Solar Radiation and Sea ice Sea Ice dynamics from climate models

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Outline

- Projections of future solar radiation for PV power
- Regional climate model uncertainty
- Challenges for functional data analysis
- Open water leads in sea ice simulations.
- Unsupervised learning.

Solar radiation project: Maggie Bailey, Soutir Bandyopadhyay Manajit Sengupta, Aron Habte, Yu Xie (National Renewable Energy Laboratory)

Sea ice: Hannah Director (Mines, Climate), Cecilia Bitz (U Washington), Marika Holland (NCAR).

Planning for future photovoltaic (PV) power facilities.



Part of NRELs contribution to the energy community is National Solar Radiation Data Base (NSRDB).

• For the US 4km \times 4km resolution, 1998–2014, hourly and 30 minute times.

• Uses a physical model for solar radiation at the surface and based on a variety of observations to create the gridded product.

• We might expect solar radiation to change over the lifetime of a facility along with the other changes to the climate system.

Building off of NSRDB

A PV facility can have a 30+ year life span

Goal: Characterize the distribution solar radiation at the same space and time resolution as NSRDB under scenarios of climate change.

- Represent the distribution of solar radiation by a *statistical ensemble* of possible outcomes all equally likely.
- Ensembles might be generated on demand to reduce the size of the stored results.

MNIST - hand written digits

Mean across 60K samples



First 20 members



• Ensembles are useful to represent variation in complex objects.

Workflow for modeling solar radiation

- Primary variable is Global Horizontal Irradiance (GHI) in watts/m².
- Use regional climate model projections to infer details of the

distribution of GHI in time and space.

Based on RCM projections

- Regrid Daily GHI from RCM on native grid \rightarrow 20km NSRDB Grid
- Predict daily total GHI Regression model with RCMs, seasonality, elevation \rightarrow to predict observed GHI based on NSRDB.

Based on NSRDB modeling

- Disaggregation to hourly radiation Daily totals of NSRBD \rightarrow predict hourly solar radiation.
- Downscaling to 4km Hourly GHI at 20km \rightarrow Hourly GHI at 4km

A hierarchical model to simulate high resolution hourly solar from RCM output.

The variation in hourly GHI is as important as the point predictions.

Regridding and prediction

The RCM output is not on the same grid as the NSRDB product.



Regridding and prediction

Regridding uncertainty (to out knowledge) is an often ignored issue in climate science.

Framework:

• A Bayesian linear model where the "X's" are uncertain.

RCMs values have error based on regridding.

 $\mathsf{NSRDB} = \mathsf{RCM}_1\beta_1 + \mathsf{RCM}_2\beta_2 + \mathsf{RCM}_3\beta_3 + \mathsf{Seasonality} + \mathsf{error}$

• Generate posterior draws from the RCM fields regridded to the NSRDB grid.

• Bayes posterior for regression coefficients and prediction and GHI conditional on draw.

Regridding and prediction results

Parameters in the linear model for a coastal grid box.



- NOTE RCMs are forced by reanalysis fields.
- Nominally we have a separate linear model for every grid box.

Daily total \rightarrow hourly at 20km

<u>Use the NSRDB data to build this conditional distribution.</u>



Hourly times series for June 1-6 2008, 4 grid boxes.



Functional boxplots - diurnal cycle 20km

Hourly times series for June months over 1998- 2019



- Strong diurnal cycle around "deepest" curves
- Substantial variability for "shallow" curves suggests a mixture model.

Principle components at 20km

• First three PCs for a single grid box and PC1 \pm PC2, PC1 \pm PC3.



Relationship of PC2 and PC3 to daily total GHI



Additional components tend to add more noise than structure.

Downscaling to 4km

 $5 \times 5 = 25$, 4km time series nested in a single 20km grid box.



June 1-6 2008 , 4km, 20km



Summary

These are tentative based on preliminary analysis!

- Some skill in predicting total GHI from the RCMs
- Regridding process does not appear to inflate uncertainty.
- Diurnal patterns appear to be a mixture of a strong daily cycle and more variable, intermittent behavior. (*No surprises here.*)

- Also true for 20km to downscaling to 4km.

• Diurnal and coefficients pattern appear to be coherent over space. Suggesting a multivariate spatial model on PCs.

• *LatticeKrig* spatial model and related SPDE work could be useful for the multivariate spatial and temporal models for the PC coefficients.



Identification and Uncertainty of Sea Ice Leads

- Rapid decline in Arctic, more complex changes in Antarctica
- Understood via physics-based models, remote sensing, and direct measurement



Deformation features

- Leads: long narrow cracks in sea ice
- Pressure ridges: small "mountains" that form on top of the ice
- Linear Kinematic Features (LKFs): discontinuities in kinematic features of sea ice (deformation), encompasses both leads and ridges



Pressure ridge

Resolution

- Leads emerge in high-resolution simulations
- Leads are rarely present in typical low-resolution simulations
- Want to understand high-resolution leads to improve low-resolution approximations
- Statistics of leads Daily grow interesting on their own as May/June) a coherent structure emerging from the model dynamics.



Daily growth rate (Antarctica, April/-May/June)

Data

- High-resolution Community Earth System Model
 - Physical simulation of the whole Earth system
 - Widely-used and extensively tested
 - ► Focus on Sea Ice component.
- Pre-industrial control run
 - Stable climate
 - Useful for understanding sea ice physics and interactions of sea ice with surrounding environment

Although leads are produced by the model they are not identified explicitly as a coherent structure.



Data transformation: subgrid-scale leads

Sea ice concentration: proportion of area in each grid box that is ice-covered Model **y**, the difference between high-resolution and smoothed output



Difference is the potential adjustment/parametrization for a low resolution simulation.

Finding Leads

Model the lead's path as a chain of M + 1 connected spatial points: $\ell = (p_1, \ldots, p_{M+1})$.



Model the expected difference in sea increase in the sea increase increase increase increase increase increase increase increase increase increas



• The hardest part is estimating the end points because of the ambiguity of when a lead ends.

• Taken together provide a model for the ice concentration field localized around a lead.

• Difference function estimated using a nonparametric curve estimate.

Examples of identification

Finding multiple leads



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Analysis of the ice model output



• Certain vs Possible based on amplitude of difference function.

Summary

- Speedup Bayesian version to improve uncertainty quantification.
- Find difference function in fully objective manner.
- One of the first times, leads have been explicitly quantified from the ice component of CESM.

Thank you



