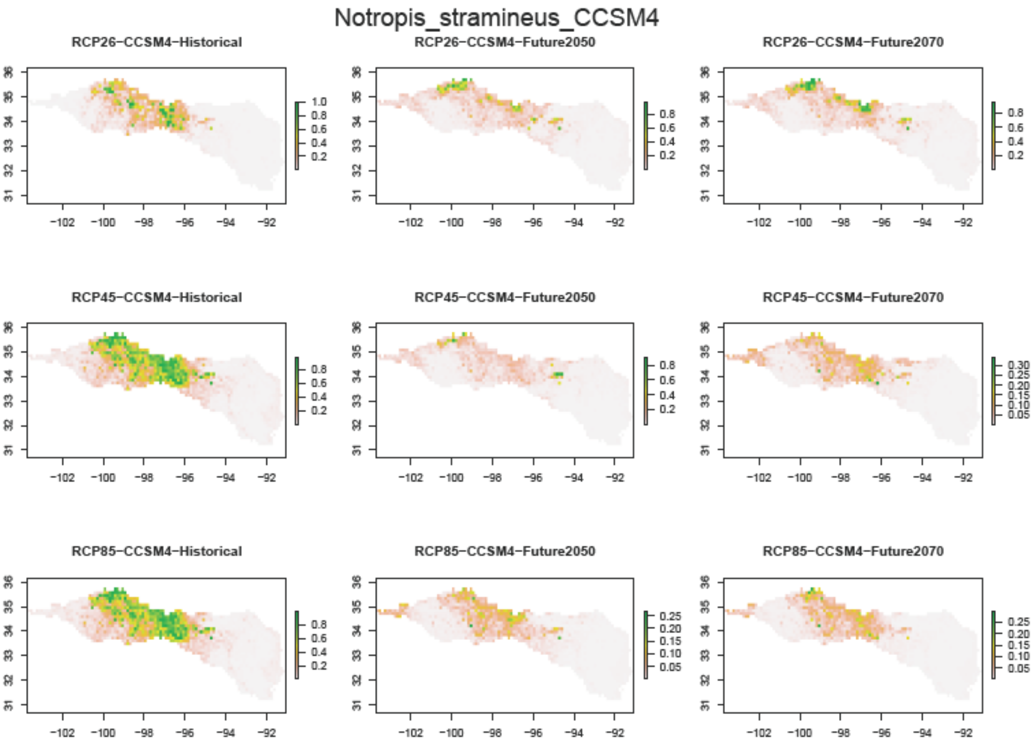


Figure 1*: Example of raw model output from Maxent. Historical distribution (left) is each respective GCM/RCP scenario's historical occurrence and used for Maxent and BRT model training. Projections using SC-CASC climatic and hydrologic variables alter the distribution for species in 2050 (middle) and 2070 (right).*

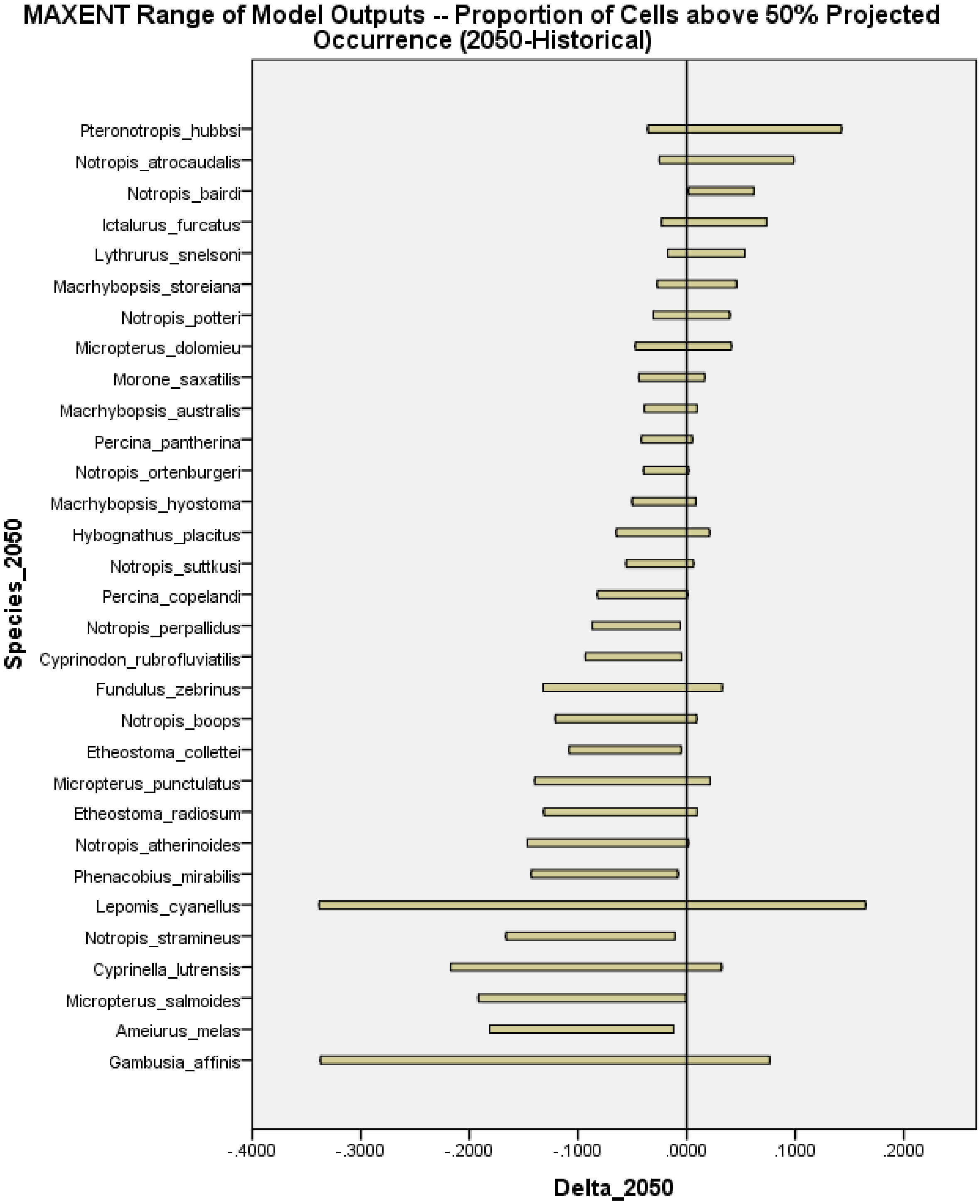


Figure 2: *Variability in species' distributional shifts across 9 future climate scenarios in the Red River. For each species, the horizontal axis gives the difference in the proportion of raster cells with > 50% projected occurrence between the year 2050 and the recent historical period (year 1970 to 2000) based on our Maxent models. The endpoints of each bar give the minimum and maximum value of Delta_2050 observed across the 9 climate scenarios.*

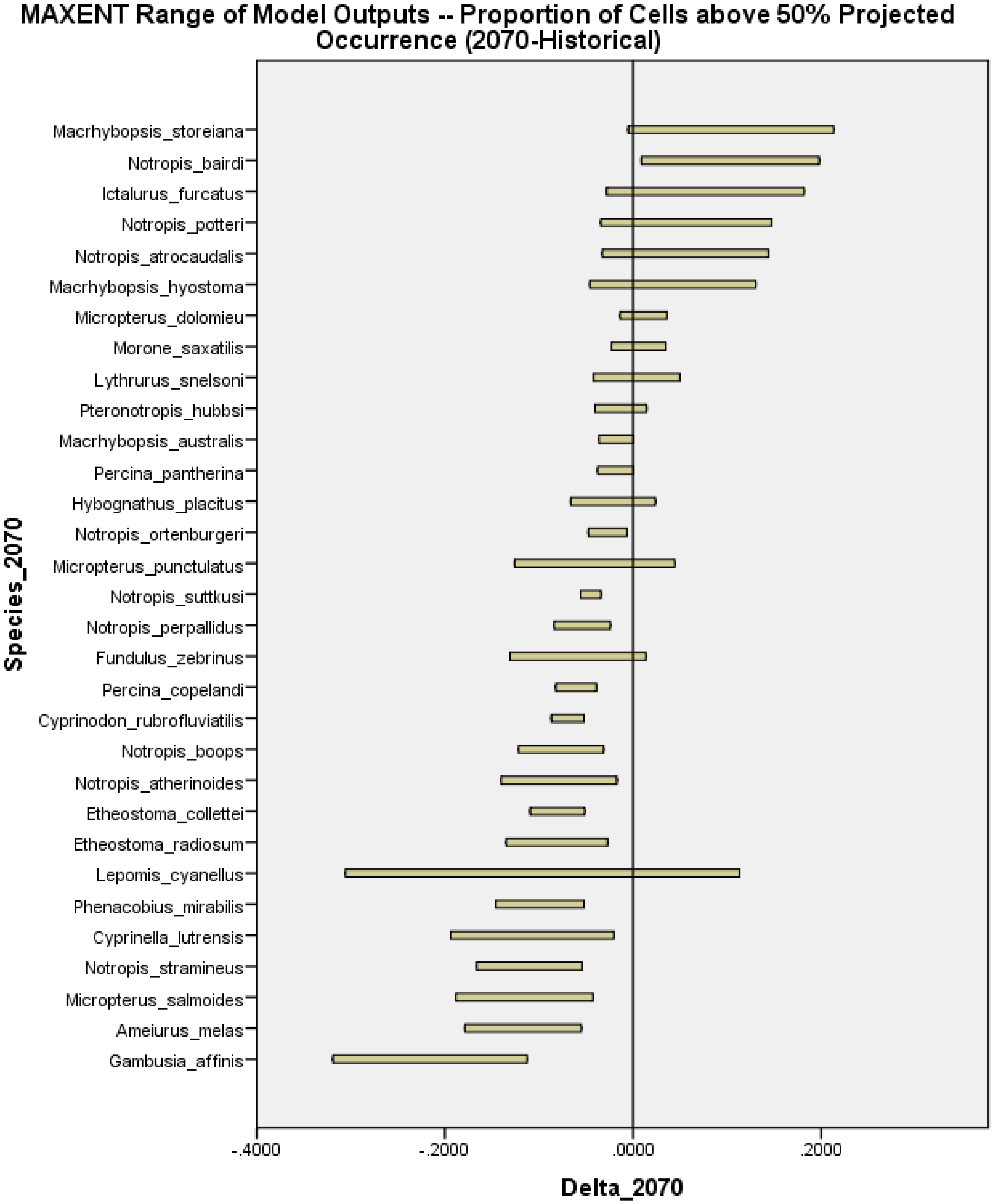


Figure 3: *Variability in species' distributional shifts across 9 future climate scenarios in the Red River. For each species, the horizontal axis gives the difference in the proportion of raster cells with > 50% projected occurrence between the year 2070 and the recent historical period (year 1970 to 2000) based on our Maxent models. The endpoints of each bar give the minimum and maximum value of Delta_2070 observed across the 9 climate scenarios.*

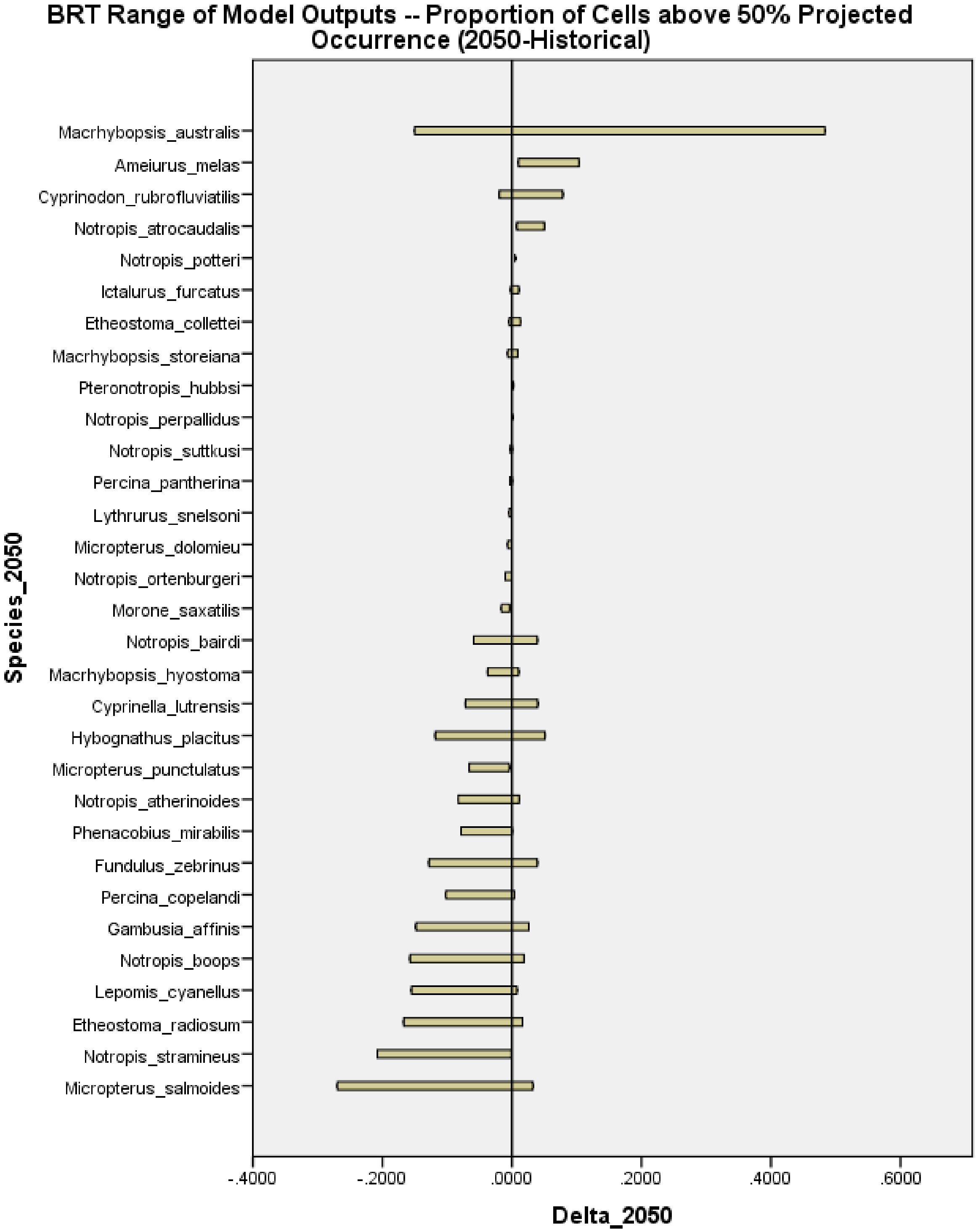


Figure 4: *Variability in species' distributional shifts across 9 future climate scenarios in the Red River. For each species, the horizontal axis gives the difference in the proportion of raster cells with > 50% projected occurrence between the year 2050 and the recent historical period (year 1970 to 2000) based on our BRT models. The endpoints of each bar give the minimum and maximum value of Delta_2050 observed across the 9 climate scenarios.*

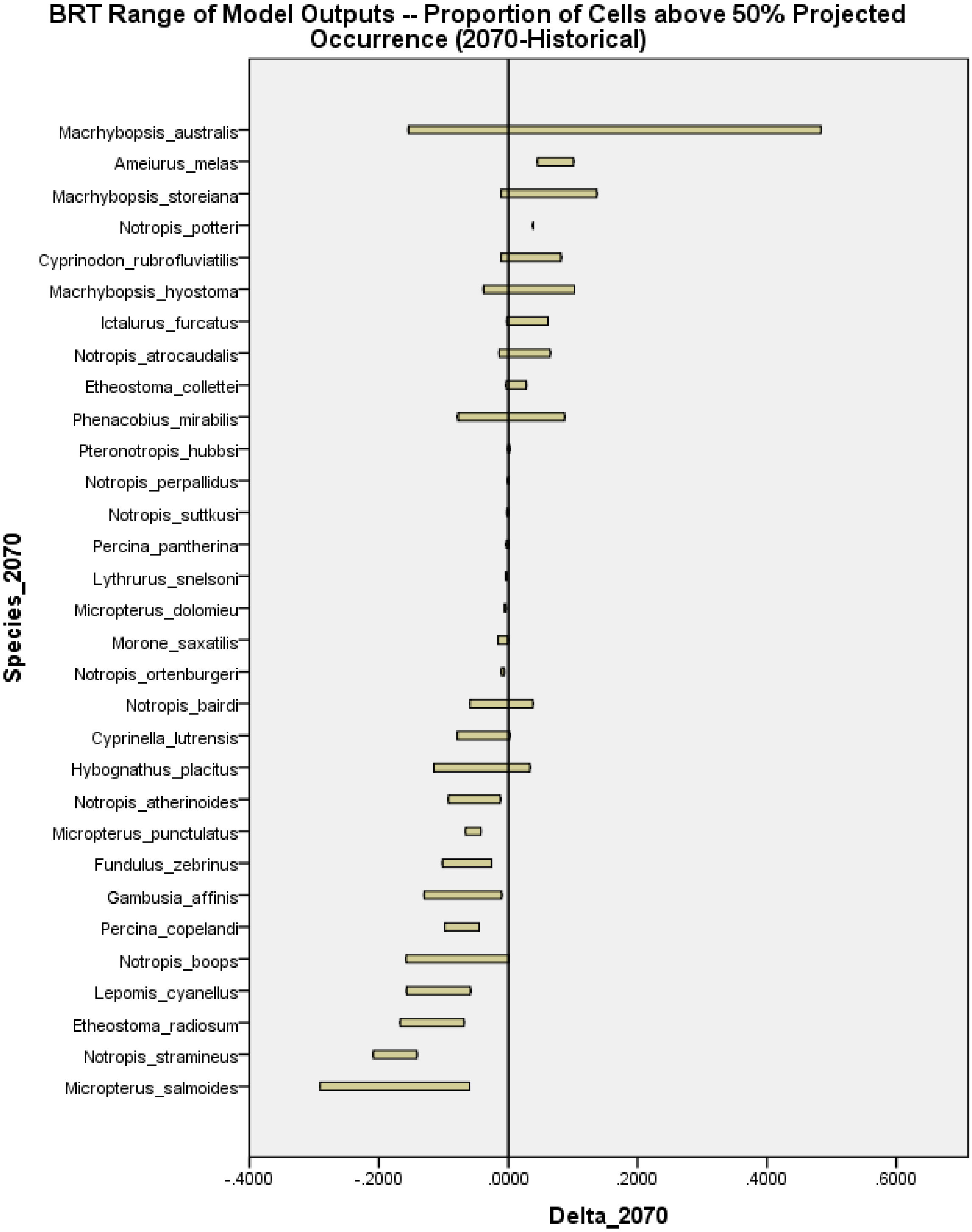


Figure 5: *Variability in species' distributional shifts across 9 future climate scenarios in the Red River. For each species, the horizontal axis gives the difference in the proportion of raster cells with > 50% projected occurrence between the year 2070 and the recent historical period (year 1970 to 2000) based on our BRT models. The endpoints of each bar give the minimum and maximum value of Delta_2070 observed across the 9 climate scenarios.*

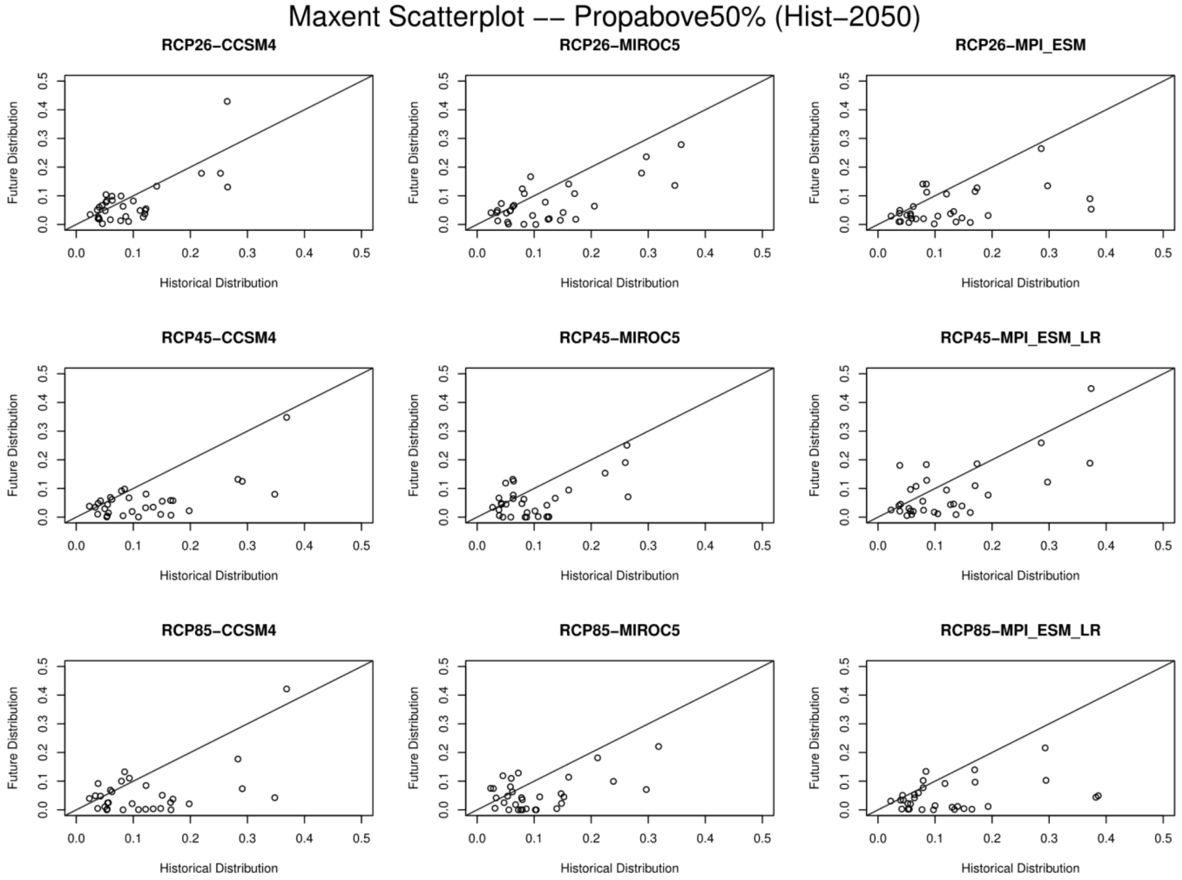


Figure 6*: Comparison of historical vs. future range width for each species in the year 2050 as projected by our Maxent models. Each point on these scatterplots represents a species. Points that fall below the 1:1 line indicate that the range width of that species is projected to contract across the Red River Basin. Alternatively, points that lie above the trend line indicate that the range width of that species is projected to increase across the Red River Basin.*

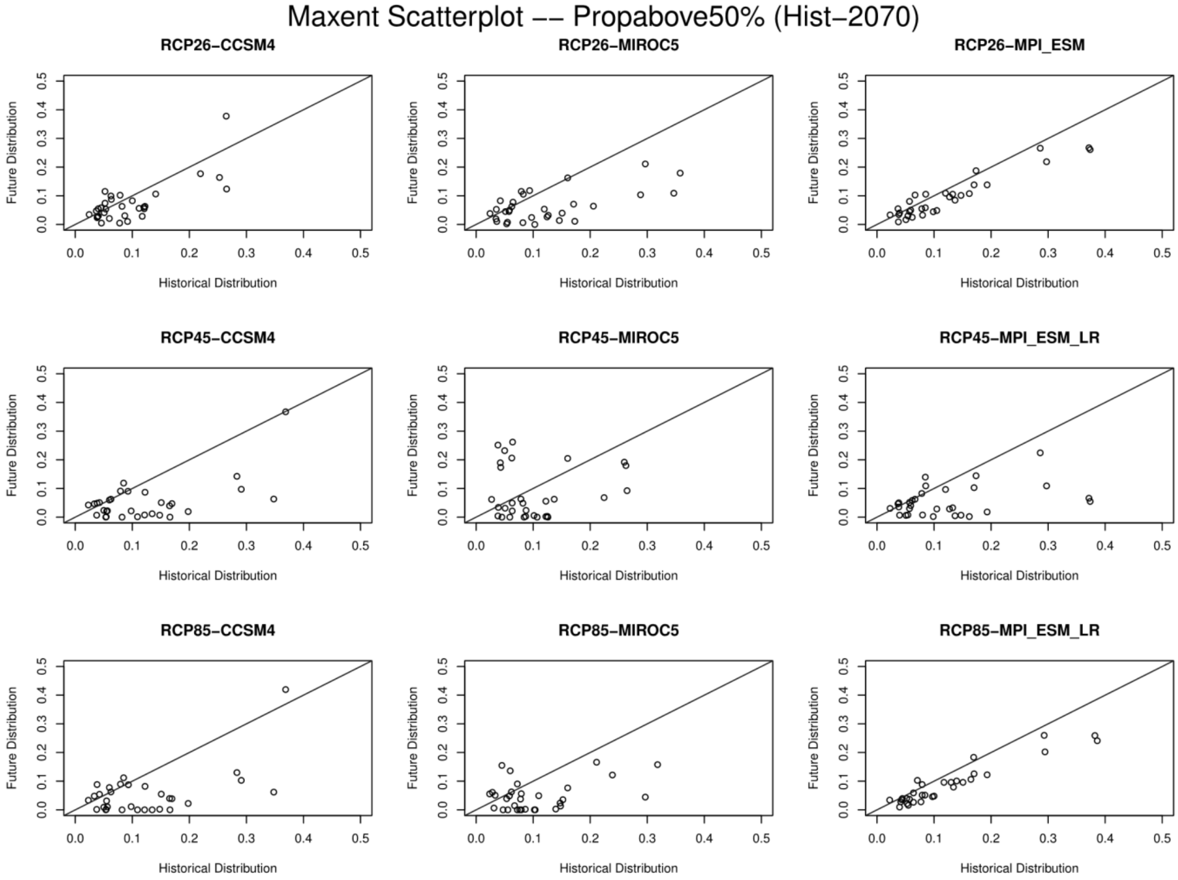


Figure 7*: Comparison of historical vs. future range width for each species in the year 2070 as projected by our Maxent models. Each point on these scatterplots represents a species. Points that fall below the 1:1 line indicate that the range width of that species is projected to contract across the Red River Basin. Alternatively, points that lie above the trend line indicate that the range width of that species is projected to increase across the Red River Basin.*

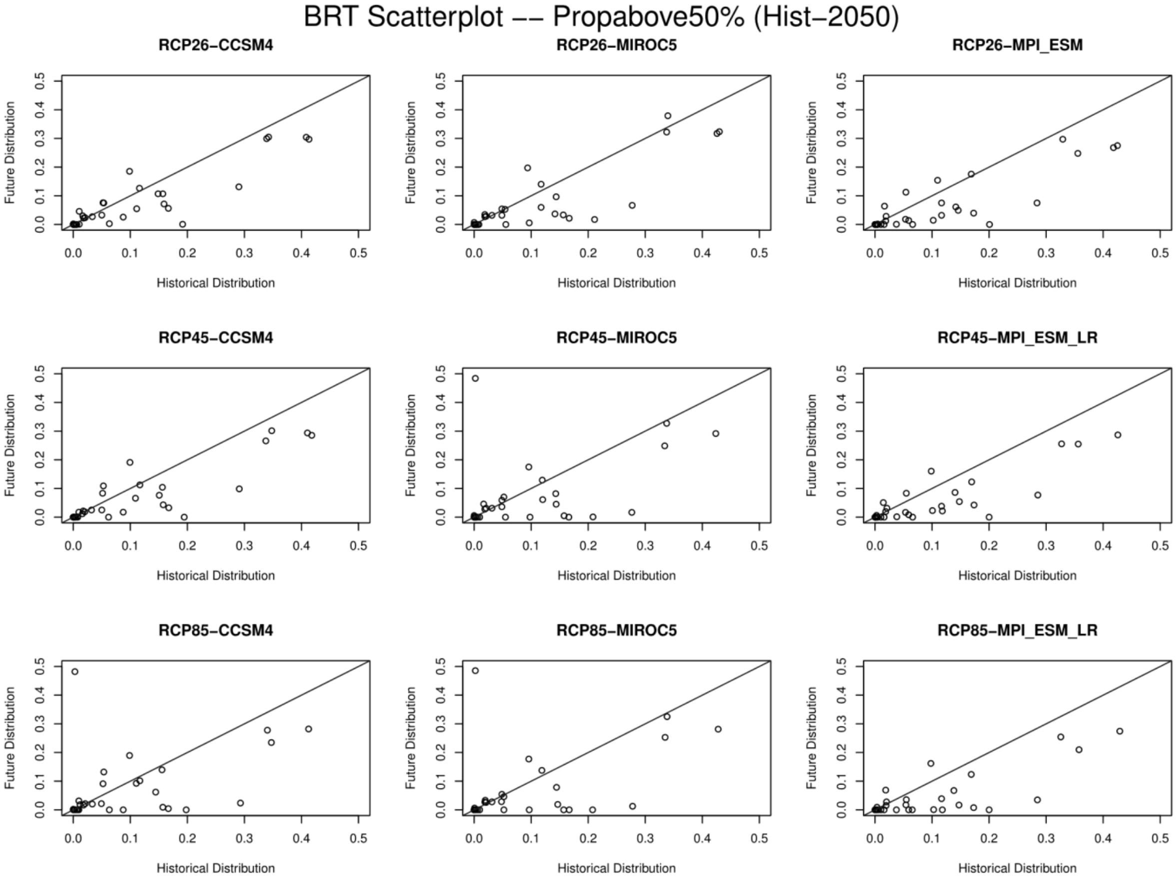


***Figure 8**: Comparison of historical vs. future range width for each species in the year 2050 as projected by our BRT models. Each point on these scatterplots represents a species. Points that fall below the 1:1 line indicate that the range width of that species is projected to contract across the Red River Basin. Alternatively, points that lie above the trend line indicate that the range width of that species is projected to increase across the Red River Basin.*

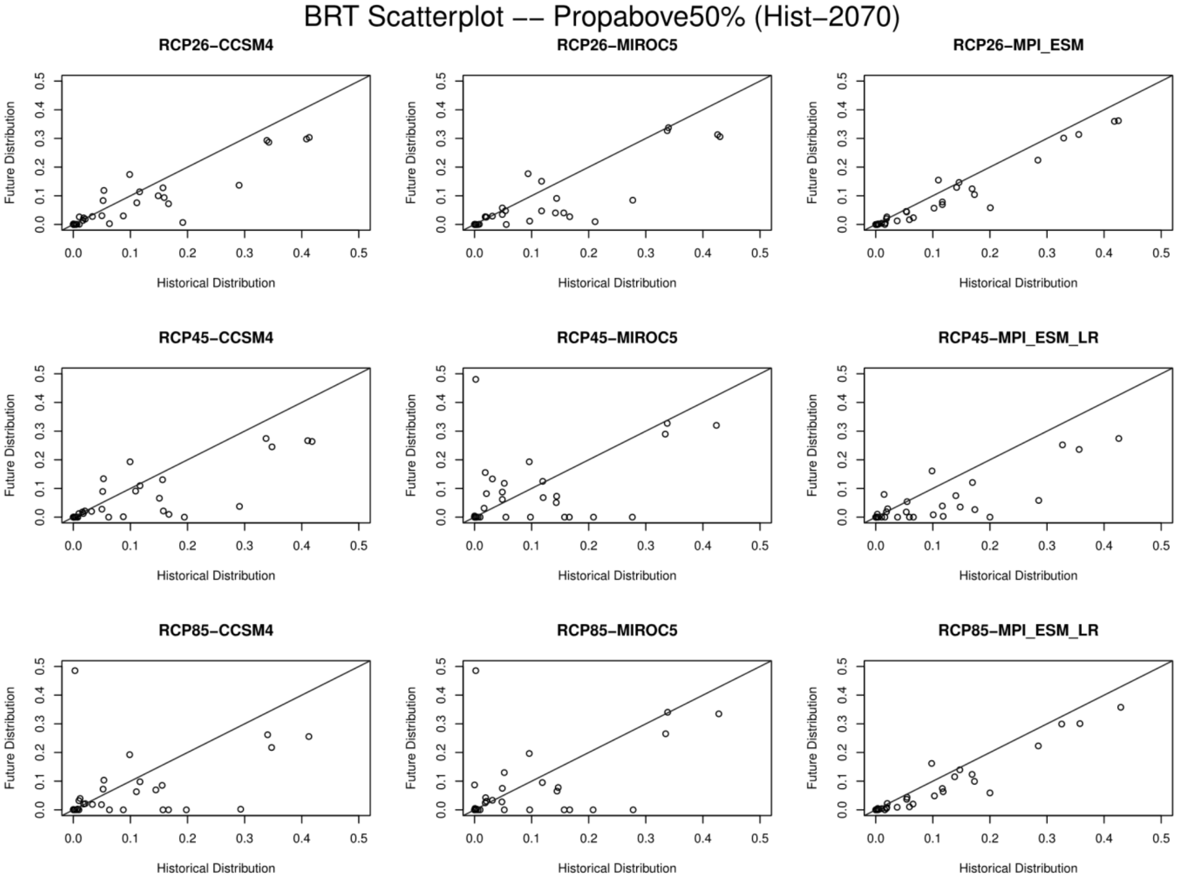


***Figure 9**: Comparison of historical vs. future range width for each species in the year 2070 as projected by our BRT models. Each point on these scatterplots represents a species. Points that fall below the 1:1 line indicate that the range width of that species is projected to contract across the Red River Basin. Alternatively, points that lie above the trend line indicate that the range width of that species is projected to increase across the Red River Basin.*

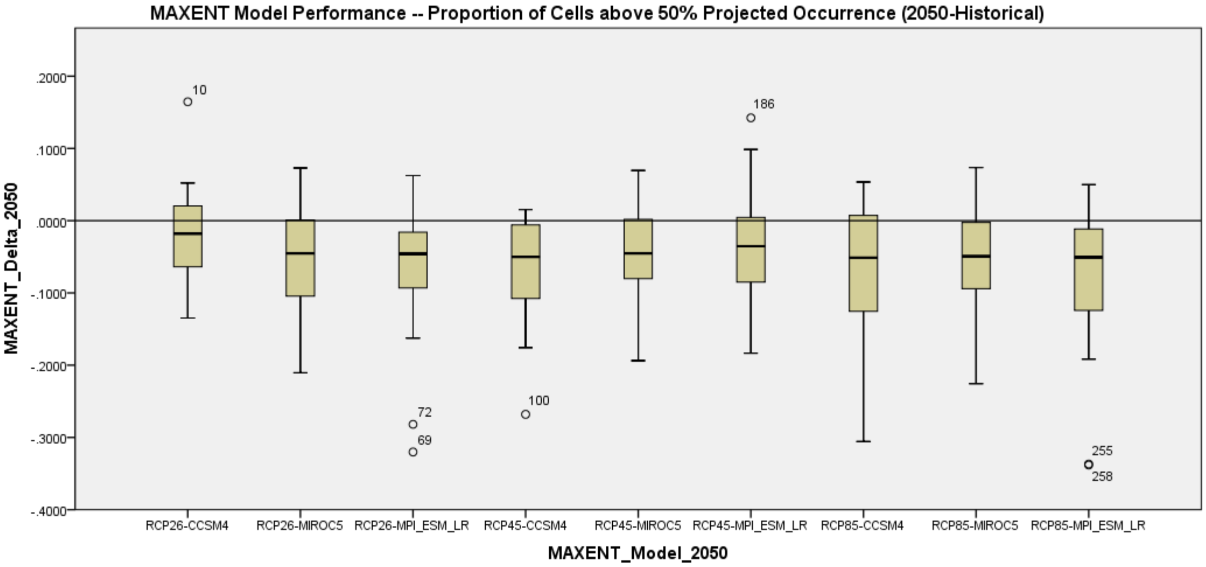


Figure 10*: Summary of the variability among species in changes to their range width across climate scenarios (horizontal axis) in the year 2050 as projected by our Maxent models. Each segment of the boxplot expresses the range of the delta of projected occurrence (50% or greater) for each of the respective GCM/RCP scenarios among all 31 fish.*

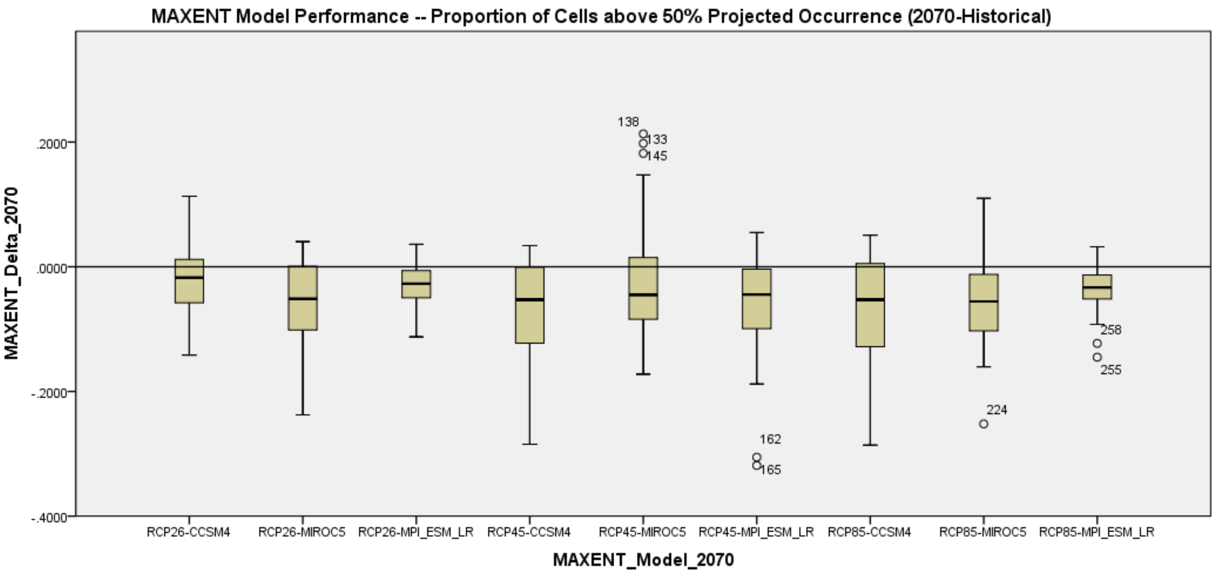


***Figure 11**: Summary of the variability among species in changes to their range width across climate scenarios (horizontal axis) in the year 2070 as projected by our Maxent models. Each segment of the boxplot expresses the range of the delta of projected occurrence (50% or greater) for each of the respective GCM/RCP scenarios among all 31 fish.*

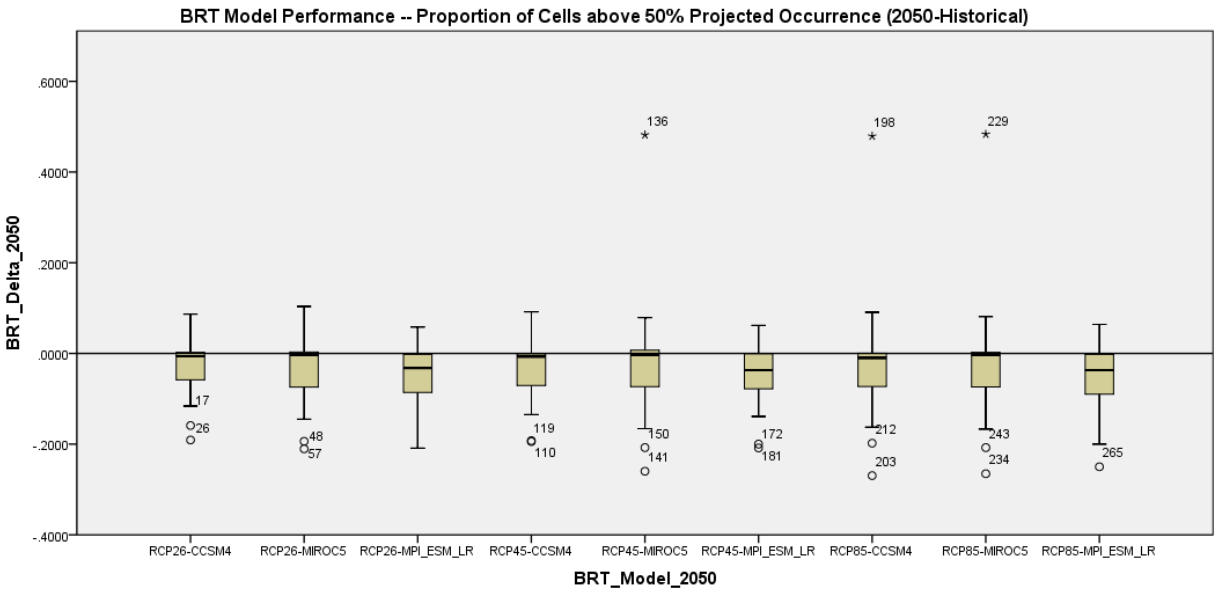


***Figure 12**: Summary of the variability among species in changes to their range width across climate scenarios (horizontal axis) in the year 2050 as projected by our BRT models. Each segment of the boxplot expresses the range of the delta of projected occurrence (50% or greater) for each of the respective GCM/RCP scenarios among all 31 fish.*

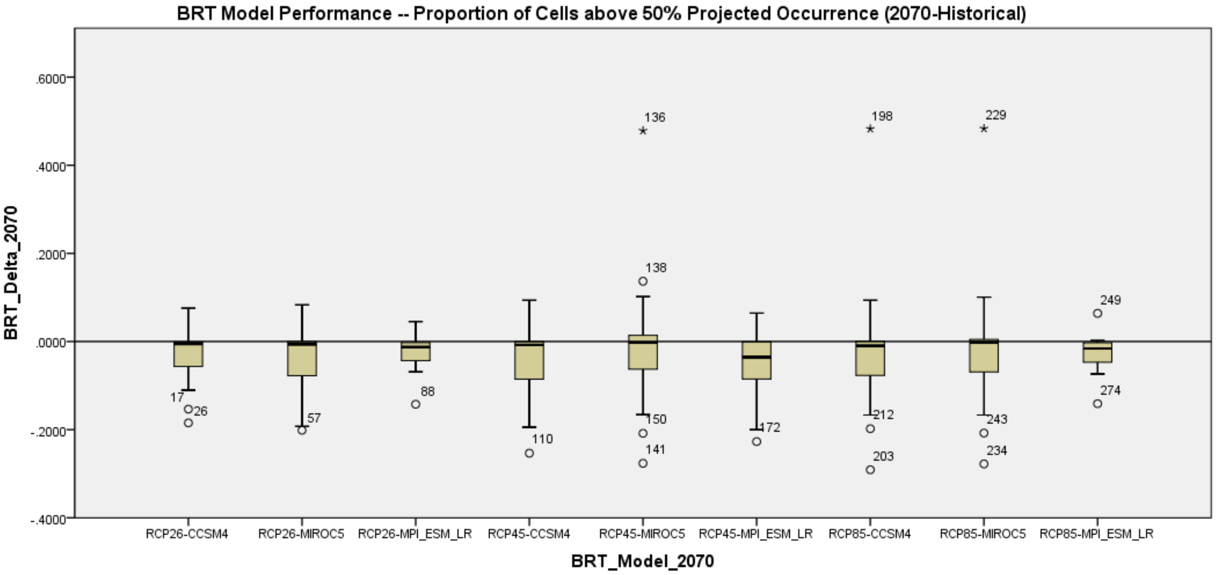


Figure 13*: Summary of the variability among species in changes to their range width across climate scenarios (horizontal axis) in the year 2070 as projected by our BRT models. Each segment of the boxplot expresses the range of the delta of projected occurrence (50% or greater) for each of the respective GCM/RCP scenarios among all 31 fish.*

Table 6*: Average contribution of each climatic, hydrologic and lithospheric covariate averaged for each GCM/ RCP scenario for both Maxent and BRT. Contributions were calculated mutually exclusive from one another with respect to modeling techniques.*

Covariates	**Pelagic Broadcast Spawners**									
	H. placitus		*M. australis*		*N. bairdi*		*M. hystoma*		*M. storeriana*	
	Maxent	BRT	Maxent	BRT	Maxent	BRT	Maxent	BRT	Maxent	BRT
Annual Mean Temp.	0.25	1.37	0.04	3.68	0.21	1.69	0.26	1.39	1.34	1.16
Annual Mean Rainfall	8.72	2.95	21.15	2.67	24.57	3.31	0.71	1.32	0.90	1.00
Mean Temp. of Wettest Qtr.	15.03	50.61	37.44	42.14	24.69	59.17	6.21	3.66	1.30	6.21
Mean Temp.of Driest Qtr.	37.25	3.79	3.36	9.23	6.33	6.72	6.86	10.81	4.17	6.75
Mean Annual Flow	1.64	1.05	2.64	2.47	1.29	0.70	5.18	0.03	0.58	0.36
Mean Flow of Wettest Qtr.	13.68	9.27	15.17	12.60	25.96	3.42	20.77	3.00	23.31	0.44
Mean Flow of Driest Qtr.	0.92	6.22	0.20	1.36	0.70	2.36	4.34	0.26	5.23	2.18
Strahler Stream Order	2.65	1.21	0.45	0.68	1.54	0.82	2.99	0.02	0.27	0.15
NABD Density	0.33	2.87	1.26	0.15	3.05	4.27	0.10	0.33	0.16	0.47
Topography	5.12	10.67	1.03	22.88	1.57	7.60	10.83	10.83	5.05	15.71
Lithology Type	2.54	1.67	1.89	1.30	2.02	0.35	2.22	0.09	6.75	0.44
Land Cover	9.79	5.28	9.38	0.41	7.36	4.29	39.28	67.06	50.73	64.16
NFHAP Disturbance Index	2.07	3.05	5.99	0.43	0.71	5.30	0.26	1.19	0.28	0.94

Covariates	**Riverine Spawners**											
	N. boops		*N. atrocaudalis*		*P. hubbsi*		*N. potteri*		*N. atherinoides*		*N. ortenburgeri*	
	Maxent	BRT	Maxent	BRT	Maxent	BRT	Maxent	BRT	Maxent	BRT	Maxent	BRT
Annual Mean Temp.	29.74	5.84	0.07	0.37	0.00	4.47	1.29	5.74	1.92	2.24	21.25	0.80
Annual Mean Rainfall	0.88	4.86	16.16	22.27	25.04	18.79	0.05	1.95	1.90	1.53	6.00	10.99
Mean Temp. of Wettest Qtr.	0.61	0.49	0.07	0.47	0.00	0.20	20.18	11.88	2.21	5.28	0.05	5.69
Mean Temp.of Driest Qtr.	31.79	33.61	34.58	17.89	0.12	6.01	3.39	2.08	20.93	10.90	1.18	14.53
Mean Annual Flow	0.90	0.02	1.17	0.00	5.70	0.77	5.70	1.69	2.30	4.44	1.97	0.03
Mean Flow of Wettest Qtr.	16.79	5.64	21.38	6.08	51.57	2.06	19.41	1.34	19.91	3.97	23.80	4.13
Mean Flow of Driest Qtr.	0.15	0.16	0.60	3.47	0.23	2.94	3.58	1.36	3.22	4.77	3.66	0.03
Strahler Stream Order	0.47	0.55	0.19	1.26	0.05	0.63	0.58	1.29	2.57	1.49	0.09	0.09
NABD Density	0.08	1.02	0.19	0.21	7.95	9.60	4.08	1.72	0.42	5.52	1.36	0.03
Topography	14.35	45.00	15.56	45.25	0.15	52.00	6.33	16.94	12.32	30.17	0.06	48.96
Lithology Type	4.64	0.82	3.06	0.69	6.21	1.96	3.21	2.57	8.89	0.50	4.34	0.01
Land Cover	1.44	1.46	6.74	0.93	2.63	0.15	30.53	48.02	16.27	9.46	32.65	7.96
NFHAP Disturbance Index	1.02	0.53	0.24	1.11	0.36	0.42	1.94	3.44	7.71	19.74	3.60	6.74

Covariates	**Riverine Spawners (Cont.)**													
	L. snelsoni		*N. perpallidus*		*F. zebrinus*		*C. lutrensis*		*N. suttkusi*		*N. stramineus*		*P. mirabilis*	
	Maxent	BRT	Maxent	BRT	Maxent	BRT	Maxent	BRT	Maxent	BRT	Maxent	BRT	Maxent	BRT
Annual Mean Temp.	1.87	15.89	21.25	0.80	0.09	1.51	0.20	0.97	11.22	0.92	1.96	2.45	0.44	1.15
Annual Mean Rainfall	2.64	19.62	6.00	10.99	7.73	2.84	5.10	1.99	6.55	0.53	11.63	7.13	4.08	4.88
Mean Temp. of Wettest Qtr.	6.45	31.86	0.05	5.69	2.71	4.55	4.66	15.35	0.08	4.34	6.21	10.56	1.78	18.82
Mean Temp.of Driest Qtr.	2.32	14.39	1.18	14.53	68.86	39.01	52.89	19.30	23.34	26.55	28.29	35.97	58.65	28.92
Mean Annual Flow	0.09	1.27	1.97	0.03	0.68	0.48	1.01	0.44	4.70	0.91	4.01	0.27	0.72	4.46
Mean Flow of Wettest Qtr.	66.72	12.00	23.80	4.13	8.58	24.35	8.39	7.49	19.22	6.03	10.42	6.58	13.61	12.89
Mean Flow of Driest Qtr.	0.40	0.00	3.66	0.03	0.66	1.41	2.77	1.28	0.13	0.27	0.53	4.93	3.14	1.56
Strahler Stream Order	6.79	0.01	0.09	0.09	0.81	1.87	1.86	2.10	0.03	0.01	7.45	1.47	9.13	2.30
NABD Density	1.35	0.19	1.36	0.03	0.15	0.55	0.07	0.46	0.03	1.03	1.56	0.93	0.10	0.54
Topography	7.49	0.67	0.06	48.96	2.14	18.07	12.09	43.97	20.82	35.74	14.35	25.90	1.00	22.57
Lithology Type	8.01	0.08	4.34	0.01	5.20	3.07	4.43	3.17	4.20	0.00	9.04	1.64	2.16	0.58
Land Cover	0.43	3.72	32.65	7.96	1.94	2.04	5.71	2.75	1.45	0.35	0.86	1.44	2.83	0.48
NFHAP Disturbance Index	0.26	0.30	3.60	6.74	0.45	0.25	0.86	0.71	10.37	23.31	3.71	0.73	2.41	0.34

Covariates	**Egg Burriers/ Attachers**									
	P. copelandi		*E. collettei*		*P. pantherina*		*E. radiosum*		*C. rubrofluviatilis*	
	Maxent	BRT	Maxent	BRT	Maxent	BRT	Maxent	BRT	Maxent	BRT
Annual Mean Temp.	27.16	41.42	2.72	0.89	0.18	5.93	20.72	53.00	0.15	1.83
Annual Mean Rainfall	0.46	0.14	36.93	8.04	1.95	0.68	1.45	1.34	30.83	2.49
Mean Temp. of Wettest Qtr.	0.00	3.45	7.79	0.12	0.00	3.51	0.78	0.72	7.10	35.62
Mean Temp.of Driest Qtr.	1.90	4.46	3.75	32.33	0.33	2.76	35.11	24.21	27.92	22.98
Mean Annual Flow	3.30	0.25	3.06	0.07	2.41	0.11	0.61	0.10	1.16	0.03
Mean Flow of Wettest Qtr.	21.75	0.26	33.44	32.26	77.92	1.27	8.69	2.97	17.59	17.30
Mean Flow of Driest Qtr.	3.12	1.94	0.01	0.09	1.11	8.90	0.46	0.50	0.83	0.60
Strahler Stream Order	0.75	0.06	1.73	0.54	7.15	4.24	0.26	0.21	2.58	0.62
NABD Density	0.23	1.02	5.21	0.74	0.79	38.41	0.29	0.64	1.34	0.67
Topography	8.75	6.85	0.62	22.65	0.37	14.49	32.03	10.18	0.28	10.07
Lithology Type	1.59	0.10	3.85	1.41	6.80	0.43	2.02	0.29	2.56	0.33
Land Cover	17.24	12.50	0.60	0.13	1.06	1.47	0.11	2.77	5.25	5.51
NFHAP Disturbance Index	18.72	27.56	0.66	0.73	0.06	17.81	2.60	3.07	2.44	1.95

Covariates	**Generalist Species**															
	I. furcatus		*A. melas*		*L. cyanellus*		*M. salmoides*		*M. dolomieu*		*M. punctulatus*		*M. saxatilis*		*G. affinis*	
	Maxent	BRT	Maxent	BRT	Maxent	BRT	Maxent	BRT	Maxent	BRT	Maxent	BRT	Maxent	BRT	Maxent	BRT
Annual Mean Temp.	0.00	0.46	1.06	2.68	2.38	8.78	0.27	0.56	0.81	23.56	2.02	14.38	0.28	2.42	1.31	1.56
Annual Mean Rainfall	0.16	5.24	2.55	2.33	1.32	4.72	1.16	1.25	1.55	7.77	2.93	7.63	9.19	6.99	2.17	1.82
Mean Temp. of Wettest Qtr.	4.48	1.63	2.93	9.69	0.60	6.02	2.73	3.58	1.96	1.88	0.17	1.64	0.31	12.74	1.40	4.95
Mean Temp.of Driest Qtr.	10.20	13.73	27.23	10.21	24.73	19.95	34.21	21.50	10.40	13.60	41.08	39.57	5.15	17.83	47.06	9.26
Mean Annual Flow	1.14	0.03	1.58	0.94	1.12	0.69	5.40	0.03	2.51	0.30	3.82	0.19	5.41	0.08	1.47	0.48
Mean Flow of Wettest Qtr.	42.43	1.38	34.61	28.14	15.93	5.82	25.42	11.66	59.14	10.72	16.35	18.73	34.93	0.25	18.63	15.25
Mean Flow of Driest Qtr.	5.16	4.95	2.12	0.48	1.62	2.79	1.73	2.74	0.36	11.27	0.73	3.72	4.36	0.37	3.84	4.05
Strahler Stream Order	0.77	0.69	1.11	1.43	0.11	0.87	0.65	0.66	0.68	0.53	0.43	2.86	2.46	0.05	0.46	1.07
NABD Density	1.65	0.28	0.16	0.33	0.04	0.26	0.42	0.87	1.10	1.02	0.22	0.35	0.42	0.99	0.65	0.70
Topography	2.14	25.88	9.67	38.63	41.74	45.70	17.59	48.05	11.89	5.29	19.72	6.10	4.87	11.97	13.48	52.98
Lithology Type	10.30	0.04	10.89	0.27	5.89	2.88	4.71	4.30	4.76	0.13	3.20	0.36	16.19	0.54	3.46	3.47
Land Cover	21.38	44.46	5.98	3.90	3.80	0.68	3.17	1.80	0.23	2.96	6.12	3.31	17.28	43.82	4.58	2.69
NFHAP Disturbance Index	0.18	1.23	0.11	0.99	1.58	0.85	2.64	3.00	5.76	20.97	3.97	1.15	0.88	1.96	1.72	1.72

Discussion

Our analysis of fish species distributions under nine future climate scenarios highlights a wide range of outcomes across species and across scenarios in the Red River. We found that the range width of most fish species in the Red River Basin will contract by 2050 and 2070; this was true for both Maxent and BRT models and across all GCM/RCP scenarios (Figs. 2-5). Species also varied dramatically in the uncertainty associated with their future distributions, with the range in outcomes across climate scenarios being more than 10 times higher for some species (e.g., *Lepomis cyanellus)* than for others which showed little variability across scenarios (e.g., *Notropis suttkusi)* Our analysis also revealed that the greatest absolute changes in range width are projected to occur for those species which have been the most widespread historically (Figs. 6-9).

We observed a range of outcomes across species with high societal value (e.g., sportfish), species of greatest conservation need, and other focal species. In some cases, species of conservation importance are projected to expand their ranges under future climate scenarios. The Bluehead Shiner (*P. hubbsi*), for example, is listed as “Vulnerable” by NatureServe and “Near Threatened” by IUCN. Our Maxent models suggest that the future range of this species will increase by 2050 under most climate scenarios (Fig. 2), while our BRT models predict small positive changes in all climate scenarios (Fig. 4). In other cases, our models project substantial habitat loss for species of conservation importance like the endangered Leopard Darter (*P. pantherina*). For this species, a significant loss in habitat is found in Maxent models, paired with a small predicted loss found in our BRT models. Similar dichotomies can be found in the predicted distributions of valuable sportfish. For example, the Blue Catfish (*I. furcatus*) is projected to increase in distribution in most models for 2050 and 2070 while the Largemouth

Bass (*M. salmoides*) is projected to decrease in distribution in all our models. Interestingly, some sportfish project differently between our two modeling techniques: Maxent models show that the Black Bullhead (*A. melas*) will decrease in distribution while BRT predicts that *A. melas* will increase in distribution (Figs. 2-5).

The projected occurrence rates for most species were generally higher in the Maxent models than in the BRT models. However, the proportional change in projected occurrence was similar in both models. Maxent models were more optimistic and had higher raw projected occurrence values when compared to BRT. Despite this, the change in the proportion of cells with a > 50% occurrence was similar between both Maxent and BRT (Figs. 2-5). Nearly all of our model outputs showed a definitive decrease in generalist species. For example, *G. affinis*, *C lutrensis*, *A. melas* and *M. salmoides* will experience drastic loss in occurrence. Species of greatest conservation need (*P. pantherina*, *H. placitus* and *L. snelsoni*) had mixed outputs but generally followed the decreasing trend in occurrence.

The relative importance of each environmental covariate differed greatly among fish species (Table 6). Species with limited historical ranges endemic to the Red River Basin were heavily influenced by lithospheric covariates. Generalist species like. *G. affinis* and *C. lutrensis*, on the other hand, were more heavily influenced by variables representing climatic extremes. Species with a smaller quantity of documented historical occurrence were heavily influenced by topography, anthropogenic barriers and land cover (Table 6). In this sense, these fish species (*P. hubbsi*, *P. pantherina* and *N. ortenburgeri*) have lower projected occurrence as categorical covariates were more susceptible to drive results. This influence of lithospheric covariates can be explained by their localized collinearity driving the distribution to a greater extent than it does for historically more widely distributed fish (De Marco and Nóbrega 2018). Alternatively, generalist species with more historical occurrence points were heavily impacted by dynamic climatic variables. “Mean Temperature of Driest Quarter” and “Mean Flow of Driest Quarter” were among the most influential covariates for generalist species. As the SC-CASC data shows a general increase in temperature and decrease in flow, the models suggest a decrease in range for the generalist species. In all, the anthropogenic restriction of biological parameters within these fish drives change in occurrence. Additionally, we found that SC-CASC projected seasonally extreme temperatures and reduced streamflow are key drivers in future fish distributions within the basin.

Model performance shows that each GCM/RCP scenario under both BRT and Maxent was statistically similar; each respective model run returned a statistically significant AUC value. Variable contribution toward model projections varied across fish species, temporal scale and GCM/RCP scenarios but standalone variables (from jackknife variable analysis) were rarely statistically predictive of a specific fish. The compilation of the 13 variables used in each model was necessary both to accurately calculate model projections and to construct a statistically significant model.

Our analysis of projected fish species distributions under future climate scenarios highlights opportunities for conservation practitioners and decision-makers to make pro-active investments in fish conservation. Climate change conservation strategies vary greatly (Pacifici et al. 2015; Hannah et al. 2002) and require inputs from various methodologies. This project is one of many climate change focused papers primed to provide conservation recommendations. Increased climatic volatility and reduced streamflow within the basin will limit the distribution of generalist species within the basin causing damage to ecological biodiversity and stream health. Despite the difficulty in accurately creating predictive SDMs that account for climate change (Elith and Leathwick 2009), these results show that definitive actions mitigating ill effects of climate change will improve the outlook for aquatic ecosystems (Lawler 2009). Anthropogenic factors such as barriers and land use directly impact SGCN species (Table 1); removal of key anthropogenic barriers (Perkin et al. 2015) paired with improved land use planning (Labay and Hendrickson 2014) can mitigate the negative effects driving occurrence loss for these key species.

Chapter 3: Conclusions

This project demonstrates the ability to utilize downscaled GCM/RCP scenarios for future species distribution model output creation with both Maxent and BRT. In the first chapter, I reviewed various species distribution modeling techniques for stream fishes within semi-arid stream basins. I found that both Maxent and BRT were the most effective species distribution modeling techniques for the size and scale of our project. These techniques were utilized for 31 different stream fish species within the Red River basin over 13 covariates through 2050 and 2070.

In the second chapter we utilized both Maxent and BRT species distribution modeling techniques to produce projected occurrence distribution maps for 2050 and 2070. These outputs can be utilized as key input for future conservation projects. Additionally, the results of this project isolate specific environmental covariate factors which are projected to impact future stream fish distribution the greatest. We found that rainfall and streamflow volatility during the driest quarter of each year show that large scale climate change mitigation is necessary for the survival of biodiversity success within the basin. Additionally, anthropogenic factors like barrier construction and land use further constrain the distribution of vulnerable species endemic to the Red River. The results of this project provide quantitative results crucial to conservation managers specific to the Red River basin and are expected results based off of previous research (Perkin et al. 2015).

Model performance shows that utilizing both Maxent and BRT SDM techniques can be effective approaches in determining the future distribution of our select stream fishes. Similar steps through the species distribution modeling method and covariate selection can be utilized for other semi-arid stream systems. Mainstream integration of conservation practices requires multi-level approach cooperation from the state level action plan with the implementation of best management practices from conservation practitioners (Labay and Hendrickson 2014). Based off of our results, carefully orchestrated implementation of barrier dam removal, water resource reallocation and land use management has the potential to positively impact the range width and population status of key stream fish species within the Red River Basin.

Data gathered from this study could serve as a springboard to additional research focused on species targeted for greatest conservation need or valuable sportfish. Future analysis on stream fishes in Red River basin could include a year by year analysis on each fish as their distribution changes with respect to climate change. Additionally, future studies could take into account different types of SDM techniques, stream fishes or environmental covariates. These future analyses could further refine the temporal changes for specific species distribution with respect to climate change and anthropogenic effects.

Bibliography

"A Working Guide to Boosted Regression Trees - Elith - 2008 - Journal of Animal Ecology - Wiley Online Library." n.d. Accessed May 9, 2018. https://besjournals.onlinelibrary.wiley.com/doi/epdf/10.1111/j.1365-2656.2008.01390.x.

Adger, W. Neil, Saleemul Huq, Katrina Brown, Declan Conway, and Mike Hulme. 2003. "Adaptation to Climate Change in the Developing World." *Progress in Development Studies* 3 (3): 179–95. https://doi.org/10.1191/1464993403ps060oa.

Altieri, Miguel A., and Clara I. Nicholls. 2017. "The Adaptation and Mitigation Potential of Traditional Agriculture in a Changing Climate." *Climatic Change* 140 (1): 33–45. https://doi.org/10.1007/s10584-013-0909-y.

Annis, Gust, Aaron Garringer, Phillip Hanberry, and Michael Morey. 2012. "Modeling Fish Species Distributions throughout the Arkansas, Red, and White River Basins," 1343.

Beck, Jan, Marianne Böller, Andreas Erhardt, and Wolfgang Schwanghart. 2014. "Spatial Bias in the GBIF Database and Its Effect on Modeling Species' Geographic Distributions." *Ecological Informatics* 19 (January): 10–15. https://doi.org/10.1016/j.ecoinf.2013.11.002.

Bond, Nick, Jim Thomson, Paul Reich, and Janet Stein. 2011a. "Using Species Distribution Models to Infer Potential Climate Change-Induced Range Shifts of Freshwater Fish in South-Eastern Australia." *Marine and Freshwater Research* 62 (9): 1043. https://doi.org/10.1071/MF10286.

Bouska, Kristen L., Gregory W. Whitledge, and Christopher Lant. 2015. "Development and Evaluation of Species Distribution Models for Fourteen Native Central U.S. Fish Species." *Hydrobiologia* 747 (1): 159–76. https://doi.org/10.1007/s10750-014-2134-8.

Buisson L., Blanc L., and Grenouillet G. 2007. "Modelling Stream Fish Species Distribution in a River Network: The Relative Effects of Temperature versus Physical Factors." *Ecology of Freshwater Fish* 17 (2): 244–57. https://doi.org/10.1111/j.1600-0633.2007.00276.x.

Buisson, Laëtitia, Wilfried Thuiller, Sovan Lek, Puy Lim, and Gaël Grenouillet. 2008. "Climate Change Hastens the Turnover of Stream Fish Assemblages." *Global Change Biology* 14 (10): 2232–48. https://doi.org/10.1111/j.1365-2486.2008.01657.x.

Carpenter, G., A. N. Gillison, and J. Winter. 1993. "DOMAIN: A Flexible Modelling Procedure for Mapping Potential Distributions of Plants and Animals." *Biodiversity and Conservation* 2 (6): 667–80. https://doi.org/10.1007/BF00051966.

Christopher M. Taylor, Matthew R. Winston, and William J. Matthews. 1993. "Fish Species-Environment and Abundance Relationships in a Great Plains River System." *Ecography* 16 (1): 16–23.

De Marco, Paulo, and Caroline Corrêa Nóbrega. 2018. "Evaluating Collinearity Effects on Species Distribution Models: An Approach Based on Virtual Species Simulation." *PLoS ONE* 13 (9). https://doi.org/10.1371/journal.pone.0202403.

Domisch, Sami, Sonja C. Jähnig, and Peter Haase. 2011. "Climate-Change Winners and Losers: Stream Macroinvertebrates of a Submontane Region in Central Europe." *Freshwater Biology* 56 (10): 2009–20. https://doi.org/10.1111/j.1365-2427.2011.02631.x.

Domisch, Sami, Sonja C. Jähnig, John P. Simaika, Mathias Kuemmerlen, and Stefan Stoll. 2015. "Application of Species Distribution Models in Stream Ecosystems: The Challenges of Spatial and Temporal Scale, Environmental Predictors and Species Occurrence Data."

Fundamental and Applied Limnology, February, 45–61. https://doi.org/10.1127/fal/2015/0627.

Elith, Jane, Catherine H. Graham, Robert P. Anderson, Miroslav Dudík, Simon Ferrier, Antoine Guisan, Robert J. Hijmans, et al. 2006a. “Novel Methods Improve Prediction of Species’ Distributions from Occurrence Data.” *Ecography* 29 (2): 129–51. https://doi.org/10.1111/j.2006.0906-7590.04596.x.

Elith, Jane, Michael Kearney, and Steven Phillips. 2010. “The Art of Modelling Range-Shifting Species: The Art of Modelling Range-Shifting Species.” *Methods in Ecology and Evolution* 1 (4): 330–42. https://doi.org/10.1111/j.2041-210X.2010.00036.x.

Elith, Jane, and John R. Leathwick. 2009. “Species Distribution Models: Ecological Explanation and Prediction Across Space and Time.” *Annual Review of Ecology, Evolution, and Systematics* 40 (1): 677–97. https://doi.org/10.1146/annurev.ecolsys.110308.120159.

Fick, Stephen E., and Robert J. Hijmans. 2017. “WorldClim 2: New 1-Km Spatial Resolution Climate Surfaces for Global Land Areas: NEW CLIMATE SURFACES FOR GLOBAL LAND AREAS.” *International Journal of Climatology* 37 (12): 4302–15. https://doi.org/10.1002/joc.5086.

Fitzpatrick Matthew C., Gotelli Nicholas J., and Ellison Aaron M. 2013. “MaxEnt versus MaxLike: Empirical Comparisons with Ant Species Distributions.” *Ecosphere* 4 (5): art55. https://doi.org/10.1890/ES13-00066.1.

Gaitán, C. F., et al. "Statistically Downscaled Datasets for the Red River Basin, South Central USA." (2016).

Gomes, Vitor H. F., Stéphanie D. IJff, Niels Raes, Iêda Leão Amaral, Rafael P. Salomão, Luiz Souza Coelho, Francisca Dionízia Almeida Matos, et al. 2018. “Species Distribution Modelling: Contrasting Presence-Only Models with Plot Abundance Data.” *Scientific Reports* 8 (1): 1003. https://doi.org/10.1038/s41598-017-18927-1.

Guthery, Fred S., Kenneth P. Burnham, and David R. Anderson. 2003. “Model Selection and Multimodel Inference: A Practical Information-Theoretic Approach.” *The Journal of Wildlife Management* 67 (3): 655. https://doi.org/10.2307/3802723.

Hannah, L., G. F. Midgley, and D. Millar. 2002. “Climate Change-Integrated Conservation Strategies.” *Global Ecology and Biogeography* 11 (6): 485–95. https://doi.org/10.1046/j.1466-822X.2002.00306.x.

Hansen, J., M. Sato, R. Ruedy, K. Lo, D. W. Lea, and M. Medina-Elizade. 2006. “Global Temperature Change.” *Proceedings of the National Academy of Sciences* 103 (39): 14288–93. https://doi.org/10.1073/pnas.0606291103.

Hawkins, Ed, and Rowan Sutton. 2009. “The Potential to Narrow Uncertainty in Regional Climate Predictions.” *Bulletin of the American Meteorological Society* 90 (8): 1095–1108. https://doi.org/10.1175/2009BAMS2607.1.

Hayhoe, Katharine & Edmonds, James & Kopp, Robert & LeGrande, Allegra & Sanderson, Benjamin & Wehner, Michael & Wuebbles, Donald. (2017). Climate models, scenarios, and projections.

Hermoso Virgilio, Kennard Mark J., Schmidt Daniel J., Bond Nick, Huey Joel A., Mondol Rashedul K., Jamandre Brian W., and Hughes Jane M. 2016. “Species Distributions Represent Intraspecific Genetic Diversity of Freshwater Fish in Conservation Assessments.” *Freshwater Biology* 61 (10): 1707–19. https://doi.org/10.1111/fwb.12810.

Hernandez, Justin Matthew. 2015. “Ecological Niche Modeling of Pteronotropis Hubbsi, the Bluehead Shiner: Evaluating the Effects of Spatial Filtering and Maxent Features Across Various Spacial Extents,” 207.

Hijmans, Robert J., et al. "Package ‘dismo’." *Circles* 9.1 (2017).

Hoagstrom, Christopher W., James E. Brooks, and Stephen R. Davenport. 2011. “A Large-Scale Conservation Perspective Considering Endemic Fishes of the North American Plains.” *Biological Conservation* 144 (1): 21–34. https://doi.org/10.1016/j.biocon.2010.07.015.

Hoagstrom, Christopher W, and Thomas F Turner. 2015. “Recruitment Ecology of Pelagic-Broadcast Spawning Minnows: Paradigms from the Ocean Advance Science and Conservation of an Imperilled Freshwater Fauna.” *Fish and Fisheries* 16 (2): 282–99. https://doi.org/10.1111/faf.12054.

Khatchikian, C., F. Sangermano, D. Kendell, and T. Livdahl. 2011. “Evaluation of Species Distribution Model Algorithms For Fine-Scale Container Breeding Mosquito Risk Prediction.” *Medical and Veterinary Entomology* 25 (3): 268–75. https://doi.org/10.1111/j.1365-2915.2010.00935.x.

Labay, Ben, and Dean Hendrickson. 2014. “Final Report: Conservation Assessment and Mapping Products for GPLCC Priority Fish Taxa.” . . *Final Report*, 46.

Lawler, Joshua J. 2009. “Climate Change Adaptation Strategies for Resource Management and Conservation Planning.” *Annals of the New York Academy of Sciences* 1162 (1): 79–98. https://doi.org/10.1111/j.1749-6632.2009.04147.x.

Leathwick, J. R., J. Elith, and T. Hastie. 2006. “Comparative Performance of Generalized Additive Models and Multivariate Adaptive Regression Splines for Statistical Modelling of Species Distributions.” *Ecological Modelling*, Predicting Species Distributions, 199 (2): 188–96. https://doi.org/10.1016/j.ecolmodel.2006.05.022.

Leathwick, J. R., D. Rowe, J. Richardson, J. Elith, and T. Hastie. 2005. “Using Multivariate Adaptive Regression Splines to Predict the Distributions of New Zealand’s Freshwater Diadromous Fish.” *Freshwater Biology* 50 (12): 2034–52. https://doi.org/10.1111/j.1365-2427.2005.01448.x.

McNyset K. M. 2005. “Use of Ecological Niche Modelling to Predict Distributions of Freshwater Fish Species in Kansas.” *Ecology of Freshwater Fish* 14 (3): 243–55. https://doi.org/10.1111/j.1600-0633.2005.00101.x.

Merow, Cory, Matthew J. Smith, and John A. Silander. 2013a. “A Practical Guide to MaxEnt for Modeling Species’ Distributions: What It Does, and Why Inputs and Settings Matter.” *Ecography* 36 (10): 1058–69. https://doi.org/10.1111/j.1600-0587.2013.07872.x.

Olden Julian D., and Jackson Donald A. 2002. “A Comparison of Statistical Approaches for Modelling Fish Species Distributions.” *Freshwater Biology* 47 (10): 1976–95. https://doi.org/10.1046/j.1365-2427.2002.00945.x.

Pacifici, Michela, Wendy B. Foden, Piero Visconti, James E. M. Watson, Stuart H.M. Butchart, Kit M. Kovacs, Brett R. Scheffers, et al. 2015. “Assessing Species Vulnerability to Climate Change.” *Nature Climate Change* 5 (3): 215–24. https://doi.org/10.1038/nclimate2448.

Perkin, Joshuah S., and Keith B. Gido. 2011. “Stream Fragmentation Thresholds for a Reproductive Guild of Great Plains Fishes.” *Fisheries* 36 (8): 371–83. https://doi.org/10.1080/03632415.2011.597666.

Joshuah S. Perkin, and Keith B. Gido. 2012. “Fragmentation Alters Stream Fish Community Structure in Dendritic Ecological Networks.” *Ecological Applications* 22 (8): 2176–87.

Perkin, Joshuah S., Keith B. Gido, Arthur R. Cooper, Thomas F. Turner, Megan J. Osborne, Eric R. Johnson, and Kevin B. Mayes. 2015. “Fragmentation and Dewatering Transform Great Plains Stream Fish Communities.” *Ecological Monographs* 85 (1): 73–92. https://doi.org/10.1890/14-0121.1.

Phillips, Steven. n.d. “A Brief Tutorial on Maxent,” 29.

Radosavljevic, Aleksandar, and Robert P. Anderson. 2014. “Making Better M AXENT Models of Species Distributions: Complexity, Overfitting and Evaluation.” Edited by Miguel Araújo. *Journal of Biogeography* 41 (4): 629–43. https://doi.org/10.1111/jbi.12227.

Ralph W. Tingley III, Arthur Cooper, Daniel Wieferich, Dana M. Infante, Peter C. Esselman, Lizhu Wang, William W. Taylor, And Jacqueline Fenner. 2013. “National Fish Habitat Action Plan (NFHAP) 2010 HCI Scores and Human Disturbance Data for Hawaii Linked to NFHAP Catchments (Developed Using the 1:24,000 Scale National Hydrography Dataset) VERSION 2.0.” U.S. Geological Survey. https://doi.org/10.5066/F7V9863B.

Sauer, Jan, Sami Domisch, Carsten Nowak, and Peter Haase. 2011. “Low Mountain Ranges: Summit Traps for Montane Freshwater Species under Climate Change.” *Biodiversity and Conservation* 20 (13): 3133–46. https://doi.org/10.1007/s10531-011-0140-y.

Stockman, Amy K., David A. Beamer, and Jason E. Bond. 2006. “An Evaluation of a GARP Model as an Approach to Predicting the Spatial Distribution of Non-Vagile Invertebrate Species.” *Diversity <html_ent Glyph="@amp;" Ascii="&"/> Distributions* 12 (1): 81–89. https://doi.org/10.1111/j.1366-9516.2006.00225.x.

Strayer, David L., and David Dudgeon. 2010. “Freshwater Biodiversity Conservation: Recent Progress and Future Challenges.” *Journal of the North American Benthological Society* 29 (1): 344–58. https://doi.org/10.1899/08-171.1.

Swets, J.A. 1988. Measuring the accuracy of diagnostic systems. Science. 240: 1285– 1293.

Taylor, Christopher M. 2010. “Covariation Among Plains Stream Fish Assemblages, Flow Regimes, and Patterns of Water Use,” 14.

Taylor, Christopher M., Matthew R. Winston, and William J. Matthews. 1993. “Fish Species-Environment and Abundance Relationships in a Great Plains River System.” *Ecography* 16 (1): 16–23. https://doi.org/10.1111/j.1600-0587.1993.tb00054.x.

VanDerWal, Jeremy, Luke P. Shoo, Christopher N. Johnson, and Stephen E. Williams. 2009. “Abundance and the Environmental Niche: Environmental Suitability Estimated from Niche Models Predicts the Upper Limit of Local Abundance.” *The American Naturalist* 174 (2): 282–91. https://doi.org/10.1086/600087.

Vorosmarty, C. J. 2000. “Global Water Resources: Vulnerability from Climate Change and Population Growth.” *Science* 289 (5477): 284–88. https://doi.org/10.1126/science.289.5477.284.

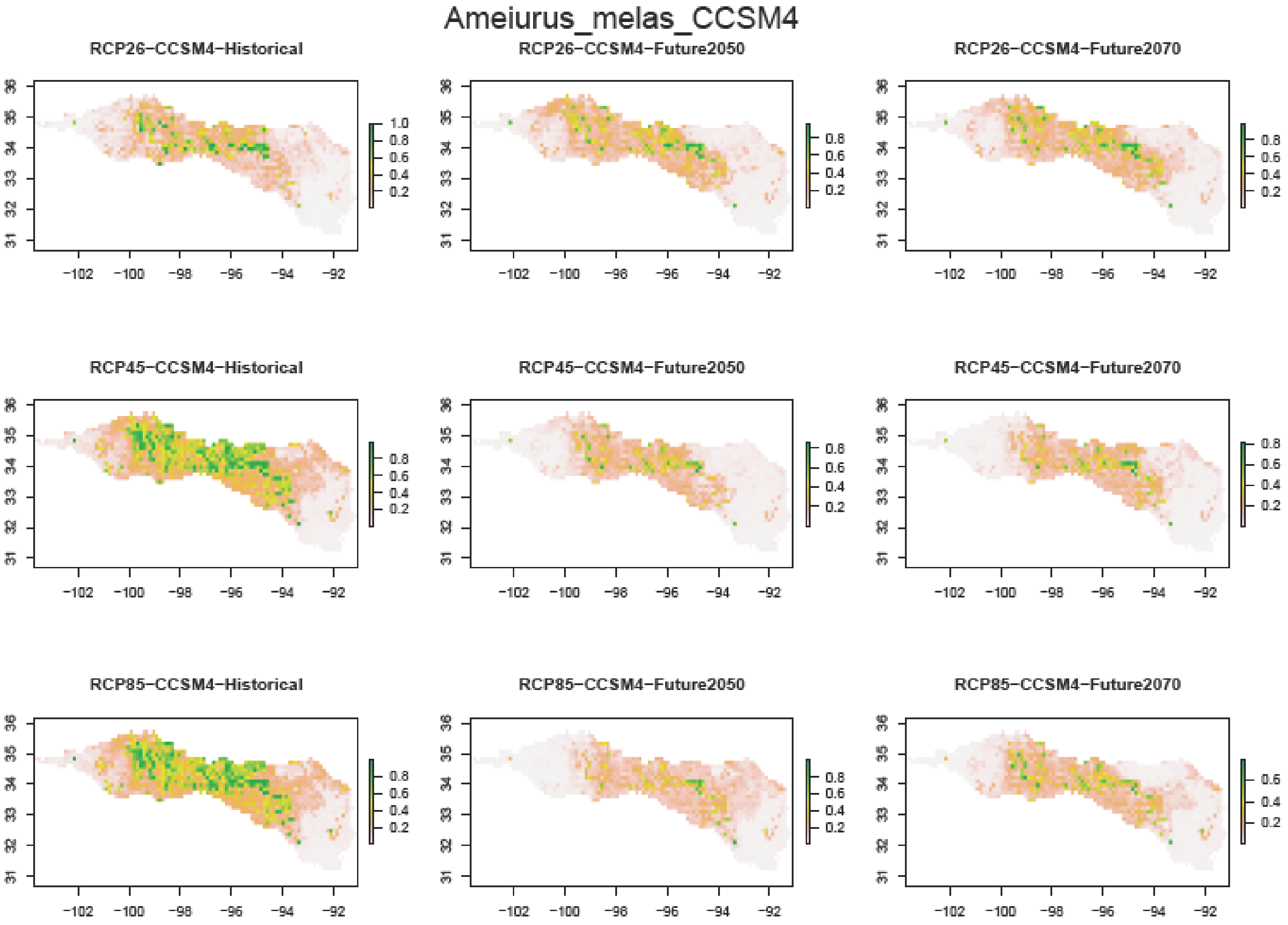
Xue, Xianwu, Ke Zhang, Yang Hong, Jonathan J. Gourley, Wayne Kellogg, Renee A. McPherson, Zhanming Wan, and Barney N. Austin. 2016. “New Multisite Cascading Calibration Approach for Hydrological Models: Case Study in the Red River Basin Using the VIC Model.” *Journal of Hydrologic Engineering* 21 (2): 05015019. https://doi.org/10.1061/(ASCE)HE.1943-5584.0001282.

Zamani Sabzi, Hamed, Shalamu Abudu, Reza Alizadeh, Leili Soltanisehat, Naci Dilekli, and James Phillip King. 2018. “Integration of Time Series Forecasting in a Dynamic Decision Support System for Multiple Reservoir Management to Conserve Water Sources.”

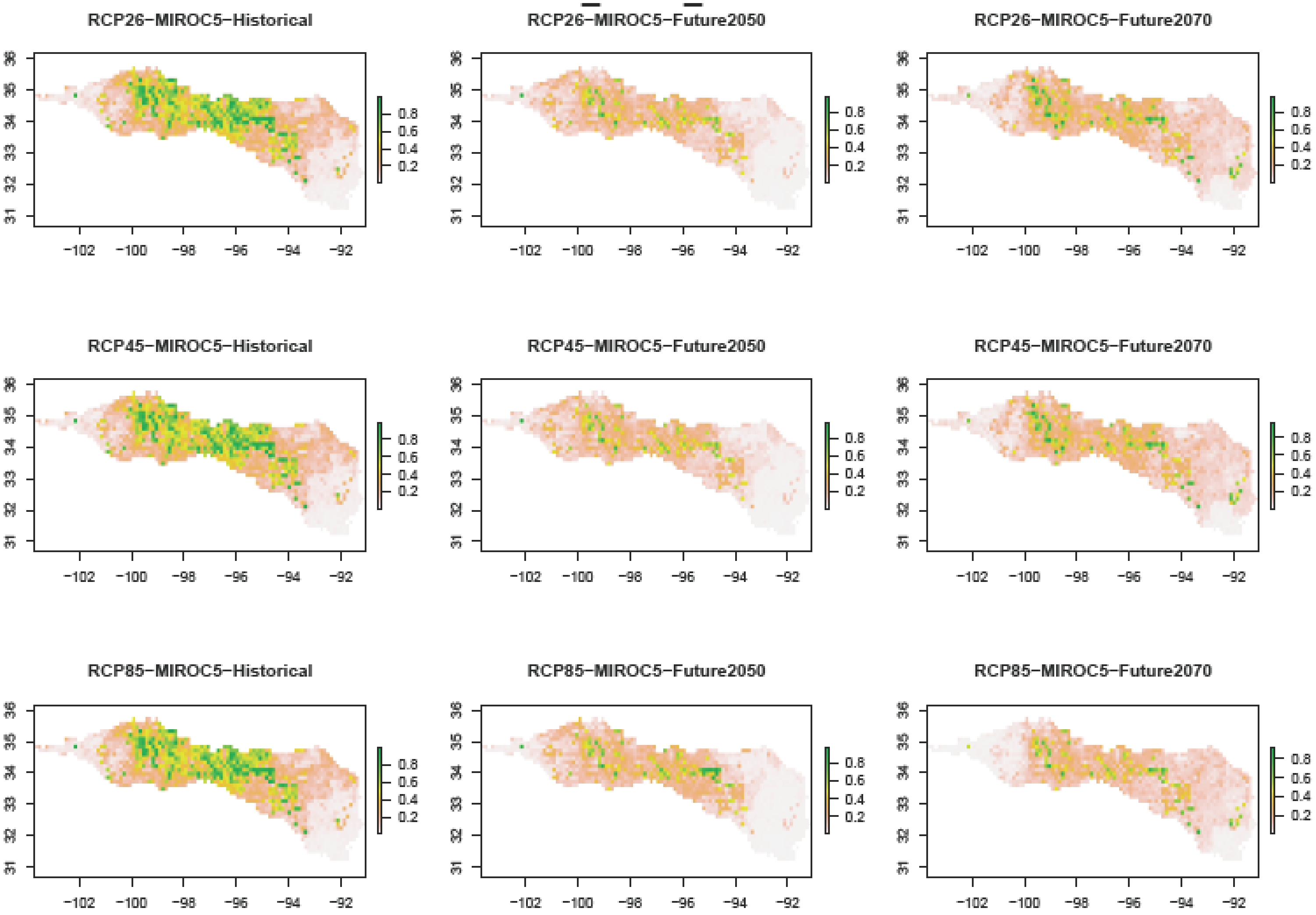
Energy Sources, Part A: Recovery, Utilization, and Environmental Effects 40 (11): 1398–1416. https://doi.org/10.1080/15567036.2018.1476934.

Appendix 1: Raw Model Outputs

Maxent: *Ameiurus melas*



Ameiurus_melas_MIROC5



RCP26−MIROC5−Historical

RCP26−MIROC5−Future2050

RCP26−MIROC5−Future2070

RCP45−MIROC5−Historical

RCP45−MIROC5−Future2050

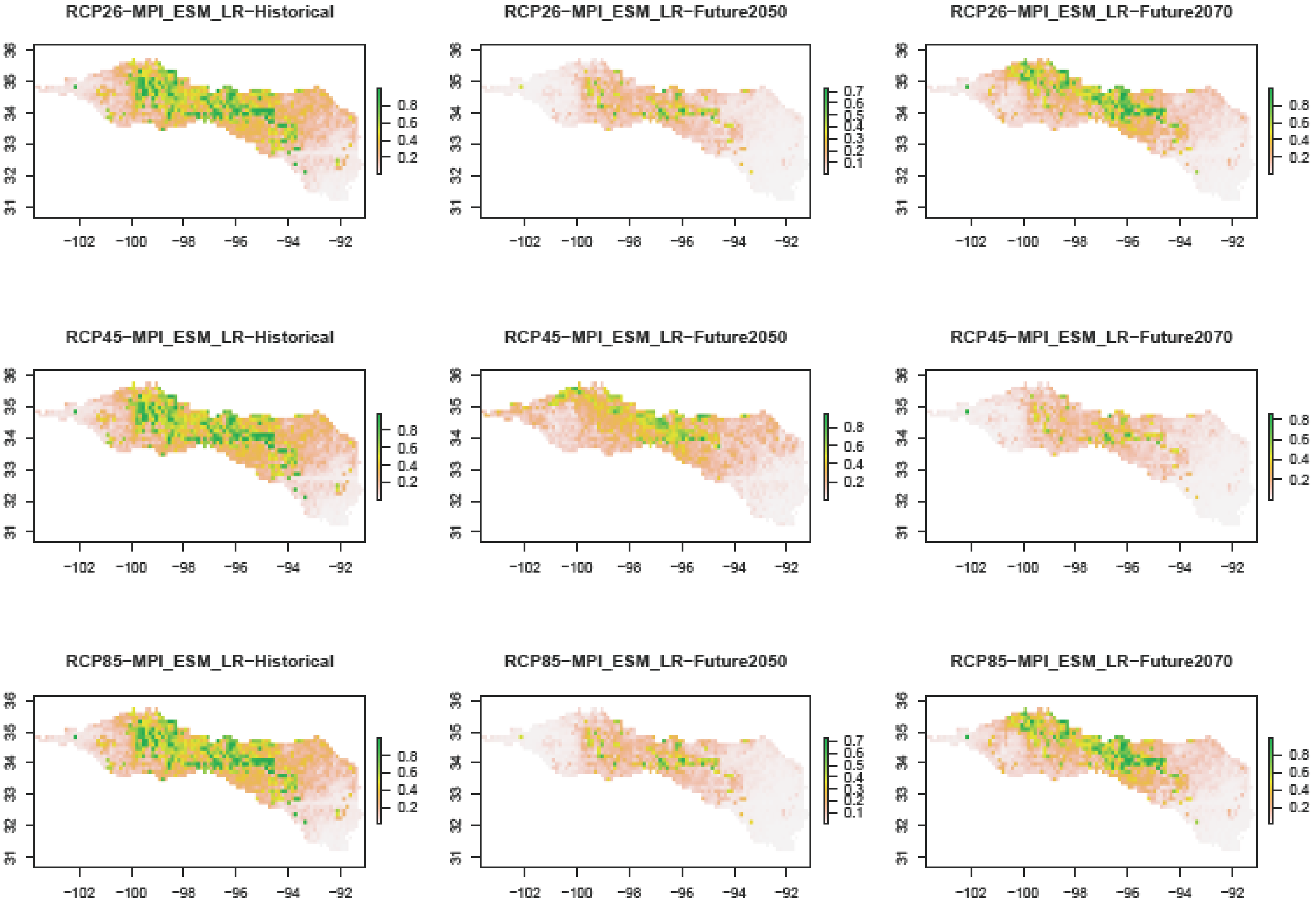
RCP45−MIROC5−Future2070

RCP85−MIROC5−Historical

RCP85−MIROC5−Future2050

RCP85−MIROC5−Future2070

Ameiurus_melas_MPI_ESM_LR



RCP26-MPI_ESM_LR-Historical

RCP26-MPI_ESM_LR-Future2050

RCP26-MPI_ESM_LR-Future2070

RCP45-MPI_ESM_LR-Historical

RCP45-MPI_ESM_LR-Future2050

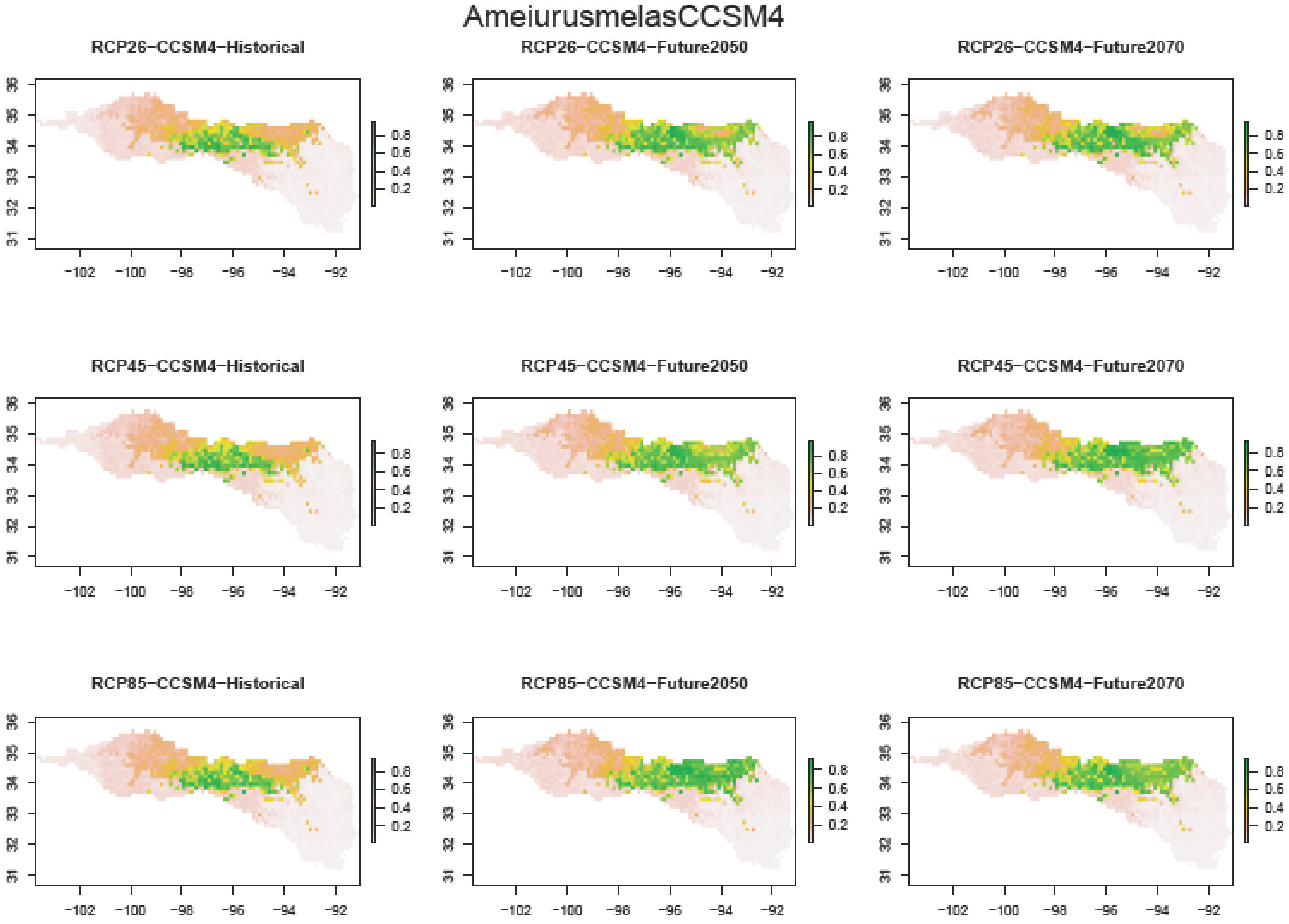
RCP45-MPI_ESM_LR-Future2070

RCP85-MPI_ESM_LR-Historical

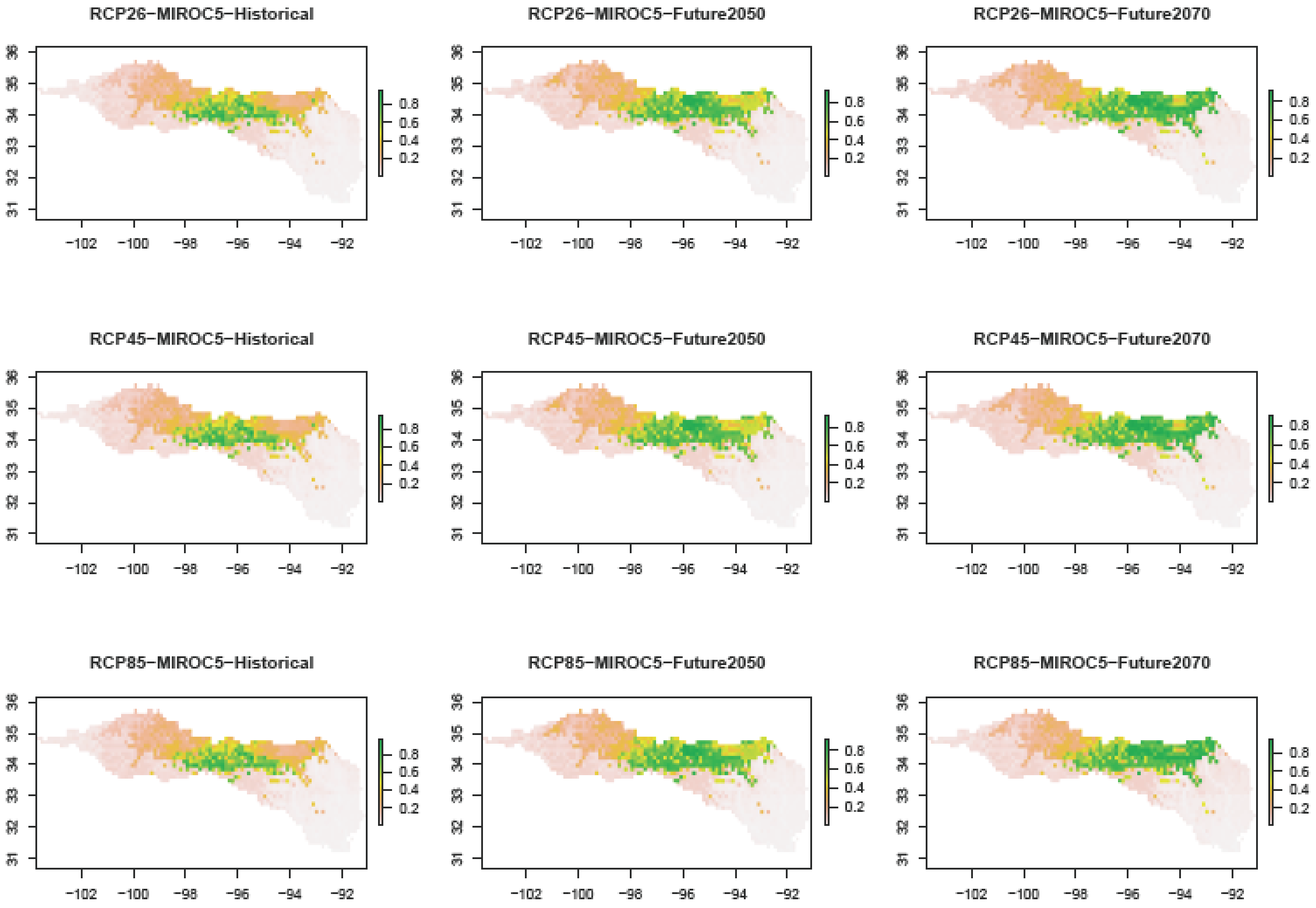
RCP85-MPI_ESM_LR-Future2050

RCP85-MPI_ESM_LR-Future2070

BRT: *Ameiurus melas*



AmeiurusmelasMIROC5



RCP26-MIROC5-Historical

RCP26-MIROC5-Future2050

RCP26-MIROC5-Future2070

RCP45-MIROC5-Historical

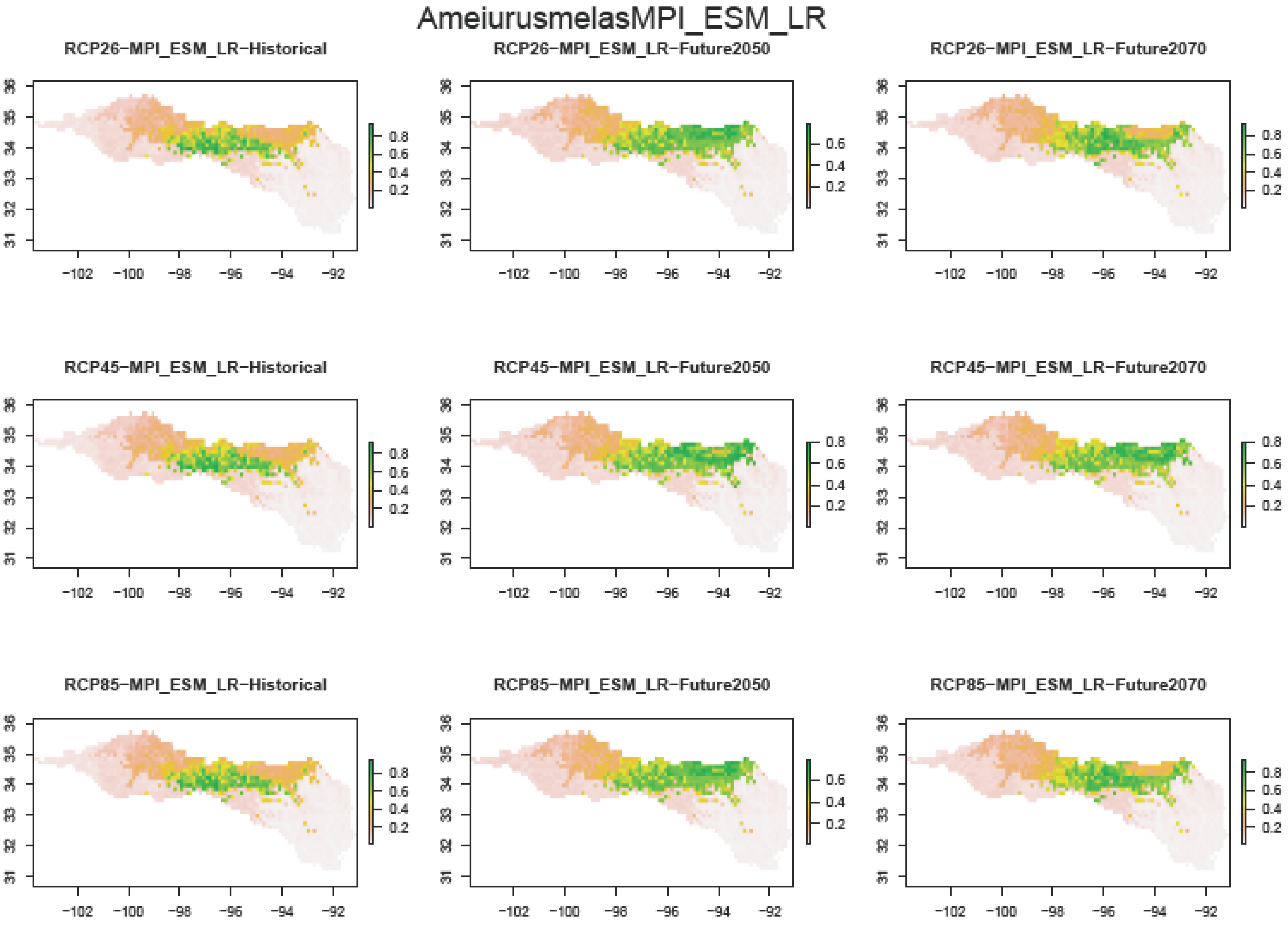
RCP45-MIROC5-Future2050

RCP45-MIROC5-Future2070

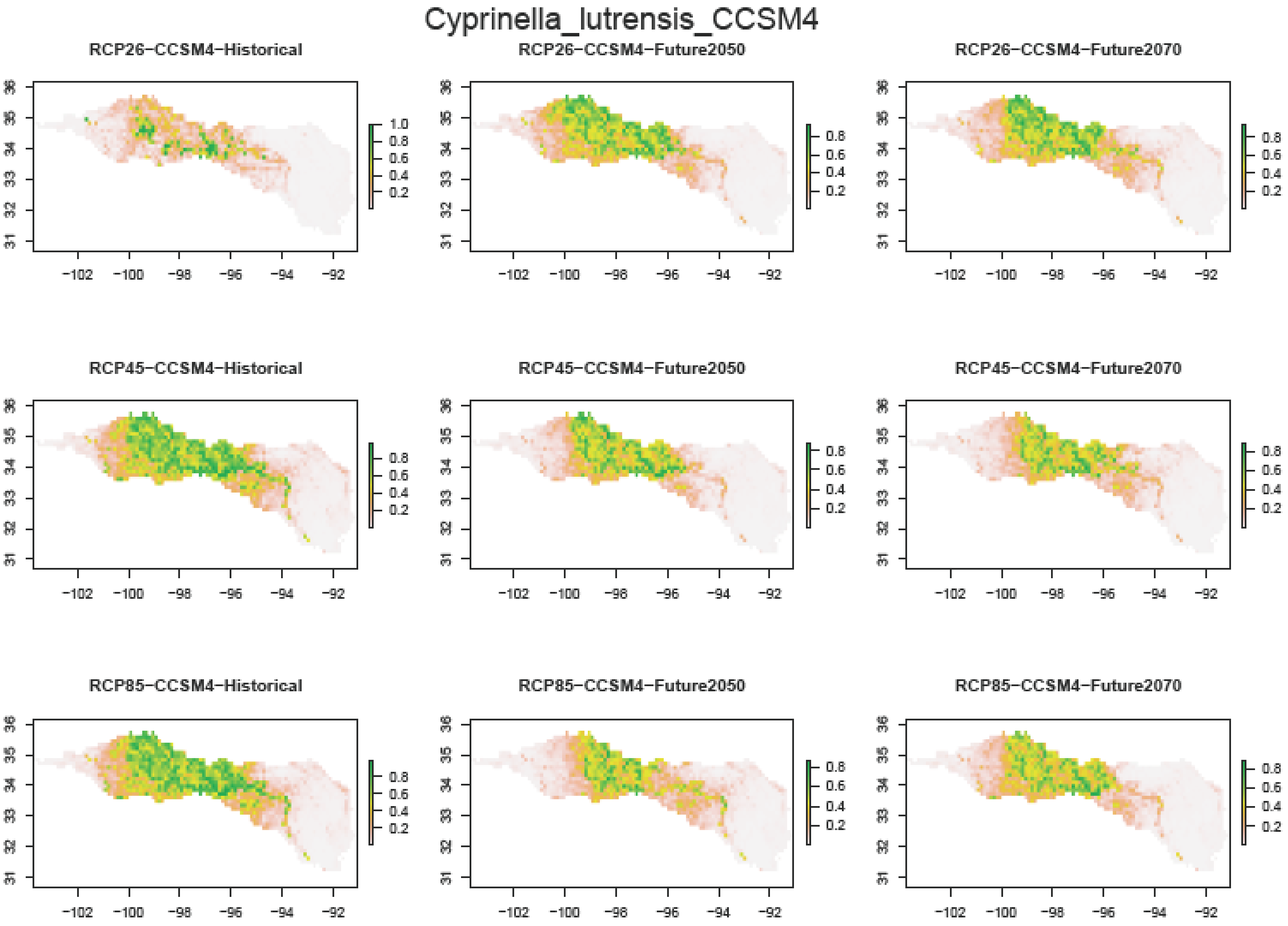
RCP85-MIROC5-Historical

RCP85-MIROC5-Future2050

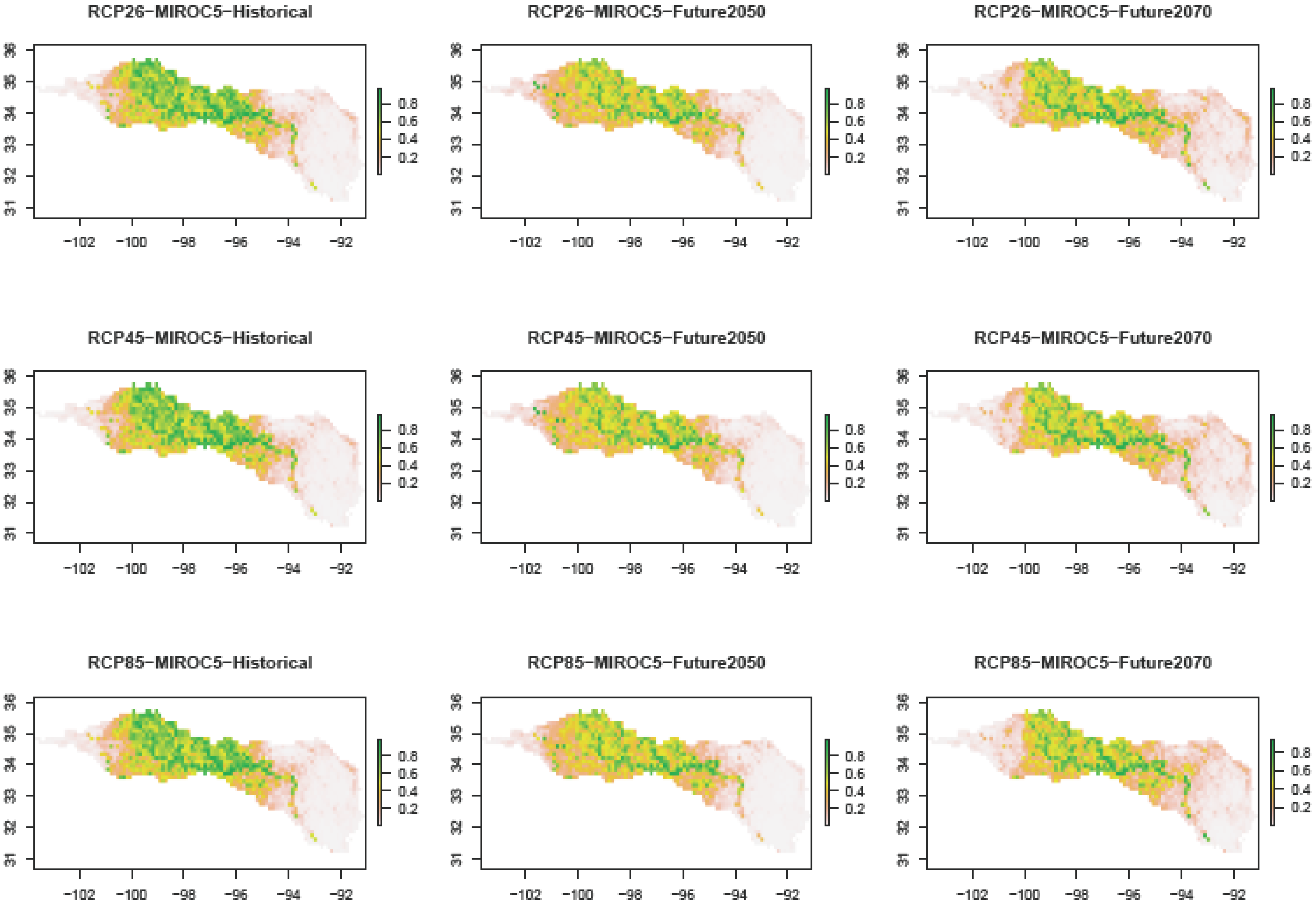
RCP85-MIROC5-Future2070


AmeiurusmelasMPI_ESM_LR
RCP26-MPI_ESM_LR-Historical
RCP26-MPI_ESM_LR-Future2050
RCP26-MPI_ESM_LR-Future2070
RCP45-MPI_ESM_LR-Historical
RCP45-MPI_ESM_LR-Future2050
RCP45-MPI_ESM_LR-Future2070
RCP85-MPI_ESM_LR-Historical
RCP85-MPI_ESM_LR-Future2050
RCP85-MPI_ESM_LR-Future2070
31
32
33
34
35
36
−102
−100
−98
−96
−94
−92
0.2
0.4
0.6
0.8

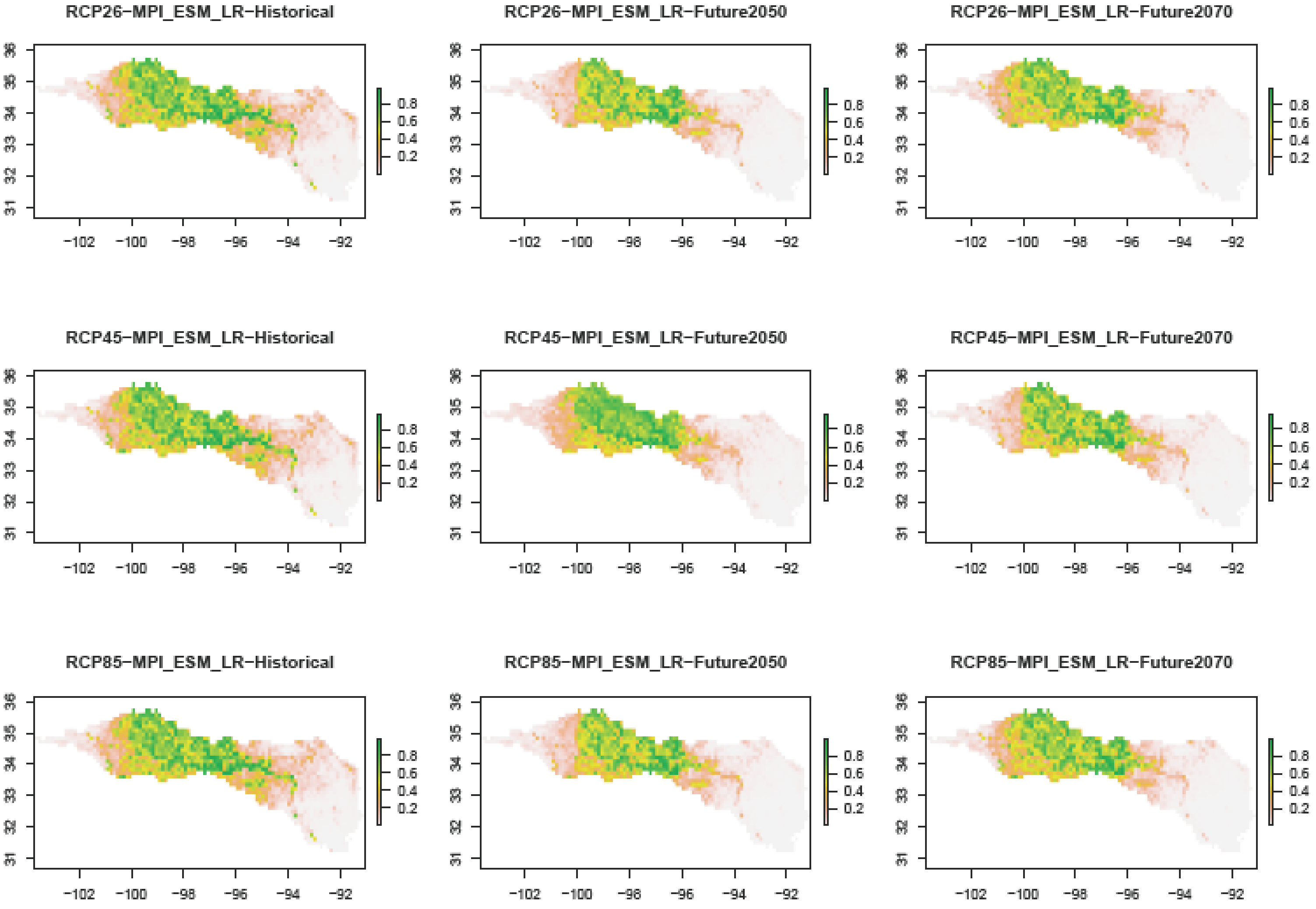
Maxent: *Cyprinella lutrensis*



Cyprinella_lutrensis_MIROC5


RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070

Cyprinella_lutrensis_MPI_ESM_LR



RCP26-MPI_ESM_LR-Historical

RCP26-MPI_ESM_LR-Future2050

RCP26-MPI_ESM_LR-Future2070

RCP45-MPI_ESM_LR-Historical

RCP45-MPI_ESM_LR-Future2050

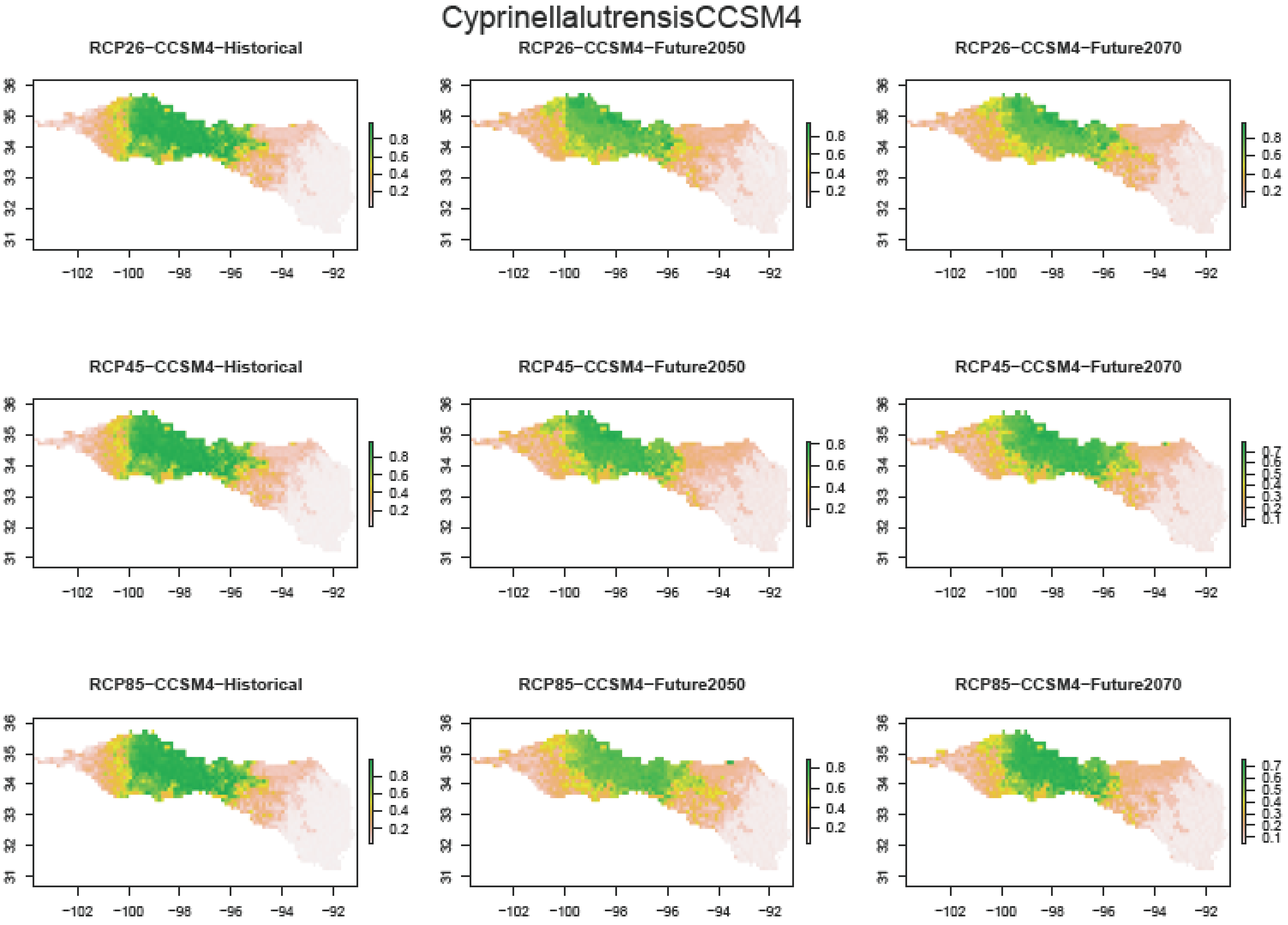
RCP45-MPI_ESM_LR-Future2070

RCP85-MPI_ESM_LR-Historical

RCP85-MPI_ESM_LR-Future2050

RCP85-MPI_ESM_LR-Future2070

BRT: *Cyprinella lutrensis*


CyprinellalutrensisCCSM4

RCP26−CCSM4−Historical

RCP26−CCSM4−Future2050

RCP26−CCSM4−Future2070

RCP45−CCSM4−Historical

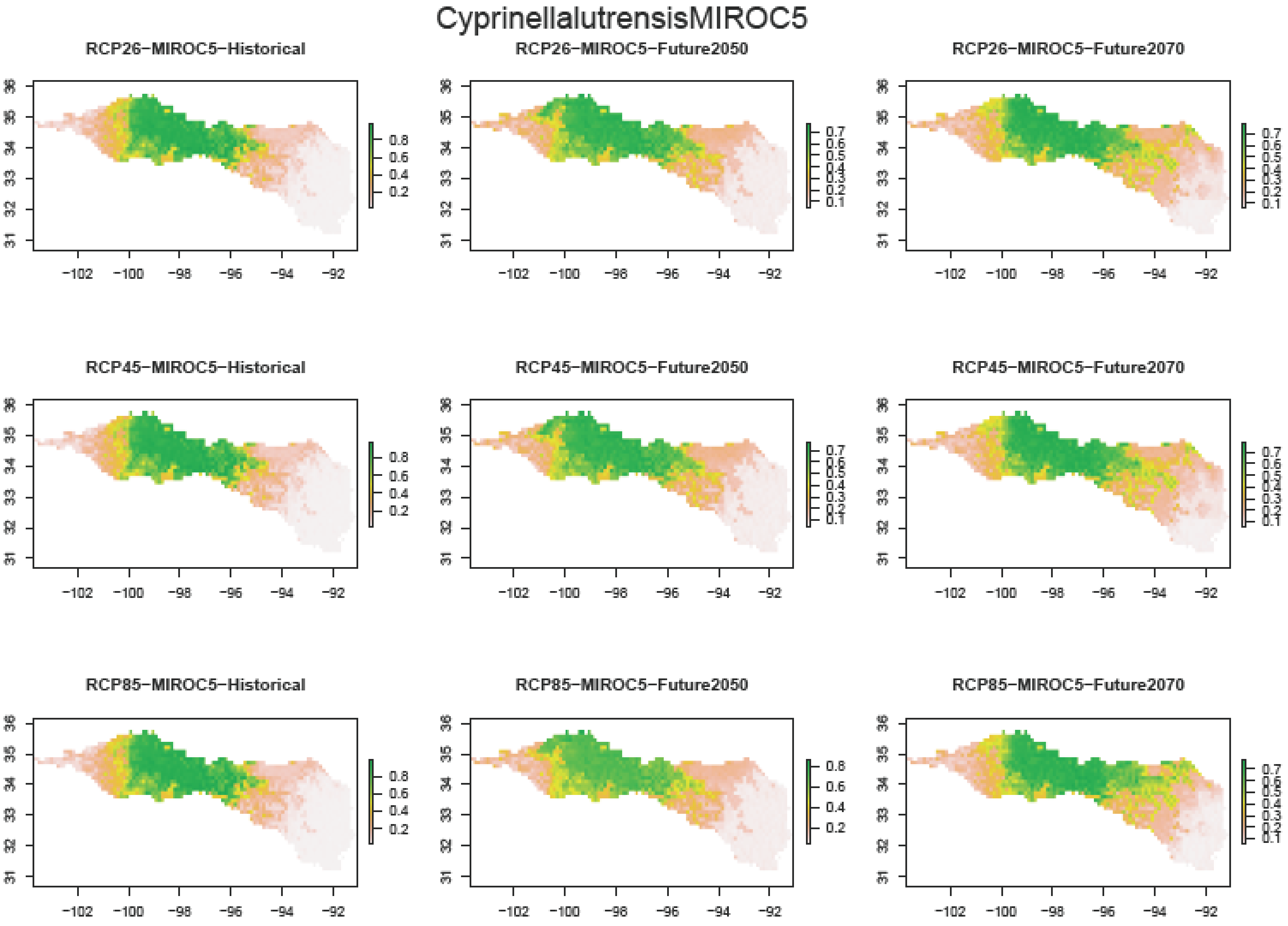
RCP45−CCSM4−Future2050

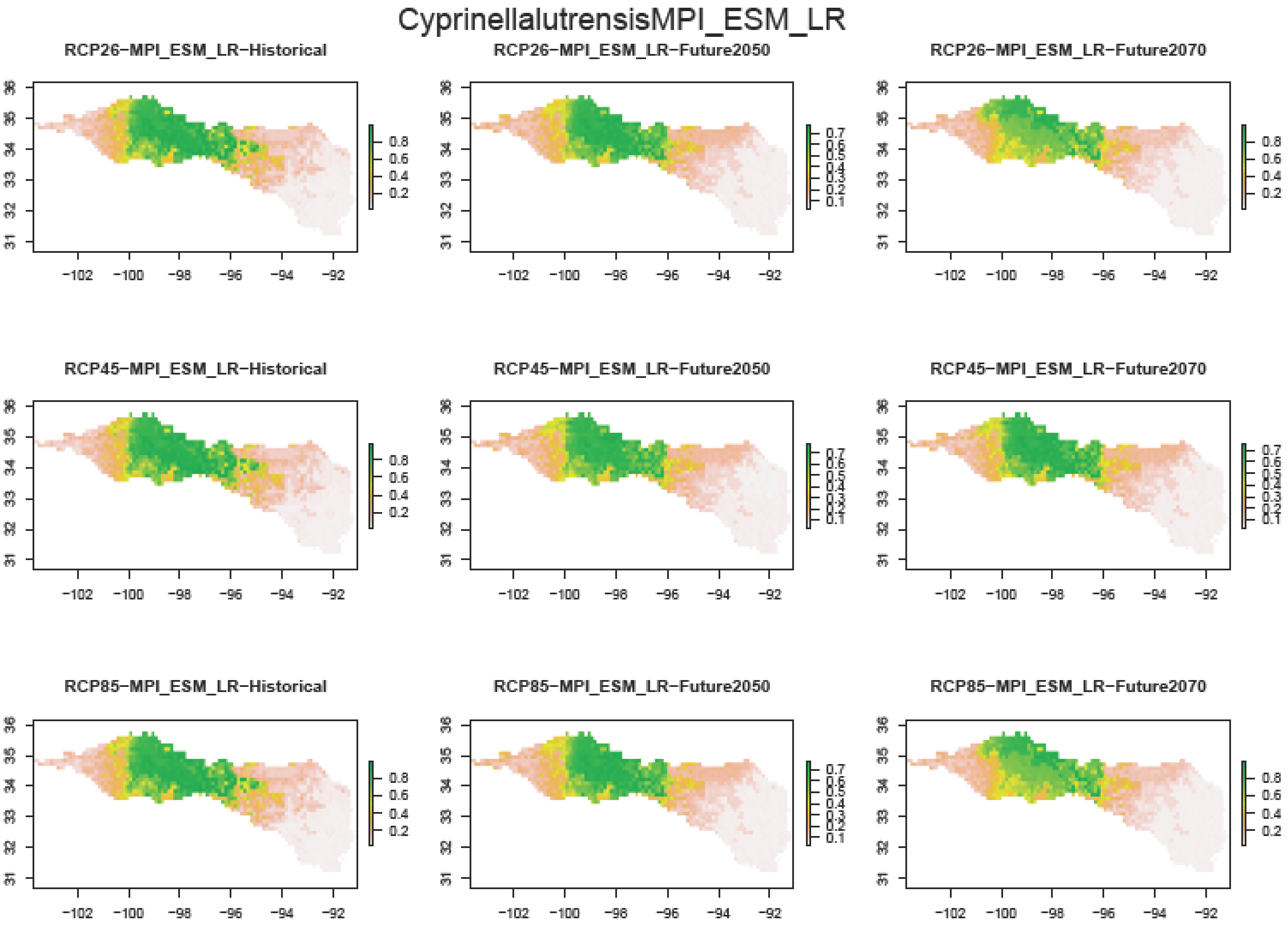
RCP45−CCSM4−Future2070

RCP85−CCSM4−Historical

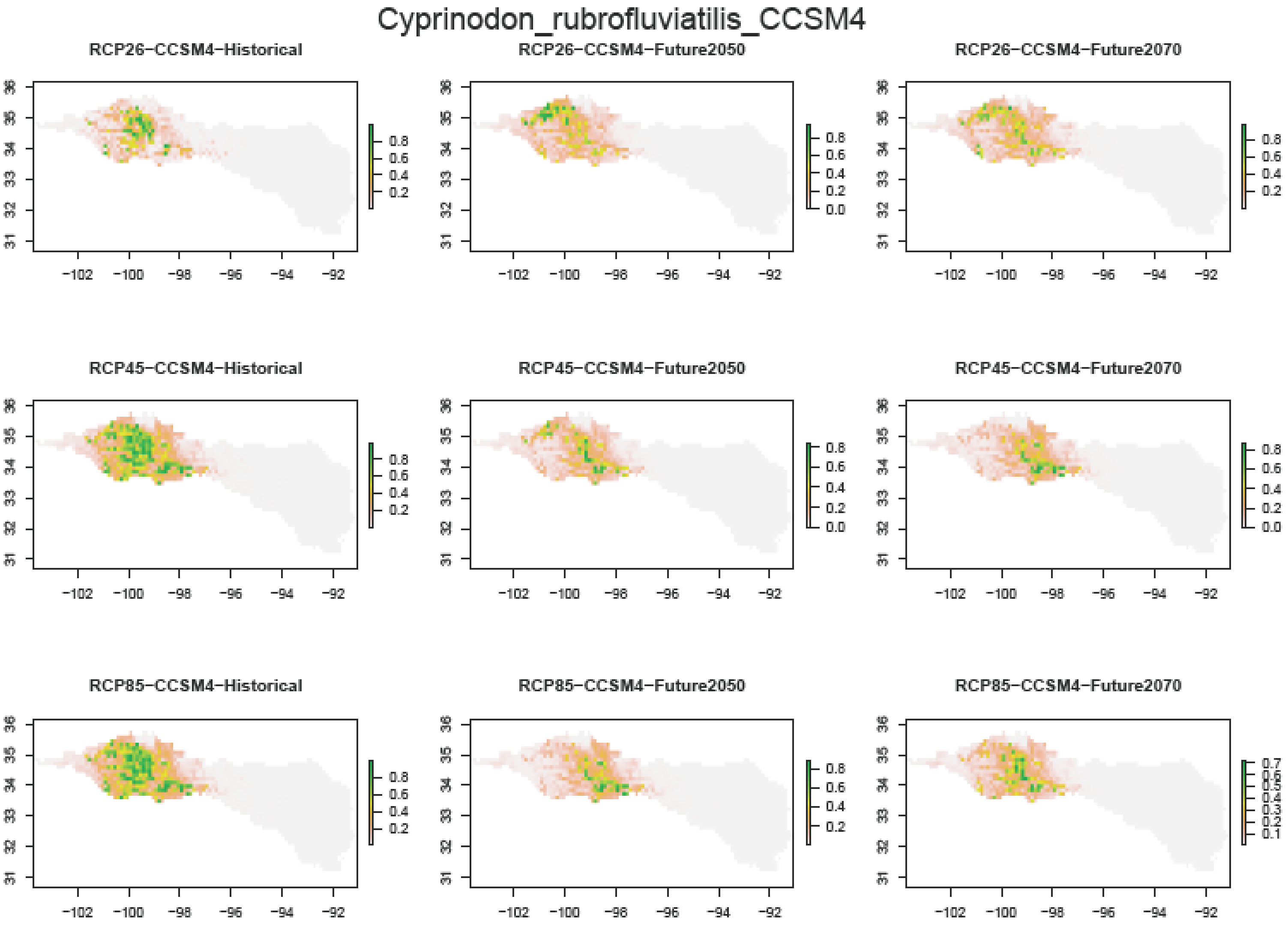
RCP85−CCSM4−Future2050

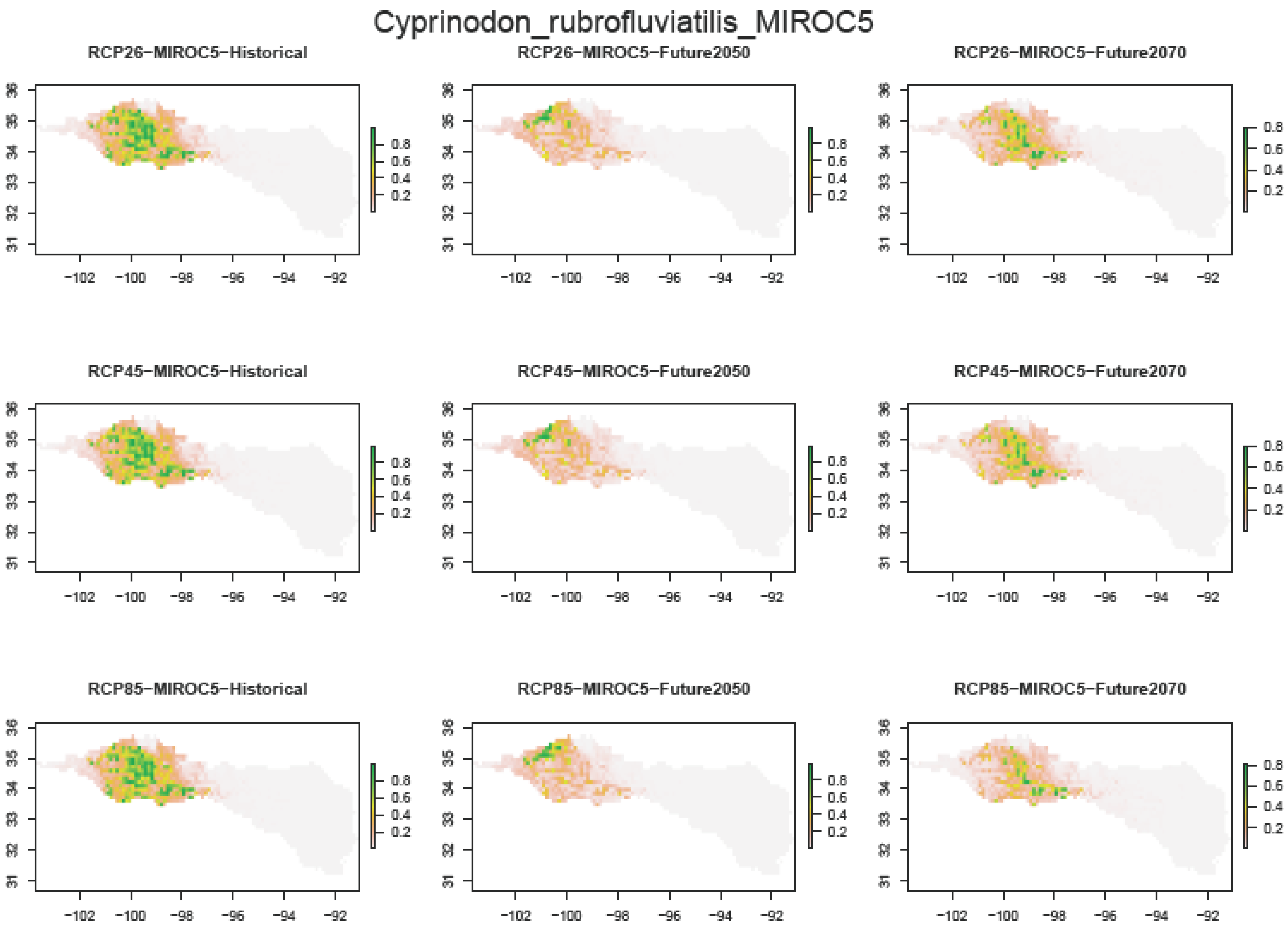
RCP85−CCSM4−Future2070


CyprinellalutrensisMIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070
31
32
33
34
35
36
−102
−100
−98
−96
−94
−92
0.2
0.4
0.6
0.8
0.1
0.2
0.3
0.4
0.5
0.6
0.7

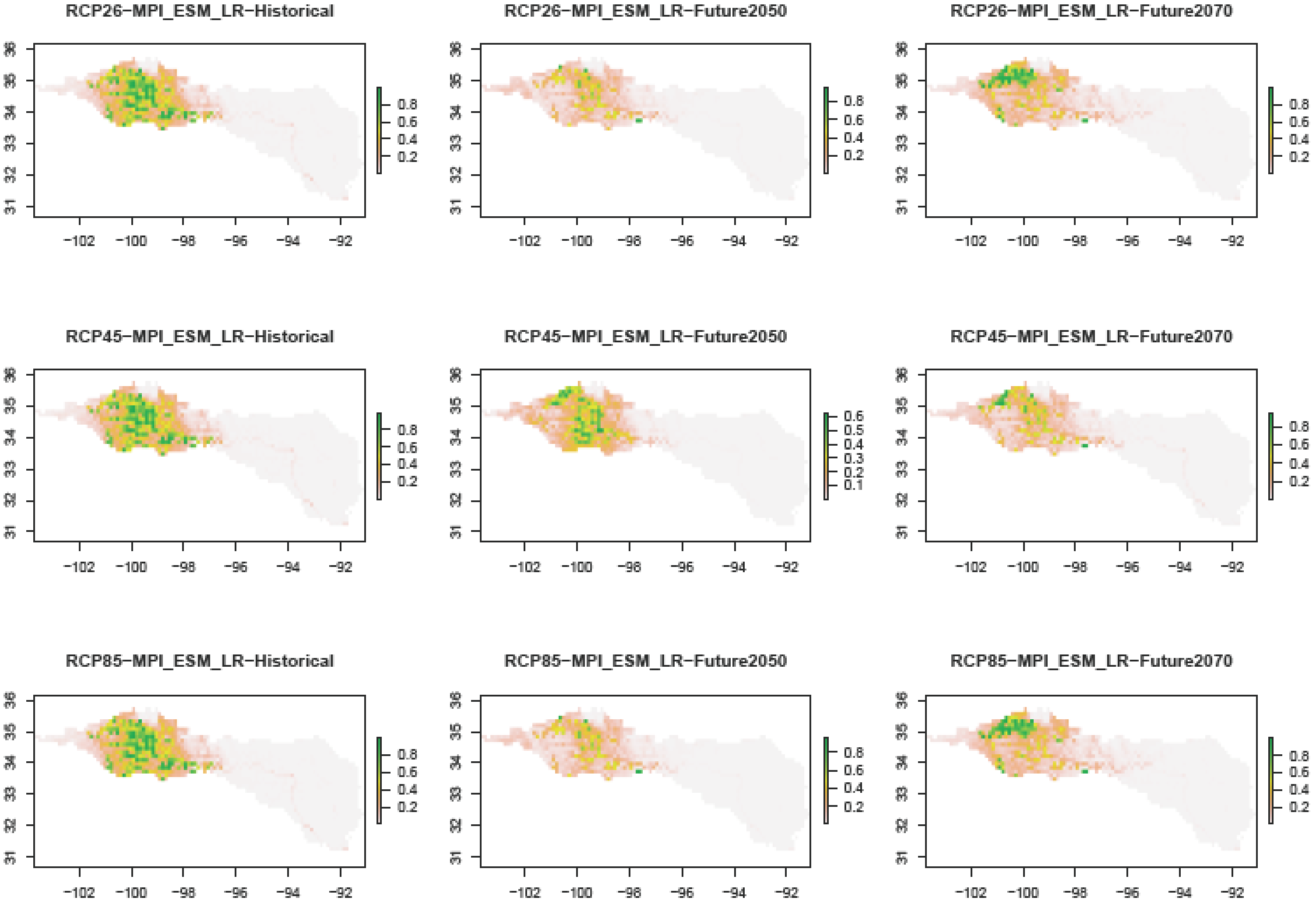

CyprinellalutrensisMPI_ESM_LR
RCP26−MPI_ESM_LR−Historical
RCP26−MPI_ESM_LR−Future2050
RCP26−MPI_ESM_LR−Future2070
RCP45−MPI_ESM_LR−Historical
RCP45−MPI_ESM_LR−Future2050
RCP45−MPI_ESM_LR−Future2070
RCP85−MPI_ESM_LR−Historical
RCP85−MPI_ESM_LR−Future2050
RCP85−MPI_ESM_LR−Future2070
31
32
33
34
35
36
−102
−100
−98
−96
−94
−92
0.2
0.4
0.6
0.8
0.1
0.2
0.3
0.4
0.5
0.6
0.7

Maxent: *Cyprinodon rubrofluviatilis*




Cyprinodon_rubrofluviatilis_MIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070
31
32
33
34
35
36
−102
−100
−98
−96
−94
−92
0.2
0.4
0.6
0.8

Cyprinodon_rubrofluviatilis_MPI_ESM_LR



RCP26−MPI_ESM_LR−Historical

RCP26−MPI_ESM_LR−Future2050

RCP26−MPI_ESM_LR−Future2070

RCP45−MPI_ESM_LR−Historical

RCP45−MPI_ESM_LR−Future2050

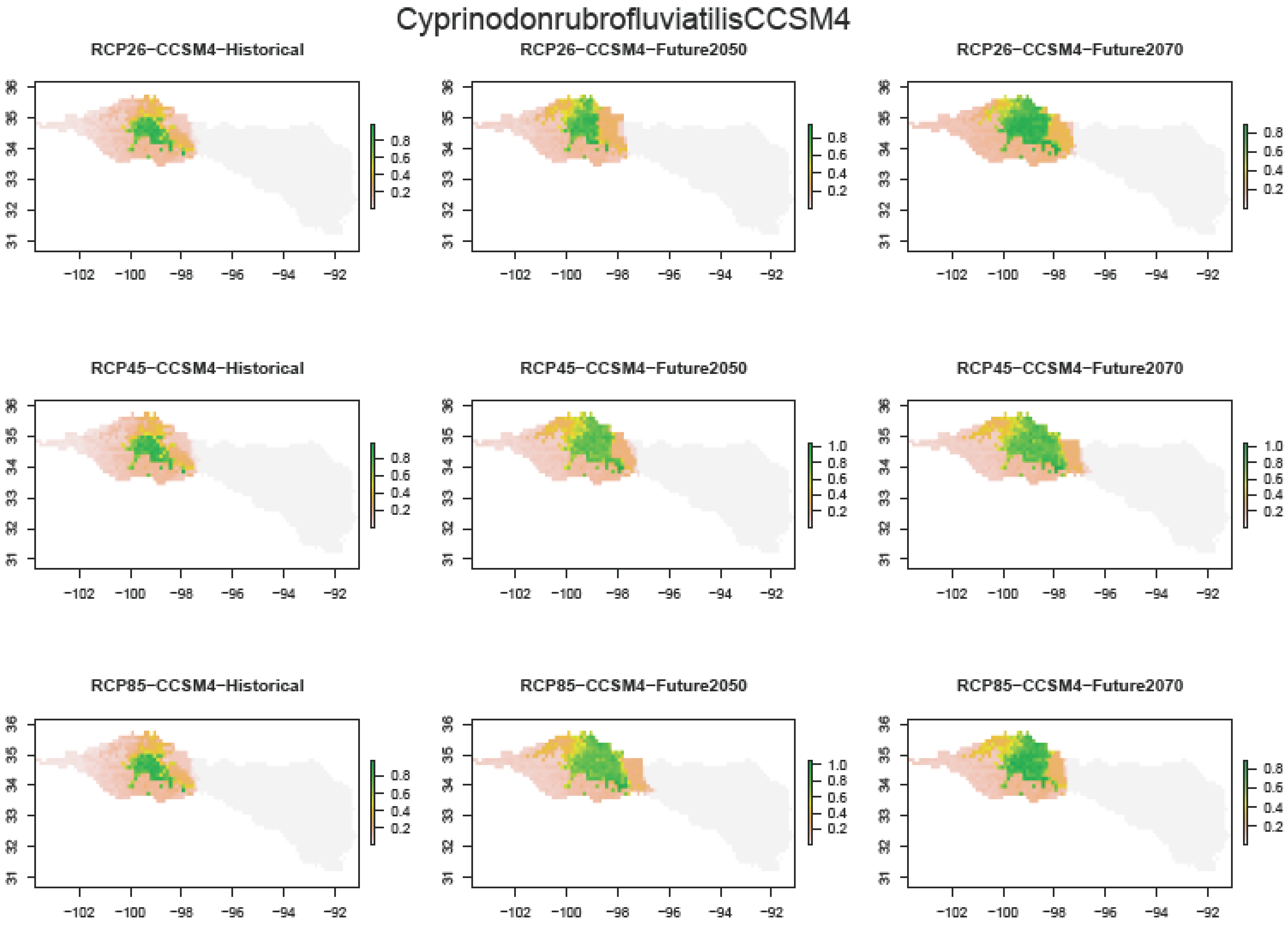
RCP45−MPI_ESM_LR−Future2070

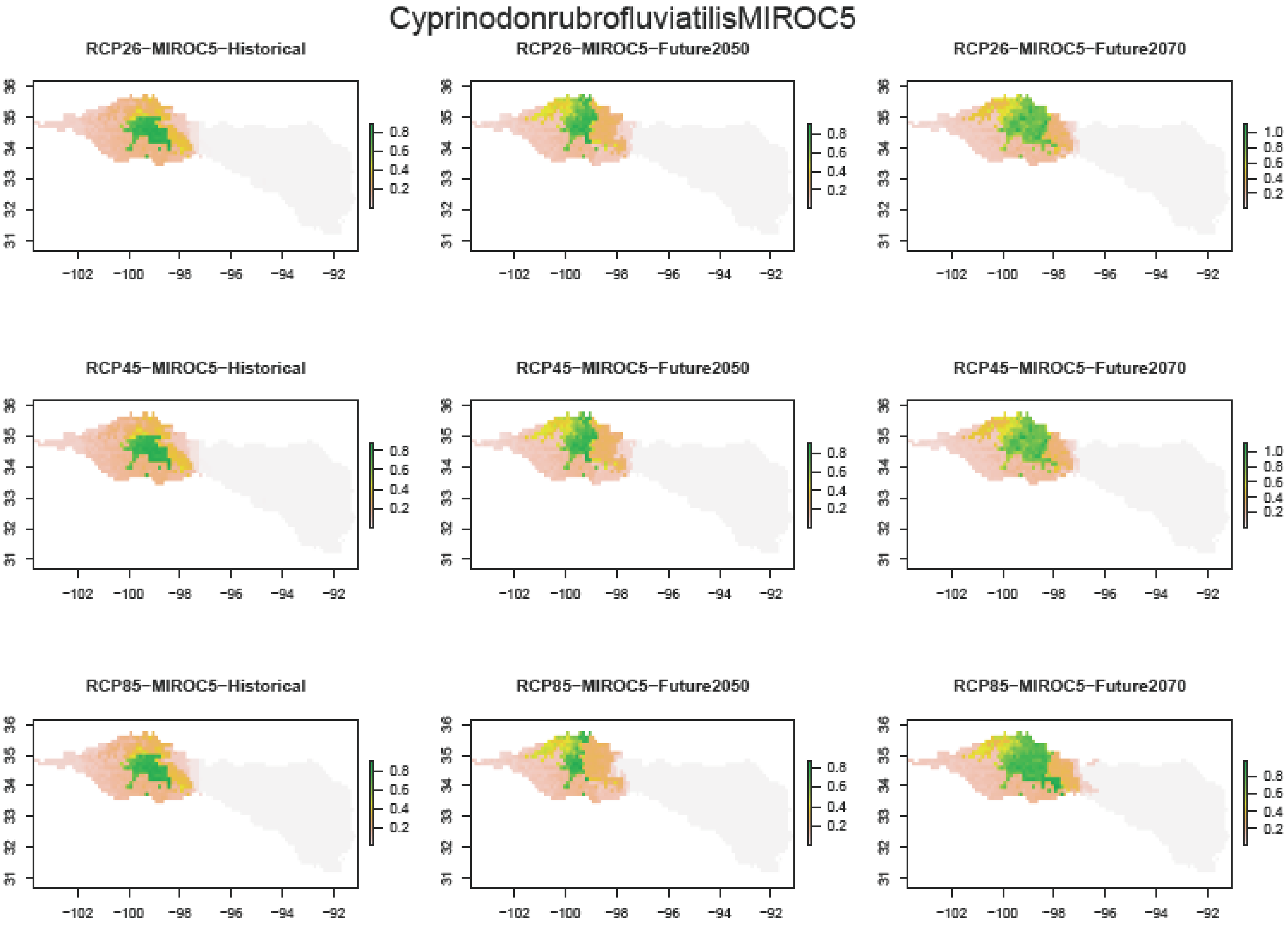
RCP85−MPI_ESM_LR−Historical

RCP85−MPI_ESM_LR−Future2050

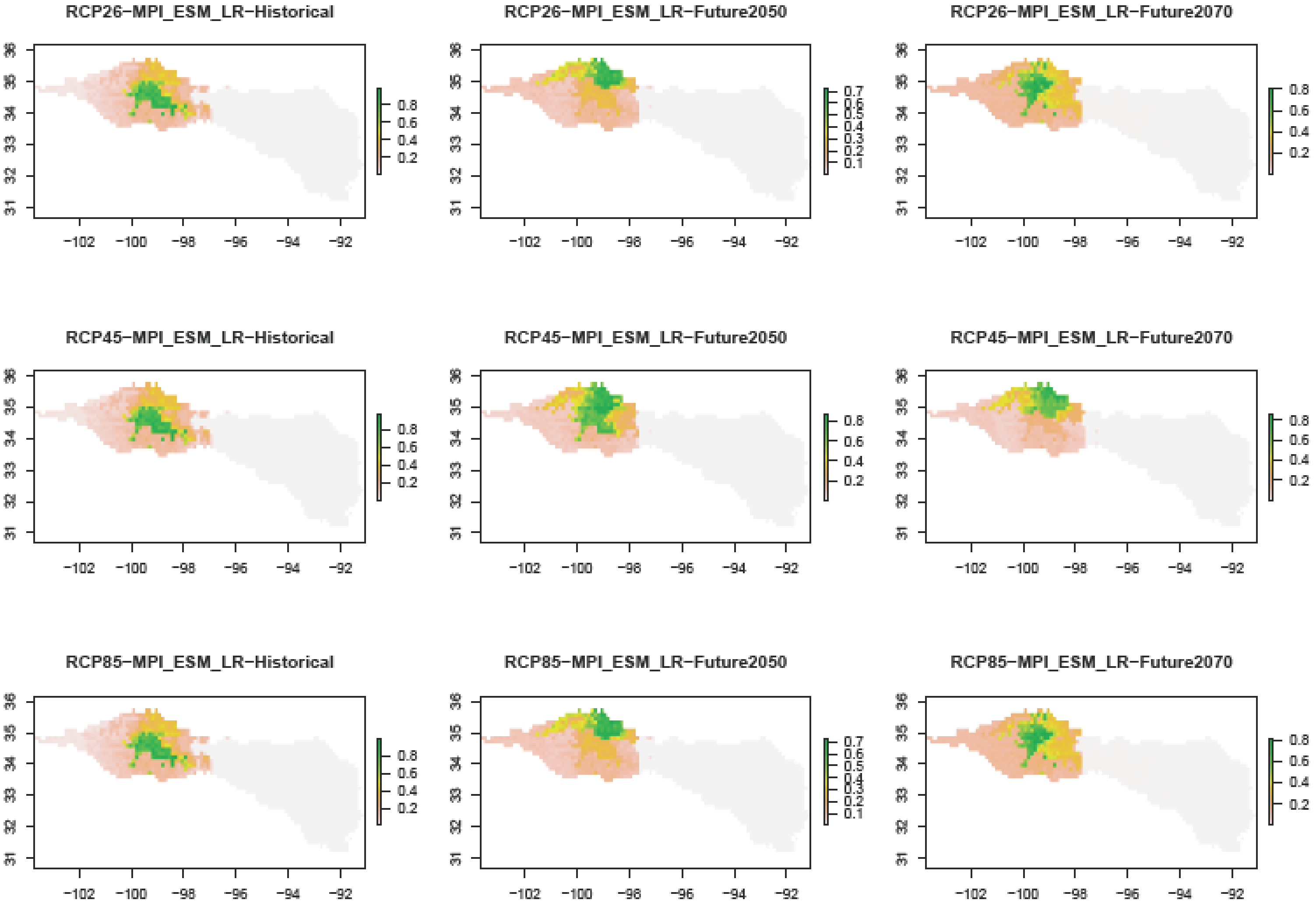
RCP85−MPI_ESM_LR−Future2070

BRT: *Cyprinodon rubrofluviatilis*

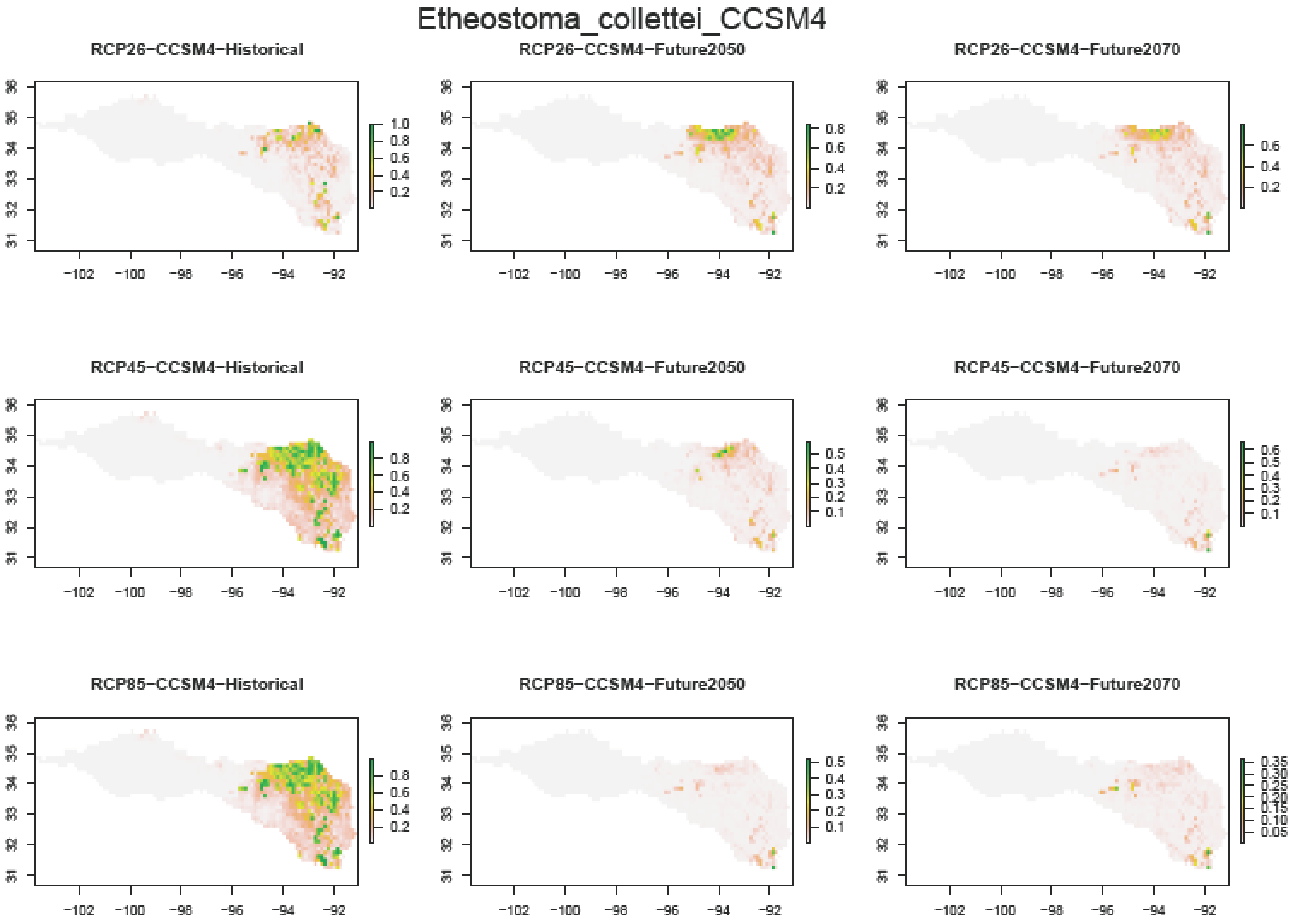



CyprinodonrubrofluviatilisMIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070
31
32
33
34
35
36
−102
−100
−98
−96
−94
−92
0.2
0.4
0.6
0.8
1.0

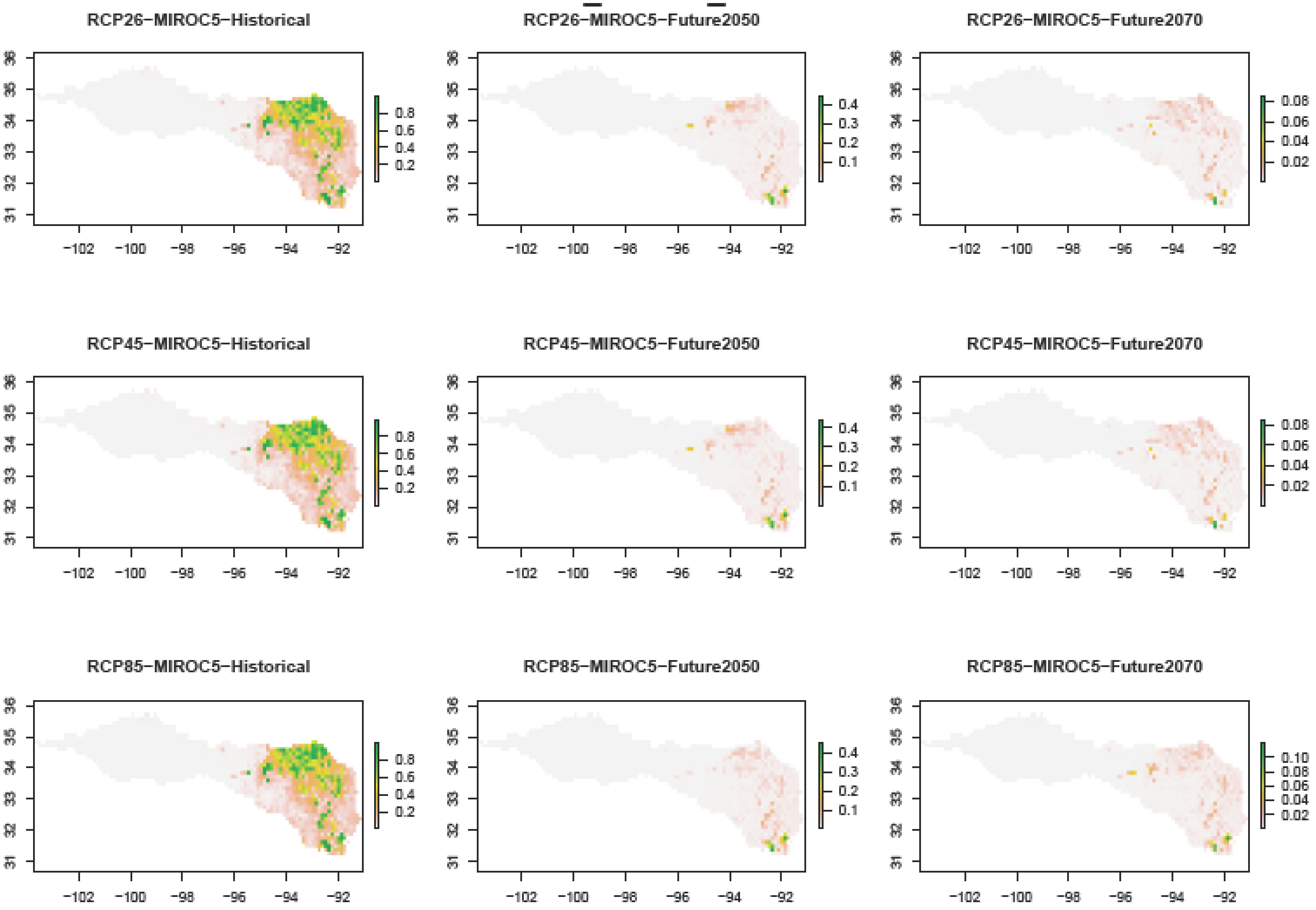
CyprinodonrubrofluviatilisMPI_ESM_LR



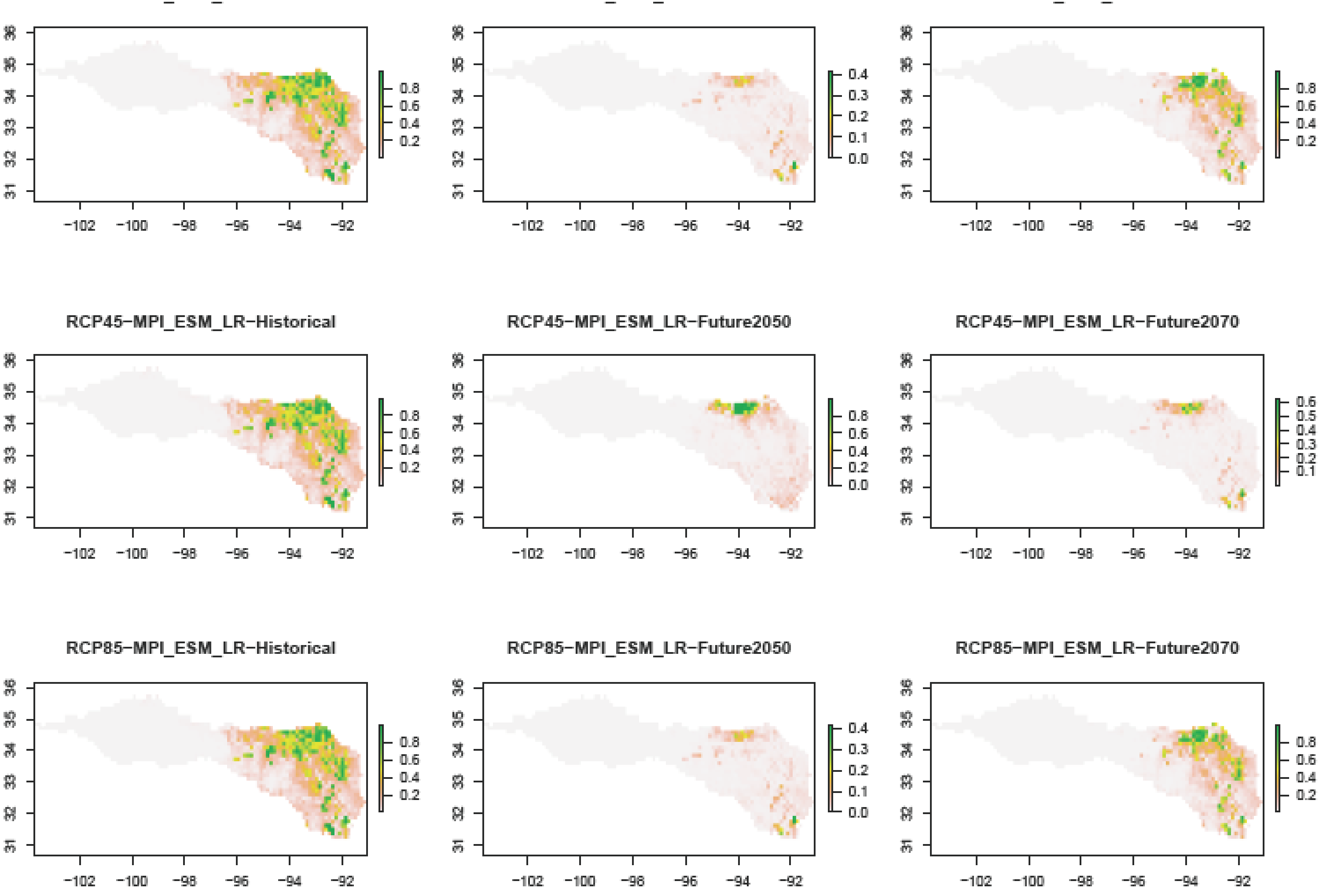
Maxent: *Etheostoma collettei*



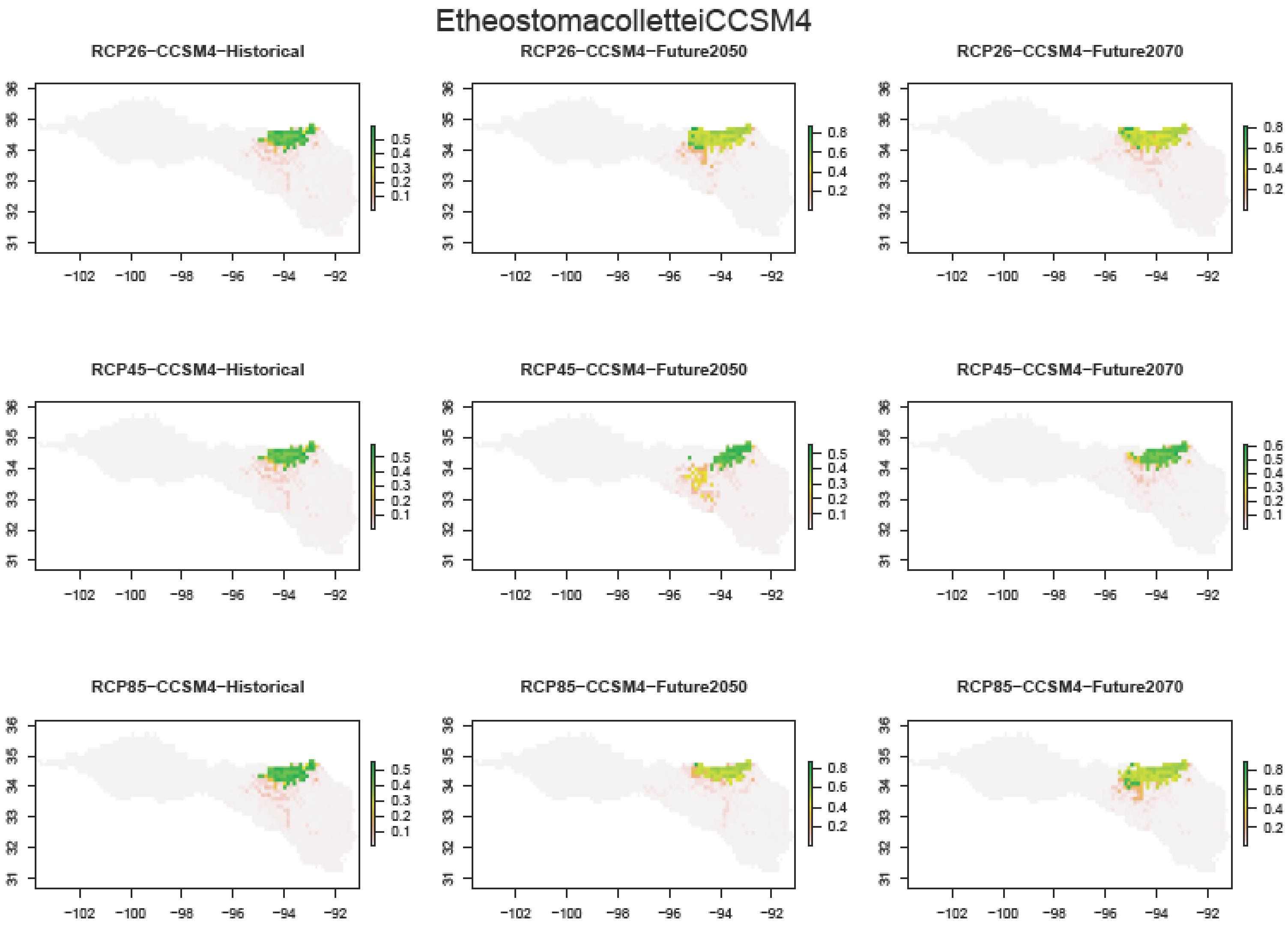
Etheostoma_collettei_MIROC5



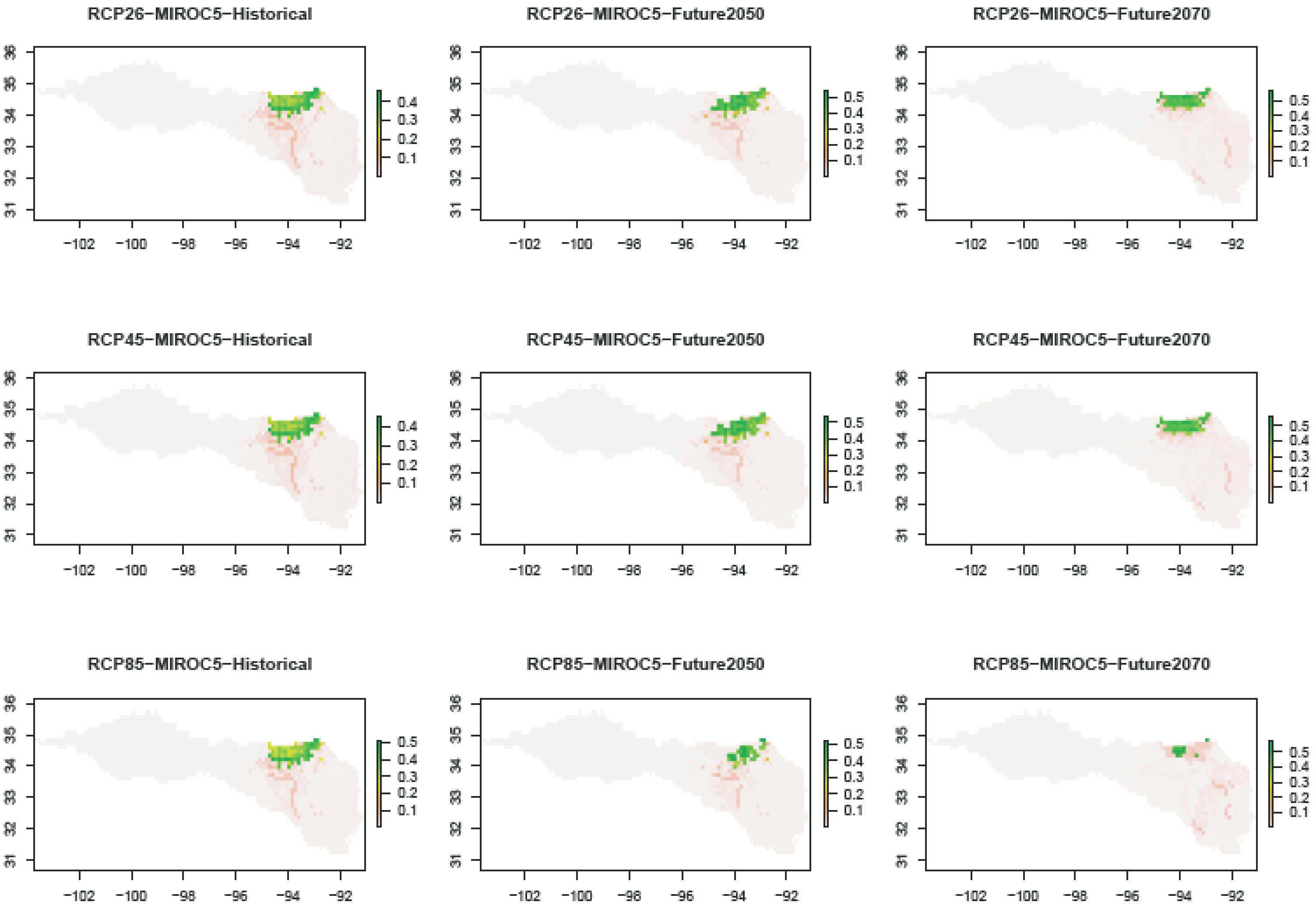
Etheostoma_collettei_MPI_ESM_LR

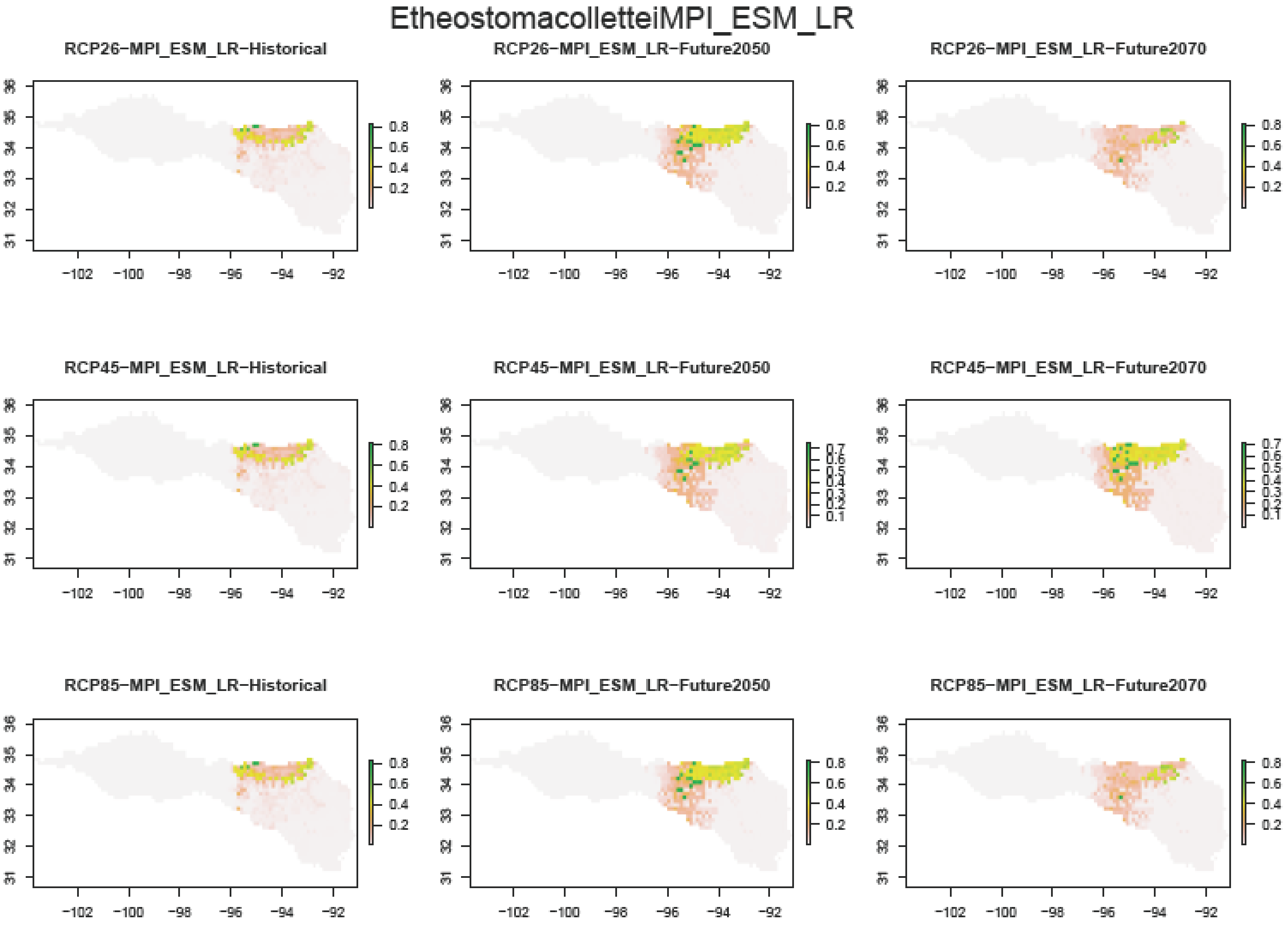


BRT: *Etheostoma collettei*



EtheostomacolletteiMIROC5





EtheostomacolletteiMPI_ESM_LR

RCP26-MPI_ESM_LR-Historical

RCP26-MPI_ESM_LR-Future2050

RCP26-MPI_ESM_LR-Future2070

RCP45-MPI_ESM_LR-Historical

RCP45-MPI_ESM_LR-Future2050

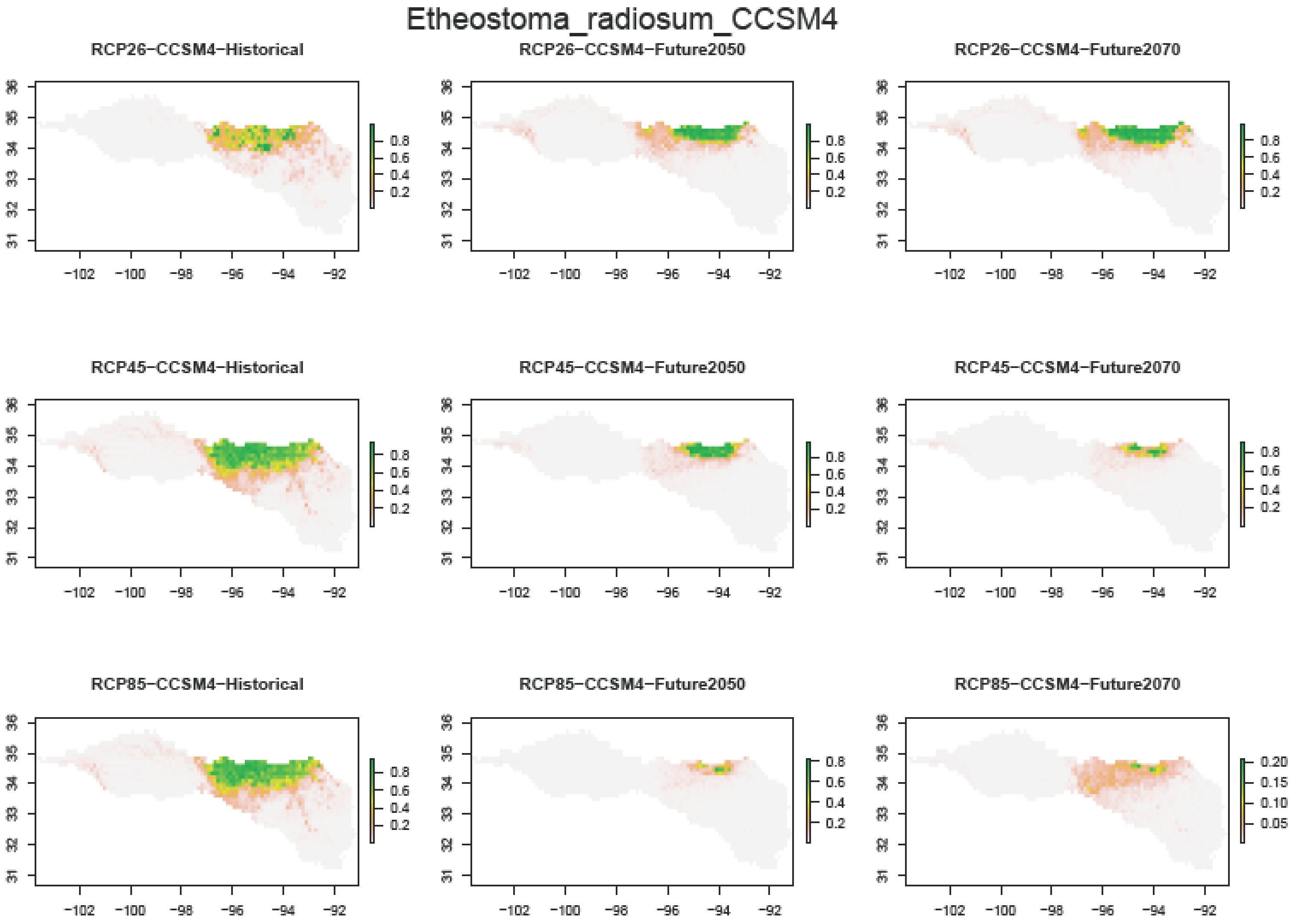
RCP45-MPI_ESM_LR-Future2070

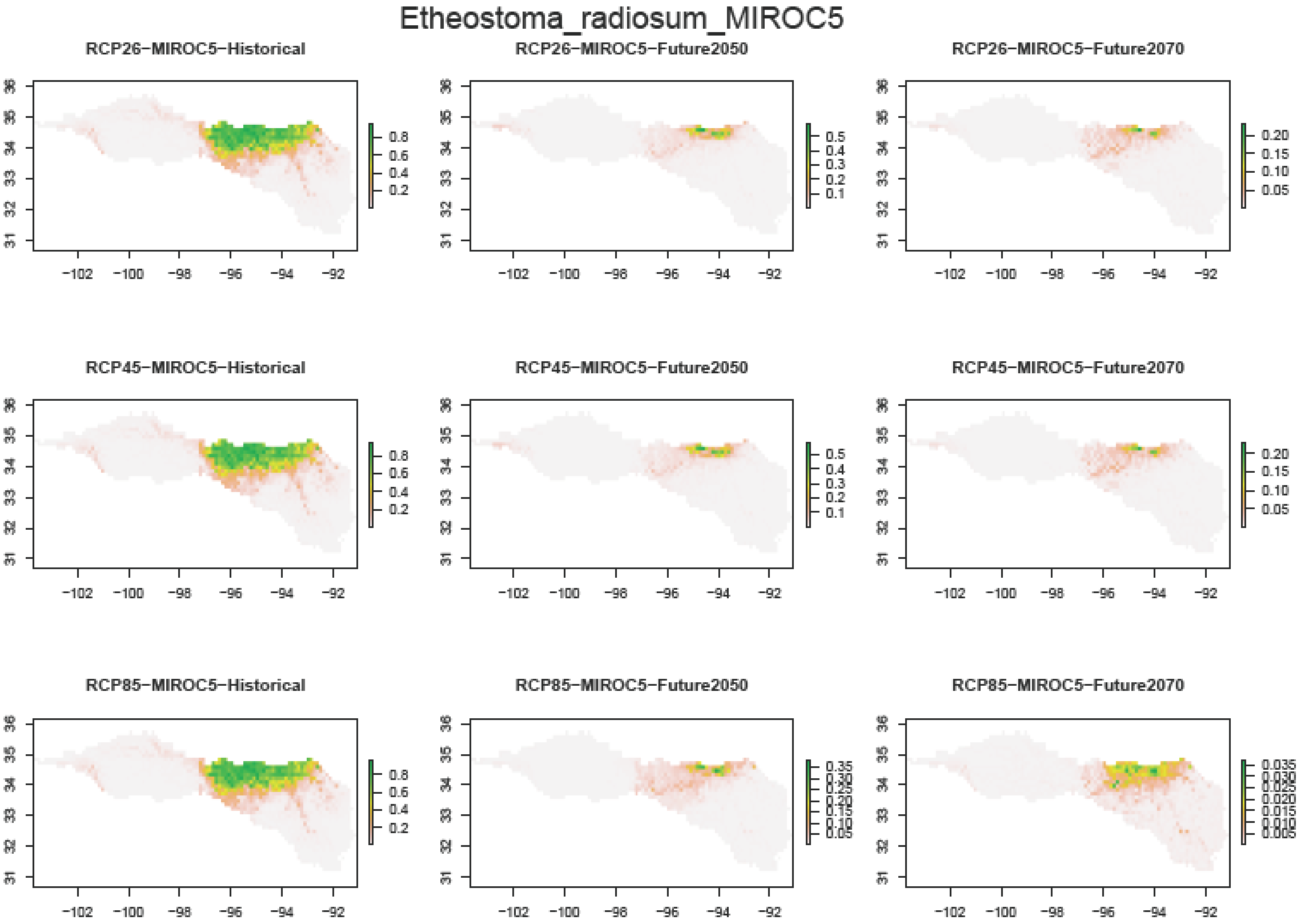
RCP85-MPI_ESM_LR-Historical

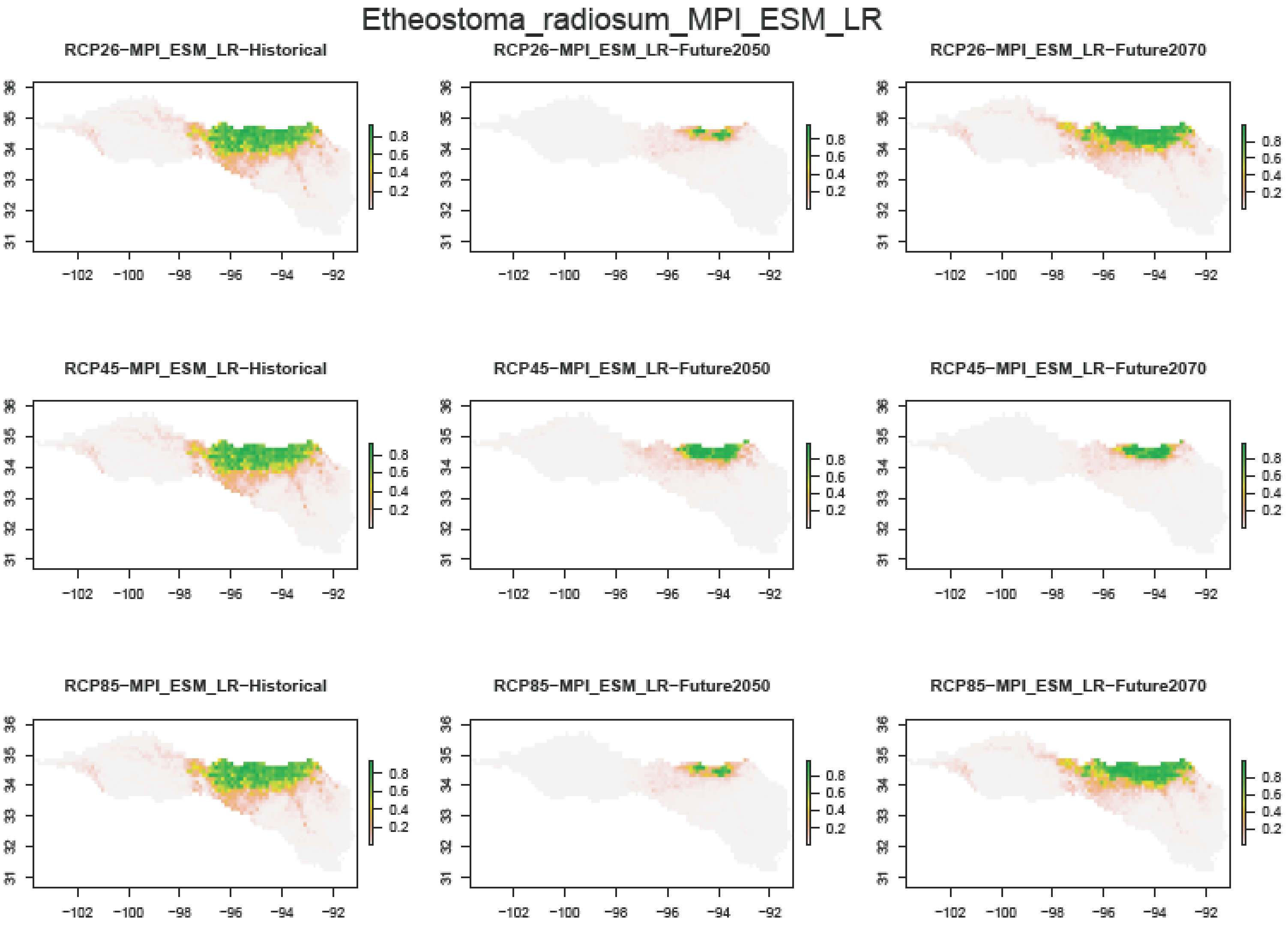
RCP85-MPI_ESM_LR-Future2050

RCP85-MPI_ESM_LR-Future2070

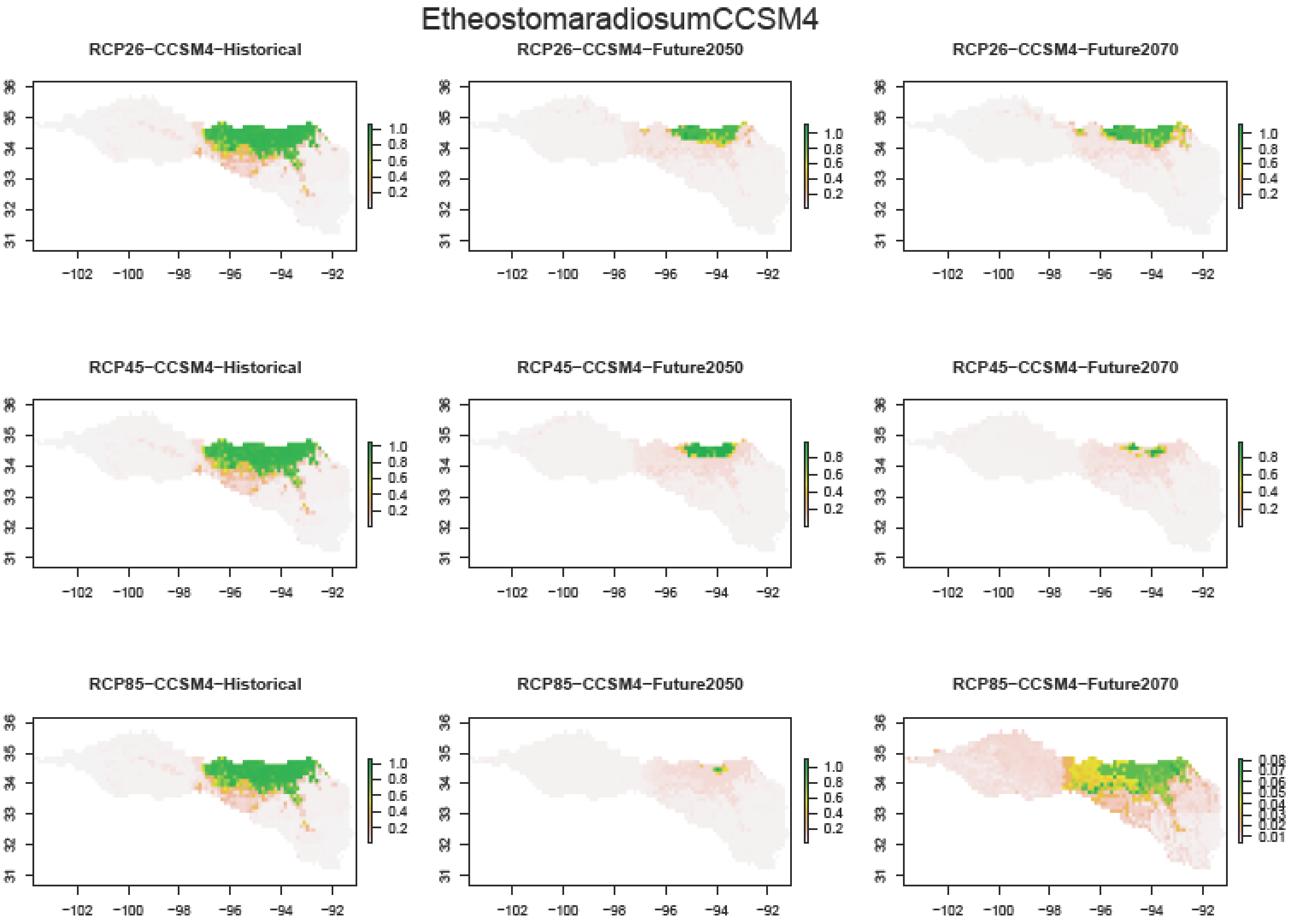
Maxent: *Etheostoma radiosum*

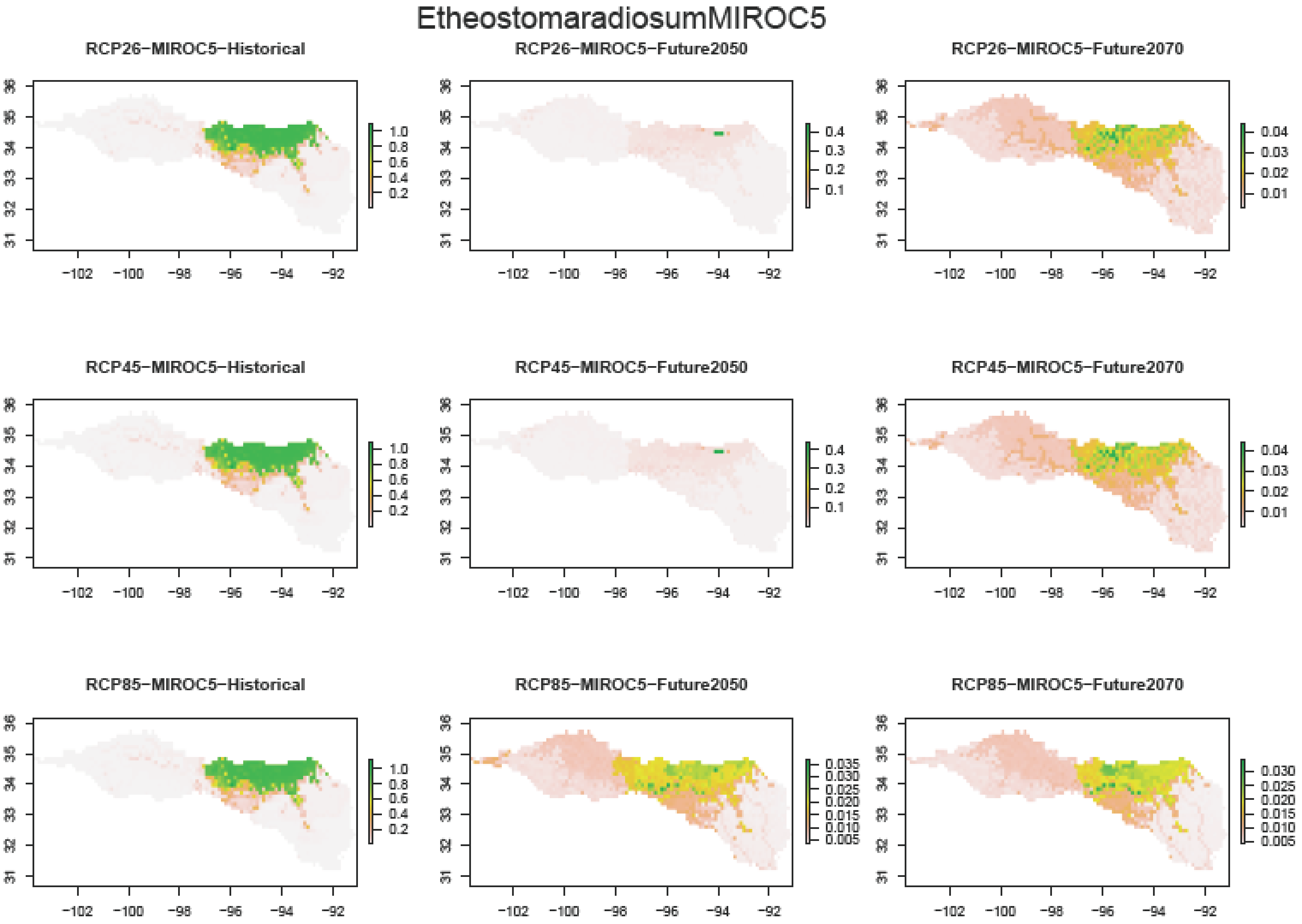



Etheostoma_radiosum_MIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070
31 32 33 34 35 36
−102 −100 −98 −96 −94 −92
0.2 0.4 0.6 0.8
0.1 0.2 0.3 0.4 0.5
0.05 0.10 0.15 0.20
0.05 0.10 0.15 0.20 0.25 0.30 0.35
0.005 0.010 0.015 0.020 0.025 0.030 0.035


Etheostoma_radiosum_MPI_ESM_LR
RCP26−MPI_ESM_LR−Historical
RCP26−MPI_ESM_LR−Future2050
RCP26−MPI_ESM_LR−Future2070
RCP45−MPI_ESM_LR−Historical
RCP45−MPI_ESM_LR−Future2050
RCP45−MPI_ESM_LR−Future2070
RCP85−MPI_ESM_LR−Historical
RCP85−MPI_ESM_LR−Future2050
RCP85−MPI_ESM_LR−Future2070
31
32
33
34
35
36
−102
−100
−98
−96
−94
−92
0.2
0.4
0.6
0.8

BRT: *Etheostoma radiosum*





EtheostomaradiosumMIROC5

RCP26−MIROC5−Historical

RCP26−MIROC5−Future2050

RCP26−MIROC5−Future2070

RCP45−MIROC5−Historical

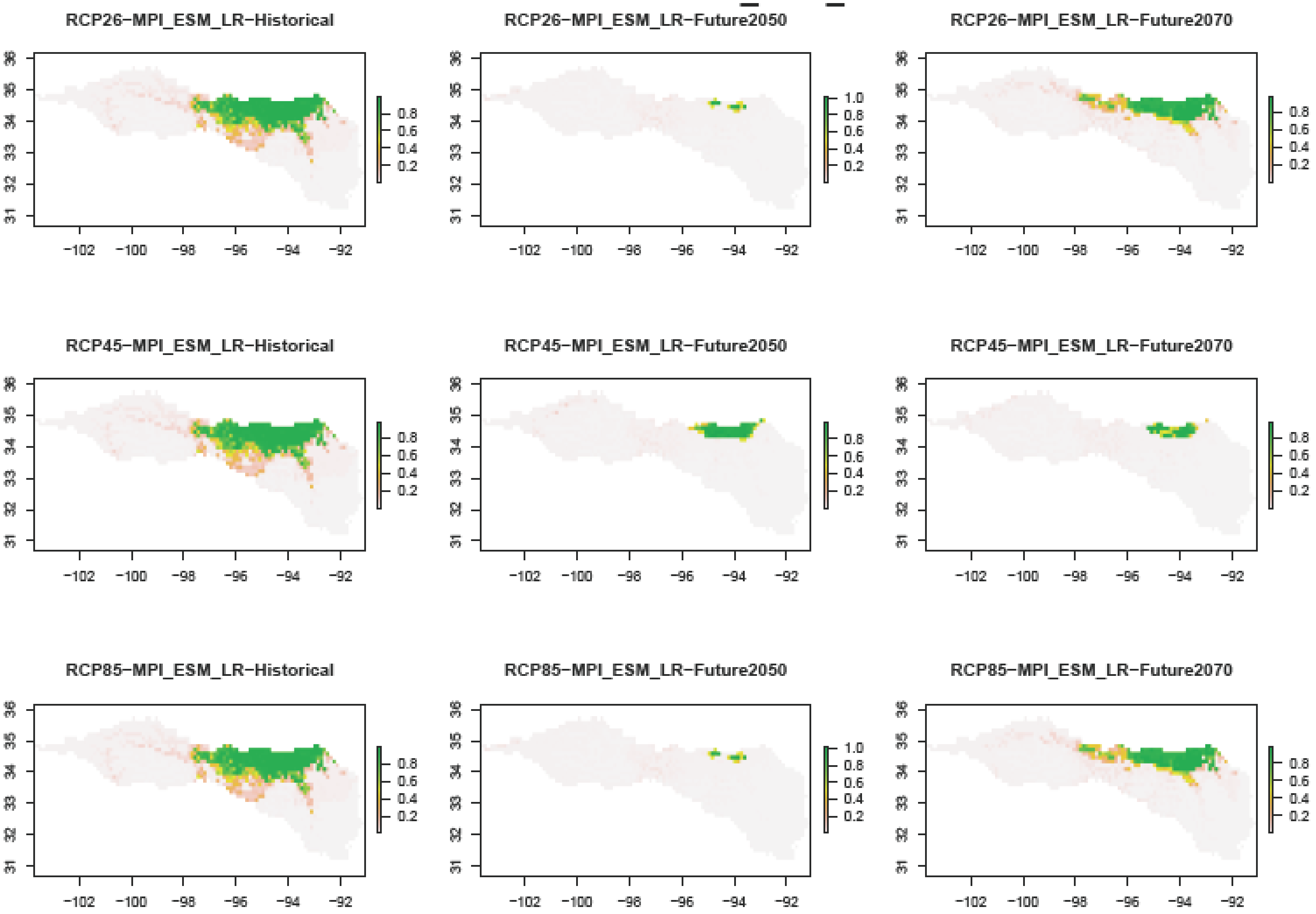
RCP45−MIROC5−Future2050

RCP45−MIROC5−Future2070

RCP85−MIROC5−Historical

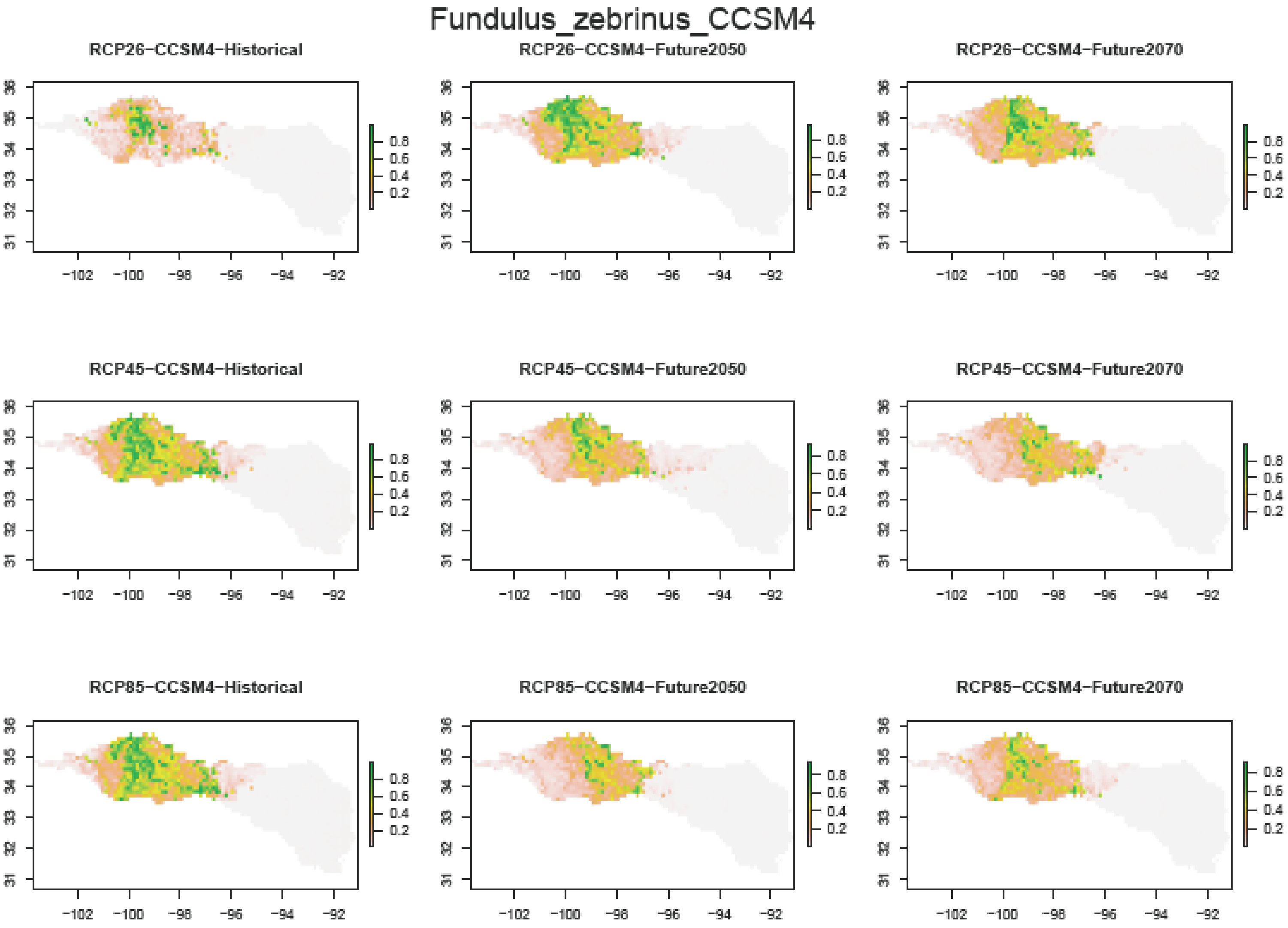
RCP85−MIROC5−Future2050

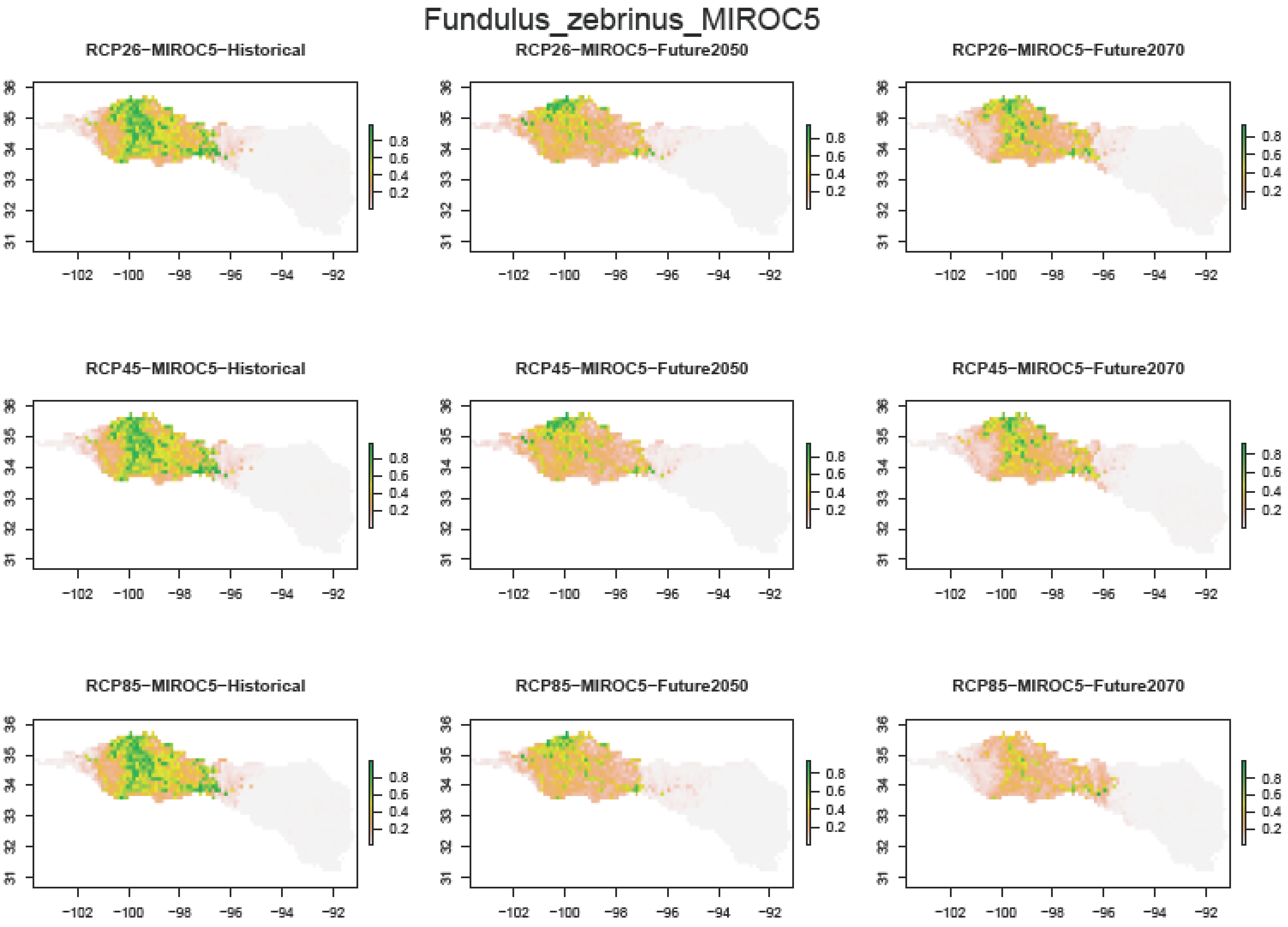
RCP85−MIROC5−Future2070



EtheostomaradiosumMPI_ESM_LR

Maxent: *Fundulus zebrinus*





Fundulus_zebrinus_MIROC5

RCP26-MIROC5-Historical

RCP26-MIROC5-Future2050

RCP26-MIROC5-Future2070

RCP45-MIROC5-Historical

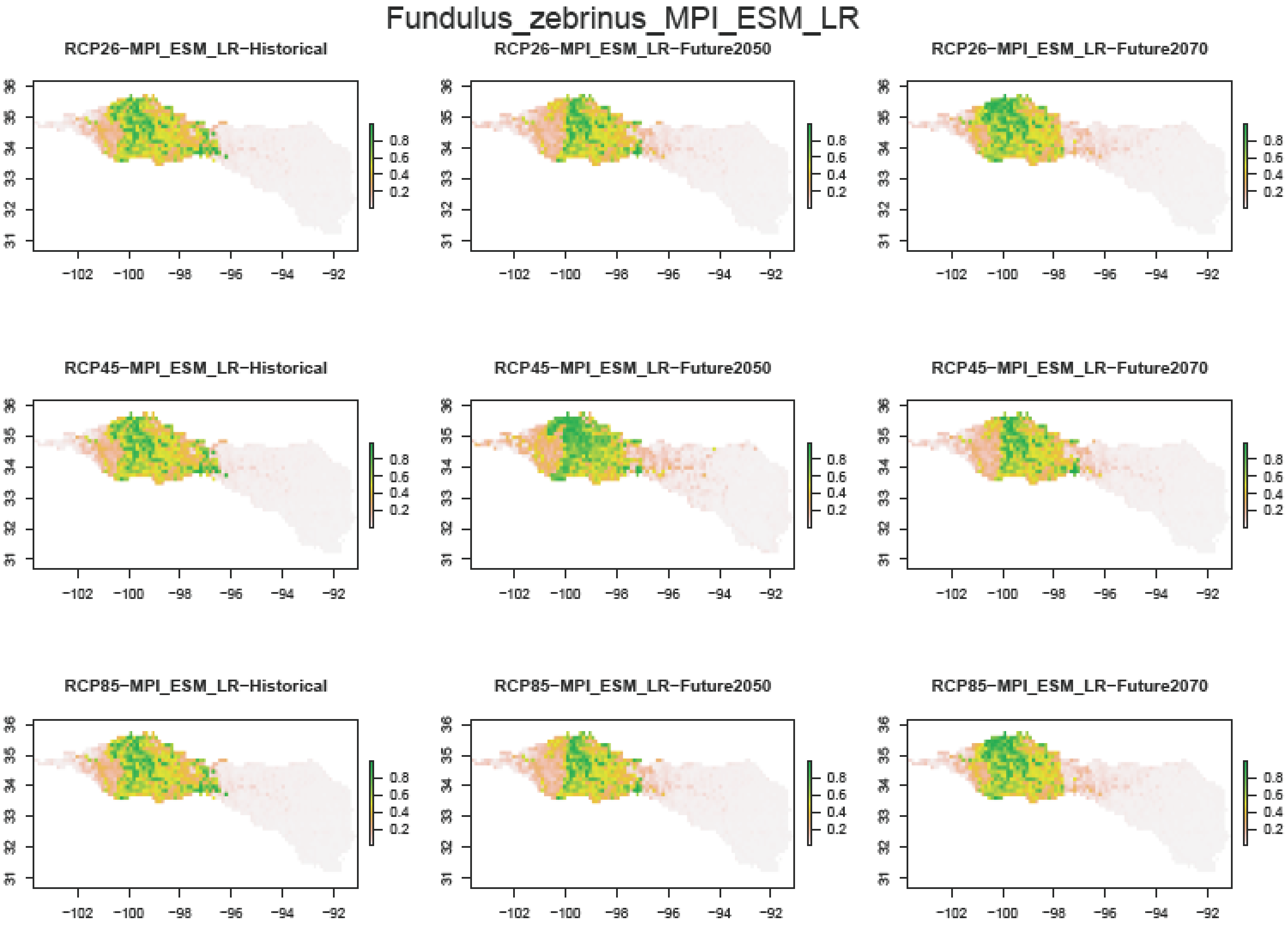
RCP45-MIROC5-Future2050

RCP45-MIROC5-Future2070

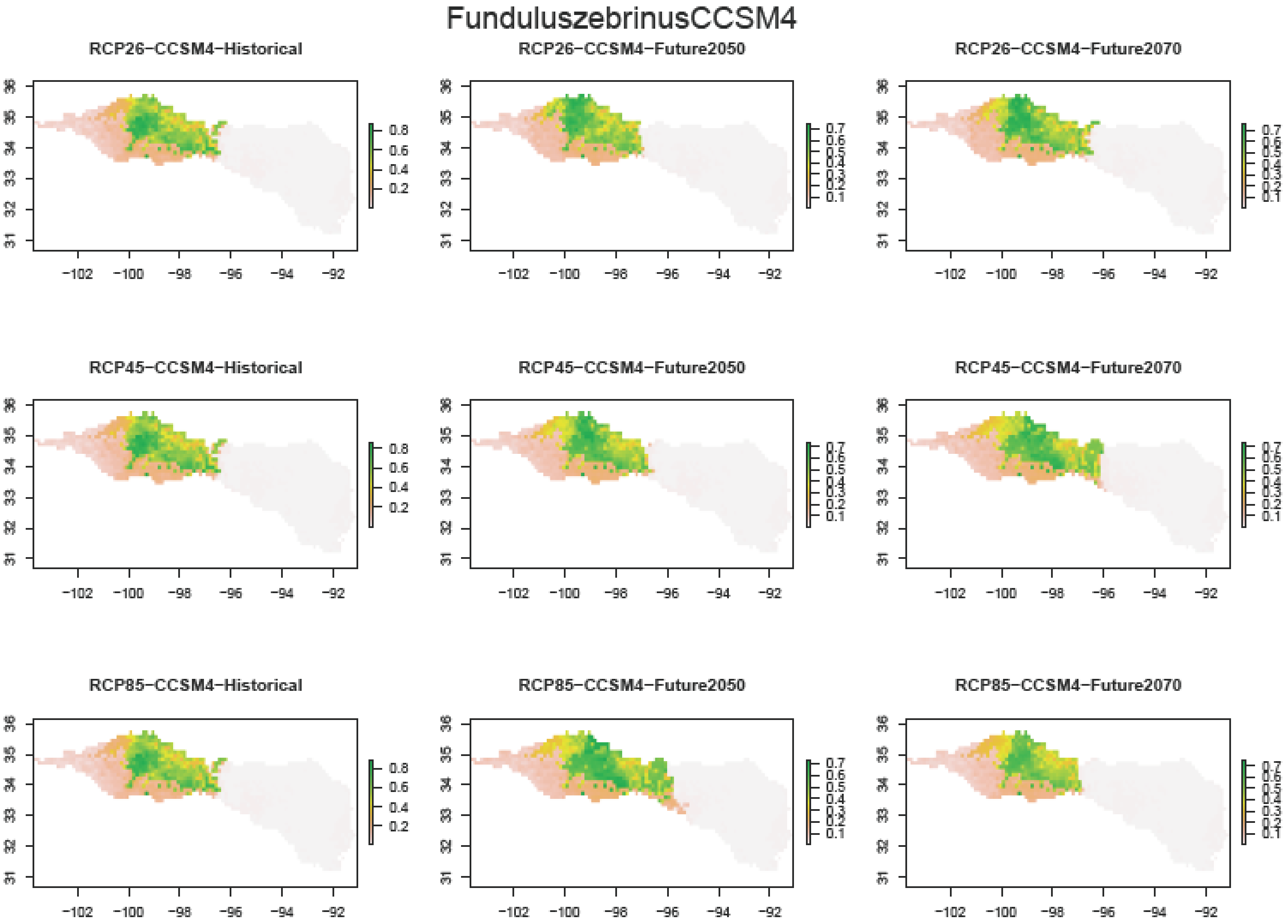
RCP85-MIROC5-Historical

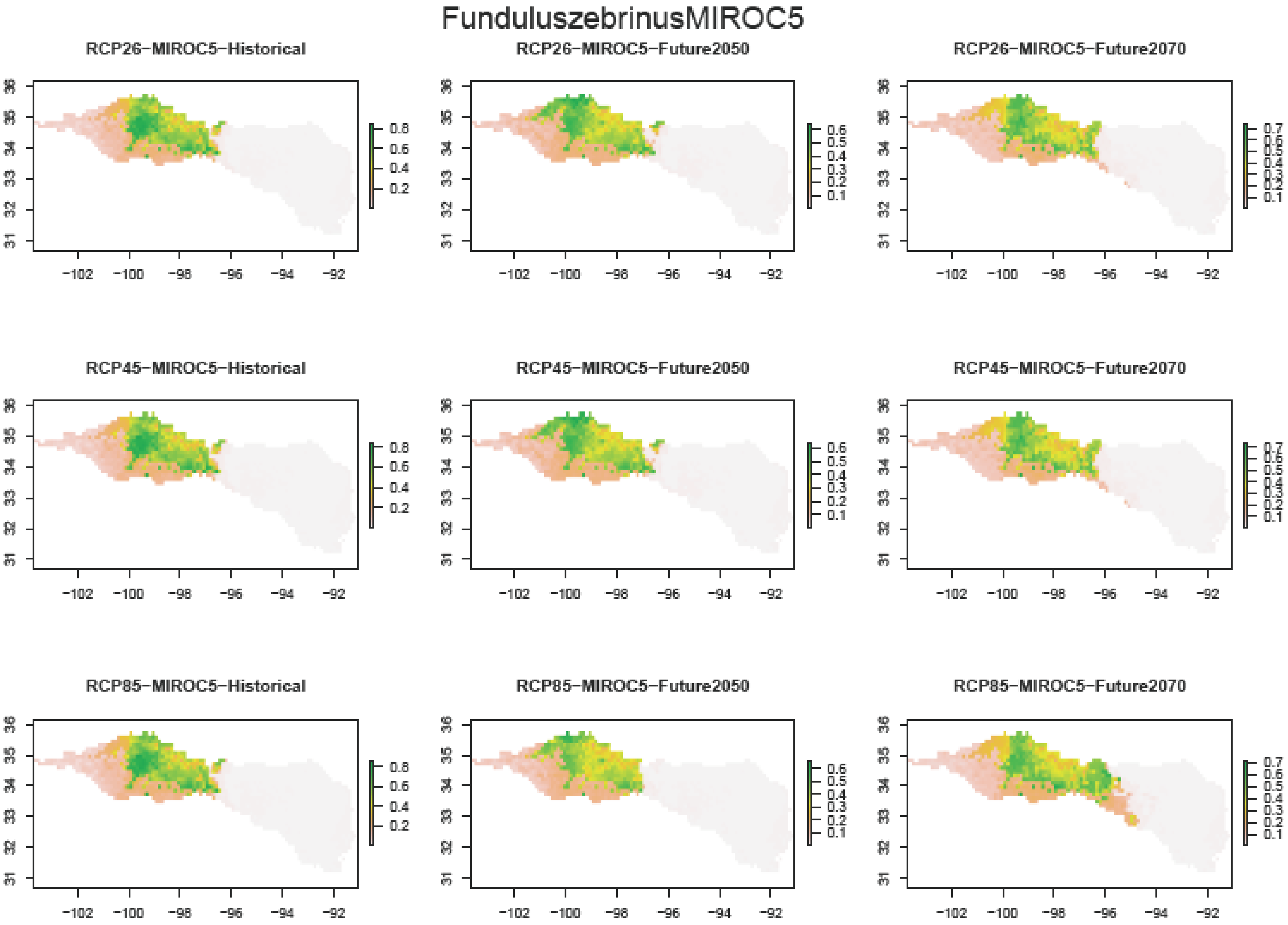
RCP85-MIROC5-Future2050

RCP85-MIROC5-Future2070

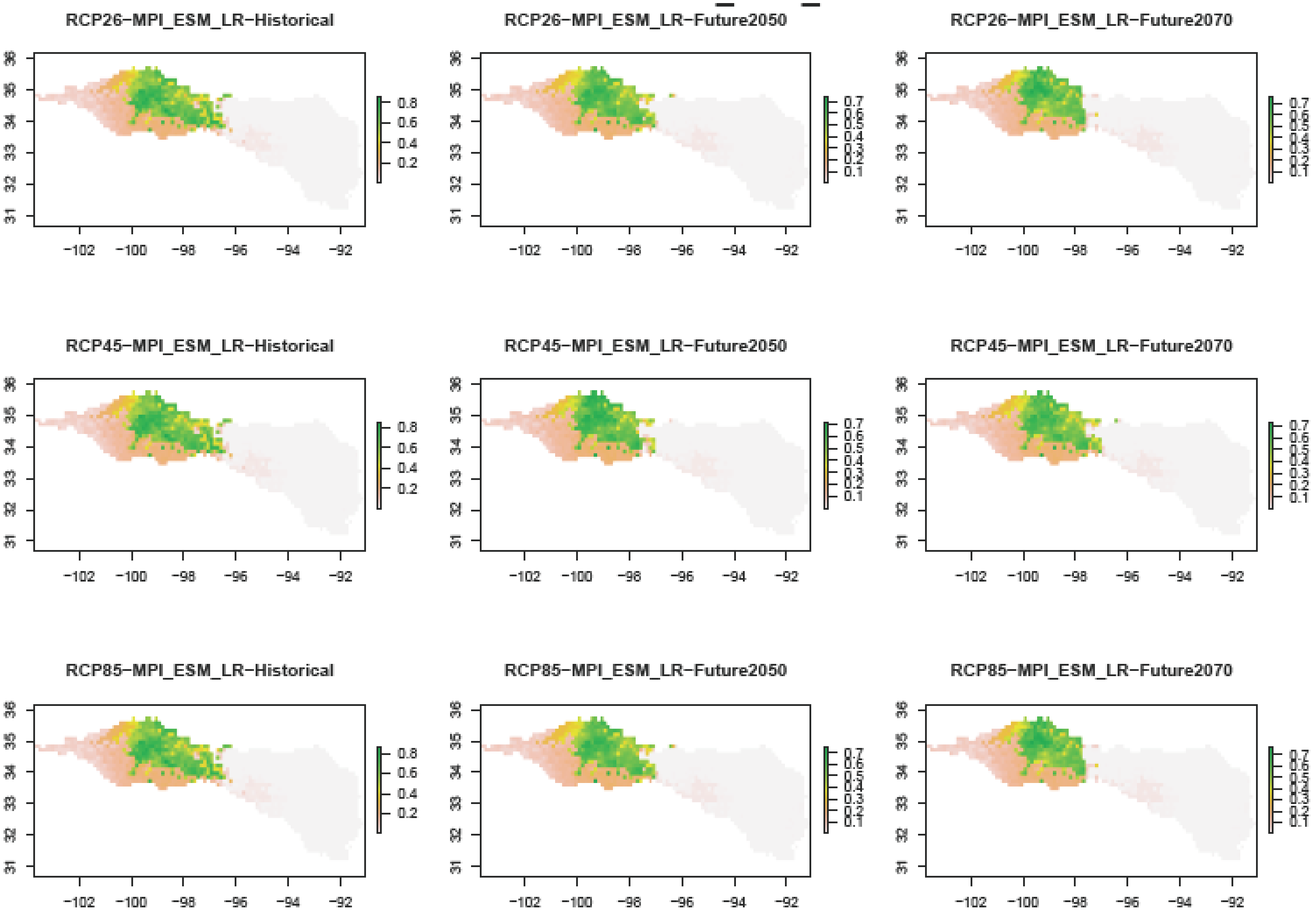

Fundulus_zebrinus_MPI_ESM_LR
RCP26−MPI_ESM_LR−Historical
RCP26−MPI_ESM_LR−Future2050
RCP26−MPI_ESM_LR−Future2070
RCP45−MPI_ESM_LR−Historical
RCP45−MPI_ESM_LR−Future2050
RCP45−MPI_ESM_LR−Future2070
RCP85−MPI_ESM_LR−Historical
RCP85−MPI_ESM_LR−Future2050
RCP85−MPI_ESM_LR−Future2070
31
32
33
34
35
36
−102
−100
−98
−96
−94
−92
0.2
0.4
0.6
0.8

BRT: *Fundulus zebrinus*

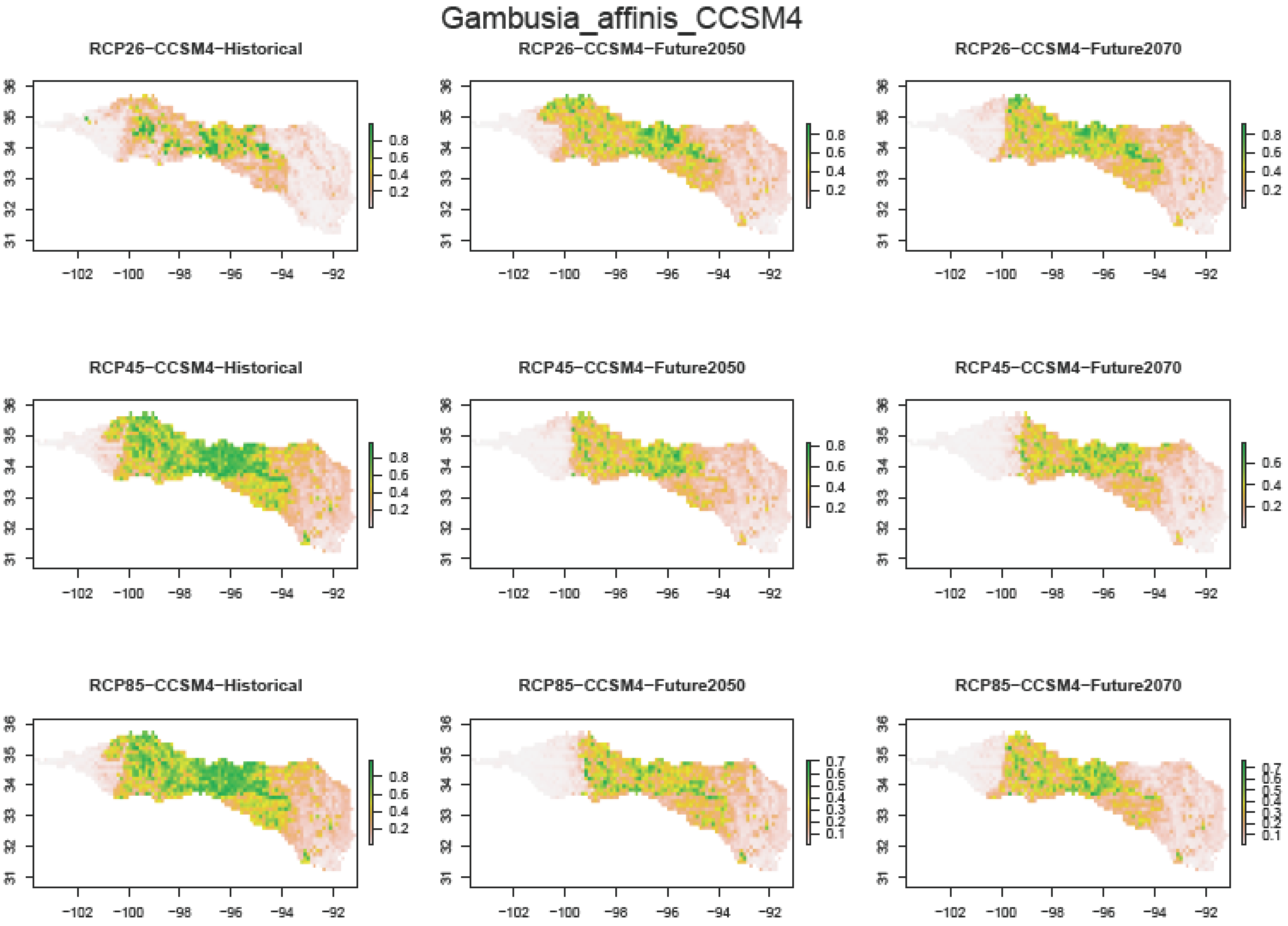



FunduluszebrinusMIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070
31
32
33
34
35
36
−102
−100
−98
−96
−94
−92
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8

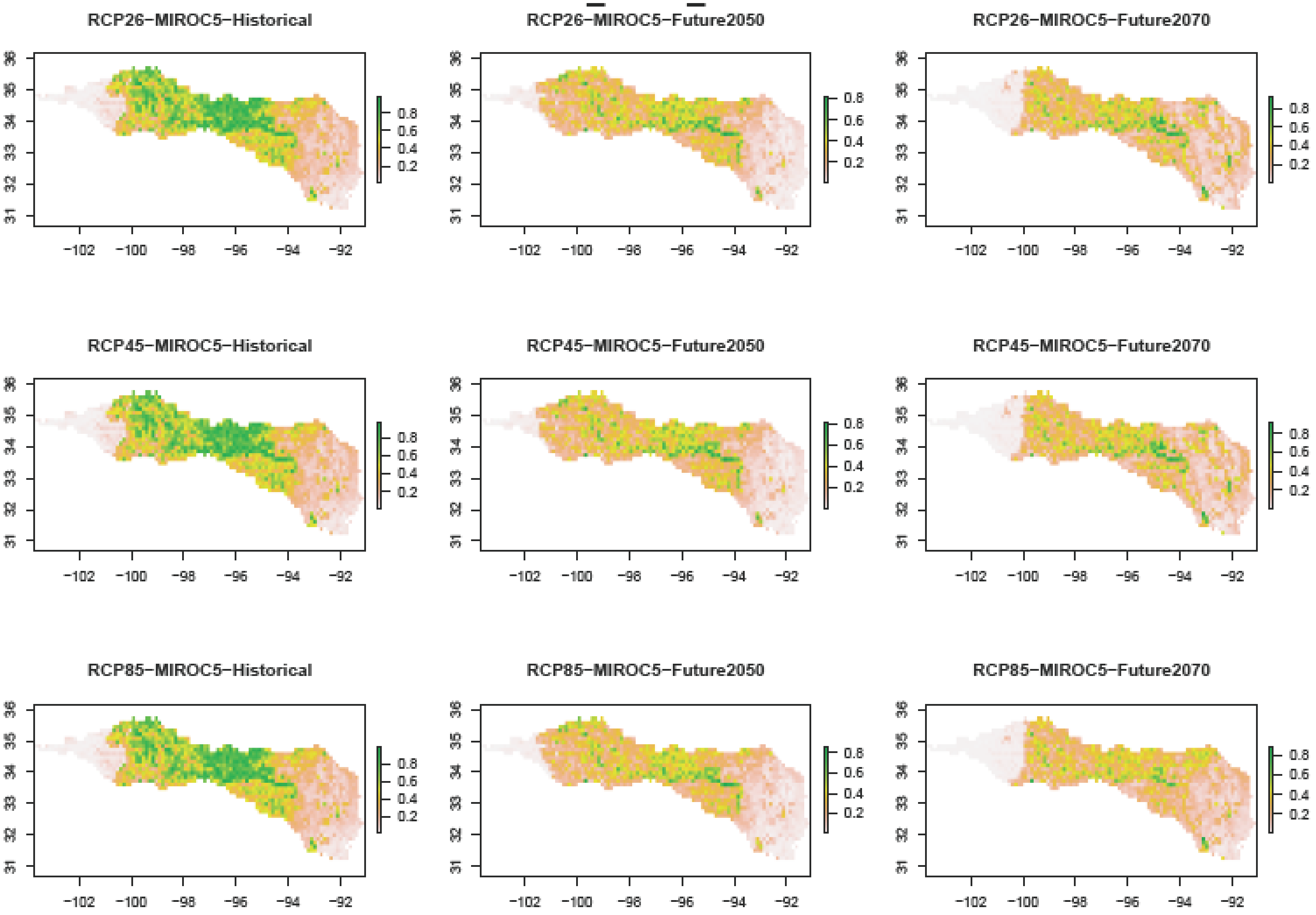
FunduluszebrinusMPI_ESM_LR

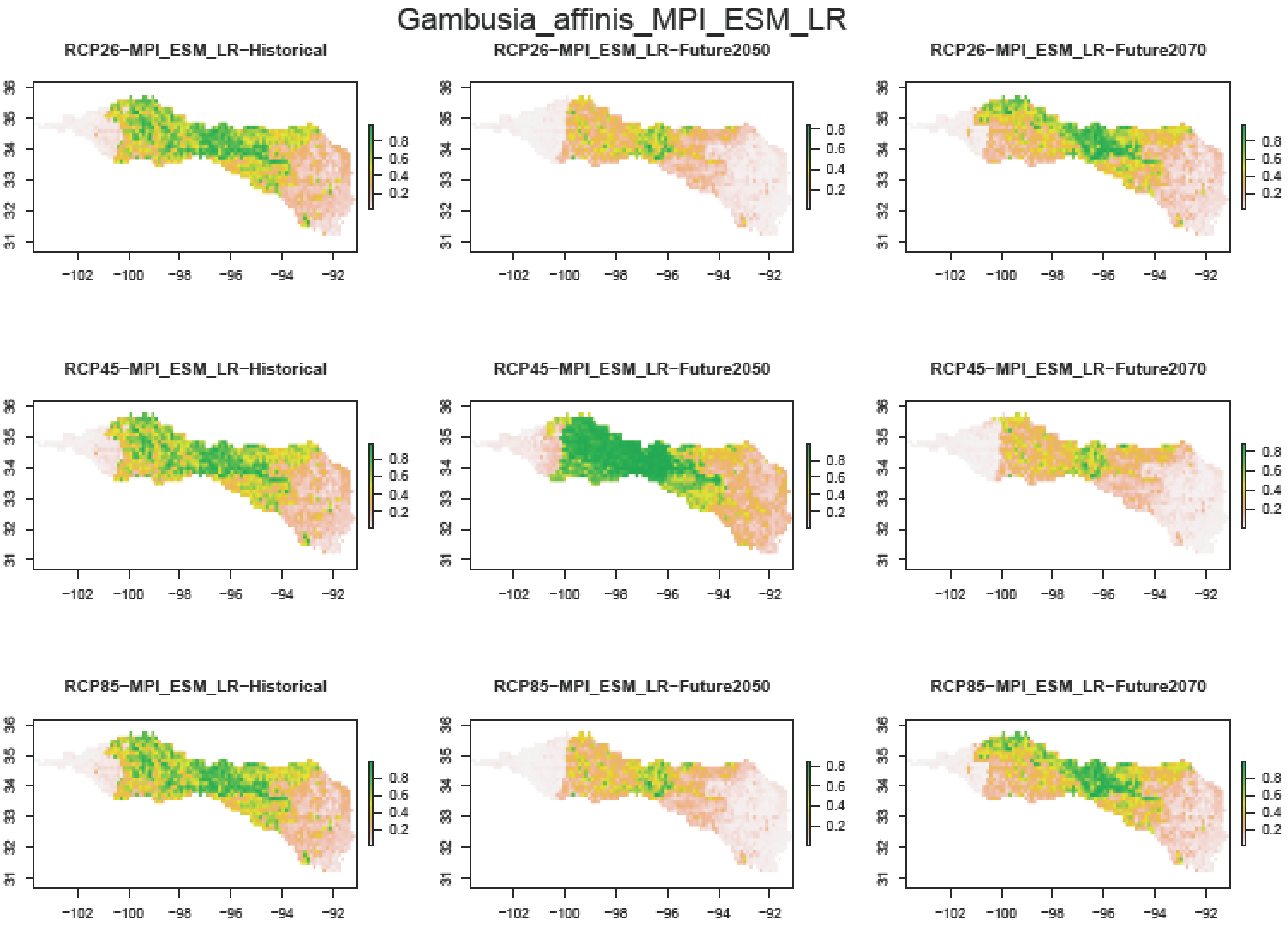


Maxent: *Gambusia affinis*



Gambusia_affinis_MIROC5





Gambusia_affinis_MPI_ESM_LR

RCP26-MPI_ESM_LR-Historical

RCP26-MPI_ESM_LR-Future2050

RCP26-MPI_ESM_LR-Future2070

RCP45-MPI_ESM_LR-Historical

RCP45-MPI_ESM_LR-Future2050

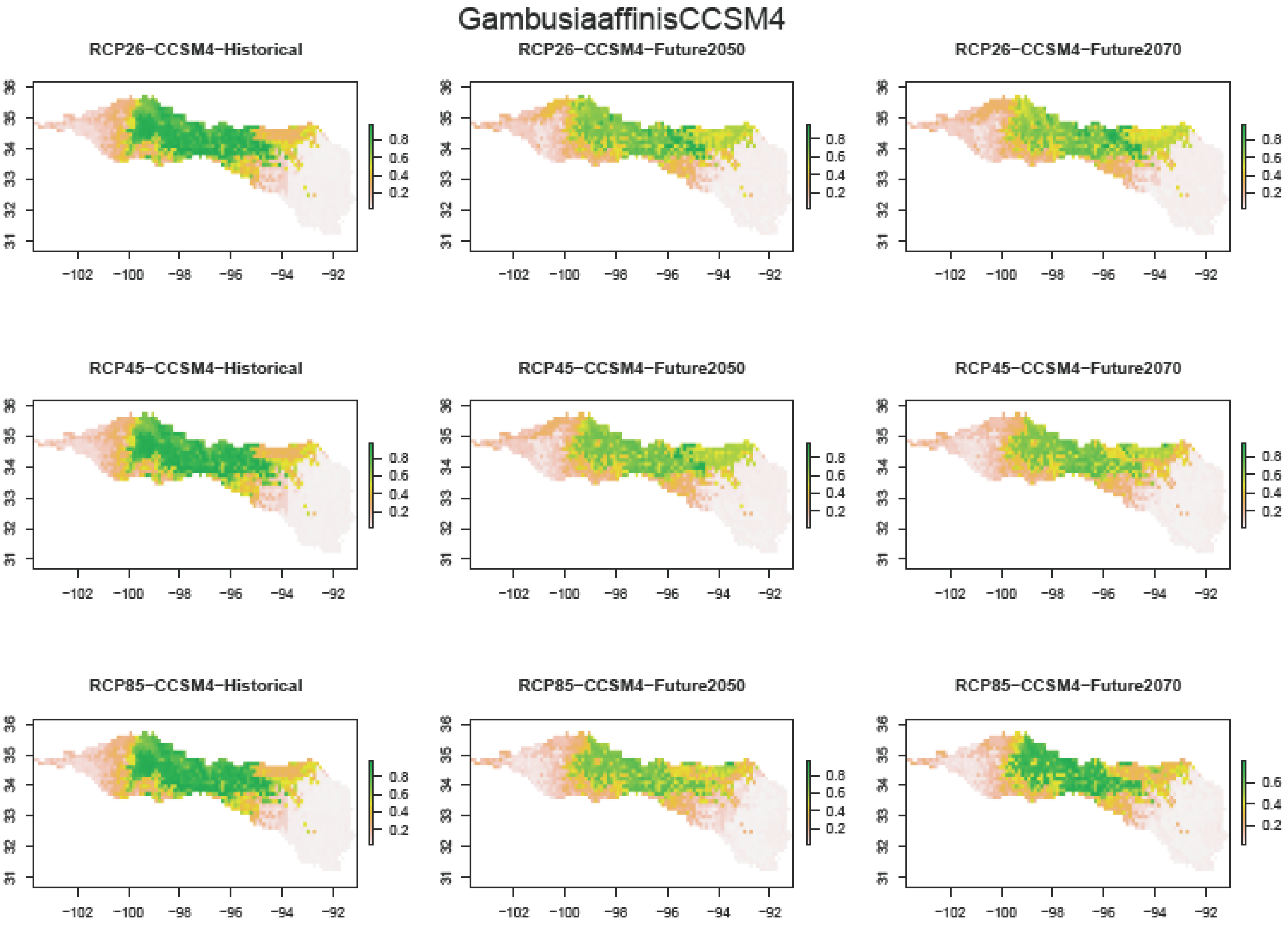
RCP45-MPI_ESM_LR-Future2070

RCP85-MPI_ESM_LR-Historical

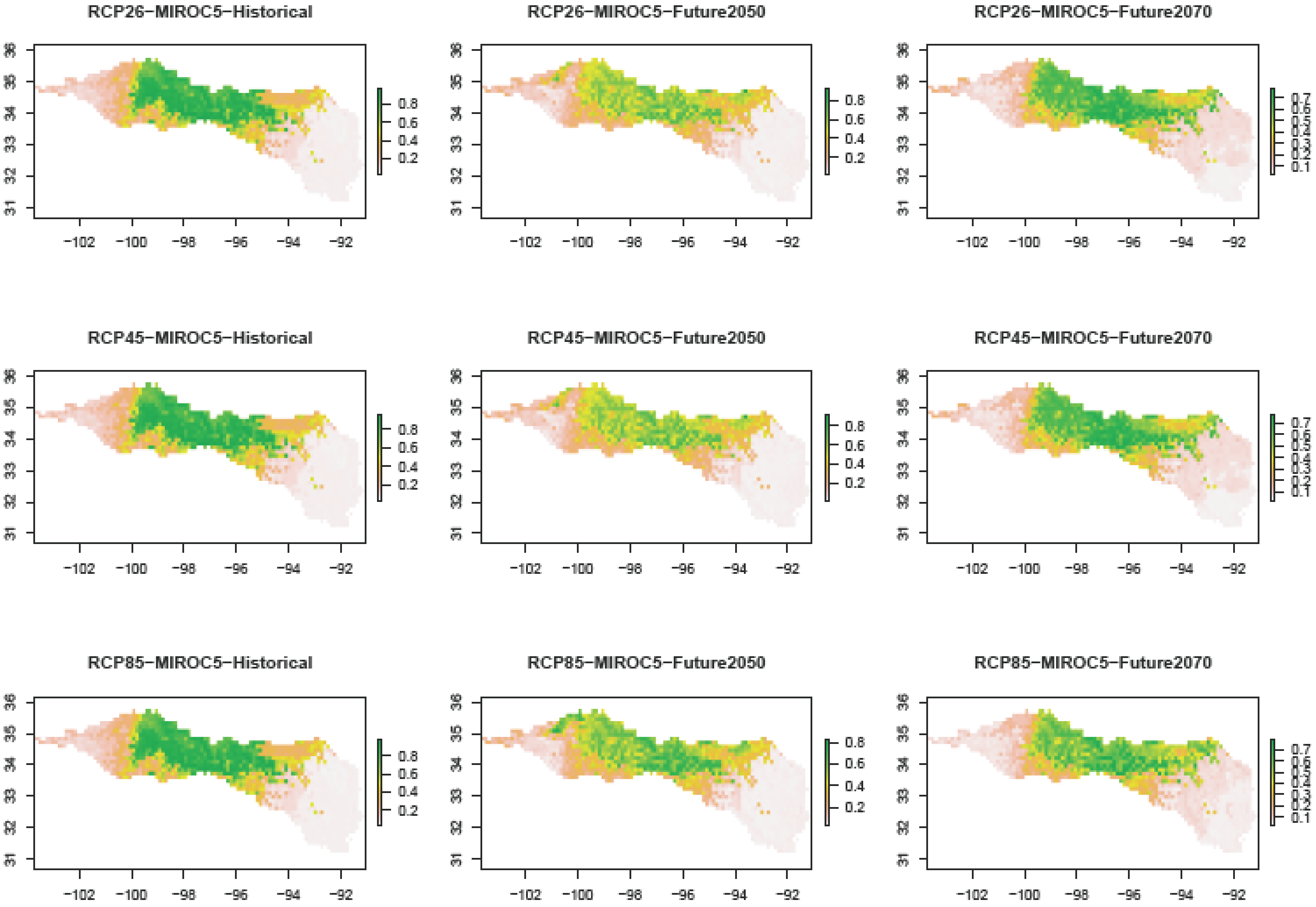
RCP85-MPI_ESM_LR-Future2050

RCP85-MPI_ESM_LR-Future2070

BRT: *Gambusia affinis*



GambusiaaffinisMIROC5



RCP26−MIROC5−Historical

RCP26−MIROC5−Future2050

RCP26−MIROC5−Future2070

RCP45−MIROC5−Historical

RCP45−MIROC5−Future2050

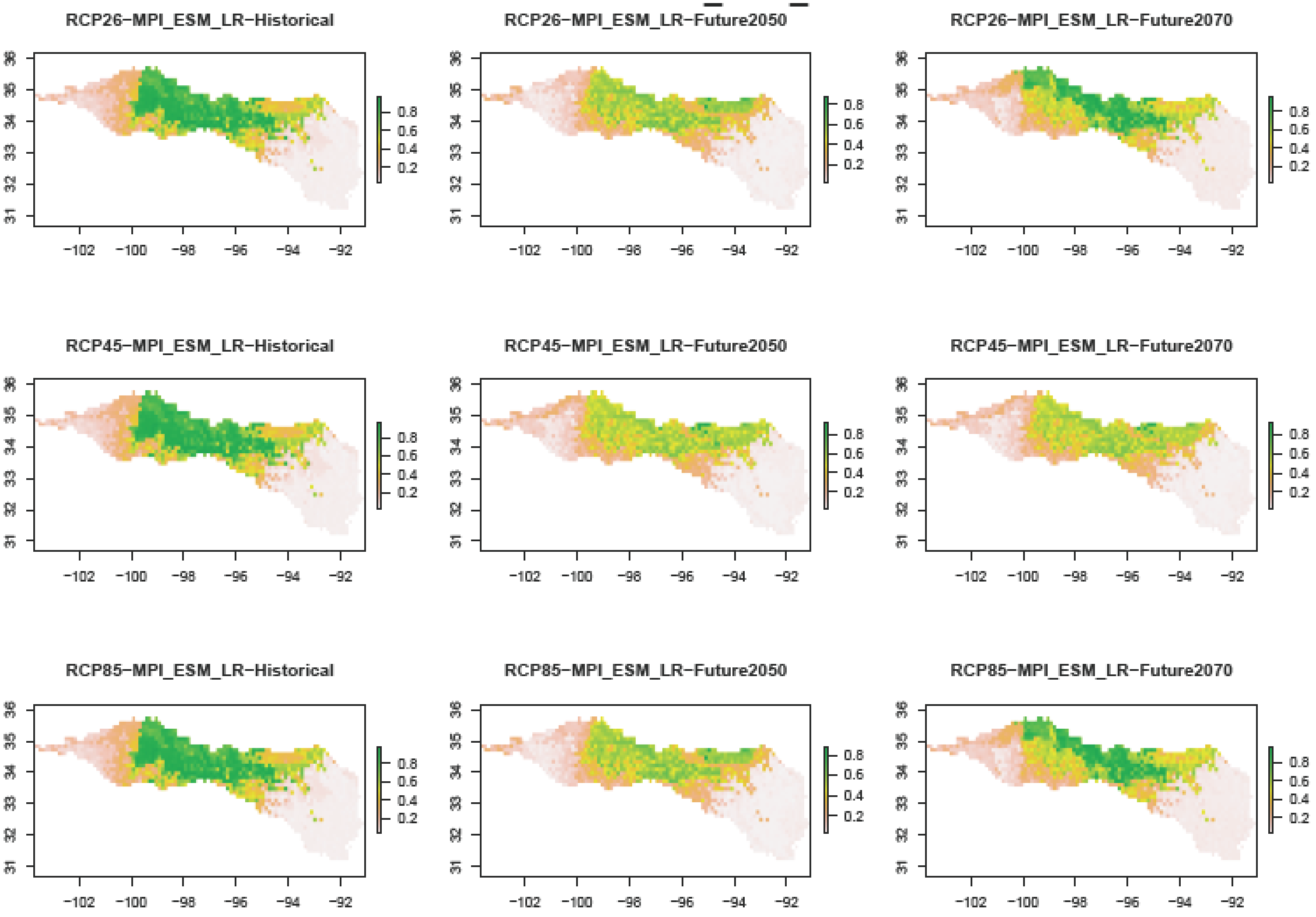
RCP45−MIROC5−Future2070

RCP85−MIROC5−Historical

RCP85−MIROC5−Future2050

RCP85−MIROC5−Future2070

GambusiaaffinisMPI_ESM_LR



RCP26−MPI_ESM_LR−Historical

RCP26−MPI_ESM_LR−Future2050

RCP26−MPI_ESM_LR−Future2070

RCP45−MPI_ESM_LR−Historical

RCP45−MPI_ESM_LR−Future2050

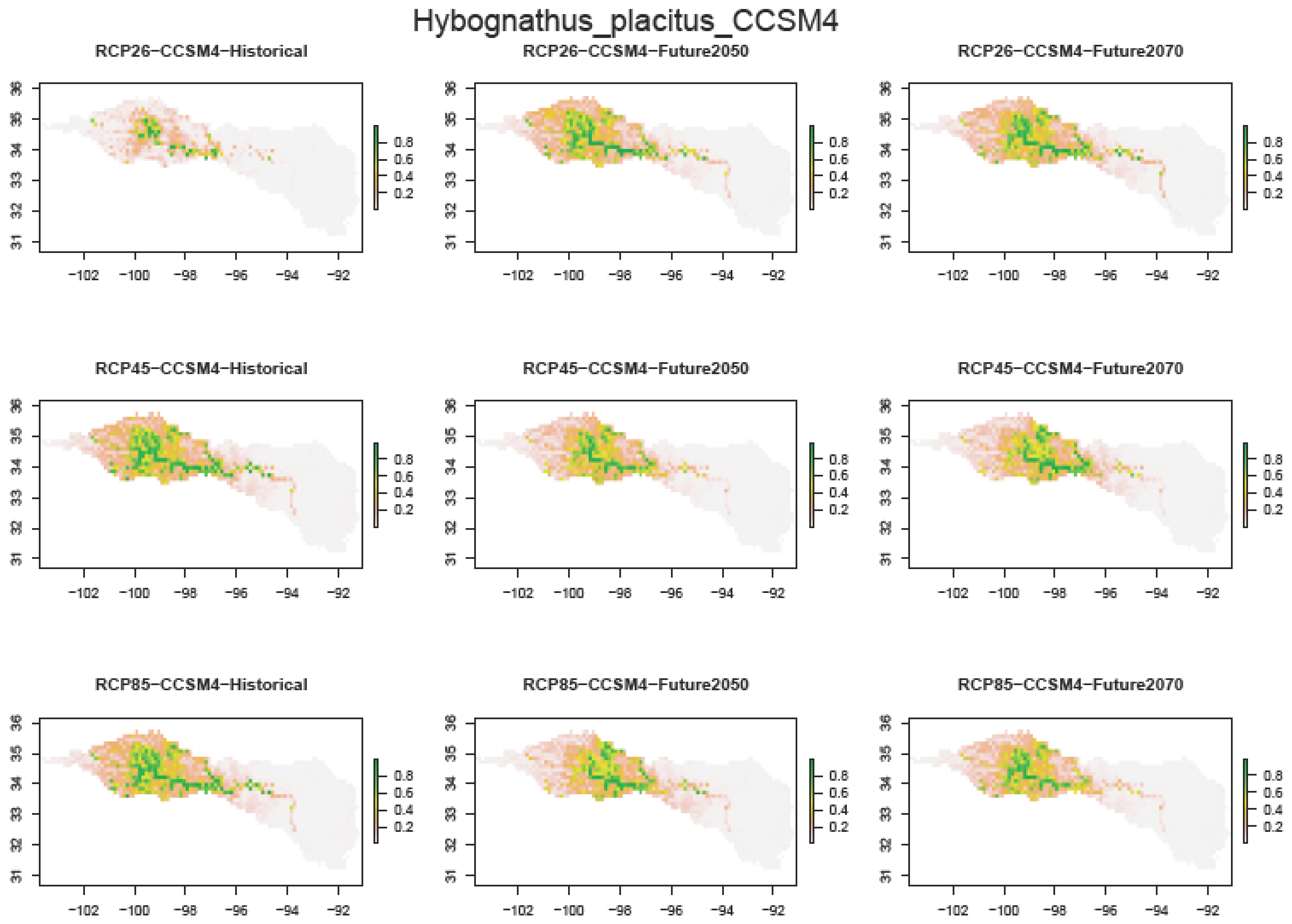
RCP45−MPI_ESM_LR−Future2070

RCP85−MPI_ESM_LR−Historical

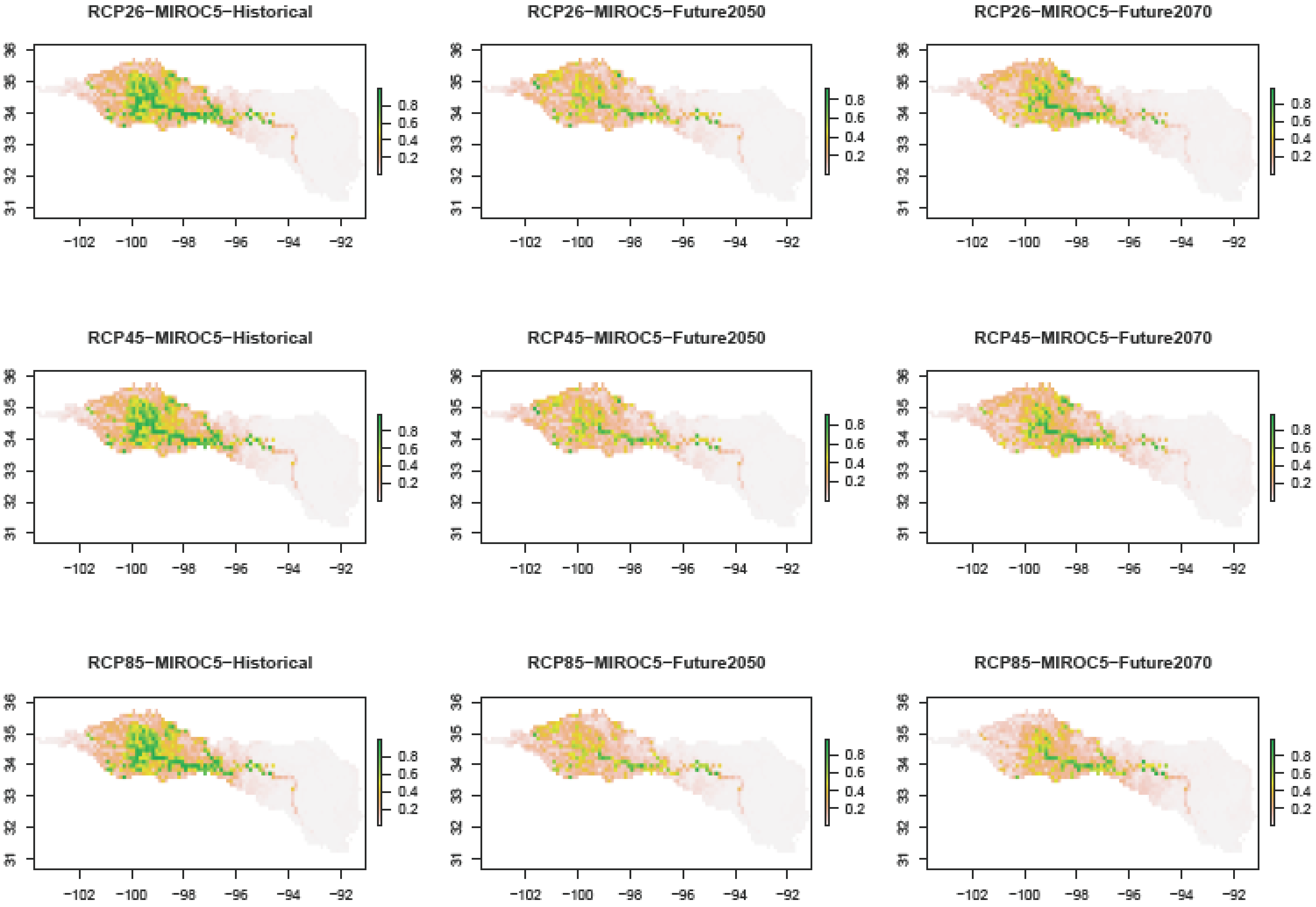
RCP85−MPI_ESM_LR−Future2050

RCP85−MPI_ESM_LR−Future2070

Maxent: *Hybognathus placitus*



Hybognathus_placitus_MIROC5



RCP26-MIROC5-Historical

RCP26-MIROC5-Future2050

RCP26-MIROC5-Future2070

RCP45-MIROC5-Historical

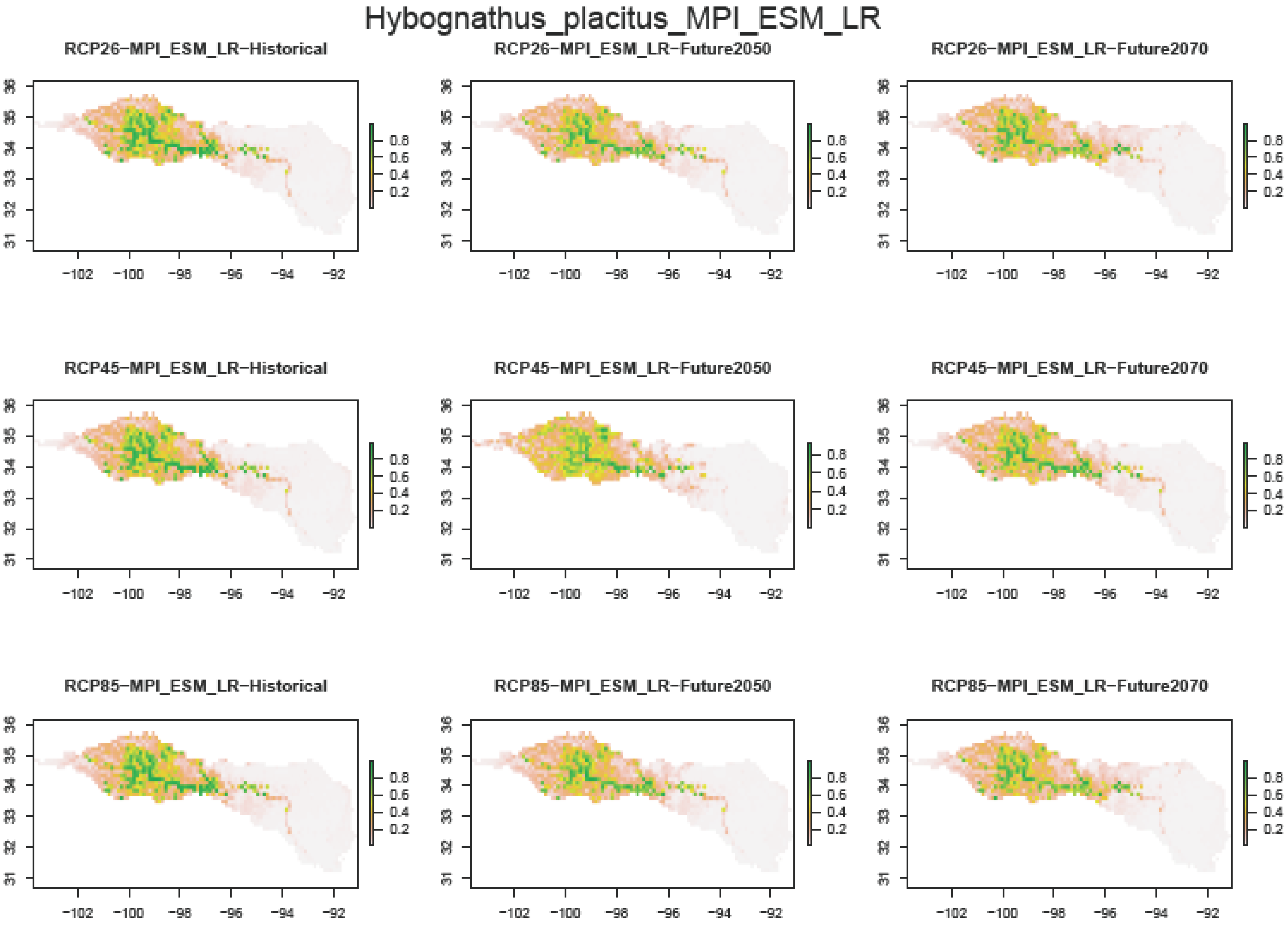
RCP45-MIROC5-Future2050

RCP45-MIROC5-Future2070

RCP85-MIROC5-Historical

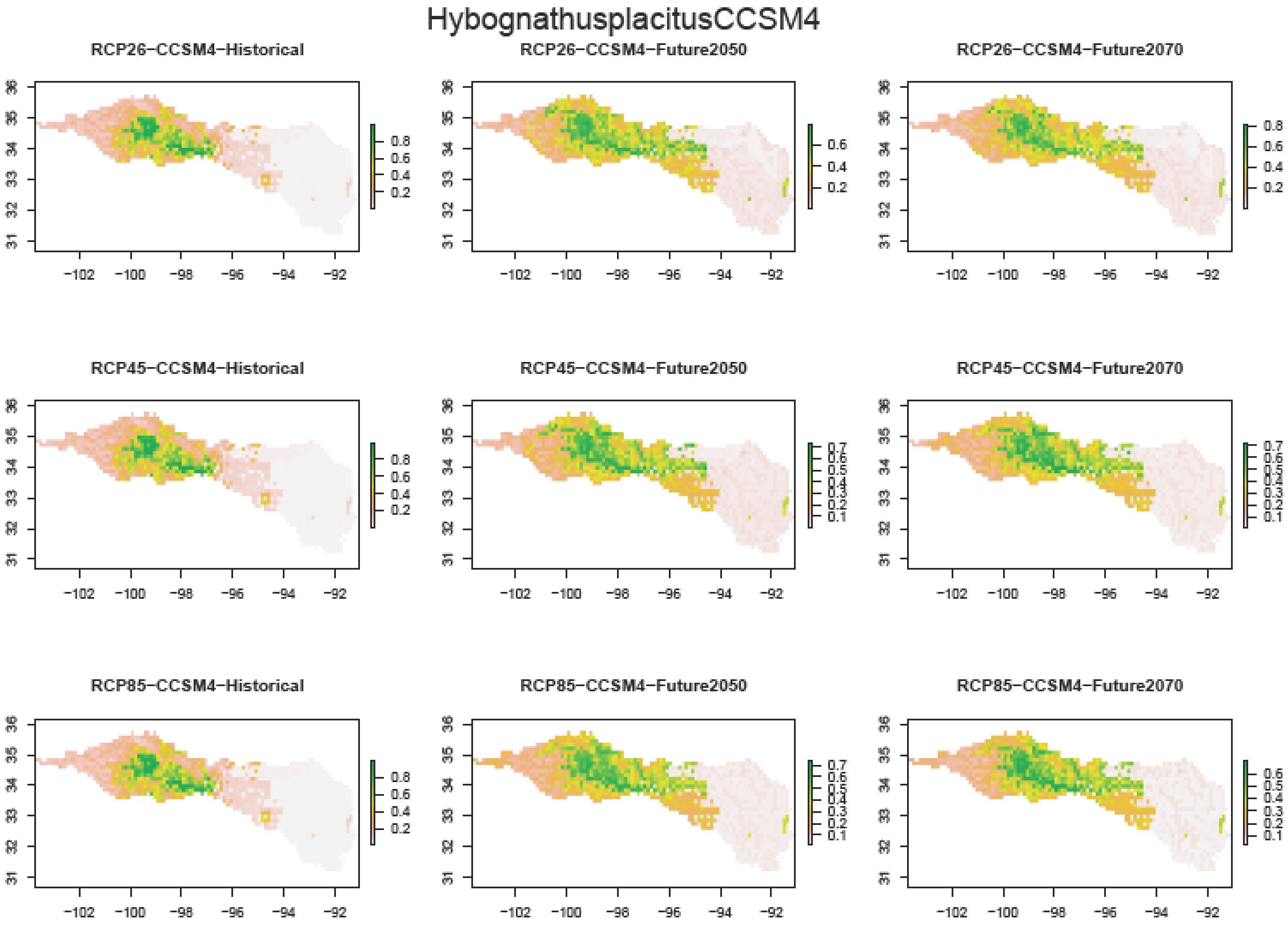
RCP85-MIROC5-Future2050

RCP85-MIROC5-Future2070

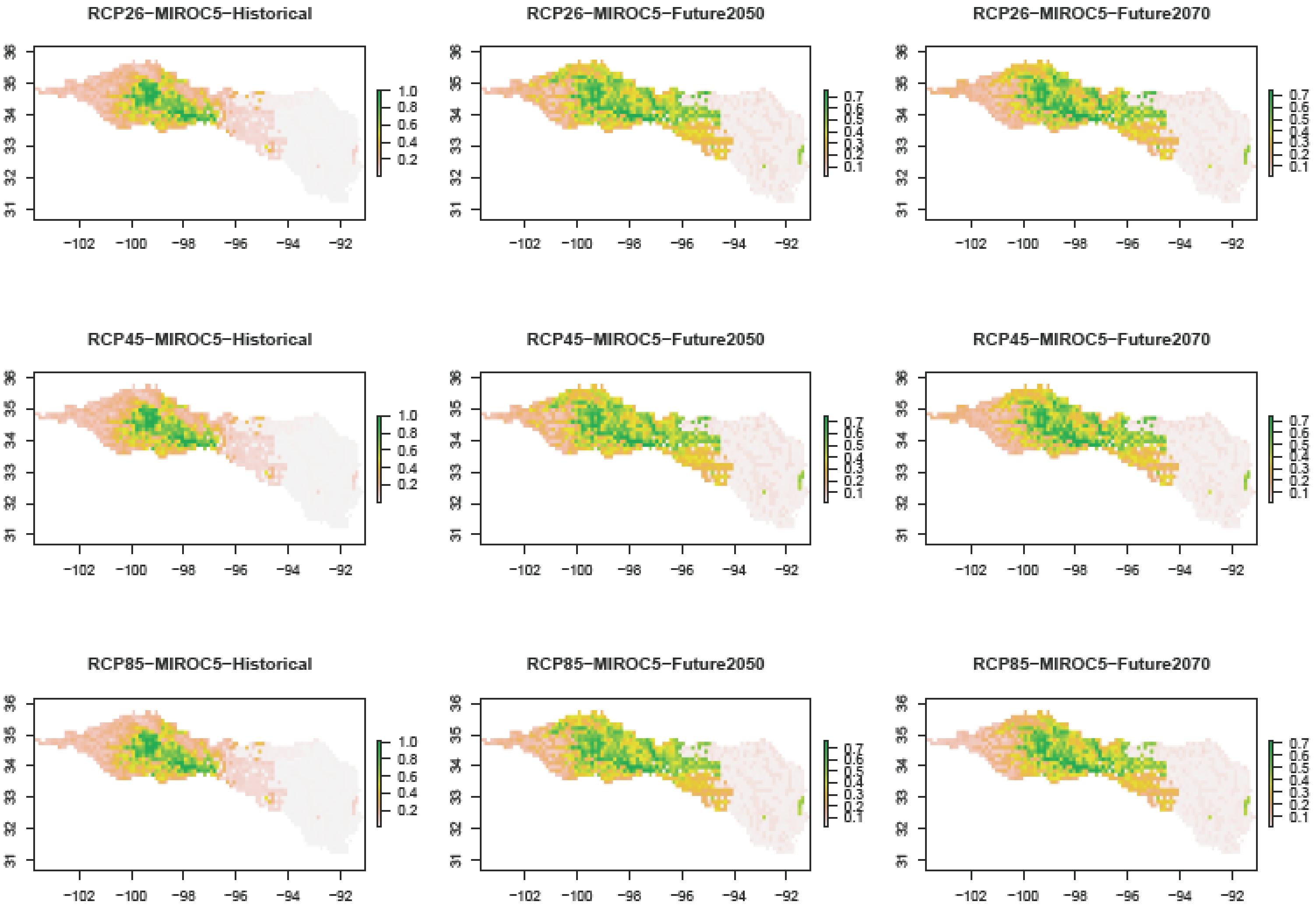


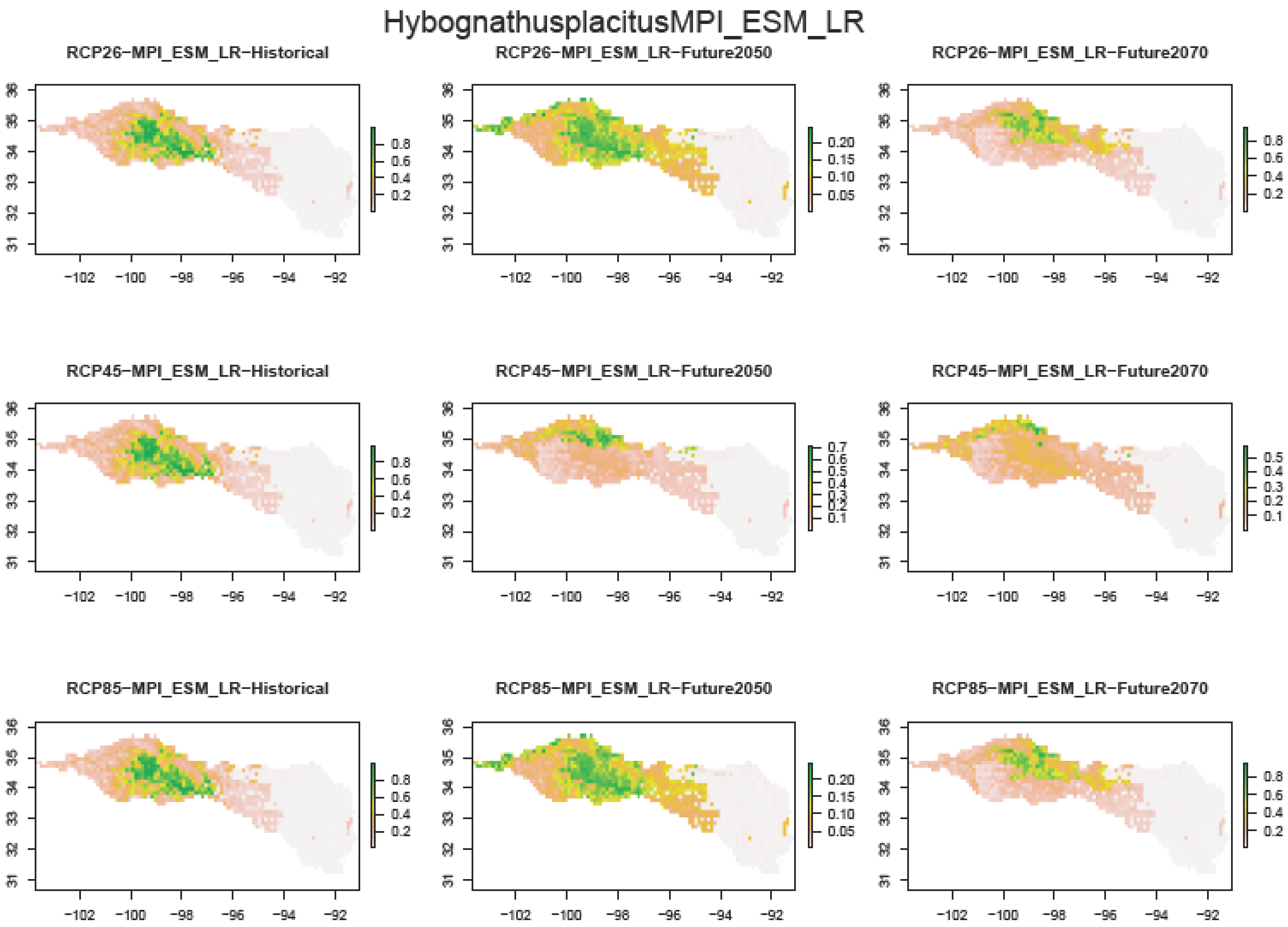
Hybognathus_placitus_MPI_ESM_LR

BRT: *Hybognathus placitus*



HybognathusplacitusMIROC5




HybognathusplacitusMPI_ESM_LR

RCP26-MPI_ESM_LR-Historical

RCP26-MPI_ESM_LR-Future2050

RCP26-MPI_ESM_LR-Future2070

RCP45-MPI_ESM_LR-Historical

RCP45-MPI_ESM_LR-Future2050

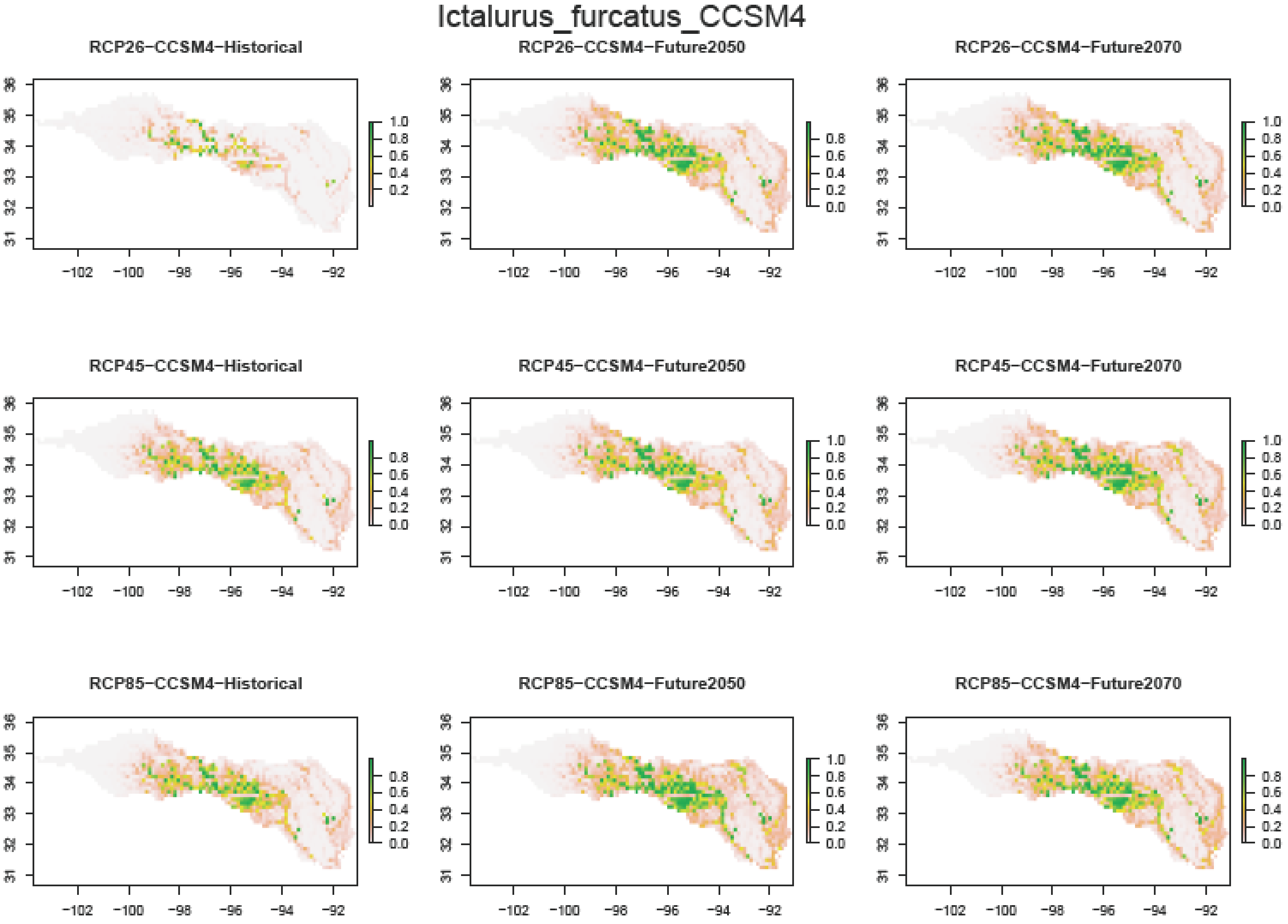
RCP45-MPI_ESM_LR-Future2070

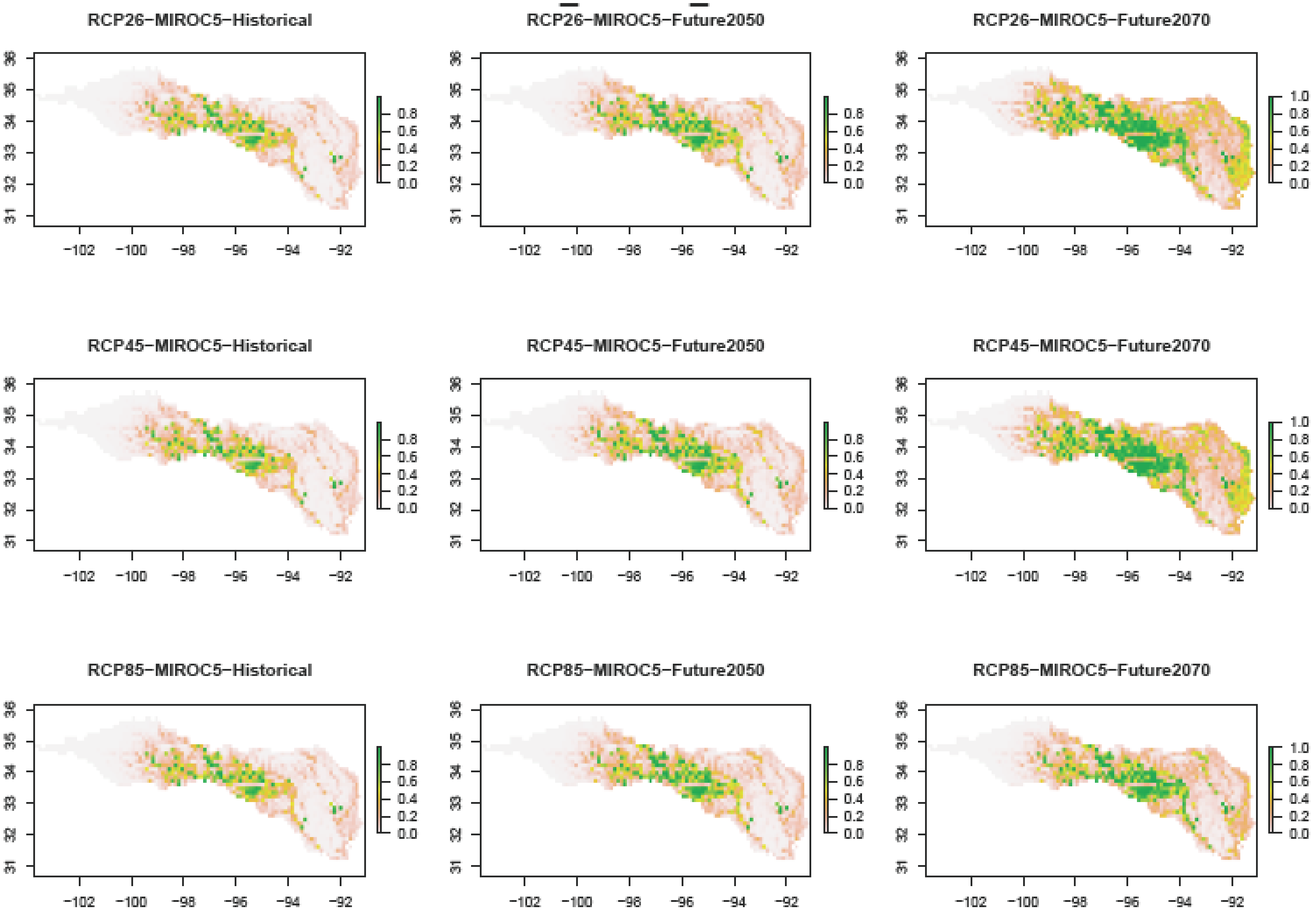
RCP85-MPI_ESM_LR-Historical

RCP85-MPI_ESM_LR-Future2050

RCP85-MPI_ESM_LR-Future2070

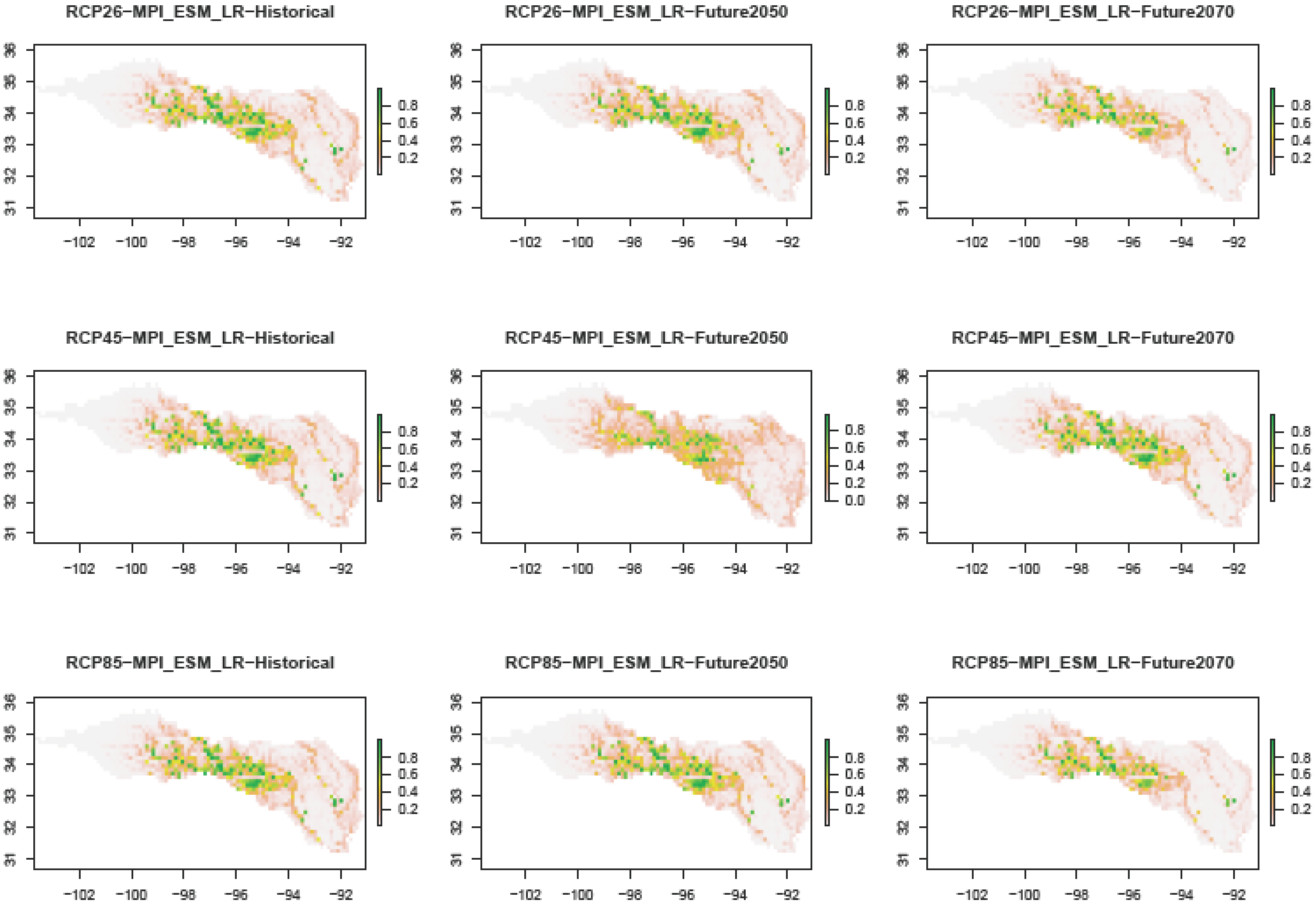
Maxent: *Ictalurus furcatus*





Ictalurus_furcatus_MIROC5

Ictalurus_furcatus_MPI_ESM_LR



RCP26−MPI_ESM_LR−Historical

RCP26−MPI_ESM_LR−Future2050

RCP26−MPI_ESM_LR−Future2070

RCP45−MPI_ESM_LR−Historical

RCP45−MPI_ESM_LR−Future2050

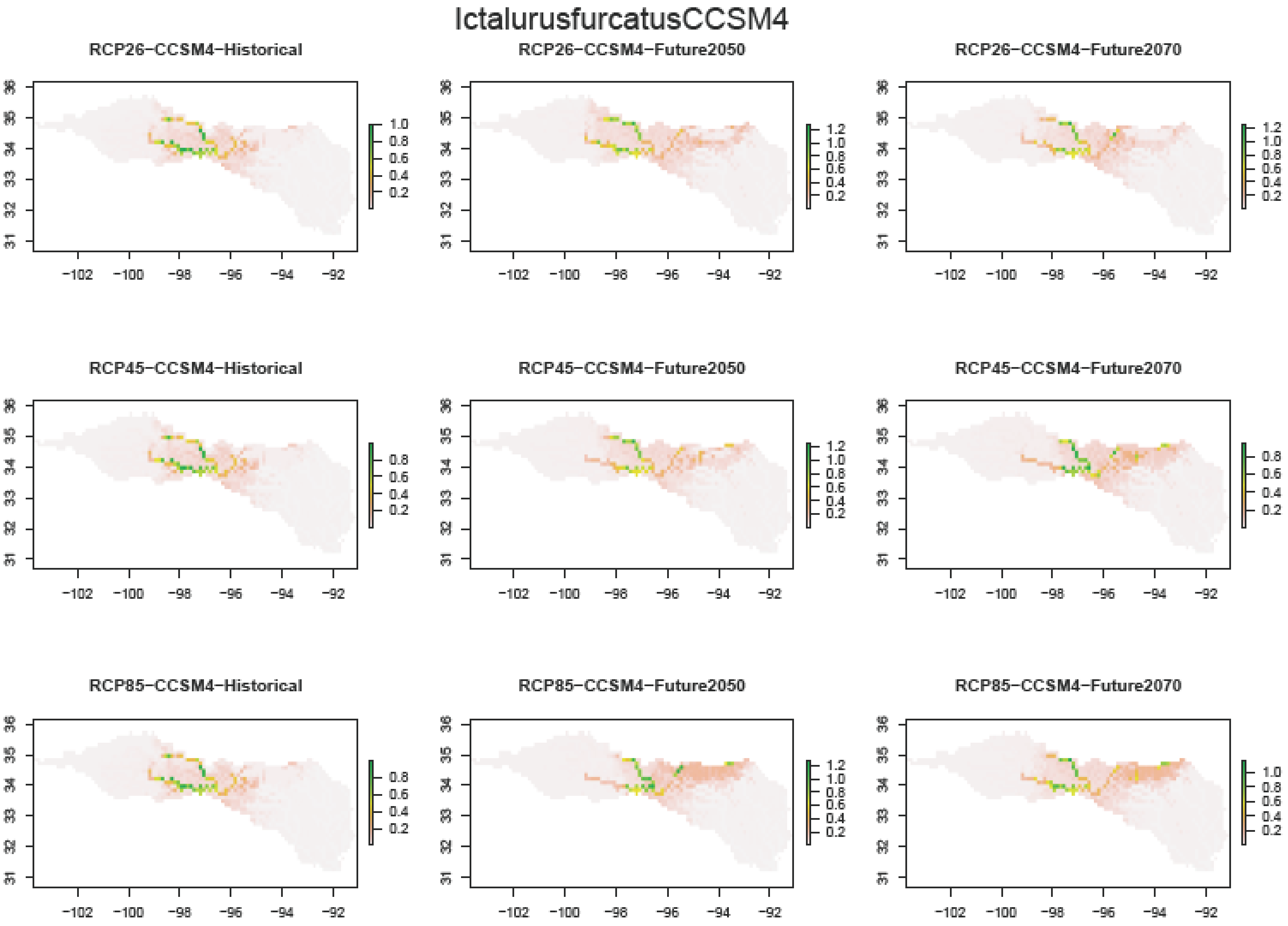
RCP45−MPI_ESM_LR−Future2070

RCP85−MPI_ESM_LR−Historical

RCP85−MPI_ESM_LR−Future2050

RCP85−MPI_ESM_LR−Future2070

BRT: *Ictalurus furcatus*



IctalurusfurcatusCCSM4

RCP26−CCSM4−Historical

RCP26−CCSM4−Future2050

RCP26−CCSM4−Future2070

RCP45−CCSM4−Historical

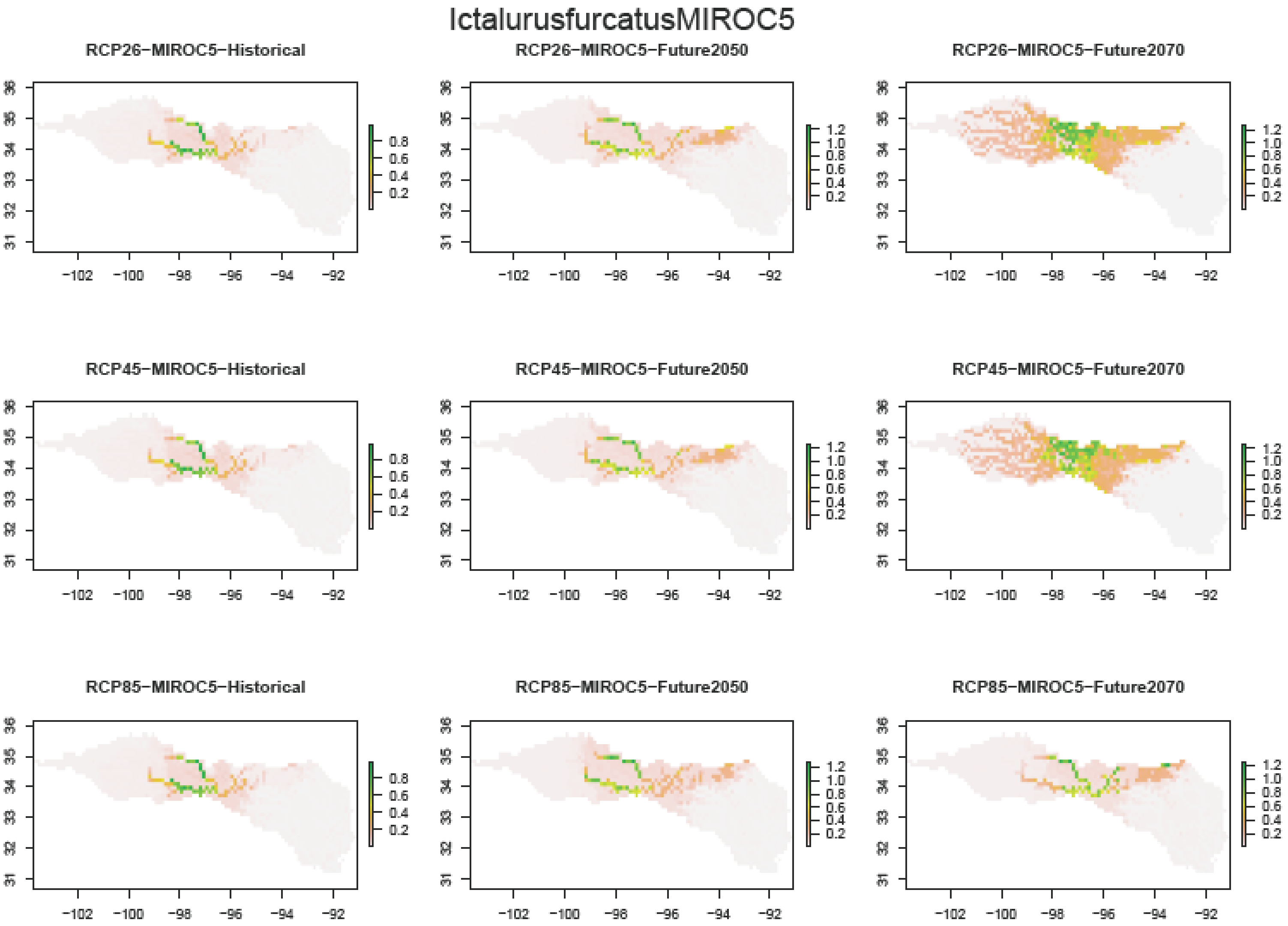
RCP45−CCSM4−Future2050

RCP45−CCSM4−Future2070

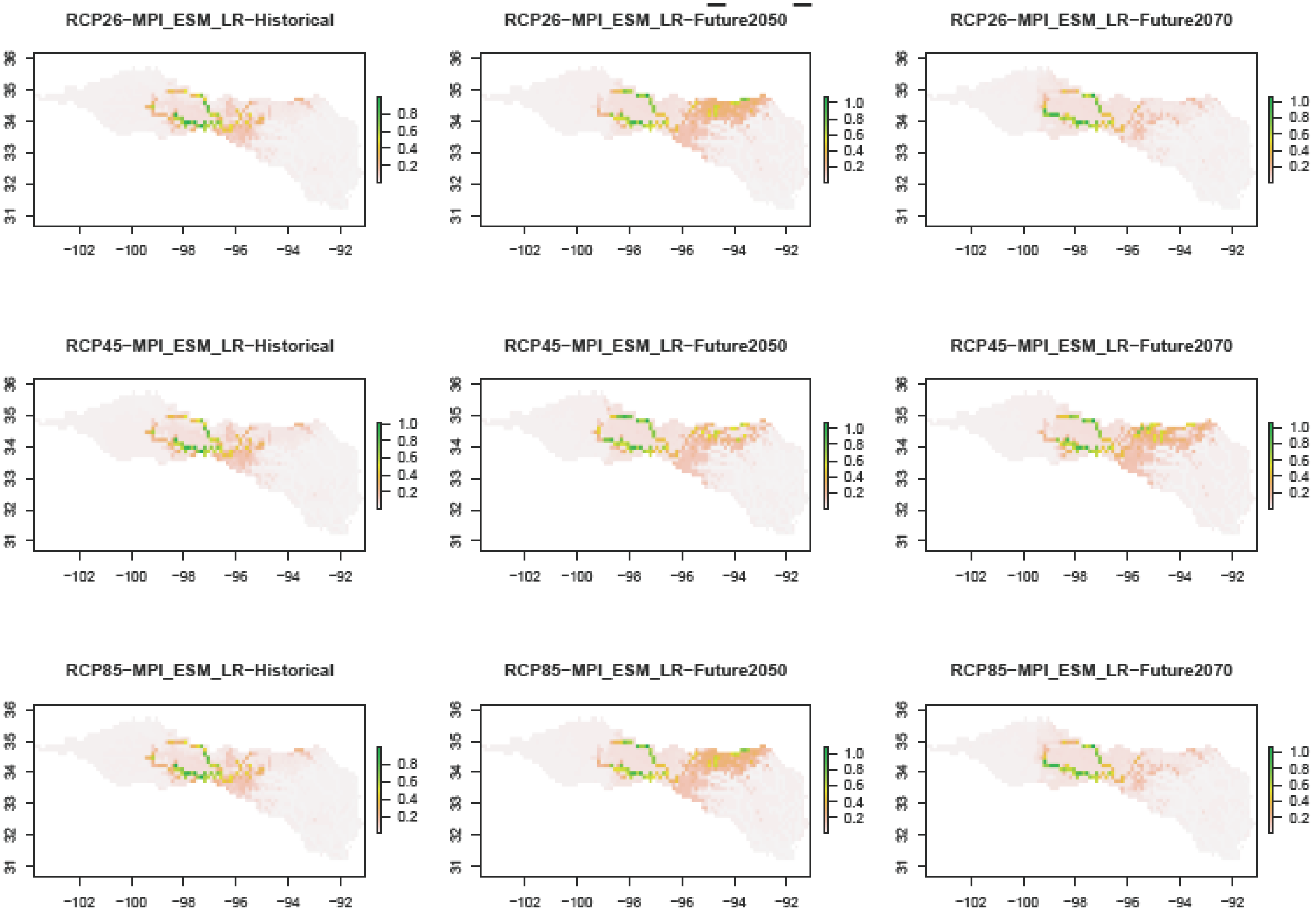
RCP85−CCSM4−Historical

RCP85−CCSM4−Future2050

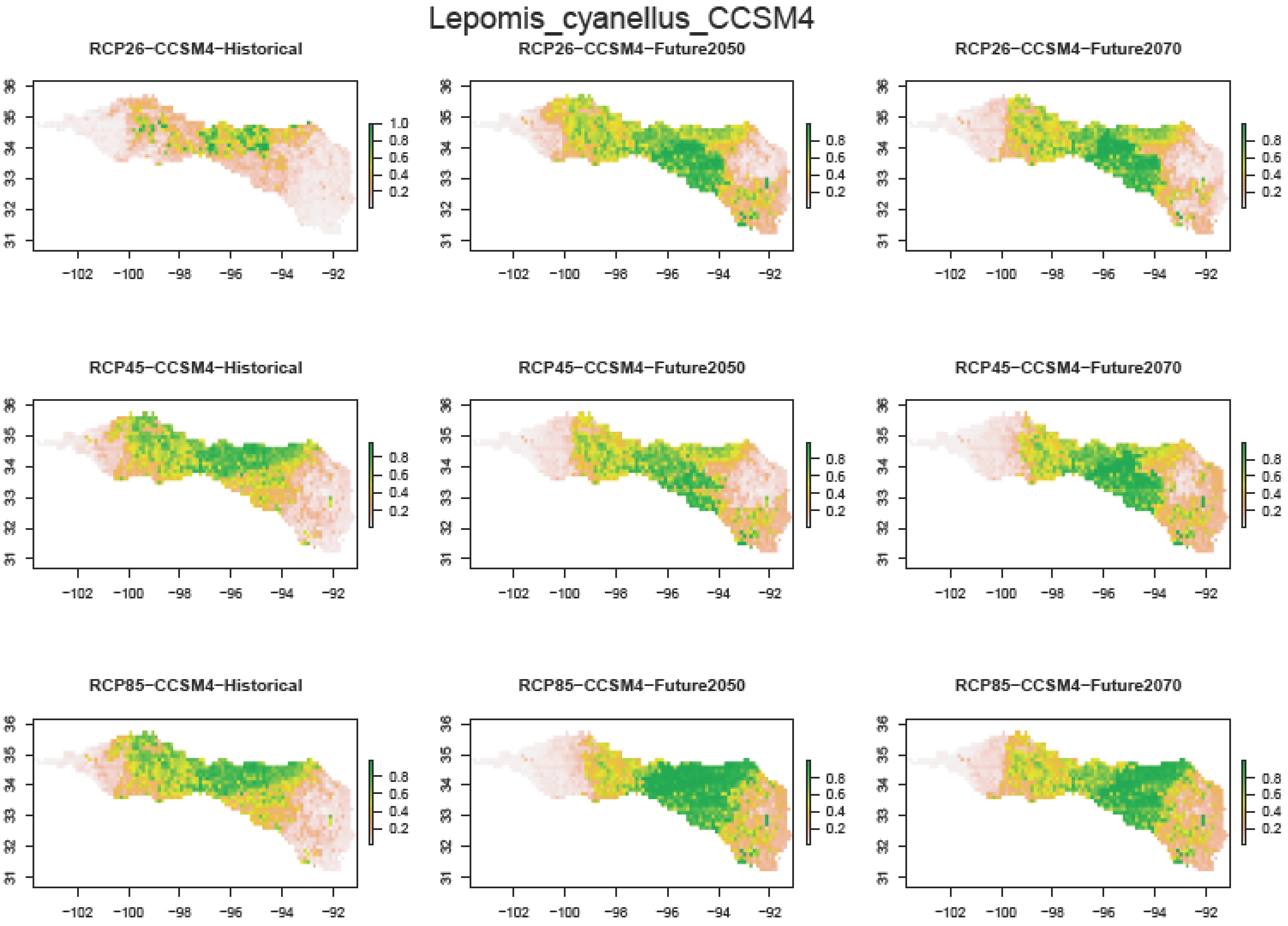
RCP85−CCSM4−Future2070

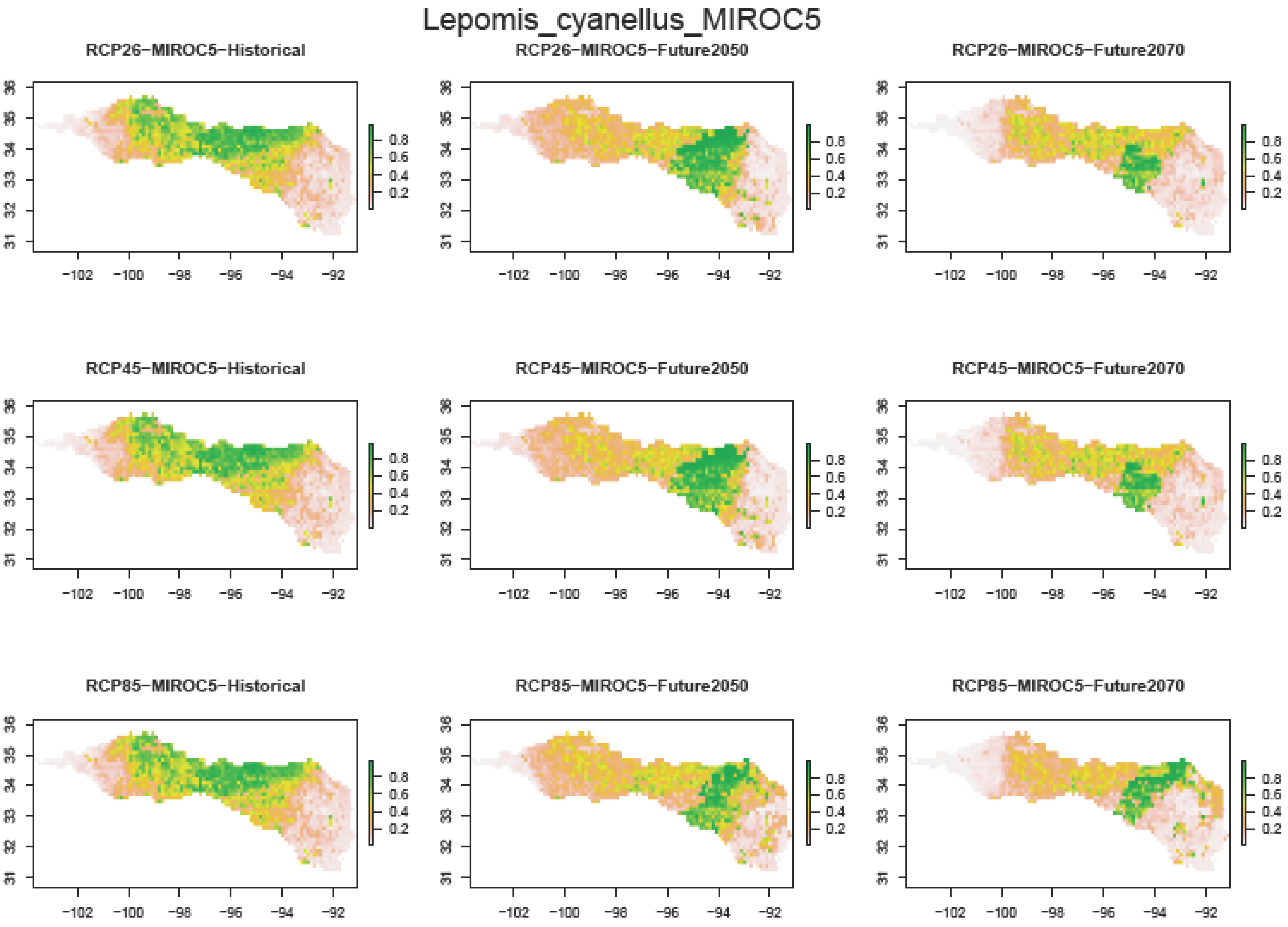

IctalurusfurcatusMIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070
31
32
33
34
35
36
−102
−100
−98
−96
−94
−92
0.2
0.4
0.6
0.8
1.0
1.2

IctalurusfurcatusMPI_ESM_LR


RCP26−MPI_ESM_LR−Historical
RCP26−MPI_ESM_LR−Future2050
RCP26−MPI_ESM_LR−Future2070
RCP45−MPI_ESM_LR−Historical
RCP45−MPI_ESM_LR−Future2050
RCP45−MPI_ESM_LR−Future2070
RCP85−MPI_ESM_LR−Historical
RCP85−MPI_ESM_LR−Future2050
RCP85−MPI_ESM_LR−Future2070

Maxent: *Lepomis cyanellus*





Lepomis_cyanellus_MIROC5

RCP26−MIROC5−Historical

RCP26−MIROC5−Future2050

RCP26−MIROC5−Future2070

RCP45−MIROC5−Historical

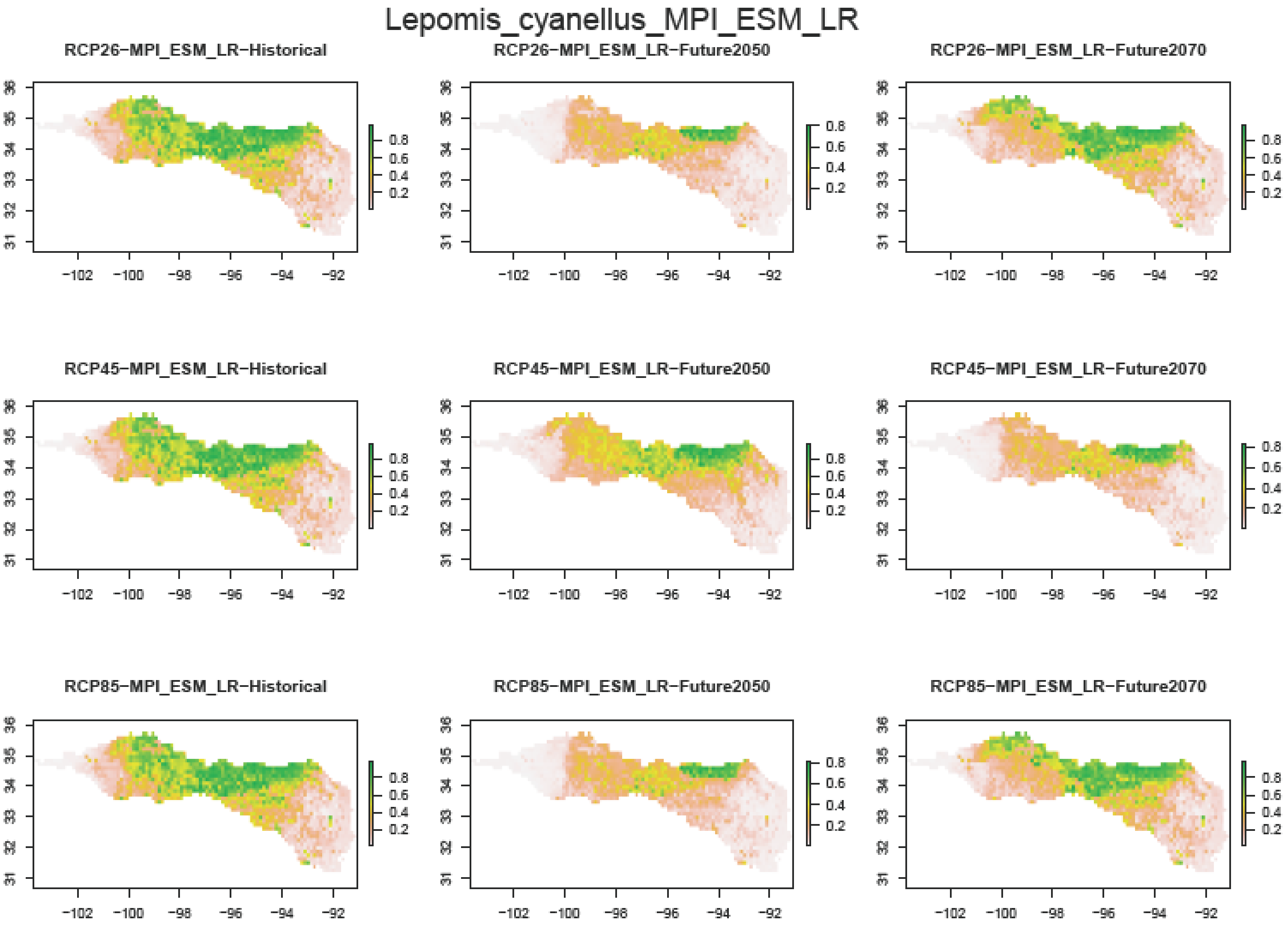
RCP45−MIROC5−Future2050

RCP45−MIROC5−Future2070

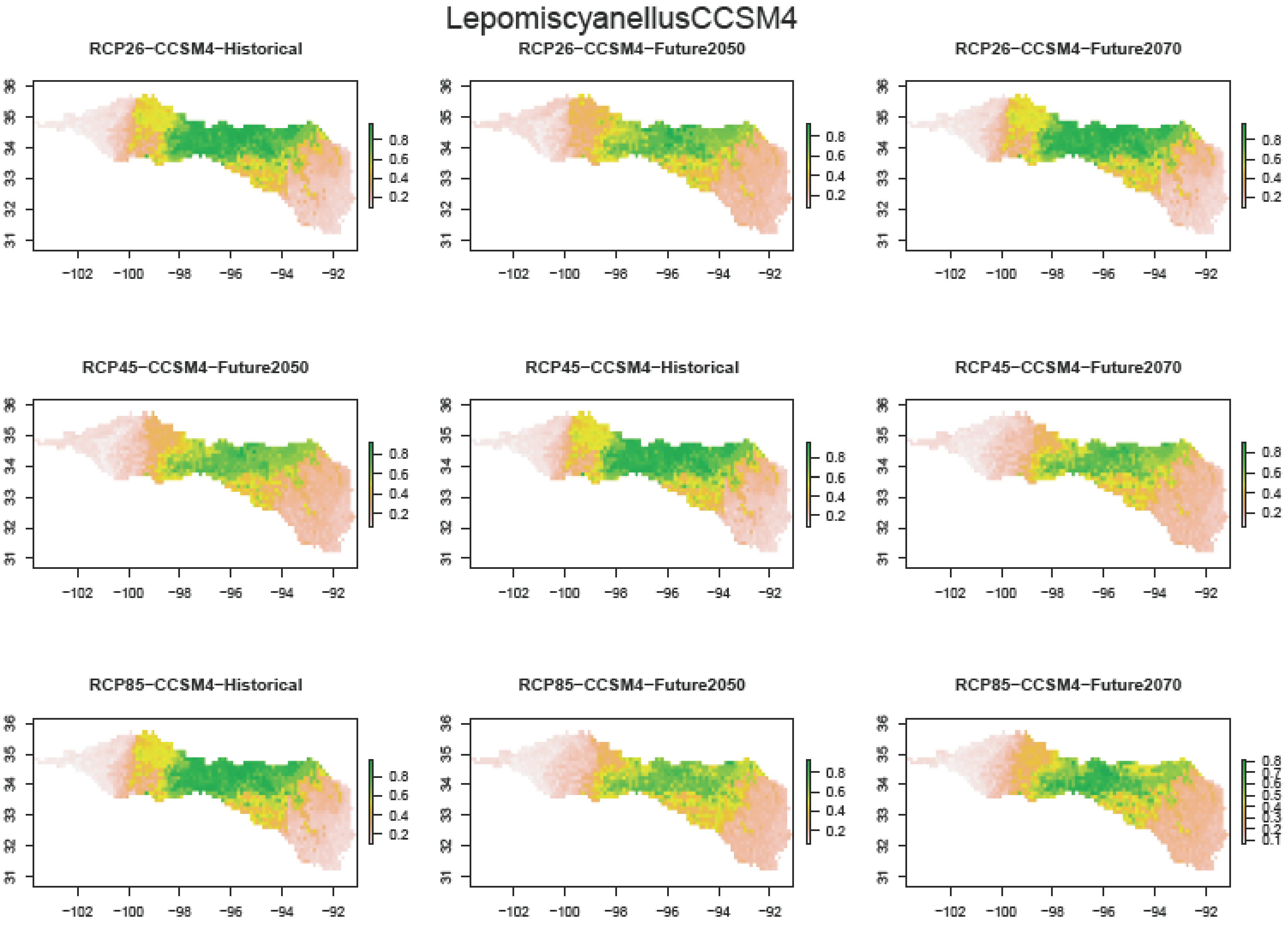
RCP85−MIROC5−Historical

RCP85−MIROC5−Future2050

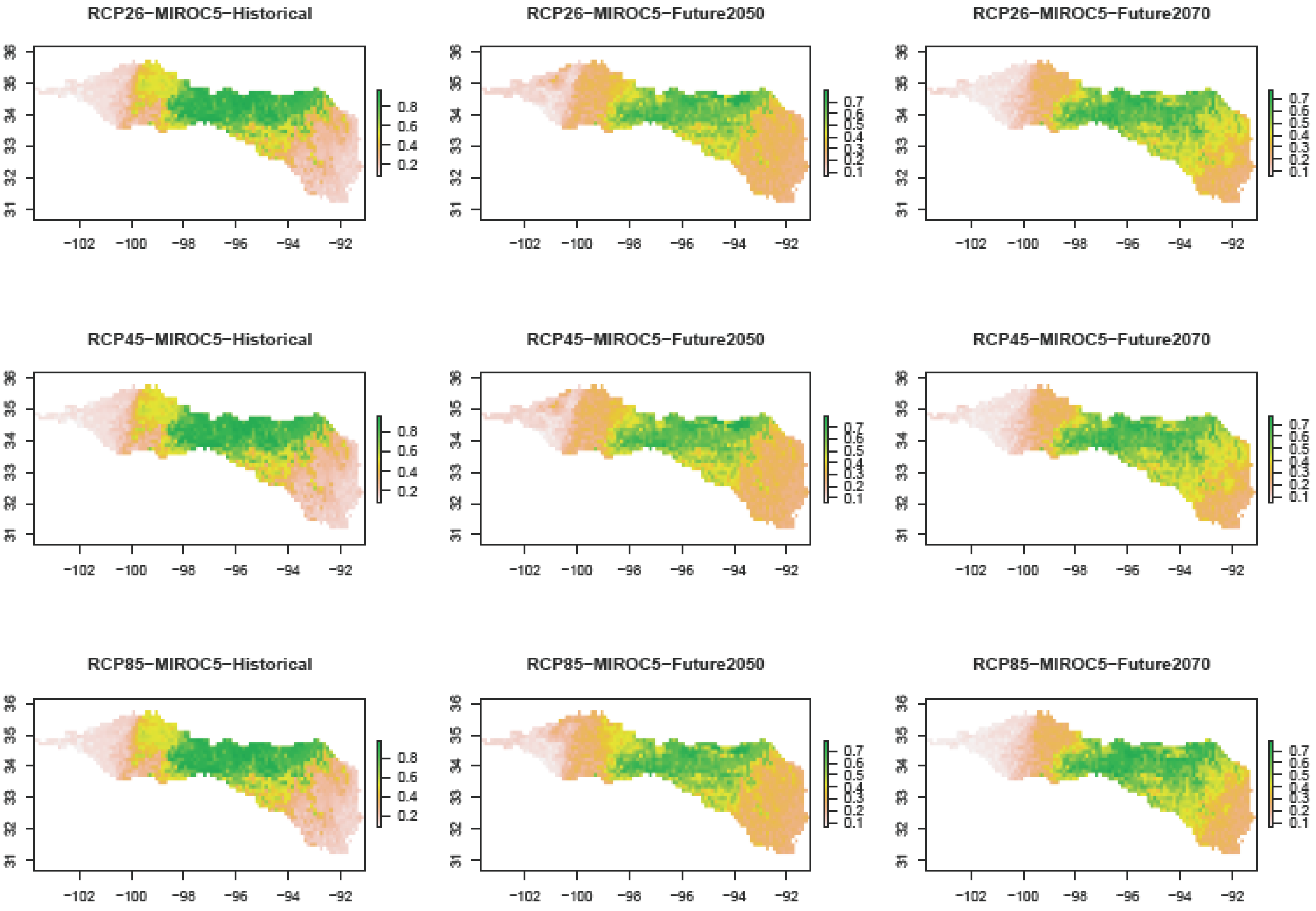
RCP85−MIROC5−Future2070

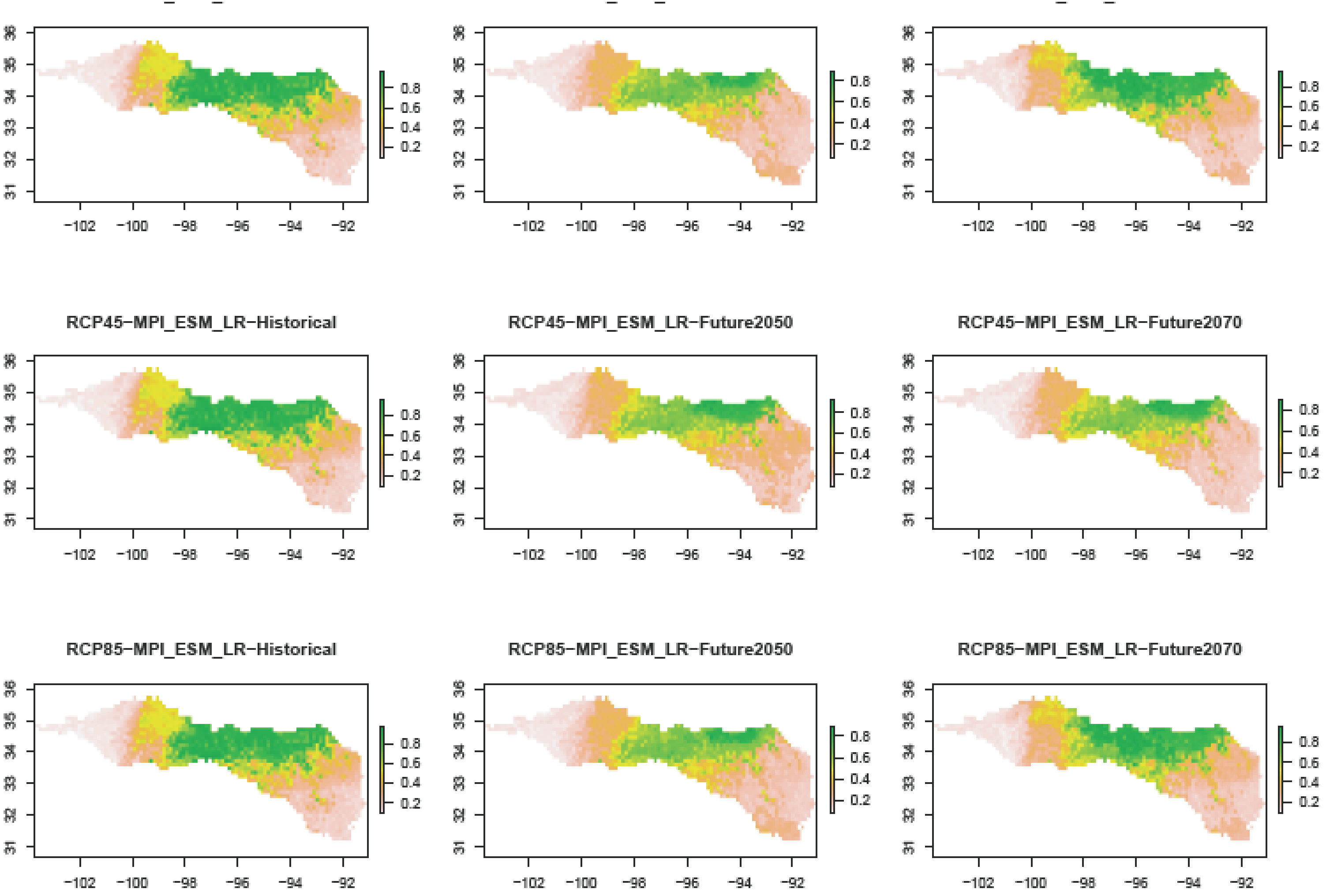

Lepomis_cyanellus_MPI_ESM_LR
RCP26−MPI_ESM_LR−Historical
RCP26−MPI_ESM_LR−Future2050
RCP26−MPI_ESM_LR−Future2070
RCP45−MPI_ESM_LR−Historical
RCP45−MPI_ESM_LR−Future2050
RCP45−MPI_ESM_LR−Future2070
RCP85−MPI_ESM_LR−Historical
RCP85−MPI_ESM_LR−Future2050
RCP85−MPI_ESM_LR−Future2070
31
32
33
34
35
36
−102
−100
−98
−96
−94
−92
0.2
0.4
0.6
0.8

BRT: *Lepomis cyanellus*



LepomiscyanellusMIROC5





LepomiscyanellusMPI_ESM_LR

RCP26−MPI_ESM_LR−Historical

RCP26−MPI_ESM_LR−Future2050

RCP26−MPI_ESM_LR−Future2070

RCP45−MPI_ESM_LR−Historical

RCP45−MPI_ESM_LR−Future2050

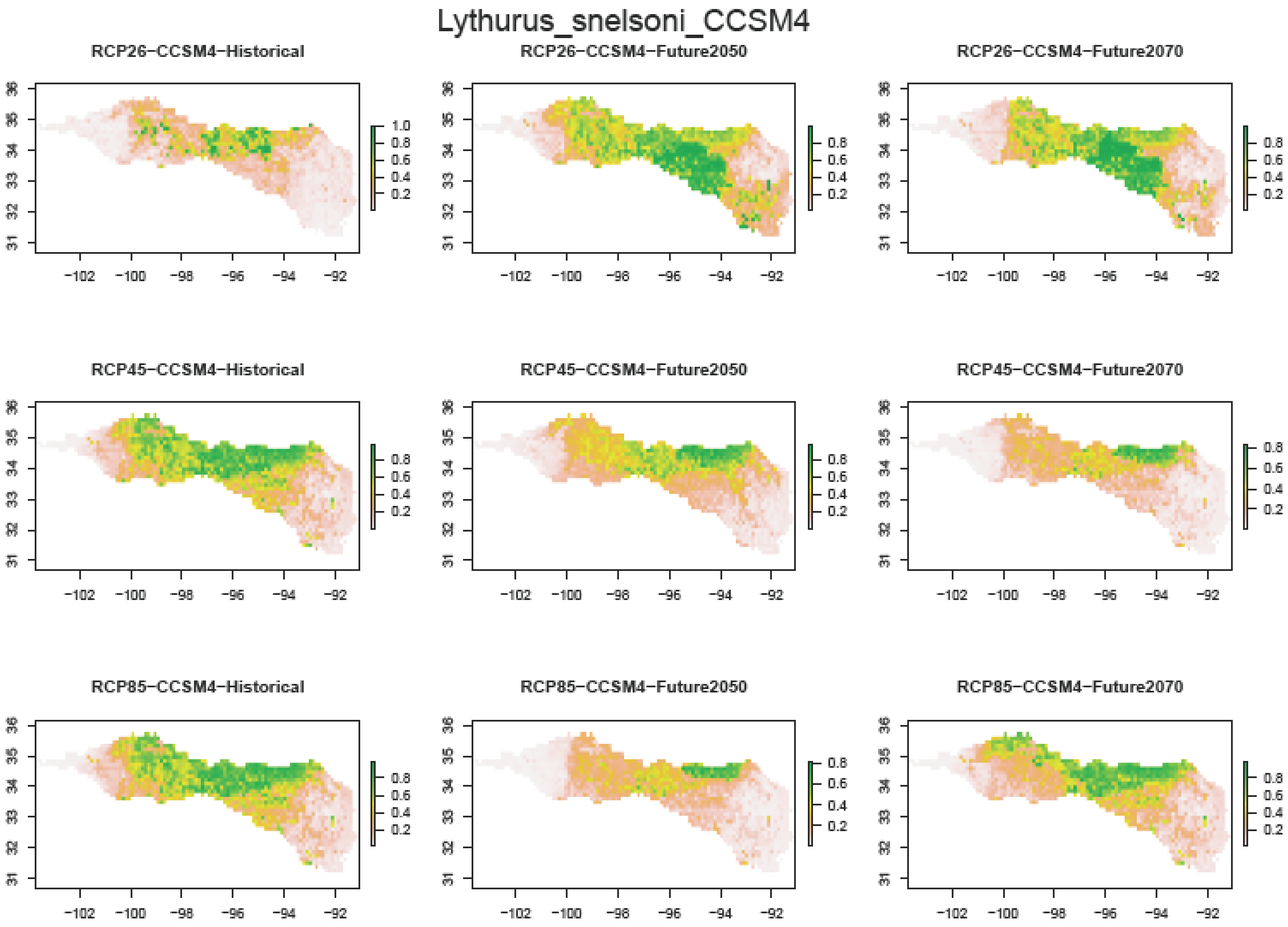
RCP45−MPI_ESM_LR−Future2070

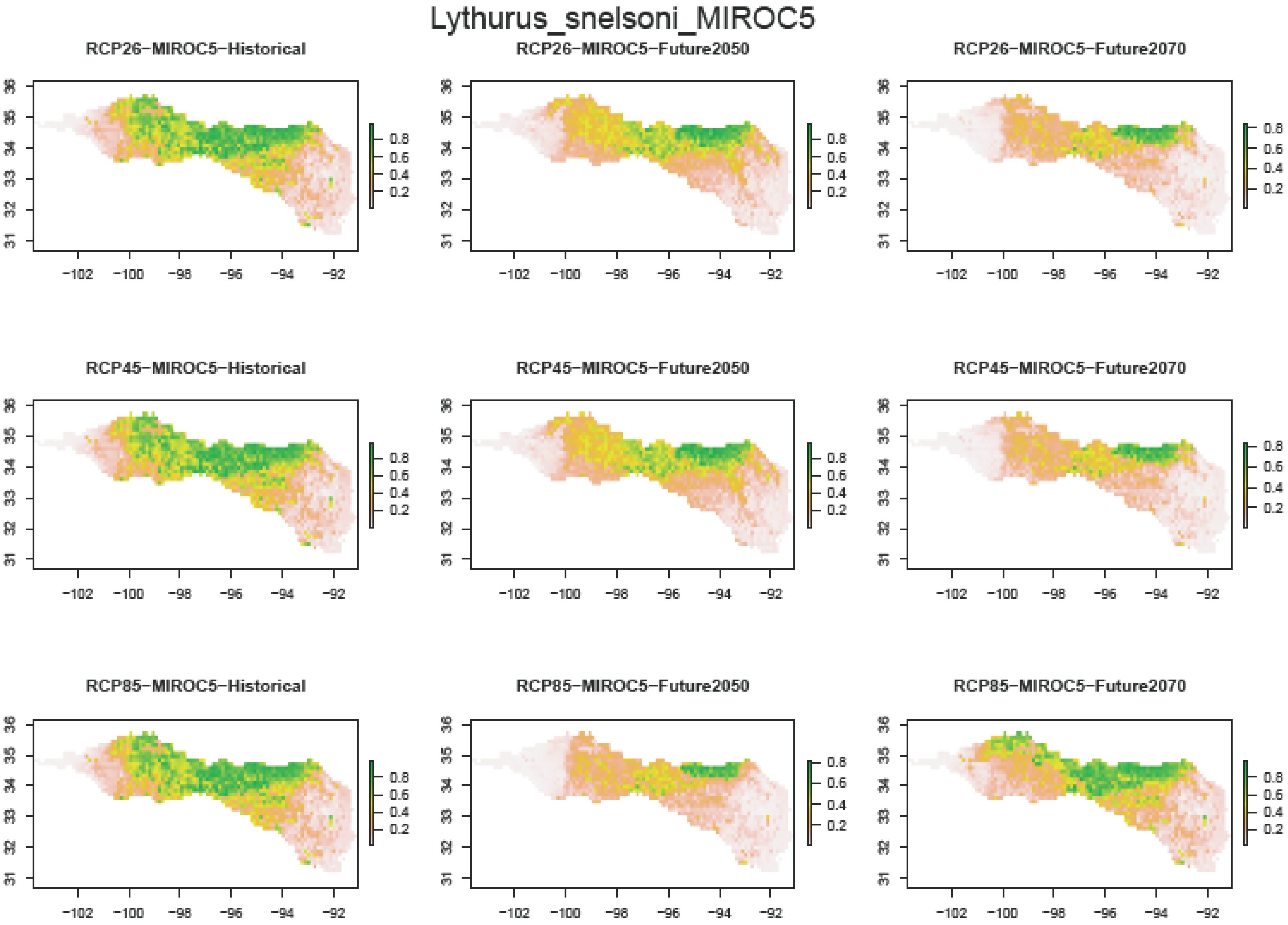
RCP85−MPI_ESM_LR−Historical

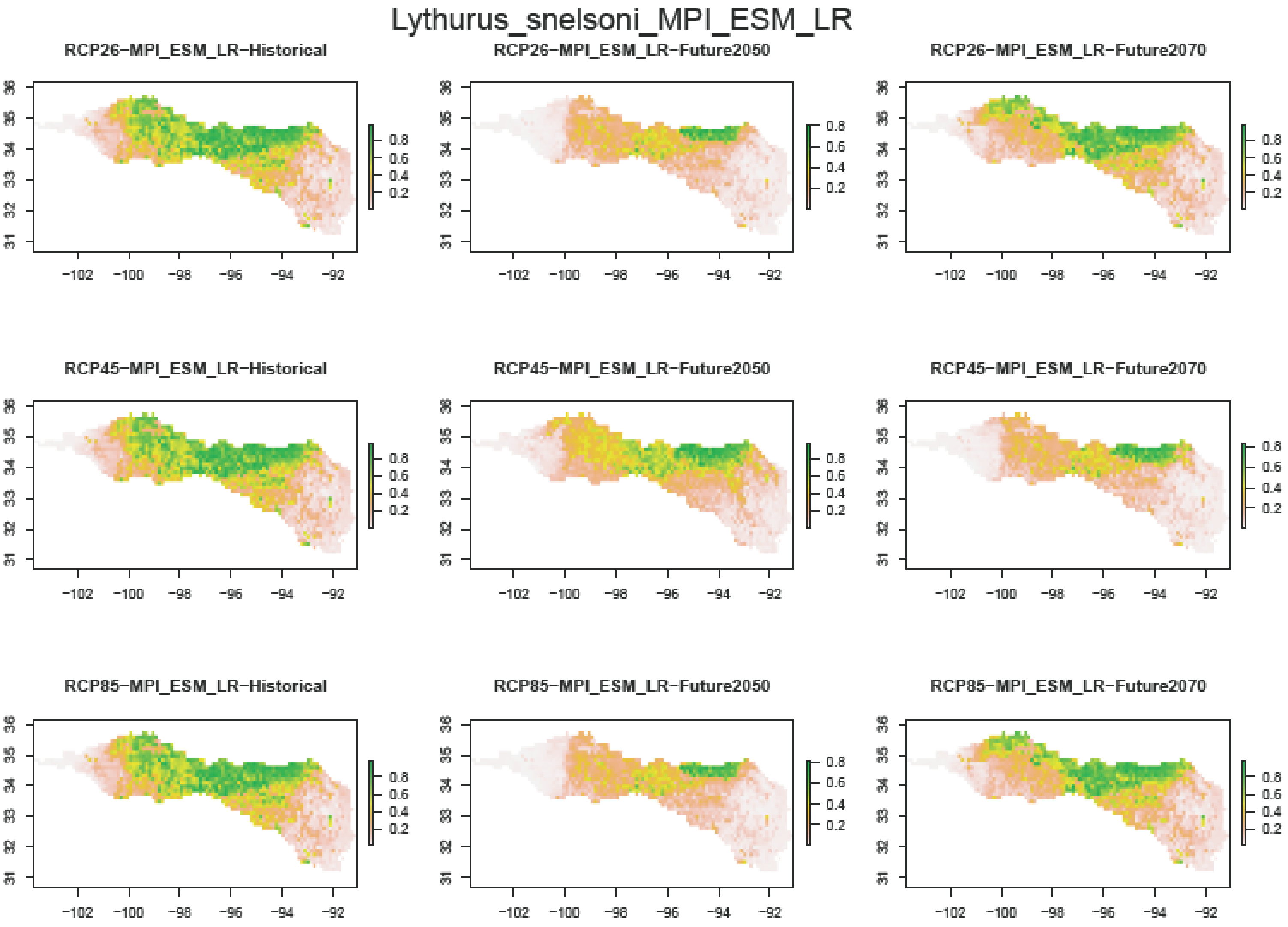
RCP85−MPI_ESM_LR−Future2050

RCP85−MPI_ESM_LR−Future2070

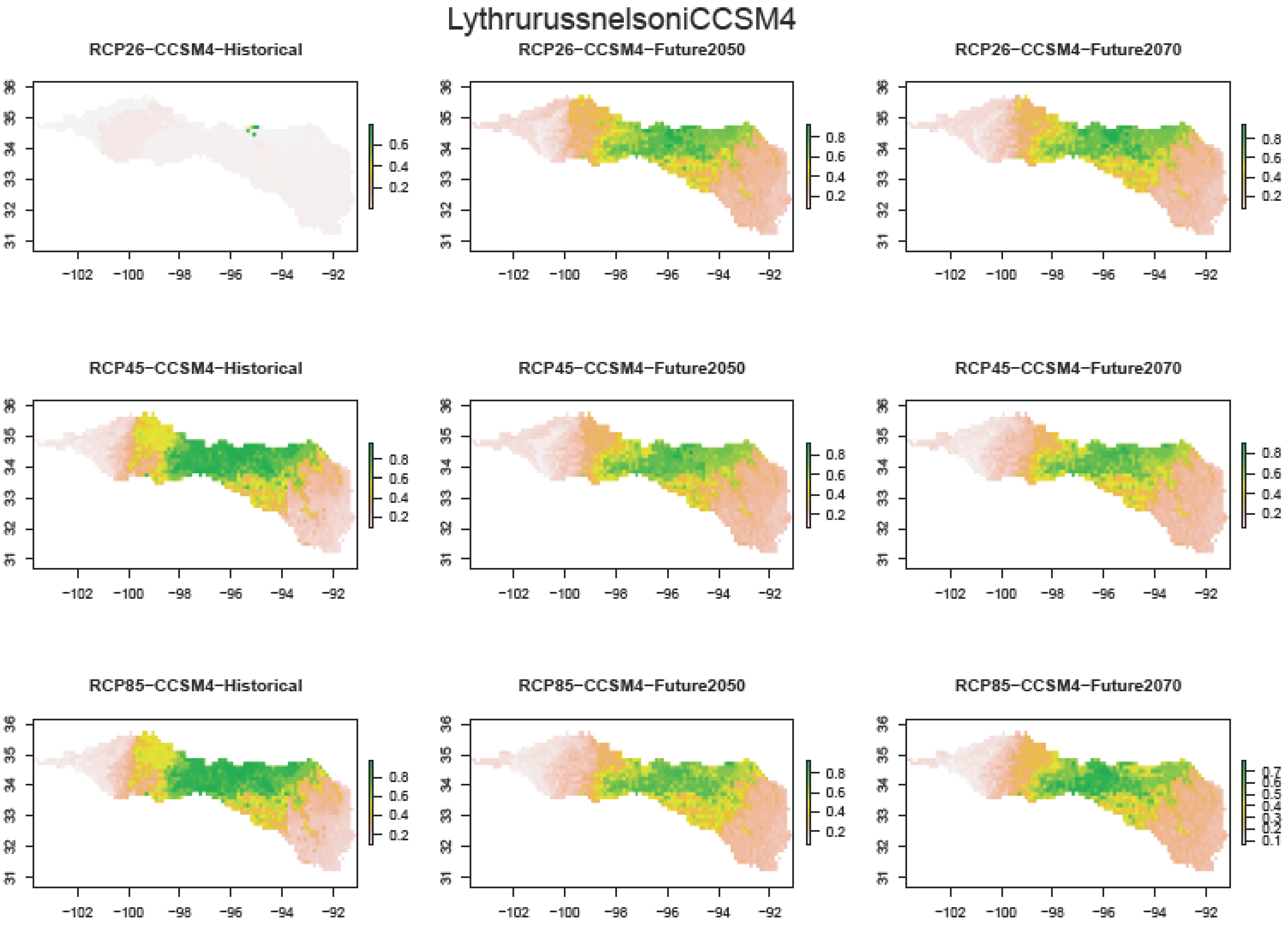
Maxent: *Lythrurus snelsoni*



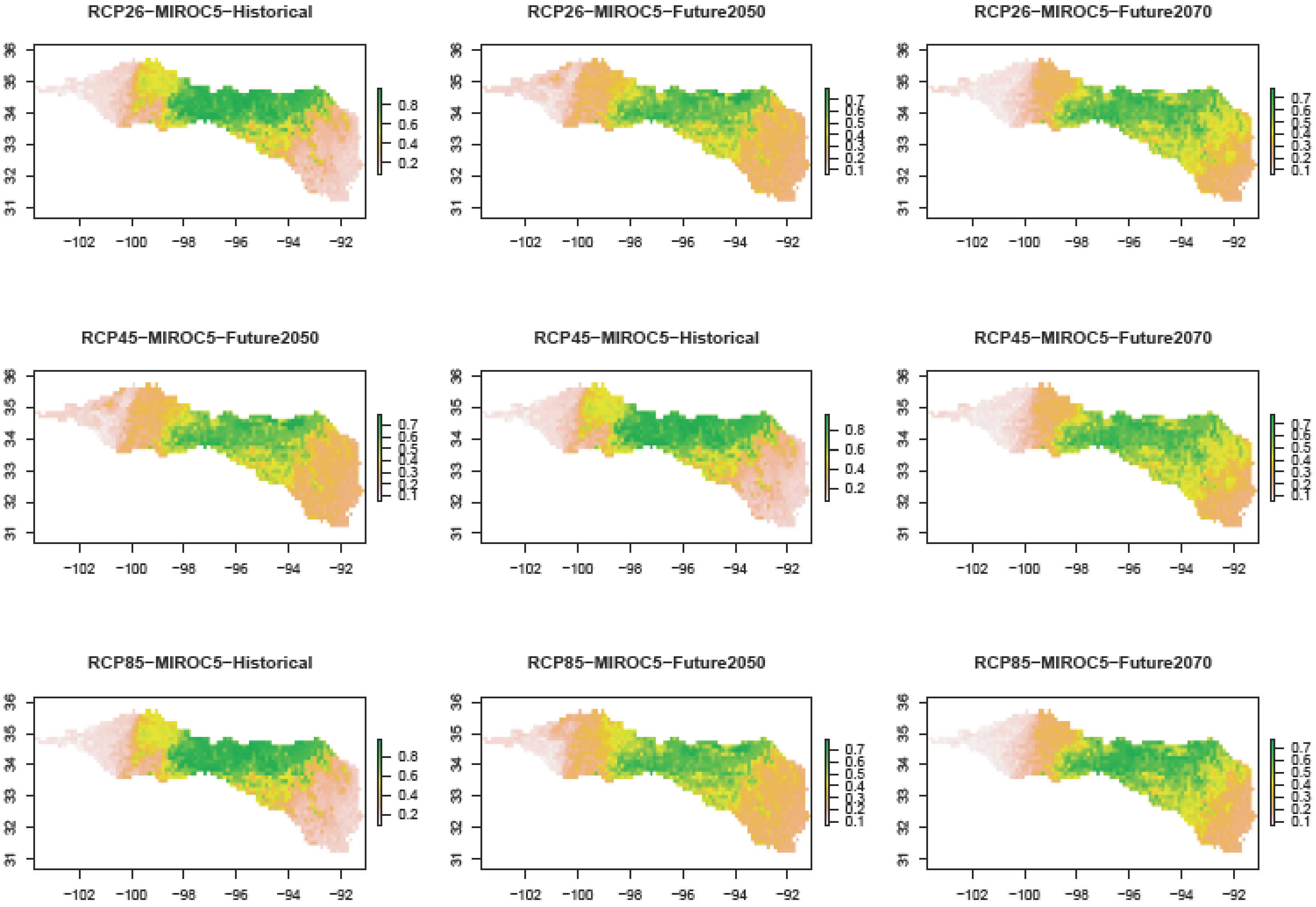

Lythurus_snelsoni_MIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070
31
32
33
34
35
36
−102
−100
−98
−96
−94
−92
0.2
0.4
0.6
0.8


Lythurus_snelsoni_MPI_ESM_LR
RCP26−MPI_ESM_LR−Historical
RCP26−MPI_ESM_LR−Future2050
RCP26−MPI_ESM_LR−Future2070
RCP45−MPI_ESM_LR−Historical
RCP45−MPI_ESM_LR−Future2050
RCP45−MPI_ESM_LR−Future2070
RCP85−MPI_ESM_LR−Historical
RCP85−MPI_ESM_LR−Future2050
RCP85−MPI_ESM_LR−Future2070
31
32
33
34
35
36
−102
−100
−98
−96
−94
−92
0.2
0.4
0.6
0.8

BRT: *Lythrurus snelsoni*



LythrurussnelsoniMIROC5


RCP26-MIROC5-Historical

RCP26-MIROC5-Future2050

RCP26-MIROC5-Future2070

RCP45-MIROC5-Future2050

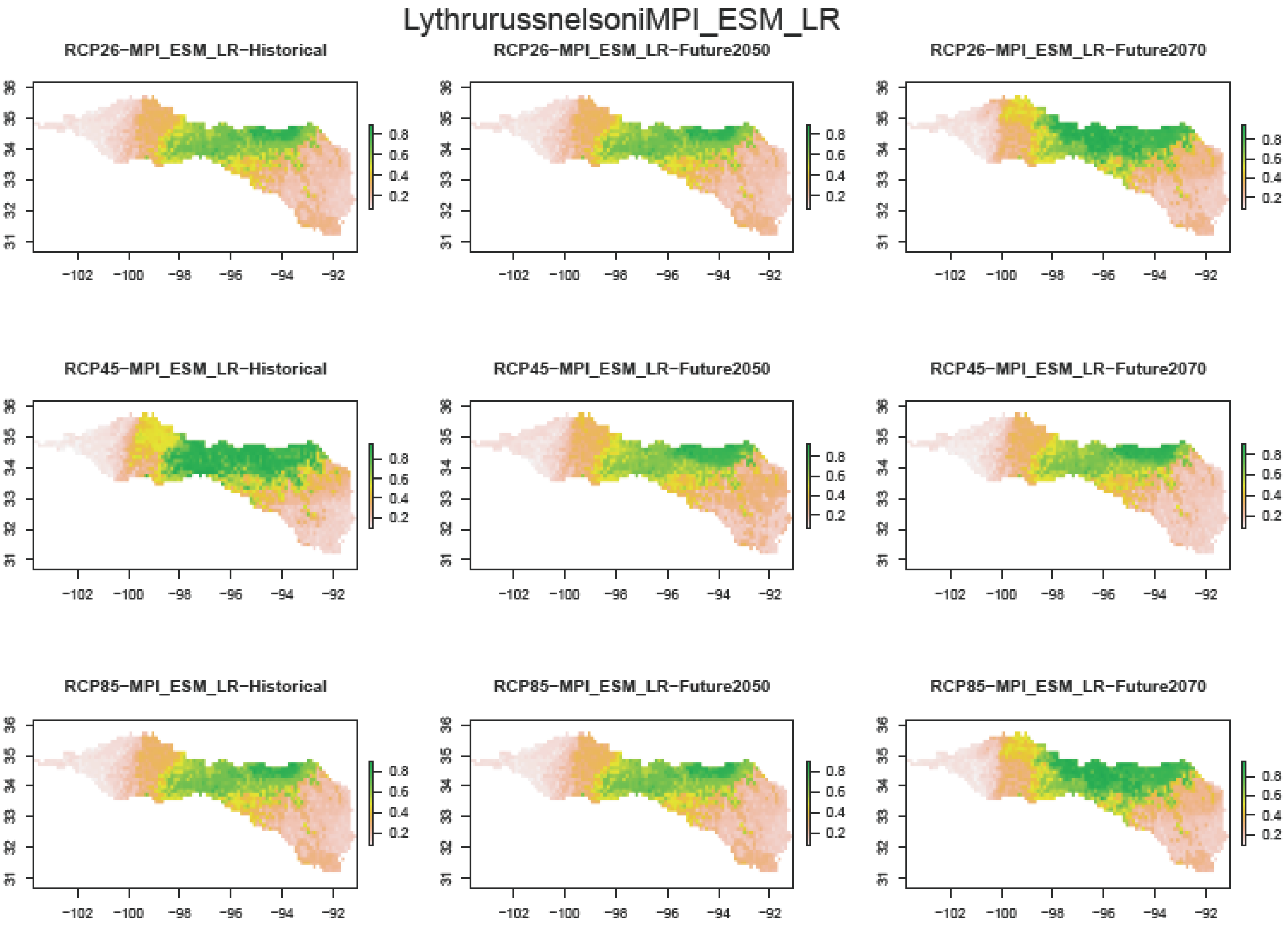
RCP45-MIROC5-Historical

RCP45-MIROC5-Future2070

RCP85-MIROC5-Historical

RCP85-MIROC5-Future2050

RCP85-MIROC5-Future2070



LythrurussnelsoniMPI_ESM_LR

RCP26−MPI_ESM_LR−Historical

RCP26−MPI_ESM_LR−Future2050

RCP26−MPI_ESM_LR−Future2070

RCP45−MPI_ESM_LR−Historical

RCP45−MPI_ESM_LR−Future2050

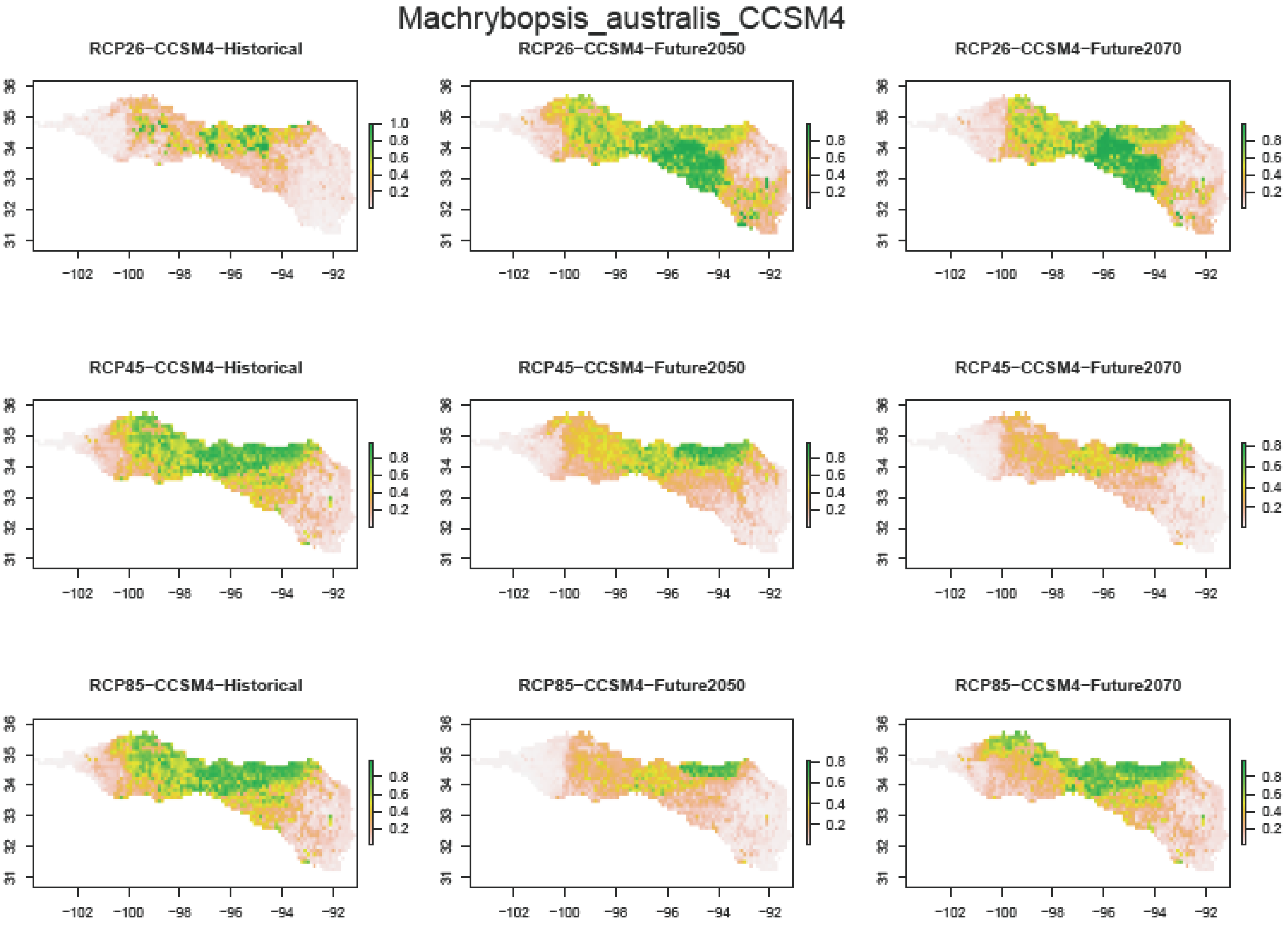
RCP45−MPI_ESM_LR−Future2070

RCP85−MPI_ESM_LR−Historical

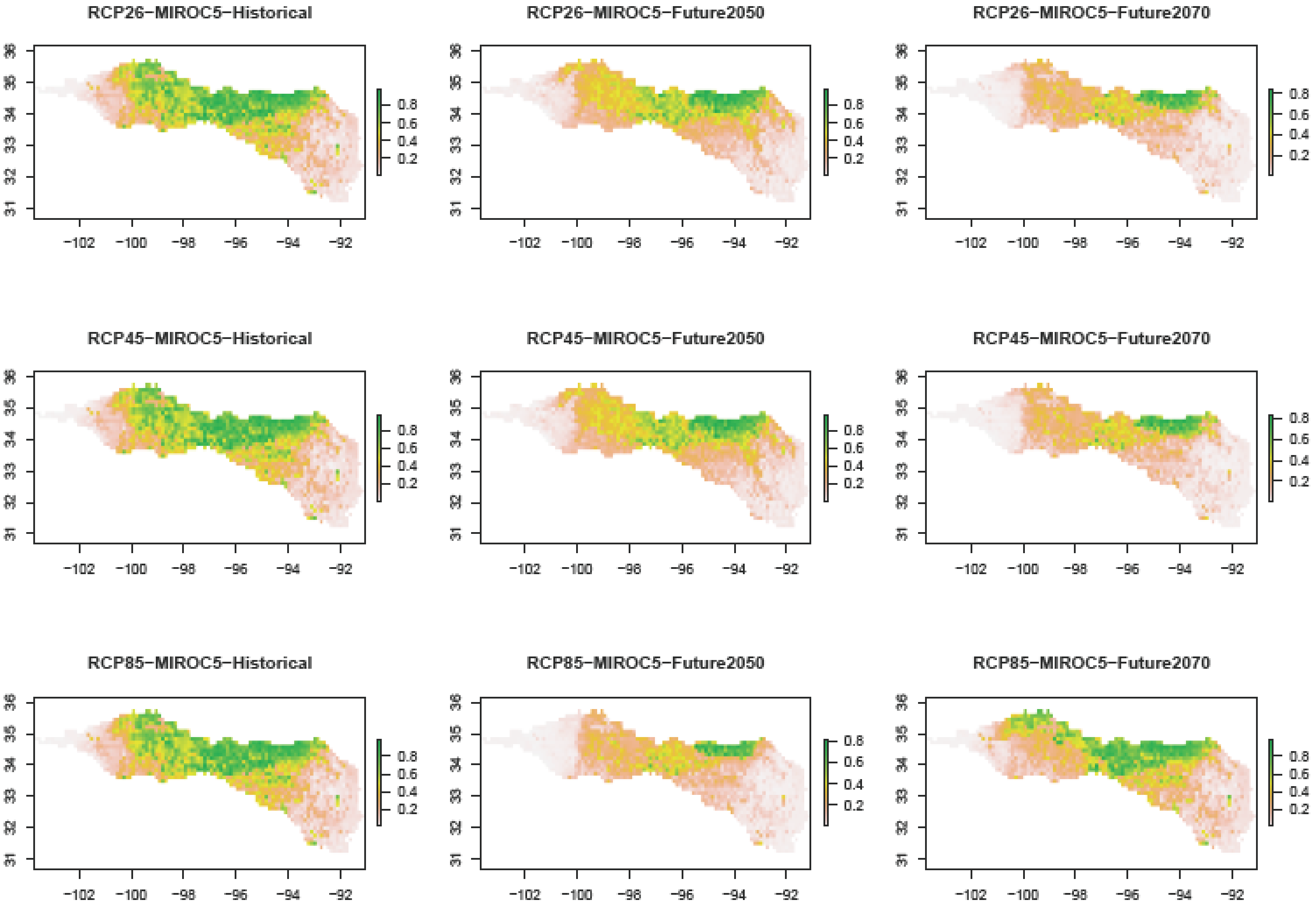
RCP85−MPI_ESM_LR−Future2050

RCP85−MPI_ESM_LR−Future2070

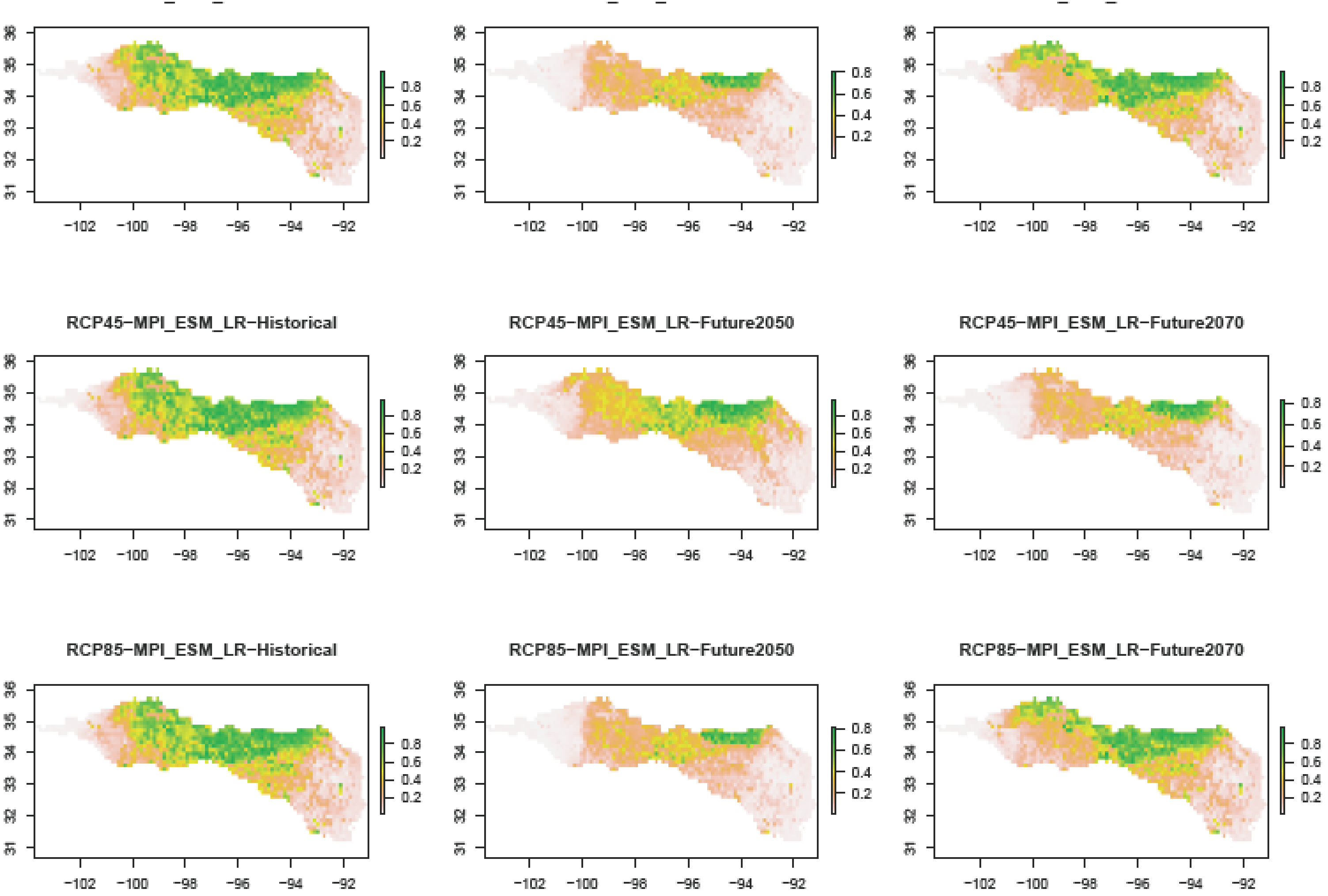
Maxent: *Macrhybopsis australis*



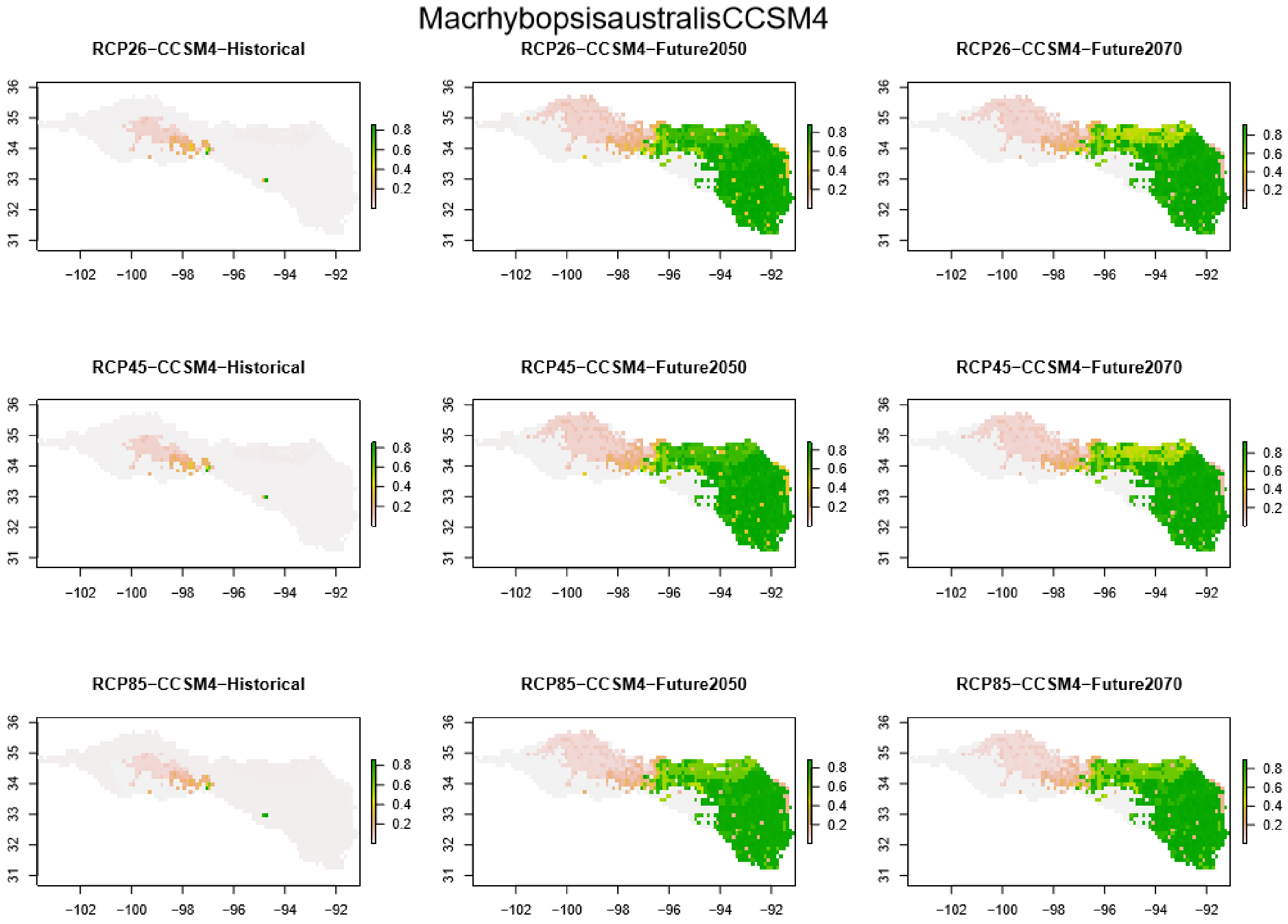
Machrybopsis_australis_MIROC5

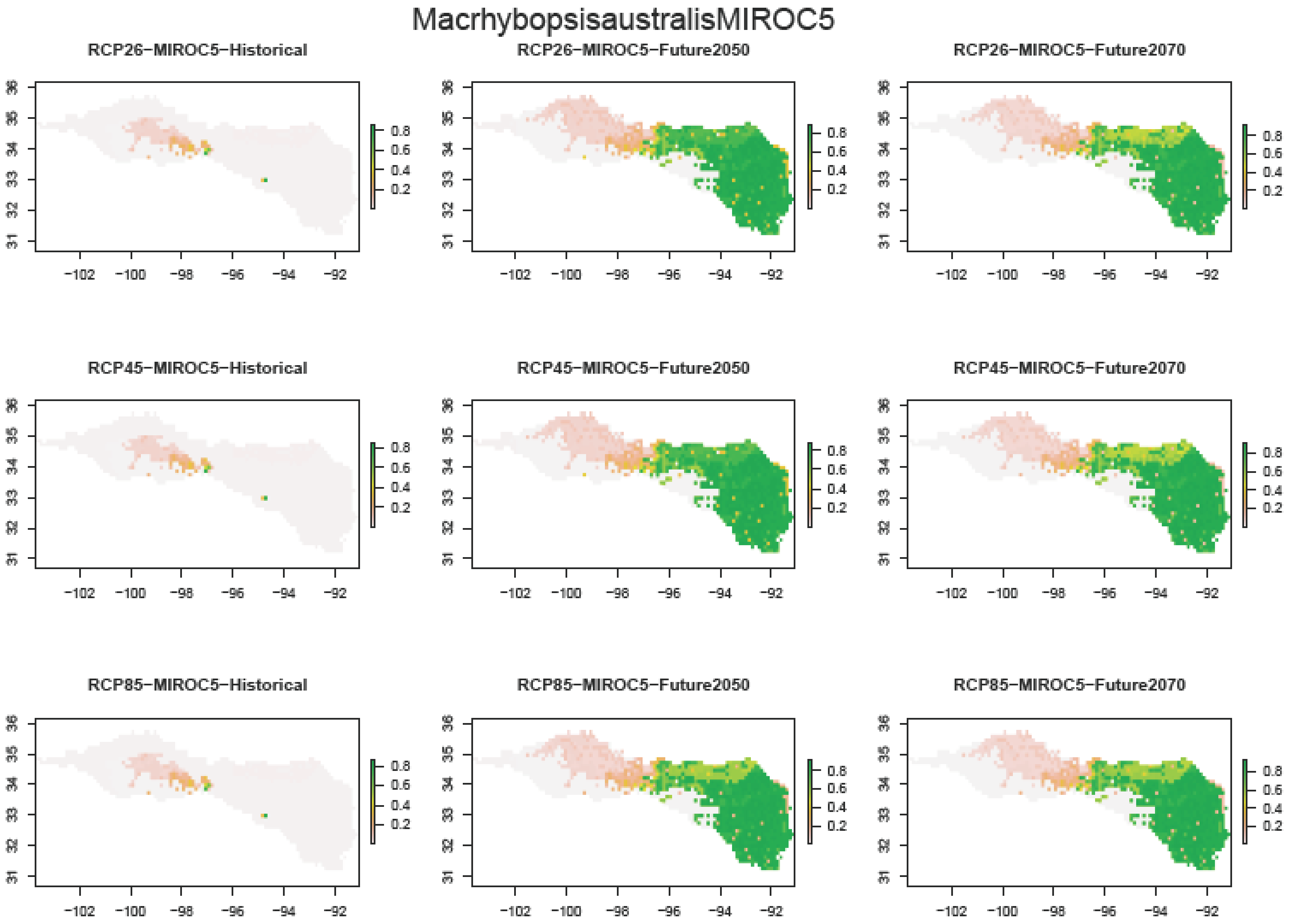


Machrybopsis_australis_MPI_ESM_LR

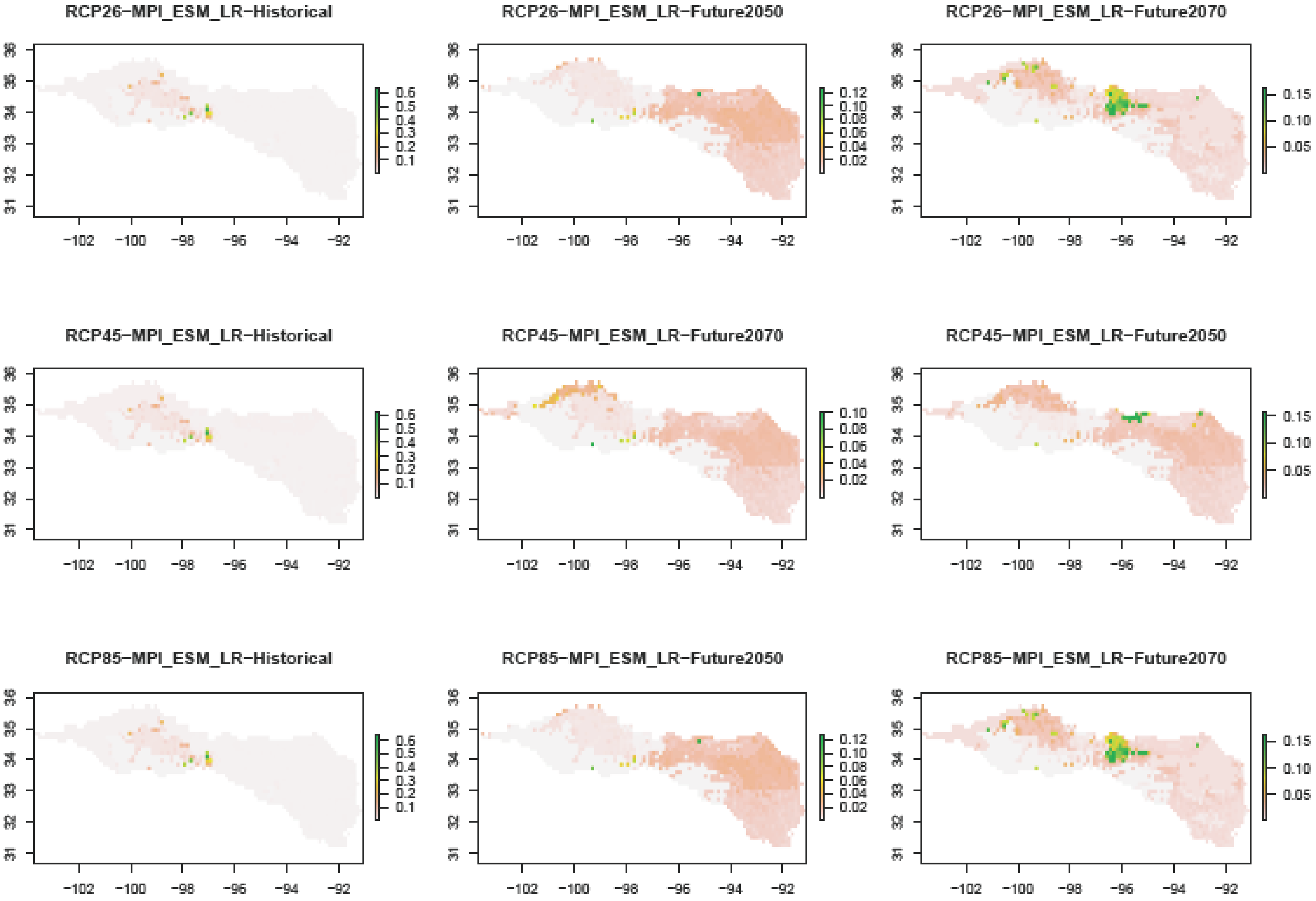


BRT: *Macrhybopsis australis*




MacrhybopsisaustralisMIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070
31
32
33
34
35
36
−102
−100
−98
−96
−94
−92
0.2
0.4
0.6
0.8

MacrhybopsisaustralisMPI_ESM_LR



RCP26−MPI_ESM_LR−Historical

RCP26−MPI_ESM_LR−Future2050

RCP26−MPI_ESM_LR−Future2070

RCP45−MPI_ESM_LR−Historical

RCP45−MPI_ESM_LR−Future2070

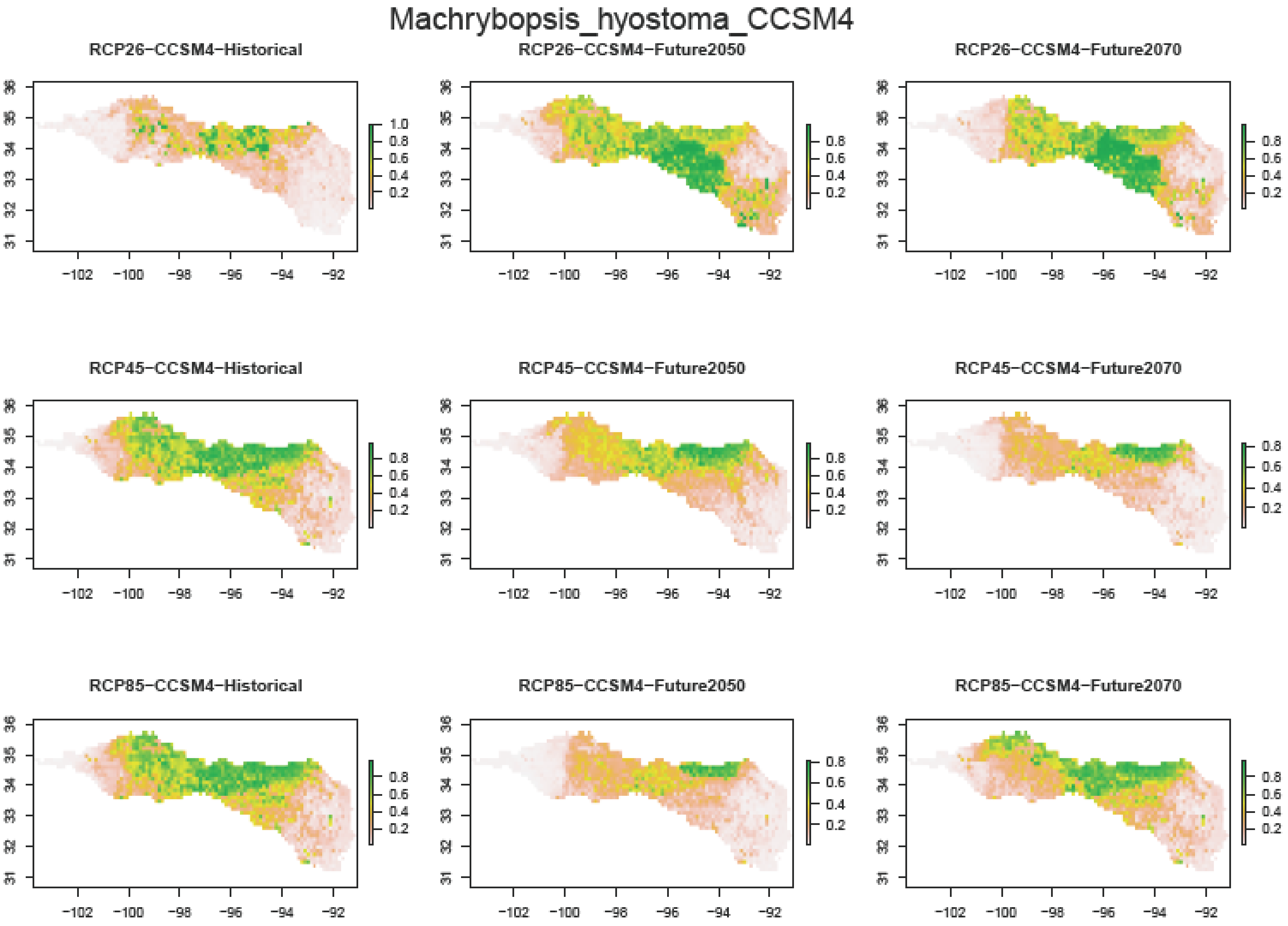
RCP45−MPI_ESM_LR−Future2050

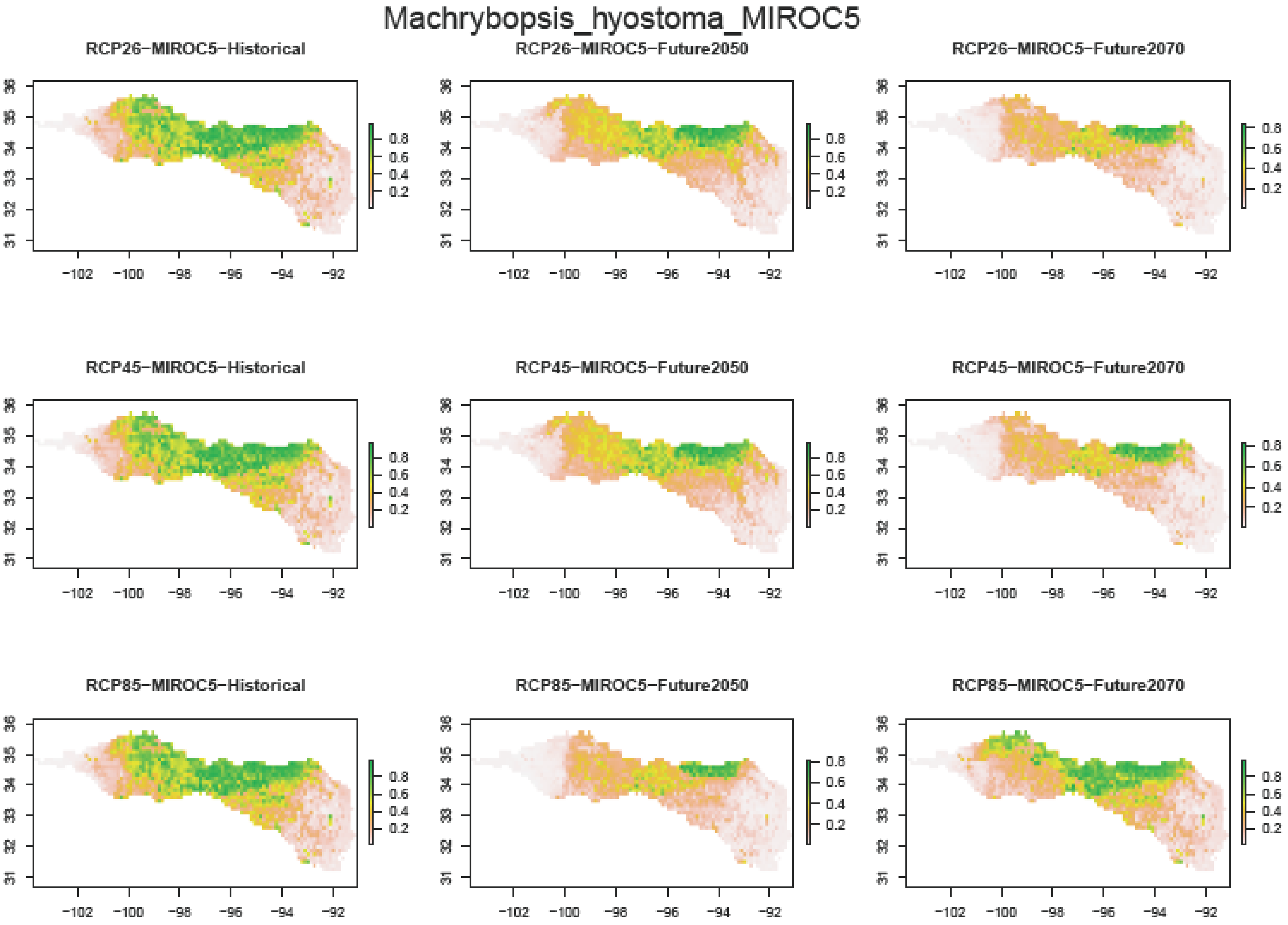
RCP85−MPI_ESM_LR−Historical

RCP85−MPI_ESM_LR−Future2050

RCP85−MPI_ESM_LR−Future2070

Maxent: *Machrybopsis hyostoma*




Machrybopsis_hyostoma_MIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070
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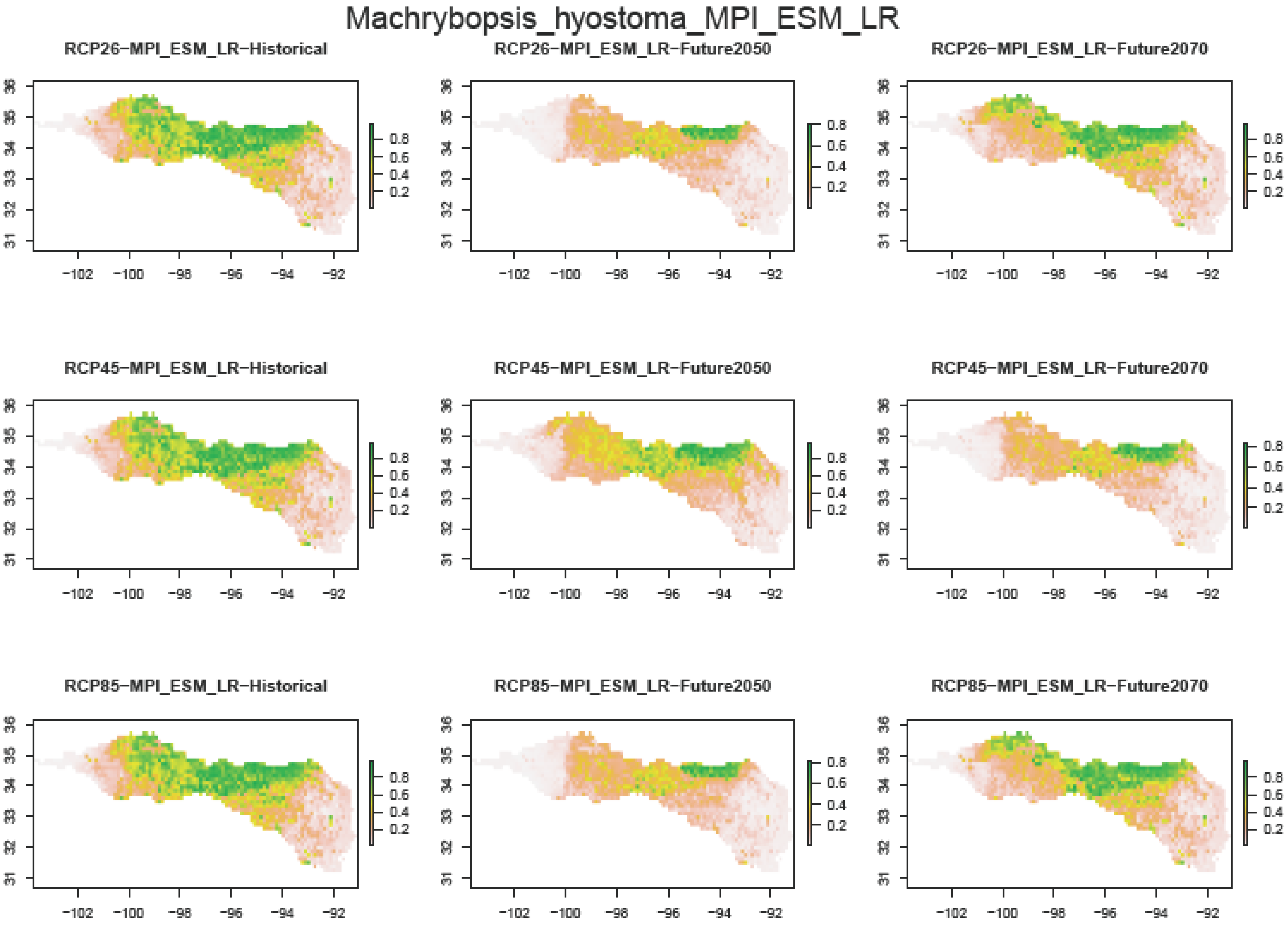
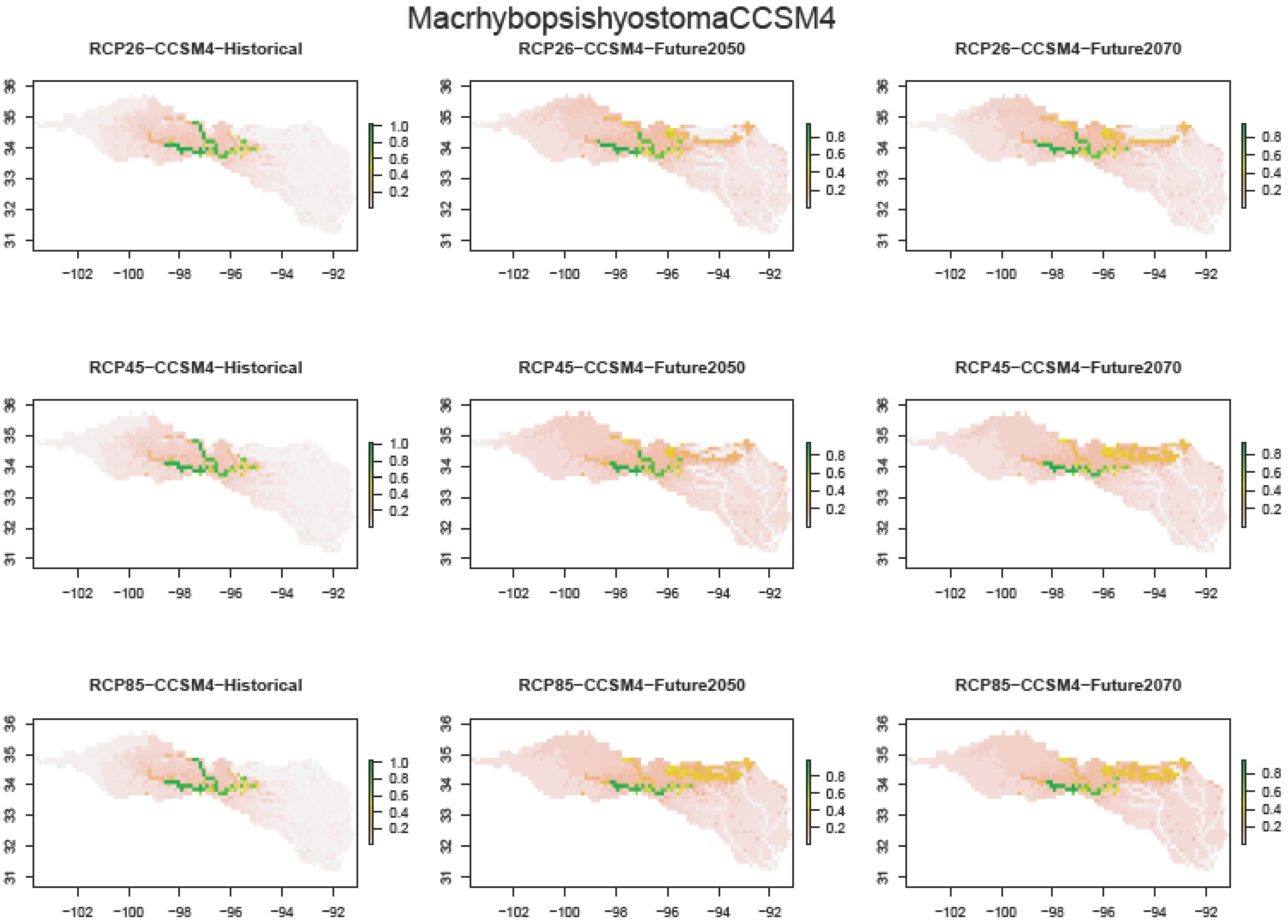
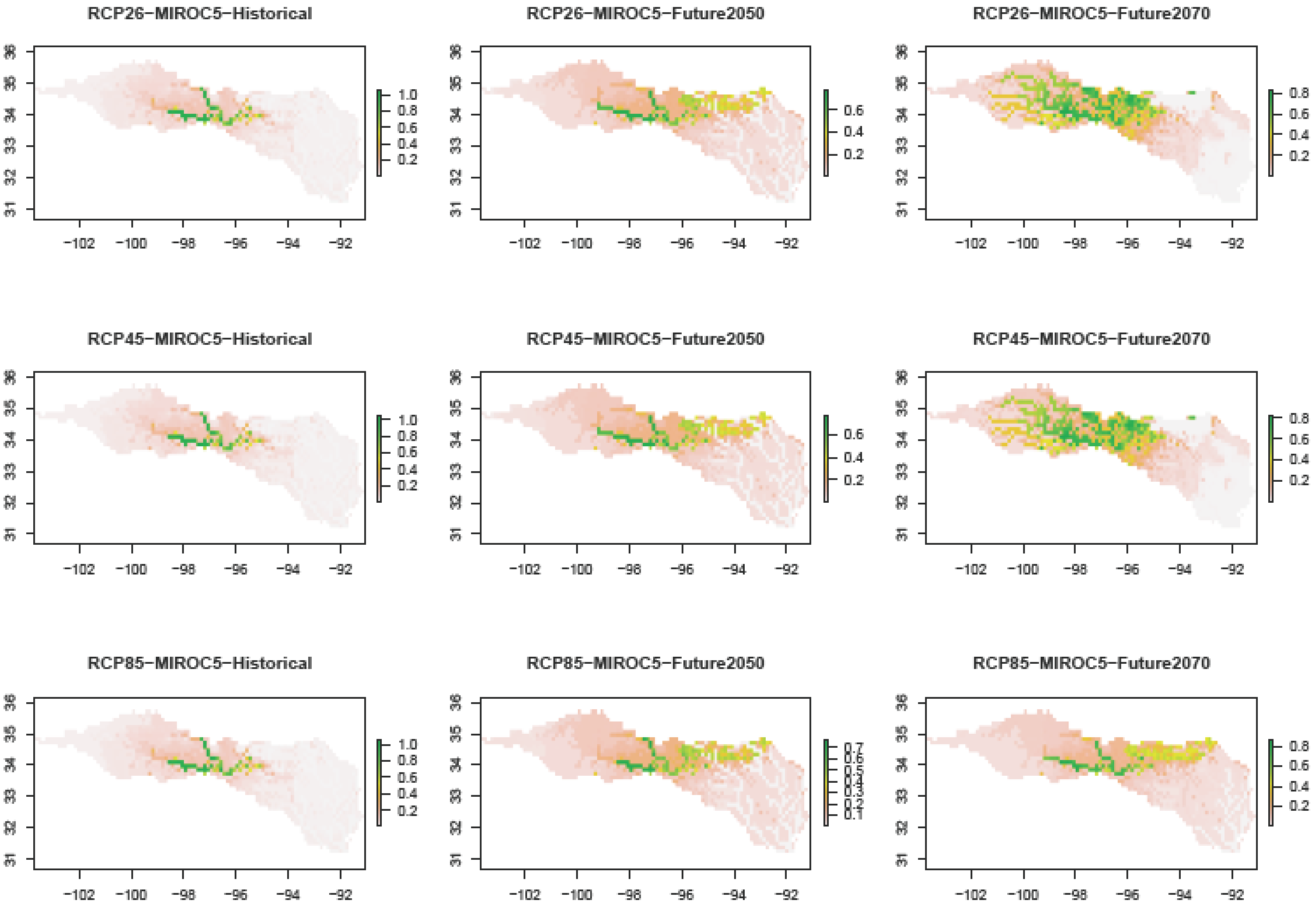
0.4
0.6
0.8


Machrybopsis_hyostoma_MPI_ESM_LR

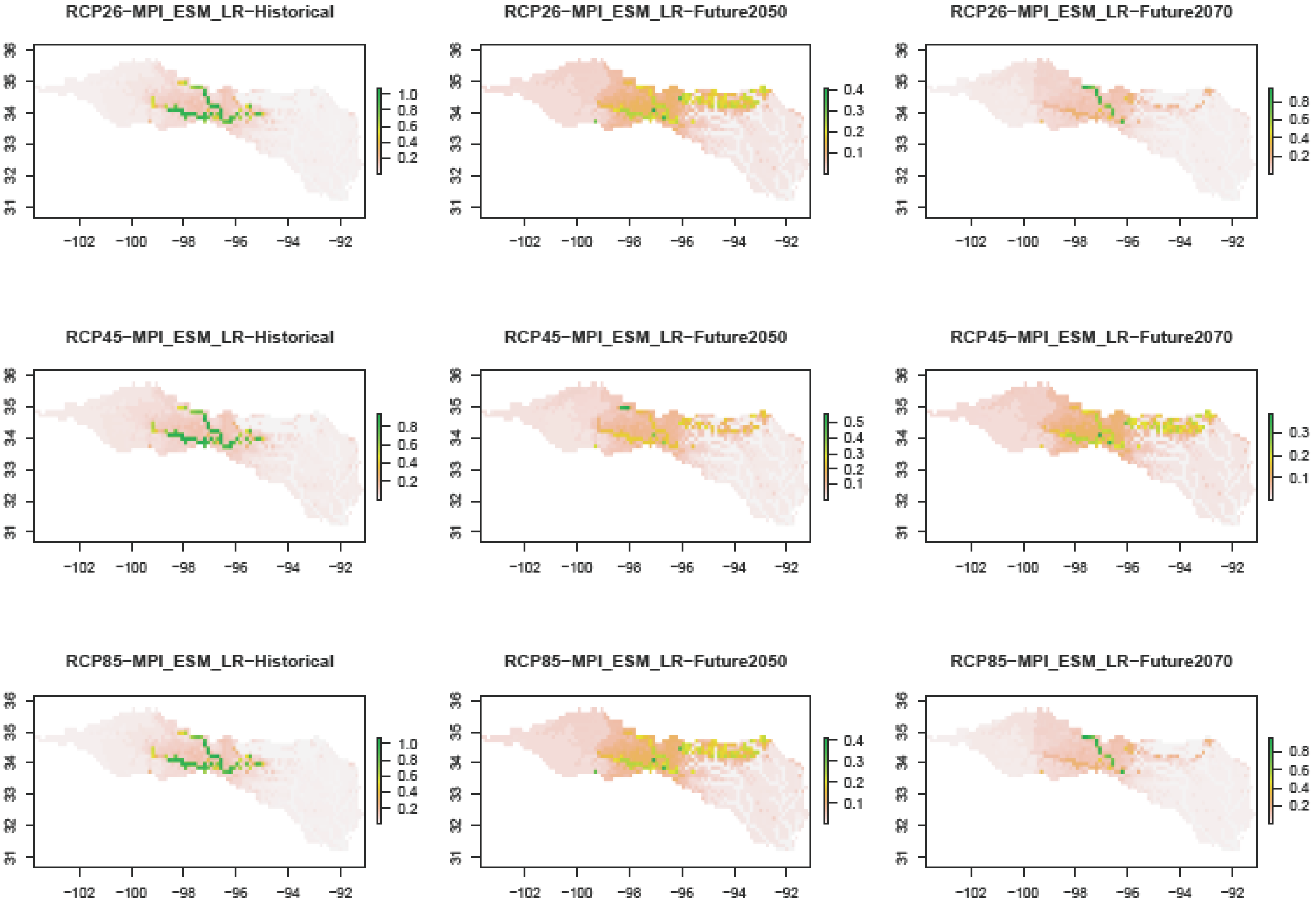
BRT: *Machrybopsis hyostoma*



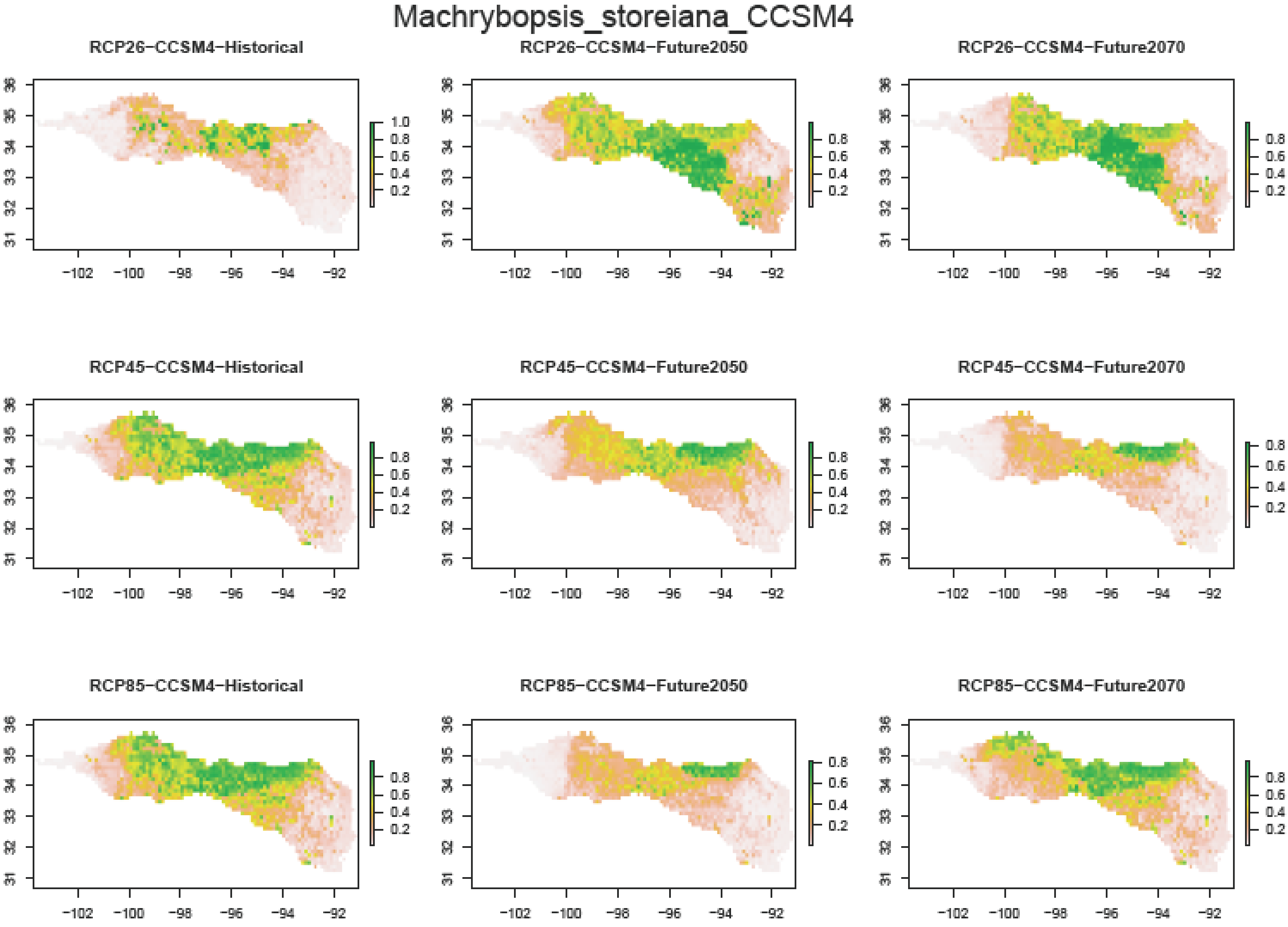
MacrhybopsishyostomaMIROC5

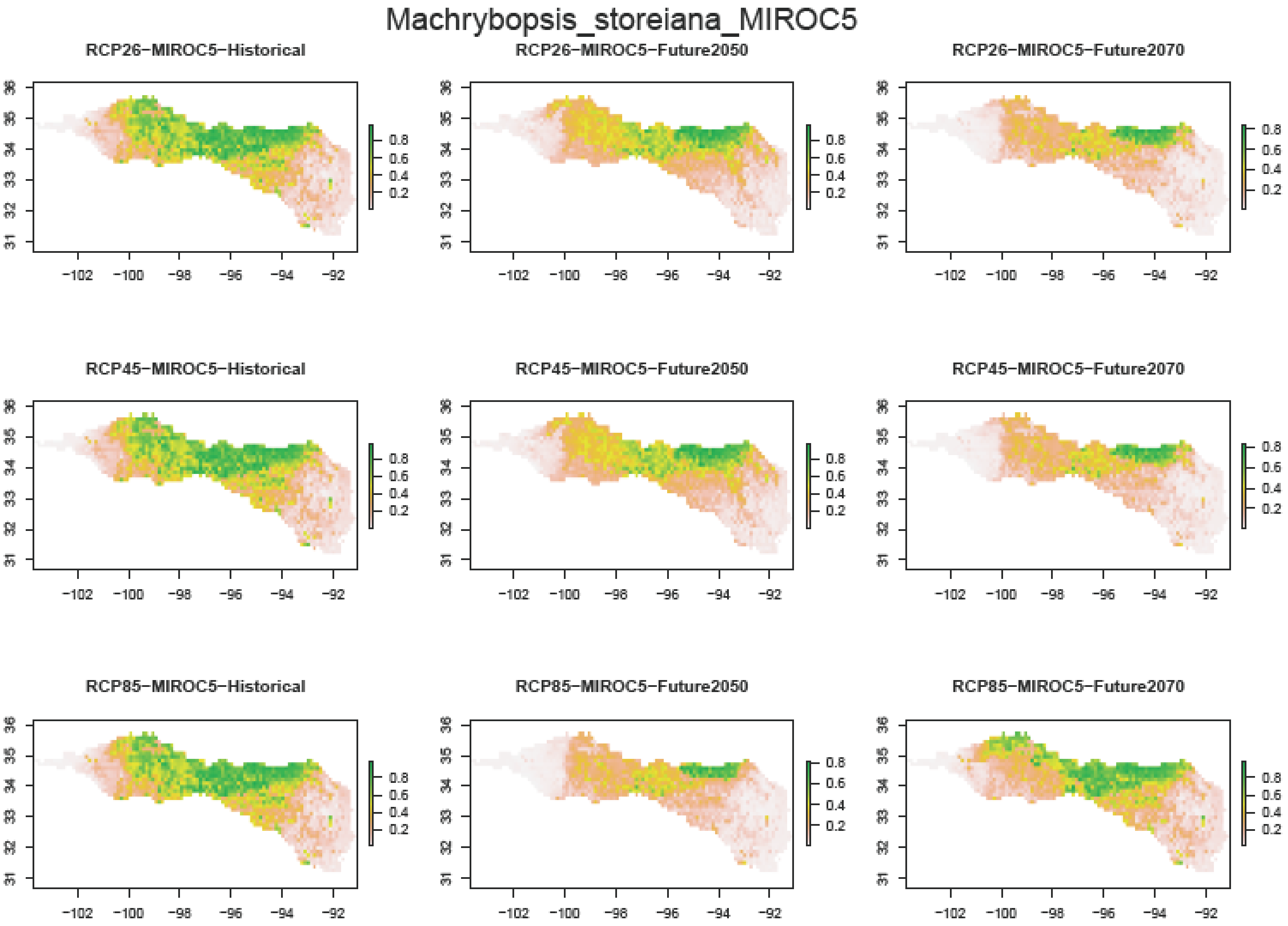


MacrhybopsishyostomaMPI_ESM_LR



Maxent: *Macrhybopsis storeriana*





Machrybopsis_storeiana_MIROC5

RCP26−MIROC5−Historical

RCP26−MIROC5−Future2050

RCP26−MIROC5−Future2070

RCP45−MIROC5−Historical

RCP45−MIROC5−Future2050

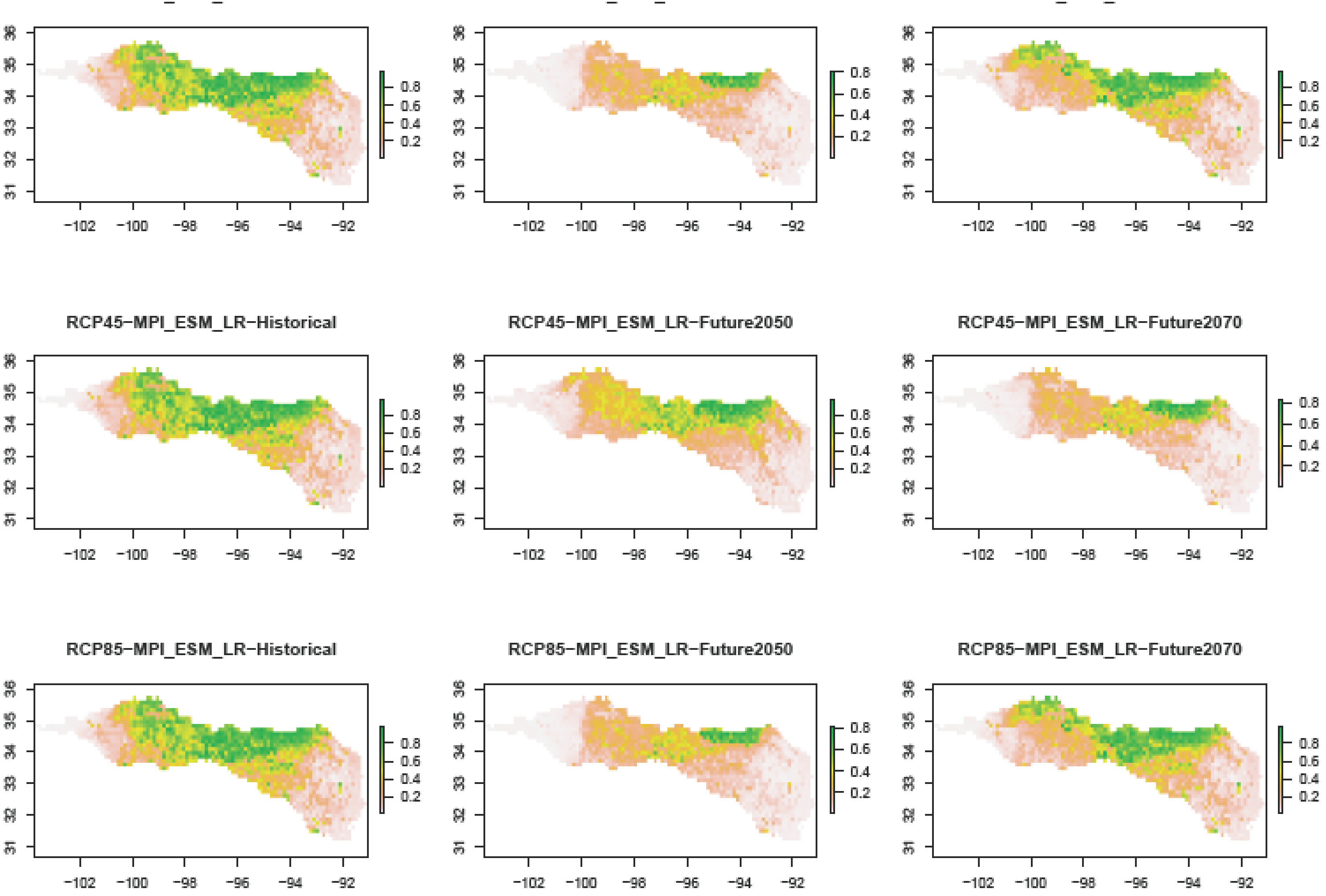
RCP45−MIROC5−Future2070

RCP85−MIROC5−Historical

RCP85−MIROC5−Future2050

RCP85−MIROC5−Future2070

Machrybopsis_storeiana_MPI_ESM_LR



RCP26−MPI_ESM_LR−Historical

RCP26−MPI_ESM_LR−Future2050

RCP26−MPI_ESM_LR−Future2070

RCP45−MPI_ESM_LR−Historical

RCP45−MPI_ESM_LR−Future2050

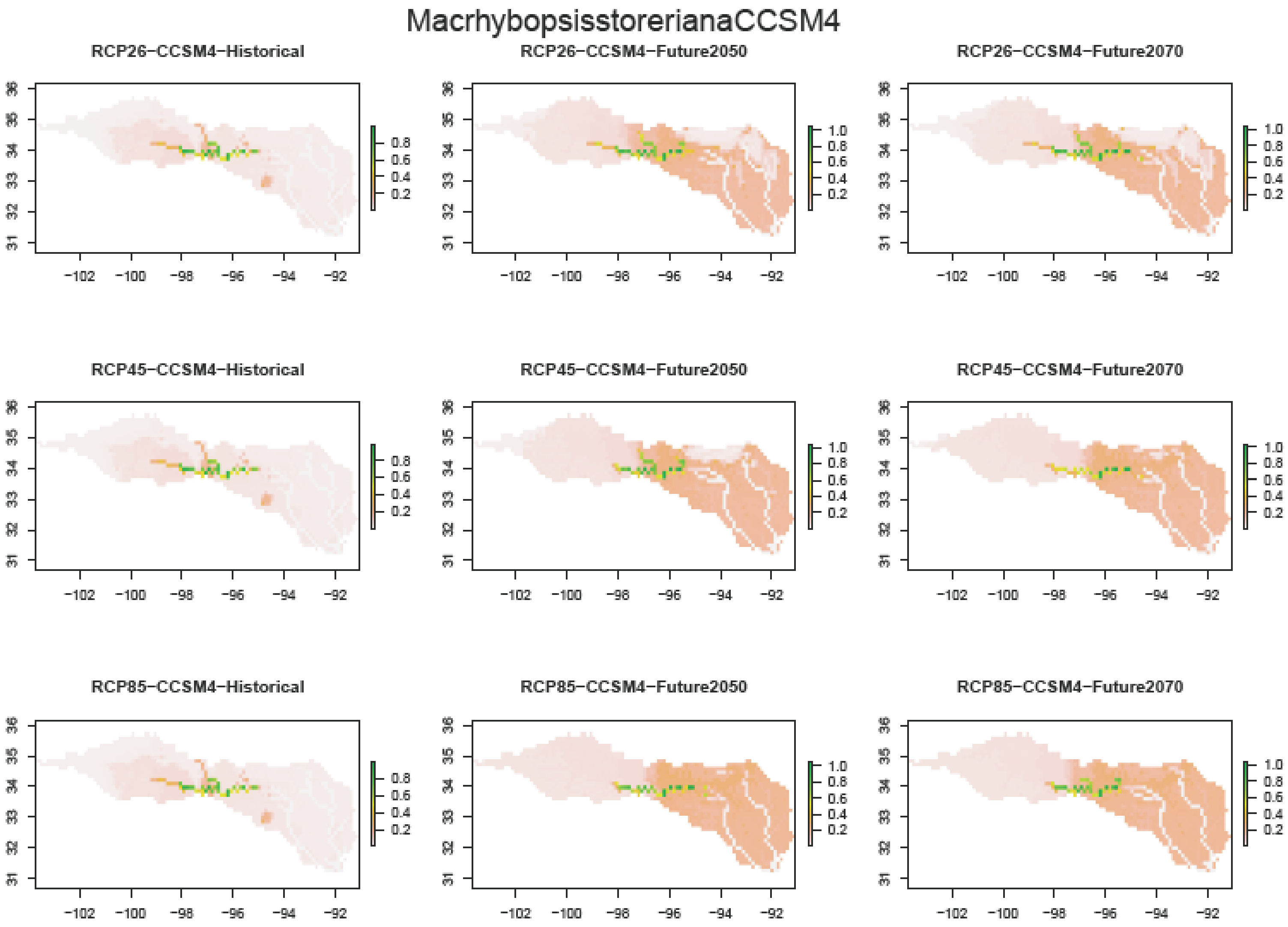
RCP45−MPI_ESM_LR−Future2070

RCP85−MPI_ESM_LR−Historical

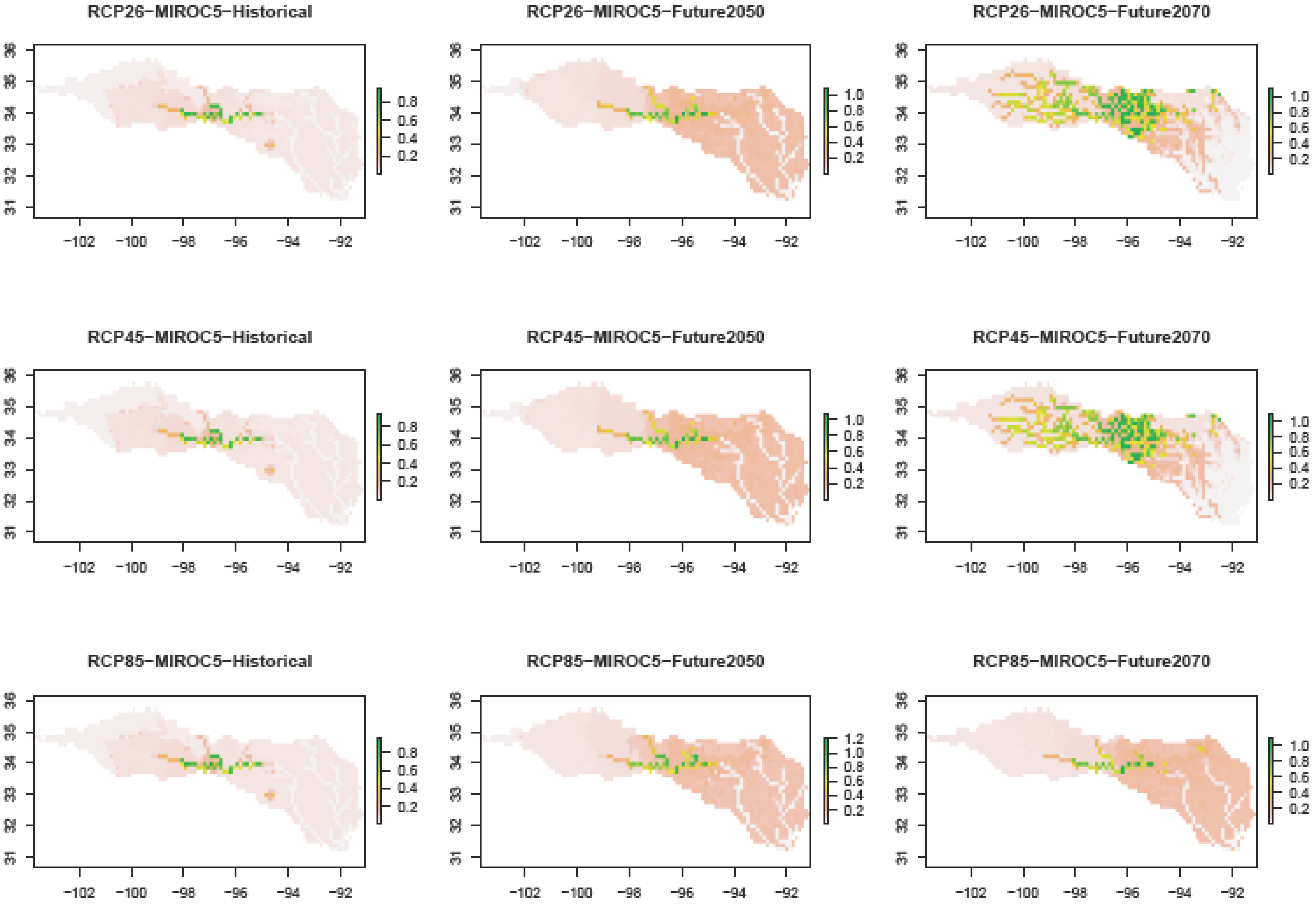
RCP85−MPI_ESM_LR−Future2050

RCP85−MPI_ESM_LR−Future2070

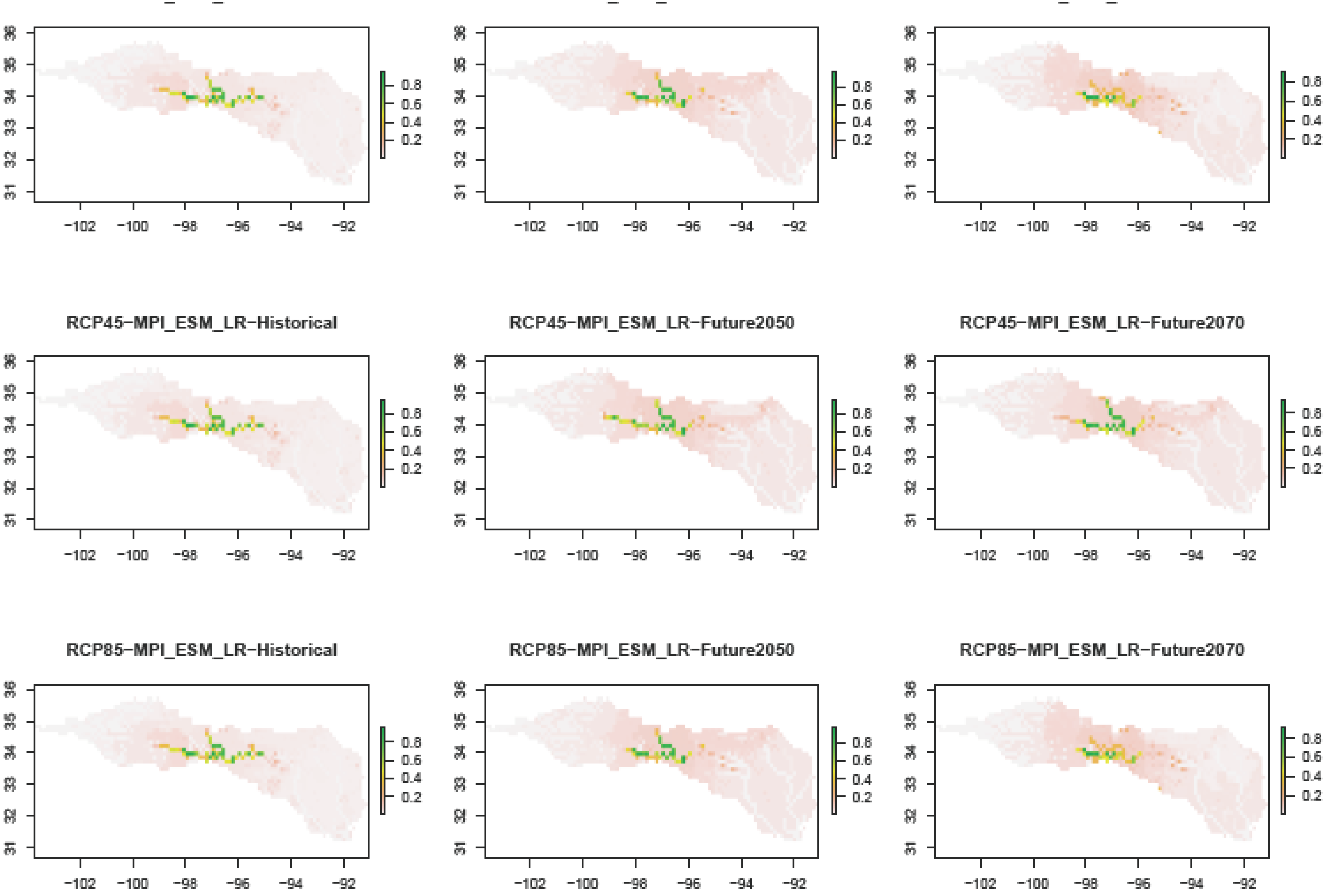
BRT: *Macrhybopsis storeriana*



MacrhybopsisstorerianaMIROC5



MacrhybopsisstorerianaMPI_ESM_LR


RCP26−MPI_ESM_LR−Historical

RCP26−MPI_ESM_LR−Future2050

RCP26−MPI_ESM_LR−Future2070

RCP45−MPI_ESM_LR−Historical

RCP45−MPI_ESM_LR−Future2050

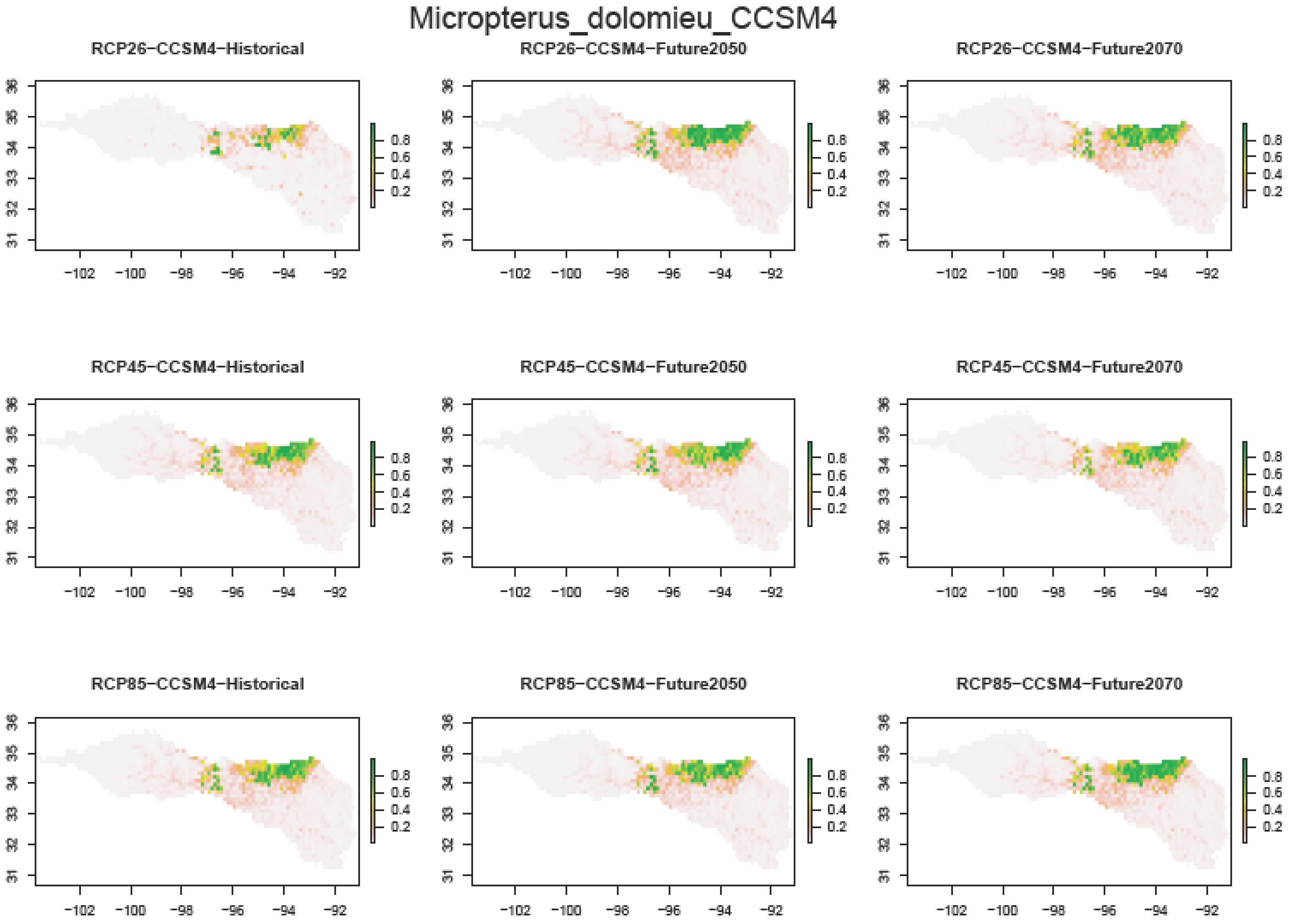
RCP45−MPI_ESM_LR−Future2070

RCP85−MPI_ESM_LR−Historical

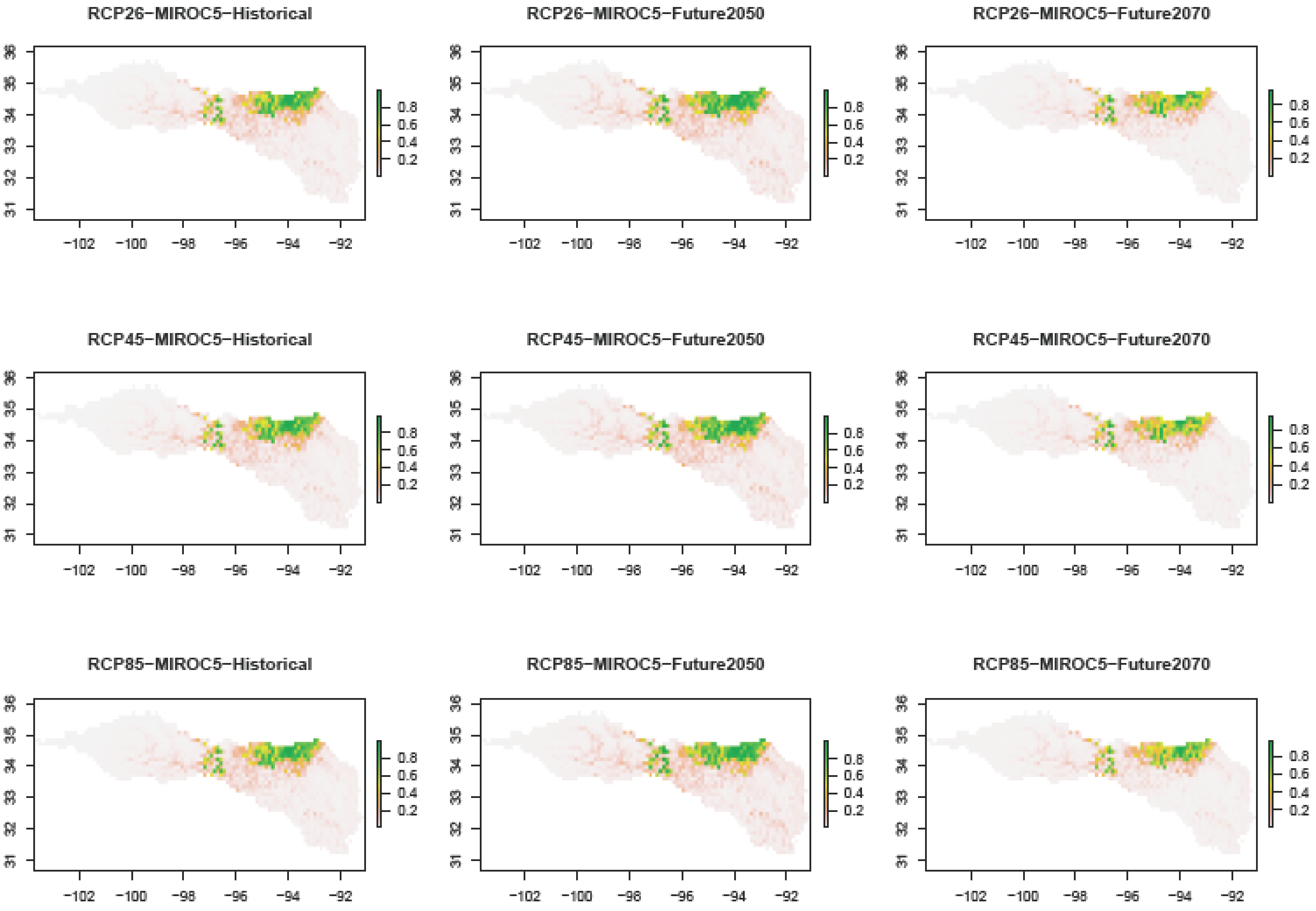
RCP85−MPI_ESM_LR−Future2050

RCP85−MPI_ESM_LR−Future2070

Maxent: *Micopterus dolomieu*



Micropterus_dolomieu_MIROC5


RCP26−MIROC5−Historical

RCP26−MIROC5−Future2050

RCP26−MIROC5−Future2070

RCP45−MIROC5−Historical

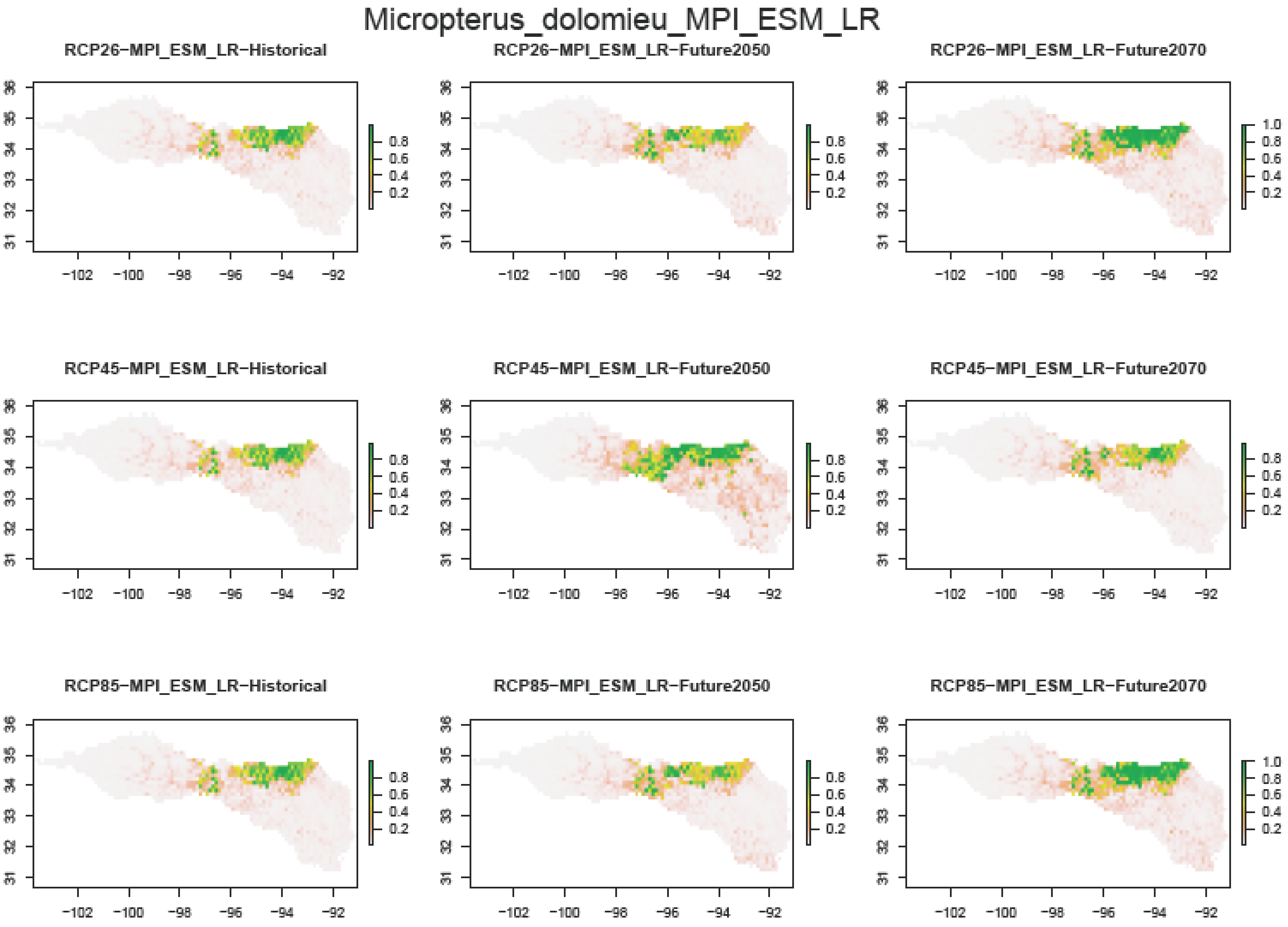
RCP45−MIROC5−Future2050

RCP45−MIROC5−Future2070

RCP85−MIROC5−Historical

RCP85−MIROC5−Future2050

RCP85−MIROC5−Future2070



Micropterus_dolomieu_MPI_ESM_LR

RCP26-MPI_ESM_LR-Historical

RCP26-MPI_ESM_LR-Future2050

RCP26-MPI_ESM_LR-Future2070

RCP45-MPI_ESM_LR-Historical

RCP45-MPI_ESM_LR-Future2050

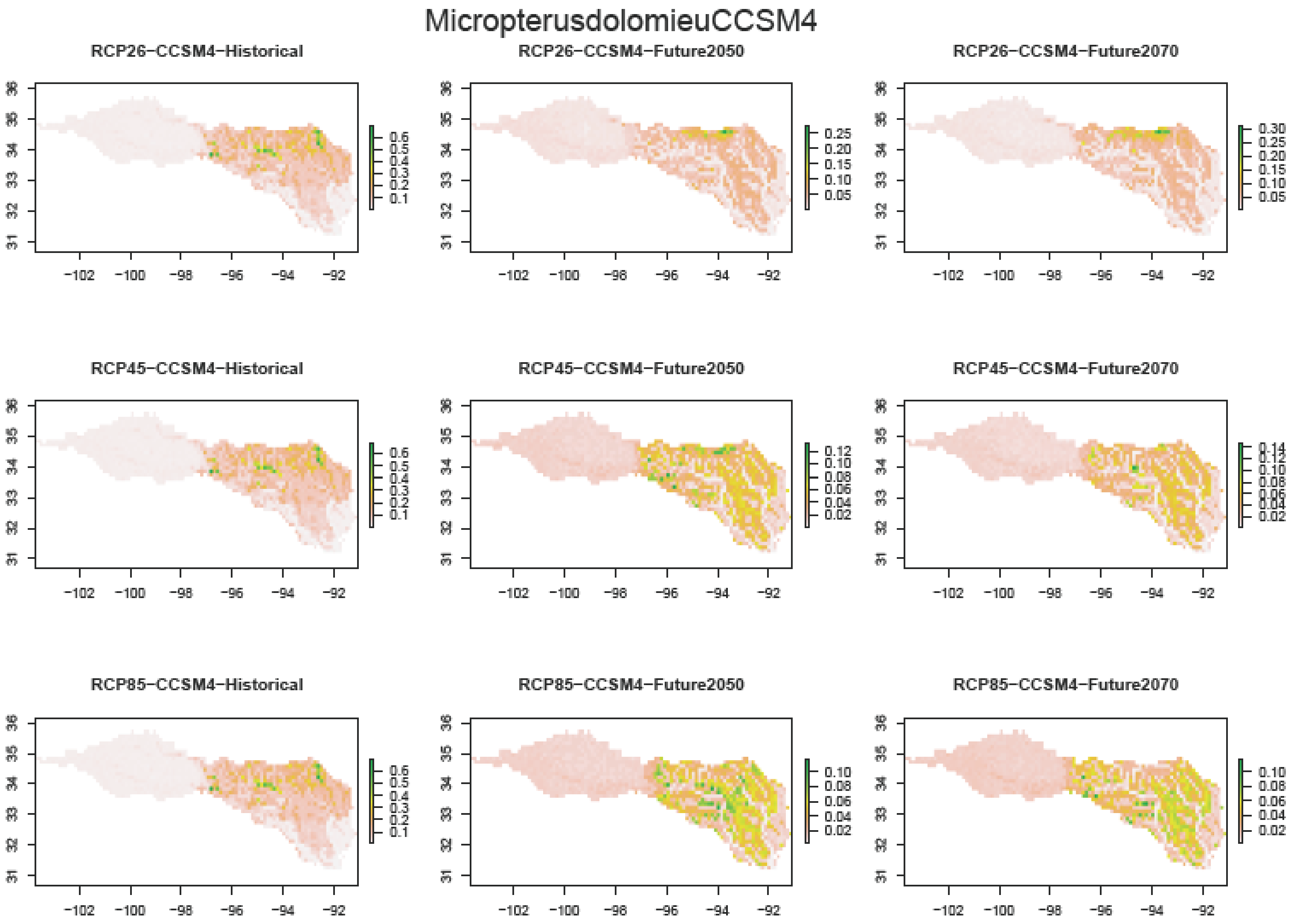
RCP45-MPI_ESM_LR-Future2070

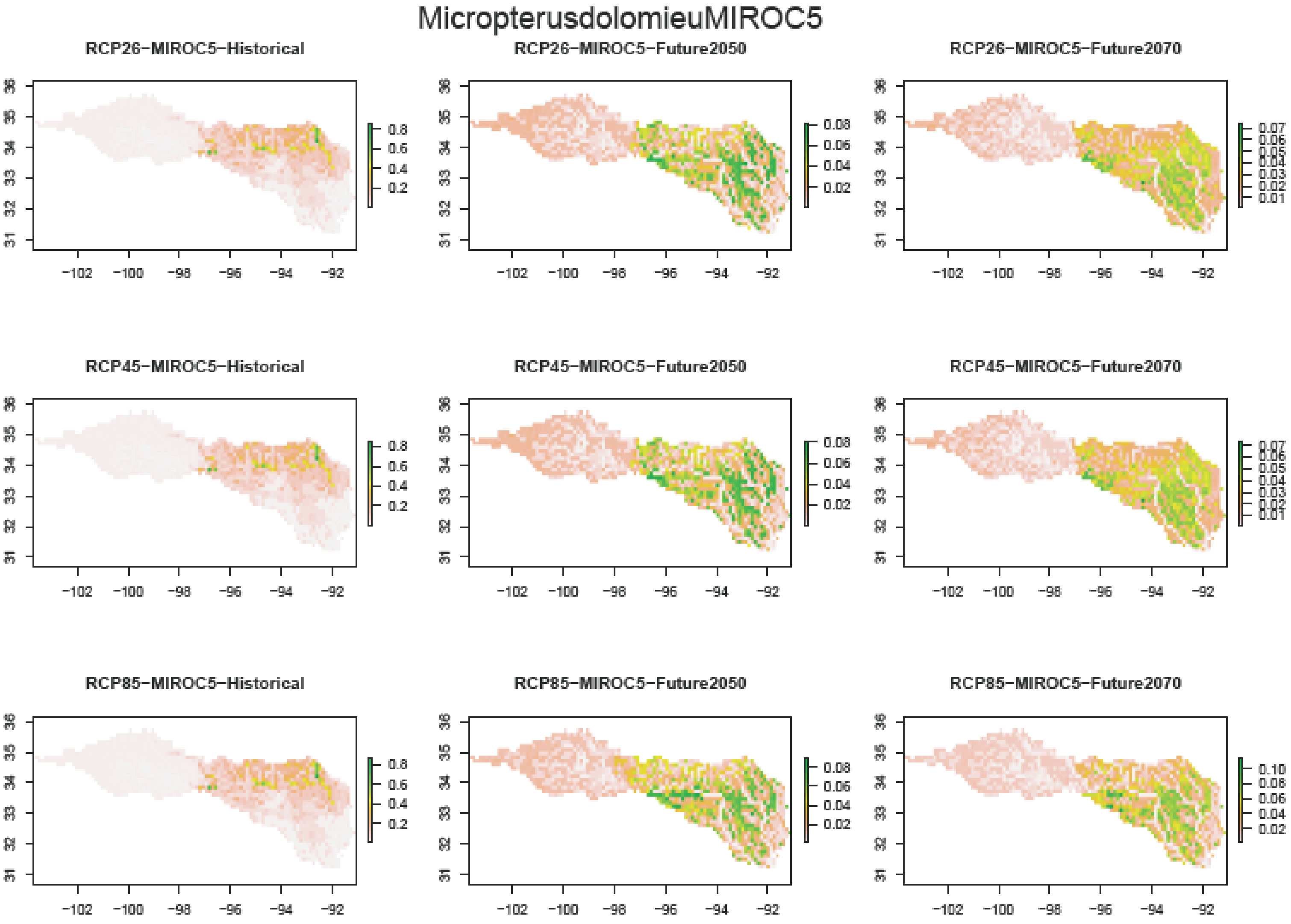
RCP85-MPI_ESM_LR-Historical

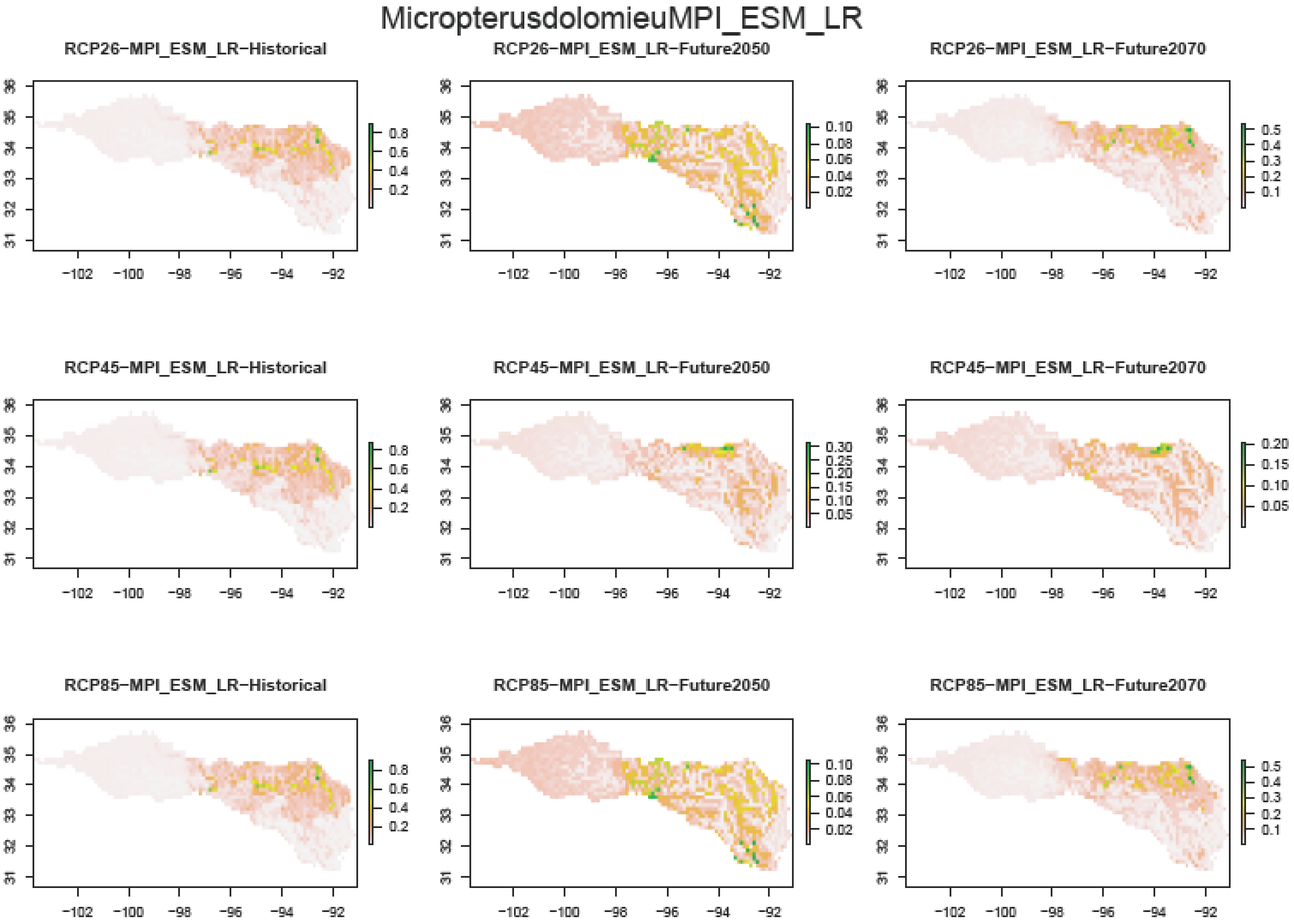
RCP85-MPI_ESM_LR-Future2050

RCP85-MPI_ESM_LR-Future2070

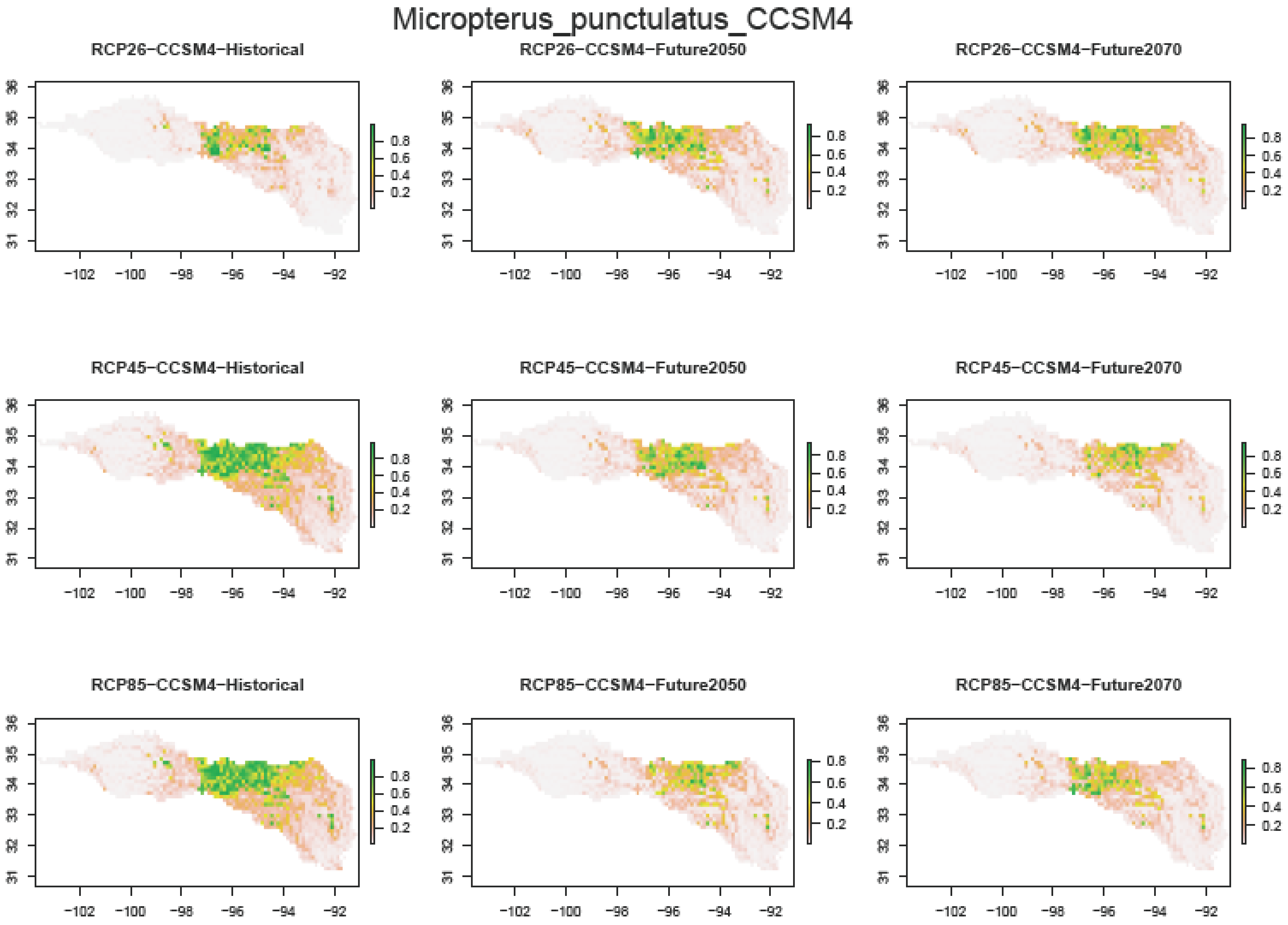
BRT: *Micropterus dolomieu*

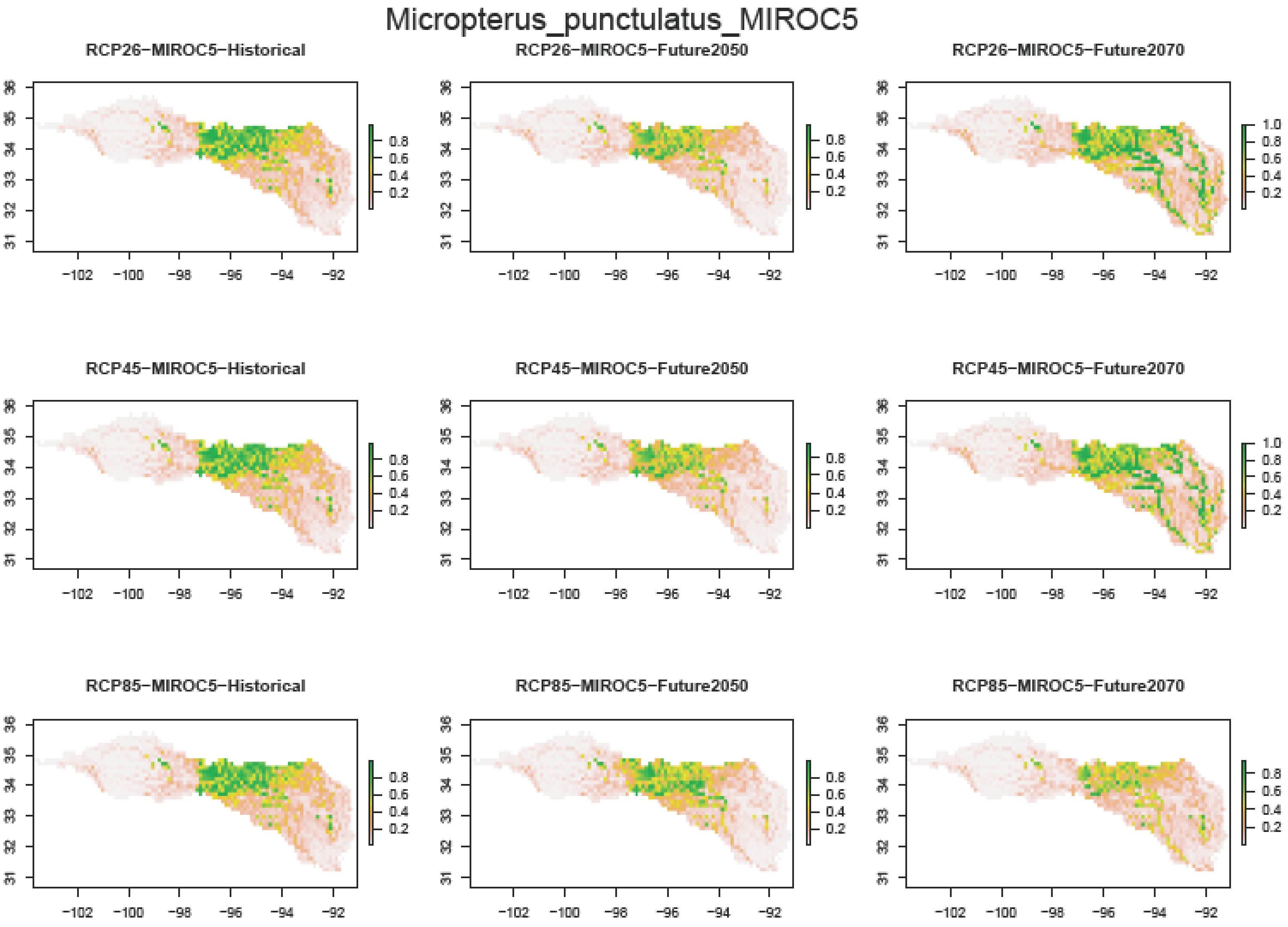



MicropterusdolomieuMIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070
−102
−100
−98
−96
−94
−92
31
32
33
34
35
36
0.2
0.4
0.6
0.8
0.02
0.04
0.06
0.08
0.01
0.02
0.03
0.04
0.05
0.06
0.07
0.10

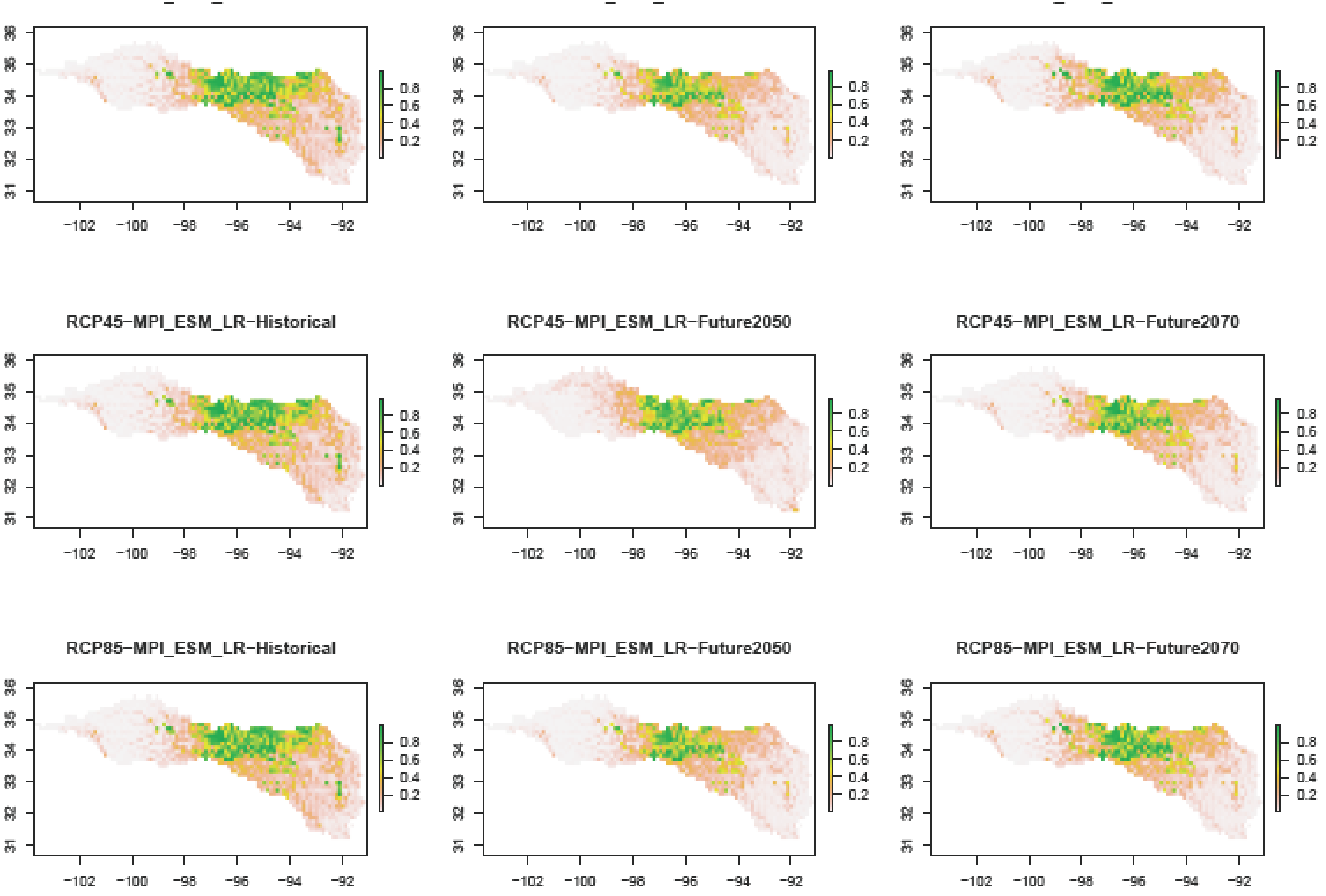

MicropterusdolomieuMPI_ESM_LR
RCP26−MPI_ESM_LR−Historical
RCP26−MPI_ESM_LR−Future2050
RCP26−MPI_ESM_LR−Future2070
RCP45−MPI_ESM_LR−Historical
RCP45−MPI_ESM_LR−Future2050
RCP45−MPI_ESM_LR−Future2070
RCP85−MPI_ESM_LR−Historical
RCP85−MPI_ESM_LR−Future2050
RCP85−MPI_ESM_LR−Future2070
31
32
33
34
35
36
−102
−100
−98
−96
−94
−92
0.8
0.6
0.4
0.2
0.10
0.08
0.06
0.04
0.02
0.5
0.4
0.3
0.2
0.1
0.30
0.25
0.20
0.15
0.10
0.05
0.20
0.15
0.10
0.05

Maxent: *Micropterus punctulatus*

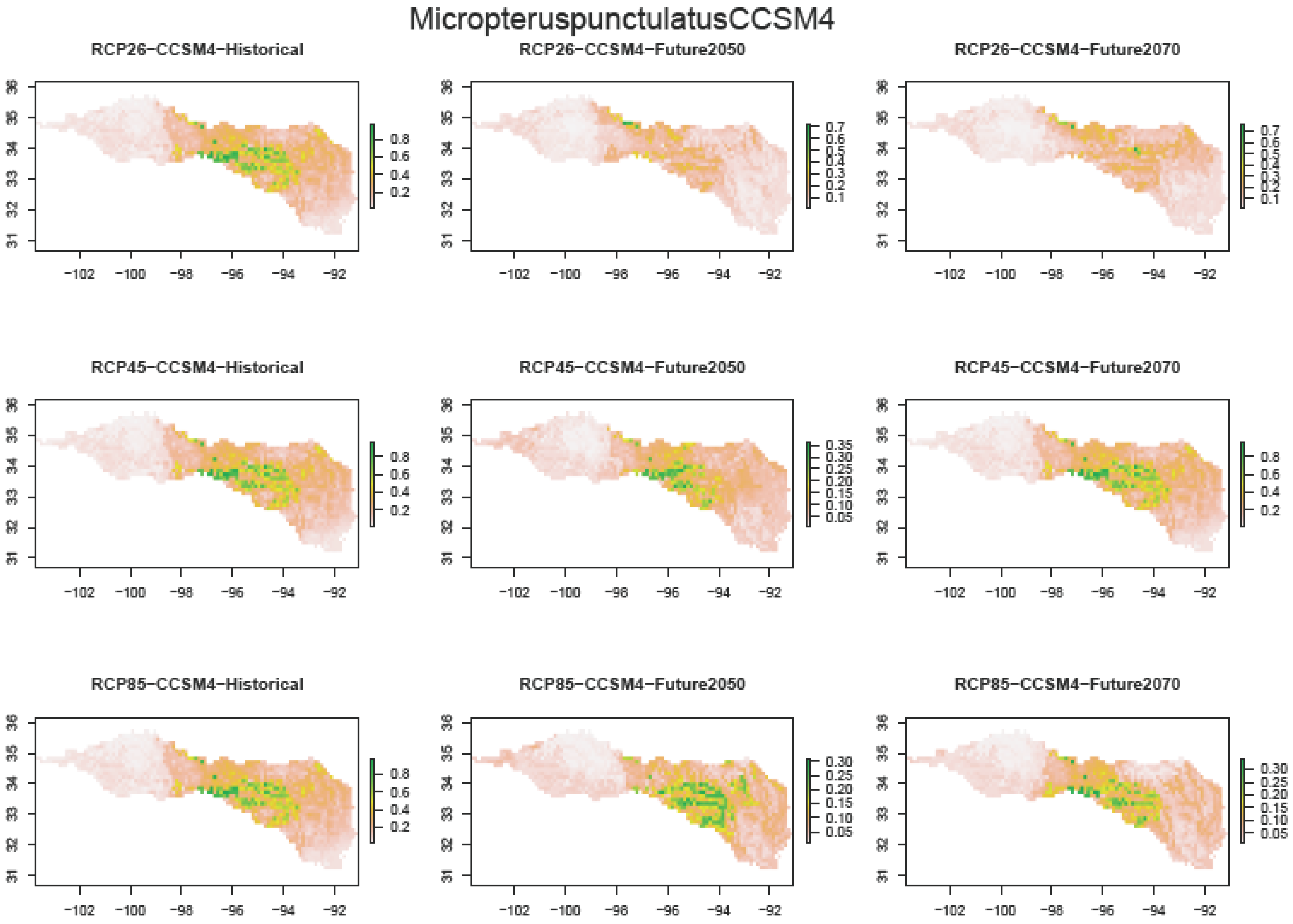


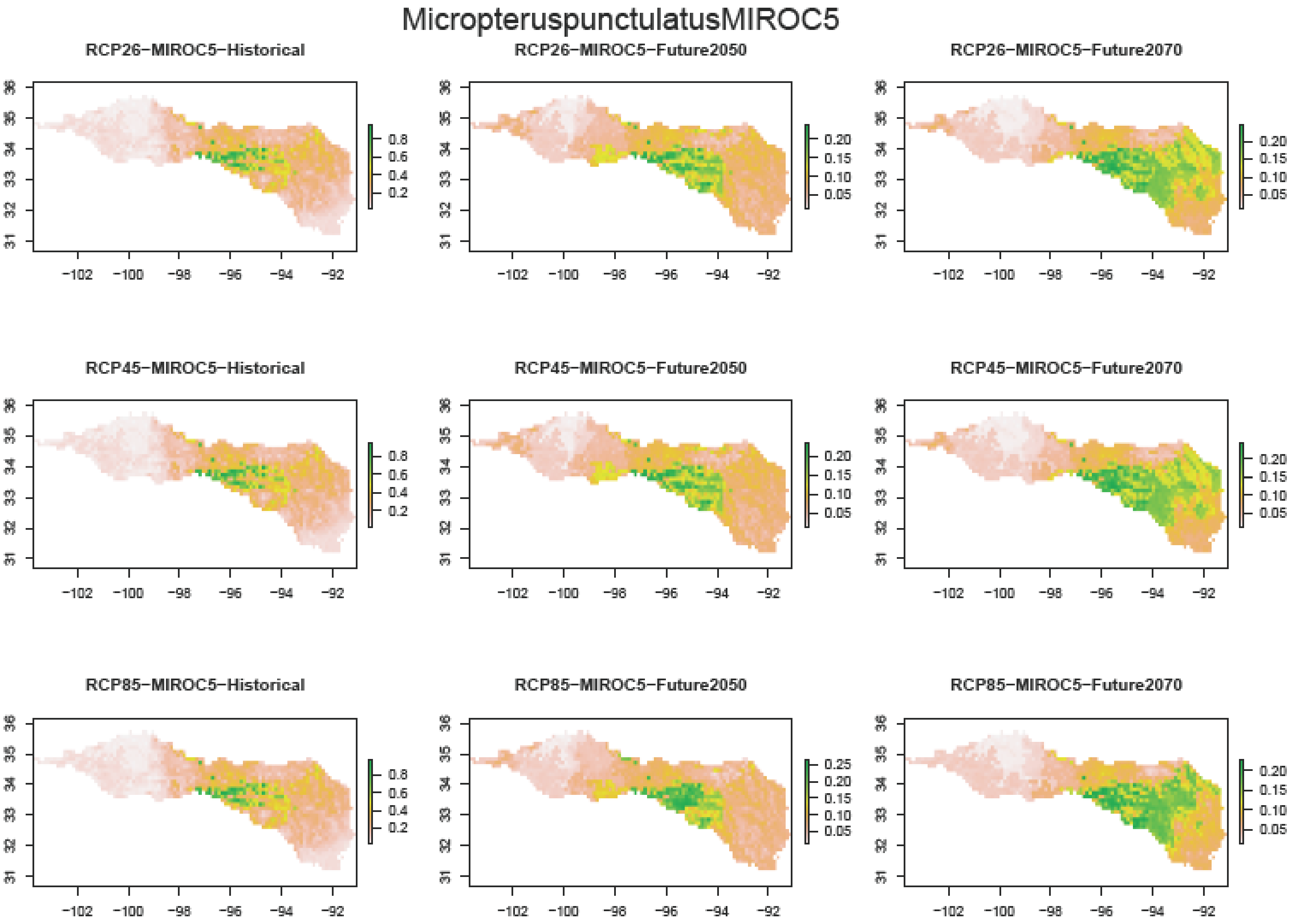

Micropterus_punctulatus_MIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070
31
32
33
34
35
36
−102
−100
−98
−96
−94
−92
1.0
0.8
0.6
0.4
0.2

Micropterus_punctulatus_MPI_ESM_LR

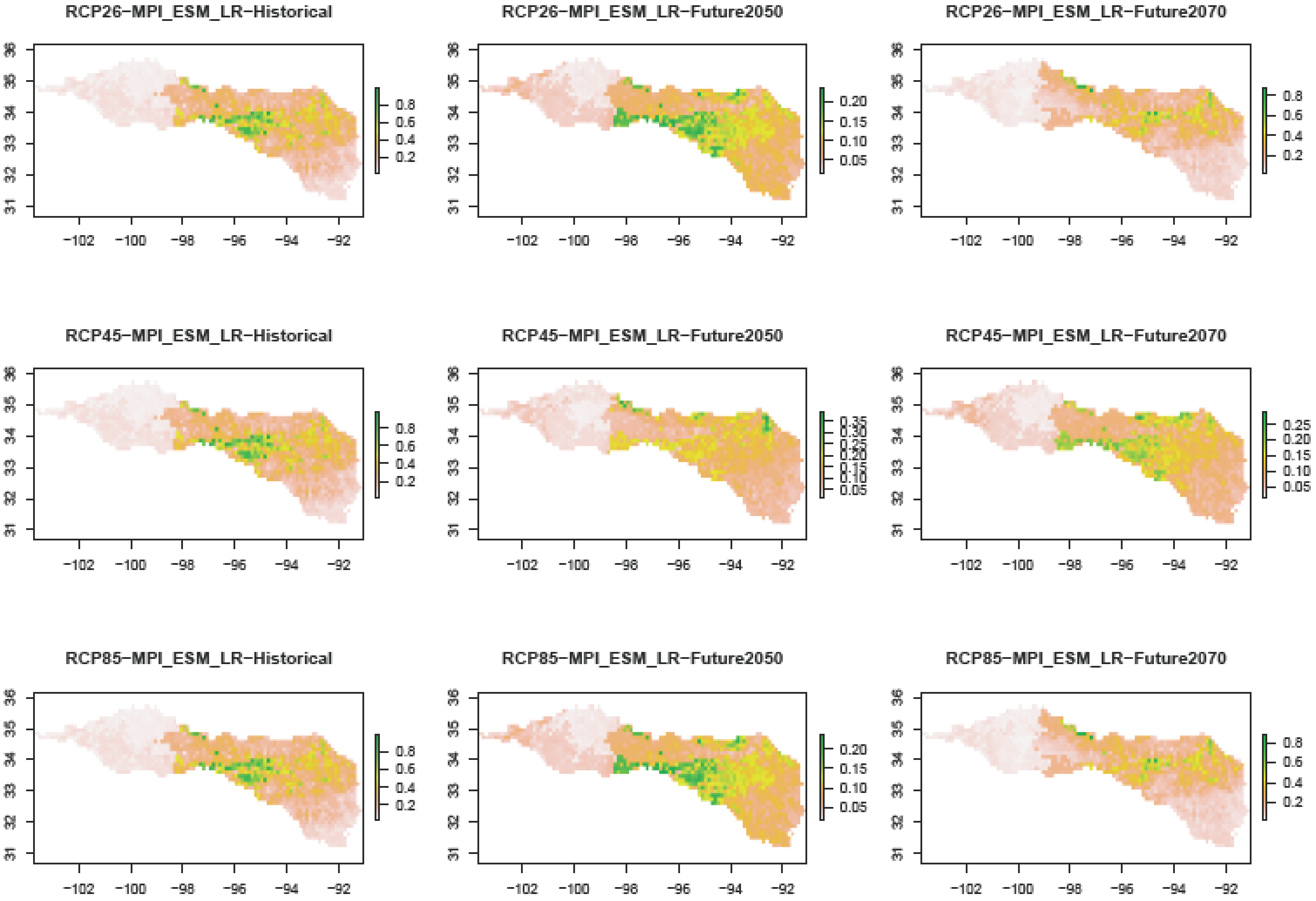


BRT: *Micropterus punctulatus*




MicropteruspunctulatusMIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070
31
32
33
34
35
36
−102
−100
−98
−96
−94
−92
0.8
0.6
0.4
0.2
0.25
0.20
0.15
0.10
0.05

MicropteruspunctulatusMPI_ESM_LR



RCP26−MPI_ESM_LR−Historical

RCP26−MPI_ESM_LR−Future2050

RCP26−MPI_ESM_LR−Future2070

RCP45−MPI_ESM_LR−Historical

RCP45−MPI_ESM_LR−Future2050

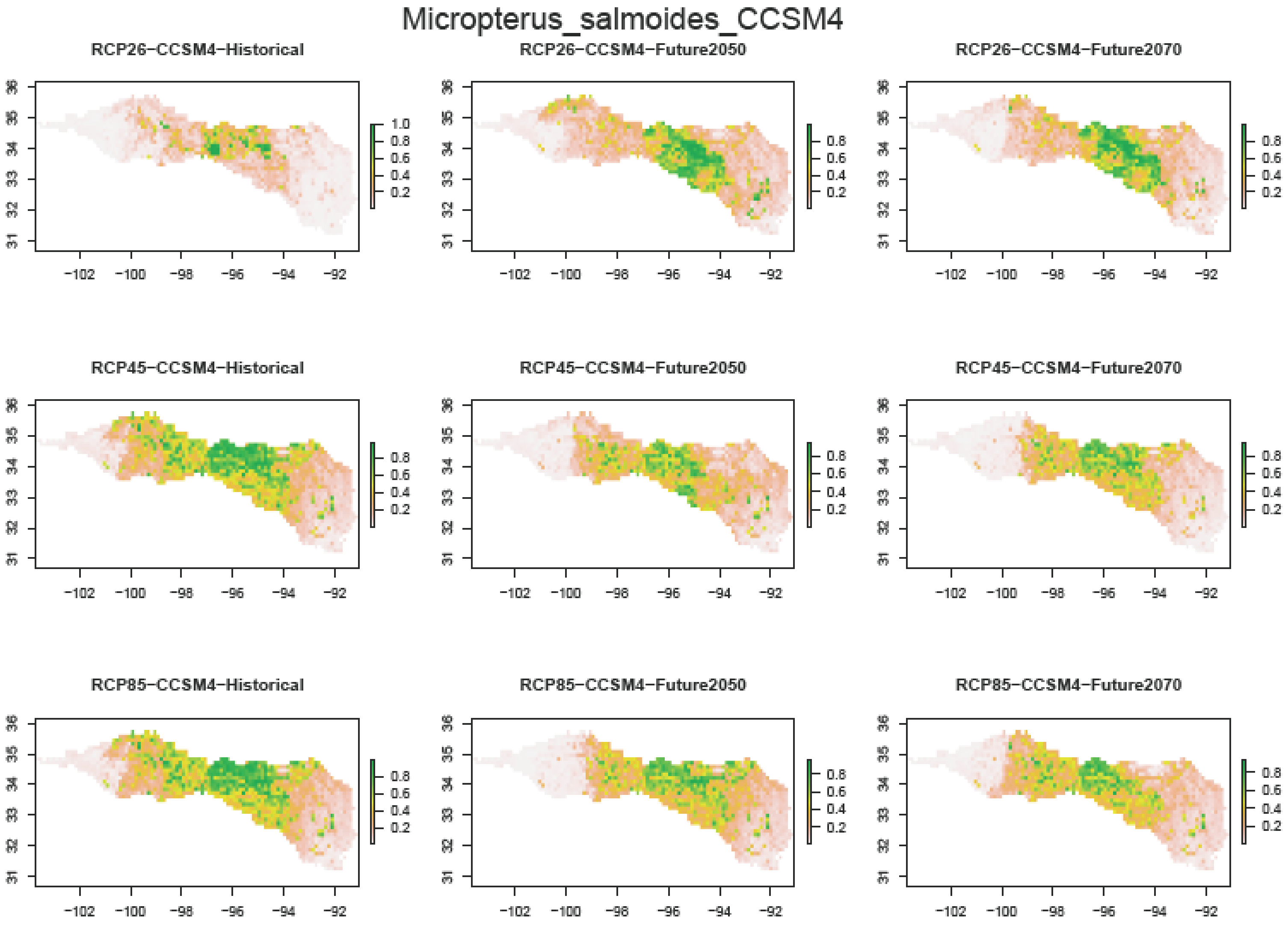
RCP45−MPI_ESM_LR−Future2070

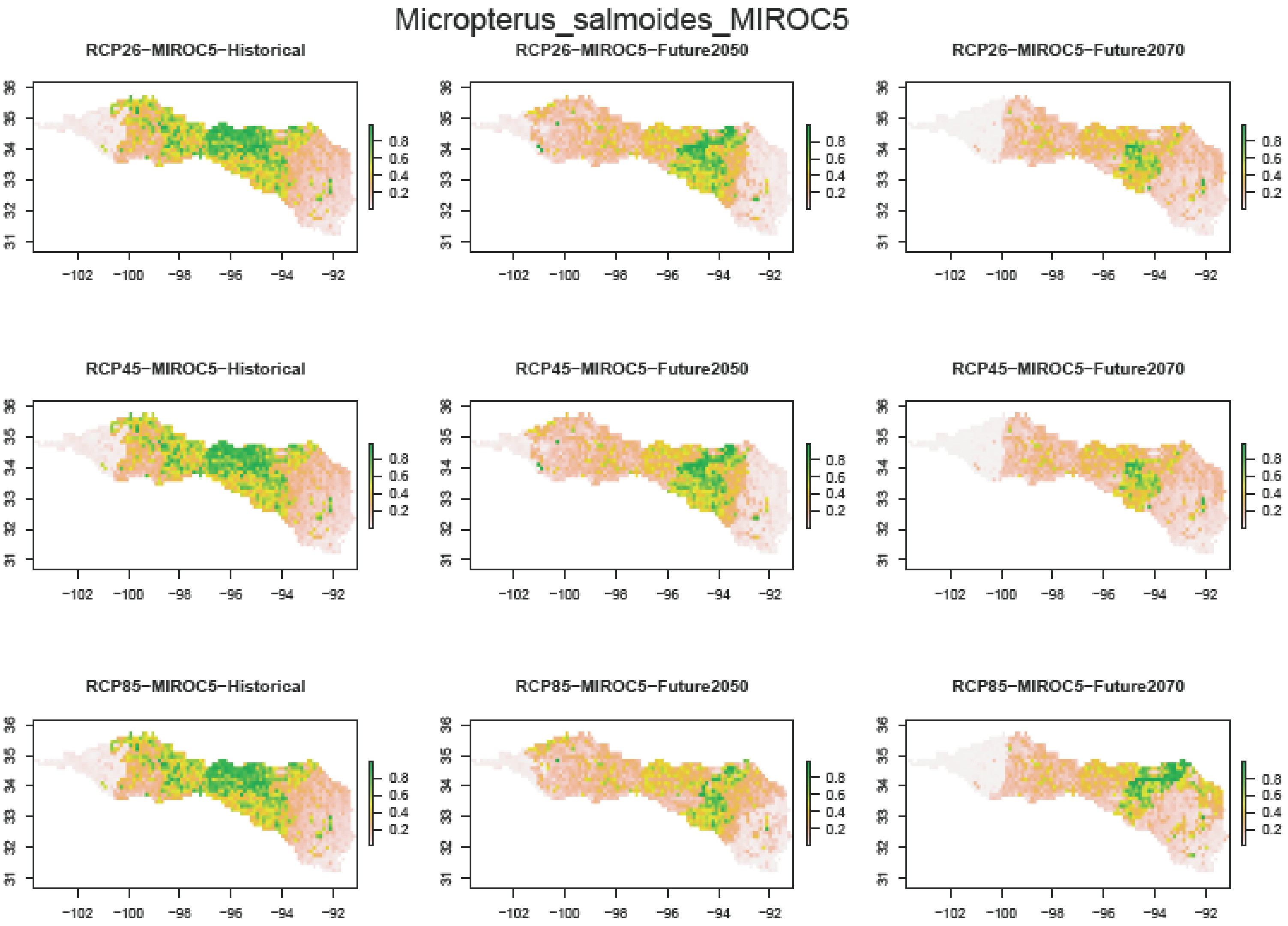
RCP85−MPI_ESM_LR−Historical

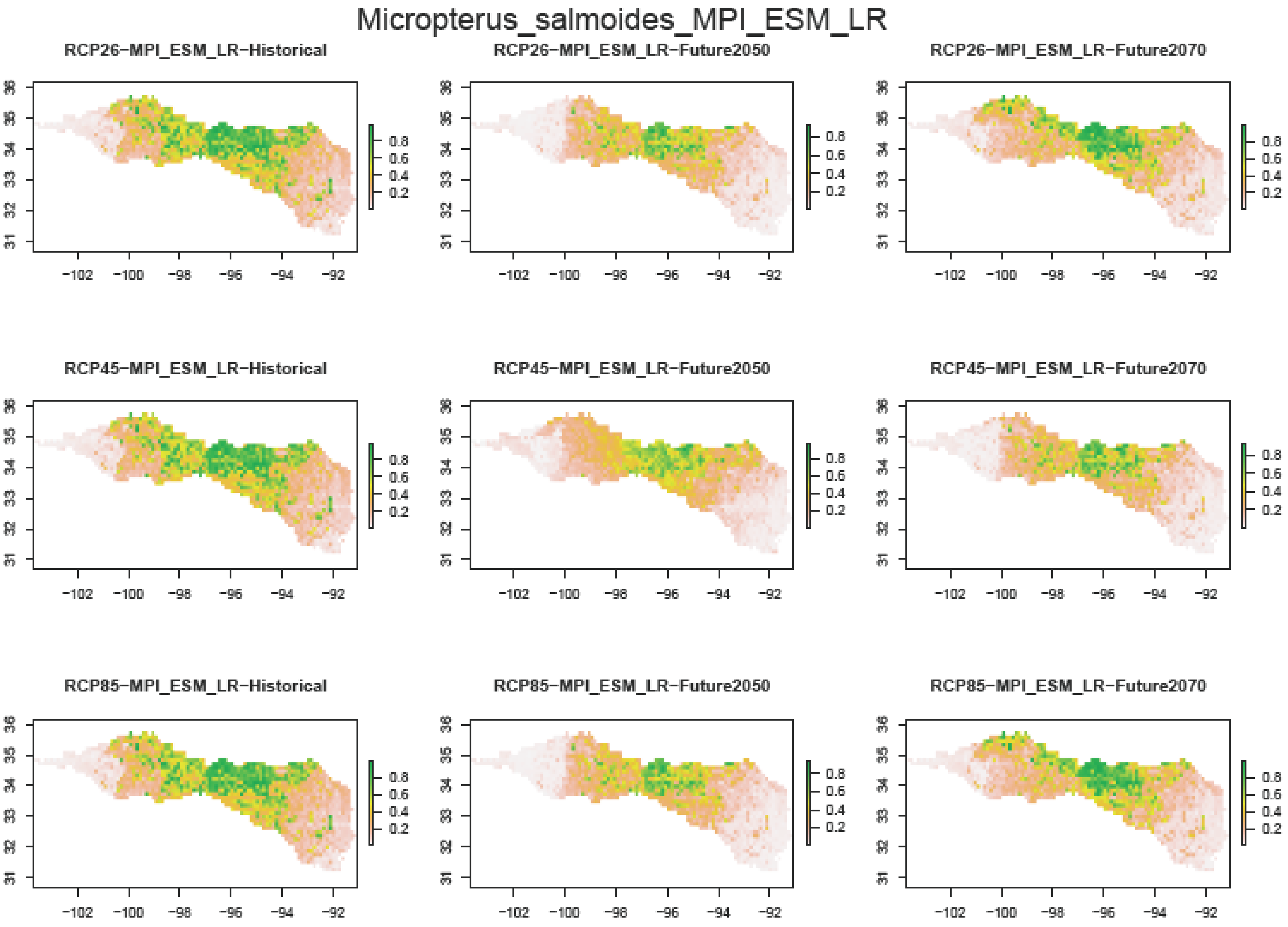
RCP85−MPI_ESM_LR−Future2050

RCP85−MPI_ESM_LR−Future2070

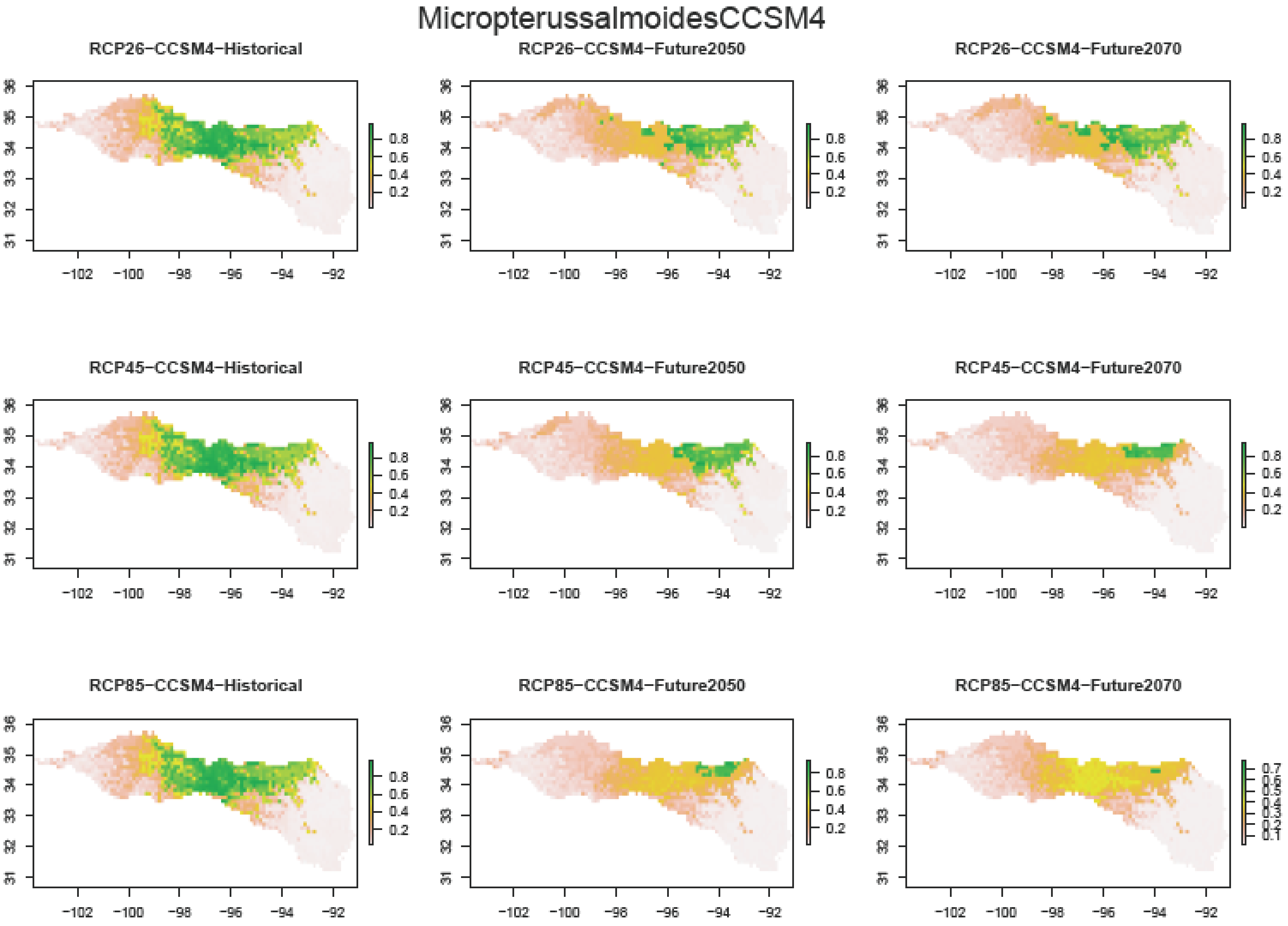
Maxent: *Micropterus salmoides*

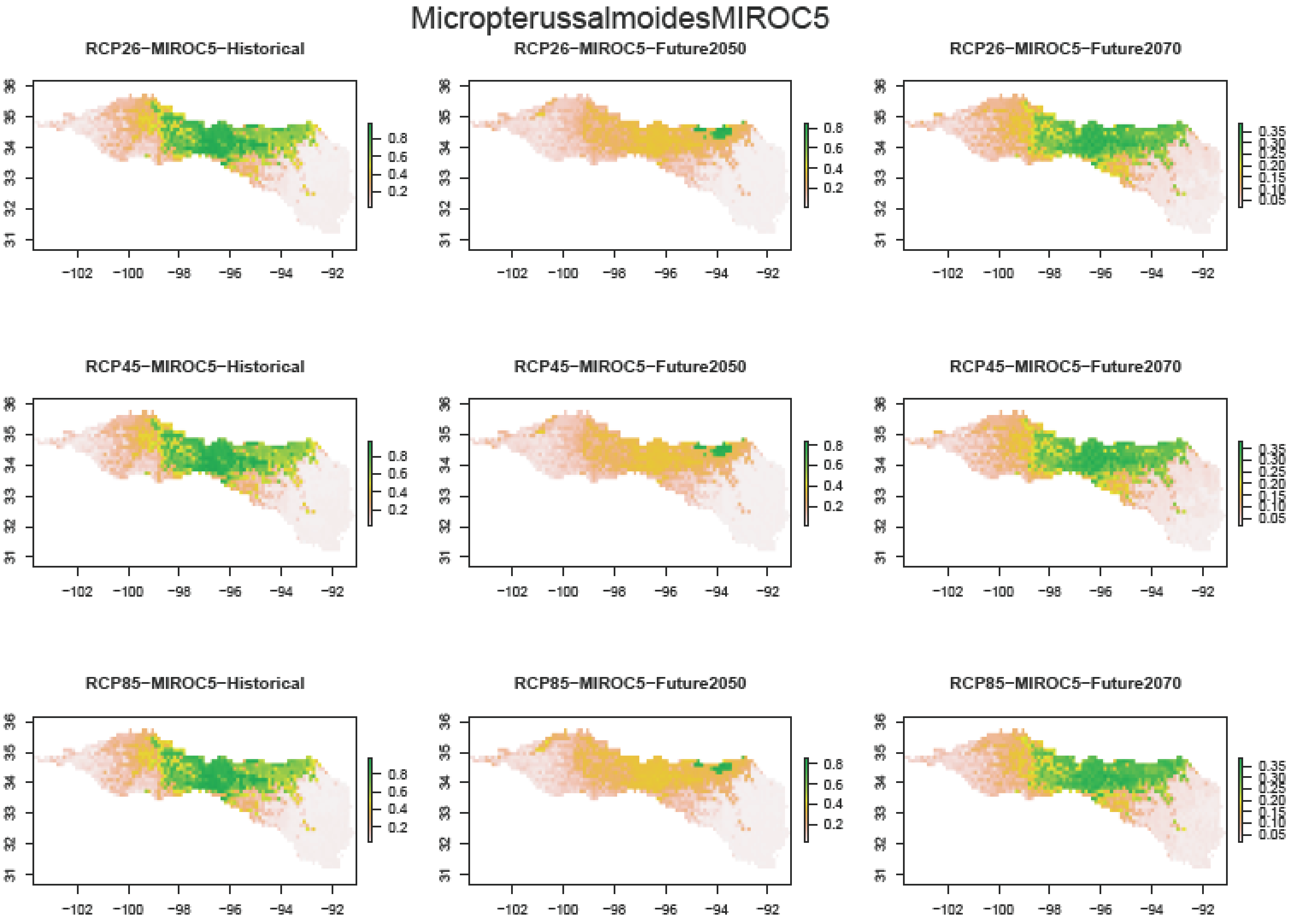



Micropterus_salmoides_MIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070
31
32
33
34
35
36
−102
−100
−98
−96
−94
−92
0.8
0.6
0.4
0.2


Micropterus_salmoides_MPI_ESM_LR
RCP26−MPI_ESM_LR−Historical
RCP26−MPI_ESM_LR−Future2050
RCP26−MPI_ESM_LR−Future2070
RCP45−MPI_ESM_LR−Historical
RCP45−MPI_ESM_LR−Future2050
RCP45−MPI_ESM_LR−Future2070
RCP85−MPI_ESM_LR−Historical
RCP85−MPI_ESM_LR−Future2050
RCP85−MPI_ESM_LR−Future2070
31
32
33
34
35
36
−102
−100
−98
−96
−94
−92
0.8
0.6
0.4
0.2

BRT: *Micropterus salmoides*




MicropterussalmoidesMIROC5

RCP26−MIROC5−Historical

RCP26−MIROC5−Future2050

RCP26−MIROC5−Future2070

RCP45−MIROC5−Historical

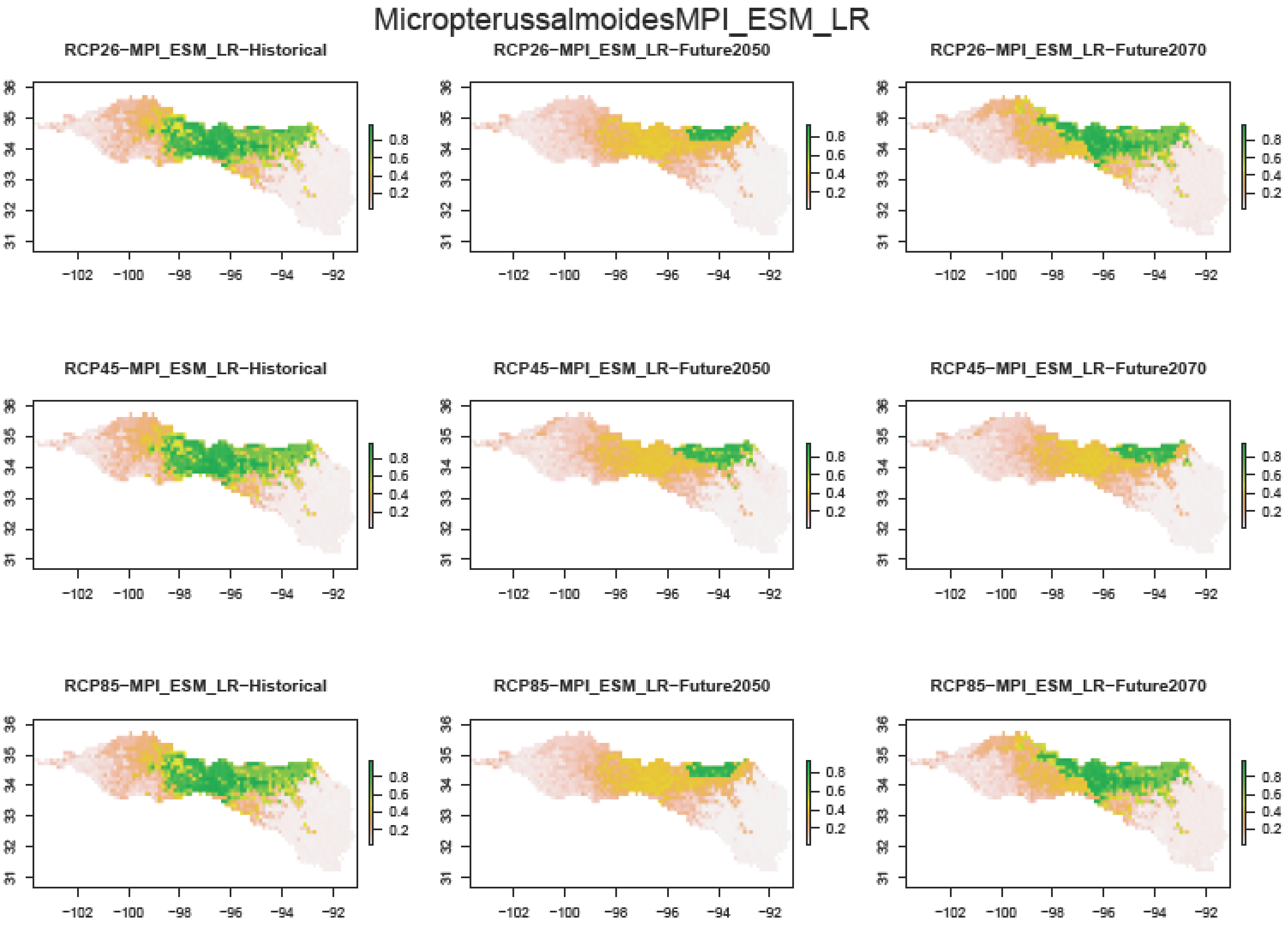
RCP45−MIROC5−Future2050

RCP45−MIROC5−Future2070

RCP85−MIROC5−Historical

RCP85−MIROC5−Future2050

RCP85−MIROC5−Future2070



MicropterussalmoidesMPI_ESM_LR

RCP26−MPI_ESM_LR−Historical

RCP26−MPI_ESM_LR−Future2050

RCP26−MPI_ESM_LR−Future2070

RCP45−MPI_ESM_LR−Historical

RCP45−MPI_ESM_LR−Future2050

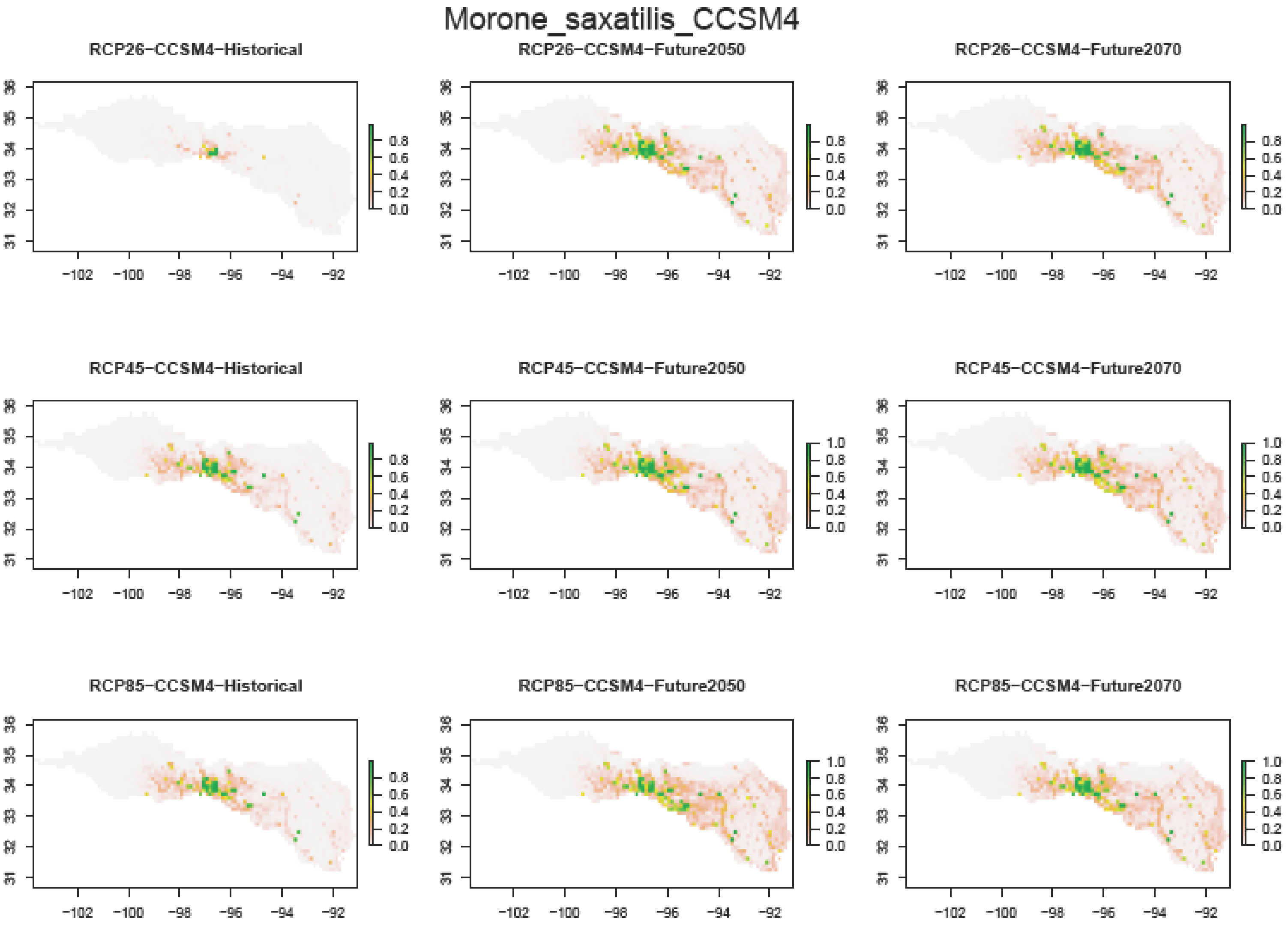
RCP45−MPI_ESM_LR−Future2070

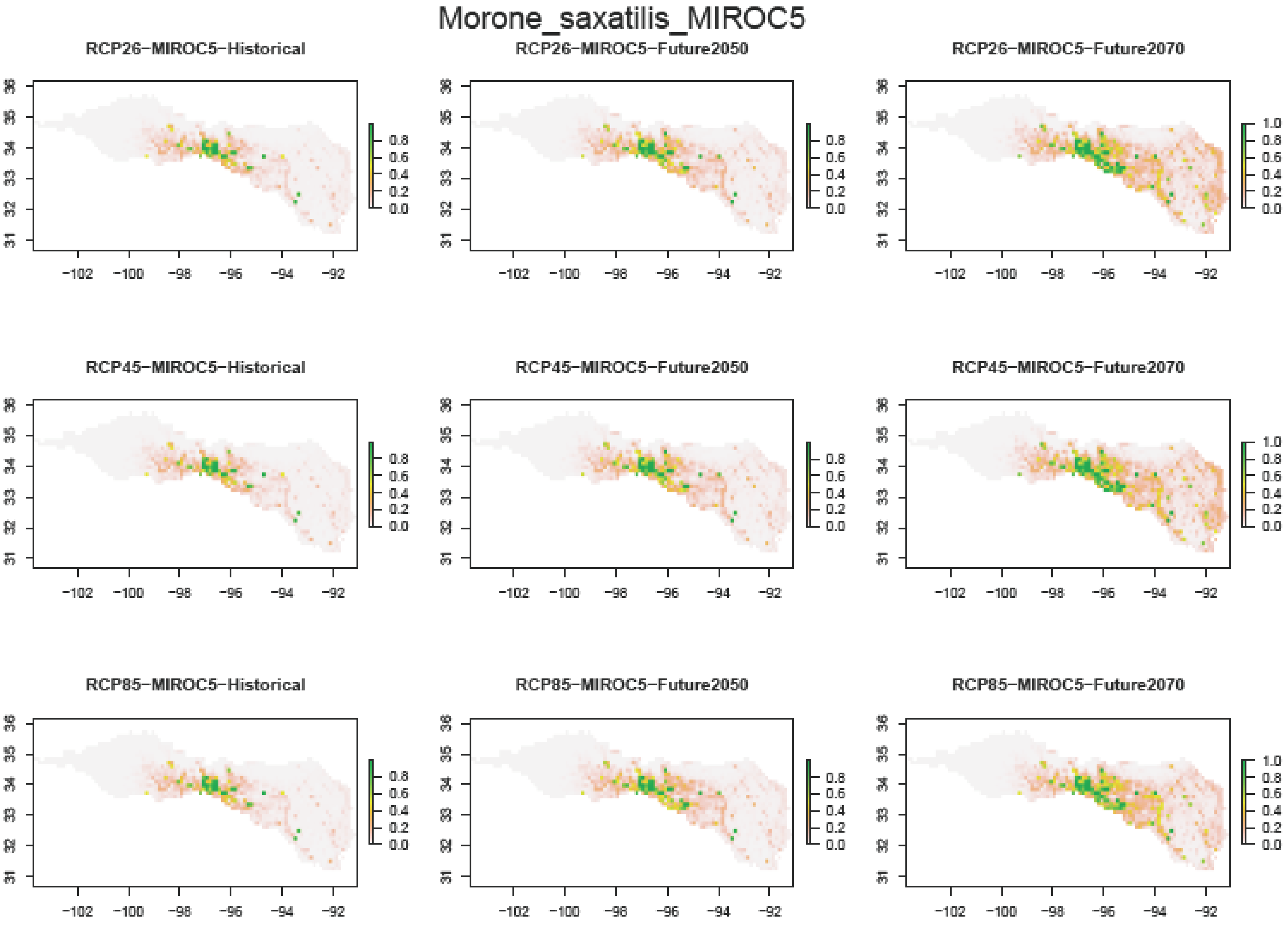
RCP85−MPI_ESM_LR−Historical

RCP85−MPI_ESM_LR−Future2050

RCP85−MPI_ESM_LR−Future2070

Maxent: *Morone saxatilis*





Morone_saxatilis_MIROC5

RCP26−MIROC5−Historical

RCP26−MIROC5−Future2050

RCP26−MIROC5−Future2070

RCP45−MIROC5−Historical

RCP45−MIROC5−Future2050

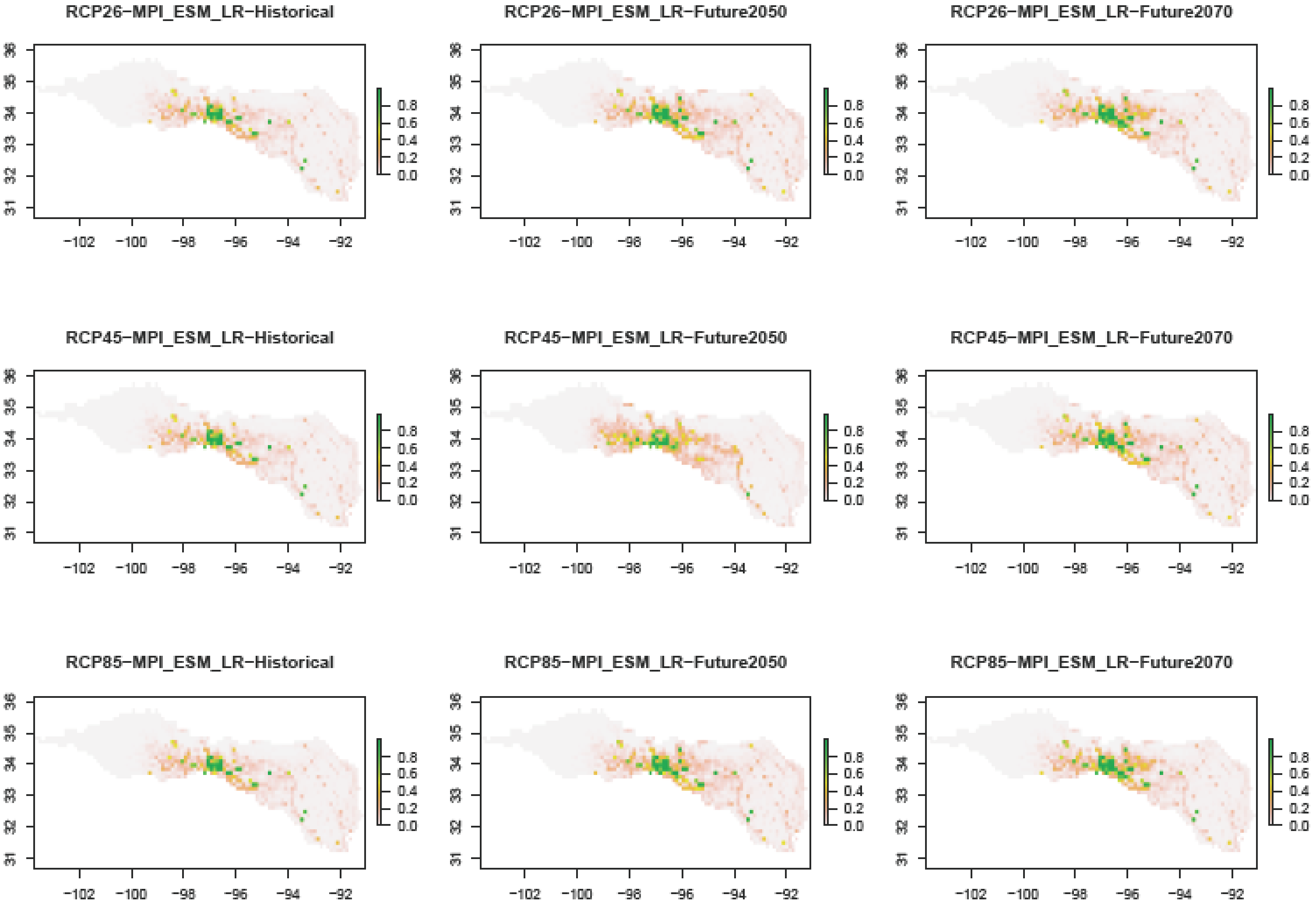
RCP45−MIROC5−Future2070

RCP85−MIROC5−Historical

RCP85−MIROC5−Future2050

RCP85−MIROC5−Future2070

Morone_saxatilis_MPI_ESM_LR



RCP26−MPI_ESM_LR−Historical

RCP26−MPI_ESM_LR−Future2050

RCP26−MPI_ESM_LR−Future2070

RCP45−MPI_ESM_LR−Historical

RCP45−MPI_ESM_LR−Future2050

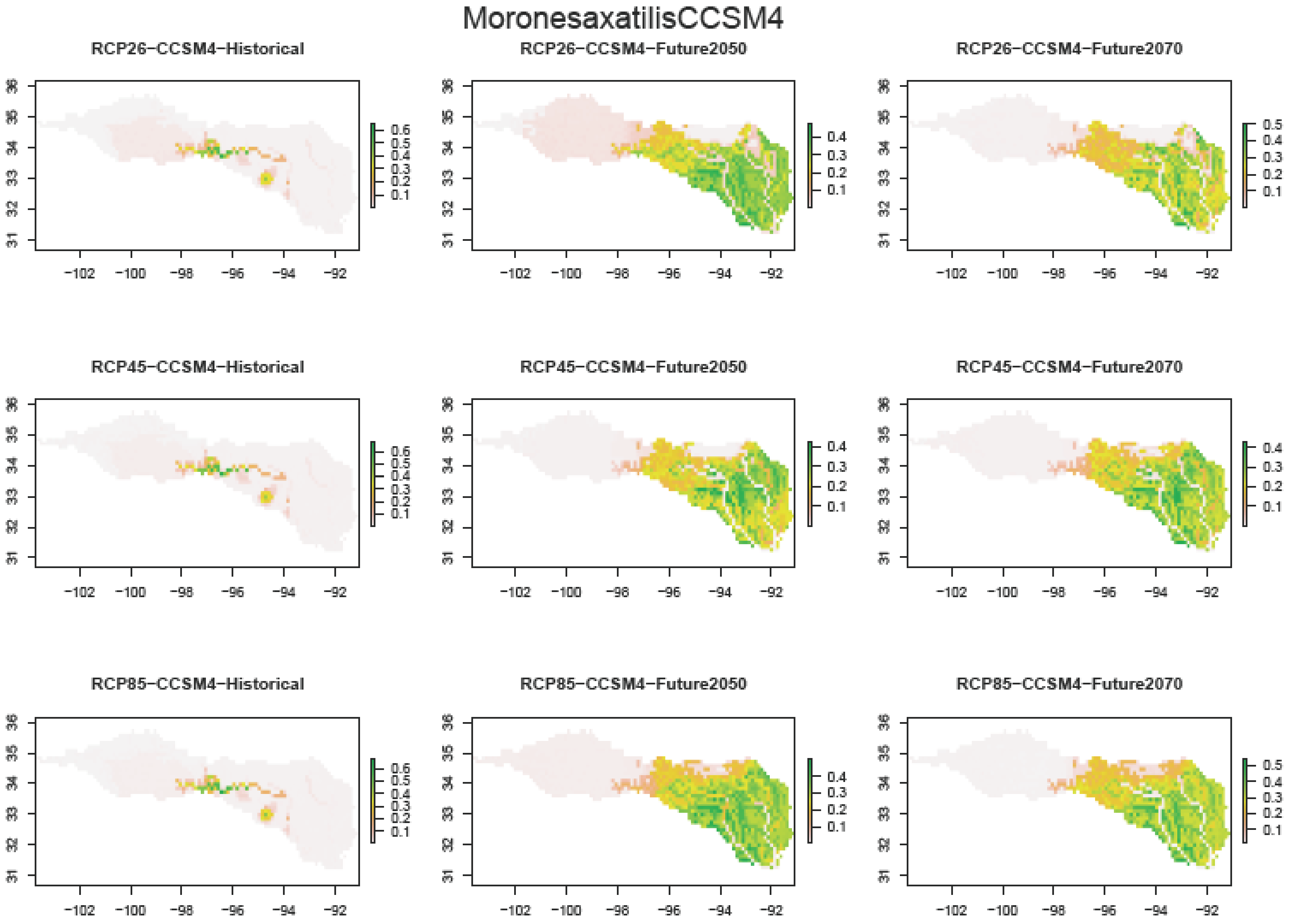
RCP45−MPI_ESM_LR−Future2070

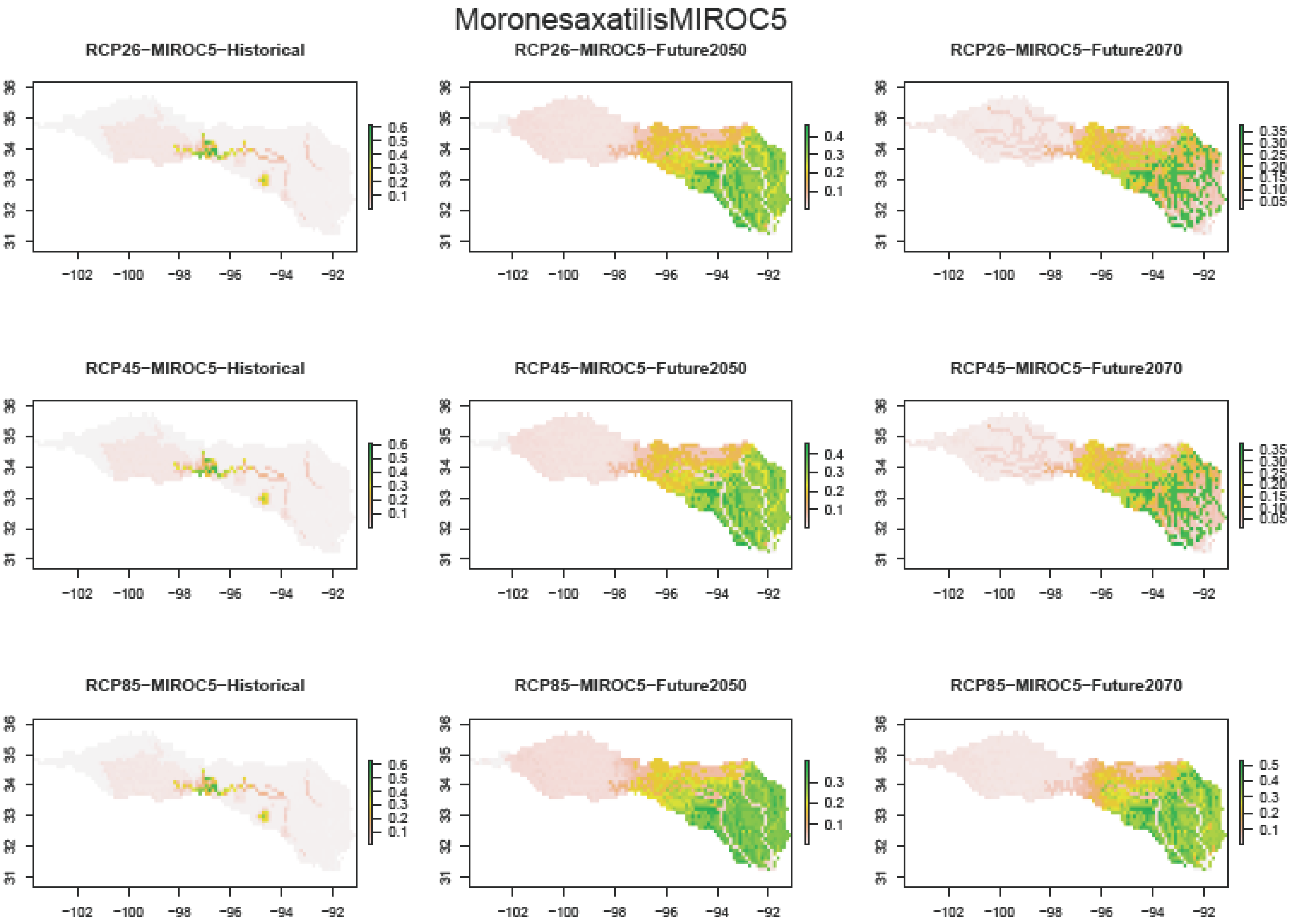
RCP85−MPI_ESM_LR−Historical

RCP85−MPI_ESM_LR−Future2050

RCP85−MPI_ESM_LR−Future2070

BRT: *Morone saxatilis*




MoronesaxatilisMIROC5

RCP26−MIROC5−Historical

RCP26−MIROC5−Future2050

RCP26−MIROC5−Future2070

RCP45−MIROC5−Historical

RCP45−MIROC5−Future2050

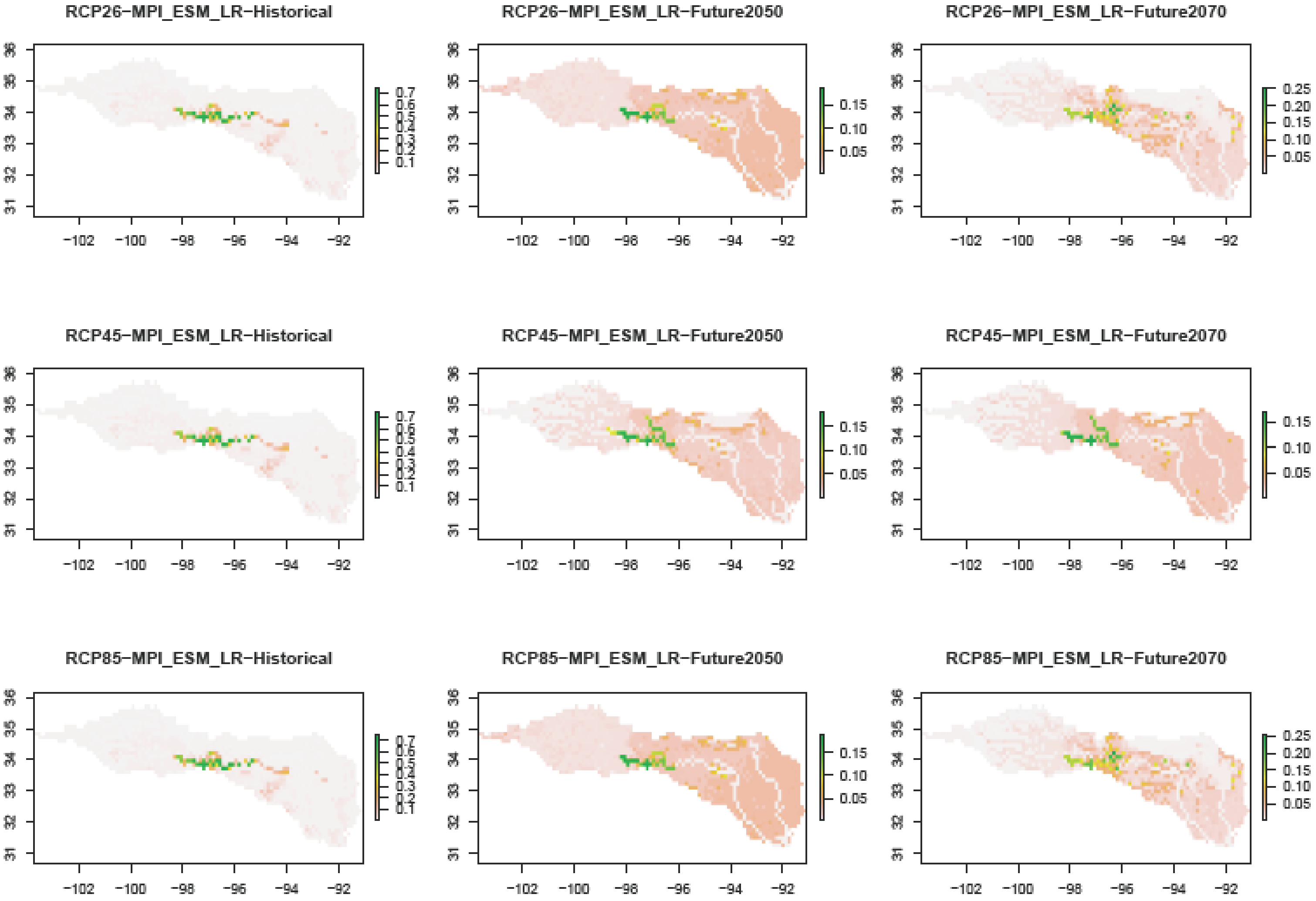
RCP45−MIROC5−Future2070

RCP85−MIROC5−Historical

RCP85−MIROC5−Future2050

RCP85−MIROC5−Future2070

MoronesaxatilisMPI_ESM_LR


RCP26−MPI_ESM_LR−Historical

RCP26−MPI_ESM_LR−Future2050

RCP26−MPI_ESM_LR−Future2070

RCP45−MPI_ESM_LR−Historical

RCP45−MPI_ESM_LR−Future2050

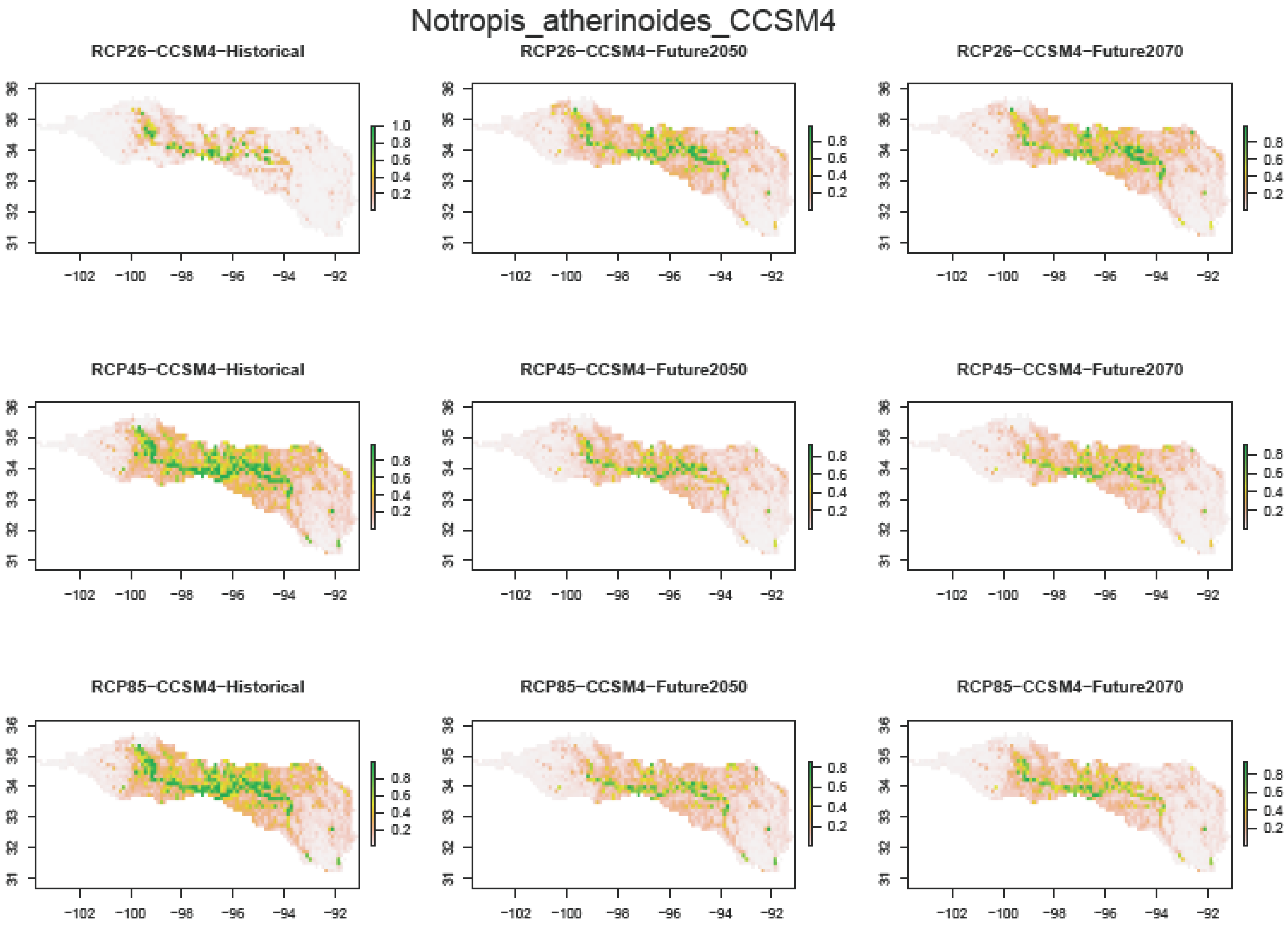
RCP45−MPI_ESM_LR−Future2070

RCP85−MPI_ESM_LR−Historical

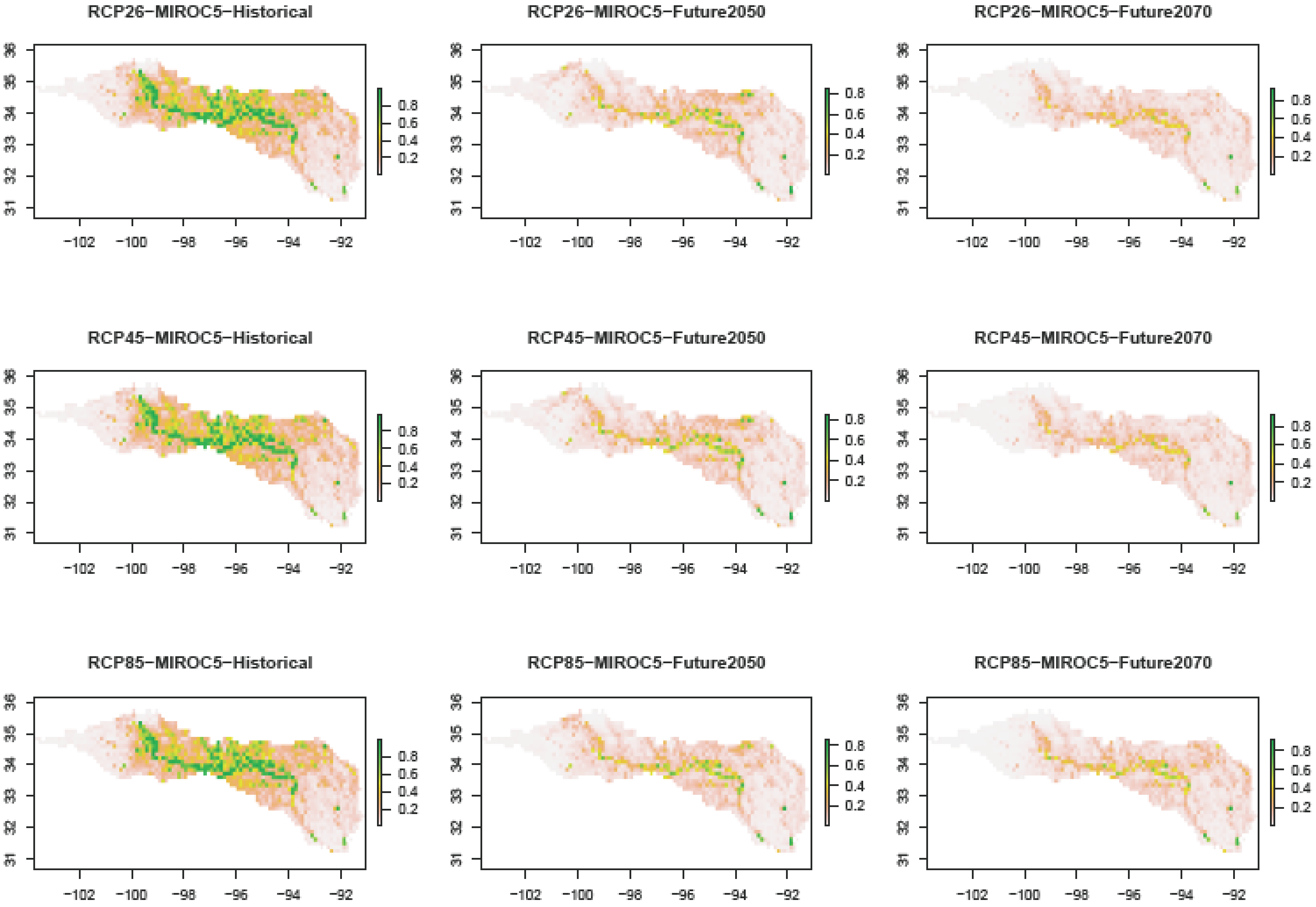
RCP85−MPI_ESM_LR−Future2050

RCP85−MPI_ESM_LR−Future2070

Maxent: *Notropis atherinoides*



Notropis_atherinoides_MIROC5



RCP26−MIROC5−Historical

RCP26−MIROC5−Future2050

RCP26−MIROC5−Future2070

RCP45−MIROC5−Historical

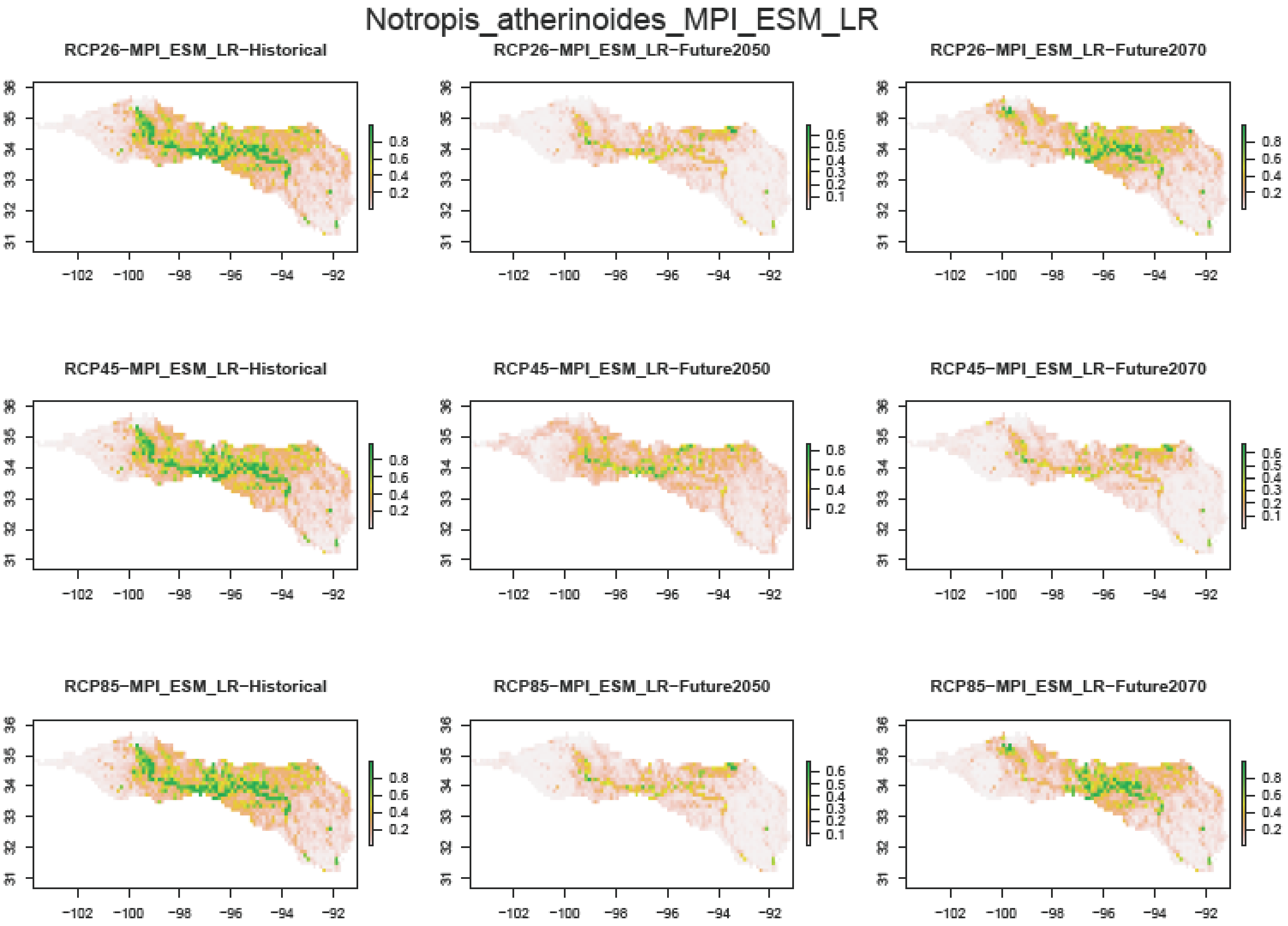
RCP45−MIROC5−Future2050

RCP45−MIROC5−Future2070

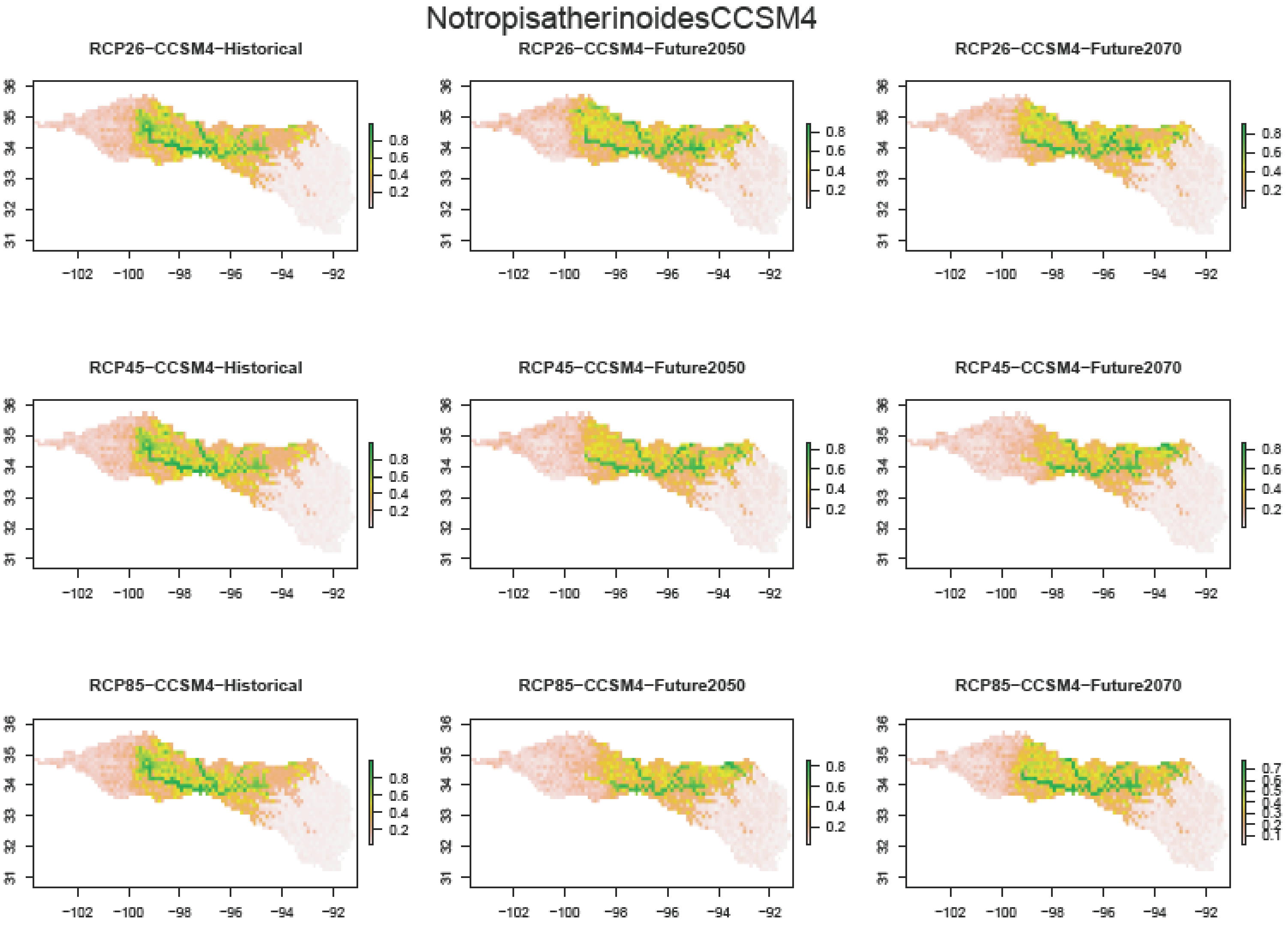
RCP85−MIROC5−Historical

RCP85−MIROC5−Future2050

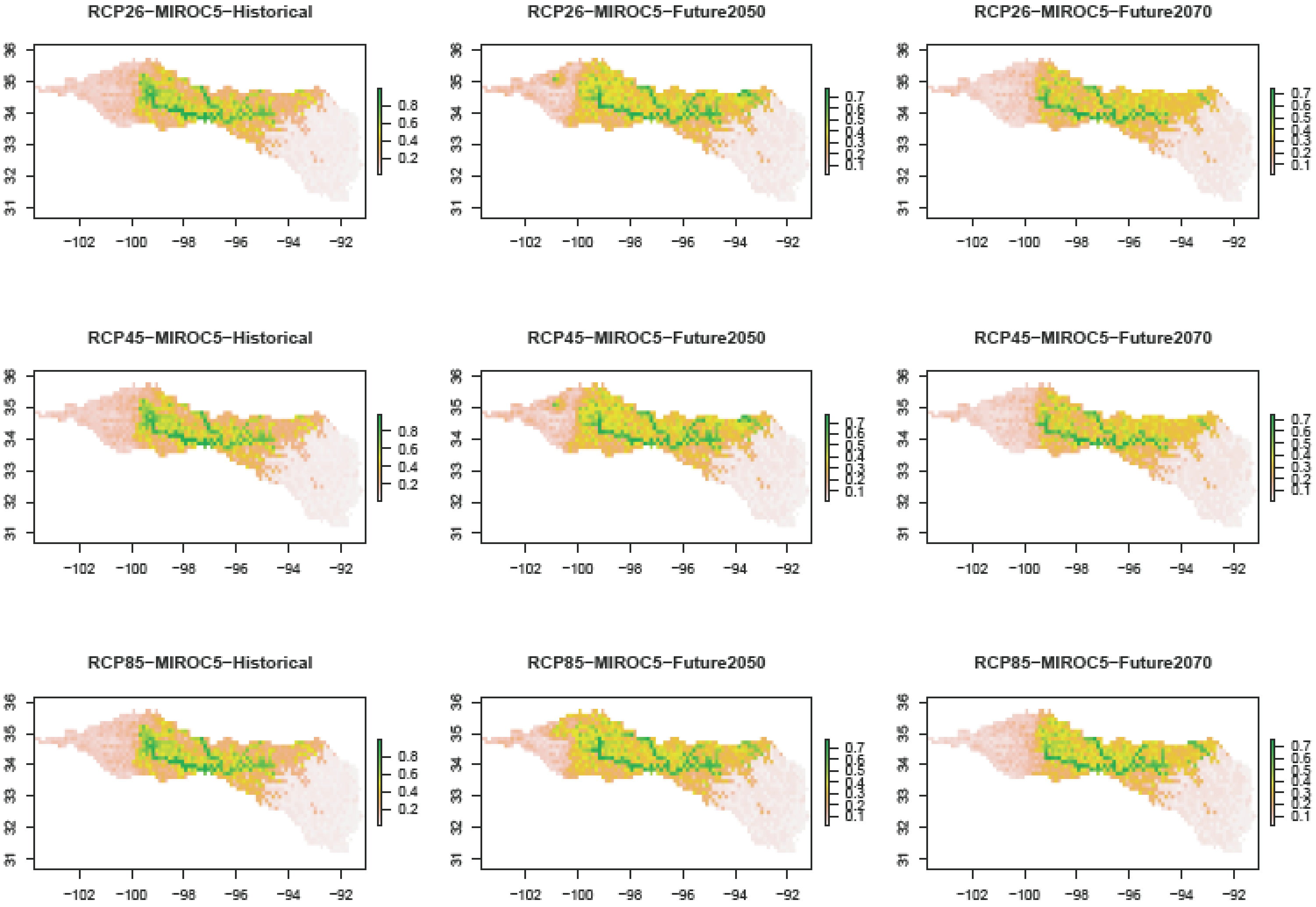
RCP85−MIROC5−Future2070


Notropis_atherinoides_MPI_ESM_LR
RCP26-MPI_ESM_LR-Historical
RCP26-MPI_ESM_LR-Future2050
RCP26-MPI_ESM_LR-Future2070
RCP45-MPI_ESM_LR-Historical
RCP45-MPI_ESM_LR-Future2050
RCP45-MPI_ESM_LR-Future2070
RCP85-MPI_ESM_LR-Historical
RCP85-MPI_ESM_LR-Future2050
RCP85-MPI_ESM_LR-Future2070
31
32
33
34
35
36
-102
-100
-98
-96
-94
-92
0.1
0.2
0.3
0.4
0.5
0.6
0.8

BRT: *Notropis atherinoides*



NotropisatherinoidesMIROC5



RCP26−MIROC5−Historical

RCP26−MIROC5−Future2050

RCP26−MIROC5−Future2070

RCP45−MIROC5−Historical

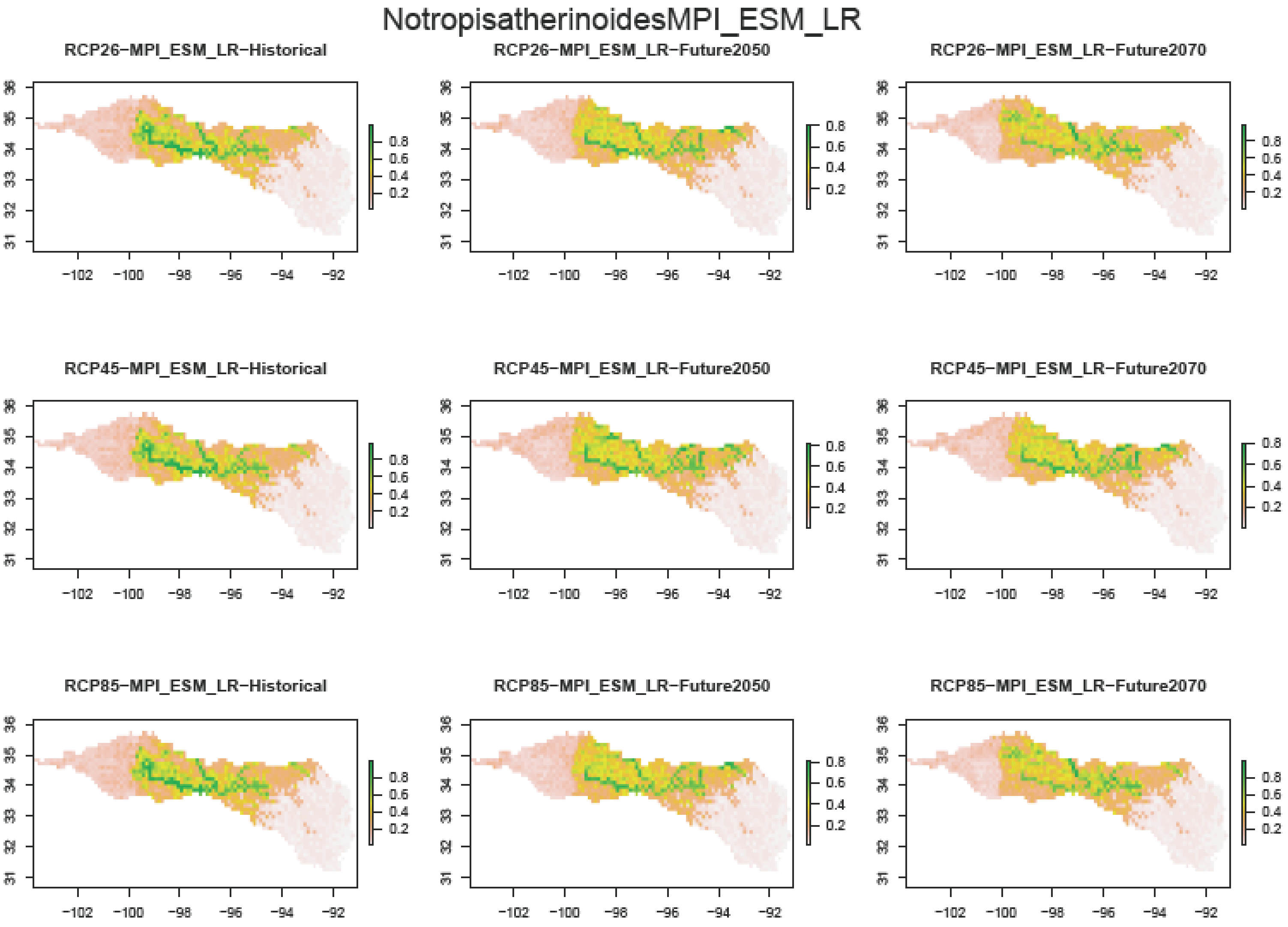
RCP45−MIROC5−Future2050

RCP45−MIROC5−Future2070

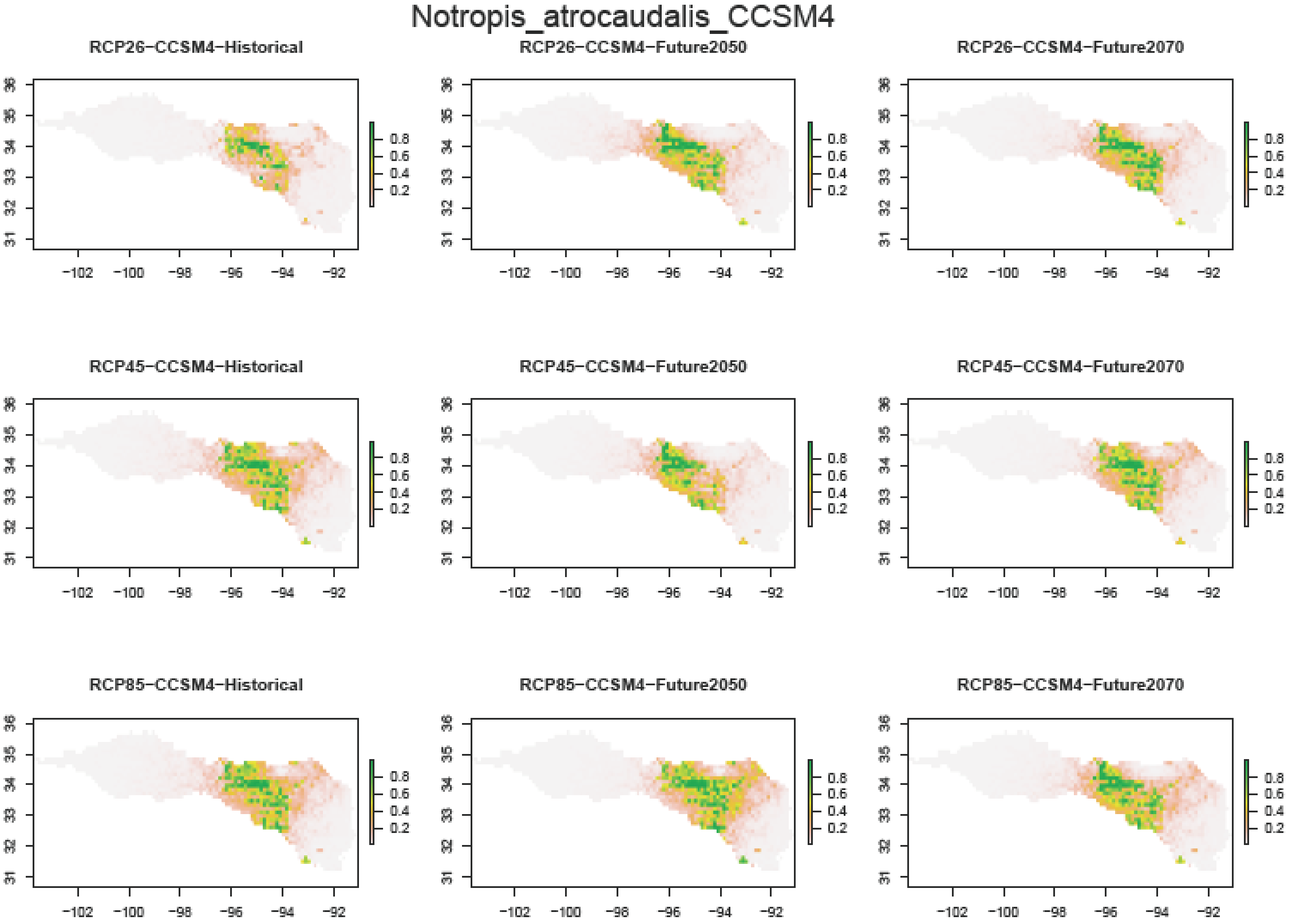
RCP85−MIROC5−Historical

RCP85−MIROC5−Future2050

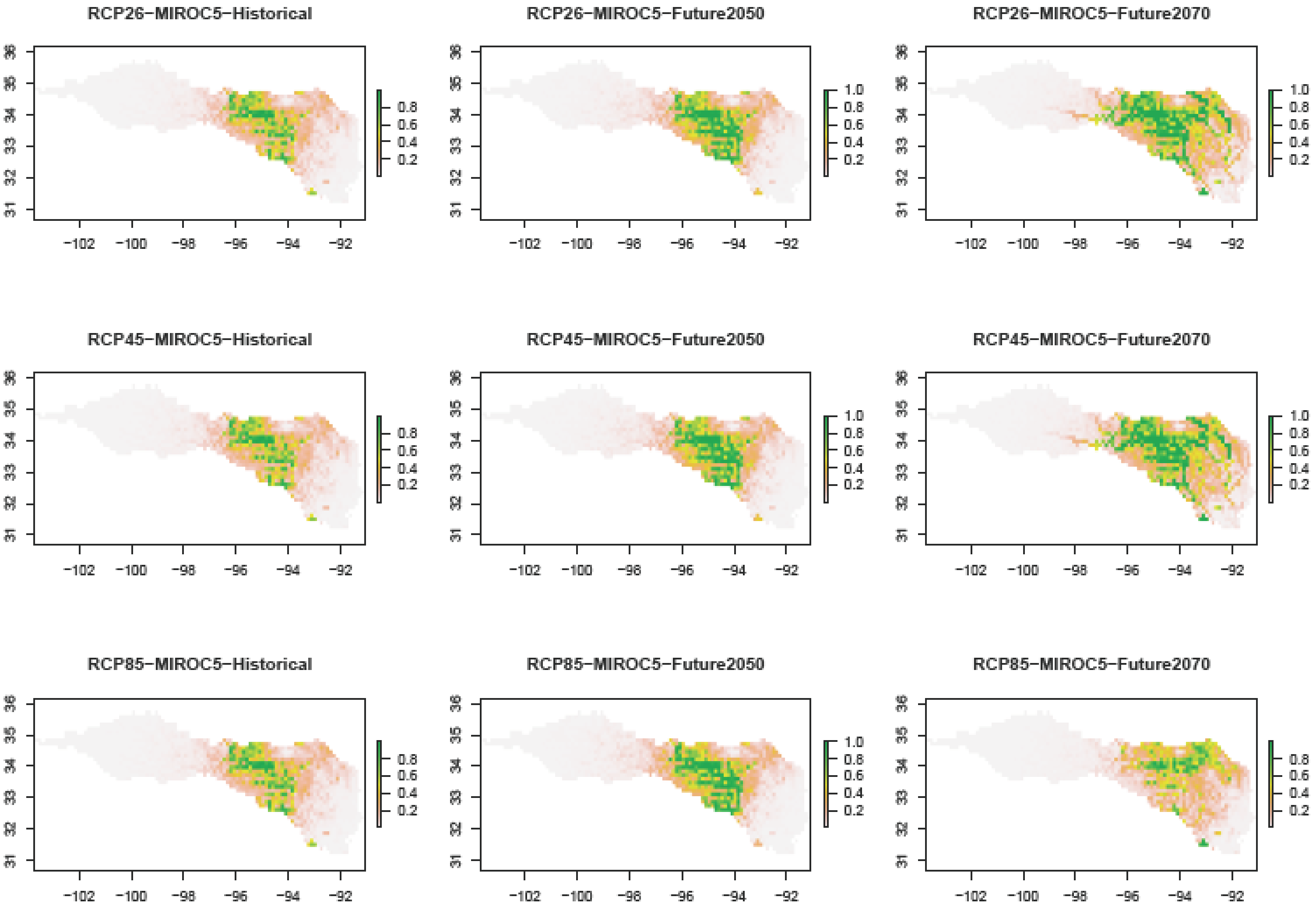
RCP85−MIROC5−Future2070


NotropisatherinoidesMPI_ESM_LR
RCP26−MPI_ESM_LR−Historical
RCP26−MPI_ESM_LR−Future2050
RCP26−MPI_ESM_LR−Future2070
RCP45−MPI_ESM_LR−Historical
RCP45−MPI_ESM_LR−Future2050
RCP45−MPI_ESM_LR−Future2070
RCP85−MPI_ESM_LR−Historical
RCP85−MPI_ESM_LR−Future2050
RCP85−MPI_ESM_LR−Future2070
31
32
33
34
35
36
−102
−100
−98
−96
−94
−92
0.2
0.4
0.6
0.8

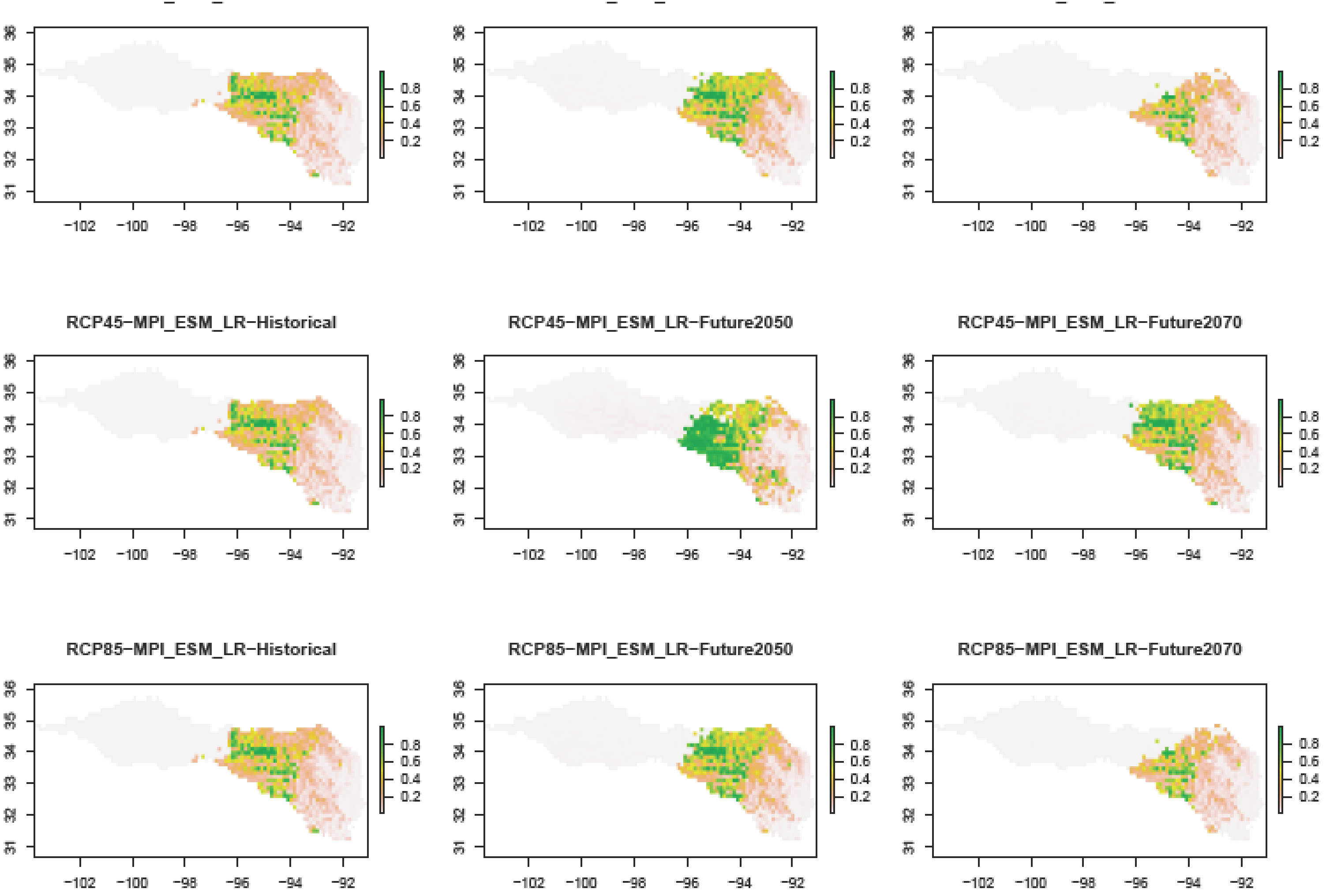
Maxent: *Notropis atrocaudalis*



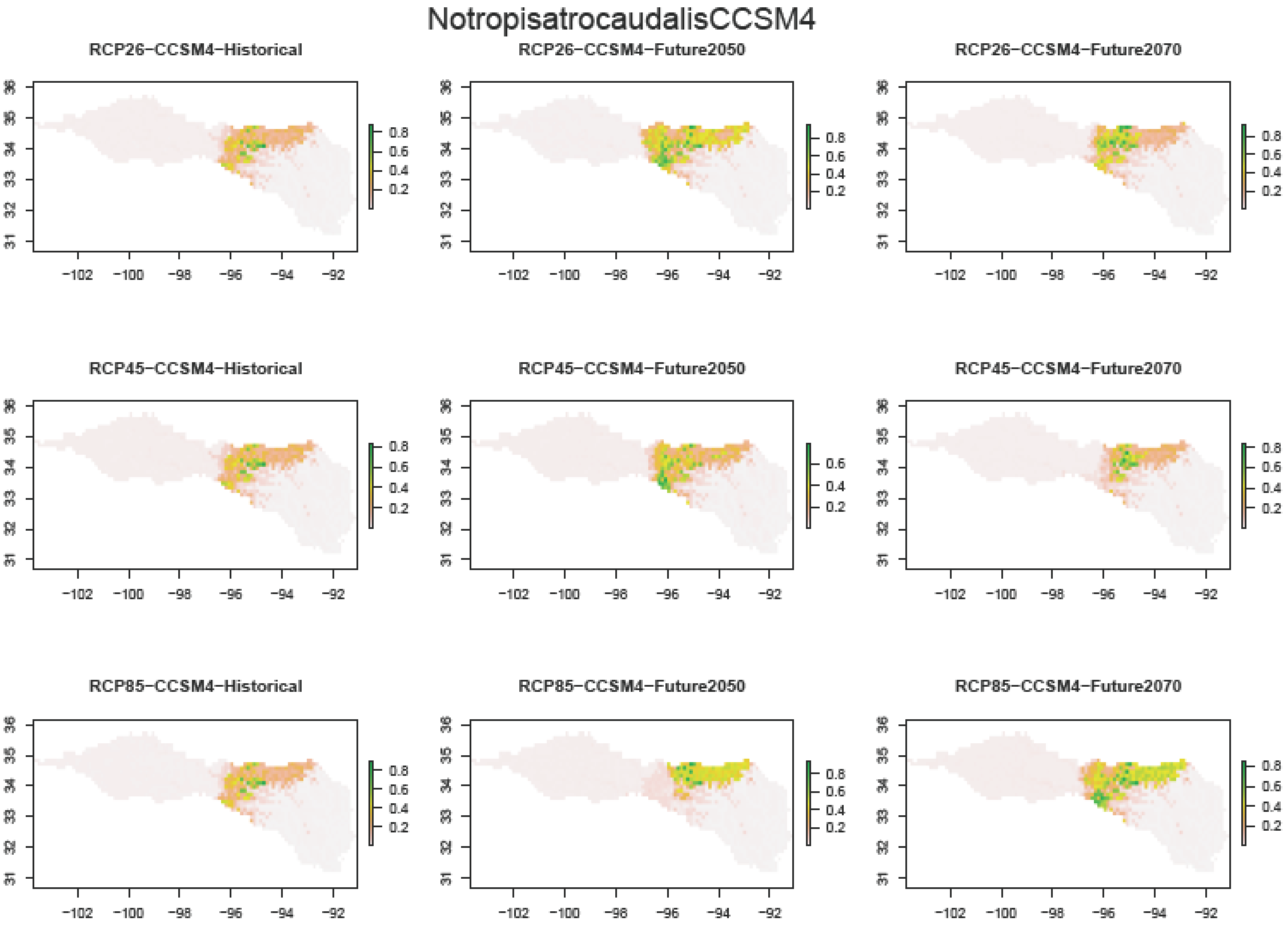
Notropis_atrocaudalis_MIROC5

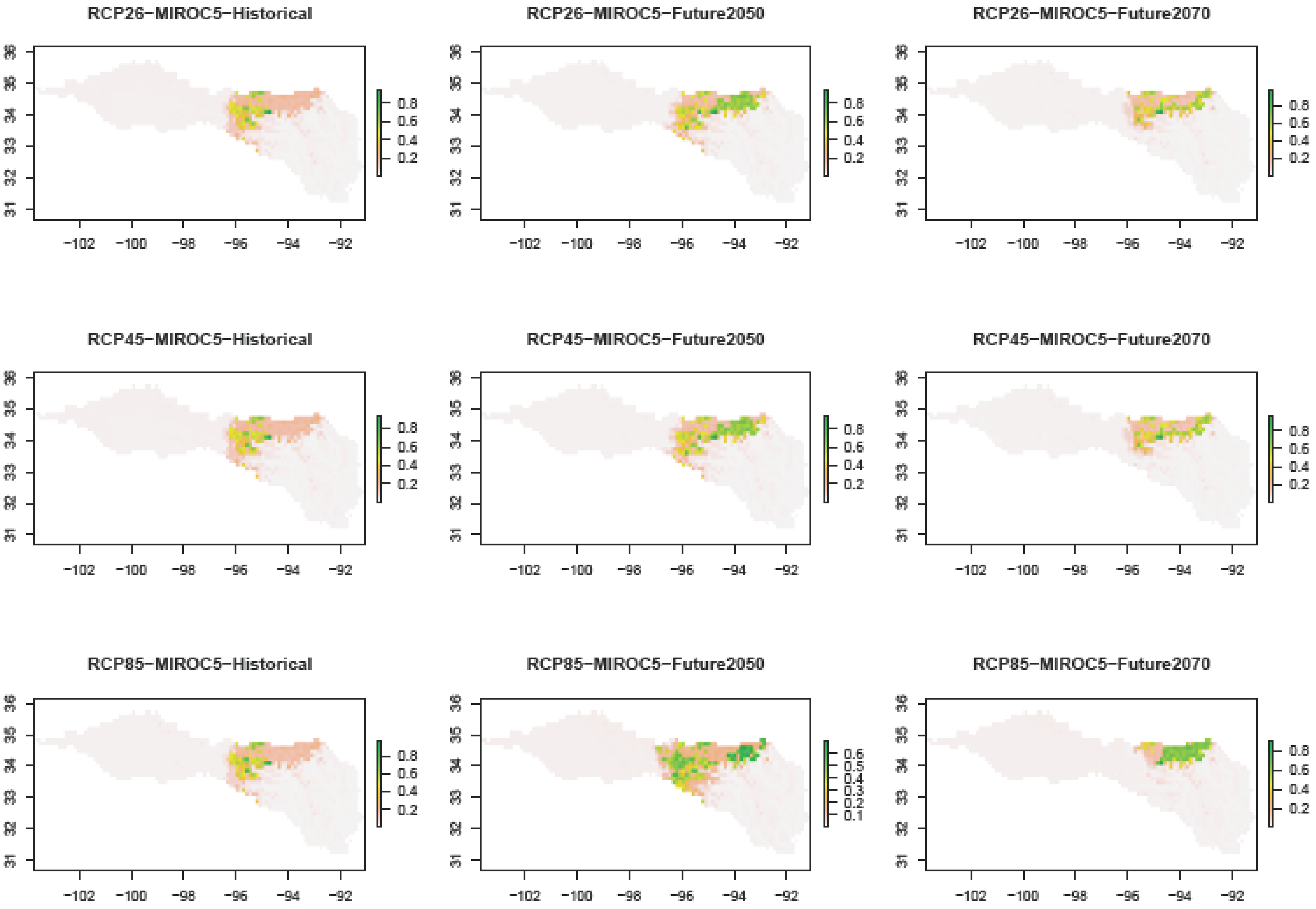


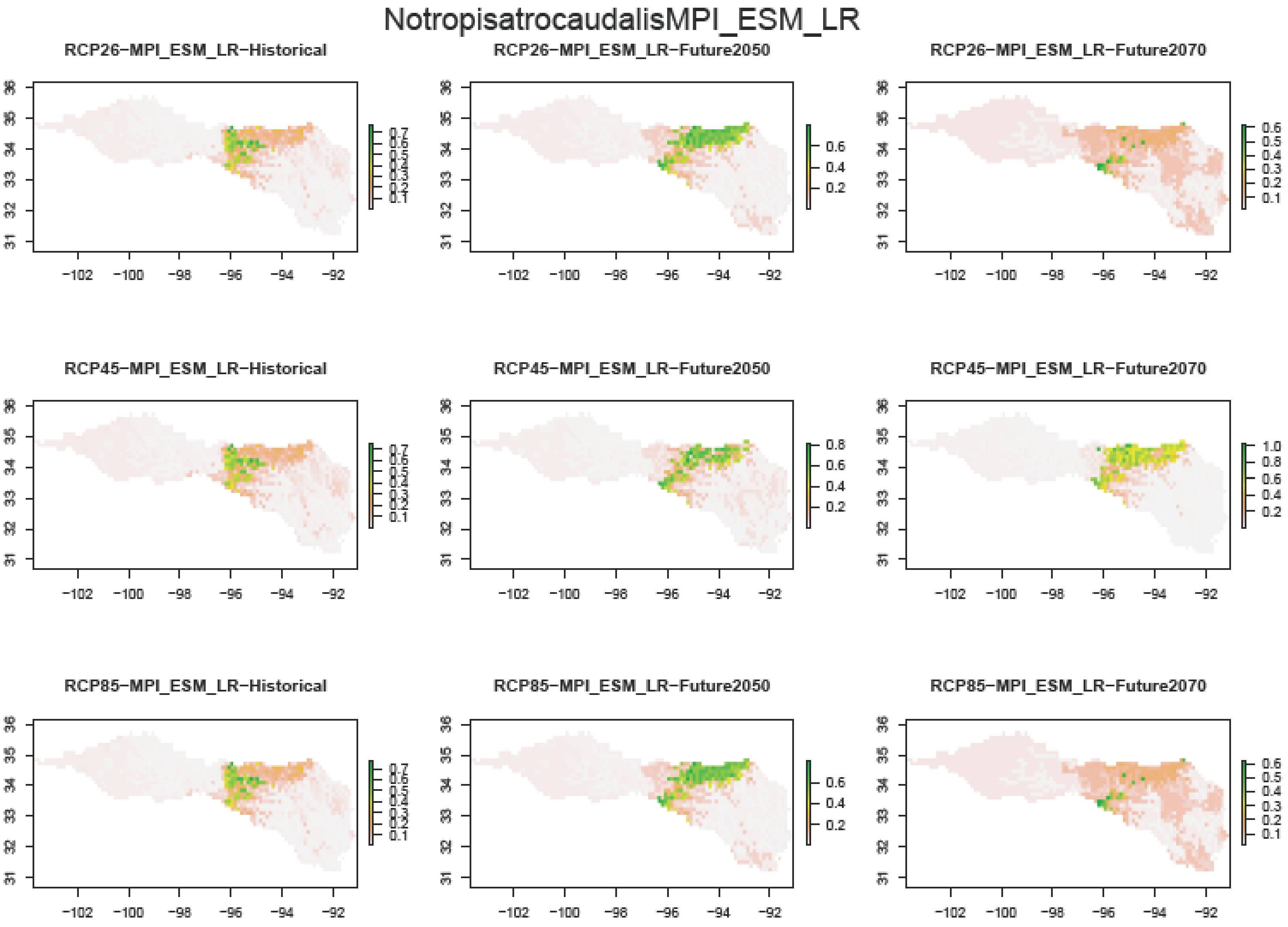
Notropis_atrocaudalis_MPI_ESM_LR



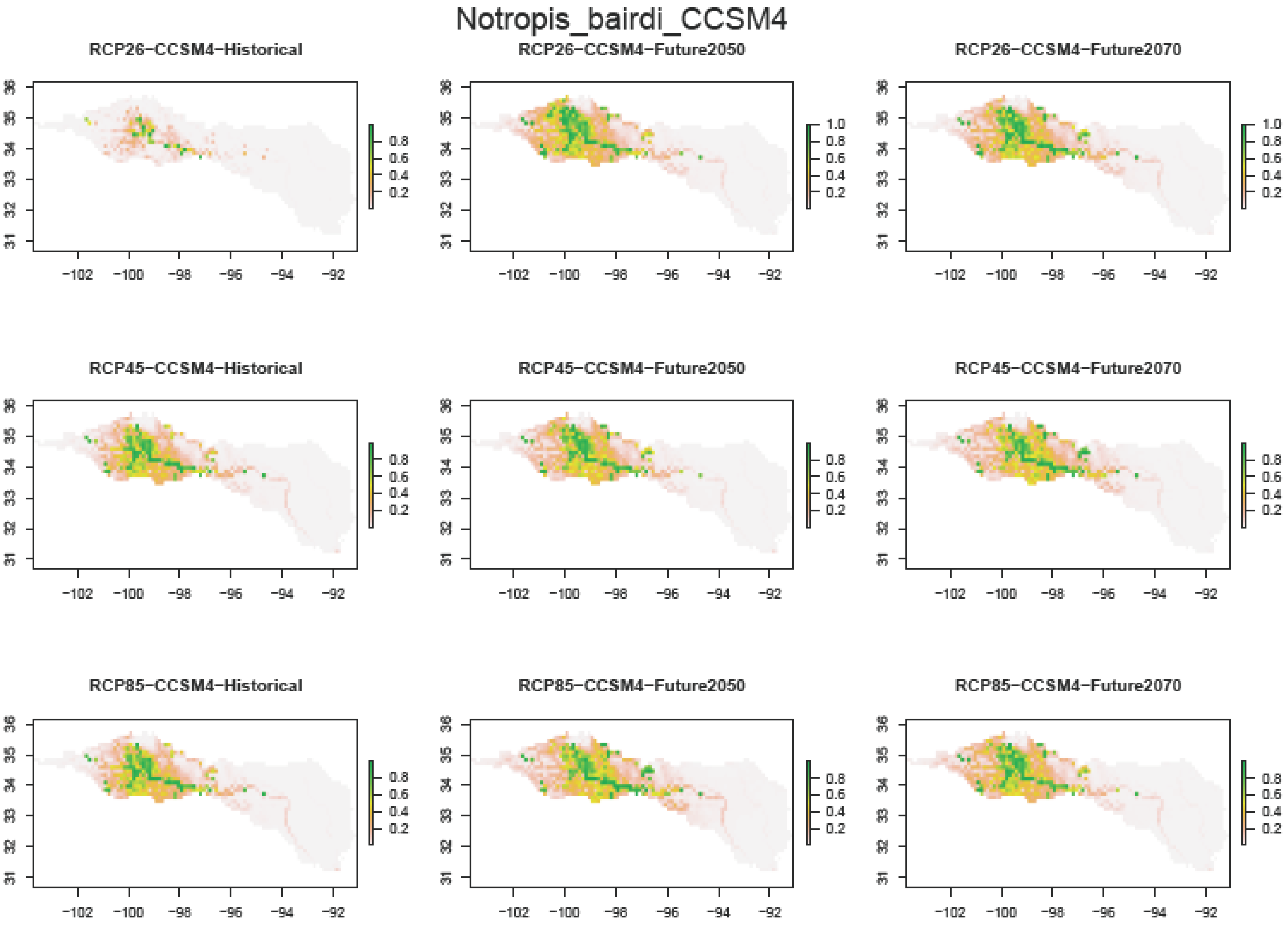
BRT: *Notropis atrocaudalis*



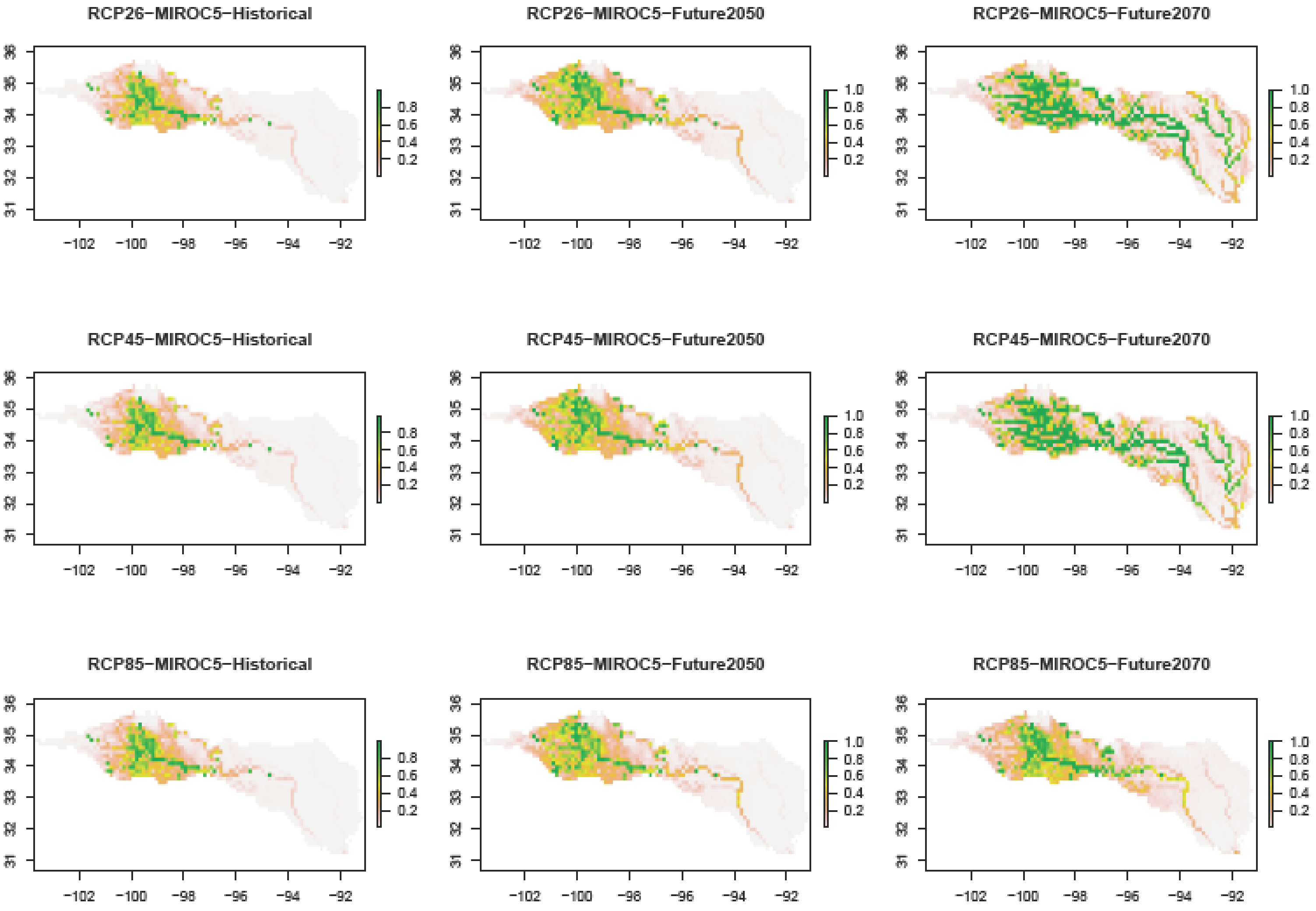

NotropisatrocaudalisMIROC5


NotropisatrocaudalisMPI_ESM_LR
RCP26−MPI_ESM_LR−Historical
RCP26−MPI_ESM_LR−Future2050
RCP26−MPI_ESM_LR−Future2070
RCP45−MPI_ESM_LR−Historical
RCP45−MPI_ESM_LR−Future2050
RCP45−MPI_ESM_LR−Future2070
RCP85−MPI_ESM_LR−Historical
RCP85−MPI_ESM_LR−Future2050
RCP85−MPI_ESM_LR−Future2070
−102
−100
−98
−96
−94
−92
31
32
33
34
35
36
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
1.0

Maxent: *Notropis bairdi*



Notropis_bairdi_MIROC5



RCP26−MIROC5−Historical

RCP26−MIROC5−Future2050

RCP26−MIROC5−Future2070

RCP45−MIROC5−Historical

RCP45−MIROC5−Future2050

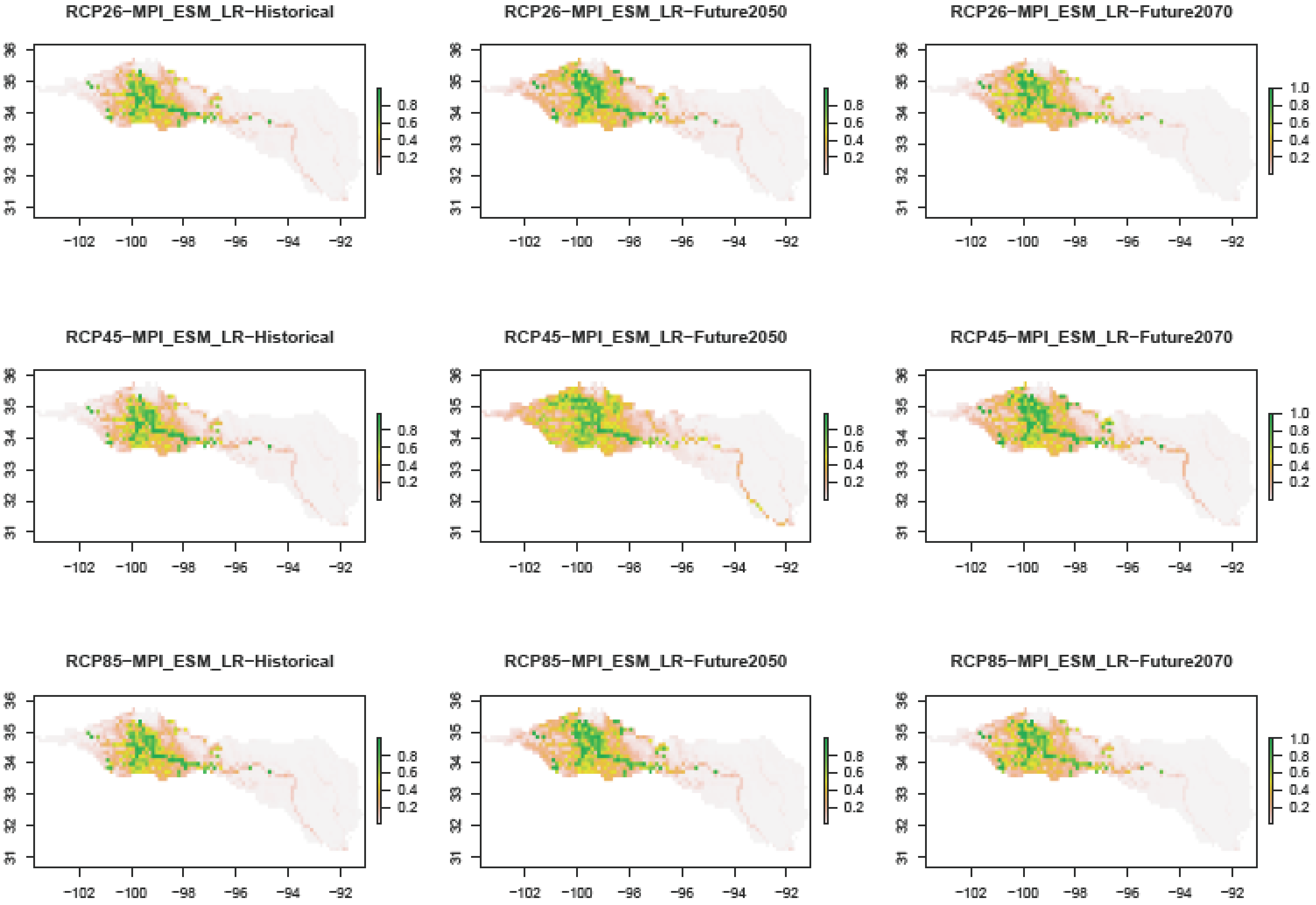
RCP45−MIROC5−Future2070

RCP85−MIROC5−Historical

RCP85−MIROC5−Future2050

RCP85−MIROC5−Future2070

Notropis_bairdi_MPI_ESM_LR



RCP26-MPI_ESM_LR-Historical

RCP26-MPI_ESM_LR-Future2050

RCP26-MPI_ESM_LR-Future2070

RCP45-MPI_ESM_LR-Historical

RCP45-MPI_ESM_LR-Future2050

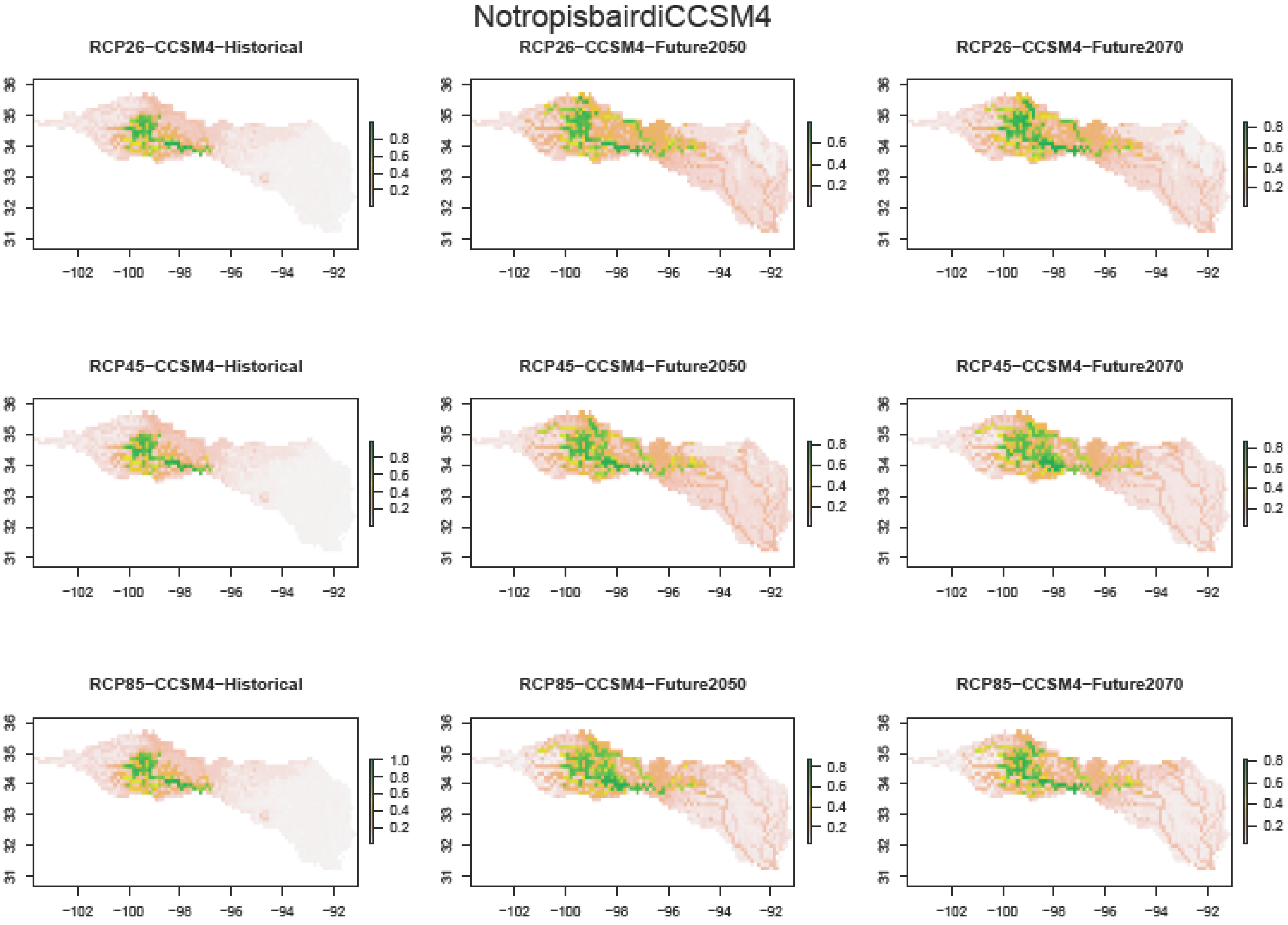
RCP45-MPI_ESM_LR-Future2070

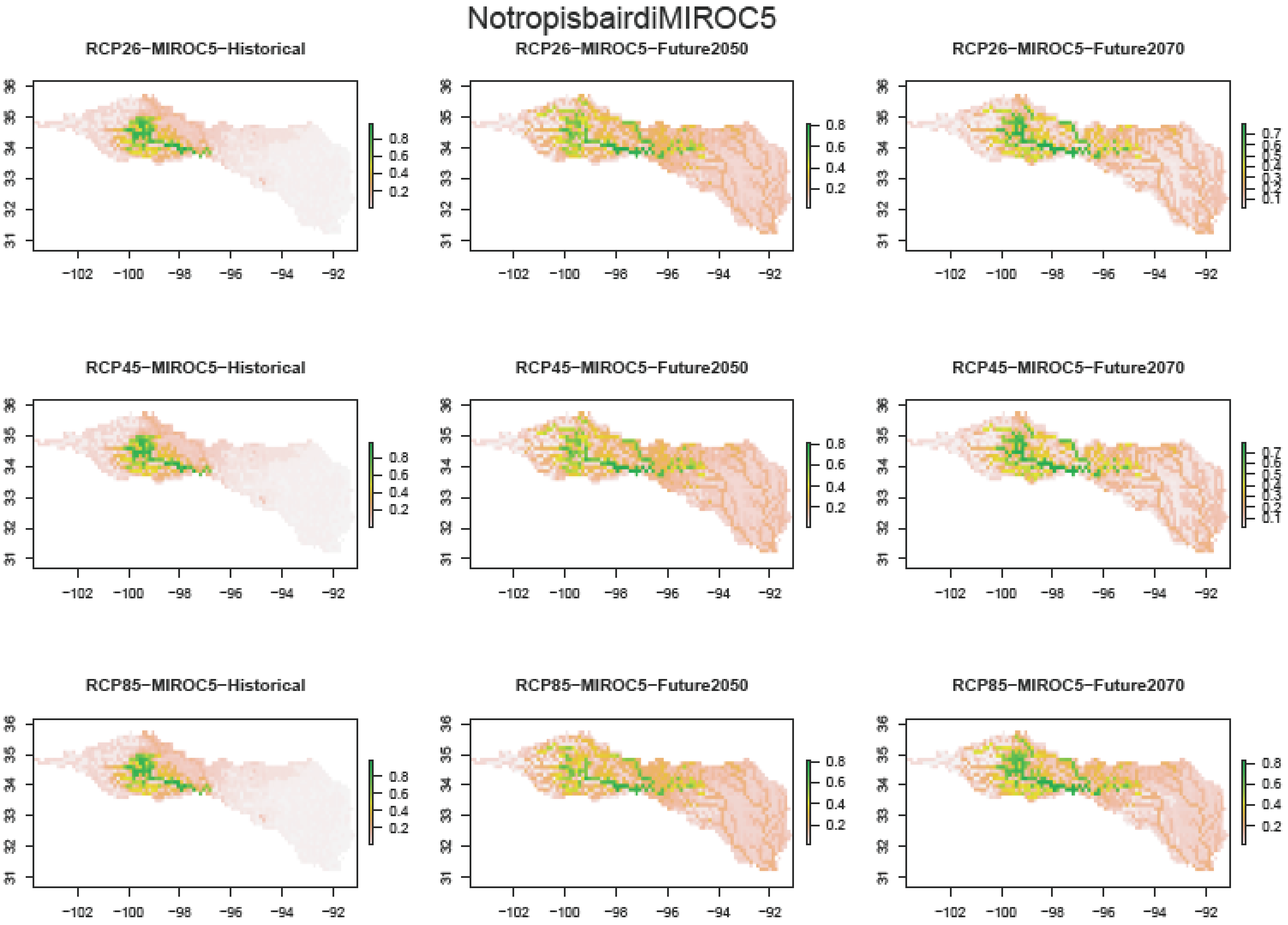
RCP85-MPI_ESM_LR-Historical

RCP85-MPI_ESM_LR-Future2050

RCP85-MPI_ESM_LR-Future2070

BRT: *Notropis bairdi*




NotropisbairdiMIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070
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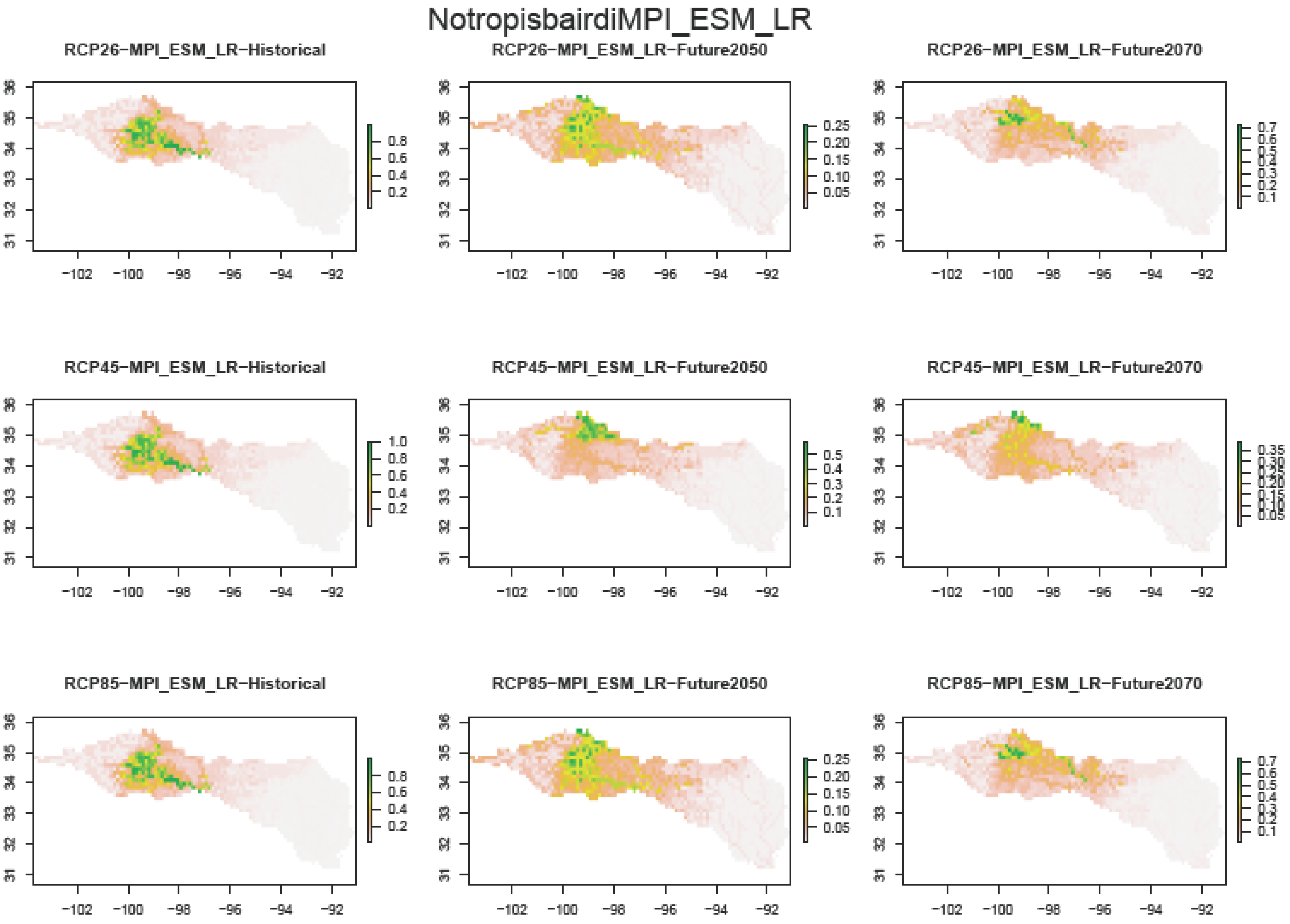
NotropisbairdiMPI_ESM_LR
RCP26-MPI_ESM_LR-Historical
RCP26-MPI_ESM_LR-Future2050
RCP26-MPI_ESM_LR-Future2070
RCP45-MPI_ESM_LR-Historical
RCP45-MPI_ESM_LR-Future2050
RCP45-MPI_ESM_LR-Future2070
RCP85-MPI_ESM_LR-Historical
RCP85-MPI_ESM_LR-Future2050
RCP85-MPI_ESM_LR-Future2070
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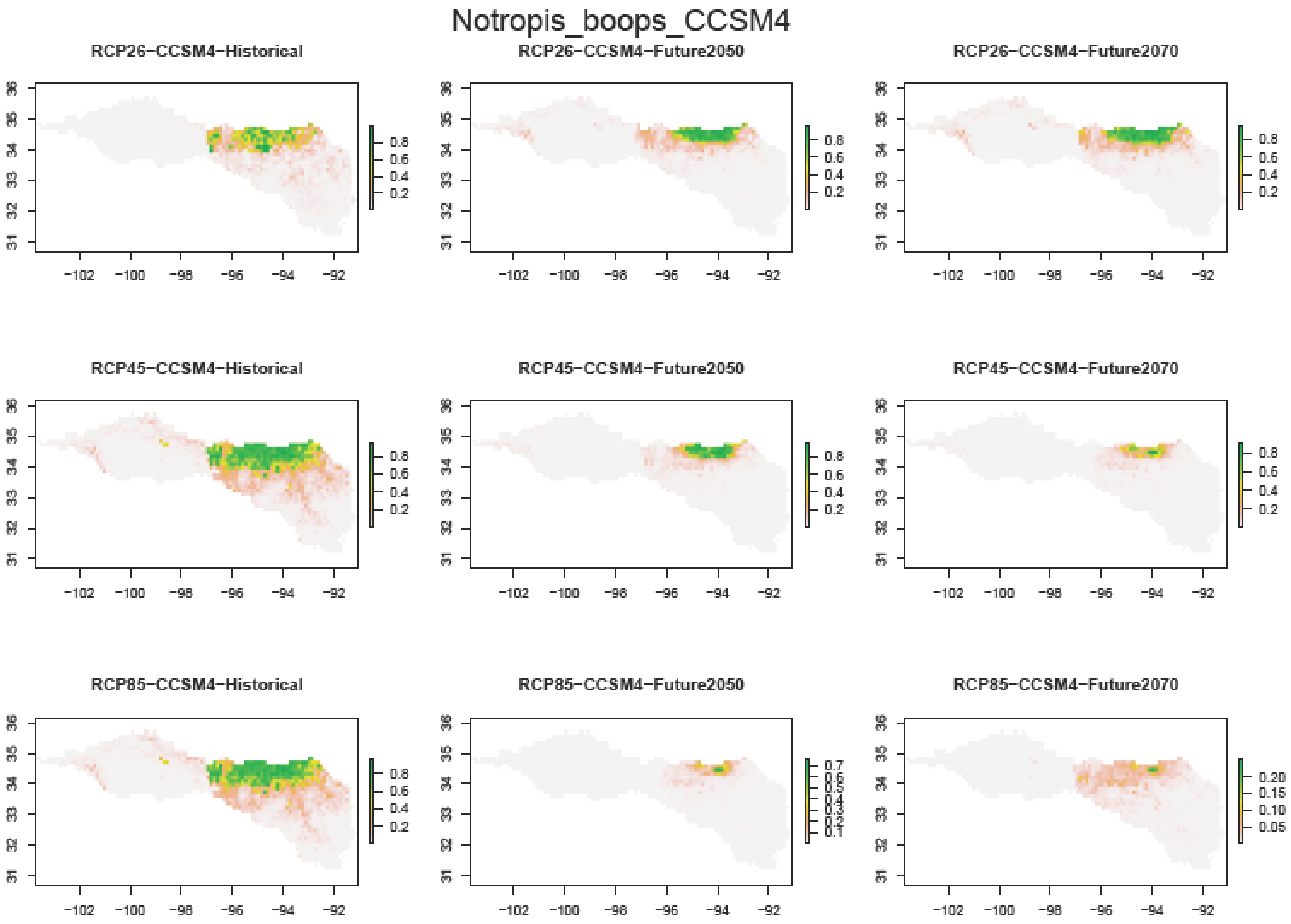
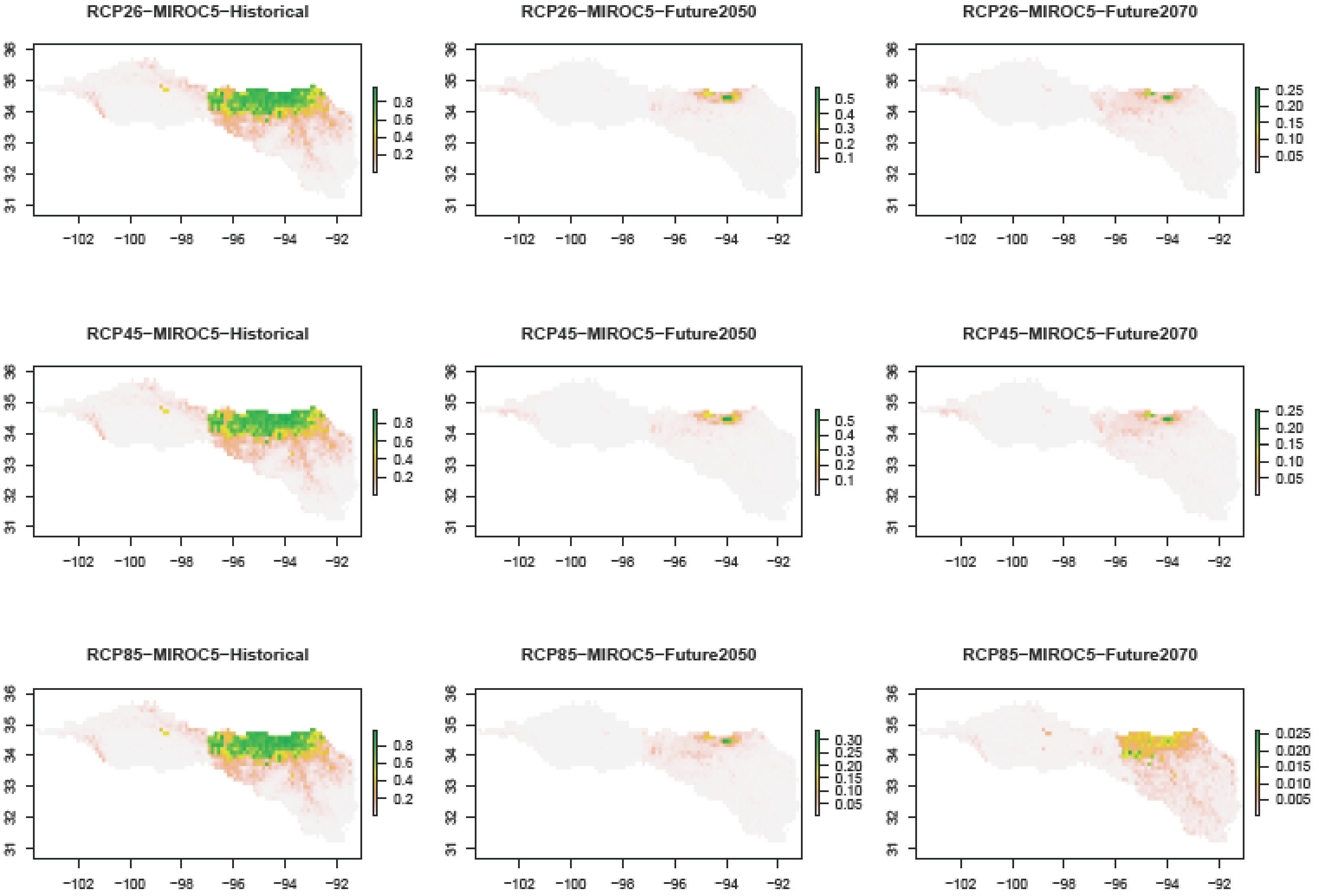
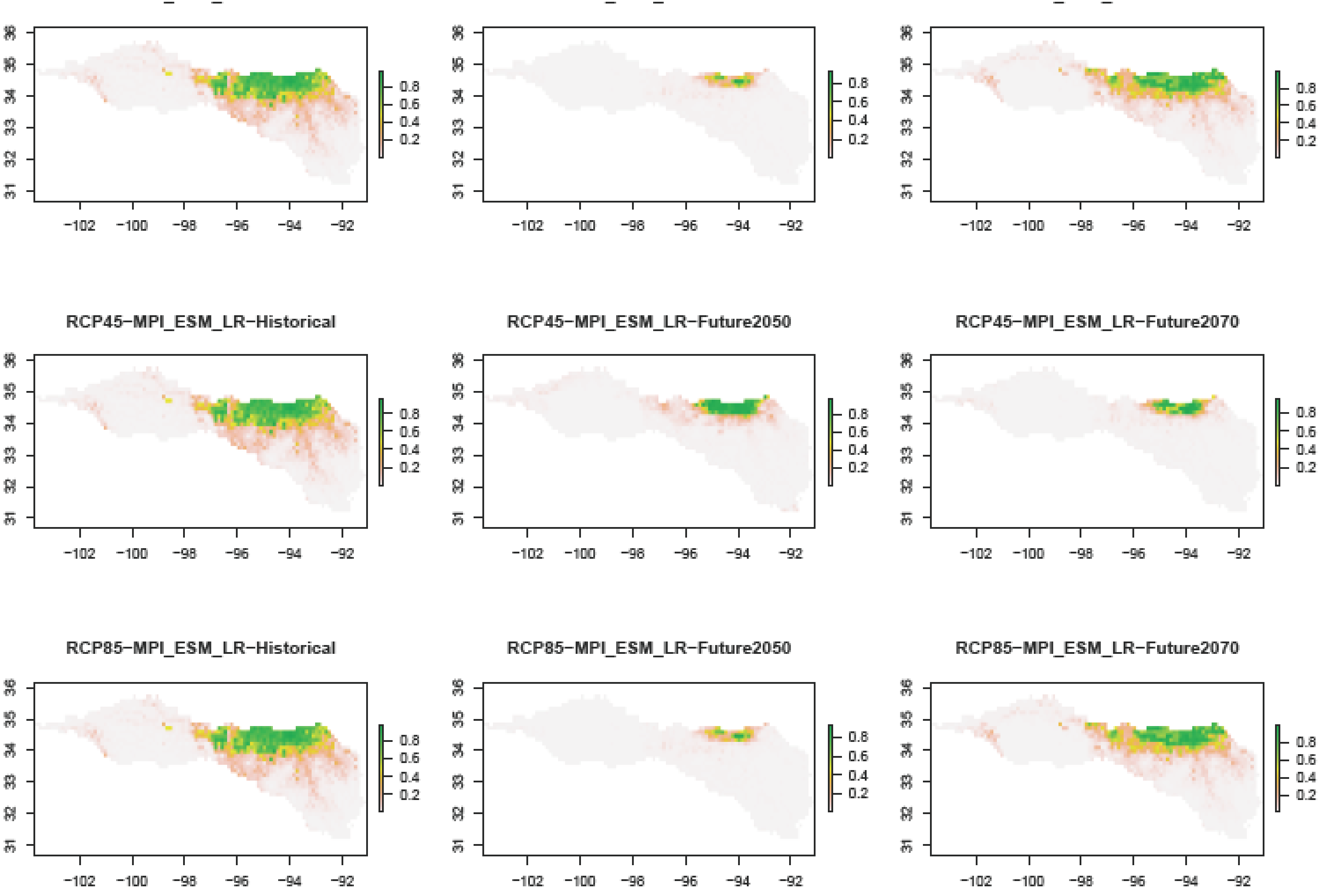
Maxent: *Notropis boops*



Notropis_boops_MIROC5



Notropis_boops_MPI_ESM_LR



RCP26−MPI_ESM_LR−Historical

RCP26−MPI_ESM_LR−Future2050

RCP26−MPI_ESM_LR−Future2070

RCP45−MPI_ESM_LR−Historical

RCP45−MPI_ESM_LR−Future2050

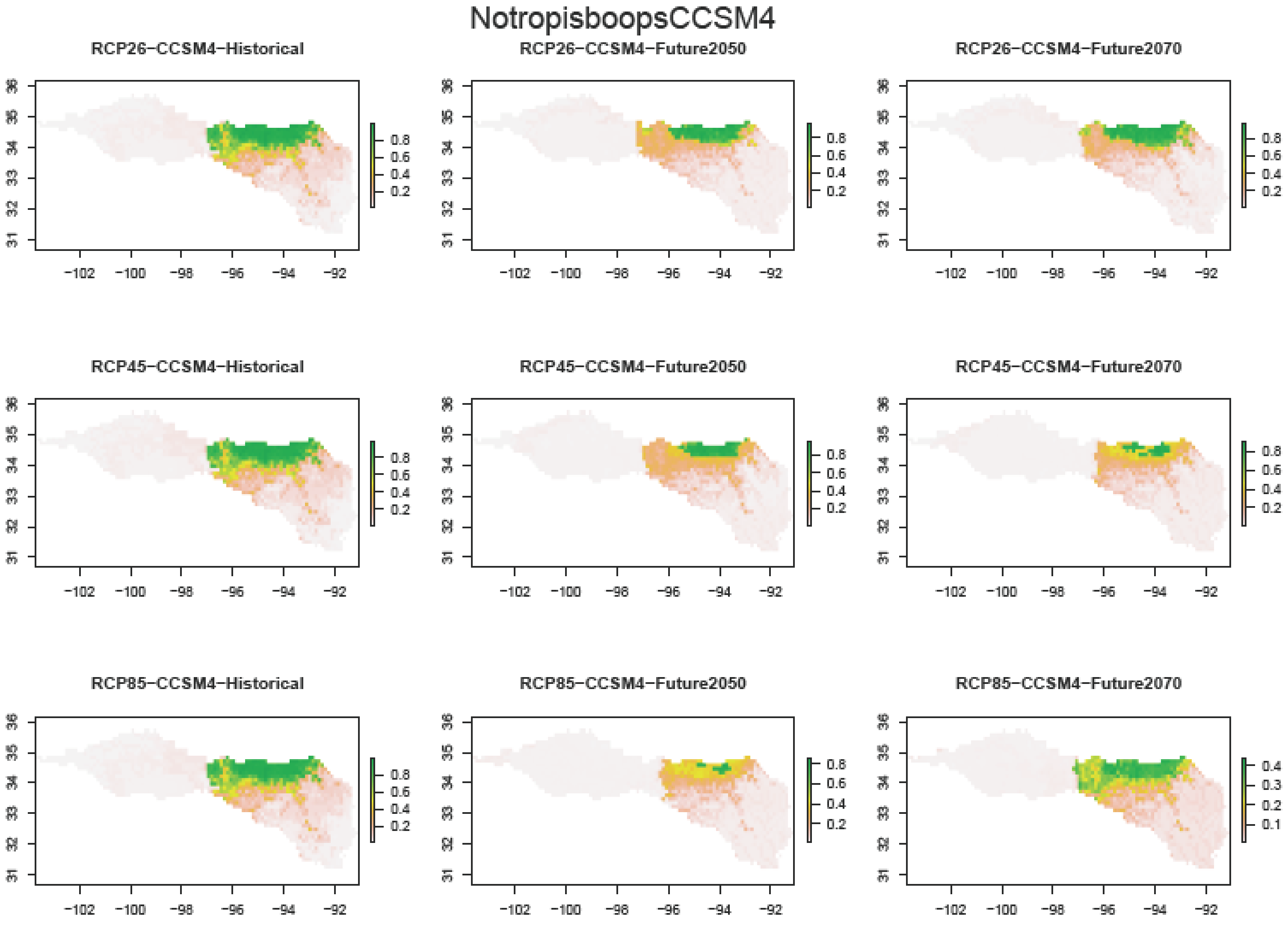
RCP45−MPI_ESM_LR−Future2070

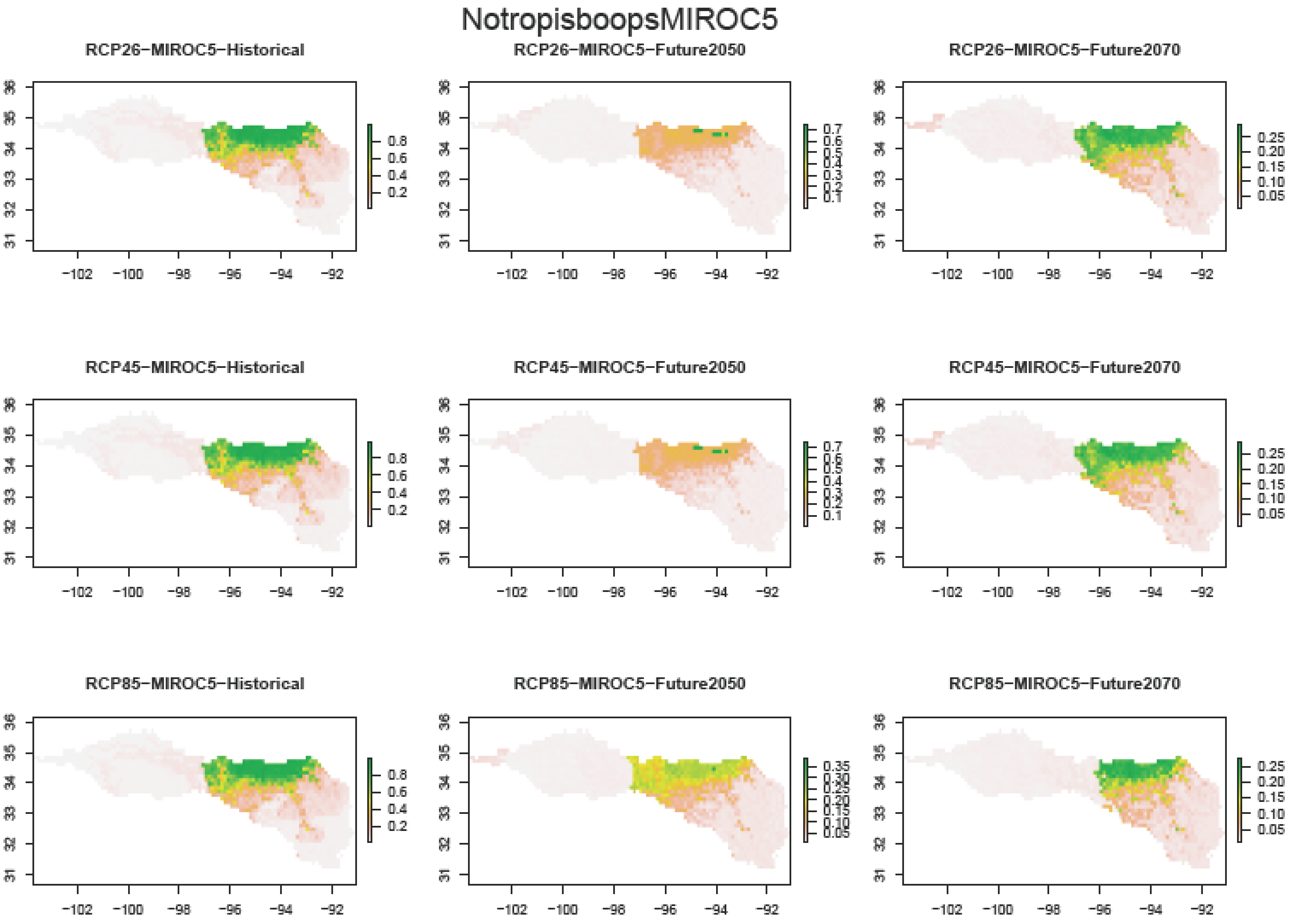
RCP85−MPI_ESM_LR−Historical

RCP85−MPI_ESM_LR−Future2050

RCP85−MPI_ESM_LR−Future2070

BRT: *Notropis boops*




NotropisboopsMIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070
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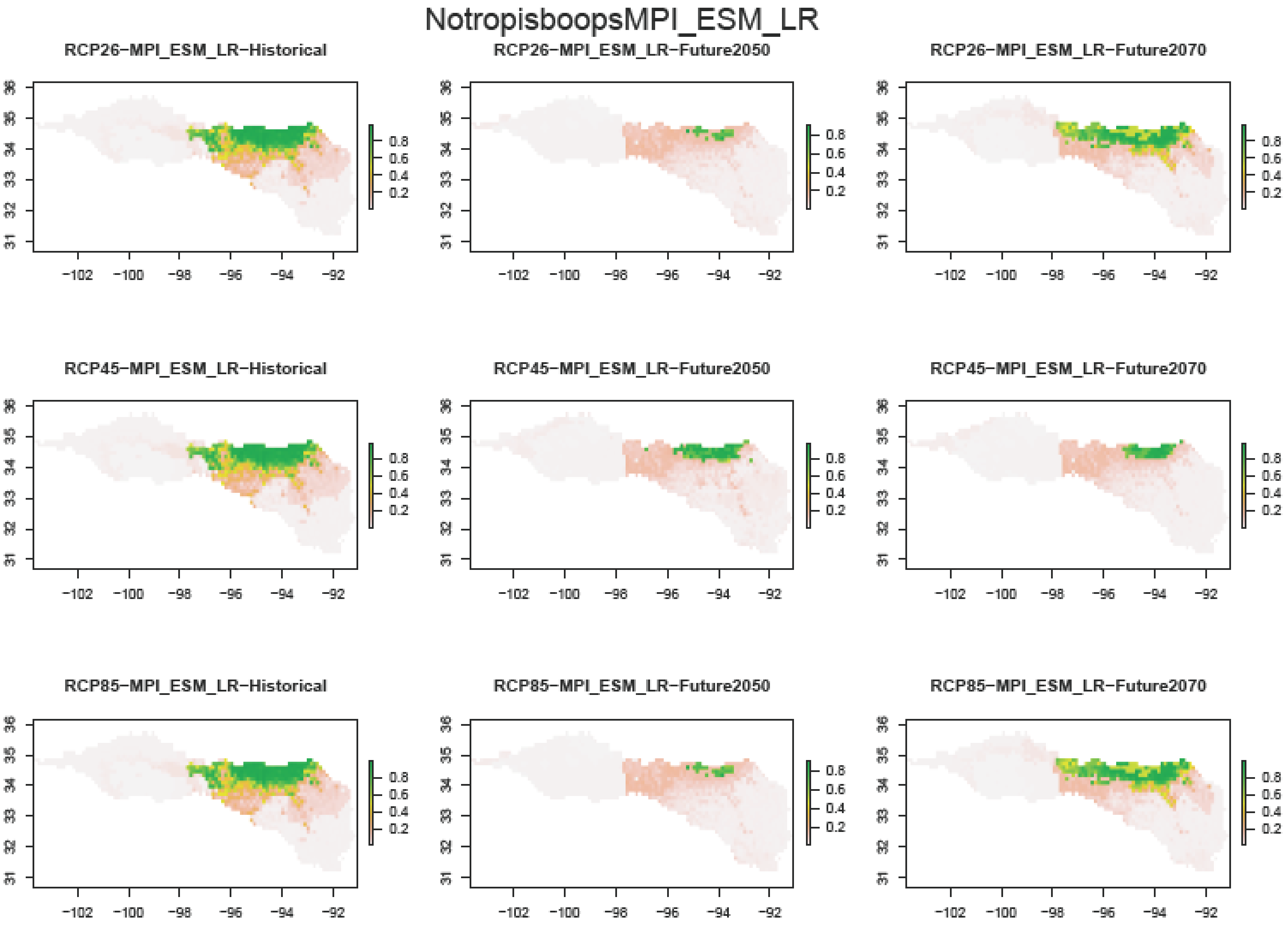
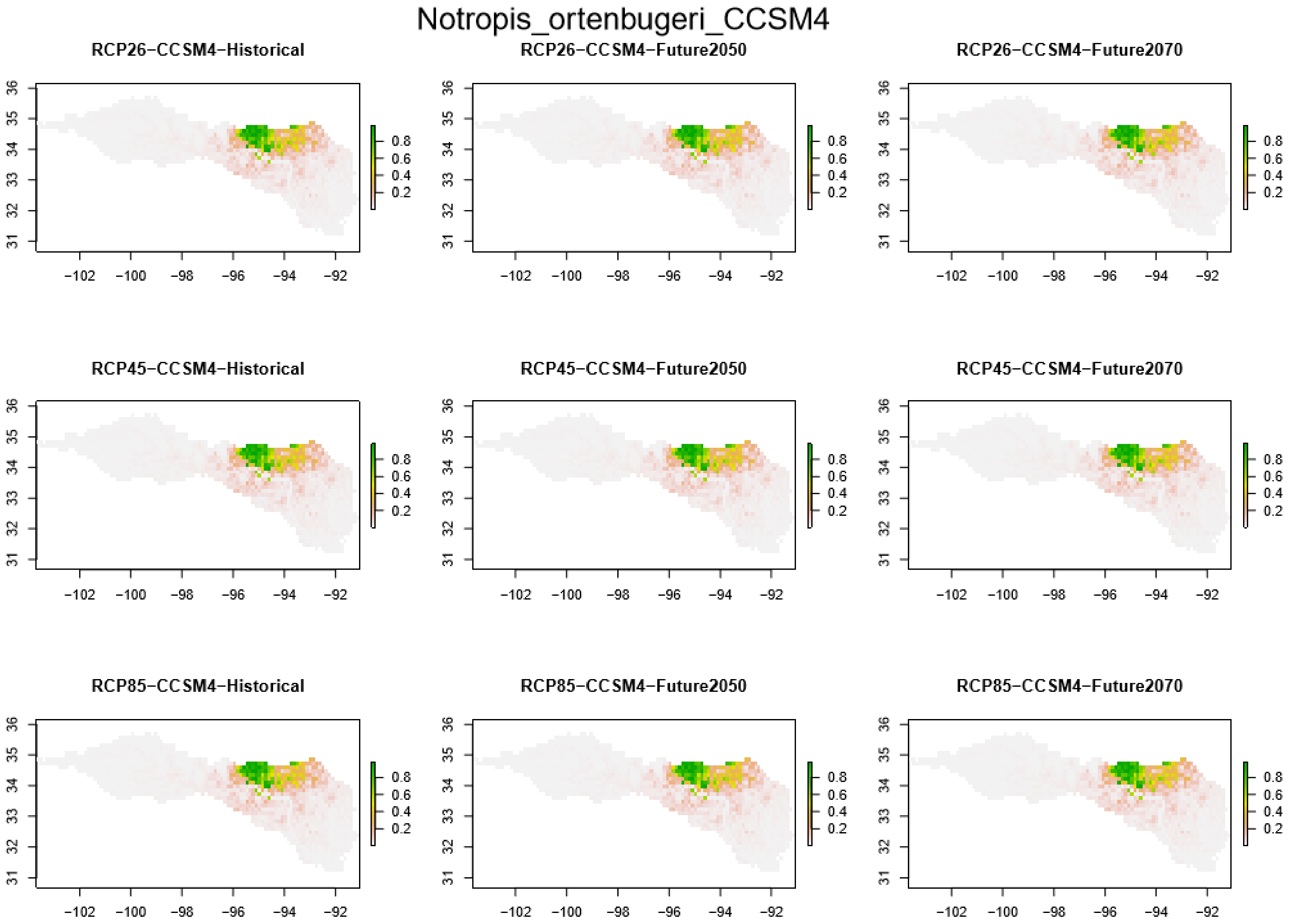
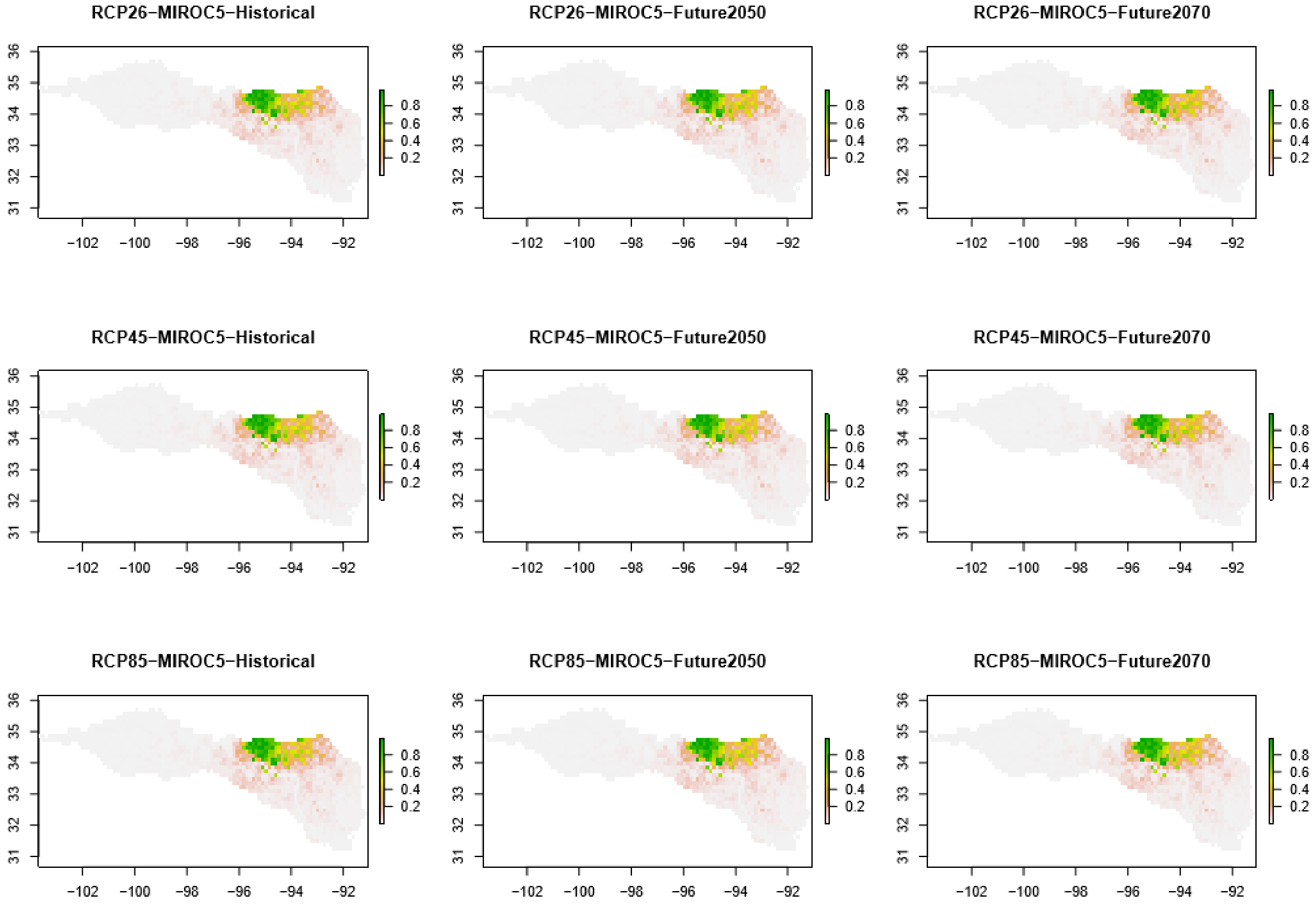

NotropisboopsMPI_ESM_LR

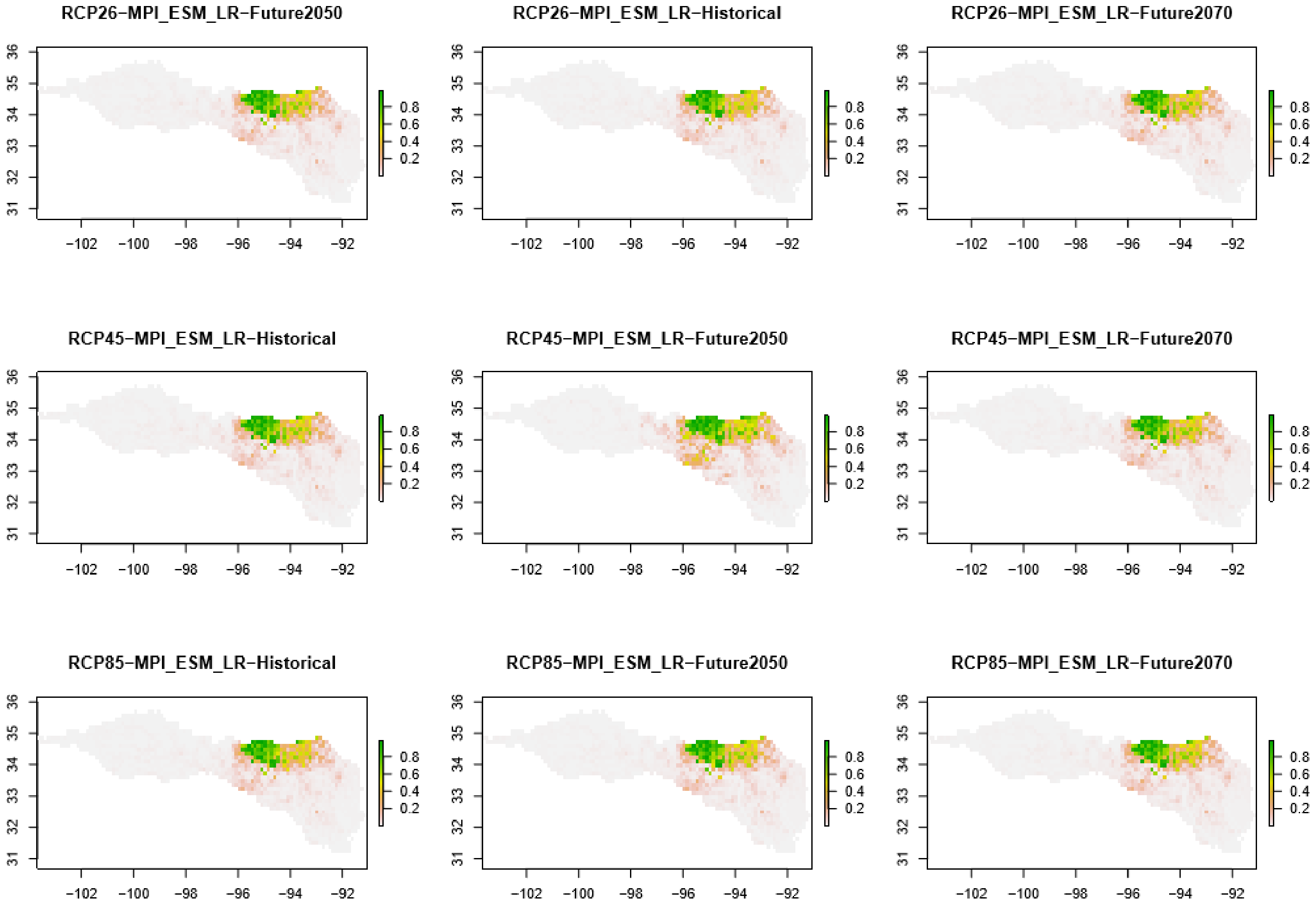
Maxent: *Notropis ortenburgeri*



Notropis_ortenbugeri_MIROC5



Notropis_ortenbugeri_MPI_ESM_LR



RCP26−MPI_ESM_LR−Future2050

RCP26−MPI_ESM_LR−Historical

RCP26−MPI_ESM_LR−Future2070

RCP45−MPI_ESM_LR−Historical

RCP45−MPI_ESM_LR−Future2050

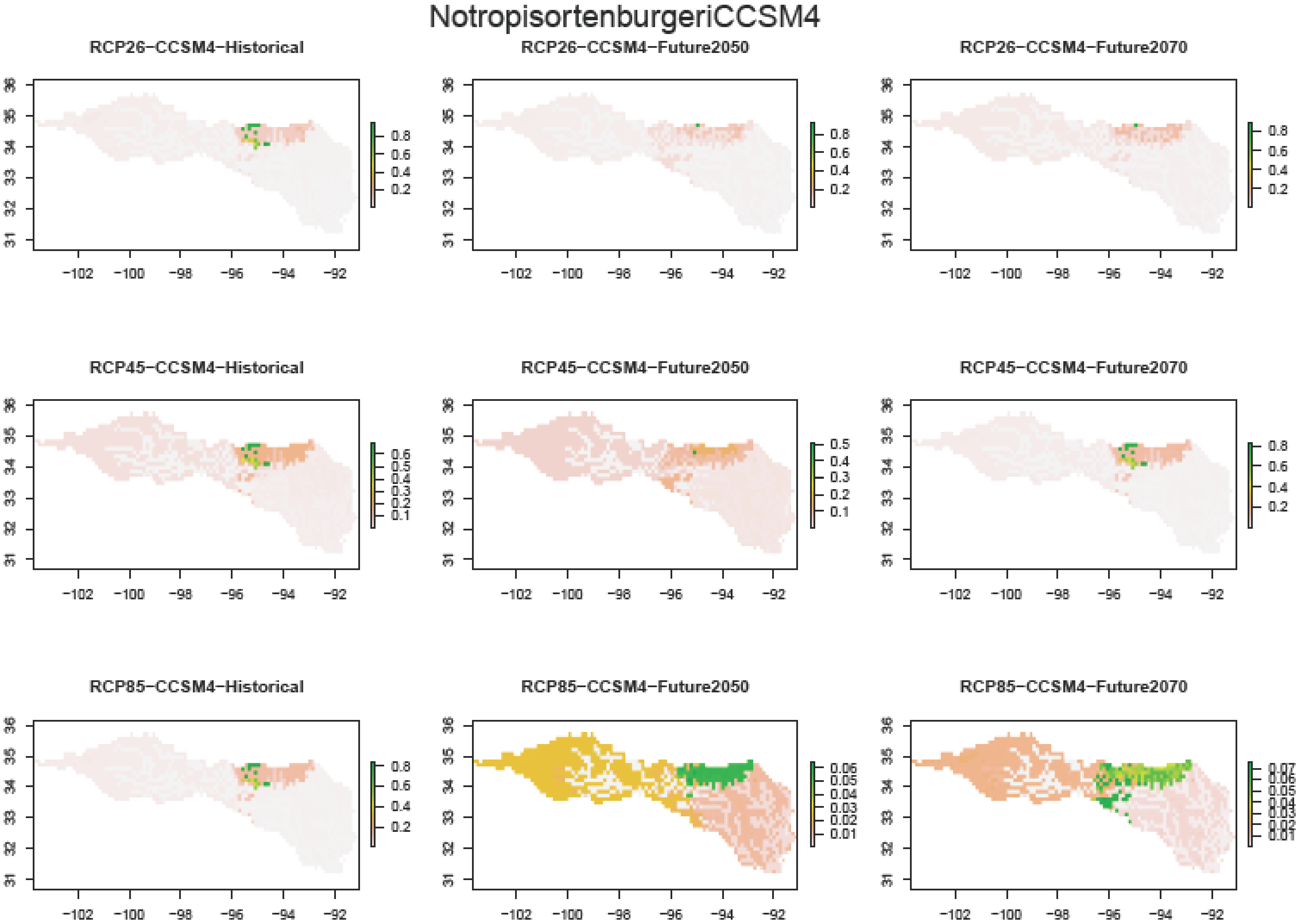
RCP45−MPI_ESM_LR−Future2070

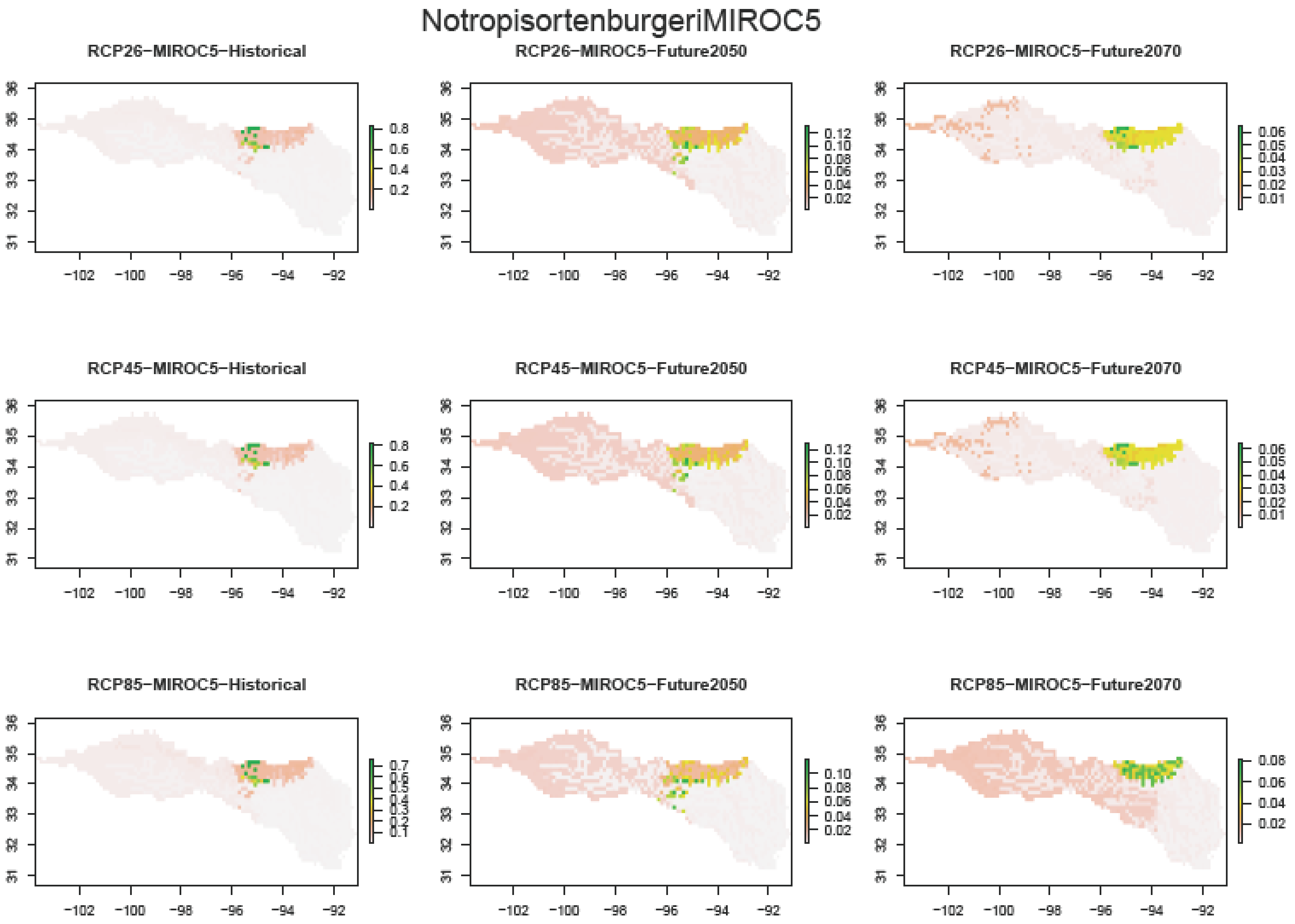
RCP85−MPI_ESM_LR−Historical

RCP85−MPI_ESM_LR−Future2050

RCP85−MPI_ESM_LR−Future2070

BRT: *Notropis ortenburgeri*




NotropisortenburgeriMIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070
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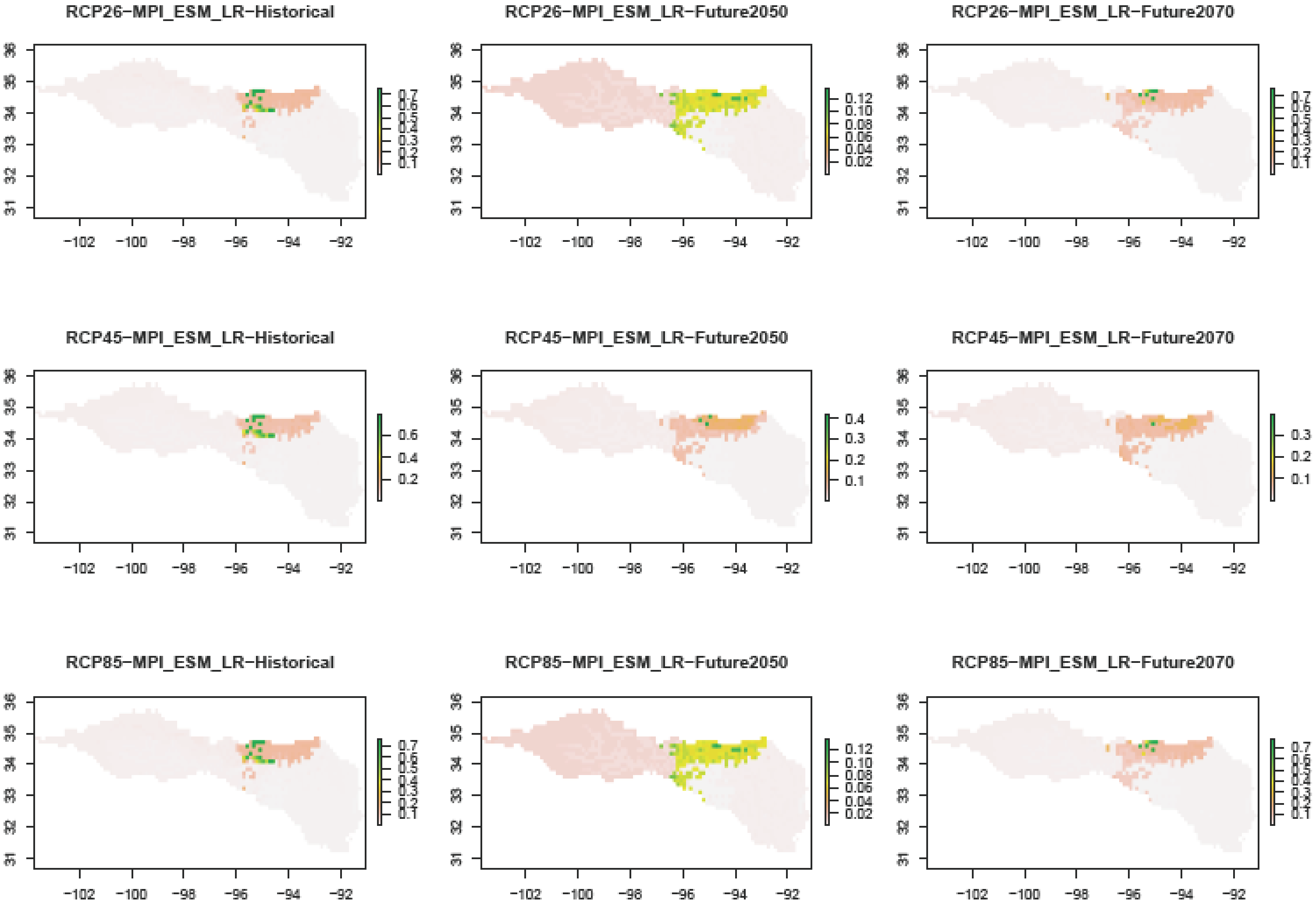
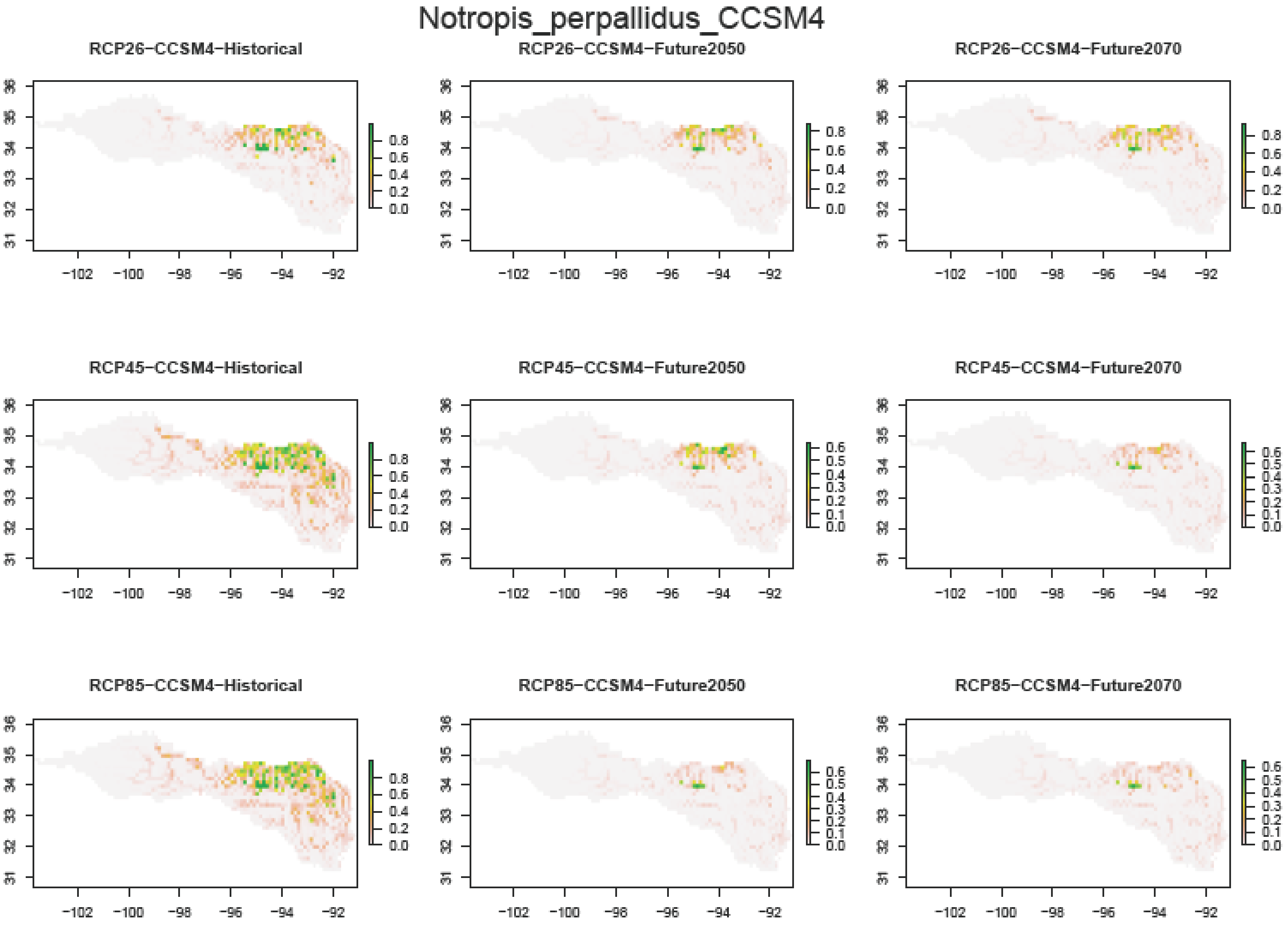
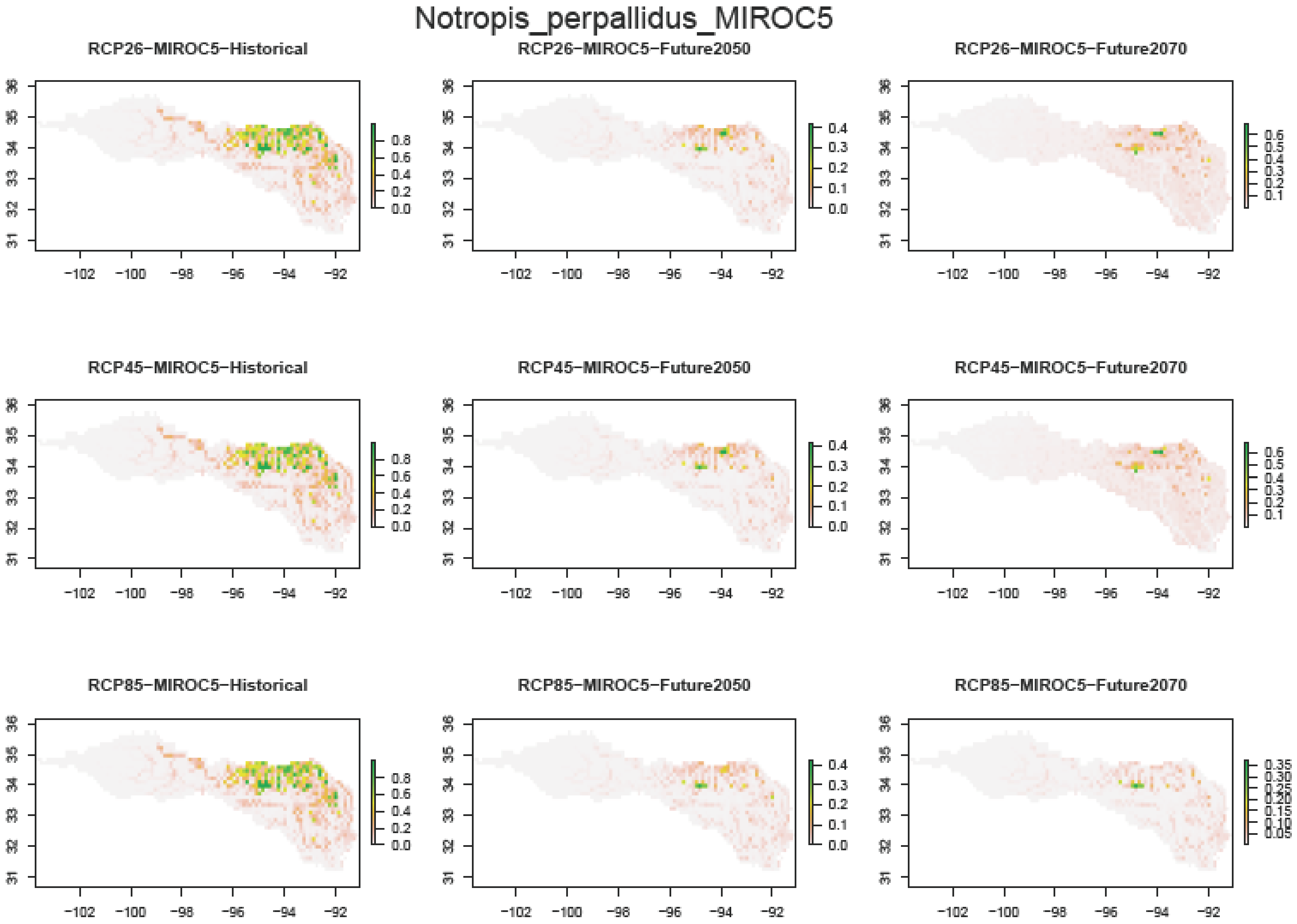
NotropisortenburgeriMPI_ESM_LR



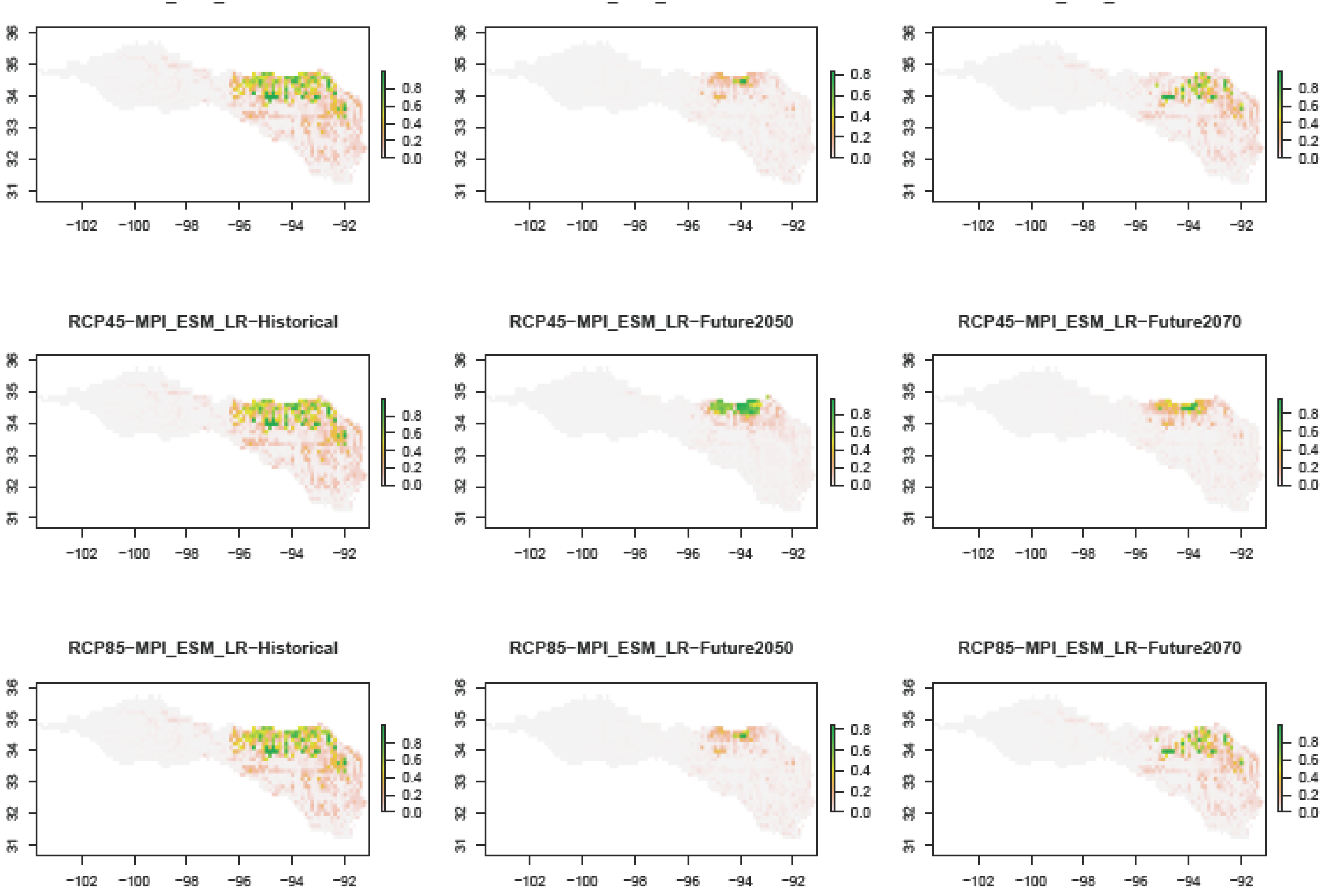
Maxent: *Notropis perpallidus*



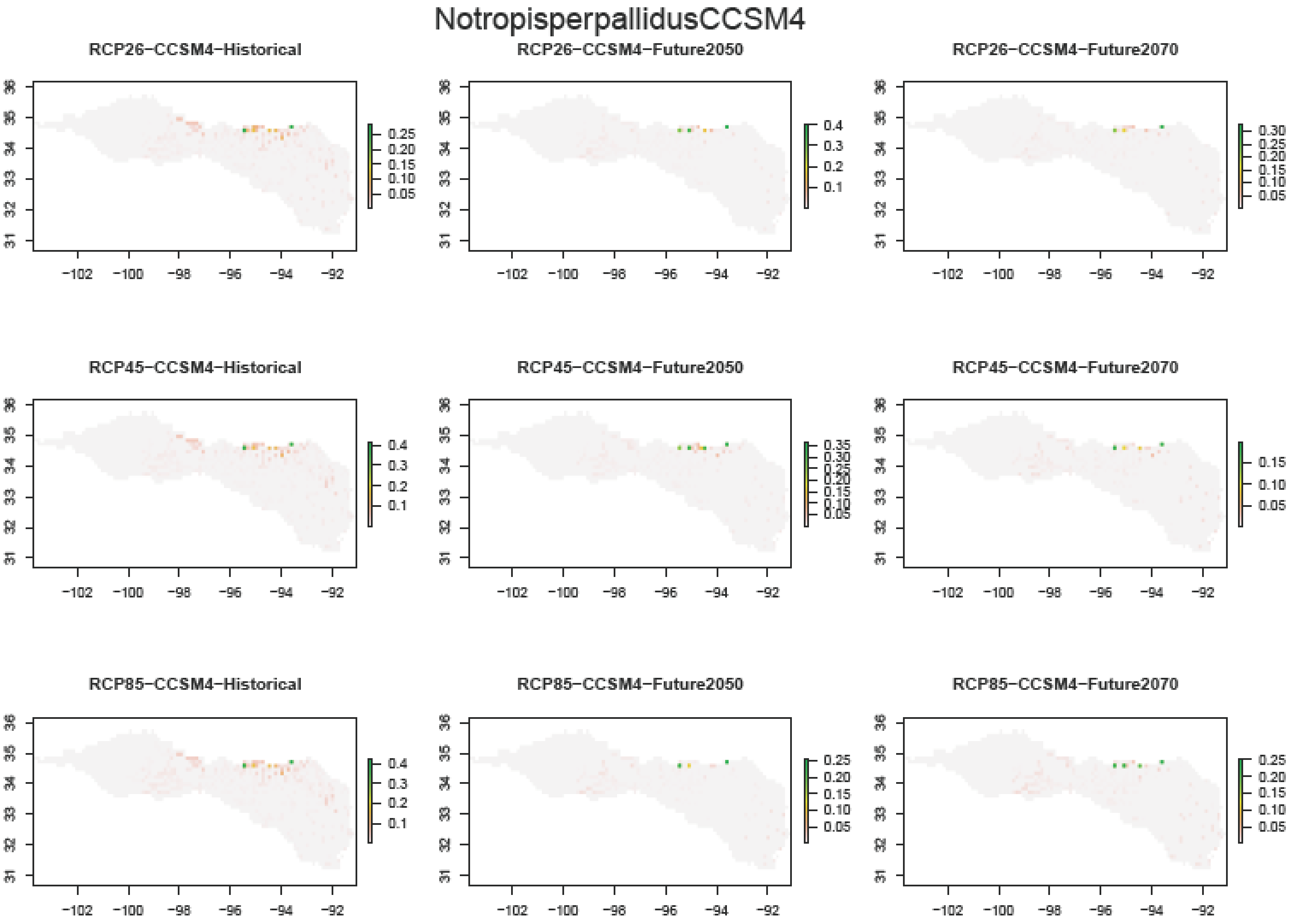


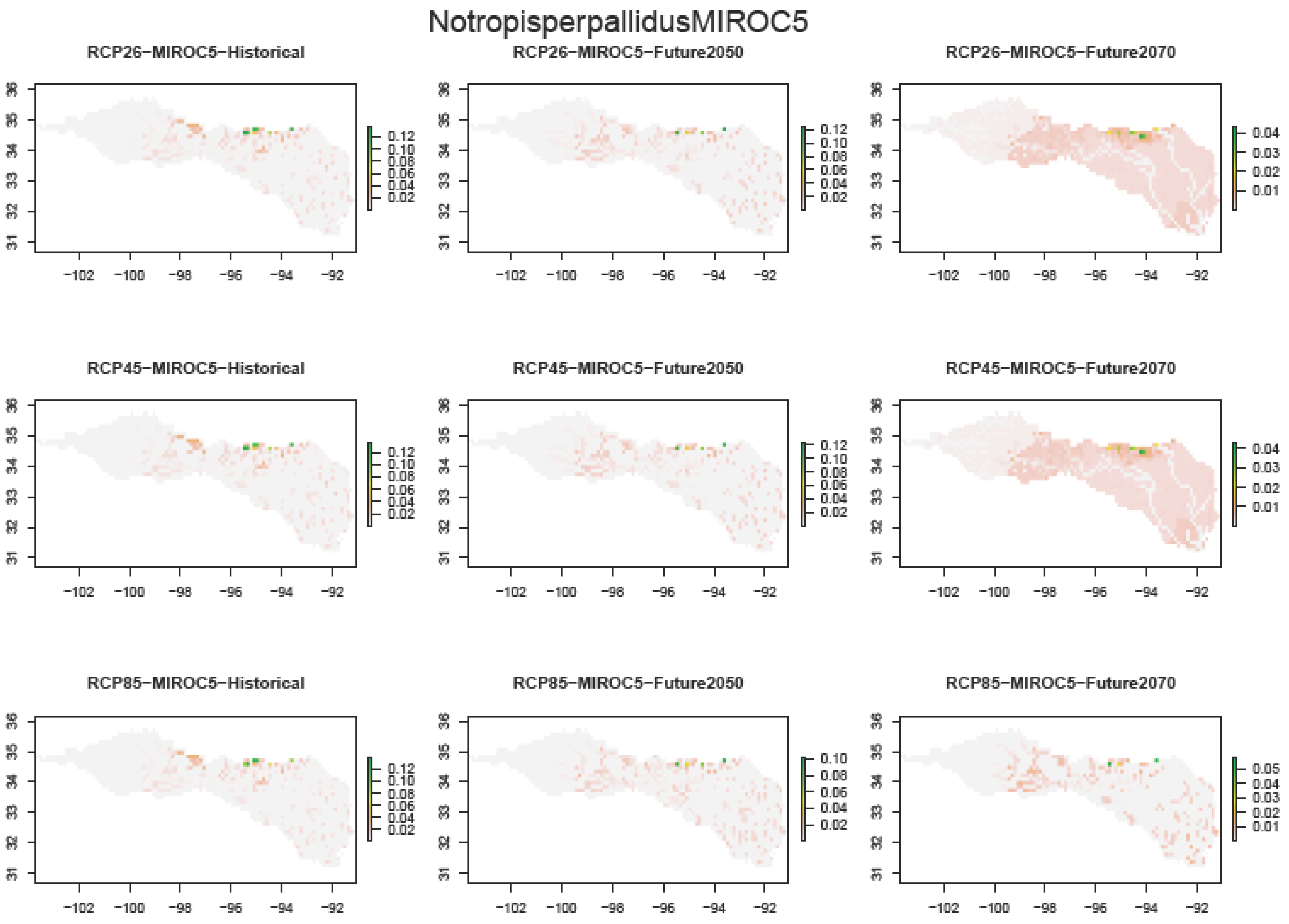
Notropis_perpallidus_MIROC5

Notropis_perpallidus_MPI_ESM_LR



BRT: *Notropis perpallidus*




NotropisperpallidusMIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070
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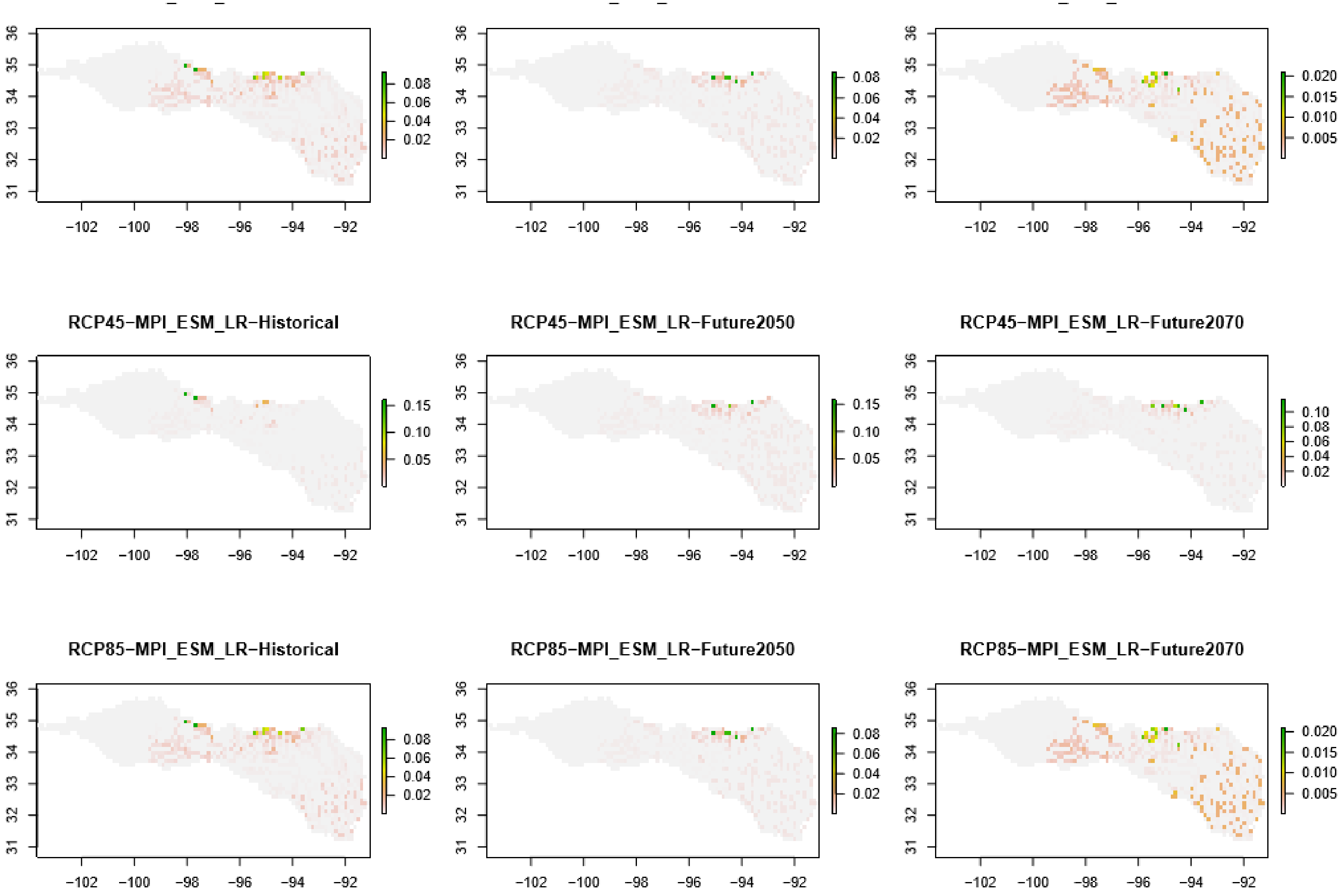
NotropisperpallidusMPI_ESM_LR



RCP26−MPI_ESM_LR−Historical

RCP26−MPI_ESM_LR−Future2050

RCP26−MPI_ESM_LR−Future2070

RCP45−MPI_ESM_LR−Historical

RCP45−MPI_ESM_LR−Future2050

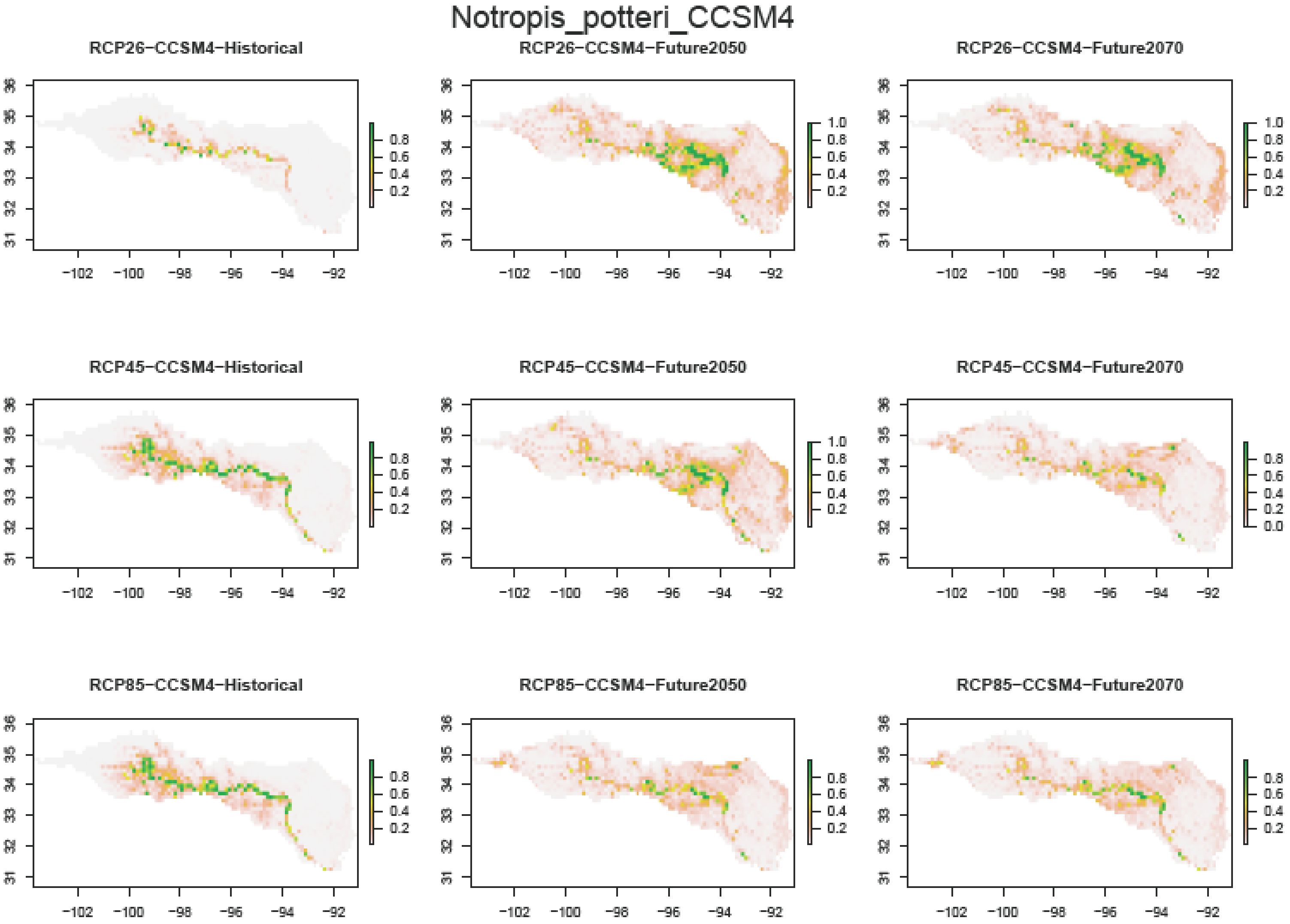
RCP45−MPI_ESM_LR−Future2070

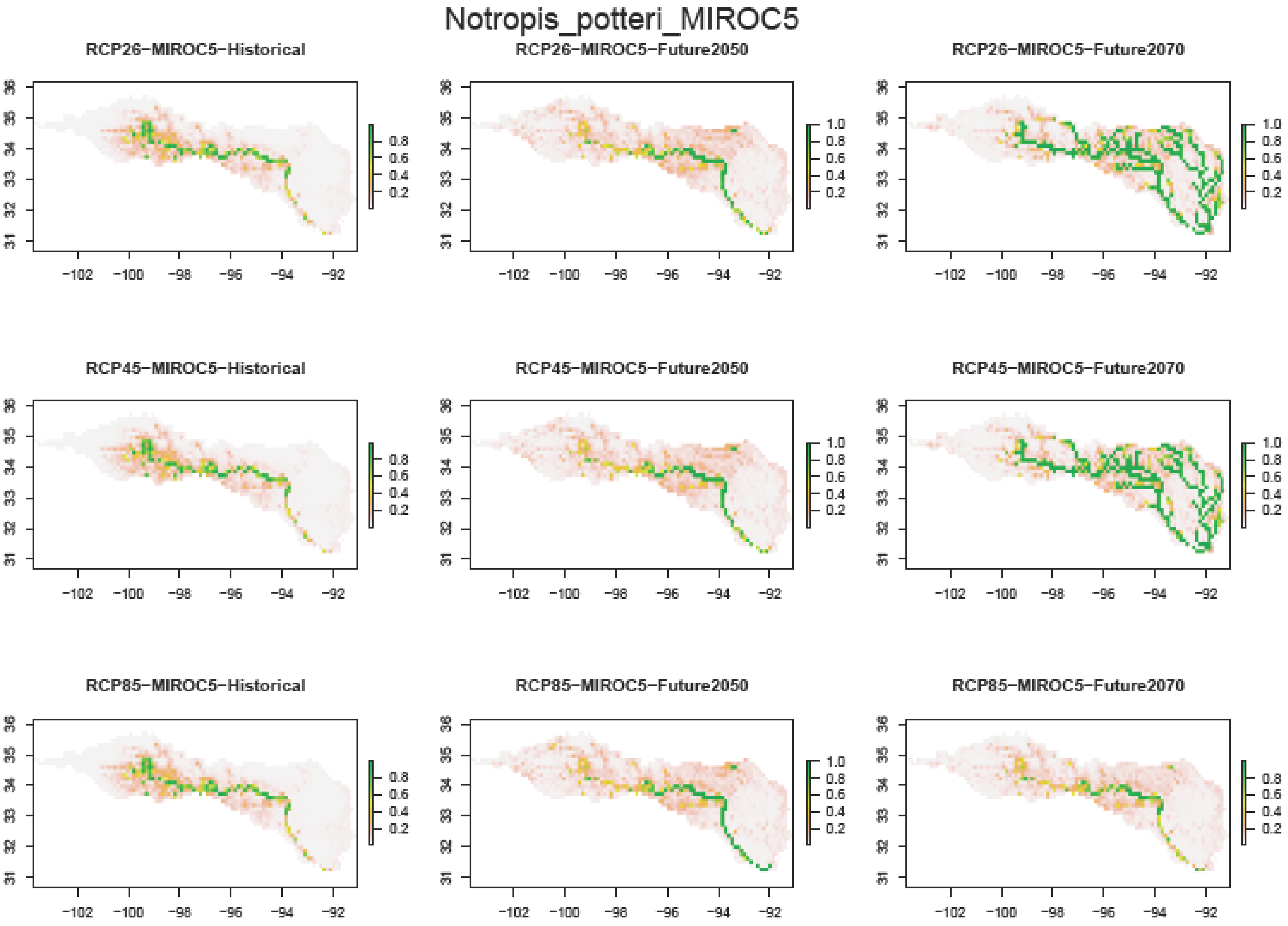
RCP85−MPI_ESM_LR−Historical

RCP85−MPI_ESM_LR−Future2050

RCP85−MPI_ESM_LR−Future2070

Maxent: *Notropis potteri*




Notropis_potteri_MIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070
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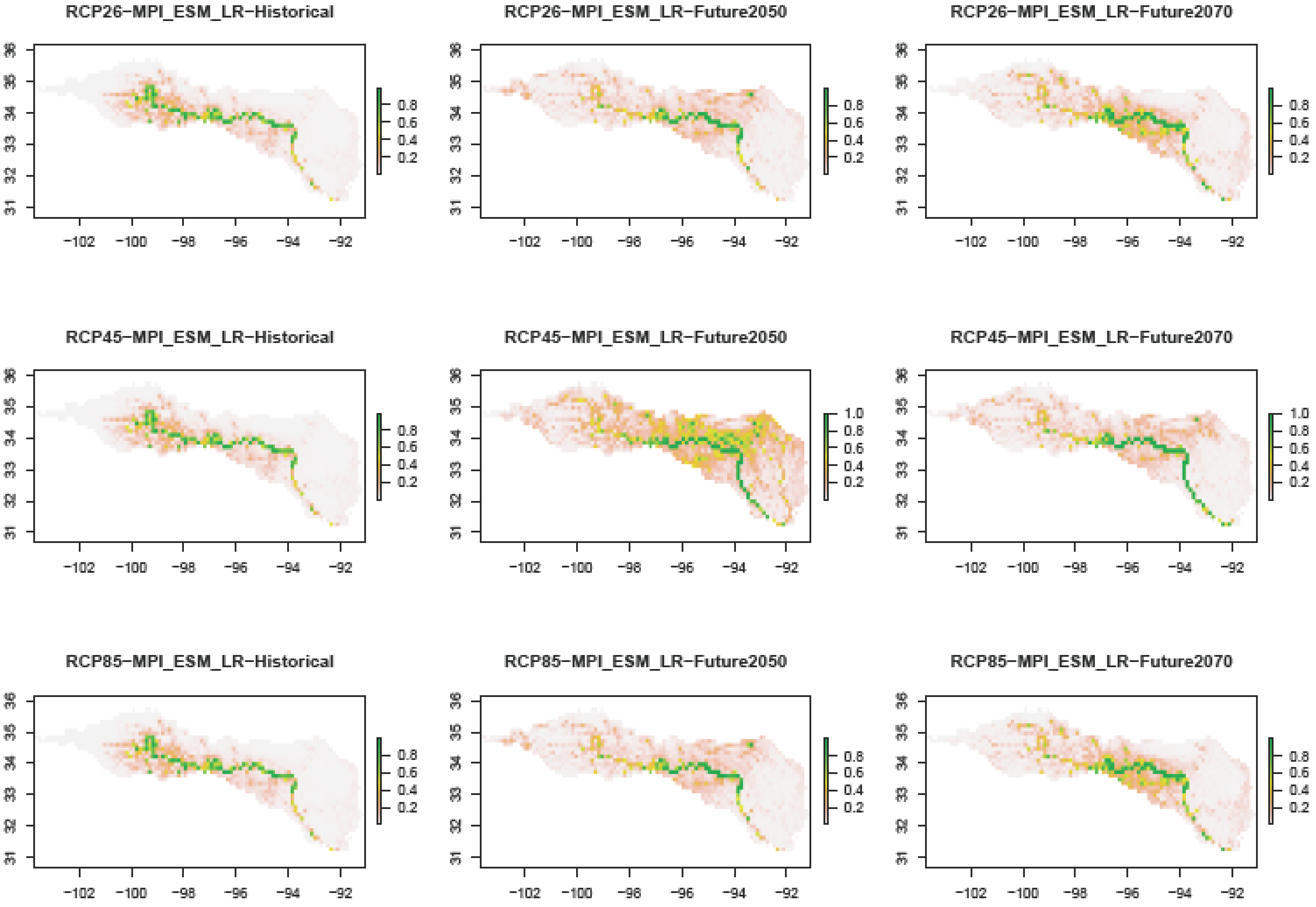
Notropis_potteri_MPI_ESM_LR


RCP26-MPI_ESM_LR-Historical

RCP26-MPI_ESM_LR-Future2050

RCP26-MPI_ESM_LR-Future2070

RCP45-MPI_ESM_LR-Historical

RCP45-MPI_ESM_LR-Future2050

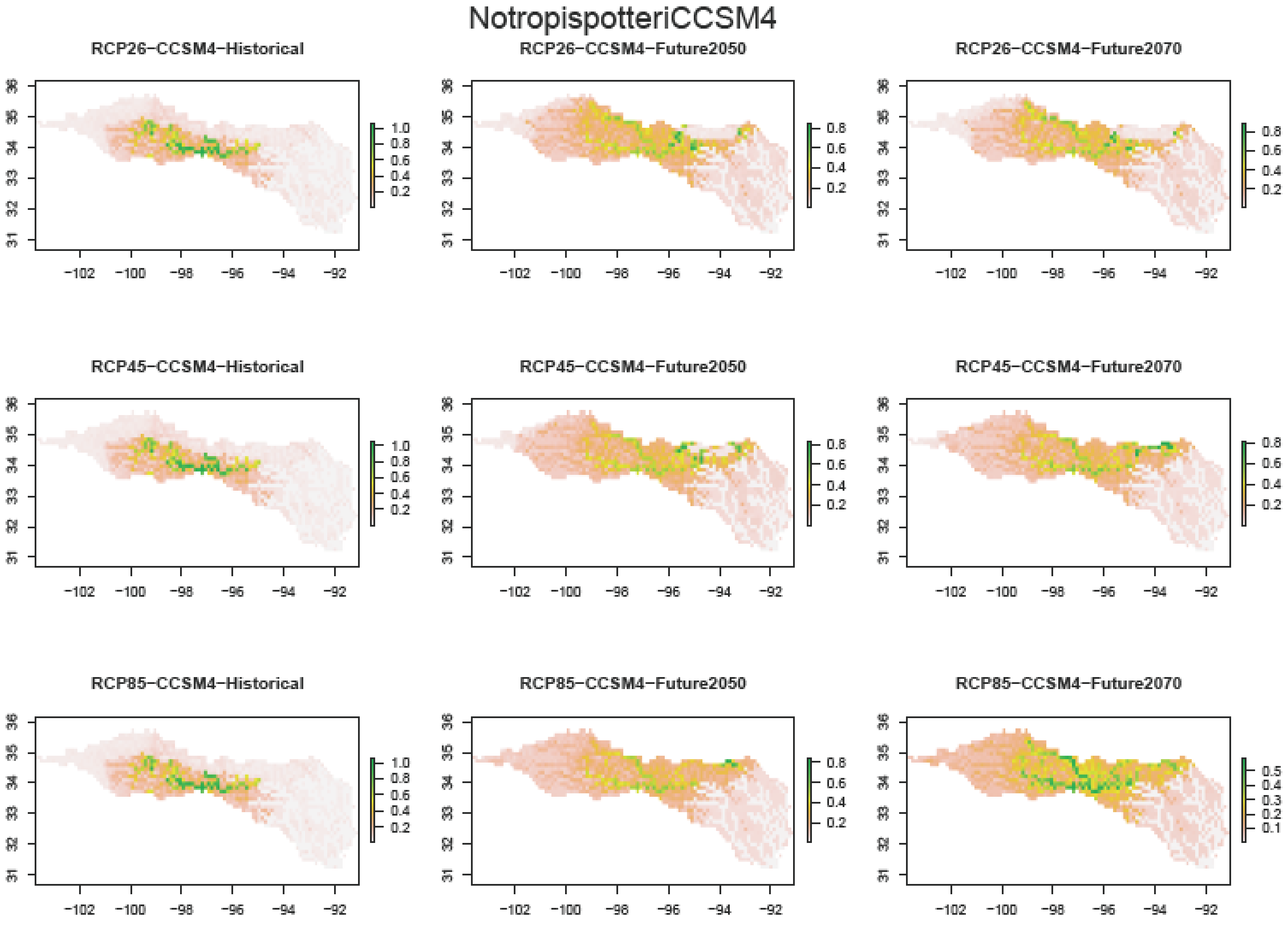
RCP45-MPI_ESM_LR-Future2070

RCP85-MPI_ESM_LR-Historical

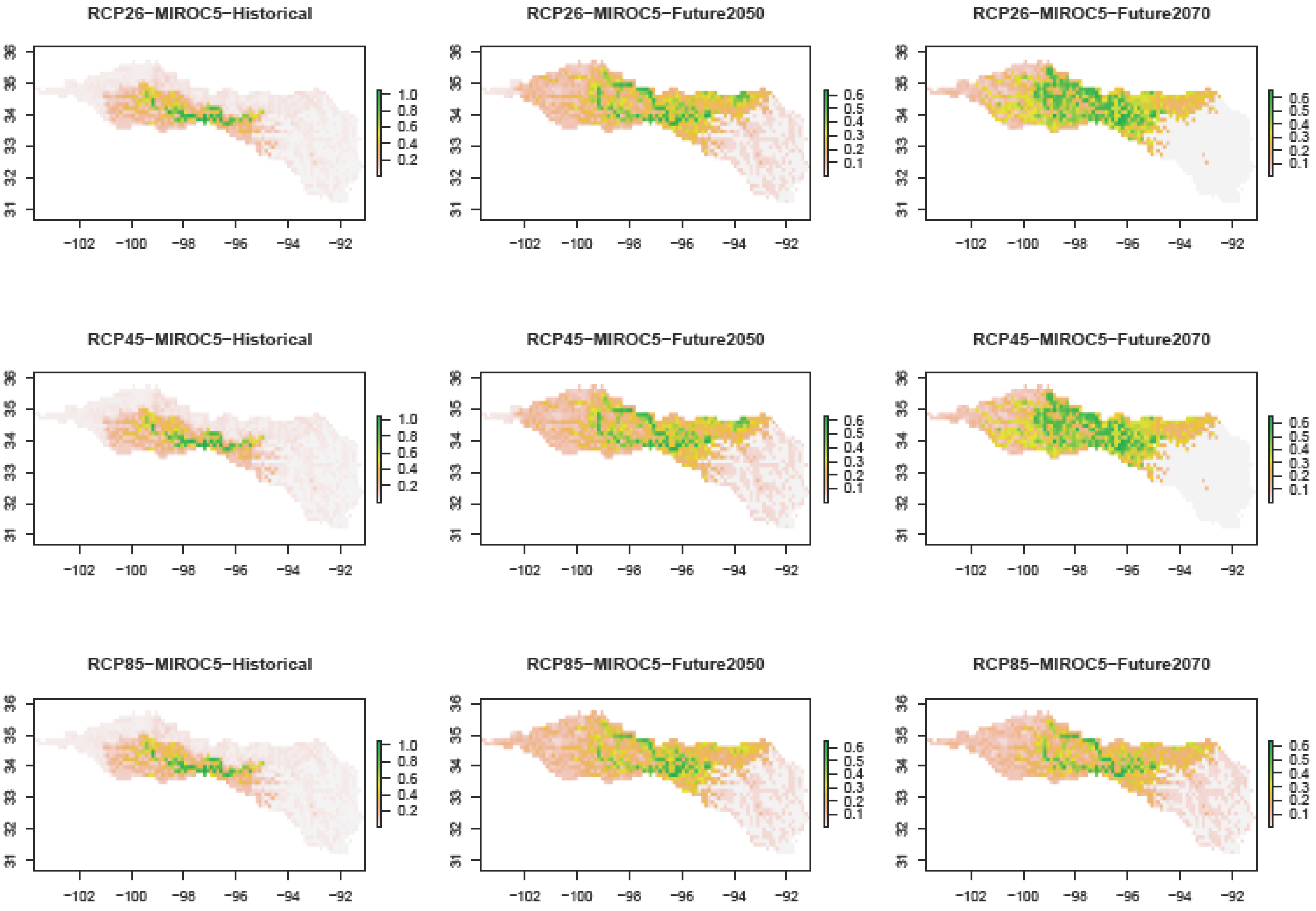
RCP85-MPI_ESM_LR-Future2050

RCP85-MPI_ESM_LR-Future2070

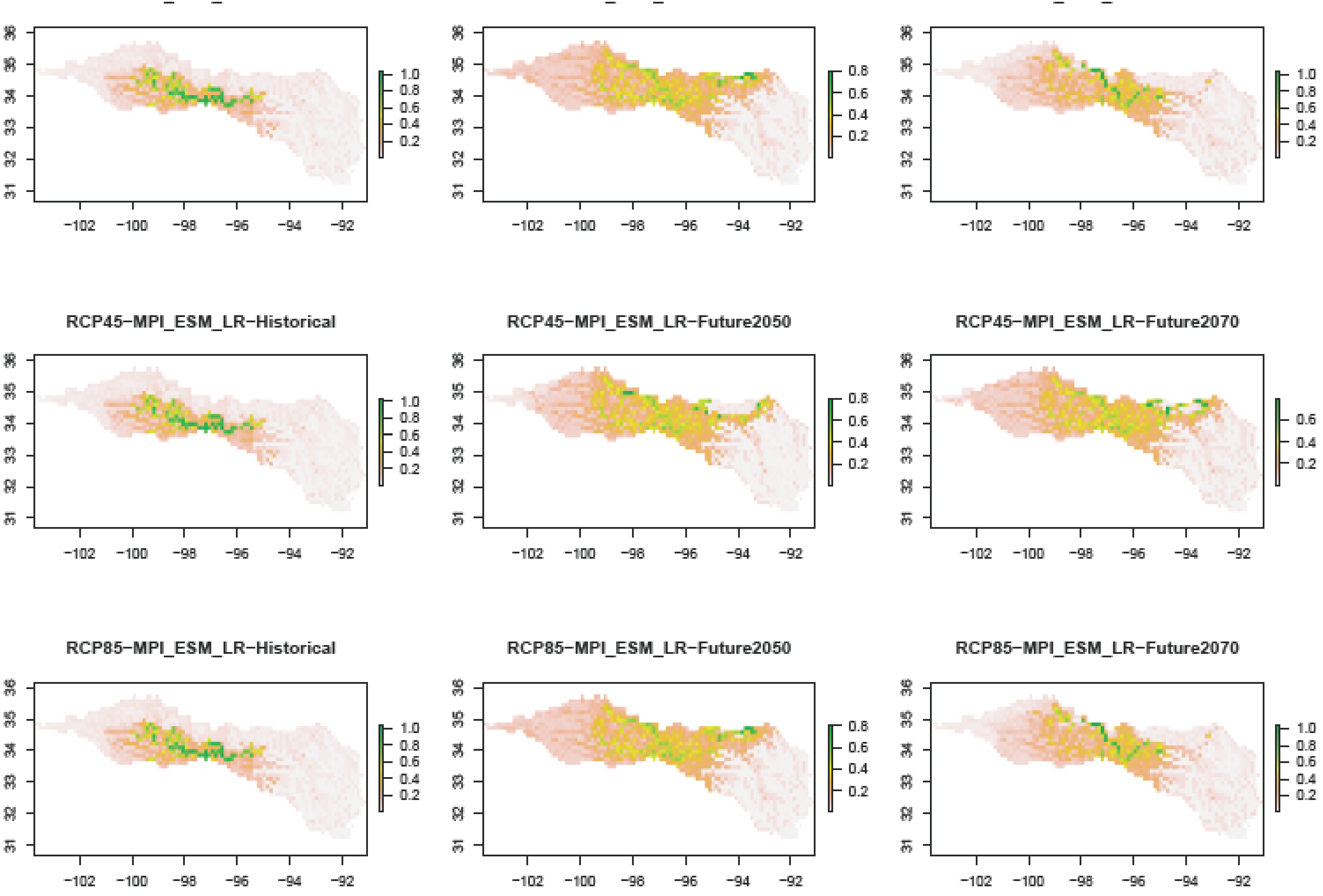
BRT: *Notropis potteri*



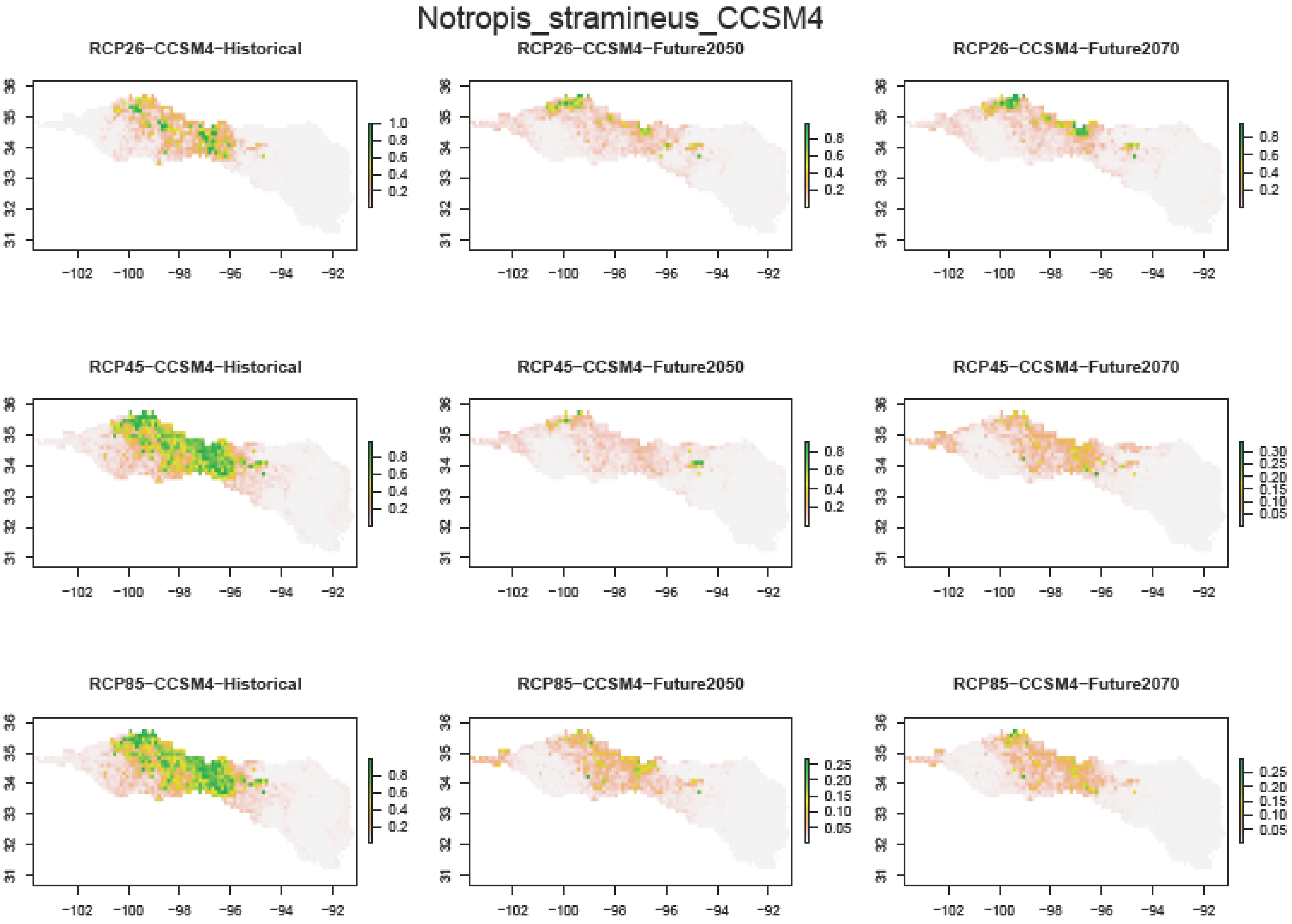
NotropispotteriMIROC5

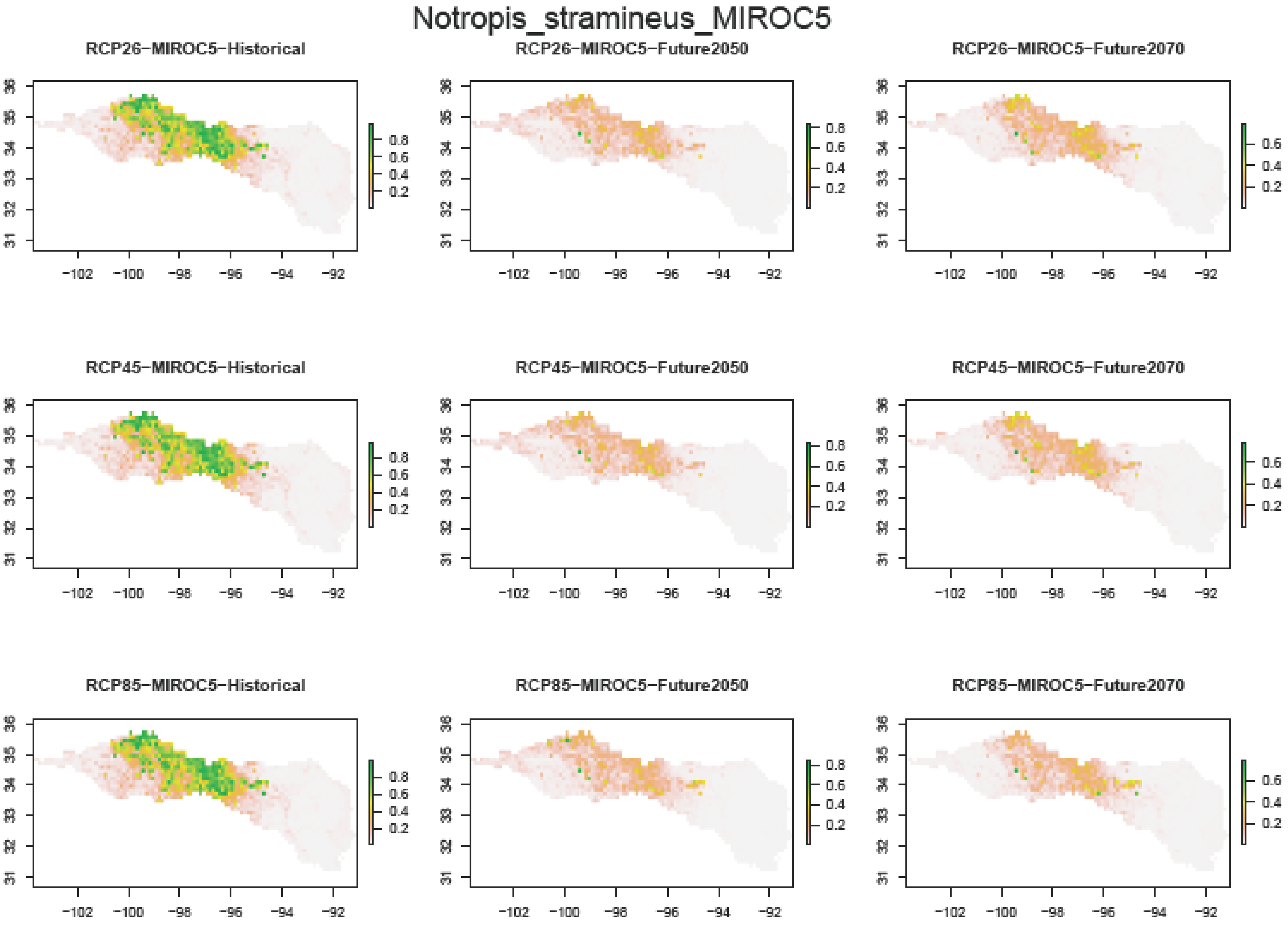


NotropispotteriMPI_ESM_LR



Maxent: *Notropis stramineus*





Notropis_stramineus_MIROC5

RCP26−MIROC5−Historical

RCP26−MIROC5−Future2050

RCP26−MIROC5−Future2070

RCP45−MIROC5−Historical

RCP45−MIROC5−Future2050

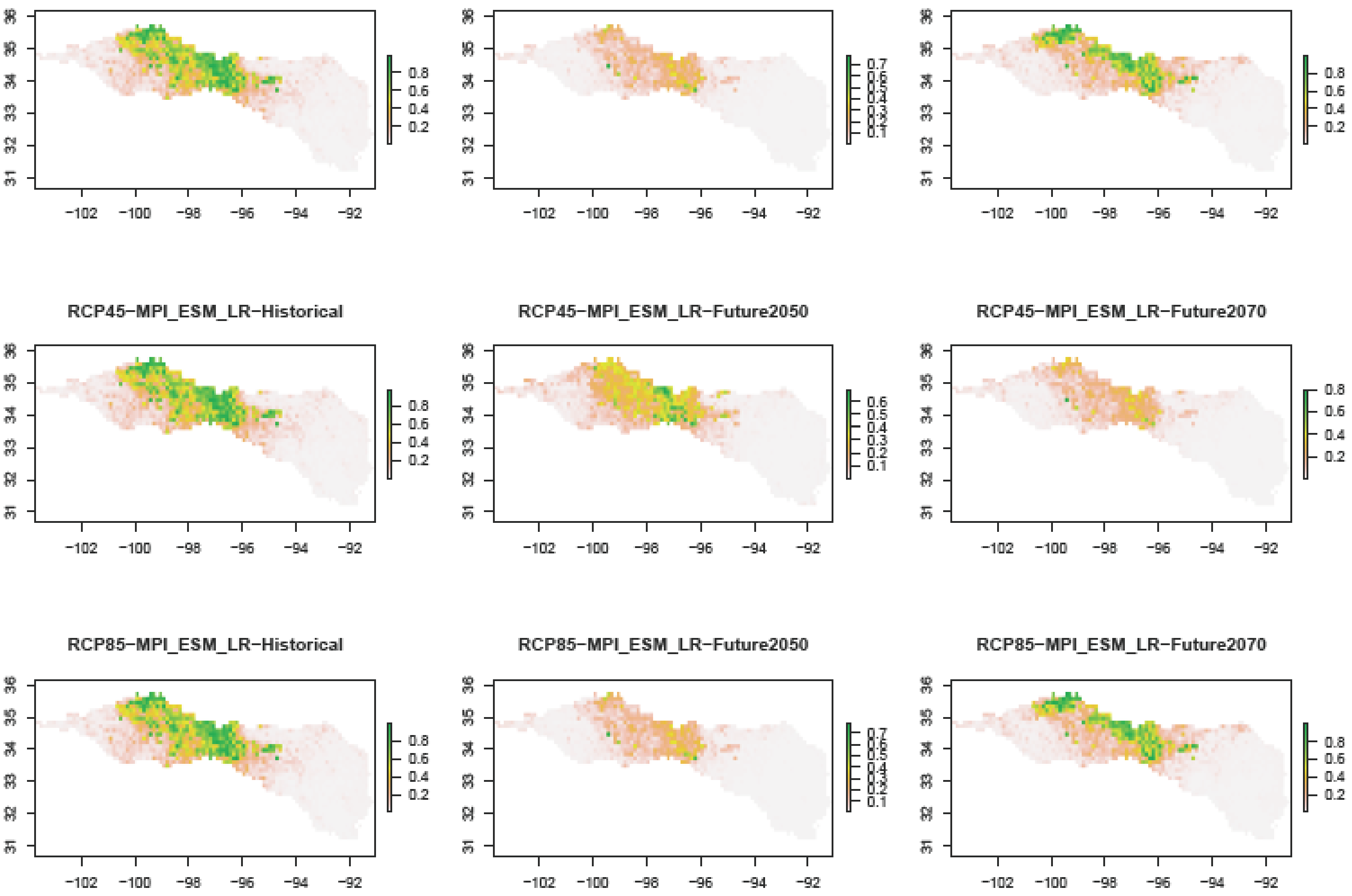
RCP45−MIROC5−Future2070

RCP85−MIROC5−Historical

RCP85−MIROC5−Future2050

RCP85−MIROC5−Future2070

Notropis_stramineus_MPI_ESM_LR


RCP26−MPI_ESM_LR−Historical

RCP26−MPI_ESM_LR−Future2050

RCP26−MPI_ESM_LR−Future2070

RCP45−MPI_ESM_LR−Historical

RCP45−MPI_ESM_LR−Future2050

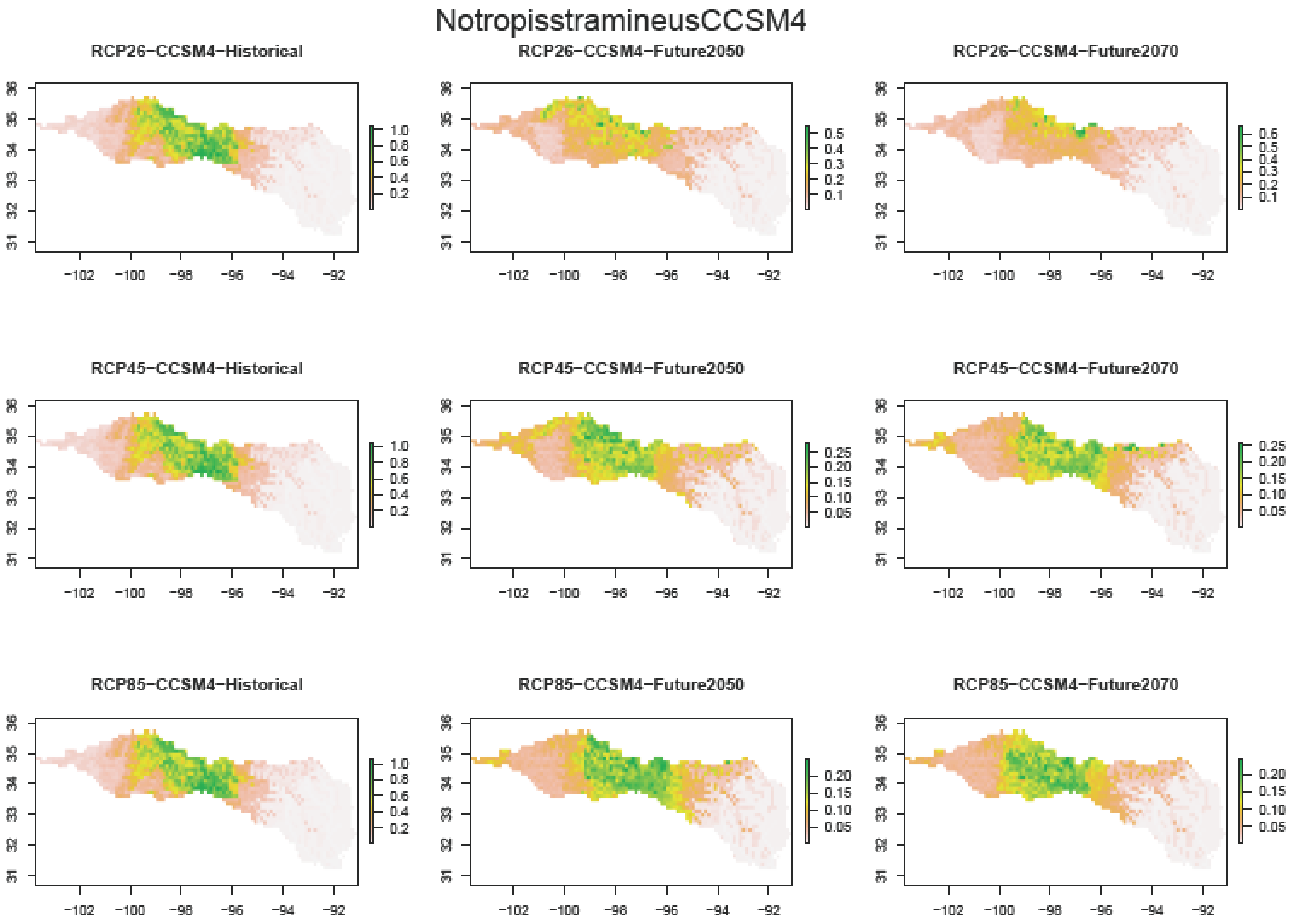
RCP45−MPI_ESM_LR−Future2070

RCP85−MPI_ESM_LR−Historical

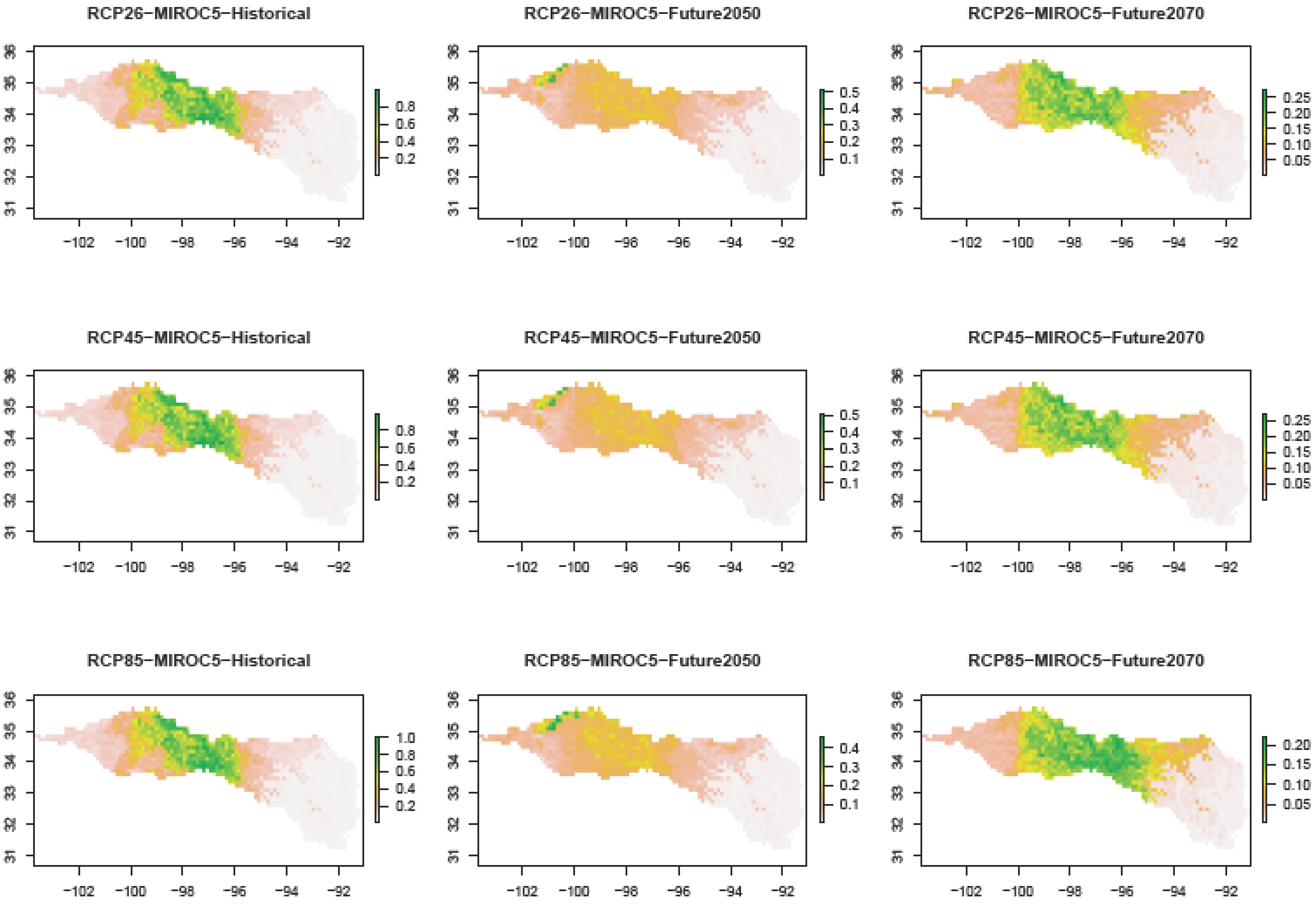
RCP85−MPI_ESM_LR−Future2050

RCP85−MPI_ESM_LR−Future2070

BRT: *Notropis stramineus*



NotropisstramineusMIROC5



RCP26-MIROC5-Historical

RCP26-MIROC5-Future2050

RCP26-MIROC5-Future2070

RCP45-MIROC5-Historical

RCP45-MIROC5-Future2050

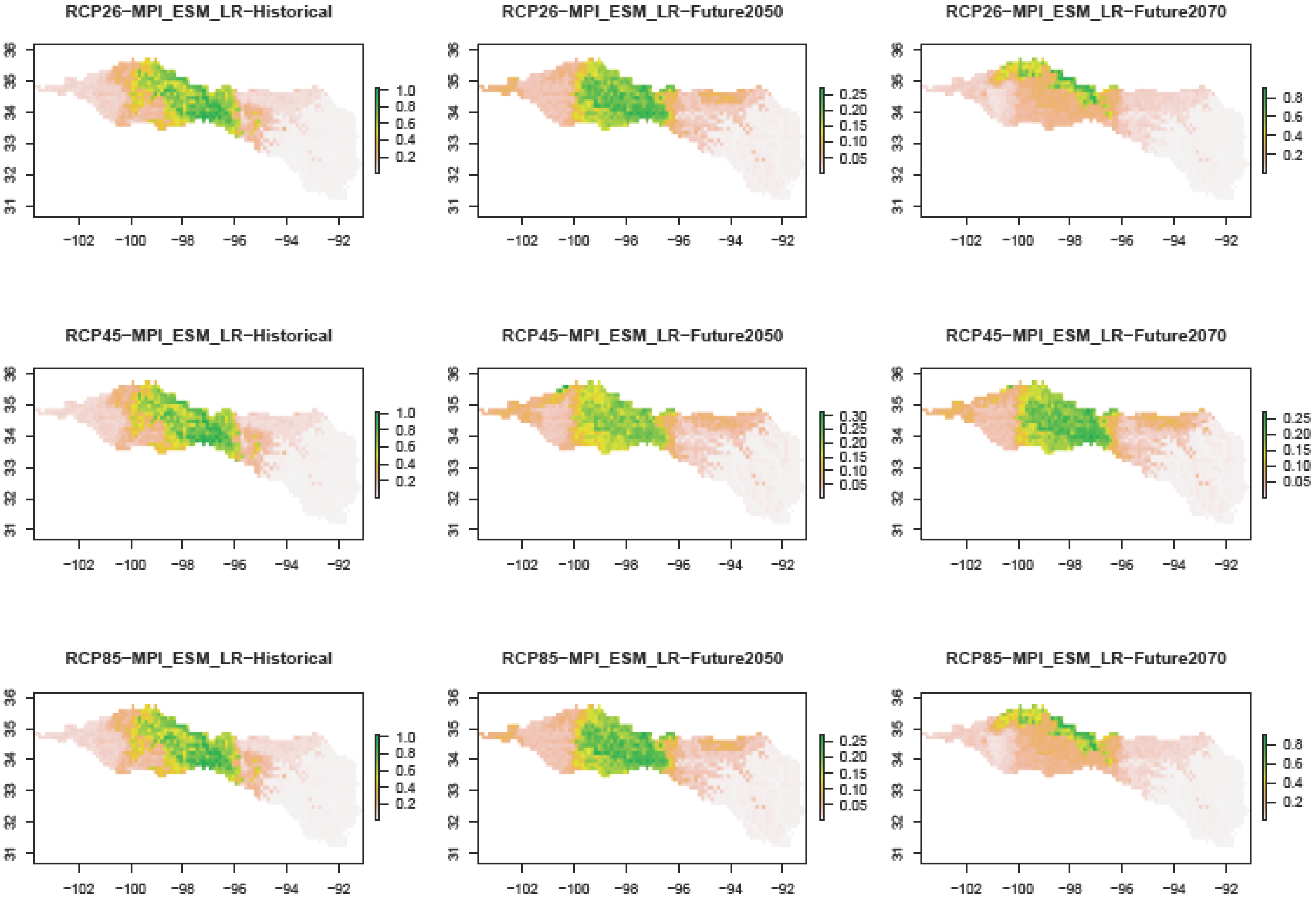
RCP45-MIROC5-Future2070

RCP85-MIROC5-Historical

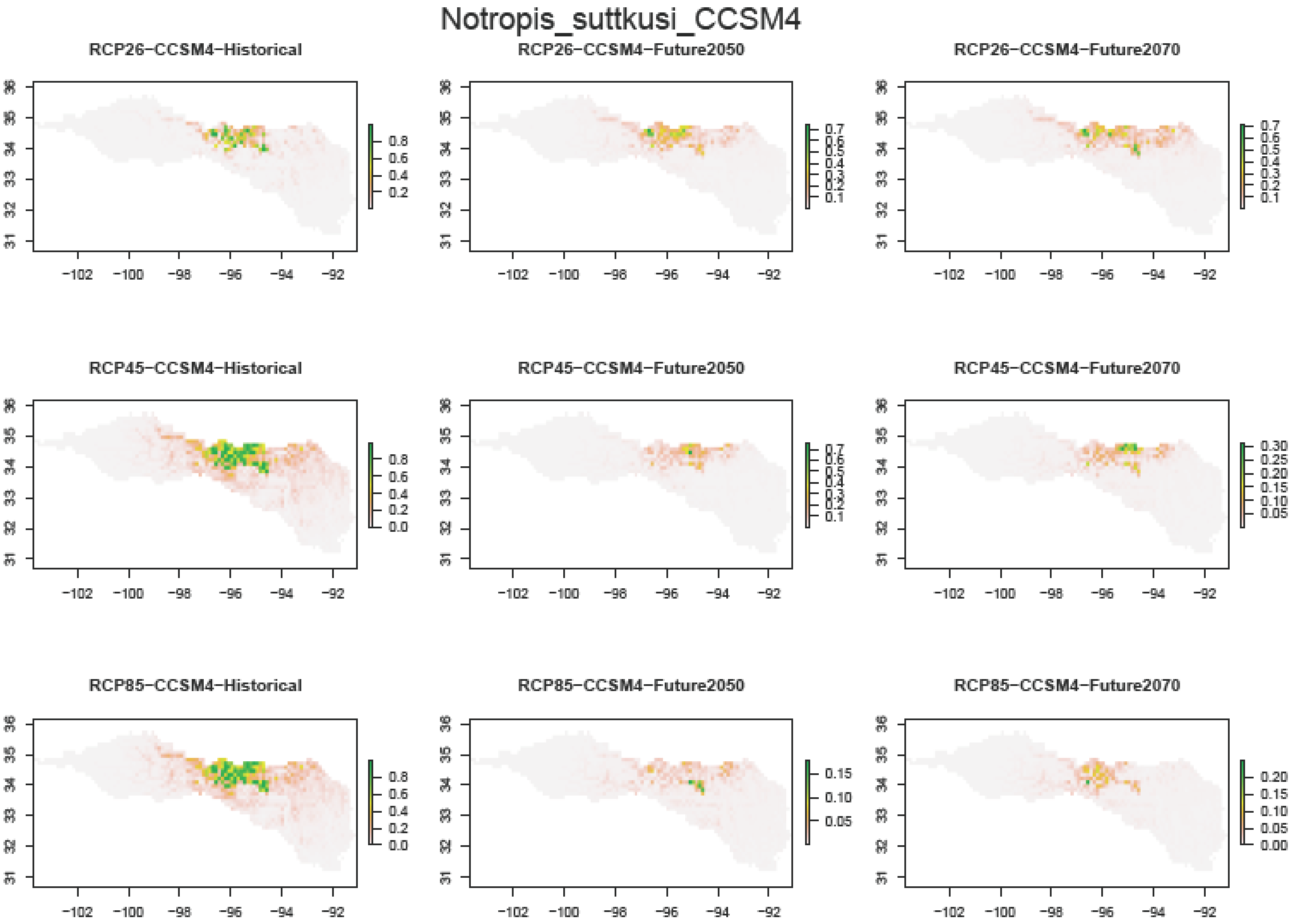
RCP85-MIROC5-Future2050

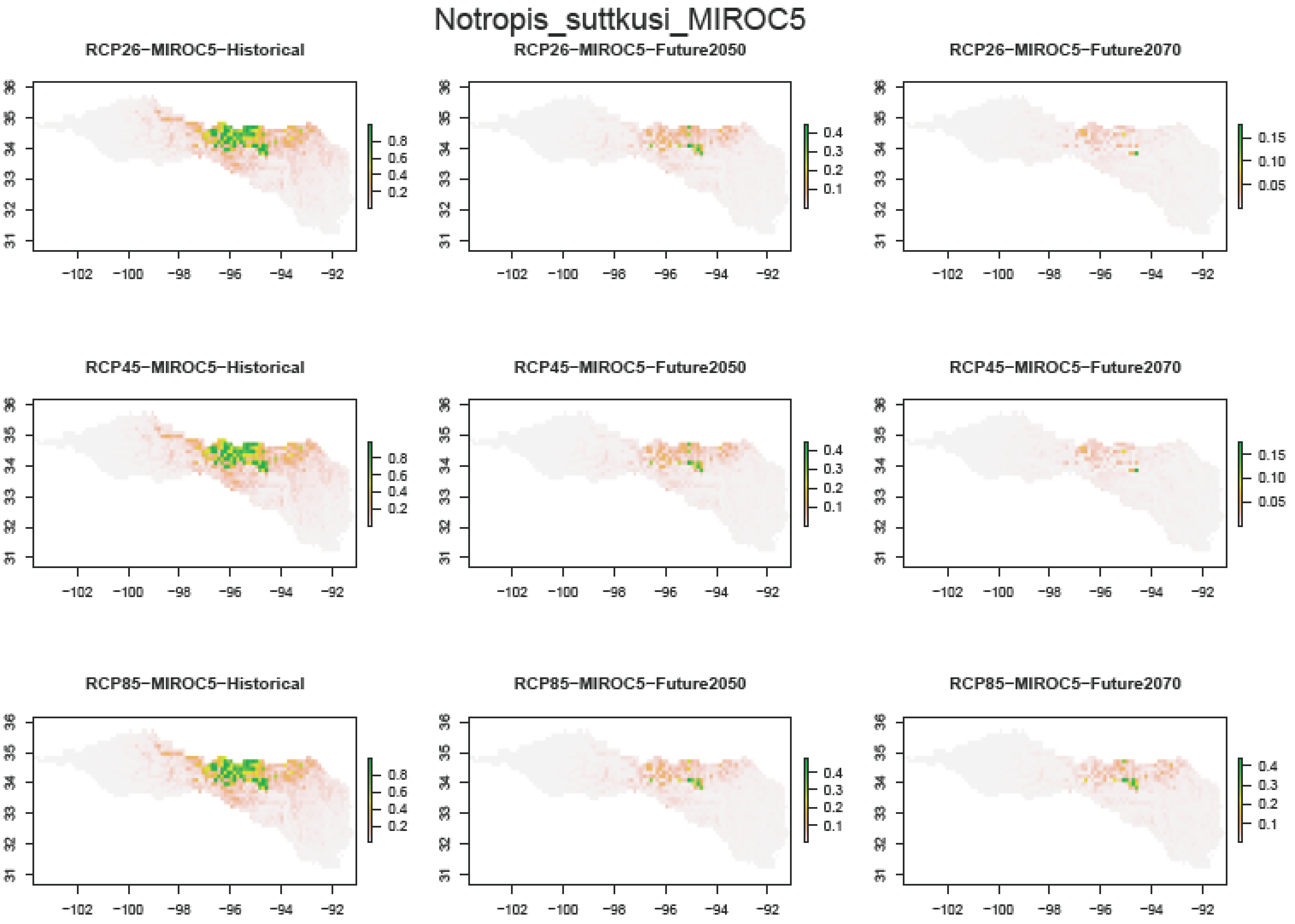
RCP85-MIROC5-Future2070

NotropisstramineusMPI_ESM_LR



Maxent: *Notropis suttkusi*




Notropis_suttkusi_MIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070
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0.6
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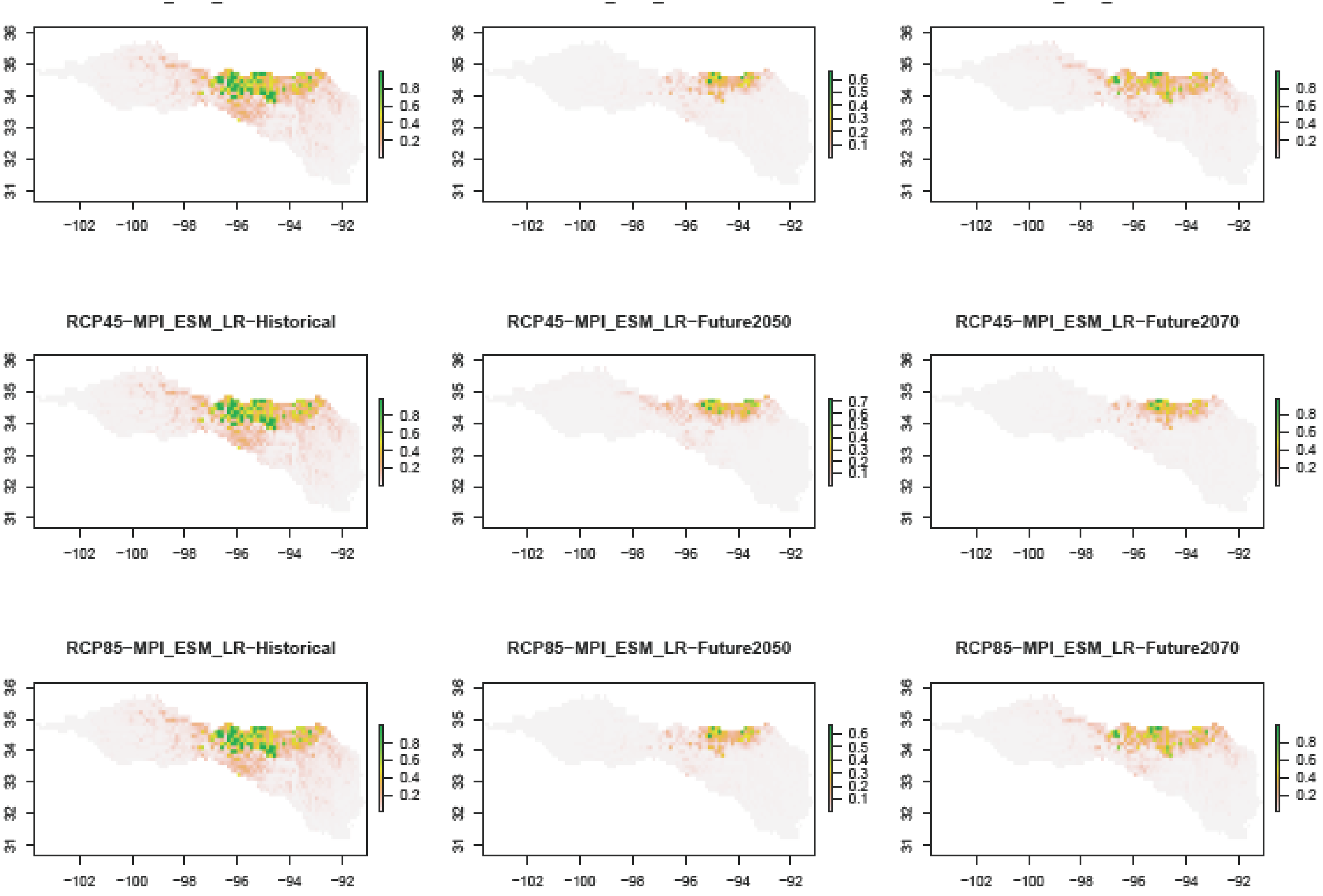
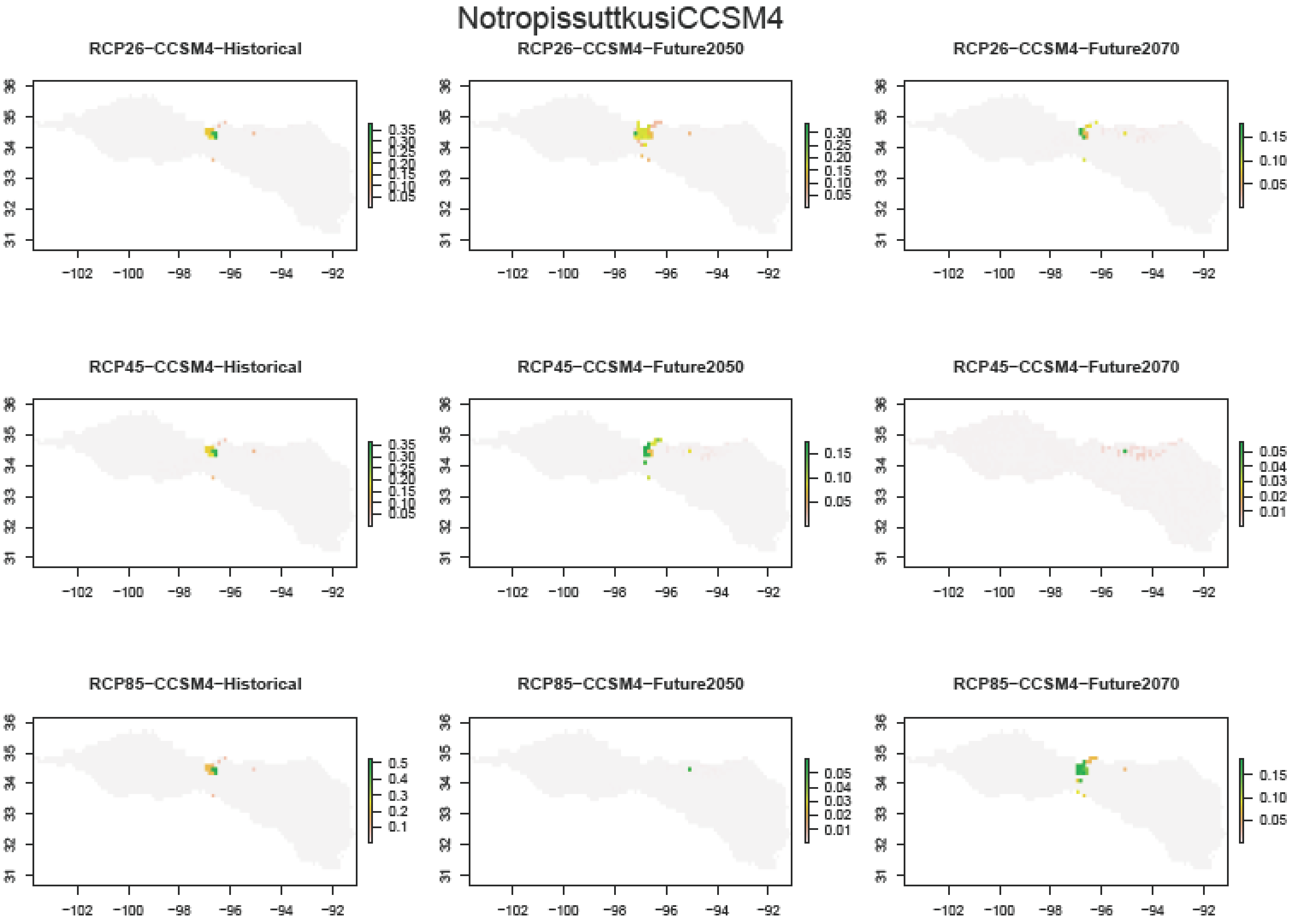
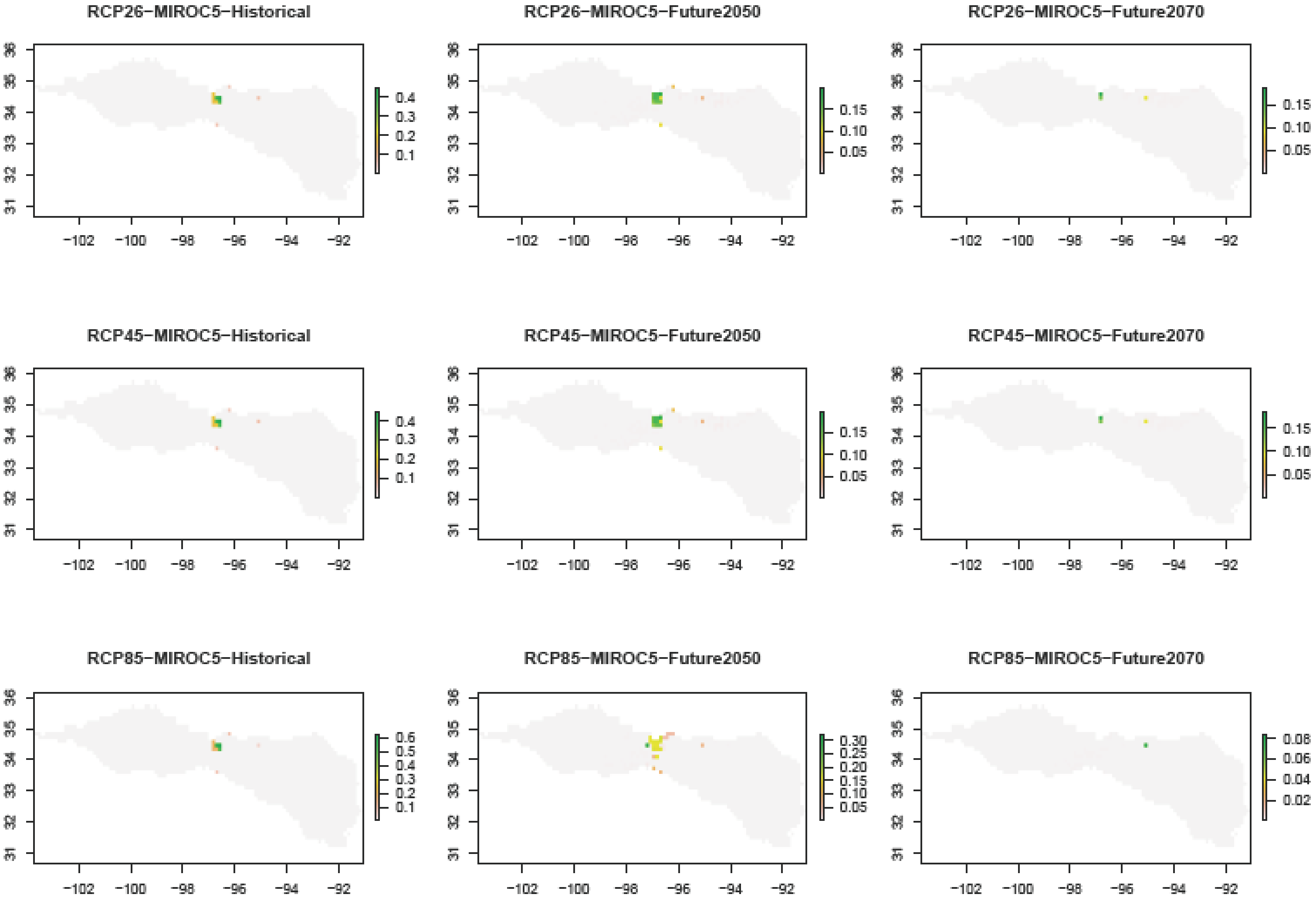
Notropis_suttkusi_MPI_ESM_LR



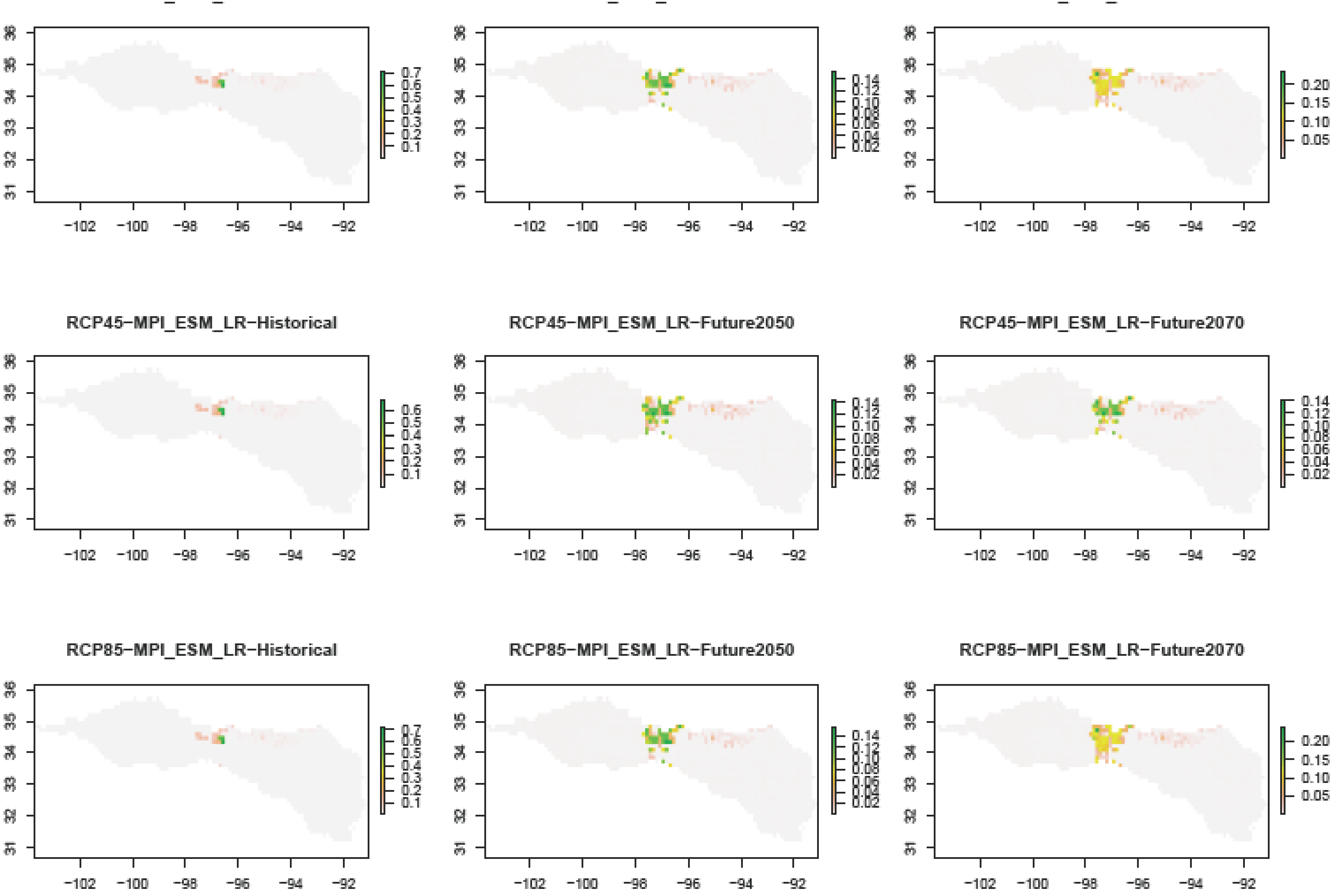
BRT: *Notropis suttkusi*



NotropissuttkusiMIROC5



NotropissuttkusiMPI_ESM_LR


RCP26-MPI_ESM_LR-Historical

RCP26-MPI_ESM_LR-Future2050

RCP26-MPI_ESM_LR-Future2070

RCP45-MPI_ESM_LR-Historical

RCP45-MPI_ESM_LR-Future2050

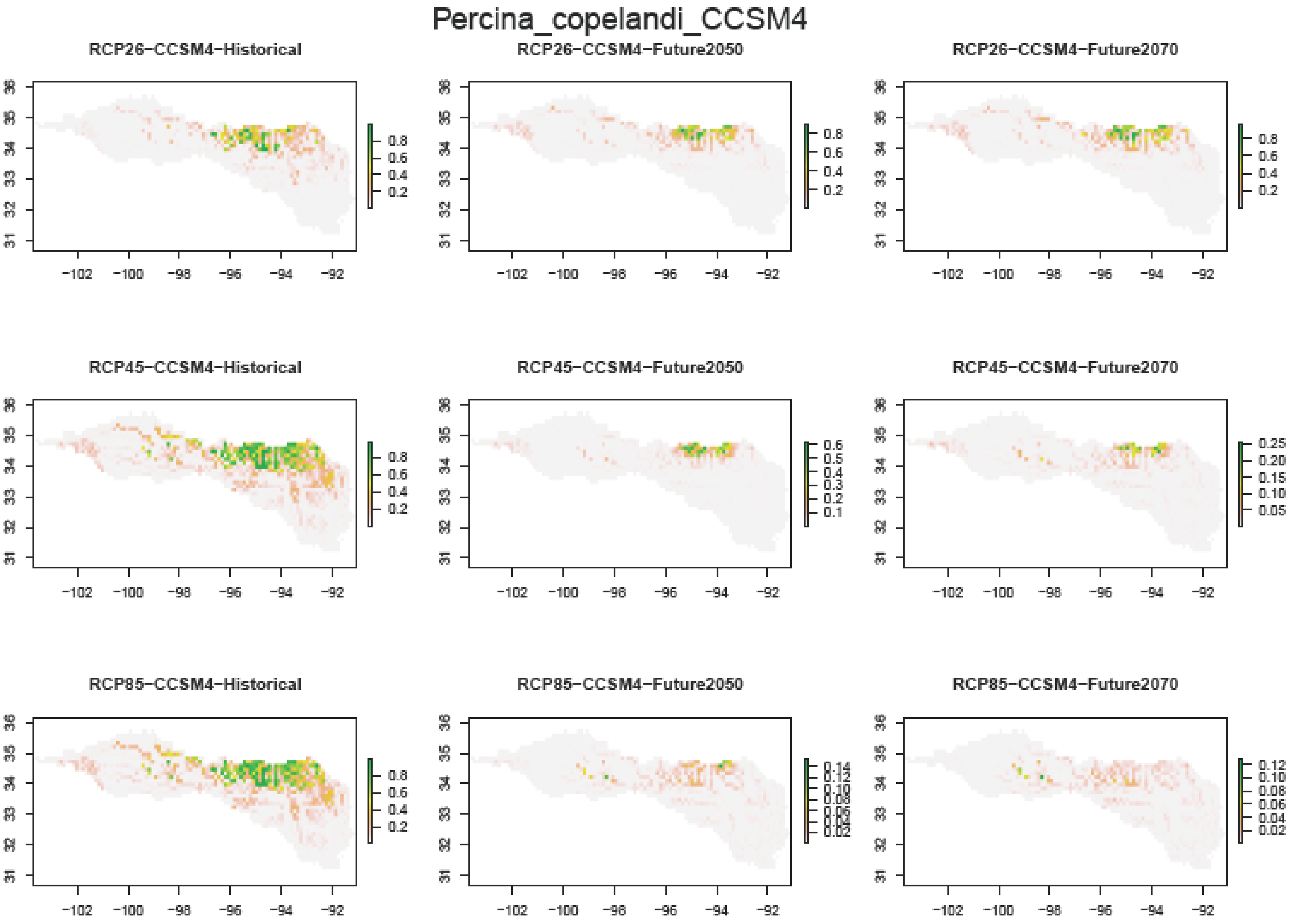
RCP45-MPI_ESM_LR-Future2070

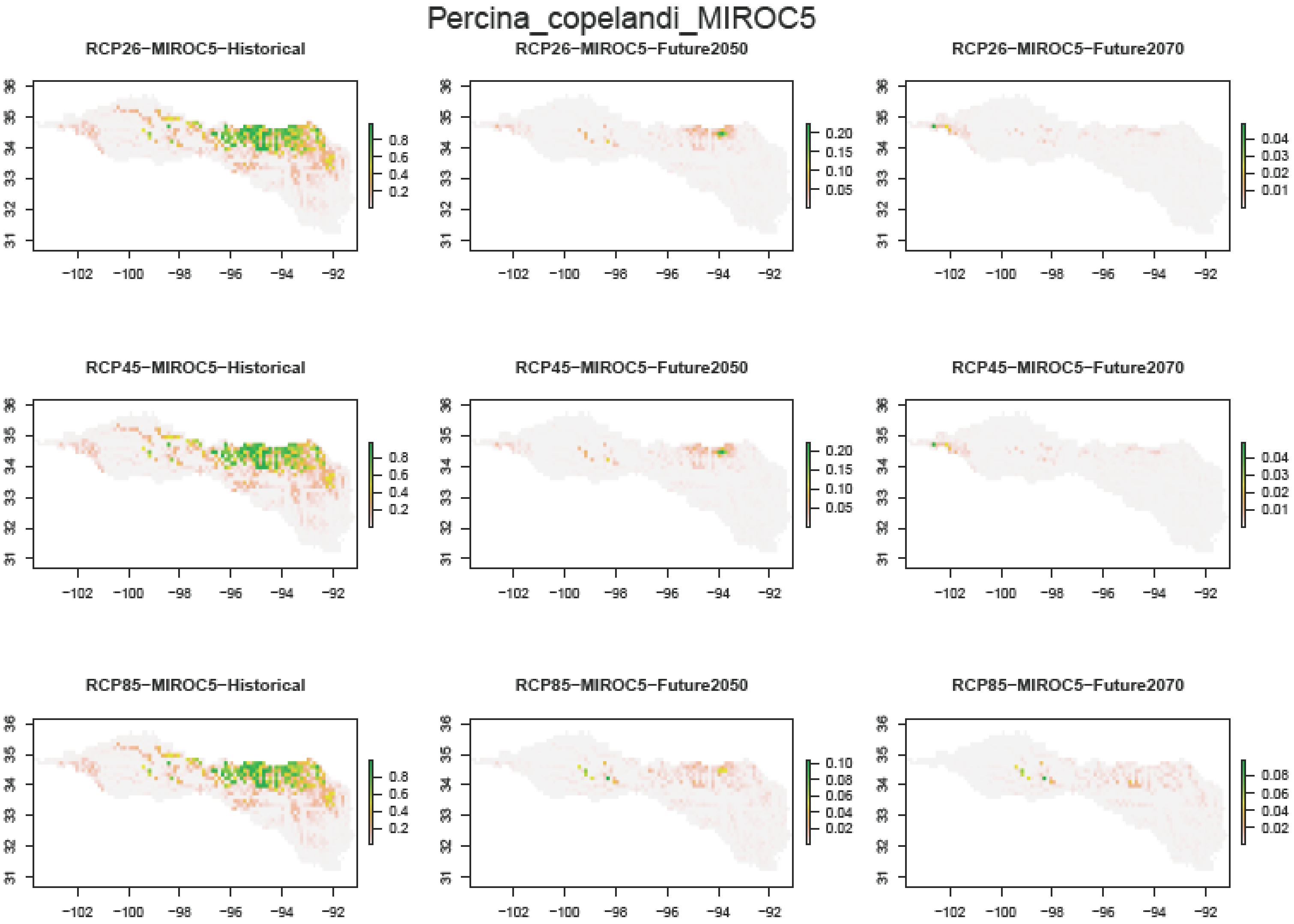
RCP85-MPI_ESM_LR-Historical

RCP85-MPI_ESM_LR-Future2050

RCP85-MPI_ESM_LR-Future2070

Maxent: *Percina copelandi*




Percina_copelandi_MIROC5
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RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070
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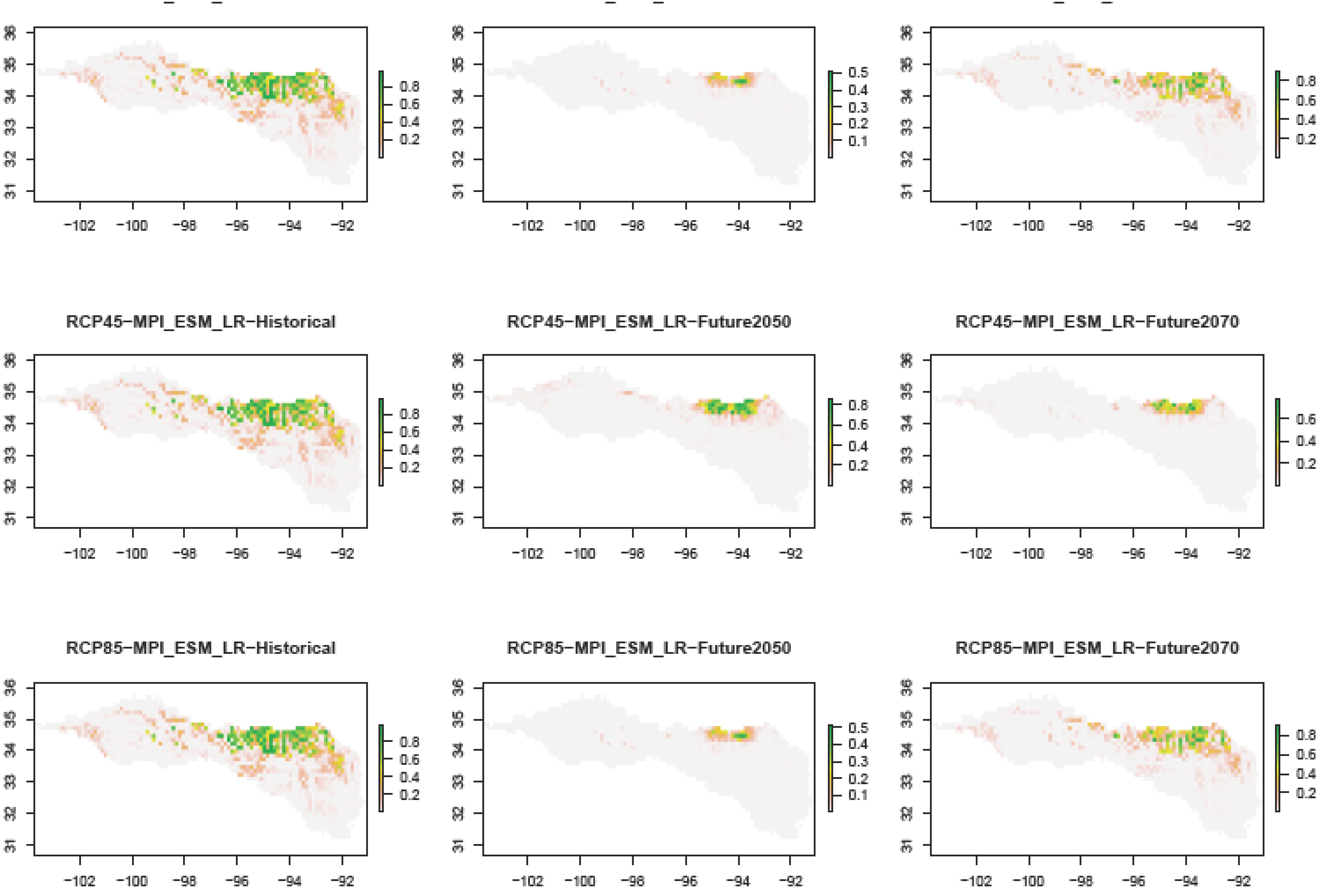
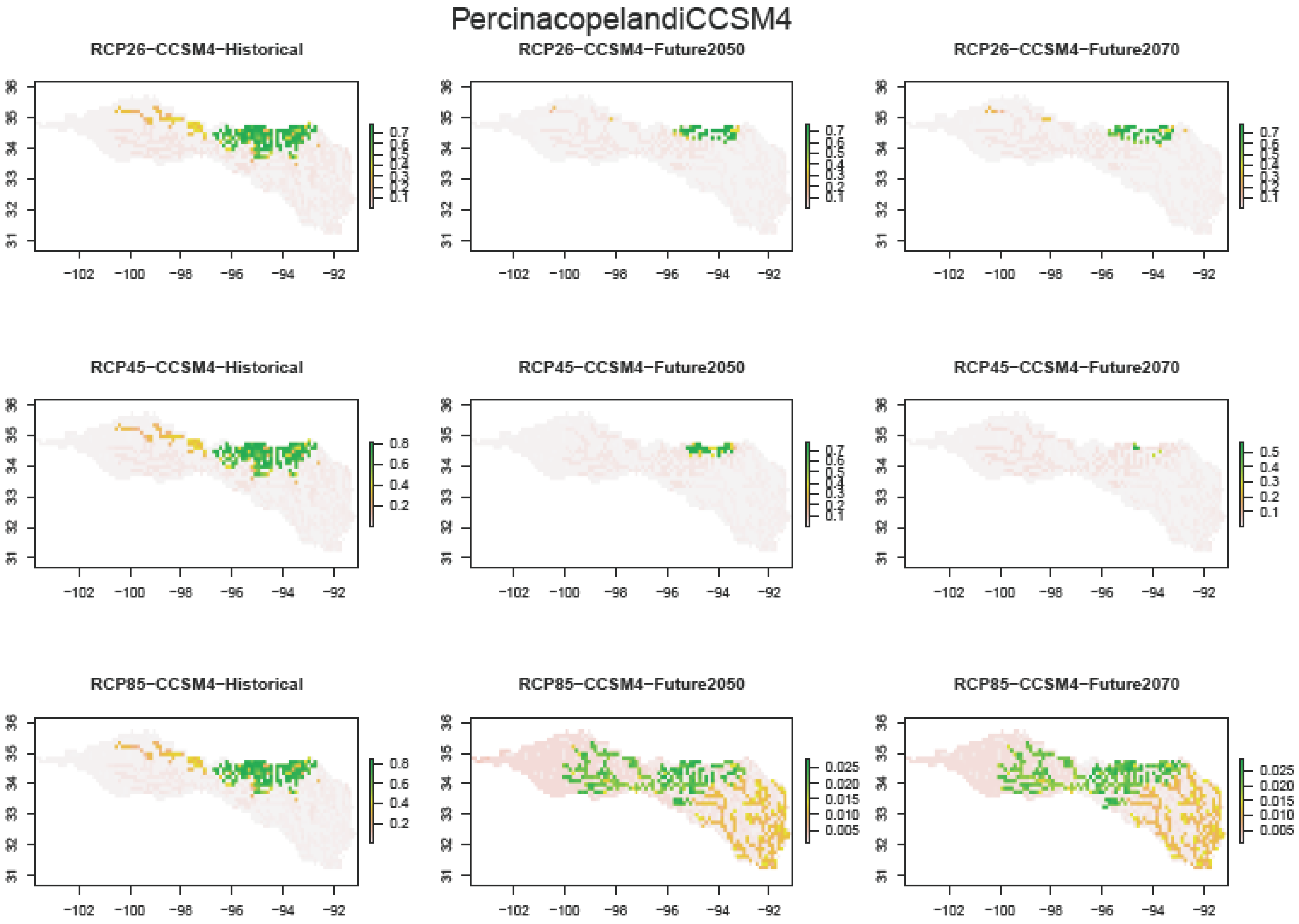
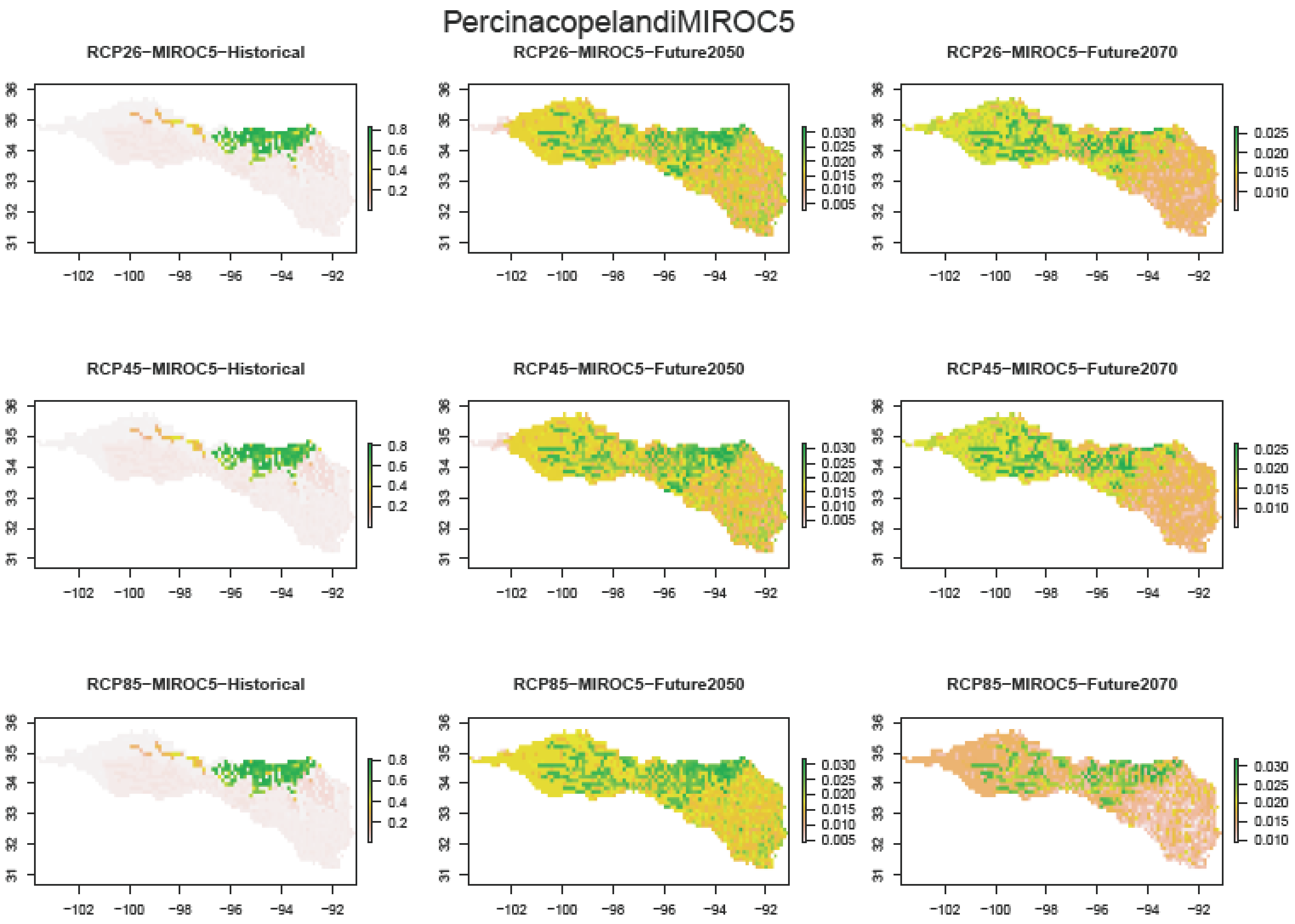
−92
0.8
0.6
0.4
0.2
0.20
0.15
0.10
0.05
0.04
0.03
0.02
0.01
0.10
0.08
0.06
0.04
0.02
0.08
0.06
0.04
0.02

Percina_copelandi_MPI_ESM_LR



BRT: *Percina copelandi*





PercinacopelandiMIROC5

RCP26−MIROC5−Historical

RCP26−MIROC5−Future2050

RCP26−MIROC5−Future2070

RCP45−MIROC5−Historical

RCP45−MIROC5−Future2050

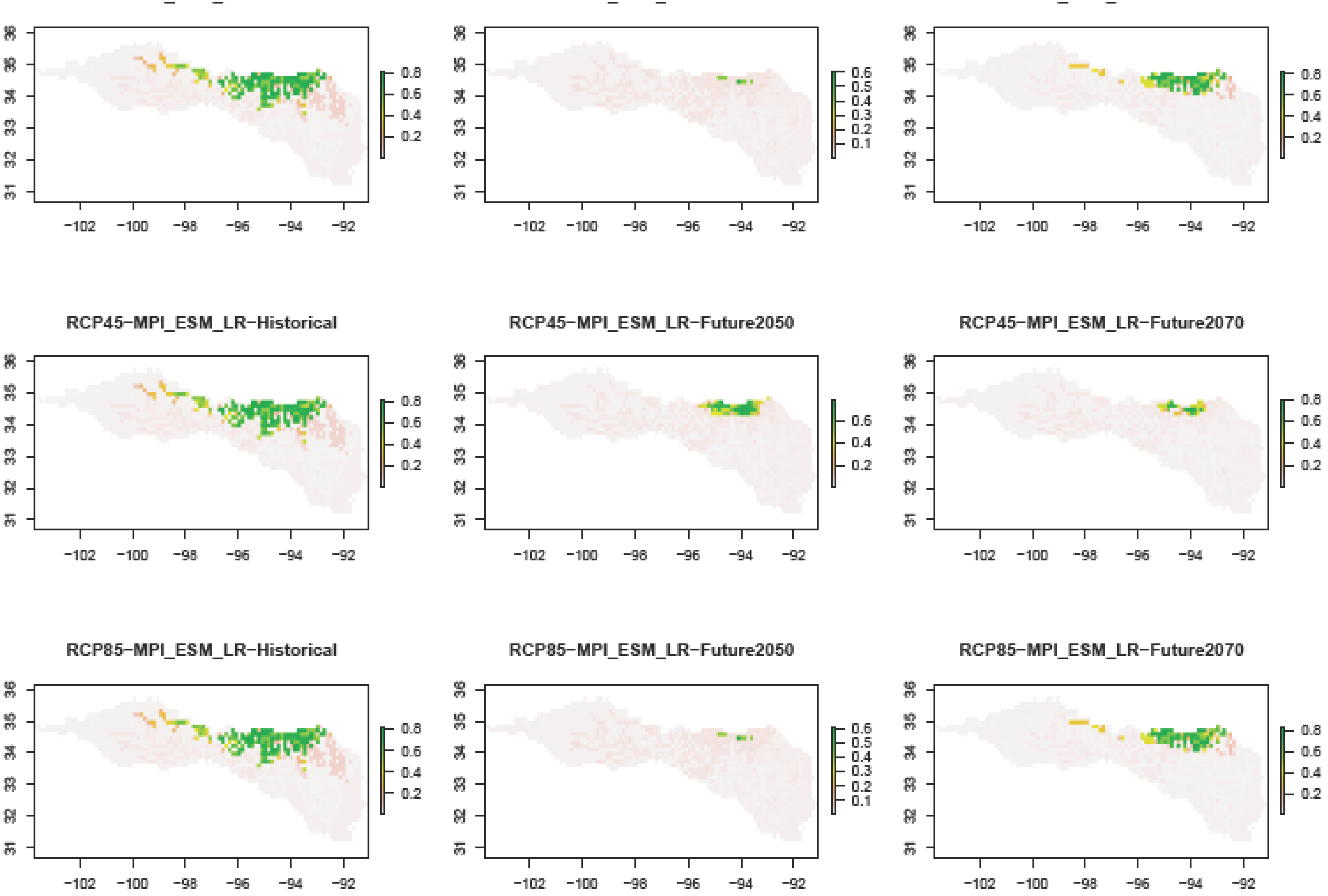
RCP45−MIROC5−Future2070

RCP85−MIROC5−Historical

RCP85−MIROC5−Future2050

RCP85−MIROC5−Future2070

PercinacopelandiMPI_ESM_LR



RCP26-MPI_ESM_LR-Historical

RCP26-MPI_ESM_LR-Future2050

RCP26-MPI_ESM_LR-Future2070

RCP45-MPI_ESM_LR-Historical

RCP45-MPI_ESM_LR-Future2050

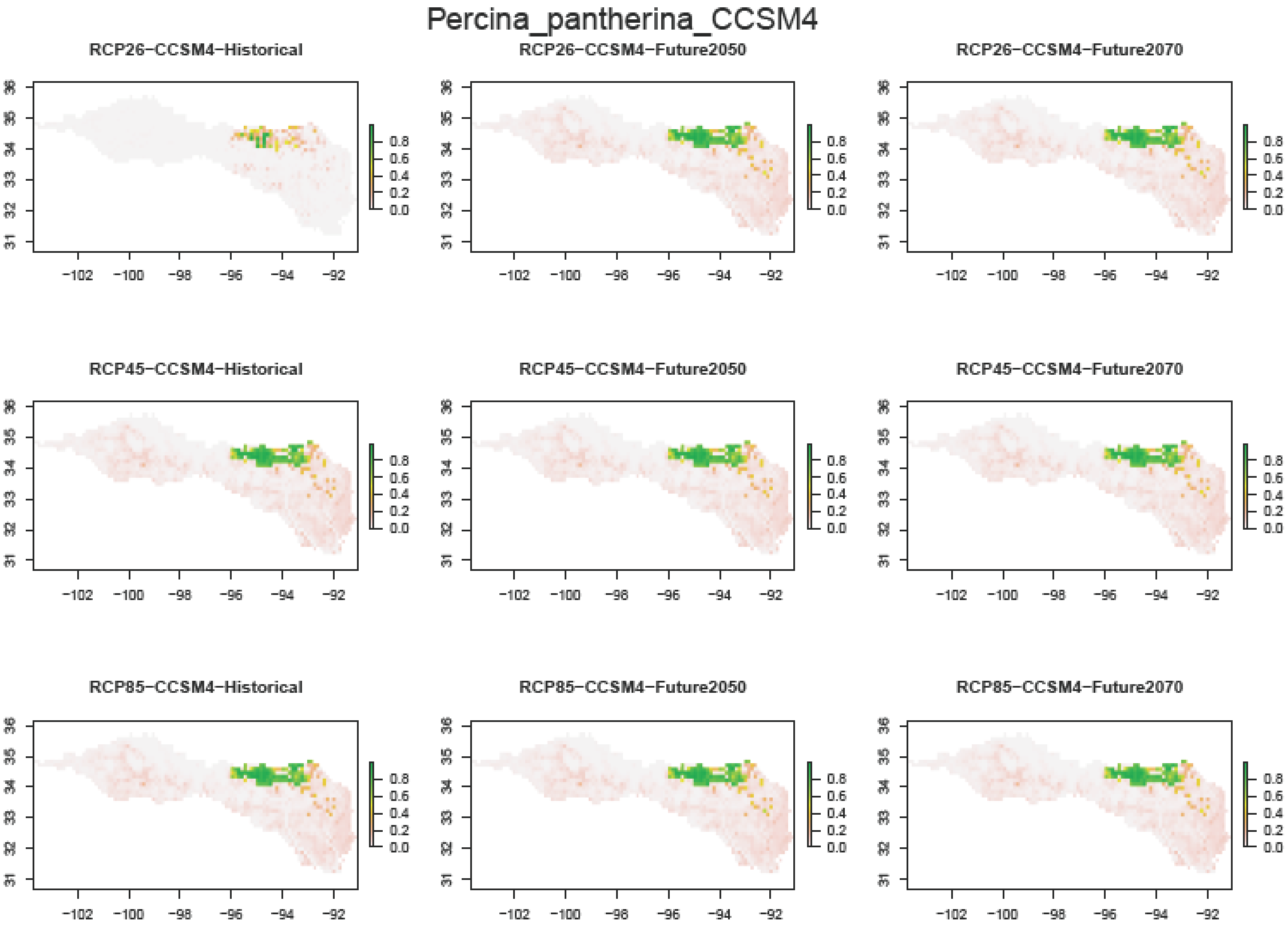
RCP45-MPI_ESM_LR-Future2070

RCP85-MPI_ESM_LR-Historical

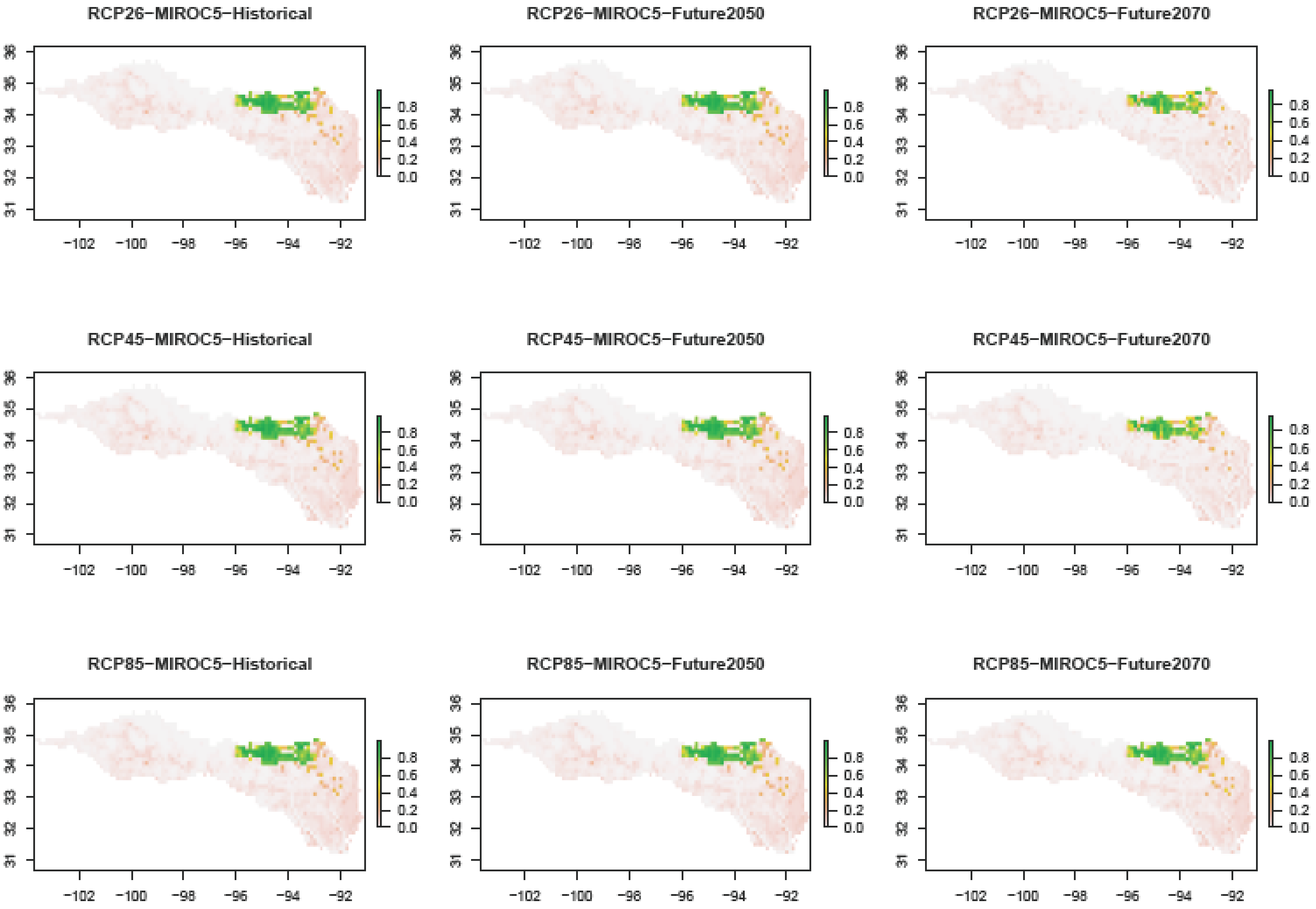
RCP85-MPI_ESM_LR-Future2050

RCP85-MPI_ESM_LR-Future2070

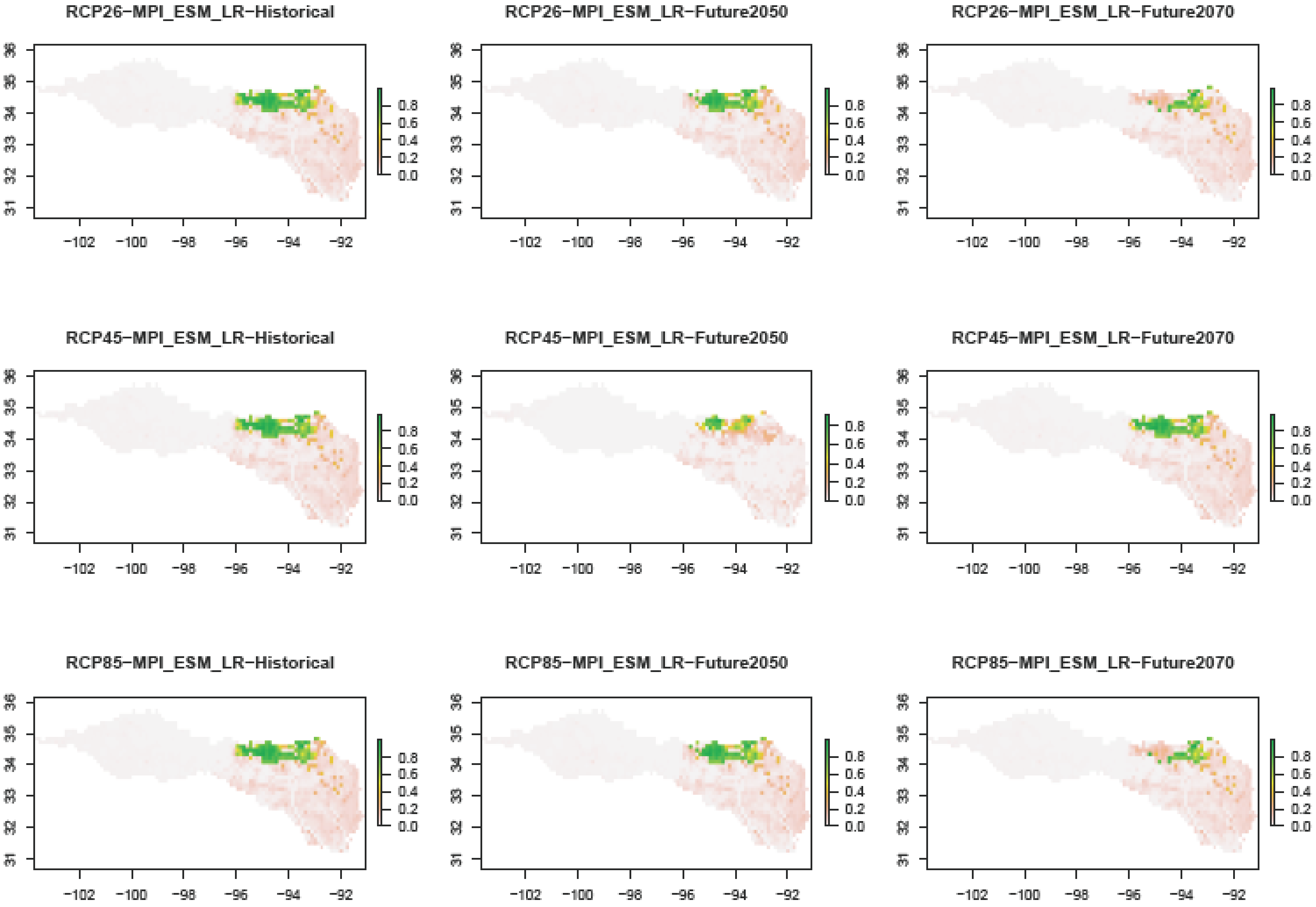
Maxent: *Percina pantherina*



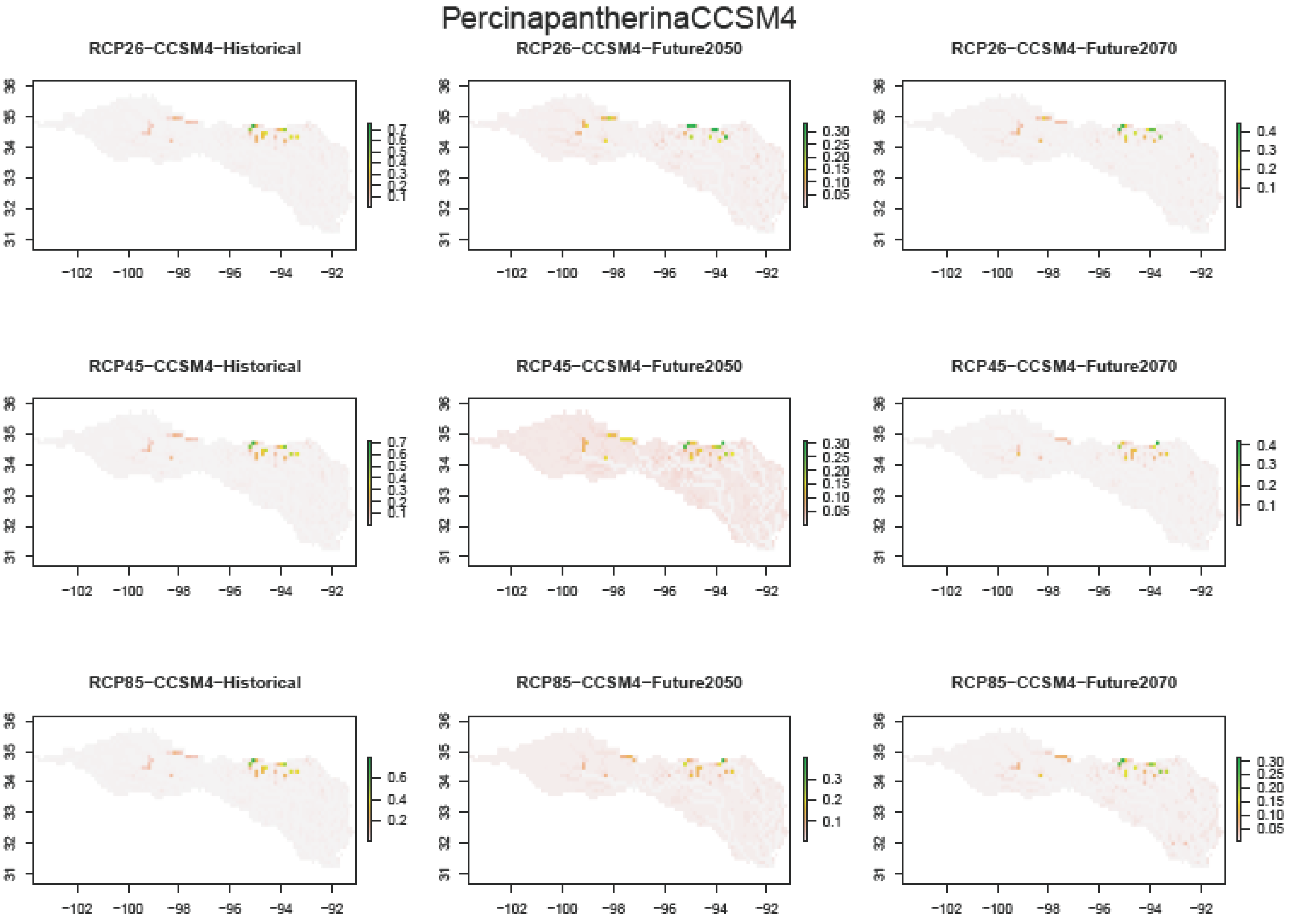
Percina_pantherina_MIROC5



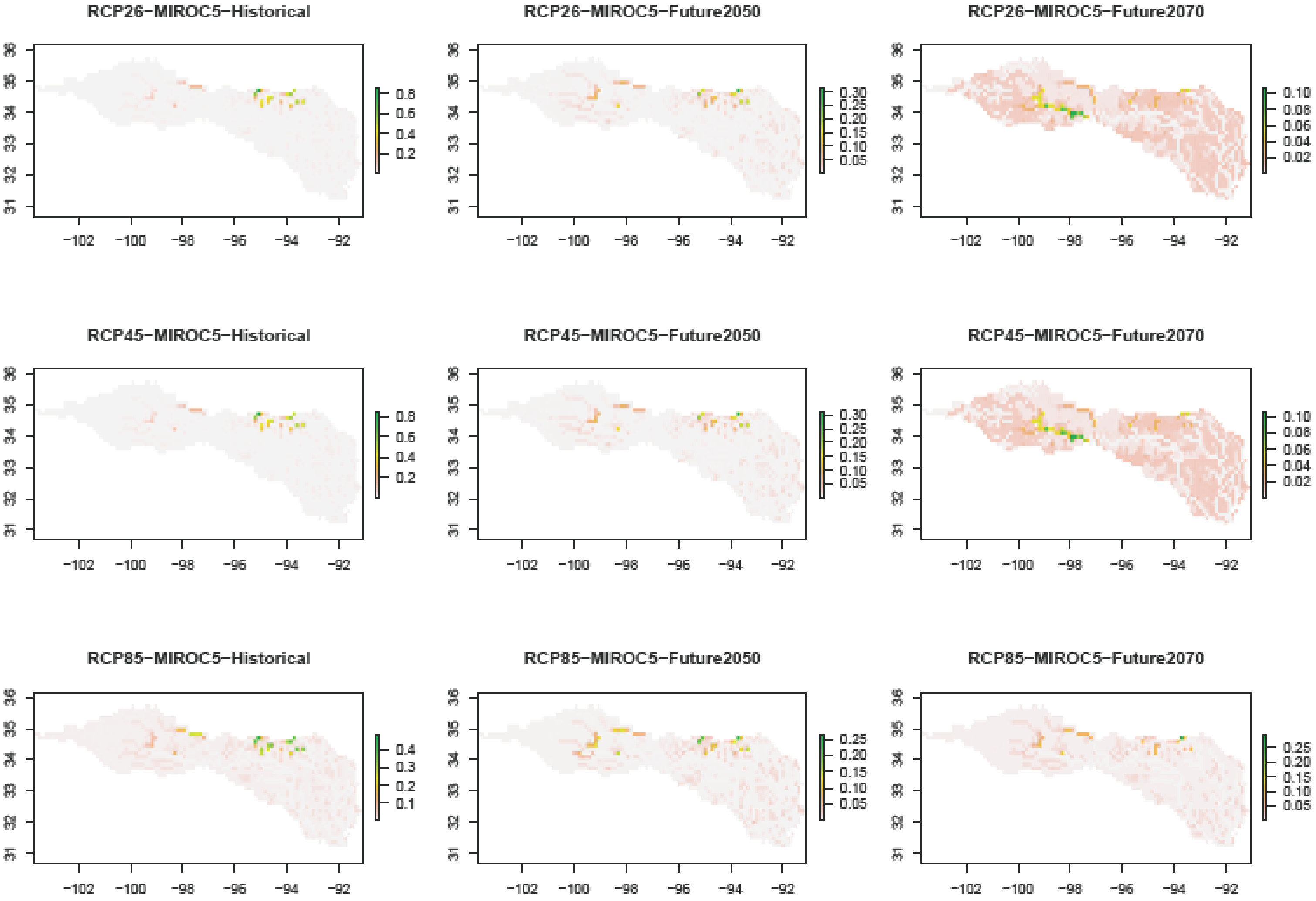
Percina_pantherina_MPI_ESM_LR



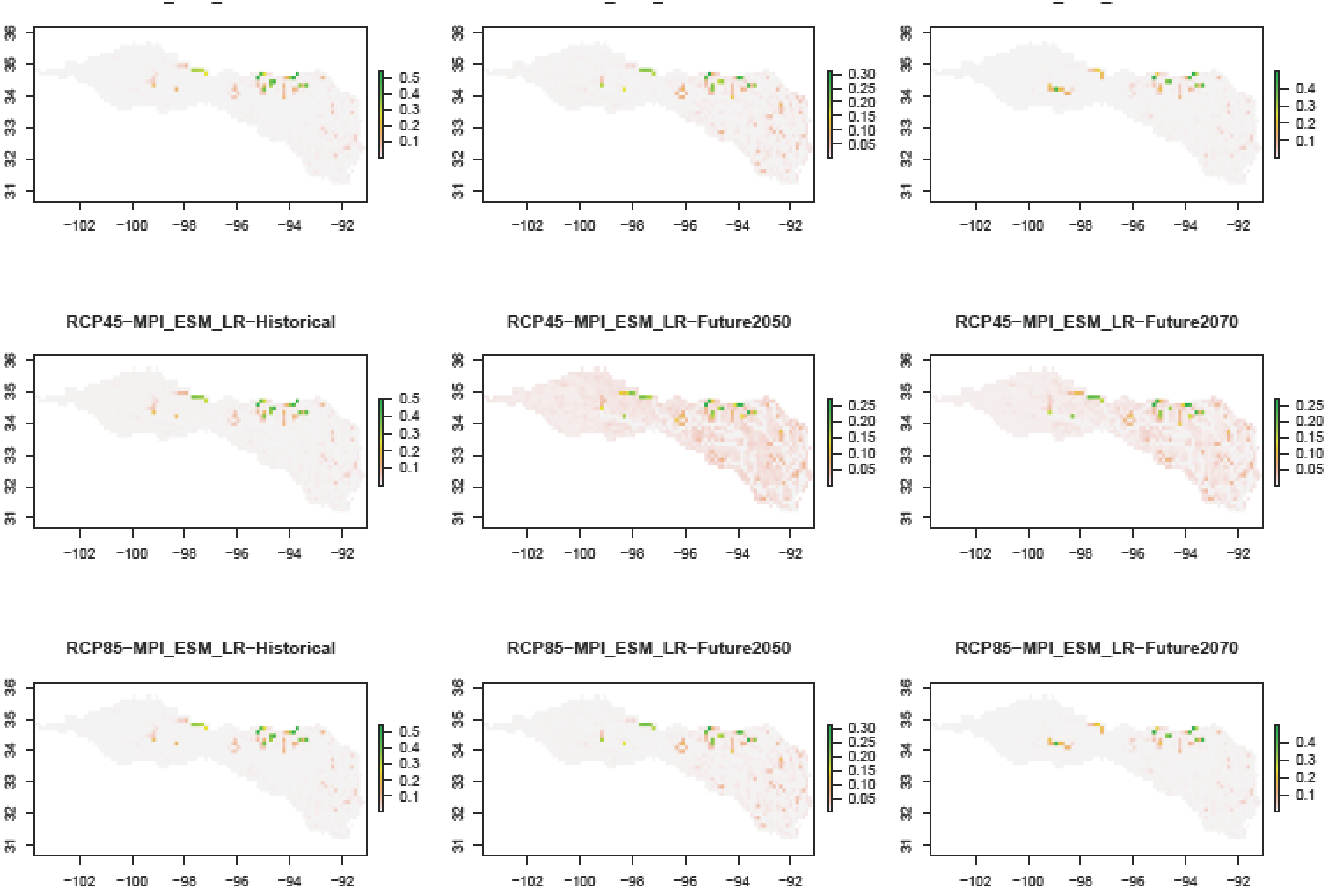
BRT: *Percina pantherina*



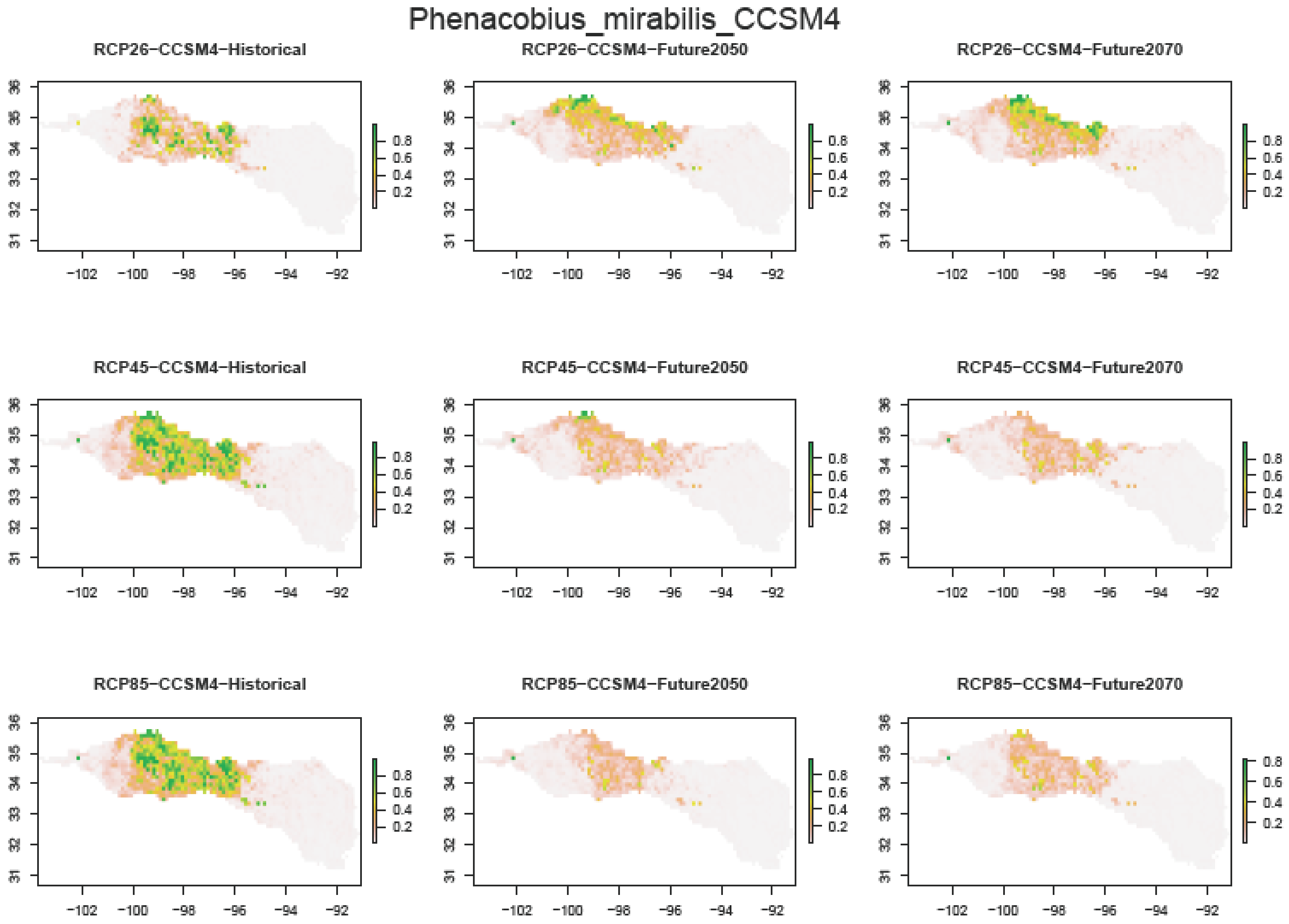
PercinapantherinaMIROC5



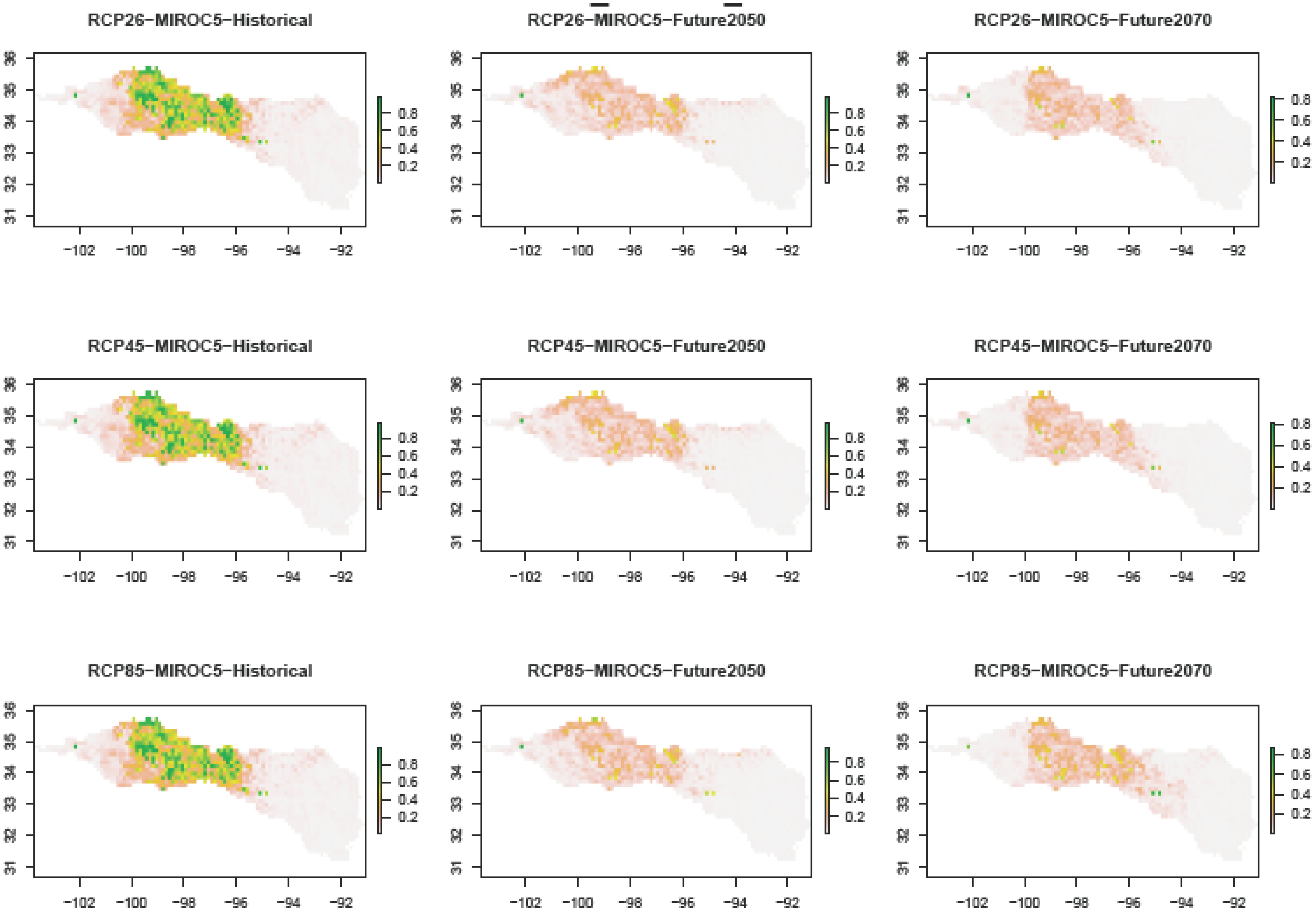
PercinapantherinaMPI_ESM_LR



Maxent: *Phenacobius mirabilis*



Phenacobius_mirabilis_MIROC5


RCP26−MIROC5−Historical

RCP26−MIROC5−Future2050

RCP26−MIROC5−Future2070

RCP45−MIROC5−Historical

RCP45−MIROC5−Future2050

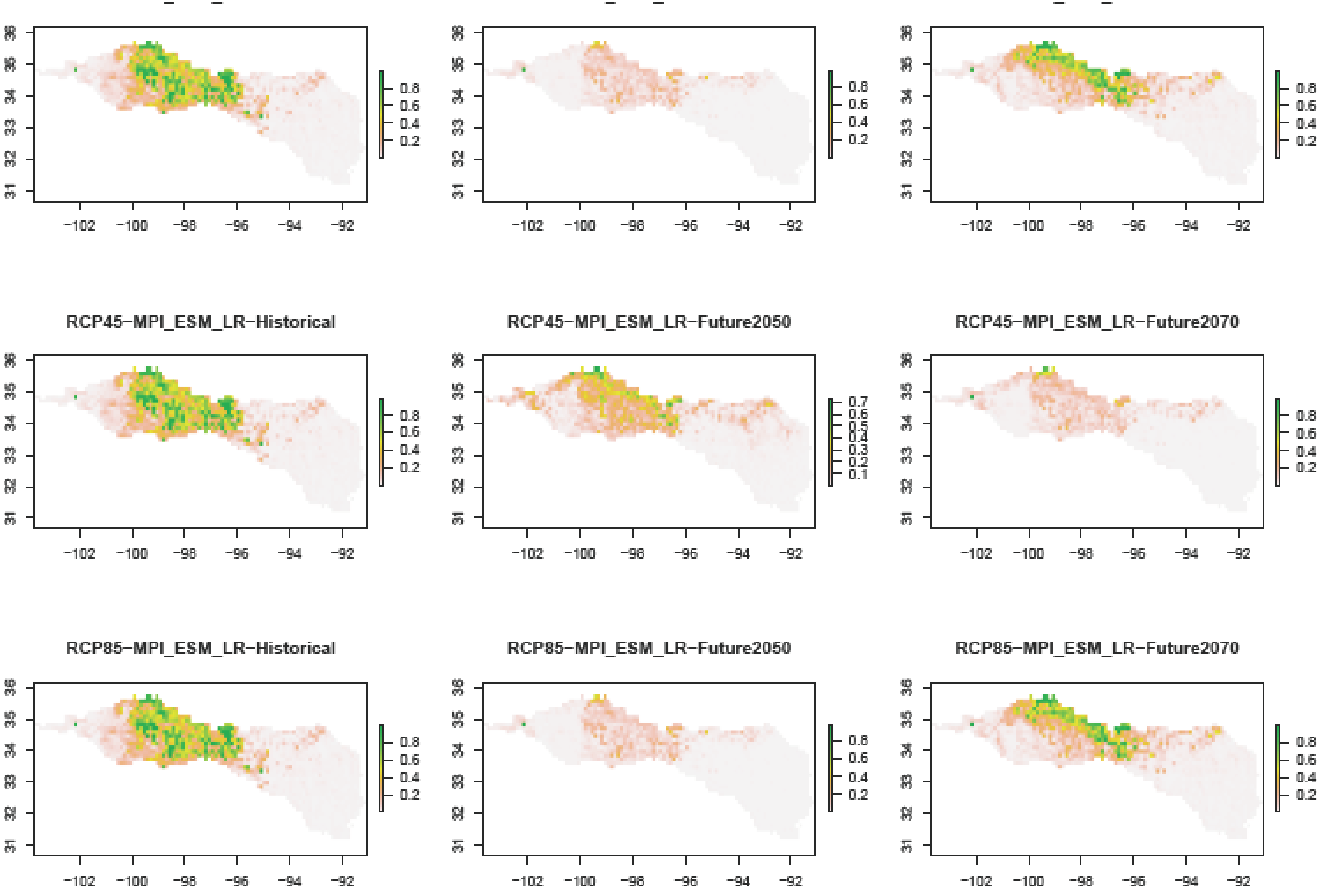
RCP45−MIROC5−Future2070

RCP85−MIROC5−Historical

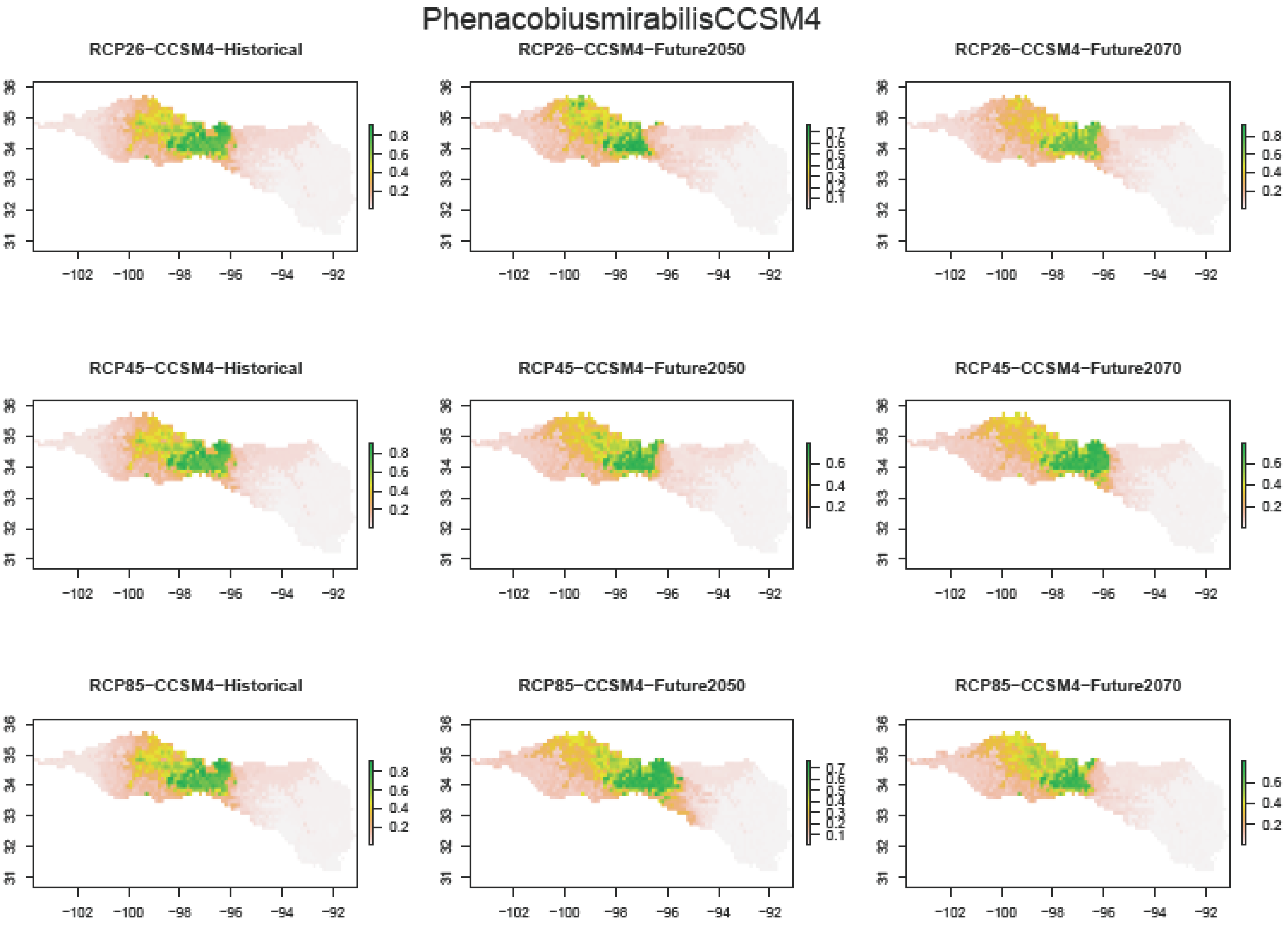
RCP85−MIROC5−Future2050

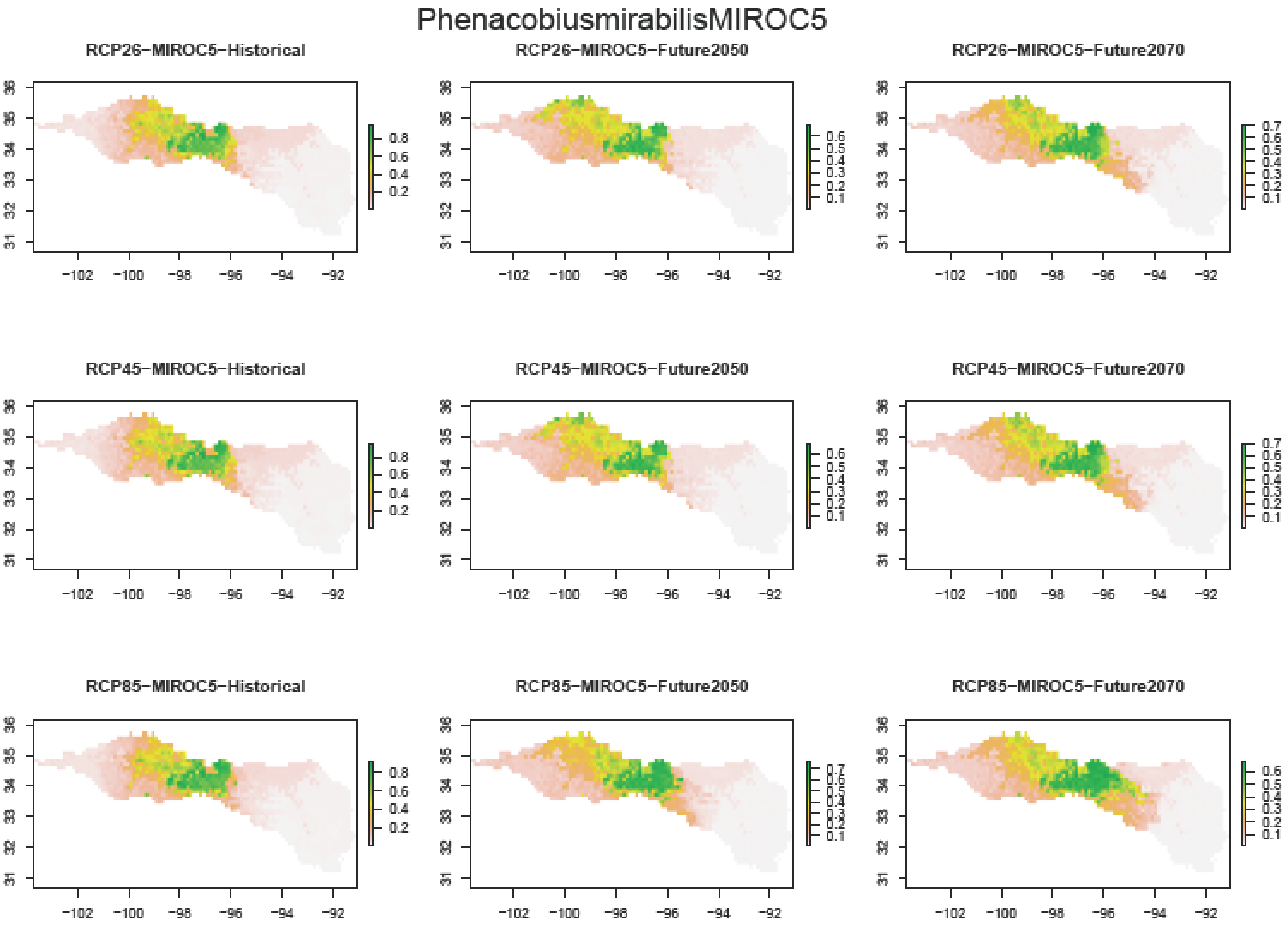
RCP85−MIROC5−Future2070

Phenacobius_mirabilis_MPI_ESM_LR

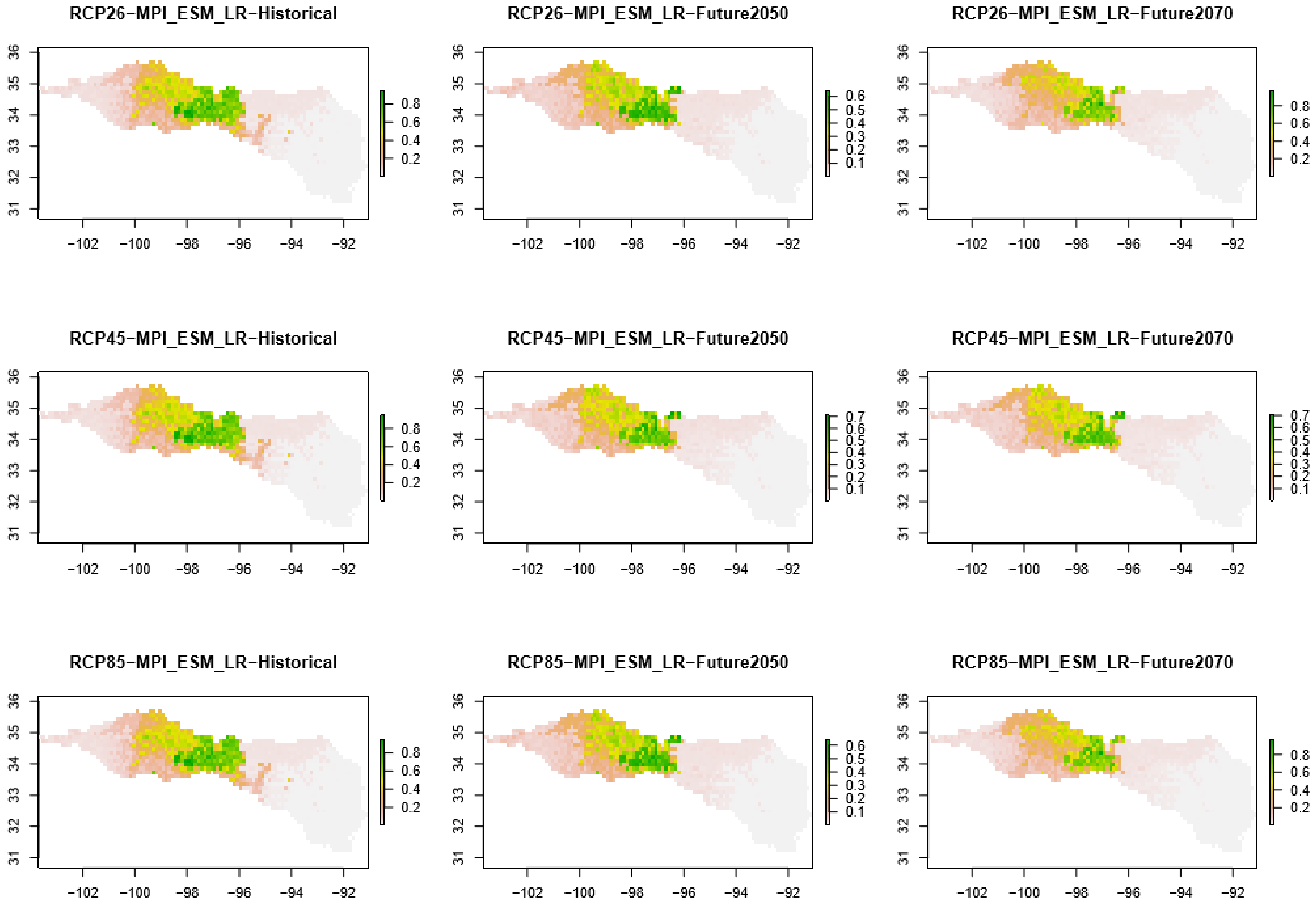


BRT: *Phenacobius mirabilis*




PhenacobiusmirabilisMIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070
31
32
33
34
35
36
−102
−100
−98
−96
−94
−92
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8

PhenacobiusmirabilisMPI_ESM_LR


RCP26−MPI_ESM_LR−Historical

RCP26−MPI_ESM_LR−Future2050

RCP26−MPI_ESM_LR−Future2070

RCP45−MPI_ESM_LR−Historical

RCP45−MPI_ESM_LR−Future2050

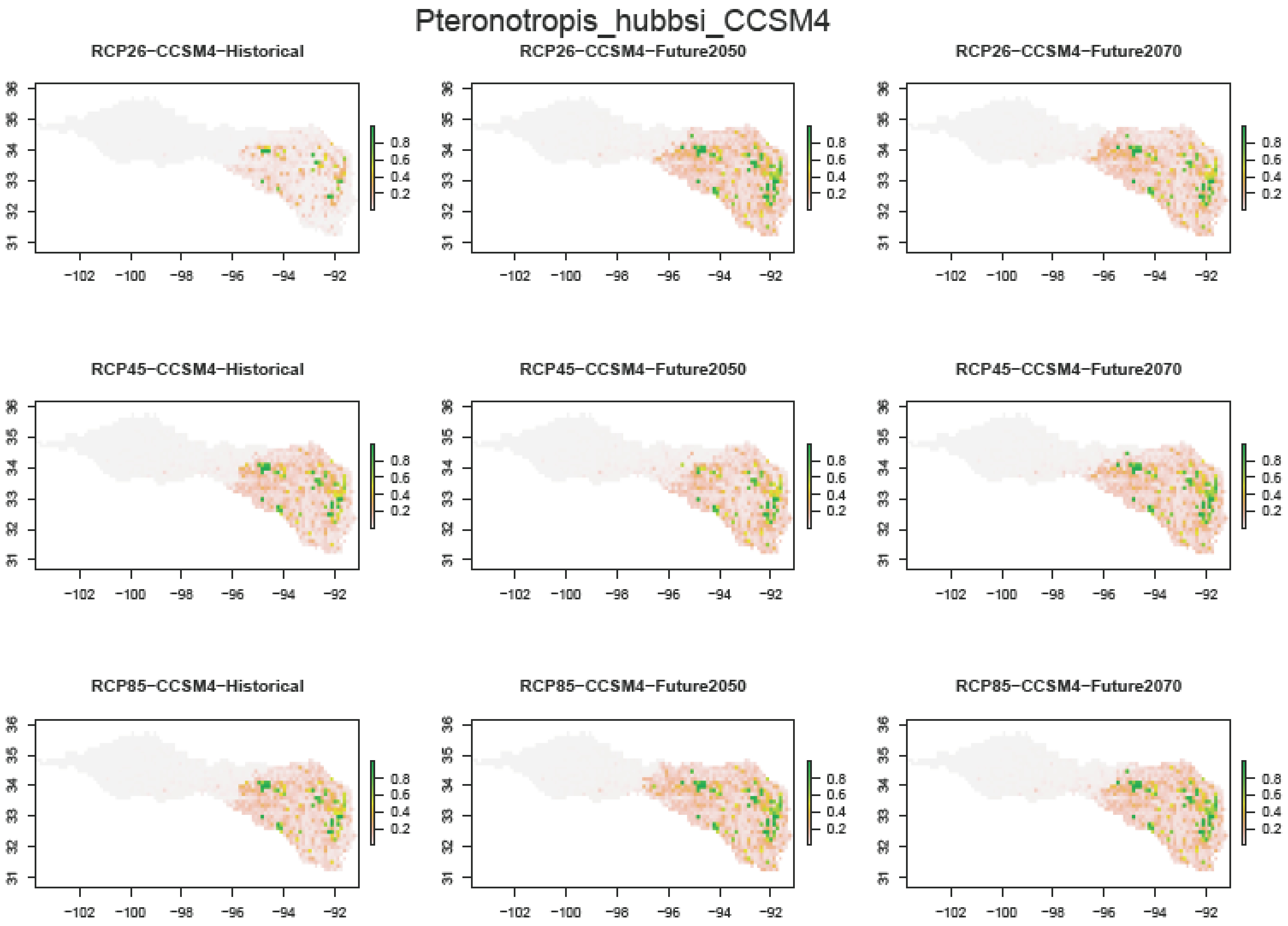
RCP45−MPI_ESM_LR−Future2070

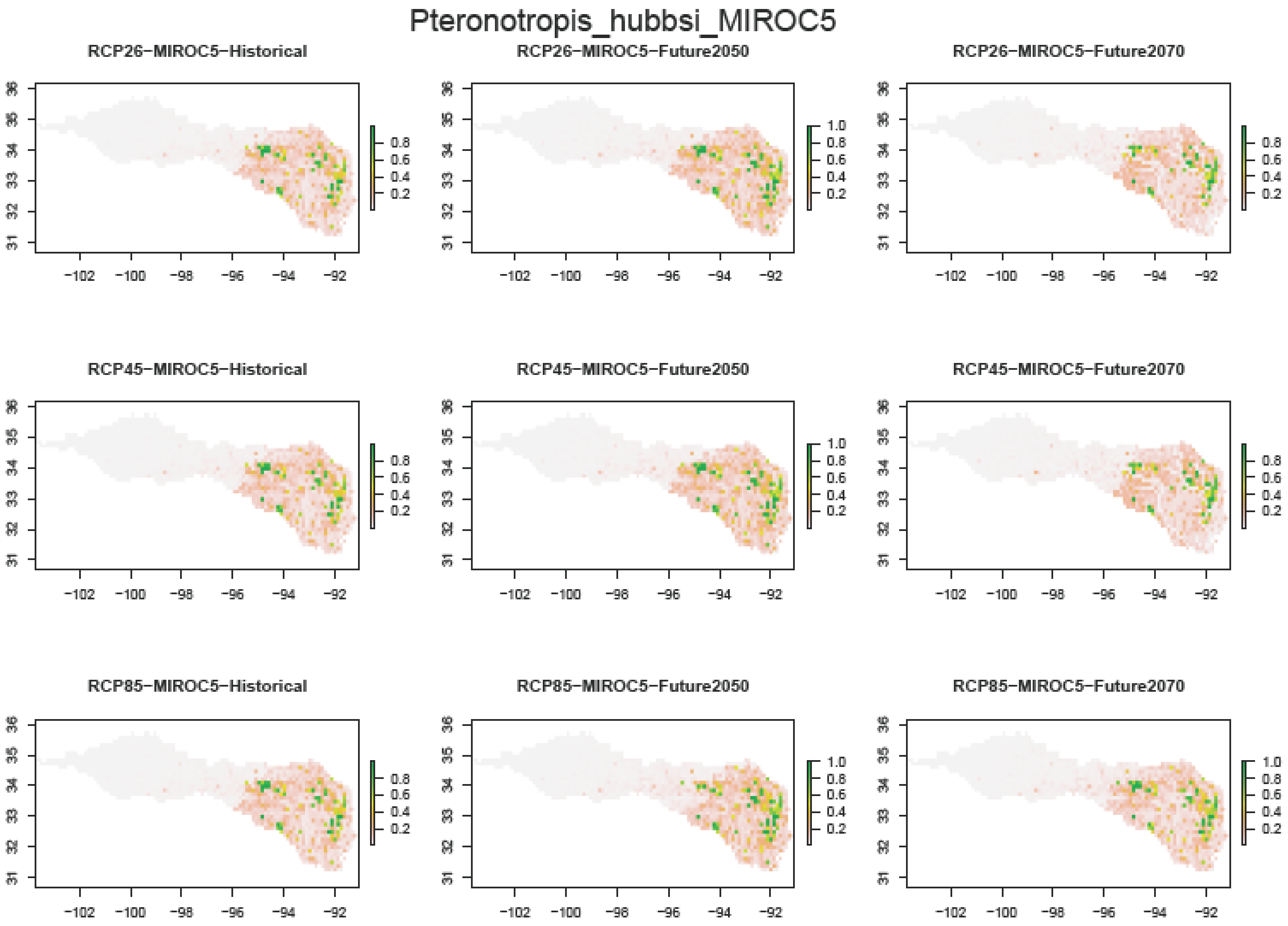
RCP85−MPI_ESM_LR−Historical

RCP85−MPI_ESM_LR−Future2050

RCP85−MPI_ESM_LR−Future2070

Maxent: *Pteronotropis hubbsi*





Pteronotropis_hubbsi_MIROC5

RCP26-MIROC5-Historical

RCP26-MIROC5-Future2050

RCP26-MIROC5-Future2070

RCP45-MIROC5-Historical

RCP45-MIROC5-Future2050

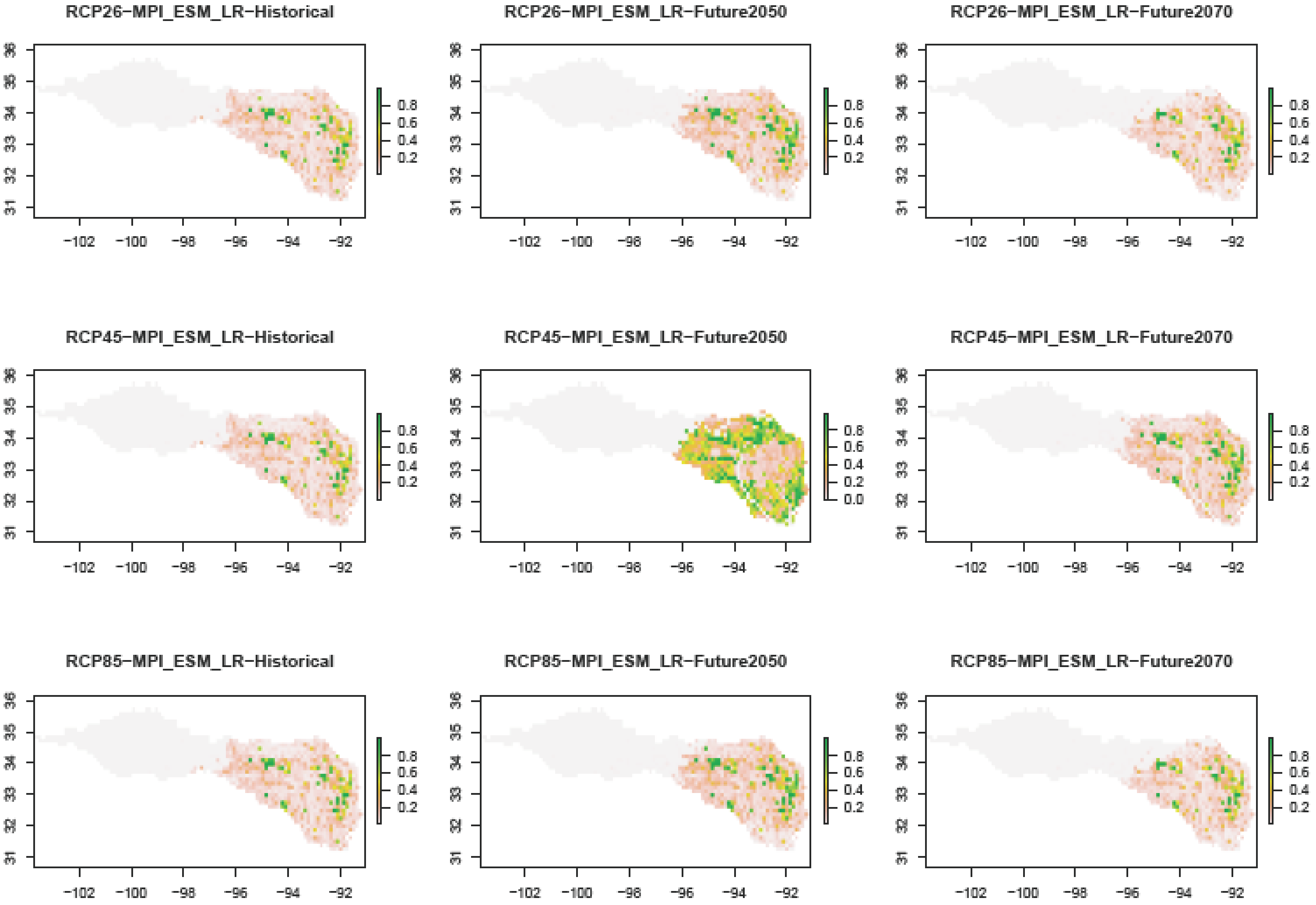
RCP45-MIROC5-Future2070

RCP85-MIROC5-Historical

RCP85-MIROC5-Future2050

RCP85-MIROC5-Future2070

Pteronotropis_hubbsi_MPI_ESM_LR



RCP26-MPI_ESM_LR-Historical

RCP26-MPI_ESM_LR-Future2050

RCP26-MPI_ESM_LR-Future2070

RCP45-MPI_ESM_LR-Historical

RCP45-MPI_ESM_LR-Future2050

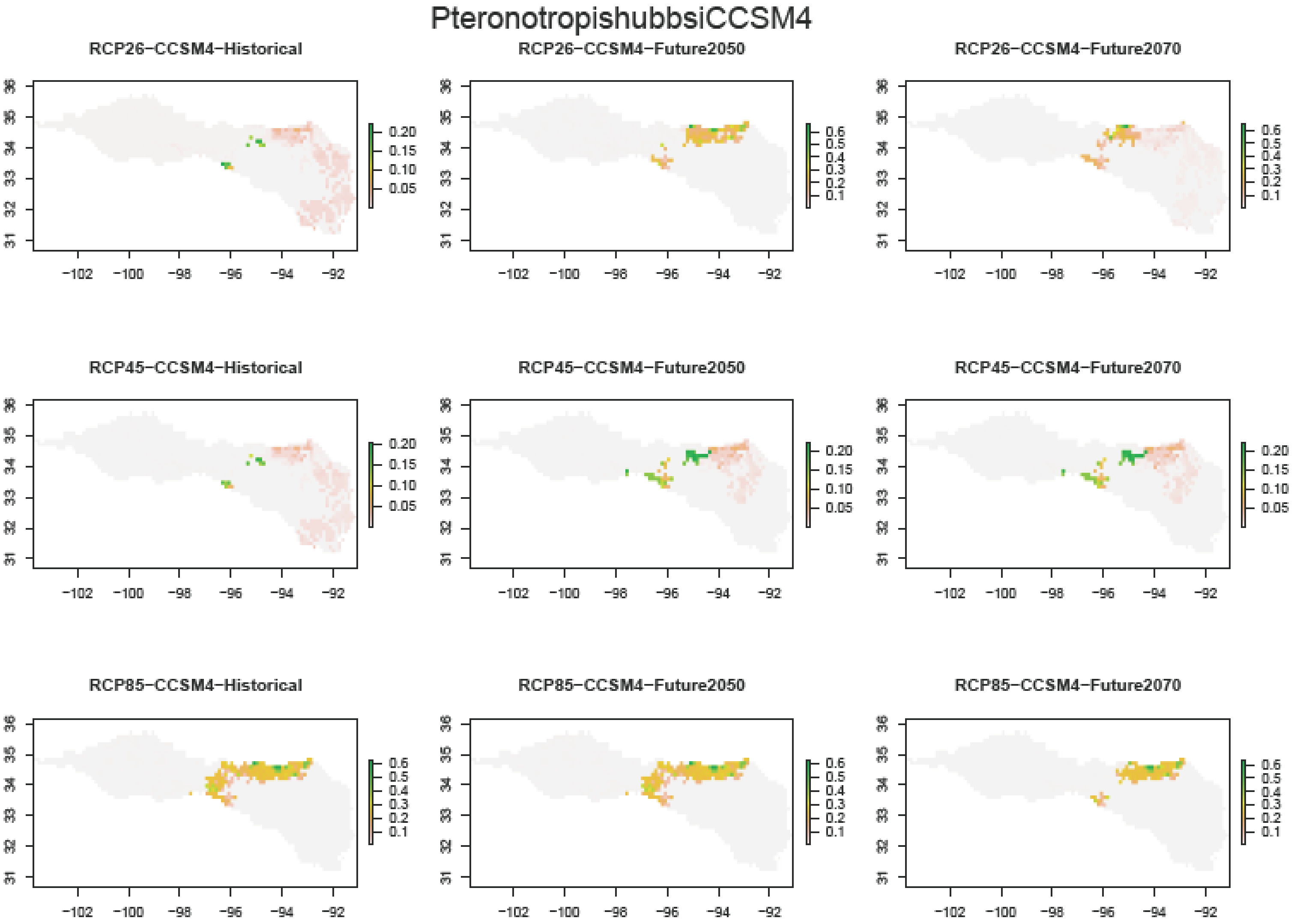
RCP45-MPI_ESM_LR-Future2070

RCP85-MPI_ESM_LR-Historical

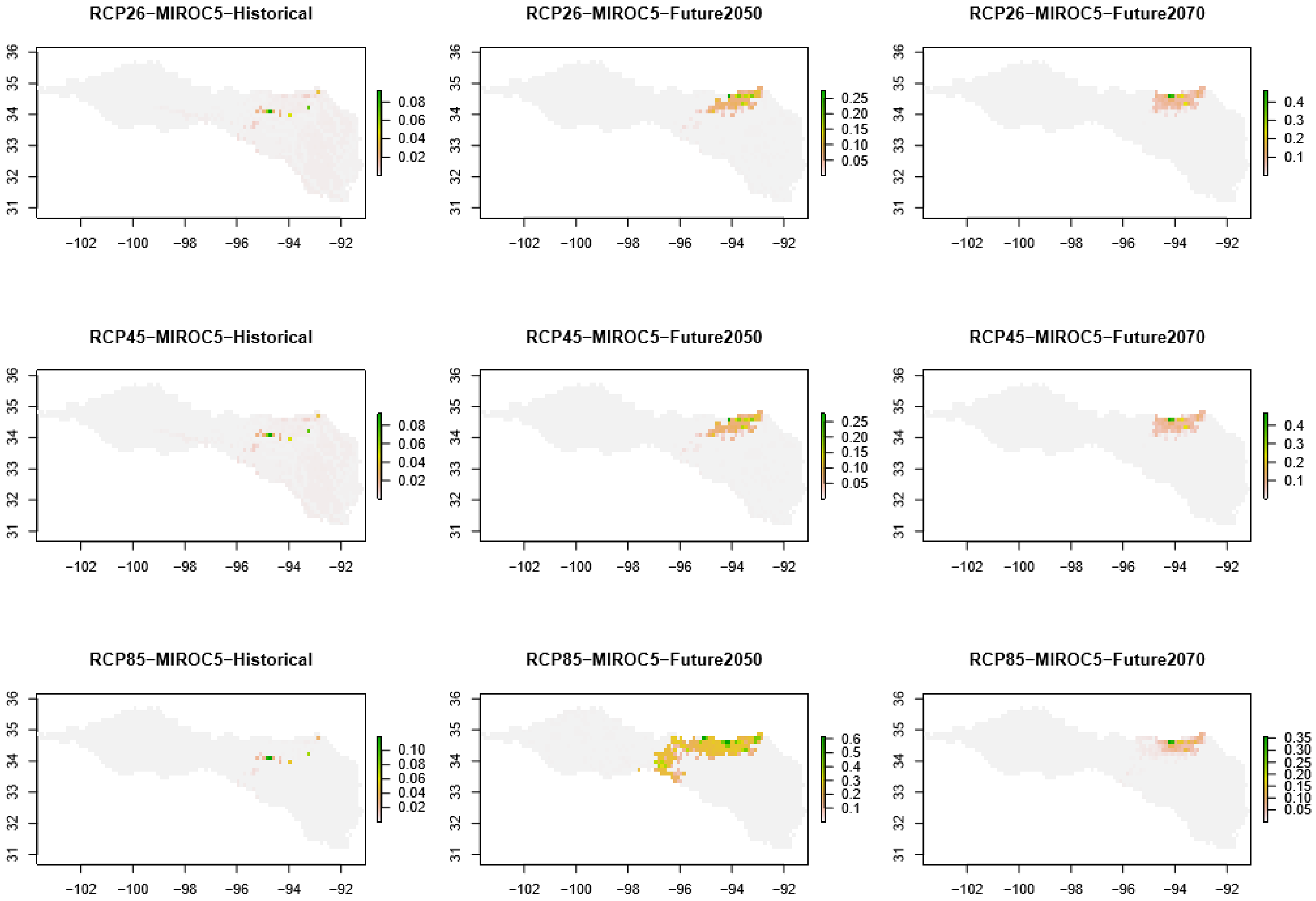
RCP85-MPI_ESM_LR-Future2050

RCP85-MPI_ESM_LR-Future2070

BRT: *Pteronotropis hubbsi*



PteronotropishubbsiMIROC5



RCP26−MIROC5−Historical

RCP26−MIROC5−Future2050

RCP26−MIROC5−Future2070

RCP45−MIROC5−Historical

RCP45−MIROC5−Future2050

RCP45−MIROC5−Future2070

RCP85−MIROC5−Historical

RCP85−MIROC5−Future2050

RCP85−MIROC5−Future2070

PteronotropishubbsiMPI_ESM_LR