Remote Sensing Effects and Invariants in Land Surface Studies

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Full Text

Preamble

Remote Sensing Effects and Invariants in Land Surface Studies

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Keywords: Remote sensing effects; Remote sensing invariants; Theoretical remote sensing; Remote sensing science

Introduction

Remote sensing obtains information about Earth from a distance without any physical contact with the target. The characteristics of the information received from a sensor, whether near-surface, airborne, or spaceborne, depend on many factors, particularly the reflectance or emittance of the target, the nature and magnitude of the atmosphere, the topography of the ground, and the geometry of the sun-target-sensor system. Consequently, our capability to retrieve information is determined by these factors, collectively referred to as remote sensing effects.

There is no commonly agreed definition for "remote sensing effect" since "effect" itself is a very broad term. It can be generally defined as any factor, phenomenon, or events that need to be considered in remote sensing processes. In theory, it is difficult to disentangle all effects since many of them are closely related to each other. However, there do exist some effects that are critical for obtaining high-quality information and have been widely studied. These effects will be the focus of this paper. In addition to remote sensing effects, there are also some features that remain essentially unchanged during remote sensing data analysis. This property has been commonly utilized in parameter retrieval, where some parameters are kept invariant while deriving other variables. One such example is the pseudo-invariant calibration sites (PICS) commonly used in radiometric calibration [1, 2], where the radiation properties of these sites are assumed invariant over time. Remote sensing effects and invariants exist through all aspects of remote sensing study, including satellite-measured radiance, radiative transfer (RT) process, physical parameter retrieval, and product validation and applications. Although many studies have covered various effects and invariants individually, there is currently no comprehensive synthesis of remote sensing effects and invariants.

The objective of this paper is to provide a meta-analysis of various remote sensing effects and invariants. This study classifies and synthetically analyzes current progresses, challenges, and future prospects in the study of remote sensing effects and invariants. The ultimate goal is to enhance our understanding of these concepts and to advance theoretical remote sensing studies. Section 2 provides an overview of ten selected remote sensing effects. It is not our intention to present an exhaustive description of all known effects; for more comprehensive information, readers are referred to the cited references for each effect. Section 3 offers a synthetic analysis of remote sensing effects. Sections 4 explores the remote sensing invariants. Section 5 concludes the paper.

2. Remote Sensing Effects in Various Links

A large number of remote sensing effects have been proposed and investigated (Appendix A). They vary in different degrees of completeness and advancement. The remote sensing process can be treated as a chain of events or steps leading to a final output [3]. Remote sensing effects play distinct roles throughout this chain, beginning with the electromagnetic (EM) data source, such as solar radiation, thermal emission, and active EM radiation (LiDAR or radar). The illumination effect indicates the properties of the EM radiation and the distribution of luminance over the sky, whether it is directionally uniform or varies with weather conditions. The properties of the target, such as material composition, homogeneity, roughness, water content, salinity, temperature, texture, reflectance and emittance, and anisotropy properties are central to remote sensing signal processing.

Moreover, the relative position and motion state of targets will cause radiance differences in different wavelengths. The location, altitude, and environmental conditions, such as disease, drought, dust, and fire, can also impact remote sensing data acquisition.

In field biophysical measurements, optical instruments, such as digital hemispherical photography (DHP), are affected by exposure setting, blooming and vignetting effects, segment size, file format, and environmental contamination [4]. LAI-2200, a standard field leaf area index (LAI) measurement instrument, is particularly susceptible to the ring effect [5]. For LiDAR measurements, the occlusion and saturation effects must be considered [6]. Woody and non-green element effects also require attention in LAI measurements using DHP, LAI-2200 and LiDAR. In general, all field measurements are subject to sampling effects, whether random, systematic, or stratified.

Satellite remote sensing is influenced by many effects, such as sensor spectral wavelength, spectral response, sensitivity, field-of-view, radiometric, spatial and spectral resolutions, active or passive observation modes, observation geometry, temporal variation, orbital shift, among others. Recent studies have found that most land products derived from MODIS are affected by the orbital drift, especially for the fraction of absorbed photosynthetically active radiation (FAPAR) because of variations in solar illumination angle and light conditions [7].

Remote sensing models simulate the RT process in the atmosphere and vegetation systems. Typically, the radiation is decomposed into direct and diffuse components. The models need to account for photon interactions with the atmospheric and vegetation elements. The understory or background soil plays an important role in vegetation remote sensing, especially for sparse canopy. For a water surface, the air-water interface effect must be considered in RT simulations of coupled air-water systems. Polarization effects are explicitly incorporated in polarized RT models [8, 9].

Many factors affect remote sensing data storage, processing, and transmission. Data compression prior to transmission or storage may reduce data quality and lose critical details. Transmission delays or partial data loss from communication issues can result in incomplete or outdated datasets. In image classification, different classifiers may introduce varying uncertainties in final products. Image interpretation inherently involves artificial effects that may cause systematic errors. Scale differences, temporal coherence, and spectral consistency disparities between remote sensing products and reference data can introduce errors in product evaluation and applications.

2.2 Connections Among Remote Sensing Effects

Remote sensing effects are not isolated phenomena but rather interconnected with each other. Some effects exhibit similarities or equivalences and can be studied collectively, while others demonstrate opposing characteristics. These relationships are broadly categorized as follows.

2.2.1 Generic and Integrated Effects Generic effects are those that should be considered across multiple aspects of remote sensing studies. The scaling effect is one such example that exists in field measurements, satellite observations, product generation and evaluation, and applications. Another example is the temporal effect, which affects instruments, targets, observers, and environmental conditions. The human factor permeates nearly all remote sensing processes. In contrast to generic effects, certain effects hold particular importance for specific applications. These effects are also more independent, such as the texture effect, which is commonly used for image classification. The clumping effect, while predominantly significant at local scales, may also contribute at landscape and regional scales [10].

Many effects are an integration of several sub-effects. Topographic effects contain elevation, slope, and aspect effects, and are coupled with directional effects in affecting land surface reflectance. Spatial and temporal effects are usually analyzed together as spatio-temporal effects. The latitude, longitude, topographic, and elevation effects may be subsumed in spatial effects. The adjacency effect is a combination of atmospheric and surface effects, while one of them may play a primary role and the other secondary. Directional effects is a category of geometric effects, which are affected by Earth's shape and rotation, sun-target-sensor configurations, terrain influences, and geo-reference projection. Temporal effects are usually combined with variations of spectral, angular, and textural characteristics. In mountainous areas, topographic effects need to be incorporated into atmospheric correction in surface reflectance estimation and land cover classification [11-13].

2.2.2 Equivalent, Facilitating and Neutralizing Effects Many effects are literally equivalent. For example, heterogeneity effect and mixing effect are often interchangeable in different fields. Both phenology and seasonal effects are similar to each other and are subcategories of temporal effects. Directional effects are closely related to angular effect, sun glint effect, specular effect, non-Lambertian effect, hotspot and darkspot effects, shading effect and others.

Some effects mutually reinforce each other in remote sensing studies, while others may compensate with each other. Leaf biochemical components (e.g., chlorophyll content) and canopy structural properties (e.g., LAI) jointly influence canopy reflectance, which makes it difficult to decouple them in parameter retrieval. Similarly, canopy clumping, woody components, and non-green foliage collectively complicate the LAI retrieval from optical remote sensing. In practice, the clumping and woody effects may be compensated in forest LAI estimation [10, 14].

2.2.3 Beneficial and Detrimental Effects Depending on the user's purpose, remote sensing effects can be either beneficial or detrimental. Beneficial effects are helpful for a user; for example, the temporal effect is beneficial for time series analysis and thematic classification. Many effects are beneficial and can be utilized in remote sensing studies. The usefulness of an effect depends on the purpose of the application. Traditional visual interpretation and digital classification have long capitalized on spatial patterns, spectral characteristics, and temporal variations, while temporal effects have been commonly utilized for global land cover classification [15].

Detrimental effects introduce complications for a user. For a coupled atmosphere and surface system, the atmospheric influence hinders surface detection, and vice versa. For a coupled soil-vegetation system, detecting one of them needs to consider the other's effect. However, bright background effects can enhance vegetation detection and quantification. Thermally emitted radiance from any surface depends on the surface temperature and emissivity; estimating either one needs to account for their mutual dependence.

3. Overview of Selected Remote Sensing Effects

This section focuses on a selected group of ten effects that have received significant attention in land surface remote sensing. These effects are well-defined and have been extensively studied in the literature. Their key characteristics are summarized below with examples and references.

3.1 Atmospheric Effect

Atmosphere effect is a joint result of all kinds of atmospheric components, such as atmospheric molecules, aerosols, water vapor, ozone, methane, carbon monoxide, nitrous oxide, and carbon dioxide [16]. The main atmospheric effects include scattering, absorption, cloud cover, aerosol, water vapor, refraction, and thermal effects. Atmospheric effects modify signals received by sensors on satellites or other platforms, making it challenging to interpret accurately without compensating for them. Atmospheric conditions also impact optical instruments used for canopy biophysical structural measurements, such as DHP, LAI-2200, and AccuPAR. Therefore, diffuse conditions are generally recommended for optimal performance, particularly for forests, to avoid the impact of direct irradiance [17-19]. Among these instruments, DHP has been found more robust due to its lower sensitivity to illumination conditions [20].

Atmospheric correction technique aims to remove or reduce atmospheric distortions, so that the true surface parameters can be more accurately retrieved [21]. Atmospheric corrections enhance image quality and improve classification accuracy [22]. Numerous studies have reviewed and evaluated atmospheric correction methods [23-25]. Aerosols and water vapor, which exhibit greater spatial and temporal variability than other atmospheric components, introduce significant uncertainties in atmospheric correction. Therefore, accurately characterizing these components is essential for effective atmospheric correction. Various techniques, including physical modeling [26] and deep learning methods [27], have been proposed to provide processing solutions for all kinds of illumination conditions. Commonly used atmospheric correction algorithms include the ATmospheric CORrection (ATCOR3) [28], the Landsat Surface Reflectance Code (LaSRC) [29], and Sen2Cor implemented in SeNtinel's Application Platform (Sen2Cor-SNAP) [30]. Atmospheric models, such as MODTRAN [31] and 6S [32], are commonly used to simulate and compensate for the effects of scattering, absorption, and other atmospheric phenomena.

Remote sensing data contaminated by atmospheric effects can be processed using various filtering approaches [33-35]. Combining data from multiple bands or using images acquired at different times can help mitigate the atmospheric influence. Specialized vegetation indices (VIs), such as the atmospherically resistant vegetation index (ARVI) [36] and infrared simple ratio (ISR) [37], were developed to minimize atmospheric impacts. Notably, atmospheric correction may not be necessary for classification and change detection applications when training data and target data maintain consistent relative scales [38].

Validation of atmospheric correction results is crucial to ensure that the processed remote sensing data accurately represent surface reflectance or radiance. Field-measured surface reflectance data such as those from SpecNet [39] and HyperNav [40] are thus critical in validation of the corrected data. When there are no concurrent field measurements, atmospheric parameters derived from satellite images can be used to reconstruct atmospheric conditions and verify corrections [41, 42]. By combining visual inspection, quantitative analysis, and cross-validation, one can ensure that atmospheric correction improves data accuracy for downstream applications like land cover classification and environmental monitoring.

3.2 Background Effect

Background effects refer to the mixture of both target and background information in the sensor. Background effects primarily arise from soil, snow, understory, or water background. In forest environments, background may refer to all the materials below the canopy such as understory plants, leaf litter, grasses, lichens, mosses, rocks, soil, snow, water, or their mixtures [43, 44]. Typically in forests, a moss or lichen layer covers the ground surface beneath grasses. Similarly, in agricultural fields, a thin weed layer commonly exists beneath the main crop canopy.

Background materials influence vegetation canopy reflectance and VIs, consequently affecting canopy parameter retrieval. Combining information from different bands can eliminate some background effects and significantly enhance canopy information extraction. Several VIs have been specifically developed for this purpose, including as the soil-adjusted vegetation index (SAVI) [45], the modified soil-adjusted vegetation index (MSAVI) [46], the reduced simple ratio (RSR) [47], and the normalized difference phenology index (NDPI) [48].

Forest background information can be retrieved from remote sensing techniques, especially from multiangle sensors such as CASI and MISR [45, 49, 50]. In canopy reflectance models, background contributions are represented in different schemes [51-53]. For example, the MODIS LAI algorithm uses 25 patterns of effective ground reflectance to parameterize the contribution of sub-canopy surface (soil and/or understory) [54]. In practice, background characteristics for low-to-medium density forests are usually considered similar within a geographical area, although local variations may occur between adjacent stands of different densities [55]. When the overstory coverage is high (e.g., $> 70\%$), the background has little effect on canopy reflectance and albedo [56].

The background reflectance estimated from remote sensing can be used to retrieve the overstory parameters [57]. However, the background information retrieval in forests may be partly influenced by non-green materials in the canopy (trunks and branches) [58]. For dense forest (e.g., LAI > 4), there is no ability to retrieve background reflectivity. Furthermore, separating different understory components is still difficult; the model-retrieved background reflectance may not represent the true ground conditions but is more like an effective value from model inversion [59, 60].

More attention is necessary for complicated snow backgrounds [61, 62]. However, it is challenging to map the snow-covered area using optical satellite sensors, particularly during snowmelt [63]. A normalized difference snow index (NDSI) has been used to identify whether snow or ice background is present [64]. On the other hand, snow cover benefits wintertime forest LAI estimation from airborne imagery by providing a uniformly bright background for hemispherical image analysis [62, 65].

3.3 Clumping Effect

Canopy clumping effect characterizes the spatial distribution of leaves or needles within a vegetation canopy, which is critical in determining the transmission and interception of light and precipitation [10, 66, 67]. Canopy clumping effect is usually quantified using the canopy clumping index (CI), defined as the ratio of the effective LAI (LAIe) to the true LAI. In landscape ecology, an aggregation index has also been used to measure the spatial aggregation of ecological adjacencies and class patches [68-70].

CI can be estimated in the field using direct, indirect optical, and allometric methods [10]. Direct methods derive CI by separately estimating LAIe and LAI. Indirect methods estimate CI through the analysis of canopy gap fractions, while allometric methods use relationships with other biophysical parameters. Both passive optical sensors and active LiDAR systems, including terrestrial, airborne, and spaceborne platforms, have been successfully applied for CI estimation, following similar principles to field measurements [71, 72]. Currently, most global CI products are generated through empirical relationships with the normalized difference hotspot and darkspot (NDHD) index derived from POLDER, MODIS, and MISR data [73-75].

Clumping effect is scale-dependent and tends to intensify with higher spatial resolution [76, 77]. For broadleaf forests, foliage clumping patterns vary at within-crown and between-crown scales. For coniferous forests, foliage clumping can be described at shoot, branch, crown, and landscape levels [10].

Clumping effect generally increases (decreasing CI value) with view elevation angle and canopy height, primarily because of the larger gaps in the upper canopy than in the lower canopy. Seasonally, canopy clumping is more pronounced during the peak growing season compared to early and later growing periods [75].

The clumping effect significantly influences LAI field measurements, remote sensing modeling, and parameter retrieval and should be considered in canopy reflectance and land surface models. It is critical in partitioning the total LAI into sunlit and shaded components for the estimation of gross primary production (GPP) [78], solar-induced fluorescence (SIF) [79], and surface evaporation [80, 81].

Seasonal clumping variations have been used to explore their effects on canopy radiation absorption and GPP dynamics [82, 83]. However, the interannual clumping variability has not been fully considered in current land surface models for climate change studies. Future studies should focus on implementing automated wireless measurement techniques, developing advanced remote sensing estimation methods, enhancing fundamental understanding of clumping characteristics, and improving clumping parameterization in land surface models.

3.4 Directional Effect

Directional effect represents the variation of object properties with angles, such as variations in solar illumination, surface characteristics, and observed radiances. Surface directional effect is an intrinsic surface property and is crucial for the modeling and estimation of land surface parameters.

Surface directional property is usually characterized by the bidirectional reflectance factor (BRF) and bidirectional reflectance distribution function (BRDF), which can be measured using various instruments in the field [84]. For vegetation canopy, directional gap distribution represents another crucial directional property and can be obtained through photographic (e.g., DHP) or radiometric (e.g., LAI-2200) field measurement techniques [85].

Satellite observations acquired at off-nadir viewing angles inherently incorporate directional effects in surface reflectance measurements. Even for surfaces with constant properties, apparent reflectance varies with solar zenith angle [86]. Correcting directional effects is particularly important for time-series analysis and the generation of long-term data records [87, 88]. The influence of directional effects propagates from surface reflectance to VIs and therefore impacts the estimation of canopy biophysical variables such as LAI using the VI approach. To limit the impact of directional effects, one common option is to use VIs such as the normalized difference vegetation index (NDVI) and enhanced vegetation index (EVI). However, the VIs may still contain significant directional signatures [89].

Directional effects can be effectively reduced with angular normalization and BRDF models [90]. Various canopy reflectance models have been developed to characterize these directional variations [52, 91, 92]. The MODIS processing chain, for instance, employs a kernel-driven BRDF model to produce nadir BRDF-adjusted reflectance (NBAR) products [93, 94]. Additional metrics such as the anisotropic factor [95] and anisotropy index [96] have been developed to quantify surface reflectance anisotropy.

Consideration of directional effects is important due to the strong non-Lambertian scattering properties of vegetation surfaces and the directional influence of model parameters on the canopy reflectance [91]. Multi-angle observations generally improve LAI retrieval accuracy compared to single-angle measurements [97, 98], as demonstrated by the MODIS LAI product derived from directional reflectance data [54, 99]. However, the magnitude of angular effects tends to decrease with increasing LAI values [100]. Some researchers have suggested using angularly normalized VIs or directionally based indices for LAI estimation [101-103].

3.5 Heterogeneity Effect

Heterogeneity effect refers the mixing of different objects within a study target, for example, mixed pixels in land surface classification. Surface heterogeneities are associated with horizontal and vertical arrangements of target components. Therefore, comprehensive characterization of the effect needs to account for both horizontal and vertical dimensions. Surface heterogeneity effect is scale-dependent and is directly related to the resolution of the sensor. The greater the spatial detail registered in the image, the greater its sensitivity in detecting the internal variations of a category contained under a larger pixel [104].

Vegetation heterogeneity can be determined in horizontal and vertical directions. In the horizontal direction, surface mixture of vegetation and soil can be expressed by the fractional vegetation cover (FVC), which is usually determined along transects in field measurements. In the vertical direction, heterogeneity mainly stems from variations in biophysical and biochemical properties throughout the canopy profile. Foliage area density profiles can be measured with various vertical sampling methods [105]. LiDAR and radar sensors are particularly effective for capturing three-dimensional heterogeneity patterns [106]. Both horizontal and vertical heterogeneity characteristics have been incorporated in canopy RT models [107-109].

Multiple approaches exist for quantifying spatial heterogeneity at satellite footprint scales [110]. Field-based methods include spatial variogram analysis for assessing autocorrelation patterns [93, 111]. High-resolution imagery combined with pixel unmixing techniques can mitigate heterogeneity effects by decomposing mixed pixels into constituent endmembers with respective abundance fractions.

However, an increase in spatial resolution does not always improve the discrimination of features, as the internal heterogeneity within categories may increase as well [104, 112]. Since greater heterogeneity means greater mixing with similar classes and greater risk of confusions, an increase in spatial resolution may even complicate digital classification.

Surface heterogeneity significantly impacts multiple aspects of remote sensing, including field sampling, radiometric calibration, land surface classification, and remote sensing modeling and retrieval. A representative example is land cover classification, where the selection of appropriate spatial resolution depends on specific research objectives. For regional and global agricultural monitoring, moderate spatial resolution sensors (e.g., MODIS) provide an optimal balance between data volume and temporal coverage [113]. Conversely, in highly fragmented areas, even 10-30 m resolution data from sensors like Sentinel-2 and Landsat may prove insufficient and meter-resolution data are necessary. Regarding visual analysis, higher spatial resolution generally enables more accurate interpretation of the imagery [114].

3.6 Saturation Effect

Saturation effect refers to the phenomenon where sensor readings reach their maximum detection limit and can no longer accurately represent further increase in signal intensity. Saturation effect occurs in the estimation of canopy properties, e.g., LAI, from VIs and spectral data. As vegetation develops, these indices and spectral measurements often lose sensitivity to canopy changes and saturate at medium-to-high LAI values or during late growth stages [115]. The red band demonstrates earlier saturation than the NIR band due to greater light attenuation in the visible spectrum caused by scattering and absorption processes [91, 116].

Saturation thresholds are usually defined as the point where a VI reaches 90-95% of its maximum potential value [117, 118].

In the field, LAI is usually estimated from the canopy gap fraction following the Beer-Lambert law [119, 120]:

$$P(\theta) = \exp\left(-\frac{G(\theta) \cdot \Omega(\theta) \cdot LAI}{\cos(\theta)}\right)$$

where $P(\theta)$, $G(\theta)$, and $\Omega(\theta)$ are the canopy gap fraction, leaf projection function, and canopy CI at zenith angle θ, respectively. Eq. (1) shows that LAI follows an asymptotic relationship with the canopy gap fraction and would saturate at high values. Documented saturation thresholds vary by vegetation type: approximately 5-6 for forests [121, 122], 3.5 for paddy rice [123], and 5.0 for giant reed [124]. The saturation effect persists when Eq. (1) is applied to derive LAI from LiDAR data [72, 125].

Seasonal variations in saturation are influenced by canopy clumping dynamics, particularly during peak growing periods [10]. In addition to LAI, saturation effects similarly affect the estimation of leaf chlorophyll content [126], canopy water content [127], canopy photosynthesis [80], and above ground biomass. When the radiation intensity is low, the leaf photosynthesis rate increases rapidly with the increase of the incident radiation; however, the increase rate becomes much slower when the radiation intensity is high, i.e., photosynthesis tends to saturate at high radiation intensity [128, 129].

Saturation effect adversely impacts data interpretation and analysis by causing inconsistent spectral responses [130]. To reduce the saturation effect, new VIs, e.g., the Wide Dynamic Range Vegetation Index (WDRVI), and new retrieval methods have been explored [131-133]. The red-edge channels are useful to improve the LAI estimation; however, these channels are also sensitive to leaf chlorophyll content and may cause problems for LAI estimation [134-136]. Incorporating thermal infrared (TIR) bands [137], texture information [138, 139], and LiDAR technology [140, 141] were shown to partly alleviate saturation issues in dense canopies. Additionally, non-parametric machine-learning algorithms, e.g., support vector machine [142], the Gaussian processes regression (GPR) [143] have shown potential in reducing saturation effects. However, it remains difficult to solve this intrinsic problem.

3.7 Scaling Effect

Remote sensing data are often collected from platforms operating at different spatial scales, e.g., field, UAV, airborne, and spaceborne sensors, and thus, the data characteristics change due to differences in the spatial resolution [144]. The scaling effect needs to be considered in land surface characterization, modeling, product generation and validation. Canopy reflectance and land surface models, in their hierarchical forms, integrate data from different scales and simulate how small-scale features contribute to larger-scale processes [145]. In LAI validation, a direct comparison between sparsely sampled field measurements and moderate-resolution satellite products may suffer from the problem of scale-mismatch [146]. To address this issue, it is recommended to scale up LAI estimates derived from high-resolution imagery to moderate-resolution pixels, thereby bridging the scale gap between ground measurements and satellite products [146, 147].

The magnitude of the scaling bias increases with both the model nonlinearity and the surface heterogeneity [148-151]. Raffy [148] estimated the scaling bias as half the amplitude of the transfer function's convex hull. Hu and Islam [150] quantified NDVI scaling errors by comparing two upscaling approaches: (1) calculating NDVI at fine resolution before upscaling, and (2) upscaling reflectance first and then calculating NDVI at coarse resolution. Garrigues et al. [152] proposed a method to estimate scaling bias based on the degree of transfer function nonlinearity and intra-pixel spatial heterogeneity.

To understand the influence of scaling effects, various techniques have been developed. Remote sensing classification at different spatial scales can be investigated using metrics like accuracy, Kappa coefficient, or F1 score to assess how scale influences classification results. Machine learning techniques, such as convolutional neural networks, random forests, and support vector machines, can be trained on data at various resolutions to analyze scale effects. Wavelet transforms and fractal model have been found useful for examining the relationship between spatial scale and surface complexity [153, 154]. Geostatistical tools like Kriging can be used to model spatial continuity at different scales, predict data at intermediate spatial scales, and understand how scale affects spatial variability [155].

Space analysis techniques like Gaussian pyramids or multi-resolution image pyramids can model spatial features at multiple scales and help understand how image features (e.g., edges, textures, shapes) evolve with spatial resolution changes. Scalable models, such as the allometric methods, can be applied at different scales in LAI and above ground biomass estimation [156].

3.8 Temporal Effect

Temporal effect broadly refers to changes and variations in the Earth's surface over time caused by natural or human factors. Temporal effects are fundamental in studying seasonal and long-term vegetation dynamics. In field measurements, temporal variations are monitored through continuous and automatic measurements of land surface parameters. Satellite remote sensing provides instantaneous measurement during the overpass time, which can be integrated into daily measurements and further combined to generate continuous products.

Temporal effects can limit the effectiveness and generality of empirical methods for estimating canopy biophysical variables from VIs. Some studies have found improved relationships by partitioning the growing season into two phases separated by the maximum VI [157], while others have reported no significant improvement [158]. The relationships between VIs and biophysical variables should be carefully considered during the leaf senescence stage, especially for LAI estimation [5, 159].

Temporal variations in land surface need to be considered in remote sensing models. Several researchers have suggested to use temporally resistant bands [160] and incorporate temporal factors into statistical models [161]. Adding temporal information in RT models is considered to enhance their explanatory power. Rebelo et al. [162] proposed a temporal kernel-based BRDF model for change detection. The isotropic term of the BRDF model varies as a cubic function of time, while the BRDF shape parameters remain constant over time. The model essentially combines both directional and temporal effects to improve its prediction power.

Time series analysis is widely used in the examining and analyzing of temporal effects [163, 164]. This process includes change detection and trend analysis at different temporal scales (daily, monthly, seasonally, yearly, and long-term). Time series analysis may be hindered by data gaps and thus temporal smoothing and data harmonization are needed to reduce noise and improve accuracy. The purpose of data harmonization is to address sensor degradation for individual sensors and cross-sensor differences for multiple sensors [165]. Many temporal filtering, interpolation, data reconstruction and integration techniques have been proposed to obtain temporally continuous and fine-spatial-resolution satellite imagery. Multi-sensor fusion algorithms are developed to increase product temporal resolution and accuracy. The Spatial and Temporal Adaptive Reflectance Fusion Model (STARFM) provides a tool to obtain high-resolution product by blending MODIS and Landsat data from common acquisition dates [166]. Essentially, STARFM provides a fusion of both scaling and temporal effects.

Temporal mismatch is one of the first issues that need to be considered in temporal analysis. Data interpolation and smoothing may also alter the original observations and bring artifacts in amplitude and frequency. Sensor degradation may affect product quality and complicate time series analysis [167].

Temporal stability is an important metric in time series analysis. The Global Climate Observation System (GCOS) defined product stability as the maximum acceptable change in systematic error over decadal timescales [168]. In practice, other forms of stability metrics, such as coefficient of variation [169], change of accuracy [170], and yearly drift [171] were also used.

3.9 Topographic Effect

Topographic effect refers to the influence caused by variations in elevation, slope, aspect, terrain, roughness and openness of the Earth's surface. Local topography significantly modulates surface illumination conditions and surface BRDF, which affects field measurements, land cover classification, land surface RT modeling and parameter retrieval, especially for fine resolution (<100 m) remote sensing data [172]. Surface microtopography is related to surface roughness, which is important to the interpretation of remote sensing imagery [173, 174]. Ground surveys and remote sensing methods, such as LiDAR, SAR, stereo satellite imagery, and aerial photogrammetry, are commonly employed to determine surface topography [175, 176]. Global topographic data are available as digital elevation models (DEMs), such as those from the Shuttle Radar Topographic Mission (SRTM) [177] and ASTER Global Digital Elevation Model (GDEM). However, retrieving accurate topographic information from dense forest environments remains challenging [178].

Topographic correction is necessary for both field measurements and remote sensing data acquired in topographically complicated areas [49, 179, 180]. The goal of topographic correction is to create harmonized and radiometrically stable remote sensing data. Numerous topographic correction methods have been developed and can be roughly classified into physical, semi-empirical, and empirical models [180]. One simple way to mitigate topographic effect is to build different VI models for different slope, aspect, and elevation classes [181]. A more thorough way is to create VIs that are inherently robust to different kinds of topographic conditions [182]. Different topographic correction methods have been evaluated but diverse and even conflicting conclusions have been reported [180, 183, 184]. These diverse conclusions could be attributed to the limited ground truth data and evaluation strategies that largely depend on selected images [13].

The benefits of topographic correction have been shown in many applications, such as land cover classification [11, 12] and biophysical parameter retrieval from airborne LiDAR [185]. For example, Ma et al. [186] proposed a refined albedo estimation algorithm for mountain areas by integrating a 3D RT approach that accounts for various terrain conditions (e.g. slope, aspect, elevation, and vegetation structure). Carmon et al. [187] reported that incorporating dynamic topography directly into joint surface and atmospheric models during the retrieval process could reduce errors in the retrieved surface reflectance.

Topographic correction converts physically observed signals to a hypothetical horizontal plane. Since this hypothetical plane does not physically exist, it's impossible to validate the correction effectiveness due to the absence of reference data. Although simulation studies may offer some insights, they inevitably introduce artifacts. Moreover, current correction methods do not consider spectral wavelength variations; therefore, further correction methods may be developed for different wavelengths.

3.10 Human Effect

The influence of human factors permeates nearly all aspects of remote sensing, including experiment design and implementation, data collection and analysis, research documentation, and policy recommendation. The utility of remote sensing data is fundamentally dependent on the expertise and knowledge of human users. Image interpretation relies not only on the imagery characteristics but also on the interpreter's knowledge, skill, and experience. Although automatic image processing techniques have been significantly improved in recent years, relying on computer only remains inadequate for remote sensing data analysis [188]. Serious errors may occur because of insufficient human interactions or artificial anomalies. Therefore, some remote sensing products such as China's National Land Use/cover Database [189] and GlobeLand30 [190] have adopted hybrid approaches incorporating human interpretations for quality assurance.

Human effects can act at individual, organization, and societal levels. Research organizations determine their remote sensing objectives based on organizational structure, available resources, and management approaches. Professional communities and committees within the remote sensing field establish standards, protocols, and requirements for remote sensing activities. The development of classification algorithms, classification systems, and the proliferation of land cover products are largely driven by various national and international initiatives. Human-induced land use and land cover changes, environmental and climate changes are crucial research themes in remote sensing.

Political and social factors are critical for the successful development and management of remote sensing programs, such as those for the sustainable development goals [191]. Sustained government funding is essential for maintaining space programs and supporting remote sensing research. The policy of open access to Landsat data since 2005 sets a good example of how such decisions can dramatically expand data application [192].

4. Perspectives on Remote Sensing Effect Studies

Remote sensing effects may be suppressed using various VIs. Many forms of remote sensing effects, such as illumination, atmospheric, cloud shadow, and topographic effects, show similar influences across multiple spectral bands and may thus be reduced using ratio vegetation index (RVI) and NDVI. For example, NDVI can partially cancel the bidirectional effect on observed radiances [193], while the difference vegetation index (DVI) helps reduce the scale effect [194]. However, the effectiveness and generality of empirical VI to mitigate remote sensing effects are constrained by many factors such as vegetation type, sun-surface-sensor geometry, leaf chlorophyll content, background reflectance, and atmospheric conditions. For example, both RVI and NDVI are sensitive to the soil background effect, showing positive biases when soils are dark or wet. To reduce this influence, modified VIs have been proposed, such as the soil-adjusted vegetation index (SAVI) [45], transformed SAVI (TSAVI) [195], and modified SAVI (MSAVI) [46]. Kaufman and Tanré [36] developed an ARVI to specifically correct for atmospheric effects, particularly aerosols, in vegetation remote sensing.

The spectral signal recorded in each pixel comes from surrounding areas as a consequence of multiple effects such as instrument optics, atmospheric effects, and image resampling. These effects can be characterized using a point spread function (PSF), which quantifies a sensor's response to point signals [196, 197]. Spatiotemporal data fusion methods address data gap problems by blending temporally sparse fine-resolution images with temporally dense coarse-resolution imagery. These methods leverage spectral, spatial, and temporal properties to accomplish diverse fusion tasks under different environmental conditions and using different sensor datasets [198].

A more general solution is to incorporate remote sensing effects directly into physical canopy reflectance models. Essentially, canopy reflectance models aim to integrate various effects induced by background, leaf, canopy, observation geometry, and environment. For example, Verhoef [199] developed a simple model to simulate the effects of canopy structure, surface heterogeneity, and background on canopy reflectance. Canopy reflectance models are further integrated with atmospheric RT models to simulate satellite observations [200]. Wang et al. [201] systematically quantified uncertainty sources in the daily VIIRS nighttime light radiance products and found that the uncertainty is dominated by angular and atmospheric effects. Specialized software was developed in their subsequent research to correct for cloud, atmosphere, terrain, snow, lunar, and stray light effects in the Day/Night Band (DNB) radiances [201, 202]. As a potential future study, the angular, atmosphere, adjacency, scaling, saturation, and temporal effects could be incorporated in surface reflectance modeling, e.g., in a kernel-based model similar to Rebelo et al. [162]. This kind of models could be evaluated using both field data and actual images.

Several unification schemes of various degrees of complexity and integration have been developed in land surface models. The coupled land surface and atmosphere models attempt to integrate all different kinds of effects in a sophisticated manner. The formulation of surface processes needs to carefully consider the effects of surface heterogeneity, the influence of surface processes on planetary boundary layer stability and moist convection, and the large-scale observational parameter specifications [203]. Carmon et al. [187, 204] demonstrated a scheme to incorporate topography into the joint surface-atmospheric modeling. The joint modeling scheme improved atmospheric and surface property inversion and provided more accurate surface reflectance estimates.

In the above sections, we have focused only on the most fundamental effects in land surface remote sensing. Some important but more indirect effects were not addressed, e.g., ecological, geographic, hydrological, greenhouse, and CO_2 fertilization effects, because of their more tangential relationship with direct remote sensing observations. One important effect is the spectral variability caused by different sensors. To ensure spectral stability between sensors, cross-sensor correction and spectral normalization need to be performed for reflectance and VI comparability and continuity and large-scale vegetation monitoring [205-207]. Other minor effects, such as the lateral radiation effect, have received less attention and can be neglected when the radiation regime is analyzed in a rather extended canopy [208]. Further studies of these effects can be performed in a broader context.

5. Remote Sensing Invariants

Remote sensing invariants can be categorized into five primary types: spectral, spatial, temporal, directional, and thematical invariants, each corresponding to different dimensions of remote sensing data. These invariants relate either to field measurement and RT processes or to external environmental conditions and driving factors.

5.1 Spectral Invariants

Spectral invariance refers to the properties of objects that show similar reflectance, emittance, transmittance, or absorptance at different wavelengths. In field reflectance measurements, white reference panels are assumed to have constant reflectance (100%) in the shortwave range. In canopy RT modeling, leaves and soil backgrounds may be considered as black bodies that absorb all incident radiation in all wavelengths. If no polarization is considered in RT modeling, it means that the polarization property is assumed spectrally invariant.

Spectral invariance also refers to the static relationships between different bands. This relationship is useful for band restoration. The MODIS aerosol algorithms have traditionally assumed a fixed ratio between surface reflectance in visible channels and that at 2.12 m [209-211]. Similarly, soil reflectance in the blue, green and NIR bands can be expressed using various linear relationships with the red band reflectance [212].

Over the past decades, the spectral invariant theory has gained increasing attention in canopy reflectance modeling [54, 213, 214]. Spectral invariants in this theory represent the canopy variables that remain constant in different wavelengths, such as gap fraction, canopy interceptance, photon escape and recollision probabilities [215-217]. The invariants can be determined in field measurements and remote sensing studies based on empirical relationships with other biophysical and biochemical variables, spectral or scale transformations, or a direct relationship with other structural parameters at different levels. It provides a simple way for canopy spectral modeling and biophysical and biochemical parameter retrieval.

5.2 Spatial and Scale Invariants

Spatial and scale invariance refers to the properties that remain consistent despite location and scale changes. In geography, closer areas tend to be more similar with one another than with those further away [218]. This spatial similarity property is frequently used in the restoration of missing values, e.g., by using neighboring pixel values. In the estimation of remote sensing variables, a common procedure is to establish a relationship between canopy biophysical or biochemical variables and VIs at representative sites. The relationship is then applied to a larger area to predict these variables from remote sensing data. In this process, the empirical relationship derived locally is assumed invariant at the larger area [219].

Scale invariants represent those parameters whose characteristics do not change with spatial scales [220]. If the value of a parameter is independent of the scale of sampling, the parameter can be considered scale-invariant, such as LAI, vegetation coverage, and tree height. For these parameters, the spatial scale has been included in the parameter definitions, and the variation of spatial precision has been taken into account in the sampling process.

Spatial invariance also exists in the vertical direction. For canopy simulation models, one-layer turbid-medium models assume that leaf properties are invariant within the layer, whereas 3D models consider vertical variations of leaf properties [221, 222]. Similarly, in land surface models, one-layer model assumes constant vertical canopy profiles, whereas multi-layer models consider vertical canopy and microclimate variations [223, 224].

Several indices of scale-invariants have been used in remote sensing data processing and modeling. Scale invariant features are widely applied in remote sensing image matching to handle geometric distortions [225]. Scale-invariant feature transform (SIFT) algorithms [226] are used to extract distinct points from an image, which remain invariant in affine transformations or illumination changes. Fractional dimensions quantify self-organizing properties of a certain feature and is essential for understanding and scaling RT and photosynthetic processes from individual leaf to canopy levels [108].

5.3 Temporal Invariants

Temporal invariants, or time invariants, refer to features or patterns that do not change over specific time periods. The time frame could be an hour, a day, a week, a month, a year, or even longer. Remote sensing sensors are often assumed stable within a given timeframe for trend analysis. However, since sensors degrade over time, radiometric matching between different dates may be performed based on a series of control pixels that are assumed invariant through time. It should be noted that as the temporal window expands, the probability of feature variation may increase.

In instrument calibration, cloud detection, and atmospheric correction, the surface properties are considered stable over a specific time window [48, 227]. This feature allows for better classification and interpretation of surface materials. In the standard MODIS LAI algorithm, eight biome types are used as a priori information to constrain the structural and optical parameters of the vegetation

[228]. In the comparison of RT model simulations and physical reality, environment properties are commonly kept constant over space and time [229]. In some land surface model simulations, constant LAI [230] and stem area index (SAI) values [231, 232] are used.

PICS are spatially uniform, spectrally stable, and temporally invariant locations that are widely used for sensor calibration and radiometric correction. These sites support RT simulations of satellite sensor measurements [1]. They can also be used to integrate data from new platforms and contribute to satellite program continuity [233].

5.4 Directional Invariants

Directional invariance relates to the properties that remain stable under different observation and solar angles. Directional invariance is essential in texture analysis, pattern recognition, and feature extraction as they help to extract features that are not sensitive to these variations [138, 139]. Directional invariance is a common assumption in quantitative remote sensing studies. One typical example is the Lambertian assumption for white reference panels in field reflectance measurements. Likewise, in the atmosphere and ground interaction, the surface is usually assumed as Lambertian. In atmospheric correction, the solar illumination is decomposed into direct and isotropic diffuse radiations. Satellites in geosynchronous orbit observe the same areas on Earth at constant view angles.

In kernel-driven BRDF models, an isotropic kernel is used to represent nadir-view nadir-sun reflectance [74]. With a proper BRDF model, many angularly dependent variables can be normalized to obtain angular invariant measures, such as NBAR and albedo. Various BRDF shape indices, such as the structural scattering index (SSI) [234], anisotropic flat index (AFX) [235], and Hotspot–Dark-spot index (HDS) [102], have been proposed to describe the relationship between different directions.

Vermote et al. [236] suggested that the yearly BRDF shape variations are limited and linked to the NDVI. Shuai et al. [237] also assumed that the surface BRDF shape is time-invariant.

Rotational invariance is another directional invariance property and is essential in object detection, classification, and change detection [238, 239]. Rotational invariance focuses on ensuring that an object's fundamental properties remain consistent despite changes in orientation.

5.5 Thematical Invariants

Thematical invariants refer to spectral reflectance, BRDF shapes, and VIs that remain consistent for different surface types, atmospheric conditions, or vegetation properties. When Landsat is used to estimate global reflectance, it is assumed that the BRDF shape of ground objects is constant for similar land cover types [237]. Lee et al. [240] proposed a modified aerosol free vegetation index (AFRI) which is not affected by aerosol presence. Fernandes et al. [37] reported that ISR is robust to atmospheric and species variability within forests and offers better LAI estimation compared to SR and RSR. Several studies have suggested that the NIR reflectance is unaffected by leaf chlorophyll variations and can be used for LAI estimation in densely vegetated areas [91, 241, 242]. Further investigations also found that the normalized difference red-edge index (NDRE, 710~780 nm) is insensitive to chlorophyll concentration and canopy clumping in LAI estimation [134]. To minimize the variable background effect, different kinds of VIs have been developed, such as SAVI, RSR, and NDPI (section 3.2). These VIs are considered invariant to the background variation. Carmon et al. [187] proposed a unified topographic and atmospheric correction approach and obtained terrain-invariant reflectance estimates.

5.6 Synthesis

All remote sensing invariants are related to some remote sensing effects. When a feature is unaffected by the effect, it can be considered as an invariant to that specific effect. Literally, temporal invariants are considered unaffected by temporal effects. An object may exhibit invariance in multiple dimensions simultaneously. For example, surface radiance may remain invariant in spectral, spatial, temporal, and directional dimensions. The geometric pattern of roads or buildings may remain invariant in different viewing angles, observation times, and atmospheric conditions.

Other remote sensing invariants may also be explored. One such example is the relationship invariant, which represents constant correlations used in remote sensing analysis. For example, in phenology study, the onset of greenness is usually defined as the half-maximum time during spring growth [243-245] because this threshold is stable and consistent across different ecosystems.

Remote sensing invariance features are critical in remote sensing modeling, parameter estimation, product generation and validation, and land surface and Earth system models. Certainly, these invariants maintain relative validity under specific assumptions. By understanding invariant properties, researchers can focus on other changing properties, such as in land cover or environmental conditions.

Remote sensing invariants may also be disrupted by external factors due to environmental change and thus, should be monitored constantly.

6. Conclusion

This paper provides a synthetic overview of various effects and invariants in land surface remote sensing. Remote sensing effects and invariants are fundamental in remote sensing science as they involve different factors from atmosphere, land surface, water, instrument, and human. Remote sensing effects and invariants are crucial for RT modeling, parameter retrieval, feature interpretation, and various applications. They provide a unified framework for remote sensing systems, methodologies, algorithms, products, and applications. Significant research efforts have been carried out for better understanding, quantification, mitigation and adaptation of different remote sensing effects. A unification of multiple effects may be further pursued.

The concepts of effects and invariants are intertwined. The description of invariants is the description of invariant effects. The quantification of effects requires the determination of invariants. Thus, the identification of invariants is an entree into the identification of effects. Studying remote sensing effects and invariants provides the greatest potential for the advancement of remote sensing science. Continued efforts are necessary for future quantification, evaluation, and validation of the effects and invariants. Remote sensing effects and invariants involve very broad and diversified disciplines. The list of effects and invariants in this review is not in any way complete. The presented framework offers new perspectives to understanding remote sensing and should help stimulate a collaborative study of theoretical remote sensing.

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Appendix A. Remote Sensing Effects in the Eyes of Graduate Students

From 2022 to 2025, I taught a course titled "Geo-analysis of Remote Sensing" each spring to first-year graduate students from the College of Resources and Environment at the University of Chinese Academy of Sciences (UCAS). The course was delivered by five to six lecturers with diverse specialties, focusing on vegetation remote sensing. The graduate students came from various academic backgrounds but had all completed introductory remote sensing courses.

During the class, I initially presented several common remote sensing effects—such as atmospheric effects, directional effects, and scaling effects—and then asked students to identify additional effects they could conceptualize. The student response was remarkable, yielding 70, 77, 97, and 69 distinct effects across the four years from 2022 to 2025 (the full list is omitted for brevity).

After eliminating redundant and irrelevant submissions, Table A1 presents the top 25 remote sensing effects identified through this exercise. This compilation reveals the key remote sensing effects that resonate with emerging graduate scholars.

Table A1. Top 25 remote sensing effects submitted in UCAS graduate seatwork (2022-2025). BRDF: bidirectional reflectance distribution function; RS: remote sensing.

Rank	Spring 2022	Spring 2023	Spring 2024	Spring 2025
1	Temporal	Scale	Scale	Atmosphere
2	Adjacency	Angular	Angular	Scale
3	Atmosphere	Hotspot	Temporal	Mixed pixel
4	Heat-island	Temporal	Hotspot	Angular
5	Topography	Shade	Atmosphere	Temporal
6	Spatial	Adjacency	Topography	Topography
7	Temperature	Atmosphere	Spatial	Polarization
8	Scale	Spatial	Adjacency	Adjacency
9	Spectral	Heat-island	Spectral	Shade
10	Polarization	Doppler	Shade	Geometric distortion
11	Radiation	Spectral	Radiation	Spectral variability
12	Distance	Polarization	Heat-island	Specular reflectance
13	Viewing	Topography	Doppler	Thermal infrared
14	Phenology	Dry island	Mixed pixel	Hotspot
15	Shade	Ecology	Reflection	Propagation
16	Patching	Red-edge	Directional	Radiance
17	Multispectral	Reflection	Phenology	Doppler
18	Angular	Acoustic	Geometry	Multi-path
19	Greenhouse	Instantaneous temperature	Scattering	Spectral confusion
20	Red-edge	Multispectral	Polarization	Scattering
21	Altitude	Multitemporal	Overlay	Heat-island
22	Latitude	Azimuth	Absorption	Spectral
23	Tyndall	Foehn	Multispectral	Ground object
24	Cold island	Elevation angle	RS system	
25	Human			

Note: Figure translations are in progress. See original paper for figures.

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