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Landsat–MODIS Assessment of Paddy Residue Burning in Northwestern India: District-Level Comparison of Burn-Affected Cropland During the 2021 Post-Monsoon Season

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Abstract

*Across northwestern India, a large part of the post-harvest agricultural fire activity is associated with paddy residue burning. The amount detected in regional satellite-based monitoring is not necessarily the same at different spatial resolutions, since smaller or fragmented burning areas may be represented differently. This study compares Landsat-derived probable burn-affected cropland with the MODIS MCD64A1 burnt-area product across seven validation districts in Punjab, Haryana and Rajasthan which focusing on the 2021 post-monsoon burning season within a comparison framework built from 2005 to 2025 data. Landsat Collection 2 surface reflectance imagery was processed using fixed pre- and post-burning seasonal composites to derive the Normalized Burn Ratio, Normalized Difference Vegetation Index, and their differenced forms, dNBR and dNDVI. A dNBR threshold of 0.65, established through long-term calibration against MODIS, was used to estimate probable burn-affected cropland for 2021. Landsat gave higher burn-area estimates than MODIS in all seven districts, despite this there is a difference between the two varied across the districts. Sangrur–Malerkotla showed the closest agreement, with Landsat and MODIS estimates of 2904.98 and 2795.59 km^2 respectively, a ratio of 1.039, the largest difference was observed in Sonipat, where the Landsat estimate was more than six times higher than the MODIS value. The seven district-level observations produced a strong positive correlation between the two products (Pearson's $r = 0.949$, $R^2 = 0.900$, $p = 0.0011$), consistent with the pattern observed in the larger 2005 to 2025 clean-record dataset ($n = 120$, $r = 0.850$, $R^2 = 0.722$). The largest differences between the two products were seen in districts outside the main Punjab burning belt**.** The findings of the study suggest that MODIS-based estimates of burning in this region may be lower in areas where agricultural fields are smaller and more fragmented, and that Landsat's finer spatial resolution captures a greater extent of probable burning activity than the coarser MODIS product resolves.*

Keywords: *Paddy residue burning; Landsat; MODIS MCD64A1; dNBR; Burn-affected cropland; Remote sensing; Northwestern India.*

1. Introduction

Paddy residue burning is a recurring feature of the post-monsoon agricultural calendar in Punjab and Haryana, occurring each October and November as farmers clear rice stubble before sowing wheat crop. The practice is closely related to the use of mechanization process in harvesting, since combine harvesters leave large volumes of loose paddy straws in the field, and burning provides a rapid method of residue clearance within the short interval time span between rice harvest and wheat establishment ***(Gupta et al., 2004; Sidhu et al., 2007)***. The effects of this burning are not only limited to the fields where it occurs. Crop residue fires release substantial amount of fine particulate matter and trace gases, and the resulting smoke is regularly transported into the Indo-Gangetic Plain, compounding already severe urban air pollution in cities such as Delhi during the same weeks each year ***(Cusworth et al., 2018)***. Given the scale of this public health burden (***WHO, 2021***), accurate monitoring of where and how much burning occurs each season is a direct input into regional air quality management rather than a purely academic concern.

Satellite remote sensing is widely used to monitor agricultural burning at the regional scale because it is not practical to count fires on the ground across the many small fields involved. The MODIS sensor has served as the principal tool for regional fire monitoring for nearly two decades, offering the daily revisit frequency needed to capture a fast-moving burning season (***Justice et al., 2002***). Its MCD64A1 burned-area product, built on a dedicated burnt-area detection algorithm, remains the standard reference for tracking burnt area at this scale ***(Giglio et al., 2009)***. This temporal advantage comes with a corresponding spatial limitation. Each MODIS pixel covers an area of 500 meters, because a MODIS pixel can cover several individual agricultural fields, burning that affects only part of the pixel may produce a signal too weak for the pixel to be classified as burnt. This limitation has been documented specifically in Punjab and Haryana. ***Liu et al. (2019***) compared MCD64A1 against household survey data in the region and found that the product consistently underestimated burning, especially in areas where fires were small and scattered. ***Vadrevu and Lasko (2018)*** reported a related pattern using a different sensor pairing, finding that the finer-resolution VIIRS active-fire product detected fires in Punjab at nearly five times the rate of MODIS. More recently, ***Arbain and Imasu (2025)*** used 10-meter Sentinel-2 imagery to illustrate the practical scale of this difference, estimating PM2.5 emissions for a single month in 2022 more than twenty times higher than the figure implied by a coarser global emissions inventory covering the same period.

Landsat can help examine these differences at a finer spatial scale, making it possible to see whether coarser satellite products are missing actual burning activity or simply showing it differently. This approach is not new. ***Singh, Kant and Dadhwal (2009)*** demonstrated that combining multiple sensors improved burnt-area estimation accuracy in Punjab when validated against ground observations. More recently, ***Bawa et al. (2022)*** applied a Landsat-based trend analysis to burned-area detection across northwestern India, while ***Anand et al. (2025***) used a deep learning segmentation model on high-resolution Sentinel-2 imagery specifically to improve detection of small agricultural burn areas in Punjab. However, few studies have made a systematic, quality-screened comparison of Landsat and MODIS at the district level across the same validation regions. Most existing work has focused on the Punjab burning belt, with less attention given to districts in Haryana and Rajasthan. This study also looks at how and where the two products differ, rather than simply treating those differences as measurement errors.

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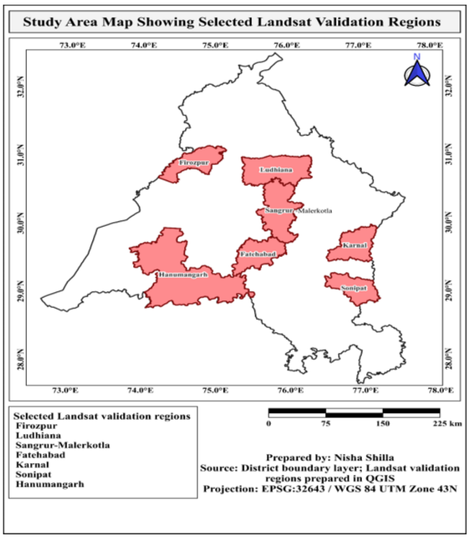
This study focuses on the gap using 2021 as a representative post-monsoon burning season, evaluated within a Landsat-MODIS calibration framework spanning 2005 to 2025. Landsat Collection 2 surface reflectance imagery was processed to derive dNBR across seven validation districts in Punjab, Haryana and Rajasthan, with a threshold for probable burn-affected cropland established through comparison against MODIS over the full study period. Within this framework, the study addresses three specific questions. First, to what extent do Landsat and MODIS agree at the district level during the 2021 season? Second, where does this agreement hold, and where does it diverge most sharply? Third, what do the observed patterns of divergence suggest about the influence of sensor resolution and field-scale agricultural characteristics on burnt-area detection in this region? The intention is not to establish either product as more accurate in an absolute sense, but to characterize how much confidence regional burning estimates derived from MODIS alone can reasonably support, and to identify where finer-resolution observation contributes meaningfully to that assessment.

2. Study Area and Data

The study covers seven agricultural districts in Punjab, Haryana and Hanumangarh district of Rajasthan, selected to represent a range of burning conditions rather than the only districts which is associated with heavy fire incidents. Sangrur–Malerkotla, Firozpur and Ludhiana fall within the Punjab burning belt, a region consistently identified in satellite fire records as a major concentration of post-monsoon agricultural burning. Fatehabad, Karnal and Sonipat represent Haryana, where burning is generally more dispersed and based on the prior regional assessments here the fire activity is less intense than in central Punjab. Hanumangarh extends the study into Rajasthan, a district with similar cropping patterns to its Punjab and Haryana neighbours but comparatively limited representation in the existing literature. The selected areas represent different agricultural conditions, rather than only the areas where burning is highest.``

Figure 1. Study area map showing the seven selected Landsat validation regions across Punjab, Haryana and Rajasthan



The analysis uses two satellite products. Landsat surface reflectance imagery was obtained from Collection 2 Level 2 products, drawing on four sensors that together span the full 2005 to 2025 study period, Landsat 5 TM, Landsat 7 ETM+, Landsat 8 OLI and Landsat 9 OLI-2. No single Landsat mission covers the entire study period. Therefore, data from different sensors were combined with Landsat 5 and 7 used for the earlier years while Landsat 8 and 9 were used for the later years. Each scene was filtered using the QA_PIXEL and QA_RADSAT quality bands to remove cloud, cloud shadow, snow, cirrus and saturated pixels, and the analysis was restricted throughout to cropland using the ESA WorldCover 2021 land cover product.

Another dataset which is used in the study to draw a comparison was the MODIS MCD64A1 product, a widely used 500-meter burnt-area product applied extensively in existing research on this region. MCD64A1 was used here as an established, operational comparison product rather than as independently verified ground truth, and therefore, the analysis compares the two satellite products rather than validating either one against a confirmed reference dataset.

The Landsat and MODIS data from 2005 to 2025 were used for threshold selection and quality screening, as described in the following section., but the core comparison presented in this study targets the 2021 post-monsoon season specifically. This year was selected as a representative burning season, consistent with the broader temporal pattern established across the study period while remaining recent enough to reflect current agricultural practices and sensor performance. The analysis combines a detailed assessment of the 2021 season across seven districts with Landsat and MODIS data from the previous two decades used for threshold selection and comparison.

3. Methods

3.1 Landsat Preprocessing and Spectral Index Calculation

Each Landsat scene was processed through a consistent workflow before the analysis. Surface reflectance values were rescaled using the standard Collection 2 scale factors, and only pixels passing the QA_PIXEL and QA_RADSAT quality checks were retained. Two spectral indices were then calculated from the Red, Near Infrared and Shortwave Infrared 2 bands. The Normalized Difference Vegetation Index characterized vegetation condition, while the Normalized Burn Ratio captured the spectral signature typically associated with burning.

The same seasonal period was used for all years from 2005 to 2025. Images from 15 September to 10 October were used to create the pre-burning composite, showing field conditions before the main burning period. Images from 1 to 30 November were used for the post-burning composite. Instead of using just one image before and after burning, the analysis used the maximum NBR and NDVI values from the pre-burning period and the minimum values from the post-burning period. This approach helped capture the largest seasonal change within each time window, since field conditions can change quickly after harvesting or burning.

The differenced NBR, or dNBR, was calculated as the pre-burning maximum NBR minus the post-burning minimum NBR, with dNDVI derived using the equivalent NDVI values. Higher values indicate a stronger seasonal spectral change. It should be noted that dNBR alone cannot fully distinguish burning from other post-harvest activities such as residue removal or ploughing which can produce a broadly similar spectral response. dNDVI was calculated alongside dNBR to provide supporting spectral evidence of the same underlying seasonal change, rather than as an independent confirmation derived from separate observations.

3.2 Cropland Masking and District-Level Extraction

All dNBR and dNDVI layers were masked to cropland using the ESA WorldCover 2021 product, excluding spectral change associated with forests, water bodies or built-up land from the analysis. Mean dNBR and dNDVI were then calculated for each district in each year from all valid cropland pixels.

3.3 Threshold Calibration

Positive dNBR values do not always represent actual burning. Therefore, a low threshold could classify normal vegetation changes as fire-related. Three candidate thresholds were therefore evaluated against the MODIS reference product, dNBR ≥ 0.45, ≥ 0.55 and ≥ 0.65. At each threshold, the resulting Landsat-derived burnt-area was compared with MODIS across the full 2005 to 2025 record, with agreement assessed using Pearson correlation and R^2. The dNBR $\geq$ 0.65 threshold produced the strongest and most consistent agreement with MODIS across the seven districts and was adopted as the operational threshold for all burnt-area estimates in this study, including the 2021 comparison.

3.4 Quality Screening

A two-stage screening procedure was applied to the long-term dataset before the statistical analysis, because some district-year observations were more reliable than others. The first stage, Tier 1, identified district-years where valid Landsat pixel coverage fell below 10 percent of total cropland area. Two such cases were identified across the full dataset, both in 2011, corresponding to a known reduction in Landsat 5 availability during the transition to Landsat 7 and 8. These records were excluded entirely, as coverage was insufficient to support a meaningful comparison for that year.

The second stage, Tier 2, identified district-years where the Landsat-MODIS area ratio fell outside a 0.1 to 10 range. Twenty-five district-years met this criterion. These were not treated as data errors and were retained in the complete dataset, since substantial divergence between the two products may reflect genuine differences in detection capability rather than a processing fault. They were, however, excluded from the clean-record statistics used to characterize overall agreement, resulting in a final clean-record dataset of 120 district-year observations from the original 147.

3.5 Statistical Analysis

Agreement between Landsat and MODIS was assessed using Pearson's correlation coefficient and simple linear regression, with MODIS treated as the reference variable and Landsat as the predicted value. This direction was adopted because MODIS represents the established, operational product against which Landsat's finer-resolution estimates are being compared. The coefficient of determination, R^2, indicated the proportion of variation in Landsat's estimates explained by MODIS, and statistical significance was assessed at the 0.05 level.

For the 2021 comparison specifically, the same statistical approach was applied to the seven paired district-level observations available for that year. Given the limited sample size, the resulting correlation is reported as a district-level relationship characteristic of a single representative year, and is considered alongside the larger long-term dataset rather than being used on its own to make broader claims about Landsat-MODIS agreement.

4. Results

4.1 Landsat Observation Availability During 2021

Before examining burn area, it is necessary to confirm that sufficient Landsat data were available in 2021 to support a reliable comparison.

Table 1. Landsat image availability during the 2021 burn season across the seven validation districts

District	Pre-burning images	Post-burning images	Total images
Sangrur–Malerkotla	8	14	22
Firozpur	11	19	30
Ludhiana	10	18	28
Fatehabad	11	20	31
Karnal	13	16	29
Sonipat	7	8	15
Hanumangarh	14	24	38

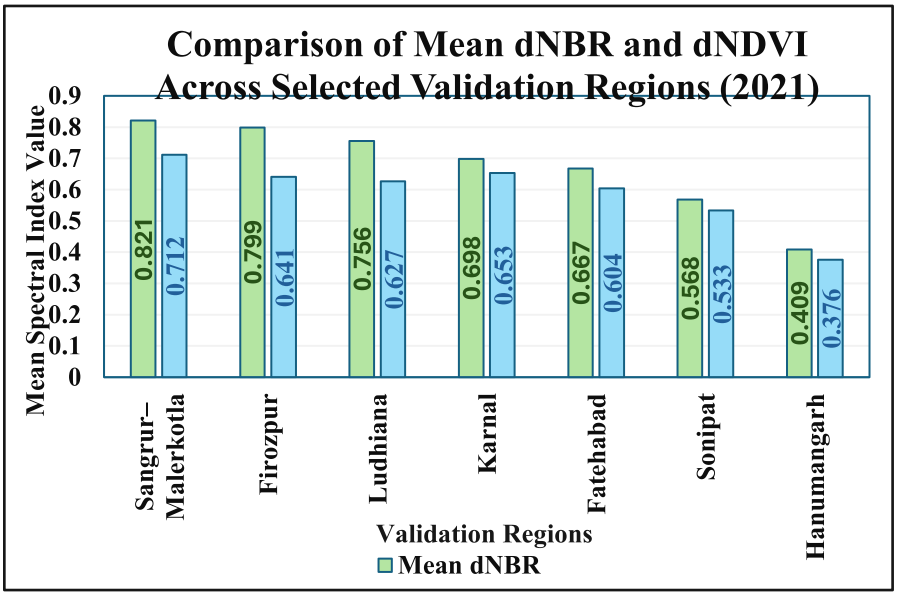
Pre-burning image counts ranged from 7 in Sonipat to 14 in Hanumangarh, and post-burning counts ranged from 8 to 24 across the same districts. Every district met the minimum coverage needed for a reliable maximum-minimum composite, and none of the districts came close to the coverage level used for exclusion in the long-term dataset. Therefore the 2021 dataset was complete and no observations were excluded because of data quality.

4.2 District-Level dNBR and dNDVI

Table 2. District-wise Landsat surface-change indicators for 2021

District	Mean dNBR	Mean dNDVI	dNBR Rank	dNDVI Rank
Sangrur–Malerkotla	0.821	0.712	1	1
Firozpur	0.799	0.641	2	3
Ludhiana	0.756	0.627	3	4
Karnal	0.698	0.653	4	2
Fatehabad	0.667	0.604	5	5
Sonipat	0.568	0.533	6	6
Hanumangarh	0.409	0.376	7	7

Figure 2. Comparison of mean dNBR and dNDVI across the selected validation regions, 2021.



The three Punjab districts had the highest dNBR values among the seven validation regions. Sangrur–Malerkotla had the highest value followed by Firozpur and Ludhiana. Karnal ranked fourth followed by Fatehabad while Sonipat and Hanumangarh recorded the lowest values.

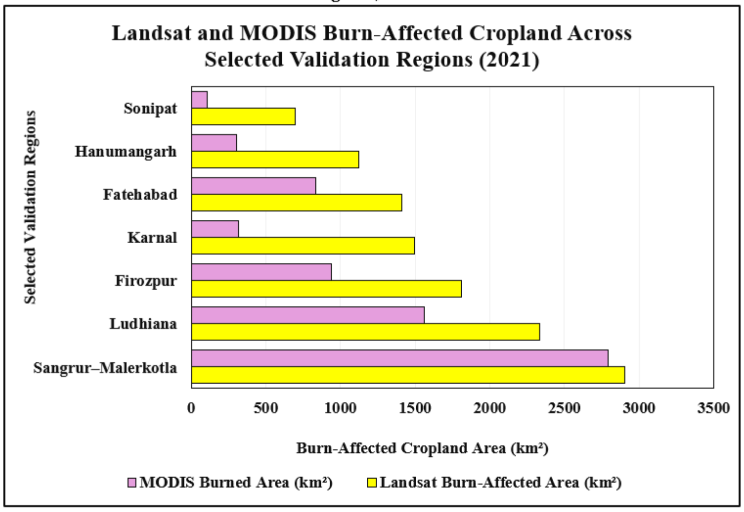
dNDVI followed a broadly similar pattern, but not an identical one. Sangrur–Malerkotla again ranked highest, but Karnal's dNDVI value ranked second overall, ahead of both Firozpur and Ludhiana, despite Karnal’s ranking was lower than both on dNBR. This kind of divergence between the two indices is not unexpected, since dNBR and dNDVI respond to somewhat different aspects of post-harvest surface change rather than measuring identical phenomena.

4.3 District-Level Landsat-MODIS Burn Area Comparison

Table 3. District-level comparison of Landsat-derived probable burn-affected cropland area and MODIS MCD64A1 burned area, 2021

District	Landsat (km^2)	MODIS (km^2)	Difference (km^2)	Landsat/MODIS Ratio	Rank
Sangrur–Malerkotla	2904.982	2795.590	109.392	1.039	1
Ludhiana	2335.953	1558.979	776.974	1.498	2
Firozpur	1810.901	937.874	873.028	1.931	3
Karnal	1496.073	316.986	1179.087	4.720	4
Fatehabad	1409.736	836.163	573.573	1.686	5
Hanumangarh	1126.126	306.940	819.187	3.669	6
Sonipat	694.813	109.696	585.117	6.334	7

Figure 3. Landsat and MODIS burn-affected cropland area across the selected validation regions, 2021.



Landsat-derived probable burn-affected area exceeded the MODIS burnt-area estimate in all seven districts, though the magnitude of the difference varied considerably. Sangrur–Malerkotla showed the closest agreement between the two products, with a ratio of 1.039. The divergence increased progressively through Ludhiana, Firozpur and Fatehabad, before reaching its largest values in Karnal, Hanumangarh and particularly Sonipat, where the Landsat estimate exceeded the MODIS estimate by a ratio of 6.334, the largest observed in this comparison.

4.4 State-Level Spectral Response

At the state level, Punjab recorded the highest mean dNBR and dNDVI values, followed by Haryana, with Rajasthan, represented here by Hanumangarh, recording the lowest values on both indices. This pattern agrees with the district-level results and shows that the stronger spectral response in Punjab is not simply due to the way the districts were grouped**.**

Table 4. State-wise mean Landsat surface-change indicators, 2021

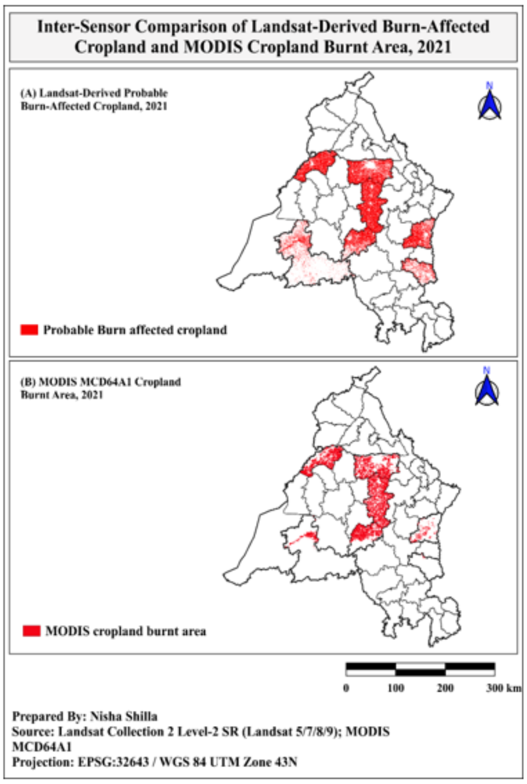
State	Districts	Mean dNBR	Mean dNDVI
Punjab	Sangrur–Malerkotla, Firozpur, Ludhiana	0.792	0.660
Haryana	Fatehabad, Karnal, Sonipat	0.644	0.596
Rajasthan	Hanumangarh	0.409	0.376

4.5 Spatial Comparison of Landsat and MODIS

The spatial distribution of the 2021 results is consistent with the district-level pattern reported above. The strongest Landsat dNBR response is concentrated in the Sangrur–Malerkotla, Firozpur and Ludhiana belt, and the MODIS burnt-area product identifies burning within largely the same area, particularly around Sangrur–Malerkotla and Ludhiana. The two products differ primarily in the extent of the response mapped rather than in its general location. The Landsat dNBR response extends further into Haryana and Hanumangarh than the corresponding MODIS burnt-area detection, a pattern consistent with the possibility that a 500-meter MODIS pixel may not register burning where only part of the pixel is affected. Across the seven districts examined, Landsat-derived probable burn-affected area exceeded the

MODIS estimate in every case, indicating that the observed divergence between the two products was consistently one-directional at the district level during 2021.

Figure 4. Inter-sensor spatial comparison of Landsat dNBR-based surface change and MODIS MCD64A1 burnt area across the selected validation regions, 2021.



4.6 Statistical Relationship Between Landsat and MODIS

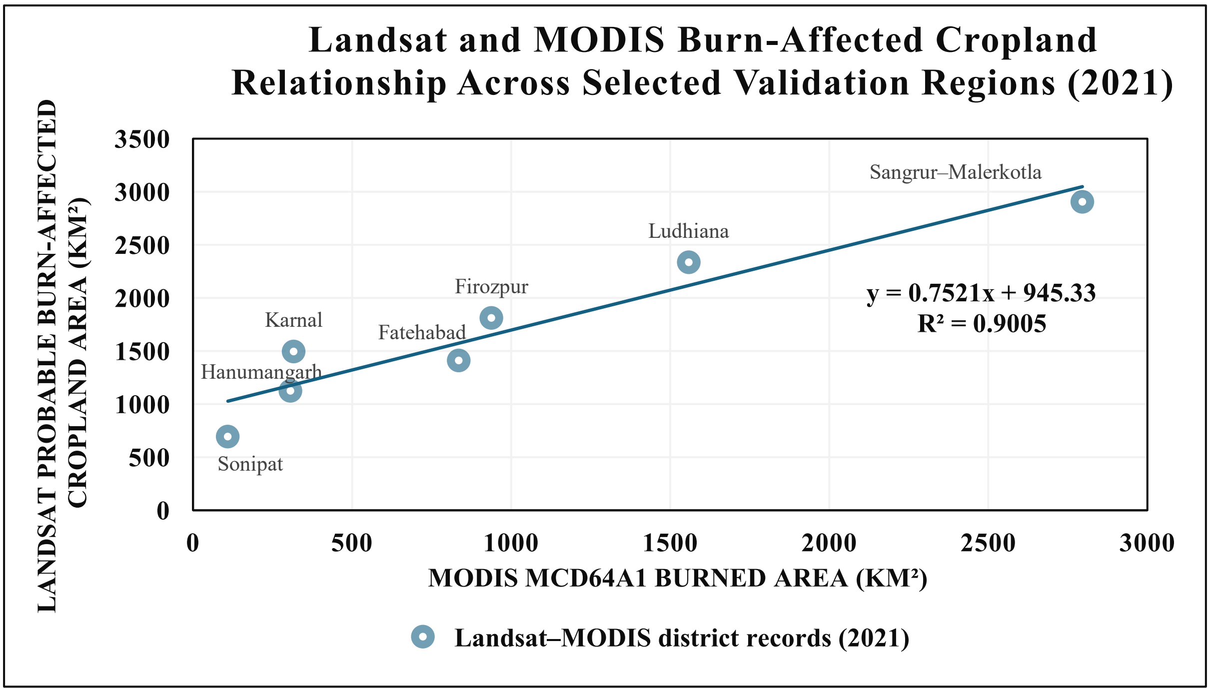
The strength of agreement between Landsat and MODIS was assessed statistically at both the district level for 2021 and across the longer-term clean-record dataset. This section presents the correlation, regression, and error statistics from both comparisons alongside each other.

Table 5. Statistical relationship between Landsat and MODIS burn-area estimates, 2021 district-level comparison (n = 7) and long-term clean-record dataset (n = 120)

Statistic	2021 (n = 7)	Long-term clean-record dataset (n = 120)
Pearson's r	0.949	0.850
R^2	0.900	0.722
p-value	0.0011	<0.001
Regression equation	Landsat = 0.752 × MODIS + 945.33	Landsat = 0.745 × MODIS + 762.34
RMSE (regression residual)	217.67 km^2	397.56 km^2
MAE (regression residual)	197.31 km^2	316.31 km^2
Mean difference (Landsat − MODIS)	702.34 km^2	509.22 km^2

RMS difference (Landsat − MODIS)	766.30 km²	682.20 km²

Figure 5. Relationship between Landsat-derived probable burn-affected cropland area and MODIS MCD64A1 burned area across seven validation districts, 2021 (n = 7).



The seven district-level observations for 2021 showed a strong positive relationship between the two products, with a Pearson correlation of 0.949 and an R^2 of 0.900, significant well below the 0.05 threshold despite the limited sample size. The regression model had an RMSE of 217.67 km², showing an average difference of 217.67 km² between the observed values and the fitted values. This is distinct from the RMS difference between the raw Landsat and MODIS estimates, 766.30 km^2, which reflects the average magnitude of the gap between the two products directly, independent of the fitted line. Both measures are informative in different respects. The regression-based statistics indicate that the relationship between the two products is close and predictable, while the raw difference indicates that, even given this close relationship, Landsat consistently identifies a substantially larger area of probable burning than MODIS across the districts examined.

This district-level result is consistent with the pattern established in the substantially larger long-term clean-record dataset, where 120 observations spanning 2005 to 2025 produced a correlation of 0.850 and an R^2 of 0.722. The 2021 relationship is marginally stronger, though given the difference in sample size, the long-term dataset provides the more statistically robust basis for characterizing Landsat-MODIS agreement across this region. Interestingly, the long-term dataset shows a smaller mean difference between Landsat and MODIS estimates than the 2021 comparison alone, 509.22 km^2 against 702.34 km^2, despite its slightly weaker correlation. This suggests that 2021 was a comparatively active burning season in which the absolute gap between the two products widened even as their underlying statistical relationship remained tight, a distinction that becomes visible only once both the correlation strength and the raw difference are examined together rather than either measure in isolation.

5. Discussion

5.1 Direction and Consistency of the Landsat-MODIS Disagreement

The direction of disagreement observed in this study is notably consistent. Landsat-derived probable burn-affected area exceeded the MODIS estimate in all seven districts, without exception. A pattern this uniform suggests a structural rather than random source of divergence. This difference may be partly related to the different spatial resolutions of the two products. A MODIS pixel covers an area of 500 meters, large enough to encompass several individual agricultural fields given the fragmented land holdings characteristic of Punjab and Haryana. Where only part of a pixel burns, the resulting spectral signal may not be sufficient to meet MODIS's burned-area classification criteria. Landsat, at 30-meter resolution, is considerably less susceptible to this limitation. This interpretation is consistent with ***Liu et al. (2019***), who compared MCD64A1 against household survey data in the same broader region and found that the product consistently underrepresented small and scattered fires that ground observations confirmed had occurred.

5.2 Agreement in Sangrur–Malerkotla

Sangrur–Malerkotla is the one district where Landsat and MODIS estimates converge closely. Two factors possibly contribute to this. First, burning in this district is more extensive than elsewhere in the study area, and where fires cover large, continuous areas rather than isolated patches, a greater proportion of MODIS pixels are likely to be substantially or fully burned, reducing the detection limitation described above. Second, this district lies at the core of the region most consistently identified in the existing literature as the principal paddy-burning belt, meaning both the intensity and the spatial extent of burning may work in Favor of MODIS detection simultaneously. This near-agreement should not be read as uniform across time. Firozpur, for instance, shows two very different reasons for falling outside the strongest-agreement tier in different years of the longer 2005–2025 record, once due to a documented data-quality limitation and due to a genuine shift in another district's burning extent overtaking it. Divergence between Landsat and MODIS in any single district can therefore arise from more than one underlying cause, a distinction the single-year 2021 comparison alone cannot fully separate

5.3 Divergence Outside the Core Punjab Belt

The pattern reverses in Sonipat, Karnal and Hanumangarh, which showed the largest divergence between the two products. The larger differences observed outside the main Punjab burning belt may reflect differences in burn-patch size, spatial fragmentation and sensor resolution, though this study did not directly quantify field size or fragmentation, and this explanation should be regarded as a possibly interpretation rather than a demonstrated mechanism. A similar pattern has also been reported in studies using other sensors**. *Vadrevu and Lasko (2018***) found that MODIS consistently detected fewer fires than the finer-resolution VIIRS product in Punjab, a result broadly consistent with the resolution-dependent explanation offered here. Sonipat's divergence from MODIS is not specific to 2021. Across the full 2005–2025 record, Sonipat records the lowest long-term mean MODIS-detected burnt area of any validation district, consistently below even Hanumangarh, suggesting this gap reflects a persistent limitation in MODIS's ability to resolve burning in this specific district rather than a feature particular to the 2021 season.

5.4 Implications for Regional Monitoring

These findings do not indicate that MODIS is an unreliable monitoring tool. Its correlation with Landsat remained strong throughout this study, both in the seven-district 2021 comparison and across the substantially larger long-term dataset. The results suggest that MODIS may give lower estimates of burn-affected area in districts where agricultural fields are smaller or more fragmented. For researchers and policymakers using MODIS-based estimates to assess the scale of a burning season or support emissions modelling, these results suggest that the actual extent of burning outside the main Punjab belt may be greater than MODIS alone indicates. MODIS-derived estimates should therefore be interpreted with some caution in regions where small and fragmented agricultural burning is prevalent, while Landsat's finer spatial resolution appears to capture a meaningfully larger extent of probable burn-affected cropland in exactly these settings.

5.5 Limitations

Several limitations should be acknowledged. The 2021 district-level statistical relationship is based on only seven paired observations, and although the correlation was strong and statistically significant, a sample of this size limits how far the specific result can be generalized. The long-term clean-record dataset, comprising 120 observations across 2005 to 2025, provides a more robust statistical basis and should be treated as the primary evidence for claims about Landsat-MODIS agreement in this region. Landsat itself carries limitations not fully addressed in this study. Its revisit interval of approximately sixteen days means short-lived burn scars may be missed between successive overpasses, and dNBR-based detection can, in principle, respond to post-harvest activities such as residue removal or ploughing in addition to genuine burning. dNDVI was calculated alongside dNBR to provide supporting spectral evidence of the same seasonal change, however, this does not completely remove the uncertainty. Finally, this study relies on a single representative year for its detailed spatial and statistical comparison. While 2021 was selected deliberately and evaluated against the longer-term pattern, interannual variation in weather, harvest timing and burning intensity means the specific results reported here should not be assumed to apply uniformly to every season.

6. Conclusion

This study compared Landsat-derived probable burn-affected cropland with the MODIS MCD64A1 burnt-area product across seven districts in Punjab, Haryana and Rajasthan, using 2021 as a representative post-monsoon burning season, with data covering the period from 2005 to 2025. Landsat-derived estimates exceeded the corresponding MODIS estimate in all seven districts, with the closest agreement observed in Sangrur–Malerkotla and the largest divergence observed in Sonipat, Karnal and Hanumangarh. The two products showed a strong and statistically significant positive correlation, consistent between the 2021 district-level comparison and the substantially larger long-term clean-record dataset, even as the absolute difference between the two estimates remained considerable in several districts. Together, these results indicate that the Landsat-derived dNBR identifies a greater extent of probable burn-affected cropland than MCD64A1, while the two products retain a strong positive district-level relationship rather than representing fundamentally inconsistent measurements of the same phenomenon.

These findings suggest that MODIS-derived estimates of burning in this region should be interpreted with some caution where agricultural fields are small and fragmented, since the coarser product's estimates may not fully capture the extent of burning that finer-resolution observation reveals. This does not reduce the usefulness of MODIS for regional monitoring, but it suggests that MODIS-based estimates of total burning may be lower than the actual amount in these areas.

Data Availability Statement

The Landsat imagery used in this study is publicly available from the United States Geological Survey (USGS) Earth Explorer platform and via Google Earth Engine (Collection 2 Level 2 Surface Reflectance products for Landsat 5, 7, 8 and 9). The MODIS MCD64A1 burnt-area product is publicly available through NASA's Land Processes Distributed Active Archive Center (LP DAAC). The ESA WorldCover 2021 cropland mask used for spatial restriction is publicly available through the European Space Agency's WorldCover portal. The processed district-level dNBR, dNDVI and burnt-area datasets generated during this study, including the annual calibration dataset and quality-screening classifications, are available from the corresponding author upon reasonable request.

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