



Vulnerability and adaptation to climate change in water hazard assessments using regional climate scenarios in the Tokyo region

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Dynamic Downscaling



Dynamic Downscaling Categories

Castro, C.L., R.A. Pielke Sr., and G. Leoncini, 2005: Dynamical downscaling: Assessment of value retained and added using the Regional Atmospheric Modeling System (RAMS). *J. Geophys. Res. - Atmospheres*, 110, No. D5, D05108, doi:10.1029/2004JD004721.

Downscaling Categories

Type 1

Regional Day-to-day regional weather prediction

Type 2

Regional Seasonal weather simulation

Type 3

Regional Season weather prediction

Type 4

Regional Multiyear climate prediction

From top to bottom of table: more constraints to fewer constraints; from bottom to top of table: less predictive skill to greater

Type 1 = Regional Numerical Weather Prediction

Type 1: The regional dynamic model is forced by lateral boundary conditions from a numerical global model weather prediction or global data reanalysis at regular time intervals (typically 6 or 12 h), by bottom boundary conditions (e.g., terrain, soil moisture, etc.), and **specified regional atmospheric initial conditions**. A numerical global model weather prediction is one in which the initial atmospheric conditions are not yet forgotten.

Type 1 are called **“numerical weather prediction models”**. This application of dynamic downscaling is of considerable value as it is the basis for our short-term weather forecasts.

Type 2 = Regional Weather Simulations

Type 2: The regional dynamic model initial atmospheric conditions have been **forgotten**, but results are still dependent on the lateral boundary conditions from a numerical global model weather prediction model (in which the initial atmospheric conditions are not yet forgotten) or a global data reanalysis, and on the bottom boundary conditions.

Type 2 includes using regional runs using ERA-40 or NCEP Reanalyses, for example, as the best-estimate of the large scale atmospheric structure at selected time intervals (e.g., 6 hours). Reanalyses use a combination of real world observations that are inserted into a model in order to obtain the most accurate description (diagnosis) of the atmospheric distribution of temperature, humidity, winds, etc as possible. **This type of dynamic downscaling permits us to test the maximum forecast skill that is achievable with Type 3 and 4 downscaling.**

Type 3 = Regional Seasonal Weather Prediction

Type 3: The regional dynamic model lateral boundary conditions are provided from a numerical global model prediction model which is forced with specified real-world surface boundary conditions, but in which its initial atmospheric conditions are forgotten. Type 3 includes seasonal forecasts in which certain climate system attributes, such as sea surface temperature are prescribed. This type of dynamic downscaling is at the frontier of assessing how far into the future we can produce skillful weather forecasts.

Multi-RCM Ensemble Downscaling of Multi-GCM Seasonal Forecasts (MRED)

Raymond W. Arritt, Iowa State University, Ames, Iowa

Multi-RCM Ensemble Downscaling of multi-GCM Seasonal Forecasts

Objective: Demonstrate the usefulness of multi-model downscaling of global seasonal forecasts for hydrologic applications.

- Evaluate usefulness of dynamical downscaling for seasonal prediction over the coterminous U.S.:
 - Studies of dynamical downscaling have mostly focused on climate projections.
 - Evaluate strategies for producing **ensembles of downscaled seasonal predictions.**
- Provide predictions at higher resolution and regional level for **hydrologic applications.**

From:

http://www.eol.ucar.edu/projects/cppa/meetings/200809/presentations/Tuesday/T0930_Arritt.pdf

Type 4 = Regional Climate Prediction

Type 4: Lateral boundary conditions from a coupled earth system global climate model in which the atmosphere-ocean-biosphere and cryosphere are interactive. **Other than terrain, all other components of the climate system are predicted and are not constrained by real world observations.** Type 4 includes the 2007 IPCC runs that claim to predict climate decades from now. Type 4 downscaling, while the basis for 21st century climate change impacts, has not demonstrated predictive skill.

Dependence of Regional Model on Indicated Real World **Constraints** – Bottom Boundary Conditions

- Type 1 – e.g., terrain; soils; observed vegetation [LDAS]; prescribed deep soil moisture and temperatures; observed SSTs
- Type 2- e.g., terrain; soils; observed vegetation (perhaps); prescribed deep soil moisture and temperatures; observed ocean temperatures
- Type 3- e.g., terrain; climatological vegetation (perhaps) ; observed ocean temperatures; prescribed deep soil moisture and temperatures
- Type 4 – e.g., terrain; soils – **vegetation, ocean temperatures, deep soil moisture and temperatures must be predicted.**

Dependence of Regional Model on Indicated Constraints – Real World Initial Conditions

- Type 1 – e.g., ETA analysis field
- Type 2 - none
- Type 3 - none
- Type 4 – none

The atmospheric structure in the interior of the regional model must be predicted and/or nudged from the global model (or reanalysis)

Dependence of Regional Model on Indicated Constraints – Real World Lateral Boundary Conditions

Type 1 – e.g., Global Forecast System
Atmospheric – Real world observations are included

Type 2 – e.g., NCEP Reanalysis – Real world observations are included

Type 3 – e.g., global model forced by observed SSTs – **Global atmospheric structure must be skillfully predicted**

Type 4 – e.g., IPCC; U.S. National Assessment global model runs – **Global atmospheric and ocean structure must be skillfully predicted**

However, accurate (regional resolution) Lateral Boundary Conditions Require REGIONAL SCALE Information FROM A GLOBAL MODEL WHICH DOES NOT HAVE REGIONAL SCALE RESOLUTION!

This Is A Classic “Catch-22”.

A **Catch-22** a logical paradox arising from a situation in which the regional model needs something that can only be acquired by a regional model (or regional observations); therefore, the acquisition of this lateral boundary conditions with the needed spatial resolution becomes logically impossible.

The Catch-22

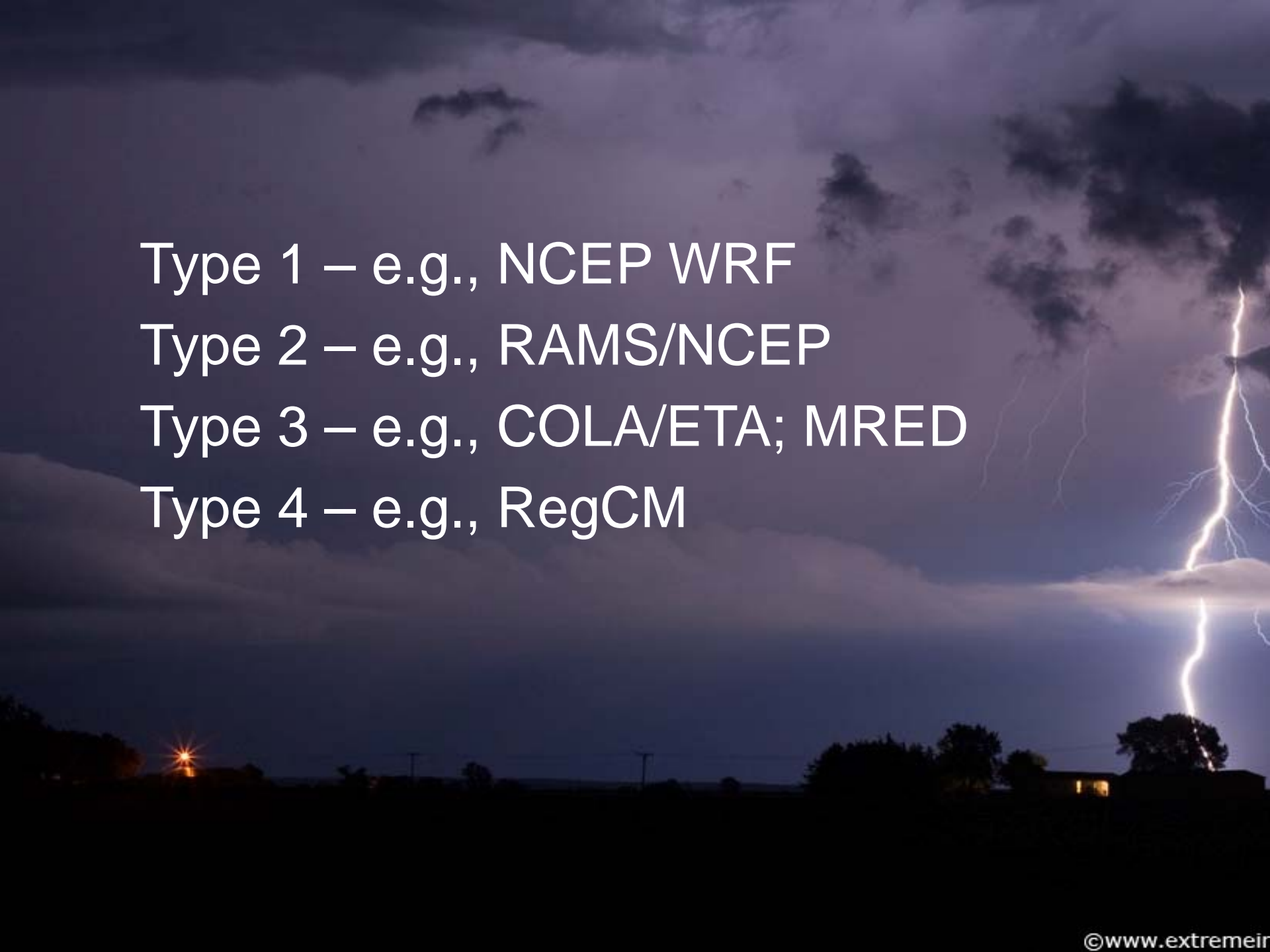
The Catch-22 is that:

With a global reanalysis the data is sampled from the real world which does have regional and smaller effects implicit in the data.

*With a global prediction model, once it has forgotten its initial conditions, **it knows nothing about the regional and smaller scales.***

Another Issue - One-Way Versus Two-Way Downscaling

One-Way Interaction Between The Regional and Global Models Is Not Physically Consistent

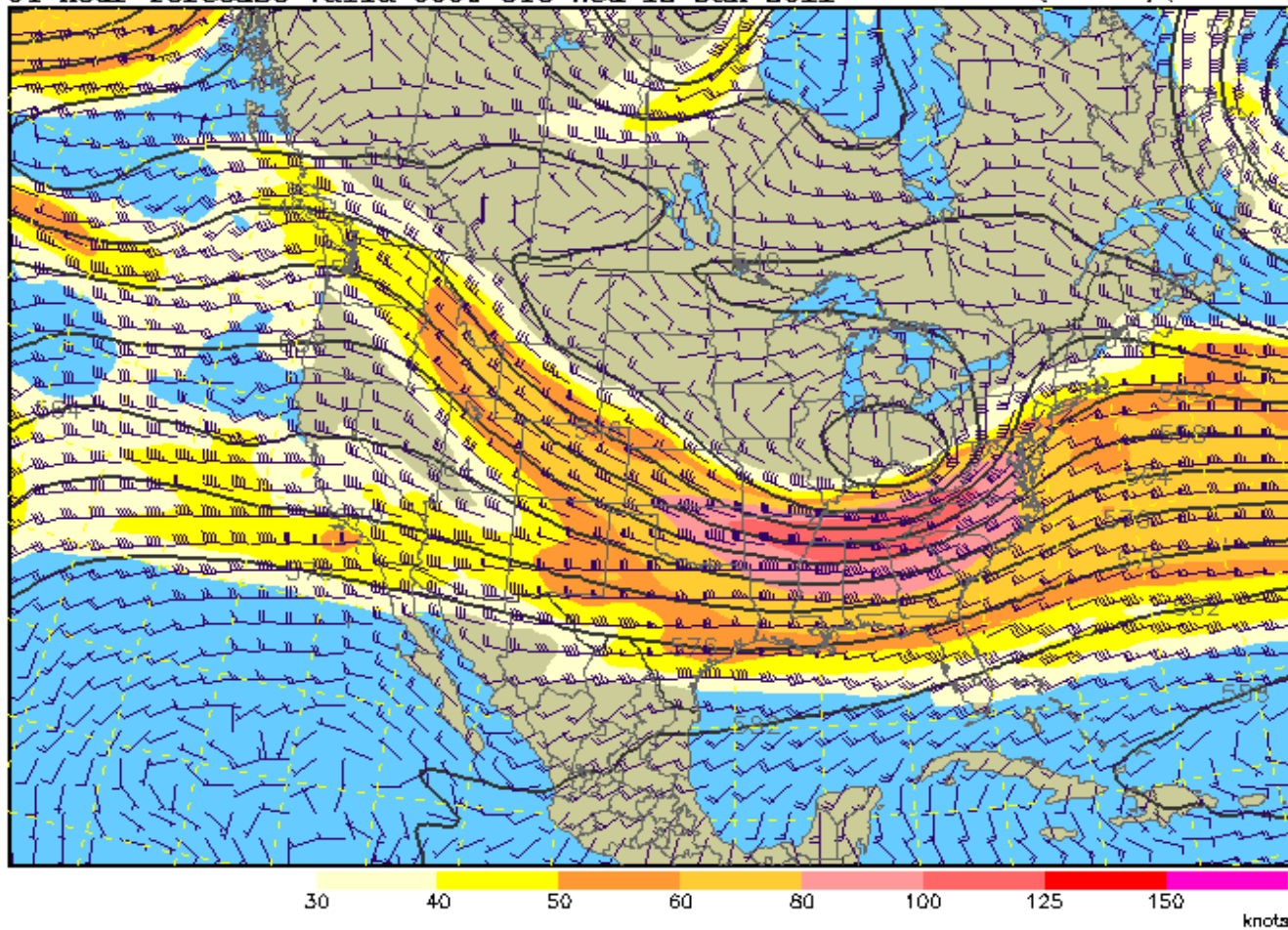


Type 1 – e.g., NCEP WRF
Type 2 – e.g., RAMS/NCEP
Type 3 – e.g., COLA/ETA; MRED
Type 4 – e.g., RegCM

500 mb Heights (dm) / Isotachs (knots)

84-hour forecast valid 0000 UTC Wed 12 Jan 2011

NAM (WRF-NMM) (12z 08 Jan)



Deterioration Of Predictability



Necessarily, the prediction skill decreases as one moves from Type 1 to Type 2 to Type 3 to Type 4 since progressively more climate variables must be predicted rather than prescribed from observations

Dynamic Downscaling Prediction Skill Level Of Climate Scenarios In The Tokyo Region

Type 1 > Type 2 > Type 3

>Type 4 = ~0

The Multi-Decadal Global Climate Model Predictions Must Include All First-Order Climate Forcings and Feedbacks That Impact Lateral Boundary Conditions Of The Regional Model

They Do Not; e.g., see

National Research Council, 2005: Radiative forcing of climate change: Expanding the concept and addressing uncertainties. Committee on Radiative Forcing Effects on Climate Change, Climate Research Committee, Board on Atmospheric Sciences and Climate, Division on Earth and Life Studies, The National Academies Press, Washington, D.C., 208 pp.

Comparing With Observations To Assess Regional Forecast Skill

Type 1 – Millions of Times – Numerical Weather Prediction

Type 2 - Numerous papers where a Regional Reanalysis (e.g., NARR) can be used to compare with the regional model prediction

Type 3 - On the Frontier of Testing; e.g.,

Castro, C.L., R.A. Pielke Sr., J. Adegoke, S.D. Schubert, and P.J. Pegion, 2007: Investigation of the summer climate of the contiguous U.S. and Mexico using the Regional Atmospheric Modeling System (RAMS). Part II: Model climate variability. *J. Climate*, 20, 3866-3887.

Castro, C.L., R.A. Pielke Sr., and J. Adegoke, 2007: Investigation of the summer climate of the contiguous U.S. and Mexico using the Regional Atmospheric Modeling System (RAMS). Part I: Model climatology (1950-2002). *J. Climate*, 20, 3844-3865.

Arritt, R. (current project underway) Multi-RCM Ensemble Downscaling of Multi-GCM Seasonal Forecasts (MRED)

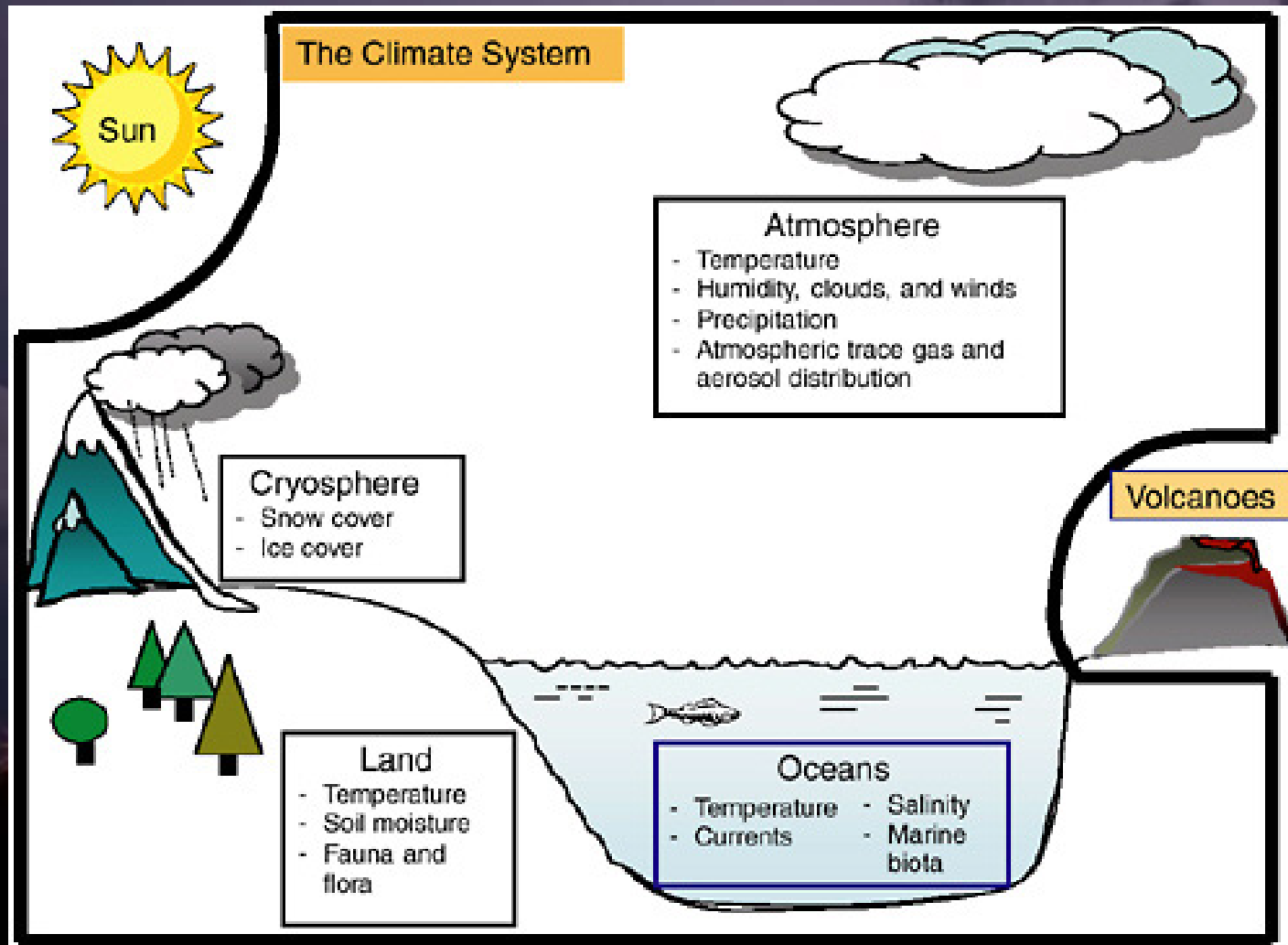
Type 4 - None

Forecasting Weather Versus Weather Statistics (Climatology)

The only difference between weather forecasts of daily weather and the forecasts of the statistics of weather (i.e., “climatology) is **the averaging time.**

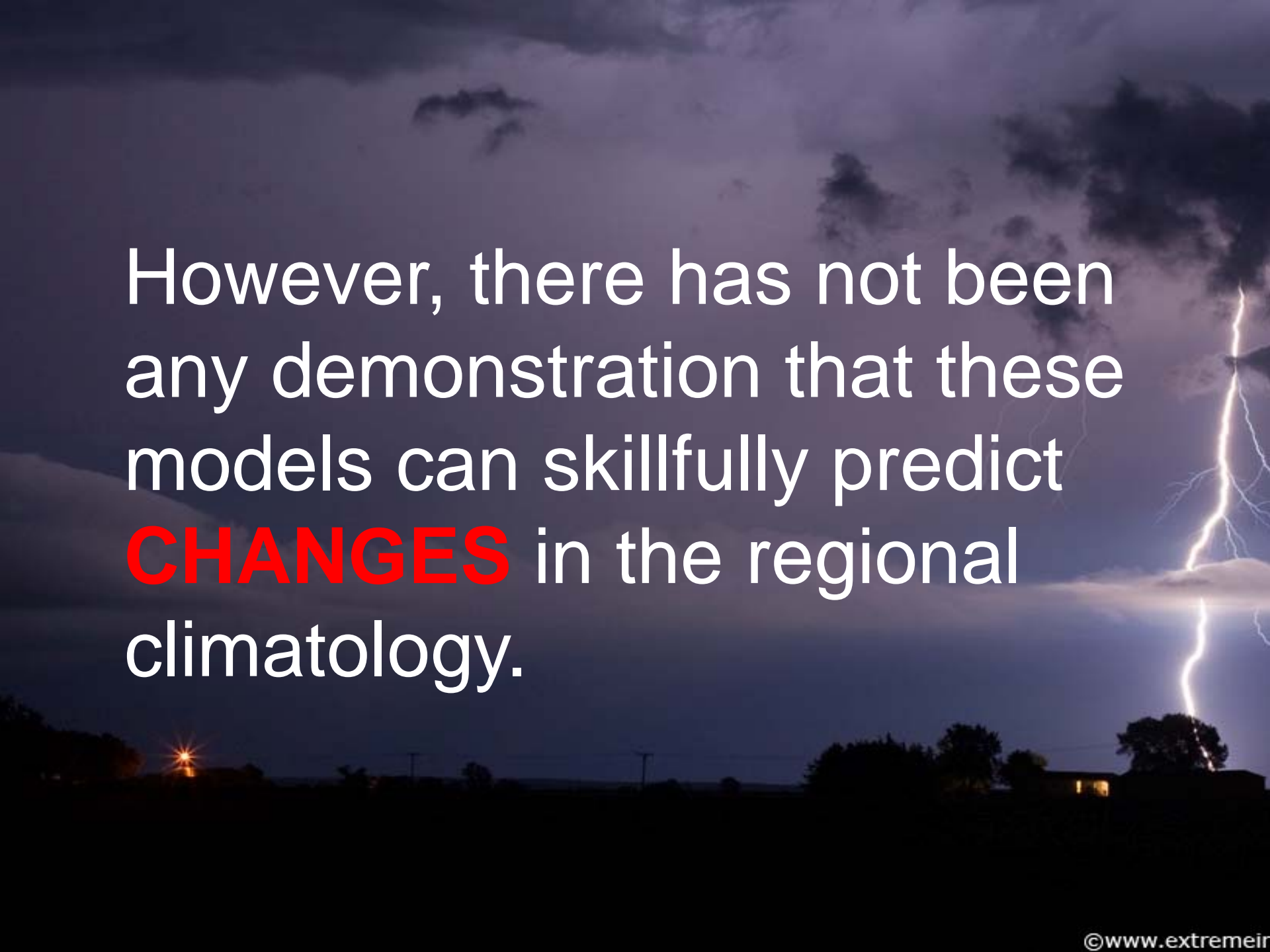
For example, a 24 hour average temperature for tomorrow, January 20 2011 is clearly considered weather. However, so is the 2011-2020 average temperature for those ten January 20^{ths}.

Climatology, however, is not the same as Climate!



The Challenge For Type 4 Dynamic Downscaling For The Impacts Community

- The Impacts community needs the best estimates of both the regional climatology and, more broadly, the regional climate of the future.
- For the downscaling regional (and global) models to add value over and beyond what is available from the historical, recent paleo-record, and worse case sequence of days, is to be able to skillfully predict the **CHANGES** in the regional weather statistics.



However, there has not been any demonstration that these models can skillfully predict **CHANGES** in the regional climatology.

Conclusion #1

**Type 4 Dynamic Downscaling
From Multi-Decadal Global
Model Projections Cannot Add
Spatial and Temporal Accuracy
Of Value To The Impacts
Community**

Statistical Downscaling



Value Of Statistical Downscaling As The “Benchmark Of Skill”

Statistical downscaling from the parent global model should be used as the benchmark (control) with which dynamic downscaling would have to improve on.

An excellent example of this type of testing is given in the paper Landsea, C.W., Knaff, J.A., 2000: “How much skill was there in forecasting the very strong 1997-98 El Niño?” Bulletin of the American Meteorological Society, 81.

Among their insight conclusions from this seminal paper is

“..... the use of more complex, physically realistic dynamical models does not automatically provide more reliable forecasts. Increased complexity can increase by orders of magnitude the sources for error, which can cause degradation in skill.”

Type 1 Statistical Downscaling

Type 1: The regional statistical model is trained from the output of a numerical global model weather prediction and/or a regional dynamically downscaled numerical weather prediction model, or a global data reanalysis, at regular time intervals (e.g., 6 or 12 h). A numerical global model weather prediction is one in which the initial atmospheric conditions are not yet forgotten.

The Method of Model Output Statistics (MOS) and the Perfect Prog Method are two approaches of the statistical downscaling method. MOS permits the method to correct for systematic biases, while the Perfect Prog Method does not.

Type 1 statistical downscaling has been shown to be of considerable value in producing skillful short-term weather forecasts.

Type 2 Statistical Downscaling

Type 2: The regional statistical model is trained from the output of a numerical global model weather prediction, or a global data reanalysis, at regular time intervals (e.g. 6 or 12 h). A numerical global model weather prediction is one in which the initial atmospheric conditions are not yet forgotten (in which the initial atmospheric conditions are not yet forgotten), or a global data reanalysis. The initial conditions from a dynamically downscaled model, however, have been forgotten.

Type 2 statistical downscaling has less skill than Type 1 statistical downscaling since skillful finer (regional) scale real world observationally constrained information is not available as a predictor.

Type 3 Statistical Downscaling

Type 3: The regional statistical model conditions are provided from a numerical global model prediction model which is forced with specified real-world surface boundary conditions, but in which the initial atmospheric conditions of the global model have been forgotten.

Type 3 has even less skill than Type 2 since less real world observations are available as input to the predictors for the statistical downscaling model. However, since the equations used to train the statistical model were developed from real world observations, there is an assumption that the same relationship will hold for the dynamically predicted numerical model results.

Type 4 Statistical Downscaling

Type 4: The regional statistical model from a coupled earth system global climate model in which the atmosphere-ocean-biosphere and cryosphere are interactive and their evolution over time is predicted. Other than terrain, all other components of the climate system are predicted and are not constrained by real world observations.

As long as the relationship between the real world observations and the statistically predicted model results does not change, **the main issue is how accurate are the dynamically predicted Type 4 dynamic numerical model results. However, IF the statistical relationship changes in the future, this method will not provide the actual real world response.**

Conclusion #2

Statistical downscaling does add prediction skill for Type 1, 2, and perhaps, Type 3 applications. These downscaled results should be the benchmark to compare with dynamically downscaled regional model results.

Bias Corrected and Downscaled WCRP CMIP3 Climate Projections

“The principal weakness of any statistical downscaling method is the assumption of some stationarity.....the assumption is made that the relationship between large-scale precipitation and temperature and fine-scale precipitation and temperature in the future will be the same as in the past.”

WCRP CMIP3 Climate Projections

The WCRP CMIP3 Climate Projections are Type 4 statistical downscaling. They have the fundamental issues that they have to assume the statistical relationships are invariant in a changing climate AND the dynamically predicted numerical model results from which they derive their predictions are accurate.

The dynamic model predictions that they use, however, are the same as Type 4 that is used for dynamic downscaling! Type 4 dynamic downscaling has not been shown to have skill, and there is no reason to expect a better behavior for Type 4 statistical downscaling.

Wilby, R.L. and Fowler, H.J. 2010. Regional climate downscaling. In: Fung, C.F., Lopez, A. and New, M. (Eds.) Modelling the impact of climate change on water resources. Blackwell Publishing, Oxford.

*“The scientific community is developing regional climate downscaling (RCD) techniques to reconcile the scale mismatch between coarse-resolution OA/GCMs and location-specific information needs of adaptation planners.....It is becoming apparent, however, that downscaling also has serious practical limitations, especially where the meteorological data needed for model calibration may be of dubious quality or patchy, the links between regional and local climate are poorly understood or resolved, and where technical capacity is not in place. **Another concern is that high-resolution downscaling can be misconstrued as accurate downscaling (Dessai et al. 2009). In other words, our ability to downscale to finer time and space scales does not imply that our confidence is any greater in the resulting scenarios.”***

Conclusion # 3

The bottom line is that vast amounts of money are being spent for both dynamic and statistical downscaling predictions for decades from now that have absolutely no demonstrative skill.

Policymakers are being provided information that is at best, no worse than one can be achieved by using historical and recent paleo-climate information and/or worst case sequences of climate events.

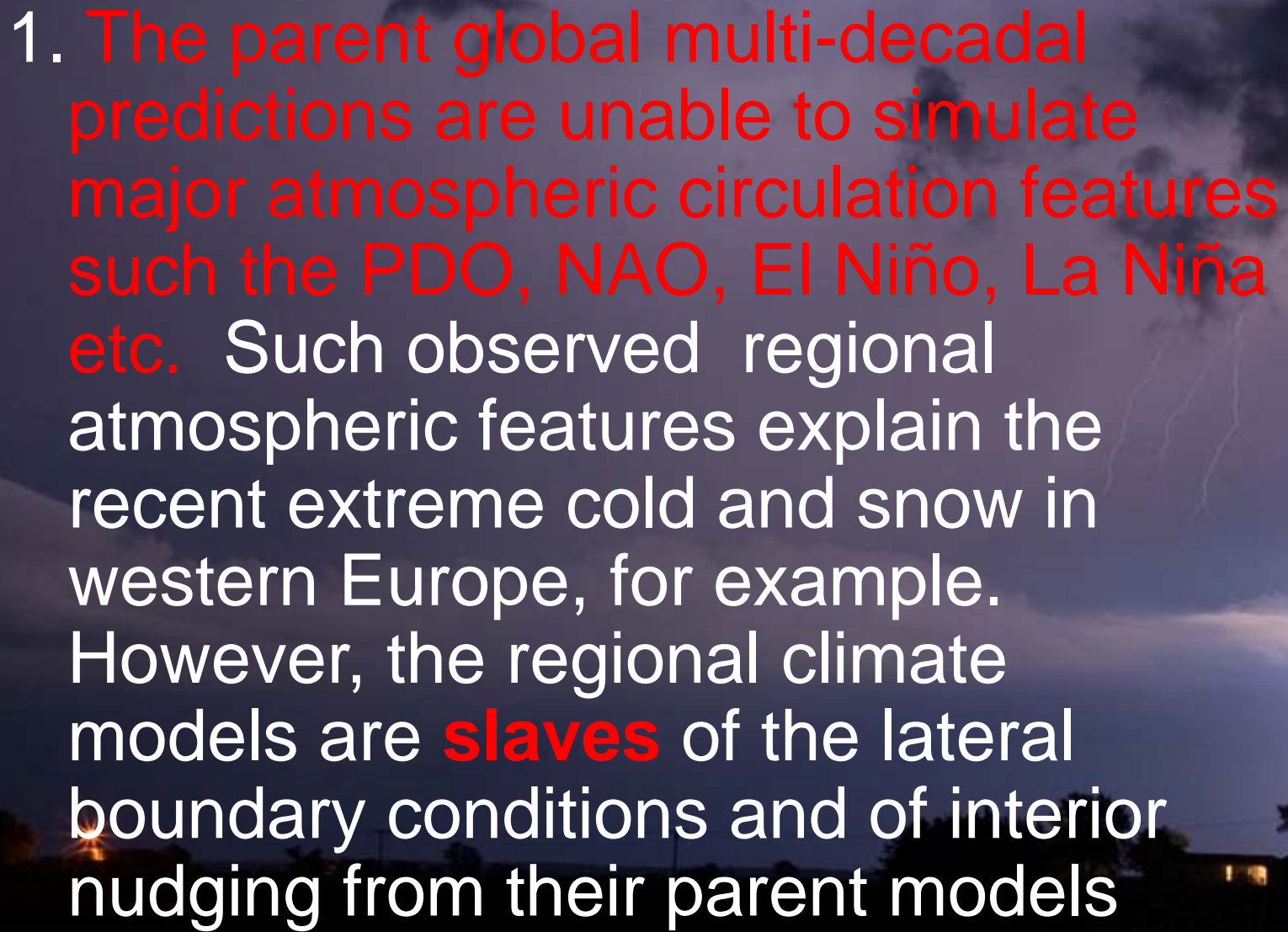
At worse, however, these predictions could be significantly misleading policymakers to the actual threats that our key resources of water, energy, food, human health and ecosystem face in the coming decades.

Conclusion #4

Statistical Downscaling From Multi-Decadal Global Model Projections (Type 4) Does Not Add Spatial and Temporal Accuracy Of Value To The Impacts Community

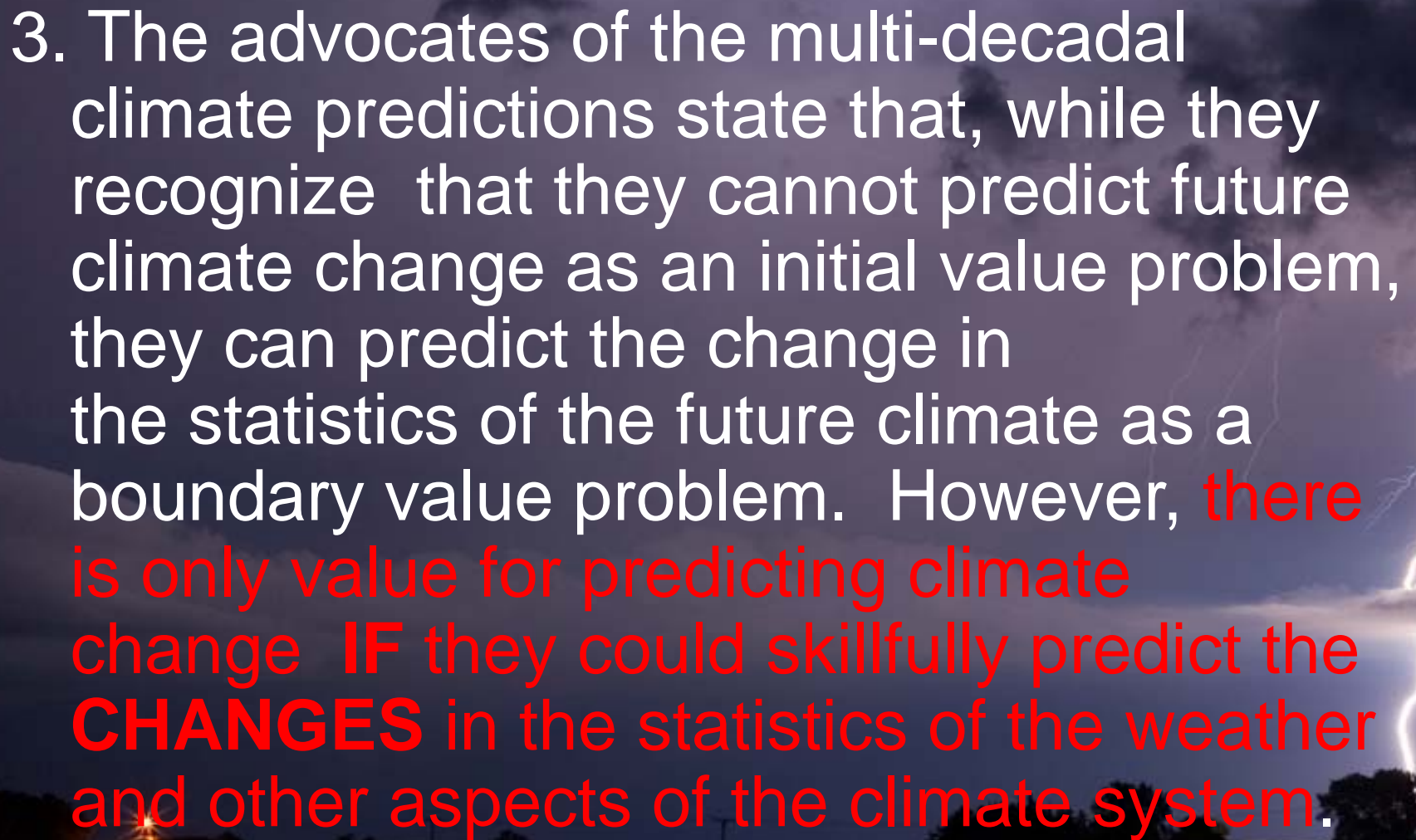
The Failure of Type 4 Dynamic and Statistical Downscaling

The reason for the necessary failure of the regional climate models (as a dead-end engineering and science tool) can be summarized in the following:

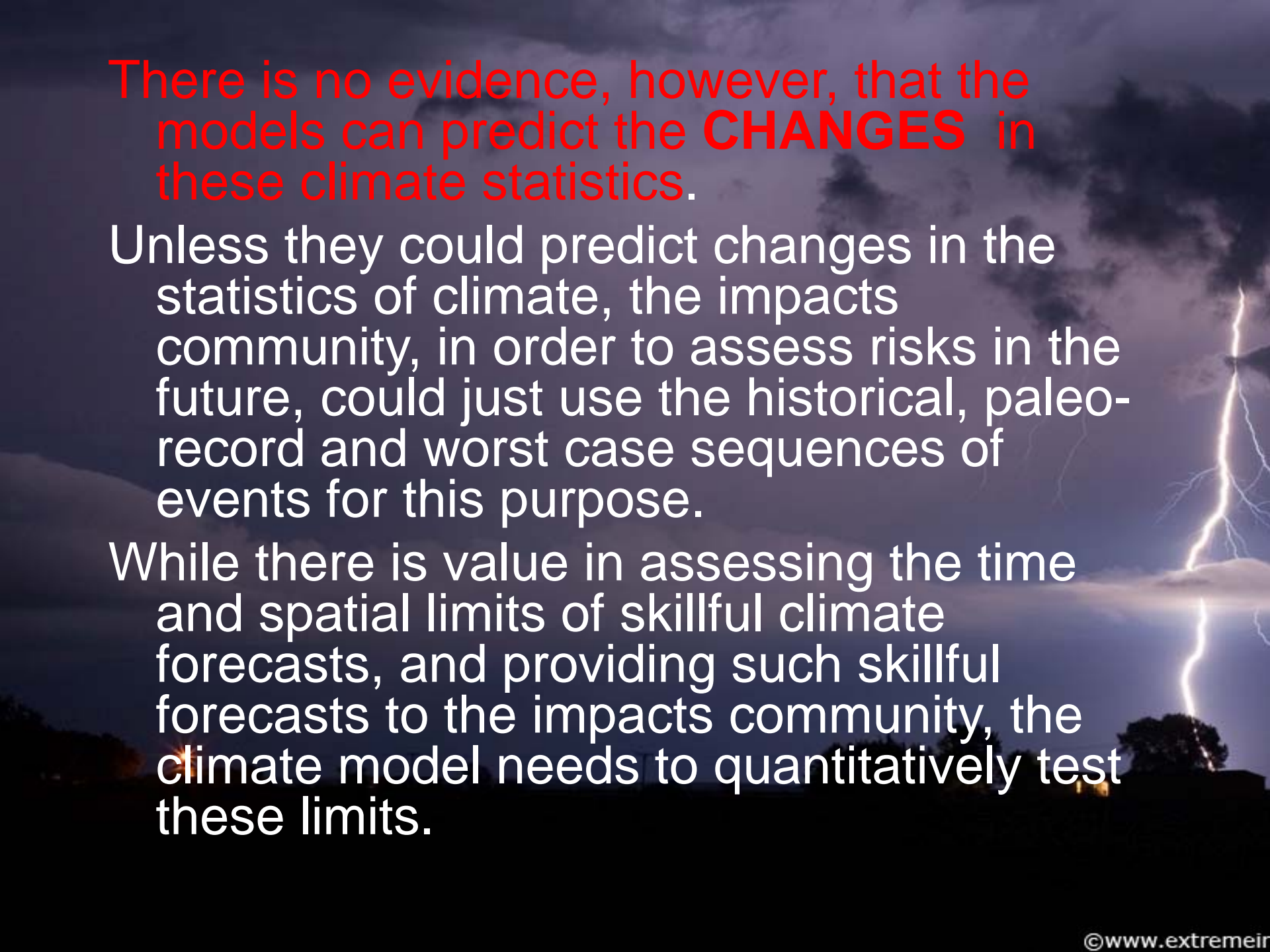


1. The parent global multi-decadal predictions are unable to simulate major atmospheric circulation features such the PDO, NAO, El Niño, La Niña etc. Such observed regional atmospheric features explain the recent extreme cold and snow in western Europe, for example. However, the regional climate models are **slaves** of the lateral boundary conditions and of interior nudging from their parent models

2. If the global multi-decadal climate model predictions cannot accurately predict the larger scale circulation features of PDO, NAO, El Niño, La Niña etc, there is no way they can provide accurate lateral boundary conditions and interior nudging to the regional climate models (RCMs). The RCMs themselves do not have the domain scale (or two-way interaction) to skillfully predict these larger scale atmospheric features.



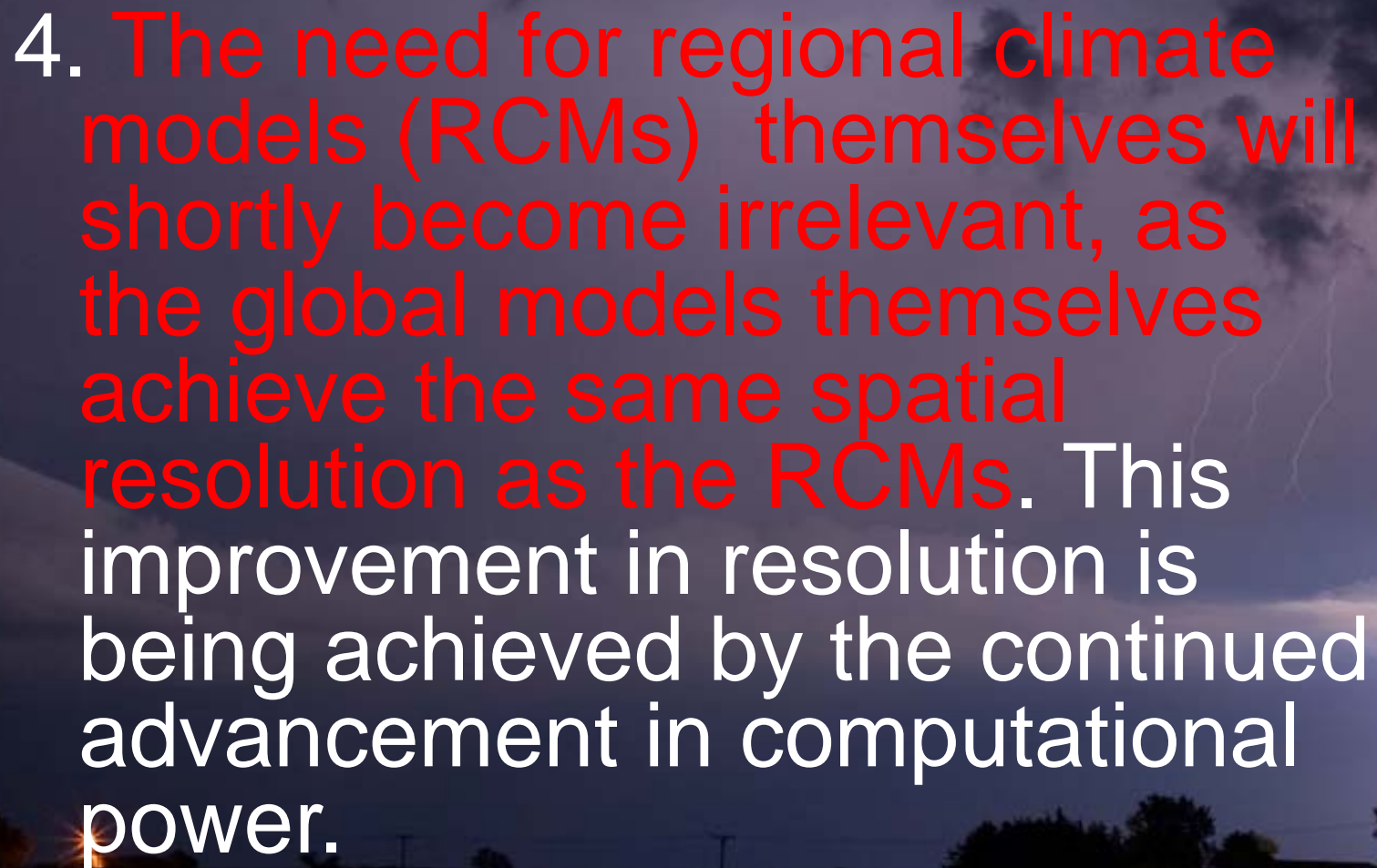
3. The advocates of the multi-decadal climate predictions state that, while they recognize that they cannot predict future climate change as an initial value problem, they can predict the change in the statistics of the future climate as a boundary value problem. However, **there is only value for predicting climate change IF they could skillfully predict the CHANGES in the statistics of the weather and other aspects of the climate system.**



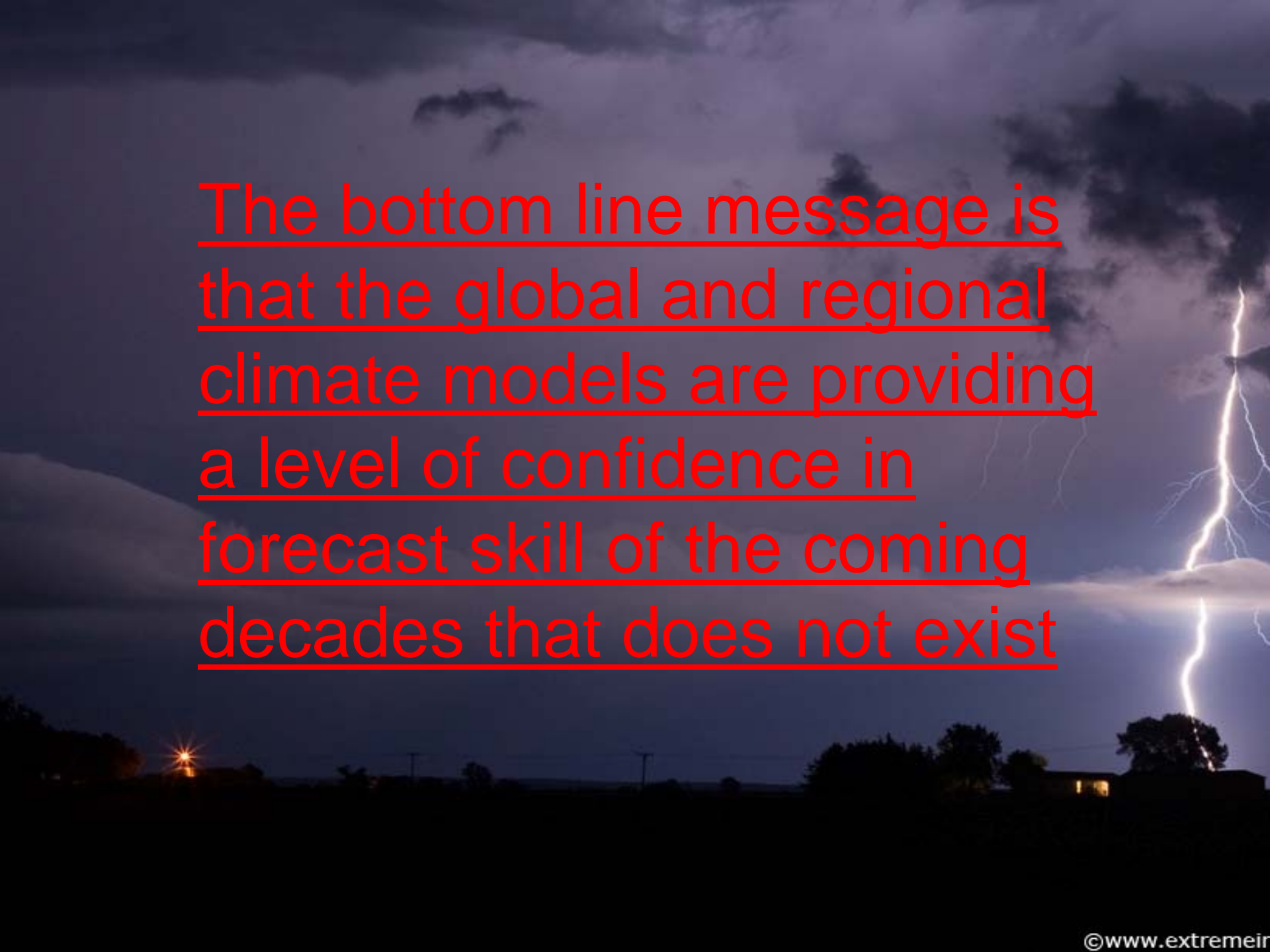
There is no evidence, however, that the models can predict the **CHANGES** in these climate statistics.

Unless they could predict changes in the statistics of climate, the impacts community, in order to assess risks in the future, could just use the historical, paleo-record and worst case sequences of events for this purpose.


While there is value in assessing the time and spatial limits of skillful climate forecasts, and providing such skillful forecasts to the impacts community, the climate model needs to quantitatively test these limits.



4. The need for regional climate models (RCMs) themselves will shortly become irrelevant, as the global models themselves achieve the same spatial resolution as the RCMs. This improvement in resolution is being achieved by the continued advancement in computational power.



The bottom line message is
that the global and regional
climate models are providing
a level of confidence in
forecast skill of the coming
decades that does not exist




I do, of course, support the goal of assessing the **predictability** of global and regional climate on seasonal, yearly and decadal time scales.

Predictability

The assessment of the ability to make skillful climate forecasts (by comparing with real-world observations – this is the evaluation of predictability), however, is not the same as providing predictions (forecasts) of climate change decades into the future for the impacts community. **Large amount of research funds are being wasted on multi-decadal climate change forecasts.**

Scientific Test Requirement

As a test for predictability, the dynamic downscaled predictions need to show skill over that achieved by using statistical downscaling from the parent model in a forecast (e.g., NCEP WRF) and/or hindcast mode. Unless the dynamic models can show skill above that achieved by the statistically downscaled results, they are not useful, and, indeed, will provide misleading, inaccurate results to policymakers and others.



As I have suggested, there is a much more effective and scientifically robust approach, as summarized in my post

A Way Forward In Climate Science Based On A Bottom-Up Resource-Based Perspective.

A Bottom-Up Resource-Based Focus

There are 5 broad areas that we can use to define the need for vulnerability assessments: **water, food, energy, human health, and ecosystem function**. Each area has societally critical resources. The vulnerability concept requires the determination of the major threats to these resources from climate, but also from other social and environmental issues.

After these threats are identified for each resource, then the relative risk from natural- and human-caused climate change (estimated from global and regional climate model predictions that have been shown to have quantifiable skill, but also from the historical, paleo-record and worst case sequences of events) can be compared with other risks in order to adopt the optimal mitigation/adaptation strategy.

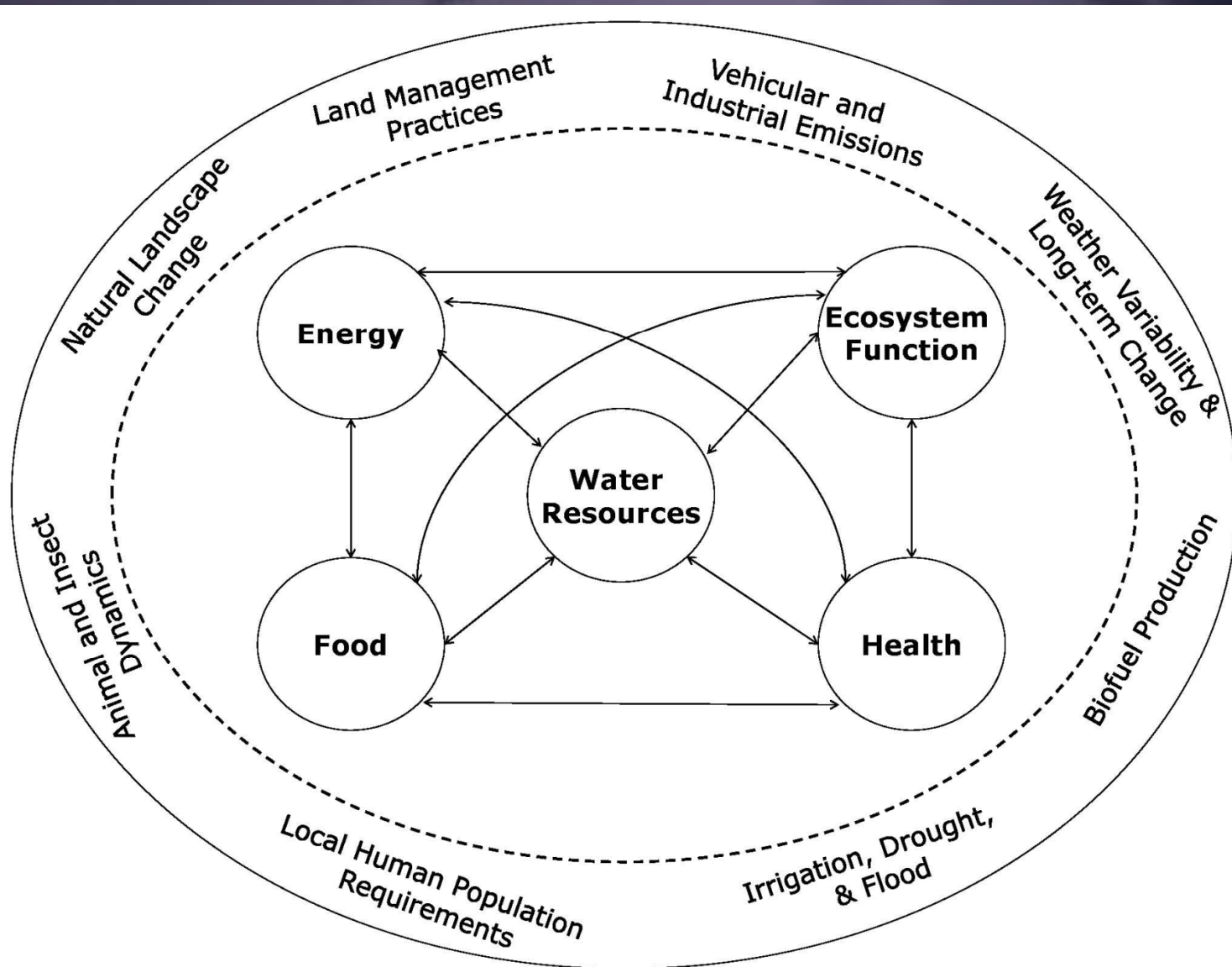
Stakeholder Questions

- 1. Why is this resource important? How is it used? To what stakeholders is it valuable?
- 2. What are the key environmental and social variables that influence this resource?
- 3. What is the sensitivity of this resource to changes in each of these key variables? (this includes, but is not limited to, the sensitivity of the resource to climate variations and change on short (e.g., days); medium (e.g., seasons) ,and long (e.g., multi-decadal) time scales.
- 4. What changes (thresholds) in these key variables would have to occur to result in a negative (or positive) response to this resource?
- 5. What are the best estimates of the probabilities for these changes to occur? What tools are available to quantify the effect of these changes. Can these estimates be skillfully predicted?
- 6. What actions (adaptation/mitigation) can be undertaken in order to minimize or eliminate the negative consequences of these changes (or to optimize a positive response)?
- 7. What are specific recommendations for policymakers and other stakeholders?

A Schematic Of The Bottom-Up, Resource-Based Perspective

Faisal Hossain, Dev Niyogi, James Adegoke, George Kallos, and Roger A. Pielke Sr., 2011: Making sense of the water resources that will be available for future use. Submitted to EOS.

Hossain et al. 2011 : Making sense of the water resources that will be available for future use. EOS (submitted)



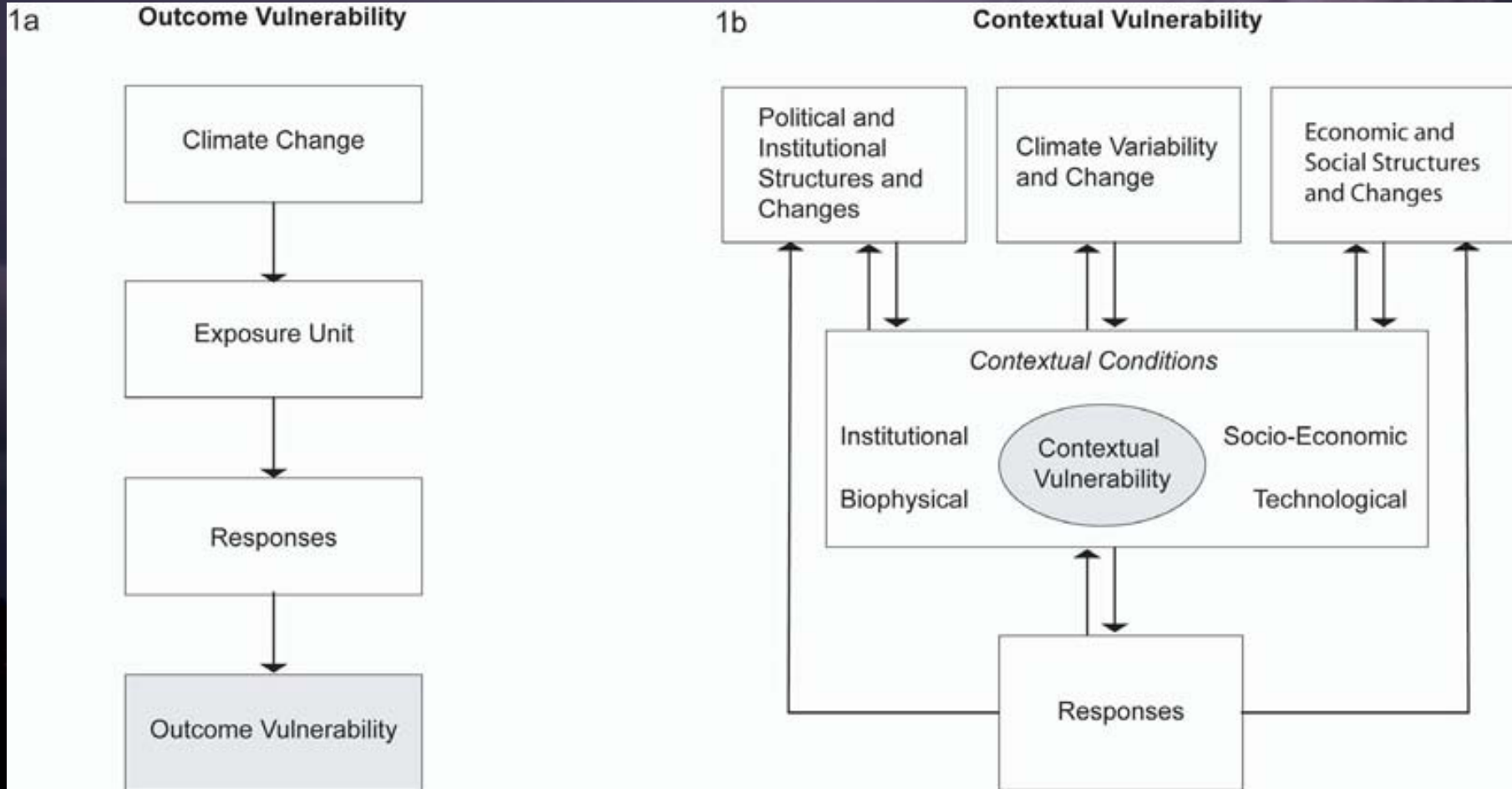
Types Of Vulnerability Frameworks

REVIEW AND QUANTITATIVE ANALYSIS
OF INDICES OF CLIMATE CHANGE
EXPOSURE, ADAPTIVE CAPACITY,
SENSITIVITY, AND IMPACTS

by

Hans-Martin Füssel Potsdam Institute for
Climate Impact Research (PIK), Germany

Figure 1: Frameworks depicting two interpretations of vulnerability to climate change: (a) outcome vulnerability; (b) contextual vulnerability.
Source: [O'Brien et al. 2007]



Two interpretations of vulnerability in climate change research. Source: [Füssel 2007]

	End-point interpretation	Starting-point interpretation
Root problem	Climate change	Social vulnerability
Policy context	Climate change mitigation, compensation, technical adaptation	Social adaptation, sustainable development
Illustrative policy question	What are the benefits of climate change mitigation?	How can the vulnerability of societies to climatic hazards be reduced?
Illustrative research question	What are the expected net impacts of climate change in different regions?	Why are some groups more affected by climatic hazards than others?
Vulnerability and adaptive capacity	Adaptive capacity determines vulnerability	Vulnerability determines adaptive capacity
Reference for adaptive capacity	Adaptation to future climate change	Adaptation to current climate variability
Starting point of analysis	Scenarios of future climate hazards	Current vulnerability to climatic stimuli
Analytical function	Descriptive, positivist	Explanatory, normative
Main discipline	Natural sciences	Social sciences
Meaning of 'vulnerability'	Expected net damage for a given level of global climate change	Susceptibility to climate change and variability as determined by socioeconomic factors
Qualification according to the terminology from Section 2	Dynamic cross-scale integrated vulnerability [of a particular system] to global climate change	Current internal socioeconomic vulnerability [of a particular social unit] to all climatic stressors
Vulnerability approach	Integrated, risk-hazard	Political economy
Reference	McCarthy et al. (2001)	Adger (1999)

From Pielke, R.A. Sr., and L. Bravo de Guenni, 2004: Conclusions. Chapter E.7 In: Vegetation, Water, Humans and the Climate: A New Perspective on an Interactive System. Global Change - The IGBP Series, P. Kabat et al., Eds., Springer, 537-538.

Table E.7. General characteristics of the scenario and vulnerability approaches as typically used

Approach	Scenario	Vulnerability
Assumed dominant stress	Climate, recent greenhouse gas emissions to the atmosphere, ocean temperatures, aerosols, etc.	Multiple stresses: climate (historical climate variability), land use and water use, altered disturbance regimes, invasive species, contaminants/pollutants, habitat loss, etc.
Usual timeframe of concern	Long-term, doubled CO ₂ , 30 to 100 years in the future.	Short-term (0 to 30 years) and long-term research.
Usual scale of concern	Global, sometimes regional. Local scale needs downscaling techniques. However, there is little evidence to suggest that present models provide realistic, accurate, or precise climate scenarios at local or regional scales.	Local, regional, national and global scales.
Major parameters of concern	Spatially averaged changes in mean temperatures and precipitation in fairly large grid-cells with some regional scenarios for drought.	Potential extreme values in multiple parameters (temperature, precipitation, frost-free days) and additional focus on extreme events (floods, fires, droughts, etc.); measures of uncertainty.
Major limitations for developing coping strategies	<p>Focus on single stress limits preparedness for other stresses.</p> <p>Results often show gradual ramping of climate-change-limiting preparedness for extreme events.</p> <p>Results represent only a limited subset of all likely future outcomes – usually unidirectional trends.</p> <p>Results are accepted by many scientists, the media, and the public as actual "predictions".</p> <p>Lost in the translation of results is that all models of the distant future have unstated (presently unknowable) levels of certainty or probability.</p>	<p>Approach requires detailed data on multiple stresses and their interactions at local, regional, national and global scales – and many areas lack adequate information.</p> <p>Emphasis on short-term issues may limit preparedness for abrupt "threshold" changes in climate some time in the short- or long-term.</p> <p>Requires preparedness for a far greater variation of possible futures, including abrupt changes in any direction – this is probably more realistic, yet difficult.</p>

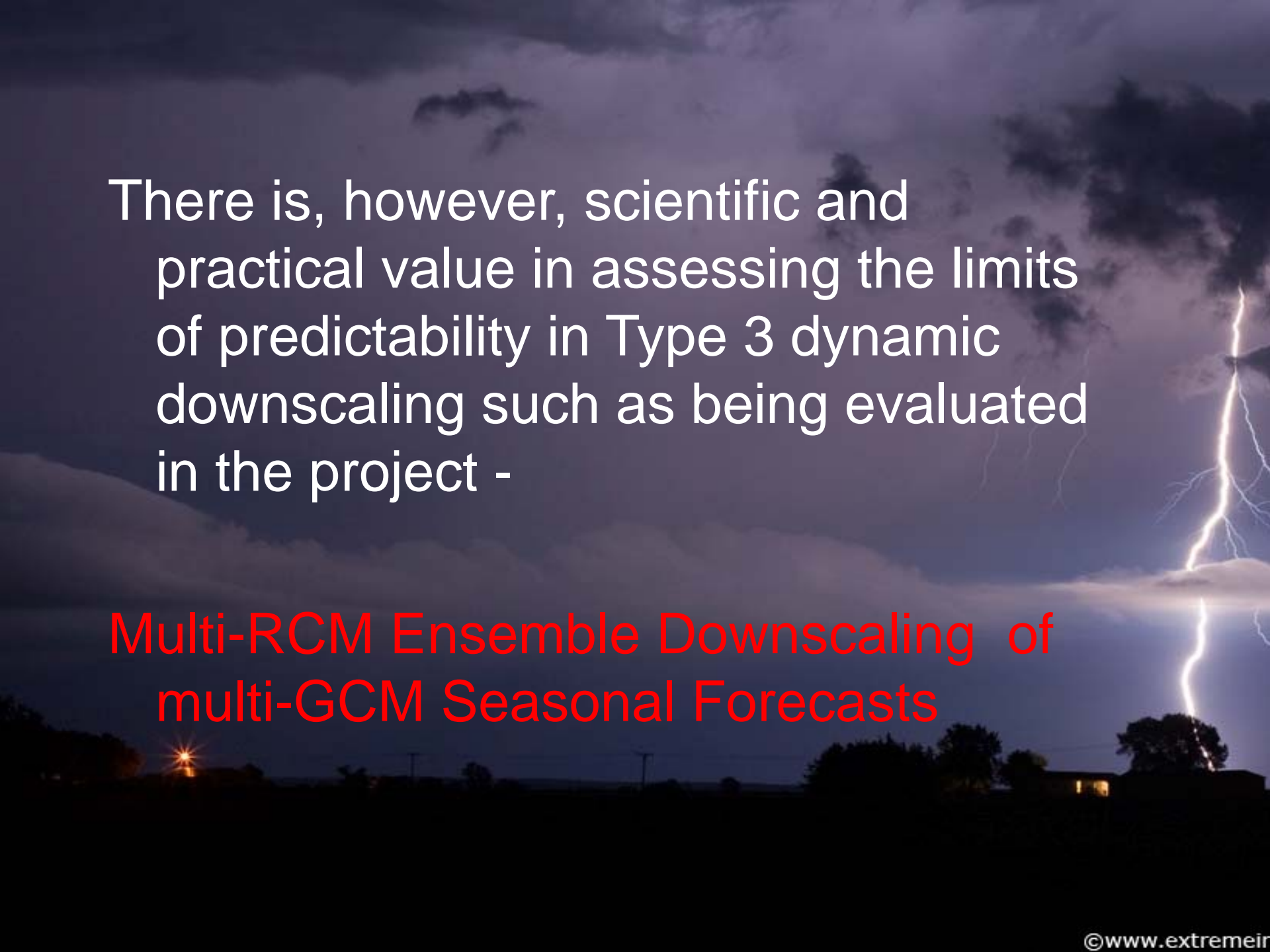
Conclusion

Is there value-added using regional climate scenarios in the Tokyo region?

Yes- But not with Type 4 dynamic and statistical downscaling.

A more scientifically robust approach is to use for “what if” scenarios include;

- The historical record
- The recent pale-record
- Worst case sequence of weather events
- Arbitrary changes of water vapor, temperatures, etc at the lateral boundaries of a regional model downscaled from a global reanalysis



There is, however, scientific and practical value in assessing the limits of predictability in Type 3 dynamic downscaling such as being evaluated in the project -

Multi-RCM Ensemble Downscaling of multi-GCM Seasonal Forecasts



Thank you for inviting
me to present my talk!

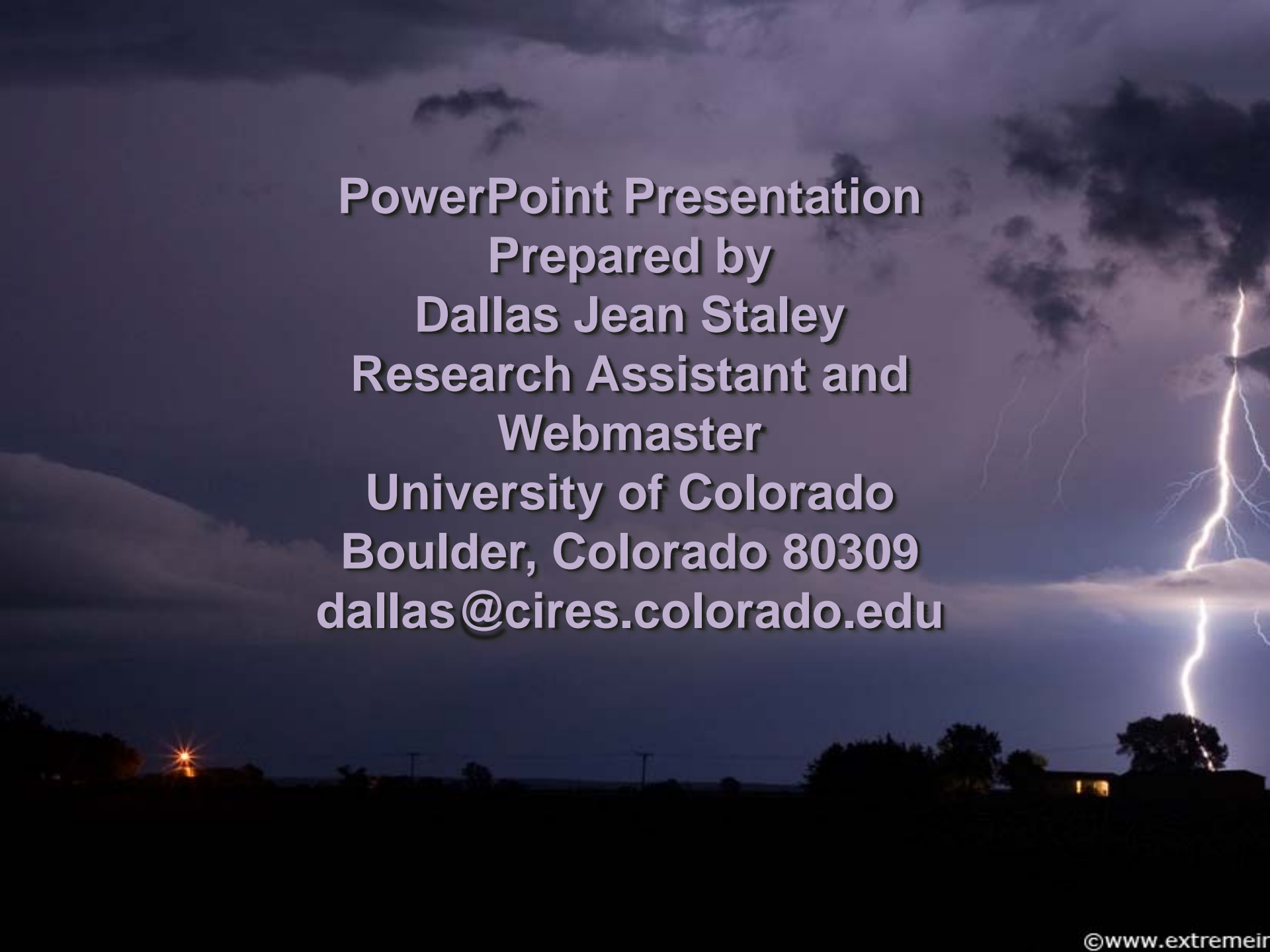


**Background Photograph Courtesy
of Mike Hollingshead
<http://www.extremeinstability.com/>**

Roger Pielke Sr. Research Websites

<http://pielkeclimatesci.wordpress.com/>

<http://cires.colorado.edu/science/groups/pielke/>



PowerPoint Presentation
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