

```
for (k in 1:length(file.names)){
  basin <- read.delim(file.names[k],sep=" ",na.strings="-9999.000")
  names(basin) <- c("JJ", "DD","MM","YYYY","Qm3","P","T","PET","SM","AET","Peff")
  # basin <- basin[which(is.na(basin$Q)==FALSE),] #leave out data gaps
  basin$Date <- as.Date(paste(basin$DD,basin$MM,basin$YYYY,sep="."),format="%d.%m.%Y")
  basin$Q <- basin$Qm3*3.6*24/area$Area[k]
  thresh <- quantile(basin$Q,pVal,na.rm=TRUE)
  basin$Station <- as.numeric(gsub("sub_1.txt","",file.names[k]))

  index <- 1
  basin$Event <- NA #prepare output vectors/dataframe
  basin$EventID <- NA
  for(m in (max(lag)+1):length(basin[,1])){#assign flood event numbers to each day
    #start from max-lag+1 to allow for calculation of preconditions below
```

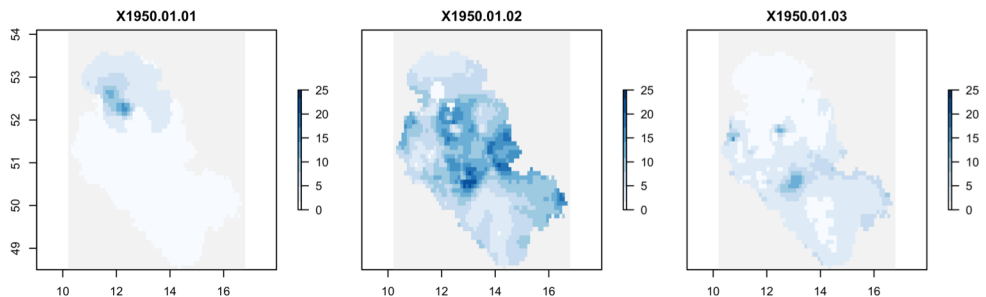


## DeepHydro: Petrus 2.0

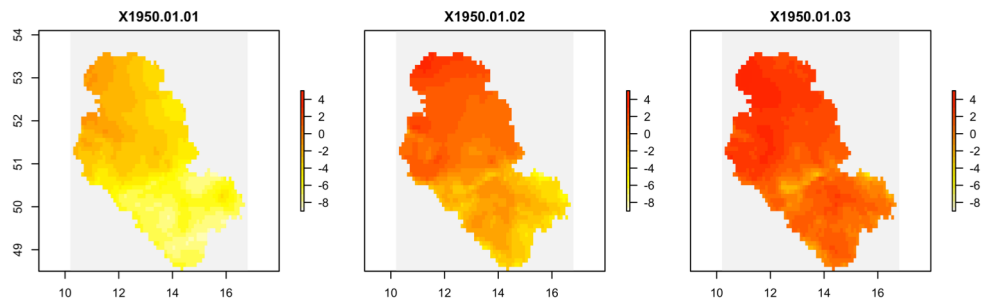
Lennart Schmidt, Elona Gusho, Walter de Back, Kira Vinogradova

# Data

## Precipitation



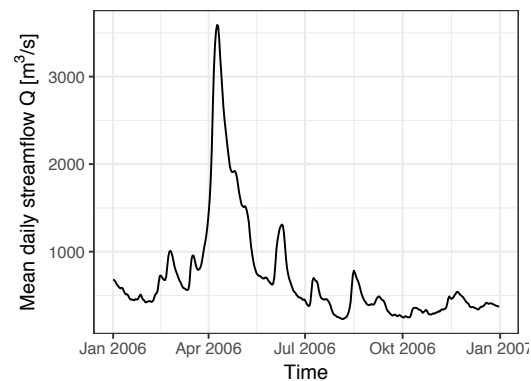
## Air temperature



Input

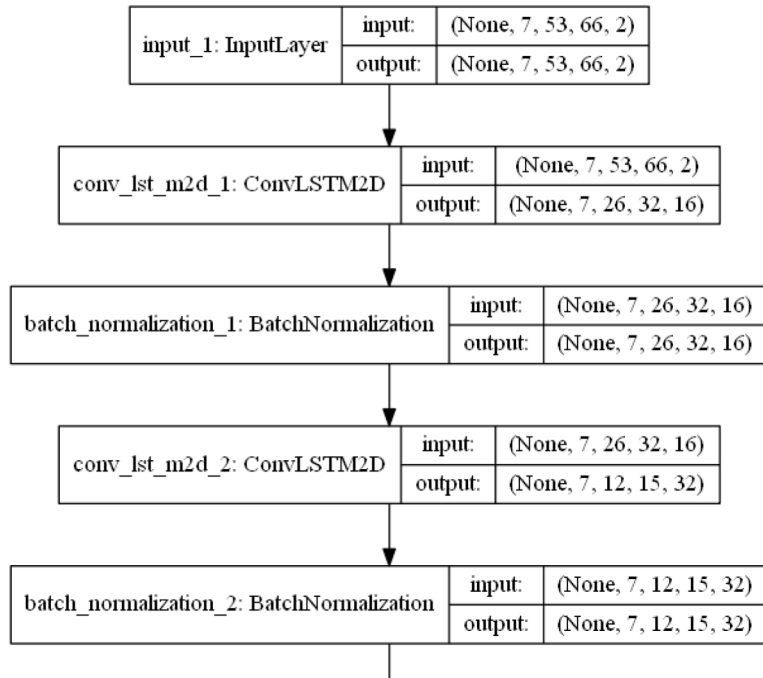
ConvLSTM

- Patterns
- Time-lags

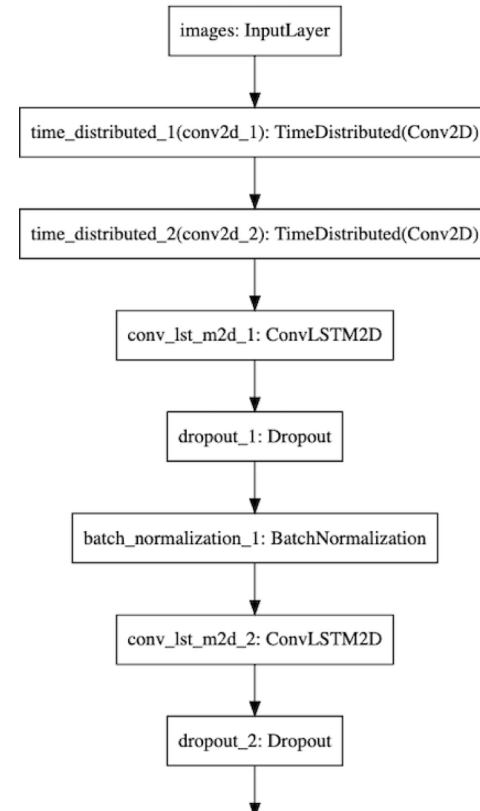


Target

# Old vs. new architecture

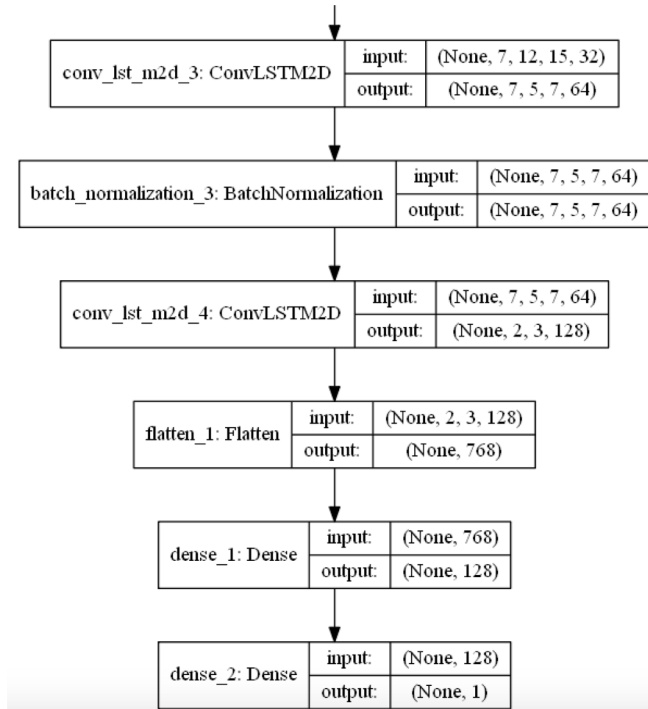


Old

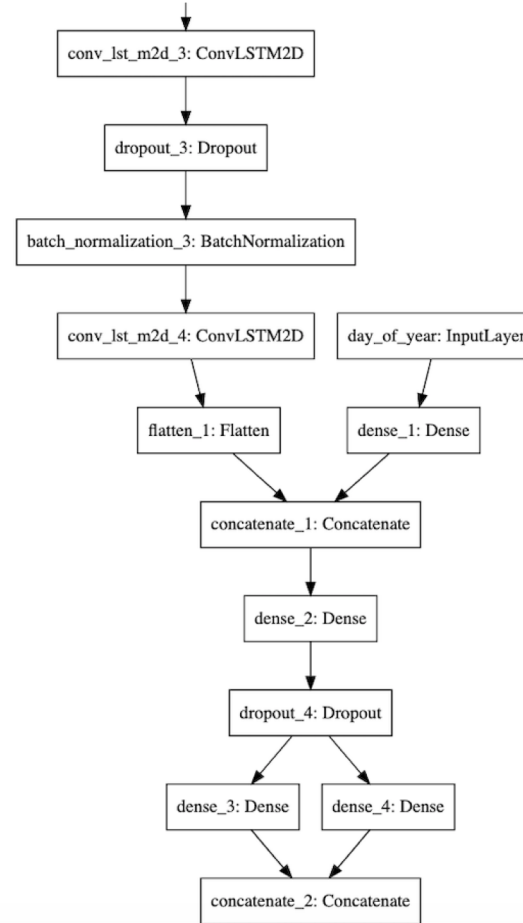


New

# Old vs. new architecture



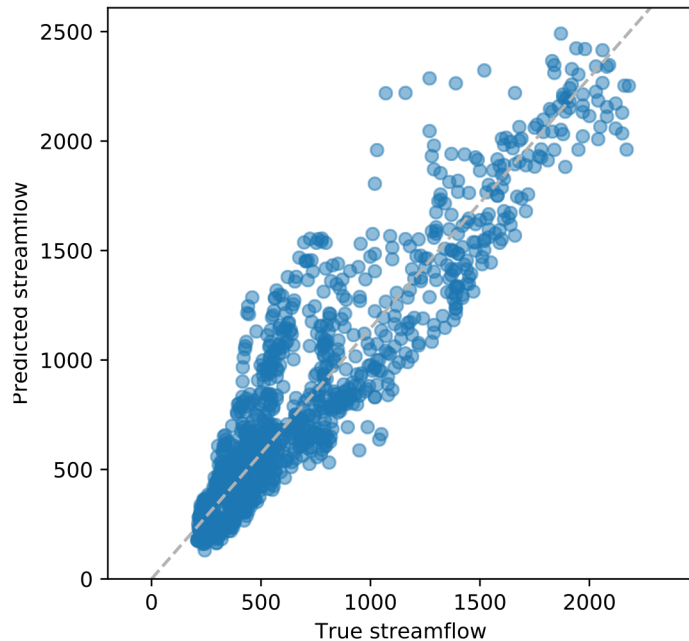
Old



New

# ConvLSTM

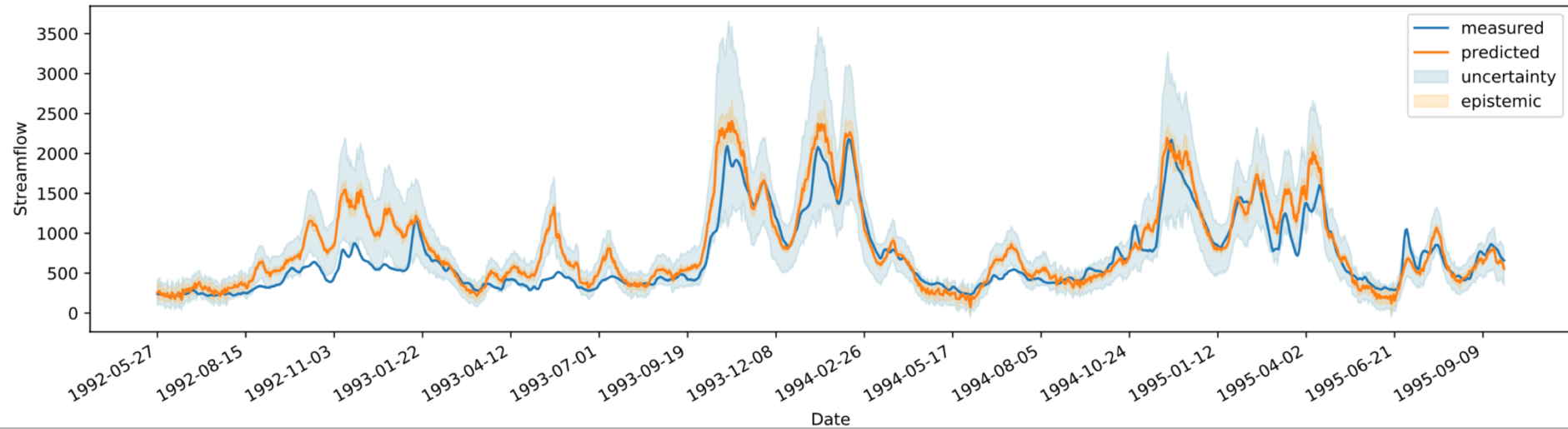
Concordance correlation coefficient = 0.879



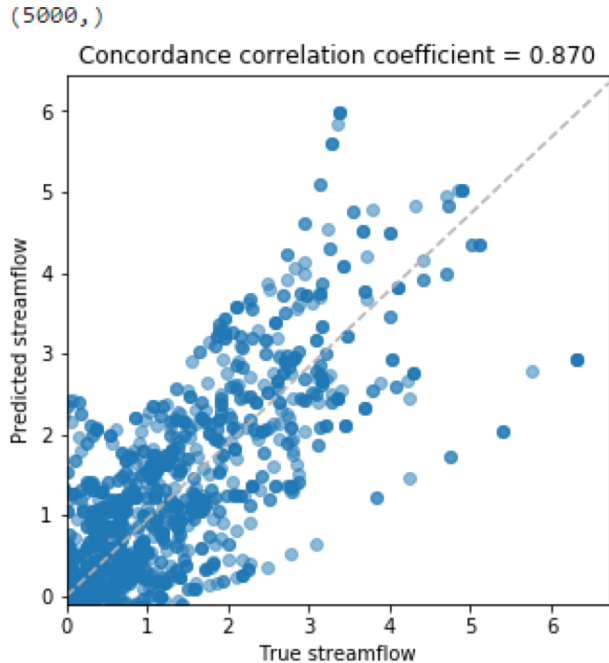
Changes:

- (non-recurrent) 2D-convolutions in top layers
- Dropout
- Add day of the year
- Longer input sequence
- Add estimation of uncertainties (aleatoric+epistemic)

# ConvLSTM



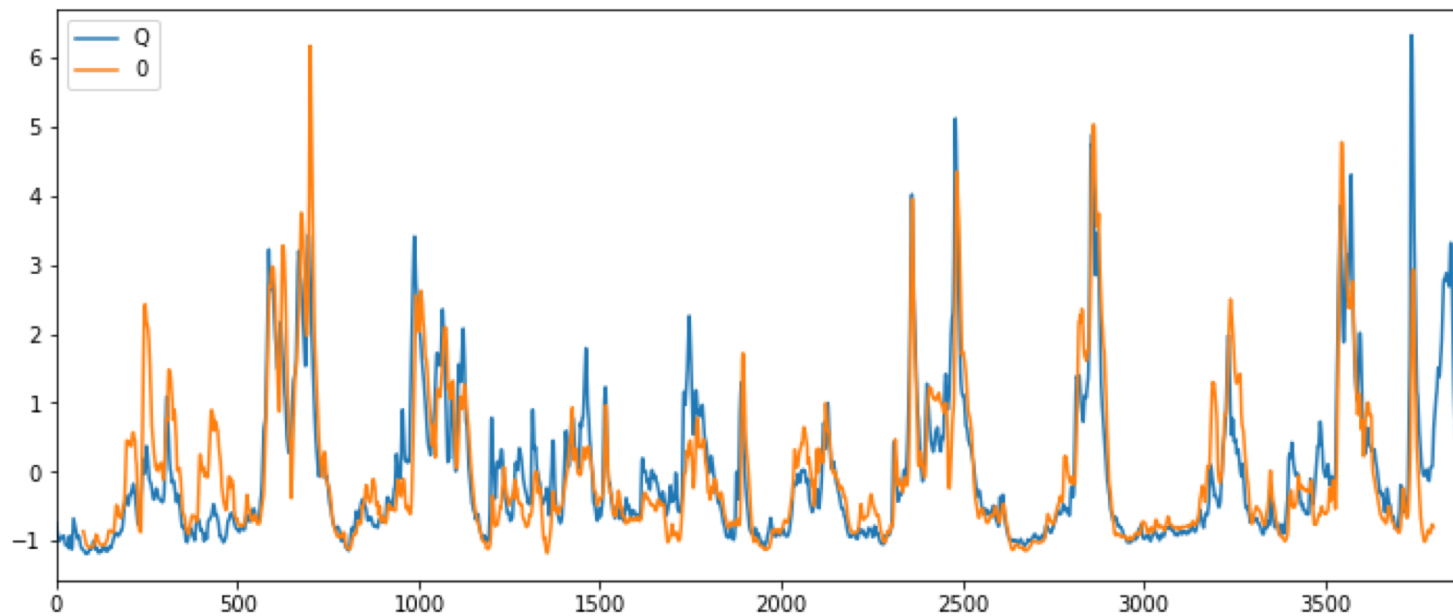
# 1D-LSTM



- Catchment Averages = Baseline
  - Surprisingly high ccc
  - Accurate modeling of timeseries
- We do not exploit all of the spatial information

# 2D-LSTM

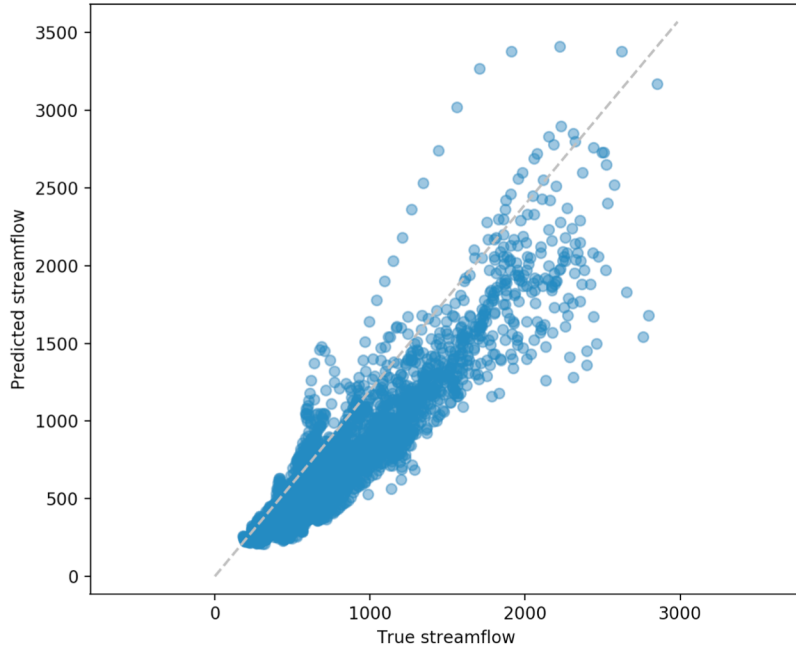
```
[118]: <matplotlib.axes._subplots.AxesSubplot at 0x2000c9ef85f8>
```





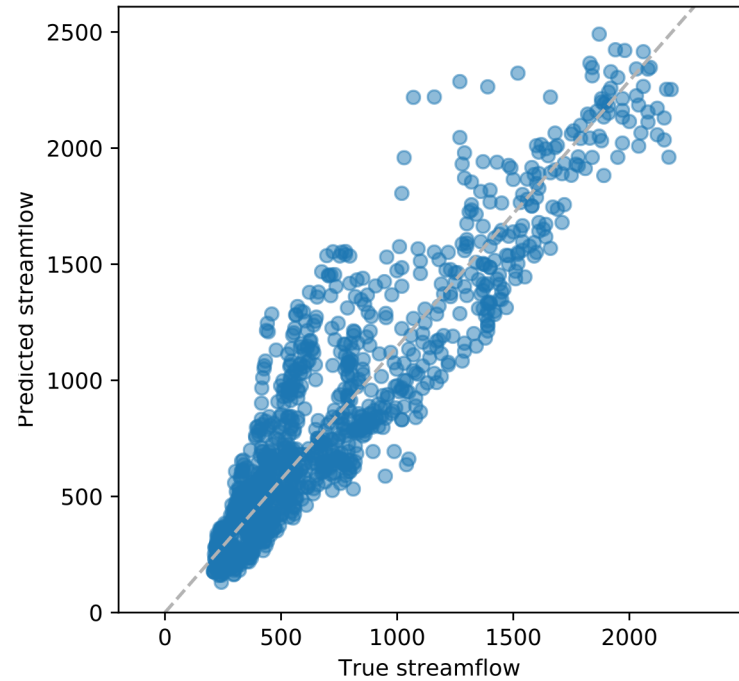
# Physical model: mHm

Concordance correlation coefficient = 0.916



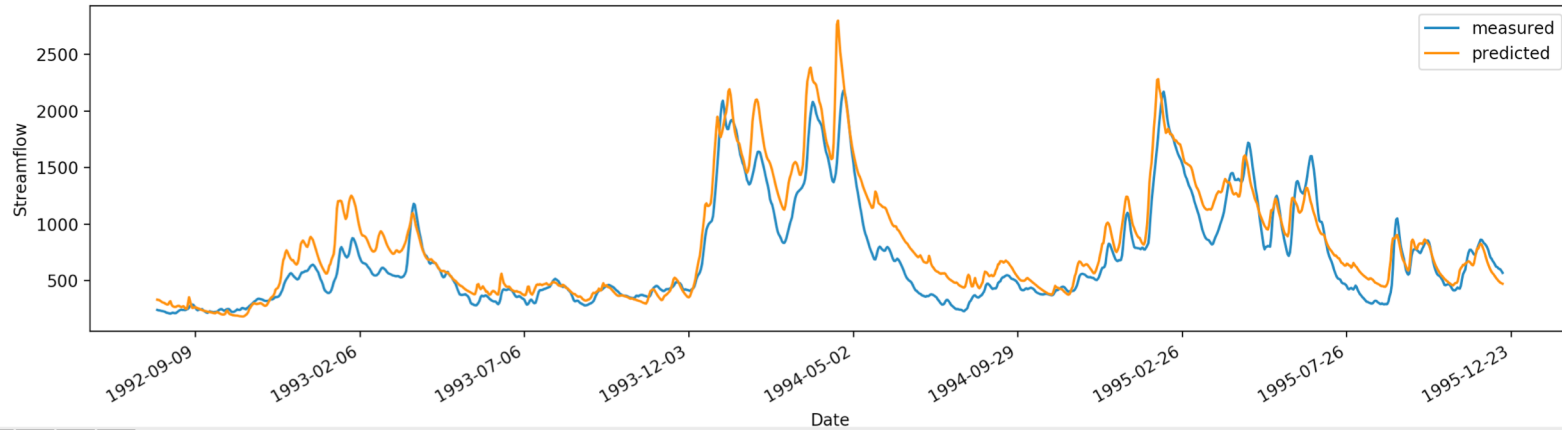
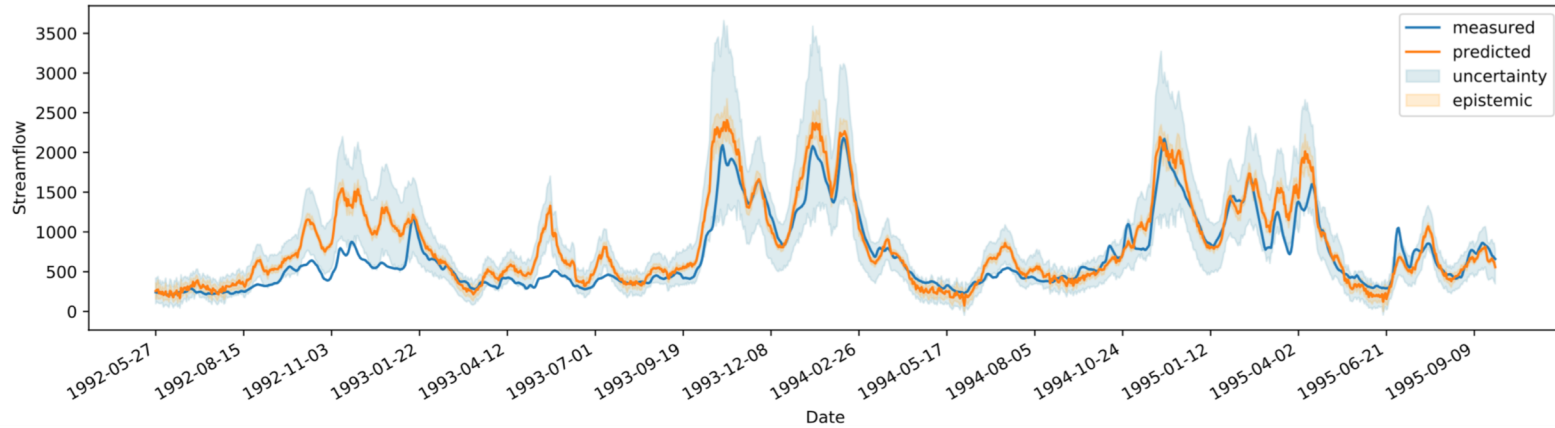
mHm

Concordance correlation coefficient = 0.879



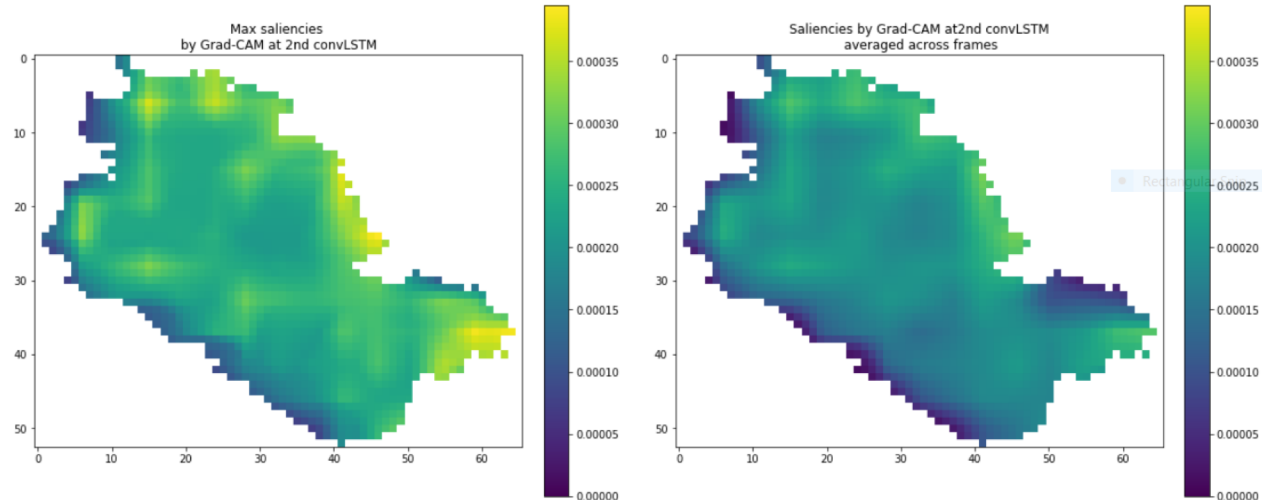
ConvLSTM

# ConvLSTM vs. mHm

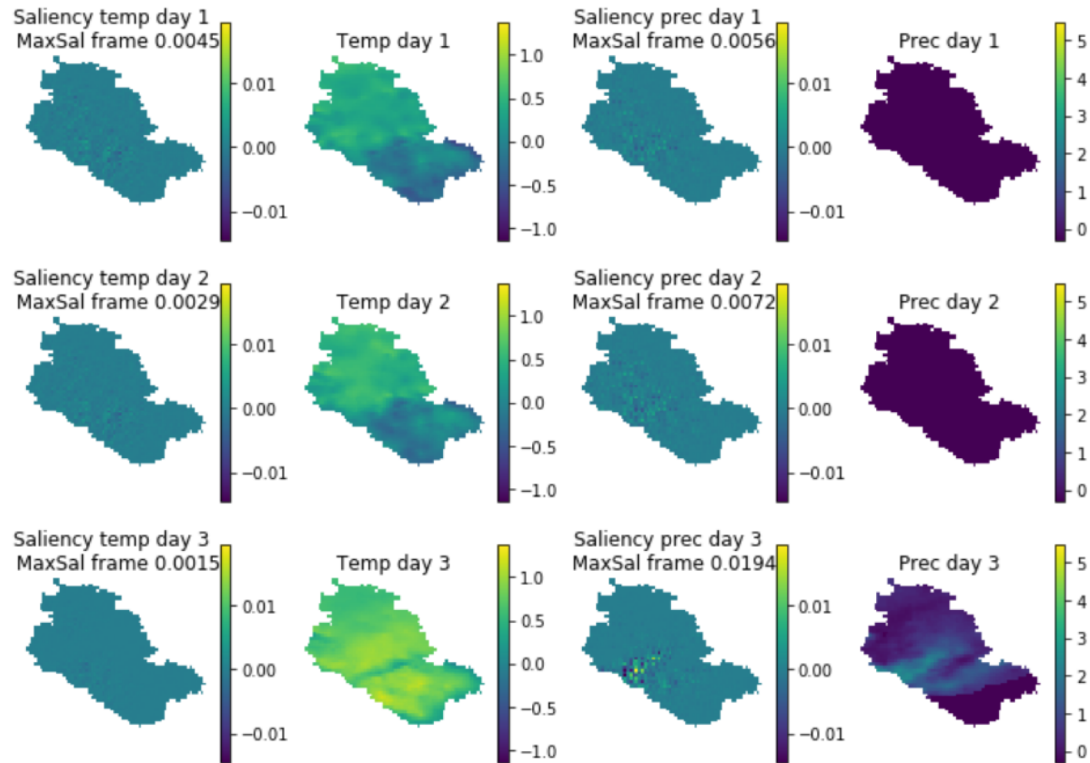


# Saliency maps

- Grad-CAM and SHAP implemented
- Spatial and temporal importance
- Grad-CAM: Difficult to implement for LSTM
- SHAP: Model-agnostic

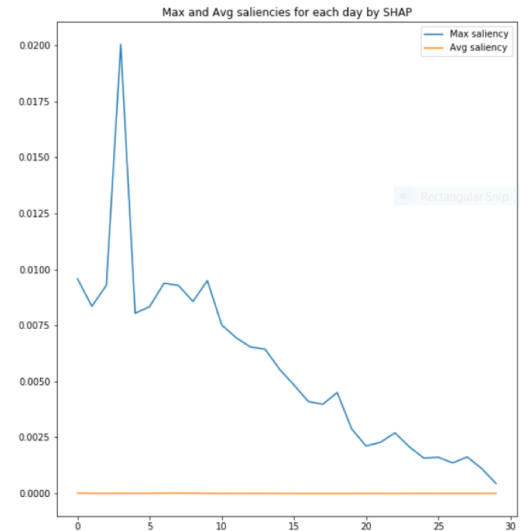
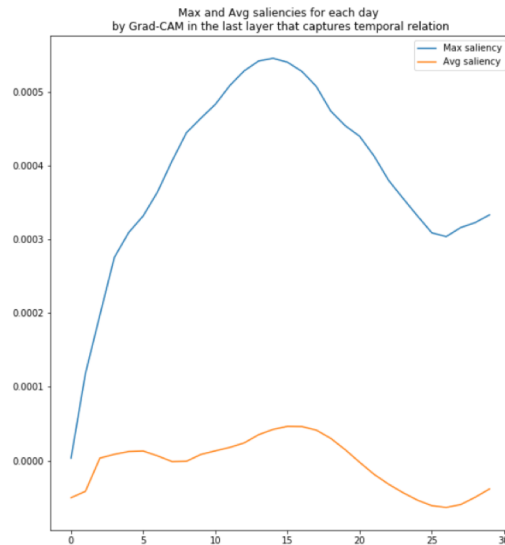


# Saliency maps: SHAP



# Saliency maps

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# Summary

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- Further tuning needed to exploit spatial information
- On par with physical model
- Saliency maps to be finished

**Thanks for your attention!**

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