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Reducing Uncertainties in Climate Projections with Emergent Constraints: Concepts, Examples and Prospects

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Abstract

Models disagree on a significant number of responses to climate change, such as climate feedback, regional changes, or the strength of equilibrium climate sensitivity. Emergent constraints aim to reduce these uncertainties by finding links between the inter-model spread in an observable predictor and climate projections. In this paper, the concepts underlying this framework are recalled with an emphasis on the statistical inference used for narrowing uncertainties, and a review of emergent constraints found in the last two decades. Potential links between highlighted predictors are explored, especially those targeting uncertainty reductions in climate sensitivity, cloud feedback, and changes of the hydrological cycle. Yet the disagreement across emergent constraints suggests that the spread in climate sensitivity can not be significantly narrowed. This calls for weighting the realism of emergent constraints by quantifying the level of physical understanding explaining the relationship. This would also permit more efficient model evaluation and better targeted model development. In the context of the upcoming CMIP6 model intercomparison a growing number of new predictors and uncertainty reductions is expected, which call for robust statistical inferences that allow cross-validation of more likely estimates.

1 Introduction

For more than two centuries, steadily increasing carbon dioxide concentrations in the atmosphere have been warming the Earth. Today it is 0.8°C warmer than in the preindustrial period in the middle of the 19th century [Morice *et al.*, 2012]. Global climate models (GCMs) project how this global warming will continue given the expected continuous increase in human-made carbon dioxide emissions. While models agree on the sign of a number of climate change signals, they often disagree on their amplitude [Flato *et al.*, 2013]. A well-known example is the equilibrium climate sensitivity (ECS), i.e. the equilibrium global-mean surface temperature increase resulting from a sustained doubling of carbon dioxide concentrations [Gregory *et al.*, 2004]. For decades, models have exhibited widely differing climate sensitivities, yet with a range remaining roughly between 2 and 5°C [Charney *et al.*, 1979; Bony *et al.*, 2013]. To correctly predict how much the Earth will warm, one must know at least (1) how carbon dioxide concentration will evolve [Stocker *et al.*, 2013], and (2) the correct value of climate sensitivity.

A doubling of the carbon dioxide concentration would warm the Earth by $1.2 \pm 0.1^{\circ}\text{C}$ [Dufresne and Bony, 2008]. However, this warming induces changes that can amplify or dampen the initial temperature response through feedback processes [Bony *et al.*, 2006]. For example, the CO_2 -induced global warming allows the atmosphere to hold more water vapor. This acts as a positive feedback

44 on the surface warming, because water vapor itself is a powerful greenhouse gas that, like CO₂,
45 absorbs and re-emits long-wave radiation back to the surface. This is somewhat compensated by the
46 negative temperature lapse rate feedback that allows more outgoing long wave emission to be emitted
47 out of the atmosphere. The initial warming also reduces the surface albedo by melting snow and
48 sea-ice, which also constitutes a positive feedback because snow and ice are effective reflectors of
49 sunlight. Models agree on the sign and approximately the amplitude of these two feedback processes
50 [Ceppi *et al.*, 2017]. The water vapor, lapse-rate, and ice-albedo feedbacks in isolation enhance the
51 global warming due to increasing CO₂ concentrations to around +2.2°C [Dufresne and Bony, 2008].
52 Models disagree on the cloud response to surface warming, which is primarily why they produce
53 a wide range of ECS values, e.g. between 2.1 and 4.7°C for the CMIP5 model intercomparison
54 [Flato *et al.*, 2013]. Since clouds have dynamical scales in the order of tens to hundreds of
55 meters, climate models with grid boxes of hundred of kilometers cannot explicitly resolve cloud
56 processes. Empirically-based assumptions are thus used to relate unresolvable small-scale dynamics
57 to properties (temperature, humidity etc.) on the models' grid scale. Those parameterizations are
58 the heart of biases in reproducing the present-day climate and of uncertainties in climate change
59 projections [e.g. Qu *et al.*, 2013; Webb *et al.*, 2015; Brient *et al.*, 2016; Geoffroy *et al.*, 2017].
60 This calls for new efficient process-oriented methods for understanding leading causes behind these
61 uncertainties and for establishing better model evaluation and development.

62 **2 Emergent constraints**

63 **2.1 Definition**

64 Recently, a methodology called emergent constraint has been developed for reducing uncertain-
65 ties in climate-change projections. This framework is based on :

- 66 1. identifying responses to climate change perturbation in which model disagree (e.g., cloud
67 feedback)
- 68 2. relating the inter-model spread in the climate-change responses to present-day biases or short-
69 term variations that can be observed.

70 This could be achieved by identifying an empirical relationship between the inter-model spread of an
71 observable variable (hereafter named A) and the inter-model responses B to a given perturbation. The
72 variable A is called the predictor and the variable B the predictand. Because observed measurements
73 of the predictor A can then be used to constrain the models' responses B, the relationship between A
74 and B is called an emergent constraint [Klein and Hall, 2015]. The variable A may represent a metric

75 that characterize the climate system (humidity, winds,...) or may characterize natural variability
76 (e.g., in the seasonal cycle, or from year to year). The response B can be the global-mean response of
77 the climate system (e.g. ECS) or a local response to perturbations (e.g. a regional climate feedback).
78 Therefore, the goal is to find a predictor that, given its relation to a climate response, emerges as a
79 constraint on future projections.

80 Once the variable A is estimated observationally, the emergent constraint can be used to assess
81 models' realism and to eventually narrow the spread of climate change projections. As an idealized
82 example, Figure 1 shows a randomly-generated relationship between a predictor A simulated by
83 29 climate models and a projection of future climate changes (in principle any climate-change
84 response may be considered). The green distribution represents an observational measurement and
85 its uncertainties. We see that differences in A are significantly associated with differences in B,
86 here with a correlation coefficient of $r=0.83$. By constraining A through potential observations
87 (green distribution), this example suggests that some models are more realistic and, by inference,
88 are associated with more realistic predictand. The degree to which the models' A deviates from
89 the observed A can be used to derive weights for the models to compute a weighted average of the
90 models' response B (see section 2.2.3).

91 **2.2 Criterion and uncertainties**

92 **2.2.1 Physical understanding**

93 An emergent constraint can be trusted if it meets certain criteria. The most important one
94 is an understanding of physical mechanisms underlying the empirical relationship, which is the
95 key to increase the plausibility of a proposed emergent constraint. Several methods have been
96 recently suggested to verify the level of confidence of emergent constraints [Caldwell *et al.*, 2018;
97 Hall *et al.*, 2019]. One of them consists in checking the reliability of an emergent constraint by
98 developing sensitivity tests that would modify A for some models (if there is a straightforward way
99 of manipulating A). For accurate model comparison, this would require coupled model simulations
100 with global-mean radiative balance as performed for CMIP intercomparison. If the models' behavior
101 after the modification deviates from that expected from the emergent constraint, the relationship may
102 have been found by chance. A study showed that this risk is not negligible [Caldwell *et al.*, 2014],
103 primarily because climate models are not independent but many are derived from each other [Masson
104 and Knutti, 2011; Knutti *et al.*, 2013]. Keeping only models with enough structural differences
105 often reduces the reliability of identified emergent constraints. The search for correlations with no

106 obvious physical understanding could lead to such spurious results. Conversely, if those sensitivity
107 tests confirm the inter-model relationship, the credibility of assumed physical mechanisms and
108 observational constraints on climate change projections increases. Those tests could be performed
109 through an ensemble of simulations over which either parameterizations or uncertain parameters are
110 modified. This would help (1) disentangle structural and parametric influence on the multi-model
111 spread in predictor A and (2) highlight underlying processes explaining the empirical relationship
112 [*Kamae et al.*, 2016].

113 **2.2.2 Observation uncertainties**

114 The second criterion is related to the correct use of observations. Uncertainties tied to the
115 observation of the predictor must be small enough so that not all models remain consistent with the
116 data. This criterion may not be satisfied if observations are available only over a short time period (as
117 is the case for the vertical structure of clouds, [e.g. *Winker et al.*, 2010]), or if the predictor is defined
118 through low-frequency variability (trends, decadal variability), or if there is a lack of consistency
119 among available datasets (as in the case for global-mean precipitation and surface fluxes, [e.g.
120 *Găinușă-Bogdan et al.*, 2015]). Finally, some *observational* constraints rely on parameterizations
121 used in climate models, e.g. reanalysis that use sub-grid assumptions for representing clouds [e.g.
122 *Dee et al.*, 2011] or data product for clouds that use sub-grid assumptions for radiative transfer
123 calculations [*Rossow and Schiffer*, 1999].

124 **2.2.3 Statistical inference**

125 Emergent constraints can allow us to narrow uncertainties and quantify more likely estimates
126 of climate projections, i.e. constrained posterior range of a prior distribution. However, not all
127 emergent constraints should be given the same trust. *Hall et al.* [2019] suggested to relate this trust
128 to the level of physical understanding associated with the emergent relationship. This means making
129 predictions only for confirmed emergent constraints.

130 Posterior estimates are influenced by the way the statistical inference has been performed.
131 However, no consensus has yet emerged for this inference. A first method for quantifying this
132 constraint is to directly use uncertainties underlying the observational predictor and project it onto the
133 vertical axis using the emergent constraint relationship. This method takes into account uncertainties
134 in both observations and the estimated regression model, through bootstrapping samples for instance
135 [*Huber et al.*, 2011]. Most studies use this straightforward framework. In our idealized example,

136 this would give a posterior estimate slightly larger and narrower than the prior estimate (Figure 1).
137 However, several problems with this kind of inference might be highlighted as suggested by *Schneider*
138 [2018]:

- 139 • Most fundamentally, the inference generally revolves around assuming that there exists a
140 linear relationship, and estimating parameters in the linear relationship from climate models.
141 But it is not clear that such a linear relationship does in fact exist, and estimating parameters
142 in it is strongly influenced by models that are inconsistent with the observations (extreme
143 values). In other words, the analysis neglects structural uncertainty about the adequacy of the
144 assumed linear model, and the parameter uncertainty the analysis does take into account is
145 strongly reduced by models that are "bad" by this model-data mismatch metric. Outliers thus
146 strongly influence the result. However, the influence of models consistent with the data but
147 off the regression line is diminished. Given that there is no strong a priori knowledge about
148 any linear relationship – this is why it is an "emergent" constraint – it seems inadvisable to
149 make one's statistical inference strongly dependent on models that are not consistent with the
150 data at hand.
- 151 • Often analysis parameters are chosen so as to give strong correlations between the response
152 of models to perturbations and the predictor. This introduces selection bias in the estimation
153 of the regression lines. This leads to underestimation of uncertainties in parameters, such
154 as the slope of the regression line, which propagates into underestimated uncertainties in the
155 inferred estimate.
- 156 • When regression parameters are estimated by least squares, the observable on the horizontal
157 axis is treated as being a known predictor, rather than as being affected by error (e.g., from
158 sampling variability). This likewise leads to underestimation of uncertainties in regression
159 parameters. This problem can be mitigated by using errors-in-variables methods.

160 A second method consists of estimating a posterior distribution by weighting each model's
161 response by the likelihood of the model given the observations of the predictor. This can be
162 accomplished by a Bayesian weighting method [e.g. *Hargreaves et al.*, 2012] or through information
163 theory [e.g. *Brient and Schneider*, 2016], such as the Kullback-Leibler divergence or relative entropy
164 [*Burnham and Anderson*, 2010]. This method does not use the linear regression for estimating
165 the posterior distribution and therefore favor realistic models and deemphasize outliers inconsistent
166 with observations. For instance, the Kullback-Leibler divergence applied to our idealized example

167 (assuming an identical standard deviation between observation and each model) suggests an posterior
168 estimate lower and narrower than the prior estimate (Figure 1).

169 This more justifiable inference still suffers from several shortcomings [*Schneider, 2018*]. For
170 example, it suffers from selection bias, and it treats the model ensemble as a random sample (which it
171 is not). It also only weights models, suggesting that climate projections far outside the range of what
172 current models produce will always come out as being very unlikely. Given uncertainties underlying
173 each method, posterior estimates should thus be quantified using different methods (as previously
174 done in *Hargreaves et al. [2012]* for instance) and methods should be significantly described.

175 Figure 2 provides a tangible example for explaining the importance of statistical inference.
176 It shows the relation in 29 current climate models between ECS and the strength with which the
177 reflection of sunlight in tropical low-cloud regions covaries with surface temperature [*Brient and
178 Schneider, 2016*]. That is, the horizontal axis shows the percentage change in the reflection of
179 sunlight per degree surface warming, for deseasonalized natural variations. It is clear that there
180 is a strong correlation (correlation coefficient about -0.7) between ECS on the vertical axis and
181 the natural fluctuations on the horizontal axis. The green line on the horizontal axis indicates
182 the probability density function (PDF) of the observed natural fluctuations. What many previous
183 emergent-constraint studies have done is to take such a band of observations and project it onto
184 the vertical ECS axis using the estimated regression line between ECS and the natural fluctuations,
185 taking into account uncertainties in the estimated regression model. If we do this with the data
186 here, we obtain an ECS that likely lies within the blue band: between 3.1 and 4.2 K, with a most
187 likely value of 3.6 K. Simply looking at the scatter of the 29 models in this plot indicates that this
188 uncertainty band is too narrow. For example, model 7 is consistent with the observations, but has
189 a much lower ECS of 2.6 K. The regression analysis would imply that the probability of an ECS
190 this low or lower is less than 4%. Yet this is one of 29 models, and one of relatively few (around
191 9) that are likely consistent with the data. Obviously, the probability of an ECS this low is much
192 larger than what the regression analysis implies. As explained before, these flaws could be reduced
193 by weighting ECS by the likelihood of the model given the observations. Models such as numbers 2
194 and 3, which are inconsistent with observations, would receive essentially zero weight (unlike in the
195 regression-based analysis, they do not influence the final result). No linear relationship is assumed
196 or implied, so models such as 7 receive a large weight because they are consistent with the data,
197 although they lie far from any regression line. The resulting posterior PDF for ECS is shown by
198 the orange line in Figure 1b. The most likely ECS value according to this analysis is 4.0 K. It is
199 shifted upward relative to the regression estimate, toward the values in the cluster of models (around

200 numbers 25 and 26) with relatively high ECS that are consistent with the observations. The likely
201 ECS range stretches from 2.9 to 4.5 K. This is perhaps a disappointingly wide range. It is 50 %
202 wider than what the analysis based on linear regressions suggests, and it is not much narrower than
203 what simple-minded equal weighting of raw climate models gives (gray line in Figure 1b). But it is
204 a much more statistically defensible range.

205 In order to generalize the sensitivity of inferred estimates to the statistical methodology, 10^4
206 random emergent relationships are generated. Figure 3 shows statistics of inferences (mode, confi-
207 dence intervals) as a function of averaged correlation coefficients. Averaged modes and confidence
208 intervals are consistent between the two inference methods for this set of relationships. However, the
209 variance of inferred best estimates (modes) using the weighting method is larger than the one using
210 the inference method. This is in agreement with results obtained from the tangible example from
211 *Brient and Schneider* [2016], which show different most likely values. Therefore, this suggests the
212 best estimate is significantly influenced by the way statistical inference is performed.

213 Finally, uncertainties underlying these estimates may be influenced by the level of structural
214 similarity between climate models. Indeed, adding models with only weak structural differences
215 (e.g. model version with different resolution, interactive chemistry) can artificially strengthen the
216 correlation coefficient of the empirical relationship and the inferred best estimate [*Sanderson et al.*,
217 2015]. This coefficient is usually the first criterion that quantify the statistical credibility of an
218 emergent constraint, i.e. the larger the correlation coefficient, the more trustworthy the regression-
219 based inference will be. However, it remains unknown what level of statistical significance justifies
220 an emergent constraint and whether these correlation best characterize their credibility.

221 **3 Pioneering studies**

222 In the following sections, emergent constraints that have been highlighted within the last two
223 decades are listed and described. Table 1 summarize them, along with prior and posterior estimates of
224 the models' predictand. Mean and uncertainties (one standard deviation) are based on the inference
225 provided in the reference if available, or roughly derived through their empirical relationship and
226 observational uncertainties otherwise (for qualitative assessment).

227 In the late 1990s, signs of climate feedback started to be constrained from climate models and
228 observations [e.g. *Hall and Manabe*, 1999]. Usually analyzing one unique model, these studies
229 improved our understanding of physical mechanisms driving climate feedback. However, the lack
230 of inter-model comparisons in these studies did not allow quantifying the relative importance of

231 feedbacks in driving uncertainties in climate change projections. Model intercomparisons during
232 this period identified the cloud response to global warming as being the key contributor of inter-model
233 spread in climate projections [Cess *et al.*, 1990, 1996]. Both types of studies thus pave the way toward
234 process-oriented investigation for understanding inter-model differences in climate projections.

235 To my knowledge, the first attempt at introducing the concept of emergent constraint was
236 made by Allen and Ingram [2002]. The authors tried to constrain the spread in global-mean future
237 precipitation change simulated by the set of climate models participating in the CMIP2 model
238 intercomparison project [Meehl *et al.*, 2000] through observable temperature variability and a simple
239 energetic framework. Despite the inability to robustly narrow future precipitation changes, they
240 introduced the concepts that establish emergent constraints: the need for physical understanding and
241 the ability of observations to constrain the model predictor.

242 An early application of emergent constraints concerns the snow-albedo feedback. Hall and
243 Qu [2006] showed that differences among models in seasonal northern hemisphere surface albedo
244 changes are well correlated with global-warming albedo changes in CMIP3 models. The three main
245 criteria for a robust emergent constraint are satisfied: the physical mechanisms are well understood,
246 the statistical relationship between the quantities of interest is strong, and uncertainties in the observed
247 variations are weak, allowing the authors to constrain the northern hemisphere snow-albedo feedback
248 under global warming. Despite this successful application, the generation of models that followed
249 (CMIP5) continued to exhibit a large spread in seasonal variability of snow-albedo changes [Qu and
250 Hall, 2014]. This could be narrowed through targeted process-oriented model development based
251 on the evaluation of snow and vegetation parameterizations [Thackeray *et al.*, 2018]. Yet this study
252 can be seen as the first confirmed emergent constraint [Klein and Hall, 2015; Hall *et al.*, 2019].

253 The success of the Hall and Qu study led a number of studies to seek emergent constraints able
254 to narrow climate-change responses. In the following sections, these studies aiming to constrain
255 equilibrium climate sensitivity, cloud feedback, or various changes in Earth system components,
256 such as the hydrological cycle or the carbon cycle, are described.

257 **4 Model biases and equilibrium climate sensitivity**

258 Uncertainties in ECS usually scale with uncertainties in regional climate changes [Seneviratne
259 *et al.*, 2016]. So constraining ECS would help estimating regional responses to climate change,
260 which matter the most for impact studies and risk assessment. Therefore, a majority of emergent
261 constraints prioritize providing a better range for ECS, as shown on table 1.

262 The main predictors used to constrain the spread in ECS consist of observable climatological
263 characteristics of the current climate. The first study using this approach was *Volodin* [2008], which
264 found that CMIP3 models with large ECS are more likely to exhibit (1) large differences in cloud
265 cover between the tropics and the extra-tropics and (2) low tropical relative humidity.

266 The first estimate suggested by *Volodin* [2008] uses a cloud climatology from geostationary
267 satellites to derive a more likely ECS range of 3.6 ± 0.3 K. This range is slightly higher than the
268 multi-model average, with a reduced variance (Table 1). However this study does not address the
269 physical understanding of links between clouds, moisture, and climate feedbacks, which reduce the
270 credibility of this estimate. A more recent study, *Siler et al.* [2018], provides a physical interpretation
271 underlying this cloud constraint. They hypothesize that the need for a global-mean radiative balance
272 (through model tuning) forces a link between warm and cold regions, i.e. models having less clouds
273 in the tropical area will very likely simulate more extratropical clouds in the current climate. Given
274 that the global warming will expand tropical warm regions at the expense of extratropical cold
275 regions, these models will increase the spatial coverage of areas with weak cloudiness relative to the
276 multi-model mean, leading to more positive low-cloud feedback and high climate sensitivity. Using
277 observations for characterizing the spatial coverage of cloud albedo, *Siler et al.* [2018] find a best
278 ECS estimate of 3.7 ± 1.3 K, in agreement with *Volodin* [2008]. The credibility of this estimate is
279 yet questionable because physical mechanisms explaining the emergent relationships are not testable
280 [*Caldwell et al.*, 2018].

281 The second estimate suggested by *Volodin* [2008] is related to relative humidity and uses re-
282 analysis outputs to provide a more likely ECS range of 3.4 ± 0.3 K. In CMIP3, models with largest
283 zonal-mean relative humidity over the subtropical free troposphere are those with the lowest climate
284 sensitivity. Given that models generally overestimate this predictor, this suggests the highest ECS
285 values are more realistic. This is in agreement with *Fasullo and Trenberth* [2012], which found
286 the same relationship and a best ECS estimate of around 4 K (Table 1). This emergent relationship
287 is somewhat explained by the broadening of the tropical dry zones with global warming, which
288 imply a drying of the subsiding branches. Thus, the drier the free troposphere in the current climate
289 the stronger the boundary-layer drying and cloud feedback with global warming. This mechanism
290 may also explain the positive low-cloud feedback in climate models, e.g. the IPSL-CM5A model
291 [*Brient and Bony*, 2013]. Conversely, *Volodin* [2008] hypothesized that the relationship is related to
292 the role of relative humidity in convective parameterization. These different physical interpretations
293 suggest that emergent constraints arise from inter-model differences in structural (local) uncertainties,
294 (remote) biases in large-scale dynamics, and the interactions between them.

295 This dichotomy is addressed by *Sherwood et al.* [2014]. They quantify the low-tropospheric
296 convective mixing through the sum of two metrics : an index related to small-scale mixing and an
297 index linked to large-scale mixing. The former aims to represent errors in parameterized processes
298 such as shallow convection, turbulence, or precipitation. The latter quantifies model errors in
299 reproducing the tropical dynamical circulation, which can also be affected by parameterizations of
300 deeper convection remotely affecting low-clouds. The CMIP3 and CMIP5 inter-model spread of this
301 predictor is well correlated to uncertainties in ECS. Observations (here reanalysis) suggest that most
302 models underestimate this large-scale mixing, indicating a most likely ECS value larger than 3 K
303 (Table 1). The level of confidence in this estimate is related to the trust one gives to the link between
304 the low-tropospheric characteristics these indices aim to quantify and the low-cloud feedback, which
305 primarily controls the intermodel spread in ECS. In that regards *Caldwell et al.* [2018] suggest that
306 constraints suggested by *Sherwood et al.* [2014] are only partly credible and metrics need to be
307 studied separately. The observational constraint should also be viewed with caution since it is based
308 on re-analysis data and hence is influenced by parameterizations.

309 The mixing indexes suggested by *Sherwood et al.* [2014] highlight that errors in representing the
310 coupling between low-clouds and tropical dynamics explain a significant part of the spread in ECS, in
311 agreement with *Volodin* [2008] and *Fasullo and Trenberth* [2012]. This was confirmed by follow-up
312 studies that suggested significant correlations between ECS and indexes of the tropical dynamics,
313 such as the strength of the double-ITCZ bias [*Tian*, 2015] or the strength of the Hadley circulation
314 [*Su et al.*, 2014]. Both show that models better representing the tropical large-scale dynamics are
315 those with the highest climate sensitivities (≈ 4 K). However the lack of robust physical mechanisms
316 explaining these emergent constraints reduces the trustfulness of these inferences, but it also prompts
317 for better theoretical understanding of links between cloud and circulation. This question can be
318 investigated by analyzing the driving influence of clouds on the energetic balance of the atmosphere
319 for explaining large-scale dynamical biases, whether clouds are located in the southern hemisphere
320 [*Hwang and Frierson*, 2013] or in the tropical subsiding regions [*Adam et al.*, 2016, 2017]. Together
321 these studies suggest hidden relationships between low clouds, circulation, and climate sensitivity,
322 which remain to be clarified.

323 The spread in ECS can also be constrained through the past variability in global-mean tempera-
324 ture, as suggested by *Cox et al.* [2018]. Observations suggest that a majority of models overestimate
325 temperature variations and year-to-year autocorrelation, providing a most likely posterior ECS es-
326 timate of 2.8 ± 0.6 K (Table 1). Contrary to most of emergent constraints, this study thus suggests
327 a relative low best estimate for climate sensitivity. The absence of links between the mathematical

328 framework used to build the predictor and clouds might reduce the confidence in this estimate,
329 despite the fact that the constraint is *Cox et al.* [2018] seems strongly dominated by the spread in
330 SW cloud feedback [*Caldwell et al.*, 2018]. Given that low-frequency natural variability of tropical
331 temperature are partly related to cloud variability [e.g. *Zhou et al.*, 2016], it can not be excluded that
332 all these emergent constraints are related to each other through cloud processes. Process-oriented
333 cross-metric analysis would be necessary to support this hypothesis [e.g. *Wagman and Jackson*,
334 2018].

335 5 Cloud feedback

336 The spread of climate sensitivity is significantly related to the spread in cloud feedback, and
337 mostly to uncertainties in low-cloud responses. It therefore appears obvious that constraining how
338 low clouds respond to global warming would very likely reduce the spread of climate sensitivity
339 among models, and that many emergent constraints on ECS can be understood as encoding properties
340 of shortwave low-cloud feedbacks [*Qu et al.*, 2018]. Conversely, emergent constraints that are only
341 indirectly related to clouds should be viewed with caution.

342 A number of studies have highlighted relationships between low-cloud amount changes under
343 global warming and modeled variations of low clouds with changes in specific meteorological
344 conditions, such as surface temperature, inversion strength, subsidence [*Qu et al.*, 2013, 2015; *Myers*
345 *and Norris*, 2013, 2015; *Brient and Schneider*, 2016]. These studies suggest two robust low-cloud
346 feedbacks: a decrease in low-cloud amount with surface warming (related to increasing boundary-
347 layer ventilation) and an increase of low-cloud amount with inversion strengthening (related to a
348 reduced cloud-top entrainment of dry air). Models show that the former feedback mostly dominates
349 the latter under a global warming, and that the more realistic models exhibit larger low-cloud
350 feedback [*Qu et al.*, 2013, 2015; *Brient and Schneider*, 2016]. The convergence of studies using
351 different methodologies and different observations increases our confidence that low-cloud amount
352 feedback more likely lie in the upper range of simulated estimates. Given the credibility of physical
353 mechanisms explaining cloud feedback emergent relationships, reproducibility with the CMIP6
354 models is expected but yet to be confirmed.

355 Given that the strength of low-cloud amount feedback strongly correlates with ECS, temporal
356 variations in low-cloud albedo appears as one of the most credible metric for constraining ECS [*Cald-*
357 *well et al.*, 2018]. Observations suggests most likely ECS estimates around 4 K, roughly identical for
358 different temporal frequencies of cloud variations [*Zhai et al.*, 2015; *Brient and Schneider*, 2016].

359 Despite this robustness, these conclusions are sensitive to the short time period (around a decade)
360 over which observations provide accurate enough characteristics of low-clouds. Low-cloud short-
361 term variations might only partly reflect long-term feedback [Zhou *et al.*, 2015], likely because of
362 slow evolving spatial pattern of surface temperature that delay inversion changes and cloud feedback
363 in subsiding regions [Ceppi and Gregory, 2017; Andrews *et al.*, 2018].

364 Although low-cloud amount feedback is the main driver of uncertainties in climate sensitivity,
365 other cloud responses contribute to the spread as well. One of them is the low-cloud optical feedback,
366 which is defined by the radiative influence of changes in optical properties given unchanged cloud
367 amount and altitude. Gordon and Klein [2014] show that the natural variability of mid-latitude
368 cloud optical depth with temperature is well correlated with its changes with global warming.
369 This relationship stems from fundamental thermodynamics, i.e. the increase in water content with
370 warming [Betts and Harshvardhan, 1987], and microphysical changes, i.e. the relative increase of
371 liquid content relative to ice within clouds [Mitchell *et al.*, 1989]. This supports a robust negative
372 cloud optical feedback with warming. Observations suggest that models are usually biased high, thus
373 overestimating the negative mid-latitude low-cloud optical feedback. A misrepresentation of mixed-
374 phase processes within these extratropical clouds may explain this bias [McCoy *et al.*, 2015], which
375 has been pinpointed as being a key driver of differences in cloud feedback and climate sensitivity
376 estimates [Tan *et al.*, 2016].

377 The cloud altitude response to global warming may also amplify the original warming, and
378 models continue to disagree on the strength of this feedback [Zelinka *et al.*, 2013]. Physical
379 mechanisms of high cloud elevation with warming are well understood [Hartmann and Larson, 2002],
380 making high-cloud altitude feedback very likely positive. Yet it remains unknown to what extent the
381 high-cloud amount and the high-cloud optical depth change with warming. These changes are related
382 to upper-tropospheric divergence and microphysics, which need to be constrained individually. Some
383 studies suggest a decreasing high-cloud amount due to more efficient large-scale organization with
384 warming [e.g. Bony *et al.*, 2016], which point the way towards mechanistic emergent constraints on
385 high-cloud feedback.

386 Better constraining cloud feedback will therefore very likely lead to better constraints on the
387 equilibrium climate sensitivity. This target should be addressed through process-based understanding
388 of individual cloud changes, such as how the relative coverage of tropical low clouds evolves, how
389 high cloud fraction change as they move upward, or to what extent small-scale microphysical changes

390 perturb the climate system. Merging realistic estimates of these feedbacks would give a step forward
391 for accurately constraining the equilibrium climate sensitivity.

392 **6 Constraining Climate Changes**

393 In the last decade, the concept of emergent constraints has begun to be widely applied in different
394 branches of climate science that allowed constraining uncertain responses of the Earth system, such
395 as the hydrological cycle, the carbon cycle, or various regional changes.

396 **6.1 The hydrological cycle**

397 Uncertainties in the response of precipitation to global warming are important and remain to be
398 narrowed. Increasing the confidence in precipitation changes would provide important benefits for
399 regional climate projections and risk assessment [*Christensen et al.*, 2013]. Links between natural
400 variability of extreme precipitation and temperature offer possible observational constraints for
401 changes in climate extremes, especially because the underlying physical mechanisms are relatively
402 well understood [*O’Gorman and Schneider*, 2008]. These constraints usually suggest a strong
403 intensification of heavy rainfall with warming [*O’Gorman*, 2012; *Borodina et al.*, 2017]. Changes in
404 the hydrological cycle can partly be attributed to changes in the clear-sky shortwave absorption, which
405 is related to models’ radiative transfer parameterizations [*DeAngelis et al.*, 2015]. *Watanabe et al.*
406 [2018] follow this path for providing a best estimate for both hydrological sensitivity and shortwave
407 cloud feedback, through the surface longwave cloud radiative effect climatology. This study then
408 connects inter-model spread of changes in the water cycle and ECS. That emphasis on processes
409 that explain inter-model difference in the predictor might lead to targeted model development for
410 narrowing climate projections.

411 **6.2 The carbon cycle**

412 A second topic that has also received great emphasis is the sensitivity of the carbon cycle to
413 climate change. *Cox et al.* [2013] found a robust relationship that links interannual co-variations
414 between tropical temperature and carbon release into the atmosphere (the predictor) and the weak-
415 ening in carbon storage under global warming. Observations highlight that most climate models
416 overestimate the present-day sensitivity of land CO₂ changes, suggesting a too strong weakening of
417 the CO₂ tropical land storage with climate change (Table 1). This constraint has been confirmed
418 by following analysis [*Wang et al.*, 2014; *Wenzel et al.*, 2014]. Additional studies have aimed to

419 constrain other aspects of the climate-carbon cycle feedback, such as the land photosynthesis [Wenzel
420 *et al.*, 2016], sinks and sources of carbon dioxide [Hoffman *et al.*, 2014; Winkler *et al.*, 2019], and
421 the tropical ocean primary production [Kwiatkowski *et al.*, 2017].

422 **6.3 Geoengineering**

423 Constraining uncertainties in geoengineering simulations has also been addressed. Inter-model
424 differences in the climate response to an artificial increase of sulfate concentrations are correlated to
425 inter-model differences in the simulated cooling by past volcanic eruptions [Plazzotta *et al.*, 2018].
426 Physical assumptions underlying this relationship consists in assuming that volcanic eruptions can be
427 understood as an analogue of solar radiation management [Trenberth and Dai, 2007]. Observations
428 from satellites suggest that models overestimate the cooling by volcanic eruptions, thus overestimating
429 the potential cooling effect by an addition of aerosols in the stratosphere.

430 **6.4 Regional climate changes**

431 While most emergent constraints focus on global scales, several aim to better understand and
432 constrain regional climate changes. So far these studies mostly focus on extratropical climate
433 responses, as was the case for the pioneering work of Hall and Qu [2006]. Attempts in constraining
434 changes of extreme temperature have recently showed that models slightly overestimate the increasing
435 frequency of heat extremes with global warming in Europe and North America [Donat *et al.*,
436 2018], in relation with a too strong soil drying [Douville and Plazzotta, 2017]. Changes in the
437 extratropical circulation have also been studied. Models show a robust poleward shift of the South
438 Hemisphere jet with global warming, and are uncertain about the sign of the North Hemisphere jet
439 shift. Emergent constraints and statistical inference suggest that models overestimate the southern
440 hemispheric poleward shift [Kidston and Gerber, 2010; Simpson and Polvani, 2016] and predict
441 that the northern hemisphere jet will likely move poleward [Gao *et al.*, 2016]. Finally, a number of
442 studies aim to constrain changes over the Arctic region. They show that a majority of models delays
443 the year when summertime sea-ice cover would likely disappear [Boé *et al.*, 2009; Massonnet *et al.*,
444 2012] and slightly overestimates the strength of the polar amplification [Bracegirdle and Stephenson,
445 2013].

446 Regional emergent constraints remain rare, which reduce the ability to compare metrics and
447 observations to one another. Results are thus not robust yet, and should be viewed with caution.
448 However, knowing the large uncertainties underlying regional climate projections and the advantages

449 local populations will get from better model projections [*Christensen et al.*, 2013], I expect to see
450 numerous new emergent constraints aimed to narrow uncertainties in regional climate changes in the
451 near future. Nevertheless, this should be addressed through rigorous physical understanding given
452 the numerous multi-scale interactions and adjustments that induce regional differences.

453 **6.5 Paleoclimate**

454 The sensitivity of global-mean temperature to Earth's orbital variations and/or CO₂ natural
455 changes might be considered an analogue of the warming induced by the artificial CO₂ increase,
456 i.e. the climate sensitivity to past climate change an analogue to the equilibrium climate sensitivity
457 (as defined by *Gregory et al.* [2004]). When imposing such past variations, climate models suggest
458 different responses in the strength of global-mean cooling that may be related to the spread in ECS.
459 For instance, *Hargreaves et al.* [2012] shows that the simulated global-mean cooling during the
460 Last Glacial Maximum (LGM, 19-23 ka before present) is inversely correlated with ECS in CMIP3
461 models. Constraining the LGM cooling from proxy data yields a most likely climate sensitivity
462 around 2.3 K, which is lower than emergent constraints based on the mean state or variability
463 (Table 1). A number of criticisms may arise from this inference, such as the realism of the LGM
464 CMIP simulations, uncertainties underlying proxies used for observational reference, and the use
465 of paleoclimates as a surrogate for global warming (differences in temperature patterns, albedo
466 feedback etc.). These uncertainties may partly explain the frequent weak correlations found between
467 paleoclimate indices and climate projections, and the difficulty in narrowing the spread in models'
468 climate sensitivity estimates from paleoclimate-based emergent constraints [*Schmidt et al.*, 2013;
469 *Harrison et al.*, 2015].

470 **7 Do emergent constraints narrow the spread of climate sensitivity so far?**

471 Table 1 lists 14 emergent constraints that provide best estimates for climate sensitivity using
472 various predictors (without paleoclimate indexes). Here I inquire whether taken all together they
473 reduce the raw model uncertainty (e.g., 3.4 ± 0.8 K for CMIP5 models). For that purpose, a density
474 estimate is generated based on 11 ECS emergent constraints that provide mean and standard deviation
475 of more likely ranges (Table 1). These values correspond to moments provided by the authors if
476 available, or estimated from the emergent relationship otherwise (and thus correspond to a raw
477 estimate of the real posterior estimate). Due to the small sample, I use a kernel bandwidth of
478 1.0°C. This provides a density distribution with with 5–95% range of 2.2–4.9°C and a median of
479 3.8°C. Figure 4 shows that this unweighted distribution is really close to the prior distributions, yet

480 slightly skewed towards high ECS values (explained by a majority of emergent constraints suggesting
481 higher-than-average ECS values).

482 Here an equal weight is attributed to each distribution, which assume that emergent constraints
483 are equally valuable. Knowing the various level of credibility emergent constraints could receive
484 [*Caldwell et al.*, 2018], this assumption remains a crude approximation. Conversely, quantifying this
485 credibility would permit weighting each emergent constraint and providing more reliable posterior
486 distributions. However it exists various ways of combining and weighting the constraints. Standard
487 deviation σ associated with each constraint are somehow related to this level of confidence, given
488 its relationship with model samples (section 2.2.3) and observation uncertainties (section 2.2.2). We
489 thus attribute a relative weight of $\frac{1}{\sigma^2}$ to each emergent constraint, which correspond to an optimal
490 weighting method under the assumption that distributions are independent and normally distributed.
491 Figure 4 shows that the weighted density distribution is closer to the raw CMIP distributions and
492 narrower than the unweighted distribution (a 5–95% range of 2.3–4.6°C and a median of 3.7°C).
493 Differences between unweighted and weighted distributions are partly related to the strong relative
494 weight given to some emergent constraints [e.g. *Volodin*, 2008]. The weighting framework suffers
495 from several biases, such as the lack of statistical consistency across various constraints, the over-
496 confidence of observational estimates or the different set of models used for computing emergent
497 constraints.

498 The disagreement between emergent constraints and their large uncertainties therefore do not
499 significantly narrow the original spread in ECS. This suggests that emergent constraints need to be
500 better assessed through a verification of physical mechanisms explaining the relationship [*Caldwell*
501 *et al.*, 2018; *Hall et al.*, 2019]. This would help providing better weights quantifying the credibility
502 of emergent constraints and thus provide more reliable averaged ranges for narrowing the spread
503 in climate change projections. Finally, statistical inference and observational uncertainties must be
504 better informed for cross-validation of posterior estimates.

505 **8 Conclusions**

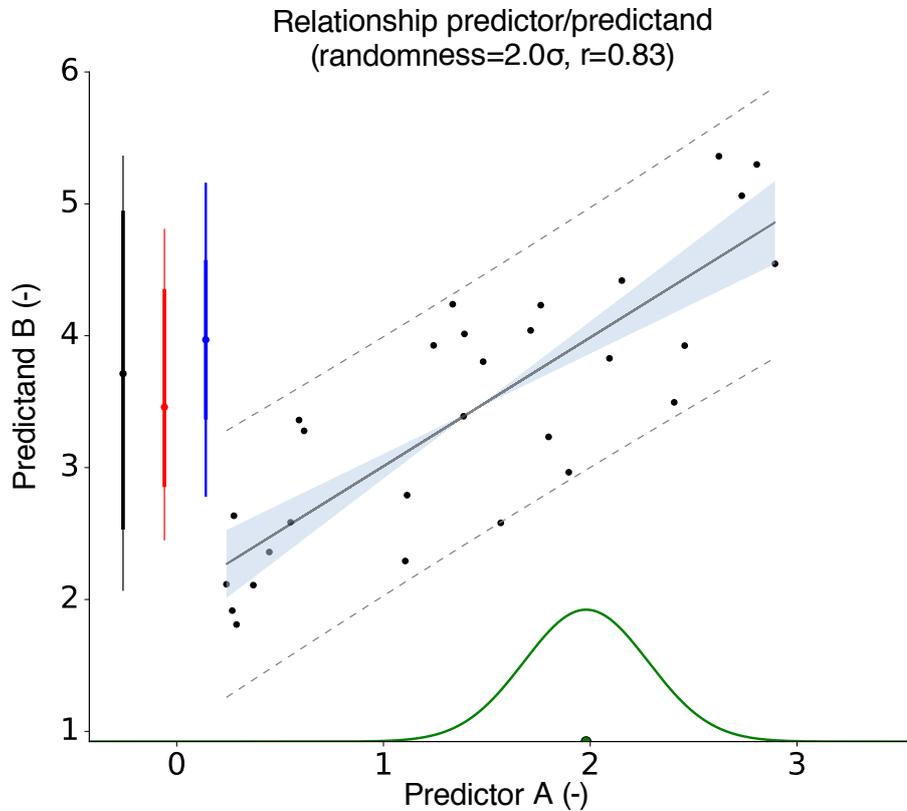
506 This paper presents the concept of emergent constraints, a methodology that aim to narrow
507 uncertainties in climate change projections by identifying a link between them and the inter-model
508 spread in an observable predictor. In the last decade, the number of studies that used this frame-
509 work grew significantly and provided constraints on various climate projections (an exhaustive list
510 of published emergent constraints is presented on table 1). The majority focused on narrowing

511 uncertainties in equilibrium climate sensitivity, cloud feedback, and carbon cycle feedbacks. Others
512 focused on components of the climate system in relation with changes of the hydrological cycle, the
513 cryosphere, or the dynamical shift of mid-latitude jet, among others. Predictors can be gathered in
514 two main categories: natural variations of the variable of interest with temperature variability or
515 a mean feature of the climate system. This sometimes leads to metrics not directly related to the
516 considered predictand. Physical explanations for emergent constraints are diverse and thus a majority
517 of them remain to be confirmed. Weighting the credibility of emergent constraints would very likely
518 increase the confidence in posterior estimates aimed to narrow the spread in climate projections.

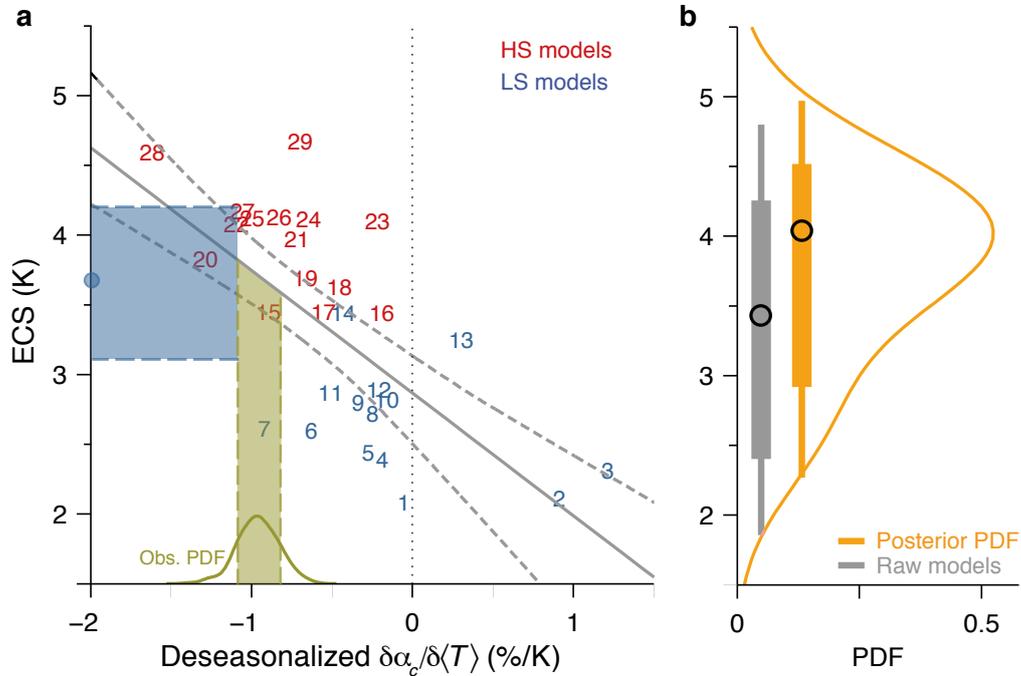
519 The diversity of emergent constraints highlight the commitment of the climate community to
520 narrowing uncertainties in climate projections. This interest will likely continue to grow since a
521 large number of changes in climate phenomena simulated by models remain uncertain, even when
522 fundamental mechanisms are relatively well understood (e.g., changes in monsoons, heat waves,
523 cyclones). The emergent constraint framework can thus be seen as a new promising way to evaluate
524 climate models [Eyring *et al.*, 2019; Hall *et al.*, 2019], especially with the upcoming CMIP6 project
525 that will very likely boost this enthusiasm. However, this calls for robust statistical inference for
526 providing credible uncertainty reductions. In that purpose, the code used for quantifying inference
527 and uncertainties in Figure 4 with two different methods is shared¹. Quantifying posterior estimates
528 with different frameworks (either from inference or model weighting) allows testing the confidence
529 in predictions. Further improvements would consists in continuing testing difference statistical
530 inference procedures and building multi-predictor weighting method to benefit from the number of
531 proposed emergent constraints .

532 Beyond the post-facto model evaluation, it will finally be interesting to see whether new climate
533 models take advantage of emergent constraints to improve their simulation of present-day climate
534 and to reduce uncertainties in future projections.

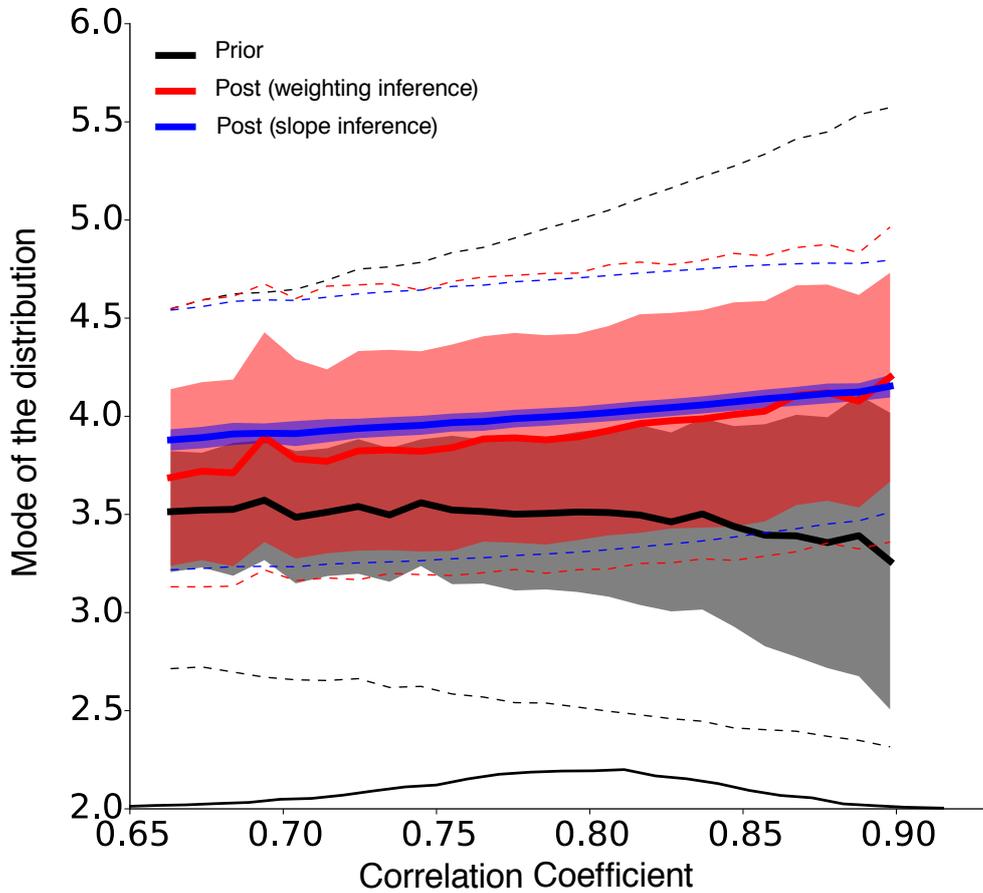
¹ https://github.com/florentbrient/emergent_constraint



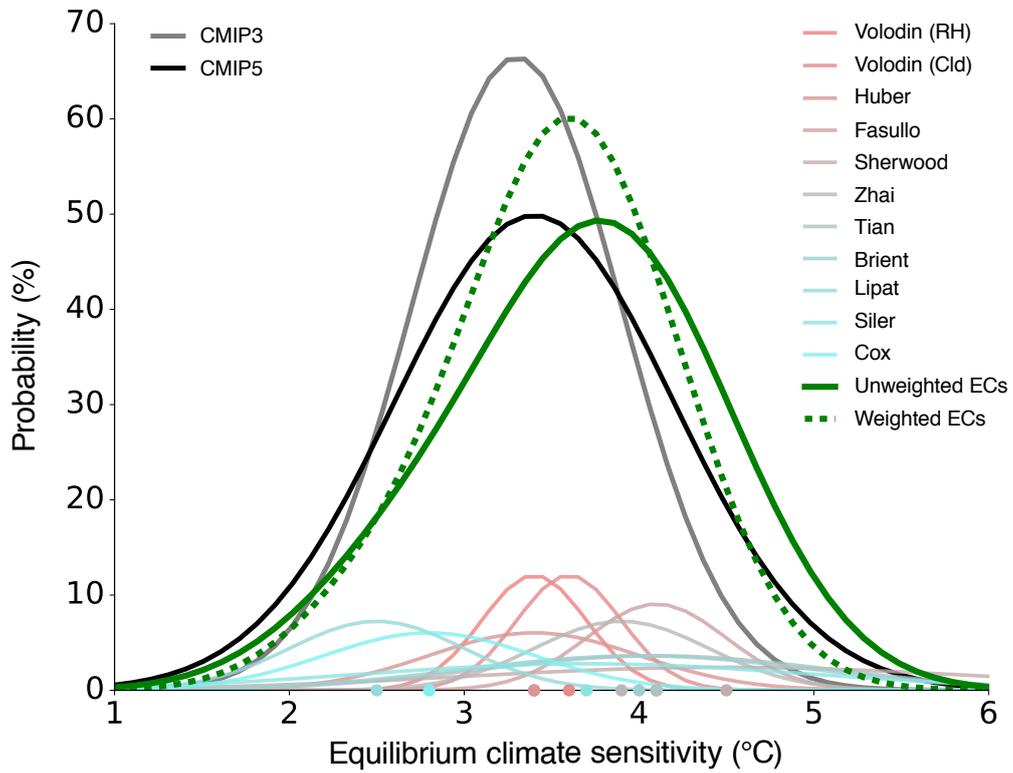
535 **Figure 1.** Idealized relationship between a predictor and a predictand. The 29 models (dots) are associated
 536 with randomly-generated values of the predictor A (x here between 0 and 3). The predictand B on the y-axis
 537 follows the idealized relationship ($y' = ax + b$ with $a=1.$ and $b=2.$) plus a random deviation Δ following a
 538 normal distribution with $\sigma=2$ (such as $y = y' + \Delta(y')$). The dashed lines and blue shades represent the 90%
 539 prediction limits and the 90% confidence limits of the slope respectively. The green distribution on the x-axis
 540 represents an idealized observed distribution of the predictor, assuming a normal distribution (here with $\mu=1.98$
 541 and $\sigma=0.3$). Prior and posterior distributions of the predictand are represented as vertical lines on the left part,
 542 with mode (circle), 66% (thick) and 90% (thin) confidence intervals. Black lines represent the prior distribution,
 543 red lines represent the posterior distribution obtained by a weighted average of the climate models through a
 544 Kullback-Leibler divergence and blue lines are the one inferred using the slope and its uncertainties. In that
 545 randomly generated example, posterior estimates are sensitive to the way inference is computed.



546 **Figure 2.** (a) Scatterplot of ECS vs deseasonalized covariance of marine tropical low-cloud (TLC) reflectance
 547 α_c with surface temperature T in CMIP5 models (numbered in order of increasing ECS). Gray lines represent
 548 a robust regression line (solid), with the 90% confidence interval of the fitted values (dashed) estimated by a
 549 bootstrap procedure. The green line at the lower axis indicates the PDF of the deseasonalized TLC reflectance
 550 variation with surface temperature inferred from observations. The vertical green band indicates the 66% band
 551 of the observations. The blue circle and horizontal band shows the mode and the likely (66%) ECS range inferred
 552 from a linear regression procedure respectively, taking into account uncertainties estimated by bootstrapping
 553 predictions with estimating regression models. (b) Posterior PDF of ECS (orange) obtained by a weighted
 554 average of the climate models, given the observations. The bars with circles represent the mode and confidence
 555 intervals (66% and 90%) implied by the posterior (orange) PDF and the prior (gray) PDF. Adapted from *Brient*
 556 *and Schneider* [2016].



557 **Figure 3.** Relationship between modes and correlation coefficient (r) of 10^4 randomly-generated emergent
 558 constraints, as the example shown on Figure 1. Thick lines, dashed lines and shades represent the average mode,
 559 the average 66% confidence interval and the standard deviation of mode across the set of emergent relationship.
 560 Characteristics of the prior distributions are represented in black color. Posterior estimates using the slope
 561 inference or the weighting averaging are represented in blue and red respectively, using an idealized observed
 562 distribution of the predictor as defined on Figure 1. The probability density function of correlation coefficients
 563 is shown as a thin black line on the x-axis. This figure shows that average modes and confidence intervals
 564 remain independent of the inference method, but the uncertainty of the mode value is larger for the weighting
 565 method.



566 **Figure 4.** Probability density distributions of equilibrium climate sensitivity (ECS). The black and grey
 567 density distributions shows original CMIP3 and CMIP5 model distributions. The 11 emergent constraints
 568 of ECS are shown as a normal distributions with mean (color dots) and standard deviation listed on table 1.
 569 Unweighted and weighted density distributions aggregated over the 11 emergent constraints are shown as green
 570 full and dashed lines respectively. A kernel bandwidth of 1.0°C is used and weights are computed as the
 571 reciprocal of the variance.

572 **Table 1.** List of 45 published emergent constraints, the predictand they constrain, the original and the constrained ranges. Mean and standard deviations of prior and posterior estimates are listed when available. The
 573 * sign signifies that the moments of the distribution are not directly quantified in the reference paper but derived
 574 from their emergent relationship and the observational constraint, and thus should be understood only as
 575 qualitative assessment.
 576

Reference	Predictand	Original	Constrained
<i>Covey et al.</i> [2000] <i>Volodin</i> [2008] (RH) <i>Volodin</i> [2008] (Cloud) <i>Trenberth and Fasullo</i> [2010] <i>Huber et al.</i> [2011] <i>Fasullo and Trenberth</i> [2012] <i>Sherwood et al.</i> [2014] <i>Su et al.</i> [2014] <i>Zhai et al.</i> [2015] <i>Tian</i> [2015] <i>Brient and Schneider</i> [2016] <i>Lipat et al.</i> [2017] <i>Siler et al.</i> [2018] <i>Cox et al.</i> [2018]	ECS (K)	3.4±0.8 3.3±0.6 3.4±0.8	– 3.4±0.3 3.6±0.3 >4.0 3.4±0.6 4.1±0.4* 4.5±1.5* >3.4 3.9±0.5 4.1±1.0* 4.0±1.0* 2.5±0.5* 3.7±1.3 2.8±0.6
<i>Qu et al.</i> [2013] <i>Gordon and Klein</i> [2014] <i>Brient and Schneider</i> [2016]	Low-cloud amount feedback (%/K) Low-cloud optical depth feedback (K ⁻¹) Low-cloud albedo change (%/K)	-1.0±1.5 0.04±0.03 -0.12±0.28	– – -0.4±0.4*
<i>Siler et al.</i> [2018]	Global cloud feedback (%/K)	0.43±0.30	0.58±0.31
<i>Allen and Ingram</i> [2002] <i>O’Gorman</i> [2012] <i>DeAngelis et al.</i> [2015] <i>Li et al.</i> [2017] <i>Watanabe et al.</i> [2018]	Global-mean precipitation Tropical precipitation extremes (%/K) Clear-sky shortwave absorption (W/m ² /K) Indian Monsoon rainfall changes (%/K) Hydrological sensitivity (%/K)	– 2-23 0.8±0.3 +6.5±5.0 2.6±0.3	– 6-14 1.0±0.1 +3.5±4.0 1.8±0.4
<i>Cox et al.</i> [2013] <i>Wang et al.</i> [2014] <i>Wenzel et al.</i> [2014] <i>Hoffman et al.</i> [2014] <i>Wenzel et al.</i> [2016] <i>Kwiatkowski et al.</i> [2017] <i>Winkler et al.</i> [2019]	Tropical land carbon release (GtC/K) CO ₂ concentration in 2100 (ppm) Gross Primary Productivity (%) Tropical ocean primary production (%/K) Gross Primary Production (PgC/yr)	69±39 79±43 49±40 980±161 +34±15 -4.0±2.2 2.1±1.9	53±17 70±45* 44±14 947±35 +37±9 -3.0±1.0 3.4±0.2
<i>Plazzotta et al.</i> [2018]	Global-mean cooling by sulfate (K/W/m ²)	0.54±0.33	0.44±0.24
<i>Hall and Qu</i> [2006] <i>Qu and Hall</i> [2014] <i>Boé et al.</i> [2009] <i>Massonnet et al.</i> [2012] <i>Bracegirdle and Stephenson</i> [2013]	Snow-albedo feedback (%/K) Remaining Arctic sea-ice cover in 2040 (%) Years of summer Arctic ice free Arctic warming (°C)	-0.8±0.3 -0.9±0.3 67±20* [2029-2100+] ~2.78	-1.0±0.1* -1.0±0.2* 37±10* [2041-2060] <2.78
<i>Kidston and Gerber</i> [2010] <i>Simpson and Polvani</i> [2016] <i>Gao et al.</i> [2016] <i>Gao et al.</i> [2016] <i>Douville and Plazzotta</i> [2017] <i>Lin et al.</i> [2017] <i>Donat et al.</i> [2018]	Shift of the South Hemispheric Jet (°) Shift of the North Hemispheric Jet (°) Summer midlatitude soil moisture Summer US temperature changes (°C) Frequency of heat extremes (-)	-1.8±0.7 ~-3 ~0 ~+1.5 – +6.0±0.8 –	-0.9±0.6 ~-0.5* (Winter) ~-2 (Winter) ~-1 (Spring) – +5.2±1.0* –
<i>Hargreaves et al.</i> [2012] <i>Schmidt et al.</i> [2013]	ECS (K)	3.1±0.9 3.3±0.8	2.3±0.9 3.1±0.7

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 581 the randomly-generated relationship and the statistical inferences are available on the Github website
 582 (https://github.com/florentbrient/emergent_constraint/).

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