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Pervious area change as surrogate to diverse climatic variables trends in the CONUS: A county-scale assessment

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ABSTRACT

The increase in worldwide population is putting much pressure on the existent urban management plans. In this context, strategies and policies should be updated to conserve natural resources, but more importantly, to improve inhabitants' well-being. Studies focusing on pervious areas have many potentials, particularly regarding the assessment of potential green infrastructures within the vicinities of cities. This study highlights the pervious area change between 2001 and 2016 within every county in the CONtiguous United States (CONUS) based on the National Land Cover Database (NLCD). The study found that 43 different counties can be considered dense. A statistical analysis is followed, highlighting the air temperature, wind speed, precipitation, solar radiation, and Normalized Difference Vegetation Index (NDVI) trends in five characteristic counties. These datasets were retrieved from diverse remote sensing and satellite platforms between 1980 and 2019. The main results also found that air temperature was significantly (at $\alpha = 0.95$) increasing for the same period. The other climatic variables depict fluctuating and usually insignificant trends. Such information would benefit decision- and policy-makers to focus their initiatives towards the most vulnerable counties while projecting different scenarios based on their current and historical conditions. Furthermore, this approach can be portable to other countries.

1. Introduction

Even within a lack of standard terminology (e.g. Ewers et al., 2009; European Commision, 2013; Langemeyer et al., 2020), Green Infrastructure (GI) functions along a two-pronged approach. It aims to conserve biodiversity and ecosystem services while improving human well-being (Elbakidze et al., 2017). In this context, several previous studies have tried to tackle the establishment of a least-environmentally-disturbed green corridors (e.g. Sanesi et al., 2017; Zhang et al., 2019). Some of them were based on the integration of the Geographic Information System (GIS) (e.g. Cohen, 2016; Langemeyer et al., 2020; Ramyar et al., 2020), while others relied on expert-led, top-down or bottom-up approaches (e.g. Schilling and Logan, 2008; Weber et al., 2006; Elbakidze et al., 2017). The usage of Remote Sensing (RS) and GIS techniques proved their effectiveness in many research studies trying to document, monitor, and assess a changing land feature (e.g. Faour et al., 2013; Mhawej et al., 2017; Faour et al., 2018).

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Much of the extant literature focuses on the ecosystem services and their direct or indirect benefits to local dwellers (Demuzere et al., 2014; Pochee and Johnston, 2017). These benefits could be categorized into physical and psychological and social. The physical impact includes reduced pollution (e.g. Pugh et al., 2012; Abhijith et al., 2017), thermal comfort (e.g. Di Leo et al., 2016; Reynolds et al., 2019), reduced energy use (e.g. Kumar et al., 2019; Susca, 2019), reduced problems with flooding and drought (e.g. Raquel et al., 2016; Ghofrani et al., 2017), and an improvement of water and air quality (e.g. Pappalardo et al., 2017; Hewitt et al., 2020). The psychological and social effect encompasses health and restoration benefits (e.g. Tzoulas et al., 2007; Suppakittpaisarn et al., 2019), social and individual coping capacities (e.g. Lertzman, 2012; Kaźmierczak, 2013), and education (e.g. Barthel et al., 2010; Hashimoto-Martell et al., 2012). Furthermore, other studies have assessed the best GI practices based on the most adequate financial and economic plan (e.g. Horwood, 2011; Newman et al., 2019), aligned with the climate change and global warming effect (e.g. Foster et al., 2011; Venter et al., 2020). Still, most of these previous studies have discussed the GI impact at the block-, neighborhood- or even city-scales (Demuzere et al., 2014). This is particularly observable when considering temperature-related studies.

In this paper, a focus on the different climatic variables will be carried out at the county scale throughout the CONtiguous United States (CONUS). More precisely, climatic and vegetation health parameters will be assessed for the past 40 years. This was done through the usage of the proposed pervious area percentage, which could potentially enable a better characterization and aggregation of the CONUS's similar counties. Thus, this article will address the question as to whether knowing the pervious area percentage change would determine the change in climatic variables. Such findings will help decision- and policy-makers to investigate the pervious area in each county, while deriving the current and future severity of the increasing air temperature. As the proposed approach was produced using GIS techniques and RS datasets, it could be portable to other spatial and temporal settings.

2. Materials and methods

2.1. Study area

The considered study area is the Contiguous United States, also known as CONUS. It is located in 22 different climatic zones as shown in Fig. 1. The temperate, dry summer, cold summer climate exists in a small region of 277 km^2. The prevailing climate is arid, steppe, cold stretching to over 2,884,301 km^2. It is followed by the temperate, no dry season, hot summer and the cold, no dry season,

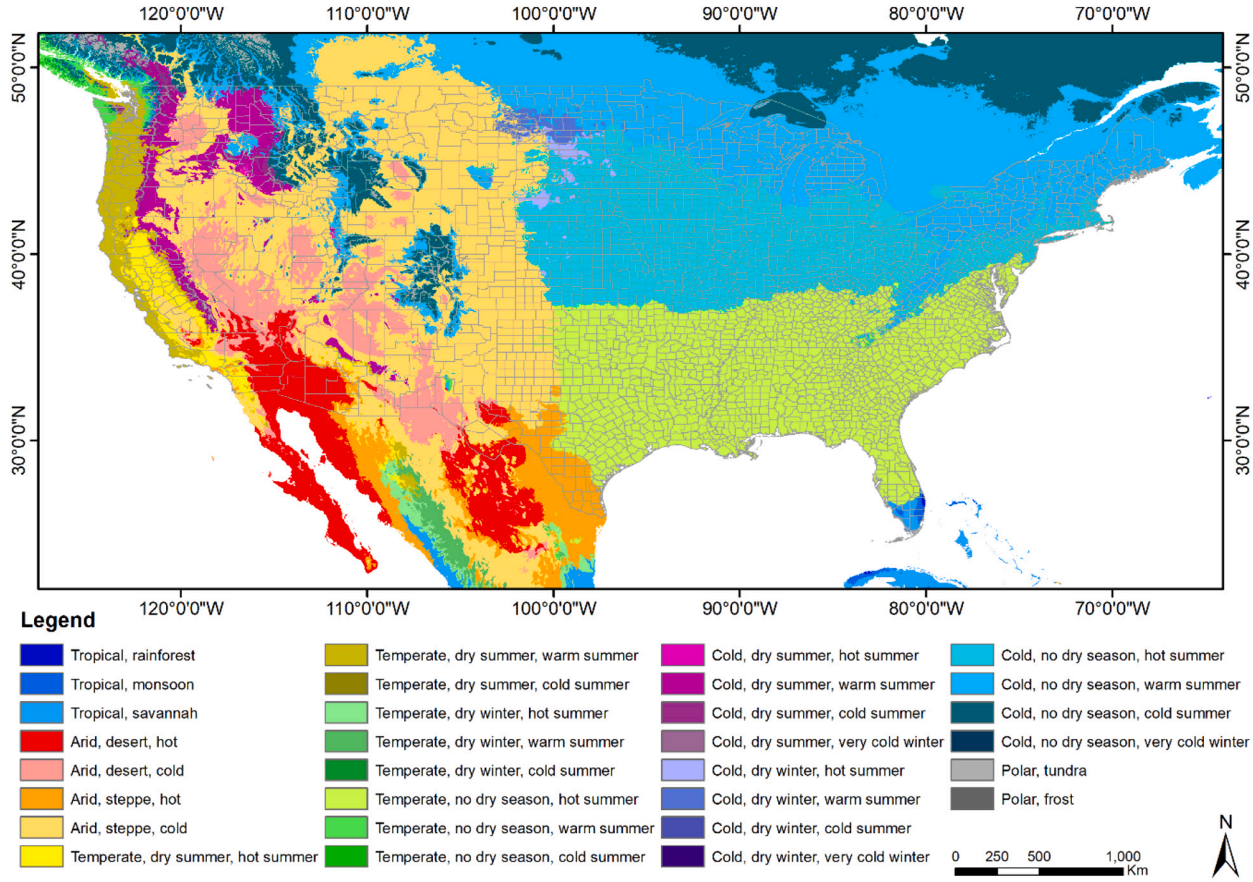

Fig. 1. Koppen classification in CONUS based on Beck et al. (2018).

hot summer climates with an area of 2,551,300 and 2,240,920 km^2, respectively. Based on circa 2005 images, impervious surface in the CONUS was estimated at 2.4% (Nowak and Greenfield, 2012). Still, within urban settlement areas, impervious area percentage increased to 17.5% (Nowak and Greenfield, 2012). These changes varied significantly among states and counties, highlighting the existence of diverse development and planning patterns. Moreover, the health and well-being of urban residents is affected by the recently highlighted trend of a decreasing tree cover within urban lands at a rate of 700 km^2/year, corresponding to 36 million trees per year (Nowak and Greenfield, 2018).

2.2. Data background

The National Land Cover Database (NLCD) of 2001 and 2016 were downloaded from the Multi-Resolution Land Characteristics Consortium (MRLC) official website (i.e. https://www.mrlc.gov/). NLCD is an ongoing land cover modeling production effort providing twenty different land cover sub-classes under seven major classes (i.e. water, developed, barren, forest, shrubland, herbaceous, planted/cultivated and wetlands). Further information can be found in many previous studies (e.g. Fry et al., 2009; Wickham et al., 2013; Yang et al., 2018; Jin et al., 2019).

Climatic and vegetation health data were collected from two different sources. More precisely, air temperature, wind speed, precipitation, and solar radiation information were provided by the North American Land Data Assimilation System (NLDAS). Since 1979, this project enables the construction of quality-controlled, and spatially and temporally consistent, land-surface model (LSM) datasets, based on the best available observations and reanalysis. The data was downloaded from the Land Data Assimilation System (LDAS) official website at https://ldas.gsfc.nasa.gov/. Further description of this product can be found in Cosgrove et al. (2003).

The second source corresponds to another satellite sensor which is the Moderate Resolution Imaging Spectroradiometer (MODIS) on Terra satellite. Its product is the MODIS vegetation indices, producing 16-day intervals and 250-m consistent spatial and temporal vegetation canopy greenness (i.e. Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI)). The data was downloaded from the National Aeronautics and Space Administration's earth data directory at https://earthdata.nasa.gov.

2.3. Methods

As NLCD database are produced in a raster TIFF format, further processing is required within a GIS-based software. Such processing enables the classification of the NLCD 2001 and 2016 into pervious and impervious surface layers. Pervious classes include open space areas, barren lands, forests, shrublands, herbaceous, and planted and cultivated lands. Impervious areas are the low, medium, and high intensity developed lands. Based on the previous classification, two layers each showing the percentage of pervious areas, one in 2001 and the other in 2016, were produced for the CONUS. A zonal statistic was required as well in order to assess the pervious areas'

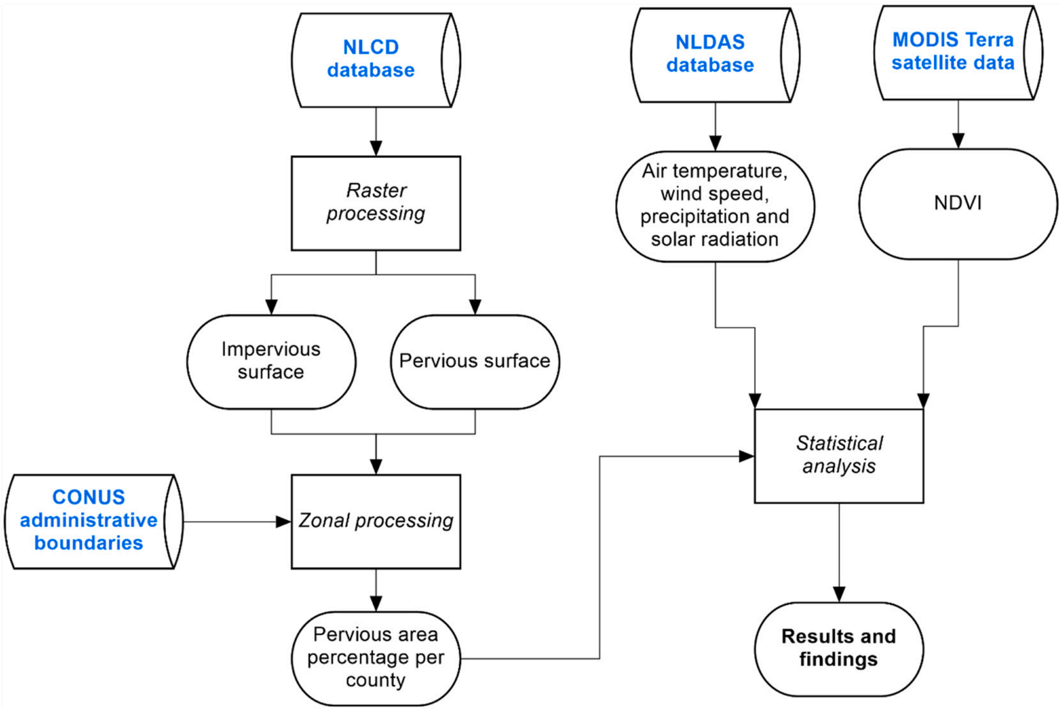

Fig. 2. Simplified flowchart of the methods used (blue: inputs; italic: processing and analysis). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

percentage at the county level.

Moreover, database and satellite data from NLDAS and MODIS were collected and compared to the randomly selected similar pervious areas' percentage counties using statistical tests (e.g. Pearson correlation, student test and Theil–Sen estimator). It was produced using the MAKESENS application designed by the Finnish Meteorological Institute. The included factors in these tests correspond to air temperature, wind speed, precipitation, and solar radiation. A simplified flowchart of the followed method is available in Fig. 2.

Furthermore, two counties were randomly selected to highlight major increase or decrease of pervious area percentage. To enable a better assessment at the county level, the selection considered a county showing high increase/decrease in the percentage of pervious areas bordered by other counties showing opposite conditions. Thus, McPherson was considered to represent the class 1 (i.e. increase of more than 10%), whereas, Dimmit is within the class 5 (i.e. decrease of more than 20%). Dense counties, showing an average pervious area of lower than 50%, represented a total number 43 counties.

3. Results

3.1. CONUS pervious area assessment, 2001–2016

Counties with coastal boundaries show one of the lowest pervious area percentage across the CONUS in 2001 (Fig. 3). A similar finding is also noticeable in 2016. Still, some other landlocked counties, particularly at the north and south of the CONUS boundaries highlight low pervious areas in both 2001 and 2016. It is important to note that eastern counties show high pervious percentage (i.e. more than 90%) in comparison to its western counterpart (Fig. 3). Thus, the pervious area change map presents a decrease of more than 20% of pervious area in many western counties. Only a limited number of counties show an increase of pervious area, particularly visible in landlocked regions and at the eastern part of the CONUS. Most of the counties represent a pervious area change between 0% and 10%.

3.2. Dense counties pervious area assessment, 2001–2016

Fig. 4 shows the distribution of dense counties with their pervious change between 2001 and 2016. It was also noticeable that, for

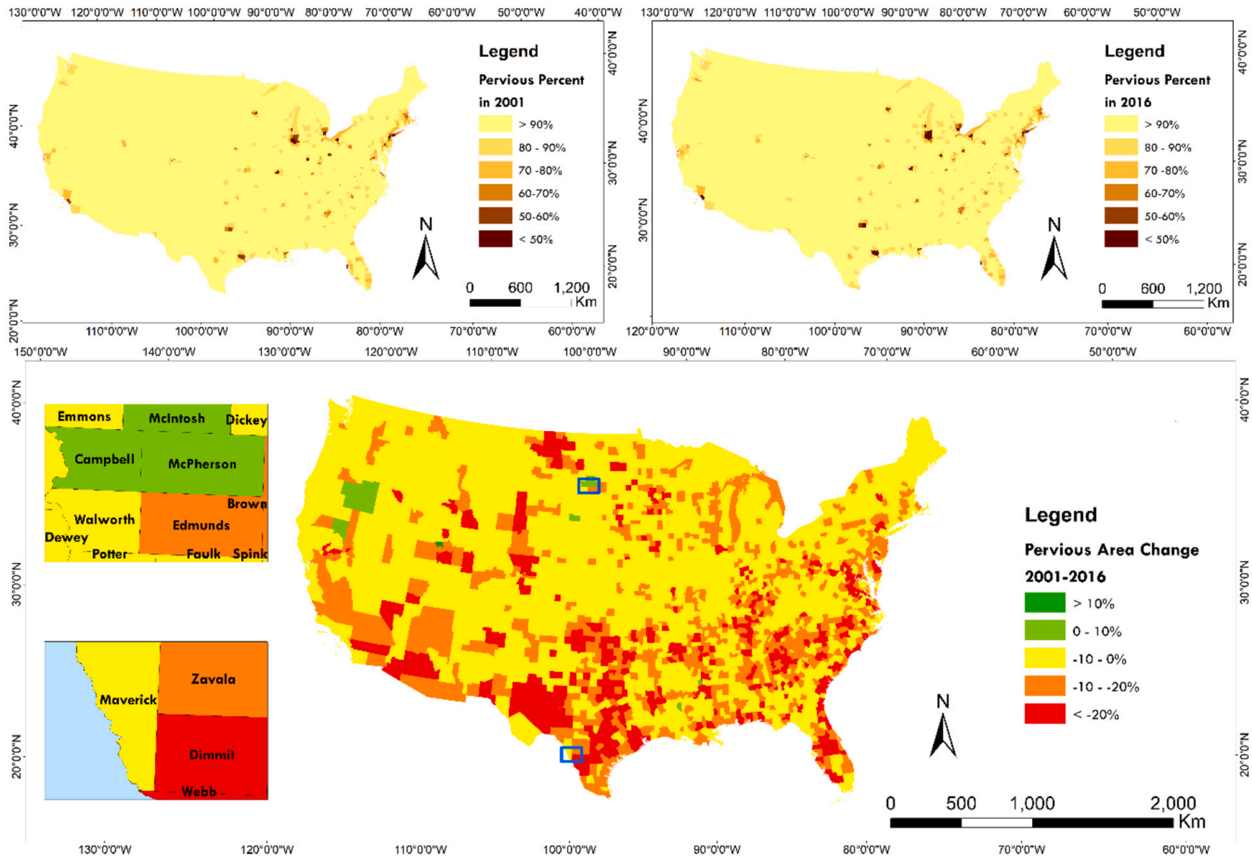

Fig. 3. Pervious area in 2001 (upper left), in 2016 (upper right) and the pervious area change between 2001 and 2016 (bottom) in the CONUS.

instance, Suffolk county exists within a pervious area change between 0% and − 10%. Dallas shows more decrease in pervious area with a negative change of 12%. Harris presents approximately 22% of negative change in pervious areas. A detailed list of dense counties and their respective changes is shown in Table 1. Virginia district highlights the largest number of dense counties with 17 counties, followed by New York district with a total of 6 counties. Still, as average pervious area change, Texas district shows the highest value of 17%, much higher than the second largest decrease of pervious change which is presented in Virginia district with 8% of negative change. On the other hand, districts such as Massachusetts and New York have a decrease of less than 2%.

3.3. *Climatic and vegetation variables trends*

3.3.1. *McPherson*

An area-averaged time series in McPherson county shows an increase in air temperature, wind speed, precipitation, and solar radiation but with no significant trends between 1980 and 2019 (Fig. 5). McPherson county is selected as it is showing very high increase in the percentage of pervious areas bordered by other counties showing opposite conditions. The NDVI trend was not plotted as the change is minimal with still very large vegetation areas.

3.3.2. *Dimmit*

An area-averaged time series in Dimmit county show a significant at $\alpha = 0.95$ increase of air temperature in the region (Fig. 6). Wind speed over the selected time frame (i.e. 1980–2019) appears to have no clear change. Precipitation values are showing a non-significant decrease aligned with a non-significant increase in solar radiation values. Dimmit county is considered as it is showing very high decrease in the percentage of pervious areas bordered by other counties showing opposite conditions. The NDVI trend was not plotted as the change is minimal with still very large vegetation areas.

3.3.3. *Suffolk*

Because not all CONUS counties could provide adequate information for climatic and vegetation assessments, as many appear to have more than 90% of pervious areas, only dense counties were identified. Three random cases were selected representing median (i.e. Suffolk), high (i.e. Dallas) and very high (i.e. Harris) change in the percentage of pervious areas.

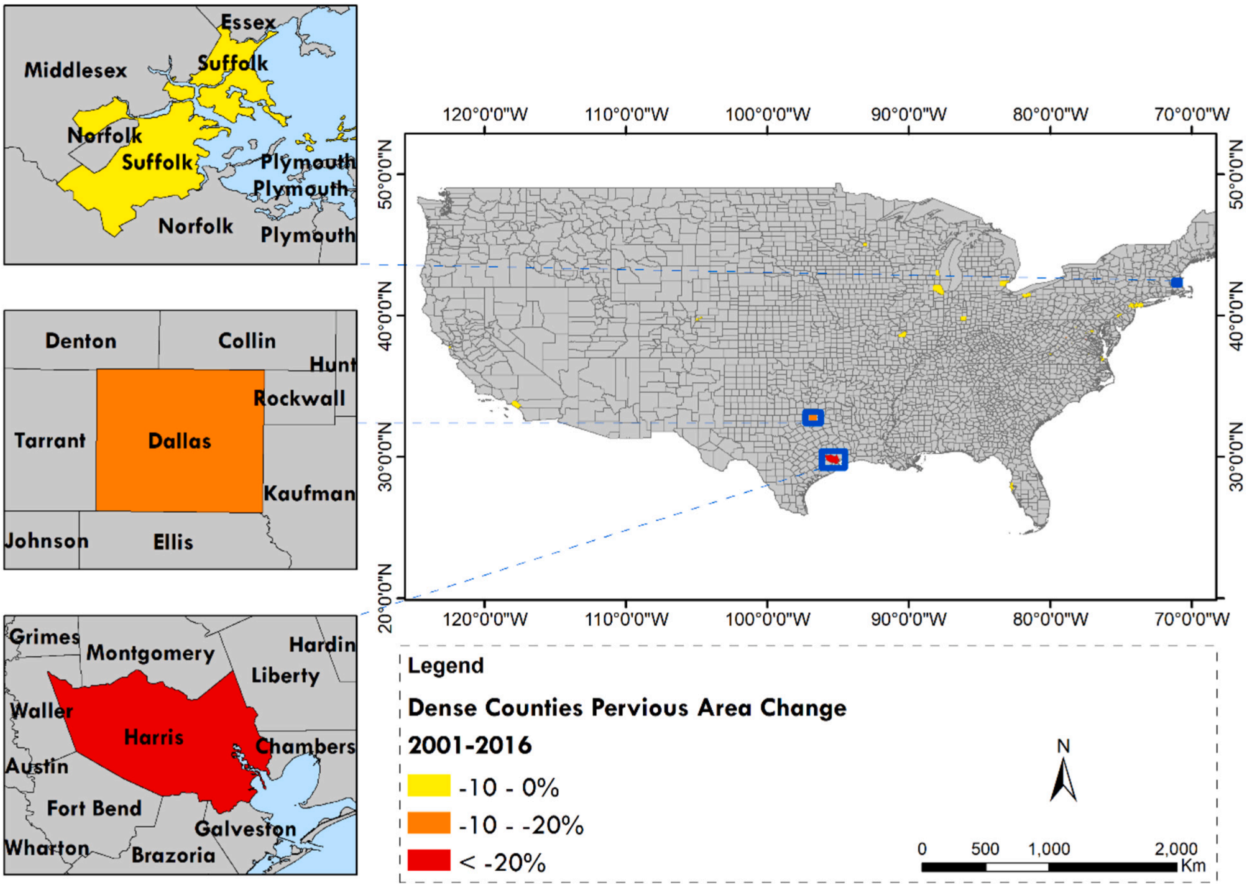

Fig. 4. Pervious area change between 2001 and 2016 for dense counties.

Table 1
List of dense counties showing pervious area change between 2001 and 2016, as well as their climatic zones.

District	County	Pervious area in 2001 (% of the total area)	Pervious area in 2016 (% of the total area)	Pervious area change (%)	Koppen climatic zone (Beck et al., 2018)
Virginia	Fredericksburg	0.60	0.49	−0.27	Temperate, no dry season, hot summer
Virginia	Manassas Park	0.51	0.40	−0.23	Temperate, no dry season, hot summer
Texas	Harris	0.58	0.48	−0.22	Temperate, no dry season, hot summer
Texas	Dallas	0.53	0.48	−0.12	Temperate, no dry season, hot summer
Virginia	Harrisonburg	0.46	0.40	−0.12	Cold, no dry season, hot summer
Virginia	Hopewell	0.52	0.47	−0.10	Temperate, no dry season, hot summer
Virginia	Winchester	0.39	0.33	−0.10	Cold, no dry season, hot summer
Virginia	Charlottesville	0.44	0.38	−0.09	Temperate, no dry season, hot summer
Virginia	Portsmouth	0.45	0.40	−0.09	Temperate, dry winter, cold summer
Virginia	Manassas	0.44	0.39	−0.09	Temperate, no dry season, hot summer
Virginia	Hampton	0.54	0.50	−0.08	Temperate, dry winter, cold summer
Colorado	Denver	0.40	0.36	−0.08	Arid, steppe, cold
Indiana	Marion	0.49	0.45	−0.07	Cold, no dry season, hot summer
Virginia	Lexington	0.50	0.47	−0.06	Temperate, no dry season, hot summer
Ohio	Cuyahoga	0.49	0.46	−0.05	Cold, no dry season, hot summer
California	Orange	0.51	0.49	−0.05	Arid, steppe, cold
Virginia	Fairfax City	0.48	0.46	−0.05	Temperate, no dry season, hot summer
Minnesota	Ramsey	0.44	0.41	−0.04	Cold, no dry season, hot summer
Wisconsin	Milwaukee	0.36	0.34	−0.04	Cold, no dry season, hot summer
Missouri	Saint Louis	0.48	0.46	−0.04	Cold, no dry season, hot summer
New Jersey	Essex	0.48	0.46	−0.03	Cold, no dry season, hot summer
Florida	Pinellas	0.35	0.33	−0.03	Temperate, dry winter, cold summer
New York	Richmond	0.38	0.36	−0.03	Cold, dry winter, cold summer
Virginia	Alexandria	0.26	0.24	−0.03	Temperate, no dry season, hot summer
Virginia	Arlington	0.38	0.36	−0.03	Temperate, no dry season, hot summer
Virginia	Norfolk	0.29	0.27	−0.03	Temperate, dry winter, cold summer
Illinois	Dupage	0.33	0.31	−0.03	Cold, no dry season, hot summer
Virginia	Roanoke City	0.34	0.32	−0.03	Temperate, no dry season, hot summer
New York	Bronx	0.22	0.20	−0.03	Cold, dry winter, very cold winter
District of Columbia	District of Columbia	0.32	0.30	−0.03	Temperate, no dry season, hot summer
Michigan	Wayne	0.36	0.35	−0.02	Cold, no dry season, hot summer
New Jersey	Hudson	0.16	0.14	−0.02	Cold, dry winter, very cold winter
Virginia	Salem	0.36	0.34	−0.02	Temperate, no dry season, hot summer
Pennsylvania	Philadelphia	0.25	0.24	−0.02	Cold, dry summer, very cold winter
Illinois	Cook	0.26	0.24	−0.02	

(continued on next page)

Table 1 (*continued*)

District	County	Pervious area in 2001 (% of the total area)	Pervious area in 2016 (% of the total area)	Pervious area change (%)	Koppen climatic zone (Beck et al., 2018)
					Cold, no dry season, hot summer
New York	New York	0.15	0.13	−0.02	Cold, dry winter, very cold winter
New Jersey	Union	0.40	0.39	−0.02	Cold, no dry season, hot summer
Massachusetts	Suffolk	0.17	0.16	−0.02	Cold, dry winter, cold summer
New York	Nassau	0.39	0.39	−0.01	Cold, dry winter, very cold winter
Virginia	Covington	0.50	0.49	−0.01	Temperate, no dry season, warm summer
California	San Francisco	0.18	0.17	−0.01	Temperate, dry summer, warm summer
New York	Kings	0.10	0.09	−0.01	Cold, dry winter, very cold winter
New York	Queens	0.13	0.12	−0.01	Cold, dry winter, very cold winter

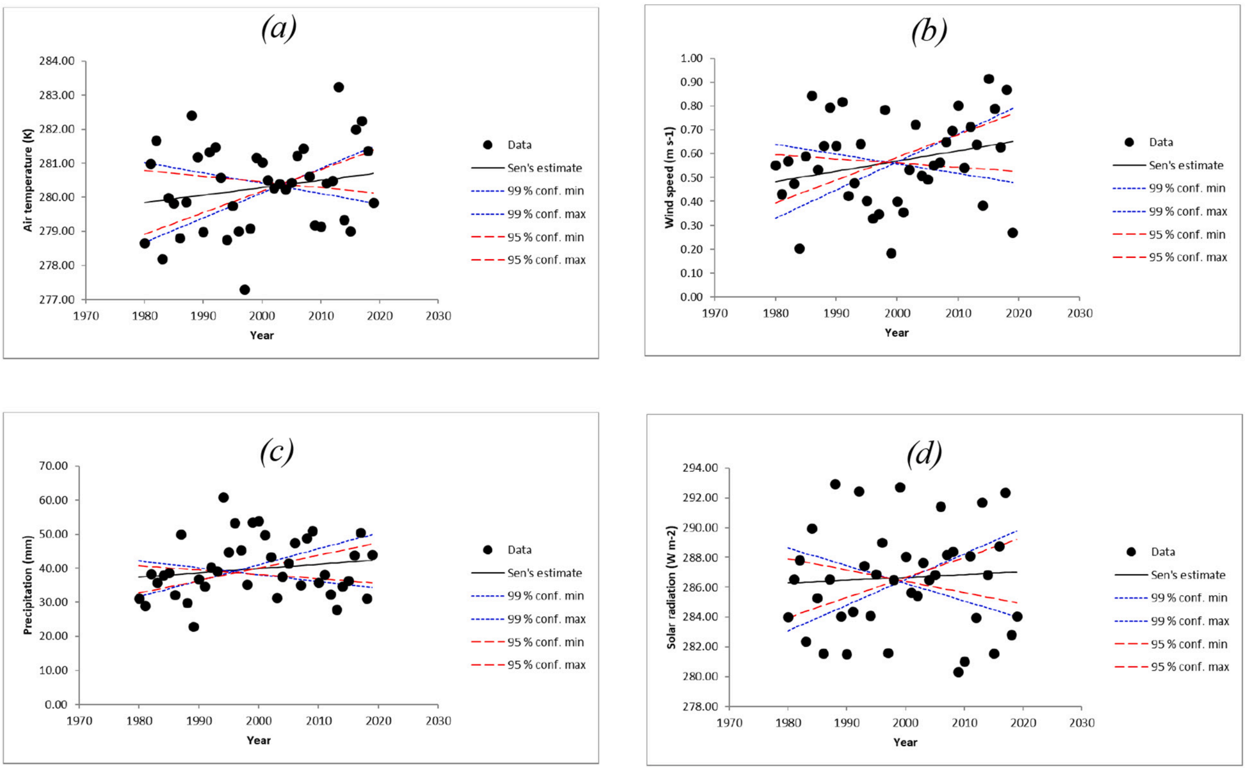

Fig. 5. Air temperature (a), wind speed (b), precipitation (c) and solar radiation (d) area-averaged time series in McPherson county, 1980–2019.

The area-averaged time series in Suffolk county show a significant at α = 0.99 increase of air temperature (Fig. 7). NDVI values show a non-significant increasing trend between 2000 and 2019. Suffolk is a dense county representing a median change in the percentage of pervious areas. The other climatic factors showed similar patterns to what was seen in McPherson and Dimmit, and thus is not included in Fig. 7.

3.3.4. Dallas

The area-averaged time series in Dallas county show a significant at α = 0.95 increase of air temperature (Fig. 8). NDVI values show almost a stable trend between 2000 and 2019. Dallas is a dense county representing a high change in the percentage of pervious areas. The other climatic factors showed similar patterns to what was seen in McPherson and Dimmit, and thus is not included in Fig. 8.

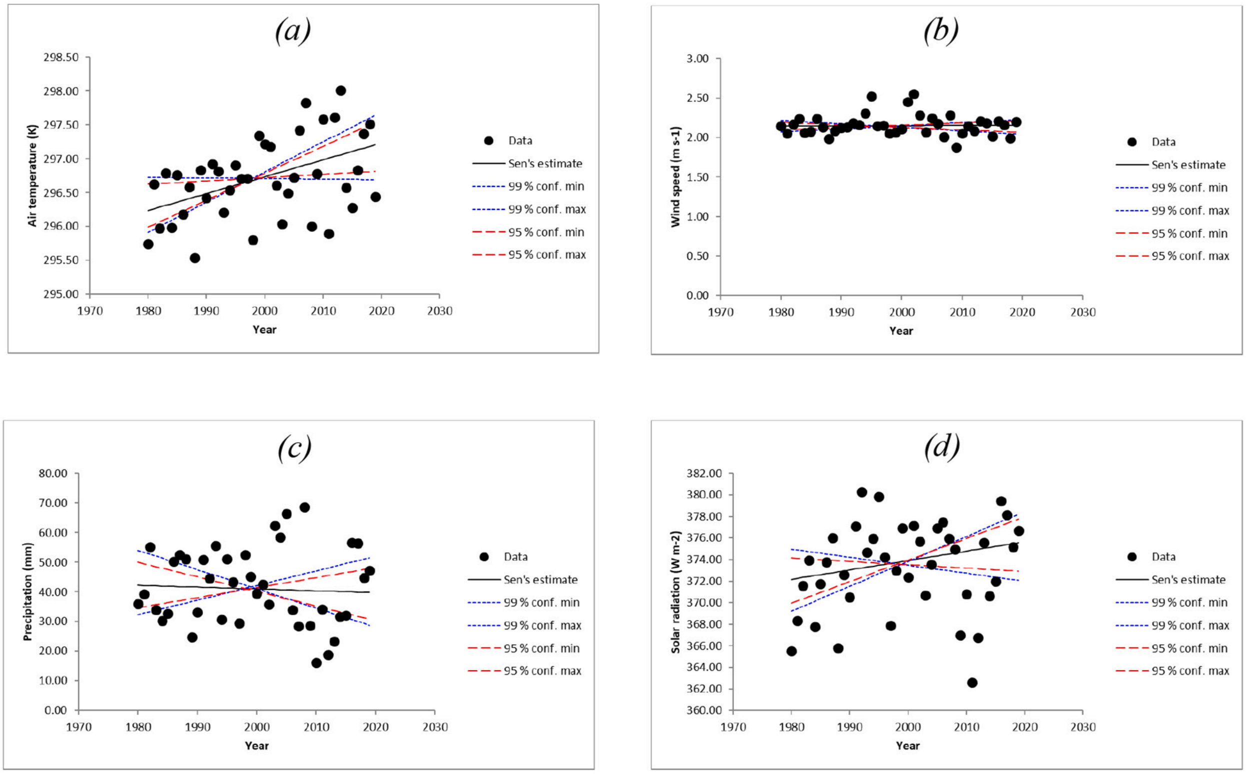

Fig. 6. Air temperature (a), wind speed (b), precipitation (c) and solar radiation (d) area-averaged time series in Dimmit county, 1980–2019.

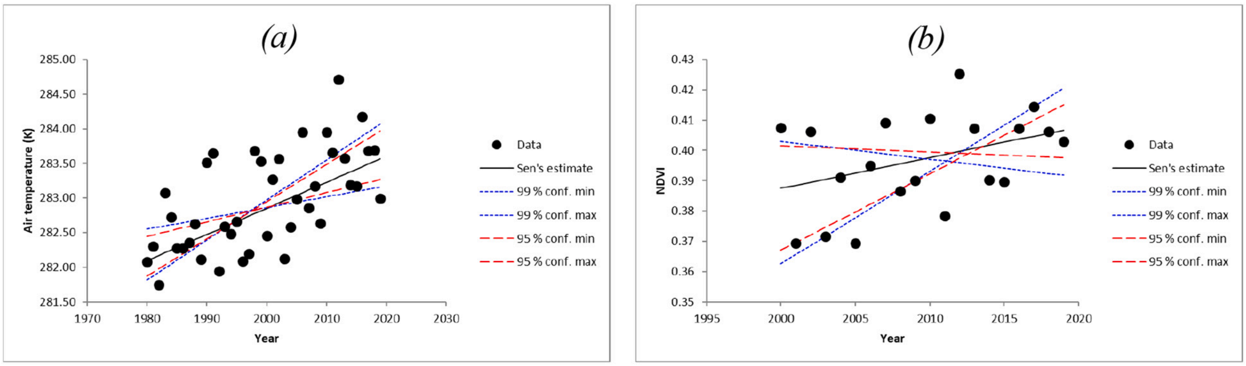

Fig. 7. Air temperature (a) and NDVI (b) area-averaged time series in Suffolk county, 1980–2019.

3.3.5. *Harris*

The area-averaged time series in Harris county show a significant at $\alpha = 0.95$ increase of air temperature (Fig. 9). NDVI values show a non-significant decreasing trend between 2000 and 2019. Harris is a dense county representing a very high change in the percentage of pervious areas. The other climatic factors showed similar patterns to what was seen in McPherson and Dimmit, and thus is not included in Fig. 9.

4. Discussion

Historically, humans tend to live on coastlines (Ghoussein et al., 2018), particularly because of their proximity to natural resources and the main commercial hubs. In this context, coastal regions showed the lowest pervious area percentage across the CONUS in both 2001 and 2016. The other high human agglomerations counties appear to exist on the boundary between the United States and Canada, as well as between the United States and Mexico, which could be also attributed to the commercial and transport hubs between these countries. The interesting part concerns the high pervious percentage counties existent at the western part of the CONUS,

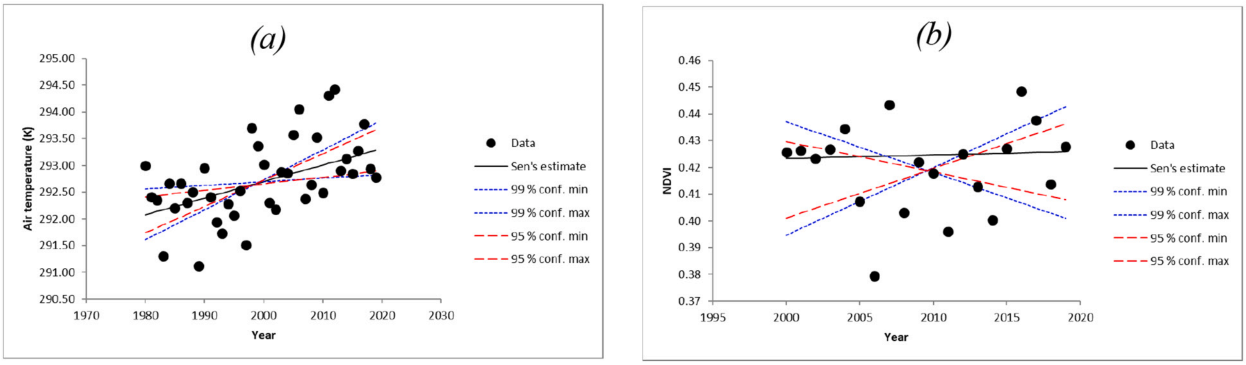

Fig. 8. Air temperature (a) and NDVI (b) area-averaged time series in Dallas county, 1980–2019.

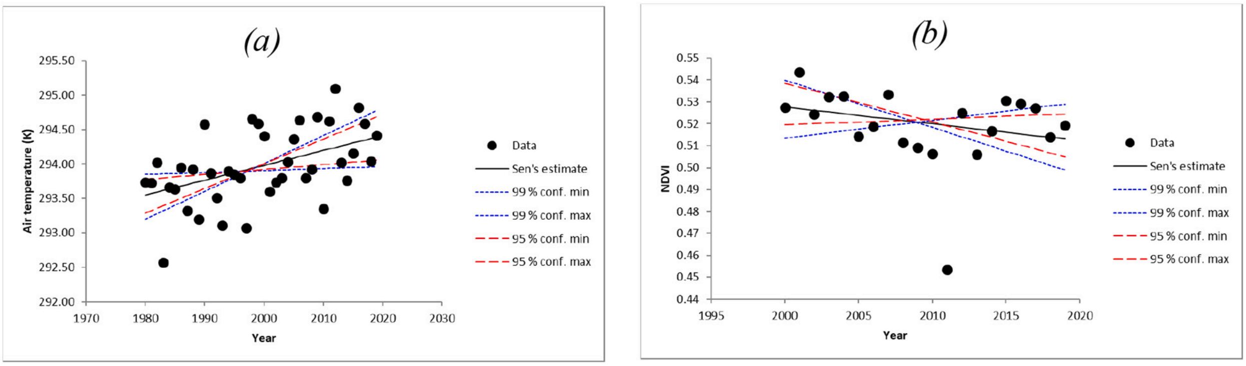

Fig. 9. Air temperature (a) and NDVI (d) area-averaged time series in Harris county, 1980–2019.

which is mainly due to the prevalence of desertic and cold climates as shown in the Koppen classification climatic zones (Fig. 1).

But more importantly, the built-up areas have greatly increased, more than 20% in many eastern counties, which is aligned with a population increase of nearly 13% between 2001 and 2016 according to the United States Census Bureau. Such increase has put much pressure on the government to answer increasing social- and health-related issues, such as water sustainability (e.g. Yigzaw and Hossain, 2016), increasing cancer patients (e.g. Hao et al., 2019), and increasing suicidal rates (e.g. Curtin et al., 2016).

On the other hand, the limited increase shown in some counties could be related to the implemented policies that encourage the establishment of new green infrastructures within the vicinity of the cities (Schilling and Logan, 2008; Kimmel et al., 2013). More in-depth investigation needs to be conducted at county-level to retrieve the root causes behind such an increase. That being said, the majority of CONUS' counties showed negative pervious areas between 1% and 10%.

The considered climatic factors, including wind speed, precipitation, and solar radiation showed fluctuating changes in different pervious area percentages. Thus, these elements could be considered irrelevant when describing pervious or impervious areas. Inversely, the significant increase of temperatures throughout the selected counties is alarming. Thus, a regional warming across the CONUS could be deduced, which is aligned with many previous studies (e.g. Kellstedt et al., 2008; Rahmstorf et al., 2017; Cooke and Kim, 2019; Susskind et al., 2019).

To further assess the impact of warming at the county-level, only dense counties representing less than 50% of pervious areas were considered. The district of Virginia showed the largest number of dense counties due to the existence of major cities with large populations such as Fairfax and Norfolk counties. Still, the district of Texas represented the greatest decrease in pervious area percentage due the large urban expansion as discussed in Georgescu et al. (2014). The availability of lands might also be the main cause behind such huge decrease. On the other hand, the limited decrease shown in Massachusetts and New York counties can be related to the saturation of demand for land (Sharmina et al., 2016) and their limited availability (Faour and Mhawej, 2014).

Increasing NDVI values in Suffolk aligned with an increase in air temperatures, even though this county represents one of the less negative pervious area change among the 43 dense CONUS's counties. The NDVI trend was nearly constant for Dallas, whereas, for Harris that has one of the major negative pervious area changes showed a decrease in NDVI values. Thus, the area-averaged NDVI per county did not directly affect the change in air temperature, as some counties with high NDVI value (e.g. Harris with an average NDVI of 0.5) have alarming air temperature trends.

Still, further investigation needs to be done into these 43 dense counties to assess the direct effect of NDVI on the change in temperatures. Our findings suggest that the pervious area percentage change cannot alone describe the change in climatic variables. Future research could focus on increasing factors as well as to derive those which could be statistically significant. This can be done through data covering more than three decades. The usage of Landsat-8 or the Advanced Very-High-Resolution Radiometer (AVHRR) satellites could help retrieve NDVI values since the 1980's. Furthermore, studies focusing on more regional- or neighborhood-scales are advisable to understand future temperature changes at both regional and national levels (Faour et al., 2016).

Nevertheless, the importance of this study lies in providing the pervious area percentage change between the years, 2001 and 2016, for the entirety of CONUS's counties. Such percentage proved to be reliable when classifying counties that require more attention. More in-depth assessment should be conducted to clearly define the relation between climatic factors and other urban-related indices as well as to improve their accuracies by integrating other factors, maybe also by using an Ordinary Least Square (OLS) approach (Mhawej et al., 2016). More importantly, the proposed approach is replicable and can be portable to other countries and to other years, particularly when the new NLCD 2019 will be available. This approach offers an easy-to-implement and straightforward assessment of the counties to enable policy makers and planners a better implementation of the national effort to curb the effect of regional warming.

5. Conclusion

The concept of Green Infrastructure has been gaining much attention in recent years, coinciding with a global attention on improving human well-being while conserving natural resources for future generations. This paper has proposed an approach to assess the pervious area in each county while identifying the 43 dense counties across CONUS. The significant increase at $\alpha = 0.95$ in air temperatures between 1980 and 2019 is alarming. The other considered factors (e.g. precipitation, wind speed, and solar incoming radiation) appear to show no effect on the pervious area percentage change, nor on air temperature trends. Furthermore, assessments should be made to derive the impact of such an increase on each county, in terms of experiencing a longer hot season, a higher flood frequency, and an increased disease outbreak, among other direct and in-direct consequences. More importantly, human well-being should be always monitored enabling an improved happiness index for a more productive society (Shin and Johnson, 1978; Pavot and Diener, 2009).

Author statement

With the submission of this manuscript I would like to undertake that:

- All authors of this research paper have directly participated in the planning, execution, or analysis of this study;
- All authors of this paper have read and approved the final version submitted;
- The contents of this manuscript have not been copyrighted or published previously;
- The contents of this manuscript are not now under consideration for publication elsewhere;
- The contents of this manuscript will not be copyrighted, submitted, or published elsewhere, while acceptance by the Journal is under consideration;
- There are no directly related manuscripts or abstracts, published or unpublished, by any authors of this paper;

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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