Extreme Weather Prediction using Deep Learning

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Introduction

- **Problem Statement**: An important scientific goal for climate researchers is weather nowcasting, which can be used effectively to predict extreme weather events. This problem of weather nowcasting can be formulated as the prediction of the next data point or frame in sequence, given a fixed window of sequence that precedes the said data point. Using these short-term predictions, the system should be able to identify areas where the cloud systems or humidity levels can lead to extreme conditions in the future.
- **Objective**: We propose a 2 phase deep learning pipeline. In the first phase, we nowcast frames captured by the INSAT-3D satellite sensors. In the second phase, we use these predictions to identify hotspots of meteorological variables that signal towards genesis of extreme weather events.

Data

The complete data that we have worked on was captured using the INSAT-3D Imager sensor. In the first phase, we used the 6 channel standard disk products as given in Table 1.

Table: L1B Standard Products (INSAT-3D). Used in Phase 1.

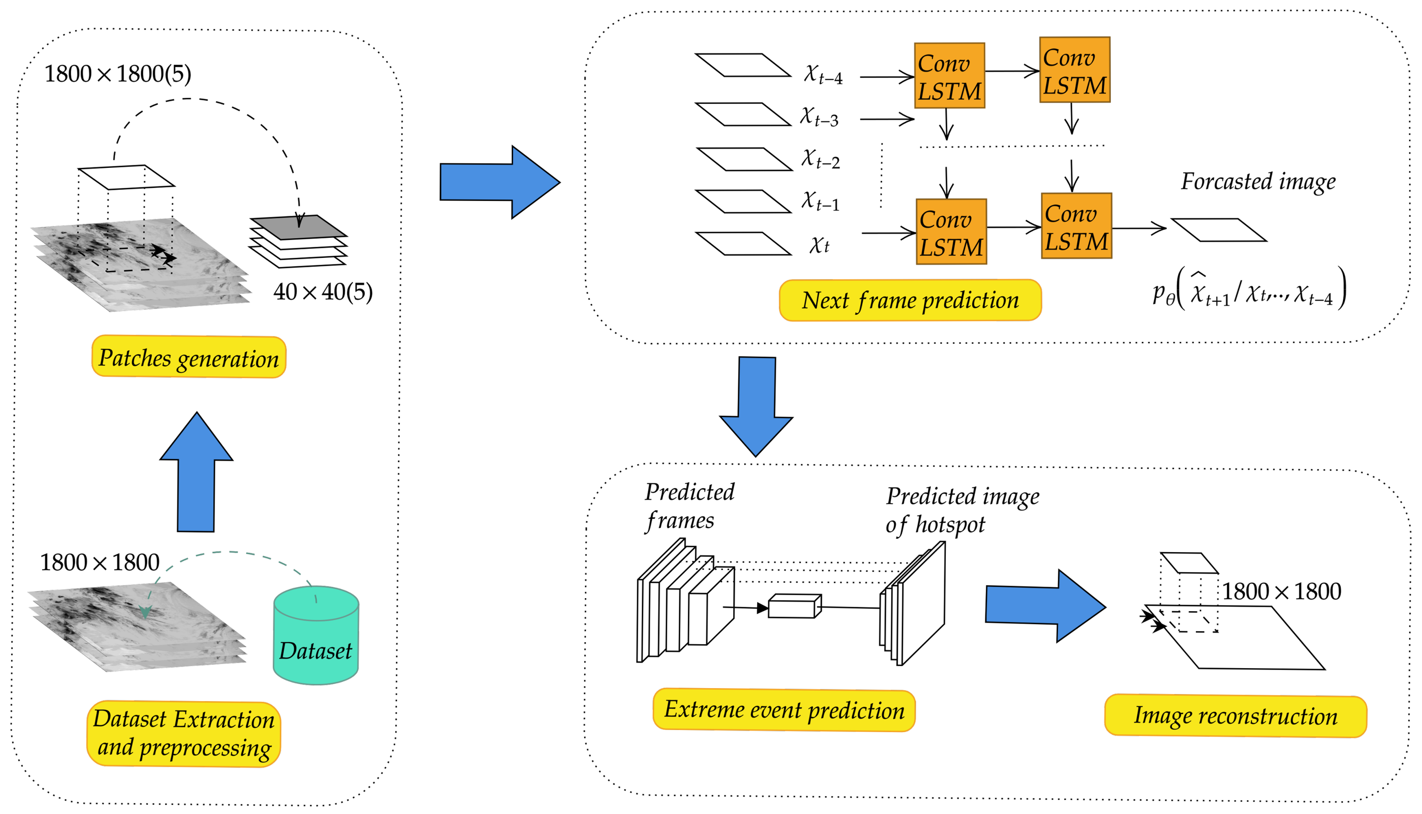
Sr. No.	Channel Name	Spatial Resolution	Description
1	IMG_VIS	1km	Rad. for Visible Channel
2	IMG_SWIR	1km	Rad. for Shortwave Infrared Channel
3	IMG_TIR1	4km	B.T. for Thermal Infrared Channel 1
4	IMG_TIR2	4km	B.T. for Thermal Infrared Channel 2
5	IMG_MIR	4km	B.T. for Middlewave Channel
6	IMG_WV	8km	B.T. for Water Vapor Channel

This data consists of the L1B standard products that are used to derive geophysical products like hydro-estimator precipitation or land surface temperature is given in Table 2. The spatial resolution of the image in coordinates is 60°N to 60°S and 30°E to 130°E, with varying pixel based resolution as given in Table 1. The temporal resolution of the data is 30 minutes.

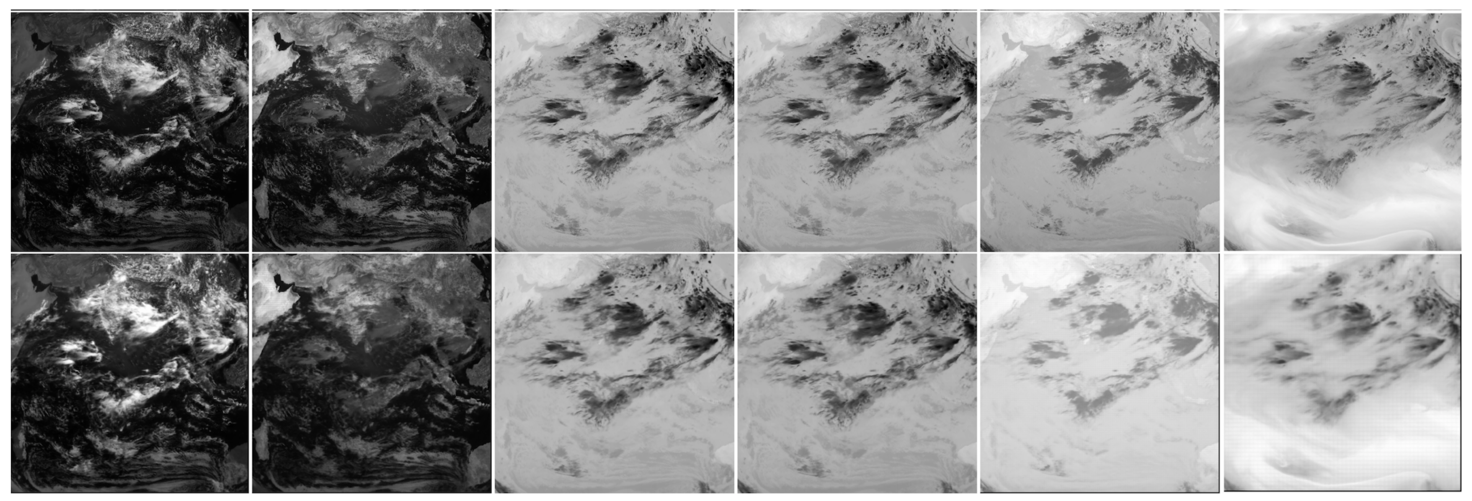
Table: Derived Products. Used in Phase 2.

Sr. No.	Product Name	Resolution	Application	Dataset Period
1	Hydro-Estimator Precipitation	4km	Used for extreme rainfall events	July to August 2018
2	Land Surface Temperature	4km	Used for extreme heat events	April to May 2018

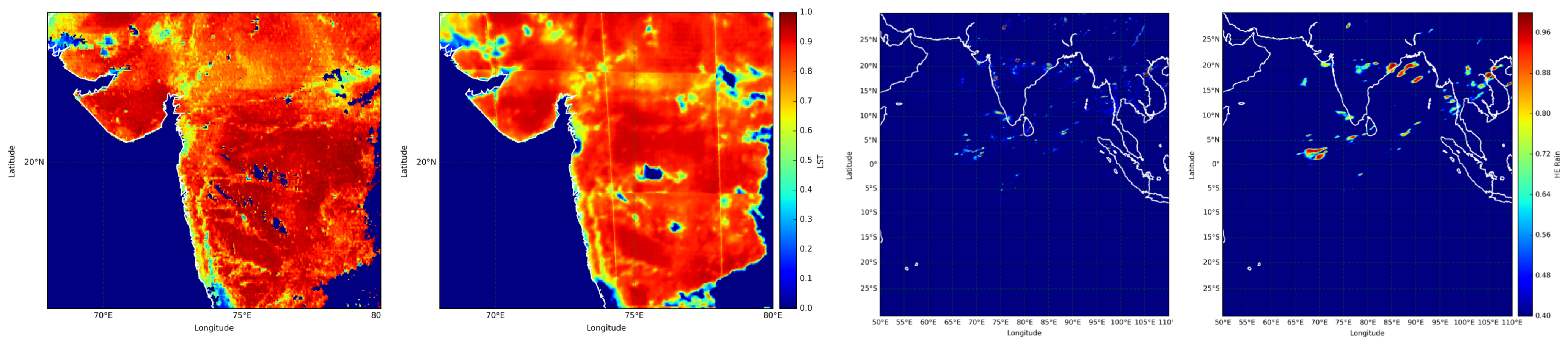
Implementation Pipeline



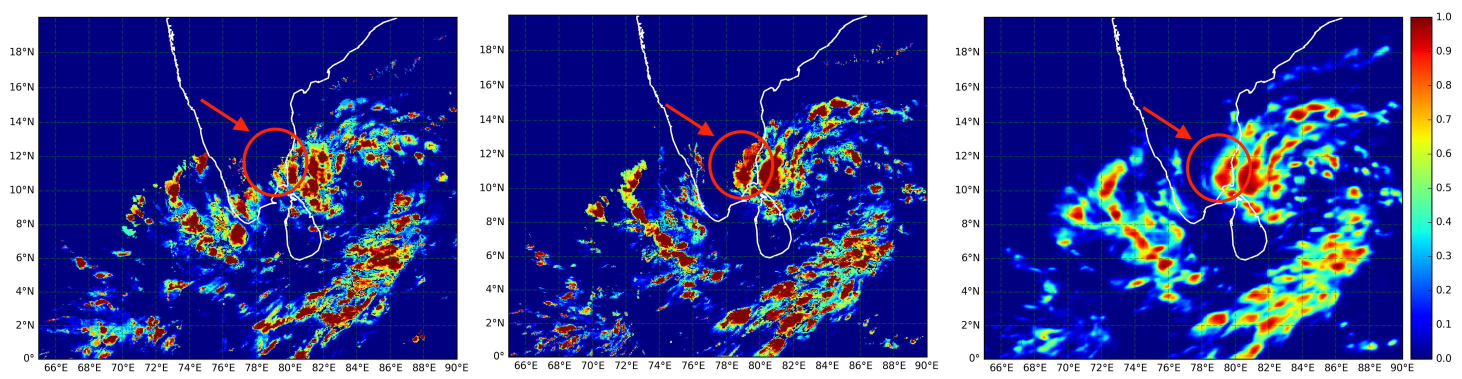
Results



Top to bottom:actual $(t+1)^{th}$ frame, predicted frame. Left to right: as listed in Table 1.



Left: Actual, predicted $(t+1)^{th}$ LST frames. Right: Actual, predicted $(t+1)^{th}$ HE values.



Left to right: $(t-4)^{th}$ frame, actual$(t+1)^{th}$ frame and predicted frame of HE rain on 8 November 2015 at Chennai

Dataset Preprocessing and Model

For practical training purposes, we convert the full frames into patches of 40×40 with a stride of 20. During reconstruction, we compute the pixel by overlapping and averaging the patches based on positioning.

Phase 1: Given 5 sequence frames as input, predict next frames (+00:30, +01:00, +01:30, +02:00, +02:30) of all 6 channels sequentially. Model: ConvLSTM. Normalization: min-max scaling. Loss: binary cross-entropy. Optimizer: Adam.

Phase 2: Given predicted images from Phase 1, predict the meteorological variable frame corresponding to given extreme event. Model: U-Net. Normalization: tanh (for extreme event classification). Loss: binary cross-entropy. Optimizer: Adam.

Results

Table: Result metrics

(a) Phase 1 results.

Channels	+00:30	+01:00	+01:30	+02:00	+02:30
VIS	28.264	26.053	24.598	23.929	24.066
SWIR	27.538	24.921	22.358	20.404	20.200
TIR1	28.504	24.202	21.146	19.046	17.604
TIR2	31.239	28.481	26.447	24.747	23.256
MIR	26.178	22.210	19.275	17.084	15.443
WV	31.100	27.970	25.384	23.822	22.565
Avg.	28.804	25.639	23.201	21.505	20.522

(b) Phase 2 results.

Extreme event parameters	SSIM	PSNR
Hydro-Estimator	0.923	24.36
Land Surface Temperature	0.803	22.96

Scope & Future Work

Apart from the direct benefit of being able to forecast the next-hour weather, we explore the advantages of being able to extract derived features like hydro-estimator rain or surface temperature. Hence, we explore the possibility of a prediction system that can predict any feature of the next half-hour and next hour, given the underlying standard feature set.

As future work, we can focus on the slow processing of the ConvLSTM as the three dimensional processing with gated properties. So, we can replace the ConvLSTM with U-Net for faster results by slightly reducing accuracy.

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