Convolutional Neural Networks for Climate Downscaling

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CLIMATE DOWNSCALING

WHY DOWNSCALE?

To study the impact of global change on local to regional scale climate, including precipitation and temperature.

DYNAMIC DOWNSCALING:

Limited area physical/dynamical models can directly simulate smaller-scale physical processes and capture local topographical features such as lake effects, but are computationally expensive.

STATISTICAL DOWNSCALING:

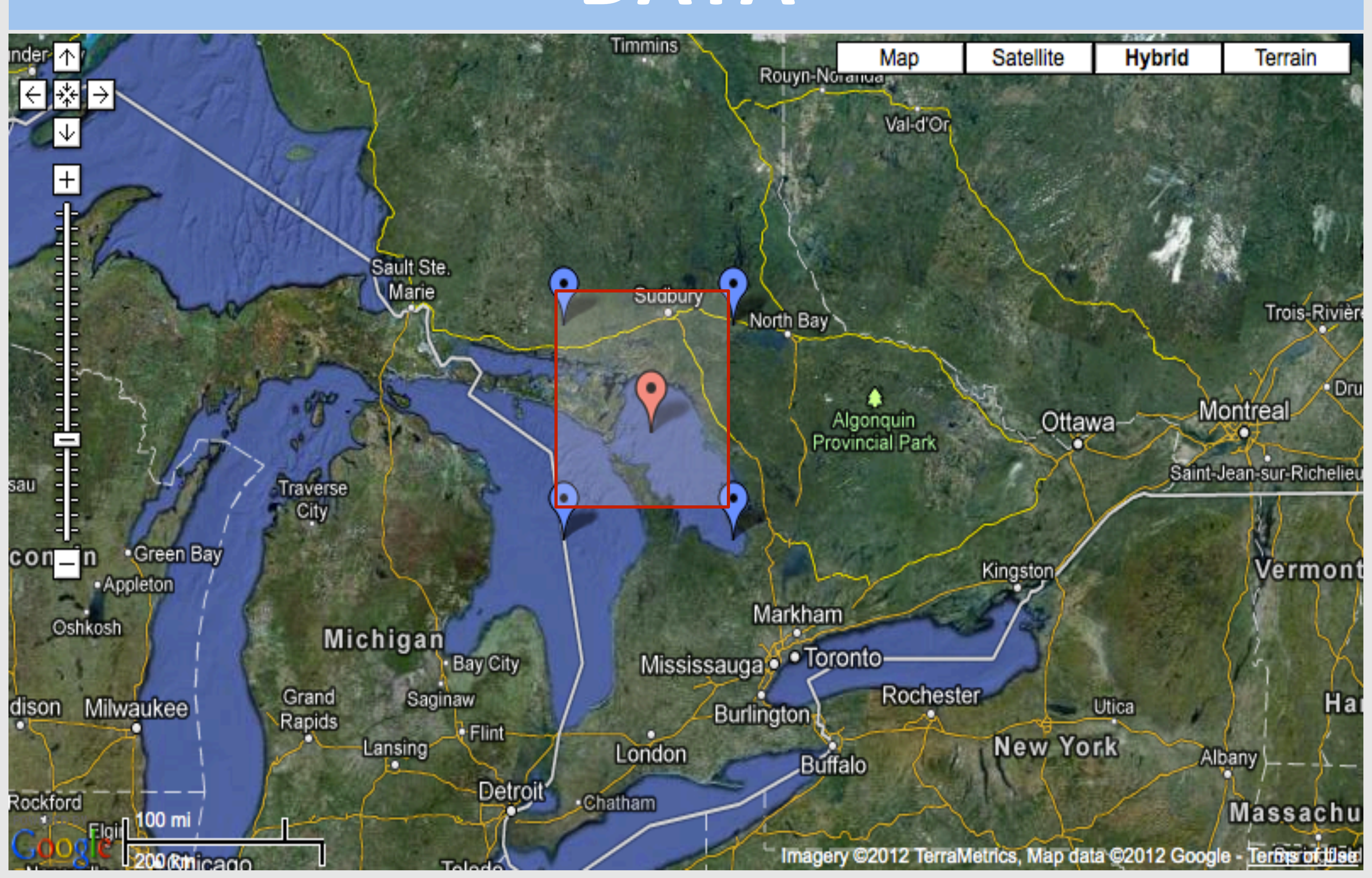
Statistical models trained on historical relationships between large-scale circulation and high-resolution observations are more cost and time efficient, but assume stationarity in future relationships.

RESEARCH HYPOTHESIS

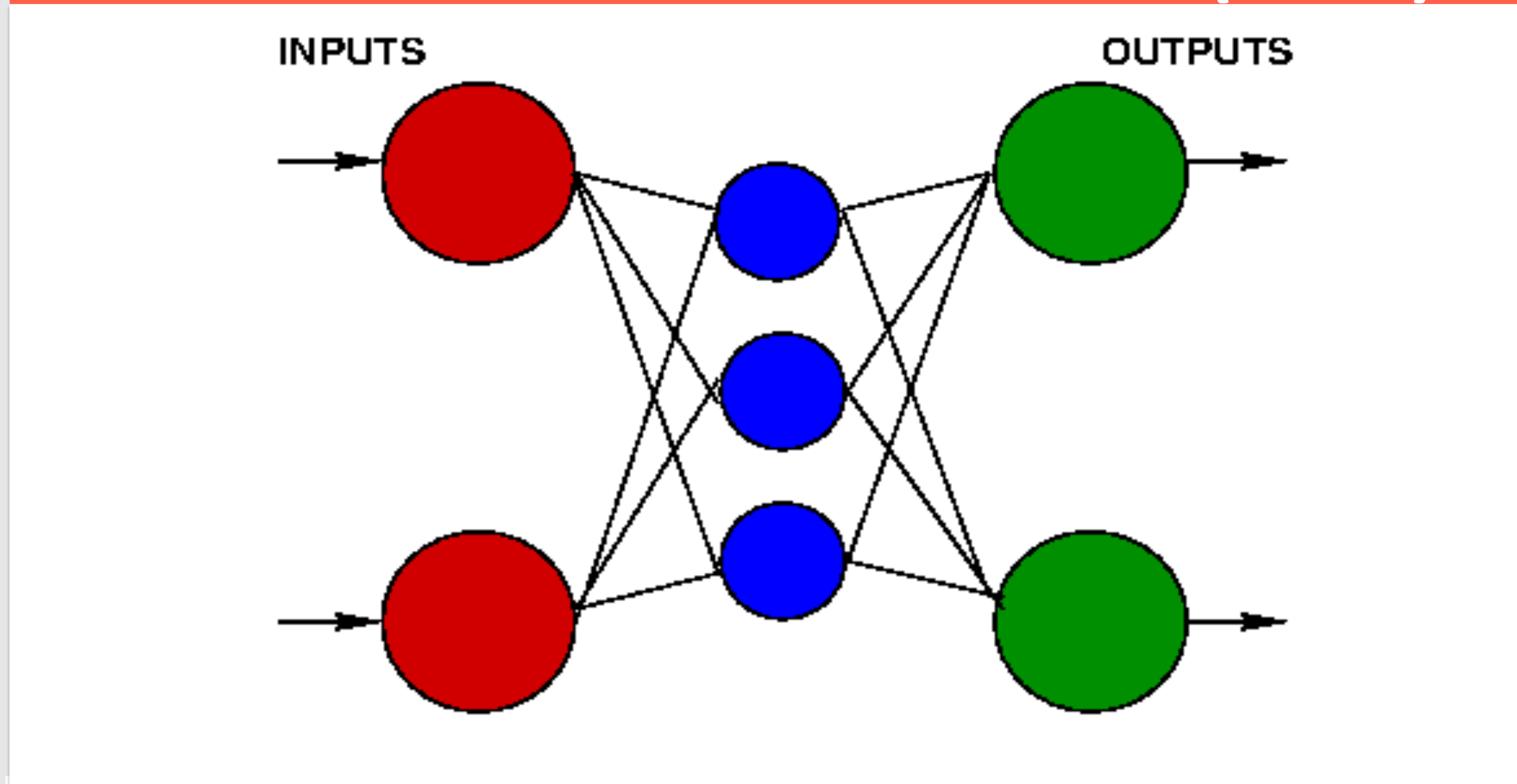
Deep architectures such as Convolutional Neural Networks and Deep Belief Networks can more robustly model the complex relationships between global climate model output and observed local climate because:

- The input parameters are not treated as independent variables but as arising from some spatial structure whose topology is captured by the model.
- Deep architectures provide the flexibility of using a larger number of layers (in comparison to multilayer perceptrons), automatically varying the number of layers to provide better generalization.

DATA

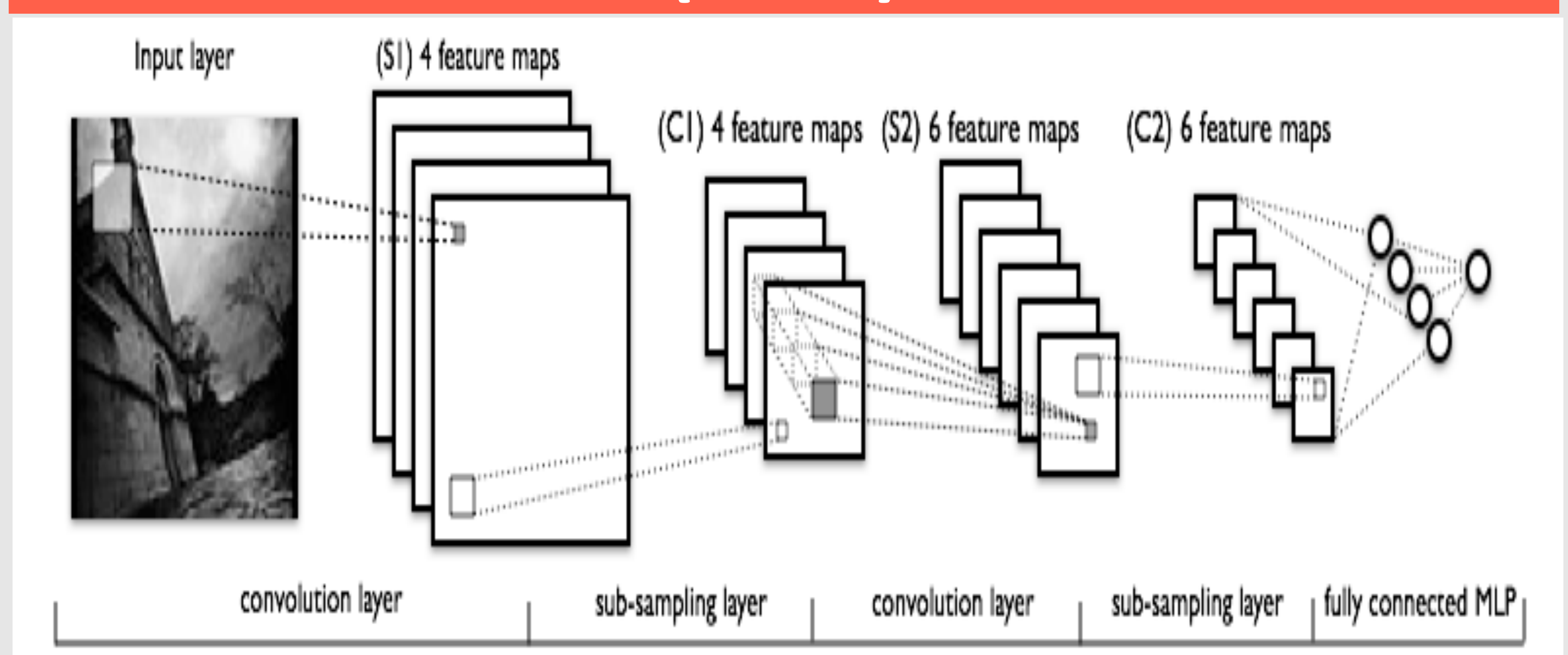


MULTILAYER PERCEPTRON (MLP)



- Represent relationships between inputs and outputs to extract complex patterns.
- Can result in local minima.
- Can lead to overfitting.

CONVOLUTIONAL NEURAL NETWORK (CNN)



FEATURES

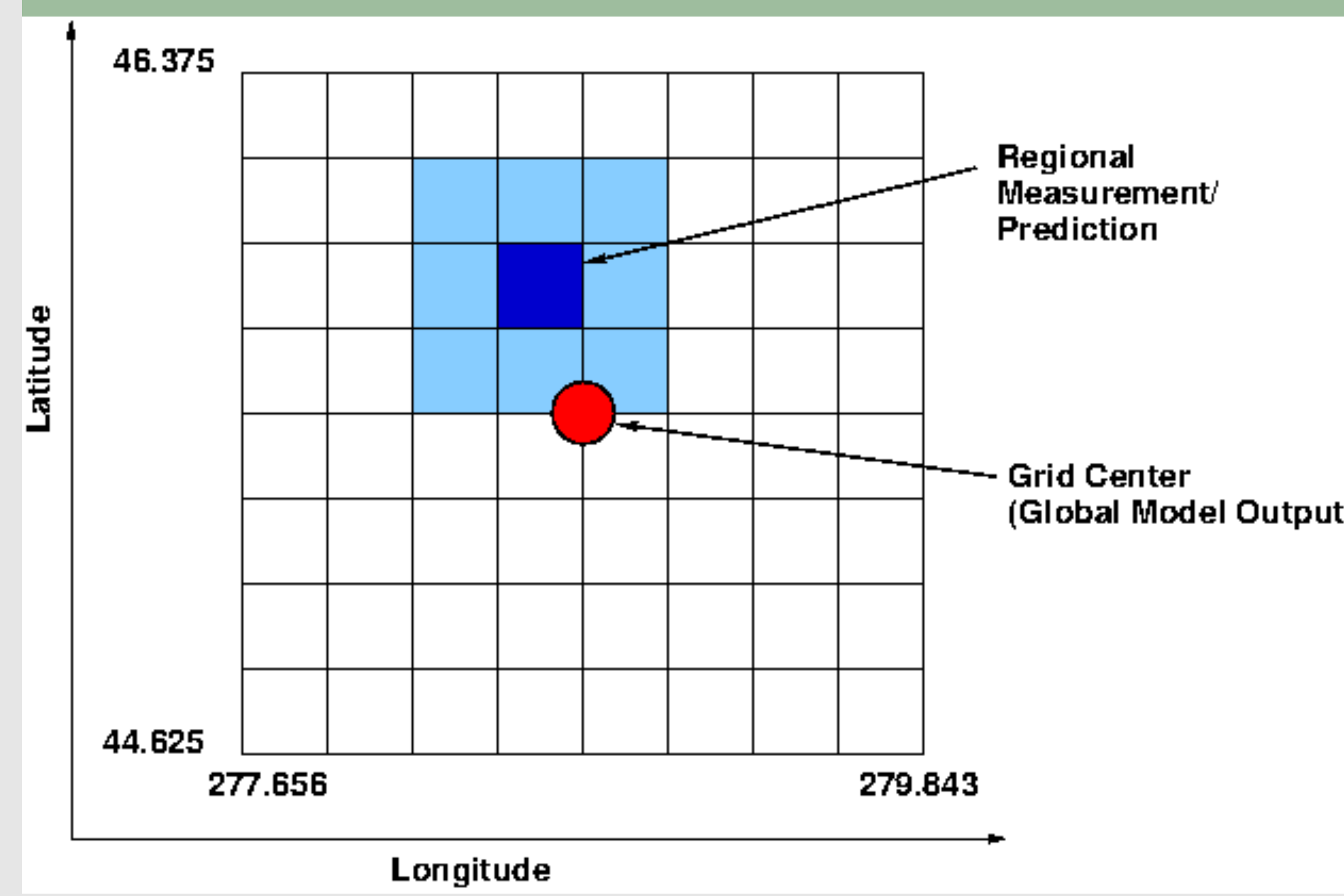
- Multilayered network of neurons.
- Local receptive fields → capture input topology.
- Shared weights → shift invariance.
- Spatial or temporal subsampling → higher level abstractions.

EXPERIMENTAL SETUP

We compare the performance of MLPs, CNNs and DBNs in representing the relationship between large-scale climate and local conditions, we conduct an idealized experiment consisting of 30 years of daily maximum temperature and 24h cumulative precipitation for:

- One coarse resolution global model grid cell ~200 by 200 km (predictor; red square, centered on red balloon)
- 64 high-resolution global model grid cells ~25 by 25km (predictand; nested within the global model grid cell)

CNNs FOR CLIMATE VARIABLES



PRELIMINARY RESULTS

Our initial experiments for climate downscaling have shown that :

- Root Mean Square Error of the MLP predictions is about 1.66 and 5 times that of the CNN and DBN for temperature and precipitation respectively.
- CNN and DBN were consistent in their predictions for regions across topographical variations.

Preliminary results show that deep architectures such as CNN and DBN may be better suited to model complex relationships between global climate model outputs and regional climate.

FUTURE WORK

- Understand the effect of variables as predictors of other variables.
- Identify best predictors for long-term changes in climate and trends in variability
- Downscale infrequently observed (e.g. soil moisture) and highly variable (e.g. wind) climate variables.

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