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Exploring geomasking methods for geoprivacy: a pilot study in an environment with built features

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Abstract

This study discusses the ethical use of geographical information systems (GIS) data with a focus on geomasking for upholding locational privacy. As part of a pilot study in Jeddah City, Saudi Arabia, we used open-source geomasking methods to ensure geoprivacy while examining built environment features that determine the quality of life among individuals with type-II diabetes. We employed the open-source algorithms Maskmy.XYZ and NRand-k for geomasking 329 data points. The results showed no differences between global and city-level spatial patterns, but significant variations were observed with respect to local patterns. These findings indicate the promising potential of the chosen geomasking technologies with respect to ensuring locational privacy but it was noted that further improvements are needed. We recommend developing enhanced algorithms and conducting additional studies to minimize any negative impact of geomasking in spatial analysis with the overall aim of achieving a better understanding of ethical considerations in GIS sciences. In conclusion, application of geomasking is straightforward and can lead to enhanced use for privacy protection in geospatial data analysis.

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Introduction

Debates regarding the ethics of geographical information systems (GIS), mentioned by Onsrud (1995) and Crampton (1995), are not no longer new. Privacy concerns related to spatial data and the responsible use of GIS emphasized by Blatt (2012) have become important issues with the rapid proliferation of geospatial technology over the past two to three decades. The widespread adoption of maps in everyday life has led to a growing consensus on the need for adherence to a code of conduct in various applications of GIS (Armstrong & Ruggles, 2005; Crampton, 2003). In urban planning and the spatial study on urban health, where personal information of individuals is extensively used, professionals involved in the collection, storage, cataloguing and distribution of data need to know about issues such as privacy and ethics (Blatt, 2012). Additionally, urban planning has recently witnessed a promising data revolution known as *The Urban Data Deluge* (Kourtit *et al.,* 2020), which has brought about emerging challenges in data privacy (Engin *et al.*, 2020). The use of big data, including spatial data, has raised ethical concerns, particularly with regard to data privacy (Jain et al., 2016).

GIS and ethics

No technology is value-neutral (Onsrud, 1995) and GIS is no exception. Therefore, scientific research (Lo et al., 2008) and related professional practices in all disciplines (Banville & Torres, 2017) should be guided by ethical considerations. However, the majority of GIS professionals still do not take the ethical use of

GIS data and locational privacy seriously (Scull *et al.,* 2016). Among the various issues, truthful use of GIS data is a dominant topic of debate in the field of GIS ethics. The ethical debate on GIS and ethics has become prominent since GIS, to some extent, moved past its earlier dilemma of being considered just a *science tool* in the late 1990s. This has led to a vibrant proposal to set the research agenda on the interaction between *GIS and Society* with *Privacy*, with *Access and Ethics* one of the seven key thematic areas (Sheppard, 1995), with Onsrud (1995) emphasising the need to identify unethical conduct when using GIS. Indeed, *How to Lie with Maps* (Monmonier 2005), a classic text in cartography, has been heavily criticised by scholars due to rapidly growing concern about ethics in spatial disciplines.

The US-based non-profit association Urban and Regional Information Systems Association (URISA) is probably the first to give voice to the ethics issue for GIS professionals by drafting *The Code of Ethics* document (URISA, 2002). It consists of four categories: obligations to society; role of employers and funders; role of colleagues and professions; and impact on individuals in society. The United Nations International Children's Emergency Fund (UNICEF) has also outlined a robust framework of ethical considerations related to the usage of GIS data (Berman *et al.*, 2018). In a recent publication (Nelson *et al.*, 2022), the authors further highlight the importance of *the 3 Es* related to GIS, namely ethics, empathy and equity. According to them, cartographic integrity and locational privacy are key ethical concerns in GIS.

The case for locational privacy

Data related to individual locations are often gathered and analysed through advanced spatial analytical tools and methods in many projects of scientific research, including spatial econometrics (Aljoufie & Tiwari, 2020; Tiwari & Aljoufie, 2021; Tiwari, 2022). In recent decades, Web maps as a tool for locational surveillance have raised concerns (Monmonier 2003), while the use of individual locational research data in GIS and related disciplines has become common, which brings up the concern about the need for privacy (Bridwell, 2007). Many scholars have recognized the importance of addressing locational privacy concerns in GIS research, e.g., Cremonini *et al.* (2013), who defines locational privacy as the "right of individuals to decide how, when, and for which purposes their location information could be released to other parties". There is now increased emphasis on the need to respect individuals' preferences regarding timing, mode and extent of revealing their personal, locational data (Kerski, 2016). Other scholars have highlighted ability to make locational data inaccessible since that privacy is a human right that requires this kind of information should not be available without consent for whatever use without consent (Beresford & Stajano, 2003; Blumberg, 2010). Indeed, compromising locational privacy can have serious consequences for the individual as it often results in unsolicited advertising, user profiling and tracking, persecution (for political, religious and gender-based reasons), discrimination, denial of service and even physical attack or harassment (Ardagna *et al.*, 2006). In extreme cases, the unethical use of locational information can lead to *geoslavery*, where institutions enforce locational control over individuals (Dobson & Fisher, 2003). Violations of locational privacy can not only be ethically problematic but also legally so, as it can involve the potential exercise of coercive powers based on law (Schäffer *et al*., 2010; Cetl *et al*., 2019).

Without doubt, efforts to prevent any violation of locational privacy should be prioritized. In this context, Bridwell (2007) proposed the concept of *consent*, which defines scenarios where users should be allowed to control data regarding their individual locations. This includes aspects, such as data types; data-sharing rights; time of data collection; longevity of data storage; and purpose of data collection. The advancement of geospatial technologies together with lax laws governing geoprivacy, as well as lack of experience among writers and publishers, are the main causes of geoprivacy breaches (Kounadi & Leitner, 2014). The legal debate surrounding the use of locational data during the COVID-19 pandemic has revolved around the tension between public health surveillance and individual privacy rights (Frith & Saker, 2020). While it has enabled contact tracing and containment efforts, concerns over potential abuse and long-term data retention have sparked contentious discussions on the necessity and limits of this kind of data collection (Cann & Price, 2023). Striking the right balance between health protection and civil liberties remains a complex challenge for lawmakers. The Data Protection Regulation 2016/679 of the European Union (EU) is, to some extent, relevant in protecting the privacy of health data, including locational data, as it prioritizes individual privacy while promoting responsible and secure data usage, ensuring the necessary balance in the era of data-driven healthcare innovations (Lopes & Oliveira, 2018).

Protection of locational privacy

Numerous studies have identified various methods to protect geoprivacy, ranging from self-regulation to technical solutions aimed at hiding locational data (Onserud et al., 1994). With the constant advancements in GIS technologies and emerging ethical considerations related to the use of GIS data, innovative applications such as geomasking have been developed (Wang *et al.*, 2022). These developments have paved the way for new approaches in protecting geoprivacy.

The importance of locational privacy depends on the nature of the data and the potential impact. For example, while mapping influenza cases may not require strict locational privacy, the mapping of human immunodeficiency virus (HIV) cases may necessitate the use of geomasking due to the higher social stigma associated with this infection (Allshouse *et al.*, 2010). Similarly, a recent study found that socially vulnerable groups have a higher perceived risk of locational disclosure compared to non-vulnerable groups (Kim *et al.*, 2021). These findings highlight the varying levels of sensitivity associated with different types of data and the need for careful consideration of locational privacy measures based on the nature of the data and the potential impact on individuals or communities. In fact, point-level spatial data are strong identifiers of someone's place of residence or work, leading to invasion of individual privacy or posing risks of reverse identification from maps published on the web or in scientific publications (Brownstein *et al.*, 2006; Kounadi & Leitner, 2014). Therefore, geomasking are instituted with the intension to curtail the revelation of locational data, while permitting disaggregate spatial analyses with the least distortion to spatial information (Bridwell, 2007; Charleux & Schofield, 2020; Seidl *et al.*, J 2016; Venter *et al.*, 2020). Additionally, the problem of false identification is nascent and arises from geomasked data linked to incorrect households or persons (Seidl *et al.*, 2016; Kim *et al.*, 2021). So far, several simple and rigorous geomasking techniques have been proposed to ensure the locational privacy of individuals, including, but not limited to, affine transformation (Ribeiro *et al.* 2022), aggregation (Armstrong *et al.*, 1999; Wang *et al.*, 2022) and random perturbation (Angulo & Bueso, 2001). In fact, over the past couple of years, several easy-to-use tools have been developed by experts to protect geoprivacy through geographical masks. Some common, open-source applications (apps) developed to perform geomasking are MaskMy.XYZ (Swanlund *et al.*, 2020) and GeoPriv plugin for QGIS software (Ordonez *et al.*, 2019). Affine transformation and random perturbation uphold both the number of records and the type of data, while aggregation either drops the number of records or their spatial resolution (Wang *et al.*, 2022). Affine transformation is a fundamental, geomasking technique (Swanlund *et al.*, 2020), which includes translation, rotation and scale, while aggregation joins the locational data and allocates combined attributes to a spatial data entry at certain spatial resolutions, such as an administrative district or a census block (Armstrong *et al.*, 1999), and random perturbation relocates every individual's locational record in a dataset using a randomizing movement algorithm.

GIS scientists have developed several geomasking algorithms, some of which are highly sophisticated, e.g., location privacy protection mechanisms (LPPMs) (Zurbarán *et al.*, 2018); adaptive areal elimination (Kounadi & Leitner, 2016); adaptive areal masking (Charleux & Schofield, 2020); street masking (Swanlund *et al.*, 2020); and adaptive Voronoi masking (Polzin 2020). All these methods and algorithms have their own pros and cons but most of them are compatible with commercial software. MaskMy.XYZ and NRand-k are open-source geomasking algorithms and therefore freely available over the Internet web. The former is a browser-based, modified random perturbation technique that randomly shifts original data points (ODPs) (Swanlund et al. 2020) and the latter an addition to the QGIS environment (Zurbarán *et al.*, 2018), which combines noise-based masking or obfuscation (NR) and anonymity based on the number of individuals (k) involved (in fact, the larger the k value, the stronger the anonymity). NRand-k tackles the threat of re-identification through linkage to another dataset, with anonymity attained when the minimum k-threshold is surpassed for each set of quasi-identifiers from the dataset (Ghinita *et al.*, 2010). This algorithm generates evenly dispersed random points and selects the remotest point from the ODP within a spatial data frame of circular shape. Largely, the NRand-k algorithm curtails the effect on exploratory spatial data analysis (ESDA) as explained by Haining *et al.* (1998) and is useful in cluster detection, where it returns inferences like those from the ODP (Zurbarán *et al.*, 2018). While many authors have examined the disclosure risks of individual-level geospatial data, e.g., Onsrud *et al.* (1994) and Kounadi & Leitner (2014), very few of them have assessed the effectiveness of geomasking techniques to protect individual-level, locational data. The need for the study presented here arose during a pilot study in the city of Jeddah, Saudi Arabia where we aimed to examine the impact of built environment features on the quality of life among people with type-II diabetes where the use of individual, locational data was required. During the study we realized that most respondents, especially women, did not wish to give their consent to map their office or home location because of privacy concerns. Hence, to protect privacy of respondents, we wished to examine the efficiency of two open-source geomasking algorithms, the approach of which is presented here.

Materials and Methods

Study site and participants

During October-November 2022, we collected 391 random ODPs in Jeddah City, Saudi Arabia (Figure 1). The respondents were asked to give their consent to show their home or office location, which is an obligatory code of conduct for the ethical use of GIS data (Berman *et al.*, 2018; URISA 2002). Out of this collection, 5.9% (n=23) of the respondents were not willing to reveal their individual spatial location in any way, while 9.9% (n=39) of them had no objection to reveal their geolocations. The remaining

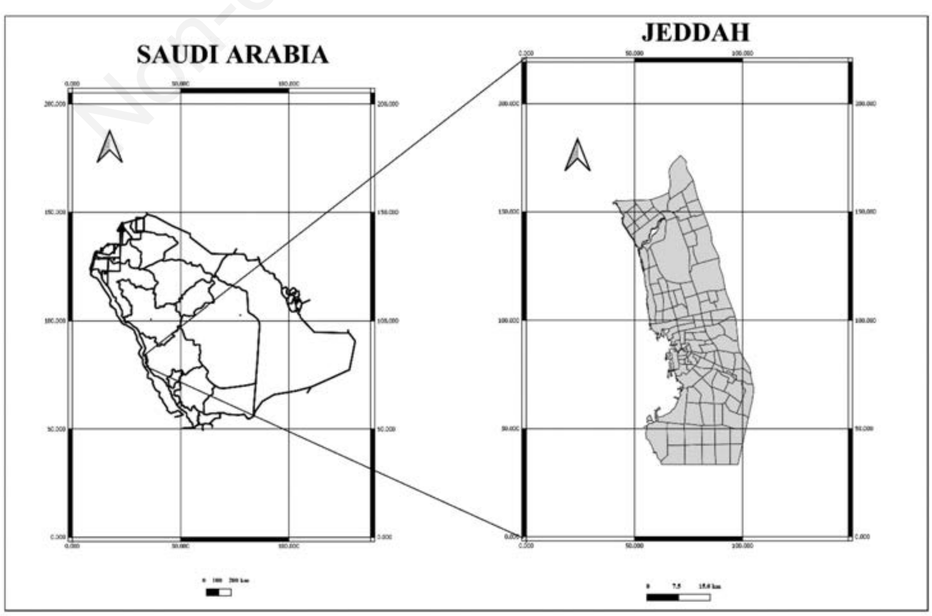

Figure 1. The study site in Jeddah City, Saudi Arabia.

329 respondents accepted to disclose their office or work location only if geomasking was provided.

Methods

Haining *et al.* (1998) described an extended form of for the examination of spatial traits of a dataset having locational references, i.e. exploratory data analysis (ESDA). We decided to apply this approach previously used by us (Aljoufie & Tiwari, 2020; Tiwari & Aljoufie 2021), this time examining two open-source algorithms for geomasking, namely MaskMy.XYZ (https://maskmy.xyz/#about) described by Swanlund *et al.* (2020) and NRand-k (Zurbarán *et al.*, 2018). We assessed the effectiveness and analytical accuracy of the selected geomasking methods through ESDA in agreement with the recommendations made in a recent paper by Wang *et al.* (2022). GeoDa (Anselin, 2003; Anselin *et al.*, 2006) software was used for ESDA, which reports global and local spatial autocorrelations through Moran's *I* (1948, 1950) and local indicators of spatial association (LISA) maps (Anselin, 2010). Figure 2 gives a schematic overview of our approach.

The strength of spatial dependence between the value of one observation of a spatial entity and the values of nearby observations of the same variable is known as *spatial autocorrelation* (Grekousis, 2020). In fact, spatial analysis will be of no use in the absence of spatial autocorrelation (O'Sullivan & Unwin, 2003). Moran's *I* is the most widely used measure of spatial autocorrelation in the form of inferential statistic assessed using a *p*-value and a z-score based on the expected value derived under the null hypothesis of no spatial autocorrelation or a complete spatial randomness. Global indices of spatial autocorrelation can tell whether or not a variable's values are clustered, but they cannot tell where the clusters are. On the other hand, LISA makes it possible to determine their precise location and extent.

We noted that the basic aim of the developers of MaskMy.XYZ was the development of a simple, usable algorithm for researchers. The speed of masking in this method is extremely quick: 2000 points can be masked in less than 1 second by an Internet browser. The ODPs are randomly shifted into a zone delimited by an outer and inner circumferential area isolated from each ODP, which is located at the centre of both these circular, surrounding areas. In contrast, the NRand-k technique, produces four trails to determine an obfuscated location far from each ODP investigated that falls in a newly created, circular borderline with the assumed ODP in its epicentre (Zurbarán *et al.*, 2018). To ease the visualization of LISA results, Voronoi or Thiessen polygons (Tatalovich *et al.*, 2006; Abellanas & Palop, 2008) can be used in addition to point-data on LISA maps.

Results

The ESDA results of global spatial autocorrelation are presented for the ODPs and the geomasked data points through MaskMy.XYZ technique on the one hand and the NRand-k approach on the other. The comparison, carried out based on *p*-value, z value, mean, standard deviation (SD) and global Moran's *I* based on 999 permutations, indicated no significant differences after geomasking globally (Table 1). Clustering of data points is shown by increased z values (>2.58) along higher Global Moran's *I* outcomes (>0.80). Results of local spatial autocorrelation measures are presented through LISA cluster maps (Figure 3), where it can be observed that 260 locations were not significantly different, though the numbers were slightly higher with the Maskmy.XYZ algorithm (+7.2%), and somewhat lower with NRand-k one (-

Table 1. Comparison of ESDA results.

Item	ODP	MaskMy.XYZ	NR-k
p-value	0.001000	0.00100	0.00100
z-value	4.3756	3.9578	3.3270
Mean	0.1243	0.1223	0.1240
SD	0.0240	0.0249	0.0245
Global Moran's *I*	0.2294	0.1994	02060
Permutation (no.)	999	999	999

ESDA, exploratory spatial data analysis; ODP, original data point; MaskMy.XYZ GIS & NRand-k, data-masking algorithms; SD, standard deviation.

Table 2. Results of LISA analysis.

LISA cluster	ODP	MaskMy.XYZ	NR-k
Not significant	260	280	259
High-high	27	27	24
Low-low	27	10	31
Low-high	5	5	5
High-low	10	6	10

LISA, localindicators of spatial association; ODP, original data point; MaskMy.XYZ GIS & NRand-k, data-masking algorithms.

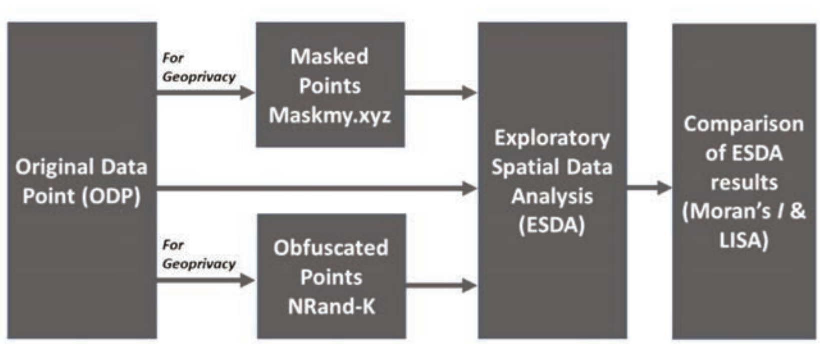

Figure 2. Flowchart of ESDA methods used for comparison.

7.5%). Consequently, the number of High-High clusters was similar with MaskMy.XYZ but little lower with NRand-k. Low-low clusters were slightly higher with NRand-k (+14.8%), while significantly lower (-62.95) with Mask-my.XYZ. Among the outliers, Low-High clusters were similar in all three cases noted; however the High-Low clusters were similar with the NRand-*k* technique but lower with the MaskMy.XYZ one (Table 2). In conclusion, the cluster analysis revealed notable variations between the two geomasking methods when considering local spatial autocorrelation measures. The discernible disparity in the count of High-High clusters with the NRand-k method, coupled with the contrasting numbers of Low-Low clusters evident with both MaskMy.XYZ and NRand-k, serves as a compelling illustration of the divergence in significant outcomes after geomasking. Visual inspection of geomasked maps demonstrated that shifted points were between 250 and 450 meters away from the ODPs thereby reducing the risk of re-identification considerably as predicted by the approach used by Swanlund *et al.* (2020).

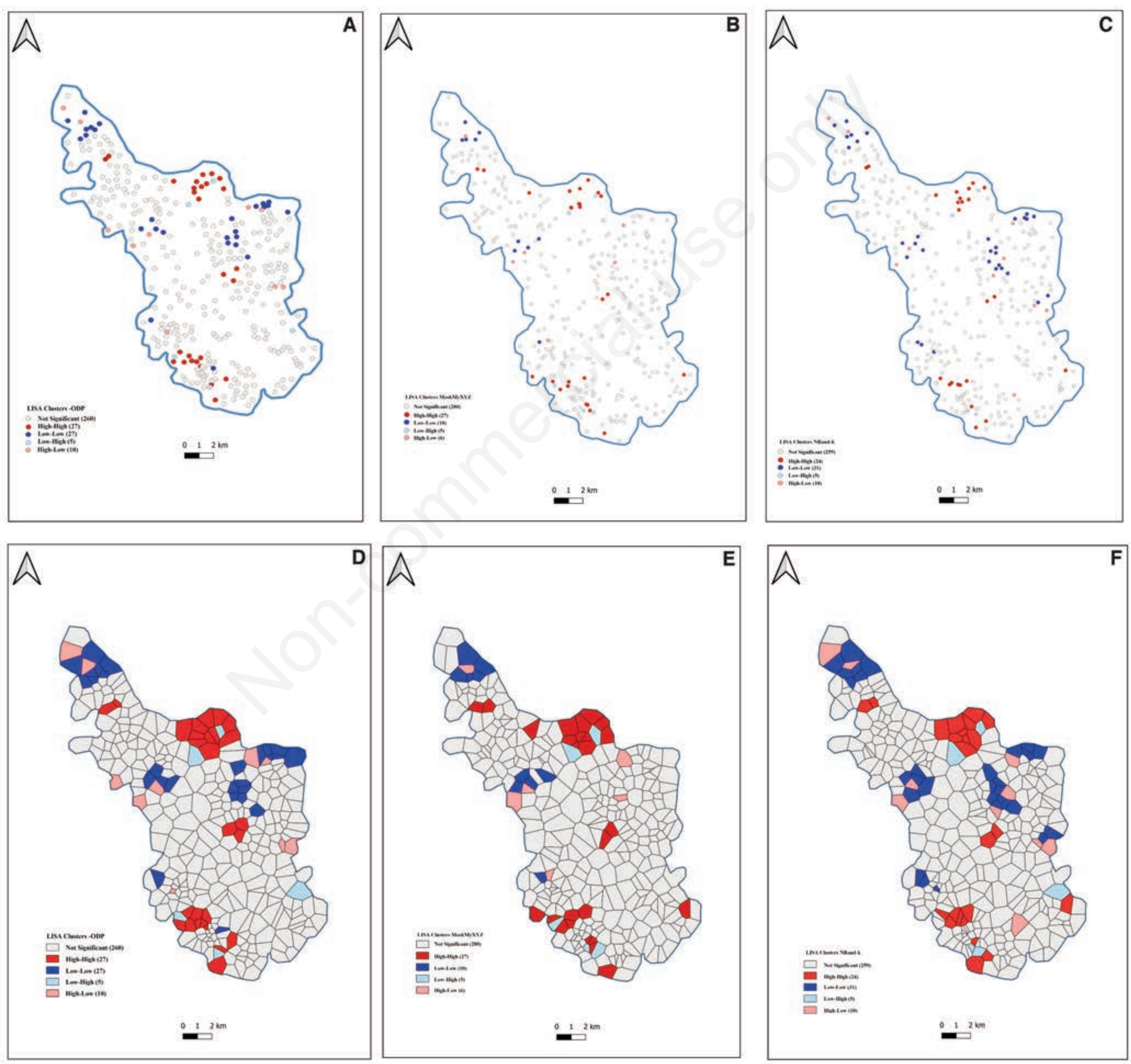

Figure 3. A) LISA clusters point map for ODP, B) LISA clusters point map after MaskMyXYZ application, C) LISA clusters point map after NRand-k application, D) LISA clusters based on a Voronoi polygon map, E) LISA cluster map based on Voronoi polygons after MaskMyXYZ application, F) LISA cluster map based on Voronoi polygons after NRand-k application.

Discussion

We conducted our study in the context of protecting the spatial privacy of the respondents as a part of a pilot study examining built environment features and determining the quality of life for people with lifestyle-related diabetes (type-II diabetes) in the Saudi city of Jeddah. The growing debate over ethical considerations in GIS sciences is a move in the right direction, and so is the work by various professional and voluntary organisations (Berman *et al.*, 2018; URISA 2002) to develop codes of conduct (COC) for ethical use of GIS. The protection of the privacy of individual-level geospatial data has thus come into focus (Wang et al. 2022), and there is now strong support among researchers and professionals for only publishing personal data after consent from study subjects. In this context, researchers have taken an interest in developing new algorithms to protect geoprivacy. As a result, several new geomasking techniques (Charleux and Schofield, 2020; Kounadi & Leitner, 2016; Polzin, 2020; Swanlund *et al.*, 2020; Wightman *et al.*, 2011; Zurbarán *et al.*, 2018) have been proposed.

Wang *et al.* (2022) carried out an exploratory assessment of the effectiveness of geomasking methods on privacy protection and analytical accuracy for individual-level geospatial data. In agreement with Haining *et al.* (1998) and the work based on GWR by Brunsdon and Comber (2021), they suggest the use of ESDA to measure efficacy and analytical accuracy of geomasking methods. We also used ESDA but with the novelty of testing two open-source algorithms, MaskMy.XYZ and NRand-k, with spatial autocorrelation and its subsets of Global Moran's *I* and LISA. Before this study, Zurbarán *et al.* (2018) also used ESDA to examine the impact of locational obfuscation on spatial analysis in NRand-k; however, our approach differed from theirs since they deployed heatmaps involving kernel density function for spatial visualization and hotspot analysis through Getis–Ord local statistic Gi* (Griffith 2021).

The results of our study suggest that both MaskMy.XYZ and NRand-k produce promising results at the global or city level. However, we observed significant variations with respect to cluster formation at the local level that was reflected both by High-High and Low-Low clusters Additionally, the algorithms under study moved the ODPs to an optimum location 250-450 meters away from the true one to reduce the re-identification risk. To eliminate the possibility of false identification (Seidl *et al.*, 2016; Wang *et al.*, 2022), we recommend combining other algorithms with the ones investigated here, e.g., adaptive Voronoi masking (Polzin, 2020) that first creates adoptive Voronoi polygons based on the population density, with boundaries over street intersections that shifts masked points over the nearest boundary. Overall, we suggest developing more open-source algorithms that are ubiquitous and enhance the precision of geomasked data points with the least distortion to the spatial patterns as proposed by Grekousis (2020). Our study is an extension of the study of Wang *et al.* (2022) from a user point of view and protection of locational privacy is a work in progress requiring further studies are to find improved ways to deal with this issue.

Conclusions

The prohibition to use individual level locational data without the consent of study participants, as expressed by COC for GIS data,protects privacy. The study presented based on two open-source algorithms,Maskmy.XYZ (Swanlund *et al.*, 2020) and NR-k (Zurbarán *et al.*, 2018), with efficiency examined through ESDA (Haining *et al.*, 1998)clearly shows the current limitations as there wasno change in spatial patterns after geomasking by Moran's *I*at the global level. However significant variations were observed in the local patterns. The technologies we choose are promising though there is an urgent need to develop available algorithms further to reduce the impact of geomasking in spatial analysis.

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