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IMPACTS OF SENSOR SPATIAL RESOLUTION ON REMOTE SENSING IMAGE CLASSIFICATION

Thomas U. Omali

Department of Geoinformatics and Surveying
University of Nigeria Enugu Campus
Enugu, Nigeria
E-mail: t.omali@yahoo.com

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ABSTRACT

There has been a significant upsurge in the development of satellite platforms with enormous number of sensors in recent years. Several remotely sensed data with spatial resolutions extending from 0.5 to 25,000m are accessible for diverse applications. This advancements result in novel and substantial modifications as well as challenges in the methodology of remotely sensed data analysis, integration, and the efficient spatial modelling of these data. This paper critically reviews the impacts of sensor spatial resolution on remote sensing image classification. First and foremost, an introductory background was presented. Second, spatial resolution was characterized in terms of four classes including low, medium, high, and very high resolutions. Third, basic perception on sensor spatial resolution was discussed. The fourth session dealt with sensor spatial resolution and mixed pixel challenge. And the fifth session elaborated the suitability of specific spatial resolution for image classification. Finally, it was revealed that, even though, higher spatial resolution remotely sensed data may deliver improved data, it may not always be desired due to intricate nature of interpretation, data volume and data acquisition costs. And despite the increasing propensity for more satellites with improved spatial characteristics and to develop applications for the same, the lower spatial resolution satellites remain invaluable.

1.0 INTRODUCTION

Remote sensing technique has increasingly become a predominant tool in diverse areas of application. It has proven its capacity in addressing a variety of global applications including food security, forestry, global conflict, ecological issues, land sustainability, and the host of other areas of specific interest. This evolution can be predominantly ascribed to technological advances in the field of remote sensing as well as progress of critical technologies such as increased computing power, mobile technology adoption, efficient distributed computing and dissemination, advanced pattern recognition technologies from medical imaging, robotics and machine learning, and many more. The emergences of more Earth Observation satellites have increased the use of satellite imagery in applications like land cover detection, and environment monitoring [1]. Remotely sensed data have the provision of a synoptic view of the surface area of interest, thereby capturing the spatial variability in attributes of interest like tree height, crown closure, etc. [2]. These data can be processed in order to derive map-like products, through certain processes ranging from data capture to map production. Of all the processes in remote sensing, image classification is the most significant. This is because information is generally extracted from satellite images by classification techniques [1].

The intent of the classification procedure is to categorize all pixels in a digital image into one of numerous land cover classes, or "themes". This grouped data may then be used to produce thematic maps of the land cover existing in an image. Typically, multispectral data are used to perform the classification and, indeed, the spectral pattern existing within the data for each pixel is used as the numerical basis for grouping. The goal of image classification is to identify and portray, as a unique gray level (or color), the features occurring in an image in terms of the object or type of land cover these features actually represent on the ground. Yet, most results of remotely sensed data classification operations are subjected to various influences. For instance, spatial resolution is an important factor that affects classification details and accuracy [3].

Spatial resolution commonly referred to as 'pixel size' in digital images [4] is by far the most important characteristics of a remote sensing system [5]. Spatial resolution is the ability to sharply and clearly define the extent or shape of features within an image [6]. It is related to the sensor characteristics that define the degree of spatial detail it provide about features on the earth's surface. In analogue photography, the spatial resolution of photograph refers to the sharpness of the image [5] whereas digital image spatial resolution refers to the size of the individual physical sample unit on the ground that is sensed by a given detector at any instant in time [4]. It is noteworthy that, the spatial resolution in a digital image is limited by the pixel size, i.e. the smallest resolvable object is usually bigger than the pixel size.

The inherent resolution of a sensor is determined principally by the instantaneous field of view of the sensor. The instantaneous field-of-view (IFOV) defines the (nominal) angle, subtended at the sensor, over which the instrument records radiation emanating from the Earth's surface at a given instant in time [7]. The area on the Earth's surface to which this corresponds, known as the ground resolution element (GRE), is therefore controlled by the IFOV and the height of the sensor above the ground [7]. For high spatial resolution, the sensor has to have a small IFOV [6]. However, this reduces the amount of energy that can be detected as the area of ground resolution cell within the IFOV becomes smaller [6], and in consequence affects the classification of features present in the image produced. In other words, the spatial resolution of a sensor whether high or low determine the accuracy of classification operation performed on images produced by the sensor. Thus, the aim of this paper is to critically review the impacts of sensor spatial resolution on remote sensing image classification

2.0 CHARACTERIZATION OF SENSOR SPATIAL RESOLUTIONS

Over the past half century, remote sensing imagery has been acquired by a range of airborne and space-borne sensors from multispectral sensors to hyperspectral sensors with wave- lengths ranging from visible to microwave, with spatial resolutions ranging from sub-meter to kilometres and with temporal frequencies ranging from 30 min to weeks or months [8], [9]. In principle, any sensor can be used for any problem; for instance, it would be possible to address global land-cover using one-meter hyperspectral imagery [4]. There are classes of problems that require specific spatial characteristics of remotely sensed data to solve efficiently. For example, the range of resolution required to detect a distinct tree is by far smaller as compared to that required to detect a large block of building, and resolution required for mapping vegetation cover may differ from that used for mapping vegetation types. Spatial autocorrelation existing in each class is an important factor influencing classification results at each resolution level [10].

Generally, sensor spatial resolution may be categorized into low or coarse, medium or moderate, fine or high, and very high resolutions. These descriptors denote the degree of the surface feature or surface detail that a satellite sensor can discriminate. Objects that are smaller than a sensor's spatial resolution cannot be distinctly differentiated, so the smaller the dimensions of the resolution, the more detail one can see or 'resolve' in an image, and thus the 'higher' or 'finer' the resolution. 'Low' or 'coarse' spatial resolution means that the smallest area resolved by a sensor is relatively large, which means less detail.

Often the ground sampling distance (pixel size) in an image after image re-sampling is used to represent the spatial resolution, but it can be different from the spatial resolution of the sensor that records the image [3]. The rough guidelines for definitions of spatial resolution based on ground sampling distance (GSD) was defined by Navulur (2006) [8], [9] as (i) low or coarse resolution is defined as pixels with ground sampling distance (GSD) of 30m or greater, (ii) medium resolution has GSD in the range of 2.0–30m, (iii) high resolution has GSD 0.5–2.0m, and (iv) very high resolution has pixel sizes <0.5m GSD.

Generally, remote sensing systems having spatial resolution that are more than 1km are categorized as low resolution systems. There are many available low resolution system including Geostationary Satellites, Polar Orbiting Meteorological Satellites (NOAA-AVHRR, DMSP-OLS), Orbview2-SeaWiFS, SPOT4-Vegetation, ADEOS-OCTS, and MODIS etc. Moderate resolution systems are remote sensing systems with spatial resolution ranging from 100m to 1km, such as bands 1-7 of TERRA-MODIS, ENVISAT-MERIS, IRS WiFS, ADEOS2-GLI, and band 6 of Landsat TM etc. Furthermore, satellite sensors having spatial resolution roughly ranging between 5-100m are classified as high resolution systems. For instance, NigeriaSat–1, Landsat ETM+, SPOT (1, 2, 4), MOS, EO1, RESURS IRS LISS- III and AWiFS,. Very high resolution systems are the remote sensors which provide less than 5m spatial resolution including IKONOS2, EROS-A1, Quickbird2, Orbview3, SPOT5, and GeoEye etc.

3.0 BASIC PERCEPTION ON SENSOR SPATIAL RESOLUTION

The effects of spatial resolution on the accuracy of mapping land use/cover types have received increasing attention as a large number of multi-scale earth observation data become available [11]. Spatial resolution is an important factor that affects classification details and accuracy, which influences the selection of a classification approach [12]. Unseemly choice of different spatial resolution can lead to misleading interpretation [13]. In order to comprehend spatial resolution in the best manner, Strahler et al. [14] explained in reference to the size of the objects that we want to sense. They described H- and L- resolution (high- and low-resolution) scene models based on the relationships between the sizes of the scene elements and the resolution cell of the sensor. Of course, the size of ground objects relative to the spatial resolution of a sensor is directly related to image variance [15]. High or H- resolution images will contain multiple pixels for each object, which adds to the overall variance of the image [4]. For instance, in an image in which individual trees are represented by multiple pixels, each pixel may be shadowed or sunlit, young foliage or old, or may contain one of a variety of different understorey components [4]. The scene elements in the H- resolution model are larger than the resolution cell and can, therefore, be directly detected [16], whereas, the scene elements in the L-resolution model are smaller than the resolution cells, and cannot be directly identified. For image pixels of low resolution imagery, radiance is a function of multiple objects, and the averaging impact is worthwhile by reducing high spatial frequency variance. This is useful, for example, in that it creates the kind of stable and representative spectral classes needed for many types of image processing [16]. Yet, pixels with much larger size as compared to the objects of concern have the propensity of averaging multiple objects of dissimilar attributes.
When the scene objects become progressively smaller comparatively to the cell size resolution, they may no longer be considered as individual objects. Hence, the reflectance measured by the sensor can be treated as a sum of interactions among various classes of scene elements as weighted by their relative proportions [14]. Medium spatial resolution data such as Landsat TM/ETM + or coarse spatial resolution data such as AVHRR and MODIS are attributed to the L-resolution model [16]. The second factor which influences classification accuracy is that finer spatial resolution increases the spectral-radiometric variation of land cover types [17].

4.0 SENSOR SPATIAL RESOLUTION AND MIXED PIXEL CHALLENGE

The synoptic view is a significant strength of remote sensing for the study of planetary surfaces and global processes [18]. As an important source of urban information, remote sensing data provide a spatially consistent coverage of large areas with both high spatial detail and high temporal frequency [19]. The entire coverage is usually categorized into land cover classes as thematic maps or for onward processing. Images produced by digital sensors are represented in 2-dimensional arrays of data cells called picture elements or pixels. The sizes of these cells in terms of the area that they represent on the ground are defined by the spatial resolution of the sensor.

Most classification approaches are based on per-pixel information, in which each pixel is classified into one category and the land-cover classes are mutually exclusive [16]. Due to the heterogeneity of landscapes and the limitation in spatial resolution of remote-sensing imagery, mixed pixels are common in medium and coarse spatial resolution data [20], [16]. In other words, remote sensing image contains a mix of pure and mixed pixels. While pure pixel contains only one feature, mixed pixel (or mixels) contains more than one feature. The occurrence of mixed pixel comes to play when the spatial frequency is more than the interval between pixels. In this case, two or more surface materials may fall within a single pixel, that is, each cell in the image contains energy from different land-cover types, called mixed pixels. Mixed Pixels are major cause of uncertainty in image classification process [1]. Of course, without overcoming the issue of mixed pixel, the possibility of extracting meaningful data will remain unrealized [21]. The manifestation of mixels is a function of sensor spatial resolution and the spatial variability of the observed surface. Of course, the presence of mixels is a principal problem against effective use of per-pixel technique of satellite data classification. First, the detected spectral response of a mixel will be some composite of the individual spectral signals from the constituent surface materials [22]. Second, the size, shape, and spatial arrangement (pattern) of the major spatial entities present within the scene will be to some extent obscured [15].

Usually, urban areas are heterogeneous and most urban image pixels at the resolution of Landsat and similar sensors are mixed with varying proportions of different components and/or materials [23]. In most situations, the components in urban environments are mixed together within individual pixels. For example, pixels assigned as residential may represent between 20 – 100% impervious surfaces while also representing between 0 – 60% tree canopy coverage [24]. Each pixel within an image provides a single measurement for an area that comprises multiple components [18]. Mixed pixels are very difficult to discriminate from each other, and have been recognized as a major problem in image classification especially when per-pixel classifiers are used. Obviously, certain feature might not be recognized at a low or medium resolution, but with a finer spatial resolution, more details about objects in a scene become available.

5.0 Suitability of Specific Spatial Resolution for Image Classification

The selection of suitable sensor data is the first important step for a successful classification for a specific purpose [4]. Scale, image resolution, and the user's need are the most important factors affecting the selection of remotely sensed data [16]. The user's need determines the nature of classification and the scale of the study area, thus affecting the selection of suitable spatial resolution of remotely sensed data [16]. One of the fundamental characteristics of a remotely sensed image is its spatial resolution, or the characteristic size on the ground associated with the radiance measurement of a pixel [15], [3]. Appropriate spatial resolution is a function of the type of environment, the kind of information desired and the techniques used to extract information [3]. Consequently, selecting a specific spatial resolution from various spatial resolutions for particular purpose can lead to ambiguous image interpretation. For example, in a Landsat Multi- Spectral Scanner image, the urban residential environment is sensed as a relatively homogeneous entity [3]. However, when observed at finer resolution, the residential area is mostly made of individual houses, roads and plants [3]. Thus, selection of appropriate spatial resolution becomes more complex as resolutions increase, [13], [3].

The basic information contained in a remotely sensed image is strongly dependent on spatial resolution [15], [13] and the spatial resolution of an image extensively affects every stage of image classification [13]. In mapping vegetation for instance, images with low resolutions may be adopted only when the high level of vegetation classes are to be identified, while the images with relatively higher resolutions are used for fine-detailed classifications of vegetation [8]. From the mapping scale point of view, vegetation mapping at a small scale usually requires high-resolution images, while low- resolution images are used for a large-scale mapping [8]. In general, a fine-scale classification system is needed for a classification at a local level, thus high spatial resolution data such as IKONOS and SPOT 5 HRG data are helpful [16]. At a regional scale, medium spatial resolution data such as Landsat TM/ETM +, and Terra ASTER are the most frequently used data [16]. At a continental or global scale, coarse spatial resolution data such as AVHRR, MODIS, and SPOT Vegetation are preferable [16].

High resolution (HR) images are useful in many applications such as remote sensing, video frame freezing, medical diagnostics, and military information gathering, etc. However, because of the high cost and physical limitations of the high precision optics and image sensors, it is not easy to obtain the desired HR images in many cases [25]. Therefore, super resolution (SR) image reconstruction techniques, which can reconstruct one or a set of HR images from a sequence of low resolution (LR) images of the same scene, have been widely researched in the last two decades [25]. Numerous methods have been used to evaluate suitable spatial resolutions for image classification over the years. Although a particular classification can achieve the best result from a single resolution appropriate to the class, there is no single resolution which would give the best results from all classes [26]. In fact, different features require either finer or coarser resolutions for adequate classification. This is because various objects require different analysis scales according to the image scene model [15]. Thus, even though there is growing application of high-resolution data, medium-resolution imagery is still the preferred data source. This is because, medium-resolution remotely sensed data is globally accessible, and it is exclusively composed of the only long-term, consistent digital dataset. Nevertheless, commonly used detection techniques, such as the calculation of classification and vegetation indices from medium spatial resolution imagery, may be ineffective in quantifying physically fine-resolution information related to urban greenness.

6.0 Conclusion

There has been upsurge in the development of satellite platforms with enormous number of sensors in recent years. Several remotely sensed data with spatial resolutions ranging from 0.5 to 25,000m are accessible for diverse applications. This advancements result in novel and substantial modifications as well as challenges in the methodology of remotely sensed data analysis, integration, and the efficient spatial modelling of these data. This discussed the impacts of sensor spatial resolution on remote sensing image classification. Spatial resolution may be broadly categorized into four including low, medium, high, and very high resolutions. These characterizations depend on the amount of the surface feature or surface detail that a satellite sensor can discriminate and/or the Ground Sampling Distance. Choosing suitable spatial resolution(s) is obviously one of the basic factors when employing remotely sensed data for land use and land cover classification and mapping. This is because the choice of different spatial resolution can lead to misleading interpretation since it affects classification details and accuracy. One can easily understand spatial resolution in terms of the feature to be sensed. This may be achieved through high- and low- resolution scene models based on the relationships between the sizes of the scene elements and the resolution cell of the sensor. Of course, the size of ground features relative to the spatial resolution of a sensor is directly related to image variance. Mixed Pixels is a major challenge in image classification especially when per-pixel classifiers are used. It is manifested depending mostly on sensor spatial resolution and the spatial variability of the observed surface. Each pixel within an image provides a single measurement for an area that comprises multiple components called endmembers. Mixed pixels are very difficult to discriminate from each other. Obviously, certain feature might not be recognized at a low or medium resolution, but with a finer spatial resolution, more details about objects in a scene become available. The suitability of specific spatial resolution for image classification depends on certain factors including the type of environment, the kind of information desired and the techniques used to extract information. Thus, selecting a specific spatial resolution from various spatial resolutions for particular purpose can lead to ambiguous image interpretation. Finally, it was revealed that, even though, higher spatial resolution remotely sensed data may deliver improved data, it may not always be desired due to intricate nature of interpretation, data volume and data acquisition costs. And despite the increasing propensity for more satellites with improved spatial characteristics and to develop applications for the same, the lower spatial resolution satellites remain invaluable. Selecting suitable spatial resolution(s) of remotely sensed data is one of the most essential considerations prior to remotely sensed data classification. When defining the appropriate spatial resolution for analysis, certain factors are very salient including spatial resolution of available data, environmental conditions, anticipated information, and procedures employed in extracting information. Proper image classification is to a great extent dependent on the knowledge of certain spatial attributes of the data so as to determine the appropriate classification procedure and parameters to use. The reason for this is because the spatial resolution of remotely sensed data largely affects each of the stages involve in image classification. With the increased availability of very high resolution multi-spectral images spatial resolution variation will play an increasingly important role in the employment of remotely sensed imagery. Though, higher spatial resolution remotely sensed data may deliver enhanced data, it may not always be desired due to intricate nature of interpretation, data volume and data acquisition costs. And despite the increasing propensity for more satellites with improved spatial characteristics and to develop applications for the same, the lower spatial resolution satellites remain invaluable

References

[1] M. Arif, M. Suresh, K. Jain, and S. Dundhigal, ''Sub Pixel Classification of High Resolution Satellite Imagery,'' *International Journal of Computer Applications*, vol. 129, no.1, 2015.

[2] L. Kumar, P. Sinha, S. Taylor, and A. F. Alqurashi, "Review of the Use of Remote Sensing for Biomass Estimation to Support Renewable Energy Generation," *Journal of Applied Remote Sensing*, vol. 9, 2017

[3] D. Chen, D. A. Stow, and P. Gong, ''Examining the Effect of Spatial Resolution and Texture Window Size on Classification Accuracy: An Urban Environment Case,'' *Int. J. Remote Sensing* 25(00), pp. 1–16, 2004.

[4] M. A. Lefsky, and W. B. Cohen, ''Selection of Remotely Sensed Data. Current Affiliation: Department of Forest Sciences, Colorado State University, Fort Collins, Colorado, 80523-1470, USA, pp. 78-87, 2003.

[5] S. K. Duggal, ''Surveyin,'' Tata Mc Graw-Hill Publishing Company Limited, New Delhi, pp. 351-352, 2004.

[6] F. I. Okeke, and C. D. Anejionu, ''Investigating the Usefulness of Fusing NigeriaSat–1 Data and NOAA–AVHRR Images as well as High–Resolution Aerial Photograph,'' *Nigerian Journal of Space Research*, 4, pp. 73–90, 2007.

[7] M. R. B. Forshaw, A. Haskell, P. F. Miller, D. J. Stanley, and J. R. G. Townshend, ''Spatial Resolution of Remotely- Sensed Imagery: A Review Paper,'' *International Journal of Remote Sensing*, vol. 4, pp. 497–520, 1983.

[8] Y. Xie, Z. Sha, and M. Yu, ''Remote Sensing Imagery in Vegetation Mapping: A Review,'' *Journal of Plant Ecology*, vol. 1, no. 1, pp 9–23, 2008.

[9] K. I. Nwosu, and A. I. Ugwuoti, ''Vegetation Mapping for Nigeria from Remotely- Sensed Imagery: Prospect,'' *The Tropical Environment*, vol. 10, no. 1, p. 157, 2011.

[10] D. Chen and D. A Stow, D.A., ''Strategies for integrating information from multiple spatial resolutions into land-use/land-cover classification routines,'' *Photogrammetric Engineering & Remote Sensing*, vol. 69, no. 11, pp. 1279-1287, 2003.

[11] J. L. Dungan, ''Scaling up and scaling down: the relevance of the support effect on remote sensing of vegetation,'' *In Modeling Scale in Geographic Information Science*, N.J. Tate and P.M. Atkinson (eds). John Wiley&Sons, Ltd., pp. 221-235, 2001.

[12] S. V. Prasad, T. S Savithri, and I. V. K. Murali, ''Techniques in Image Classification: A Survey,'' *Global Journal of Researches in Engineering: Electrical and Electronics Engineering* vol. 15, no. 6, 2015.

[13] C. Suwanprasit, and N. Srichai, ''Impacts of Spatial Resolution on Land Cover Classification,'' Proceedings of the Asia-Pacific Advanced Network 33, pp. 39-47, 2012.

[14] A. Strahler, C. E. Woodcock, and J. Smith, ''On the Nature of Models in Remote Sensing,'' *Remote Sensing of Environment*, vol. 20, pp. 121–139, 1986

[15] C. E. Woodcock, and A. H. Strahler, '' The Factor of Scale in Remote Sensing,'' *Remote Sensing of Environment*, vol. 21, no. 3, pp. 311-332, 1987.

[16] Lu, D., and Q. Weng, ''A Survey of Image Classification Methods and Techniques for Improving Classification Performance,'' *International Journal of Remote Sensing*, vol. 28, no. 5, pp. 823–870, 2007.

[17] B. M. Markham, and J. R. G. Townshend, ''Land Cover Classification Accuracy As A Function Of Sensor Spatial Resolution,'' Proceedings of the 15th International Symposium on Remote Sensing of Environment, pp. 1075–1090, 1981.

[18] S. Tompkins, J. F. Mustard, C. M. Pieters, and D. W. Forsyth, ''Optimization of Endmembers for Spectral Mixture Analysis,'' *Remote Sensing of Environment*, vol. 59, pp. 472-489, 1997.

[19] J. S. Deng, K. Wang, Y. Hong, and J. C. Qi, ''Spatio-Temporal Dynamics and Evolution of Land Use Change and Landscape Pattern in Response to Rapid Urbanization,'' *Landscape and Urban Planning*, vol. 92, pp. 187–198, 2009.

[20] L. P. Zhang and D. R. Li, ''Study of the Spectral Mixture Model of Soil and Vegetation in Poyang Lake Area, China,'' *International Journal of Remote Sensing*, vol. 9, no. 11, pp. 2077-2084, 1998.

[21] G. M. Foody, ''Sub-Pixel Methods in Remote Sensing,'' In: S. M. D. Jong, and F. D. Meer, (Eds.), *Remote Sensing Image Analysis.* Springer, 2006.

[22] M. O. Smith, P. E. Johnson, J. B. Adams, ''Quantitative Determination Of Mineral Types And Abundances From Reflectance Spectra Using Principal Components Analysis,'' *Journal of Geophysical Research*, vol. 90, pp. 792–804, 1985.

[23] P. Pu, P. Gong, and R. Michishita, ''Spectral Mixture Analysis for Mapping Abundance of Urban Surface Components from the Terra/Aster Data,'' ASPRS Annual

Conference Tampa, Florida, May 7-11, 2007.

[24] W. B. Clapham, Jr., ''Continuum-Based Classification of Remotely Sensed Imagery to Describe Urban Sprawl on a Watershed Scale,'' *Remote Sensing of Environment*, vol. 86, pp. 322-340, 2003.

[25] L. Zhang, and X. Huang, ''Advanced processing techniques for remotely sensed imagery,'' *Journal of Remote Sensing*, vol. 13, no. 4, pp. 559-569. 2009.

[26] D. J. Marceau, P. . Howarth, D. J. Gratton, ''Remote Sensing and the Measurement of Geographical Entities in a Forest Environment 2: The Optimal Spatial Resolution,'' *Remote Sensing of Environment, vol.* 49, pp. 105-117, 1994.