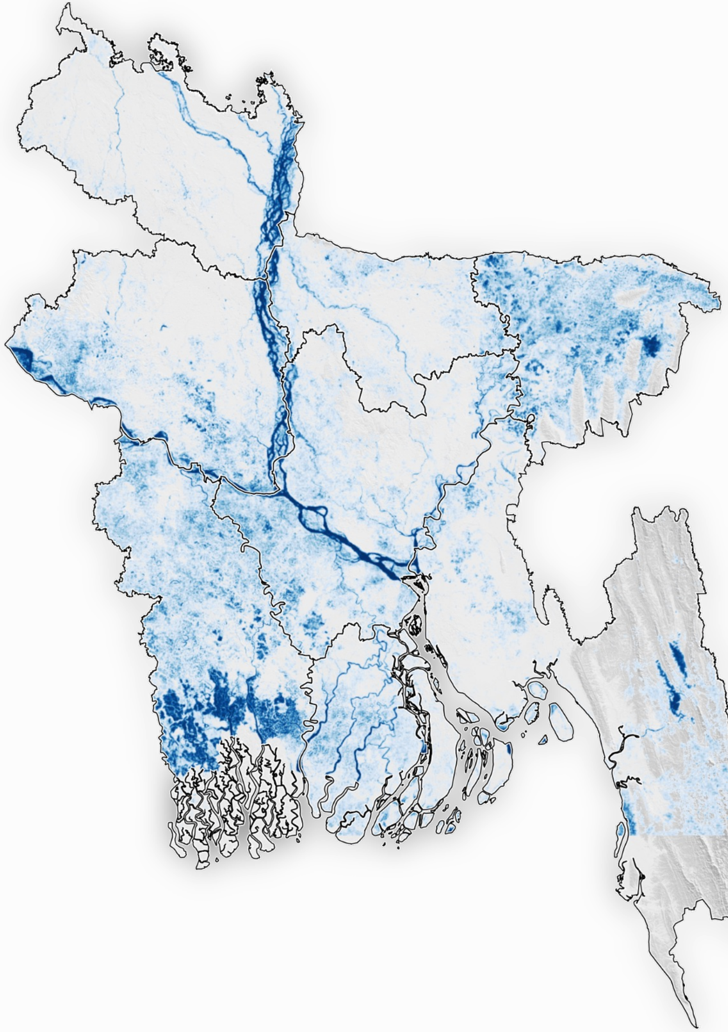
Deep Learning Satellite Fusion Based Historical Inundation Estimates for Accurate Return Period Estimates in Bangladesh

Jonathan Giezendanner,
Rohit Mukherjee, Matthew Purri, Mitchell Thomas,
Max Mauerman, A.K.M. Saiful Islam, **Beth Tellman**

jgiezendanner@arizona.edu
jgiezendanner.com
Twitter: @JoGiezi



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Inundations affect crops

15% of flood losses absorbed by the agricultural sector (FAO 2015)

Asia lost 48 billion USD in agricultural production from 1980-2013 (60% due to floods) (FAO 2015)

Insurance can support farmers' sustainable development (Benami et al 2021)

<1% insurance penetration in Bangladesh!

Bangladesh: world's first satellite based agricultural flood index insurance

Interpress News Service: Mintu Deshwara/ Sheikh Nasir

Index Based Insurance

PREMIUM

Payout amount ($200M)

Transaction cost (15%)

$$R_\theta = Pp_{exc} + kPsp_{exc} + f1 + f2P$$

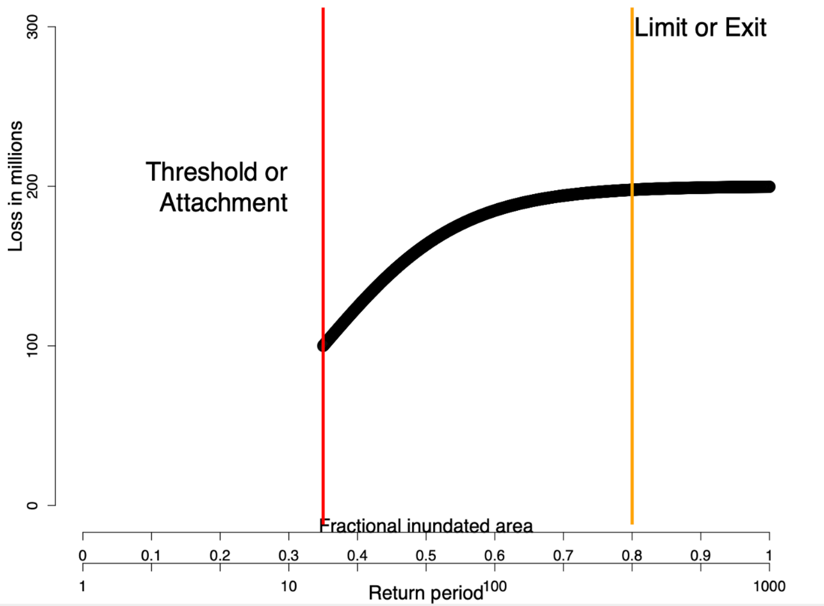
Risk price factor

Trigger: Probability of exceedance (0.4)

5|95 spread of probability of exceedance (uncertainty)

Profit margin (6%)

Tellman et al, 2022



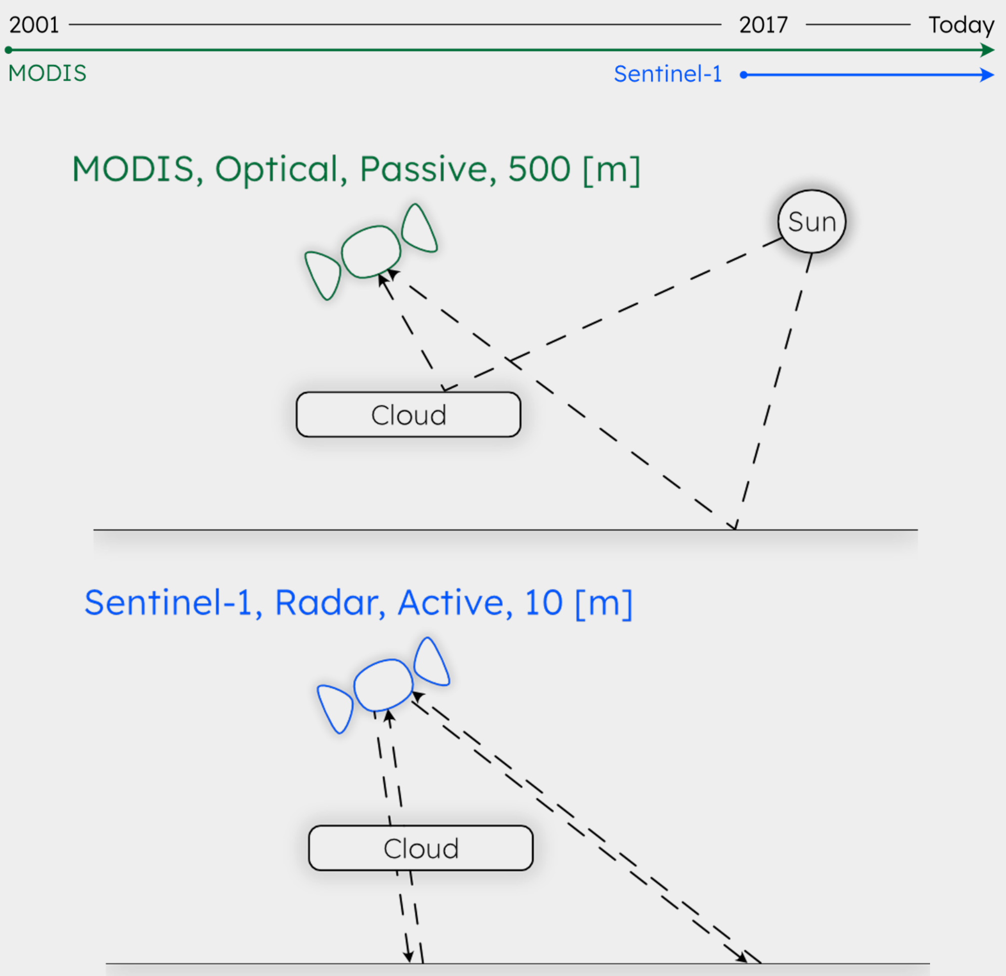
Payout based on **measurable proxy** for losses

Payout issued when **pre-defined threshold** is reached

Interesting in remote areas, generates cheap premiums, less moral hazard

For Floods: based on **Return Period** vs **Fractional Inundated Area** estimates

Requires accurate **historical** estimate of **yearly maximum inundation extent** (capture peaks)



Insurance requires >15 year time series to establish contracts, best satellites for flood mapping start ~2017

Longest Consistent Time Series: MODIS

MODIS: 500 m resolution, only Optical, can't see through clouds, difficult for floods

Sentinel-1: active imagery (radar, can see through clouds) at 10 meters resolution

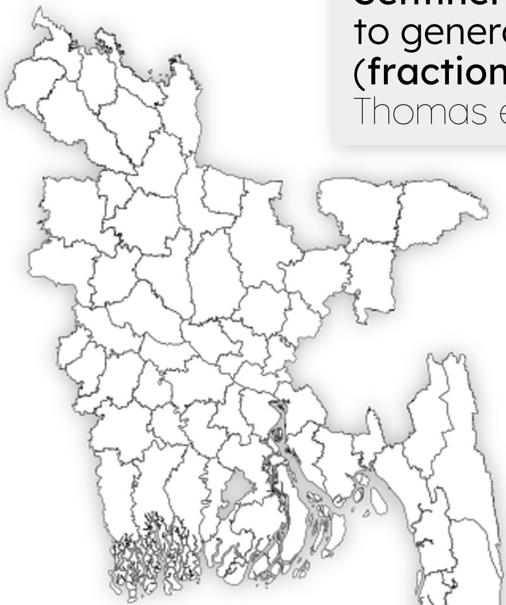
Higher spatial accuracy and temporal consistency, more correlated to damage

Only consistently available since 2017

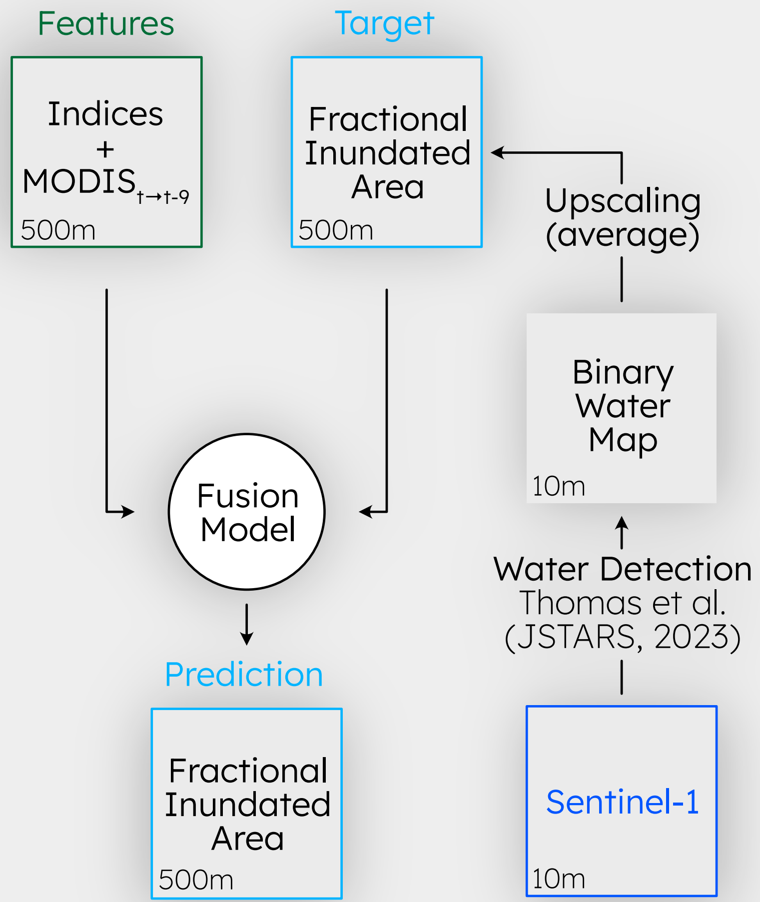
Goal: create historical (20+ years) time series of inundated areas over Bangladesh for return period estimates

Create a **Fusion** algorithm (**Deep Learning**) to estimate **fraction of inundated area** for each **MODIS** pixel

Sentinel-1 data (2017 - 2021) to generate weak labels (**fraction of inundated area**)
Thomas et al., JSTARS, 2023



Infer time series based on MODIS historical data (2001 – 2022) and indices over all Bangladesh



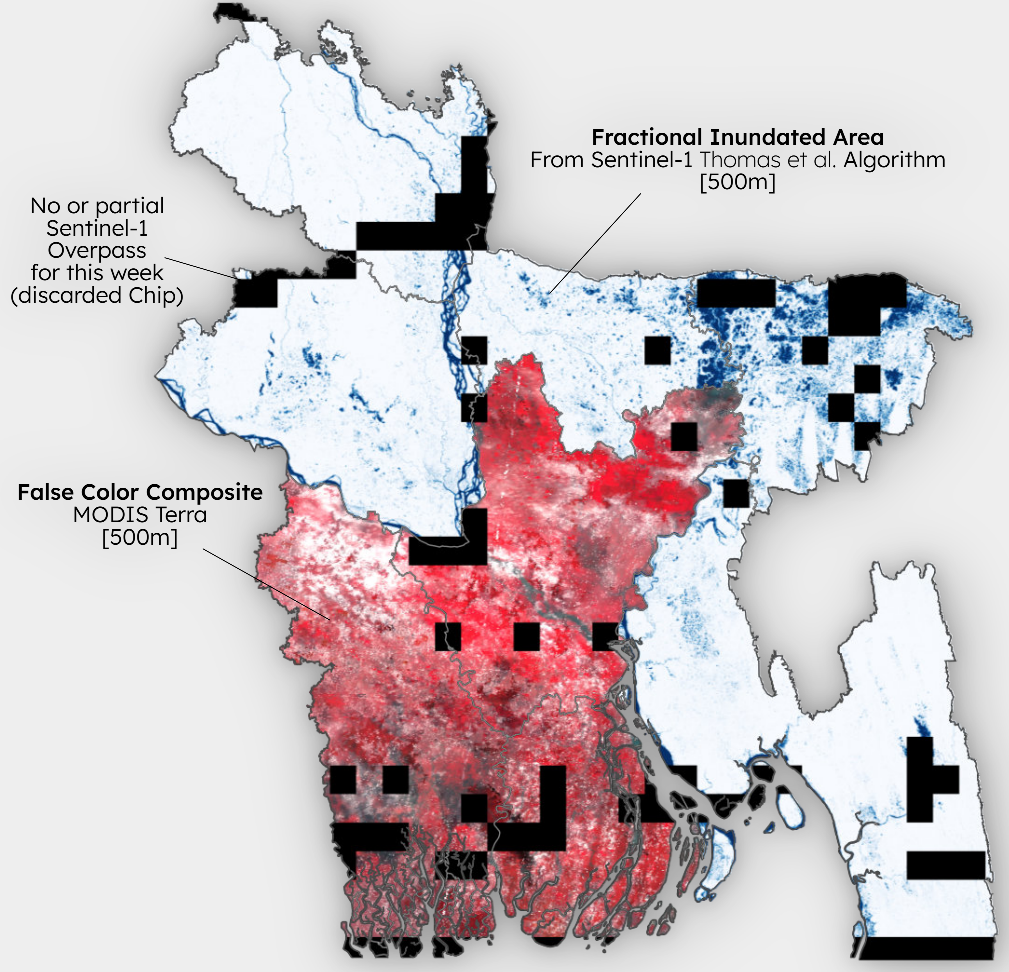
Data

Target: Fraction of Inundated Area at 500 meter resolution

- Based on Sentinel-1
- Dynamic thresholding algorithm creates a **binary** map at **10** [m] resolution Thomas et al., JSTARS, 2003
- Calculate **fraction of inundated** area (∈ [0,1]) for each **MODIS** pixel at **500** [m] resolution

Features:

- 8-Days MODIS Terra composite image at 500 [m] resolution
- Elevation FABDEM
- Slope FABDEM
- Height Above Nearest Drainage (HAND) MERIT Hydro



Deep Learning Fusion Model

Long-Short-Term-Memory (**LSTM**) Network coupled with Convolutional Neural Networks (**CNNs**)

For each image **t**:

- 10 MODIS images up to time **t** run through **CNN** A
➔ Provides the **spatial** context

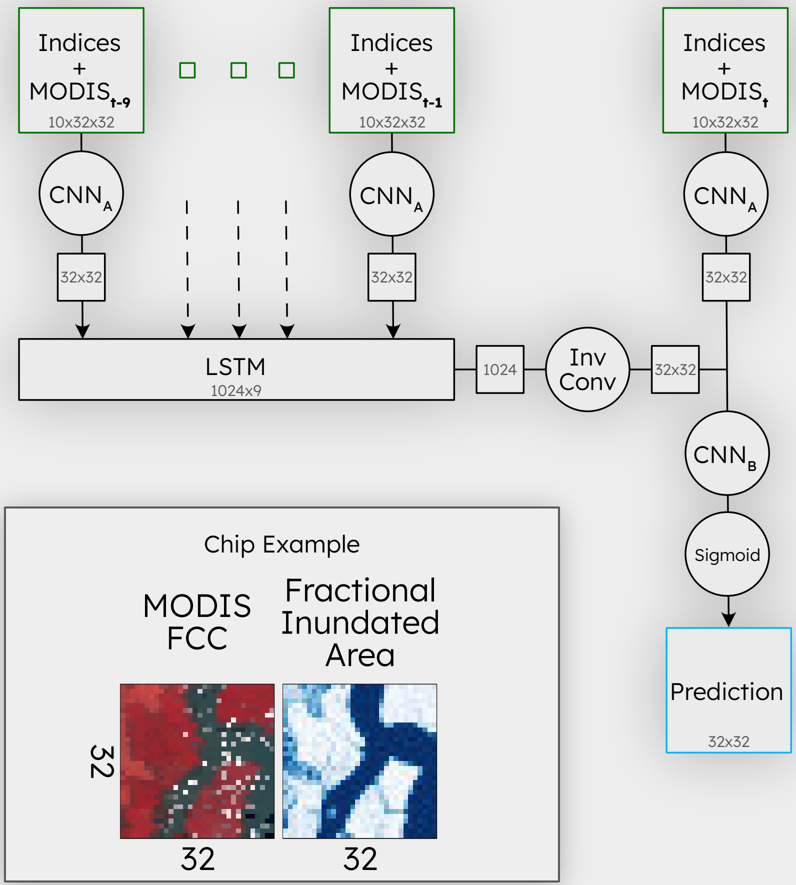
- 9 previous CNN outputs are run through a **LSTM**
➔ Provides the **temporal** context

- LSTM output combined with CNN at time t and run through CNN B ➔ **prediction**

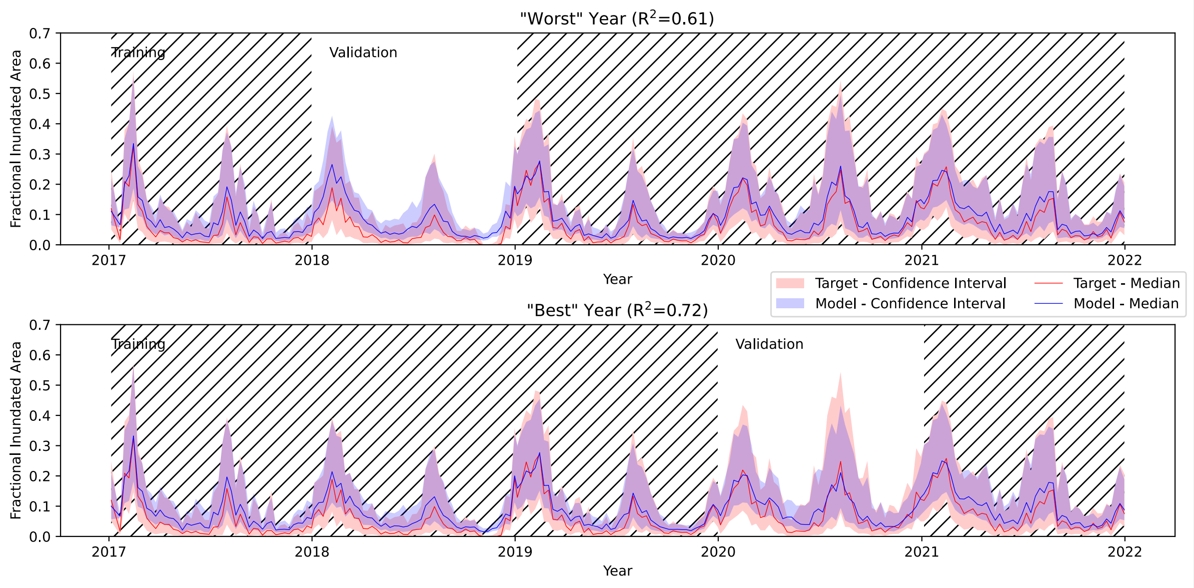
Training and Testing:

- Each Chip is **32x32** pixels at 500 [m]
- The total dataset contains **150'946** chips
- Cross-validation: Iterate over years

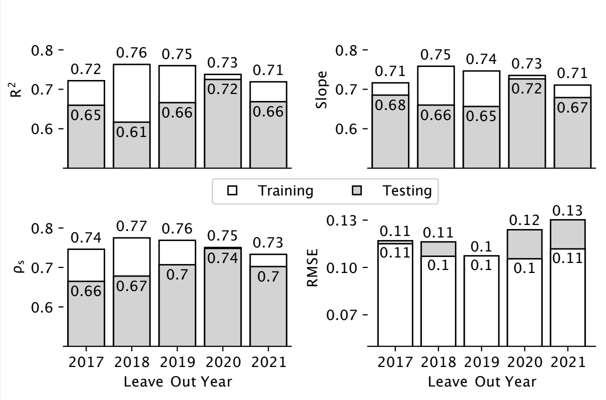
Deep Learning Model



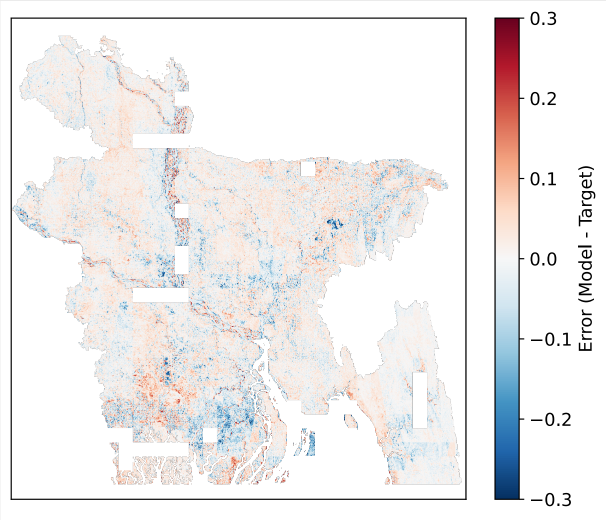
Time Series of "Worst" and "Best" Cross-Validated Year



Cross-Validation Statistics



Model vs Observation



Results

Time series shows that the **flood peaks** and **valleys** are well reproduced

Overall R^2 of **.66** for the validation

Per region analysis shows that the model struggles with more **mountainous** and **coastal regions**

CNN Baseline Comparison

CNN-LSTM outperforms CNN Baseline

Spatial patterns and inundation intensity closer matched

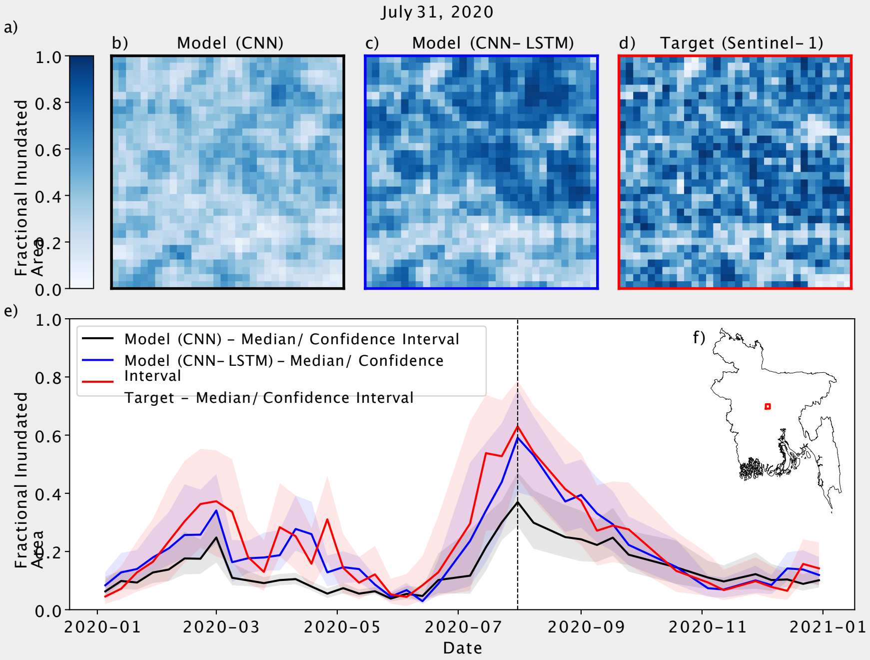
CNN-LSTM captures temporal dynamics

CNN-LSTM captures signature of the inundation, i.e. captures rising and falling of inundation level

CNN vs CNN-LSTM Cross-Validated R^2

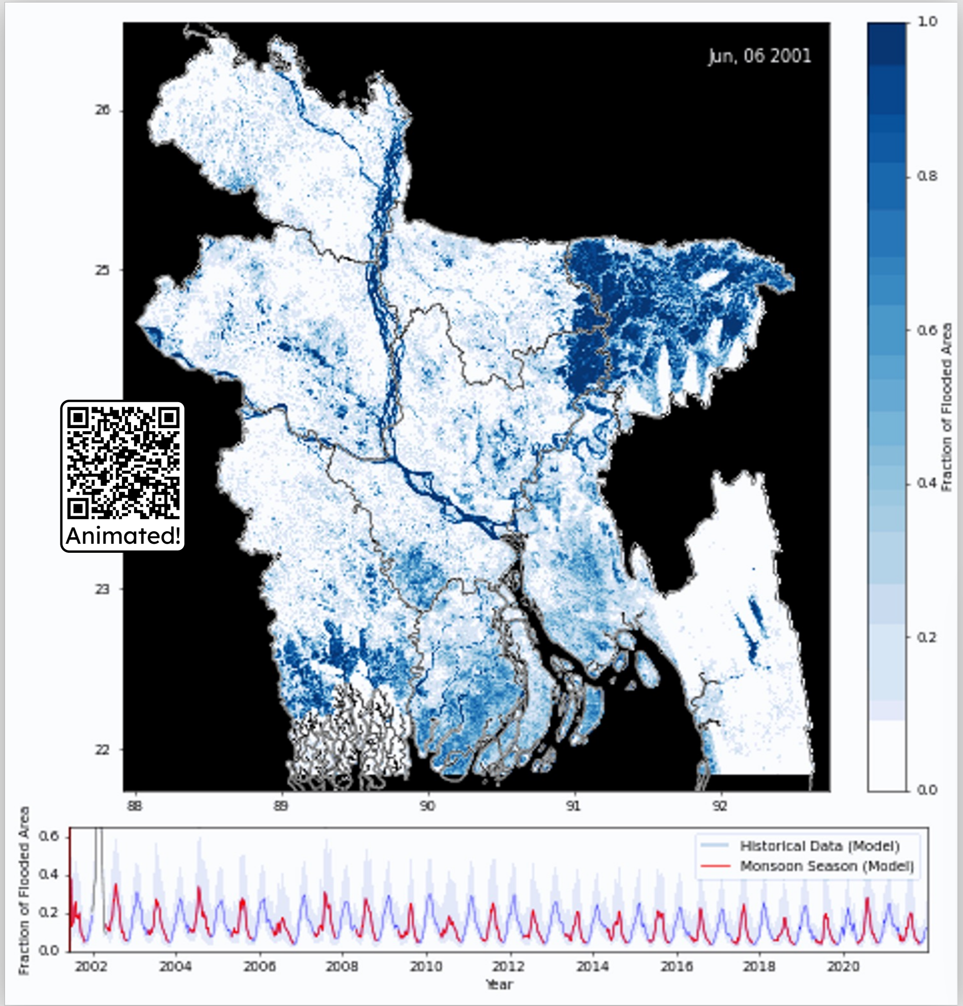
Year	CNN	CNN–LSTM
2017	0.62	0.66
2018	0.55	0.62
2019	0.55	0.67
2020	0.63	0.72
2021	0.60	0.67

Comparison to CNN baseline (chosen chip)



Historical Inference

Inferred time series

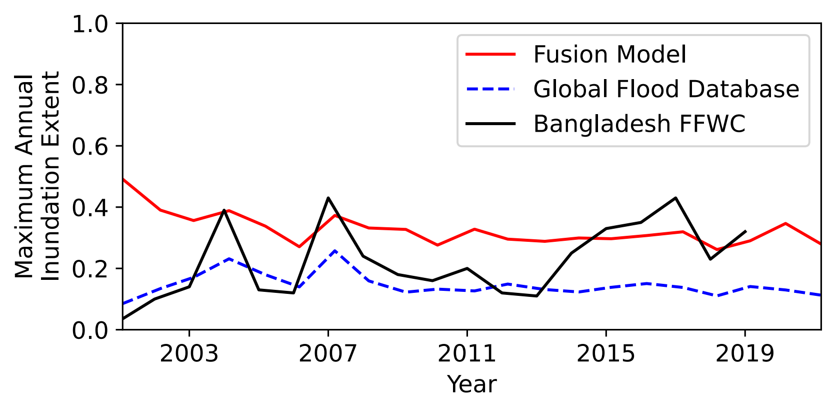


Infer time series of fraction of flooded area based on MODIS Fusion algorithm (20 years)

Extract yearly maximum extent

Compare to Global Flood Database Algorithm (GFD) and Bangladesh Flood Forecasting and Warning Center (FFWC, Mike 11)

Yearly Maximum Extent



Return Period Estimates

Return period estimates for **Fractional Flooded Area** using **Beta-2 distribution**

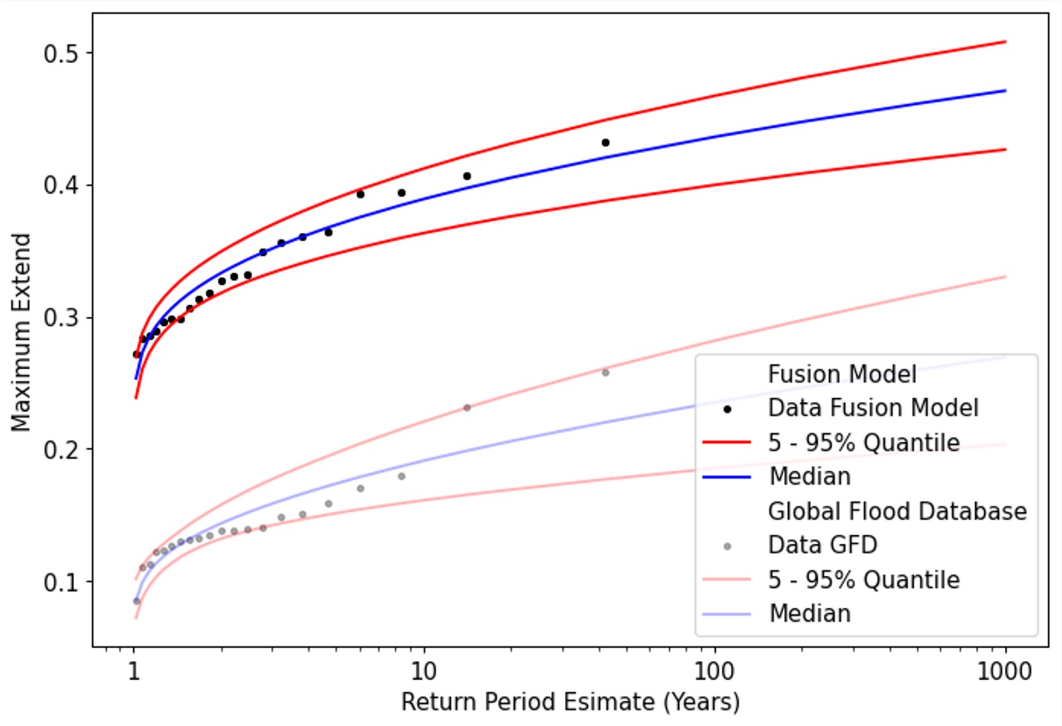
Tellman et al., 2022

Less uncertainty in the Fusion Model

GFD seems to underestimate flood extents compared to Fusion model

Reduced uncertainty and more accurate flood estimate could reduce base risk

Calculated Return Periods



Conclusions and Outlook

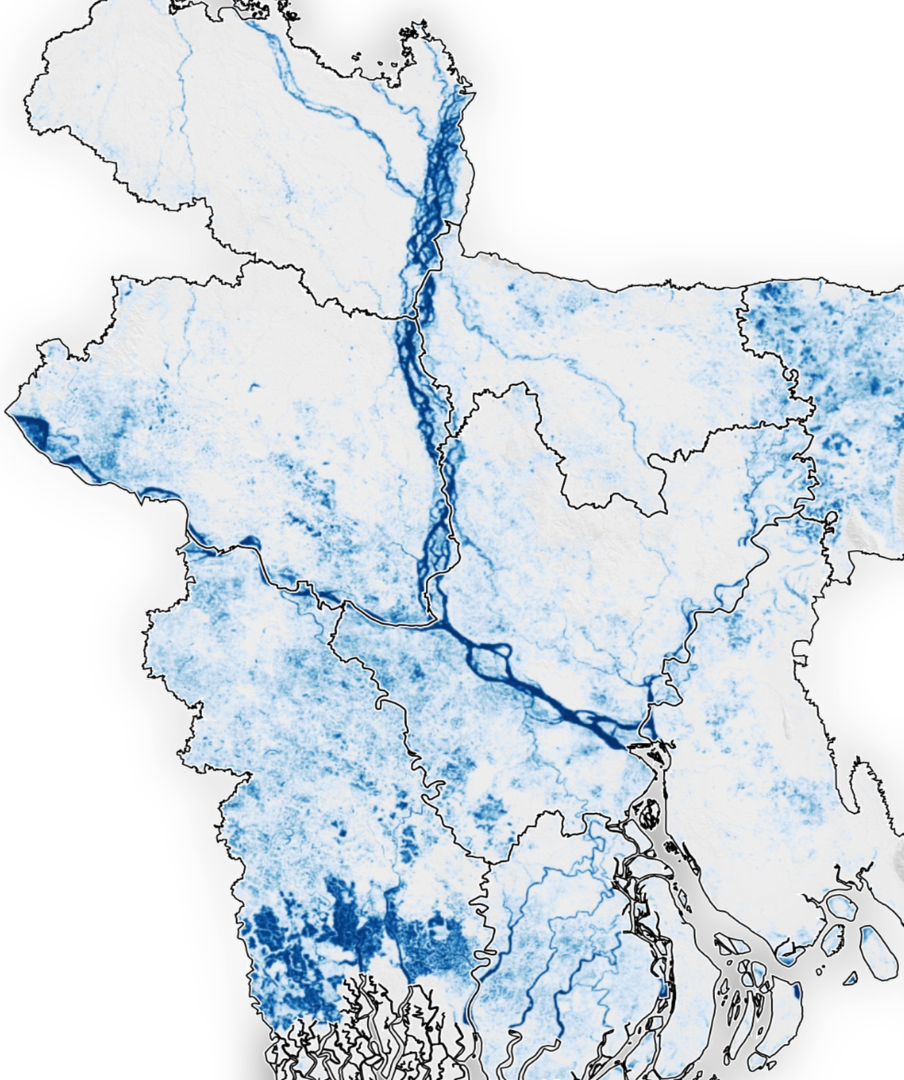
Fusion Algorithm seems to provide an accurate historical time series for return period estimates

Filling gaps under clouds by understanding inundation dynamic (c.f. Saunders et al. (2023), IGARSS for validation against other products)

Algorithm needs further work to improve estimates in coastal and mountainous regions

Gap the bridge between MODIS and VIIRS

Bayesian return period estimation based on region or district grouping



Thank you for your attention!

jgiezendanner@arizona.edu
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Twitter: @JoGiezi

Paper, Data and Code

Giezendanner et al (2023) *Inferring the past: a combined CNN-LSTM deep learning framework to fuse satellites for historical inundation mapping*, CVPR Earthvision Workshop

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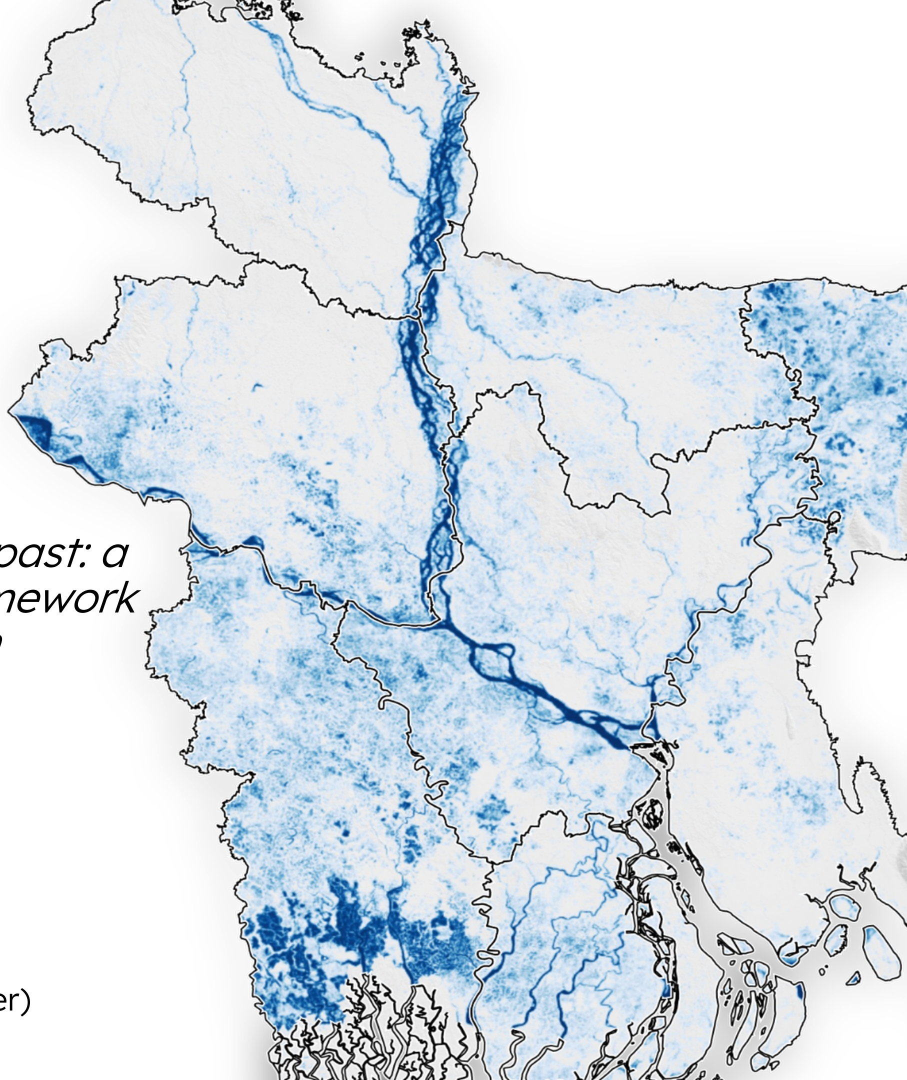

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