Selection of Global Climate Model Data for Downscaling With Generative Machine Learning and Use in the Power Planning for Alignment of Climate and Energy Systems Project

Laura Vimmerstedt, Brandon Benton, Grant Buster, and Slater Podgorny

National Renewable Energy Laboratory

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Preface

A multi-institutional team is developing data and methods that will help the energy sector plan for climate change through the Power Planning for Alignment of Climate and Energy Systems project. The team and roles are shown here:

- City University of New York: Hydropower and thermal cooling water modeling
- Electric Power Research Institute: Risk metrics and engagement with the utility community
- Evolved Energy Research: Development of load data based on climate-impacted meteorology
- Los Alamos National Laboratory: Stochastic capacity expansion development and equitable energy pricing analysis
- Oak Ridge National Laboratory: Continental hydrological modeling
- National Renewable Energy Laboratory: Global climate model downscaling and power system planning
- Southern Company: Utility case study
- Tennessee Valley Authority: Utility case study
- University of Connecticut and University of Wisconsin: Hydrological modeling.

This project relies on downscaled data based on the results of global climate models (GCMs). This report documents a fundamental building block of the project: the selection of datasets for downscaling. Readers of this report will learn why certain GCMs were used as well as the relationship between the range of values in key parameters in this subset compared to a broader set of GCMs.

This project is part of the Grid Modernization Laboratory Consortium, a partnership of the U.S. Department of Energy and the national laboratories.

Acknowledgments

This research was supported by the Grid Modernization Initiative of the U.S. Department of Energy (DOE) as part of its Grid Modernization Laboratory Consortium, a strategic partnership between DOE and the national laboratories to bring together leading experts, technologies, and resources to collaborate on the goal of modernizing the nation's grid.

The research was performed using computational resources sponsored by the DOE Office of Energy Efficiency and Renewable Energy and located at the National Renewable Energy Laboratory (NREL).

Thanks to the Tennessee Valley Authority for providing perspectives as a power provider and balancing authority and for review. We would like to thank Andrew Kumler (NREL), Deeksha Rastogi (Oak Ridge National Laboratory) for review comments, and Emily Horvath (NREL) for editing.

List of Acronyms

CMIP6	Coupled Model Intercomparison Project Phase 6
CONUS	contiguous United States
GCM	Global Climate Model
GMLC	Grid Modernization Laboratory Consortium
m	meters
mm	millimeters
NREL	National Renewable Energy Laboratory
ORNL	Oak Ridge National Laboratory
PACES	Power Planning for Alignment of Climate and Energy Systems
Sup3rCC	Super-Resolution for Renewable Energy Resource Data with Climate Change Impacts
TVA	Tennessee Valley Authority

Abstract

The range of results from climate models and scenarios is important to the understanding of uncertainty in power planning analysis. A U.S. Department of Energy-funded analytic project called Power Planning for Alignment of Climate and Energy Systems is developing data and analytic methods to reflect the effects of climate change on key variables for power system planning, as part of the Grid Modernization Lab Consortium. This project will select and prepare global climate model results for use in power system planning models. A related report (*Evaluation of Global Climate Models for Use in Energy Analysis*) assesses the performance of various global climate models from the Coupled Model Intercomparison Project Phase 6 data archive for their historical skill with respect to energy system performance and for their future projections under multiple climate change scenarios. Building from that report, we describe the selection of a climate scenario (Shared Socioeconomic Pathway [SSP] 2-4.5) and five climate models: TaiESM1, EC-Earth3-CC, GFDL-CM4, EC-Earth3-Veg, and MPI-ESM1-2-HR. We describe the model selection criteria, which were based on the quality of the match between model results under historical conditions and on the representation of the range of future values for several variables. These results will be downscaled via an open-source generative machine learning method called Super-Resolution for Renewable Energy Resource Data with Climate Change Impacts.

Executive Summary

The U.S. Department of Energy funded a project through the Grid Modernization Lab Consortium called Power Planning for Alignment of Climate and Energy Systems (PACES). Among other activities, this project is developing data and analytic methods to reflect the effects of climate change on key variables for power system planning. One part of these methods is the selection of global climate model (GCM) results to use. The project will prepare GCM results for power system planning models in two ways: downscaling via an open-source generative machine learning method—Super-Resolution for Renewable Energy Resource Data with Climate Change Impacts (Sup3rCC) (Buster et al. 2024)—and a dynamical downscaling method that uses the Weather Research and Forecasting model (NCAR 2024). The GCM results that are selected via the process described in this report will be downscaled using Sup3rCC.

Our starting point for the selection of GCM results was the Coupled Model Intercomparison Project Phase 6 (CMIP6) (Eyring 2016; PCMDI 2022). A related report (Buster et al. 2024) screened these datasets for their representation of variables of interest for power system planning. This dataset included multiple climate scenarios, from which we selected a single emissions scenario—the Shared Socioeconomic Pathway (SSP2-4.5) (Riahi 2017)—and multiple climate models.

This report describes the selection of GCM results from CMIP6 SSP2-4.5 datasets, based on the quality of the match between model results under historical conditions and on the representation of the range of future values for several variables. The report recommends the selection of datasets from five models for the PACES project: TaiESM1, EC-Earth3-CC, GFDL-CM4, EC-Earth3-Veg, and MPI-ESM1-2-HR. See the section on References for GCMs and Appendix A for GCM acronyms.

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1 Introduction

1.1 PACES Project Requirements for GCM Data

The Power Planning for Alignment of Climate and Energy Systems (PACES) project aims to develop data and analytic methods to reflect the effects of climate change on key variables for power system planning. The project will prepare global climate model (GCM) results for power system planning models in two ways: downscaling via an open-source generative machine learning method—Super-Resolution for Renewable Energy Resource Data with Climate Change Impacts (Sup3rCC) (Buster et al. 2024)—and a dynamical downscaling method that uses the Weather Research and Forecasting model (NCAR 2024). The GCM results that are selected via the process described in this report will be downscaled using Sup3rCC.

Requirements for the data to be developed using Sup3rCC and input to power system models inform our approach to dataset selection. These requirements include the following:

1. Inclusion of variables relevant to power system planning (see Buster et al. 2024)
2. Selection of a limited number of datasets to avoid excess computational expense
3. Use of synchronous multivariate data from individual GCM outputs rather than ensemble-averaged, aggregated, or interpolated data to retain relationships across variables and preserve extreme events that could stress the power system
4. Selection of GCMs that will enable us to study an appropriate range of uncertainty in the impacts of climate change on relevant variables.

This report explains how these requirements are applied to the selection of GCM datasets for the PACES project.

1.2 Global Climate Models

Our starting point for the selection of GCM results is the Coupled Model Intercomparison Project Phase 6 (CMIP6) (Eyring 2016; PCMDI 2022). This data archive is the primary public source of GCM results. Buster et al. (2024) identifies climate model datasets from CMIP6 that have the relevant variables for a comprehensive power system planning analysis. The report also presents and discusses the variability and uncertainty across various climate models and emission scenarios, which should be considered in any robust planning activity. See the References for GCMs section of that report for documentation of the models.

1.3 Emissions Scenario

The CMIP6 dataset includes multiple emissions scenarios from the standardized Shared Socioeconomic Pathways. The most commonly used scenarios are SSP2-4.5 and SSP5-8.5. As discussed in Buster et al. (2024), GCMs differ in the sensitivity of their response to emissions, so a given model may be more or less extreme than other models from one emissions scenario to another. For the PACES project, we focus on planning timelines through midcentury to support utility decision-making timescales. On that time frame, the differences between SSP2-4.5 and

SSP5-8.5 are less pronounced than later in the century, as shown in Buster et al. (2024), Wootten et al. (2017), and Hawkins and Sutton (2009). Buster et al. (2024) noted that some arguments support the selection of the SSP5-8.5 climate scenario, but others consider it too extreme. For the Sup3rCC downscaling effort in the PACES project, we choose a single climate scenario to focus on with opportunities to consider additional scenarios if time and budget allow in later years. After discussion with the PACES utility partners, we decided to study SSP2-4.5 because of documented assertions that it is one of the more likely scenarios. Perspectives about another commonly used scenario, SSP5-8.5, differ: Hausfather and Peters (2020) and Pielke and Ritchie (2021) criticize its common use as a "business as usual" scenario, but Schwalm et al. (2020) assert that it is the best match for historical emissions through 2020 and projected emissions under current and stated policies through midcentury. For a more detailed discussion of scenario selection and a literature review on the topic, see Buster et al. (2024).

This report describes the selection of GCM results from CMIP6 SSP2-4.5 datasets, based on the quality of the match between model results under historical conditions and on the representation of the range of future values for several variables. The report recommends the selection of results data from five models for the PACES project: TaiESM1, EC-Earth3-CC, GFDL-CM4, EC-Earth3-Veg, and MPI-ESM1-2-HR.

1.4 GCM Results

We focused this analysis on results for variables relevant to power systems planning: air temperature (2-meter [m]), relative humidity (2-m), precipitation, global horizontal irradiance, and windspeed (100-m), as described in Buster et al. (2024), Table 2. That table also shows the sources of historical data used to estimate the accuracy of each GCM in replicating historical estimates of each variable, termed "historical skill." We use the historical skill as estimated in Buster et al. (2024) and reported in the companion online dataset (https://nrel.github.io/gcm_eval/) as part of the selection process described in this report. These GCM rankings, variables, and values used to estimate historical skill are shown in Appendix A.

2 Target GCM Datasets for Downscaling

Thirty-three GCMs were surveyed in Buster et al., and 20 were screened out as described in that report. The remaining 13 were considered in this report for potential selection for downscaling and use in the PACES project (Table 1). Of these remaining GCMs, we decided to downselect to no more than five GCMs based on the results presented here. As described in Buster et al. 2024, Pierce et al. (2009) considered five climate models to be adequate, and applied studies generally use 5 to 20 climate models (Miara et al. 2019; Craig et al. 2020; Kao et al. 2022; Szinai et al. 2023; Ralston Fonseca et al. 2021).

For the PACES project, five GCMs were chosen as driving a reasonable compute requirement while not overwhelming power system planning models. Although the machine-learning-based downscaling used in PACES is highly efficient and could be used to downscale all 13 viable GCMs (Buster et al. 2024), more data from additional GCMs would not necessarily be useful to power system planning activities—which have typically not considered all hours in a single year (Ho et al. 2021).

Although the PACES project targeted a subset of the GCM datasets for downscaling because of the computational intensity of later project steps, the downscaling itself could readily be performed on additional datasets for other purposes in the future (Buster et al. 2024).

Table 2. Summary of GCMs Used in This Report
(Notes are quoted from Buster et al. 2024)

GCM Name	Used	Notes and Reference
CESM2	Yes	Used variant r4i1p1f1; other variants (r1i1p1f1, r2i1p1f1, and r3i1p1f1) do not include daily min/max temperatures (Danabasoglu 2019a)
CESM2-WACCM	Yes	Used variant r3i1p1f1; other variants (r1i1p1f1 and r2i1p1f1) do not include daily min/max temperatures (Danabasoglu 2019b)
EC-Earth3	Yes	EC-Earth Consortium (2019a)
EC-Earth3-CC	Yes	EC-Earth Consortium (2021b)
EC-Earth3-Veg	Yes	EC-Earth Consortium (2019b)
GFDL-CM4	Yes	Guo et al. (2018)
GFDL-ESM4	Yes	John et al. (2018)
INM-CM4-8	Yes	Volodin et al. (2019a)
INM-CM5-0	Yes	Volodin et al. (2019b)
MPI-ESM1-2-HR	Yes	Schupfner et al. (2019)
MRI-ESM2-0	Yes	Yukimoto et al. (2019)
NorESM2-MM	Yes	Bentsen et al. (2019)
TaiESM1	Yes	Lee et al. (2020)

To select a subset of GCMs for use in the PACES project, we considered the accuracy of the models in representing selected variables historically as well as other selection rationales, as described in the following sections.

3 Rationale for GCM Selection

We consider three criteria for GCM selection: historical skill, consistency with other analyses, and representation of the range of potential future values for key variables.

3.1 Historical Skill

Buster et al. (2024) describes a methodology and results of a historical skill ranking of the GCMs. From this analysis, the models that ranked in the top half of the GCMs—based on average skill ranking for all variables—are shown in **Table 2**, with their ranking. Based on historical skill alone, the top five models for the contiguous United States (CONUS) would be TaiESM1, EC-Earth3-CC, GFDL-CM4, EC-Earth3-Veg, and MPI-ESM1-2-HR. This is similar to the historical skill ranking for our utility focus regions. In Tennessee (representing the Tennessee Valley Authority [TVA] territory), the top five models are GFDL-CM4, TaiESM1, EC-Earth3-Veg, NorESM2-MM, and EC-Earth3-CC, with MPI-ESM1-2-HR coming in 7th. In Alabama and Georgia (representing the Southern Company territory), the top five models are NorESM2-MM, GFDL-CM4, EC-Earth3-Veg, EC-Earth3-CC, and MPI-ESM1-2-HR, with TaiESM1 coming in 9th.

3.2 Consistency With Other Analyses

Previous analysis by members of the PACES project team is described in Kao et al. (2022), which used several GCMs to perform extensive analysis on the climate impacts to hydropower systems and included three GCMs: MRI-ESM2-0, MPI-ESM1-2-HR, and NorESM2-MM. Note that although the original work by Kao et al. (2022) focused on SSP5-8.5 and did not include EC-Earth3-Veg, follow-on work by the same team with TVA focused on the SSP2-4.5 scenario and included EC-Earth3-Veg—so candidate combinations of scenario and GCMs that provide consistency are SSP2-4.5 with MRI-ESM2-0, MPI-ESM1-2-HR, and EC-Earth3-Veg. Selection of these three climate models would support consistency and comparison with previous and ongoing work. Two of the three (EC-Earth3-Veg and MPI-ESM1-2-HR) are included in the top five by historical skill as shown in the last column of **Table 2**.

In addition to these related efforts, part of the PACES project will prepare GCM results for power system planning models using the Weather Research and Forecasting model (NCAR 2024). That effort is currently expected to use a bias-corrected version of the MPI-ESM1-2-HR data based on work by Xu et al. (2021) and includes SSP5-8.5 in addition to SSP2-4.5. As shown in the last column of **Table 2**, this means the MPI-ESM1-2-HR SSP2-4.5 runs will provide an important overlap for consistency between other work with TVA, the PACES analysis that uses the Weather Research and Forecasting model, and the PACES analysis that uses Sup3rCC.

Table 2. GCMs Based on Historical Skill

GCM Name	Rank			Notes and Reference	Other Analyses
	CONUS	TVA	Southern		
EC-Earth3	6	6	6	EC-Earth Consortium (2019a)	
EC-Earth3-CC	**2**	5	4	EC-Earth Consortium (2021b)	
EC-Earth3-Veg	**4**	3	3	EC-Earth Consortium (2019b)	TVA-ORNL
GFDL-CM4	**3**	1	2	Guo et al. (2018)	
NorESM2-MM	7	4	1	Bentsen et al. (2019)	
MPI-ESM1-2-HR	**5**	7	5	Schupfner et al. (2019)	TVA-ORNL NREL WRF
TaiESM1	**1**	2	9	Lee et al. (2020)	

ORNL = Oak Ridge National Laboratory; NREL = National Renewable Energy Laboratory; WRF = Weather Research and Forecasting model

3.3 Representation of Ranges for Key Variables

Another rationale for GCM selection is the representation of the range of potential future values for key variables. This rationale is grounded in the idea that intermodel variation in GCM results may be considered useful as a limited proxy for uncertainty in the future climate. Considering four sources of uncertainty in GCM results—natural variability, model uncertainty, emissions scenario, and downscaling method—the first two are the main sources through 2050, whereas emissions scenario increases in importance thereafter and the effects of downscaling method vary by region, experiment, and variable and are sensitive to treatment of extreme values (Buster et al. 2024; Wootten et al. 2017; Hawkins and Sutton 2009; Kao et al. 2022; Rastogi et al. 2022).

Buster et al. define and discuss the key variables—and an online repository provides their values by region, model, and year—for the 13-model set as well as for historical data. We determined the range of values for key variables and then calculated how much of that range was covered by each of two sets of models. The range of the variables identified a minimum and a maximum value for each year from modeled and historical data. The two sets were 1) the full 13-model set of GCMs (called "full set") and 2) the GCMs that are in the top five for historical skill—TaiESM1, EC-Earth3-CC, GFDL-CM4, EC-Earth3-Veg, and MPI-ESM1-2-HR (called "subset"). The key variables include values as well as percent changes in values for air temperature, relative humidity, precipitation, global horizontal irradiance, and windspeed.

Figure 1 shows the percent of the range of each variable that is covered by the subset, for years 2020 through 2055, for CONUS, TVA, and Southern Company. Because no historical data are available for these years, the maximum and minimum of the full set coincide with the overall maximum and minimum for each year. (The dataset for years before 2020 is available in the data supplement.) The year 2055 may be present or absent, depending on the size of the time period for moving average calculation. See Buster et al. (2024) for additional discussion of moving averages. The final column shows the percent of the range that is covered for each variable, considering ranges over all years. This may be a better indicator of coverage for volatile variables.

The subset does not cover the full range for some variables and years. In particular, the coverage of the range in 10-year minimum annual precipitation in CONUS is 67%, the coverage of the range in percent change in global horizontal irradiance is 73% and 78% for Southern and TVA regions, respectively, and the coverage for percent change in windspeed in TVA is 76%.

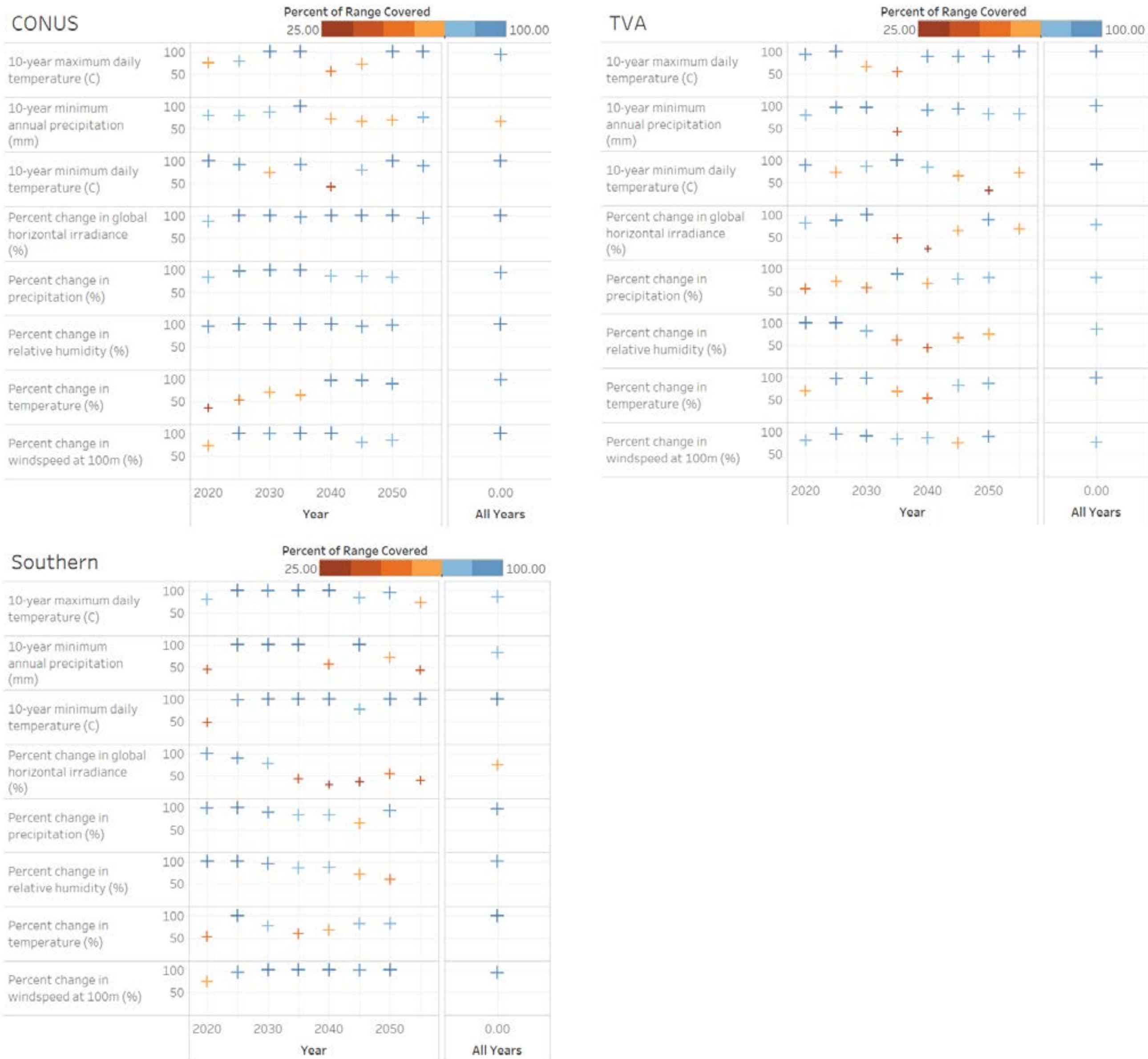

Figure 1. Percent of range of metrics covered by subset

Default metric height = 2 m; moving average = 20 years for percent change in precipitation, relative humidity, temperature, and windspeed and 10 years for global horizontal irradiance;
mm = millimeters

4 GCM Results Selection

We propose to use a subset of GCMs for downscaling and use in the PACES project that consists of the top five GCMs based on the historical skill ranking from Buster et al. (2024): TaiESM1, EC-Earth3-CC, GFDL-CM4, EC-Earth3-Veg, and MPI-ESM1-2-HR. This subset includes two GCMs that were used in prior TVA–Oak Ridge National Laboratory (ORNL) analyses (EC-Earth3-Veg, MPI-ESM1-2-HR); MPI-ESM1-2-HR is also being used in the part of the PACES project that uses the Weather Research and Forecasting model. This subset also covers more than 90% of the range in key variables for CONUS for all future years for all variables except global horizontal irradiance, for which it covers 67% of the range.

The proposed subset will enable us to consider the majority of intermodel climate uncertainty in key climate variables such as temperature and precipitation. The GCM subset also covers most of the range of projections in wind and solar resources. The proposed GCM subset covers less of the possible range of change in irradiance in our two focus regions, but the overall magnitude of projected change for this variable is relatively small. The subset covers most of the range while also remaining tractable for computational efforts in downscaling and power system planning.

Figures 2–9 show CONUS results for the selected subset of GCMs in color, with the results for the other models from the full set shown in gray. In color are TaiESM1, EC-Earth3-CC, GFDL-CM4, EC-Earth3-Veg, and MPI-ESM1-2-HR. In gray are CESM2, CESM2-WACCM, EC-Earth3, GFDL-ESM4, INM-CM4-8, INM-CM5-0, NorESM2-MM, and MRI-ESM2-0. Results for Tennessee Valley Authority and Southern Company regions appear in Appendices B and C. To view these results interactively with labels on each trace, see https://nrel.github.io/gcm_eval/.

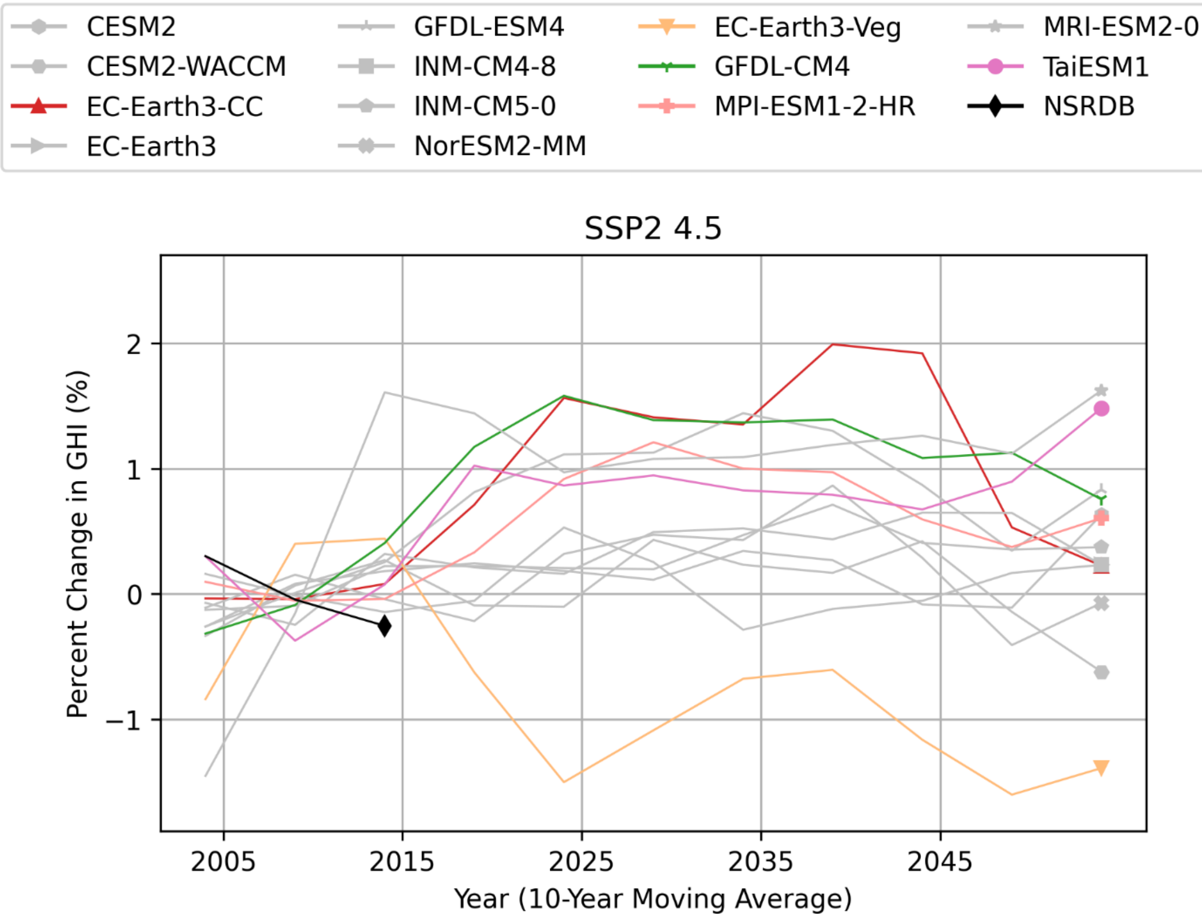

Figure 2. Percent change in global horizontal irradiance

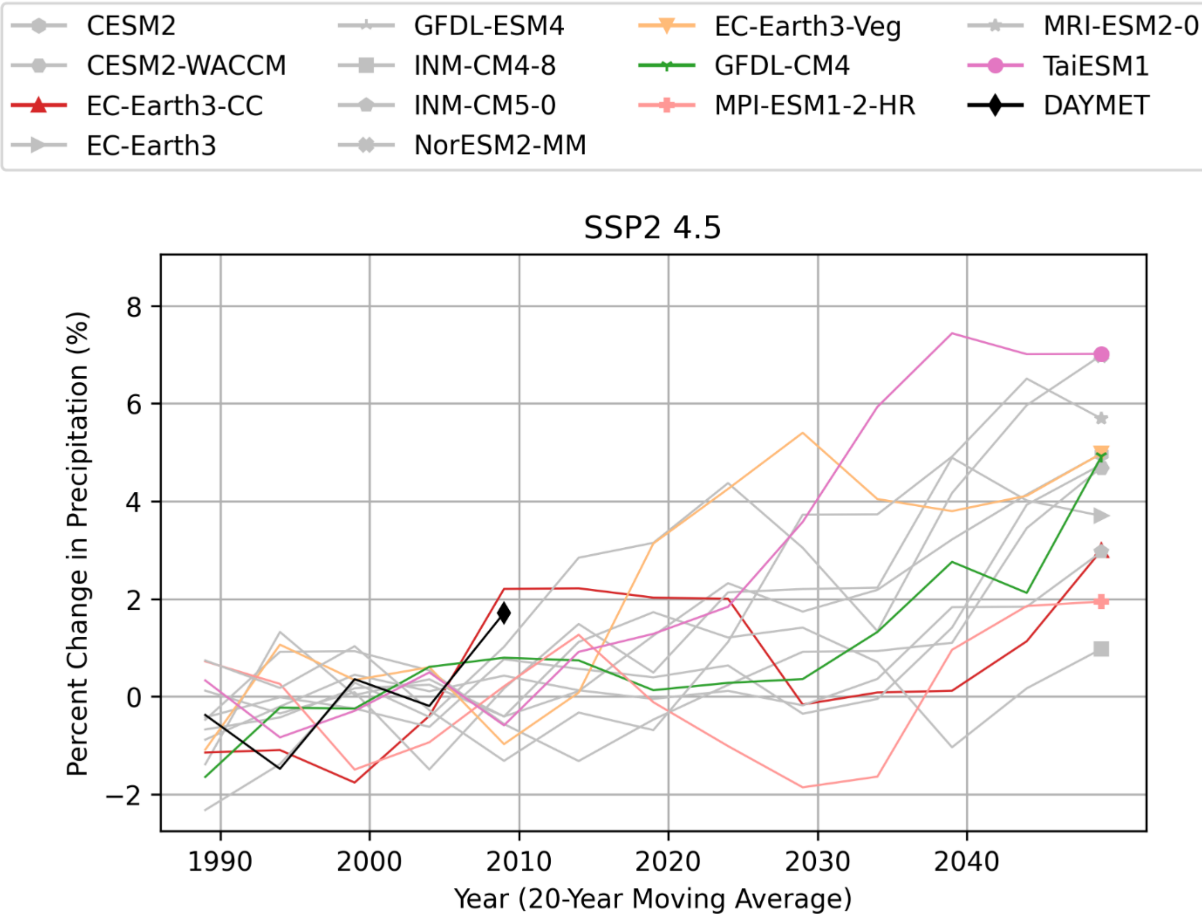

Figure 3. Percent change in precipitation

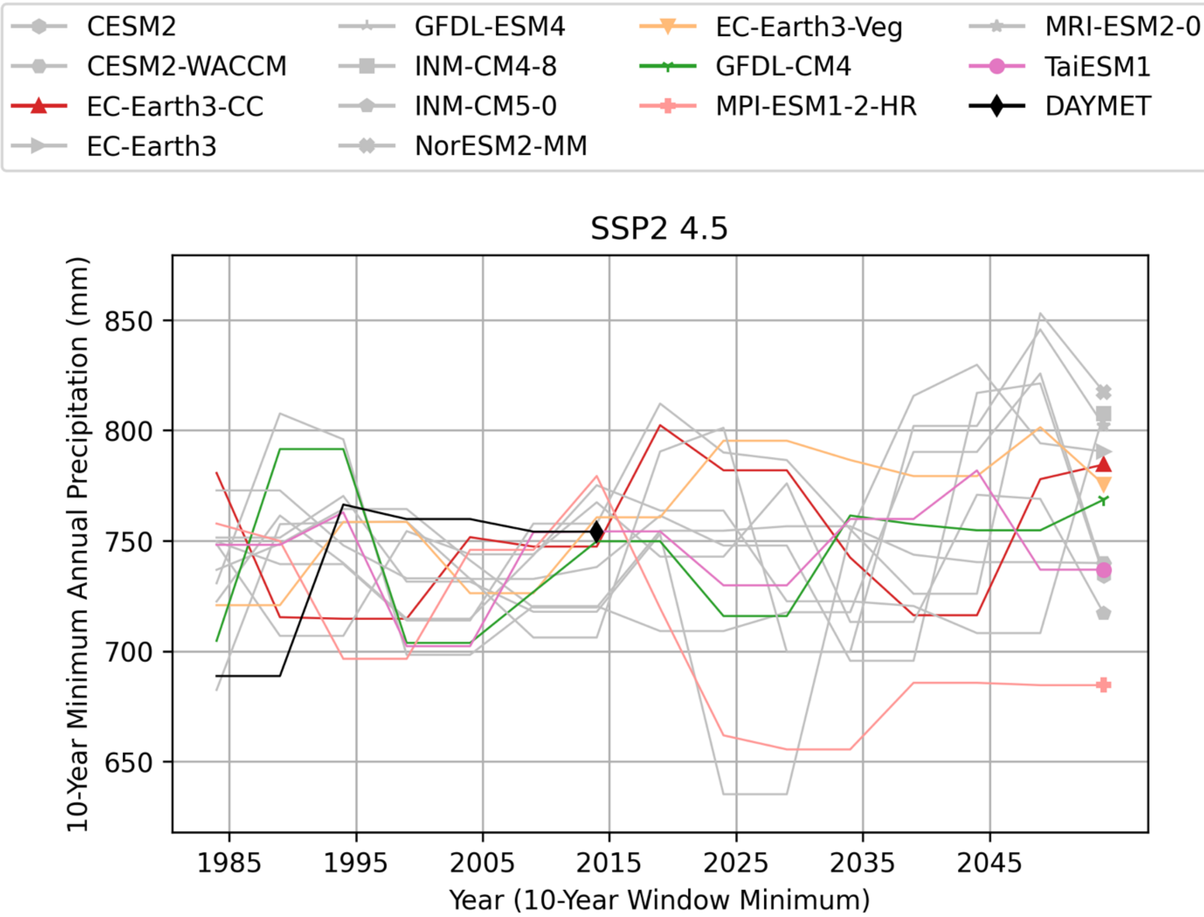

Figure 4. 10-year minimum annual precipitation

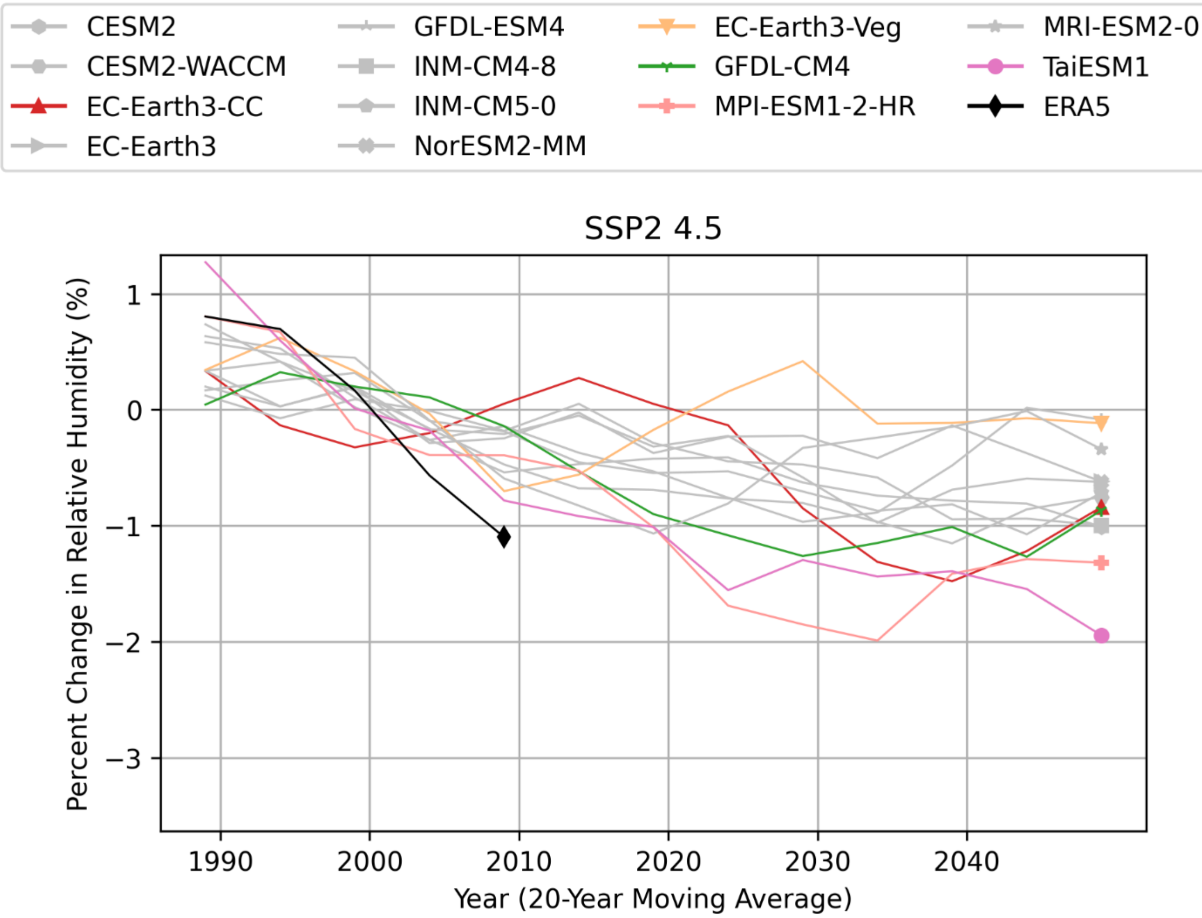

Figure 5. Percent change in relative humidity

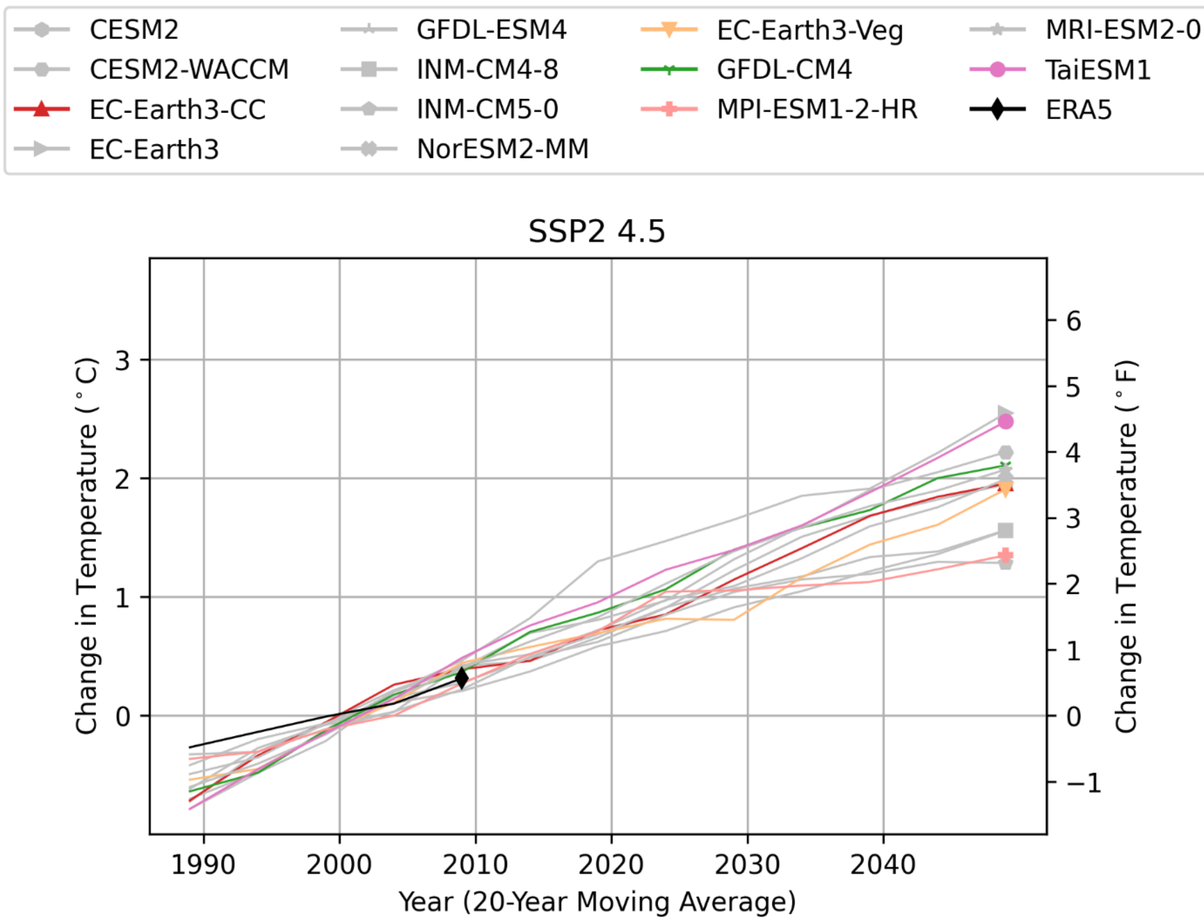

Figure 6. Change in temperature

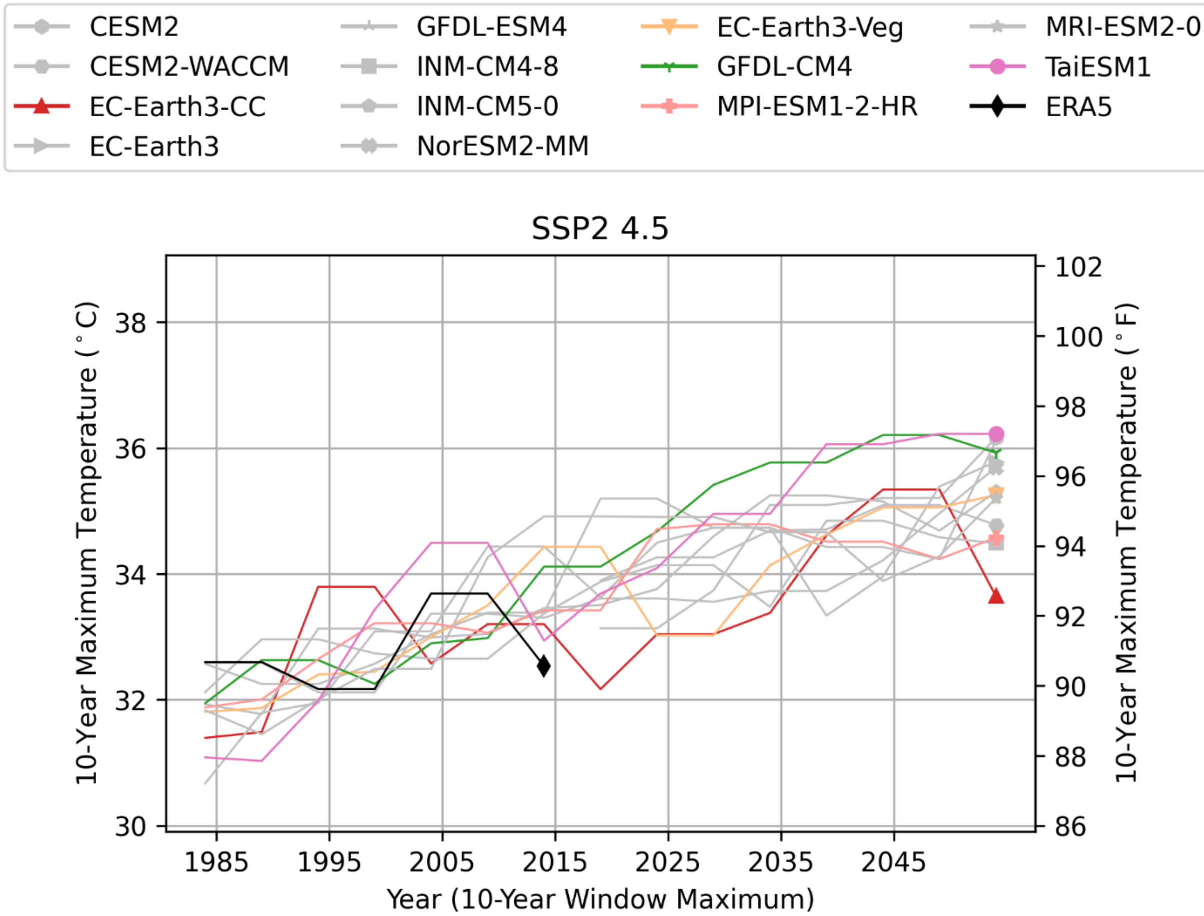

Figure 7. 10-year maximum temperature

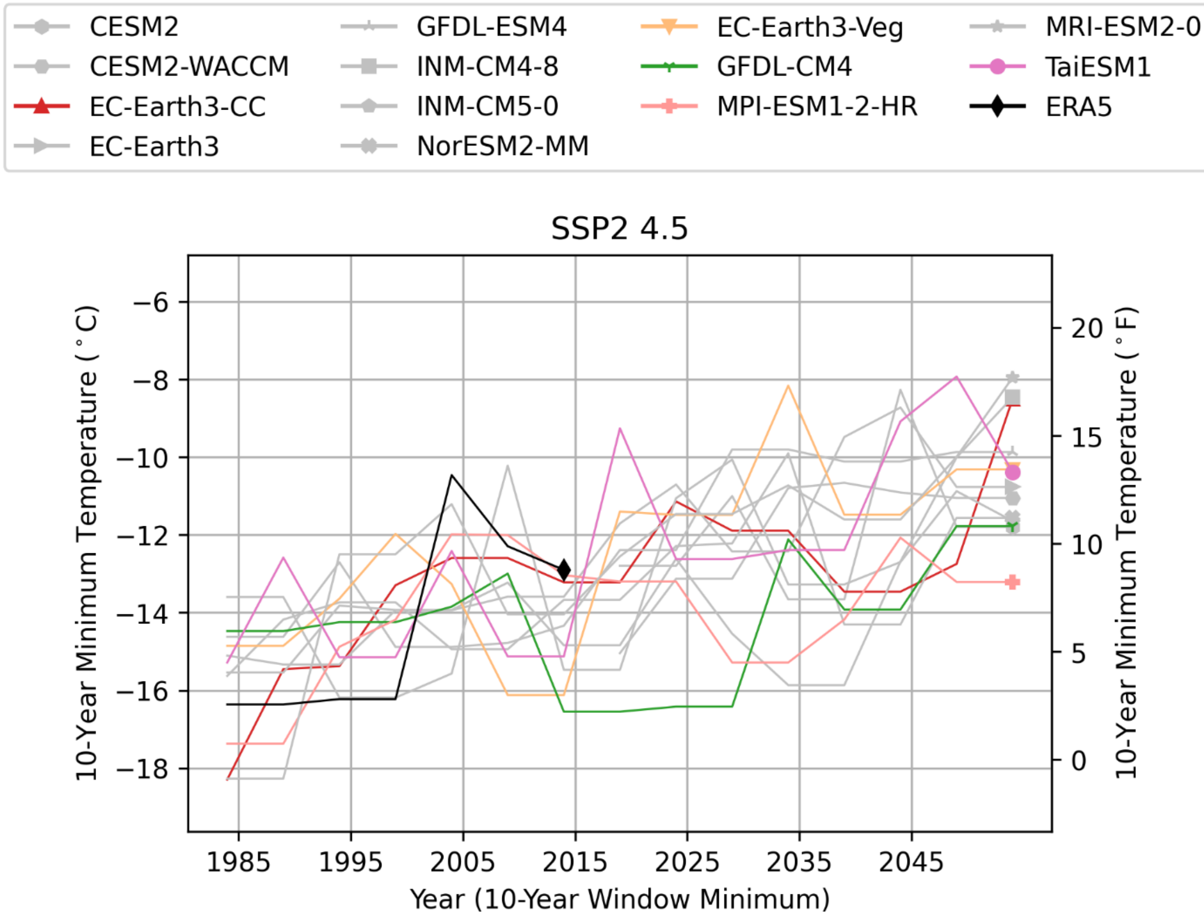

Figure 8. 10-year minimum temperature

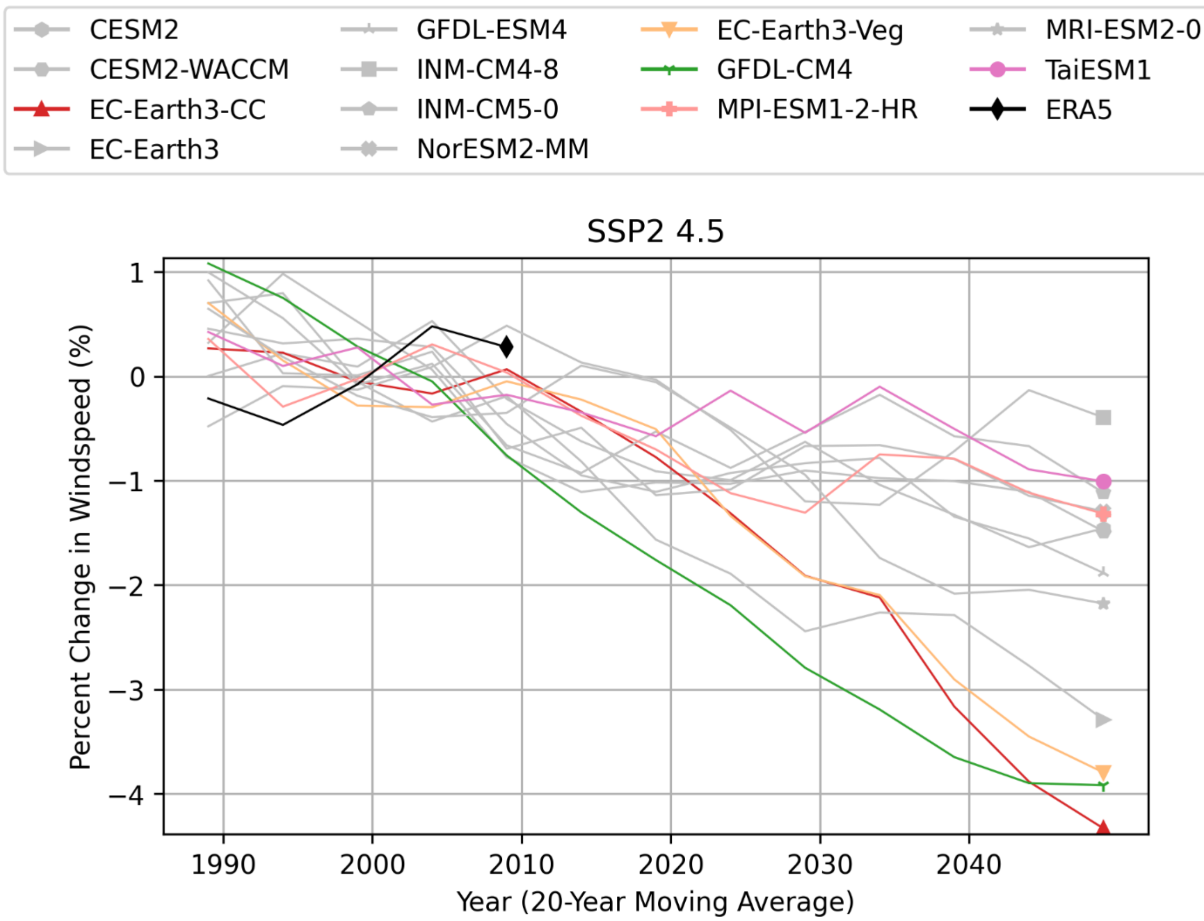

Figure 9. Percent change in windspeed

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Appendix A. Results of Historical Skill Ranking

The following tables show GCM ranking by historical skill, as described in Buster et al. (2024) with additional tables for the two utility focus regions in the PACES project. The model names appear in the column labels, ranked from best to worst. The metrics that contributed to the ranking appear in the row labels. The quantitative values in the body of the matrix are the mean-centered Kolmogorov-Smirnov statistic and bias metrics. Best skill is dark blue; worst skill is dark red.

For the GCM names and sources, see references. The following acronyms are used in these tables:

T temperature

2M 2 meters from the surface

KS Kolmogorov-Smirnov statistic

PXX percentile at which bias is measured (e.g., P50 is the difference between GCM and historical value at the 50^{th} percentile)

RH relative humidity

PR precipitation

GHI global horizontal irradiance

WS windspeed

Table A-1. Historical Skill Ranking With Contributing Metric for CONUS (Buster et al. 2024, Table 3)

	TaiESM1	EC-Earth3-CC	GFDL-CM4	EC-Earth3-Veg	MPI-ESM1-2-HR	EC-Earth3	NorESM2-MM	CESM2	GFDL-ESM4	CESM2-WACCM	MRI-ESM2-0	INM-CM5-0	INM-CM4-8
T2M KS	0.04	0.05	0.05	0.05	0.06	0.06	0.06	0.05	0.05	0.05	0.06	0.05	0.06
T2M Bias P50 (°C)	0.29	-1.04	-2.28	-1.30	-0.73	-1.88	1.38	1.92	-2.41	1.89	-1.15	0.12	0.84
T2M Max KS	0.05	0.05	0.05	0.06	0.06	0.06	0.07	0.07	0.06	0.06	0.07	0.07	0.09
T2M Max Bias P95 (°C)	1.04	0.22	-1.46	0.08	0.07	-0.45	3.13	2.97	-1.04	-3.48	-0.88	2.55	4.03
T2M Min KS	0.04	0.05	0.05	0.05	0.06	0.06	0.06	0.07	0.05	0.09	0.06	0.06	0.06
T2M Min Bias P5 (°C)	-1.74	-2.43	-1.39	-2.57	-0.83	-3.83	0.90	3.01	-0.48	7.53	2.27	1.78	2.39
RH2M KS	0.08	0.07	0.07	0.07	0.13	0.07	0.10	0.09	0.13	0.09	0.09	0.13	0.15
RH2M Bias P50 (%)	7.5	9.2	12.8	8.7	7.9	10.1	-12.6	-8.9	18.3	-8.7	10.2	2.4	-2.8
RH2M Max KS		0.09	0.14	0.09	0.21	0.09					0.19	0.23	0.25
RH2M Max Bias P95 (%)		1.76	7.43	1.68	10.95	1.80					3.76	5.62	5.31
RH2M Min KS		0.09	0.09	0.09	0.12	0.09					0.10	0.11	0.11
RH2M Min Bias P5 (%)		7.8	4.7	6.7	5.9	9.6					13.8	-11.0	-15.4
PR KS	0.10	0.09	0.10	0.09	0.07	0.09	0.08	0.09	0.12	0.09	0.12	0.16	0.14
PR Bias P50 (%)	1.67	2.75	4.60	2.47	1.53	2.77	0.43	1.73	7.52	1.99	6.77	13.21	10.28
GHI KS	0.04	0.05	0.03	0.05	0.04	0.05	0.04	0.04	0.04	0.04	0.04	0.03	0.04
GHI Bias P50 (%)	-0.30	0.60	-2.12	3.01	0.42	1.82	10.72	5.79	-6.41	5.09	6.33	4.82	7.81
WS 100m KS	0.08	0.09	0.07	0.09	0.14	0.09	0.14	0.27	0.08	0.27	0.14	0.19	0.20
WS 100m Bias P50 (%)	-17.4	-1.2	-16.1	-0.8	-2.9	-16.4	7.3	45.2	-19.6	45.3	-27.9	-56.5	-56.1
Process Skill	0.29	0.05	0.06	0.06	0.09	0.06	0.04	0.20	0.14	0.16	0.34	0.82	0.85

Table A-2. Historical Skill Ranking With Contributing Metrics for TVA

	GFDL-CM4	TaiESM1	EC-Earth3-Veg	NorESM2-MM	EC-Earth3-CC	EC-Earth3	MPI-ESM1-2-HR	CESM2-WACCM	MRI-ESM2-0	CESM2	GFDL-ESM4	INM-CM5-0	INM-CM4-8
T2M KS	0.04	0.03	0.05	0.05	0.05	0.05	0.06	0.04	0.06	0.03	0.05	0.05	0.06
T2M Bias P50 (°C)	-2.45	-0.53	-1.81	1.61	-1.51	-2.07	-1.50	1.77	-1.36	1.76	-3.21	-0.98	-0.28
T2M Max KS	0.03	0.06	0.06	0.05	0.06	0.06	0.05	0.04	0.06	0.07	0.06	0.07	0.09
T2M Max Bias P95 (°C)	-2.07	-0.01	0.13	3.03	0.86	0.02	-2.33	-3.42	-0.02	3.21	-2.48	3.82	5.55
T2M Min KS	0.05	0.03	0.03	0.05	0.04	0.04	0.06	0.03	0.06	0.07	0.04	0.06	0.04
T2M Min Bias P5 (°C)	-2.81	-2.92	-1.78	1.01	-1.96	-2.94	-2.89	5.60	0.25	1.53	-1.00	2.73	2.37
RH2M KS	0.06	0.07	0.07	0.10	0.07	0.06	0.08	0.08	0.06	0.09	0.19	0.14	0.15
RH2M Bias P50 (%)	9.8	9.0	10.4	-10.6	10.1	10.4	17.6	-6.2	5.2	-6.8	22.5	-0.7	-4.5
RH2M Max KS	0.21		0.11		0.11	0.11	0.13		0.25			0.31	0.32
RH2M Max Bias P95 (%)	2.56		0.40		0.36	0.45	4.62		0.67			2.97	2.98
RH2M Min KS	0.08		0.07		0.07	0.07	0.06		0.06			0.10	0.11
RH2M Min Bias P5 (%)	17.9		18.4		18.2	20.6	34.7		18.2			-16.2	-19.6
PR KS	0.09	0.08	0.09	0.07	0.09	0.09	0.09	0.08	0.07	0.08	0.12	0.12	0.10
PR Bias P50 (%)	5.90	4.61	6.88	3.41	6.77	7.21	5.38	6.13	5.95	5.79	13.78	13.81	9.51
GHI KS	0.02	0.03	0.04	0.03	0.04	0.04	0.06	0.03	0.04	0.03	0.03	0.03	0.04
GHI Bias P50 (%)	-1.59	-3.94	-4.79	9.65	-6.88	-5.86	-4.01	0.03	7.12	1.74	####	7.34	10.12
WS 100m KS	0.05	0.06	0.08	0.12	0.07	0.07	0.12	0.31	0.16	0.31	0.05	0.25	0.26
WS 100m Bias P50 (%)	-12.4	-22.1	1.1	4.1	1.9	-19.5	-8.0	64.6	-48.6	64.5	-23.6	-72.3	-73.3
Process Skill	0.06	0.29	0.06	0.04	0.05	0.06	0.09	0.16	0.34	0.20	0.14	0.82	0.85

Table A-3. Historical Skill Ranking With Contributing Metrics for Southern Company

	NorESM2-MM	GFDL-CM4	EC-Earth3-Veg	EC-Earth3-CC	MPI-ESM1-2-HR	EC-Earth3	CESM2	MRI-ESM2-0	TaiESM1	CESM2-WACCM	GFDL-ESM4	INM-CM4-8	INM-CM5-0
T2M KS	0.03	0.05	0.03	0.04	0.04	0.03	0.03	0.06	0.04	0.03	0.07	0.08	0.10
T2M Bias P50 (°C)	1.17	-1.85	-1.00	-0.87	-0.93	-1.25	1.74	-0.64	-0.31	1.69	-2.43	-0.54	-0.95
T2M Max KS	0.03	0.03	0.05	0.06	0.04	0.05	0.04	0.05	0.05	0.05	0.06	0.08	0.10
T2M Max Bias P95 (°C)	1.34	-1.70	-0.28	0.32	-2.88	-0.61	1.45	-0.99	-0.27	-5.16	-2.24	-0.55	-1.95
T2M Min KS	0.03	0.05	0.04	0.04	0.03	0.04	0.05	0.06	0.03	0.10	0.06	0.11	0.14
T2M Min Bias P5 (°C)	0.33	-2.78	-0.49	-0.51	-0.95	-1.06	0.76	0.30	-1.91	6.12	-2.51	2.47	3.15
RH2M KS	0.08	0.04	0.06	0.06	0.04	0.06	0.08	0.06	0.06	0.08	0.12	0.10	0.09
RH2M Bias P50 (%)	-3.7	6.4	8.5	8.3	9.0	8.9	-1.2	2.9	8.7	-0.3	16.6	5.5	7.6
RH2M Max KS		0.15	0.09	0.09	0.14	0.09		0.24				0.27	0.26
RH2M Max Bias P95 (%)		2.08	0.50	0.48	3.01	0.54		0.32				2.34	2.35
RH2M Min KS		0.06	0.06	0.06	0.06	0.05		0.05				0.12	0.12
RH2M Min Bias P5 (%)		6.9	19.1	17.7	29.5	21.1		21.3				-3.6	-0.5
PR KS	0.10	0.09	0.10	0.10	0.08	0.10	0.11	0.08	0.11	0.12	0.11	0.16	0.18
PR Bias P50 (%)	2.3	2.7	0.0	0.0	0.0	0.0	3.2	1.8	3.2	3.5	5.5	29.4	35.0
GHI KS	0.02	0.02	0.02	0.03	0.06	0.03	0.02	0.03	0.04	0.02	0.02	0.03	0.02
GHI Bias P50 (%)	3.38	-3.12	-5.61	-7.10	-1.75	-6.13	-3.07	5.05	-7.59	-4.54	-6.72	4.20	1.89
WS 100m KS	0.07	0.04	0.04	0.04	0.04	0.04	0.25	0.16	0.06	0.25	0.07	0.19	0.18
WS 100m Bias P50 (%)	-11.6	-30.2	-7.6	-6.9	-24.7	-27.2	27.9	-52.5	-24.8	27.1	-13.2	-53.9	-53.4
Process Skill	0.04	0.06	0.06	0.05	0.09	0.06	0.20	0.34	0.29	0.16	0.14	0.85	0.82

Appendix B. Selected GCM Subset Results in Context of Full GCM Results in the Tennessee Valley Authority Region

The figures in this appendix show results for the selected subset of GCMs in color, with the results for the other models from the full set shown in gray. In color are TaiESM1, EC-Earth3-CC, GFDL-CM4, EC-Earth3-Veg, and MPI-ESM1-2-HR. In gray are CESM2, CESM2-WACCM, EC-Earth3, GFDL-ESM4, INM-CM4-8, INM-CM5-0, NorESM2-MM, and MRI-ESM2-0.

CONUS is shown previously; Tennessee Valley Authority appears here.

We use a simple state mask to represent the utility territory, e.g., Tennessee for TVA.

To view these results interactively with labels on each trace, see https://nrel.github.io/gcm_eval/. For GCM names and sources, see references.

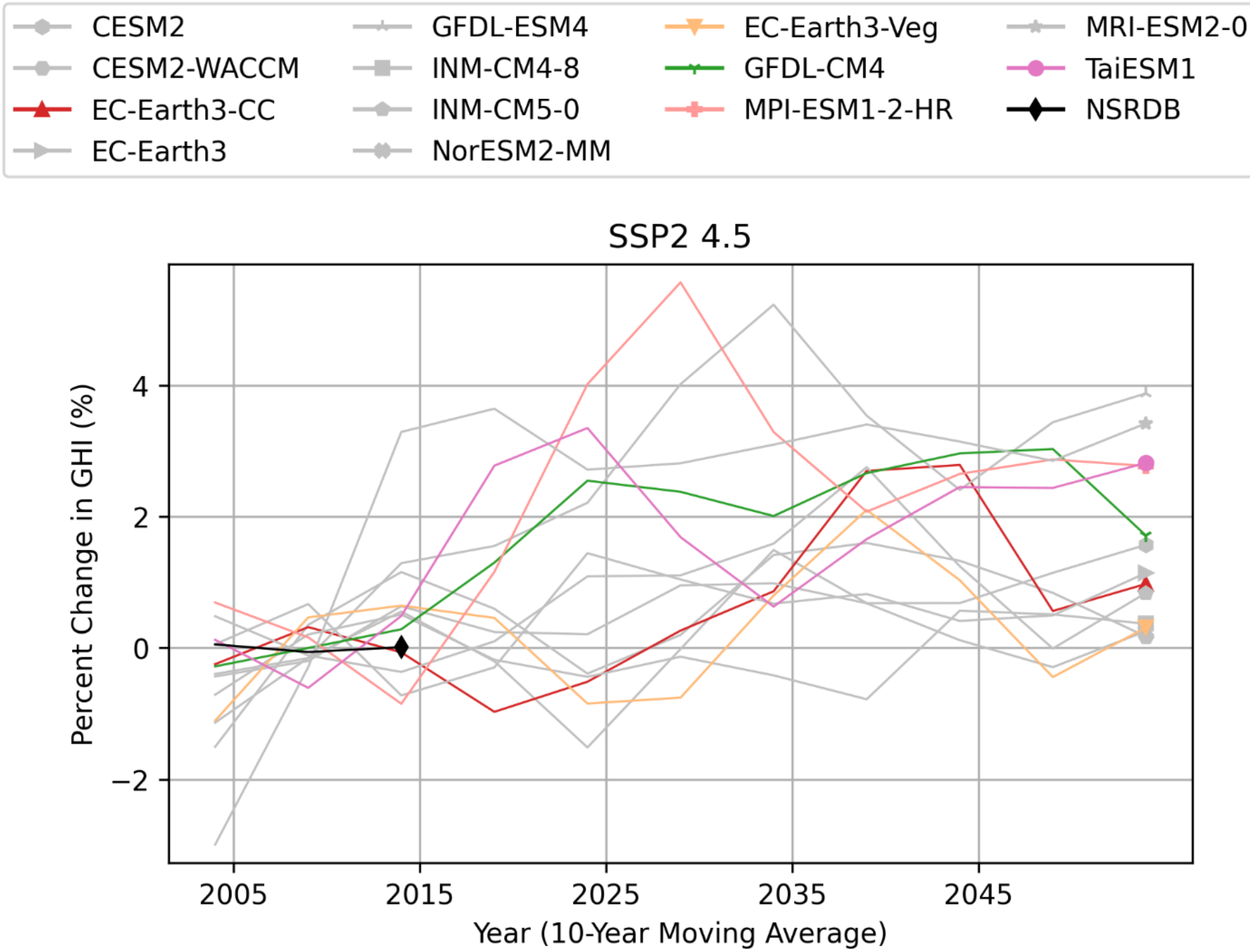

Figure B-1. Comparison of GCM trends in changes to GHI for TVA

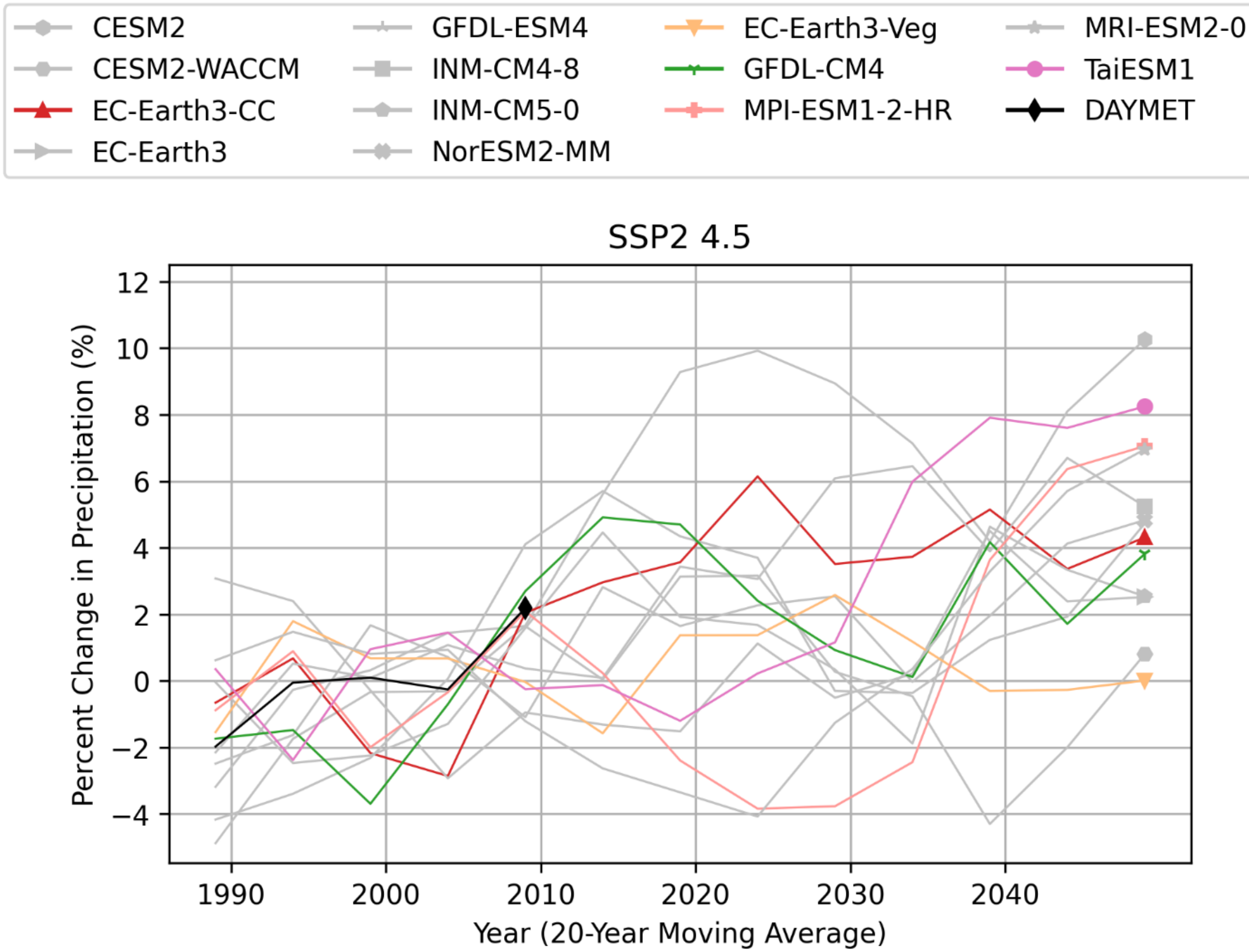

Figure B-2. Comparison of GCM trends in changes to precipitation for TVA

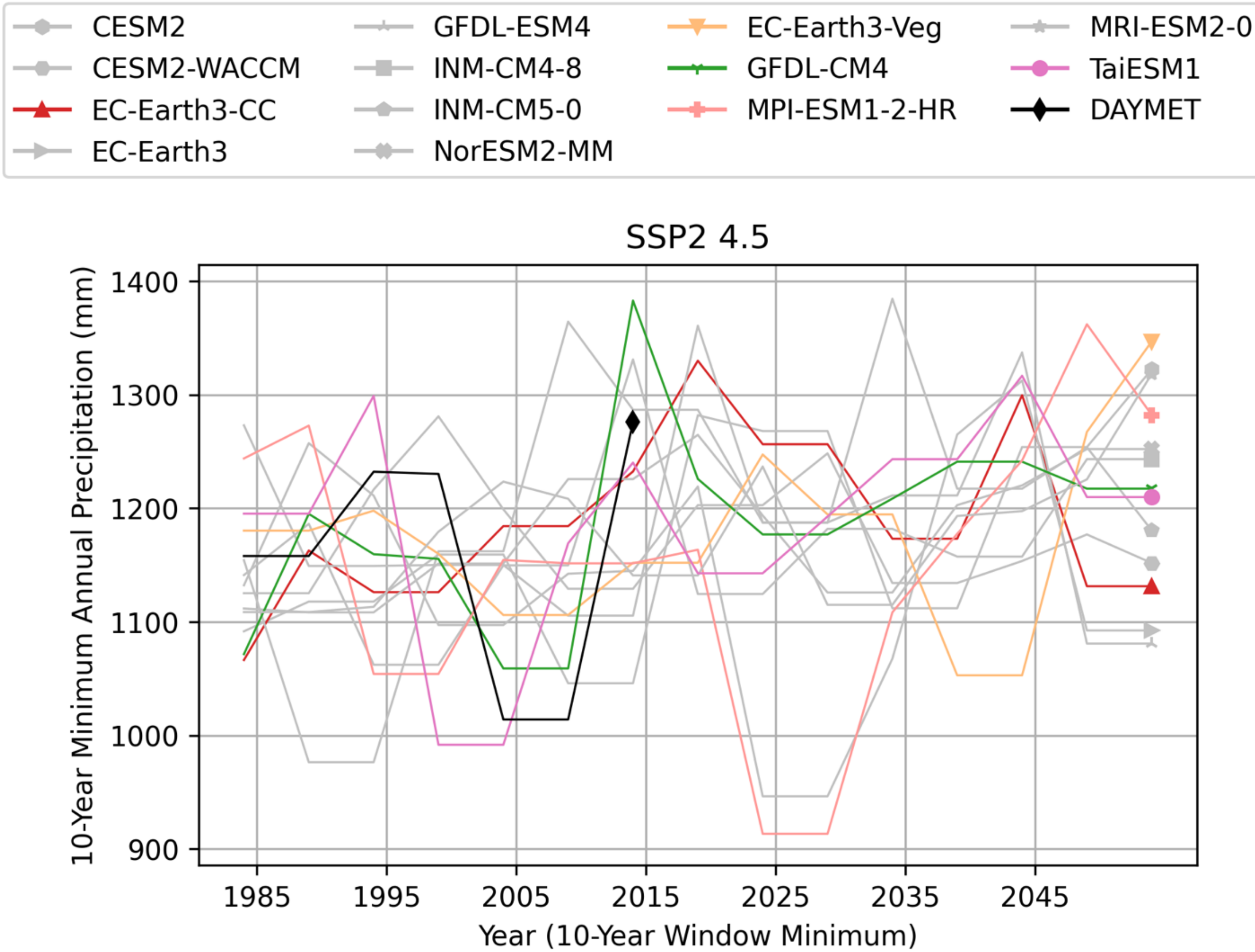

Figure B-3. Comparison of GCM trends in 10-year minimum annual precipitation for TVA

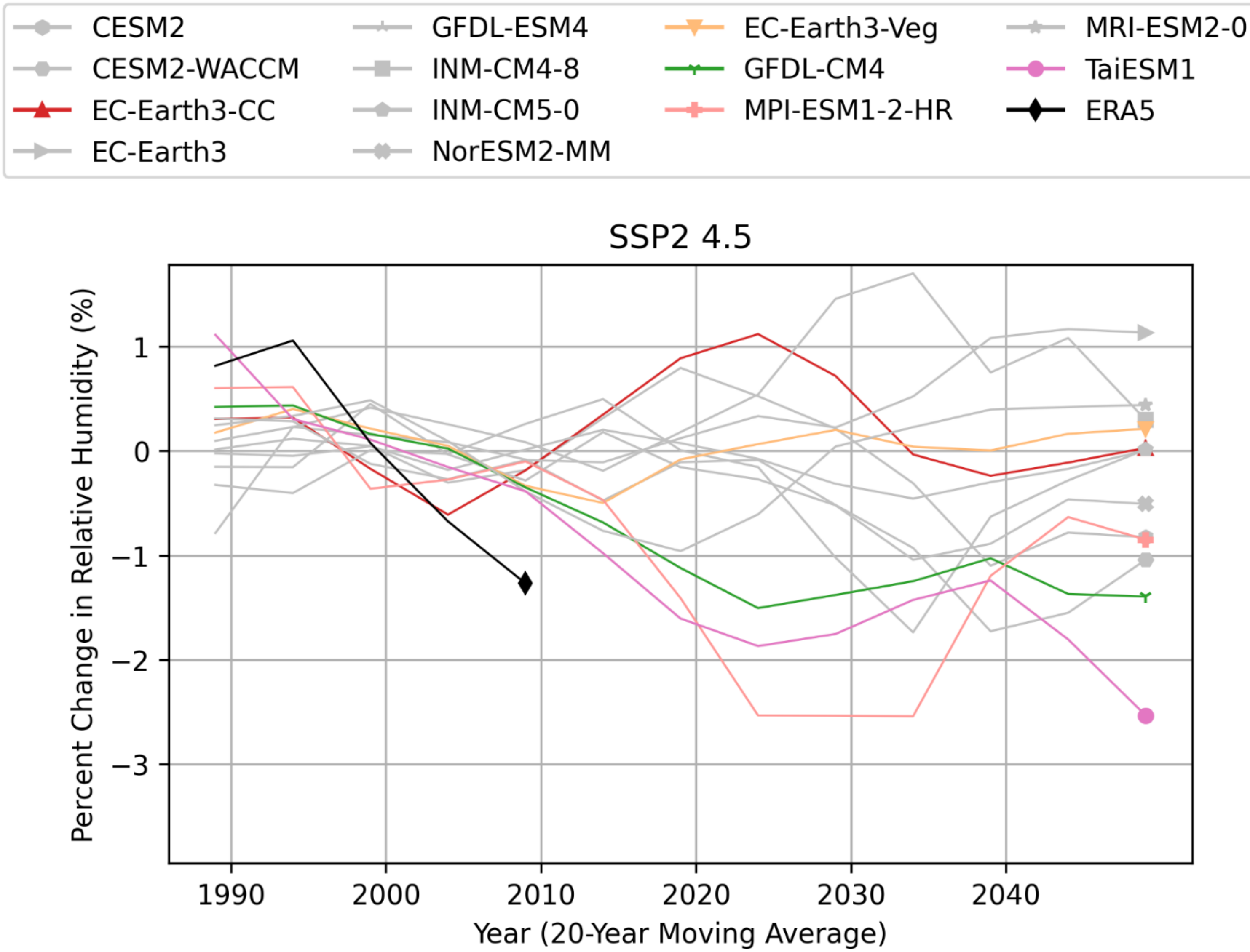

Figure B-4. Comparison of GCM trends in changes to relative humidity for TVA

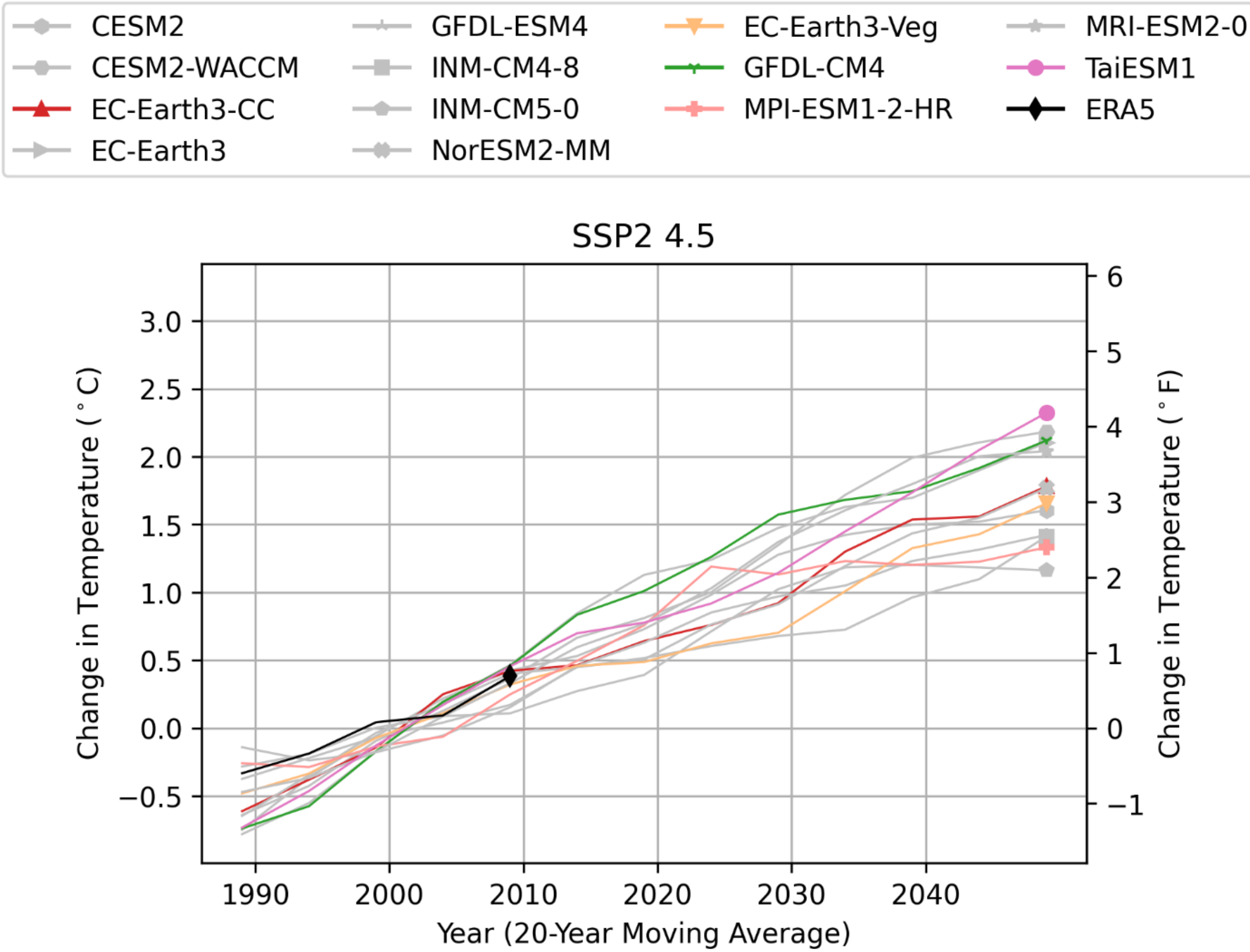

Figure B-5. Comparison of GCM trends in changes in temperature for TVA

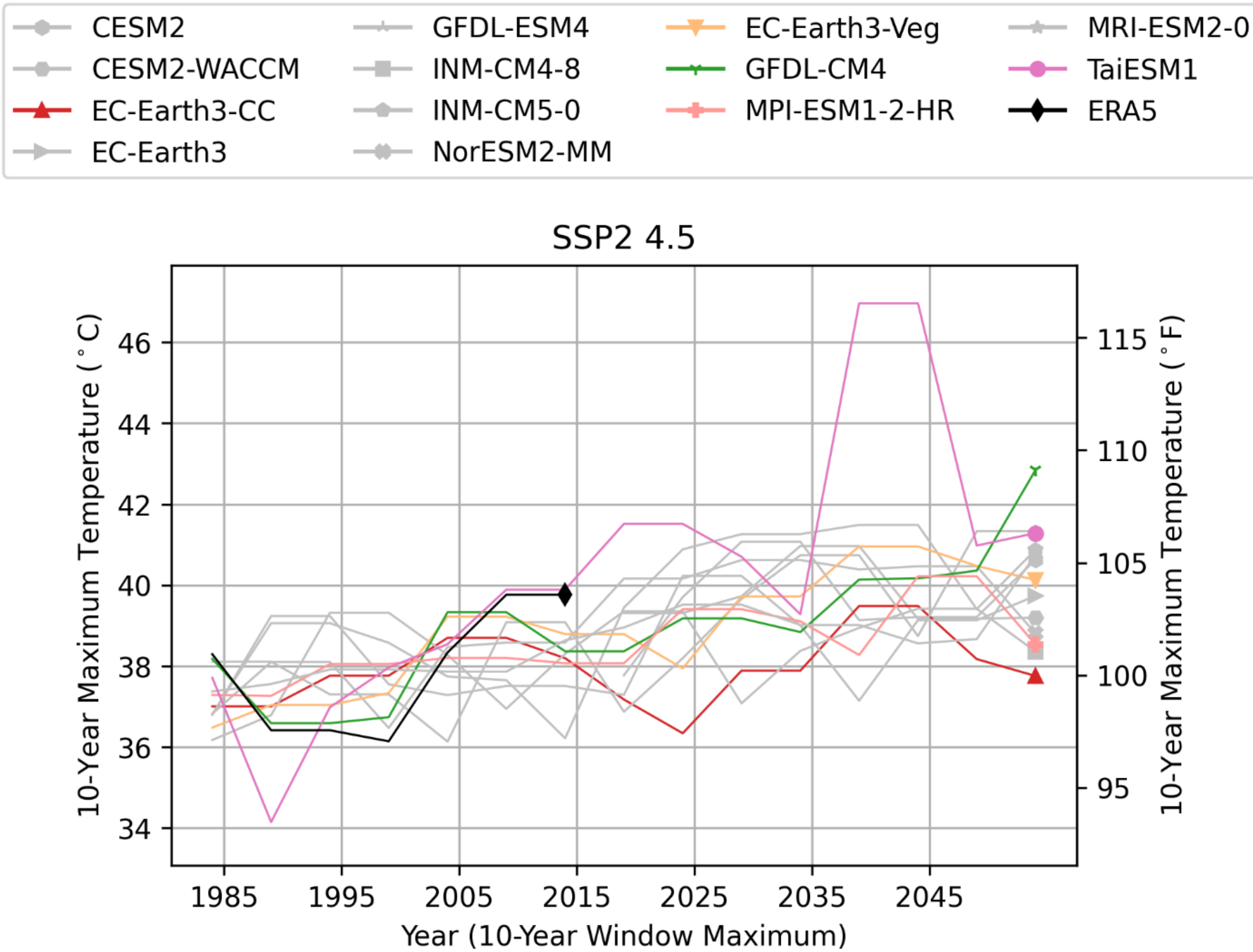

Figure B-6. Comparison of GCM trends in 10-year maximum temperature for TVA

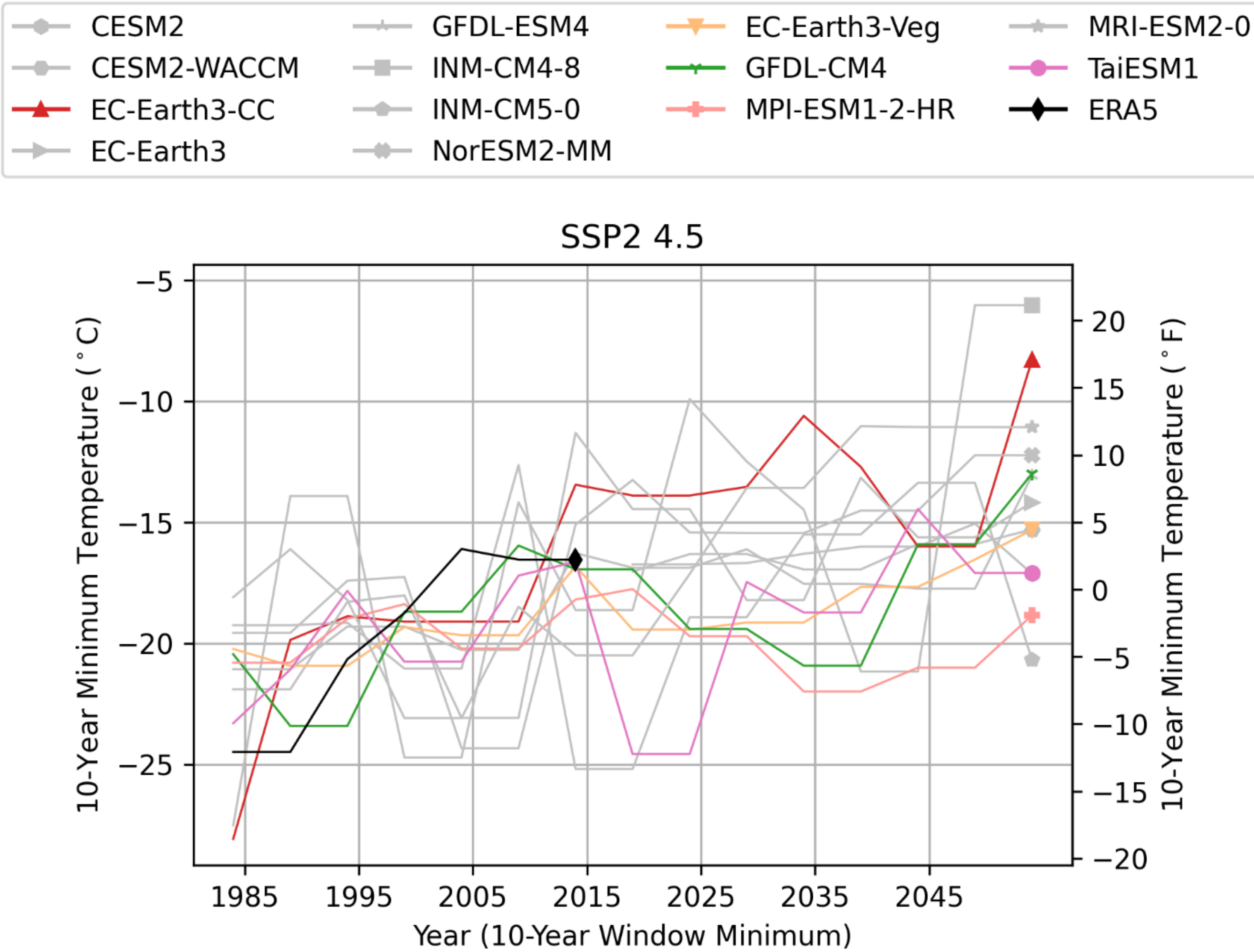

Figure B-7. Comparison of GCM trends in 10-year minimum temperature for TVA

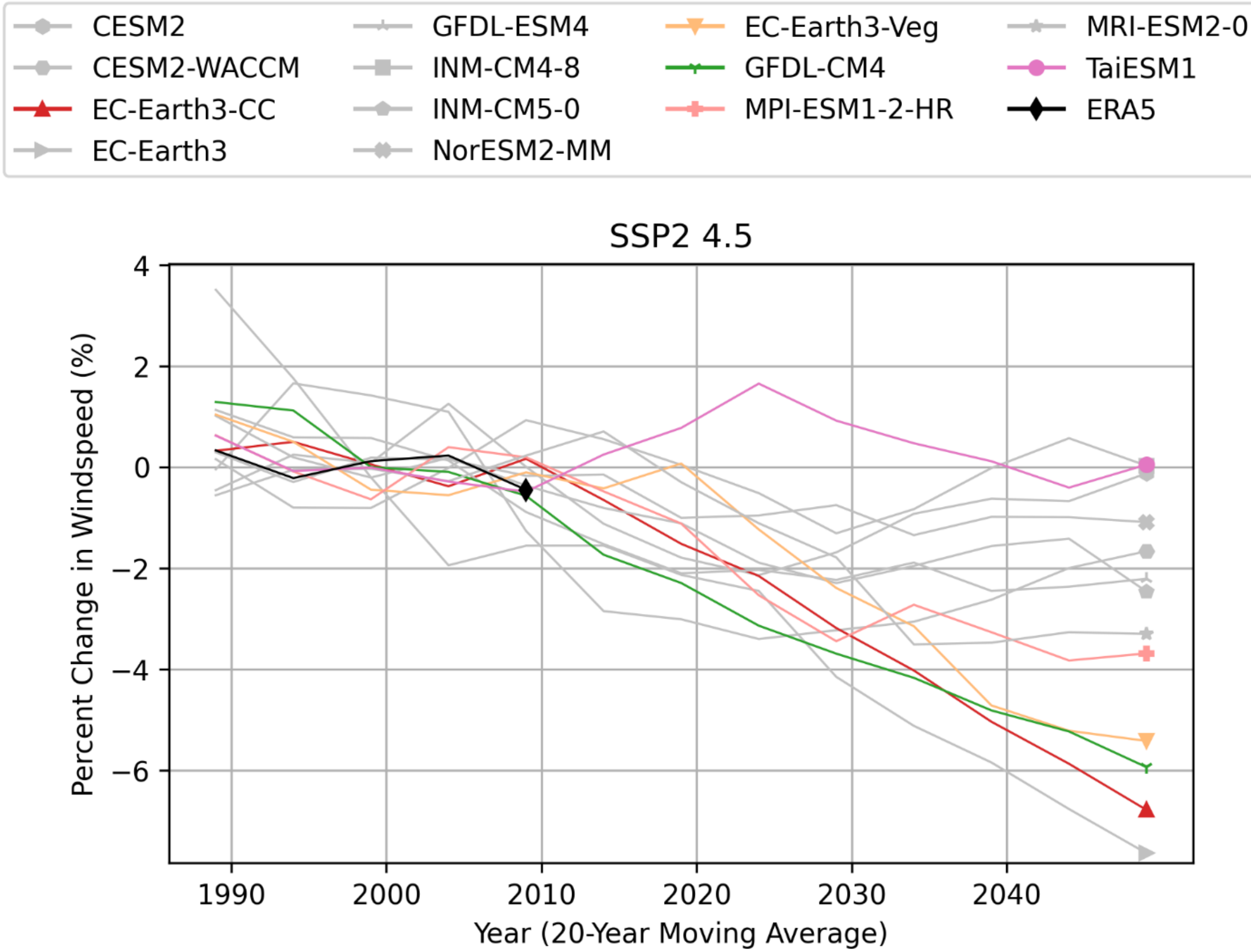

Figure B-8. Comparison of GCM trends in percent change in windspeed for TVA

Appendix C. Selected GCM Subset Results in Context of Full GCM Results in the Southern Company Region

The figures in this appendix show results for the selected subset of GCMs in color, with the results for the other models from the full set shown in gray. In color are TaiESM1, EC-Earth3-CC, GFDL-CM4, EC-Earth3-Veg, and MPI-ESM1-2-HR. In gray are CESM2, CESM2-WACCM, EC-Earth3, GFDL-ESM4, INM-CM4-8, INM-CM5-0, NorESM2-MM, and MRI-ESM2-0.

CONUS is shown previously; Southern Company appears here.

We use a simple state mask to represent the utility territory, e.g., Alabama and Georgia for Southern Company.

To view these results interactively with labels on each trace, see https://nrel.github.io/gcm_eval/. For GCM names and sources, see references.

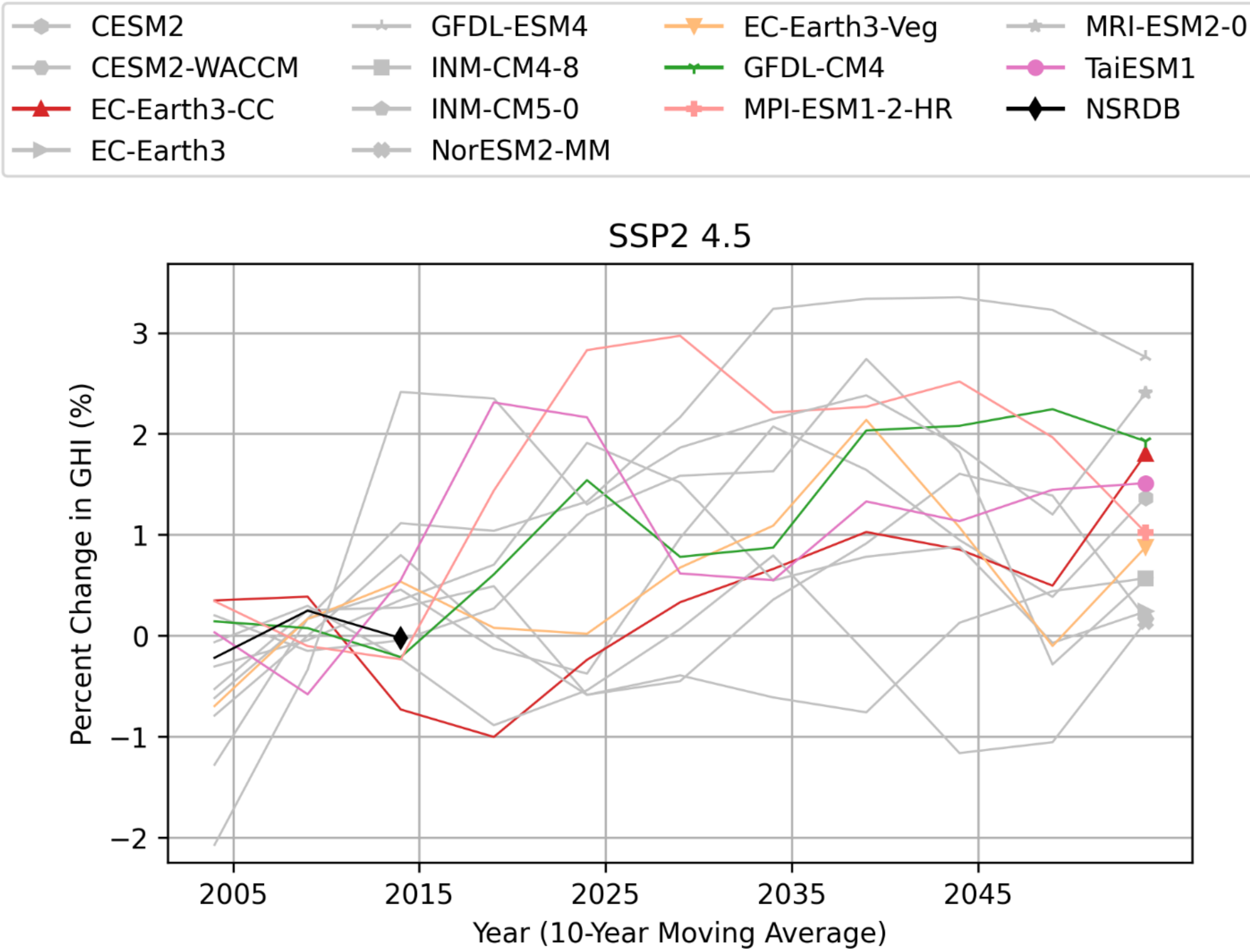

Figure C-1. Comparison of GCM trends in changes to GHI for Southern Company

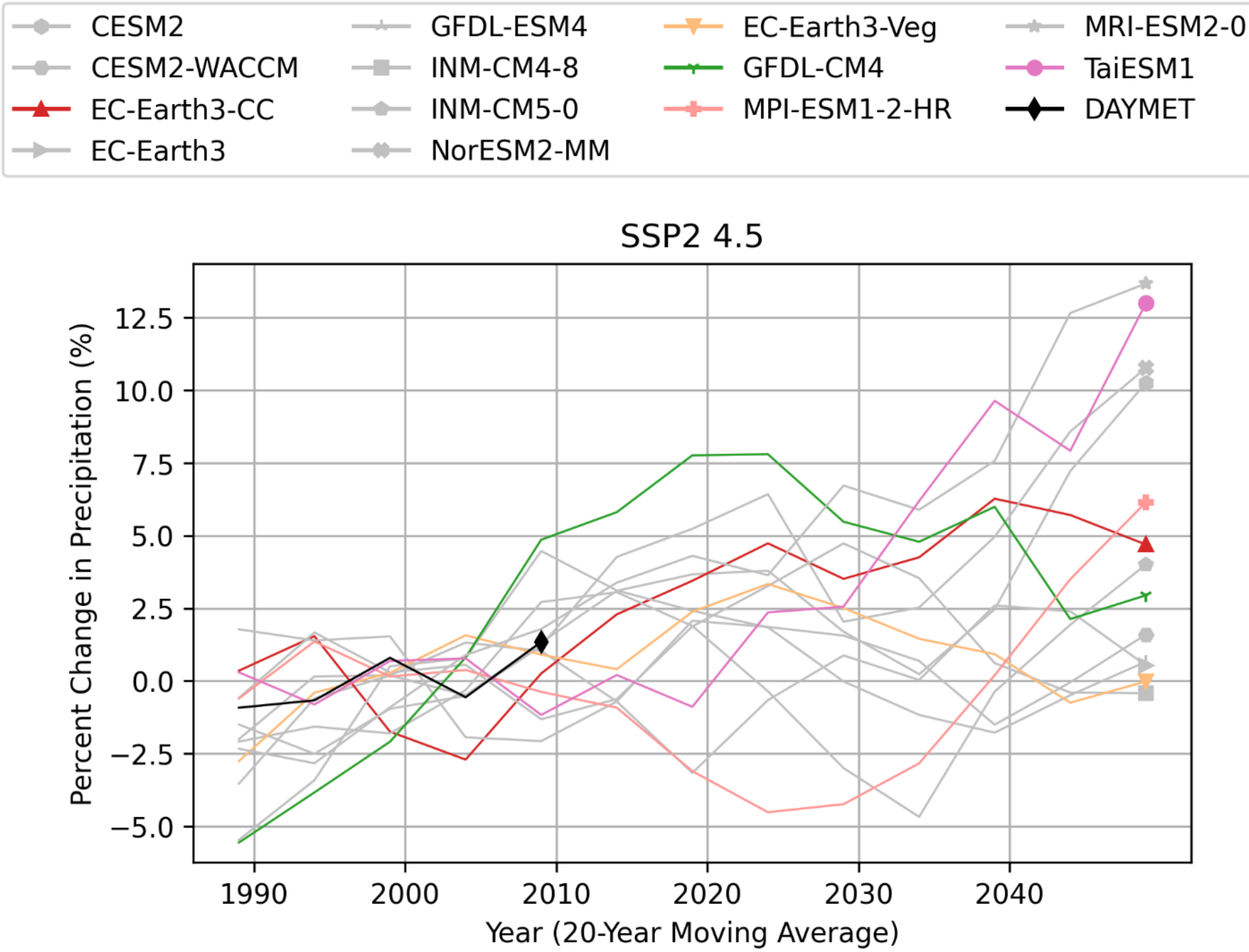

Figure C-2. Comparison of GCM trends in changes to precipitation for Southern Company

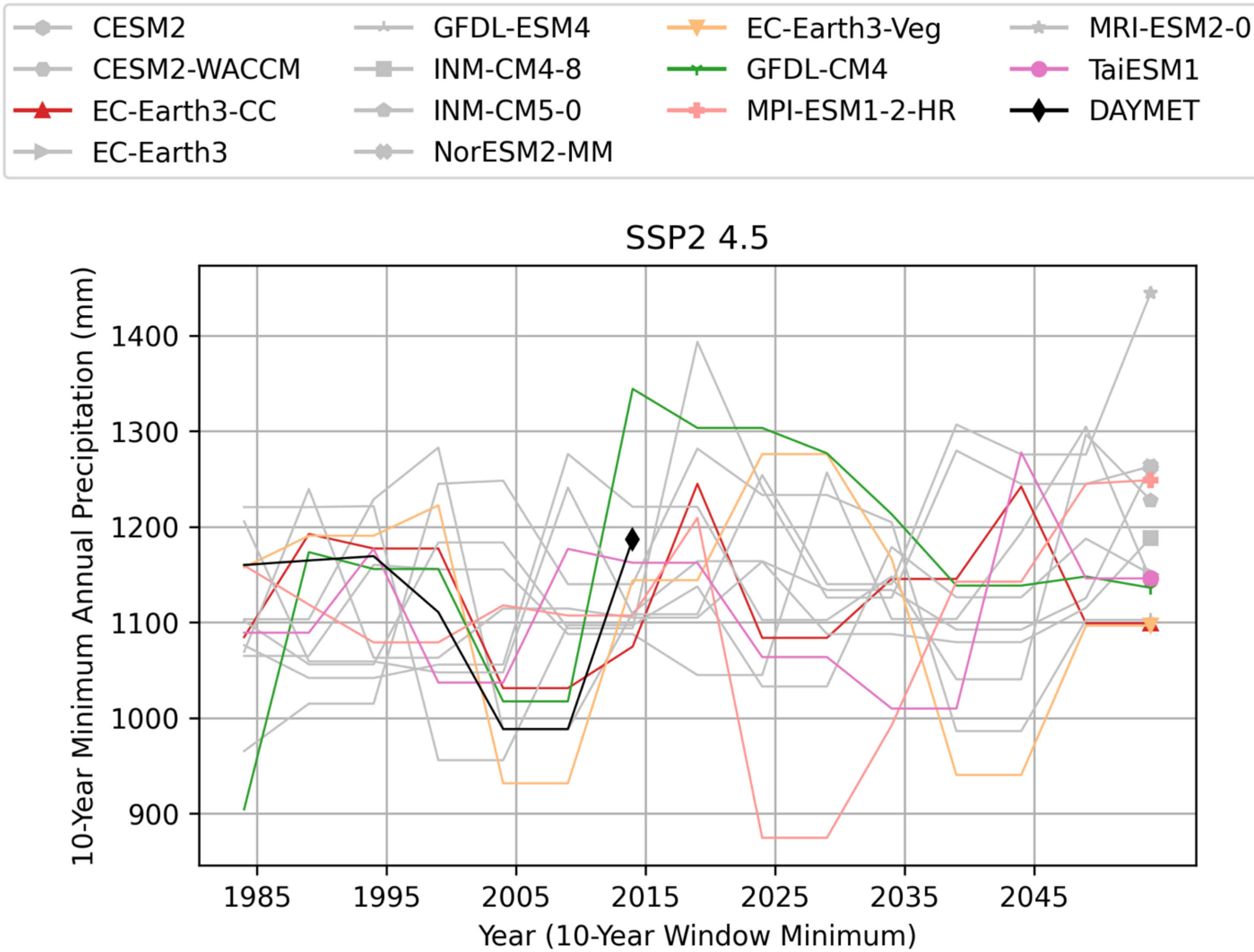

Figure C-3. Comparison of GCM trends in 10-year minimum annual precipitation for Southern Company

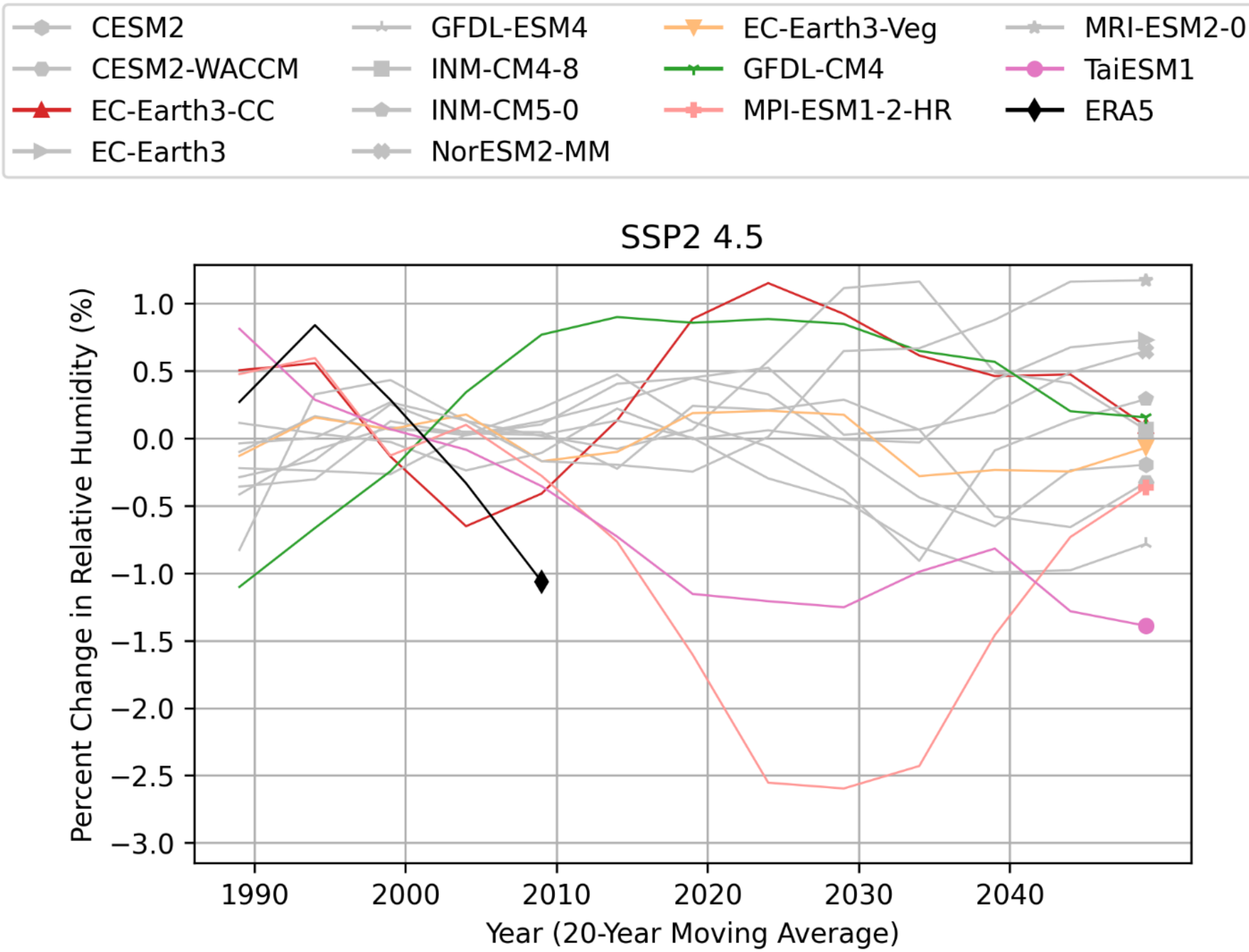

Figure C-4. Comparison of GCM trends in changes to relative humidity for Southern Company

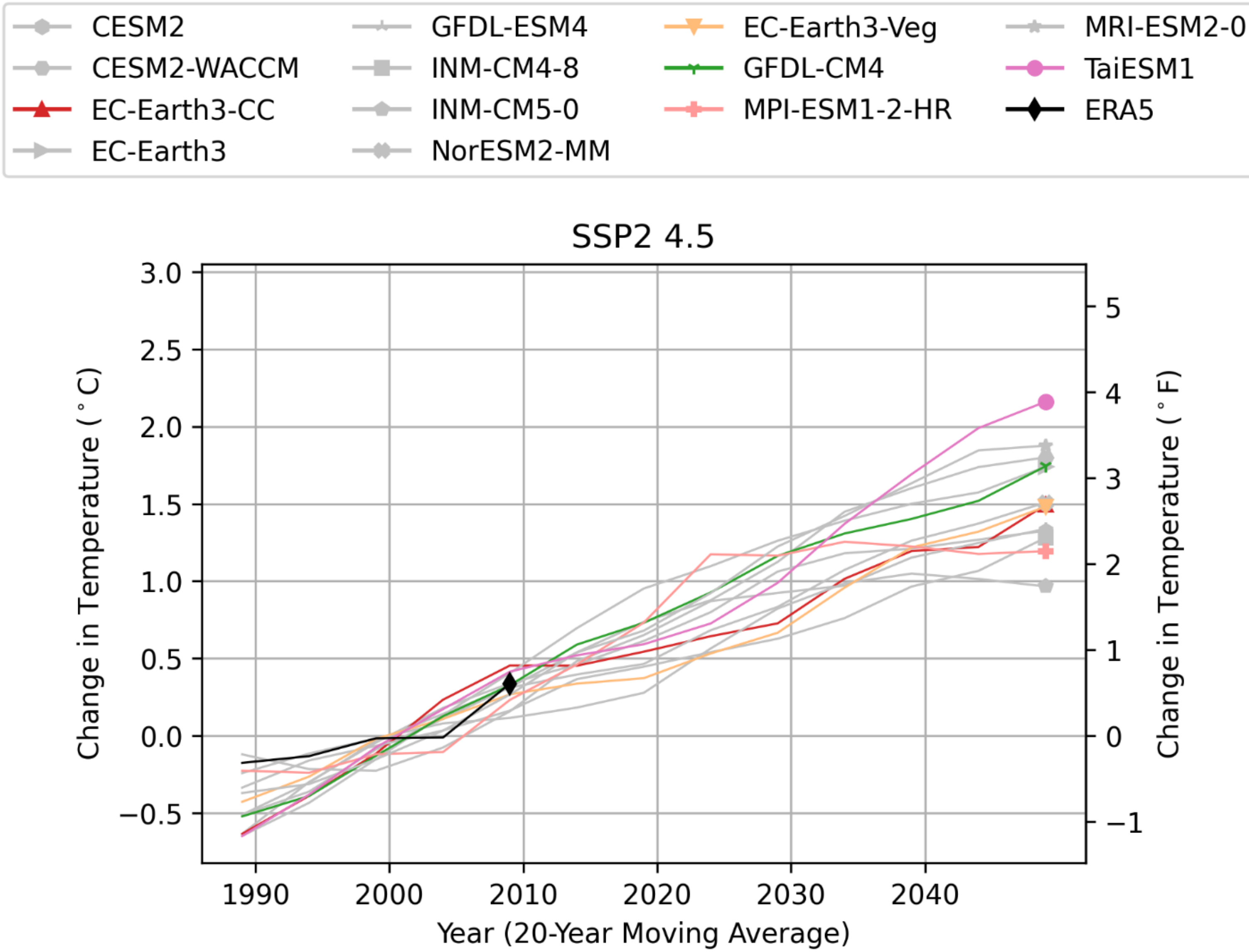

Figure C-5. Comparison of GCM trends in changes in temperature for Southern Company

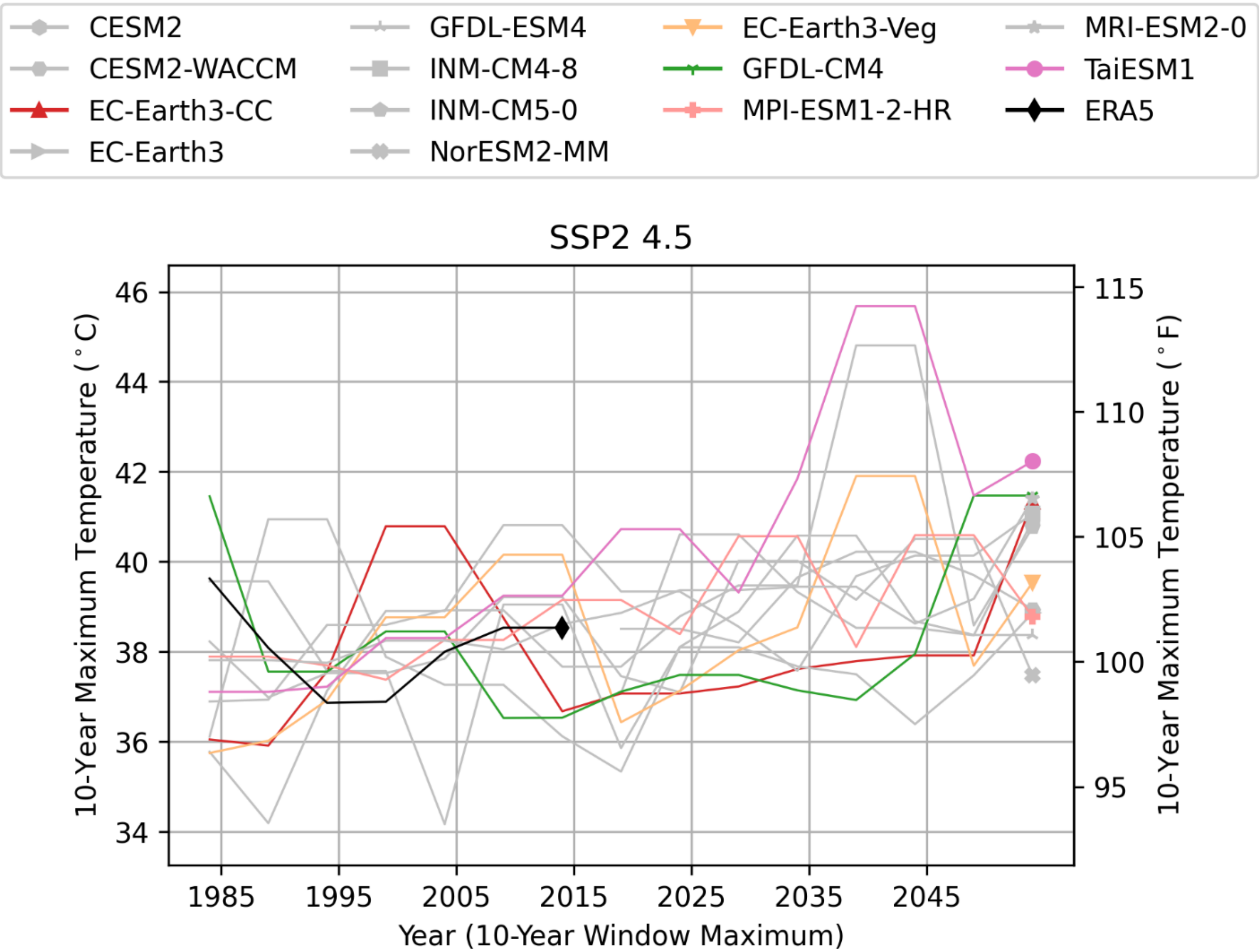

Figure C-6. Comparison of GCM trends in 10-year maximum temperature for Southern Company

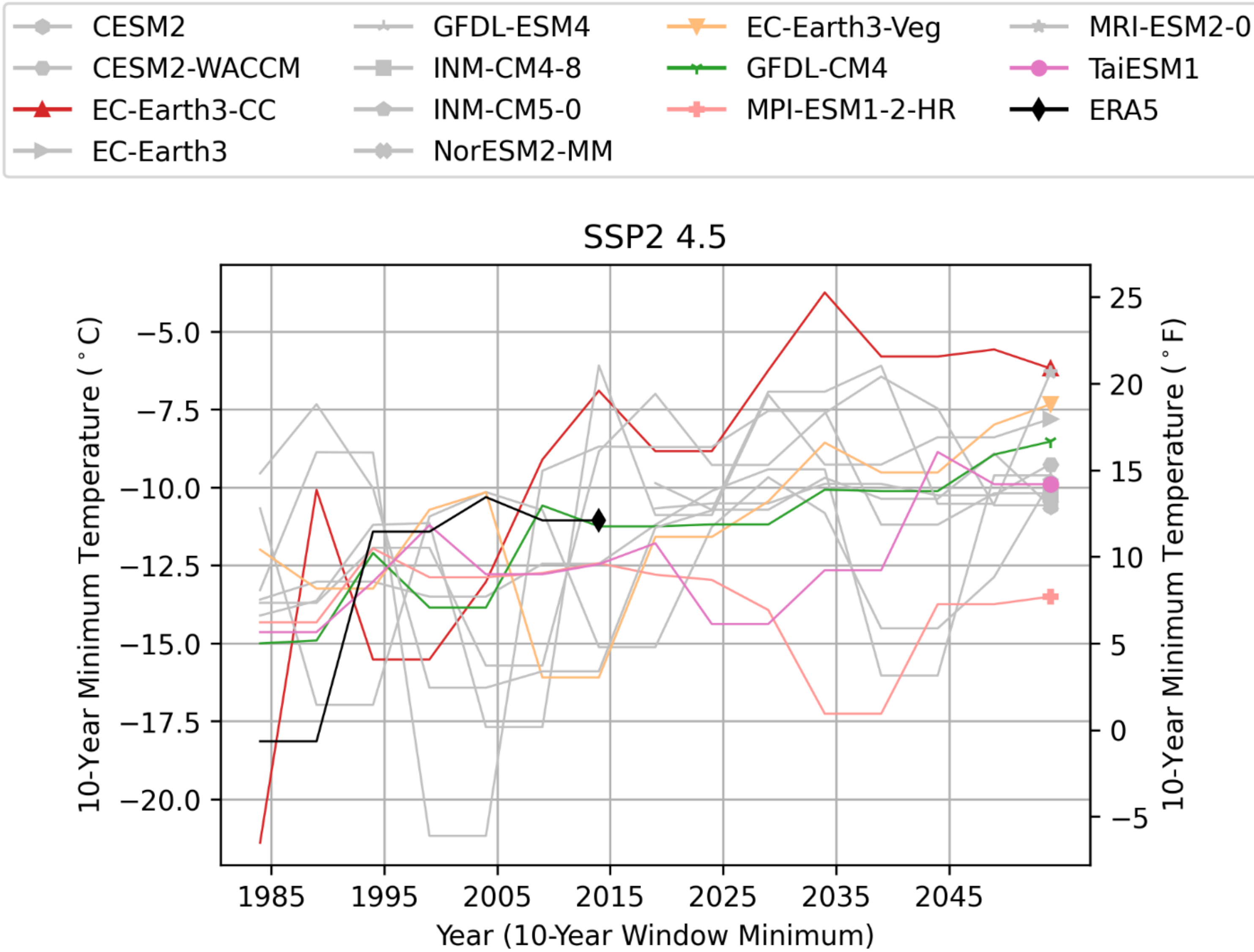

Figure C-7. Comparison of GCM trends in 10-year minimum temperature for Southern Company

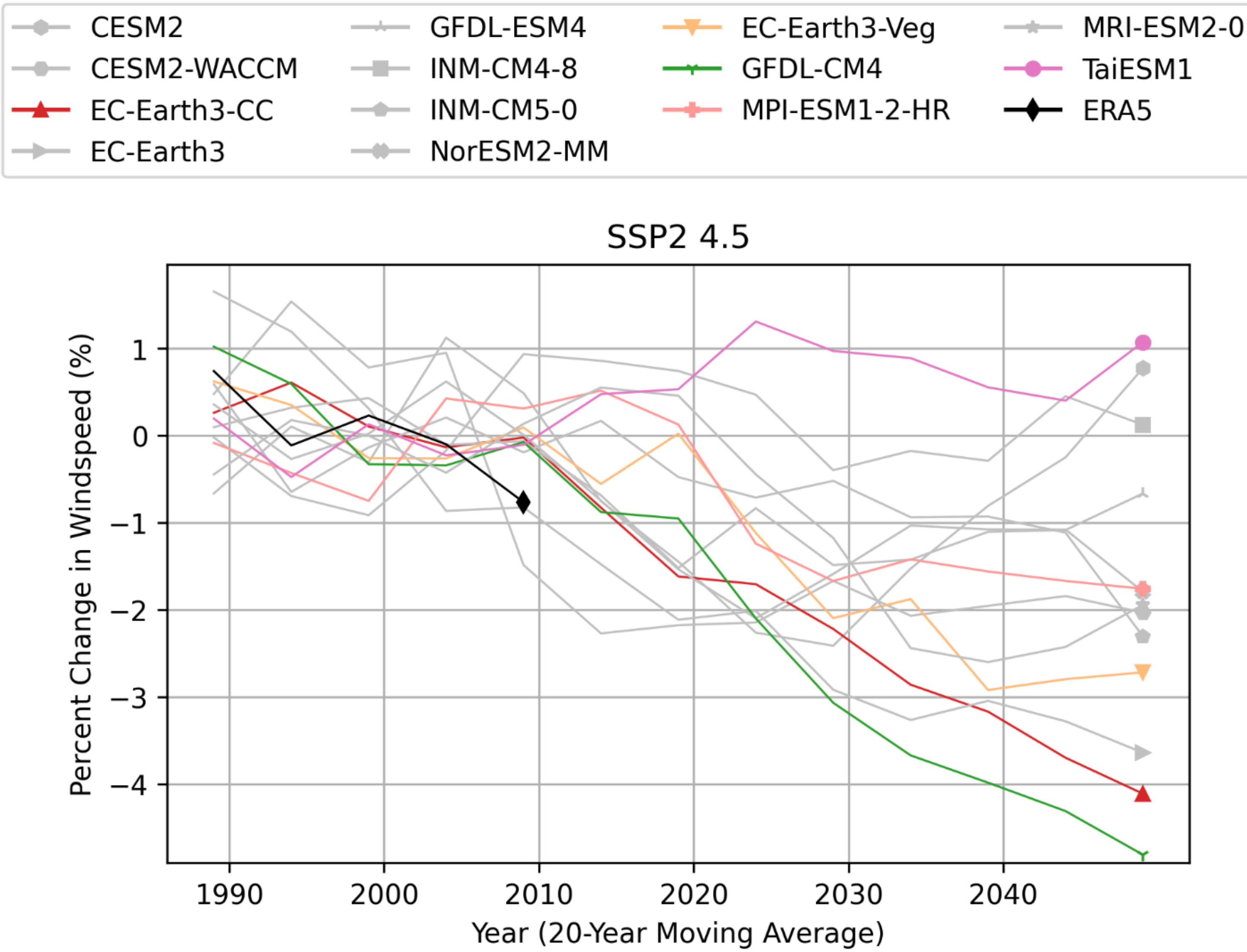

Figure C-8. Comparison of GCM trends in percent change in windspeed for Southern Company