Sub-daily Statistical Downscaling of Meteorological Variables Using Neural Networks

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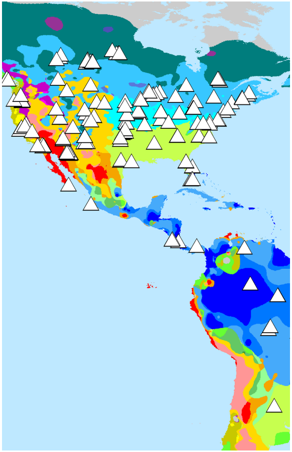
Rationale for scaling climate data with neural networks

- Model validation (Jung et al. 2011, Biogeosciences)
- Extrapolation/interpolation of climate model projections (Coulibaly et al., 2005, J. Hydromet.)
- Synthesizing driver data consistent with observed weather (PalEON)

Example sparse network and rep. clim. zones

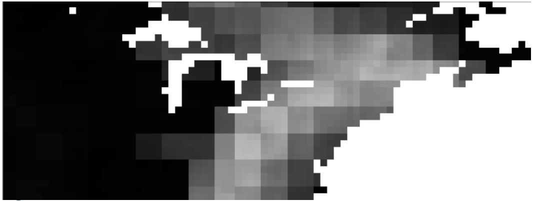
fig. taken from http://fluxnet.ornl.gov



Key points of past neural network downscaling performance

- Wilby et al. 1998, Water Resour. Rsrch., ANN's synthesize temp. and precip. poorly due to wet day occurrence
- Haylock et al. 2006, Intl. Jnl. Clim., ANN synthesize precip well, especially at interannual variability, but consistently underestimate precip. intensity. Mixture model approach greatly improved performance.
- For difficult met. variables (precip.) combining ANN's and sparse regularization models (e.g., Ebtehaj et al. 2012, JGR Atm.) may be needed to capture full space and time variance.

6-hourly total precipitation snapshot (March, 2000) over eastern U.S. Taken from CRU-NCEP reanalysis



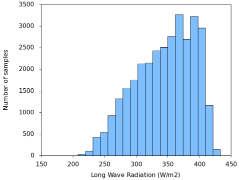
Downscaling framework

To downscale multiple meteorological variables that are coherent between var's we developed an easy-to-use, fast, and open-source (C-code) downscaling framework based on artificial neural networks (ANNs) called the Climate Observations and Model Data Analysis and Synthesis Toolkit (COMDAST), which includes an optional mixture model approach for handling precipitation.
http://www.climatemodeling.org/comdast/ (GNU GPL License)

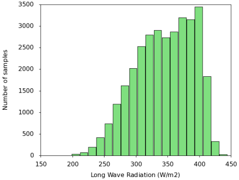
Variable	Short Name	Model type
Downwelling longwave radiation	lwdown	ANN only
Total precip. (stratif.+conv.)	precipf	mixture model
Surface pressure	psurf	ANN only
Specific humidity	qair	ANN only
Downwelling shortwave radiation	swdown	ANN only
2 meter air temperature	tair	ANN only
wind speed	wind	ANN only

Representativeness test: variance & model data mismatch

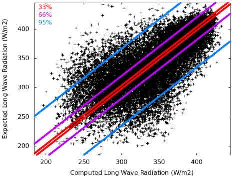
Histograms and scatter plots with CI's of 0.5° longwave (top) and shortwave radiation (bot). Target vs. coarsened-then-dwnsc. data



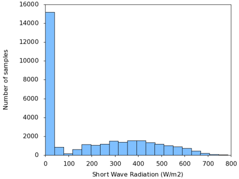
(a) Expected



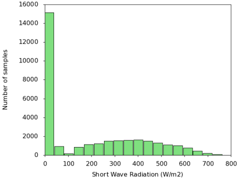
(b) Computed



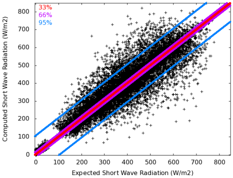
(c) E/C



(d) Expected



(e) Computed



(f) E/C

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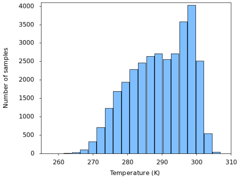
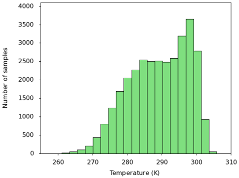
Representativeness test: variance & model data mismatch

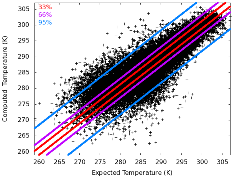
Histograms and scatter plots with CI's of 0.5° 2m air temp. (top) and tot. precip. (bot). Target vs. coarsened-then-dwnsc. data



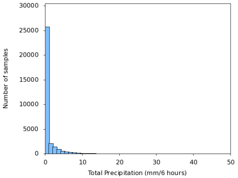
(g) Expected



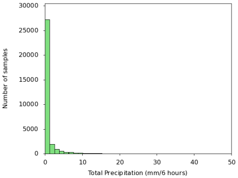
(h) Computed



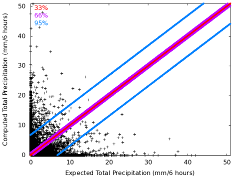
(i) E/C



(j) Expected



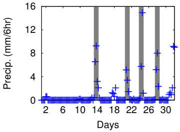
(k) Computed



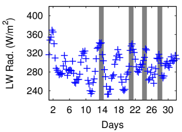
(l) E/C

Consistency across meteorological variables

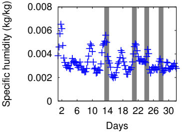
Case study comparison of consistency between meteorological variables for several precipitation events (Jan, 2000).



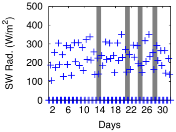
(m) Ex. precip



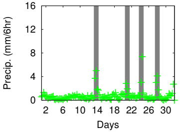
(n) Ex. lwdown



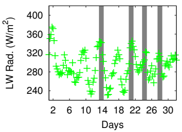
(o) Ex. qair



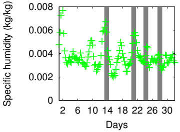
(p) Ex. swdown



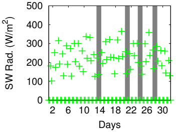
(q) Co. precip



(r) Co. lwdown



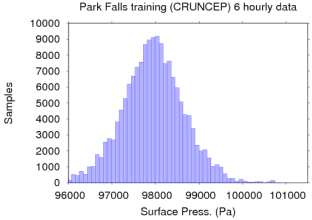
(s) Co. qair

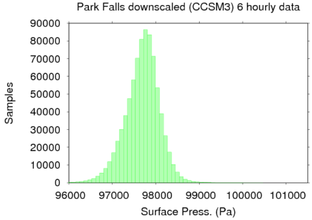


(t) Co. swdown

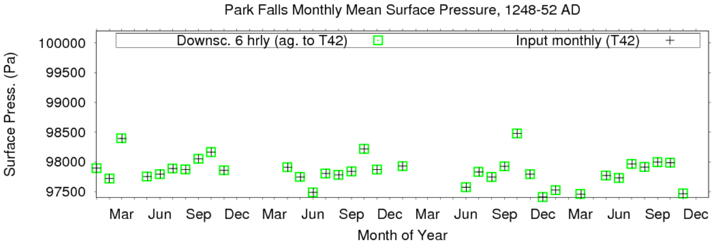
Consistency between ‘testing’ input & downscaled output

Histg. showing diff. in mean, var. & time series showing mean consrvn.





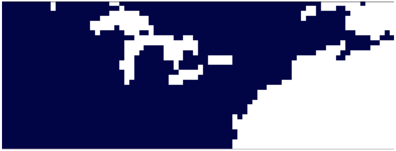
*Training (CRUNCEP) data — Testing (CCSM3) data

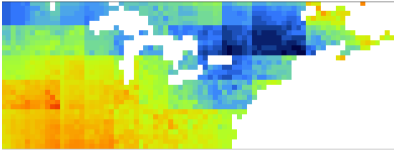


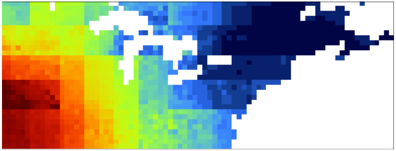
Mean conservation: coarse input & means of downscaled output

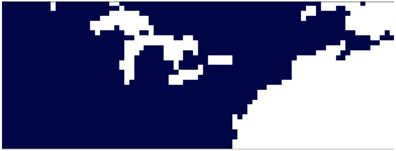
Spatial coherence in downscaled data

Maps representing four 6-hour snapshots (April, 1250 C.E.) from downscaled CCSM3 insolation (monthly, $\sim 3^\circ$ to 6-hourly, 0.5°)


0-6 LT

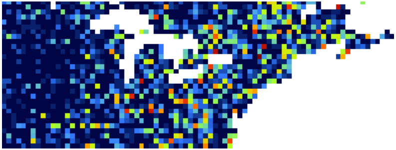

6-12 LT


12-18 LT

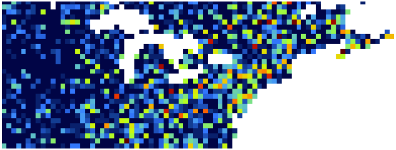

18-24 LT

Spatial coherence in downscaled precipitation data

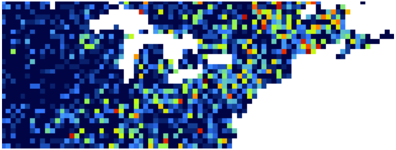
Maps representing four 6-hour snapshots (April, 1250 C.E.) from downscaled CCSM3 precipitation (monthly, $\sim 3^\circ$ to 6-hourly, 0.5°). Note the loss of spatial contiguousness. Spatial coherence is reduced by our mixture model approach.



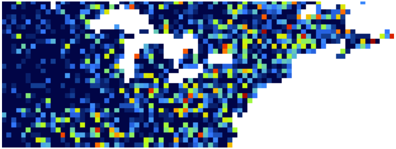
0-6 LT



6-12 LT



12-18 LT



18-24 LT

Summary

- Our neural network temporal downscaling approach allows for downscaling of many variables across hundreds of years of monthly means to 6 hourly values in minutes per location.
- Validation tests indicate accuracy of monthly means to within 1% across all variables. Expected and computed standard deviations were similar to within 1% for longwave, shortwave radiation, specific humidity, and air temperature, and were 4%, 10% and 11% for surface pressure, wind, and precipitation.
- A trained network that is applied to downscale a new 'testing' dataset can require use of the optional mixture model approach if the testing data are significantly different from training data

'Parting words' & acknowledgments

- This presentation: www.climatemodeling.org/∼bjorn/talks/
- www.climatemodeling.org/comdast/
- www.paleonproject.org

- For data contributions we thank Yafang Zhong for providing the CCSM-3 model output
- We thank Nicolas Viovy for generating CRU-NCEP– Natnl Center for Environmental Prediction (NCEP)– Climate Research Unit, Univ. of East Anglia who produced the base datasets for CRU+NCEP.
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