Opinion: Why all emergent constraints are wrong but some are useful - a machine learning perspective

Peer Nowack[1,2] and Duncan Watson-Parris[3,4]

[1]Institute of Theoretical Informatics, Karlsruhe Institute of Technology, 76131 Karlsruhe, Germany
[2]Institute of Meteorology and Climate Research (IMK-ASF), Karlsruhe Institute of Technology, 76131 Karlsruhe, Germany
[3]Scripps Institution of Oceanography, University of California San Diego, San Diego, USA
[4]Halicioglu Data Science Institute, University of California San Diego, San Diego, USA

Correspondence: Peer Nowack (peer.nowack@kit.edu) and Duncan Watson-Parris (dwatsonparris@ucsd.edu)

Abstract. Global climate change projections are subject to substantial modelling uncertainties. A variety of emergent constraints, as well as several other statistical model evaluation approaches, have been suggested to address these uncertainties. However, they remain heavily debated in the climate science community. Still, the central idea to relate future model projections to already observable quantities has no real substitute. Here we highlight the validation perspective of predictive skill in the machine learning community as a promising alternative viewpoint. Building on this perspective, we review machine learning ideas for new types of controlling factor analyses (CFA). The principal idea behind these CFA is to use machine learning to find climate-invariant relationships in historical data, which also hold approximately under strong climate change scenarios. On the basis of existing data archives, these climate-invariant relationships can be validated in perfect-climate-model frameworks. From a machine learning perspective, we argue that such approaches are promising for three reasons: (a) they can be objectively validated both for past data and future data, (b) they provide more direct - by design physically-plausible - links between historical observations and potential future climates and (c) they can take higher dimensional relationships into account that better characterize the still complex nature of large-scale emerging relationships. We demonstrate these advantages for two recently published CFA examples in the form of constraints on climate feedback mechanisms (clouds, stratospheric water vapour), and discuss further challenges and opportunities using the example of a climate forcing (aerosol-cloud interactions).

1 Introduction

Machine learning applications are now ubiquitous in the atmospheric sciences (e.g., Huntingford et al., 2019; Reichstein et al., 2019; Hess et al., 2022; Hickman et al., 2023). However, there is not a single recipe for machine learning to advance the field. Prominently, there is an important distinction between machine learning for weather forecasting (e.g., Dueben and Bauer, 2018; Rasp and Thuerey, 2021; Keisler, 2022; Bi et al., 2023; Lam et al., 2023; Kurth et al., 2023; Bouallègue et al., 2024) and machine learning for accelerating and observationally constraining climate change projections (e.g. Mansfield et al., 2020; Watson-Parris, 2021; Watson-Parris et al., 2022; Kaltenborn et al., 2023; Nowack et al., 2023). In weather forecasting, the aim is to predict a relatively short time-horizon over which any new influences of climate change are supposedly negligible. In stark contrast, the science of climate change is interested in how changing boundary conditions will affect Earth's climate

system on long timescales. The need to go beyond what has previously been observed poses specific, hard challenges to the application of machine learning in climate science. It is the classic differentiation that is often coined as 'ML models are good at interpolation (weather forecasting) but not at extrapolation (climate change response)'. In this Opinion Article, we highlight a few ideas of how machine learning can nonetheless help reduce the substantial modelling uncertainties in climate change projections, addressing a major scientific challenge of this century.

In the remaining sections of the introduction, we first briefly review the concept of model uncertainty as well as current observational constraint methods, including some of their limitations. In section 2, we discuss controlling factor analyses (CFA) using linear machine learning methods as an alternative approach, highlighting several advantages, exemplified for the cases of constraints on global cloud feedback and stratospheric water vapour feedback. In section 3, we discuss key challenges in constraining future responses on the basis of present-day data, in particular non-linearity and confounding. We illustrate these on the example of constraining the effective radiative forcing (ERF) from aerosol-cloud interactions. In section 4, we highlight potential avenues for future work, also in terms of addressing model uncertainty with machine learning frameworks more generally. In section 5, we summarize key ideas for observational constraints and suggest that machine learning ideas could also help to improve climate model tuning frameworks in the future.

1.1 Model uncertainty

Three sources of climate model projection uncertainty are commonly distinguished (Hawkins and Sutton, 2009; Deser et al., 2012; O'Neill et al., 2014):

1. *scenario uncertainty* given different anthropogenic emission scenarios of greenhouse gases and aerosols. Typical scenarios range from strong mitigation of climate change to unmitigated growth of emissions.

2. *internal variability uncertainty* due to noise from climate variability superimposed on any scenario-driven trends. For example, any given year might be colder or warmer than the climate-dependent expected average value for temperature.

3. *model uncertainty* arising from varying scientific design choices for climate models developed by different institutions. For example, climate models can differ in terms of which and how specific processes are represented, including parameterizations of cloud processes, aerosols, and convection (Carslaw et al., 2013a, b; Sherwood et al., 2014; Kasoar et al., 2016; Bellouin et al., 2020; Sherwood et al., 2020), or in their representations of the carbon cycle and atmospheric chemistry (Cox, 2019; Nowack et al., 2017, 2018a). Ultimately, the resulting model uncertainty describes the long-term projection uncertainty in e.g. regional surface temperature or precipitation changes under the same emissions scenario.

Despite decades-long model development efforts, model uncertainty in key climate impact variables such as temperature and precipitation, globally and regionally, has remained stubbornly high (Sherwood et al., 2020; IPCC, 2021). The apparent lack of net progress might be the result of the competition between (a) improved individual process representations in climate models and (b) the continuously growing number of (uncertain) climate processes being considered in the first place (Cox, 2019;

55 Eyring et al., 2019; Saltelli, 2019). Whatever the reason may be; empirically, we probably need to accept large inter-model spread in climate change projections for the foreseeable future.

In Figure 1, we illustrate the three uncertainty contributions for temperature projections for an area in Central Europe. Scenario and model uncertainty clearly start to dominate over time, whereas at the beginning (around the years 2014-2030) internal variability uncertainty renders even very different forcing scenarios difficult to distinguish. In climate science, scenario

60 and internal variability uncertainty are often taken as given. To characterize scenario uncertainty, it is common to consider a range of socioeconomic development pathways, from strong mitigation scenarios targeting e.g. less than 2° C global warming, to high forcing business-as-usual scenarios (O'Neill et al., 2016). Internal variability uncertainty, in turn, is usually reduced by averaging responses across multiple ensemble members for the same climate model and forcing scenario (Sippel et al., 2015; O'Reilly et al., 2020; Labe and Barnes, 2021). In this paper, we focus on methods that tackle model uncertainty.

65 Clearly, in order to make meaningful climate risk assessments, society and policymakers require better (more certain) information than the range of raw model ensembles are currently able to provide (Figure 1). Here we will suggest a machine learning perspective on this challenging yet important task, contrasting and comparing our view to other concepts to observationally constrain model uncertainty (e.g. Knutti, 2010; Eyring et al., 2019; Hall et al., 2019; Williamson et al., 2021). Our viewpoint still shares the fundamental idea that from the complexity of the climate system, simpler relationships may emerge over time

70 and space, which may be used to robustly compare climate model behaviour to observed relationships as to distinguish more realistic models from the rest (Allen and Ingram, 2002; Held, 2014; Huntingford et al., 2023).

1.2 Methods to address model uncertainty

As mentioned above, international climate model development efforts have not resulted in reduced model uncertainty over time (e.g. Zelinka et al., 2020). To address this longstanding issue, a variety of approaches have been suggested to evaluate climate

75 models and to weight their projections, in particular through systematic comparisons of the modelled climate statistics and relationships against those found in Earth observations. Current methods can be broadly separated into two major groups: (a) statistical climate model evaluation approaches and (b) emergent constraints.

1.2.1 Statistical model evaluation frameworks

There are several widely used frameworks that use a defined set of standard statistical measures to compare model behaviour to

80 observations. Model projections are for example weighted by performance metrics relating to historical trends and variability in key variables such as temperature or precipitation (e.g. Giorgi and Mearns, 2002; Tebaldi et al., 2004; Reichler and Kim, 2008; Räisänen et al., 2010; Lorenz et al., 2018; Brunner et al., 2020a, b; Tokarska et al., 2020; Hegerl et al., 2021; Ribes et al., 2021; Douville et al., 2022; Ribes et al., 2022; Qasmi and Ribes, 2022; Douville, 2023; O'Reilly et al., 2024), with further examples found e.g. in atmospheric chemistry (Karpechko et al., 2013). In addition, methods to account for model-interdependencies

85 (due to shared model development backgrounds, or components) in these weighting procedures have been proposed (Bishop
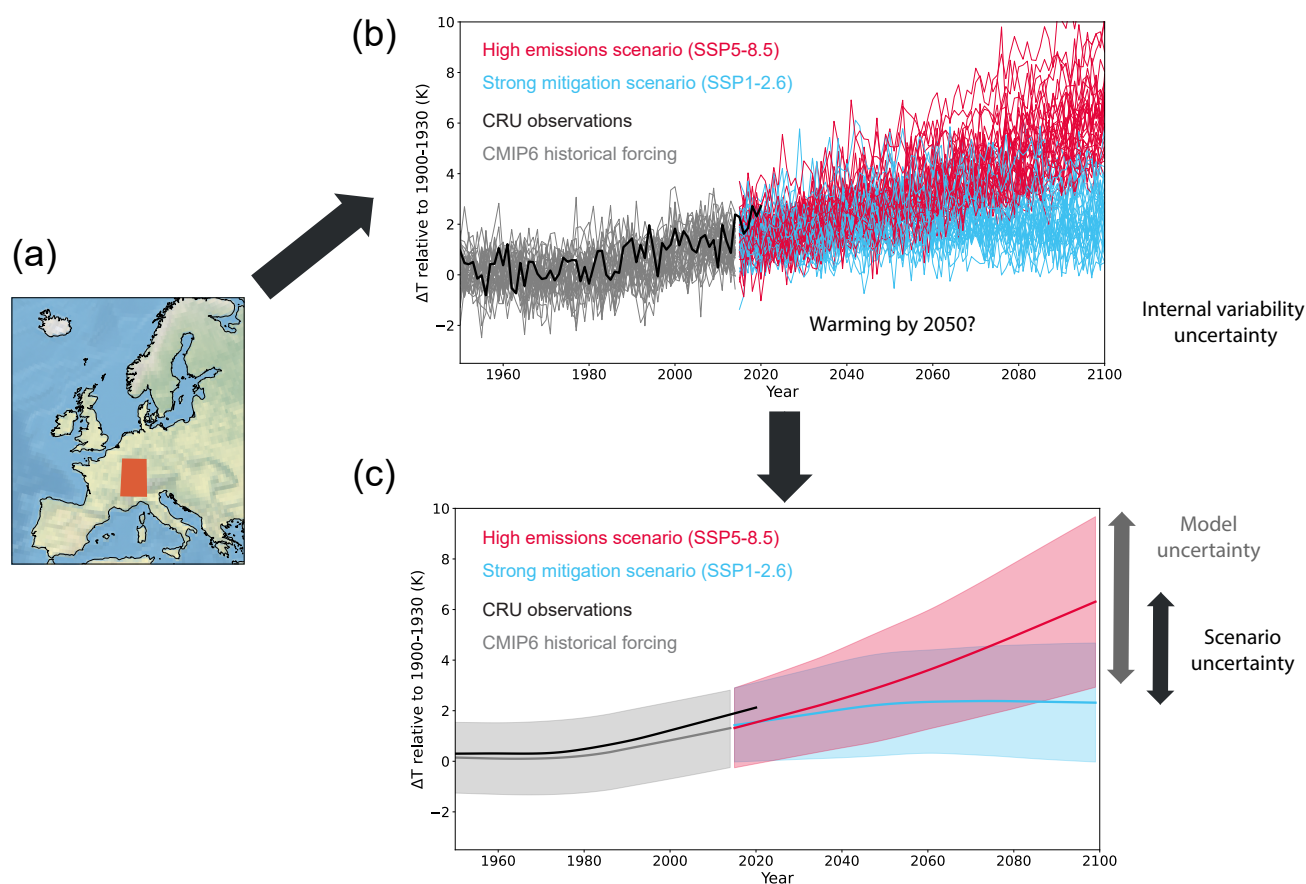
Figure 1. Surface air temperature climate model projections and observations for a $5° \times 5°$ grid box in Central Europe. The region is indicated in orange in (a). The raw projections, relative to their 1900-1930 average, are shown for 34 Coupled Model Intercomparison Project phase 6 (CMIP6) models in (b). Gray lines show one ensemble member of each model for simulations under historical forcing conditions. The same ensemble members and CMIP6 models are shown for the years 2014 to 2100 under a high emission (red) and a strong mitigation scenario (blue). SSP stands for Shared Socioeconomic Pathway. Observational data according to the Climatic Research Unit (CRU, version TS4.05, Harris et al., 2020) are shown in solid black. In (b), internal variability uncertainty for individual ensemble members makes it difficult to, e.g., answer the question of how much the region is projected to have warmed by the year 2050. This uncertainty could be better characterized by considering the average across multiple ensemble members for each model (not done here). Instead, we applied a Lowess smoothing to approximately remove internal variability and indicate the remaining $\pm 2\sigma$ intervals for each scenario in (c). This, in turn, highlights more clearly the scenario uncertainty, best exemplified by the differences in the multi-model-means provided as solid central lines in (c). Finally, the model uncertainty - i.e. the spread in projection for a given scenario after removing internal variability uncertainty - makes an evidently large contribution to the projections here. For example, for the high emission scenario, model responses range between ca. 3 and 10 K of warming by 2100. For the Lowess smoothing, we considered a data fraction of 0.5, individually for each time series.

and Abramowitz, 2013; Abramowitz and Bishop, 2015; Sanderson et al., 2015; Knutti et al., 2017; Sanderson et al., 2017; Abramowitz et al., 2019).

A disadvantage of many conventional model evaluation approaches is that past statistical measures (e.g. standard deviation or climatological means and trends) are not necessarily reliable indicators for each model's future response. Instead, a model that performs worse on certain past performance measures might actually be more informative about the true future response. Possible reasons for the missing direct correlation of past and future responses might be that simple metrics can be blind to offsetting model biases (Nowack et al., 2020) and could even be targeted by model tuning (Mauritsen et al., 2012; Hourdin et al., 2017). From a machine learning perspective, this could lead to situations akin to overfitting training data (e.g., apparent skill on historical data used to tune climate models, or selecting past evaluation metrics on the basis of seemingly constraining correlations), whereas the same model might - as a result - actually be less informative/predictive in new situations, i.e. in this case under climate change.

Overall, due to the indirect link between historical performance measures and future responses in conventional model evaluation frameworks, it is not a priori clear which of the evaluation metrics to trust most. This point was for example demonstrated in the review by Hegerl et al. (2021). Basically, different weighting approaches provide different constraints (both in terms of median and uncertainty ranges) and it remains difficult to establish which approach to trust most and to find ways to make them directly comparable. Another practical limitation is that standard model evaluation measures used to constrain climate change projections are typically based on relatively large-scale spatial and long-term temporal averaging to find significant correlations between historical climate model skill and future projections. This, in turn, makes robust constraints on changes in extreme weather events particularly difficult to establish (Sippel et al., 2017; Lorenz et al., 2018).

1.2.2 Emergent constraints

Emergent constraints more directly target relationships between shorter-term variability within the Earth system ('observables', e.g. seasonal cycle characteristics, observed trends, and other aspects of internal and inter-annual variability) and future climate change, even under strong and century-long climate forcing scenarios (see also review papers by Hall et al., 2019; Eyring et al., 2019). Among the prominent examples are proposed constraints on changes in snow albedo (Hall and Qu, 2006), the highly uncertain cloud feedback and equilibrium climate sensitivity (Sherwood et al., 2014; Klein and Hall, 2015; Tian, 2015; Brient and Schneider, 2016; Lipat et al., 2017; Cox et al., 2018; Dessler and Forster, 2018), climate-driven changes in the hydrological cycle (O'Gorman, 2012; Deangelis et al., 2015; Li et al., 2017; Chen et al., 2022; Shiogama et al., 2022; Thackeray et al., 2022) and in the carbon cycle (Cox et al., 2013; Wenzel et al., 2014; Cox, 2019; Winkler et al., 2019b, a), wintertime Arctic amplification (Bracegirdle and Stephenson, 2013; Thackeray and Hall, 2019), marine primary production (Kwiatkowski et al., 2017), permafrost (Chadburn et al., 2017), atmospheric circulation (Wenzel et al., 2016), and mid-latitude daily heat extremes (Donat et al., 2018).

A central aspect of emergent constraint definitions is that a measure of historical, already observable, climate is consistently linked to future responses. Since the latter is only available from climate model simulations (i.e. is 'unobserved'), it is self-

explanatory that emergent constraint relationships can only be validated and, effectively, constructed using climate models. As a result, the identification of potential constraint candidates fundamentally requires climate change projections simulated by large ensembles of climate models, as for example widely available in the form of the CMIPs.

1.3 Limitations of current constraint frameworks

The challenge to constrain future projections on the basis of observations is a difficult one. Any attempt to establish robust relationships between the (observable) past and simulated future will be hampered by the non-stationary nature of the climate system (Beucler et al., 2024). Any information content that can be gained from observations will naturally, and intuitively, diminish as the climate changes. In addition, once relationships of this kind have been put forward, the various methods discussed in section 1.2 typically lead to different suggested constraints for median climate change responses and confidence intervals (e.g. Brunner et al., 2020a; Hegerl et al., 2021). This raises the next central question: which of the methods should we trust (most)? By any means, this is not a small question considering the significant possible impacts associated with future changes in climate.

We identify three broad issues which make progress on this central question particularly difficult, and which we suggest can be addressed by incorporating machine learning ideas into observational constraint frameworks. Further limitations are for example discussed in section IV of Williamson et al. (2021). The three we wish to highlight here are:

1. *The indirect nature of the link between the past performance measures and the future response to be constrained.* While nowadays most emergent constraints are suggested together with a plausible theoretical link between the observable measure and the future response (Williamson et al., 2021), the connection is by design indirect (Caldwell et al., 2018). In many cases, this might indeed lead to a scientifically robust relationship, however, this robustness is in practice difficult to evaluate objectively. Clearly, the situation is not much different in model evaluation methods which, for example, aim to correlate the historical model-consistent standard deviation in precipitation with its future response. The indirect nature of these links means that one can attempt to manipulate x (the observed) to better match the observational record. If this leads to the desired improvement in y (i.e. the simulated response) that would be a targeted away to improve climate models. However, there is clearly no guarantee that apparent improvements in modelling historical x will translate into constrained future responses (Hall et al., 2019).

2. *Low-dimensionality equals oversimplification?* The reliance on a few, relatively simple, historical performance measures could be argued to have played a key role in limiting progress to date, even if they have the advantage to be relatively easy to conceptualize. For example, it is hard to imagine that very simple measures can truly reflect the complexity of the climate system driving model uncertainty (Caldwell et al., 2018; Bretherton and Caldwell, 2020; Schlund et al., 2020; Nowack et al., 2020). A natural focus on the best-performing of the resulting constraints, even if linked to plausible physical mechanisms, will likely overfit the relationships between past model performance and projected change, returning back to point 1. In addition, the constantly ongoing quest to find such relationships is somewhat akin to issues with multiple hypothesis testing in statistics, which directly leads us to point 3.

3. *Risk of data mining correlations, even if based on a scientifically grounded search.* A key issue with finding relationships such as emergent constraints, which aim for finding a high correlation between a past (uncertain) metric and future (uncertain) responses across climate model ensembles, is the fact that correlations of this kind will always be present in big data climate archives. As a result, if scientists keep searching for such relationships long enough, they will eventually find a few. Those relationships in turn, for a high-dimensional and highly coupled climate system, will likely be at least partly explainable on the basis of actual scientific mechanisms operating in the system, whereas other correlations will occur by chance. A natural focus on the best-performing of the resulting constraints, even if linked to plausible physical mechanisms, will likely overfit the relationships between past model performance and projected change, often even falling victim to coincidental correlations. This "data mining" criticism has been prominently made in previous publications (e.g. Caldwell et al., 2014; Sanderson et al., 2021; Williamson et al., 2021; Breul et al., 2023).

A good indicator for potentially non-robust, coincidental and statistically over-confident relationships can be seen in tendencies for emergent constraints to perform better on the CMIP archive for which they were suggested than for later phases. Indeed this was found for a number of constraints when moving from CMIP3 to CMIP5, or from CMIP5 to CMIP6 (Caldwell et al., 2018; Pendergrass, 2020; Schlund et al., 2020; Williamson et al., 2021; Simpson et al., 2021; Thackeray et al., 2021).

2   Climate-invariant controlling factor analysis

We suggest machine learning-guided CFAs as a promising alternative to establish more robust relationships tested to hold across climate states and climate model ensembles. Specifically, these CFAs establish functions that are only trained on data representative of the observational record but which are subsequently also tested for future responses, as can be evaluated across ensembles of future climate model projections. These functions therefore establish a direct link between the past and the future. This *climate-invariance* can be evaluated across sets of climate models, or even sets of CMIP ensembles, addressing limitation (1). The use of machine learning allows us to learn higher-dimensional, less simplifying, relationships, addressing limitation (2). Finally, the design of the CFA functions will be motivated by known physical relationships between target variables to be constrained (the predictand) and environmental controlling factors (the predictors), addressing limitation (3). The fact that the resulting functions can be validated both under past and future conditions further enables an objective validation and uncertainty quantification, and reduces the risk to fall victim to coincidental correlations.

Low-dimensional CFA frameworks have been popular in climate science for some time, especially in the context of constraining uncertainty on cloud feedback mechanisms (e.g. Klein et al., 2017). Here we focus on recent machine learning ideas to improve their performance for specific constraints on climate feedback mechanisms. We often found that CFA are at first interpreted as a type of emergent constraint. In the following, we instead highlight key differences between the two frameworks; arguing for a separate treatment. We will illustrate central aspects by reviewing two recently published examples of constraining highly uncertain changes in Earth's cloud cover (Ceppi and Nowack, 2021) and in stratospheric water vapour (Nowack et al., 2023).

2.1 Framework definition

185 The central idea behind CFA for observational constraints is the definition of a function f relating multiple large-scale environmental variables $\mathbf{X}$ to a target variable y over time t

$$y(t) \approx f(\mathbf{X}(t); \boldsymbol{\theta}) \qquad (1)$$

Ultimately, we wish to constrain climate model uncertainty in projected changes in y (e.g. changes in clouds or stratospheric water vapour) given already observed relationships between $\mathbf{X}$ and y. A first major difference to emergent constraints is that

190 the functions are trained only on historical data (observations or, for consistency, climate model simulations under historical forcing conditions). The parameters $\boldsymbol{\theta}$, which characterize the function f, measure the importance of the controlling factor relationships found. Again, in this data-driven framework, f (and thus $\boldsymbol{\theta}$) can be learned individually both from sets of observational (providing observational functions f_{obs}) and climate model data (providing model-derived functions $f_{\mathrm{CMIP,k}}$).

The workflow of the CFA framework is illustrated in Figure 2. Expert knowledge is pivotal when selecting the factors $\mathbf{X}$

195 (yellow box) that are thought to 'control' y (violet box). Machine learning is used to derive the strength of the relationships between the factors and y. The generalization skill of these functions trained on the historical data is easily validated on independent test data, which is a crucial component of any data-driven method. A good first test case is again the already observable data or historical simulations (e.g. left out years not used during training and cross-validation), especially on extreme historical events such as the 2015/2016 El Niño event (Kemsley et al., 2024). Of course, this test data is not used during training

200 and cross-validation/the hyperparameter tuning (see longer discussions on these issues in e.g. Bishop, 2006; Nowack et al., 2021). In Figure 2, an example is shown for a hypothetical observational test case for the year 2012, if data from that year was not used for training. We re-iterate that separate functions can be learned and then validated in such a fashion for both observational data (f_{obs}) and for simulations conducted with various climate models (typically, historical simulations run with different climate models, indexed by k, leading to functions $f_{\mathrm{CMIP,k}}$).

205 To clarify, emergent constraints in combination with machine learning frameworks have been suggested as well (e.g. Williamson et al., 2021). However, CFA are different in two ways: firstly, the relationships learned are established entirely on the already observed period, or equivalent individual climate model output. In contrast, emergent constraint functions learn from emergent behaviour across climate change responses of an entire model ensemble, by correlating variables characterizing the models' past behaviour (e.g. a measure of internal variability) to the model-consistent future responses in a quantity of

210 interest (e.g. the equilibrium climate sensitivity). CFA instead learns *from* internal variability and uses these relationships in a climate-invariant context to also constrain the future response, without the latter being involved in the fitting process. Secondly, because the sample size for the relationships learned is no longer limited by the number of models in the ensemble (as is the case for emergent constraints; typically in the range of around 10-60 CMIP models), the general setting is more suitable for the application of machine learning, which strongly depends on the availability of a sufficient number of training samples. The

215 review examples below used monthly-mean data. However, in principle, even much higher temporal resolutions could be used,
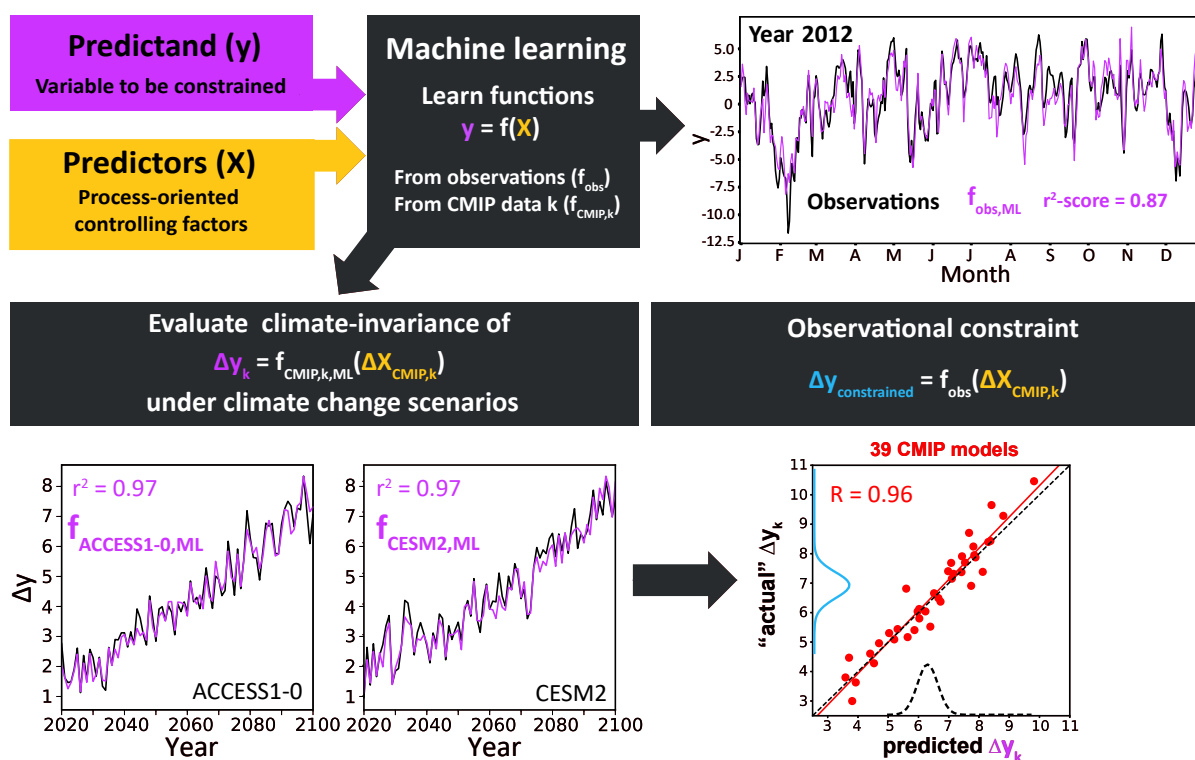
Figure 2. Example workflow for a CFA with machine learning. First, the regression set-up is defined so that the predictand y can be modelled well on the basis of a set of controlling factors $\mathbf{X}$. These functions are learned individually for observational datasets and climate model simulations under historical climate forcing conditions. Out-of-sample predictive skill is evaluated in each case on held-out test data; illustrated here for a hypothetical test year 2012. Next, it is tested if the relationships learned also hold under climate change scenarios. This step is only possible for climate models; demonstrated here for two example SSP projections. The black lines mark the true model responses; the violet lines the predictions of the functions are fed with the model-consistent changes in the controlling factors. Imperfections in the machine learning predictions can be measured across an ensemble of climate models, e.g. from the CMIPs, and as such incorporated into the overall uncertainty quantification. This is sketched in the bottom right for a set of 39 CMIP models (red dots), here showing 30-year averages of the predictions vs. true responses for the years 2070–2100. Finally, to obtain an observational constraint on model uncertainty in Δy (cf. inter-model spread along the y-axis), the function(s) f_{obs} are combined with the 39 different CMIP controlling factor responses, leading to an observationally constrained distribution for the predicted responses $\Delta y_{\mathrm{constrained}}$. The latter is shown (dashed distribution) on the x-axis in the bottom right figure. This preliminary distribution is then combined with the prediction error (cf. spread around the 1:1 line across the 39 CMIP models) to obtain a final observational constraint, indicated by the wider distribution (light blue) along the y-axis.

up to e.g. daily extremes, which might open up new routes for constraining changes in specific high-frequency extreme events (Wilkinson et al., 2023; Shao et al., 2024).

The next important step is to validate - across a representative climate model ensemble - that the functions learned on historical data also perform well under climate change scenarios, i.e. if $f_{\mathrm{CMIP,k}}$ can also skillfully predict the model-consistent

220 climate change response (indicated by Δ) if provided with model-consistent changes in the controlling factors:

$$\Delta y_{\mathrm{CMIP,k}}(t) \approx f_{\mathrm{CMIP,k}}(\Delta \mathbf{X}_{\mathrm{CMIP,k}}(t)) \tag{2}$$

Note that for most predictand and controlling factor variables, this will pose an extrapolation step to previously unobserved value ranges. As discussed in the introduction, this extrapolation step under e.g. strong CO_2 forcing poses particular challenges for non-linear ML techniques that one might want to apply to any given CFA analysis. In the stratospheric water vapour ex-

225 ample, we will show how linearizations might help tackle non-linear observational constraint problems. However, alternative approaches, e.g. to turn extrapolation into approximate interpolation problems (Beucler et al., 2024), might be one of many other helpful pathways to pursue. In the examples below, CFA-based constraints will be derived for annually-averaged responses normalized by the global mean surface temperature T_g, as is common in climate feedback analyses (e.g. Andrews et al., 2012).

230 If the projections are reproduced well across the ensemble of climate models, this implies that the learned relationships are approximately climate-invariant, thus opening up a new link between historically observable relationships and the future climate response, at least to the degree that is currently represented in state-of-the-art climate models. This is exciting, because it provides a more direct approach to constrain model uncertainty than emergent constraints are able to provide. In the end, one can then simply obtain an observational constraint on each model's response by combining the observed function(s) f_{obs} with

235 each individual model response in the controlling factors:

$$\Delta y_{\mathrm{CMIP, constrained,k}}(t) = f_{\mathrm{obs,m}}(\Delta \mathbf{X}_{\mathrm{CMIP,k}}(t)) \tag{3}$$

Finally, since the machine learning predictions will not be perfect, the resulting distribution of observationally constrained climate model responses will further need to be combined with the method-intrinsic prediction error, see Figure 2 and the explanation in its caption, to obtain a final observationally constrained distribution for Δy. Note that we also indexed the

240 function f_{obs} with the index m here, to indicate that both Ceppi and Nowack (2021) and Nowack et al. (2023) trained a number of different observational functions to create the observationally constrained distribution, to also sample and represent observational uncertainty in the relationships learned.

2.2 Taking a step back

Before we discuss the two specific applications of the machine learning-based CFA framework, it is important to point out two

245 built-in assumptions in the nature of the resulting observational constraints:

1. By compartmentalising the prediction of y into two contributors in the form of parameters Θ and controlling factors $\mathbf{X}$, the constraint will be based on the observed θ_{obs}. However, current versions of CFA do not address uncertainty in the controlling factor responses across the climate model ensemble, which essentially remains untouched.

2. The CFA observational constraints are therefore conceptually closest to emergent constraints in the point that the choice
250   of controlling factors will be crucial for finding a constraint. If the resulting sensitivities Θ for the controlling factors are not actually uncertain, there will be no constraint. For emergent constraints, this situation is akin to cases where there would be no spread along the x-axis for the observable quantity across the models. A key difference is that one first identifies process-oriented relationships between $\mathbf{X}$ and y in climate model data and observations, representing internal climate variability (and, possibly, historical trends), instead of directly targeting quantities that have a large spread across
255   the model ensemble for both the predictors and the long-term response.

2.3   Application I: cloud-controlling factor analysis

Changes in Earth's cloud cover are the leading uncertainty factor in global warming projections under increasing atmospheric CO_2 (Ceppi et al., 2017; Sherwood et al., 2020; Zelinka et al., 2020). A driving force behind this uncertainty is the still relatively coarse spatial resolution of global models, meaning that processes involved in cloud formation have to be parameterized
260 instead of being explicitly resolved. Improvements to parameterizations relying on machine learning ideas have been suggested elsewhere (e.g. Schneider et al., 2017) and will not be discussed further here. Instead, as first example, we will focus on CFA as an alternative viewpoint to constrain uncertainty in global cloud feedback. As such, CFA attempts to find constraining relationships at larger spatial scale, similar to - but as outlined above in important points different to - emergent constraints. CFA have already been used extensively to constrain uncertainty related to specific cloud feedback types, however primarily
265 with low-dimensional multiple linear regression approaches including < 10 controlling factors. A few CFA studies used non-linear machine learning methods as well, but only to understand historical cloud variations rather than to derive observational constraints on future projections (e.g. Andersen et al., 2017; Fuchs et al., 2018; Andersen et al., 2022).

Previous observational constraint studies with lower-dimensional multiple linear regression, in turn, mostly focused on regionally confined major low-cloud decks (e.g. Qu et al., 2015; Zhou et al., 2015; Myers and Norris, 2016; McCoy et al.,
270 2017; Scott et al., 2020; Cesana and Genio, 2021; Myers et al., 2021), because changes in their cumulative shortwave reflectivity contribute a large fraction to the overall uncertainty in global cloud feedback (Sherwood et al., 2020). Building on this work, Ceppi and Nowack (2021) developed a statistical learning analysis using ridge regression (Hoerl and Kennard, 1970) as a linear form of machine learning. This new approach to CFA allowed them to improve on previous CFA constraints and to expand the scope beyond the low cloud decks and to global scale; for both shortwave (clouds are reflective, thus cooling climate) and
275 longwave (clouds can trap terrestrial radiation, thus warming climate) cloud radiative effects. Here, we will briefly review these results, as an example of how CFA can be developed to constrain model uncertainty more effectively, by including machine learning ideas. A sketch of the framework is shown in Figure 3.

As in previous lower-dimensional CFA for clouds, Ceppi and Nowack (2021) focused on a relatively short, well-observed period during the satellite era. In their set-up, this translates into a regression approach in which cloud-radiative anomalies at grid point r, $\mathrm{d}C(r)$, to be be approximated as a linear function of anomalies in a set of M meteorological cloud-controlling factors $\mathrm{d}\boldsymbol{X}_i(r)$:

$$\mathrm{d}C(r) \approx \sum_{i=1}^{M} \frac{\partial C(r)}{\partial \boldsymbol{X}_i(r)} \cdot \mathrm{d}\boldsymbol{X}_i(r) = \sum_{i=1}^{M} \boldsymbol{\Theta}_i(r) \cdot \mathrm{d}\boldsymbol{X}_i(r). \tag{4}$$

where the parameters $\boldsymbol{\Theta}_i(r)$ represent the *sensitivities* of $C(r)$ to the controlling factors. Here, $C(r)$ could in principle be different types of measures to characterize cloud contributions to shorter-term variations (here, monthly) and long-term changes (including the climate change response) in Earth's energy budget. For example, Ceppi and Nowack (2021) separated shortwave from longwave cloud radiative effects, and further common decompositions are into high cloud and low cloud contributions, as well as changes in cloud fractions, cloud top pressure, and cloud optical depth (e.g. Kemsley et al., 2024). As a key difference to previous studies, which focused on grid-point-wise relationships, e.g. between surface temperature at point r and $C(r)$, Ceppi and Nowack (2021) regressed cloud-radiative anomalies at grid point r as a function of the controlling factors within a $105° \times 55°$ (lon × lat) gridded domain centered on r (Figure 3), rendering the regression high-dimensional. The contribution of each controlling factor to $\mathrm{d}C(r)$ is then obtained by the scalar product of the spatial vectors $\boldsymbol{\Theta}_i(r)$ and $\mathrm{d}\boldsymbol{X}_i(r)$.

An important choice is the set of controlling factors. Heuristics that motivate various predictors for low cloud decks can be found in Klein et al. (2017) and for high clouds in Kemsley et al. (2024). In Ceppi and Nowack (2021), the authors used five different patterns of cloud controlling factors, which were used to train the predictions on historical data. However, for an effective constraint on the cloud feedback under abrupt-4xCO₂ forcing across CMIP5 and CMIP6 models, they only considered two factors that drive the main part of the climate change response (rather than variability), at least when averaged globally. These were patterns of surface temperature (the most important factor) and of the estimated inversion strength (EIS, an important modulating factor). Overall, the study demonstrated that the use of machine learning ideas opens the door to consider a larger spatial context, which improved the CFA function in terms of its predictions, and eventually also the overall observational constraint. It further allowed for the extension of CFA frameworks of cloud feedback from specific low-cloud analyses to global scale and to new cloud types (in particular, high clouds; cf. Kemsley et al. (2024)).

2.4 Application II: an observational constraint on the stratospheric water vapour feedback

The linearity assumption appears to work well to first order for global cloud feedback, but this is not guaranteed for many other uncertain Earth system feedbacks. A first counter-example can be found in Nowack et al. (2023) who adapted the framework presented in Ceppi and Nowack (2021) to constrain uncertainty in changes in specific humidity across the stratosphere. This 'stratospheric water vapour feedback' is indeed highly uncertain in CMIP models, with model responses ranging from virtually no response to more than a tripling of concentrations relative to present-day values in 4xCO₂ simulations. This, in turn, makes significant contributions to uncertainties in global warming projections (Stuber et al., 2005; Joshi et al., 2010; Dietmüller et al.,
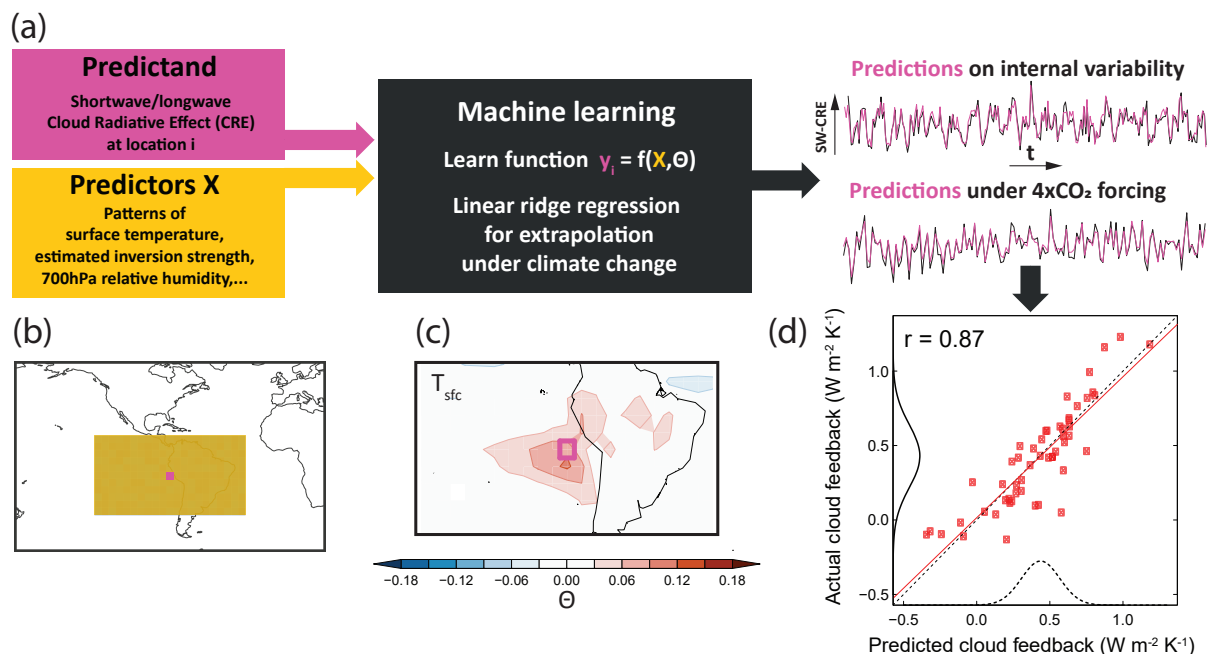
Figure 3. Cloud example for a CFA with machine learning. (a) Cloud radiative effects are predicted at a given grid location as a function of a set of controlling factors. Linear machine learning approaches such as ridge regression are currently recommended due to the need to extrapolate when using the learned relationships for predictions under climate change scenarios. (b) Example sketch of the regional context (yellow) of many grid points surrounding a target grid point (purple) for which the cloud radiative effects are predicted. (c) Example map of CMIP multi-model-mean ridge regression coefficients Θ for one of the controlling factors - surface temperature - when predicting shortwave cloud radiative effects. In (d), the final constraint on the global cloud feedback is illustrated: the predicted cloud feedback is obtained by combining the functions learned from slices of historical simulations (of same length as the satellite data observational record) with model-consistent changes in the controlling factors. This is regressed against the 'actual' cloud feedback of the same climate models, as inferred from the actual abrupt-4xCO$_2$ simulations available from the CMIP5/6 archives. Across 52 CMIP models, a strong relationship (r = 0.87) is obtained. Here, four different observationally derived functions resulted in $4 \times 52 = 208$ observationally constrained projections, shown as uncertainty distribution along the x-axis (dashed line). This distribution is combined with the methodological uncertainty to provide a final observational constraint distribution for the global cloud feedback shown along the y-axis (solid line).

2014; Nowack et al., 2018b; Keeble et al., 2021), the tropospheric circulation response (Joshi et al., 2006), and the recovery of
310 the ozone layer (Dvortsov and Solomon, 2001; Stenke and Grewe, 2005).

To address this uncertainty, Nowack et al. (2023) defined a CFA using ridge regression (Hoerl and Kennard, 1970) in
which they predicted monthly-mean water vapour concentrations in the tropical lower stratosphere (q_{strat}) as a function of
temperature variations in the upper troposphere and lower stratosphere (UTLS). Their analysis was directly motivated by the
strong mechanistic link between tropical UTLS temperature and water vapour entry rates, see e.g. Fueglistaler et al. (2009) for
315 a review. Their final controlling factor function was defined as follows:

$$\log\left(q_{\mathrm{strat}}(t)\right) = f(\boldsymbol{\Theta}, \mathbf{T}; t, \tau_{\max}) = \sum_{\mathrm{i}}^{\mathrm{lat}} \sum_{\mathrm{j}}^{\mathrm{lon}} \sum_{\mathrm{k}}^{\mathrm{p}} \sum_{\tau}^{\tau_{\max}} \Theta_{\mathrm{ijk},\tau} \, \mathrm{d}T_{\mathrm{ijk}}\left(t - \tau\right) \tag{5}$$

which takes into account temperature anomalies dT across a whole longitude-latitude-altitude cube of the tropical to mid-
latitude UTLS region, over $\tau_{\max}$ monthly time lags. Using this function, both internal variability in q_{strat} (for observations and
CMIP models) as well as the long-term climate change response (CMIP models) could be predicted well.

320 However, under abrupt-4xCO₂ forcing, the function notably only held true after log-transforming the predictand before
training, which apparently led to a quasi-linearization of the relationships to be learned (Figure 4). The need for such a trans-
formation is not unexpected due to the known approximately exponential relationship between temperature and saturation
water vapour concentrations, and simply underlines that similar CFA could be designed for many other uncertain Earth system
feedbacks, even if non-linear, if appropriate physics-informed transformations can be applied.

3 Challenges

3.1 Dealing with non-linearities

As already implied by the stratospheric water vapour example, not all relationships we wish to constrain will be linear. For
example, while not typically considered in the emergent constraint literature, the aerosol effective radiative forcing (ERF) is
defined with reference to an un-observed pre-industrial atmospheric state and so faces many of the same challenges described
330 above (see also Figure 5). Since the relationships between aerosol emissions and cloud properties, and cloud properties and
radiative forcing are known to be non-linear (Carslaw et al., 2013a) extrapolating from observed to unobserved climate states,
while necessary, is fraught with danger.

Besides the obvious risk that if we naively attempted to fit non-linear functions to such relationships we could easily over-fit
our data, Figure 5 shows the opposite risk that assuming the non-linearities to be small based on the observed data (inset) could
335 lead us to under-fitting the response over larger ranges. If at all possible we should look to collect observations in these outlying
regions, perhaps looking at particularly clean atmospheric conditions in the case of aerosol (Carslaw et al., 2013a; Gryspeerdt
et al., 2023). Failing that, we must either either rescale our data such that we are no-longer extrapolating, or linearize the
relationship using physical understanding (Beucler et al., 2024).
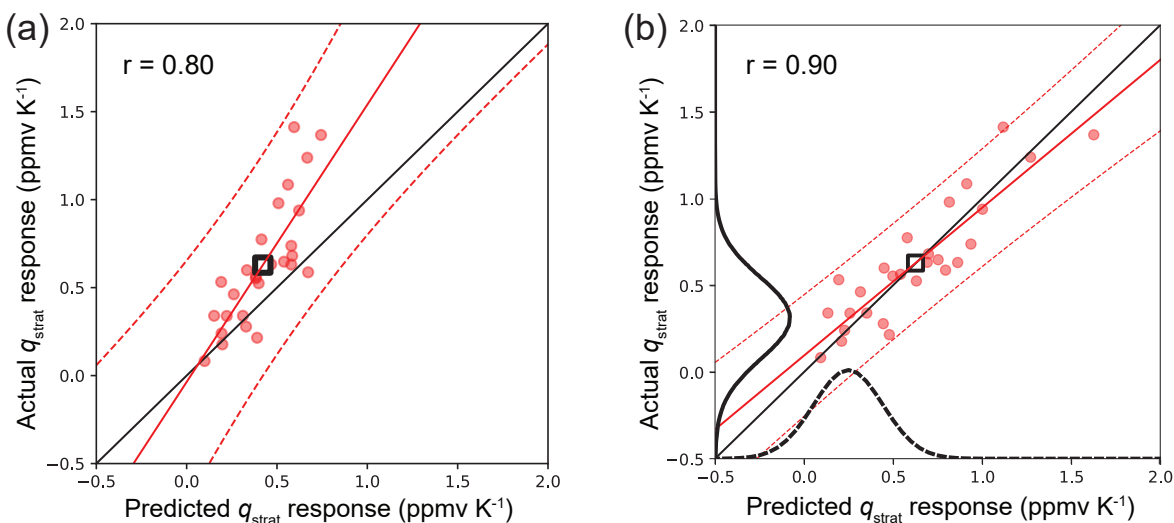
Figure 4. Constraint on stratospheric water vapour projections requiring a nonlinear transformation. (a) linear ridge regression without transformation of the predictand. (b) After log-transforming the predictand before training on historical data. Without the log-transformation, the predictions for large changes increasingly underestimate the actual responses in the corresponding abrupt-4xCO$_2$ simulations and the scatter in the predictions also increases (lowering r). With the transformation, the predicted water vapour responses agree well with the actual simulated responses (provided in parts per million volume/ppmv; normalized by model-consistent global mean surface temperature change). The final observational constraint is calculated similar to the cloud example; for further details see Nowack et al. (2023). The dashed red lines mark the predictions intervals, the solid red lines the linear regressions (Wilks, 2006).

3.2 Confounding

340   Confounding occurs when an extraneous variable influences both the dependent variable and an independent variable, leading to a spurious association. This is particularly challenging in climate science, where numerous interacting processes can lead to complex relationships between variables. For instance, in the context of Figure 5, the apparent influence of an observed variable on an unobserved variable may actually be mediated or obscured by another uncontrolled variable, such as temperature. This confounding can severely compromise the identification and validation of emergent constraints or controlling-factor rela-

345   tionships. Machine learning methods, though powerful in detecting patterns, are not inherently equipped to distinguish causal relationships from mere correlations unless specifically designed to do so.

4 Opportunities

With care, however, machine learning has the potential to be a powerful tool to learn more sophisticated, objective (emergent) constraints that can be validated through cross-validation and perfect model tests. On top of the machine learning-augmented
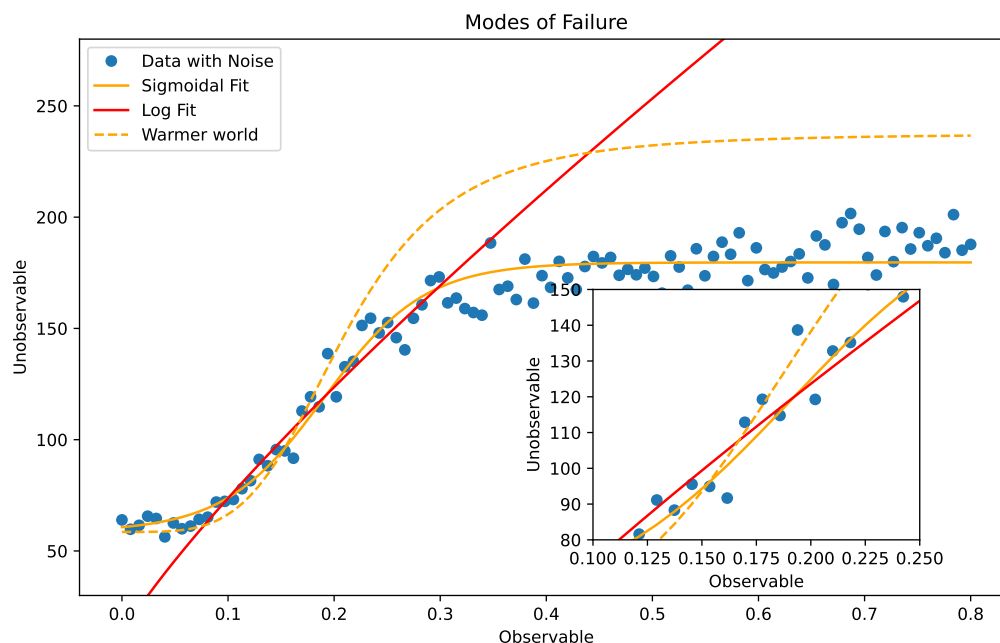
Figure 5. A schematic diagram of a typical emergent constraint showing the relationship between an unobserved quantity (Y; say effective radiative forcing/ERF) and an observed quantity (X). This holds well over a limited region of X (inset). This relationship may fail to hold outside the observed region though, particularly if the response is (or becomes) non-linear. This relationship can also breakdown if a (possibly) unobserved variable Z affects both X and Y, causing a confounding that changes the relationship in e.g. in a warmer world (or the past).

350   CFA outlined in section 2, we here highlight a few more ways in which machine learning can be used to find, and improve the robustness of, observational constraints.

4.1 Physical priors

In many cases we already have a reasonable approximation of the functional form of a physical response but would like to capture uncertain elements, such as free parameters or closures, in a consistent and transparent way. In the stratospheric

355   water vapour example above, this was the known non-linear relationship between temperature and saturation water vapour. In Bayesian terms, we already have an informative prior. As such, using a Bayesian approach can be a powerful way of encoding this information and updating it with observations to provide predictions with well calibrated uncertainties.

   One recent example of this utilizes the functional form of a simple energy balance model (FaIR in this case; Leach et al. (2021)) as a prior for a Gaussian process (GP) emulation of the temperature response to a given forcing (Bouabid et al., 2023).

360   By constructing the statistical (machine learning) model to respect the physical form of the response, it is able to better predict
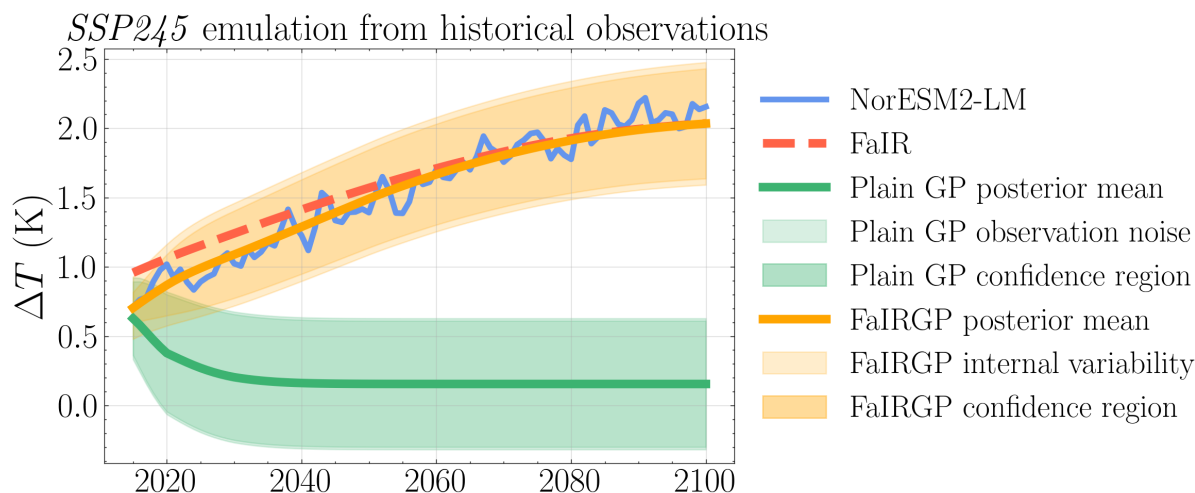
Figure 6. Example of using a Bayesian model with a physical prior to enable accurate and well calibrated *extrapolation* of climate projections. Both the FaIR model and the FaiRGP model (which encodes the FaIR response in the covariance function) accurately reproduce the NorESM2 warming under SSP2-4.5 - despite having only seen historical temperatures. The Plain GP has a no physical regularisation and quickly reverts to its mean function.

future warming. Importantly for this discussion, this approach performs significantly better than an unconstrained GP when making out-of-sample predictions (extrapolating). For example, by training both GPs only on outputs from a GCM representing the historical period, the physical GP is able to accurately predict future warming under SSP-2-4.5, while the plain GP quickly reverts to its mean function. This behaviour is not confined to GPs, any highly parameterised regression technique (such as a neural network) would produce spurious results without the strong regularisation that the physical form provides. Similarly, physical constraints imposed on machine learning cost functions, as is the case in physics-informed machine learning (Chen et al., 2021; Karniadakis et al., 2021; Kashinath et al., 2021), could be powerful tools to be used in this context.

4.2 Discovering controlling factors

Causal discovery and inference techniques allow us to robustly detect potential constraints and to address the challenge of confounding variables respectively (Runge et al., 2019; Camps-Valls et al., 2023). Methods such as causal discovery or the use of instrumental variables could help in distinguishing true climate signals from confounding noise. Furthermore, enhancing the datasets with more comprehensive metadata that captures potential confounders and applying robust statistical techniques to explicitly model these confounders can aid in mitigating their effects. Such approaches would strengthen the reliability of machine learning-driven analyses, ensuring that the emergent constraints or CFAs reflect more accurate and physically plausible relationships that hold under various climate change scenarios. An interesting analogy is that with CFA from section 2, significant confounding which might change the detected historical relationships under climate change should also lead to a corresponding decrease in predictive skill of the climate change response under, e.g., 4xCO$_2$ forcing. As such, poorly perform-

ing CFA extrapolations might be a good indicator of poorly designed causal (proxy) relationships among the controlling factors and the predictand.

4.3 Perturbed parameter ensembles

Perturbed Physics Ensembles (PPEs) (Murphy et al., 2004; Mulholland et al., 2017) present a significant opportunity in the realm of CFA by allowing researchers to systematically explore the sensitivity of climate models to changes in physical parameterizations. By adjusting various parameters within a climate model, PPEs generate a range of plausible climate outcomes, which can then be analyzed to understand how specific processes impact model outputs. This systematic variation of parameters helps isolate the influence of individual factors, thereby providing deeper insights into the workings of climate models than is possible by simply comparing a small ensemble of qualitatively different models.

The utility of PPEs extends beyond the internal processes of models to potentially enhance our understanding of real-world observations. By identifying which parameters and model configurations yield the best alignment with observed climate data, researchers can infer which physical processes might be driving observed changes in the climate system. This transfer of learning from models to observations is crucial for improving the robustness and credibility of climate projections. Moreover, the knowledge gained through PPEs can guide the development of more refined machine learning algorithms that are capable of incorporating complex, non-linear interactions discovered in observations. Thus, combined with the causal discovery approaches outlined above, PPEs not only enrich our understanding of climate model behavior but can also serve as a resource for informing robust (physical) CFAs.

5 Conclusions

While all climate change studies with machine learning necessarily face the challenge of extrapolation in the presence of (potential) non-linearity, there are clearly opportunities and methods to make the power of machine learning accessible to the scientific challenge. Here, we took the perspective of how machine learning can help us provide better observational constraints on the still substantial uncertainties in climate model projections. In particular, we highlighted controlling factor analyses (CFA) combined with machine learning as a promising route to pursue, and contrasted this approach to emergent constraints. Ultimately, CFA might also help to validate proposed emergent constraints in the future. Existing emergent constraints could thus, in many ways, be considered as useful starting points for this new field. We further provided a wider perspective on the challenges of using machine learning for observational and, specifically, emergent constraints, such as non-linearity and confounding. Key opportunities to address these challenges we see in physics-informed data transformations, physics-informed machine learning, causal algorithms, perturbed physics ensembles, and in imposing physical knowledge through physical priors in Bayesian methods.

Finally, we underline an analogy between the development of machine learning and climate models. This analogy, in turn, could motivate adjustments to frameworks for climate model development and evaluation cycles. Specifically, in the context of training machine learning models, the process bears some similarities to the tuning of climate models to historical observations

410 (e.g. Mauritsen et al., 2012; Hourdin et al., 2017). As a result, one might argue that model intercomparisons, weightings, and evaluations against that same data are far less meaningful, similar to how one should not evaluate machine learning models against their training data (a good fit could simply - and in the most cases - imply overfitting rather than good generalizable predictive skill). Of course, there are intrinsically regularizing features in the form of physical laws in any physics-based modelling system, which will somewhat mitigate such effects, as compared to fitting a neural network without physical constraints.

415 Still, we see scope for defining dedicated historical test datasets as part of future model intercomparison exercises. These test datasets should not be included during climate model tuning. For example, one could agree that all model tuning should stop by the year 2005 (the typically last year of historical simulations for CMIP5), which would leave around two decades for objective model evaluation of recent trends and variability. Through continued scientific exchange, there might be many different ways for academic 'transfer learning' of this kind between the disciplines of machine learning and climate science.

420 *Author contributions.* Both authors co-designed and co-wrote the paper. For the initial draft, PN focused on sections 1 and 2, DWP on sections 3 and 4.

Competing interests. At least one of the (co-)authors is a member of the editorial board of Atmospheric Chemistry and Physics.

Acknowledgements. The authors were supported by the UK Natural Environment Research Council (grant no. NE/V012045/1). The authors thank Paulo Ceppi (Imperial College London) for helpful comments.

References

Abramowitz, G. and Bishop, C. H.: Climate model dependence and the ensemble dependence transformation of CMIP projections, Journal of Climate, 28, 2332–2348, https://doi.org/10.1175/JCLI-D-14-00364.1, 2015.

Abramowitz, G., Herger, N., Gutmann, E., Hammerling, D., Knutti, R., Leduc, M., Lorenz, R., Pincus, R., and Schmidt, G. A.: ESD Reviews: Model dependence in multi-model climate ensembles: Weighting, sub-selection and out-of-sample testing, https://doi.org/10.5194/esd-10-91-2019, 2019.

Allen, M. R. and Ingram, W. J.: Constraints on future changes in climate and the hydrologic cycle., Nature, 419, 224–232, https://doi.org/10.1038/nature01092, 2002.

Andersen, H., Cermak, J., Fuchs, J., Knutti, R., and Lohmann, U.: Understanding the drivers of marine liquid-water cloud occurrence and properties with global observations using neural networks, Atmospheric Chemistry and Physics, 17, 9535–9546, https://doi.org/10.5194/acp-17-9535-2017, 2017.

Andersen, H., Cermak, J., Zipfel, L., and Myers, T. A.: Attribution of Observed Recent Decrease in Low Clouds Over the Northeastern Pacific to Cloud-Controlling Factors, Geophysical Research Letters, 49, 1–10, https://doi.org/10.1029/2021gl096498, 2022.

Andrews, T., Gregory, J. M., Webb, M. J., and Taylor, K. E.: Forcing, feedbacks and climate sensitivity in CMIP5 coupled atmosphere-ocean climate models, Geophysical Research Letters, 39, L09 712, https://doi.org/10.1029/2012GL051607, 2012.

Bellouin, N., Quaas, J., Gryspeerdt, E., Kinne, S., Stier, P., Watson-Parris, D., Boucher, O., Carslaw, K. S., Christensen, M., Daniau, A. L., Dufresne, J. L., Feingold, G., Fiedler, S., Forster, P., Gettelman, A., Haywood, J. M., Lohmann, U., Malavelle, F., Mauritsen, T., McCoy, D. T., Myhre, G., Mülmenstädt, J., Neubauer, D., Possner, A., Rugenstein, M., Sato, Y., Schulz, M., Schwartz, S. E., Sourdeval, O., Storelvmo, T., Toll, V., Winker, D., and Stevens, B.: Bounding Global Aerosol Radiative Forcing of Climate Change, Reviews of Geophysics, 58, e2019RG000 660, https://doi.org/10.1029/2019RG000660, 2020.

Beucler, T., Gentine, P., Yuval, J., Gupta, A., Peng, L., Lin, J., Yu, S., Rasp, S., Ahmed, F., O'gorman, P. A., Neelin, J. D., Lutsko, N. J., and Pritchard, M.: Climate-invariant machine learning, Science Advances, 10, eadj7250, https://www.science.org, 2024.

Bi, K., Xie, L., Zhang, H., Chen, X., Gu, X., and Tian, Q.: Accurate medium-range global weather forecasting with 3D neural networks, Nature, 619, 533–538, https://doi.org/10.1038/s41586-023-06185-3, 2023.

Bishop, C. H. and Abramowitz, G.: Climate model dependence and the replicate Earth paradigm, Climate Dynamics, 41, 885–900, https://doi.org/10.1007/s00382-012-1610-y, 2013.

Bishop, C. M.: Pattern recognition and machine learning, Springer Science+Business Media, https://link.springer.com/book/9780387310732, 2006.

Bouabid, S., Sejdinovic, D., and Watson-Parris, D.: FaIRGP: A Bayesian Energy Balance Model for Surface Temperatures Emulation, arXiv, pp. 1–64, http://arxiv.org/abs/2307.10052, 2023.

Bouallègue, Z. B., Weyn, J. A., Clare, M. C. A., Dramsch, J., Dueben, P., and Chantry, M.: Improving Medium-Range Ensemble Weather Forecasts with Hierarchical Ensemble Transformers, Artificial Intelligence for the Earth Systems, 3, e230 027, https://doi.org/10.1175/aies-d-23-0027.1, 2024.

Bracegirdle, T. J. and Stephenson, D. B.: On the robustness of emergent constraints used in multimodel climate change projections of arctic warming, Journal of Climate, 26, 669–678, https://doi.org/10.1175/JCLI-D-12-00537.1, 2013.

Bretherton, C. S. and Caldwell, P. M.: Combining emergent constraints for climate sensitivity, Journal of Climate, 33, 7413–7430, https://doi.org/10.1175/JCLI-D-19-0911.1, 2020.

Breul, P., Ceppi, P., and Shepherd, T. G.: Revisiting the wintertime emergent constraint of the southern hemispheric midlatitude jet response to global warming, Weather and Climate Dynamics, 4, 39–47, https://doi.org/10.5194/wcd-4-39-2023, 2023.

Brient, F. and Schneider, T.: Constraints on climate sensitivity from space-based measurements of low-cloud reflection, Journal of Climate,

465   29, 5821–5835, https://doi.org/10.1175/JCLI-D-15-0897.1, 2016.

Brunner, L., McSweeney, C., Ballinger, A. P., Befort, D. J., Benassi, M., Booth, B., Coppola, E., Vries, H. D., Harris, G., Hegerl, G. C., Knutti, R., Lenderink, G., Lowe, J., Nogherotto, R., O'Reilly, C., Qasmi, S., Ribes, A., Stocchi, P., and Undorf, S.: Comparing Methods to Constrain Future European Climate Projections Using a Consistent Framework, Journal of Climate, 33, 8671–8692, https://doi.org/10.1175/JCLI-D-19-0953.1, 2020a.

470   Brunner, L., Pendergrass, A., Lehner, F., Merrifield, A., Lorenz, R., and Knutti, R.: Reduced global warming from CMIP6 projections when weighting models by performance and independence, Earth System Dynamics, 11, 995–1012, https://doi.org/10.5194/esd-11-995-2020, 2020b.

Caldwell, P. M., Bretherton, C. S., Zelinka, M. D., Klein, S. A., Santer, B. D., and Sanderson, B. M.: Statistical significance of climate sensitivity predictors obtained by data mining, Geophysical Research Letters, 41, 1803–1808, https://doi.org/10.1002/2014gl059205, 2014.

475   Caldwell, P. M., Zelinka, M. D., and Klein, S. A.: Evaluating Emergent Constraints on Equilibrium Climate Sensitivity, Journal of Climate, 31, 3921–3942, https://doi.org/10.1175/JCLI-D-17, 2018.

Camps-Valls, G., Gerhardus, A., Ninad, U., Varando, G., Martius, G., Balaguer-Ballester, E., Vinuesa, R., Diaz, E., Zanna, L., and Runge, J.: Discovering causal relations and equations from data, https://doi.org/10.1016/j.physrep.2023.10.005, 2023.

Carslaw, K. S., Lee, L. A., Reddington, C. L., Mann, G. W., and Pringle, K. J.: The magnitude and sources of uncertainty in global aerosol,

480   Faraday Discussions, 165, 495, https://doi.org/10.1039/c3fd00043e, 2013a.

Carslaw, K. S., Lee, L. A., Reddington, C. L., Pringle, K. J., Rap, A., Forster, P. M., Mann, G. W., Spracklen, D. V., Woodhouse, M. T., Regayre, L. A., and Pierce, J. R.: Large contribution of natural aerosols to uncertainty in indirect forcing, Nature, 503, 67–71, https://doi.org/10.1038/nature12674, 2013b.

Ceppi, P. and Nowack, P.: Observational evidence that cloud feedback amplifies global warming, Proc. Natl. Acad. Sci. USA, 118,

485   e2026290118, https://doi.org/10.1073/pnas.2026290118, 2021.

Ceppi, P., Brient, F., Zelinka, M., and Hartmann, D. L.: Cloud feedback mechanisms and their representation in global climate models, Wiley Interdisciplinary Reviews: Climate Change, 8, 1–21, https://doi.org/10.1002/wcc.465, 2017.

Cesana, G. V. and Genio, A. D. D.: Observational constraint on cloud feedbacks suggests moderate climate sensitivity, Nature Climate Change, 11, 213–220, https://doi.org/10.1038/s41558-020-00970-y, 2021.

490   Chadburn, S. E., Burke, E. J., Cox, P. M., Friedlingstein, P., Hugelius, G., and Westermann, S.: An observation-based constraint on permafrost loss as a function of global warming, Nature Climate Change, 7, 340–344, https://doi.org/10.1038/nclimate3262, 2017.

Chen, Z., Liu, Y., and Sun, H.: Physics-informed learning of governing equations from scarce data, Nature Communications, 12, https://doi.org/10.1038/s41467-021-26434-1, 2021.

Chen, Z., Zhou, T., Chen, X., Zhang, W., Zhang, L., Wu, M., and Zou, L.: Observationally constrained projection of Afro-Asian monsoon

495   precipitation, Nature Communications, 13, 2552, https://doi.org/10.1038/s41467-022-30106-z, 2022.

Cox, P. M.: Emergent Constraints on Climate-Carbon Cycle Feedbacks, https://doi.org/10.1007/s40641-019-00141-y, 2019.

Cox, P. M., Pearson, D., Booth, B. B., Friedlingstein, P., Huntingford, C., Jones, C. D., and Luke, C. M.: Sensitivity of tropical carbon to climate change constrained by carbon dioxide variability, Nature, 494, 341–344, https://doi.org/10.1038/nature11882, 2013.

Cox, P. M., Huntingford, C., and Williamson, M. S.: Emergent constraint on equilibrium climate sensitivity from global temperature variability, Nature, 553, 319–322, https://doi.org/10.1038/nature25450, 2018.

Deangelis, A. M., Qu, X., Zelinka, M. D., and Hall, A.: An observational radiative constraint on hydrologic cycle intensification, Nature, 528, 249–253, https://doi.org/10.1038/nature15770, 2015.

Deser, C., Phillips, A., Bourdette, V., and Teng, H.: Uncertainty in climate change projections: The role of internal variability, Climate Dynamics, 38, 527–546, https://doi.org/10.1007/s00382-010-0977-x, 2012.

Dessler, A. E. and Forster, P. M.: An estimate of equilibrium climate sensitivity from interannual variability, Journal of Geophysical Research: Atmospheres, 123, 1–12, https://doi.org/10.1029/2018JD028481, 2018.

Dietmüller, S., Ponater, M., and Sausen, R.: Interactive ozone induces a negative feedback in CO2-driven climate change simulations, Journal of Geophysical Research: Atmospheres, 119, 1796–1805, https://doi.org/10.1002/2013JD020575, 2014.

Donat, M. G., Pitman, A. J., and Angélil, O.: Understanding and Reducing Future Uncertainty in Midlatitude Daily Heat Extremes Via Land Surface Feedback Constraints, Geophysical Research Letters, 45, 10,627–10,636, https://doi.org/10.1029/2018GL079128, 2018.

Douville, H.: Robust and perfectible constraints on human-induced Arctic amplification, Communications Earth and Environment, 4, https://doi.org/10.1038/s43247-023-00949-5, 2023.

Douville, H., Qasmi, S., Ribes, A., and Bock, O.: Global warming at near-constant tropospheric relative humidity is supported by observations, Communications Earth and Environment, 3, https://doi.org/10.1038/s43247-022-00561-z, 2022.

Dueben, P. D. and Bauer, P.: Challenges and design choices for global weather and climate models based on machine learning, Geoscientific Model Development, 11, 3999–4009, https://doi.org/10.5194/gmd-11-3999-2018, 2018.

Dvortsov, V. L. and Solomon, S.: Response of the stratospheric temperatures and ozone to past and future increases in stratospheric humidity, Journal of Geophysical Research, 106, 7505–7514, https://doi.org/10.1029/2000JD900637, 2001.

Eyring, V., Cox, P., Flato, G., Gleckler, P., Abramowitz, G., Caldwell, P., Collins, W., Gier, B., Hall, A., Hoffman, F., Hurtt, G., Jahn, A., Jones, C., Klein, S., Krasting, J., Kwiatkowski, L., Lorenz, R., Maloney, E., Meehl, G., and Pen, M.: Taking climate model evaluation to the next level, Nature Climate Change, 9, 102–110, https://doi.org/10.1038/s41558-018-0355-y, 2019.

Fuchs, J., Cermak, J., and Andersen, H.: Building a cloud in the southeast Atlantic : understanding low-cloud controls based on satellite observations with machine learning, pp. 16 537–16 552, 2018.

Fueglistaler, S., Dessler, A. E., Dunkerton, T. J., Folkins, I., Fu, Q., and Ote, P. W.: Tropical tropopause layer, Reviews of Geophysics, 47, RG1004, 2009.

Giorgi, F. and Mearns, L. O.: Calculation of average, uncertainty range, and reliability of regional climate changes from AOGCM simulations via the "Reliability Ensemble Averaging" (REA) method, Journal of Climate, 15, 1141–1158, https://doi.org/10.1175/1520-0442(2003)016<0883:COCOAU>2.0.CO;2, 2002.

Gryspeerdt, E., Povey, A. C., Grainger, R. G., Hasekamp, O., Hsu, N. C., Mulcahy, J. P., Sayer, A. M., and Sorooshian, A.: Uncertainty in aerosol-cloud radiative forcing is driven by clean conditions, Atmospheric Chemistry and Physics, 23, 4115–4122, https://doi.org/10.5194/acp-23-4115-2023, 2023.

Hall, A. and Qu, X.: Using the current seasonal cycle to constrain snow albedo feedback in future climate change, Geophysical Research Letters, 33, https://doi.org/10.1029/2005GL025127, 2006.

Hall, A., Cox, P., Huntingford, C., and Klein, S.: Progressing emergent constraints on future climate change, Nature Climate Change, 9, 269–278, https://doi.org/10.1038/s41558-019-0436-6, 2019.

Harris, I., Osborn, T. J., Jones, P., and Lister, D.: Version 4 of the CRU TS monthly high-resolution gridded multivariate climate dataset, Scientific Data, 7, 109, https://doi.org/10.1038/s41597-020-0453-3, 2020.

Hawkins, E. and Sutton, R.: The potential to narrow uncertainty in regional climate predictions, Bulletin of the American Meteorological Society, 90, 1095–1108, https://doi.org/10.1175/2009BAMS2607.1, 2009.

540 Hegerl, G. C., Ballinger, A. P., Booth, B. B., Borchert, L. F., Brunner, L., Donat, M. G., Doblas-Reyes, F. J., Harris, G. R., Lowe, J., Mahmood, R., Mignot, J., Murphy, J. M., Swingedouw, D., and Weisheimer, A.: Toward Consistent Observational Constraints in Climate Predictions and Projections, Frontiers in Climate, 3, 678 109, https://doi.org/10.3389/fclim.2021.678109, 2021.

Held, I.: Simplicity amid complexity, https://doi.org/10.1126/science.1248447, 2014.

Hess, P., Drüke, M., Petri, S., Strnad, F. M., and Boers, N.: Physically constrained generative adversarial networks for improving precipitation
545 fields from Earth system models, Nature Machine Intelligence, 4, 828–839, https://doi.org/10.1038/s42256-022-00540-1, 2022.

Hickman, S. H. M., Griffiths, P. T., Nowack, P. J., and Archibald, A. T.: Short-term forecasting of ozone air pollution across Europe with transformers, Environmental Data Science, 2, e43, https://doi.org/10.1017/eds.2023.37, 2023.

Hoerl, A. E. and Kennard, R. W.: Ridge Regression: Biased Estimation for Nonorthogonal Problems, Technometrics, 12, 55–67, https://doi.org/10.2307/1271436, 1970.

550 Hourdin, F., Mauritsen, T., Gettelman, A., Golaz, J. C., Balaji, V., Duan, Q., Folini, D., Ji, D., Klocke, D., Qian, Y., Rauser, F., Rio, C., Tomassini, L., Watanabe, M., and Williamson, D.: The art and science of climate model tuning, Bulletin of the American Meteorological Society, 98, 589–602, https://doi.org/10.1175/BAMS-D-15-00135.1, 2017.

Huntingford, C., Jeffers, E. S., Bonsall, M. B., Christensen, H. M., Lees, T., and Yang, H.: Machine learning and artificial intelligence to aid climate change research and preparedness, Environ. Res. Lett, 14, 124 007, https://doi.org/10.1088/1748-9326/ab4e55, 2019.

555 Huntingford, C., Cox, P. M., Williamson, M. S., Clarke, J. J., and Ritchie, P. D. L.: Emergent constraints for the climate system as effective parameters of bulk differential equations, Earth System Dynamics, 14, 433–442, https://doi.org/10.5194/esd-14-433-2023, 2023.

IPCC: Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Press, https://doi.org/doi/10.1017/9781009157896, 2021.

Joshi, M. M., Charlton, A. J., and Scaife, A. A.: On the influence of stratospheric water vapor changes on the tropospheric circulation,
560 Geophysical Research Letters, 33, L09 806, https://doi.org/10.1029/2006GL025983, 2006.

Joshi, M. M., Webb, M. J., Maycock, A. C., and Collins, M.: Stratospheric water vapour and high climate sensitivity in a version of the HadSM3 climate model, Atmospheric Chemistry and Physics, 10, 7161–7167, https://doi.org/10.5194/acp-10-7161-2010, 2010.

Kaltenborn, J., Charlotte, L., Ramesh, V., Brouillard, P., Gurwicz, Y., Nagda, C., Runge, J., Nowack, P., and Rolnick, D.: ClimateSet: A Large-Scale Climate Model Dataset for Machine Learning, Advances in Neural Information Processing Systems, 36, https://papers.nips.
565 cc/paper_files/paper/2023/hash/44a6769fe6c695f8dfb347c649f7c9f0-Abstract-Datasets_and_Benchmarks.html, 2023.

Karniadakis, G. E., Kevrekidis, I. G., Lu, L., Perdikaris, P., Wang, S., and Yang, L.: Physics-informed machine learning, Nature Reviews Physics, 3, 422–440, https://www.nature.com/articles/s42254-021-00314-5, 2021.

Karpechko, A. Y., Maraun, D., and Eyring, V.: Improving antarctic total ozone projections by a process-oriented multiple diagnostic ensemble regression, Journal of the Atmospheric Sciences, 70, 3959–3976, https://doi.org/10.1175/JAS-D-13-071.1, 2013.

570 Kashinath, K., Mustafa, M., Albert, A., Wu, J. L., Jiang, C., Esmaeilzadeh, S., Azizzadenesheli, K., Wang, R., Chattopadhyay, A., Singh, A., Manepalli, A., Chirila, D., Yu, R., Walters, R., White, B., Xiao, H., Tchelepi, H. A., Marcus, P., Anandkumar, A., Hassanzadeh, P., and Prabhat: Physics-informed machine learning: Case studies for weather and climate modelling, Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 379, 20200 093, https://doi.org/10.1098/rsta.2020.0093, 2021.

Kasoar, M., Voulgarakis, A., Lamarque, J. F., Shindell, D. T., Bellouin, N., Faluvegi, G., and Tsigaridis, K.: Regional and global temperature
575   response to anthropogenic SO2 emissions from China in three climate models, Atmospheric Chemistry and Physics, 16, 9785–9804,
       https://doi.org/10.5194/acp-16-9785-2016, 2016.

Keeble, J., Hassler, B., Banerjee, A., Checa-garcia, R., Chiodo, G., Davis, S., Eyring, V., Griffiths, P. T., Morgenstern, O., Nowack, P.,
       Zeng, G., Zhang, J., Bodeker, G., Burrows, S., Cameron-Smith, P., Cugnet, D., Danek, C., Deushi, M., Horowitz, L. W., Kubin, A., Li,
       L., Lohmann, G., Michou, M., Mills, M. J., Nabat, P., Olivie, D., Park, S., Seland, O., Stoll, J., Wieners, K.-H., and Wu, T.: Evaluating
580   stratospheric ozone and water vapour changes in CMIP6 models from 1850 to 2100, Atmospheric Chemistry and Physics, 21, 5015–5061,
       https://doi.org/https://doi.org/10.5194/acp-21-5015-2021, 2021.

Keisler, R.: Forecasting Global Weather with Graph Neural Networks, http://arxiv.org/abs/2202.07575, 2022.

Kemsley, S. W., Ceppi, P., Andersen, H., Cermak, J., Stier, P., and Nowack, P.: A systematic evaluation of high-cloud controlling factors,
       Atmospheric Chemistry and Physics Discussions, pp. 1–33, 2024.

585   Klein, S. A. and Hall, A.: Emergent Constraints for Cloud Feedbacks, Current Climate Change Reports, 1, 276–287,
       https://doi.org/10.1007/s40641-015-0027-1, 2015.

Klein, S. A., Hall, A., Norris, J. R., and Pincus, R.: Low-Cloud Feedbacks from Cloud-Controlling Factors: A Review, Surveys in Geophysics,
       38, 1307–1329, https://doi.org/10.1007/s10712-017-9433-3, 2017.

Knutti, R.: The end of model democracy?, Climatic Change, 102, 395–404, https://doi.org/10.1007/s10584-010-9800-2, 2010.

590   Knutti, R., Rugenstein, M. A. A., and Hegerl, G. C.: Beyond equilibrium climate sensitivity, Nature Geoscience,
       https://doi.org/10.1038/ngeo3017, 2017.

Kurth, T., Subramanian, S., Harrington, P., Pathak, J., Mardani, M., Hall, D., Miele, A., Kashinath, K., and Anandkumar, A.: FourCast-
       Net: Accelerating Global High-Resolution Weather Forecasting Using Adaptive Fourier Neural Operators, Association for Computing
       Machinery, Inc, https://doi.org/10.1145/3592979.3593412, 2023.

595   Kwiatkowski, L., Bopp, L., Aumont, O., Ciais, P., Cox, P. M., Laufkötter, C., Li, Y., and Séférian, R.: Emergent constraints on projections of
       declining primary production in the tropical oceans, Nature Climate Change, 7, 355–358, https://doi.org/10.1038/nclimate3265, 2017.

Labe, Z. M. and Barnes, E. A.: Detecting Climate Signals Using Explainable AI With Single-Forcing Large Ensembles, Journal of Advances
       in Modeling Earth Systems, 13, https://doi.org/10.1029/2021ms002464, 2021.

Lam, R., Sanchez-Gonzalez, A., Willson, M., Wirnsberger, P., Fortunato, M., Alet, F., Ravuri, S., Ewalds, T., Eaton-Rosen, Z., Hu, W.,
600   Merose, A., Hoyer, S., Holland, G., Vinyals, O., Stott, J., Pritzel, A., Mohamed, S., and Battaglia, P.: Learning skillful medium-range
       global weather forecasting, Science, 382, 1416–1421, https://www.solarsystemscope.com/textures/], 2023.

Leach, N. J., Jenkins, S., Nicholls, Z., Smith, C. J., Lynch, J., Cain, M., Walsh, T., Wu, B., Tsutsui, J., and Allen, M. R.: FaIRv2.0.0:
       A generalized impulse response model for climate uncertainty and future scenario exploration, Geoscientific Model Development, 14,
       https://doi.org/10.5194/gmd-14-3007-2021, 2021.

605   Li, G., Xie, S. P., He, C., and Chen, Z.: Western Pacific emergent constraint lowers projected increase in Indian summer monsoon rainfall,
       Nature Climate Change, 7, 708–712, https://doi.org/10.1038/nclimate3387, 2017.

Lipat, B. R., Tselioudis, G., Grise, K. M., and Polvani, L. M.: CMIP5 models' shortwave cloud radiative response and climate sensitivity
       linked to the climatological Hadley cell extent, Geophysical Research Letters, 44, 5739–5748, https://doi.org/10.1002/2017GL073151,
       2017.

610 Lorenz, R., Herger, N., Sedláček, J., Eyring, V., Fischer, E. M., and Knutti, R.: Prospects and Caveats of Weighting Climate Models for Summer Maximum Temperature Projections Over North America, Journal of Geophysical Research: Atmospheres, 123, 4509–4526, https://doi.org/10.1029/2017JD027992, 2018.

Mansfield, L., Nowack, P., Kasoar, M., Everitt, R., Collins, W., and Voulgarakis, A.: Predicting global patterns of long-term climate change from short-term simulations using machine learning, npj Climate and Atmospheric Science, 3, 44, https://doi.org/10.1038/s41612-020-615 00148-5, 2020.

Mauritsen, T., Stevens, B., Roeckner, E., Crueger, T., Esch, M., Giorgetta, M., Haak, H., Jungclaus, J., Klocke, D., Matei, D., Mikolajewicz, U., Notz, D., Pincus, R., Schmidt, H., and Tomassini, L.: Tuning the climate of a global model, Journal of Advances in Modeling Earth Systems, 4, M00A01, https://doi.org/10.1029/2012MS000154, 2012.

McCoy, D. T., Eastman, R., Hartmann, D. L., and Wood, R.: The change in low cloud cover in a warmed climate inferred from AIRS, 620 MODIS, and ERA-interim, Journal of Climate, 30, 3609–3620, https://doi.org/10.1175/JCLI-D-15-0734.1, 2017.

Mulholland, D. P., Haines, K., Sparrow, S. N., and Wallom, D.: Climate model forecast biases assessed with a perturbed physics ensemble, Climate Dynamics, 49, 1729–1746, https://doi.org/10.1007/s00382-016-3407-x, 2017.

Murphy, J. M., Sexton, D. M. H., Barnett, D. N., Jones, G. S., Webb, M. J., Collins, M., and Stainforth, D. A.: Quantification of modelling uncertainties in a large ensemble of climate change simulations, Nature, 430, 768–772, https://doi.org/10.1038/nature02770.1., 2004.

625 Myers, T. A. and Norris, J. R.: Reducing the uncertainty in subtropical cloud feedback, Geophysical Research Letters, 43, 2144–2148, https://doi.org/10.1002/2015GL067416, 2016.

Myers, T. A., Scott, R. C., Zelinka, M. D., Klein, S. A., Norris, J. R., and Caldwell, P. M.: Observational constraints on low cloud feedback reduce uncertainty of climate sensitivity, Nature Climate Change, 11, 501–507, https://doi.org/10.1038/s41558-021-01039-0, 2021.

Nowack, P., Braesicke, P., Haigh, J., Abraham, N. L., Pyle, J., and Voulgarakis, A.: Using machine learning to build temperature-based 630 ozone parameterizations for climate sensitivity simulations, Environmental Research Letters, 13, 104 016, https://doi.org/10.1088/1748-9326/aae2be, 2018a.

Nowack, P., Runge, J., Eyring, V., and Haigh, J. D.: Causal networks for climate model evaluation and constrained projections, Nature Communications, 11, 1415, https://doi.org/10.1038/s41467-020-15195-y, 2020.

Nowack, P., Konstantinovskiy, L., Gardiner, H., and Cant, J.: Machine learning calibration of low-cost NO2 and PM10 sen-635 sors: non-linear algorithms and their impact on site transferability, Atmospheric Measurement Techniques, 14, 5637–5655, https://doi.org/https://doi.org/10.5194/amt-14-5637-2021, 2021.

Nowack, P., Ceppi, P., Davis, S. M., Chiodo, G., Ball, W., Diallo, M. A., Hassler, B., Jia, Y., Keeble, J., and Joshi, M.: Response of stratospheric water vapour to warming constrained by satellite observations, Nature Geoscience, https://doi.org/10.1038/s41561-023-01183-6, 2023.

640 Nowack, P. J., Braesicke, P., Abraham, N. L., and Pyle, J. A.: On the role of ozone feedback in the ENSO amplitude response under global warming, Geophysical Research Letters, 44, 3858–3866, https://doi.org/10.1002/2016GL072418, 2017.

Nowack, P. J., Abraham, N. L., Braesicke, P., and Pyle, J. A.: The impact of stratospheric ozone feedbacks on climate sensitivity estimates, Journal of Geophysical Research: Atmospheres, 123, 4630–4641, https://doi.org/10.1002/2017JD027943, 2018b.

O'Gorman, P. A.: Sensitivity of tropical precipitation extremes to climate change, Nature Geoscience, 5, 697–700, 645 https://doi.org/10.1038/ngeo1568, 2012.

O'Neill, B. C., Kriegler, E., Riahi, K., Ebi, K. L., Hallegatte, S., Carter, T. R., Mathur, R., and van Vuuren, D. P.: A new scenario framework for climate change research: The concept of shared socioeconomic pathways, Climatic Change, 122, 387–400, https://doi.org/10.1007/s10584-013-0905-2, 2014.

O'Neill, B. C., Tebaldi, C., Vuuren, D. P. V., Eyring, V., Friedlingstein, P., Hurtt, G., Knutti, R., Kriegler, E., Lamarque, J. F., Lowe, J., Meehl, G. A., Moss, R., Riahi, K., and Sanderson, B. M.: The Scenario Model Intercomparison Project (ScenarioMIP) for CMIP6, Geoscientific Model Development, 9, 3461–3482, https://doi.org/10.5194/gmd-9-3461-2016, 2016.

O'Reilly, C. H., Befort, D. J., and Weisheimer, A.: Calibrating large-ensemble European climate projections using observational data, Earth System Dynamics, 11, 1033–1049, https://doi.org/10.5194/esd-11-1033-2020, 2020.

O'Reilly, C. H., Brunner, L., Qasmi, S., Nogherotto, R., Ballinger, A. P., Booth, B., Befort, D. J., Knutti, R., Schurer, A. P., Ribes, A., Weisheimer, A., Coppola, E., and McSweeney, C.: Assessing observational constraints on future European climate in an out-of-sample framework, npj Climate and Atmospheric Science, 7, 95, https://doi.org/10.1038/s41612-024-00648-8, 2024.

Pendergrass, A. G.: The Global-Mean Precipitation Response to CO2-Induced Warming in CMIP6 Models, Geophysical Research Letters, 47, https://doi.org/10.1029/2020GL089964, 2020.

Qasmi, S. and Ribes, A.: Reducing uncertainty in local climate projections, Science Advances, 8, eabo6872, https://doi.org/doi.org/10.1126/sciadv.abo6872, 2022.

Qu, X., Hall, A., Klein, S. A., and Deangelis, A. M.: Positive tropical marine low-cloud cover feedback inferred from cloud-controlling factors, Geophysical Research Letters, 42, 7767–7775, https://doi.org/10.1002/2015GL065627, 2015.

Rasp, S. and Thuerey, N.: Data-Driven Medium-Range Weather Prediction With a Resnet Pretrained on Climate Simulations: A New Model for WeatherBench, Journal of Advances in Modeling Earth Systems, 13, https://doi.org/10.1029/2020MS002405, 2021.

Reichler, T. and Kim, J.: How Well Do Coupled Models Simulate Today ' s Climate ?, Bulletin of the American Meteorological Society, 819, 303–311, https://doi.org/10.1175/BAMS-89-3-303, 2008.

Reichstein, M., Camps-Valls, G., Stevens, B., Jung, M., Denzler, J., Carvalhais, N., and Prabhat: Deep learning and process understanding for data-driven Earth system science, Nature, 566, 195–204, https://doi.org/10.1038/s41586-019-0912-1, 2019.

Ribes, A., Qasmi, S., and Gillett, N. P.: Making climate projections conditional on historical observations, Science Advances, 7, eabc0671, https://doi.org/10.1126/sciadv.abc0671, 2021.

Ribes, A., Boé, J., Qasmi, S., Dubuisson, B., Douville, H., and Terray, L.: An updated assessment of past and future warming over France based on a regional observational constraint, Earth System Dynamics, 13, 1397–1415, https://doi.org/10.5194/esd-13-1397-2022, 2022.

Runge, J., Nowack, P., Kretschmer, M., Flaxman, S., and Sejdinovic, D.: Detecting and quantifying causal associations in large nonlinear time series datasets, Science Advances, 5, aau4996, https://doi.org/10.1126/sciadv.aau4996, 2019.

Räisänen, J., Ruokolainen, L., and Ylhäisi, J.: Weighting of model results for improving best estimates of climate change, Climate Dynamics, 35, 407–422, https://doi.org/10.1007/s00382-009-0659-8, 2010.

Saltelli, A.: A short comment on statistical versus mathematical modelling, https://doi.org/10.1038/s41467-019-11865-8, 2019.

Sanderson, B. M., Knutti, R., and Caldwell, P.: Addressing interdependency in a multimodel ensemble by interpolation of model properties, Journal of Climate, 28, 5150–5170, https://doi.org/10.1175/JCLI-D-14-00361.1, 2015.

Sanderson, B. M., Wehner, M., and Knutti, R.: Skill and independence weighting for multi-model assessments, Geoscientific Model Development, 10, 2379–2395, https://doi.org/10.5194/gmd-10-2379-2017, 2017.

Sanderson, B. M., Pendergrass, A. G., Koven, C. D., Brient, F., Booth, B. B., Fisher, R. A., and Knutti, R.: The potential for structural errors in emergent constraints, Earth System Dynamics, 12, 899–918, https://doi.org/10.5194/esd-12-899-2021, 2021.

Schlund, M., Lauer, A., Gentine, P., Sherwood, S. C., and Eyring, V.: Emergent constraints on equilibrium climate sensitivity in CMIP5: Do
    they hold for CMIP6?, Earth System Dynamics, 11, 1233–1258, https://doi.org/10.5194/esd-11-1233-2020, 2020.

Schneider, T., Lan, S., Stuart, A., and Teixeira, J.: Earth system modeling 2.0 : a blueprint for models that learn from observations and
    targeted high-resolution simulations, Geophysical Research Letters, 44, 12 396–12 417, https://doi.org/10.1002/2017GL076101, 2017.

Scott, R. C., Myers, T. A., and Norris, J. R.: Observed Sensitivity of Low Cloud Radiative Effects to Meteorological Perturbations over the
    Global Oceans, Journal of Climate, 33, 7717–7734, https://doi.org/10.1175/JCLI-D-19-1028.1., 2020.

Shao, Y., Bishop, C. H., Hobeichi, S., Nishant, N., Abramowitz, G., and Sherwood, S.: Time Variability Correction of CMIP6 Climate
    Change Projections, Journal of Advances in Modeling Earth Systems, 16, https://doi.org/10.1029/2023MS003640, 2024.

Sherwood, S., Webb, M. J., Annan, J. D., Armour, K. C., Forster, P. M., Hargreaves, J. C., Hegerl, G., Klein, S. A., Marvel, K. D., Rohling,
    E. J., Watanabe, M., Andrews, T., Braconnot, P., Bretherton, C. S., Foster, G. L., Hausfather, Z., von der Heydt, A. S., Knutti, R., Mauritsen,
    T., Norris, J. R., Proistosescu, C., Rugenstein, M., Schmidt, G. A., Tokarska, K. B., and Zelinka, M. D.: An assessment of Earth's climate
    sensitivity using multiple lines of evidence, Reviews of Geophysics, 58, e2019RG000 678, https://doi.org/10.1029/2019RG000678, 2020.

Sherwood, S. C., Bony, S., and Dufresne, J.-L.: Spread in model climate sensitivity traced to atmospheric convective mixing, Nature, 505,
    37–42, https://doi.org/10.1038/nature12829, 2014.

Shiogama, H., Watanabe, M., Kim, H., and Hirota, N.: Emergent constraints on future precipitation changes, Nature, 602, 612–616,
    https://doi.org/10.1038/s41586-021-04310-8, 2022.

Simpson, I. R., McKinnon, K. A., Davenport, F. V., Tingley, M., Lehner, F., Fahad, A. A., and Chen, D.: Emergent constraints on the large-
    scale atmospheric circulation and regional hydroclimate: Do they still work in CMIP6 and how much can they actually constrain the
    future?, Journal of Climate, 34, 6355–6377, https://doi.org/10.1175/JCLI-D-21-0055.1, 2021.

Sippel, S., Mitchell, D., Black, M. T., Dittus, A. J., Harrington, L., Schaller, N., and Otto, F. E.: Combining large model en-
    sembles with extreme value statistics to improve attribution statements of rare events, Weather and Climate Extremes, 9, 25–35,
    https://doi.org/10.1016/j.wace.2015.06.004, 2015.

Sippel, S., Zscheischler, J., Mahecha, M. D., Orth, R., Reichstein, M., Vogel, M., and Seneviratne, S. I.: Refining multi-model pro-
    jections of temperature extremes by evaluation against land-Atmosphere coupling diagnostics, Earth System Dynamics, 8, 387–403,
    https://doi.org/10.5194/esd-8-387-2017, 2017.

Stenke, A. and Grewe, V.: Simulation of stratospheric water vapor trends: impact on stratospheric ozone chemistry, Atmospheric Chemistry
    and Physics, 5, 1257–1272, https://doi.org/10.5194/acp-5-1257-2005, 2005.

Stuber, N., Ponater, M., and Sausen, R.: Why radiative forcing might fail as a predictor of climate change, Climate Dynamics, 24, 497–510,
    https://doi.org/10.1007/s00382-004-0497-7, 2005.

Tebaldi, C., Mearns, L. O., Nychka, D., and Smith, R. L.: Regional probabilities of precipitation change: A Bayesian analysis of multimodel
    simulations, Geophysical Research Letters, 31, L24 213, https://doi.org/10.1029/2004GL021276, 2004.

Thackeray, C. W. and Hall, A.: An emergent constraint on future Arctic sea-ice albedo feedback, Nature Climate Change, 9, 972–978,
    https://doi.org/10.1038/s41558-019-0619-1, 2019.

Thackeray, C. W., Hall, A., Zelinka, M. D., and Fletcher, C. G.: Assessing Prior Emergent Constraints on Surface Albedo Feedback in
    CMIP6, Journal of Climate, May, 3889–3905, https://doi.org/10.1175/JCLI-D-20, 2021.

Thackeray, C. W., Hall, A., Norris, J., and Chen, D.: Constraining the increased frequency of global precipitation extremes under warming,
    Nature Climate Change, 12, 441–448, https://doi.org/10.1038/s41558-022-01329-1, 2022.

Tian, B.: Spread of model climate sensitivity linked to double-Intertropical Convergence Zone bias, pp. 4133–4141, https://doi.org/10.1002/2015GL064119.Received, 2015.

Tokarska, K. B., Stolpe, M. B., Sippel, S., Fischer, E. M., Smith, C. J., Lehner, F., and Knutti, R.: Past warming trend constrains future warming in CMIP6 models, Science Advances, 6, eaaz9549, https://doi.org/10.1126/sciadv.aaz9549, 2020.

725 Watson-Parris, D.: Machine learning for weather and climate are worlds apart, https://doi.org/10.1098/rsta.2020.0098, 2021.

Watson-Parris, D., Rao, Y., Olivié, D., Seland, , Nowack, P., Camps-Valls, G., Stier, P., Bouabid, S., Dewey, M., Fons, E., Gonzalez, J., Harder, P., Jeggle, K., Lenhardt, J., Manshausen, P., Novitasari, M., Ricard, L., and Roesch, C.: ClimateBench v1.0: A benchmark for data-driven climate projections, Journal of Advances in Modeling Earth Systems, 14, e2021MS002 954, https://doi.org/10.1029/2021ms002954, 2022.

Wenzel, S., Cox, P. M., Eyring, V., and Friedlingstein, P.: Emergent constraints on climate-carbon cycle feedbacks in the CMIP5 Earth system

730 models, Journal of Geophysical Research: Biogeosciences, 119, 794–807, https://doi.org/10.1002/2013JG002591, 2014.

Wenzel, S., Eyring, V., Gerber, E. P., and Karpechko, A. Y.: Constraining future summer austral jet stream positions in the CMIP5 ensemble by process-oriented multiple diagnostic regression, Journal of Climate, 29, 673–687, https://doi.org/10.1175/JCLI-D-15-0412.1, 2016.

Wilkinson, S., Nowack, P., and Joshi, M.: Observations-based machine learning model constrains uncertainty in future regional warming projections, pp. EGU23–7869, European Geosciences Union, https://doi.org/10.5194/egusphere-egu23-7869, 2023.

735 Wilks, D. S.: Statistical Methods in the Atmospheric Sciences, Academic Press, 2006.

Williamson, M. S., Thackeray, C. W., Cox, P. M., Hall, A., Huntingford, C., and Nijsse, F. J.: Emergent constraints on climate sensitivities, Reviews of Modern Physics, 93, https://doi.org/10.1103/RevModPhys.93.025004, 2021.

Winkler, A. J., Myneni, R. B., Alexandrov, G. A., and Brovkin, V.: Earth system models underestimate carbon fixation by plants in the high latitudes, Nature Communications, 10, https://doi.org/10.1038/s41467-019-08633-z, 2019a.

740 Winkler, A. J., Myneni, R. B., and Brovkin, V.: Investigating the applicability of emergent constraints, Earth System Dynamics, 10, 501–523, https://doi.org/10.5194/esd-10-501-2019, 2019b.

Zelinka, M. D., Myers, T. A., McCoy, D. T., Po-Chedley, S., Caldwell, P. M., Ceppi, P., Klein, S. A., and Taylor, K. E.: Causes of Higher Climate Sensitivity in CMIP6 Models, Geophysical Research Letters, 47, e2019GL085 782, https://doi.org/10.1029/2019GL085782, 2020.

Zhou, C., Zelinka, M. D., Dessler, A. E., and Klein, S. A.: The relationship between interannual and long-term cloud feedbacks, Geophysical

745 Research Letters, 42, 10 463–10 469, https://doi.org/10.1002/2015GL066698, 2015.