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

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

A THESIS APPROVED FOR THE DEPARTMENT OF GEOGRAPHY AND ENVIRONMENTAL SUSTAINABILITY

BY

Dr. Thomas M. Neeson, Chair

Dr. Bruce Hoagland

Dr. Rebecca Loraamm

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# 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 | MAX ENT | 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/ MAR S | 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 /MAR S | 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/M ARS | 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 | GAR P | 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 | MAR S | 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 | MAX ENT | 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 $5^{th}$ and top $5^{th}$ 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 $21^{st}$ 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% |

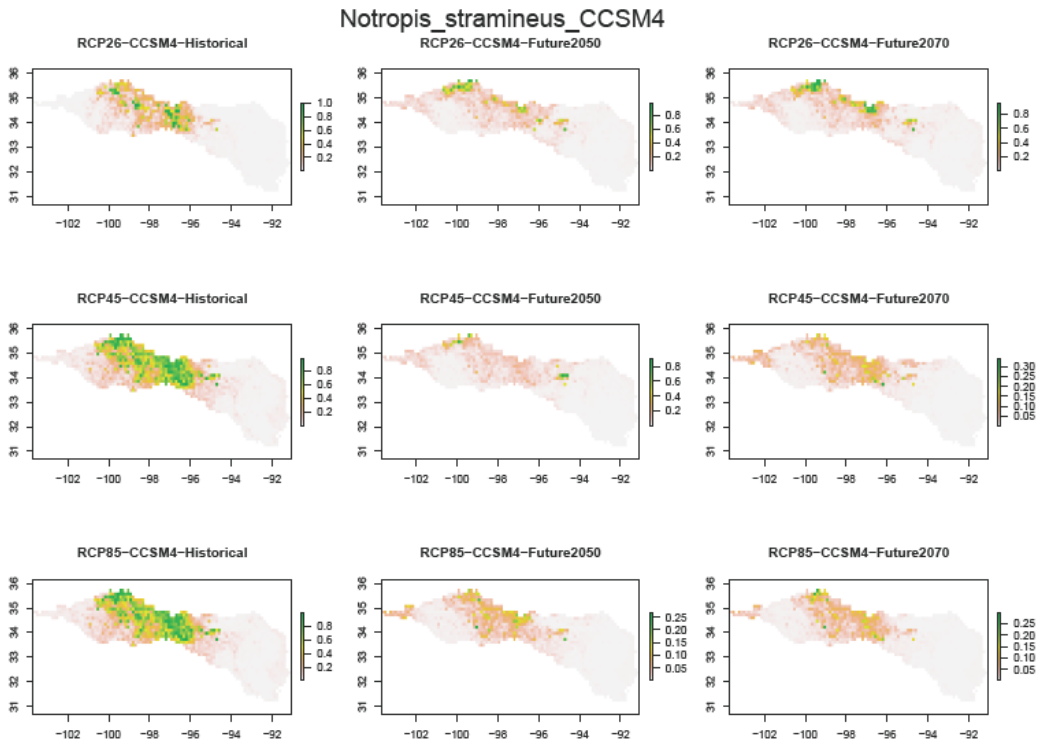



***Figure 1****: Example of raw model output from Maxent. Historical distribution (left) is each respective GCM/RCP scenario's historical occurrence and used for Maxent and BRT model training. Projections using SC-CASC climatic and hydrologic variables alter the distribution for species in 2050 (middle)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

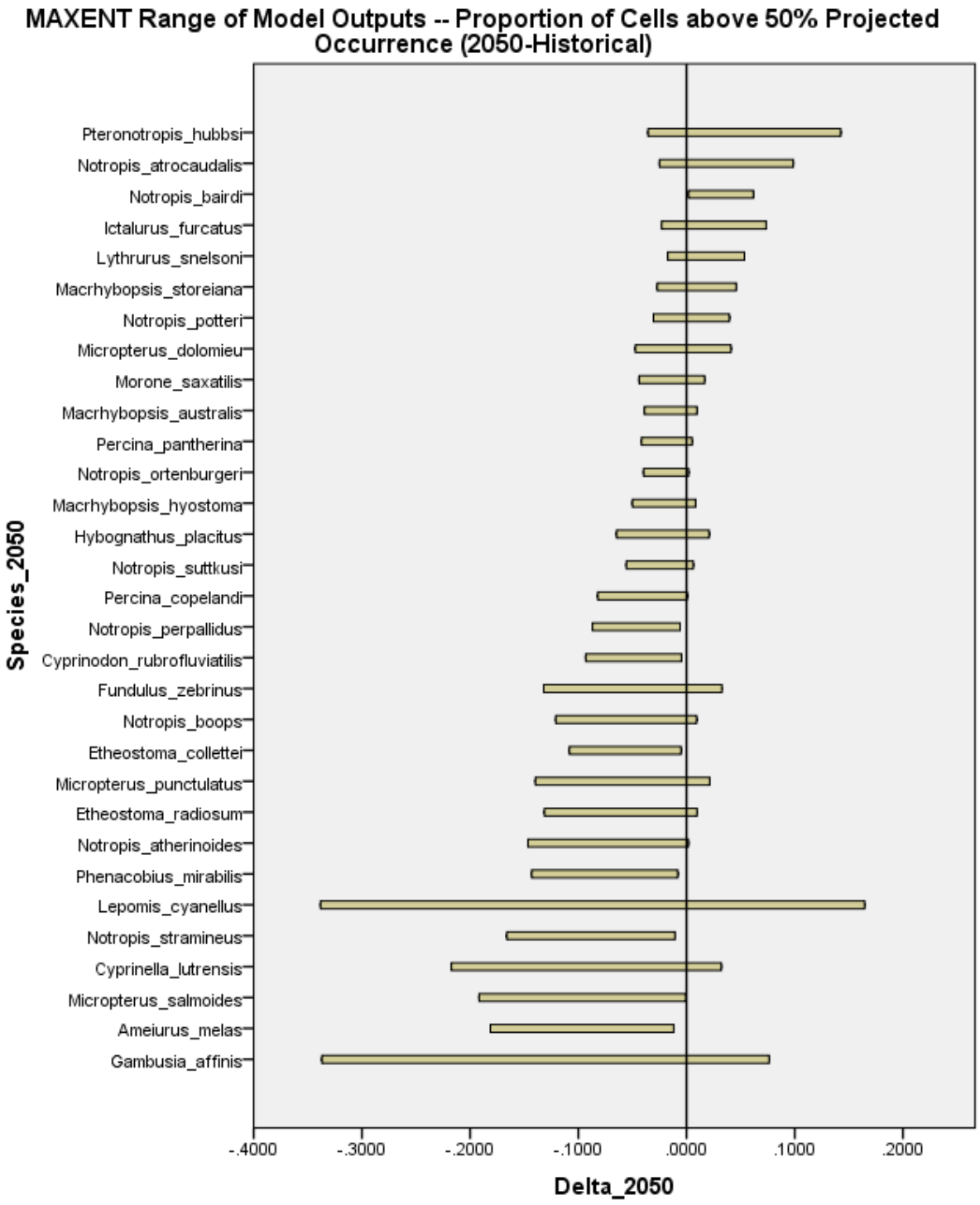



***Figure 2:*** *Variability in species' distributional shifts across 9 future climate scenarios in the Red River. For each species, the horizontal axis gives the difference in the proportion of raster cells with > 50% projected occurrence between the year 2050 and the recent historical period (year 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.*

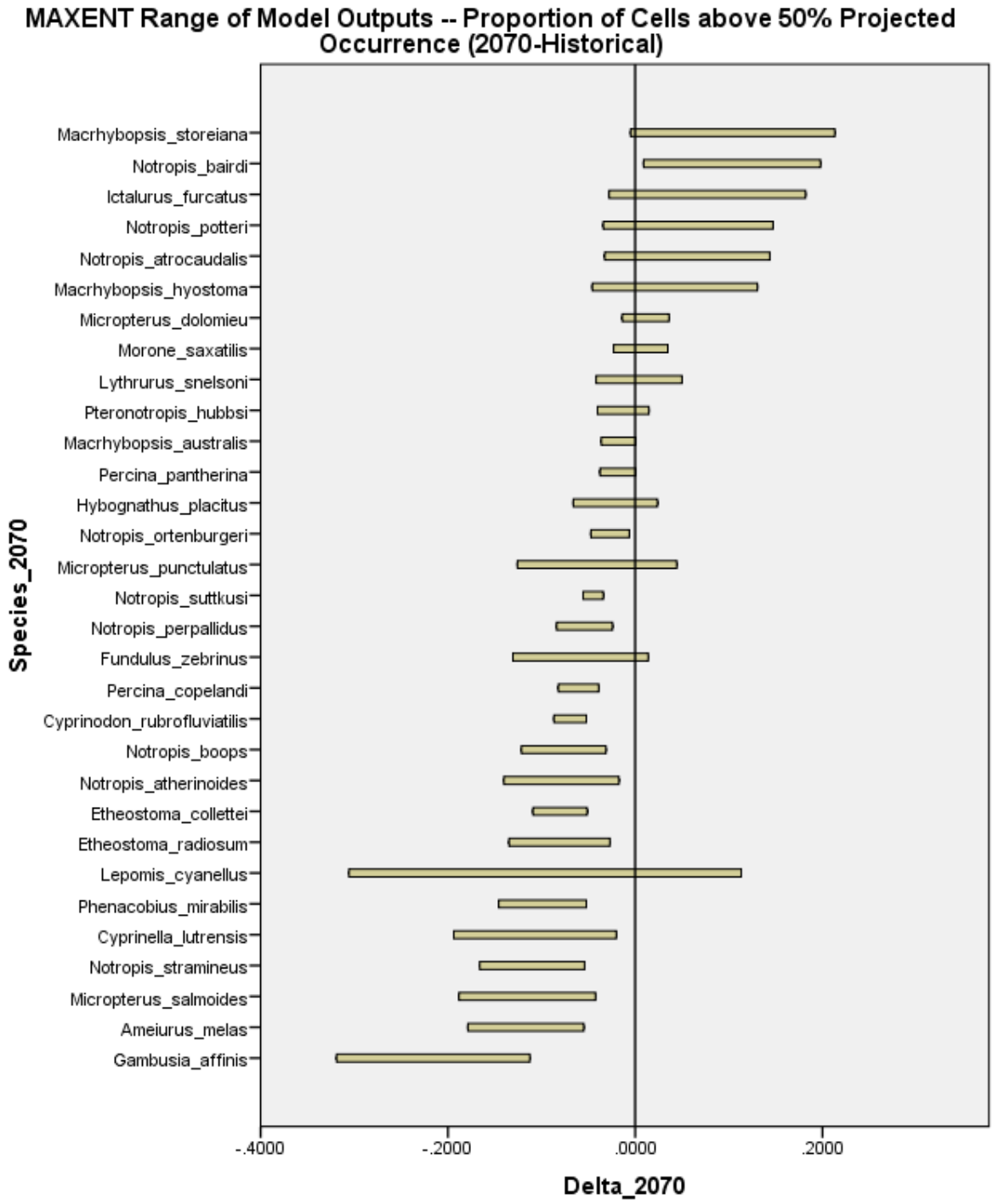



***Figure 3:*** *Variability in species' distributional shifts across 9 future climate scenarios in the Red River. For each species, the horizontal axis gives the difference in the proportion of raster cells with > 50% projected occurrence between the year 2070 and the recent historical period (year 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.*

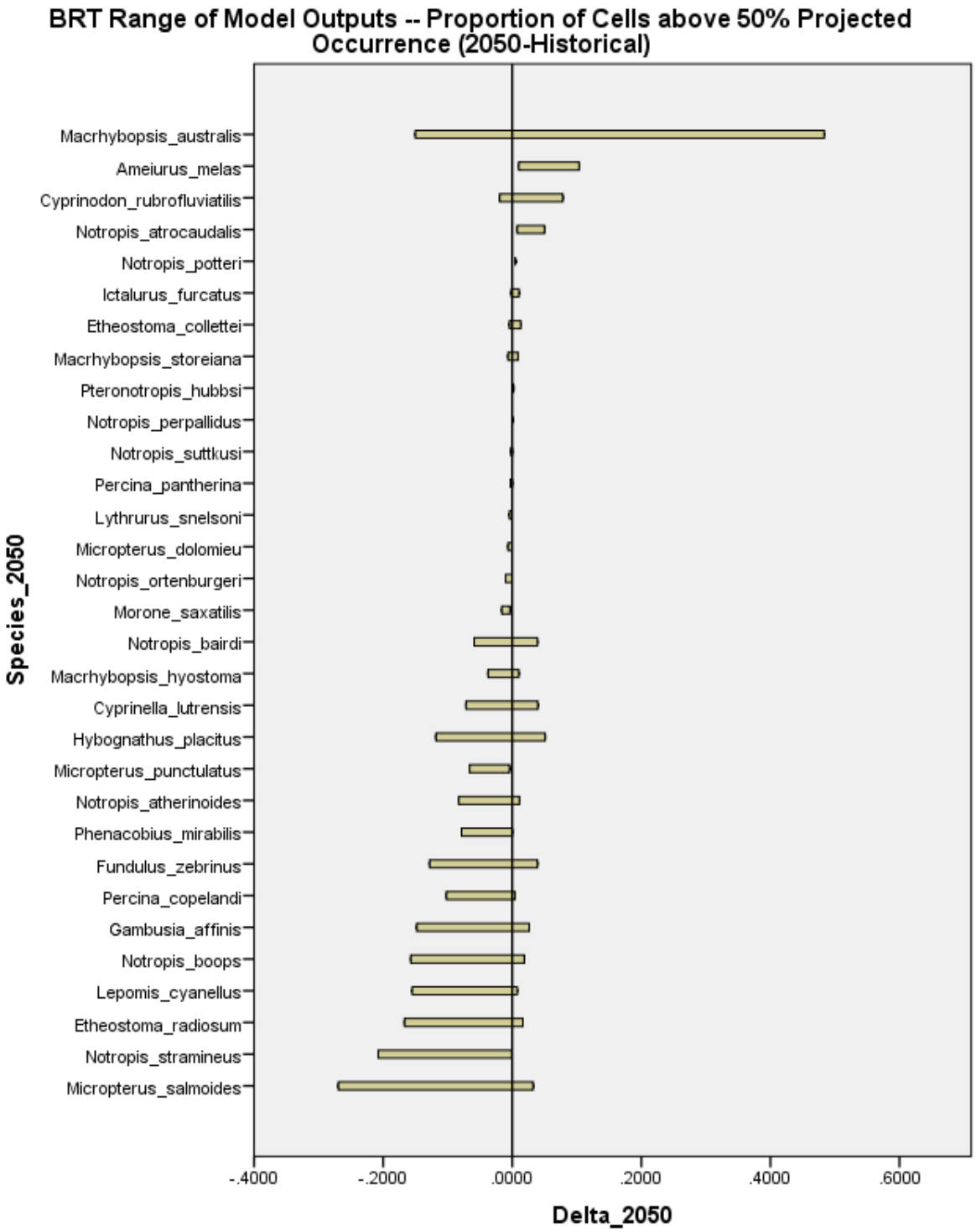



***Figure 4:*** *Variability in species' distributional shifts across 9 future climate scenarios in the Red River. For each species, the horizontal axis gives the difference in the proportion of raster cells with > 50% projected occurrence between the year 2050 and the recent historical period (year 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.*

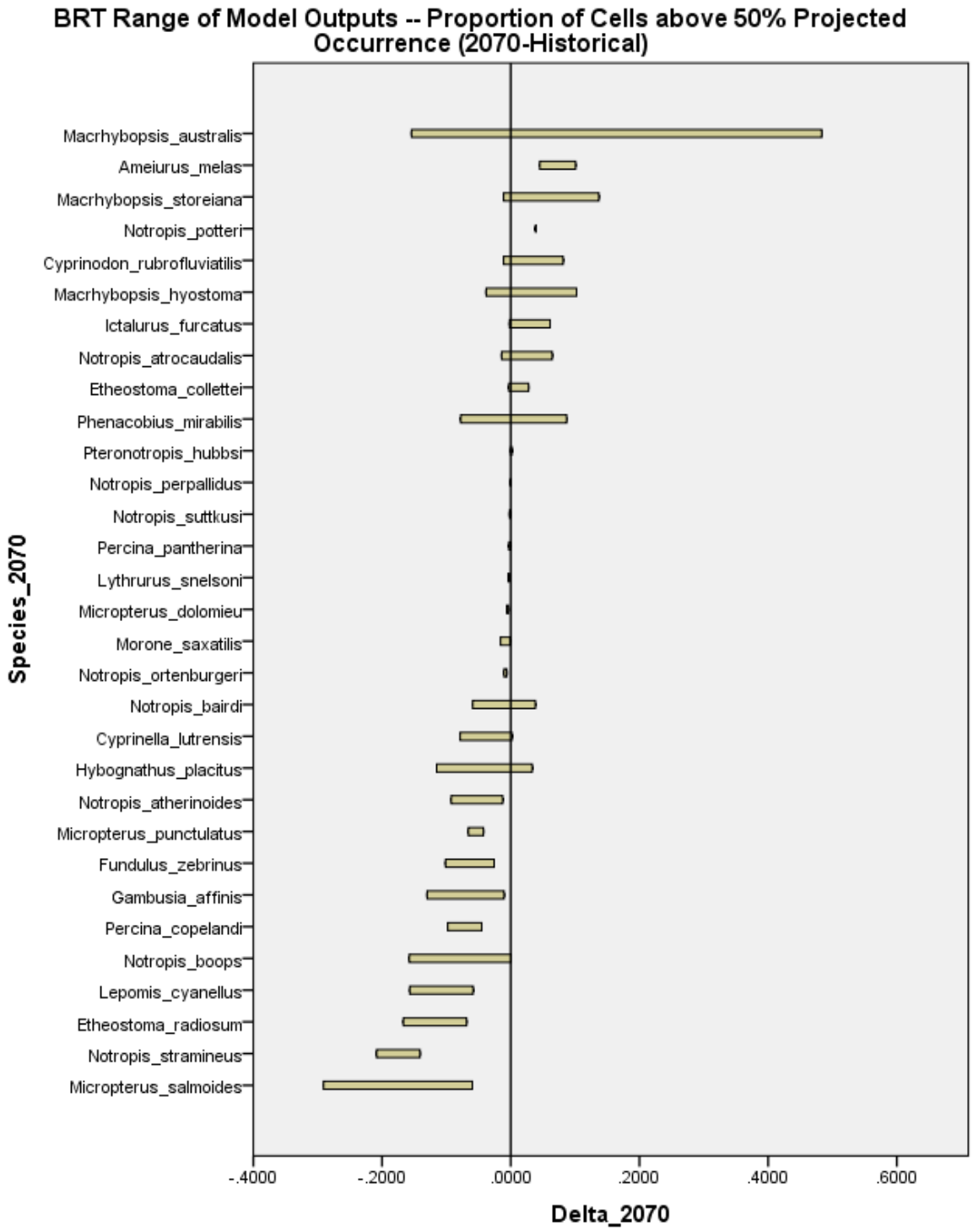



***Figure 5:*** *Variability in species' distributional shifts across 9 future climate scenarios in the Red River. For each species, the horizontal axis gives the difference in the proportion of raster cells with > 50% projected occurrence between the year 2070 and the recent historical period (year 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.*

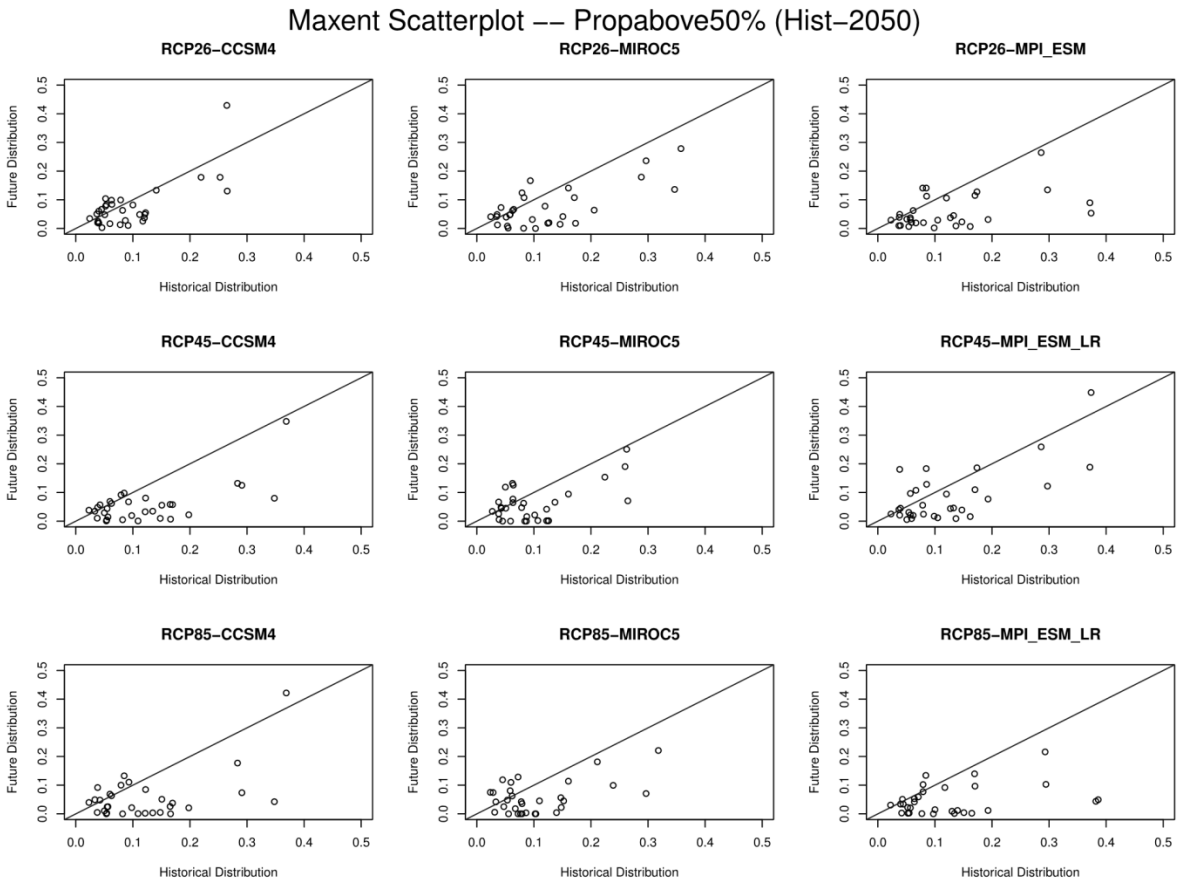



***Figure 6****: Comparison of historical vs. future range width for each species in the year 2050 as projected by our Maxent models. Each point on these scatterplots represents a species. Points that fall below the 1:1 line indicate that the range width of that species is projected to contract across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

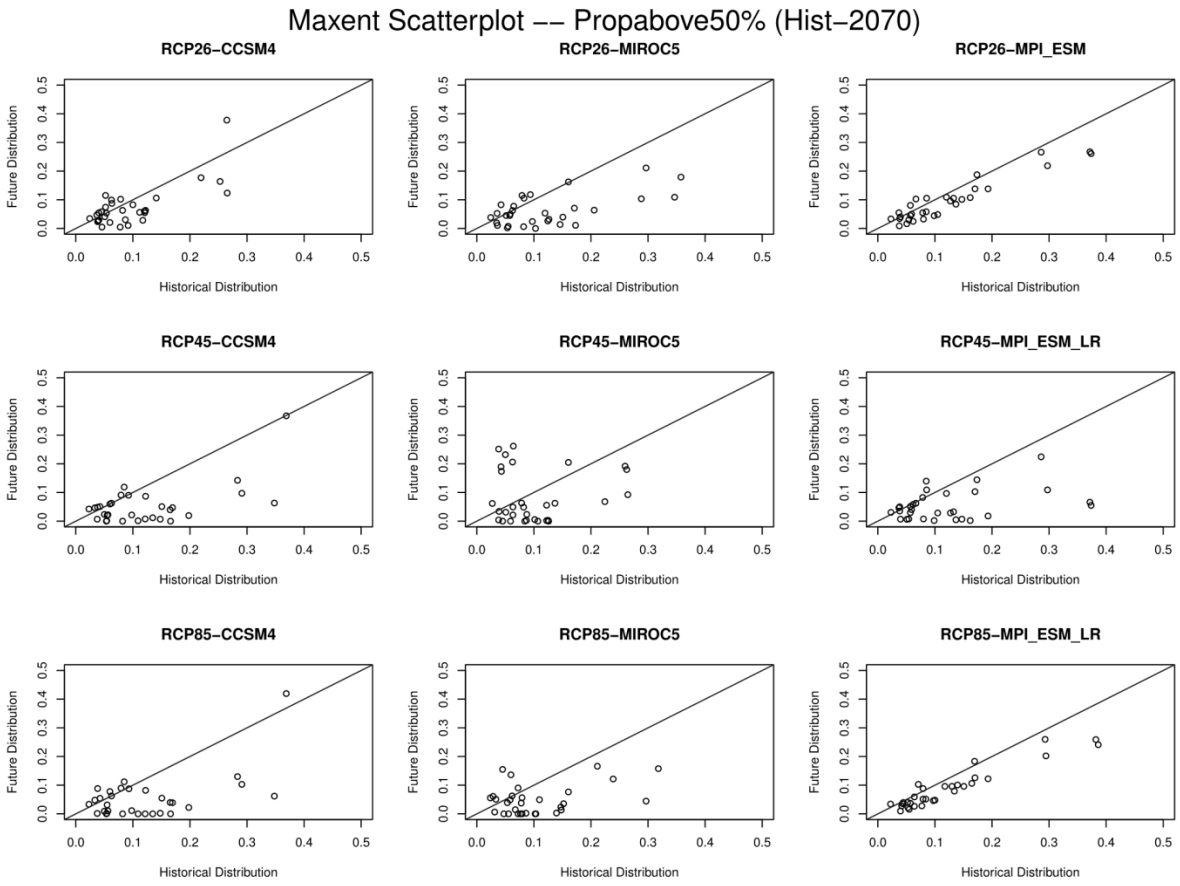



***Figure 7****: Comparison of historical vs. future range width for each species in the year 2070 as projected by our Maxent models. Each point on these scatterplots represents a species. Points that fall below the 1:1 line indicate that the range width of that species is projected to contract across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

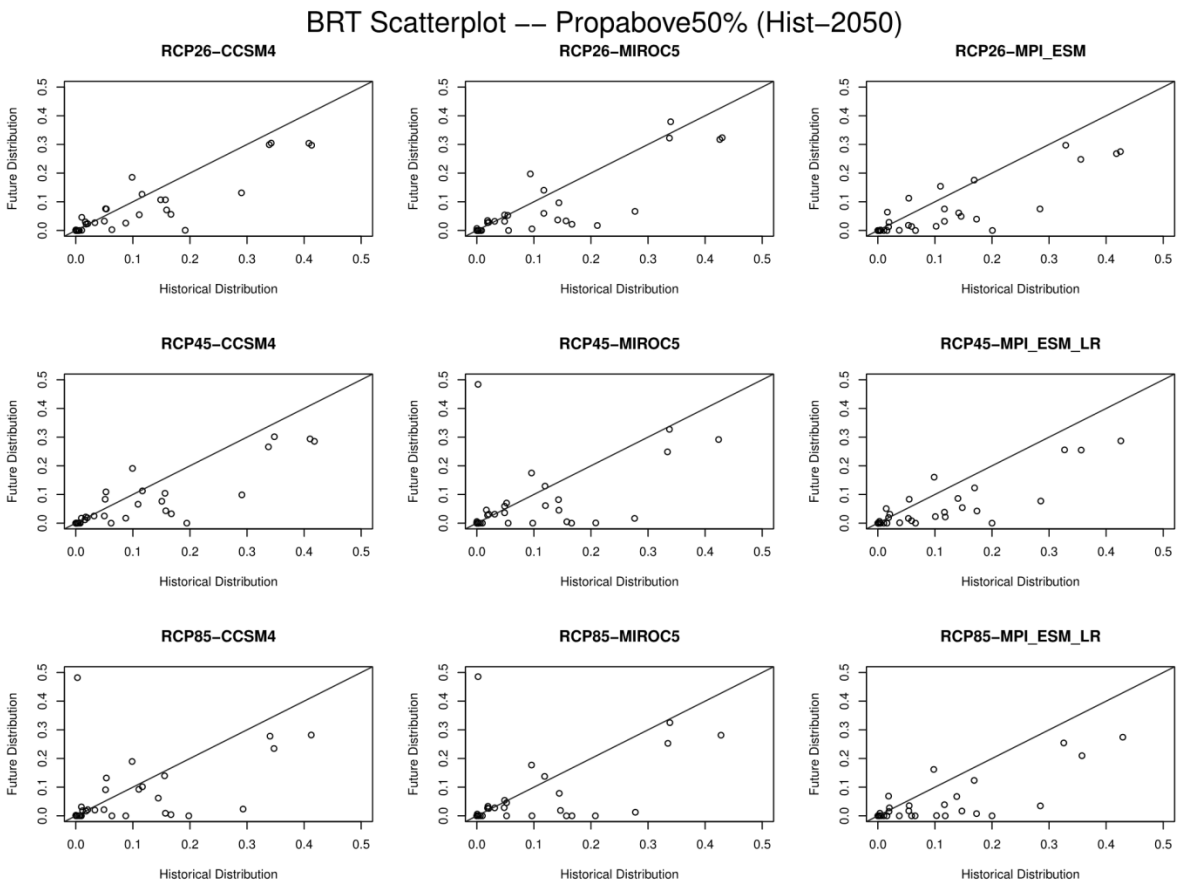



***Figure 8****: Comparison of historical vs. future range width for each species in the year 2050 as projected by our BRT models. Each point on these scatterplots represents a species. Points that fall below the 1:1 line indicate that the range width of that species is projected to contract across the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

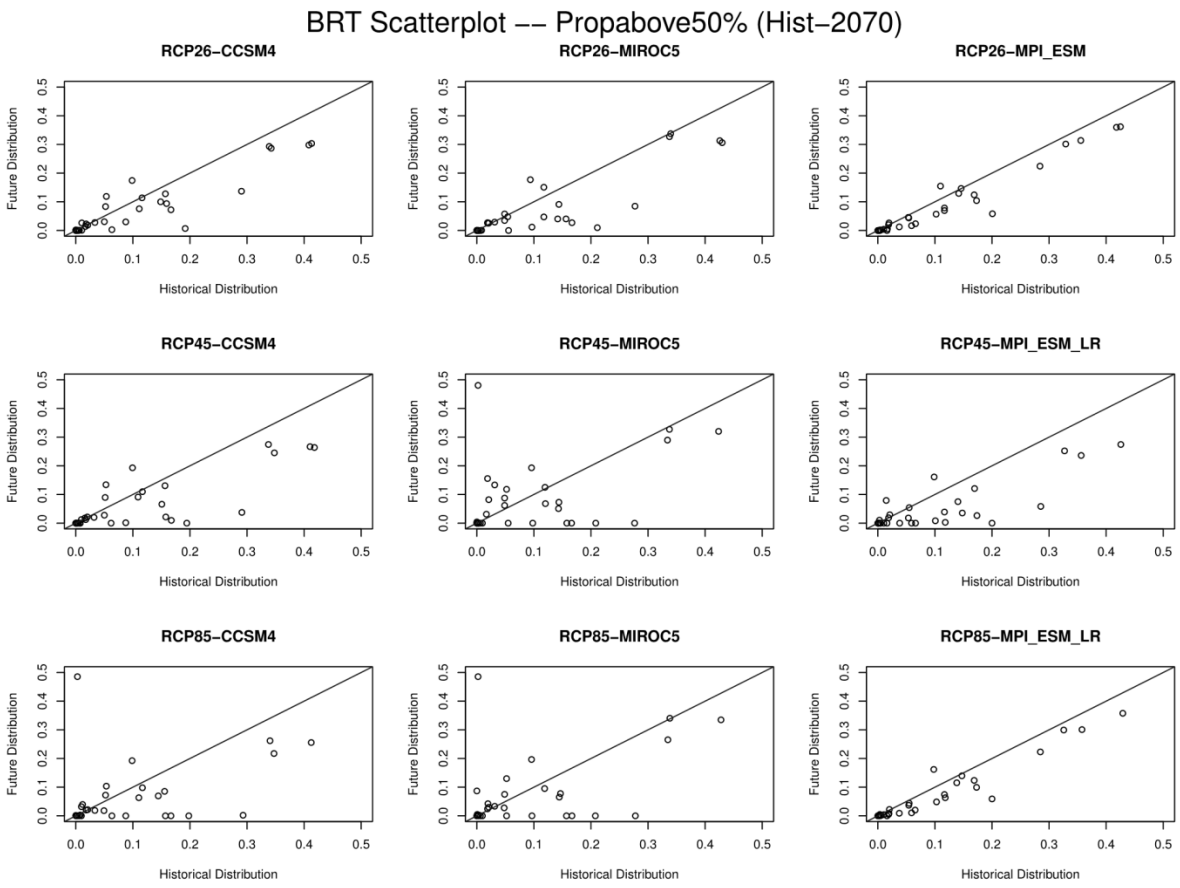



***Figure 9****: Comparison of historical vs. future range width for each species in the year 2070 as projected by our BRT models. Each point on these scatterplots represents a species. Points that fall below the 1:1 line indicate that the range width of that species is projected to contract across the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

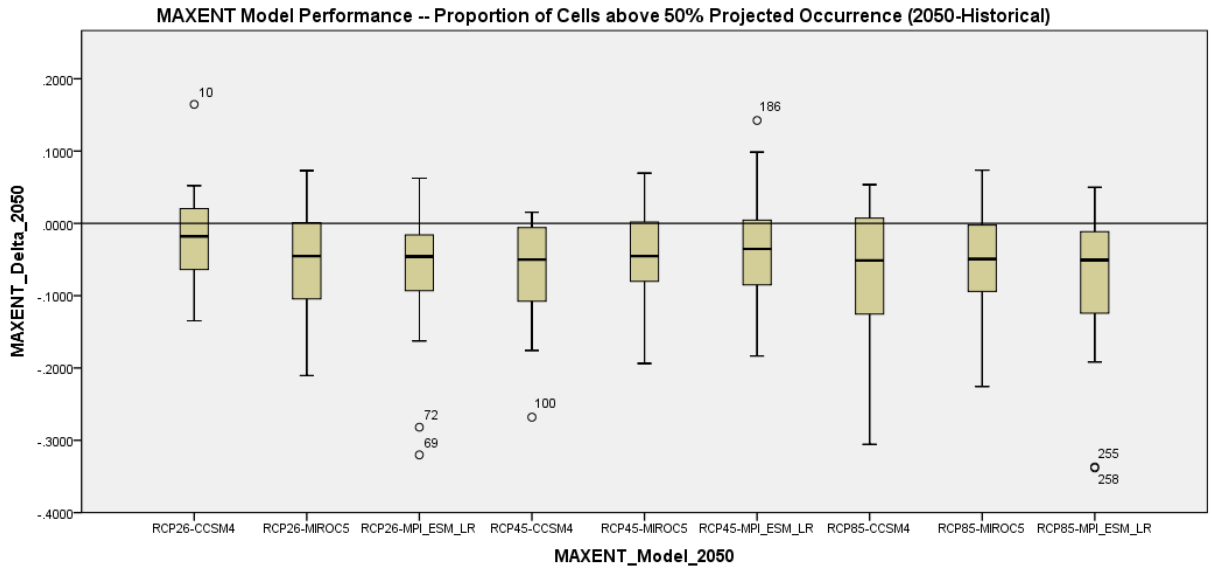



***Figure 10**: Summary of the variability among species in changes to their range width across climate scenarios (horizontal axis) in the year 2050 as projected by our Maxent models. Each segment of the boxplot expresses the range of the delta of projected occurrence (50% or greater) for each of the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

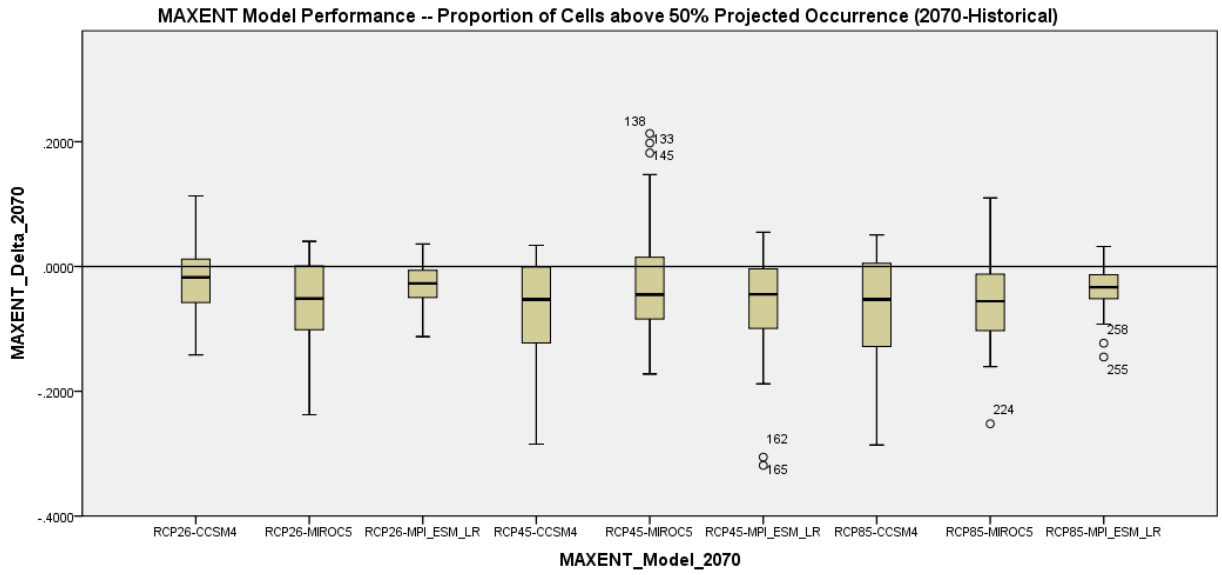



***Figure 11****: Summary of the variability among species in changes to their range width across climate scenarios (horizontal axis) in the year 2070 as projected by our Maxent models. Each segment of the boxplot expresses the range of the delta of projected occurrence (50% or greater) for each of the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

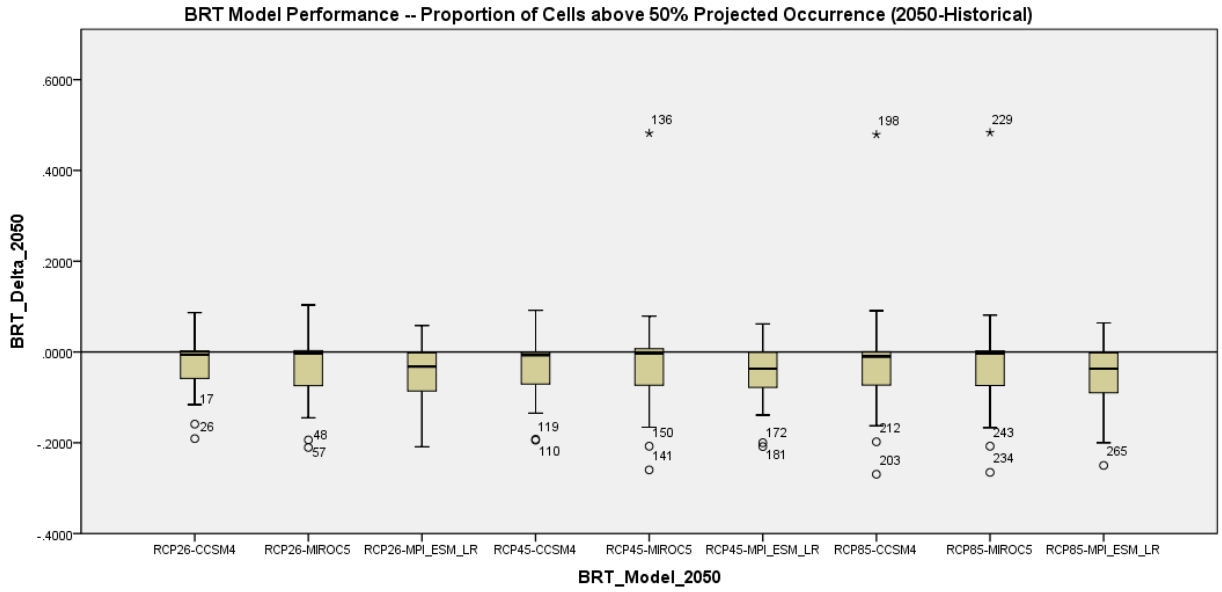



***Figure 12****: Summary of the variability among species in changes to their range width across climate scenarios (horizontal axis) in the year 2050 as projected by our BRT models. Each segment of the boxplot expresses the range of the delta of projected occurrence (50% or greater) for each of the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

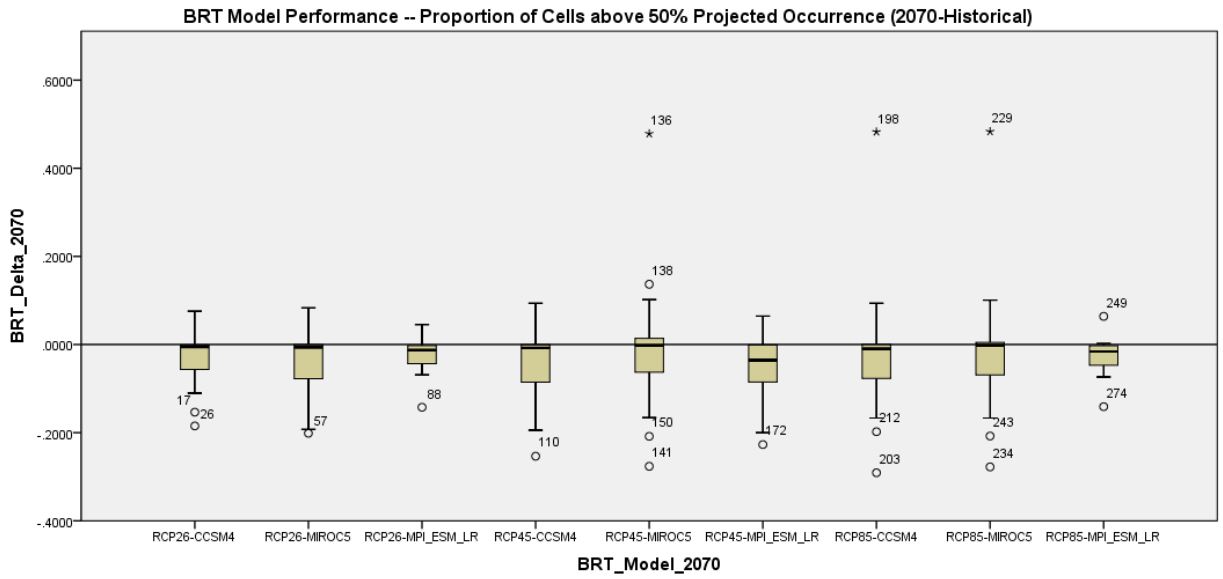



***Figure 13****: Summary of the variability among species in changes to their range width across climate scenarios (horizontal axis) in the year 2070 as projected by our BRT models. Each segment of the boxplot expresses the range of the delta of projected occurrence (50% or greater) for each of the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

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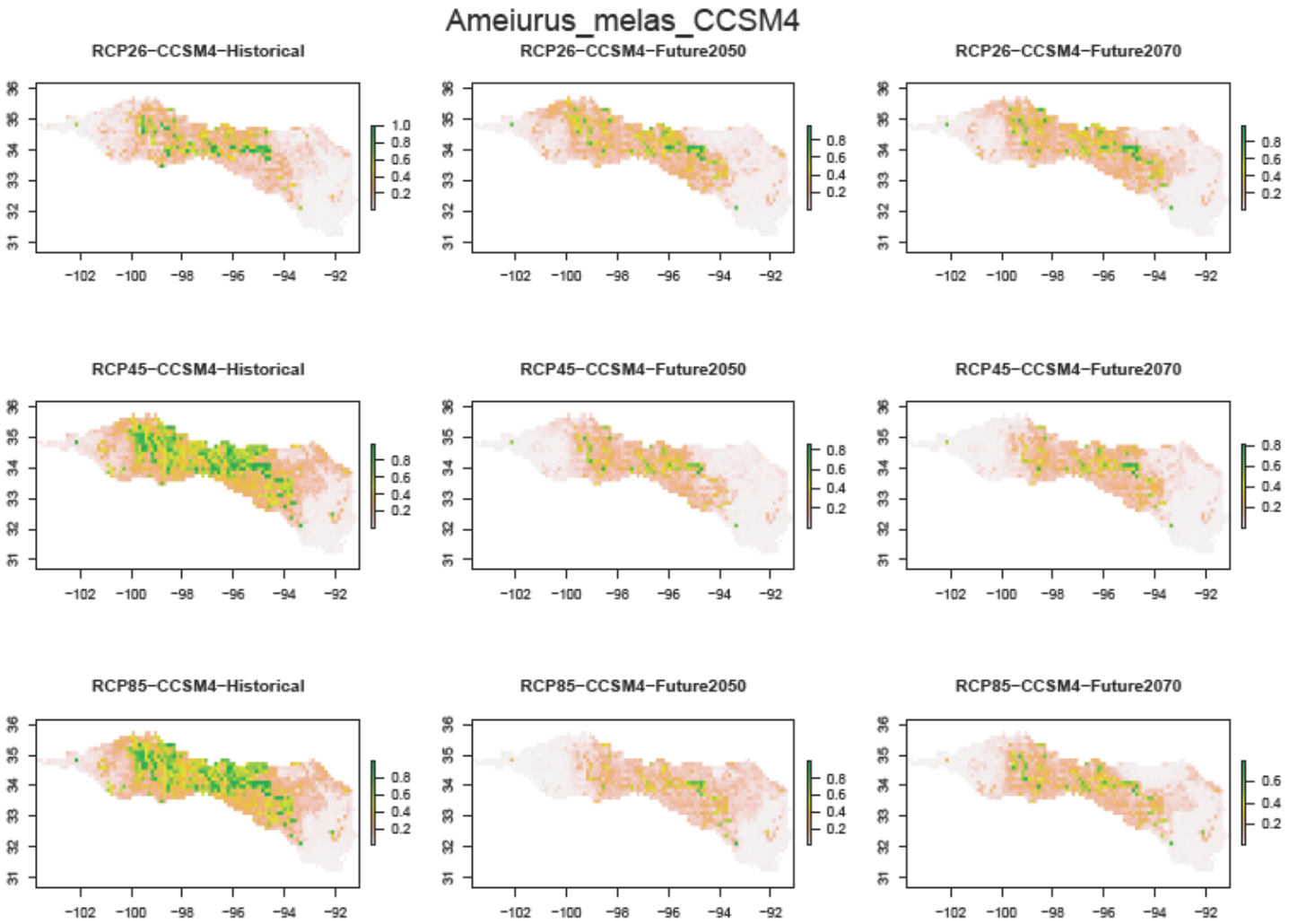
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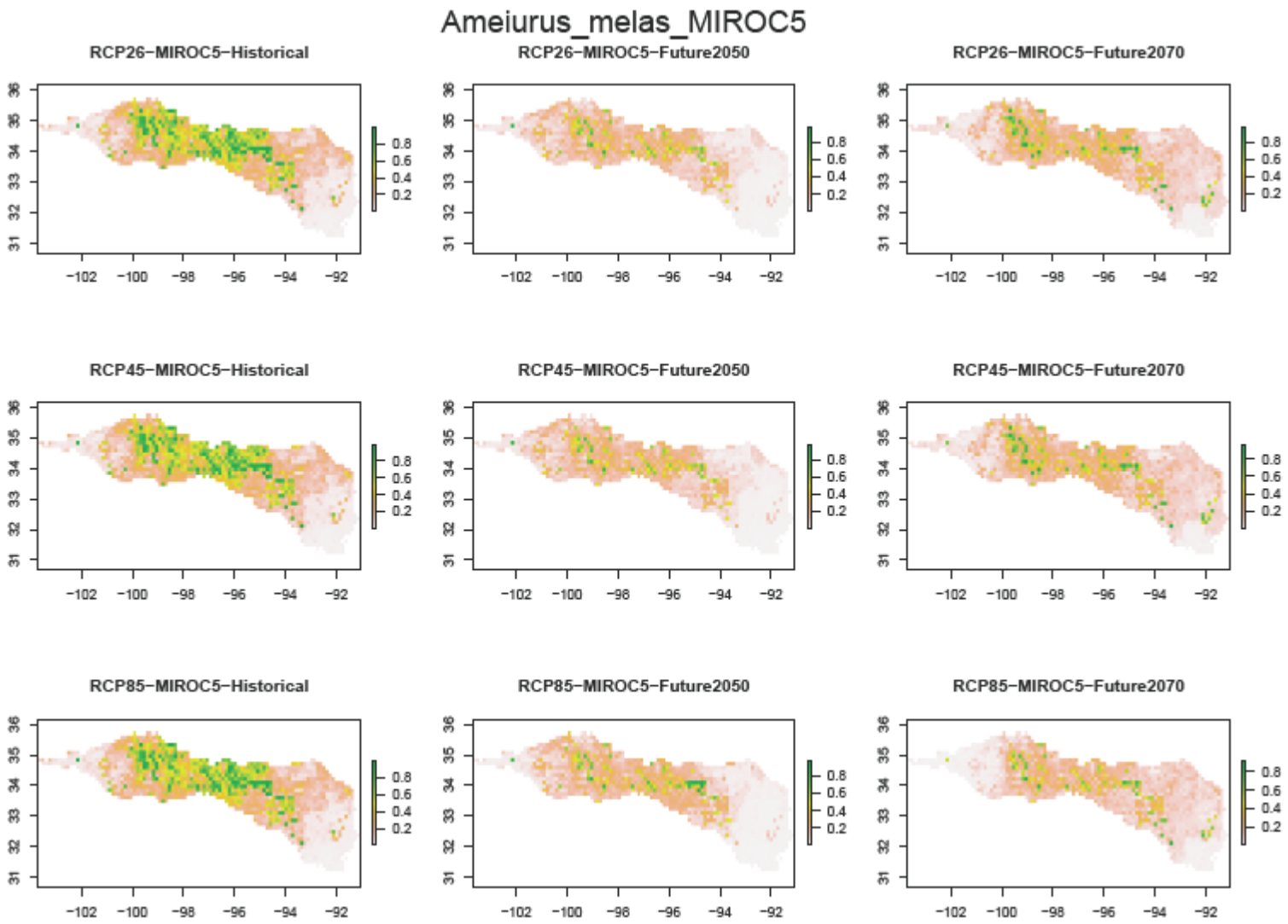
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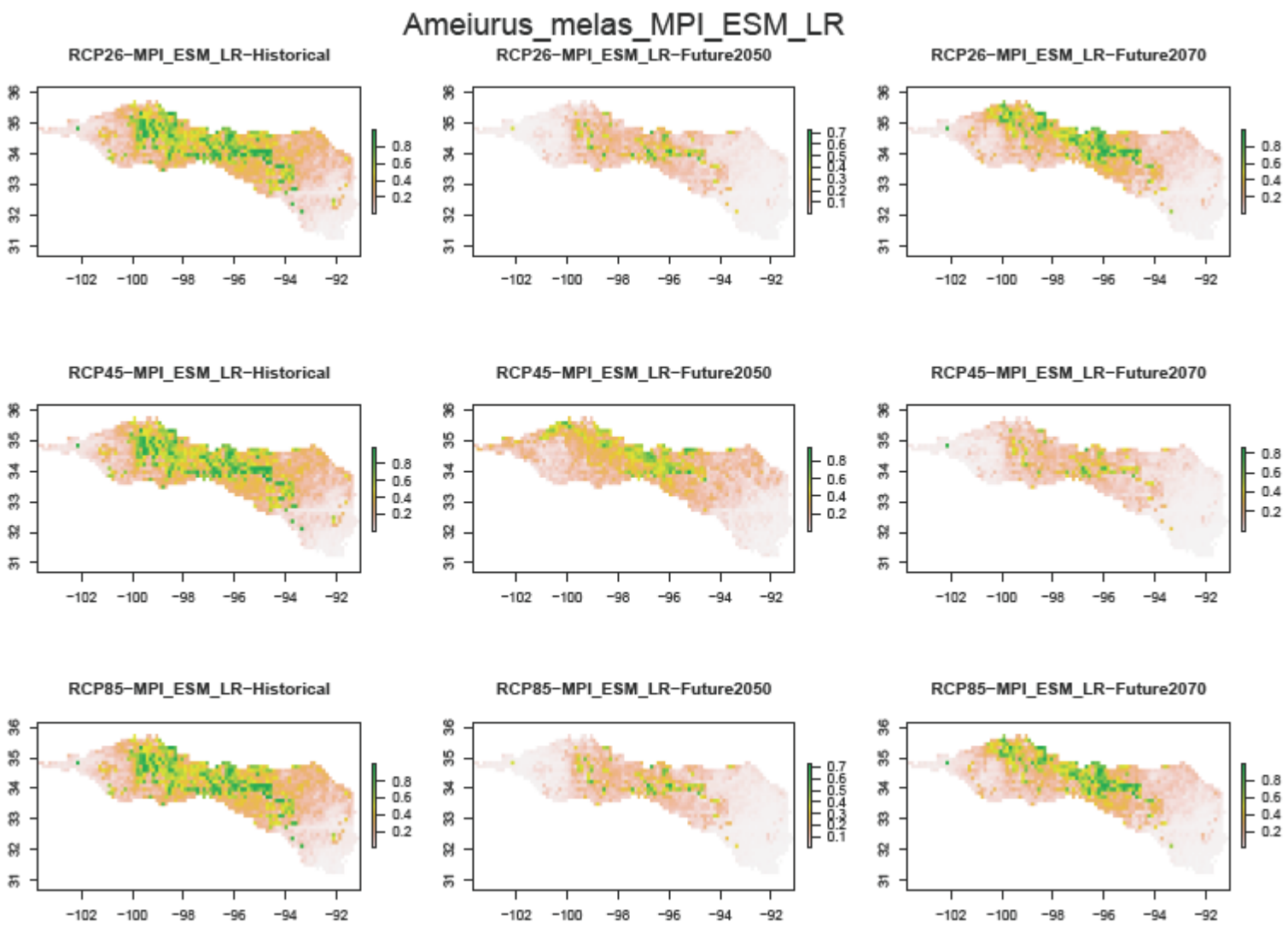
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## Appendix 1: Raw Model Outputs

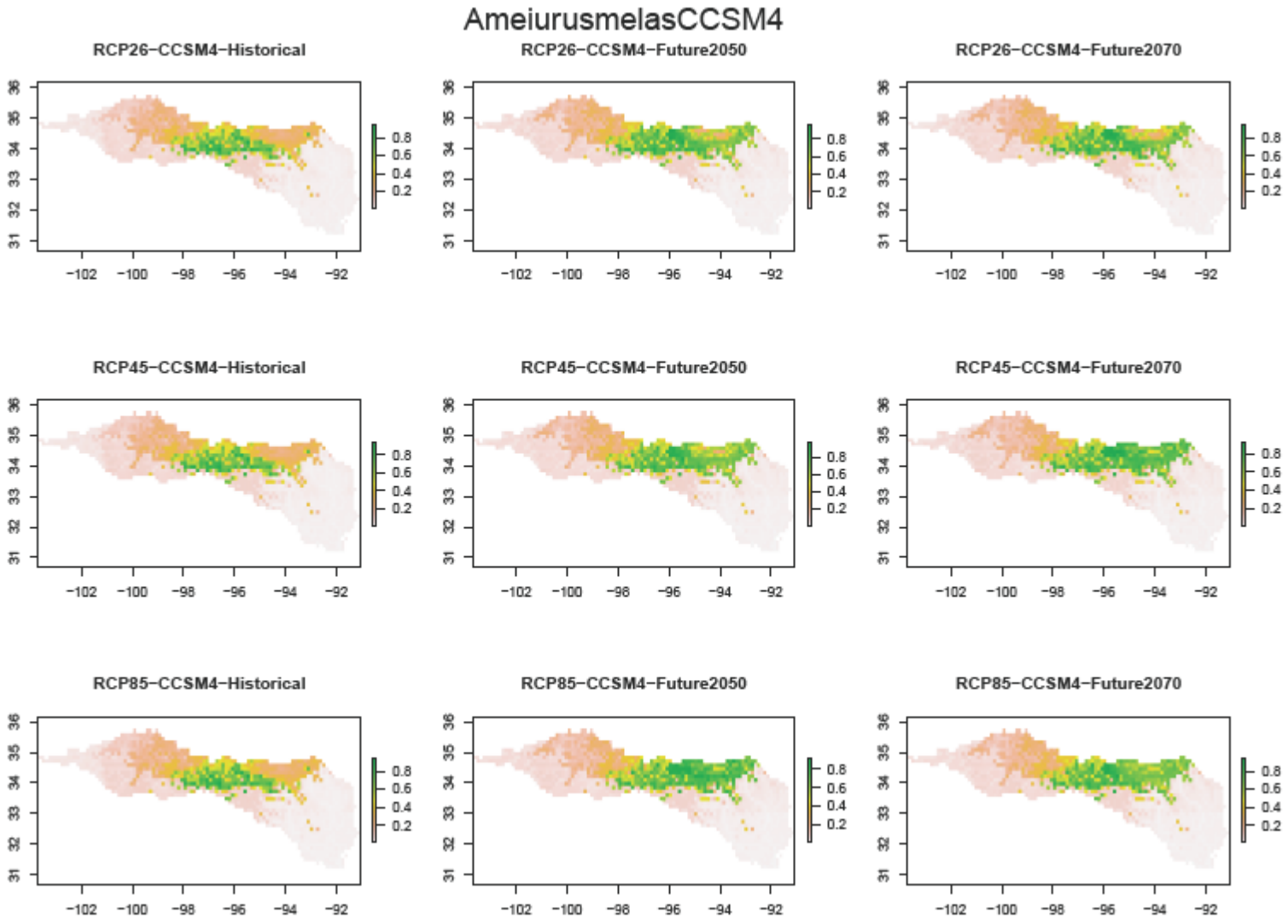
Maxent: *Ameiurus melas*

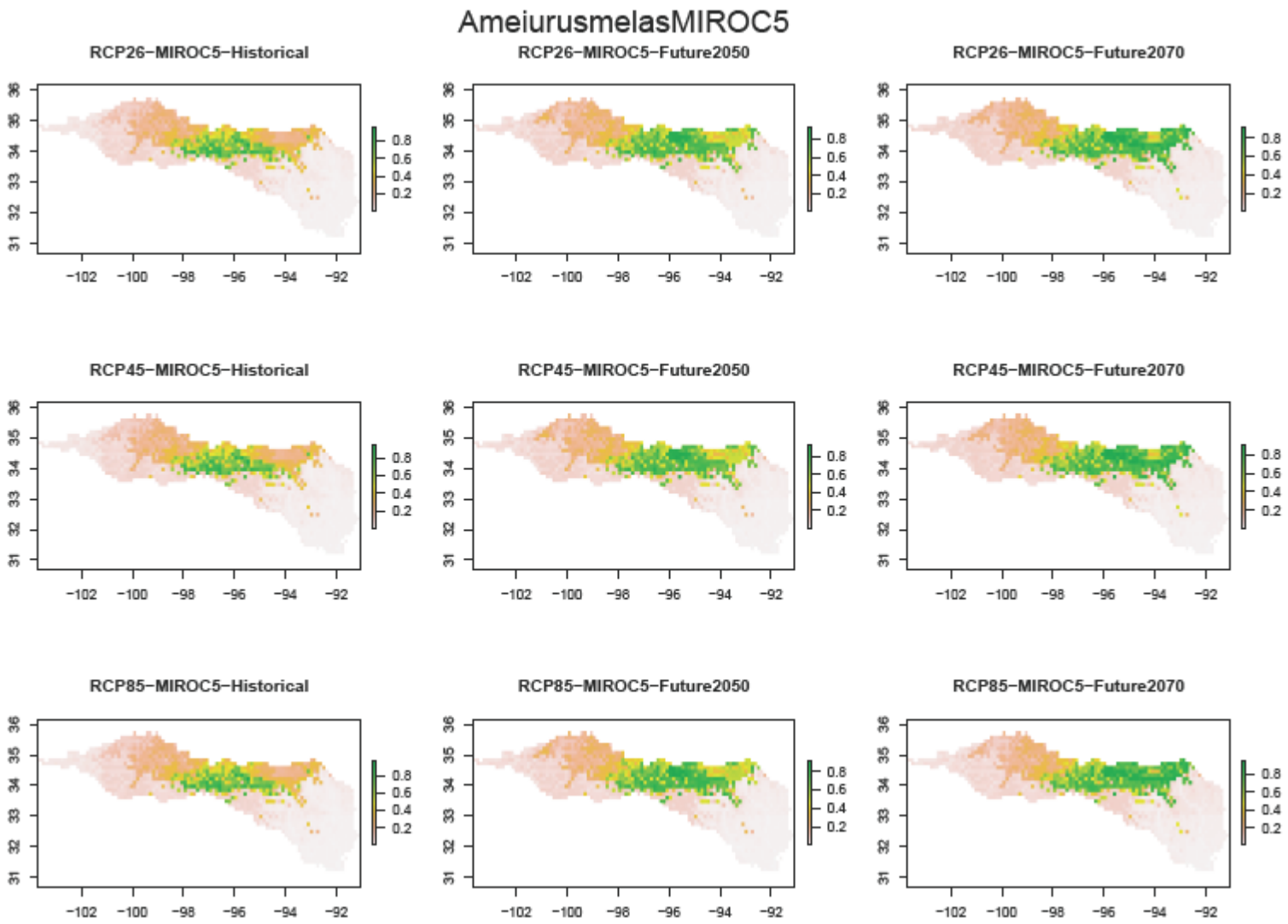


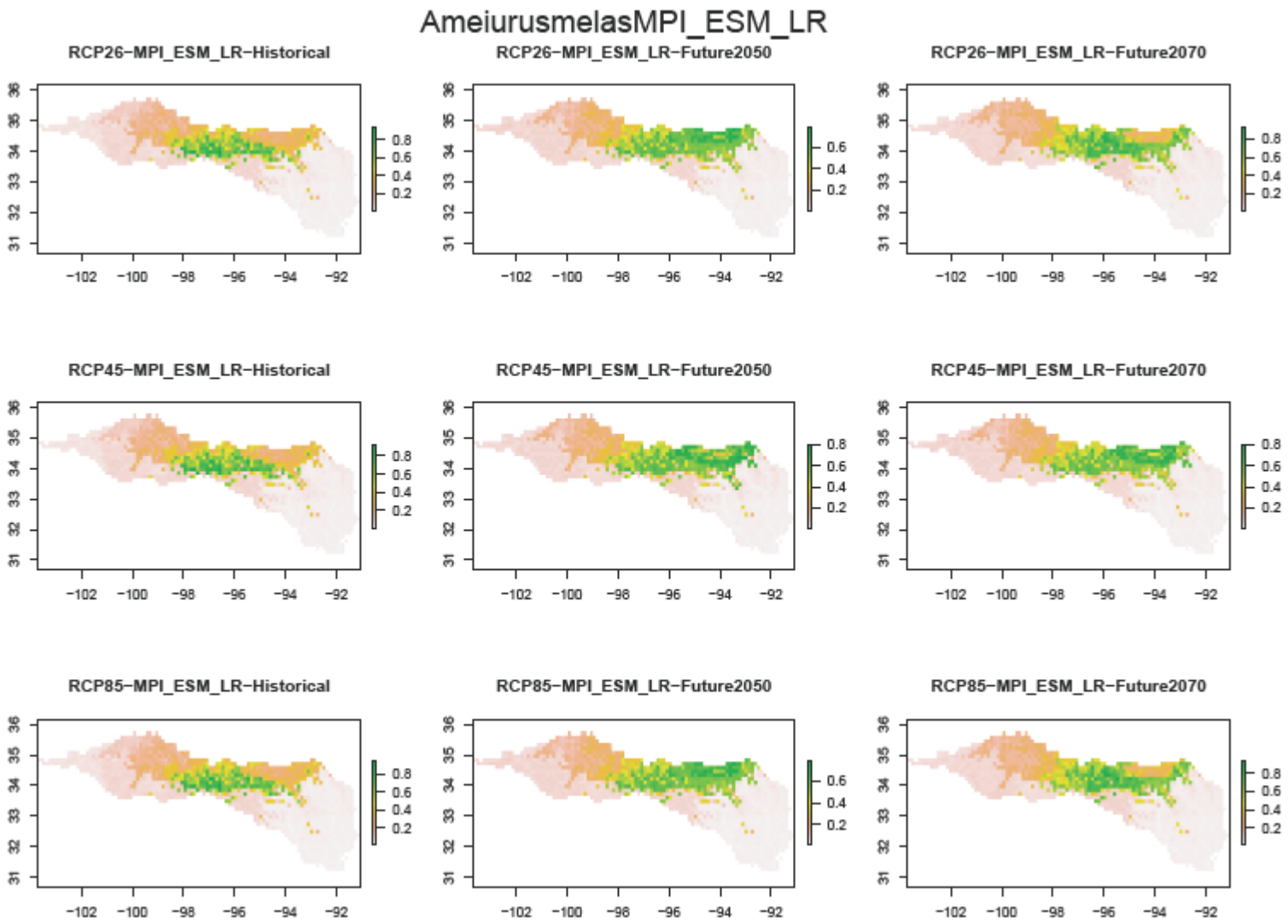

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RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070
31
32
33
34
35
36
−102
−100
−98
−96
−94
−92
0.2
0.4
0.6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


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

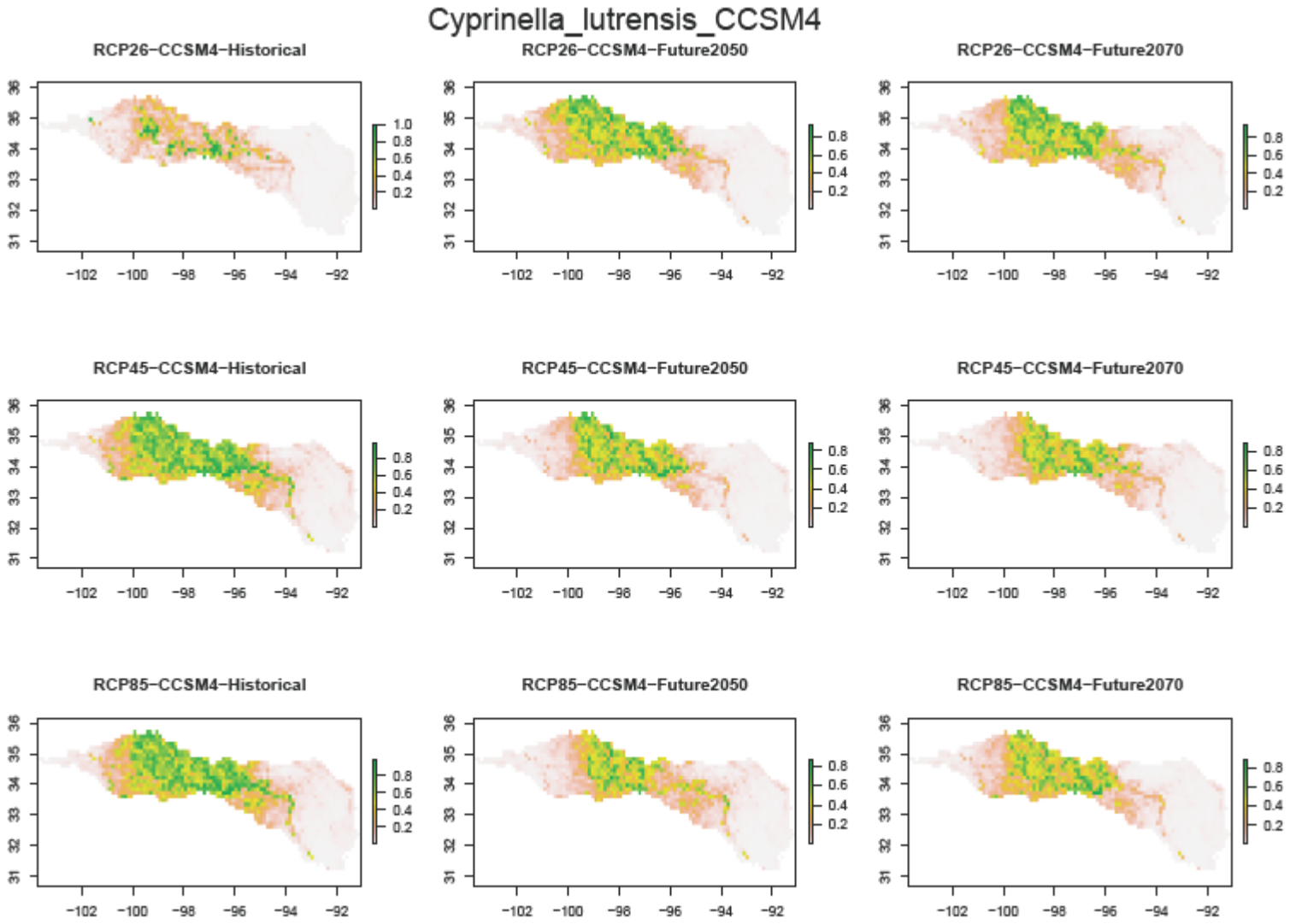
BRT: *Ameiurus melas*

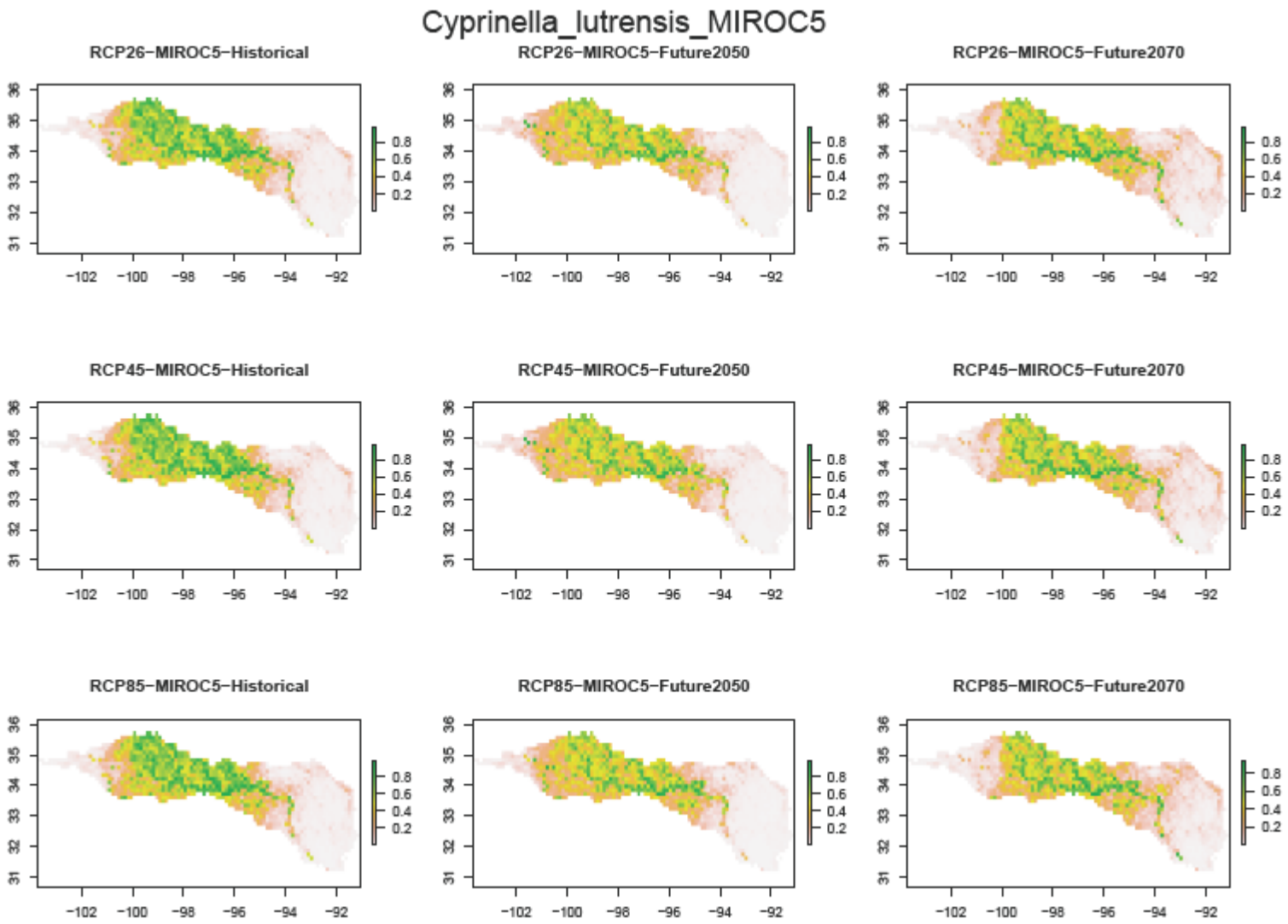


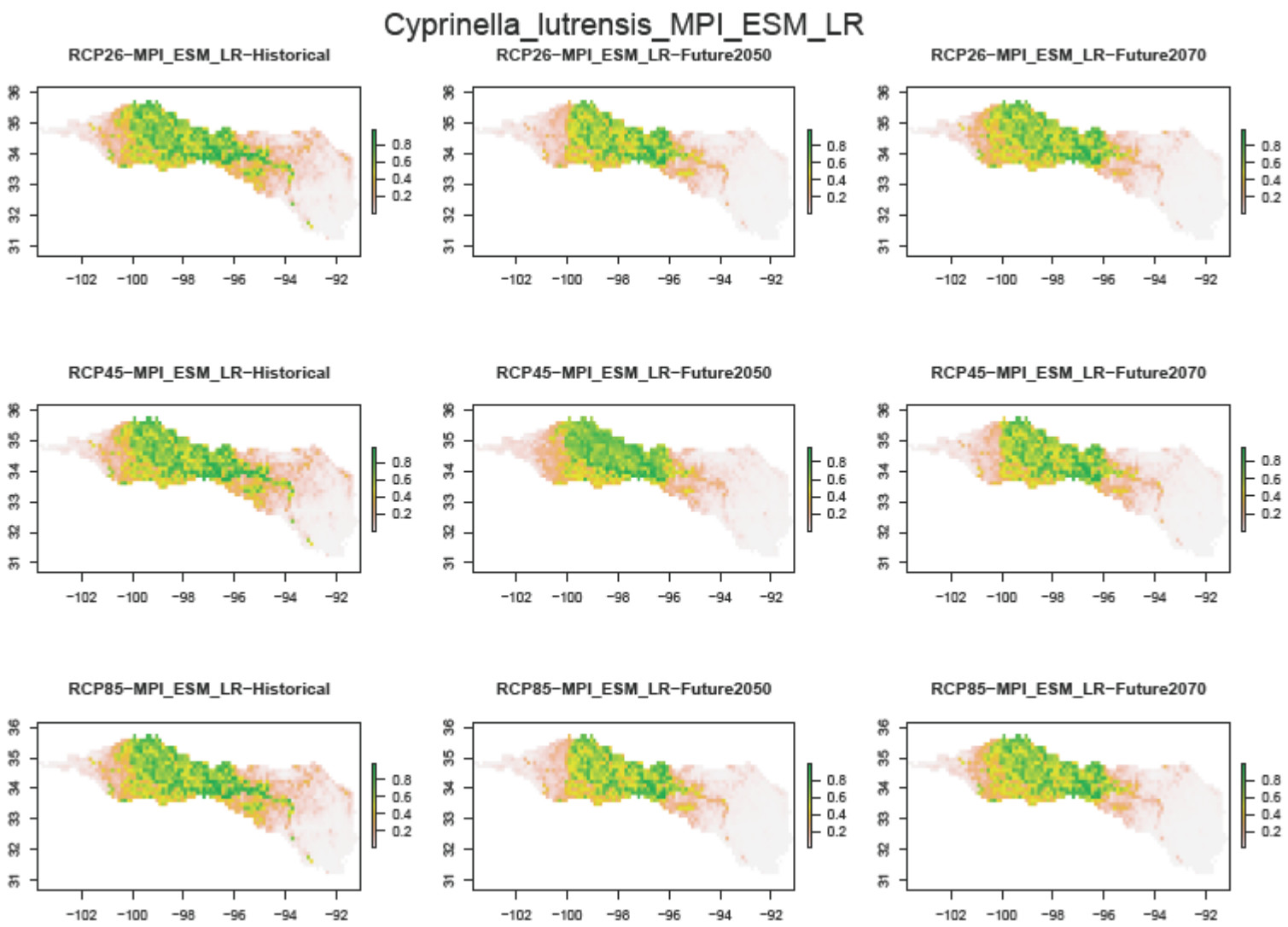

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RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070
31
32
33
34
35
36
−102
−100
−98
−96
−94
−92
0.2
0.4
0.6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


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
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−102 −100 −98 −96 −94 −92
0.2 0.4 0.6 0.8

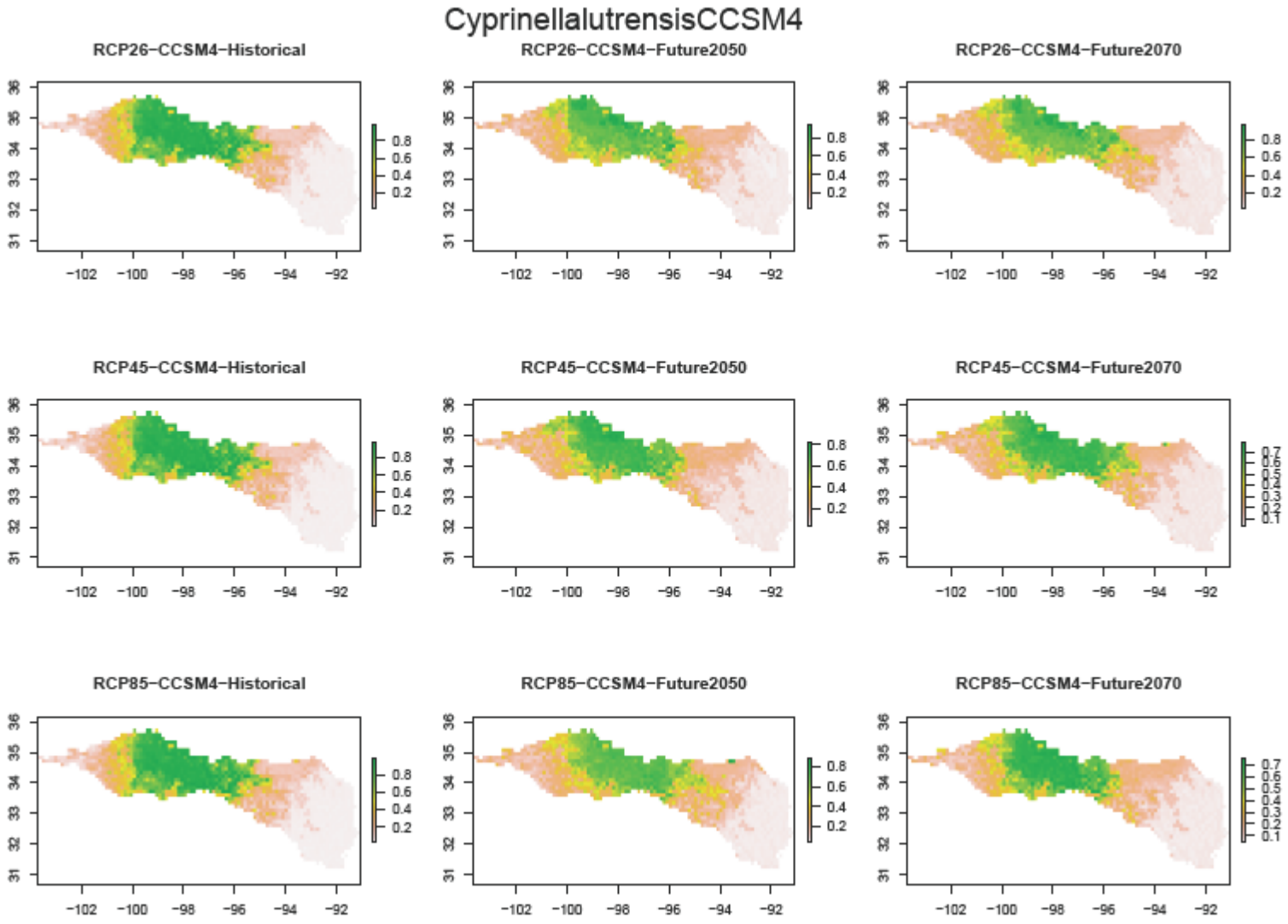
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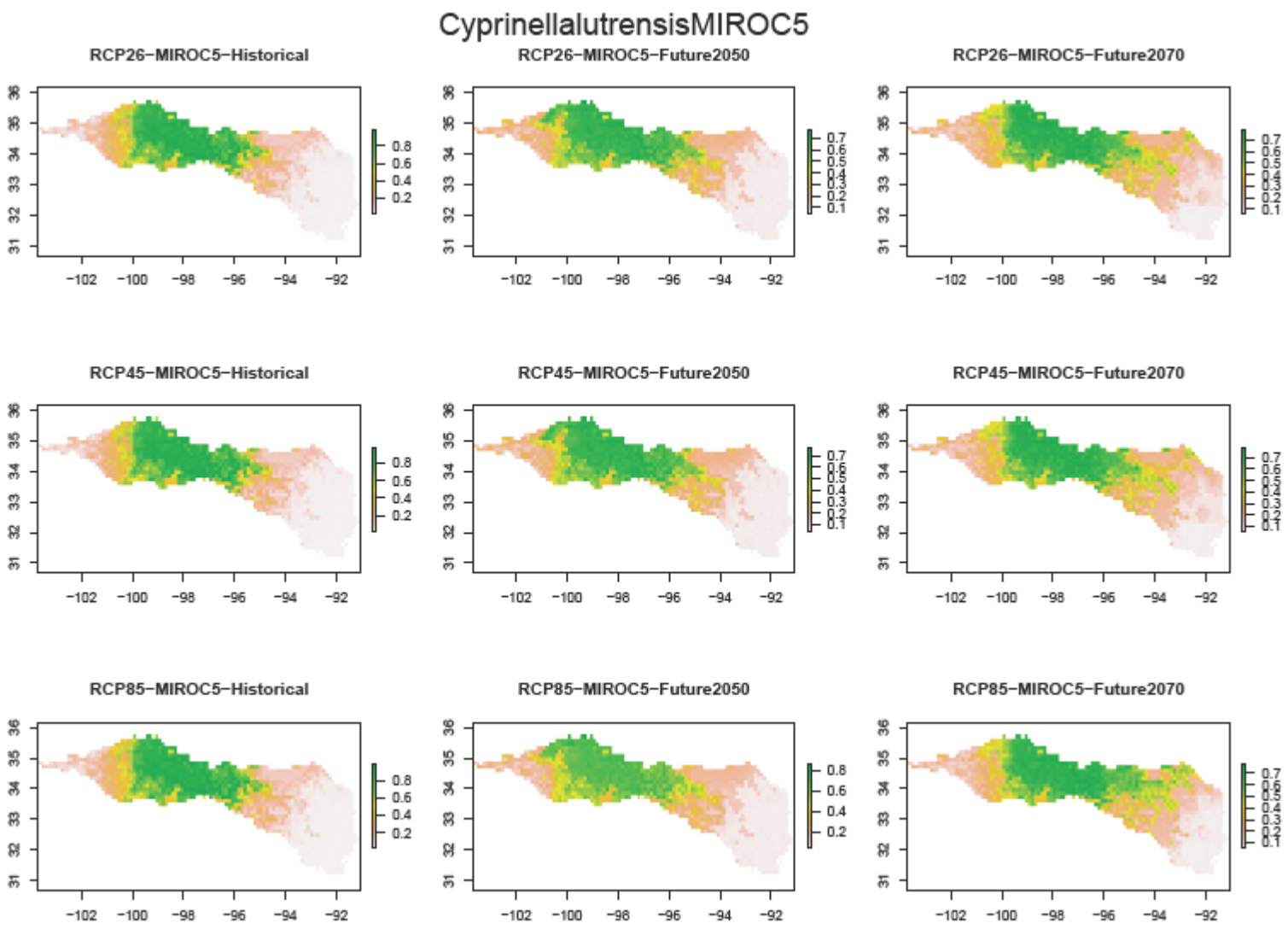


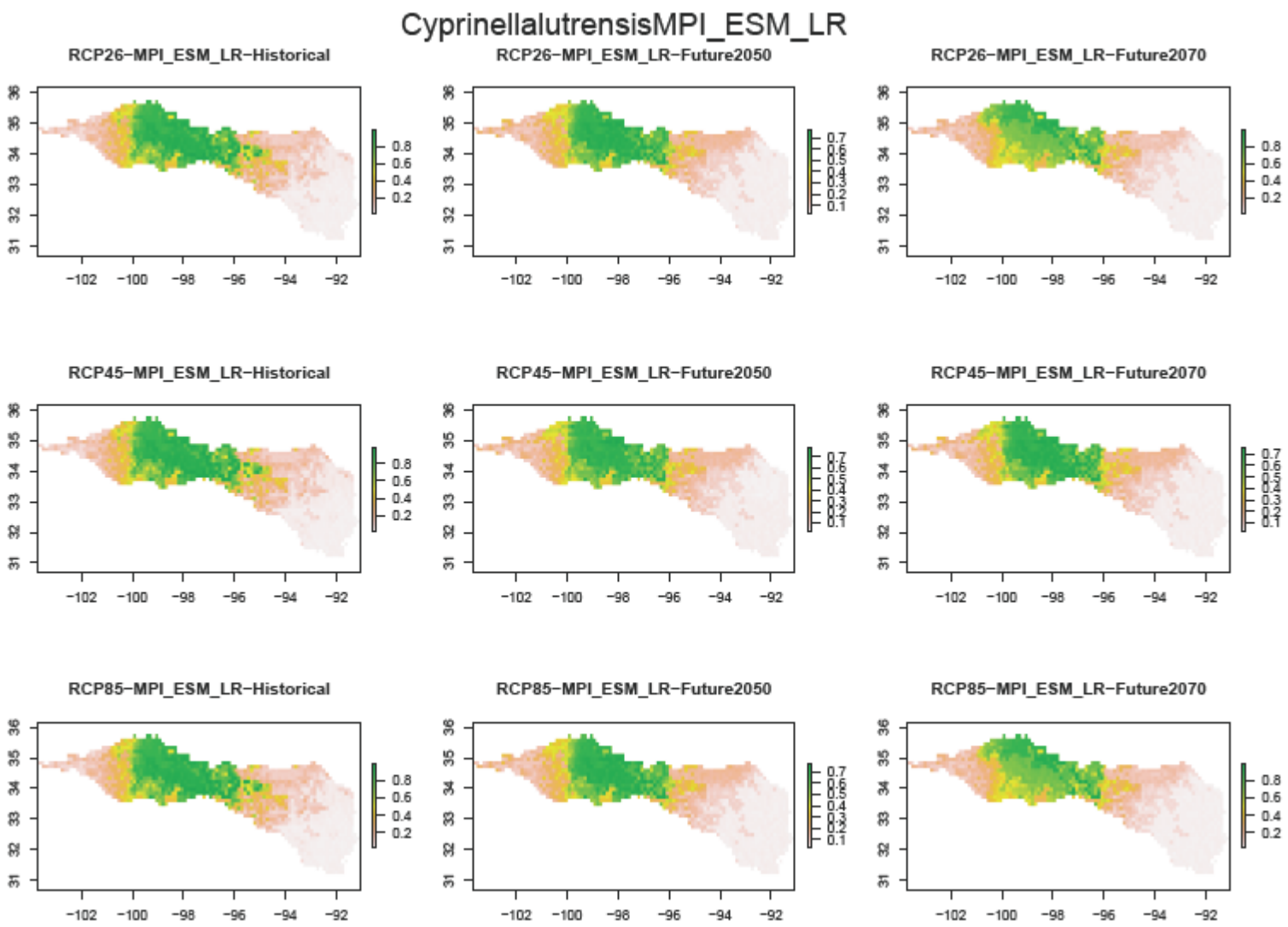

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RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070
31
32
33
34
35
36
−102
−100
−98
−96
−94
−92
0.2
0.4
0.6
0.8


Cyprinella_lutrensis_MPI_ESM_LR
RCP26-MPI_ESM_LR-Historical
RCP26-MPI_ESM_LR-Future2050
RCP26-MPI_ESM_LR-Future2070
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RCP85-MPI_ESM_LR-Historical
RCP85-MPI_ESM_LR-Future2050
RCP85-MPI_ESM_LR-Future2070
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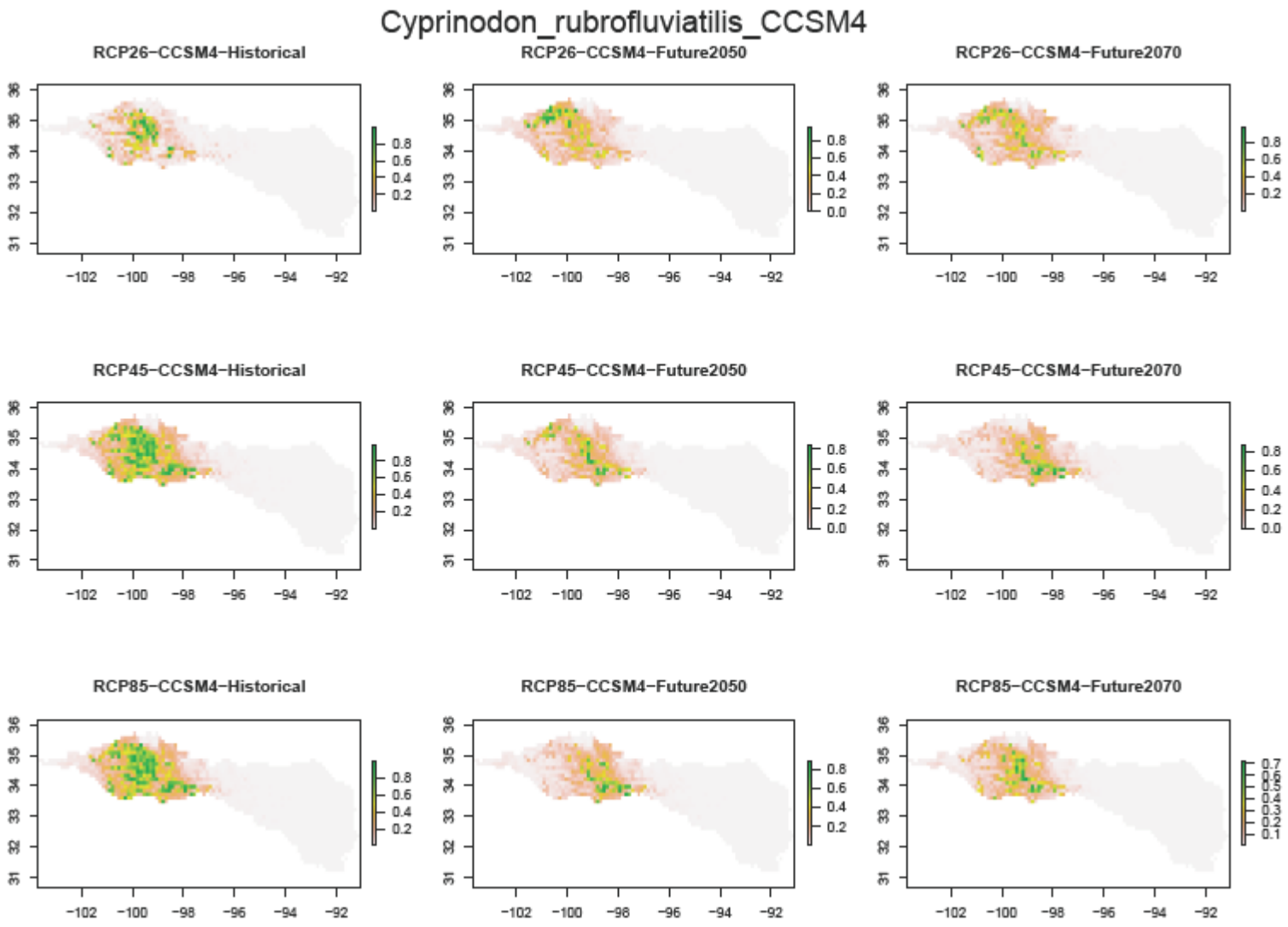
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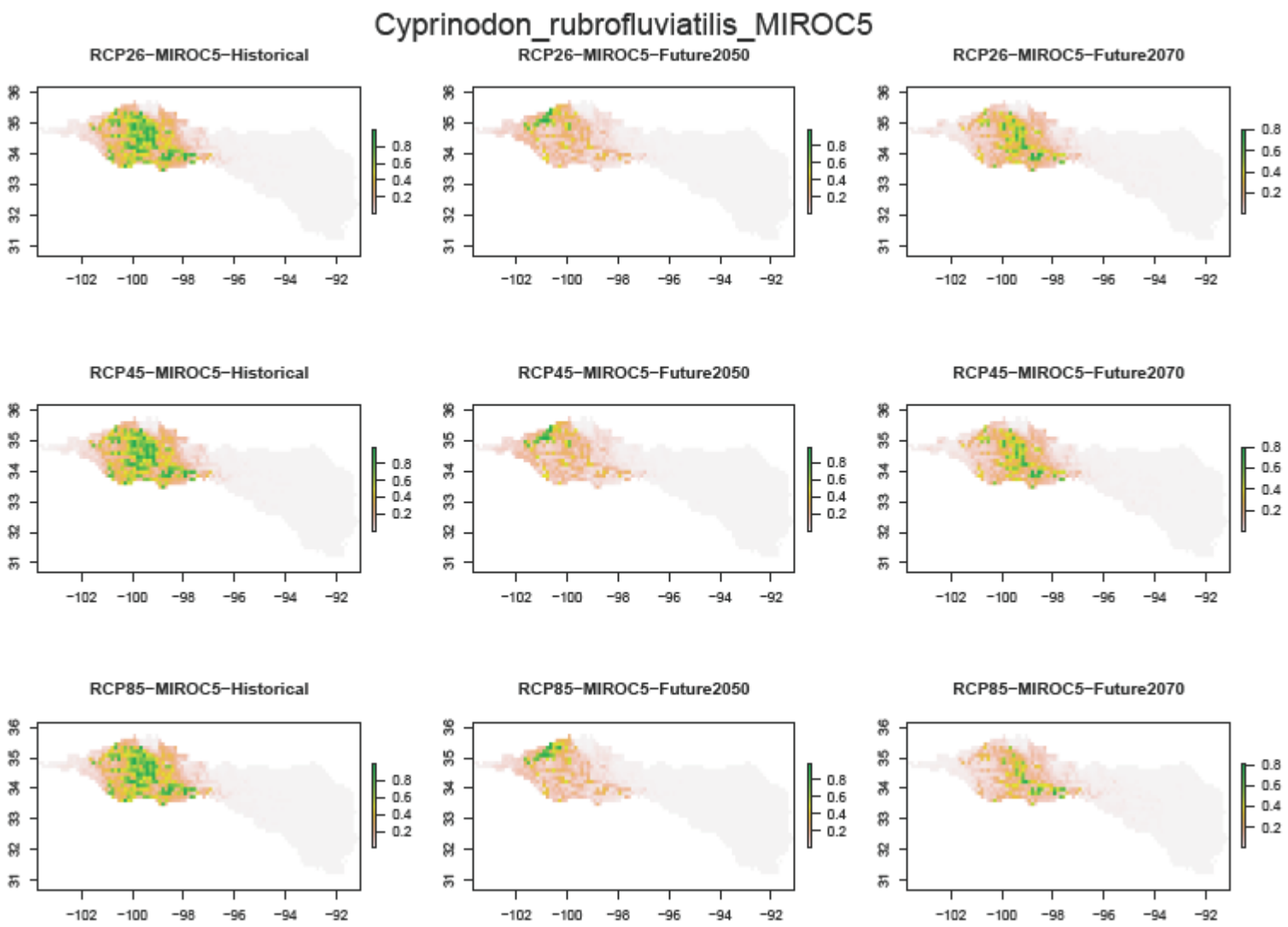


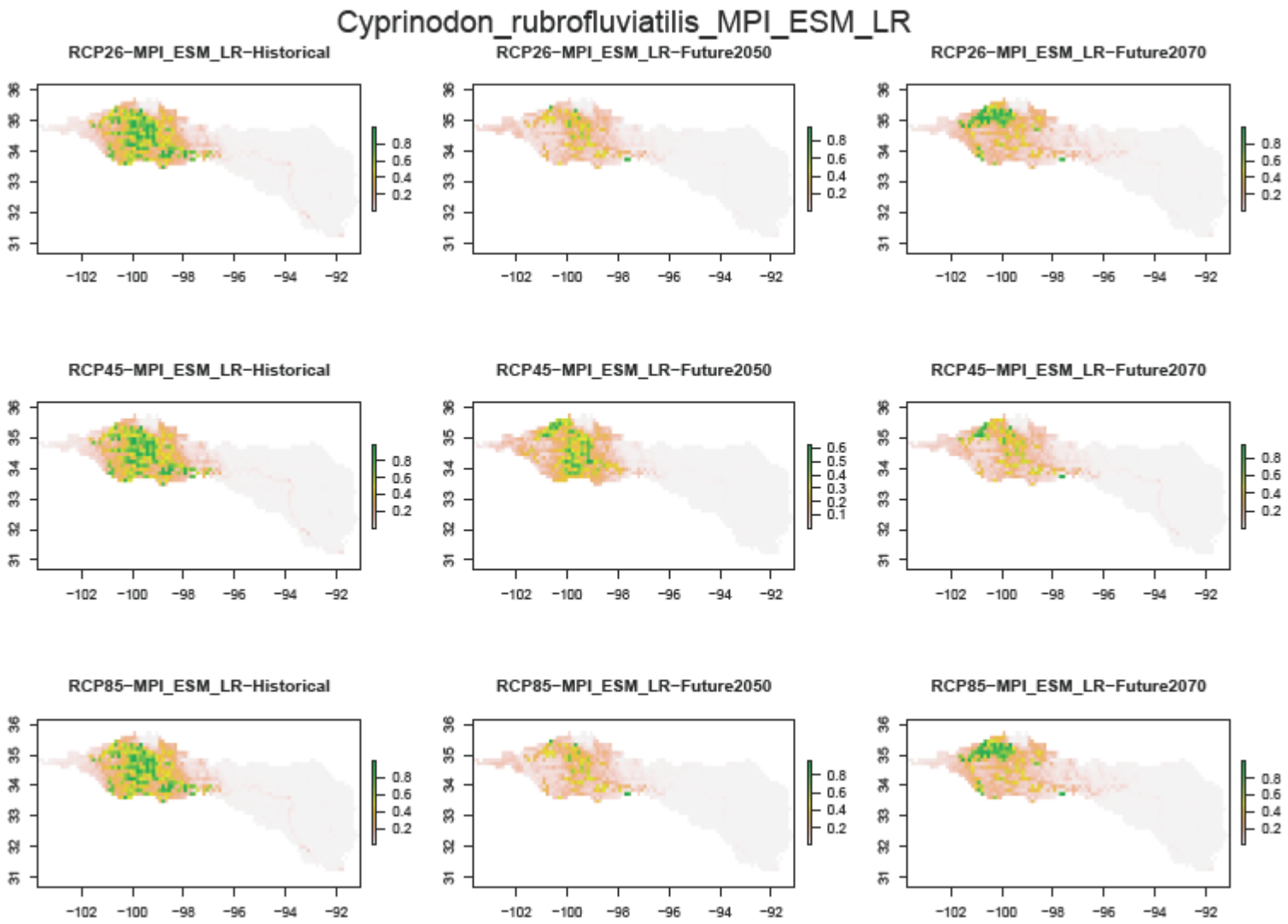

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RCP26−MIROC5−Future2070
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RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070


CyprinellalutrensisMPI_ESM_LR
RCP26-MPI_ESM_LR-Historical
RCP26-MPI_ESM_LR-Future2050
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RCP45-MPI_ESM_LR-Future2050
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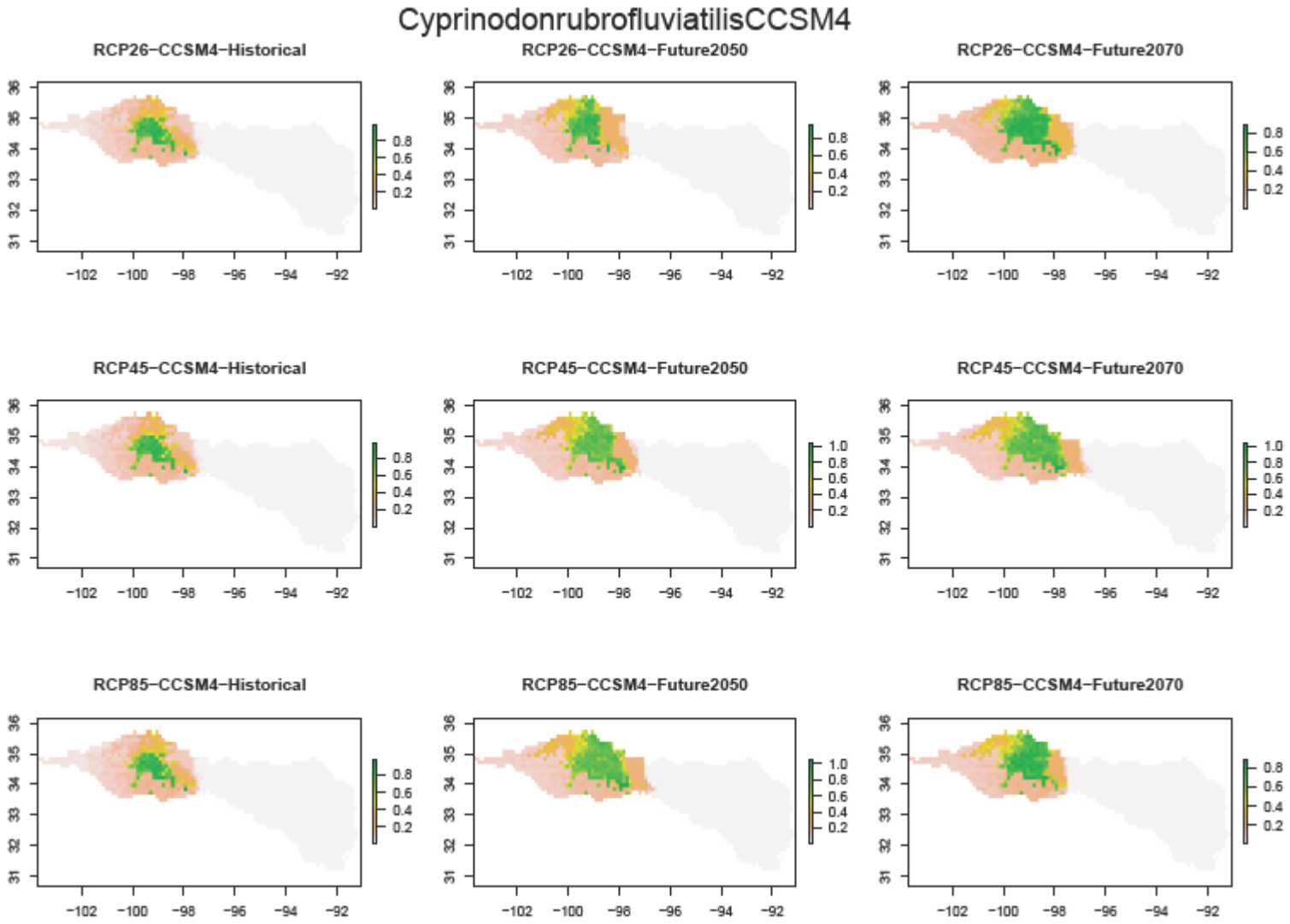
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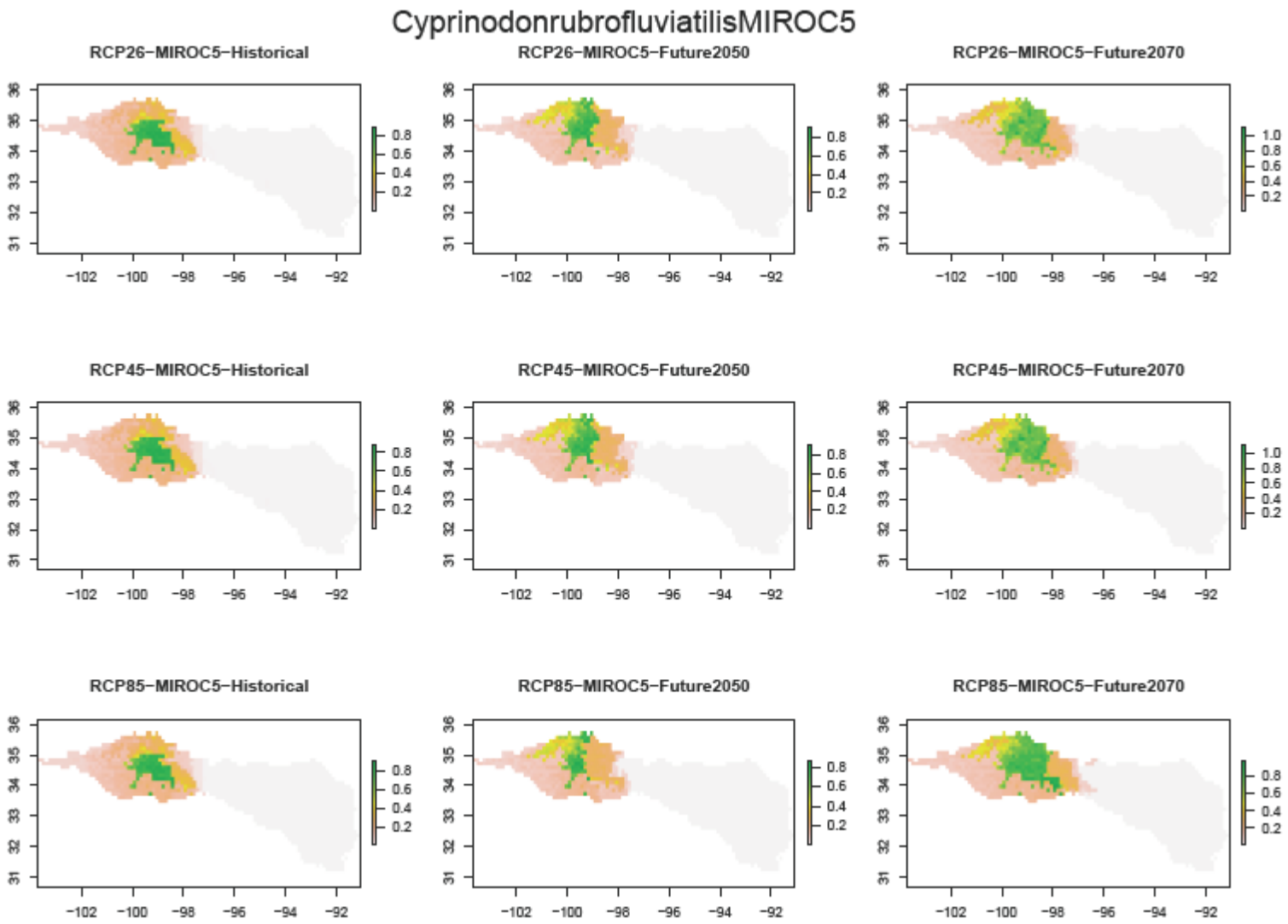


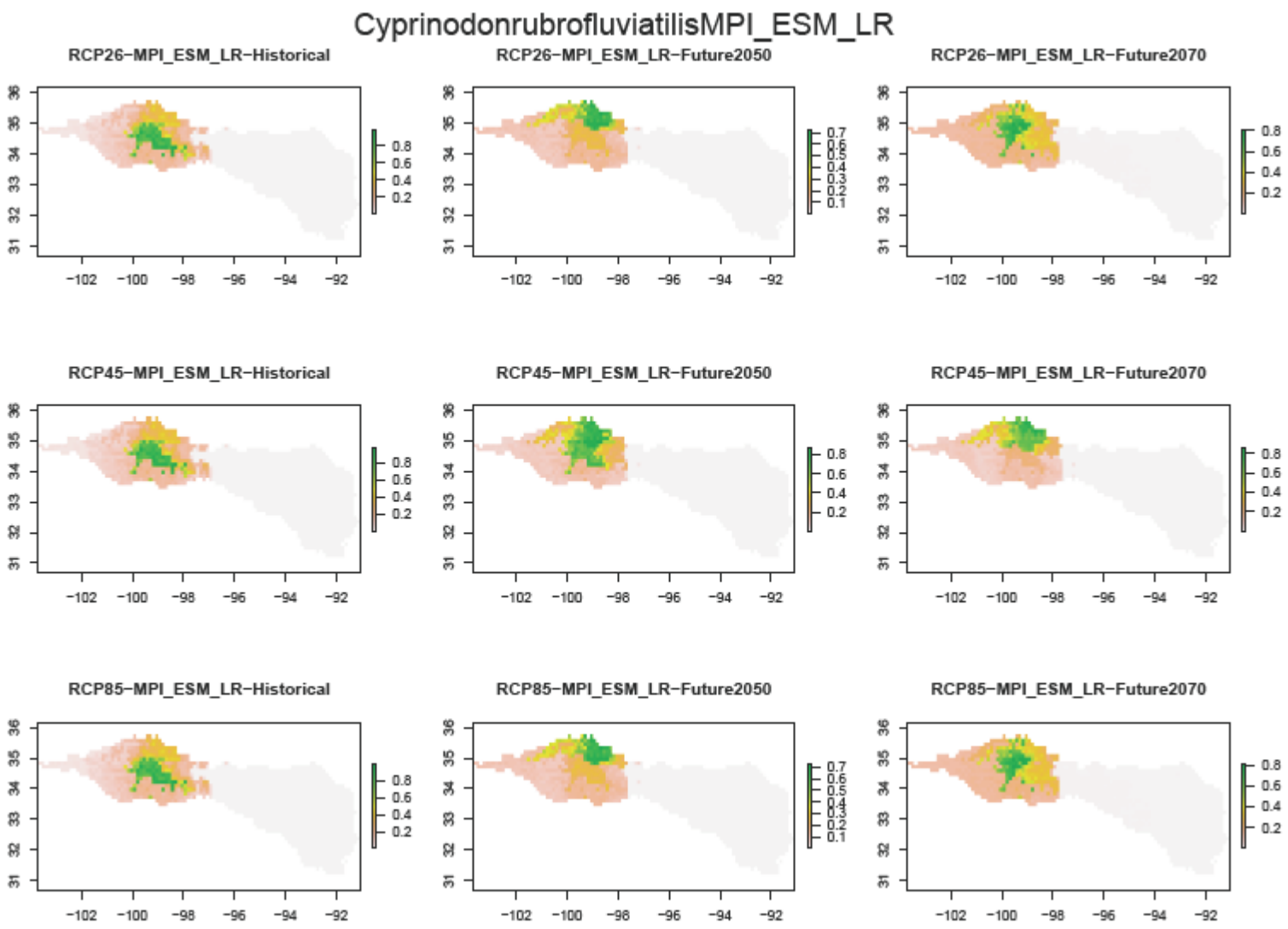

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RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070
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Cyprinodon_rubrofluviatilis_MPI_ESM_LR
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RCP26-MPI_ESM_LR-Future2050
RCP26-MPI_ESM_LR-Future2070
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RCP45-MPI_ESM_LR-Future2050
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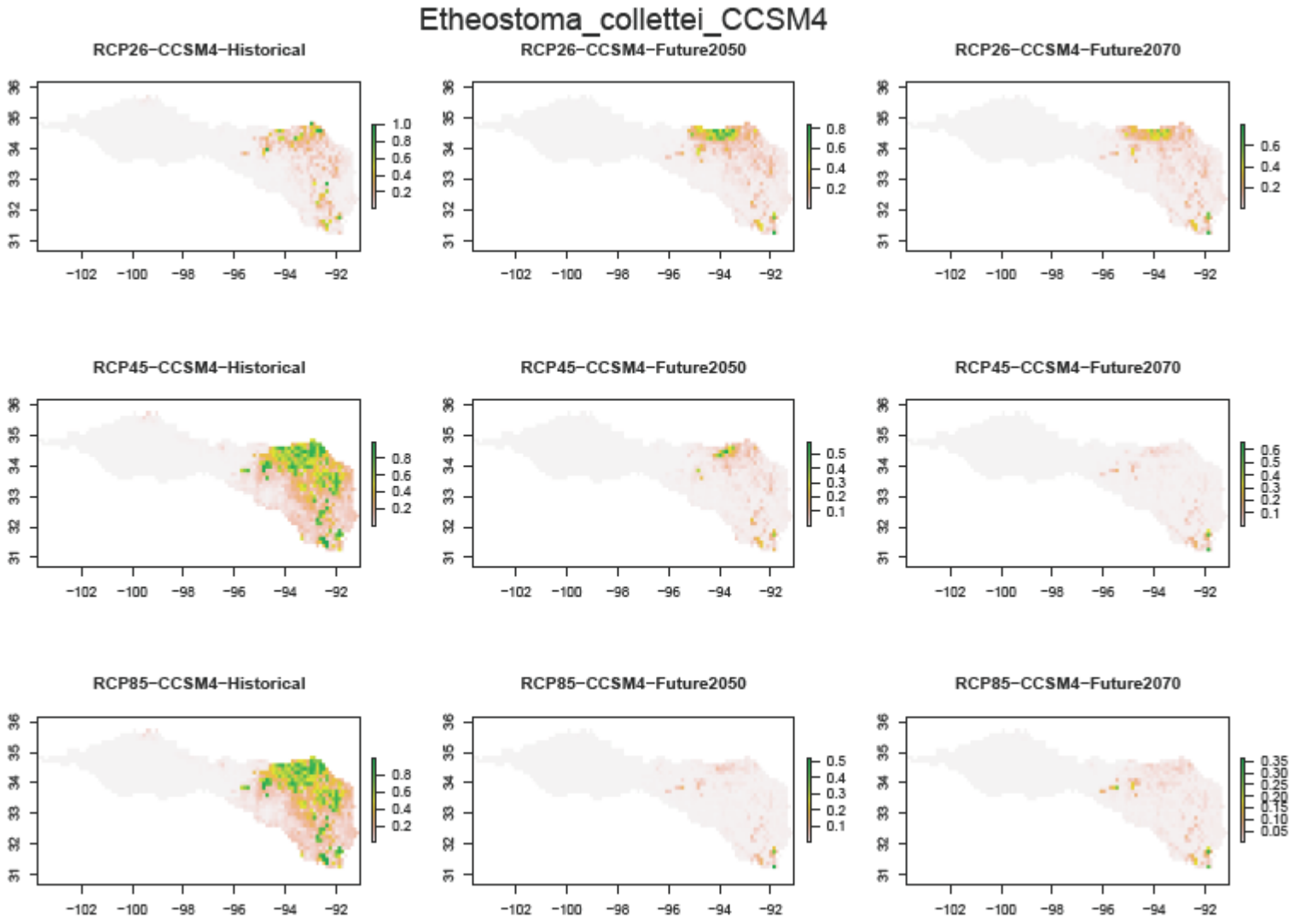
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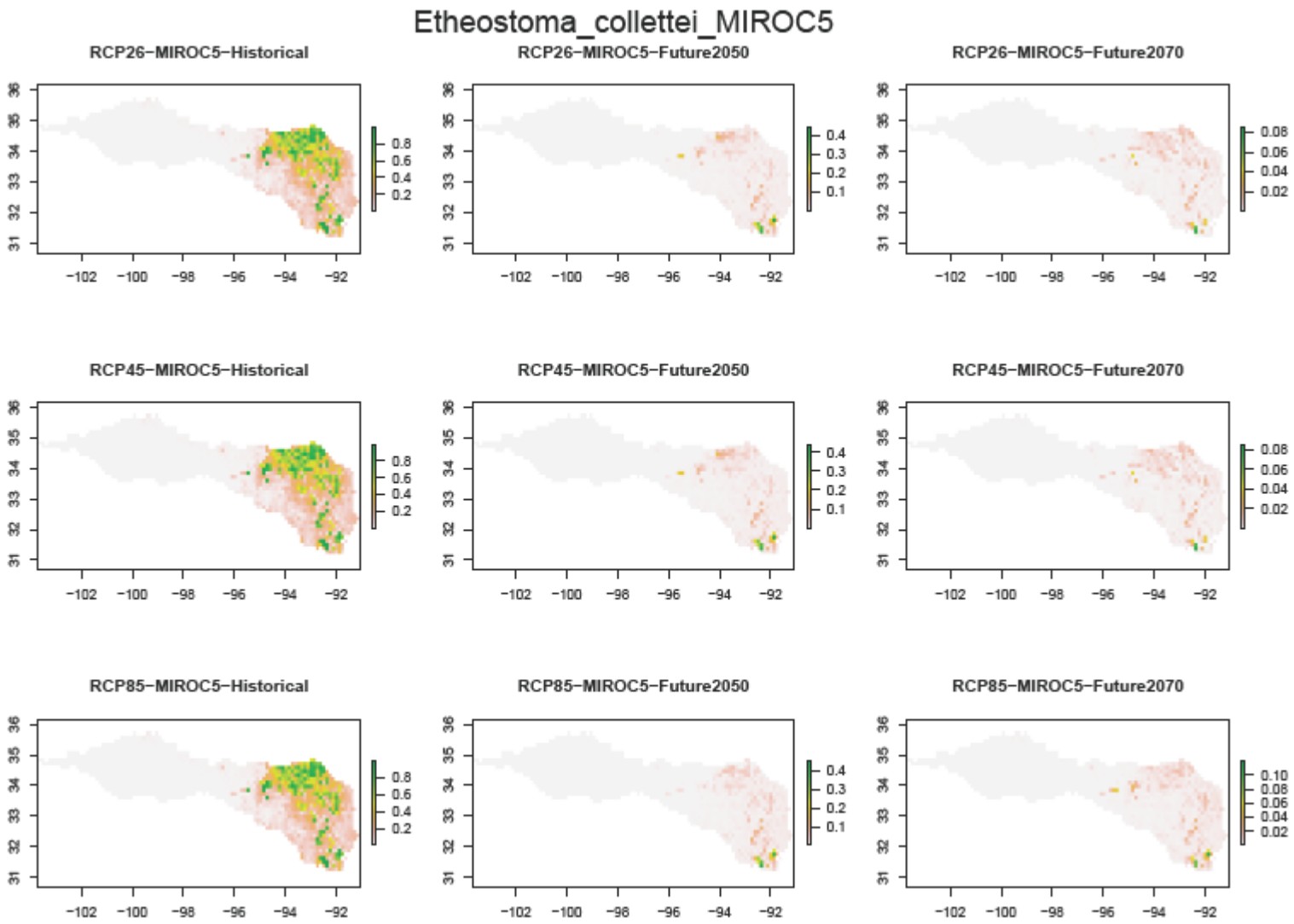


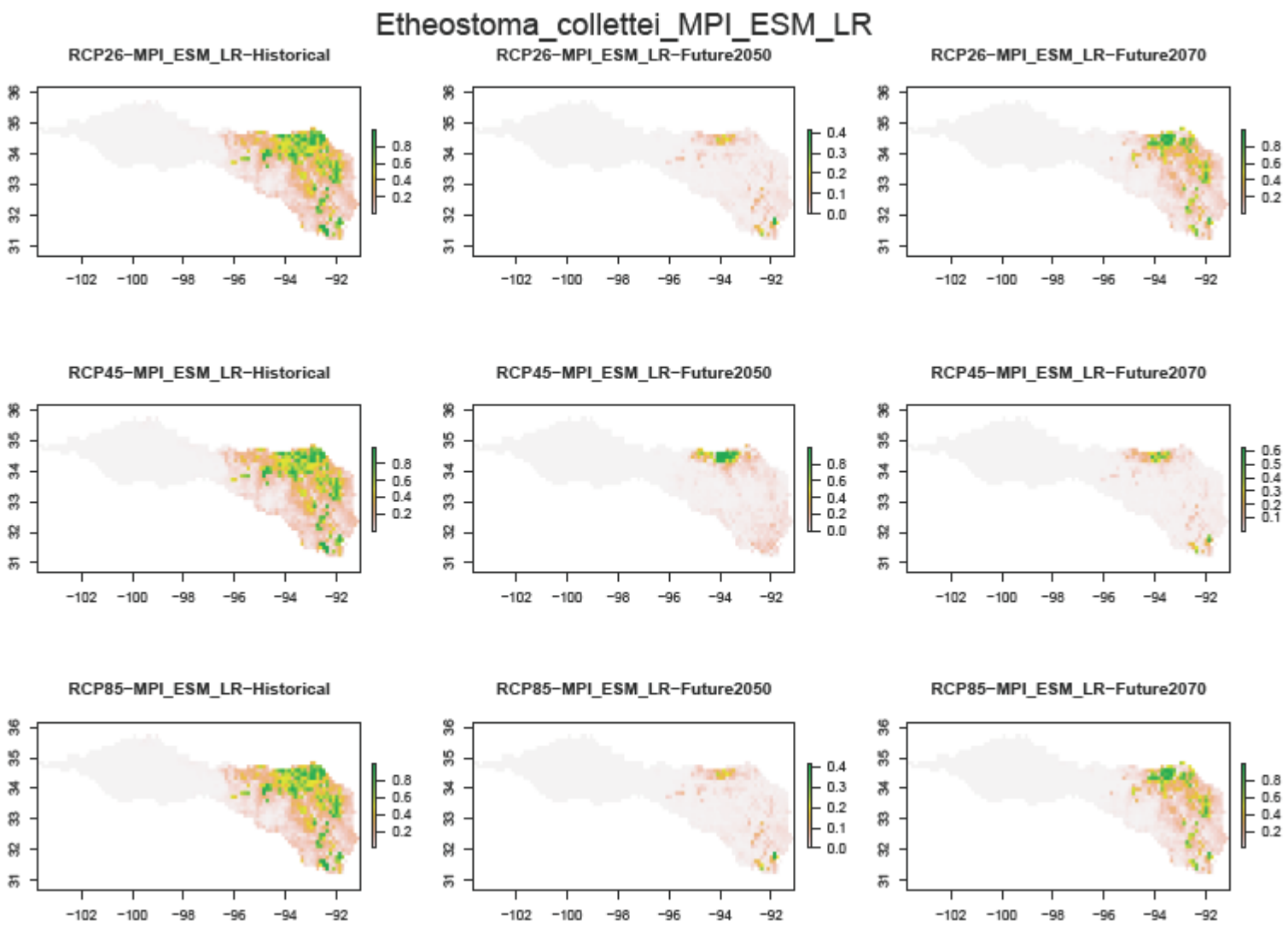

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RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070
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0.4
0.6
0.8
1.0


CyprinodonrubrofluviatilisMPI_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
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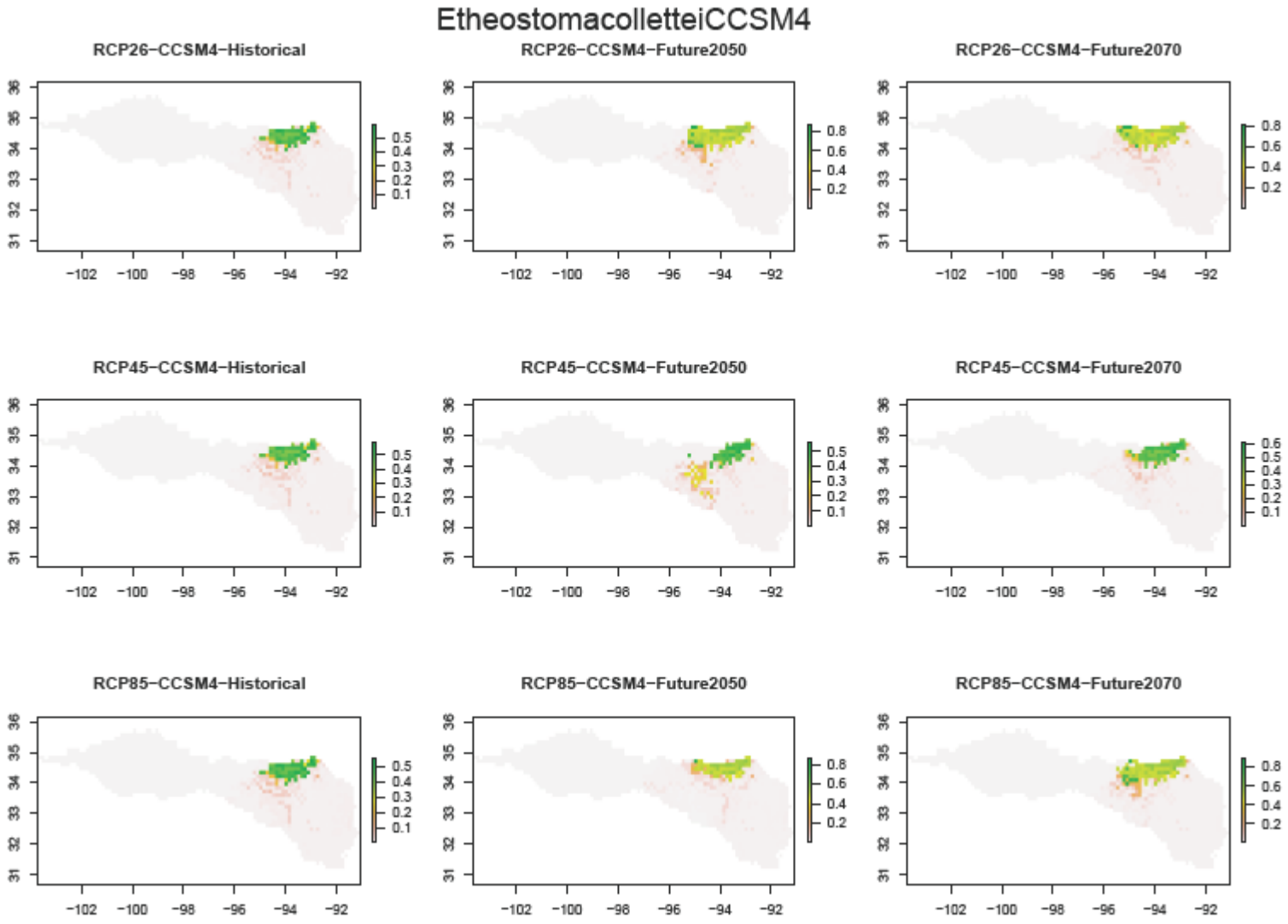
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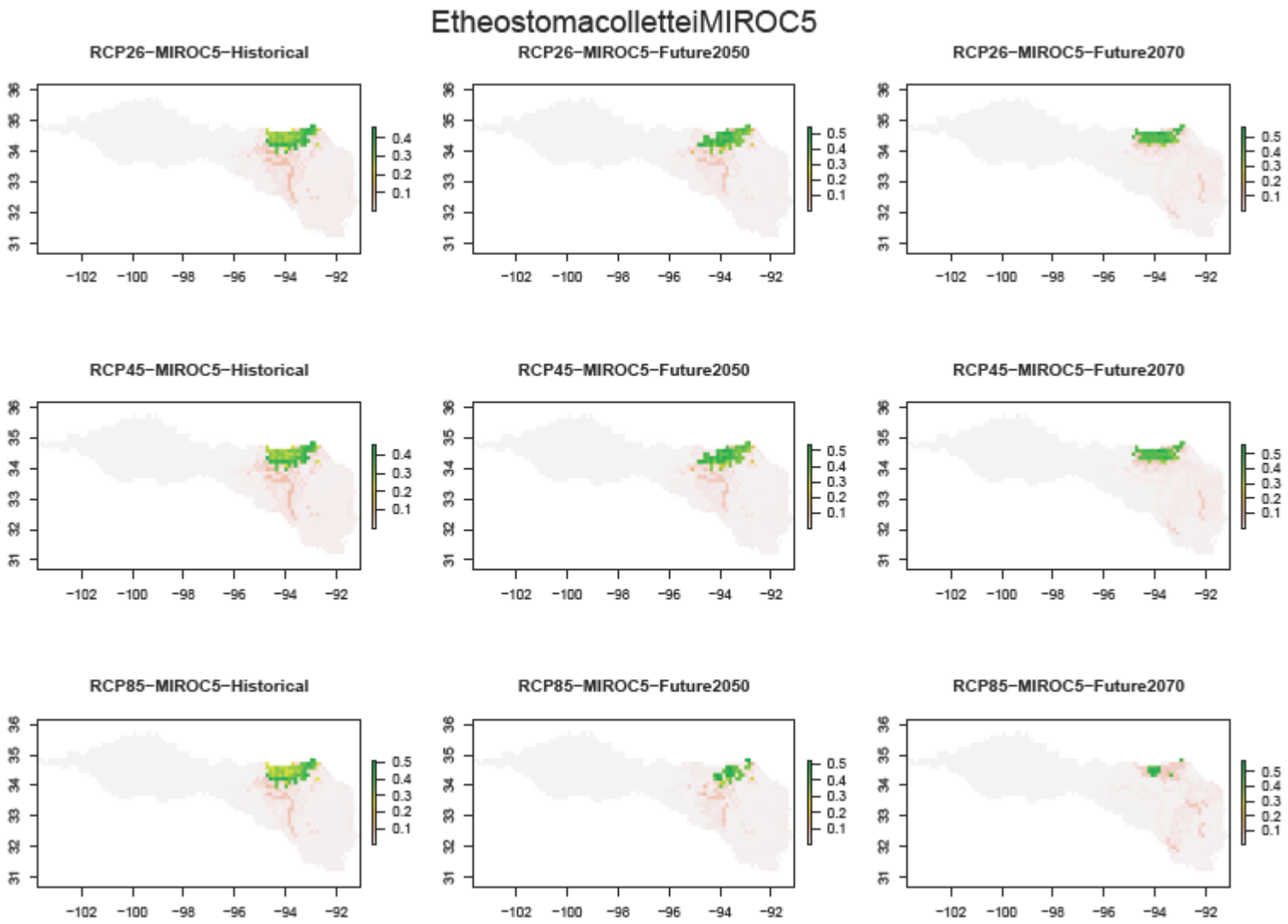


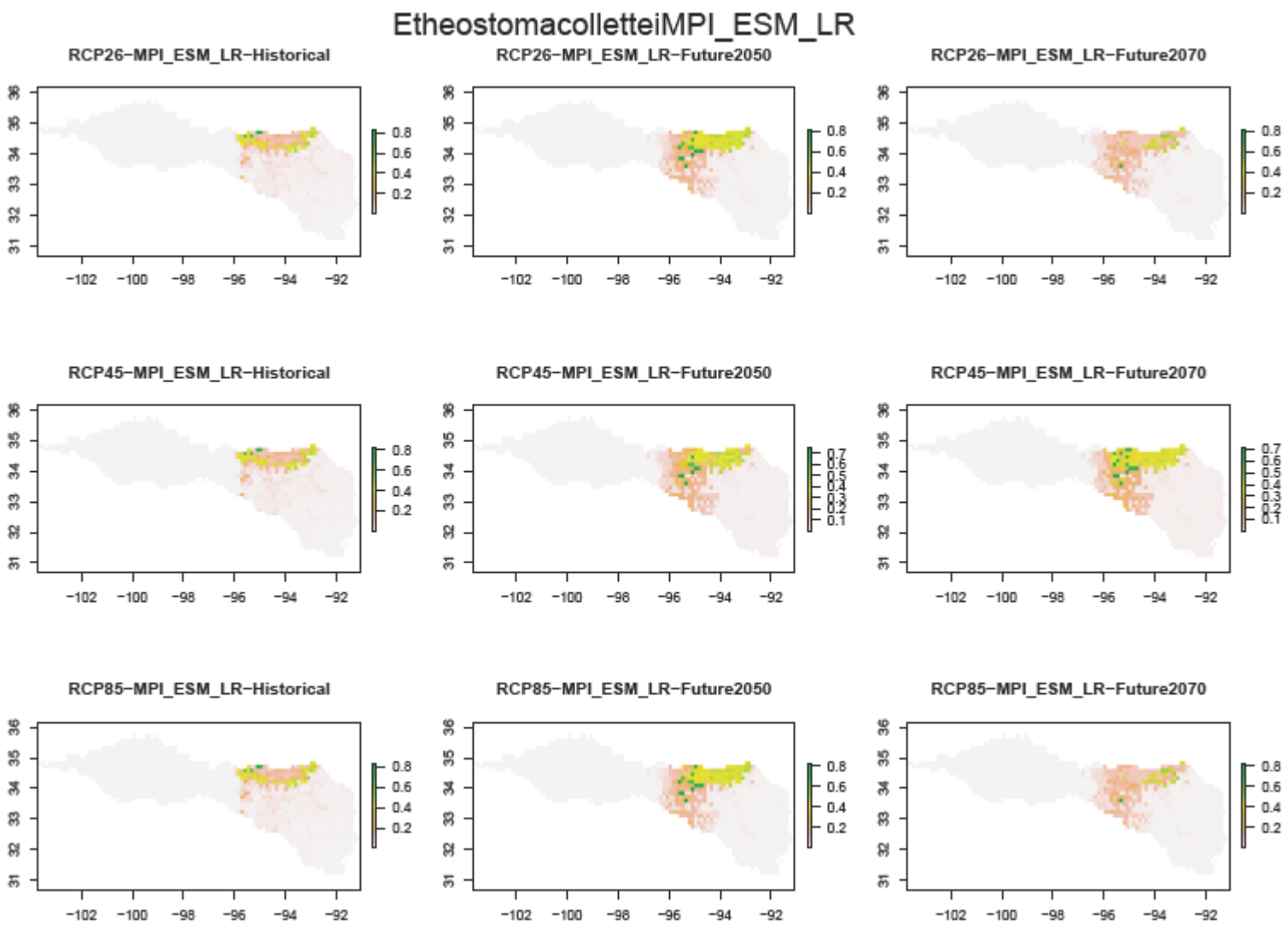

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RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070
−102 −100 −98 −96 −94 −92
31 32 33 34 35 36
0.8 0.6 0.4 0.2
0.4 0.3 0.2 0.1
0.08 0.06 0.04 0.02
0.10 0.08 0.06 0.04 0.02


Etheostoma_collettei_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
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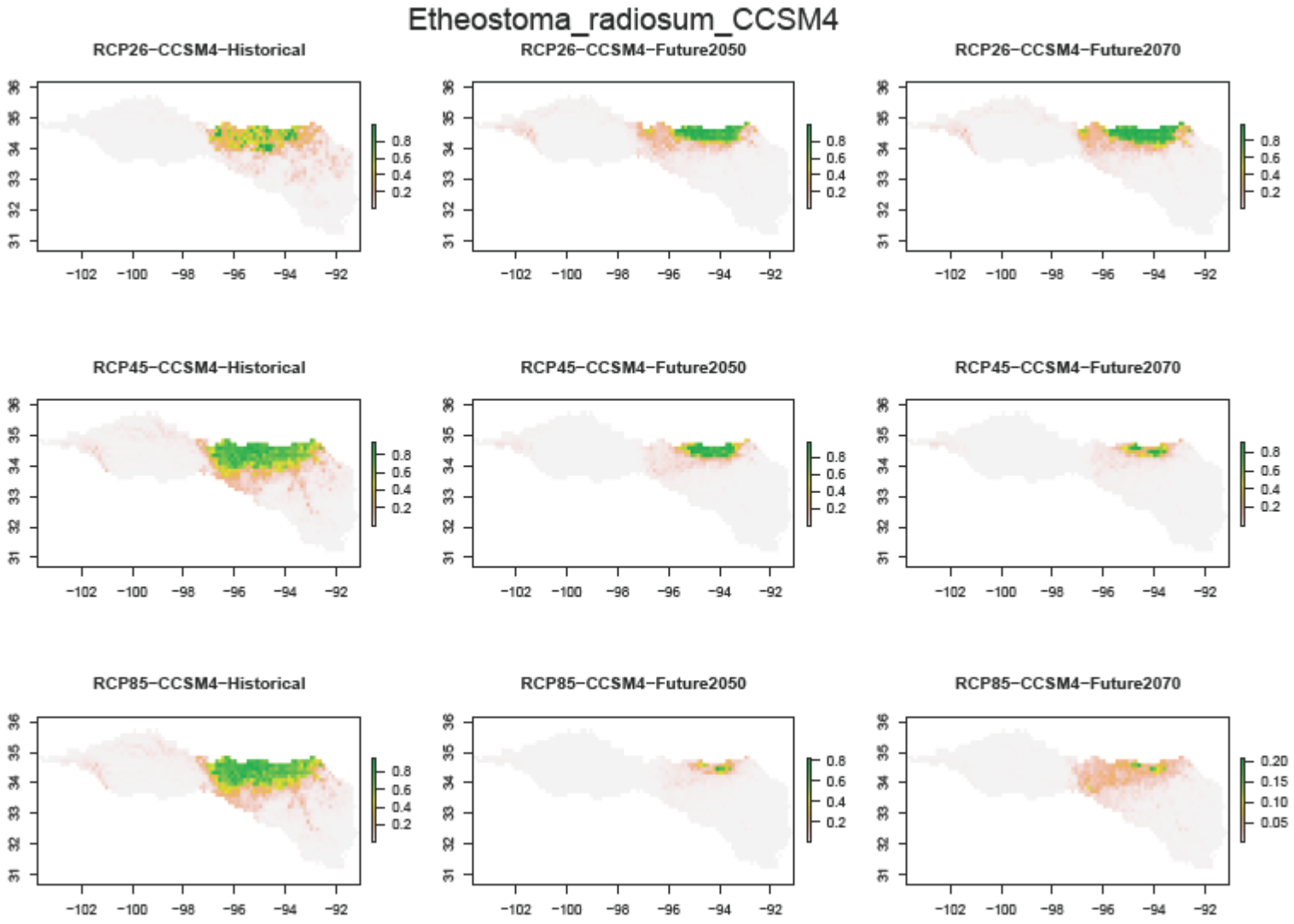
BRT: *Etheostoma collettei*

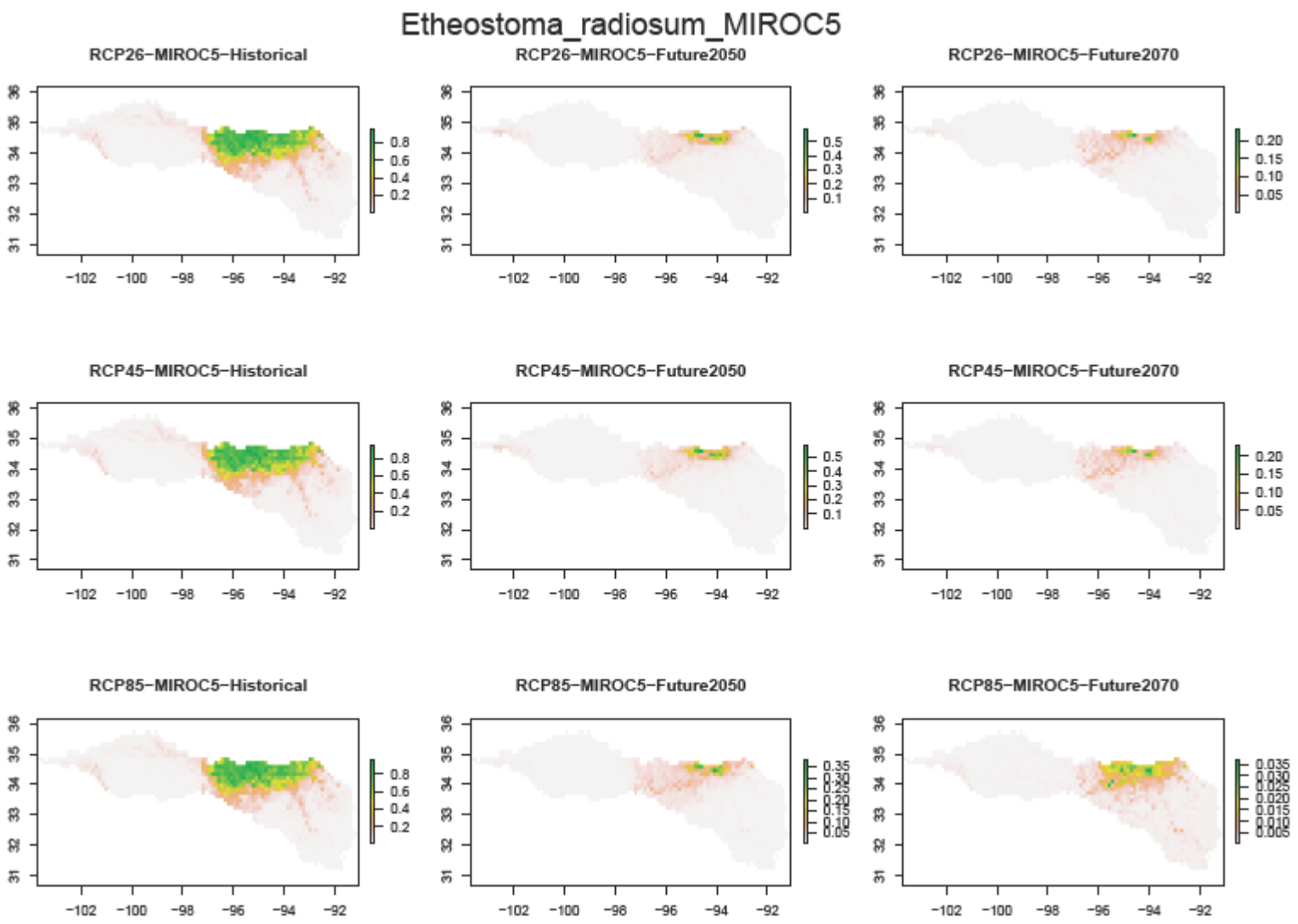


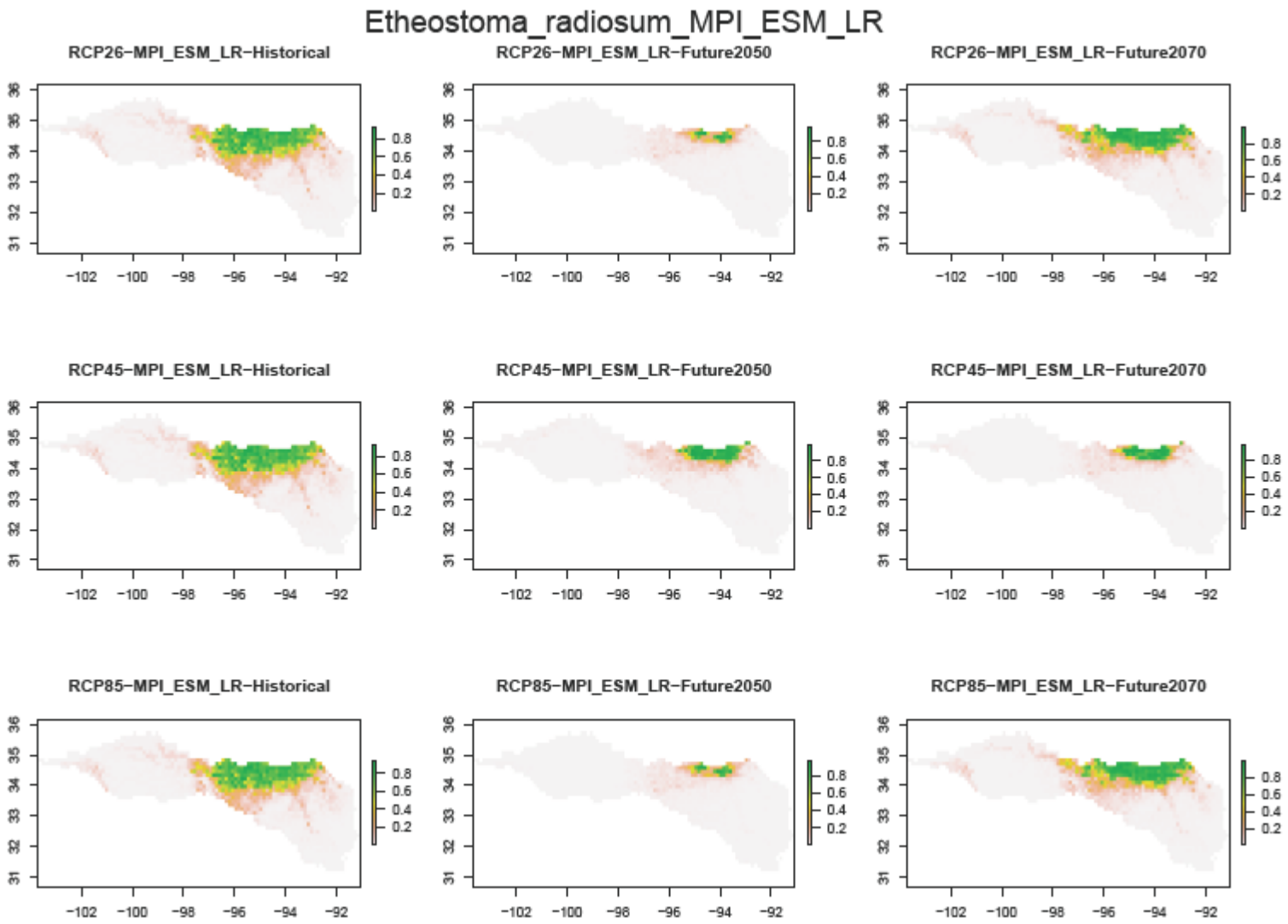

EtheostomacolletteiMIROC5
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RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070
−102 −100 −98 −96 −94 −92
31 32 33 34 35 36
0.1 0.2 0.3 0.4 0.5


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
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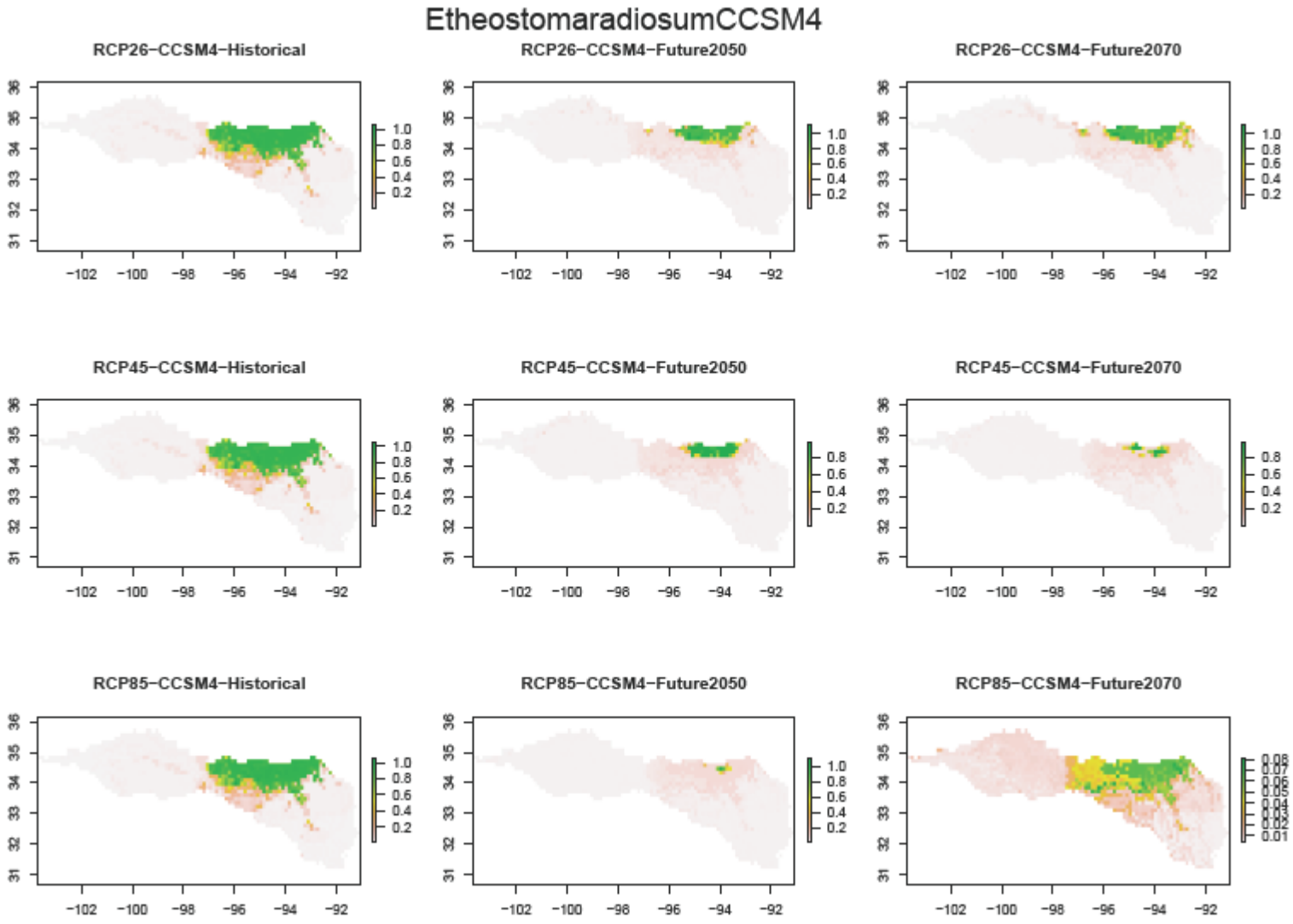
Maxent: *Etheostoma radiosum*

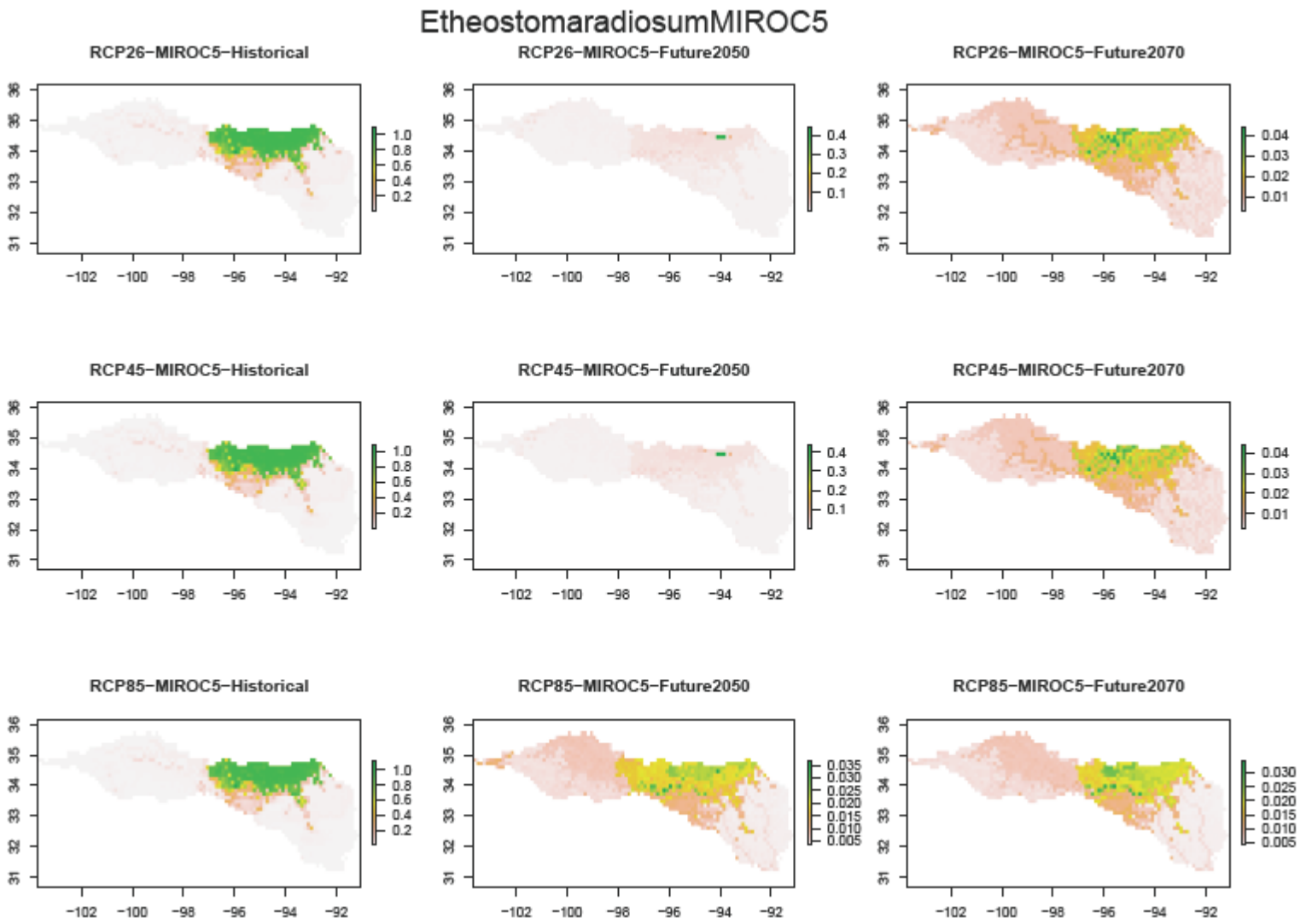


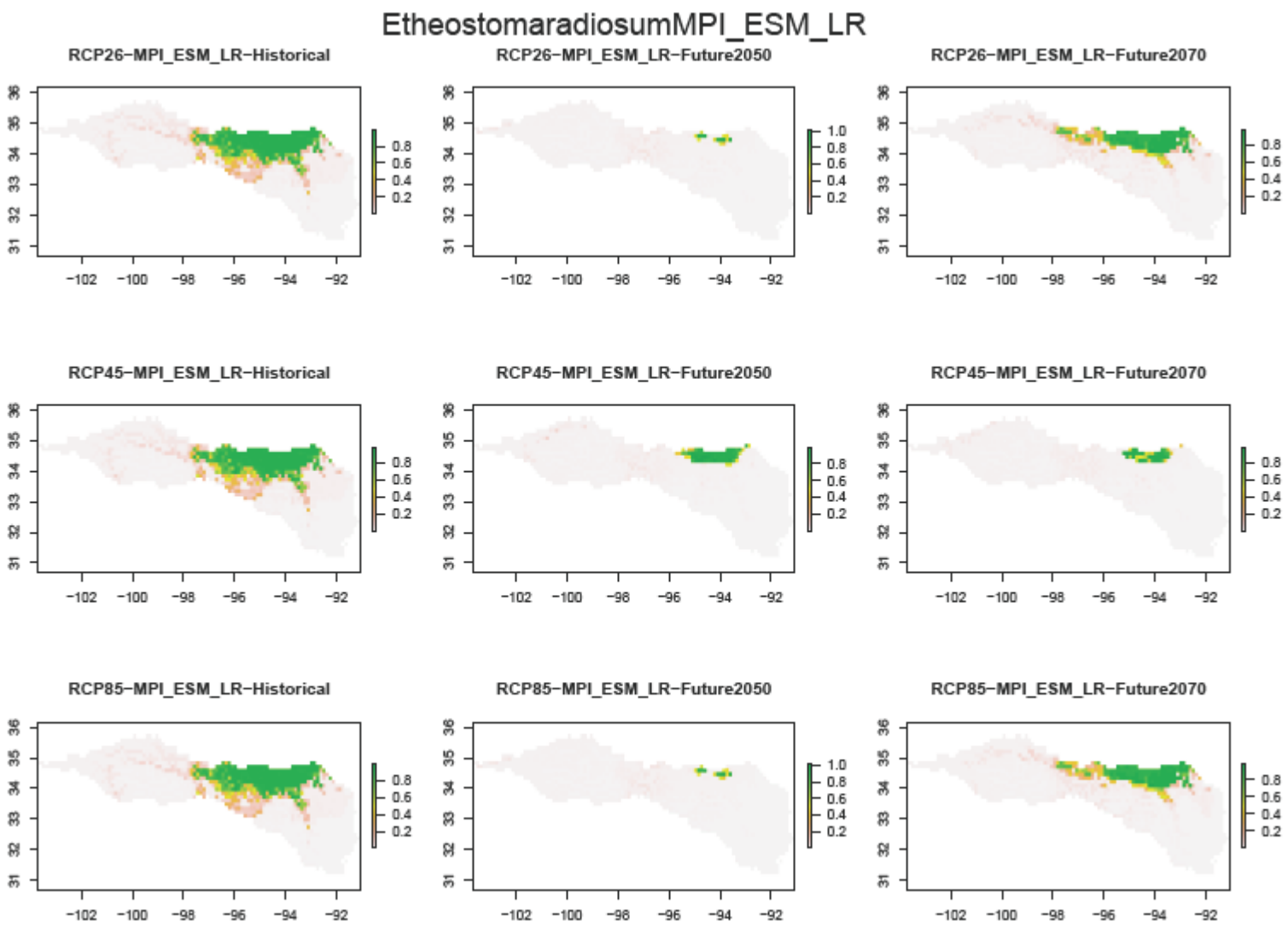

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RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070


Etheostoma_radiosum_MPI_ESM_LR
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RCP26-MPI_ESM_LR-Future2050
RCP26-MPI_ESM_LR-Future2070
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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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0.8

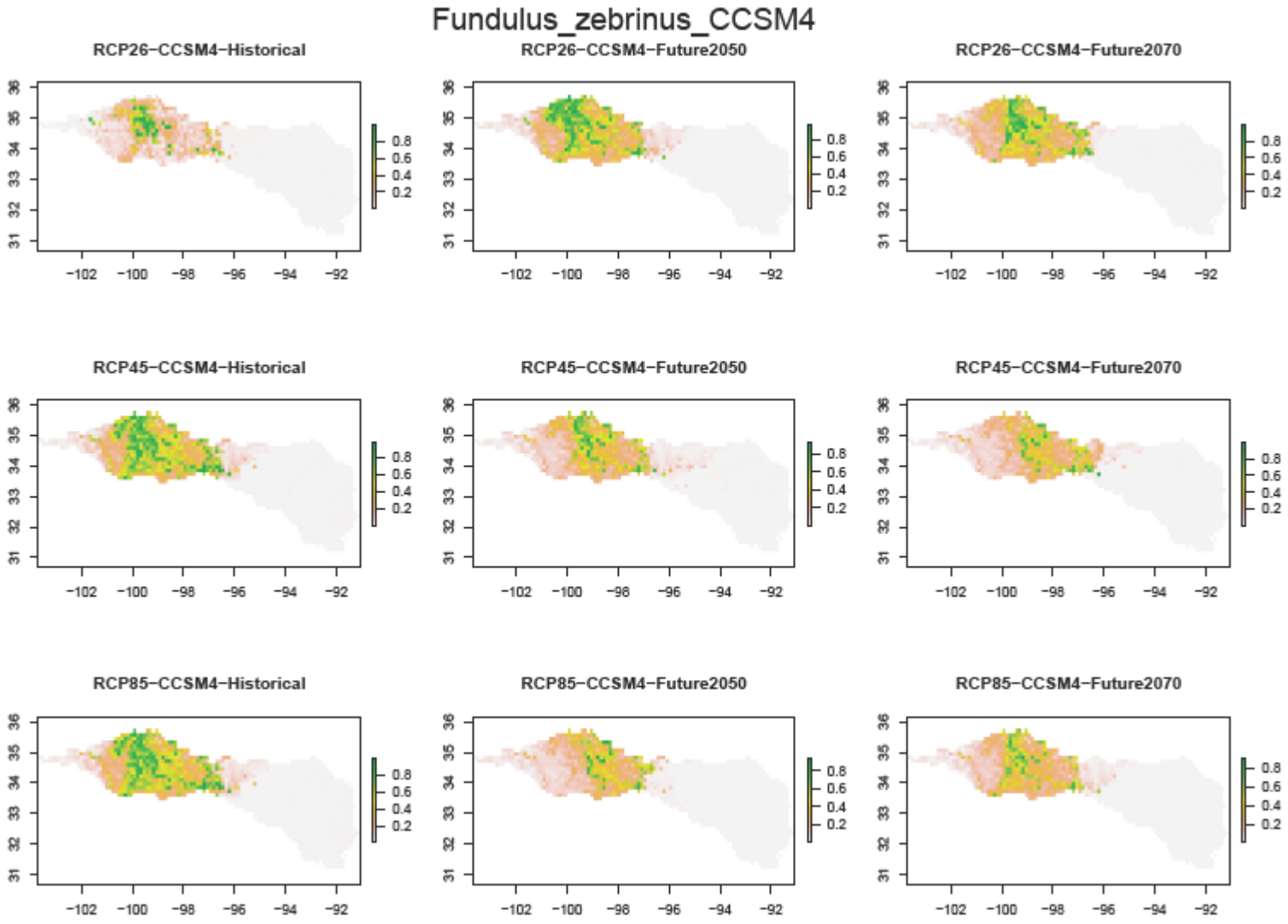
BRT: *Etheostoma radiosum*

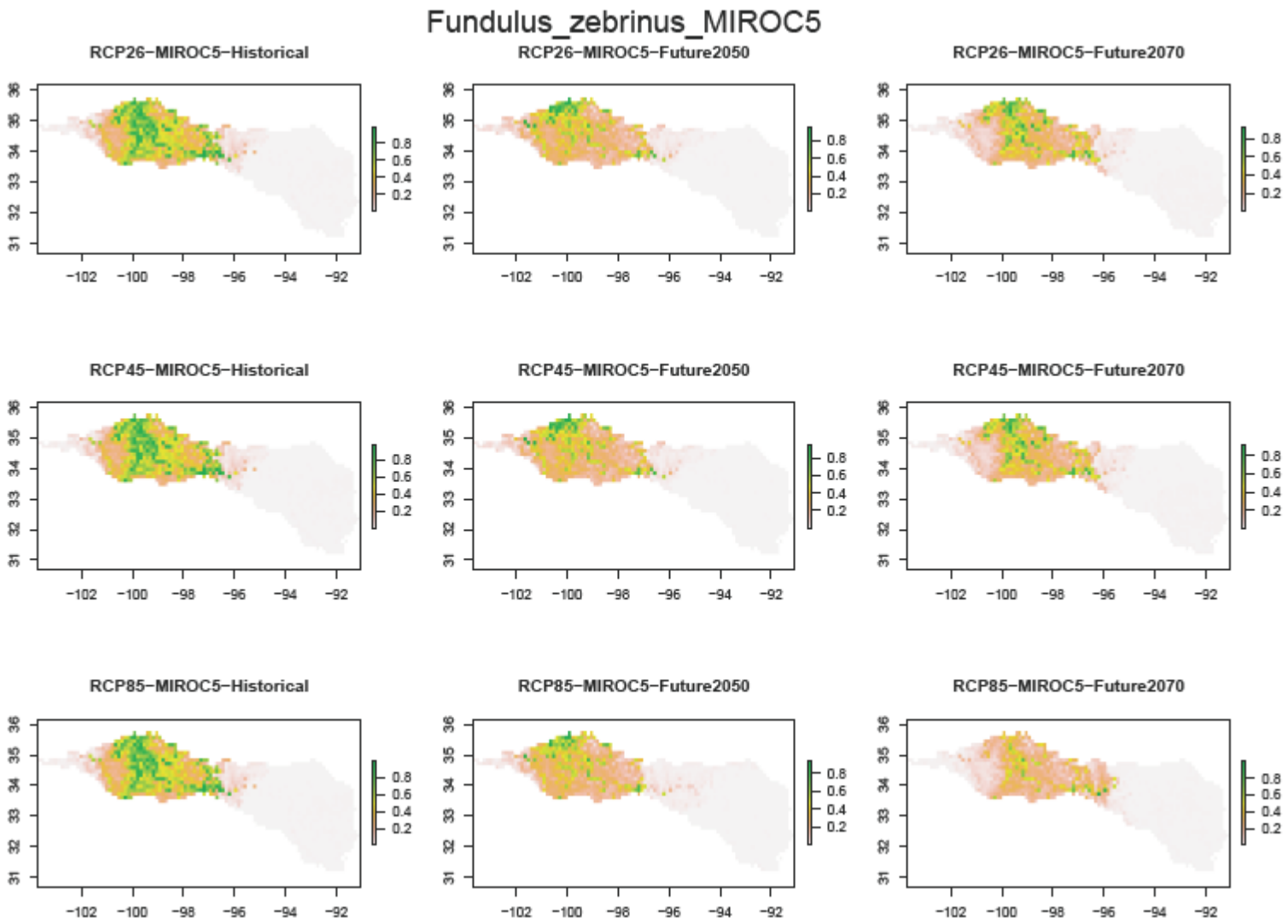


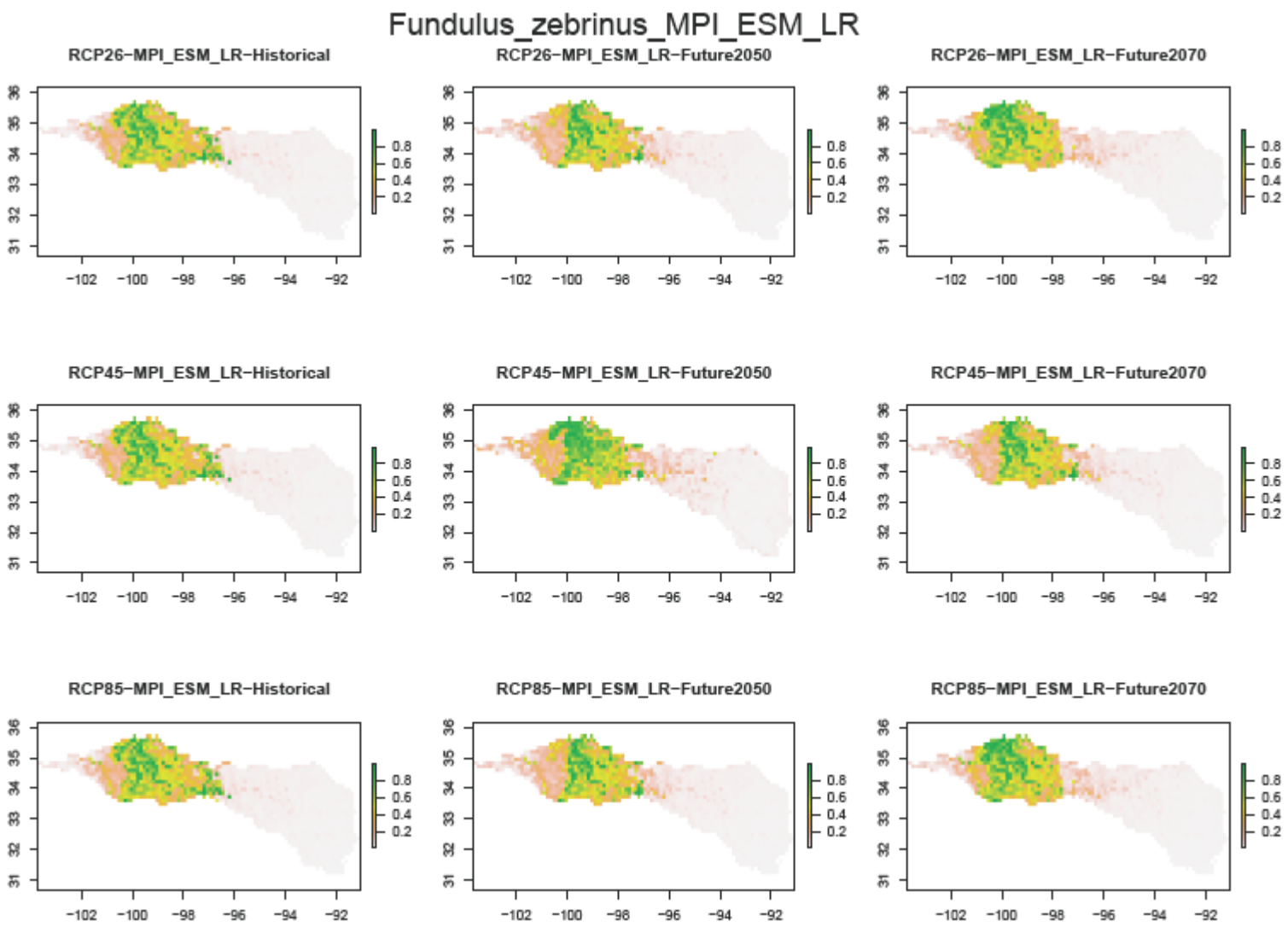

EtheostomaradiosumMIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070


EtheostomaradiosumMPI_ESM_LR
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 1.0

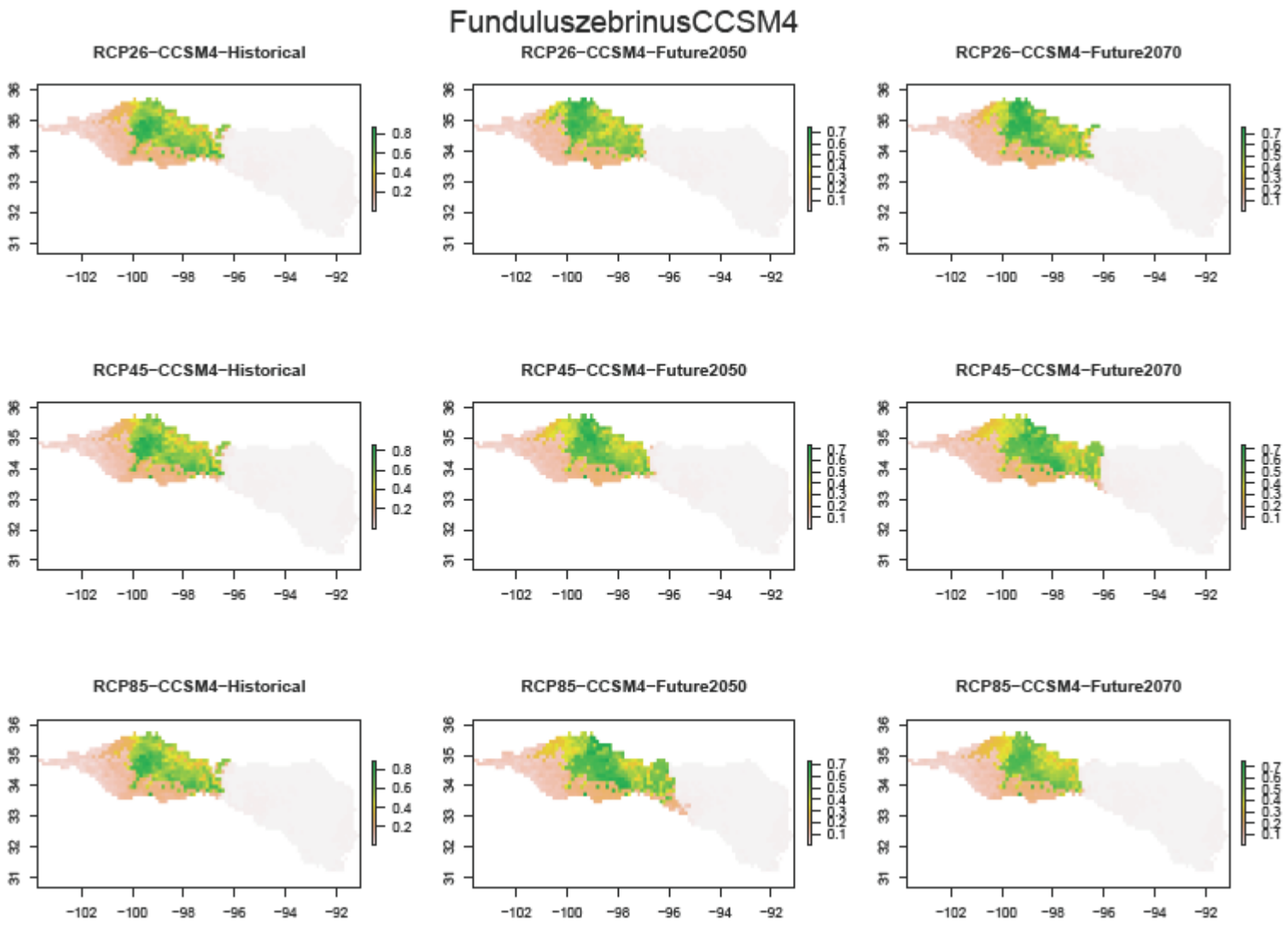
Maxent: *Fundulus zebrinus*

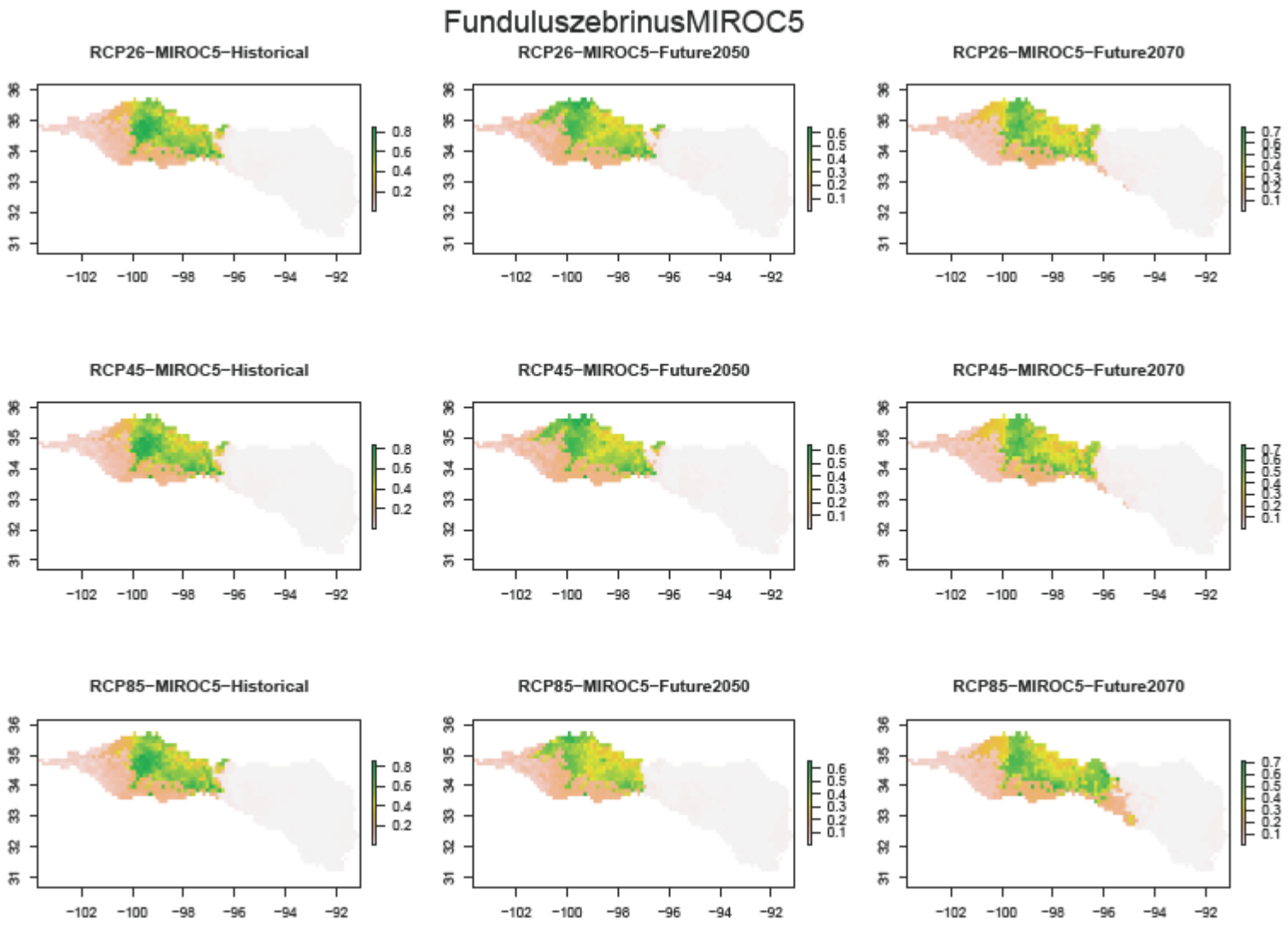


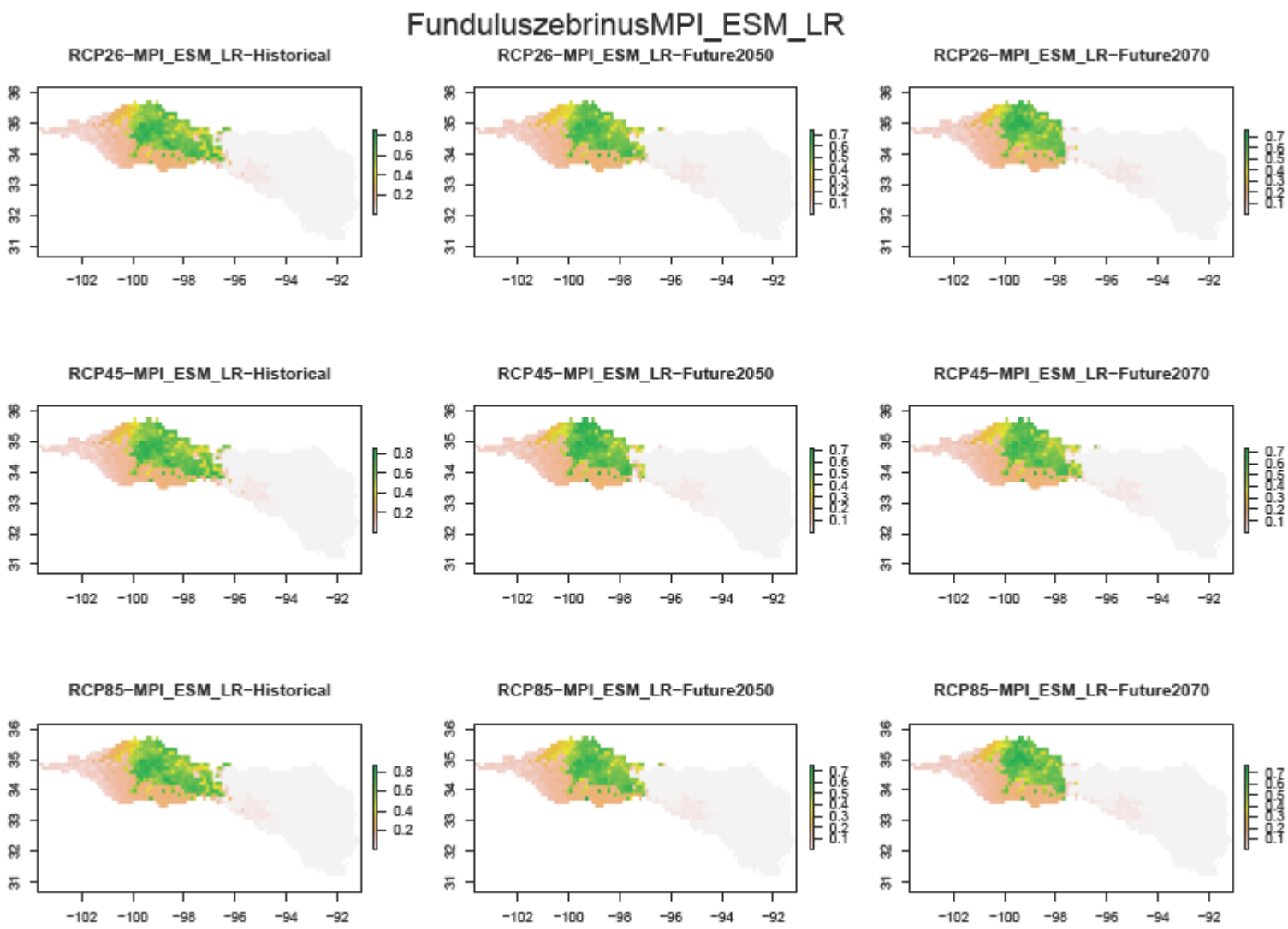

Fundulus_zebrinus_MIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070
36
35
34
33
32
31
−102
−100
−98
−96
−94
−92
0.8
0.6
0.4
0.2


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
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0.4
0.6
0.8

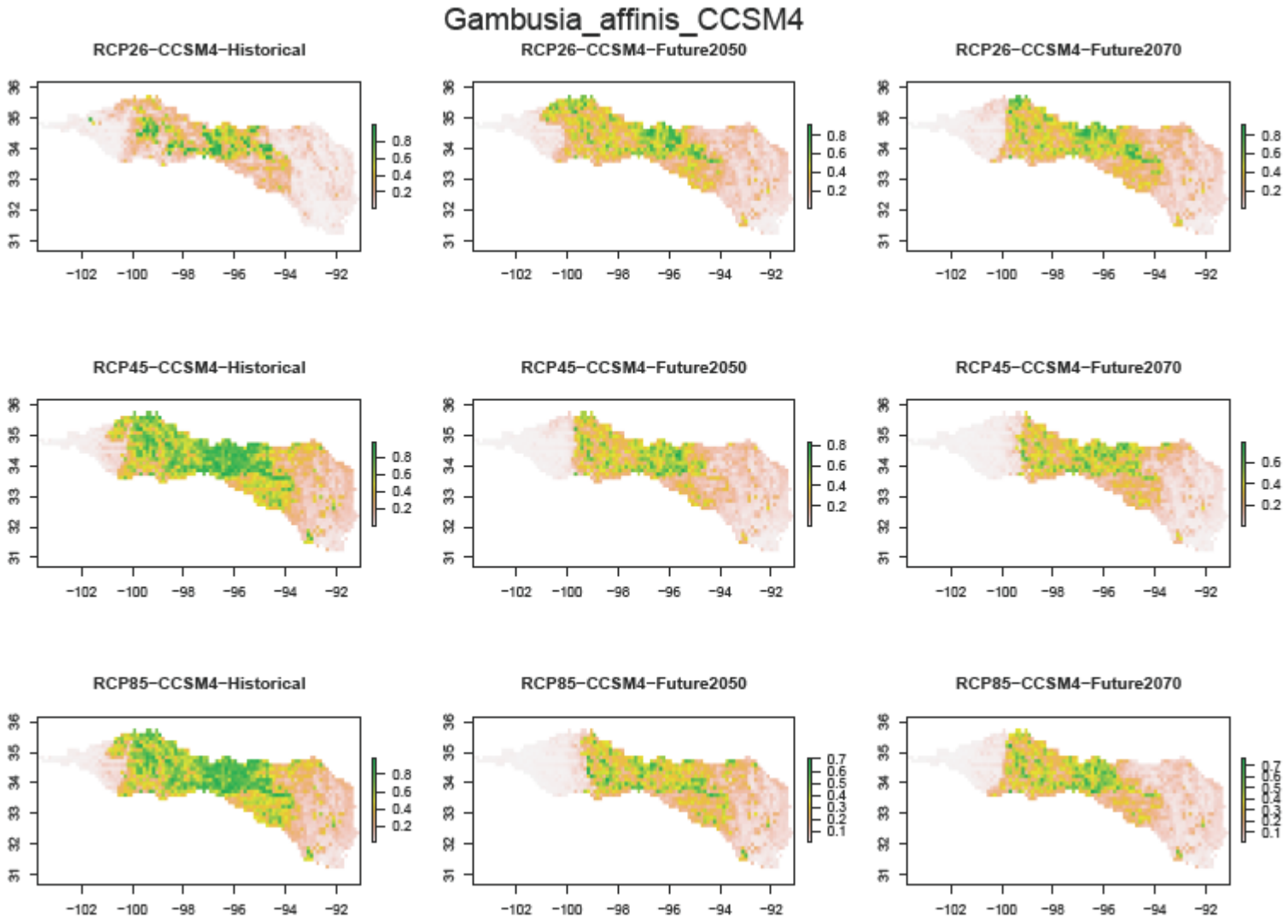
BRT: *Fundulus zebrinus*

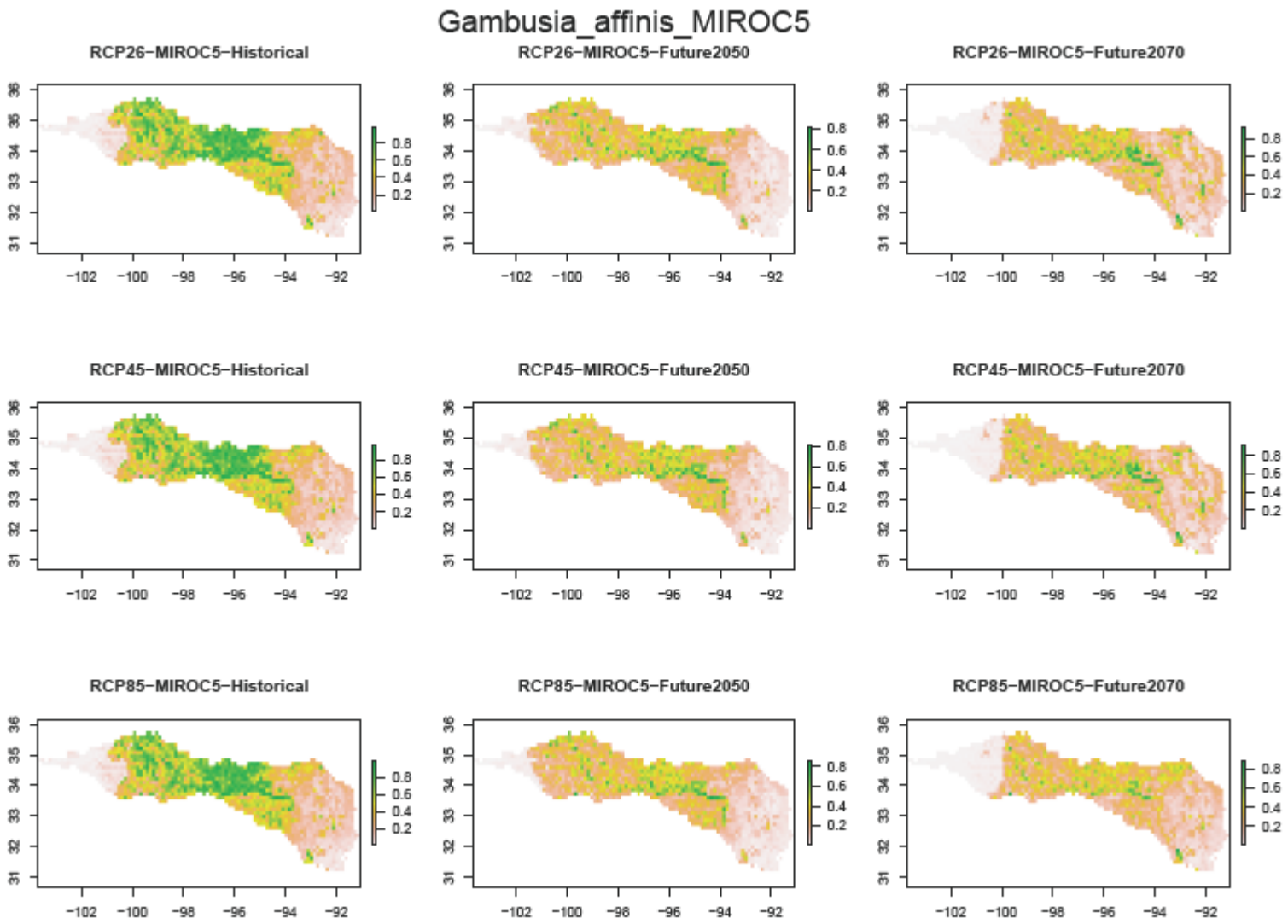


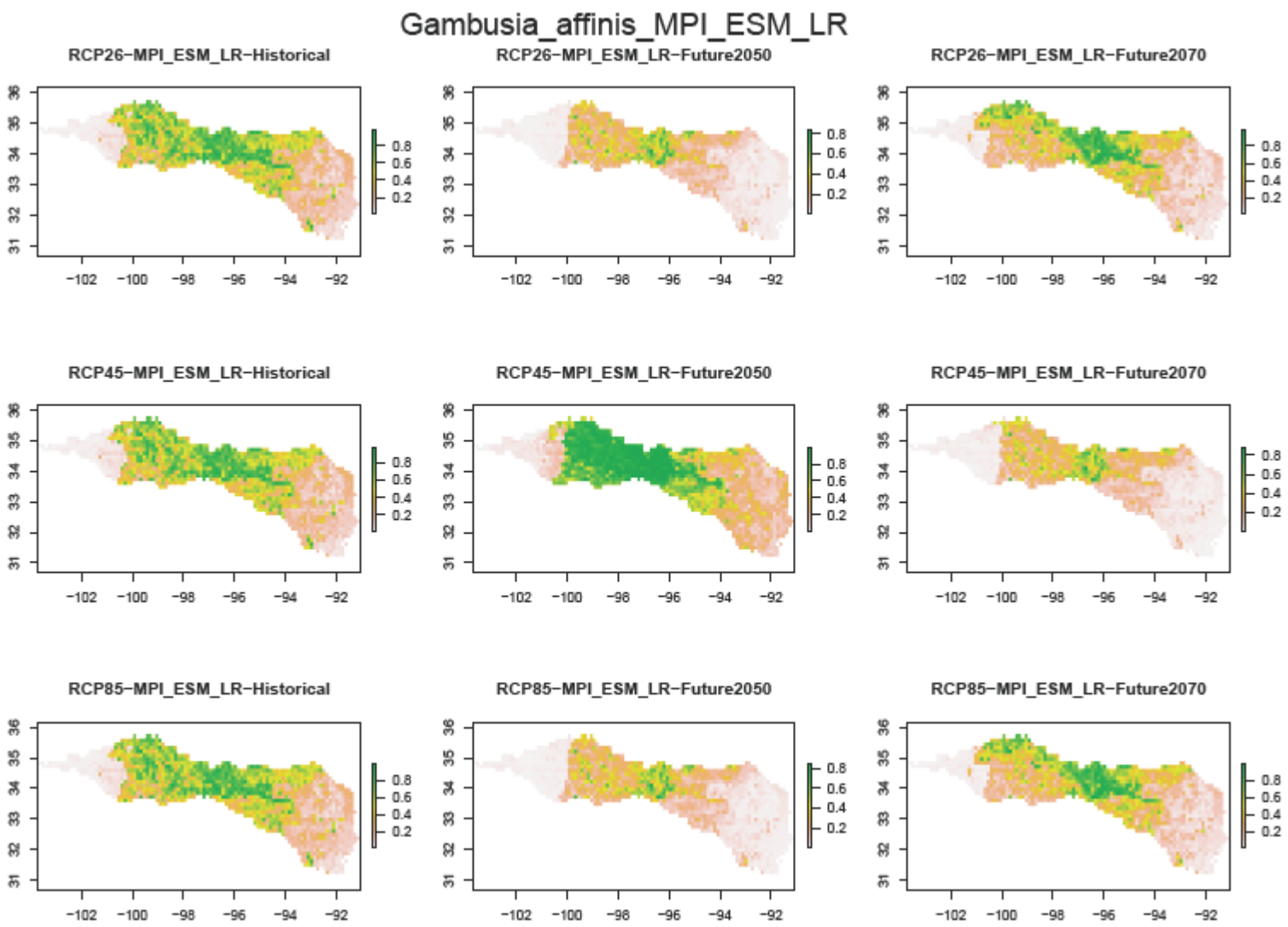

FunduluszebrinusMIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070


FundulusZebrinusMPI_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
0.7 0.6 0.5 0.4 0.3 0.2 0.1

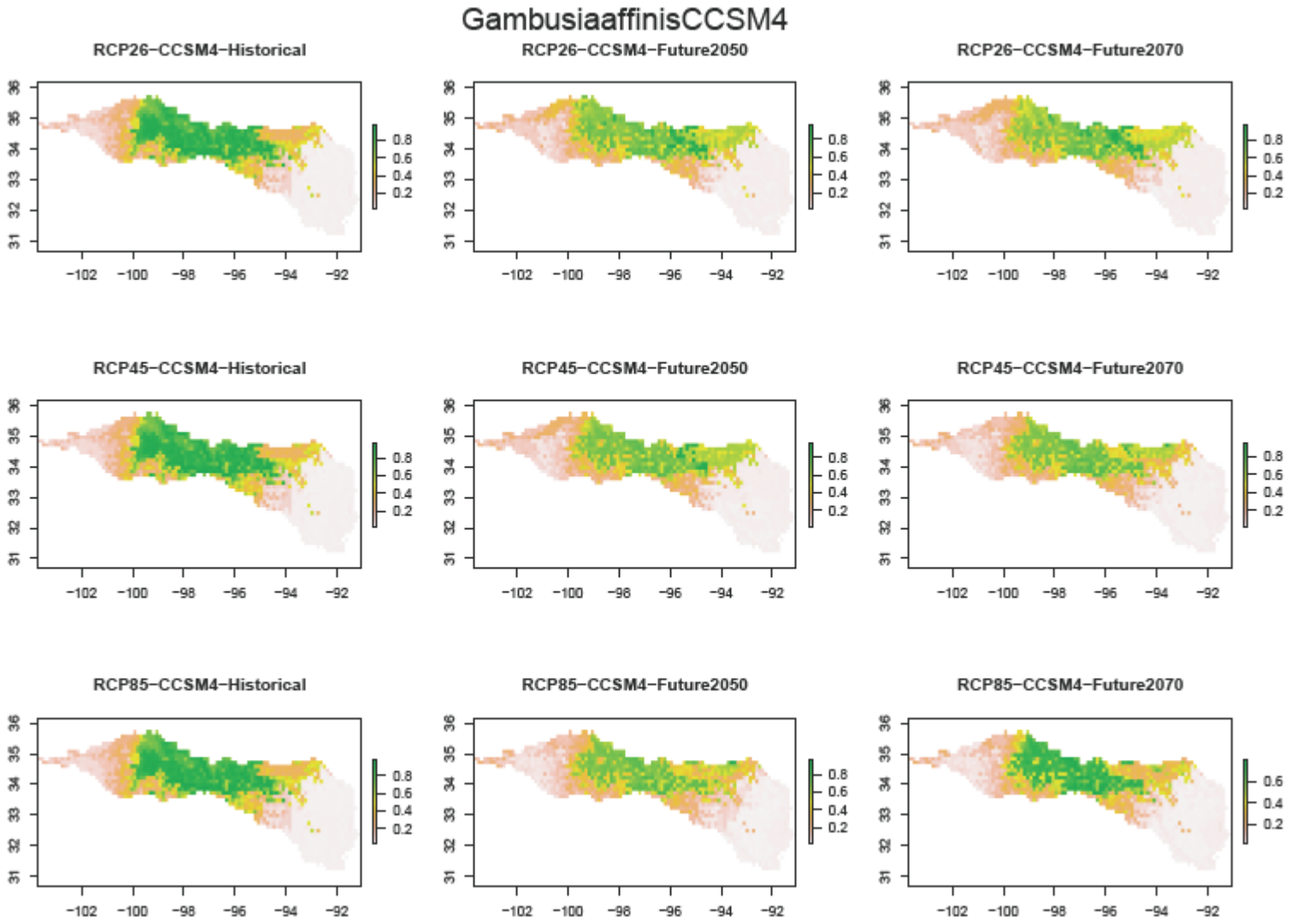
Maxent: *Gambusia affinis*

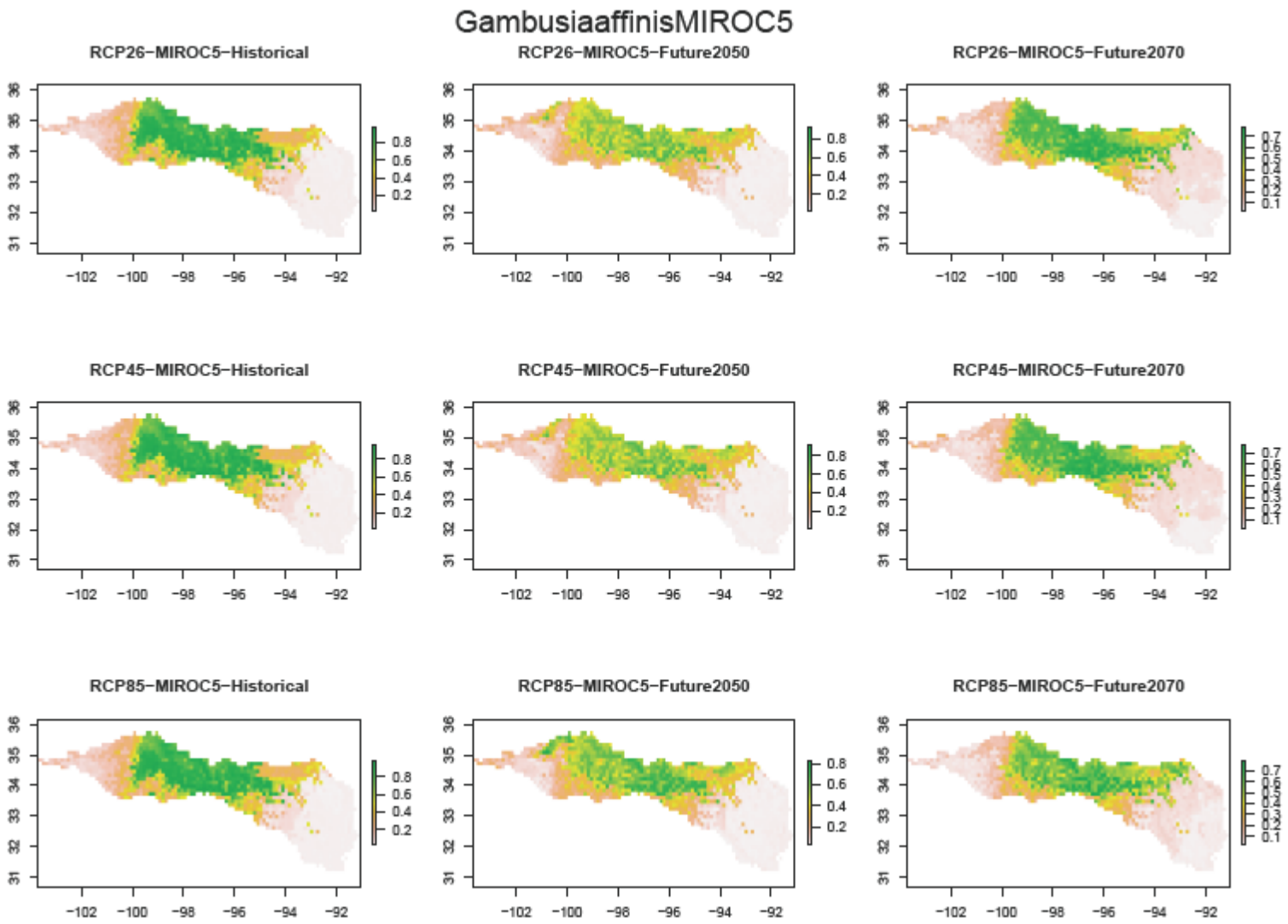


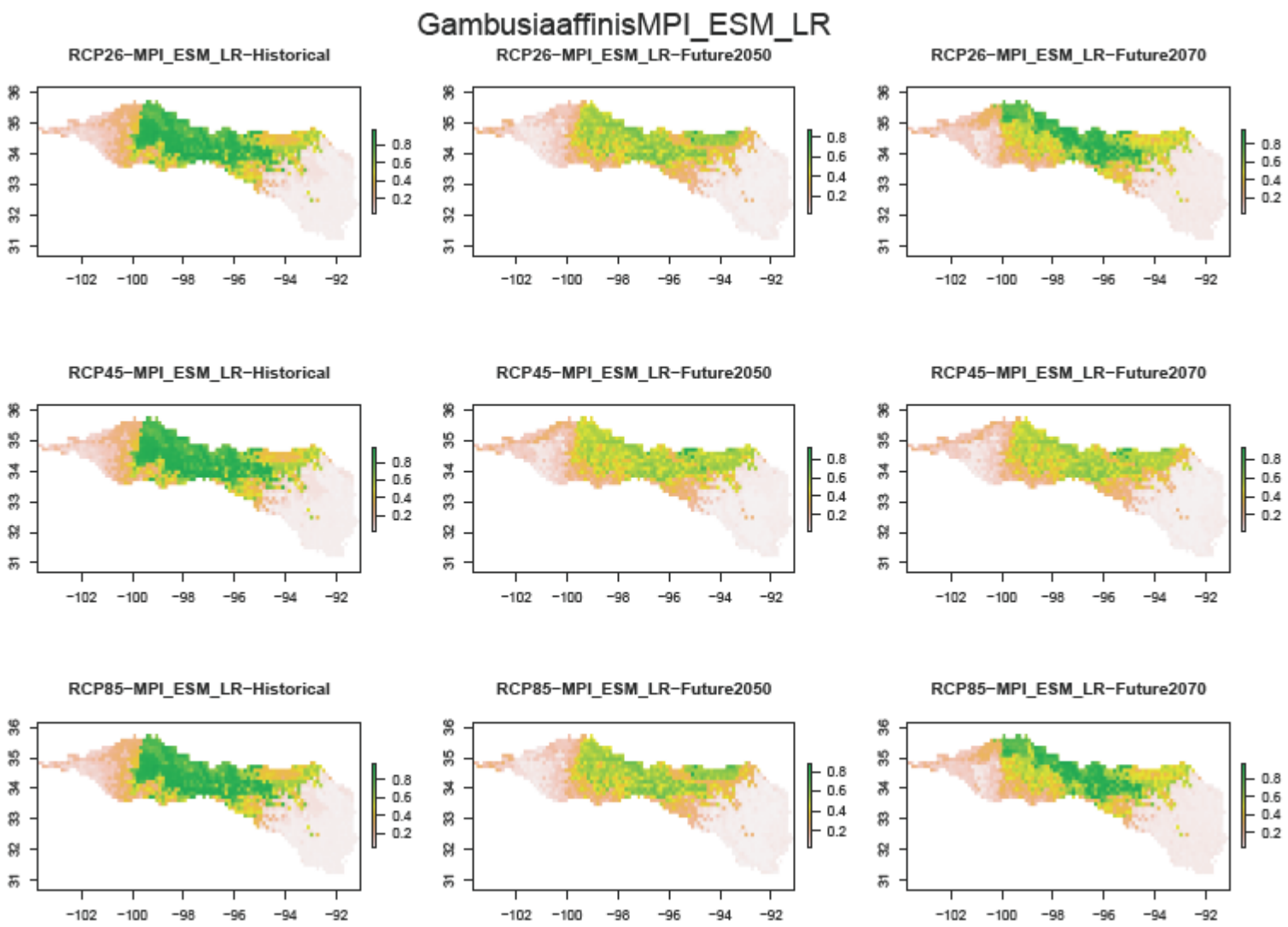

Gambusia_affinis_MIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070
0.8
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−94
−92
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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
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-102 -100 -98 -96 -94 -92
0.2 0.4 0.6 0.8

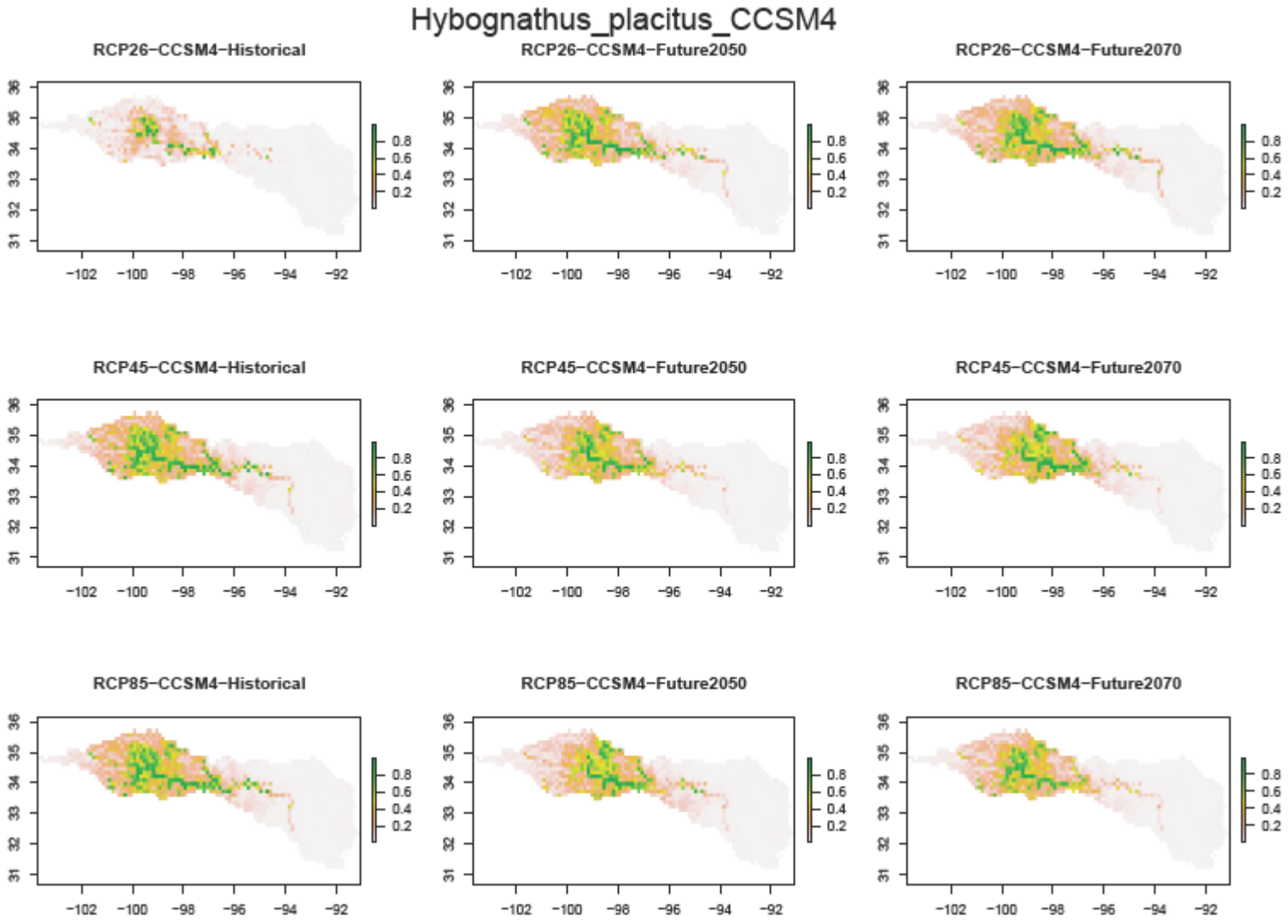
BRT: *Gambusia affinis*

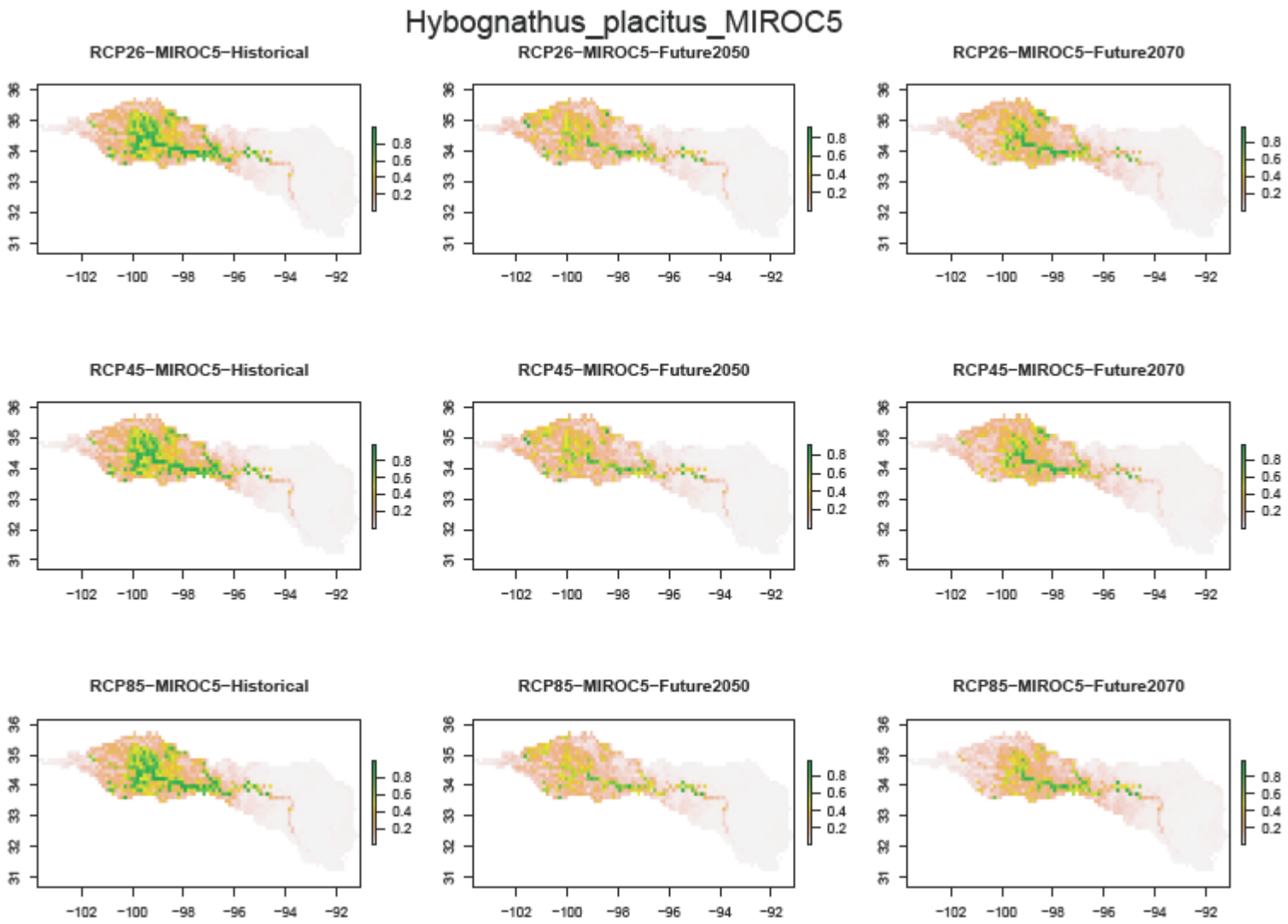


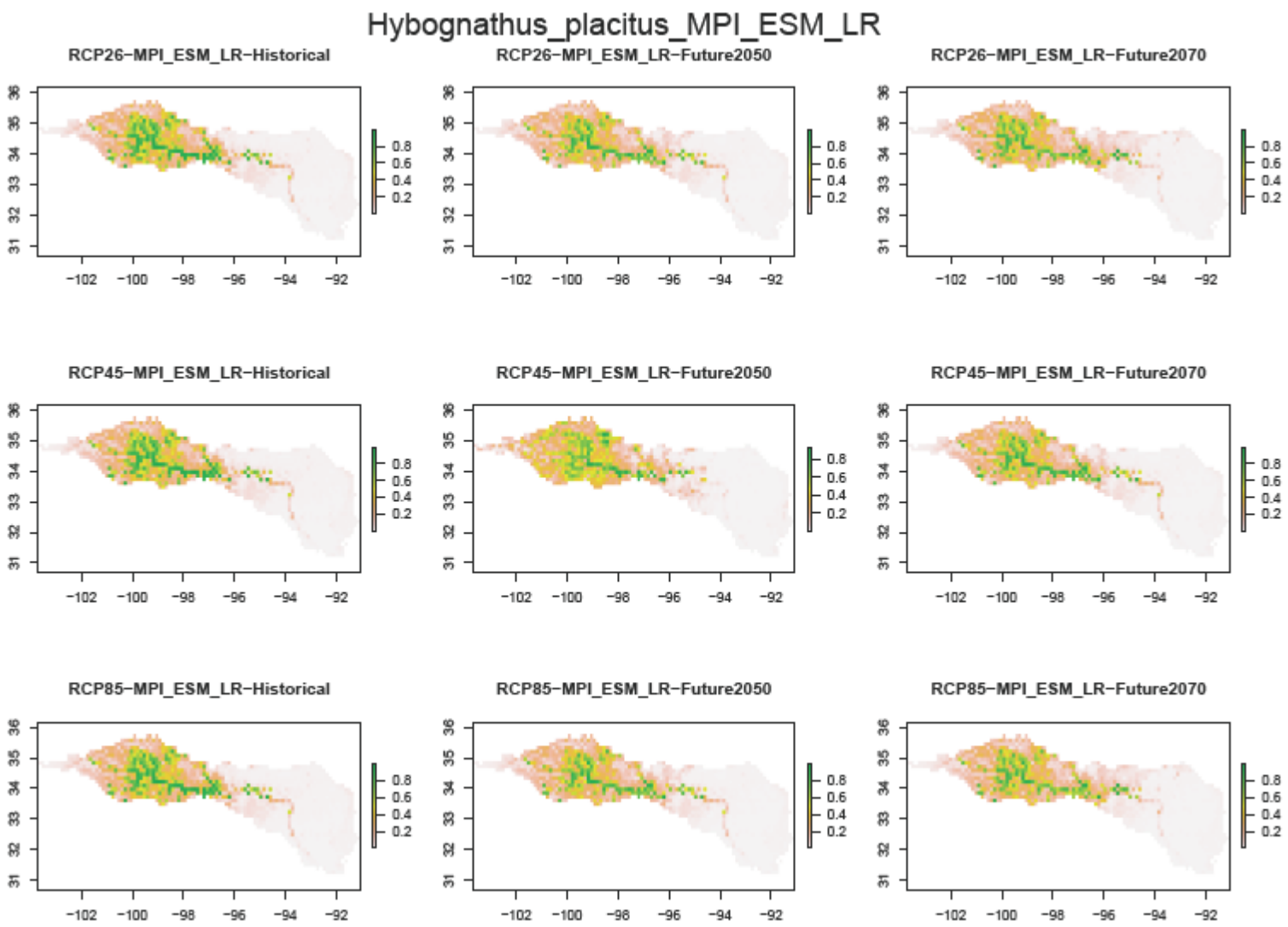

GambusiaaffinisMIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070


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
31
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36
-102
-100
-98
-96
-94
-92
0.2
0.4
0.6
0.8

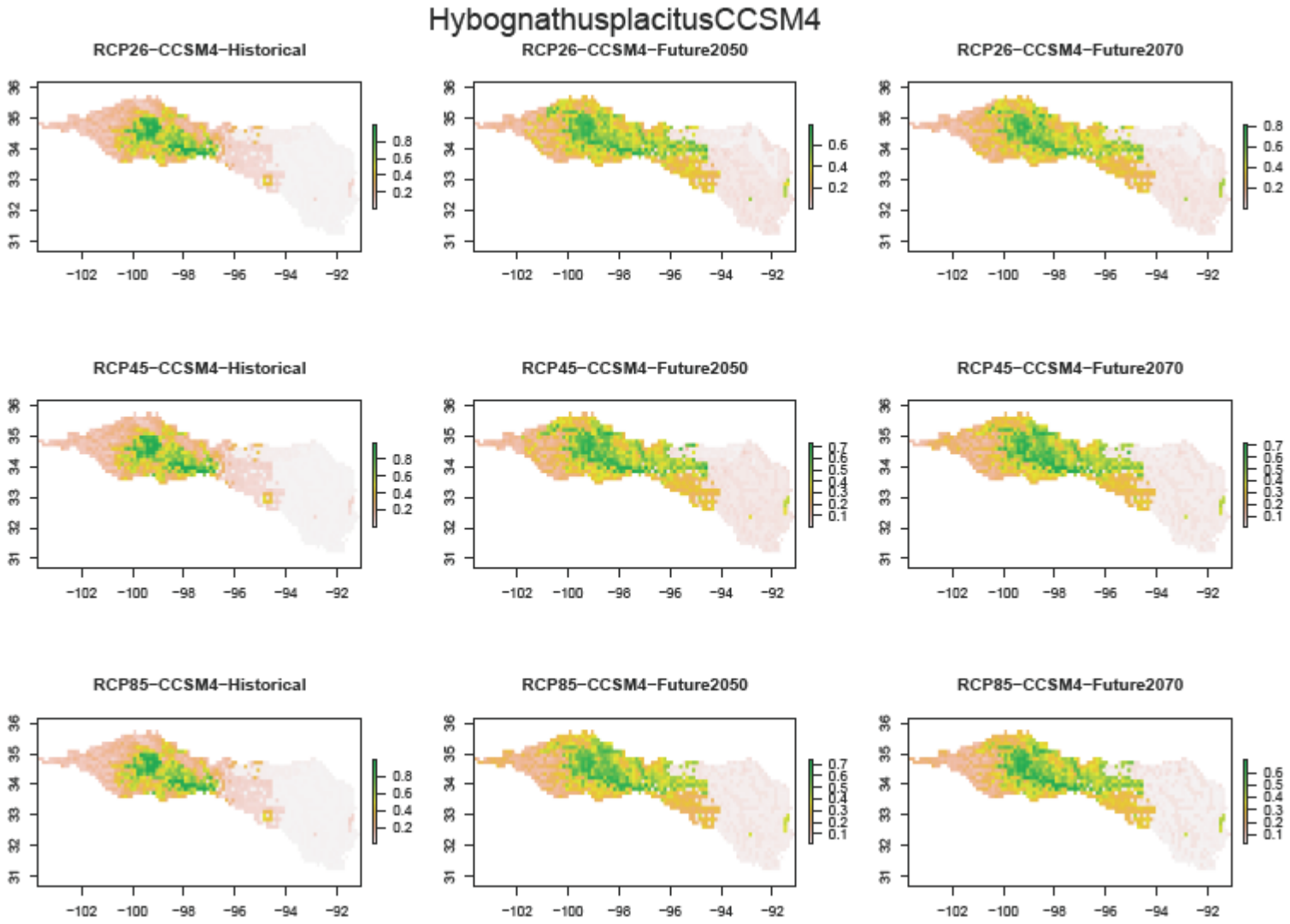
Maxent: *Hybognathus placitus*

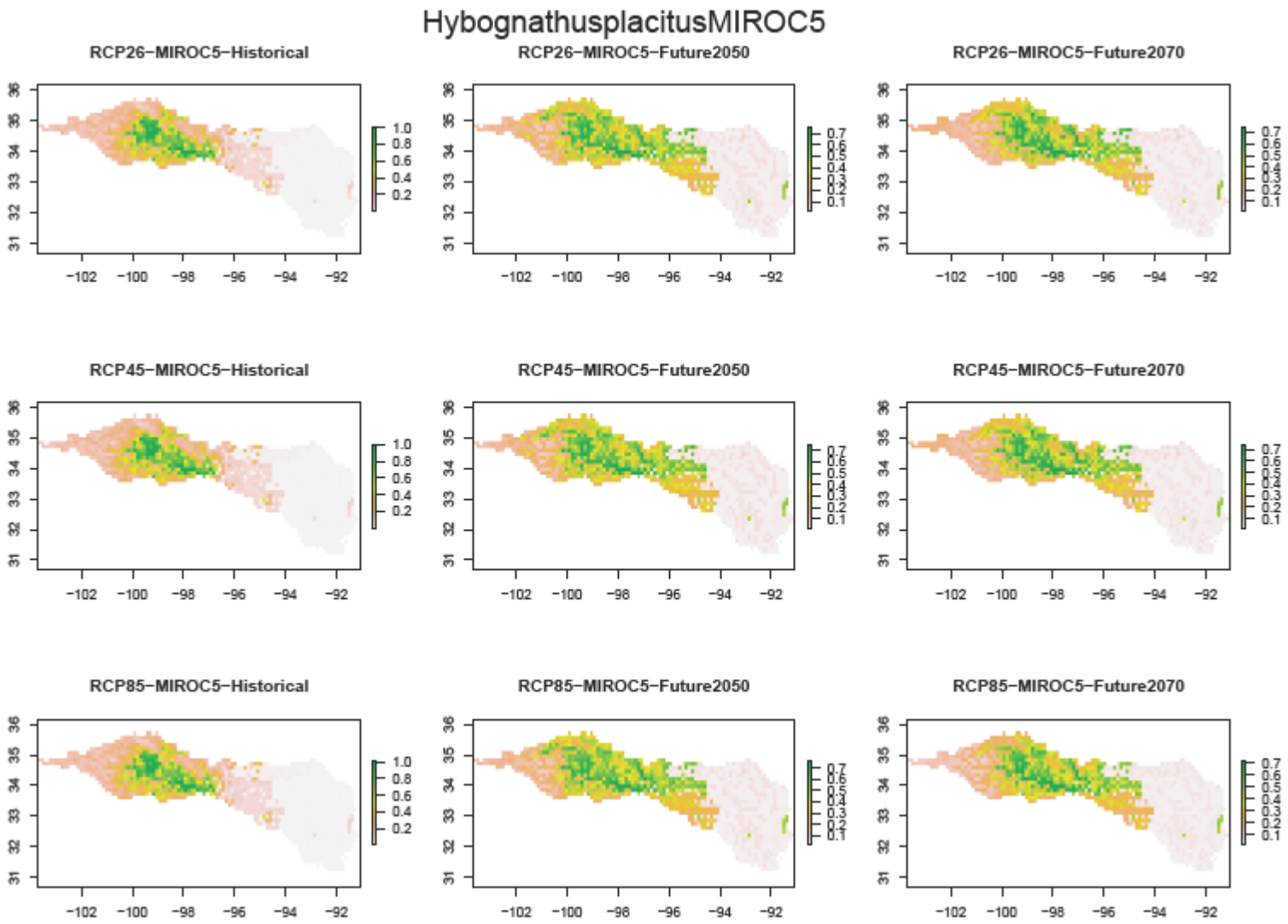


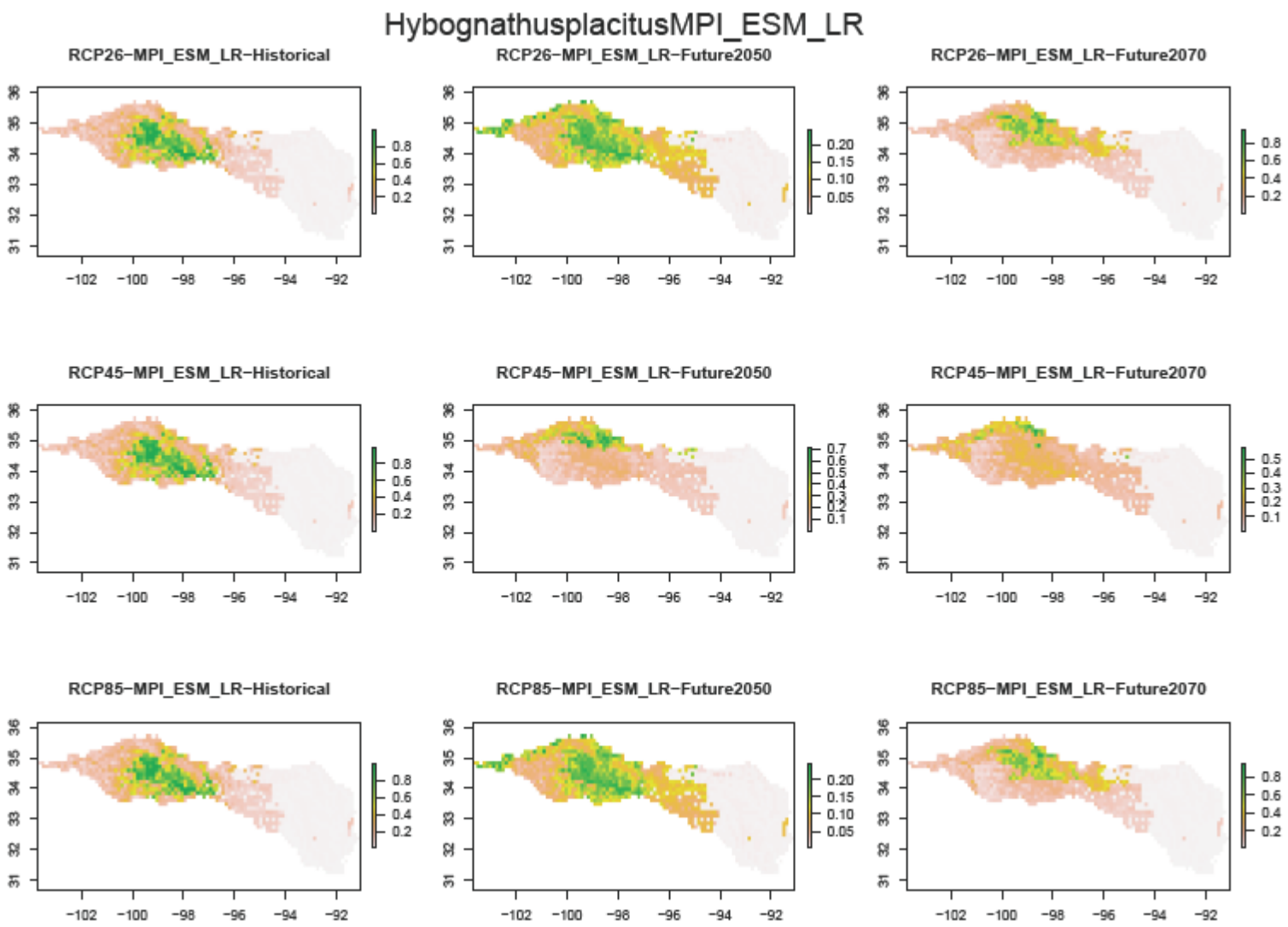

Hybognathus_placitus_MIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070
31
32
33
34
35
36
−102
−100
−98
−96
−94
−92
0.2
0.4
0.6
0.8


Hybognathus_placitus_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

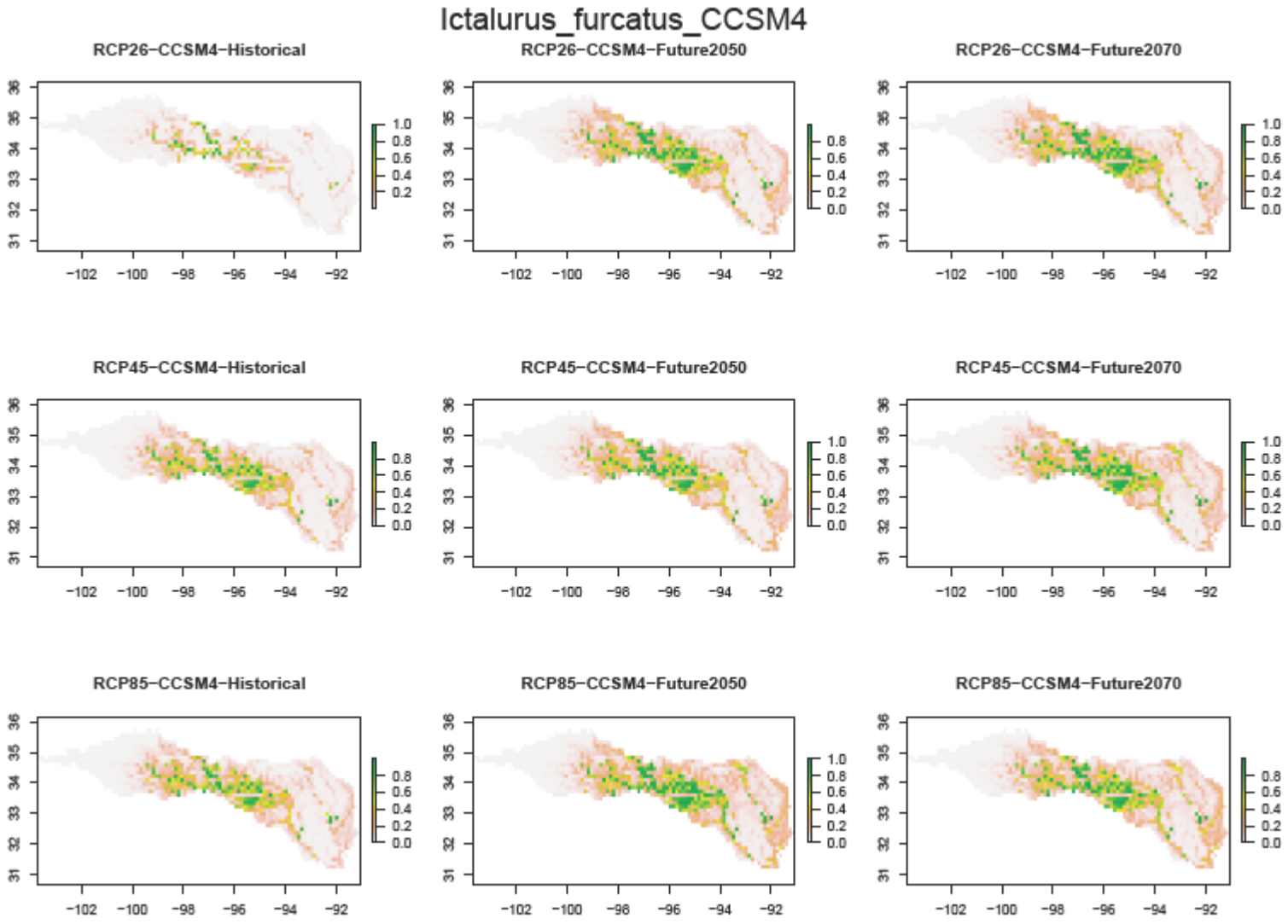
BRT: *Hybognathus placitus*

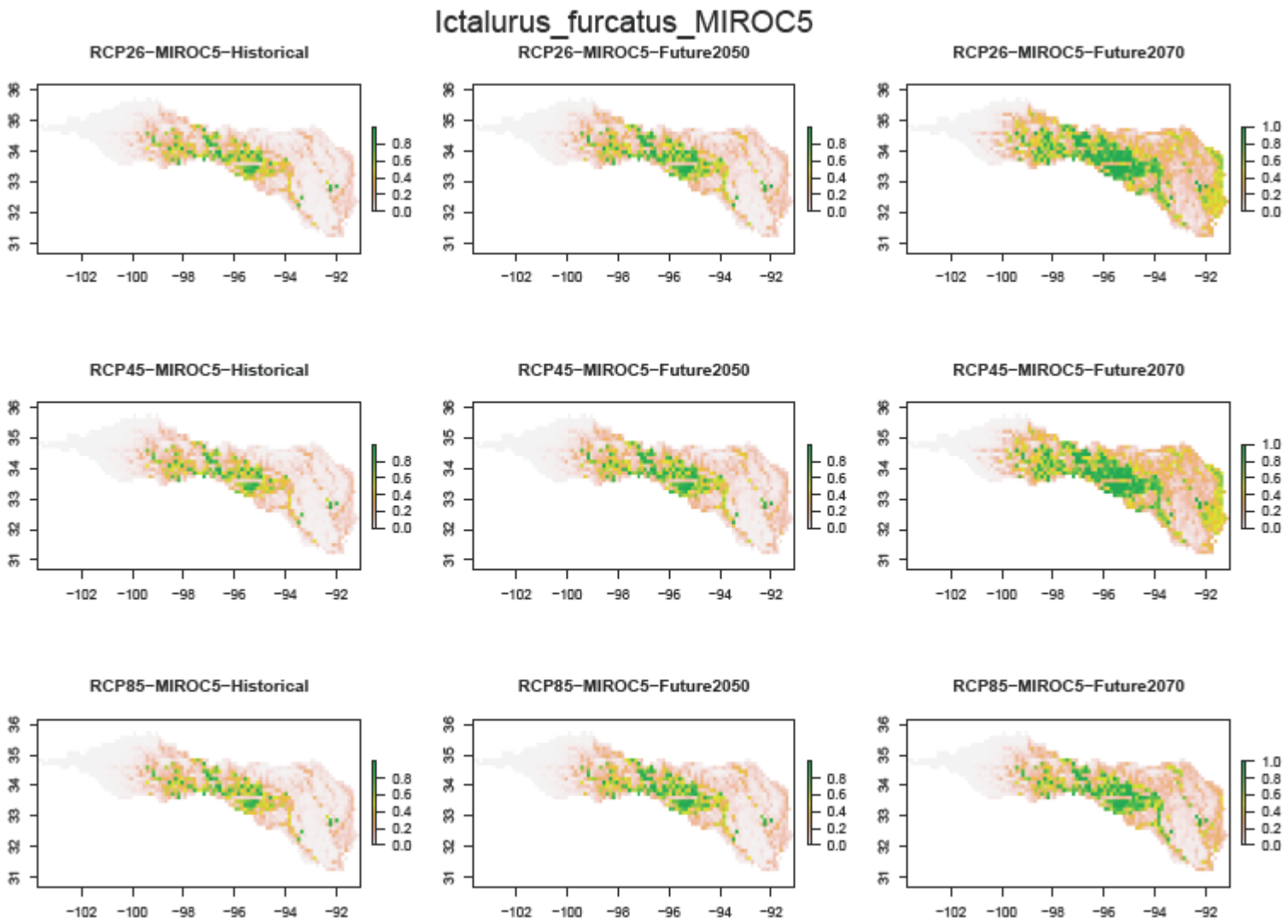


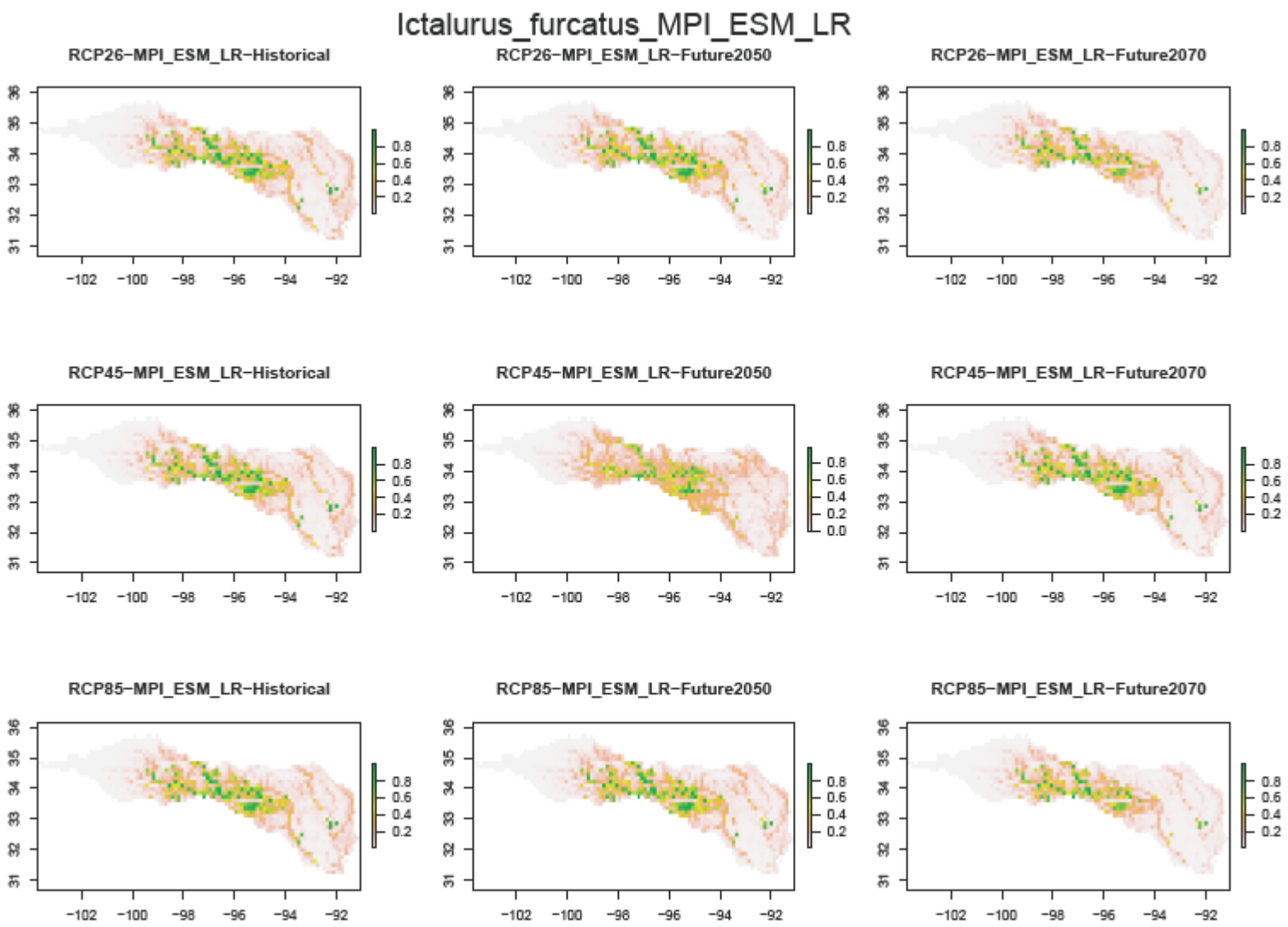

HybognathusplacitusMIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070


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
31 32 33 34 35 36
-102 -100 -98 -96 -94 -92
0.8 0.6 0.4 0.2
0.20 0.15 0.10 0.05
0.7 0.6 0.5 0.4 0.3 0.2 0.1
0.5 0.4 0.3 0.2 0.1

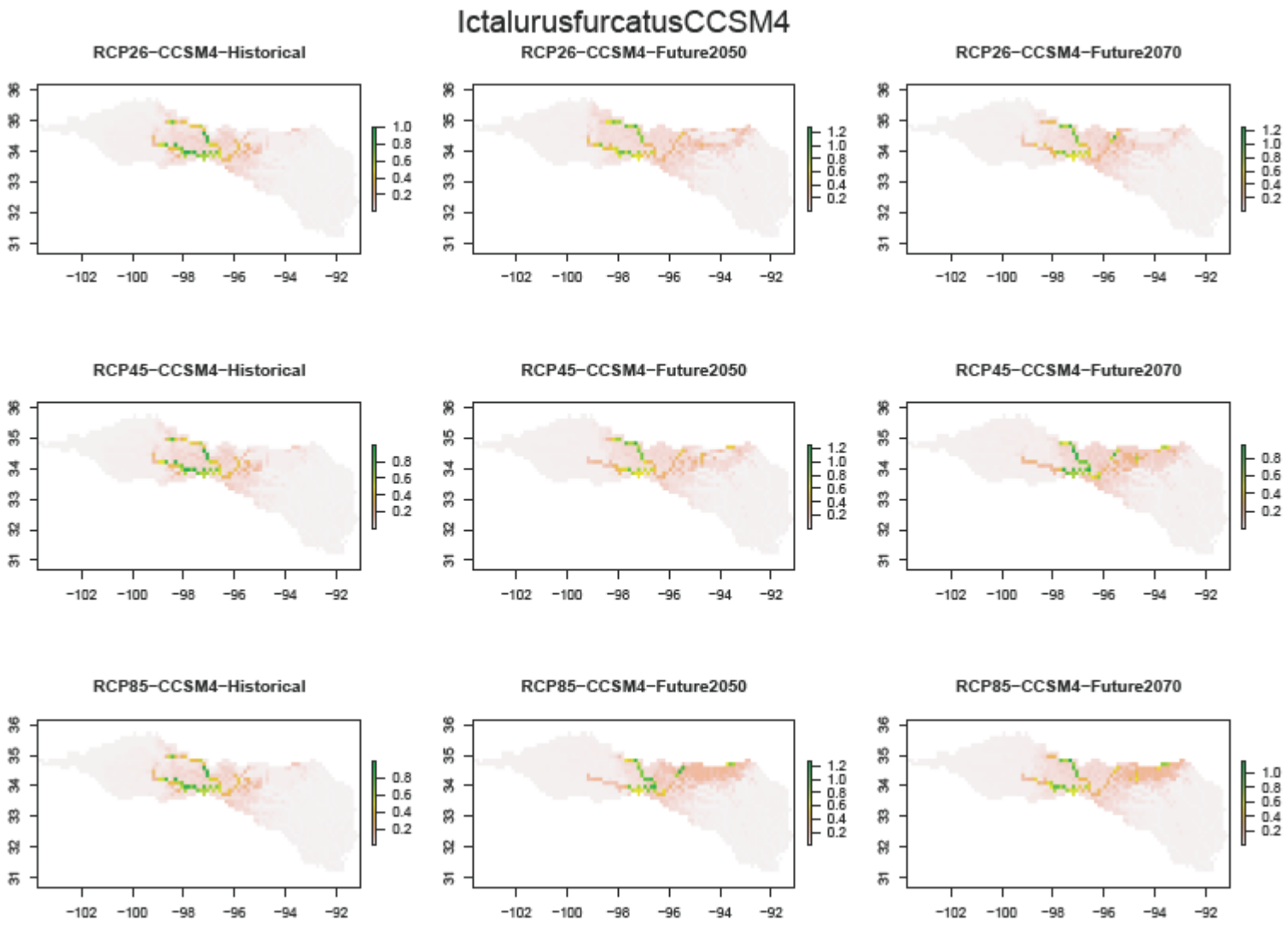
Maxent: *Ictalurus furcatus*

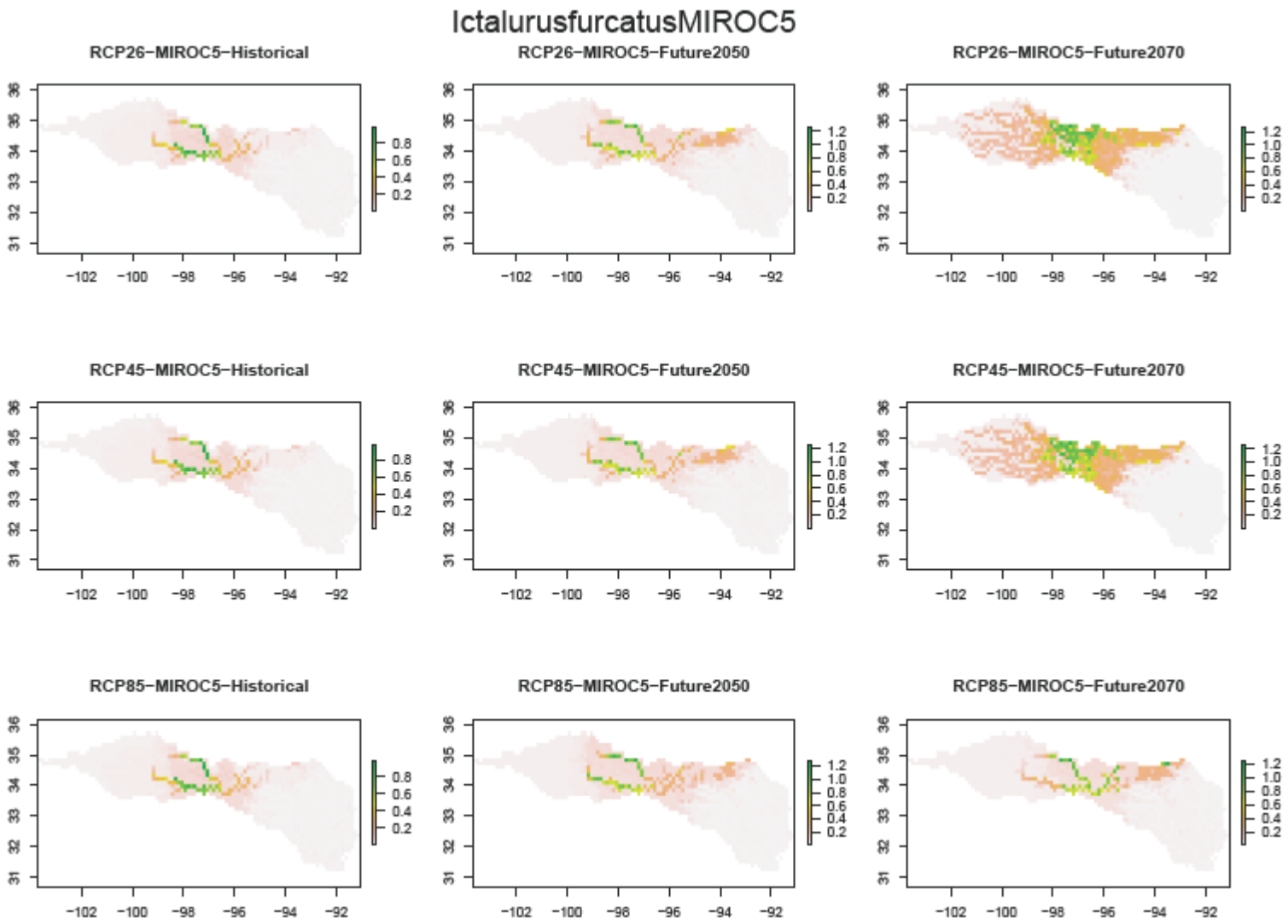


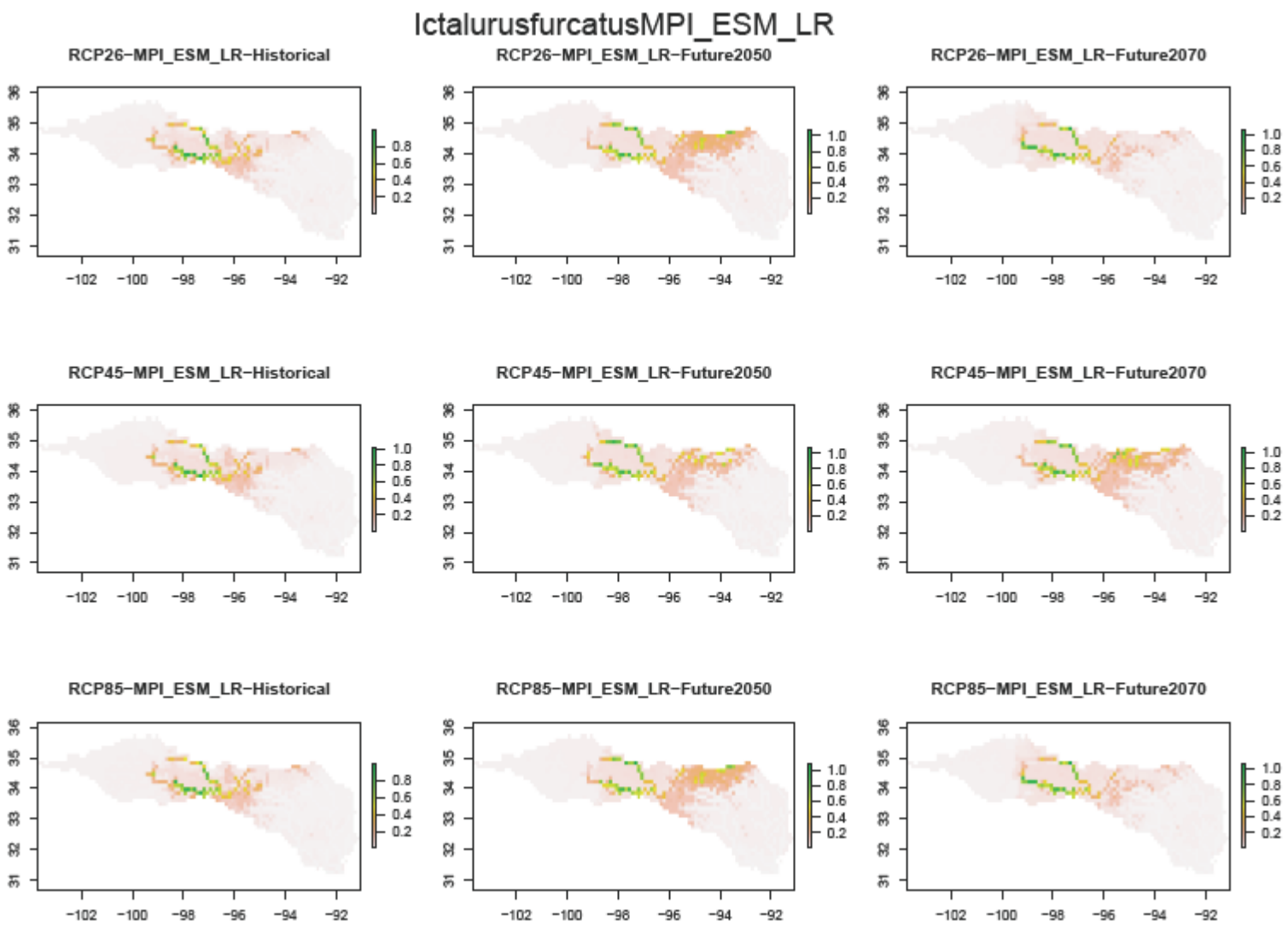

Ictalurus_furcatus_MIROC5
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RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070


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
31 32 33 34 35 36
-102 -100 -98 -96 -94 -92
0.0 0.2 0.4 0.6 0.8

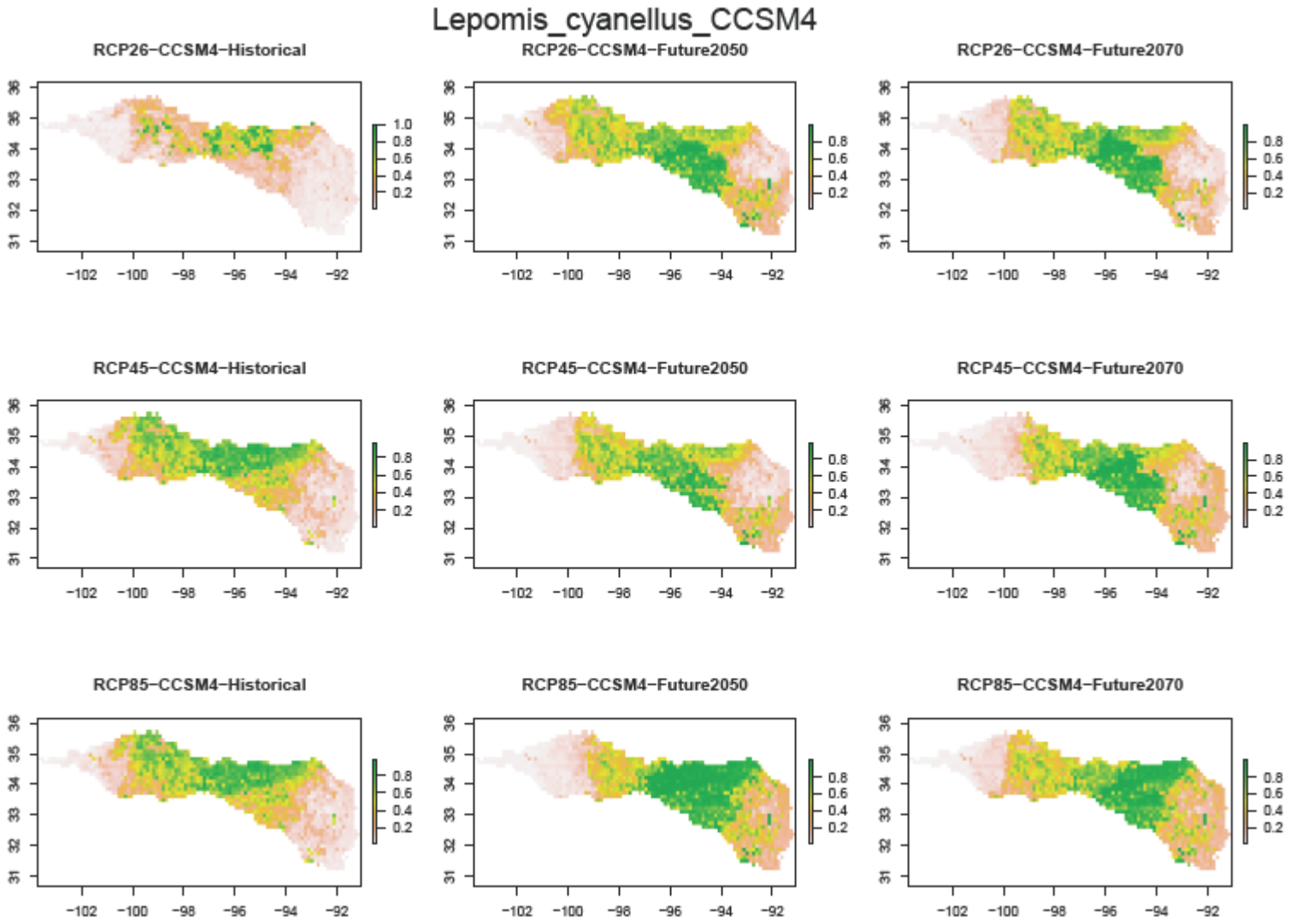
BRT: *Ictalurus furcatus*

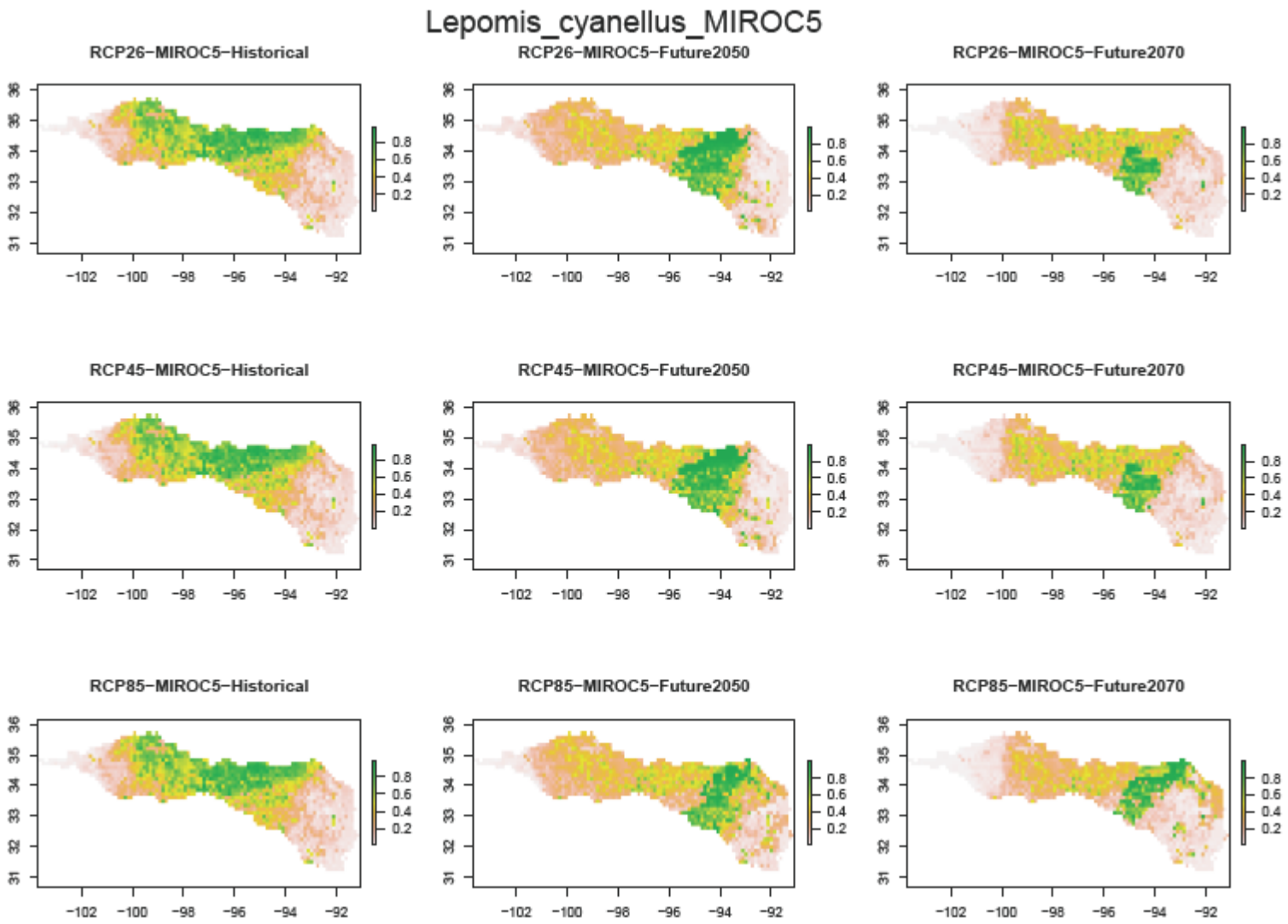


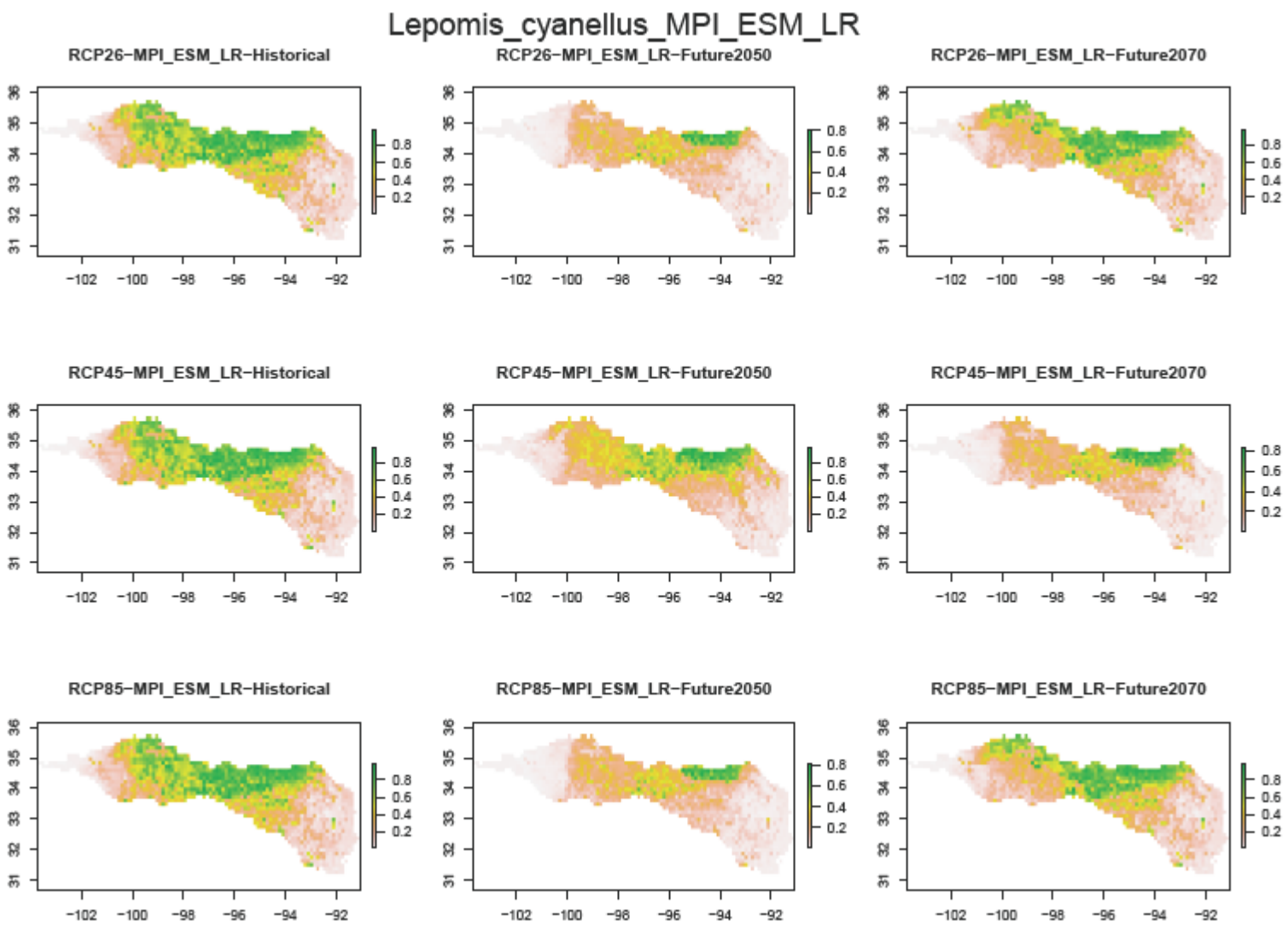

IctalurusfurcatusMIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070


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
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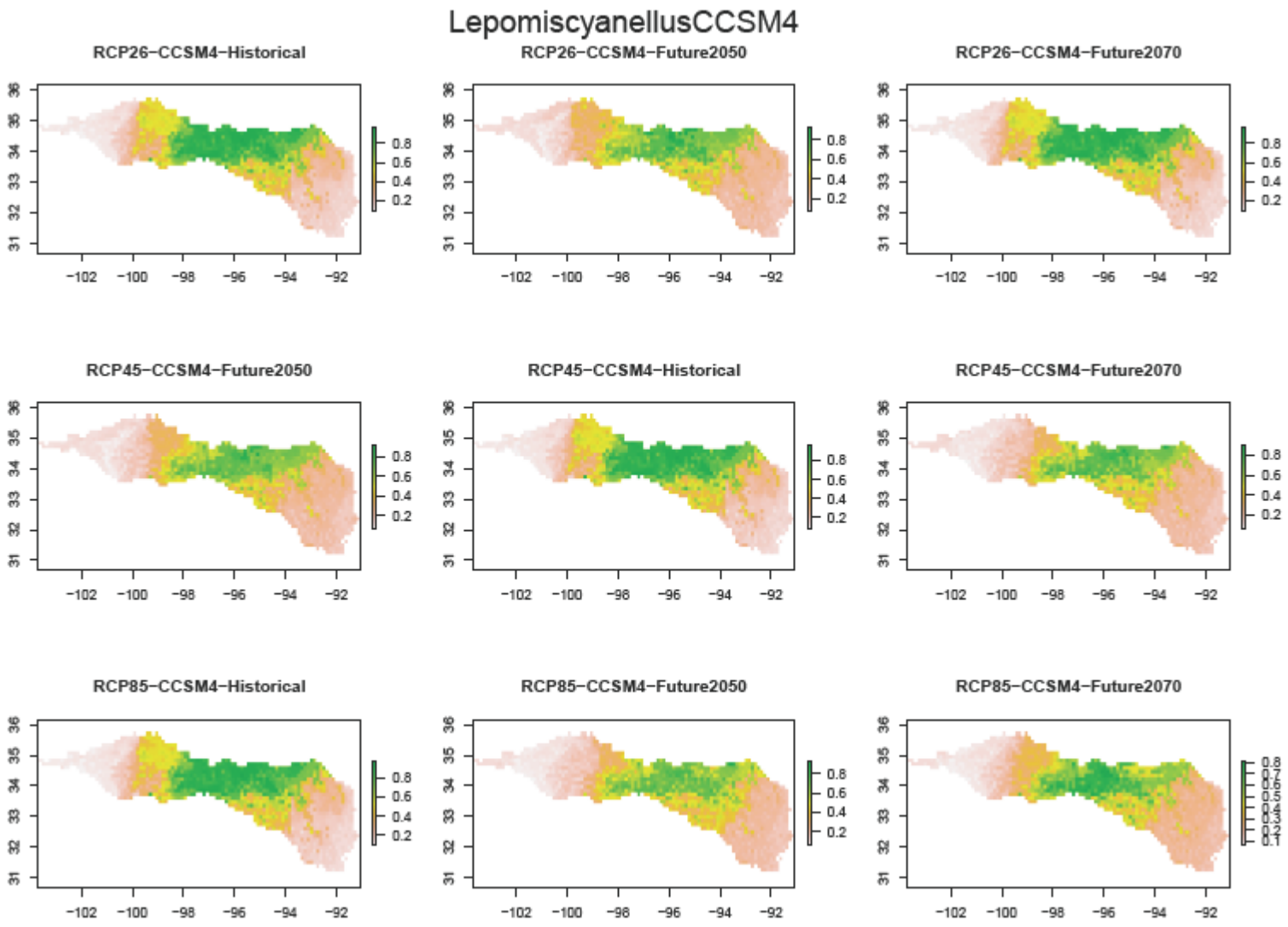
Maxent: *Lepomis cyanellus*

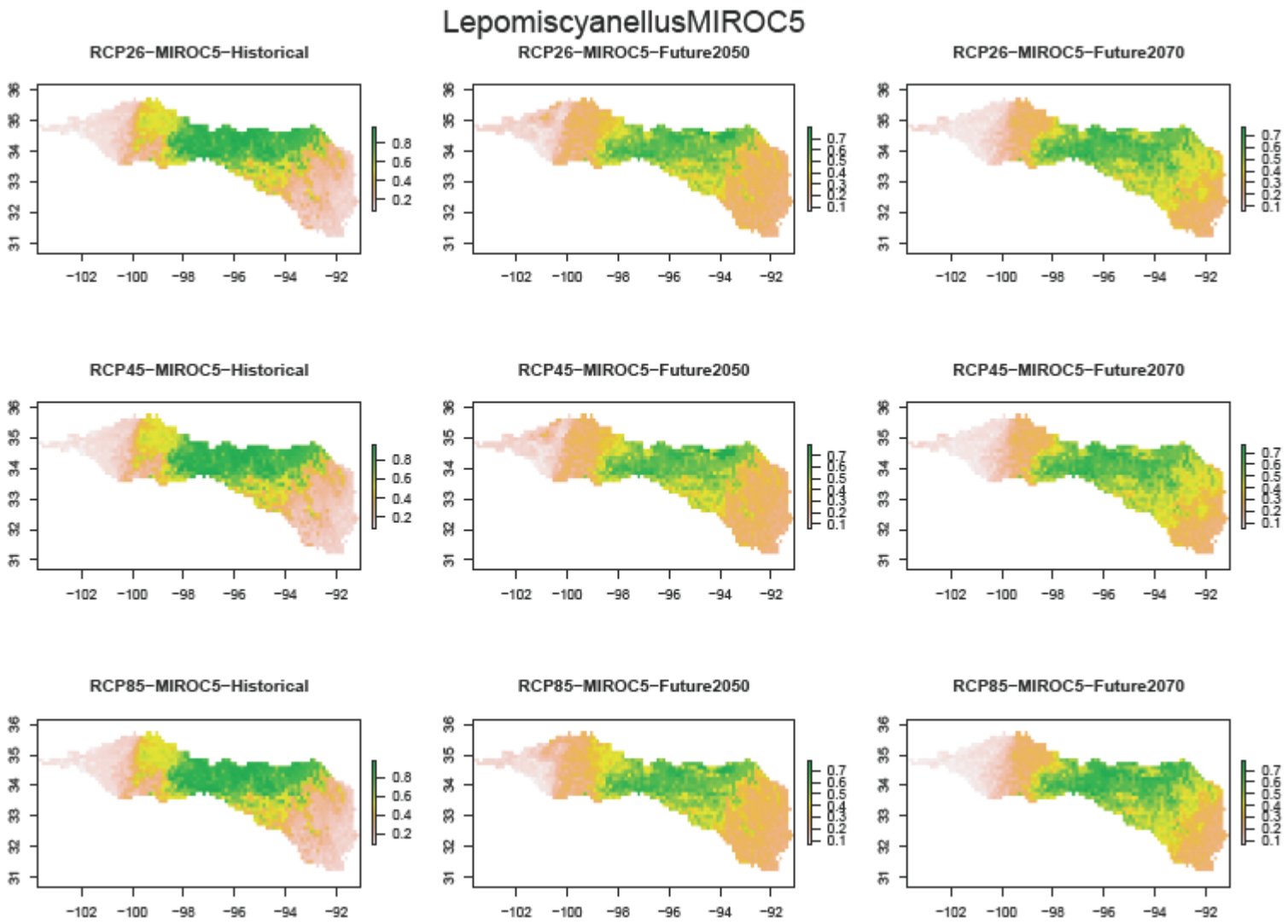


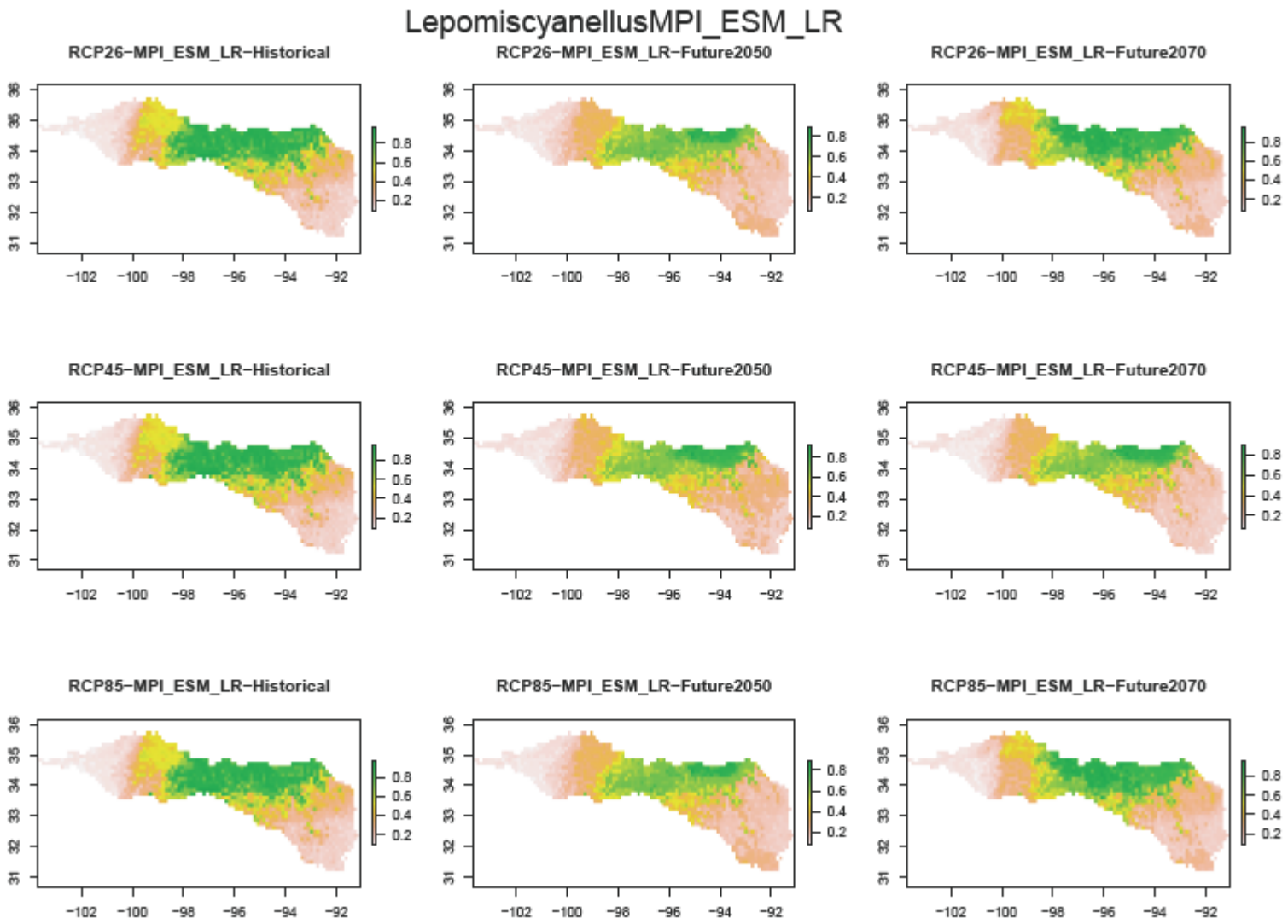

Lepomis_cyanellus_MIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070
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−100
−98
−96
−94
−92
0.2
0.4
0.6
0.8


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

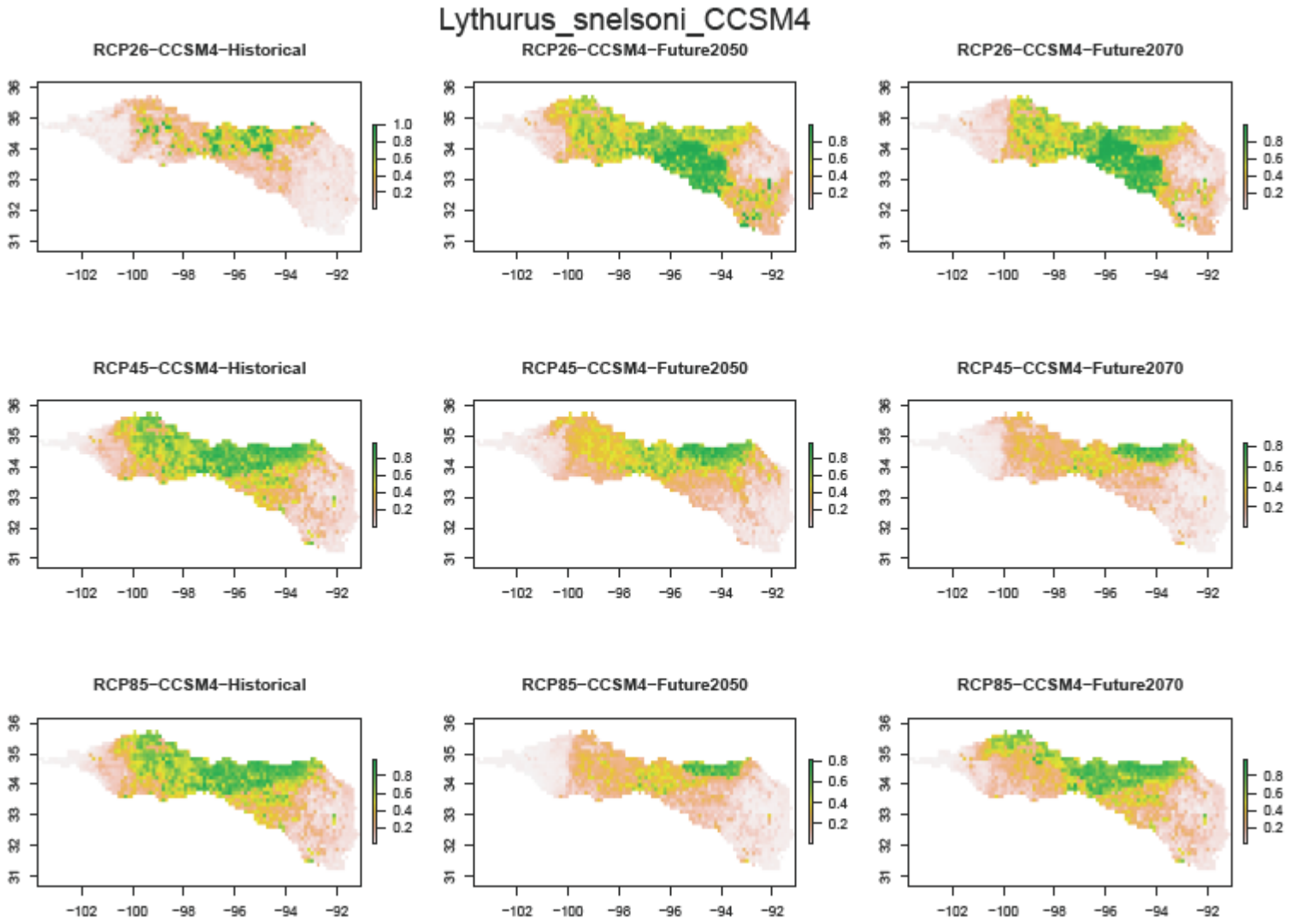
BRT: *Lepomis cyanellus*

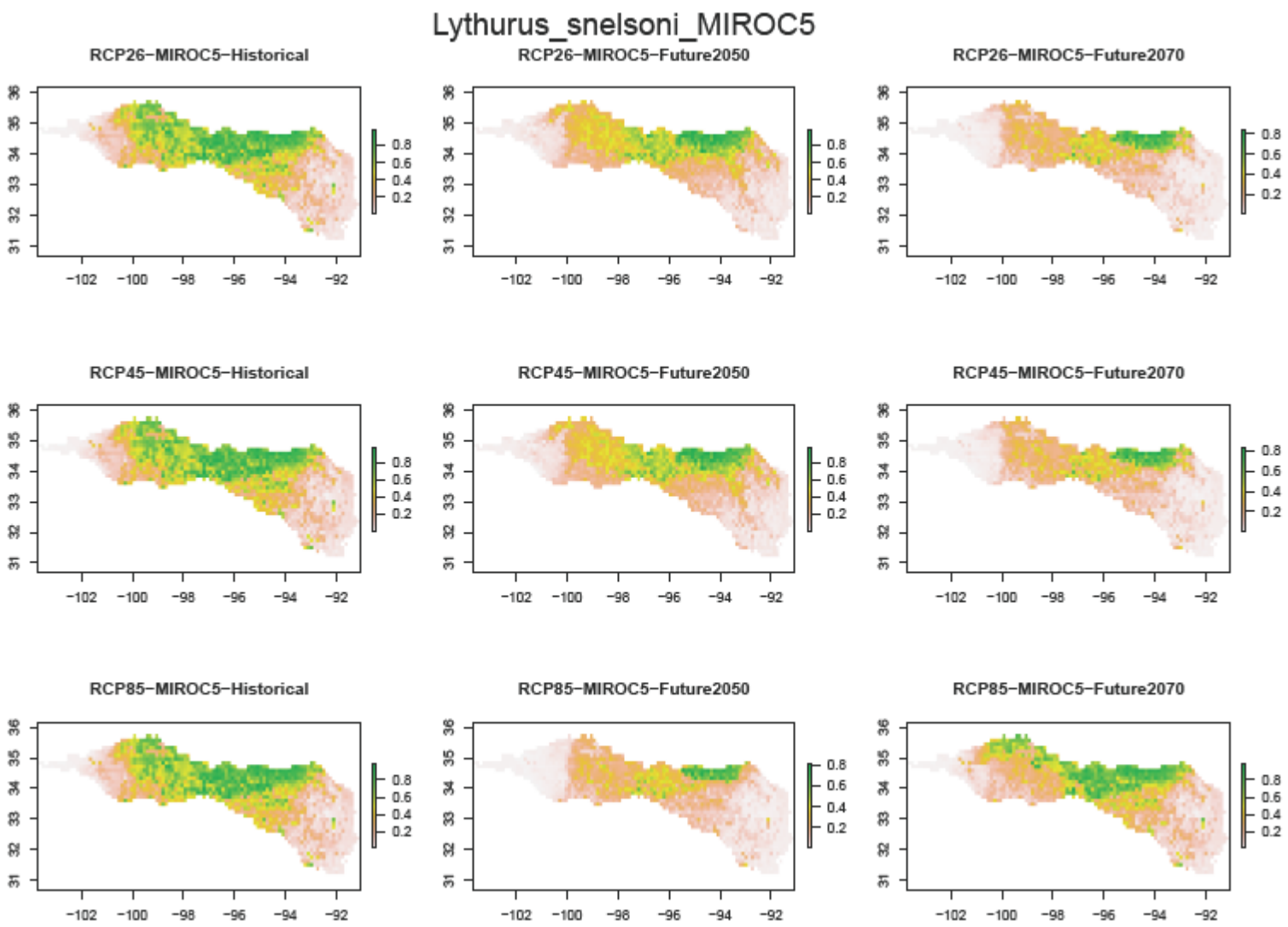


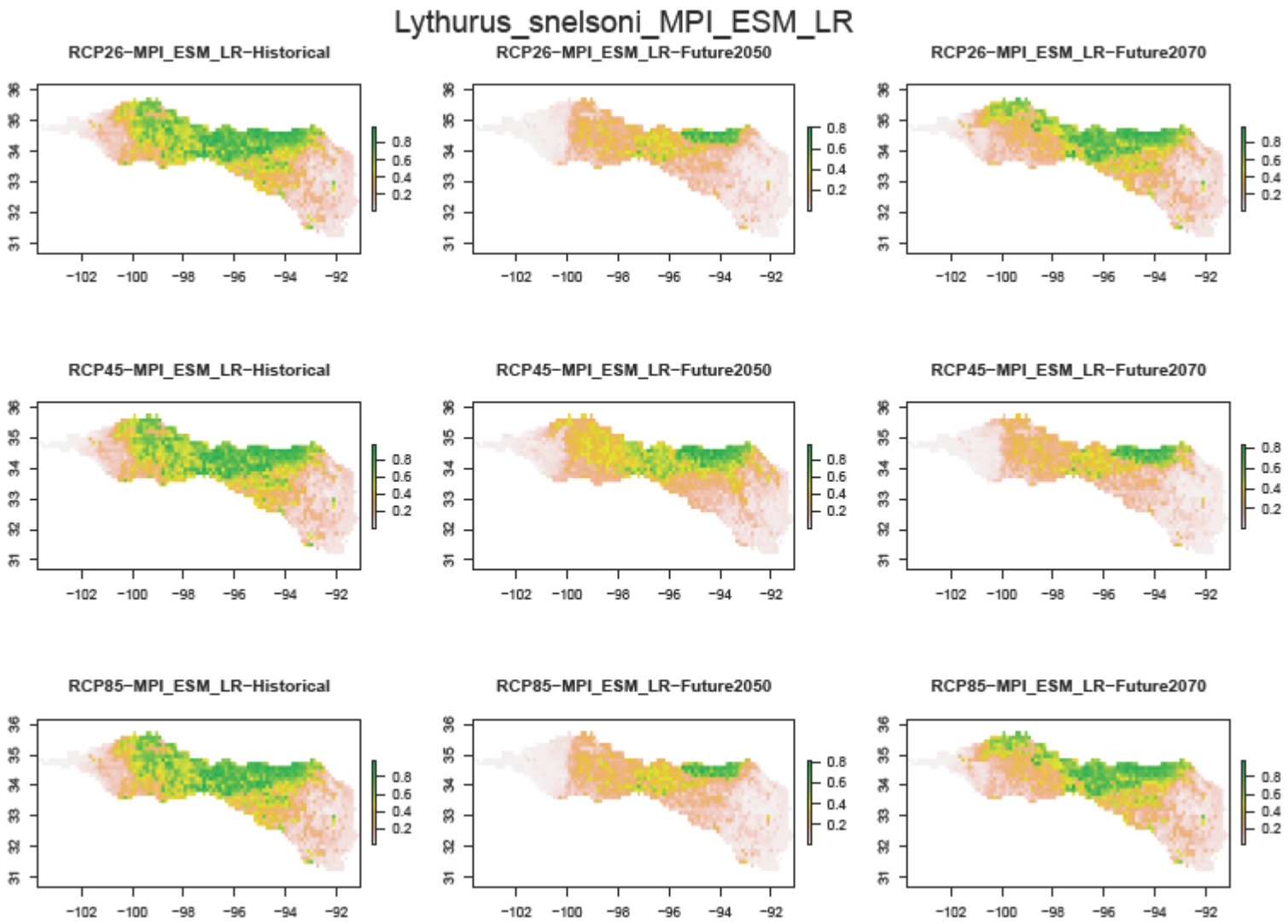

LepomiscyanellusMIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070


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
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−94
−92
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0.6
0.8

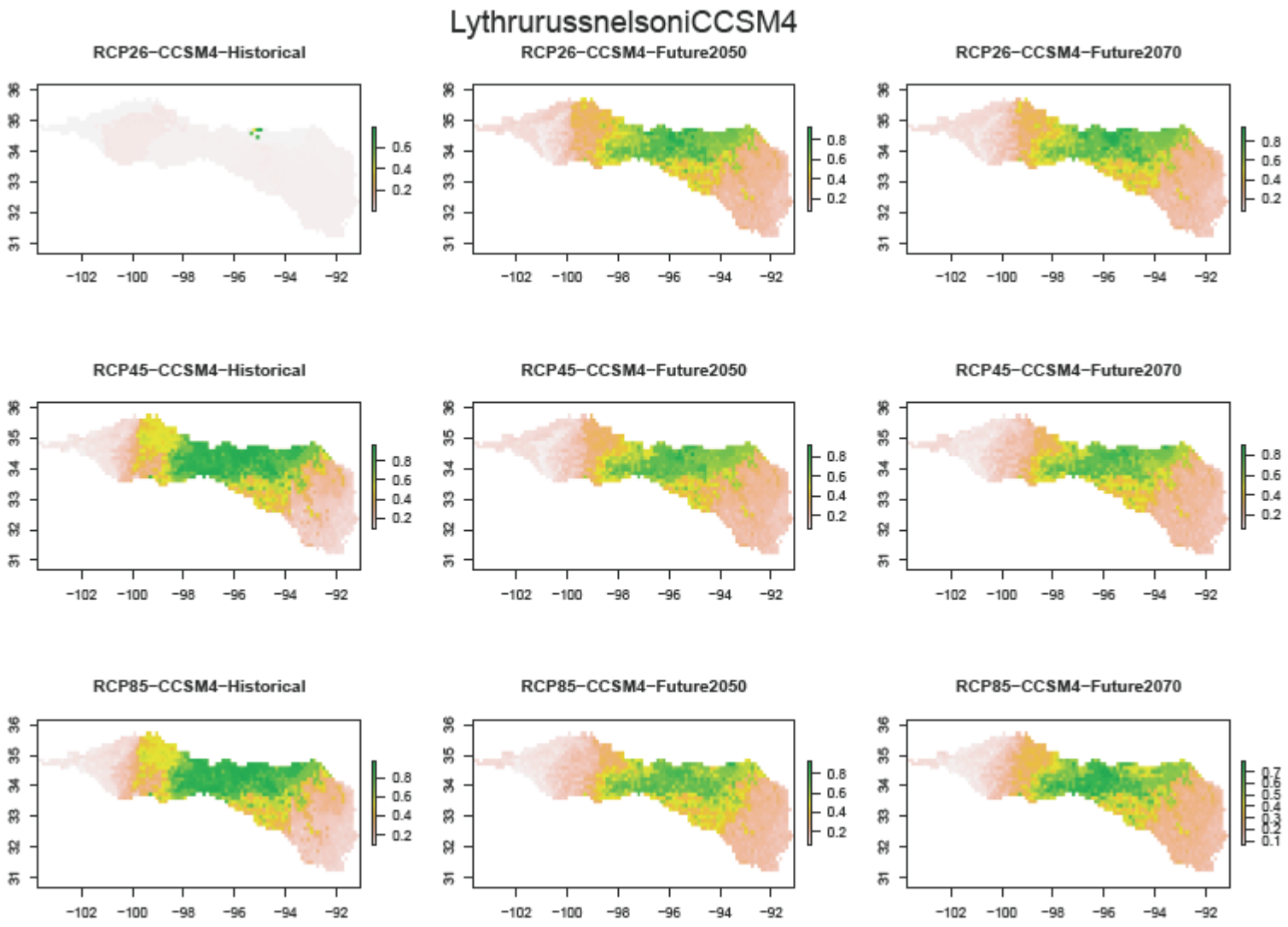
Maxent: *Lythrurus snelsoni*

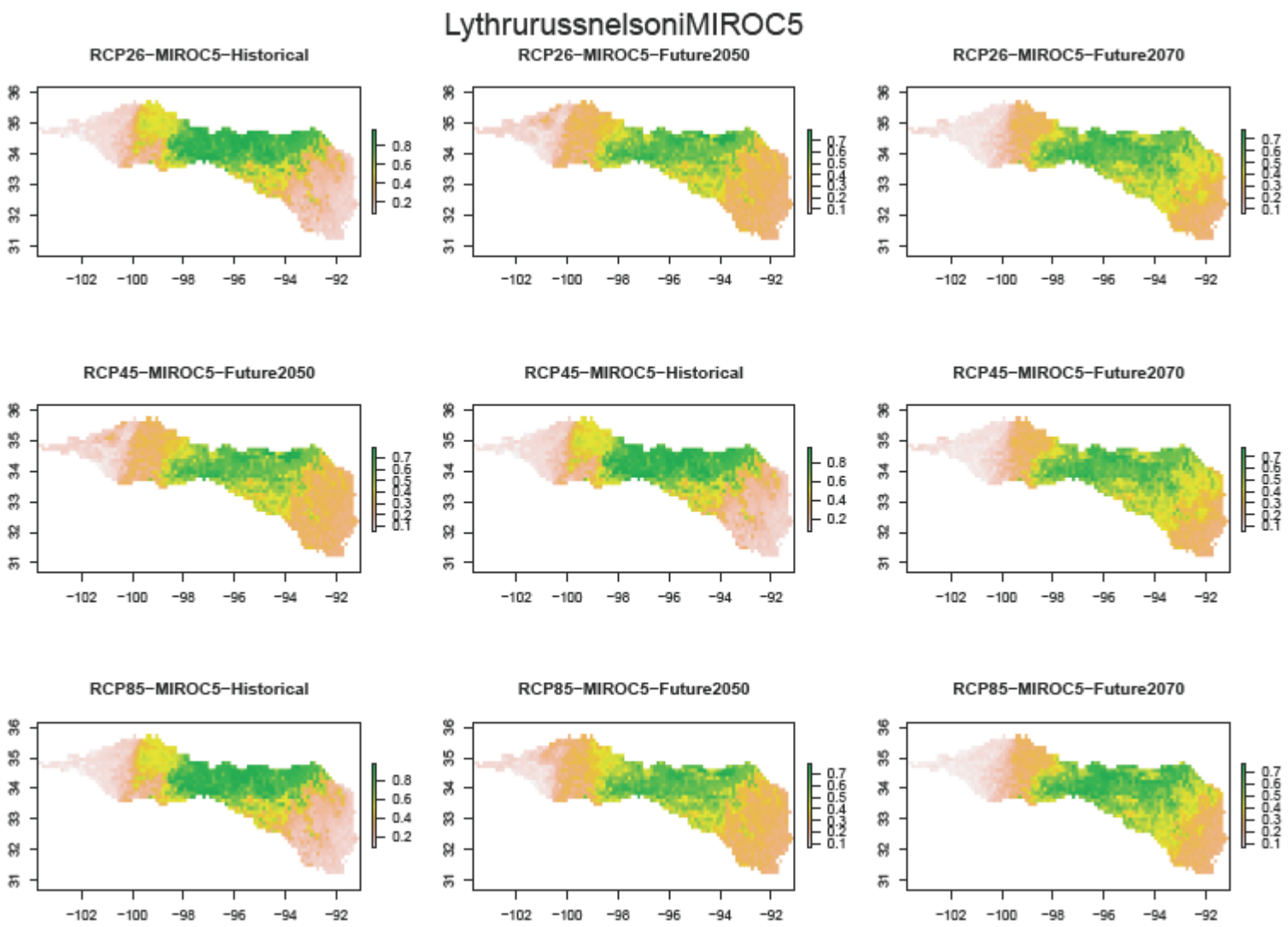


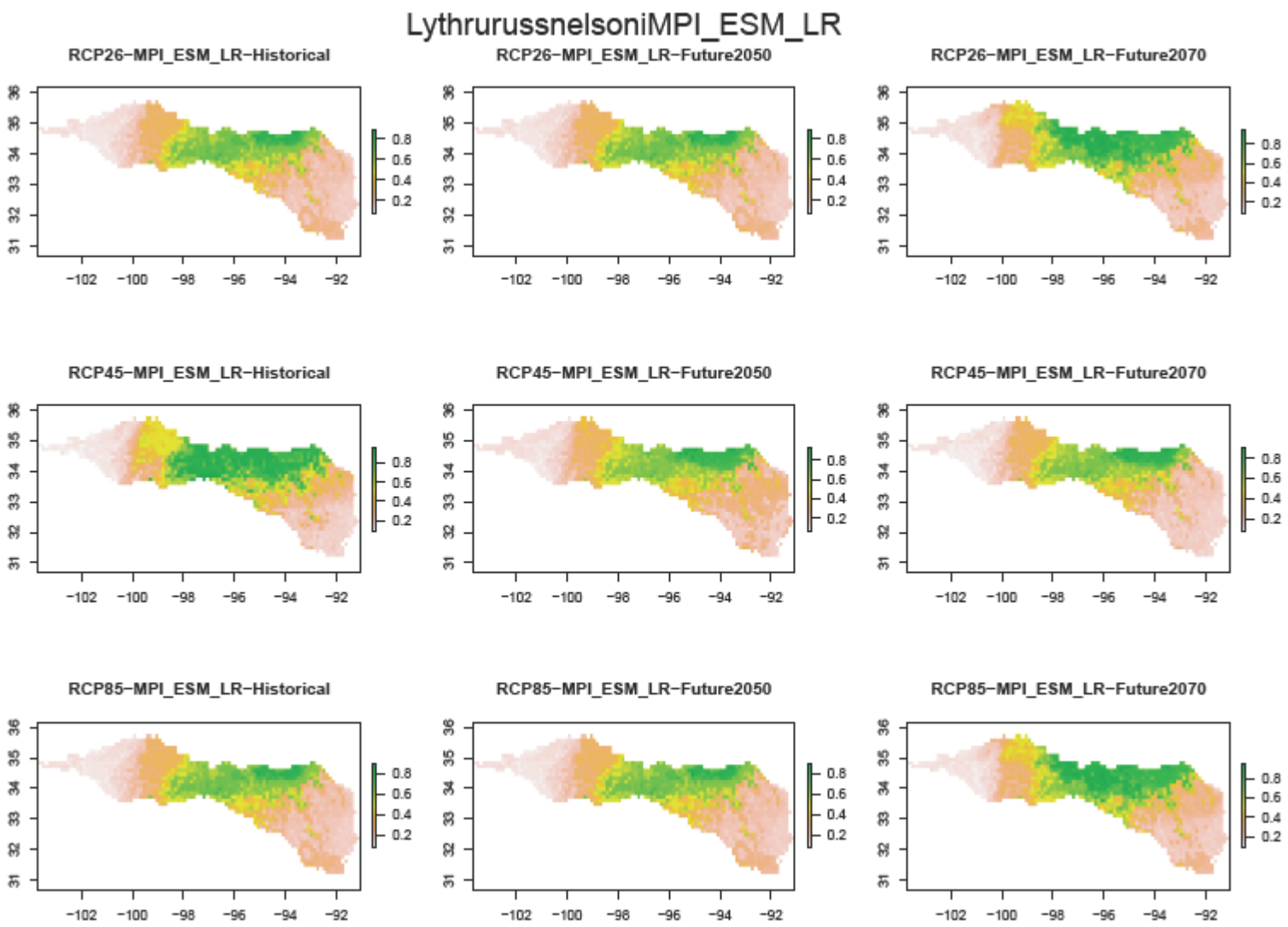

Lythurus_snelsoni_MIROC5
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RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070
0.8
0.6
0.4
0.2
−102
−100
−98
−96
−94
−92
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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

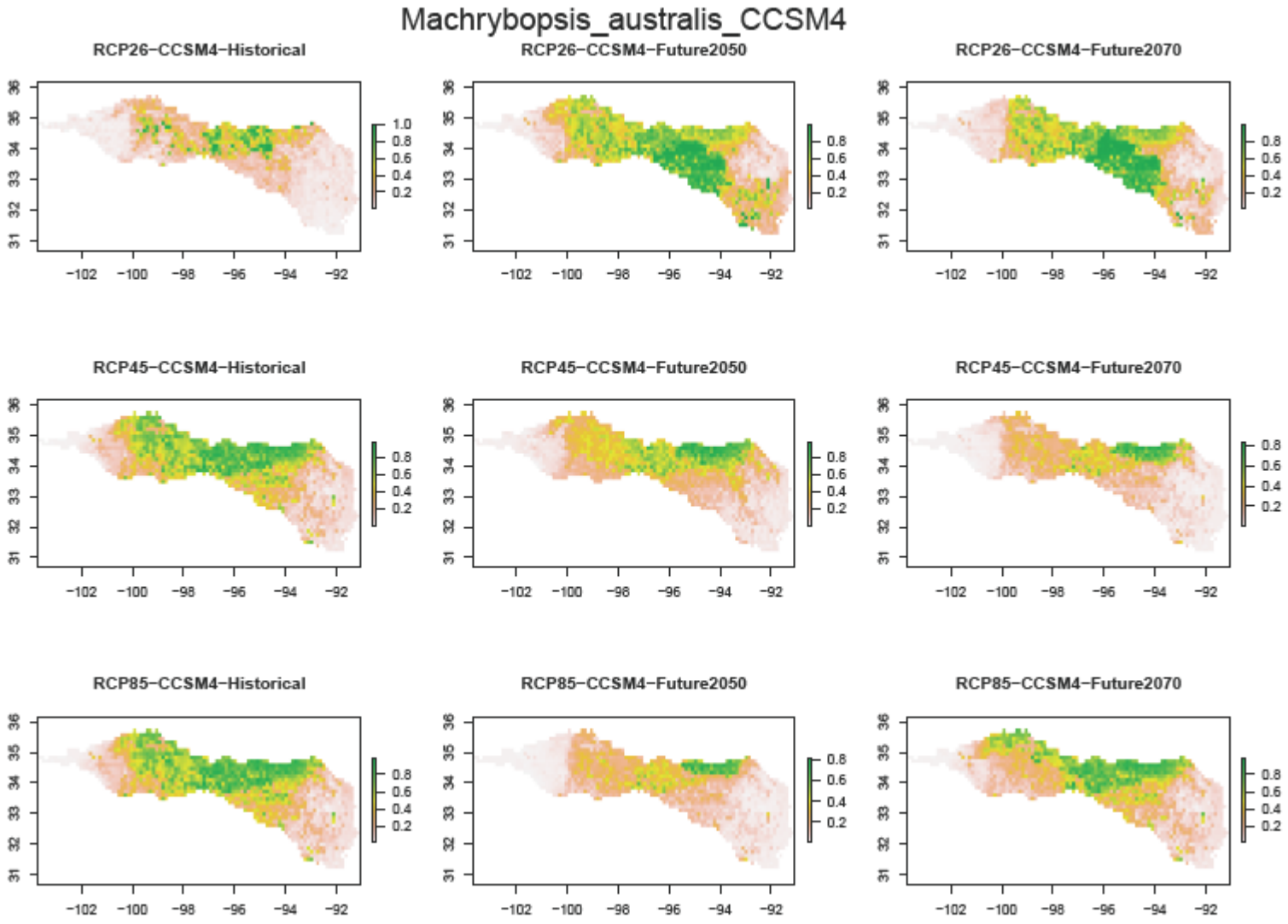
BRT: *Lythrurus snelsoni*

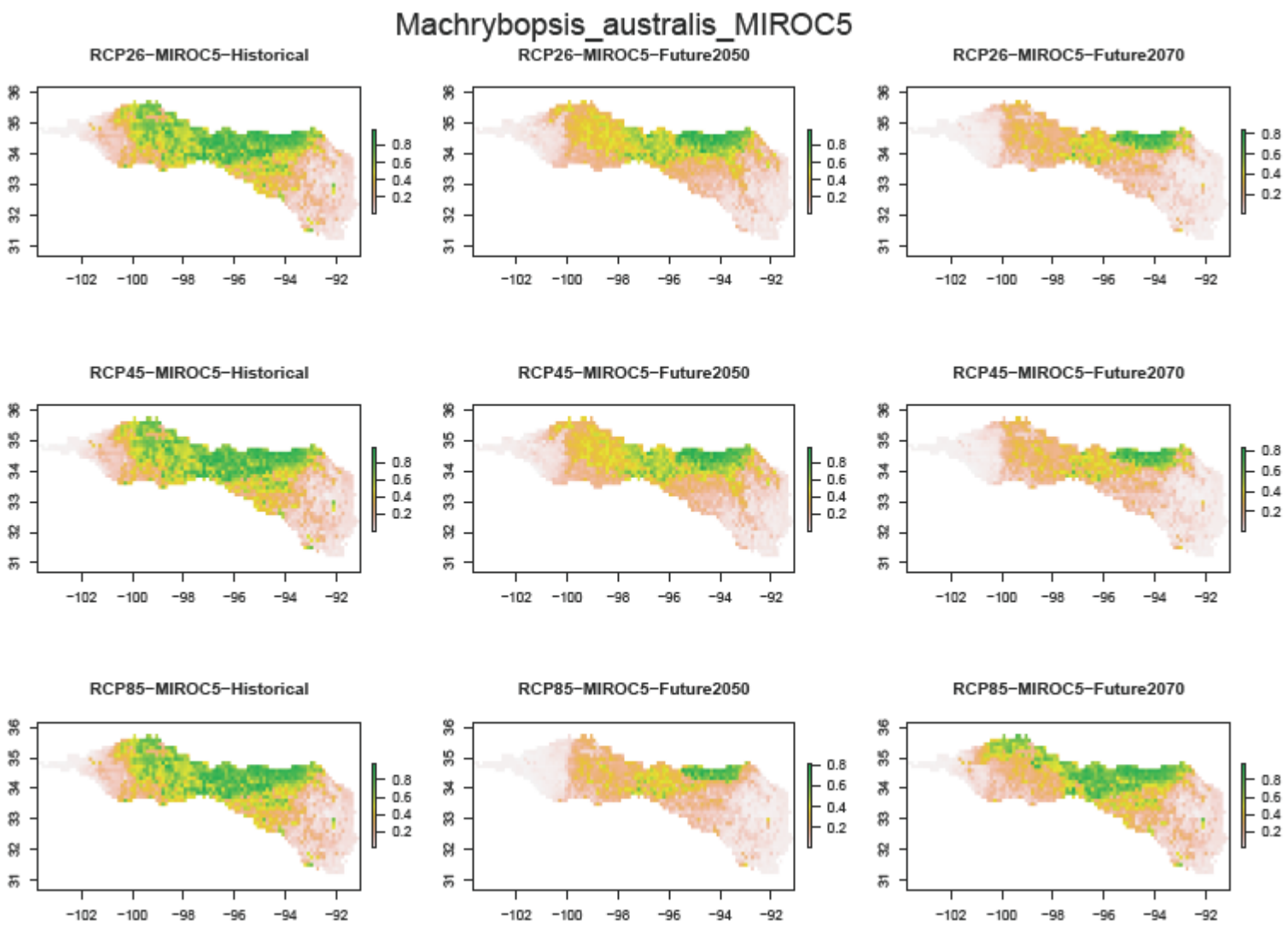


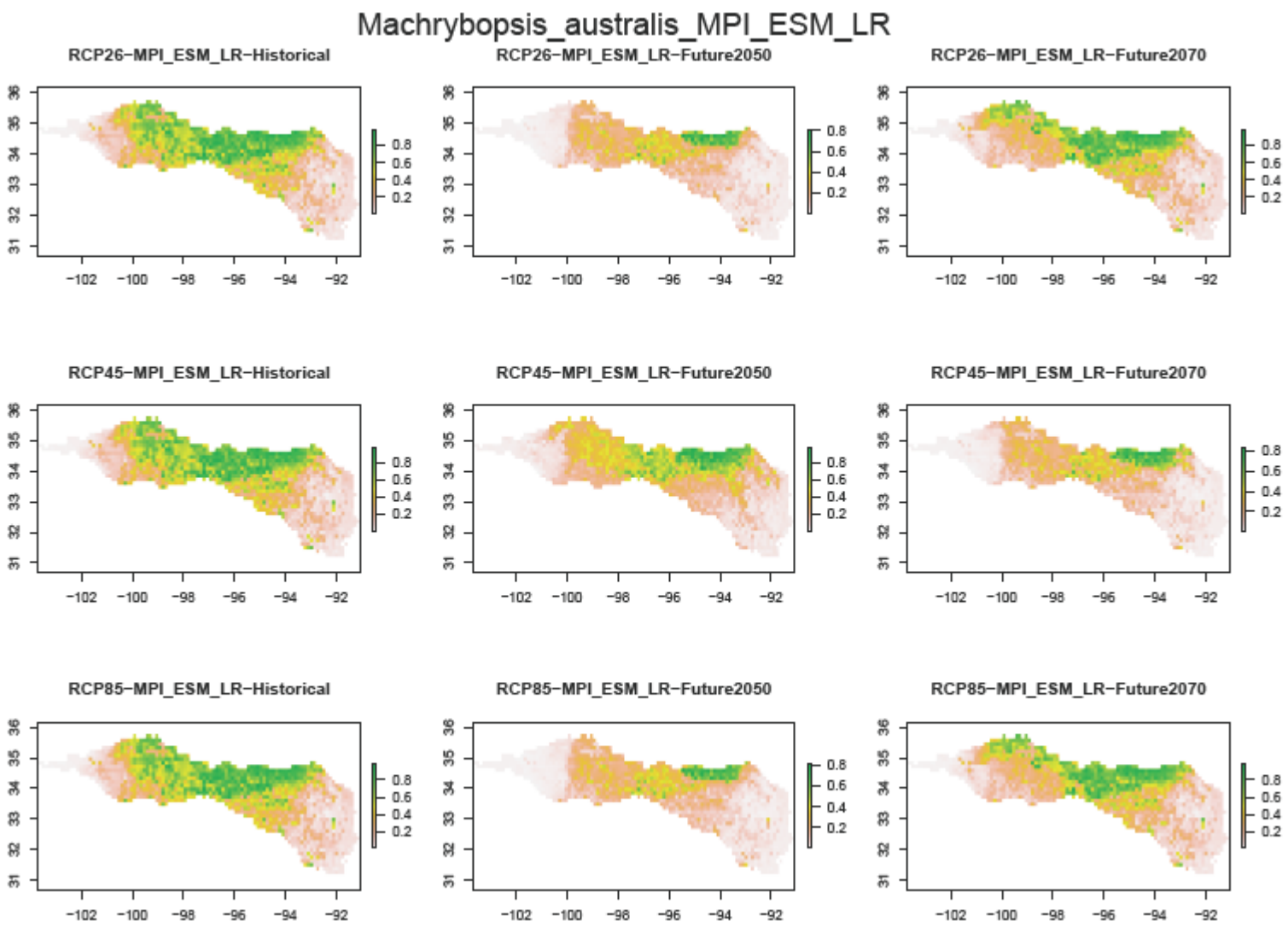

LythrurussnelsoniMIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Future2050
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070


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
31 32 33 34 35 36
-102 -100 -98 -96 -94 -92
0.2 0.4 0.6 0.8

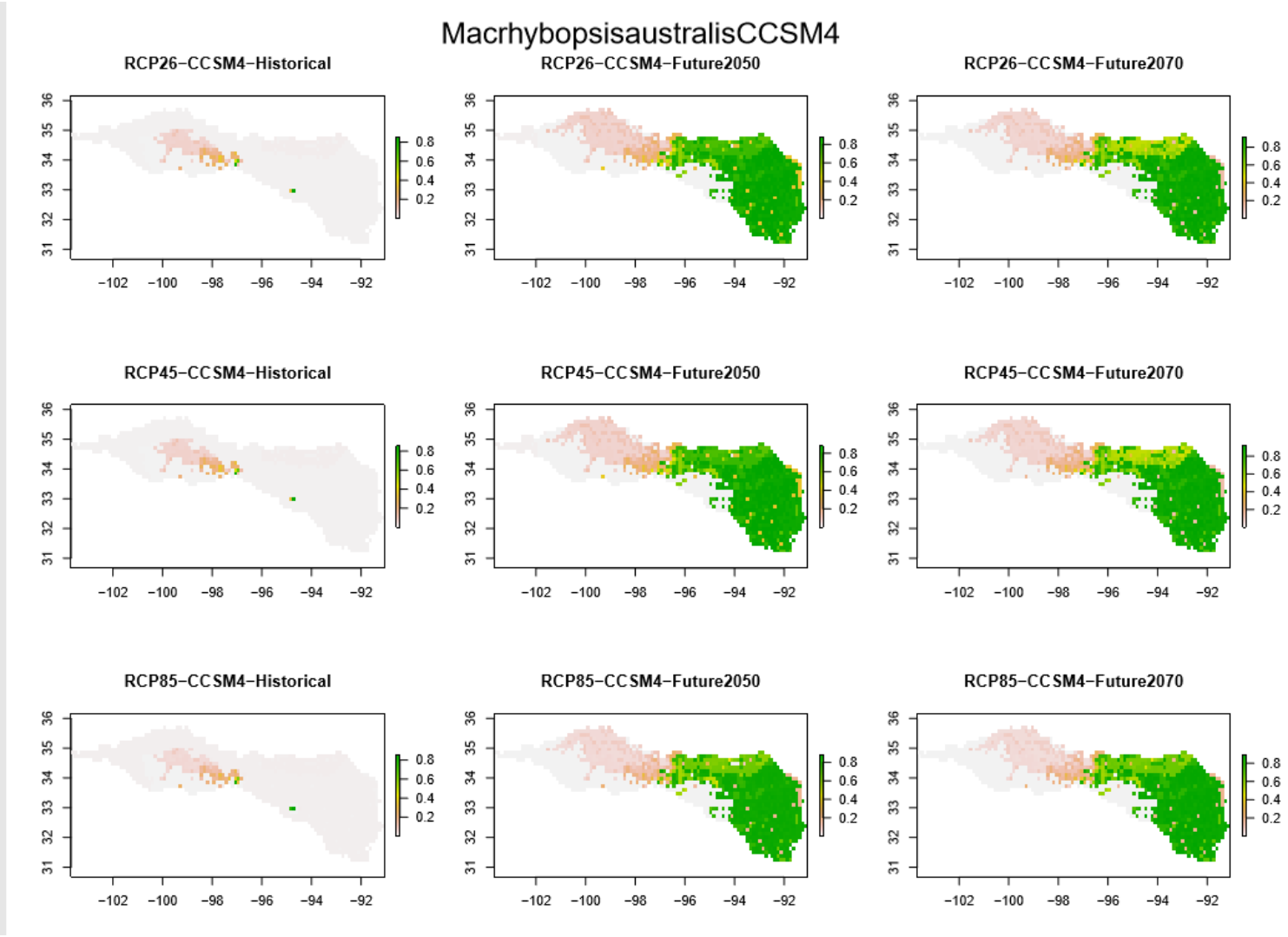
Maxent: *Macrhybopsis australis*

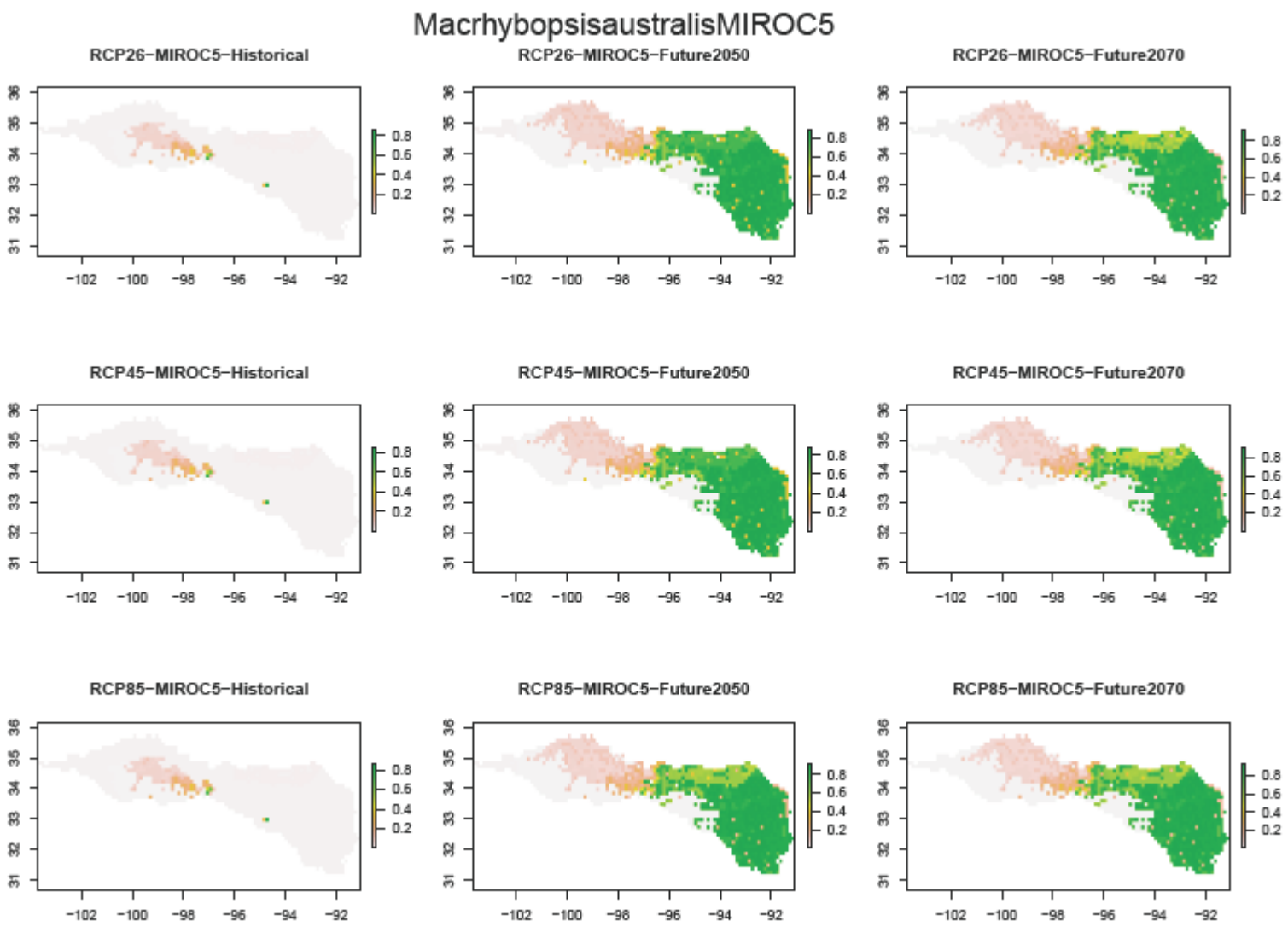


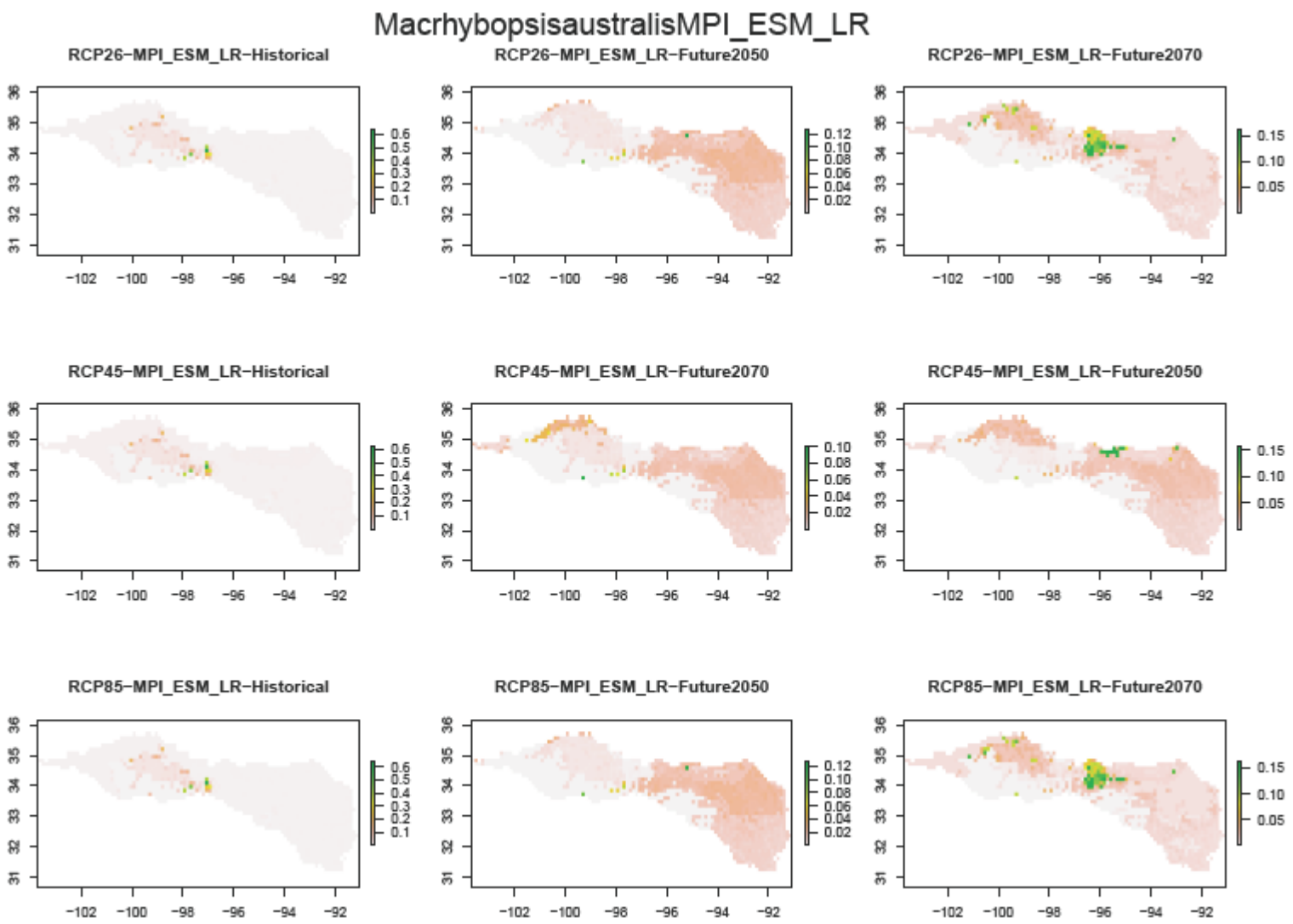

Machrybopsis_australis_MIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070
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Machrybopsis_australis_MPI_ESM_LR
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
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0.2 0.4 0.6 0.8

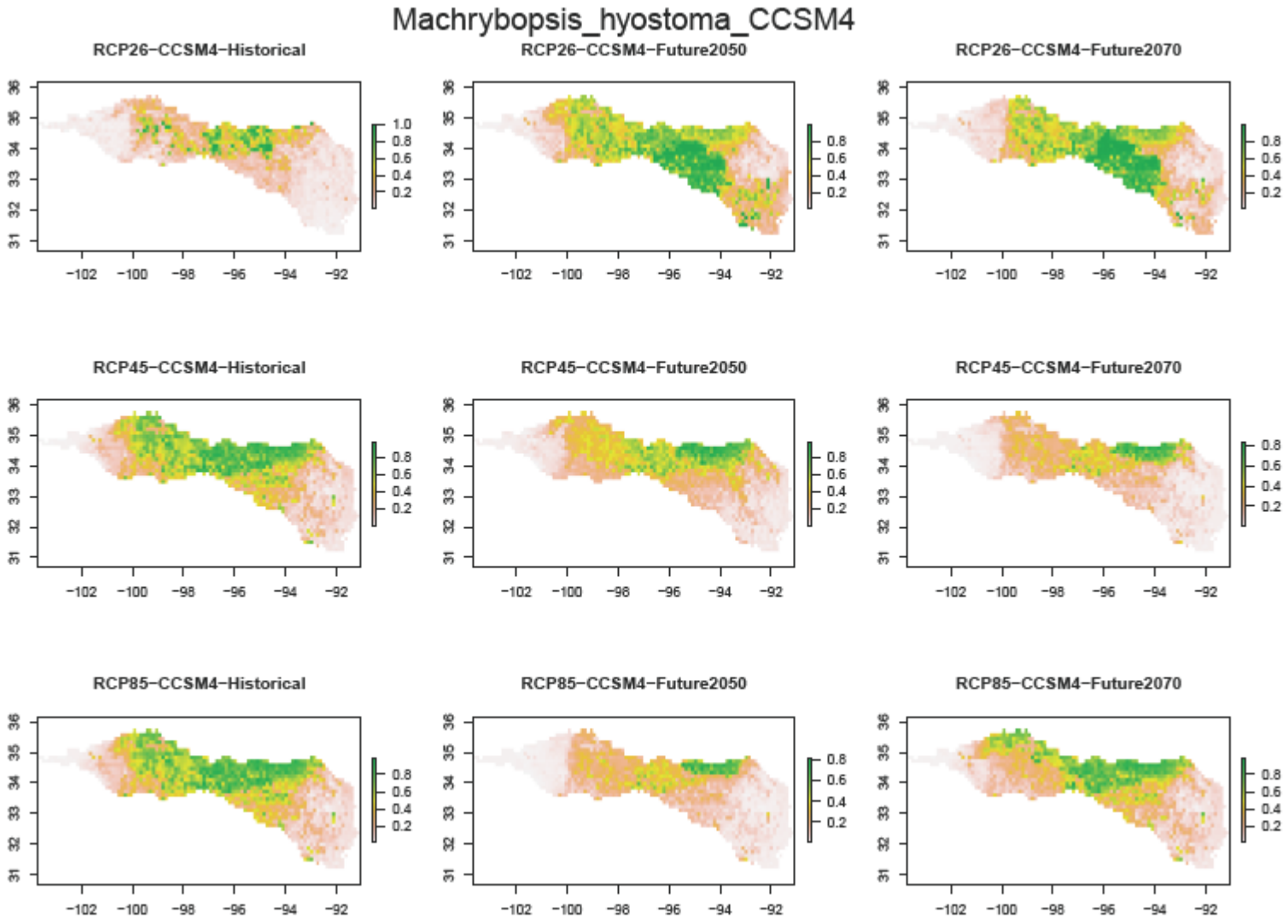
BRT: *Macrhybopsis australis*

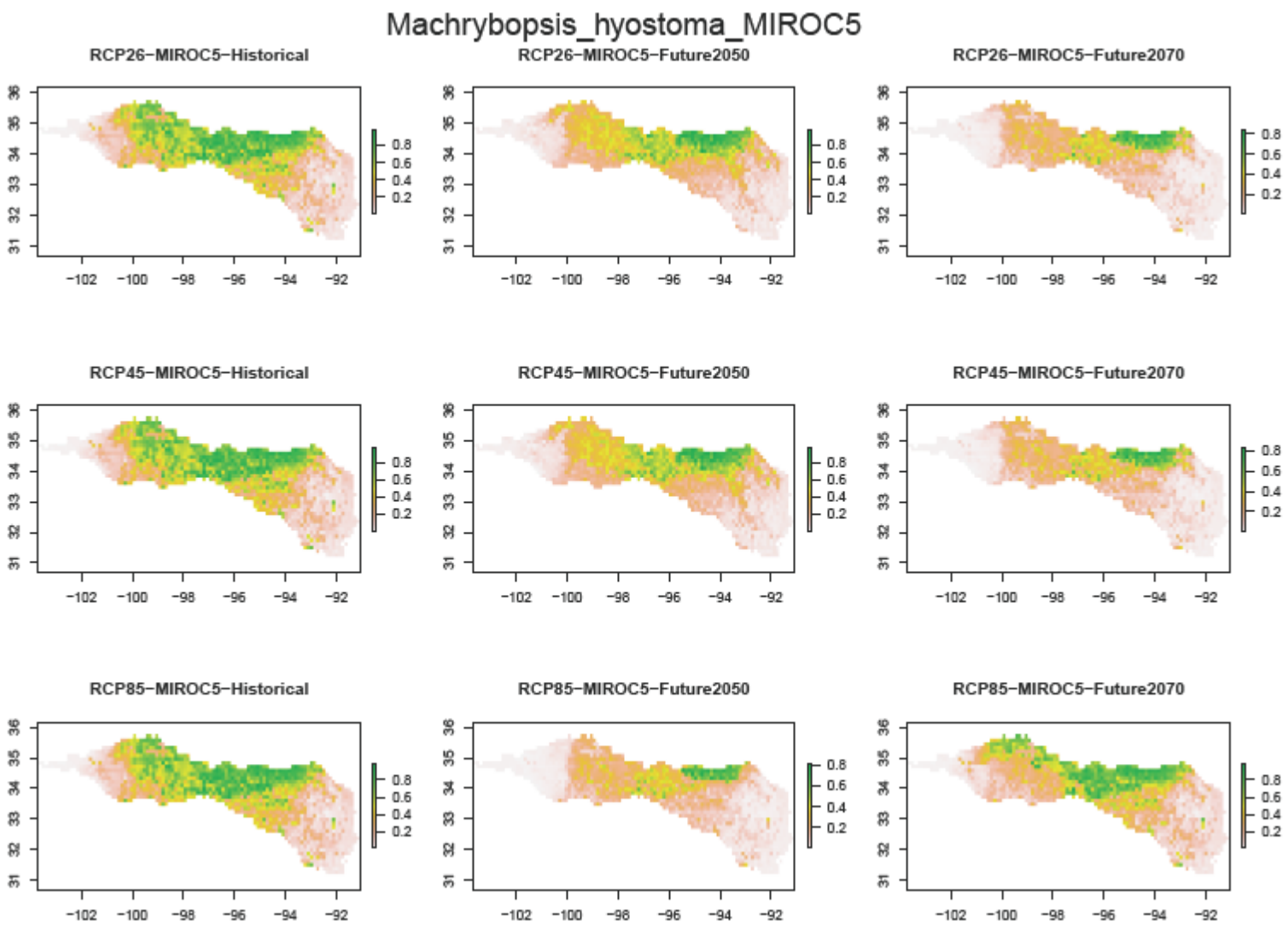


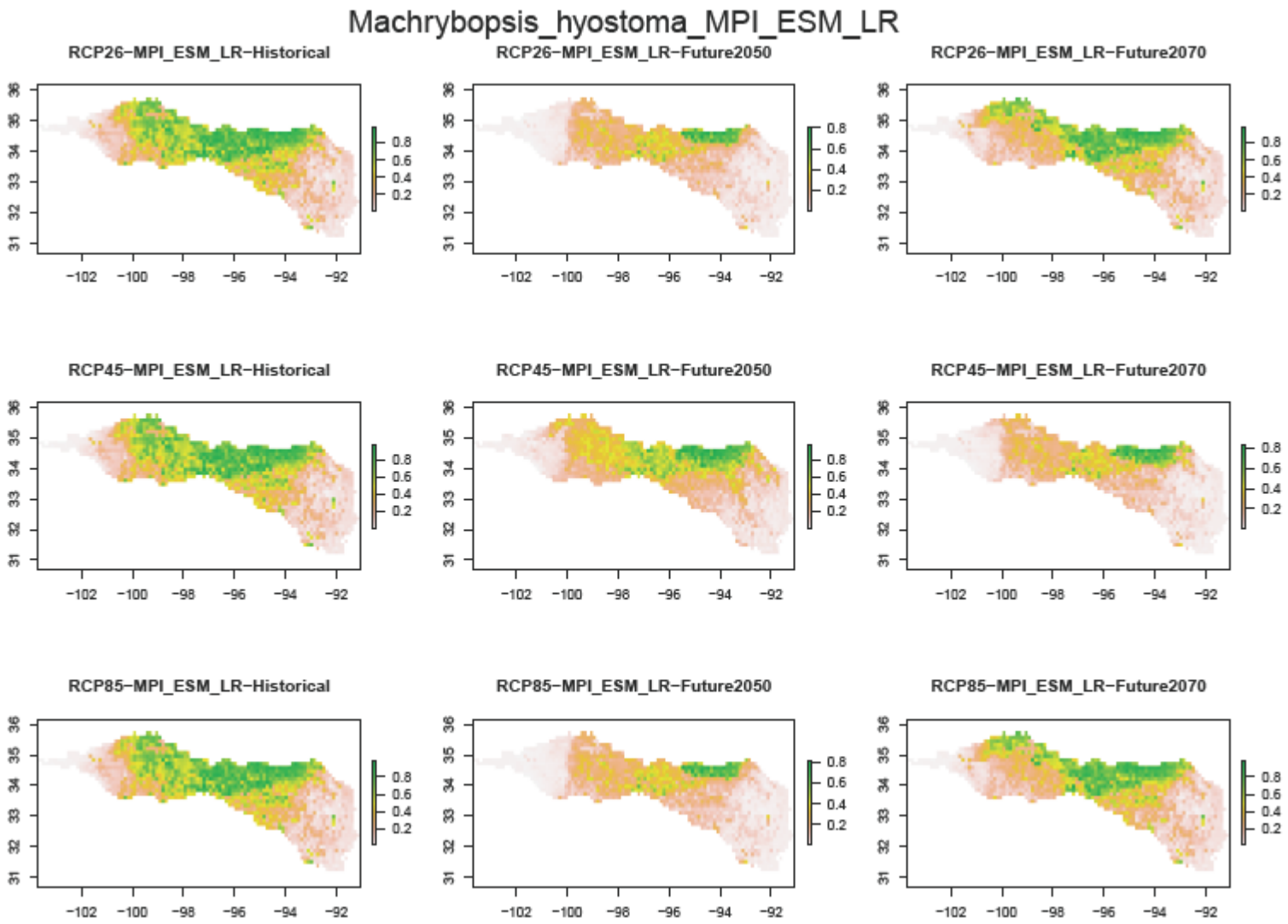

MacrhybopsisaustralisMIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070
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MacrhybopsisaustralisMPI_ESM_LR
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

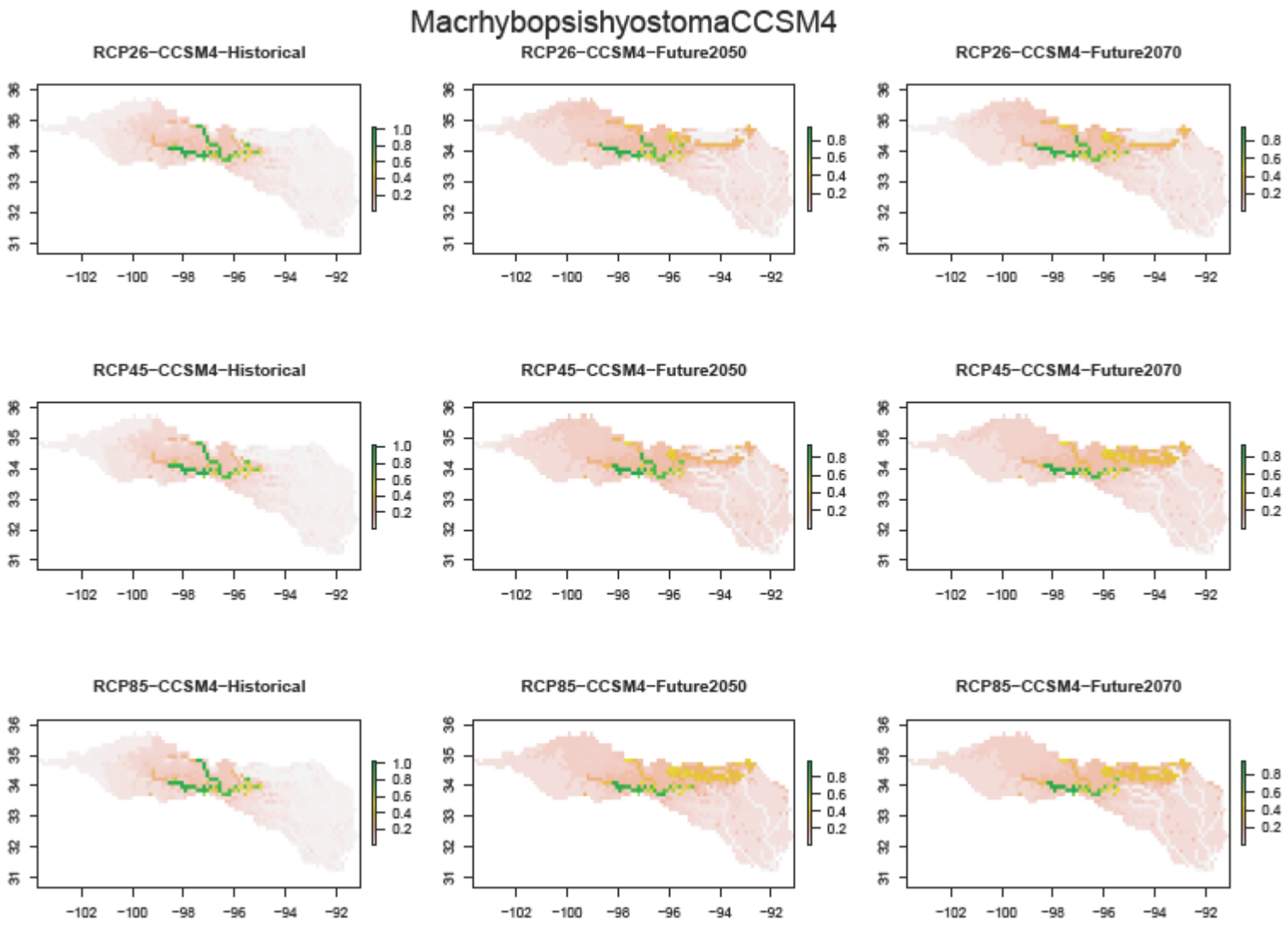
Maxent: *Machrybopsis hyostoma*

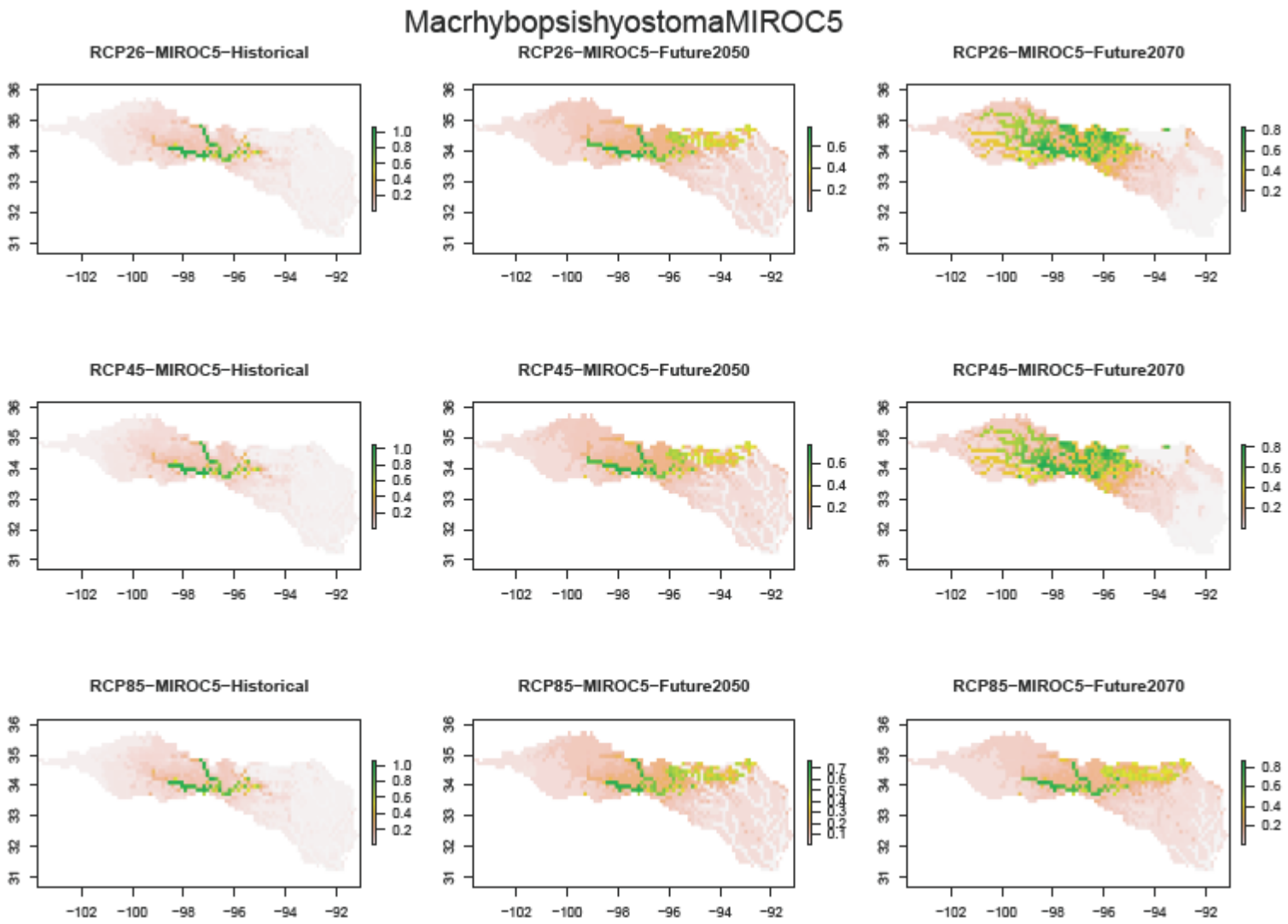


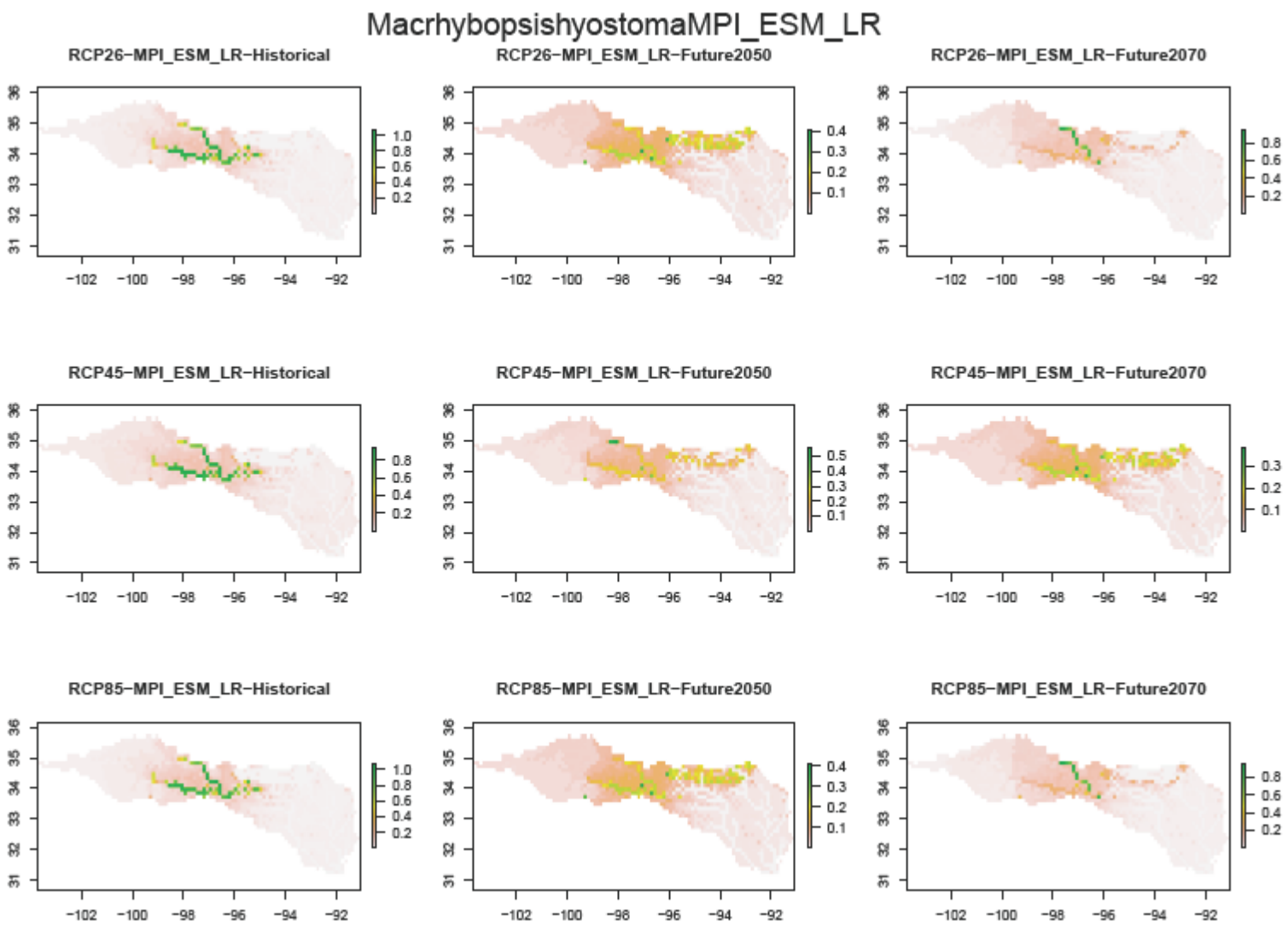

Machrybopsis_hyostoma_MIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070
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Machrybopsis_hyostoma_MPI_ESM_LR
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
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-92
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0.6
0.8

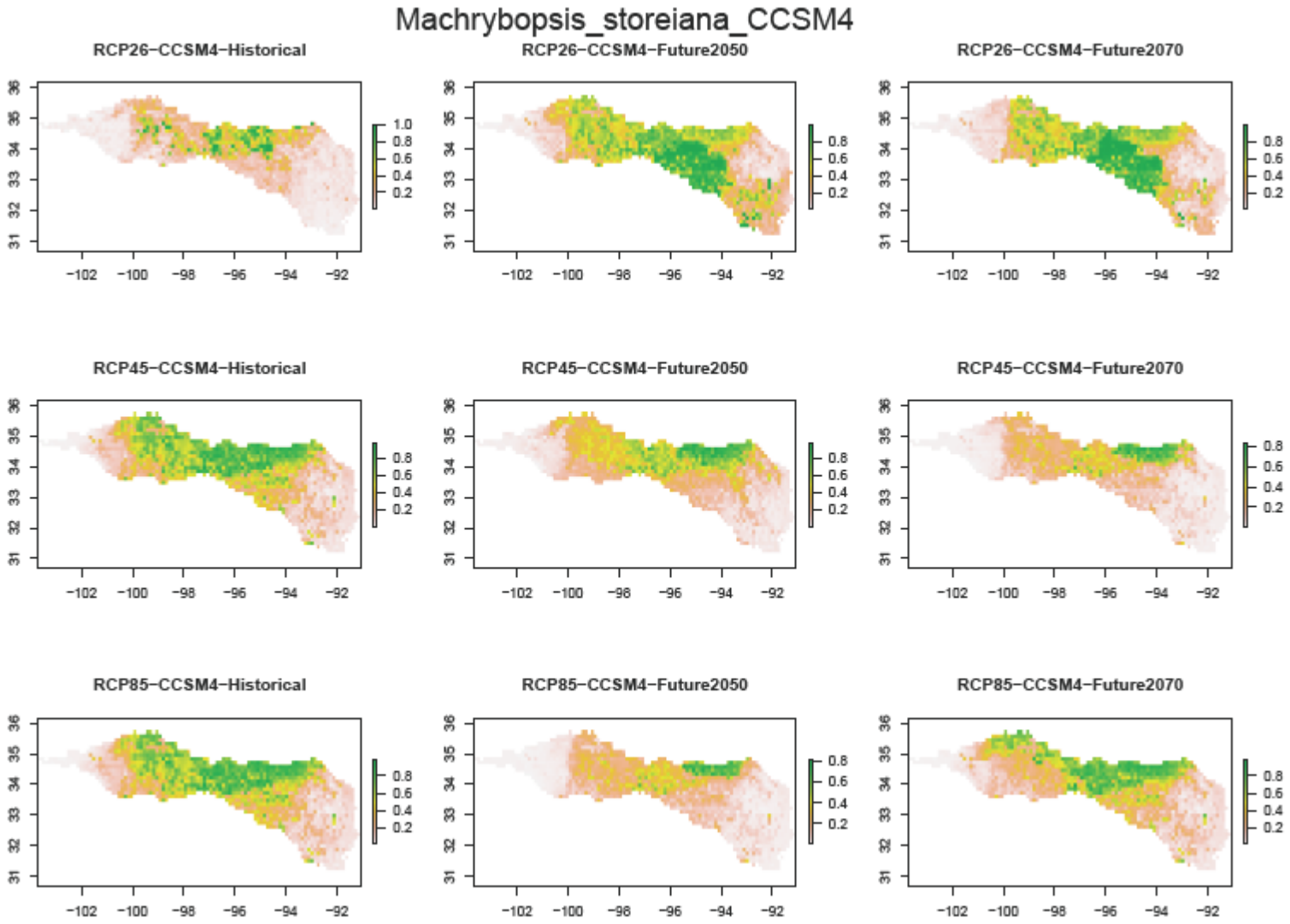
BRT: *Machrybopsis hyostoma*

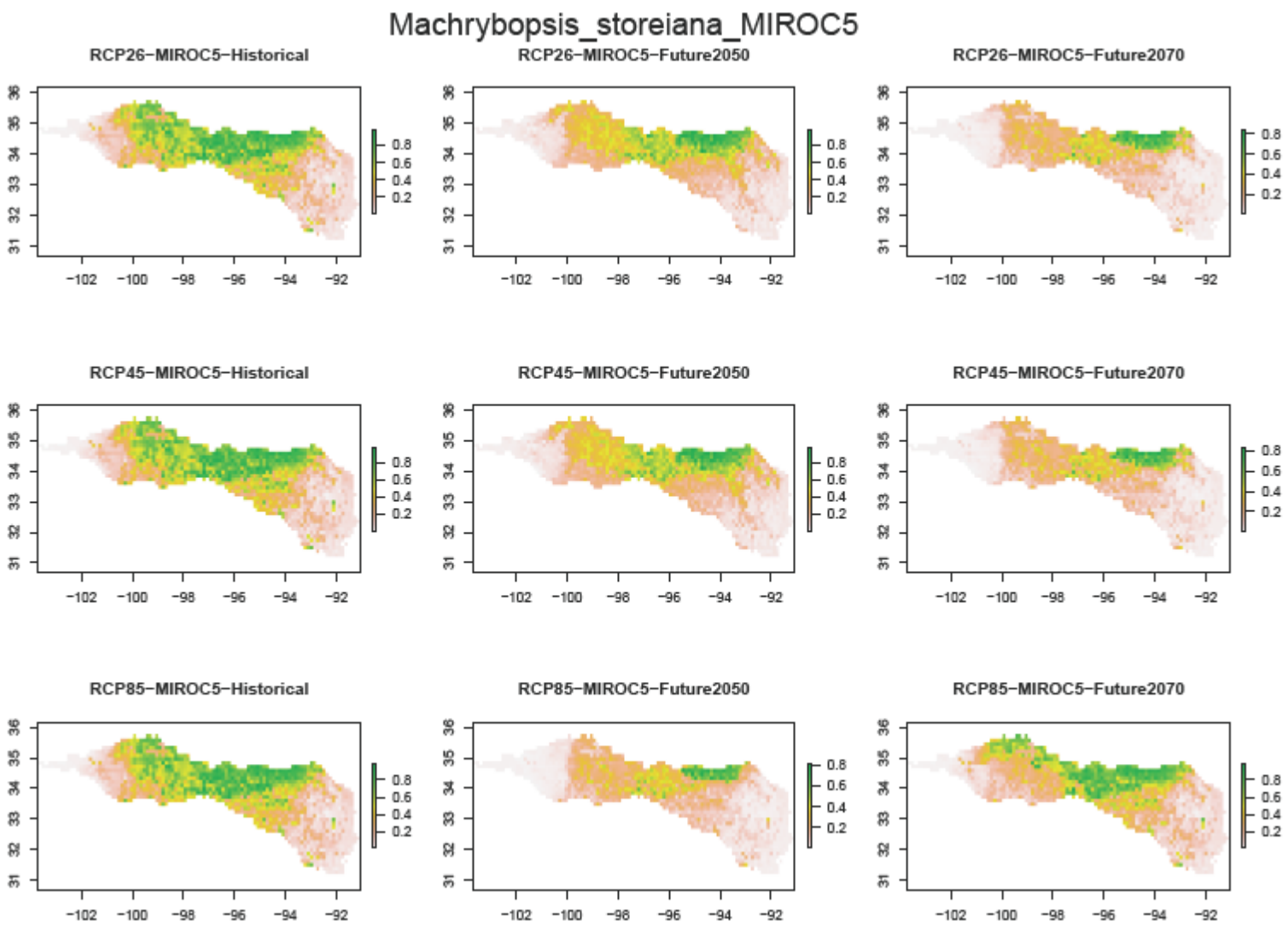


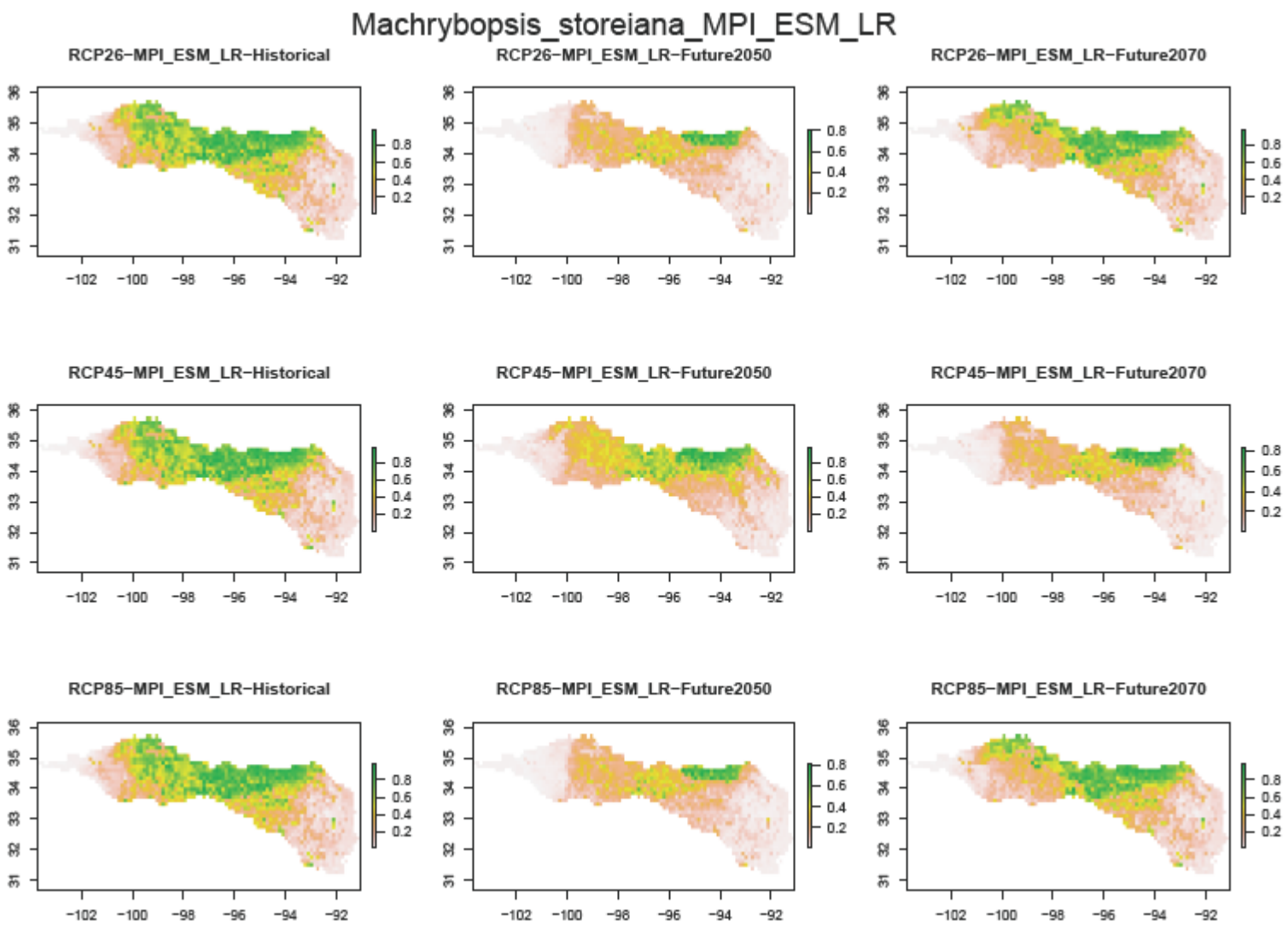

MacrhybopsishyostomaMIROC5
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RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070


MacrhybopsishyostomaMPI_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

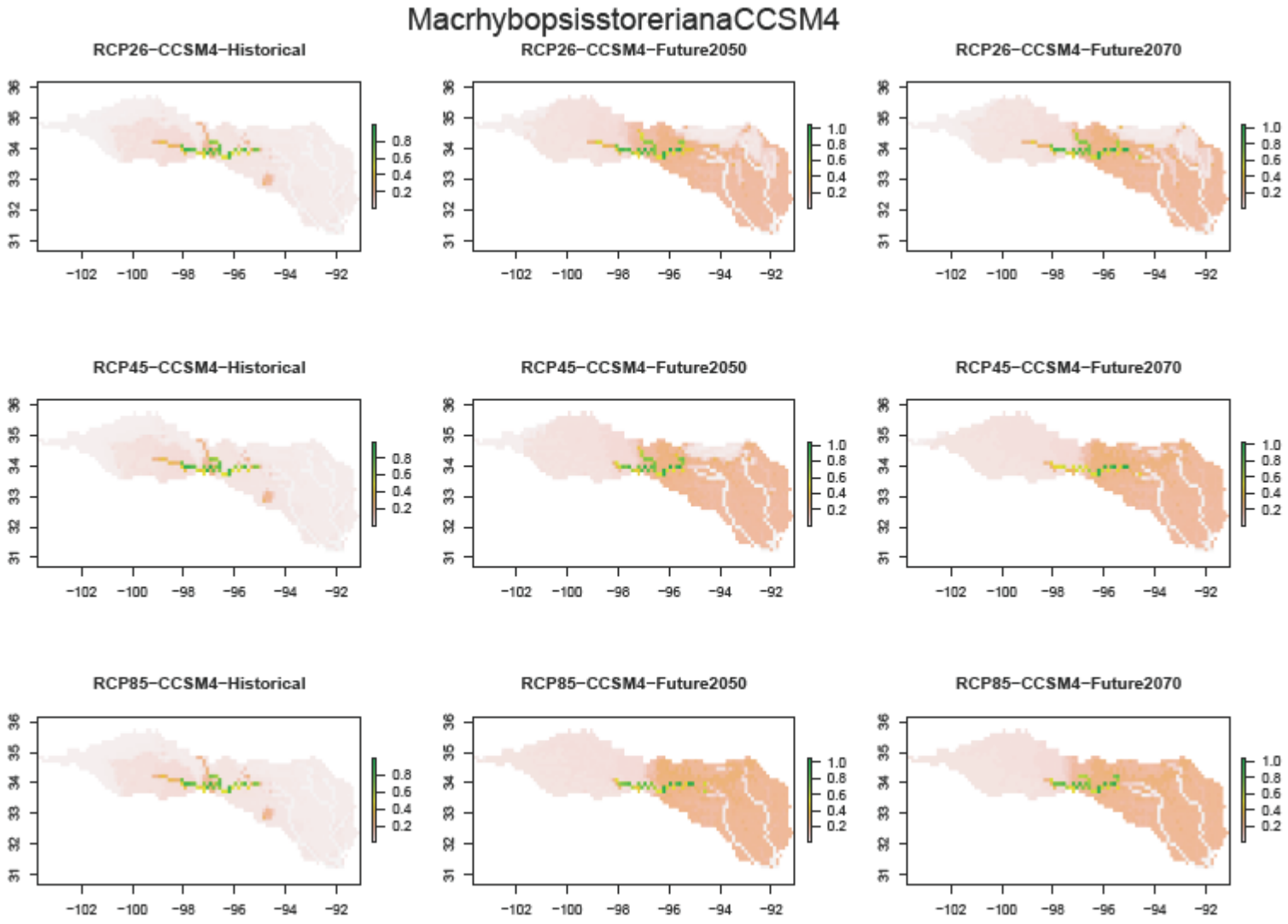
Maxent: *Macrhybopsis storeriana*

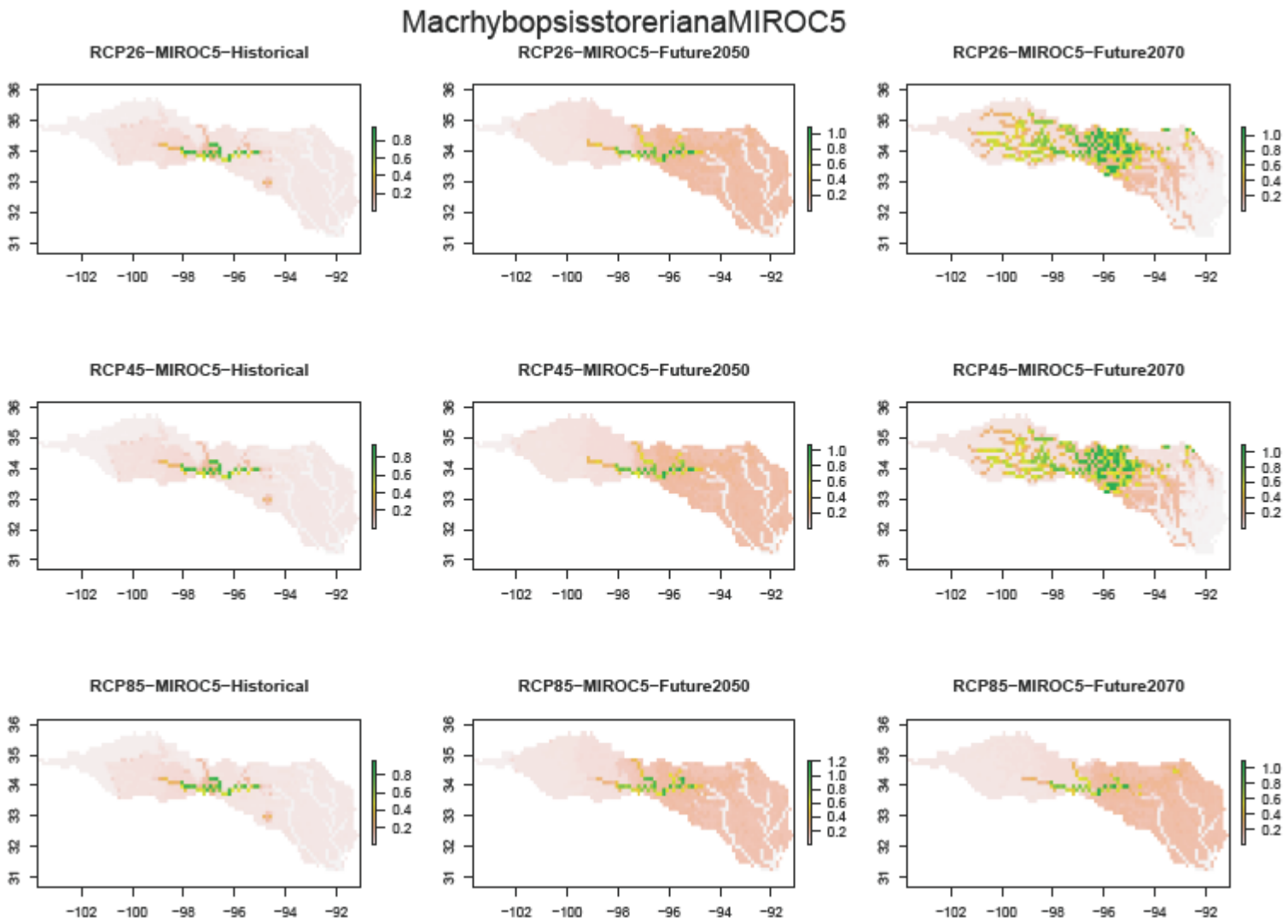


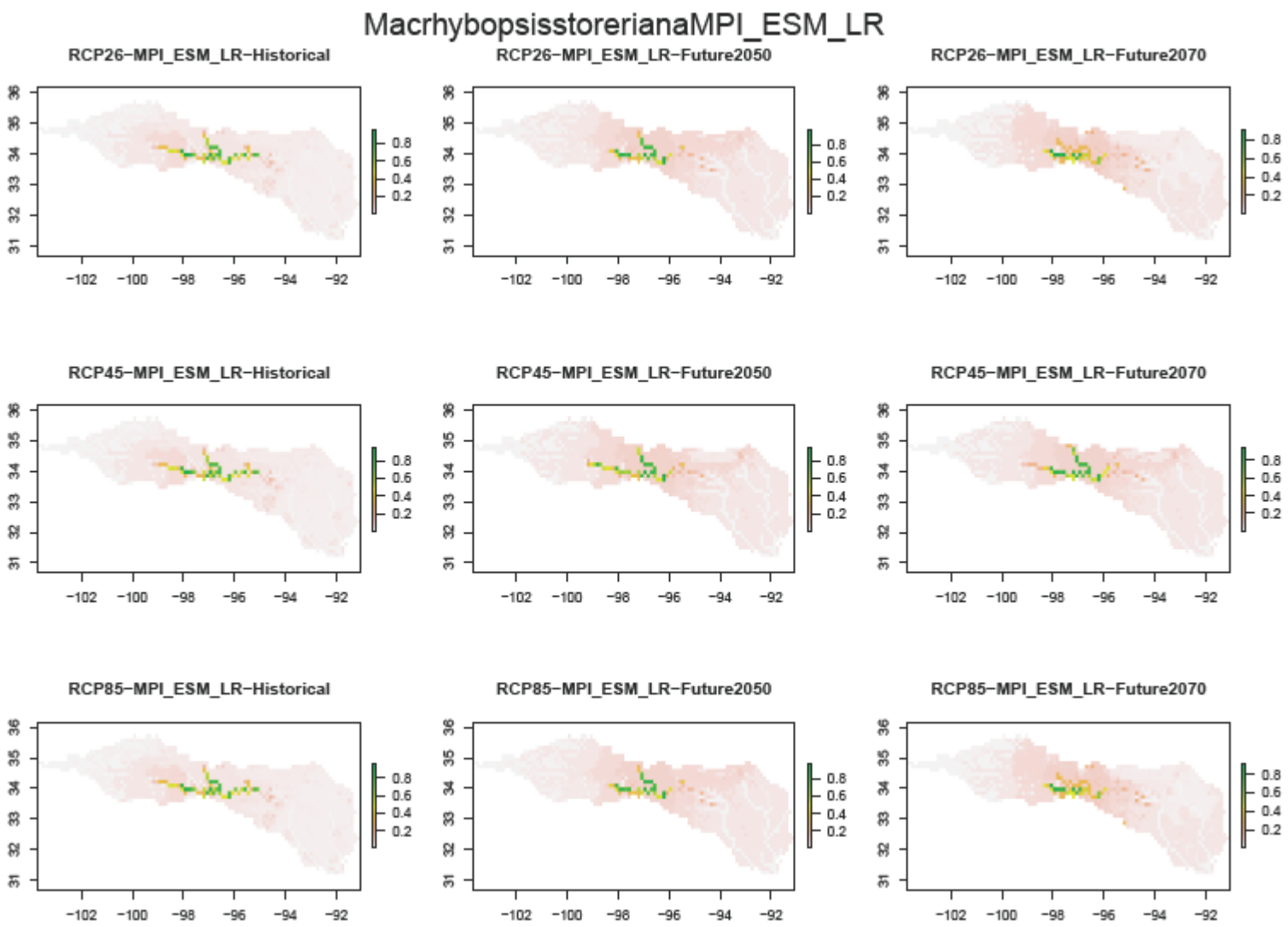

Machrybopsis_storeiana_MIROC5
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RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070
0.8
0.6
0.4
0.2
−102
−100
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−96
−94
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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
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-92
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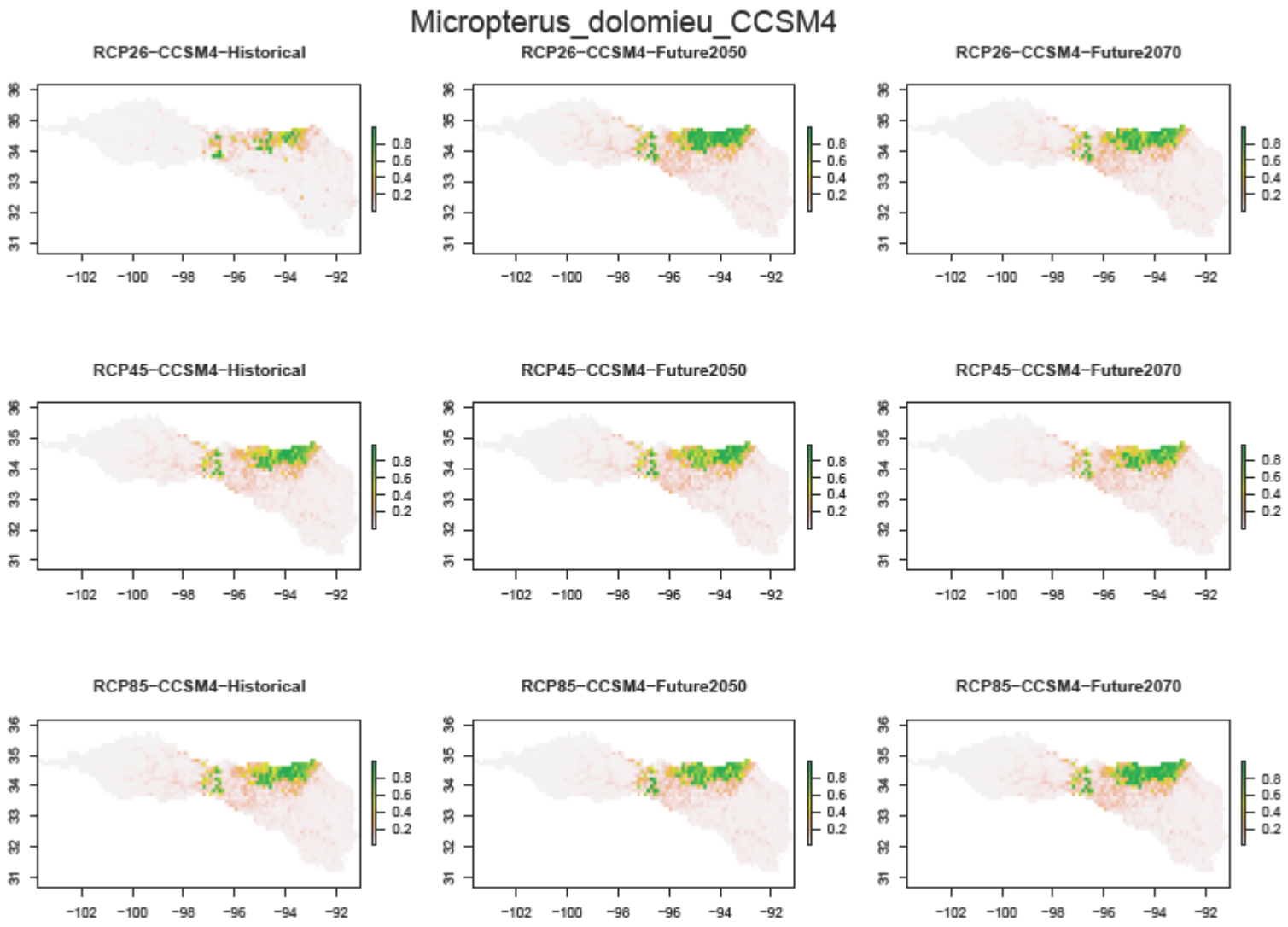
BRT: *Macrhybopsis storeriana*

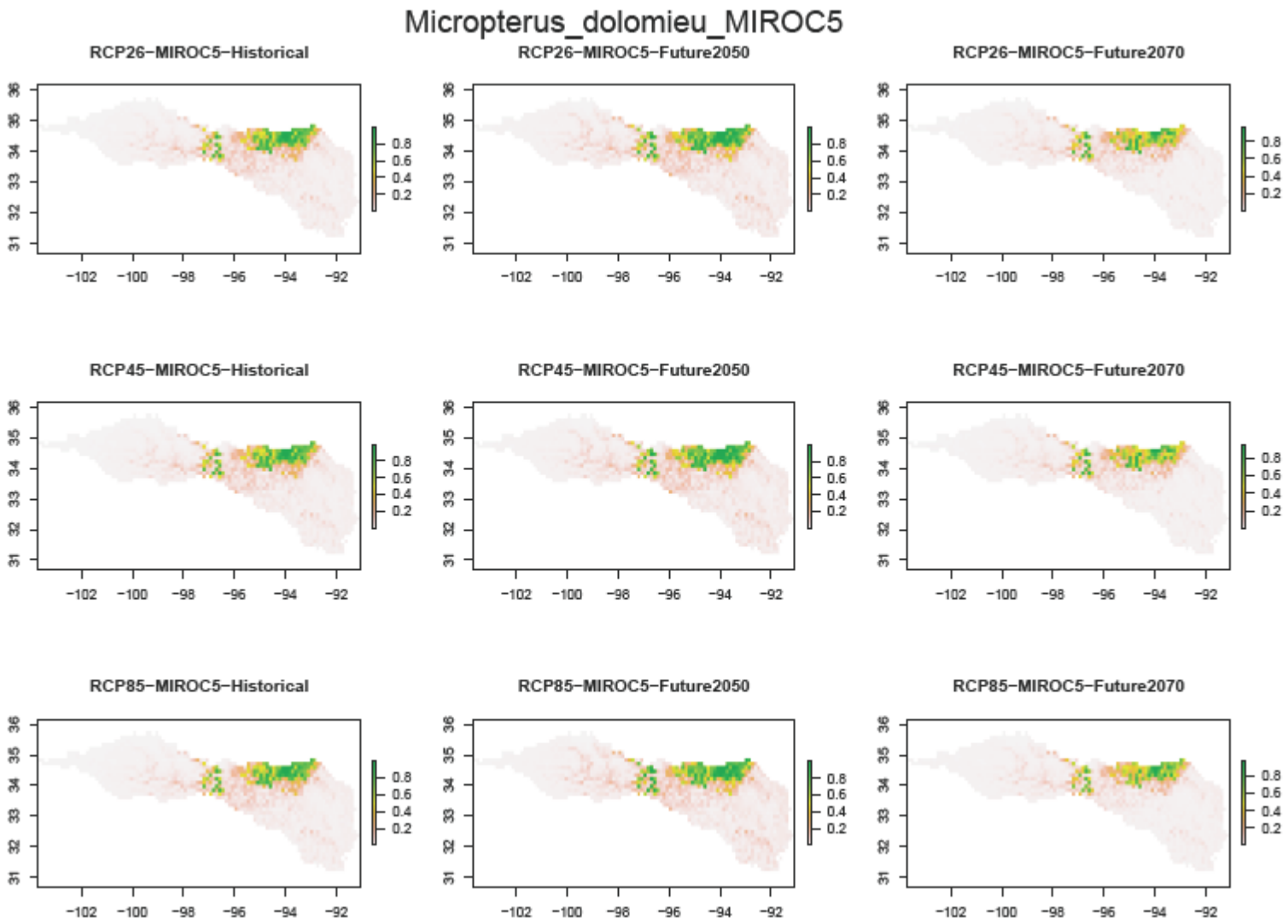


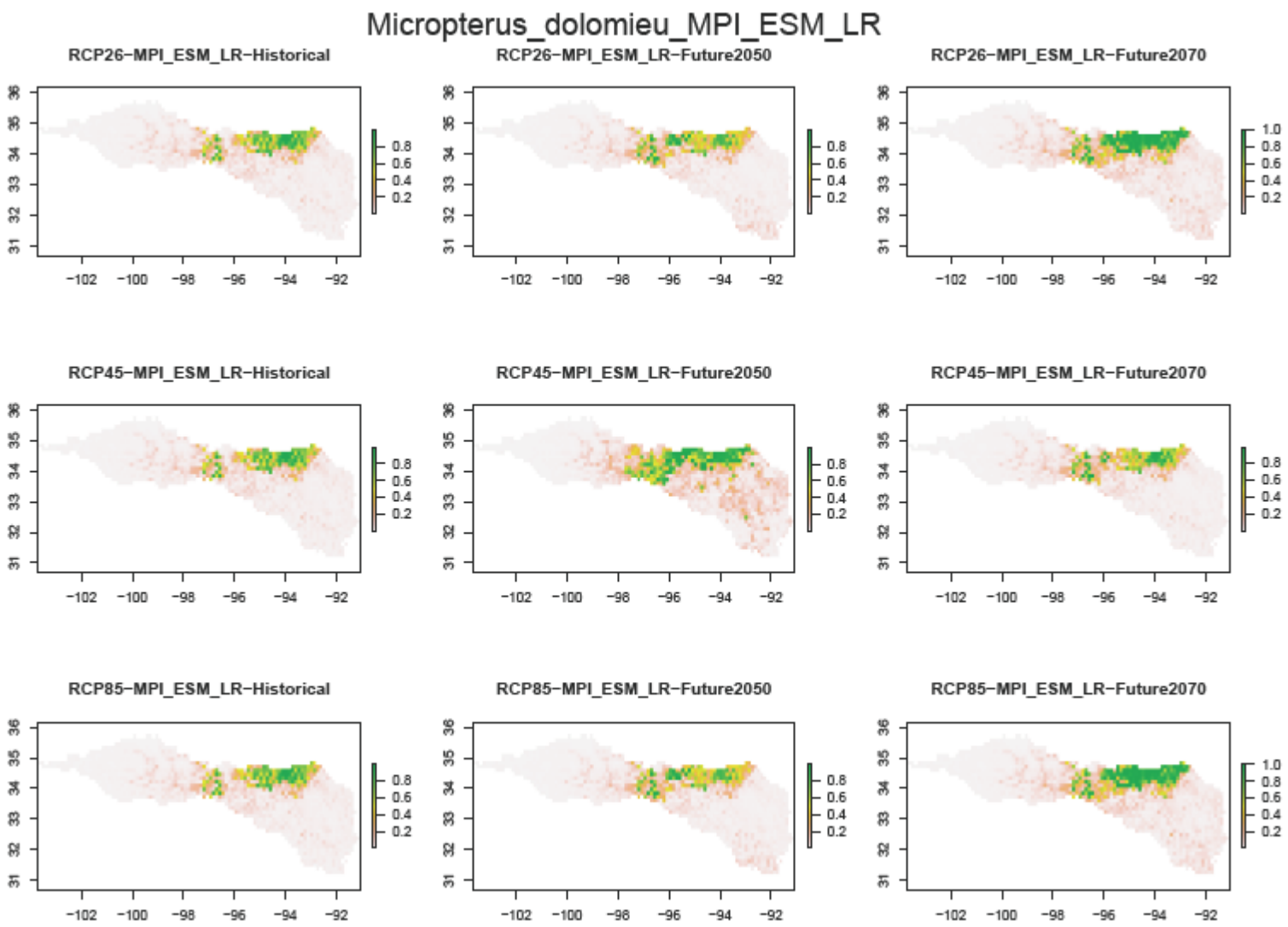

MacrhybopsisstorerianaMIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070


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
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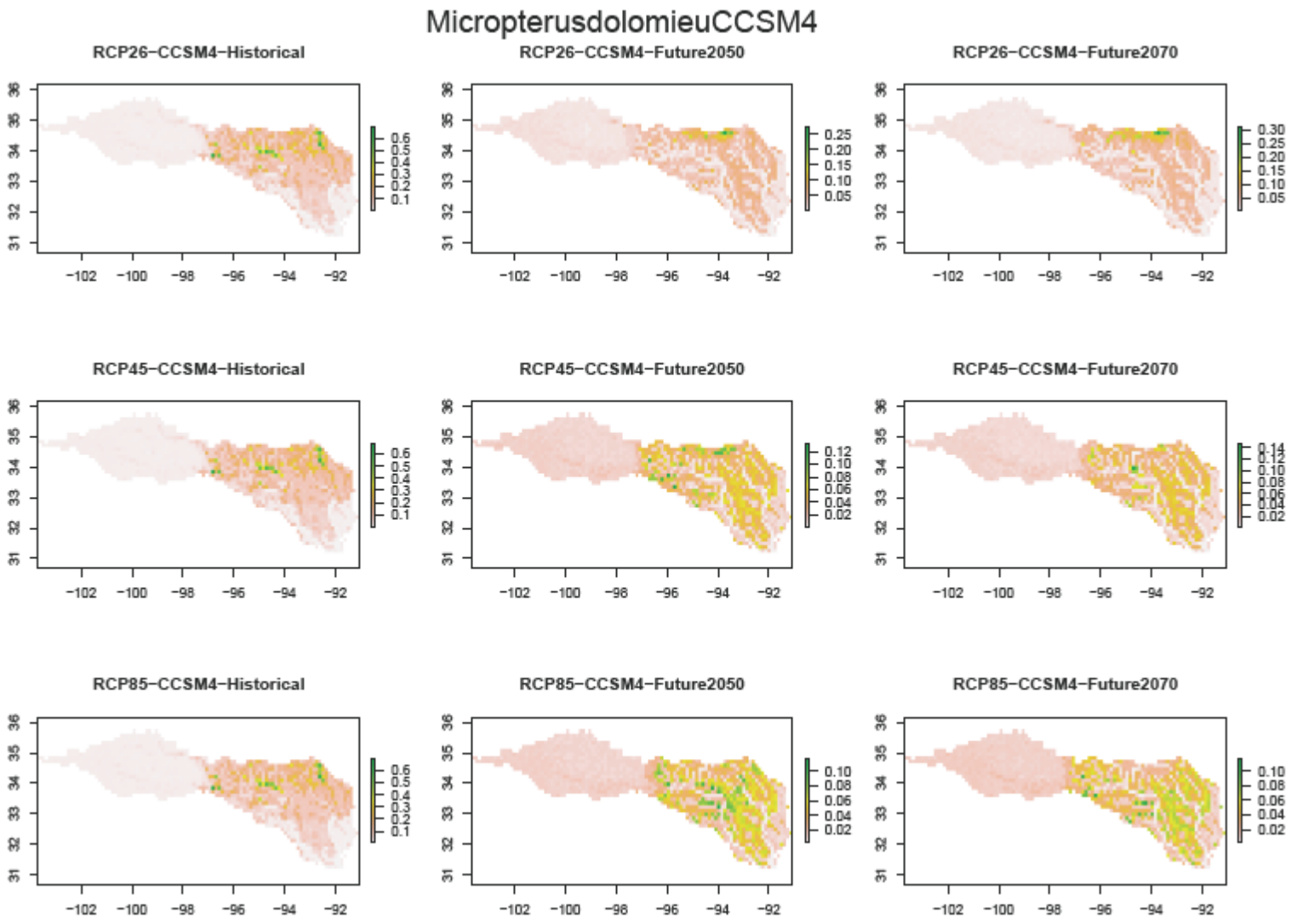
Maxent: *Micopterus dolomieu*

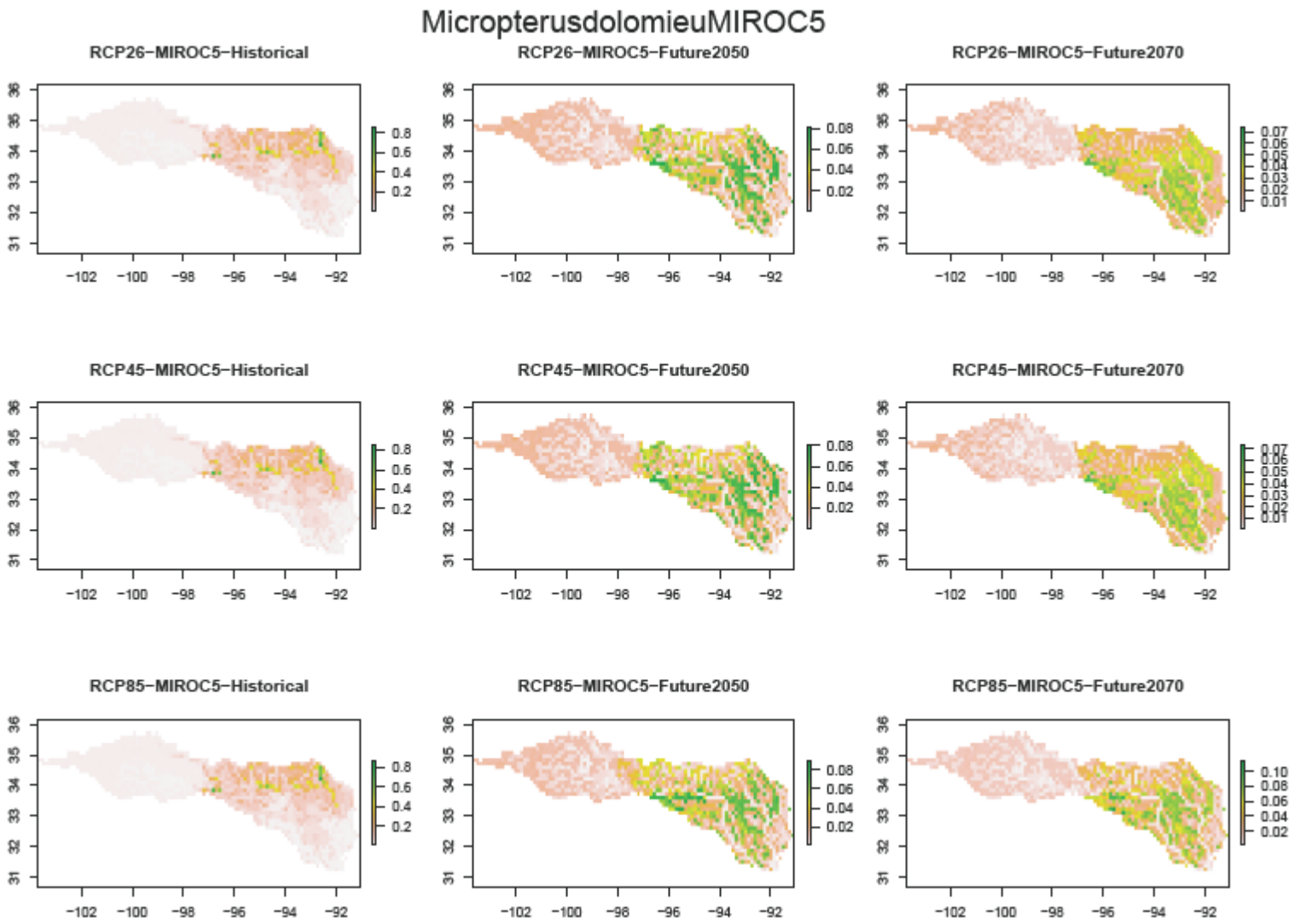


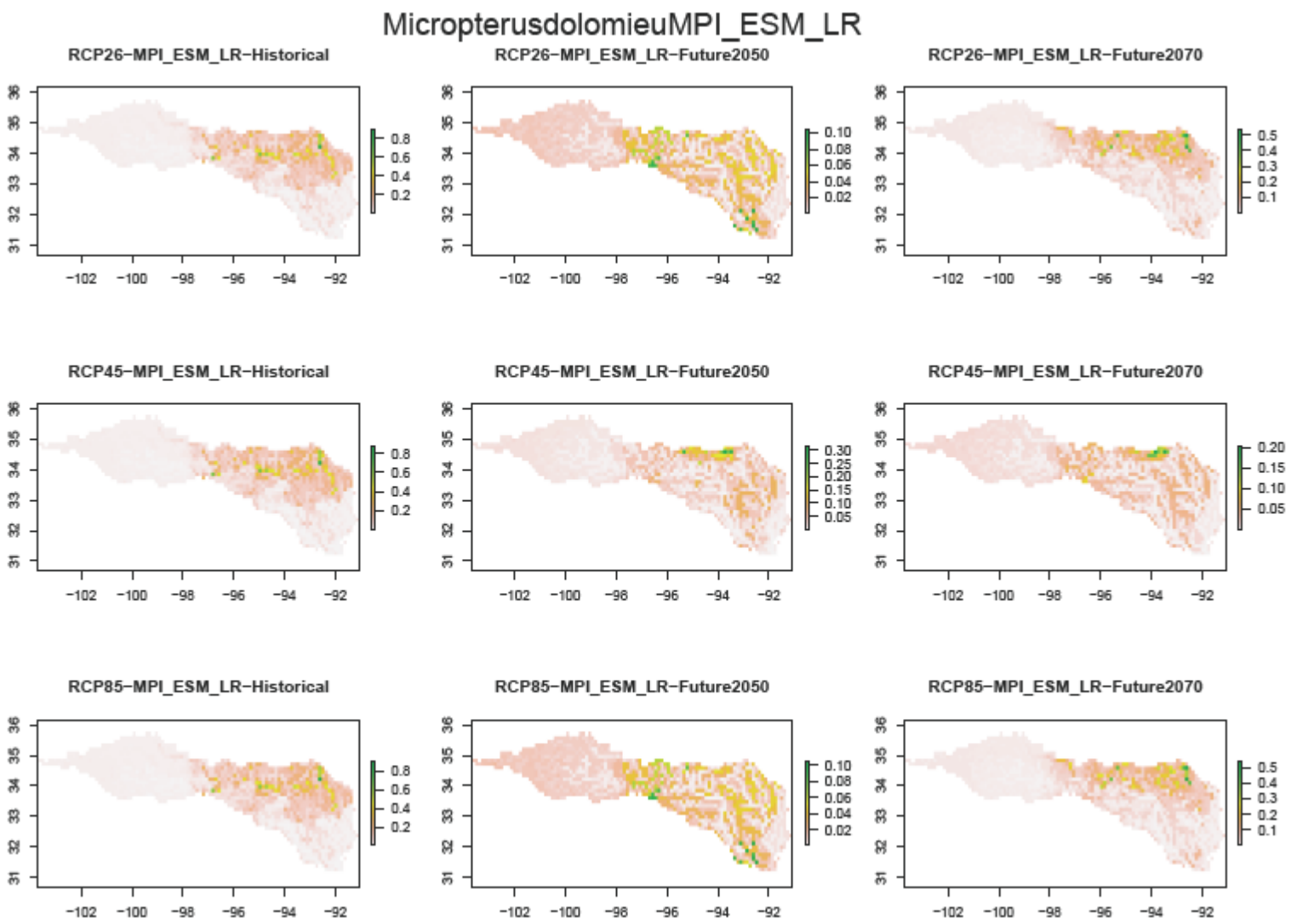

Micropterus_dolomieu_MIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070
0.8
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Micropterus_dolomieu_MPI_ESM_LR
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
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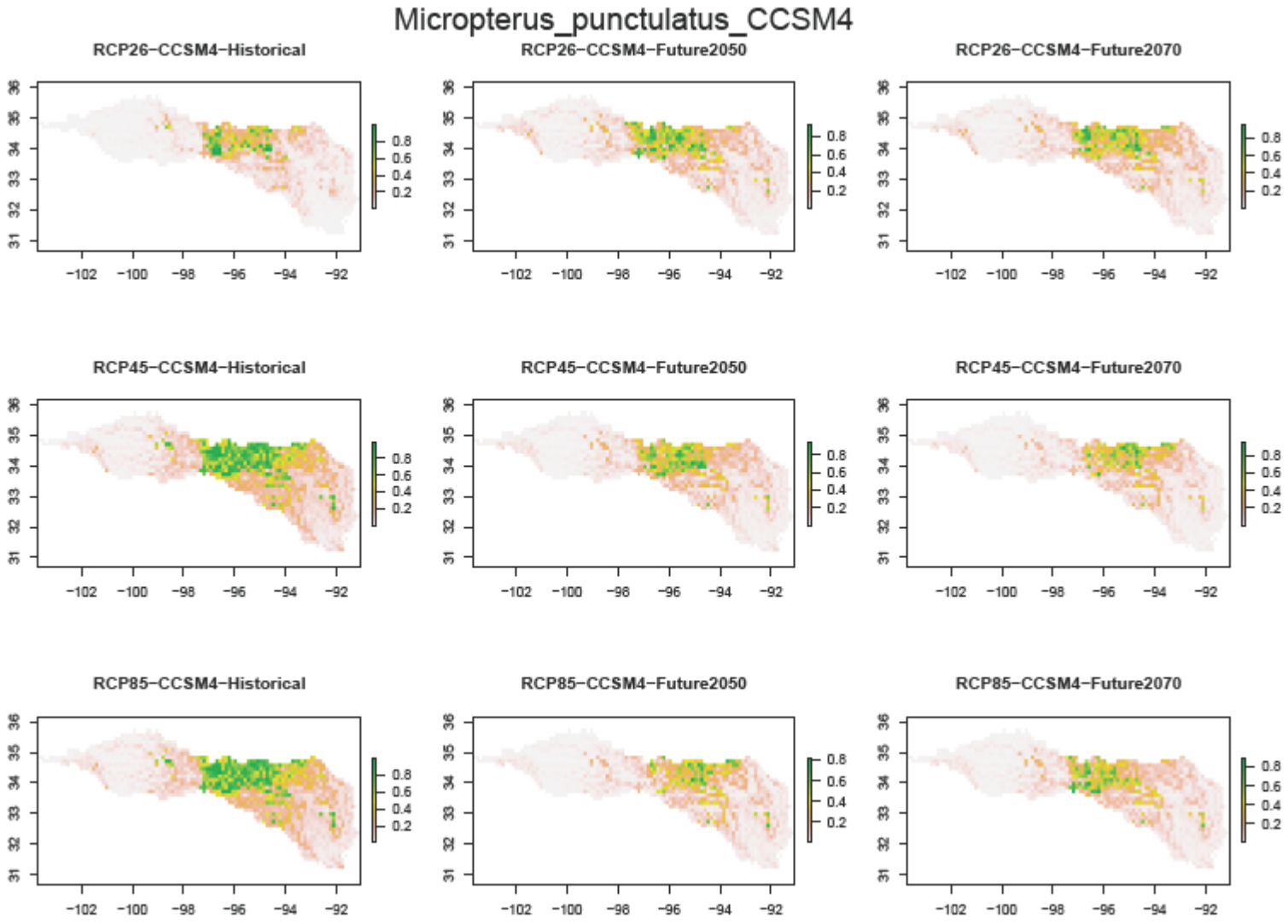
BRT: *Micropterus dolomieu*

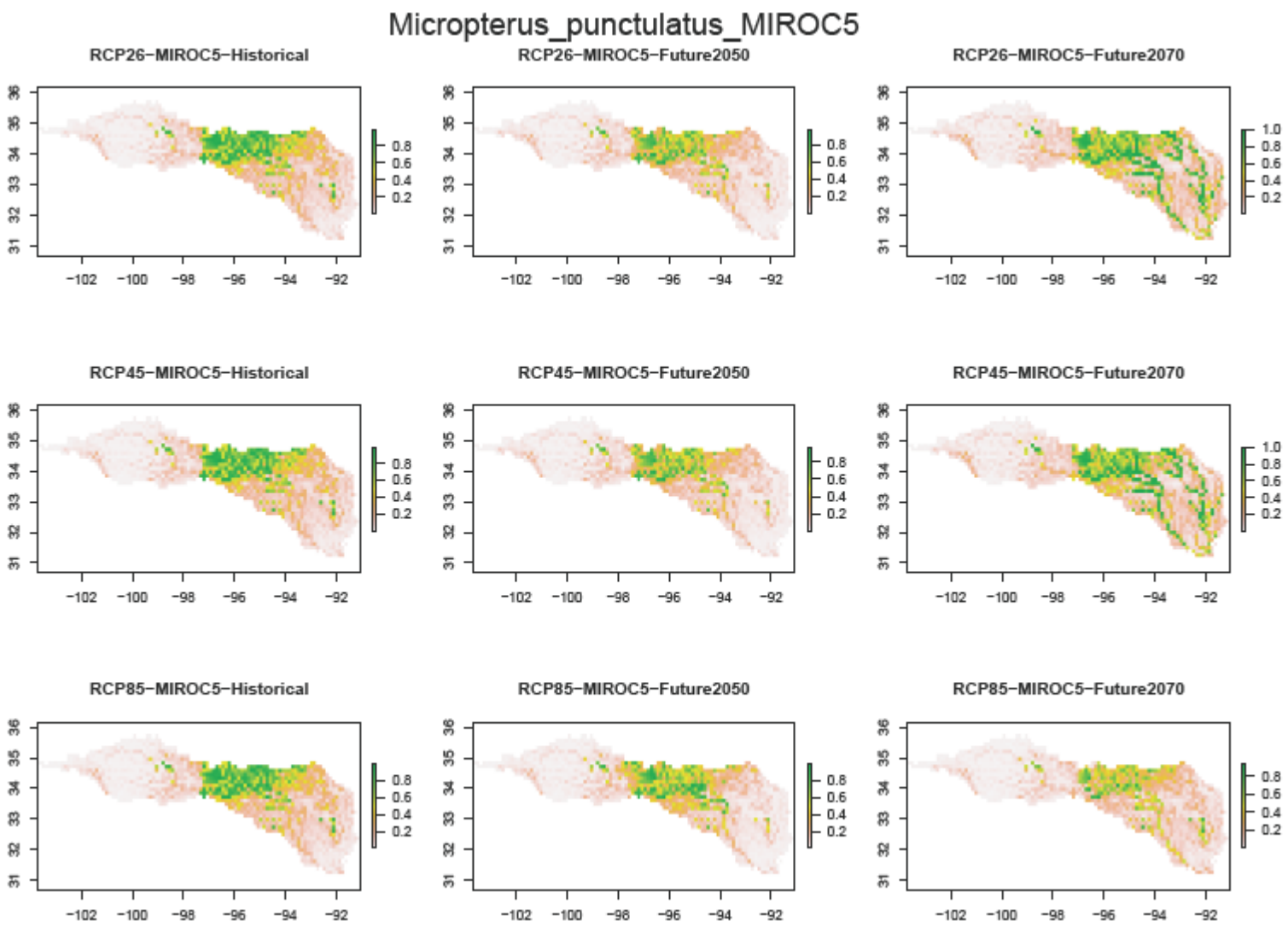


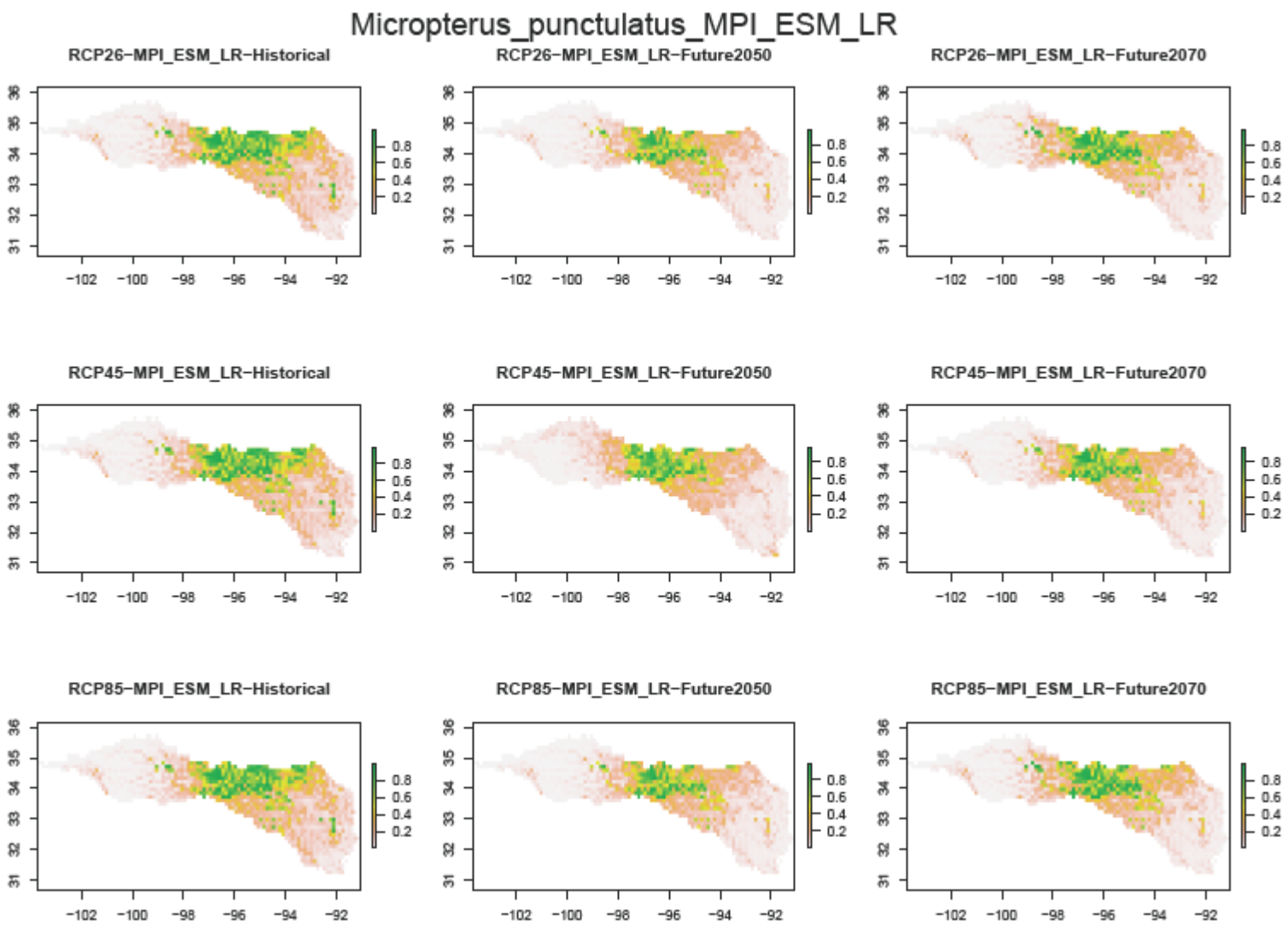

MicropterusdolomieuMIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070


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
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RCP85-MPI_ESM_LR-Future2050
RCP85-MPI_ESM_LR-Future2070

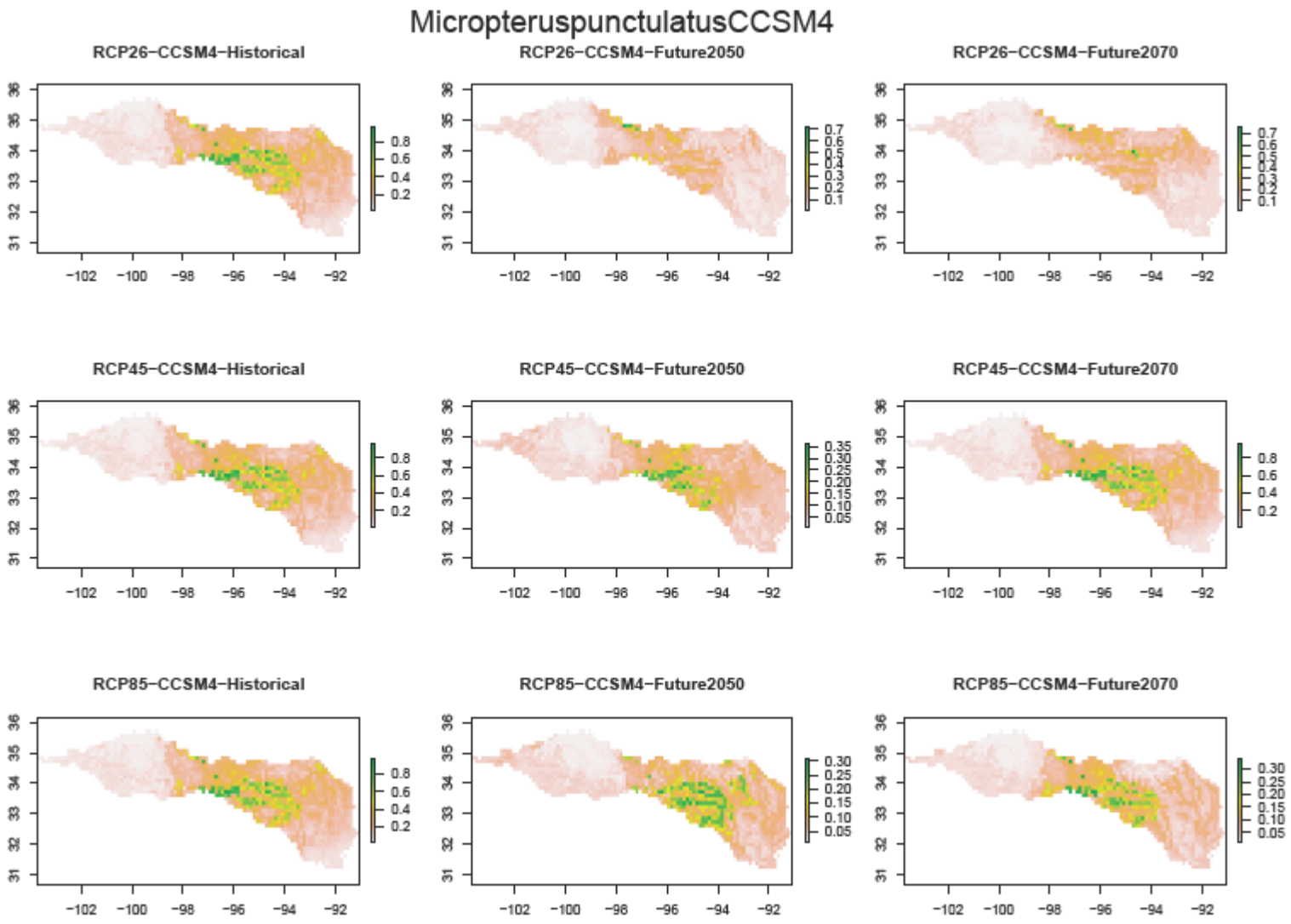
Maxent: *Micropterus punctulatus*

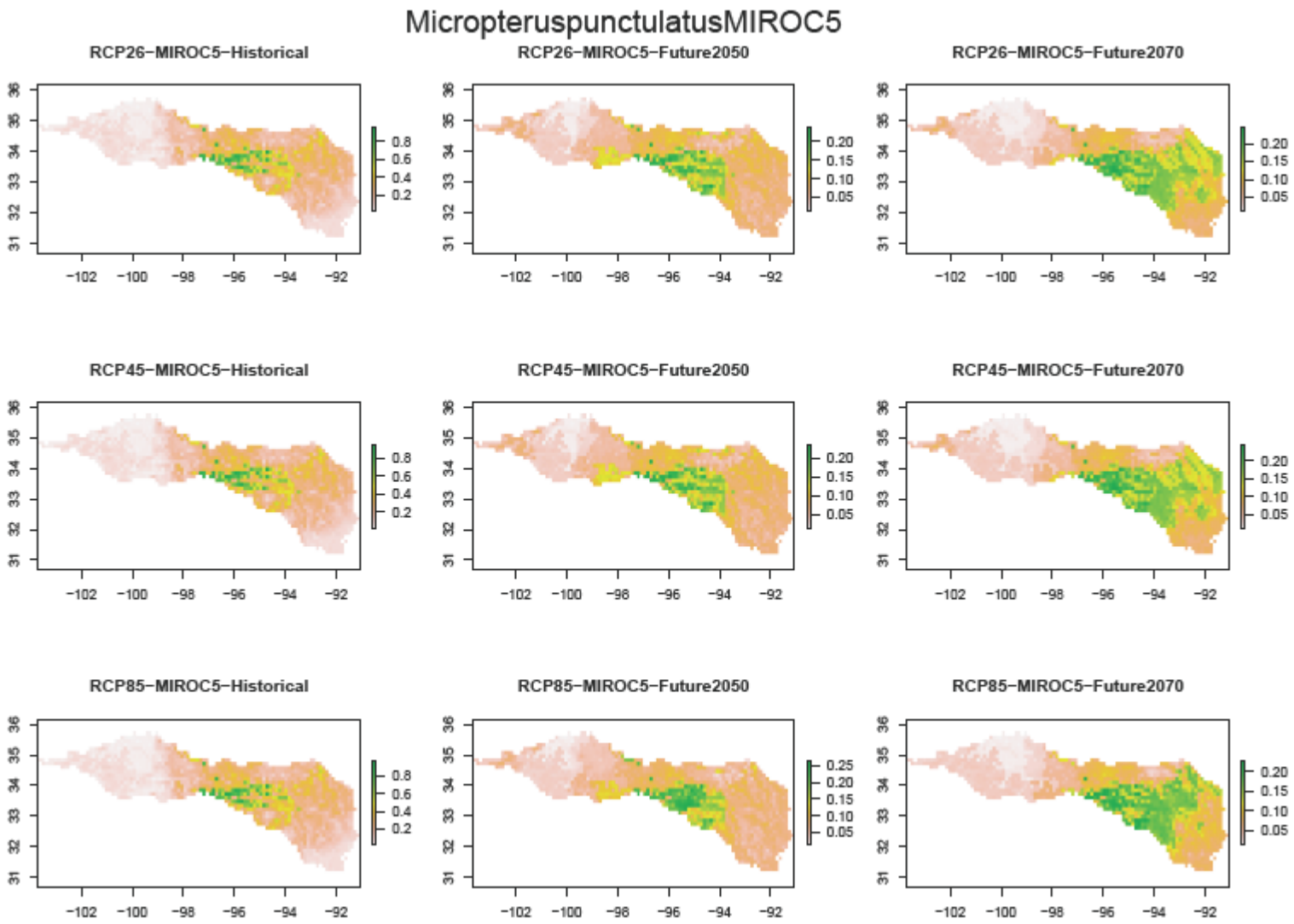


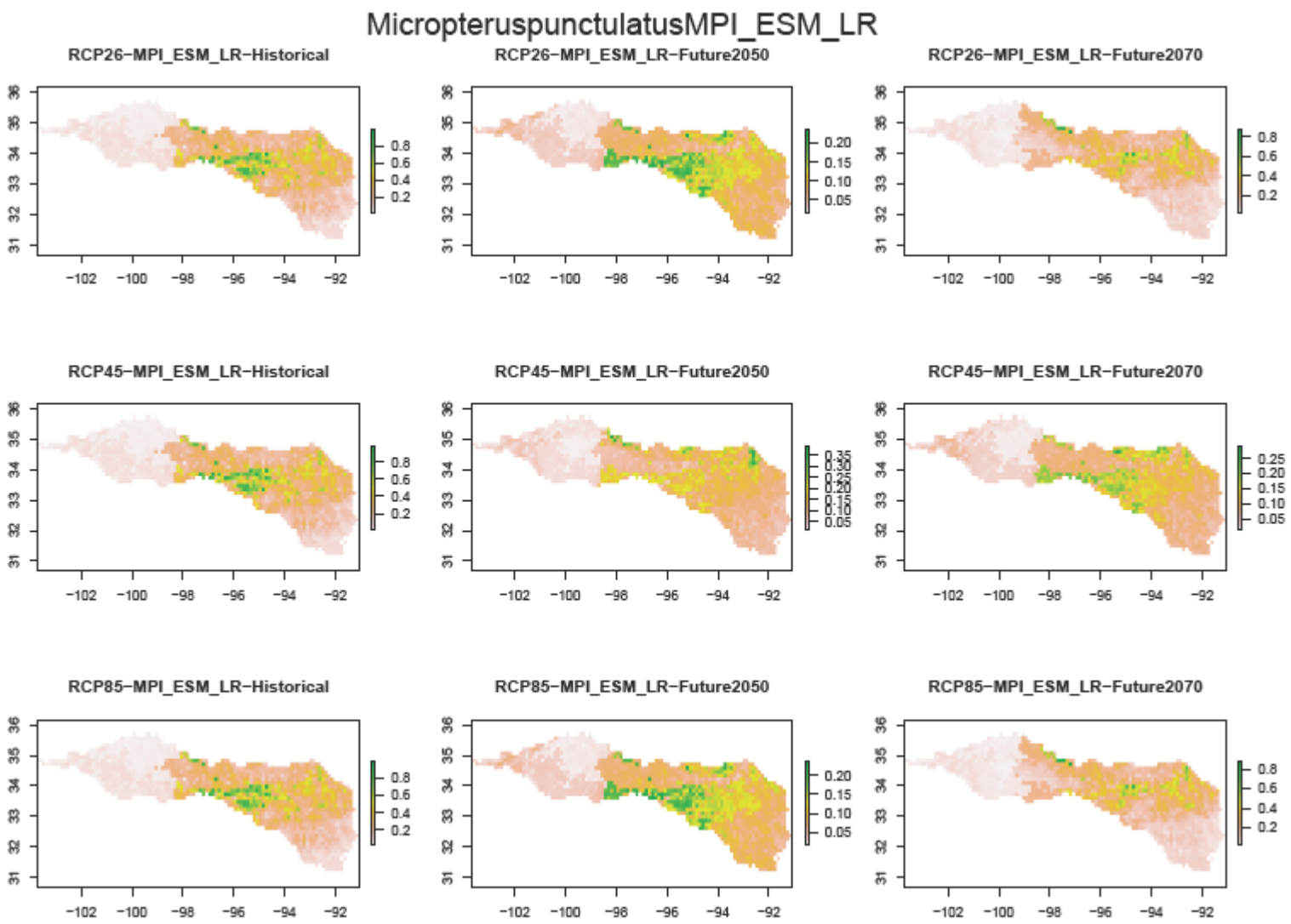

Micropterus_punctulatus_MIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070


Micropterus_punctulatus_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
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0.4
0.6
0.8

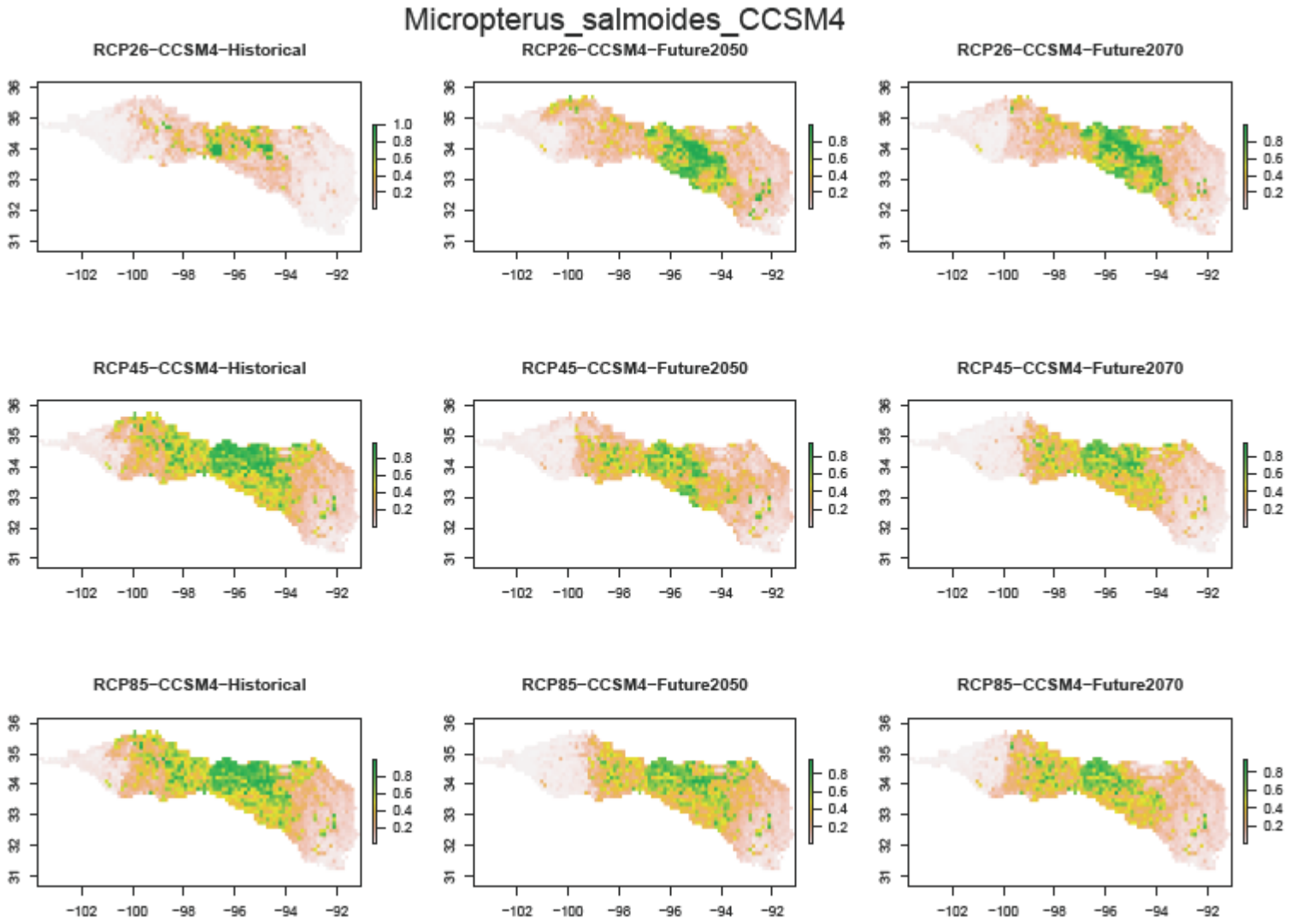
BRT: *Micropterus punctulatus*

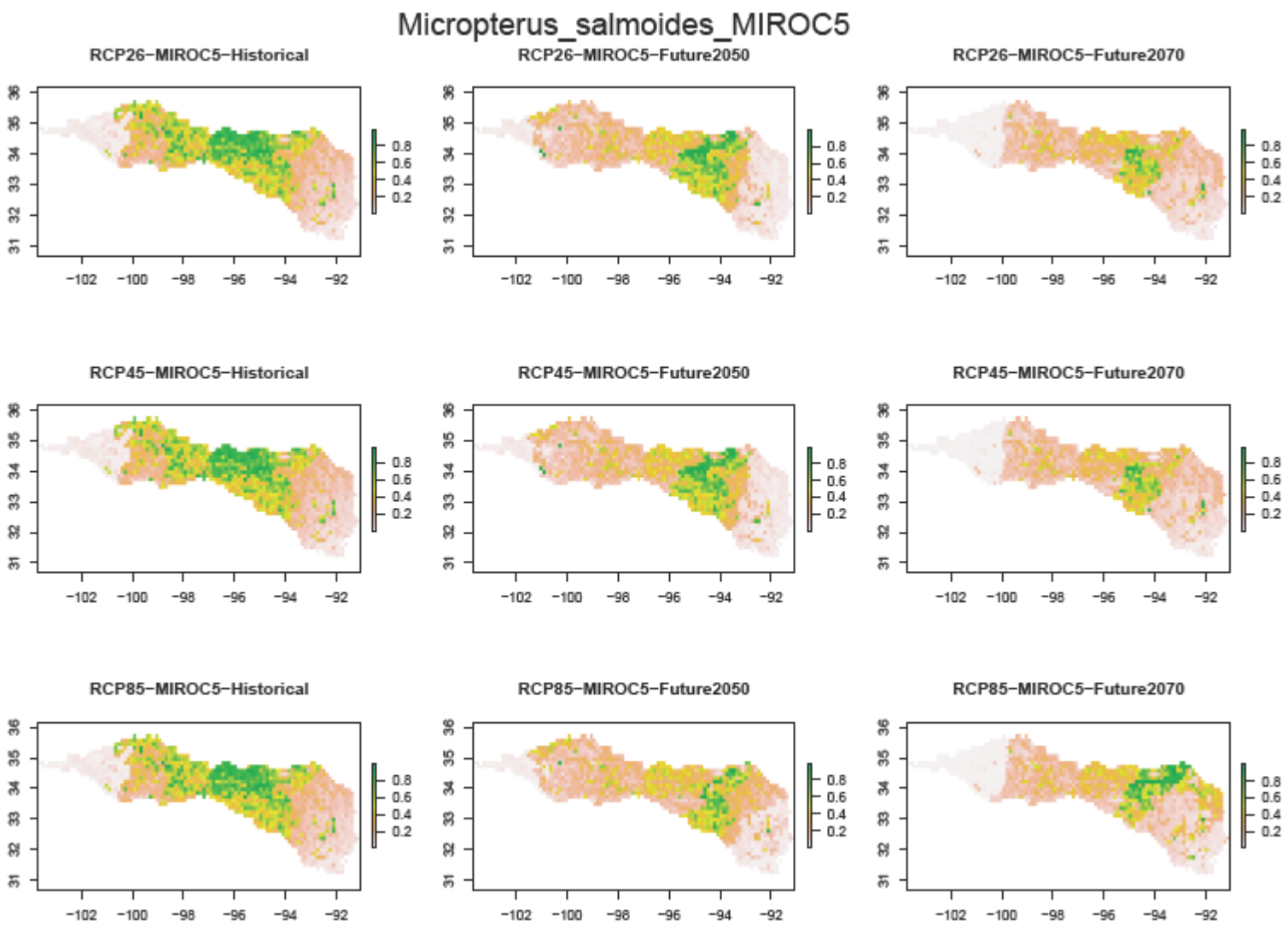


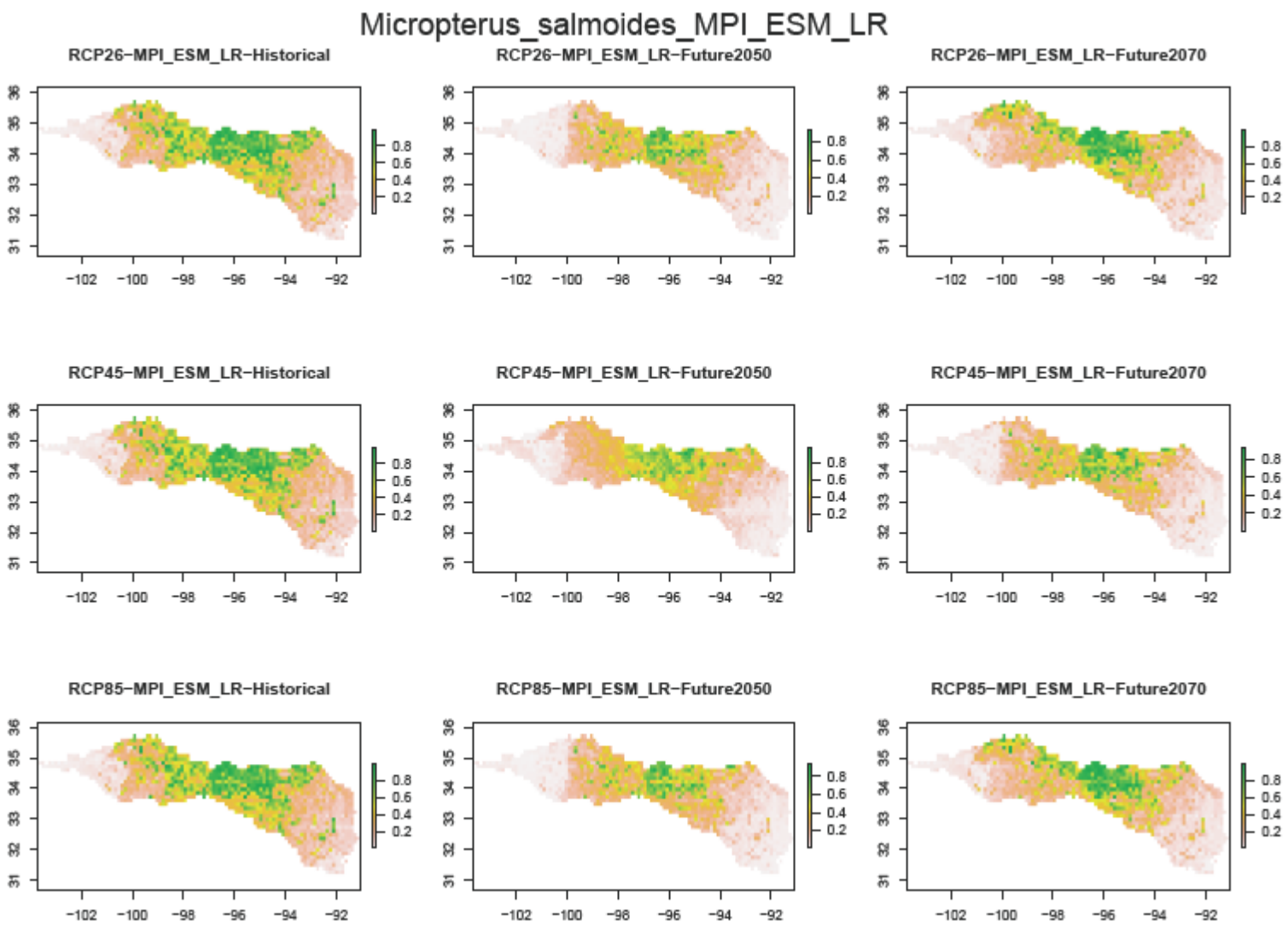

MicropteruspunctulatusMIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070


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

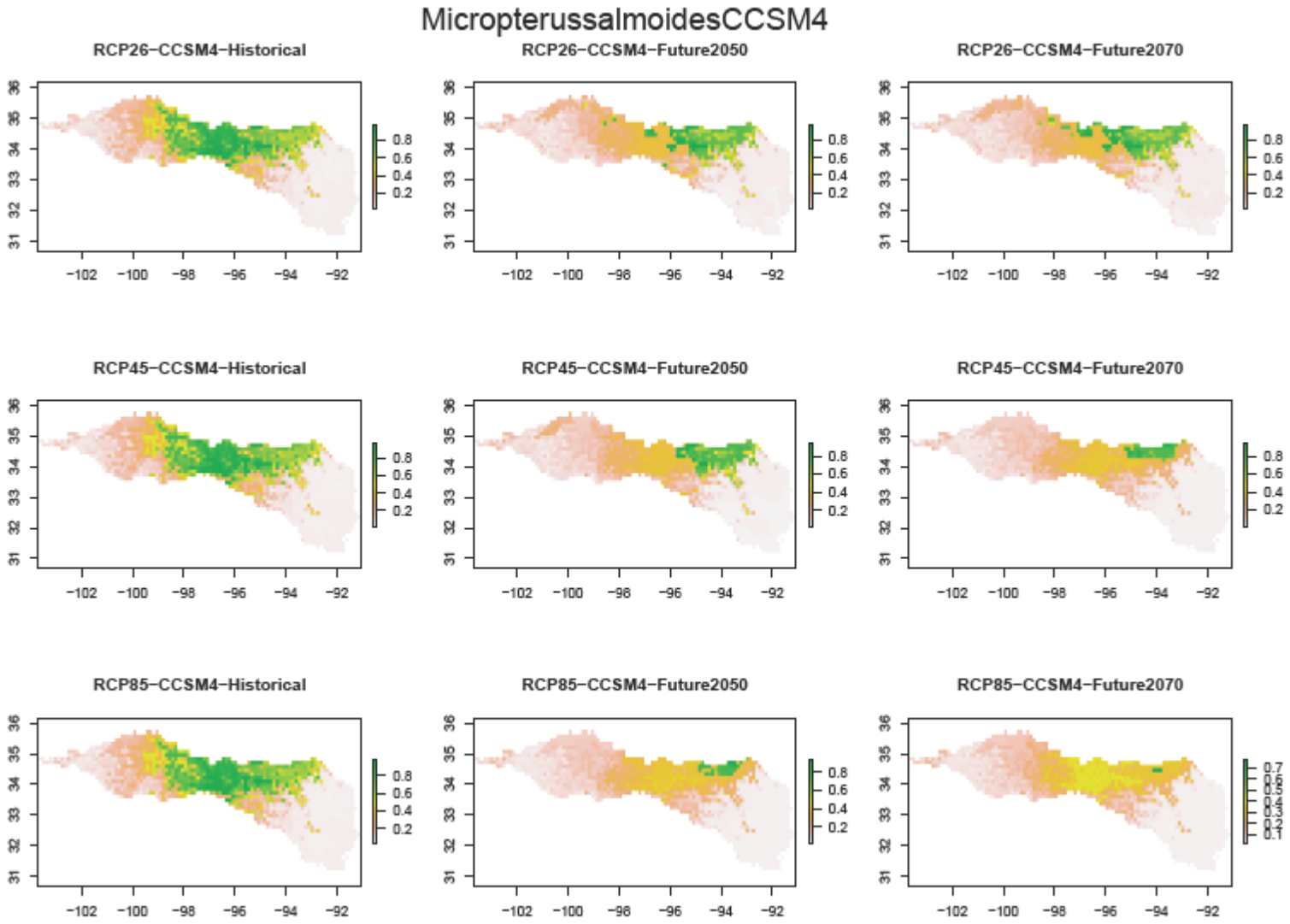
Maxent: *Micropterus salmoides*

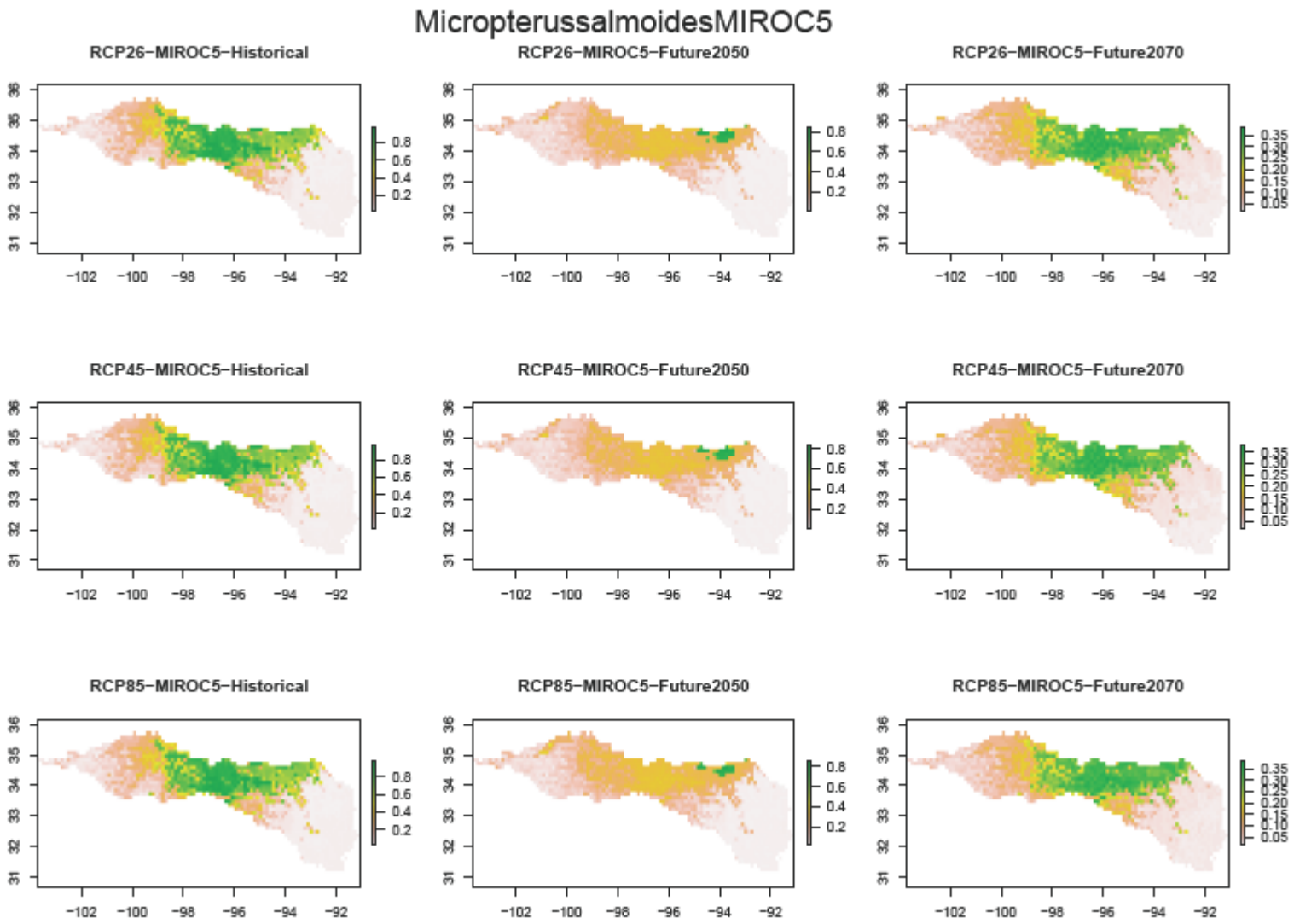


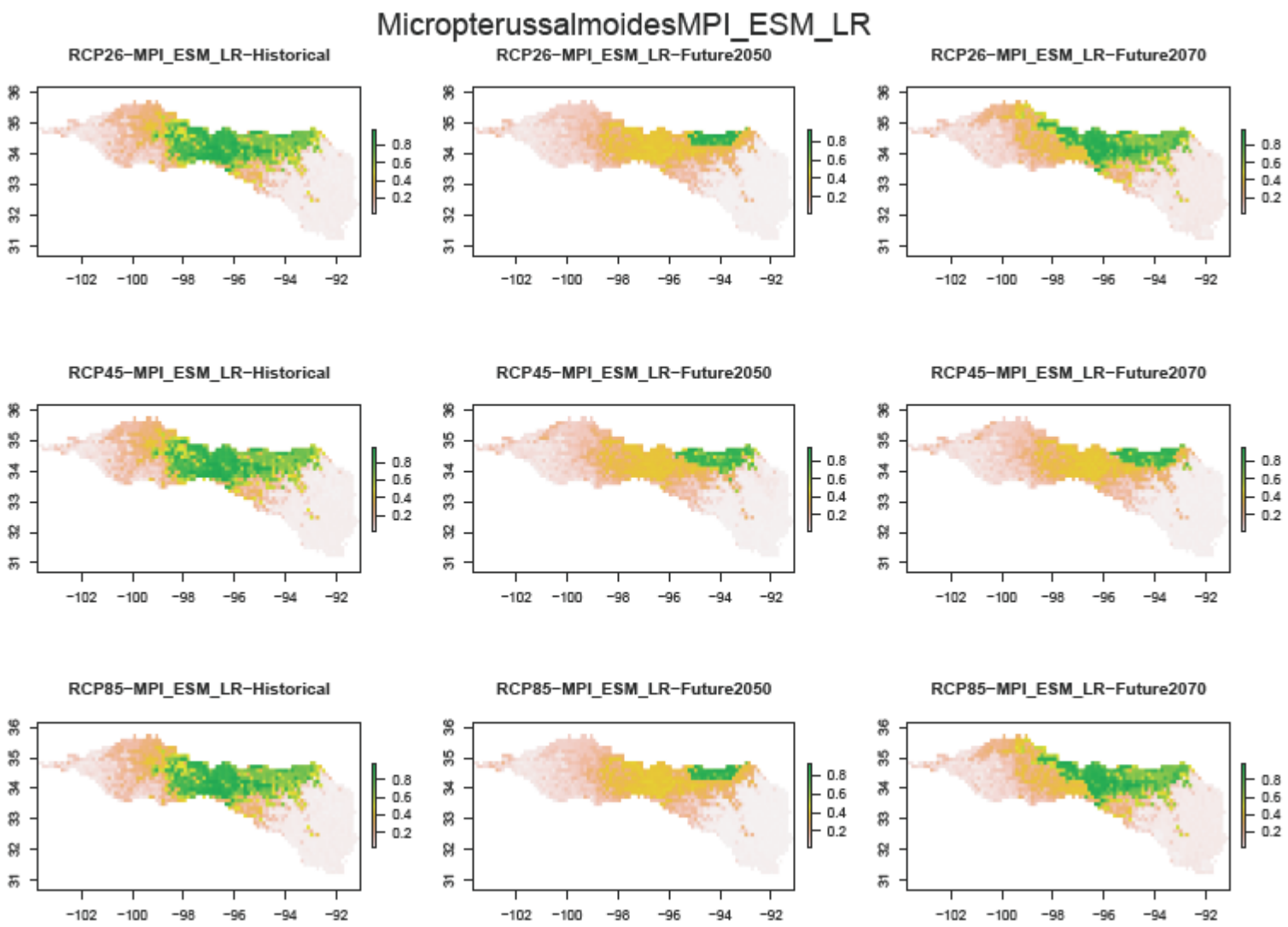

Micropterus_salmoides_MIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070
0.8
0.6
0.4
0.2
−102
−100
−98
−96
−94
−92
31
32
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36


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
0.2 0.4 0.6 0.8

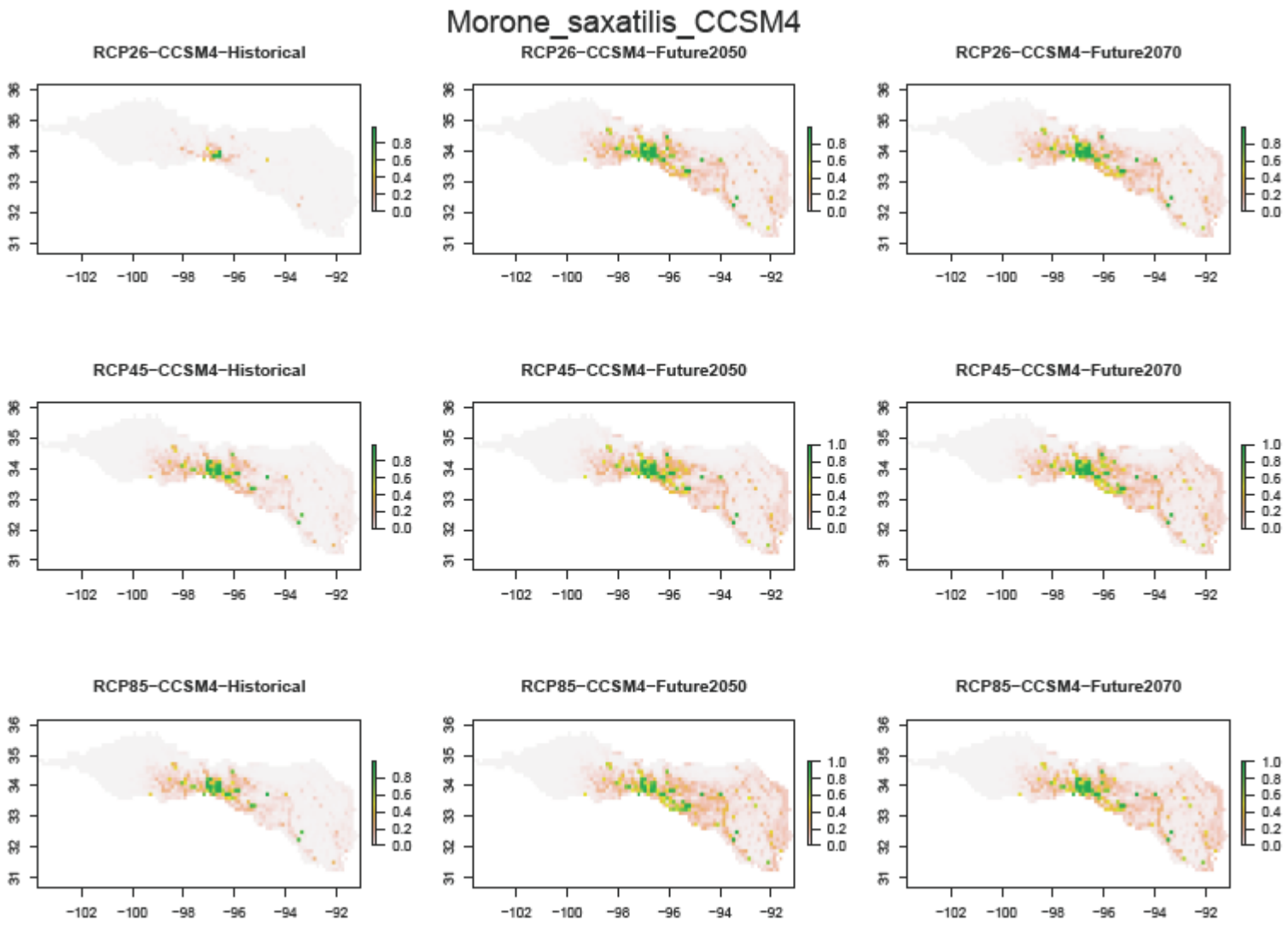
BRT: *Micropterus salmoides*

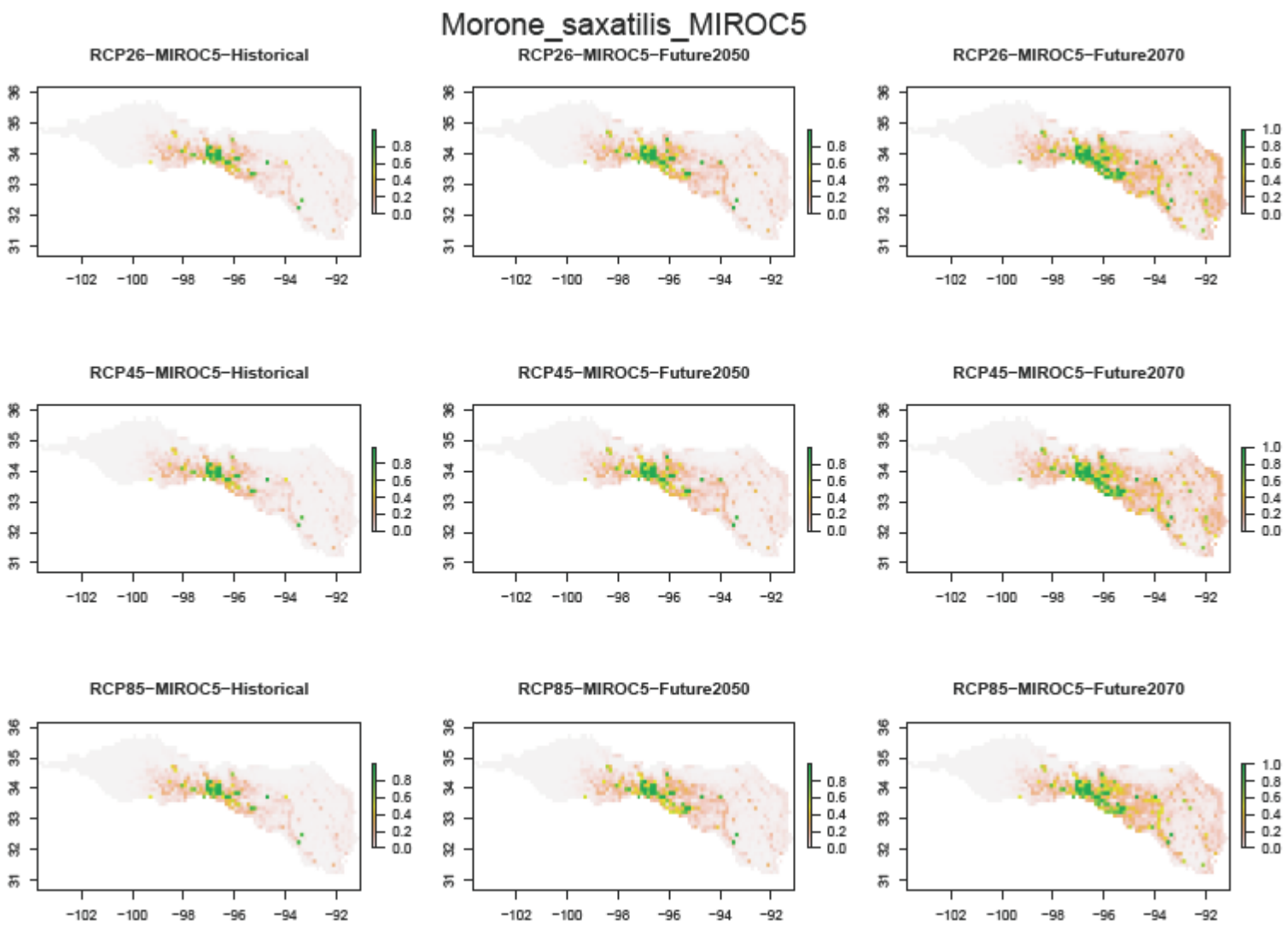


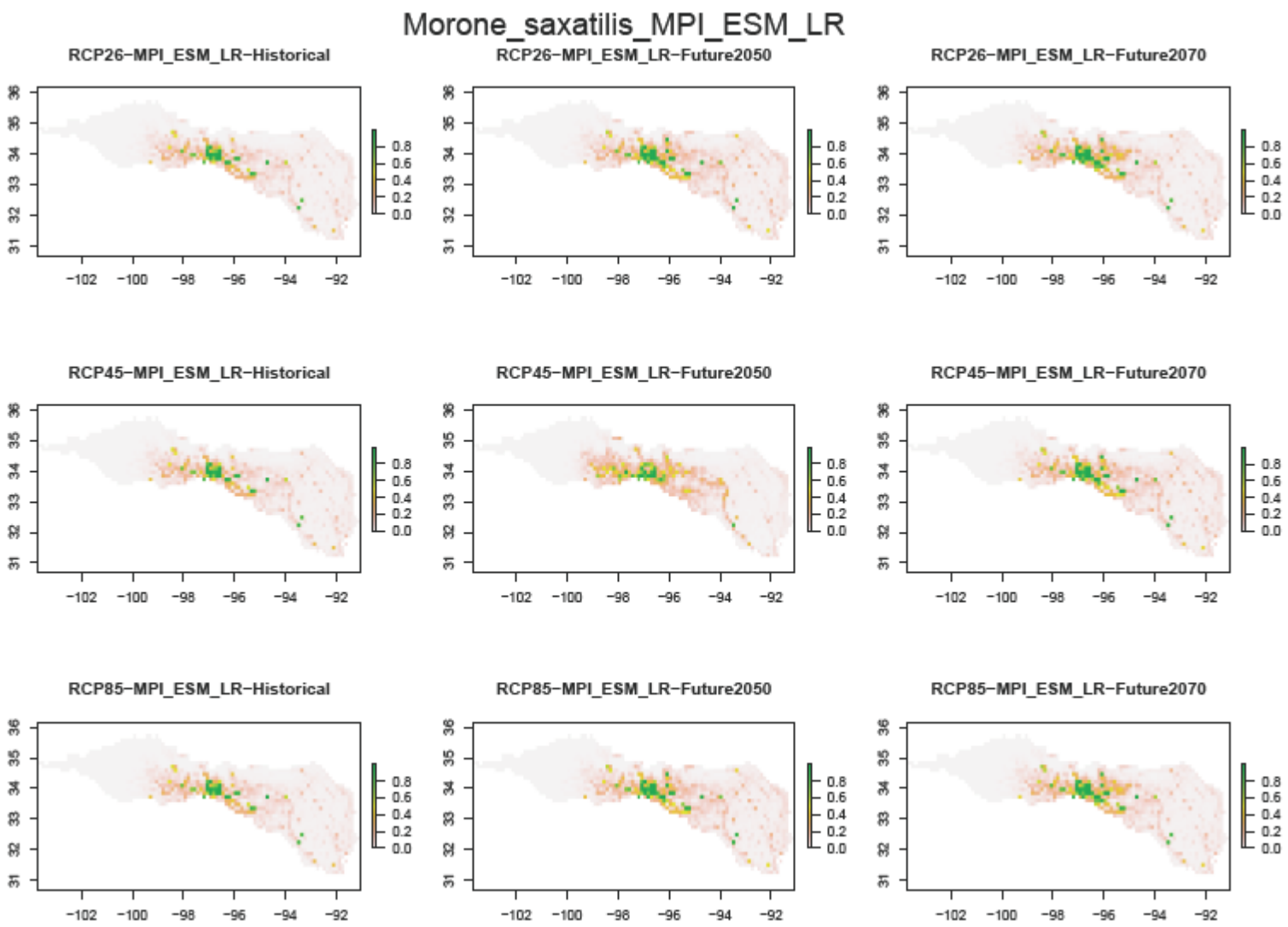

MicropterussalmoidesMIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070


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
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36
-102
-100
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-96
-94
-92
0.2
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0.6
0.8

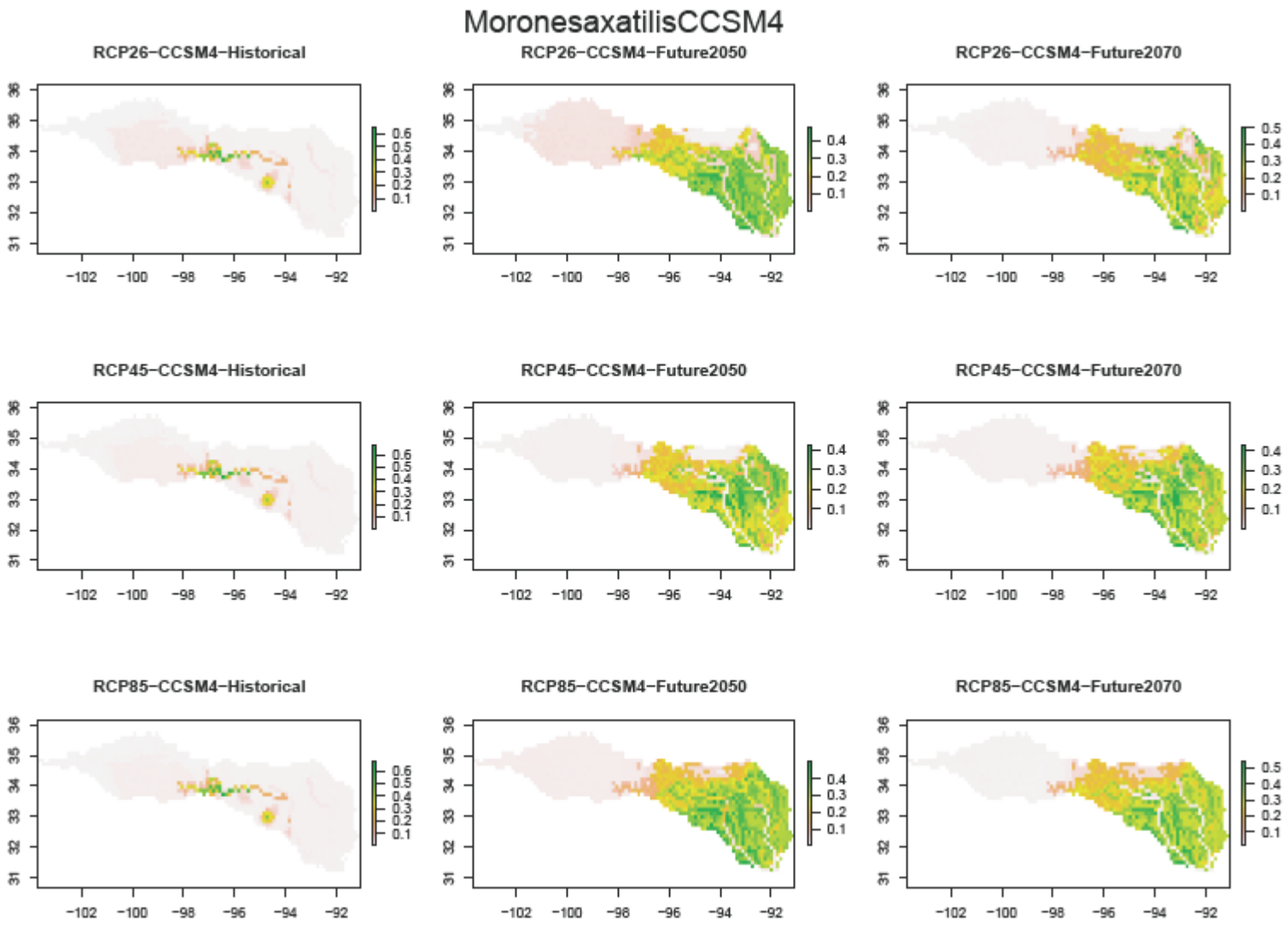
Maxent: *Morone saxatilis*

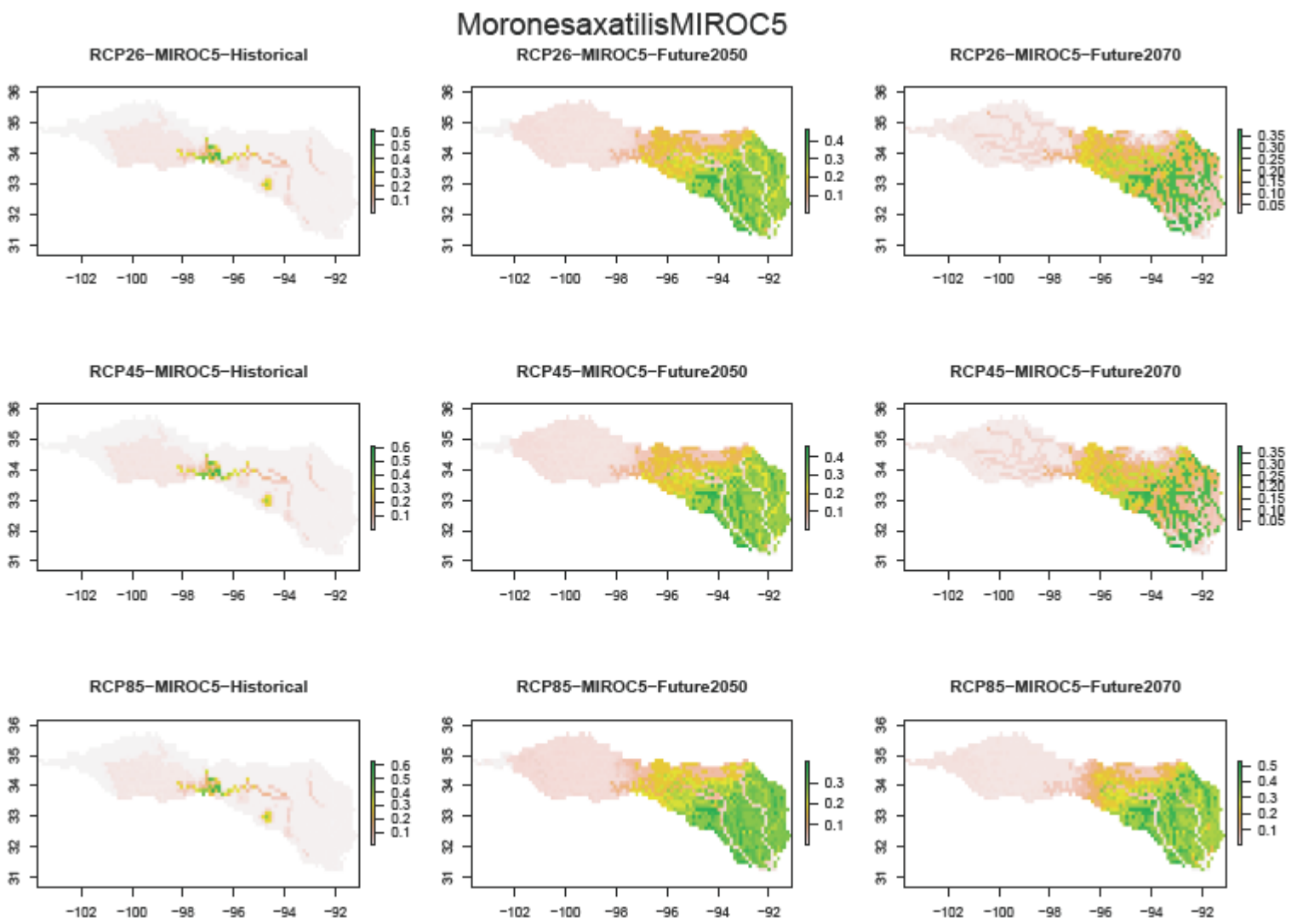


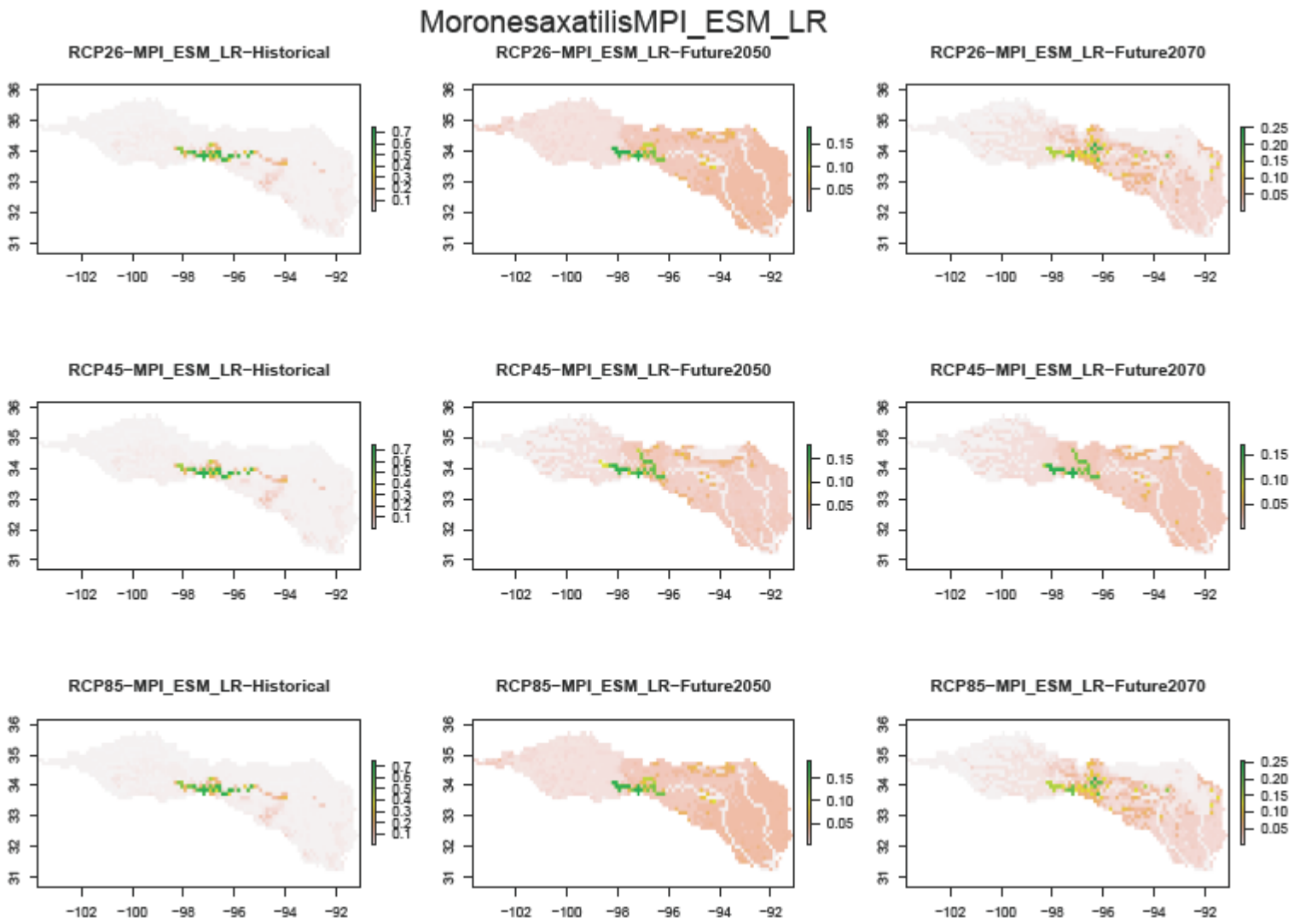

Morone_saxatilis_MIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070
31
32
33
34
35
36
−102
−100
−98
−96
−94
−92
0.0
0.2
0.4
0.6
0.8
1.0


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
31 32 33 34 35 36
-102 -100 -98 -96 -94 -92
0.0 0.2 0.4 0.6 0.8

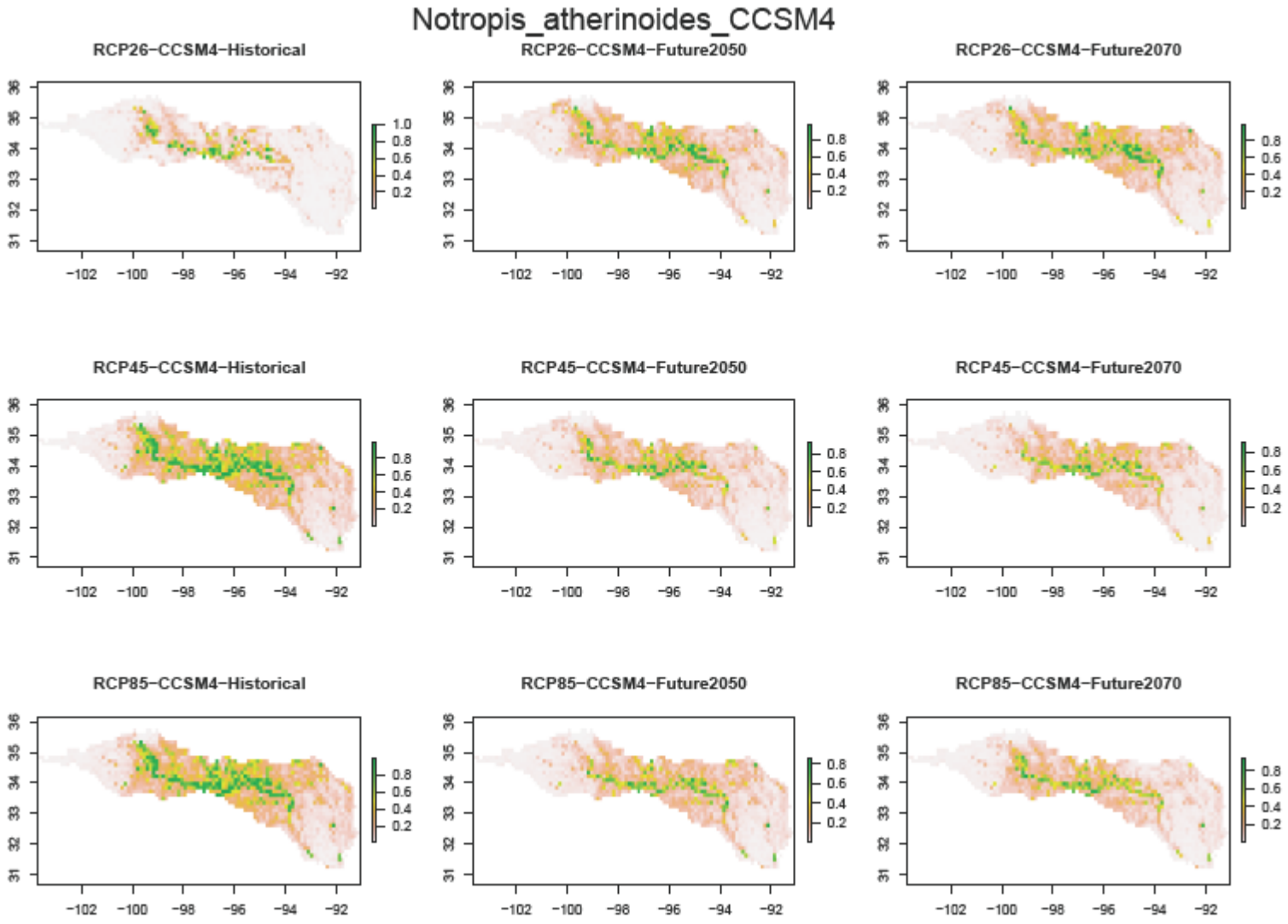
BRT: *Morone saxatilis*

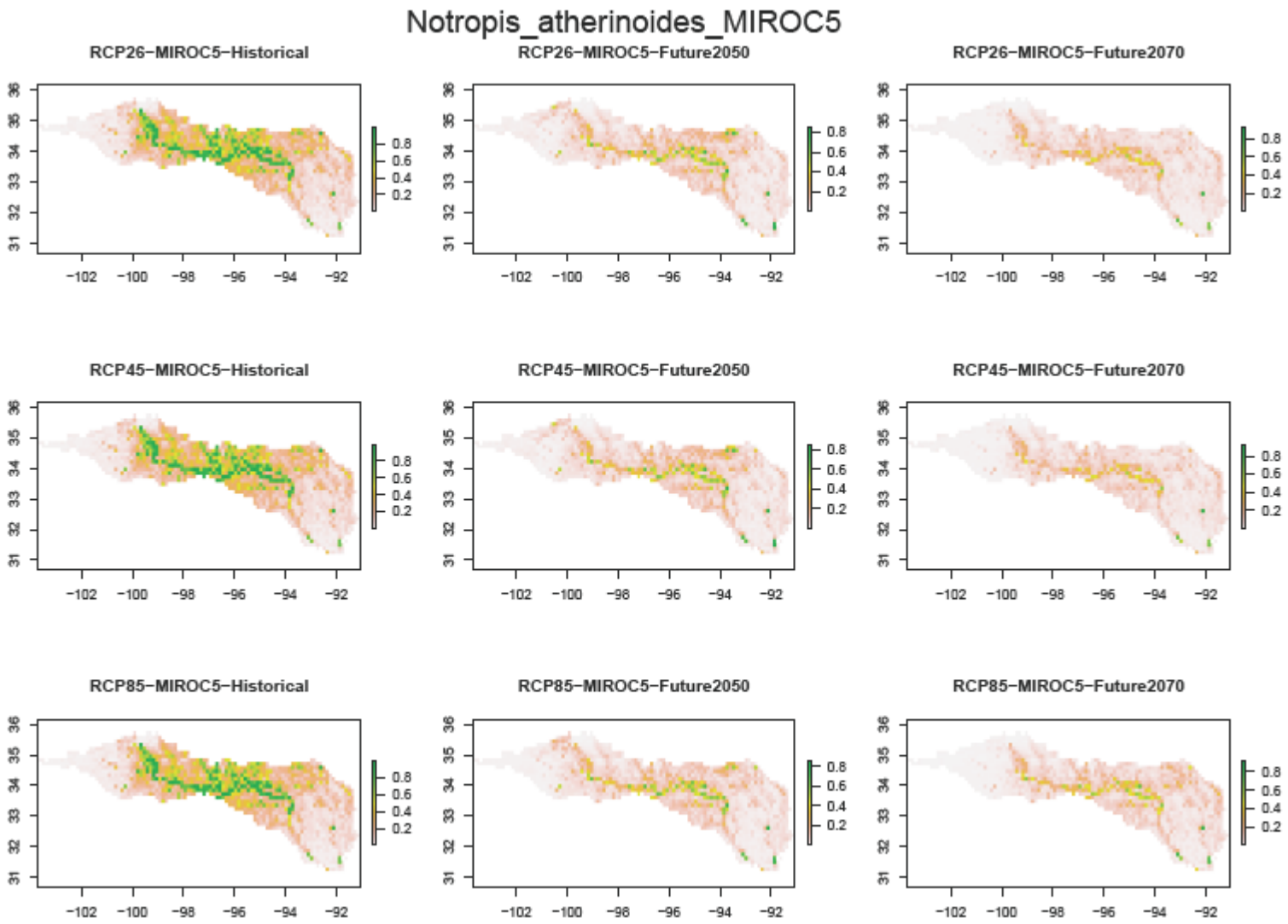


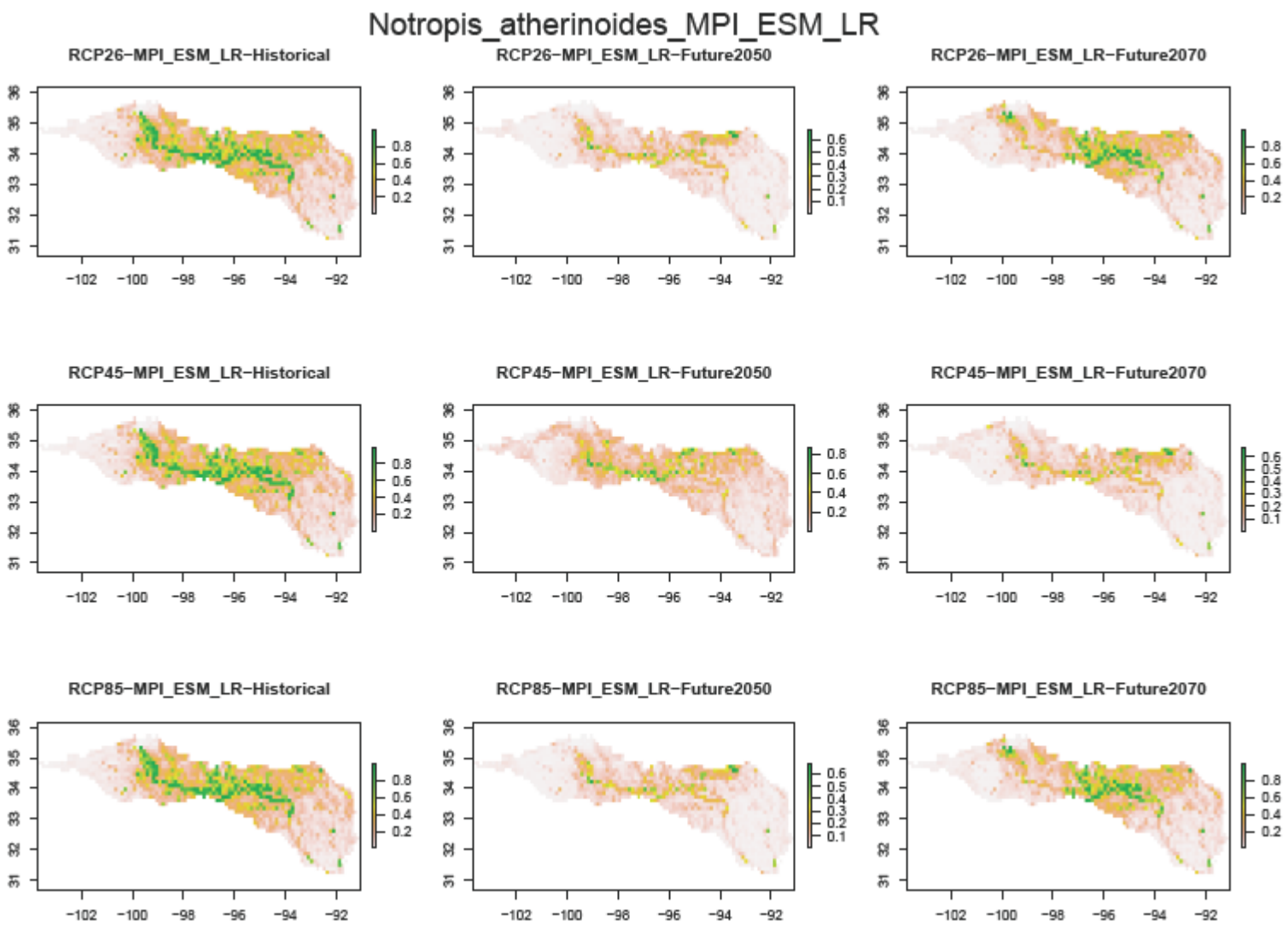

MoronesaxatilisMIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070


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

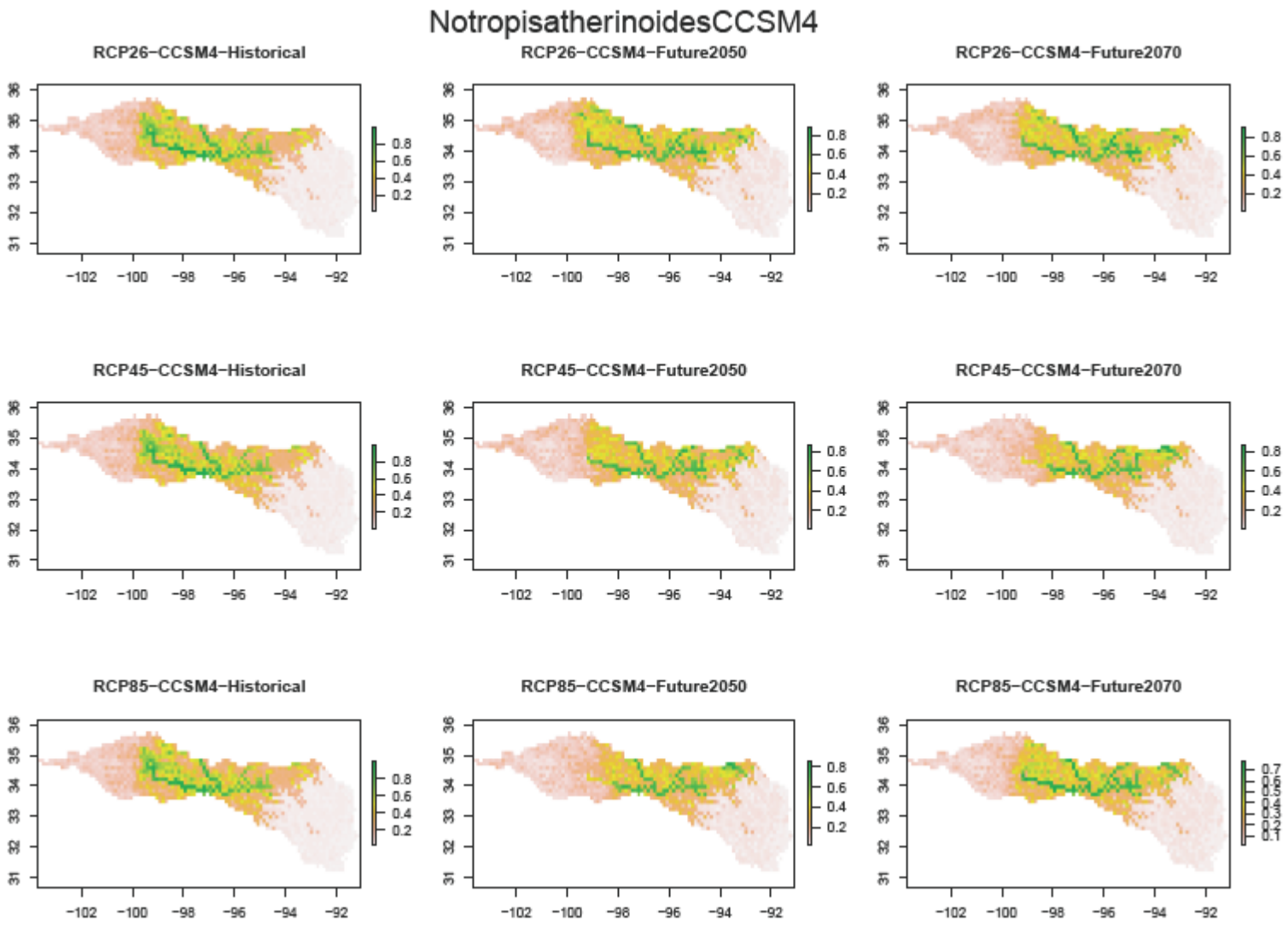
Maxent: *Notropis atherinoides*

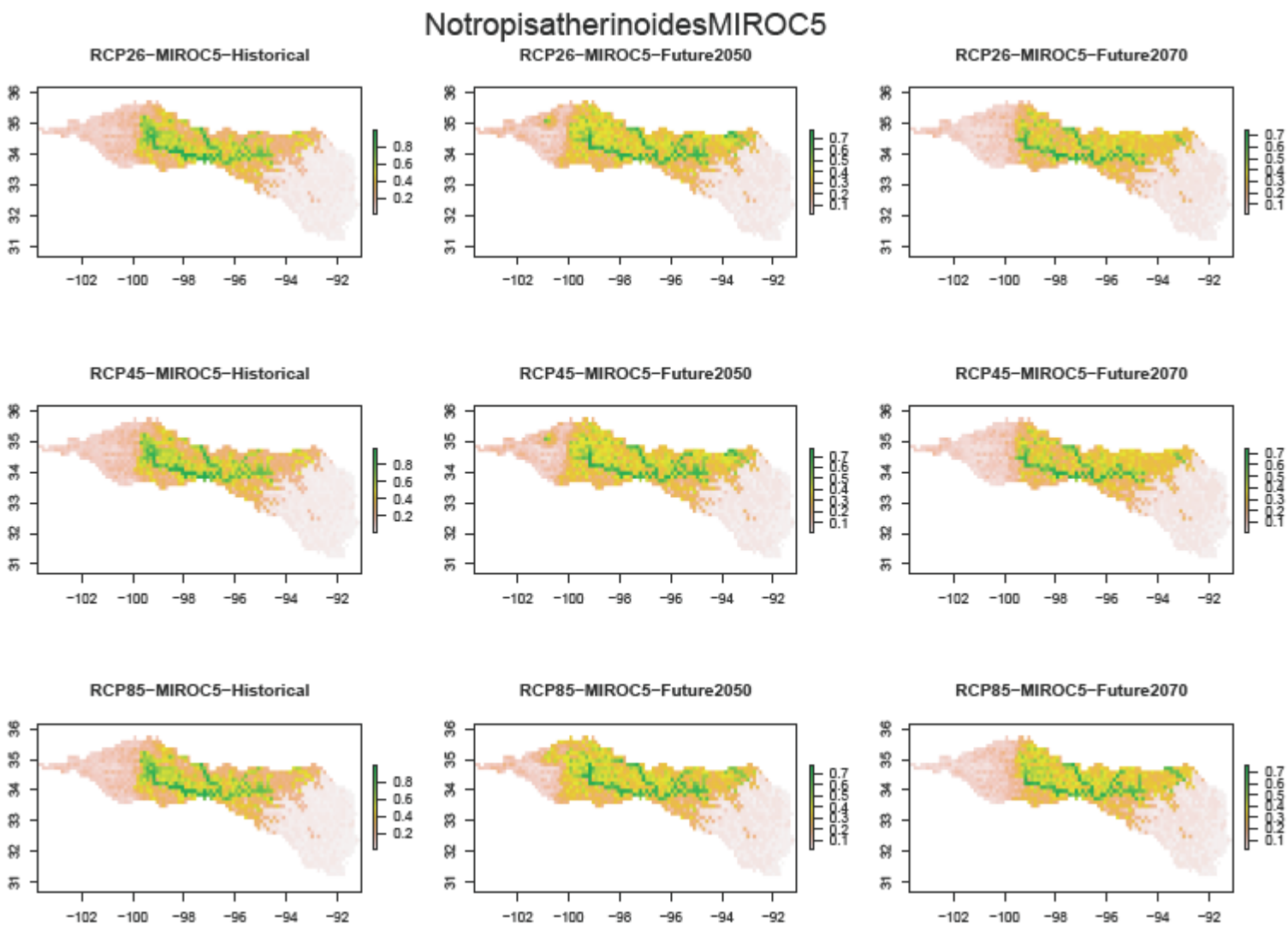


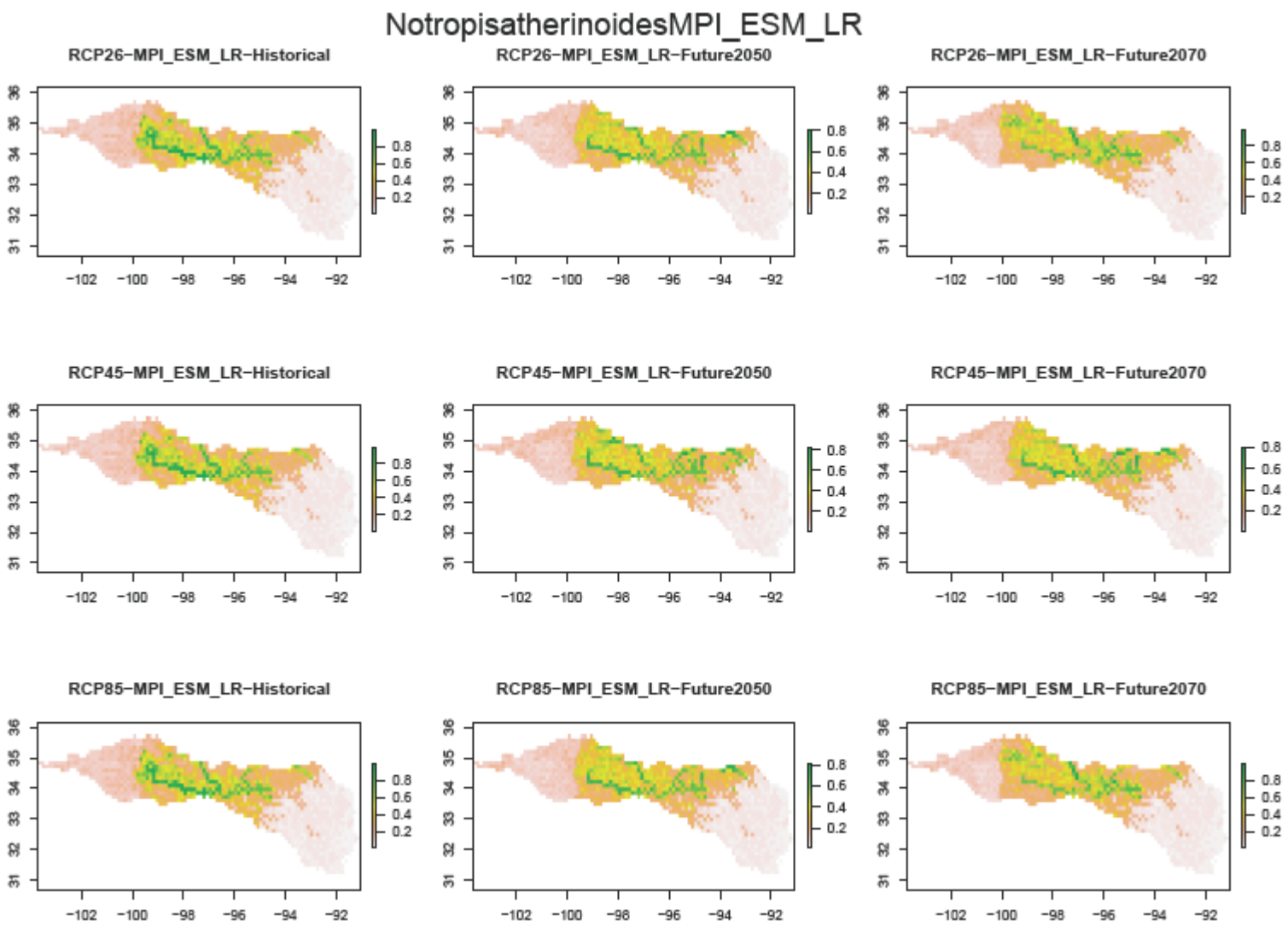

Notropis_atherinoides_MIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070
0.8
0.6
0.4
0.2
−102
−100
−98
−96
−94
−92
31
32
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35
36


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

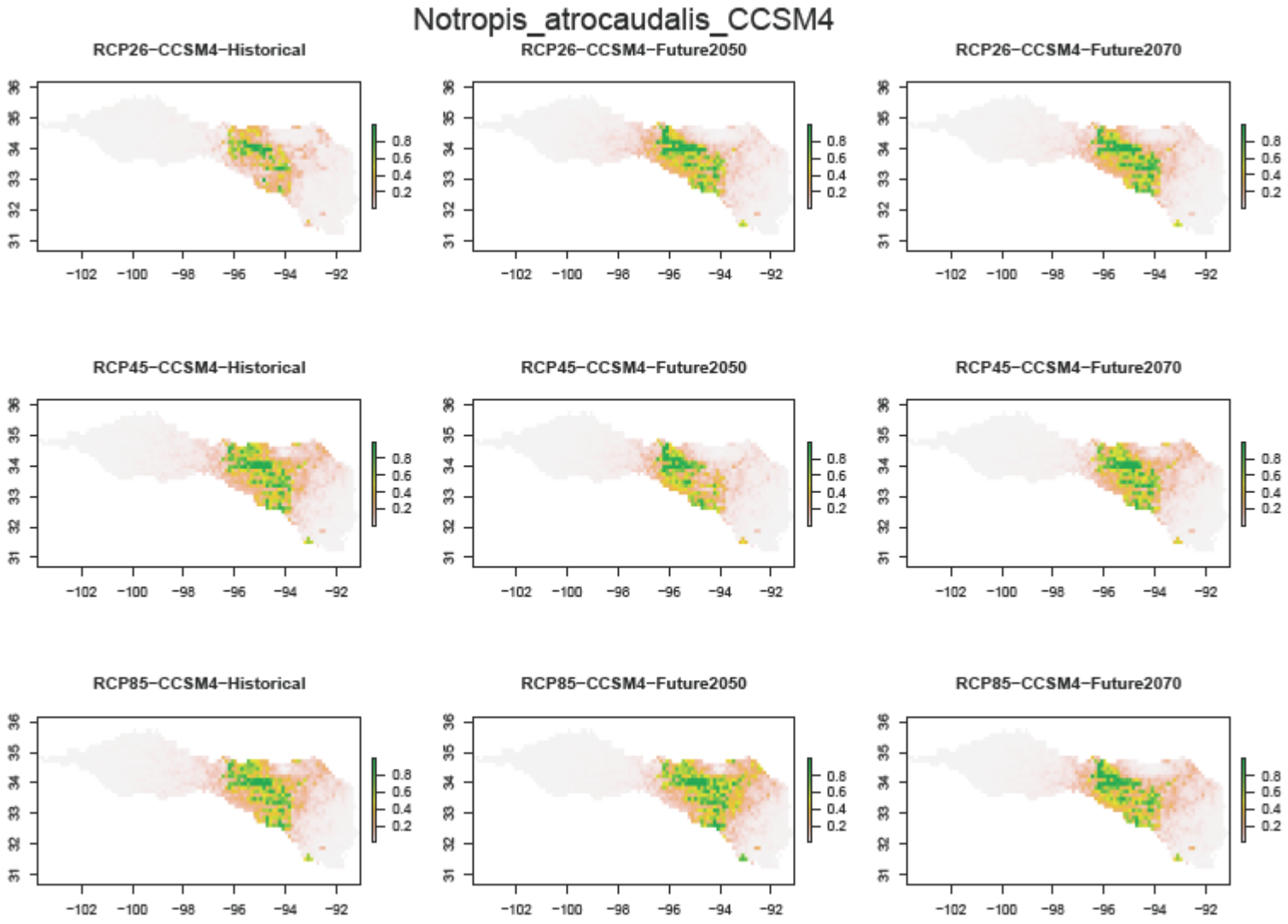
BRT: *Notropis atherinoides*

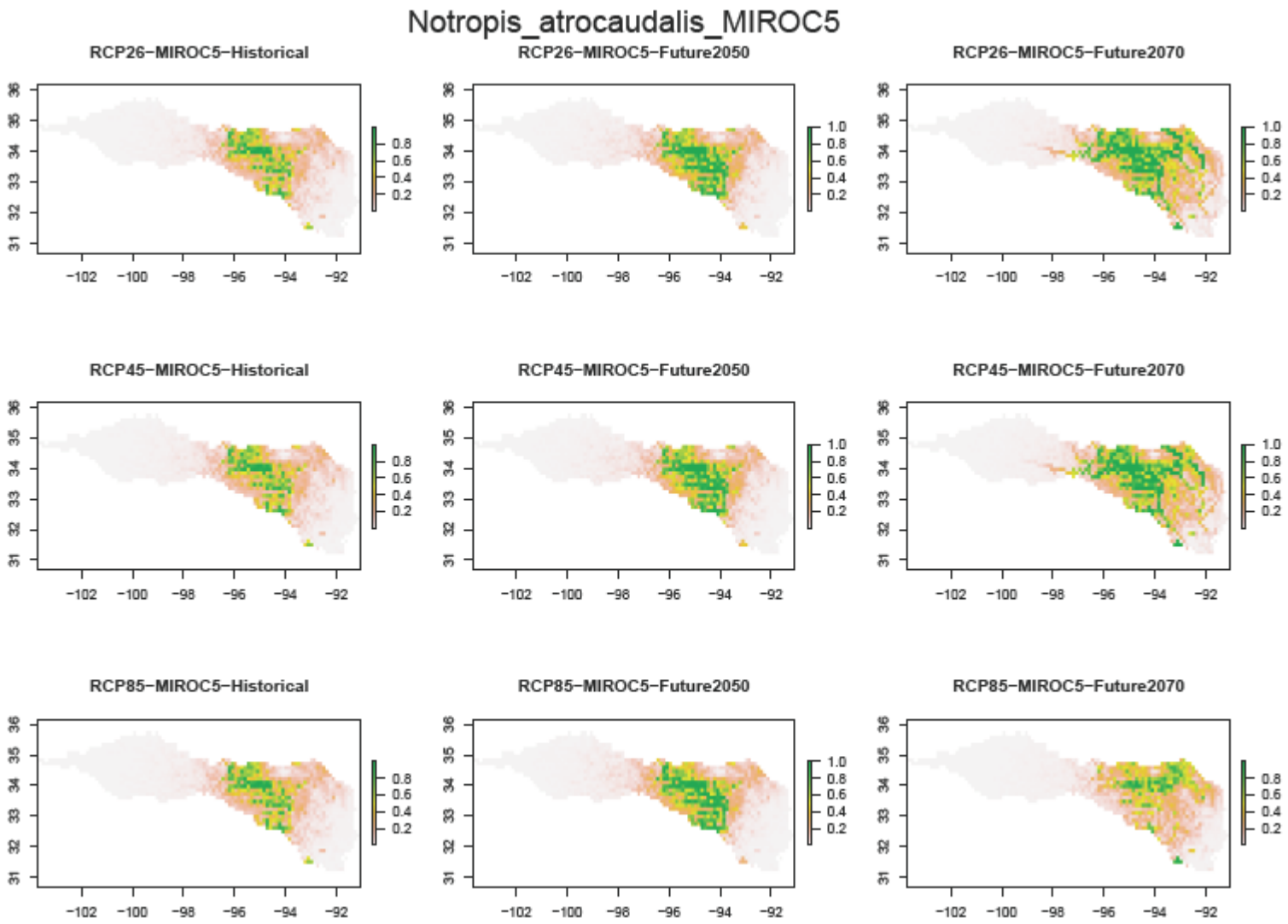


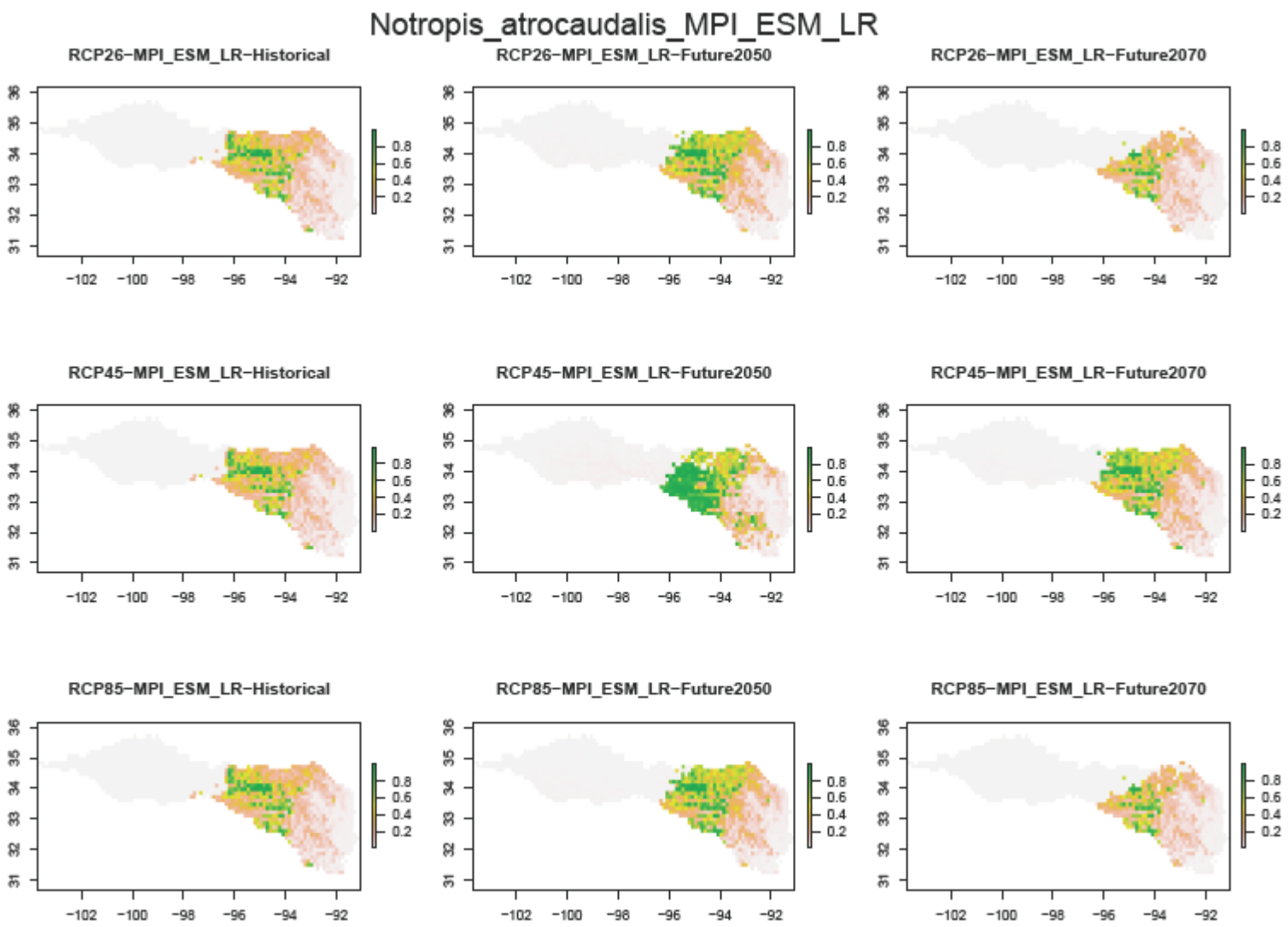

NotropisatherinoidesMIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070


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
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31
-102
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-98
-96
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-92
0.8
0.6
0.4
0.2

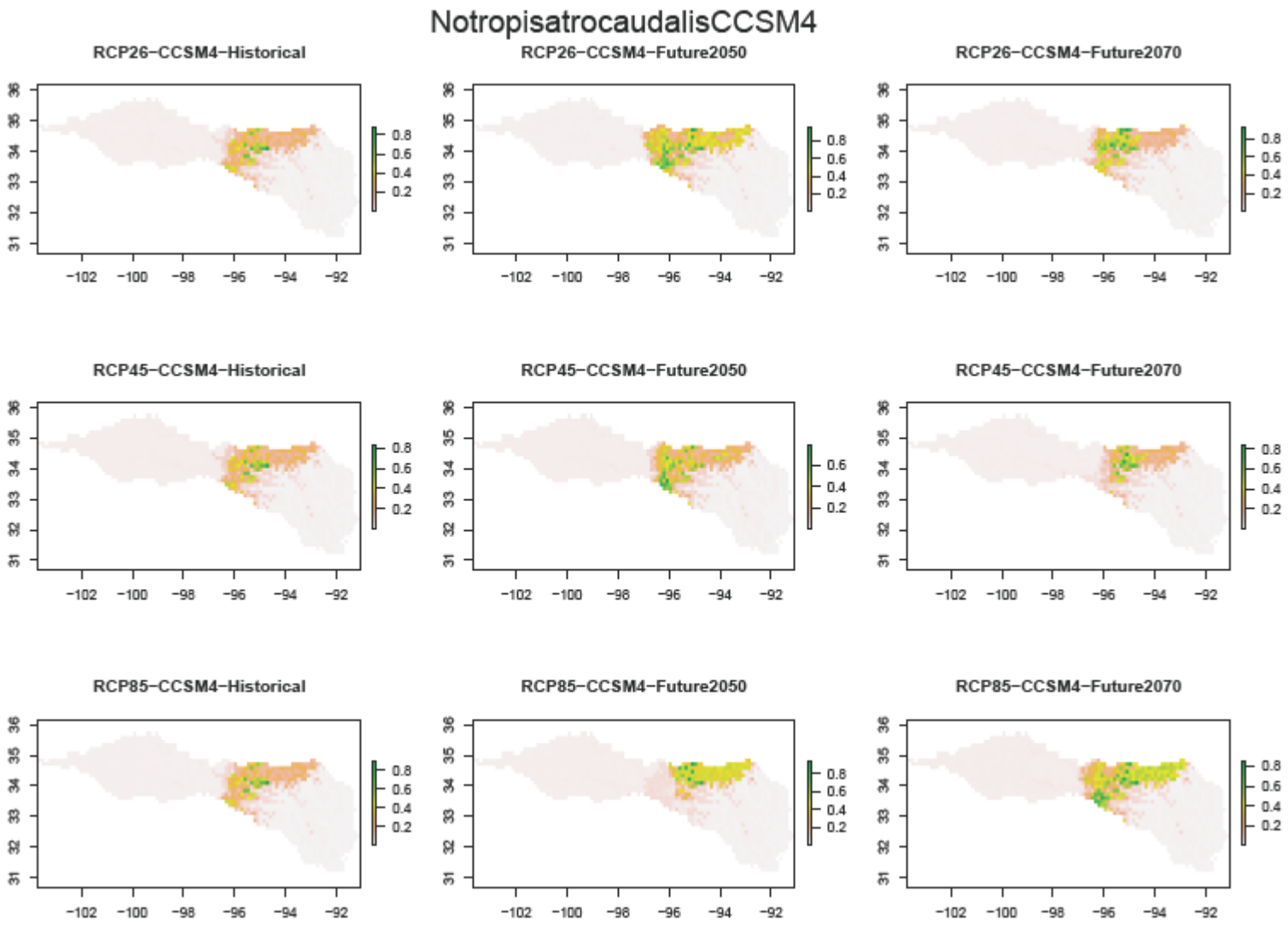
Maxent: *Notropis atrocaudalis*

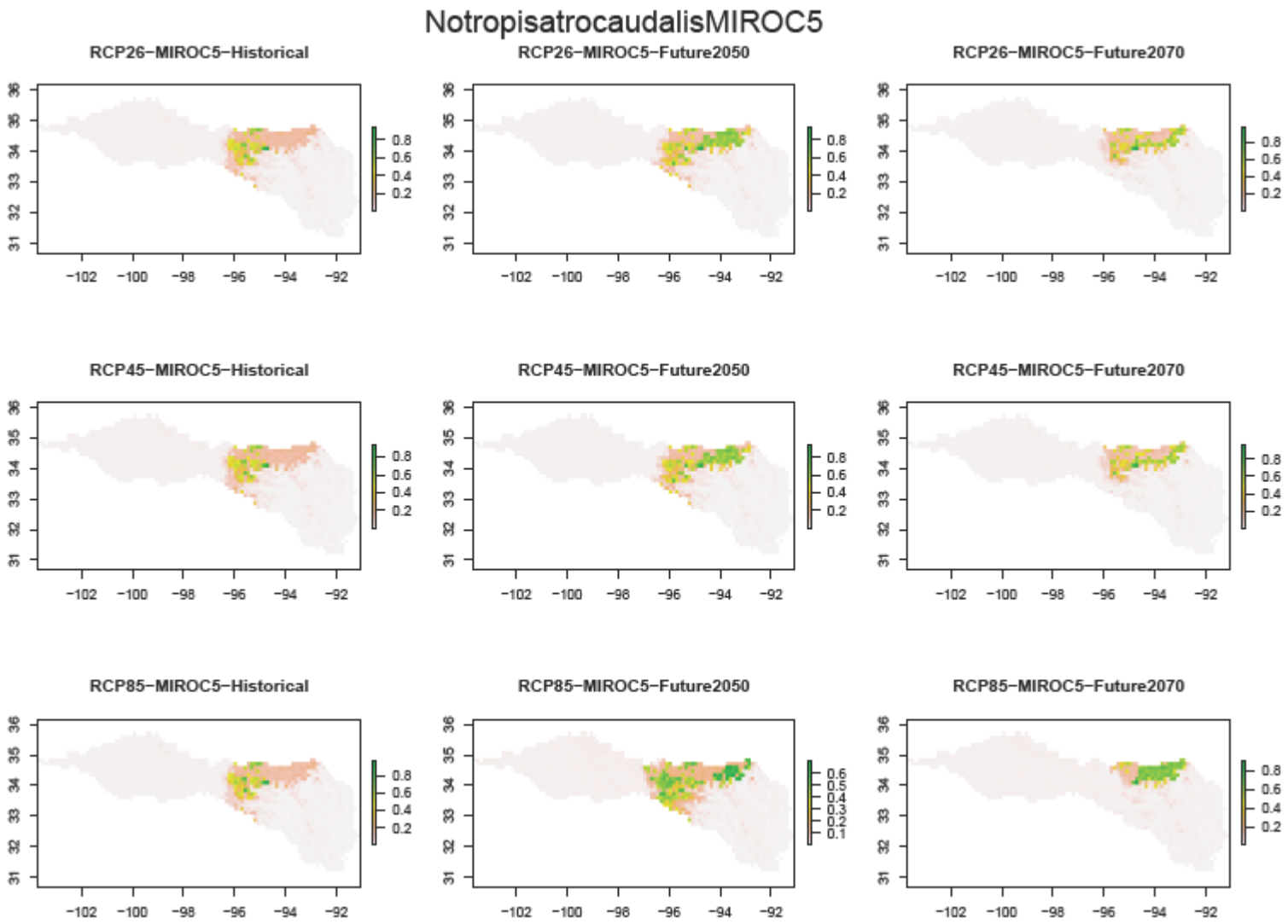


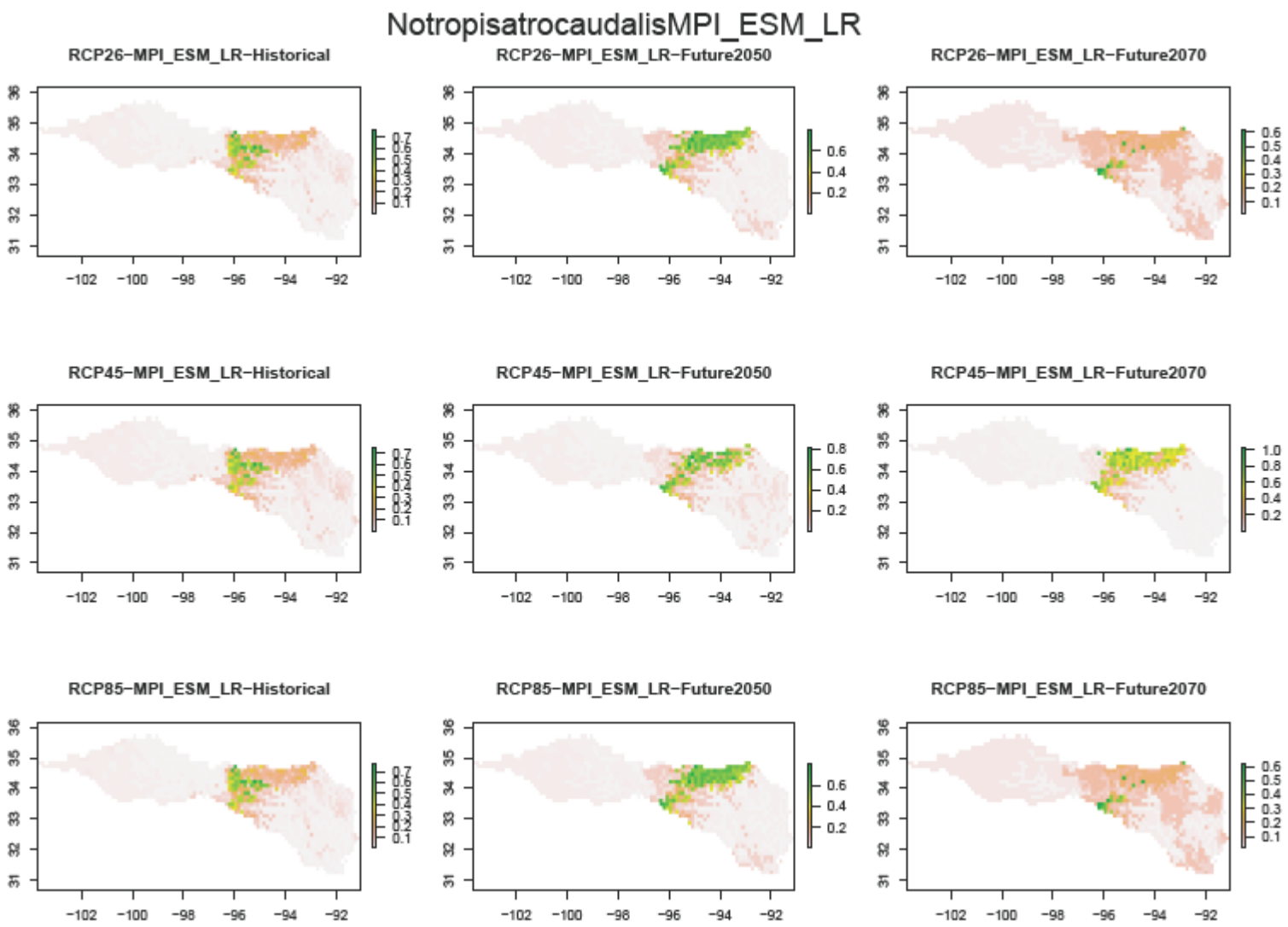

Notropis_atrocaudalis_MIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070
31
32
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34
35
36
−102
−100
−98
−96
−94
−92
0.2
0.4
0.6
0.8
1.0


Notropis_atrocaudalis_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

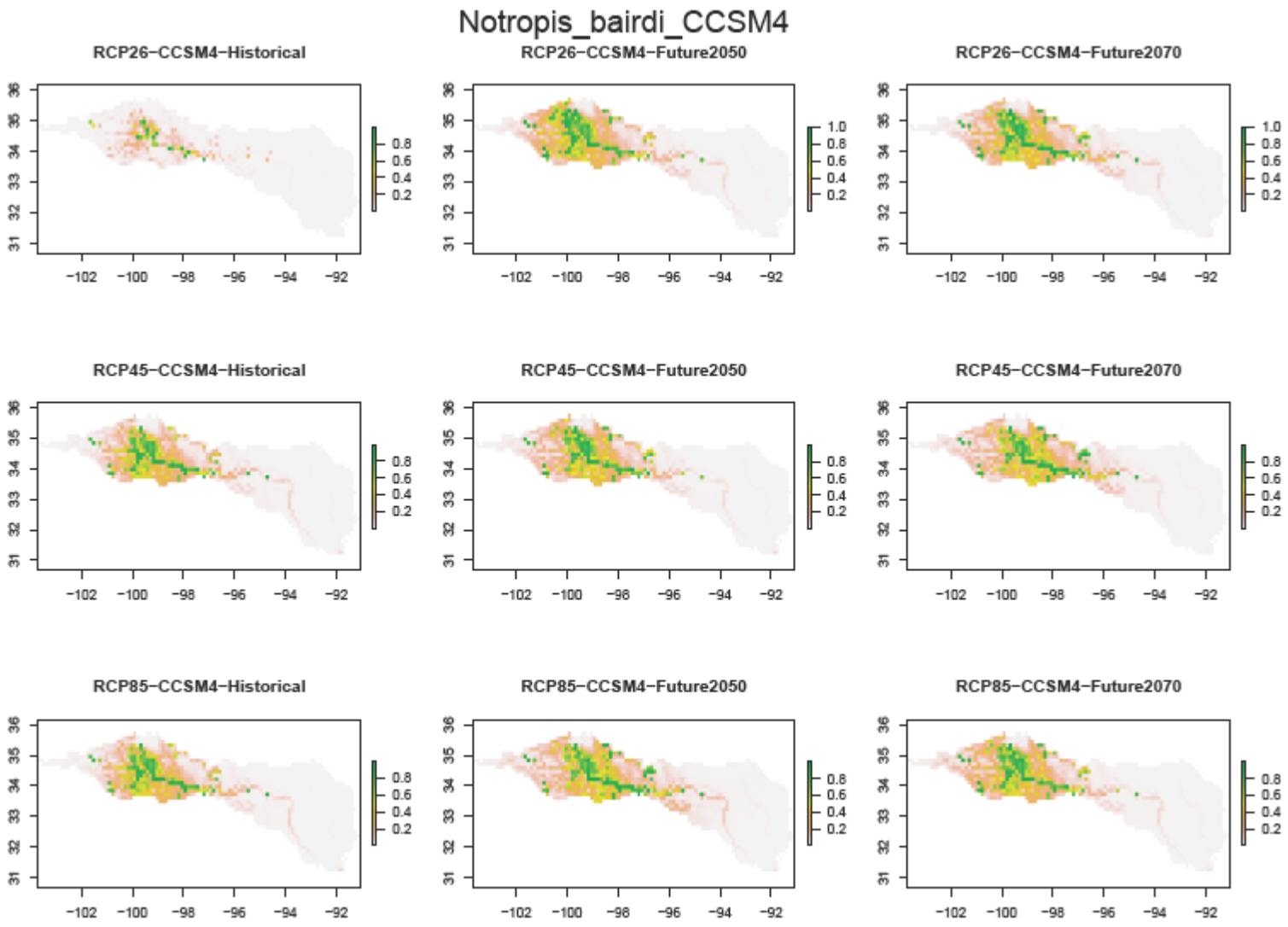
BRT: *Notropis atrocaudalis*

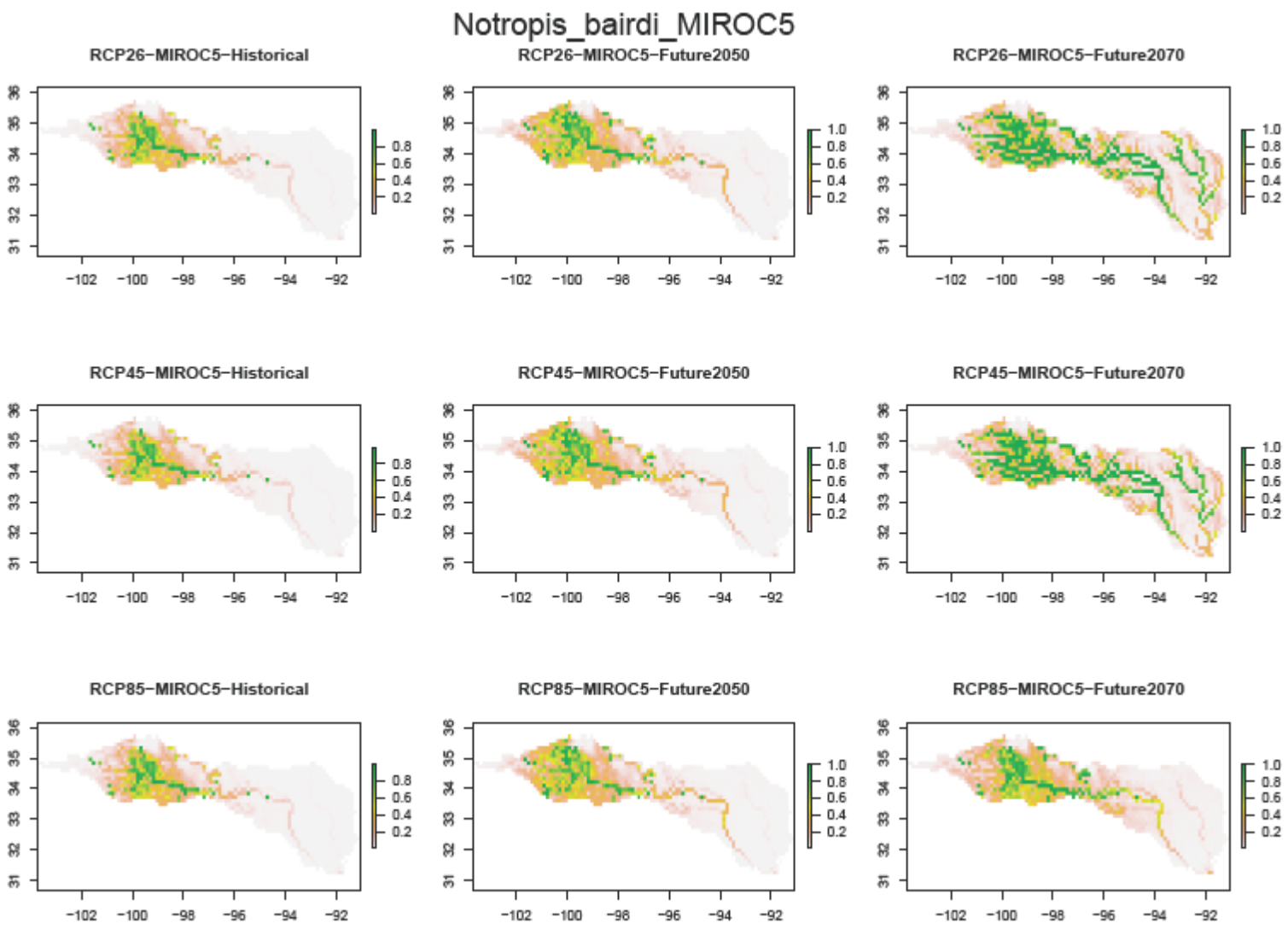


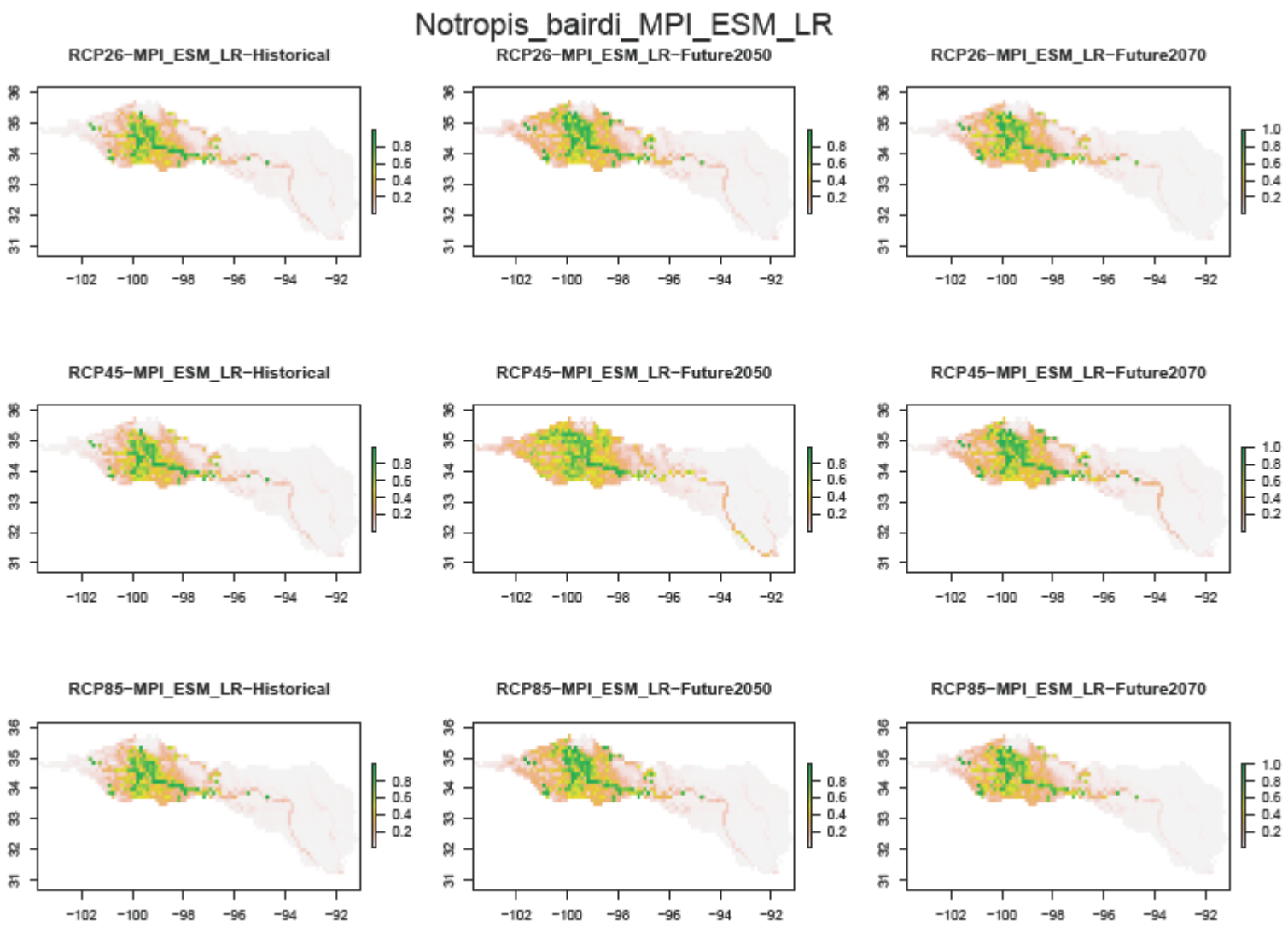

NotropisatrocaudalisMIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070


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
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RCP85-MPI_ESM_LR-Future2050
RCP85-MPI_ESM_LR-Future2070

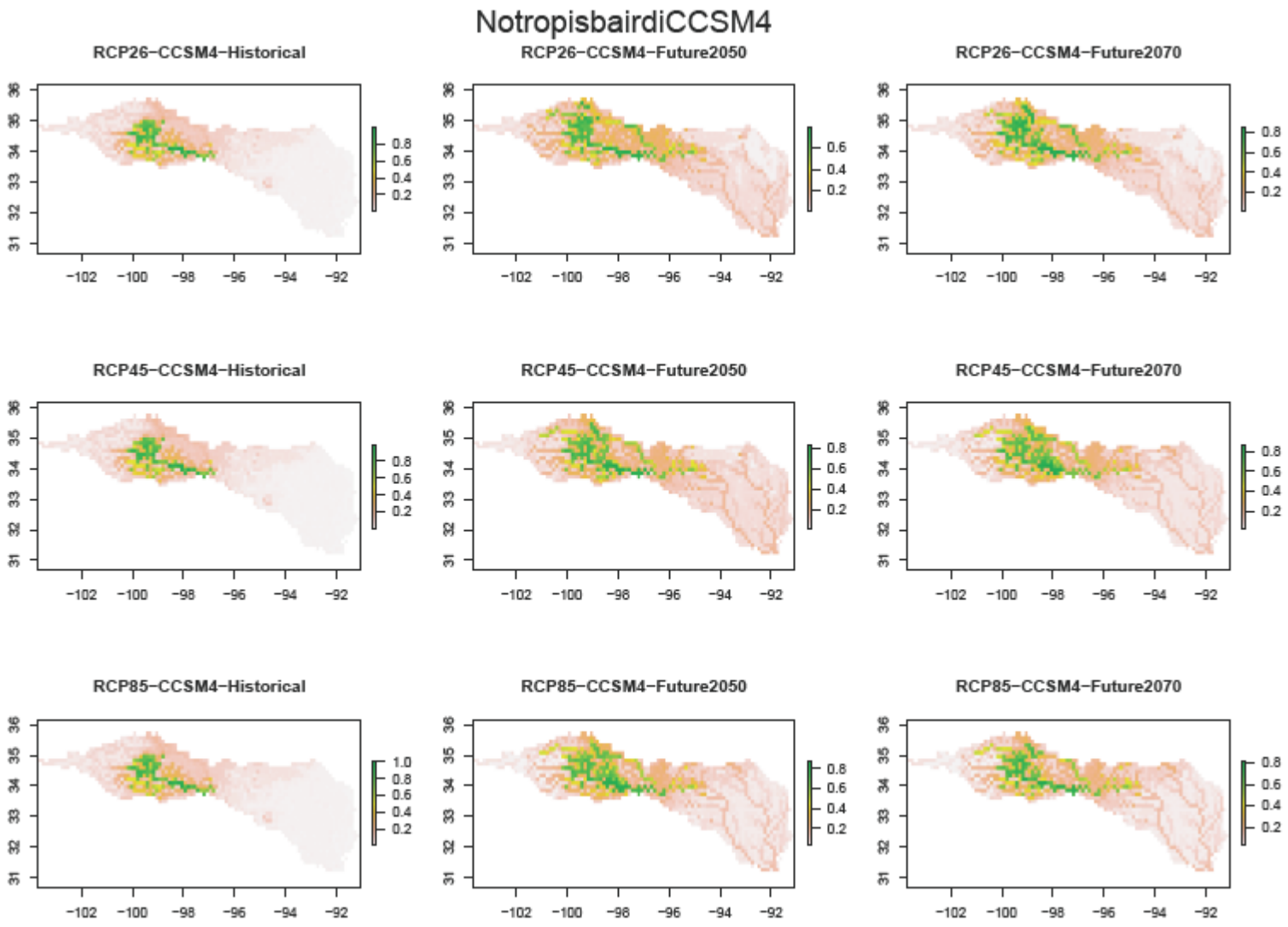
Maxent: *Notropis bairdi*

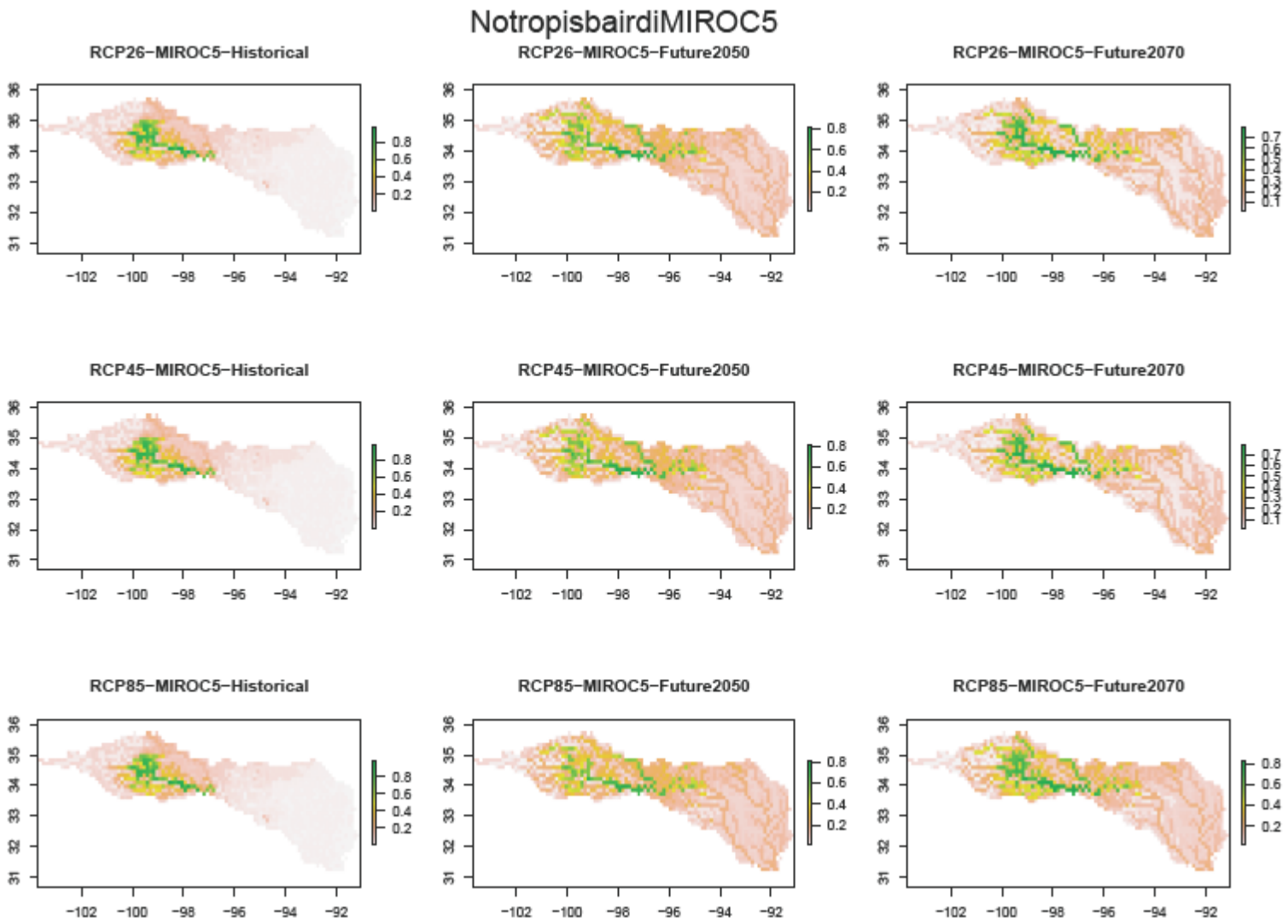


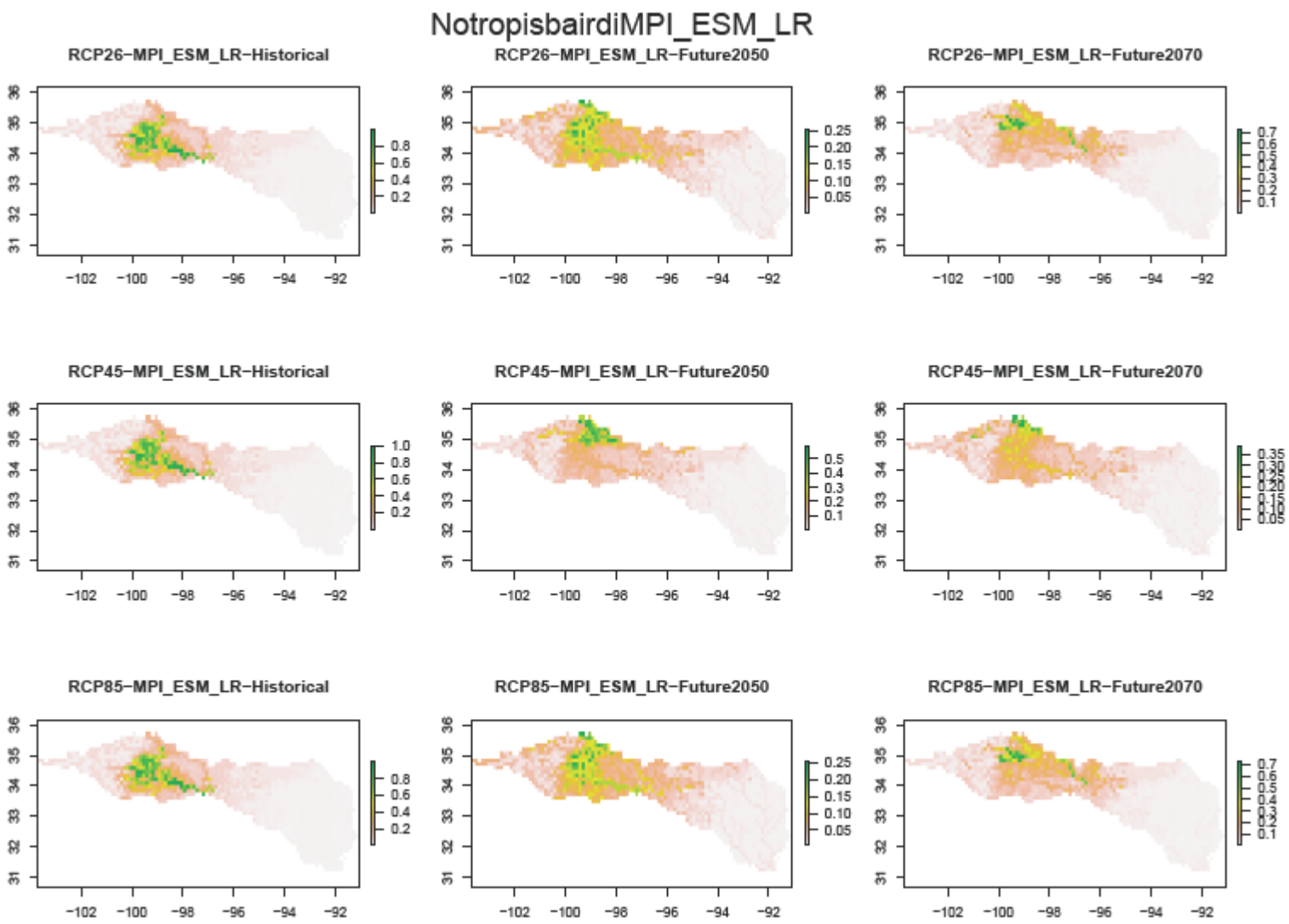

Notropis_bairdi_MIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070
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−102
−100
−98
−96
−94
−92
0.2
0.4
0.6
0.8
1.0


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
31
32
33
34
35
36
-102
-100
-98
-96
-94
-92
0.2
0.4
0.6
0.8
1.0

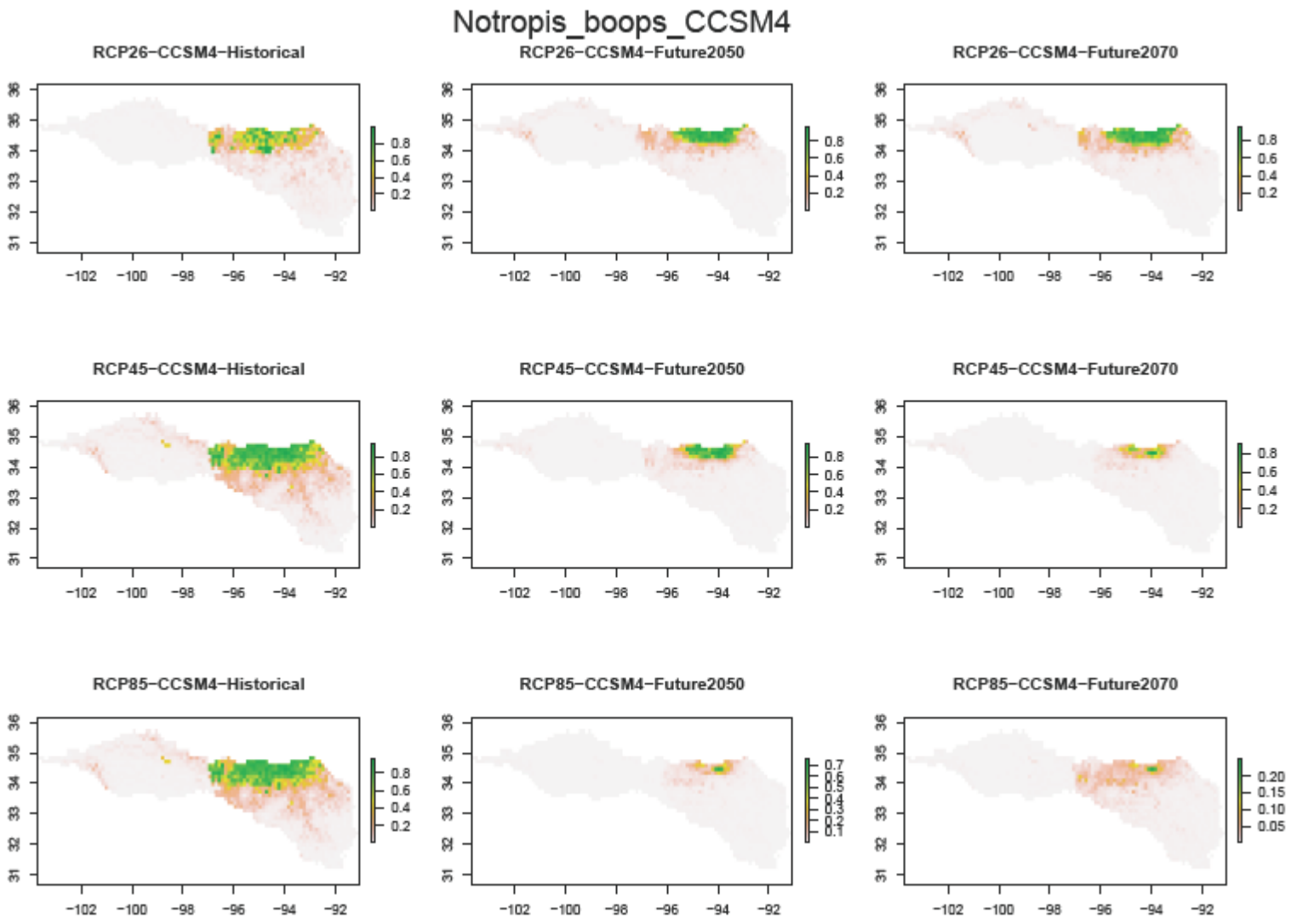
BRT: *Notropis bairdi*

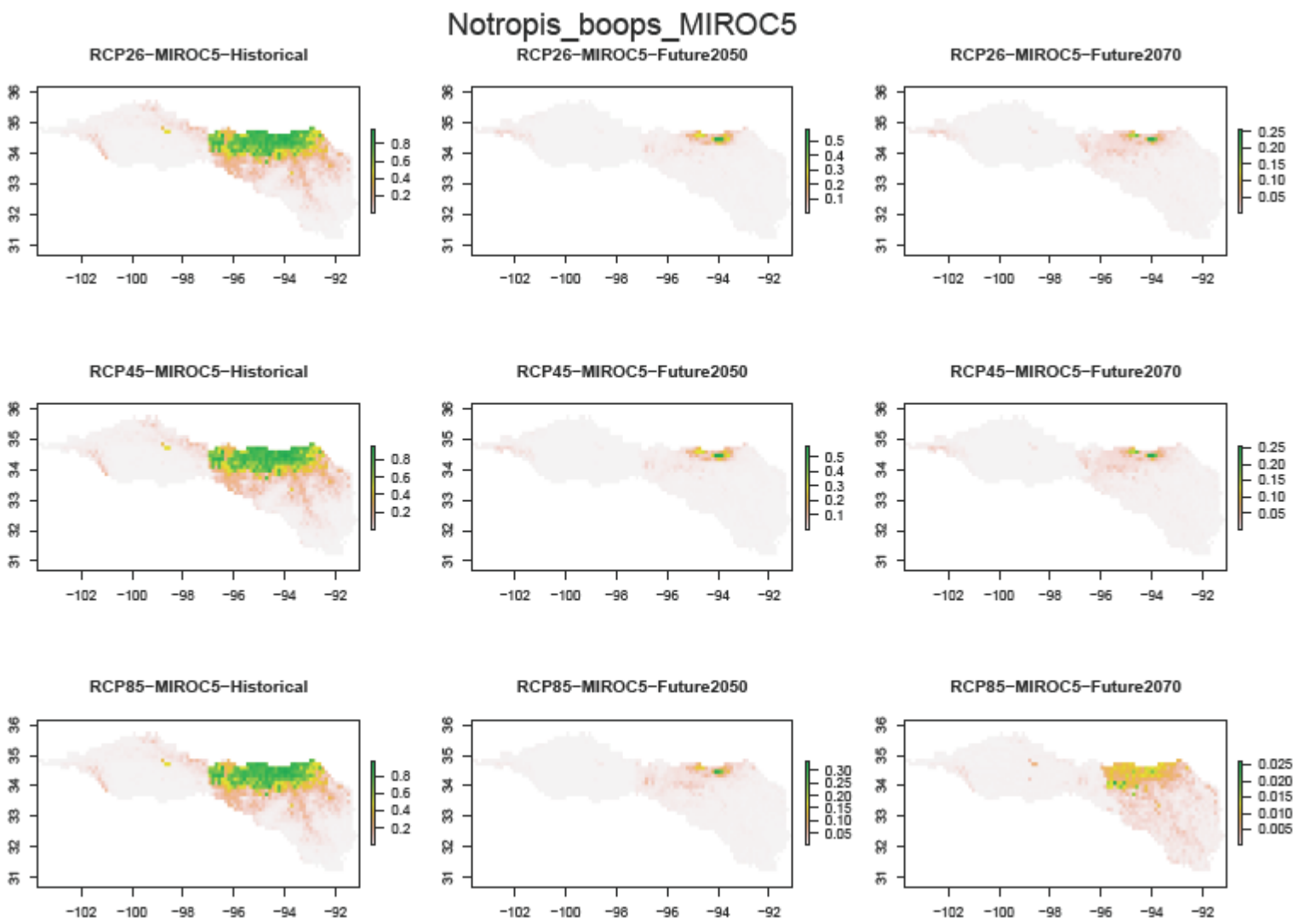


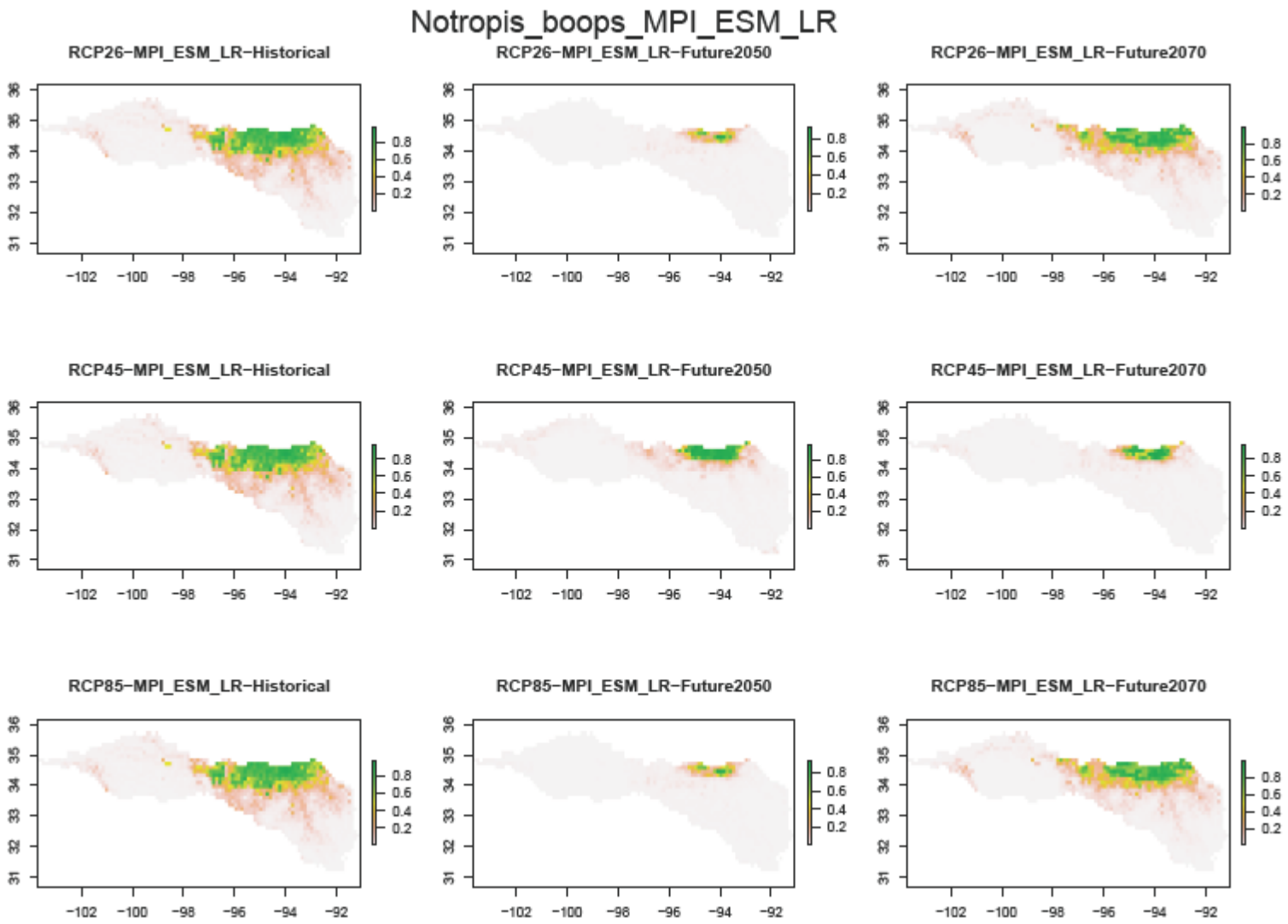

NotropisbairdiMIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070


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

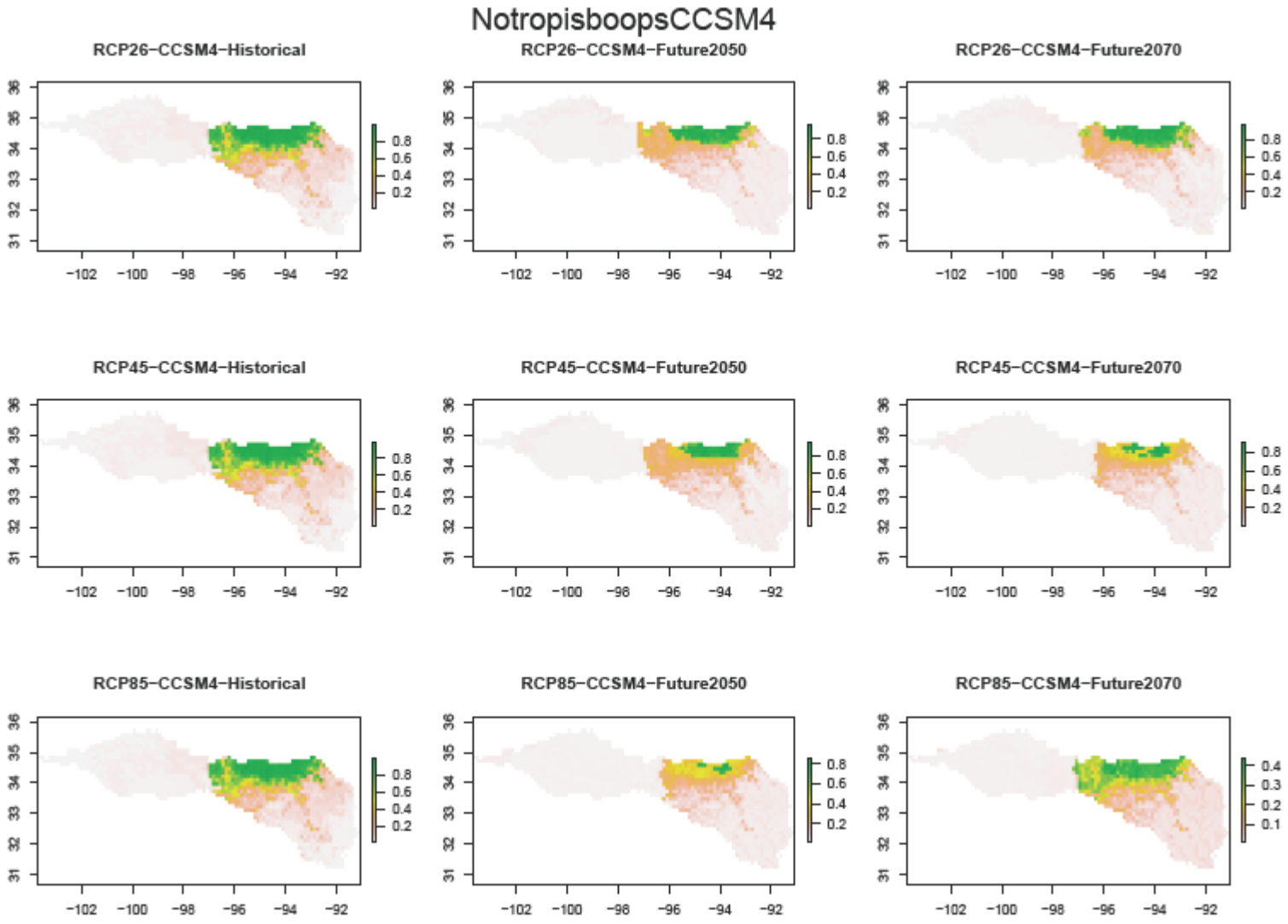
Maxent: *Notropis boops*

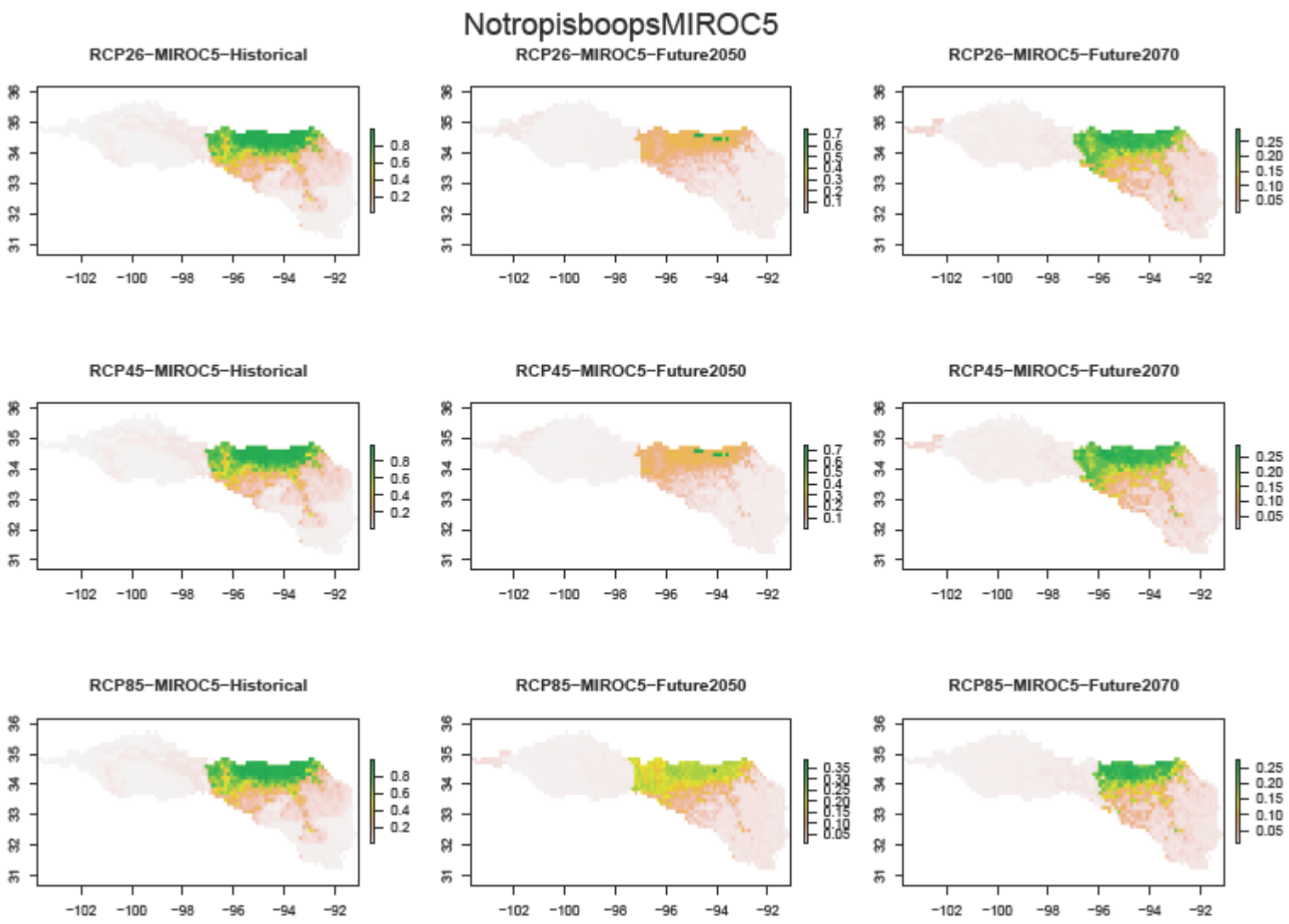


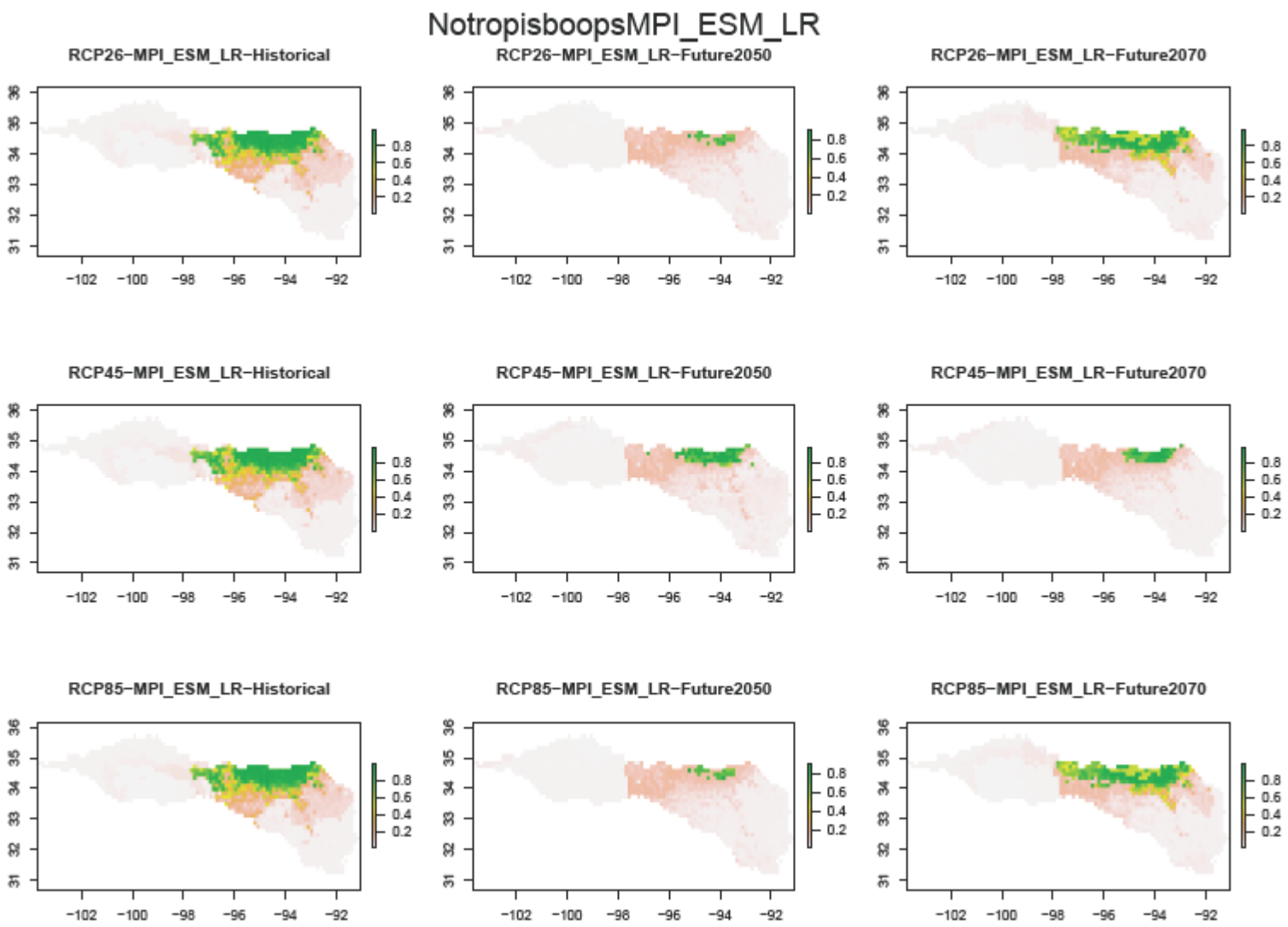

Notropis_boops_MIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070


Notropis_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
31 32 33 34 35 36
-102 -100 -98 -96 -94 -92
0.2 0.4 0.6 0.8

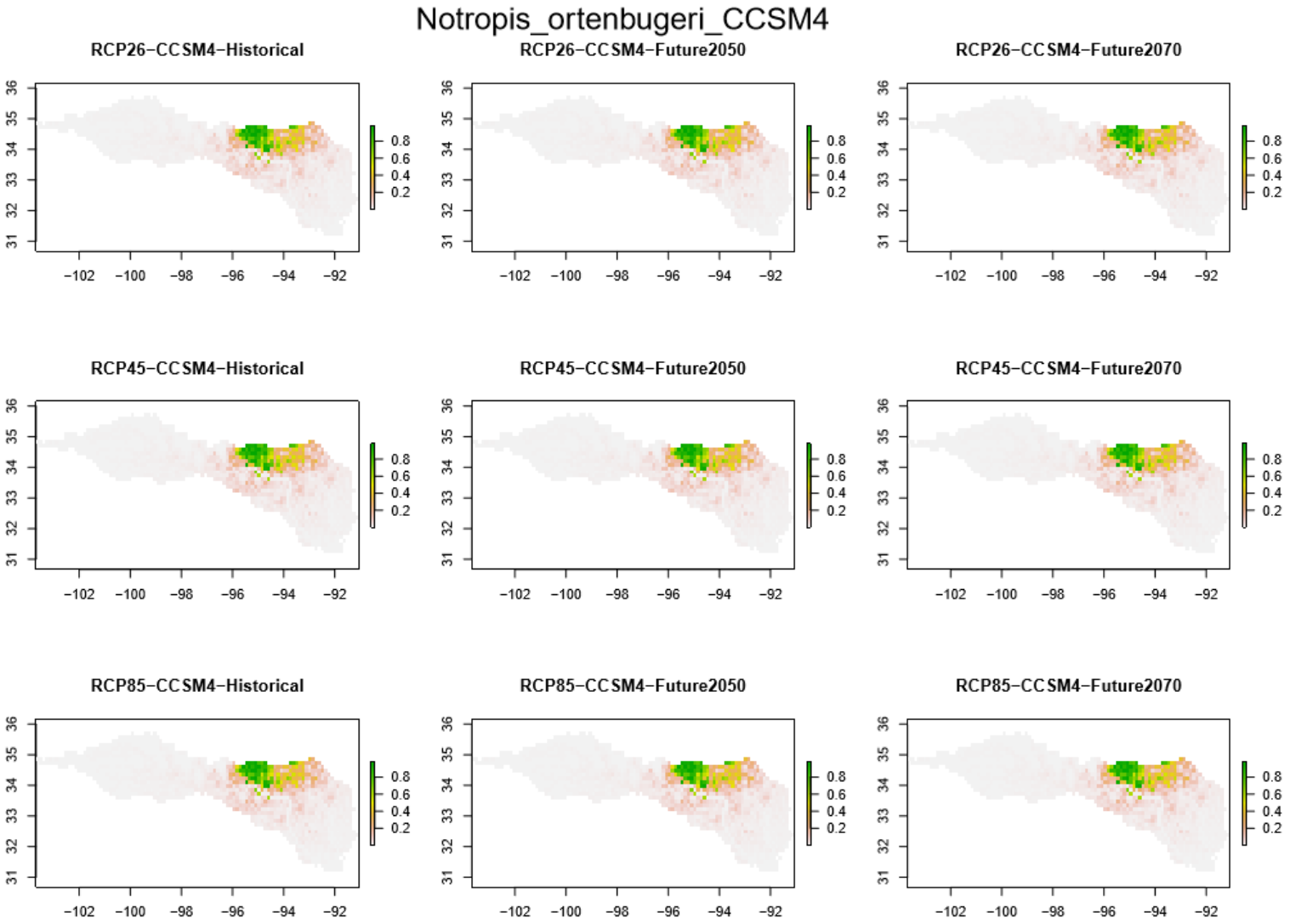
BRT: *Notropis boops*

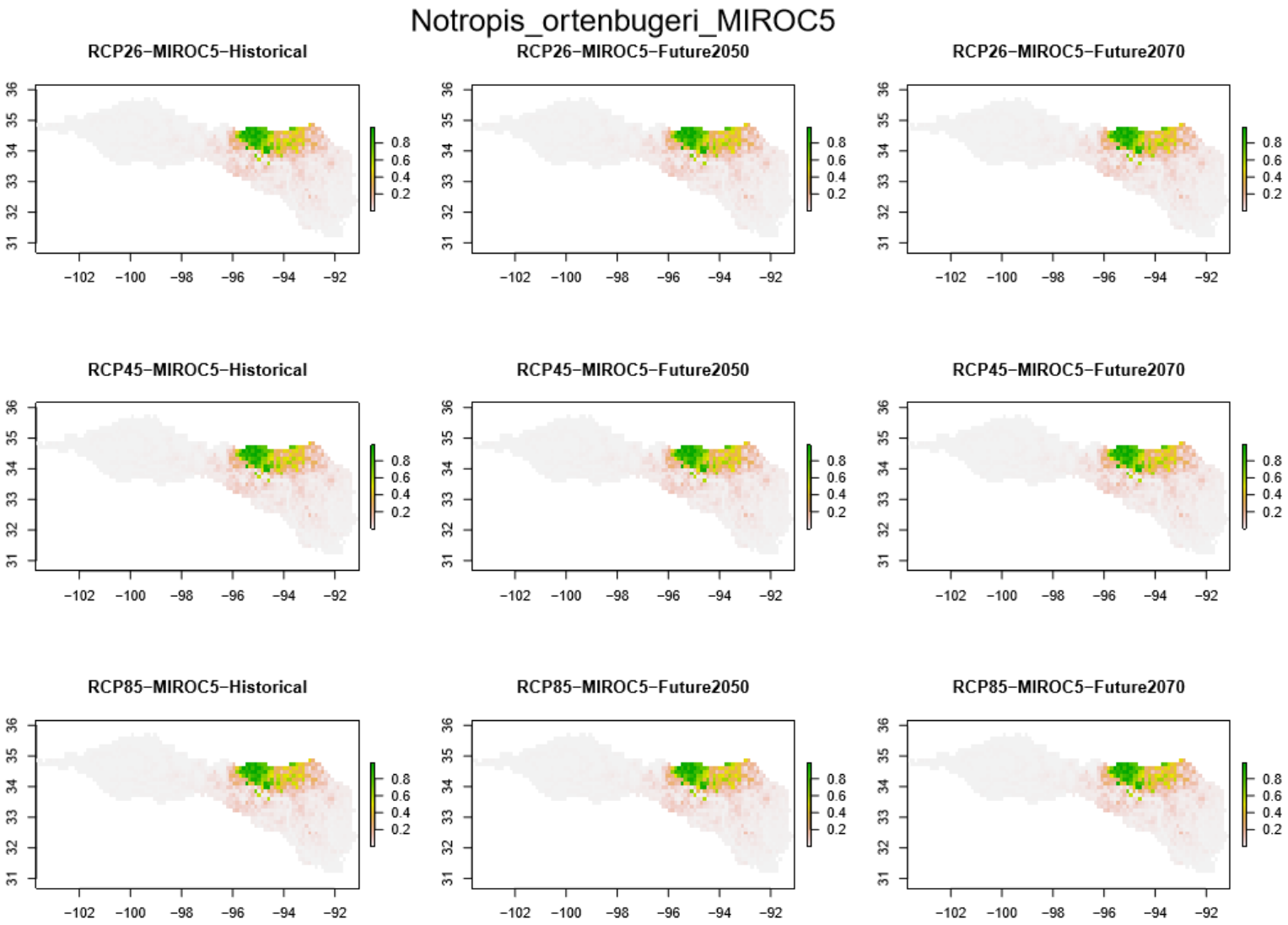


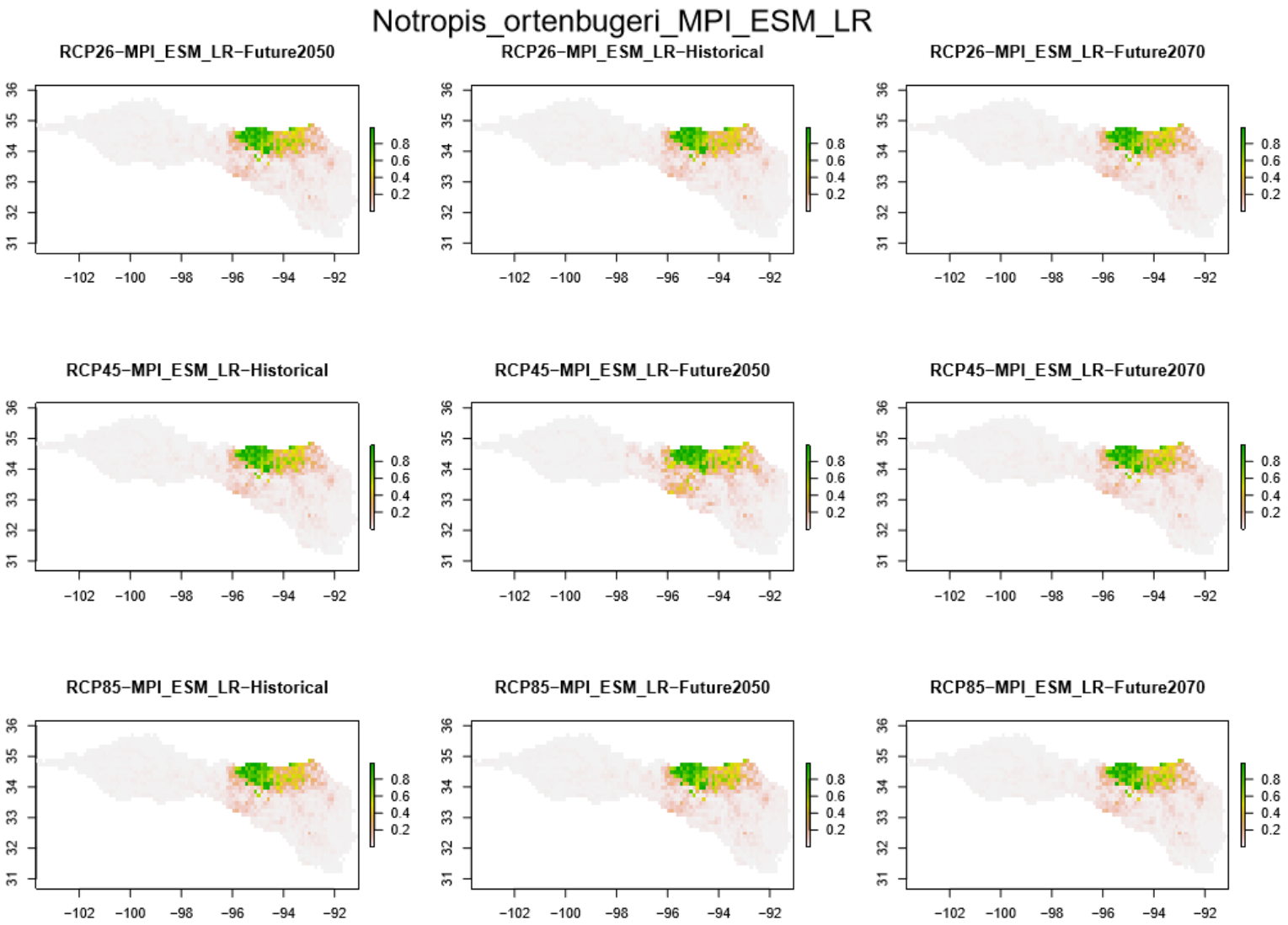

NotropisboopsMIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070


NotropisboopsMPI_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
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35
36
-102
-100
-98
-96
-94
-92
0.2
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0.6
0.8

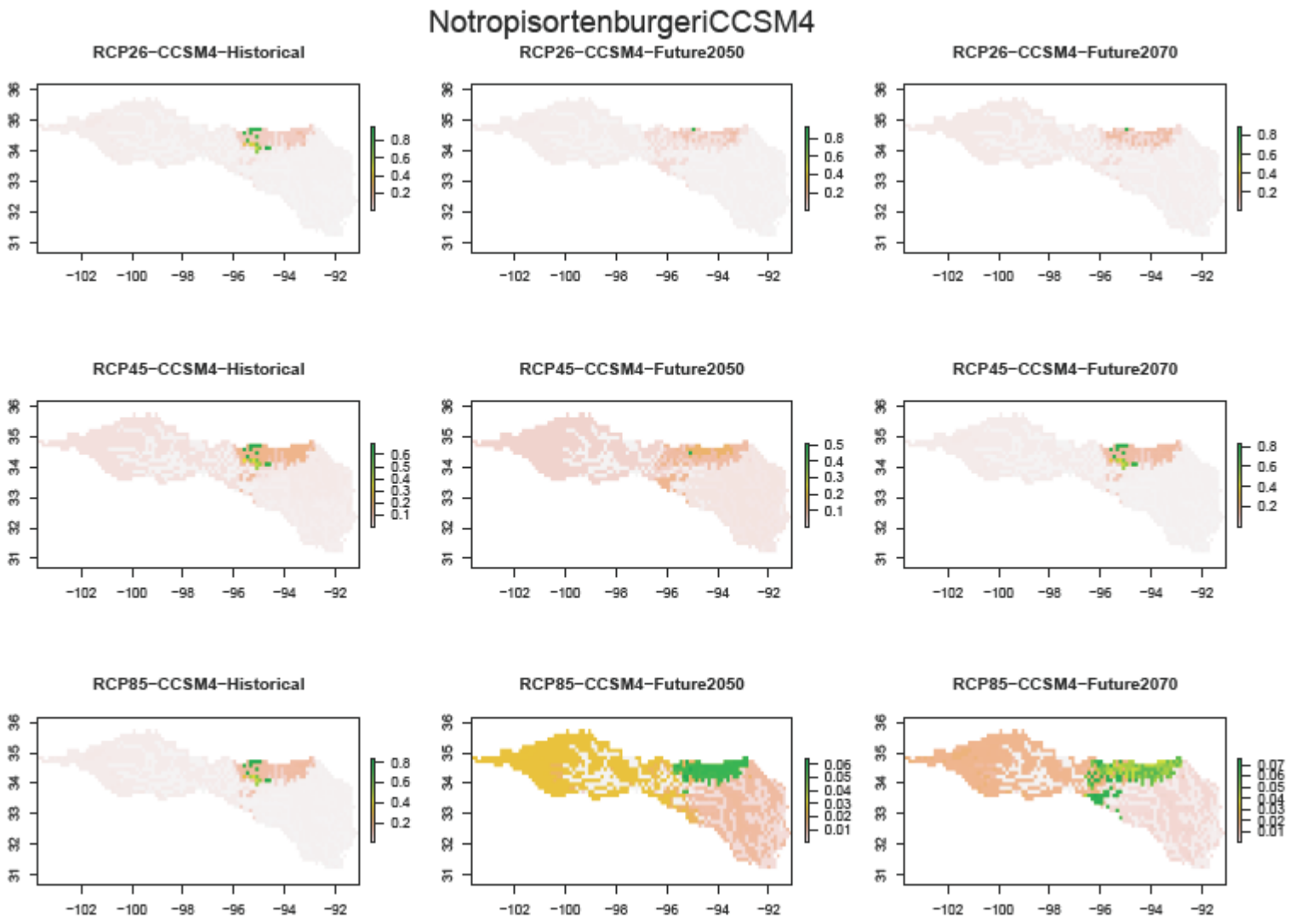
Maxent: *Notropis ortenburgeri*

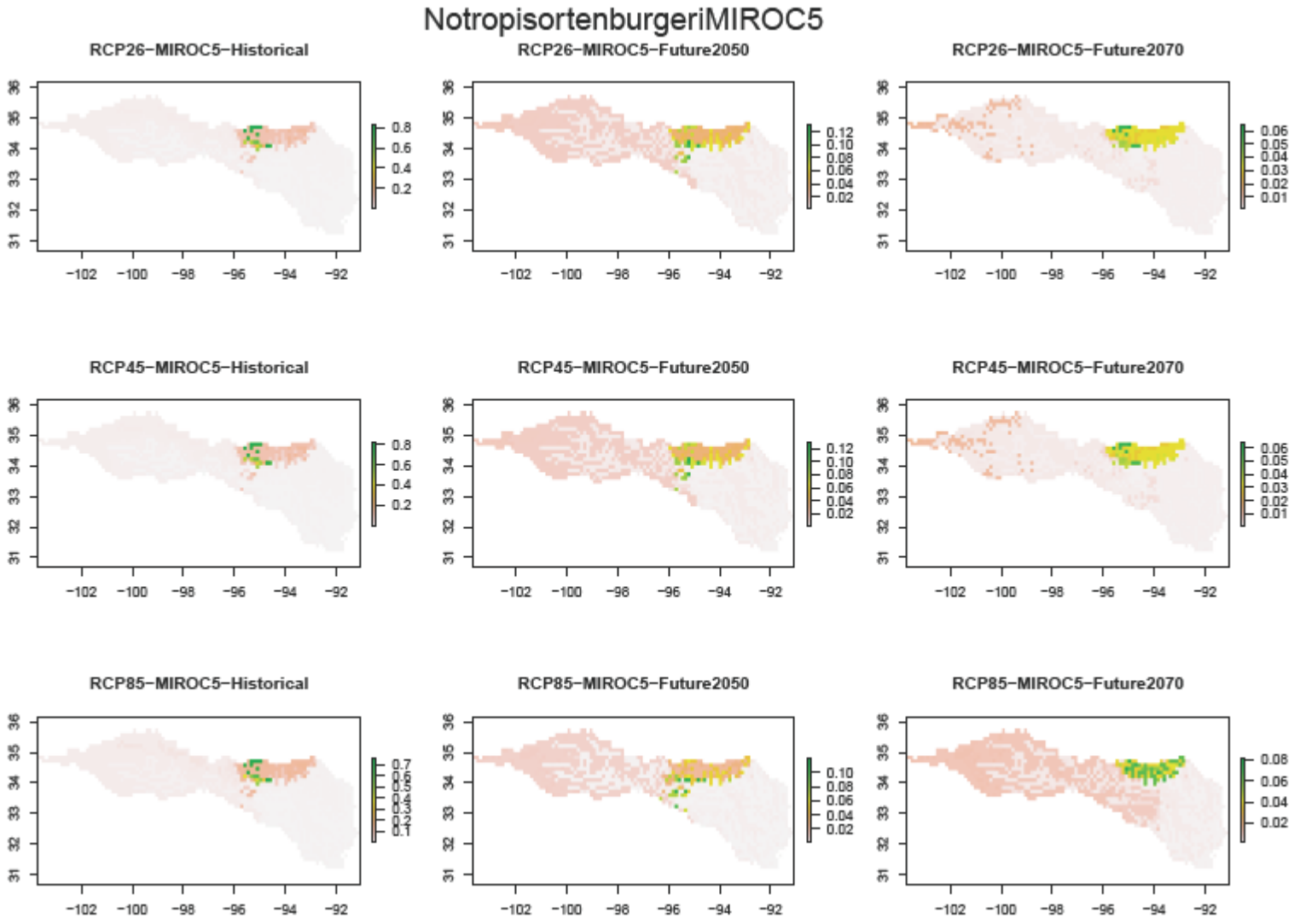


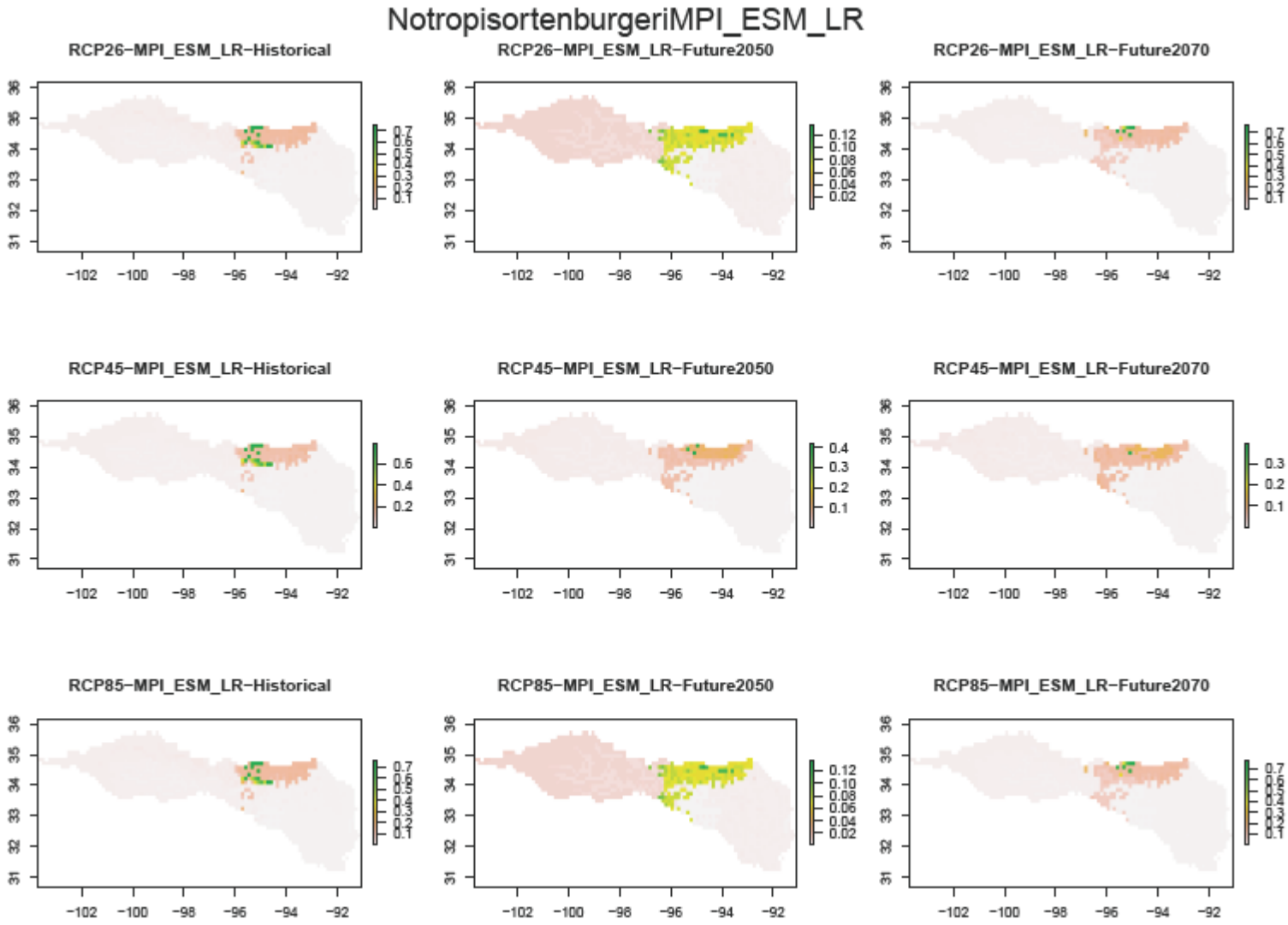

Notropis_ortenbugeri_MIROC5
RCP26-MIROC5-Historical
RCP26-MIROC5-Future2050
RCP26-MIROC5-Future2070
RCP45-MIROC5-Historical
RCP45-MIROC5-Future2050
RCP45-MIROC5-Future2070
RCP85-MIROC5-Historical
RCP85-MIROC5-Future2050
RCP85-MIROC5-Future2070
31 32 33 34 35 36
−102 −100 −98 −96 −94 −92
0.8 0.6 0.4 0.2


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
36
35
34
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32
31
-102
-100
-98
-96
-94
-92
0.8
0.6
0.4
0.2

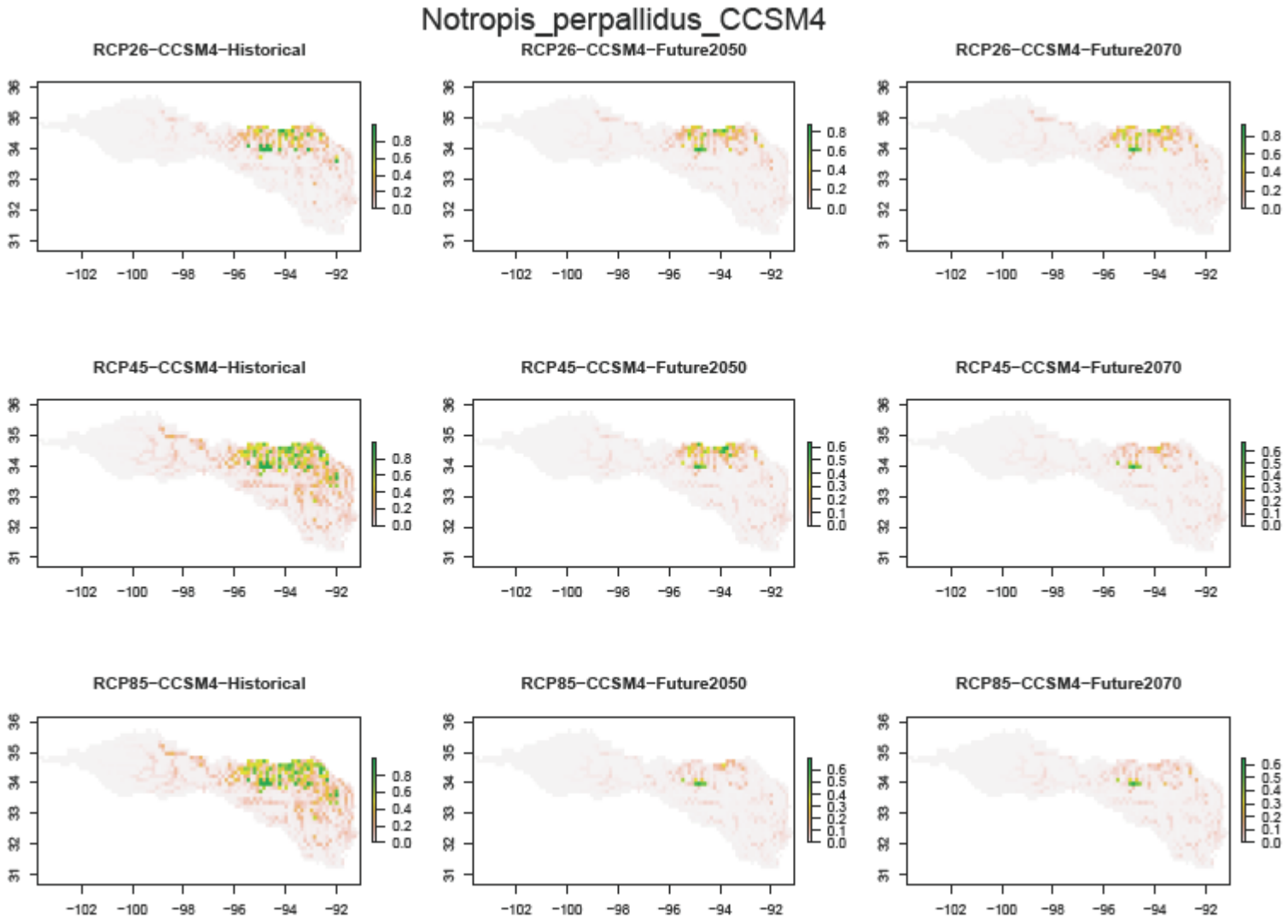
BRT: *Notropis ortenburgeri*

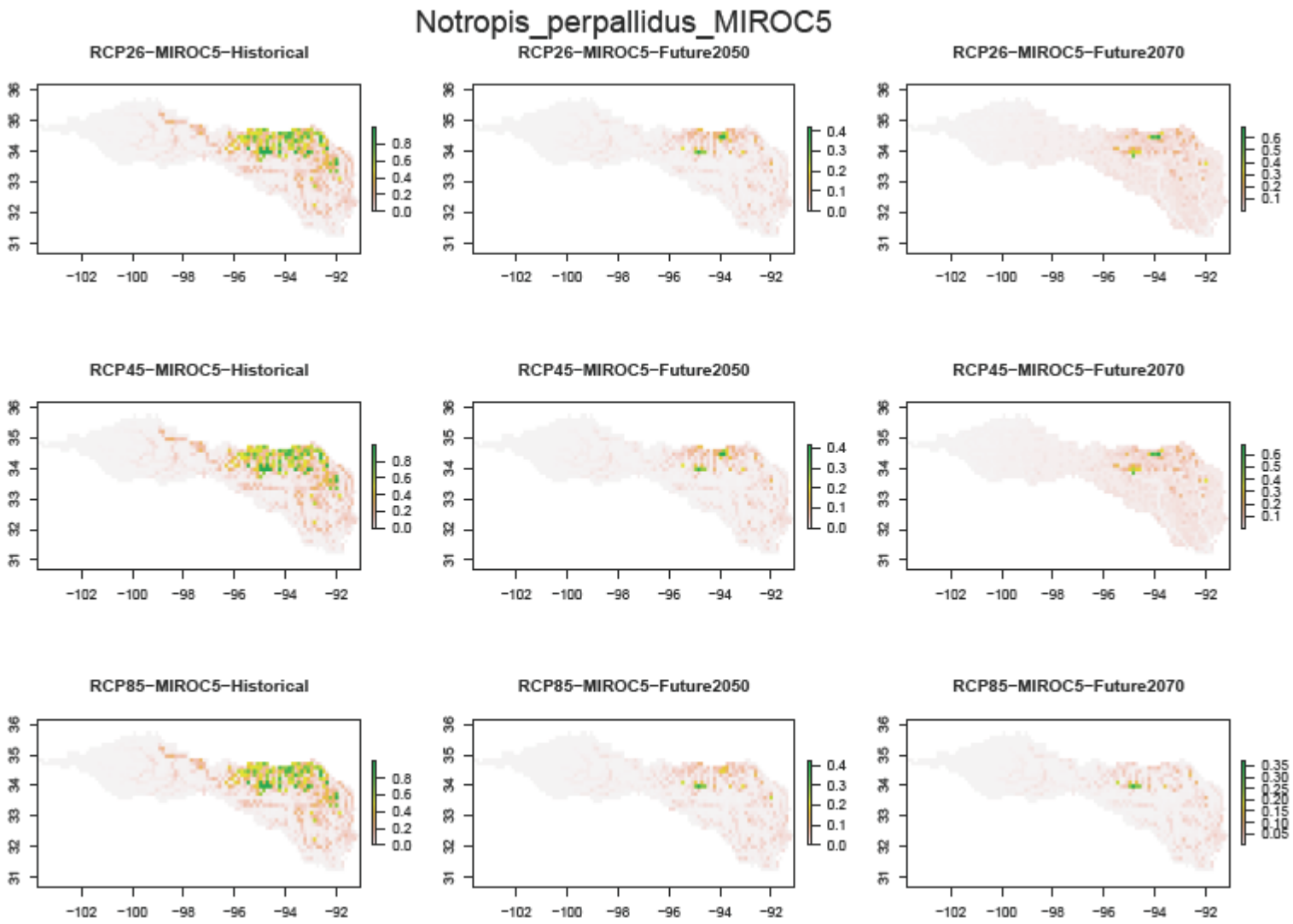


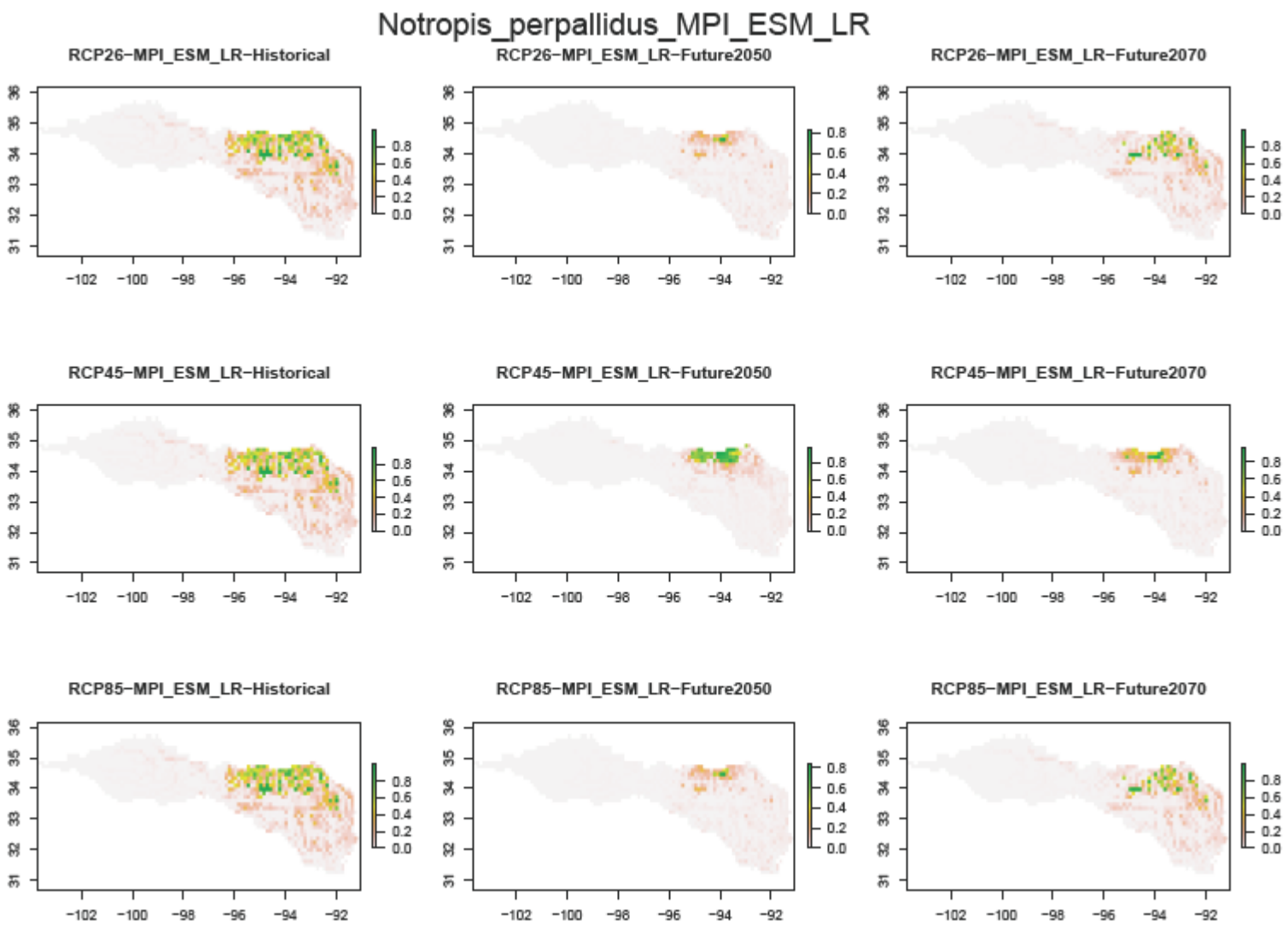

NotropisortenburgeriMIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070


NotropisortenburgeriMPI_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

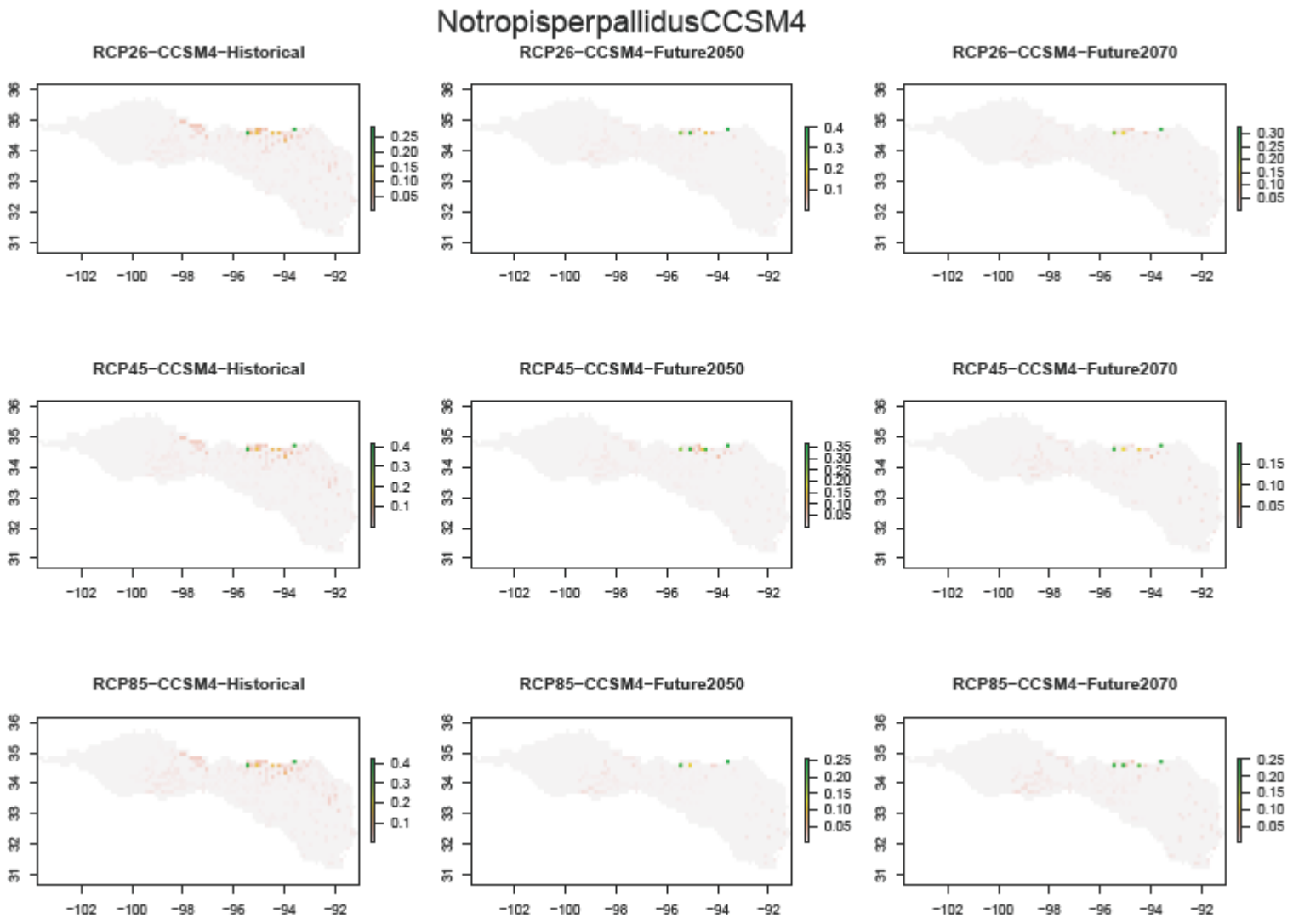
Maxent: *Notropis perpallidus*

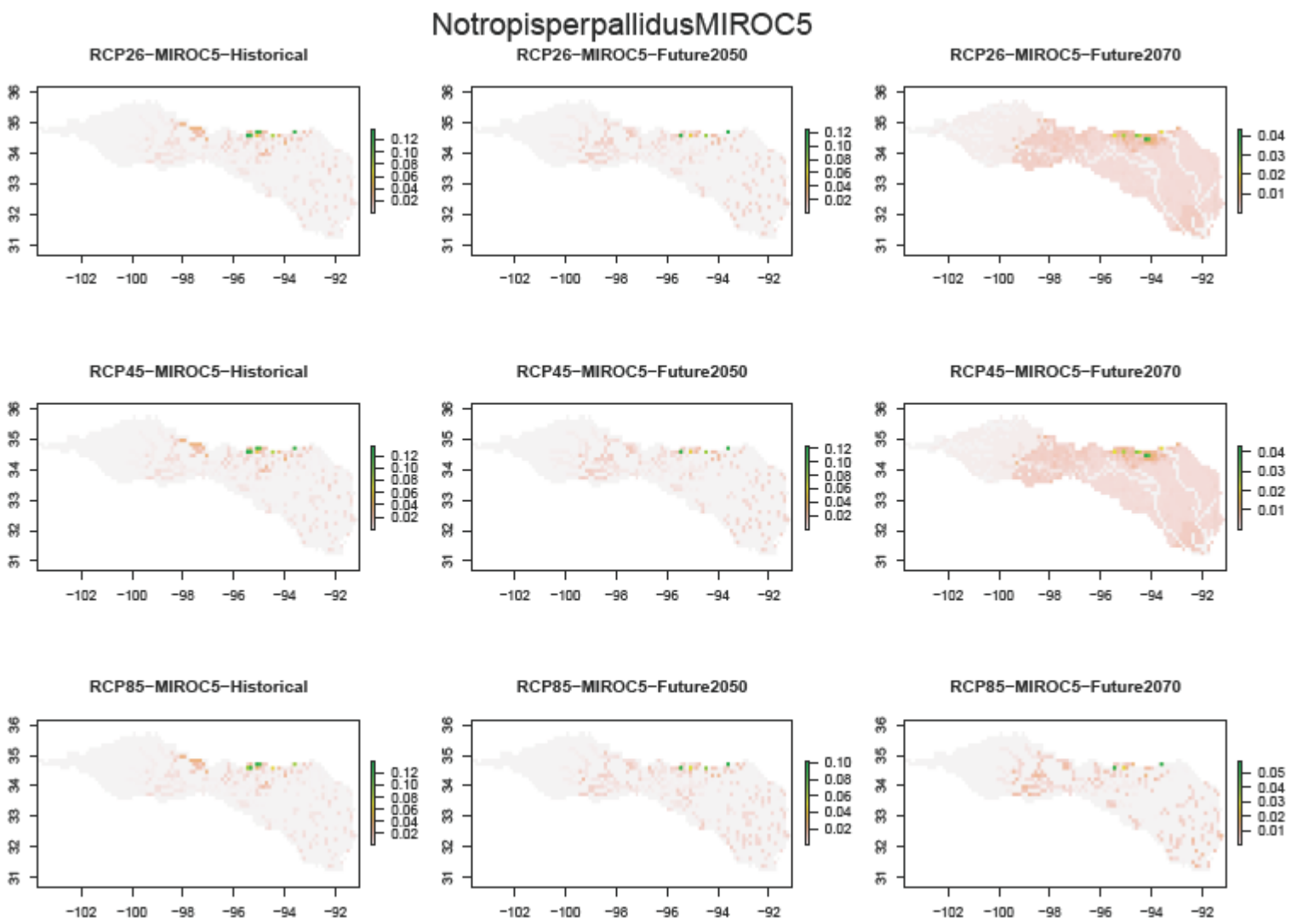



Notropis_perpallidus_MIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070

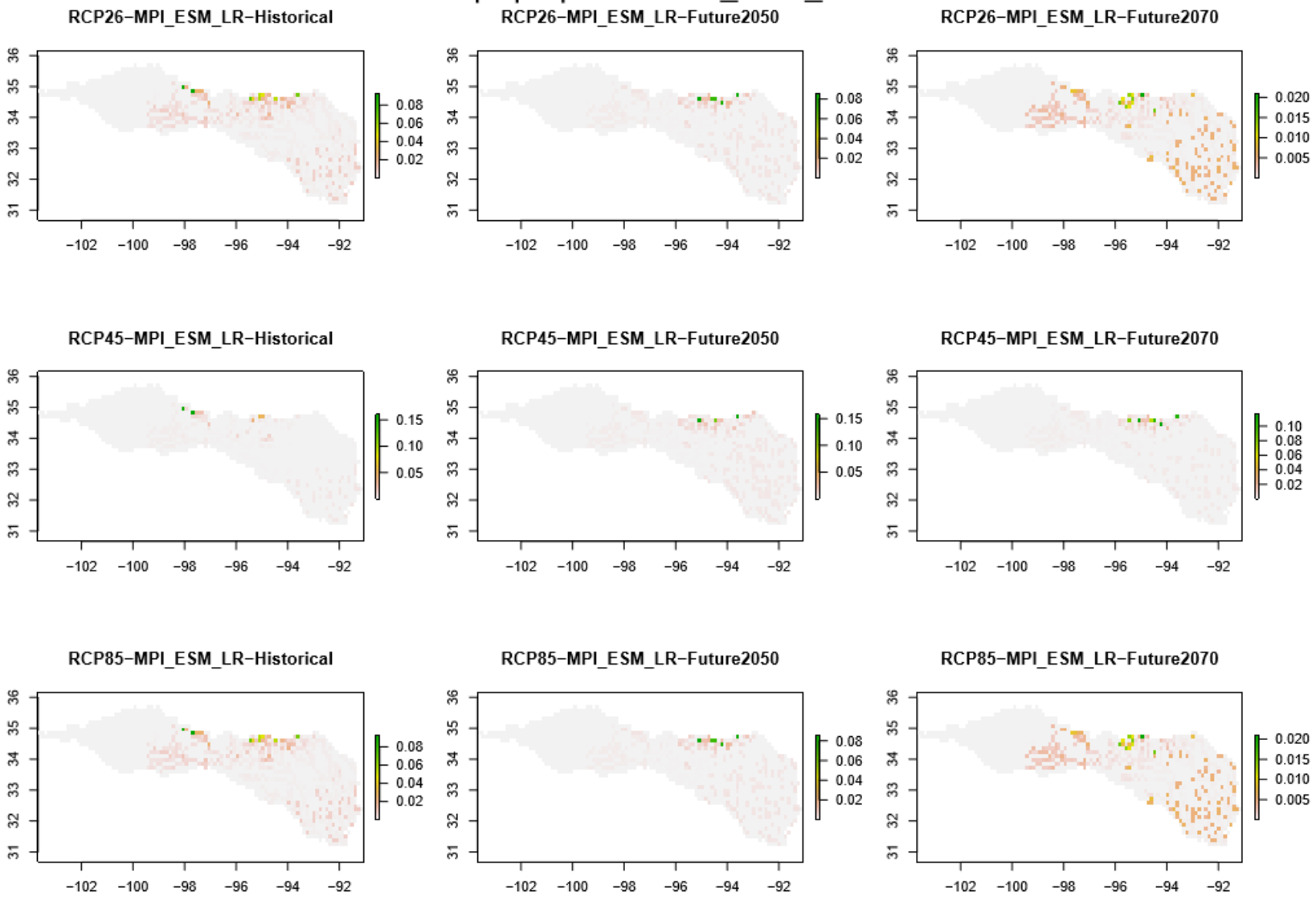

Notropis_perpallidus_MPI_ESM_LR
RCP26-MPI_ESM_LR-Historical
RCP26-MPI_ESM_LR-Future2050
RCP26-MPI_ESM_LR-Future2070
RCP45-MPI_ESM_LR-Historical
RCP45-MPI_ESM_LR-Future2050
RCP45-MPI_ESM_LR-Future2070
RCP85-MPI_ESM_LR-Historical
RCP85-MPI_ESM_LR-Future2050
RCP85-MPI_ESM_LR-Future2070
31 32 33 34 35 36
-102 -100 -98 -96 -94 -92
0.0 0.2 0.4 0.6 0.8

BRT: *Notropis perpallidus*

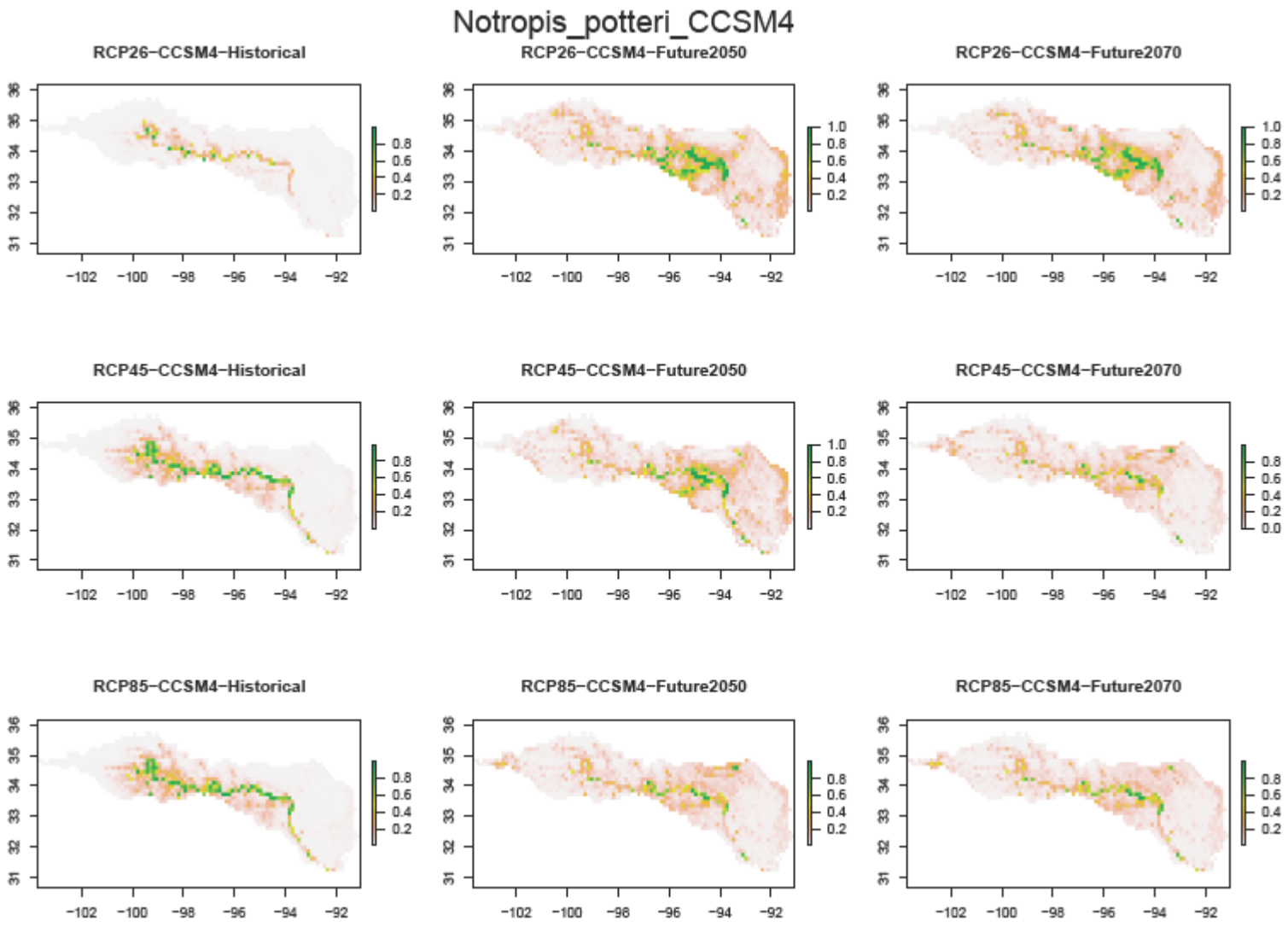


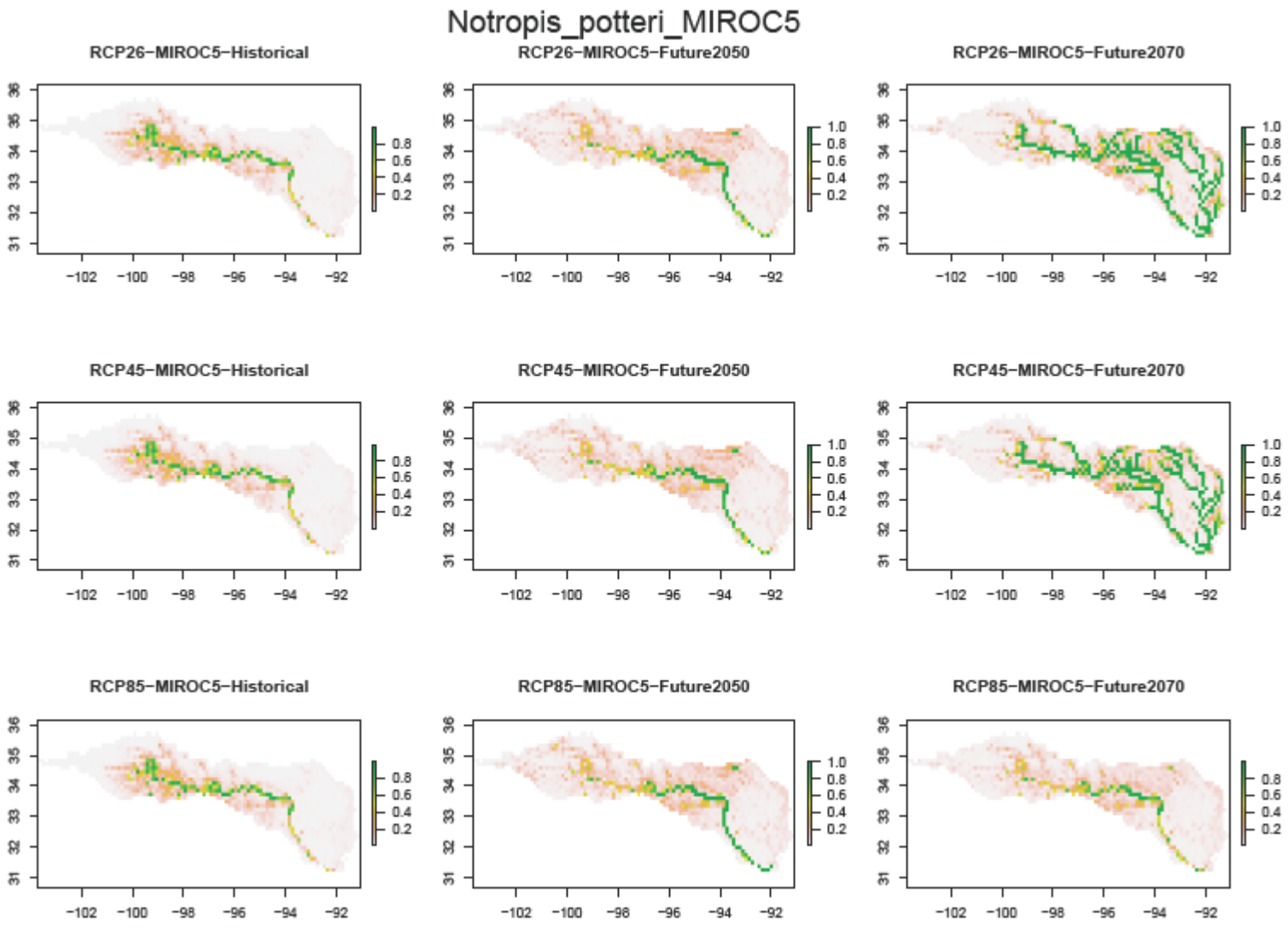

NotropisperpallidusMIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070

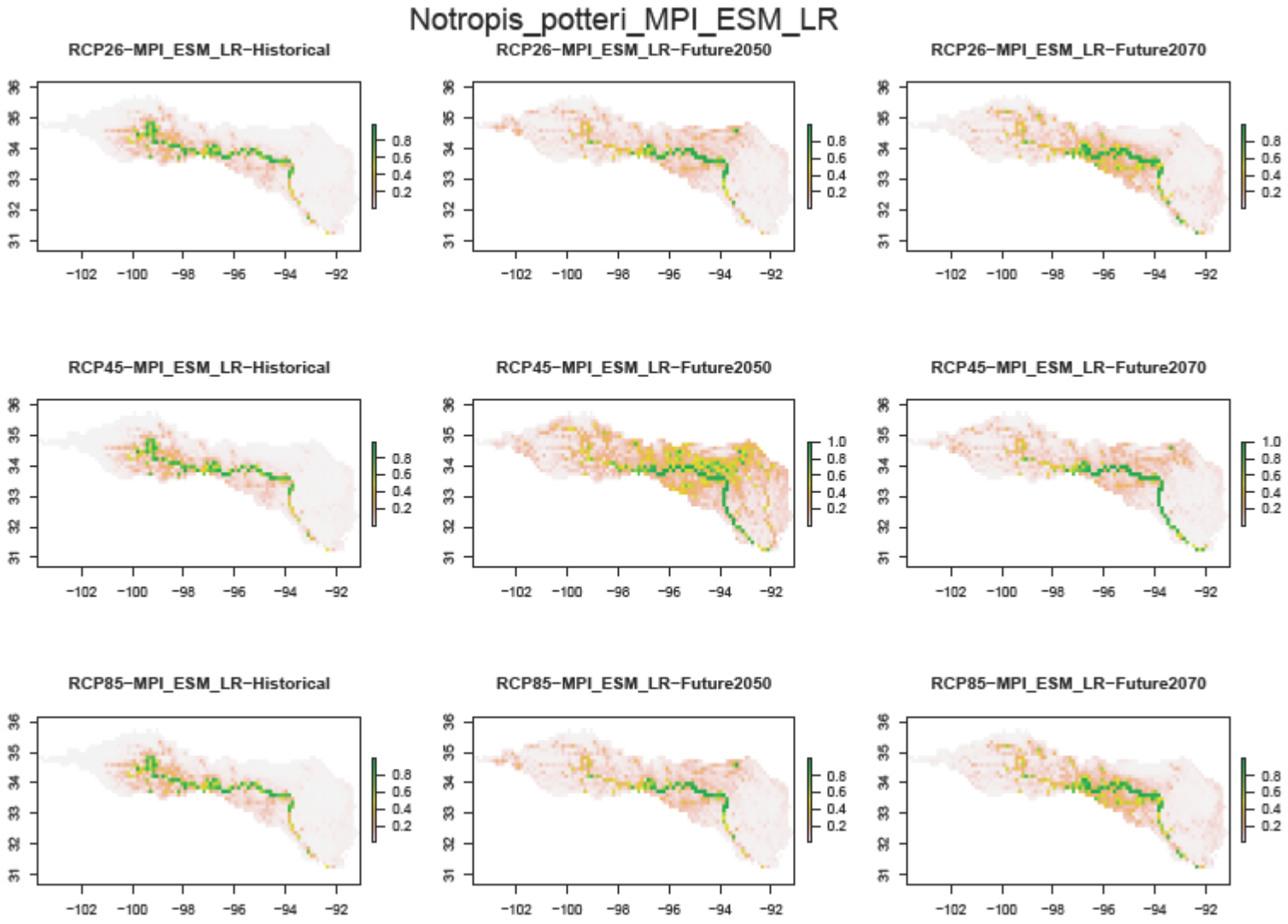
# NotropisperpallidusMPI_ESM_LR



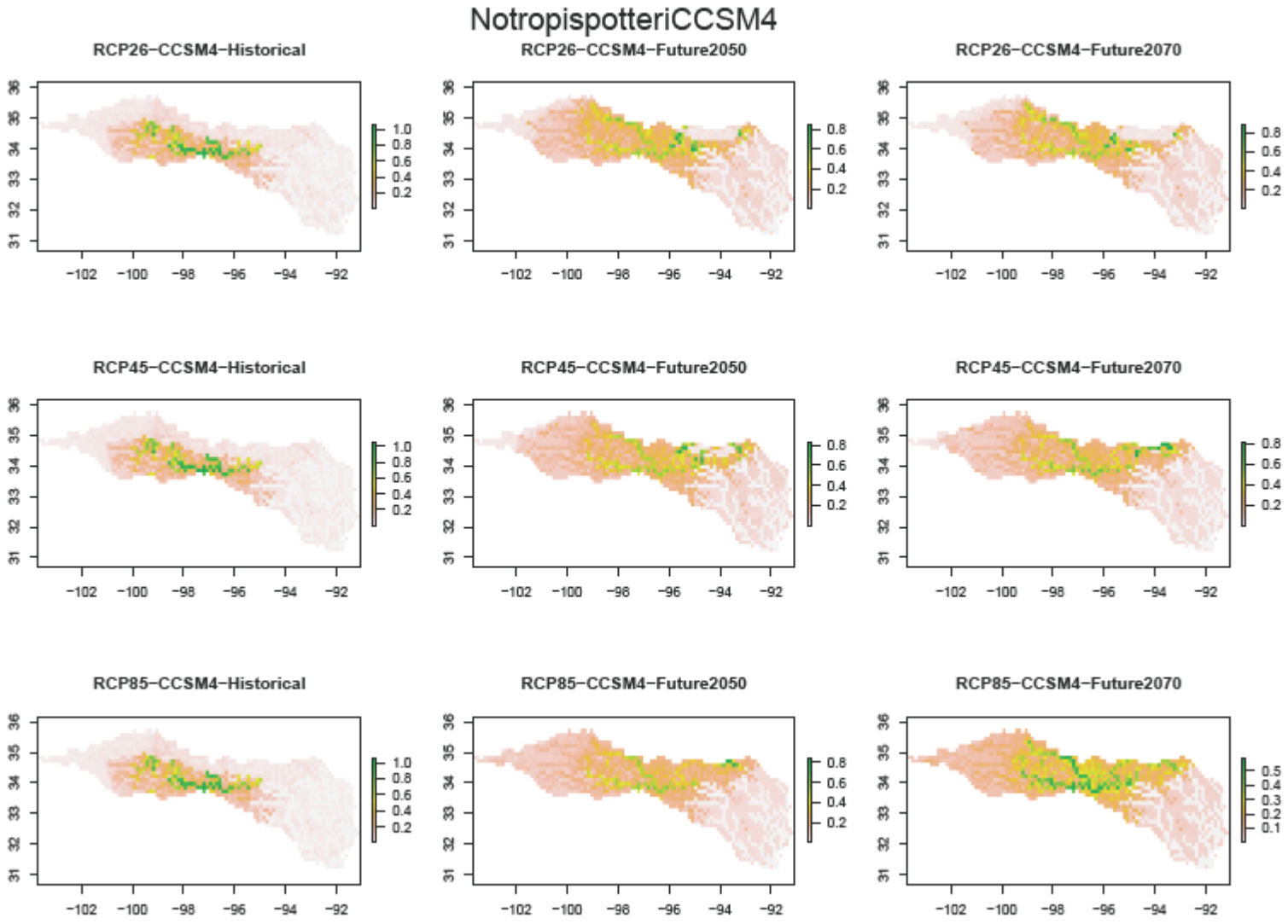
Maxent: *Notropis potteri*

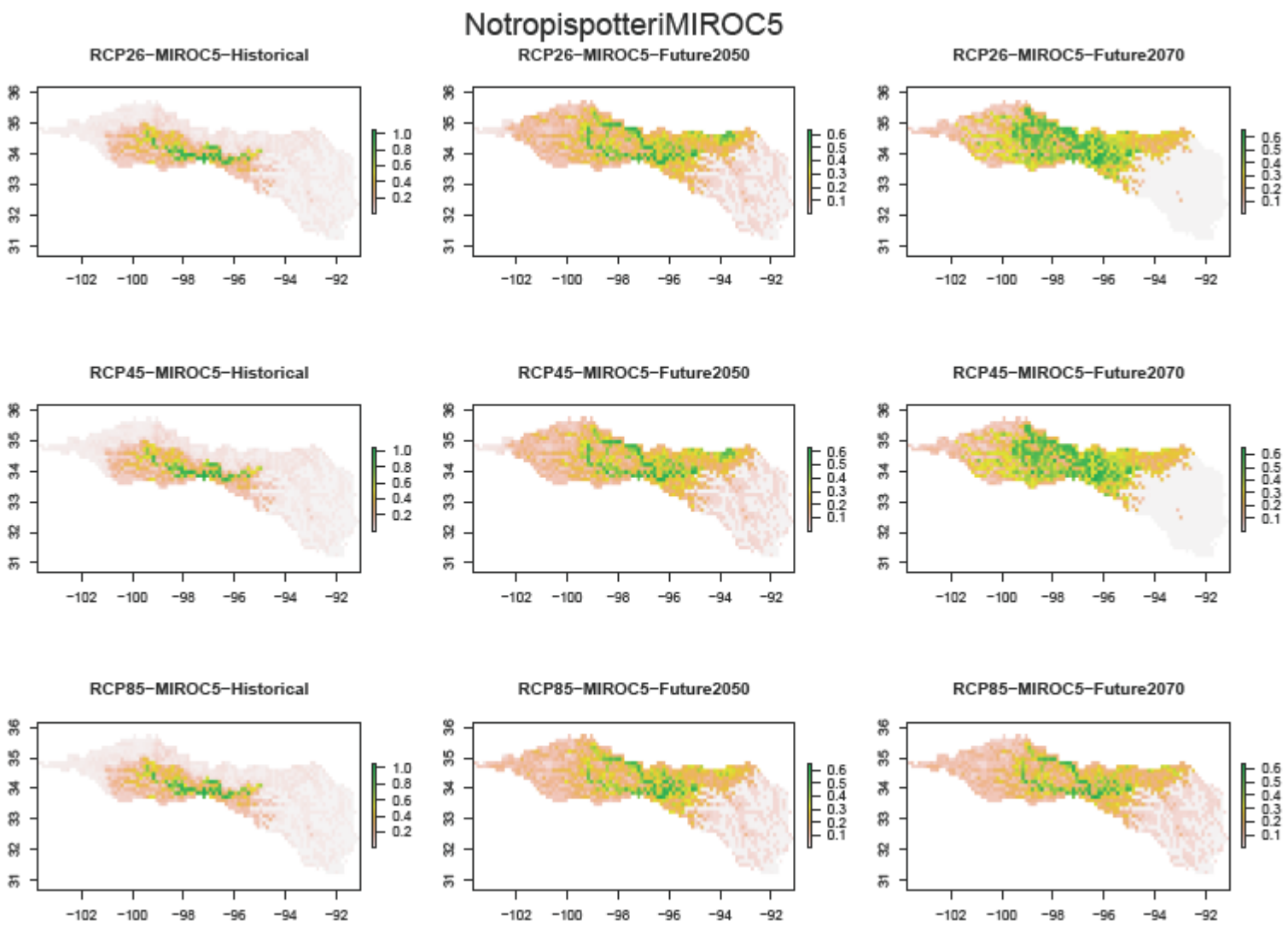


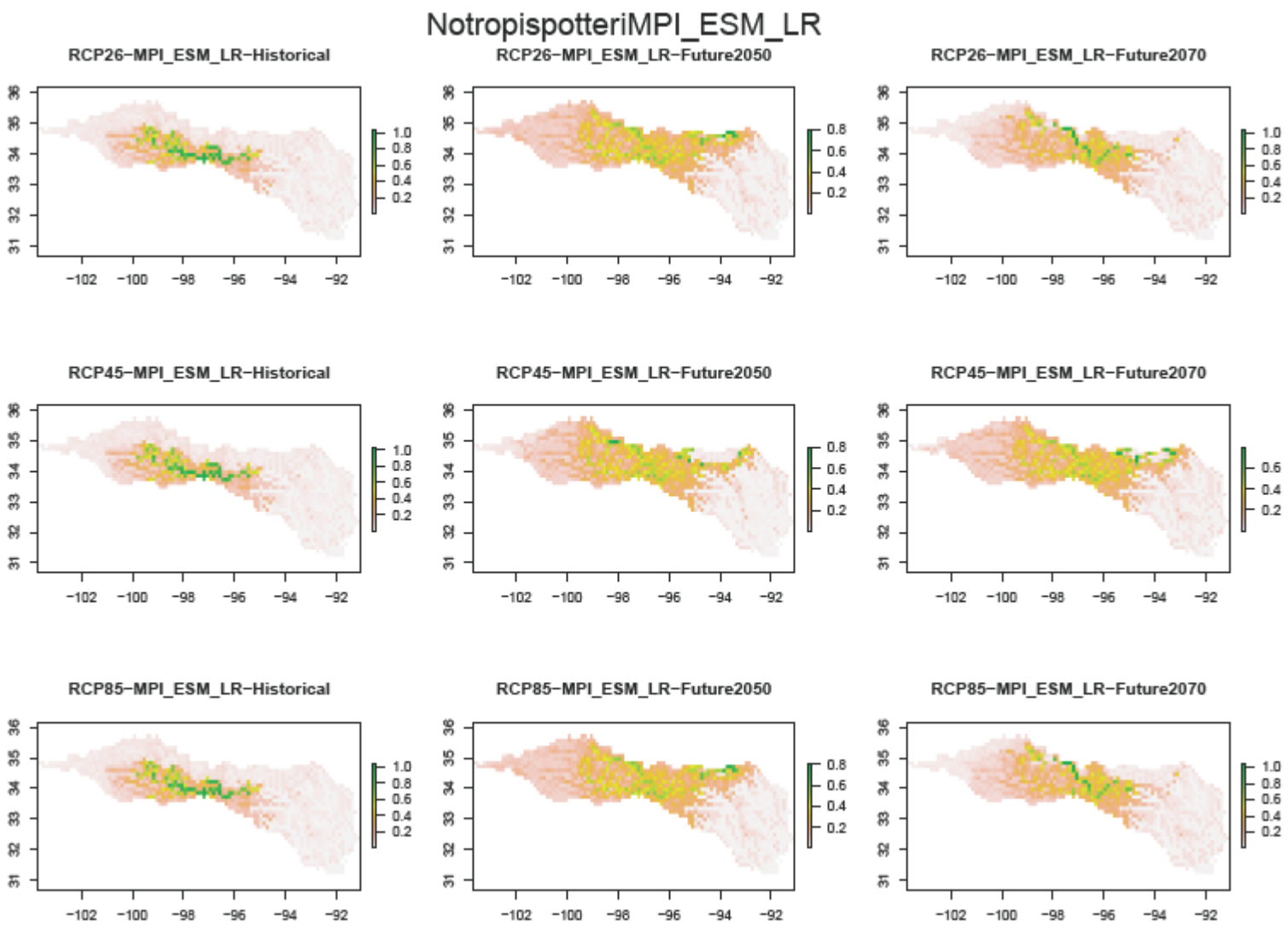

Notropis_potteri_MIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070
−102 −100 −98 −96 −94 −92
31 32 33 34 35 36
0.2 0.4 0.6 0.8 1.0


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
31 32 33 34 35 36
-102 -100 -98 -96 -94 -92
0.2 0.4 0.6 0.8 1.0

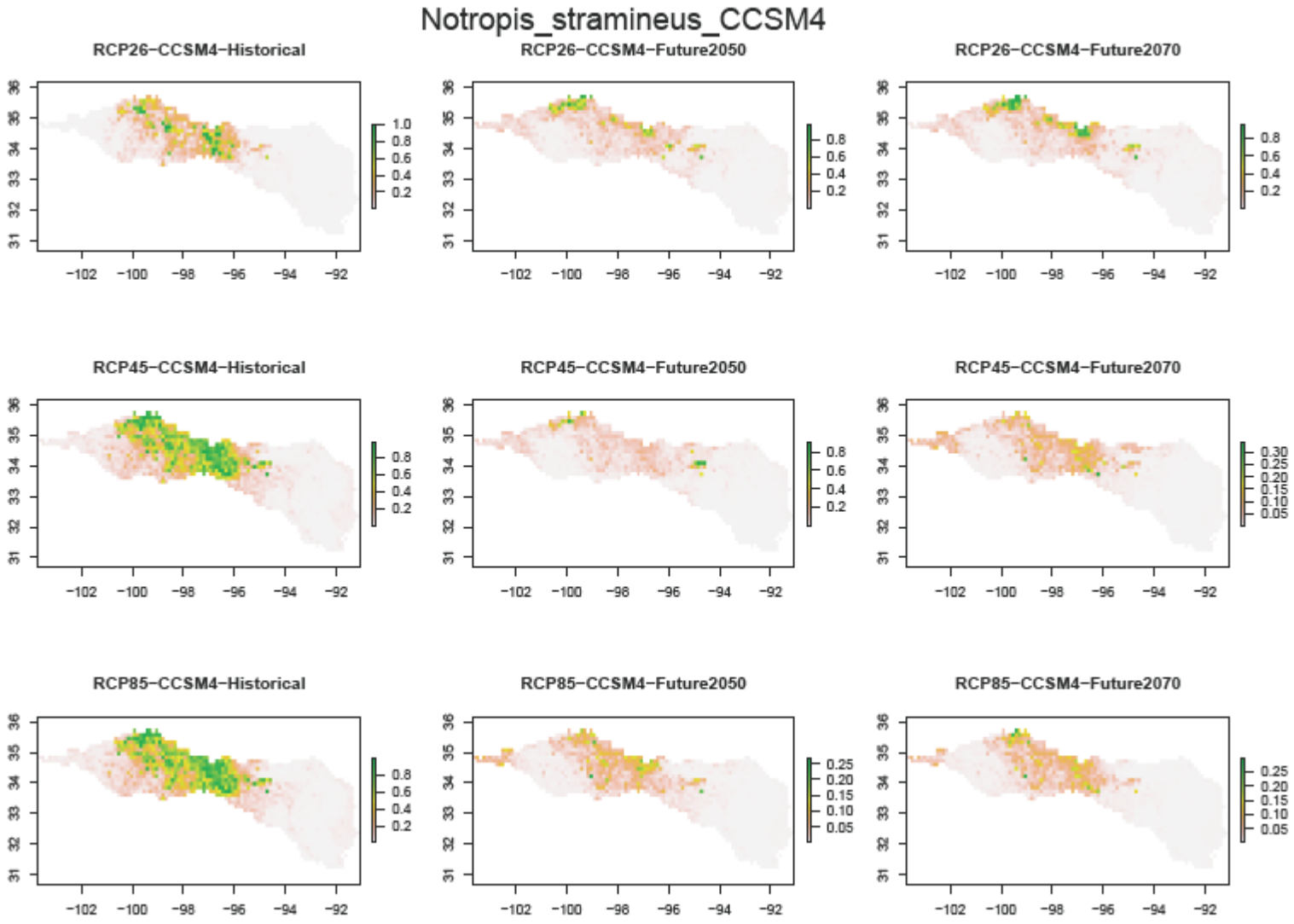
BRT: *Notropis potteri*

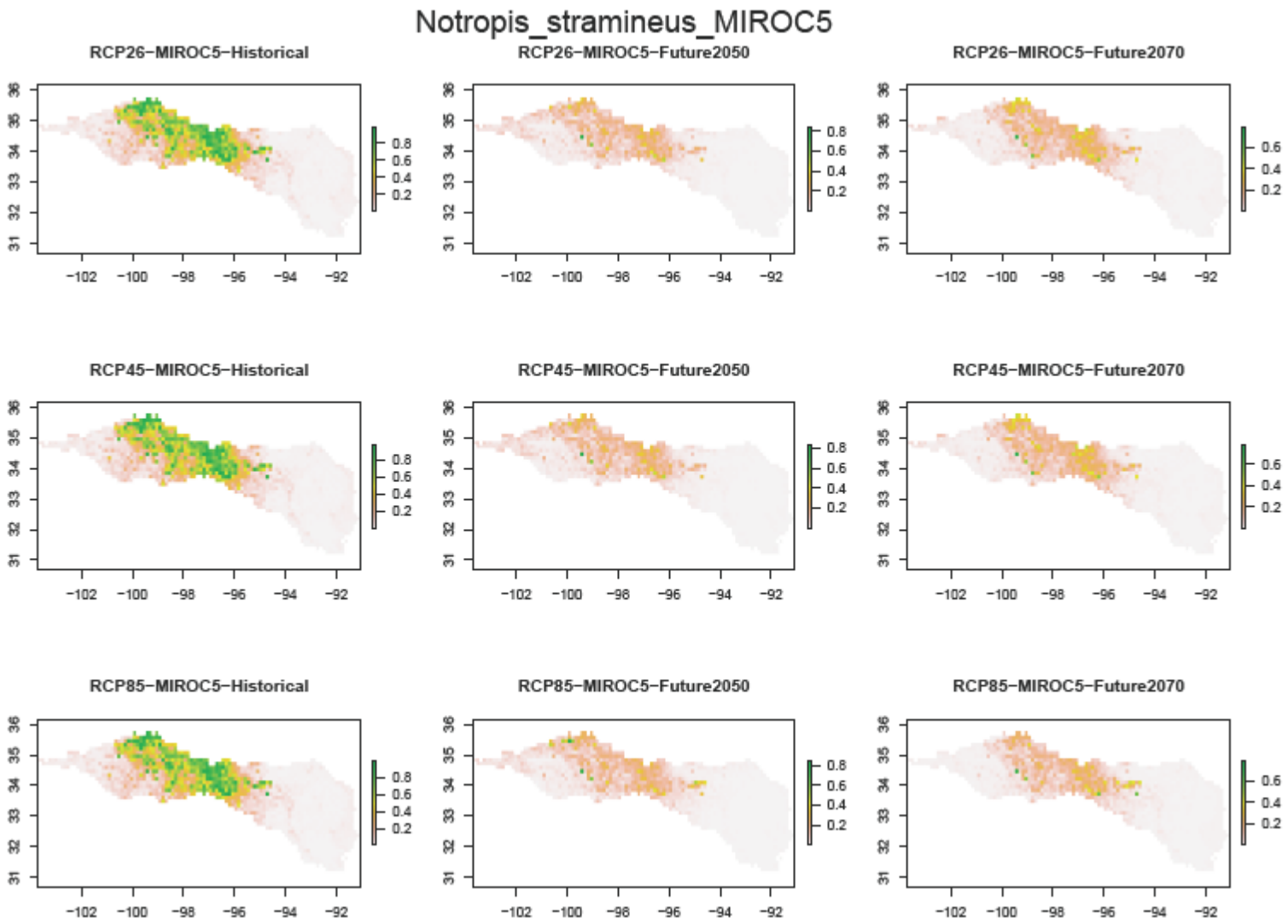


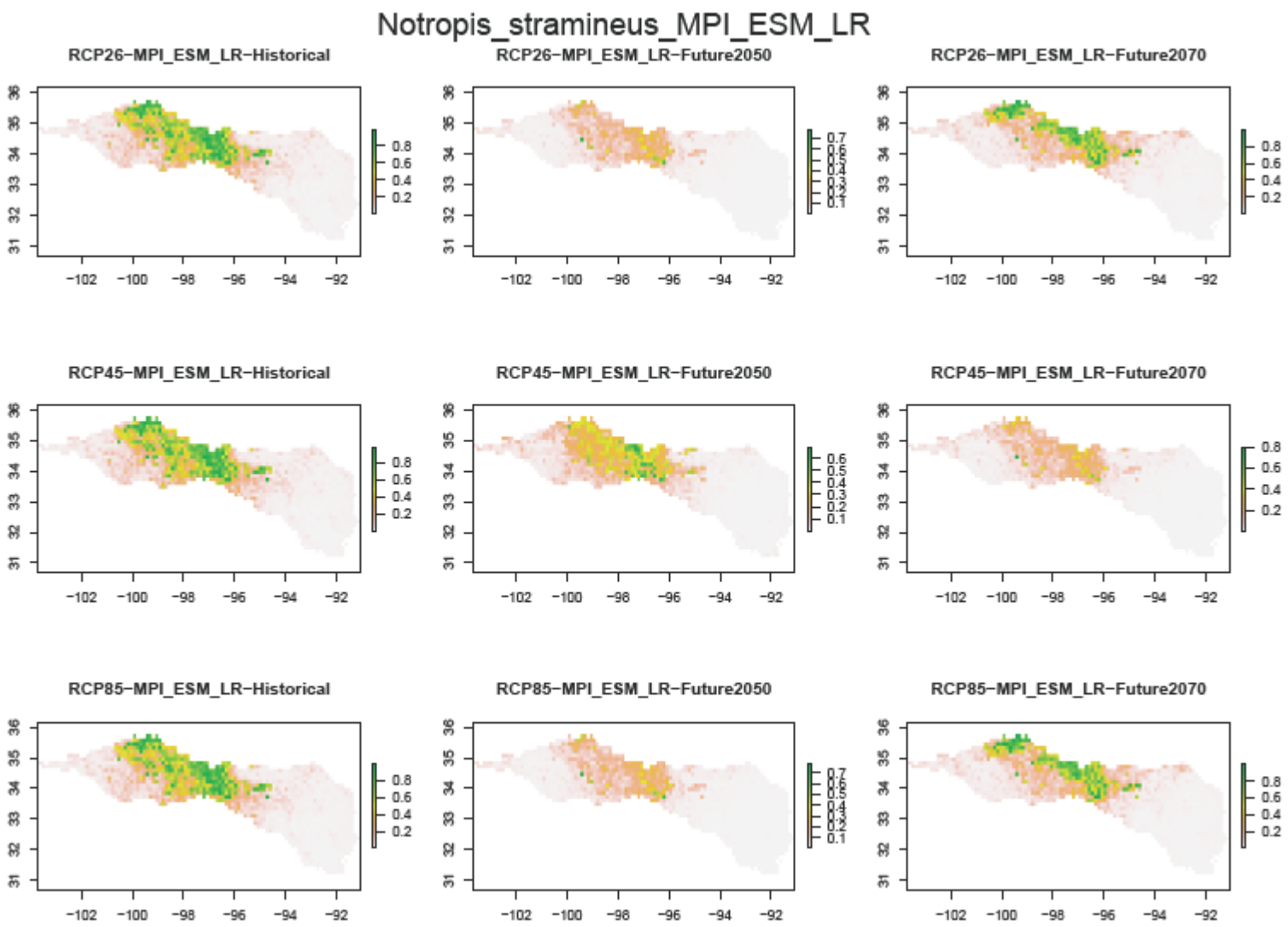

NotropispotteriMIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070


NotropispotteriMPI_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

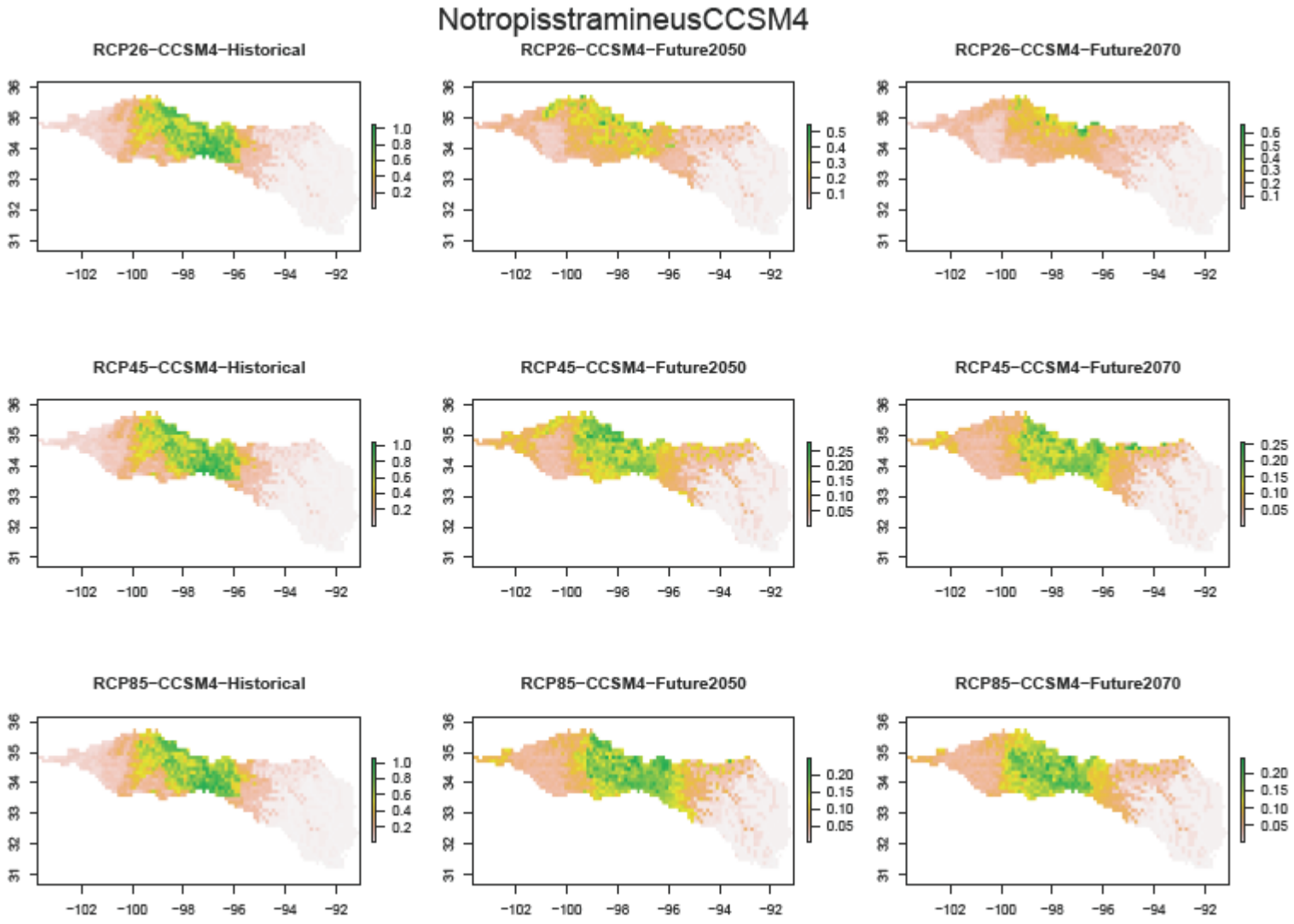
Maxent: *Notropis stramineus*

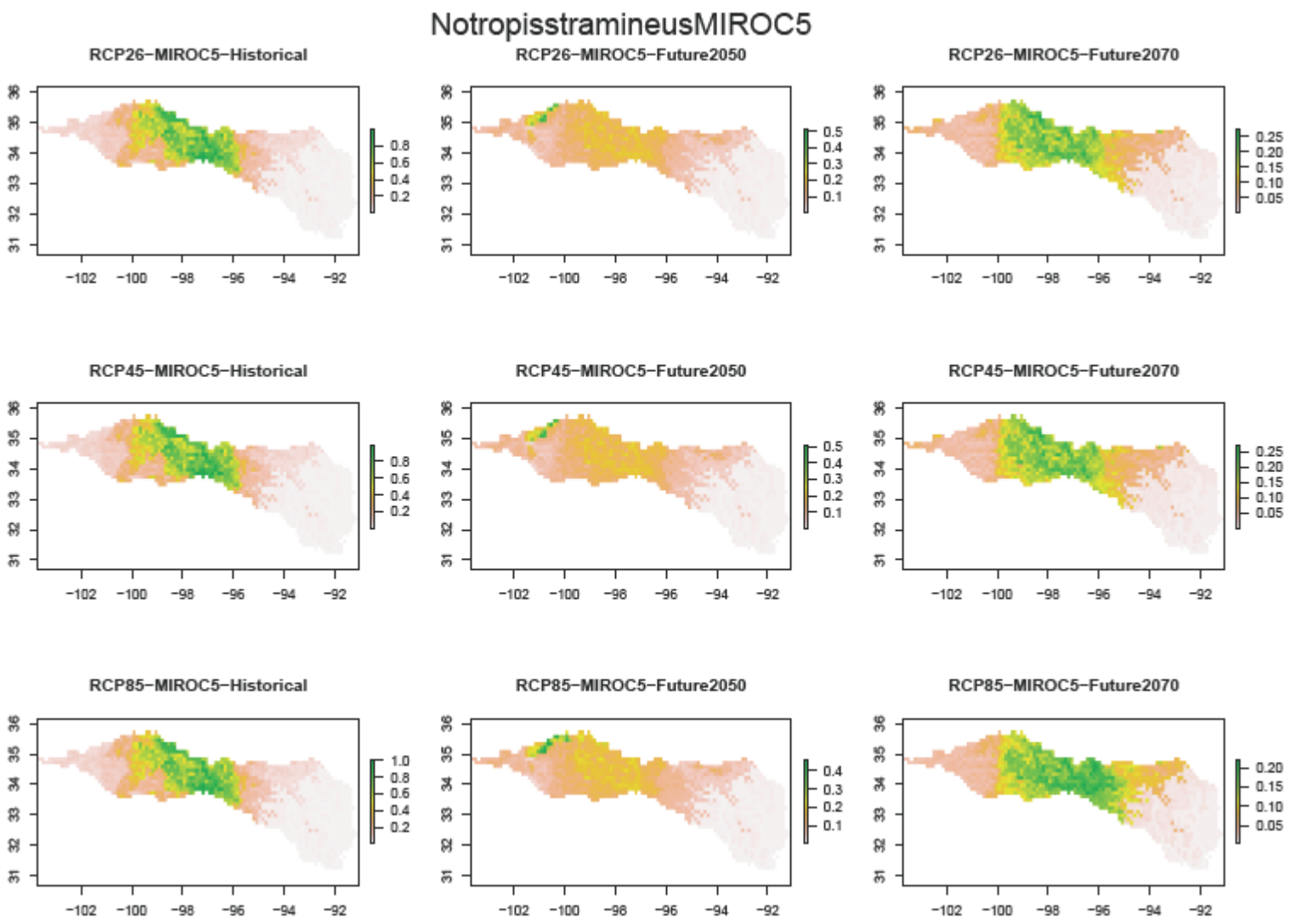


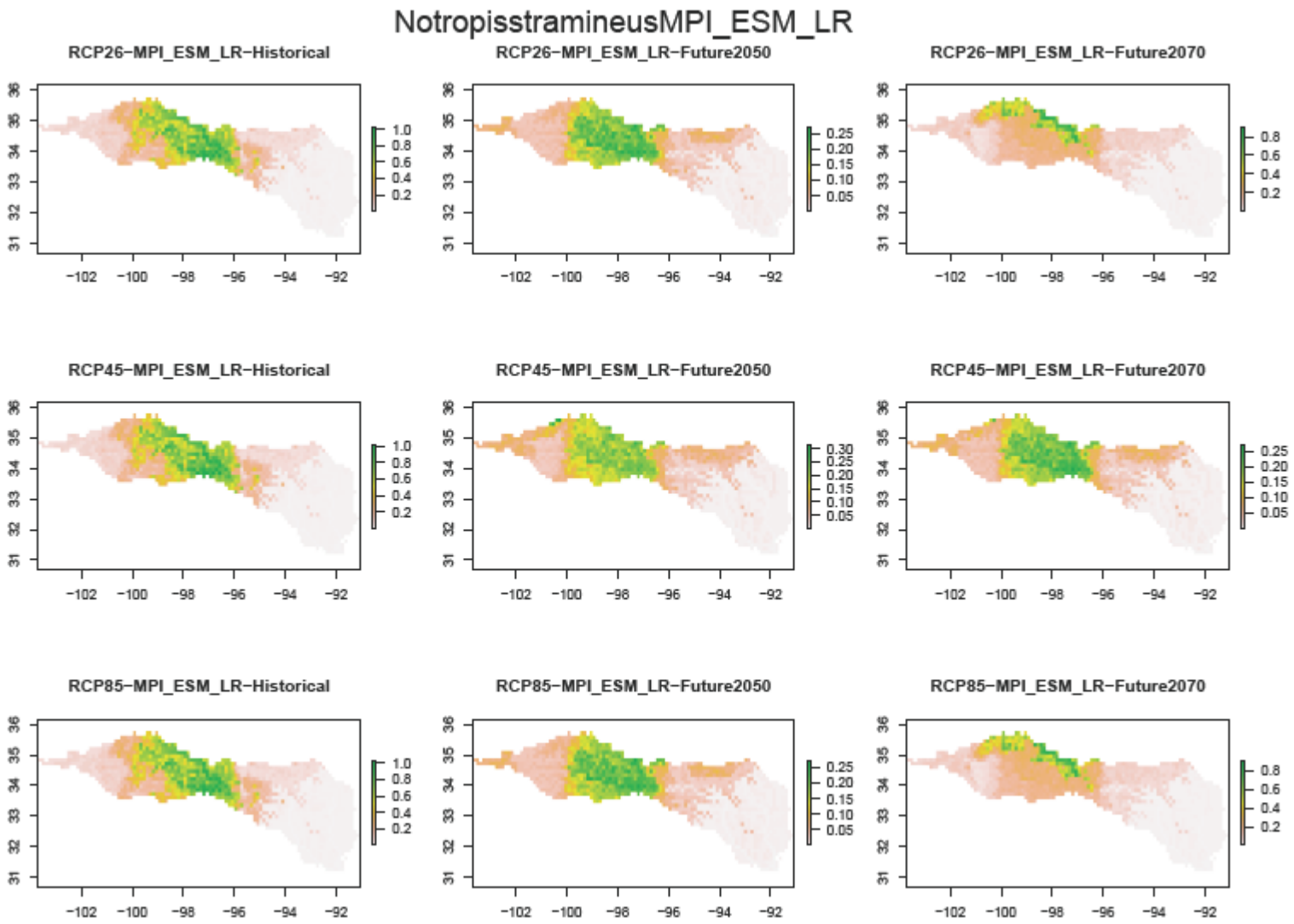

Notropis_stramineus_MIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070
31
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−102
−100
−98
−96
−94
−92
0.2
0.4
0.6
0.8


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

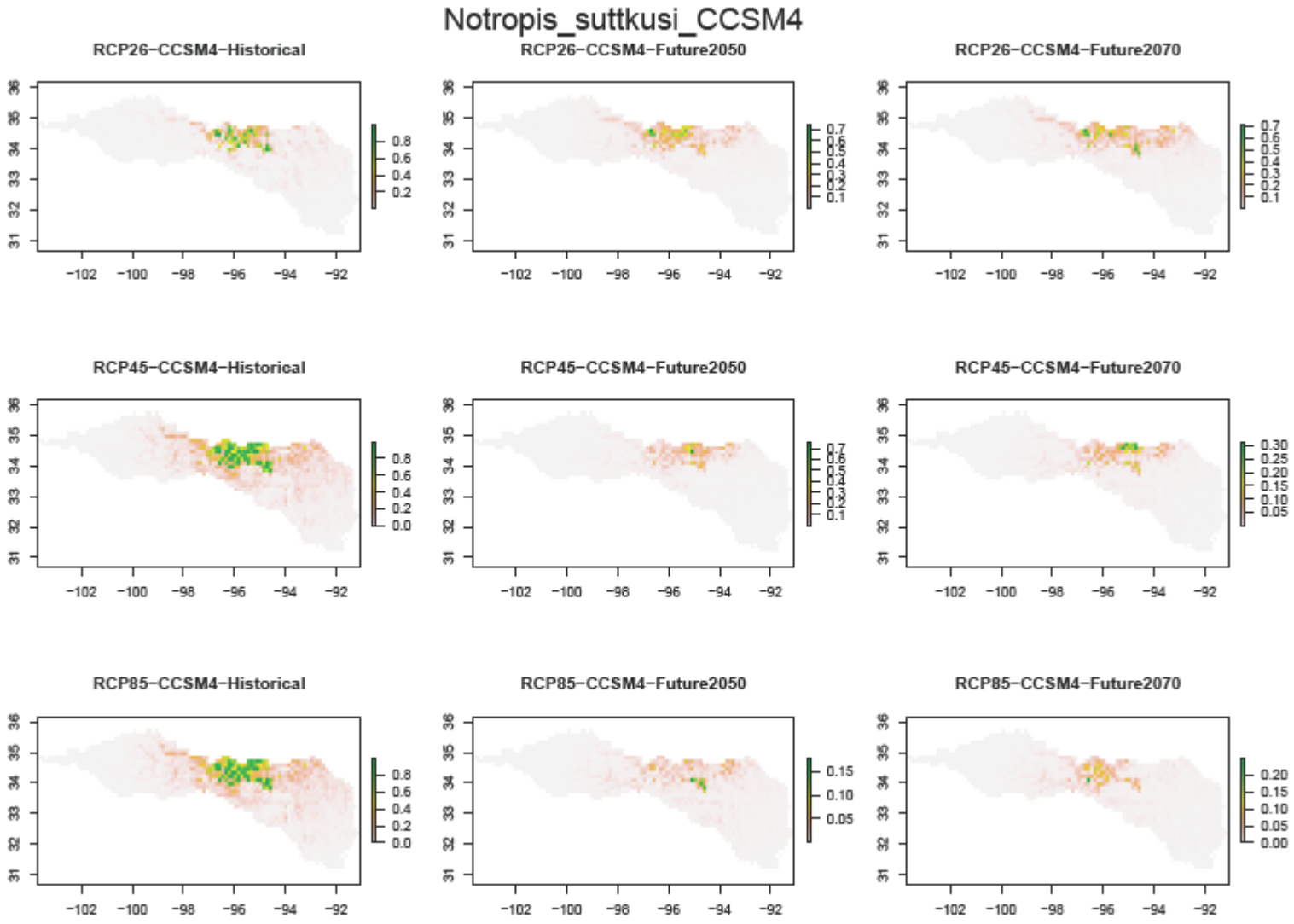
BRT: *Notropis stramineus*

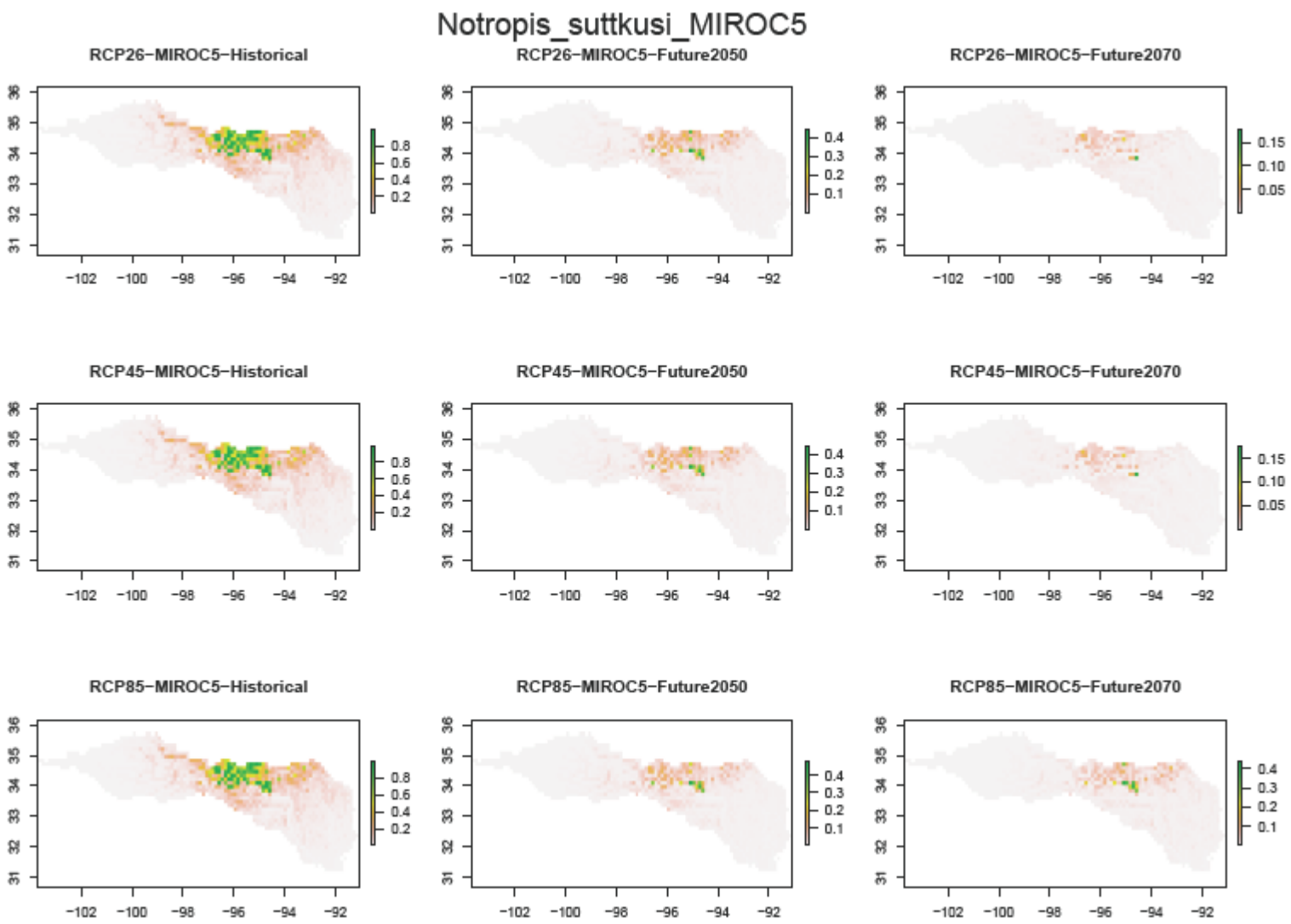


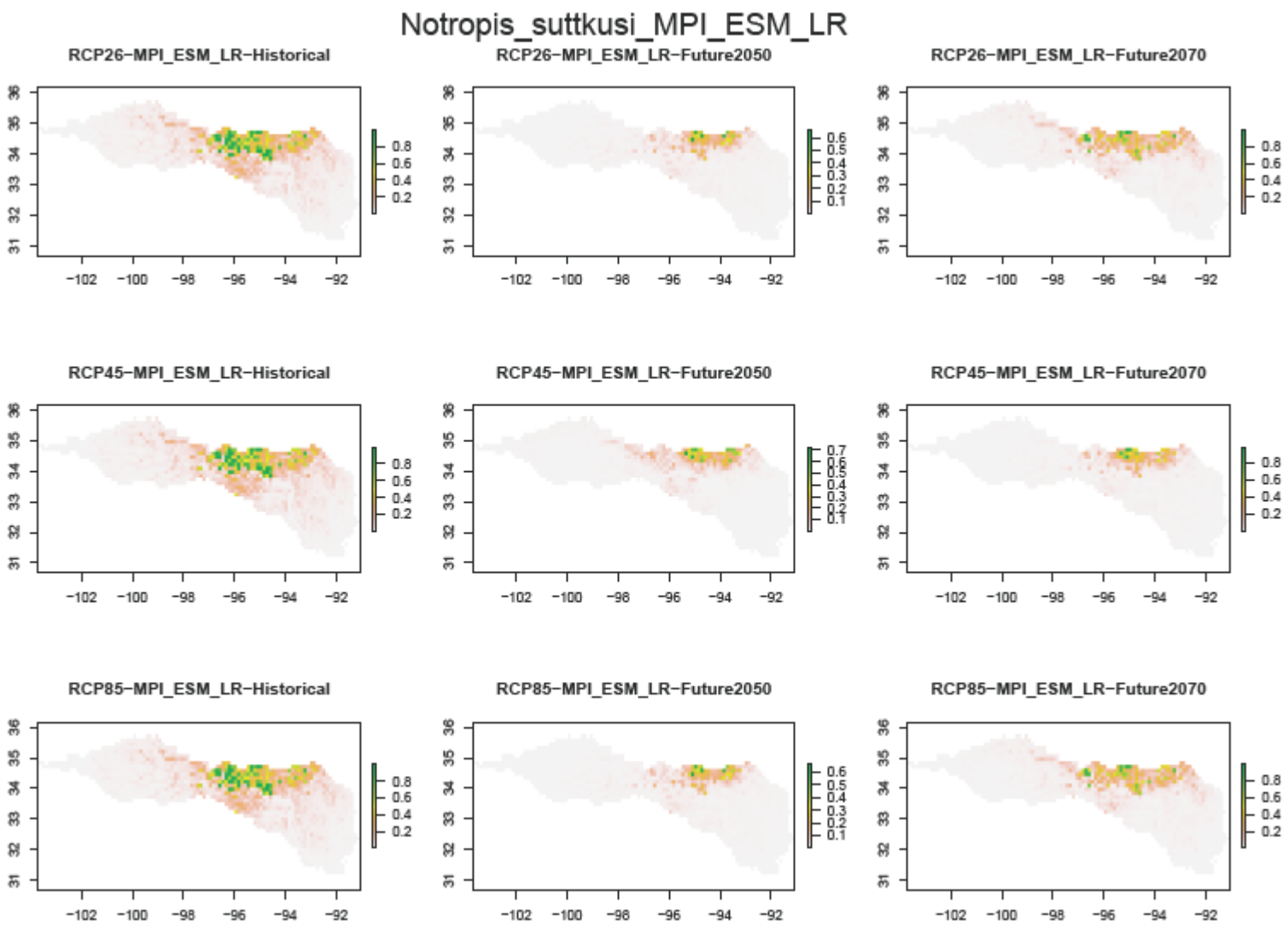

NotropisstramineusMIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070


NotropisstramineusMPI_ESM_LR
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

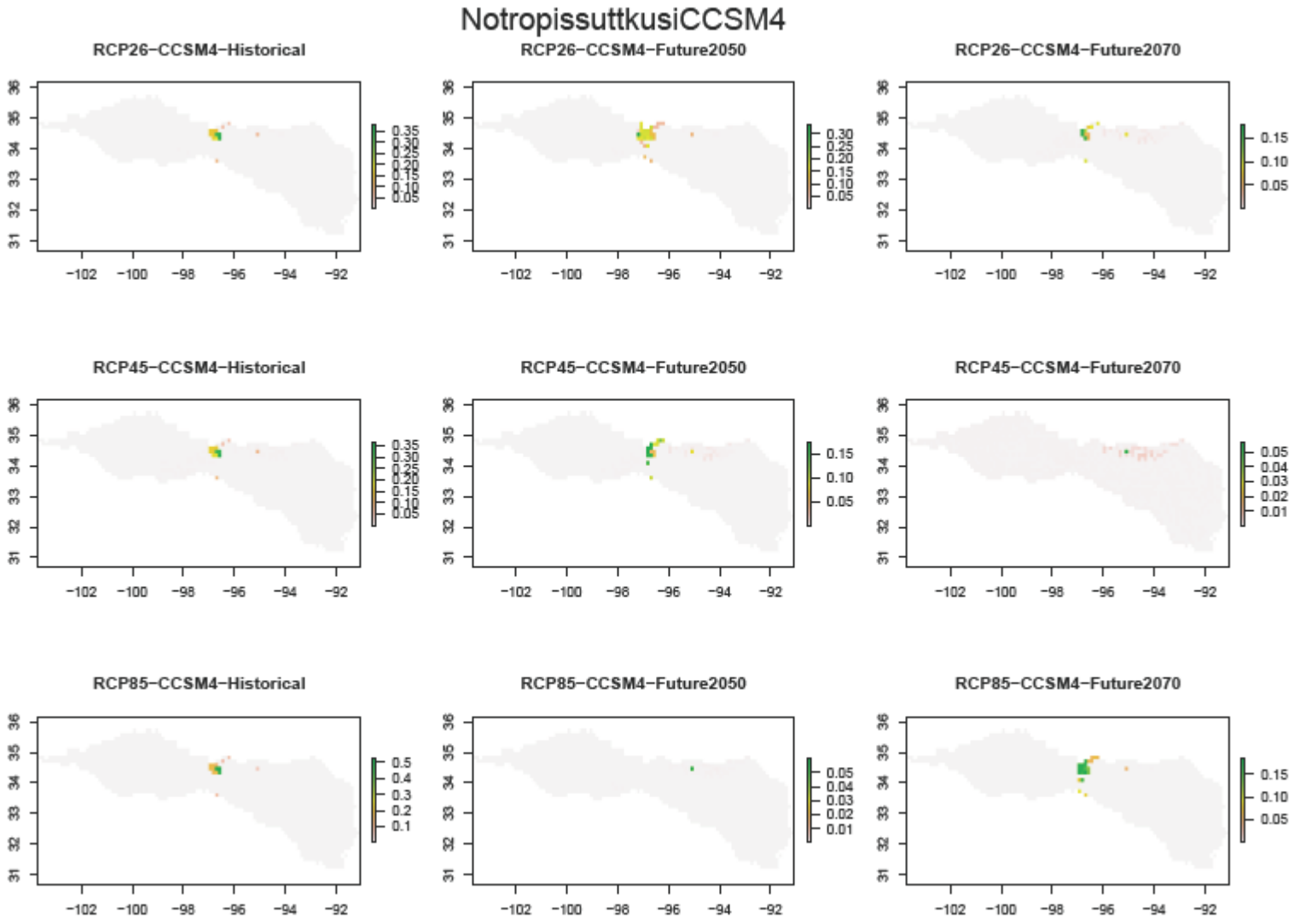
Maxent: *Notropis suttkusi*

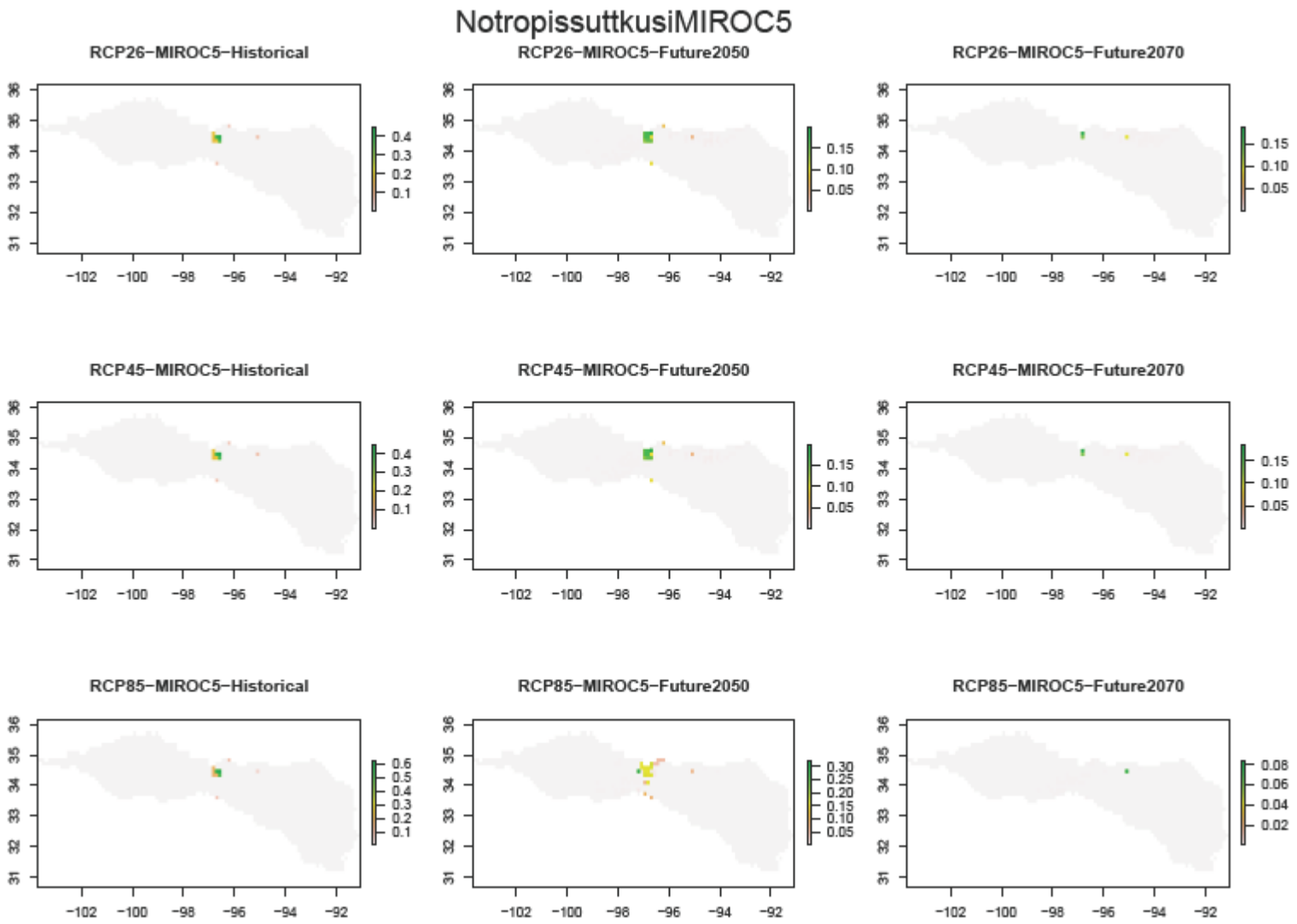


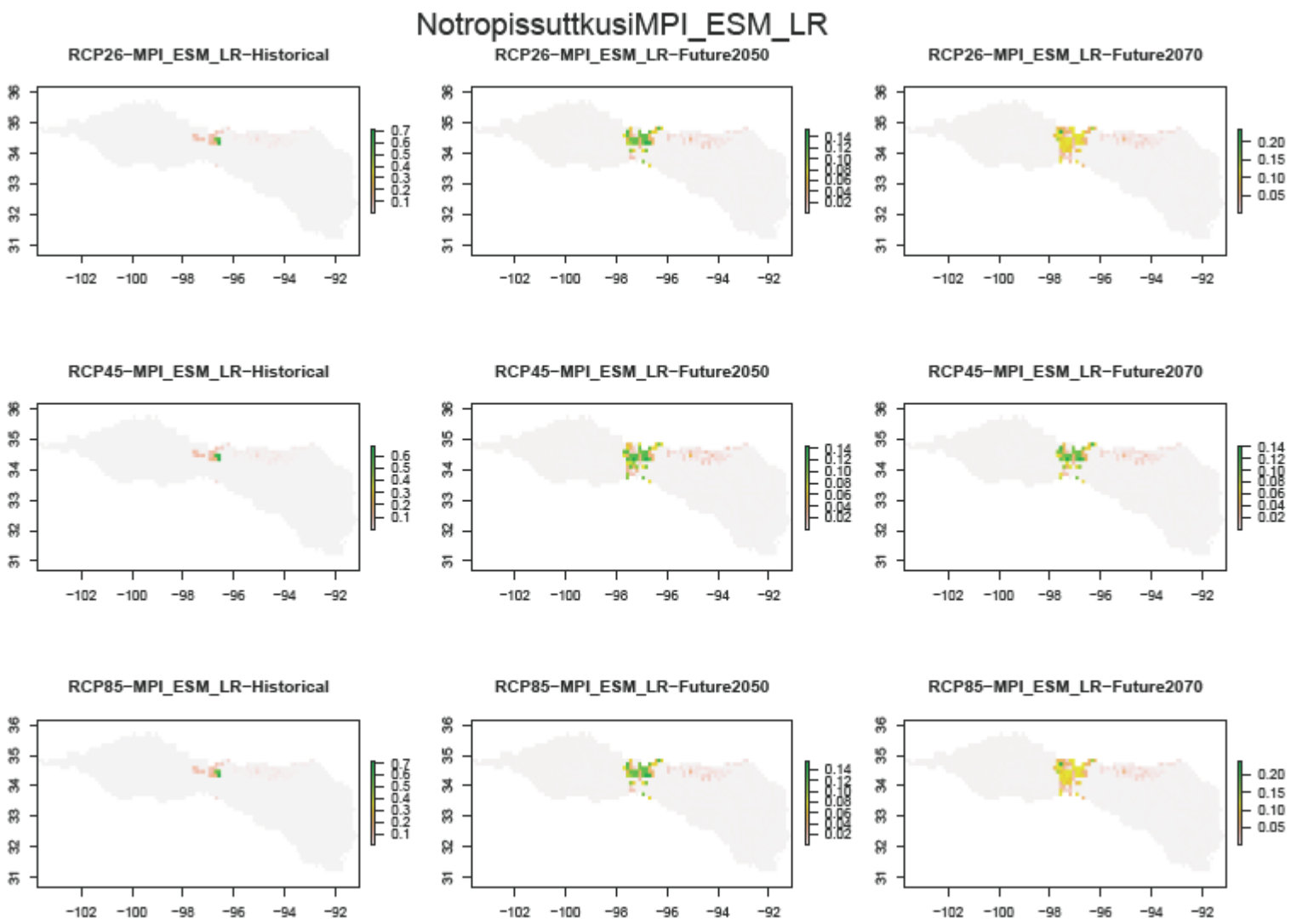

Notropis_suttkusi_MIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070


Notropis_suttkusi_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

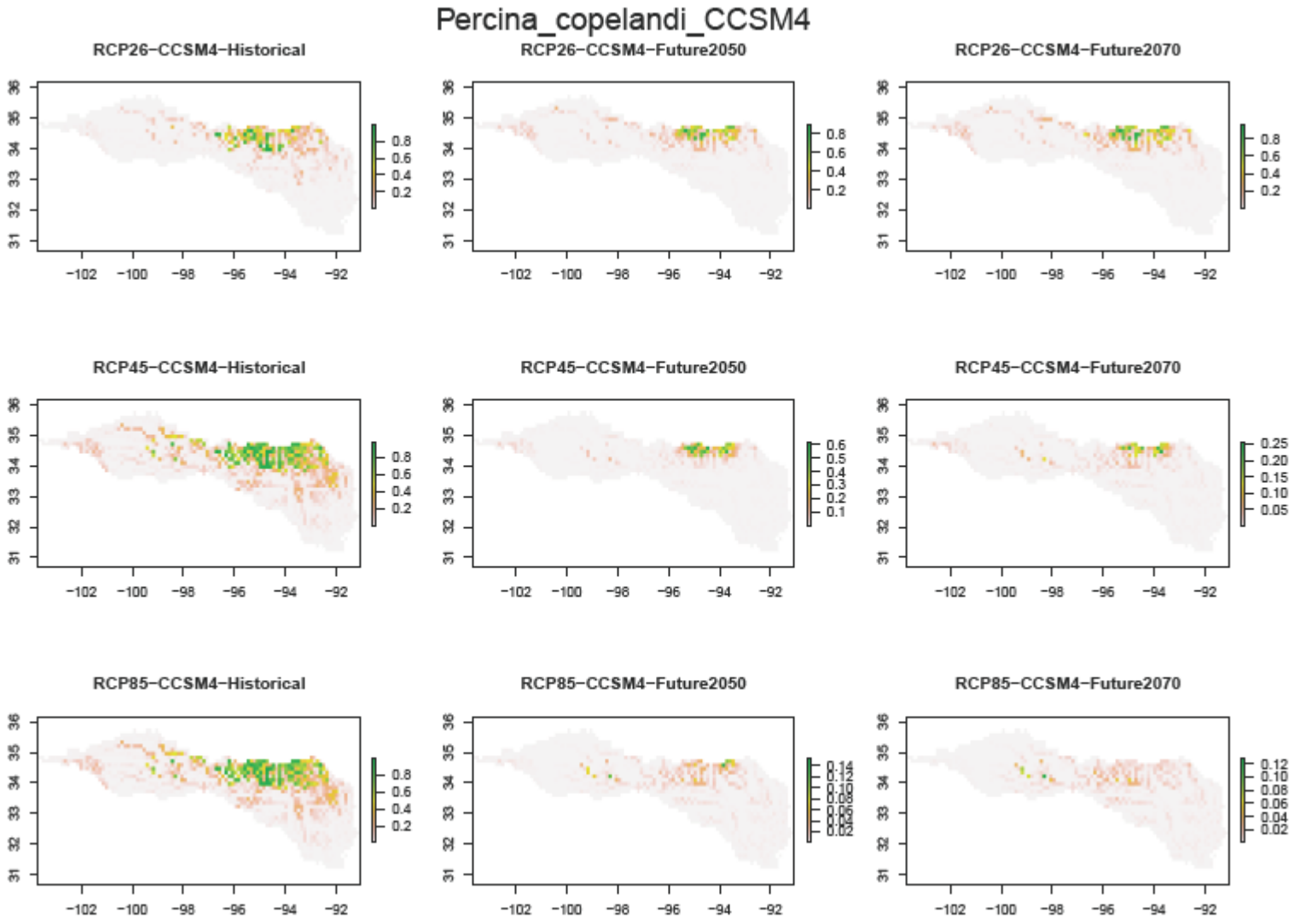
BRT: *Notropis suttkusi*

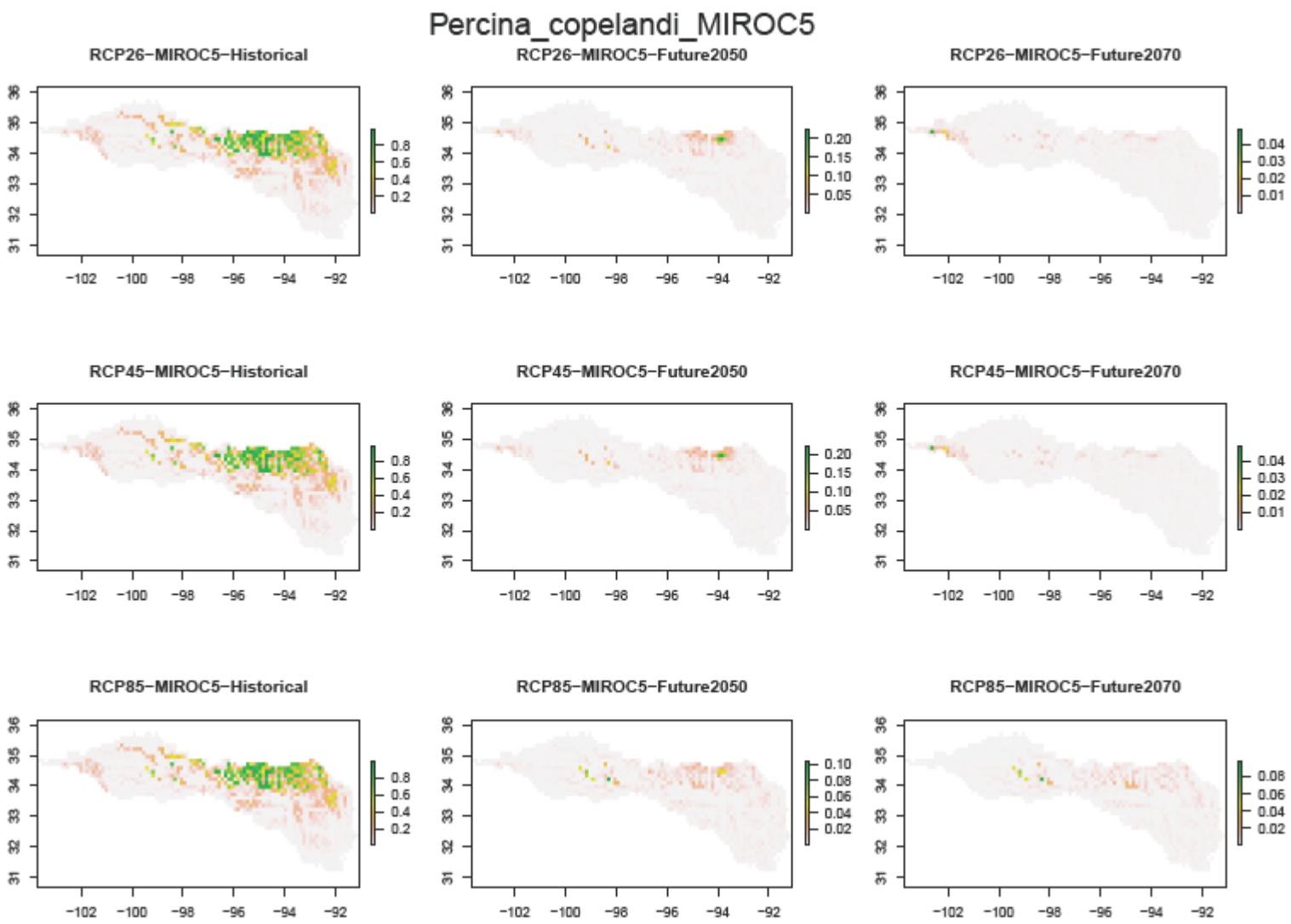


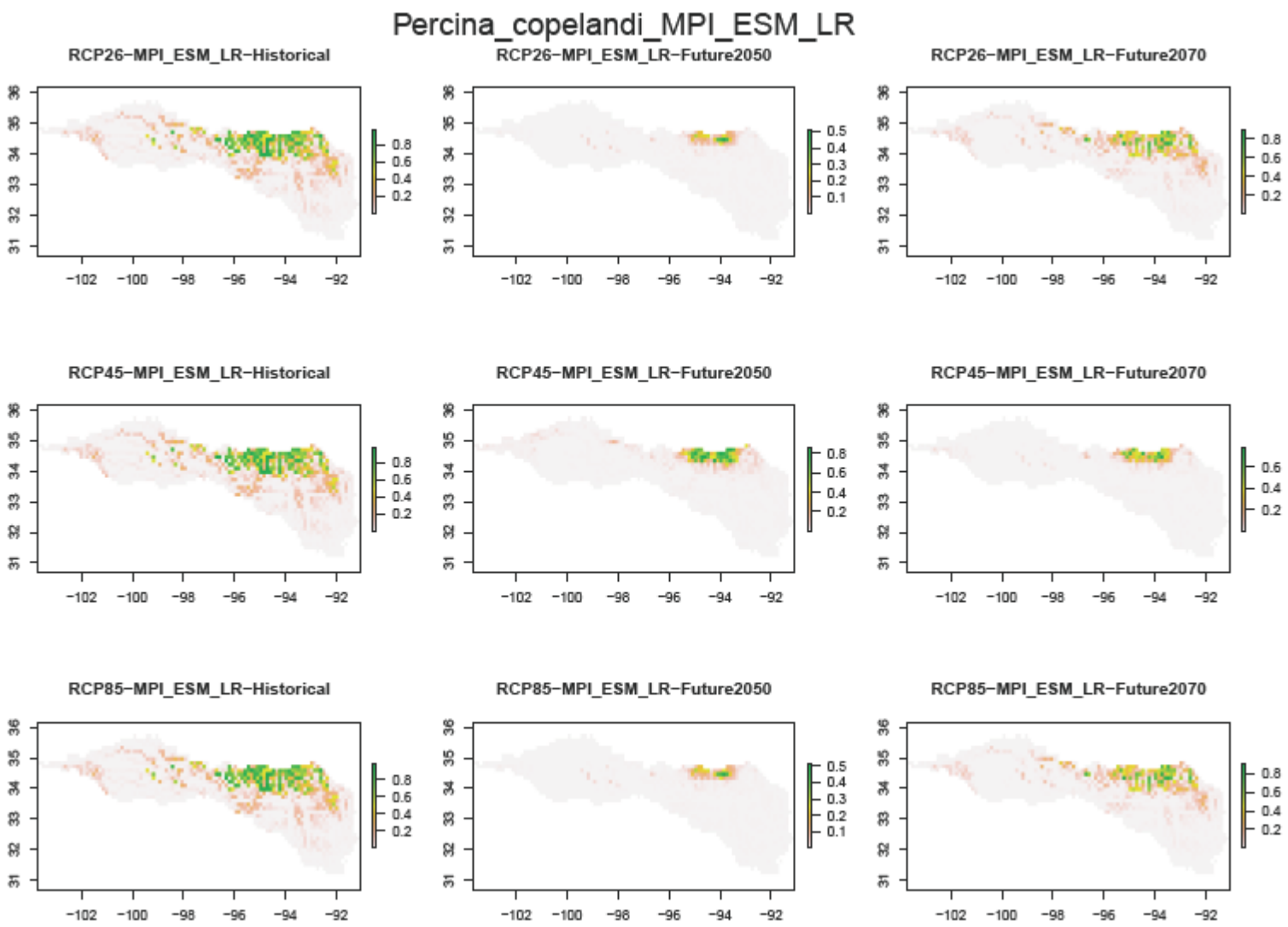

NotropissuttkusiMIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070


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

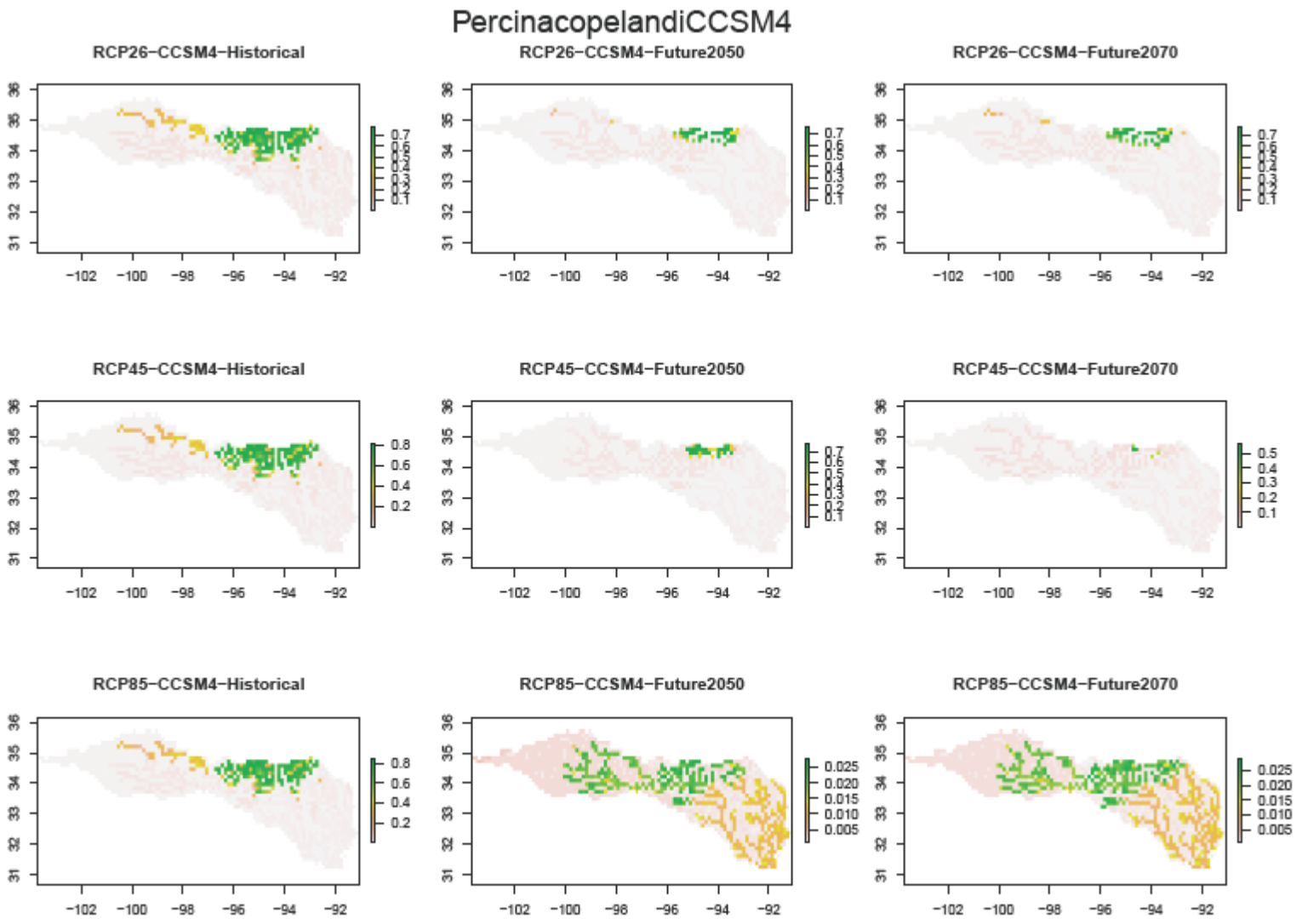
Maxent: *Percina copelandi*

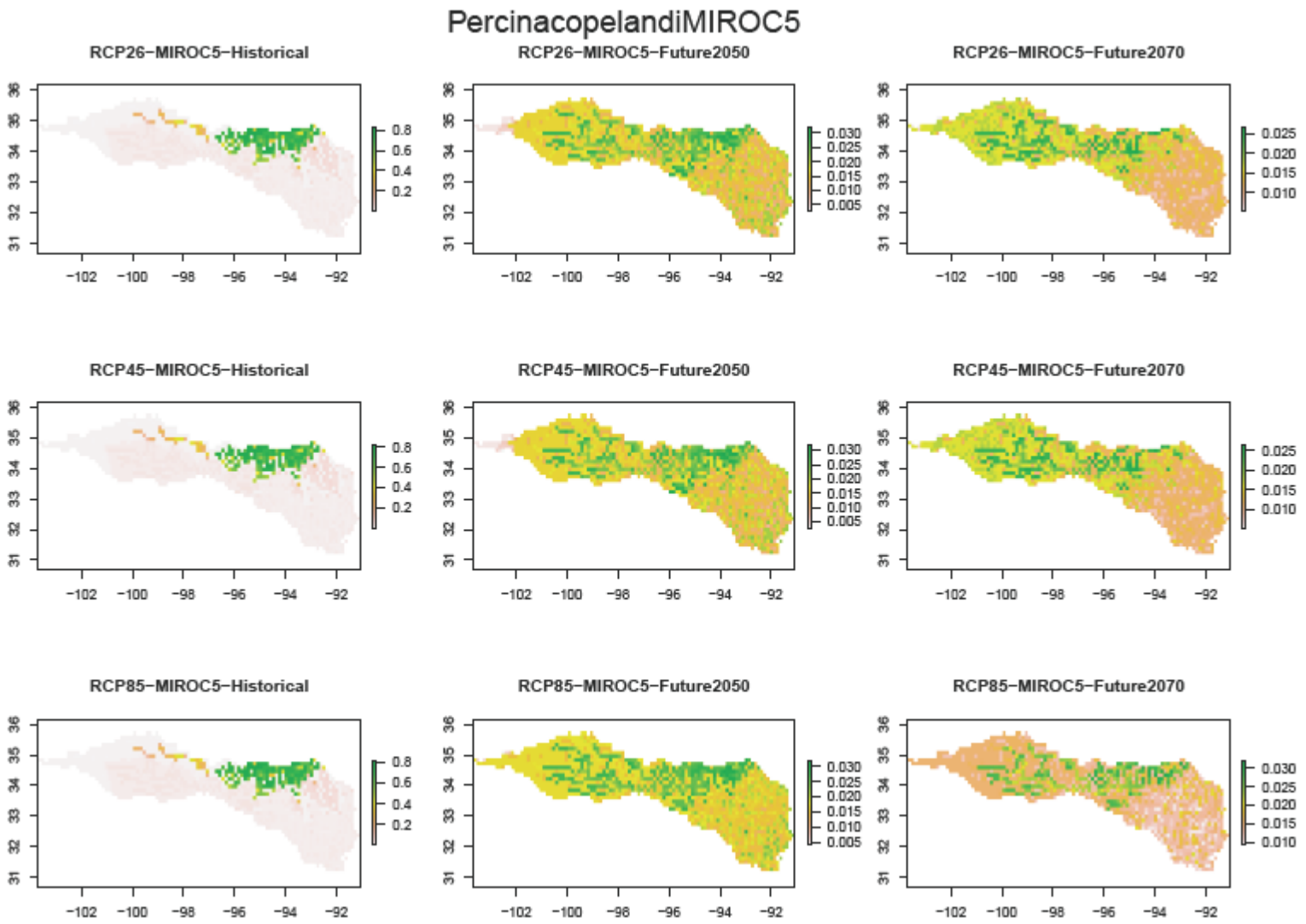


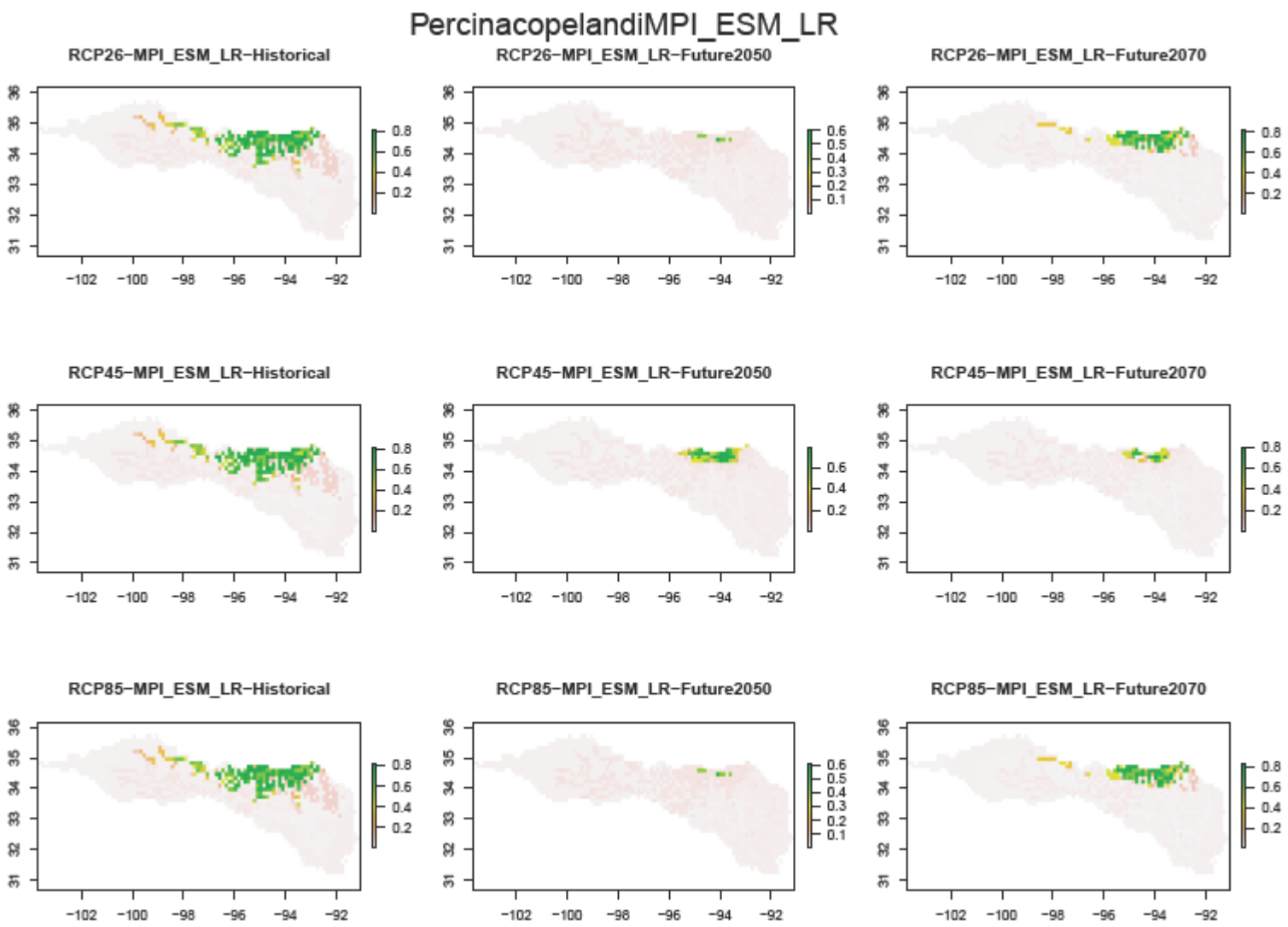

Percina_copelandi_MIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070


Percina_copelandi_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

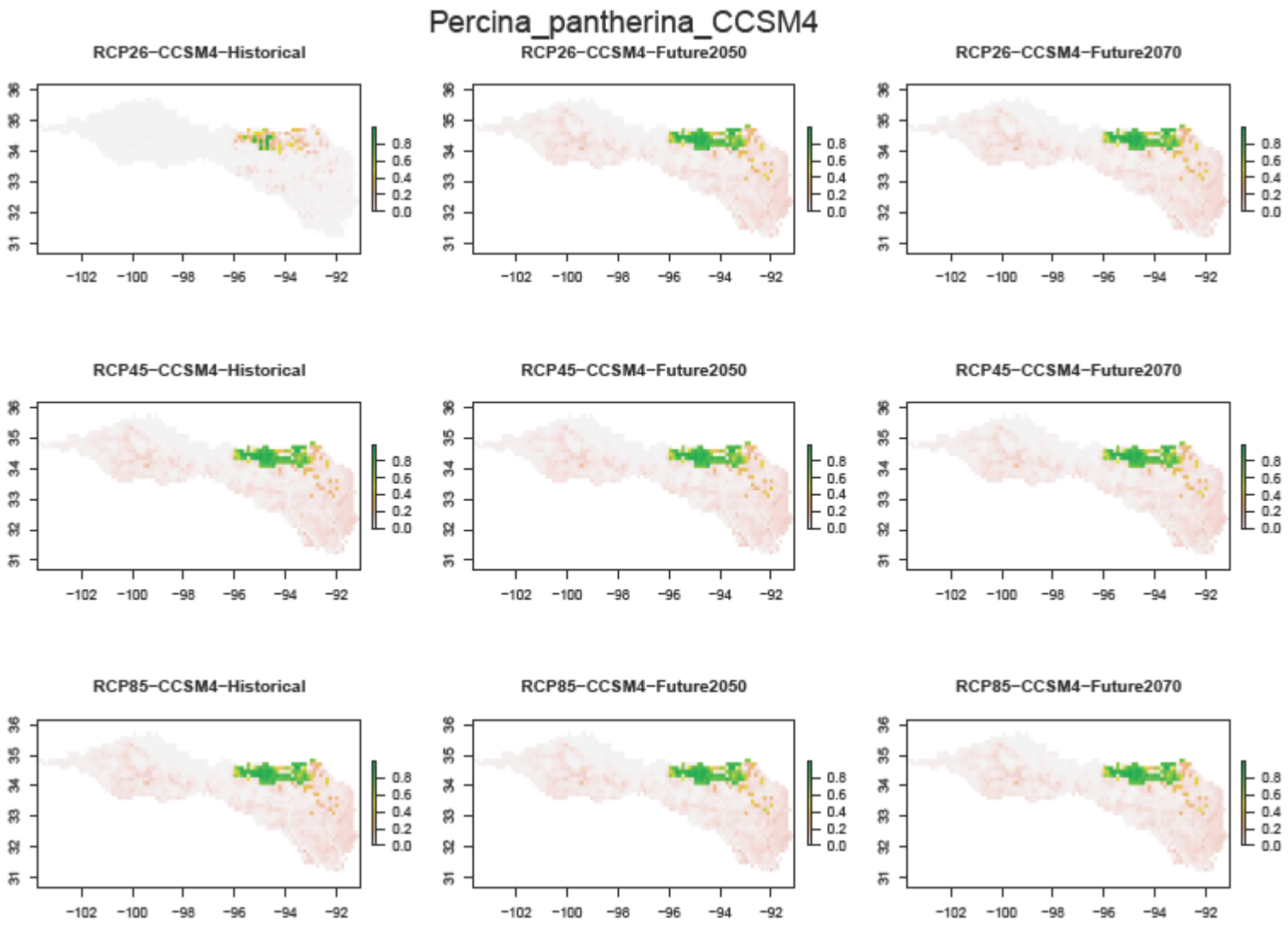
BRT: *Percina copelandi*

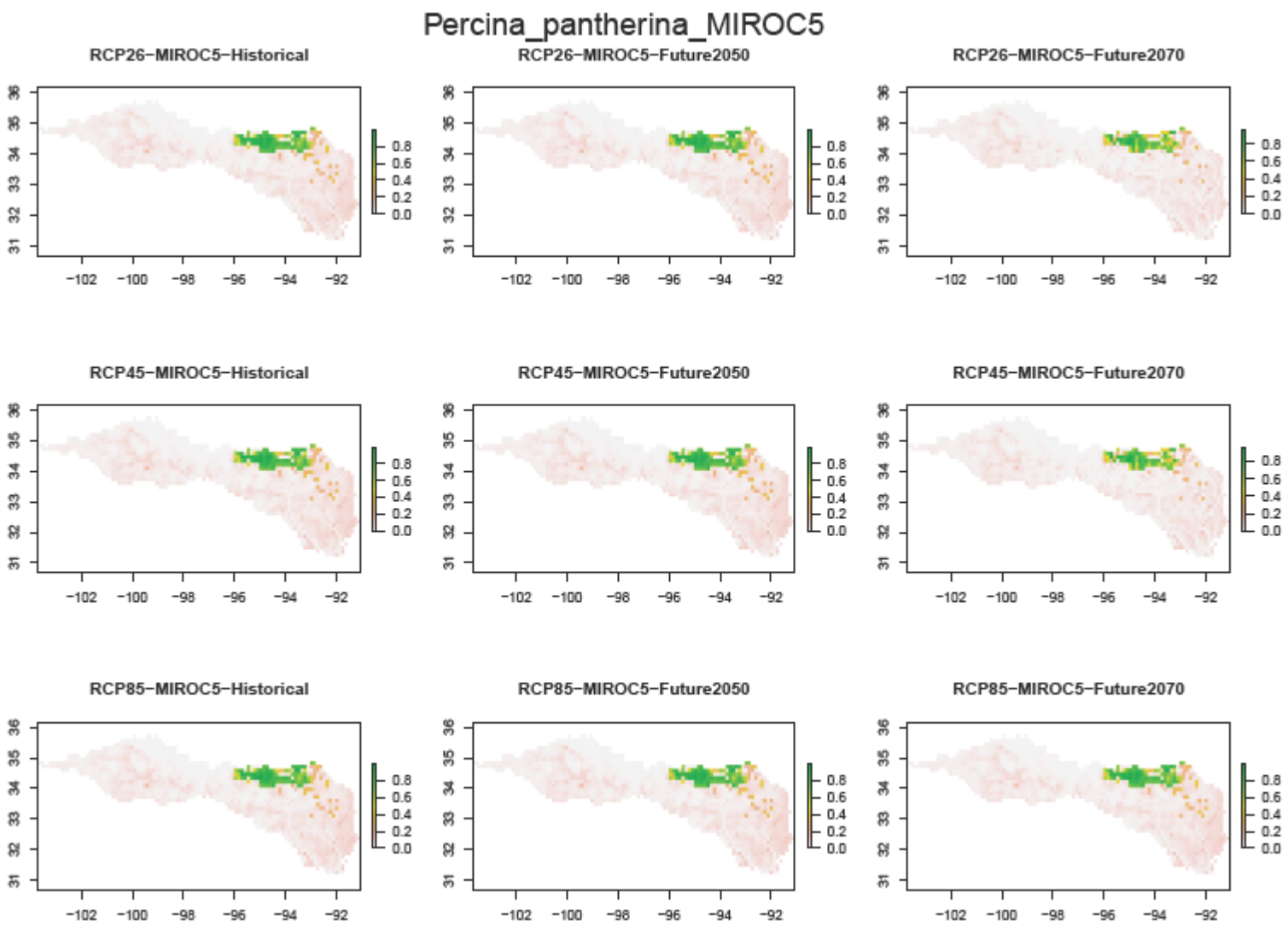


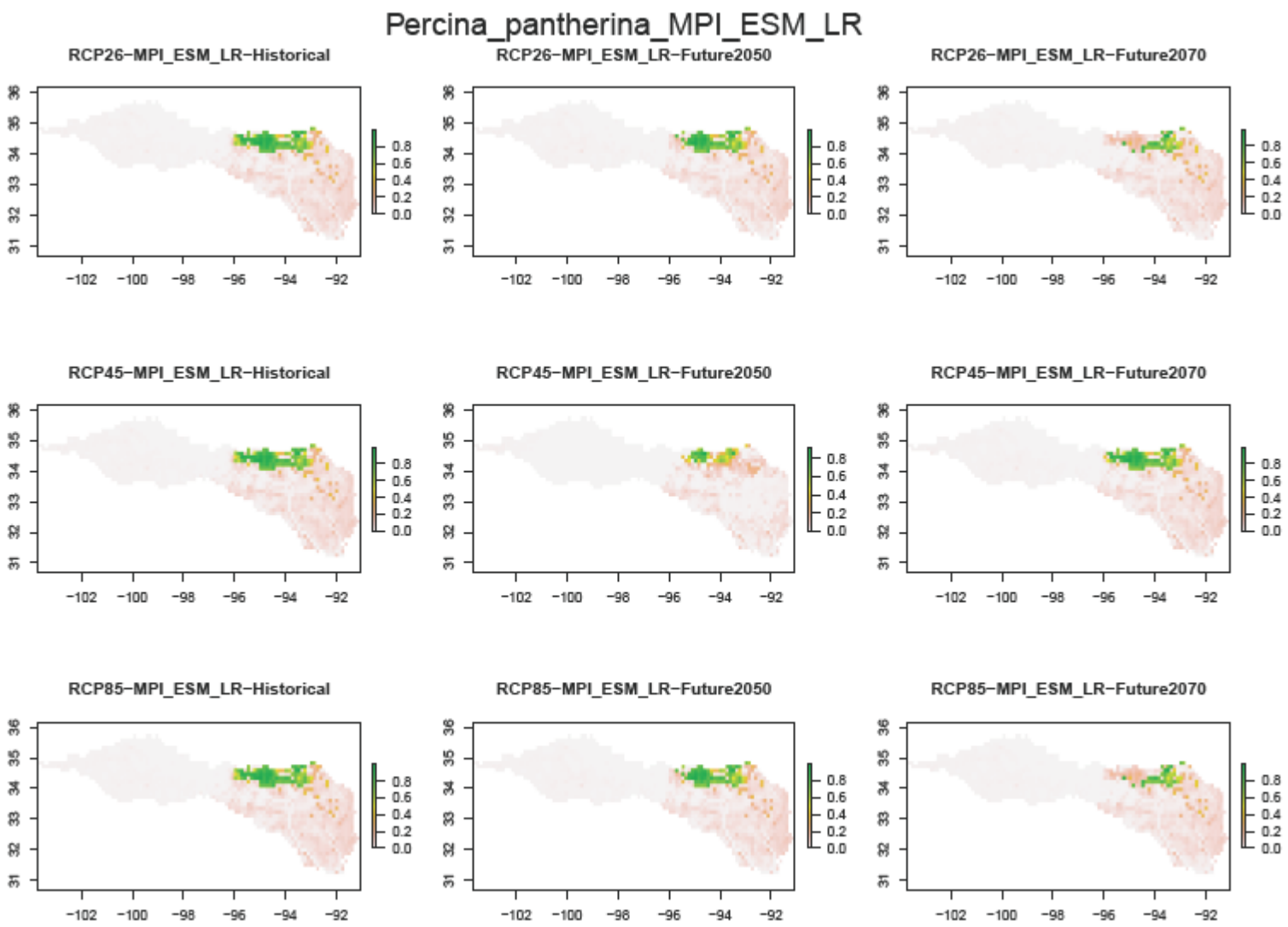

PercinacopelandiMIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070
31
32
33
34
35
36
−102
−100
−98
−96
−94
−92
0.8
0.6
0.4
0.2
0.030
0.025
0.020
0.015
0.010
0.005


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

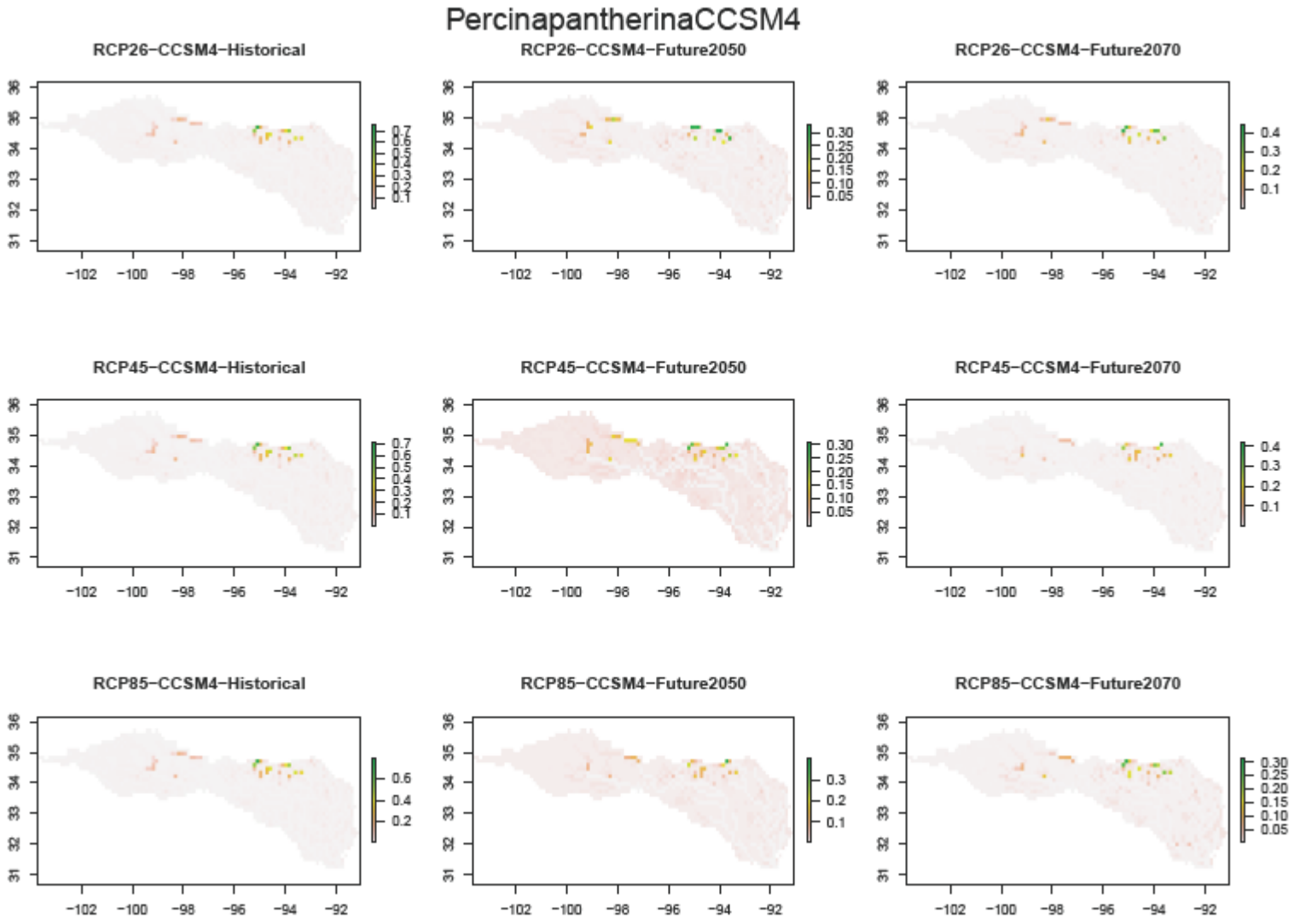
Maxent: *Percina pantherina*

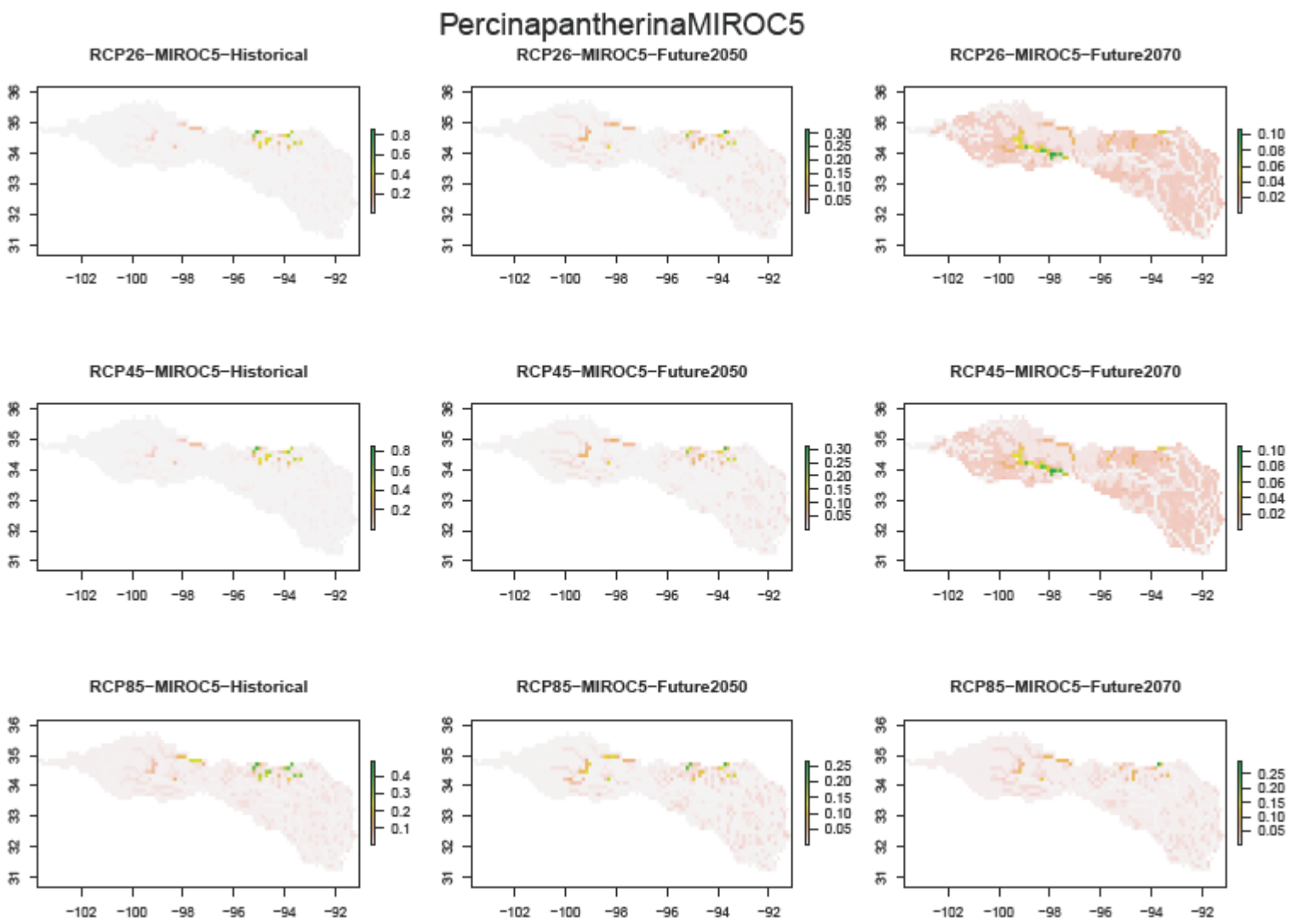


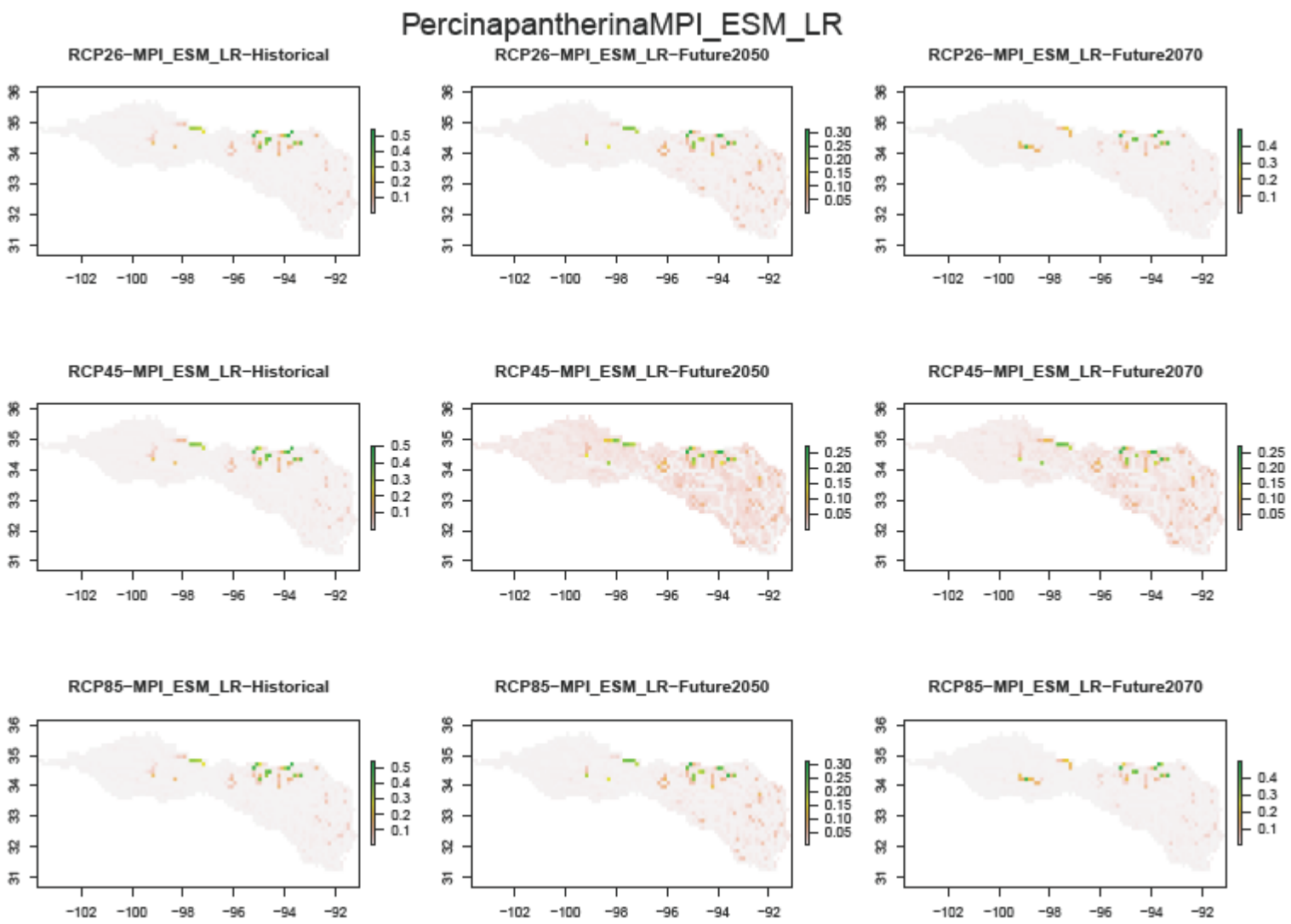

Percina_pantherina_MIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070
31
32
33
34
35
36
−102
−100
−98
−96
−94
−92
0.0
0.2
0.4
0.6
0.8


Percina_pantherina_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
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36
-102
-100
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-96
-94
-92
0.0
0.2
0.4
0.6
0.8

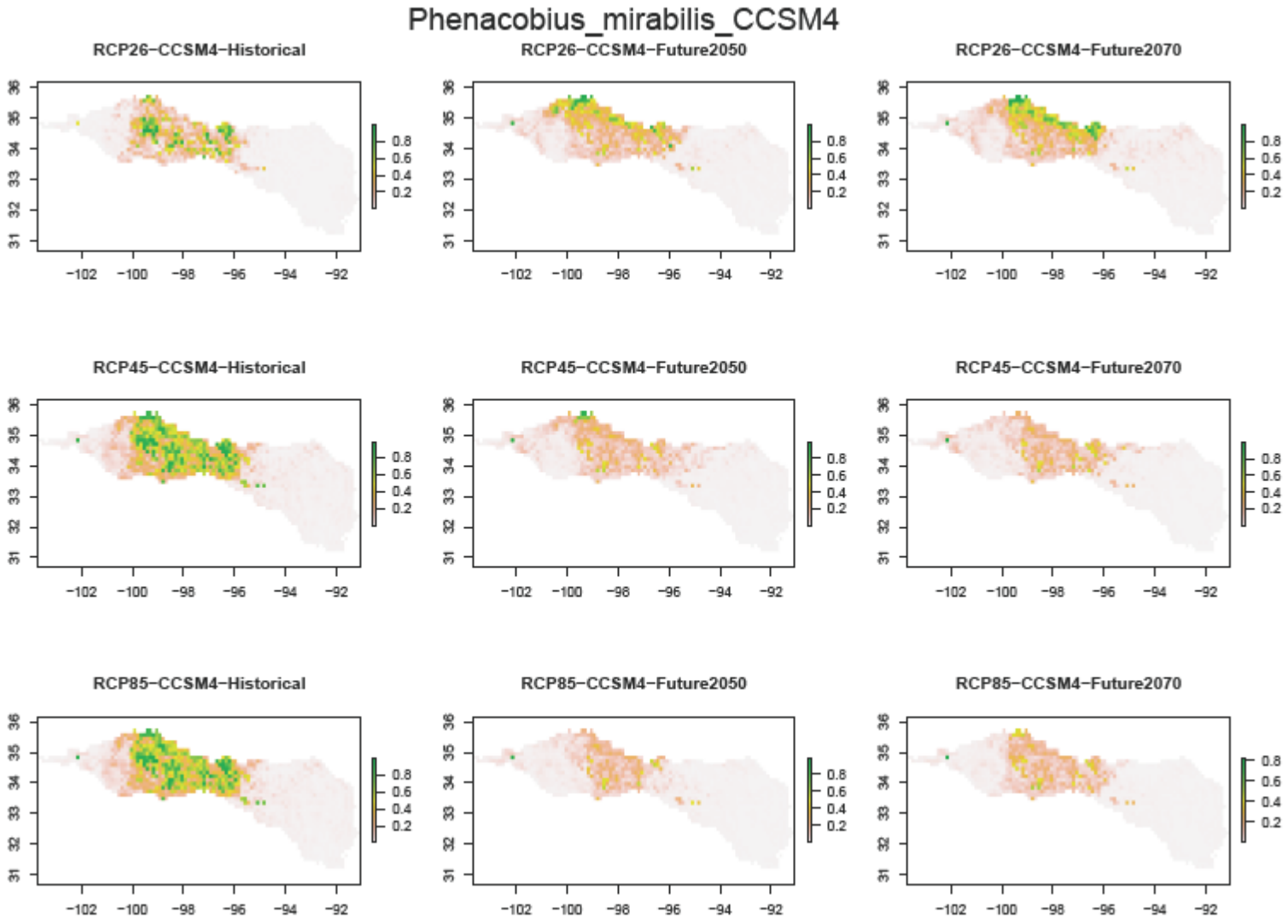
BRT: *Percina pantherina*

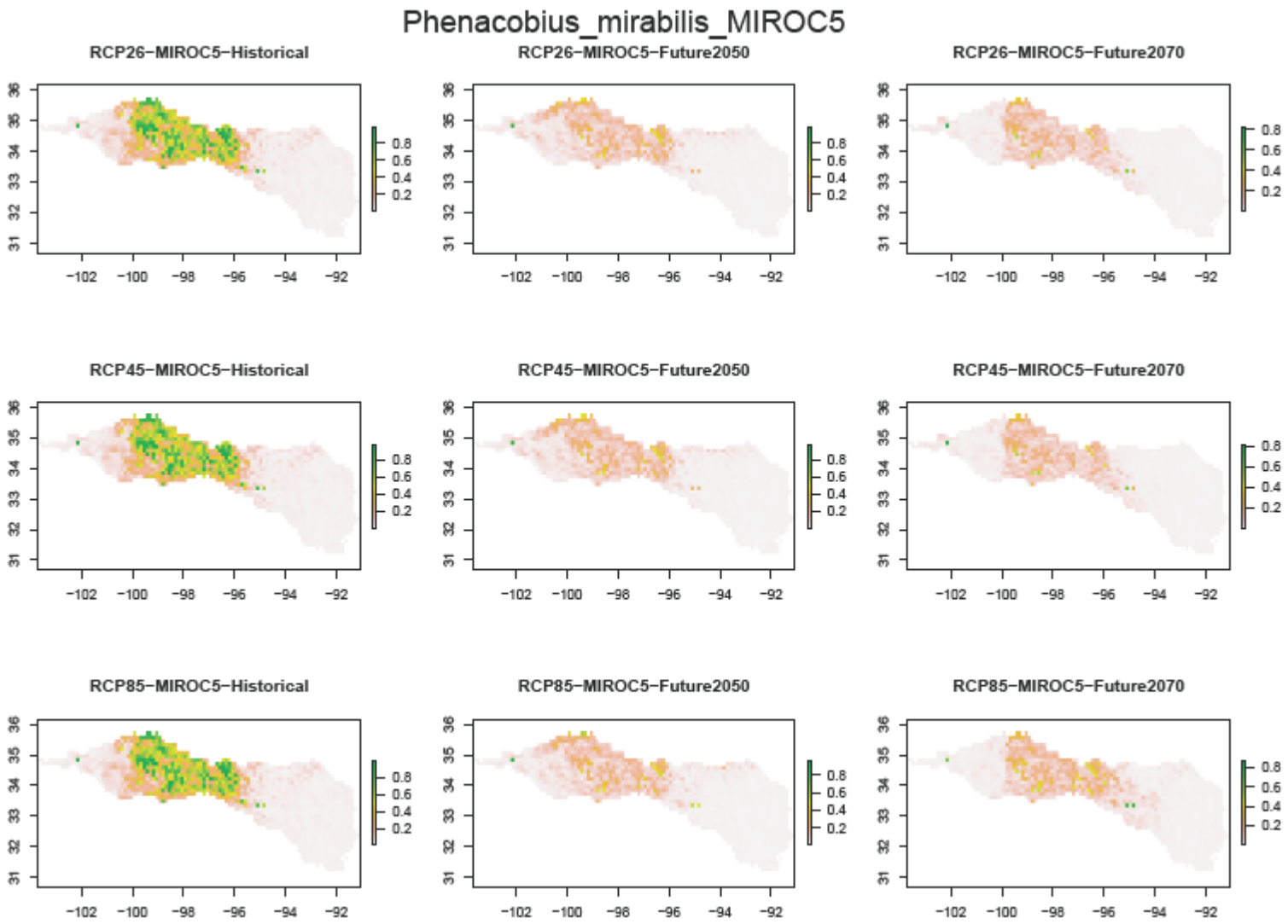


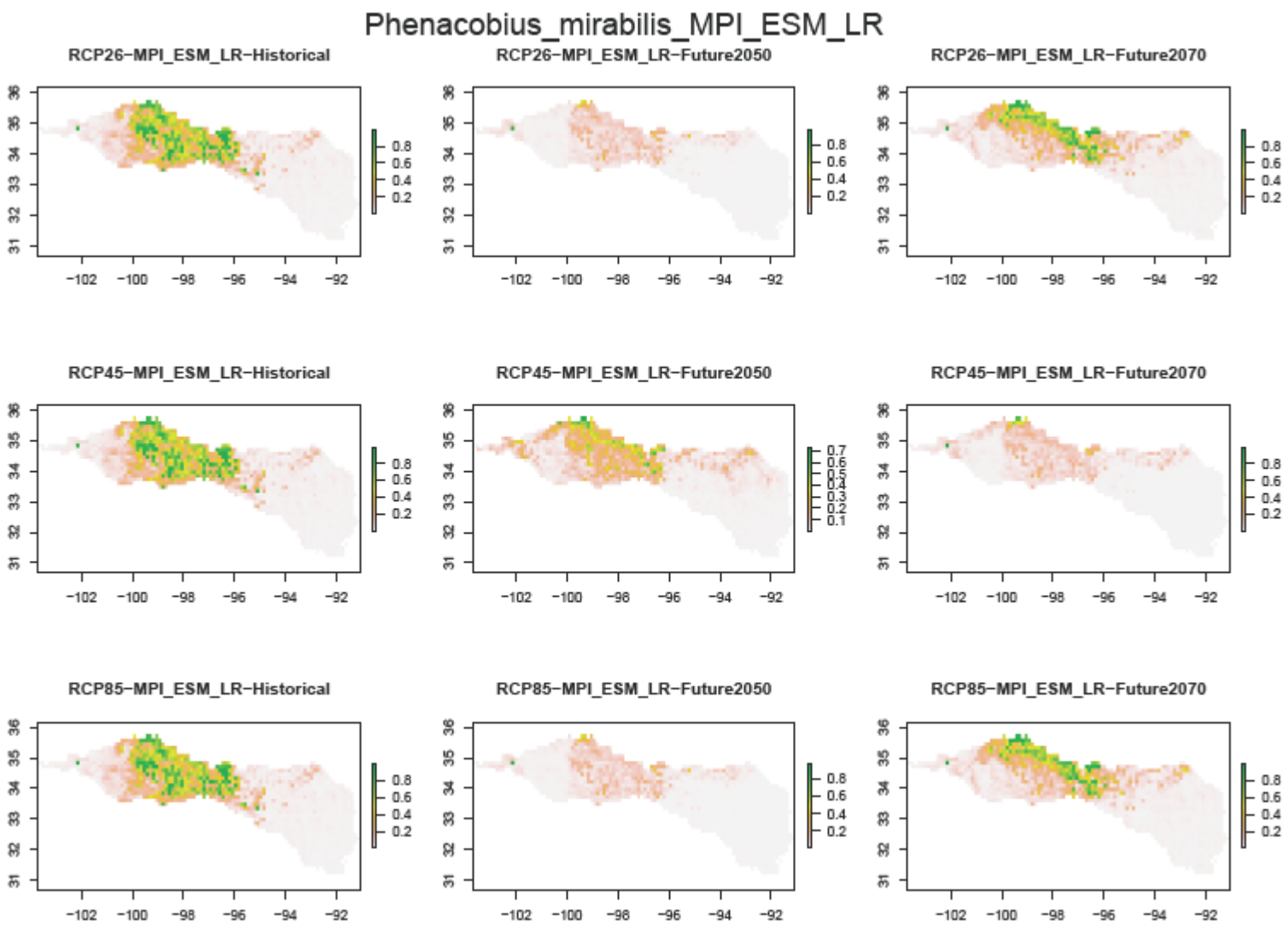

PercinapantherinaMIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070


PercinapantherinaMPI_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

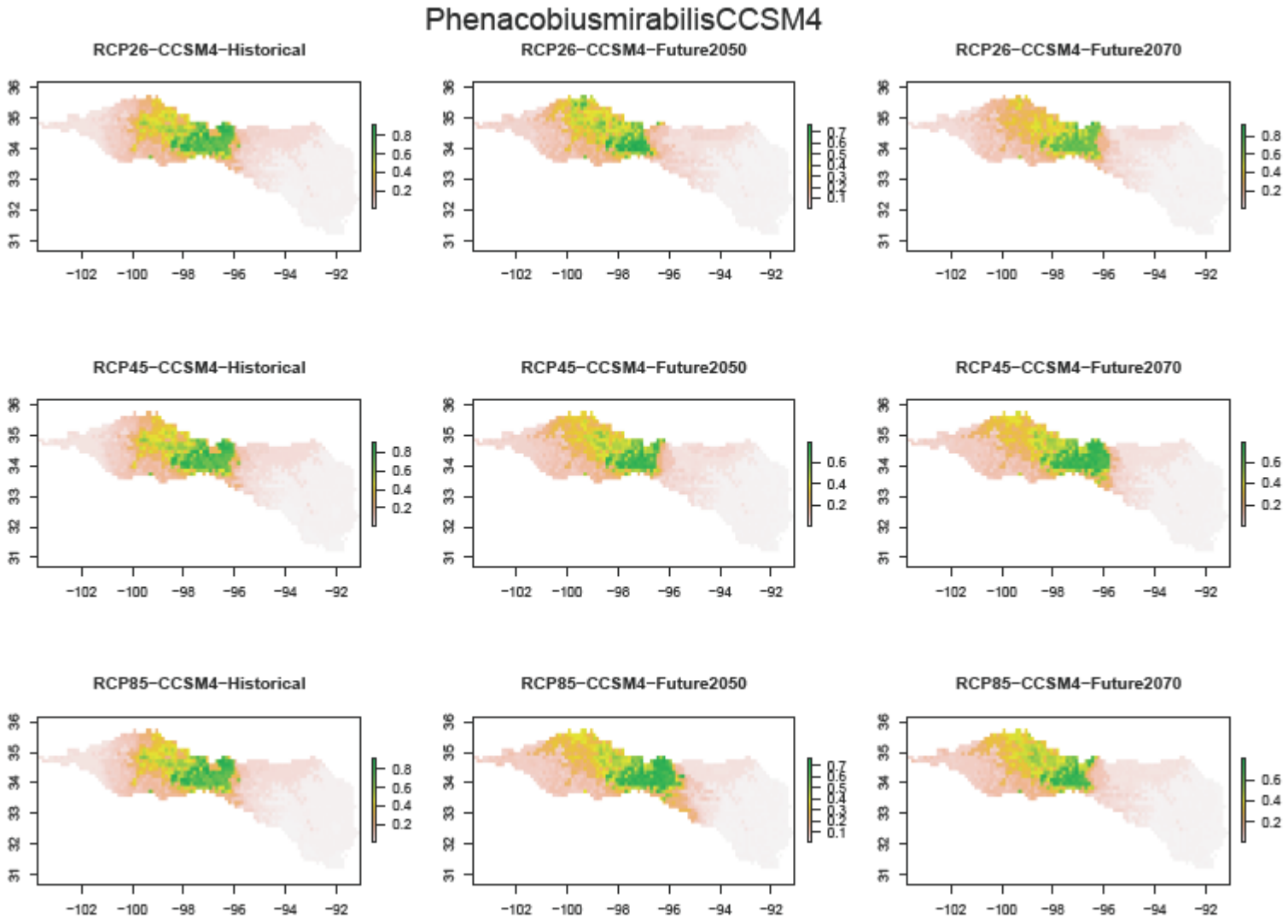
Maxent: *Phenacobius mirabilis*

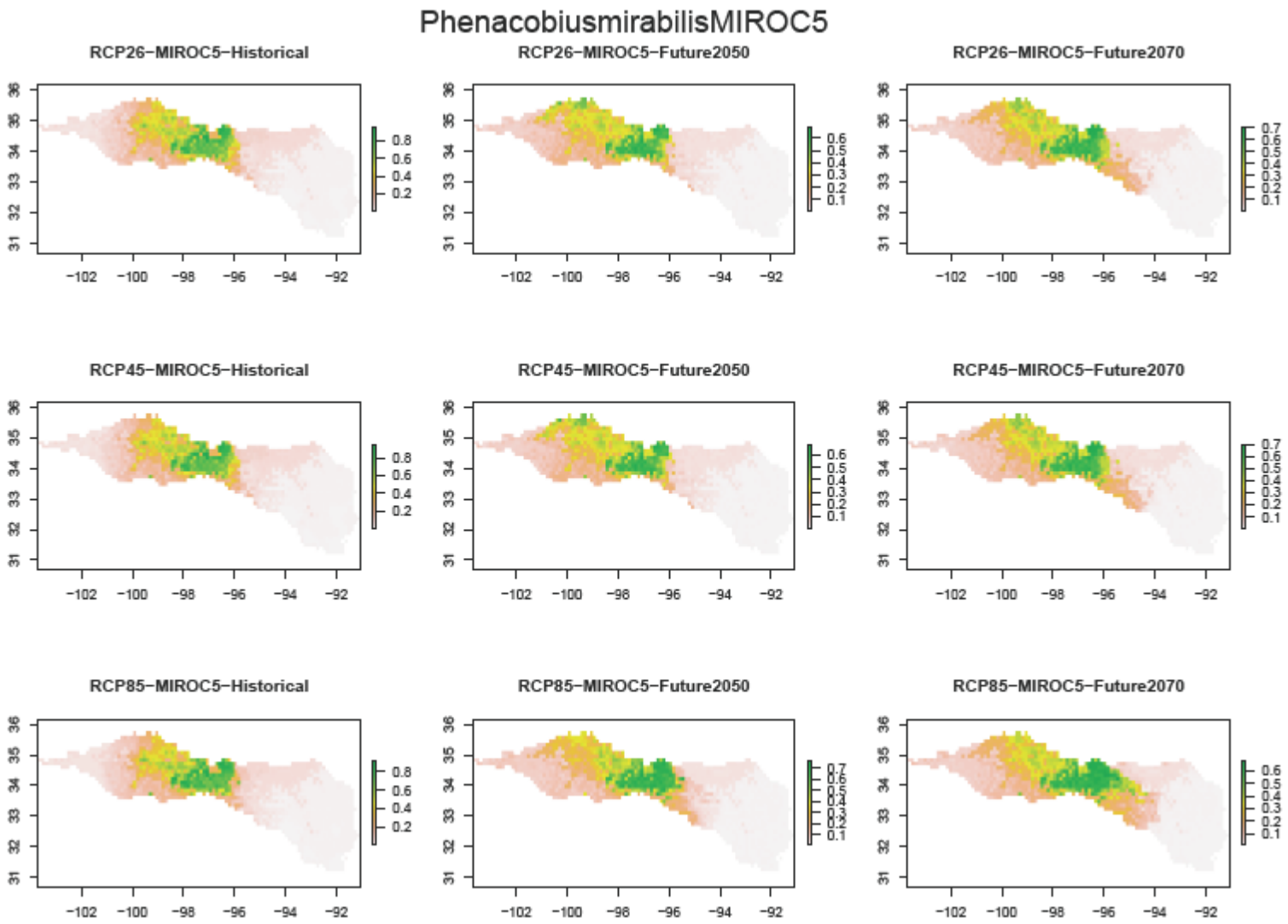



Phenacobius_mirabilis_MIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070
0.8
0.6
0.4
0.2
−102
−100
−98
−96
−94
−92
31
32
33
34
35
36


Phenacobius_mirabilis_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

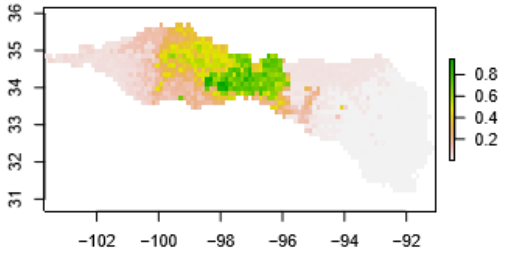
BRT: *Phenacobius mirabilis*



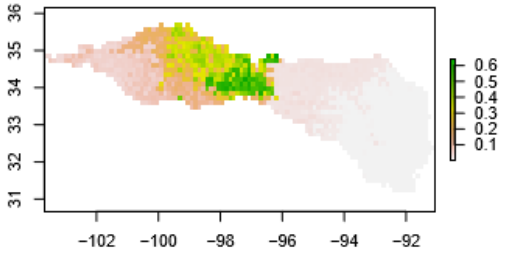

PhenacobiusmirabilisMIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070

# PhenacobiusmirabilisMPI_ESM_LR

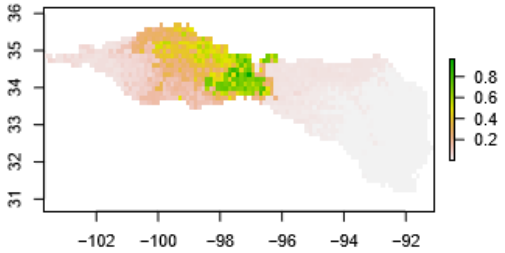
RCP26-MPI_ESM_LR-Historical



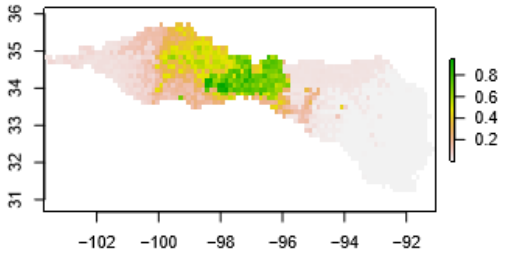

RCP26-MPI_ESM_LR-Future2050



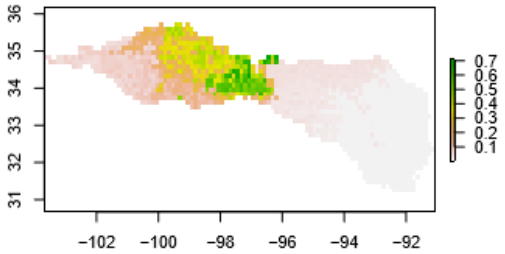

RCP26-MPI_ESM_LR-Future2070



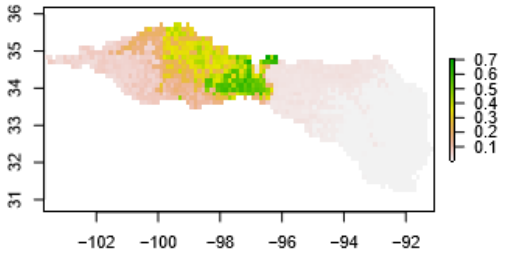

RCP45-MPI_ESM_LR-Historical



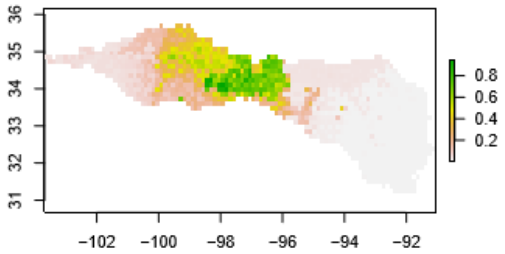

RCP45-MPI_ESM_LR-Future2050



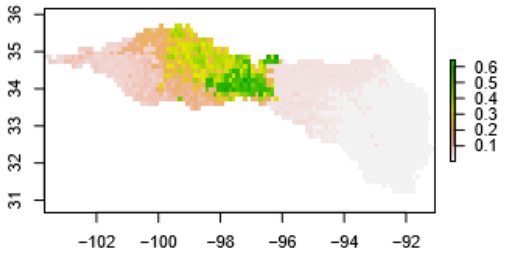

RCP45-MPI_ESM_LR-Future2070



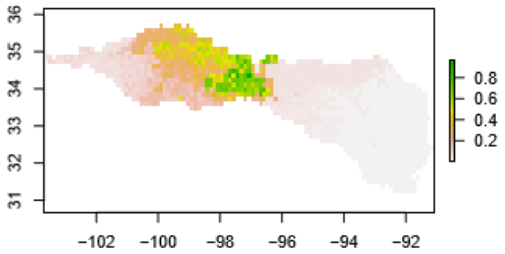

RCP85-MPI_ESM_LR-Historical



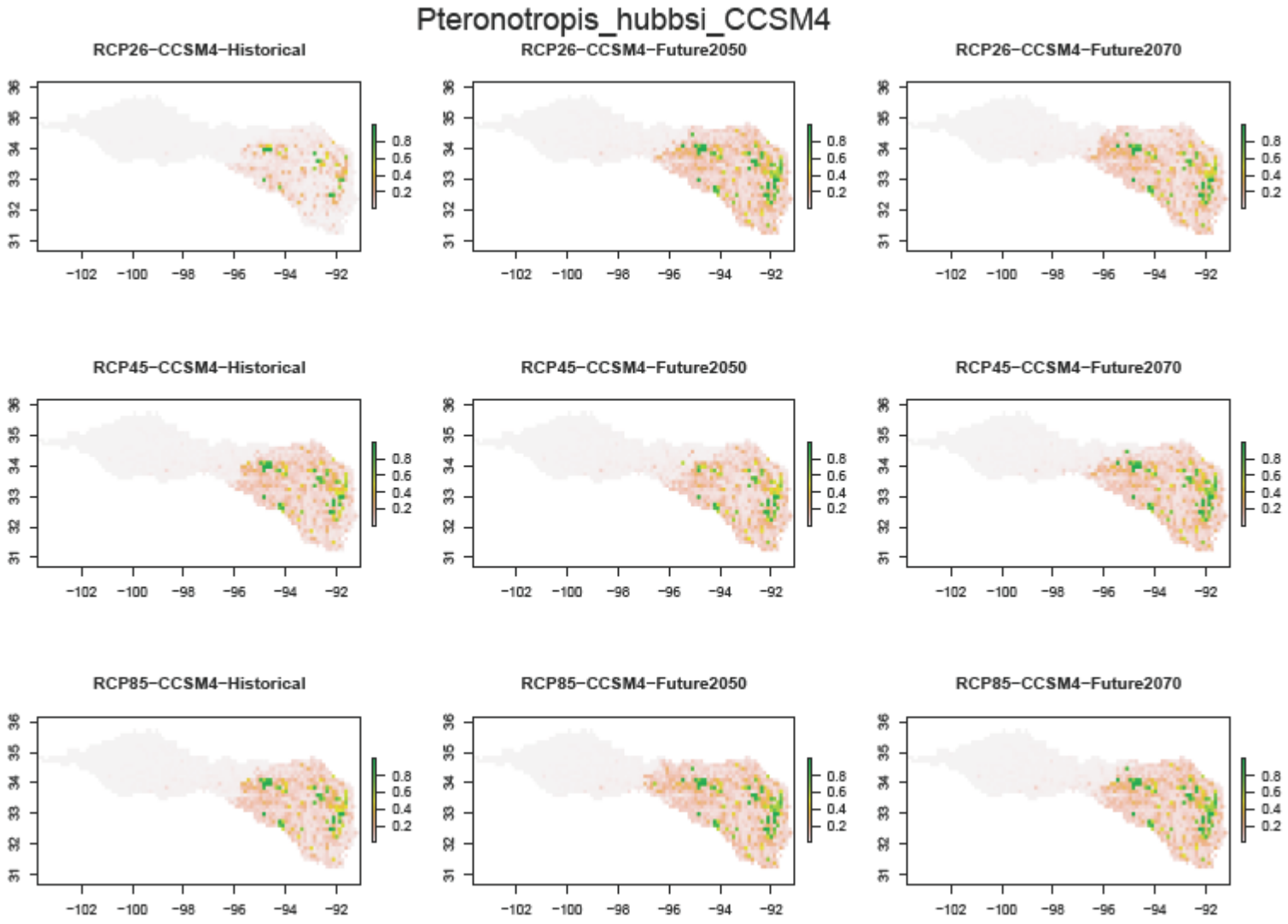

RCP85-MPI_ESM_LR-Future2050

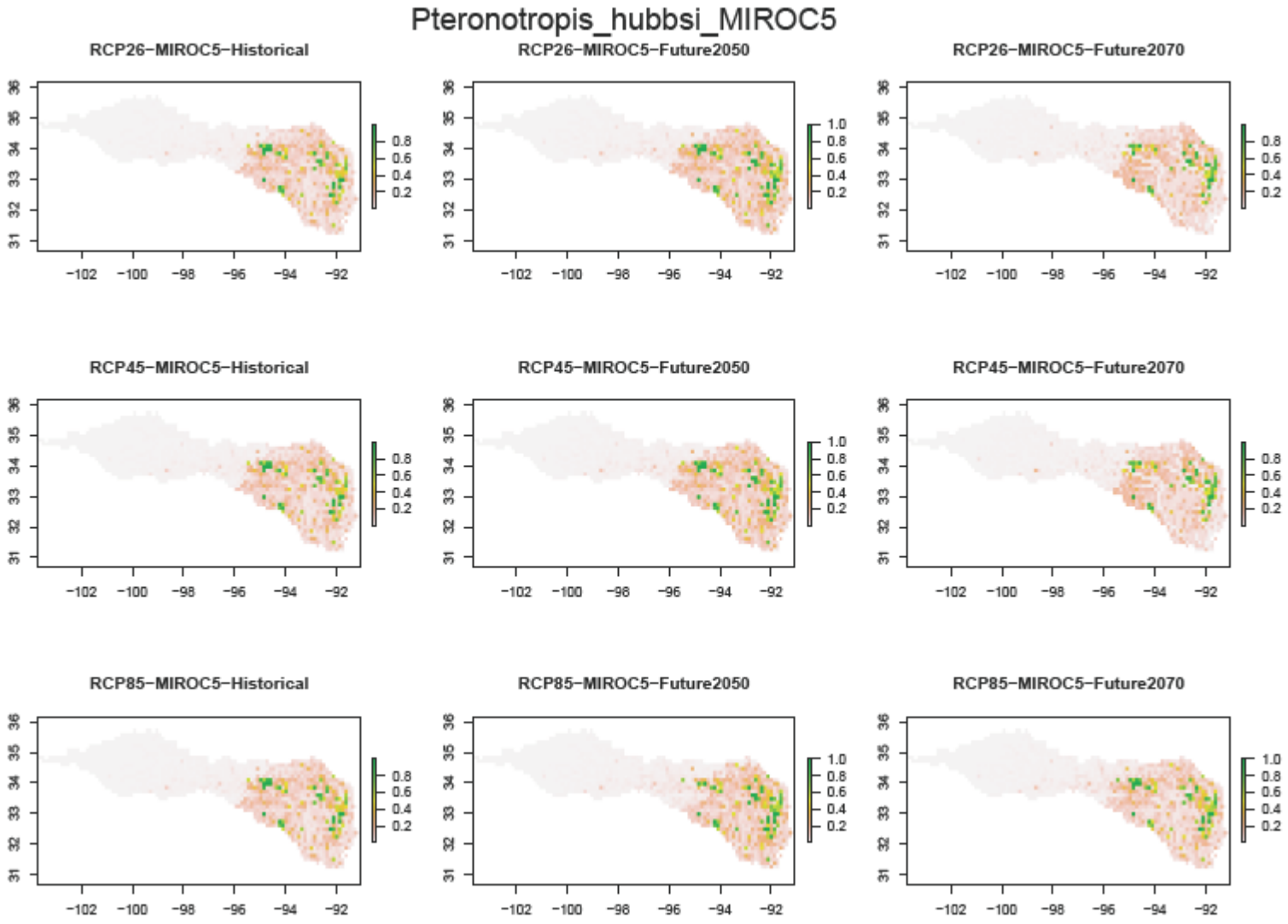


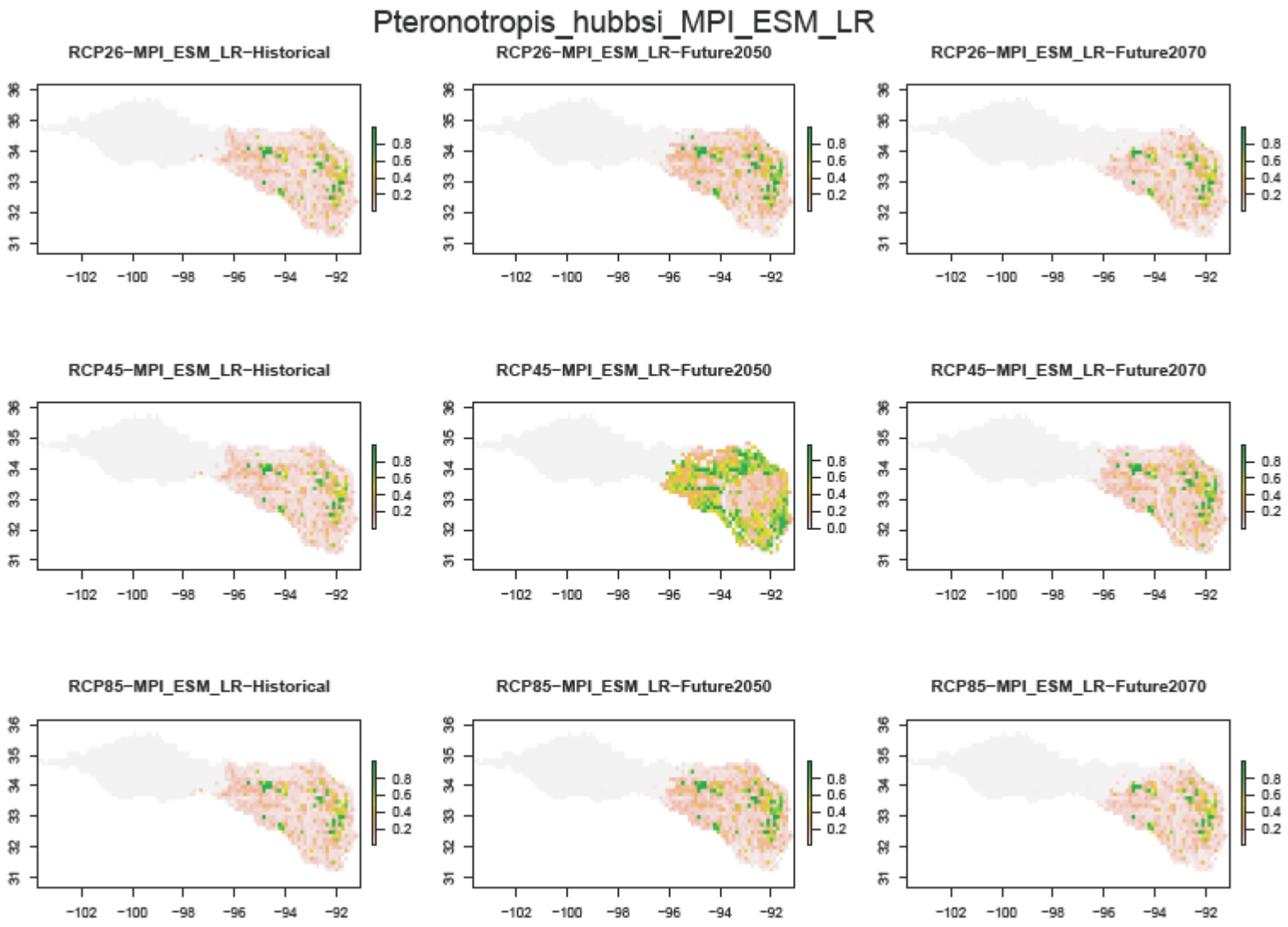

RCP85-MPI_ESM_LR-Future2070



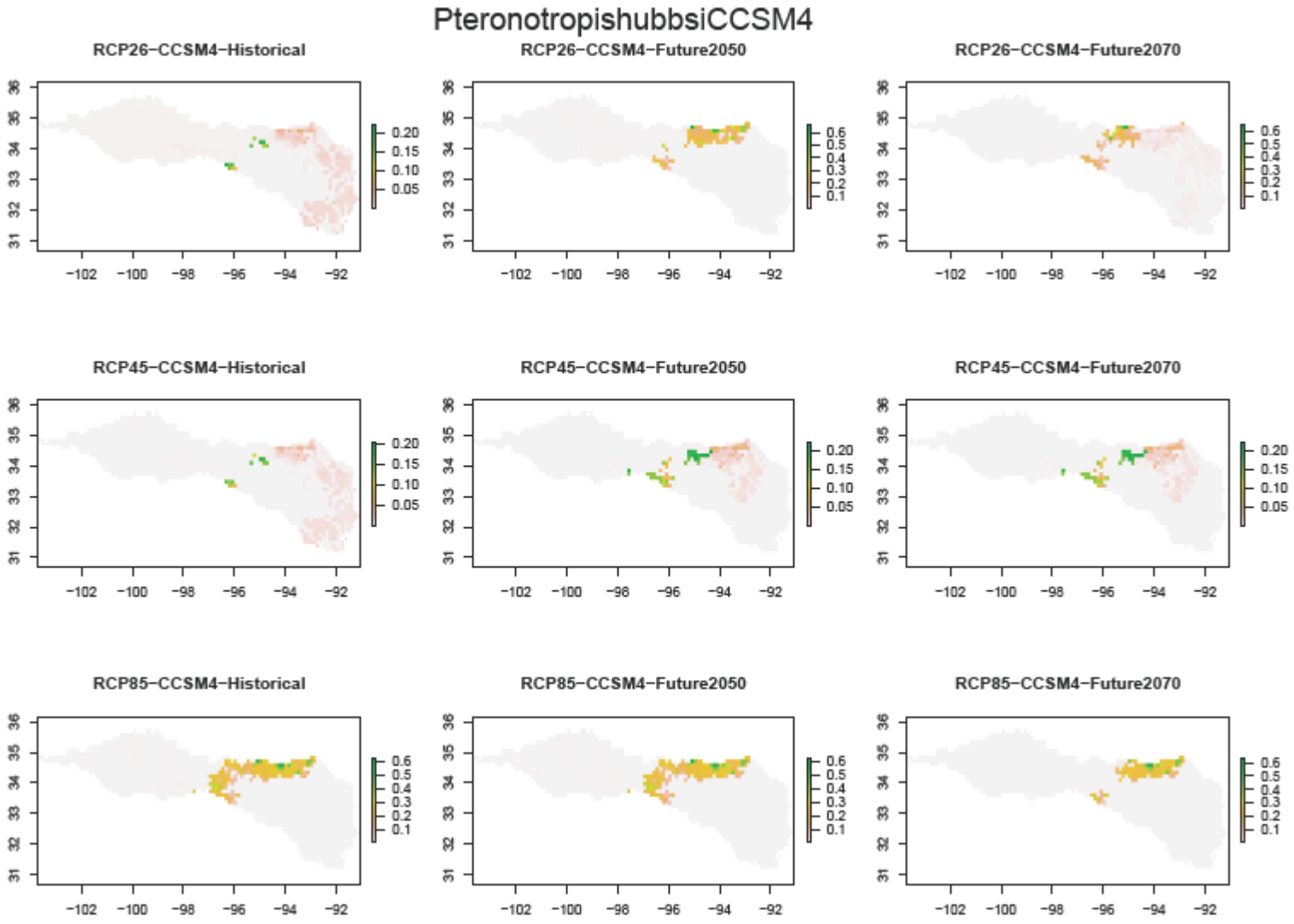
Maxent: *Pteronotropis hubbsi*

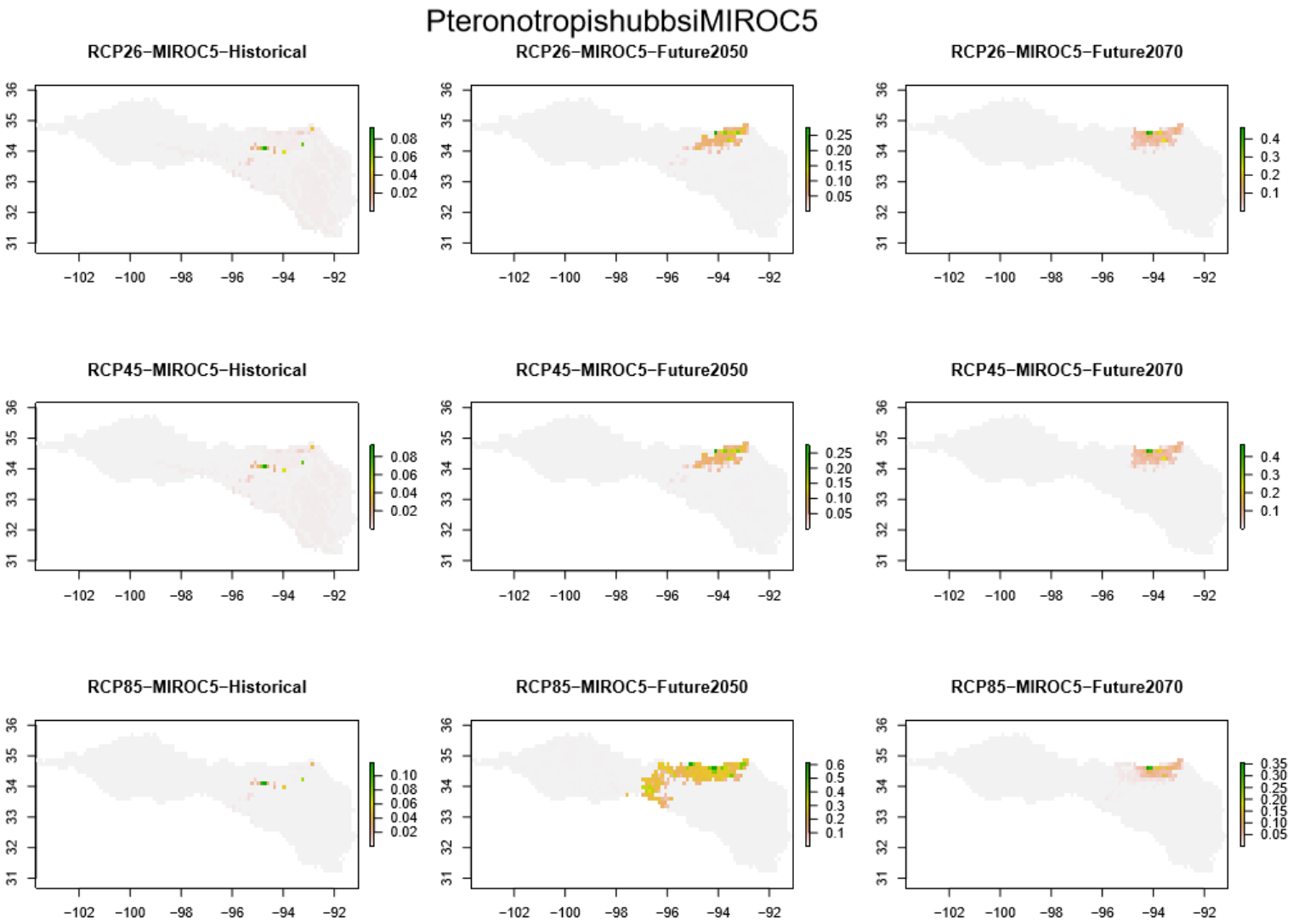


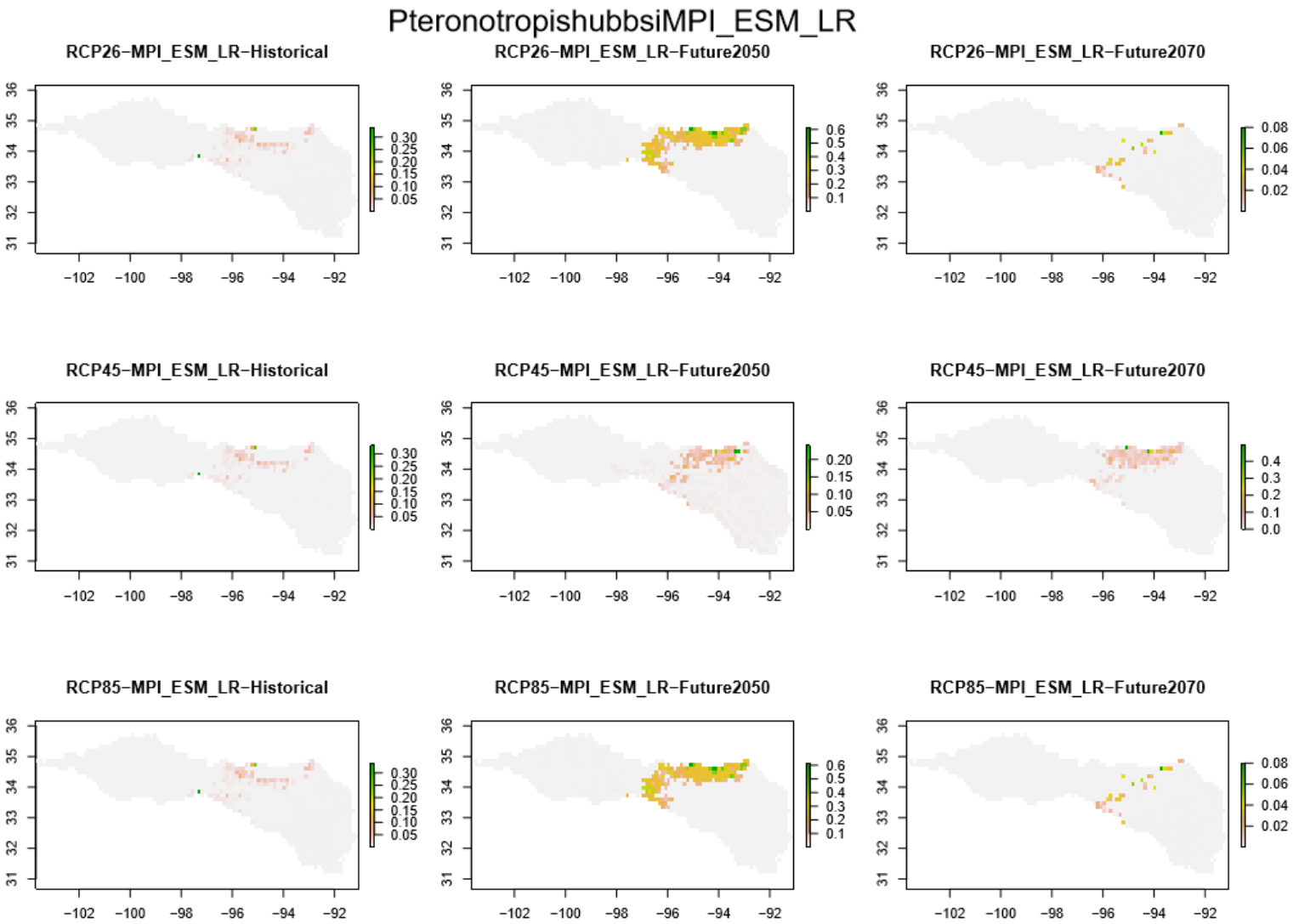

Pteronotropis_hubbsi_MIROC5
RCP26−MIROC5−Historical
RCP26−MIROC5−Future2050
RCP26−MIROC5−Future2070
RCP45−MIROC5−Historical
RCP45−MIROC5−Future2050
RCP45−MIROC5−Future2070
RCP85−MIROC5−Historical
RCP85−MIROC5−Future2050
RCP85−MIROC5−Future2070


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
31 32 33 34 35 36
-102 -100 -98 -96 -94 -92
0.0 0.2 0.4 0.6 0.8

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
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