

Composite Population–Road–Vegetation Index for Assessing Anthropogenic Vulnerability of Protected Areas in the Western Himalaya, India

Vipin Bihari Yadav^{1*}, Nirbhay Tiwari²

¹Research Scholar, Department of Computer Science, Babasaheb Bhimrao Ambedkar University (A Central University),
Lucknow, Uttar Pradesh, India

¹Corresponding Author Email: vipin884060@gmail.com

²Department of Computer Science and Information Systems, Shri Ramswaroop Memorial University, Lucknow-Deva
Road, Uttar Pradesh, India

²Email: nirbhaytiwari00000@gmail.com

Abstract

Protected areas are the principal instrument of in-situ biodiversity conservation, yet the intensity of human pressure on them varies widely from one reserve to the next, and no simple, transferable procedure exists for ranking that pressure across a large, administratively fragmented landscape. This study proposes such a ranking for the southern flank of the Indian Himalaya — the Union Territory of Jammu & Kashmir and Ladakh together with the states of Uttarakhand, Himachal Pradesh, and Punjab — a region that contains 69 named protected areas but has not previously been assessed as a single analytical unit. District-level population density and road density were each rescaled to a common 0–1 range and combined into a composite anthropogenic-pressure indicator, while sixteen-day MODIS MOD13Q1 NDVI composites were mosaicked, masked to the protected-area boundaries, and reduced to a per-reserve mean vegetation score. Two independent scoring schemes — a rank-based average and an exponential weighting function — were used to combine the pressure indicator with the vegetation score, and the two schemes were compared for internal consistency. Both approaches agree that the Talra Wildlife Sanctuary segment in Uttarkashi district, Uttarakhand, and several sanctuaries in the Kullu and Mandi districts of Himachal Pradesh obtain the most favourable combined scores (least vulnerable), while the Manali Wildlife Sanctuary segment in Kangra district is consistently the lowest-scoring (most vulnerable) reserve in the pixel-inclusive analysis; when open-water pixels are excluded from the vegetation calculation, Bir Gurdialpura in Patiala district, Punjab, replaces Manali as the lowest-scoring site. Across the region, mean NDVI is positively rather than negatively rank-correlated with district-level population–road pressure (Spearman $\rho \approx 0.53$ across 36 districts), because the lowest NDVI values occur in high-altitude, sparsely populated trans-Himalayan reserves; low NDVI in this dataset therefore appears to reflect elevation and aridity more than anthropogenic degradation. Because the analysis is based on a single vegetation-index composite rather than a multi-year time series, these patterns describe present-day spatial variation in reserve condition rather than a temporal trend, and are presented accordingly. The resulting ranked table offers state forest and wildlife departments a transparent and repeatable basis for prioritising monitoring and enforcement resources among competing reserves.

Keywords: Protected areas; NDVI; MODIS MOD13Q1; population density; road density; composite index; Western Himalaya; conservation prioritisation

1. Introduction

Protected areas remain the single most widely used instrument for in-situ biodiversity conservation, combining statutory governance and scientific monitoring with, in many landscapes, traditional and community-based stewardship. The designation “protected,” however, is not by itself a guarantee of an undisturbed condition: encroachment, grazing, road-building, and settlement continue inside notified boundaries across much of the developing world, and the degree of that pressure differs sharply between reserves that sit, on paper, under the same legal regime.

Vegetation cover is one of the most sensitive and most frequently monitored proxies for this pressure. Remote sensing combined with GIS has become the standard tool for tracking vegetation condition at the regional and landscape scale, largely because it is one of the few methods capable of repeatedly covering large, often inaccessible mountainous terrain. The Normalized Difference Vegetation Index (NDVI) is the workhorse metric for this purpose: it correlates with photosynthetic activity, standing biomass, and canopy condition, and, because protected areas are in principle less exposed to direct human modification than their surroundings, NDVI has been used both as a sentinel for climate-driven ecosystem change and as an indicator of direct anthropogenic disturbance [1].

A growing body of work has applied this logic to specific mountain systems. On the Tibetan Plateau, sixty-two of sixty-nine protected areas showed no significant change in mean NDVI between 1982 and 2015, and seven showed a significant increase, even as the human population inside protected areas rose overall between 2000 and 2015, and the analysis concluded that vegetation change in most reserves was largely independent of local population pressure [2] — a pattern this study revisits, independently, for a different mountain system. A parallel literature has used the human-footprint framework — which folds population density, built-up land, and road distribution into a single pressure surface — to evaluate whether protected status measurably suppresses these pressures relative to unprotected land, generally finding that protection helps but does not eliminate anthropogenic pressure [3–5]. Roads matter in this context because their ecological footprint extends well beyond their physical footprint: they fragment habitat, alter hydrology and fire regimes, and facilitate the spread of invasive species, and, importantly for a ranking exercise of this kind, road density is one of the few anthropogenic variables that can be derived directly from vector road networks across an entire multi-state study area, although the completeness of mapped roads varies with the level of human influence [6].

The southern Himalayan arc examined here — Jammu & Kashmir and Ladakh, Uttarakhand, Himachal Pradesh, and Punjab — is a demanding test case for this kind of assessment. It spans an elevational gradient from the Indo-Gangetic plain to the trans-Himalayan cold desert, it contains 69 protected areas ranging from small sanctuaries of a few square kilometres to reserves larger than some Indian states, and it has received considerable conservation attention at the level of individual reserves or individual threats [7]; however, to the authors’ knowledge, it has not previously been ranked as a single set using a population–road–vegetation composite index. That gap motivates the present study.

Three questions guided the analysis. First, what is the current spatial pattern of vegetation condition across the protected areas of this region, and how much does it vary from reserve to reserve? Second, is that pattern related to the level of human engagement — population density and road development — within the districts containing each reserve, and does the direction of that relationship match the expectation that higher engagement corresponds to lower greenness? Third, can a simple, transparent, and repeatable composite index reproduce the same ranking of “most” and “least” pressured reserves under two different mathematical formulations, which would suggest that the ranking reflects a genuine underlying pattern rather than an artefact of one particular scoring choice? Because the vegetation data used here represent a single seasonal composite rather than a multi-date archive, these questions are

addressed as a spatial-pattern assessment; a genuine temporal-trend analysis would require a separate, multi-year NDVI time series and is identified in Section 4.4 as a direction for future work rather than treated as already available.

The remainder of this paper is organised as follows. Section 2 describes the study area. Section 3 sets out the datasets, the population- and road-density formulation, the NDVI processing chain, and the two ranking models. Section 4 presents the results, discusses them against the wider literature, and states the limitations of the approach. Section 5 concludes and identifies directions for future refinement.

2. Study Area

The study area (Fig. 1) covers the Union Territory of Jammu & Kashmir and Ladakh and the states of Uttarakhand, Himachal Pradesh, and Punjab, treated jointly as a single southern-Himalayan analytical unit. District boundaries were used as the base administrative unit for population and road statistics, and 69 named protected areas — national parks, wildlife sanctuaries, and related reserve categories — falling within these districts were extracted for the reserve-level analysis. Because several reserves straddle more than one district, the underlying spreadsheet used for the ranking (Appendix, Table 1) contains 126 protected-area–district occurrences rather than 69 rows; each occurrence records the local composite pressure and mean NDVI applicable to the portion of that reserve lying in the given district, while the reserve itself remains the ecological and administrative unit of interest throughout the narrative results.

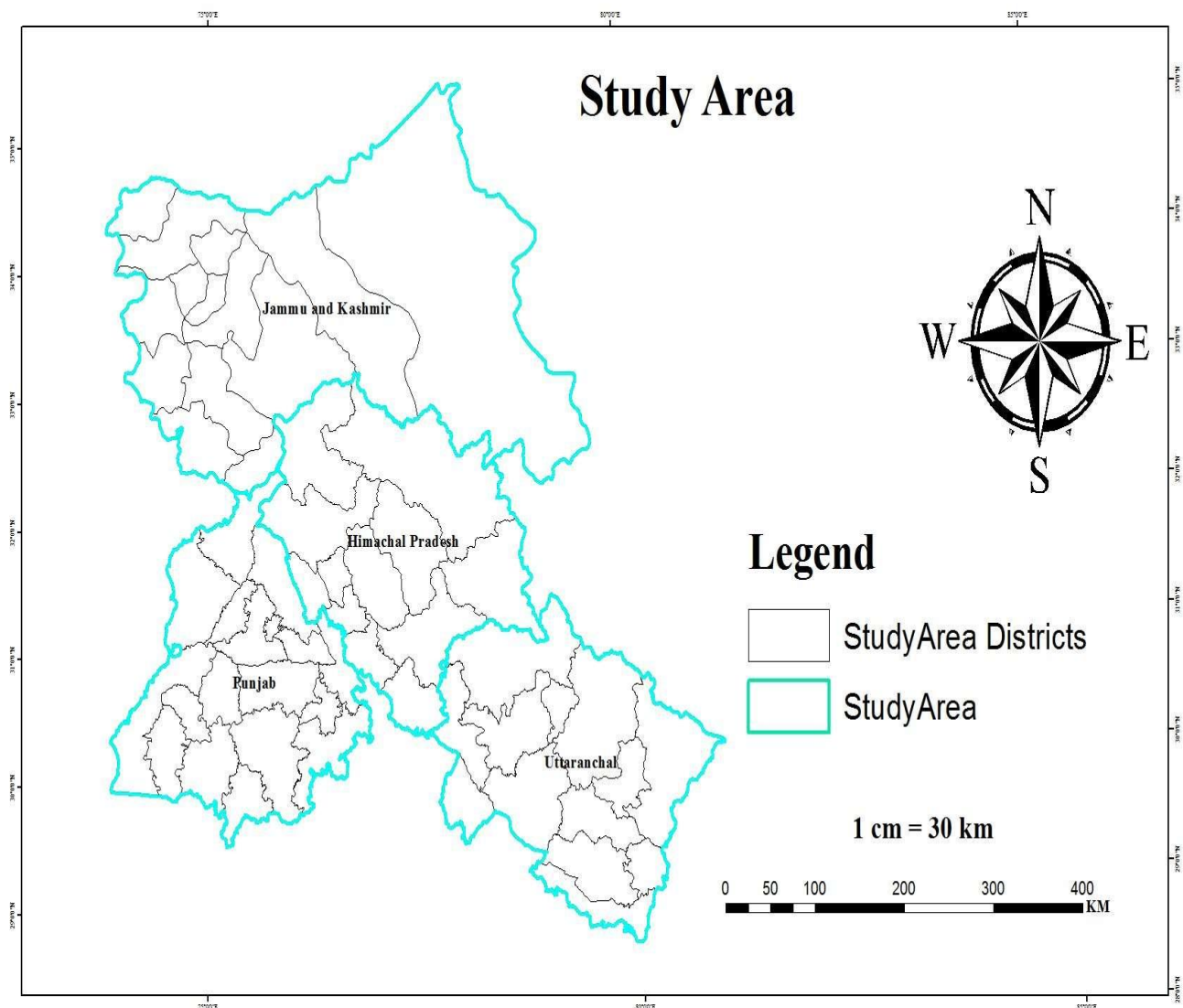


Figure 1. Study area: districts of Jammu & Kashmir and Ladakh, Uttarakhand, Himachal Pradesh, and Punjab.

3. Methods and Material

The methodological workflow, from the source data through the two independent ranking models to the final composite vulnerability ranking, is summarised in Fig. 2.

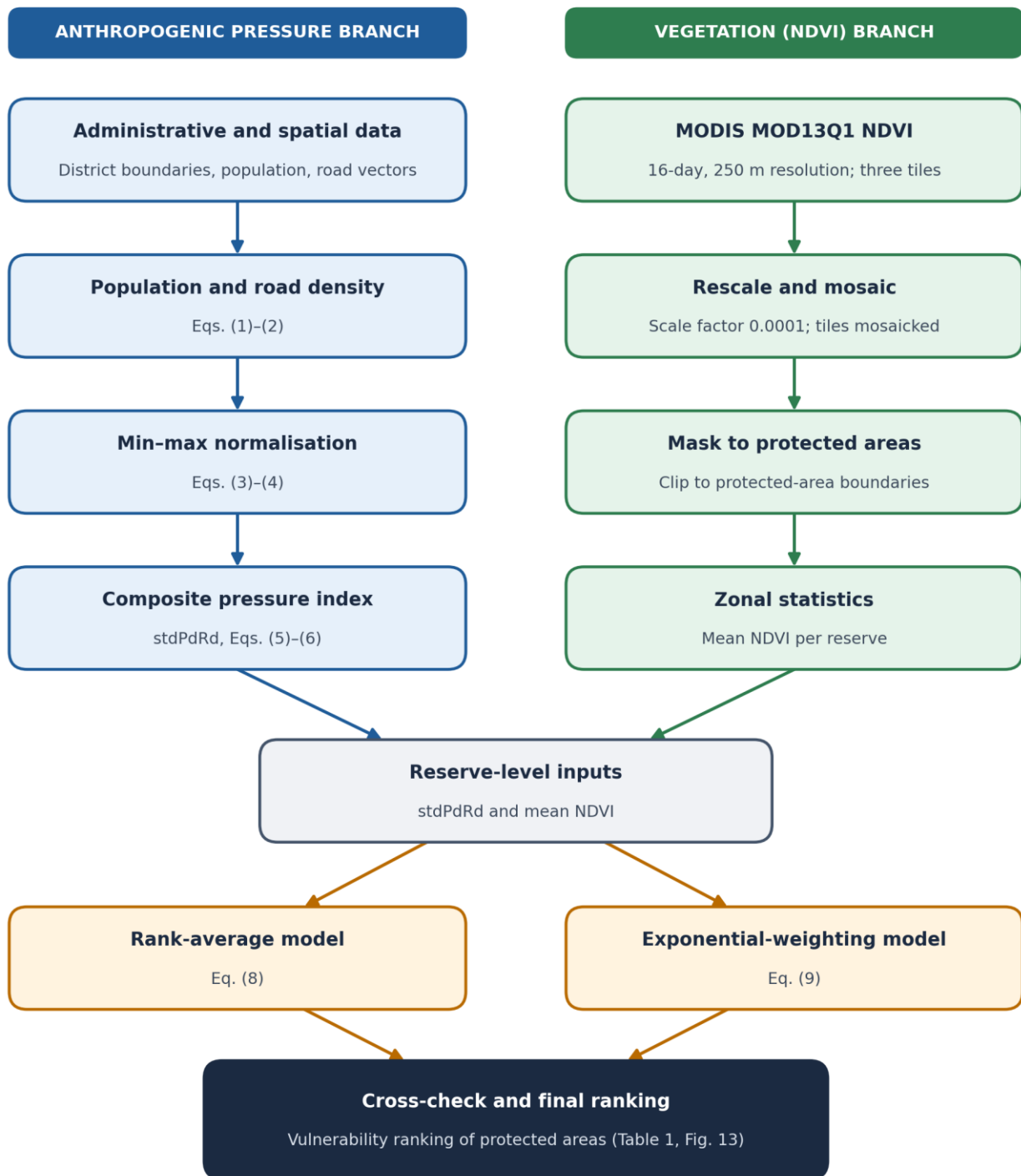


Figure 2. Methodological workflow, from source data through the two independent ranking models to the final composite vulnerability ranking.

3.1. Datasets

Three categories of data were used. First, administrative and demographic data — district boundaries, area, population, and road-network vector layers — from which district-wise population density and road density were derived. Second, protected-area boundaries: polygon layers for the 69 reserves falling inside the study region. Third, vegetation data: the MODIS Terra Vegetation Indices 16-Day L3 Global 250 m product, MOD13Q1 [8], which delivers NDVI and EVI composites every sixteen days at 250 m spatial resolution together with surface-reflectance

bands and per-pixel quality-assurance layers. The compositing algorithm retains, for each pixel and each sixteen-day window, the observation with the lowest cloud contamination, the lowest view angle, and the highest NDVI/EVI value, which is what makes the product usable for consistent multi-tile mosaicking over mountainous terrain. Only sub-dataset 0 (the 250 m 16-day NDVI layer) was used in this study; three MOD13Q1 tiles were required to cover the full study extent.

3.2. Population Density and Road Density

For each district i , population density and road density were computed as simple area-normalised ratios:

$$PD_i = \frac{P_i}{A_i} \quad (1)$$

where P_i is the district population and A_i is the district area in square kilometres, giving PD_i in persons per km^2 .

$$RD_i = \frac{L_i}{A_i} \quad (2)$$

where L_i is the total mapped road length in kilometres within district i . Population density and road density were chosen as the two anthropogenic-pressure variables because both are measurable consistently across the full multi-state study area from routinely available administrative data, and because both are widely used, individually and in combination, as proxies for the broader human footprint on natural ecosystems [3,6].

3.3. Standardisation and Composite Pressure Index

Because PD_i and RD_i are measured in different units and span very different numeric ranges across the study area, both were rescaled to a common $[0,1]$ interval using min–max normalisation before being combined, following standard composite-indicator practice:

$$\text{stdPD}_i = \frac{PD_i - PD_{\min}}{PD_{\max} - PD_{\min}} \quad (3)$$

$$\text{stdRD}_i = \frac{RD_i - RD_{\min}}{RD_{\max} - RD_{\min}} \quad (4)$$

The two normalised variables were then summed and renormalised to give a single composite pressure indicator, stdPdRd_i , bounded between 0 and 1:

$$\text{Sum}_i = \text{stdPD}_i + \text{stdRD}_i, \quad 0 \leq \text{Sum}_i \leq 2 \quad (5)$$

$$\text{stdPdRd}_i = \frac{\text{Sum}_i - \text{Sum}_{\min}}{\text{Sum}_{\max} - \text{Sum}_{\min}} \quad (6)$$

stdPdRd_i therefore expresses, on a common scale, how heavily populated and how heavily road-served district i is relative to every other district in the study area; this district-level value was subsequently attached to each protected area lying within, or spanning, that district. Assigning a district-level pressure value to a reserve is a simplification — it does not capture pressure gradients within a district — and is discussed as a limitation in Section 4.4.

3.4. NDVI Mosaicking and Zonal Reduction

The three MOD13Q1 tiles required to cover the study area were imported into ArcMap, and the raw digital-number NDVI layer was rescaled to its physical range by multiplying by the product's scale factor of 0.0001 [8]. The three rescaled tiles were mosaicked into a single continuous NDVI surface, which was then clipped (“extracted by mask”) to the union of the 69 protected-area boundaries, producing an area-of-interest NDVI raster (Fig. 9). For each protected area, the mean NDVI of all pixels falling inside its boundary was computed using zonal statistics, giving a single representative value, mean NDVI_j , for reserve j (Fig. 10). This value was also min–max normalised across the 69 reserves for comparability, following the same procedure as Eqs. (3)–(4):

$$\text{stdNDVI}_j = \frac{\text{NDVI}_j - \text{NDVI}_{\min}}{\text{NDVI}_{\max} - \text{NDVI}_{\min}} \quad (7)$$

The mean NDVI used throughout this study is a single 16-day composite rather than a multi-date time series. It therefore describes the present-day spatial condition of vegetation within each reserve and should not be read as evidence of a temporal increase or decrease; a genuine trend analysis would require repeating this procedure across multiple years, which is identified in Section 4.4 as a priority extension.

3.5. Ranking Models

Two independent, non-nested scoring schemes were used to combine reserve-level vegetation condition with reserve-level anthropogenic pressure, so that the final ranking would not depend on a single arbitrary choice of aggregation function. In both schemes, a higher final score denotes a reserve that is comparatively greener and less pressured — that is, less vulnerable — and a lower final score denotes a more vulnerable reserve; this convention is used consistently in the results, in Figs. 11–13, and in the Appendix (Table 1).

3.5.1. Rank-average model

Each protected area j was first ranked on mean NDVI $_j$ alone, in descending order (a higher mean NDVI receiving a better, numerically lower, rank), giving Rank1 $_j$. It was independently ranked on stdPdRd $_j$ in ascending order (a lower pressure score receiving a better rank), giving Rank2 $_j$. The rank-average score was the arithmetic mean of the two component ranks:

$$\text{RankScore}_j = \frac{\text{Rank1}_j + \text{Rank2}_j}{2} \quad (8)$$

A lower RankScore $_j$ corresponds to a reserve that is simultaneously greener and less exposed to population/road pressure than average. Note that, in the Appendix and in Fig. 13, RankScore $_j$ is not shown; both instead report the exponential-model scores described next, on which a higher value denotes lower vulnerability. The rank-average calculation was implemented in Python using pandas' rank(method='average') function (Fig. 11).

3.5.2. Exponential-weighting model

As a second, independent formulation, an exponential composite score was computed for each reserve as the sum of the exponential of the mean NDVI and the negative exponential of the composite pressure index:

$$S_j = e^{\text{NDVI}_j} + e^{-\text{stdPdRd}_j} \quad (9)$$

Algebraically, the reciprocal-exponential term used in the original computation, $1/e^{\text{stdPdRd}_j}$, is equivalent to $e^{-\text{stdPdRd}_j}$; Eq. (9) states this in its simplified form. The function rewards high vegetation cover through the exponential NDVI term while penalising high pressure through the negative-exponential term, giving disproportionately more weight to reserves that are simultaneously very green and very lightly pressured, rather than treating the two components as linearly interchangeable as in Eq. (8). Reserves were sorted by S_j in descending order, with the highest S_j corresponding to the least disturbed reserve; this implementation and its output are shown in Fig. 12.

Agreement between the two independently derived orderings — one rank-based and linear, the other value-based and exponential — was used as an internal consistency check on the overall ranking. A formal statistical test of rank agreement (for example, Spearman's rank correlation or Kendall's tau between the two orderings) was not computed for this version of the manuscript.

4. Results and Discussion

4.1. Spatial pattern of pressure and vegetation

District-level area, population density, and road density (Figs. 3–5) show a familiar Himalayan gradient: the trans-Himalayan and high-altitude districts of Ladakh, Lahaul & Spiti, and Kinnaur combine very large areas with very low population and road density, while the sub-montane and plains districts of Punjab and the outer Shivalik belt of Himachal Pradesh and Uttarakhand combine small areas with high population and road density. After min–

max normalisation and summation (Figs. 6–8), the composite pressure surface stdPdRd shows the sharpest concentration of anthropogenic pressure in the Kullu–Mandi–Shimla belt of Himachal Pradesh and along the Punjab plains, consistent with the widespread use of road density as a spatially traceable proxy for cumulative human footprint where fine-grained land-use data are unavailable, although mapped road networks tend to be less complete where human influence is low [6].

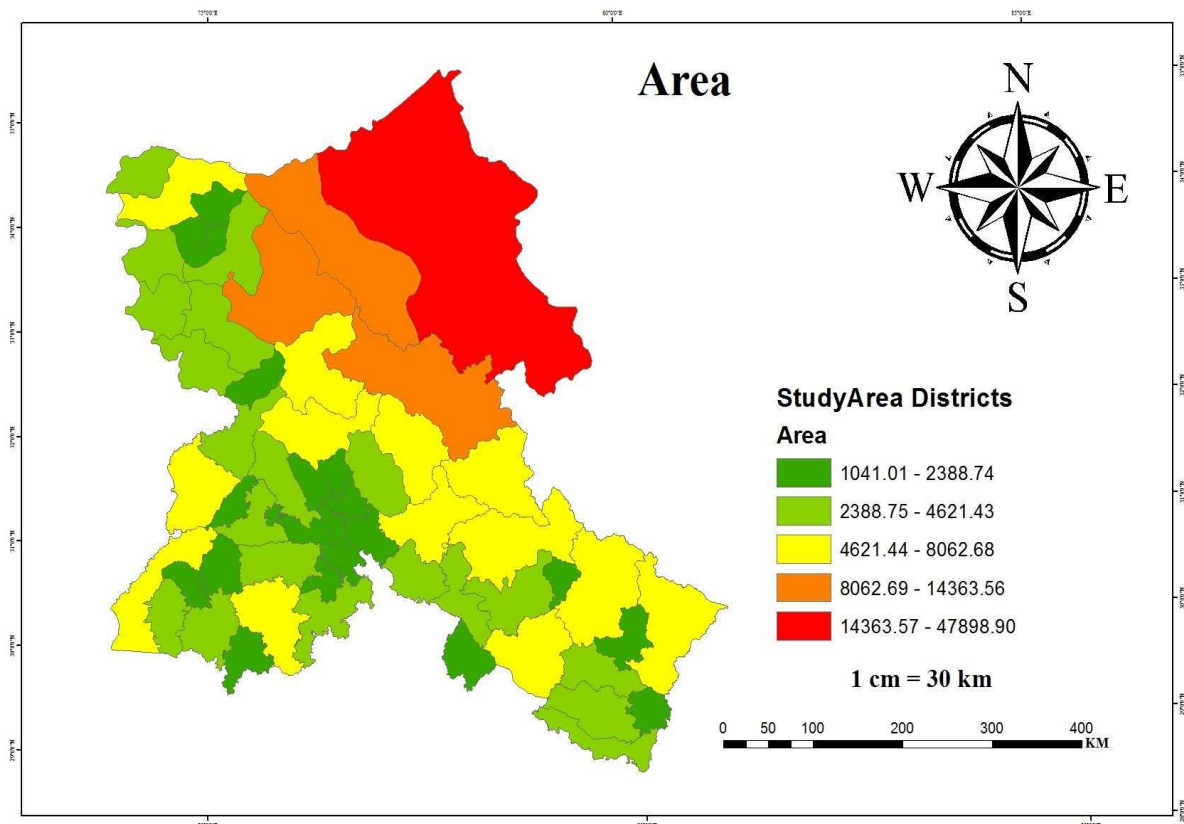


Figure 3. District area.

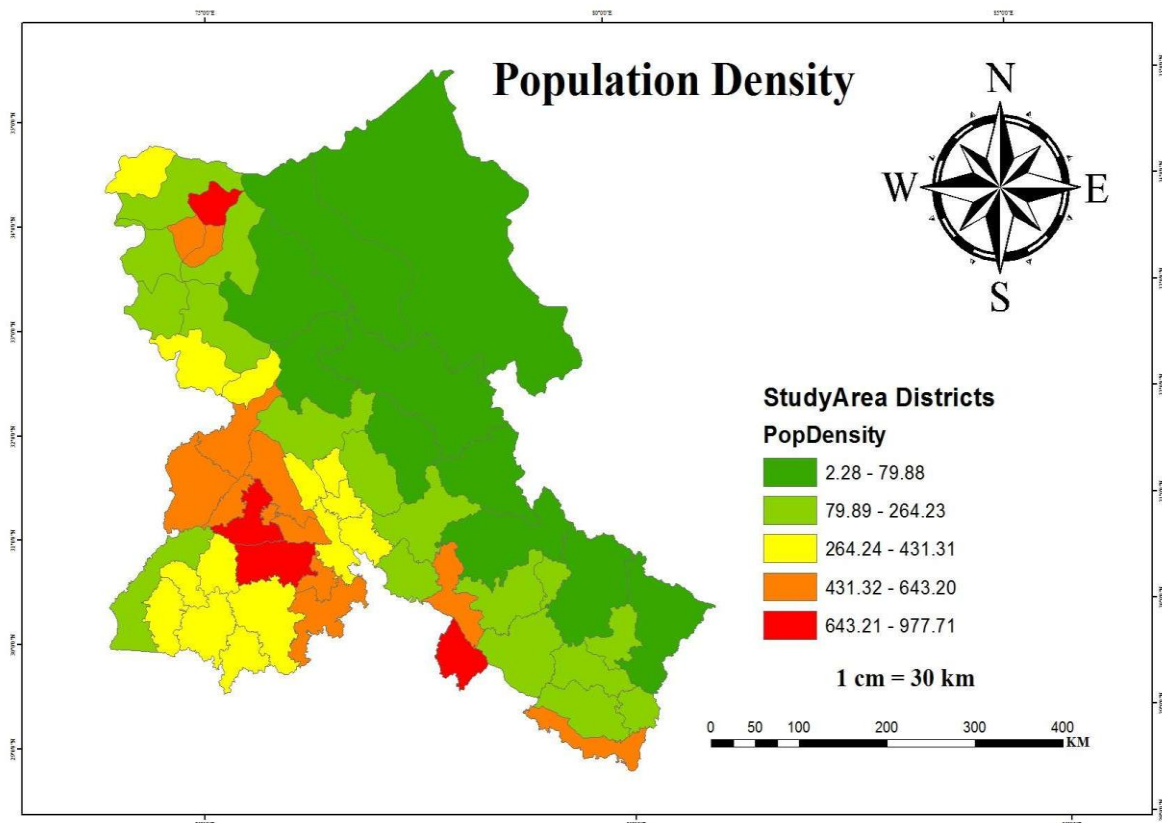


Figure 4. Population density.

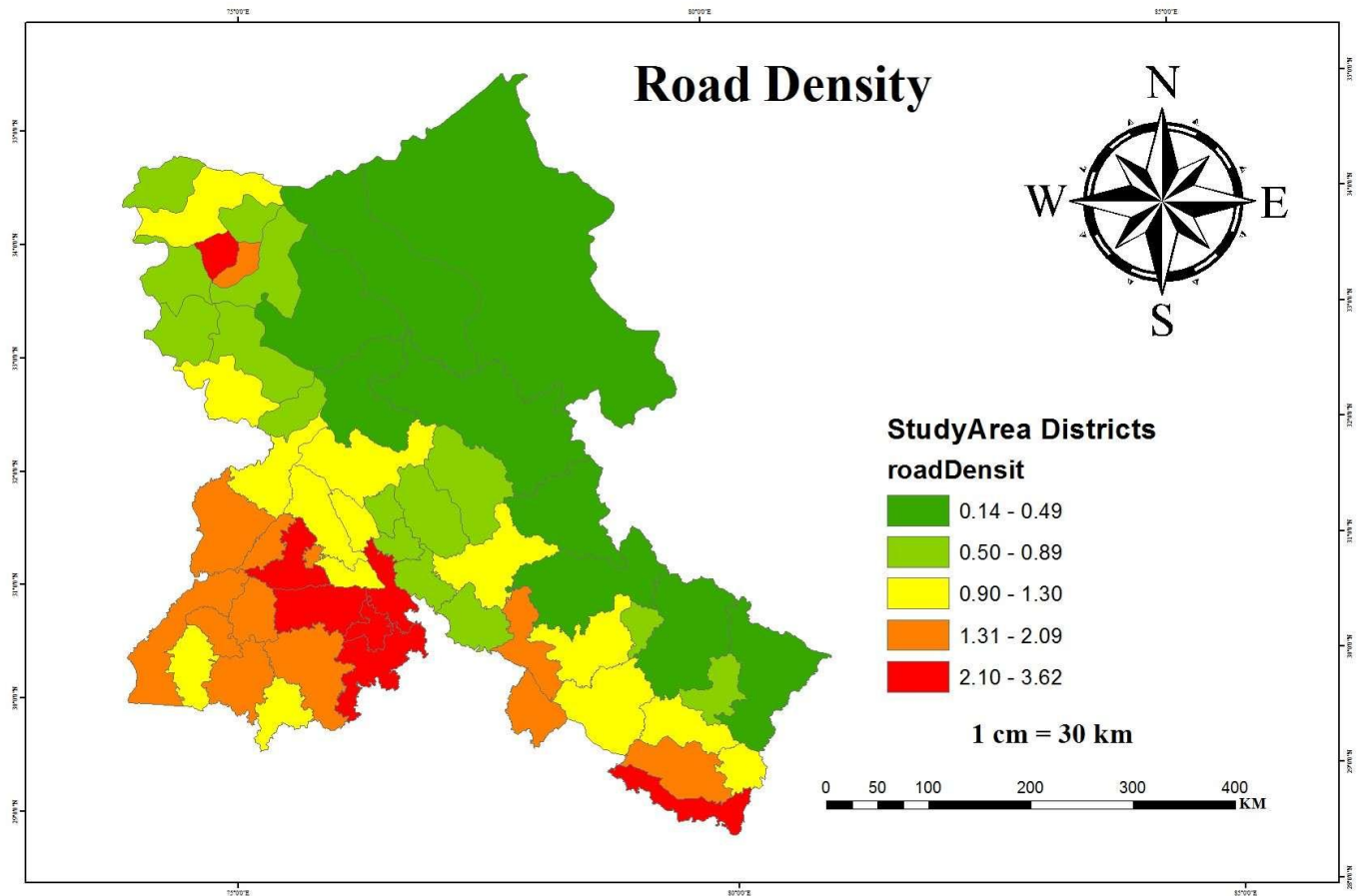


Figure 5. Road density.

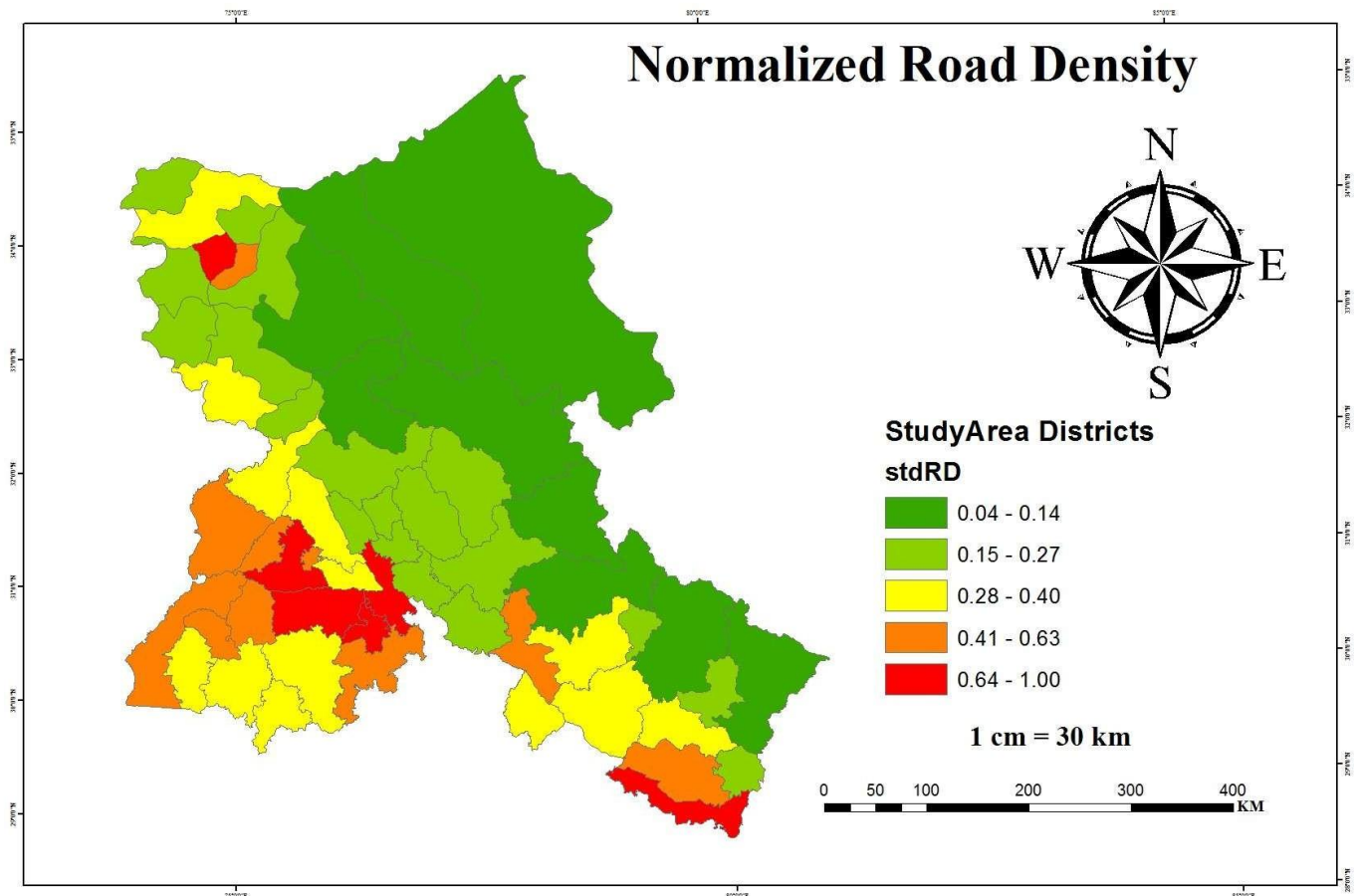


Figure 6. Normalised road density.

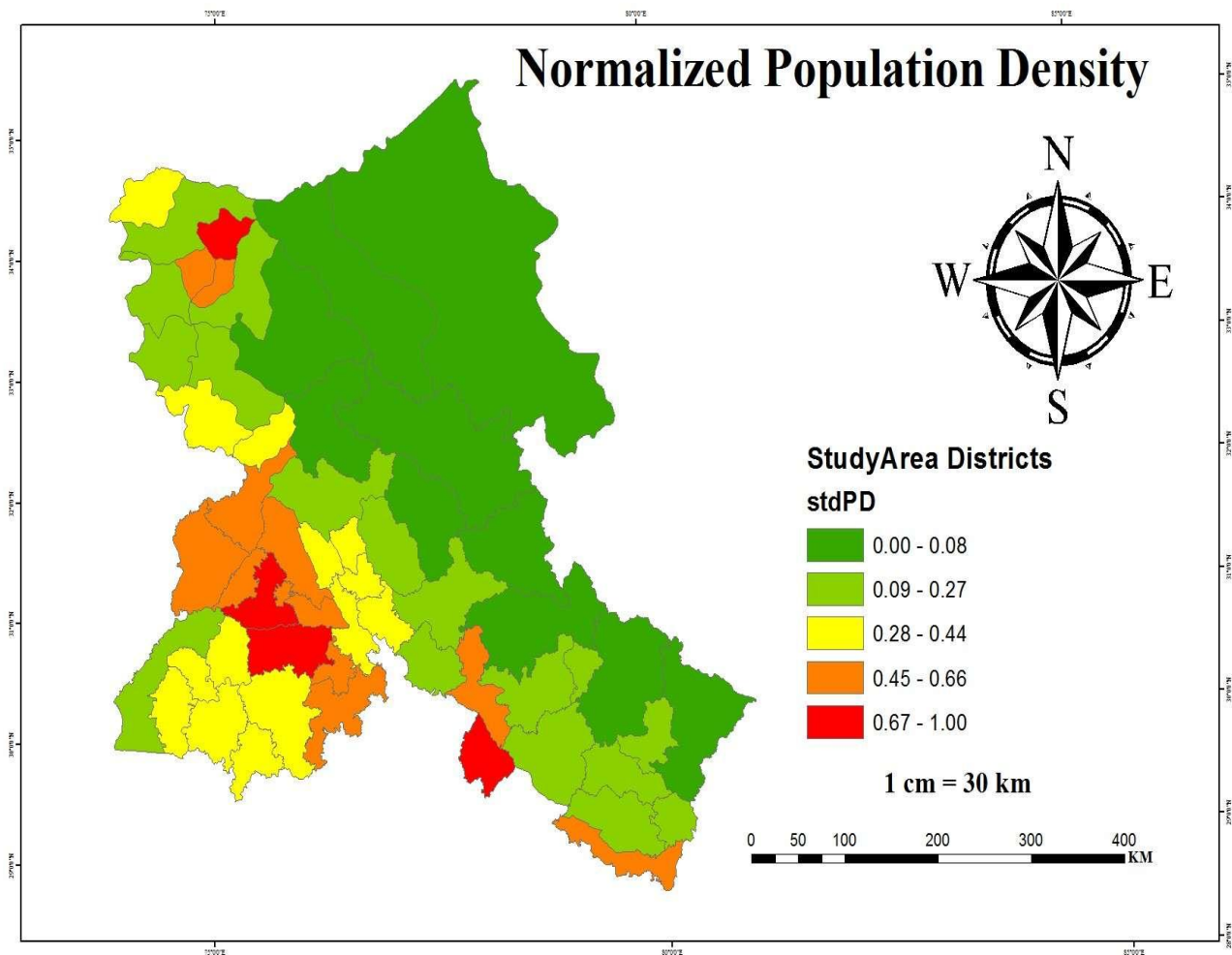


Figure 7. Normalised population density.

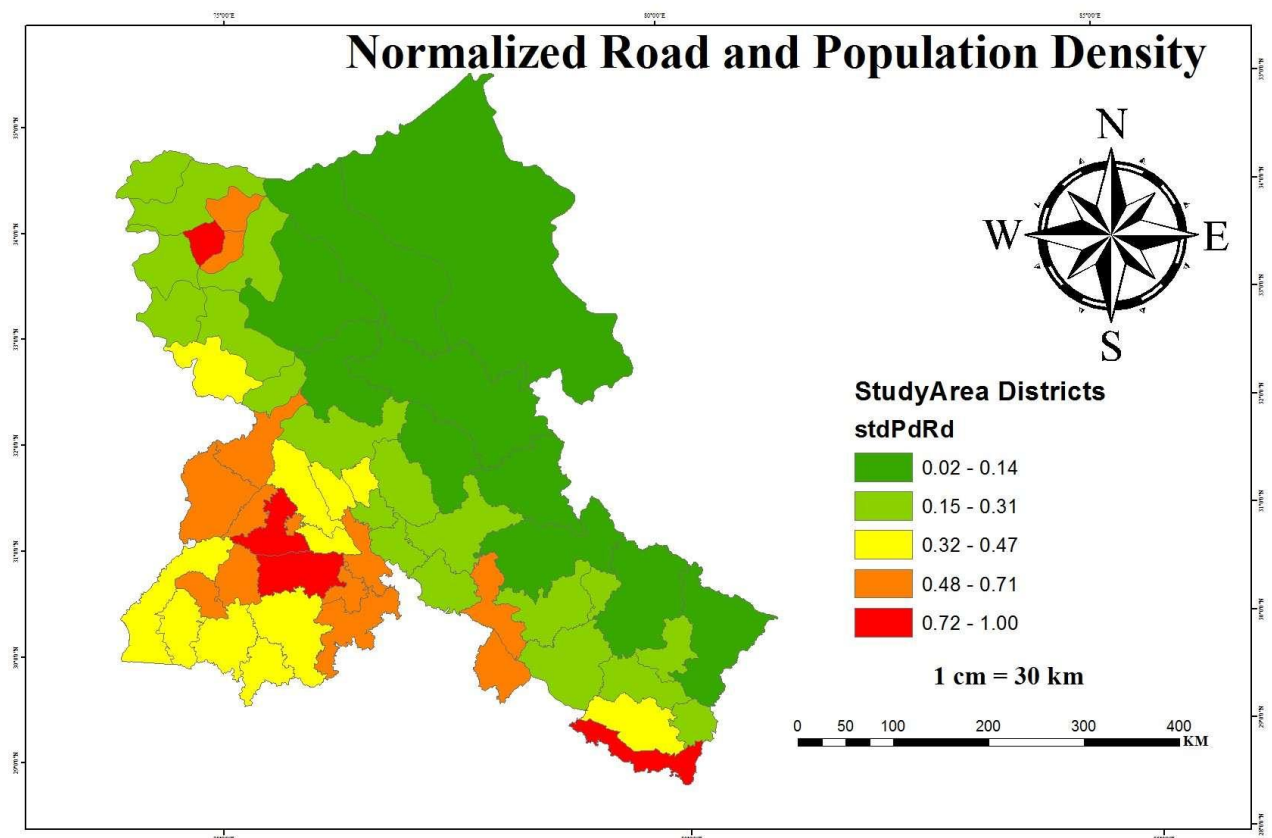


Figure 8. Normalised composite pressure index, stdPdRd.

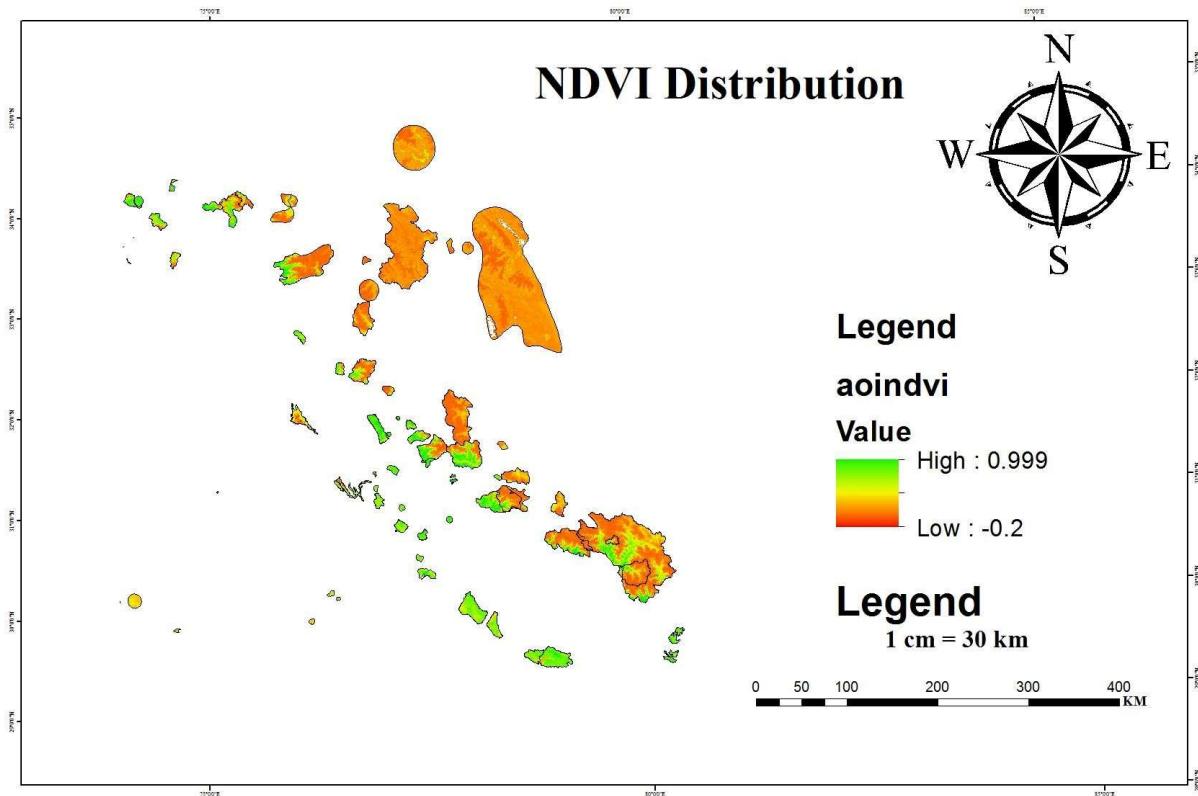


Figure 9. Area-of-interest NDVI raster obtained after mosaicking and masking the three MOD13Q1 tiles to the 69 protected-area boundaries.

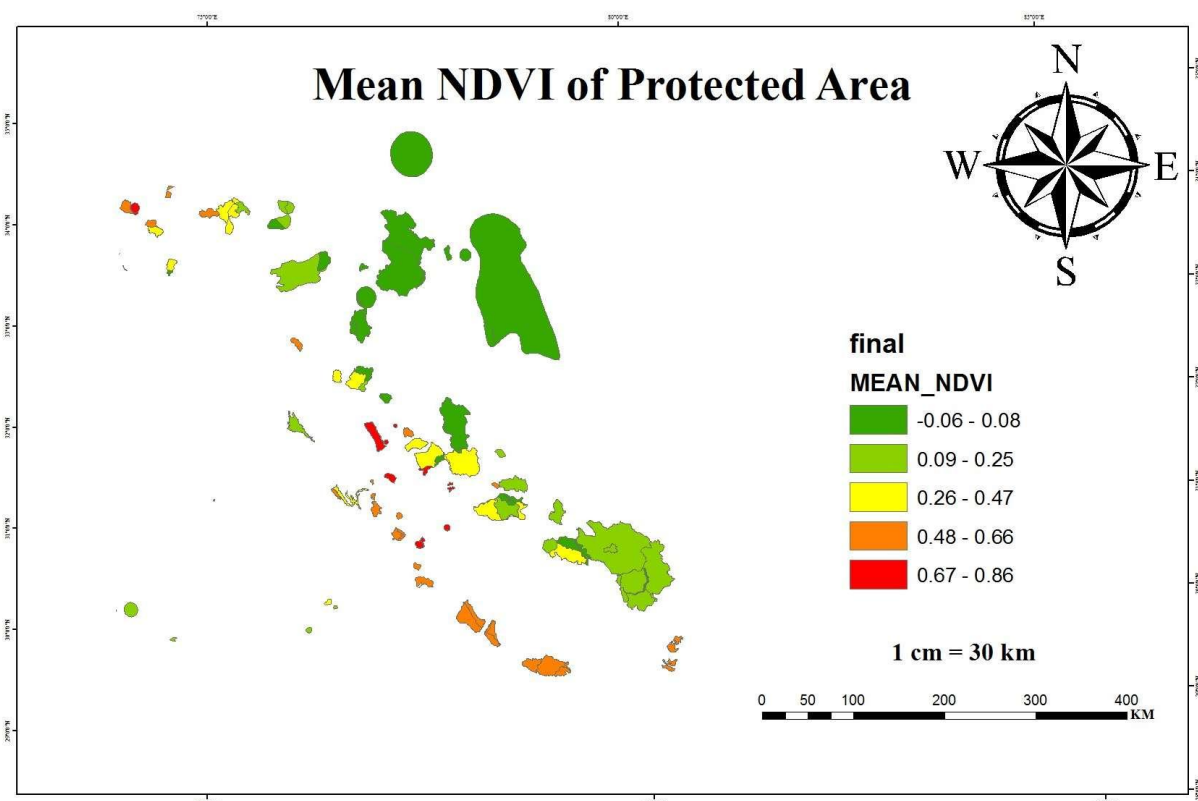


Figure 10. Mean NDVI per protected area, obtained via zonal statistics on the masked raster in Fig. 9.

4.2. Ranking outcomes

Both scoring schemes converge on the same reserves at the least-vulnerable end of the ranking: the Talra Wildlife Sanctuary segment in Uttarkashi district, Uttarakhand, ranks first or near-first under both formulations, alongside a cluster of Himachal Pradesh reserves in the Kullu, Mandi, and Shimla districts (Khokhan, Nargu, Daranghati, Kais, Tirthan) that combine high mean NDVI with low composite pressure. At the most-vulnerable

end, the Manali Wildlife Sanctuary segment in Kangra district returns the lowest composite score in the pixel-inclusive analysis under both the rank-average and the exponential model (Figs. 11–13). When open-water pixels — which register spuriously low or highly variable NDVI values and are common in reserves containing rivers, lakes, or reservoirs — are excluded from the zonal NDVI calculation, the identity of the most vulnerable reserve changes: Bir Gurdialpura, a small reserve in Patiala district, Punjab, replaces Manali as the lowest-scoring site, consistent with Bir Gurdialpura's location in a densely populated, heavily cultivated part of the Punjab plains rather than reflecting an actual change in Manali's vegetation condition. This sensitivity to water-pixel handling is itself informative: any operational use of this ranking should treat small, water-influenced reserves with additional caution, and a masked, land-only NDVI recalculation should be treated as more reliable than the unmasked version for such reserves. This sensitivity run is reported from the authors' own analysis and its full output is not tabulated here. Because each row of Table 1 is a reserve segment defined by the overlay of reserve and district boundaries, the values quoted above refer to individual segments rather than to whole reserves: Talra scores 3.05 in its Uttarkashi segment and 2.85 in its Shimla segment, and Manali scores 1.95 in its Kullu segment and 1.69 in its Kangra segment. Across the 36 districts in Table 1, district-level pressure and the district mean of segment NDVI are positively rank-correlated (Spearman $\rho = 0.53$, $p = 0.001$).

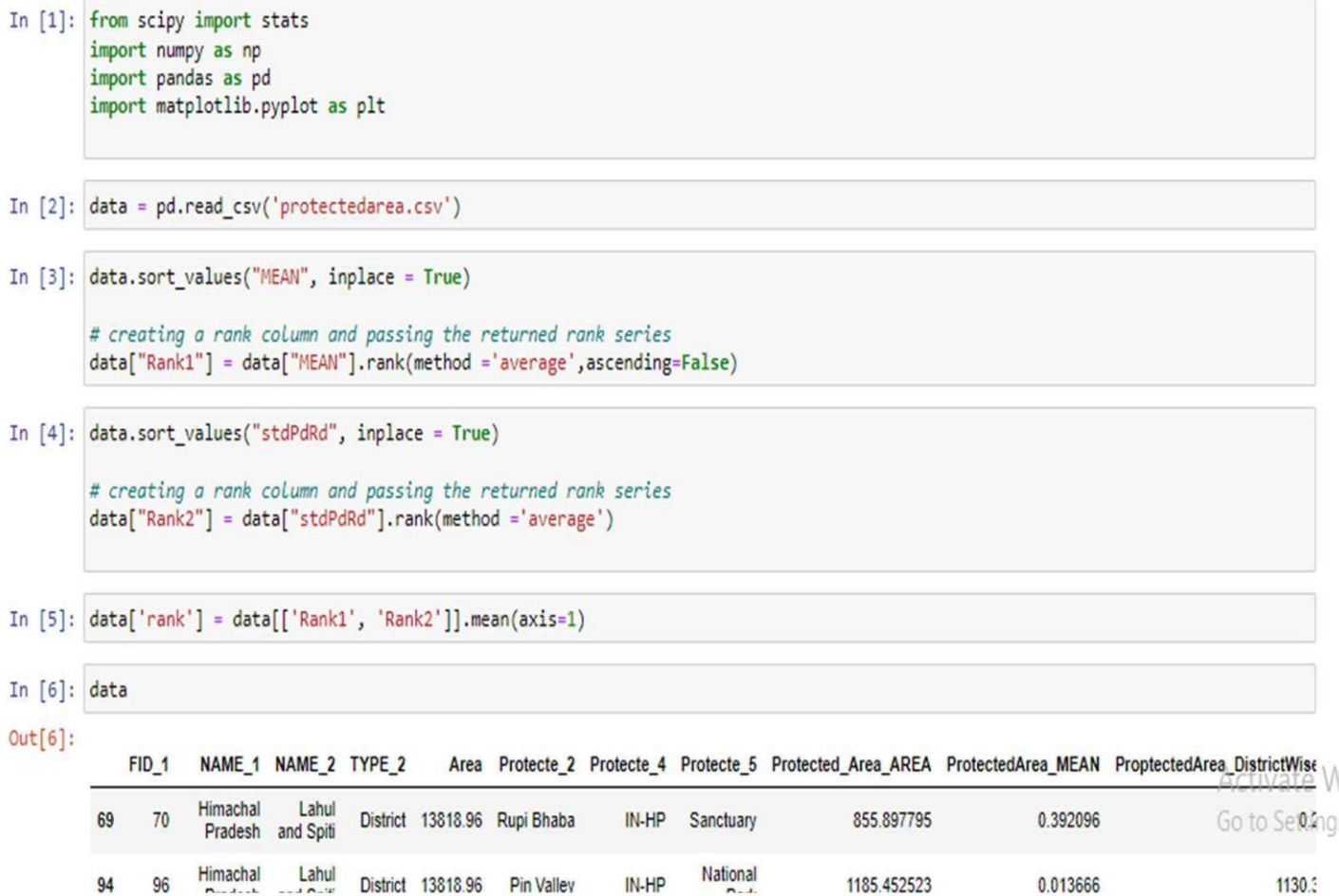


Figure 11. Python implementation of the rank-average model (Eq. 8).

```

In [1]: import numpy as np
        import pandas as pd

In [2]: df = pd.read_csv("table1.csv")      # stdPdRd, MEAN_NDVI
In [3]: df["X"] = np.exp(df["MEAN_NDVI"])   # e^NDVI
In [4]: df["Y"] = np.exp(-df["stdPdRd"])    # e^(-stdPdRd) = 1 / e^stdPdRd
In [5]: df["S"] = df["X"] + df["Y"]         # Eq. (9)
In [6]: df = df.sort_values("S", ascending=False)
In [7]: pd.concat([df.head(4), df.tail(3)])

```

Out[7]:

	Protected_Area	District	stdPdRd	MEAN_NDVI	X	Y	S
0	Talra	Uttarkashi	0.090	0.760	2.138	0.914	3.052
1	Khokhan	Mandi	0.280	0.830	2.293	0.756	3.049
2	Nargu	Kullu	0.140	0.770	2.160	0.869	3.029
4	Khokhan	Kullu	0.140	0.770	2.160	0.869	3.029
...							
124	Overa-Aru	Pulwama	0.650	0.200	1.221	0.522	1.743
123	Bir Gurdialpura	Patiala	0.660	0.200	1.221	0.517	1.738
125	Manali	Kangra	0.310	-0.040	0.961	0.733	1.694

Figure 12. Python implementation and output of the exponential-weighting model (Eq. 9). The listing implements Eq. (9) exactly; the output shows the highest- and lowest-scoring rows, computed from the two-decimal values given in Table 1.

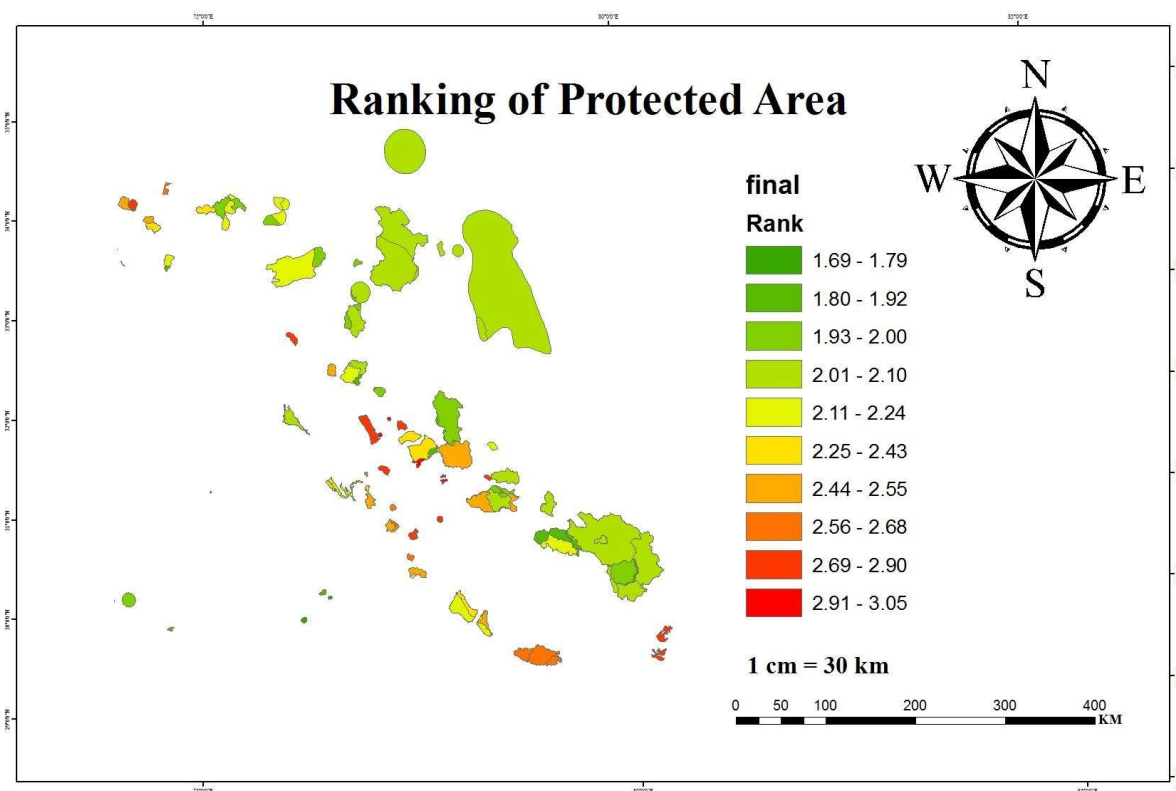


Figure 13. Final ranking of the 69 protected areas by combined population–road–vegetation vulnerability score. Values are the exponential-model scores of Eq. (9) as tabulated in Table 1; higher values (red) denote lower vulnerability and lower values (green) higher vulnerability.

Table 1 (Appendix) lists the full composite ranking for every protected-area–district occurrence in the study region; several reserves span more than one district and therefore appear more than once, each row reflecting the local stdPdRd and mean NDVI combination for that portion of the reserve. The distribution of rank values shows that most rows cluster in the middle of the ranking, with scores changing gradually rather than in sharp steps, which is consistent with a genuine underlying gradient of pressure rather than a small number of sharply separated “disturbed” and “pristine” clusters.

4.3. Interpretation against the wider literature

The overall pattern observed here — most reserves showing only a modest vegetation gradient that is not negatively related to district-level population pressure, alongside a smaller subset of clearly identifiable high-pressure reserves — can be compared, with caution (that study examined temporal NDVI change rather than spatial variation), with the result reported for protected areas of the Tibetan Plateau, where the great majority of sixty-nine reserves showed no significant NDVI change over a thirty-year record even as population inside protected areas rose overall [2]. It is also consistent with global-scale evidence that formally protected status measurably slows, but does not eliminate, anthropogenic pressure relative to unprotected land [4,5], and with human-footprint-based reserve evaluations elsewhere that combine population, land use, and road distribution into a single pressure surface [9]. Within the Himalayan region specifically, a systematic review found that restoration effort in the Western Himalaya has been concentrated in Uttarakhand and Himachal Pradesh and that monitoring of outcomes has been inconsistent, which underlines the value of a simple, repeatable screening index of the kind proposed here [7]. These comparisons are offered as associations rather than causal claims: the present design cannot separate the effect of population and road pressure on vegetation condition from other factors that co-vary with it, such as elevation, precipitation, and underlying land-cover type.

4.4. Limitations

Four limitations should be kept in mind when using this ranking operationally.

- District-level pressure. Population and road density are district-level averages rather than values measured at the reserve boundary itself, so a large district containing a small reserve in an otherwise sparsely settled corner will understate the local pressure actually experienced by that reserve, and vice versa. A protected-area buffer analysis, in which population and road statistics are recomputed within a fixed distance of each reserve boundary, would address this directly.
- Single-period vegetation index. The NDVI mean used here is a single 16-day composite rather than a multi-year trend; it describes the current vegetation condition of each reserve well, but on its own it cannot distinguish a long-standing, naturally sparse landscape (much of trans-Himalayan Ladakh, for example) from a recently degraded one. A multi-temporal NDVI extension is needed to make that distinction with confidence and is identified as the most direct methodological priority for future work.
- Water-pixel sensitivity. Open-water pixels within reserve boundaries register spuriously low or unstable NDVI values, and, as shown in Section 4.2, their inclusion or exclusion changes the identity of the most vulnerable reserve. Results for small, water-influenced reserves should therefore be treated with additional caution.
- Unvalidated ranking models. The rank-average and exponential models in Eqs. (8)–(9) were chosen for their transparency and intuitive behaviour rather than fitted or validated against an independent disturbance dataset, and formal rank-agreement statistics between them have not yet been computed. Their scores should be read as an ordinal ranking device rather than as a calibrated probability or severity scale.

5. Conclusion

Combining district-level population and road density into a single normalised anthropogenic-pressure index, and pairing it with reserve-level mean NDVI drawn from MODIS MOD13Q1 composites, produces a ranking of the 69 protected areas of the southern Himalayan study region that is stable across two independently constructed scoring functions. The Talra Wildlife Sanctuary segment in Uttarkashi district, Uttarakhand, together with a cluster of reserves in the Kullu, Mandi, and Shimla districts of Himachal Pradesh, consistently emerges as the least vulnerable (highest-scoring) group in the study area, while the Manali Wildlife Sanctuary segment in Kangra district is the most vulnerable (lowest-scoring) reserve once water pixels are included in the NDVI calculation, a position

taken over by Bir Gurdialpura in Patiala district, Punjab, once water pixels are excluded. Mean NDVI is positively rather than negatively rank-correlated with district-level population–road pressure (Spearman $\rho \approx 0.53$ across 36 districts), because the lowest NDVI values occur in high-altitude, sparsely populated reserves; the vegetation term of the index should therefore be interpreted with care in the trans-Himalayan zone, where low NDVI reflects natural conditions as well as any human pressure. Because the underlying inputs — population, road vector data, and MOD13Q1 composites — are all routinely updated, this index can be recomputed on a rolling basis at comparatively low cost, offering state forest and wildlife departments a transparent, repeatable basis for allocating monitoring and enforcement attention among reserves that would otherwise be compared only qualitatively. Extending the vegetation component from a single-period mean to a multi-year trend, replacing district-level pressure values with pressure measured directly within each reserve's buffer zone, and computing a formal rank-agreement statistic between the two scoring models are the three most promising directions for improving the precision of this ranking in future work.

Acknowledgements

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Data Availability Statement

The MODIS MOD13Q1 vegetation index data used in this study are openly available from the NASA LP DAAC [8]. District-level population and road-network data were sourced from the Census of India and publicly available road vector layers.

Conflict Of Interest

The authors declare no conflict of interest.

Appendix

Table 1. Composite ranking of the 126 protected-area–district occurrences, sorted by the exponential-model score (Eq. 9) in descending order; a higher score denotes lower vulnerability. stdPdRd is the normalised composite pressure of the district; mean NDVI is the zonal mean of MOD13Q1 NDVI over the part of the reserve lying in that district.

Protected area	State	District	stdPdRd	Mean NDVI	Score (Eq. 9)
Talra	Uttarakhand	Uttarkashi	0.09	0.76	3.05
Khokhan	Himachal Pradesh	Mandi	0.28	0.83	3.05
Nargu	Himachal Pradesh	Kullu	0.14	0.77	3.03
Daranghati	Himachal Pradesh	Shimla	0.25	0.81	3.03
Khokhan	Himachal Pradesh	Kullu	0.14	0.77	3.03
Kais	Himachal Pradesh	Kullu	0.14	0.77	3.03
Tirthan	Himachal Pradesh	Kullu	0.14	0.74	2.97
Churdhar	Himachal Pradesh	Shimla	0.25	0.75	2.90
Talra	Himachal Pradesh	Shimla	0.25	0.73	2.85
Limber	Jammu and Kashmir	Baramulla	0.29	0.74	2.84
Askot Musk Deer	Uttarakhand	Pithoragarh	0.10	0.65	2.82
Nargu	Himachal Pradesh	Mandi	0.28	0.71	2.79
Churdhar	Himachal Pradesh	Sirmaur	0.25	0.70	2.79
Kanawar	Himachal Pradesh	Kullu	0.14	0.64	2.77
Dachigam	Jammu and Kashmir	Budgam	0.93	0.86	2.76
Lachipora	Jammu and Kashmir	Baramulla	0.29	0.70	2.76
Gangul Siahbehi	Himachal Pradesh	Chamba	0.12	0.61	2.73
Shikari Devi	Himachal Pradesh	Mandi	0.28	0.68	2.73
Raksham Chitkul	Himachal Pradesh	Kinnaur	0.03	0.56	2.72
Chail	Himachal Pradesh	Shimla	0.25	0.64	2.68
Shilli	Himachal Pradesh	Solan	0.31	0.66	2.67
Corbett	Uttarakhand	Pauri Garhwal	0.23	0.62	2.65

Protected area	State	District	stdPdRd	Mean NDVI	Score (Eq. 9)
Bandli	Himachal Pradesh	Mandi	0.28	0.64	2.65
Shimla Catchment	Himachal Pradesh	Shimla	0.25	0.62	2.64
Corbett	Uttarakhand	Almora	0.29	0.63	2.63
Sonanadi	Uttarakhand	Pauri Garhwal	0.23	0.59	2.60
Corbett	Uttarakhand	Nainital	0.40	0.65	2.59
Renuka	Himachal Pradesh	Sirmaur	0.25	0.59	2.58
Wular Lake	Jammu and Kashmir	Baramulla	0.29	0.60	2.57
Simbalbara	Himachal Pradesh	Sirmaur	0.25	0.57	2.55
Chail	Himachal Pradesh	Solan	0.31	0.59	2.54
Darlaghat	Himachal Pradesh	Shimla	0.25	0.56	2.53
Gulmarg	Jammu and Kashmir	Baramulla	0.29	0.58	2.53
Govind Pashu Vihar	Uttarakhand	Uttarkashi	0.09	0.47	2.51
Dachigam	Jammu and Kashmir	Baramulla	0.29	0.56	2.50
Gobindsagar	Himachal Pradesh	Solan	0.31	0.56	2.48
Darlaghat	Himachal Pradesh	Solan	0.31	0.56	2.48
Chail	Himachal Pradesh	Sirmaur	0.25	0.53	2.48
Rajaji	Uttarakhand	Pauri Garhwal	0.23	0.52	2.48
Tundah	Himachal Pradesh	Chamba	0.12	0.45	2.46
Rupi Bhaba	Himachal Pradesh	Kinnaur	0.03	0.39	2.45
Kazinag	Jammu and Kashmir	Poonch	0.23	0.50	2.44
Naina Devi	Himachal Pradesh	Bilaspur	0.29	0.52	2.43
Great Himalayan	Himachal Pradesh	Kullu	0.14	0.43	2.41
Gobindsagar	Himachal Pradesh	Mandi	0.28	0.50	2.40
Majathal	Himachal Pradesh	Solan	0.31	0.51	2.40
Killan	Jammu and Kashmir	Poonch	0.23	0.47	2.39
Rajaji	Uttarakhand	Dehradun	0.63	0.62	2.39
Gangotri	Himachal Pradesh	Kinnaur	0.03	0.35	2.39
Dachigam	Jammu and Kashmir	Srinagar	0.53	0.57	2.36
Majathal	Himachal Pradesh	Bilaspur	0.29	0.47	2.35
Dachigam	Jammu and Kashmir	Poonch	0.23	0.42	2.32
Majathal	Himachal Pradesh	Mandi	0.28	0.43	2.29
Kugti	Himachal Pradesh	Chamba	0.12	0.30	2.24
Rajaji	Uttarakhand	Haridwar	0.70	0.55	2.23
Overa-Aru	Jammu and Kashmir	Anantnag	0.24	0.36	2.22
Gobindsagar	Himachal Pradesh	Bilaspur	0.29	0.38	2.21
Gobindsagar	Punjab	Rupnagar	0.59	0.50	2.20
Kanji	Jammu and Kashmir	Kargil	0.03	0.19	2.18
Kistwar	Jammu and Kashmir	Doda	0.06	0.20	2.16
Baltal-Thajwas	Jammu and Kashmir	Srinagar	0.53	0.45	2.16
Rangdum	Jammu and Kashmir	Kargil	0.03	0.17	2.16
Rupi Bhaba	Himachal Pradesh	Shimla	0.25	0.31	2.14
Hirapora	Jammu and Kashmir	Poonch	0.23	0.30	2.14
Kedarnath	Uttarakhand	Rudraprayag	0.22	0.28	2.13
Lippa Asrang	Himachal Pradesh	Kinnaur	0.03	0.15	2.13
Boodkharbu	Jammu and Kashmir	Kargil	0.03	0.14	2.12
Govind	Uttarakhand	Uttarkashi	0.09	0.17	2.10
Nanda Devi	Uttarakhand	Bageshwar	0.17	0.23	2.10
Nanda Devi	Uttarakhand	Chamoli	0.11	0.18	2.09
Sangla	Himachal Pradesh	Kinnaur	0.03	0.10	2.08
Karakoram	Jammu and Kashmir	Leh	0.03	0.08	2.05
Gya-Miru	Jammu and Kashmir	Leh	0.03	0.08	2.05
Gangotri	Uttarakhand	Uttarkashi	0.09	0.13	2.05
Sechu Tuan Nala	Himachal Pradesh	Lahaul and Spiti	0.02	0.06	2.04
Kugti	Himachal Pradesh	Lahaul and Spiti	0.02	0.06	2.04
Hemis	Jammu and Kashmir	Leh	0.03	0.06	2.03
Changthang	Jammu and Kashmir	Leh	0.03	0.06	2.03

Protected area	State	District	stdPdRd	Mean NDVI	Score (Eq. 9)
Valley of Flowers	Uttarakhand	Chamoli	0.11	0.13	2.03
Pong Dam Lake	Himachal Pradesh	Kangra	0.31	0.25	2.02
Nanda Devi	Uttarakhand	Pithoragarh	0.10	0.11	2.02
Hemis	Jammu and Kashmir	Kargil	0.03	0.04	2.01
Lung Nag	Jammu and Kashmir	Kargil	0.03	0.04	2.01
Rupshu	Jammu and Kashmir	Leh	0.03	0.04	2.01
Govind Pashu Vihar	Himachal Pradesh	Kinnaur	0.03	0.03	2.00
Pin Valley	Himachal Pradesh	Lahaul and Spiti	0.02	0.02	2.00
Nanda Devi	Uttarakhand	Chamoli	0.11	0.10	2.00
Simbalbara	Uttarakhand	Dehradun	0.63	0.38	1.99
Govind Pashu Vihar	Himachal Pradesh	Shimla	0.25	0.18	1.98
Rangdum	Jammu and Kashmir	Doda	0.06	0.04	1.98
Govind	Himachal Pradesh	Kinnaur	0.03	0.00	1.97
Tingri	Jammu and Kashmir	Kargil	0.03	0.00	1.97
Kistwar	Jammu and Kashmir	Kargil	0.03	-0.01	1.96
Abohar	Punjab	Firozpur	0.37	0.24	1.96
Rupi Bhaba	Himachal Pradesh	Lahaul and Spiti	0.02	-0.02	1.96
Sechu Tuan Nala	Himachal Pradesh	Chamba	0.12	0.06	1.95
Manali	Himachal Pradesh	Kullu	0.14	0.08	1.95
Lung Nag	Himachal Pradesh	Lahaul and Spiti	0.02	-0.03	1.95
Pin Valley	Himachal Pradesh	Kinnaur	0.03	-0.02	1.95
Sechu Tuan Nala	Jammu and Kashmir	Kargil	0.03	-0.03	1.94
Overa-Aru	Jammu and Kashmir	Srinagar	0.53	0.30	1.94
Baltal-Thajwas	Jammu and Kashmir	Anantnag	0.24	0.13	1.93
Kedarnath	Uttarakhand	Tehri Garhwal	0.25	0.13	1.92
Great Himalayan	Himachal Pradesh	Kinnaur	0.03	-0.06	1.91
Kugti	Himachal Pradesh	Kangra	0.31	0.15	1.90
Lung Nag	Jammu and Kashmir	Doda	0.06	-0.04	1.90
Kedarnath	Uttarakhand	Uttarkashi	0.09	-0.02	1.89
Bir Motibagh	Punjab	Patiala	0.66	0.32	1.89
Indo-Pak Border	Punjab	Firozpur	0.37	0.18	1.89
Kedarnath	Uttarakhand	Chamoli	0.11	-0.02	1.88
Kedarnath	Uttarakhand	Chamoli	0.11	-0.02	1.88
Nanda Devi	Uttarakhand	Uttarkashi	0.09	-0.05	1.87
Kedarnath	Uttarakhand	Uttarkashi	0.09	-0.05	1.87
Nanda Devi	Uttarakhand	Pithoragarh	0.10	-0.04	1.87
Hirapora	Jammu and Kashmir	Rajouri	0.24	0.07	1.86
Chautala	Punjab	Muktsar	0.41	0.18	1.86
Great Himalayan	Himachal Pradesh	Shimla	0.25	0.07	1.85
Pin Valley	Himachal Pradesh	Kullu	0.14	-0.04	1.83
Nanda Devi	Uttarakhand	Bageshwar	0.17	-0.05	1.79
Nanda Devi	Uttarakhand	Rudraprayag	0.22	-0.04	1.76
Kedarnath	Uttarakhand	Rudraprayag	0.22	-0.04	1.76
Bir Bunerheri	Punjab	Patiala	0.66	0.21	1.75
Harike Lake	Punjab	Amritsar	0.59	0.18	1.75
Bir Gurdialpura	Punjab	Patiala	0.66	0.20	1.74
Overa-Aru	Jammu and Kashmir	Pulwama	0.65	0.20	1.74
Manali	Himachal Pradesh	Kangra	0.31	-0.04	1.69

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