

Storyline approach to the construction of regional climate-change information

Article

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41 **1. Introduction**

42 Although there is high confidence in thermodynamic aspects of climate
43 change (global warming, sea-level rise, atmospheric moistening, melting of
44 ice), the levels of confidence concerning dynamical aspects of climate change,
45 such as the location and strength of storm tracks, are much lower [1]. None of
46 the three key lines of evidence used in climate-change science — predicated
47 by accepted theory, detected in observations, and consistently represented in
48 climate models — apply to aspects of climate change that are closely related
49 to large-scale atmospheric circulation. This includes, notably, mean
50 precipitation changes over many of the most populated regions on Earth
51 (Figure 1). It is in striking contrast to thermodynamic aspects of change, at
52 least when sufficiently aggregated [3], where all three lines of evidence apply
53 [2].

54 Lack of agreed-upon theoretical predictions is related to the fact that different
55 drivers of change can act in opposite directions, so the result is often a small
56 difference of large terms [4,5]. Lack of detection in observations is related to
57 the small signal-to-noise ratio of forced circulation changes, reflecting the fact
58 that climate variability is primarily a dynamical phenomenon [6]. Lack of
59 model agreement is related to both these issues, and to the fact that
60 circulation changes are often quite sensitive to model biases, which can be
61 substantial [7-9].

62 Furthermore, thermodynamic aspects of climate can be described by
63 extensive quantities (e.g. heat content or ocean volume), which can be readily
64 aggregated, and strong conclusions can be drawn from thermodynamic
65 principles alone, often in terms of global budgets [10]. In contrast, circulation
66 aspects of climate are inherently regional, and involve dynamics (Newton's
67 second law) as well as thermodynamics. Since dynamics is also inherently
68 chaotic, the challenge of atmospheric circulation should come as no surprise.

69 Ways must therefore be found to construct useful scientific information on
70 the regional scale, and even on the local scale, that reflect an appropriate level
71 of uncertainty yet retain the relevant information about climate risk. It has
72 recently been argued [11] that *storylines* — physically self-consistent
73 unfoldings of past events, or of plausible future events or pathways —
74 provide a potential way forward, both for the interpretation of the observed
75 record and for the description of plausible futures. However, storylines are
76 inherently subjective and thus would seem to be at odds with more
77 probabilistic approaches, which give the appearance of objectivity. The
78 purpose of this paper is to place storylines within a broader epistemological
79 framework.

80 It is first shown (Section 2) how the standard, confidence-based framework
81 for the construction of climate information prioritizes reliability (the
82 avoidance of Type 1 errors, or false alarms) over informativeness (the

83 avoidance of Type 2 errors, or missed warnings), and thus has ethical
84 implications. It follows that there is no such thing as value-free climate
85 science. In Section 3, the difference between epistemic and aleatoric
86 (random) uncertainty is shown to be critical to the treatment of climate risk.
87 Since epistemic uncertainty is deterministic and inherently subjective, it
88 follows that there is no objective basis for a probabilistic approach, and no
89 such thing as objective climate information. This motivates a re-framing of the
90 climate risk question from the ostensibly objective prediction space into the
91 explicitly subjective decision space (Section 4). Finally, it is shown in Section
92 5 how such a re-framing can be cast within the mathematical framework of a
93 causal network, thereby reconciling storyline and probabilistic approaches.

94 **2. The confidence straightjacket**

95 The most authoritative statements on physical aspects of climate change
96 come from Working Group I (WGI) of the Intergovernmental Panel on Climate
97 Change (IPCC). In the Summary for Policymakers of the last (5th) IPCC WGI
98 Assessment Report [2], atmospheric circulation is scarcely mentioned, and all
99 the statements of confidence are based on thermodynamics. This remarkable
100 fact evidences better than anything else the lack of scientific consensus on
101 dynamical aspects of climate change. Moreover, the statements of confidence
102 are crafted to be reliable, generally by emphasizing global rather than
103 regional aspects of change. A good example is the headline statement on the
104 water cycle:

105 “Changes in the global water cycle in response to the warming over the
106 21st century will not be uniform. The contrast in precipitation between
107 wet and dry regions and between wet and dry seasons will increase,
108 although there may be regional exceptions.” [2]

109 This statement is based on the sound physical principle that, all else being
110 equal, a moister atmosphere will exhibit an accelerated hydrological cycle
111 [10]. The statement achieves its reliability in the tropics by including oceanic
112 regions (see Figure 1); indeed a key observation supporting the statement is
113 the increased salinity in the subtropical upper oceans (due to increased
114 evaporation). However, it is precipitation over land that matters for climate
115 impacts, and there have been many studies showing that the “wet get wetter,
116 dry get drier” paradigm does not hold over land regions [12-14], as is
117 reflected in the general lack of stippling over these regions (apart from the
118 high northern latitudes) in Figure 1. The statement is perfectly reliable as an
119 explanation of how the global climate system works, but it does not provide
120 useful information at the regional scale, as the final caveat makes clear. In this
121 way, reliability is achieved at the price of informativeness.

122 To find a high-level statement on dynamical aspects of climate change in the
123 IPCC WGI 5th Assessment Report, one must look one level down, in the
124 Technical Summary [2]. The statements are uniformly characterized by low

125 levels of confidence and a lack of informativeness at the regional scale. An
126 illustrative example is the statement on changes in Northern Hemisphere
127 (NH) storm tracks, which are an important determinant of midlatitude
128 weather:

129 “Substantial uncertainty and thus low confidence remains in projecting
130 changes in NH storm tracks, especially for the North Atlantic basin.” [2]

131 Furthermore, IPCC WGI uses a likelihood scale in which the term “unlikely” is
132 used to describe likelihoods of up to 33%. This terminology seems rather
133 perverse from a lay perspective; in most areas of life, one would pay attention
134 to likelihoods that high, especially if the consequences were serious — as they
135 are with climate change. (Would you board an airplane if you were told that it
136 had a 33% chance of crashing?) Yet in the WGI report, the term “unlikely” is
137 generally used to dismiss rather than to highlight a possibility. Consider this
138 example from the Technical Summary, again with reference to the North
139 Atlantic storm track:

140 “...it is unlikely that the response of the North Atlantic storm track is
141 a simple poleward shift” [2]

142 The context here is that, despite the lack of an agreed-upon theoretical
143 explanation, the concept of a poleward storm track shift under climate change
144 has become a general expectation [5]. However, projected changes in the
145 North Atlantic storm track do not conform to that expectation [15]. An
146 equivalent version of the statement would be “...it is likely that the response
147 of the North Atlantic storm track [to climate change] is not a simple poleward
148 shift”. Because in the present state of knowledge a consensus statement could
149 not be crafted on what was likely to happen, the authors instead chose to
150 emphasize what was not likely to happen. Yet there are several possibilities
151 for what might happen, each with their own implications for climate risk,
152 which could have been articulated (e.g. [16]). However, the simultaneous
153 consideration of contradictory futures is not naturally expressed through
154 statements of confidence. Thus, reliability is again achieved at the price of
155 informativeness.

156 These examples illustrate the fact that by employing a confidence framework,
157 which seeks to attribute what has happened and to predict what will happen
158 (for a given climate forcing scenario), climate science winds up in something
159 of a straightjacket when it comes to aspects of regional climate change that
160 are closely related to large-scale atmospheric circulation, such as drought and
161 storminess.

162 It is notable in this respect that IPCC Working Group II, which deals with
163 impacts and adaptation, defines climate change as any observed change, not
164 necessarily one that has been attributed to anthropogenic forcing [17]. This is

165 done to avoid the confidence straightjacket, but it creates a knowledge gap
166 between the WGI and WGII science domains [18].

167 There is always a trade-off to be made between reliability and
168 informativeness [19]. Yet a focus on reliability, guarding preferentially
169 against Type 1 errors (false positives, i.e. false alarms), increases the
170 likelihood of Type 2 errors (false negatives, i.e. missed warnings). It follows
171 that much as though climate science might strive to be value-free, it cannot
172 be: the way in which climate information is constructed has ethical
173 implications [20]. Lloyd and Oreskes [20] raise the important question of why
174 in climate science it has become normative that scientific rigour is associated
175 with a focus on reliability. They point out that the decision on whether to
176 preferentially guard against Type 1 or Type 2 errors is not a scientific one, but
177 one of values. For example, in deciding whether to bring a new drug to market,
178 one assesses both the drug's efficacy (guarding against Type 1 errors) and
179 whether it has any unwanted side effects (guarding against Type 2 errors).
180 Similarly, in deciding whether to issue an evacuation order for a city in the
181 face of a forecasted storm, a balance of concern between Type 1 and Type 2
182 errors will be considered. Thus, there is nothing unscientific about seeking to
183 guard against Type 2 errors.

184 It would seem entirely appropriate to preferentially guard against Type 1
185 errors when making high-level definitive statements concerning global
186 climate change such as "Warming of the climate system is unequivocal" [2].
187 However, the framework is not so evidently appropriate when it comes to
188 regional aspects of change (see also [21]). This situation seems to be an
189 example of Kuhn's [22, p.37] important observation that "a paradigm can ...
190 insulate the [scientific] community from those socially important problems
191 that ... cannot be stated in terms of the conceptual and instrumental tools the
192 paradigm supplies". Thus, it is imperative to find alternative paradigms.

193 **3. Epistemic vs aleatoric uncertainty**

194 Broadly, uncertainty in climate projections arises from three sources:
195 uncertainty in future climate forcing, in the climate system response to that
196 forcing (i.e. the change in climate), and in the actual realization of climate for
197 a particular time window, which is subject to internal variability. The nature
198 of these uncertainties is very different (e.g. [23]). The first depends primarily
199 on human actions and is called the scenario, and the projections are normally
200 made conditional on the scenario. The second is what is known as an
201 *epistemic* uncertainty; there is only one truth, but we do not know what it is.
202 The third is what is known as an *aleatoric* uncertainty; there is a random
203 element to what will occur, whose probability is known to some extent. Any
204 discussion of climate risk must address the central fact that the nature of the
205 second and third uncertainties is fundamentally different. This is especially
206 important for circulation-related aspects of climate change at the regional
207 scale, for which these two sources of uncertainty tend to dominate the overall

208 uncertainty (see [24] for regional precipitation changes). Yet it is standard
209 practice in climate science to mingle the two sources of uncertainty together,
210 e.g. in the multi-model ensembles (with one realization taken from each
211 model) that are in such widespread use [2]. In such ensembles the differences
212 between the individual model projections include both the systematic
213 differences between different model climates (epistemic) and the random
214 differences that arise from the limited sampling of internal variability
215 (aleatoric), which poses challenges in interpretation [25].

216 We first discuss the uncertainty arising from internal variability, since it is
217 conceptually much easier to deal with. Internal variability is a property of the
218 physical climate system, whose random character arises from the chaotic
219 nature of atmospheric and oceanic dynamics, and which can be characterized
220 from observations. Indeed, the definition of climate includes internal
221 variability, which is characterized through statistical measures such as
222 variances and co-variances of physical fields, as well as higher-order
223 moments such as skewness or extremes, and includes coherent modes of
224 variability such as the El Niño/Southern Oscillation phenomenon. The
225 uncertainty from internal variability is fundamentally irreducible (leaving
226 aside the possibility of finite-time prediction from specified initial conditions),
227 and users of climate information need to understand that the mantra of
228 “reducing uncertainty” is inappropriate in this case; rather, the scientific goal
229 is to better quantify the uncertainty. The magnitude of the uncertainty for any
230 particular quantity can be reduced by taking coarser spatial and temporal
231 averages, but that operation changes and may simultaneously reduce the
232 value of the information provided.

233 The concept of internal variability is not without ambiguity since climate has
234 various sources of non-stationarity, and what is meant by internal variability
235 is conditional on any non-stationary influence, including climate change itself.
236 Furthermore, knowledge of internal variability is limited by the finite
237 observational record, and there is uncertainty in how internal variability will
238 respond to global warming. Nevertheless, in most cases, the main uncertainty
239 in what climate conditions will be experienced at a particular place and time
240 arising from internal variability can be considered to be aleatoric, and thus
241 amenable to a straightforward (i.e. frequentist) probabilistic interpretation.
242 The reliability of model simulations of internal variability can be similarly
243 assessed, at least in principle.

244 The uncertainty in the climate response to forcing is conceptually very
245 different. It is not a property of the physical climate system; rather, it is a
246 property of a state of knowledge, or degree of belief, and it *can* be reduced as
247 knowledge improves. In contrast to aleatoric uncertainty, which is objective,
248 such epistemic uncertainty is *subjective* [26]. Therefore, treating epistemic
249 uncertainty as if it were aleatoric, with a focus on the multi-model mean as a
250 best estimate, has no epistemological justification. This has been recognized

251 for some time [27,28,21], but the practice continues to be normative (e.g. as
252 in Figure 1). It is interesting to consider why this is so, since in most areas of
253 science the essential distinction between systematic and random sources of
254 uncertainty is well recognized. One of the reasons may be that the extent of
255 the epistemic uncertainty is not particularly well known. First, climate models
256 are imperfect representations of reality and share many deficiencies, thus
257 may exhibit a collective bias and fail to explore important aspects of climate
258 change. Second, even within the world represented by climate models, the
259 forced circulation response of any particular model is obscured by internal
260 variability.

261 As an example of the latter, Deser et al. [29] estimate that for NH wintertime
262 midlatitude surface pressure (whose spatial gradient provides an indicator of
263 circulation changes), ensemble sizes of around 30 are generally needed to
264 determine the forced decadal changes of a given model over a 45-year period.
265 This is in striking contrast to surface temperature changes, where the signal-
266 to-noise ratio of the forced response is much larger, and even single
267 simulations can be informative. One might be tempted to think that if such a
268 large ensemble size is needed to detect the signal, then the signal must be
269 small. However, Deser et al. [29] show that such a change in surface pressure
270 patterns can alter the risk of regional drought or heavy precipitation by a
271 factor of two, which is hardly negligible. Most climate model simulations are
272 performed with much smaller ensemble sizes, although there is a growing
273 interest in large single-model ensembles in order to better characterize the
274 epistemic uncertainty within current models.

275 Another conceptual challenge in dealing with the epistemic uncertainty of
276 climate change is that the concept of “error” is not well defined. Although in
277 principle there may be one truth, it is not knowable: there will never be
278 sufficient observations to define all relevant aspects of future climate; future
279 climate will in any case be non-stationary; and model projections are based
280 on climate forcing scenarios that will not be the ones actually realized. Thus,
281 there has been interest in trying to understand the relationship between
282 model errors in observable aspects of climate and the forced response
283 simulated by that model — so-called “emergent constraints” (e.g. [30]). Such
284 an approach permits a Bayesian probabilistic interpretation of epistemic
285 uncertainty [31]. However, there is a danger that any such relationship is
286 merely statistical and not causal, and many published emergent constraints
287 have been subsequently debunked (see [32-34]). In any case, subjective
288 choices are required in the application of any such constraints.

289 That an aleatoric interpretation of multi-model ensembles can blur the
290 climate information contained within those ensembles is not difficult to
291 appreciate. Circulation aspects of climate are related to features such as jet
292 streams. Over Europe during wintertime, some models show an increase in
293 jet strength under climate change and others a decrease (see Figure 4 of [1]),

294 moreover the location of the changes varies between models. Whilst all
295 models predict a significant jet response somewhere, averaging over the
296 models will lead to a washed-out response. Thus the multi-model mean may
297 not only be unlikely, but even implausible. The situation is analogous to the
298 idealized case of a bi-modal Probability Density Function, whose mean may
299 not be a physically realizable state.

300 A related issue is apparent in Figure 1. Because precipitation increases in
301 some regions and decreases in others, the multi-model mean change
302 inevitably passes through zero, and will be small compared to internal
303 variability on either side of that line. However, that does not mean that the
304 change in those regions can be expected to be small compared to internal
305 variability; it just reflects uncertainty in the sign of the change. When there
306 are equally plausible futures that point in different directions, averaging
307 those futures buries relevant information and underestimates risk.

308 The essential point is that epistemic uncertainties are deterministic, which
309 means that they introduce correlations; unless those correlations are
310 accounted for, inferences may be flawed. For example, Madsen et al. [35]
311 show that the spread across CMIP5 model projections in temperature and
312 precipitation changes at the gridpoint scale is significantly exaggerated when
313 treating the gridpoints independently, as compared to when the models are
314 ranked by the global mean changes (where the spread comes mainly from
315 climate sensitivity). This illustrates the general point that with an
316 inhomogeneous distribution of estimators, one should examine the
317 distribution of responses to a perturbation rather than the overall response of
318 the distribution to the perturbation.

319 **4. Re-framing the question**

320 If the construction of regional climate information inevitably involves ethical
321 choices, then those choices should be made by the users of the climate
322 information, based on their values. If the uncertainties in the climate
323 information involve a significant epistemic component, then subjectivity is
324 inevitable and the epistemic uncertainties similarly need to be
325 understandable and assessable by the users of the climate information, within
326 their particular context. Both imperatives move the climate risk problem
327 outside the domain of pure climate science. Moreover, the recognition that
328 epistemic uncertainties are deterministic removes the impulse to provide
329 probabilities, which can give the illusion of objectivity and thereby reduce
330 transparency. Instead, epistemic uncertainty can be represented through a
331 discrete set of (multiple) storylines — physically self-consistent, plausible
332 pathways, with no probability attached [11,36].

333 Rather than asking what will happen (as in the traditional, scenario-driven
334 approach), which we may not be able to answer with any confidence,
335 storylines allow us to ask what would be the effect of particular interventions

336 — e.g. different climate forcing scenarios, or different adaptation measures —
337 across a range of plausible futures. The latter questions are in any case the
338 societally relevant ones. This re-framing of the climate risk question from the
339 prediction space to the decision space avoids the confidence straightjacket.
340 Storylines have much in common with scenario planning and other methods
341 of robust decision-making under uncertainty [37,38]. What is novel is their
342 application to physical climate science, where, perhaps because the system
343 obeys known physical laws, the operative paradigm up to now has been
344 probabilistic, which gives the impression of objectivity.

345 The different uncertainties that are relevant to climate risk, and the different
346 human decision points, can be broadly represented as follows. There is
347 uncertainty in the future climate forcing, which is mainly anthropogenic in
348 origin, and represents the mitigation options. This combines with the
349 epistemic uncertainty in climate sensitivity to determine the global-mean
350 warming level. Whilst there is some aleatoric uncertainty in the global-mean
351 warming, it is small compared with the forced response on decadal or longer
352 timescales. A given global-mean warming level will be associated with distinct
353 patterns of regional warming (e.g. land warms more than ocean, the Arctic
354 warms more than lower latitudes during the winter season), including
355 changes in lapse rate [39]. These regional warming patterns are largely
356 explainable from thermodynamic principles and thus are fairly well
357 understood, though have substantial quantitative epistemic uncertainty
358 (including the possibility of tipping points). A given global-mean warming
359 level will also be associated with particular dynamical conditions in any
360 specific region (including the circulation effects of coupled atmosphere-ocean
361 variability), which have a very large aleatoric component but whose forced
362 changes are also highly uncertain. The regional warming patterns and
363 dynamical conditions together produce hazards such as weather or climate
364 extremes, which then combine with the non-climatic anthropogenic factors of
365 vulnerability and exposure to create climate impacts.

366 This representation of the climate risk problem provides a natural framework
367 for storyline approaches. For example, from the perspective of the Paris
368 Agreement, one may ask the question of what the climate impacts would be at
369 different levels of global-mean warming, and what different mitigation
370 pathways would lead to those warming levels [40]. The epistemic uncertainty
371 in climate sensitivity now no longer affects the estimation of climate impacts,
372 but is instead relevant to the carbon budget allowed by the given level of
373 warming. The epistemic uncertainty in future dynamical conditions (for a
374 given level of global-mean warming) can then be managed via storylines, the
375 simplest of which is that the changes in hazard are dominated by the
376 thermodynamic effects arising from the regional temperature changes, with
377 the forced changes in dynamical conditions assumed to be negligible. Given
378 the large uncertainties in the forced dynamical changes, this can be
379 considered a reasonable null hypothesis for climate change [41,42], and it is

380 far from uninformative. It is in fact the basis for all of the predicted changes in
381 extremes shown in Table SPM.1 of the IPCC AR5 [2]. It also underlies the
382 “surrogate climate change” (also known as “pseudo-global warming”)
383 methodology [43,39] which is widely used in regional climate change
384 simulations, and the circulation-analogue methodology [44] which is widely
385 used in extreme-event attribution. However, specific storylines of forced
386 circulation change can also be considered [42,16].

387 Reframing the climate risk question in this way increases the signal-to-noise
388 ratio of the climate information by explicitly accounting for the correlated
389 nature of epistemic uncertainty. An example is provided by Figure 2. The
390 Mediterranean region receives most of its precipitation during the winter
391 season, so the predicted wintertime drying of the region, which is a robust
392 feature of climate model projections (see Figure 1), has important
393 consequences. The extent of the drying will depend on the global-warming
394 level, and it is relevant to ask, for instance, what would be the difference
395 between 1.5C and 2.0C of global warming. However the extent of the drying
396 will also depend on the pattern of circulation change in the region — an
397 epistemic uncertainty — which can be characterized by physically coherent
398 storylines [16]. Considering just the range between the low-impact and high-
399 impact storylines shown in Figure 2, the difference in drying between 1.5C
400 and 2.0C of global-mean warming under the standard probabilistic framing is
401 the difference between 0.09 [0.04 to 0.15] and 0.12 [0.05 to 0.20] mm/day
402 (left panel), which would be considered indeterminate within the stated
403 uncertainties. The storyline framing of the difference is, in contrast, a
404 deterministic 0.04 vs 0.05 for the low-impact circulation storyline, 0.09 vs
405 0.12 for the median storyline, and 0.15 vs 0.20 for the high-impact storyline
406 (right panel). This is a more informative way of representing the uncertainty,
407 because it quantifies different plausible outcomes. For reference, 0.08
408 mm/day corresponds to a change that is statistically detectable, and 0.19 to
409 one standard deviation of the interannual variability — quite a large change,
410 likely requiring significant adaptation measures. The distinction between the
411 two approaches is analogous to that between accuracy and precision;
412 sometimes, the latter is all that is needed for decision-making.

413 Storylines are ideal vehicles for quantifying the impacts of climate change and
414 adaptation measures. They provide a way of dealing with singular historical
415 events, which within the probabilistic framework are merely accidents within
416 a phase space of unrealized possibilities, yet often provide benchmarks for
417 resilience; and with the local context, where the human element becomes part
418 of the analysis rather than a confounding factor. For example, rather than
419 seeking to determine the recurrence likelihood of a particularly damaging
420 storm (an inherently fuzzy question since every storm is unique), one can ask
421 how much worse the flooding would be in a warmer, moister climate [41], or
422 under a particular urban development scenario. Such conditioning of the
423 question enormously reduces the dimension of the problem and thereby

424 allows the use of much more realistic modelling tools, which users of climate
425 information can relate to. In this way, the storyline approach addresses the
426 needed re-framing of the climate risk problem whilst representing the
427 epistemic uncertainties in a traceable manner.

428 That there is relevant information concerning climate risk contained even in
429 single historical events is illustrated by Figure 3, which shows a small region
430 in central France during one day in August 2000 and another day in August
431 2003 during the severe heat wave that affected Europe that summer [45].
432 From a statistical perspective, it may seem meaningless to compare two
433 single days because they will each be strongly influenced by synoptic
434 variability. However, the images show that the crops and grasses in the
435 agricultural plots died out during the 2003 heat wave, and the surface
436 temperature difference between the two days over those parts of the scene
437 was 20 C, vs only 11 C in the forested region. Since a difference of 9 C over a
438 distance of several hundred metres cannot be explained by synoptic
439 variability (which has much larger correlation scales), this clearly shows the
440 impact of land cover on the climate risk from heat waves. (Moreover, the
441 average temperature difference in the agricultural plots rises to 24 C if the
442 hedgerows are excluded, and the temperature difference in fields that were
443 bare in both 2000 and 2003 is 11 C.) Whilst it may not be possible to predict
444 the future statistics of heat waves in this region, it is possible to make
445 informative statements about how those heat waves would be affected by
446 land cover and thus inform adaptation strategies.

447 The tension between global and local descriptions (in time or space) is not
448 unique to climate science, of course. It arises in any scientific context where
449 statistical power is achieved by aggregation over an inhomogeneous
450 population, and thus blurs information. There is a growing move in many
451 fields towards analysis methods that aim to consider information in context
452 rather than in aggregate, especially when that information is sparse (e.g.
453 safety in health care: [46]). Storyline approaches to climate risk can be seen
454 as part of that movement.

455 **5. Causal networks**

456 In the above, storylines have been presented in contrast to probabilistic
457 representations of uncertainty. However, if storylines are to provide an
458 alternative scientific paradigm for the construction of regional climate change
459 information, they must be somehow reconcilable with the conventional,
460 probabilistic approach, in order to effectively bridge between climate science
461 and climate impacts, and from the global to the local scale.

462 The narrative description of the regional climate risk problem in the previous
463 section is represented graphically in Figure 4. Figure 4 is a *directed acyclic*
464 *graph*, which means that the climate risk problem can be represented
465 mathematically as a causal network [47,48]. This observation provides the

466 key to reconciling storyline and probabilistic approaches. Following [48], a
 467 joint probability of n variables $P(x_1, \dots, x_n)$ can be expressed as the product of
 468 conditional probabilities $P(x_j | pa_j)$, where pa_j are the ‘parent’ factors
 469 influencing x_j , according to

$$470 \quad P(x_1, \dots, x_n) = \prod_j P(x_j | pa_j). \quad (1)$$

471 The representation (1) factorizes the uncertainty, which is extremely useful
 472 when the different uncertainties have rather different characteristics, as in
 473 the climate risk problem. A storyline $x_i = x'_i$ for a particular i can be defined by
 474 imposing that particular condition within (1), represented symbolically by \hat{x}'_i ,
 475 which leads to [48, pp. 72-73]

$$476 \quad P(x_1, \dots, x_n | \hat{x}'_i) = \begin{cases} \prod_{j \neq i} P(x_j | pa_j) = \frac{P(x_1, \dots, x_n)}{P(x'_i | pa_i)} & \text{if } x_i = x'_i \\ 0 & \text{if } x_i \neq x'_i \end{cases} . \quad (2)$$

477 The expression (2) is thus a *truncated factorization* of the expression (1) for
 478 the unconditional probability, representing a blend of probabilistic and
 479 deterministic factors. Multivariate storylines can be treated by repeated
 480 application of this procedure. In this way, storylines can be cast within the
 481 context of a probabilistic framework.

482 We illustrate this for the system represented in Figure 4. The traditional
 483 scenario-driven prediction problem aims to estimate the joint probability of
 484 the climate state conditional only on the climate forcing F :

$$485 \quad P(H, D, R, G, S | F) . \quad (3)$$

486 According to the causal linkages represented in Figure 4, this factorizes to

$$487 \quad P(H | D, R) P(D | G) P(R | G) P(G | S, F) P(S) . \quad (4)$$

488 Within this perspective, it is necessary to have knowledge of the climate
 489 sensitivity S . However, from the perspective of the Paris Agreement, one can
 490 define a storyline consisting of a particular global warming level, say $G = G_1$,
 491 which specifies G deterministically. This condition blocks the influence of S ,
 492 leaving the truncated factorization

$$493 \quad P(H | D, R) P(D | G = G_1) P(R | G = G_1) \quad (5)$$

494 where now the hazard H depends only on the dynamical conditions D and the
 495 regional warming R . Note that (5) does not imply that D and R are
 496 independent; they share a common dependence through G , hence storylines
 497 of R may be correlated with storylines of D . This is precisely the basis of the
 498 approach of [16].

499 Interestingly, imposing a global-mean warming target builds in a relationship
 500 between the climate sensitivity S and the climate forcing F . This is in contrast

501 to the traditional scenario-driven formulation of climate risk, where these
 502 quantities are treated as independent. [In (3), S , as a property of the climate
 503 system, would be assumed independent of F .] Such a relationship expresses
 504 the policy-relevant information that society will need to act more aggressively
 505 on controlling emissions if climate sensitivity turns out to be high, but may
 506 allow itself more time if climate sensitivity turns out to be low.

507 If R is taken to be a deterministic function of G , i.e. the uncertainty in R is
 508 considered to be mainly epistemic, then (5) simplifies to

$$509 \quad P(H | D, R = R_1) P(D | G = G_1) , \quad (6)$$

510 where $R_1 = R(G_1)$. The first term in (6) represents the thermodynamic effects
 511 of a particular regional warming R_1 on H , given knowledge of D , whilst the
 512 second term represents the dynamical effects of climate change. As already
 513 discussed, the epistemic uncertainty in the latter can be very high, but is
 514 representable through storylines. The simplest storyline is that dynamics
 515 remains unchanged, in which case the conditionality in the second term drops
 516 out and we are left with

$$517 \quad P(H | D, R = R_1) P(D) , \quad (7)$$

518 where $P(D)$ can be based, for example, on observations. This is exactly the
 519 formulation of the “surrogate climate change” methodology mentioned earlier,
 520 which is widely used in regional climate change simulations. However, one
 521 can certainly also specify different dynamical storylines to represent
 522 plausible changes in dynamics. Since (6) essentially describes the regional
 523 climate modelling paradigm, it may provide a useful framework for the
 524 construction of regional climate-change information and the design of
 525 ensembles of simulations using regional climate models, including the
 526 representation of particularly extreme forms of internal variability.

527 Without this factorization of the probabilities, the regional climate risk
 528 problem for a given global warming level is representable instead in the form

$$529 \quad P(H, D, R | G) , \quad (8)$$

530 which lends itself to a probabilistic interpretation of the dynamical aspects of
 531 climate change. This hides the implicit assumptions concerning the epistemic
 532 uncertainties that are made explicit in the representation (6). Moreover, the
 533 comparatively unconditional nature of (8) requires the use of global models,
 534 whereas (6) permits the use of regional models, which can provide a more
 535 physically realistic representation of regional climate risk [49-51].

536 By casting storylines within the context of a probabilistic framework, it
 537 becomes clear that there is nothing to prevent assigning probabilities to
 538 storylines, if the scientific basis exists to do that. At the very least, physically
 539 implausible behaviours could be excluded [50]. As epistemic uncertainties are

540 reduced, this knowledge can be immediately incorporated into a revised risk
541 analysis. Thus, storylines provide a very flexible, transparent representation
542 of epistemic uncertainty.

543 Not only do causal networks reconcile storyline and probabilistic approaches
544 to climate risk, they are also ideally suited for moving the risk question into
545 the decision space. That is because the calculus of causal networks explicitly
546 allows the consideration of counter-factual outcomes [48], and decision-
547 making is precisely the consideration of counter-factual outcomes. Within this
548 context, storylines correspond to what Halpern and Pearl [52] define as
549 explanations: “a fact that is not known for certain but, if found to be true,
550 would constitute an actual cause of the fact to be explained, regardless of the
551 agent's initial uncertainty”.

552 More generally, causal networks are a way of combining expert knowledge
553 with probability [47]. The factorization (1) allows for the ready incorporation
554 of knowledge within a local semantics, and yields results that are
555 comprehensible to humans [53]. In the published Discussion of Lauritzen and
556 Spiegelhalter [47, p. 210] J. Pearl invokes the following statement (attributed
557 to G. Halter): “Probability is not really about numbers; it is about the structure
558 of reasoning.” Making the subjective assumptions explicit leads to
559 transparency in the subsequent analysis [54] and provides an audit trail for
560 decision-makers [55]. This is important since, as Beven [55] puts it, “Decision
561 and policy makers are ... far more interested in evidence than uncertainty.”

562 The challenge for regional climate-change science then becomes that of
563 constructing suitable causal networks. Causal networks are necessarily a
564 simplification, because they entail the reduction of continuous fields to a
565 finite-dimensional system. However, they very much correspond to how
566 climate scientists reason. For example, the El Niño variability in tropical sea-
567 surface temperatures drives a Rossby-wave teleconnection pathway which
568 affects circulation and weather regimes in the mid-latitudes, and all these
569 elements can be represented to a reasonable extent with physical climate
570 indices. Thus, atmospheric dynamics already provides the building blocks for
571 the construction of causal networks relevant to regional climate risk. (In
572 practice, the “Dynamical conditions” node in Figure 4 could be expanded into
573 a sub-network.) Comprehensive climate simulation models are still needed to
574 explore uncertainty space, but causal networks can provide the diagnostic
575 framework within which to extract the relevant climate information from
576 those simulations, and combine it with other sources of information in a
577 format that is suitable for decision-making.

578 The causal network depicted in Figure 4 incorporates two emergent aspects
579 of climate change. Both aspects are simplifications, but they are extremely
580 powerful and are widely used in the interpretation of climate information.
581 The first is what is known as “pattern scaling” [56,57]: namely that regional
582 climate change is a function of global-mean warming. In practice, the patterns

583 of regional warming are time-dependent [58] so are different for transient
584 and equilibrated warming levels, and short-lived climate forcers such as
585 aerosol can have distinct regional effects [59]. Such additional degrees of
586 freedom, as well as global tipping points, could be incorporated by making the
587 node G suitably multivariate. The second emergent aspect is the distinction
588 between thermodynamic and dynamical aspects of regional climate change,
589 which has already been discussed. Whilst the distinction is not precise and
590 has its limitations, it is useful (e.g. [60]); it has even been used for the last two
591 Dutch Climate Change Scenarios [61]. As with the other simplifications
592 implicit in Figure 4, e.g. the lack of any arrows pointing back from the right to
593 the left, the validity of all these simplifications can be assessed *a posteriori*.

594 Note that linearity is not assumed in causal networks. However, if certain
595 relationships can be shown to be linear to a suitable level of approximation
596 for the problem at hand, then the analysis is enormously simplified. This is
597 generally necessary for any observational analysis, because of the limited
598 sample size [62].

599 **6. Discussion**

600 This paper has argued that the storyline approach to regional climate-change
601 information avoids the straightjacket that hampers the standard confidence-
602 based approach, by allowing a reframing of the climate risk question from the
603 prediction space into the decision space. Whilst in principle such a reframing
604 is possible from probabilistic estimates of risk, the challenge for regional
605 climate-change information is that the level of epistemic uncertainty is
606 sufficiently high that subjective choices must inevitably be made, and the
607 range of users sufficiently inhomogeneous that there is no consensus on
608 values. Under such conditions, probabilistic ‘rational-choice’ approaches to
609 decision-making are ineffective [63,64] and the decision framework needs to
610 be one where the subjective and ethical choices are both flexible and
611 transparent [65]. Since epistemic uncertainty is inherently deterministic and
612 subjective, there is no imperative to represent it probabilistically [23], and
613 probabilistic representations can give a false impression of objectivity.

614 The reframing of the risk question from the prediction space to the decision
615 space may seem uncomfortable from a physical science perspective, but is in
616 fact quite orthodox from the perspective of statistical inference. Despite the
617 widespread use of p-values as an ostensibly objective measure of statistical
618 significance, the inference derived from data concerning a particular
619 hypothesis is far from a straightforward matter and involves many
620 assumptions [66]. In the Neyman-Pearson framework, the inference problem
621 is regularized by placing it in a decision context between two alternative
622 hypotheses, which takes into account the possibility of both Type 1 and Type
623 2 errors [67]. In the Bayesian framework, the strength of evidence between
624 these alternative hypotheses (H_1 and H_2) provided by the data D is given by

625
$$\frac{P(H_2 | D)}{P(H_1 | D)} = \frac{P(D | H_2) P(H_2)}{P(D | H_1) P(H_1)}, \quad (9)$$

626 which follows directly from Bayes' theorem. The Bayes factor
 627 $P(D|H_2)/P(D|H_1)$ is independent of the prior likelihoods $P(H_2)$ and $P(H_1)$, so
 628 can be considered objective, but it does not represent any sort of absolute
 629 knowledge — only an increment in knowledge, relative to the prior beliefs.

630 Moving the climate risk problem out of the domain of pure climate science
 631 requires humility on the part of climate scientists. To quote Funtowicz and
 632 Ravetz [63] — who used sea-level rise as an example — “the traditional
 633 domination of ‘hard facts’ over ‘soft values’ [is] inverted... traditional
 634 scientific inputs... become ‘soft’ in the context of the ‘hard’ value
 635 commitments that will determine the success of policies for mitigating the
 636 effects of [climate change]”. Indeed, it has been argued that humility is one of
 637 the four core elements — the others being integrity, transparency, and
 638 collaboration — that should be intrinsic to the production of regional climate
 639 information [68]. In this way, the goal is not so much to be authoritative,
 640 which has something of a gatekeeper connotation, but to be trustworthy [69].
 641 This involves a loss of control, because one’s trustworthiness is a judgement
 642 made by others.

643 This perspective also involves an acknowledgement that climate-relevant
 644 decisions, especially at the local scale, are not usually made on the basis of
 645 climate change alone but involve many other changing factors, most of which
 646 are highly uncertain. If climate impacts I are a product of hazard H ,
 647 vulnerability V and exposure E , then, conceptually, the anthropogenic changes
 648 in I can be represented as

649
$$\delta I = \delta(HVE) = HV\delta E + HE\delta V + VE\delta H. \quad (10)$$

650 It may well be that the largest terms on the right-hand side of (10) are the
 651 first two, where it is the combination of climate and weather *variability* with
 652 changing vulnerability and exposure that is the main determinant of climate
 653 risk [70]. In this case the decision framework is not so much that of dealing
 654 with climate change as it is that of bringing climate information into decisions
 655 that need to be made in any case. There are calls for this sort of complex-
 656 systems thinking in other areas of science, such as public health [71]: “Instead
 657 of asking whether an intervention works to fix a problem, researchers should
 658 aim to identify if and how it contributes to reshaping a system in favourable
 659 ways.”

660 To return to Kuhn [22], the construction of regional climate-change
 661 information is not most usefully viewed as a search for an objective truth, but
 662 rather as a search for more complete descriptions of the realities that people
 663 have experienced and may experience in the future, and how those depend on
 664 contingent factors that are under human control. Kuhn’s version of the

665 Bayesian perspective described above, and the cutting of the Gordian Knot it
666 enables, is as follows [22, p. 170]: “If we can learn to substitute evolution-
667 from-what-we-know for evolution-toward-what-we-wish-to-know, a number
668 of vexing problems may vanish in the process.” In such an enterprise, physical
669 knowledge of the climate system provides the foundation for the construction
670 of regional climate information.

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675

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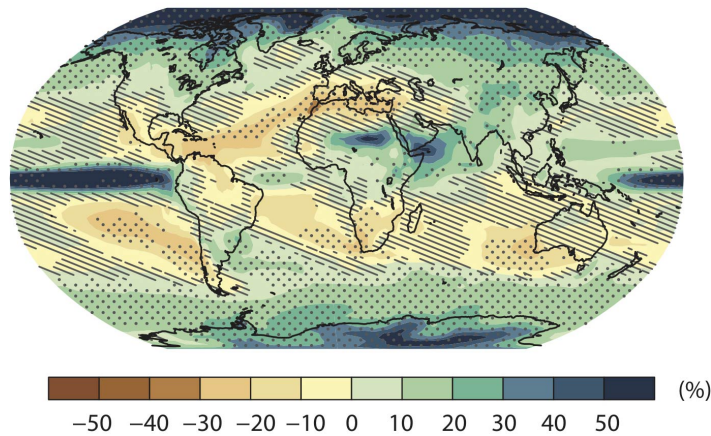
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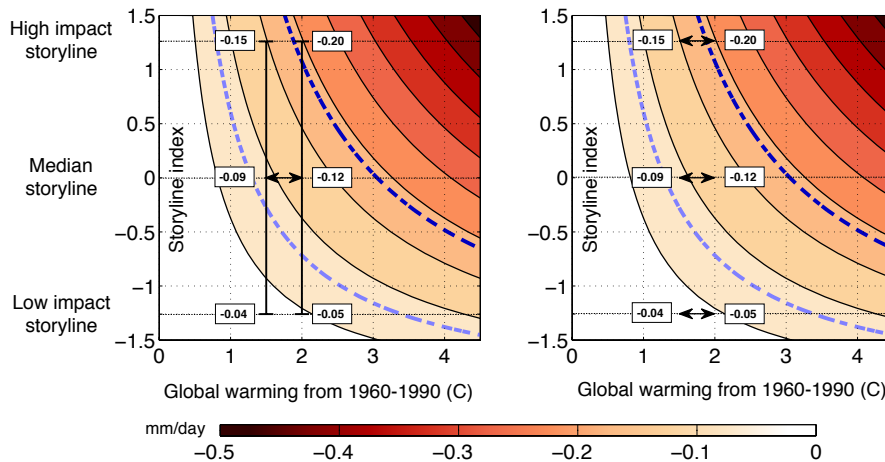
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Change in precipitation



889

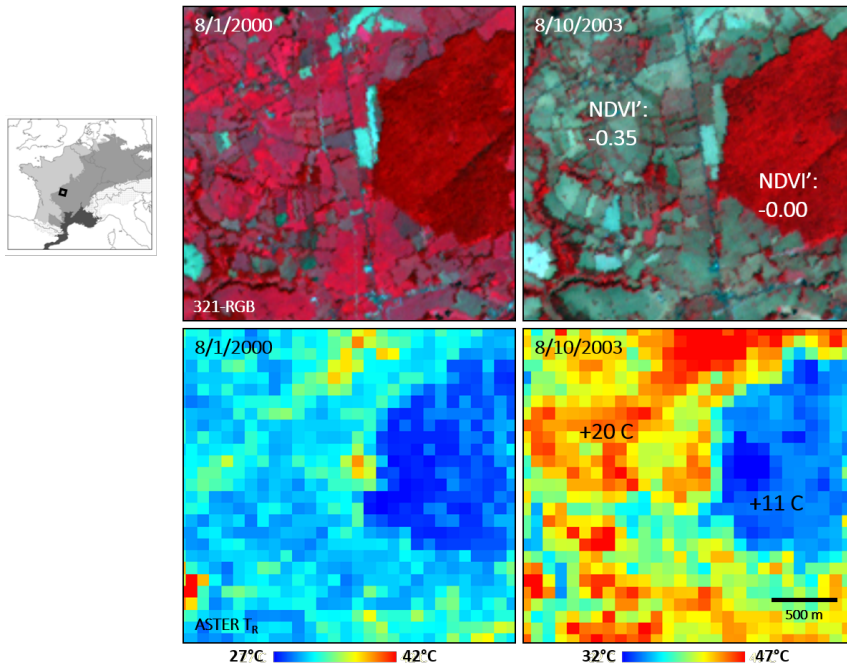
890 **Figure 1.** Projected changes in precipitation (in %) over the 21st century
 891 under a high climate forcing scenario (RCP8.5). Stippling indicates where the
 892 multi-model mean change is large compared with natural internal variability
 893 in 20-year means (greater than two standard deviations) and where at least
 894 90% of models agree on the sign of change. Hatching indicates where the
 895 multi-model mean change is small compared with internal variability (less
 896 than one standard deviation), but this does not mean that individual model
 897 changes are small. From the Summary for Policymakers of [2].



898

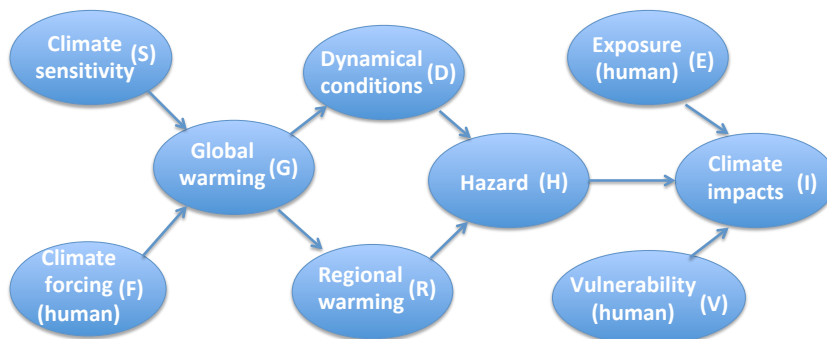
899 **Figure 2.** Projected average wintertime precipitation change (in mm/day)
 900 over the Mediterranean basin plotted as a function of global warming level (in
 901 C) and a 'storyline index' that represents the uncertainty in the pattern of
 902 circulation change in the region. The high impact storyline corresponds to the
 903 combination of strong tropical upper tropospheric amplification of surface
 904 warming and a strengthening of the stratospheric polar vortex, and the low
 905 impact storyline to weak tropical upper tropospheric amplification of surface
 906 warming and a weakening of the polar vortex. The light blue dashed line
 907 represents a magnitude of change that is statistically detectable, and the dark
 908 blue dashed line to one standard deviation of the interannual variability. In

909 the left panel, the standard representation of the difference between global
 910 warming levels of 1.5 C and 2.0 C is shown, taking the low and high impact
 911 storylines as spanning a range of uncertainty. In the right panel, differences
 912 are shown conditioned on different storylines. Adapted from [16].



913

914 **Figure 3.** Surface conditions derived from infrared remote sensing for a small
 915 region in central France, for 1 August 2000 (left panels) and 10 August 2003
 916 (right panels). The top panels show the normalized difference vegetation
 917 index (NDVI), with the red colours indicative of vegetation. The lower panels
 918 show the radiometric temperature, with the colour scale at the bottom. The
 919 distance scale is shown in the lower-right panel, and the values given in the
 920 right panels indicate the average differences in those parts of the scene
 921 between the left and right panels. Adapted from [45].



922

923 **Figure 4.** A causal network describing regional climate risk. The arrows
 924 indicate the directions of causal influence. See text for details.