Gridding Artifacts on Medium-Resolution Satellite Image Time Series: MERIS Case Study

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Abstract—Earth observation satellites provide a valuable source of data which when conveniently processed can be used to better understand the Earth system dynamics. In this regard, one of the prerequisites for the analysis of satellite image time series is that the images are spatially coregistered so that the resulting multitemporal pixel entities offer a true temporal view of the area under study. This implies that all the observations must be mapped to a common system of grid cells. This process is known as gridding and, in practice, two common grids can be used as a reference: 1) a grid defined by some kind of external data set (e.g., an existing land-cover map) or 2) a grid defined by one of the images of the time series. The aim of this paper is to study the impact that gridding has on the quality of satellite time series. More precisely, the impact of the so-called gridding artifacts is quantified using a time series of 12 images acquired over The Netherlands by the Medium Resolution Imaging Spectrometer (MERIS). First, the impact of selecting a reference grid is evaluated in terms of geolocation errors and pixel overlap. Then, the effect of observation geometry is studied as non-geostationary satellites, like MERIS, can acquire images from the same area from a number of orbits. Finally, a high-resolution land-cover data set is used to account for temporal information consistency (pixel homogeneity in terms of land-cover composition). Results have shown an average pixel overlap with the nearest pixel between 20% and 41% depending on the selected reference grid and on the differences in observation geometry. These results indicate that inappropriate gridding might result in collocated time series that are not adequate for temporal studies at pixel level (particularly over nonhomogeneous areas) and that, in any case, it is interesting to identify areas with low pixel overlap in order to further analyze the reliability of the products derived over these areas.

Index Terms—Gridding, mapping, MERIS, pixel overlap, resampling, satellite image, time series.

I. INTRODUCTION

Obtaining reliable and up-to-date information about the Earth’s surface is essential to better understand the Earth’s system. In this respect, data derived from medium spatial resolution earth observation sensors, such as the ESA’s ENVISAT/MERIS [1], the NASA’s TERRA/MODIS [2], or the forthcoming OLCI on board GMES Sentinel-3 [3], have a great potential for multitemporal studies at both regional and global scales. This is because medium spatial resolution sensors provide multispectral data with a high revisit time (one to three days). Therefore, time series from this kind of sensors is a valuable source of data that can be used to monitor the Earth dynamics with unique spatial, spectral, and temporal resolutions [4], [5].

However, the preprocessing and analysis of satellite image time series poses some challenges that, if unaddressed, can severely hamper the operational exploitation of such data sets [6]–[9]. For instance, an important assumption is that all the images that form the time series are perfectly coregistered, so that image pixels are different (temporal) views of the same object or multitemporal pixel entity [10]. To achieve such a coregistration, the images must be mapped to a common system of grid cells. This process, known as gridding, implies that the geolocated observations of each acquisition are allocated into an (predefined) output grid cell [11]. Image gridding is a critical preprocessing phase because it could introduce the so-called gridding artifacts, which are undesirable effects because of the different dimensions and orientations of the observations and the grid cells. Gridding effects have been extensively studied for wide field-of-view whiskbroom sensors like MODIS by analyzing the following: the mismatch between observations and grid cells [11] and between observations of different dates [9]; the band-to-band coregistration [6]; the impact of the misregistration for change detection [12], biophysical parameter retrieval [5], or temporal unmixing [13]; the point spread function (PSF) [14]; and even proposing alternative vector-based preprocessing of the images [15]. Whiskbroom sensors present progressively overlapping observations further from nadir, which produces really different pixel overlaps depending on the view zenith angle. These angular effects are relatively lower in pushbroom sensors, if pushbroom-related optical aberrations like keystone are neglected [16], [17], and probably, this explains why there are much more MODIS than MERIS studies on these effects [18]. To the authors’ knowledge, little attention has been paid to the impact of misregistration between MERIS products in a time series. Moreover, misregistration between MERIS products and other geospatial data has not been quantitatively evaluated. For example, the MERIS sensor has a large swath that allows a high revisit time of two to three days while maintaining a high spatial resolution of 300 m (full-resolution (FR) mode),
II. DATA MATERIAL

A. MERIS Level-1b Products

The MERIS data analyzed in this paper consist of a time series of FR images of geolocated and radiometrically calibrated top of the atmosphere radiance [24], i.e., the so-called MERIS FR level-1b (L1b) product. In this section, the basics of the MERIS acquisition principles and of the L1b processing are described.

Pushbroom sensors like MERIS have an array of detectors, placed transversally to the platform movement, that provides spatial sampling in the across-track direction, while the satellite’s motion provides scanning in the along-track direction. Therefore, all measurements (pixels) in an image line are acquired simultaneously and correspond to a straight line on the Earth’s surface if no instrumental errors (e.g., keystone or detector misalignment) occur. In the case of MERIS, the Earth is imaged with a spatial resolution of 260-m across track and 290-m along track at the nominal orbit, and the instrument’s field of view of 68.5° around nadir covers a swath width of 1150 km. As MERIS sensor elements have a nearly even angular spacing in the across-track direction, the distance between their projections on Earth surface increases toward the sides of the image lines (extreme look directions of MERIS swath), thus increasing the pixel footprint (integration area of the pixel), which will be larger in the across-track direction than the along-track direction [24]. In general, the size of the sensor’s footprint depends on the instantaneous field of view, the distance from the platform to the target, and the observation angle with respect to nadir. However, the L1b products delivered to the users contain MERIS observations in a regularly spaced along- and across-track grid. This is because the ESA systematically applies a nearest neighbor resampling to the original MERIS observations (level-0), which implies a partial loss of the geolocation of the original MERIS observations. In this process, if the original observation covers two product pixels, the original radiances are copied to both product pixels, and both are marked as duplicate in the MERIS quality flags.

B. MERIS FR Time Series Over the Netherlands

A time series of MERIS FR L1b images acquired over The Netherlands in 2003 was selected to illustrate this work. The image acquisition dates were chosen attending to two criteria: 1) to maximize the number of different orbits and 2) to have multiple images acquired from the same orbit so that both the inter- and intraorbit differences could be analyzed.

The orbit tracks of the images that form the time series are depicted in Fig. 1. The first thick solid line on the right side highlights the orbit #423, and the dashed lines depict the corresponding MERIS swath, which completely encompasses the territory of The Netherlands. The orbit #423, and particularly the image acquired in October 15, is used as reference image in our experiments (cf. Section IV). In Fig. 1, one can also appreciate that the selected time series includes the full range of orbits that cover The Netherlands.

The time series of MERIS images was projected onto the Dutch national coordinate system (RD) so that they could be integrated with the Dutch land use database used in the experiments (cf. Section IV-C). Fig. 2 shows the red–green–blue color composites of these images (1083 × 939 pixels in the RD system at 300 m). The relative acquisition orbit number of each image is indicated in parenthesis. It is important to notice that the images were automatically coregistered using the geolocation information provided in the corresponding MERIS products [24]. A visual inspection of the projected MERIS images did not show any major shift between them (apart from...
the expected differences due to different acquisition orbits). This can be considered as a preliminary quality proof of the automatic projection of the images [25], [26]. Although a quantitative assessment of the geolocation accuracy might have been more appropriate [27], the aim of this paper is to test the operational use of MERIS FR L1b time series.

III. METHODOLOGY

A. Mapping Image Pixels to the Grid Cells

The processing of satellite image time series requires the coregistration of all the images into a common grid, which usually implies two steps that are intimately related:

1) to define the location and extension of the regions (grid cells) where the temporal evolution is analyzed;
2) to interpolate the observations of each date contributing to each generated multitemporal pixel entity.

The first step usually consists in defining a regular map grid in a predefined coordinate system (e.g., geographic latitude–longitude, Universal Transverse Mercator, or the Dutch RD coordinate systems) for georeferencing the resulting temporal composite. However, if one only wants to coregister the images in the time series without mapping them onto a fixed grid of geodetic coordinates, it is possible to use the pixel center coordinates of a reference image in the time series to define the mapping for the rest of the images (i.e., one of the images of the time series acts as a reference image). In the second step, the spectrum assigned to each grid cell is obtained as a function of the observations contributing to the signal in the grid cell center. Several interpolation and resampling methods can be used at this step [28]–[30]. From a theoretical point of view, a signal respecting the Shannon’s sampling theorem can be interpolated without any error. However, moderate resolution remote sensing instruments like MERIS are really far from respecting the Shannon’s sampling theorem. This is particularly true in land applications over heterogeneous areas where the surface signal is not smooth and the interpolation errors at the grid locations are expected to be high regardless of the interpolation method (linear, cubic, and windowed sinc). In this case, an antialiasing filter can be applied before interpolating at the expense of a lower effective spatial resolution. However, the MERIS spatial resolution of 300 m is in the limit to analyze most of the surface targets of interest (e.g., agricultural crops). In consequence, the use of antialiasing filters before interpolating yet adequate is not very common. Thus, in practice, a simple method, namely, nearest neighbor interpolation, is often used. In this method, the observation falling closest to the grid cell center is selected, which leaves the signal measured by the sensor unaltered and preserves the MERIS spectral signature. Despite its simplicity, the nearest neighbor interpolation has some drawbacks since it presents the highest error in the interpolated radiance, and spurious effects may appear as a result of the repetition or omission of pixels [10]. Moreover, this resampling method implies a spatial shift (geolocation error) between the observations and the assigned location that might mask a low correspondence (overlap) between pixels of different dates when applied operationally. In this context, the nearest neighbor interpolation represents a perfect worst-case scenario to show the effect of gridding artifacts in satellite image time series.

It is important to note that the aim of this paper is not to suggest or analyze a particular interpolation methodology but...
to study the following: 1) the impact of the reference map grid selection (i.e., satellite acquisition geometry or geographical product) and 2) the effect of observation geometry due to the fact that time series images are acquired from slightly different orbits. This is evaluated in terms of the pixel footprint overlap and the geolocation errors between the nearest pixels/cells in the time series. Both measurements are intrinsic to the given images and independent of the interpolation method used afterward. Certainly, the radiometric error of the interpolated spectra for each date at the final grid coordinates will depend on the employed interpolation method, but this interpolation error cannot be directly measured in a real application. Therefore, the quality indicators proposed in the next section identify regions with a poor spatial matching, which will presumably have high interpolation errors and, thus, are useful and practical measures of the consistency of the satellite time series.

Fig. 3 illustrates how the measurement of pixel overlap and the geolocation errors\(^1\) strongly depend on the following: 1) the criteria used to select the pixel to be analyzed (rows) and 2) the reference frame used to make the comparison (columns). The selection of the nearest pixel (used to compute the quality indicators) can be done by minimizing its distance to the center of the map grid cell (top row) in order to minimize geolocation errors or to the center of the reference image pixel (bottom row) in order to maximize the matching between observations (pixel overlap). Additionally, one also has to consider that the overlap and the geolocation errors of the image pixels can be computed with respect to the map grid (left column) or the reference image (right column). These two geometric measurements are used to provide some insights into the quality of each generated multitemporal pixel entity. For instance, the upper-right plot in Fig. 3 illustrates how, if the series of images is projected onto a predefined map grid, some pixels might have very little overlap with the pixels of other images (in this case, the image acting as a reference). On the other hand, the matching between georeferenced image pixels and grid cells (left column) is less important when analyzing the impact of gridding artifacts on satellite image time series, but it is relevant when the MERIS time series is going to be combined with an already existing geographic information system (GIS) product in a given coordinate system.

### B. Time Series Quality Indicators

In order to quantify the gridding effects on satellite image time series, one can compute the matching of image pixels from each date with both the map grid cells and the reference image pixels. In this paper, the root mean square (rms) absolute geolocation error (distance) and the pixel overlap (area) are used to quantify the matching. These quality indicators are computed between each pixel of a given image \((t)\) and both the assigned grid cell \((g)\) and the associated pixel from the reference image \((r)\). In addition, they are computed for both pixel selection approaches (depending on if the selection of the pixel is done attending to a reference image or to the map grid) as presented in Fig. 3.

Given an image pixel \(i\) at an acquisition time \(t\), let us define its center coordinates as \(x_i^{(t)}\) and its corresponding footprint (modeled as a polygon that characterizes the geographical area observed at this time) as \(P_i^{(t)}\).

1. The rms geolocation error is computed as the distance (lat–lon coordinates) between the centers of the pixel of the analyzed image and the associated map grid cell

\[
d_i^{(g)} = \left\| x_i^{(t)} - x_i^{(g)} \right\|^2. \tag{1}
\]

Analogously, the distance with the pixel from the reference image is computed as \(d_i^{(r)} = \left\| x_i^{(t)} - x_i^{(r)} \right\|^2\).

2. The relative pixel overlap is computed as the ratio of the intersection area over the union area of the polygons defined for the image pixel and the map grid cell (or with the pixel of the reference image \(i^{(r)}\))

\[
o_i^{(g)} = \frac{\text{area} \left( P_i^{(t)} \cap P_i^{(g)} \right)}{\text{area} \left( P_i^{(t)} \cup P_i^{(g)} \right)} \tag{2}
\]

where operators \(\cap\) and \(\cup\) represent the intersection and union of polygons, respectively.

\(^1\)Geolocation error is defined as the distance between the center of the MERIS pixel and the center of the grid cell to which this pixel is assigned.
Fig. 4. Pixel overlap for different pixel selection approaches and reference grids. (a) $5 \times 5$ cells of (black solid lines) the map grid overlaid with pixel footprints of (blue and red dashed lines, respectively) the reference image and the analyzed image from May 31. The rest of the plots shows results in a $100 \times 100$ cell window. (b) Pixels that (white) change depending on the pixel selection criterion. Overlap with (c) grid cells and with (e) reference image pixels when selecting pixels by their distance to grid cells. Overlap with (d) grid and with (f) reference image pixels when selecting pixels by their distance to reference image pixels. Please note the correspondence between plots (c)-(f), and the plots in Fig. 3.

It must be noted that the overlap in (2) is relative to the common area (union area) so it ranges from zero (no overlap) to one (equal polygons), and thus, it can be expressed in percentage (e.g., an overlap of 33% represents the case of two equal-size pixels with their centers separated by a half-pixel).

A different overlap measure is described in [11], which divides the intersection area between the observation and the grid cell by the area of the observation, but (2) is used in this paper since it can also compare pixel footprints of different sizes. In this paper, the overlap has been obtained by first projecting an image with the index number of all pixels onto a fix grid with a $5 \times 5$ coordinate system of a region in the center of The Netherlands.

The overlap between the selected image pixel and the grid cell $o_i^{(g)}$ is shown in Fig. 4(c) and (d), whereas the overlap between the selected image pixel and the reference image pixel $o_i^{(r)}$ is shown in Fig. 4(e) and (f). Note that two subplots are needed for each case because of the different criterion to select the pixels. Thus, the subplots Fig. 4(c) and (e) illustrate the pixel selection based on minimizing the distance to the grid cell, and the subplots Fig. 4(d) and (f) illustrate the selection based on minimizing the distance to the reference image pixels. In order to emphasize the differences between these two pixel selection criteria, Fig. 4(b) highlights the grid cells in white where the selected image pixel changes depending on the pixel selection criterion (43% of changes).

Results, when image pixels are selected by their distance to the grid cells, are analyzed first, since this is the most com-

![Image 40x559 to 286x722]

![Image 303x604 to 549x722]
mon approach in multitemporal remote sensing applications. In Fig. 4(c), one can appreciate a fairly homogeneous distribution of pixel overlap with the grid cells that can be explained since the image pixels assigned to each grid cell have been selected by minimizing its distance to the grid cell $d_i^{(g)}$, which in turn maximizes the overlap $o_i^{(g)}$ between them. However, with this approach, pixels of different dates are selected attending only to their relation to the grid without imposing any relation between the pixels that will form the multitemporal pixel entity. This can be seen in Fig. 4(e) where, in some grid cells, the overlap between the analyzed and the reference image pixels drops off drastically and even would produce temporal composites with no spatial overlap in some elements. Obviously, this situation is unacceptable for the analysis of time series (except over extremely homogeneous regions where a spatial shift will not deviate the combined radiance from the ideal case).

The other option is to select the image pixels by their distance to the pixel centers of a reference image of the time series (note that, in this case, only locations highlighted in Fig. 4(b), where the selected image pixel changes from the previous case, will show different values). In Fig. 4(f), the distribution of pixel overlap with the reference image pixels shows the same Moiré pattern than before, but in this case, all cells present an overlap of, at least, 17%. Therefore, by selecting the image pixels assigned to each grid cell by minimizing their distance to the reference image pixels $d_i^{(r)}$, the overlap between pixels $o_i^{(r)}$ is maximized, and the extreme low overlap values visible in Fig. 4(e) disappear. On the contrary, the overlap with the grid cells [Fig. 4(d)] in those pixels that change is reduced.

In order to better analyze the results, Fig. 5 shows the histograms of the pixel overlap and the geolocation error for all the cases but taking into account the whole region over The Netherlands ($1083 \times 939$ cells). In these plots, one can better analyze the distribution of values and their limits. First, one can observe the complementary behavior of the overlap between the pixels of the analyzed image and (red lines) the grid cells or (black lines) the reference image pixels depending on the used (dashed and solid lines) selection criterion. Basically, with regard to overlap, results show that, independently of the selection approach, the overlap with the map grid cells is never higher than 80%. Overlap with the reference image occasionally reaches 100%; however, the greatest number of cases fall below 50%. It is important to note that whenever the selection and the overlap use different criteria, the pixel overlap goes down to zero with the maximum of the histogram about 20%. On the other hand, regarding geolocation errors, the distance to a reference image is always smaller than the distance to a grid. Thus, it can be concluded that, for multitemporal analysis, it is better to use a reference image to select the appropriate pixels to construct the multitemporal pixel entity, as the distance between centers is minimized throughout the image, while the overlap is maximized reaching cases with almost 100% overlap. Finally, it is important to recall that the obtained overlap values depend on the assumptions made on the sensor PSF. However, the overlap maps are still relevant to assess the consistency of the products derived from MERIS time series. In addition, one should realize that the errors on the interpolated spectral values (e.g., radiances) are inversely related to the pixel overlap (although it will strongly depend on the selected interpolation method).

In summary, the selection of the reference map grid has a great impact on the results, so the choice depends on the requirements of the application. Applications aimed at combining MERIS and ancillary (GIS) data or those aimed at obtaining high geolocation accuracy should use a predefined coordinate system as reference grid. However, in this case, the user should be aware of the grid cells where the overlap is extremely low, since in these locations the retrieved biophysical products may be less accurate or even wrong. Therefore, in multitemporal applications, the overlap image, shown in Fig. 4(e), should be computed and used as a quality indicator (e.g., quality flags can be obtained to identify all pixels under a given overlap threshold). Analogous conclusions are obtained when the image pixels assigned to the grid cells are selected by minimizing their distance to the reference image pixels $d_i^{(r)}$. This approach is more suitable for applications where the consistency of the temporal information in a given area is critical (e.g., crop phenology, vegetation dynamics, desertification, urban monitoring, etc.). Furthermore, the overlap information in Fig. 4(f) is also relevant to know in which areas the retrieved products are more consistent (higher overlap), and Fig. 4(d) allows identifying cells where the provided information does not correspond to the map location accurately.

### B. Impact of the Orbit Selection on Satellite Image Time Series

Once the effects of the pixel selection criterion and the resampling have been analyzed, this section explores their dependence on the orbit difference between images for the full time series. In order to properly interpret the results, one should recall Fig. 1 and observe that orbits of the satellite image time series are distanced from the reference orbit ($\#423$) westward at constant increments (although the time series does not comprise all possible orbits in this range and some gaps can be observed). This longitudinal increment in the west direction from the reference orbit (hereinto referred to as orbit shift, $\delta$) is used to sort the image results in Fig. 6 since it expresses the difference between the orbits and the observation geometries. Therefore, orbit order from left to right corresponds to an increase in the distance in the west direction with respect to the reference orbit. Pixel overlap in the second row in Fig. 6 shows the expected Moiré patterns where the orientation of the patterns depends on the orbit inclination, which determines the orientation of the sensor scanning. Moreover, the spatial frequency of the patterns increases as the longitudinal distance between orbits increases, which produces an increasing angular shift between the pixel footprint gratings of the images (as can be seen in the first row in Fig. 6). The third row in Fig. 6 shows the histograms of the pixel overlap for the whole region over The Netherlands (1083 × 939 cells). Despite the apparent differences between the overlap spatial patterns depending on the orbits, the overlap histograms show almost identical curves to the ones presented in Fig. 5. Results show that the pixel overlap between images acquired from different orbits ranges from 0% up to 80% when the selection of the image pixel is done by its distance to the center of the map grid (solid red line with an average overlap...
around 32%) and from 17% up to almost 100% when it is done by its distance to the center of the reference pixel (solid black line with an average overlap around 41%). These results are valid for images acquired at The Netherlands latitudes, but similar behavior is expected at other latitudes.

In order to analyze in more detail the differences in the pixel overlap patterns as a function of the orbit shift \( \delta \), Fig. 7 shows the properties of the overlap patterns of the whole scene in the Fourier spectral domain. It shows the period and the frequency of the fundamental frequency of the 2-D Fourier transform of the overlap patterns in the second row in Fig. 6. The spatial frequency of the patterns presents a linear dependence with the orbit shift \( \delta \), which can be explained since the variation in \( \delta \) produces a linear variation in the angle between the pixel gratings of the images. Moreover, the average pixel overlap for all the orbits is 41% approximately, which demonstrates that the produced overlap patterns present different spatial distributions but the same values (only the spatial frequency changes).

In the case of images acquired from the same orbit, one would expect that the average pixel overlap should be much higher since they present almost the same observation geometry. However, and very importantly, when there are small shifts in the satellite position or geolocation uncertainties (across-track direction) or shifts in the starting acquisition time (along-track direction), the pixel grating for both images is the same but with a constant spatial shift. Therefore, the mismatch between pixels from the two dates is the same for all the image pixels, and depending on the shifts, the relative pixel overlap for the whole image might be lower than 20% (these images being useless for temporal studies). The top plots in Fig. 8 show a subset of the map grid (5 × 5 cells) overlaid with pixel footprints of the reference image of October 15 and the images of April 23, May 28, and August 6 acquired from the same relative orbit (#423). These examples illustrate three different scenarios that clearly affect the resulting pixel overlap.

Fig. 6. Results for images with an orbit different from that of the reference image (October 15, orbit #423) sorted by the longitudinal distance between the orbit of the reference image and the orbit of the analyzed image (number of orbit shifts \( \delta \) in parenthesis). First row: map grid (5 × 5 cells) overlaid with pixel footprints of the reference image and the analyzed image. Second row: overlap with reference image pixels when selecting pixels by their distance to reference image pixels (100 × 100 cells). Third row: histograms of pixel overlap for the whole region over The Netherlands (1083 × 939 cells).

Fig. 7. Spatial period, frequency, and average value of the overlap patterns as a function of the orbit shift \( \delta \) with respect to the reference orbit.

Fig. 8. Results for images with same orbit as the reference image (#423, October 15, \( \delta = 0 \)). First row: map grid (5 × 5 cells) overlaid with pixel footprints of the reference image and the analyzed image. Second row: overlap with reference image pixels when selecting pixels by their distance to reference image pixels (100 × 100 cells).
overlap displayed in the bottom plots in Fig. 8. In the first case (April 23), the two pixel gratings are accurately collocated (small shift in the across-track direction can be observed), and the average pixel overlap for the whole image is 60%. In the second case (August 6), the shift between the grids in the across-track direction is approximately half pixel (worst case in the across-track direction), and the overlap decreases to 37%. Finally, the third case (May 28) presents a small shift in the across-track direction and a shift of half pixel in the along-track direction (due to differences in the starting acquisition time) that drastically drop off the overlap to 25%, which is close to the worst-case scenario.

Attending to the previous results, for both selection approaches and independently of the image orbits, it is of paramount importance to identify the areas with rather small overlaps in order to analyze the validity of further multitemporal studies in these areas and dates (e.g., biophysical parameter estimation). Moreover, one cannot assume that the matching between images acquired from the same orbit is perfect. Therefore, possible spatial shifts between image pixels should be taken into account to discard from the time series those images with low average overlap.

C. Pixel Matching Based on Subpixel Land-Cover Differences

Despite the relatively low pixel overlap found in the experiments (~41%), most of the multitemporal remote sensing applications do not even consider these effects. However, results from these applications are mostly valid since a mismatch between observations does not necessarily imply that the formed temporal profile is wrong: Over a homogeneous land cover with the same temporal evolution, a spatial shift will not affect the temporal spectral signature corresponding to this surface, while the same mismatch over heterogeneous areas will lead to mixed temporal spectra and thus misleading results.

This section is devoted to provide a quality indicator accounting for both the actual pixel footprints and the consistency of the temporal information combined from the time series in terms of land-cover composition consistency. The main limitation of the proposed approach is that an accurate land-cover map of the region of interest, with a higher spatial resolution than the analyzed satellite images, is required.

The Netherlands was selected as study area because of the heterogeneity of its landscapes and the availability of an up-to-date high spatial resolution land use database, which is needed to compute the pixel coincidence between different dates based on subpixel land-cover differences [20], [38]. The fifth version of the Dutch land use database (also known as the LGN5) is used as a reference in this study. This geographical database is based on a multitemporal classification of high-resolution satellite data acquired in 2002 and 2003; several types of ancillary data were also used to produce the land use database (see [39] for more details). The LGN5 is provided in the Dutch national RD coordinate system at 25 m (13 000 × 11 274 pixels) and maps 39 classes. Most of the classes are rather small and/or sparsely distributed and/or heavily based on available ancillary data, which mainly describes land uses rather than land-cover types. Consequently, the LGN5 was thematically aggregated into the main nine land-cover types of The Netherlands. The aggregation to nine classes is meant to offer a detailed distribution of the following classes (Fig. 9): grassland, arable land, deciduous forest, coniferous forest, water, built-up, greenhouses, bare soil (including sand dunes), and natural vegetation.

The proposed time-series quality indicator is basically a land-cover difference that consists in the difference of land-cover abundances of the nine LGN5 classes between the two pixels. Fig. 10(a) shows a small region of the LGN5 land-cover map at 25 m overlaid with the map grid (5 × 5 cells) and the MERIS pixel footprints (February 18th image), (b) at 300 m computed by considering the area circumscribed by the grid cells, and (c) by considering the area circumscribed by the MERIS pixel footprint.

![Fig. 9. LGN5 land-cover map of The Netherlands with nine classes.](image)

![Fig. 10. Land-cover classes of the LGN5 (a) at 25 m overlaid with the map grid (5 × 5 cells) and the MERIS pixel footprints (February 18th image), (b) at 300 m computed by considering the area circumscribed by the grid cells, and (c) by considering the area circumscribed by the MERIS pixel footprint.](image)

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3Alternatively, the spatial pattern of the present land covers at high spatial resolution may be obtained from other satellite images [34], [36], [37].
original 25-m grid of the LGN5. Then, the abundances of the different land-cover types present in the area observed by each MERIS pixel \( P_{i}^{(t)} \) were computed as a simple percentage of their areas. The class having the highest abundance was also used to produce a land-cover classification for each date. After this, the subpixel abundances and land-cover map were projected onto the RD coordinate system of the reference LGN5 data set but this time with a grid of 300 \( \times \) 300 m (i.e., MERIS FR nominal pixel size). Fig. 10(c) shows these land-cover classes at 300 m computed by considering the area circumscribed by the pixel footprints. This provided us with slightly different abundances \( f_{i}^{(t)} \) for each date \( (t) \) that can be used to measure the differences in the composition of the mixed pixels.

Once the subpixel land-cover fractions are obtained, these fractional maps can be used to assess the self-consistency of the land covers observed by pixels. Similarly to [13], the rms error between the fractions, \( ||f_{i}^{(g)} - f_{i}^{(t)}||^{2} \), can be used to do the quality assessment. However, in order to provide a similarity measure sensitive to the agreement between the abundance vectors, the overall subpixel accuracy (OSA) is computed as follows [40]:

\[
OSA_{i} = \sum_{c=1}^{n_{c}} \min \left\{ f_{i,c}^{(t)}, f_{i,c}^{(g)} \right\}
\]

where \( n_{c} = 9 \) is the number of land-cover classes present in the LGN5; \( f_{i,c}^{(t)} \) and \( f_{i,c}^{(g)} \) are the abundances for class \( c \) computed from the LGN5 for the particular observation geometry of the analyzed image and the map grid, respectively; and \( \min\{ f_{i,c}^{(t)}, f_{i,c}^{(g)} \} \) indicates the coincident fractions for class \( c \). Note that OSA values range between 0 and 1 (or 0 and 100 in percentage) since land-cover fractions in a given pixel sum to one \( (\sum_{c} f_{i,c} = 1) \).

Fig. 11 shows the pixel overlap between the image pixels and the map grid cells analyzed in the previous sections including the OSA between the subpixel land-cover fractions corresponding to the image and the grid cells. The top row shows a subset of 200 \( \times \) 200 cells in the center of The Netherlands, and the bottom row shows the whole scene.

V. Conclusion and Discussion

The impact of gridding artifacts on medium spatial resolution satellite image time series has been analyzed in this paper. The geometric matching between images has been quantified in terms of geolocation errors (distances) and spatial overlap (areas) between the actual pixels constituting each multitemporal pixel entity. This information may be used to elaborate enhanced products and to improve the usability of satellite image time series coming from the same or different orbits. In particular, when the images are resampled with the nearest neighbor method, the geometric matching between pixel footprints (overlap) can be used in order to decide whether it is better to coregister the images to a predefined coordinate system or to a given acquisition used as a reference. This paper has also described a procedure to identify regions where coregistration requirements might be relaxed (depending on the application), which is based on the land-cover heterogeneity along the temporal composite. The main assumption is that whenever the land-cover composition of the observed footprint for each date is similar, the measured temporal profile is consistent.

All these analyses are supported by a set of experiments carried out using a time series of MERIS L1b FR images acquired over The Netherlands in 2003. Results have shown that the average pixel overlap between images acquired from different orbits is around 32% when the selection of the image pixel is done by its distance to the center of the map grid and around 41% when it is done by its distance to the center of the reference pixel. Therefore, in both cases, it is of paramount
importance to identify the areas with rather small overlaps in order to analyze the reliability of further estimated biophysical parameters in these areas. In the case of images acquired from the same orbit, the average pixel overlap can be much higher. However, under certain conditions (e.g., subpixel shifts), it might be lower than 20% being this image pair inappropriate for temporal studies. It is also important to note that the obtained overlap values depend on the assumptions made on the sensor PSF. In addition, one should be aware of the fact that the selected interpolation method will greatly influence the errors on the gridded spectral values. For instance, the commonly used nearest neighbor interpolation will provide a high interpolation error. More appropriate interpolation and/or filtering techniques might be used to mitigate such interpolation errors at the expense of a lower spatial resolution.

Further work is needed in order to obtain more realistic and accurate pixel footprint characterization. For example, in current MERIS L1b products, a regular sampling in the along- and across-track directions is imposed by ESA. This preprocessing step implies that some geometric information is lost because a nearest neighbor resampling is applied to generate the L1b product. In this process, if two resampled product pixels come from the same MERIS observation, both are marked as duplicate. However, this flag only allows a partial reversibility of the image-to-product resampling process.

For future satellite missions, more geolocation information about the ungridded observations might be provided together with the products distributed to the users: the geographic coordinate of each pixel’s center (so-called image geometry map) or the subpixel shifts in the across-track and along-track directions; the footprint dimension, shape, and orientation for every pixel; as well as other parameters that might be found relevant during this study, such as an accurate model of the PSF of instrument. As a consequence, working with nonrectified georeferenced images and incorporating the additional information require new processing algorithms able to find geographically matching pixels in different images and estimate the corresponding overlap, as well as rectify the images to a geographically matching pixels in different images and estimate information require new processing algorithms able to find georeferenced images and incorporating the additional parameters in these areas. In the case of images acquired from the same MERIS observation, both are marked as duplicate. However, this flag only allows a partial reversibility of the image-to-product resampling process.

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References


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