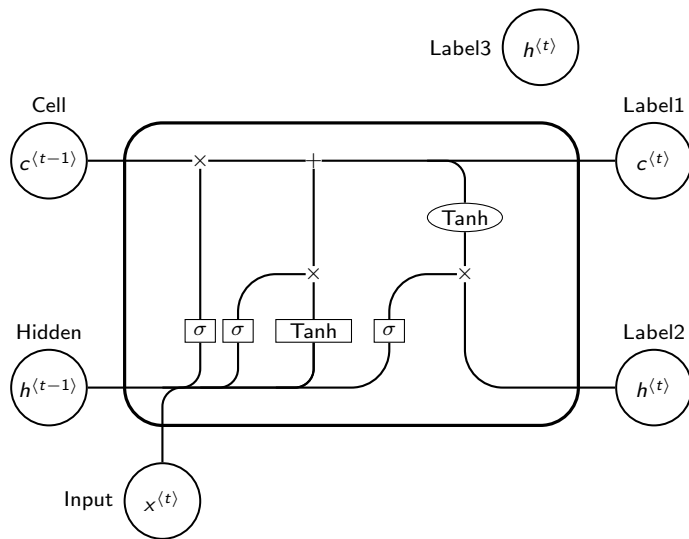


LSTM-RNN Results for GPP

January 28, 2019

- Daily/monthly outputs of sELM are time series
- Outputs dependent on each day (and also other outputs)
- Recurrent Neural Network can be used to train outputs from sELM
- Need a Gated Type Method
 - LSTM (long short term memory)
 - GRU (gated recurrent unit)
- No longer need to deal with vanishing/exploding gradients
- Can handle history of time sequences

LSTM Cell



LSTM Cell summary

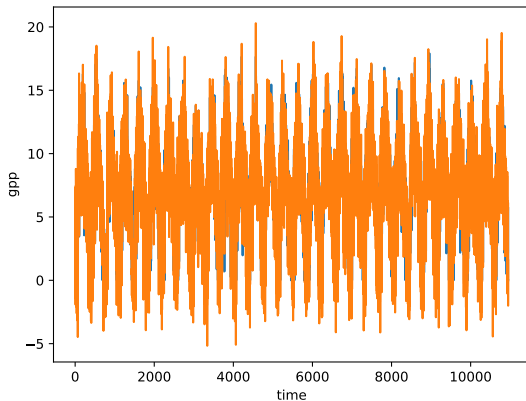
$$\begin{aligned}f_t &= \sigma(W_f x + U_f h_{t-1} + b_f) \\i_t &= \sigma(W_i x + U_i h_{t-1} + b_i) \\o_t &= \sigma(W_o x + U_o h_{t-1} + b_o) \\c_t &= f_t \odot c_{t-1} + i_t \odot \sigma_c(W_c x_t + U_c c_{t-1} + b_c) \\h_t &= o_t \odot \sigma_h(c_t)\end{aligned}\tag{1}$$

RNN Structure

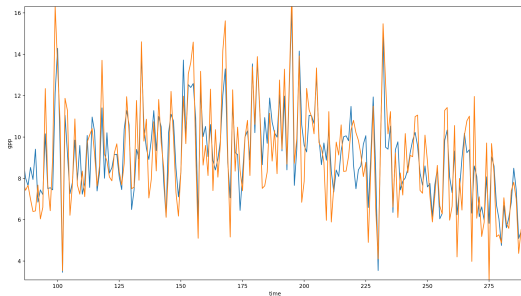
- Trained RNN on regional sELM for a particular lon, lat region
- Inputs: Forcings
 - TMIN
 - TMAX
 - BTRAN
 - FSDS
 - DAYL
 - DOY
- Inputs: Stochastic Inputs (e.g. frootcn, fpg, etc.)
- OUTPUTS
 - GPP
 - LAI
 - NEE
 - GR
 - HR
- Trained on 90 samples
- 2 layers, 53 hidden neurons

Model 1

Pearson-r = 0.81

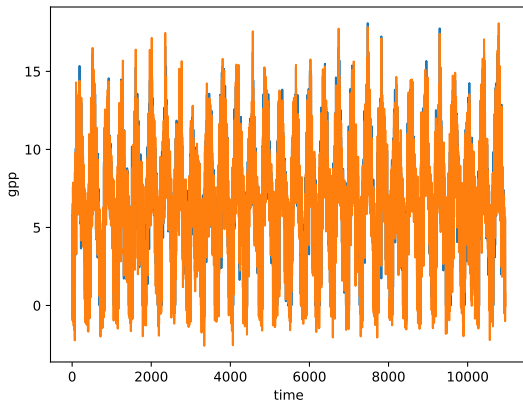


Model 1 zoom

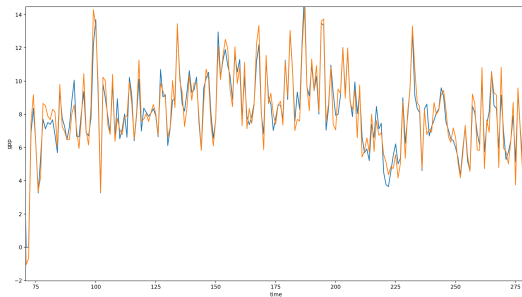


Model 2

Pearson-r = 0.78

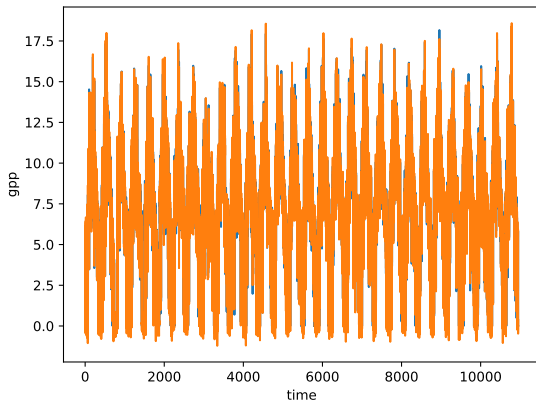


Model 2 zoom

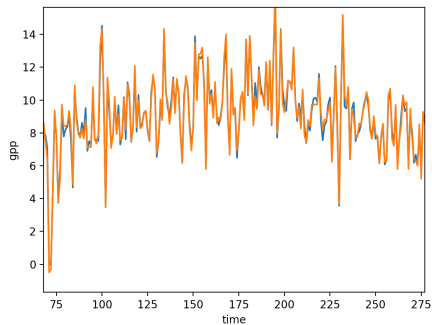


Model 3

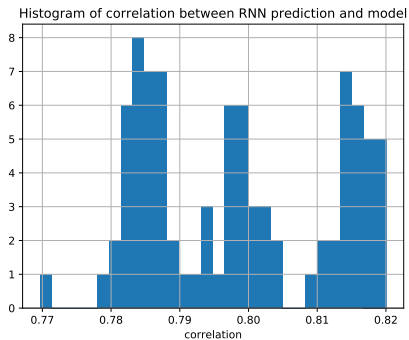
Pearson-r = 0.814



Model 3 zoom

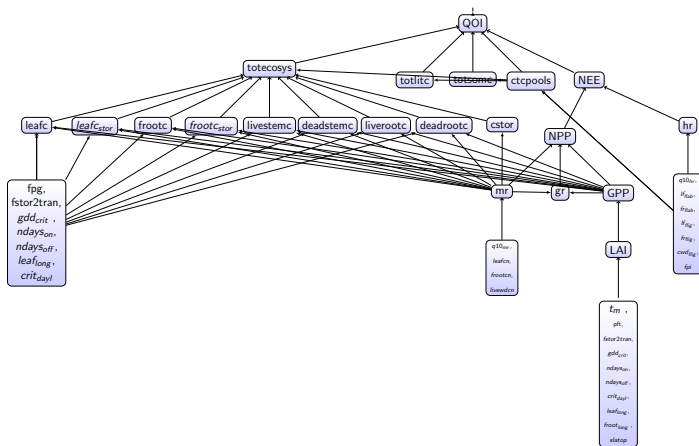


Pearson Coefficient Summary (Histogram)



In Progress

- sELM has hierarchical structure (graph-like)
- Adapt RNN to fit that structure
- account for noise/error in observations/states



- Better to train on Average monthly or daily history
- Noise/error in forcings (quantifiable)-periods where forcings are too noisy
- Time history of daily outputs of interest (by year)
- Seasonal history of interest (perhaps during certain years)
- Sites have correlations (any way to quantify those)
- Acceptable range for stochastic inputs (noticed overflow errors)