Progressing Emergent Constraints on Future Climate Change

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In recent years, an evaluation technique for Earth System Models (ESMs) has arisen – emergent constraints (ECs) – which rely on strong statistical relationships between aspects of current climate and future change across an ESM ensemble. Combining the EC relationship with observations could reduce uncertainty surrounding future change. Here we articulate a framework to assess ECs, and provide indicators whereby a proposed EC may move from a strong statistical relationship to confirmation. The primary indicators are verified mechanisms and out-of-sample testing. Confirmed ECs have the potential to improve ESMs by focusing attention on the variables most relevant to climate projections. Looking forward, there may be undiscovered ECs for extremes and teleconnections and ECs may help identify climate system tipping points.

ESMs involving both atmosphere and ocean components were first developed in the 1970s and 1980s, prompting individual modelling groups to evaluate their quality through comparison of simulations against observations of basic climate system features, such as spatial variation in mean temperature and precipitation. The exercise was perfectly sensible: a climate model should simulate rudimentary metrics of the current climate. Since then, observations have improved dramatically, both in spatial and temporal coverage and in the numbers of observed variables. ESMs have also become more complex, encompassing many more elements of the Earth system, most notably aggregated components of the biosphere that simulate the global carbon cycle. These advances have led to ever more comprehensive evaluations of ESMs, expanding the number of variables examined and including higher order statistics characterizing variability.

Despite greater ESM complexity, the fundamental nature of model evaluation has not changed: if an ESM can simulate a suite of observed variables believed to characterize the current climate system's basic features reasonably well, it is considered appropriate for producing simulations of future climate. However, even for the basic variables, it is unclear how relevant these are to an ESM's ability to simulate the climate perturbation that results from increasing greenhouse gases. Thus this approach has been unkindly, but perhaps not inaccurately, compared to a 'beauty contest'. While traditional evaluation may make sense as a basic first step in certifying that an ESM is in fact an ESM, its utility in identifying those that produce trustworthy simulations of future climate is unclear. Conversely, an ESM regarded as less attractive in a 'beauty contest' could be dismissed; yet it may contain more accurate and useful estimates of some key attribute of future change.

The disconnect between the traditional form of model evaluation and the core ESM purpose of credibly simulating future climate change may explain a key disappointment of the climate science community in recent decades. Even as ESMs agree on basics aspects of climate change, the spread across ESM ensembles remains uncomfortably large, as seen in the IPCC reports. The most recent 5th Assessment Report (AR5) [1] bases assessment of expected changes in climate on ESMs contributing to the CMIP5 ensemble [2]. However, there remains a large spread in even the most basic quantities, such as equilibrium global warming for a doubling of atmospheric CO_2. How to reduce these uncertainties is more than an interesting academic question, with accurate information needed by policymakers to plan climate mitigation and adaptation measures.

In recent years, a new model evaluation method - the "Emergent Constraint" (EC) approach - has gained prominence that offers hope to constrain projections of future quantities of interest. It is a novel way to achieve uncertainty reduction through the combination of an ensemble of climate simulations with contemporary measurements. The core concept is that despite major differences across ESMs, relationships between elements of current and future climate (X and Y) are implicit within ESM solutions of the partial differential equations governing physical and biogeochemical systems and associated parameterizations. The spread in contemporary variable X and future variable Y may be large across ESMs, but the relationship f linking the two is sometimes clear. That is, $Y=\mathrm{f}(X)+\varepsilon$, where ε is a relatively small departure from f. If X is also a quantity that can measured, then relationship *f* may place a useful "constraint" on *Y*, provided the measurement uncertainty in *X* is small compared to the range of simulated values. This approach has the label "emergent" because the function *f* cannot be diagnosed from a single ESM. It only becomes apparent through analysis of a suitably large and structurally diverse ESM ensemble such as CMIP3, CMIP5, or the nascent CMIP6 ensemble. Indeed the EC technique would not have been possible without the high level of organization and systematisation of ESM climate change experiments in CMIP. Figure 1 illustrates differences between traditional model evaluation and the EC approach.

Though we have differentiated between traditional model evaluation and the EC technique, traditional model evaluation and associated tuning of ESM parameters has sometimes focused on climate variables seen as very important for simulating climate change. The attention on such variables often arose because they were perturbed within a single ESM, and shown to be important for that model's climate change signals. One example is the sensitivity of the water vapor response to temperature and the failure of models without such a water vapor feedback to reproduce the observed response to external forcing[3,4]. Another is the demonstration in the mid 1990s of the influence of biases in sea ice extent and thickness on climate sensitivity within a single ESM[5,6], which may have led to those variables being included in traditional model evaluation studies[7,8]. Such proto-EC research enabled the development of the EC technique before the advent of the CMIP-type ESM ensembles. It illustrates how even traditional model evaluation has been inclusive of variables thought to matter for future projections. However, with the EC approach, there is a deliberate and much more targeted search for those observable aspects of current climate, *X*, that matter most to the aspect of future projections, *Y*. Moreover, the emergent relationship between *X* and *Y* across structurally-diverse ESM ensembles is made quantitative. Finally, it is worth emphasising that the EC technique is complementary to traditional model evaluation, which the scientific community must keep doing. As ESMs become more complex, there will be a continued need to document basic model quality, which traditional model evaluation now does very efficiently[9].

Note that the EC technique is limited by the knowledge space represented by the ESM ensemble, that is there may be uncertainty in *Y* that the ESMs collectively fail to capture. For example, if the ESMs are systematically biased, say by sharing some unrealistically simple parameterization of a process affecting *Y*, the EC technique cannot identify this bias and correct for it. Similarly, if the ESMs are all missing an important process relating to future climate change, the EC technique cannot be used to identify that process. Rather, the technique identifies spread in *Y* values that cannot be justified given how the ESMs are formulated.

1. Emergent constraints found so far

As an example, we describe the earliest documented EC, for the snow-albedo feedback [10]. This feedback amplifies simulated surface warming over northern hemisphere continents through snow retreat and the associated reduction in land surface albedo. Its strength in amplifying future warming can be quantified in ESMs, and the magnitude varies by roughly a factor of three across contemporary ESMs. This feedback has an analogue in contemporary climate. As springtime proceeds in the northern hemisphere, the snow retreat amplifies seasonal warming through surface albedo reduction. The strength of this seasonal cycle version of the feedback can be diagnosed in individual ESMs. A comparison of the feedback strength in future climate change (i.e. "*Y*") versus in the seasonal cycle (i.e. a different, but related "*X*" quantity), reveals a linear, nearly one-to-one relationship (Figure 1a). This relationship suggests that the simulated feedback strength in the seasonal cycle is predictive of its strength in climate change. Moreover, *X* in this case is measurable in the real climate, with smaller observational uncertainty bounds than the ESM spread in *X*. Thus it possible to declare certain ESMs biased, which may be consequential for their ability to simulate snow-albedo feedback in future climate.

Another prominent example of the technique involves constraining uncertain elements of climate-carbon cycle feedbacks. In this case, *Y* is the projected carbon loss from tropical land under climate change [11]. The simulated tropical land carbon released per degree warming exhibited a spread of more than a factor of four in the ESM ensemble associated with AR4. The ecological and carbon cycle implications of this spread are potentially dramatic, as the upper end of the range corresponds to catastrophic "dieback" of the Amazon rainforest [12,13]. Similar to snow albedo feedback, this dimension of future climate can be related to an observable quantity in the current climate – the present-day sensitivity of the annual atmospheric CO_2-growth-rate to temperature variation, a quantity strongly influenced by carbon storage fluctuations in tropical land areas. Creating a scatter plot across ESMs of the modelled tropical land carbon sensitivity to future warming (*Y*) against the *X* sensitivity variable, a nearly linear relationship is found (Figure 1b). As with the above example, the CO_2-growth-rate sensitivity to temperature is observable, and hence this EC allows for inferences about future tropical land carbon stability under climate change.

Many other ECs spanning physical and biogeochemical components of the Earth System have been proposed in roughly the past decade. To capture the growing number, we list nearly three dozen examples (Table 1), grouped by component, an indication of the intensity of interest in EC research.

2. Why Emergent Constraints might exist

Given the extent to which ECs have become commonplace in climate research, there is a need to develop a more theoretically-based understanding of how, when, and why they should work. The most basic question is whether emergent relationships should be expected in ESM ensembles. A starting null hypothesis might be that they emerge by chance and are not indicative of deeper mechanistic relationships. With enough analyses of systems as complex as GCMs, some correlations between two analysed variables will be high by chance. Indeed, blind data mining has shown that it is possible to obtain statistically-significant correlations between current and future climate variables that are devoid of any obvious mechanistic interpretation [14].

Alternatively, there are two reasons strong relationships between *X* and *Y* variables might emerge from an ESM ensemble: (1) There is a broadly-accepted and profound mechanistic relationship between variability and sensitivity in near-linear systems, as characterised by the Fluctuation-Dissipation Theorem [15]. ESMs are highly complex, with a mix of relatively linear thermodynamics and biogeochemical processes, and highly nonlinear dynamics in many key subsystems such as the atmosphere and ocean [16]. Such complexity may prevent direct application of the Fluctuation-Dissipation Theorem to ESMs [17,18,19] especially where the slower feedbacks relevant to climate projections are not evident in shorter-term internal variability. However, emergent relationships between variability and sensitivity might be expected to be common where the sensitivity of a net flux, say energy or carbon, and the sensitivity of a near-linear store of those same quantities, are connected by a conservation principle[20,21]. The two types of sensitivity are indeed connected in a broad-class of models[22]. (2) It is not unreasonable that there would be similarities in how ESMs respond to relatively short-time-scale natural forcings such as the diurnal cycle, annual cycle, and volcanic forcing, and their response to more sustained anthropogenic forcing. Analogous feedback processes may be at work in the two cases; in fact, this intuition was behind the snow-albedo-feedback example.

These considerations underscore the possibility that ESM-simulated climate variations on a variety of time scales captured within the observational record might be mechanistically-linked to the responses of those ESMs to future increasing greenhouse gases. In the next section, we argue that demonstrating those mechanisms is key to full development of an EC.

3. Confirmation indicators

With so many ECs documented in the literature (Table 1), there is a need to evaluate their validity, meaning, and usefulness. As a starting point, we offer a classification of ECs into two categories. The first is a “proposed” EC, which is an emergent relationship with strong statistical underpinnings, but which is not accompanied by a strong physical or theoretical explanation, or even intuition that the two variables will be linked. An example of a proposed emergent constraint is the strong correlation between Intertropical Convergence Zone (ITCZ) bias and climate sensitivity [23], two quantities both shaped by multiple processes that currently are not connected in any obvious way. The second category is a “confirmed” EC, where in addition to strong statistical underpinnings, it has been documented that an emergent relationship arises from a mechanism at work in the ESM ensemble. Though we have differentiated between proposed and confirmed ECs, in practice probably no EC can ever be completely confirmed, and is associated with degrees of confirmation. As we discuss below, an emergent relationship becomes increasingly useful, i.e. it can be combined with observations to constrain future climate, as evidence mounts that a mechanism underpins it, and it migrates from proposed to confirmed. What, therefore, are the indicators that a mechanism underpins an emergent relationship? Here we argue that there are three such confirmation indicators (illustrated schematically in Figure 3).

Plausible mechanism. The first, and most basic, is that the emergent relationship has some plausible and intuitive proposed mechanism associated with it. This initial requirement involves expert judgment to determine the emergent relationship's credibility. An example of an EC associated with a plausible mechanism is the high correlation between sensitivity of extratropical cloud reflectivity to temperature in the current climate (*X*) and in climate change (*Y*) in CMIP5 models[24,25]. The main mechanism proposed is that a warm temperature anomaly causes a general microphysical conversion of cloud particles from ice to liquid, increasing the cloud optical depth and brightening the clouds, whether the temperature anomaly is internally-generated or externally-forced. The reason for the brightening with warmer temperatures is that liquid drops are typically smaller and precipitate less efficiently than their frozen counterparts[26,27]. CMIP5 ESMs all show this brightening of extratropical clouds as temperature increases, though the magnitude of the effect varies significantly. In this case the mechanism was not proven to be at work in the ESMs when the EC was first proposed, but it was plausible because it was linked to previously observed thermodynamic and microphysical behaviour of clouds[28].

Verification of mechanism. The second indicator builds on the first, and involves scientific understanding of the proposed mechanism underpinning the emergent relationship. The evidence leading to this understanding could take the form of more detailed analysis of ESM output, demonstrating the mechanistic links whereby intermodel variation in *X* leads to corresponding intermodel variations in *Y*. This approach was undertaken for the snow albedo feedback example [29,30]. Verification of mechanism could also take the form of theoretical arguments that support the existence of the emergent relationship, possibly even through formal analytical solution of a reduced equation set that retains the dominant equation terms. Verification of mechanism may be most straightforward for ECs involving the same feedback process for both *X* and *Y* variables, the only difference being the time scale on which the process operates. It becomes less straightforward as the number of processes shaping *X* and *Y* variables increases. For example, verification of mechanism is more difficult for *X* variables that are outcomes of complex system interactions, such as ENSO frequency, or *Y* variables where multiple feedbacks are inputs, such as climate sensitivity. We do not wish to discourage ECs based on such variables. However, confirming those ECs is more challenging because discovering the true mechanism behind the emergent relationship involves the disentanglement of processes.

Out-of-sample testing. A third indicator operates in parallel to the first two, and involves neither naming nor understanding of a mechanism, but rather indirect empirical evidence that a mechanism is at work: The emergent relationship can be seen in an ESM ensemble that is independent of the one in which the relationship was first diagnosed. The benefits of such out-of-sample testing can be also stated in statistical terms. Testing the emergent relationship with a new ensemble is equivalent to enlarging the original ensemble and checking whether the high correlation of the emergent relationship remains. If so, then the probability the relationship emerged by chance has declined accordingly. Out-of-sample verification of a previously-diagnosed emergent relationship can take place when a new ESM ensemble is generated through climate model coordination activities (i.e. CMIP). However, ESMs are developed based on a previous version, and so successive generations of ESMs are not entirely independent of another [31-34]. Thus true out-of-sample verification is not possible. Indeed, even within an ensemble, ESMs are not entirely independent, effectively reducing the statistical significance of any emergent relationship [33]. Nevertheless, when a previously-diagnosed emergent relationship is seen in a new ensemble in which each the ESMs have evolved from the previous generation, and which may include new ESMs, this is useful evidence of an underlying, mechanistically-based emergent relationship. A form of out-of-sample testing may also be done with perturbed parameter or physics ensembles of single models [35,36] providing additional testing in ensembles of larger size, but reduced structural diversity. Out-of-sample testing was done for the snow-albedo-feedback and tropical carbon loss examples described above. For both cases, the emergent relationship was found to be equally strong in the CMIP5 models after having first been discovered in an earlier ensemble (Figure 1). Conversely, failure of out-of-sample testing occurred for some ECs when tested in an ensemble other than the one in which they were originally proposed [37]. We consider such a failure to be a strong indicator that the EC cannot be confirmed, and therefore cannot offer a constraint on future climate change.

Ideally, a published EC in the proposed category should migrate to the confirmed category. This migration may require multiple analyses and related publications to produce indicators of confirmation. An example is the further research that has been done to demonstrate that the plausible mechanism associated with the previously discussed brightening of extratropical cloud with warmer temperatures is at work in ESMs [38]. While process understanding from the outset is desirable, it would be inappropriate to discourage publication of research on ECs if they are initially only in the proposed category, as early publication provides an incentive to discover mechanistic links. Openness to emergent relationships that are purely statistical allows for more complex emergent relationships requiring many years of verification to be fully vetted. In fact, there is evidence this process is occurring for the strong correlation between ITCZ bias and climate sensitivity, the example we cited above as being an EC in the "proposed" category[39]. It is also possible that the scientific community will eventually demonstrate that a particular proposed EC arose by chance in the ESM ensemble, in which case it is appropriate to discard it entirely. Likewise, further work could demonstrate that the research showing confirmation of a proposed EC is flawed, in which case the EC can be "demoted" back to the proposed category. Such back-and-forth may be frustrating, and may not always be conclusive. But we believe it is the only way to develop confidence in those emergent relationships that truly reflect mechanisms at work in ESM ensembles, and discard those that do not.

4. Using emergent constraints for uncertainty reduction now

If an emergent relationship becomes a confirmed EC, then it can be confidently combined with observations to produce a constraint on the value of "*Y*", i.e. it can reduce uncertainty in *Y*. However, as discussed above, few ECs may show all confirmation indicators, and the confirmation process may take years. This raises questions about the extent to which the scientific community can rely on only partially confirmed ECs for uncertainty reduction. This is a dilemma, because the time scale of knowledge generation about the climate system (of order decades) is comparable to the time frame of decision-making surrounding climate change adaptation and mitigation (the coming decades). Should emergent relationships be used now to provide answers to urgent societally-relevant questions about the future, even if there is not complete confidence they are real? As it can take years to confirm an emergent relationship, we argue that it would be omitting important evidence ***not*** to use them in this way, as long as their constraints on future climate are associated with likelihood statements. Such statements should be informed by how far along the emergent relationship is in the confirmation process we have described here.

We give an illustration of this dilemma. Projections of Arctic sea ice extent made in AR5 are a prime example of how emergent relationships have been invoked to narrow uncertainty surrounding elements of future climate. When AR5 was drafted, it had been shown that simulated September Arctic sea ice trends in CMIP3 models showed significant biases compared to observations, with most models exhibiting unrealistically weak trends [40]. Emergent relationships between simulated Arctic sea ice characteristics of the current climate and the 21st century timing of future summertime Arctic sea ice loss had been documented for CMIP3 models [41,42], and the IPCC AR5 authors found similar relationships in the CMIP5 models [43]. Mean extent, volume, and seasonal cycle amplitude, as well as recent sea ice trends are each correlated in varying degrees with the first year of Arctic sea ice disappearance (Figure 4). Collectively, these four *X*s appear to be systematically biased in the ESMs, when compared to measurements. When the emergent relationships are taken into account, they mostly favour a significantly earlier disappearance of sea ice than the ensemble mean would suggest. The IPCC authors decided to select ESMs that were as realistic as possible in the four *X* variables, as compared to data. The resultant EC-based sea ice projections were described in the Summary for Policymakers[44]: "A nearly ice-free Arctic Ocean in September before mid-century is likely for RCP8.5," i.e. roughly two decades earlier than the CMIP5 ensemble-mean. The mechanisms underpinning the individual ECs in Figure 4 are currently imperfectly understood. Although plausible, they remain unanalysed. An additional gap in understanding is their likely connection to one another, and the difficulty in devising an objective means of combining them to produce a single narrow bound of uncertainty about the future. (See New Directions below.) Yet despite this lack of understanding, it would have been problematic to ignore the evidence from these ECs. The CMIP5 ESMs are systematically biased in a way that likely matters for their ability to simulate a very consequential attribute of future climate. Considering this evidence, the approach taken by the IPCC authors can be justified. If they had waited until the emergent relationships were fully analysed and based their projections on the conventional ensemble-mean, they risked inappropriately deflating the urgency about the future of Arctic sea ice.

When ECs are used to make predictions, care must be taken to characterise the uncertainty in the observational values of the *X* variable. The translation of observed *X* values into predicted *Y* values is not trivial. It is certainly not as simple as finding the intersection of the most likely value of observed *X* and the regression line relating *Y* to *X*, and "reading off" the predicted *Y* value. Instead both observed *X* and predicted *Y* must be treated probabilistically. In one recent work[45], a probability density function for predicted *Y* is derived given observational uncertainty in *X* and the correlation between *X* and *Y*. As one might expect, tighter bounds on observed *X* and higher correlations between *X* and *Y* produce the least uncertainty in *Y*.

5. New directions

We have discussed existing ECs, emphasizing how they gain credibility and usefulness through a confirmation process, and examined the circumstances under which they can be used now to reduce uncertainty, even if not completely confirmed. Now we shift to the future of EC research, and suggest four directions that the technique could take the scientific community.

Targeted Model Development. An appealing feature of ECs is their use to narrow uncertainty surrounding a particular aspect, *Y*, of future climate change. ECs can be also used to launch a process of ESM improvement and bias reduction in the current climate variable (*X*) correlated with *Y*. Once this ESM development process is complete, the ESMs themselves will exhibit less spread in *Y* if the EC is confirmed. That is, when spread in *X* is reduced through ESM improvement, a corresponding spread reduction in *Y* will occur provided *Y*'s correlation with *X* is underpinned by a mechanism. In such cases, it is unlikely the ESM model development community will be able to reduce biases in *X* without further analysis as to how specific structural and parametric variations in the ESM ensemble lead to spread in *X*. This type of analysis has only been completed for ECs relating to hydrologic cycle intensification [46] and snow albedo feedback [47]. Unfortunately, these publications appeared after the CMIP5 model development cycle, but it will be interesting to see whether spread will be reduced in the forthcoming CMIP6 ensemble.

For all confirmed ECs, the scientific community should be encouraged to perform analysis to understand why ESMs produce spread in their associated values of *X*. An advantage of activities along these lines is that other climate system components affected by the corresponding values of *Y* will also exhibit less spread, consistent with the climate system's internal dynamics. In this way, uncertainty surrounding many linked attributes of climate change will be generally reduced. Paradoxically these efforts could eventually lead to the disappearance of the confirmed ECs. That is, if model development removes the spread in the *X* and then the *Y* quantities, the emergent relationship resulting from the variation of each is no longer available. Despite this effect, we believe general uncertainty reduction is always worthwhile, and is arguably a principal demand made of climate science.

These EC-led activities must be coordinated as the task of improving models to agree with *X* variables in confirmed ECs will typically not be a small effort. Coordination would also allow EC-led model development activities to occur prior to the ESM development cycles set in motion by CMIP. Such a disciplined approach has the potential to significantly reduce climate change uncertainty. It could also help determine the limits beyond which uncertainty reduction is not possible, an important issue the scientific community has only partly confronted [48].

New and Important Climate Variables. The ECs proposed to date have tended to focus on constraining globally-aggregated quantities *Y*. That is, on variables related to the climate system's mean state, e.g. variables relating to climate sensitivity. We believe that part of the unrealized promise of the EC technique is to apply it to a much broader suite of variables, including higher order moments of climate statistics, many of which are of societal importance.

For example, features of simulated temporal distributions of precipitation in the current climate may be systematically related across ensembles to how ESMs simulate future changes in the precipitation distribution, including in extremes. Satellite-based time series are now long enough to characterize observed precipitation distributions, putting in place the observational element necessary for development of ECs in this category. Spatial variability may be another underexploited dimension of climate. For example, pattern biases in teleconnections within the current climate may be systematically related to ESM response of those patterns to external forcing. Biases in the position and strength of key features of the climate system, such as jet streams, subtropical highs, monsoon systems, and the ITCZ, are likely related in systematic ways across ESM ensembles to future changes in those features. Initial research has begun [49,50,51], but we believe there are many more latent spatial relationships to be discovered, a process that may be guided in part by the high spatial fidelity of emerging Earth Observations.

Combining Predictions from Multiple Constraints. A new challenge is how to combine information content from multiple emergent constraints for the same *Y* variable into a single rational prediction, such as for the Arctic sea ice example (viz. Figure 4). It also exists for climate sensitivity – a critical variable associated with approximately a dozen ECs (Table 1) in varying degrees of confirmation [37]. When various *X* variables converge on a prediction, combining ECs may be relatively straight-forward, although one must consider whether various constraints are independent or merely different manifestations of the same underlying mechanism. As many constraints for climate sensitivity exhibit statistical relationships with each other [37], predictions that do not consider dependencies may be over-confident. ECs for the same *Y* could also make contradictory predictions. It is easy to see how this situation might arise if *Y* variables involve multiple processes. For example, suppose statistically significant emergent relationships between two different *X* variables and climate sensitivity exist, but that the emergent relationships arise because the *X* variables are each tightly linked to different feedbacks shaping climate sensitivity. The two ECs may give different predictions for the true climate sensitivity, but it makes little sense to consider them as two independent and valid estimates. Instead, the fact that the ECs contradict one another should be taken as an indication that neither is confirmed. The ECs should be reformulated to focus on the feedbacks that lead to the correlations with climate sensitivity in the first place. This recommendation echoes our earlier remarks that ECs are easiest to confirm if the *X*s and *Y*s of the emergent relationship involve as few processes as possible. We urge the scientific community to think more carefully about the circumstances under which ECs can and cannot be combined, and how to perform such combinations.

Detecting Tipping Points. ECs linking Earth System sensitivities (*Y*) to temporal variability (*X*) are closely related to tipping point precursors [52]. Both depend on a relationship between a system's internal variability and its sensitivity to external forcing, as embodied mathematically in the Fluctuation-Dissipation Theorem [19] and linear response theory [53]. Some ECs depend on relationships between variability and sensitivity across a model ensemble [20]. Similarly, in the case of tipping point precursors, temporal changes in variability within a system are used to detect the reducing system resilience that occurs prior to many tipping points [54]. The most common technique is to check for 'critical slowing down' as the tipping point is approached, identified by increased autocorrelation of a state variable such as global mean temperature [55]. The underlying assumption of tipping point precursors is that changes in system variability indicate changes in sensitivity, and there is circumstantial evidence this occurred in many past climate transitions [52].

Building stronger links between those working on tipping point precursors and on ECs could have major benefits. As an example, we highlight the issue of tropical forest dieback under climate change, evident in early climate-carbon cycle projections [12,13], and also detectable in a subset of CMIP5 models [56]. It is difficult to detect the imminent transition to forest dieback via the critical slowing-down metrics typically used in the tipping points community [57]. This is because the rate of climate change, in conjunction with the relatively slow response-time of forest cover, means the system is far from the quasi-equilibrium state where variability changes most clearly reveal changes in sensitivity. By contrast, take an *X* variable designed to provide an EC on carbon loss from tropical forests under climate change [11] – a metric that relies on the sensitivity of the tropical land carbon fluxes, rather than forest cover, to tropical climate variability. This *X* variable provides a much clearer signal of future tropical forest dieback in a given model realization [57]. In cases where the EC community is focused on Earth System components suspected of harbouring tipping points (e.g. the cryosphere and carbon cycle), it may be fruitful to consider the *X* variables in question as possible tipping point precursors.

6. Conclusions

ECs are attractive in this era of multiple impressive – albeit imperfect – ESMs because the full ensemble of models along with observations is exploited to reduce uncertainties in the real climate system. Indeed, ECs are dependent on a collection of ESM biases. It is rare that model inter-comparison approaches find value in ESM biases, and offer the promise of '*more than the sum of the parts*'. Since the first emergent relationship was discovered in an ESM ensemble [10], there has been great interest among climate scientists in the potential of ECs to reduce climate change uncertainty. This interest has translated into a very large number of proposed ECs. However, as might be expected for a rapidly developing methodology, there has been some confusion as to its capabilities. Indeed, ECs remain widely misunderstood, and sometimes emergent relationships are combined with observations and assumed to have constraining power even if they are unconfirmed. Such overinterpretations risk undermining this promising approach.

This Perspective article strives to clarify issues surrounding ECs, and to provide a hierarchy of approaches to assess the credibility of proposed ECs. At the top of this hierarchy is a form of hypothesis testing, in which physical reasoning, or simpler mathematical models, are used to explain a relationship between an observable aspect of current climate and some uncertain aspect of future climate. This hypothesis is then tested through analysis of outputs of complex ESMs. Even where analysis of full complexity ESMs looks to be consistent (or at least not inconsistent) with the hypothesis, most ECs identified so far remain in essence statistical relationships between observables and projections, i.e. in the proposed category. Hence it is advantageous to test them out-of-sample, which has been difficult to date owing to the relatively small number (~20-30) of ESMs available in the CMIP5 archive. However, with next generation CMIP6 models coming online, there is the unique opportunity to test ECs derived from CMIP5 against the new CMIP6 models. It would be useful for such analyses to include an assessment of how and whether the ESMs have evolved in the simulation of variables used to construct the emergent relationship. This exercise would shed light on whether the CMIP6 ensemble offers an out-of-sample test of the CMIP5-derived EC.

The reasons why emergent relationships should exist in an ESM ensemble provide a guide to those searching for ECs in CMIP6: When trying to connect variability to sensitivity, researchers should examine system components that behave the most linearly. When trying to connect the system's forced response on the shorter time scales of the historical record to the response to future anthropogenic forcing, focus should be placed on feedbacks and processes that behave similarly on both time scales. Data-mining of an ESM ensemble may also be a pathway to discovery of ECs, with the caveat that they, like all other purely statistical emergent relationships, must remain in the proposed category until associated with confirmation indicators.

Despite major advances in representation of key processes, model resolution, and the inclusion of Earth System feedbacks, the spread in climate change projections has not reduced substantially. The lack of progress represents a disappointment for climate science, and hinders society's ability to plan for future impacts. We believe the EC approach offers a promising way to reduce key uncertainties in future climate. However, it will require a concerted effort from theorists, modellers, and observational scientists to ensure the ECs produced are valid. If best practices in EC research are adopted, we expect these can pave the way for further discoveries about climate system behaviour and true uncertainty reduction in critical aspects of climate change, some of which have so far received little attention. Here we envisioned what a few of those aspects might be – climate extremes, teleconnections, combinations of ECs, and warning of system tipping points. But it will be up to the scientific community to apply the EC technique to the forthcoming CMIP6 ensemble, and in so doing take it to the next levels of credibility and sophistication.

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Statement of the individual contributions

AH drafted large portions of the paper, informed by discussions with CH, PC, and SK, and an earlier manuscript drafted mainly by CH. CH, PC, and SK each also drafted pieces of the paper. AH revised the paper in response to reviewer comments, after gathering feedback from CH, PC, and SK. CH managed the references throughout the drafting process.

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Earth System Component	**Future constrained quantity (*Y*)**	**Contemporary quantity for which measurement exists (*X*)**	**Ref.**
Climate Sensitivity	Equilibrium climate sensitivity	Height of tropical low clouds	Ref[58]

Climate Sensitivity	Equilibrium climate sensitivity	Sensitivity of the reflection by subtropical low clouds to sea-surface temperature	Ref[59]
Climate Sensitivity	Equilibrium climate sensitivity	Seasonal sensitivity of low cloud in the 20°–40° latitude band to sea-surface temperature	Ref[60]
Climate Sensitivity	Equilibrium climate sensitivity	Climatological top-of-atmosphere net radiation balance in the Southern Hemisphere	Ref[61]
Climate Sensitivity	Equilibrium climate sensitivity	Variation in relative humidity and cloud extent	Ref[62]
Climate Sensitivity	Equilibrium climate sensitivity	Vertically resolved zonally-average relative humidity and clouds between 40°N and 45°S	Ref[63]
Climate Sensitivity	Equilibrium climate sensitivity	Contemporary features of TOA radiation fluxes from Earth Observation	Ref[64,65]
Climate Sensitivity	Equilibrium climate sensitivity	Seasonal cycles of temperature	Ref[66]
Climate Sensitivity	Equilibrium climate sensitivity	Statistics of interannual temperature variability	Ref[20]
Climate Sensitivity	Equilibrium climate sensitivity	Cloudy-sky radiative flux sensitivity to temperature	Ref[67]
Climate Sensitivity	Equilibrium climate sensitivity	Vertical mixing between the boundary layer and lower troposphere over tropical oceans	Ref[68]
Climate Sensitivity	Equilibrium climate sensitivity	Climatological precipitation in the "double-ITCZ" region	Ref[23]
Climate Sensitivity	Equilibrium climate sensitivity	Climatological latitude of the Southern Hemisphere Hadley Cell edge in December-January-February	Ref[69]
Climate Sensitivity	Equilibrium climate sensitivity	Climatological difference between tropical and Southern Hemisphere midlatitude total cloud fraction	Ref[70]
Cloud Feedback & Climate Sensitivity	Global mean cloud feedback and Equilibrium climate sensitivity	Climatological latitudinal gradient in the reflectivity of clouds	Ref[71]
Cloud feedback	Low cloud feedback sign	Low cloud sensitivity to Pacific internal variability	Ref[72]

Cloud feedback	Low cloud optical depth change per degree climate warming	Low cloud optical depth response to temperature anomalies	Ref[24]
Cloud feedback	Low cloud cover change under climate warming	Low cloud cover response to inter-annual temperature and stability anomalies	Ref[73]
Snow-albedo feedback	Snow-albedo feedback (climate change)	Snow-albedo feedback (seasonal cycle)	Refs[10, 30]
Hydrologic Cycle	Indian summer monsoon rainfall increase with climate warming	Climatological mean precipitation in the Western Tropical Pacific	Ref[51]
Hydrologic Cycle	Global mean precipitation increase with climate warming	Sensitivity of shortwave radiation absorption to changes in column water vapor	Ref[46]
Hydrologic Cycle	Change in tropical precipitation extremes under climate warming	Sensitivity of tropical precipitation extremes to temperature variability	Ref[74]
Circulation Sensitivity	Poleward shift of Southern Hemisphere eddy-driven jet stream with climate warming	Climatological latitudinal position of Southern Hemisphere eddy-driven jet stream	Ref[50]
Circulation Sensitivity	Poleward jet shifts under climate warming	Climatological Position of jet stream	Ref[49]
Regional warming	Summertime increase in surface air temperature over the Central U. S. A. with climate warming	Climatological summertime surface air temperature over the Central U. S. A.	Ref[75]
Radiative forcing	Anthropogenic Ozone radiative forcing	Tropospheric ozone effect on outgoing longwave radiation	Ref[76]
Arctic sea ice	Time in 21st century when Arctic becomes ice-free in summer	September Arctic sea ice trend over satellite era	Ref[41]
Arctic warming	Arctic thermal feedbacks	Different aspects of Northern Latitude regional temperatures	Ref[77]
Carbon Cycle	Tropical land carbon carbon store response to climate warming	Simultaneous tropical fluctuations in temperature and CO_2 concentration	Refs[11, 21]
Carbon Cycle	Permafrost extent	Permafrost extent in temperature features	Ref[78]
Carbon Cycle	Vegetation fertilisation and photosynthesis	Fluctuations in CO_2 concentration	Ref[79]
Carbon Cycle	Change in tropical primary production to temperature anomalies	Sensitivity of tropical primary production	Ref[80]

Table 1: List of existing ECs derived from CMIP3 and CMIP5 models. Note that some of these ECs involve correlations that are lower than those portrayed in Figure 1, with correspondingly less potential for uncertainty reduction.