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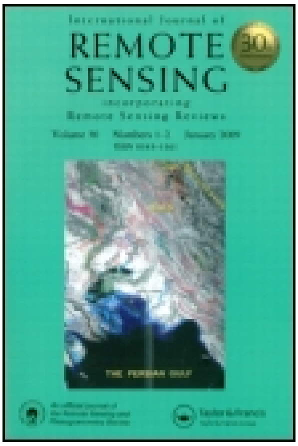

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TECHNICAL NOTE

Fourier transforms for detecting multitemporal landscape fragmentation by remote sensing

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Remote sensing is a useful tool for detecting landscape fragmentation, typically by creating land-use maps from remotely sensed images acquired at different dates. Nonetheless, classification may present a number of drawbacks since it degrades the information content of images leading to the loss of continuous information about fragmentation processes. For exploratory purposes, methods to detect landscape change based on continuous information should not require any *a-priori* assumptions about landscape characteristics. Accordingly, Fourier transforms may represent the best algorithmic solution. In this paper, we describe a Fourier transform tool developed in a free and open-source environment to detect potential fragmentation over the landscape. We briefly introduce Fourier transforms applied to remotely sensed imagery by further showing their potential application with an empirical example. We argue that Fourier transforms represent a straightforward approach for detecting spatial fragmentation of the landscape, on the strength of their potential to detect trends in increase or decrease of complexity/heterogeneity of the landscape in an objective manner. To our knowledge, this is the first open-source tool for analysing fragmentation of the landscape in multitemporal series based on Fourier transforms, which guarantees a high robustness and reproducibility of the applied algorithms.

1. Introduction

Landscape fragmentation is known to be related to human-induced ecosystem processes such as ecosystem degradation (Mertens and Lambin 1997). Multitemporal analysis based on remotely sensed data has played an important role in detecting fragmentation, typically by creating land-use maps from remotely sensed images acquired at different dates. However, generally, classification may present a number of drawbacks (Foody 1996), in particular: (1) an implicit degradation of the information content, coupled with (2) the loss of the continuous information about fragmentation processes, and (3) problems related to downscaling once images are classified with different resolutions. Strictly speaking, classification is expected to degrade continuous original data provoking a loss of information (Palmer et al. 2002).

Alternative approaches based on continuous information for detecting landscape changes, including fragmentation, have been proposed by relying on fuzzy set theory

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(Ivan 2012), spectral unmixing (Michishita, Jiang, and Xu 2012), support vector machines (Li and Xu 2010), and neural networks (Ghosh, Patra, and Ghosh 2009).

When seeking a method to detect landscape change based on continuous rather than classified information, one should rely on a (continuous) function that requires neither (1) *a-priori* field information nor (2) a specific model based on the data being used. In this view, Fourier transforms (Fourier 1822) may represent the best algorithmic solution. While Fourier transforms have been used in the past to smooth data for summarizing landscape patterns (e.g. Lobo et al. 1998; Lundquist and Sommerfeld 2002; Saunders et al. 2005), no specific studies have been performed to show their potential in the detection of landscape fragmentation.

The aim of this paper is to show the potential application of a Fourier transform tool in a free and open-source environment to detect fragmentation over the landscape. We will briefly introduce Fourier transforms applied to remotely sensed imagery and then show an empirical example.

2. A theoretical introduction to Fourier transforms applied to remote sensing

Let $f(x)$ be a continuous function described in a spatial domain. Based on the Fourier theorem (Fourier 1822), every $f(x)$ can be transformed into a continuum of sinusoidal functions of varying frequency, as:

$$\hat{F}(\omega) = \int_{-\infty}^{\infty} f(x) \mathrm{e}^{-2\pi i \omega \omega} \mathrm{d}x, \quad (1)$$

where ω = frequency, also known as radian frequency since it is expressed in radians per spatial unit (Figure 1).

Extending Equation (1) to two dimensions implies consideration of a two-dimensional function $f(x,y)$ (e.g. a raster matrix (Figure 2)). Its Fourier transform then becomes

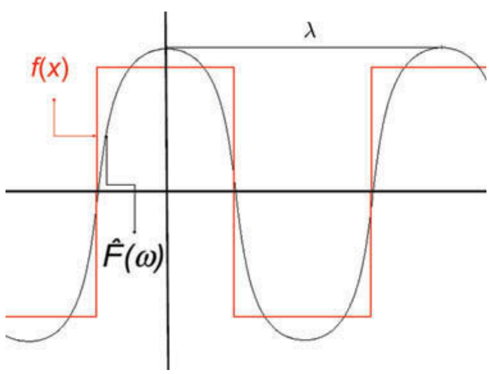

Figure 1. A continuous function *f(x)* can be transformed into a continuum of sinusoidal functions of varying frequency according to the Fourier theorem (Fourier 1822). Refer to the main text for detailed explanation.

$$\hat{F}(\omega, v) = \iint\limits_{-\infty} f(x, y)\mathrm{e}^{-2\pi i(\omega x + vy)}\mathrm{d}x\mathrm{d}y, \tag{2}$$

where ω, v = frequency coordinates.

Equation (2) associates with the space defined by $f(x,y)$, an alternative coordinate space $\hat{F}(\omega, v)$, also referred to as the frequency domain in Figure 2, based on the frequency components ω, v.

Considering two different two-dimensional functions, $f(x_{t_0}, y_{t_0})$ and $f(x_{t_1}, y_{t_1})$ acquired at different dates t_0 and t_1, Equation (2) applied to $f(x_{t_0}, y_{t_0})$ and $f(x_{t_1}, y_{t_1})$ will provide the frequencies of each image distributed into the coordinate space defined by $\hat{F}(\omega_{t_0}, v_{t_0})$ and $\hat{F}(\omega_{t_1}, v_{t_1})$, such as:

$$\hat{F}(\omega_{t_0}, v_{t_0}) = \iint\limits_{-\infty} f(x_{t_0}, y_{t_0})\mathrm{e}^{-2\pi i\left(\omega_{t_0}x_{t_0} + v_{t_0}y_{t_0}\right)}\mathrm{d}x_{t_0}\mathrm{d}y_{t_0}, \tag{3}$$

$$\hat{F}(\omega_{t_1}, v_{t_1}) = \iint\limits_{-\infty} f(x_{t_1}, y_{t_1})\mathrm{e}^{-2\pi i\left(\omega_{t_1}x_{t_1} + v_{t_1}y_{t_1}\right)}\mathrm{d}x_{t_1}\mathrm{d}y_{t_1}. \tag{4}$$

Once a Fourier transform has been applied, lower frequencies are generally plotted at the centre of the Fourier spectrum, while higher frequencies are plotted outward (Figure 2). Hence, low-frequency homogeneous images are expected to show high values to the centre of the ω, v scatterplot and very low values at the outward (Figure 2(*a*)). An increase in fragmentation should provoke an increase in higher frequencies, resulting in a more complex (heterogeneous) Fourier spectrum with higher values in the high-frequency part of the frequency domain (Figure 2(*b*)).

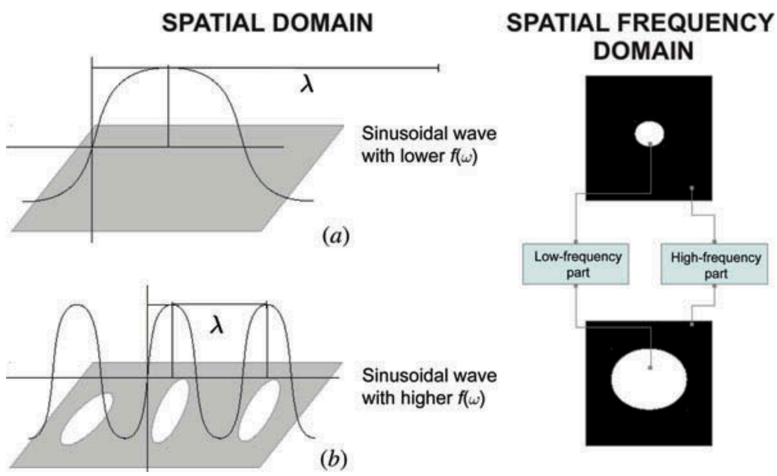

Figure 2. In regard to two landscapes or the same landscape at different points in time, once a Fourier transform has been applied, lower frequencies are generally plotted at the centre of the Fourier spectrum, while higher frequencies are plotted outward. (*a*) Homogeneous landscape, (*b*) heterogeneous landscape. Fragmentation of the landscape results in an increase in higher frequencies resulting in a more complex (heterogeneous) Fourier spectrum with higher values in the high-frequency part of the frequency domain. Refer to the main text for additional explanations.

An extensive mathematical description of Fourier transforms is provided by De Bie (2012). The following example helps explain the power of Fourier spectra in detecting the presence of fragmentation processes.

3. A free and open-source tool for applying Fourier transforms to the detection of fragmentation

The use of open-source software guarantees that the applied algorithms are robust and peer-reviewed. Following Stallman (1985) and later stressed by Rocchini and Neteler (2012), the freedom to run, adapt, redistribute, and improve programs is essential in science to perform robust and reproducible analysis.

In this manuscript, we will rely on the most commonly used free and open-source software applied to geosciences, namely, Geographical Resources Analysis Support System (GRASS GIS, see Neteler and Mitasova (2008) and Neteler et al. (2012)), although different software packages, such as ImageJ (http://rsbweb.nih.gov/ij/download.html), can be used. GRASS GIS includes more than 350 modules for managing and analysing geographical data and has been widely used in the geosciences (e.g. Baker, Egbert, and Frazier 1991; Grohmann 2004; Carrera-Hernández and Gaskin 2008; Jasiewicz and Metz 2011).

The modular software design of GRASS GIS facilitates the introduction of new functionalities without affecting the overall performance of the system. Moreover, its scripting capabilities enable automated processing of a large volume of data and a wide-ranging use of the achieved results. In particular, recent developments also allow GRASS users and developers to make use of the Python programming language (van Rossum 1995, 1997), to introduce new features. Refer to Neteler et al. (2012), for a throughput review of GRASS GIS.

The tool on which we rely is the Fast Fourier Transform (FFT) i.fft function of GRASS GIS devised by Satnik and Clements (refer to the GRASS GIS manual page, http://grass.osgeo.org/grass64/manuals/i.fft.html). Such FFT implementation is based on the open-source FFTW library (Frigo and Johnson 2005), which in turn is related to the Fourier transform algorithm described by Cooley and Tukey (1965).

Considering, as an example, a single band of a Landsat 7 image (e.g. the first principal component), the command to be used to calculate its Fourier transform is straightforward:

```
i.fft input_image=lsat7_2002_pca.1 real=lsat7_2002_pca1.real imaginary=lsat7_2002_pca1.imag
```

where real = real part of Equation (3) and Equation (4) and imaginary = imaginary part of Equation (3) and Equation (4), both stored as raster maps. The following section presents an empirical example of the application of Fourier transforms into GRASS GIS for multitemporal analysis. The complete code is available at http://grasswiki.osgeo.org/wiki/Fourier_transforms_for_multitemporal_analysis.

The output produced by i.fft may be further processed by statistical techniques such as those described in the following empirical example: (1) frequency plots based on kernel density functions (Bowman and Azzalini 1997, 2013) and (2) linear models (by hexagon binning, Carr, Lewin-Koh, and Maechler 2013), which may help to show changes in the distribution of the FFT output values and their relative relationship, respectively, over different time periods.

4. Empirical example

An application for the detection of fragmentation by the Fourier transform function i.fft is provided in Figure 3, which shows Landsat TM data (1987 and 2002 images, First Principal Components, explaining 83% and 81% of variance, respectively) derived from the GRASS free data set 'North Carolina' available at: http://www.grassbook.org/data_menu3rd.php.

The 1987 Landsat TM5 PC1 image (top left in Figure 3(*a*)) shows a homogeneous environment before the landscape became fragmented, mainly by expanding urban areas (2002 Landsat TM7 PC1 image to the right, Figure 3(*a*)). A comparison of the i.fft Fourier transforms of the two images shows that the homogeneous frequency pattern of 1987 shifts to a heterogeneous pattern in 2002 (Figure 3(*b*)). Using a red-to-green colour table, one colour (red) dominated the 1987 image while a higher mixture of green and red was apparent in the 2002 Fourier image (Figure 3(*b*)). In fact, in the Fourier space, the 1987 image shows very similar (and low) values in the high-frequency part of the spectrum (external part of Figure 3(*b*)), while a higher equitability/heterogeneity is found in the 2002 image (Figure 3(*b*)).

Applying a kernel density function (see Bowman and Azzalini (1997)) to the Fourier output by R software (R Development Core Team 2013, sm package, Bowman and Azzalini 2013) demonstrated a skewed distribution of Fourier frequency values in 1987 (Figure 4, blue line) with the dominance (peak) of only a few values, indicating high homogeneity over the landscape. Once fragmentation occurred in the landscape, the

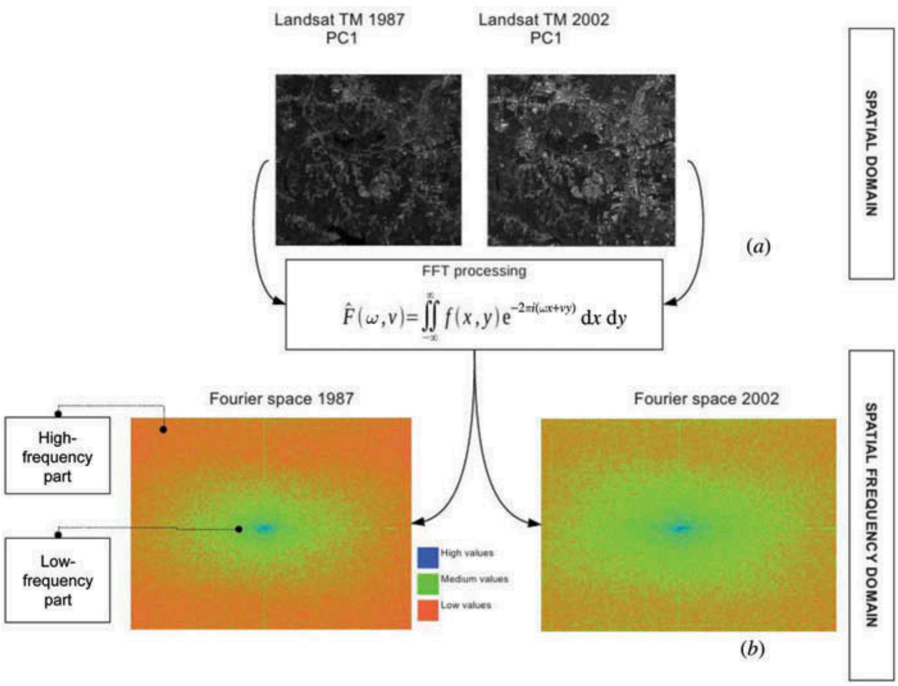

Figure 3. A 1987 Landsat TM5 PC1 image and a 2002 Landsat TM7 PC1 image (*a*) processed by the i.fft Fourier transform algorithm (*b*). The 1987 image shows a higher homogeneity in values with a peak at low values (in the high-frequency part of the spectrum). High values (spread of the green-coloured cloud) in the outer part are related to a higher heterogeneity once fragmentation occurs in the landscape. The real part of Equations (3) and (4) is shown.

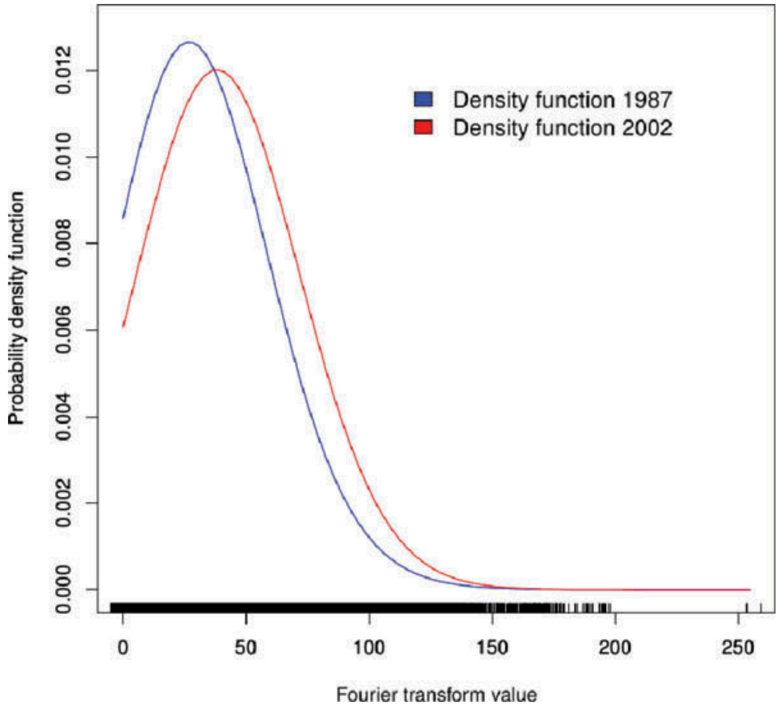

Figure 4. Density function applied to the Fourier output of Figure 3. A skewed distribution of Fourier frequency values in 1987 (blue line) with the dominance (peak) of some values is shown, indicating high homogeneity over the landscape. The equitability of values increased (higher heterogeneity, red line) in 2002, as a consequence of a fragmentation process over the landscape mainly due the spread of urban areas (see Figure 3(*a*)), with a lower skewness of value distribution.

equitability of values inevitably increased (higher heterogeneity, Figure 4, red line), with a lower skewness of value distribution.

Finally, in plotting the Fourier-transformed values by hexagon binning (hexbin package of the R software; Carr, Lewin-Koh, and Maechler 2013), the 2002 image generally showed higher values than the 1987 image as shown when plotting the 1:1 line (Figure 5). This is particularly true considering the left part of the scatterplot (Figure 5), where 2002 frequency values are always higher than the 1:1 line. This is related to the spread of the green-coloured cloud of Figure 3(*b*) (i.e. to the increase from 1987 to 2002 of values in the high-frequency part of the frequency domain (Figure 3(*b*))).

5. Concluding remarks

In this manuscript, we described the potential of a tool implementing Fourier transforms in a free and open-source environment for approximating functions that allows the analysis of fragmentation of the landscape considering its continuous variability, thus maintaining uncertainty information over space rather than creating thresholds by classification (see Rocchini et al. (2013)). It is worth noting that a proper atmospheric correction is mandatory before performing Fourier transform analysis, since light conditions or noise may have an impact on final results.

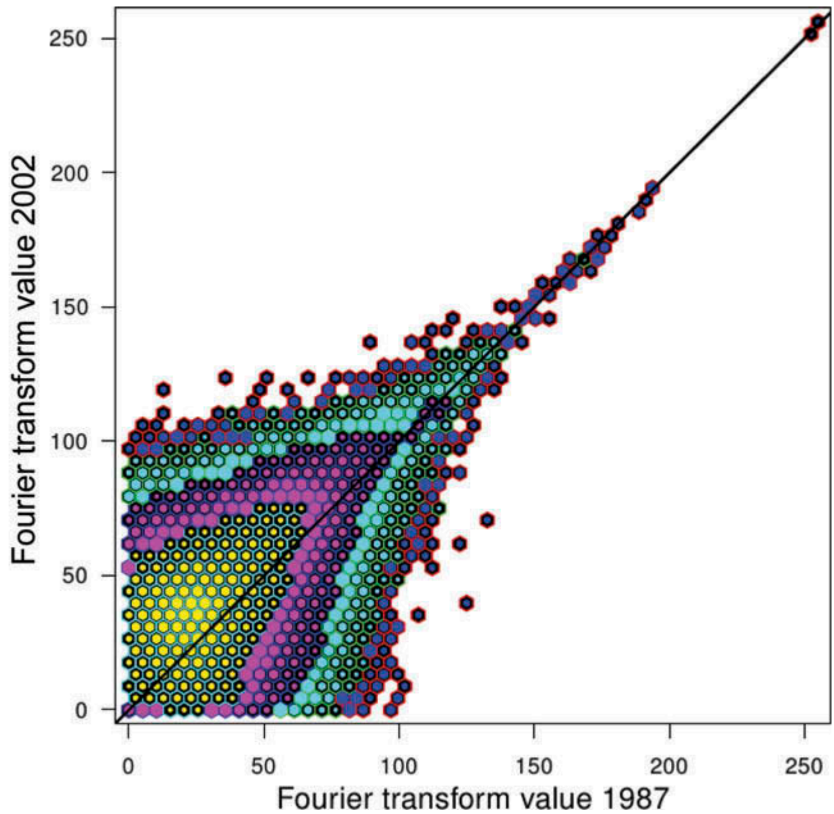

Figure 5. Plot of frequency values by hexagon binning. Yellow hexagons, thousands of pixels; violet hexagons, hundreds of pixels; light blue hexagons, tens of pixels; blue hexagons, single pixels. The 2002 image shows higher values than those of the 1987 image (spread of the green-coloured cloud in Figure 3), i.e. with respect to the 1:1 plotted line, demonstrating a change of values in the spatial frequency domain over time towards a higher heterogeneity related to fragmentation.

We showed how continuous information could be profitably used to perform multi-temporal analysis by relying on frequency changes in a multitemporal set of images, without losing continuous information by the creation of discrete classes (Rocchini et al. 2013). From a theoretical point of view, this is similar to approximation theory in mathematics in which, once searching for a function that best approximates a more complex one, the characterization of uncertainty is of primary importance (e.g. Fourier 1822).

Fourier transforms have been used in remote sensing for resolving a number of issues such as calibrating remote sensing imagery (Peleg 1998), removing systematic noise from satellite images (Emch et al. 2005), appropriate scaling of satellite imagery for landscape scale studies (Lundquist and Sommerfeld 2002), and fusing high-resolution data (Ling et al. 2007). We argue that Fourier transforms may also represent a straightforward approach for detecting spatial fragmentation of the landscape, on the strength of their potential to detect increasing/decreasing trends in the complexity/heterogeneity of the landscape in an objective manner, because no *a-priori* assumptions about landscape characteristics need to be made. We also refer to Figure 6 for an additional example of

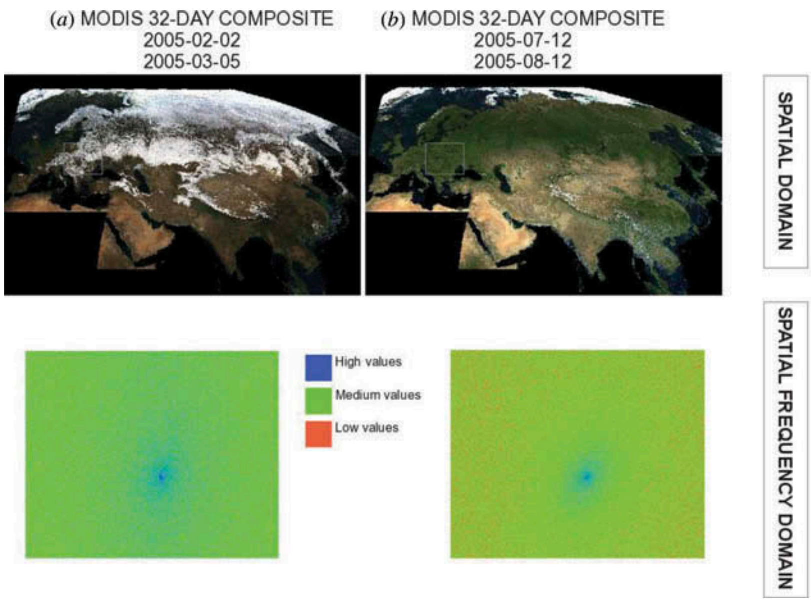

Figure 6. Fourier transforms applied to two different MODIS 32-day composites freely downloadable from http://glcfapp.glcf.umd.edu:8080/esdi/. (*a*) Image covering a temporal period from 2 February 2005 to 5 March 2005; (*b*) image covering a temporal period from 12 July 2005 to 12 August 2005. Image (*a*) has a higher spatial heterogeneity than image (*b*), due to mixed classes including snow. This is reflected in the spatial frequency domain where the high-frequency part of the graph (external part of the frequency domain) is dominated by higher values in image (*a*). Conversely, image (*b*) shows lower values (red) in the high-frequency part of the graph. Refer also to Figure 3, with the same increase in values in the high-frequency part of the frequency domain, in the case of higher heterogeneity/complexity. The test was performed by subsetting the MODIS images (grey rectangle) and using band 2 (spectral range: 841–876 nm, spatial resolution: 250 m). Since fragmented landscapes are expected to show a higher spatial heterogeneity/complexity, Fourier transforms can ensure the detection of fragmentation strictly related to high frequencies in the frequency domain space.

image complexity detection by Fourier transforms relying on MODIS 32-day composite imagery, which demonstrates the robustness of the method not only for detecting long-term fragmentation but also for studying seasonal fluctuations in landscape complexity.

To our knowledge, this is the first open-source tool for analysing fragmentation of the landscape in multitemporal series based on Fourier transforms.

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