Multi-Input ConvLSTM for Flood Extent Prediction

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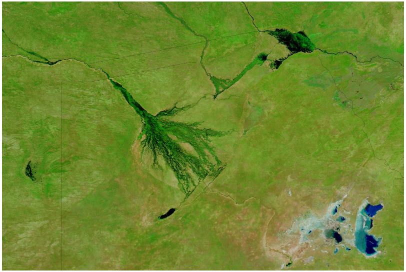
Flood Forecasting vs Flood Extent Prediction

- Flood Forecasting is generally focused on predicting **when** a flood is going to happen
  - e.g. when will the Zambezi river overflow?

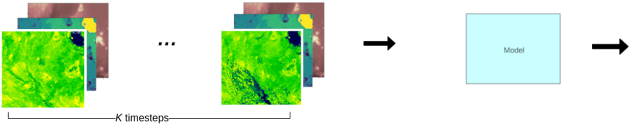
- Flood Extent Prediction determines **where** the flood is going to happen and to **what** extent
  - e.g. given that the Zambezi river has overflowed, where in the Zambezi river basin has flooded the most?

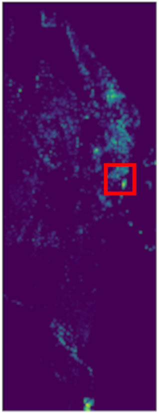


Source: *NASA Earth Observatory*

Flood Extent Prediction

Flood Conditioning Factors





Model Formulation

Given $\mathcal{X} = \left\{ \mathbf{x}_t^{(i)} : t \in K \right\}_{i=1}^{N}$, find $\mathcal{F} : \mathcal{X} \rightarrow y$ where $y^i \in [0, 1]$

Problem & Solution

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1. How can we effectively exploit features that have varying frequencies of observation?
   - Example: Land Elevation vs. Soil Moisture
   - **Proposal**: Adopt Multi-Input Architecture

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   - Flood conditioning factors have inherent spatio-temporal patterns
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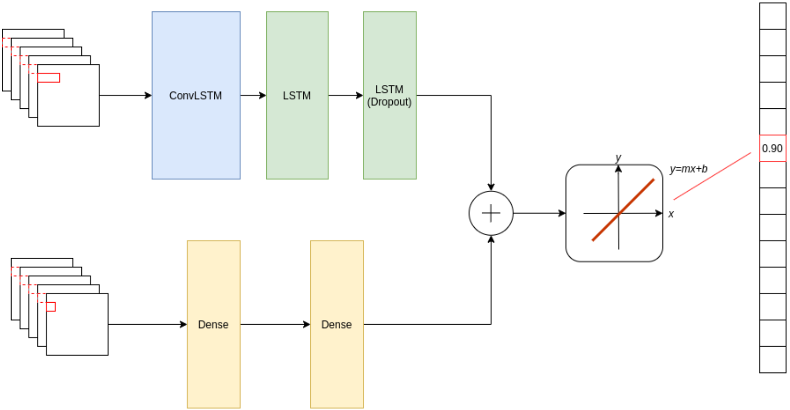
Solution

Combine to create novel Multi-Input ConvLSTM technique

Multi-Input ConvLSTM



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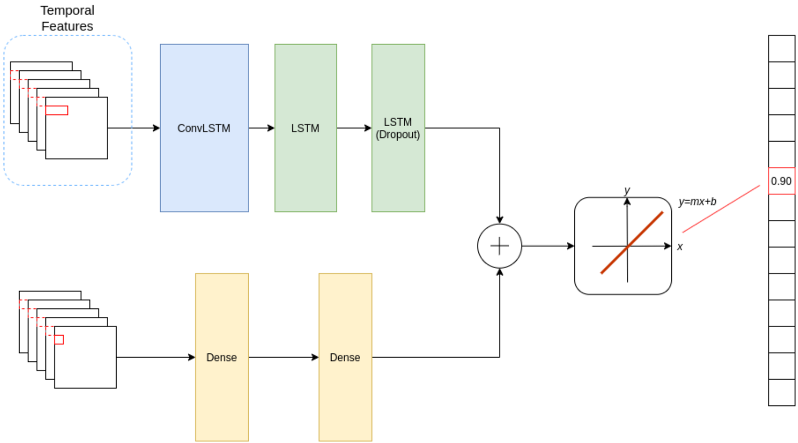

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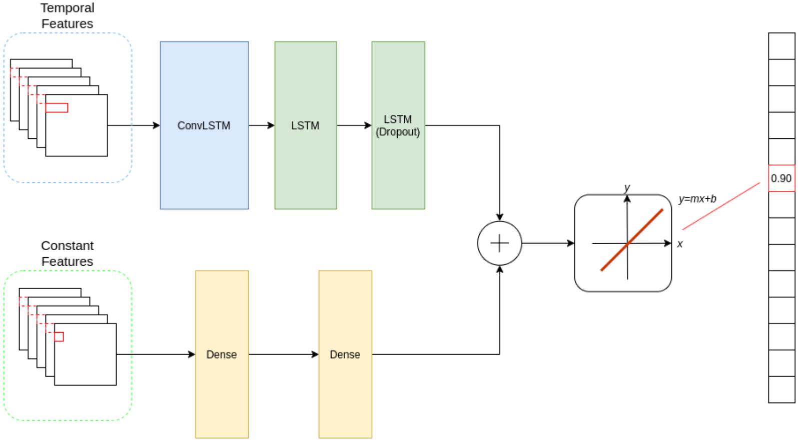
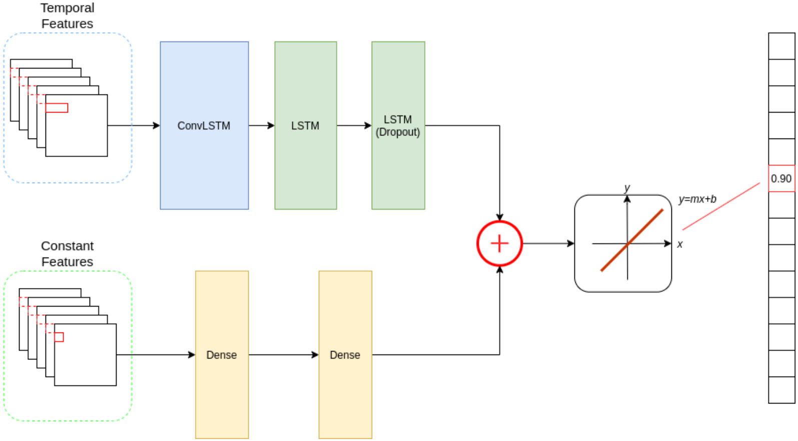


Multi-Input ConvLSTM



Experiments

Datasets

- Choose a variety of historical flood events from East Africa
  - Homogeneous: training and test sets originate from nearby geo-locations
  - Heterogeneous: training and test sets originate from distant geo-locations

Benchmark

- Winning solution for the UNICEF Arm 2030 Vision Competition
  - Competition Goal: Determine flood extent in Malawi
  - Model: Light Gradient Boosting Machine (LGBM)

Results

- Homogeneous Data
  1. Malawi dataset used for training and testing

Model	**RMSE**
LSTM	0.0525 ± 0.0004
LSTM-Autoencoder	0.0542 ± 0.01
Multi-Input LSTM	0.0532 ± 0.001
ConvLSTM	0.0519 ± 0.0002
Multi-Input ConvLSTM	0.0572 ± 0.001
LGBM	0.1021 ± 0.0001

Results

- Heterogeneous
  1. Mozambique used for training and Malawi used for testing
  2. Mozambique used for training and Kenya used for testing

Model	**Malawi**	**Kenya**
LSTM	0.1471 ± 0.03	0.2270 ± 0.01
LSTM-Autoencoder	0.1117 ± 0.02	0.2333 ± 0.01
Multi-Input LSTM	0.0803 ± 0.01	0.2120 ± 0.01
ConvLSTM	0.1350 ± 0.02	0.2180 ± 0.01
Multi-Input ConvLSTM	0.0890 ± 0.01	0.2169 ± 0.02
LGBM	0.2815 ± 0.002	0.2554 ± 0.01

Summary

Main Steps

- Split input features based on the frequency of satellite observation of a given feature
- Add ConvLSTM layers to model the spatio-temporal patterns
- Combine layers subsequently

Main Results

- ConvLSTM architectures are effective when training and test sets are similar
- Multi-Input architectures are effective when training and test sets are dissimilar
- Multi-Input ConvLSTM are particularly effective at generalising to various flood events

Thank you!

github.com/leomuckley