

13 **Abstract**

14 Stratospheric aerosol injection (SAI) has been proposed as a possible complementary solution to
15 limit global warming and its societal consequences. However, the climate impacts of such
16 intervention remain unclear. Here, we introduce an explainable artificial intelligence (XAI)
17 framework to quantify how distinguishable an SAI climate might be from a pre-deployment
18 climate. A suite of neural networks is trained on Earth system model data to learn to distinguish
19 between pre- and post-deployment periods across a variety of climate variables. The network
20 accuracy is analogous to the “climate distinguishability” between the periods, and the
21 corresponding distinctive patterns are identified using XAI methods to gain insights into the
22 emerging signals from SAI. For many variables, the two periods are less distinguishable under
23 SAI than under a no-SAI scenario, suggesting that the specific intervention modeled decelerates
24 future climatic changes. Other climate variables for which the intervention has negligible effect
25 are also highlighted.

26

27

28

29 **Keywords**

30 Solar climate intervention, Stratospheric Aerosols Injection (SAI), eXplainable Artificial
31 Intelligence (XAI), deep learning, climate distinguishability, climatic impacts.

32

33

34

35

36

37

38 **Plain Language Summary**

39 We use Earth system model predictions for two scenarios of the future: one policy-relevant climate
40 change scenario where global temperatures continue rising in the coming decades, and that same
41 scenario but with humans intervening in the climate system to limit warming to 1.5°C. We then
42 train a machine to learn to classify annual maps of climate variables based on whether they
43 originate from the period before or after the intervention. The more successful the machine is at
44 this task, the more distinguishable the pre- and post-intervention periods are with respect to the
45 variable analyzed. Our results show that for many climate variables, the two periods are less
46 distinguishable under the climate intervention scenario than the no-intervention scenario. In those
47 cases, the intervention ends up decelerating future climate change. However, we also show that
48 there are important climate variables for which the intervention has a negligible effect.

49

50 **Key points**

- 51 • An explainable artificial intelligence framework is introduced to quantify the “climate
52 distinguishability” under a climate intervention scenario.
- 53 • The distinctive patterns between the pre- and post-intervention climates are not predefined
54 but are learned directly from the data.
- 55 • For the Earth system model simulations analyzed, stratospheric aerosol injection is shown
56 to decelerate future changes for some climate variables, while it shows a negligible effect
57 for others.

58

59

60 1. Introduction

61 In order to limit the adverse impacts of global warming on weather, climate and society, various
62 climate intervention strategies have been proposed as complementary to cutting CO₂ emissions.
63 The two main categories of such strategies are greenhouse gas removal and solar climate
64 intervention (Herzog, 2001; Vaughan and Lenton, 2011; National Research Council, 2015;
65 National Academies of Sciences, Engineering and Medicine, NASEM 2021; Xu et al., 2020). Solar
66 climate intervention consists of technologies that aim to increase the reflection of the incoming
67 solar radiation and cool down the planet. A particularly popular strategy of solar climate
68 intervention is stratospheric aerosol injection (SAI), which involves the deliberate injection of tiny
69 particles (i.e., aerosols) into the stratosphere to reflect incoming solar radiation (Crutzen, 2006;
70 Robock et al., 2009; Niemeier and Tilmes, 2017; MacMartin et al., 2017; Tilmes et al., 2018; 2020;
71 Richter et al., 2022). The natural analog of SAI is large volcanic eruptions (e.g., the Mount
72 Pinatubo eruption in 1991), during which, tiny particles are expelled into the atmosphere, resulting
73 in a temporary (for a handful of years) cooling of the planet (Robock and Mao, 1995; Parker et al.,
74 1996; Robock, 2000; Soden et al., 2002).

75 Although SAI has been shown to be a relatively inexpensive and effective strategy to limit
76 global warming (Smith and Wagner, 2018; Tilmes et al., 2018; 2020; MacMartin et al., 2018),
77 large uncertainties remain as to how such intervention would affect the climate system *beyond* the
78 global mean temperature. For example, the degree to which the intervened Earth system would
79 exhibit a similar climate to the pre-deployment system, whether ongoing/future climatic changes
80 apart from global warming would be decelerated or halted, and the likelihood that SAI would
81 introduce *new* adverse impacts are all questions of great interest (Jones et al., 2018; MacMartin et
82 al., 2019; Kravitz and MacMartin, 2020; NASEM, 2021). Here, we propose an explainable
83 artificial intelligence (XAI) framework to gain insights into these questions. We consider model
84 simulations from the Community Earth System Model 2 under two future scenarios (spanning the

85 years 2015-2069): an intermediate climate change scenario where global temperatures continue
86 rising, and an identical climate change scenario except where SAI is deployed to limit warming to
87 1.5°C relative to the preindustrial era (Richter et al., 2022). We then focus on quantifying the
88 “climate distinguishability” between the pre- and post-SAI worlds, by tasking an artificial neural
89 network to distinguish between the two across a variety of climate variables. The more successful
90 the network is at this task the more “distinguishable” the pre- and post-SAI worlds are in terms of
91 their climate.

92 Specifically, to quantify the climate distinguishability after SAI, we train a neural network
93 to distinguish between maps of a variable of interest that originate from the SAI climate (i.e., the
94 SAI climate is defined as the 2040-2059 climate under the SAI scenario; see blue box in Figure
95 1a) vs maps that originate from the pre-deployment/reference climate (the reference climate is
96 defined as the 2020-2039 climate under the intermediate climate change scenario; O’Neill et al.,
97 2017; see gray box in Figure 1a). Although the prediction itself is not useful in this setting (i.e.,
98 we already know which map originates from which set of simulations), the accuracy of the network
99 informs us about the climate distinguishability between the two periods for the variable analyzed.
100 In this way, we quantify the degree of climate distinguishability with a single number: the accuracy
101 of the network. To put this number into context, we compare the network accuracy with its
102 “baseline” value, i.e., the network accuracy in the case where there was no intervention. That is,
103 we repeat the above prediction task but this time the network is trained to distinguish between the
104 reference climate and the future SSP climate with no intervention taking place (i.e., the future SSP
105 climate is defined as the 2040-2059 climate under the intermediate climate change scenario; see
106 magenta box in Figure 1a). The network’s accuracy from this second task serves as a “baseline”
107 value of climate distinguishability for the variable analyzed and is compared with the results from
108 the first task to help assess the potential benefits (or risks) of deploying SAI.

109 We highlight that the main advantages of the proposed framework are that i) it provides a
110 way to quantify with a single number the impact of an intervention on the reference climate, by
111 assessing how much distinguishable the pre- and post-deployment climates would be, and ii) it is
112 purely data-driven, thus, one does not need to predefine the form of change between the two
113 compared climates. Instead, with our framework, we let the data tell us “the ways” that the two
114 climates might be different. To gain insight into these distinctive patterns that make the two
115 climates distinguishable, we use tools of explainable artificial intelligence (XAI). XAI tools aim
116 to elucidate the decision-making process of deep learning models and have been increasingly
117 applied in the geosciences in the recent years (see McGovern et al., 2019; Toms et al., 2020;
118 Mamalakis et al., 2022a-c). Based on the climate simulations analyzed, SAI is shown to decelerate
119 future changes for some of the variables, while showing negligible effect for others, highlighting
120 the diversity in the potential effects of such climate interventions. In section 2, we provide details
121 about the data, the prediction task of our framework and methods used, and in section 3 we present
122 our results. Section 4 discusses our conclusions and future research directions.

123 **2. Data and methodology**

124 **2.1. Data**

125 We use data from an ensemble of Earth system model simulations: “Assessing Responses and
126 Impacts of Solar climate intervention on the Earth system with Stratospheric Aerosol Injection”
127 (ARISE-SAI; publicly available at <https://www.cesm.ucar.edu/community-projects/arise-sai>;
128 Richter et al., 2022). The ARISE-SAI experiment consists of two sets of parallel simulations
129 performed with the Community Earth System Model 2, using the Whole Atmosphere Community
130 Climate Model version 6 as its atmospheric component (CESM2(WACCM6); Gettelman, et al.,
131 2019; Danabasoglu, et al., 2020; Tilmes, et al., 2020; Richter et al., 2022): i) 10 ensemble members
132 from 2015 to 2069 under the Shared Socioeconomic Pathway 2-4.5 (SSP2-4.5; O’Neill et al.,
133 2017), which represents an intermediate climate change scenario; and ii) 10 ensemble members

134 from 2035 to 2069 under an SAI deployment scenario. In the latter, SO₂ is injected every day at
135 roughly 21 km height at 180° longitude and 30°S, 15°S, 15°N, and 30°N using a “controller”
136 algorithm (MacMartin et al., 2014; Kravitz et al., 2017). The SAI simulations aim to keep the
137 global-mean surface air temperature near 1.5°C above the preindustrial temperature. For more
138 detailed information on the ARISE-SAI experiment, the reader is referred to Richter et al. (2022).

139 We quantify climate distinguishability for a list of 21 climate variables that are provided
140 in Table S1. Prior to training the network, all variables are bi-linearly re-gridded to a 2.5° by 2.5°
141 resolution from an approximate 1° by 1° resolution to reduce the dimensionality of the prediction
142 task. Since this re-gridding is applied to the climate data of both scenarios, it is not expected to
143 affect the conclusions about the impacts of SAI.

144 **2.2. Prediction task**

145 We define the CESM2(WACCM6) output over the period 2020-2039 under the SSP2-4.5 scenario
146 as our reference climate, following the original study of ARISE-SAI (Richter et al., 2022). The
147 reference climate represents the climatic conditions before a potential deployment of SAI. We then
148 train a network to *distinguish* between the reference climate (see gray box in Figure 1a) and the
149 climate under SAI over the period 2040-2059 (see blue box in Figure 1a). Specifically, given a
150 randomly chosen map of a variable of interest as an input (e.g., a map of annual mean surface
151 temperature or annual maximum precipitation, see Table S1), a fully connected network is tasked
152 with estimating the probability that the map originated from the 2040-2059 SAI climate. A
153 probability value less than 0.5 indicates that the map is predicted to belong to the reference climate,
154 while a probability value greater than 0.5 indicates that the map is predicted to belong to the SAI
155 climate; see Figure 1b. Framing the prediction task in this way requires the network to identify
156 patterns that serve as robust and distinctive indicators to separate the pre- and post-deployment
157 periods. The more successful the network is at this task, the more the two periods are “climatically
158 distinguishable” under the SAI scenario. In contrast when the network is not successful (e.g., if it

159 performs similarly to a random chance-based model), the climatic conditions between the two
160 periods are deemed indistinguishable with respect to the variable analyzed and based on the
161 network used. We highlight here that the patterns used by the network could be of any form: local,
162 global or any type of combination of patterns, pointing out to the generic nature of the suggested
163 framework.

164 To place climate distinguishability under SAI into context, we compare it to the climate
165 distinguishability under the scenario of no intervention. We do this by we repeating the same
166 approach, but by tasking the network to distinguish between the reference climate and the climate
167 in the period 2040-2059 under the SSP2-4.5 scenario (see magenta box in Figure 1a). The
168 comparison between the climate distinguishability with and without SAI gives insights into the
169 potential of SAI to counter the impacts of climate change. For instance, in the specific case of the
170 ARISE-SAI simulations, it may be concluded that SAI reduces future climate change if the degree
171 of climate distinguishability is significantly lower under the SAI scenario than under the SSP
172 scenario. For details on the training approach and the architectures of the networks, please see
173 Supplementary Text S1.

174 **2.3. Explainable AI method**

175 We use the local attribution method Deep SHAP (Lundberg and Lee, 2017) to explain the
176 predictions of the network. We have chosen this method for two reasons: 1) it allows the user to
177 define the baseline for which the attribution is derived (see Mamalakis et al., (2023) on the
178 importance of baselines); and 2) it satisfies the *completeness* property (Sundararajan et al., 2017),
179 which holds that the attributions add up to the difference between the network output at the current
180 sample and the one at the baseline. For further details on the Deep SHAP algorithm, please see
181 Supplementary Text S2. We note that we have also used the method Integrated Gradients
182 (Sundararajan et al., 2017) to explain the network's predictions, and the results were very similar
183 to those based on Deep SHAP (not shown).

184 3. Results

185 We start by presenting the results for the case of annual maximum daily precipitation in Figure 2.
186 We first discuss the results for a future climate with no intervention. The global-mean annual
187 maximum precipitation exhibits an increase throughout the century but with large ensemble spread
188 (magenta lines, Figure 2a). The largest increases occur in the deep tropics, specifically over the
189 tropical Pacific (Figure 2b; see also O’Gorman and Schneider, 2009; Kharin et al., 2013; Pfahl et
190 al., 2017). The network can successfully distinguish between the reference climate and the SSP
191 future climate 85% of the time, which is significant at a 0.01 level (Figure 2d). Moreover, the
192 probability assigned by the network that a map corresponds to the future SSP climate increases
193 linearly with the actual year of the map and maximizes in the out-of-sample years 2060-2069
194 (Figure 2d). This suggests that there are robust signals of climate change that become more and
195 more evident with time. It also suggests that the learned patterns generalize successfully, since the
196 network is able to correctly classify the years 2060-2069, although those years were not used
197 during training (see Supplementary Text S1). Based on the results from the XAI method Deep
198 SHAP, the network mainly uses precipitation extremes over the tropical eastern Pacific (and to a
199 lesser degree over the Southern Ocean and the tropical Atlantic) to make its predictions (Figure
200 2f). Interestingly, the network does not use precipitation over the western Pacific or Australia,
201 despite the fact that the corresponding ensemble mean difference between the two periods is of
202 high magnitude (Figure 2b). This implies high internal variability of precipitation extremes over
203 these regions, which does not make them robust indicators from a signal-to-noise perspective.

204 Under the SAI scenario, the overall accuracy of the network is only 58% (Figure 2e), which
205 is not statistically different from a random chance-based model (at a 0.01 significance level, a
206 random chance-based model would perform with up to 69% accuracy, derived using a binomial
207 distribution). The network-estimated probability that a map corresponds to the SAI climate is
208 almost independent from the year of the map (Figure 2e), which indicates that there are no robust

209 long-term climate signals under SAI that the network could use for distinguishing from the
210 reference climate. This is also suggested by the XAI results; note the incoherent and noisy
211 attributions in Figure 2g. Generally, the results in Figure 2 indicate that although the
212 CESM2(WACCM6) simulates a robust increase in future extreme daily precipitation under the
213 SSP2-4.5 scenario, possible deployment of SAI could preserve the conditions of the reference (i.e.,
214 pre-deployment) climate. This could be an example of a potential positive SAI impact.

215 Next, we consider the annual mean surface temperature over land (Figure 3). Under the
216 SSP scenario, a clear increase in surface temperature is shown throughout the century that is
217 evident globally (Figure 3a-b). Accordingly, the network accuracy in distinguishing between the
218 reference and the future SSP climate is high, on the order of 93%. Many regions around the globe
219 are highlighted by Deep SHAP as robust distinctive patterns; e.g., Mexico, southern South
220 America, southern Africa, Indonesia, and southern Australia. Under the SAI scenario, although the
221 global mean temperature is similar to the one under the reference climate, there are robust patterns
222 of regional cooling that make the two climates *highly* distinguishable: 91% of the time (Figure 3e).
223 Regional cooling happens mainly over southern South America, eastern Africa, eastern Australia,
224 and Greenland (Figure 3c). These are the regions that the network uses to distinguish between the
225 reference and the SAI climates (see Figure 3g). Overall, these results indicate that the
226 CESM2(WACCM6) projects that a potential SAI deployment would lead to a less warm climate
227 than SSP; however, the annual mean surface temperature over land in an SAI world would also be
228 distinguishable from the reference climate. Importantly, the distinctive patterns in the two
229 scenarios are quite different, with warming being the distinctive difference under the SSP scenario,
230 while regional cooling patterns being the most robust distinctive patterns under SAI.

231 We have repeated the same analysis as in Figures 2-3 for a list of 21 variables (see Table
232 S1), and we summarize the results in Figure 4. For all variables, the network accuracy under the
233 SSP scenario (magenta circles in Figure 4a) is statistically significant. This means that even under

234 the intermediate climate change scenario SSP2-4.5, the CESM2(WACCM6) projects that the Earth
235 system would exhibit climatic conditions that are distinguishable from the reference climate in the
236 coming decades. However, for the majority of variables examined here, SAI would lead to a less
237 distinguishable climate than the SSP scenario, although (with a few exceptions) one that would
238 also be distinguishable from the reference climate (note that the network accuracy (light blue
239 circles) is higher than the random chance-based accuracy). In particular, SAI would decelerate
240 many future greenhouse-gas driven climate changes, especially for surface temperature extremes,
241 precipitation, drought occurrence, sea level pressure, and Arctic sea ice (see also Xu et al., 2020;
242 Tye et al., 2022; Lee et al., 2020; 2023). It is important to note, however, that there are variables
243 for which SAI is projected to have minimal impact relative to climate change. Examples include
244 soil moisture, evapotranspiration, and ocean acidity.

245 We next explore how distinctive patterns might be modified from SAI; note that the
246 network accuracy alone does not provide this information. For example, as is shown in Figure 3,
247 the climate distinguishability under the SSP and the SAI scenarios is very similar, but the
248 corresponding distinctive patterns are different. To explore this further, the spatial correlation
249 between the XAI heatmaps under the SSP and SAI scenarios are presented in Figure 4b. In most
250 cases, the correlation is not statistically different from zero, which means that SAI is projected to
251 introduce different distinctive patterns relative to those from the SSP scenario. Exceptions are for
252 cases where the correlation is high, such as for ocean acidity and ocean heat, which means that the
253 anticipated SSP-driven distinctive patterns are projected to remain almost unchanged under SAI.

254 The results in Figure 4 indicate the diverse impacts of SAI on different components of the
255 climate system, which highlights the need for systematic and thorough investigations into the
256 possible impacts of SAI on the Earth system beyond only the global-mean temperature response.
257 Such research is needed for a well-informed policy making regarding potential deployment of
258 climate intervention approaches (NASEM, 2021). The framework introduced here allows for such

259 data-driven and generic investigations to uncover the ways in which an SAI climate would be
260 different from a pre-deployment one.

261 **4. Conclusions**

262 In this study, a new framework was used that allows quantification (with a single number)
263 of the degree of climate distinguishability between a reference climate and future climate states
264 from both SAI and no-SAI worlds. The framework is based on the use of machine learning and
265 leverages XAI tools to identify robust distinctive patterns under the intervention and the no-
266 intervention scenarios. The framework is purely data driven, nonlinear, nonlocal, and it accounts
267 for underlying uncertainties in the data that may originate from internal stochastic variability or
268 uncertainties in Earth system model physics.

269 We applied this framework to data from ensembles of simulations that were developed to
270 examine the potential impacts of stratospheric aerosol injection; namely, the ARISE-SAI project
271 (Richter et al., 2022). In these simulations, SAI was shown to have diverse impacts on the
272 simulated climate. These include minimizing changes due to greenhouse gas forcing in
273 temperature and precipitation extremes, while having negligible effect on ocean acidification.
274 Also, for the majority of variables examined here, the simulated deployment of SAI led to new
275 patterns of change with respect to the reference climate that were different from the SSP patterns.
276 This raises the possibility of SAI leading to *new* (and perhaps unwanted) changes in specific
277 components of the Earth system or in certain regions of the world.

278 We do note some potential limitations of the presented framework. One is the dependence
279 of the results on the amount of data. Neural networks are known to be “data-thirsty” models
280 (LeCun et al., 2015), so it is possible that certain patterns that were not identified as robust
281 indicators during training could become robust with more data. However, the dependence on the
282 amount of data is present in virtually all climate settings involving questions of signal-to-noise and
283 statistical significance. Another limitation is the possible dependence of the results on the network

284 architecture. In order to address this issue here, we searched over many different architectures and
285 combinations of hyperparameters before training the network, as described in Supplementary Text
286 S1. That way, we let the data guide us as to what architecture we should use for each climate
287 variable. Yet, we acknowledge that it is possible that some of these results depend on the adopted
288 architectures.

289 Our work highlights the need to further research the impacts of possible intervention
290 approaches *beyond* just global mean temperatures, as has been done in other studies, examining
291 ARISE-SAI data in particular (Keys et al., 2022; Labe et al., 2023; Hueholt et al., 2023). In doing
292 so, we envision that the notion of “quantifiable climate distinguishability” will be a relevant and
293 informative metric to assess impacts and to expand the design space of possible interventions (Lee
294 et al., 2020), as illustrated by the presented results. Further investigation could include further
295 assessing the climate distinguishability by considering multiple variables at the same time (i.e., the
296 network input consists of many channels each of which refers to a different variable), to assess
297 potential impacts on the dependence structure of different components of the Earth system and the
298 occurrence of compound events. Future work could also focus on analyzing the output of more
299 than one model and of more than one climate intervention strategy to establish a more holistic
300 picture of the potential impacts of proposed climate intervention strategies.

301

302

303 **Acknowledgments**

304 This work was supported by Defense Advanced Research Projects Agency (DARPA) Grant No.
305 HR00112290071. The views expressed here do not necessarily reflect the positions of the U.S.
306 government. The authors would also like to thank the efforts of the ARISE-SAI team for making
307 their data publicly available.

308

309

310 **Data availability**

311 The ARISE-SAI data is publicly available at [https://www.cesm.ucar.edu/community-](https://www.cesm.ucar.edu/community-projects/arise-sai)
312 [projects/arise-sai](https://www.cesm.ucar.edu/community-projects/arise-sai). The code to reproduce the presented results is publicly available at
313 https://github.com/amamalak/Quantify_SAI_impacts.

314

315

316

317

318 **References**

- 319 Crutzen, P.J. (2006) Albedo Enhancement by Stratospheric Sulfur Injections: A contribution to
320 Resolve a Policy Dilemma? *Clim. Change*, **77**(3-4), 211-220, doi:10.1007/s10584-006-9101-
321 y.
- 322 Danabasoglu, G., et al. (2020) The Community Earth System Model Version 2 (CESM2), *J. Adv.*
323 *Model. Earth Sy.*, **12**, e2019MS001916, <https://doi.org/10.1029/2019MS001916>.
- 324 Gettelman, A., et al. (2019) The whole atmosphere community climate model version 6
325 (WACCM6), *J. Geophys. Res.-Atmos.*, **124**, 12380–12403,
326 <https://doi.org/10.1029/2019JD030943>.
- 327 Herzog, H.J., (2001) What Future for Carbon Capture and Sequestration?, *Environ. Sci. Technol.*,
328 **35**(7), 148A-153A.
- 329 Hueholt, D.M., E.A. Barnes, J.W. Hurrell, J.H. Richter, and L. Sun (2023) Assessing Outcomes in
330 Stratospheric Aerosol Injection scenarios shortly after deployment, authorea preprints.
- 331 Jones, A.C., M.K. Hawcroft, J.M. Haywood, A. Jones, X. Guo, and J.C. Moore (2018) Regional
332 climate impacts of stabilizing global warming at 1.5 K using solar geoengineering, *Earth's*
333 *Future*, **6**, 230-251.
- 334 Keys, P.W., E.A. Barnes, N.S. Diffenbaugh, J.W. Hurrell, and M.B. Curtis (2022) Potential for
335 perceived failure of Stratospheric Aerosol Injection deployment, *PNAS*, **119**(40),
336 e2210036119.
- 337 Kharin, V.V., F.W. Zwiers, X. Zhang, et al. (2013) Changes in temperature and precipitation
338 extremes in the CMIP5 ensemble, *Climatic Change*, **119**, 345-357.
- 339 Kravitz, B., et al. (2017) First simulations of designing stratospheric sulfate aerosol
340 geoengineering to meet multiple simultaneous climate objectives, *J. Geophys. Res.-Atmos.*,
341 **122**, 12616-12634.

342 Kravitz, B., and D.G. MacMartin (2020) Uncertainty and the basis for confidence in solar
343 geoengineering research, *Nat Rev Earth Environ*, **1**, 64-75.

344 Labe, Z.M., E.A. Barnes, and J.W. Hurrell (2023) Identifying the regional emergence of climate
345 patterns in the ARISE-SAI-1.5 simulations, *Environmental Research Letters*,
346 <https://doi.org/10.1088/1748-9326/acc81a>.

347 LeCun, Y., Y. Bengio, and G. Hinton (2015) Deep learning, *Nature*, **521**, 436-444,
348 <https://doi.org/10.1038/nature14539>.

349 Lee, W., D. MacMartin, D. Visoni, and B. Kravitz (2020) Expanding the design space of
350 stratospheric aerosol geoengineering to include precipitation-based objectives and explore
351 trade-offs, *Earth Syst. Dynam.*, **11**(4), 1051-1072.

352 Lee, W.R., et al., (2023) High-latitude stratospheric aerosol injection to preserve the Arctic,
353 *Earth's Future*, **11**(1), e2022EF003052.

354 Lundberg, S. M. and S. I. Lee (2017) A unified approach to interpreting model predictions,” *Proc.*
355 *Adv. Neural Inf. Process. Syst.*, pp. 4768-4777.

356 MacMartin, D.G., B. Kravitz, D.W. Keith, and A. Jarvis (2014) Dynamics of the coupled human-
357 climate system resulting from closed-loop control of solar geoengineering, *Clim. Dynam.*, **43**,
358 243-258.

359 MacMartin, D.G., et al. (2017) The Climate Response to Stratospheric Aerosol Geoengineering
360 Can Be Tailored Using Multiple Injection Locations, *J. Geophys. Res. Atmos.*, **122**(23),
361 12,574-12,590, doi:10.1002/2017JD026868.

362 MacMartin, D.G., K.L. Ricke, and D.W. Keith (2018) Solar geoengineering as part of an overall
363 strategy for meeting 1.5°C Paris target, *Philosophical Transactions of the Royal Society A*,
364 **376**, 20160454.

365 MacMartin, D.G., W. Wang, B. Kravitz, S. Tilmes, J.H. Richter, and M.J. Mills (2019) Timescale
366 for detecting the climate response to stratospheric aerosol geoengineering. *Journal of*
367 *Geophysical Research: Atmospheres*, **124**, 1233-1247.

368 Mamalakis, A., I. Ebert-Uphoff, E.A. Barnes (2022a) Explainable Artificial Intelligence in
369 Meteorology and Climate Science: Model fine-tuning, calibrating trust and learning new
370 science, in *Beyond explainable Artificial Intelligence* by Holzinger et al. (Editors), Springer
371 Lecture Notes on Artificial Intelligence (LNAI).

372 Mamalakis, A., I. Ebert-Uphoff, E.A. Barnes (2022b) Neural network attribution methods for
373 problems in geoscience: A novel synthetic benchmark dataset, *Environmental Data Science*,
374 **1**.

375 Mamalakis, A, E.A. Barnes and I. Ebert-Uphoff (2022c) Investigating the fidelity of explainable
376 artificial intelligence methods for applications of convolutional neural networks in geoscience,
377 *Artificial Intelligence for the Earth Systems*, **1**(4), e220012.

378 Mamalakis, A, E.A. Barnes and I. Ebert-Uphoff (2023) Carefully choose the baseline: Lessons
379 learned from applying XAI attribution methods for regression tasks in geoscience, *Artificial*
380 *Intelligence for the Earth Systems*, **2**(1), e220058.

381 McGovern, A., *et al.*, (2019) Making the black box more transparent: Understanding the physical
382 implications of machine learning,” *Bulletin of the American Meteorological Society*, vol. **100**,
383 no. 11, pp. 2175-2199.

384 National Academies of Sciences, Engineering, and Medicine (2021) Reflecting Sunlight:
385 Recommendations for Solar Geoengineering Research and Research Governance.
386 Washington, DC: The National Academies Press. <https://doi.org/10.17226/25762>.
387

388 National Research Council (2015) Climate Intervention: Carbon Dioxide Removal and Reliable
389 Sequestration. Washington, CD: The National Academies Press.
390 <https://doi.org/10.17226/18805>.

391 Niemeier, U., and S. Tilmes (2017) Sulfur injections for a cooler planet, *Science*, **357**(6348), 246-
392 248, doi:10.1126/science.aan3317.

393 O’Gorman, O.A., and T. Schneider (2009) The physical basis for increases in precipitation
394 extremes in simulations of 21st-century climate change, *PNAS*, **106**(35), 14773-14777.

395 O’Neill, et al. (2017) The roads ahead: Narratives for shared socioeconomic pathways describing
396 world futures in the 21st century, *Global Environ. Change*, **42**, 169-180.

397 Parker, D.E., H. Wilson, P.D. Jones, J.R. Christy, C.K. Folland (1996) The impact of mount
398 Pinatubo on world-wide temperatures, *Int. J. Climatol.*, **16**, 487-497.

399 Pfahl, S., P. O’Gorman, and E. Fischer (2017) Understanding the regional pattern of projected
400 future changes in extreme precipitation, *Nature Climate Change*, **7**, 423-427.

401 Richter, J.H., et al. (2022) Assessing Responses and Impacts of Solar climate Intervention on the
402 Earth system with stratospheric aerosol injection (ARISE-SAI): protocol and initial results
403 from the first simulations, *Geosci. Model Dev.*, **15**, 8221-8243.

404 Robock, A. (2000) Volcanic eruptions and climate, *Rev. Geophys.*, **38**(2), 191-219,
405 doi:10.1029/1998RG000054.

406 Robock, A., and J. Mao (1995) The Volcanic Signal in Surface Temperature Observations, *J.*
407 *Climate*, **8**(5), 1086-1103.

408 Robock, A., A. Marquardt, B. Kravitz, and G. Stenchikov (2009) Benefits, risks, and costs of
409 stratospheric geoengineering, *Geophys. Res. Lett.*, **36**(19), L19703,
410 doi:10.1029/2009GL039209.

411 Smith, W., and G. Wagner (2018) Stratospheric aerosol injection tactics and costs in the first 15
412 years of deployment, *Environ. Res. Lett.*, **13**, 124001.

413 Soden, B.J., et al. (2002) Global cooling after the eruption of mount Pinatubo: A test of climate
414 feedback by water vapor, *Science*, **296**, 727-730, doi:10.1126/science.296.5568.727.

415 Sundararajan, M., A. Taly, Q. Yan, (2017) Axiomatic attribution for deep networks,” arXiv
416 preprint, <https://arxiv.org/abs/1703.01365>.

417 Tilmes, S., et al. (2018) CESM1(WACCM) Stratospheric Aerosol Geoengineering Large
418 Ensemble Project, *Bull. Am. Meteorol. Soc.*, **99**(11), 2361-2371, doi:10.1175/BAMS-D-17-
419 0267.1.

420 Tilmes, S., et al. (2020) Reaching 1.5 and 2.0 °C global surface temperature targets using
421 stratospheric aerosol geoengineering, *Earth Syst. Dynam.*, **11**, 579–601,
422 <https://doi.org/10.5194/esd-11-579-2020>.

423 Toms, B.A., E. A. Barnes, I. Ebert-Uphoff, “Physically interpretable neural networks for the
424 geosciences: Applications to Earth system variability,” *Journal of Advances in Modeling Earth*
425 *Systems*, vol. **12**, e2019MS002002, 2020.

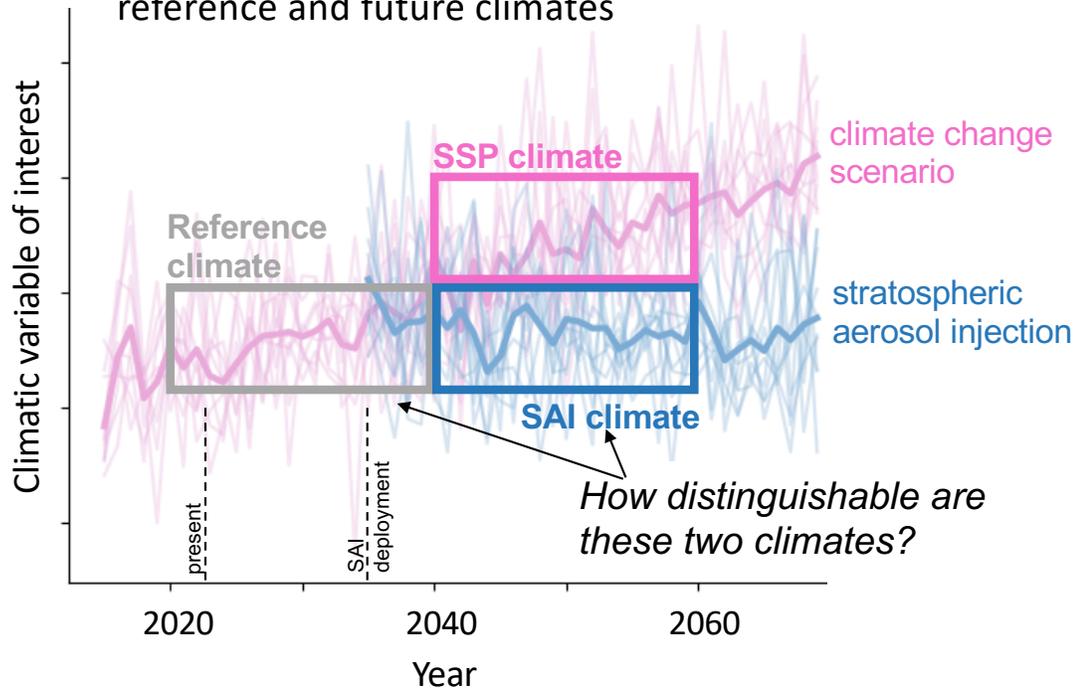
426 Tye, M.R., K. Dagon, M.J. Molina, J.H. Richter, D. Visoni, B. Kravitz, and S. Tilmes (2022)
427 Indices of extremes: geographic patterns of change in extremes and associated vegetation
428 impacts under climate intervention, *Earth Syst. Dynam.*, **13**, 1233-1257.

429 Vaughan, N.E. and T.M. Lenton (2011) A review of climate geoengineering proposals, *Clim.*
430 *Change*, **109**(3-4), 745-790.

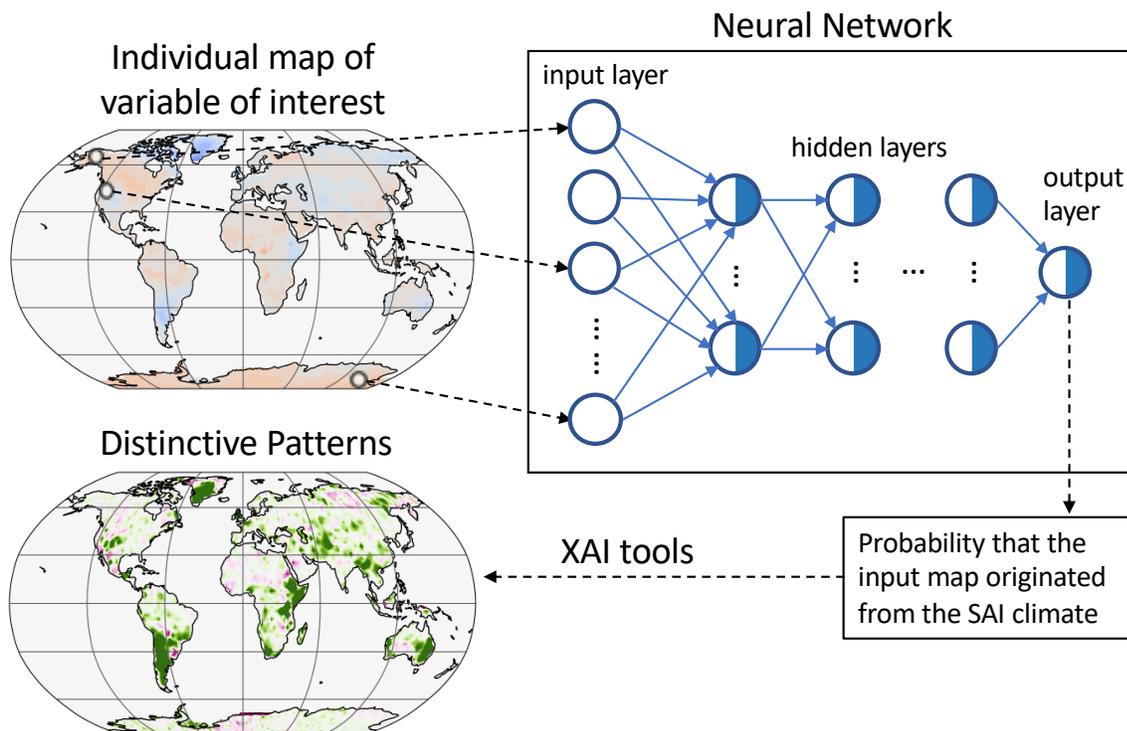
431

432

a) Climate distinguishability between reference and future climates



b) Prediction setting to quantify climate distinguishability

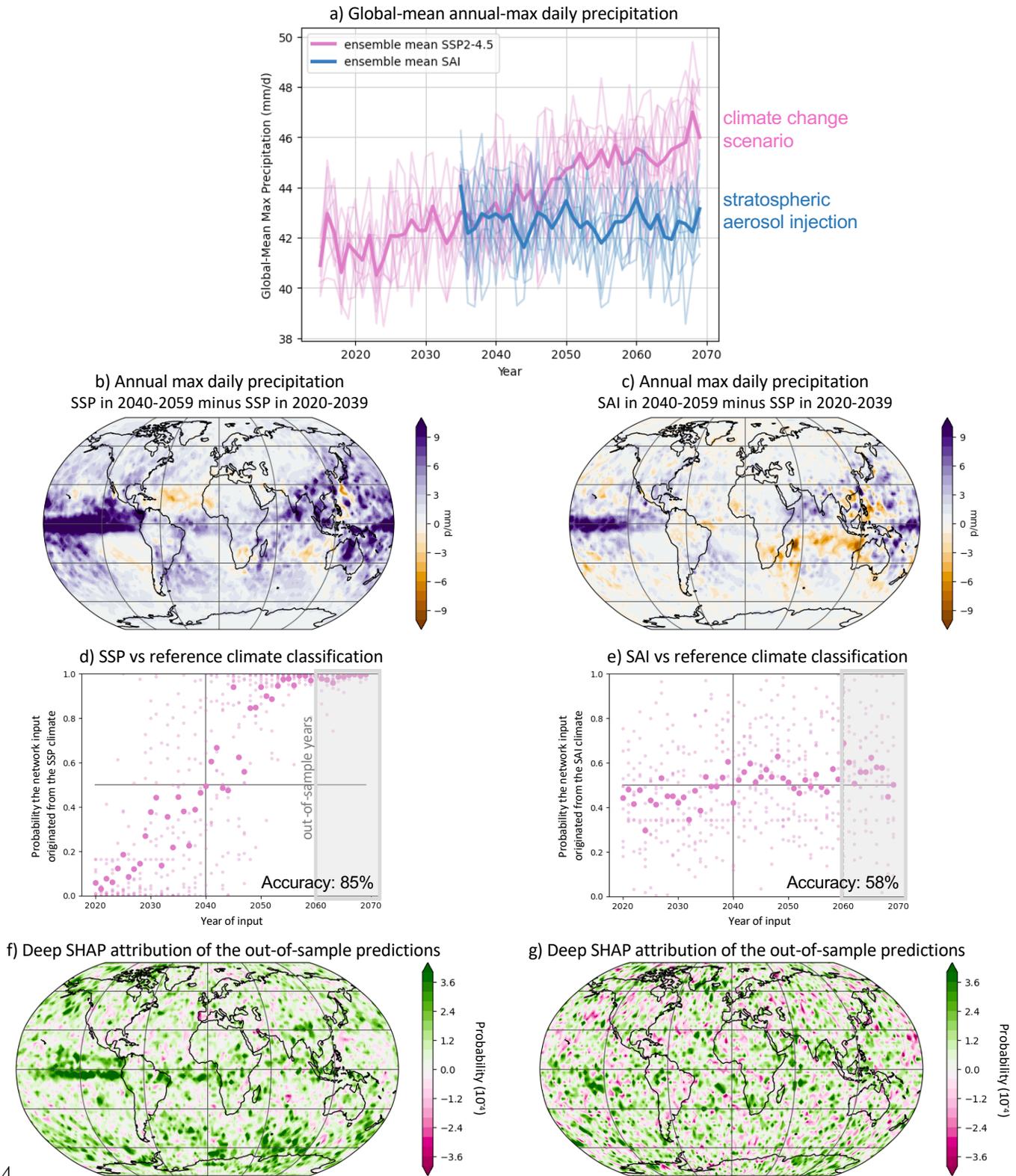


433

434 **Figure 1:** Schematic of our framework to quantify SAI impacts using XAI. a) Assessing climate

435 distinguishability between reference and future climates. Note that the pre-2040 period under an

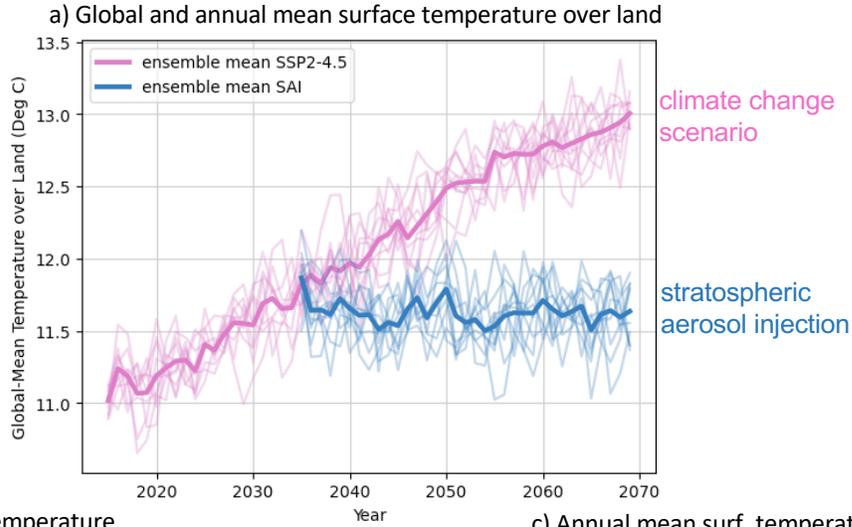
436 intermediate climate change scenario is used as the reference climate, in accordance to Richer et al (2022).
437 b) Schematic of the prediction task to quantify climate distinguishability after SAI and the use of XAI to
438 derive the distinctive patterns between the reference and SAI climates.



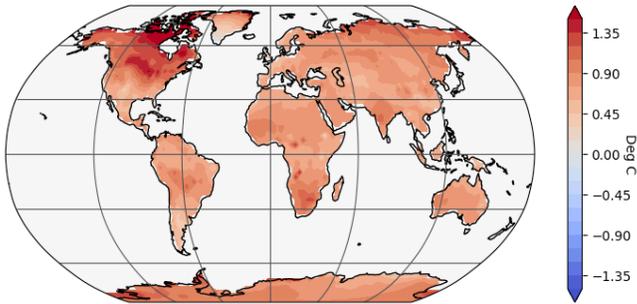
4

441 **Figure 2.** Results of our framework for annual maximum daily precipitation. a) Series of global-mean
 442 annual maximum precipitation (in mm/d) under the SSP2-4.5 scenario and the ARISE-SAI scenario. All

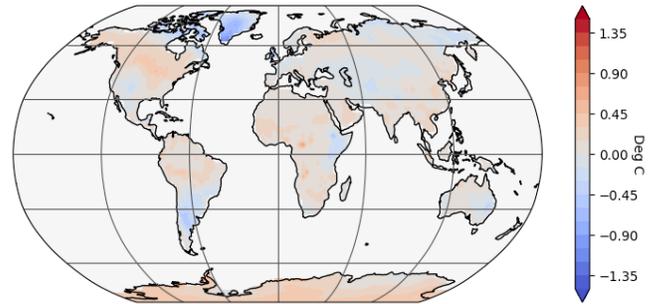
443 10 ensemble members and the ensemble mean are shown. b) Ensemble mean difference between the annual
444 maximum precipitation in the 2040-2059 SSP2-4.5 climate and the reference climate. d) Network-generated
445 probability that different annual maximum precipitation maps originated from the 2040-2059 SSP2-4.5
446 climate. The actual year of each map is provided in the horizontal axis. The overall accuracy of the network
447 is shown on the bottom right corner. f) Distinctive patterns that were used by the network to separate the
448 reference climate from the 2040-2059 SSP2-4.5 climate, as estimated using the method Deep SHAP. The
449 presented attributions correspond to the average attributions across the 2060-2069 network predictions and
450 all testing members, using the years 2035-2044 as baseline. c,e,g) Same as (b,d,f), but the network is trained
451 to separate the reference climate from the 2040-2059 ARISE-SAI climate.
452



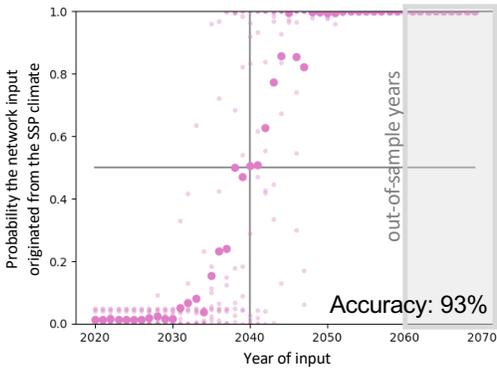
b) Annual mean surf. temperature SSP in 2040-2059 minus SSP in 2020-2039



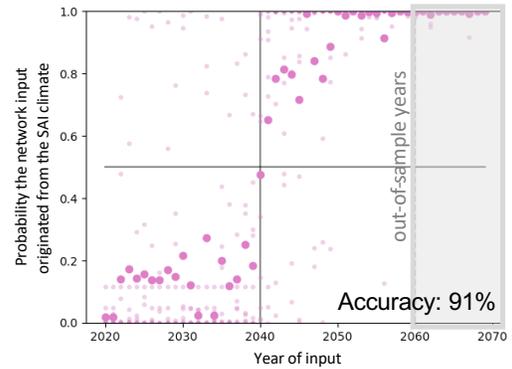
c) Annual mean surf. temperature SAI in 2040-2059 minus SSP in 2020-2039



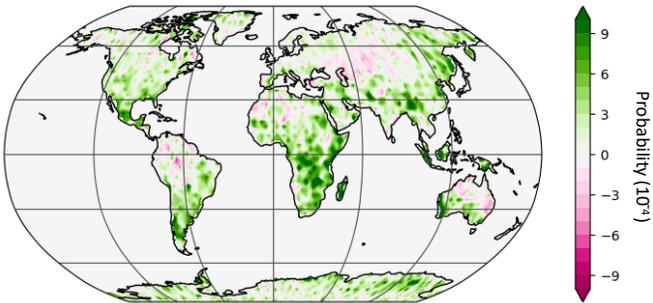
d) SSP vs reference climate classification



e) SAI vs reference climate classification



f) Deep SHAP attribution of the out-of-sample predictions



g) Deep SHAP attribution of the out-of-sample predictions

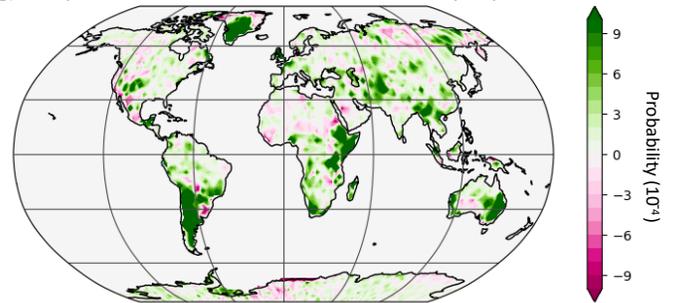
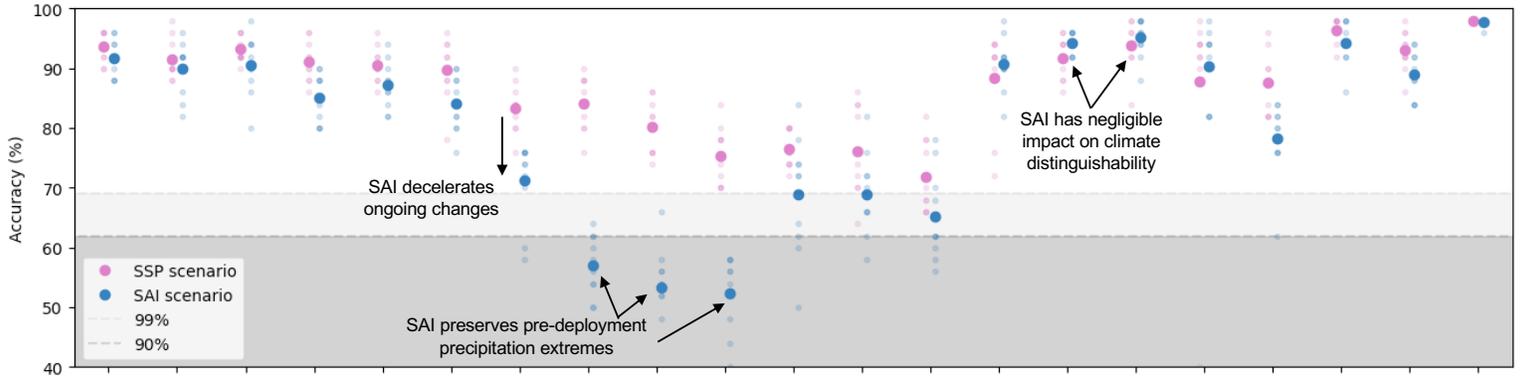
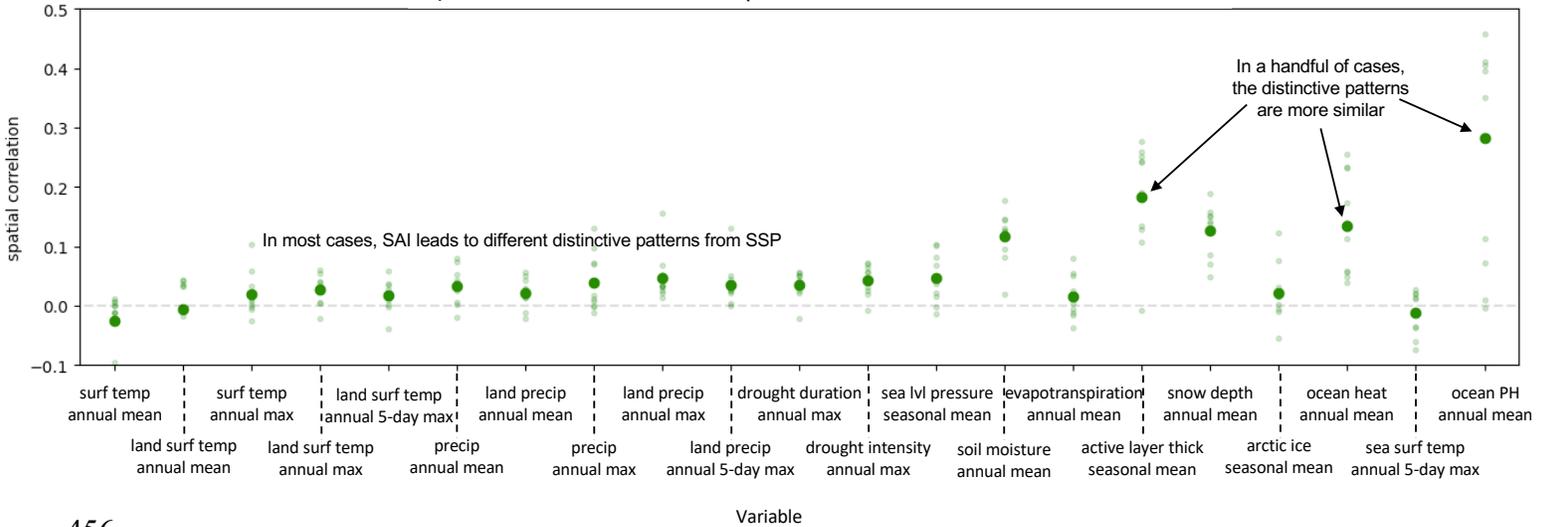


Figure 3. Same as in Figure 2, but results are for the annual mean surface temperature over land.

a) Climate distinguishability between reference and future climates



b) Correlation of distinctive patterns under SSP and SAI scenarios



456

457 **Figure 4.** a) Accuracy of the network in distinguishing between the reference climate and the future SSP
 458 2-4.5 climate (magenta) or the future ARISE-SAI climate (light blue), for all variables considered in the
 459 study (see Supplementary Table S1). Results from individual testing members (smaller circles) and the
 460 ensemble mean (bigger circles) are presented. The critical values for the 10% and 1% significance levels
 461 are derived using a binomial distribution. b) Correlation coefficient between attribution heatmaps that
 462 correspond to predicting in the two scenarios. Results from individual testing members (smaller circles)
 463 and the ensemble mean (bigger circles) are presented.