INTEGRATED LOCAL WEATHER FORECASTING WITH SURFACE SOIL MOISTURE USING REMOTE SENSING TECHNIQUES

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Abstract - *A land surface dryness index (Temperature–Vegetation Dryness Index, TVDI) based on the relationship between surface temperature (LST) and Normal Difference Vegetation index (NDVI) is done. The index is related to soil moisture and, in comparison to existing interpretations of the LST/NDVI space, the index is conceptually and computationally straightforward. It is based on satellite derived information only. The spatial pattern and temporal evolution in TVDI will be analyzed using Landsat 8 images for the year 2018. The spatial pattern in TVDI will be compared with simulations of surface soil moisture and these spatial variation in TVDI may reflect the variation in moisture on a finer scale. With this spatio-temporal variation in surface soil moisture Numerical weather predication model is generated for Local weather variables influencing the weather of the Tuticorin district. The results from the model will be validated with data obtained from the Indian Meteorological Department.*

Key Words: Weather forecasting, Surface soil moisture, ECMWF, Landsat 8, ArcGIS 10.4, NDVI, LST, TVDI, NWP, ANN.

1. INTRODUCTION

Weather forecasting is the application of science and technology to forecast the conditions of the atmosphere for a given location and time. People have attempted to predict the weather informally for millennia and formally since the 19th century. Weather forecasts are made by collecting computable data about the current state of the atmosphere at a given place and using meteorology to project how the atmosphere will change.

Meteorologists and climatologists use several methods for predicting the weather: the climatology, analogue, and persistence and trends methods along with predicting the weather by using supercomputers in numerical or statistical weather prediction. Once calculated manually based mainly upon changes in barometric pressure, current weather conditions, and sky condition or cloud cover, weather forecasting now relies on computer-based models that take many atmospheric factors into account.

Human input is still needed to pick the best possible forecast model to base the forecast upon, which involves pattern recognition skills, teleconnections, knowledge of model performance, and knowledge of model biases. The inaccuracy of forecasting is due to the confused nature of the atmosphere, the massive computational power required to solve the equations that describe the atmosphere, the error occur happens by measuring the initial conditions, and an incomplete understanding of atmospheric processes. Hence, forecasts become less accurate as the time difference between current and forecast time increases. The use of grouping and model concord help narrow the error and pick the most likely outcome.

2. STUDY AREA

Thoothukudi is a port city and an industrial city in the Indian state of Tamilnadu. The city located in the Coromandel Coast of Bay of Bengal. Thoothukudi is known as "Pearl City" because pearl fishing takes place in the town. It is a commercial seaport which serves the non-coastal cities of Southern India and is one of the sea gateways of Tamil Nadu. It is also one of the major seaports in India with a history from the 6th century AD. The major harbour of Thoothukudi is famous for pearl diving and fishing.

Thoothukudi is located at 8.53°N 78.36°E. Thoothukudi is lies in South India on the Gulf of Mannar, about 540 kilometres (340 miles) south of Chennai and 125 kilometres (78 miles) north of Kanyakumari. The hinderlands of the port of the city is connected to the districts of Madurai, Tirunelveli, Ramanathapuram and Tiruchirapalli. The city consists of loose soil with thorny shrubs in the north and salt pans in the south. The key map of the study area is shown in the figure -1.

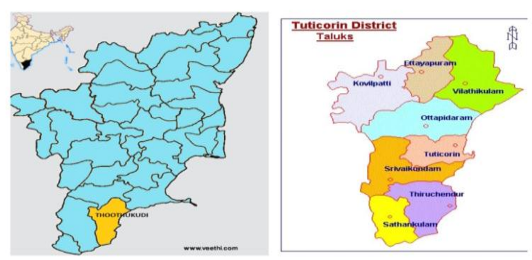

Figure -1: Key map of the study area

2.1 Data Collection

Remote sensing and GIS techniques offer a wide range of possibilities in the predicting the local weather. The unique capabilities of satellite-based sensors in providing a wide spectrum of information available through the electromagnetic spectrum in repetitive and synoptic coverage over in accessible and larger areas in frequent intervals made the remote sensing technology.

- Landsat 8 data set for the year 2018 (March & Sept) which is collected from USGS Earth Explorer website.
- Collection of field data (Temperature, Humidity, Pressure) from Indian Meteorological Department.
- Satellite-derived (Temperature, Humidity, Pressure) datasets readily available in The European Centre for Medium-Range Weather Forecasts.

2.2 Software Used

In this study, ARCGIS 10.4 version software is used. This software is user friendly and it is freely downloaded from the internet. By using this software image processing and map generation are carried out.

ArcGIS 10.4 version is a geographic information system (GIS) useful for creating and using maps compiling geographic data. It also helps for scanning mapped information sharing and discovering geographic information using maps and geographic information in a range of applications and managing geographic information in a database. This software is also capable of conversion of data from one format to another format. So that, major works for this study is done by using this software.

Matlab (Matrix Laboratory) is a multi-paradigm numerical enumerating environment and proprietary programming language developed by MathWorks. MATLAB permit matrix manipulations, plotting of functions and data, implementation of algorithms, creation of user interfaces, and interfacing with programs written in other languages.

3. METHODOLOGY

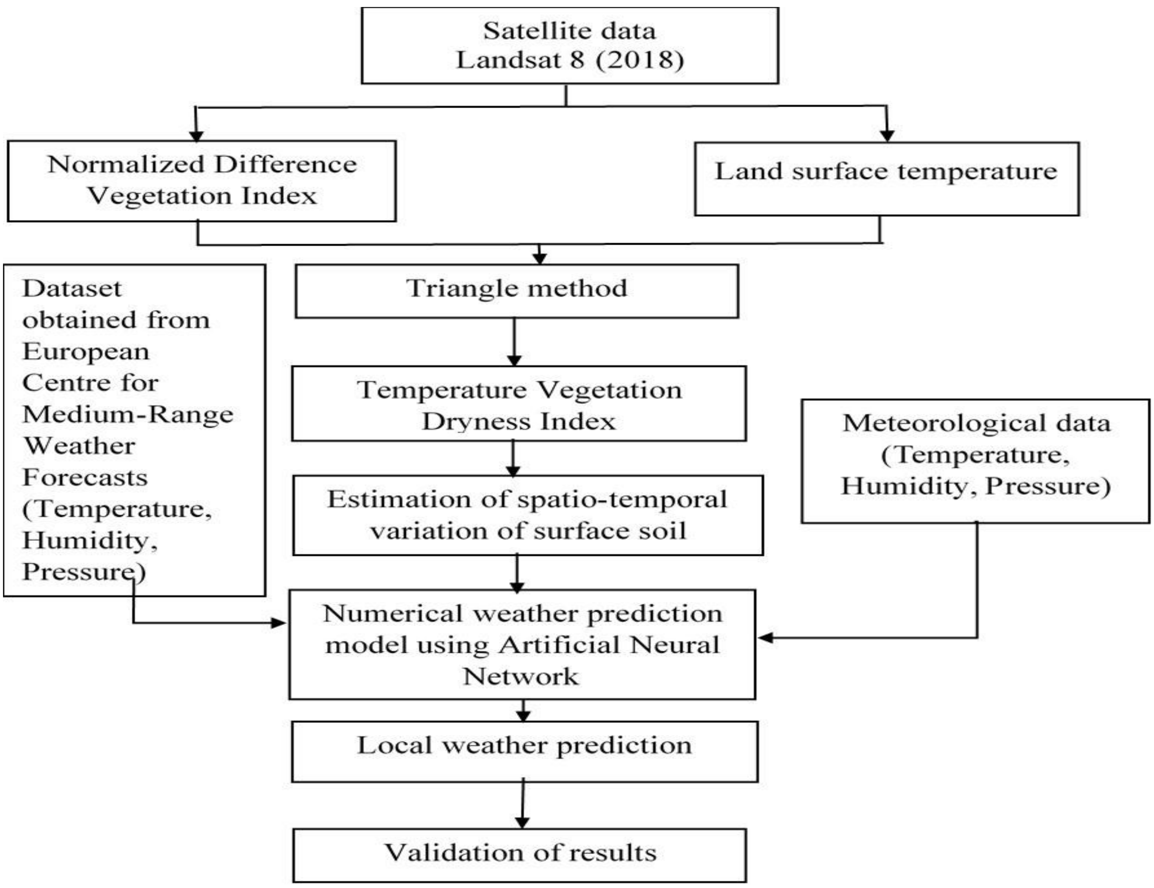

Figure -2: Flowchart for Methodology

3.1 Satellite data

Landsat 8 data set for the year 2018 which is collected from USGS Earth Explorer website. Different time period of data is downloaded to avoid the cloud cover images.

3.2 Normalized Difference Vegetation Index

The Normalized Difference Vegetation Index (NDVI)is a numerical measure that uses the visible and near – infrared bands of the electromagnetic spectrum and is adopted to analyze remote sensing measurements and check whether the target being observed contains live green vegetation or not. Generally, healthy vegetation will absorb most of the visible light that falls on it and affects a large portion of the near – infrared light. Bare soils on the other hand reflects moderately in both the red and infrared portion of the electromagnetic spectrum (Holme et al., 1987). The NDVI algorithm subtracts the red reflectance values from the near – infrared and divides by the sum of near – infrared and red bands.

NDVI=(NIR-RED)/(NIR+RED) (1)

3.3 Land Surface Temperature

i. Top of Atmosphere (TOA) Radiance:

Using the radiance rescaling factor, Thermal Infra-Red Digital Numbers can be converted to TOA spectral radiance.

Lλ = ML * Qcal + AL (2)

Lλ = TOA spectral radiance (Watts/ (m2 * sr * µm))
ML = Radiance multiplicative Band (No.)
AL = Radiance Add Band (No.)
Qcal = Quantized and measured standard product pixel values (DN)

ii. Top of the Atmosphere (TOA) Brightness Temperature:

Spectral radiance data can be converted to top of atmosphere reflectance using the thermal constant Values in Meta data file.

BT = K2 / ln (k1 / Lλ + 1) – 273 (3)

BT = Top of atmosphere brightness temperature (°C)
Lλ = TOA spectral radiance (Watts/(m2 * sr * µm))
K1 = K1 Constant Band (No.)
K2 = K2 Constant Band (No.)

iii. Normalized Difference Vegetation Index:

The Normalized Difference Vegetation Index (NDVI) is a standardized vegetation index which Calculated using Near Infra-red (Band 5) and Red (Band 4) bands.

NDVI = (NIR – RED) / (NIR + RED) (4)

RED= DN values from the RED band
NIR= DN values from Near-Infrared band

iv. Land Surface Emissivity (LSE):

Land surface emissivity (LSE) is the mean emissivity of an element of the surface of the Earth calculated from NDVI values.

PV = [(NDVI – NDVI min) / (NDVI max + NDVI min)]^2 (5)

PV = Proportion of Vegetation
NDVI = DN values from NDVI Image
NDVI min = Minimum DN of pixel from NDVI Image
NDVI max = Maximum DN values from NDVI Image

E = 0.004 * PV + 0.986 (6)

E = Land Surface Emissivity
PV = Proportion of Vegetation

v. Land Surface Temperature (LST):

The Land Surface Temperature (LST) is the radiative temperature which is calculated using Top of atmosphere brightness temperature, Wavelength of emitted radiance, Land Surface Emissivity.

LST = (BT / 1) + W * (BT / 14380) * ln(E) (7)

BT = Top of atmosphere brightness temperature (°C)
W = Wavelength of emitted radiance
E = Land Surface Emissivity

Following Meta data values are used for calculation
Radiance Add Band 10 = 0.10000
Radiance Add Band 11 = 0.10000
Radiance Multi Band_10 = 0.0003342
Radiance Multi Band_11 = 0.0003342
K1 Constant band 10 = 774.8853
K2 Constant Band 10 = 1321.0789
K1 Constant Band 11 = 480.8883
K2 Constant Band 11 = 1201.1442

3.4 Triangle method

With the feature space constructed by LST and NDVI, the concept of triangular space was first proposed. The triangle method is proposed based on surface temperatures and NDVI scatter plots obtained using satellites. Combined with the simulation results of the land surface model, the simulated feature space is stretched to the satellite by analyzing the position of the image element in space to infer the soil moisture.

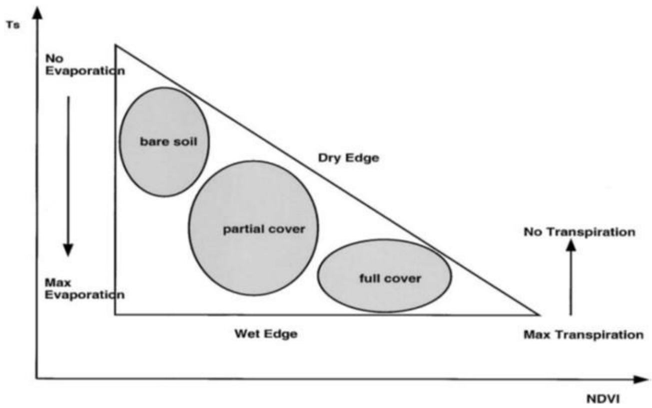

Figure -3: Triangle Method

Fig 3 represents the triangle method proposed based on land surface temperatures and NDVI scatter plots obtained using satellites.

3.5 Temperature Vegetation Dryness Index

TVDI is a simplified land surface dryness index, which is based on an empirical formula of the relationship between Ts and NDVI, and only satellite-derived information is used in the method. In the triangle, the upper sloping edge of the trapezium is defined as the dry edge, and the lower sloping edge is defined as the wet edge; they represent extreme conditions of soil moisture and evapotranspiration. TVDI ranges from 0 to 1.

$$\text{TVDI}=\frac{\boldsymbol{LST-LST_{min}}}{\boldsymbol{a+bNDVI-LST_{min}}} \quad (8)$$

where

LST_min is the minimum surface temperature in the triangle, defining the wet edge. LST is the observed surface temperature at the given certain pixel. NDVI is the observed normalized difference vegetation index. A and b are parameters defining the dry edge and wet edge modelled as a linear fit to data

$$\boldsymbol{LST_{max}} = (\text{a+bNDVI}) \quad (9)$$

where ($\boldsymbol{LST_{max}}$) is the maximum surface temperature observation for a given NDVI.

3.6 Numerical weather prediction

Numerical weather prediction (NWP) is a method of weather forecasting that utilizes a set of equations that describe the flow of fluids. These equations are translated into computer code and use governing equations, numerical methods, configuration of other physical processes and combined with initial and boundary conditions before being run over a domain.

3.7 Artificial Neural Network

A neural network is a computing model whose layered structure look like networked structure of neurons in the brain, with layers of connected nodes. A neural network can learn from data—so it can be trained to identify patterns, classify data, and forecast future events. Here the neurons are train to predict the local weather quantity (Temperature, Humidity, Pressure) with the ECMWF datasets and IMD data.

3.8 Validation of Results

The results from the Local weather quantity which is obtained from ECMWF datasets is validated with the data (Temperature, Humidity, Pressure) obtained from the Indian Meteorological Department.

4. RESULTS AND DISCUSSION

Here we will deal with the discussion about the study area extraction, NDVI map, LST map for Tuticorin District and the LST-NDVI scatter plot for the year 2018.

4.1 Extraction of Tuticorin Boundary

The study area extraction boundary of from satellite image was prepared. Figure 4,5 represents the Landsat 8 satellite image of the study area for the year 2018.

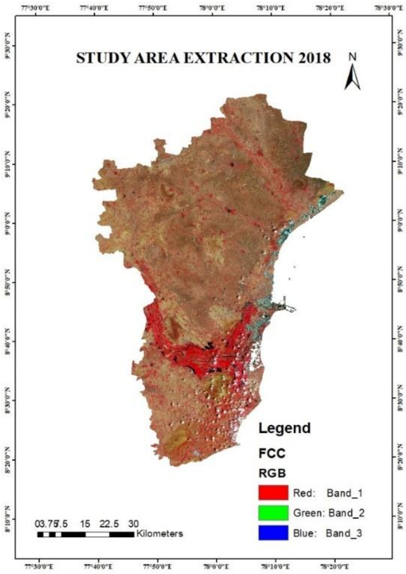

Figure-4: Landsat 8 satellite image of study area for the year 2018

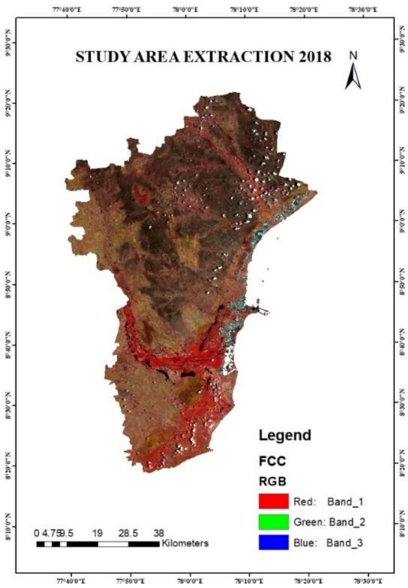

Figure-5: Landsat 8 satellite image of study area for the year 2018

4.2 Normalize Difference Vegetation Index

Low values (0.1 or less) of the NDVI function correspond to empty areas of rocks, sand or snow. Moderate values (from 0.2 to 0.3) represent shrubs and meadows, while high values (from 0.6 to 0.8) indicate temperate and tropical forests. NDVI for the study area is generated using the equation 1. Figure 6,7 represents the NDVI of the study area for the year 2018.

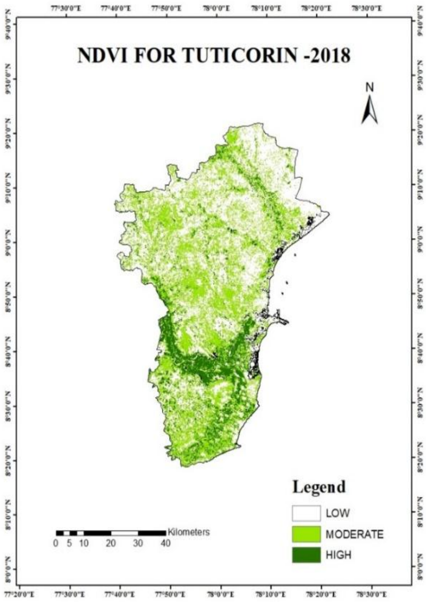

Figure-6: Spatial map of NDVI for the year 2018

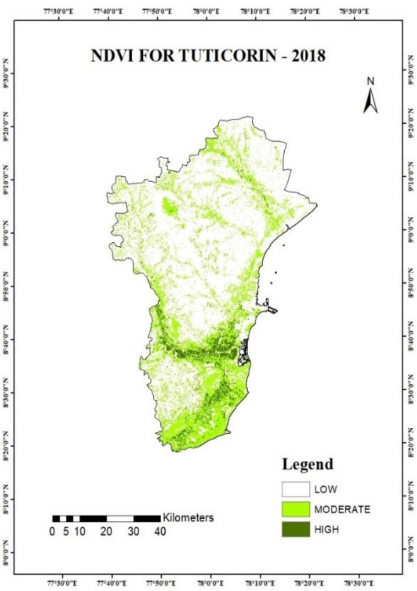

Figure-7: Spatial map of NDVI for the year 2018

4.3 Land Surface Temperature

By using the equation 7, we can be able obtain LST for the year 2018. The Spatial map of Land Surface Temperature for the year 2018 are given below in fig 8,9.

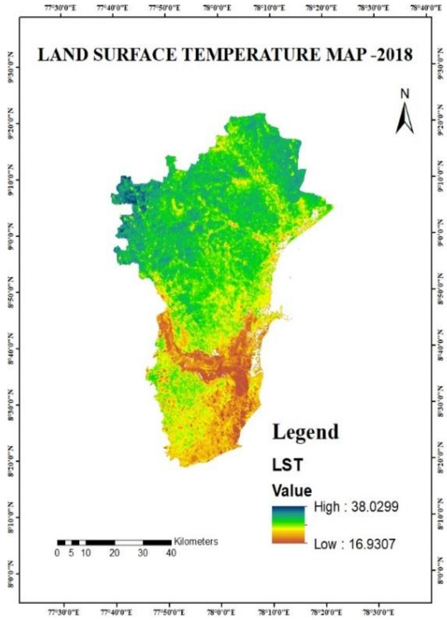

Figure-8: Spatial map of LST for the year 2018

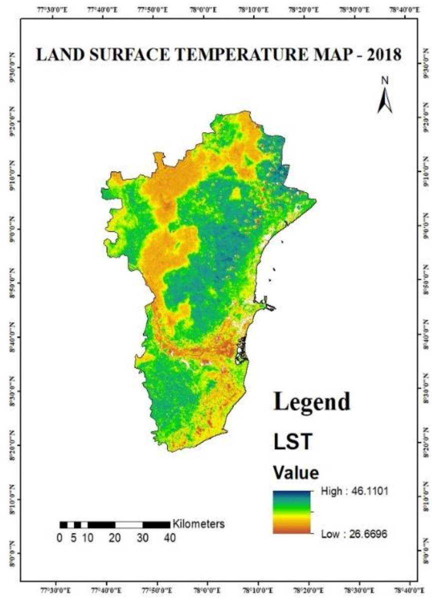

Figure-9: Spatial map of LST for the year 2018

4.4 LST/NDVI Scatter Plots

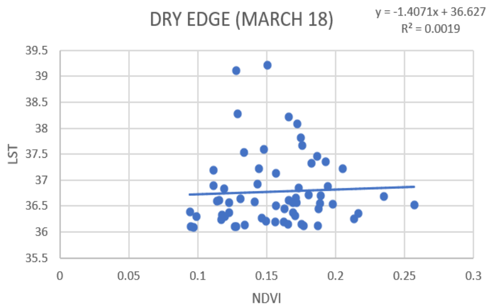

Figure-10: LST/NDVI scatter plot (dry edge) for the year 2018

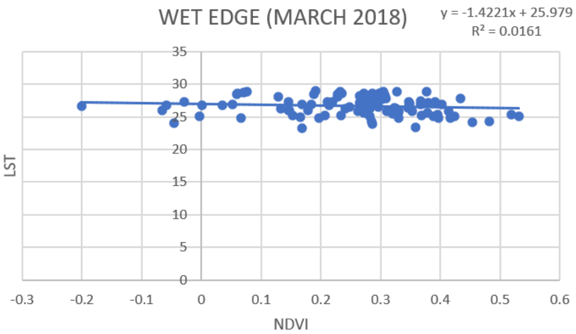

Figure-11: LST/NDVI scatter plot (wet edge) for the year 2018

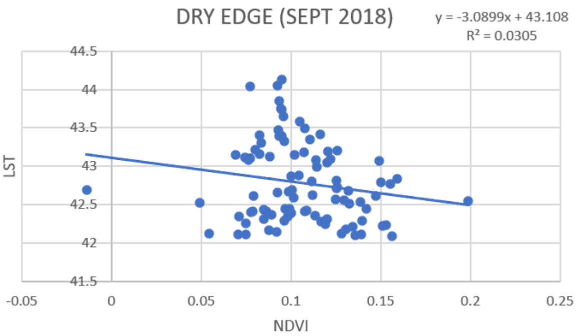

Figure-12: LST/NDVI scatter plot (dry edge) for the year 2018

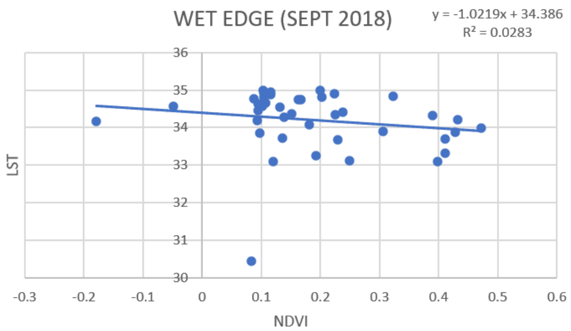

Figure-13: LST/NDVI scatter plot (wet edge) for the year 2018

Figure 10,11,12 & 13 represents LST/NDVI scatter plot (dry edge & wet edge) of the study area for the year 2018.

Table-1: Dry edges and wet edges in the LST/NDVI space for the year 2018

Dry edge	**March 03,2018**	**September 11, 2018**
LST_{max}	-1.4071 (NDVI)+36.627	-3.0899 (NDVI)+43.108
R^2	0.0019	0.0305
Wet edge	**March 03,2018**	**September 11, 2018**
LST_{min}	-1.4221 (NDVI)+25.979	-1.0219 (NDVI)+34.386
R^2	0.0161	0.0283

4.4 Temperature Vegetation Dryness Index

By using the equation 8 and 9, we can be able obtain TVDI for year 2018. The Spatial map of Temperature vegetation dryness index are given below in fig 14 & 15.

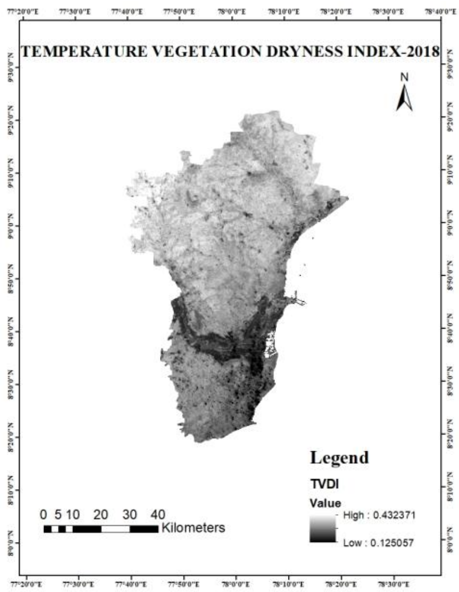

Figure-14: Spatial map of TVDI for the year 2018

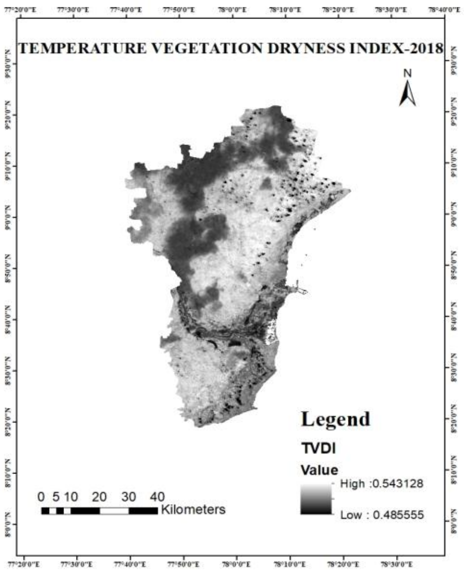

Figure-15: Spatial map of TVDI for the year 2018

4.5 LST/TVDI Scatterplots

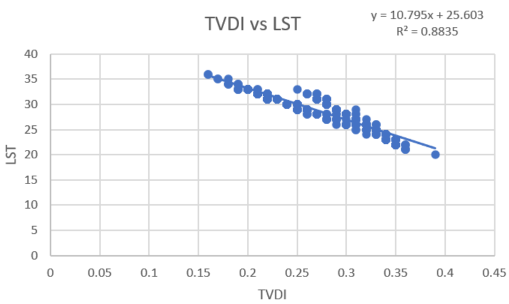

Figure -16: LST/TVDI scatter plot for the year 2018

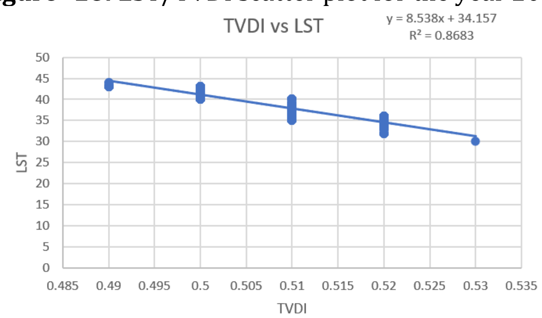

Figure -17: LST/TVDI scatter plot for the year 2018

Figure 16 & 17 represents LST/TVDI scatter plot (dry edge & wet edge) of the study area for the year 2018.

Table-2: LST/TVDI space for the year 2018

S.NO	DATE	SURFACE SOIL MOISTURE
1	March 03, 2018	**SSM**=10.795 (TVDI)+25.603 R^2= 0.8835
2	September 11,2018	**SSM**=8.538 (TVDI)+34.157 R^2= 0.8683

4.6 Surface Soil Moisture

Surface soil moisture is the water that is present in the upper 10 cm of soil. Surface soil moisture for each year was derived from the satellite images using the equation which is mentioned in the table 2. The spatial maps of the Surface soil moisture for the year 2018 are given below fig 18 & 19.

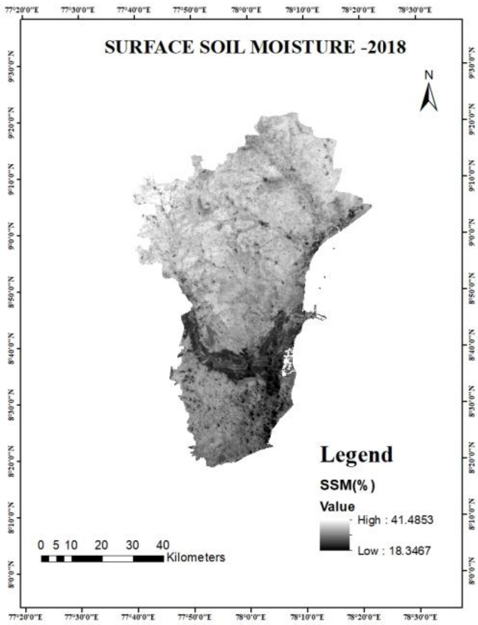

Figure-18: Spatial map of SSM for the year 2018

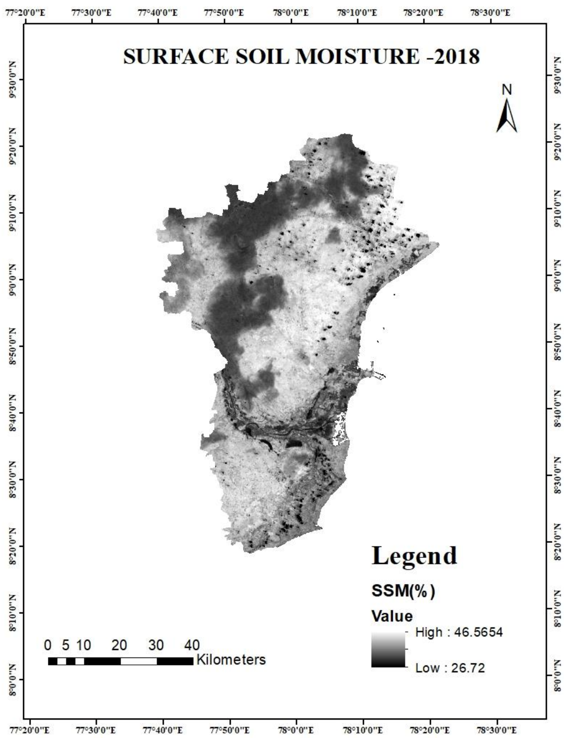

Figure-19: Spatial map of SSM for the year 2018

4.7 Model Generated to Predict Surface Soil Moisture

Table -3: Prediction of Surface soil moisture

Date	Output from the model	R value	R^2 value
March 03, 2018	Output=1*Target+0.038	0.99823	0.996431
September 11, 2018	Output=0.94*Target+2	0.99308	0.986207

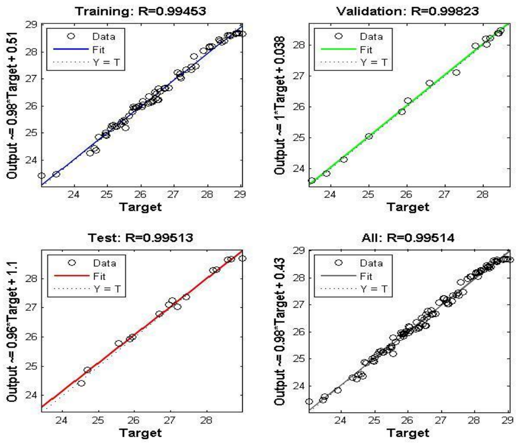

Figure-20: Prediction of Surface soil moisture for the year 2018

Figure 20 represents the results obtained from the prediction of Surface soil moisture for the year 2018.

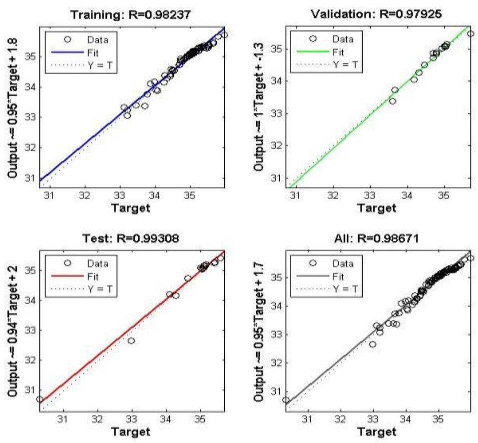

Figure-21: Prediction of Surface soil moisture for the year 2018

Figure 21 represents the results obtained from the prediction of Surface soil moisture for the year 2018.

4.8 Datasets from ECMWF

The datasets were retrieved in NetCDF format from ECMWF and converted to raster layer using Arc Map. The raster layer for Temperature, Humidity and Surface pressure for the year 2018 are given below fig 22,23,24,25,26 & 27.

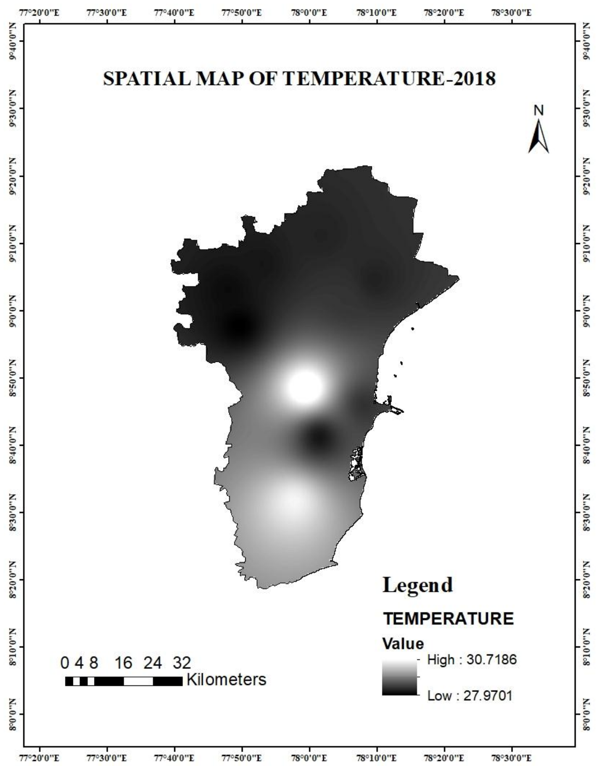

Figure -22: Spatial map of Temperature for the year 2018

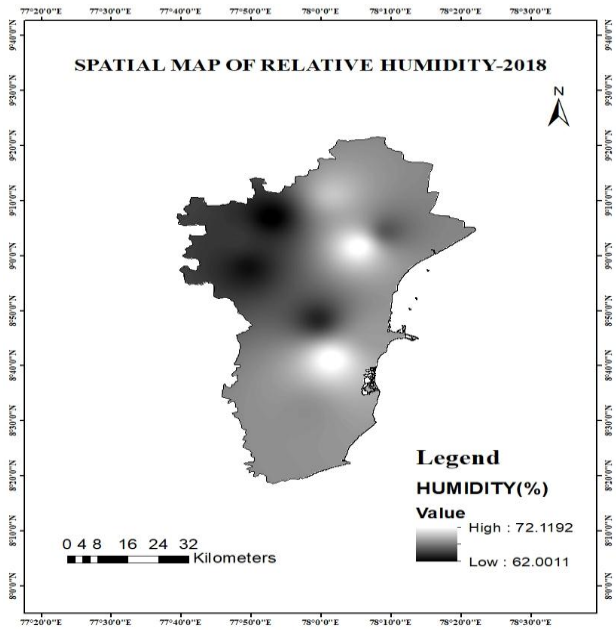

Figure -23: Spatial map of Relative Humidity for the year 2018

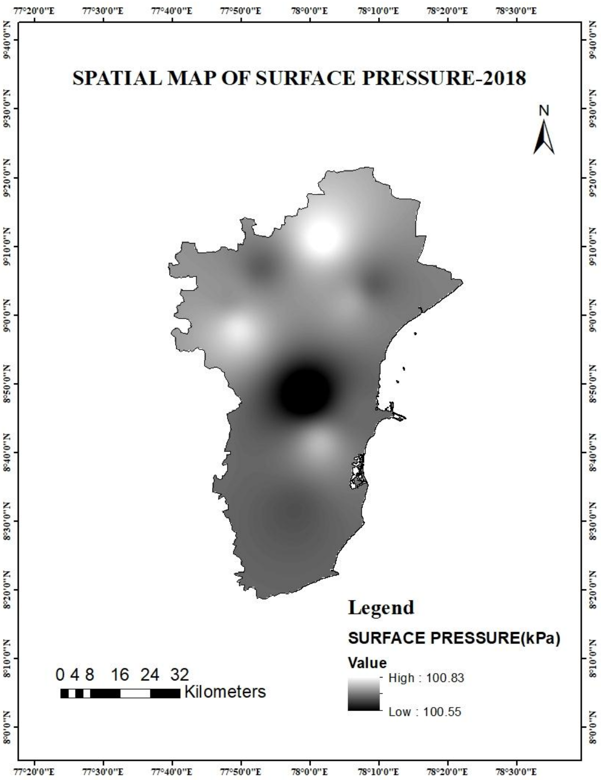

Figure -24: Spatial map of Surface Pressure for the year 2018

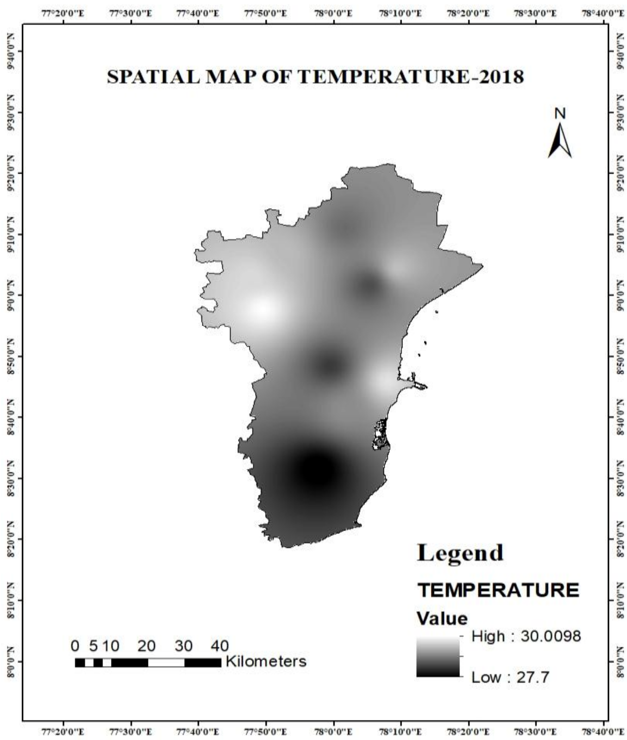

Figure -25: Spatial map of Temperature for the year 2018

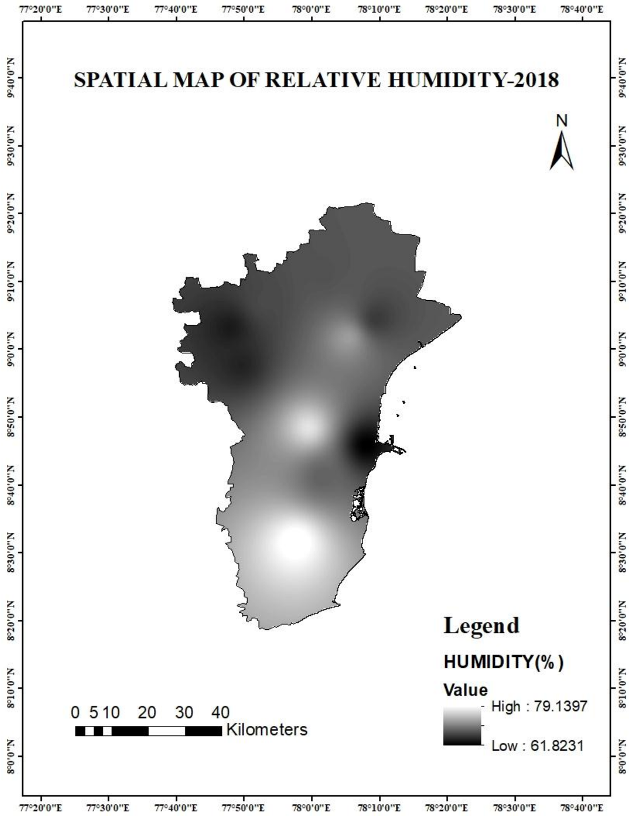

Figure -26: Spatial map of Relative Humidity for the year 2018

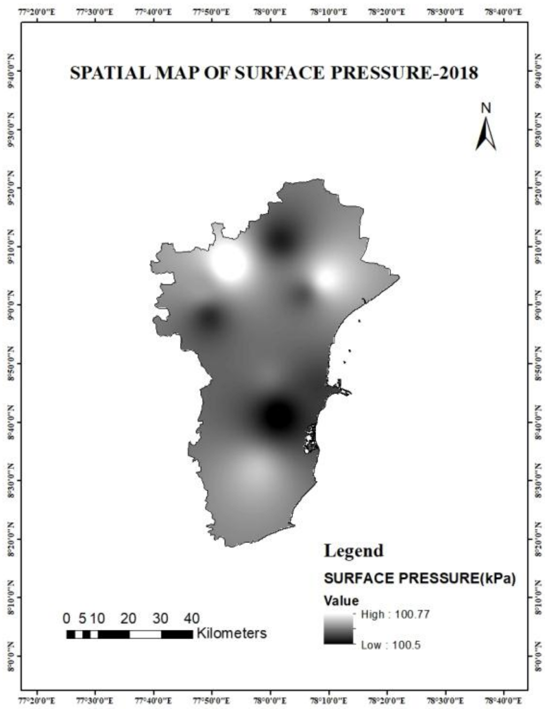

Figure -27: Spatial map of Surface Pressure for the year 2018

4.9 Model Generated using the dataset obtained from ECMWF

The results obtained from the Numerical Weather Prediction model using the datasets from ECMWF is given below in fig 28,29,30,31,32 & 33.

4.9.1 Numerical Weather Prediction model using the Temperature data from ECMWF

Output mentioned in the table 4 represents Temperature and target represents Surface soil moisture, Relative Humidity and Surface Pressure. By this set of equations we can be able to understand the influence of Surface soil moisture, Relative Humidity and Surface Pressure in Temperature. The results obtained from the Numerical Weather Prediction model using the Temperature from ECMWF is given in the table 4.

Table-4: Numerical Weather Prediction using the Temperature data obtained from ECMWF (2018)

Date	Output from the model	R value	R^2 value
March 03, 2018	Output=1.2*Target+0.21	0.93433	0.8729
September 11, 2018	Output=0.45*Target+55	0.68188	0.4649

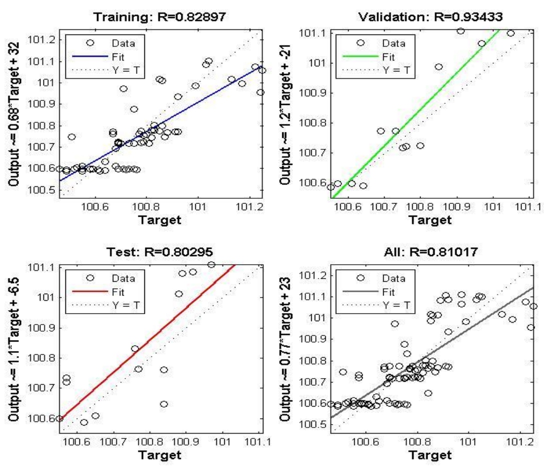

Figure -28: Prediction using Temperature data from ECMWF 2018

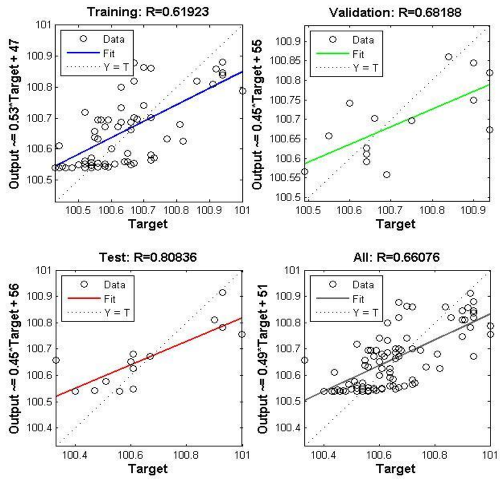

Figure -29: Prediction using Temperature data from ECMWF 2018

4.9.2 Numerical Weather Prediction model using the Relative Humidity data from ECMWF

Output mentioned in the table 5 represents Relative Humidity and target represents Surface soil moisture, Temperature and Surface Pressure. By this set of equations we can be able to understand the influence of Surface soil moisture, Temperature and Surface Pressure in Relative Humidity. The results obtained from the Numerical Weather Prediction model using the Relative Humidity from ECMWF is given in the table 5.

Table-5: Numerical Weather Prediction using the Relative Humidity data obtained from ECMWF (2018)

Date	Output from the model	R value	R^2 value
March 03, 2018	Output=0.17*Target+57	0.84926	0.72124
September 11, 2018	Output=0.49*Target+38	0.8419	0.7087

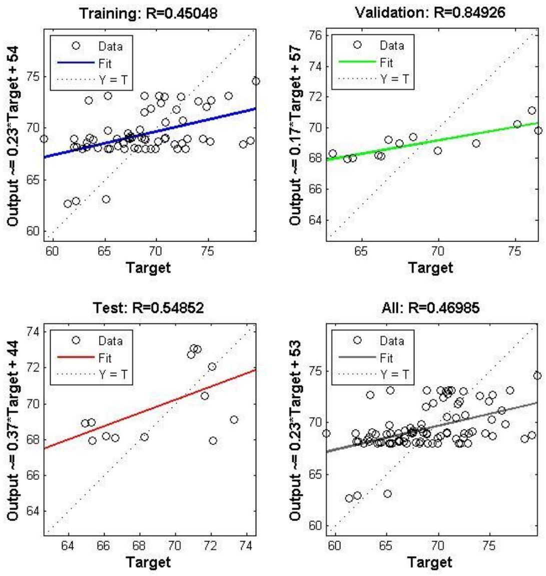

Figure -30: Prediction using Relative Humidity data from ECMWF 2018

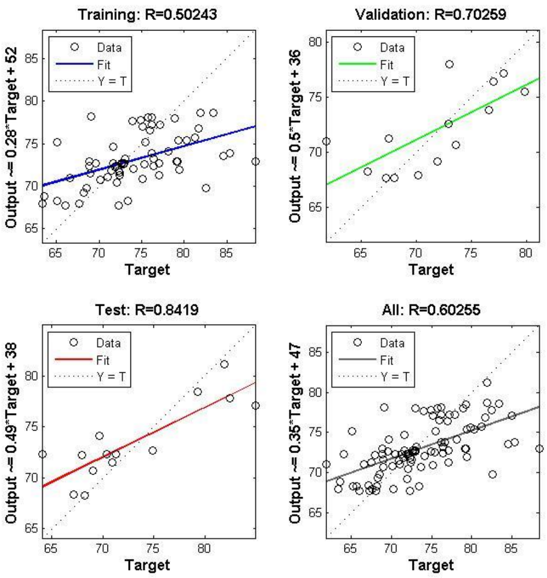

Figure -31: Prediction using Relative Humidity data from ECMWF 2018

4.9.3 Numerical Weather Prediction model using the Surface Pressure data from ECMWF

Output mentioned in the table 6 represents Surface Pressure and target represents Surface soil moisture, Temperature and Relative Humidity. By this set of equations we can be able to understand the influence of Surface soil moisture, Temperature and Relative Humidity in Surface Pressure. The results obtained from the Numerical Weather Prediction model using the Surface Pressure from ECMWF is given in the table 6.

Table-6: Numerical Weather Prediction using the Surface Pressure data obtained from ECMWF (2018)

Date	Output from the model	R value	R^2 value
March 03, 2018	Output=0.85*Target+4.1	0.93106	0.86687
September 11, 2018	Output=0.57*Target+12	0.80242	0.6438

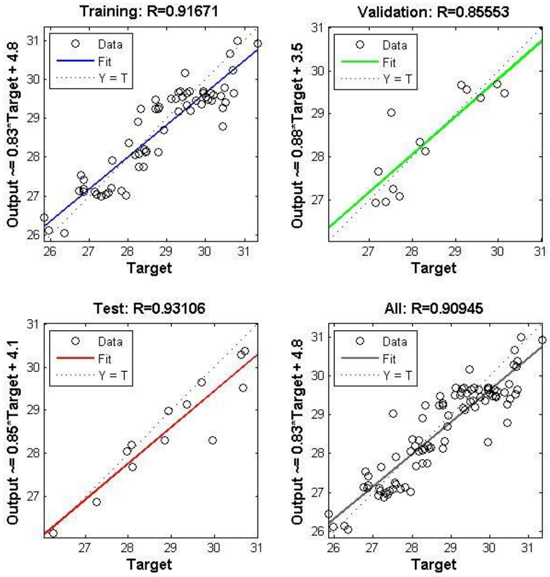

Figure -32: Prediction using Surface Pressure data from ECMWF 2018

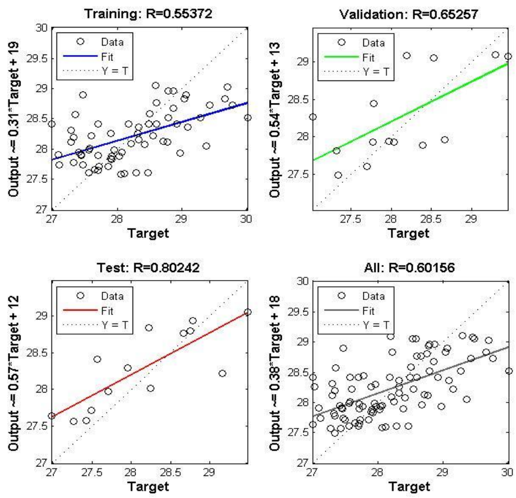

Figure -33: Prediction using Surface Pressure data from ECMWF 2018

4.10 Model Generated using the field data obtained from IMD

The results obtained from the Numerical Weather Prediction model using the data from IMD is given below in fig 34,35,36,37,38 & 39.

4.10.1 Numerical Weather Prediction model using the Temperature data from IMD

Output mentioned in the table 7 represents Temperature and target represents Surface soil moisture, Relative Humidity and Surface Pressure. By this set of equations we can be able to understand the influence of Surface soil moisture, Relative Humidity and Surface Pressure in Temperature. The results obtained from the Numerical Weather Prediction model using the Temperature from IMD is given in the table 7.

Table-7: Numerical Weather Prediction using the Temperature data obtained from IMD (2018)

Date	Output from the model	R value	R^2 value
March 03, 2018	Output=1.2*Target+4.9	0.98271	0.96571
September 11, 2018	Output=0.7*Target+8.5	0.98235	0.965011

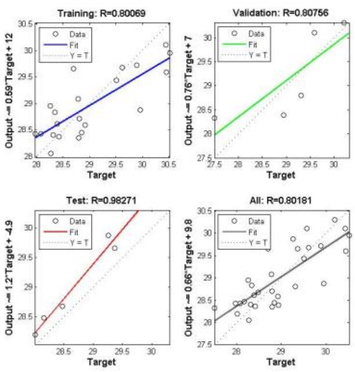

Figure -34: Prediction using Temperature data from IMD 2018

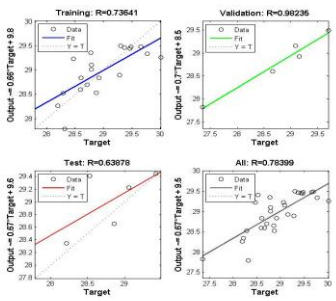

Figure -35: Prediction using Temperature data from IMD 2018

4.10.2 Numerical Weather Prediction model using the Relative Humidity data from IMD

Output mentioned in the table 8 represents Relative Humidity and target represents Surface soil moisture, Temperature and Surface Pressure. By this set of equations we can be able to understand the influence of Surface soil moisture, Temperature and Surface Pressure in Relative Humidity. The results obtained from the Numerical Weather Prediction model using the Relative Humidity from IMD is given in the table 8.

Table-8: Numerical Weather Prediction using the Relative Humidity data obtained from IMD (2018)

Date	Output from the model	R value	R^2 value
March 03, 2018	Output=0.74*Target+20	0.91471	0.83669
September 11, 2018	Output=0.75*Target+17	0.96706	0.93520

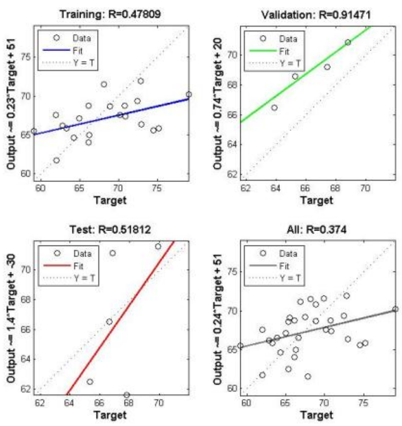

Figure -36: Prediction using Relative Humidity data from IMD 2018

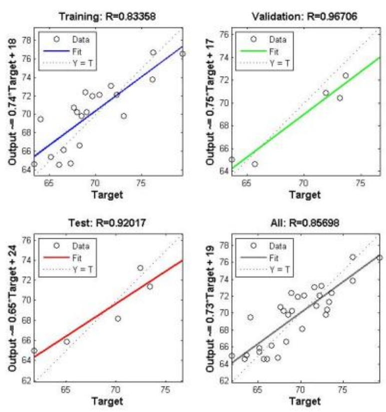

Figure -37: Prediction using Relative Humidity data from IMD 2018

4.10.3 Numerical Weather Prediction model using the Surface Pressure data from IMD

Output mentioned in the table 9 represents Surface Pressure and target represents Surface soil moisture, Temperature and Relative Humidity. By this set of equations we can be able to understand the influence of Surface soil moisture, Temperature and Relative Humidity in Surface Pressure. The results obtained from the Numerical Weather Prediction model using the Surface Pressure from IMD is given in the table 9.

Table-9: Numerical Weather Prediction using the Surface Pressure data obtained from IMD (2018)

Date	Output from the model	R value	R^2 value
March 03, 2018	Output=0.74*Target+26	0.94231	0.88794
September 11, 2018	Output=0.47*Target+54	0.96415	0.92958

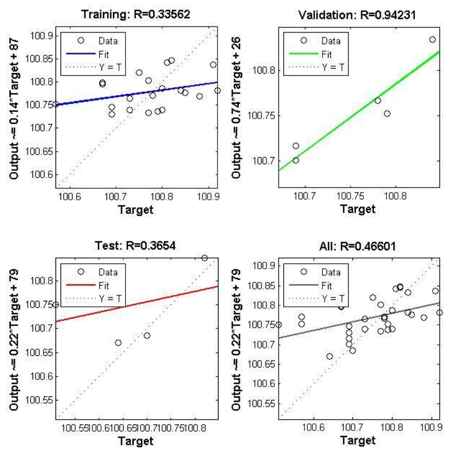

Figure -38: Prediction using Surface Pressure data from IMD 2018

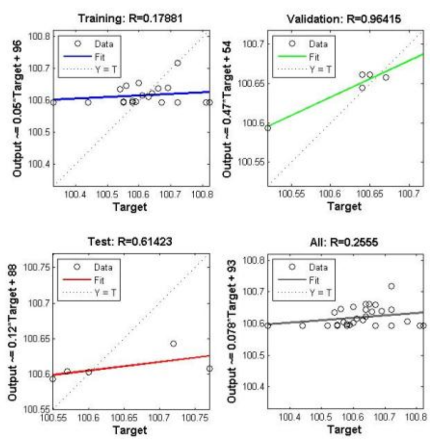

Figure -39: Prediction using Surface Pressure data from IMD 2018

4.11 Output Validation

The output obtained from the model generated for satellite-derived datasets from ECMWF and field data from IMD are validated. They are validated to check the accuracy of the model generated.

Table-10: Comparison of NWP model for Temperature data obtained from ECMWF and IMD (2018)

March 03, 2018	Output=1.2*Target+0.21 R=0.93433 R^2=0.8729	Output=1.2*Target+ 4.9 R=0.98271 R^2=0.96571
Sep11, 2018	Output=0.45*Target+55 R=0.68188 R^2=0.4649	Output=0.7*Target+ 8.5 R=0.98235 R^2=0.965011

From the table 10 Comparison of NWP model for Temperature data obtained from ECMWF and IMD for the year 2018 is done. The results from both the models are fairly similar.

Table-11: Comparison of NWP model for Relative Humidity data obtained from ECMWF and IMD (2018)

March 03, 2018	Output=0.17*Target+57 R=0.84926 R^2=0.72124	Output=0.74*Target+20 R=0.91471 R^2=0.83669
Sep11, 2018	Output=0.49*Target+38 R=0.8419 R^2=0.7087	Output=0.75*Target+17 R=0.96706 R^2=0.93520

From the table 11 Comparison of NWP model for Relative Humidity data obtained from ECMWF and IMD for the year 2018 is done. The results from both the models are fairly similar.

Table-12: Comparison of NWP model for Surface Pressure data obtained from ECMWF and IMD (2018)

Mar 03	Output=0.85*Target+4.1 R=0.93106 R^2=0.86687	Output=0.74*Target+26 R=0.94231 R^2=0.88794
Sep 11	Output=0.57*Target+12 R=0.80242 R^2=0.6438	Output=0.47*Target+54 R=0.9415 R^2=0.92958

From the table 12 Comparison of NWP model for Surface Pressure data obtained from ECMWF and IMD for the year

2018 is done. The results from both the models are fairly similar.

5. CONCLUSIONS

In the present study various indices (LST, NDVI) were derived from the satellite data for the year 2018. These indices were used and graph was plotted. From the plotted graph Triangle method was used and Temperature Vegetation Dryness Index was derived. These three indices were used to calculate the surface soil moisture for the study area. The datasets for predicting local weather were obtained from ECMWF. The datasets are the variable (Temperature, Relative Humidity, Surface Pressure) which influences the local weather. With these variables prediction of local weather was done. In order to know which variable influences the local weather Numerical weather prediction model was developed using Artificial Neural network. NWP model was developed for both the datasets obtained from ECMWF and IMD. Validation of results from both the model were done in order to check the accuracy. From the results obtained from both the models, we can be able to know that these three variable (Temperature, Relative Humidity, Surface Pressure) influences the local weather.

REFERENCES

[1] Anandababu D, B M Purushothaman, Babu, S. Suresh "Estimation of Land Surface Temperature using LANDSAT 8 Data" International Journal of Advance Research, Ideas and Innovations in Technology 2018.

[2] Drusch.M "Initializing numerical weather prediction models with satellite-derived surface soil moisture: Data assimilation experiments with ECMWF's Integrated Forecast System and the TMI soil moisture data set" journal of geophysical research, vol. 112, d03102, doi:10.1029/2006JD007478, 2007

[3] Farid.S F. Mojtahedi, Ali Khosravi, Behnaz Naeimian, S. Adel A. Hosseini Comparison of Different Techniques to Estimate Surface Soil Moisture" World Academy of Science, Engineering and Technology International Journal of Geological and Environmental Engineering Vol:11, No:2, 2017

[4] George P. Petropoulos, Gareth Ireland, Brian Barrett "Surface soil moisture retrievals from remote sensing: Current status,products & future trends Physics and Chemistry of the Earth xxx (2015) xxx–xxx

[5] Gillies.R.R , W. P. Kustas & K. S. Humes "A verification of the 'triangle' method for obtaining surface soil water content and energy fluxes from remote measurements of the Normalized Difference Vegetation Index (NDVI) and surface International Journal of Remote Sensing, 18:15, 3145-3166 (2015).

[6] Gutman.G & A. Ignatov "The derivation of the green vegetation fraction from NOAA/AVHRR data for use in numerical weather prediction models" International Journal of Remote Sensing, 19:8, 1533-1543

[7] Inge Sandholta, Kjeld Rasmussena, Jens Andersenb "A simple interpretation of the surface temperature/vegetation index space for assessment of surface moisture status" (2001) Remote Sensing of Environment 79 (2002) 213–224.

[8] Jana Sillmann, Thordis Thorarinsdottir, Noel Keenlyside, Nathalie Schaller, Lisa V. Alexander, Gabriele Hegerl , Sonia I. Seneviratne , Robert Vautard ,Xuebin Zhang , Francis W. Zwiers "Understanding, modeling and predicting weather and climate extremes: Challenges and opportunities" Weather and Climate Extremes 18 (2017) 65–74

[9] Jose´ A. Sobrino, Juan C. Jime´nez-Mun˜oz, Leonardo Paolini "Land surface temperature retrieval from LANDSAT TM 5" Remote Sensing of Environment 90 (2004) 434–440 (2004).

[10] Shulin Chen, Zuomin Wen ,Hong Jiang , Qingjian Zhao , Xiuying Zhang and

[11] Yan Chen "Temperature Vegetation Dryness Index Estimation of Soil Moisture under Different Tree Species" Sustainability 2015, 7, 11401-11417; doi:10.3390/su70911401.

[12] Thies.B and Jorg Bendix "Satellite based remote sensing of weather and climate: recent achievements and future perspectives METEOROLOGICAL APPLICATIONS Meteorol. Appl. 18: 262–295 (2011).

[13] Toby Carlson "An Overview of the "Triangle Method" for Estimating Surface Evapotranspiration and Soil Moisture from Satellite Imagery" Sensors 2007, 7, 1612-1629.

[14] Xiaohang Wen, Shihua Lyu "Integrating Remote Sensing Data with WRF for Improved Simulations of Oasis Effects on Local Weather Processes over an Arid Region in Northwestern China" Journal of Hydrometeorology · April 2012.

[15] Zhaofei Liu, Zhijun Yao and Rui Wang "Evaluating the surface temperature and vegetation index (Ts/VI) method for estimating surface soil moisture in heterogeneous regions" (2018).

[16] Zhiqiang Gao, Wei Gao, Ni-Bin Chang "Integrating temperature vegetation dryness index (TVDI) and regional water stress index (RWSI) for drought assessment with the aid of LANDSAT TM/ETM+images. International Journal of Applied Earth Observation and Geoinformation 13 (2011) 495–503 (2010).