What controls mixing in lakes?

Keith Arora-Williams

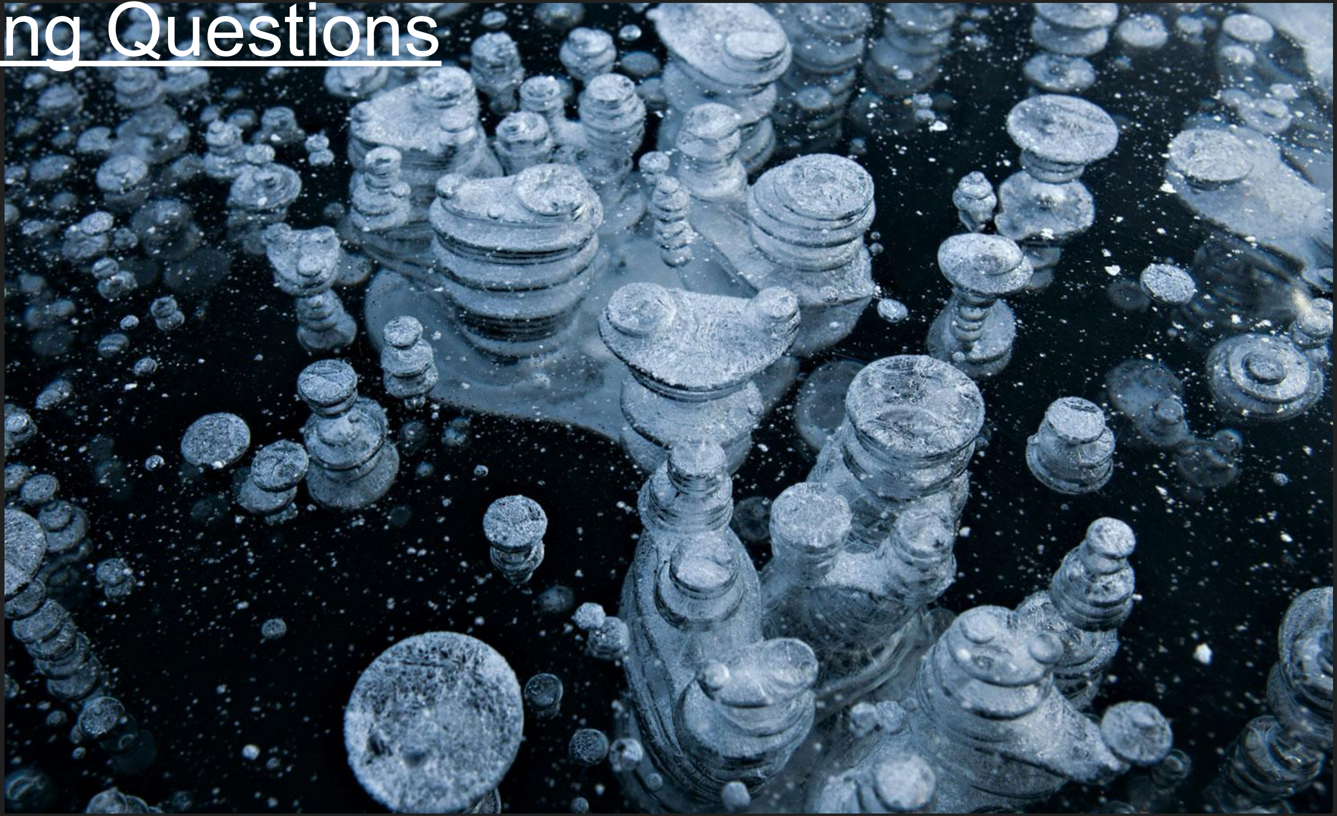
April 29, 2016

Outline

Motivation (1 slide)
Approach (2 slides)
Data Sources & Types (1 slide)
Initial Results (5 slides)
Next Steps (1 slide)

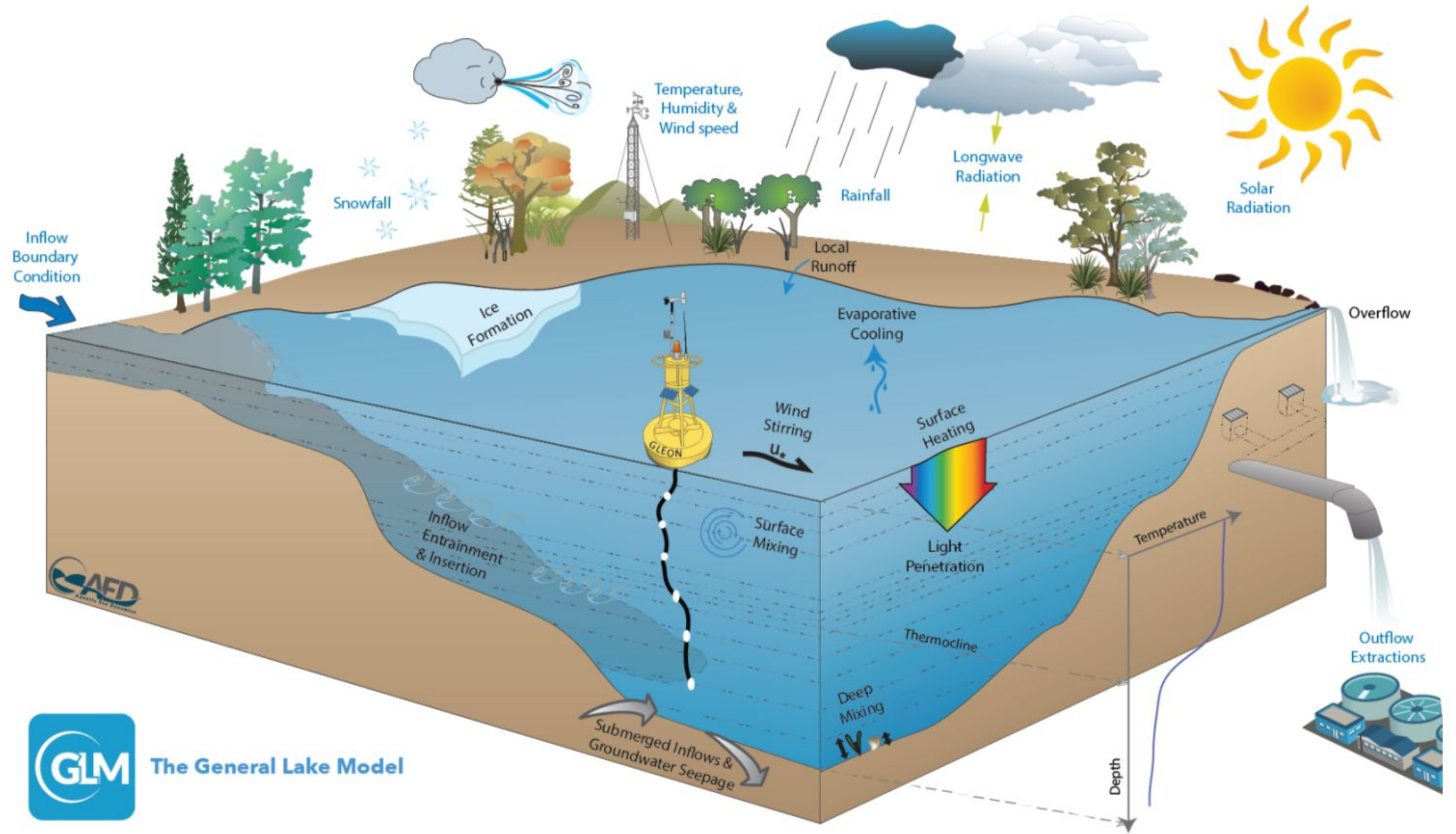
Motivating Question

Motivating Questions



- Bastviken, D., et al. *Freshwater methane emissions offset the continental carbon sink*. **Science** (2011) 331, 50 .
- Bogard, M.J., et al. *Oxic water column methanogenesis as a major component of aquatic CH4 fluxes*. **Nat Commun.** (2014)
- Itoh, M. et al. *Effect of interannual variation in winter vertical mixing on CH4 dynamics in a subtropical reservoir.* **Journal of Geophysical Research: Biogeosciences** (2015)

How to address this question?

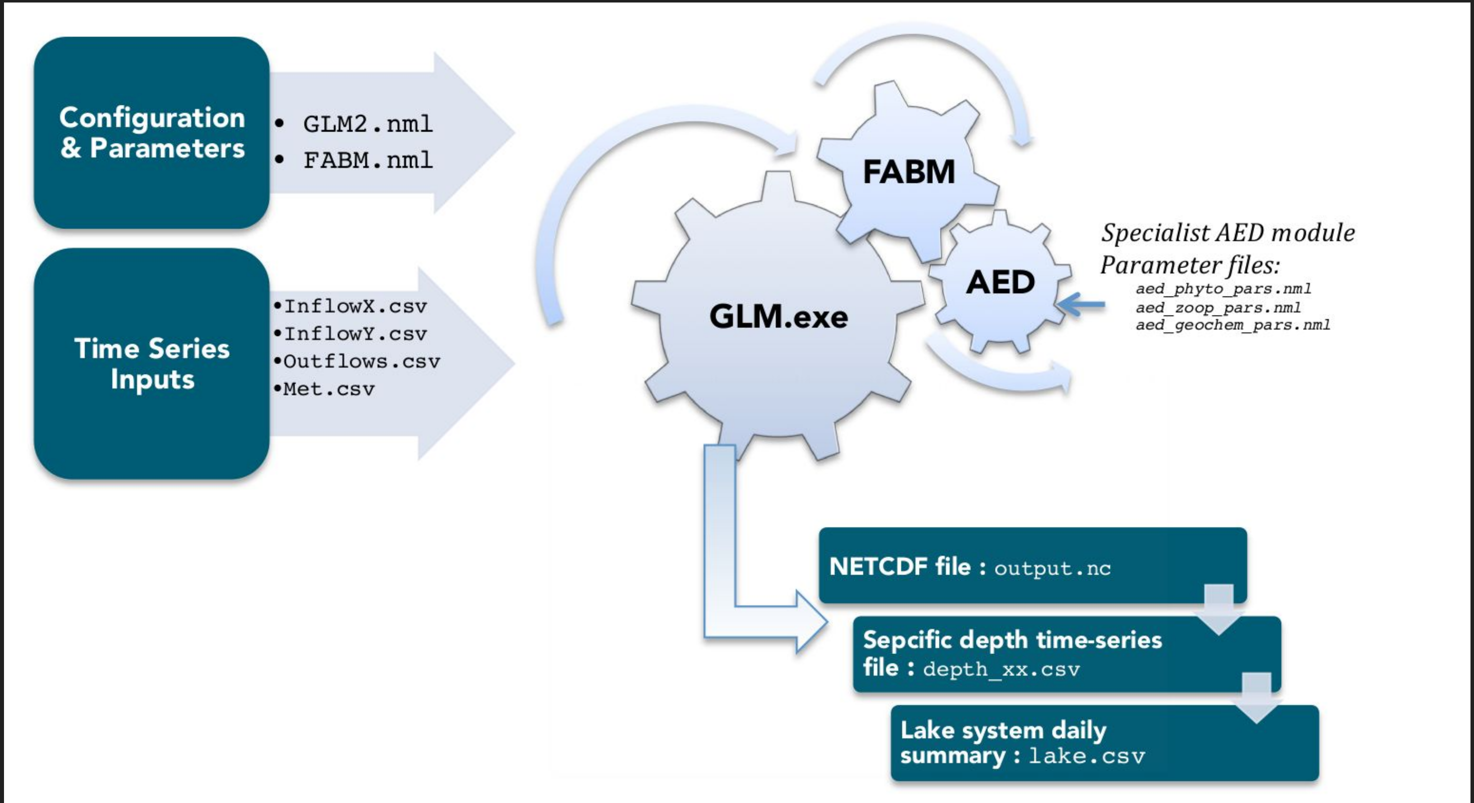


Temperature,
Humidity &
Wind speed
Snowfall
Rainfall
Longwave
Radiation
Solar
Radiation
Inflow
Boundary
Condition
Local
Runoff
Ice
Formation
Evaporative
Cooling
Overflow
Wind
Stirring
u_*
Surface
Heating
GLEON
Surface
Mixing
Light
Penetration
Inflow
Entrainment
& Insertion
Temperature
Thermocline
Outflow
Extractions
Deep
Mixing
Submerged Inflows &
Groundwater Seepage
Depth
AED
GLM
The General Lake Model

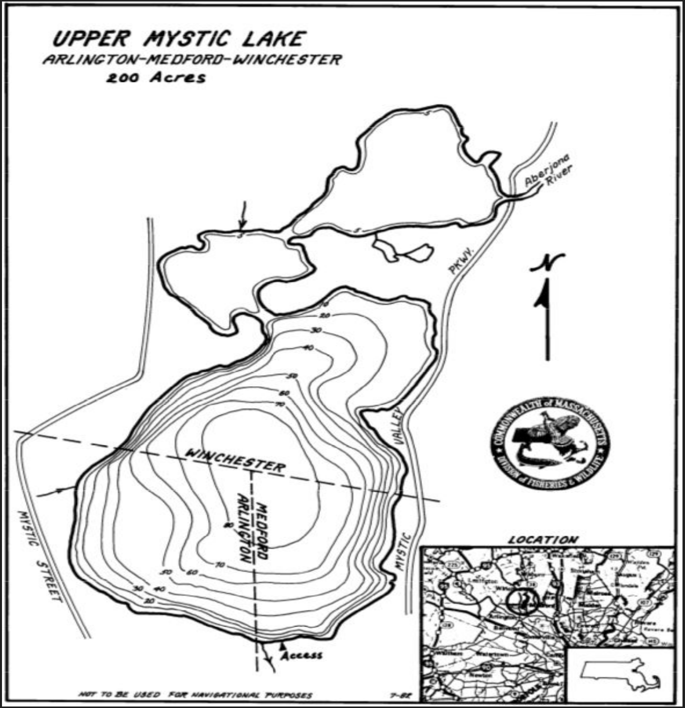
Step 1: Get Input Data

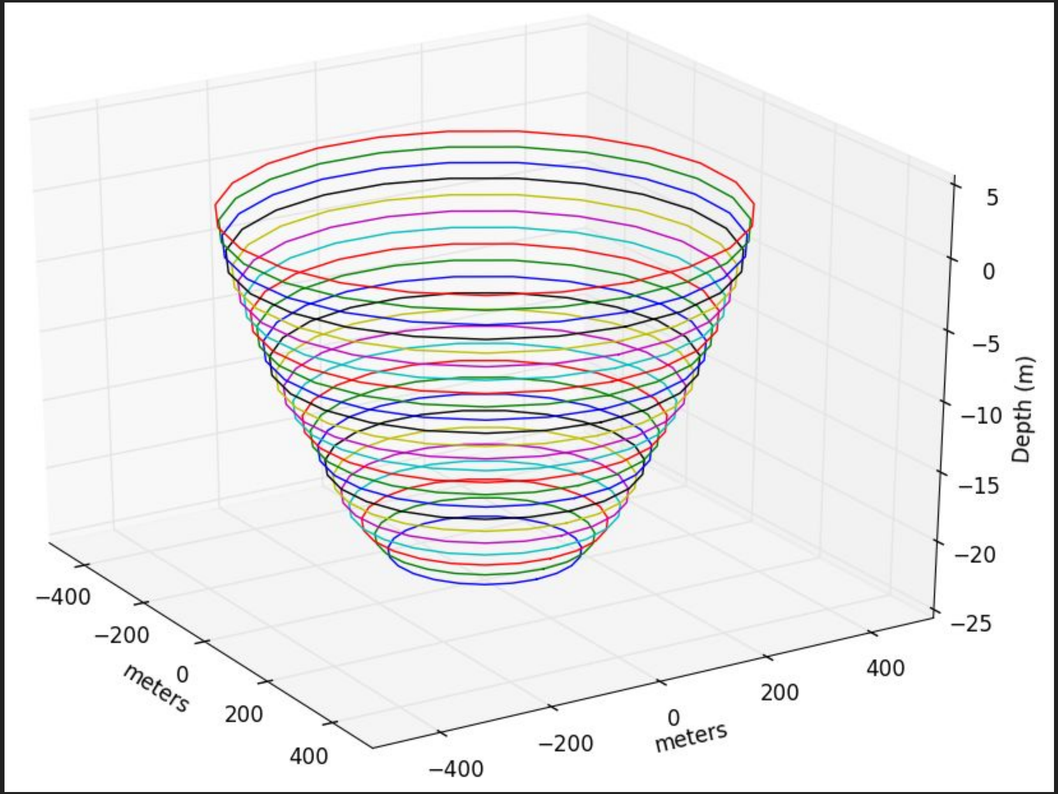
Name	Type	Interval	Source	Input File Name
Inflow Volume	Discharge	15 min	USGS	`inflows.csv`
Outflow Volume[(A)]	Discharge	15 min	USGS	`outflows.csv`
Inflow Salinity[(B)]	Spec. conductance	10 min	USGS	`inflows.csv`
Inflow Temperature[(B)]	-	10 min	USGS	`inflows.csv`
Shortwave Radiation	Irradiance	~12 hr	CERES	`met.csv`
Longwave Radiation	Irradiance	~12 hr	CERES	`met.csv`
Cloud Cover[(C)]	Fraction	~12 hr	LAADS	`met.csv`
Air Temperature[(D)]	-	~12 hr	CERES	`met.csv`
Relative Humidity[(E)]	-	~12 hr	CERES	`met.csv`
WindSpeed	Speed	24 hr	GHCN	`met.csv`
Rainfall[(F)]	Length	24 hr	GHCN	`met.csv`
Snowfall	Length	24 hr	GHCN	`met.csv`

Step 2: Write Configuration Files



Step 3: Area - Depth Relations



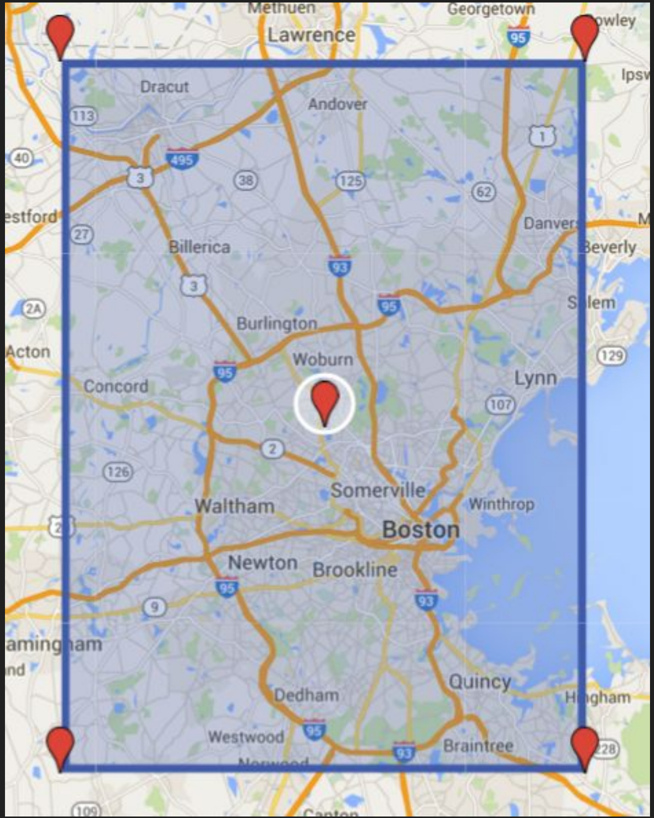


Step 4: Access & Examine Data

- General Tasks
  - Unit Conversions
- CERES-specific
  - Unpack netCDF / ‘.nc’ files
  - Converting Julian days into Calendar Days
  - Filter by position in space
  - Examine distribution in time

```
In [49]: test.net_GCHN.columns
Out[49]:
Index([u'precip', u'wind_speed', u't_max', u't_min', u'snow_fall',
       u'snow_depth'],
      dtype='object')

In [50]: test.ceres_df.columns
Out[50]:
Index([u'temp', u'windU', u'windV', u'humidity', u'cloud_frac', u'LW_rad',
       u'SW_rad'],
      dtype='object')
```



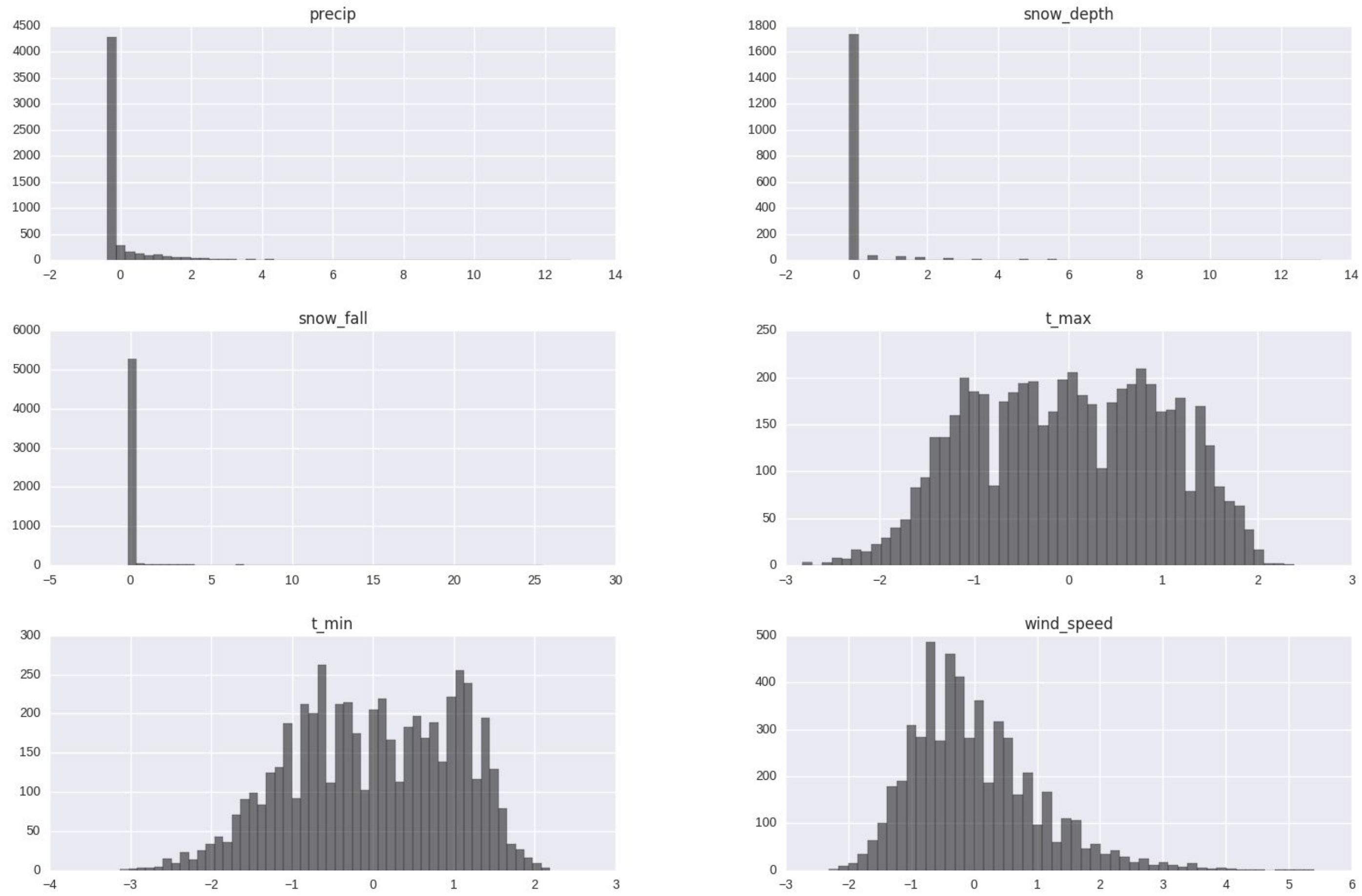
Step 5: Deal with missing data

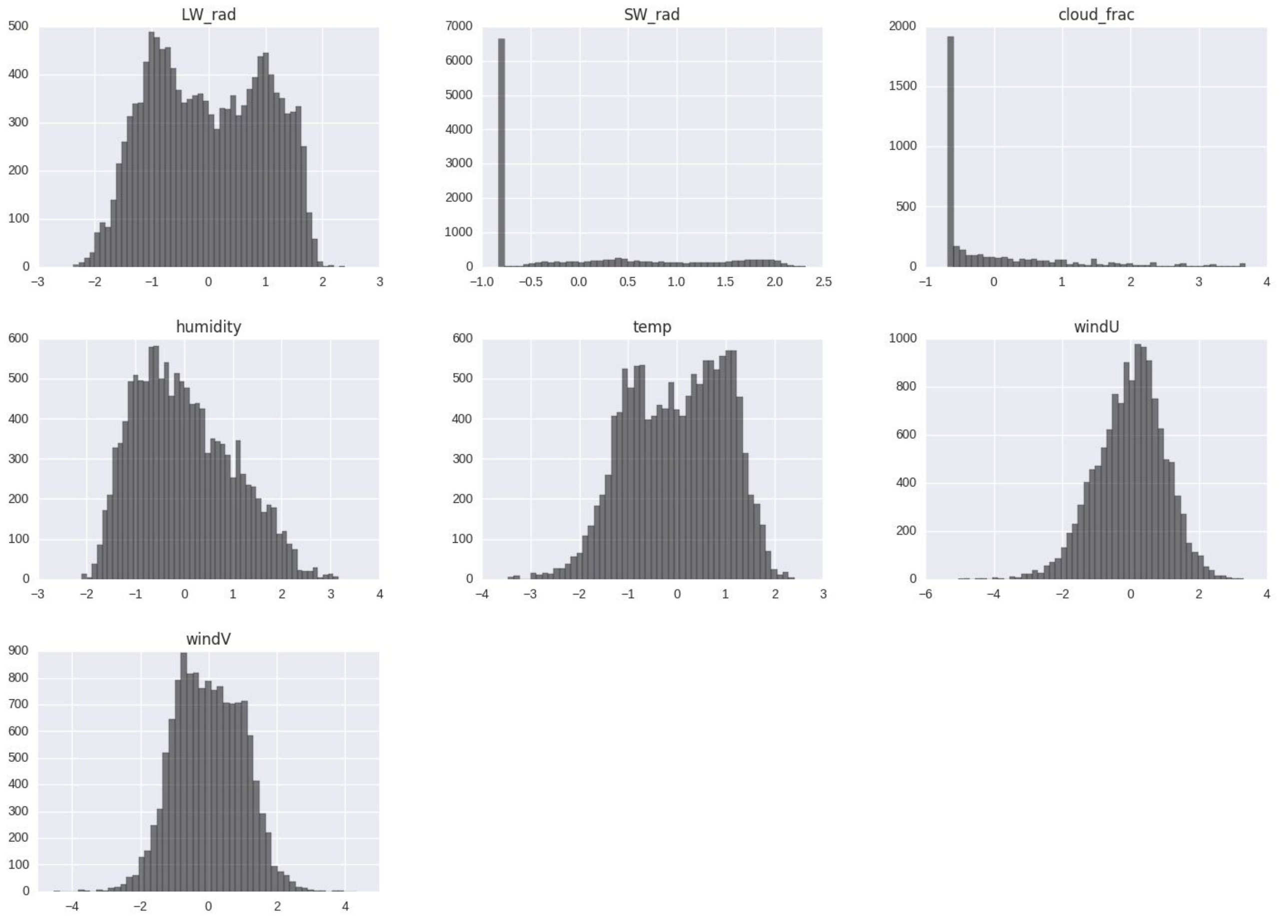
```
NaN Values read into GCHN data (<class 'pandas.core.frame.DataFrame'>)
precip           2
wind_speed       0
t_max            0
t_min            0
snow_fall        0
snow_depth    3609
dtype: int64
Total measurements per variable: 5480

NaN Values read into CERES data (<class 'pandas.core.frame.DataFrame'>)
temp             0
windU            0
windV            0
humidity         0
cloud_frac    9329
LW_rad          74
SW_rad          81
dtype: int64
Total measurements per variable: 13252
```

- Autocorrelation on:
  - Time-Scale Aggregations
  - Raw Data
- Z-scores: easy for plotting, easy for interpreting

```
Autocorrelation peaks
season_i
        temp max autocorr @ 1 = 0.38
        windU max autocorr @ 1 = 0.05
        windV max autocorr @ 1 = 0.06
        humidity max autocorr @ 1 = -0.02
        cloud_frac max autocorr @ 1 = -0.04
        LW_rad max autocorr @ 1 = -0.42
        SW_rad max autocorr @ 1 = 0.59
day_i
        temp max autocorr @ 1 = -0.10
        windU max autocorr @ 1 = -0.00
        windV max autocorr @ 1 = -0.02
        humidity max autocorr @ 1 = -0.02
        cloud_frac max autocorr @ 86 = 0.00
        LW_rad max autocorr @ 1 = -0.00
        SW_rad max autocorr @ 2 = -0.08
year_i
        temp max autocorr @ 1 = -0.98
        windU max autocorr @ 1 = -0.55
        windV max autocorr @ 1 = -0.53
        humidity max autocorr @ 1 = -0.05
        cloud_frac max autocorr @ 1 = -0.46
        LW_rad max autocorr @ 1 = -0.89
        SW_rad max autocorr @ 1 = -0.47
week_i
        temp max autocorr @ 1 = -0.10
        windU max autocorr @ 1 = -0.02
        windV max autocorr @ 1 = -0.05
        humidity max autocorr @ 1 = -0.07
        cloud_frac max autocorr @ 1 = -0.01
        LW_rad max autocorr @ 2 = -0.03
        SW_rad max autocorr @ 1 = -0.13
month_i
        temp max autocorr @ 1 = -0.13
        windU max autocorr @ 1 = -0.09
        windV max autocorr @ 1 = -0.12
        humidity max autocorr @ 1 = -0.18
        cloud_frac max autocorr @ 3 = -0.02
        LW_rad max autocorr @ 5 = -0.08
        SW_rad max autocorr @ 1 = -0.17
```


precip
snow_depth
snow_fall
t_max
t_min
wind_speed


LW_rad
SW_rad
cloud_frac
humidity
temp
windU
windV

More Steps

- Read in USGS Water Data & write out CSVs (Pandas)
- Run model (Joblib / subprocess)
- Determine Kling-Gupta Efficiency based on comparison with known water temperature distribution
- Use Hornberger-Spear-Young method to determine sensitivity between behavioural & non-behavioural simulations.