Spatial downscaling in climate models: an application for generation of alcohol production scenarios in Brazil

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Abstract

The Brazilian agribusiness has an oscillatory behavior as a function of market demand resulting from the expansion/contraction of cultivation areas. The current demand for sugarcane biofuels is a main driving force of changes in the Brazilian landscape. Some models incorporate climate as a factor to understand the dynamics of sugarcane transformation. The integration of climate data faces challenges in associated with downscaling from the coarse scale of global circulation models to the fine scales of applied studies. In this study, we relate data from different spatial scales for the prediction of spatial climate dynamics. The downscaling approach is developed and validated using Eta climate model outputs from 1961 to 1990 with 40 km (24.85 miles) resolution and observed daily mean temperature and precipitation from meteorological stations in the 1990-2010 period. A type of unsupervised artificial neural network, Self Organizing Map, and cross-validation approach are used to compare empirical downscaling techniques for climate data. Observed progresses will contribute to bring machine-learning techniques as a valid tool when dealing with multivariate data in the downscale context.

Goal, Objective

Aim: Downscale climate data for use in Sao Paulo state, Brazil
Objectives: (1) integrate spatiotemporally different climate data into a single multivariate density function; and (2) used density function to estimate missing temperature and precipitation
Challenge: data are disparate, noisy, sparse, and scale-dependent

Background

The use of regional-scale climate models (RCMs) is considered important in the future assessment and prediction of climate systems (Wang *et al.* 2004, Maraun *et al.* 2010), because they conceptually bridge spatiotemporal gaps between large-scale predictions by general circulation models (GCM) and subcatchment scale field observations. One factor limiting the development and use of RCMs is the integration of data from multiple climate sources due to their mismatch in scale and sparseness of data. Our research evaluates the efficacy of using machine-learning for the simultaneous integration of *big data;* that is, data characterized as disparate, noisy, sparse, and spatiotemporal. Specifically, we use unsupervised Self-Organizing Map (SOM) and component planes techniques to (1) find patterns and relations, and (2) estimate missing climate data among GCM and field data sets.

Methodological framework

Methodological steps

Today:

(1) Preprocessing - aggregating and normalization of sparse climate related data (location/coordinates, elevation, minimum temperature, maximum temperature and precipitation)

(2) Self-organizing map - a competitive and nonlinear training stages, in which information are compressed preserving the topological neighborhood relationship.

(3) Component planes analysis - patterns (relations) among climate variables are identified and statistics calculated;

Future:

(1) Estimation - prototype vectors of the best matching units will be used to estimate climate variables that are missing and at new (downscaled) locations based on distances among the available model vectors.

(2) Cross-validation – performance of the estimation process will be based on a leave-one-out strategy of bootstrapped samples.

(3) Forecasting – (a) climate variables at randomly generated (downscaled) locations, and (b) land-use changes.

Study area

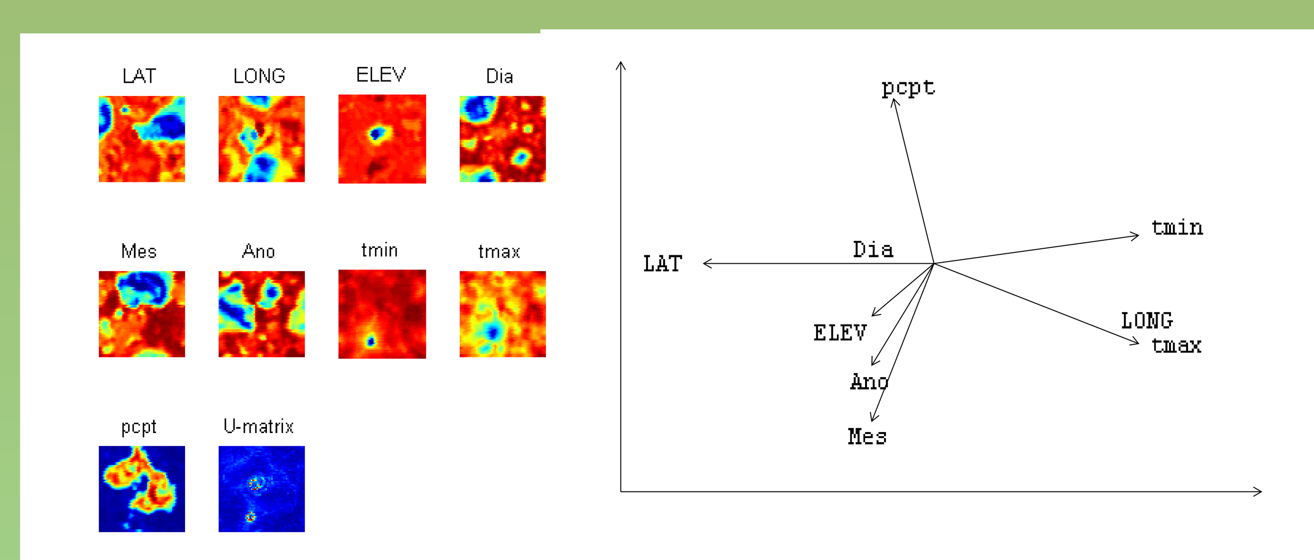
Figure 1. Distribution of Cerrado fragments at São Paulo State (Brazil)

The Cerrado (Brazilian savannahs) of São Paulo state (Brazil) represent a complex typological mosaic of uses, actors and biophysical and social restrictions, with particularities at every scale level. Among the Brazilian biomes, the Cerrado stands out by its intense conversion in the last decades into agricultural land use.

Originally, 14% of the state of São Paulo was covered by the Cerrado. Only 1% of the original composition remains fragmented into numerous relicts of biodiversity, mainly concentrated in cities of the central-eastern of the state (Figure 1). Below 10% of this composition is under the protection of Conservation Units, that consists mainly on private farms.

A relevant part of the fragments are found in areas of intense coverage change by human activities, and the greatest pressure currently comes from sugar cane cultivation, either by direct replacement of vegetation or the transition from pasture areas. In both cases, this change introduces a new dynamics landscape that, directly or indirectly, affects the established processes in the observed social and ecological systems.

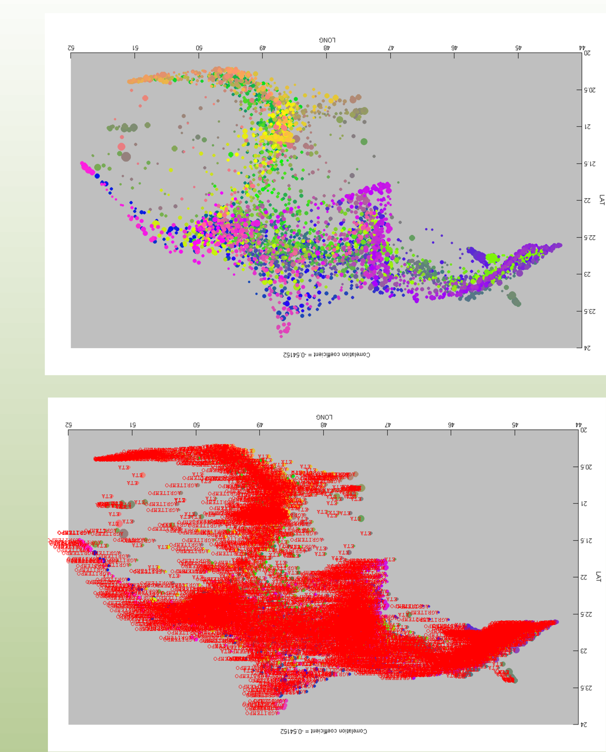
Component Planes



LAT	– Latitude	LONG	– Longitude	ELEV	– Elevation
Dia	– Day	Mes	– Month	Ano	– Year
tmin	– Minimum temperature	Tmax	– Maximum temperature	Pcpt	- Precipitation

Data

Measured and simulated climate data stations



Agritempo – climate observation stations (local)

ETA – simulated climate using global circulation model (40km spacing)

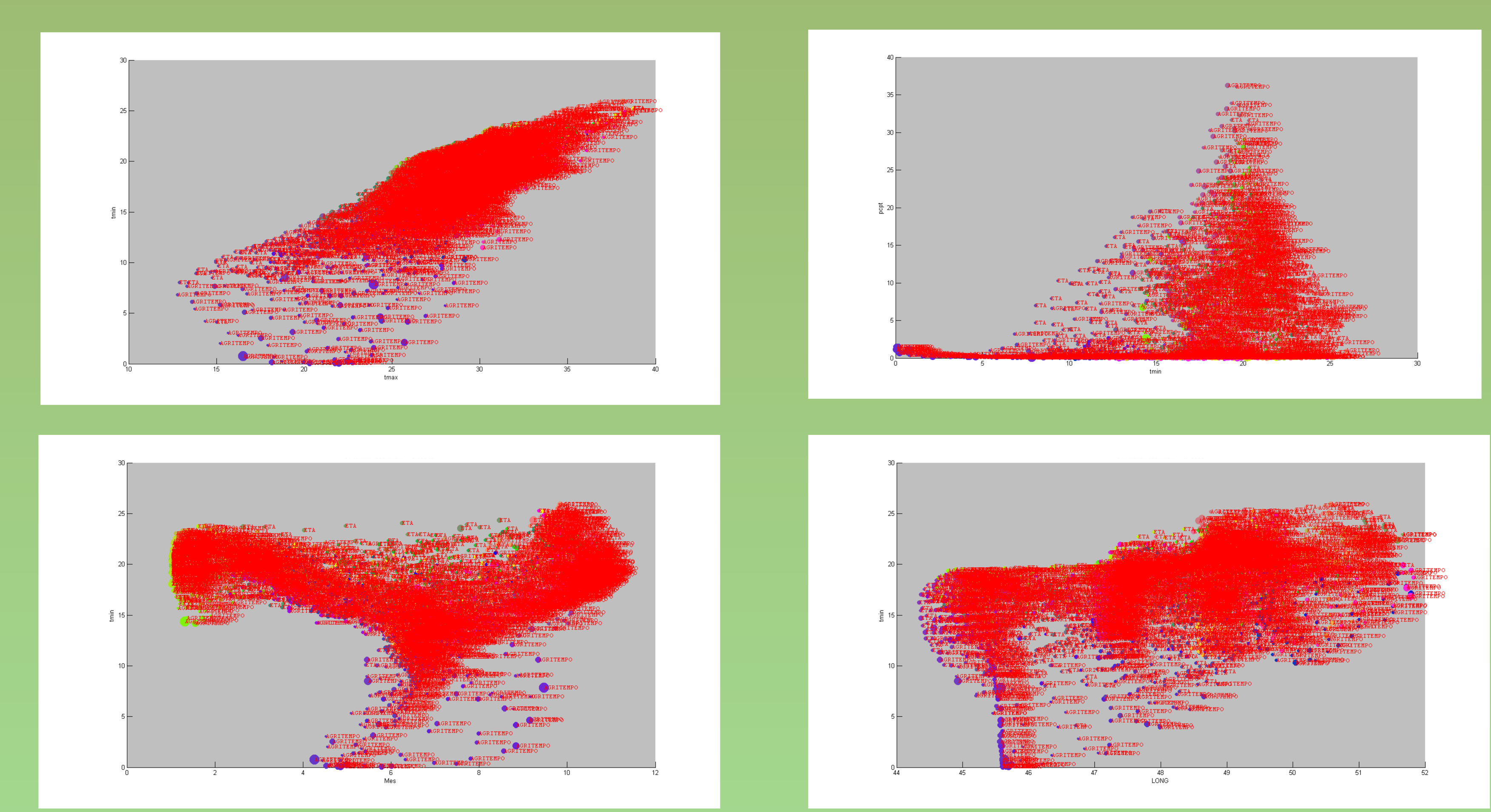
Daily precipitation and temperature measurements from 1990 to 2010

Agritempo: Observed measurements at subcatchment-scale climate from stations distributed across the tropical savanna (Cerrado) areas of Sao Paulo state (www.agritempo.gov.br). Time-series measurements are local, random, sparse, and noisy.

ETA: Simulated measurements at global-scale climate measurements from atmosphere-ocean general circulation model HadCM3 (Hadley Centre Coupled Model) at fixed grid size spacing of 40 km. The model uses as a boundary condition the. Time-series measurements are complete.

Cross-component planes

Some spatiotemporal trends among sparse climate data sets



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Conclusions

- The self-organazing map technque is able to integrate sparse climate variables across different spatial scales.
- The component planes technique reveals relations among variables in the underlying density function.