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Ndvi Based Crop Response with Lst and Spi for Vegetation Quality Analysis

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Abstract : Drought, the influencing phenomenon which affects the overall environment in every aspect. It is classified into various types since it is applied to a various sector like agricultural, meteorological and hydrological sectors. Agricultural drought monitoring has a huge impact in the field of agriculture and it helps to better decision-making, which results in an increase in yield and prevents from losses. In this study, Standard Precipitation Index (SPI) and Land Surface Temperature (LST) has been analyzed for the Gingee river basin and their influence on different crop heath (by Normalized Difference Vegetation Index) has been identified by Correlation and regression for Pre-monsoon.

Keywords: Drought, Crop health, LST, SPI, and NDVI.

I. INTRODUCTION

Drought, the alarming phenomenon which impacts every component in the ecosystem, and its effects are severe in nature. Drought for a particular location can be analyzed with the help of data like Temperature, Relative Humidity, and wind. [2] Agricultural drought is defined as the loss of soil moisture, which leads to poor yield. The loss of soil moisture is due to various aspects like poor rainfall, an increase in temperature, etc., [3][4] In order to identify agricultural drought, various methods have been introduced. In this study, Standard Precipitation Index and Land Surface Temperature for different crop health during pre-monsoon have been computed with Normalized Difference Vegetation Index. [5] Also, with the obtained data, the statistical modeling (Correlation and Regression) has been done to identify the condition of the crop in the study area, which gets high influence/tolerance with SPI and LST. Such that, those crops are cultivable for the Pre-monsoon condition (Season), thereby increasing the crop production.

Study area

Gingee sub-river basin covers approx. 900 sq.km of Villupuram District of Tamil Nadu. Puducherry district along Gingee stream between 11.9416° N, 79.8083° E. The annual rainfall of Puducherry and Villupuram more or less similar and they vary in the range of 800-1200mm.

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The main drain is Gingee River originates from Villupuram and flows along Puducherry inside the delineated sub-watershed and it is transient in nature.[6] Also, there are several water bodies (like lakes, ponds, etc.,) which are used for irrigation and influence on better crop conditions for (growth and health). Crops like Cashew, Mango, Coconut, Amla are present in the subbasin. The study area is shown in figure 1 as follows,

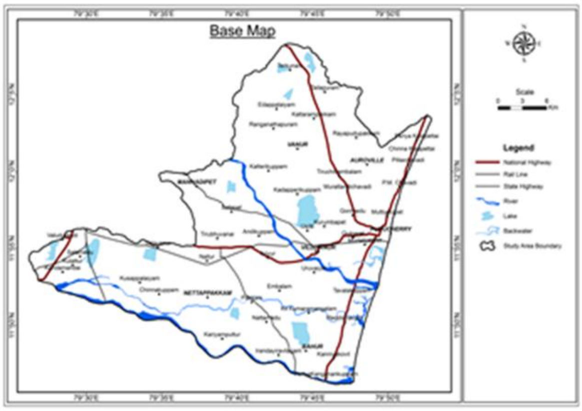

Fig 1 Base map of the study area

II. DATASET AND METHODOLOGY

Satellite data

The Landsat 8 satellite is viewing the entire Earth's surface every 18 days, acquiring data, in the wavelengths covering the visible light, near infrared, middle infrared and thermal infrared. Hence, these data can be extracted for every year in Pre-monsoon and northeast monsoon condition without any cloud cover.

Rainfall data for SPI

Daily rainfall data from 2013 were used for SPI computation. This Monthly rainfall data of 3 stations of 5 years the meteorological data are from Pondicherry government. Crop Location points are taken manually with GPS and were mentioned below in table 1 as follows,

Table 1 Crops with location details

Crop	Latitude	Longitude
CASHEW	11.9913°	79.82201°
AMLA	11.93879°	79.76512°
MANGO	11.93827°	79.76537°

WETLAND VEGETATION	11.93227°	79.76921°
COCONUT	11.9529°	79.72084°

Methodology

The satellite data are acquired for 2018 in the pre-monsoon period because the study area is affected by both drought and flood condition. The SPI was calculated from only rainfall, which elucidates the water availability of the area. The 3 meteorological observatories were used for SPI and computed for short-time range (i.e.,) 3-month SPI, and 6-month SPI, which is more suitable for analyzing Agricultural Drought[7]. Also, LST is estimated in Figure 2.

Standard Precipitation Index (SPI)

In order to assess drought, SPI is recommended by the World Meteorological Organization. It is the better index which helps to analyze drought with the help of precipitation data. Based on the timescale range, SPI helps to elucidate soil moisture (short timescale range) and storage conditions of reservoir and groundwater (Long timescale range) of any region[8]. SPI is the simple index, which only needs precipitation data and it is also the limitation since it does not consider other parameters (like Evapotranspiration, temperature, wind,etc.,) Influencing drought. SPI quantifies the rainfall (either surplus or deficit) for different timescales. If the obtained value is positive, then there is no drought and if it is in negative, it indicates drought. SPI helps to take precautionary measures with its probabilistic nature, such that the impacts of drought can be minimized The values, 2.0+ = Very wet, 1.5 to 1.99 = Actual wet, 1.0 to 1.49 is Moderately wet, -.99 to .99 is Near normal, -1.0 to -1.49 is Moderately dry, -1.5 to -1.99 is Harshly dry and -2 and less is Extremely dry. [9]

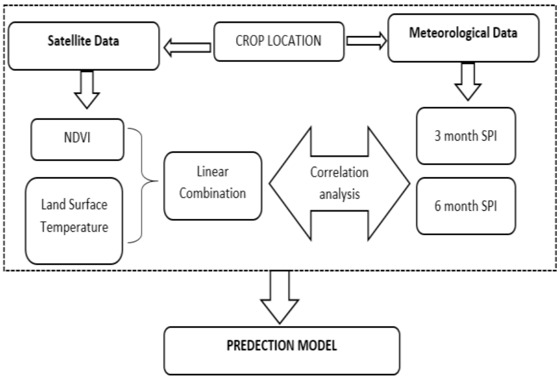

Fig 2: Methodology Flow chart

Estimation of Land Surface Temperature

Land Surface Temperature is estimated by the single window method[2]. Previous studies show the different ways for recovering LST from Thematic data in order to subsidize more employment of this band of 10 and 11 in the future. Three different single-channel methods were analyzed [10][4]. In this study, the estimation of LST by single window method was done for quality estimation with pre-monsoon acquired data of 2018.

Top of Atmospheric Spectral Radiance.

The top starting step for estimating LST algorithm is the input of band 10 or Band 11 (Thermal Bands). After entering the band, in the background, the formulas were taken from the earth explore web page for retrieving the top of atmospheric (TOA) *spectral radiance* ($L\lambda$) are mentioned in Equation 1

$$L\lambda = ML * Q\text{cal} + AL - Oi, \qquad (1)$$

Where ML signifies the band-specific fixed rescaling factor, Qcal is the Band 10 / 11 image, AL is the band-specific continuous improver rescaling factor, and Oi is the correction for Band 10 / 11

Conversion of Radiance to At-Sensor Temperature.

After the digital numbers (DNs) values are converted to reflection, the brightness temperature (BT) from the band 10/11, TIRS data should be converted from spectral radiance using the value of the thermal constant provided by the server in the metadata file. The following equation is for Thermal constant (BT) with Band 10.1 = 1321.08, $K2$ =777.89, rescaling factor of Band 10 is ML = 0.000342, AL= 0.1 and Correction Band 10 is Oi = 0.29, simultaneously same kind of factor present for band 11 the following equation 2 is denoting of Brightness temperature.

$$BT = \frac{K2}{\ln\left[\left(\frac{K1}{L\lambda}\right)+1\right]} - 273.15 \qquad (2)$$

Where $K1$ and $K2$ is constant band-specific thermal conversion constants from the metadata file. For finding the outcomes in Celsius, the radiant temperature is revised by adding the absolute zero (approx. −273.15∘ C)

NDVI Method for Emissivity Correction

Normal Difference Vegetation Index (NDVI) was calculated by Landsat Blue, Green, Red bands (Visible bands) and near-infrared bands. The NDVI is calculated to assess for the amount of vegetation present in a particular vegetation factor and also analysis of general vegetation condition by equation 1.[11] The calculation of the NDVI is important because, *the proportion of the vegetation* (*PV*) can be computed, and they are highly related with the NDVI, and emissivity (ε) should be calculated, which is related to the P_V.

$$\text{NDVI} = \frac{\text{NIR (band 5)} - \text{R (band 4)}}{\text{NIR (band 5)} + \text{R (band 4)}} \qquad (3)$$

Calculating the *Proportion of Vegetation*, P_V using the NDVI values ($NDVI_V$ = 0.5 and $NDVI_s$ = 0.2) of v and "s" are vegetation value and soil value should applied in varied

situations, in equation number 4

$$Pv = \left(\frac{NDVI - NDVIs}{NDVIv - NDVIs}\right)^2 \quad (4)$$

However, since the NDVI values changes for every area and source availability, the value for vegetated surfaces is 0.5, may low of vegetation content. Wide values from NDVI can be calculated from at-surface reflectivity, but it not be possible in the case of an NDVI computed from TOA reflectivity since $NDVI_V$ and $NDVI_s$ will depend on the atmospheric conditions.

Calculating Land Surface Emissivity.

The land surface emissivity (LSE (ε)) is the most important for the assessment of LST, since the LSE (land surface emissivity) is an independent feature that scales blackbody radiance (Planck's law) to forecast estimate reflectant radiance, and the effectiveness of transferring thermal energy across the surface area into the atmosphere. The determination of the ground emissivity is calculated conditionally is shown in equation 5,

$$\lambda = \varepsilon_{V\lambda} P_V + \varepsilon_{s\lambda}(1 - P_V) + C_\lambda, \quad (5)$$

Where ε_V and ε_s are the vegetation cover and soil emissivity, and C represents the surface irregularity (C = 0 for similar and flat surfaces) taken as a constant value of 0.005. The condition can be represented with the following formula of LST and the emissivity constant. When the NDVI is less than 0, it is defined as water, and the emissivity value of nearly about 0.991 is allocated. The values between 0 and 0.2, of NDVI it is reflected that with soil, and the emissivity value of 0.996 is assigned. Values between 0.2 and 0.5 are considered mixtures of soil and vegetation cover and are applied to retrieve the emissivity. In the last case, when the NDVI value is greater than 0.5, it is considered to be covered with good vegetation, and the value of 0.973 is assigned. The last step of retrieving the LST or the emissivity corrected land surface temperature Ts, is computed using following equation 6,

$$T_S = \frac{BT}{\{1 + [(\frac{\lambda BT}{\rho}) \ln \varepsilon_\lambda]\}} \quad (6)$$

Where Ts is the LST in Celsius (° C), BT is at-sensor BT (° C), λ is the wavelength radiance (for which the peak response and the average of the limiting wavelength (λ = 10.895) will be used), $\varepsilon\lambda$ is the emissivity calculated in following equation of 7

$$\rho = h + \frac{c}{\sigma} = 1.438 \text{ X } 10^{-2} mK \quad (7)$$

Where σ is the Boltzmann constant (1.38 × 10−23 J/K), h is Planck's constant (6.626 × 10−34 J s), and c is the velocity of light (2.998 × 108 m/s

NDVI Analysis

Normalized differentiation vegetation index (NDVI), were estimated in the LST by this condition. NDVI is the dependent variable to estimate how the NDVI responds to the rainfall and Land Surface Temperature[11][12][13] The correlation analysis was done for the short timescale range SPI-3 and 6 with NDVI, and LST with NDVI for selection of which SPI responds better to NDVI to analyze the drought.

III. RESULTS AND DISCUSSION

Correlation between mean SPI, LST with NDVI

Correlation coefficients between different NDVI and SPI 3, 6 shows that it is varied with different crop condition (Figure 4), in every pre-monsoon condition. This means NDVI is not significantly correlated with SPI of all timescales[3][11]. The SPI with timescale 3 is giving the highest correlation for the Cashew, Amla and wetland vegetation. And this crop changes by the NDVI was based on the 3-month timescale. But it is not significant for all crops. On the other hand, SPI with timescale 6-month is giving a negative correlation for all crop condition. SPI 3 and SPI 6 denotes the cumulative rainfall of past three and six months. In most cases, precipitation happening in one month does not adversely affect the vegetation, but the response is monitored over periods of the season. This study shows that NDVI response lag to precipitation was 4–8 weeks and for 3 to 4 months, the correlations did not improve, because the longer 6-month SPIs incline to reduce the variance in the precipitation data and smoothen the SPI values. Pre-monsoon crop monitoring by using NDVI and LST data was based on a corrected dataset derived. NDVI and LST behavior on a yearly basis, through the retrieval of 3 parameters was obtained by linear regression between NDVI and Normalized LST data. Correlation coefficients between different crop's mean NDVI and area mean Land Surface Temperature shows that it was varying with different crop condition (Figure 5). LST shows high correlation with Cashew, mango and wetland vegetation. Water required for the crop like cashew is less, so heat distribution is not a matter more. Mango is a drought tolerant crop since its response to the temperature is less, which grows mainly in the dry land condition. The negatively correlated crop was Amla with -0.01629 and the most negatively least correlation factor was with Wetland vegetation (-0.2086), where LST temperature increase, vapor transpiration will be more and vegetation quality will also less.

Linear regression analysis:

From correlation analysis of LST, SPI-6 month and SPI-3 month, it was found that SPI-3 month shows the strong relationship[14] with values of crops like cashew and Wetland vegetation. In the case of SPI-6 month, an only negative correlation was occurring, so it is not suitable for most of the short time analysis. SPI-6 is mainly used for long term drought analysis. Land Surface Temperature is another main impact factor for analyzing drought. Based on temperature, evaporation will be more. LST of crop shows a positive correlation with coconut, Cashew, and mango. (Table 2)

Table 2: Correlation analysis of SPI 3, SPI6 and LST with crops

Mean Values	*SPI-3 MONTH*	*SPI-6 MONTH*	*LST*
COCONUT- NDVI	-0.3132	-0.464	0.37459
CASHEW- NDVI	0.6183	-0.662	0.57919
AMLA- NDVI	0.2620	-0.426	-0.01629
MANGO- NDVI	-0.4619	-0.157	0.5521
WETLAND VEGETATION- NDVI	0.6580	-0.180	- 0.20868

Linear regression analysis:

Simple Linear regression gives the relationship between the dependent and independent parameter. Hence the SPI - 3 MONTH is used for regressions analysis, as SPI3 as an independent variable and Cashew, Wetland vegetation as the dependent variable.

Table 2 Regression analysis between the best-correlated crop

Crop	**Regression Equation**	**R Square**
Linear Regression with SPI - 3 MONTH		
Cashew	SPI 3 = -0.0291(Cashew NDVI) + 0.3585	0.601
Wetland Vegetation	SPI 3 = 0.0325 (Wetland Vegetation NDVI) + 0.3882	0.533
Linear Regression with LST		
Mango	LST = 0.0102 (Mango NDVI) + 0.1031	0.548
Cashew	LST = -0.0291(Cashew NDVI) + 0.3585	0.601

Based on regressions analysis, cashew crop has more R square (0.601) value with SPI - 3 MONTH value. Next, to this, Wetland vegetation has an R square value = 0.433 (SPI-3). The linear regression between LST, SPI-3, and SPI-6 was shown in Table 2.

The regression analysis between LST and crops shows the most regressed factor was with Cashew, where R square value of 0.5483 was obtained and it clearly denotes that however temperature increases, the cashew crop was sustainable to the drought.

Quality prediction models

Among the Regression and correlation analysis, the Cashew crop has more correlation factor with both[13], [15] [16] NDVI and SPI - 3 MONTH, and the equation were derived with SPI - 3 MONTH and NDVI, where 0.0192 is the Coefficient of LST and -0.219 is the coefficient of SPI - 3 MONTH. With the accuracy of 0.82217 with a standard error of 0.01363. So, with this crop quality prediction can be done with following equation of 8.

Quality(Y) = 0.0192(LST)-0.0219(SPI-3) +0.28322;
Significant = 0.004 (8)

Wetland vegetation shows good correlation with SPI-3, but not with LST. In this case, a single factor analysis was done. The Quality predicted model of Wetland vegetation was given in the below equation, Where Y is the Quality and coefficient of SPI is -2.3469. The accuracy of 0.710 with a standard error of 0.084 was obtained. So, with this equation, wetland vegetation quality prediction can be done with following equation of 8.

Quality (Y) = -2.34569 (SPI-3) + 1.4552; (9)
Significant = 0.0052

The crop mango shows one of the highly significant regression with LST. The quality predicted model of Wetland vegetation was given in the below equation of 10, Where Y is the Quality and coefficient of SPI is -0.02757 with an accuracy of 0.2213 and standard error of 0.0164.

Quality(Y) = -0.2757(SPI-3) + 0.368; (10)

Significant = 0.006

Compare to another prediction model, Mango quality model shows the low accuracy and significant was more than 0.005. So, it is not advised to use for analysis.

IV. CONCLUSION

This study to understand the Crop quality by remote sensing during pre-monsoon of Gingee River basin. The crop grown in this region were majorly the plantation crops, except the few areas. Remote-sensing-based quality analysis was done by NDVI for Pre-monsoon crop condition.

SPI is the major and important short-term Agriculture drought detection with rainfall and Land Surface temperature is the most important

factor derived from a thermal band of the Satellite image. By combining the factors, the crop quality (NDVI) was influenced by LST and SPI–3 and 6 were analyzed. SPI-3 and 6 were correlated with the Mean NDVI of the permanent crop.

In this analysis Wetland vegetation, amla and cashew were the positively correlated crops, where even negative correlation occurred in crops like mango and coconut. Positively correlated crops show a good response to the rainfall[11] Hence if good rainfall occurs, vegetation quality will be good. In SPI-6, all crops were in negative correlation and therefore SPI-6 was not used for further analysis. Also, previous studies mention that SPI-6 applicable for long term analysis. The land surface temperature is another important factor for analyzing the quality of crops. If temperature increases, the evapotranspiration rate will also increase and hence it creates the stress to plant. The LST shows that the positive correlation among the crops like mango and Cashew, where cashew was the more positively correlated crop in both SPI and LST. The regression analysis explained clearly that -0.029 coefficient was influencing the NDVI independent factor and R square was about 0.601. And for Wetland vegetation, the linear regression factor was with R square of 0.533. So, from this above content Wetland vegetation and cashew crop condition can be analyzed by the SPI-3 itself.

In second linear regression factor with LST, the cashew has obtained high regression value of 0.601 and next to that was mango with a value of 0.5482, the cashew was influenced by both LST and SPI-3. So, prediction modeling was done for cashew with a statistical method with high accuracy. Other than this, wetland vegetation and mango do show some accuracy in the predicted model. The future work will be done for the post-monsoon analysis with large parameters like water index and more drought indexes. Since it will enhance the accuracy of crop health prediction model. To obtain good results and interpretation (accuracy), the year-wise data for several decades is needed

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