Review

Spatiotemporal Fusion of Multisource Remote Sensing Data: Literature Survey, Taxonomy, Principles, Applications, and Future Directions

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Abstract: Satellite time series with high spatial resolution is critical for monitoring land surface dynamics in heterogeneous landscapes. Although remote sensing technologies have experienced rapid development in recent years, data acquired from a single satellite sensor are often unable to satisfy our demand. As a result, integrated use of data from different sensors has become increasingly popular in the past decade. Many spatiotemporal data fusion methods have been developed to produce synthesized images with both high spatial and temporal resolutions from two types of satellite images, frequent coarse-resolution images, and sparse fine-resolution images. These methods were designed based on different principles and strategies, and therefore show different strengths and limitations. This diversity brings difficulties for users to choose an appropriate method for their specific applications and data sets. To this end, this review paper investigates literature on current spatiotemporal data fusion methods, categorizes existing methods, discusses the principal laws underlying these methods, summarizes their potential applications, and proposes possible directions for future studies in this field.

Keywords: spatiotemporal data fusion; data blending; spatial resolution; temporal resolution; satellite images

1. Introduction

Dense time-series data from satellites are highly desired for studying dynamics of our Earth systems. For instance, dense time-series data contain the temporal information of objects on the land surface, which are extremely helpful for discriminating different land cover types [1], monitoring vegetation seasonality [2], modeling the carbon sequestration [3], estimating crop yields [4], exploring the human-nature interactions [5], and revealing the ecosystem-climate feedback [6]. Time series-based studies have become extremely popular in this decade because the number of free satellite images available to the public are increasing. For example, all Landsat data have been available at no charge since 2008 and now data from a new satellite, Sentinel-2, are also free of charge. Additionally, a free cloud computing platform, Google Earth Engine (GEE), currently promotes the use of time-series satellite data for large area monitoring of land and water dynamics because it has super ability to process massive satellite images [7].

However, these available satellite images still cannot satisfy our needs for studying high-frequency change in heterogeneous landscapes, such as monitoring the progress of construction work in cities and producing real-time map of urban hazards (e.g., landslides and floods). These studies need satellite images with high frequency as well as high spatial resolution. Due to the tradeoff between

scanning swath and pixel size, existing satellites are hard to obtain images with both high temporal resolution (or temporal frequency) and high spatial resolution [8]. Table 1 lists most of the existing multispectral satellite sensors with spatial resolution larger than 10 m. The commercial satellites with very high spatial resolutions, e.g., meter to sub-meter, are not included in Table 1 since they can be costly to composite time-series data. From Table 1, we can see that high-frequency data have coarse spatial resolutions, such as AVHRR, MODIS and SeaWiFS which collects daily images, but their spatial resolutions range from 250 m to 1000 m. On the other hand, the sub 100 m sensors, such as ASTER, Landsat (TM, ETM+, OLI), and Sentinel-2 MSI, have a relatively long revisit cycle, e.g., longer than 10 days. In addition, optical satellite images are contaminated by clouds, cloud shadows, and other atmospheric conditions. These contaminations further hinder the acquisition of dense time series data from sub 100 m sensors, especially in cloudy regions such as tropical and subtropical areas [9]. Although new technologies developed in recent years, such as Unmanned Aerial Vehicles (UAVs), provide a valuable supplement to traditional satellites, scientists still face challenges when studying land surface dynamics of the complex environment over a long period (e.g., several decades) because only satellite images documented the early years. For example, Landsat images are the only data source appropriate for studying any land cover changes in the past 40 years because of their relatively high spatial resolution and long-term archives since 1972. Therefore, how to integrate images from multiple satellites to generate high-quality dense time-series data becomes an urgent task for studies which require observations with high frequency and high spatial resolution.

Spatiotemporal data fusion is a feasible solution for the aforementioned problem. Spatiotemporal data fusion is a type of methodology for fusing satellite images from two sensors, sensor one with very high frequency but coarse spatial resolution such as MODIS and AVHRR, and sensor two with very high spatial resolution but lower frequency such as Landsat and Sentinel-2. The output of spatiotemporal data fusion is the synthesized images with temporal frequency of sensor one and spatial resolution of sensor two (Figure 1). It can also integrate two sensors with similar spatial and temporal resolutions to generate consistent observations, such as harmonizing Landsat and Sentinel-2 images [10]. Spatiotemporal data fusion provides a better dataset with higher spatial and temporal resolutions and thus it is a feasible and effective tool to overcome the limitations of current satellites. It is needed to point out that spatiotemporal data fusion is different from the traditional image fusion in the remote sensing field. Traditional data fusion focuses more on combining high-resolution panchromatic band and low-resolution multispectral bands from the same sensor and both data sets are acquired at the same time. Traditional data fusion technologies include Brovey transformation, the intensity-hue-saturation (IHS) transformation, principal component substation, wavelet decomposition, and Gram-Schmidt spectral sharpening method [11]. The major difference between traditional data fusion and spatiotemporal data fusion is that traditional data fusion cannot improve the temporal frequency of the original images.
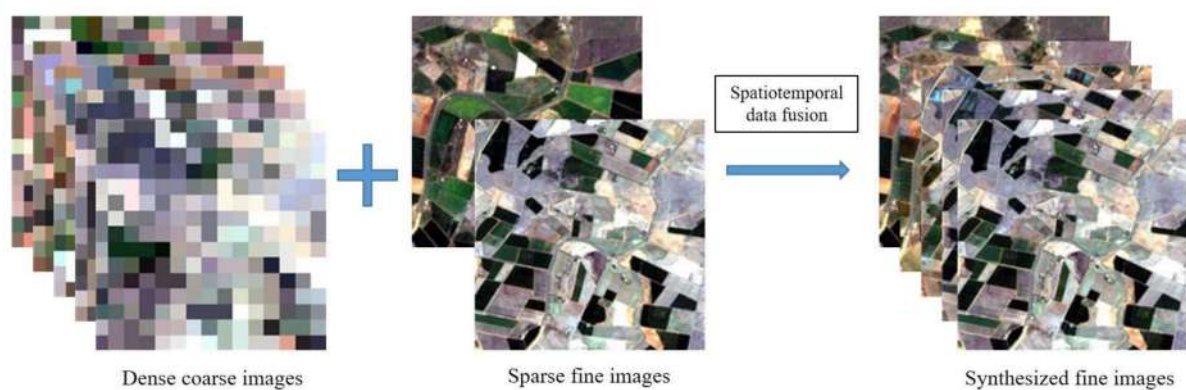

Figure 1. The input and output of spatiotemporal data fusion.

Table 1. Existing satellite sensors collecting multispectral images with spatial resolution larger than 10 m.

Satellite	Sensor	Spatial Resolution	Revisit Cycle	Operational Period
NOAA	AVHRR	1.1 km	12 h	From 1978
Terra/Aqua	MODIS	Band 1–2: 250 m Band 3–7: 500 m Band 8–36: 1000 m	1 day	From 2000
Terra	ASTER	VNIR: 15 m SWIR: 30 m TIR: 90 m	16 days	From Dec-1999
Landsat	MSS (Landsat 1–3)	79 m	18 days	From 1972 to 1983
	MSS+TM(Landsat5)	VNIR: 30 m TIR: 120 m	16 days	From 1984 to 2013
	ETM+(Landsat-7)	VNIR: 30 m TIR: 60 m	16 days	From 1999
	OLI(Landsat-8)	VNIR: 30 m TIR: 100 m	16 days	From 2013
OrbView-2	Sealifts	1 km	1 day	From 1997
SPOT	HRV(SPOT1–3) VGT(SPOT-4) HRG/HRS/VGT(SPOT-5)	20 m 1.15 km HRG-VNIR: 10 m HRG-SWIR: 20 m	26 days (VGT 1 day)	From 1986
ENVISAT	MERIS	300 m	35 days	From 2002 to 2012
Sentinel-2	MSI	10 m: (VNIR) B2,3,4,8 20 m: B5,6,7,8A,11,12 60 m: B1,9,10	10 days with one satellite and 5 days with 2 satellites	From Jun-2015
HJ-1A/1B	Multi-spectral sensor	30 m	31 days	From 2009
TH-1	Multi-spectral sensor	10 m	58 days	From Aug-2010
BJ-1	Multi-spectral sensor	32 m		From Oct-2005
CBERS-01/02	Multi-spectral sensor	Multi-spectral-CCD: 19.5 m	26 days	CBERS-01: From 1999 to 2002
		Multi-spectral-IRMSS: 78 m/156 m	26 days	CBERS-02: From Oct-2003
ZY-1 02B	Multi-spectral sensor	20 m	26 days	From Sep-2007
ZY-1 02C	Multi-spectral sensor	10 m	55 days	From Apr-2012
SJ-9A	Multi-spectral sensor	10 m	69 days	From Oct-2012
ALOS	AVNIR-2	10 m	46 days	From 2006 to 2011
ADEOS	Multi-spectral sensor	700 m	41 days	From 1996 to 1997
JERS-1	OPS	18 m	44 days	From 1992 to 1998
IRS-1A/1B	LISS-I/LISS-II/LISS-A/ LISS-B	72.5 m(LISS-I); 36 m(LISS-II)	22 days	From 1988
IRS-1C/1D	LISS-III	23.5 m; 70 m	24 days	From 1995 to 2010
IRS-P3	WiFS/MOS	188 m(WiFS); 1500 m/520 m/ 550 m(MOS)	5 days	From 1996 to 2004
IRS-P6	LISS-IV/LISS-III/AWiFS	5.8 m(LISS-IV)/23.5 m (LISS-III)/70 m(AWiFS)	24 days	From 2003
THEOS	Multi-spectral sensor	15 m	26 days	From Oct-2008

Spatiotemporal data fusion has experienced a fast development in the past decade. Up to the end of 2017, 44 different spatiotemporal data fusion methods have been published in major refereed journals in the field of remote sensing and the number of new methods increased dramatically since 2013 (Figure 2a). The total citations of these 58 papers is 2, 112 in Web of Science and shows a dramatic increase yearly (Figure 2b). The spatial and temporal adaptive reflectance fusion model (STARFM) developed in 2006 is the first operational algorithm with free code for users. It has been widely used and became the basis for many other methods which partially explains the increase in both new spatiotemporal fusion methods and citations after 2006. Although spatiotemporal data fusion garnered a lot of attention in recent years,

to our knowledge there is no thorough review article to summarize the progress on this topic. Zhang et al. generalized the spatiotemporal data fusion methods developed up to November 2014 [12]. Chen et al. did a comparison among four spatiotemporal data fusion methods [13]. Gao et al. reviewed STARFM and two extended methods as well as their applications in vegetation monitoring [14]. It is urgent to survey the current literature to guide future research on this topic.

This review investigates literature on current spatiotemporal data fusion methods, categorizes existing methods, discusses the principal laws underlying these methods, summarizes their applications, presents the key issues, and proposes possible directions of future studies on this topic.
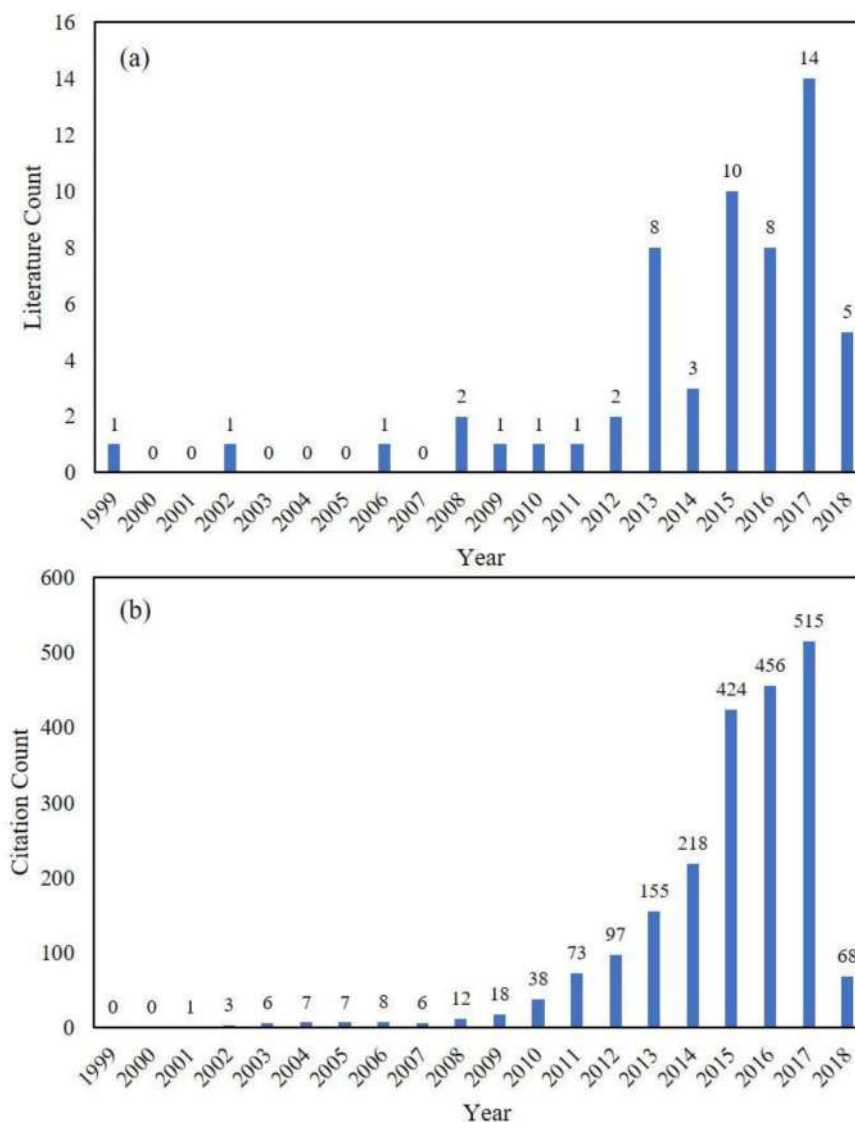

Figure 2. (**a**) Yearly literature counts of journal papers introducing spatiotemporal data fusion methods and (**b**) citation counts of these papers in Web of Science. The search was conducted on 10 March 2018.

2. Literature Survey

We collected spatiotemporal data fusion methods published in refereed journals of the remote sensing field. These 58 papers were published in 11 major international journals in the field of remote sensing (Table 2). Methods published in conference proceedings or other journals may have been omitted in this literature analysis, but majority of existing spatiotemporal data fusion methods should be included in Table 2. Among these 11 journals, 15 out of 58 methods were published in Remote

Sensing of Environment, a top journal in the field of remote sensing, which confirms that as one of new data processing techniques, spatiotemporal data fusion has attracted a lot of attention and has been widely accepted by the remote sensing community. It should be noted that papers on spatiotemporal data fusion applications were not included in this section. They are discussed in Section 5. For convenience, papers introducing new spatiotemporal fusion methods are referred as methodology papers hereinafter, and papers only applying spatiotemporal fusion methods to study scientific or practical problems are referred as application papers.

Table 2. Number of methodology papers of spatiotemporal data fusion published in 11 major journals in the field of remote sensing. The search was conducted on 10 March 2018.

Source Titles	Records	Percentage	Literature
Remote Sensing of Environment	15	25.86%	[11,15–28]
IEEE Transactions on Geoscience and Remote Sensing	14	24.14%	[8,29–41]
Remote Sensing	10	17.24%	[42–51]
International Journal of Remote Sensing	5	8.62%	[52–56]
IEEE Geoscience and Remote Sensing Letters	4	6.90%	[57–60]
International Journal of Applied Earth Observation and Geoinformation	2	3.45%	[61,62]
Journal of Applied Remote Sensing	2	3.45%	[63,64]
Sensors	2	3.45%	[65,66]
IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing	2	3.45%	[67,68]
GIScience and Remote Sensing	1	1.72%	[69]
Remote Sensing Letters	1	1.72%	[70]
TOTAL	58	100%	

Currently, "spatiotemporal data fusion" is a term commonly used to name this type of data fusion technology. This term can well distinguish this type of fusion methods from traditional pan-sharpening methods which only improve images in spatial and spectral domains. However, in the early years, the names are quite inconsistent. Developers named their methods in different ways. This can be reflected by the words used in the titles (Figure 3a) and keywords of the 58 methodology papers (Figure 3b). "fusion", "spatial", and "temporal" are frequent words used in titles and keywords which exactly reflect the nature of spatiotemporal data fusion, i.e., technology to improve spatial and temporal resolutions of multi-source satellite images. "MODIS" and "Landsat" are also frequently used in the titles and keywords, suggesting that most spatiotemporal data fusion models were proposed to fuse MODIS and Landsat data or used them as representatives of coarse images and fine images respectively. Although most spatiotemporal fusion methods were applied to data from satellites listed in Table 1, it is worthwhile to mention that spatiotemporal fusion methods can also fuse high-resolution images from commercial satellites, especially for small-scale studies. For instance, the 5 m RapidEye images was fused with 30 m Landsat images to improve the detection of local forest disturbance [71].
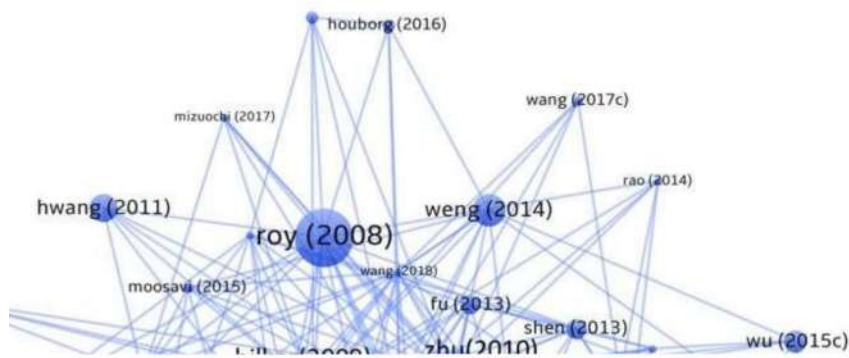
houborg (2016)

wang (2017c)

mizuochi (2017)

rao (2014)

hwang (2011)   weng (2014)

roy (2008)

moosavi (2015)   wang (2018)

fu (2013)

shen (2013)   wu (2015c)

zhu(2010)

Figure 3. (**a**) A tag cloud of the literature titles of the 58 papers introducing new spatiotemporal fusion methods, where a larger font and darker color denote a higher frequency; and (**b**) count of keywords with frequency larger than 4.

The literature citation map was plotted by VOSViewer (Figure 4). The most cited paper is the one developing STARFM [8] which has been cited by most other methodology papers. Other high-citation papers include ones developing ESTARFM [11], STAARCH [27], and a semi-physical fusion method [19]. These papers are in the center of the citation map.

Figure 4. Citation map of the literature in Table 2. The size of nodes indicates the count of citations. The citation relationship was derived from Web of Science.

3. Taxonomy

In a previous work [26], typical spatiotemporal data fusion methods were classified into three groups: unmixing-based, weight function-based, and dictionary-pair learning-based. However, this classification scheme cannot cover all spatiotemporal fusion methods. In the current review, existing spatiotemporal data fusion methods are categorized into five groups based on the specific techniques used to link coarse and fine images: unmixing-based, weight function-based, Bayesian-based, learning-based, and hybrid methods (Table 3). For convenience, the images with coarse spatial resolution but high frequency are referred as "coarse images" and pixels in these images as "coarse pixels", while the images with high spatial resolution but low frequency are called "fine images" and their pixels, "fine pixels". All the existing methods need to input one or more pairs of coarse and fine images and a coarse image at prediction date. The output is a synthetic fine image at prediction date.

Unmixing-based methods estimate the value of fine pixels through unmixing the coarse pixels based on the linear spectral mixing theory. The multisensor multiresolution technique (MMT) proposed by Zhukov, Oertel, Lanzl, and Reinhäckel (1999) is perhaps the first unmixing-based method to fuse satellite images acquired at different times and with different spatial resolutions. Other unmixing-based methods can be considered as improved versions of MMT. There are four steps in MMT to predict a fine-resolution image: (1) classify the input fine image to define endmembers; (2) compute endmember fractions of each coarse pixel; (3) unmix the coarse pixels at the prediction date within a moving window; (4) assign unmixed reflectance to fine pixels [31]. MMT has two major challenges: large errors in the spectral

unmixing and lack of within-class variability for fine pixels inside one coarse pixel. The subsequent unmixing-based methods are geared towards addressing these two challenges. For instance, LAC-GAS NDVI integration method used locally calibrated multivariate regression models to better reserve the within-class NDVI spatial variability [52]. Zurita-Milla et al. introduced constraints into the linear unmixing process to ensure that the solved reflectance values were positive and within an appropriate range [57]. STDFA estimated reflectance change through unmixing endmember reflectance at both input and prediction date in a moving window and then added the estimated change back to the base fine-resolution image to get the prediction [63]. STDFA was further improved by using adaptive moving window size [66]. The Landsat-MERIS fusion method modified the cost function to prevent the solved endmember reflectance from being greatly different from a predefined endmember reflectance [62]. OB-STVIUM employed multi-data segmentation to better define the endmember fractions for improving the estimation of the fine-scale pixel values [17].

Table 3. Categories of the existing spatiotemporal data fusion methods.

Category	Methods [1] and References
Unmixing-based	MMT [31]; LAC-GAC NDVI integration [52]; Landsat-MERIS fusion method [62]; ESTDFM [44]; STDFA [63]; MSTDFA [66]; OB-STVIUM [17]; MERIS-Landsat fusion [57]
Weight function-based	STARFM [8]; semi-physical fusion approach [19]; ESTARFM [11]; STAARCH [27]; SADFAT [21]; Topographically corrected downscaling [18]; STITFM [23]; STARFM-Sensor difference [54]; mESTARFM [45]; Bilateral Filter method [59]; ET fusion model [53]; STI-FM [64]; operational STARFM [33]; Three-step method [16]; STEM-LAI [61]; ATPPK [34]; ATPPK-STARFM [67]; STNLFFM [30]; Fast spatiotemporal fusion [55]; RWSTFM [47]; DBUX [25]; ISKRFM [56]; Temporal high-pass modulation and edge primitives method [36]; Decision-level fusion [39]; STVIFM [50]; Soil moisture downscaling [51]
Bayesian-based	BME [20]; Uni ed fusion [70]; NDVI-BSFM [46]; Bayesian data fusion approach [42]; Spatio-Temporal-Spectral fusion framework [38]
Learning-based	SPSTFM [29]; One-pair image learning method [35]; EBSPTM [32]; ELM-based method [58]; WAIFA [15]; bSBL-SCDL [48]; CSSF [37]; Regression tree-based method [69]; Evapotranspiration downscaling [49]; STFDCNN [68]; MRT [40]; Integrated sparse representation-based fusion [41]
Hybrid	FSDAF [26]; NDVI-LMGM [43]; Regularized spatial unmixing method [60]; STIMFM [22]; STRUM [24]; USTARFM [65]; BLEST [28]

[1] Names of these methods were extracted from the literature. If the methods were not named in the literature, the words describing the methods' major characteristics were used to name them here.

Weight function-based methods estimate ne pixel values through combining information of all input images by weight functions. Up to present, this category has the most methods developed (Table 3). The spatial and temporal adaptive re ectance fusion model (STARFM) is the weight function-based method developed rst [8]. STARFM assumes that changes of re ectance are consistent and comparable at coarse and ne resolutions if pixels in coarse-resolution images are "pure" pixels, in that, one coarse pixel only includes one land cover type. In this case, changes derived from coarse pixels can be directly added to pixels in ne-resolution images to get the prediction. However, this ideal situation cannot be satis ed when coarse pixels are mixed, having a mixture of different land cover types. Therefore, STARFM predicts pixels with a function that gives a higher weight to purer coarse pixels based on information from neighboring ne pixels. Given its simplicity and code available to the public, STARFM has been a popular method with 398 citations. However, it has two major issues: the assumption is not valid in heterogeneous landscapes and the weight function is empirical. Most other weight function-based methods improved STARFM with regards to the above two issues, or modi ed STARFM to fusion other products, such as land surface temperature (LST) [21], vegetation indices [50] and classi cation results [39], instead of re ectance. For example, the spatial temporal adaptive algorithm for mapping re ectance change (STAARCH) detects the change points

from dense time series of coarse images to improve STARFM's performance when land cover type change exists [27]. Enhanced STARFM (ESTARFM) introduces a conversion coefficient to improve STARFM's accuracy in heterogeneous areas [11]. SADFAT modified STARFM to blend LST data by considering annual temperature cycle and urban thermal landscape heterogeneity [21]. The original STARFM was also modified to an operational framework by integrating BRDF correction, automatic co-registration, and automatic selection of input data pairs [33]. ATPPK-STARFM first downscales 500 m MODIS images to 250 m before implementation of STARFM to increase the performance in abrupt changes and heterogeneous landscapes [67]. ISKRFM integrates image inpainting and steering kernel regression to detect land-cover changed regions and determine the weight function. These two steps improve the land cover issue and empirical weight function in the original STARFM method [56].

Bayesian-based methods use Bayesian estimation theory to fuse images in a probabilistic manner. In the Bayesian framework, the spatiotemporal fusion can be considered as a maximum a posterior (MAP) problem, i.e., the goal of spatiotemporal data fusion is to obtain the desirable fine image at the prediction date by maximizing its conditional probability relative to the input fine and coarse images [38]. Bayesian framework provides more flexibility in modeling the relationships between the input and predicted images using defined principles which allows an intuitive interpretation of fusion processes [70]. In Bayesian-based data fusion, the key is how to model the relationship between observed images (i.e., the input images) and unobserved image (i.e., the image to be predicted). In spatiotemporal data fusion, there are two types of relationships. One is the relationship between observed coarse image and fine image observed at the same date which we name as scale model, and the other one is the relationship between coarse images observed at different dates which we name as temporal model. The scale model incorporates knowledge of point spread function which maps the pixels of fine image to the pixels of the coarse image [42]. The temporal model describes the dynamics of land surface, including both gradual change such as vegetation seasonality and sudden land cover change such as forest fires and floods. Existing Bayesian-based spatiotemporal data fusion methods used different methods to model these relationships. In the Bayesian Maximum Entropy (BME) method, covariance functions were used to link coarse the Advanced Microwave Scanning Radiometer for Earth observing system (AMSR-E) sea surface temperature (SST) with 25 km resolution and fine MODIS SST with 4 km resolution [20]. In a unified fusion method, the low-pass filtering method was used to model the relationship between coarse and fine images and a linear model to model the temporal relationship [70]. In the NDVI-BSFM method, linear mixing model was used to link MODIS and Landsat NDVI and multi-year average NDVI time series was used to represent the temporal relationship [46]. In a recent Bayesian data fusion approach, integration of bilinear interpolation of coarse image and high-pass frequencies of fine image were used to model the scale model, and the joint covariance from the observed coarse images was employed as temporal model [42].

Learning-based methods employ machine learning algorithms to model the relationship between observed coarse-fine image pairs and then predict the unobserved fine images. Up to date, dictionary-pair learning [29], extreme learning [58], regression tree [69], random forest [49], deep convolutional neural networks [68], and artificial neural network [15] have been used for spatiotemporal data fusion. Dictionary-pair learning-based algorithms establish correspondences between fine- and coarse-resolution images based on their structural similarity which can be used to capture the main features, including land cover type changes, in the predictions. The Sparse-representation-based SpatioTemporal reflectance Fusion Model (SPSTFM) is perhaps the first to bring dictionary-pair learning techniques from natural image super-resolution to spatiotemporal data fusion [29]. SPSTFM establishes a correspondence between the change of two coarse and fine image pairs. Following SPSTFM, Song and Huang developed another dictionary-pair learning-based fusion method which uses only one pair of fine- and coarse-resolution images [35]. This method trains a dictionary pair on the input fine- and coarse-resolution image pair, and then downscales the coarse-resolution image at the prediction date by a sparse coding technique. To solve the problem of insufficient prior knowledge in the sparse representation, a new spatiotemporal fusion model is constructed with the semi-coupled dictionary learning and structural sparsity [48]. Furthermore,

the explicit down-sampling process from ne to coarse images were considered by compressed sensing which can further improve accuracy of the dictionary-based spatiotemporal fusion [37]. The error-bound-regularized sparse coding (EBSPTM) method is another dictionary-pair learning method which imposes a regularization on the error bounds of the dictionary perturbations to model the possible perturbations of the overcomplete dictionary [32]. The wavelet-arti cial intelligence fusion approach (WAIFA) couples wavelet transform with arti cial neural network to blend MODIS and Landsat land surface temperature data [15]. The main improvement of WAIFA is that the arti cial neural network can cope with the non-linear nature of the land surface temperature data. The extreme learning machine (ELM) method uses a powerful learning technique, extreme learning machine, to build a feature mapping function between raw pixels of coarse and ne images. Compared with SPSTFM, ELM achieves a better performance and uses less computing time [58].

Hybrid methods integrate two or more technologies from the above four categories. The aim is to improve the performance of spatiotemporal data fusion through combining the advantages of different methods. One representative of this kind is the Flexible Spatiotemporal Data Fusion (FSDAF) developed recently. FSDAF combined ideas from unmixing-based methods and the weighted function-based methods, as well as spatial interpolation. As a result, FSDAF is capable of fusing images in challenging scenarios, i.e., heterogeneous landscapes and abrupt land cover changes occurring between the input images and prediction. For the highly mixed pixels, their reflectance change can be estimated through solving the linear mixing equations. For the abrupt land cover changes, the spatial interpolation can capture it as long as it is shown in the coarse image. The idea of FSDAF was recently adapted by the BLEed Spatiotemporal Temperature (BLEST) method for fusing land surface temperature with different spatial resolutions [28]. The weight function was further used to combine the unmixing results and spatial interpolation to reduce the uncertainties. Another example is the spatial and temporal reflectance unmixing model (STRUM), which directly unmixed the change of coarse pixels by Bayesian theory to estimate the change of fine-resolution endmembers and then use the idea of STARFM to create the fused image using moving windows [24]. A recently developed method, Spatial-Temporal remotely sensed Images and land cover Maps Fusion Model (STIMFM), integrates the spectral linear mixing model and Bayesian framework for fusing multi-temporal coarse images and a few land cover maps from fine images to directly produce a series of fine-resolution land cover maps [22].

4. Principle Laws

Several fundamental laws or assumptions were used in existing spatiotemporal data fusion methods although they are not often clearly stated. This section highlights and discusses these laws in detail. The most common application scenario is that two coarse images at t_1 and t_2, and a ne image at t_1 are collected. We want to predict a ne image at t_2 by fusing the three collected images. Some notations and de nitions are given here for convenience.

m: the number of ne pixels (also named as subpixels) within one coarse pixel;

(x_i, y_i): coordinate index of the ith pixel;

$C_1(x_i, y_i, b)$ and $C_2(x_i, y_i, b)$: band b value of coarse pixel (e.g., MODIS) at location (x_i, y_i) observed at t_1 and t_2 respectively;

$F_1(x_i, y_i, b)$ and $F_2(x_i, y_i, b)$: band b value of ne pixel (e.g., Landsat) at location (x_i, y_i) observed at t_1 and t_2 respectively;

$F_1(x_{ij}, y_{ij}, b)$ and $F_2(x_{ij}, y_{ij}, b)$: band b value of the jth ne pixel within the coarse pixel at location (x_i, y_i) observed at t_1 and t_2 respectively;

fc(x_i, y_i): the fraction of class c of the coarse pixel (x_i, y_i);

F(c, b): the band b value of endmember class c at ne scale;

DC(x_i, y_i, b): change of band b value of the (x_i, y_i) coarse pixel between t_1 and t_2;

DF(x_{ij}, y_{ij}, b): change of band b value of the jth ne pixel inside the coarse pixel (x_i, y_i) between t_1 and t_2;

DF(c, b): change of band b value of class c at ne resolution between t_1 and t_2.

4.1. Linear Mixing Model

The linear mixing model can be used to link the pixels in the coarse image and ﬁne image by the equation below:

$$C(x_i, y_i, b) = \frac{1}{m} \sum_{j=1}^{m} F(x_{ij}, y_{ij}, b) + \varepsilon \tag{1}$$

For each coarse pixel, its pixel value is equal to the average of all internal ﬁne pixels adding a bias factor ε which is the systematic difference between two sensors. It can be caused by difference in bandwidth, solar geometry, and viewing angles [11]. The basic assumption for the linear mixing model is that the variable is linearly additive. For optical satellite images, the raw images record the radiance, and is often converted to reﬂectance for end users. Both radiance and reﬂectance of individual spectral bands are linearly additive. However, some higher-level products derived from the raw data are not linearly additive, such as some vegetation indices (e.g., NDVI, EVI) and land surface temperature. Existing studies show that using linear mixing model to link these products at different scales may not introduce signiﬁcant errors [72,73], so some existing methods also use linear mixing model for fusing these high-level products, such as the NDVI-LMGM model for fusing MODIS and Landsat NDVI products [43], and the SADFAT for fusing LST products [21].

Although linear mixing model is the start point of many spatiotemporal fusion methods, it is used in two fashions. In the unmixing-based method [57,62,63], the internal ﬁne pixels are aggregated into several land cover classes. Then, Equation (1) can be rewritten as:

$$C(x_i, y_i, b) = \sum_{c=1}^{l} f_c(x_i, y_i) \cdot F(c, b) \tag{2}$$

In this equation, fraction of land cover types $f_c(x_i, y_i)$ can be estimated from the classiﬁcation map of the given ﬁne image at t_1 or any ﬁne-scale land cover maps, and this fraction is assumed to be stable across different times. The endmember's spectral values of each land cover $F(c, b)$ can be estimated through solving the linear equation system composed by multiple coarse pixels:

$$\begin{bmatrix} C(x_1, y_1, b) \\ \vdots \\ C(x_i, y_i, b) \\ \vdots \\ C(x_n, y_n, b) \end{bmatrix} = \begin{bmatrix} f_1(x_1, y_1) & f_2(x_1, y_1) & & f_l(x_1, y_1) \\ \vdots & \vdots & & \vdots \\ f_1(x_i, y_i) & f_2(x_i, y_i) & & f_l(x_i, y_i) \\ \vdots & \vdots & & \vdots \\ f_1(x_n, y_n) & f_2(x_n, y_n) & & f_l(x_n, y_n) \end{bmatrix} \begin{bmatrix} F(1, b) \\ \vdots \\ F(c, b) \\ \vdots \\ F(l, b) \end{bmatrix} \tag{3}$$

All the pixel values of coarse and ﬁne images in Equations (1)–(3) can be replaced by the pixel value change between t_1 and t_2. As a result, the temporal change at ﬁne-scale $DF(c, b)$ can be estimated by solving the linear equation system. For the unmixing-based methods, their efforts are input for how to select more appropriate coarse pixels to compose the linear equation system, how to improve the accuracy of solving the equation system, how to distribute the solved endmember values to ﬁne pixels, how to compensate the residuals and how to add the inner-class variations to the fused results.

Linear mixing model is also the basis of many weighted function-based methods. Unlike the unmixing-based methods, weighted function-based methods do not solve the linear mixing equation system. They use further assumptions to simplify the mixing equation, so that the temporal change of the internal ﬁne pixels can be directly estimated from the corresponding coarse pixel. For example, STARFM just simply assumes that the temporal change of all internal ﬁne pixels is equal to the corresponding coarse pixel:

$$F_2(x_{ij}, y_{ij}, b) - F_1(x_{ij}, y_{ij}, b) = C_2(x_i, y_i, b) - C_1(x_i, y_i, b) \tag{4}$$

Equation (4) is a specific case of Equation (1) if we assume that all internal fine pixels have same temporal change. This assumption is only valid when all internal fine pixels are from same land cover type, i.e., the corresponding coarse pixel is "pure" pixel. The subsequent enhanced versions of STARFM try to improve Equation (4) to make it capable of estimating temporal change more accurately. For example, ESTARFM introduced a conversion coefficient to adjust the temporal change from coarse pixels to fine pixels [11] and STAARCH selected optimal input fine images through the change detection on dense time series of coarse images [27].

4.2. Spatial Dependence

Spatial dependence is a rule used by nearly all spatiotemporal fusion algorithms. According to Tobler's first law of geography, everything is related but nearby things are more related [74]. Satellite images observe the spectral information of objects on land surface. It is very reasonable to assume that nearby objects have similar spectral characteristics if they are from the same land cover. The pixels of these objects are named as similar pixels in the STARFM method and other STARFM-like methods (Figure 5a) [8,11,26]. Similar pixels exhibit spatial dependence, for example, in a forest region, neighboring pixels are more likely from the same tree species and have similar structural attributes, such as tree height and stem density. As a result, these pixels have higher similarity in spectral characteristics, and higher consistency in temporal change across time. In Geostatistics, for similar pixels with a spatial distance h, the spatial dependence can be estimated as covariance C(h) [75]:

$$C(h) = \frac{1}{n(h)} \sum_{d_{ij} = h} [(F_1(x_i, y_i, b) - \overline{F})(F_1(x_j, y_j, b) - \overline{F})] \tag{5}$$

where $n(h)$ is the number of similar pixel pairs with distance h, d_{ij} is the spatial distance between ith and jth similar pixels, and $\overline{F}$ is the average value of these similar pixels. Normally, the covariance is different at each spatial distance as depicted by the curve in Figure 5b. The covariance decreases with distance until a saturated point is reached.

Figure 5. (a) Diagram of similar pixels and (b) shape of normal covariance functions.

In STARFM and all STARFM-like algorithms, they use the spatial dependence property to reduce the uncertainty and block effect of fusion results, but they do not use covariance in Equation (5) to describe the spatial dependence. For simplification, these algorithms use the inverse distance (1/h) as the alternative of the covariance function. The initial fused result of an individual pixel has a lot of uncertainties due to the error in geo-referencing between two types of images and image noises, however, combining fused results of all similar pixels can average out abnormal prediction of an individual pixel. The spatial dependence is used to weight these similar pixels when they are combined [8,11]. For methods such as FSDAF, most of the calculations are implemented within each

coarse pixel, which may lead to the block effect in the fused image, i.e., showing the footprint of coarse pixels in the fused ne image. To mitigate this block effect, predictions of similar pixels from a moving window covering several coarse pixels are combined using spatial dependence as the weight [26].

In unmixing-based methods, the spatial dependence property of satellite images is used to solve ne-scale endmember values. To successfully estimate the unknown variables in the linear equations (Equation (3)), the number of coarse pixels must be equal or larger than the number of land cover classes. Assuming nearby coarse pixels should have high similarity in endmember values due to spatial dependence, then, a given coarse pixel and its spatially neighboring coarse pixels are employed to compose the equation system in Equation (3) to estimate its ne-scale endmember values [43].

4.3. Temporal Dependence

Temporal dependence means the spectral value of a pixel at t_2 is correlated to that at t_1. In other words, pixel value at t_2 can be estimated as a function of pixel value at t_1. Figure 6 shows a temporal pro le of NDVI of a pixel. Although the temporal pro le is not a linear function, it can be divided into many short linear sections. The whole pro le can be considered as a combination of all these linear sections. With this simpli cation, the temporal relationship can be expressed as:

$$F_2(x_i, y_i, b) = a(x_i, y_i, b) F_1(x_i, y_i, b) + b(x_i, y_i, b) \qquad (6)$$

or

$$F_2(x_i, y_i, b) = F_1(x_i, y_i, b) + b(x_i, y_i, b), \qquad if \qquad a(x_i, y_i, b) = 1 \qquad (7)$$

where $a(x_i, y_i, b)$ and $b(x_i, y_i, b)$ are two coef cients for the pixel (x_i, x_j) of band b. Both Equations (6) and (7) are used in existing spatiotemporal data fusion methods. Here, the key is to estimate two coef cients. Different spatiotemporal methods employ different strategies. STARFM employs Equation (7) and estimates $b(x_i, y_i, b)$ directly from coarse pixels using $C_2(x_i, y_i, b) \quad C_1(x_i, y_i, b)$ assuming this coef cient is same between coarse images and ne images if the coarse pixels are pure pixels, i.e., only including one land cover type [8]. This assumption is not valid for many cases in reality, so ESTARFM added a conversion coef cient V to adjust the estimation from coarse pixels using $V[C_2(x_i, y_i, b) \quad C_1(x_i, y_i, b)]$ [11]. In a method developed recently for fusing Sentinel-2 and Sentinel-3 images, Equation (6) is used and the two coef cients are estimated from coarse pixels in a moving window using least square regression [16]. This method assumes the coef cients in Equation (6) are scale invariant and uses a residual compensation step to reduce the errors induced by this assumption.

Figure 6. Schematic diagram of a NDVI curve and its linear segments (derived from paper [43]).

5. Applications

5.1. Agriculture

Crop progress and yield are affected by environmental conditions (e.g., groundwater or soil types) and climatic conditions (e.g., precipitation and temperature) [76,77]. Those factors vary with time and space. Coarse satellite images, such as MODIS and AVHRR, which can provide daily data were widely used to monitor the crop growth from the sowing to maturing stages and thus estimate the yield [78–81]. Although the short revisit cycle of these images can successfully monitor rapid dynamics in agriculture, the coarse resolution is often inadequate for highly heterogeneous areas such as agricultural landscapes in south China. In recent years, the high spatial and temporal resolution images generated by spatiotemporal data fusion have been explored to improve agricultural studies, such as, crop yield and gross primary productivity (GPP) estimation, crop growth monitoring and management [82–85].

As the most popular applications in agriculture remote sensing, crop yield, biomass and GPP estimation, can reflect the superiority of spatiotemporal data fusion methods. For example, a study in China blended HJ-1 CCD and MODIS images by the Spatial and Temporal Adaptive Vegetation index Fusion Model (STAVFM) to predict crop biomass. Its result shows that the correlation between winter wheat biomass estimated by STAVFM and actual observations is very high (R^2 reaches 0.876) [84]. Similarly, GPP estimated from field observation and from Landsat-MODIS fused images shows a strong agreement in wheat ($R^2 = 0.85, p < 0.01$) and sugarcane ($R^2 = 0.86, p < 0.01$) in India [86]. In addition, timely monitoring of crop growth is important for farming management [87]. Synthesized data could be used to provide near real-time estimate of external conditions (e.g., water and soil conditions) and internal attributes (e.g., leaf chlorophyll and protein content) of crops. For instance, soil evapotranspiration (ET), a key factor for crop growth, were estimated from fused ASTER-MODIS images by STARFM and compared with daily ET field observations. The results indicate that the bias and root mean squared error (RMSE) of ET estimated from fused images are smaller than a satellite-based ET product, especially in maize and vegetable sites [88].

5.2. Ecology

Traditionally, data collected from field survey are the main source for ecological studies. However, field data can hardly cover large areas and over long time periods [89,90]. Fortunately, many studies suggest that satellite images, in particular images generated by spatiotemporal data fusion, have a great potential for ecological applications [14,91,92], such as, ecological variables estimation (e.g., vegetation index and biomass), ecosystem dynamics monitoring (e.g., phenology of forest, grassland, dryland and wetland) and disturbances detecting (e.g., wild fires and tree disease) in ecosystems.

The improvement of using spatiotemporal data fusion has been demonstrated by several studies. For LAI modeling, the R^2 and RMSE between LAI derived from fused MODIS and Landsat images and ground measurement can reach 0.977 and 0.1585 $m^2 m^{-2}$ ($p < 0.005$), and such results are more accurate than MODIS LAI standard products [93]. For biomass estimation, synthetic NDVI time series from fusing MODIS-Landsat by STARFM can obtain accurate grassland biomass ($R^2 = 0.77$, RMSE = 17.22 g/m^2). It is more accurate than using NDVI from MODIS alone ($R^2 = 0.73$, RMSE = 30.61 g/m^2) [94]. For vegetation phenology detection, the synthetic EVI time series through fusing MODIS and Landsat images during 2005–2009 by STARFM can well characterize dryland vegetation phenology in Arizona, USA [95]. For forest disturbances detecting, data fusion also shows its superiority. To map forest disturbance, Landsat and MODIS reflectance data were fused using STAARCH. Compared with validation datasets, the spatial precision can reach 93% in Canada [27] and 89–92% in mixed forests of USA [96].

5.3. Land Cover Classification

Satellite images have been widely used for land cover classification. However, errors in land cover classification are unavoidable if different land covers have similar spectral characteristics in satellite images. For example, most land cover types of vegetation, such as grassland, farming land and forest,

have very similar spectral signals in the summer season; it is impossible to accurately differentiate these land cover types using only summer satellite images [97]. Data generated by spatiotemporal data fusion can improve the accuracy from two aspects: high frequency and high spatial resolution. High frequency can obtain temporal information of different land cover types which is a valuable supplement to spectral information, and high spatial resolution can reduce the number of mixed pixels.

A study applied and compared two data fusion models, STARFM and ESTARFM, in generating synthetic images from Landsat and MODIS for mapping ooded areas. Results show that both fusion methods can get ood maps with much higher accuracy than those only using MODIS images [98]. Another study classi ed the land cover using seven phenological parameters derived from NDVI with high spatial and temporal resolutions. The NDVI data was generated by STARFM fusing GF-1 and MODIS NDVI dataset in Hebei Province of China. The overall classi cation accuracy of using fused data is 88.8%, which represents an increase of 9.3 percentage compared to GF-1 spectral data alone [99]. A recent study fusing Landsat with MODIS, China Environment 1A series (HJ-1A), and Advanced Spaceborne Thermal Emission and Re ection (ASTER) digital elevation model (DEM) data, showed that the fused data, integrating temporal, spectral, angular, and topographic features can get better land cover classi cation accuracy than the original data from an individual source [100].

6. Issues and Future Directions

6.1. Precise Image Alignment

Spatiotemporal data fusion is implemented on images from two different satellite sensors. These images have many differences although they have similar spectral con guration. These differences include spatial resolution, band width, spectral response function, atmospheric conditions, solar geometry and viewing angle. In addition, with the fast development of UAVs witnessed in recent years, fusing UAV images with satellite images is needed in the future. However, the difference between UAV and satellite images is even larger than that between two satellite sensors [101]. Theoretically, spatiotemporal data fusion requires that the coarse pixel and its internal ne pixels observe the same piece of land surface with same observing geometry. A precise image alignment is then required to mitigate the differences between the two types of images. Speci cally, differences in band width, spectral response function, and even atmospheric condition (when the image size is small) more than likely cause systematic bias between the two types of images. This systematic bias can be reduced through relative calibration, such as using a linear regression or histogram matching method. However, most spatiotemporal data fusion methods, such as STARFM and ESTARFM, already take the systematic bias into account, so systematic bias is not a factor affecting the fusion accuracy very much. Different solar geometry and viewing angles of two sensors lead to pixel-wise difference because of the BRDF effect. For example, MODIS has a larger swath with larger viewing angles than Landsat, and its sun elevation is also a little bit different from Landsat. BRDF effect causes both MODIS and Landsat to not observe the exactly same part of Landsat surface. Pixel-wise difference is hard to remove during the data fusion process. As a result, BRDF adjustment may be a necessary preprocessing step to improve the accuracy of data fusion, although it is often ignored in most studies. Lastly, different spatial resolution is the reason for spatiotemporal data fusion, but it also brings the most dif cult part in geo-registration between two types of images. Geo-registration error is the major error source in data fusion. Existing studies use both manual method and automatic method for geo-registration, but the accuracy cannot reach ne-pixel level. Future studies can consider developing spatiotemporal fusion methods which are less sensitive to the above differences between two sensors, especially the geo-registration error.

6.2. Dif culty in Retrieving Land Cover Change

Currently, the most dif cult case of spatiotemporal data fusion is the abrupt land cover change happening during the fusion period. The abrupt change is recorded in two coarse images at t_1 and

t_2, but the fine image at t_1 is prior to the change. A successful fused result of the fine image at t_2 should reflect the magnitude and extent of the change at fine resolution. Figure 7 shows such a case with flood event happening during fusion period. This event was recorded in the coarse images (c) and (d), but the boundary of flooded area is blurring due to the coarse resolution. Quite a few spatiotemporal data fusion methods were developed to improve the fusion results for this challenging case. For example, FSDAF employs the thin plate spine (TPS) to downscale the coarse image to the fine resolution and then uses the result to guide the residual distribution for pixels experiencing land cover change. This strategy works well for land cover change visible in coarse image but it may not be able to recover tiny land cover change in coarse subpixels [26]. In addition, the flooded area in Figure 7 has quite a smooth and regular boundary. FSDAF can capture the boundary for this case well but it is unknown if it can capture the boundary of land cover change with irregular shapes. The machine learning-based methods may be able to capture land cover changes. For example, the one-pair learning method using sparse representation can capture land cover change in the fused image although the boundary is a little bit blurred. The problem with this method is that it also blurs the land cover boundaries without change (see Figure 3 in the paper [35]). Now, deep learning has been successfully applied to image classification, object recognition, and information mining [102,103]. It is possible to model complex relationships between input coarse and fine images and the trained model could be used to predict the fine image. In the future, we could see studies using deep learning to fuse images with different resolutions.

Figure 7. An example of flood event happening during spatiotemporal data fusion: using (a), (c), and (d) to predict (b).

6.3. Standard Method and Dataset for Accuracy Assessment

Accuracy assessment of fused results is an urgent issue for spatiotemporal data fusion eld. There are two challenges: no widely accepted assessment method and no standard data sets. Basically, accuracy assessment is the evaluation of the similarity between fused and a true image (it is a known ne image at the prediction date). The similarity includes two aspects: the closeness of spectral values of the fused image to the true image, and the spatial details the fused image reserved compared with the true image. For the accuracy assessment methods, most existing studies use some global accuracy indices, including RMSE, the correlation coef cient, absolute difference, and relative difference. However, these indices most likely re ect the image-level spectral similarity rather than pixel-wise spatial details. In a current study of assessing downscaled results of thermal images, a new index was proposed [104]. A similar idea can be extended to evaluate accuracy of spatiotemporal data fusion. In addition, a standard dataset is important for the comparison among different spatiotemporal data fusion methods. As listed in Table 3, more than 40 spatiotemporal data fusion methods have been proposed. There is a need to have a cross-comparison to guide users to select the most suitable method for their speci c cases. This standard dataset should include the most challenging cases in spatiotemporal data fusion, such as images with heterogeneous land surface and experiencing abrupt land cover change during the fusion period. A study used MODIS and Landsat images in two sites with contrasting spatial and temporal variability to compare STARFM and ESTARFM, and they released the dataset for public use [105]. This dataset has been used to test performance of some newly developed spatiotemporal data fusion methods [26,43]. This dataset can be used as a starting point to develop a future standard dataset for testing the performance of spatiotemporal data fusion methods.

6.4. Ef ciency Improvement

Low computing ef ciency is a key factor which limits the wide application of spatiotemporal fusion methods. There are two reasons for the low computing ef ciency of most spatiotemporal data fusion methods: pixel-wise calculation and moving window strategy. For weight function-based methods, they need to compute the weights from spatial, spectral, and temporal perspectives for each ne pixel. For the unmixing-based methods, they need to estimate the endmember values for each coarse pixel. In other words, pixel-wise calculation is used to model the local rules linking coarse and ne images. Meanwhile, many calculations are implemented within moving windows. Moving window is commonly used by STARFM-like methods to search for similar pixels. The demand of computing time of these methods increases dramatically with the size of moving window. Due to the above complexity, in terms of calculation, most existing spatiotemporal data fusion methods, applied to an image size of one Landsat scene, need several hours and sometimes more than one day to obtain the fused image when using a personal computer. This ef ciency is acceptable for small study areas or when a limited number of images need to be fused. The ef ciency must be largely improved for studies that cover large areas and long-length time series. There are two possible ways to improve the ef ciency: (1) balancing the pixel-wise calculation and block-wise (or image-wise) calculation based on the homogeneity of the fused images; and (2) using more advanced programming strategies, such as parallel computing and GPU computing.

7. Summary

Due to the tradeoff between swath and pixel size, most current satellites cannot provide data with both high spatial and temporal resolutions. However, this type of data is needed for many studies which monitor the land surface dynamics over complex areas and with rapid change. Spatiotemporal data fusion methods have been proposed to combine images from different satellites to solve the limitation of a single satellite. However, the development of this methodology is quite disorderly although more than 40 methods have been proposed in the past two decades. This study critically

reviewed existing methods for spatiotemporal data fusion. The facts of the authors, journals, and citations were summarized. The main accomplishments of this review are as follows:

1. Existing spatiotemporal data fusion methods were grouped into ve categories based on the speci c methodology for linking coarse and ne images. These ve categories include unmixing-based, weight function-based, Bayesian-based, learning-based, and hybrid methods. Currently, there is no agreement reached about which method is superior. More inter-comparisons among those categories are needed to reveal the pros and cons of the different methods.

2. The main principles underlying existing spatiotemporal data fusion methods were explained. These principles include spectral mixing model, spatial dependence, and temporal dependence. Existing spatiotemporal data fusion methods used above principles and employed different mathematic tools to simplify these principles to make the developed methods implementable.

3. The major applications of spatiotemporal data fusion were reviewed. Spatiotemporal data fusion can be applied to any study which needs satellite images with high frequency and high spatial resolution. Most current applications are in the eld of agriculture, ecology, and land surface process.

4. The issues and directions of further development of spatiotemporal data fusion methods were discussed. Spatiotemporal data fusion is one of the youngest research topics in the remote sensing eld. There is still a lot of space for further improvements. Four issues were listed which are worth addressing in future studies: the high demand of data preprocessing, the dif culties in retrieving abrupt land cover change, the lack of an accuracy assessment method and data sets and low computing ef ciency.

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