

Rainfall prediction for the state of Gujarat using deep learning technique

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Introduction

- Predicting rainfall is extremely challenging.
- Rainfall varies both spatially and temporally.
- Precise amount of rainfall depends on a number of factors.
- Different ways of predicting rainfall:
 - ▶ Satellite Images
 - ▶ Digital Images
 - ▶ Weather radar maps

Literature Review

- **Using only Infrared (TIR1) based algorithms, it incorrectly classify cirrus clouds as rain bearing cloud.**
- **Passive Microwave is better compared to Infrared but it has low sampling frequency, thus low temporal resolution.**
- **CMORPH and MIRA uses both Infrared and Passive Microwave but has low temporal resolution due to PMW.**

Literature Review (contd.)

- **Visual and Infrared channels have high temporal resolution but visible data is not available at night.**
- **GMSRA uses information from 5 satellite channels coupled with pre-calibrated probability of rain derived from clouds top brightness temperature groups.**
- **PERSIANN-MSA uses self-organizing map(ANN-SOFM).**

Problem Statement

Limitations of previous methods -

- Use of only one or two spectral channels.
- Daily or monthly average rainfall prediction.
- Very few studies focused on Indian regions.

Our Approach -

We have used multi-spectral channels with hourly predictions over $10km \times 10km$ for the state of Gujarat having coordinates 68W-75E and 25N-20S.

- **INSAT-3D is a geosynchronous satellite with IMAGER and SOUNDER payloads.**
- **VHRR data of multiple wavelengths has been taken from MOSDAC for each hour of each day for rainy months i.e. June-September from 2014 to 2017.**
- **5 channels out of the 25 available spectral channel are used because other channels are not related to the rain or not available.**

Features (contd.)

- **Wavelength range of each channel:**
 - ▶ **$0.52\mu\text{m}$ - $0.72\mu\text{m}$ VIS (Visible)**
 - ▶ **$1.55\mu\text{m}$ - $1.70\mu\text{m}$ SWIR (Short Wave Infrared)**
 - ▶ **$6.50\mu\text{m}$ - $7.00\mu\text{m}$ WV (Water Vapor)**
 - ▶ **$10.2\mu\text{m}$ - $11.2\mu\text{m}$ TIR-1 (Thermal Infrared)**
 - ▶ **$11.5\mu\text{m}$ - $12.5\mu\text{m}$ TIR-2 (Thermal Infrared)**
- **Temporal resolution: 1 hour**
- **Spatial resolution: 2×2 km**

Features (contd.)

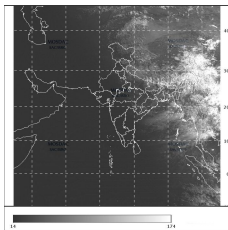


Figure 1: VIS (0.65 μ m)

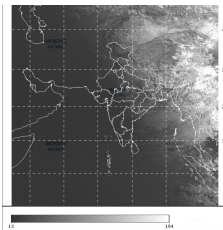


Figure 2: SWIR (1.625 μ m)

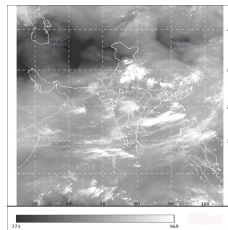


Figure 3: WV (6.8 μ m)

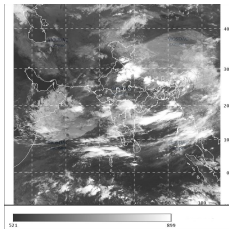


Figure 4: TIR1 (10.8 μ m)

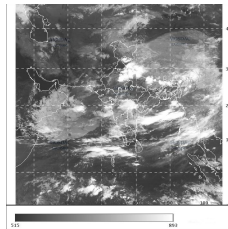


Figure 5: TIR2 (12 μ m)

Features (contd.)

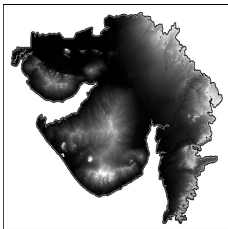


Figure 6: SRTM DEM

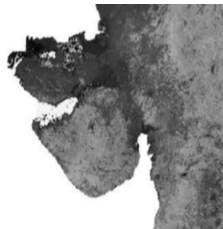


Figure 7: NDVI

- **SRTM provides Digital Elevation data with $1\text{km} \times 1\text{km}$ resolution and the vertical error less than 16m.**
- **The NDVI is a numerical indicator that shows whether targeted area contains vegetation or not. it has 15 days temporal and $1\text{km} \times 1\text{km}$ spatial resolution.**

Rainfall sources

- **Ground based rainfall observation stations (AWS data) provided by MOSDAC, ISRO.**
- **IMD rainfall data (daily average).**
- **TRMM PR hourly data with spacial resolution of $10\text{km} \times 10\text{km}$.**

Problems in AWS Rainfall Data

- Rainfall data is cumulative and the reset points are at random.
- Appearance of 1023 due to two reasons:
 - ▶ It is the highest value (10 bit number).
 - ▶ Missing data is sometimes filled with value 1023.
- Random length of increasing and decreasing numbers.
- Garbage values like 9999 appear randomly.
- Nearly $(1/3)^{rd}$ data is missing.

Datasets

Dataset	Channel	Features per channel	Other Feature	Input Dimention	Resolution
1	TIR1 (T)	5	SRTM, NDVI, WV (rad)	8	2×2 km
2	VIS (Albedo), SWIR (Rad), WV (T), WV (Rad), TIR1 (T), TIR2 (T)	5	SRTM, NDVI	32	10×10 km

Table 1: Features in each dataset

- Computing the brightness temperature mean and standard deviation of 3×3 neighbourhood for each channel.
- Computing the brightness temperature mean and standard deviation of 5×5 neighbourhood for each channel.
- SWIR and VIS are highly affected by solar zenith angle (SZA) so we adopted a correction technique of multiplying each observed value with $(\cos SZA)^{-1}$

Implementation

- Started with some linear classifier models but due to dis-satisfactory results we moved on to non-linear classifiers.
- 80% of total data was allocated for training and rest (20%) was used for validation.

class ID	Rainfall(in mm)
class 0	0
class 1	<2
class 2	<5
class 3	>=5

Table 2: Class ID and its corresponding rainfall (in mm) range

Multi layer Perceptron (MLP)

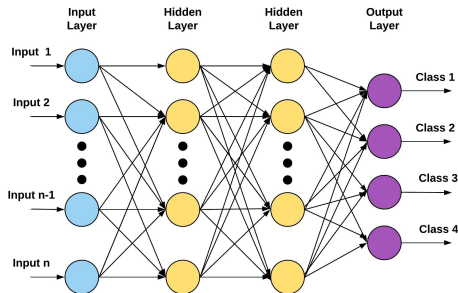


Figure 8: Multi Layer Perceptron

Input units = Number of features
Output units = 4 (one for each class)
Optimizer = Adam Optimizer

Neurons in each hidden layer = $16 \times (\text{number of input units})$
Loss Function = Categorical cross-entropy
Activation Function = relu (hidden layers) and softmax (output layer)

Synthetic Minority Oversampling Technique (SMOTE):

- SMOTE is a synthetic data generation technique which helps in balancing classes.
- If the classes are not balanced then the classifier always learns to predict the majority class.
- To avoid this and do the rightful prediction of rainfall we use SMOTE.

Long short-term memory (LSTM)

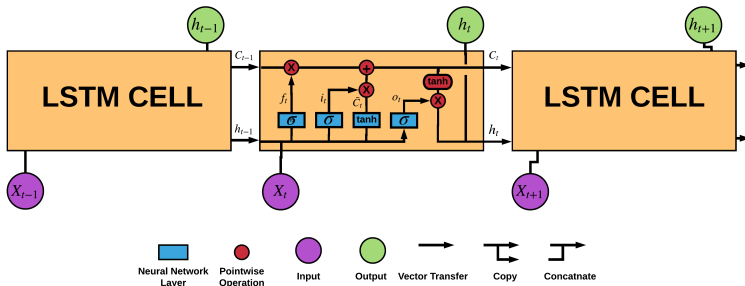


Figure 9: Long Short Term Memory Module

Input units = Number of features.

For dataset 1 first Layer = 24 LSTM cells

Next layer = time distributed dense layer

Loss Function = Categorical cross-entropy

Output layer = 4 (one for each class)

For dataset 2 First Layer = 10 LSTM

Optimizer = Adam Optimizer

Activation Function = softmax for output layer

Metrics

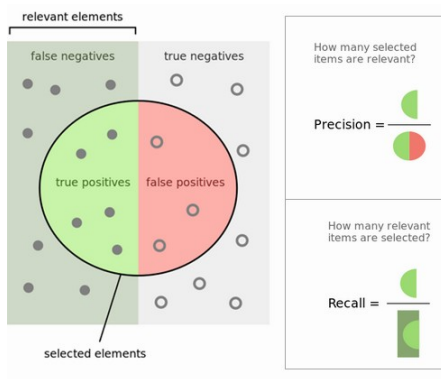


Figure 10: Precision and Recall

$$\text{Accuracy} = \frac{\text{true positive} + \text{true negatives}}{\text{true positive} + \text{false negative} + \text{false positive} + \text{true negatives}}$$

$$F\text{score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Results

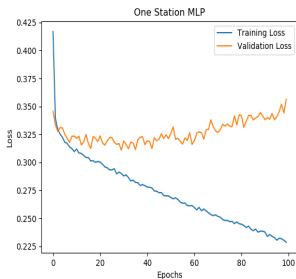


Figure 11: MLP model for SAC BOPAL without SMOTE

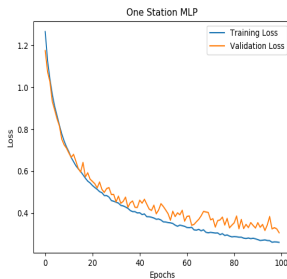


Figure 12: MLP model for SAC BOPAL with SMOTE

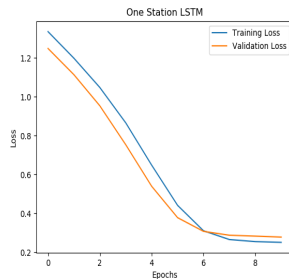


Figure 13: LSTM model for SAC BOPAL

Results (contd.)

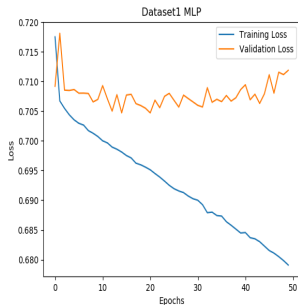


Figure 14: MLP model for Gujarat without SMOTE using Dataset 1

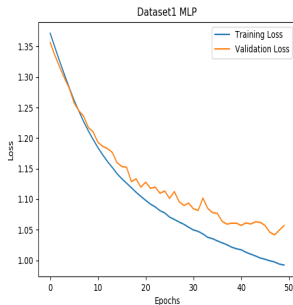


Figure 15: MLP model for Gujarat with SMOTE using Dataset 1

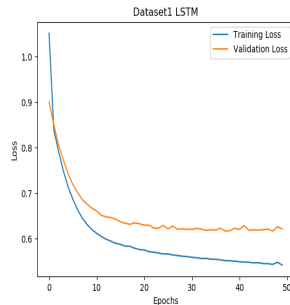


Figure 16: LSTM model for Gujarat using Dataset 1

Results (contd.)

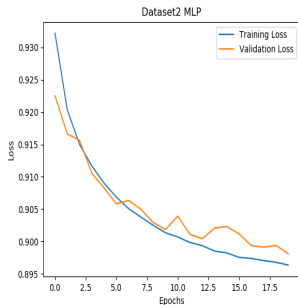


Figure 17: MLP model for Gujarat without SMOTE using Dataset 2

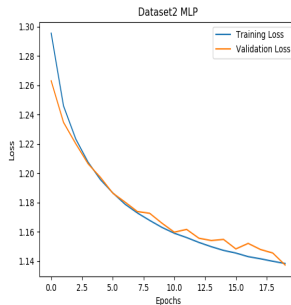


Figure 18: MLP model for Gujarat with SMOTE using Dataset 2

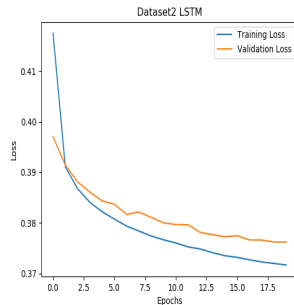


Figure 19: LSTM model for Gujarat using Dataset 2

Results (contd.)

One Station				Dataset 1			Dataset 2		
	MLP without SMOTE	MLP with SMOTE	LSTM	MLP without SMOTE	MLP with SMOTE	LSTM	MLP without SMOTE	MLP with SMOTE	LSTM
categorical_accuracy	0.93	0.91	0.95	0.80	0.5	0.85	0.62	0.46	0.84
val_categorical_accuracy	0.92	0.90	0.95	0.80	0.54	0.83	0.63	0.47	0.84
Precision overall	0.93	0.87	-	0.80	0.66	-	0.64	0.65	-
Recall overall	0.93	0.83	-	0.80	0.37	-	0.60	0.23	-
F-score overall	0.93	0.85	-	0.80	0.47	-	0.62	0.34	-
Precision_class1	0.00	0.79	-	0.50	0.62	-	0.66	0.68	-
Recall_class1	0.00	0.45	-	0.00	0.27	-	0.12	0.16	-
F-score_class1	0.00	0.57	-	0.00	0.38	-	0.20	0.26	-
Precision_class2	0.00	0.79	-	0.00	0.66	-	0.65	0.69	-
Recall_class2	0.00	0.67	-	0.00	0.37	-	0.01	0.16	-
F-score_class2	0.00	0.72	-	0.00	0.47	-	0.02	0.26	-
Precision_class3	0.00	0.83	-	1.00	0.77	-	0.68	0.78	-
Recall_class3	0.00	0.71	-	0.00	0.54	-	0.01	0.25	-
F-score_class3	0.00	0.77	-	0.00	0.63	-	0.01	0.38	-

Table 3: Results

Conclusion

- **This project discusses the importance of different parameters that determine the amount of rainfall occurring in a particular region.**
- **Using multispectral channels (in dataset 2) over TIR1 channel (in dataset 1) didn't improve the results significantly as stated in some papers.**
- **MLP gave good results with SMOTE technique for a particular station data (small dataset).**
- **LSTM performed better than MLP in general as it made predictions with an accuracy of 84% when relatively balanced dataset was used.**

- **Currently we used only 2014 year data for preparing dataset 2 and training the models due to limitation of computing resources.**
- **Here have only focused on Gujarat, like to develop this model for entire India.**
- **The IR satellite data taken from MOSDAC not entirely accurate so would try to incorporate data from NASA as well.**
- **Addition of Passive Microwave can be useful as it is directly related to the water content in the clouds.**

Acknowledgement

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Reference



Tim Bellerby, Martin Todd, Dom Kniveton, and Chris Kidd. “Rainfall estimation from a combination of TRMM precipitation radar and GOES multispectral satellite imagery through the use of an artificial neural network”. In: *Journal of applied Meteorology* 39.12 (2000), pp. 2115–2128.



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Normalized Difference Vegetation Index (NDVI), SDAPSA, National Remote Sensing Center, Bhuvan Noeda.
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Precision and Recall.
https://en.wikipedia.org/wiki/Precision_and_recall.

Reference (contd.)



Ali Behrangi, Kuo-lin Hsu, Bisher Imam, Soroosh Sorooshian, and Robert J Kuligowski. “Evaluating the utility of multispectral information in delineating the areal extent of precipitation”. In: *Journal of Hydrometeorology* 10.3 (2009), pp. 684–700.



Andy Jarvis, Hannes Isaak Reuter, Andrew Nelson, Edward Guevara, et al. “Hole-filled SRTM for the globe Version 4”. In: *available from the CGIAR-CSI SRTM 90m Database* (<http://srtm.csi.cgiar.org>) 15 (2008).



Jesse Davis and Mark Goadrich. “The Relationship Between Precision-Recall and ROC Curves”. In: *Proceedings of the 23rd International Conference on Machine Learning*. ICML '06. ACM, 2006, pp. 233–240. ISBN: 1-59593-383-2. DOI: 10.1145/1143844.1143874. URL: <http://doi.acm.org/10.1145/1143844.1143874>.

Dataset2 Distribution

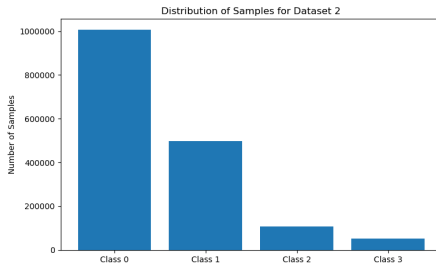


Figure 20: Sample Distribution for Dataset 2

AWS Data Problems

- Rainfall data is cumulative and the reset points are at random.
- Random length of increasing and decreasing numbers.
- Lot of missing data

@STATION_ID	LATITUDE	LONGITUDE	ALTITUDE(m)	TIME(GMT)	DATE(GMT)	AIR_TEMP(°C)	WIND_SPEED(m/s)	WIND_DIRECTION(deg)	ATMO_PRESSURE(hpa)	HUMIDITY(%)	RAIN_FALL(mm)
ISRO0009_15F009(PRL_Ahmedabad)	23.0362	72.5424	7	0	08/08/2016	24.9	0.1	264.9	1000.3	100	208
ISRO0009_15F009(PRL_Ahmedabad)	23.0362	72.5424	7	1	08/08/2016	24.7	0	359.2	1000.6	100	208
ISRO0009_15F009(PRL_Ahmedabad)	23.0362	72.5424	7	2	08/08/2016	24.9	0.3	210.2	1001.2	100	209
ISRO0009_15F009(PRL_Ahmedabad)	23.0362	72.5424	7	5	08/08/2016	26	0.8	225.8	1001.9	100	214
ISRO0009_15F009(PRL_Ahmedabad)	23.0362	72.5424	7	5	08/09/2016	27.1	1.4	243.9	1001	100	222
ISRO0009_15F009(PRL_Ahmedabad)	23.0362	72.5424	7	6	08/09/2016	27.1	2.5	224.8	1000.8	100	222
ISRO0009_15F009(PRL_Ahmedabad)	23.0362	72.5424	7	7	08/09/2016	27.1	0.6	213.1	1000.4	100	222
ISRO0009_15F009(PRL_Ahmedabad)	23.0362	72.5424	7	17	08/09/2016	26	0.2	200.9	1000.2	100	11
ISRO0009_15F009(PRL_Ahmedabad)	23.0362	72.5424	7	20	08/09/2016	25.9	0.7	252.2	999.5	100	11
ISRO0009_15F009(PRL_Ahmedabad)	23.0362	72.5424	7	3	08/10/2016	25.1	1.2	230.2	1000.3	100	34
ISRO0009_15F009(PRL_Ahmedabad)	23.0362	72.5424	7	4	08/10/2016	25.5	1	213.1	1001	100	37
ISRO0009_15F009(PRL_Ahmedabad)	23.0362	72.5424	7	20	08/10/2016	25.5	0	359.2	1002.1	100	43
ISRO0009_15F009(PRL_Ahmedabad)	23.0362	72.5424	7	21	08/10/2016	25.4	0.4	232.2	1001.2	100	43
ISRO0009_15F009(PRL_Ahmedabad)	23.0362	72.5424	7	22	08/10/2016	25.4	1.5	263	1000.8	100	43
ISRO0009_15F009(PRL_Ahmedabad)	23.0362	72.5424	7	23	08/10/2016	25.3	0	359.2	1001.3	100	43
ISRO0009_15F009(PRL_Ahmedabad)	23.0362	72.5424	7	0	08/11/2016	25.2	0.2	158.8	1001.6	100	43

Figure 21

AWS Data Problems (contd.)

- Appearance of 1023 due to two reasons:
 - ▶ It is the highest value (10 bit number).
 - ▶ Missing data is sometimes filled with value 1023.

STATION_ID	LATITUDE	LONGITUDE	ALTITUDE(m)	TIME(GMT)	DATE(GMT)	AIR_TEMP(C)	WIND_SPEED(m/s)	WIND_DIRECTION(deg)	ATMO_PRESSURE(hpa)	HUMIDITY(%)	RAIN_FALL(mm)
ISROO264_15F108(N5 Dwarika, Okha)	22.468334	69.075554	NA	8/07/13/2016	28.1	1.9	301		996.8	100	2
ISROO264_15F108(N5 Dwarika, Okha)	22.468334	69.075554	NA	9/07/13/2016	29.7	1.6	302.1		996.1	89	2
ISROO264_15F108(N5 Dwarika, Okha)	22.468334	69.075554	NA	22/07/13/2016	26.7	0	359.2		995.5	100	1023
ISROO264_15F108(N5 Dwarika, Okha)	22.468334	69.075554	NA	23/07/13/2016	26.8	0.7	353.9		995.5	100	1023
ISROO264_15F108(N5 Dwarika, Okha)	22.468334	69.075554	NA	0/07/14/2016	26.8	0	359.2		995.6	100	1023
ISROO264_15F108(N5 Dwarika, Okha)	22.468334	69.075554	NA	1/07/14/2016	26.9	0.1	137.0		996.3	100	1023
ISROO264_15F108(N5 Dwarika, Okha)	22.468334	69.075554	NA	2/07/14/2016	27.3	0.8	191.1		996.9	100	1023
ISROO264_15F108(N5 Dwarika, Okha)	22.468334	69.075554	NA	22/07/14/2016	27.4	0	359.2		996.8	98	1023
ISROO264_15F108(N5 Dwarika, Okha)	22.468334	69.075554	NA	23/07/14/2016	27.4	0	359.2		996.9	99	23
ISROO264_15F108(N5 Dwarika, Okha)	22.468334	69.075554	NA	0/07/15/2016	27.5	0	359.2		997.2	98	1023
ISROO264_15F108(N5 Dwarika, Okha)	22.468334	69.075554	NA	1/07/15/2016	27.5	0	359.2		997.7	99	1023
ISROO264_15F108(N5 Dwarika, Okha)	22.468334	69.075554	NA	2/07/15/2016	28	0	359.2		998.1	98	1023
ISROO264_15F108(N5 Dwarika, Okha)	22.468334	69.075554	NA	22/07/15/2016	27.5	0.7	181.8		996.8	96	1023
ISROO264_15F108(N5 Dwarika, Okha)	22.468334	69.075554	NA	23/07/15/2016	27.2	2.5	191.1		996.6	98	1023
ISROO264_15F108(N5 Dwarika, Okha)	22.468334	69.075554	NA	0/07/16/2016	26.2	0	359.2		996.6	100	1023
ISROO264_15F108(N5 Dwarika, Okha)	22.468334	69.075554	NA	1/07/16/2016	26.3	1	250.2		997	100	1023
ISROO264_15F108(N5 Dwarika, Okha)	22.468334	69.075554	NA	2/07/16/2016	26.6	0.9	159.8		997.5	100	108
ISROO264_15F108(N5 Dwarika, Okha)	22.468334	69.075554	NA	21/07/16/2016	27.9	0.6	187.2		998.5	95	1023
ISROO264_15F108(N5 Dwarika, Okha)	22.468334	69.075554	NA	22/07/16/2016	27	1.1	208.2		998.4	96	1023
ISROO264_15F108(N5 Dwarika, Okha)	22.468334	69.075554	NA	23/07/16/2016	26.8	0	359.2		998.5	100	1023
ISROO264_15F108(N5 Dwarika, Okha)	22.468334	69.075554	NA	0/07/17/2016	26.4	0.1	181.0		998.7	100	115
ISROO264_15F108(N5 Dwarika, Okha)	22.468334	69.075554	NA	1/07/17/2016	26.9	0.5	159.8		999	100	115
ISROO264_15F108(N5 Dwarika, Okha)	22.468334	69.075554	NA	2/07/17/2016	26.3	0	359.2		999.8	100	115
ISROO264_15F108(N5 Dwarika, Okha)	22.468334	69.075554	NA	3/07/17/2016	26.5	1.6	236.1		1000.7	100	115
ISROO264_15F108(N5 Dwarika, Okha)	22.468334	69.075554	NA	4/07/17/2016	26	1.1	229.2		1001	100	115
ISROO264_15F108(N5 Dwarika, Okha)	22.468334	69.075554	NA	5/07/17/2016	27.7	1.7	226.8		1001.1	94	115
ISROO264_15F108(N5 Dwarika, Okha)	22.468334	69.075554	NA	16/07/17/2016	26.8	2.6	217		1001.5	100	116
ISROO264_15F108(N5 Dwarika, Okha)	22.468334	69.075554	NA	17/07/17/2016	26.9	1.3	201.9		1001.7	98	1023
ISROO264_15F108(N5 Dwarika, Okha)	22.468334	69.075554	NA	18/07/17/2016	27	0	359.2		1001.8	98	1023
ISROO264_15F108(N5 Dwarika, Okha)	22.468334	69.075554	NA	19/07/17/2016	26.2	2.5	225.1		1001.4	97	1023
ISROO264_15F108(N5 Dwarika, Okha)	22.468334	69.075554	NA	20/07/17/2016	26.9	0.7	208.2		1001	99	1023

Figure 22

AWS Data Problems (contd.)

- Garbage values like 9999 appear randomly.

@STATION_ID	LATITUDE	LONGITUDE	ALTITUDE(m)	TIME(GMT)	DATE(GMT)	AIR_TEMP(°C)	WIND_SPEED(m/s)	WIND_DIRECTION(deg)	ATMO_PRESSURE(pas)	HUMIDITY(%)	RAIN_FALL(mm)
ISRO1024_15F400(Jagudan (Main Spices Research Station))	23.513332	72.39861	87	20/07/10/2016	28.4	9955	0	9999.9	35.1	9999.9	
ISRO1024_15F400(Jagudan (Main Spices Research Station))	23.513332	72.39861	87	21/07/10/2016	28.3	9955	0	9999.9	35.1	9999.9	
ISRO1024_15F400(Jagudan (Main Spices Research Station))	23.513332	72.39861	87	22/07/10/2016	28.8	1.4	276.1	997.1	78	69	
ISRO1024_15F400(Jagudan (Main Spices Research Station))	23.513332	72.39861	87	23/07/10/2016	28.7	1.3	253.2	997.2	79	69	
ISRO1024_15F400(Jagudan (Main Spices Research Station))	23.513332	72.39861	87	0/07/11/2016	28.4	1	247.8	997.1	80	69	
ISRO1024_15F400(Jagudan (Main Spices Research Station))	23.513332	72.39861	87	1/07/11/2016	28.3	0.8	236.1	997.4	82	69	
ISRO1024_15F400(Jagudan (Main Spices Research Station))	23.513332	72.39861	87	2/07/11/2016	28.6	1	236.1	997.6	81	69	
ISRO1024_15F400(Jagudan (Main Spices Research Station))	23.513332	72.39861	87	3/07/11/2016	26.8	9955	0	9999.9	35.1	9999.9	
ISRO1024_15F400(Jagudan (Main Spices Research Station))	23.513332	72.39861	87	4/07/11/2016	30.3	1.2	237	998.4	74	69	
ISRO1024_15F400(Jagudan (Main Spices Research Station))	23.513332	72.39861	87	5/07/11/2016	28.3	9955	0	9999.9	35.1	9999.9	
ISRO1024_15F400(Jagudan (Main Spices Research Station))	23.513332	72.39861	87	6/07/11/2016	28.2	9955	0	9999.9	35.1	9999.9	
ISRO1024_15F400(Jagudan (Main Spices Research Station))	23.513332	72.39861	87	7/07/11/2016	28.7	9955	0	9999.9	35.1	9999.9	
ISRO1024_15F400(Jagudan (Main Spices Research Station))	23.513332	72.39861	87	8/07/11/2016	29.2	9955	0	9999.9	35.1	9999.9	
ISRO1024_15F400(Jagudan (Main Spices Research Station))	23.513332	72.39861	87	9/07/11/2016	29.6	9955	0	9999.9	35.1	9999.9	
ISRO1024_15F400(Jagudan (Main Spices Research Station))	23.513332	72.39861	87	10/07/11/2016	29.3	9955	0	9999.9	35.1	9999.9	
ISRO1024_15F400(Jagudan (Main Spices Research Station))	23.513332	72.39861	87	11/07/11/2016	29.4	9955	0	9999.9	35.1	9999.9	
ISRO1024_15F400(Jagudan (Main Spices Research Station))	23.513332	72.39861	87	12/07/11/2016	29.4	9955	0	9999.9	35.1	9999.9	
ISRO1024_15F400(Jagudan (Main Spices Research Station))	23.513332	72.39861	87	13/07/11/2016	28.8	9955	0	9999.9	35.1	9999.9	
ISRO1024_15F400(Jagudan (Main Spices Research Station))	23.513332	72.39861	87	14/07/11/2016	28.8	9955	0	9999.9	35.1	9999.9	
ISRO1024_15F400(Jagudan (Main Spices Research Station))	23.513332	72.39861	87	15/07/11/2016	29.2	9955	0	9999.9	35.1	9999.9	
ISRO1024_15F400(Jagudan (Main Spices Research Station))	23.513332	72.39861	87	16/07/11/2016	29.3	9955	0	9999.9	35.1	9999.9	
ISRO1024_15F400(Jagudan (Main Spices Research Station))	23.513332	72.39861	87	17/07/11/2016	29.3	9955	0	9999.9	35.1	9999.9	
ISRO1024_15F400(Jagudan (Main Spices Research Station))	23.513332	72.39861	87	18/07/11/2016	29.2	9955	0	9999.9	35.1	9999.9	
ISRO1024_15F400(Jagudan (Main Spices Research Station))	23.513332	72.39861	87	19/07/11/2016	29.1	9955	0	9999.9	35.1	9999.9	
ISRO1024_15F400(Jagudan (Main Spices Research Station))	23.513332	72.39861	87	20/07/11/2016	28.6	9955	0	9999.9	35.1	9999.9	
ISRO1024_15F400(Jagudan (Main Spices Research Station))	23.513332	72.39861	87	21/07/11/2016	28.4	9955	0	9999.9	35.1	9999.9	
ISRO1024_15F400(Jagudan (Main Spices Research Station))	23.513332	72.39861	87	22/07/11/2016	28.3	9955	0	9999.9	35.1	9999.9	
ISRO1024_15F400(Jagudan (Main Spices Research Station))	23.513332	72.39861	87	23/07/11/2016	28.3	9955	0	9999.9	35.1	9999.9	
ISRO1024_15F400(Jagudan (Main Spices Research Station))	23.513332	72.39861	87	0/07/12/2016	26.7	0.3	215.1	997.8	99	84	
ISRO1024_15F400(Jagudan (Main Spices Research Station))	23.513332	72.39861	87	1/07/12/2016	0	0	0	9999.9	35.1	9999.9	

Figure 23

AWS Data Problems (contd.)

- 95% of the entries have zero rainfall.
- AWS and IMD Rainfall don't even match.

	A	B	C	D	E	F	G	H	I	J	K	L	M
1	Station ID	Latitude	Longitude	Time	Date	Top Latitude	Bottom Latitude	Rain Fall(mm)					
3344	ISRO1020_15F3FC(Khandra / Narmada Irrigation Res. Station)	22.060278	73.070274	11.09.02.2014	22.070809883	22.050951057		6					
3345	ISRO1020_15F3FC(Khandra / Narmada Irrigation Res. Station)	22.060278	73.070274	12.09.02.2014	22.070809883	22.050951057		5					
3346	ISRO1020_15F3FC(Khandra / Narmada Irrigation Res. Station)	22.060278	73.070274	22.09.02.2014	22.070809883	22.050951057		1					
3347	ISRO1023_15F3FF(Majur / Main Wheat Research Station)	23.571112	72.76111	11.09.02.2014	23.5740094791	23.5532334831		14					
3348	ISRO1023_15F3FF(Majur / Main Wheat Research Station)	23.571112	72.76111	12.09.02.2014	23.5740094791	23.5532334831		11					
3349	ISRO1023_15F3FF(Majur / Main Wheat Research Station)	23.571112	72.76111	13.09.02.2014	23.5740094791	23.5532334831		1					
3350	ISRO1023_15F3FF(Majur / Main Wheat Research Station)	23.571112	72.76111	14.09.02.2014	23.5740094791	23.5532334831		2					
3351	ISRO1023_15F3FF(Majur / Main Wheat Research Station)	23.571112	72.76111	15.09.02.2014	23.5740094791	23.5532334831		1					
3352	ISRO1023_15F3FF(Majur / Main Wheat Research Station)	23.571112	72.76111	16.09.02.2014	23.5740094791	23.5532334831		1					
3353	ISRO1026_15F402(Deesa / Potato Research Station)	24.26	72.18684	10.09.02.2014	24.2668821664	24.2456774126		1					
3354	ISRO1026_15F402(Deesa / Potato Research Station)	24.26	72.18684	11.09.02.2014	24.2668821664	24.2456774126		1					
3355	ISRO1026_15F402(Deesa / Potato Research Station)	24.26	72.18684	12.09.02.2014	24.2668821664	24.2456774126		1					
3356	ISRO1026_15F402(Deesa / Potato Research Station)	24.26	72.18684	15.09.02.2014	24.2668821664	24.2456774126		1					
3357	ISRO1028_15F404(Rudhanpur / Dry Farming Research Station)	23.838394	71.50667	22.09.02.2014	23.8451710908	23.8243271351		4					
3358	ISRO1029_15F405(Khojod / Agricultural Research Station)	23.928655	72.35111	10.09.02.2014	23.9291761777	23.9061804004		1					

	A	B	C	D	E	F	G	H	I	J	K	L	M
1	DAILY RAIN FALL DATA												
2	METEOROLOGICAL CENTRE, AHMEDABAD												
3	STATION:DEESA							YEAR:2014					
4	Date	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
5	01	000.0	000.0	000.0	000.0	000.0	000.0	000.0	003.0	015.0	000.0	000.0	000.0
6	02	000.0	000.0	000.0	000.0	000.0	000.0	000.0	065.6	000.0	000.0	000.0	000.0
7	03	000.0	000.0	000.0	000.0	000.0	000.0	000.0	040.8	240.0	000.0	000.0	000.0
8	04	000.0	000.0	000.0	000.0	000.0	000.0	000.0	000.6	068.6	000.0	000.0	000.0
9	05	000.0	000.0	000.0	000.0	000.0	000.0	000.0	000.0	022.2	000.0	000.0	000.0
10	06	000.0	000.0	000.0	000.0	000.0	000.0	000.0	001.0	000.0	000.0	000.0	000.0
11	07	000.0	000.0	000.0	000.0	000.0	000.0	000.0	004.0	000.0	000.0	000.0	000.0
12	08	000.0	000.0	000.0	000.0	000.0	000.0	000.0	006.2	000.0	000.0	000.0	000.0

Figure 24

Abbreviation

- VIS = Visual Wavelength ($1.55\mu\text{m}$ - $1.70\mu\text{m}$)
- MIR = Mid wave Infrared ($0.39\mu\text{m}$ - $0.7\mu\text{m}$)
- WV = Water Vapor Wavelength ($6.5\mu\text{m}$ - $7.0\mu\text{m}$)
- TIR1 = Thermal Infrared ($10.2\mu\text{m}$ - $11.2\mu\text{m}$)
- TIR2 = Thermal Infrared ($11.5\mu\text{m}$ - $12.5\mu\text{m}$)
- PMW = Passive Microwave (1cm - 1m)
- VHRR = Very High Resolution Radiometer
- SRTM = Shuttle Radar Topography Mission
- DEM = Digital Elevation Models
- NDVI = Normalized Difference Vegetation Index
- AWIFS = Advanced Wide Field Sensor
- MLP = Multi Layer Perceptron

Abbreviation (contd.)

- **LSTM = Long-Short Term Memory**
- **TRMM = Tropical Rainfall Measuring Mission**
- **AWS = Automatic Weather Station**
- **SZA = Solar Zenith Angle**
- **CMORPH = Climate Prediction Center morphing method**
- **MIRA = microwave/infrared rainfall algorithm**
- **GMSRA = Geostationary Operational Environmental Satellite system-Multispectral Rainfall Algorithm**
- **PERSSIAN-MSA = Rainfall prediction from Remotely Sensed information using Artificial Neural NetworksMultispectral Analysis**