Identification of Land undergoing degradation using geospatial techniques: A case study of Kohima, Nagaland

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Abstract*: *Land degradation is defined as the process of transformation of productive lands into non-productive lands which affects the living conditions of the people. Assessing land degradation vulnerability is an important step to combat land degradation. To combat the degradation process, it is necessary to understand the causes and impacts caused by the socio economic and natural parameters. The present study aims to assess the areas undergoing Land Degradation in Kohima District of Nagaland using Remote sensing and GIS techniques. Socio-economic Indices such as Economic Development Index, Amenities Index and Natural parameters such as Land utilisation Index and Soil Index are used to derive Degradation Vulnerability Index. The results indicate that, about 40.92% of land of Kohima falls under high vulnerable and 25.40% under very high vulnerable class.

***Keywords*: over-utilised, land degradation, degradation vulnerability index, amenities.**

(Article history: Received: March 2022 and accepted May 2022)

I. INTRODUCTION

Land degradation is affected by climate change and at the same time it contributes to climate change. Land degradation is defined as a negative trend in land condition, caused by direct or indirect human-induced processes including anthropogenic climate change, expressed as long-term reduction or loss of at least one of the following: biological productivity, ecological integrity, or value to humans (IPCC). It is caused by changes in rainfall pattern, reduction in vegetal cover, wrong agricultural management practices, cultivation on marginal lands, over-exploitation of the natural resources, excessive grazing, etc. [1-2]. Land degradation has been increasing in recent years globally and it is accelerated by three main processes including Physical (Wind erosion, water erosion, mass wasting, frost heaving etc.), chemical (acidification, salinization, alkalinisation etc.) and biological (vegetal degradation, shifting cultivation, biodiversity declination) [1]. There are global efforts to combat desertification and land degradation through United Nations Convention for Combating Desertification (UNCCD). In India, approximately 1/3rd of the total geographical area is undergoing the process of land degradation [3]. Identifying hotspot areas which are undergoing the process of land degradation will facilitate the experts to suggest an action plan required to reverse or slow down the process of land degradation. [4]. To identify the hotspot areas, an approach which considers socioeconomic conditions of people living in vulnerable areas as well as natural parameters is required.

In India, research is going on in desertification and land degradation in dry lands which comprises Hyper Arid, Arid, Semi-arid and Dry Sub-humid with aridity Index (ratio of Precipitation to Potential Evapotranspiration) ranges between 0.05-0.65. But there are less land degradation studies available on Northeastern states of India which falls in Humid region (AI >0.65). According to the draft report generated by the scientists of ISRO, Nagaland held third position with 47% of land under the risk of degradation after Uttar Pradesh with 53% and Rajasthan with 52%. In Nagaland, Kohima and Wokha are the two vulnerable districts having 62.43 % and 36.59% of its land getting degraded [5].

The present research was carried out to identify areas under the risk of land degradation based on natural and human induced parameters along with their severity in terms of degradation. The study is first of its kind in the Nagaland where in socio-economic parameters such as Economic Development Index (EDI), Amenities Index (AI) and

Natural parameters such as Land Utilisation Index (LUI) and Soil Index (SI) were generated to delineate the area under the risk of degradation along with the severity levels.

II. MATERIALS AND METHODS

A. Study Area

Kohima, a hilly district of Nagaland, lies between 93°19'55" and 94°20'10" East Longitude and 25°11'38" and 26°01'35" North Latitude. It shares its borders with Assam State and Dimapur District in the West, Phek District in the East, Manipur State and Peren District in the South and Wokha District in the North. Kohima records average annual rainfall of 1831.3 mm/ year and average annual temperature ranges from 14.6^0 to 22.2^0. The Location map of study area is given in the figure 1.

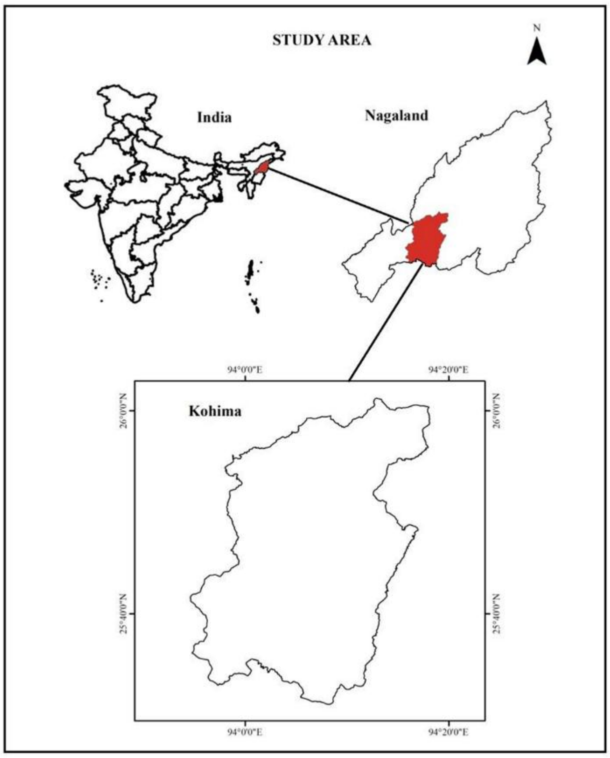

Fig. 1. Study area map

B. Data used

To derive Socio Economic Indices (SEI) such as Amenities Index (AI) and Economic Development Index (EDI), Census Data 2011, freely downloadable from https://censusindia.gov.in/ and location points of villages present in the Kohima District and boundary layer of Kohima district was used. To generate Land utilisation Index (LUI), Landuse and Land Cover (LULC) generated by NESAC, Landsat 8 annual NDVI composites were downloaded from Google Earth Engine for the years 2013-2018 and Land Capability Classification (LCC) was taken from soil layers generated by Soil and Landuse Survey of India (SLUSI) have been used. Finally, Soil Index was generated from the Soil layer provided by SLUSI. The satellite and Ancillary data used in this study is given in the table 1.

TABLE I. DATA USED

	Data used	Spatial Resolution
Satellite Data	Landsat 8(OLI)	30m
Ancillary Data	LULC	1:50,000
	Soil	1:50,000
	Census data (2011)	

III. METHODOLOGY

Social and Economic status of an area influences the area directly or indirectly and makes it vulnerable to the process of land degradation. Population pressure, unemployment and illiteracy altogether are directly proportional to poverty and degradation of environment [6]. In this study SEI such as EDI and AI were generated for all the villages in the Kohima district. The detailed methodology flowchart is given in the figure 2.

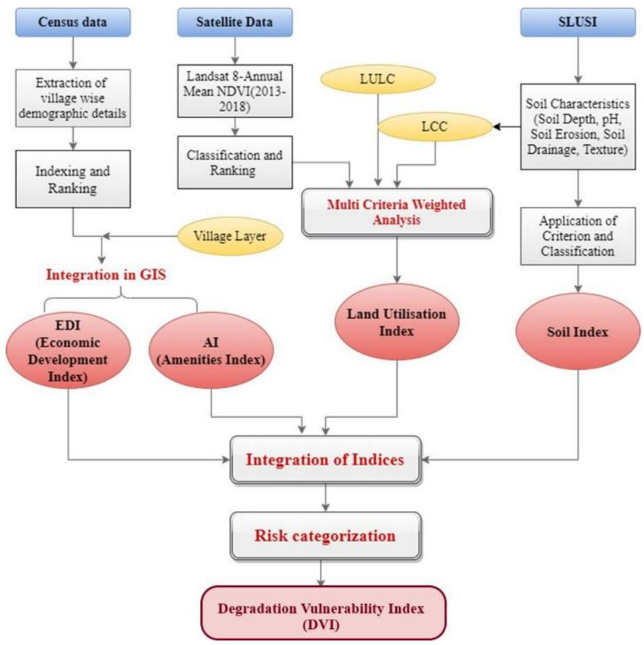

Fig. 2. Methodology Flowchart

A. Economic Development Index (EDI)

EDI is generated based on the population density and the economic status of the people residing in the villages. Land tends to degrade more when the population of unskilled employee are more in the particular area.

Economic development Index is derived [6], [7], [8] using the equation 1 given below.

$$E = \sqrt{(D * X\ (W - A)} \text{-------------------------} \quad (1)$$

Where E = Economic development status

D = Population density

X = Population Percentage

W = Proportion of employed population

A = Proportion of unskilled workers

D (Population density) is derived from the ratio of the total population to the total area and A (Proportion of unskilled workers) is defined as the ratio of the addition of unemployed, agricultural labours and marginal workers to Total population.

B. Amenities Index (AI)

AI is derived based on the facilities present in the villages and it acts as an important factor for the socio-economic development. EDI and AI are directly proportional to each other. When the economic status of the village is high, facilities in the village is also high and vice versa. In this study, Amenities such as Banking, Irrigation, Infrastructure, Medical, Education and Transportation is considered, and it is integrated to derive the cumulative amenities index.

The equation 2 used to derive AI [8], [9], [10] is given below. The Cumulative Amenities Index (AI) is calculated using the following equation:

$$AI = \sum_{c=1}^{m} I_c \text{ ---------------------- (2)}$$

Where,

c = 1 to m

AI = Cumulative Index for a particular settlement for all the facilities.

m = Number of facilities categories (In this study m is 6 which includes Banking, Irrigation, Infrastructure, Medical, Education, Transportation)

I_C= Category Index Where,

$$I_c = \sum_{i=0}^{n} (Ai * Wi) \;/\; \Sigma Wi \text{------------ (3)}$$

Where i = 1 to n,

n = number of categories under facility,

Ic = Index for a particular facility class,

Ai = Availability status of facility i.e., 0 or 1

(If Ai = 0; Not available, Ai=1; available)

Wi = Weight of the facility within a category and is defined as

$$Wi = (N - Fi)/N * 100 \text{----------------- (4)}$$

Where, N = Total number of settlements.

Fi = Number of settlements having the particular facility

After the derivation of EDI and AI for all the villages of the Kohima district, it is converted spatially in GIS platform. Due to unavailability of village boundary, thiessen polygon is used to create a boundary from the available village points. There are 109 villages in the district Kohima. From the available point shape file, thiessen polygon is generated for all 109-point shape files and it is clipped using the district shape file to get a proxy for village boundary. Then the EDI and AI is classified into 5 classes of vulnerability such as very high, high, medium, low, and very low with higher the index value, lower the vulnerability, based on the second order standard deviation.

C. Soil Index

Soil is a one of the important factors to identify land degradation process. As Northeastern states receive high rainfall there is a possibility of the soil being acidified. The pH of the soil increases after the minerals such as calcium, magnesium, sodium, and potassium are washed away by the water, leaving the soil with only hydrogen ions. The pH of soil is measured in terms of the concentration of hydrogen ions (pH) in the soil. In this study, Soil and Land Use Survey of India (SLUSI) soil data at 1:50,000 scale is used for generating Soil Index over the study area. The criterion table used in the generation of soil index is given in the table 2.

TABLE II. CRITERION TO GENERATE SOIL INDEX

Soil Properties	Rank assigned	5	4	3	2	1	0
Soil depth (cm)	Class	<25	25-50	50-75	75-100	>100	NA
	Description	Very Shallow	Shallow	Slightly Shallow	Moderately Deep	Deep	NA
pH	Class	<4.5 and 4.5-5.0	5.1-5.5	5.6-6.0	6.1-6.5	6.6-7.5	7.6- 8.4 an >8.5
	Description	Extremely acidic and very strongly acidic	Strongly acidic	Moderately acidic	Slightly acidic	Neutral	Slightly alkaline an very strongly alkaline
	Class	e4	e3	e2-e3	e2	e1	NA
	Description	Extremely severe	Very Severe	Severe	Moderate	Slight	NA
	Class	Very Poorly Drained	Poorly Drained	Imperfectly well and Excessive	Well to Excessive and moderately well	Well	NA
Soil Erosion	Class	Gravelly, Loamy Sand to Gravelly Loamy Sand, Loamy Very Fine Sand to Sand, Loamy Sand, Sand, Loamy Sand to Sandy Loam, Gravelly Sandy Loam	Sandy Loam, Gravelly Clay Loam, Gravelly Loam	Sandy Loam to Clay, Sandy Clay	Sandy Clay Loam to Clay, Sandy Loam to Sandy Clay Loam	Clay Loam, Loam, Loam to Silty Loam, Loam to Clay Loam, Sandy Clay Loam to Clay Loam, Loam	NA

D. Land Utilization Index (LUI)

Land Utilization Index (LUI) is defined as the utilization of land based on its capacity to hold the vegetation cover and to assess whether the lands are put to the proper use. If the lands are mismanaged over its capacity, it will degrade the land. To derive LUI, NDVI (Normalised Difference Vegetation Index), LCC (Land Capability Classification) and LULC (Landuse and Land Cover) is used.

In general, NDVI is used in Landuse/ Land cover change studies to identify the changes in vegetation over a period. NDVI is defined as spectral reflectance from the visible and near-infrared light by vegetation. Healthy vegetation absorbs more visible light and reflects a more near-infrared light and sparse vegetation reflects more visible light and less near-infrared light which is calculated using equation 5.

$$NDVI = (NIR-R)/(NIR+R) \text{ ----------------------------- (5)}$$

Because of the cloud cover in northeastern states, NDVI composites have been used for the period of 2013 to 2018 and the mean was calculated for all the 5 years to identify the NDVI trends. Furthermore, NDVI is classified into 2 classes <0.7 (Sparse vegetation) and >0.7 (Dense Vegetation).

The land capability classification is defined as the classification of soils into groups based on their ability to cultivate in which depth of soil, texture, soil erodibility, soil drainage, slope etc. are taken into consideration. LCC is classified into 8 major groups in which class I to IV is suitable for cultivation and V to VIII is not suitable for cultivation. In this study land capability classes are extracted from the soil data from SLUSI of 1:50000. Again, LCC is classified into 2 classes i.e., < IV and > IV.

LULC are predominantly used in land management and planning studies [11 – 13]. Landuse and Landcover which is classified into three levels of details with 1:50000 scale is used in this study.

Finally, NDVI, LCC and LULC are integrated, and unique combinations are identified. The criterion given in table 3 is applied to the unique combinations and LUI is generated with three classes viz. optimally utilized, underutilized, and over utilized.

TABLE III. CRITERION TO GENERATE LAND UTILISATION INDEX

Class	LULC	LCC	NDVI
Optimally Utilised	Kharif Crop/ Rabi Crop/ Agricultural Plantation/ Fallow Land	< IV	> 0.7
	Evergreen Forest/ Deciduous Forest/Scrub Forest/ Forest Plantation/ Tree Clad Area/Alpine Grassland	< IV	> 0.7
	Current Jhum/ Abandoned Jhum	< IV	> 0.7
	Kharif Crop/ Rabi Crop/ Agricultural Plantation/ Fallow Land	> IV	< 0.7
	Evergreen Forest/ Deciduous Forest/ Scrub Forest/ Forest Plantation/ Tree Clad Area/ Alpine Grassland	> IV	< 0.7
	Current Jhum/ Abandoned Jhum	> IV	< 0.7
Over Utilised	Kharif Crop/ Rabi Crop/ Agricultural Plantation/ Fallow Land	> IV	> 0.7
	Evergreen Forest/ Deciduous Forest/ Scrub Forest/ Forest Plantation/ Tree Clad Area/ Alpine Grassland	> IV	> 0.7
	Scrublands/ Gullied Lands/ Sandy Areas	> IV	0 - 1
	Current Jhum/ Abandoned Jhum	> IV	> 0.7
Under Utilised	Kharif Crop/ Rabi Crop/ Agricultural Plantation/Fallow Land	< IV	< 0.7
	Evergreen Forest/Deciduous Forest/ Scrub Forest/ Forest Plantation/ Tree Clad Area/ Alpine Grassland	< IV	< 0.7
	Wastelands/Scrub Land/Open	< IV	0 - 1
	Scrublands/ Gullied Lands/ sandy Areas	< IV	0 - 1
	Current Jhum/ Abandoned Jhum	< IV	< 0.7

Finally, all socio-economic and natural indices were integrated in GIS environment using geometric mean given in the equation 6 to generate the final Land degradation vulnerability map of the district.

$$(a_1 \times a_2 \times \ldots \times a_n)^{(1/n)} \text{ ---------------------- } (6)$$

Where n = Number of parameters (a) that are multiplied
a = Parameters used

Degradation Vulnerability Index (DVI) is classified into five classes viz., very low, low, moderate, high and very high vulnerability classes which is used in combating action plan.

IV. RESULTS AND DISCUSSION

EDI of the Kohima district given in the figure 3 depicts that the villages fall under the category of High, medium, low, and very low classes with most of the villages as highly vulnerable to land degradation.

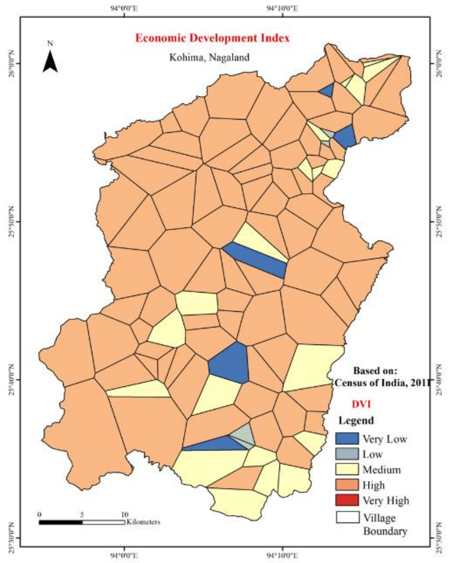

Fig. 3. EDI map

An alias proportion of unskilled workers is the most important parameter which influences land degradation. If A increases, vulnerability to desertification and land degradation increases. AI is shown in the figure 4, in which vulnerability due to lack of facilities such as banking, irrigation, infrastructure, education, medical, transportation is identified.

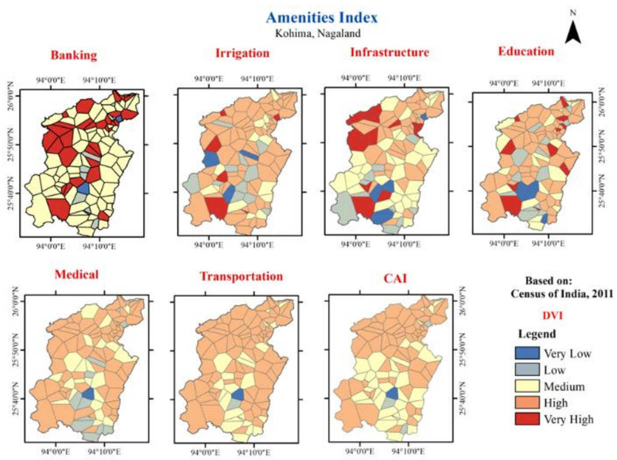

Fig. 4. AI map

If EDI and AI are low then DVI will be high, that means high vulnerability. Since EDI and AI maps (figure 3and 4) have been generated in terms of DVI thus red color has been used to represent areas with low EDI and AI values representing high vulnerability.

Cumulative facility index is also calculated which has the classes from very low to high, higher the facilities lower the vulnerability. Soil index is calculated using the physical and chemical properties of soil which is classified into five classes of vulnerability excluding built-up and waterbodies which is shown in the figure 5.

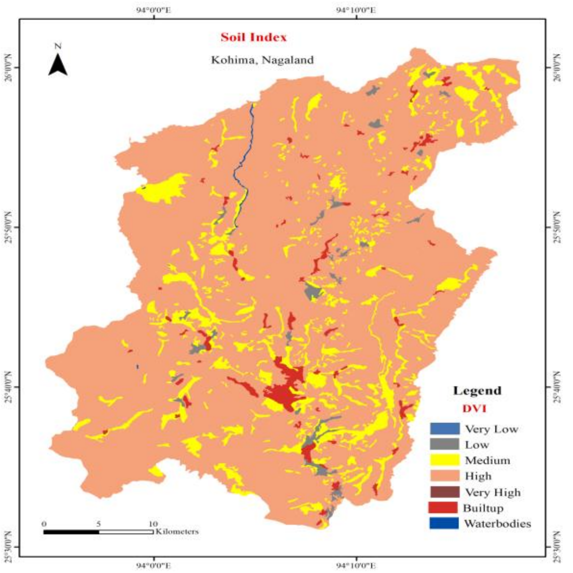

Fig. 5. Soil map

LUI is shown in the figure 6 containing optimally utilised, underutilized and over utilised classes which are classified based on multi criterion parametric analysis.

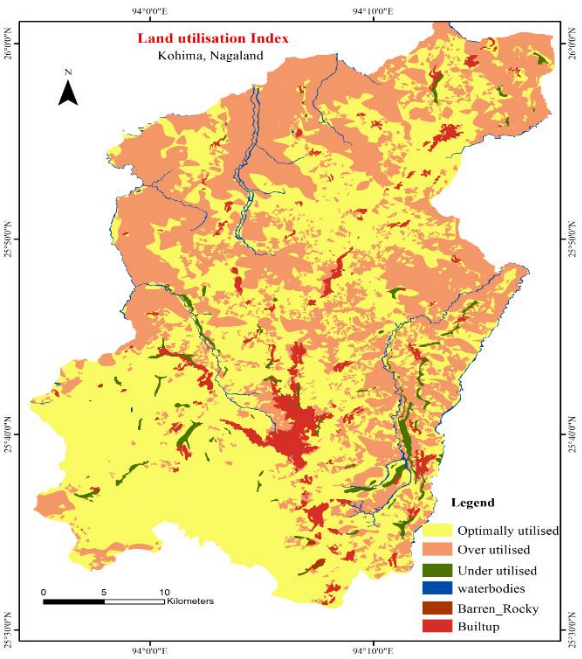

Fig. 6. Land utilisation map

The land degradation vulnerability map shown in the figure 7 and the table 4 represents the area of the land under the classes of degradation with 2.74% of area falling under very low vulnerable class, 3.52% under low vulnerable, 22.45% under moderately vulnerable, 40.92% under high vulnerable and 25.40% under very high vulnerable class. Waterbodies, built up and barren rocky occupies the land with 0.98%, 3.90% and 0.09% of the total area respectively.

TABLE IV. AREA STATISTICS OF EACH VULNERABILITY CLASS

Classes	Total Area(sq km)	Percentage
Very Low vulnerable	36.32	2.74
Low vulnerable	46.67	3.52
Moderately vulnerable	297.65	22.45
High vulnerable	542.60	40.92
Very High vulnerable	336.89	25.40
Barren rocky	1.16	0.09
Builtup	51.75	3.90
Waterbody	13.04	0.98

The reports prepared as part of DSM Atlas by SAC-ISRO [5] also show similar trends of land degradation in Kohima district

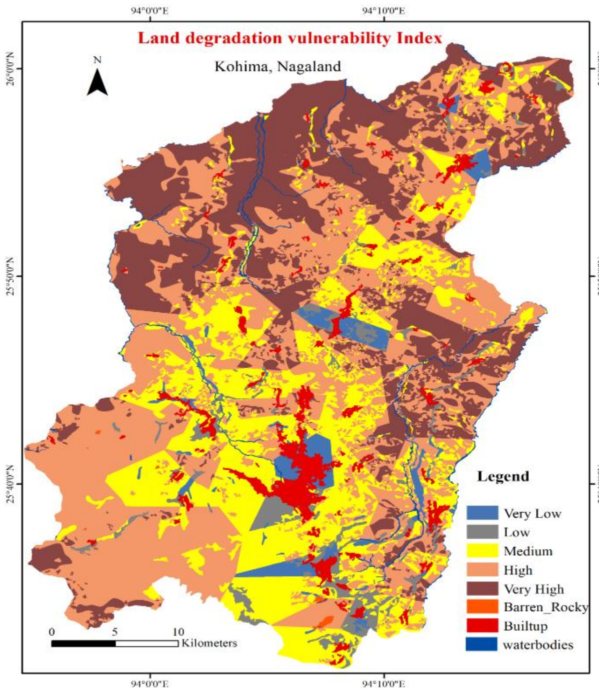

Fig. 7. Land degradation vulnerability map along with the levels of vulnerability

V. CONCLUSION

The study reveals that Indices approach permit us to have a detailed analysis of impact of socio economic and natural factors on land degradation from remotely sensed data and other ancillary data in combination. Assessing the risk of land degradation by integrating all effective factors is also possible and action plan can be suggested for this area.

The future work is to integrate these results with the DSM (Desertification Status Maps) and to identify the microwatershed which falls under the high vulnerable areas and action plan will be recommended based on the expert advice by incorporating other factors such as ground water prospects.

ACKNOWLEDGMENT

The authors acknowledge the support of Space Applications Center, Indian Space Research organisation, Ahmedabad (SAC-ISRO) for funding the work. The authors express gratitude to Northeastern Space Applications Center, Umiam, Meghalaya for providing the required data. First author expresses profound gratitude to Dr. Ajai, Emeritus Scientist SAC-ISRO, for guidance during the research.

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