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Unveiling the Vulnerability: Mapping Desertification and Land Degradation in the Eastern fringes of the Thar Desert

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Abstract: This study focuses on identifying the key drivers of desertification in the Sirsa district of Haryana, India. It takes into account several factors, such as climate, soil, regional hydrology, vegetation condition, land use, available amenities, and economic conditions. Using a hierarchy-based model within a geographic information system framework, these parameters were integrated to create the Desertification-Land Degradation Vulnerability Index (DLVI). The analysis categorizes the results into five vulnerability zones-very high, high, moderate, low, and very low-based on their relative susceptibility to desertification and land degradation. The findings highlight that areas experiencing lower rainfall, higher temperatures, and greater population density with limited social amenities face a higher risk of desertification, particularly in the south-southwest and western parts of Sirsa. To validate the DLVI map, Land Degradation Status Maps are used, employing the Receiver Operating Curve and the Area Under the Curve. This validation process demonstrates an accuracy rate of 61.6%. The model-based approach, which integrates various factors encompassing the geo-environmental and socio-economic aspects, offers valuable insights for the formulation of effective mitigation strategies to combat land degradation and desertification in the future.

Key words: Desertification, land degradation, vulnerability zones, geospatial techniques, receiver-operating-curve, desert fringe.

Desertification and Land Degradation (DLD), drought and human-induced climate change are contemporarily the most critical environmental challenges faced by the global community (Reed and Stringer 2016). Anthropogenic activities, climatic variability, vegetal degradation and soil erosion are considered significant drivers of desertification (Eskandari Dameneh *et al.*, 2021), whereby the general productivity of land decreases (Marques da Silva *et al.*, 2018). They may subsequently lead to the loss of livelihoods, bringing in poverty, marginalisation and migration. Historically DLD has been examined solely through the lens of geo-physical indicators, i.e. climate variability, vegetation condition, soil characteristics, groundwater conditions, but social and economic parameters which bear profound impacts (either positive or negative) on sensitive landscapes (Rodrigo, 2022) have largely been ignored (Oliveira *et al.*, 2018). The processes of DLD have accelerated due to overexploitation of resources, population growth, and increasing climatic variability (Prăvălie *et al.*,, 2021). Consequently, studies of Salvati and Zitti (2008), Requier-Desjardins *et al.* (2011), Kelly *et al.* (2015), and Dharumarajan *et al.*, (2018b) have incorporated various social and economic factors to assess land degradation vulnerability more comprehensively.

Globally, approximately 24% of the total land area is affected by DLD, with 9% of it under high desertification risk, supporting around one-fifth of the global population (United Nations, 2015; Pacheco *et al*., 2018).With largely an agrarian economy, steadily rising population and a diverse agro-climatic setting, India is also facing issues pertaining to land degradation (Parmar *et al.,* 2021). Space Applications Centre (SAC, 2021) has reported of a cumulative increase of 1.87 mha of DLD-affected area between 2003-05 and 2011-13, followed by an additional 1.45 mha increase between 2011-13 and 2018-19. Therefore, understanding the current DLD status, monitoring its trends, and developing effective strategies to manage and mitigate DLD are essential for an agriculture-focused country like India.

In India the Space Applications Centre, Indian Space Research Organisation (SAC-ISRO) adopted a large-scale and multi-pronged approach in identifying the various land degradation processes active in India on a district level (Dhinwa, 2003; Arya *et al.*, 2009; SAC 2007; SAC 2016; SAC 2018a; SAC 2018b; SAC 2021). These models have been validated using variety of different methods i.e. ROC (Tolche *et al.,* 2021), Z score (Parmar *et al.,* 2021), Kappa index (Dharumarajan *et al.*, 2018a) respectively. The ROC-AUC has been extensively used for its relevance in decision-making and algorithm comparison in many fields of enquiries (Das *et al.,* 2022).

Sirsa has been identified as a district exhibiting serious problems of degradation by both CAZRI (Kar *et al.,* 2009) and SAC-ISRO (SAC 2007; 2016; 2018a; 2021). The semi-arid lands of Sirsa are characterised by extreme temperature and water scarcity conditions in the summer months along with scanty vegetation and fragile soil. Increase of population in the district is further inducing pressure on the resources at disposal, thus necessitating efficient management of production. Thus, the current situation calls for constant monitoring and management of land resources to check the forces of degradation in this fringe area of The Indian desert. Several studies have examined the distribution and processes of degradation on a 1:50,000 scale (Promila *et al.,* 2018); however, none have comprehensively addressed both anthropogenic and physical factors in assessing land degradation vulnerability in the Sirsa district. Therefore, this research explores the intrinsic vulnerability of Sirsa district to desertification using a hierarchy-based integration model.

Materials and Methods

Geographical Setting

Sirsa, the westernmost district of the state of Haryana lies between the trans-Gangetic plains of Punjab (29°54′27.54″N, 74°30′6.97″E and the arid western plains of Rajasthan (29°13′53.65″N, 75°14′16.63″E). Majority of the district is covered by older alluvium which is either accumulated through fluvial processes (from the Ghaggar River and its paleo channels) or brought in by aeolian processes from the Thar Desert (Saini and Mujtaba, 2012). The region is mostly flat (elevation between 190 m to 210 m), with numerous stabilized dunes and dune complexes dotting the landscape (Moharana, 2017). Sirsa has a sub-tropical, semi-arid, continental monsoonal climate (Singh, 2005), which is associated with extreme temperature and scant rainfall. Average annual rainfall in the region varies between 230 to 450 mm. The soils in the area are classified as *Rahi* or soft loamy soils along the banks of Ghaggar, *Naili* silt clay downstream near Ottu weir and *Bhaggar* or sandy soils in the southern parts adjacent to stabilized dunes (Singh *et al.,* 2006). Preceding studies by Kumar *et al.* (2011) and SAC (2018a) revealed that nearly ~ 9% of the entire land area of Sirsa is affected by different processes of degradation; while, Promila *et al.* (2018) identified about 265 km^2 land in Sirsa district, affected by land degradation processes. Most of the district experiences wind erosion and problems related to water logging and salinization, perpetually halting agricultural practices (Mandal, 2019). Through this study,

Table 1. Data sources used in this study

Data used	Source	Scale/Spatial Resolution	Time Frame
Rainfall	IMD (Pai *et al.*, 2014)	0.25 ° * 0.25 °	1901-2010
Temperature	IMD (Srivastava *et al.*, 2009)	1 * 1	1969–2005
Potential Evapotranspiration	CGIAR-CSI	30-arc second	1970 - 2000
Aridity Index	CGIAR-CSI	30-arc second	1970 - 2000
Soil	NBSS&LUP (Panagos *et al.*, 2011) and Singh, 2005	1:500.000	1994
Groundwater	CGWB (WRIS)	Well data	2010-2019
Drainage	Google Earth	1:2,500	2020-21
Demography	Census of India	Primary Census Abstract	2011
Land use Land Cover	IRS LISS-III	24 m	2011-13 and 2020-2021
LDSM	IRS LISS-III	24 m	2018-2019
OSM – Topographical sheets	Survey of India	1:50,000	2006

a broader theme of inquiry was applied to examine the effects of desertification and other land degradation processes in the district.

Methodology

Desertification land degradation vulnerability index (DLVI) incorporates a host of different indices to showcase the extent of land degradation in the study area. These indices have been developed by integrating one or more sub-parameters from relevant sources (Table 1). Fig. 1 illustrates the comprehensive framework adopted for mapping the DLVI and the stages of development of each index. A hierarchy based multi-criteria analysis (MCDM) has been used to showcase the proximal causes of desertification by incorporating demographic and natural parameters (Sahoo *et al.*, 2016; Jafari and Bakhshandehmehr, 2016; Sastry *et al.*, 2017). All the parameters bearing different scales of resolutions (raster and vector) necessary for the calculation of DLVI were commeasured at a 1:30,000 scale at the time of geospatial integration on GIS platform. The Land Use/ Land Cover (LULC) was carried out for both 2011-12 and 2020-21, while all the other datasets bear different time-frames. A more detailed documentation of the perused datasets have been provided in Table 1.

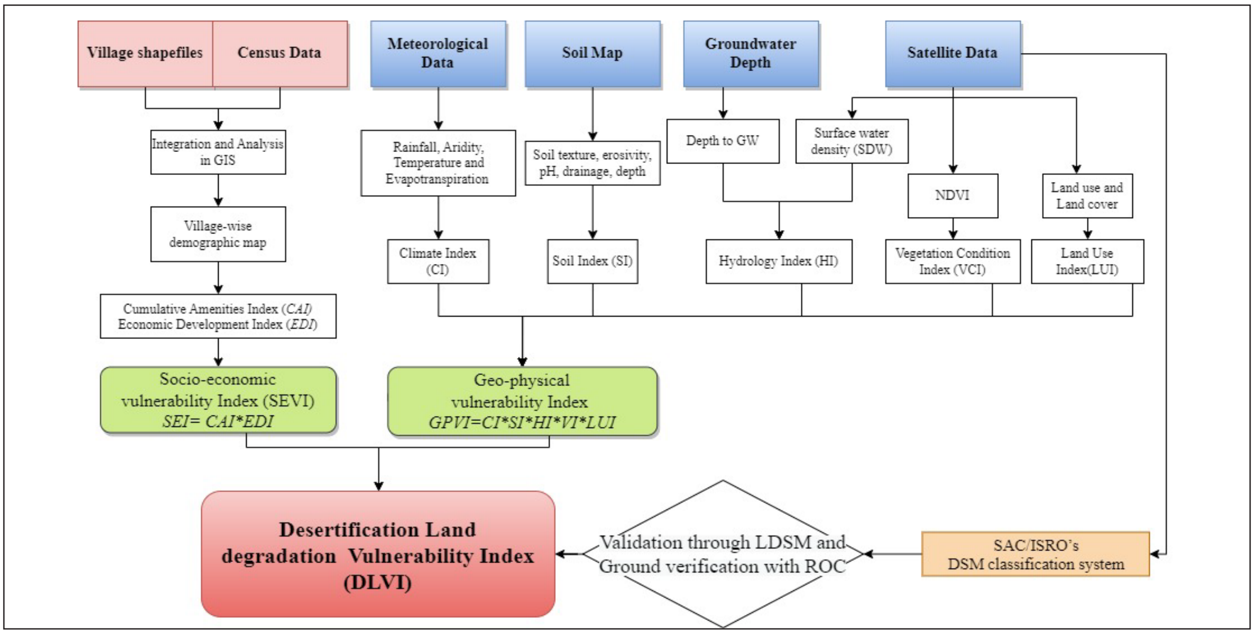

Fig. 1. A schematic flowchart is presented to illustrate the process of identifying DLVI (Desertification and Land Degradation Vulnerability Index).

Geo-environmental Indices

Climate Index and Aridity Index: To understand the effects of natural and environmental factors on desertification, several indicators were selected based on existing literatures weighing their relative contributions towards this phenomenon (Dasgupta *et al.,* 2013; Dharumarajan *et al.,* 2018a; Parmar *et al.,* 2021). For calculation of climate index gridded precipitation and temperature data set over India at spatial resolutions of 0.25° x 0.25° (Pai *et al*., 2015) and 1° x 1° respectively from IMD was used for mapping rainfall and temperature variation over the district. The aridity index was calculated from average annual rainfall/ potential evapotranspiration (ECJRC, 2018) and divided into two classes semi-arid (0.2-0.5) and dry sub-humid (0.5-0.65). Southwestern section of the district was classified as semi-arid while the northeastern part reflected dry sub-humid characteristics.

The index for each climate sub-parameter is generated individually using the following equation.

$$W_i = \sum \frac{A_i * R_i}{Total\ area} \quad ...1$$

where, W_i=Weightages for the climate parameters, A_i=Area ofthat perticular class, R_i=Rank of the i^{th} class.

Each of these climatic parameters bears values ranging from 0 to 1 and have been classified into five classes using a statistical normalization method before integrating into the GIS platform to arrive at a composite climate index using the following formula.

$$CI = RI * TI * AI * EpI \quad ...2$$

where, CI=Climate Index ndex, Ri=Rainfall Index,TI=TemperatureIndex,AI=Aridity Index, EpI=Evapotranspiration Index.

Edaphic Index (EI): The EI was arrived at by using the variables: soil texture (ST), soil erosivity (SE), soil depth (SD), soil drainage (SDr) and soil pH (SpH). The weights of each of the parameters pertaining to soil were calculated using the following Eq. 3.

These calculated weights were integrated into a GIS platform using the following formula;

$$EI = SE * ST * SDr * SD * SpH \quad ...3$$

Hydrological Index (HI): HI was calculated using two parameters viz. surface water density (SWD) and groundwater depth (GwD) to shed light upon the distribution and availability of water resources in the district.

The Ghaggar River and major canals (Singh *et al.,* 2006) have been mapped using high resolution Google Earth imagery at 1:2000 scale. A simple line density function was applied to map the density of water bodies over the district (Gregory *et al.,* 1968). The output SWD map was spatially classified into five separate zones according to surface water availability (i.e. very good, good, moderate, low and very low).

For the GwD map, time-series pre and post monsoon data from 2010-2019, was collected from India water portal (https:// www.indiawaterportal.org/). Twenty-eight groundwater observation wells with fairly continuous data availability were selected (Table 2). These wells were vectorized, and an annual average (2010-2019) GwD data was incorporated into the GIS environment. Spatial interpolation was done using IDW interpolation technique to obtain the larger GwD map for the district.

The indices of each of the hydrological parameters were calculated using Eq. 3 and were integrated into a GIS platform using the following formula:

$$HI = SWD * GwD \quad ...4$$

Vegetation index: Normalized Differential Vegetation Index (NDVI) is a technique

Table 2. Data availability of exploration wells in Sirsa district from CGWB

Source	No of wells	up to 100 *mbgl*	100-200 *mbgl*	200-300 *mbgl*	>300 *mbgl*
CGWB	14	1	0	7	6
Private	4	0	2	2	0
PHED	77	31	46	0	0
Total	95	32	48	9	6

Depth in mbgl

enumerated under spectral ratio approaches to precisely delineate vegetation boundaries as well as calculate vegetation densities over a landscape in over a RS/GIS platform (Özyavuz, 2015). NDVI at a time series over a long duration provides valuable information regarding the status of vegetation health and growth at different time scales (Masitoh and Rusydi, 2019), therefore, suitable for analysing status of land degradation associated with desertification. Here, NDVI has been applied for calculation of Vegetation Condition Index (VCI) using the following the equation (Kogan, 1995):

$$VCI = \frac{(NDVI - NDVI_{min})}{(NDVI_{max} - NDVI_{min})} \quad ...5$$

This equation normalises the NDVI values of a year by an assortment of NDVI values computed from long term monitoring of NDVI values for the study period (2013-2020). and represent the long-term minimum and maximum NDVI values used for the calculation of the composite time series (2013-2020). For the calculation of NDVI, Band 4 and Band 5 of Landsat 8 satellite imagery were used in the following equation.

$$NDVI = \frac{(Band5 - Band4)}{(Band5 + Band4)} \quad ...6$$

Normally low values represent strained vegetation conditions, moderate values represent decent and lofty values represents robust vegetal health. The values of VCI range from 0-1.

The VCI map has been classified into five classes, *viz.* dense, moderate, sparse, and very sparse and no vegetation cover. The weight of each vegetation class has been calculated using Eq. 3.

Land use index: To understand the pressure on land and environment, cloud-free Linear Imaging Self Scanning (LISS III) satellite data of 2011 and 2021 (for three different seasons, i.e. kharif, rabi and zaid) was utilised for creating LULC map of the district. The Level-I classification method was applied using the onscreen digitisation technique (Anderson, 1976). Level-II classification was used to define barren lands, fallow land and sandy areas other than beaches. Moreover, agricultural land were further classified at the Level-III classification system, viz. double/triple cropped areas, kharif crops, rabi crops (Anderson, 1976; Parmar *et al.,* 2021).

Geo-physical vulnerability index: The geo-physical index (GPI) was mapped with each of the geo-environmental indices according to their relative vulnerability towards desertification. The GPI has been derived by multiplying all the different natural parameters (i.e. climatic, edaphic, hydrologic, vegetative and land use land cover) in a GIS platform. The Geo-physical vulnerability index classifies the land into five classes, viz. excellent, good, moderate, poor and very poor respectively depending upon their relative vulnerability towards desertification.

$$GPVI = CI * EI * HI * VI * LuI \quad ...7$$

Socio-economic indices: Multivariate statistical analysis (Salvati and Zitti, 2008; Parmar *et al.*, 2021) has been performed to generate village-level composite socio-economic indices. The vulnerability associated with these indices have been calculated using the following steps; firstly, parameter normalisation using (1= available, 0= not available), secondly, calculation of different indices along with all their sub-indices, and finally, estimation of the each indices before integrating them into a village vector layer.

Cumulative amenities index: CAI calculation has been performed to understand the status of different services or amenities, i.e. communication, transportation, health and education in a particular village or settlement of the studied district. Understandably, availability of these services/amenities indirectly influences the environment, thus, they have been considered as critical social indicators of vulnerability (Dharumarajan *et al.*, 2018b). The different social amenities were enumerated using the following equation:

$$I_A = \sum_{i=0}^{n} (A|i * W_i)/W_i \quad ...8$$

where, i=1 to n, n=number of sub classes under an amenity, I_A=Index of particular variable, A_i=0 or 1(0=notavailable,1=availabele).

In addition, the weights or W_i in the particular subcategories have calculated using the following formula:

$$W_i = (T_n - F_i)/T_n * 100 \quad ...9$$

T_n is the number of villages or towns in the study area (330 and 5 respectively), and F_i is

Table 3. Indexing method used for social and economic parameters

Classes	Vulnerability category
< (μ - 2σ)	Very low
(μ - 2σ) to (μ - σ)	Low
(μ - σ) to (μ + σ)	Moderate
(μ + σ) to (μ + 2σ)	High
> (μ + 2σ)	Very high

where (σ) is standard deviation and (μ) is mean

the aggregate of villages containing a particular facility *i*.

The CAI of a specific settlement is the summation of all the facilities available of that settlement;

$$CAI = \sum_{i=1}^{n} I_A \quad ...10$$

where i=1 to n, n=number n of amenities, and I_A Index of a perticular variable derived earlier with Eq.3.

The values derived from this index was further classified using μ and σ as shown in the Table 3.

Economic development index (EDI): Economic development of a region is very intricately related to the number of working populations, which in turn may negatively affect the environment causing degradation (Salvati and Bajocco 2011). To address this issue, EDI has been included as a parameter in the study. The status of economic development for each of the village units and towns was calculated using;

$$EDI = \sqrt[2]{DI * EP * (1 - UW)} \quad ...11$$

where DI is the density of population, EP is the ratio of employed population calculated using (total engaged population/population total of the region), and UW is the ratio of unskilled workers (total unemployed population of the area + agricultural labourers of the area + workers belonging to marginal class / population total of the area). The EDI values were thereafter spatially classified into five categories using μ and σ of the calculated dataset, shown in Table 3.

Population literacy index (PLI): Population parameters in the calculation of DLVI with the employment of the have been used. PDI has been derived using the population of each village and dividing them with their respective areas (person km^{-2}). The literacy index was calculated from the primary census data using the total literate population, and using the following equation;

$$CLR = TLP/TP*100 \quad ...12$$

where CLR is crude literacy rate, TLP is total literate population, TP is total population.

Socio-economic vulnerability (SEVI): The SEVI map has been developed by overlaying the DI, EDI, PLI and CAI as layers in a GIS platform using Eq.14. The resultant values denote the socio-economic vulnerability which have further been sequentially categorised into five zones, viz., very few facility, few facility, moderate facility, plenty facility and abundant facility zones respectively.

$$SEI = DI * PLI * EDI * SCAI \quad ...13$$

Desertification-Land-degradation Vulnerability Index (DLVI): The DLVI map was generated by integrating both Geo-physical Vulnerability Index (GPI) and Socio-economic vulnerability Index (SEVI) indices into the GIS environment (Eq. 14). This exercise produced a unique set of combinations of vulnerability classes. The multi parametric model devised for DLVI strives to capture the impact of environmental and anthropogenic factors upon degradation. The final output model classified the area into five classes, i.e. extreme, high, moderate, partly and very low desertified areas respectively.

$$DLVI = GPI * SEI \quad ...14$$

Validation

In this study the model validation was done in two parts, i.e. comparison of Land Degradation Status Map (LDSM) with DLVI using ROC, as well as conducting field verifications along with the geo-tagging of locations from both the LDSM and DLVI maps. The LDSM was derived using LISS-III images of year (2018-19) for three consecutive seasons i.e. monsoon (kharif), winter (Rabi) and summer (Zaid) (SAC, 2018a; 2021). Building upon the severity levels, processes of desertification active along with the analogous land use patterns, the LDSM map was categorized in to 3 zones of vulnerability, i.e. severe, moderate and low (Table 4). The individual classes were then converted into a binary form and the same was done for the final DLVI, depending

Table 4. Classification system for LDSM as per SAC, 2021

Level-1: Land use	Code	Level-2: Process of desertification	Code	Level-3: Severity	Code
Agriculture irrigated	I	Vegetal degradation	v	Slight	1
Agriculture unirrigated	D	Water erosion	w	Moderate	2
Forest/Plantation	F	Wind erosion	e	Severe	3
Grassland/Grazing land	G	Salinity/Alkalinity	s/a		
Land with scrub	S	Water logging	l		
Barren	B	Mass movement	g		
Rocky area	R	Frost heaving	h		
Dune/Sandy area	E	Frost shattering	f		
Glacial	C	Man made	m		
Periglacial	L				
Others	T				

on their severity or intrinsic vulnerability to degradation. Using these binary values the performance of the model was validated using ROC. The information provided by the ROC is summarised using the Area Under the Curve (AUC) technique, representing the relationship between sensitivity or the True Positive Rates and the specificity or the False Positive Rates (Das *et al.,* 2022). The area under curve (AUC) refers to that excerpt of area within which the square unit which provides an indication about the performance of the implemented methodology. Therefore, a higher AUC (ranging between 0 and 1) points out towards the efficacy of the model.

Secondly, to assess the accuracy of both the final LDSM and DLVI maps, field verification was performed, geo-tagging the potential sites of Desertification.

Results and Discussion

Analysis of geo-environmental parameters

A single indicator cannot effectively describe a complex process such as desertification, hence several different indicators are necessary to predict its progression and condition (Kosmas *et al.,* 2003; Karavitis *et al.,* 2020). Environmental or biophysical indicators can provide us with information regarding the state of condition of the environment and the effects of human actions thereafter.

Climate Index: Analysis of rainfall revealed that 40% of the area falls under high rainfall category (<1600 km^2), while the rest of the districts reflects moderate (33%) to low (27%) rainfall. Surprisingly, the most densely populated areas of the district are located in low and moderate rainfall distribution zones. It is evident from Table 5, that 43% (<1800 km^2) of the area has relatively lower temperatures, while 20% (852 km^2) area falls under the higher temperature category. Similarly, aridity index divides the district into two separate regions; semi-arid and dry sub-humid. The semi-arid parts covered 38% (<1680 km^2) of the district, while the dry sub-humid areas covered 62% (<2600) of the total geographic area (TGA). Evapotranspiration (ET_0) is a significant component of the hydrological cycle (Singh and Bala, 2012). Table 5, shows that most of the district has moderate (38%.) ET_0 values, covering an area of 1600 km^2. Very high ET_0 values can be observed in the southwestern parts and cover an area which is <5% (236 km^2). From the analysis shown in Table 6, it was observed that 12% (532 km^2) of the area is highly vulnerable towards desertification and hence can be considered as highly fragile, 16% (701 km^2) of the area as fragile, 12% (541 km^2) area as considered moderate, 15% (626 km^2) of the area as stable respectively. However around 43% (1816 km^2) of the area can be considered to be highly stable.

Edaphic Index: Desertification studies in India have used different edaphic parameters, like, soil depth (Dasgupta *et al.*, 2013), drainage (Dharumarajan *et al.*, 2018b), texture (Sastry *et al.*, 2017), pH (Romshoo *et al.*, 2020), and erosivity (Khan and Romsoo 2008) to measure either the land capability or by simply observing the status of soils in a region. The analysis from Table 5 shows that most of the district has moderately deeps soils, accounting for 62% of the total area (2680 km^2), followed by very deep and shallow soils covering 15% and 14% area (664 km^2 and 616 km^2) respectively. Soil drainage in Sirsa can be classified into three

Table 5. Different GPVI sub-parameters and their areal distribution

Indicators		Categories	Class code	Area in sq. km	% Area
Climatic indicators	Aridity	Semi-arid	1	1638.37	38.49
		Dry sub-humid	2	2618.42	61.51
	Evapotranspiration	Very high	1	236.1	5.55
		High	2	1158.15	27.22
		Moderate	3	1641.32	38.57
		Low	4	1219.76	28.66
	Rainfall	Low	1	1153.62	27.09
		Moderate	2	1421.1	33.38
		High	3	1683.03	39.53
	Temperature	High	1	852.02	20.01
		Moderate	2	1586.11	37.25
		Low	3	1819.99	42.74
Soil Parameters	Depth	Very shallow	1	295.57	6.94
		Shallow	2	616.2	14.47
		Moderately deep	3	2680.87	62.97
		Very deep	4	664.77	15.61
	Drainage	Excessively Drained	1	1514.73	35.58
		Well drained	2	2116.1	49.71
		Moderately well Drained	3	626.73	14.72
	Erosivity	Severely eroded	1	28.28	0.66
		Moderately Eroded	2	1889.94	44.4
		Slightly eroded	3	2339.35	54.95
	pH	Alkali	1	650.05	15.27
		Normal	2	3607.52	84.74
	Texture	Sand	1	63.96	1.50
		Sandy loamy	2	491.02	11.53
		Sand loam sand	3	109.28	2.57
		Loamy sand	4	1971.71	46.31
		Silty loam	5	910.18	21.38
		Silty clay loam	6	196.87	4.62
		Clay loam	7	514.52	12.08
Hydrologic Parameters	Ground Water Depth (mbgl)	Very Poor	1	133.72	3.15
		Poor	2	188.27	4.44
		Moderate	3	1117.57	26.35
		Good	4	1641.11	38.69
		Very good	5	1160.89	27.37
	SWD	Low	1	3304.33	77.64
		Medium	2	840.67	19.75
		High	3	110.97	2.61
VCI Categories		Extreme	1	685.39	16.10
		Severe	2	931.52	21.88
		Moderate	3	853.67	20.05
		Light	4	664.68	15.61
		Very light	5	1122.34	26.36

categories: excessively drained, moderately well-drained, and well-drained. Most of the district, accounting for 49% (2116 km^2) is well-drained, however around 35% of the region is excessively drained (1514 km^2), while, rest of the district is moderately well-drained (14% or 626 km^2). Slight and moderate soil erosion can be observed from Table 5, covering an area of 54% and 44% (2339 and 1889 km^2) respectively. However some parts of northern Sirsa reflects a severe problem of soil erosion (0.66% or 28 km^2). Neutral soils bearing pH value of 7 is

Table 6. Different Geo-environmental parameters and their spatial distribution

Index	Area (sq. km)	% area	Class	Description
Climate	532.43	12.62	1	Very fragile
	701.64	16.63	2	Fragile
	541.77	12.84	3	Moderately fragile
	626.01	14.84	4	Stable
	1816.68	43.06	5	Highly stable
Soil	1445.62	33.97	1	Very poor
	851.2056	20.00	2	Poor
	716.3569	16.83	3	Moderate
	423.4906	9.95	4	Good
	819.385	19.25	5	Very good
VCI	685.39	16.10	1	Extreme
	931.52	21.88	2	Severe
	853.67	20.05	3	Moderate
	664.68	15.61	4	Light
	1122.34	26.36	5	Very light
Hydrology	423.365	10.04	1	Very poor
	735.0113	17.42	2	Poor
	918.6813	21.78	3	Moderate
	892.7875	21.16	4	High
	1248.513	29.60	5	Very high

widespread in Sirsa covering 84% of the total area (or 3607 km^2), but parts of central and northern Sirsa reflect basic soils, mildly alkaline in nature (pH values ranging between 7.9-8.6). Evidently, soils in Sirsa are mostly sandy in nature and texture category varies from pure sand to clay loam. Most of the district is covered in loamy sand, while significant stretches are covered by clay-loam and sandy-loam. The later soils are mostly found along the banks of Ghaggar River. The final SI map was classified into five categories on the basis of the following categories; very poor (33%), poor (20%), moderate (16%), good (9%) and very good (19%) soils (Table 6) respectively.

Hydrology Index (HI): The surface water density (SWD) data, considers both the river Ghaggar along with the many canals in the region and can be classified into three categories, i.e. excellent surface water distribution, moderate surface water distribution and poor surface water distribution. From Table 5 it is evident that only 2% of the (110 km^2) area has good SWD, while 77% (3304 km^2) of the district has poor SWD while, 19% of the district has moderate (840 km^2) SWD.

The average annual depth of the water table of Sirsa district ranges between 2.1 mbgl to 34.4 mbgl, largely follows a north-south direction. Both pre-monsoon and post-monsoon depth data have been combined and calculated for mean values before applying interpolation techniques in the GIS environment. The groundwater depth data was then classified according to its depth to water table values and grouped into five distinct zones, i.e. excellent (27.37%), good (39.69%), moderate (26.35%), poor (4.44%) and very poor (3.15%) groundwater zones respectively (Table 5).

By combining the SWD and GwD map the HI map was prepared and classified into five classes; very high (29.60%), high (21.16%), moderate (21.78%), low (17.42%) and very low (10.04%) hydrological prospect zones respectively (Table 6).

Vegetation Index (VI): While NDVI is the most commonly used vegetation indicator, it is not as effective in evaluating vegetation density or health, hence Vegetation Condition Index (VCI), derived from the minimum and maximum NDVI values were used instead.

The VCI values were calculated using Eq. 5, and then classified according to relative values

Table 7. Area under different land use categories in 2011-12 and 2020-21 and accuracy assessment

LULC classes	2011-12		2020-21		% change	Accuracy Assessment (2021)		
	Area	Area (%)	Area	Area (%)	(2011-2021)	N	n	%
Current fallow	432.30	10.20	420.93	9.94	-2.63	3	3	100.00
Double/triple crops	1614.39	38.11	1677.26	39.67	3.89	11	9	81.82
Kharif	1657.89	39.14	1603.82	37.92	-3.26	4	3	75.00
Plantation	2.62	0.06	2.62	0.06	0.00	9	8	88.89
Rabi	258.18	6.09	258.19	5.93	0.00	6	4	66.67
Scrubland	75.73	1.79	52.10	1.23	-31.20	5	4	80.00
Settlement	179.89	4.25	182.47	4.73	1.44	15	13	86.67
Water body	15.27	0.36	15.27	0.46	0.00	3	3	100.00

N= observed, n= actual value

(0-100), where 0 is extremely unfavorable and 100 is the optimal condition for vegetation health (Jiao *et al.,* 2016). Extreme vegetative condition has been observed in 16.1% of the area (Table 6), which includes the Ghaggar basin and parts of the southern sandy areas. These areas are overly exploited in terms of groundwater resources and through mono cropping practices or due to adverse climatic conditions. Moderate conditions cover around 20% of the TGA, calculated to around 850 sq. km. These areas correspond to very light dryness and are well suited for vegetation growth. Around 26% of the land is under such kind of vegetation cover. The final VCI map reveals that there is comparatively greater proportions of the TGA that faces water stress than land which has sufficient moisture condition in order to sustain vegetation.

Land use Index: Ortho-rectified cloud-free optical satellite data of IRS LISS III for the years 2011 and 2021 (three seasons, i.e. kharif, rabi and zaid) were used for generating the LULC map of the study area. The overall accuracy of the LULC types was calculated at 84% (Table 7). The indicators of LULC have been taken into consideration to show the percentage usage of available land under different categories in order to understand the changing land-use pressure. Land utilisation under sensitive categories was examined over a temporal period of 10 years (Table 7). Agriculture being the primary economic activity observes much of the land engaged in agricultural pursuits. The map (Fig. 2) illustrated that double/triple crops and kharif crops are the region's two most prominent land usage, engaging 40% and 38% of the area respectively. Whereas rabi crops constitutes an area of about 5.63%, and are mainly found in the northern and central parts of the region. The comparative study of maps made for 2011-12 and 2020-21 showed that the area under rabi crop cultivation has decreased (from 6.09% in 2011 to 5.63% in 2021) recently. Scrublands and woodlands are noted along the Ghaggar River, besides roads, canals and railway tracts respectively. In 2011-12 there was around 75 sq. km area of scrublands, however in the recent time scrublands has been confined to only about 52 sq. km. To measure the much rather direct impact of humans upon the landscape, built up lands have also been marked on the LULC map. Settlements in the region are small and are largely rural in nature, apart from the two municipal councils (Sirsa and Dabwali) and three municipal committees (Kalanwali, Ellenabd and Rania).

Land use and land cover classification states that most of the land in the district is devoted for agricultural pursuits; the area devoted to double/triple and kharif cropping practices were 1614.39 and 1657.89 sq. km respectively in 2011-12. A 3.89% positive increase in double/triple cropping area (1614.39 sq. km in 2011-12 to 1677.26 km^2 in 2020-21)and a decrease of 3.26% cropping area for kharif (1657.89 km^2in 2011-12 to 1603.82 km^2 in 2020-21) was noticed by the year 2020-21 respectively. Current fallow lands also observed a 2.63% decrease over a span of a decade 432.30 km^2 in 2011-12 and 420.93 km^2 in 2020-21), while areas devoted to plantation and rabi crops observed no change over to same timeline. A drastic reduction in scrubland (75.73 km^2 in 2011-12 to 52.10 km^2 in 2020-21) was noticed (31.20%) in 2011-12 to 2020-2021, while settlements (179.89 km^2 in 2011-12 and 182.47 km^2 in 2020-21) observed an increase on 1.44% over coeval time. Total area

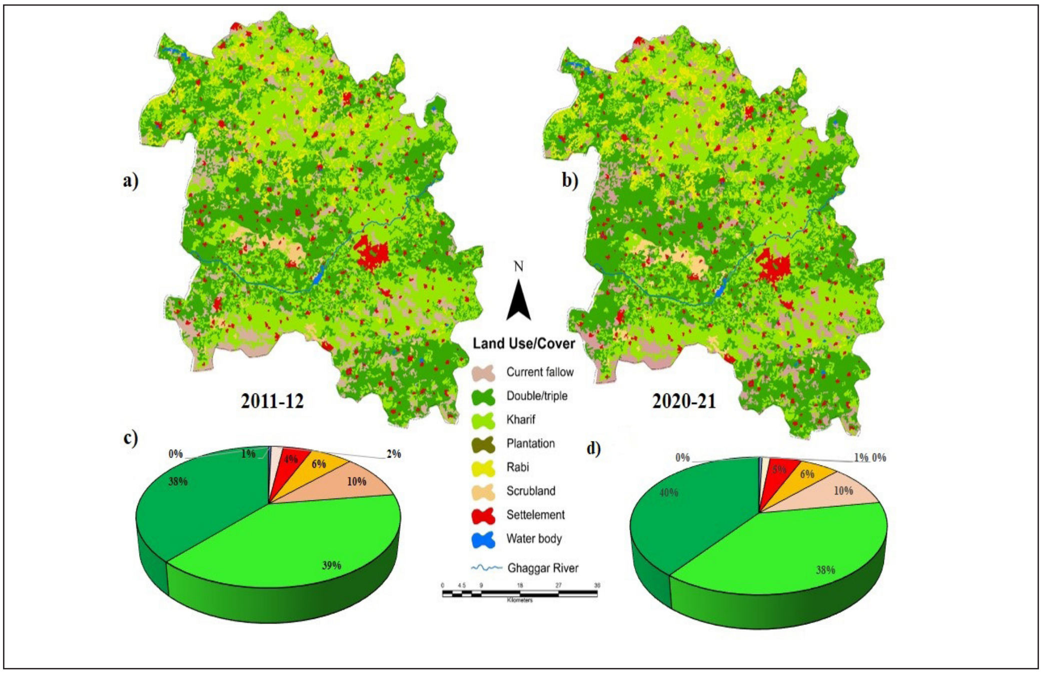

Fig. 2. The map illustrates the changes in Land Use and Land Cover (LULC) between two time periods: a) 2011-12 and b) 2020-21. Additionally, pie diagrams are provided to depict the percentage area covered by different LULC categories for c) 2011-12 and d) 2020-21.

composing of water bodies remained at 15.27 km^2 in both 2011-12 to 2020-21 notwithstanding differences in accuracy levels.

Analysis of Socio-economic parameters: Many researches have studied the role of anthropogenic factors and have come up with the argument that human actions do play a pivotal role in driving land degradation processes (Wilson and Juntti, 2005; Salvati and Zitti, 2009). The demographic variables likely to influence land degradation and subsequent desertification processes have been classified broadly into; population parameters, economic parameters and social amenities parameters respectively. Each of these indicators are further comprised of different sets of parameters which are responsible for general backwardness and vulnerability of a region, influencing the processes of desertification (Parmar *et al.*, 2021).

Cumulative amenities index: Since availability of amenities indirectly influences the sustainability of land, to assess the availability of amenities four indices is prepared (i.e. Communication, Transportation, Education and Health Index). Different parameters was chosen from the village amenities table (Census of India, 2011) and coded according to their availability; 1 (facility available) and 0 (facility not available) and normalised using Eq. 8 and Eq. 9 In order to incorporate all the different amenities (e.g. communication, transportation, health and education indexes) into the SEVI, it was classified into five classes, viz. very high, high, moderate, low and very low.

Only five settlements (all the municipal areas) was identified to have excellent connectivity and accounted for 24% of total population, whereas 134 villages has very low communication facilities (34% of the population (Table 8). According to the transportation classes, nearly 51% of the villages with a combined population of 37% falls under very low category, while only 6 settlements (four municipal areas and two villages) have very high values (Table 8,) of transport. The health index shows that good health facilities are available to about 41% of the population with around 173 villages. Only 43 and 38 villages have very low and low health infrastructure respectively. All the municipal areas have very high health facilities in comparison to the villages, accounting for nearly 23% of the population (Table 8). The education index map reveals that 310 villages with a combined population 70% of the district has little accesses to education facilities. Only 8 villages have moderate and 6 villages (including 4 municipal areas) have high education facilities. It should

Table 8. Area under different social amenities along with CAI and EDI

Amenities	Class code	Description	No of Villages/ Settlements	% of Villages/ Settlements	Area (sq.km)	Area (%)	Total Population (%)
Communication index (CI)	1	Very low	134	40.0	1748.58	41.27	34.05
	2	Low	81	24.2	769.35	18.16	13.56
	3	Moderate	102	30.4	1164.18	27.48	20.02
	4	High	13	3.9	428.12	10.11	7.72
	5	Very High	5	1.5	126.32	2.98	24.65
Transport index (TI)	1	Very low	168	50.1	2021.42	47.71	37.34
	2	Low	91	27.2	1140.56	26.92	19.84
	3	Moderate	51	15.2	660.01	15.58	12.09
	4	High	19	5.7	278.45	6.57	7.15
	5	Very High	6	1.8	136.11	3.21	23.57
Health index (HI)	1	Very low	43	12.8	602.29	14.22	10.50
	2	Low	38	11.3	471.89	11.14	9.40
	3	Moderate	75	22.4	904.47	21.35	15.40
	4	High	173	51.6	2121.80	50.08	41.13
	5	Very High	6	1.8	136.11	3.21	23.57
Education index (EI)	1	Low	310	92.5	3829.27	90.39	69.30
	2	Moderate	8	2.4	247.68	5.85	4.96
	3	High	6	1.8	107.69	2.54	11.65
	4	Very High	1	0.3	51.91	1.23	14.09
Cumulative amenities index (CAI)	1	Very low	207	61.8	2380.51	56.19	43.61
	2	Low	89	26.6	1003.82	23.69	17.25
	3	Moderate	29	8.7	580.75	13.71	11.16
	4	High	5	1.5	145.14	3.43	3.33
	5	Very High	5	1.5	126.32	2.98	24.65
Economic development index (EDI)	1	Very low	51	15.2	590.11	13.93	5.31
	2	Low	166	49.6	2029.90	47.91	38.83
	3	Moderate	106	31.6	1074.23	25.36	29.45
	4	High	11	3.3	422.29	9.97	12.32
	5	Very High	1	0.3	120.03	2.83	14.09

be noted that three villages has no data on amenities and thus they were excluded from the indices (e.g. *Chak Jiwa*, *Chak Suchan* and *Nai Dabwali*). Only the district headquarters Sirsa town has very high education facilities available (Table 8).

Economic Development Index: A region becomes more vulnerable towards land degradation and other such phenomena due to many socio-economic factors. Economic stability enables residents to better ward off against these kind of threats. Hence researches have pointed out the importance of economic activities to properly understand the situation of degradation (Tamazian and Rao 2010). To map the economic potential of the region three parameters were identified and a composite index was created using Eq.11.

Proportion of working population: The proportion of workers to total population shows how the local population is employed and also their economic stability. The data indicate that most of the workers are from rural areas. The Kamal village has the lowest proportion (11.53%) of working population whereas Shakar Mandori village has highest proportion (72.78%) of working population in the district. The villages with higher proportion of working population can be found around the towns of Kalanwali, Rania and Ellenabad. The reason for such pattern can be due to varied economic opportunities that are available in the nearby towns.

Table 9. GPVI, SEVI and DLVI, their categories and areal distribution

Index	Vulnerability	Class code	Area in sq./km	% Area
GPVI	Very high	1	1844.04	44.15
	High	2	990.31	23.71
	Moderate	3	654.50	15.67
	Low	4	518.87	12.42
	Very low	5	169.01	4.05
SEVI	Very high	1	1131.36	26.70
	High	2	1739.50	41.06
	Moderate	3	633.69	14.96
	Low	4	519.53	12.26
	Very low	5	212.48	5.02
DLVI	Very high	1	996.33	23.86
	High	2	1254.34	30.04
	Moderate	3	670.27	16.05
	Low	4	642.86	15.39
	Very low	5	612.16	14.66

Proportion of unskilled population : Skillfulness in any worker can better avert the risk posed by the physical constraints and provides better economic opportunities to sustain. In the study, the proportion of unskilled workers have been computed as the unemployed, agricultural laborers and marginal workers to the total workers population. The proportion of unskilled worker varies from 45.2% in Darewala village to nearly 100% in Kamal villages. A total of 242 out of 335 settlements have a more than 75% of worker as unskilled. The situation of towns is also gloomy. Among the towns, Ellenabad (79.48%) has maximum number of workers as unskilled, followed by Rania (76.08%), Sirsa (72.75%), Kalanwali (70.59%), and Mandi Dabwali (69.65%). The agriculturally dominated region employs agricultural labors to perform the farm jobs which requires no or little skills. The higher proportion of unskilled worker in entire district is indicative of the prevalence unorganized economic sector.

Density of population: The district has a moderate population density, <150 persons/ sq. km. The villages surrounding the municipal areas has a fairly dense population (150-300 persons/sq.km). Municipal areas, towns and the surrounding villages has dense population between 300-1200 persons/sq.km, while the district headquarters Sirsa Municipal Corporation (MC) has the highest density which is around 8488 persons/sq. km. Available literature suggest that the pressure on land is higher for densely populated land, resulting into higher level of vulnerability (Prakash *et al.,* 2016).

Literacy rate: Higher education rates have often been associated with economic development along with providing a solid base for making rational socio-economic choices. In the region, education helps adopt new land management strategies quickly and efficiently, making a positive strive towards higher economic strength, reducing vulnerability (Muttarak and Lutz, 2014). According to literacy levels, the district was classified into very high (>75%), high (60-75%), moderate (50-60%), low (40-50%) and very low (<40%) of total population respectively. Most of the district reflects moderate literacy of around 50-60%. The towns and their adjoining areas have high literacy numbers (60-75%), which includes Sirsa, Dabwali, Ellenabad, Rania, Kalanwali, Odhan, Baraguda and Nathusari Chopta. Chakbani village however, was observed with the lowest numbers of literate population (14.28%).

Geo-physical vulnerability index : The GPVI map was generated using Eq.7, and was classified into five categories upon their relative vulnerability towards desertification. Very high vulnerability has been observed in the southern and central parts of the district, accounting for nearly 44% of the TGA (Table 9). High vulnerability zones covered 23% of the district, calculated to around 1200 sq. km. The regions surrounding the canals were classified as moderately vulnerable and accounted for 15% of the TGA. The double cropping areas have Low vulnerability values, since double cropping is only possible in good soil conditions on lands that have sufficient irrigation facilities available. Low vulnerability areas encompass nearly 12% of the TGA. Very low vulnerability classes coincide with lands having good groundwater resources, deep and well drained soils, ideal land utilisation and excellent vegetation cover. Very low vulnerability zones covered about 4% of the TGA and are mainly observed in the eastern parts of the district.

Socio-economic vulnerability index: To understand the anthropogenic influence on desertification vulnerability different demographic, social and economic factors were selected from Census data sources. The SEVI map reveals that very high vulnerability zones are mostly observed in the northern and southern parts of the district encompassing 26% of the area, while high vulnerability zones have been seen in the western and southern parts covering 41% of the area. Moderately vulnerable zones are located in the vicinity of towns and cover 15% of the TGA (Table 9). Low and very low vulnerable zones are either the towns or lies just adjacent to them with 12.2% and 5% of the areas respectively. Some of the villages (e.g. Badiwala, Bajeka, Ding, and Odhan) are located in the low and very low vulnerability zone, with higher amenities at their disposal. It has been observed from the calculations (Eq. 13) that due to the centralisation of facilities in towns, a general lack of skilled labour and working populations most of the district gives rise to a perceptively high vulnerability.

Desertification and Land degradation Vulnerability Index: The DLVI map was generated by spatial integration of both GPVI and SEVI in a GIS environment using Eq.14. The map provides a general perspective of the vulnerability conditions of the district and also highlights the areas which need immediate attention for management. The district was divided into five vulnerability zones depending upon the anthropogenic and environment conditions. Very high vulnerability zones have been observed in the western parts of the district covering nearly 24% of the district (Table 9). A combination of (climatic, edaphic and anthropogenic) factors are responsible for the high vulnerability conditions in these regions. Compared to other parts of the district, this zone has much dryer weather, sandy soils, large expanses of fallow lands and low social and economic facilities. Most of the district (30% of the TGA) has been classified as highly vulnerable and have been observed in the south-western, western and central part of the district. This zone of high vulnerability boasts more amenities available than the previous category, yet, harsh climate, unsuitable soil and groundwater problems have been studied in this zone. This zone of high vulnerability has also been seen to support kharif as well as double/triple cropping system. Moderate vulnerability zone covers 16% of the TGA and is situated between the transitional areas of high and low vulnerability (Fig. 3). Low vulnerable zones covers 642 sq. km area of the district, while also bearing the highest percentages of double cropped area, good irrigation facilities, sufficient amenities and moderate climate. A section of the central part of the district has been classified in this zone.

East-central and south-eastern parts of the district have been classified as the very low vulnerability zone (Fig. 3), because of its optimal vegetal cover, well textured and well-drained soil, and transportation facilities and higher

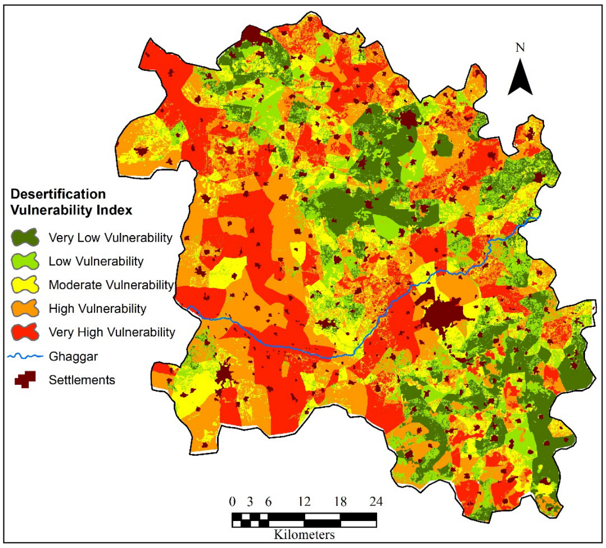

Fig. 3. The district's vulnerability to desertification and land degradation is depicted through the Desertification Land Degradation Vulnerability Map. The map categorizes the district into different levels of DLVI (Desertification Land Degradation Vulnerability Index): a) low DLVI, b) moderate DLVI, c) high DLVI, d) high DLVI, and e) high DLVI.

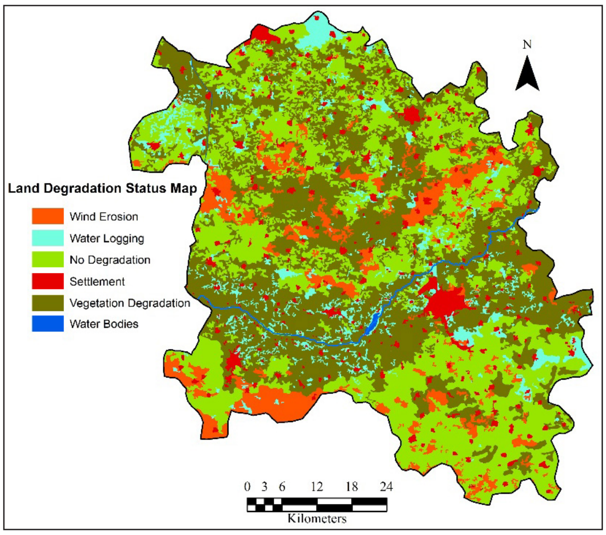

Fig. 4. Map depicting land degradation and desertification status (2018-19) of the district.

number of working population with higher literacy rates. This zone covers nearly 14% of the TGA in the district. Interestingly both Ellenabad and Rania, have been categorised under moderate and high vulnerability areas respectively, despite having good amenities and economic credentials, which points towards unsustainable development.

Validation of the model: The validation of the DVI was performed using LDSM of 2018-19. The values from the LDSM map (Table 10, Fig. 4) were transferred into R-studio and simple ROC was performed. (Fig. 5). The ROC has been used by several authors (Bradley 1997; Fawcett,

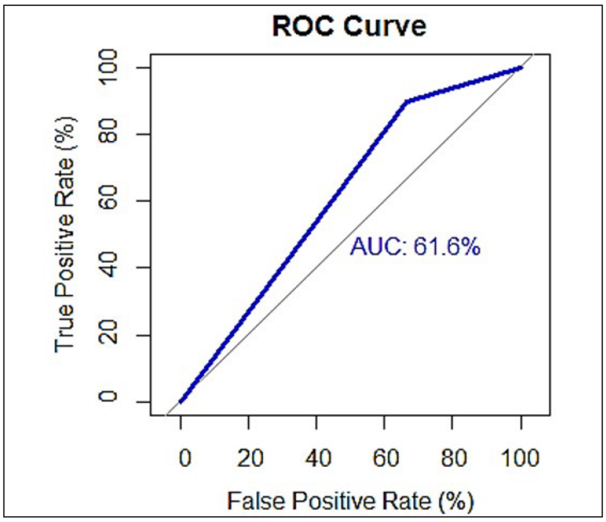

Fig. 5. The validation of the DLVI model is demonstrated through the ROC curve, which showcases an AUC (Area Under the Curve) value of 61.6%.

Table 10. Different LDSM classes and % area

Vulnerability	LDSM class	Area (%)
Very low	Not undergoing degradation	39.35
Low	Iw1, IL1, Dw1,	11.74
Moderate	Sv1, Il2. Ds1. Ss1	39.07
High	De1, Sv2, Tm2	9.17
Very high	Ee1, Ee2, Tm3	0.67

2006; Das *et al*., 2022) as a tool for evaluating the relationship between the predicted data which accurately corresponds to the ground truth. R software is used to calculate the ROC and the AUC. 105 random points have been selected to assess the exactitude of the calculated DLVI. The resultant graph shows that the DVI is fairly capable of estimating the desertification in the study area, with the AUC being 61.6%. This indicates that the DLVI correctly identifies the various zones of vulnerability and has good resemblance to the DSM, 2018.

The study presents a hierarchy-based integrated model to monitor the situation of Desertification in the westernmost district of Haryana. The study includes 14 physical and 51 socio-economic parameters and integrates them in a GIS environment. The analysis reveals that 30% of the land is under high vulnerability, and 23% under very high vulnerability towards Desertification and Land Degradation. The zones identified through this study are in immediate need of combatting plans in order to check degradation.

The model outcome has been validated against the LDSM with the help of ROC/AUC, and the study recorded an overall accuracy of 61.6% (Fig. 5). Hence, we have not just restricted the analysis to merely a geospatial examination, but have also used available information (both field and well-established measured data sets) to ascertain the validity of our results. One of the study's primary objectives was to identify the hotspots of degradation so that an adequate mitigation strategy could be developed and implemented in the selected villages or regions. The areas bordering Rajasthan in the south-western part of the district need special attention as both the model analysis as well as field investigations revealed higher prevalence degradation processes. Although the GwD map shows the presence of excellent groundwater resources in the south-western parts of the district, most of it is saline.

Climatologically the district of Sirsa falls under the BSh (semi-arid steppe type) climate (Köppen and Geiger, 1930), characterised by seasonal and diurnal temperature extremes, low rainfall, high rates of evapotranspiration (Chakravarty and Ponnusamy, 2021) high incident solar radiation with strong winds and frequent dust storms (Kumar *et al.*, 2015). These conditions make this region thin in its hydrological balance and as the soils lose moisture continuously it wakens productivity, making agriculture challenging.

The region generally exhibits an east-to-west moisture gradient; however, the development of canals and irrigation techniques has largely mitigated water shortages for agriculture. This is evident from the prevalence of kharif and double/triple cropping lands around the Ghaggar River and the numerous canals across the area. Additionally, parts of the southwestern district near Ellenabad have seen a shift from kharif to double/triple cropping, with a documented 2% increase in double/triple cropped land and a 1% decline in kharif cropped land between 2011-12 and 2020-21. As the water in this regard is considered one of the essential elements for production of crops and also for settlement (Shanzhong and Fang, 2006), availability, effective use and management of water resources remains an issue for such semi-arid regions.

Despite an extensive network of canals, groundwater remains vital for agricultural production as the canal water distribution system in Sirsa follows the 'principle of equity', which means that farmers receive canal water amount as per their proportion of land holdings, thus they use groundwater to supplement existing irrigation facilities. In spite of the above-mentioned management techniques some patches of kharif, as well as double/triple cropping land appear to be classified under the very high and high vulnerability category in the southwestern part. However, such is not the case in the double/tripled cropped northeastern part of the district in the proximities of Kalanwali and Odhan. The northeastern part of the district appears to be better equipped to deal against the processes of desertification.

A past study has shown that the soils from Sirsa are low in organic content, low in phosphorus and moderate in terms of available potassium and other minerals and nutrients (Shukla *et al.*, 2015). Sirsa is an agriculture dominated district. A sizeable part of the desertification vulnerability depends upon the edaphic vulnerabilities which includes soil quality and health as a geophysical parameter. The natural vegetation of the district has completely been wiped out due to ever increasing demand for land. Contemporarily during the period of study, only few areas (like along linear features, i.e. roads, canals, railways) have adequate vegetation cover due to lesser anthropogenic intervention in government acquired land as well as plantation activities. The effect of green revolution was faced differently by different regions across the nation. In the study area indigenous crop varieties include Jowar, Bajra and Barley as the major produce of the district. Interestingly these crops were less water intensive and best suited for this kind of climatic and environmental conditions.

With the advent of the green revolution and allied research and development in plant genetics, as well as improvement in irrigation facilities, many regions across the nation transformed with regard to choice of produce. Coarse grained produce was replaced with more commercially viable and environmentally unsustainable options (Shiva, 1991). The region presently grows wheat, rice and millets along with some amount of vegetables in sections along the Ghaggar River with deeper soil profiles and silty texture. BT cotton is another produce of the region which provides ample employment to the unskilled labour force in the unorganized sector. Further investigation may actually shed light into the interplay of several other socioeconomic practices which determine the use and maintenance of land and water as a Common Property Resource (CPR) (Hardin, 1968) in a largely moisture crunched region. Several farms were noted to use submersibles for their irrigation needs as supply of canal irrigation is often scanty and there are reports over utilization in upstream reaches (Alary and Deybe, 2005). The practice again, results into the dipping of the water-table in probably the most heavily cropped, heavily populated regions resulting in vulnerability. In such cases the socio-economic index may yield higher values, but may come at a cost of constant degradation in process.

Conclusion

The robustness and the efficacy of the model lies in the consideration of numerous physical and socio-economic parameter determining vulnerability. Regions lying in the fringes of agroclimatic regimes require special attention with respect to regional planning, as multiple specific parameters influence vulnerability levels beyond critical levels quite commonly. This hierarchy-based intergraded model helps combine geophysical index including climatic parameters, edaphic parameters, hydrologic parameters and vegetal conditions with socio-economic index including amenities available and economic development. Each of these indices have been studied to have a bearing in determining vulnerability with regard to desertification in any region.

Supplemented by our field observations alongside the careful consultation of existing literature, there is undeniably an urgent need to address water distribution problems in the whole of the district, as most the economy is agrarian and highly dependent on groundwater resources. Water-intensive crops (i.e. Rice, Wheat and Cotton) should be gradually replaced with more suited crops for such environments (i.e. *Jowar*, *Bajra* and Mustard). There is a need to identify artificial groundwater recharge sites, especially in the northern parts of the district where groundwater has been seen to be depleting more. Alternative livelihood sources apart from agriculture need to be explored with the development of both primary, secondary, as well as tertiary and vocational, in order to give rise to other livelihood pursuits. The study of the water market in the region may better shed light upon the water tariffs and reforms and their impacts upon small to large scale farmers. This technique can be extrapolated to other areas of similar environmental setting and also can be used to quickly map areas of degradation for outlining a comprehensive management strategy.

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Declarations

Conflict of interest: The authors have no conflict of interest to declare.

Author contributions: All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by SD, A.S, AB and EC. The first draft of the manuscript was written by SD and all authors commented on previous versions of the manuscript. MP and MCS edited the final manuscript. All authors read and approved the final manuscript.

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