PARADIGM SHIFTS IN ATMOSPHERIC SCIENCE

BY ROGER A. PIELKE SR
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AT

DEPARTMENT OF HYDROLOGY AND ATMOSPHERIC SCIENCES
UNIVERSITY OF ARIZONA
FEBRUARY 1 2018 4 pm in Harshbarger 206

Outline of Talk

1. GRAINEX
2. Environmental Vulnerability
3. Butterfly Effect
4. Atmospheric Dynamic and Thermal Compression Waves
5. Use of Artificial Intelligence (AI) for Weather Prediction


TOPIC #1
GRAINEX
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The Great Plains Irrigation Experiment (GRAINEX) for Understanding the Influence of Irrigation on the Planetary Boundary Layer and Weather Events

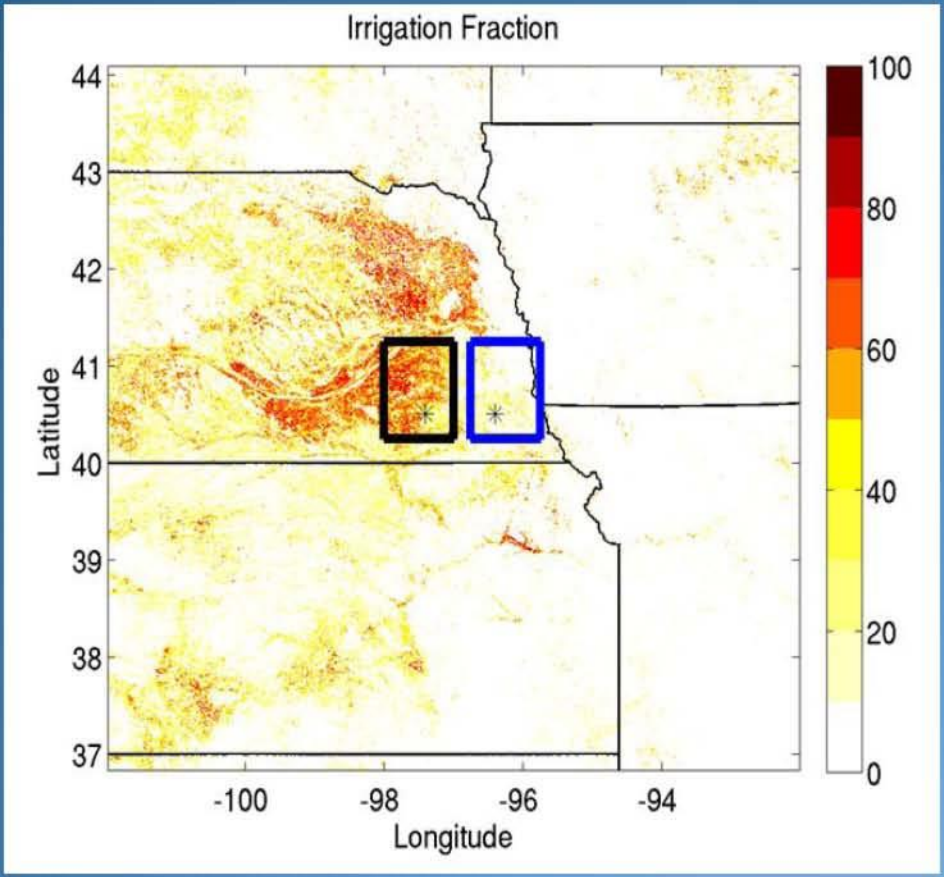
Rezaul Mahmood

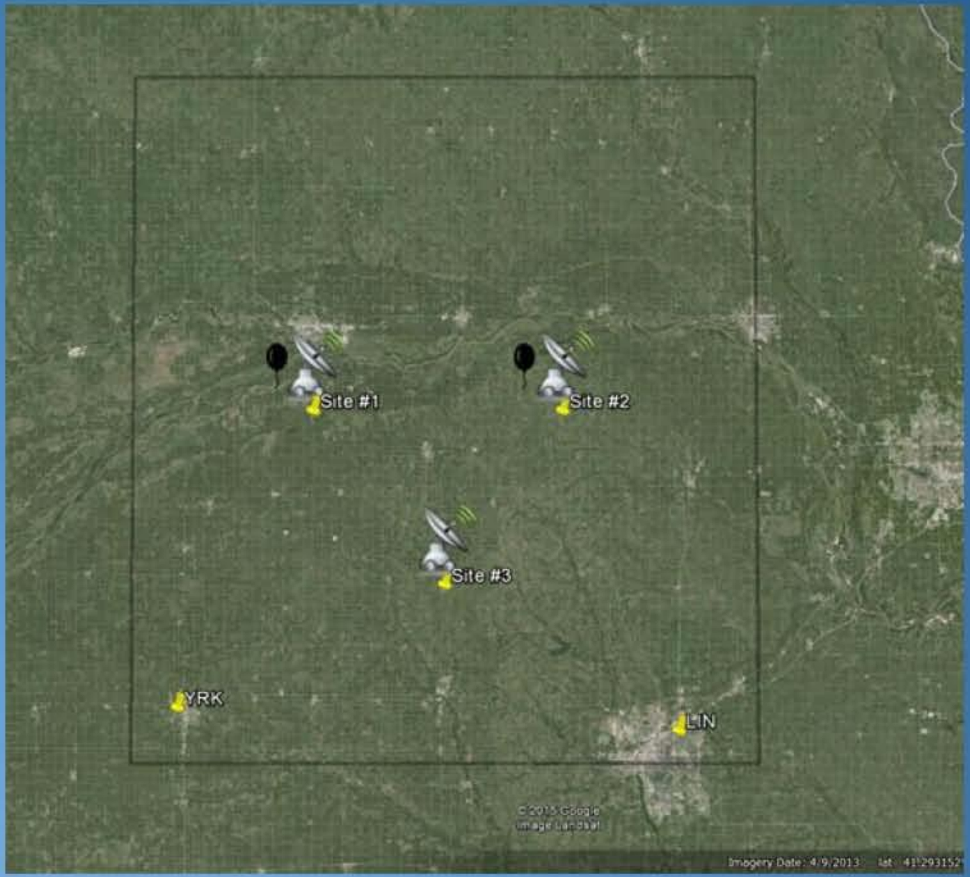
Udaysankar Nair

Eric Rappin

Roger A. Pielke Sr.

Dallas Staley





Irrigation fraction and proposed radiosonde launching sites in Nebraska (shown in asterisks). Black and blues boxes indicate irrigated and non-irrigated areas.

MISS sites: York (YRK) & Lincoln (LIN) - 100 km apart
Site 1, 2, and 3: approx. locations for DOWs
Balloon icons: Sites where additional ABL will be monitored using radiosondes and ground-based remote sensing. Sites are approximately 50 km apart

Hypothesis

Temporally rapid and spatially widespread commencement of irrigation at the beginning of the growing season in the North American Great Plains significantly alters the evolution of the planetary boundary layer, weather events, and land atmosphere coupling.

Intra-seasonal variations, including mid-growing season enhancement of irrigation due to increased crop-water demand also have similar impacts.

Objectives

- Investigate impacts of *temporally rapid and spatially widespread* commencement of irrigation in the Great Plains (GP) and resultant changes in land-atmosphere (L-A) coupling in spring at beginning of the growing season. *Annual introduction of irrigation comparable to binary switch where land surface experiences rapid transformation from low soil moisture (no irrigation) to high/saturated soil moisture (irrigation).*

- Collect observations to quantify changes in land-atmosphere coupling over a 100 km x 100 km study area in the Great Plains to *temporally rapid and spatially widespread* commencement of irrigation. Annual introduction of irrigation is comparable to *binary switch* where land surface experiences rapid transformation from water-limited conditions (no irrigation) to high/saturated soil moisture (irrigation).

Objectives cont’d

- Observationally characterize the response of boundary layer evolution to changes in land-atmosphere coupling related to irrigation.
- Observe atmospheric circulation features in the study region that are modulated by land-atmosphere coupling.
- Conduct a quantitative/modeling analysis to determine the role of irrigation forcing on process pathways that leads to changes in cloud and precipitation formation in the region.
- Develop an observational dataset that allow for the most comprehensive process study of irrigation forcing to date.

TOPIC #2

Is the current top-down global climate model based approach to assess environmental vulnerability of water resources, energy, food, ecosystem function, and human health a robust approach?

Paris 1.5 C/ 2 C Global Surface Temperature Metric Is Used to Assess Environmental Vulnerability

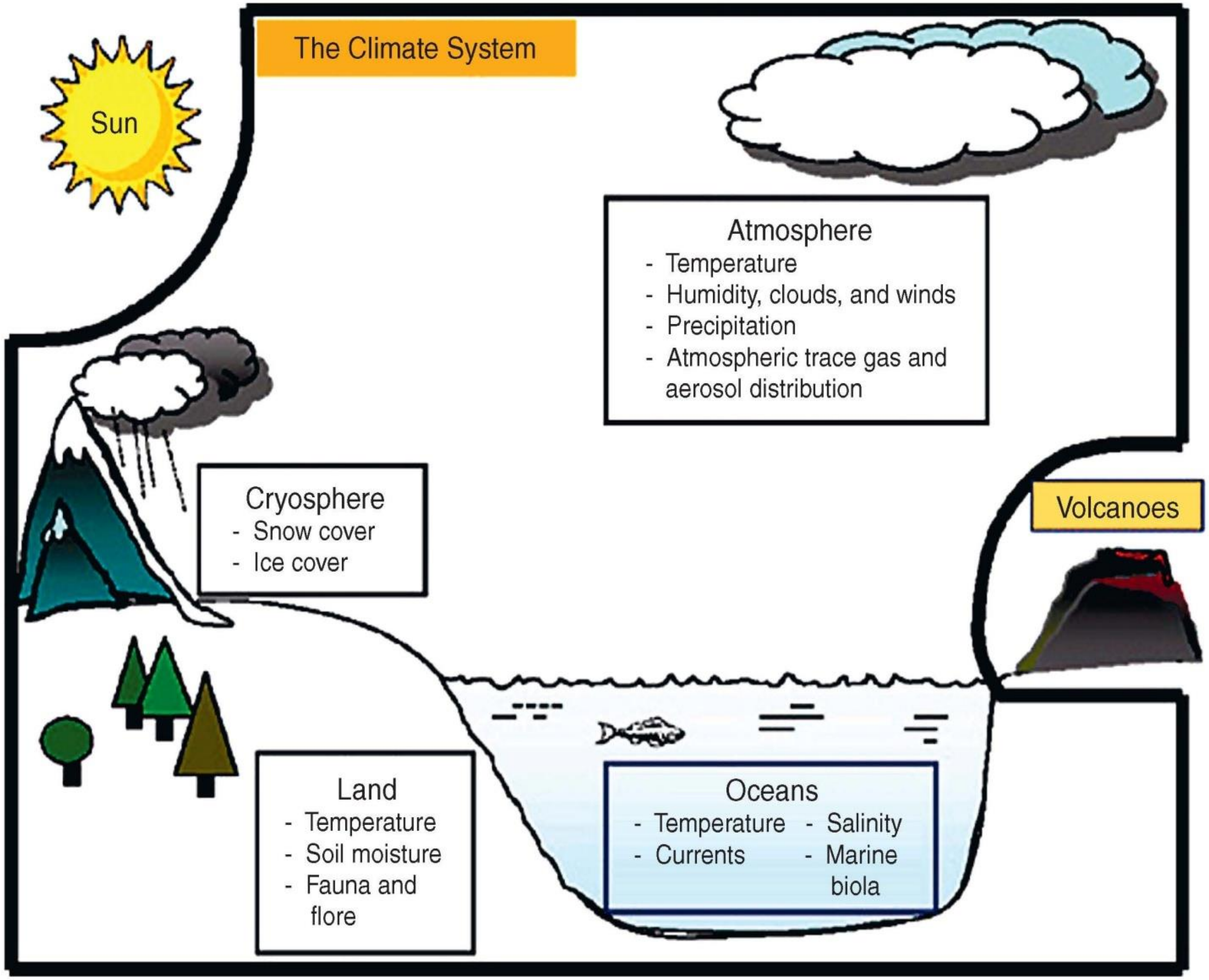


Figure 2 The climate system, consisting of the atmosphere, oceans, land, and cryosphere. Important state variables for each sphere of the climate system are listed in the boxes. For the purposes of this report, the Sun, volcanic emissions, and human-caused emissions of greenhouse gases and changes to the land surface are considered external to the climate system (NRC 2005).

Necessary Condition

Do Global Climate Models Provide Robust Multidecadal Regional Predictions of Changes in Climate Statistics?

Stephens et al. (2010) wrote

"models produce precipitation approximately twice as often as that observed and make rainfall far too lightly...The differences in the character of model precipitation are systemic and have a number of important implications for modeling the coupled Earth system ...little skill in precipitation [is] calculated at individual grid points, and thus applications involving downscaling of grid point precipitation to yet even finer-scale resolution has little foundation and relevance to the real Earth system."

van Haren et al. (2012) concluded from their study with respect to climate model predictions of precipitation that

"An investigation of precipitation trends in two multi-model ensembles including both global and regional climate models shows that these models fail to reproduce the observed trends... A quantitative understanding of the causes of these trends is needed so that climate model based projections of future climate can be corrected for these precipitation trend biases.. To conclude, modeled atmospheric circulation and SST trends over the past century are significantly different from the observed ones."

Sun et al. (2012) found that

“in global climate models, [t]he radiation sampling error due to infrequent radiation calculations is investigated .... It is found that.. errors are very large, exceeding 800 W m2 at many non-radiation time steps due to ignoring the effects of clouds..”

Kundzewicz and Stakhiv (2010) succinctly conclude that

“Simply put, the current suite of climate models were not developed to provide the level of accuracy required for adaptation-type analysis.”

Do Global Climate Models Provide Robust Multidecadal Regional Predictions of Changes in Climate Statistics?

NO

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 t o th 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	Focus on single stress limits preparedness for other stresses. Results often show gradual ramping of climate change-limiting preparedness for extreme events. Results represent only a limited subset of all likely future outcomes – usually unidirectional trends. Results are accepted by many scientists, the media, and the public as actual "predictions". Lost in the translation of results is that all models of the distant future have unstated (presently unknowable) levels of certainty or probability.	Approach requires detailed data on multiple stresses and their interactions at local, regional, national and global scales – and many areas lack adequate information. Emphasis on short-term issues may limit preparedness for abrupt "threshold" changes in climate some time in the short- or long-term. Requires preparedness for a far greater variation of possible futures, including abrupt changes in any direction – this is probably more realistic, yet difficult.

	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 climate 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 a 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]

Figure 5. Two interpretations of vulnerability in climate change research. From the work of *Füssel* [2007, 2009].

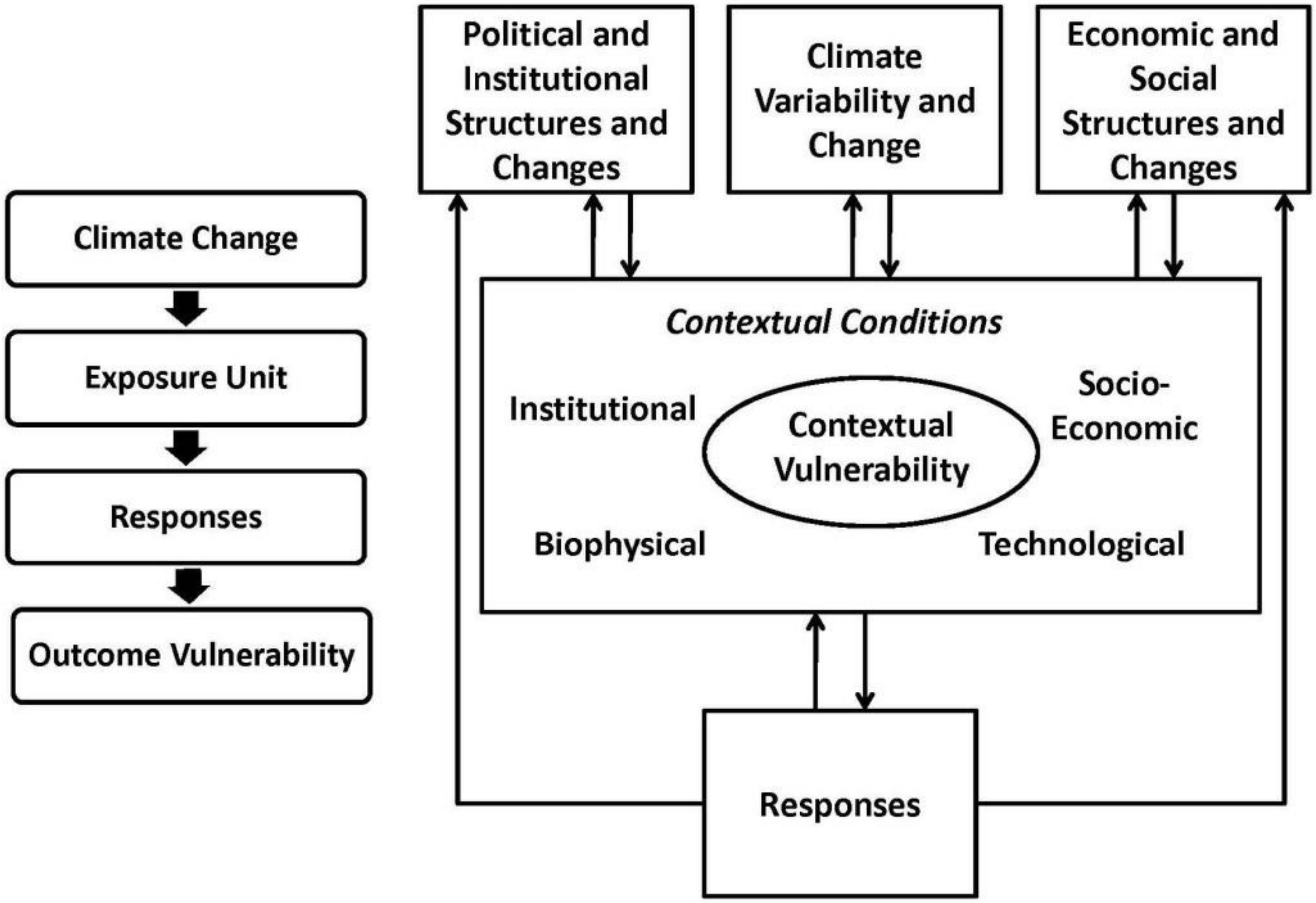
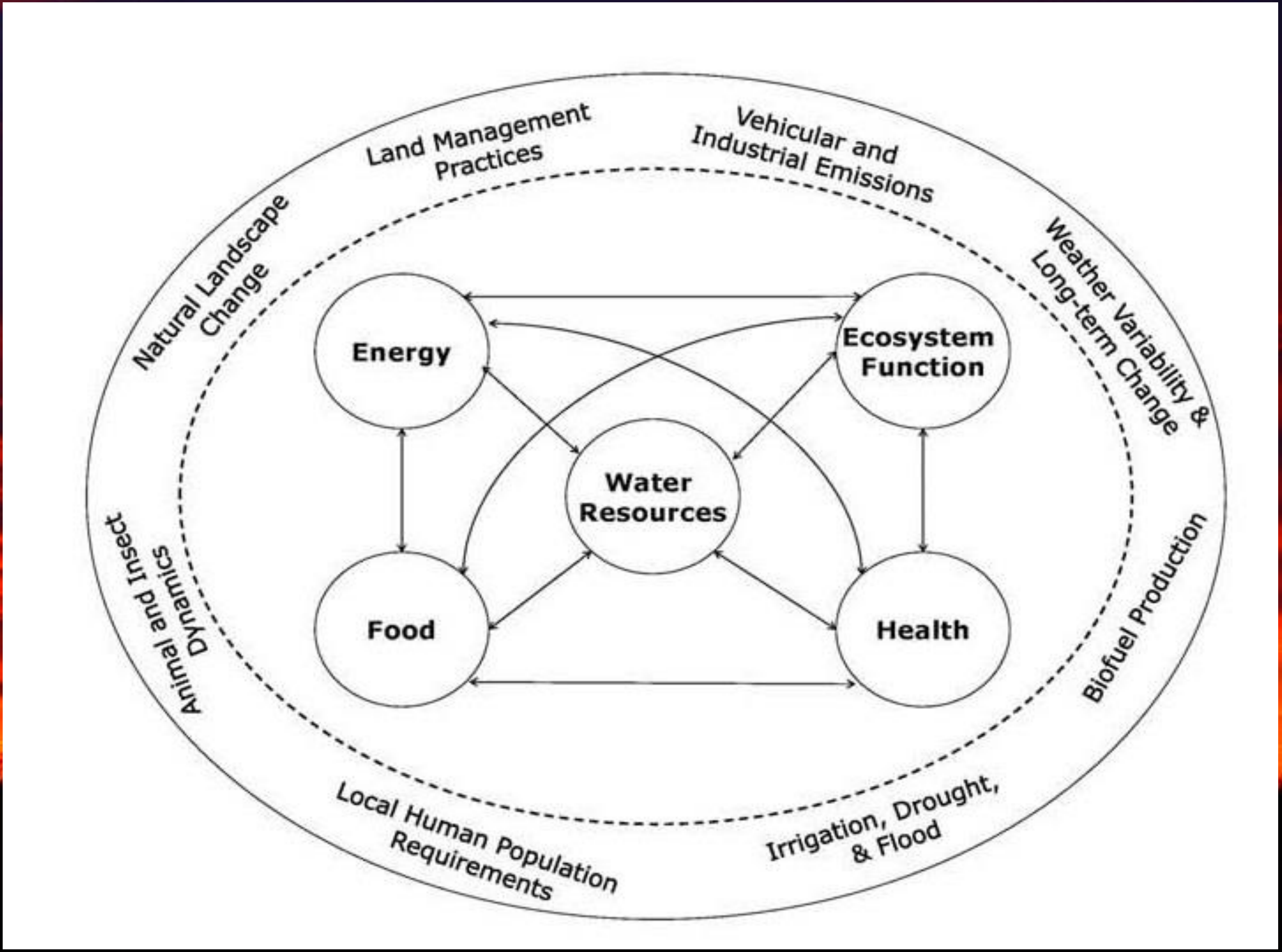
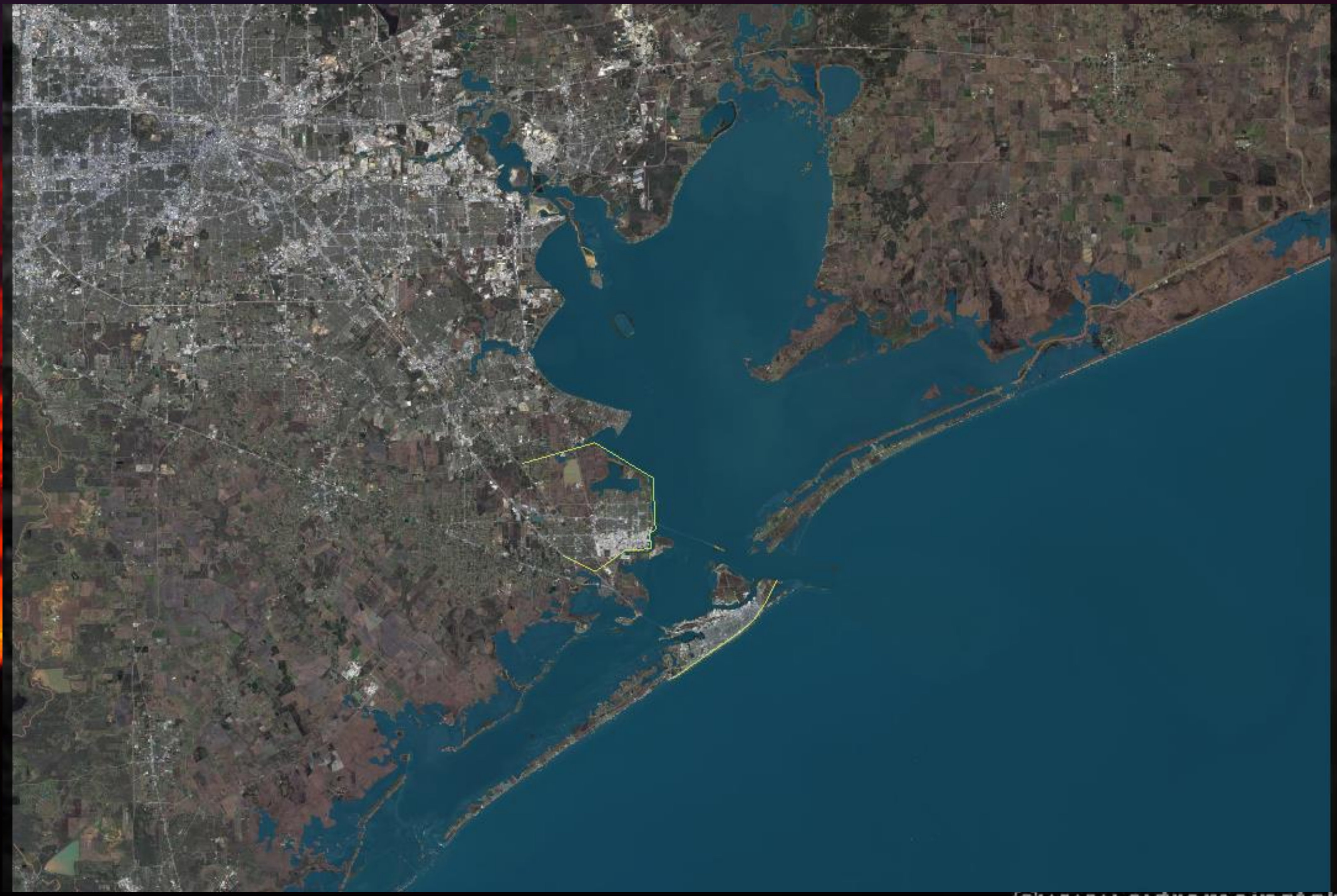


Figure 4. Framework depicting two interpretations of vulnerability to climate change: (left) outcome vulnerability and (right) contextual vulnerability. Adapted by D. Staley from the works of *Füssel* [2009] and *O'Brien et al.* [2007].


Land Management Practices
Vehicular and Industrial Emissions
Natural Landscape Change
Weather Variability & Long-term Change
Energy
Ecosystem Function
Water Resources
Food
Health
Animal and Insect Dynamics
Biofuel Production
Local Human Population Requirements
Irrigation, Drought, & Flood

Hurricane Harvey was the most significant tropical cyclone rainfall event in United States history, both in scope and peak rainfall amounts, since reliable rainfall records began around the 1880s. Max observed 60.58 inches [https://www.ksat.com/news/by-the-numbers-inside-the-national-hurricane-center-s-hurricane-harvey-report]



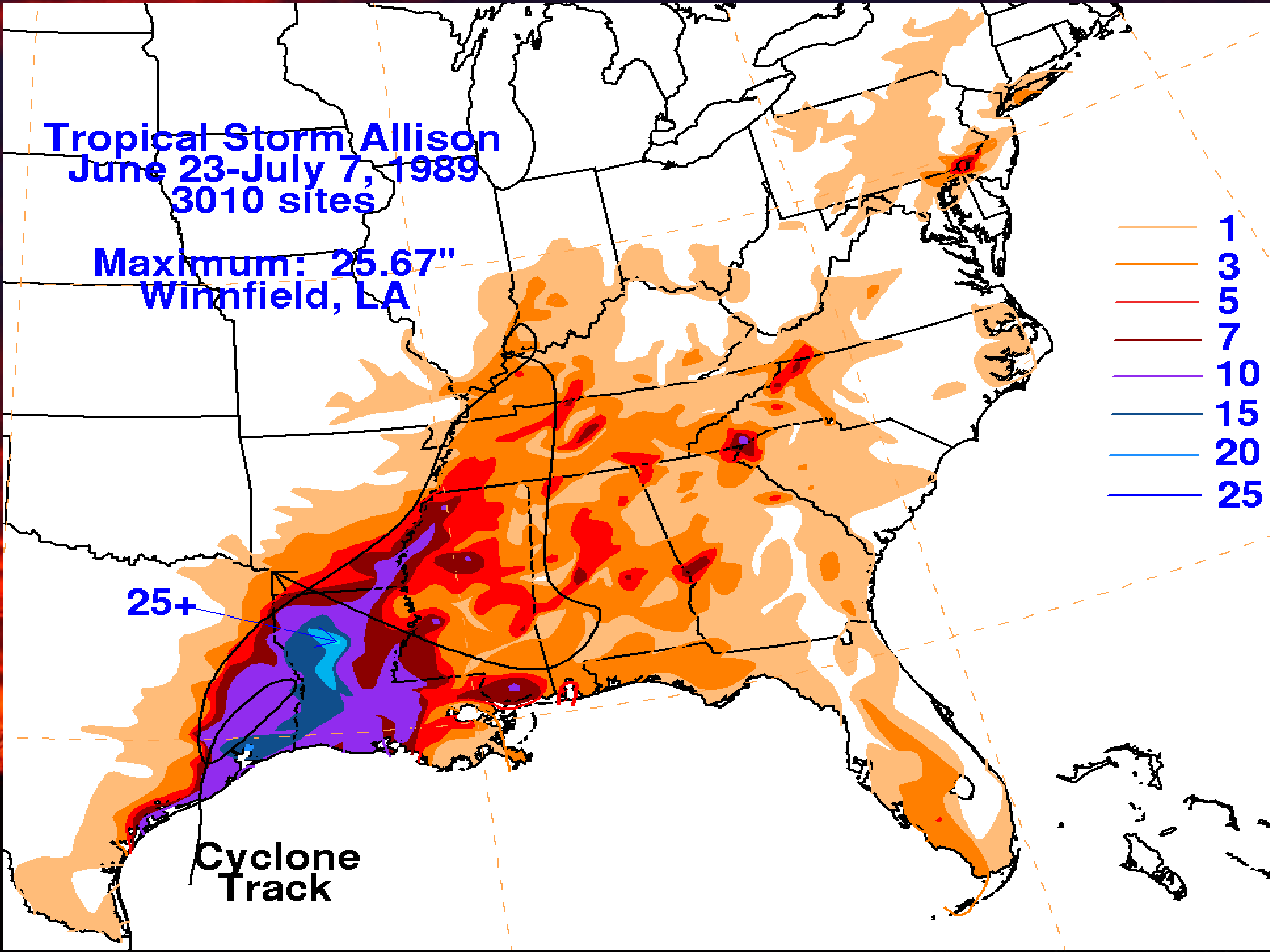
https://www.texastribune.org/hell-and-high-water/

from March 3 2016

Houston is the fourth-largest city in the country. It's home to the nation's largest refining and petrochemical complex, where billions of gallons of oil and dangerous chemicals are stored. And it's a sitting duck for the next big hurricane. Why isn't Texas ready?

https://www.texastribune.org/hell-and-high-water/

"scientists say, Houston's perfect storm is coming — and it's not a matter of if but when. The city has dodged it for decades, but the likelihood it will happen in any given year is nothing to scoff at; it's much higher than your chance of dying in a car crash or in a firearm assault, and 2,400 times as high as your chance of being struck by lightning."


Tropical Storm Allison
June 23-July 7, 1989
3010 sites
Maximum: 25.67"
Winnfield, LA
1
3
5
7
10
15
20
25
25+
Cyclone
Track

Is the current top-down GCM-based approach to assess vulnerability of water resources, energy, food, ecosystem function and human health a robust approach?

NO

TOPIC #3

Are dynamically-forced compression waves (e.g., from tornadoes) and thermally-forced compression waves (e.g., when diabatic heating occurs) an important part of weather?

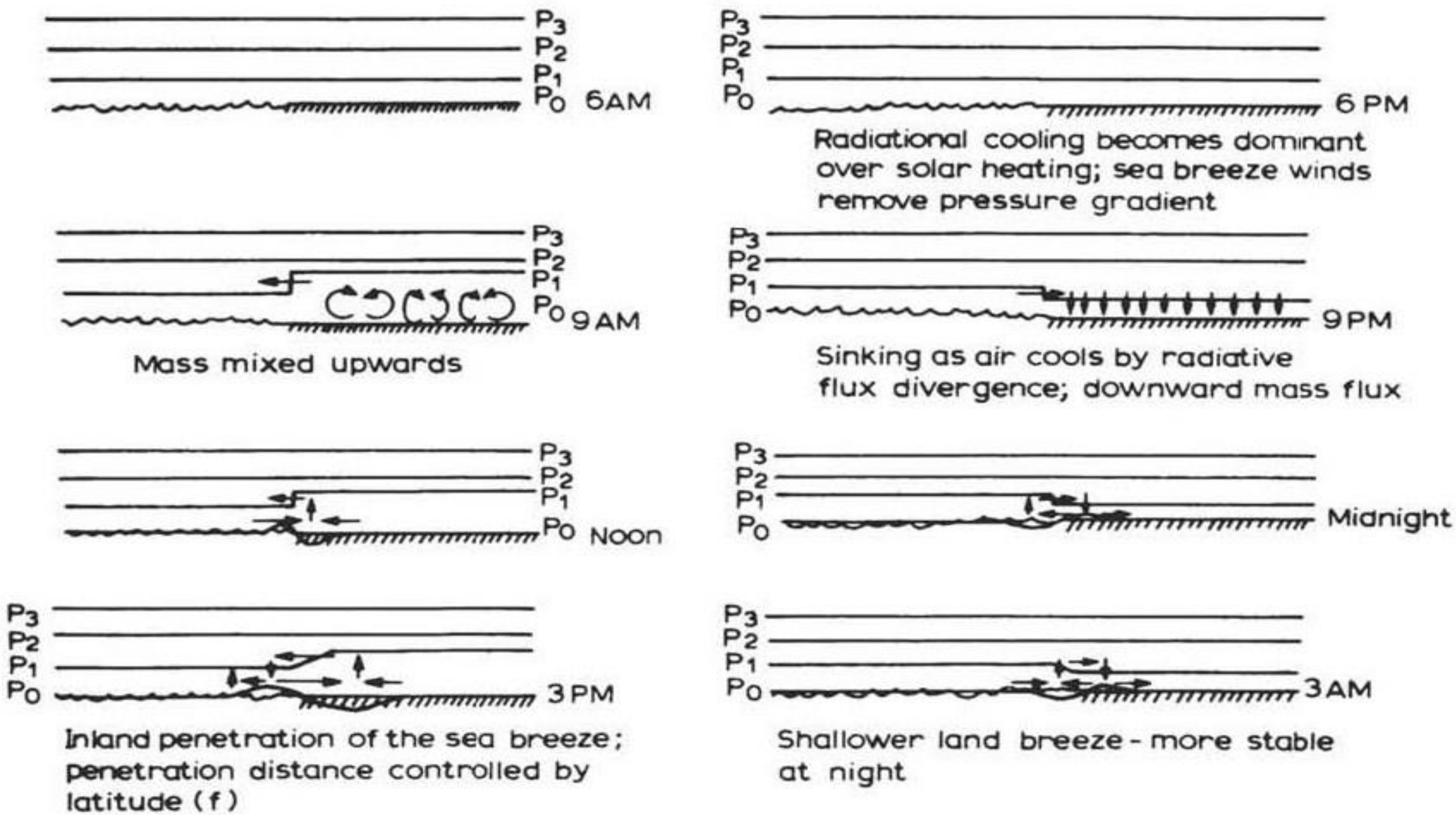


FIGURE 13.1

Schematic of the diurnal evolution of the sea and land breeze in the absence of synoptic flow (from Pielke 1981).

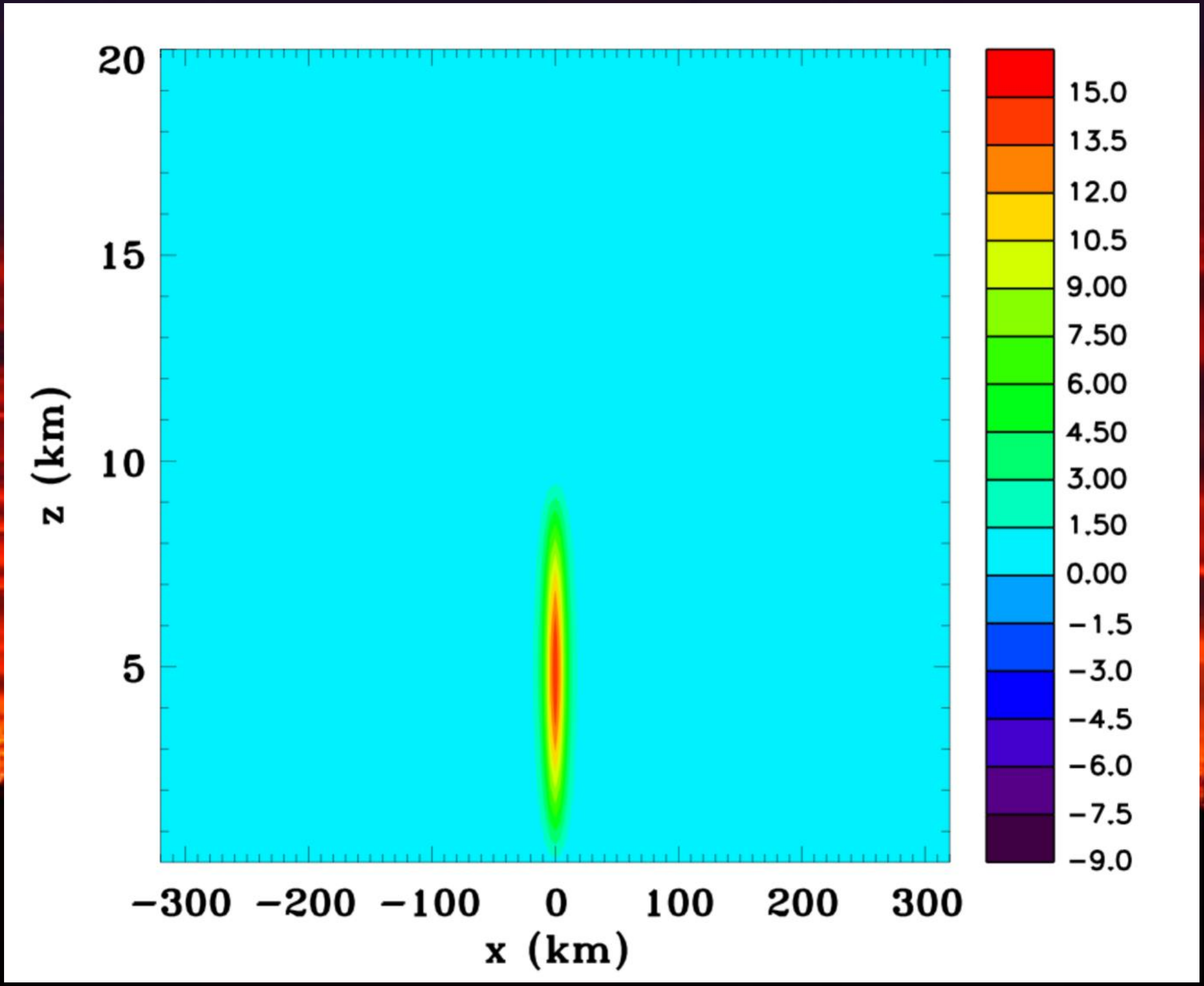
Nicholls, M.E. and R.A. Pielke, 1994: Thermal compression waves. I: Total energy transfer. Quart. J. Roy. Meteor. Soc., 120, 305-332.

Nicholls, M.E. and R.A. Pielke, 1994: Thermal compression waves. II: Mass adjustment and vertical transfer of total energy. Quart. J. Roy. Meteor. Soc., 120, 333-359.

Nicholls, M.E. and R.A. Pielke Sr., 2000: Thermally-induced compression waves and gravity waves generated by convective storms. J. Atmos. Sci., 57, 3251-3271.

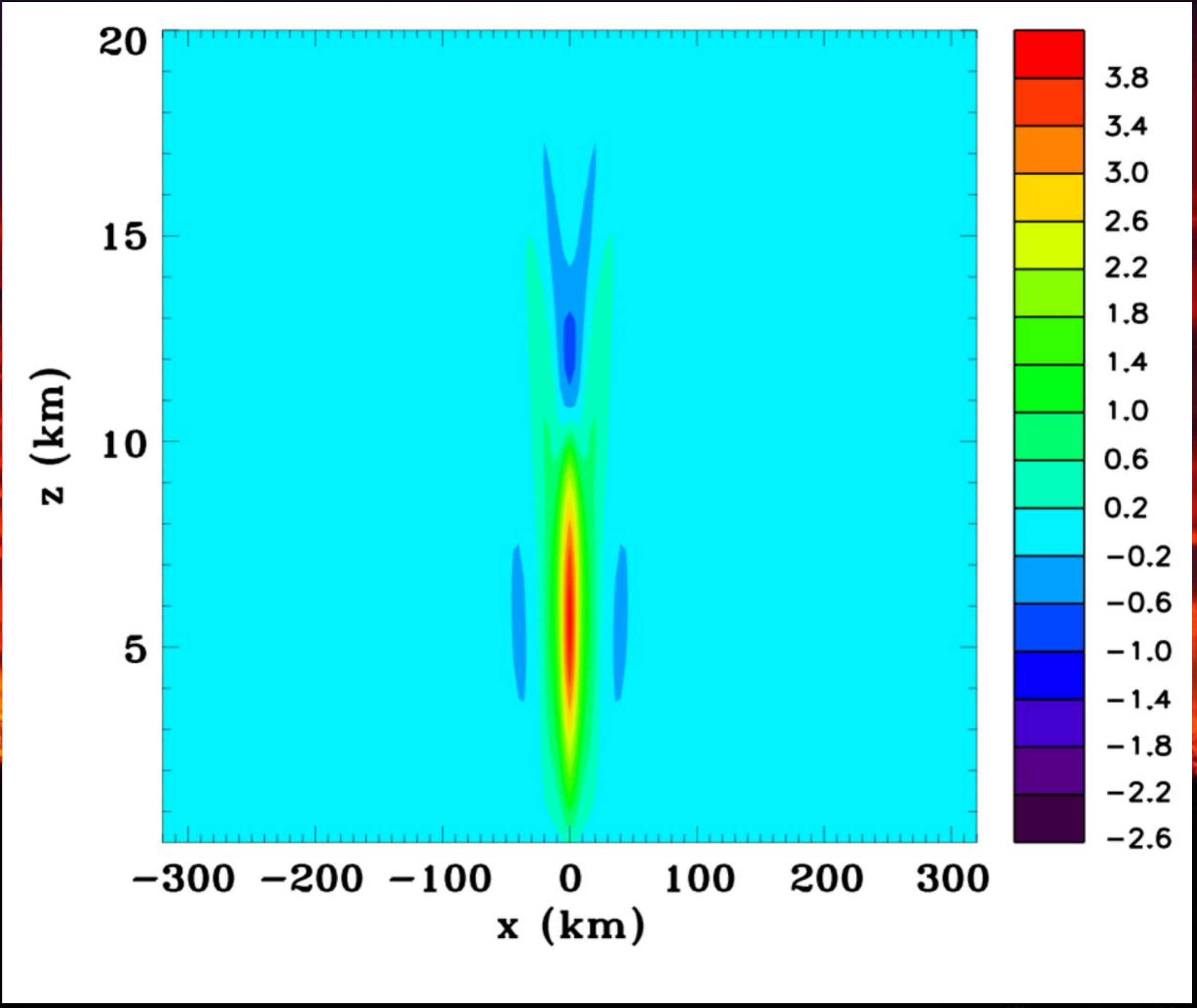
Schecter, D.A., M.E. Nicholls, J. Persing, A.J. Bedard Jr., and R.A. Pielke Sr., 2008: Infrasound emitted by tornado-like vortices: Basic theory and a numerical comparison to the acoustic radiation of a single-cell thunderstorm. J. Atmos. Sci., 65, 685-713.

Convective-scale thermally-generated compression wave – diabatic heating rate in Joules per kg per second



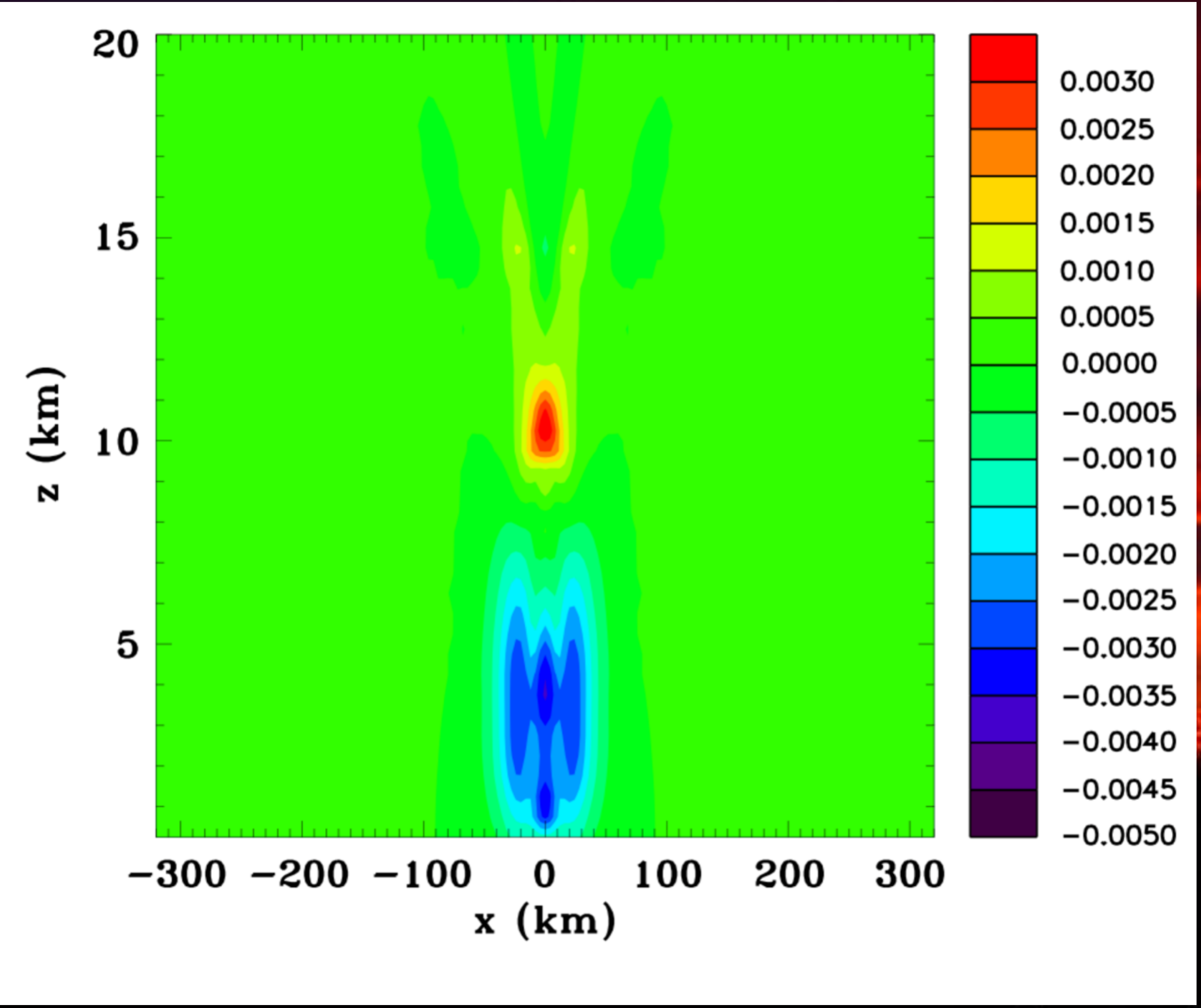
VERTICAL VELOCITY (m s^{-1}) t=15 minutes

At 15 minutes ascent of ~ 3.5 m s^{-1} occurs in the heated region and weak adiabatic descent occurs in the adjacent air



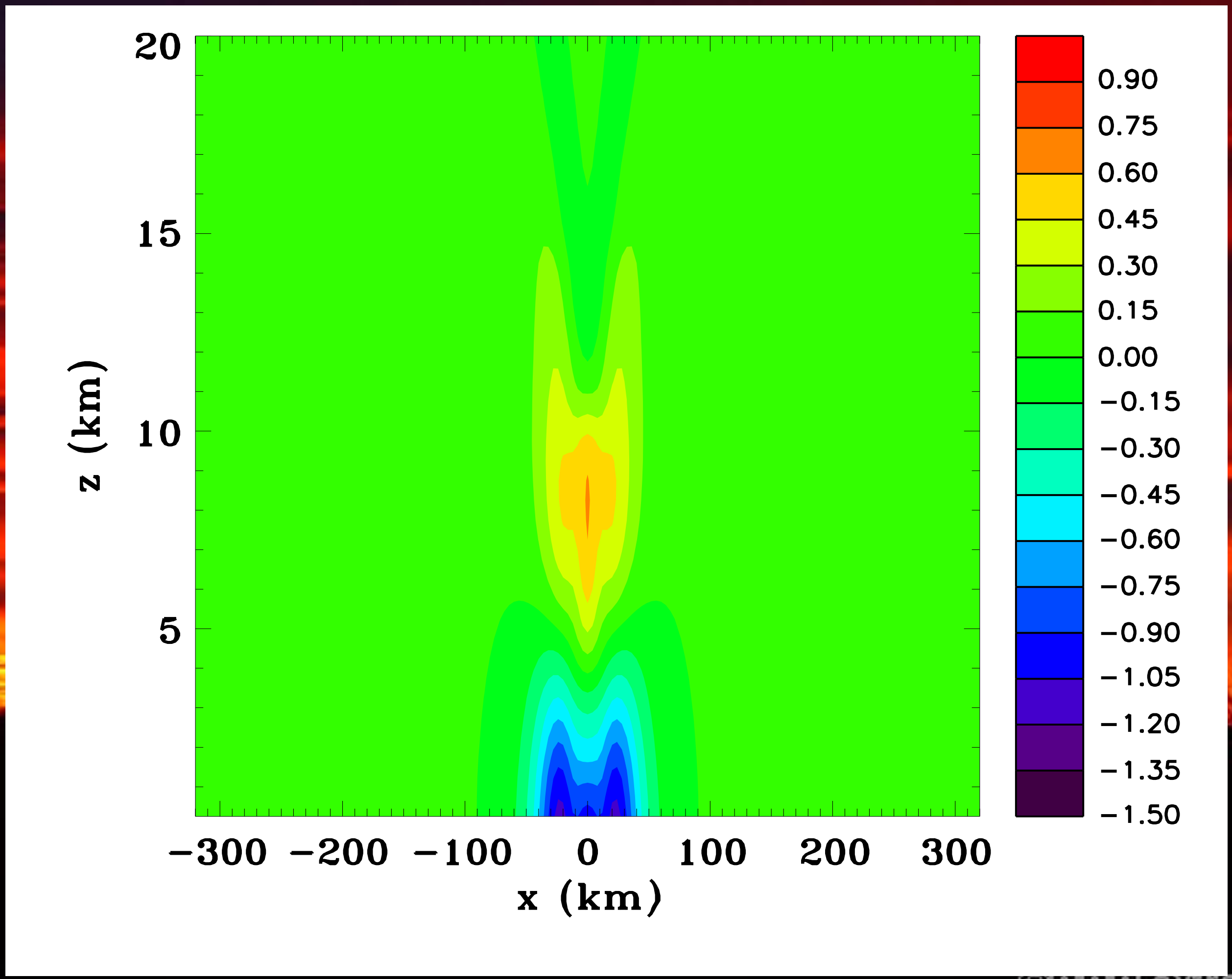
DENSITY PERTURBATION (kg m^{-3}) t=15 minutes

The density decreases in the heated region as air expands creating buoyancy and also in the adjacent region that has adiabatic descent



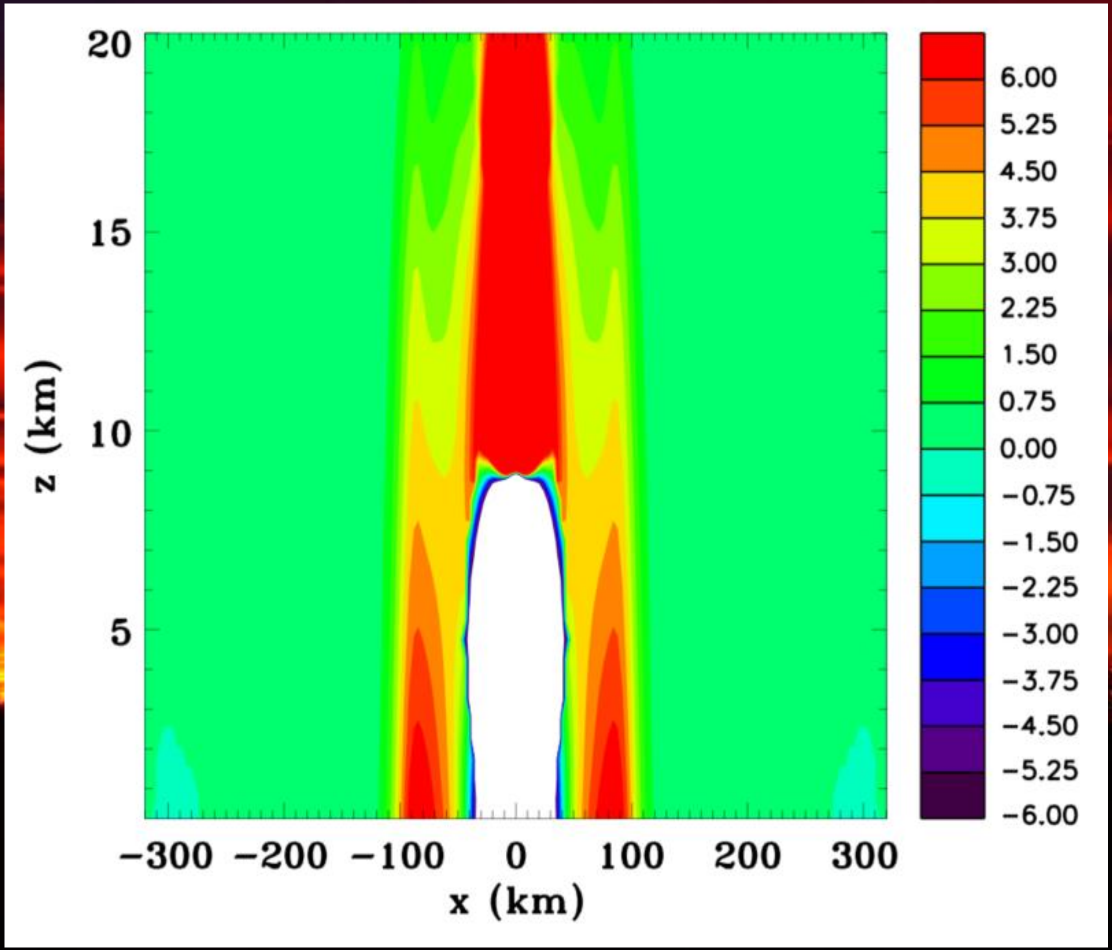
PRESSURE PERTURBATION (hPa) t=15 minutes

The pressure decreases at the surface because there has been a lateral movement of mass above the surface (as long as there is an approximate hydrostatic balance) 1000 hPa= 1 mb

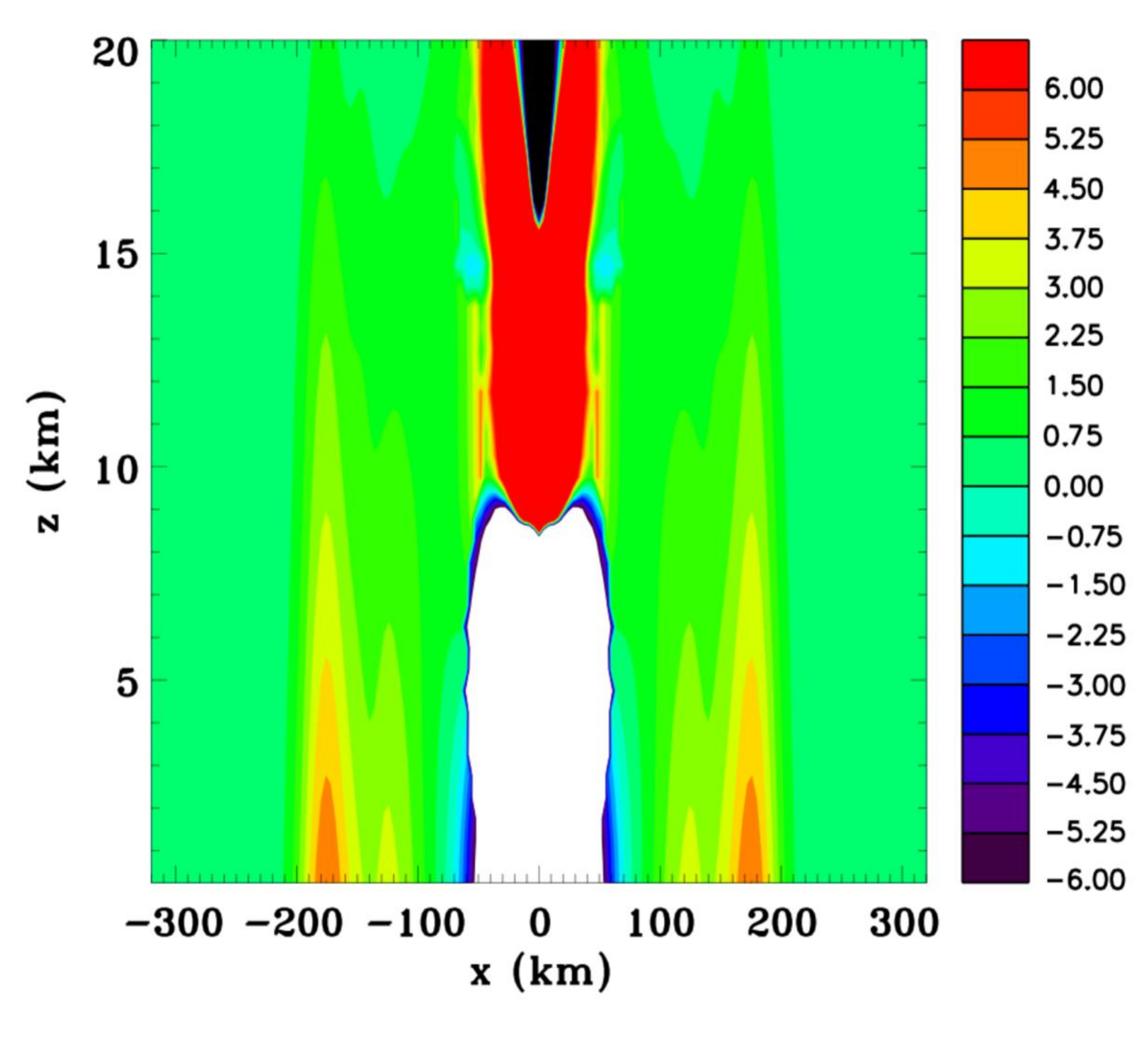


DENSITY PERTURBATION (kg m^{-3} $\times 10^{-5}$) t=5 minutes

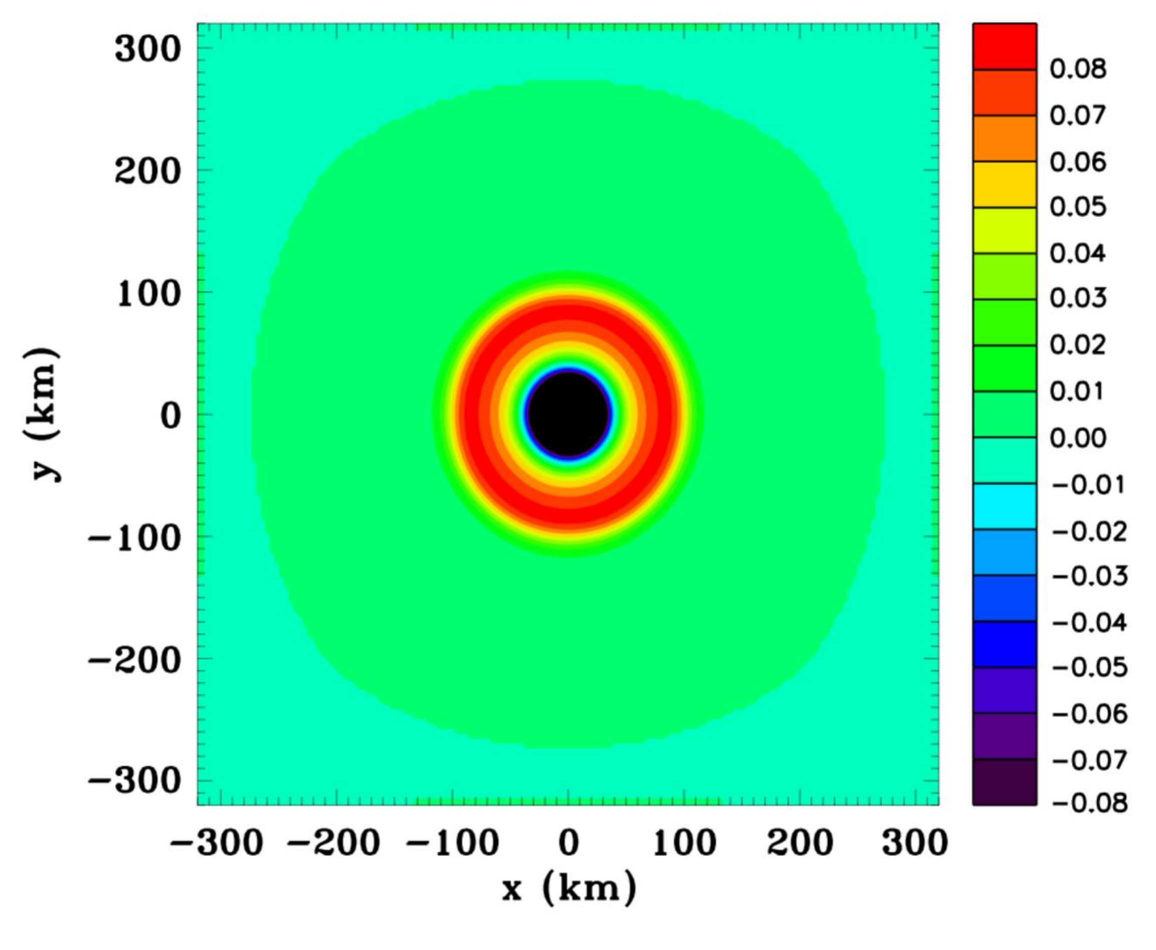
Fields contoured to illustrate the very small amplitude compression wave propagating away at the speed of sound. This shows a thermally-forced sound wave.



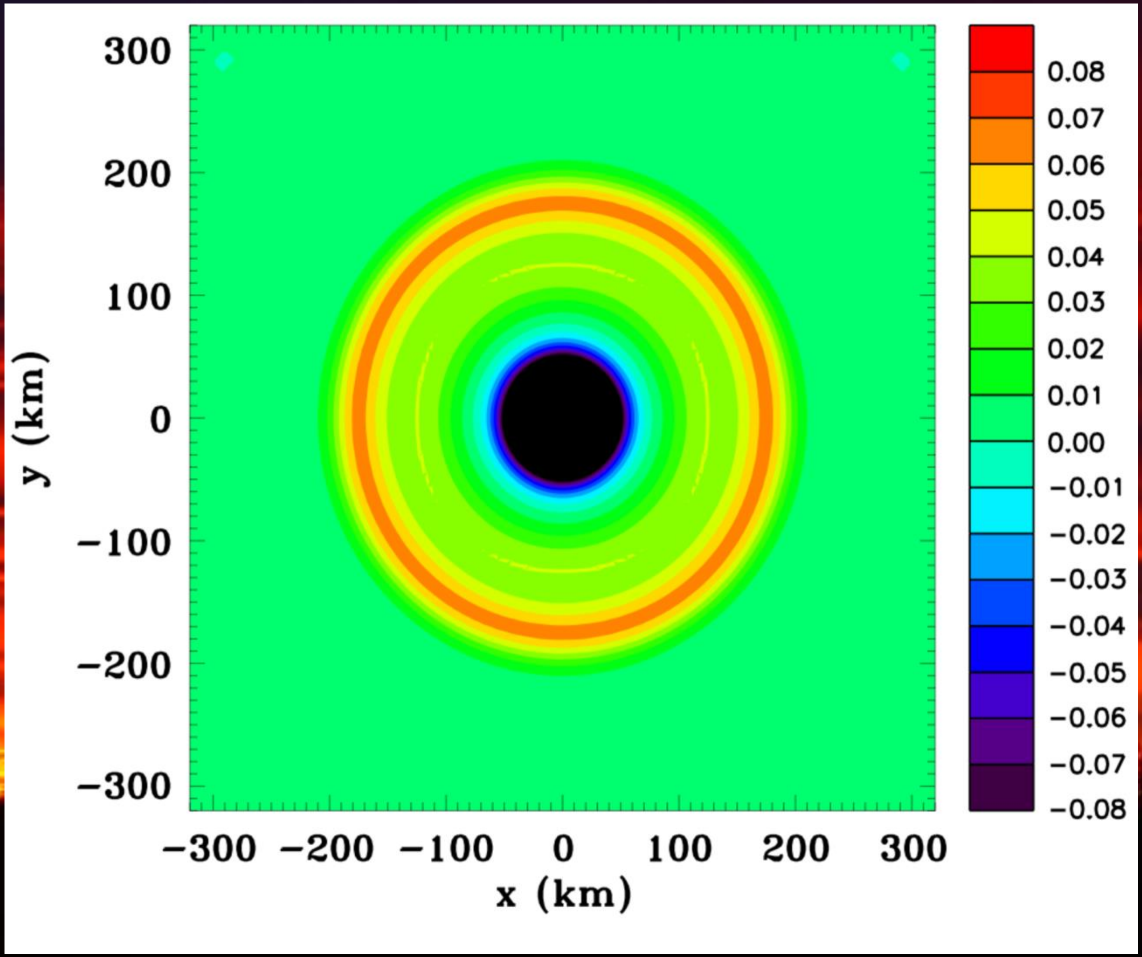
DENSITY PERTURBATION (kg m^{-3} ×10^{-5})   t=10 minutes



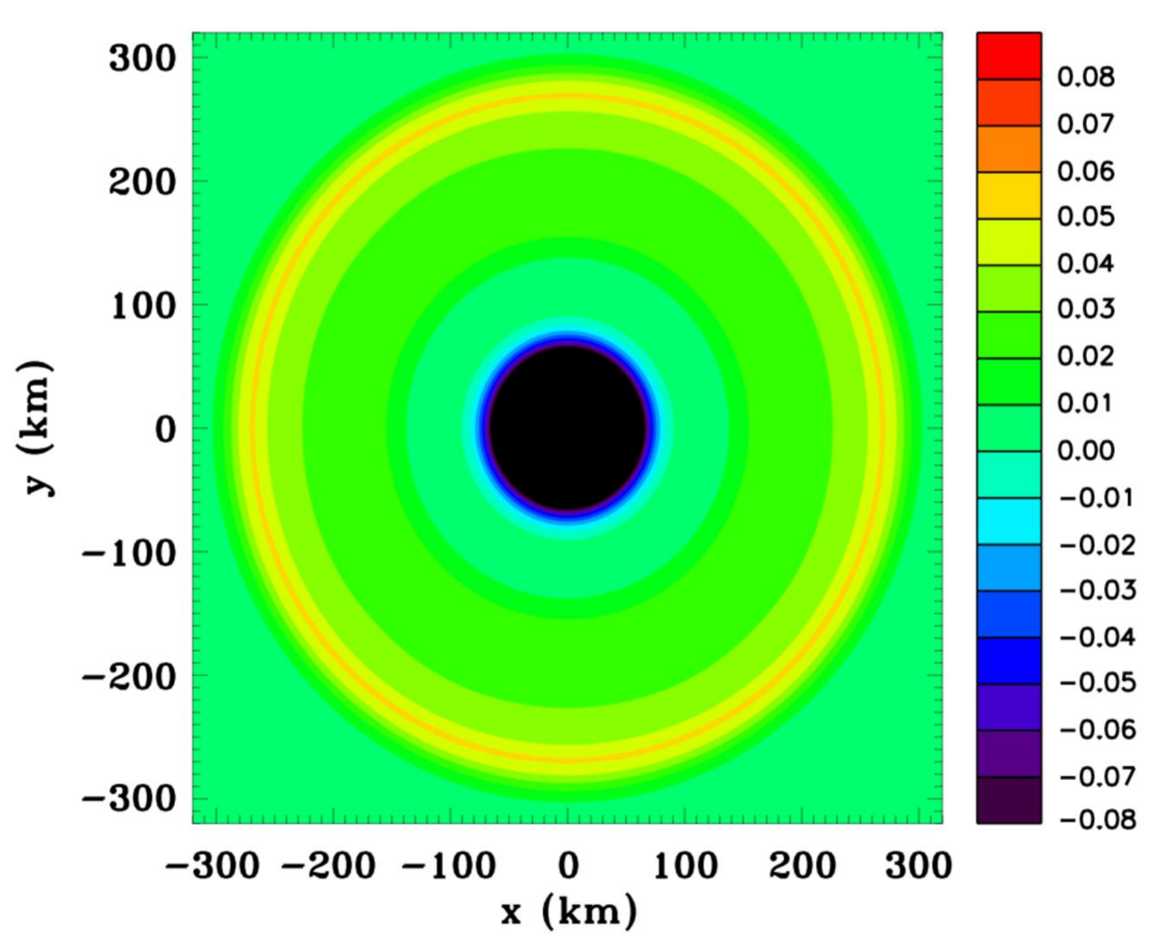
PRESSURE PERTURBATION (hPa)   t=5 minutes



PRESSURE PERTURBATION (hPa) t= 10 minutes



PRESSURE PERTURBATION (hPa) t=15 minutes



Are dynamically-forced compression waves (e.g., from tornadoes) and thermally-forced compression waves (e.g., when diabatic heating occurs) an important part of weather?

Yes in terms of monitoring weather system intensification and movement

To be still assessed with respect to affecting weather

TOPIC # 4

Can the flap of a butterfly result in a tornado thousands of kilometers away?

Butterfly Effects of the First and Second Kinds in Lorenz Models

B.-W. Shen[1], R. A. Pielke Sr.[2], X. Zeng[3], I. D. A. Santos[4], S. Faghih-Naini[1,5], J. Buchnann[6], C.-L. Shie[7], and R. Atlas[8]

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[2]CIRES and ATOC, University of Colorado at Boulder
[3]The University of Arizona
[4]Universidade Estadual do Norte Fluminense - Macae
[5]Friedrich-Alexander University Erlangen-Nuremberg
[6]Universidade Federal do Rio de Janeiro
[7]JCET, University of Maryland at Baltimore County; NASA/GSFC
[8]AOML, National Oceanic and Atmospheric Administration

2018 AMS Meeting

January 07-11, 2018, Austin, Texas

Butterfly in Lorenz Models

- The book entitled "*The Essence of Chaos*" by Lorenz in 1993 indicates that Lorenz (1963) and Lorenz (1972) are major studies regarding the Lorenz's butterfly effects.
- The title of Lorenz (1972) that includes the word "butterfly" was given by session chair Philip Merilees.
- Studies suggested that major results in Lorenz (1972) may come from Lorenz's study in 1969 (e.g., Rotunno and Snyder, 2008; Durran and Gingrich, 2014; Palmer et al. 2014).

Lorenz (1963)

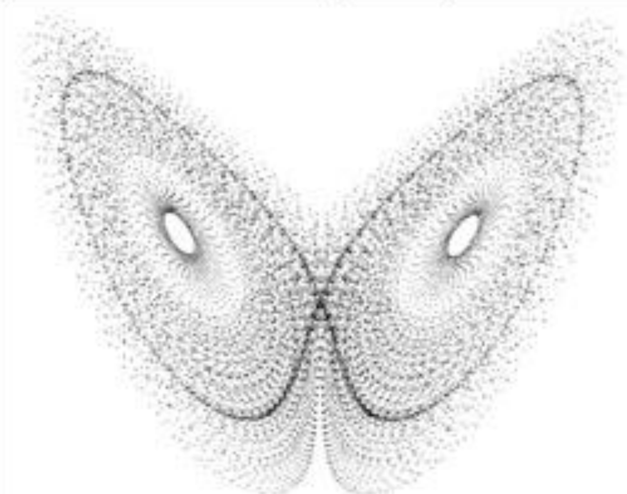


Figure 2. The butterfly.

Lorenz (1972/1969)

APPENDIX 1

The Butterfly Effect

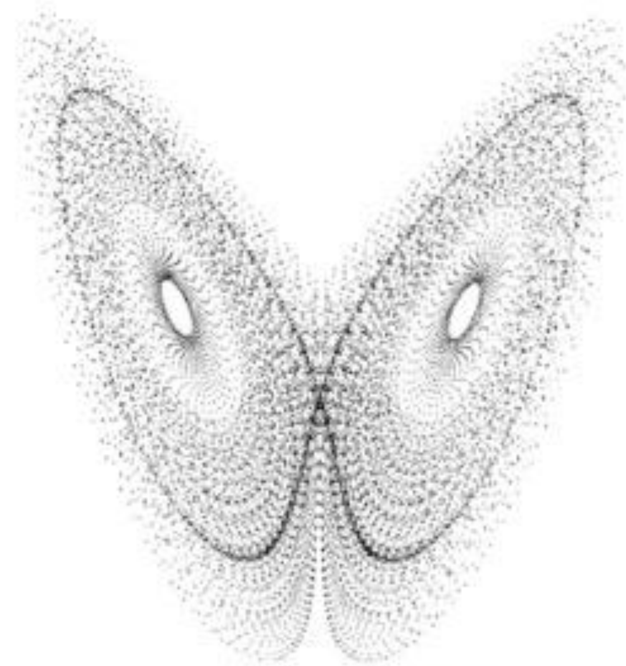
THE FOLLOWING is the text of a talk that I presented in a session devoted to the Global Atmospheric Research Program, at the 139th meeting of the American Association for the Advancement of Science, in Washington, D.C., on December 29, 1972, as prepared for press release. It was never published, and it is presented here in its original form.

Predictability: Does the Flap of a Butterfly's Wings in Brazil Set off a Tornado in Texas?

What Lorenz's Butterfly Really Reveals:

The statement of "*Orbits initially diverge and then curve back*" includes the following major features of butterfly's solutions:

- Divergence of Trajectories:
- Boundedness:
  - No "blow-up" solutions
- Recurrence:
  - Complex eigenvalues, $\lambda = \alpha + i\beta$: real part leads to the growing or decaying solution; imaginary part gives the oscillatory component.
- Error Saturations:
  - Max errors determined by the "diameter" of the butterfly's wings
- Ergodicity (Hilborn, 2000):
  - Time averages are the same as state space averages.



oscillatory

$$X(t) = e^{\alpha t}(\cos(\beta t) + i\sin(\beta t))$$

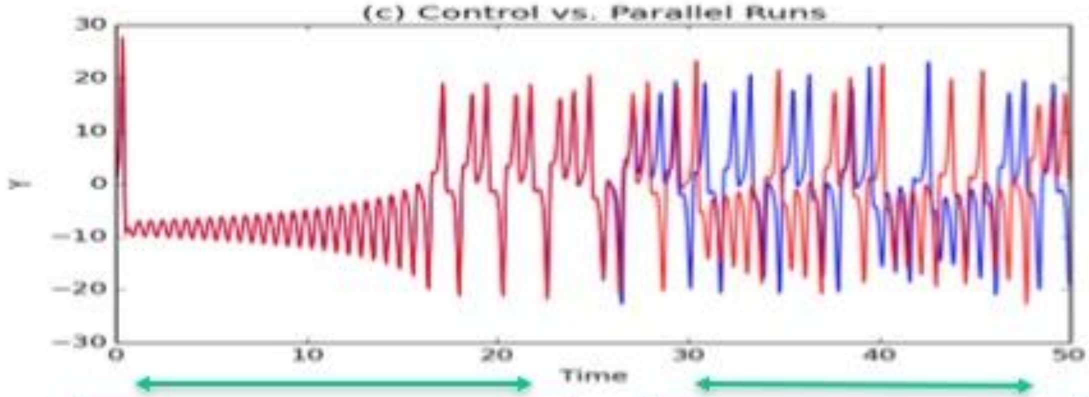
grow or decay at an exponential rate

Butterfly Effects of the First and Second Kinds

Since the studies by Lorenz (1963, 1972/1969), two kinds of butterfly effects are:

- The butterfly effect of the first kind (BE1):

  indicating the *sensitive dependence on initial conditions* (Lorenz, 1963).



continuous dependence (within an time interval)

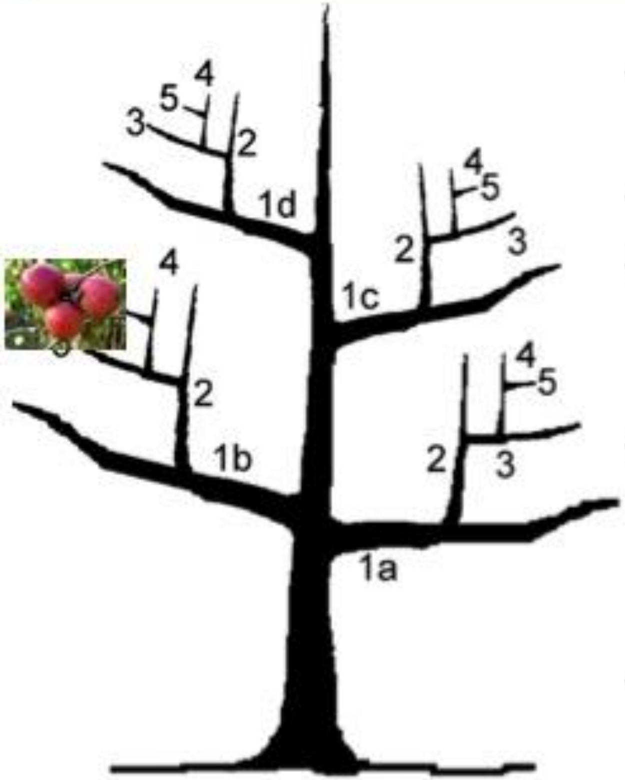
sensitive dependence

- control run (blue): $(X, Y, Z) = (0,1,0)$
- parallel run (red): $(X, Y, Z) = (0,1 + \epsilon, 0)$, $\epsilon = 1e^{-10}$

- The butterfly effect of the second kind (BE2):

  a *metaphor (or symbol) for indicating that small perturbations can alter large-scale structure* (Lorenz, 1972/1969). In this study, we refer to this as the enabling role of a tiny perturbation in producing an organized large-scale system.

A Rough Analogy using a Tree with Damping Terms



Source: google.com

- The nonlinear terms (XY and -XZ) form the nonlinear feedback loop (NFL).
- The original NFL may represent a main trunk.
- An extension of the NFL can be viewed as the growth of the main trunk or a new branch of the main trunk.
- A bigger tree that has more complicated structures may be more stable, as compared to a smaller tree, depending on the interconnectivity of the main trunk and branches.
- (Linearized NFLs enable energy transfer across scales and create incommensurate frequencies.)

- The branch mass contributes dynamic damping that acts to reduce dangerous harmonic sway motion within the trunk, therefore minimizing loads and increasing the mechanical stability of the tree.

James, K. R. , N. Haritos and P. K. Ades, 2006: Mechanical stability of trees under dynamic loads. American Journal of Botany 93(10): 1522–1530. 2006.

Can the flap of a butterfly result in a tornado thousands of kilometers away?

<u>NO</u>

TOPIC # 5

Can methods in artificial intelligence (AI) permit us to

i) replace traditional parameterizations with representations trained from real observed data and

ii) even the physics core in weather forecasting models?

Artificial Intelligence

Craig S. Pelissier GSFC

Hoshin Vijai Gupta University of Arizona

William M Putman GSFC

Grey S. Nearing GSFC

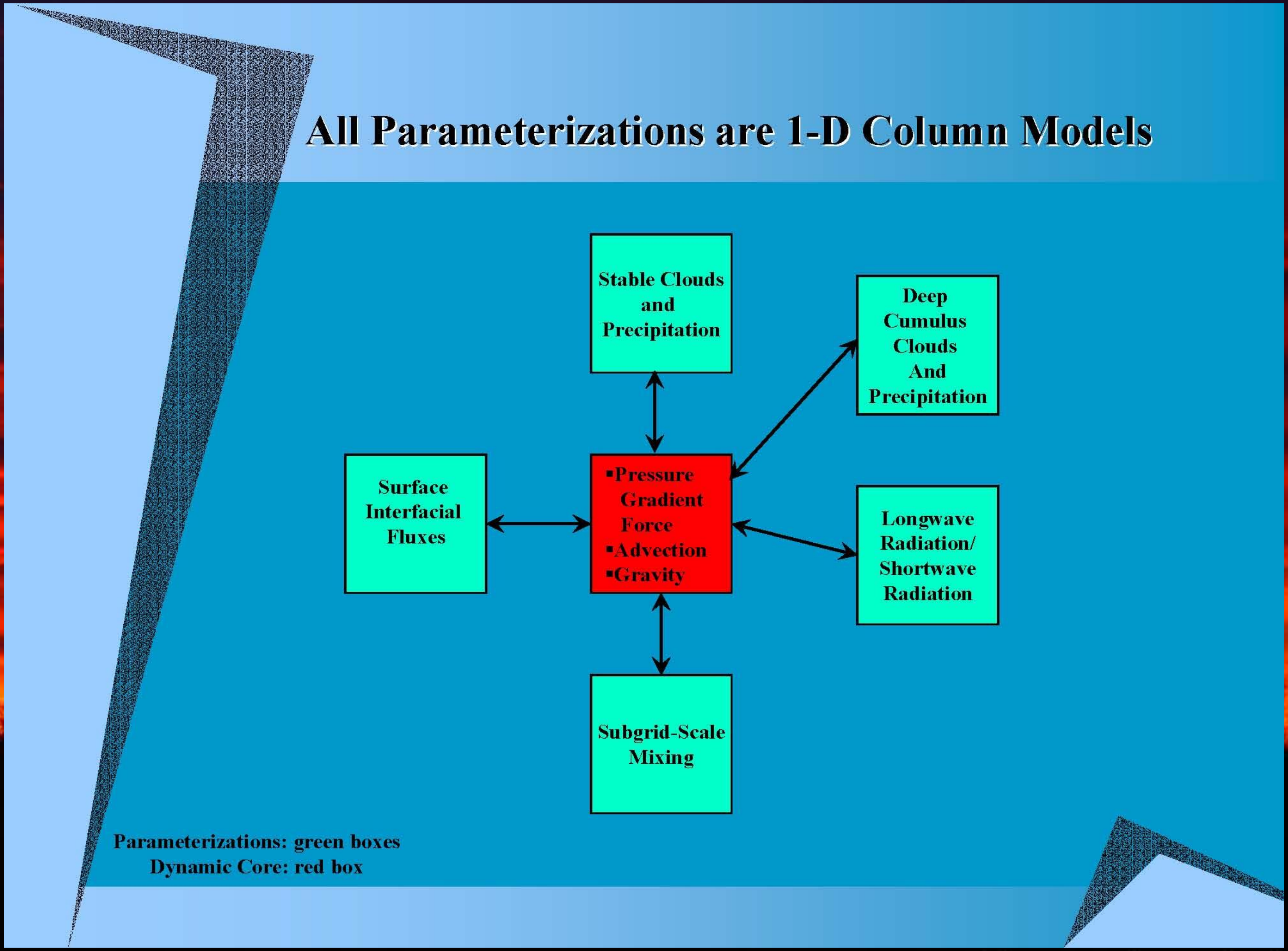
Jules Kouatchou GSFC

Daniel Q. Duffy GSFC

Roger Pielke Sr University of Colorado- Boulder

- Process studies: The application of models to improve our understanding of how the system works is a valuable application of these tools. The term sensitivity study can characterize a process study. In a sensitivity study, a subset of the forcings and/or feedback of the system may be perturbed to examine its response. The model might be incomplete and not include each of the important feedbacks and forcings. UNDERSTANDING
- Diagnosis: The application of models, in which observed data is assimilated into the model, to produce an observational analysis that is consistent with our best understanding of the system using fundamental physics constraints. MOST ACCURATE ANALYSIS
- Forecasting: The application of models to predict the future state of the system. Forecasts can be made from a single realization, or from an ensemble of forecasts which are produced by slightly perturbing the initial conditions and/or other aspects of the model. With forecasting, we may not care how we achieve the most accurate prediction as long as it is the most accurate achievable. MOST ACCURATE PREDICTION

Pielke, R.A., Sr., 2003: The Limitations of Models and Observations. COMET Symposium on Planetary Boundary Layer Processes, Boulder, Colorado, September 12, 2003. https://pielkeclimatesci.files.wordpress.com/2009/09/ppt-3.pdf



- Gupta and Nearing, 2014: *Debates—The future of hydrological sciences … Using models and data to learn: A systems theoretic perspective …*, Invited Commentary, Water Resources Research, 50
- Nearing and Gupta, 2015: *The Quantity and Quality of Information in Hydrologic Models, Water Resources Research*, 51, 524–538, doi:10.1002/2014WR015895

Recommended analogs in medical research and diagnoses from Harrison Pielke-Lombardo, University of Colorado Anschutz campus

- Ding et al. 2013: Similarity-based machine learning methods for predicting drug–target interactions: a brief review. https://academic.oup.com/bib/article-lookup/doi/10.1093/bib/bbt056.
- Livingston et al. 2015: KaBOB: ontology-based semantic integration of biomedical databases. https://doi.org/10.1186/s12859-015-0559-3.
- Libbrecht and Noble, 2015: Machine learning applications in genetics and genomics.
- Kindel et al. 2017: Using deep learning to reveal the neural code for images in primary visual cortex. https://arxiv.org/pdf/1706.06208.pdf

Ph.D. by Robert Firth, 2017: A Novel Recurrent Convolutional Neural Network for Ocean and Weather Forecasting

http://digitalcommons.lsu.edu/gradschool_dissertations/2099/

"Experimental results show that the new approach is 3.6 times more efficient at forecasting the ocean and 16 times more efficient at forecasting the atmosphere. The new approach showed forecast skill by beating the accuracy of two models, persistence and climatology, and was more accurate than the Navy NCOM model on 16 of the first 17 layers of the ocean below the surface (2 meters to 70 meters) for forecasting salinity and 15 of the first 17 layers for forecasting temperature. The new approach was also more accurate than the RAP model at forecasting wind speed on 7 layers, specific humidity on 7 layers, relative humidity on 6 layers, and temperature on 3 layers, with competitive results elsewhere."

<u>Deep Machine Learning for High-Impact Weather Forecasting</u>

Seminar Abstract by David John Gagne

"<u>Deep learning models can identify multiscale features in gridded spatio-temporal data and use that information to produce better predictions than traditional machine learning approaches.</u> A form of deep learning called generative adversarial networks will be discussed and demonstrated."

- Observing T (x,y,z) on spatial scales of 10 km and larger yields p(x,y,z) and z(x,y,p). Can, alternatively, measure height of pressure surfaces (using GPS radiosondes) to obtain average T (x,y,z) between two pressure levels (called “thickness”).
- With this information, we can compute gradient wind and thermal wind and diagnose fronts including changes of wind speed/direction with height and thus cold/warm advection, vorticity advection, extratropical cyclone development and intensification…..

On the synoptic weather scale, observing T(x,y,z) yields p(x,y,z) and z(x,y,p) – Below is an example

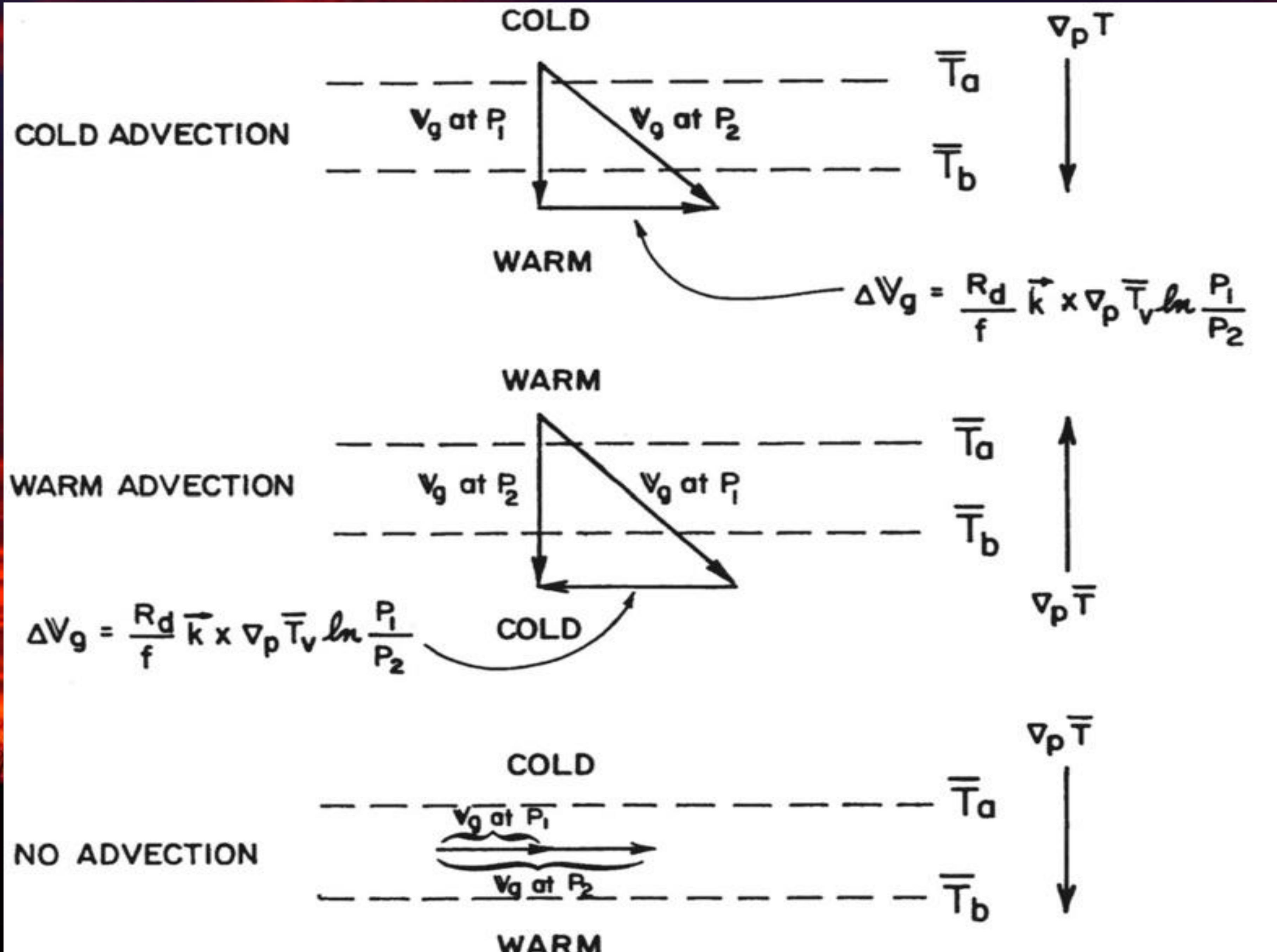
14.3.3 Thermal Wind

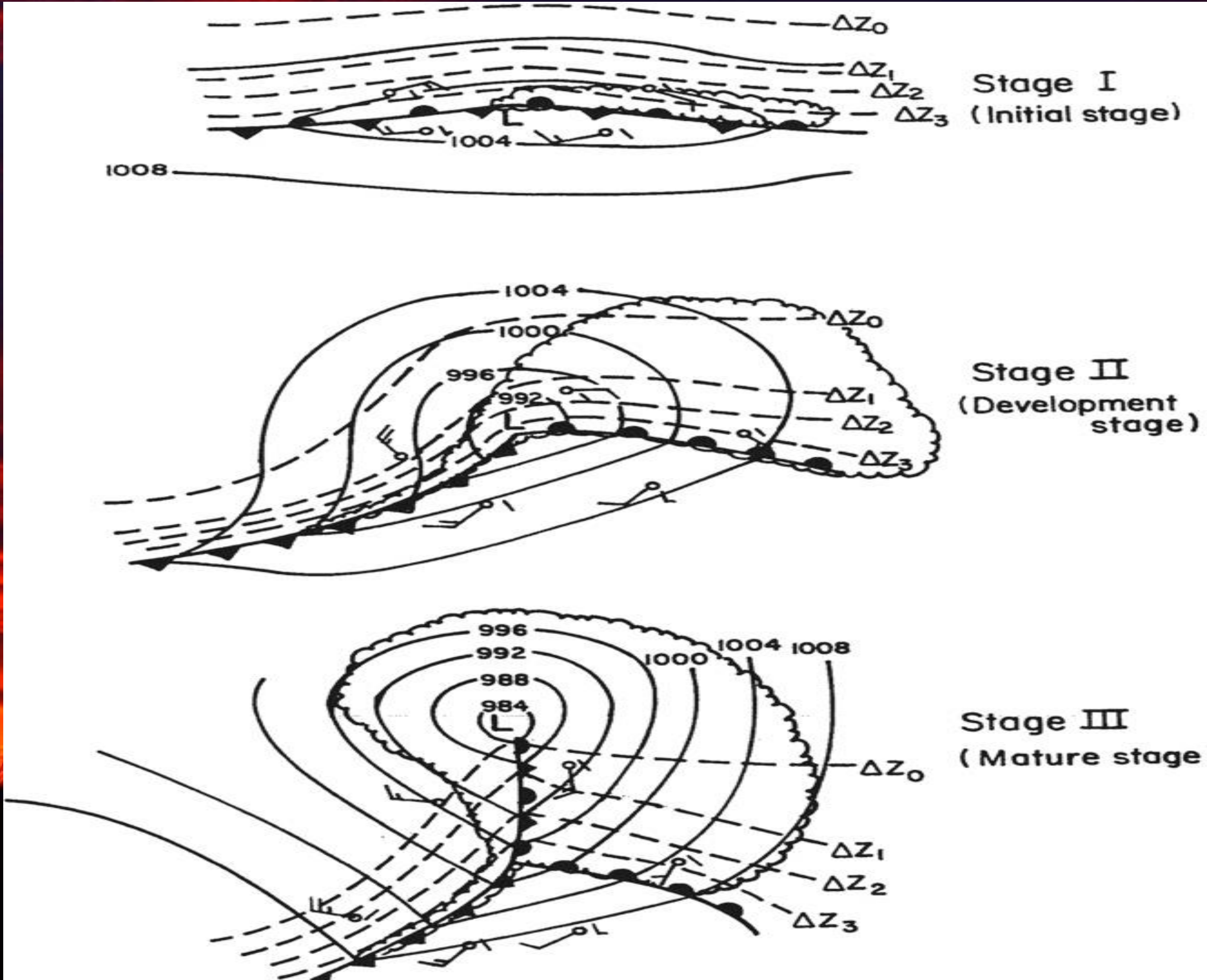
From Eq. 3.28, the geostrophic wind can be written (using vector notation) as:

$$\vec{V}_g = \vec{k} \times \frac{g}{f} \vec{\nabla}_p z$$

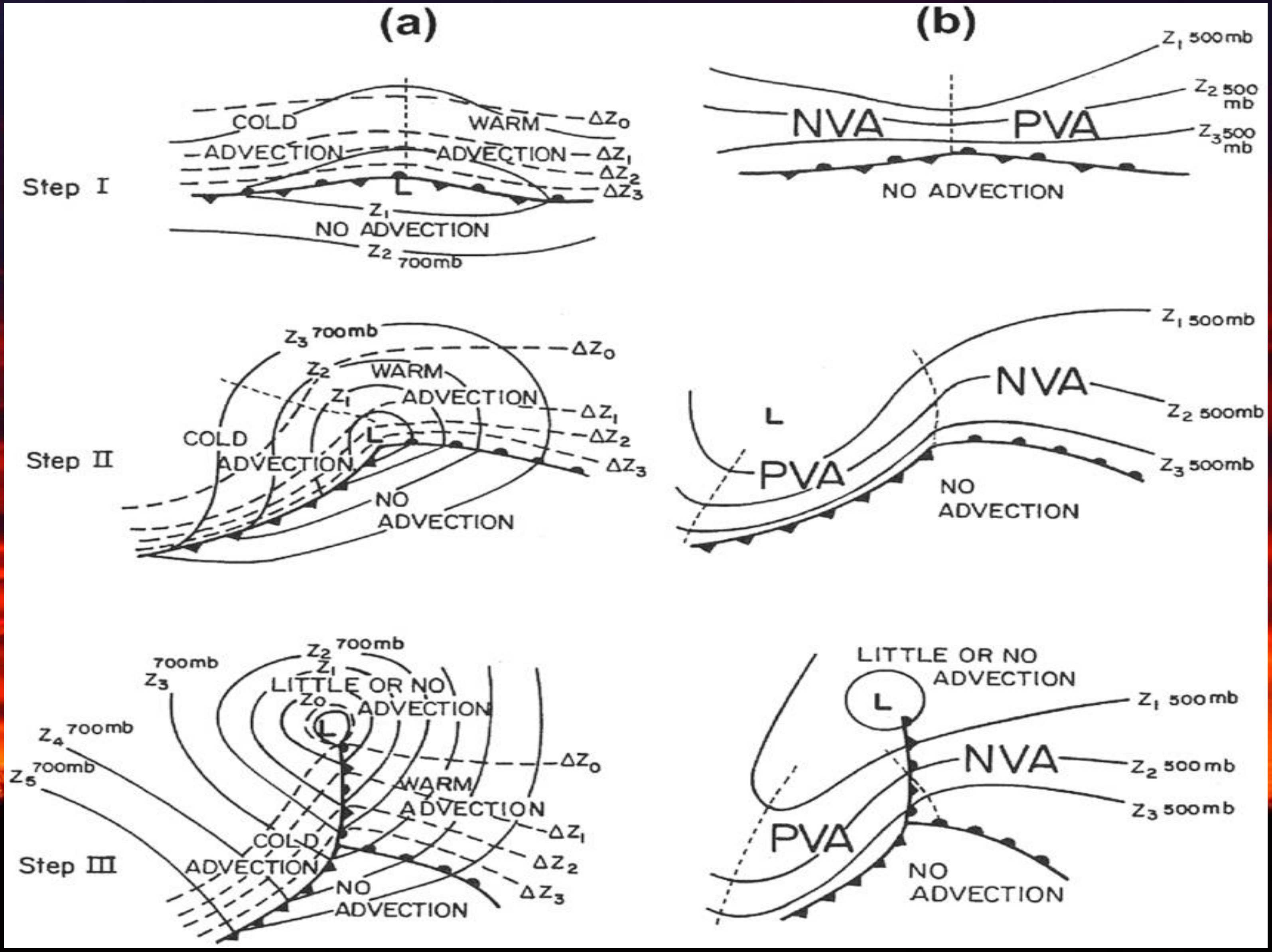
Differentiating this expression with respect to pressure yields:

$$\frac{\partial \vec{V}_g}{\partial p} = \frac{g}{f} \vec{k} \times \vec{\nabla}_p \frac{\partial z}{\partial p}$$


COLD
$\nabla_p T$
$\overline{T}_a$
COLD ADVECTION
$\mathbb{V}_g$ at P_1
$\mathbb{V}_g$ at P_2
$\overline{T}_b$
WARM
$\Delta \mathbb{V}_g = \frac{R_d}{f} \vec{k} \times \nabla_p \overline{T}_v \ln \frac{P_1}{P_2}$
WARM
$\overline{T}_a$
WARM ADVECTION
$\mathbb{V}_g$ at P_2
$\mathbb{V}_g$ at P_1
$\overline{T}_b$
$\nabla_p \overline{T}$
$\Delta \mathbb{V}_g = \frac{R_d}{f} \vec{k} \times \nabla_p \overline{T}_v \ln \frac{P_1}{P_2}$
COLD
$\nabla_p \overline{T}$
COLD
$\overline{T}_a$
$\mathbb{V}_g$ at P_1
NO ADVECTION
$\mathbb{V}_g$ at P_2
$\overline{T}_b$
WARM



ΔZ_0
ΔZ_1
ΔZ_2
ΔZ_3
Stage I
(Initial stage)
L
1004
1008
1004
1000
996
992
L
Stage II
(Development stage)
996
992
988
984
(L)
1000
1004
1008
Stage III
(Mature stage)


(a)
(b)
Step I
COLD ADVECTION
WARM ADVECTION
ΔZo
ΔZ1
ΔZ2
ΔZ3
L
Z1
NO ADVECTION
Z2 700mb
Z1 500mb
Z2 500 mb
Z3 500 mb
NVA
PVA
NO ADVECTION
Step II
Z3 700mb
Z2
Z1
WARM ADVECTION
COLD ADVECTION
L
NO ADVECTION
ΔZo
ΔZ1
ΔZ2
ΔZ3
Z1 500mb
NVA
Z2 500mb
PVA
Z3 500mb
NO ADVECTION
Step III
700mb Z3
Z2 700mb
Z1
Zo
LITTLE OR NO ADVECTION
Z4 700mb
Z5 700mb
WARM ADVECTION
COLD ADVECTION
NO ADVECTION
ΔZo
ΔZ1
ΔZ2
ΔZ3
LITTLE OR NO ADVECTION
L
Z1 500mb
NVA
Z2 500mb
Z3 500mb
PVA
NO ADVECTION


We already use AI implicitly in our weather forecasting.
Time to take the next step.
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Traditional Parameterization

In this chapter, the representation in mesoscale models of three types of physical processes are introduced. This specification of subgrid-scale and source/sink processes using experimental data and simplified fundamental concepts is called *parameterization*. Usually the parameterizations are not defined in terms of basic conservation principles. A parameterization does not necessarily have to actually simulate the physical processes it is representing, in order to be a realistic representation of these terms.

Indeed, if the quantitative accuracy of a parameterization is not sacrificed, it is desirable to make the parameterization as computationally simple as possible. The three processes to be parameterized are:

1. averaged subgrid-scale fluxes (i.e., $\rho_0\overline{u''_j u''_i}$, $\rho_0\overline{u''_j\theta''}$, etc. in Eqs. 4.21 and 4.24-4.26),
2. averaged radiation flux divergence (i.e., part of $\bar{S}_\theta$ in Eq. 4.24), and
3. averaged effects of the change-of-phase of water, including precipitation (i.e., $\bar{S}_{q_n}$ in Eq. 4.25, part of $\bar{S}_\theta$ in Eq. 4.24).

Pielke Sr., R.A., D. Stokowski, J.-W. Wang, T. Vukicevic, G. Leoncini, T. Matsui, C. Castro, D. Niyogi, C.M. Kishtawal, A. Biazar, K. Doty, R.T. McNider, U. Nair, and W.K. Tao, 2007: Satellite-based model parameterization of diabatic heating. EOS, Vol. 88, No. 8, 20 February, 96-97.

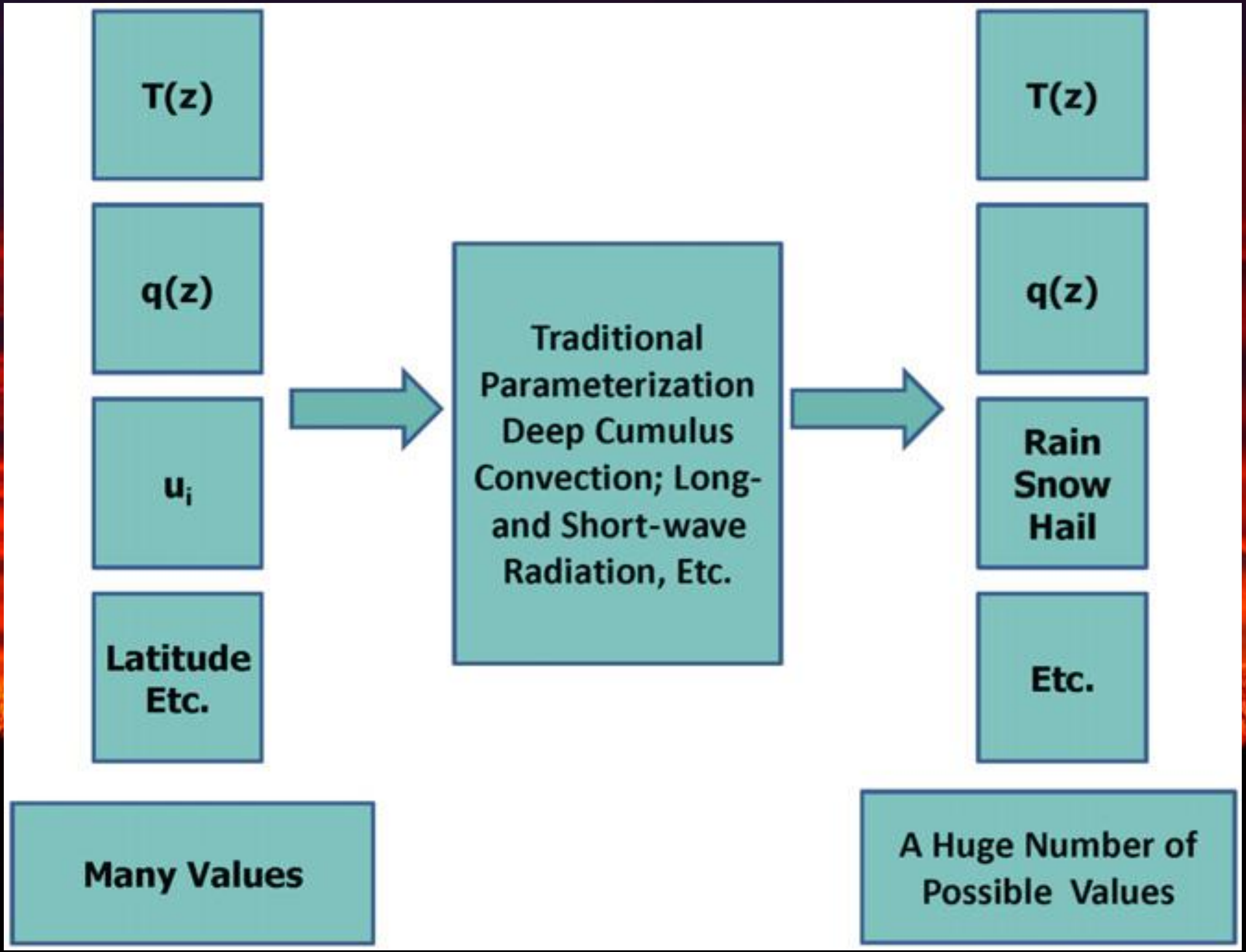
$$\partial\theta/\partial t = -u\partial\theta/\partial x - v\partial\theta/\partial y - w\partial\theta/\partial z + S_\theta \qquad (1)$$

A proposal to use AI for determining diabatic heating

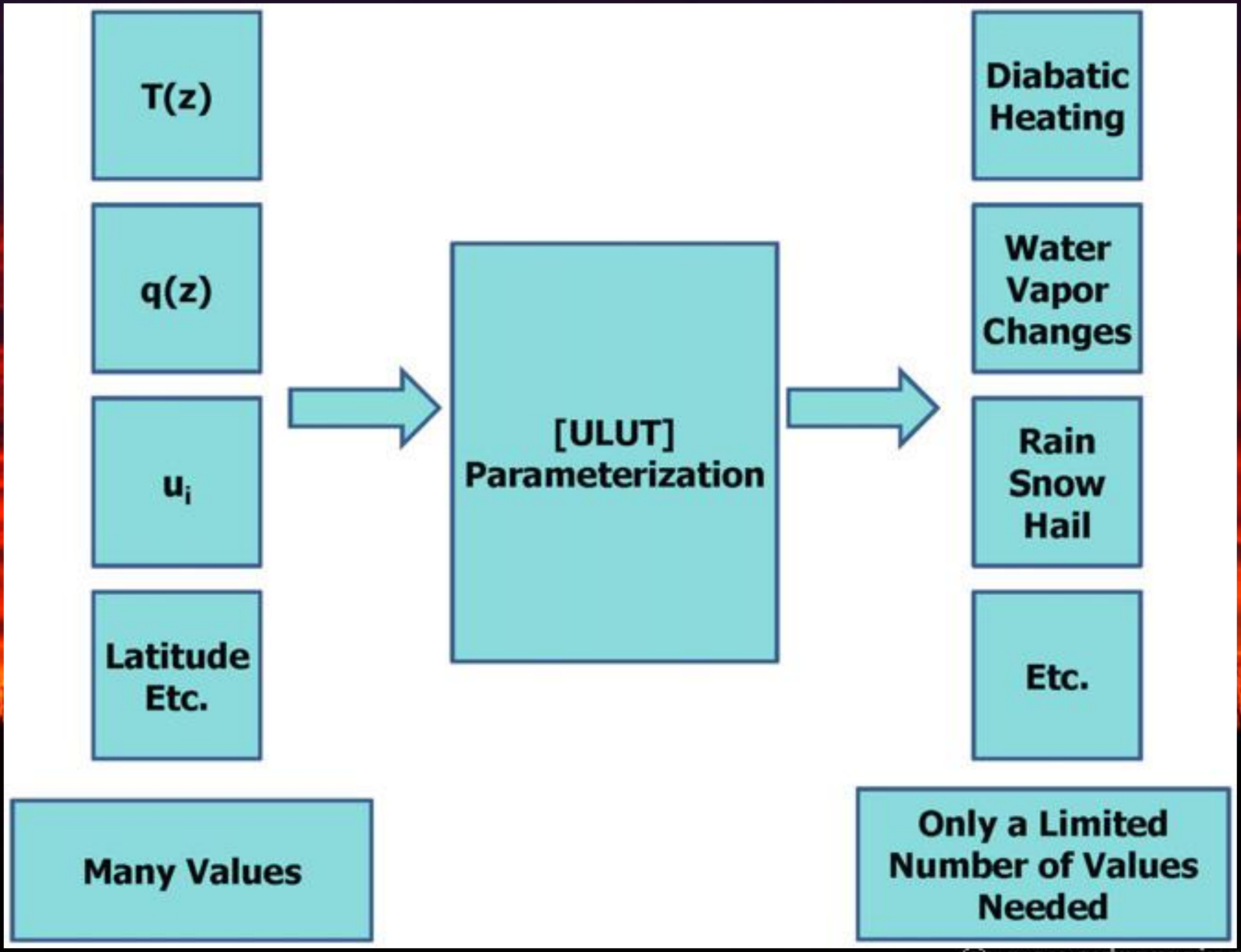
Pielke Sr., R.A., D. Stokowski, J.-W. Wang, T. Vukicevic, G. Leoncini, T. Matsui, C. Castro, D. Niyogi, C.M. Kishtawal, A. Biazar, K. Doty, R.T. McNider, U. Nair, and W.K. Tao, 2007: Satellite-based model parameterization of diabatic heating. EOS, Vol. 88, No. 8, 20 February, 96-97.

$$
\begin{aligned}
\mathrm{T} = [f(&\text{observation input of} \\
&u\partial\theta/\partial x + v\partial\theta/\partial y, \\
&\partial\theta/\partial t,\ u\partial q/\partial x + v\partial q/\partial y,\ \partial q/\partial t, \\
&\text{time of year, latitude})] \rightarrow \langle \mathbf{S}_\theta \rangle,
\end{aligned}
$$

Schematic illustration of the application of traditional parameterizations.



Schematic illustration of the application of a proposed new parameterization approach



The LUT [AI] parameterization approach can be written as

$$\text{Output}(f) = T[\text{Input}(f), c]$$

where the dependent variable response that need to be computed (the Output), are obtained from the Input values f and the prescribed constants, c of the parameterization, through the transfer function, T. The quantities f and c are vectors. The vector f includes, for example, the grid volume dependent variables, while c includes the time of year and day, the latitude etc. T is the AI parameterization.

There are several issues that permit the feasibility of this approach:

1. The physical fidelity of the parameterization is not important as long as the Output (f) is at least as accurate as the traditional parameterization.
2. Existing parameterizations are generally exercised in 1-D vertical columns with the input values of f obtained from just one x-y grid point. This simplifies significantly the number of calculations that must be performed.

3. Existing parameterizations include mathematical complexity which is not justified by the skill that it has in defining T. In other words, the dimensionality (i.e., as represented by its degrees of freedom – its resolution) of the parameterization is much greater than warranted. Such a large number of combinations results in a large number of physically meaningless inputs that result from the mathematical formulation used to construct a parameterization, rather than based on the data resolution used to construct the parameterization. No parameterization can justify a dimensionality (resolution) in the millions. This means the number of separate values of T can be much less than provided by the parent parameterization. The term graining can be used to describe the number of separate values of T.

4. The success of AI highly depends on the availability of a large repository of the precomputed values, and more critically, on fast, targeted retrieval of this information. Fortunately, commercial search engines, such as Google and Yahoo, have already demonstrated the feasibility of such an approach. For example, Google can search an index database of billions of web pages in under a second for most user queries. The AI approach has the added advantage that the total information stored is much more compact, well structured, and much easier to index.

5. In an atmospheric model, several different parameterizations usually are used to reproduce the various physical processes. However, it is generally unrealistic to separate the processes in this way since the observations and physics make no such artificial separation. These processes are, in fact, 3-D and interact with each other. Thus the most effective way to implement a LUT is to combine all of the relevant physics that result in diabatic heating and cooling, atmospheric moistening and drying, etc.

SUMMARY

Using AI, there is therefore no need for millions of data points in a LUT in order to realistically reproduce parameterization of a specific process with the accuracy needed for use in an atmospheric model. Indeed, we may want to even include the basic physics directly into the AI formulation.

Can methods in artificial intelligence (AI) permit us to i) replace traditional parameterizations with representations trained from real observed data

YES

and ii) even the physics core?

- MAYBE, BUT WHY BOTHER? H/T Anton Beljaars

THANK YOU FOR ATTENDING MY SEMINAR

Other Out of the box concepts

- What is the actual surface area of Arizona and other states? [hint: the actual surface area is not equal to its two dimensional projection.] What is their fractal dimension?
- What is the relative importance of higher altitudes and slope towards north of terrain on colder plant species at the north rim of the Grand Canyon?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Our websites

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

http://pielkeclimatesci.wordpress.com/

Thanks, as usual, to Dallas Staley in the preparation of the PowerPoint slides!