



Measurement report: Diurnal cloud variability, vertical regimes, and radiative effects over Iran from multi-sensor observations

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Abstract

Cloud cover, vertical structure, and diurnal timing jointly shape cloud radiative effects, but their observed variability has not been integrated over Iran. We combined CLAAS-3, CloudSat–CALIPSO, and CERES observations from product-specific periods between 2004 and 2025 to characterize cloud properties, vertical regimes, and top-of-atmosphere radiative effects. National mean cloud cover was highest in April (48.79 %) and lowest in September (13.30 %). Its daily maximum occurred at 16:34 local solar time, shifting to 19:35 in summer. Altostratus was the dominant classified regime across much of northern and central Iran, whereas cirrus was more common in the south and southeast; limited sampling makes some local classifications uncertain. CERES SYN1deg-MHour gave mean shortwave and longwave cloud radiative effects of -18.29 and 27.99 W m^{-2} , respectively. Their opposing associations with cloud cover were consistent with partial compensation and a weaker association with net radiative effect. Independently, CERES EBAF-TOA showed a decline in net cloud radiative effect of $-0.95 \text{ W m}^{-2} \text{ decade}^{-1}$ during 2004–2024 ($q = 0.034$), while no national CLAAS-3 cloud-property trend remained significant after multiple-testing correction. These observations indicate that cloud amount alone does not describe cloud–radiation variability across Iran. Differences in sensor resolution and sampling, and the lack of coincident observations, limit the findings to climatological associations rather than causal attribution.

Keywords: Cloud climatology; Cloud radiative effect; Diurnal cycle; Vertical cloud structure; Multi-sensor observations; Explainable machine learning; Iran

1 Introduction

Clouds simultaneously regulate the Earth's hydrological cycle and energy balance, influencing regional and global climate through the reflection of incoming solar shortwave radiation, the absorption and emission of longwave radiation, and the modulation of the atmospheric thermal structure. The sign and magnitude of cloud radiative effects depend not only on cloud cover but also on thermodynamic phase, cloud-top height and temperature, liquid and ice water content, vertical thickness and overlap, and the timing of cloud occurrence within the diurnal cycle. The importance of this complexity is further underscored by evidence that the higher climate sensitivity exhibited by some CMIP6 models has been attributed largely to differences in cloud feedbacks (Zelinka et al., 2020). Moreover, observed trends in cloud radiative effects do not necessarily imply changes in clouds themselves, as they may reflect a combination of cloud feedbacks, radiative forcing, radiative masking, and internal climate variability (Raghuraman et al., 2023). Therefore, interpreting cloud climatology over a heterogeneous region requires an integrated assessment of cloud physical properties, vertical structure, diurnal variability, the atmospheric environment, and their radiative consequences.

Iran lies at the intersection of westerly weather systems, subtropical circulations, influences from the Caspian Sea and Persian Gulf, the complex topography of the Alborz and Zagros mountain ranges, and the limited penetration of monsoonal circulation. Consequently, cloud regimes vary over relatively short spatial distances across the country. Previous studies have documented some aspects of this heterogeneity. MODIS observations have revealed a pronounced gradient in the frequency of cloudy days from the southern Caspian coast toward southeastern Iran (Hatami Bahmanbeiglou and Movahedi, 2017), while the integration of MODIS, ISCCP, and TRMM data has highlighted relationships among cloud type, topography, and precipitation intensity



(Ghasemifar et al., 2018). Analyses of cloud thermodynamic phase have further demonstrated the spatial and seasonal dependence of liquid- and ice-phase clouds on latitude, elevation, and access to moisture sources (Ahmadi et al., 2020). CloudSat observations have also provided direct information on the frequency and vertical distribution of cloud types over Iran, although this assessment was restricted to extended winter seasons and a relatively short study period (Ghasemifar et al., 2021). Thus, although the existing regional literature has characterized the major patterns of cloudiness and their relationships with precipitation and geographical factors, it has yet to provide an integrated perspective on the monthly, seasonal, diurnal, vertical, and radiative variability of clouds over Iran.

Advances in geostationary satellite observations have helped overcome some of these temporal limitations. The third edition of the CLAAS dataset, based on SEVIRI observations, provides a continuous climate record from 2004 onward that includes cloud cover and phase, cloud-top properties, and liquid and ice water paths. Its high-frequency sampling makes it particularly suitable for investigating the cloud diurnal cycle (Benas et al., 2023). Evaluations of geostationary cloud climatologies have further shown that, despite sensitivities to viewing geometry, solar zenith angle, and changes in sensor generations, these datasets offer a unique capability to resolve hourly variations in cloudiness (Bojanowski et al., 2018). This capability is physically important because identical daily-mean cloud cover does not necessarily imply an identical radiative effect. Shifts in the timing of peak cloudiness relative to the diurnal cycle of solar radiation can alter the shortwave effect and, consequently, the net cloud radiative effect, thereby contributing to intermodel spread in cloud radiative effects (Yin and Porporato, 2019). However, analyzing the diurnal cycle without consistently converting universal time to local solar time can confound longitudinal differences with physical differences in the timing of cloud formation.

Despite their favorable temporal coverage, passive geostationary observations cannot fully resolve the vertical structure and multilayer characteristics of clouds. The combination of CloudSat radar and CALIPSO lidar enables more accurate characterization of cloud-layer altitude, thickness, phase, and vertical overlap, and has demonstrated that different vertical cloud regimes can produce distinct shortwave and longwave radiative effects as well as atmospheric heating profiles (Luo et al., 2023). The importance of cloud multilayering and vertical overlap has also been demonstrated using combined CloudSat–CALIPSO products (Oreopoulos et al., 2022). In parallel, CERES products provide consistent estimates of all-sky and clear-sky radiative fluxes, enabling the quantification of shortwave, longwave, and net cloud radiative effects (Loeb et al., 2018; Rutan et al., 2015; Sun et al., 2022). Despite the complementary nature of these observing systems, differences in spatial resolution, CloudSat's narrow-swath sampling, the coarser spatial scale of CERES, and the lack of coincident overpasses complicate the direct attribution of radiative effects to specific cloud types. Consequently, a robust regional analysis must explicitly account for sampling density, the stability of dominant cloud regimes, and uncertainties associated with scale transitions, while interpreting the resulting relationships as climatological associations rather than necessarily as instantaneous estimates or causal relationships.

Linking cloud properties and their radiative effects to humidity, atmospheric stability, vertical motion, precipitation, aerosols, vegetation, snow cover, and topography cannot be fully captured by simple linear relationships because cloud radiative responses are nonlinear, seasonally dependent, and influenced by interactions among environmental variables. Explainable machine learning can characterize these relationships within a surrogate modeling framework while retaining predictive skill and enabling assessment of whether the learned responses are physically consistent with radiative processes (Hafner et al., 2025). However, random partitioning of spatiotemporal data commonly leads to overestimated model performance because of autocorrelation and information leakage; validation strategies should therefore be designed to reflect the spatial and temporal structure of the problem (Meyer et al., 2018). More recent evidence further indicates that inappropriate data partitioning can make even a model with limited predictive capability appear highly accurate (Boser, 2024). Taken together, the literature indicates that the principal gap is not merely the limited number of studies over Iran, but the absence of a long-term, multi-sensor, scale-aware, and uncertainty-conscious framework that integrates horizontal and diurnal cloud climatology, vertical cloud regimes, radiative effects, and their environmental controls within a coherent analytical design.



86 Accordingly, the present study was designed to develop a multi-sensor climatology of clouds and their radiative effects over
87 Iran using product-specific records spanning periods between 2004 and 2025. The study examines monthly, seasonal, and long-
88 term variations in cloud cover, thermodynamic phase, cloud-top properties, and cloud water path, together with metrics of the
89 diurnal cycle expressed in local solar time. It identifies the dominant CloudSat–CALIPSO vertical cloud regimes while
90 explicitly accounting for sampling adequacy and uncertainty, and relates the variability of top-of-atmosphere shortwave,
91 longwave, and net cloud radiative effects to cloud properties and environmental conditions. In the explanatory modeling stage,
92 baseline statistical models and nonlinear algorithms are compared within a spatiotemporal block cross-validation framework
93 to assess the relative contributions of cloud and environmental controls without relying on random data partitioning. The
94 novelty of this study lies not merely in its focus on Iran, but in the scale-aware integration of geostationary, vertically resolved,
95 and radiative observations; the explicit distinction between the climate data record and its interim extension; the assessment
96 of the stability of dominant cloud regimes; and the application of explainable machine learning under rigorous validation. This
97 framework provides a coherent observational baseline for understanding cloud climatology over Iran, evaluating regional
98 climate models, and investigating interactions among clouds, radiation, and the hydrological cycle.
99 Iran is being used as a heterogeneous atmospheric test bed comprising humid Caspian, mountainous, subtropical arid, and
100 monsoon-influenced environments; therefore, the analysis can inform understanding and evaluation of cloud–radiation
101 coupling in other heterogeneous dryland–mountain regions.

102 2 Materials and methods

103 2.1 Overall study design

104 This study was designed to develop a multi-sensor climatology of cloud properties, identify dominant vertical cloud regimes,
105 and investigate their relationships with cloud radiative effects over Iran. The analytical framework comprised three
106 complementary components. First, the geostationary CLAAS-3 products were used to characterize the spatial, monthly,
107 seasonal, and diurnal variability of cloud cover and physical cloud properties. Second, active CloudSat–CALIPSO
108 observations were used to characterize cloud type, thermodynamic phase, vertical thickness, and multilayer structure. Third,
109 two complementary CERES products were employed: SYN1deg-MHour for seasonal climatology, characterization of the
110 diurnal cycle, analysis of multi-sensor relationships, and modeling; and EBAF-TOA Ed4.2.1 for independent inference of long-
111 term trends in cloud radiative effects at the top of the atmosphere. Variables derived from ERA5, GPM IMERG, MAIAC,
112 ERA5-Land, NDVI, land cover, and topography were used to characterize the environmental conditions controlling clouds
113 and their radiative effects. Google Earth Engine processing was restricted to data extraction, initial quality control, and
114 preliminary aggregation, whereas all scientific calculations, scale harmonization, statistical analyses, uncertainty estimation,
115 and modeling were performed in Python.

116 2.2 Study area

117 The study area encompassed the entire political territory of Iran, extending approximately from 25° to 40° N and 44° to 63° E.
118 The original boundary dataset comprised 56 features, which, following geometric validation and repair and the dissolution of
119 internal boundaries, was converted into a single MultiPolygon feature with 24 components and a geodesic area of 1,625,138.55
120 km² in the WGS84 coordinate reference system (EPSG:4326). Figure 1 illustrates the pronounced heterogeneity of Iran's
121 topography and land surface. The mean elevation is 1,205.33 m, with elevations exceeding 2,500 m along the Zagros and
122 Alborz mountain ranges, whereas the Caspian coastal zone, Khuzestan Plain, and southern coastal regions are predominantly
123 below 500 m. Maximum local relief reaches 3,571 m and is concentrated along the major mountain belts, while the central
124 plateau and the eastern and southern plains exhibit lower topographic variability. Barren land is the dominant land-cover class,
125 accounting for approximately 60 % of the country and occurring primarily across central, eastern, and southeastern Iran,



126 followed by grasslands (21.48 %), open shrublands (12.11 %), and croplands (4.51 %); forests, wetlands, urban areas, and
127 water bodies occupy substantially smaller proportions. This pronounced heterogeneity in elevation, moisture conditions, and
128 land-surface characteristics makes Iran a suitable setting for investigating the responses of cloud regimes to topography and
129 environmental conditions. Analysis grids were defined according to the native resolution and sampling adequacy of each data
130 source: a 0.25° grid for CLAAS-3, a 1° grid for CERES, and a 2° grid for CloudSat cells with adequate sampling. This scale-
131 aware design preserves spatial detail in cloud properties while explicitly accounting for the coarser resolution of radiative
132 observations and the limitations imposed by orbital sampling.

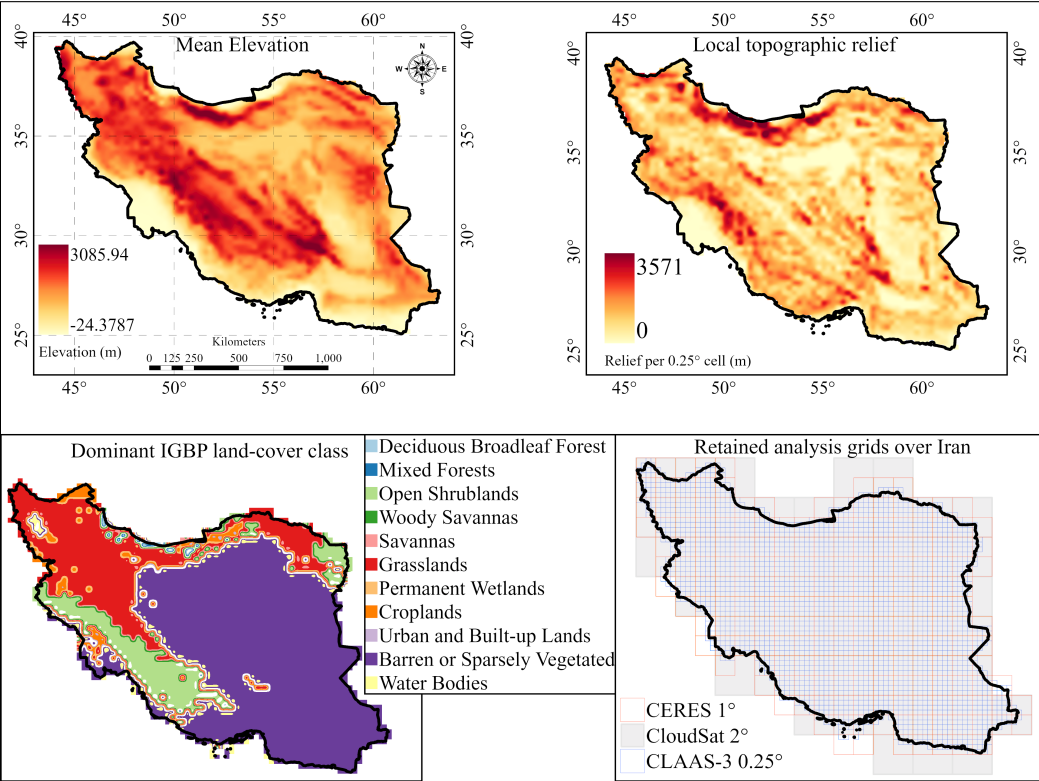


Figure 1. Study area, topographic characteristics, land cover, and analysis grids across Iran. Mean elevation and local topographic relief were derived from NASADEM, and land-cover classes were obtained from MODIS MCD12Q1 Collection 6.1 using the IGBP classification. The overlaid grids indicate the principal spatial scales used in the analysis: 0.25° for CLAAS-3 and environmental variables, 1° for CERES-based radiative and machine-learning analyses, and 2° for CloudSat–CALIPSO cloud-regime analyses. Map lines delineate the study area and do not necessarily depict accepted national boundaries.

133 **2.3 Data and data sources**

134 Table 1 summarizes the characteristics of the datasets used in this study. The data sources were selected to achieve a balance
135 among long-term temporal coverage, diurnal resolution, information on vertical cloud structure, radiative fluxes, and
136 environmental controls. CLAAS-3, based on geostationary SEVIRI observations and providing information on the cloud
137 diurnal cycle, served as the primary data source for the horizontal cloud climatology; its performance in characterizing cloud
138 properties and the diurnal cycle has been assessed through formal product evaluation (Benas et al., 2023). CloudSat–CALIPSO
139 provided information on cloud vertical structure and cloud type that cannot be retrieved from passive sensors alone (Sassen
140 and Wang, 2008). CERES products, by providing corresponding clear-sky and all-sky radiative fluxes, formed the basis for
141 calculating cloud radiative effects.



Table 1. Characteristics of the datasets used in this study

Dataset	Provider/system	Version or product	Period used	Native resolution	Variables used	Role in the study
CLAAS-3	CM SAF/EUMETSAT	CDR V004 and ICDR V004I1	February 2004–August 2025	0.25°; monthly with 24 UTC hours	CFC, CPH, CTT, CTP, CTH, LWP, and IWP	Horizontal cloud climatology and diurnal cycle
CloudSat–CALIPSO	NASA CloudSat DPC	2B-CLDCLASS-LIDAR P1_R05	2007–2020	Orbital profiles; layer-based	Cloud type, phase, base, top, thickness, and number of layers	Vertical cloud regimes and dominant cloud type
CERES SYN1deg-MHour	NASA Langley	Edition 4B; Ed4.2 label	January 2004–August 2025	1°; monthly with 24 hourly time steps	TOA and surface SW, LW, and net fluxes under all-sky and clear-sky conditions	Radiative climatology, diurnal cycle, multi-sensor relationships, and machine learning
CERES EBAF-TOA	NASA Langley	Ed4.2.1	January 2004–December 2024	1°; monthly	TOA SW, LW, and net all-sky and clear-sky fluxes	Inference of long-term trends in TOA cloud radiative effects
ERA5	ECMWF/Copernicus	ERA5 Hourly and pressure-level data	January 2004–August 2025	~0.25°; hourly	Humidity, temperature, vertical motion, and wind at 500 and 850 hPa; CAPE, CIN, TCWV, BLH, 2-m temperature, and pressure	Thermodynamic and dynamic environment
GPM IMERG	NASA/JAXA	V07 Monthly	January 2004–August 2025	0.1°; monthly	Precipitation rate and accumulation, random error, quality index, probability of liquid precipitation, and gauge weighting	Cloud–precipitation relationships
MODIS MAIAC	NASA	MCD19A2 Collection 6.1	January 2004–August 2025	Native 1 km; monthly	AOD at 550 nm, uncertainty, and frequency of valid observations	Influence of aerosol loading
NASADEM	NASA/LP DAAC	NASADEM HGT	Static	30 m; extracted at 0.01°	Elevation, slope, and relief	Topographic control
MODIS Land Cover	NASA	MCD12Q1 Collection 6.1, IGBP	2004–2024	500 m; annual	17 IGBP classes and quality flags	Land-surface characteristics
MODIS NDVI	NASA	MOD13A3 Collection 6.1	January 2004–August 2025	1 km; monthly	NDVI and SummaryQA	Vegetation condition
ERA5-Land	ECMWF/Copernicus	Monthly Aggregated	January 2004–August 2025	~0.1°; monthly	Snow cover and snow depth	Effects of snow and surface reflectivity

ERA5 data were obtained from the fifth-generation ECMWF reanalysis archive, which provides temporal consistency and a comprehensive suite of atmospheric variables (Hersbach et al., 2020). ERA5-Land was used for snow-related variables because it represents land-surface processes at a finer spatial resolution than ERA5 (Muñoz-Sabater et al., 2021). The specific Google Earth Engine dataset identifiers were ECMWF/ERA5/HOURLY, NASA/GPM_L3/IMERG_MONTHLY_V07, MODIS/061/MCD19A2_GRANULES, and ECMWF/ERA5_LAND/MONTHLY_AGGR. Two independent CERES products were used for distinct purposes. Seasonal climatology, diurnal-cycle characterization, multi-sensor relationships, and machine-learning analyses were based on the official CERES SYN1deg-MHour Terra–Aqua–NOAA20 Edition 4B dataset (DOI: 10.5067/TERRA-AQUA-NOAA20/CERES/SYN1deg-MHour_L3.004B) (CERES Science Team, 2025). The designation



“Ed4.2” was retained only when reporting the filename and metadata of the downloaded subset and was not treated as an independent dataset designation or as a replacement for Edition 4B. Long-term radiative trend inference was conducted independently using CERES EBAF-TOA Edition 4.2.1 (DOI: 10.5067/TERRA-AQUA-NOAA20/CERES/EBAF-TOA_L3B004.2.1) (CERES Science Team, 2024). Accordingly, throughout this study, SYN1deg-MHour Edition 4B refers exclusively to climatological, diurnal, multi-sensor relationship, and modeling analyses, whereas EBAF-TOA Edition 4.2.1 is used exclusively for long-term trend analysis. Consistent with CERES product-use guidance, SYN1deg-MHour was not used for any long-term trend inference and was retained solely for climatology, diurnal-cycle analysis, multi-sensor covariability, and modeling.

2.4 Data audit, preprocessing, and quality control

2.4.1 File audit

Before any analysis, an inventory of all input files was compiled based on product name, date, file size, variables, dimensions, coordinates, time information, and file readability. Checks were performed for missing and duplicate months, zero-byte files, missing required variables, infinite values, fill-value leakage, and values outside physically plausible ranges. Physical consistency constraints, including the consistency of CERES net flux with the sum of its shortwave and longwave components, were evaluated numerically. Each processing stage proceeded only after all mandatory checks had been passed; otherwise, the workflow was terminated under a fail-closed protocol.

CLAAS-3 denotes the third scientific edition of the CM SAF cloud-property dataset and is officially documented as “CLAAS-3: CM SAF Cloud Property Dataset Using SEVIRI—Edition 3” (DOI: 10.5676/EUM_SAF_CM/CLAAS/V003) (Meirink et al., 2022). In contrast, V004 and V004I1 are release labels associated with the operational files used in this study and should not be interpreted as representing a fourth scientific edition of the product. The homogeneous component of the climate data record, comprising the CDR files labeled V004, covers February 2004–December 2020. The interim extension of the record, comprising the ICDR files labeled V004I1, was used for January 2021–August 2025. The suffix I1 is part of the ICDR file-release label. Accordingly, throughout this study, “CLAAS-3 Edition 3” refers to the scientific generation of the product, whereas “CDR V004” and “ICDR V004I1” identify the record type and corresponding file release. Both components were cited using the official CLAAS-3 dataset DOI. CFC was valid across all spatiotemporal records, whereas valid-data coverage for CPH and CTO was approximately 98.6 %, and that for LWP and IWP was approximately 42.6 % and 37.1 %, respectively. These differences reflect the conditional nature of the liquid and ice water retrievals. Consequently, missing LWP and IWP values were never recoded as zero, and only valid observations were included in the denominators used to calculate conditional means.

2.4.2 Boundary preparation and fractional masks

To avoid bias in boundary cells, the actual intersection between each grid cell and the geometry of Iran was calculated, and the fraction of each cell area lying within the country was stored. Three statuses were defined for each cell: overlapping Iran, fully contained within Iran, and having its centroid within Iran. The CLAAS-3 grid comprised 2,690 overlapping cells and 2,501 centroid-in-Iran cells, whereas the CERES grid comprised 198 overlapping cells and 154 centroid-in-Iran cells. An independent 0.1° mask was also generated for GPM. All national means and cross-grid aggregations were weighted by the geodesic area of the portion of each cell located within Iran. Thus, coastal and boundary cells contributed in proportion to their actual area within the country rather than through a binary inclusion–exclusion scheme.

The area-weighted mean of a variable (x) was calculated as follows:

$$\overline{x_w} = \frac{\sum_{i=1}^n A_i x_i}{\sum_{i=1}^n A_i} \quad (1)$$



188 where A_i is the area of the portion of cell i located within Iran, x_i is the valid value of the variable in cell i , and n is the number
189 of valid cells. Cells without valid values were excluded from both the numerator and the denominator.

190 2.4.3 CloudSat–CALIPSO quality control

191 The 73 ZIP archives were read in a streaming manner to avoid the simultaneous extraction of large data volumes. After
192 verifying filenames and removing duplicate versions, 6,628 unique HDF files remained. Only profiles located within the
193 boundaries of Iran and satisfying $\text{Data_quality} = 0$ were included in the analysis. Layers with cloud-type codes outside the
194 range 1–8, phase codes outside the range 1–3, invalid geometry, or negative thickness were excluded. Phases with
195 $\text{Phase_confidence} \geq 5$ were flagged as high-confidence classifications. Lower-confidence phases, however, were not silently
196 discarded; instead, their counts were retained for sensitivity analysis. Cloud-type quality values were also checked against the
197 documented valid range of the product. The combined use of radar and lidar in 2B-CLDCLASS-LIDAR provides enhanced
198 sensitivity to optically thin clouds and multilayer cloud structures, although surface-return contamination and orbital sampling
199 remain important limitations (Wang, 2019).

200 2.4.4 Quality flags for environmental products

201 For MAIAC, the primary AOD mean was calculated from land observations characterized by clear conditions, normal
202 adjacency, the highest AOD retrieval quality, and values within the product's valid range. A broader definition, including
203 quality codes 0 or 11, was retained as a research-quality sensitivity analysis. In addition to AOD, retrieval uncertainty, the
204 effective number of observations, and the fraction of valid coverage were stored to distinguish sparsely sampled cells from
205 those with genuinely low AOD values. The MAIAC algorithm and its simultaneous retrieval of surface and aerosol properties
206 are described in the original methodological study (Lyapustin et al., 2011).

207 For MOD13A3, $\text{SummaryQA} = 0$ was adopted as the primary definition of good-quality NDVI, whereas the broader criterion
208 $\text{SummaryQA} \in \{0, 1\}$ was retained for sensitivity analysis. MCD12Q1 land-cover classes were converted, without categorical
209 interpolation, to the fractional area of each IGBP class within the target grid cell. This procedure prevented the creation of
210 artificial classes that can arise when continuous resampling methods are applied to categorical variables. The MCD12Q1
211 product and its evaluation are described by Sulla-Menashe et al. (2019), while the methodological basis of MODIS NDVI is
212 presented by Huete et al. (2002).

213 For ERA5 pressure-level data, variables at 850 hPa were masked at times when surface pressure was below 875 hPa to prevent
214 subsurface values over high-elevation terrain from entering the analysis. ERA5-Land snow cover was converted to percent by
215 applying a conversion factor of 0.01, and its native grid was completed to ensure exact alignment with the 0.25° domain. For
216 GPM, monthly precipitation totals were calculated by multiplying the mean precipitation rate by the actual number of hours
217 in each month. Conversion of the GPM random-error variable to monthly units was treated strictly as a unit conversion and
218 was not interpreted as statistical propagation of independent errors.

219 2.5 Temporal and spatial alignment

220 2.5.1 Conversion from UTC to local solar time

221 Because Iran spans approximately 19° of longitude, the direct use of UTC could introduce longitudinal shifts in the phase of
222 the diurnal cycle between the eastern and western parts of the country. Local solar time (LST) for each meridian was therefore
223 calculated as follows:

$$h_{\text{LST}} = \left(h_{\text{UTC}} + \frac{\lambda}{15} \right) \bmod 24 \quad (2)$$

224 where UTC is Coordinated Universal Time, λ is longitude in degrees east, and LST is local solar time. Hourly CLAAS-3 and
225 CERES SYN1deg-MHour data were mapped to 24 integer hours of local solar time using periodic linear interpolation. Because



226 EBAF-TOA is a monthly product with no hourly dimension, no time-of-day conversion was applied, and it was used
227 exclusively for monthly trend analysis.
228 Preservation of the daily mean before and after the time conversion was verified for each grid cell. For CERES, the nominal
229 half-hourly time centers from 0.5 to 23.5 UTC were used as the basis for the conversion, whereas CLAAS-3 was referenced
230 to integer UTC hours.

231 **2.5.2 Spatial scale harmonization**

232 Two independent target scales were defined. A 0.25° grid was used for the CLAAS-3 climatology and the environmental data
233 cube, whereas the 1° CERES grid was used for cloud radiative effect analyses and machine learning. GPM data were
234 aggregated from 0.1° to 0.25° using spherical area-weighted averaging. MAIAC data were first spatially aggregated from their
235 native resolution to 0.25° in Google Earth Engine and were subsequently converted to monthly means. This processing order
236 reduced computational demand and prevented disproportionate weighting arising from the large and uneven number of
237 granules. NASADEM, NDVI, snow, and land-cover class fractions were also transferred to the 0.25° grid using geometric
238 overlap or area-weighted averaging. For categorical data, the frequency or fractional area of each class was calculated, and
239 bilinear interpolation was not applied.
240 For the machine-learning dataset, the 0.25° CLAAS-3 and environmental data cubes were aggregated to the 1° CERES cells
241 using the area within Iran as the weighting factor. This exact geometric aggregation was preferred over simple resampling
242 because it preserves the national boundary and accounts for differences in grid-cell area. All data were stored in the WGS84
243 geographic coordinate reference system, with grid-cell ordering, centers, and boundaries explicitly verified.

244 **2.6 Cloud climatology and diurnal-cycle calculation**

245 For each calendar month, a long-term 24-h mean climatology was calculated. Seasons were defined as DJF (December–
246 January–February), MAM (March–April–May), JJA (June–July–August), and SON (September–October–November).
247 Seasonal and full-period means were weighted by the climatological number of days in each month, including 28.2425 days
248 for February. These weights summed to 365.2425 days. DJF climatologies were calculated from the corresponding
249 climatological months, whereas only complete seasons were included in seasonal trend analyses.
250 The daily mean, maximum-to-minimum range, day–night difference, and first-harmonic component were derived. Daytime
251 was defined as 06:00 to <18:00 LST and nighttime as 18:00 to <06:00 LST. The day–night difference was calculated as the
252 daytime mean minus the nighttime mean.
253 For an hourly variable (x_h), the first-harmonic coefficients and amplitude were calculated as follows:

$$\begin{aligned} a &= \frac{2}{24} \sum_{h=0}^{23} x_h \cos\left(\frac{2\pi h}{24}\right), \quad b \\ &= \frac{2}{24} \sum_{h=0}^{23} x_h \sin\left(\frac{2\pi h}{24}\right) \end{aligned} \quad (3)$$

$$A_{24} = \sqrt{a^2 + b^2}, \quad \phi_{24} = \left[\text{atan2}(b, a) \frac{24}{2\pi} \right] \text{mod} 24 \quad (4)$$

$$R^2 = 1 - \frac{\text{SSE}}{\text{SST}} \quad (5)$$

254 where A_{24} is the amplitude of the 24-h cycle in the units of the variable, and ϕ_{24} is the local solar time of the harmonic maximum.
255 The goodness of fit of the harmonic model was evaluated using $R^2 = 1 - \text{SSE}/\text{SST}$. Higher R^2 values indicate that the 24-h
256 harmonic component explains a larger proportion of the intradiurnal variability.
257 The harmonic phase was interpreted only for grid cells in which both the amplitude and goodness of fit were sufficient to
258 provide a physically meaningful estimate of the time of maximum. In regions with a very weak diurnal cycle, phase maps



259 should therefore be interpreted together with the corresponding amplitude and R^2 values and should not, on their own, be
260 regarded as indicating a definitive time of cloud formation.

261 2.7 Calculation of cloud radiative effect

262 Cloud radiative effect (CRE) at the top of the atmosphere (TOA) was calculated from the difference between clear-sky and all-
263 sky radiative fluxes. The sign convention was defined such that a positive net CRE indicates an increase in downward energy
264 within the Earth–atmosphere system:

$$\text{SWCRE}_{\text{TOA}} = \text{SW}_{\text{t,clr}} - \text{SW}_{\text{t,all}} \quad (6)$$

$$\text{LWCRE}_{\text{TOA}} = \text{LW}_{\text{out,clr}} - \text{LW}_{\text{out,all}} \quad (7)$$

$$\text{NetCRE}_{\text{TOA}} = \text{SWCRE}_{\text{TOA}} + \text{LWCRE}_{\text{TOA}} \quad (8)$$

265 where SW denotes shortwave radiation reflected to space, LWout denotes outgoing longwave radiation, and the subscripts clr
266 and all refer to clear-sky and all-sky conditions, respectively. All radiative components were expressed in W m^{-2} .
267 The cloud radiative effect equations were applied separately to the SYN1deg-MHour and EBAF-TOA products.
268 Climatological, diurnal-cycle, multi-sensor, and machine-learning analyses were based on SYN1deg-MHour, whereas EBAF-
269 TOA was used exclusively for inference of long-term trends in TOA cloud radiative effects. Surface cloud radiative effects
270 were calculated only from SYN1deg-MHour and were not included in the primary trend inference. Because of structural
271 differences between the two products, climatological means derived from SYN1deg-MHour should not be directly compared
272 with period-mean values derived from EBAF-TOA.

273 2.8 Vertical cloud regimes and dominant cloud type

274 CloudSat–CALIPSO provided eight cloud-type categories: cirrus, altostratus, altocumulus, stratus, stratocumulus, cumulus,
275 nimbostratus, and deep convection. To avoid multiple counting of the same cloud type within multilayer profiles, the presence
276 of each cloud type was counted only once per profile. The occurrence frequency of cloud type k within each grid cell and
277 analysis period was calculated as follows:

$$F_k = 100 \frac{N_{k,\text{profile}}}{N_{\text{cloudy,good}}} \quad (9)$$

278 where $N_{k,\text{profile}}$ is the number of cloudy profiles containing at least one layer of cloud type k , and $N_{\text{cloudy,good}}$ is the total
279 number of cloudy profiles meeting the quality-control criteria. Because a multilayer profile may contain more than one cloud
280 type, the sum of F_k across all cloud types is not necessarily equal to 100 %.

281 The dominant cloud type was defined as the type with the highest occurrence frequency, and the dominance margin was
282 calculated as the difference in occurrence frequency between the first- and second-ranked cloud types. The multilayer fraction
283 was calculated as the proportion of valid cloudy profiles containing more than one valid cloud layer. Monthly, seasonal, and
284 full-period cloud regimes were calculated on a 2° grid. The 1° grid was excluded from the primary inference and mapping
285 because sampling density was insufficient in many grid cells.

286 Sampling adequacy was assessed before assigning cloud regimes. The minimum requirements were 150 granules and 10 years
287 for the full-period climatology, 20 granules and 10 years for monthly climatologies, and 50 granules and 10 years for seasonal
288 climatologies. These thresholds were fixed prior to the regime analysis to prevent the resulting maps from being
289 disproportionately influenced by a limited number of orbital overpasses. Annual analyses required at least 10 granules and one
290 representative year. These filters reduce, but do not eliminate, uncertainty associated with orbital sampling. Accordingly, all
291 CloudSat results were interpreted as an orbitally sampled climatology rather than as continuous temporal coverage.



2.9 Trend analysis

2.9.1 Trends in cloud properties

To preserve instrumental and algorithmic homogeneity, the primary CLAAS-3 trend inference was restricted to the CDR period from February 2004 to December 2020. The combined CDR+ICDR record extending through August 2025 was used only for sensitivity analysis. For each variable, the climatological mean of the corresponding calendar month was subtracted from the data to obtain monthly anomalies. A linear trend was then fitted against centered decimal time:

$$y_t = \beta_0 + \beta_1(t - \bar{t}) + \varepsilon_t \quad (10)$$

where y_t is the monthly anomaly, β_1 is the trend slope, t is decimal time, and ε_t is the residual. The slope was multiplied by 10 and reported in units per decade.

Ordinary least squares (OLS) regression was selected because the analysis focused on the magnitude and direction of linear change. Given the autocorrelation and heteroskedasticity of the monthly time series, standard errors were corrected using the Newey–West heteroskedasticity- and autocorrelation-consistent (HAC) estimator with a lag of 12 months (Newey and West, 1987). For seasonal trends, a lag of one season was used. A grid cell was analyzed only when at least 80 % of the observations over the study period were valid. Two-sided 95 % confidence intervals were calculated using the t-distribution and the HAC covariance matrix.

To assess potential discontinuities between the CDR and ICDR records, a diagnostic model including time, a January 2021 step term, and a post-2021 slope-change term was fitted. This test was used solely to evaluate sensitivity to the product transition and was not included in the primary trend inference.

2.9.2 Trends in cloud radiative effects

The primary inference of long-term trends in top-of-atmosphere cloud radiative effects was based on the monthly CERES EBAF-TOA Ed4.2.1 product for the 252 complete months from January 2004 through December 2024. SYN1deg-MHour was excluded from long-term trend analysis and was used only for climatology, diurnal-cycle analysis, multi-sensor relationships, and modeling. For each EBAF component, the calendar-month climatology was removed and the linear trend was estimated using ordinary least squares. Standard errors were corrected using the Newey–West estimator with a lag of 12 months, and only grid cells with valid data for at least 80 % of the months in the study period were analyzed. The 95 % confidence intervals were calculated using the HAC covariance matrix, and spatial and national-level p-values were adjusted using the Benjamini–Hochberg procedure. Surface trends derived from SYN1deg were not included in the primary trend inference.

2.10 Multiple-testing correction

Simultaneous testing across a large number of grid cells increases the probability of false-positive detections. Therefore, p-values were adjusted using the Benjamini–Hochberg procedure with a false discovery rate (FDR) of 0.05 (Benjamini and Hochberg, 1995). Spatial correction was applied separately for each variable, whereas national-level indices were corrected within each analytical family. On the maps, stippling was used only to identify grid cells with $q < 0.05$. The sign or magnitude of a trend that did not meet this criterion was not interpreted as conclusive evidence of change.

2.11 Multi-sensor relationships

For the temporal covariability analysis, the climatological CloudSat–CERES analysis, and machine learning, the radiative target variables were derived from CERES SYN1deg-MHour because these analyses were designed to investigate covariability, climatological relationships, and predictive skill rather than long-term trend inference. SYN1deg-MHour was not used in any analysis of long-term trends in cloud radiative effects. For the temporal covariability analysis between CLAAS-3 and CERES, the common homogeneous period from February 2004 through December 2020 was selected. The calendar-month climatology



was first removed, after which each time series was linearly detrended. Spearman rank correlations were then calculated between seven cloud properties and the three TOA CRE components. Spearman correlation was selected because of its relative robustness to outliers and because it does not require a linear relationship. Uncertainty was estimated using 2,000 repetitions of a 12-month moving-block bootstrap with a random seed of 47012026. Within each target family, p-values were adjusted for FDR.

CloudSat–CERES relationships were examined at the climatological grid-cell–month scale over their common 2007–2020 period. Total cloud frequency, multilayer fraction, and the occurrence frequencies of the eight cloud types on the 2° grid were matched with the corresponding climatological TOA SWCRE, LWCRE, and net CRE. Grid-cell and calendar-month fixed effects were removed using iterative two-way demeaning, after which area-weighted rank correlations were calculated. Confidence intervals were obtained from 2,000 bootstrap repetitions with independent resampling of grid-cell blocks and calendar-month blocks, using a random seed of 482026. This design controls for time-invariant spatial differences and shared seasonality; however, it does not constitute an analysis of coincident satellite overpasses. The resulting relationships were therefore interpreted as climatological associations rather than as evidence of causal radiative forcing.

2.12 Construction of the machine-learning dataset

The machine-learning analysis was designed to predict and statistically explain three response variables—TOA SWCRE, TOA LWCRE, and TOA net CRE—at the monthly 1° grid-cell scale. The common analysis period extended from February 2004 through August 2025, comprising 259 months. The initial dataset contained 51,282 CERES grid-cell–month combinations. Model analysis was restricted to 39,886 observations corresponding to 154 grid cells whose centroids fell within Iran, thereby preventing boundary cells with only a small fraction of their area within the country from disproportionately influencing model-performance metrics.

Cloud predictors included daily-mean CFC, first-harmonic amplitude, phase of the harmonic maximum, day–night CFC difference, liquid-phase fraction, and cloud-top height. Environmental predictors included relative humidity and vertical motion at 500 hPa, CAPE, total column water vapor, monthly precipitation, highest-quality AOD, good-quality NDVI, snow cover, and mean elevation. Calendar month and the phase of the CFC diurnal cycle were represented by sine and cosine components to avoid artificial discontinuities between months 12 and 1 and between hours 23 and 0.

Missing data were not filled by interpolation or statistical imputation. Each model was fitted only to observations for which the target variable and all predictors required by that model were available. This approach avoided introducing artificial structure into conditionally retrieved variables such as LWP, IWP, and AOD. Approximately 99.89 % of observations in the primary centroid-within-Iran dataset were complete. Valid-data availability was also reported separately for each variable to ensure that the high overall completeness of the dataset did not obscure localized data limitations for individual predictors.

2.13 Models and spatiotemporal validation

2.13.1 Block design

Random partitioning of gridded climate data can underestimate prediction error because of spatial proximity and temporal persistence. Therefore, block validation was adopted in accordance with methodological recommendations for structured data (Roberts et al., 2017). The 154 modeling grid cells were partitioned into five spatially contiguous blocks using area-weighted geographic clustering. The clustering algorithm was allowed a maximum of 200 iterations, and the balance of both the number of grid cells and the area of Iran represented within each block was assessed.

The study period was also divided into five non-overlapping temporal blocks: February 2004–December 2008, January 2009–December 2012, January 2013–December 2016, January 2017–December 2020, and January 2021–August 2025. Combining the five spatial and five temporal blocks yielded 25 outer test folds. In each iteration, the test set consisted of the intersection



of the held-out spatial block and the held-out temporal block. Training data were drawn only from grid cells outside the held-out spatial block and months outside the held-out temporal block. Observations that violated only one of these two spatial or temporal conditions were excluded as a guard set. This design increased simultaneous spatial and temporal separation between the training and test data and reduced information leakage from neighboring grid cells or temporally adjacent months. No fully independent external validation dataset was available. Accordingly, the block-validation results provide an estimate of model generalization to unseen locations and periods within the domain of Iran and should not be interpreted as equivalent to independent cross-regional validation.

2.13.2 Baseline and nonlinear models

To evaluate predictive performance, five predefined model configurations were compared: a monthly climatology as a simple baseline, Ridge regression using cloud predictors only, Ridge regression combining cloud and environmental predictors, and two nonlinear algorithms, HistGradientBoosting and Random Forest. For Ridge regression, predictors were standardized using only the training data, and the resulting training-set means and standard deviations were subsequently applied to the test data. The intercept was not penalized, and the L2 regularization parameter was set to 0.01. Ridge regression provided a regularized, approximately linear benchmark against which the tree-based models could be compared, while reducing the effects of multicollinearity among atmospheric predictors. HistGradientBoosting was fitted using squared-error loss, a learning rate of 0.05, 250 iterations, a maximum of 15 leaf nodes, a minimum of 40 samples per leaf, an L2 regularization parameter of 1, no early stopping, and a random seed of 20260821. Random Forest comprised 250 trees, a maximum depth of 18, a minimum of 10 samples per leaf, 70 % of predictors considered at each split, bootstrap sampling, parallel processing, and the same random seed. Random Forest was based on the original algorithm of Breiman (2001), whereas gradient boosting followed the framework of Friedman (2001). Thus, the five predefined configurations comprised monthly climatology, cloud-only Ridge regression, cloud–environment Ridge regression, HistGradientBoosting, and Random Forest. All model hyperparameters were fixed in the code before the final blocked validation and remained unchanged across the 25 spatiotemporal test folds. No grid search, hyperparameter optimization, or selection based on test-set performance was performed. Accordingly, these settings represent fixed comparative configurations and should not be interpreted as optimized hyperparameters.

2.13.3 Performance metrics

Each observation was weighted according to the area of the corresponding CERES grid cell lying within Iran. Area-weighted RMSE, MAE, bias, and R^2 , together with Pearson correlation and the calibration slope and intercept, were calculated. The primary performance metrics were defined as follows:

$$\text{RMSE}_w = \sqrt{\frac{\sum_i w_i (y_i - \hat{y}_i)^2}{\sum_i w_i}}, \quad (11)$$

$$\text{MAE}_w = \frac{\sum_i w_i |y_i - \hat{y}_i|}{\sum_i w_i} \quad (12)$$

where y_i is the observed CRE value, $\hat{y}_i$ is the predicted value, and w_i is the grid-cell area weight. RMSE and MAE were expressed in W m^{-2} .

Valid test coverage was required to be at least 95 %. The performance of all five configurations was evaluated using out-of-sample predictions from the same 25 folds and assessed in terms of area-weighted RMSE, MAE, bias, R^2 , and calibration metrics. Results were reported for all candidate models, and no single model was presented as an independently validated final estimator following model selection. The configuration with the lowest RMSE was identified solely for comparative description and for selected interpretability analyses; consequently, its performance was not interpreted as an independent post-



406 selection estimate. Performance-stability intervals were also calculated using 2,000 two-way resamples of the spatial and
407 temporal blocks over the common set of valid observations available for all five models.

408 **2.13.4 Model interpretability**

409 Block permutation importance was calculated with 10 repetitions. In each repetition, the increase in RMSE resulting from
410 permutation of a single predictor was quantified within the blocked evaluation framework. The use of out-of-sample
411 predictions prevented optimistic estimates of variable importance based on the training data. Permutation importance
412 represents the predictive contribution of a variable in the presence of the other predictors and, because atmospheric variables
413 are often correlated, should not be interpreted as a causal effect or as an absolute measure of physical importance.
414 Accumulated local effects (ALE) were used to characterize the shapes of nonlinear relationships. Compared with partial
415 dependence plots, ALE is less reliant on predictor combinations outside the observed data domain when predictors are
416 correlated (Apley and Zhu, 2020). For continuous variables, 12 intervals were defined between the 2nd and 98th percentiles.
417 Because snow cover contained a high proportion of zero values, it was analyzed using five zero-inflated intervals. Cyclic
418 profiles for calendar month and phase were calculated on a circular scale. ALE stability intervals were obtained from 1,000
419 fold-level resamples. In addition, the six leading predictor groups were selected for each target, and all 15 possible pairwise
420 interactions among them were evaluated using 10 permutation repetitions. This interaction analysis was exploratory and
421 supplementary and was not used to infer causal mechanisms.

422 **2.14 Uncertainty and sensitivity analyses**

423 Uncertainty in the CloudSat-derived cloud regimes was estimated using 1,000 granule-level block-bootstrap repetitions
424 stratified by year, with a random seed of 20260820. The 2.5th and 97.5th percentiles defined the 95 % confidence intervals.
425 Dominance of a cloud type was considered stable only when the lower confidence bound of the occurrence-frequency
426 difference between the first- and second-ranked cloud types was greater than zero. A leave-one-year-out analysis was also
427 performed to assess the sensitivity of the identified regimes to individual years.
428 Uncertainty in model performance was estimated using 2,000 two-way spatiotemporal bootstrap repetitions. Spatial and
429 temporal blocks were independently resampled with replacement, and the weight assigned to each observation was calculated
430 as the product of its area weight and the resampling multiplicities of its spatial and temporal blocks. This procedure incorporates
431 both spatial and interperiod variability into the confidence intervals. Leave-one-block-out analyses, comparisons of Ridge
432 regression with the nonlinear models, and residual analyses were additionally performed to assess model robustness.
433 The principal sensitivity analyses included extending the CLAAS-3 trend analysis from the CDR period to the combined
434 CDR+ICDR record; retaining the incomplete year 2025 only in the extended analysis; applying broader QA definitions for
435 MAIAC and NDVI; assessing the effect of the 2021 transition in CLAAS-3; sequentially excluding individual CloudSat years;
436 and comparing baseline, regularized linear, and nonlinear models. These sensitivity analyses were kept separate from the
437 primary inference to prevent heterogeneity in product versions or temporal coverage from being misinterpreted as climatic
438 change.

439 **2.15 Generation of spatial outputs and reproducibility**

440 Analysis outputs were stored as NetCDF files for multidimensional data cubes, Parquet files for large modeling tables,
441 GeoTIFF files for rasters compatible with ArcGIS, CSV files for summaries and quality-control results, and GeoPackage files
442 for vector layers. For each primary output, dimensions, coordinates, data types, variable ranges, missing values, counts of
443 infinite values, grid alignment, algebraic consistency, and SHA-256 hashes were verified. The final results package was
444 assembled only after all 34 mandatory QA reports had been successfully passed, and all registered files were verified against
445 the hash manifest. These numbers describe the quality-control framework and do not constitute scientific findings of the study.



446 Data extraction was performed using Google Earth Engine, whereas scientific processing was conducted in Visual Studio Code
447 1.133.0 using Python 3.12.10. The principal software libraries included NumPy 2.5.2, pandas 3.0.5, xarray 2026.7.0, netCDF4
448 1.7.4, h5netcdf 1.8.1, h5py 3.16.0, cftime 1.6.5, SciPy 1.18.0, Dask 2026.7.1, Rasterio 1.5.1, scikit-learn 1.9.0, Matplotlib
449 3.11.1, GeoPandas 1.1.4, Pyogrio 0.13.0, Shapely 2.1.2, PyProj 3.7.2, PyArrow 25.0.1, and PyHDF 0.11.7. Git 2.55.0 was used
450 for code version control. All data paths, analysis periods, variables, quality-control thresholds, random seeds, and model
451 parameters were documented in the project's staged processing scripts.

452 **3 Results**

453 **3.1 Spatial and seasonal cloud climatology**

454 Figure 2 shows pronounced spatial and temporal variability in cloud cover over Iran from February 2004 through August 2025.
455 The national mean cloud cover over the entire period was 32.74 %, ranging from a monthly minimum of 13.30 % in September
456 to a maximum of 48.79 % in April. Seasonally, the highest cloud cover occurred in spring, with a mean of 44.39 %, followed
457 by winter at 39.49 %, whereas summer and autumn were the least cloudy seasons, with mean values of 23.21 % and 23.91 %,
458 respectively. Spatially, the Caspian coastal zone, the northern slopes of the Alborz Mountains, parts of northwestern Iran, and
459 areas along the Zagros Mountains exhibited greater cloud cover during most of the cold and wet months, whereas the central
460 plateau and the eastern and southeastern regions were generally less cloudy. Nevertheless, a localized increase in cloudiness
461 over southeastern Iran during June, and particularly July, indicates the influence of summer monsoonal moisture. The
462 widespread minimum in cloudiness during August and September, followed by its recovery from October through spring,
463 reflects the dominant seasonal cycle of cloud cover over Iran. Spatial values ranged from approximately 3.43 % to 80.14 %,
464 highlighting the combined influence of seasonal atmospheric circulation, proximity to moisture sources, and the complex
465 topography of the Alborz and Zagros mountain ranges on the spatial distribution of cloud cover.



466

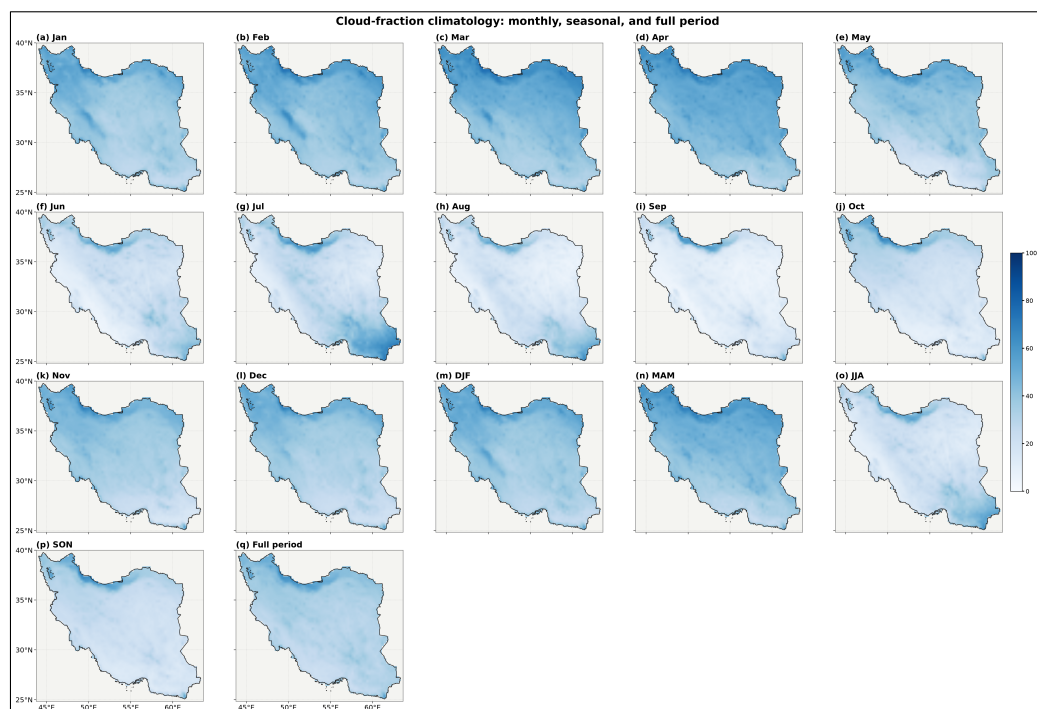


Figure 2. Monthly, seasonal, and full-period climatology of cloud fractional cover (CFC, %) over Iran derived from CLAAS-3 for February 2004–August 2025. Monthly panels represent long-term calendar-month means, seasonal panels correspond to DJF, MAM, JJA, and SON, and the full-period panel represents the day-weighted climatological mean over the complete record. Higher values indicate greater fractional cloud cover.

467 3.2 Diurnal variability and cloud physical properties

468 Figure 3 illustrates the spatial heterogeneity of the diurnal cycles of cloud cover and top-of-atmosphere net cloud radiative
 469 effect in local solar time. At the national scale, the 24-h harmonic amplitude of cloud cover was 4.06 percentage points, the
 470 day–night difference was 1.95 percentage points, and the peak-to-peak range was 12.42 percentage points, with the maximum
 471 occurring on average at 16:34 LST. However, larger amplitudes occurred over southeastern Iran, parts of the northwest, and
 472 mountainous regions, while the day–night difference shifted from negative values across parts of central and western Iran to
 473 positive values in the east and southeast. The national harmonic R^2 was 0.51, indicating that the 24-h harmonic component
 474 explained approximately half of the intradiurnal variability in cloud cover, although the strength of this cycle was spatially
 475 heterogeneous.

476 In contrast, net cloud radiative effect exhibited a substantially stronger diurnal cycle. Its national harmonic amplitude was
 477 37.16 W m^{-2} , the peak-to-peak range was 80.12 W m^{-2} , and the mean day–night difference was -44.95 W m^{-2} . The maximum
 478 net CRE occurred predominantly near midnight, with a national mean timing of 00:35 LST. Both the amplitude and day–night
 479 contrast were more pronounced over northern Iran and along the Caspian coast, reflecting the dominance of shortwave cloud-
 480 induced cooling during daytime and the persistence of the longwave warming effect of clouds at night.

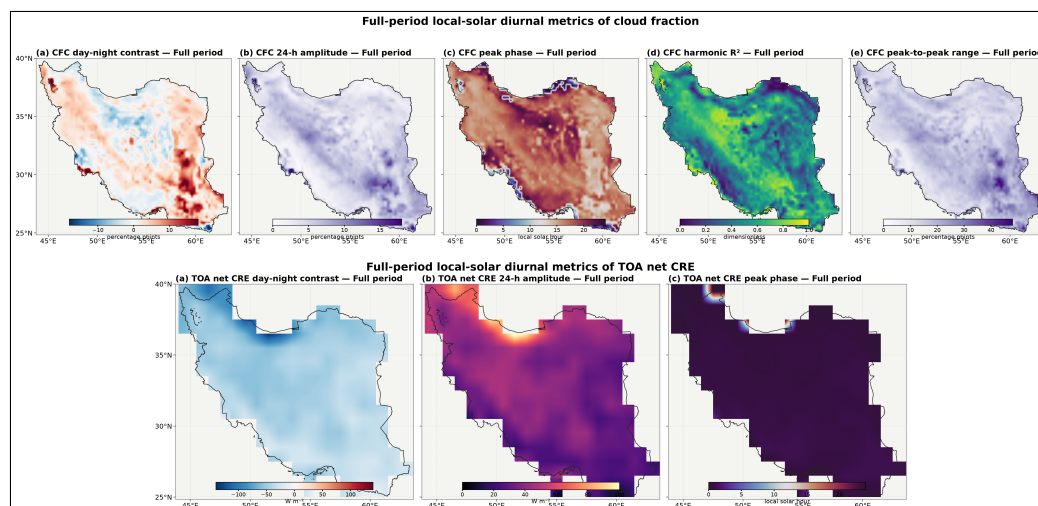


Figure 3. Spatial patterns of the local-solar-time diurnal cycle of CLAAS-3 cloud fractional cover (CFC) and CERES SYN1deg-MHour top-of-atmosphere net cloud radiative effect (net CRE) over Iran. Panels show day–night contrast, 24-h first-harmonic amplitude, local solar time of the harmonic maximum, harmonic goodness of fit (R^2), and peak-to-peak range, as applicable. CFC metrics are expressed in percentage points and net CRE in $W m^{-2}$. Phase values represent local solar time (LST) and should be interpreted together with harmonic amplitude and R^2 , particularly where the diurnal signal is weak.

Table 2 shows that the cloud regime over Iran exhibits distinct seasonal variations in cloud amount, thermodynamic phase, cloud-top height, and diurnal cycle. Mean cloud cover was highest in spring (44.39 %) and lowest in summer (23.21 %). Spring also exhibited the strongest first-harmonic diurnal variability, with a 24-h harmonic amplitude of 7.30 percentage points, and the highest mean cloud-top height, at 6.06 km. The timing of maximum cloudiness shifted from 14:44 LST in winter to 19:35 LST in summer, indicating a delay in warm-season cloud activity toward the evening hours. The liquid-phase fraction also increased from 56.13 % in spring to 79.07 % in summer, whereas liquid water path decreased from $0.143 kg m^{-2}$ in winter to $0.025 kg m^{-2}$ in summer. Thus, the higher relative frequency of liquid-phase clouds in summer does not necessarily imply a greater column-integrated liquid water content, but instead occurs under generally less cloudy conditions with lower cloud water content. Ice water path reached its maximum in spring ($0.135 kg m^{-2}$) and minimum in summer ($0.082 kg m^{-2}$), which, together with the higher cloud tops, indicates a greater contribution from deeper and colder cloud systems during spring. Over the full period, mean cloud cover was 32.74 %, the liquid-phase fraction was 66.61 %, and mean cloud-top height was 5.75 km, although the spatial coverage of valid ice water path retrievals was slightly lower in summer than in the other seasons.

Table 2. National mean characteristics of cloud cover, diurnal cycle, and cloud structure

Season or period	Mean cloud cover (%)	24-h amplitude (percentage points)	Time of maximum cloud cover (LST)	Liquid-phase fraction (%)	Cloud-top height (km)	Liquid water path ($kg m^{-2}$)	Ice water path ($kg m^{-2}$)
Winter	39.49	2.99	14:44	60.34	5.43	0.143	0.127
Spring	44.39	7.30	15:49	56.13	6.06	0.078	0.135
Summer	23.21	4.48	19:35	79.07	5.96	0.025	0.082
Autumn	23.91	3.26	16:04	70.80	5.53	0.055	0.096
Full period	32.74	4.06	16:34	66.61	5.75	0.075	0.110

Note: Decimal-hour values were converted to HH:MM local solar time (LST)

Figure 4 reveals pronounced seasonal and spatial contrasts in the physical properties of clouds over Iran. The national liquid-phase fraction increased from 56.13 % in spring to 79.07% in summer, with a full-period mean of 66.61 %. Higher values occurred predominantly across southern and eastern Iran, whereas lower values were observed over the elevated regions of western and northwestern Iran. Mean cloud-top height ranged from 5.43 km in winter to 6.06 km in spring, with a full-period mean of 5.75 km. Higher cloud tops occurred mainly over southern and southwestern Iran and along the Zagros Mountains,



particularly in spring and summer, whereas the Caspian coast and parts of northern Iran were generally characterized by lower cloud tops. Liquid water path exhibited a pronounced maximum in winter (0.143 kg m^{-2}) and decreased to 0.025 kg m^{-2} in summer, with the highest values concentrated over northwestern Iran, the Caspian coast, and the slopes of the Zagros Mountains. Ice water path likewise reached its maximum in spring (0.135 kg m^{-2}) and minimum in summer (0.082 kg m^{-2}), with higher values occurring primarily over western and northwestern Iran and mountainous regions. Thus, despite the higher relative liquid-phase fraction in summer, the concurrent reductions in both liquid and ice water paths indicate that warm-season clouds generally contain less column-integrated cloud water. White grid cells in some eastern regions indicate the absence of valid retrievals or insufficient data coverage and should not be interpreted as zero values.

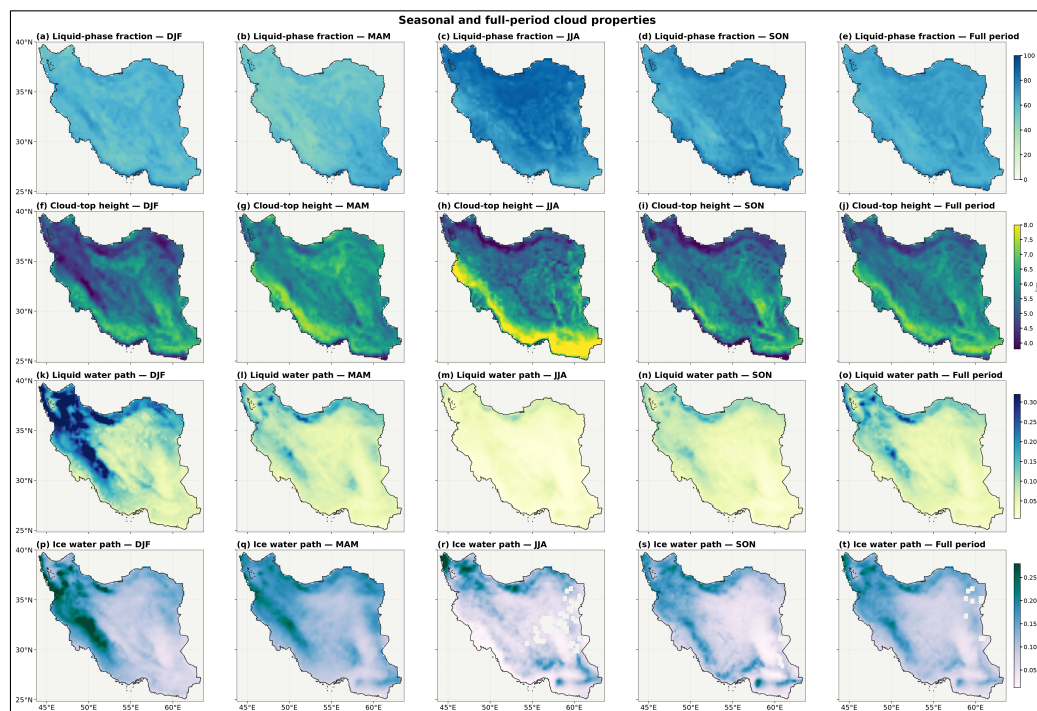


Figure 4. Seasonal and full-period spatial distributions of cloud thermodynamic phase, cloud-top height, liquid water path, and ice water path over Iran derived from CLAAS-3 for February 2004–August 2025. Liquid-phase fraction is expressed as %, cloud-top height as km, and liquid and ice water paths as kg m^{-2} . White grid cells denote missing or insufficiently valid retrievals and should not be interpreted as zero values.

3.3 Vertical cloud regimes

Figure 5 shows the dominant vertical cloud regimes in 2° grid cells with adequate sampling and statistically stable classification during 2007–2020. In winter, altostratus dominated across much of northern, central, and western Iran, whereas cirrus occurred more frequently in the south and southeast. In spring, this pattern was characterized by an expansion of cirrus into central and eastern regions, together with localized dominance of altocumulus. During summer, altocumulus became the dominant regime across much of central and northern Iran, while cirrus remained dominant in the south and southeast, and cumulus occurred sporadically in western, northern, and eastern regions. Autumn exhibited a more transitional and spatially heterogeneous pattern comprising altostratus, cirrus, altocumulus, stratocumulus, and cumulus. Over the full period, altostratus was the dominant regime across northern Iran and much of the central part of the country, whereas cirrus dominated in the south; altocumulus and cumulus were dominant in only a limited number of grid cells. Of the 54 reliable grid cells in the full-period analysis, cloud-type dominance was statistically stable with respect to uncertainty in 28 cells (51.85 %). The corresponding proportions of stable dominance among grid-cell-month and grid-cell-season combinations were 23.43 % and 33.65 %, respectively.



518 respectively. Therefore, white grid cells do not indicate the absence of clouds; rather, they represent insufficient sampling or
519 the absence of statistically stable dominance by a single cloud type. This finding underscores the need for caution when
520 spatially generalizing CloudSat-derived cloud regimes.



Figure 5. Monthly, seasonal, and full-period distributions of dominant CloudSat–CALIPSO cloud types over Iran during 2007–2020, calculated on a 2° grid after applying minimum sampling requirements and bootstrap-based dominance-stability criteria. Cloud types include cirrus, altostratus, altocumulus, stratus, stratocumulus, cumulus, nimbostratus, and deep convection. Only grid cells meeting the predefined sampling criteria are shown. Cells without a stable dominant type indicate insufficient evidence to distinguish the leading cloud type from the second-ranked type at the 95 % confidence level.

521 3.4 Cloud radiative effects and trends

522 Figure 6 shows that the shortwave cloud radiative effect (SWCRE) is predominantly negative across Iran, indicating a cooling
523 effect, with the national mean ranging from -32.21 W m^{-2} in spring to -9.24 W m^{-2} in summer. The strongest shortwave
524 cooling occurs along the Caspian coast, in northwestern Iran, and on the northern slopes of the Alborz Mountains, particularly
525 in spring, whereas it is weaker over the central plateau and the eastern and southern regions. In contrast, the longwave cloud
526 radiative effect (LWCRE) is positive in all seasons, indicating a warming effect, and ranges from 21.57 W m^{-2} in autumn to
527 40.21 W m^{-2} in spring. The largest LWCRE values are concentrated mainly over central, eastern, and southeastern Iran,
528 consistent with the occurrence of higher and colder cloud tops. The combination of these two components results in a positive
529 national mean net CRE, ranging from 5.18 W m^{-2} in winter to 15.12 W m^{-2} in summer, with a full-period mean of 9.70 W m^{-2} .
530 However, the spatial pattern is not uniform: over the Caspian coast, northwestern Iran, and parts of the Zagros Mountains,
531 shortwave cooling exceeds longwave warming, resulting in a negative net CRE, whereas over central, eastern, and southern
532 Iran, the longwave component dominates and the net CRE is positive. Thus, the sign and magnitude of net cloud radiative
533 effect reflect the combined influence of cloud amount, cloud-top height and temperature, incoming solar radiation, and
534 underlying surface characteristics.

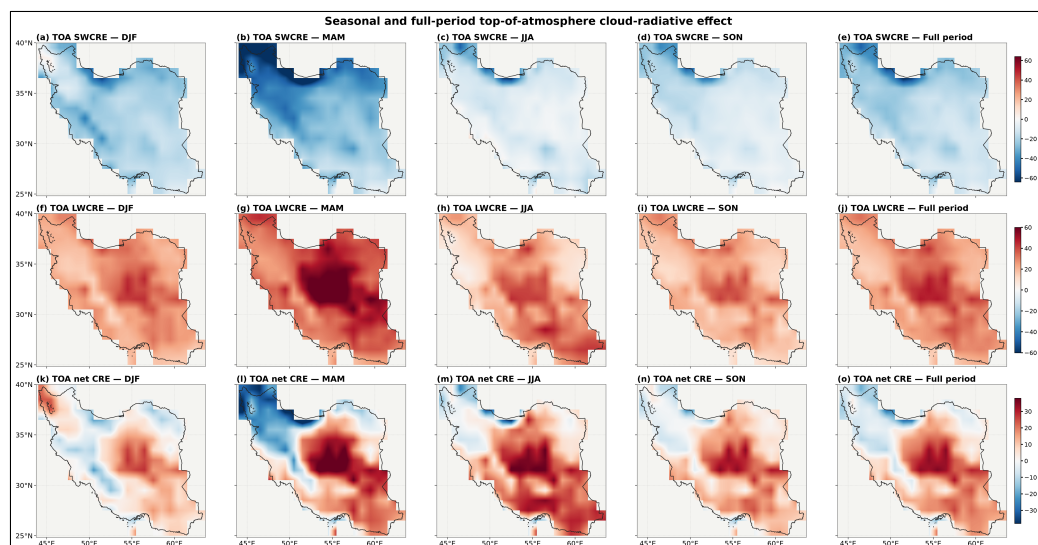


Figure 6. Seasonal and full-period climatology of top-of-atmosphere shortwave cloud radiative effect (SWCRE), longwave cloud radiative effect (LWCRE), and net cloud radiative effect (net CRE) over Iran derived from CERES SYN1deg-MHour. Values are expressed in W m^{-2} . Negative SWCRE denotes cloud-induced shortwave cooling, whereas positive LWCRE denotes cloud-induced longwave warming. Net CRE represents the combined shortwave and longwave effects according to the sign convention used in this study.

Figure 7 shows the monthly variability, 12-month moving averages, and national trends in cloud properties and cloud radiative effects. During the primary CLAAS-3 CDR period from February 2004 to December 2020, cloud cover decreased at a rate of -1.88 percentage points per decade, whereas liquid-phase fraction, cloud-top temperature, cloud-top pressure, and ice water path exhibited increasing trends, and cloud-top height decreased. However, none of the trends in cloud properties remained statistically significant after FDR correction. An independent analysis based on CERES EBAF-TOA for the complete years 2004–2024 showed trends of -0.19 , -0.75 , and $-0.95 \text{ W m}^{-2} \text{ decade}^{-1}$ in SWCRE, LWCRE, and net CRE, respectively. The SWCRE trend was not statistically significant, with a 95 % confidence interval of -1.44 to $1.06 \text{ W m}^{-2} \text{ decade}^{-1}$ and $q = 0.762$, nor was the LWCRE trend, with a 95 % confidence interval of -1.63 to $0.13 \text{ W m}^{-2} \text{ decade}^{-1}$ and $q = 0.139$. In contrast, the net CRE trend had an entirely negative 95 % confidence interval of -1.68 to $-0.22 \text{ W m}^{-2} \text{ decade}^{-1}$ and remained statistically significant after correction for multiple testing ($p = 0.011$; $q = 0.034$). Thus, the EBAF results provide evidence of a significant decrease in top-of-atmosphere net cloud radiative effect, although neither the shortwave nor longwave component individually exhibited a statistically significant trend.

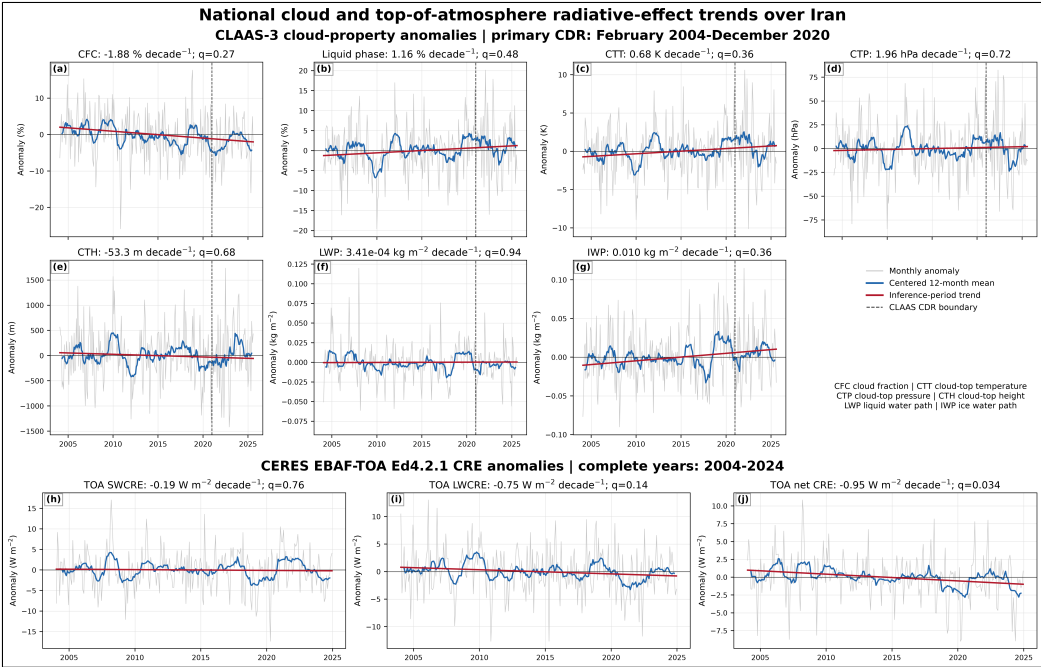


Figure 7. National monthly anomalies, 12-month moving averages, and linear trends in CLAAS-3 cloud properties and CERES EBAF-TOA top-of-atmosphere cloud radiative effects over Iran. CLAAS-3 cloud-property trends were estimated from the homogeneous CDR period February 2004–December 2020, whereas CERES EBAF-TOA Ed4.2.1 radiative trends were evaluated for January 2004–December 2024. Trend significance was assessed using Newey–West heteroskedasticity- and autocorrelation-consistent standard errors and Benjamini–Hochberg false-discovery-rate correction. Reported q-values correspond to FDR-adjusted significance.

547 Table 3 shows that none of the CLAAS-3 cloud properties exhibited a statistically significant national trend after correction
548 for multiple testing. Cloud cover decreased at a rate of -1.88 percentage points per decade and was statistically significant in
549 the unadjusted test; however, after FDR correction, the q-value increased to 0.266. In contrast, the EBAF-TOA analysis showed
550 that net cloud radiative effect decreased at a rate of $-0.95 \text{ W m}^{-2} \text{ decade}^{-1}$, with an entirely negative confidence interval, and
551 this trend remained statistically significant after correction for multiple testing ($p = 0.011$; $q = 0.034$). The trends in SWCRE
552 and LWCRE were also negative, but their confidence intervals included zero and were not statistically significant. Therefore,
553 the principal radiative finding is a significant decrease in net CRE, which should not be interpreted as evidence of separate
554 significant trends in either the shortwave or longwave component.

Table 3. Summary of national trends in CLAAS-3 CDR cloud properties and CERES EBAF-TOA Ed4.2.1 top-of-atmosphere cloud radiative effects over Iran

Variable and unit	Primary inference period	Period mean	Trend per decade	95 % confidence interval	p	q	FDR ($q < 0.05$)
Cloud cover (%)	Feb 2004–Dec 2020	33.32	-1.88	-3.65 to -0.10	0.038	0.266	No
Liquid-phase cloud fraction (%)	Feb 2004–Dec 2020	66.43	1.16	-0.92 to 3.24	0.274	0.479	No
Cloud-top temperature (K)	Feb 2004–Dec 2020	251.67	0.68	-0.18 to 1.54	0.122	0.357	No
Cloud-top pressure (hPa)	Feb 2004–Dec 2020	464.62	1.96	-5.72 to 9.64	0.615	0.718	No
Cloud-top height (m)	Feb 2004–Dec 2020	5735.57	-53.26	-203.20 to 96.69	0.485	0.678	No
Liquid water path (kg m^{-2})	Feb 2004–Dec 2020	0.076	0.000341	-0.008886 to 0.009567	0.942	0.942	No
Ice water path (kg m^{-2})	Feb 2004–Dec 2020	0.109	0.009669	-0.003618 to 0.022955	0.153	0.357	No
TOA SWCRE (W m^{-2})	Jan 2004–Dec 2024	-17.91	-0.19	-1.44 to 1.06	0.762	0.762	No
TOA LWCRE (W m^{-2})	Jan 2004–Dec 2024	19.38	-0.75	-1.63 to 0.13	0.092	0.139	No



Table 3. Summary of national trends in CLAAS-3 CDR cloud properties and CERES EBAF-TOA Ed4.2.1 top-of-atmosphere cloud radiative effects over Iran

Variable and unit	Primary inference period	Period mean	Trend per decade	95 % confidence interval	p	q	FDR (q < 0.05)
TOA net CRE (W m ⁻²)	Jan 2004–Dec 2024	1.46	−0.95	−1.68 to −0.22	0.011	0.034	Yes

Note: CLAAS-3 trends were calculated from the homogeneous CDR record, whereas radiative trends were derived from CERES EBAF-TOA Ed4.2.1. Benjamini–Hochberg correction was applied separately to the family of seven CLAAS-3 variables and the family of three EBAF components. Because of structural differences between the products, the EBAF period means reported here should not be directly compared with the SYN1deg-MHour climatology.

Figure 8 shows the spatial heterogeneity of trends in CLAAS-3 CDR cloud properties from February 2004 to December 2020 and CERES EBAF-TOA cloud radiative effects over the complete years 2004–2024. The CLAAS-3 spatial patterns remained unchanged: decreasing cloud cover across most central, eastern, and southeastern regions was accompanied by increases in liquid-phase fraction, cloud-top temperature, and cloud-top pressure over much of western and northern Iran, whereas cloud-top height generally decreased in these regions. In the EBAF analysis, SWCRE, LWCRE, and net CRE trends were negative in 56.1 %, 83.3 %, and 93.4 %, respectively, of the 198 grid cells overlapping Iran. After spatial FDR correction, 2, 19, and 14 grid cells remained statistically significant for SWCRE, LWCRE, and net CRE, respectively, and all significant trends were negative. Grid cells with significant LWCRE trends were concentrated mainly in northern and northwestern Iran and in western–central regions, whereas significant decreases in net CRE occurred in clusters across the northwest, west, southwest, south, and along the eastern border. Thus, the national-scale decrease in net CRE is spatially widespread, although its magnitude and statistical significance are not spatially uniform. The color scale is independently defined for each variable; therefore, color intensity should not be compared directly among different variables.

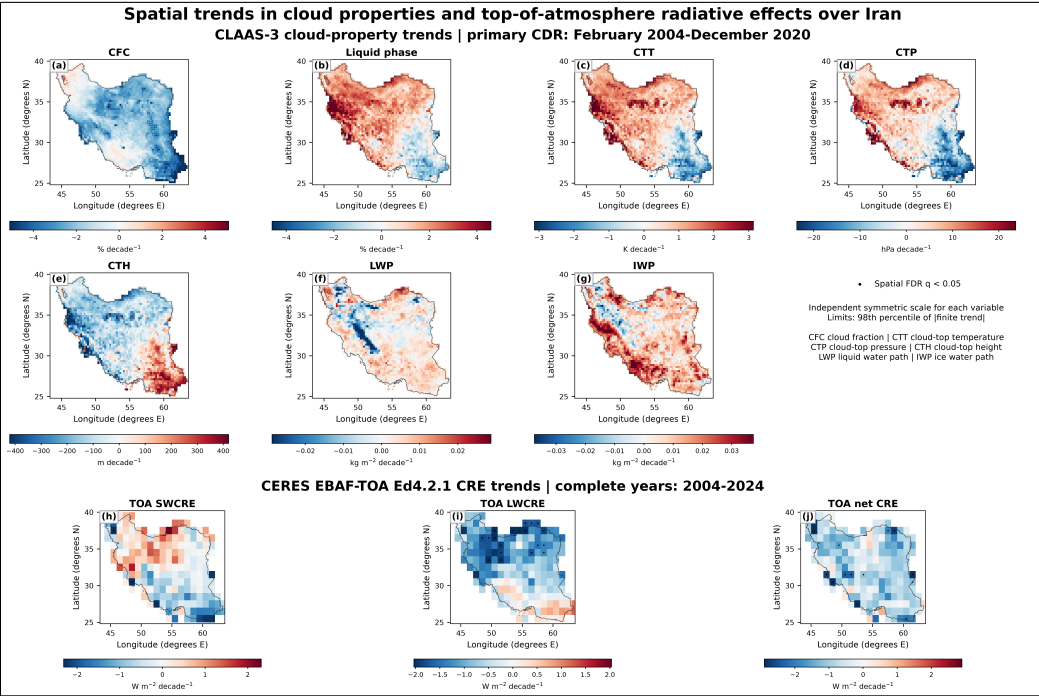


Figure 8. Spatial patterns of trends in CLAAS-3 CDR cloud properties over February 2004–December 2020 and CERES EBAF-TOA Ed4.2.1 top-of-atmosphere cloud radiative effects over January 2004–December 2024. Trends are expressed per decade in the units of each variable. Stippling identifies grid cells that remain statistically significant after Benjamini–Hochberg false-discovery-rate correction ($q < 0.05$). Color scales are defined independently for each variable and should therefore not be compared directly across panels.



3.5 Multi-sensor relationships and machine-learning performance

The complete comparison of the five model configurations showed that both nonlinear models achieved lower RMSE values than the monthly climatology and Ridge models for all three radiative components. For SWCRE, HistGradientBoosting and Random Forest yielded RMSE values of 9.24 and 9.43 W m^{-2} , respectively, with corresponding R^2 values of 0.715 and 0.703, compared with an RMSE of 14.99 W m^{-2} for the monthly climatology. For LWCRE, Random Forest and HistGradientBoosting achieved RMSE values of 10.55 and 10.86 W m^{-2} , respectively, with corresponding R^2 values of 0.532 and 0.504. The two nonlinear models also performed similarly in predicting net CRE: RMSE was 13.72 W m^{-2} for Random Forest and 13.77 W m^{-2} for HistGradientBoosting, with corresponding R^2 values of 0.452 and 0.448. Thus, the nonlinear models showed a clear improvement over the monthly climatological baseline, but the small performance differences between the two nonlinear algorithms, particularly for net CRE, do not support a definitive claim of superiority for either algorithm.

Table 4. Model performance and strongest significant multi-sensor relationships
(a) Performance of all candidate configurations under spatiotemporal block validation

Radiative component	Monthly climatology	Cloud-only Ridge	Cloud–environment Ridge	HistGradientBoosting	Random Forest
SWCRE	14.99; 0.251	11.62; 0.550	10.58; 0.626	9.24; 0.715	9.43; 0.703
LWCRE	13.83; 0.196	12.17; 0.377	11.61; 0.433	10.86; 0.504	10.55; 0.532
Net CRE	19.42; -0.099	17.07; 0.151	15.11; 0.335	13.77; 0.448	13.72; 0.452

Values are reported as RMSE (W m^{-2}); R^2 . All models were evaluated on the common data support using the same 25 spatiotemporal folds. The minimum RMSE values indicate only the best observed performance among the fixed configurations and should not be interpreted as independent post-selection estimates of model performance.

(b) Strongest significant multi-sensor relationships and vertical cloud regimes

Analysis type	Cloud property	Target radiative component	Sample size	Spearman correlation coefficient	95 % confidence interval	Adjusted p-value
Multi-sensor temporal variability	Cloud cover	TOA SWCRE	203 months	-0.856	-0.882 to -0.815	0.001
Multi-sensor temporal variability	Ice water path	TOA SWCRE	203 months	-0.641	-0.727 to -0.544	0.001
Multi-sensor temporal variability	Cloud cover	TOA LWCRE	203 months	0.835	0.783 to 0.878	0.001
Multi-sensor temporal variability	Cloud-top temperature	TOA LWCRE	203 months	-0.467	-0.559 to -0.358	0.001
Multi-sensor temporal variability	Cloud-top pressure	TOA net CRE	203 months	-0.459	-0.567 to -0.345	0.001
Multi-sensor temporal variability	Cloud-top height	TOA net CRE	203 months	0.432	0.329 to 0.523	0.001
CloudSat vertical regime	Cloud occurrence	TOA SWCRE	589 grid-cell–months	-0.459	-0.622 to -0.279	0.010
CloudSat vertical regime	Cloud occurrence	TOA LWCRE	589 grid-cell–months	0.552	0.352 to 0.716	0.010
CloudSat vertical regime	Multilayer cloud fraction	TOA LWCRE	589 grid-cell–months	0.385	0.206 to 0.536	0.010

4 Discussion

Cloud cover varied markedly across Iran, with persistent maxima along the southern Caspian coast, in the northwest, and over the Zagros Mountains. This pattern agrees with earlier regional climatologies (Hatami Bahmanbeiglou and Movahedi, 2017; Ghasemifar et al., 2018). Moisture supply and orographic ascent are plausible contributors to these contrasts, whereas the lower cloudiness of the central plateau and east is compatible with drier conditions and subsidence. Because these mechanisms were not isolated experimentally or through process attribution, the spatial correspondence should not be treated as evidence of their relative causal contributions.

Cloud amount also conceals differences in cloud phase and water content. The higher summer liquid-phase fraction coincided with lower liquid and ice water paths, showing that a larger fraction of liquid clouds need not imply more column-integrated



cloud water. Conditional retrievals and variable-specific sampling further limit direct comparison of these properties. In time, the afternoon maximum in cloud cover shifted towards evening in summer. Comparable seasonal variation in cloud timing has been reported elsewhere (Chen et al., 2022; Ge et al., 2021; Zhao et al., 2023), but differences in cloud regime, topography, and time reference preclude a quantitative regional equivalence. The moderate fit of the first diurnal harmonic also warrants interpreting its peak time alongside amplitude and goodness of fit.

The CloudSat–CALIPSO observations suggest a broad transition from altostratus-dominated northern and central regions to more frequent cirrus in the south and southeast, broadly consistent with earlier CloudSat-based work over Iran (Ghasemifar et al., 2021). Yet statistically stable dominance occurred in only 28 of 54 reliable full-period grid cells, and was less frequent at monthly and seasonal scales. Orbital sampling and classification uncertainty therefore constrain the spatial detail that can be inferred from these maps. They represent sampled climatological regimes, not exclusive cloud-type assignments. Although cloud vertical structure can affect radiation (Luo et al., 2023), the present regime and radiative products are not coincident measurements and cannot establish the radiative effect of an individual regime.

The opposite signs of shortwave and longwave cloud radiative effects explain why cloud cover was strongly associated with each component but only weakly with their net effect. Spatial contrasts in the sign of net cloud radiative effect further indicate that cloud amount is an incomplete descriptor of the regional radiation budget. Cloud timing and vertical structure offer physically relevant context (Yin and Porporato, 2019; Luo et al., 2023), but their separate contributions to the observed net effect were not identified here. Nonlinear models improved prediction over the climatological and regularized linear baselines under spatiotemporal block validation; the small differences between the two nonlinear algorithms do not establish a consistently superior model. Permutation importance and accumulated local effects describe predictive dependence, not intervention effects or causal controls.

The long-term trends require a separate interpretation from the climatological associations. No national CLAAS-3 cloud-property trend remained significant after false-discovery-rate correction, whereas EBAF-TOA showed a significant negative national trend in net cloud radiative effect over 2004–2024. The shortwave and longwave component trends were individually non-significant, so neither component alone can be identified as the driver of the net trend. Changes in clouds, clear-sky conditions, aerosols, water vapour, temperature, and internal variability may all affect the cloud radiative effect record (Raghuraman et al., 2023). The different CLAAS-3 and EBAF record lengths also prevent a simple attribution of their trend contrast to a particular cloud property.

5 Conclusions

Over Iran, national mean cloud cover ranged from 48.79 % in April to 13.30 % in September, and its mean daily maximum shifted from 16:34 local solar time to 19:35 in summer. Altostratus was the dominant classified regime across much of the north and centre, whereas cirrus was more common in the south and southeast. Stable dominance by one cloud type was supported in 28 of 54 reliable full-period CloudSat–CALIPSO grid cells, underscoring the uncertainty of finer-scale regime assignments.

At the top of the atmosphere, mean shortwave and longwave cloud radiative effects had opposing signs (-18.29 and 27.99 W m^{-2}), yielding a mean net effect of 9.70 W m^{-2} . Their partial compensation helps explain the weak association between cloud cover and net radiative effect despite stronger associations with each component. Separately, EBAF-TOA indicated a decline in net cloud radiative effect of $-0.95 \text{ W m}^{-2} \text{ decade}^{-1}$ during 2004–2024 ($q = 0.034$), while no national CLAAS-3 cloud-property trend remained significant after multiple-testing correction. These findings support considering cloud timing and structure alongside cloud fraction when describing radiative variability in this heterogeneous region.

The evidence does not identify which cloud property or physical mechanism caused the EBAF net trend, nor does it quantify the radiative effect of a particular CloudSat regime. Differences in sensor resolution and record length, sparse orbital sampling,



and the absence of exact temporal coincidence restrict the multi-sensor results to climatological associations. Longer vertically resolved records and temporally collocated measurements would be needed to test the proposed mechanisms and assess whether the observed relationships extend to other dryland and mountain regions.

Code and data availability

The original satellite and reanalysis products used in this study are publicly available from their respective data providers, including CM SAF, the NASA CloudSat Data Processing Center, NASA CERES, ECMWF/Copernicus, NASA LP DAAC, and Google Earth Engine. The corresponding product names, versions, temporal coverage, and data sources are provided in Sect. 2.3 and Table 1.

The processed datasets, numerical values behind the principal figures and tables, cross-validation folds, quality-control records, analysis code, software-environment files, and integrity manifests are openly available at <https://doi.org/10.5281/zenodo.22306721> (Soureh and Rezaei Banafsheh, 2026).

Author contribution

Ehsan Soureh: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Visualization, Writing – original draft, Writing – review and editing.

Majid Rezaei Banafsheh: Supervision, Validation, Writing – review and editing.

Competing interests

The authors declare that they have no conflict of interest.

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