Chapter 10
Metropolitan Cartography, Remote Sensing and Geographic Information Systems

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10.1 Georeferenced Products for Green-Grey-Blue Infrastructures Detection

All metropolitan areas identified in the world have some common features and elements (see Zhao et al., 2019; Costa et al., 2019), that can be used to determine, from many points of view (e.g. socioeconomic indices, demographic definition, urban planning rules), what a metropolitan system is and is made of (see, f.i., Toure et al., 2018). Several studies on metropolitan areas show that monocenter structures have been evolving into complex and interconnected spatial organizations (Contin et al., 2014b), described by the same basic features that can shape metropolitan aggregates (see Lan et al., 2019; Li, 2020), through the composition of green, grey, and blue infrastructures (GGBIs). Effectively recognizing this basic structures and analyzing their localization choices and evolution is a relevant activity for the metropolitan development of the future (Leyk et al., 2019), to mitigate the effects of risks and catastrophes (from anthropic and/or natural sources; see WHO, 2017) and to promote a sustainable use and organization of existing and future resources in urban systems (see UN, 2017).

Useful datasets (free/paid, public/private domain), that can be retrieved for this purpose, can be divided into several main classes, starting from aerial and satellite images (ASIs), produced by official sources or private users (using drones, aerial or satellites surveys) for one or many different possible goals, that determine different interpretation strategies and outputs (e.g. Padrò et al., 2019). The most interesting

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data sources are represented by vector and raster maps, produced using land or aerial surveys, having different covering and detailing levels, depending on the location. To draw and thematize maps for a specific purpose (e.g. Campi et al., 2017), zenithal images, when available, can be processed through aerial photographic and satellite image interpretation techniques.

The main element determining the potential use of ASIs is the spatial resolution (SR), that is the size of a pixel on the ground, which defines the dimension of the smallest detail that can be obtained and recorded on a map. SR is essentially a function of the sensor distance from the ground. In addition to this, there are three other resolutions that are significant for the ASIs possible use: spectral (the capability of capturing images in different wavelengths bands, from the most common RGB images to 'invisible' ones, such as infrared, to detect different surfaces), temporal (i.e. the revisiting time of the same area) and radiometric (which reveals distinct shades of the same 'color' to better detect objects). This means that images can be used in many ways for metropolitan studies about GGBIs and the most interesting ones are identified as follows.

Satellite images. They're related to Earth surface description in thematic mapping at large scale, e.g. to identify land use and/or coverage (LU/LC) classes, or to study natural or anthropic trends evolution through change detection (multitemporal analysis using archive data about urban growth, desertification, deforestation, floods, fires, ecological studies, water quality assessment, and so on). In agriculture: crop extension mapping, monitoring in different phenological phases, yield prediction, physical parameters of soils, water bodies, vegetation (f.i. biomass or Leaf Area Index maps).

Aerial images. These images are used worldwide to produce and update technical cartography, in a wide scale range (from 1:500 to 1:100,000), and topographical databases (DBT). Plus, photogrammetric techniques of stereoscopic images are used to create 3D surface and terrain models and aerial orthomosaics. With digital multispectral cameras, it is now possible to obtain high resolution thematic maps.

Drone images. Digital images (DIs) acquired by a drone (Unmanned Aerial Vehicle – UAV) can have centimetric resolutions and are used for detailed surveys on archaeological excavations, structural surveys, precision agriculture, critical events, emergency management, dangerous/remote areas, 3D building modelling, and many others.

On a large scale, ASIs provide reliable and updated geospatial information on large areas, with high geometric, spectral and temporal resolutions (GSTRs), allowing the description of the three main LC/LU categories: vegetation, built-up areas, water bodies – that is to say, GGBIs. Moreover, long time series in archives can help studying their changes in time (Osgouei & Kaya, 2017). For large regions lacking in cartographic data, ASIs can provide valuable georeferenced and up-to-date information.

Despite the wide range of available data, knowing which kind of images should be used and how to get them involves some experience, due to the intrinsic complexity of data. Though there are large archives of images, even finding and downloading them can be complicated: of course, resulting analyses and elaborations, and extracting the desired information in usable forms, needs higher skills development.

Another kind of data that is fundamental to understand local occurrences is the digital translation of the orography description: digital terrain models (DTM), that cover the entire Earth surface, are available nowadays, but with very different geometric resolutions (GRs), depending on the original satellite or aerial surveys (and, again, different geometric details can be 'seen' in the DTMs, depending on images resolution), from 1×1 km to 30×30 m, up to local ones, from aerial photos or Lidar, with cells of few meters, which are not available everywhere (terrain models made by drones can have resolutions that are significantly lesser than 1 m, but on very limited areas).

To view, overlay, and map in a common reference (and coordinate) system different kinds of geographic information, existing databases and maps, DTMs and 'raw' images, Geographic Information Systems (GIS) platforms and Remote Sensing specialized software packages can be used. Plus, using historical archives of ASIs (from 1950s onwards), the evolution of different areas can be researched (change detection).

Through GIS imagery tools, users can turn images, DTMs or CAD data into georeferenced databases, in manual, semi- or fully automatic ways. Once the dataset is ready, users can analyze the raster information content using processing functions (preset, or customized), to perform several tasks, such as data management, visualization, and analysis. In the analysis tasks, it is often convenient to convert images to set specific indices and simplify the identification of certain occurrences in imagery, such as vegetation, geology, water, or landscape units. At higher levels, the classification process allows to segment, select samples and post-process raster and vector layers, to extract selected features from images and datasets.

10.2 Existing Georeferenced Products and Related Uses

Satellite optical sensors provide DIs that consist of many 'single colour' images: this means not only the three colour bands - Red Green Blue (RGB), but also many different 'channels', covering information about the reflected light intensity in several portions of the electromagnetic spectrum (EMS) (Fig. 10.1).

By recording many different wavelengths, in fact, different kinds of surfaces can be distinguished more accurately in the images. Objects, that are similar in visible colours, may reveal significant differences in the invisible (for human eyes) EMS part, e.g. in the infrared section. In technical terms, surfaces made of different materials have 'spectral signatures' that can be similar in visible bands, but very different in other wavelengths (Fig. 10.2).

These multiband raster images (tiff, or jpeg, or other formats) can be observed on a screen by using only the three RGB video channels, that is why we can only display three bands at a time, in a 'false colour' way, that can give evidence to different objects types lying on the Earth surface (Fig. 10.3).

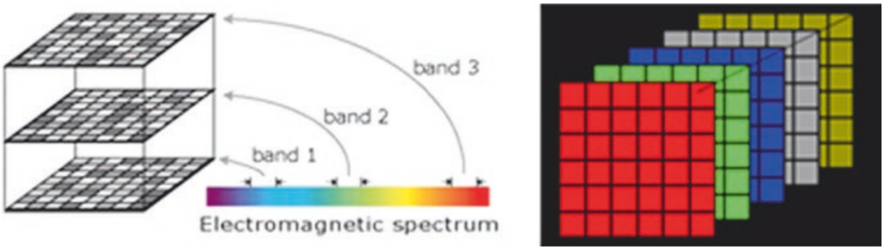

Fig. 10.1 Multispectral digital images formed by many rasters (bands)

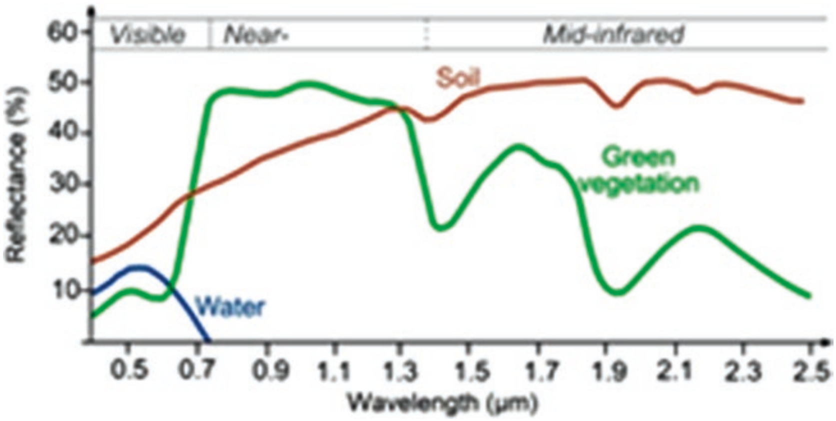

Fig. 10.2 Typical spectral signatures of Vegetation, Soil and Water

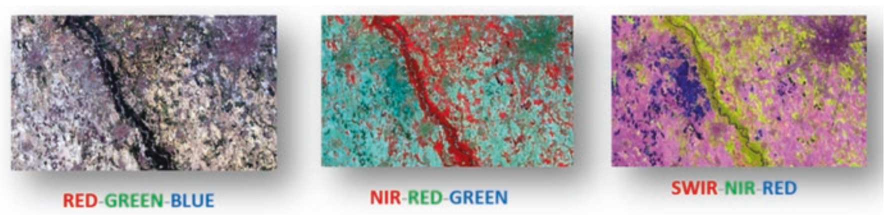

Fig. 10.3 False color visualization of multispectral images

Each band is described by digital numbers in a very 'dense' scale (very high dynamic range) of different values, from zero to the maximum intensity, a wider range compared to common RGB images, that have 256 hues for each band. In this way, the information content of each band increases, and the performance of automatic analysis, too, though involving heavy files and time-consuming elaborations.

Nowadays, many specialized sw interfaces have been developed, to search and download satellite images, for a given area and temporal interval, providing useful help in selecting only specific regions and bands and in discarding bad quality images (e.g. cloudy frames), as per step.esa, plugin.qgis and schihub.copernicus references (see Webliography).

Typically, 'products' of different 'levels' (that imply several enhancement steps, to provide accurate information) are available, instead of raw images, which are corrected after several geometric and radiometric distortions (radiometric calibration, atmospheric effect, geometric distortions due to topography and central projection, georeferencing in the due coordinate system, cloud masking, and so on), to let frames be actually representative of the Earth surface (Bottom of Atmosphere, BOA). Furthermore, some derived maps are included in downloadable files, together with quality indicators, auxiliary data and metadata (see sentinel.esa reference in Webliography).

For customized mapping purposes, the most useful products are the BOA orthophotos, which are orthogonal reprojections, in a geographic or cartographic reference system, of images, pixel by pixel, on a 3D terrain model (DTM). The orthophoto can be, then, overlapped with existing digital cartography. Other useful products are 'pansharpened' images, that are true/false colour images, with increased GRs compared to the original raw ones.

The 'products' coordinate and reference system must be checked carefully, before using them to create new maps, but also to overlay or integrate other geolocated data; a common (shared) reference system is mandatory to ensure the spatial coherence of different datasets. It is very important to check also the images georeferencing accuracy, which is the precision in pixels positioning, that is often of the same order of the pixel size (e.g. 10 m for SPOT images, as per providers).

Nowadays, satellite images are available at many different GSTRs (ranging from 1 km to 0.5 m) and bands (3 visible ones, MultiSpectral - MS, from 4 to 12 bands, Hyperspectral - hundreds of bands), revisiting from monthly to daily. Free images at 10–30 m resolutions come from Landsat, Sentinel, SPOT and other satellite systems, with revisiting times from 15 to 1 day, and many spectral bands. Commercial images can reach geometric resolution of less than 1 m and very short revisiting time, but most of them have few bands, thus preventing advanced processing. Many websites and providers can be found helping in the search of free or commercial images (e.g. see directory.eoportal, satimagingcorp, gisgeography and landinfo references in Webliography). Some companies release free of charge archive data for research or specific purposes (Fig. 10.4).

From a MS SI, specific features can be extracted by visual inspection, with the help of a GIS, to digitize specific maps, but it is more convenient to implement automatic feature extraction methods. The human view process, that lets us recognize different kinds of surfaces/objects by observing a colour image, has been partially translated into algorithms, that can automatically separate them. The use of more than three (RGB) bands enhances the automatic recognition. To detect the three main classes of LU/LC - vegetation (green), water (blue), built-up (grey), multiband classification analyses are much more effective compared to RGB images. Near Infrared (NIR) highlights vegetation, whilst water is more visible in different IR bands (SWIR short wave infrared).

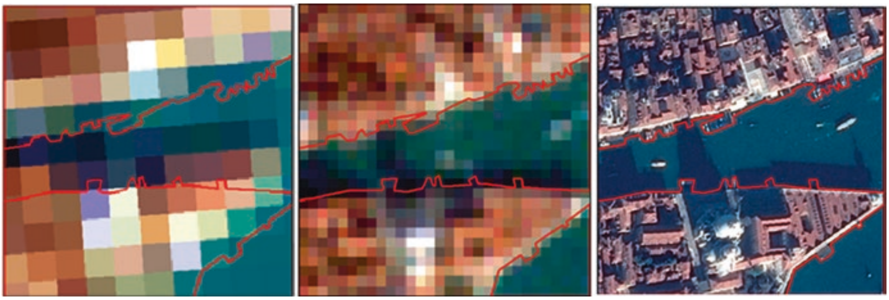

Fig. 10.4 Portion of SIs: Landsat 8 (30 m), Sentinel 2 (10 m), and Pleiades (50 cm). (From Wang et al. 2018)

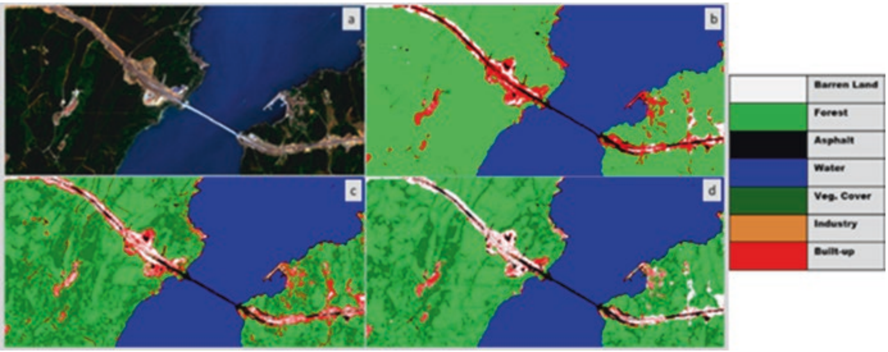

Fig. 10.5 (**a**) Sentinel-2A RGB image, (**b**) classified Sentinel-2A, (**c**) classified multi-index (NDBI, NDVIre, and MNDWI, (d) classified multi-index (NDTI, NDVIre, and MNDWI). (From Osgouei et al., 2019)

To enhance automatic classifications, it is possible to combine raster bands through specific computations, generating raster of ‘indices’ that emphasize a given kind of surface: NDVI (Normalized Difference Vegetation Index, computed with Red and NIR bands) to highlight vegetation, NDWI (Normalized Difference Water Index, computed with Green and NIR bands) for water bodies and NDBI (Normalized Difference Built-up Index, computed with SWIR and NIR bands) for bare surfaces. Many studies, with the aim of accurately extracting these features, using similar indices, highlighted that their values are affected by many factors. E.g., the NDBI cannot properly separate bare soil from built-up areas, therefore the Built-Up Index should be used (BUI = NDBI – NDVI). Similarly, NDVIre (with Red Edge band in place of NIR) gives better results for vegetation, and MNDW (Modified NDWI, with SWIR band in place of NIR) enhances water bodies selection.

The main issue in using indices is, then, the choice of the value (threshold) that marks a specific coverage (f.i. NDWI >0.5 = water). Better results can be reached by combining the indices of the three main classes (Osgouei et al., 2019) (Fig. 10.5).

To increase the cover classes accuracy and number, and produce more detailed maps, advanced analyses use 'classification' algorithms, that automatically group image pixels according to their radiometric intensity. The two main kinds of classification algorithms are called 'unsupervised' and 'supervised'. The first group can create pixels classes with similar radiometry in all bands, identified ex-post; the second one is 'trained' to group pixels by matching the radiometry of 'samples' target surfaces (water, asphalt, roofs, grass, and so on). The training samples are extracted from images, sometimes adding in-field surveyed information (ground truth). GIS and Remote Sensing software packages include programs that perform these classifications, and, with proper check on 'validation samples', yield maps with associated classification accuracies. By using satellite images with high geometric and spectral resolutions, very detailed maps can be created. The simultaneous use of images at different dates (multitemporal datasets) enhances classifications of some surfaces, typically vegetation (forests, crops), that show strong seasonal phenological changes (Immitzer et al., 2019).

Another relevant set of tools comes from DTMs, which contain the metric description of Earth surface and provide complementary information for geospatial analyses. The most used formats are regular cell grids of given size with associated heights in each of them (raster), or a list of 3D coordinates for many points (vector, Triangular Irregular Network). Maps of local slopes, exposure (aspect) and isolines (level curves) can be computed using a GIS, and a selection of slopes or heights can support specific studies (Hirt, 2015).

Many global and local DTMs are available, coming from satellite or aerial surveys, with spatial resolutions ranging from 100 km to 5–10 m; again, the coordinate and reference system must be checked carefully, as different countries use distinct systems, as well as the height data accuracy (see landinfo and gisgeography references in Webliography).

10.3 Comparing Metropolitan Contexts Using Maps for Possible Future Developments

Detecting the evolution of GGBIs to a worldwide level, starting from metropolitan contexts, can be a significant way to understand past and future dynamics, using protocol maps (Contin et al., 2014a). Comparing metropolitan areas using a prospective indicators research can provide new experimental understandings, relating and evaluating different urban systems using one single method, to be adapted to local specific factors. To create a common informative background, a protocol to create appropriate and accurate maps is needed, starting from a common set of definitions and operations:

1. Data should be retrieved from existing databases, having common features (resolution) worldwide, using similar algorithms to define different elements of the GGBIs in a common and comparable way.

2. Using the same aerial photographic and satellite image interpretation techniques, GGBIs should be extracted in a homogeneous and comparable way (e.g. through specific algorithms, as described in the previous paragraph), using the same definition to maximize comparative levels.
3. Sending vector data to local authorities is due to validate the GGBIs detection and improve data accuracy levels, crossmerging information with existing raster and vector databases (possibly, using official Geoinformation portals), e.g. datasets coming from official cartographic platforms or other geographic services, such as DUSAF, that is an Italian project aimed at producing elaborations about agriculture and forestry coverage for the Lombardy area. The last version (2018) started from orthophotos and ASIs to classify data in 5 hierarchical levels, including Corine Land Cover classes (urban, agricultural, forestry, seminatural, humid and water), further defined in local subclasses intersecting information with secondary databases. Another possible example comes from ERSAF, the Lombardy Region Agriculture and Forestry Agency, which used multitemporal images (2014), including NDVIs (calculated with ISODATA unsupervised algorithm), to detect the green areas evolution through ERDAS Imagine SW, comparing RGB false color images. The result is a multilevel classification, ensuring the correct recognition of green areas, deselecting high-reflectance pixels (built-up) and cleaning datasets by excluding single or small groups of pixels and comparing them with existing vector ones.
4. Data post-processing to detect possible evolution trends.
5. Definition of comparison maps to build a protocol mapping dataset to different scales (XL to XS).

Actually, from the point of view of metropolitan trends and dynamics, the problem of finding different definitions to represent metropolitan aggregates and their possible limits can be effectively solved using a geographical approach, instead of a purely statistical one, which embodies the traditional governance management style, based on authorities and institutional architectures (Contin et al., 2014a). Describing metropolitan aggregates using open source data becomes, then, the most effective way of building protocol maps to outline the GGBIs in urban areas, delineating the balance between GGIs, hazard elements, instable and changing borders (e.g. with buffer mixed zones), landscape and development units, ecosystem services and other hot topics (WHO, 2017). Relating a set of selected, comparable data will, then, help highlighting past and future trends.

The correct planning of urban contexts can help moderating some of the most important risks for human health, even in the built environment, through the correct identification and monitoring of green, grey, and blue infrastructures (GGBIs). The poor localization choices of settlements can even trigger multiple risks, causing significant effects and deaths reasons, that can be easily prevented by correctly teaching urban managers and citizens how to deal with these issues. The goal is to highlight a new planning and design approach for developing countries, using modern technological tools to drive conscious localization choices, even in highly fragmented urban contexts, where self-constructed housing is the standard.

The changing conditions of metropolitan planning basics, that determine the variability of our local and national contexts, can be effectively measured thanks to quantitative and qualitative indicators (Pandolfi, 2019). These values could be calculated through procedures implemented thanks to GIS, using elements of geostatistics and numeric cartography. The speculative basics of the need of using GIS for the localization analysis is strongly connected to the necessity of finding a steadier definition of its variability in time and space (Campi et al., 2017).

In the light of the general and specific measure provided by local authorities, it is crucial to implement new tools for the identification and assessment of metropolitan areas, using quantitative and qualitative procedures that can be widely applied using the same process, to be referred as best practices. This is even more important in the light of the fact that many international establishments demand for specific best practices to be implemented in all the relevant fields (see WASH_1.0, 2017). The process of identification and assessment is still far to be closed, as it is lacking a common methodology, that a set of some basic standards could spread.

This is why a worldwide research program based on protocol maps should be addressed to identify tools, indexes, methods, and best practices for the metropolitan planning best practices definition, to assess the correct planning approaches related to moderating some of the most important risks for human health (WHO, 2017), even in the built environment, considering the values assigned to them by the interested parties and populations. Most of these objectives and measures could be efficiently implemented through GIS procedures, involving quantitative and qualitative analysis techniques, that could lead to the complete identification of the relevant factors which metropolitan aggregates consists of, to define quality objectives for Planning rules.

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