Philosophy and Targeted Applications of ML/AI Techniques for Climate Risk Analytics at Jupiter

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JUPITER

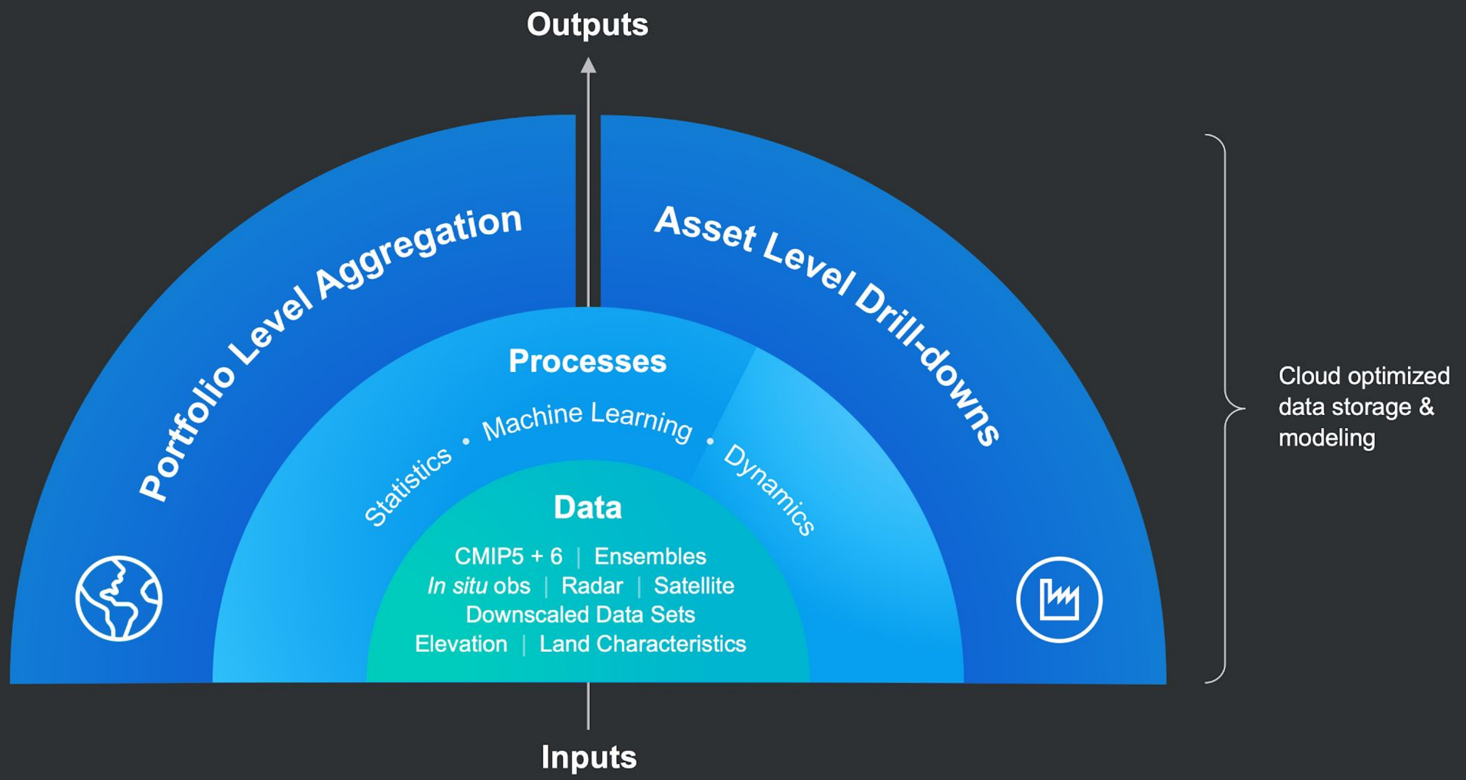
Jupiter Intelligence:
A Scientific Approach to Building Resiliency

- **We integrate best available Science & Information Tech**
  - Peer-reviewed models
  - Academic collaborations
  - Cloud / scale computing
  - Machine learning / AI
- **Facility-level, probabilistic climate risk data** for operational (1 – 120 hours) and long-term asset planning (6 months – 50 years)
- Customized for use cases across **energy, engineering design, reinsurance, financial, real estate, & public sectors**

Perils Modeled

- Flood
- Fire
- Heat
- Drought
- Wind
- Hail

Jupiter's end-to-end methods



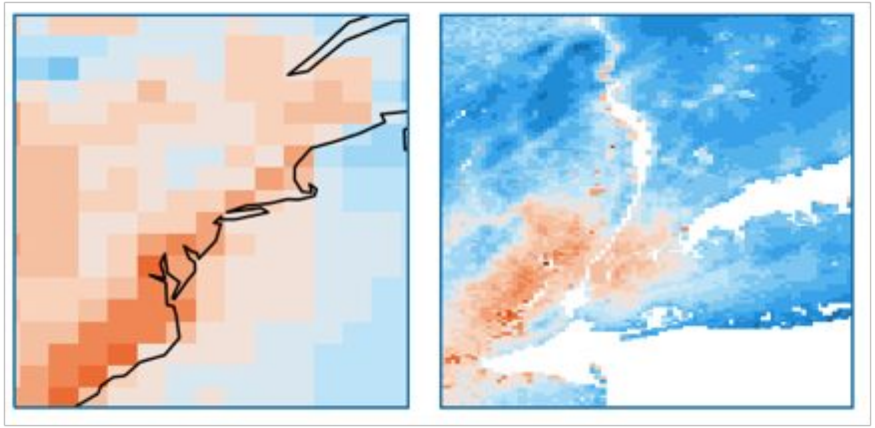
Tenets for Use of ML/AI at Jupiter

- ***Balance between established and cutting-edge techniques***
- Clear expectations of the potential for success
- Must maintain quality
- ***Efficient and deployable at scale***
- ***Explainability and transparency***

Example Applications of ML/AI at Jupiter

Example Application: Urban-Scale Downscaling

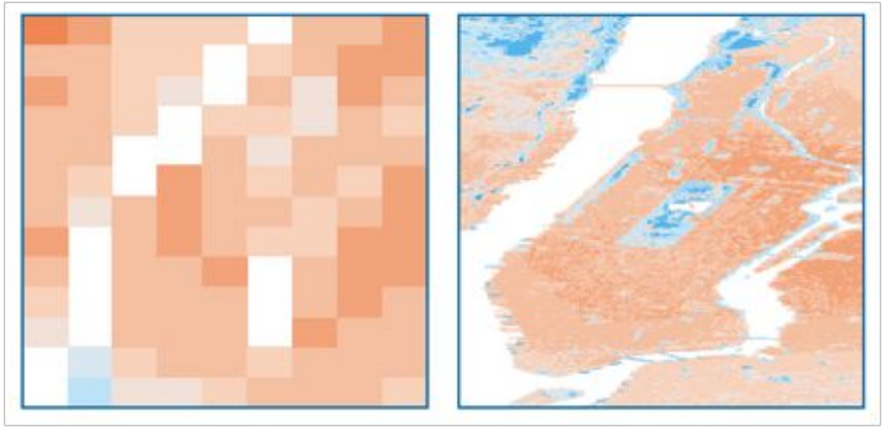
Dynamic Downscaling from 100 km to 1 km



Global Climate Model
~1 degree (100km)

Dynamic Weather Model
1km Downscaling

Machine Learning from 1 km to 30 m



Dynamic Weather Model
1km Downscaling

Machine Learning
30m Downscaling

Using a set of high-resolution dynamical simulations as training data with satellite-derived land use characteristics as predictors, a random-forest model was used to further downscale projections of heat to the urban scale.

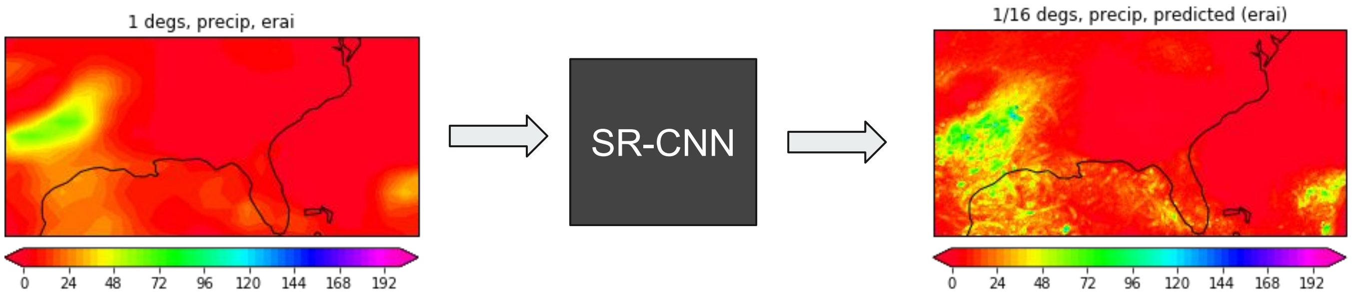
Example Application: Precipitation Downscaling

Brian Groenke | Data Science Intern | 2019 | doi: 10.1145/3429309.3429318

Idea: View statistical downscaling as an *image super-resolution* problem

- Applied well known ML model to downscaling ERA-I ➞ WRF
  - SR-CNN (Dong et al. 2015), a convolutional neural network for image super resolution

- Biggest challenges were mostly related to *data preprocessing* and *engineering*



Example Application: Model Emulation and Synthetic Generation

Challenge: surge + precip

- Flooding from hurricanes comes from multiple sources, e.g. surge and precipitation
- Nonlinear interactions
- How do we incorporate them simultaneously?

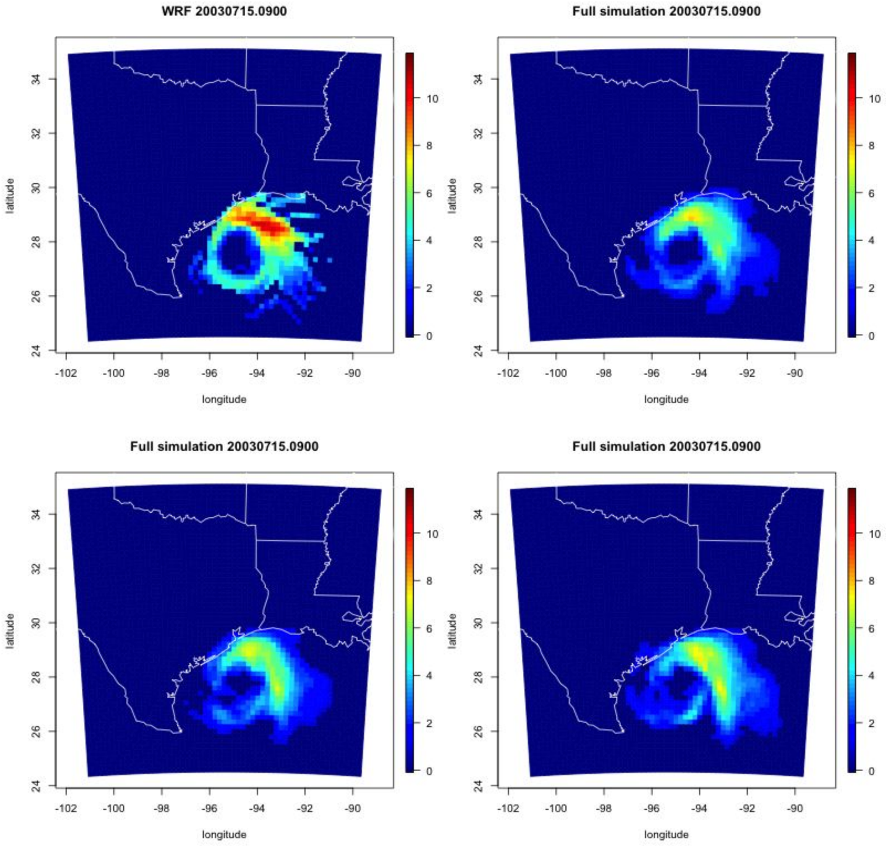
$$Y(r,\theta,t) = \sum_i c_i(t)\phi_i(r,\theta) + Z(r,\theta,t)$$

- $\phi_1(r,\theta),\ldots$ are EOFs
- $c_1(t),\ldots$ are time-varying principal components modeled via:

$$c_i(t) = \mu_i(t) + W_i(t)$$

  - $\mu_i(t)$ is a random forest with physiographic predictors
  - $W_i(t)$ is an AR(1) process
- $Z(r,\theta,t)$ is a space-time process

Collaborative project with Will Kleiber, CU APPM



Pushing Forward with ML/AI

- **Tread carefully -- reception to ML/AI techniques can vary**
    - Too “black-box” and not transparent enough to be defensible
    - Users have been “burned before” by the “over-promise” of ML/AI techniques
    - ***Is the method clearly explainable?***
- **Wealth of established statistical and dynamical methods available -- why commit to ML/AI?**
    - Beyond proof-of-concept...why have you chosen an ML/AI technique for this particular problem?
- **Transferability of models**
    - For geophysical problems, training data is often limited
    - Climate change is global -- we want models that can be applied anywhere

Questions