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1st International Electronic Conference on Remote Sensing
22 June - 5 July 2015

Conference Proceedings Paper – Remote Sensing

Assessing the Impact of Natural Factors on Desertification in Tamilnadu, India using Integrated Remote Sensing

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Abstract: Desertification is one of the major threats to the environment and the global community. Changing climate, deforestation, changing agriculture methods and increasing demand for resources are important drivers of desertification. Due to dependency of human life on land, monitoring and mitigating the desertification effect is getting more attention over the years. The main objective of the study was to assess the impact of natural factors on desertification process on a regional level by using the remotely sensed parameters like TRMM - precipitation, MODIS - Evapotranspiration (PET), MODIS - Net Primary Productivity (NPP), and

ASTER-DEM with the aid of AHP - GIS model. From the above mentioned sensor parameters, the indices like aridity, precipitation, Rain Use Efficiency (RUE), NPP and slope are prepared for 2000-2012. For analytical purpose, the TRMM data were downscaled to 1km spatial resolution to match the spatial scale of the other parameters. All the parameters were classified using the frequency distribution. Based on the classes, ranks were assigned. The weight of the parameters were assigned based upon the expert's opinions gathered through a questionnaire- based survey. We converted each data into an annual scale for time series analysis. Results showed that 18.17% of the state is characterized by highly sensitive to desertification which is the southeast part of the state. 9.26% comes under the very high sensitive area. Most of the area comes under the moderate sensitive area (63.93%) and 3.84% comes under the low sensitive area. The very low sensitive area exhibits only 4.8 %, which is the hilly region of the study area. We discuss the impact of climatic, vegetation and topography parameters on desertification in the study area.

Keywords: Desertification; MODIS; TRMM; NPP; RUE; AHP; Quantification of desertification; land degradation

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Introduction

Desertification is one of the major threats to the environment and the global community. It is a long term process caused due to both natural as well as human activities and may be exacerbated through combined effects of different land degradation process. In essence, it is the temporary or permanent lowering of the productive capacity of land [1]. The intensity of desertification depends on several factors like physical, chemical and biological drivers and thus their impacts vary across place and time. Continuous monitoring can be helpful to understand the intensity and the spatial patterns of land degradation.

International community already started the initiatives to control the impact of desertification. Assessing the land degradation is a crucial step towards combating the desertification. By mapping the land degradation, the problems could be understood across its spatial dimension while also enabling us to monitor the degree of degradation. Such monitoring can help to frame and adopt sound mitigation strategies. The first global level map of desertification was prepared by FAO and UNESCO for the 1977 World Conference, to a scale of 1:250 000. Later a methodology was developed for evaluating and mapping desertification in 1979[2]. In 1987, United nations Environment Programme (UNEP) and International Soil Reference and Information Centre (ISRIC) agreed to develop a world map on the status of soil degradation at a scale of 1:10M under the Global Assessment of Soil Degradation Project of 1:10M under the Global Assessment of Soil Degradation Project (GLASOD) [3]. According to GLASOD, 15% of the total land area comes under the degradation.

Atthe national level, India ratified the convention to combat desertification on December 17, 1996. As per the MoeF, 32.75% of the total area are affected by various forms and degree of desertification in India [4]. India has committed a 20 year comprehensive National Action Programme (NAP) to combat desertification in this country [5]. In this connection, the 10th five year plan of India has some component for action on desertification. It is proposed that, assessment and mapping of land degradation, drought monitoring and early warning system will be taken up. In this concern, mapping the sensitivity gets more important and it could be the initial step towards the mitigation action plan.

It is difficult to map the desertification of a vast country like India by using the traditional mapping and survey methods. Because traditional methods are more site specific and the methods does not consider the spatial extent [6]. Using remote sensing techniques for mapping the desertification can enable us to address this lacuna.

A number of studies successfully used the satellite products to study the land degradation and desertification analysis [7-13]. Vegetation indices have been widely used for land degradation and desertification studies. Miao et al. [14] used the AVHRR NDVI data to predict the impact of future climatic dynamics on land degradation. In this study, the vegetation changes used as a proxy for land degradation and the historical relationship between the vegetation and climate factors used to project the spatial trends of future land degradation. Vicente-Serrano et al. [15] used the AVHRR NDVI to investigate the influence of drought events on land degradation process. Other than that, Earth Observation satellites like MODIS, NOAA and SPOT gives data throughout the year for continuous monitoring data which is helpful to study the degradation [16]. Monitoring the vegetation productivity by using AQUA/TERRA-Moderate Resolution Imaging Spectroradiometer (MODIS) observation was successfully done on earlier studies [17&18]. Lu et al. [19] evaluated the suitability of different vegetation indices from MODIS for monitoring the vegetation dynamics in dryland environment. Besides that, TRMM provided crucial precipitation information for this kind of studies [20&21]. In recent years, remote sensing data products combined together or with other sensor derived factors are mostly used to study the desertification. Landmann & Dubovyk [22] used the MODIS NDVI and TRMM data to study the spatiotemporal vegetation productivity impacts on land degradation. Wang et al. [23] assessed the land degradation condition using MODIS NDVI and metrological data such as rainfall, temperature and solar radiation. The NPP and RUE was derived and used for this time series trend analysis study. Khire and Agarwadkar [24] used multiple satellite products to study the desertification process by deriving the landuse, vegetation and albedo indices with the aid of GIS. In that case, LISS I, AWiFS, SRTM and ASTER data were used to study the desertification severity in Aurangabad district, Central India. Like the vegetation indices, drought indices based on remote sensing has also been used to monitor the drought conditions which are the main cause of land degradation [25-29].

Analytical Hierarchy Process (AHP) is one of the multi criteria approaches which were used in many environmental studies. Satty stated that, AHP is a rational decision-making approach which simplifies complicated problems by breaking down into small parts with hierarchical structuring [30]. Its ability to check inconsistence and its flexibility makes the AHP better than other multi criteria methods [31].

The objective of this research is to examine the spatial and temporal effects of natural factors on land degradation severity changes using remote sensing data. This study applies the AHP model integrated with GIS to assess the desertification sensitivity and its changes over the years from 2000 to 2012.

2. Experimental Section

The current study was carried out for the state of Tamil Nadu, India, which is situated in the northern hemisphere in the tropical zone between 8° and 13°N latitude and between 78° and 80°E longitude (Figure.1). The state situated in the southeast part of the India. It is one of the water starved states and has a population over 62 million. The average rainfall in the state is 911.6mm. The size of the study area is approximately 1, 30,069 sq.km (~4% of the total land area of India) with a peak elevation point of 2632m.

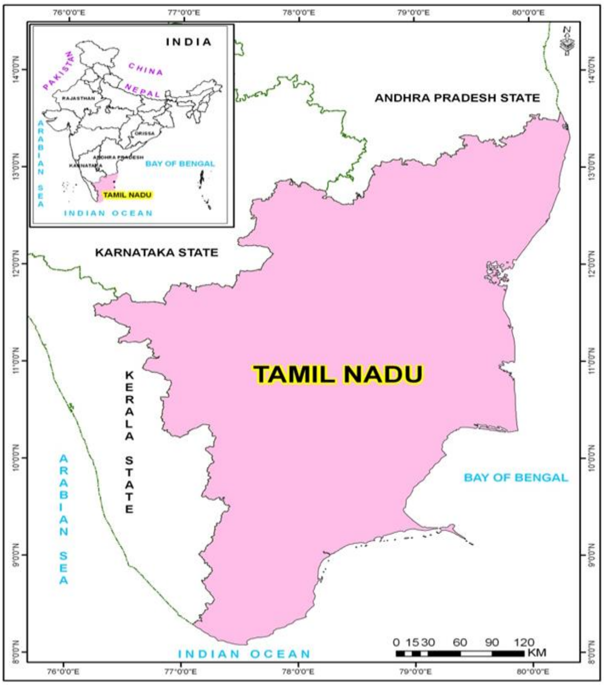

Figure 1: Study area map

2.1. Datasets

Many studies, carried out in the countries affected by desertification only concentrated on a small study area or less number of parameters or using thematic maps. In this research, remote sensing based parameters are used to analyses the impact of natural factors in the desertification process. Climate, vegetation and topographic parameters are the natural factors considered for this state level desertification analysis. Precipitation and PET are the climatic factors taken into account. Because these are the main factors which can induce the drought process. NPP and RUE are taken to understand the vegetation factors impact. The slope was taken to understand the impact of topographic pressure on desertification.

2.1.1. Precipitation

Tropical Rainfall Measuring Mission (TRMM) data was obtained from the NASA precipitation measurement mission website [32].TRMM has multiple products for different applications. Here we used 3B43 gridded product which has monthly temporal and 0.25° spatial resolution. The unit of the data is mm hr^{-1}. Then the downloaded product downscaled in to 1km spatial resolution following the methodology outlined in [33] for further analysis.

2.1.2. ET/PET

MODIS ET (MOD16) global evapotranspiration (ET)/latent heat flux (LE)/potential ET (PET)/potential LE (PLE) data was downloaded from the Land Processes Distribution Active Archive Center (LPDAC 34). It covers the time period of 2000-2012 and in sinusoidal projection. The monthly data is the sum of monthly ET which was developed from 30daily composites. The potential ET has 1km spatial resolution and in the unit of (0.1mm/month) [35].

2.1.3. NPP

MODIS GPP/NPP project (MOD 17) provides Gross/Net Primary Production (GPP/NPP) for entire earth.NPP data are downloaded from the USGS website. MOD17A3 operates over the global set of 1km land pixels and the units are in kg_C/m2. Then the monthly data converted to annual data for the next process.

2.1.4. Slope

Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) GDEM which is having vertical accuracies generally between 10 and 25m are downloaded by the GDEx tool. The data were rescaled into 1km per pixel and then the slope was created.

2.2. Methods of Analysis

All the data products were projected into a common projection (UTM) and rescaled into 1km spatial resolution grid. Then the monthly data are converted into annual time frame to do the time series analysis. Aridity index was prepared by using the UNESCO (1979) aridity index equationwhich is the ratio of precipitation and potential evapotranspiration. Aridity index is one of the important indices which could show the process of desertification in the spatial scale. It isdirectly relatedto precipitation and NPP would help to understand the degree of changes in land degradation. RUEwas prepared from the NPP and precipitation.

Subsequently, all the factors were classified into the following 5 classes: very high, high, moderate, low, very low. The weightage of classes are created by the pairwise comparison method. Aridity has the high weight 0.540 among the others and 0.25, 0.113, 0.06 and 0.037 weights are with respect to precipitation, NPP, RUE and slope. Then the ranks and weights are assigned to the factors to get the sensitive area map. These exercises repeated for all the layers from the year 2000 and 2012.

Sensitivity maps of 2000 and 2012 were taken for change detection analysis to understand the changes in degradation sensitivity with spatial distribution patterns. The change analyses were carried out using Idrisi land change modeler.

3. Results and Discussion

Figure 2. Shows, the time series of the four factors from the year of 2000 to 2012. When the factors regressed against time, it shows no trend occurs in the data. It means the correlation between the factors and time is low.

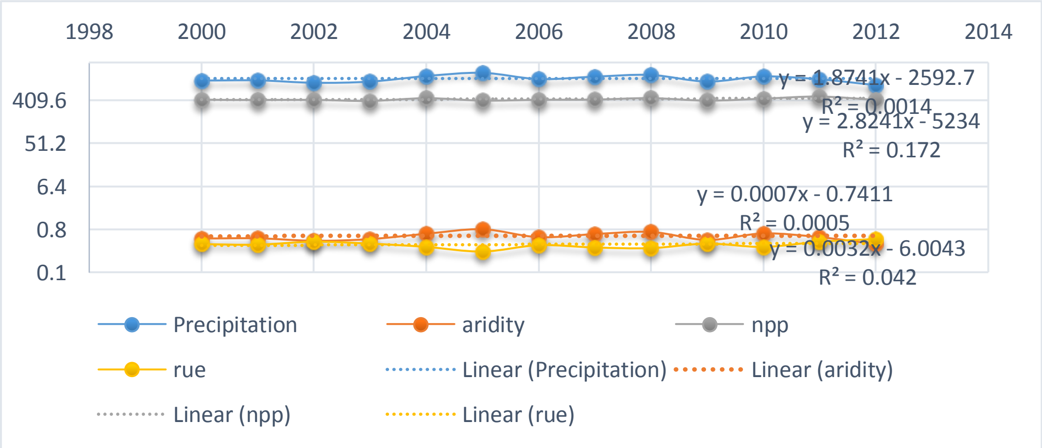

Figure 2: Time series of Precipitation, Aridity, NPP and RUE from the year 2000 to 2012

3.1. Precipitation

The precipitation time series analysis is based on TRMM precipitation data is shown in the Figure 2. Tamil Nadu, one of the drier states of India, which has an average annual rainfall of 900mm over the last 50 years of which 60% of the rainfall occurs during the north-east monsoon (November to February). Based on the monthly TRMM precipitation estimation, the annual precipitation was retrieved and plotted for all the 13 years to analyses the variation of precipitation in the study area. Tamil Nadu gets lower precipitation compared to the adjacent state of Kerala because it falls in the rain shadow zone of the Western Ghats. In general, as shown in Figure 2, the precipitation going down on every three to four year cycle in this study area. The high values were recorded during 2005, 2008 and 2010 and compared to the other years. Among these 2005 yielded high precipitation, that was because of the cyclone Fannos which resulted in almost 80% higher rainfall compared to the normal seasonal rainfall (450mm) of north-east monsoon. Year 2008 and 2010 also has the influence of cyclones Nisha and Jal. 2012 has the lowest precipitation over the 13years. It has lowest northeast monsoon recorded for the last 13 years (370mm) [36].

3.2.Aridity Index

The aridity indices time series analysis is based on the annual aridity indices mean over the time period of 13 years. Year 2002, 2009 and 2012 values go down.Figure 2, clearly shows that, most of the values falls into the dry sub-humid classification category than semi-arid category. It means the whole study area hasn't met serious drought issue over the last 13 years. It's only comes low on 2002, 2009 and 2012 when the rainfall is pretty low than other years. Year 2005 has highest value (0.82) which is because of cyclone Fannos.

3.3.NPP

The annual NPP which has an average of 431 in the 13 years, which goes down in 2003 (399.8) and goes higher in 2011 (494.5). The annual fluctuationsare lower compared to the other factors. That is because the NPP is not only affected by the climatic but also the ecological, geochemical and human influences also integrated [37]. Figure 2, show that the trends of NPP over the years from 2000 to 2012.

3.4.RUE

The RUE is calculated as npp/precipitation indicating that RUE will be highly determined by the levels of precipitation. The RUE time series analysis shown in Figure 2. The RUE ranges vary from 0.28 to 0.51 and it reached the high in 2012 and met the low value in 2005. The rain-use efficiency could be used as aparameter where the precipitation limiting the productivity [38].

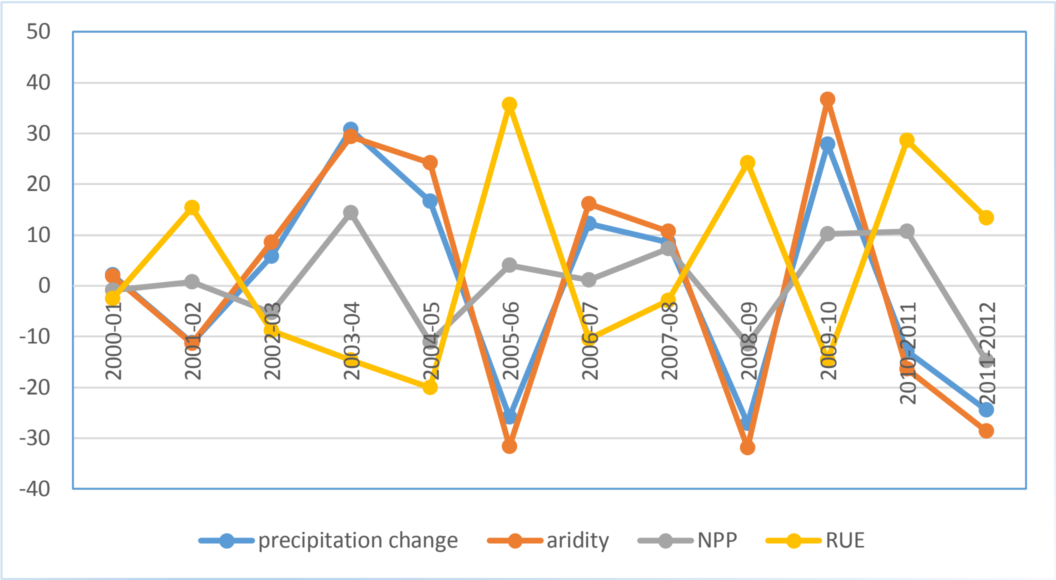

Figure 3: Temporal trend of annual mean % change of precipitation, Aridity, NPP and RUE

Annual mean percentage change analysis also carried out for this study to understand the changes and relationship between the factors on land degradation. Figure 3. Shows the annual mean percentage change of precipitation, aridity, NPP and RUE for the 13 years. Aridity follows the trend of precipitation, because precipitation is one of the input for aridity index. The change in RUE was increasing when the precipitation change has decreased. It shows there is a positive relationship between RUE and precipitation. The change of NPP over the years is -14% (2011-12) to +14 %(2003-04).Most of the years the changes in NPP also influenced by the precipitation. The highest change in NPP was recorded in 2003-04 when the changes in precipitation also high. The lowest NPP changes occurred in 2008 when the precipitation changes went negative. But year 2002-03 has negative NPP change when the precipitation had positive change trend and 2005-06 and 2010-11 has positive change trend when the precipitation change goes negative. Henceforth, the relationship between NPP and precipitation is positive in this area. Overall the changes in the four factors are fluctuate dramatically over the years and there is no sharp decline or incline in the changes. It's quit understandable, because of the short term analysis.

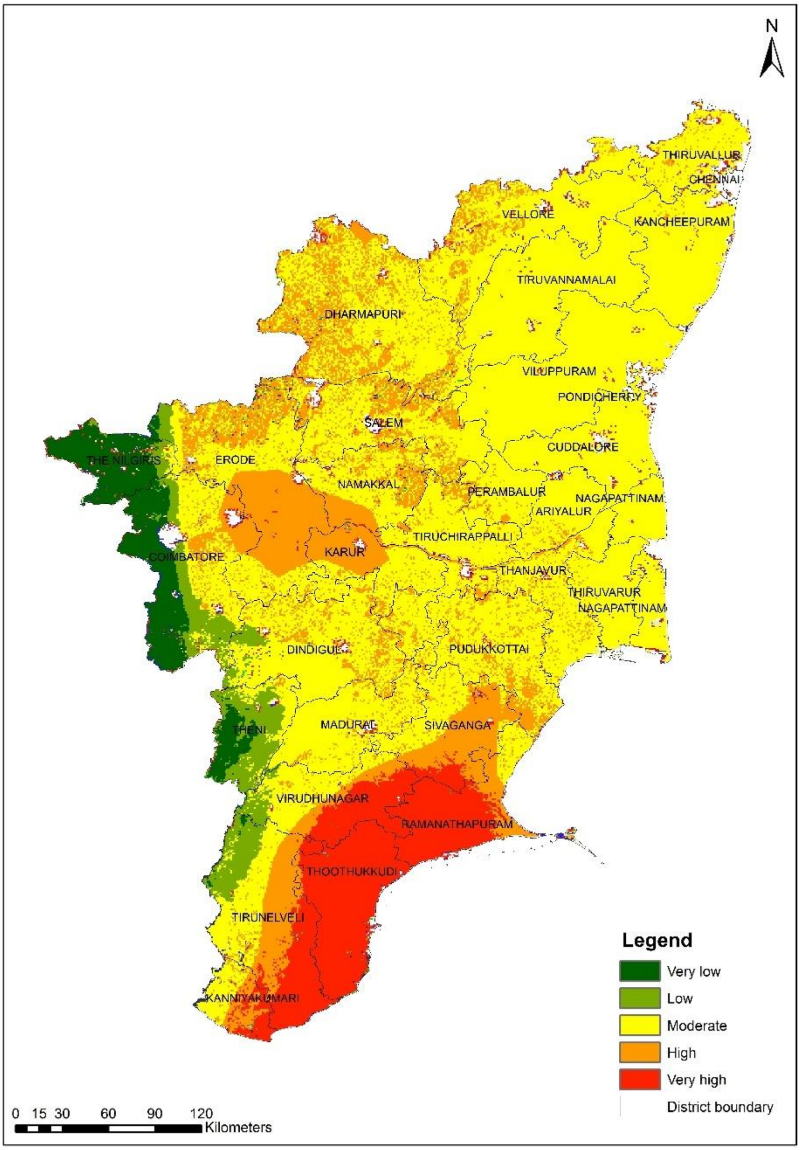

Figure 4: Shows the severity zones of desertification over the years of 2000-2012.

3.5. Desertification Severity Zone in Tamilnadu State

The condition of severity from the last 13 years also mapped and shown in Figure 4. The west side of the study area has the influence of Western Ghats. This area has well protected vegetation and good soil and water specialty. Hence it comes below the very low to low severity category. The southeast side of the study region, comes under the high to very high sensitivity category. Overall, 63% Tamilnadu State the study area comes under the moderate sensitivity zone. 18% area comes under the highly sensitive area and 10 % area comes under the very high sensitive area. Ramanathapuram, Thoothukkudi, Tirunelveli, Kanyakumari, Virudhunagar and Sivagangai districts are the most affected and severe districts in the state. The northern districts are known as a drought prone area where the drought frequency is less than five years. It means the drought occurrence is 100% high than the other districts (i.e. 5-10 years per drought as per ground water control board report [39].

3.6.Change Analysis

Change analysis also carried out for this study to understand the changes in spatial dimension too. Figure 5 clearly shows that there are significant changes among all the sensitivity classes during the period 2000 to 2012. Low, moderate and very high sensitive areas changed greatly in the last 13 years. Very high class has lost 42.61% and gained 74.24% during the year 2000-2012. Interestingly the very low category has lost 46.05% while gaining a mere 0.14 %. The more changes occurred in the low sensitive area category. There the loss was 94.06% and the gain was 98.13%.

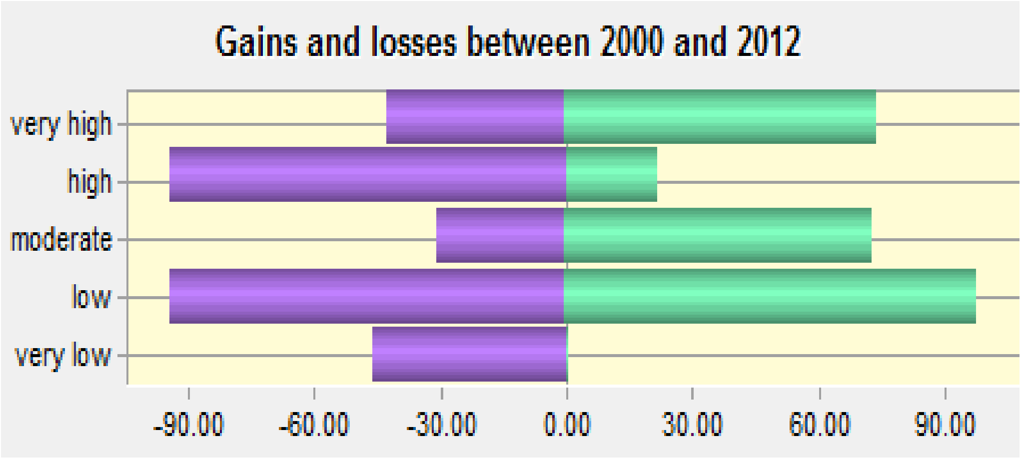

Figure 5: Gain and Losses of land degradation severity between 2000 and 2012

Figure 6 shows the spatial pattern of changes between land degradation severity classes. From figure 5&6, it is clear that changes happened in all categories and all over the state. But the degree of sensitivity was not constant over the years and the degree of changes are not gradual over the classes. Most of the high sensitive area turned into moderate sensitive. The eastern side of the state doesn’t change much over the period.

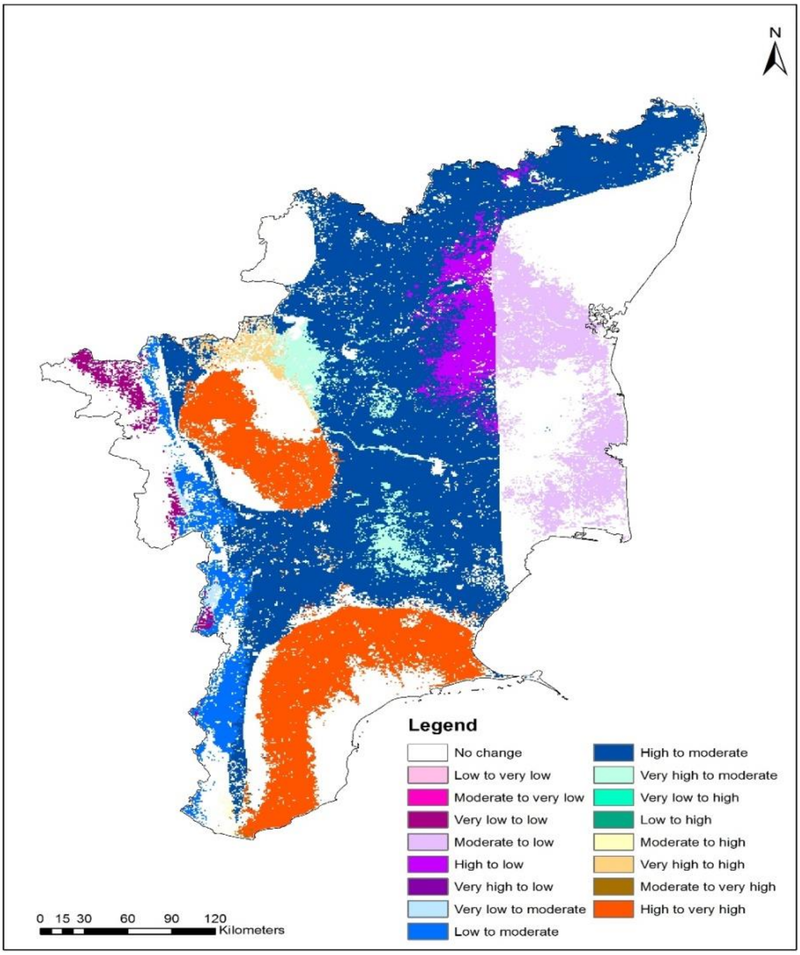

Figure 6: Land degradation changes from 2000 to 2012

4. Conclusions

In this study, we used the multiple remote sensing datasets to analyse the trends in land degradation severity over the 13 years. Even though, it's a short time period to understand the complete land degradation process it is important to know the magnitude of changes which is stimulated by the natural factors. We investigate the impact of precipitation, evapotranspiration, net primary productivity and slope on changes in land degradation.

This study demonstrated the importance of remote sensing sensor products on land degradation mapping and continuous monitoring.TRMM is one of the important remote sensing sensors which provide the crucial information on precipitation that is important to analysis the trend in desertification severity. NPP and RUE plays an important role in the stimulation of land degradation. When combining all these factors together by the use of multi-criteria analysis method, we could see the spatial changes in land degradation. The AHP used in this study proved to be important in terms of assigning weightages over the parameters which makes the GIS analysis better. The results show the severity of desertification over the years and the spatial distribution of their sensitivity. The change detection map could be a reference for the decision makers to set the spatial priority to all the mitigation plans. Based on the results, combating efforts such as an early warning system could be carried out by the spatial priorities. Nonetheless to achieve such a state, there has to be abundant and adequate data to enable confident predictions and changing patterns. Combining with the historical data and other available satellite product data like AVHRR could improve the quality of this research.

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