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NDVI, scale invariance and the modifiable areal unit problem: An assessment of vegetation in the Adelaide Parklands

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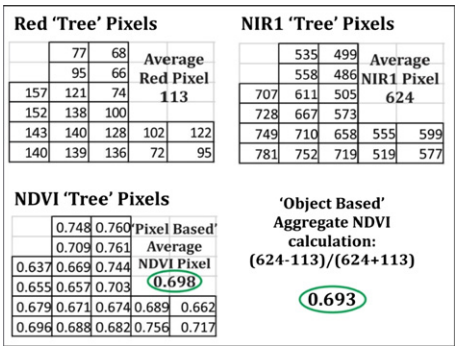
HIGHLIGHTS

- Investigating MAUP effects on pure vegetation pixels using the two different platforms of satellite and airborne imagery
- Employing two different approaches to calculate NDVI using pure pixels of vegetation
- Comparing these two different approaches in an urban parkland in Australia and in the Colorado River Delta

GRAPHICAL ABSTRACT



NDVI calculations for pure pixels of urban vegetation: 1) pixel-based NDVI; and 2) object-based NDVI for the three vegetation categories of trees, shrubs and turf grasses.

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ABSTRACT

This research addresses the question as to whether or not the Normalised Difference Vegetation Index (NDVI) is scale invariant (i.e. constant over spatial aggregation) for pure pixels of urban vegetation. It has been long recognized that there are issues related to the modifiable areal unit problem (MAUP) pertaining to indices such as NDVI and images at varying spatial resolutions. These issues are relevant to using NDVI values in spatial analyses. We compare two different methods of calculation of a mean NDVI: 1) using pixel values of NDVI within feature/object boundaries and 2) first calculating the mean red and mean near-infrared across all feature pixels and then calculating NDVI. We explore the nature and magnitude of these differences for images taken from two sensors, a 1.24 m resolution WorldView-3 and a 0.1 m resolution digital aerial image. We apply these methods over an urban park located in the Adelaide Parklands of South Australia. We demonstrate that the MAUP is not an issue for calculation of NDVI within a sensor for pure urban vegetation pixels. This may prove useful for future rule-based monitoring of the ecosystem functioning of green infrastructure.

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1. Introduction

The Normalised Difference Vegetation Index (NDVI) is a numerical indicator used to characterize the greenness of live vegetation (Rouse et al., 1974a; Tucker, 1979). NDVI has been used in numerous studies of plant extent and magnitude using satellite imagery (Leon et al., 2012). The NDVI of a multispectral image takes advantage of the differential reflection characteristics of two bands, namely chlorophyll absorption in the Red band and the high reflectivity of plant cell structure in the near-infrared (NIR) band (Fensholt and Proud, 2012; Glenn et al., 2008; Glenn et al., 2010; Vina et al., 2011). NDVI can be calculated on a per pixel basis and is simply: (NIR − Red)/(NIR + Red). Healthy or dense vegetation absorbs more visible light and reflects a large portion of the NIR while unhealthy and sparse vegetation reflects more visible and less NIR (Dutta et al., 2015; Mulmi et al., 2016). This results in high NDVI values where there is a high density of healthy 'green' vegetation. NDVI values can vary from −1.0 to +1.0. The potential of NDVI time series to investigate and record the difference between natural and anthropogenically designed flora has made this one of the most well-known and frequently used indices in vegetation studies (Blaes et al., 2016; Lanorte et al., 2014; Wang et al., 2011).

Ratios or differences using energy from two bands were first developed by Jordan (1969) to assess green vegetation spectral features for estimating energy accumulation in plant canopies, biomass, and the leaf area per unit ground (LAI, leaf area index). The provenance of the NDVI is a slight mystery. It seems that NDVI was introduced by Rouse et al. (1974a) 1974Rouse et al. (1974b). However, its use since then has grown significantly. For example, 1196 journal articles in ScienceDirect in 2016 alone relate to the use of the NDVI. The Advanced Very High Resolution Radiometer (AVHRR) is the longest running series of NDVI products for regional and global scale vegetation studies. AVHRR is carried on board the National Oceanic and Atmospheric Administration (NOAA) polar-orbiting weather satellites. Its daily repeat cycle produces 1 km resolution images that have led to the generation of an archive of NDVI-based images of the world's land surface dating from 1982. These data have been used to portray seasonal and annual changes in vegetation (Guyot, 1990; Jensen and Cowen, 1999; Los, 1998). The last generation of high spatial resolution platforms including WorldView, IKONOS, GeoEye as well as airborne images all provide detailed information appropriate for microscale studies such as forestry and urban landscapes (Blaes et al., 2016; Dragozi et al., 2016; Singh et al., 2012). In addition, some satellites such as WorldView-2 and WorldView-3 have multispectral sensors which are more sensitive to the NIR and Red bands. These two satellites have two Red bands (red and red-edge) and two NIR bands (NIR1 and NIR2). These developments have progressed the studies on vegetation canopies and vegetation indices including NDVI (Karlson et al., 2016; Muller and van Niekerk, 2016; Nouri et al., 2014; Nouri et al., 2016a; Pu and Cheng, 2015).

The modifiable areal unit problem (MAUP) is a fundamental challenge associated with the representation and analysis of spatial data

Table 1
Review of MAUP studies.
After Davis (2012).

Authors	Scale aggregate problem	Zoning problem	Hotspot	Moving window	Upscaling	OSA (object specific analysis)	OSU (object specific upscaling)	COSP (change of support problem)	Geocoded data	LISA (local indicators of spatial association)
Dark and Bram (2007)	X				X					
Ratcliffe and McCullagh (1999)	X		X	X					X	X
Shriner et al. (2006)	X		X							
Mu and Wang (2008)	X						X			
MacEachren (1982)		X								
Bhati (2005)		X							X	
Hipp (2007)		X								
Hayward and Parent (2009)	X	X								
Jelinski and Wu (1996)	X	X								
Gotway and Young (2002)	X	X			X			X		
Nakaya (2000)	X	X								
Hay, Parceau, Dube, and Bouchard (2001)	X	X			X	X	X			
Pawitan and Steel (2009)	X	X								
Tagashira and Okabe (2002)	X	X								
Chainey, Thompson, and Uhlig (2008)	X	X	X						X	
Gatrell, Bailey, Diggle, and Rowlinson (1996)				X						
Chainey, Thompson, and Uhlig (2008)			X							
Fotheringham and Wong (1991)	X									
Lentz, Blackburn, and Curtis (2011)	X	X	X							
Amrhein (1993)	X	X								
Amrhein and Reynolds (1996)	X	X								
Amrhein and Reynolds (1997)					X					
Rushton and Lolonis (1996)				X						
Rushton (1998)				X						

(Openshaw, 1984). MAUP refers to the fact that the observed aggregated values will vary according to how the area boundaries are drawn. MAUP comprises both scale and aggregation effects. The scale effect relates to the size of the areal units that are used and the aggregation effect relates to the exact way in which they are assembled at a given scale. Changes in either can bring about changes in the apparent geographical distribution of the variable in question. MAUP can present particular difficulties in the field of landscape ecology because of its influence on many landscape indices (Jelinski and Wu, 1996; Li and Wu, 2004).

Consideration has been given to the role of zones and the effect of aggregation in these kinds of analysis. There is extensive work in this area in the MAUP literature (Pawitan and Steel, 2009). However, very few studies have compared the effects of MAUP in spatial studies of urban vegetation. Davis (2012) summarised several prominent studies of MAUP in a table (Table 1). Most studies mainly emphasized either the scale problem (Ratcliffe and McCullagh, 1999; Shriner et al., 2006) or the zoning effect (Bhati, 2005; Hipp, 2007; MacEachren, 1982). For instance, Dark and Bram (2007) focused on the effect of the scale problem in physical geography. Mu and Wang (2008) investigated different approaches of the diminishing scale effect. In contrast, Hipp (2007) comprehensively discussed common problems associated with neighbourhood and aggregated information from various zonal settings. There are few studies which have considered both the scale and aggregation effects of MAUP. Different approaches result in different outcomes. Jelinski and Wu (1996) examined the impact of MAUP on NDVI. In particular, they investigated the impact of two aggregation approaches at different scales "with an equal number of pixels per zone". The same approach was reproduced by Dark and Bram (2007) who claimed that "from a hierarchical point of view, the MAUP is not really a problem".

Mathematically we can generate NDVI in multiple ways. Both approaches that are argued here are supported in the literature for the pixel-based approach (Gamon et al., 1995; Lunetta et al., 2006) and for the object-based approach (Mutanga et al., 2012; Pu and Landry, 2012).

The scope of our analysis is narrower than these broader questions of landscape ecology because it focuses on the characterization of urban parkland vegetation. We use high and very high spatial resolution imagery to ensure that we have pure pixels of trees, shrubs and turf grasses.

2. Previous studies using NDVI in the Adelaide Parklands

Vegetation indices, and particularly NDVI, have proved useful for predicting the water demand of both agricultural crops and urban landscape vegetation. The relationship between NDVI derived from high spatial resolution WorldView imagery and evapotranspiration from urban vegetation has previously been investigated in Veale Gardens, which is one of 29 parks that comprise the Adelaide Parklands, Australia (Nouri et al., 2014). Using 64 possible band combinations of WorldView-2, the bands of Red (band 5) and NIR1 (band 7) were selected as the most reliable bands to calculate NDVI in Veale Gardens. The area was hand digitized to characterize five landscape covers, namely trees, shrubs, turf grasses, impervious pavements and water bodies (Fig. 1). In winter the NDVI values for trees, shrubs and turf grasses are high and similar to one another. Previous studies in Veale Gardens (Nouri et al., 2014; Nouri et al., 2016a) indicated a verdant winter in Adelaide due to its Mediterranean climate with mild winters and dry and hot summers. Rainfall arrives mainly in winter. In summer all these vegetation types exhibit significantly lower NDVI values with grasses showing the largest decrease. The irrigation regimes required to maintain these three vegetation types are different. Having separate NDVI characterizations for these three types of vegetation is therefore useful for park managers for establishing optimal irrigation schedules.

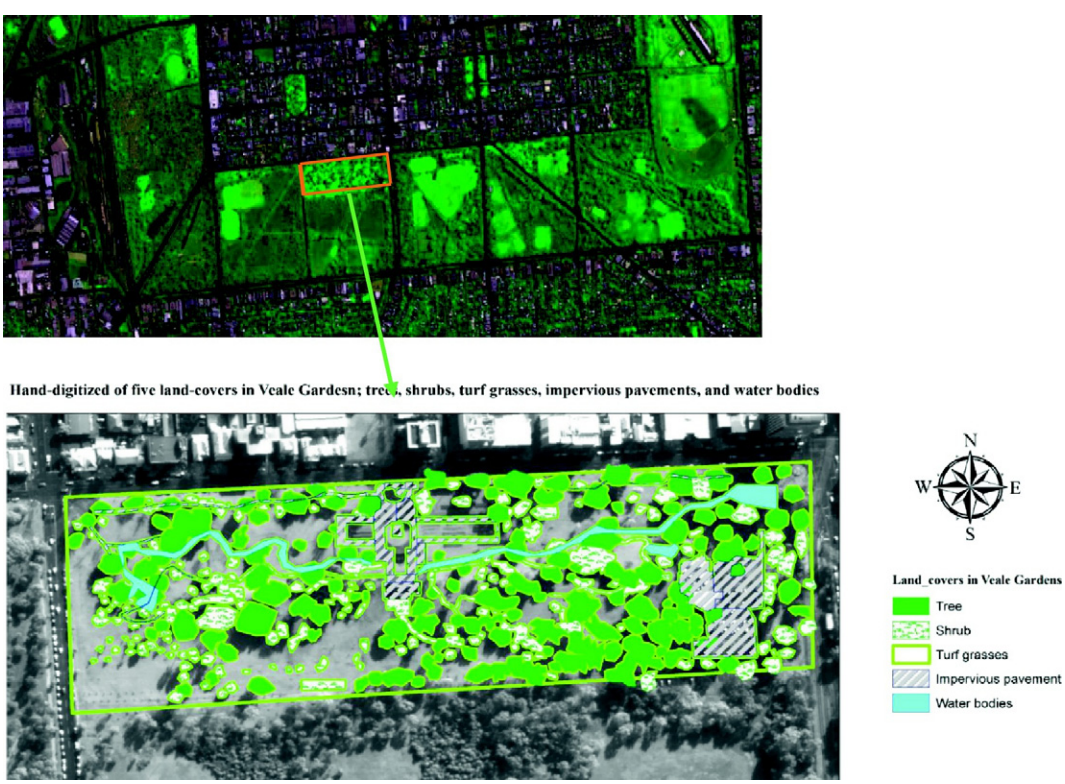

Fig. 1. Five land cover types in Veale Gardens: trees, shrubs, turf grasses, impervious pavements and water bodies.

Fig. 2. WorldView-3 image of the Adelaide Parklands.

3. Methods

Here the following question is explored: *Is NDVI in Veale Gardens scale-invariant between the 1.24 m pixel size of WorldView-3 imagery and the 0.1 m resolution of digital aerial photography?* A WorldView-3 image (March 21, 2015) with 0.31 m panchromatic resolution and 1.24 m multispectral resolution (Fig. 2) and an aerial image (January 2005) with 0.1 m resolution (Fig. 3) were used. The ground truth for image classification was derived from a landscape cover map that was digitized using a WorldView-2 image by categorizing the landscape into the five categories of trees, shrubs, turf grasses, water bodies and pavements (Fig. 1). Band 5 (Red) and band 7 (NIR1) of the WorldView-3 image and the Red and NIR bands of the aerial image were used to calculate NDVI. The NDVI was calculated for three vegetation types, namely trees, shrubs and turf grasses using the two aforementioned approaches.

Aerial images were collected with 15 cm horizontal accuracy for the City of Adelaide by AEROmetrex (http://aerometrex.com.au/). These were collected as a three band image: NIR, Red and Green. The data were acquired in late summer when there is the largest difference in irrigated and non-irrigated grasses. However, our study area is irrigated all year round.

Since there was no comparison between satellite images of a specific location at different times/dates in this research, the atmospheric correction was not applied. In a previous study in Veale Gardens (Nouri et al., 2014), atmospheric correction was applied due to differences in sun positions for the time of day and day of the year, changes in solar elevation angle from summer to winter and terrain effects that may cause differential solar illumination.

This enabled us to assess whether or not the MAUP has a significant impact on NDVI calculations for pure pixels of urban vegetation: 1) pixel-based NDVI; and 2) object-based NDVI for the three vegetation categories of trees, shrubs and turf grasses. The first method, pixel-based NDVI, uses pixel values of the Red band and the NIR1 band for each pixel and then calculates an NDVI value for each pixel by replacing the Red and NIR1 values of each pixel in the NDVI equation, as $NDVI_{WV3} = (NIR1 - Red)/(NIR1 + Red)$.

The second method, object-based NDVI, first calculates the mean Red and mean NIR across the region of interest (e.g. trees) and then calculates an NDVI by using the mean values of Red and NIR1.

We explored the nature and magnitude of these differences in another experimental site captured from a 30 m resolution Landsat image in the Colorado River Delta (CRD) in Mexico (Nouri et al., 2016b).

For the CRD in Mexico, we used the Sample tool in ArcGIS v10.3 and a point file corresponding to 64 cells (30 m) to extract values from the red and near-infrared bands of a single Landsat 8 scene (overpass date: 22 April 2013). The sampling location was chosen based on cells that exhibited a relatively wide range of values (Fig. 4).

4. Results

Applying these two methods to a patch of trees demonstrates the difference between the pixel-based and the object-based approaches (Fig. 5). This is a specific examination of the effects of the MAUP on pure pixels of urban vegetation. We extracted values of the Red and NIR1 bands for a patch of trees from the WorldView-3 image. Tables in the first row of Fig. 5 show these values and the average of the Red band (113, left table) and NIR band (624, right table) in this region of interest. Using the average values of the left and right tables resulted in 0.693 as the object-based mean value of NDVI. The table in the second row shows NDVI values for each pixel and then averages all the pixel NDVIs resulting in the pixel-based NDVI value of 0.698.

We applied this approach for three regions of interest that contained different types of vegetation, namely trees, shrubs and turf grasses. Table 2 shows the resulting pixel-based and object-based NDVI values for each vegetation category.

We repeated these steps using an aerial image of the Adelaide Parklands by extracting values of the Red and NIR bands for the same three vegetation types. Table 3 shows the pixel-based and object-based NDVI values for each vegetation category.

Fig. 6 is a specific examination of the effects of the MAUP on total of 64 pixels of an experimental site in the Colorado River Delta. We extracted values of the Red and NIR bands from the Landsat image. The

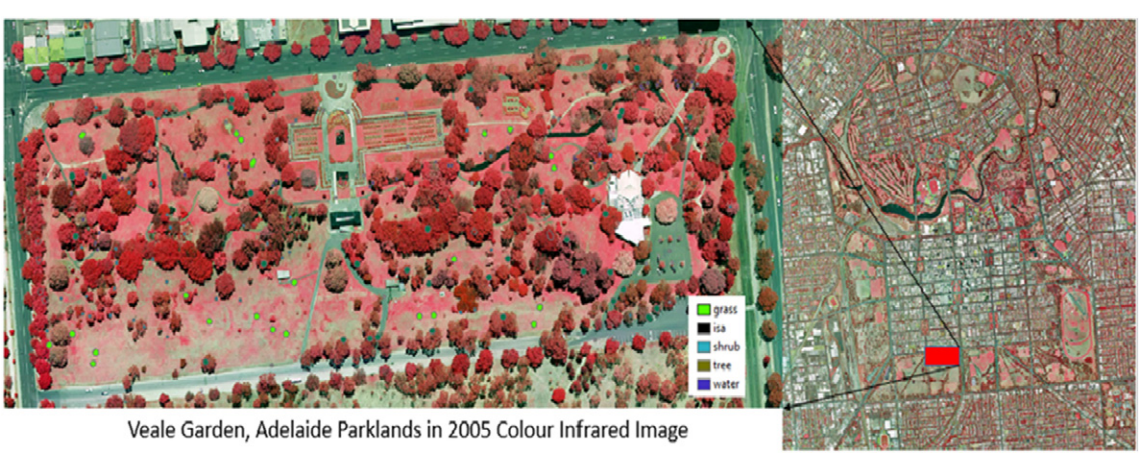

Fig. 3. Aerial image of the Adelaide Parklands.

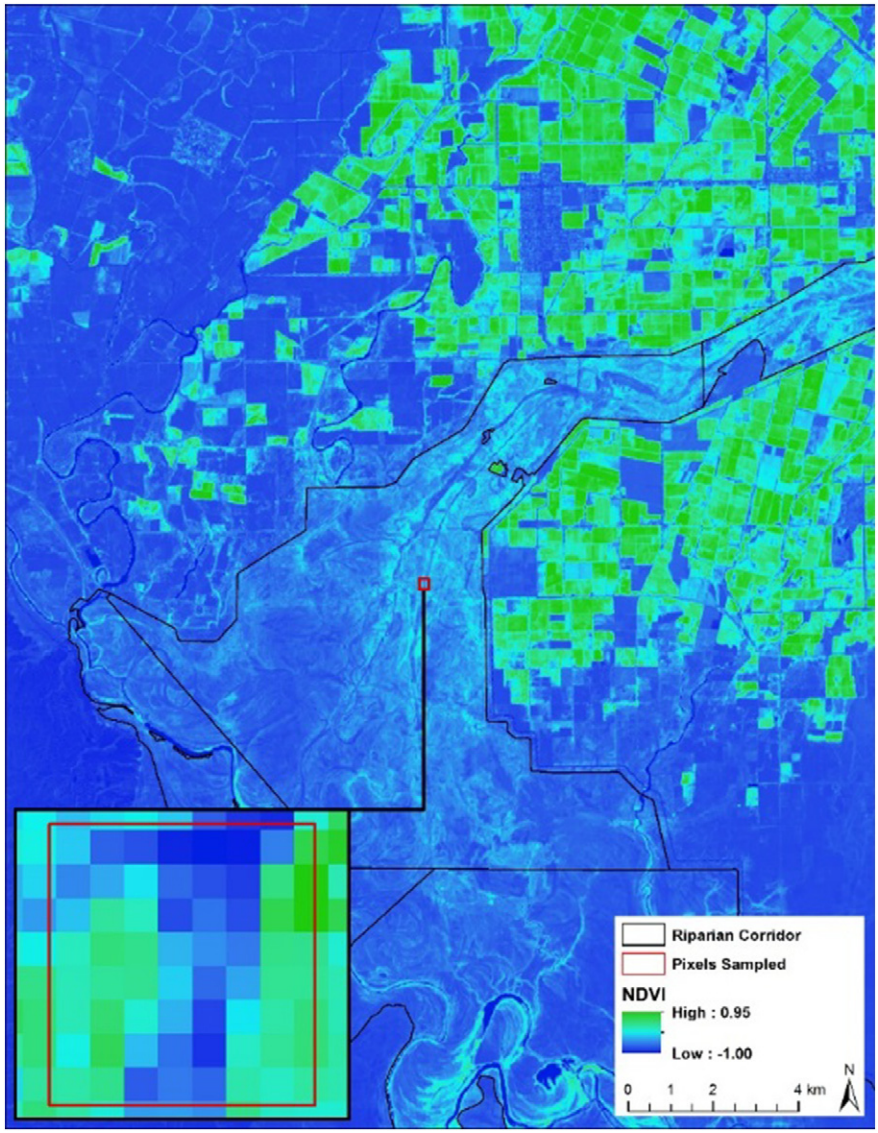

Fig. 4. Experimental site at the Colorado River Delta.

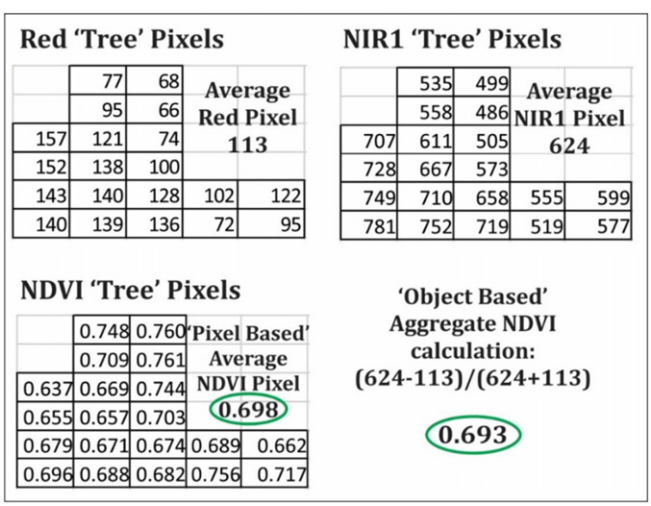

Fig. 5. NDVI calculations using pixel-based and object-based methods.

first table in Fig. 6 shows these values and the average of the NIR band (0.291400). The second table in Fig. 6 shows the NIR band values of 64 pixels and the average Red value (0.162075) in this region of interest. The third table in Fig. 6 shows the NDVI values for each pixel and then averages all the pixel NDVIs resulting in the pixel-based NDVI value.

The differences between the pixel-based and the object-based approaches in the Colorado River Delta were reported in Table 4. We extracted values of the Red and NIR bands for 64 pixels from the Landsat image. Using the average Red value of 0.162075 for 64 pixels and the average NIR value of 0.29140007 for 64 pixels resulted in an average NDVI of 0.285186 as the object-based mean value of NDVI. The third table in Fig. 6 shows an average NDVI value of 0.289836 which results from calculating NDVI for each pixel and then averaging all the pixel NDVIs.

Table 2
Pixel-based and object-based NDVI values for trees, shrubs and turf grasses from a WorldView-3 image.

WorldView-3 image	Trees	Shrubs	Turf
Pixel-based NDVI	0.72764	0.71760	0.71934
Object-based NDVI	0.72665	0.71659	0.71994

Table 3
Pixel-based and object-based NDVI values for trees, shrubs and turf grasses from an aerial image.

Aerial image	Trees	Shrubs	Turf
Pixel-based NDVI	0.46937	0.21857	0.17571
Object-based NDVI	0.46275	0.21882	0.17556

Table 4
Pixel-based and object-based NDVI values for the Colorado River Delta from a Landsat image.

Landsat image	Mixed pixels
Object-based NDVI	0.285186
Pixel-based NDVI	0.289836

By comparing Tables 2, 3 and 4 we note that there is not a significant difference in NDVI values between the object-based and pixel-based NDVIs. Since we used two different satellite platforms (Landsat & WorldView-3) and digital aerial photography, there are many potential reasons for these small differences including the sensors (bandwidth of detectors, etc.) and the season of acquisition (phenology and sensor-sun-object angles). The point of this study is to demonstrate scale invariance within an observation system and not between observation systems. Our study shows that there is no significant difference in NDVI values resulting from two methods of NDVI calculation for the Adelaide Parklands, Australia. This finding is supported by an analysis of our second experimental site in the Colorado River Delta, USA. Hall et al. (1992) suggested that NDVI is scale-invariant, which supports our findings here.

5. Discussion and conclusions

NDVI is ubiquitous as an index of vegetation. Healthy vegetation is gaining more attention because of its value in providing ecosystem services. However, monitoring and assessment of these types of vegetation requires appropriate spatial resolution imagery. It is likely that future mapping and monitoring of vegetation will take place via 'big data' image processing systems. These systems may use pixel- or object-based algorithms to assess vegetation health, evapotranspiration, and other ecosystem functions. It is useful to know that both pixel-based indices of NDVI and object-based indices of NDVI will produce very similar values for pure pixels observed in urban vegetation. However, this does not allow for scaling from a fine resolution image to a coarse resolution image. This study was also conducted using a particular sun angle for

NIR pixels

0.287589	0.311958	0.292917	0.276192	0.277653	0.273584	0.259039	0.250362
0.330751	0.309103	0.296312	0.293547	0.291209	0.290264	0.256814	0.256184
0.331268	0.306158	0.307147	0.297143	0.291748	0.299279	0.306338	0.316117
0.342059	0.318455	0.317758	0.305259	0.308136	0.315802	0.320658	0.308856
0.347994	0.333494	0.309822	0.305236	0.300605	0.292715	0.297728	0.286398
0.342688	0.330819	0.293479	0.281025	0.287117	0.289792	0.297076	0.291793
0.296469	0.28107	0.280643	0.281295	0.272168	0.270572	0.265401	0.269718
0.250969	0.254116	0.246743	0.258567	0.260276	0.250992	0.242539	0.234626
Average NIR							**0.291400**

Red pixels

0.162914	0.184428	0.165454	0.144818	0.144008	0.142614	0.141918	0.131374
0.201625	0.177256	0.148167	0.140614	0.144818	0.139422	0.124405	0.130835
0.205559	0.167567	0.157137	0.145559	0.144053	0.155945	0.172153	0.194454
0.2217	0.19324	0.199534	0.17276	0.169995	0.178403	0.192903	0.185911
0.22669	0.207785	0.187485	0.180044	0.184383	0.187058	0.193105	0.177324
0.223408	0.210595	0.186226	0.171142	0.166893	0.158036	0.152888	0.147043
0.17865	0.139265	0.131195	0.13868	0.136949	0.138815	0.135016	0.14239
0.122202	0.113165	0.114514	0.132206	0.133375	0.126541	0.123574	0.12463
Average Red							**0.162075**

NDVI pixels

0.276747	0.256918	0.278077	0.312046	0.316948	0.314681	0.292106	0.311701
0.242547	0.271088	0.3333	0.35225	0.335739	0.351052	0.347329	0.323885
0.234171	0.292555	0.323101	0.342406	0.338904	0.314864	0.280432	0.238288
0.213494	0.244706	0.228543	0.277182	0.288918	0.27802	0.248763	0.248489
0.211078	0.232245	0.245999	0.257979	0.23964	0.220223	0.213154	0.235214
0.210706	0.222056	0.223581	0.243015	0.264805	0.294212	0.320444	0.32985
0.247977	0.337362	0.362882	0.339578	0.330513	0.321838	0.325623	0.308968
0.34506	0.383768	0.366024	0.323362	0.322369	0.329642	0.324942	0.306176
Average NDVI							**0.289836**

Fig. 6. NDVI calculations using pixel-based and object-based methods in the Colorado River Delta.

each image. Further studies may demonstrate that NDVI is scale invariant with varying sun angle for pure pixels but this is an avenue for future research. In addition, other studies have demonstrated that NDVI is not scale invariant for mixed pixels (Jiang et al., 2006).

We have applied two methods of estimating NDVI indices for urban vegetation (trees, shrubs and turf grasses) at a very high spatial resolution using two different sensors and two different dates. For a given sensor the only variation we see in this study is at the third decimal place which is typically not even reported in the literature. The NDVI values for these categories are not the same between sensors for two major reasons: 1) Phenological changes due to seasonal effects, and 2) sensor design such as bandwidth mean and range, sensor angle, sun angle, and repeat coverage timing.

When a category of vegetation consists of multiple pixels, the calculation of a 'mean' can be a mean of NDVI values for each pixel (pixel-based), or a mean of the Red values and a mean of the NIR values for all the pixels in which the mean NDVI is the ratio of these (object-based). NDVI can suffer from the intractable problems that are associated with MAUP. However, we have demonstrated that pure vegetation pixels in an urban environment are not significantly impacted by MAUP. Consequently, it is reasonable to use either approach (object-based or pixel-based) to calculate the NDVI of pure pixels of vegetation provided there is a consistency of sensors and adequate spatial resolution. Measures of this nature can be used to assess the ecosystem functioning of green infrastructure with an eye towards optimizing the ecosystem services they provide.

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