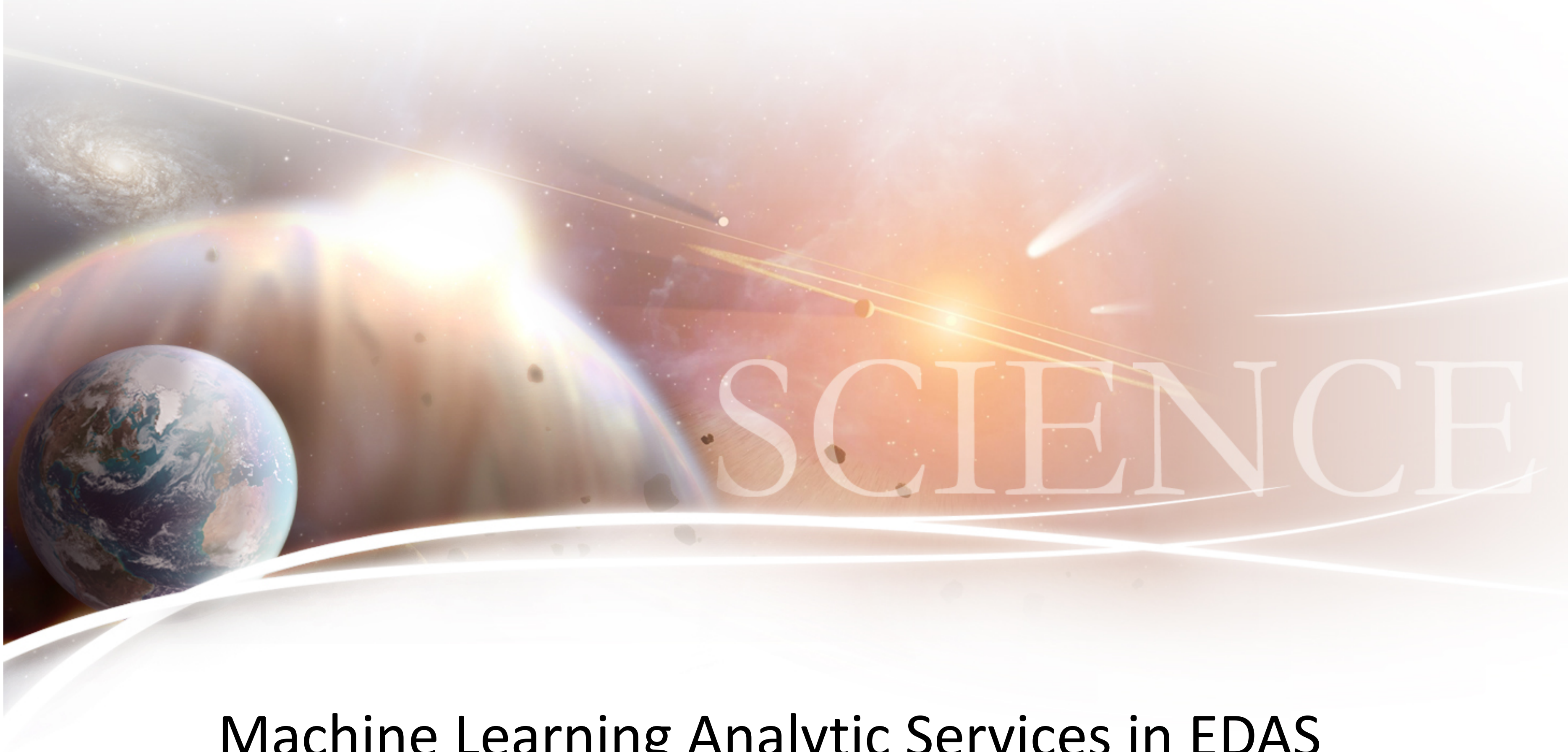
National Aeronautics and Space Administration



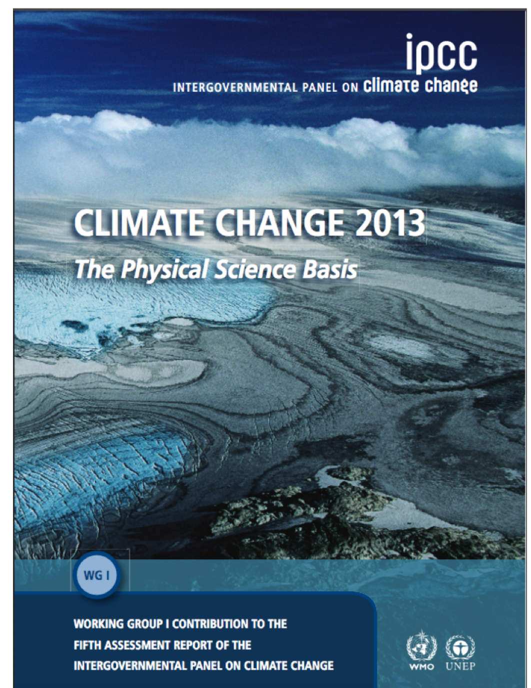
Machine Learning Analytic Services in EDAS

Thomas Maxwell, Thomas Favata, Dan Duffy, Laura Carriere, Jerry Potter

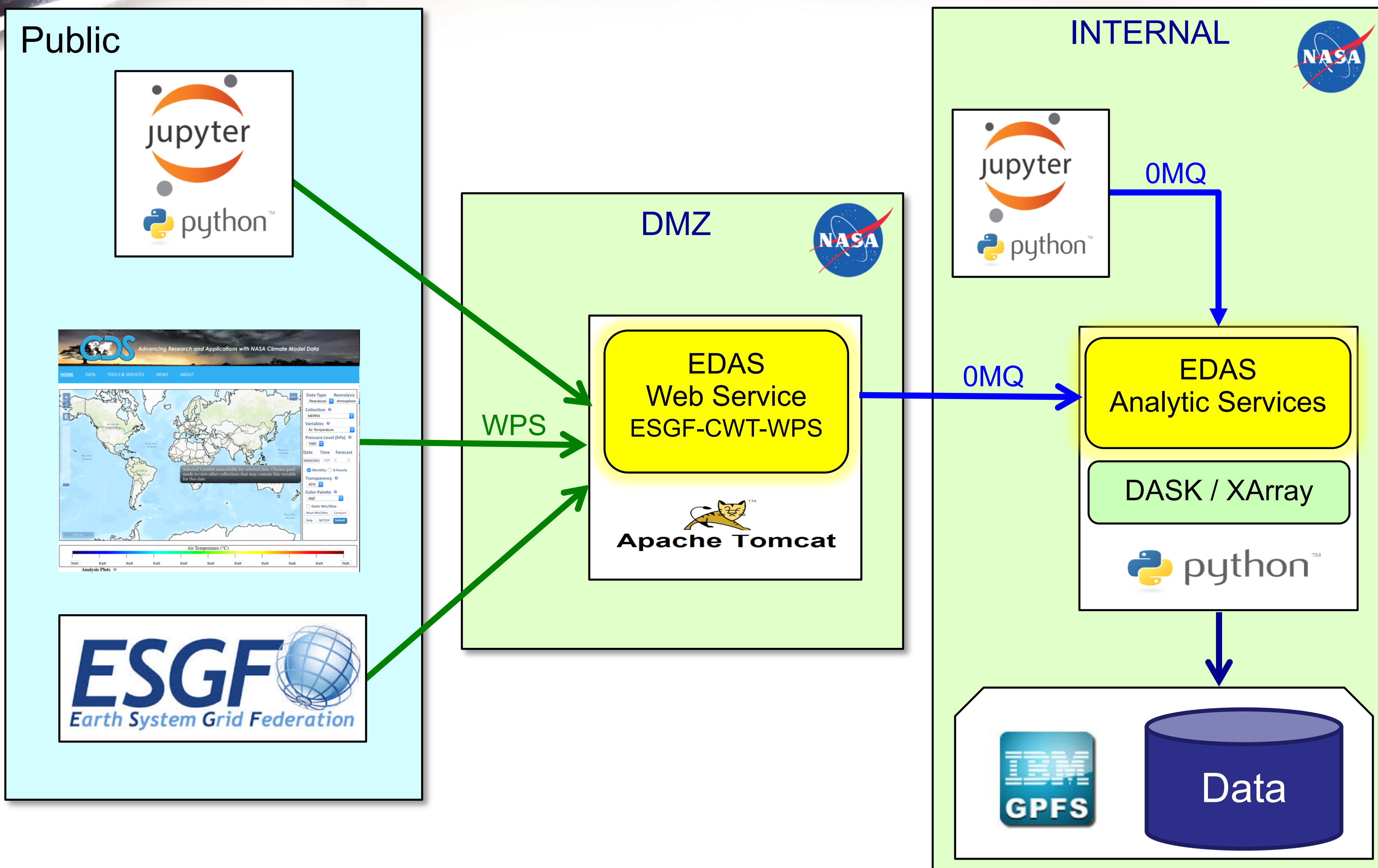
Earth System Grid Federation Compute Working Group

- ESGF distributes the data that supports the IPCC Assessment Reports
- CWT provides server-side analytics for ESGF
- CWT has defined a python API and a WPS service
- NASA-NCCS has implemented an ESGF-CWT analytics server (EDAS)
- Enables distributed, high-performance analytics close to the data

<u>Estimated Data Growth of ESGF</u>
2012 AR5 – 2 to 5 petabytes
2017 AR6 – 25 to 50 petabytes
2022 AR7 – 100 to 1,000 petabytes



NASA ESGF CWT Analytics (EDAS)



EDAS Analytic Services Framework

- Implemented in 100% python
  - Access to full python analytics ecosystem
- Built on Dask/Xarray
  - Dask-distributed parallelism
- Restful WPS interface
  - Esgf-cwt compliant
- Workflow framework
  - Compose graphs of canonical operations
- Parallel data access
  - Directly from POSIX or OpenDAP

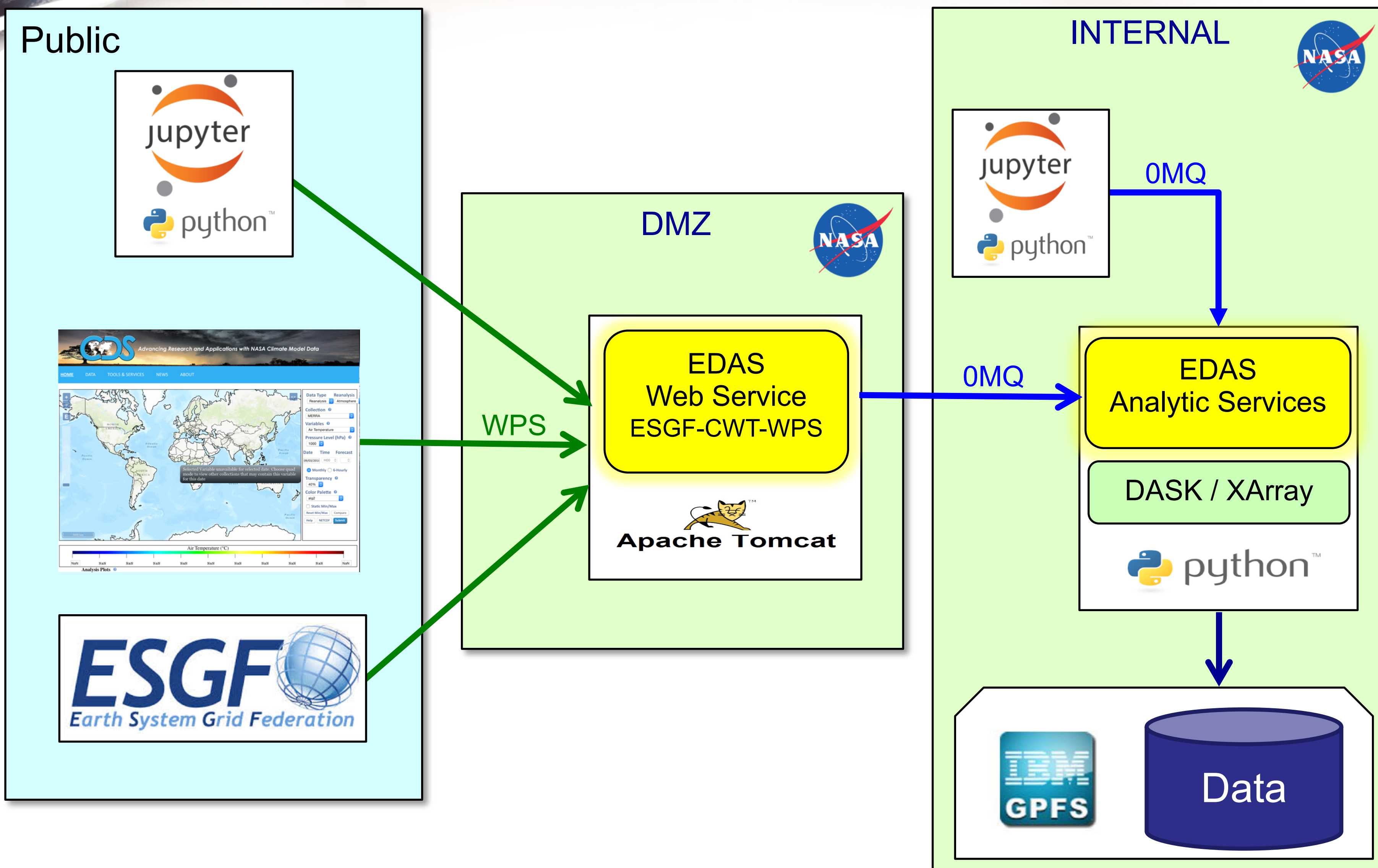
Dask-distributed parallelism

- Familiar APIs:
  - XArray builds on numpy and netCDF APIs.
  - High level constructs and automatic parallelism simplify development
- Pure Python:
  - Built in Python using well-known technologies
- Large group of developers
- Low latency:
  - Each task suffers about 1ms of overhead
- Peer-to-peer data sharing:
  - Workers communicate with each other to share data
- Complex Scheduling:
  - Supports complex workflows (not just map/filter/reduce)
- Data Locality:
  - Scheduling algorithms cleverly execute computations where data lives

Xarray Data Analysis Toolkit

- Extends Pandas to support N-dimensional arrays.
    - Inherits performance and power of Pandas.
- Tight integration with numpy and netCDF
    - In memory representation of netCDF data using np.ndarray
- Integrated with Dask for streaming data parallelism
    - Transparent distributed (chunked) arrays
    - Lazy, streaming computation on datasets that don’t fit in memory
    - Builtin parallel NetCDF IO
    - Automatically parallelizes xarray workflows
    - Parallelized numpy builtin and ufunc operations.

EDAS Architecture



Request Structure

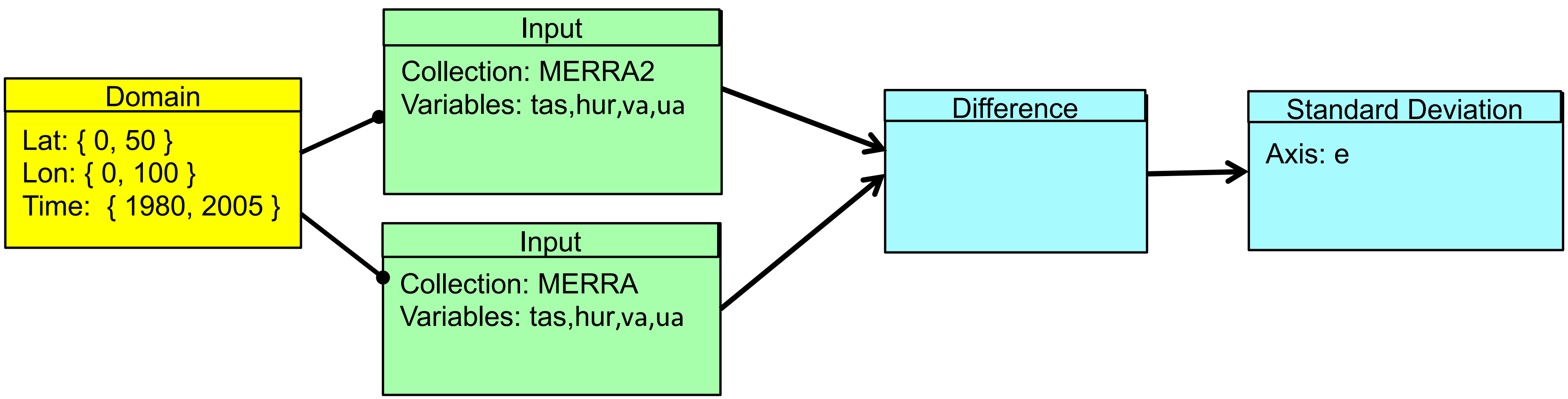
domains = [{ name: d0,   lat: {0, 50},   lon: {0, 100}, time: { '1980-01-01','2005-01-01' } }]

variables = [{ col: merra,   name: tas,hur,va,ua,   domain: d0, result: v0 }

{ col: merra2,   name: tas,hur,va,ua,   domain: d0, result: v1 }]

operations = [{ name: xarray.diff, input: v0,v1, result: vdiff   }

{ name: xarray.std, input: vdiff, axes: e }   ]



Kernels

Canonical operations:

- Data access & subset
- Average (weighted and unweighted)
- Maximum
- Minimum
- Sum
- Difference
- Product
- Standard Deviation
- Variance
- Anomaly
- Median
- Norm
- Filter
- Decycle
- Highpass/Detrend
- Lowpass/Smooth

Specialized operations:

- EOF
- PC
- TeleconnectionMap
- Neural Network Kernels:
  - Layer
  - Trainer
  - Model

Canonical Operation Options

- Domain: subset to region of interest
- Axes: reduce over axes
  - X (latitude), Y (longitude) , Z (levels), T (time), E (ensemble)
- Groupby: split-apply-combine
  - Custom or existing Axis
  - Pandas groups
- Resample: upsampling and downsampling
  - Pandas resample API

Example (for 10 years of data):

Operation	Interpretation	Size
ave(axis: t)	Time average	1
ave(axis: te)	Time ensemble average	1
ave(axis: t, groupby: t.month)	Monthly climatology	12
ave(axis: t, resample: t.month)	Monthly means	120

Simple Kernel Definition

```python
class StdKernel(OpKernel):
    def __init__( self ):
        OpKernel.__init__( self, KernelSpec("mean", "Standard Deviation Kernel",
                "Computes the standard deviation of the array elements "
                "along the given axes." ) )

    def processVariable( self, request: TaskRequest, node: OpNode, variable: EDASArray,
                        attrs: Dict[str,Any], products: List[str] ) -> List[EDASArray]:
        return [variable.std( node.axes )]
```

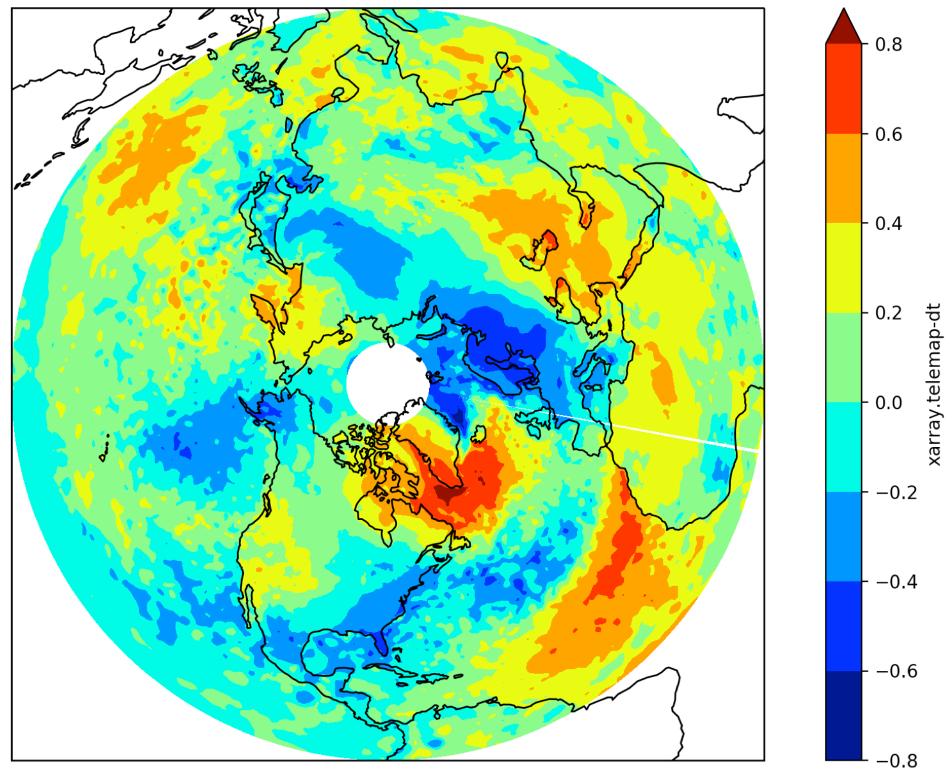
More Complex Kernel Definition

```
class TeleconnectionKernel(OpKernel):
    def __init__( self ):
        OpKernel.__init__( self, KernelSpec("telemap", "Teleconnection Kernel",
                                        "Produces teleconnection map by computing covariances at each point "
                                        "(in roi) with location specified by 'lat' and 'lon' parameters." ) )

    def processVariable( self, request: TaskRequest, node: OpNode, variable: EDASArray,
                                attrs: Dict[str,Any], products: List[str] ) -> List[EDASArray]:
        parms = self.getParameters( node, [ Param("lat"), Param("lon")])
        aIndex = variable.xr.get_axis_num('t')
        center: xa.DataArray = variable.selectPoint( float(parms["lat"]), float(parms["lon"]) ).xr
        cmean = center.mean(axis=aIndex)
        data_mean = variable.xr.mean(axis=aIndex)
        cstd = center.std(axis=aIndex)
        data_std = variable.xr.std(axis=aIndex)
        cov = np.sum((variable.xr-data_mean)*(center-cmean),axis=aIndex)/variable.xr.shape[aIndex]
        cor = cov / (cstd * data_std)
        return [ EDASArray( variable.name, variable.domId, cor ) ]
```

Teleconnection Maps

Computes a map of covariances between a chosen point and all other points in the ROI.



Domain
Lat: { 0, 80 }
Time: { 1980, 2010 }

Input
Collection: CFSR
Variables: tas

Input
Collection: 20CR
Variables: tas

Input
Collection: ECMWF
Variables: tas

Input
Collection: MERRA2
Variables: tas

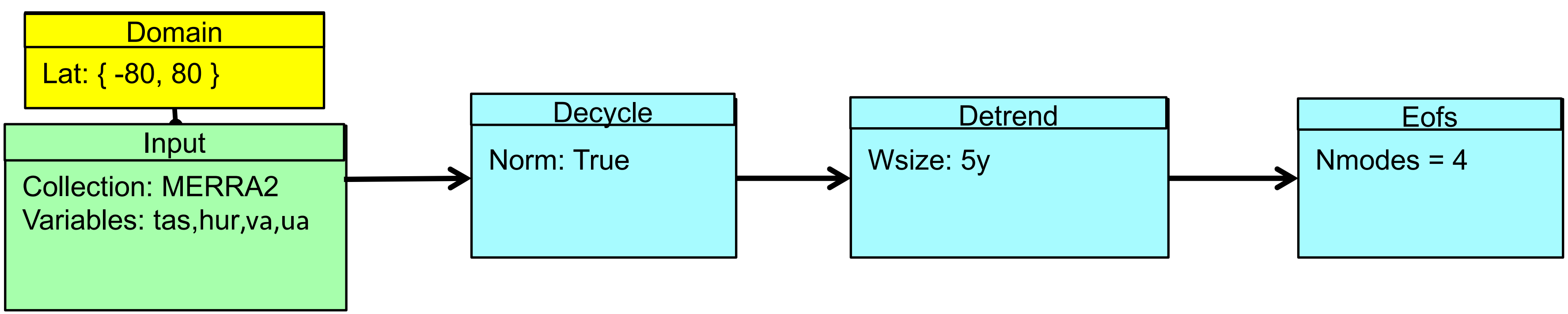
filter
Axis: t
Selection: djf

detrend
Wsize: 15

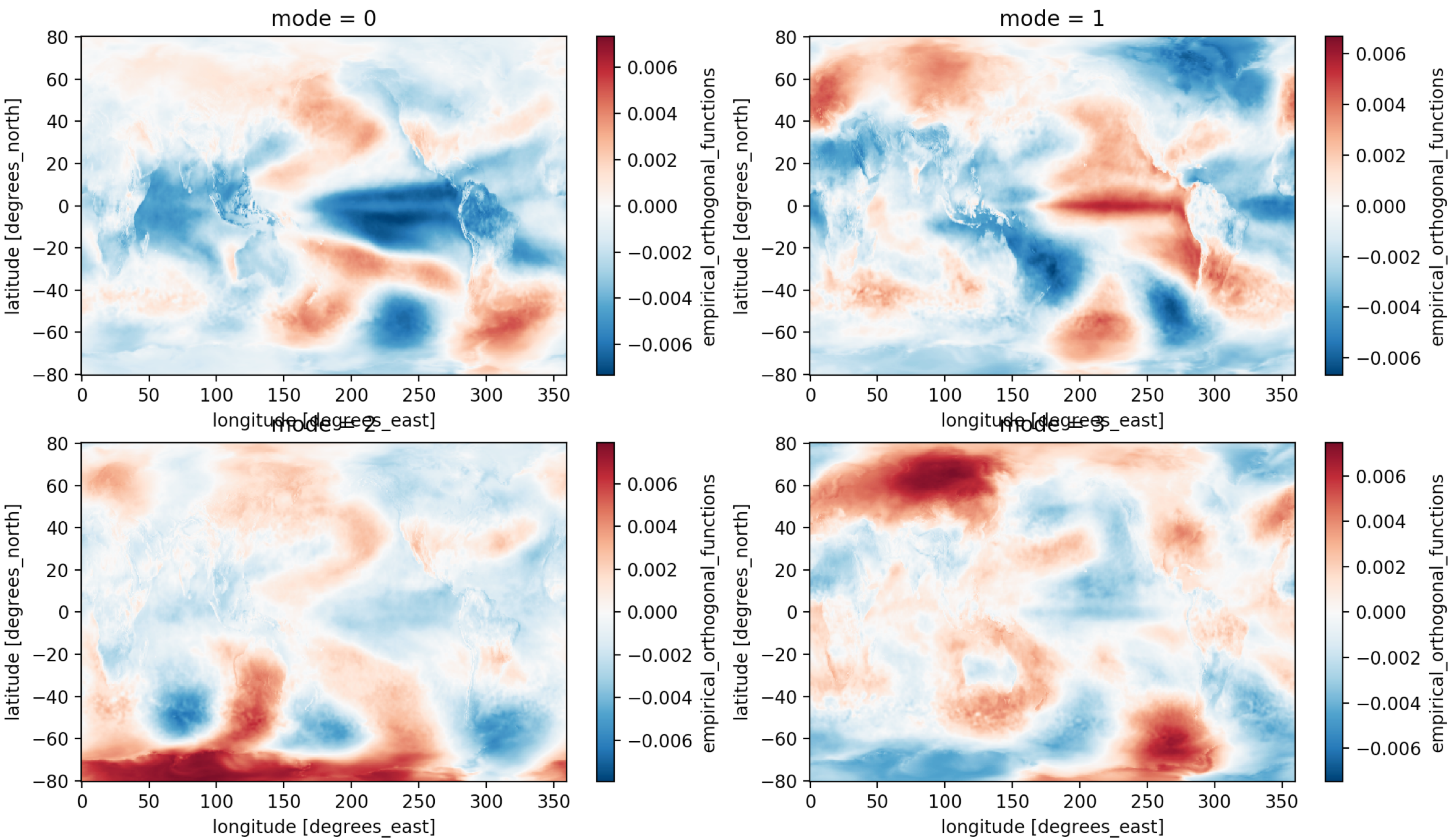
telemap
Lat: 60
Lon: 310

EOF Workflow

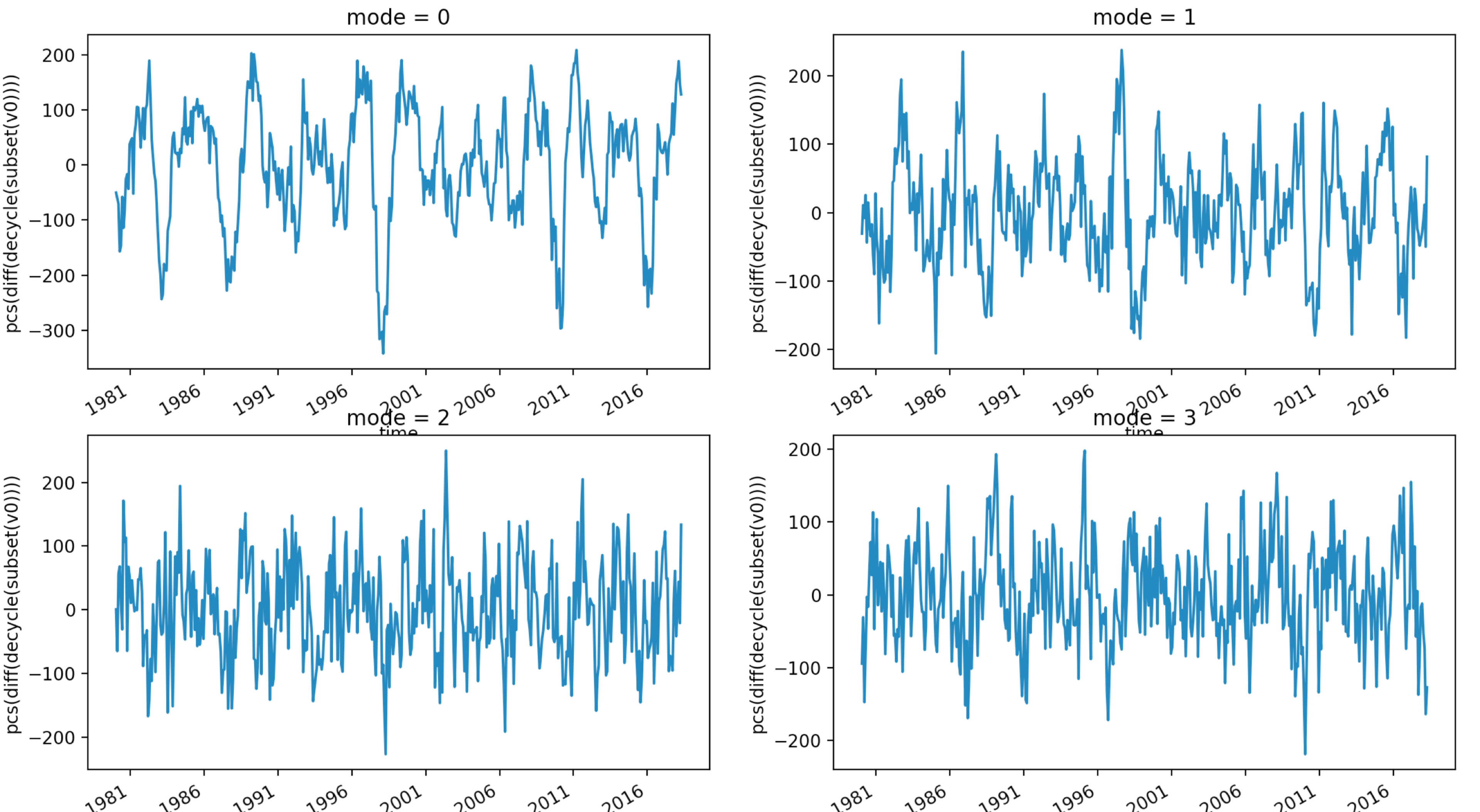
EOF Decomposition: $$X(t, \mathbf{s}) = \sum_{k=1}^{M} c_k(t) u_k(\mathbf{s}),$$



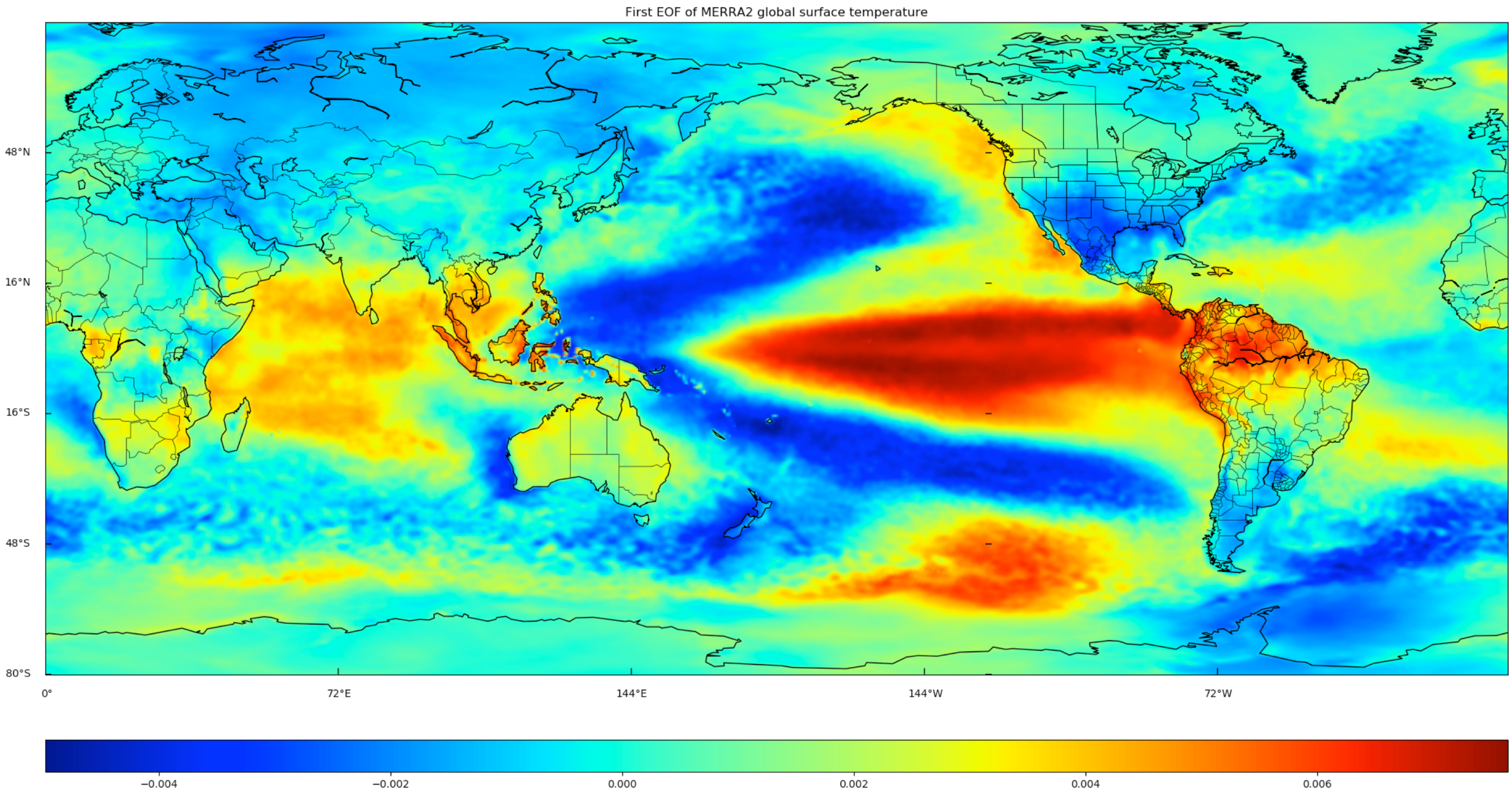
MERRA2 Global Surface Temperature
EOF Modes



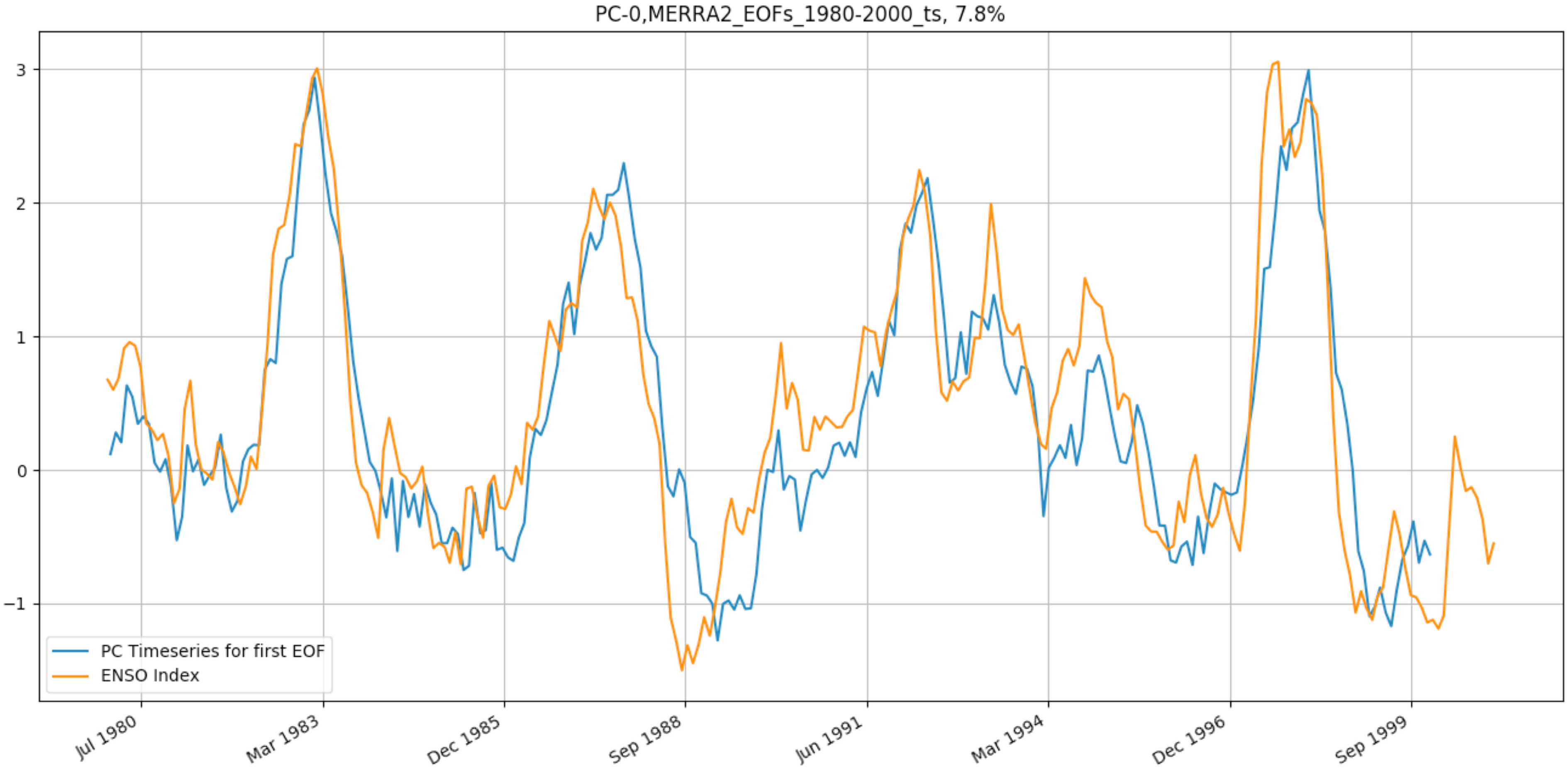
MERRA2 Global Surface Temperature
Principal Component Timeseries



MERRA2 Global Surface Temperature First EOF

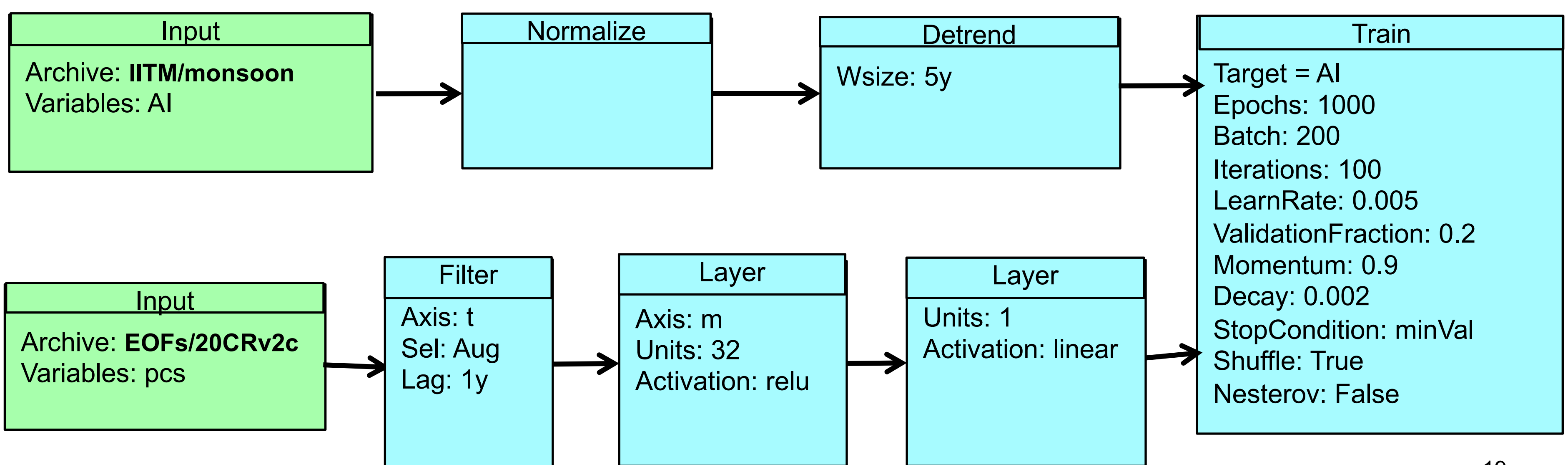


PC1 – ENSO Index Comparison



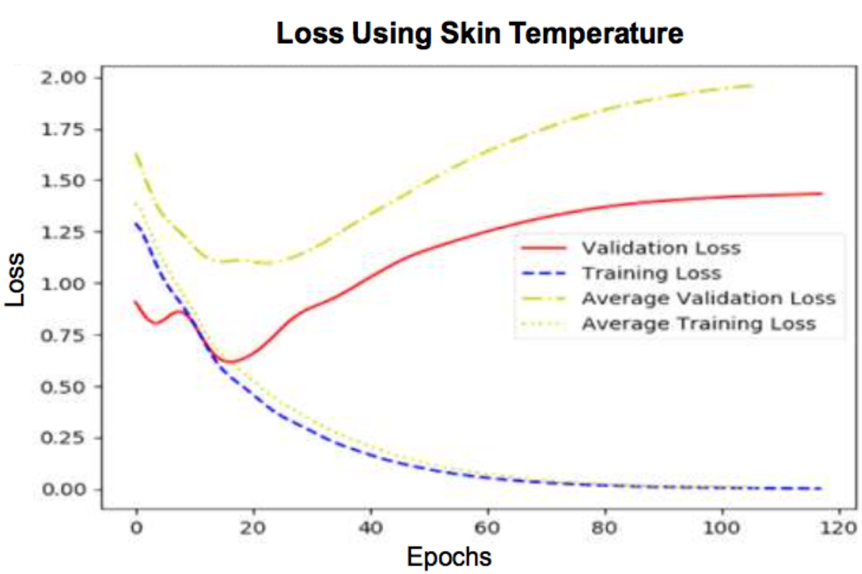
Machine Learning Workflow

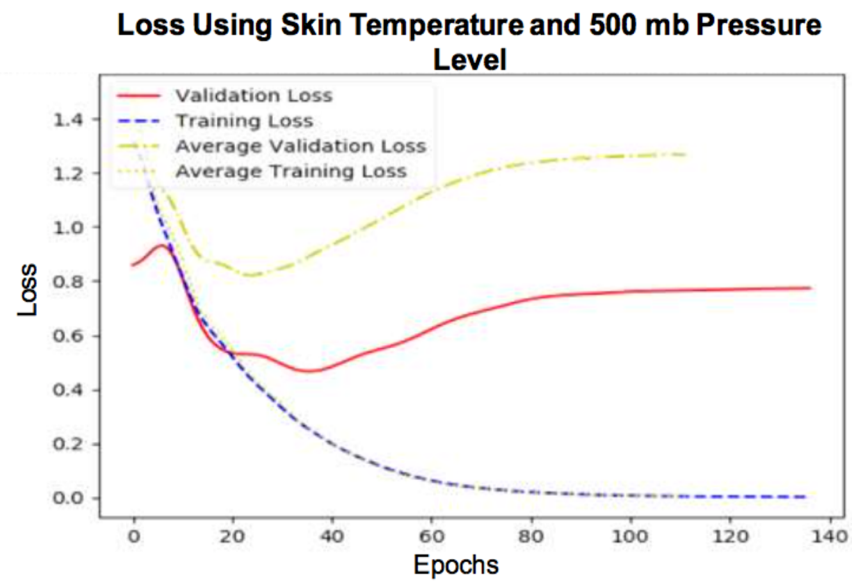
- Predict All-India Monsoon rainfall accumulation one year in advance
- Use a two-layer neural network
- Inputs: First 32 PCs of global surface temperature, 1 year lag time



Training Performance

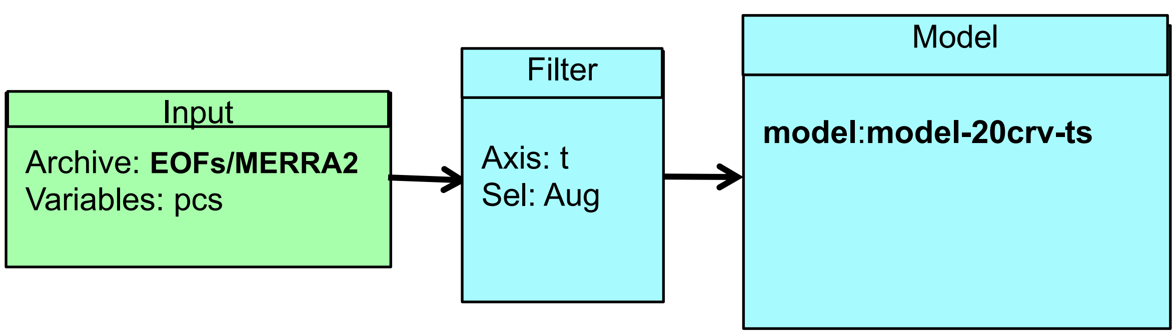
- Loss Function: Mean square error
  - Output node results vs. IITM-AI timeseries
- Last 20% of data reserved for validation
- Choose model with minimum error on validation data





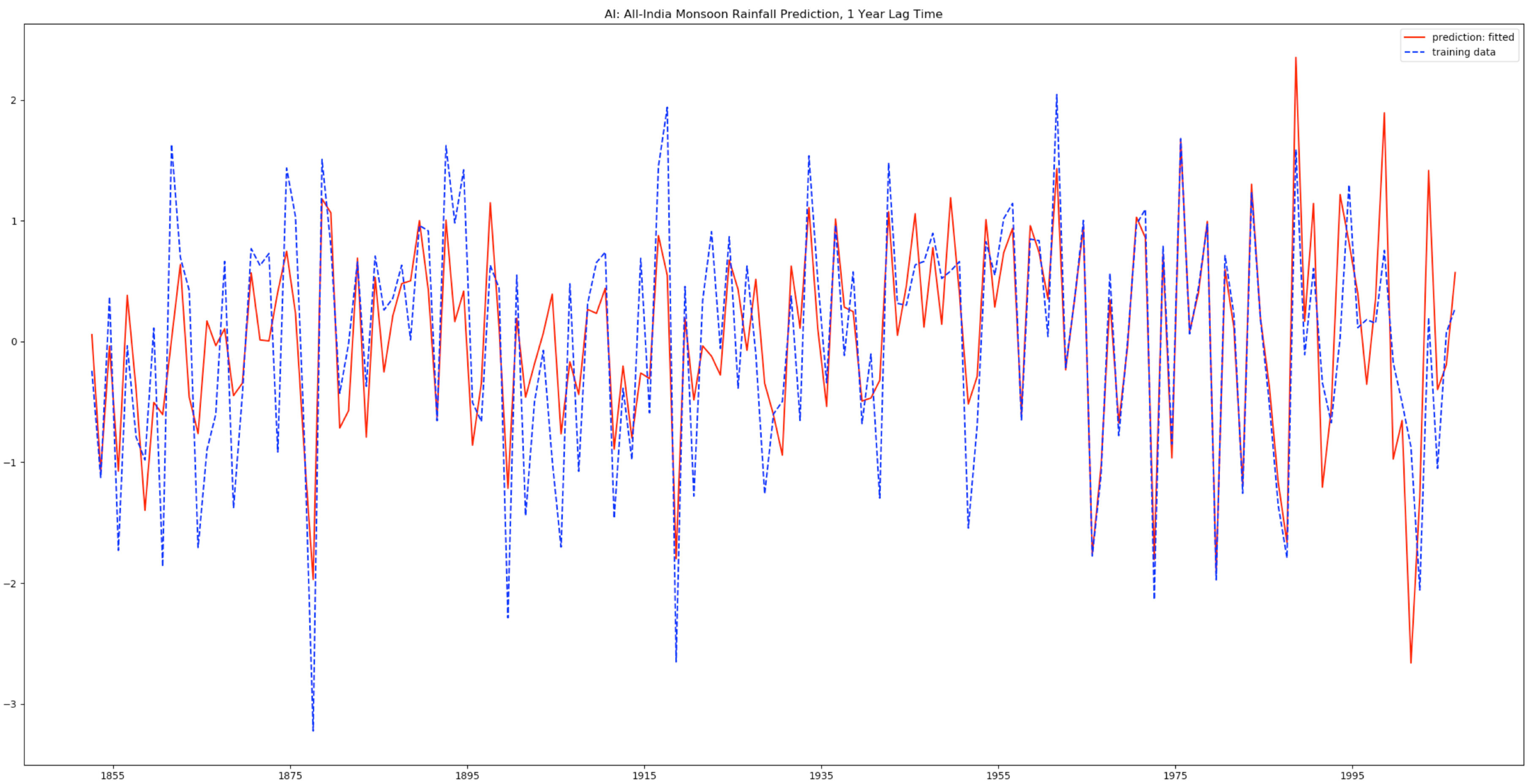
Applying the Neural Network Model

- Model kernel reads generated network structure and weights
- Generates a projection from a set of PCs



Results

- Comparison of predicted to actual monsoon precipitation
- Result of two month project by summer intern



Conclusions

- Big data analytics is moving closer to the data
- Workflows of canonical ops facilitate exploratory analytics
- Machine learning can exploit non-local climate dynamics