Renewable Resource Interannual Variability under Current and Future Climate Scenarios

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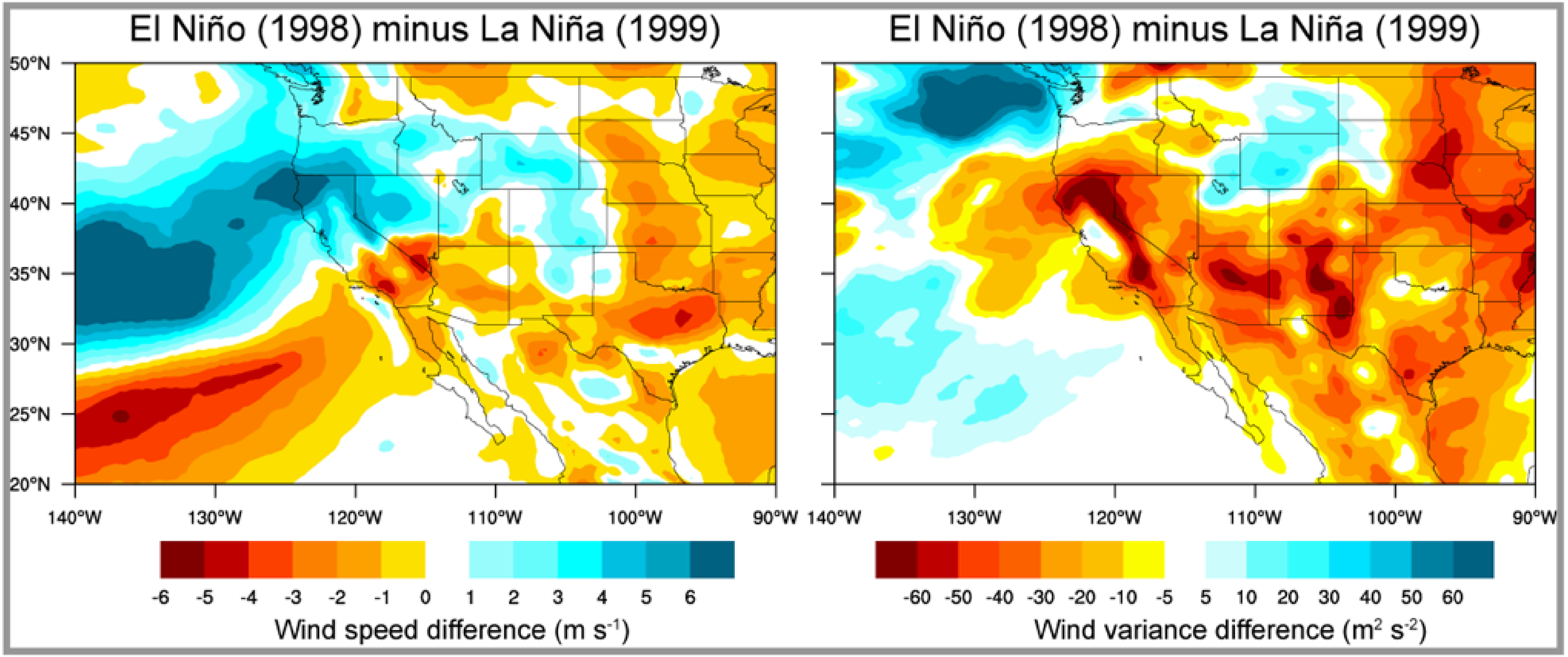
NCAR is sponsored by the National Science Foundation under CA # 1852977.

Interannual Wind Flow Challenges

Quantifying interannual variability

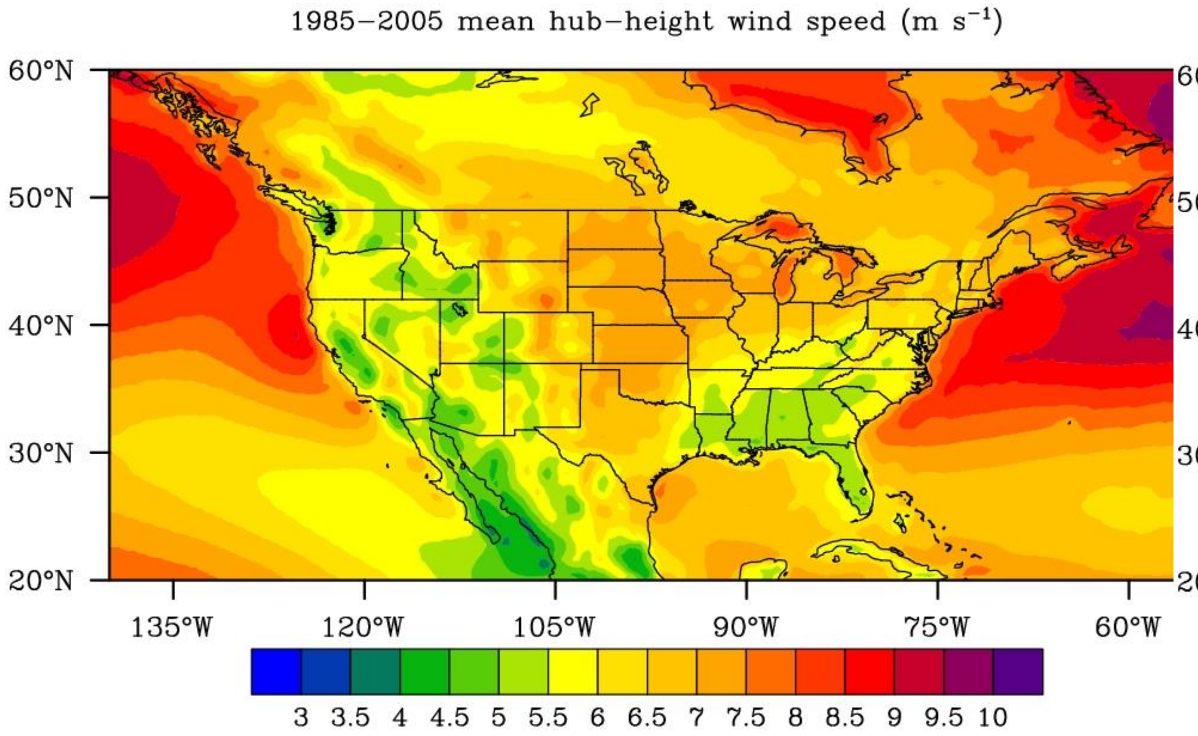


January winds at 0600 UTC (2300 MST)

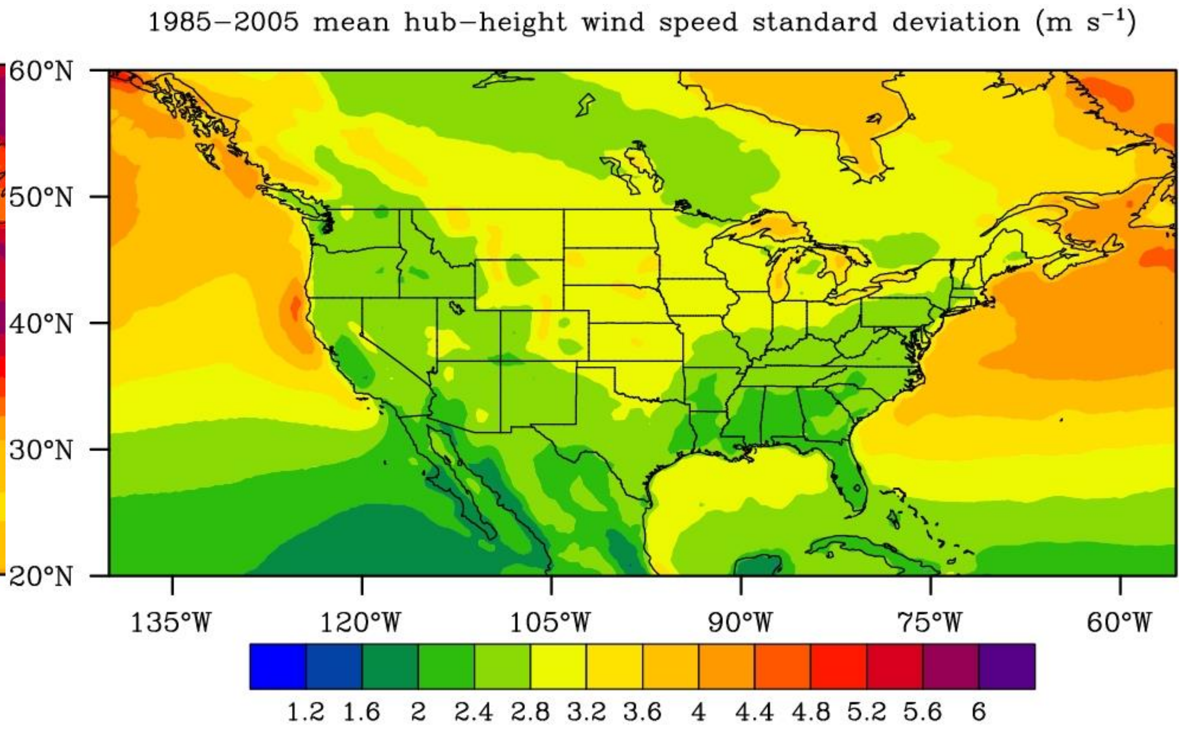
Courtesy: Daran Rife and Andrea Hahmann, Danish Technical University

Changes and Variability in Wind and Solar Resource

Maps formed from NCAR's 20 year Climate Four Dimension Data Assimilation Database (CFDDA)



Mean 80-m Wind Speed



StDev 80-m Wind Speed

Haupt, S.E., J. Copeland, W.Y.Y. Cheng, C. Amman, Y. Zhang, and P. Sullivan, 2016: Quantifying the Wind and Solar Power Resource and their Inter-annual Variability over the United States under Current and Projected Future Climate, *Journal of Applied Meteorology and Climatology*, **55**, pp. 345-363, DOI: 10.1175/JAMC-D-15-0011.1

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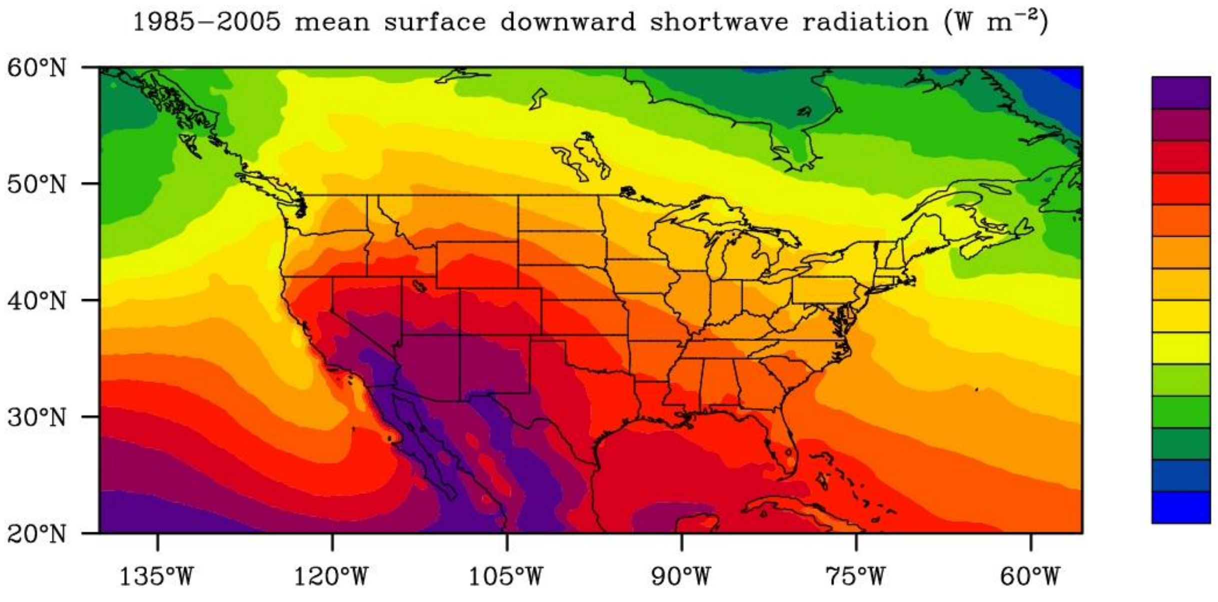
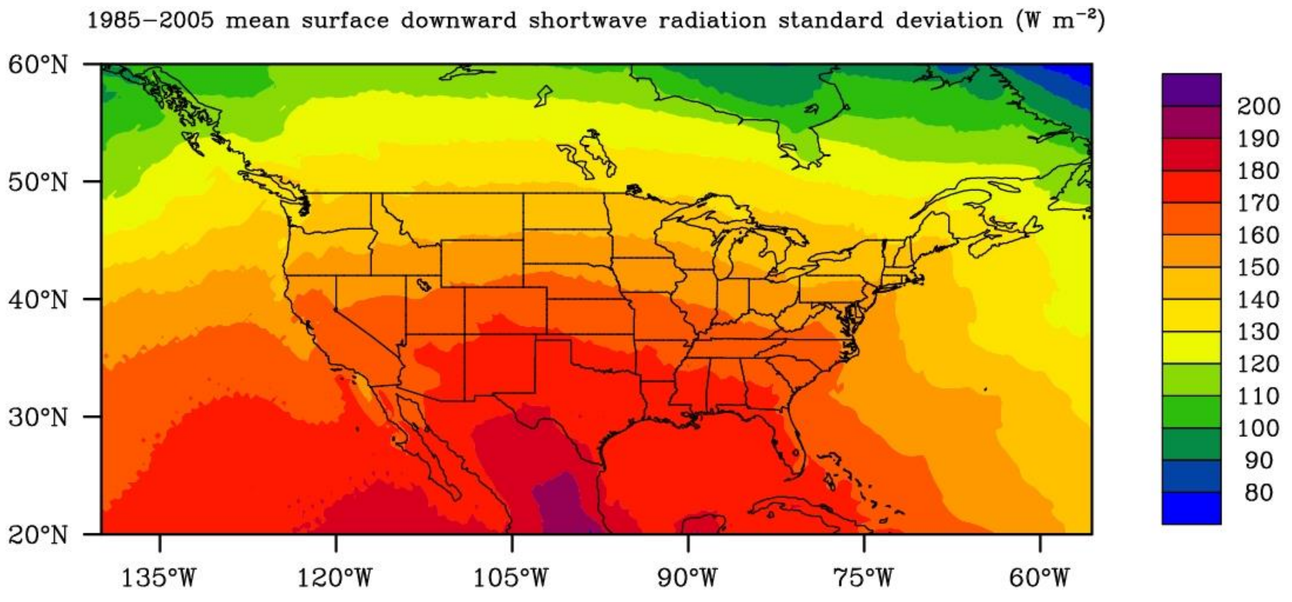


Mean Surface Downward Shortwave Radiation



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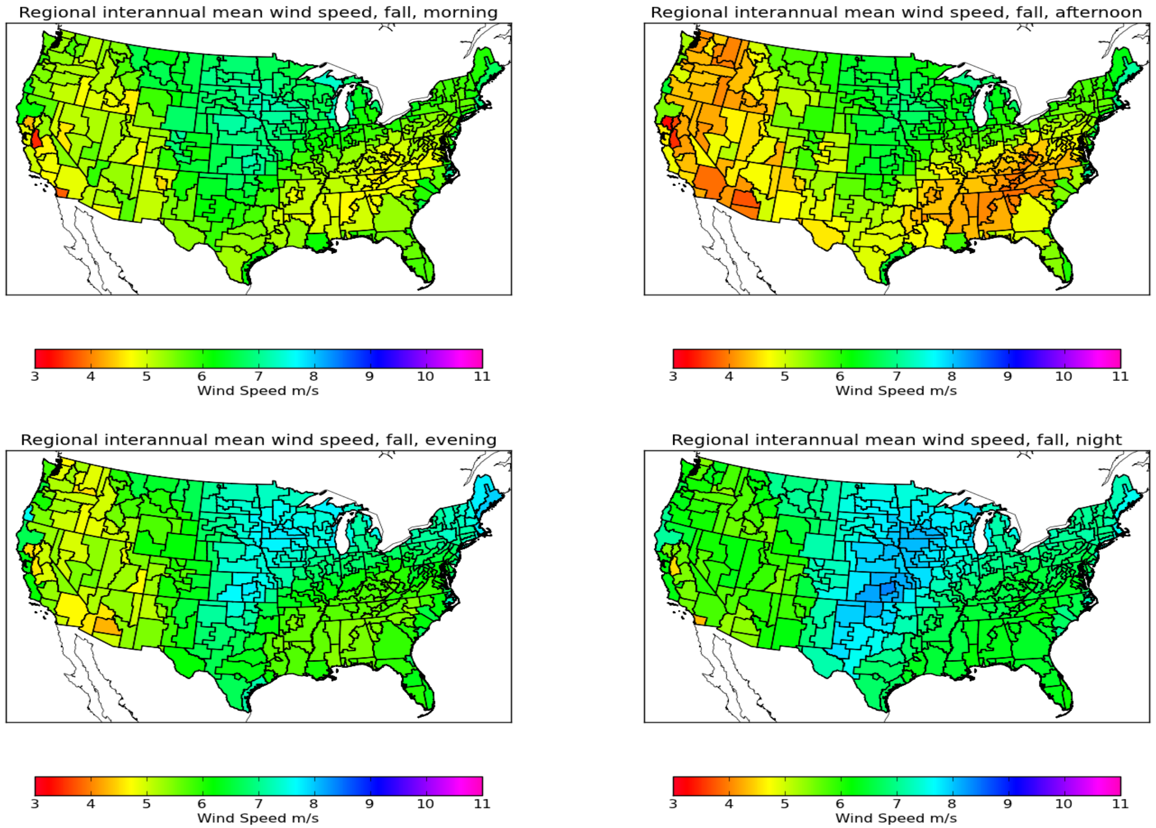
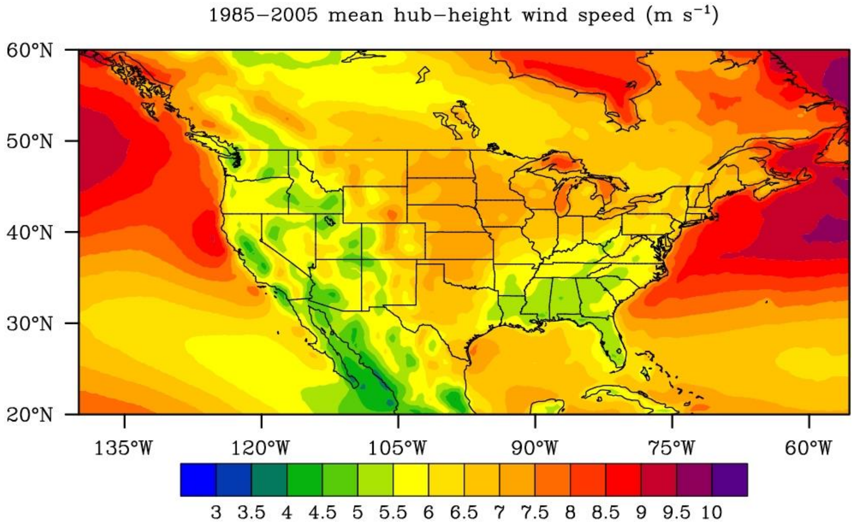
Current Climate Wind Speed by Region, Time of Day, and Season



Daily Time Slices (Local Time)	Morning	Afternoon	Evening	Night
	0600-1300	1300-1700	1700-2200	2200-0600
Seasons	Summer	Fall	Winter	Spring
	June-August	September-October	November-February	March-May

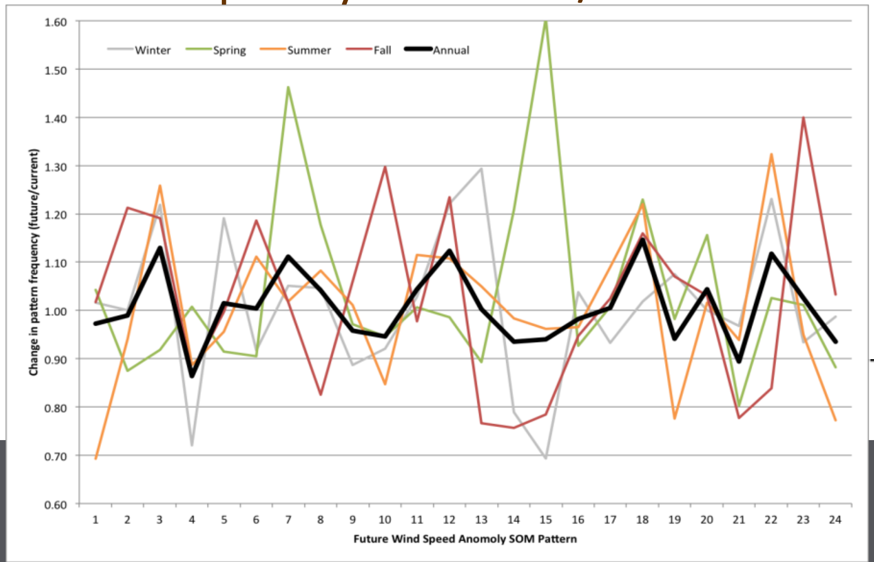
Using AI to Determine Climatic Changes in Wind and Solar Resource

Maps formed from NCAR's 20 year Climate Four Dimension Data Assimilation Database (CFDDA)

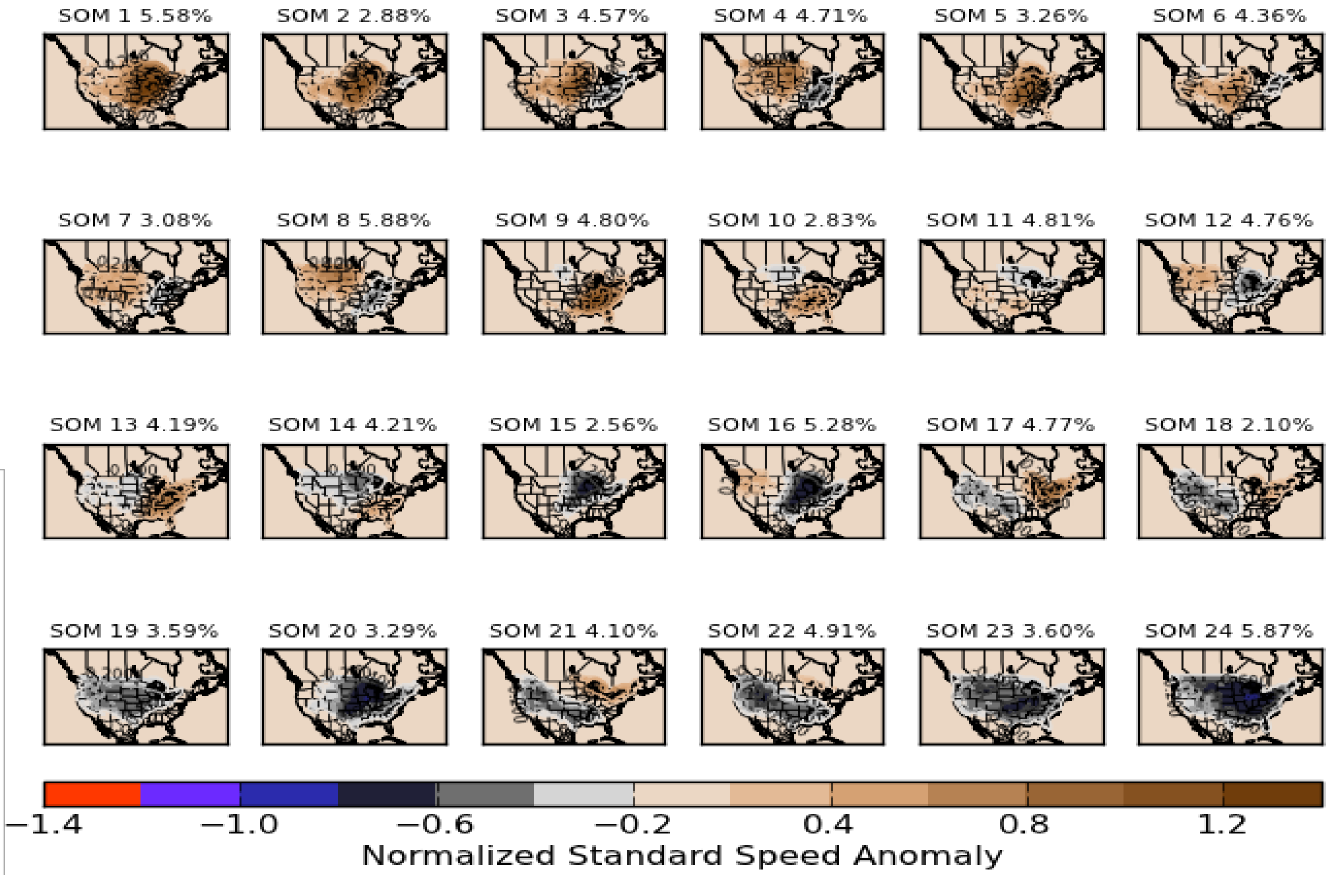


Mean 80-m Wind Speed

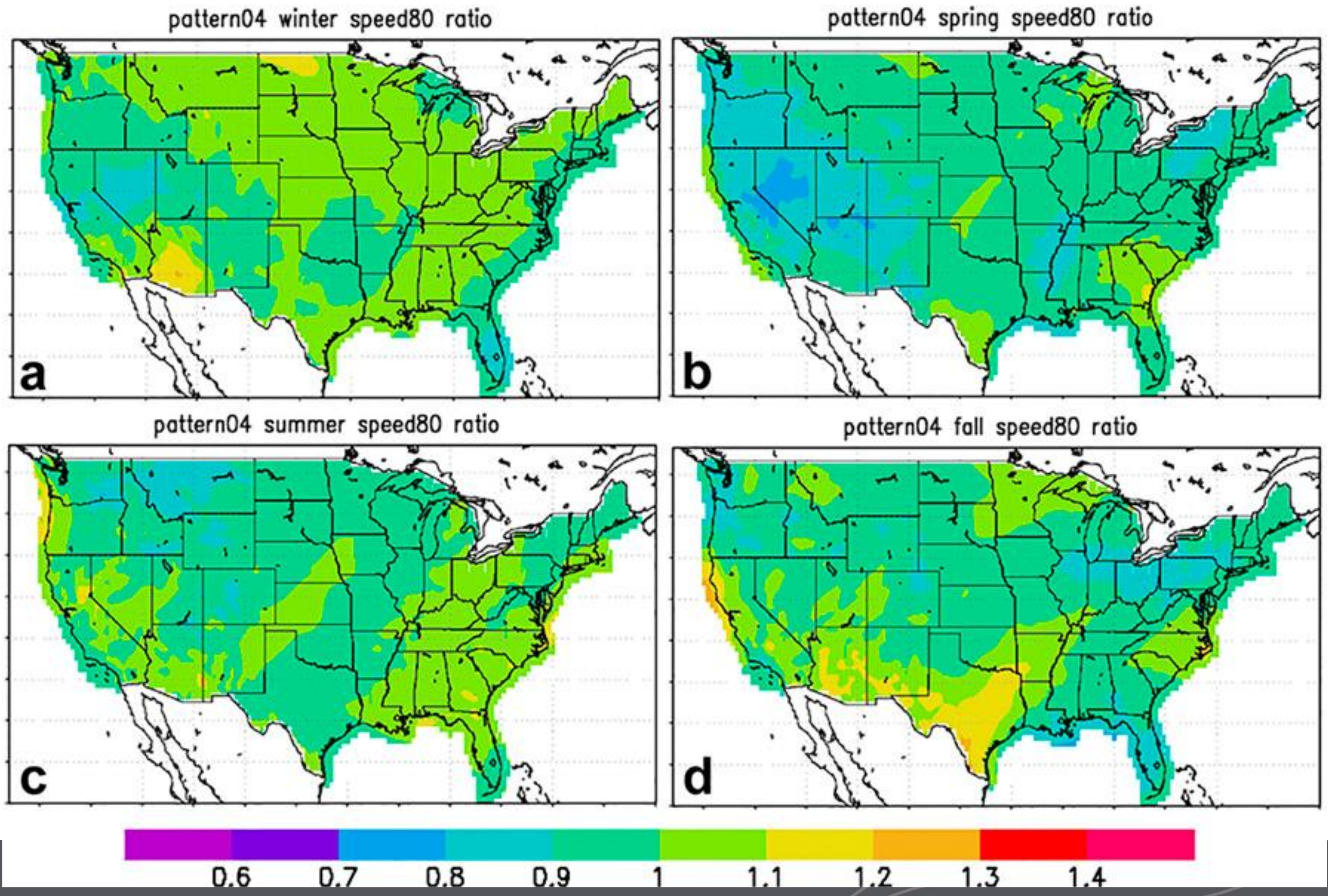
Change in seasonal pattern frequency for CRCM/CCSM



24 Self Organizing Map (SOM) analysis performed on daily standard anomalies – Based on Artificial Neural Networks

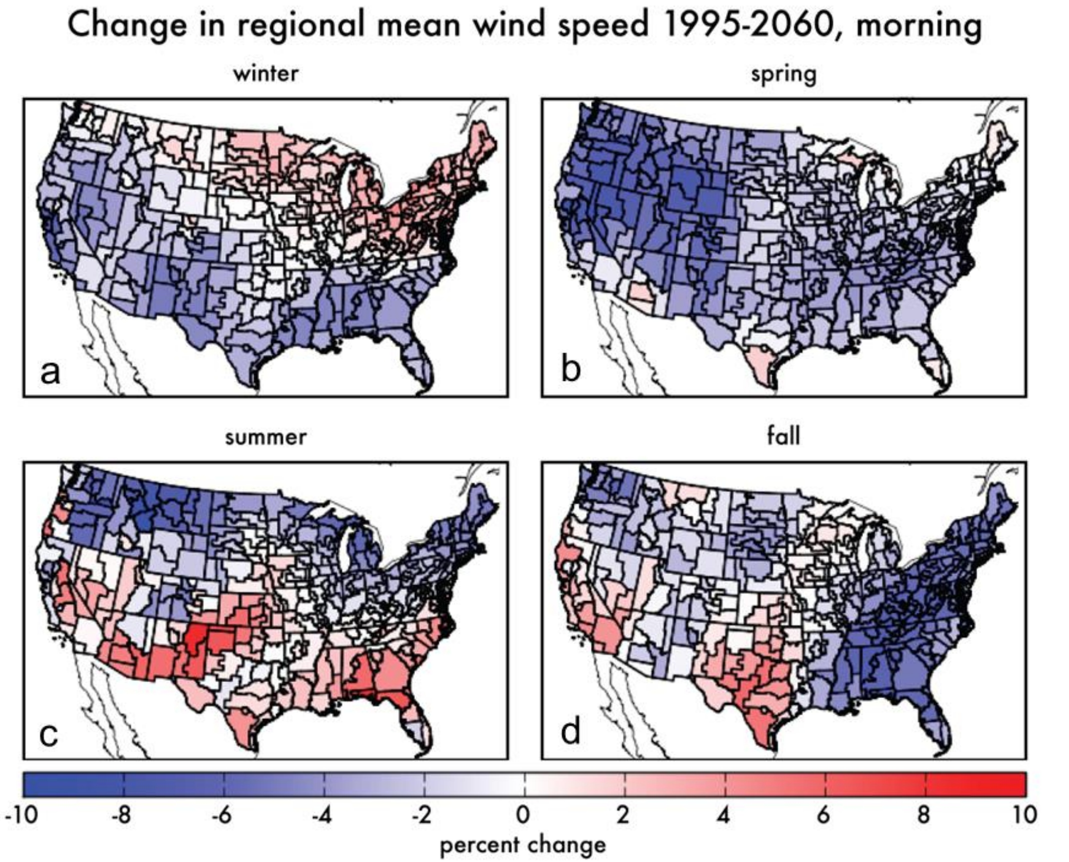


Apply SOM specific climate adjustment factors by season

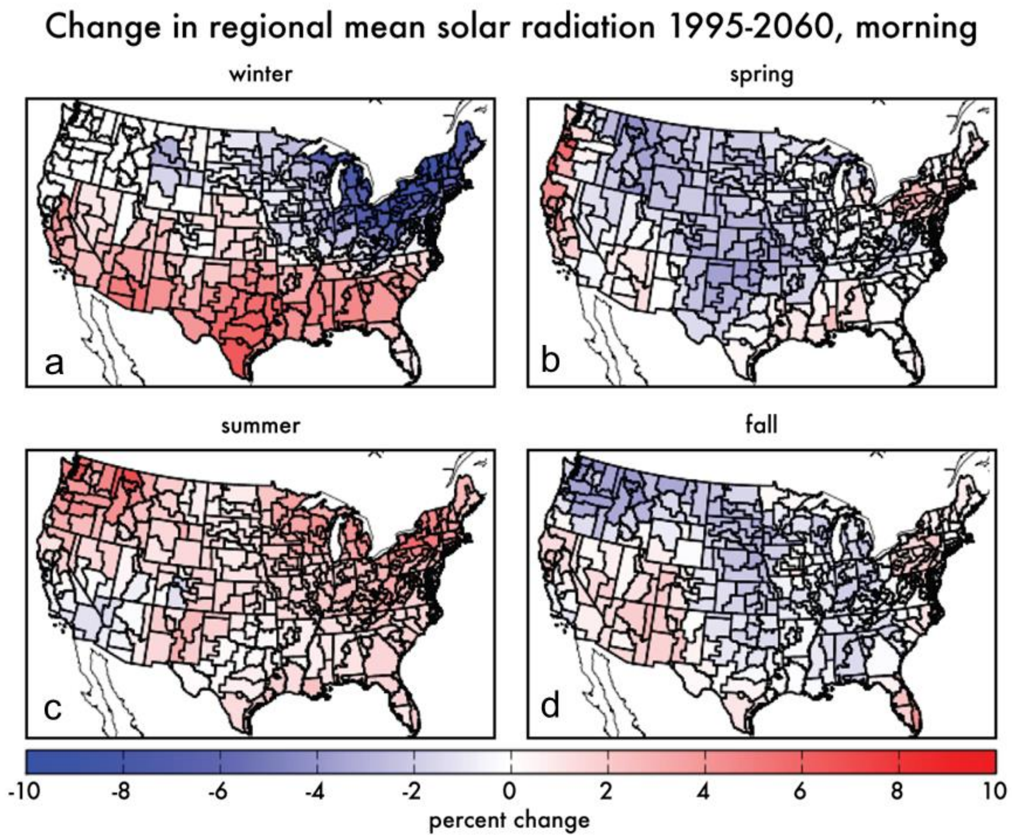


Using Output to Determine Energy Impacts

Is **Wind Speed** likely to change over the U.S. in a changing climate and will it vary by time of day and season?



Is **Solar Irradiance** likely to change over the U.S. in a changing climate and will it vary by time of day and season?



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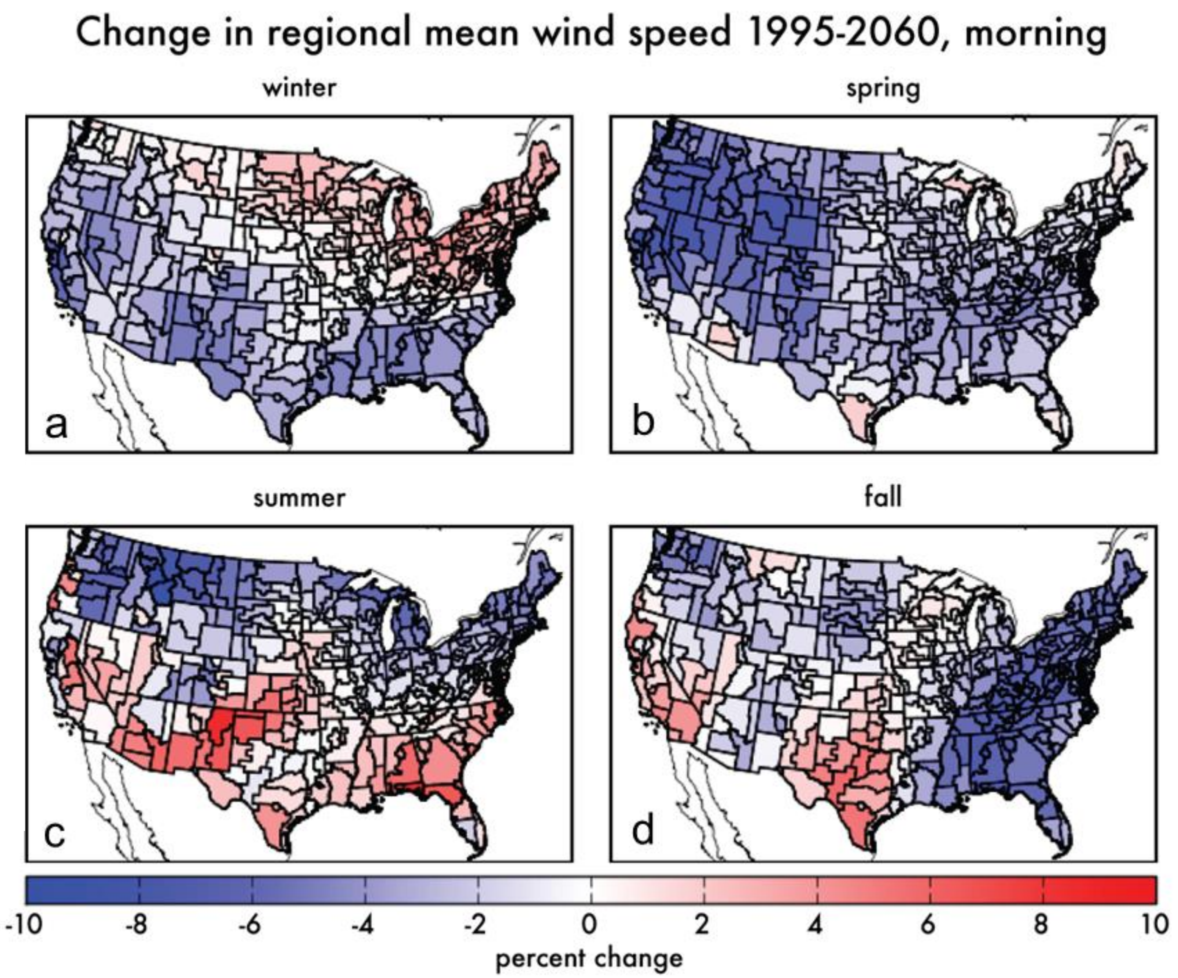
Proxy Future Climate

- ✓ Predicted change in the frequency of occurrence of the patterns is typically ±10% though this can exceed ±20% for certain patterns
- ✓ Regional changes are predicted to be within ±10% of current values
- ✓ Seasonal dependence for result

Projected Change in Wind Speed by Season



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Changing Climate

Table S1: Mean and likely range of temperature changes by 2100 for SRESs and RCPs and emissions pathway label used in this review to facilitate comparisons between sets of scenarios.

Emissions Scenario		Temperature Change (°C) by 2100		
		Mean	Likely Range	Emissions Pathway Label in this Review
RCP[a]	2.6	1.0	0.3–1.7	Low
	4.5	1.8	1.1–2.6	Medium
	6.5	2.2	1.4–3.1	Medium
	8.5	3.7	2.6–4.8	High
SRES[b]	B1	1.8	1.1–2.9	Low
	B2	2.4	1.4–3.8	Medium
	A1B	2.8	1.7–4.4	Medium
	A2	3.4	2.0–5.4	High

[a] Mean temperature changes given for 2081–2100 relative to 1986–2005. Likely range of temperature change based on 5%–95% interval across GCM outputs. Source: [1].

[b] Mean temperature changes given for 2090–2099 relative to 1980–1999. Likely range of temperature change based on +/- 1 standard deviation of model averages. Source: [2].

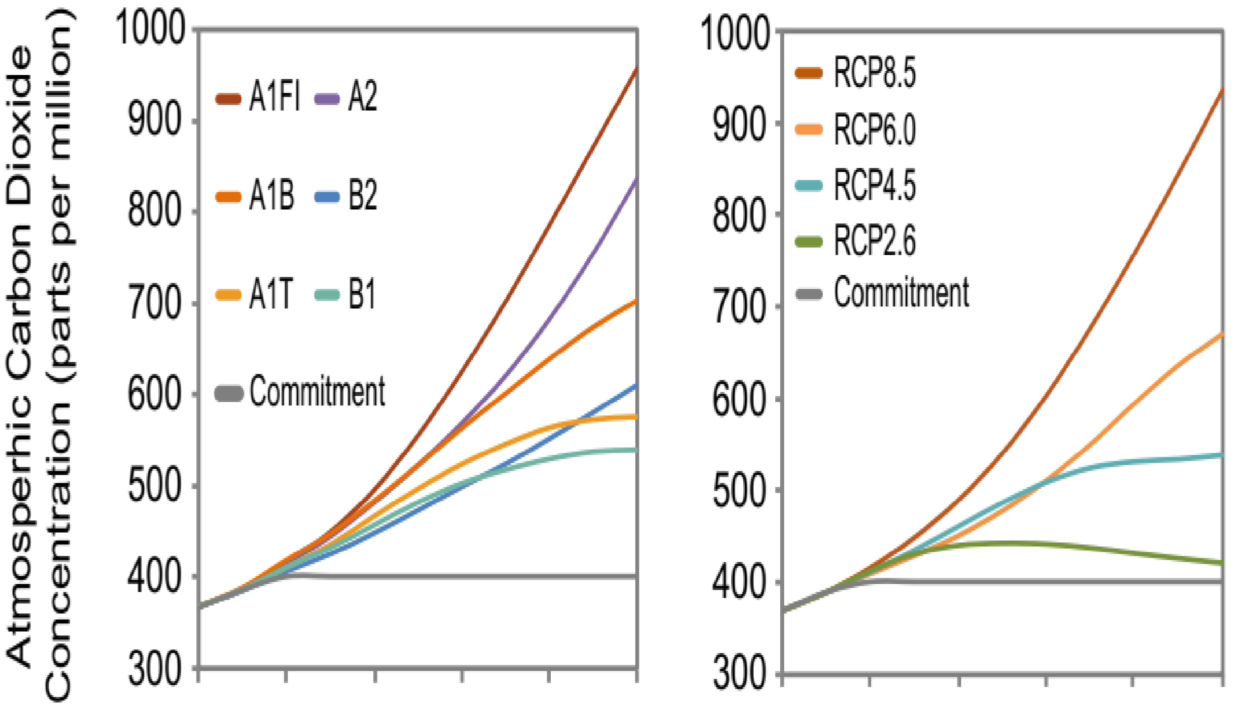

Figure S1: Atmospheric CO_2 concentrations under SRES (left) and RCP (right) emission scenarios. “Commitment” indicates a hypothetical scenario where CO_2 concentrations stabilize at roughly 400 ppm

Energy Sector Implications

Power System Component	Component-Level Impacts (Agreement among Studies, Quality of Evidence, and Confidence in our Evaluation)	Potential Power System Planning and Operations Implications
Electricity demand	Increased annual total and, to a greater extent, peak electricity demand (high, robust, high)	Increased total generation Increased investment requirement in generation or demand response and more peaked electricity prices
Thermal generators	Increased summertime curtailments largely contingent on enforcement of thermal discharge regulations (high, robust, high)	Reduced capacity value of thermal units, requiring additional capacity investments If curtailments correlated, increased operational reserve requirements
Transmission	Reduced transmission capacity during peak demand periods (medium, low, medium)	Increased transmission investment Exacerbated congestion and contingencies

Craig, M.T., S. Cohen, J. Macknick, C. Draxl, O.J. Guerra, M. Sengupta, S.E. Haupt, B.-M. Hodge, and C. Brancucci, 2018: A Review of the Potential Impacts of Climate Change on Bulk Power System Planning and Operations in the United States, *Renewable and Sustainable Energy*, DOI: 10.1016/j.rser.2018.09.022

Energy Sector Implications

Hydropower	Reduced summertime hydropower resource in California and the Pacific Northwest (medium, medium, medium) Reduced annual hydropower resource across South (medium, medium, medium)	Reduced capacity value, depending on release schedule and head height, requiring additional capacity investments Increased dispatching of other units
Wind	Decreased wind resources on average across US (low, medium, low) Large regional and temporal (seasonal and time of day) heterogeneity in wind resource changes (medium, medium, medium)	Increased wind investment or reliance on other zero-carbon technologies to meet decarbonization targets Regional changes in capacity values, requiring increased capacity investments
Solar	Decreased solar PV resource in California (medium, low, low) Increased solar PV and CSP resource in the Southeast (high, medium, medium) Greater average increases in CSP than solar PV resource across US (high, medium, high) Large regional and temporal (seasonal and time of day) heterogeneity in solar resource changes (medium, medium, medium)	Increased solar investment or reliance on other zero-carbon technologies to meet decarbonization targets Regional changes in capacity values, requiring increased capacity investments Increased investment in CSP relative to PV plants

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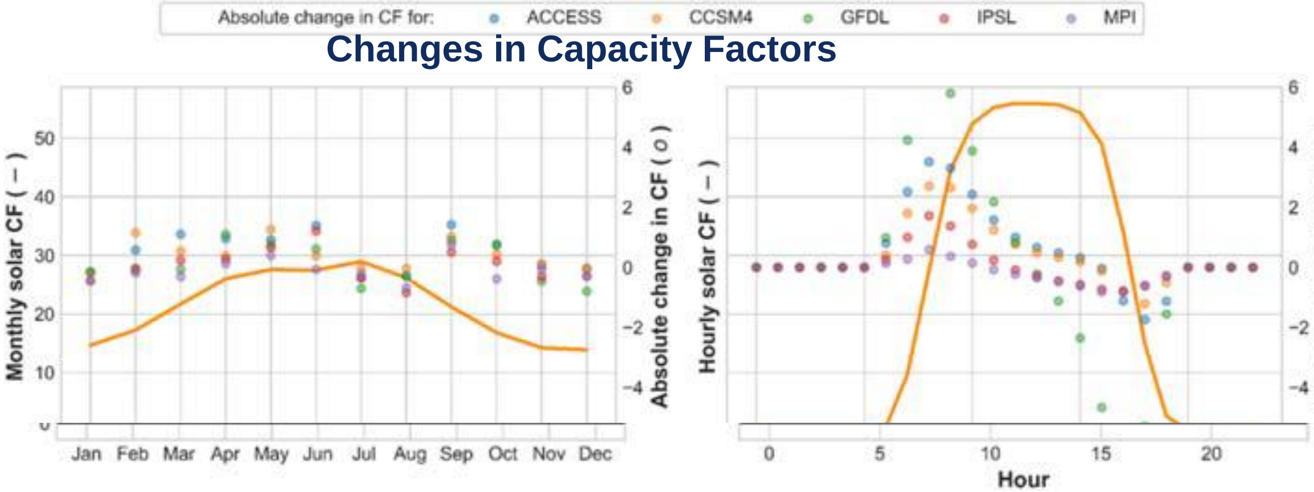
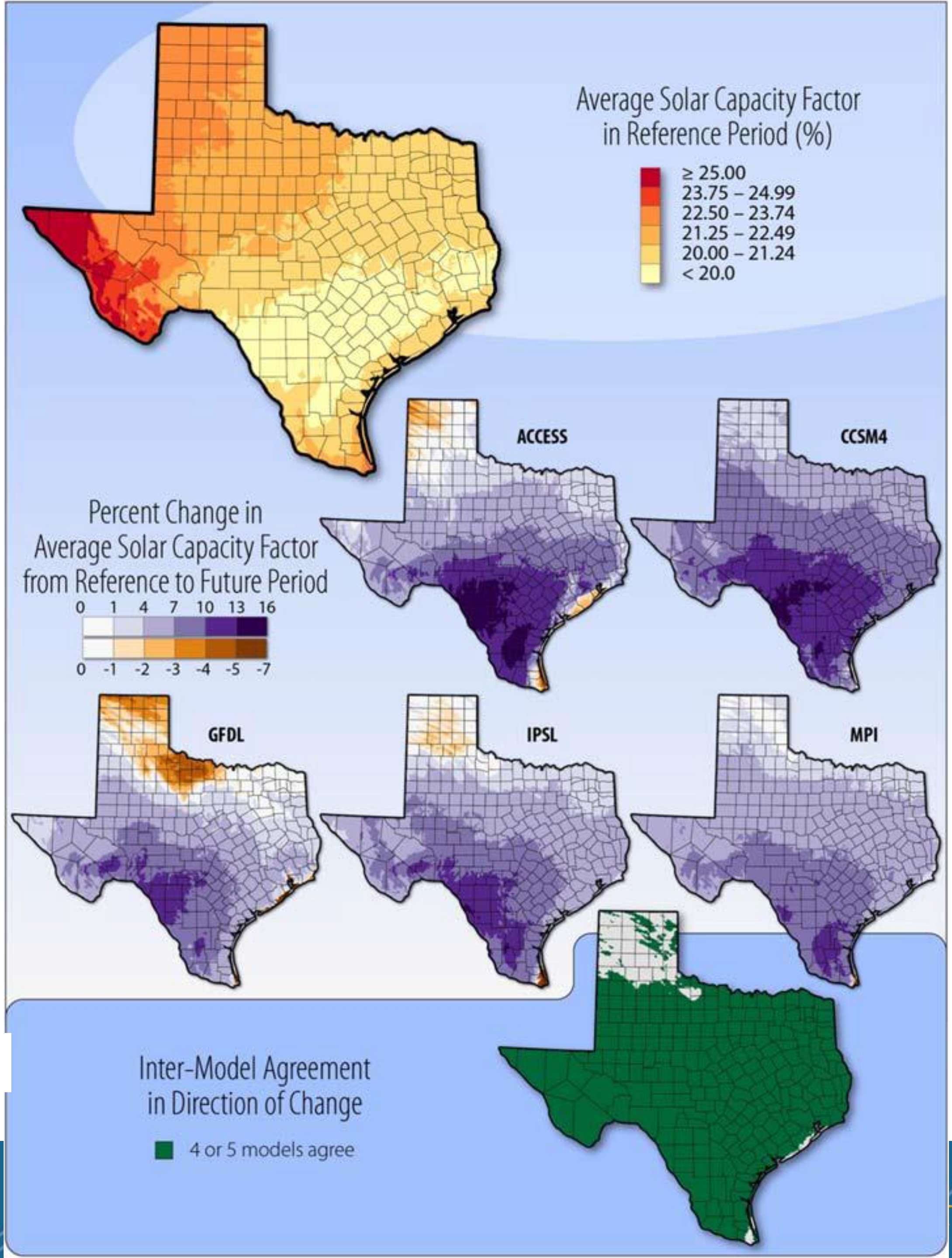
Case Study – Texas - Solar

- Dynamically downscale 5 climate models to cloud resolving (4 km)
- Changes in Solar capacity factor agree well across models.
  - Changes range from -0.6 to 2.5% ann avg
  - Increases CF in S & SW TX
  - Decreases in Panhandle
  - Decrease CF in winter & late summer
  - Increase CF n late morning



Seasonal Variations

Diurnal Variations

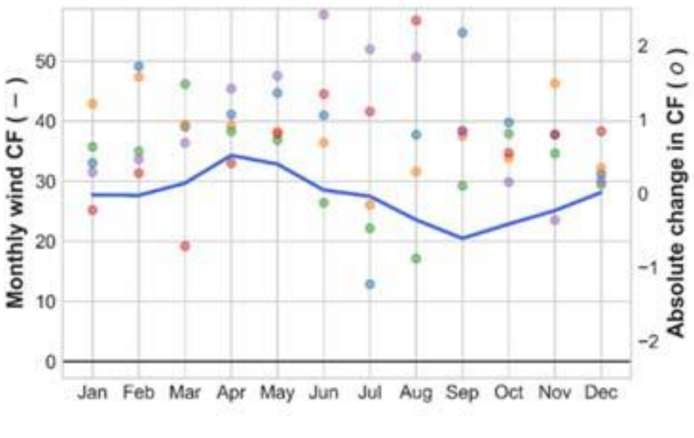


Reference and future periods correspond to 1995–2005 and 2040–2050, respectively.

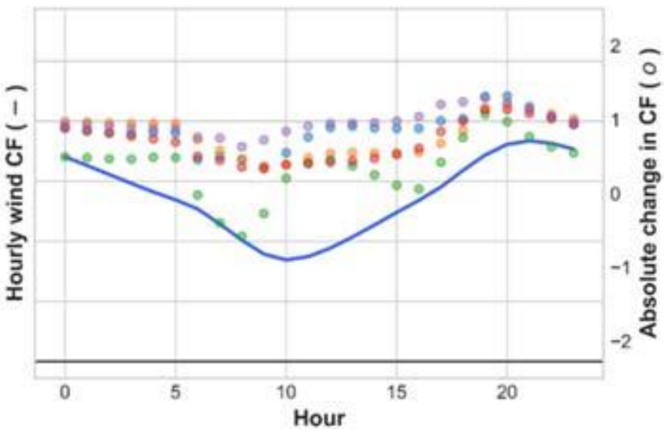
Case Study – Texas - Wind

- Changes in Wind capacity factor agree well across models.
  - Changes from +1.3 to 3.5% ann avg
  - Increases in W and E TX
  - Decreases in Panhandle & S TX
  - Seasonal changes rather small
  - Increase CF over most of day

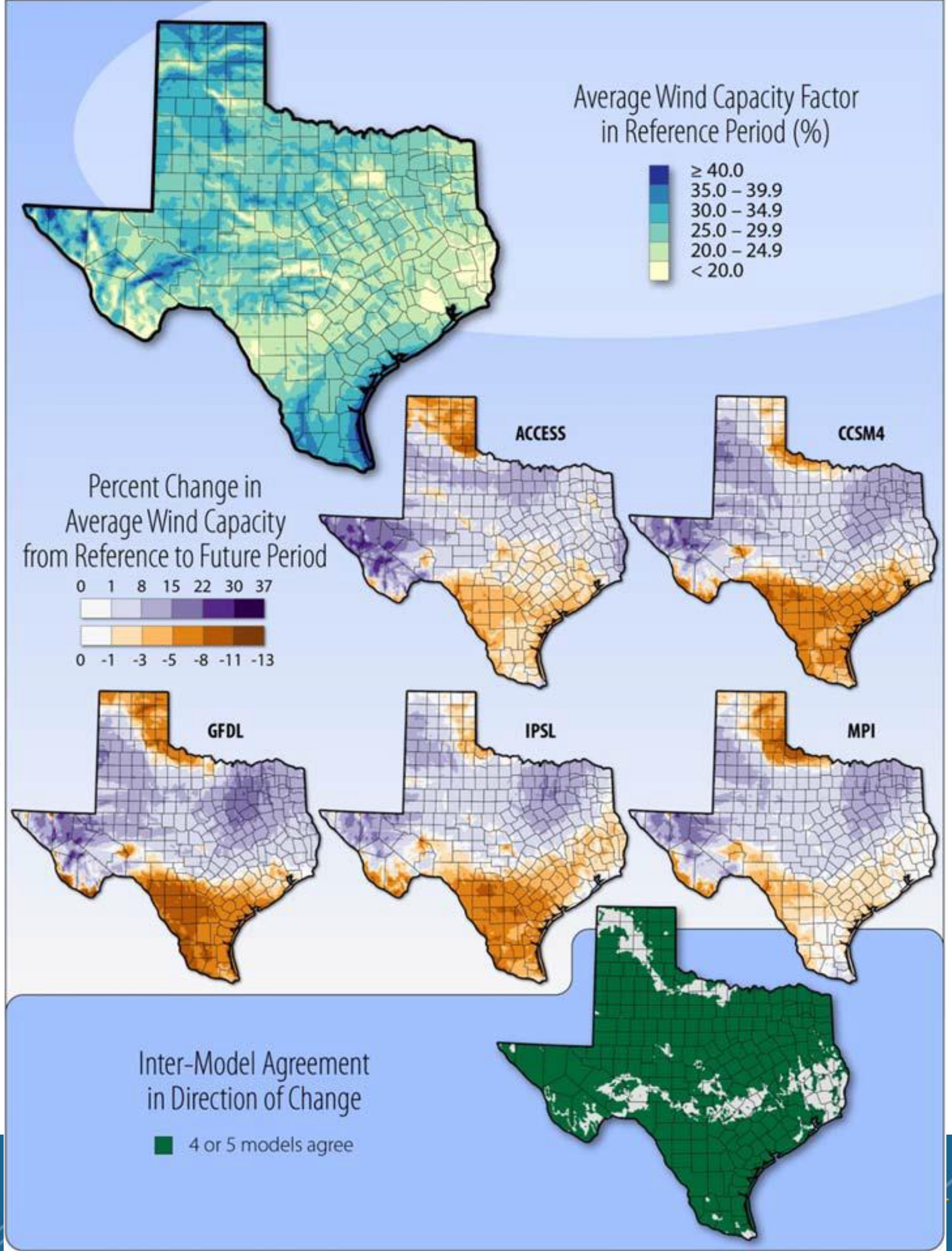
Changes in Capacity Factors



Seasonal Variations



Diurnal Variations



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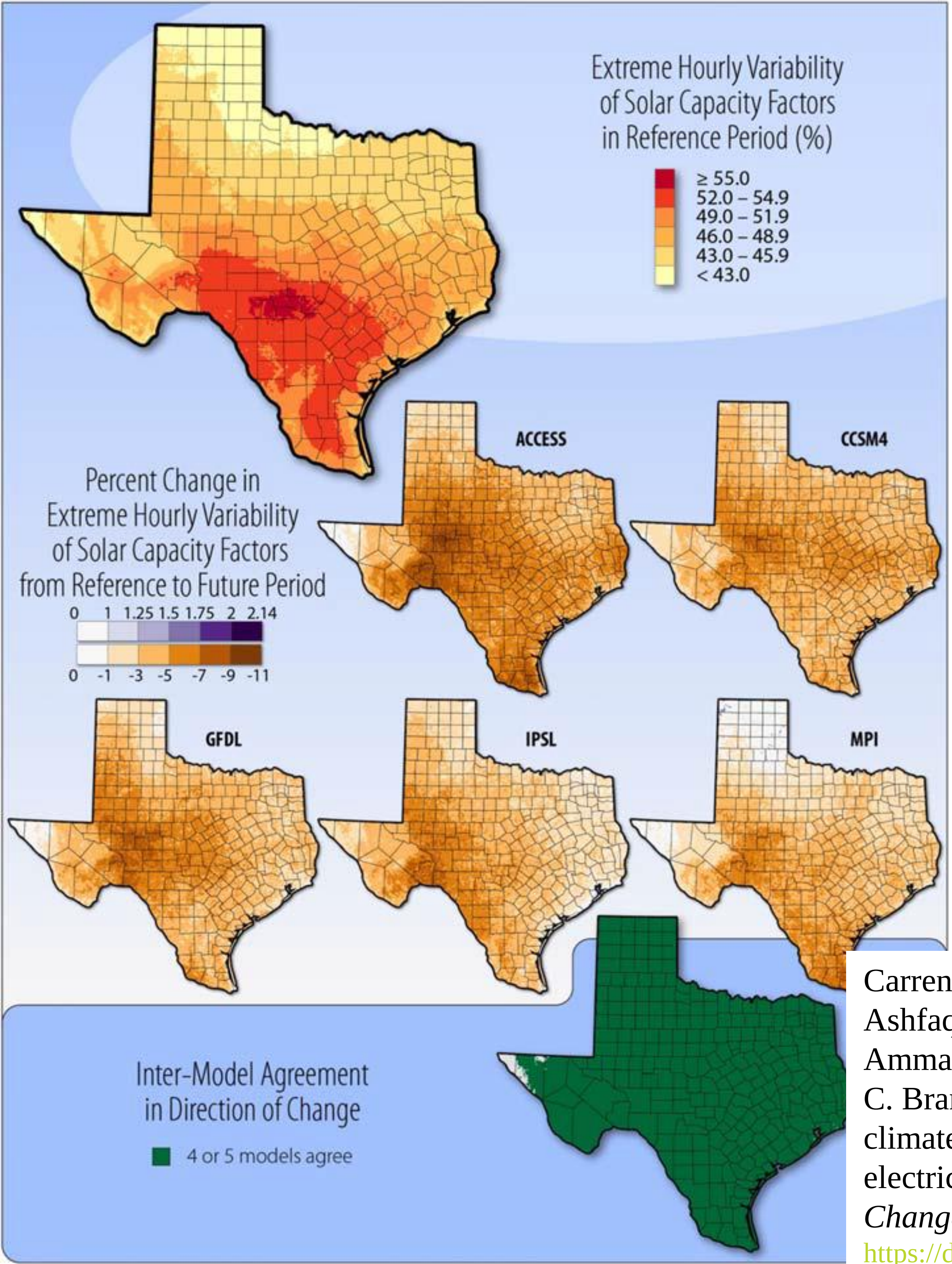
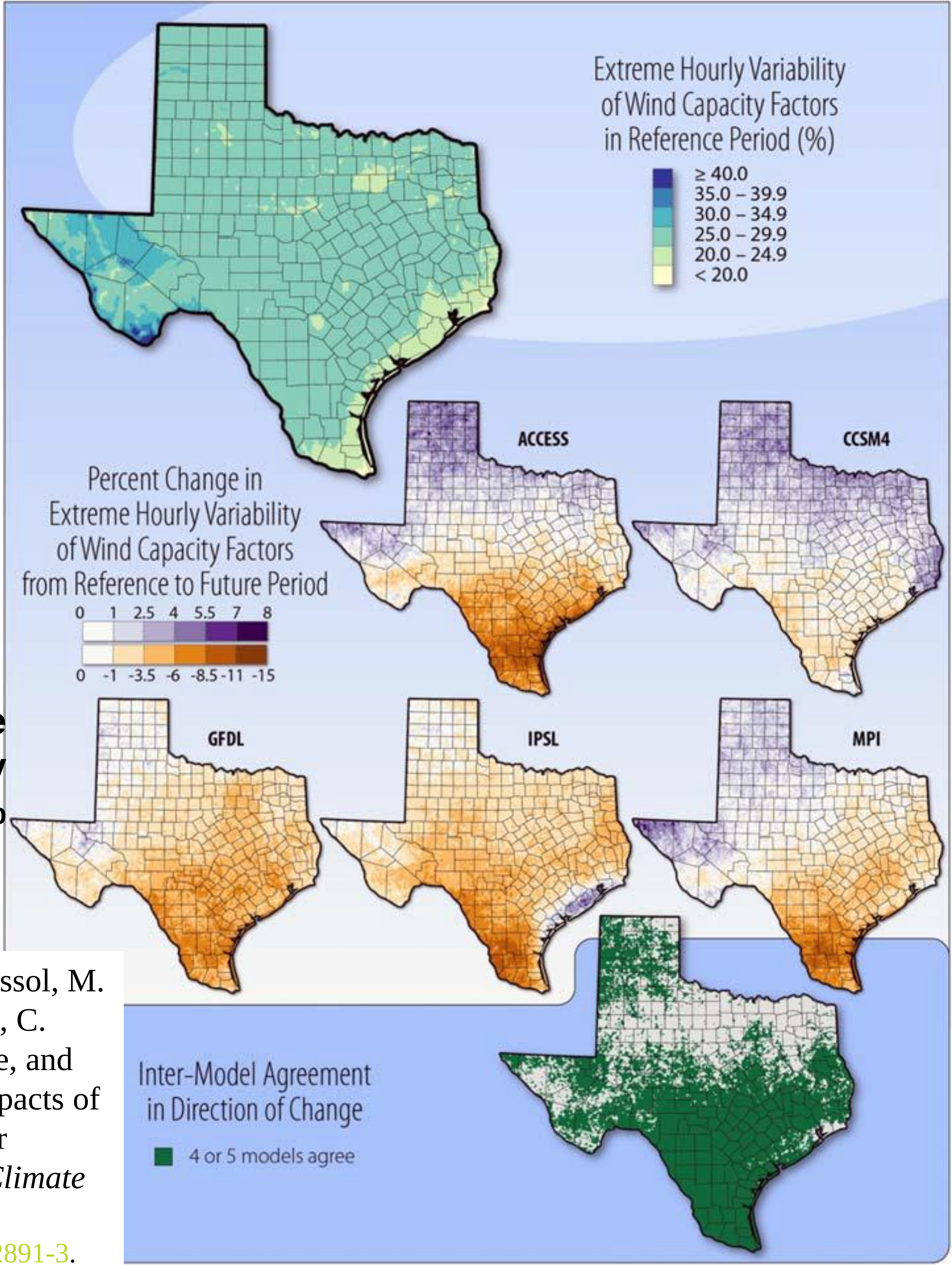
Case Study Texas



95th percentile of hourly variability (Extremes/ramps)

Reference Solar Variability 42-57%

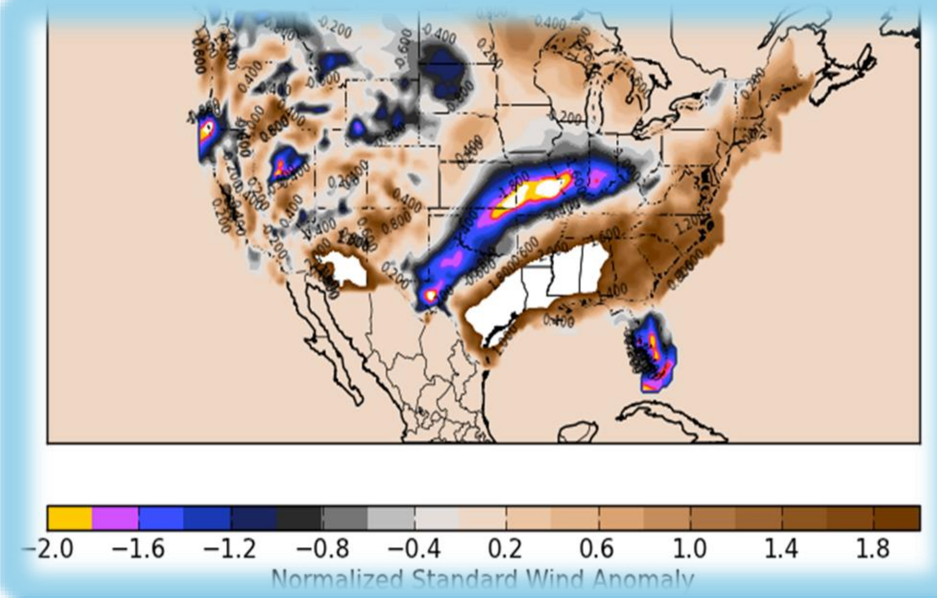
Reference Wind Variability 17-49%



Carreno, I.L., M.T. Craig, M. Rossol, M. Ashfaq, F. Gatibeniz, S.E. Haupt, C. Ammann, C. Draxl, B.-M. Hodge, and C. Brancucci, 2020: Potential impacts of climate change on wind and solar electricity generation in Texas, *Climate Change*, **163,** 745-766. https://doi.org/10.1007/s10584-020-02891-3.

Summary:

- Climate projections should include information on variability on multiple temporal and spatial scales to be most useful.
- Estimates require high-resolution model simulations (cloud-resolving scales)



Ideally, one needs to have a consistent database of correlated wind, irradiance, temperature, humidity, … , both current and future climate, for coordinated planning.