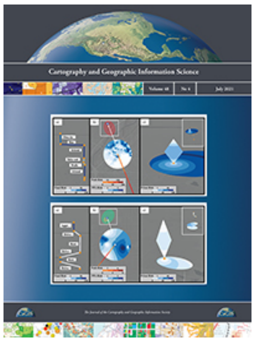

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Deep fake geography? When geospatial data encounter Artificial Intelligence

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ABSTRACT

The developing convergence of Artificial Intelligence and GIScience has raised a concern on the emergence of deep fake geography and its potentials in transforming human perception of the geographic world. Situating fake geography under the context of modern cartography and GIScience, this paper presents an empirical study to dissect the algorithmic mechanism of falsifying satellite images with non-existent landscape features. To demonstrate our pioneering attempt at deep fake detection, a robust approach is then proposed and evaluated. Our proactive study warns of the emergence and proliferation of deep fakes in geography just as “lies” in maps. We suggest timely detections of deep fakes in geospatial data and proper coping strategies when necessary. More importantly, it is encouraged to cultivate a critical geospatial data literacy and thus to understand the multi-faceted impacts of deep fake geography on individuals and human society.

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Artificial Intelligence; geospatial data; deep fake; fake geography; GeoAI; fake satellite image; Generative Adversarial Networks

1. Introduction

Geospatial Artificial Intelligence (GeoAI), for its potential to provide groundbreaking capabilities to leverage GIScience with a series of Artificial Intelligence (AI) advances, such as natural language process, unstructured data classification, computer vision, or map style transfer (Hu et al., 2019; Kamel Boulos et al., 2019; Sirosh, 2018), has been hailed by both industry pundits (e.g. the seamless integration of deep learning functions in ArcGIS Pro, GeoAI solution launched on Microsoft Azure) and scholars alike (e.g. a series of GeoAI sessions in AAG annual conferences 2018, 2019, and 2020, Critical GeoAI session in AAG annual conference 2021, GeoAI workshops at ACM SIGSPATIAL 2017, 2018, and 2019, special issues on GeoAI sponsored by *International Journal of Geographical Information Science* and *International Journal of Geo-Information*). Such a wide applause of GeoAI is not the first time when GIS practitioners paid close attention to the use of AI in improving our capacity of understanding various geographical phenomena though; similar efforts can be traced back to mid-1980s (Couclelis, 1986; Estes et al., 1986; Nystuen, 1984; Smith, 1984). AI was a major driving force to form the subfields like automated geography (Dobson, 1983) and GeoComputation (Openshaw & Abrahart, 1996), which later became significant components of today’s prosperous GIScience. This early wave of AI in GIScience was well documented in Openshaw’s book “Artificial Intelligence in Geography” (Openshaw & Openshaw, 1997).

Besides the above-mentioned technical merits brought by AI, scholars have also witnessed problematic and unexpected implications of the convergence of AI and GIScience, such as fabricated GPS signals (Tippenhauer et al., 2011), fake locational information on social media (Zhao & Sui, 2017), simulated trajectories of online game bots (Pao et al., 2010), and fake photos of geographical environments (Isola et al., 2017). Even so, deep fake, as a problematic use of AI, has not widely proliferated in GIScience yet. Deep fake is often referred to as the deceptive and/or misleading synthetic media (e.g. image, audio, or video) that are created by AI. The deep fakes of politician speech and celebrity pornography spreading on social media that have received wide public attention in recent years. It has been regarded as a serious threat to individual privacy and national security (Chesney & Citron, 2019; Sayler & Harris, 2019), and has thus incurred responses from both industry and government to restrain its use. Big tech companies, including Amazon, Facebook and Microsoft, have jointly launched a deep fake detection challenge (DFDC, 2019), and Microsoft published a tool to identify artificially manipulated media (Burt, 2020). The proliferating misuse of AI also brought up serious concerns with the appearance of deep fakes in geography. For example, the automation lead at the National Geospatial-Intelligence Agency

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(NGA, known as the National Imagery and Mapping Agency from 1996–2003), a combat support agency under the United States Department of Defense and a member of the United States Intelligence, openly unveiled that AI was used to manipulate scenes and pixels to create artifacts on satellite images for malicious purposes (Tucker, 2019). Due to the often-sensitive nature of deep fake satellite imagery in similar settings as such, we could not get convenient and safe access to existing deep fake satellite images for this study and publication. Even though, we cannot ignore the appearance, or underestimate the development, of deep fake in satellite images or other types of geospatial data.

While many GIS practitioners have been celebrating the technical merits of deep learning and other types of AI for geographical problem solving, few have publicly recognized or criticized the potential threats of deep fake to the field of geography or beyond. Therefore, we would like to take the lead to explore the potential influences of deep fake on geospatial data and GIScience. Indeed, the emergence of deep fakes in GIScience is inevitable just as "lies" are essential in maps. As Monmonier (1991, p. 1) argued, "Not only is it easy to lie with maps, it's essential … To present a useful and truthful picture, an accurate map must tell white lies." Therefore, expecting the proliferating deep fakes of geospatial data, it is necessary to develop proper coping strategies and critically analyze their complicated social implications. Thus, in the remaining sections of this paper, we review the development of fake geography since before AI and introduce the basic technical details of deep fake in relevance to geography today. Then, we detail a case study of fake satellite images of Tacoma, Washington in order to closely examine the algorithmic mechanism of deep fake techniques in simulating fake satellite images – a primary type of geospatial data. Next, we introduce a feasible detecting approach to assessing the authenticity of a satellite image. We conclude this paper with a summary of our research findings and a critical discussion of "fake" from a broader humanistic geography perspective.

2. Related works

2.1. Fake geography

Although the term "Fake Geography" first appeared to describe an AI-generated fake digital geographical environment and warn us of its detrimental effects (Maclenan, 2018), its theoretical connotation and potential significance for geography is far more profound and broader. We could trace the origin of fake geography all the way back to the false or mythological interpretation of the world that could be illustrated from some ancient maps such as the Babylonian cuneiform map in the 5th century B.C. However, in this paper we situated fake geography in the context of modern science and technology. In doing so, we realized the importance of the correspondence theory of truth as epistemological guidance on the determination of what is true and its opposites (David, 2016). This theory is premised on a clear binary relationship between an object and its measurement: if the measurement is in correspondence with the object, a truth is thus established and the object can be represented by the measurement. For those measurements that are not deemed as "truth," various terms have been used, such as "error," "false," "outlier" or "anomaly" that are often used to indicate inconsistent measurements in scientific research, and also "lie," "fake," "misinformation" or "disinformation" that are commonly used in public media and political debates to describe a deliberately generated inconsistent representation.

Monmonier is one of the first geographers whose work can be enlightening for today's debates on fake geography. In his famous book "*How to lie with maps*," a variety of ways in which maps (or geospatial data) distortedly represent the real world have been systematically explored (Monmonier, 1991). Early fake geographies would also include, for example, propaganda maps in wartime that distortedly illustrated the real battle situations in order to shake the enemy's morale (Herb, 2002); fictitious geographical entries, also called paper towns, phantom settlements, or trap streets, that are labeled on the map to help unveil copyright infringements (S. Zhang, 2015). It is worth noting that the term "lie" in the book title cannot be simply taken as some negative intentions in map making. Indeed, cartographic generalization is a type of "white lie" – any map needs to simplify and thus reduce the complexity of the real-world phenomenon in order to enable an efficient and legible visual communication.

Monmonier's book, republished several times by now, has influenced generations of cartographers and GIScientists. It did not foresee, but inspired us to understand more critically and holistically, the emerging "lies" or fake geographies in today's data-intensive and networked environments. For example, GPS signals were spoofed to mislead superyachts off the course (Shepard et al., 2012), and selfies in fake scenery spots (e.g. beach, national parks) were shared on social media to show off "fakations" (a.k.a. fake vacations) (M. Zhang, 2015). Starting from 2017, Zhao and his collaborators have conducted a series of studies on location spoofing and its existence on multiple digital platforms, such as Twitter (Zhao & Sui, 2017), Facebook (S. Zhang et al., 2020) and the online mobile game Pokémon GO (Zhao & Zhang, 2019). Location spoofing, a relatively new geographical phenomenon of fake geography, refers to a deliberate inconsistency between the reported geospatial information and the ground truth. Zhao and Sui (2017) also proposed a detection approach through combining time geography principles and the Bayesian statistics, and further explored Twitter users' intentions in generating fake geo-tags. Zhao and Zhang (2019) further explored the spoofing issues in Pokémon GO and discussed its underlying social implications. As indicated by this study, although location spoofing was considered as cheating by the game company as well as some game players, it can be used to overcome the spatial disparity of game resources (e.g. between black and white neighborhoods in New York City) and promote fairness in accessing game resources. Moreover, S. Zhang et al. (2020) examined a cyber protest on Facebook. During this protest, the AI-powered recommendation algorithm referred the posts about the protest to Facebook users who may be interested in this topic. As a result, a great number of Facebook users remotely spoofed their location check-ins to show their support to the local protesters. AI plays an increasingly significant role in building fake geographies that are essential to the recent debates on misinformation and post-truth (Maclenan, 2018; Oscar, 2018; S. Zhang et al., 2020).

The fast penetration of AI in various areas of today's society is driving fake geography to another level, *deep fake geography*, which has triggered heated debates on its controversial capacity and unforeseeable impact on society. The NGA, as mentioned earlier, has seriously reminded us of the risk of deep fake satellite images being used as a terrifying AI-powered weapon (Tucker, 2019). Considering the increasing number of fake satellite images emerged during the past two years, such as satellite images of night light in India during "Diwali" – a Hindu festival of lights (Kundu, 2019) or of fake fire in the central park of New York City (Markuse, 2019), it is highly likely in the near future if not yet that deep fake techniques could be implemented to create fake satellite images containing uncannily real landscape features. If so, deep fake can potentially develop into a new mode of unpredictable and even terrifying fake geography (Kwok & Koh, 2020; Maclenan, 2018; Tucker, 2019).

2.2. Deep fake and its detection

To understand such a new mode of fake geography, it is necessary to comprehend the basic algorithm of deep fake techniques in making fake geospatial data and thus to inspire us to explore possible detection approaches. From an algorithmic perspective, deep fake techniques primarily rely on Generative Adversarial Networks (GANs), which is a class of unsupervised deep learning algorithms that can simulate synthetic media (e.g. image, video, audio) that appear authentic (Charleer, 2018; Oscar, 2018). The GANs generate two networks – a "generator" and a "discriminator"; and enable them to contest with one another through a multiple-epoch training process. In the training process, the generator creates a latent space of candidate datasets, and then the discriminator evaluates whether the candidate datasets are qualified by satisfying an evolving statistical characteristics criterion. The candidate data from the generator, after several training epochs of tuning, can reach an acceptable similarity to the required statistical characteristics (Goodfellow et al., 2014; Salimans et al., 2016). Similarly, if we use a GAN to simulate geospatial data, the GAN's generator will create candidates of geospatial data and ask the discriminator whether the candidates meet the characteristics of a typical geospatial data. Here, the geospatial data can be as simple as a point, polyline or polygon, or relative complex data like satellite images, or even 3D point clouds. After several epochs' training, the candidates could eventually meet the criteria of qualified geospatial data. At this stage, the candidates, recognized as seemingly authentic geospatial data, embody a new mode of fake geography.

With a thorough review of the existing deep fake detection methods, we categorized these methods into two groups based on the detecting feature selection process – manually defined or automatically extracted (Afchar et al., 2018; Galbally & Marcel, 2014; Hsu et al., 2020; Matern et al., 2019; Zhu et al., 2017). The detection methods using manually defined features were developed prior to those using automatically extracted features. Galbally and Marcel (2014) proposed 14 general image quality metrics to distinguish between legitimate face images and impostor samples generated by deep learning algorithms and achieved competitive results. When it comes to videos, by summarizing visual artifacts arising from global consistency, illumination estimation and geometry estimation, Matern et al. (2019) were able to recognize face manipulations in videos with acceptable accuracy only using shallow classifiers such as logistic regression models. For detection methods using automatically extracted features, Hsu et al. (2020) proposed a two-step approach for general fake image detection. The first step extracts the discriminative features using the common fake feature network (CFFN) learning process, and the following step feeds these salient features into a small convolutional neural network (CNN) concatenated to the last convolutional layer of CFFN. This method achieved a precision at least 0.92 on a variety of image datasets generated by state-of-the-art GANs, significantly superior to other existing fake image detectors.

3. Data and method

Despite the significant progress in deep fake detection, specific methods for detecting deep fake satellite images have not been explored yet. We thus designed an empirical study to closely examine deep fake techniques and explore feasible means to detect deep fakes in satellite images. Since no existing GANs-generated satellite image has been publicized or easily accessible, this empirical study began with our own experiment of simulating a baseline dataset of satellite imagery of Tacoma, Washington. The simulated satellite images were developed on the basic urban structure on the CartoDB basemap, but with the landscape features extracted from two other cities, Seattle, Washington and Beijing, China. Such GANs-generated satellite images could be viewed as fake since the displaying landscapes did not exist in the real world and hence were used experimentally in this study for testing our deep fake detection approach. It has never been our objective to show how to fake satellite images; in fact, we acknowledged that the satellite image simulation process not only provided a baseline of simulated or fake satellite images, but also offered a demonstrative example of the essential deep fake mechanism. The baseline dataset enabled us to analyze the characteristics of fake satellite images, thereby facilitating the process of proposing an approach to detecting the deep fakes in satellite images.

3.1. Deep faking satellite image using GANs

Cycle-Consistent Adversarial Networks (CycleGAN), as a popular model of GANs, is frequently adopted for generating deep fakes (Zhu et al., 2017). In our study, we used CycleGAN to translate the basemap of a city to satellite images into landscape features of other cities. If the newly simulated images embodied any fake geographical environment but appeared to be real, we would consider them as fake images.

Specifically, CycleGAN translates between two different domains (i.e. X and Y), where X and Y should share some underlying relationship. CycleGAN aims to learn the relationship by developing two mapping functions, G: X → Y and F: Y → X. Two associated adversarial discriminators D_Y and D_X are developed to facilitate the mapping between the two domains by encouraging the G and F functions to generate the output indistinguishable from the corresponding domain (i.e. Y and X, respectively). CycleGAN aims to solve Equation (1) (Zhu et al., 2017):

$$
\begin{aligned}
G^*, F^* = L(G, F, Dx, Dy) = {} & L_{GAN}(G, Dy, X, Y) \\
& + L_{GAN}(F, Dx, Y, X) \\
& + \beta L_{cyc}(G, F)
\end{aligned} \tag{1}
$$

where β is a parameter that controls the relative importance of the two losses: adversarial losses L_{GAN} and cycle consistency losses $L_{cyc}(G, F)$, which are defined as follows:

$$
\begin{aligned}
L_{GAN}(G, Dy, X, Y) = {} & E_{y \sim p_{data}(y)}([\log D_Y(y)] \\
& + E_{x \sim p_{data}(x)}[\log(1 - D_Y(G(x)))]
\end{aligned} \tag{2}
$$

$$
\begin{aligned}
L_{cyc}(G, F) = {} & E_{x \sim p_{data}(x)}[\| F(G(x)) - x\|_1] \\
& + E_{y \sim p_{data}(y)}[\| G(F(y)) - y\|_1]
\end{aligned} \tag{3}
$$

In Equation (2), the first item is the expectation (E) of discriminator (D) output given y where y is sampled from a data distribution p_data(y). For the second item, the input to the discriminator is the output from the generator G, after being feeded in data from X domain.

In Equation (3), the loss of CycleGAN is to minimize the forward cycle consistency (the first item) and backward cycle consistency (the second item). The cycle consistency is used to depict the process that the original image (x or y) should be reconstructed (y or x) after image transformation (mapping function G, F) using CycleGAN.

To demonstrate the deep faking process, we conducted an experiment to simulate satellite images of City A to embody the landscape features of City B using CycleGAN (Figure 1). Two types of web map tile datasets from Google Earth's satellite imagery and CartoDB positron basemap were collected as the model input. The high-resolution imagery in Google Earth provided fine details of the spatial pattern at different zoom levels and has been widely used as the ground truth reference for image interpretation. The monochrome CartoDB positron basemap presented basic urban structural information of the geospatial context without any geoname label. Collected through the QTile plugin in QGIS, both datasets are in 256*256-pixel tiles at the zoom level 16, which is equivalent to the scale of 1:8,000.

In our empirical study, we collected the landscape features from two big cities – Seattle and Beijing (See Figure 2). Seattle is located between the saltwater Puget Sound to the west and Lake Washington to the east, on

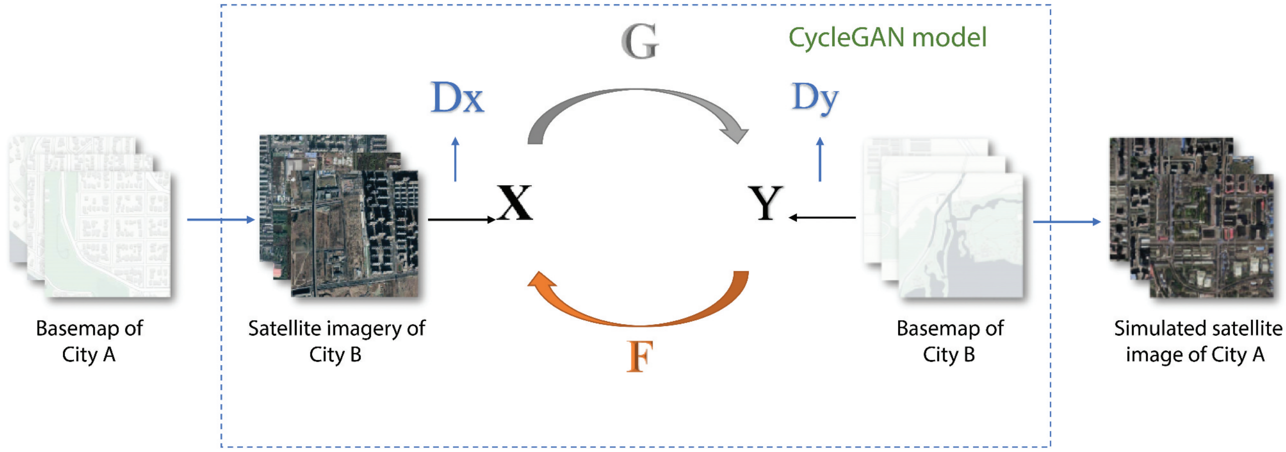

Figure 1. Dataflow of CycleGAN model in this study. The CycleGAN model is trained using the Basemap and satellite imagery dataset of City B to build the mapping relationships between two data domains. In this model, G function maps satellite imagery to basemap, while F function maps basemap to satellite imagery. Then the CycleGAN model is applied to the basemap of City A to generate the simulated satellite imagery. This CycleGAN illustration is modified from Zhu et al. (2017).

the northwest coast of the United States. It is featured as one of the largest employment bases in the country but being ranked as low in terms of the population density compared to other big cities in the United States. Beijing is located in North China, and is the world's most populous capital city, combining both modern and traditional architectures. Beijing presents rapid urban growth in the past few decades, and it witnessed the most intense conversion of the land through the urban sprawl and renewal process. These two cities present different spatial arrangements and configurations, which can be identified by the spectral and spatial features at the street scale on the high-resolution satellite imagery. Next, the dataset of the basic urban structural information was collected from Tacoma, Washington. Tacoma (see Figure 2) is a mid-sized port city located in Pierce County, Washington, and is adjacent to the southwest of Seattle. Geographically, the spatial features of Tacoma are similar to Seattle. At the zoom level 16, 1196 and 1122 pairs of satellite imagery and map tiles were collected for Seattle and Beijing, respectively, and 758 image tiles were covering for Tacoma.

Figure 3 shows the training process with five different training epochs from the beginning to end. At the early epoch (i.e. epoch = 1 in the figure), the CycleGAN generally caught the structure of the road network, but it falsely generated a large area of shadow for the road network. The land parcels were made in gray color which rarely existed in the real world. Besides, a noticeable haloing feature could be clearly found on the top edge of the image. This haloing feature did not exist in the real world. It is yet unknown why CycleGAN created such a non-geographical object. One possible reason is that, compared to the base map, the satellite image had relatively more geospatial texture; thus, it was more challenging for CycleGAN to capture the underlying relationship when mapping from the base map to the satellite image. As the epoch increased from 50 to 100, more geographical features appeared, such as green space, open land, water bodies, and buildings. Due to the cyan color, it was difficult to differentiate the green spaces from water bodies. The area of shadows for the road network disappeared. However, some urban areas such as local communities seemed clustered and thereby hard to recognize its land use type and internal structure. For the last two epochs (150 and 200), an authentically visual feeling of the simulated satellite images increased to a great extent: more geographical details were found; and the colors for open land and water bodies became differentiated and natural. Overall, with the 200-epoch training, CycleGAN successfully generated the mapping from the base map to the satellite images. This pilot experiment demonstrates the capability of GANs in generating satellite images with non-existent geographical features. The simulated satellite imagery is not perfect yet, but it looks authentic and uncovers the potential of the algorithms in falsifying satellite images that cannot be easily identified by humans.

3.2. *Detecting fake satellite images*

With our own eyes, it was nearly impossible to tell whether the simulated satellite image (see the epoch 200 in Figure 3) was authentic or fake. To investigate whether and to what extent these fake images can be

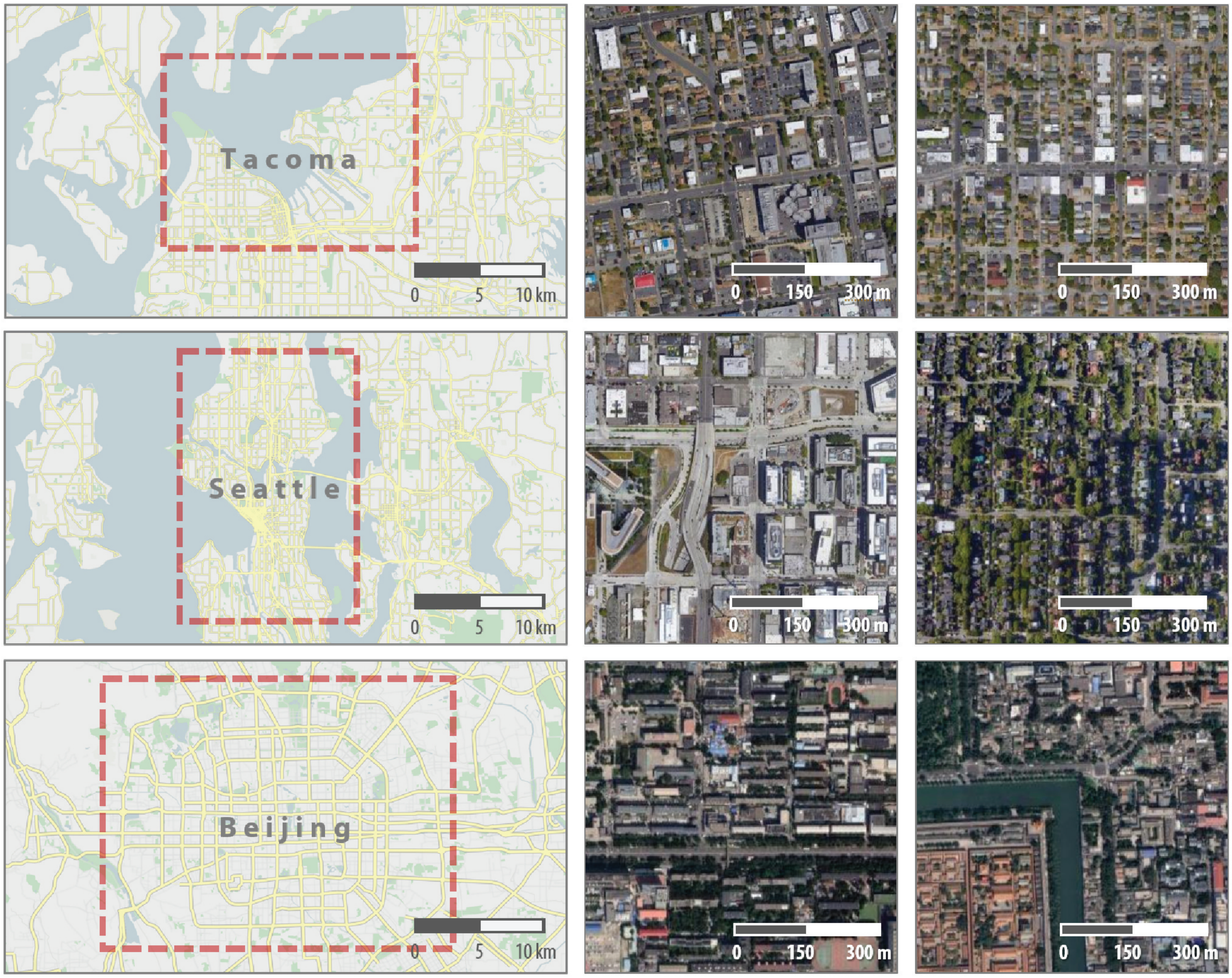

Figure 2. The study areas – Tacoma, Seattle and Beijing and their local landscape characteristics.

identified, we have learned some clues from previous studies. Scholars found that GAN-generated fake images were different from authentic ones in multiple visual features such as color, texture and details, and in frequency domain features such as a certain type of periodic replications (Galbally & Marcel, 2014; Wang et al., 2020; X. Zhang et al., 2019). Thus, to incorporate these early findings into our detection approach, we examined the GAN-generated satellite images using a suite of graphical features of color histogram, spatial domains, and frequency domains as shown in Table 1.

To explore the spatial domain, we chose Image Colorfulness Index (CFI) to describe the difference in the perception of colorfulness between the authentic image and the fake ones (Haralick et al., 1973). Besides, an image with higher definition appears with sharper edges and has larger gradient value, so the image clarity can be characterized by summing up the image gradient values. Three non-reference image quality evaluation features using Brenne, Tenengrad and Laplacian gradients were employed in this study to measure the clarity of satellite images. The clearer the image, the greater the value of these features (Mittal et al., 2012).

Among a variety of image texture description methods, gray level concurrence matrix (GLCM) is simple and effective. Haralick et al. (1973) defined 14 GLCM quadratic statistics in image classification research. Ulaby et al. (1986) further pointed out that among the aforementioned quadratic statistics, four independent features – angular second moment (ASM), contrast (CON), entropy (ENT), and inverse different moment (IDM) – are effective in recognizing land use variations. These four features were used in this study to describe the texture of satellite images. In addition to the texture of the spatial domain, replications in the frequency domain can be considered as a texture characteristic as

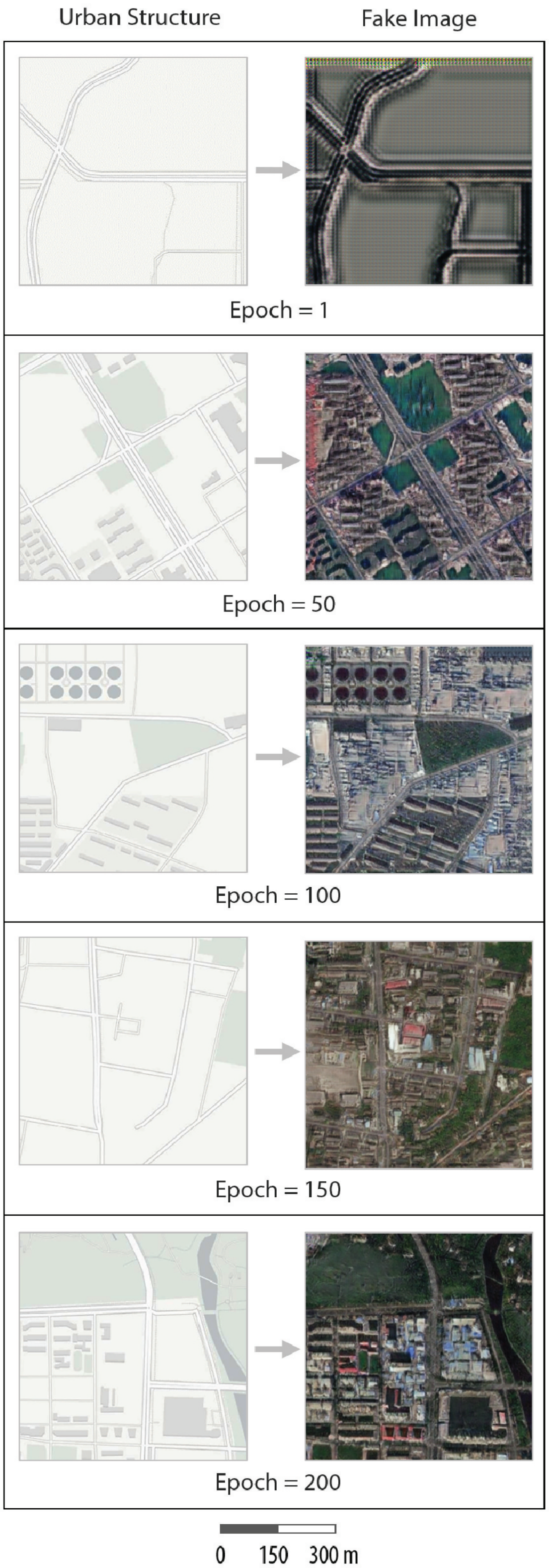

Figure 3. Training process illustrated by five image pairs of different epochs.

well. Therefore, the aforementioned four quadratic statistics were recalculated based on GLCM of frequency spectra to describe the frequency characteristics.

Table 1. Features of authentic and fake satellite images.

Code	Feature description
Spatial	
CFI	Image Colorfulness Index: A larger value indicates a more colorful image
BIQ	Brenne Image Quality Index: A larger value indicates a clearer image
TIQ	Tenengrad Image Quality Index: A larger value indicates a clearer image
LIQ	Laplacian Image Quality Index: A larger value indicates a clearer image
ASM	Angular Second Moment of GLCM: A larger value indicates a more uniform and regularly changing texture pattern
CON	Contrast of GLCM: The greater the CON, the deeper the grooves of the texture, and the clearer the visual effect
ENT	Entropy of GLCM: The more complex and uneven the texture in the image, the greater the ENT value
IDM	Inverse Different Moment of GLCM: The larger the IDM, the smaller the change between areas of the image texture, or the local pattern is more uniform
Frequency	
FASM	ASM at Frequency Domain: Similar to ASM
FCON	CON at Frequency Domain: Similar to CON
FENT	ENT at Frequency Domain: Similar to ENT
FIDM	IDM at Frequency Domain: Similar to IDM
Histogram	
MEAN	Mean of GLH, The larger the value the brighter the image
STD	Standard Deviation of GLH, the larger the value less concentrated the GLH
SKEW	Skewness of GLH, the larger the value more skewed the GLH
KURT	Kurtosis of GLH, the larger the value the steeper the GLH
GET	Entropy of GLH, the larger the value, the less even the GLH
CM1_R/G/B	First Order Color Moment of Red (Green/Blue): mean of color histogram
CM2_R/G/B	Second Order Color Moment of Red (Green/Blue): variance of color histogram
CM3_R/G/B	Third Order Color Moment of Red (Green/Blue): skewness of color histogram

GLCM means gray level concurrence matrix; GLH refers to gray level histogram.

Furthermore, a number of features were calculated to quantify the difference between the histogram of the authentic images and that of the fake ones. First, we used the mean (MEAN), standard deviation (STD), skewness (SKEW), kurtosis (KURT), and entropy (GET) to describe the grayscale histogram. Then, color moments (CM) were employed to indicate the characteristics of single channel histograms. Since the color distribution information is mainly concentrated in low-order moments, only the first (CM1), second (CM2), and third moments of color (CM3) are sufficient to express the color distribution of an image (Stricker & Orengo, 1995).

The above-mentioned 26 features can assist us to develop specific strategies of fake satellite image detection. In practice, an independent t-test is conducted on these 26 features in order to identify salient features that have significant mean value difference between all authentic and fake satellite images and thus to use these identified features for fake satellite image detection (Galbally & Marcel, 2014; Matern et al., 2019). Moreover, considering prior studies in satellite data classification (Maghsoudi et al.,

2013) and deep fake detection (Matern et al., 2019), we proposed a fake satellite image detection approach by feeding these salient features to a Support Vector Machine (SVM). By constructing a hyperplane that has the largest distance to the nearest sample of any class in a high-dimensional space, a SVM can efficiently perform data classification functions and then differentiate fake satellite images from the authentic ones. We further employed indicators like precision, recall and F1 score to evaluate the performance of our approach. In the context of fake satellite image detection, precision is the ratio of successfully detected fake satellite images to the total number of satellite images that our approach considers fake. This indicator reflects the credibility of our approach in judging a satellite image as fake or not; Recall is the ratio of successfully detected fake satellite images to all fake satellite images. This indicator measures the capability of our approach to detect fake satellite images. F1 score is the weighted average of precision and recall. This indicator evaluates the overall performance of our approach in detecting fake satellite images.

4. Results

4.1. Satellite images with non-existent landscape features

After applying the deep fake approach proposed in section 3.1, we simulated/faked satellite images of Tacoma that embodied landscape features similar to those of Beijing and Seattle (see Figure 4). Since these landscape features do not exist in Tacoma, we considered the simulated satellite images of Tacoma as fake. In general, the road network, green space, and buildings are captured by fake satellite images in the visual pattern of either Seattle or Beijing, whereas the geospatial details differ from one another. The fake satellite image in the visual pattern of Seattle presents similar landscape features such as low-rise buildings, whereas the one in the visual pattern of Beijing presents different landscapes such as high-rise compact buildings with large shadow areas.

Moreover, the CycleGAN models show stability in generating fake satellite images in a large geographical region. Figure 5(b,c) shows two fake satellite images covering a neighborhood in Tacoma made up of four fake mosaic tiles in the visual patterns of Beijing and Seattle, respectively. The fake satellite image in the visual pattern of Beijing contains more landscape details compared to those in the visual pattern of Seattle, especially in open areas where there is lack of geospatial information on the CartoDB basemap. For example, buildings were generated at the left-bottom corner on Figure 5(b) but did not appear on Figure 5(c).

According to our results, CycleGAN performs excellently in recognizing and simulating green space, which may be due to its simple color feature. Unsurprisingly, the number of details differ between the two visual patterns. Overall, the above experiment demonstrates that satellite imagery can be faked by CycleGAN.

4.2. Deep fake detection

With the successfully simulated fake satellite imagery, this section presents our pioneering attempt in detecting the deep fakes in satellite imagery. Specifically, we constructed a deep fake detection dataset containing 8064 satellite images in the size of 256*256 pixels. The dataset includes authentic satellite images of Tacoma (2016 pieces), Seattle (1008 pieces), and Beijing (1008 pieces), as well as fake satellite images of Tacoma in the visual pattern of Seattle (2016 pieces) and in the visual pattern of Beijing (2016 pieces).

According to the result of the independent two-sample t-test (Table 2), 21 out of 25 features have a significantly different mean value, and they are further considered salient features. These salient features indicate a significant difference between authentic and fake satellite images. To be more specific, from the view of the spatial domain, a significantly smaller image colorfulness index (CFI) of fake satellite images shows a relatively less colorful visual perception in comparison to authentic ones. When it comes to the clarity of satellite images, a significantly larger Brenne Image Quality Index (BIQ) of fake satellite images shows more sharp edges on them. Besides, fake satellite images have a significantly smaller angular second moment (ASM) and inverse different moment (IDM) of gray level concurrence matrix (GLCM), and a significantly larger entropy of GLCM (ENT). It indicates that fake satellite images have more complex and uneven texture in comparison to authentic satellite images.

Regarding the histogram features, fake satellite images have a significantly smaller mean value of gray level histogram (MEAN) and first-order color moment of both red, green and blue (CM1_R/G/B). It means fake satellite images have a dimmer visual appearance, and we can observe a gray level or color histogram closer to the left. Besides, the second-order color moment of the fake satellite image is significantly smaller on the red channel (CM2_R) and larger on the green channel (CM2_G). Since the skewness, kurtosis, and entropy of gray level histogram (SKEW, KURT, GET) of fake satellite images is significantly larger than authentic ones, the gray level histogram of fake satellite images appears more skewed, steeper and less even. A significant larger third color moment in all channels (CM3_R/G/B) of

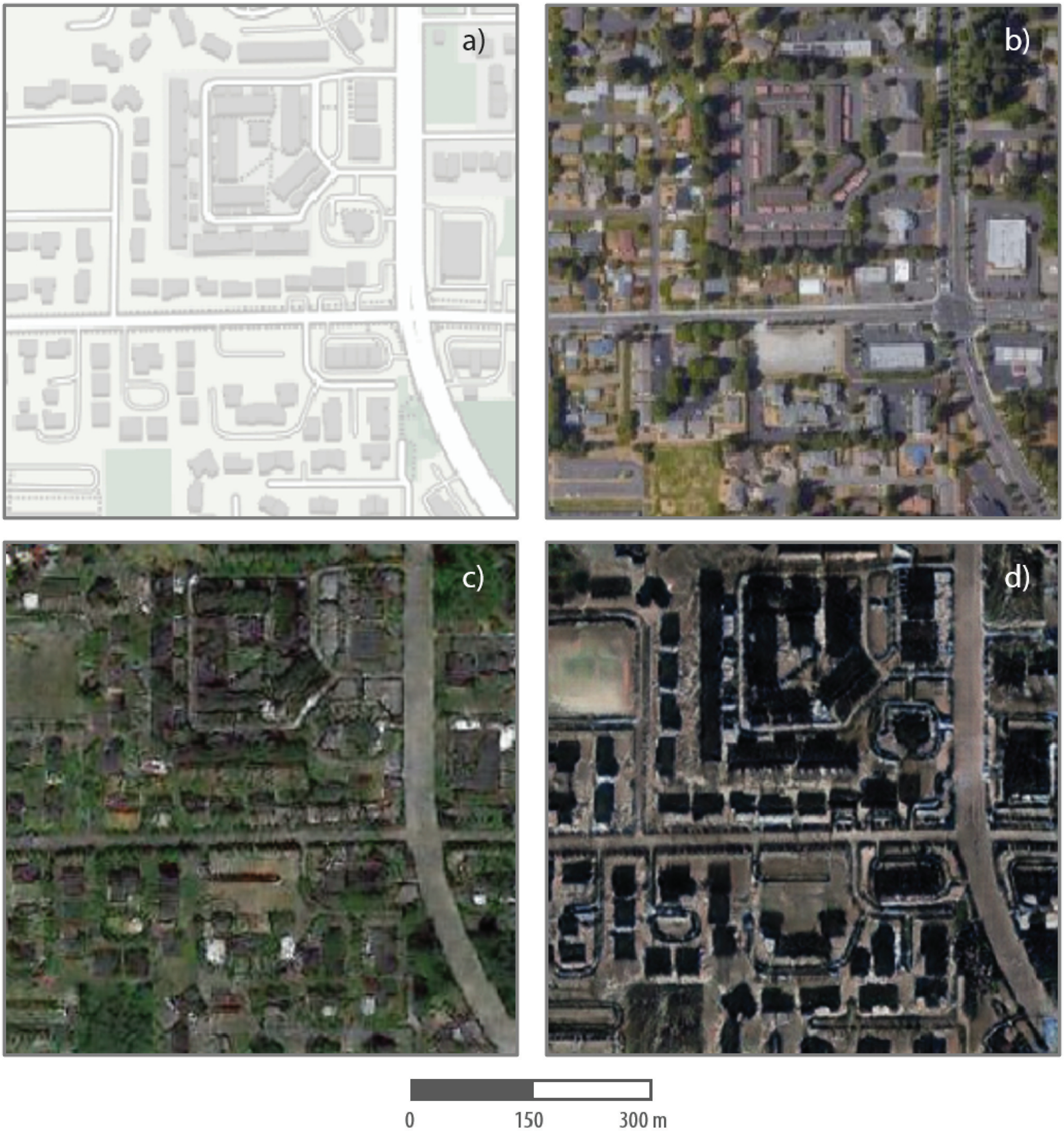

Figure 4. Fake satellite images of a neighborhood in Tacoma with landscape features of other cities. (a) The original CartoDB basemap tile; (b) the corresponding satellite image tile. The fake satellite image in the visual patterns of (c) Seattle and (d) Beijing.

fake satellite images indicates that color histograms of fake ones tend to be more skewed.

From a frequency domain perspective, fake satellite images have a significantly smaller FASM and FCON, and a significantly larger FNET and FIDM in comparison to authentic ones. It indicates the texture on frequency domain of authentic satellite images is more uniform and has deeper grooves, while the frequency domain of the fake satellite images a more complex but locally consistent texture.

When comparing specific authentic and fake satellite images, we can visually observe differences in the salient features. For example, the three authentic satellite images in Figure 6 are brighter and more colorful than the two fake ones, and these fake ones have more sharp edges such as the edges of the road. Moreover, the authentic satellite image of

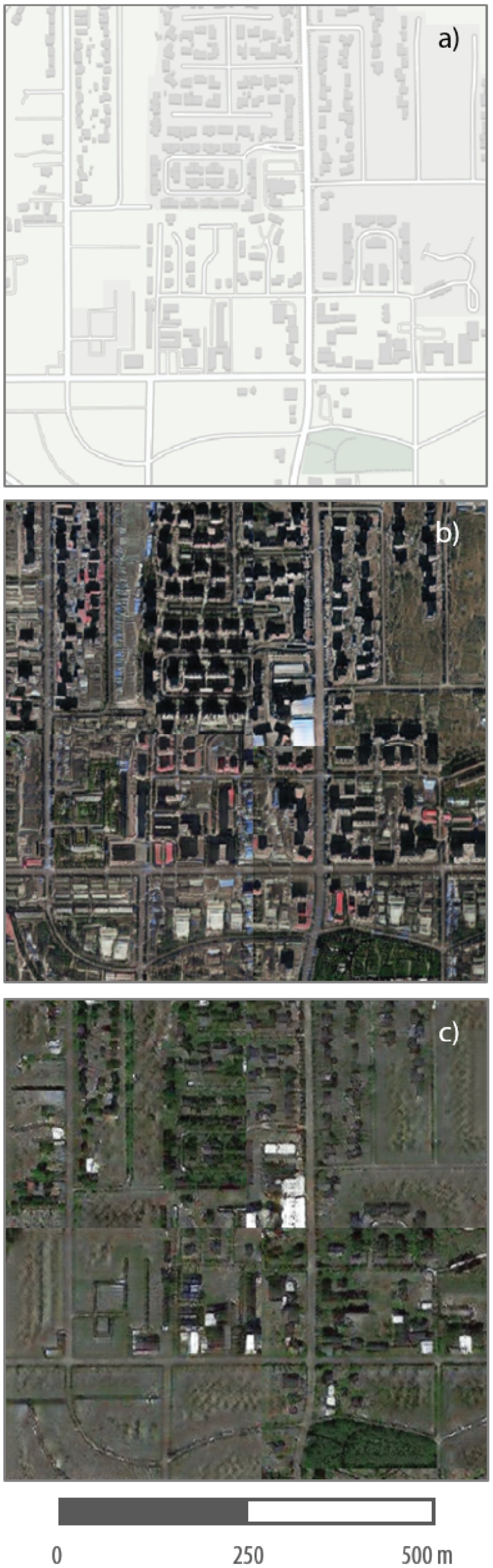

Figure 5. (a) A CartoDB basemap covering a neighborhood area in Tacoma; a fake satellite image with the transferred visual pattern of (b) Beijing; and (c) Seattle.

Seattle contains clear light-colored roofs, whereas those light-colored roofs on the fake image in the visual pattern

Table 2. The independent *t*-test between features of authentic and fake satellite images.

Feature	Mean Fake	Mean Authentic	Diff.
Spatial			
CFI	12.1343	20.6602	−8.5259***
BIQ	496.2755	462.3757	33.8998**
TIQ	19284.5431	19472.7016	−188.1585
LIQ	4897.4112	4937.9481	−40.5369
ASM	0.0089	0.0258	−0.0169***
CON	373.3451	364.6969	8.6482
ENT	7.7601	7.5506	0.2096**
IDM	0.1767	0.2764	−0.0997***
Histogram			
MEAN	79.0960	91.1394	−12.0434***
STD	28.8618	28.5261	0.3357
SKEW	0.9246	0.7465	0.1781***
KURT	5.9737	3.5810	2.3927***
GET	6.2897	6.1589	0.1308**
CM1_R	80.3252	89.2334	−8.9084***
CM2_R	30.4465	31.710	−1.2675***
CM3_R	25.1773	13.3325	11.8447***
CM1_G	80.7005	92.9016	−12.2011***
CM2_G	28.9633	28.5668	0.3965**
CM3_G	26.4078	15.7421	10.6658***
CM1_B	75.4713	88.3756	−12.9042***
CM2_B	29.1654	29.6676	−0.5022
CM3_B	28.6201	23.1306	5.4895***
Frequency			
FASM	0.0007	0.0047	−0.0041***
FCON	245.7877	251.9979	−6.2102***
FENT	8.2935	8.2288	0.0648***
FIDM	0.0956	0.0903	0.0054***

Mean Fake (Authentic) refers to the mean value of different features of all fake (authentic) samples, Diff. indicates difference between the mean value of features for all authentic samples and all fake samples; *, $p < 0.05$; **, $p < 0.01$; ***, $p < 0.001$.

of Seattle contain some mottled textures. This textural difference can be used to identify the fakes. Besides, similar to the empirical results found by X. Zhang et al. (2019) and Wang et al. (2020), periodic replications of spectra can be observed in fake satellite images in either the visual pattern of Seattle or that of Beijing.

Taking one or more types (spatial, histogram, and frequency) of salient features as input, SVMs are trained and adjusted. The performance of different models in the test dataset is shown in Table 3. All models achieved a recall more than 0.94, which indicates more than 94% fake satellite images can be detected. When only taking frequency salient features into consideration, the precision had a relative lower value 0.7283 in comparison to other models. In other words, when the model labels a satellite image as fake, it is only 73% reliable. Taking its highest recall 0.9697 into consideration, its relative lower precision may be due to that periodic replications of spectra may also be observed in some authentic satellite images. The model fed with only salient features of spatial domain obtains an F1 score of 0.9399, it indicates that we can distinguish the fake satellite images by taking a closer look at their color, edge clarity, and texture characteristics. When all spatial, histogram, and frequency salient features are taken into

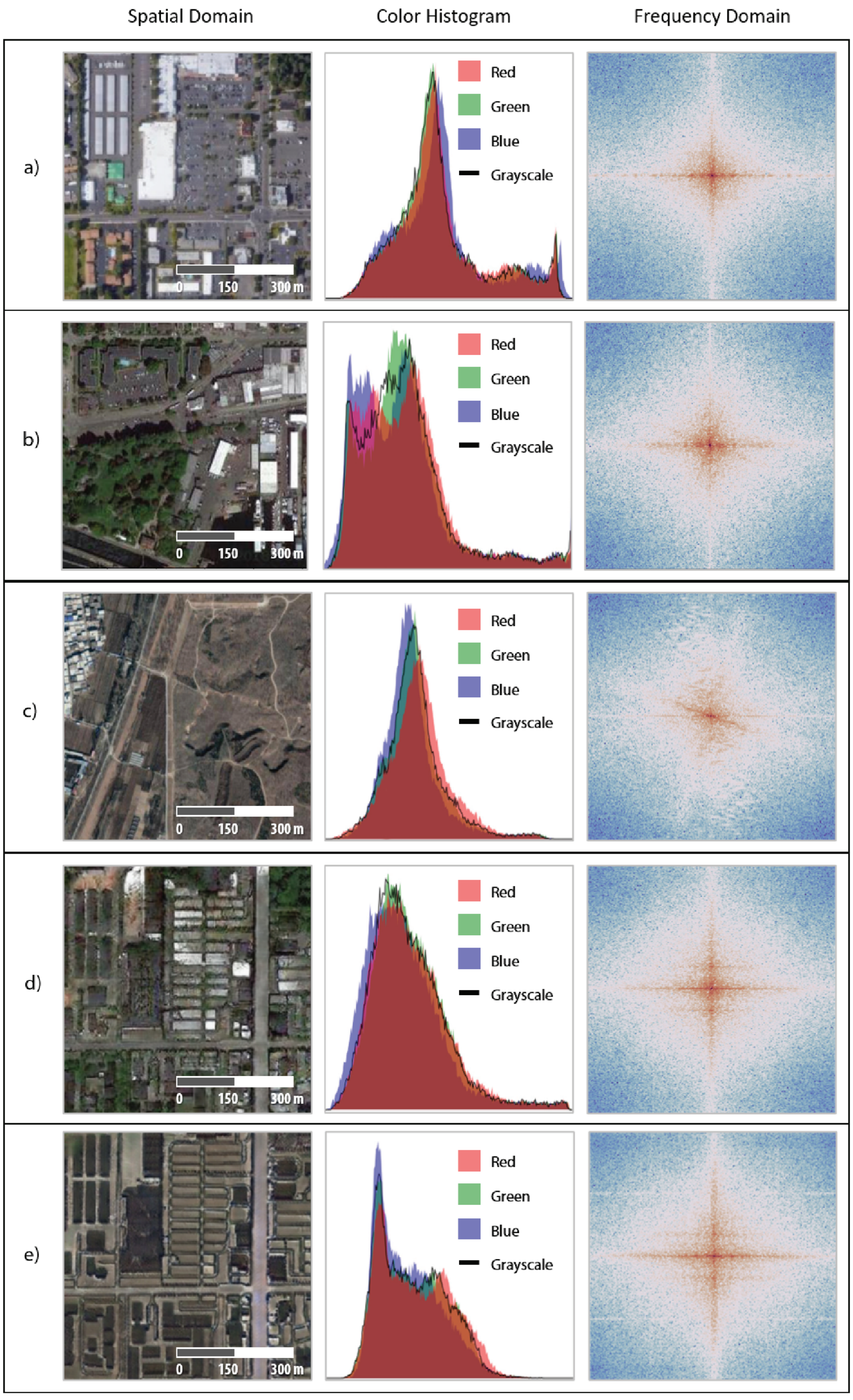

Figure 6. The comparison between authentic and fake satellite image records with respect to their spatial domains, color histograms, and frequency domains. Three authentic satellite image records showing (a) an area in Tacoma, (b) an area in Seattle, and (c) another area in Beijing, respectively. Two fake satellite image records of Tacoma in (d) a transferred visual pattern of Seattle and in (e) another transferred visual pattern of Beijing, respectively.

Table 3. Performance of different fake satellite images detection models.

Model	F1 score	Precision	Recall
Spatial	0.9399	0.9316	0.9483
Histogram	0.8795	0.8196	0.9484
Frequency	0.8324	0.7283	0.9697
Spatial + Histogram	0.9484	0.9472	0.9516
Spatial + Frequency	0.9387	0.9308	0.9468
Histogram + Frequency	0.8879	0.8347	0.9481
Spatial + Histogram + Frequency	0.9530	0.9482	0.9579

consideration, the F1 score will rise to a competitive level of 0.9530.

Therefore, the results indicate that the proposed approach can effectively detect CycleGAN-generated fake satellite images. To enhance the current approach, it is necessary to include a few other cities rather than just Tacoma to our empirical study as a means to represent a variety of landscape structures. Moreover, if this approach is applied to fake satellite images that are generated by other GAN models (e.g. pix2pix, styleGAN), its performance may decline. Further, the current approach can only provide a binary result – an image is either authentic or totally fake, it is still a challenge to detect whether an image contains both authentic and fake landscape features, or even to delineate which landscape in an image is fake or not. To address the above-listed issues, the proposed approach can be further improved by establishing a more comprehensive database of satellite images that represents different types of existent and non-existent landscape features, and thereby training a baseline dataset that incorporates a variety of authentic and fake satellite image scenarios. In addition to an enlarged dataset, we should also optimize the algorithmic mechanism to detect fake images generated by other deep fake techniques, such as FaceForensics++ (Rössler et al., 2019). Although further enhancement can be effectively made through the above-listed directions by us or other scholars who are also interested in this timely topic, our ultimate goal of this paper is not to develop a universal approach that can effectively detect all kinds of fake satellite images. A universal approach is perhaps a mission impossible anyways due to the complexity of the landscape features in the real world and the diversity of deep fake approaches.

5. Concluding remarks

In this paper, we took a proactive and critical approach to the well-recognized capabilities of GeoAI and attempted to raise public awareness of how this technology may transform our perceptions about the geographic world. We used GANs – a deep learning technique to transfer satellite images of Tacoma into new or fake ones in order to demonstrate whether and how GeoAI can falsify satellite images. Further, based on a close examination of a series of satellite image characteristics, we proposed and applied a feasible approach to detecting fake satellite images. The approach achieved a F1 score more than 0.95 when taking all salient features into consideration in an independent test set. The methods and results in our study could be very useful as they enable us to better understand the deep fakes in geospatial data expecting further development and potential impacts of fake geography. However, few existent fake satellite images do not mean the topic is unnecessary to investigate. Instead, it is one of the key missions for scholars to envision prospective developments and suggest proper coping strategies.

This study is meant to encourage proper precautions toward the upcoming development of deep fake in geography. If we continue being unaware of and unprepared for deep fake, we run the risk of entering a "fake geography" dystopia (Maclenan, 2018). With this warning, the detection approach proposed in this paper would be crucial to discover fake satellite images, and to inspire our fellow cartographers and GIS practitioners to develop approaches to coping with other types of fake geospatial data. That said, we also need to remind ourselves of another extreme situation – when the existence of a few deep fake cases may force us to verify the trustworthiness of every piece of geospatial data. This could be so far beyond inconvenient that we would feel helpless and anxious, especially in this data-intensive era– when geospatial data has become such a fundamental resource for everyday life such as in real-time traffic provided by Google Maps, Autopilot offered by Tesla vehicles, and location-based restaurant recommendations provided by Yelp.

Therefore, we humans may easily fall into a dilemma, in which we are uncertain of implementing all-weather detection toward the rare cases of deep fakes in geography or simply taking no interventions. The former makes us anxious while the latter put us in danger. Instead of providing a simple solution to this dilemma, we suggest recalling the humanistic geography perspective toward fake geography introduced earlier with Monmonier. The emergence of deep fakes in GIScience and human society at large is inevitable just as "lies" are essential in maps. We ought to admit that fake, for good or ill, is an inevitable component of human civilization. In some cases, lyings, deceptions, or spoofings can smooth our social life. An apt example is the story "The Emperor's New Clothes," in which two dressmakers, chancellors, the public, and even the king himself would rather believe, for various reasons, that the non-existent clothes are the "most beautiful" in the world, and eventually, only the "uncivilized" child is willing to expose that lie. This may imply that the cost of civilization is the integration of lying into human societies no matter whether we humans like or dislike fakes. In this sense, the existence of fakes seems inevitable or even natural; Deep fakes in geography as well as other deceptive phenomena in this world may also facilitate our social life and become an integrated part of human civilization. Indeed, deep fakes of satellite imagery can be misleading or even threatening to national security, but can also be very useful, such as in predicting land-use change scenarios, reconstructing and preserving historical scenes, and automated making of reference and topographic maps (Kang et al., 2019). From this broader human geography perspective, what is urgent for human society is to properly utilize the underlying GeoAI technique (e.g. GANs), and to understand more comprehensively and critically its fast emergence and powerful impacts. We indeed need timely detection of deep fakes in geospatial data and proper coping strategies when necessary, for example, when satellite images of fake fires in the city center to trigger panic (Markuse, 2019), or 3d point cloud of fake road obstacles being transmitted to an autonomous driving vehicle to mislead its navigation system (Cao et al., 2019).

Overall, in today's increasingly data-intensive environment, neither a simple optimistic nor a pessimistic attitude would be the most helpful. While recognizing the tremendous opportunities expected in the latest AI advances, GIS practitioners should also be aware of possible falsification of geospatial data and get prepared for that by developing detection approaches for identifying fake geospatial data and utilizing such an approach when necessary. Further, it is encouraged to cultivate a critical geospatial data literacy instead of anxiously implementing the detection all the time. This critical data literacy would not only enable us to interpret fake geospatial data, but also further raise the public awareness toward the complicated and multi-faceted social implications of geospatial technologies that are being transformed dramatically by AI advances.

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Data availability statement

The data and codes that support the findings of this study are available in "figshare.com" with the identifier at https://figshare.com/s/eeedcd150e759ef4353c.

References

Afchar, D., Nozick, V., Yamagishi, J., & Echizen, I. (2018). MesoNet: A compact facial video forgery detection network. In *2018 IEEE International Workshop on Information Forensics and Security (WIFS)* (pp. 1–7). IEEE. https://doi.org/10.1109/WIFS.2018.8630761

Burt, T. (2020). *New steps to combat disinformation*. Microsoft on the Issues. https://blogs.microsoft.com/on-the-issues/2020/09/01/disinformation-deepfakes-newsguard-video-authenticator/

Cao, Y., Zhou, Y., Chen, Q. A., Xiao, C., Park, W., Fu, K., Cyr, B., Rampazzi, S., & Morley Mao, Z. (2019). Adversarial sensor attack on LiDAR-based perception in autonomous driving. In L. Cavallaro & J. Kinder (Eds.), *Proceedings of the 2019 ACM SIGSAC conference on computer and communications security* (pp. 2267–2281). ACM. https://doi.org/10.1145/3319535.3339815

Charleer, S. (2018). *Family fun with deepfakes: Or how I got my wife onto the Tonight Show* [Sven Charleer, PhD]. http://svencharleer.com/2018/02/02/family-fun-with-deepfakes-or-how-i-got-my-wife-onto-the-tonight-show/

Chesney, B., & Citron, D. (2019). Deep fakes: A looming challenge for privacy, democracy, and national security. *California Law Review*, *107*(6), 1753–1819. https://doi.org/10.2139/ssrn.3213954

Couclelis, H. (1986). Artificial Intelligence in geography: Conjectures on the shape of things to come. *Professional Geographer*, *38*(1), 1–11. https://doi.org/10.1111/j.0033-0124.1986.00001.x

David, M. (2016). The correspondence theory of truth. In E. N. Zalta (Ed.), *The Stanford encyclopedia of philosophy (Fall 2016)* (pp. 1–65). Metaphysics Research Lab, Stanford University. https://plato.stanford.edu/archives/fall2016/entries/truth-correspondence/

DFDC. (2019). *Deepfake detection challenge: Identify videos with facial or voice manipulations*. Kaggle. https://www.kaggle.com/c/deepfake-detection-challenge

Dobson, J. E. (1983). Automated geography. *The Professional Geographer*, *35*(2), 135–143. https://doi.org/10.1111/j.0033-0124.1983.00135.x

Estes, J. E., Sailer, C., & Tinney, L. R. (1986). Applications of artificial intelligence techniques to remote sensing. *Professional Geographer*, *38*(2), 133–141. https://doi.org/10.1111/j.0033-0124.1986.00133.x

Galbally, J., & Marcel, S. (2014). Face anti-spoofing based on general image quality assessment. In *2014 22nd international conference on pattern recognition* (pp. 1173–1178). https://doi.org/10.1109/ICPR.2014.211

Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., & Bengio, Y. (2014). Generative adversarial nets. In Z. Ghahramani, M. Welling, C. Cortes, N. Lawrence, & K. Weinberger (Eds.), *Proceedings of the 27th international conference on neural information processing systems - Volume 2* (pp. 2672–2680). MIT Press. https://doi.org/10.5555/2969033.2969125

Haralick, R. M., Shanmugam, K., & Dinstein, I. H. (1973). Textural features for image classification. *IEEE Transactions on Systems, Man, and Cybernetics*, *SMC-3*(6), 610–621. https://doi.org/10.1109/TSMC.1973.4309314

Herb, G. H. (2002). *Under the map of Germany: Nationalism and propaganda 1918–1945* (1st ed.). Routledge. https://doi.org/10.4324/9780203433720

Hsu, C. C., Zhuang, Y. X., & Lee, C. Y. (2020). Deep fake image detection based on pairwise learning. *Applied Sciences (Switzerland)*, *10*(1), 370. https://doi.org/10.3390/app10010370

Hu, Y., Gao, S., Newsam, S. D., & Lunga, D. D. (2019). GeoAI 2018 workshop report the 2nd ACM SIGSPATIAL international workshop on GeoAI: AI for geographic knowledge discovery Seattle, WA, USA - November 6, 2018, In A. Züfle (Ed.), *SIGSPATIAL special* (Vol. 10(3), pp. 2–29). ACM. https://doi.org/10.1145/3307599.3307609

Isola, P., Zhu, J.-Y., Zhou, T., & Efros, A. A. (2017). Image-to-image translation with conditional adversarial networks. In R. Chellappa, Z. Zhang, & A. Hoogs (Eds.), *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)* (pp. 5967–5976). IEEE. https://doi.org/10.1109/CVPR.2017.632

Kamel Boulos, M. N., Peng, G., & Vopham, T. (2019). An overview of GeoAI applications in health and healthcare. *International Journal of Health Geographics*, *18*(1), 1–9. https://doi.org/10.1186/s12942-019-0171-2

Kang, Y., Gao, S., & Roth, R. E. (2019). Transferring multiscale map styles using Generative Adversarial Networks. *International Journal of Cartography*, *5*(2–3), 115–141. https://doi.org/10.1080/23729333.2019.1615729

Kundu, C. (2019). Fact check: All that glitters is not Diwali. *Indian Today*. https://www.indiatoday.in/fact-check/story/fact-check-all-that-glitters-is-not-diwali-1613464-2019-10-28

Kwok, A. O. J., & Koh, S. G. M. (2020). Deepfake: A social construction of technology perspective. *Current Issues in Tourism*, 1–5. Advance online publication. https://doi.org/10.1080/13683500.2020.1738357 .

Maclenan, A. (2018). *Fake geography*. GeoConnexion International. https://flickread.com/edition/html/5a4b7cdbe3415#18

Maghsoudi, Y., Collins, M. J., & Leckie, D. G. (2013). Radarsat-2 polarimetric SAR data for boreal forest classification using SVM and a wrapper feature selector. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *6*(3), 1531–1538. https://doi.org/10.1109/JSTARS.2013.2259219

Markuse, P. (2019). *It's a faaaake ... — Or not?* Medium. https://medium.com/sentinel-hub/its-a-faaaake-or-not-bace4f0c01ec

Matern, F., Riess, C., & Stamminger, M. (2019). Exploiting visual artifacts to expose deepfakes and face manipulations. In *2019 IEEE Winter Applications of Computer Vision Workshops (WACVW)* (pp. 83–92). IEEE. https://doi.org/10.1109/WACVW.2019.00020

Mittal, A., Moorthy, A. K., & Bovik, A. C. (2012). No-reference image quality assessment in the spatial domain. *IEEE Transactions on Image Processing*, *21*(12), 4695–4708. https://doi.org/10.1109/TIP.2012.2214050

Monmonier, M. (1991). *How to lie with maps*. University of Chicago Press. https://doi.org/10.7202/022356ar

Nystuen, J. D. (1984). Comment on "artificial intelligence and its applicability to geographical problem solving". *Professional Geographer*, *36*(3), 358–359. https://doi.org/10.1111/j.0033-0124.1984.00358.x

Openshaw, S., & Abrahart, R. J. (1996). Geocomputation. In R. J. Abrahart (Ed.), *Proceedings of the 1st international conference on geocomputation* (pp. 665–666). University of Leeds.

Openshaw, S., & Openshaw, C. (1997). *Artificial intelligence in geography*. Wiley. https://doi.org/book/10.5555/549314

Oscar, S. (2018). You thought fake news was bad? Deep fakes are where truth goes to die. *The Guardian*. https://www.theguardian.com/technology/2018/nov/12/deep-fakes-fake-news-truth

Pao, H. K., Chen, K. T., & Chang, H. C. (2010). Game bot detection via avatar trajectory analysis. *IEEE Transactions on Computational Intelligence and AI in Games*, *2*(3), 162–175. https://doi.org/10.1109/TCIAIG.2010.2072506

Rössler, A., Cozzolino, D., Verdoliva, L., Riess, C., Thies, J., & Niessner, M. (2019). FaceForensics++: Learning to detect manipulated facial images. In K. Lee, D. Forsyth, M. Pollefeys, & X. Tang (Eds.), *2019 IEEE/CVF International Conference on Computer Vision (ICCV)* (pp. 1–11). IEEE. https://doi.org/10.1109/ICCV.2019.00009

Salimans, T., Goodfellow, I., Zaremba, W., Cheung, V., Radford, A., & Chen, X. (2016). Improved techniques for training GANs. In D. Lee, U. Luxburg, R. Garnett, M. Sugiyama, & I. Guyon (Eds.), *Proceedings of the 30th international conference on neural information processing systems* (pp. 2234–2242). ACM. https://doi.org/10.5555/3157096.3157346

Sayler, K. M., & Harris, L. A. (2019). Deep fakes and national security (CRS Report No. IF11333). *Congressional Research Service*. https://crsreports.congress.gov/product/pdf/IF/IF11333

Shepard, D. P., Humphreys, T. E., & Fansler, A. A. (2012). Evaluation of the vulnerability of phasor measurement units to GPS spoofing attacks. *International Journal of Critical Infrastructure Protection*, *5*(3), 146–153. https://doi.org/10.1016/j.ijcip.2012.09.003

Sirosh, J. (2018). *Microsoft and Esri launch geospatial AI on Azure*. Microsoft Azure Blog. https://azure.microsoft.com/en-us/blog/microsoft-and-esri-launch-geospatial-ai-on-azure/

Smith, T. R. (1984). Artificial intelligence and its applicability to geographical problem solving. *The Professional Geographer*, *36*(2), 147–158. https://doi.org/10.1111/j.0033-0124.1984.00147.x

Stricker, M. A., & Orengo, M. (1995). Similarity of color images. *Storage and Retrieval for Image and Video Databases III*, *2420*, 381–392. https://doi.org/10.1117/12.205308

Tippenhauer, N. O., Pöpper, C., Rasmussen, K. B., & Capkun, S. (2011). On the requirements for successful GPS spoofing attacks. In *Proceedings of the 18th ACM conference on computer and communications security* (pp.75–86). https://doi.org/10.1145/2046707.2046719

Tucker, P. (2019). *The newest AI-enabled weapon: 'deep-faking' photos of the earth*. Defense One. https://www.defenseone.com/technology/2019/03/next-phase-ai-deep-faking-whole-world-and-china-ahead/155944/

Ulaby, F. T., Kouyate, F., Brisco, B., & Williams, T. H. L. (1986). Textural Information in SAR Images. *IEEE Transactions on Geoscience and Remote Sensing*, *GE-24*(2), 235–245. https://doi.org/10.1109/TGRS.1986.289643

Wang, S.-Y., Wang, O., Zhang, R., Owens, A., & Efros, A. A. (2020). CNN-generated images are surprisingly easy to spot … for now. In T. Boult, G. Medioni, & R. Zabih (Eds.), *2020 IEEE/CVF conference on computer vision and pattern recognition* (pp. 8692–8701). IEEE. https://doi.org/10.1109/cvpr42600.2020.00872

Zhang, M. (2015). *KFC's new tray liners let you take "fakation" photos*. PetaPixel. https://petapixel.com/2015/08/05/kfcs-new-tray-liners-let-you-take-fakation-photos/

Zhang, S. (2015). *The fake places that only exist to catch copycat mapmakers*. Gizmodo. https://gizmodo.com/the-fake-places-that-only-exist-to-catch-copycat-cartog-1695414770

Zhang, S., Zhao, B., Tian, Y., & Chen, S. (2020). Stand with #StandingRock: Envisioning an epistemological shift in understanding geospatial big data in the "post-truth" era. *Annals of the American Association of Geographers*, 1–21. Advance online publication. https://doi.org/10.1080/24694452.2020.1782166 .

Zhang, X., Karaman, S., & Chang, S. F. (2019). Detecting and simulating artifacts in GAN fake images. In *2019 IEEE international Workshop on Information Forensics and Security (WIFS)* (pp. 1–6). IEEE. https://doi.org/10.1109/WIFS47025.2019.9035107

Zhao, B., & Sui, D. Z. (2017). True lies in geospatial big data: Detecting location spoofing in social media. *Annals of GIS*, *23*(1), 1–14. https://doi.org/10.1080/19475683.2017.1280536

Zhao, B., & Zhang, S. (2019). Rethinking spatial data quality: Pokémon Go as a case study of location spoofing. *Professional Geographer*, *71*(1), 96–108. https://doi.org/10.1080/00330124.2018.1479973

Zhu, J. Y., Park, T., Isola, P., & Efros, A. A. (2017). Unpaired image-to-image translation using cycle-consistent adversarial networks. In K. Ikeuchi, G. Medioni, & M. Pelillo (Eds.), *2017 IEEE International Conference on Computer Vision (ICCV)* (pp. 2242–2251). IEEE. https://doi.org/10.1109/ICCV.2017.244