

Article

Multispectral Assessment of Net Radiations Using Comprehensive Multi-Satellite Data

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Abstract: Precise estimation of net radiation (R_n) is fundamental to understanding surface energy balance and is critical for accurately determining crop water requirements, especially using remote sensing and geospatial techniques. The core objective of this study is to evaluate multi-satellite-based net radiations on major cropped areas of the Punjab and Sindh provinces of Pakistan. In this study, overlapping scenes from the Moderate Resolution Imaging Spectroradiometer (MODIS), Landsat 8, and Sentinel 2 were used from 2016 to 2020 along with three temperature products MOD11A1, Landsat 8 (brightness temperature), and ERA5. The multi-satellite-based net radiation estimations on overlapping days were compared with the Global Land Data Assimilation System (GLDAS) dataset. The models based on Landsat 8 and Sentinel 2 data exhibited good performance, with a Nash–Sutcliffe Efficiency (NSE) of 68.9%, a mean error (ME) of 13.918 W/m², and a bias of 50.669 W/m². The results indicated that Landsat 8 and Sentinel 2 data produced reliable estimations of net radiation, while MODIS data tended to overestimate due to its higher spatial resolution and broader coverage area. Landsat 8-based estimations are good compared to others, as it has good correlation coefficient and lower RMSE values. The study concludes that Landsat 8 provides the most reliable estimates of net radiation for determining crop water requirements, outperforming other datasets in accuracy. The findings underscore the importance of using high-resolution multi-satellite data for precise agricultural water management, recommending its use in future studies and water resource planning in Pakistan.

Keywords: net radiation; Landsat; MODIS; Sentinel 2; ERA5; GLDAS

1. Introduction

The agricultural sector is a mainstay of Pakistan's economic development [1,2] that contributes to food security [3], food fiber [4], employment creation [5], and poverty mitigation [6], especially in rural areas. The agriculture sector produces approximately 42.3% of the labor force, contributes around 20% of the Gross Domestic Product (GDP), and greatly affects the economy in other areas as well [7,8]. More than 90% of irrigation is used in Pakistan's wheat, the majority of pulses, and nearly all other crops, which are also major contributors to the country's overall crop production [9,10]. With a growing population, there is less water per person available, and groundwater is being overused. Pakistan's irrigated land dramatically enhanced in the early and middle decades of the 20th century due to rapid population expansion and rising food consumption [11]. Irrigated agriculture contributes around 90% of Pakistan's crop production, whereas dryland (rainfed) agriculture makes for about 10% of it because of the country's infrequent and poor rainfall [12]. Farmers apply water to crops manually in which most of the water is wasted [13]. Due to inadequate management, farmers lose more than two thirds of the available water. For instance, there are around 25–40% water losses when applying irrigation, which severely decreases water availability for Pakistan's agricultural production [14]. Saving water losses is not only important for increasing agricultural water production, but it may also help to increase the irrigated area [15]. To save water losses when applying irrigation, evapotranspiration (ET) estimation is necessary for defining crop water requirements [16].

ET is the synthesis of both evaporation and transpiration that includes loss from waterbodies, soil, and vegetation to the atmosphere. ET controls water availability, and is a critical element in hydrological management and planning, along with precipitation and runoff [17,18]. Accurate estimation of ET is important for crop modelling, hydrological modelling, climatic research, and agricultural management at all scales (from locally to globally) [19]. There is a lack of direct observable evidence of the intensification of global land ET because there are only approximately 400 flux stations globally, and their temporal records are very short [20,21]. ET uses about three fifths of annual solar radiation available to the surface of the Earth [22]. Computation of evapotranspiration (ET), which consists of soil surface evaporation and vegetation transpiration, has traditionally relied on conventional methods that often pose challenges, especially when estimating ET on a basin-wide basis [23]. These conventional methods typically involve the use of climatic data and require assumptions and simplifications that may not accurately capture the spatial and temporal patterns in ET within a basin. In recent years, satellite imaging observations have emerged as a valuable implement for estimating real and potential water loss through transpiration and evaporation, respectively, in areas dominated by uniform crop types. Remote sensing technologies, such as satellite imagery, give a comprehensive view of the Earth's surface and can capture information on vegetation characteristics, land surface temperature, and other relevant parameters [24]. By leveraging remote sensing data, it becomes possible to estimate ET over large areas, such as an entire basin, by sampling a representative number of fields [25]. This approach offers several advantages compared to traditional methods. Firstly, it allows for the assessment of real averages for an irrigated region, providing a more accurate representation of ET at a broader scale. Secondly, remote sensing-based estimation considers not only the planting dates and some agronomic management practices but also the actual conditions and variations within the fields, leading to more reliable estimates [26]. For ET estimations, satellite data enable a more comprehensive and spatially explicit analysis [27]. Instead of relying on small sample areas, remote sensing allows for gathering information over the entire basin at each point, providing a more detailed understanding of the ET dynamics [28]. This can be particularly valuable for water resource management, irrigation scheduling, and agricultural planning at the basin scale [29]. Furthermore, remote sensing-based estimation of ET can capture variations in ET across different land cover types, topography, and climate conditions within the basin [30].

There are many empirical methods for determining ET, which are as follows: the Priestley and Taylor method [31], ASCE Penman–Monteith method [32], Penman–Monteith

(FAO 56) standard [33], Surface Energy Balance System (SEBS) [34], Surface Energy Balance Algorithm for Land (SEBAL) [35], and Mapping Evapotranspiration at High Resolution and with Internalized Calibration (METRIC) model [36]. In all the above models, surface net radiation (R_n) is a vital factor for estimating the water requirements for crops. This radiative energy is essential for accurately calculating the amount of water needed to ensure successful crop growth. To ensure effective agricultural production, it is necessary to accurately estimate R_n , as this will help farmers determine the amount of water needed for their crops [37–40]. R_n is a crucial factor which has various implications in crop water requirements, the hydrologic cycle, and climate studies [41]. It is radiative energy present at the terrestrial surface that is the quantity of energy which is received and emitted back into the atmosphere as heat. This energy balance is measured across different wavelengths in the electromagnetic spectrum, including both shortwave (visible light) and longwave (infrared) radiation. The quantity of radiant flux accessible at the land's exterior is calculated by the variation between the energy absorbed and emitted [42–45]. The Sun serves as the fundamental energy source driving the various physical and chemical processes occurring at the boundary between the soil and surrounding air, in addition to heat and water management, plant photosynthesis [46], and evapotranspiration [42,47], which all contribute to the input data used in predicting global and regional effects of climate change and water cycle interactions. The global energy balance and net radiation are critical for the formation of the atmospheric boundary layer [42]. The relationship between the radiations and climate has a crucial role in R_n estimation [48]. R_n comprises two components: (i) net shortwave radiations and (ii) net longwave radiations [37,48,49].

R_n estimation is significantly important, particularly in research concerned with determining evapotranspiration using remote sensing techniques [40,50,51]. These methods for determining net radiation are most often used to determine net shortwave and net longwave radiation [39,52]. Various climatic models can be employed to assess the global distribution of solar radiation [53,54]. Estimation of longwave radiation is possible through geospatial approaches and various empirical models [55,56]. Normalized Difference Vegetation Index (NDVI), Soil Adjusted Vegetation Index (SAVI), and Leaf Area Index (LAI) can be determined for net longwave radiations [57,58]. Many agricultural applications and models that estimate ET need daily average net radiation (DANR) or a diurnal radiation flux cycle. Many equations have been presented, which may be summarized as two techniques. Technique 1 is based on air temperature [59,60] and Technique 2 involves both air and surface temperature [61,62]. In Technique 2, it is necessary to determine daily air emissivity. Evaluation of these techniques showed that they can make accurate predictions under a clear sky. All substantially overstate air emissivity under cloudy and nighttime conditions [63,64]. The net radiation determined by Technique 1 is slightly higher at night than that of Technique 2 because of higher air temperatures at night [63]. DANR gives overestimated net radiation as compared to ground-based estimation [65,66]. The thermal-transducer-type net radiometer [67] instrument also determines net radiation. SEBAL can be used for the estimation of evapotranspiration by using net radiation, soil heat flux, and latent heat flux [40,68].

Different satellites like MODIS, Landsat 8, and Sentinel 2 can be used for mapping of net radiation, temperature, and solar radiation. The MODIS sensor offers information on atmosphere, land, cryosphere, and the ocean through its 36 spectral bands, ranging from 0.405 to 14.385 μm with a spatial resolution of 250 m, 500 m, and 1 km and coverage with roughly four passes per day. MODIS data can be used not only as inputs for hydrological models but also to assess their accuracy by calculating various elements of the surface energy budget. The Landsat 30 m satellite offers a unique view of the world's land surfaces with a resolution of 30 m and provides a 40-year historical record of these conditions, accessible through time-series Landsat data [69]. Due to their widespread usage, Landsat5/TM and Landsat7/ETM+ have become the preferred data for determining the surface radiation budget [70]. Landsat data have been chosen to determine the relationship between Top-Of-Atmosphere (TOA) radiance and the incident insolation at the surface.

These data can be used to calculate insolation and SSNR based on simulations of the radiation transfer [71]. The advancement of optical remote sensing has led to the availability of high-resolution satellites such as Sentinel 2, which can provide detailed images of surface conditions with a 10 m spatial resolution. Additionally, the faster revisit rate of Sentinel 2 compared to the Landsat series allows for the daily calculation of key parameters in ET estimation, such as NDVI and surface albedo, by interpolating data over short periods to capture limited variability [72]. One of the main issues in using satellite remote sensing for optimizing irrigation management is finding the right balance between revisit rate of the sensor and its spatial resolution. Daily coverage sensors like MODIS have a low spatial resolution (>250 m), while medium-resolution sensors like the Landsat series have longer revisit periods (16 days). Although optical sensors are useful for field crop monitoring, their temporal resolution can be reduced in cloudy conditions, making them impractical.

The majority of studies have focused on net radiation using data from individual satellite platforms, such as MODIS [65], Aster [73], and Landsat-ETM [38]. Although these satellites offer valuable data, dependence on a single platform constrains the depth of analysis, as each satellite has unique strengths and drawbacks in terms of spatial resolution, revisit rate, and radiometric precision [74,75]. There is a significant gap in comparative analyses of different satellite platforms for simultaneous radiation estimations, particularly for agricultural and bare soil land use types. This limits the ability to generalize findings and assess the performance of different satellites in varying environmental conditions [76]. Although individual satellite-based approaches have been validated for net radiation estimation, there is a significant lack of comprehensive studies that evaluate the accuracy of net radiation estimates from multiple satellite platforms (e.g., MODIS, Landsat 8, and Sentinel 2) under uniform conditions and on the same day of data acquisition [77]. While some studies have integrated satellite-based radiation estimates with ground-based observations, few have utilized globally available datasets such as the Global Land Data Assimilation System (GLDAS) for comparison. The lack of comprehensive validation across multiple datasets and satellite sources limits the resilience of current net radiation estimation methods. Cross-comparison with global datasets would provide a more reliable framework for improving the accuracy of satellite-based radiation estimates, especially in regions with in situ data [78]. There is also a significant gap in understanding the effect of different satellite-based temperature products (e.g., MODIS, Landsat 8, and ERA5) on net radiation estimation. While temperature is essential for radiation flux calculations, there are few studies that have methodically compared these temperature datasets to evaluate their impact on the accuracy of net radiation estimates across diverse land use types [79].

In this paper, the core objective of this research is evaluation of land use-based net radiation estimated using different temperature products in Punjab and Sindh. The first objective of this study is to compare multi-satellite-based estimation of net radiation on the same day of image acquisition of all the mentioned satellites over an agricultural area with Global Land Data Assimilation System (GLDAS) datasets. The second objective of this study is to reveal the effect of different satellite-based temperature products for estimation of net radiation for all the satellites. In this study, Landsat 8, Sentinel 2, and MODIS satellites were used for estimation of net radiation on the concurrent day in overlapped areas. We used land surface temperature of Landsat 8, MODIS, and ERA5 and developed several combinations for comparison to reveal the effect of different satellite-based land surface temperatures. In future, researchers who want to conduct research on crop water requirements may decide more easily to pick a satellite according to precision and accuracy of net radiation.

2. Materials and Methods

2.1. Study Area

This study was focused in Punjab and Sindh, Pakistan as shown in Figure 1. The geographical extent of Punjab lies in Pakistan in the domain of 69–75.4 E and 27–34.02 N and elevation ranges from 182 to 185 m a.s.l., while Sindh lies 67–71.2.4 E and 24–28.5 N.

Our study area has 8 distinct agro-ecological zones (5 for Punjab, 3 for Sindh) based on climatic factors [80]. The semi-arid lowland region is located in Punjab, the second-largest province by area in Pakistan. It is watered by five rivers, including the Indus, Chenab, Sutlej, and Jhelum, and is regarded as Pakistan's lifeblood. Punjab has a total agricultural land area of 16.52 million hectares. The 36 districts of Punjab are separated into regions: south Punjab, north Punjab/Pothohar, and the southwest region. In terms of weather, Punjab has distinct seasons: the hot season, the cold or moderate season, and the rainy season. Punjab's landscape is made up of the Suleiman Range in the southwest, the Margalla Hills in the north, the Salt Range, and other mountain ranges and deserts, such as Rajasthan in the south and parts of Thal and Cholistan. The agricultural industry in Punjab consists of main crops like maize, rice, cotton, wheat, and sugarcane as well as minor crops like onion, potato, chilies, mash, mung, and masoor. Kharif and Rabi are the two cropping seasons that are observed. The average temperature of Punjab is between 2 and 45 °C; however, in certain places it is over 50 °C. The average annual max temperature is 28–32 °C, and the mean minimum temperature is 15–19 °C. Punjab's rain, which is mostly caused by spring winds, falls in many different places. The rain-fed (Barani) zone receives the most rain, followed by the flooded fields, the Thal area, and the fringe land. Monsoon rainfall occurs from July to September. The sub-mountain area receives 1140 to 1270 mm of yearly rainfall, whereas the plains receive 508 to 630 mm; with changes in climate, humidity fluctuates from 53% to 62%. With a total population of 47.9 million people and a land area of over 14.1 million hectares, Sindh is the second most populous province in Pakistan and the third biggest overall. The total agricultural area is 7.67 million hectares in Sindh. Wheat, cotton, rice, and sugarcane are the main field crops, and they take up 68 percent of all cropped land. Horticultural foods like mangoes, bananas, dates, and chilies are also grown. Climatically, Sindh is situated in tropical and semi-tropical conditions, with the maximum and minimum temperatures varying from 52 °C to 2 °C. The mean monthly maximum temperature in the summer season is about 43 °C to 44 °C, while during the winter, the minimum temperature is about 7 °C.

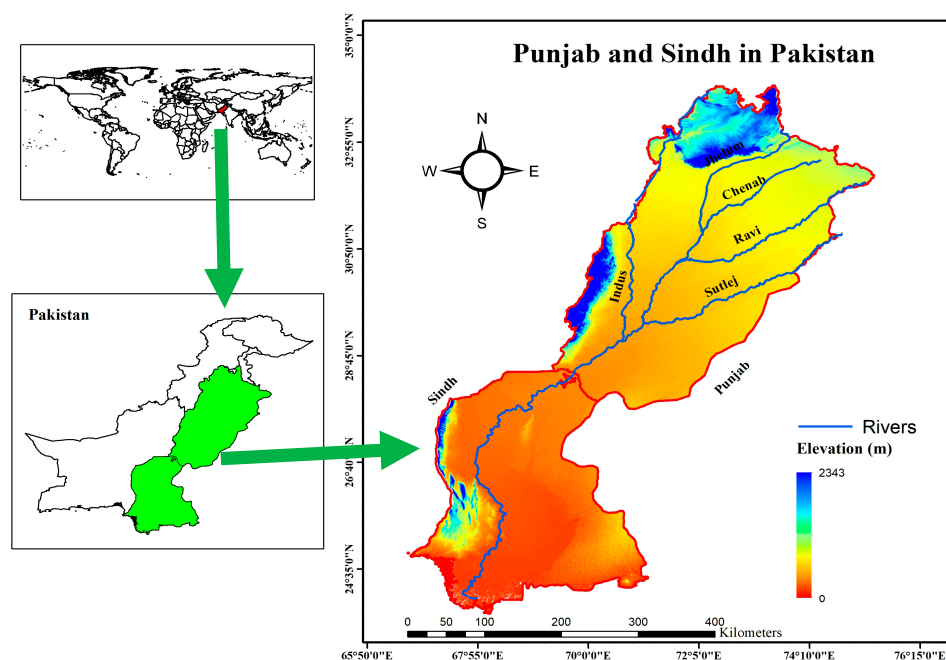


Figure 1. Topographic map of the Punjab and Sindh. The Punjab includes 5 rivers and the Sindh includes 1 major river. The blue line shows the rivers, which are essential for understanding the surface energy balance dynamics in these regions.

2.2. Datasets Used in the Study

Three kinds of satellites were used in this study: Moderate Resolution Imaging Spectroradiometer (MODIS), Landsat 8, and Sentinel 2. The specifications of these satellites are shown in Table 1 below. Different products and bands were used to achieve our objectives. SRTM was used for elevation of the study area. Different temperature products, i.e., ERA5, Landsat 8, and MOD11A1 were used in the study. The characteristics of these products are shown in Table 2 below. The data processing for net radiation was performed using overlapping dates, as presented in Table 3.

Table 1. Different specifications of observed satellites.

Specifications	MODIS (MOD09GA)	Landsat 8	Sentinel 2
Bands	36	8	12
Sensors	MODIS	TIRS/OLI	MSI
Spatial Resolution (m)	250–500	15–30	10–60
Temporal Resolution (days)	1	16	10
Orbit Type	Polar Orbit	Sun-Synchronous	Sun-Synchronous

Table 2. Different characteristics of temperature products.

Specifications	MOD11A1	Landsat 8 Brightness Temperature	ERA5
Bands	36	8	69
Spatial Resolution (m)	500–1000	15–30	11,132
Temporal Resolution (days)	1	16	1
Temperature Unit	Kelvin	Kelvin	Kelvin

Table 3. Overlapping date with Julian day and solar elevation angle of all satellite used in this study.

Date	Julian Day	Solar Elevation Angle
1 May 2016	122	39.86712
8 October 2016	223	39.96391
31 October 2016	305	46.27108
27 December 2016	362	45.28562
17 March 2017	76	45.36283
9 April 2017	97	43.22337
5 June 2017	156	36.38664
16 September 2017	261	44.74274
18 September 2017	339	45.41327
5 December 2017	341	45.37595
7 December 2017	31	46.09333
31 January 2018	56	46.28489
25 February 2018	111	41.37004
21 April 2018	136	38.12117
16 May 2018	191	36.55348

Table 3. Cont.

Date	Julian Day	Solar Elevation Angle
10 July 2018	216	39.04771
4 August 2018	269	45.41623
28 September 2018	271	45.55645
23 October 2018	296	46.35114
17 December 2018	351	45.26024
11 January 2019	11	45.54117
7 March 2019	66	45.96798
1 April 2019	91	43.93689
26 May 2019	146	37.11361
20 June 2019	171	35.92352
8 September 2019	251	43.67385
21 January 2020	12	45.56626
15 February 2020	46	46.34508
10 April 2020	101	42.71461
5 May 2020	126	39.33964
27 June 2020	179	36.00628
29 June 2020	181	36.06289

2.3. Surface Energy Balance Algorithm for Land

Evapotranspiration (ET) is based on a combination of satellite images and climate data, employing the surface energy balance concept. SEBAL determines the instantaneous ET flux only during the time of the picture, which is only available during the satellite's overhead. As a "residual" of the surface energy budget equation, the ET flow is calculated for each pixel. By utilizing this approach, SEBAL can estimate ET at the moment of satellite image acquisition, taking into account the various energy exchanges occurring at the surface. Equation (1) is proposed by [40].

$$\lambda ET = R_n - G - H \quad (1)$$

where λET is the latent heat flux (W/m^2), R_n is the net radiation flux at the surface (W/m^2), G is the soil heat flux (W/m^2), and H is the sensible heat flux to the air (W/m^2).

Net Radiation by Using Surface Energy Balance Equation

Net radiation was estimated by using the surface energy budget equation proposed by Brunt [81] in 1932. It was calculated by subtracting incoming radiation from outgoing radiation. The following equation was used for finding net radiation [40]:

Net surface radiation = gains – losses

$$R_n = RL_{\downarrow} - RL_{\uparrow} - (1 - \epsilon_0) RL_{\downarrow} + (1 - \alpha) RS_{\downarrow} \quad (2)$$

where $RS_{\downarrow}$ = incoming shortwave radiation (W/m^2), α = surface albedo (dimensionless), $RL_{\downarrow}$ = incoming longwave radiation (W/m^2), $RL_{\uparrow}$ = outgoing longwave radiation (W/m^2), and ϵ_0 = surface thermal emissivity (dimensionless).

Surface albedo is defined as the proportion of long-wave radiated energy that is reflected relative to that which is incident. Surface albedo was estimated from albedo top of atmosphere (α_{toa}) by using Equation (4), NIR, and Red bands.

$$\alpha_{toa} = (0.545 \times Red) + (0.32 \times NIR) + 0.035 \quad (3)$$

$$\alpha = \frac{\alpha_{toa} - \alpha_{path\_radiance}}{\tau_{sw}^2} \quad (4)$$

$$\tau_{sw} = 0.75 + 0.00002Z \quad (5)$$

where $\alpha_{path\_radiance}$ is 0.04 for SEBAL as proposed by [82], and τ_{sw} is atmospheric transmissivity estimated by using elevation (Z).

Surface thermal emissivity (ϵ_o) is defined as radiant heat from the Earth's surface divided by the heat given out by a black substance at that temperature. For determination of ϵ_o , NDVI was used. In this index, we utilized NIR and Red bands. The following equation was used for this estimation of NDVI:

$$NDVI = \frac{NIR - Red}{NIR + Red} \quad (6)$$

The maximum and minimum pixels of NDVI were also found. These minimum and maximum NDVI values were employed for estimation of fraction of vegetation (fv) by using following the equation:

$$fv = \left(\frac{(NDVI - NDVI_{min})}{(NDVI_{max} - NDVI_{min})} \right)^2 \quad (7)$$

After estimation of fv, emissivity was estimated by the following equation:

$$\epsilon_o = 0.004 \times fv + 0.986 \quad (8)$$

Energy balance is greatly influenced by LST. In our research, satellite data utilized LST obtained from the Moderate Resolution Imaging Spectroradiometer (MODIS), Landsat 8, and ERA5. MOD11A1 provides land surface temperature measurements at a spatial resolution of 1 km, obtained from the Terra and Aqua Satellites' MODIS sensors. We took the average of night and day temperature. Landsat 8 LST was estimated by using thermal infrared band. The following equation was used for estimation of LST for Landsat 8—see Figure 2

$$LST = \frac{TIR}{(1 + (0.0015 \times \left(\frac{TIR}{1.438} \right)) \times \ln(\epsilon_o))} \quad (9)$$

where TIR is the thermal infrared band. The third temperature product was ERA5. We estimated LST by using ERA5 at each pixel of crops.

Incoming shortwave radiation is the term used to describe the sum of the Sun's rays that hit Earth, both directly and indirectly, and it is measured in W/m^2 .

$$Rs_{\downarrow} = G_{sc} \times \cos \theta \times dr \times \tau_{sw} \quad (10)$$

In this equation, G_{sc} is the solar constant ($1367 W/m^2$), $\cos \theta$ is the cosine of the solar incidence angle, dr is the inverse square of the distance between the Earth and the Sun, and τ_{sw} is the atmospheric transmissivity, as previously mentioned in Equation (5). Using the Excel data on Sun elevation angle (β), where $\beta = (900 - \beta)$, cosine is calculated.

$$dr = 1 + 0.033 \times \cos\left(\frac{DOY \times 2 \times \pi}{365}\right) \quad (11)$$

In the given equation, the term "DOY" represents the Julian day. The angle $(DOY \times 2\pi/365)$ is expressed in radians. The values for "dr" are dimensionless and typically range from 0.97 to 1.03, reflecting variations in the Earth's distance from the Sun throughout the year. $Rs_{\downarrow}$ readings may be anything from 200 to $1000 W/m^2$ depending on when and where the picture was taken.

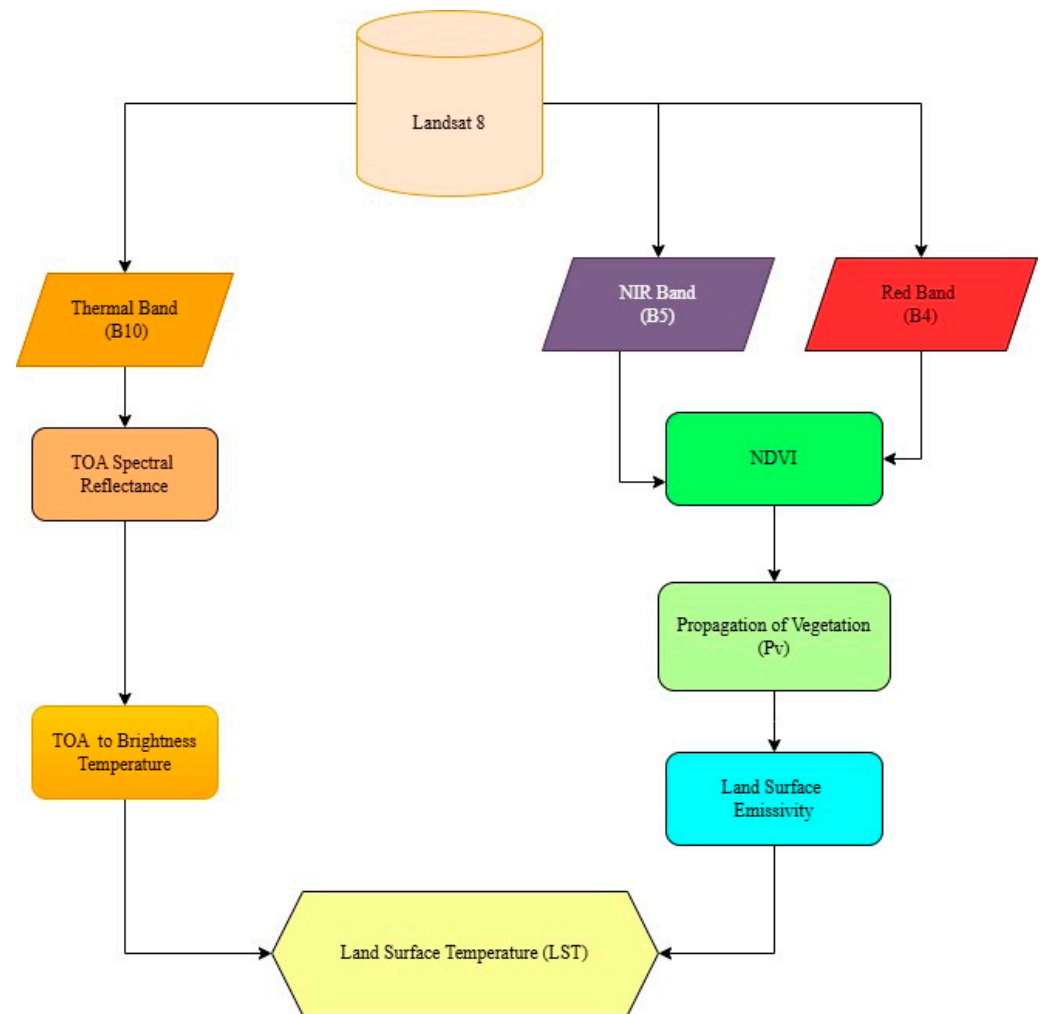


Figure 2. Schematic diagram of estimation of land surface temperature by using Landsat 8. Starting from data acquisition from the Landsat 8 satellite, the process involves multiple stages including pre-processing, band selection, calculation of NDVI and LSE, and conversions to radiance and brightness temperature. Atmospheric corrections are applied to ensure accuracy, and the final LST is calculated using established formulas.

The thermal radiation flux (W/m^2) that space-borne signals pick up from the ground is known as the outgoing longwave radiation. Using the Stefan–Boltzmann equation developed by Josef Stefan, the quantity of $\text{RL}\uparrow$ was estimated. To estimate outgoing longwave radiation, surface temperature (LST) and emissivity (ϵ) were utilized:

$$\text{RL}\uparrow = \epsilon \sigma \times \text{LST}^4 \quad (12)$$

where σ is the Stefan–Boltzmann constant ($5.67 \times 10^{-8} \text{ W}/\text{m}^2/\text{K}^4$), ϵ is the “broad-band” surface emissivity (dimensionless), and LST is the surface temperature (K). The upward longwave radiation ($\text{RL}\uparrow$) values can range from 200 to 700 W/m^2 , based on the image’s time and location.

Two “anchor” pixels are used in the SEBAL procedure to set boundary conditions for the energy balance computations. The “hot” and “cold” pixels, which are the anchor pixels, are situated in the region. The “cold” pixel depicts vegetation that is completely covered in plants and is moist and well irrigated. At this pixel, it is assumed that LST and the air temperature near a surface are comparable. A “hot” pixel, on the other hand, depicts a dry, barren field of crops where evapotranspiration (ET) is thought to be small or nil. In our investigation, cold pixels were used as the lowest LST and hot pixels as the maximum LST.

Incoming longwave radiation refers to the entry of the thermal radiation emitted by the atmosphere (expressed in W/m^2). Incoming longwave radiation ($\text{RL}_{\downarrow}$) was also determined from the Stefan–Boltzmann equation. Air temperature (T_a) and air transmissivity (ϵ_a) were used for the estimation of incoming and outgoing radiation. The following equation was used for estimation of $\text{RL}_{\downarrow}$.

$$\text{RL}_{\downarrow} = \epsilon_a \times \sigma \times \text{LST}^4 \quad (13)$$

where ϵ_a is the atmospheric emissivity (dimensionless), σ is the Stefan–Boltzmann constant, and LST is the near-surface air temperature (K). The following empirical equation for ϵ_a by [40] is applied using data from alfalfa fields in Idaho:

$$\epsilon_a = 0.85 \times (\ln(\tau_{\text{sw}}))^{0.09} \quad (14)$$

Equation (14) replaces into Equation (13), and replacing the air temperature (T_a) with the temperature of the “cold” pixel (T_c), the resulting equation can be expressed as follows:

$$\text{RL}_{\downarrow} = 0.85 \times (\ln(\tau_{\text{sw}}))^{0.09} \times \sigma \times T_c^4 \quad (15)$$

The downward longwave radiation ($\text{RL}_{\downarrow}$) values can vary between 200 and 500 W/m^2 .

The net surface radiation (R_n) was calculated using Equation (1), taking into account the surface albedo (α), outgoing longwave radiation ($\text{RL}_{\uparrow}$), surface emissivity (ϵ_o), incoming shortwave radiation ($\text{RS}_{\downarrow}$), and incoming longwave radiation ($\text{RL}_{\downarrow}$). R_n values range from 100 to 700 W/m^2 depending on the properties of the surface under consideration. The complete flowchart of the methodology is presented in Figure 3.

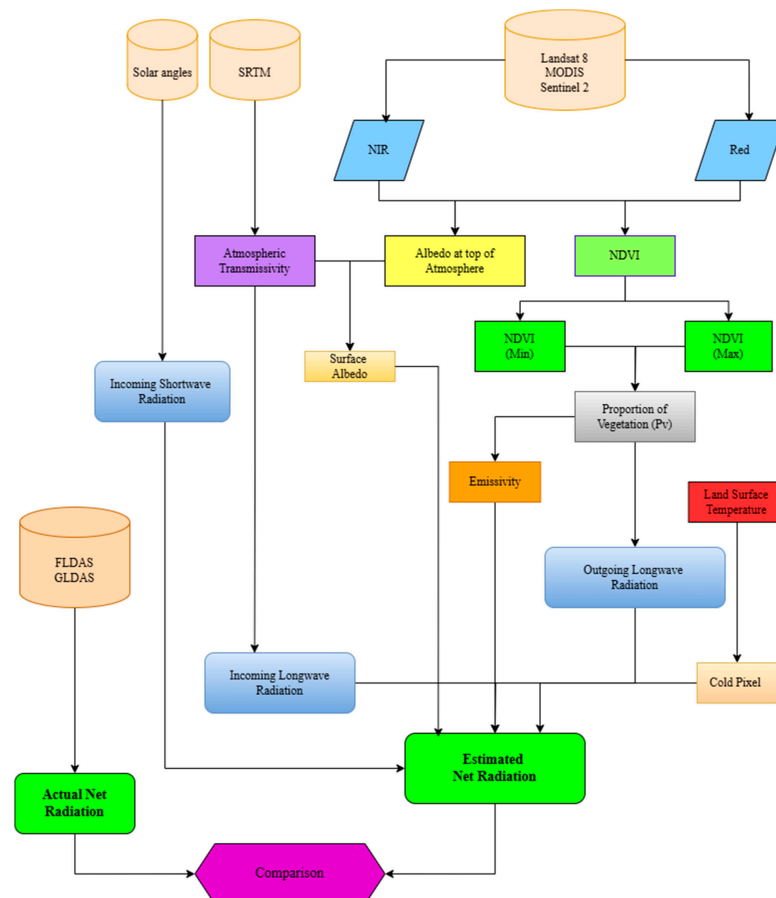


Figure 3. Flow chart for estimation of net radiation by using Landsat 8, MODIS, and Sentinel 2 with different temperature products of ERA5, MODIS, and Landsat 8.

2.4. Statistical Approaches

Validation of the results was conducted using four statistical techniques. Additionally, comparisons were made with GLDAS (Global Land Data Assimilation System) data for comparison purposes. The Nash–Sutcliffe Efficiency (NSE), Mean Error (ME), Root Mean Square Error (RMSE), and Pearson correlation coefficient (Pearson r) were used for validation of results.

$$NSE = 1 - \frac{\sum_{i=1}^n (Rn_{obs} - Rn_{est})^2}{\sum_{i=1}^n (Rn_{obs} - \text{Mean}(Rn_{obs}))^2} \quad (16)$$

$$ME = \frac{1}{n} \sum (Rn_{est} - Rn_{abs}) \quad (17)$$

$$RMSE = 100 \sqrt{\frac{1}{n} \sum (Rn_{est} - Rn_{abs})^2} \quad (18)$$

3. Results

3.1. Comparison of Net Radiation on Overlapping Days

Table 4 presents the statistical parameters of net radiation values for Landsat 8, MODIS, and Sentinel 2 satellites with the three temperature products from 2016 to 2020. In the case of the Landsat 8 satellite, the ERA5 temperature product recorded the highest and lowest net radiation value at 586.7275 W and 200.1064 W/m², respectively. In the case of the MODIS satellite, the ERA5 temperature product recorded the highest net radiation value at 639.6317 W/m², with the lowest value with the Landsat 8 temperature product noted at 211.8415 W/m², respectively. In the case of the Sentinel 2 satellite, the ERA5 temperature product recorded the highest net radiation value at 601.5395 W/m², with the lowest value with the Landsat 8 temperature product noted at 200.0032 W/m², respectively. It can be concluded that combination of the ERA5 temperature product with any satellite gives maximum value and overall, MODIS with ERA5 gives the highest net radiation among all the satellite and temperature product combinations during the study period. while the temperature product of Landsat 8 combined with Sentinel 2 gives the lowest value at 200.0032 W/m². Among all combinations, the highest standard deviation of 85.16643 W/m² was observed for the Sentinel 2 using the MODIS temperature product, indicating higher variability in net radiation values. Conversely, the lowest standard deviation of 63.0793 W/m² was recorded for MODIS with the ERA5 temperature product.

Table 4. Statistical parameters for analysis of net radiation.

Satellites	Temperature Products	Maximum	Minimum	Mean	SD
Landsat 8	ERA5	586.7275	200.1064	411.0769	75.7448
	Landsat 8	576.5881	200.1911	365.0422	74.11454
	MODIS	550.9826	200.4894	379.999	83.38002
MODIS	ERA5	639.6317	287.0346	541.06749	63.0793
	Landsat 8	639.5667	211.8415	493.3916	69.89179
	MODIS	623.2462	357.9417	515.1535	73.35691
Sentinel 2	ERA5	601.5395	200.1471	421.4046	77.3709
	Landsat 8	591.4503	200.0032	381.5748	80.94944
	MODIS	565.7946	200.0255	387.8346	85.16643

3.2. Model Performance

The GLDAS was utilized as an in situ measurement dataset, providing 1-day averaged data at overlapping time intervals. The model data, obtained from various satel-

lite and temperature product combinations, were compared with the net radiation flux data from GLDAS. The estimated net radiation results from 2016 to 2020 were compared with the GLDAS on overlapping dates, as shown in Figure 4. The comparison of GLDAS with the Landsat 8 using the temperature products of ERA5, Landsat 8, and MODIS revealed correlation coefficients of 0.073, -0.005 , and -0.007 , and RMSE values of 86.282 W/m^2 , 86.122 W/m^2 , and 85.86 W/m^2 , respectively. The comparison of GLDAS with the MODIS satellite using the temperature products of ERA5, Landsat 8, and MODIS revealed correlation coefficients of 0.018, -0.035 , and 0.056 , and RMSE values of 170.617 W/m^2 , 133.840 W/m^2 , and 154.624 W/m^2 , respectively. The comparison of GLDAS with the Sentinel 2 satellite using the three temperature products revealed correlation coefficients of 0.055, 0.068 , and -0.002 , and RMSE values of 93.357 W/m^2 , 86.723 W/m^2 , and 92.039 W/m^2 , respectively.

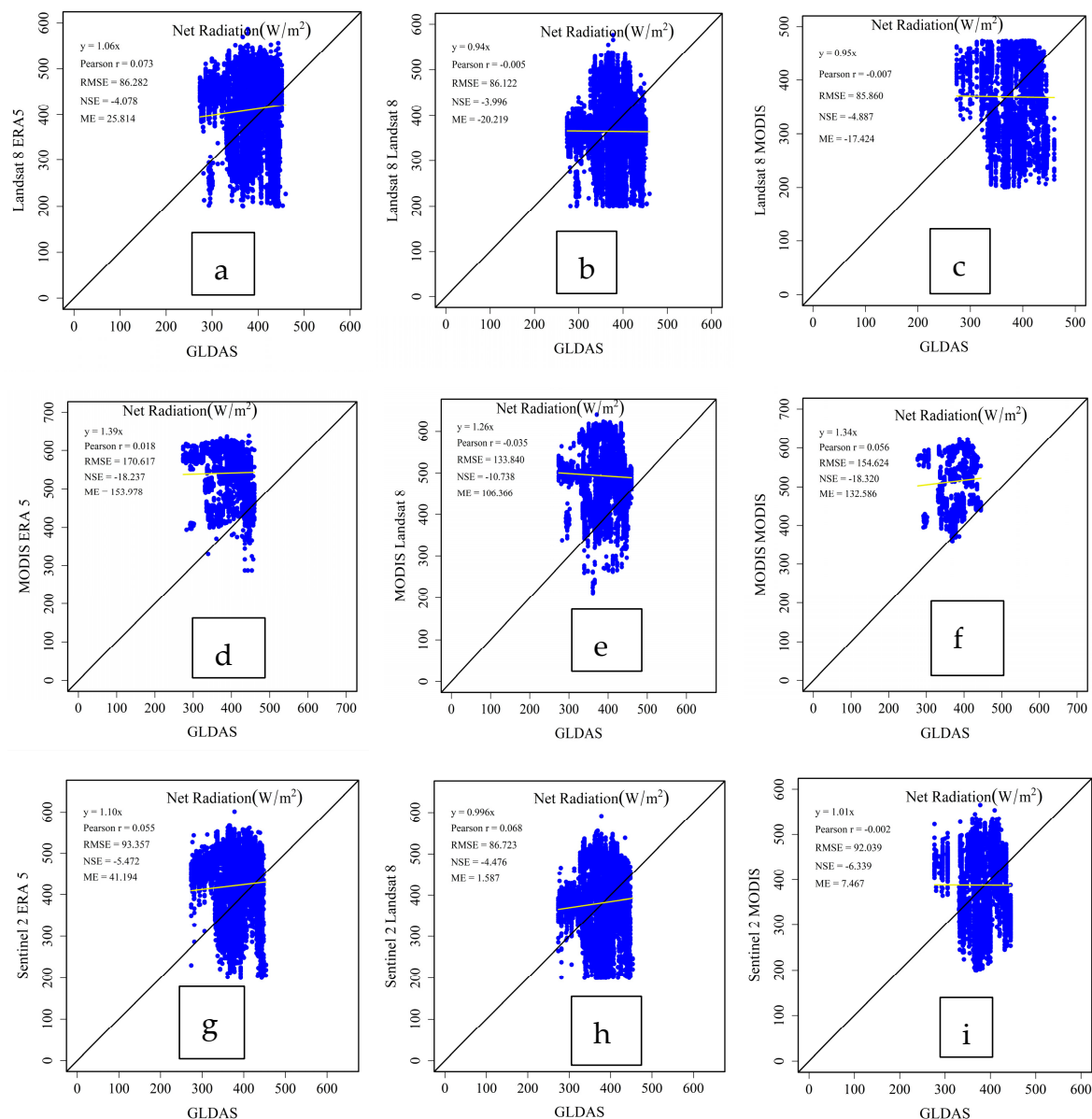


Figure 4. Comparison of net radiation (W/m^2) estimated from different satellites and temperature products with GLDAS; (a) Landsat 8 ERA5, (b) Landsat 8 Landsat 8, (c) Landsat 8 MODIS (MOD11A1), (d) MODIS ERA5, (e) MODIS Landsat 8, (f) MODIS MODIS (MOD11A1), (g) Sentinel 2 ERA5, (h) Sentinel 2 Landsat 8, (i) Sentinel 2 MODIS (MOD11A1).

Furthermore, the NSE values were estimated for each combination, and the results indicated relatively poor performance. The comparison of GLDAS with Landsat 8, MODIS, and Sentinel 2 using the temperature products of ERA5, Landsat 8, and MODIS revealed NSE values of -4.078 , -3.996 , -4.887 , -18.435 , -10.738 , -18.237 , -5.472 , -4.476 , and -6.339 , respectively. These negative NSE values suggest that the model estimations of net radiation using surface energy balance are in poor agreement with the GLDAS data. This indicates that Landsat 8 estimations of net radiation using are slightly better than the other satellites.

3.3. Time Series Analysis of Net Radiation over Punjab and Sindh

The time series analysis of net radiation estimated from MODIS, Landsat 8, and Sentinel 2, using temperature of ERA5, Landsat 8, and Sentinel 2, respectively, is presented in Figure 5a–c.

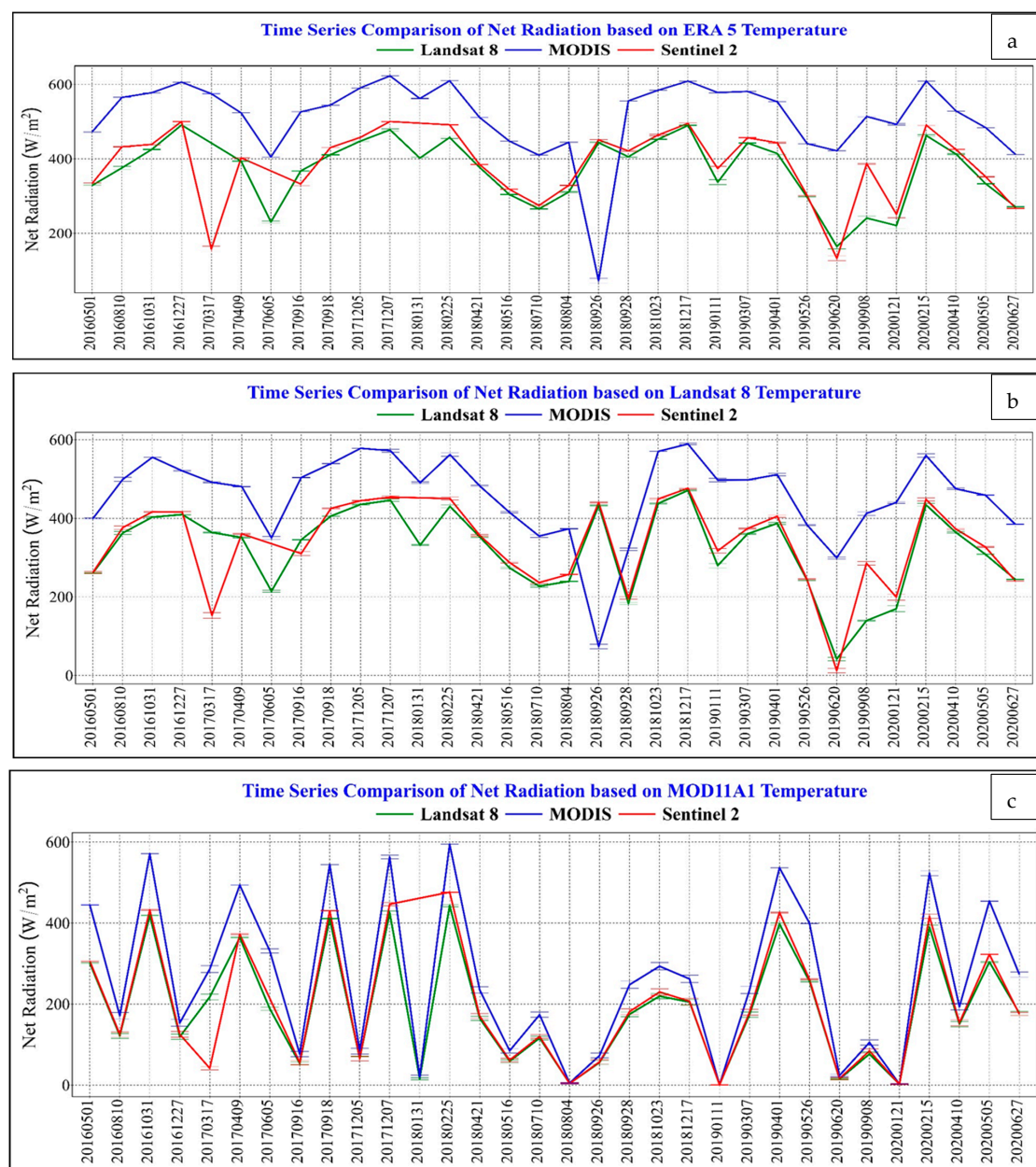


Figure 5. (a–c). Time series graph of net radiation estimated by using (a) ERA5, (b) Landsat 8, and (c) MOD11A1.

It is clear from Figure 5a,b that the MODIS-based estimations of net radiation highly overestimated the net radiation based on Landsat 8 and Sentinel 2, while the overall trend of Landsat 8 and Sentinel 2 is the same in Figure 5a,b. Figure 5c indicates very close agreement for all the net radiation estimations using the temperature of MODIS. However, in Figure 5c, many lower net radiation values are observed for Landsat 8 and the Sentinel 2 satellite in some of the summer months, indicating uncertainties in the MODIS temperature product.

There are huge variations in all the net radiation estimations, with notable events such as a sharp increase in MODIS-based net radiation in September 2018 and a significant decrease in Sentinel 2 net radiation. Most of the peak values of net radiation of Landsat 8 range from 400 to 450 W/m², with the highest net radiation observed in the summer months, while the lower values are about 200 W/m² or slightly below during the end of 2018 and mid-2019. MODIS shows the lowest net radiation values at the end of 2018 and mid-2019, even very close to 180–200 W/m². The variations in net radiation values are associated with several factors such as different temperature products, seasonal changes, meteorological conditions, land cover dynamics, and possible sensor and algorithmic differences. The variations in net radiation estimations highlight the need to carefully select the sources of satellite data.

3.4. Inter-Comparison of Net Radiation

The scatter plots of comparison of net radiation of all the satellite sources are presented in Figure 6a–c. The scatter plots reveal that the comparison of net radiation estimations using Landsat 8 and Sentinel 2 have the highest correlation coefficient of 0.85, lowest value of 50.669 W/m², and highest NSE value of 0.68. Overestimations and underestimations were observed in the comparison of net radiation of Landsat 8 and Sentinel 2. The comparison of net radiation of MODIS and Landsat 8, and MODIS and Sentinel 2, indicated higher ME values of −138.48 and −125.12, representing poor agreement. The comparison of MODIS with Landsat 8 and Sentinel 2 indicated overestimation in MODIS estimations, which may be due to its coarser spatial resolution.

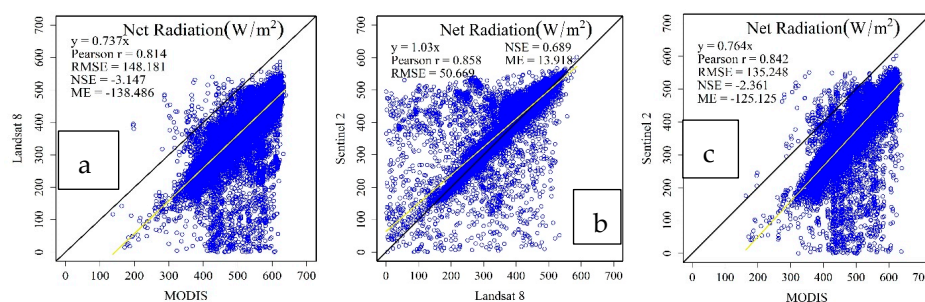


Figure 6. (a–c). Statistical performance of net radiation models: (a) Landsat 8 vs. MODIS, (b) Sentinel 2 vs. Landsat 8, (c) Sentinel 2 vs. MODIS.

4. Discussion

Surface net radiation (R_n), an important factor in the surface radiation budget, has been a focus of researchers worldwide. The accurate measurement of R_n is important for estimation of the reference evapotranspiration (ET_0), which plays a crucial role in assessing crop water requirements. In this study, we conducted a comparative analysis of net radiation using different satellite data and temperature products. GLDAS was used for comparison of net radiation using each satellite and temperature product. The net radiation from paddies in this study was in the range of 200.1064 to 586.7275 W/m² using Landsat 8. The researchers [83] also reported net radiation estimation for agriculture was around 560 to 600 W/m² in a study conducted using Landsat 8 satellite in the Lagudi block of Trichy district, Tamil Nadu, India.

The researchers [84] estimated net radiations on agriculture area in the range of 498.25 to 606.05 W/m² using satellite sensor Landsat 5 TM data in the city of Rio de Janeiro. They

compared net radiation estimated from Landsat 5 with the Penman–Monteith method (FAO-56) with a Standard Error of 84.44 W/m^2 , and correlation coefficient (r) of 0.90. However, in this study, we observed a significantly lower correlation when compared to GLDAS data, and several factors may be associated with this discrepancy. First, the quality and accuracy of the data utilized, particularly the GLDAS dataset, must be scrutinized to ensure the reliability of the variables. Additionally, differences in spatial and temporal resolution between the data sources may also be a source of uncertainties. Furthermore, variations in the underlying assumptions and methodologies of SEBAL, FAO-56, and GLDAS methods may lead to discrepancies in the estimation of net radiation values. To enhance the correlation and gain a comprehensive understanding of the discrepancies observed, a thorough review of data sources, methodologies, and data processing procedures is essential. Identifying and rectifying any potential discrepancies or errors in the research can improve the overall results in the estimation in the future.

Xu et al. [85] introduced a method known as Point-Surface Matching Estimation (PSME) to increase the accuracy of surface net radiation (R_n) estimation by using RCNN using data of AVHRR from 1981 to 2019. The R^2 , RMSE, and bias were found to be 0.84, 26.77 W/m^2 (31.54%), and 1.16 W/m^2 (1.37%), respectively. They concluded that the AVHRR-based R_n displayed higher accuracy in a variety of surface and atmospheric conditions, particularly in situations including thick clouds or hazy conditions. Abraham et al. [86] evaluated net radiation in San Luis Potosí City, México, with remote sensing processes in 2022. The conclusions of their study showed that net radiation was higher during the rainy season and less during the dry season. Furthermore, it was concluded by the researchers that incident radiation had a dominant impact on the city's impermeable surfaces by raising the surface temperatures. Jiang et al. [87] developed two techniques for estimating global R_n using Landsat data: the Downhill Shortwave Radiation (DSR)-based algorithm and the Top-Of-Atmosphere (TOA)-based methodology. They found R^2 of 0.93, RMSE of 17.58 W/m^2 , and a bias of -4.27 W/m^2 on validation against ground measurements, indicating that the DSR-based approach was more accurate than the TOA-based algorithm.

In a study conducted by Ferreira et al. [37], they assessed the influence of estimated net radiation in a prominent agricultural area located within the Brazilian semiarid region, utilizing a combination of remote sensing and in situ data. The net radiation values obtained in their research were within the range of 260.8 W/m^2 to 722.0 W/m^2 , which is closely related to the results of our study. The researchers [88] used MODIS temperature and emissivity datasets for estimation of net radiation and found bias of -33.3 W m^{-2} and a RMSE of 39.6 W m^{-2} on validation with ground-based measurements in Baiyangdian watershed in North China. The researchers [38] found 15–20% uncertainties in estimations of net radiations using Landsat images in lower Rhône Valley, South-Eastern France. However, a combined study on overlapping days was still missing in order to correlate the uncertainties in agricultural areas. The net radiation values derived from different satellite platforms represent average conditions across large areas, and any variations in land cover or human activity within those areas can significantly impact the accuracy of the estimations. However, this also suggests that, in the absence of anthropogenic influences, the net radiation potential of agricultural and bare soil areas may be substantial under the current climatic conditions. This is evident in the analysis of overlapping satellite data, where discrepancies in net radiation estimates become apparent when comparing different temperature products. Therefore, optimizing the use of satellite-based temperature data and enhancing the precision of net radiation estimations are crucial for improving the understanding of water resource dynamics in agricultural ecosystems.

5. Conclusions

This paper evaluated net radiation by using three satellites (MODIS, Landsat 8, and Sentinel 2) and three temperature products (MOD11A1, Landsat 8, and ERA5) using the Surface Energy balance algorithm for land over Punjab and Sindh from 2016 to 2020. The

findings of time series analysis indicate that there is good agreement between the net radiation of Landsat 8 and Sentinel 2 estimated using the temperature of ERA5 and Landsat 8, while huge overestimations were observed in both cases. The times series net radiation plot developed using the MODIS temperature product indicates reliable agreement among the net radiation values using all three satellite sources. The comparison of the scatter plots of net radiation estimations using all the satellite imagery and temperature products with the GLDAS-based net radiation shows very poor correlation coefficients. The scatter plots further reveal that the comparison of net radiation estimations using Landsat 8 and Sentinel 2 have the highest correlation coefficient of 0.85 and NSE value of 0.68. Overestimations and underestimations were observed in the comparison of net radiation of Landsat 8 and Sentinel 2. The comparison of net radiation of MODIS and Landsat 8, and MODIS and Sentinel 2, indicated lower NSE values, representing poor agreement. In both cases, the MODIS-based net radiation estimations overestimated Landsat 8 and Sentinel 2, owing to its coarser spatial resolution.

The comparison of net radiation estimations of all the satellites with the GLDAS estimations revealed poor correlation. The validation of net radiation values of all three satellite sources with ground measurements is recommended to improve the accuracy of net radiation estimations. The study has important implications for estimation of crop water requirements on large field scales and can be useful in decision making in agricultural water management under climate change.

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