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# Mapping biophysical variables from solar and thermal infrared remote sensing: focus on agricultural landscapes with spatial heterogeneity.

Frederic Jacob, *Member, IEEE* and Marie Weiss, *Member, IEEE*

**Abstract**—This paper closes a special Stream that focuses on spatial heterogeneity when mapping biophysical variables over agricultural landscape from solar and thermal infrared remote sensing. We propose an overview of the highlights from prior research, we report the main results of the special stream, and we discuss future directions. The main outcomes of the special stream are related to: 1) the impact on the remotely sensed signal of canopy vertical distribution, shadowing effects, and multiple scattering; 2) the notion of spatial resolution limit in relation to spatial heterogeneity; and 3) the definition of an optimal sampling strategy to spatialize ground measurements.

**Index Terms**—Remote sensing, spatial heterogeneity, upscaling, downscaling, agricultural landscape, forestry.

## I. INTRODUCTION

AGRICULTURAL landscapes, including crops, rangelands and managed forests, are typical instances for studying global changes. Their evolution is influenced by several factors, either natural (e.g., climate) or anthropogenic (e.g., farmer practices, regional management, governmental incentives). Adapting anthropogenic forcing requires decision-making systems that rely on diagnostic and prognostic tools. In this context, land surface processes are described with biophysical models that must be parameterized, calibrated and validated. This can be achieved with Earth observation data.

Remote sensing is one of the most efficient means to capture spatial patterns related to land surface processes, at given temporal sampling and spatial resolution. The remote sensing technique is usually chosen according to the targeted variable: solar domain to retrieve fraction of absorbed photosynthetically active radiation (fAPAR), leaf area index (LAI) and gross primary production (GPP), or thermal infrared (TIR) domain to retrieve land surface temperature (LST).

A large part of the literature has addressed this topic [1, 2]. Due to technical and methodological limitations, most investigations have been conducted under quite homogeneous and flat conditions, with the use of decametric to kilometric spatial resolution sensors. However, agricultural landscapes are highly heterogeneous, due to crop mosaics and canopy structures.

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Recent observing systems and modeling improvements now allow the investigation of such complex terrains and canopies.

The IEEE Geoscience and Remote Sensing Letters (IEEE-GRSL) opened a call for submission of research papers, through a Special Stream devoted to solar and thermal infrared remote sensing of biophysical variables in agricultural landscapes characterized by spatial heterogeneity. Among 23 submissions, eight papers were accepted for publication, temporally distributed from July 2013 to January 2014. The papers addressed the implications of spatial heterogeneity when mapping a panel of biophysical variables (surface reflectance, chlorophyll fluorescence, LST, LIDAR waveform, GPP, and fAPAR), over various agrosystems (forests, orchards, vineyards, crops, and grasslands), using different remote sensing techniques (active and passive sensors over the solar and thermal infrared spectral domains), onboard different platforms (airborne and satellite).

This paper concludes the Special Stream by focusing on the main outcomes in light of prior research. Section II discusses how spatial heterogeneity is considered in the literature. Section III presents the methodological strategies that have been developed to overcome the difficulties induced by spatial heterogeneity. Section IV provides an overview of the highlights from prior research. Section V details the outcomes from the Special Stream. Section VI concludes the paper by identifying some critical issues to be addressed in the future.

## II. SPATIAL HETEROGENEITY IN REMOTE SENSING

In relation to technological constraints and intrinsic characteristics, any remotely sensed measurement corresponds to a mixed pixel that depicts horizontal and vertical heterogeneities. As stated by [3], there is no single definition of spatial heterogeneity, because it is usually regarded according to the considered scales and the targeted variables.

Spatial heterogeneity results from the patterns observed at a given scale that is driven by the sensor sampling capabilities [4, 5]. At the landscape scale, spatial heterogeneity is characterized either by the length scale beyond which it cannot be captured (textural features) or by the sizes and shapes of landscape elements (contextual features) [6]. In this case, spatial heterogeneity can be described with land use maps [7] or geomorphological maps [8]. It can also be characterized through semi-empirical parameters derived from the angular signature of the bidirectional reflectance [9, 10]. At the field scale, spatial heterogeneity is usually defined according to canopy vertical structure [11], horizontal structure [12], or both [13].

Spatial heterogeneity also results from radiative transfer

processes that are driven by spatial structures and land surface processes. The solar observations are influenced by several factors such as shadowing effects or multiple scattering [12]. The thermal observations are also affected by multiple scattering and shadowing effects, as well as by vegetation and soil water status [14].

As driven by spatial patterns and land surface processes, spatial heterogeneity varies with scale and time. It decreases with larger scale [5], and varies with the temporal evolution of the elements within the spatial patterns or vertical strata [15].

### III. METHODOLOGICAL STRATEGIES

In the context of using solar and thermal remote sensing to map biophysical variables over agricultural landscapes, several methods were developed to account for spatial heterogeneity. We provide an overview of these approaches by dividing them into two types: bottom-up and top-down approaches.

Bottom-up approaches aim to estimate biophysical variables over a given extent by accounting for spatial heterogeneity within this extent. This includes simulating remotely sensed measurements with radiative transfer models (RTM, Section III.A), spatializing local ground measurements (Section III.B), and correcting errors induced by spatial heterogeneity within coarse-resolution pixels (Section III.C).

Top-down approaches use ancillary information to retrieve biophysical variables for scene components horizontally or vertically distributed within the pixel. They rely on unmixing methods (Section III.D). Spatial heterogeneity is characterized by both the description level (e.g., the number of components) and the type of ancillary information used for unmixing (e.g., LAI, temperature, land use).

#### A. Spatial heterogeneity and radiative transfer modeling

Radiative transfer models (RTM) simulate the remotely sensed signal according to a given representation of the scene within the pixel. The representation accounts for spatial heterogeneity with different levels of complexity in terms of spatial structures and radiative transfer processes.

At the basic level of complexity, spatial heterogeneity can be described by considering few scene components that are distributed vertically (e.g., soil and vegetation, eventually shaded and sunlit) or horizontally (e.g., land use classes). The radiative transfer modeling is then restricted to linear or quadratic combinations of radiative properties such as reflectance or temperature [16, 17].

At the intermediate level of complexity, 1-D structures are associated to turbid RTM to describe vertical heterogeneity. They encompass several layers, including the soil, and each layer can include several elements with different radiative properties [18, 14]. 2-D structures are associated to geometric-optics models with a limited number of inputs, to describe both horizontal and vertical heterogeneity. They include geometrical elements such as parallelepipeds, cylinders, or ellipsoids in relation to the shapes of trunks, stems, or foliage [19].

At the highest level of complexity, 3D mock-ups are associated to radiosity or ray tracing methods with a large number of inputs [20, 21]. They describe the scene as an ensemble of

elements such as triangles or cells.

#### B. Spatial heterogeneity and spatialization methods

Spatialization methods aim to produce biophysical variable maps from a limited number of local measurements distributed over a given extent. This requires two steps: first to develop spatial sampling strategies and second to apply spatialization methods. Both steps rely on using ancillary information to characterize the spatial heterogeneity.

The ancillary information must be strongly correlated with the biophysical variable of interest. Different sources of information are used and can be related to anthropogenic factors (e.g., land use), biophysical variables (e.g., GPP), or geomorphological drivers (e.g., soil properties).

Sampling strategies generally use classification maps to optimize the number and location of the measurements [22]. Spatialization methods rely on either transfer functions (e.g., relationships between the measurements and the ancillary information), or geostatistics with or without ancillary information (e.g., ordinary or collocated kriging) [23].

#### C. Spatial heterogeneity and coarse resolution pixel

The biophysical variable value at coarse resolution is the arithmetic average of the biophysical variable at finer resolution. When estimating the biophysical variable from remote sensing data, this is still the case when the surface is homogeneous or when the surface is heterogeneous and the relationship  $\mathcal{F}$  between the remotely sensed signal and the variable is linear. However, when  $\mathcal{F}$  is nonlinear and the surface is heterogeneous, arithmetic averaging is not valid [24]. The associated biases have been quantified in different ways: by comparing the biophysical variable value obtained by averaging the fine resolution estimates with the one issued from the coarse resolution [25, 26], or by combining  $\mathcal{F}$  non-linearity derived from Taylor decomposition with spatial heterogeneity quantified from variogram analysis [27]. As heterogeneity is scale dependent, the biases depend upon the resolution difference between the coarse and fine pixels [28].

#### D. Spatial heterogeneity and unmixing methods

Unmixing methods consist of retrieving the biophysical variable for each homogeneous scene component within the pixel. These components are horizontally (e.g., crop mosaic) or vertically (e.g., understory and trees) distributed.

Vertical heterogeneity is commonly addressed by inverting linear RTM to retrieve biophysical variables for canopy strata (e.g., the LAI for understory and tree crown [17] or the temperature for soil and vegetation [16]). Linear RTMs consider only single scattering, which assumes that the vertically distributed elements do not interact. This is equivalent to projecting the vertical distribution on a horizontal plane in the viewing direction. The inversion of nonlinear RTM has been mainly conducted using LIDAR data, in order to characterize forest canopy structure [29].

Horizontal heterogeneity in unmixing methods is commonly addressed by disaggregating pixels, with ancillary information at finer spatial resolution. The goal is to use fine spatial infor-

mation from high-resolution sensors and high revisit frequency of coarse-resolution sensors. Disaggregation is usually achieved by fitting multi-linear regressions between the biophysical variable at coarser resolution and the ancillary information at finer resolution. Ancillary information can be the same biophysical variable at the resolution of homogeneous land units [30], or a panel of other variables [31]. This assumes that the biophysical variable of interest is spatially correlated with the ancillary information [32].

#### IV. RESULTS FROM PRIOR RESEARCH

In relation to the topics addressed in Section III, we discuss here breakthroughs from prior research. Therefore, some outcomes are not considered, because they have been widely published. Most of them stated that applying methods designed for homogeneous surfaces over heterogeneous areas is not adequate.

Before designing methods for mapping biophysical variables over heterogeneous surfaces, it is necessary to characterize spatial heterogeneity, according to the limited capabilities of existing sensors. Capturing spatial heterogeneity requires that the pixel size is lower than the length scale of the biophysical variable [33]. Furthermore, pixel shape could be optimized as a function of spatial heterogeneity [34].

The signal simulated by RTM depends on both the degree of the scene heterogeneity and the ability of the model to describe this heterogeneity. Many models have been improved to account for specific heterogeneities (e.g., leaf or plant clumping, rows, or shadowing effects) [15, 35]. However, when comparing models with different complexities over a range of spatial heterogeneity, [36] showed that concluding on the best model is difficult because of differences in model assumptions.

When spatializing ground measurements to validate biophysical variable products at coarse resolution, it is necessary to associate an error estimate to the spatialized and/or upscaled variable. Only few studies investigated the quantification of this error, and they all rely on kriging methods ([37]).

When considering spatial heterogeneity within the coarse

resolution pixel, [27] showed that the biases induced by the  $\mathcal{F}$  non-linearity (Section III-C) can reach up to 20% for LAI at 1 km spatial resolution. The largest biases are observed for agricultural areas due to crop patches. These biases are scale dependent, and decrease with pixel resolution [24], similarly to spatial heterogeneity (Section II). They result from observation conditions [38, 5], including landscape patterns that change with time, radiative transfer processes such as multiple scattering and adjacency effects, and instrumental effects such as the point spread function (PSF). Finally, the impact of spatial heterogeneity on biophysical variable retrieval depends on the degree of the  $\mathcal{F}$  non-linearity: for LST, [25] reported that it is moderate, with uncertainties ranging from 0.5 K to 1 K.

Unmixing methods from RTM inversion usually rely on linear RTM, and address the retrieval of biophysical variables for a few scene components only. A critical issue is to make a compromise between the number of components describing the spatial heterogeneity and the retrieval accuracy of the corresponding biophysical variables. It is possible to increase the number of scene components by using multi-angular observations. Thus, [17] retrieved LAI of understory and crowns, and [39] estimated temperature of sunlit and shaded components, additionally to soil and vegetation.

Unmixing methods based on pixel disaggregation mostly deal with surface temperature [32]. This is motivated by the low revisit frequency of high-resolution sensors in relation to the high temporal variability of temperature, compared to other variables that monotonously and slowly change with time (e.g., LAI). Throughout the last decade, an increasing amount of ancillary information has been included in the disaggregation schemes (e.g., NDVI, emissivity, and microwave brightness temperature) [40, 31]. This requires characterizing the relationships between surface temperature and ancillary information. However, [41] questioned the scale invariance of these relationships. Overall, the obtained accuracy, between 2 K and 3 K, is still far from the requirements.

Topography is another source of spatial heterogeneity that has been addressed in few studies. Over the solar domain, [42]

TABLE I: OVERVIEW OF THE SPECIAL STREAM PAPER CONTENT.

Paper	Spatial Heterogeneity	Scale	Agrosystem	Type of Scene	Radiative Transfer Modeling	Spectral Domain	Variable of Interest	Scientific Question
[45]	Horizontal	Field	Vineyards	2D	Linear aggregation	TIR	LST	Directional effect on mixed pixel
[46]	Horizontal	Landscape	Sparse Vegetation	2D	Linear aggregation	TIR	LST	Directional effect on mixed pixel
[47]	Horizontal	Field	Orchard	2D	Linear aggregation Hybrid model	Solar	Fluorescence	Fluorescence of mixed pixel
[48]	Horizontal	Field	Orchard	2D	Linear aggregation	Solar	fAPAR	Spatial information from high resolution data
[49]	Both	Landscape	Spruce	3D	Ray tracing	Solar	fAPAR	Multiple scattering & spatial resolution
[50]	Both	Field	Corn, Forest, Orchard	3D	Ray tracing	LIDAR	LIDAR Waveform	Multiple scattering & spatial resolution
[51]	Vertical	Field & Landscape	Forest	2D	Linear aggregation	Solar	Reflectance	Understory impact on signal
[52]	Horizontal	Landscape	Grassland Forest	2D	-	Solar	GPP	Ground sampling strategy

showed the benefit of including topographic correction within turbid RTM. Over the TIR domain, [25] reported an increase in accuracy of 1 K when accounting for terrain-induced angular effects in surface temperature aggregation scheme.

Finally, an original direction was explored by [43], who took advantage of the temporal dynamics of spatial heterogeneity. They used the scene component dynamics as a priori information to constrain the inversion of an RTM. Similarly, [44] constrains RTM inversion by assuming different spatial variabilities for each model variable (e.g., unique value within the field or within an  $N * N$  pixel window).

## V. OUTCOMES FROM THE SPECIAL STREAM

Among the four types of methodological strategy discussed in Section III and IV, the eight papers published in the Special Stream dealt with the bottom-up approach: seven papers addressed the simulation of remotely sensed measurements, and one focused on the spatialization of local ground measurements. The top-down approach was not addressed. Table I summarizes the content of the papers in relation to the different items discussed in Sections II and III.

Four papers of the Special Stream addressed the shadowing effect on remotely sensed measurements. [45] and [46] brought up the influence of these effects on the angular signature of LST. [46] showed the consequences when intercomparing and validating coarse resolution LST. In the solar domain, [47] identified shadowing effects as the cause of discrepancies between fluorescence estimates at the tree level and those at lower spatial resolutions ( $\geq 50$  m). Finally, [48] took advantage of the very high spatial resolution to identify shadowed and sunlit soil to improve fAPAR estimates.

Three papers of the Special Stream addressed the notion of spatial resolution limit in relation to spatial heterogeneity. On the one hand, [49] and [50] showed that multiple scattering can no longer be neglected when refining the spatial resolution up to a few meters. On the other hand, [47] investigated the impact of degrading the spatial resolution when mapping vegetation fluorescence. They showed that spatial heterogeneity, induced by vegetation cover fraction, strongly affects the fluorescence signal within a mixed pixel.

Vertical heterogeneity was addressed by [51] only. The authors showed that, for boreal forests, the understory could contribute up to 40% to the canopy reflectance. They concluded that it is necessary to account for the understory contribution when monitoring the temporal dynamics of tree LAI.

In the unique paper dealing with the spatialization of local ground measurements [52], the benefit of using geostatistical methods with remote sensing data was investigated. To optimize ground sampling, the authors showed the interest of considering the anisotropic feature of horizontal heterogeneity.

## VI. FUTURE DIRECTIONS

Each of the studies cited in this paper addressed a specific heterogeneity. Therefore, the proposed methods and associated outcomes are not general since they are not representative of any range of agricultural landscapes.

There is a lack of studies dealing with vertical heterogeneity. Unmixing methods that rely on RTM inversion must focus on multi-layer models rather than simple linear models. This requires using multispectral and multiangular observations.

We recommend accounting for the difference between temporal dynamics of canopy elements (e.g., understory or tree crown). A possible solution is to exploit these dynamics as a priori information for RTM inversion, or to decompose the time series of the composite signal through wavelet analysis.

The influence of inherent measurement factors is rarely investigated when addressing spatial heterogeneity. Multiple scattering or topography must be taken into account in both RTM direct and inverse modes. We also suggest developing correction methods for sensor PSF and gridding artefacts [53].

Forthcoming sensors with high spatiotemporal resolution [54, 55] will offer new possibilities to address these issues. Thus, the scientific community can benefit from observations compatible with the temporal dynamics and spatial patterns of agricultural landscapes.

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## REFERENCES

- [1] F. Baret and S. Buis, "Estimating Canopy Characteristics from Remote Sensing Observations: Review of Methods and Associated Problems," in *Advances in Land Remote Sensing*, S. Liang, Ed., ed: Springer Netherlands, 2008, pp. 173-201.
- [2] F. Jacob, T. Schmugge, A. Olioso, *et al.*, "Modeling and Inversion in Thermal Infrared Remote Sensing over Vegetated Land Surfaces," in *Advances in Land Remote Sensing*, S. Liang, Ed., ed: Springer Netherlands, 2008, pp. 245-291.
- [3] D. J. Marceau and G. J. Hay, "Remote sensing contributions to the scale issue," *Can. J. Remote Sens.*, vol. 25, pp. 357-366, 1999.
- [4] G. Duveiller and P. Defourny, "A conceptual framework to define the spatial resolution requirements for agricultural monitoring using remote sensing," *Remote Sens. Environ.*, vol. 114, pp. 2637-2650, 2010.
- [5] E. Tarnavsky, S. Garrigues, and M. E. Brown, "Multiscale geostatistical analysis of AVHRR, SPOT-VGT, and MODIS global NDVI products," *Remote Sens. Environ.*, vol. 112, pp. 535-549, 2008.
- [6] J. M. Chen, "Spatial Scaling of a Remotely Sensed Surface Parameter by Contexture," *Remote Sens. Environ.*, vol. 69, pp. 30-42, 1999.
- [7] S. G. Plexida, A. I. Sfougaris, I. P. Ispikoudis, *et al.*, "Selecting landscape metrics as indicators of spatial heterogeneity—A comparison among Greek landscapes," *International Journal of Applied Earth Observation and Geoinformation*, vol. 26, pp. 26-35, 2014.
- [8] C. Gomez, P. Lagacherie, and G. Coulouma, "Regional predictions of eight common soil properties and their spatial structures from hyperspectral Vis-NIR data," *Geoderma*, vol. 189-190, pp. 176-185, 2012.
- [9] J. M. Chen, C. H. Menges, and S. G. Leblanc, "Global mapping of foliage clumping index using multi-angular satellite data," *Remote Sens. Environ.*, vol. 97, pp. 447-457, 2005.
- [10] B. Pinty, J. L. Widlowski, N. Gobron, *et al.*, "Uniqueness of multiangular measurements. I. An indicator of subpixel surface heterogeneity from MISR," *IEEE Trans. Geosci. Remote Sens.*, vol. 40, pp. 1560-1573, 2002.
- [11] Q. Wang and P. Li, "Canopy vertical heterogeneity plays a critical role in reflectance simulation," *Agric. For. Meteorol.*, vol. 169, pp. 111-121, 2013.
- [12] J.-L. Widlowski, B. Pinty, T. Lavergne, *et al.*, "Horizontal radiation transport in 3-D forest canopies at multiple spatial resolutions: Simulated

- impact on canopy absorption," *Remote Sens. Environ.*, vol. 103, pp. 379-397, 2006.
- [13] P. Stenberg, M. Möttöus, and M. Rautiainen, "Modeling the Spectral Signature of Forests: Application of Remote Sensing Models to Coniferous Canopies," in *Advances in Land Remote Sensing*, S. Liang, Ed., ed: Springer Netherlands, 2008, pp. 147-171.
- [14] C. van der Tol, W. Verhoef, J. Timmermans, *et al.*, "An integrated model of soil-canopy spectral radiances, photosynthesis, fluorescence, temperature and energy balance," *Biogeosciences*, vol. 6, pp. 3109-3129, 2009.
- [15] R. López-Lozano, F. Baret, M. Chelle, *et al.*, "Sensitivity of gap fraction to maize architectural characteristics based on 4D model simulations," *Agric. For. Meteorol.*, vol. 143, pp. 217-229, 2007.
- [16] J. Li, Z. I. Li, M. Menenti, *et al.*, "A practical algorithm to infer soil and foliage component temperatures from bi-angular ATSR-2 data," *Int. J. Remote Sens.*, vol. 24, pp. 4739-4760, 2003.
- [17] J. Pisek, M. Rautiainen, J. Heiskanen, *et al.*, "Retrieval of seasonal dynamics of forest understory reflectance in a Northern European boreal forest from MODIS BRDF data," *Remote Sens. Environ.*, vol. 117, pp. 464-468, 2012.
- [18] S. Jacquemoud, W. Verhoef, F. Baret, *et al.*, "PROSPECT + SAIL models: A review of use for vegetation characterization," *Remote Sens. Environ.*, vol. 113, pp. S56-S66, 2009.
- [19] T. Yu, G. XingFa, T. Guoliang, *et al.*, "Modeling directional brightness temperature over a maize canopy in row structure," *IEEE Trans. Geosci. Remote Sens.*, vol. 42, pp. 2290-2304, 2004.
- [20] M. I. Disney, P. Lewis, and P. R. J. North, "Monte Carlo ray tracing in optical canopy reflectance modelling," *Remote Sens. Rev.*, vol. 18, pp. 163-196, 2000.
- [21] S. Y. Kotchenova, N. V. Shabanov, Y. Knyazikhin, *et al.*, "Modeling lidar waveforms with time-dependent stochastic radiative transfer theory for remote estimations of forest structure," *J. Geophys. Res. (D Atmos.)*, vol. 108, p. 4484, 2003.
- [22] B. Martínez, F. J. García-Haro, and F. Camacho-de Coca, "Derivation of high-resolution leaf area index maps in support of validation activities: Application to the cropland Barrax site," *Agric. For. Meteorol.*, vol. 149, pp. 130-145, 2009.
- [23] M. Berterretche, A. T. Hudak, W. B. Cohen, *et al.*, "Comparison of regression and geostatistical methods for mapping Leaf Area Index (LAI) with Landsat ETM+ data over a boreal forest," *Remote Sens. Environ.*, vol. 96, pp. 49-61, 2005.
- [24] S. Liang, "Numerical experiments on the spatial scaling of land surface albedo and leaf area index," *Remote Sens. Rev.*, vol. 19, pp. 225-242, 2000.
- [25] Y. Liu, T. Hiyama, and Y. Yamaguchi, "Scaling of land surface temperature using satellite data: A case examination on ASTER and MODIS products over a heterogeneous terrain area," *Remote Sens. Environ.*, vol. 105, pp. 115-128, 2006.
- [26] M. Weiss, F. Baret, R. B. Myneni, *et al.*, "Investigation of a model inversion technique to estimate canopy biophysical variables from spectral and directional reflectance data," *Agronomie*, vol. 20, pp. 3-22, 2000.
- [27] S. Garrigues, D. Allard, F. Baret, *et al.*, "Influence of landscape spatial heterogeneity on the non-linear estimation of leaf area index from moderate spatial resolution remote sensing data," *Remote Sens. Environ.*, vol. 105, pp. 286-298, 2006.
- [28] Y. Tian, C. E. Woodcock, Y. Wang, *et al.*, "Multiscale analysis and validation of the MODIS LAI product: I. Uncertainty assessment," *Remote Sens. Environ.*, vol. 83, pp. 414-430, 2002.
- [29] B. Koetz, F. Morsdorf, G. Sun, *et al.*, "Inversion of a lidar waveform model for forest biophysical parameter estimation," *IEEE Geosci. Remote Sens. Lett.*, vol. 3, pp. 49-53, 2006.
- [30] L. Busetto, M. Meroni, and R. Colombo, "Combining medium and coarse spatial resolution satellite data to improve the estimation of sub-pixel NDVI time series," *Remote Sens. Environ.*, vol. 112, pp. 118-131, 2008.
- [31] O. Merlin, F. Jacob, J. P. Wigneron, *et al.*, "Multidimensional Disaggregation of Land Surface Temperature Using High-Resolution Red, Near-Infrared, Shortwave-Infrared, and Microwave-L Bands," *IEEE Trans. Geosci. Remote Sens.*, vol. 50, pp. 1864-1880, 2012.
- [32] W. Zhan, Y. Chen, J. Zhou, *et al.*, "Disaggregation of remotely sensed land surface temperature: Literature survey, taxonomy, issues, and caveats," *Remote Sens. Environ.*, vol. 131, pp. 119-139, 2013.
- [33] S. Garrigues, D. Allard, F. Baret, *et al.*, "Quantifying spatial heterogeneity at the landscape scale using variogram models," *Remote Sens. Environ.*, vol. 103, pp. 81-96, 2006.
- [34] P. C. Stoy, M. Williams, L. Spadavecchia, *et al.*, "Using Information Theory to Determine Optimum Pixel Size and Shape for Ecological Studies: Aggregating Land Surface Characteristics in Arctic Ecosystems," *Ecosystems*, vol. 12, pp. 574-589, 2009.
- [35] H. Ren, G. Yan, R. Liu, *et al.*, "Impact of sensor footprint on measurement of directional brightness temperature of row crop canopies," *Remote Sens. Environ.*, vol. 134, pp. 135-151, 2013.
- [36] J. L. Widlowski, M. Taberner, B. Pinty, *et al.*, "Third Radiation Transfer Model Intercomparison (RAMI) exercise: Documenting progress in canopy reflectance models," *J. Geophys. Res. (D Atmos.)*, vol. 112, p. D09111, 2007.
- [37] M. Williams, R. Bell, L. Spadavecchia, *et al.*, "Upscaling leaf area index in an Arctic landscape through multiscale observations," *Global Change Biol.*, vol. 14, pp. 1517-1530, 2008.
- [38] G. Duveiller, F. Baret, and P. Defourny, "Crop specific green area index retrieval from MODIS data at regional scale by controlling pixel-target adequacy," *Remote Sens. Environ.*, vol. 115, pp. 2686-2701, 2011.
- [39] J. Timmermans, W. Verhoef, C. van der Tol, *et al.*, "Retrieval of canopy component temperatures through Bayesian inversion of directional thermal measurements," *Hydrol. Earth Syst. Sci.*, vol. 13, pp. 1249-1260, 2009.
- [40] A. K. Inamdar and A. French, "Disaggregation of GOES land surface temperatures using surface emissivity," *Geophys. Res. Lett.*, vol. 36, p. L02408, 2009.
- [41] C. Xuehong, Y. Yamaguchi, C. Jin, *et al.*, "Scale Effect of Vegetation-Index-Based Spatial Sharpening for Thermal Imagery: A Simulation Study by ASTER Data," *IEEE Geosci. Remote Sens. Lett.*, vol. 9, pp. 549-553, 2012.
- [42] B. Combal, H. Isaka, and C. Trotter, "Extending a turbid medium BRDF model to allow sloping terrain with a vertical plant stand," *IEEE Trans. Geosci. Remote Sens.*, vol. 38, pp. 798-810, 2000.
- [43] C. Lauvernet, F. Baret, L. Hascoët, *et al.*, "Multitemporal-patch ensemble inversion of coupled surface-atmosphere radiative transfer models for land surface characterization," *Remote Sens. Environ.*, vol. 112, pp. 851-861, 2008.
- [44] C. Atzberger and K. Richter, "Spatially constrained inversion of radiative transfer models for improved LAI mapping from future Sentinel-2 imagery," *Remote Sens. Environ.*, vol. 120, pp. 208-218, 2012.
- [45] J. P. Lagouarde, S. Dayau, P. Moreau, *et al.*, "Directional anisotropy of brightness surface temperature over vineyards: case study over the Medoc region (SW France)," *IEEE Geosci. Remote Sens. Lett.*, vol. 11, pp. 574-578, 2014.
- [46] P. C. Guillevic, A. Bork-Unkelbach, F. M. Gottsche, *et al.*, "Directional Viewing Effects on Satellite Land Surface Temperature Products Over Sparse Vegetation Canopies - A Multisensor Analysis," *IEEE Geosci. Remote Sens. Lett.*, vol. 10, pp. 1464-1468, 2013.
- [47] P. J. Zarco-Tejada, L. Suarez, and V. Gonzalez-Dugo, "Spatial Resolution Effects on Chlorophyll Fluorescence Retrieval in a Heterogeneous Canopy Using Hyperspectral Imagery and Radiative Transfer Simulation," *IEEE Geosci. Remote Sens. Lett.*, vol. 10, pp. 937-941, 2013.
- [48] M. L. Guillen-Climent, P. J. Zarco-Tejada, and F. J. Villalobos, "Estimating Radiation Interception in Heterogeneous Orchards Using High Spatial Resolution Airborne Imagery," *IEEE Geosci. Remote Sens. Lett.*, vol. 11, pp. 579 - 583, 2013.
- [49] H. Kobayashi, R. Suzuki, S. Nagai, *et al.*, "Spatial Scale and Landscape Heterogeneity Effects on FAPAR in an Open-Canopy Black Spruce Forest in Interior Alaska," *IEEE Geosci. Remote Sens. Lett.*, vol. 11, pp. 564 - 568, 2013.
- [50] T. Ristorcelli, D. Hamoir, and X. Briottet, "Simulating Space Lidar Waveforms From Smaller-Footprint Airborne Laser Scanner Data for Vegetation Observation," *IEEE Geosci. Remote Sens. Lett.*, vol. 11, pp. 534 - 538, 2013.
- [51] M. Rautiainen and J. Heiskanen, "Seasonal Contribution of Understory Vegetation to the Reflectance of a Boreal Landscape at Different Spatial Scales," *IEEE Geosci. Remote Sens. Lett.*, vol. 10, pp. 923-927, 2013.
- [52] J. Wang, Y. Ge, G. B. M. Heuvelink, *et al.*, "Spatial Sampling Design for Estimating Regional GPP With Spatial Heterogeneities," *IEEE Geosci. Remote Sens. Lett.*, vol. 11, pp. 539 - 543, 2013.
- [53] B. Tan, C. E. Woodcock, J. Hu, *et al.*, "The impact of gridding artifacts on the local spatial properties of MODIS data: Implications for validation, compositing, and band-to-band registration across resolutions," *Remote Sensing of Environment*, vol. 105, pp. 98-114, 2006/11/30 2006.
- [54] M. Drusch, U. Del Bello, S. Carlier, *et al.*, "Sentinel-2: ESA's Optical High-Resolution Mission for GMES Operational Services," *Remote Sens. Environ.*, vol. 120, pp. 25-36, 2012.
- [55] J.-P. Lagouarde, M. Bach, J. A. Sobrino, *et al.*, "The MISTIGRI thermal infrared project: scientific objectives and mission specifications," *Int. J. Remote Sens.*, vol. 34, pp. 3437-3466, 2012.