International Journal of
Geo-Information

MDPI

Article

Crime Geographical Displacement: Testing Its Potential Contribution to Crime Prediction

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Received: 9 July 2019; Accepted: 29 August 2019; Published: 2 September 2019

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Abstract: Crime geographical displacement has been examined in many Western countries. However, little is known about its existence, distribution, and potential predictive ability in large cities in China. Compared to the existing research, this study contributes to the current research in three ways. (1) It provides confirmation that crime geographical displacement exists in relation to burglaries that occur in a large Chinese city. (2) A crime geographical displacement detector is proposed, where significant displacements are statistically detected and geographically displayed. Interestingly, most of the displacements are not very far from one another. These findings confirm the inferences in the existing literature. (3) Based on the quantitative results detected by the crime geographical displacement detector, a crime prediction method involving crime geographical displacement patterns could improve the accuracy of the empirical crime prediction method by 7.25% and 3.1 in the capture rate and prediction accuracy index (PAI), respectively. Our current study verifies the feasibility of crime displacement for crime prediction. The feasibility of the crime geographical displacement detector and results should be verified in additional areas.

Keywords: crime geographical displacement; detector; crime prediction; repeat and near-repeat

1. Introduction

As a response to crime prevention initiatives, displacements refer to the activities that offenders, consciously or unconsciously, change in their original crime implementation plans due to the potential high risk [1]. According to the existing literature, such displacement could be classified into five types: a temporal change to a different time of the day, geographical displacement to another location, tactical adoption of a new modus operandi, searching for a new target, or considering a change (optimize/learn) in crime type [1–4].

The existence of crime displacement brings great uncertainty to the emergence of crime victimizations and, therefore, increases the difficulty in crime prediction, which calls for additional studies from researchers and practical efforts of practitioners [5]. For instance, crime may be displaced into lower crime neighborhoods, where the crime rate may match frequent-crime communities and where less crime is predicted or fewer police forces are allocated [1].

In our current research, we focus on geographical displacement, which is the form most commonly recognized [6]. Geographical displacement refers to offenders moving from one place to another as a result of crime prevention initiatives. Studies of crime spatial displacements provide important empirical evidence and experimental support for our current study [1,3,5,7,8]. Many of the analyses and the techniques addressed could be applicable to other types of displacement.

Geographical displacement has mostly been interpreted as a response to crime intervention initiatives [9,10]. For the affected area, the empirical studies observed significant deterrent effects of policing patrols on crime rates [7,11]. Consequently, intensive police enforcement efforts were suggested for deployment in high-crime areas. Eventually, displacement occurs when "the offender is continually being displaced from one potential target to another until he finds a suitable opportunity" [12].

Geographical displacement could bring negative consequences to crime prevention efforts, "but even when displacement does occur, it can still provide some benefit" [10]. For example, the volume of displaced crime could be less due to a decreased number of opportunities resulting from the crime prevention efforts. Additionally, crime displacement from more serious to less serious types of crime is also beneficial because less harm is produced. Displacement can also lead to more harmful consequences. For example, more serious offenses may occur after crime displacement [3]. Crimes may concentrate on a smaller group of victims or special places where it has greater impact on the community [10]. According to the existing literature, crime prevention efforts are still considered beneficial because the harm and/or volume of displaced crime is less than the overall net reduction in crime.

Further explanations for why crime displacement occurs can be found in theories of routine activity and crime pattern and rational choice theories [13–15]. Many offenders have "mental maps," consisting of nodes (homes, place of work, and other places) on their daily routes. The environment of the nodes is acknowledged by potential offenders and evaluated as to whether it was suitable for crime. When the opportunity to commit another crime at the same place as the previous crime disappears, the offenders would likely displace to another node for a crime. Not all offenders are capable of exploiting all opportunities in their cognitive maps. Some will repeat the knowledge learned in the previous crime at a similar target/place. From this view, places similar to previously victimized places are more likely to be displaced into than others. Such similarities could be interpreted as characteristics attractive to potential offenders or a comprehensive consideration of benefit, risk, and cost [14,15]. As such, the new targets will not be too far away from the previous targets when the distance is considered as a kind of cost [5,6]. Displacement will not happen when suitable opportunities are too far away for the offenders. By contrast, when the opportunities are close to the offenders, near-repeat victimizations are more likely to occur. Considering the fact that it is difficult to distinguish between "far" and "near," near-repeat and displacement are not distinguished based on the concept of "far" and "near."

Regarding aims at enriching the existing research body of crime geographical displacement, great efforts have contributed to the quantitative analysis of crime displacement. Based on the analysis of crime placement and displacement, Barr and Pease conceptualized the framework of present patterns of crime as a response to the distribution of criminal opportunities and crime risk [3]. Furthermore, two types of measures were suggested for the quantitative analysis of crime displacement. Following this study, further research examined the existence of crime displacement and measured geographical displacement [1,7,16–18]. Using the geographic information system (GIS) technique, Nakaya and Yano statistically examined the existence of crime displacement and vividly displayed this phenomenon in a space-time cube [19].

The aforementioned explorations provide a solid theoretical basis and experimental support for the study of crime geographical displacement. However, investigation of crime geographical displacement using China's crime record is still limited. Moreover, marginal studies have assessed the potential ability of crime geographical displacement for crime prediction. Inspired by the research of repeat and near-repeat (RNR) victimization, a crime displacement detector will be introduced [20].

Research of RNR phenomena suggests that the crime risk after one crime will be increased for a period of time at the same location or in close proximity [20]. The strong relation between spatiotemporally-close crimes is emphasized by RNR phenomena. Two hypotheses accounting for such phenomena have been put forward: "flag" and "boost." The "boost" hypothesis suggests that the heightened risk of future victimization is boosted by the past victimizations [21–24]. The "flag" hypothesis argues that certain target properties may be flagged by opportunistic offenders [23,25,26]. Both the boost and flag accounts have been tested and used in many studies.

In this study, I investigate spatial displacement by introducing a quantitative model. This research is expected to improve crime prediction accuracy and benefit the policing patrol effect. The current study will contribute to the literature by confirming the following hypotheses.

(1) The existence of crime displacement in a large Chinese city is to be confirmed.

Criminology research in China has verified the existence of RNR in the crime records. Combined with the fact that many criminology theories are useful in interpreting crime distribution and crime risk, it seems plausible to hypothesize the existence of geographical displacement in the crime of China's large cities. This is probably the first attempt at investigating the existence of crime displacement in a large Chinese city.

(2) The quantitative results for spatial-temporal displacement could improve the accuracy of crime prediction.

RNR emphasizes strong relations between near-crimes, while crime geographical displacement argues for a strong connection between distant crimes. The two crime phenomena follow distinct patterns. Consequently, the quantitative analysis based on crime geographical displacements could ideally improve the accuracy of crime prediction by contributing additional information to the existing literature. Whether this hypothesis is true or not is to be investigated.

2. Methodology

2.1. Overview

Following hypothesis 1, the spatial-temporal crime displacement (STCD) detector is introduced to test whether spatial displacement exists in the study area. Subsequently, in response to hypothesis 2, the potential ability for crime prediction is further examined by the capture rate and prediction accuracy index (PAI). For comparison purposes, the principle of the Knox test and its predictive capability are introduced as well.

2.2. Repeat and Near-Repeat Calculator

To investigate whether the RNR phenomenon exists in N city's burglary records, a near-repeat calculator was conducted following the same process proposed by Ratcliffe and Johnson et al. [27,28]. In this calculator, each crime event pair is calculated and counted by space and time. This statistical result is compared to the results derived by a Monte-Carlo simulation. The outcome of this calculation is usually presented in terms of a matrix within which the values represent the risk levels after one crime event. The greater the value, the higher the risk level. The number of iterations of a Monte-Carlo simulation corresponds to the statistical significance of the risk value. For example, if the number of crime pairs in one bandwidth is greater than the numbers in 19 simulated crime pairs, then the significance of this bandwidth value is as low as 0.01.

Before the process of the near-repeat calculator, a spatial-temporal bandwidth is specified as the threshold. In the existing literature, many different bandwidths have been adopted for near-repeat pattern analysis [28]. Our current study follows the existing research by adopting 200 m and seven days as the space and time bandwidth, respectively. As such, six spatial (same location, 200, 400, 600, 800, and 1000 m) and seven temporal (7, 14, 21, 28, 35, 42, and >42 days) bandwidths are used and evaluated in the framework of a risk analysis.

2.3. Crime Spatial-Temporal Displacement Detector

Inspired by the Knox method, the STCD detector follows a similar process as the near-repeat calculator in detecting significant connections. The study area is separated into several cells. Following the bandwidth selected in the RNR calculator, the 200 × 200 m space bandwidth is selected for the spatial-temporal displacement analysis. Each crime is assigned to a cell based on its coordinates. Then, all crimes are connected to each other and marked as crime pairs. In each pair, the crime committed earlier with no subsequent crime at the same location is called the starter of the pair (Figure 1). The later crime, which had no previous crime at the same location, is called the follower of the pair. The crime pairs containing a start point and an end point are identified and marked as one space-time displacement between the two cells.

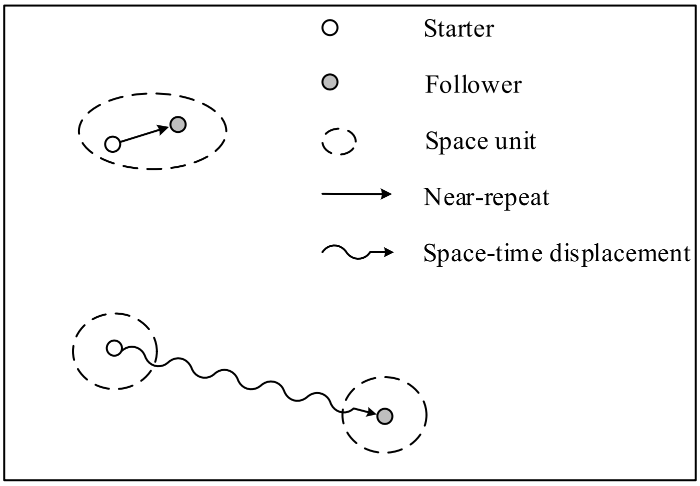

Figure 1. Near-repeat and space-time displacement.

The identification of the space-time displacement could be processed in several steps. Additionally, several assumptions are also being made around the space-time displacement. The theoretical set of steps by which offenders may commit burglary are as follows.

Step 1: Property A is burgled (by an offender or co-offenders).

Step 2: Property A does not experience repeat victimization (RV) within a given time period.

In this step, if RV did occur at Property A, then the RV will not be considered as a part of the displacement. Therefore, only crimes with no subsequent crime at the same location are considered as starters in displacements.

Step 3: Property A receives some form of crime prevention measure (e.g., target hardening, new burglary alarm, or increased police patrols).

In this step, it is assumed that some form of situational crime prevention measure has been introduced at Property A and prevented RV. Nevertheless, it is possible that Property A did not suffer from RV even though no security measures were put into place. When matched with some new burglary committed elsewhere (by the same or different offenders), the burglary committed at Property A may be wrongly recognized as a starter. To rule out such false detection, a Monte-Carlo simulation is conducted to statistically identify geographical displacement. Therefore, it is assumed that the statistically significant geographical displacement occurred under the condition that Property A received some form of effective situational crime prevention measure.

Step 4A: Property A does not experience repeat victimization but Property B nearby is burgled (by the same or other offenders).

If Property B is close to Property A, then crimes at Property B should be classified as near-repeats. In our current research, there is no definition to distinguish whether B is near or far from A. As such, crimes committed at Property B may be recognized as displacement and NR at the same time. Theoretically, the assumption in this step is that the situational crime prevention measure at Property A did not have any diffusion of benefit (or the diffusion of benefit did not reach the place of Property B), which could have protected nearby properties from near-repeats. Considering the difficulty of measuring effects of situational crime prevention initiatives, phenomena occurring in step 4 are simply classified as displacement. This classification method may result in overlaps between near-repeat victimization (NRV) and geographical displacement. Acknowledging such a situation, our current study investigates the contribution of geographical displacement on crime prediction, besides RV and NRV. From this point of view, the confusion about classification of crimes committed at Property B can be statistically alleviated in crime prediction.

Step 4B: After Property A is burgled, and it does not experience RV, there are few or no NRV burglaries in the vicinity of Property A.

It is assumed that, after Property A was burgled, some new situational crime prevention was introduced that protected both Property A and the surrounding properties (diffusion of benefit), for example, police patrols in the area or information campaigns warning of increased risk in the area. It could be argued that after Property A was burgled, there were no situational crime prevention measures introduced either at Property A or in nearby areas, but that for other reasons Property A did not experience RV and no nearby properties experienced situational crime prevention measures. In this case, some new and emerging crime trends could possibly be identified as displacements. The Monte-Carlo simulation is expected to rule out the false detections. Only statistically significant displacement will be recognized.

Step 5: After Property A was burgled, the situational crime prevention introduced was effective at preventing RV, and there was also a diffusion of benefit and no NRV nearby. Offenders were required to search for alternative locations to offend, and thus, there was displacement of crime.

By using matched pairs, it is assumed that the crime levels before Property A was burgled and after the crime at Property B are the same. Considering the assumption that crime prevention intervention may lead to an overall reduction in net crime, not all crimes would have a second pair that matched.

Following the five steps and the theoretical assumptions, each pair of crimes is considered as a connection between the two places where the two crimes are located. Ideally, many pairs of points can be observed in a large number of crime records. However, many of these pairs may not be geographical displacement. For example, two unrelated crimes may be connected just because they were committed in close time. To avoid false detection, only places that have significant connections are observed and recorded. The Monte-Carlo simulation is conducted to determine whether the connections between places are significant or not. In this process, a number of randomly distributed crimes are generated with the same volume as the crime incidents. The space-time displacements are identified and counted followed by the estimation of simulated connections between each pair of cells. Such a simulation is repeated a number of times to evaluate the risk level and significance of the displacements, as in the Knox test. In our current study, the Monte-Carlo simulation is generated by 999 permutations. As such, the risk level of a connection indicates the possibility of displacement from one cell to another. It could be calculated by the count of observed crime connections against the average number of simulated connections.

$$\text{Risk level of displacement} = \frac{count\ of\ crime\ connections}{count\ of\ simulated\ connections} \tag{1}$$

A large value corresponds to a high possibility of displacement, while a small value indicates a low possibility of displacement. The significance level for each displacement is determined by the possibility of observed displacements exceeding the simulated displacements. For instance, when the number of observed displacements from cell A to cell B is greater than the count of displacements in 998 simulations, the significance level is 1–998/999 = 0.002. Obviously, a small value means a high significance level, and the higher values correspond to a low significance level.

2.4. Accuracy Assessment

To assess the predictive ability of the two methods, the results are compared, first, by capture rate and, second, by a prediction accuracy index (PAI). The capture rate indicates how many crimes could be predicted, whereas the prediction accuracy index tells the efficiency of a method using the percentage of offenses in one unit of the study area.

The capture rate, as a common index in crime prediction literature, indicates the proportion of crime events for the measured data (N) time period falling into the areas where crimes are predicted to occur (n).

$$capture\ rate = \frac{n * 100}{N * 100}. \quad (2)$$

A high capture rate indicates a high percentage of crimes captured in the predicted crime areas. In this index, the prediction areas are not considered. The prediction accuracy index, therefore, is involved in assessing the predictive accuracy of the results [29]. This index measures how efficient a prediction method is in capturing future crimes. It is calculated by the proportion of predicted events (n) from the total number of events (N) divided by the proportion of the size of the prediction area (a) related to the entire study area (A).

$$PAI = \frac{n/N}{a/A}. \quad (3)$$

A large PAI value means that a method is highly efficient at capturing a high percentage of crimes with a small prediction area.

3. Study Area and Data

In our current study, city N was selected as the study area due to its strong representation in China (Figure 2). As a large city in the Yangtze River Delta region, N is a transportation hub. The convenient transportation system and geographical advantage enabled N's economy to develop rapidly, similar to many of China's other large cities. The gross domestic product (GDP) of N ranked in the top 20 most developed cities in China over the last 10 years. Similar to many of China's other large cities, N undertook a long period of urbanization. Over the past few decades, many new urban areas have been developed, while many ancient buildings have been retained. These economic and environmental characteristics make N highly representative in China.

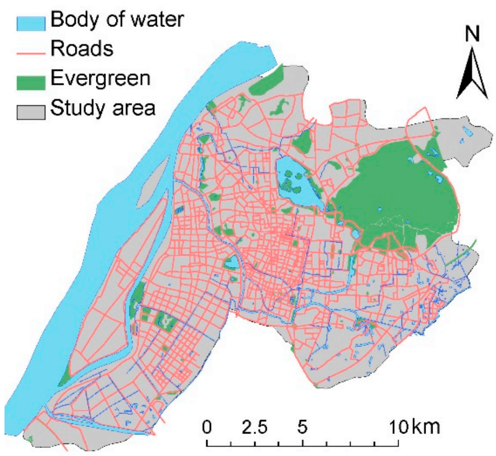

Figure 2. The study area.

The crime records were collected by the Public Security Bureau (PSB) of N city. Every reported crime was reported to the PSB and recorded in the emergency response system (ERS) with the date, address, and other descriptive fields. After a geocoding process, the coordinates and dates of the crimes were adopted for our current study. The complete dataset included a total of 8561 burglaries from 1 January, 2013, to 30 December, 2013. All crimes were registered on the map based on the recorded coordinates, and the full dataset was used to quantitatively analyze crime displacement.

4. Results and Analysis

4.1. Crime Prediction Ability of RNR and STCD

In this section, we investigate whether there is a pattern of RNR victimization for burglaries in N city. According to the existing research results, the crime events are expected to cluster in space and in time. Table 1 displays the results from the NRV. The spatial distance starts from the same location to over 1000 m. In this table, "same location" indicates the risk value of repeat victimization occurring at the same location as the previous crime. The values in the other rows correspond to the risk of near-repeats within the area distant from the previous crimes. The temporal distance corresponds to the time period after each crime. Each value in Table 1 indicates the ratio of observed crime event pairs within a similar distance and time over the expected number. Consequently, a high value indicates a high level of risk, while a small value indicates a low level of risk. The significance is calculated by a Monte-Carlo simulation and indicates whether the risk level is statistically significant or not.

Table 1. Repeat and near-repeat matrix of burglaries.

Space Distance (meter)	Time Distance (day)						
	0–7	8–14	15–21	22–28	29–35	36–42	>43
Same location	2.76 **	1.33 **	1.18 **	1.21 **	1.13 *	1.18 *	1.18 *
1–200	1.39 **	1.08 **	1.06 *	1.11 **	1.05 *	1.08 *	1.09 *
201–400	1.20 **	1.09 *	1.10 **	1.08 **	1.10 *	1.08 *	1.08 *
401–600	1.14 **	1.10 **	1.08 *	1.04 *	1.07 *	1.07 *	1.08 *
601–800	1.12 **	1.07 *	1.07 *	1.06 *	1.04 *	1.06 *	1.07 *
801–1000	1.12 **	1.05 *	1.04 *	1.06 *	1.03	1.05 *	1.07 *
>1000	1.07 *	1.03 *	1.03 *	1.04	1.06 *	1.07 *	1.07 *

* $p < 0.01$; ** $p < 0.001$.

The distribution of risk values follows a similar pattern to the previous research results [25,30–32]. The greatest value of 2.76 is located in the upper-left cell of Table 1 and indicates that the burglary risk in seven days at the same location after one burglary is nearly three times higher than would be expected. The other values in Table 1 decay over space and time. At the highest spatial-temporal distance cell, the risk value is only marginally greater than 1, indicating a slightly higher risk than would be expected. Overall, a significant RNR pattern can be observed for the burglary records in N city.

4.2. Significant STCD

To detect the displacements, the study area is first divided into a number of 200 m × 200 m spatial units. Subsequently, the displacements between each space unit pair were detected and counted. The risk level and significance value of each displacement were calculated with the count of displacements against the simulated results. The significance test was conducted on two levels, 0.01 and 0.001, corresponding to 99 Monte-Carlo simulations and 999 Monte-Carlo simulations, respectively. Furthermore, the distances of spatial-temporal displacements were statistically analyzed.

For the 0.01 significance level, there are 2919 observed displacements (Figure 3). These displacements were represented by event pairs. The histogram of the distances of the displacements shows how far away the displacements usually occur. Most displaced crimes are nearly 5 km away from the previous crime. The long-distance transfer and short-distance transfer represent a very low percentage of all the displacements.

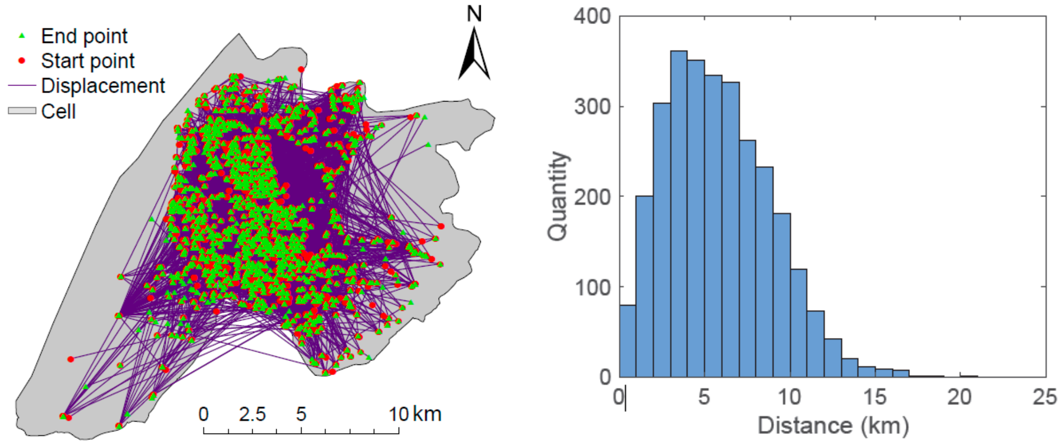

Figure 3. Displacements (significance < 0.01) and histogram of the distances.

For the 0.001 significance level, 237 pairs of crime incidents are identified as significant displacements, which is much fewer than that of the 0.01 significance level (Figure 4). The cell pairs where the crime pairs are located are considered significantly related (at the 0.001 level). Similar to the results of the 0.01 level, the displacement distances are mostly concentrated approximately 5 km away. The short distance displacement and long distance displacement represent a very low percentage, like the displacements conducted on the 0.01 level.

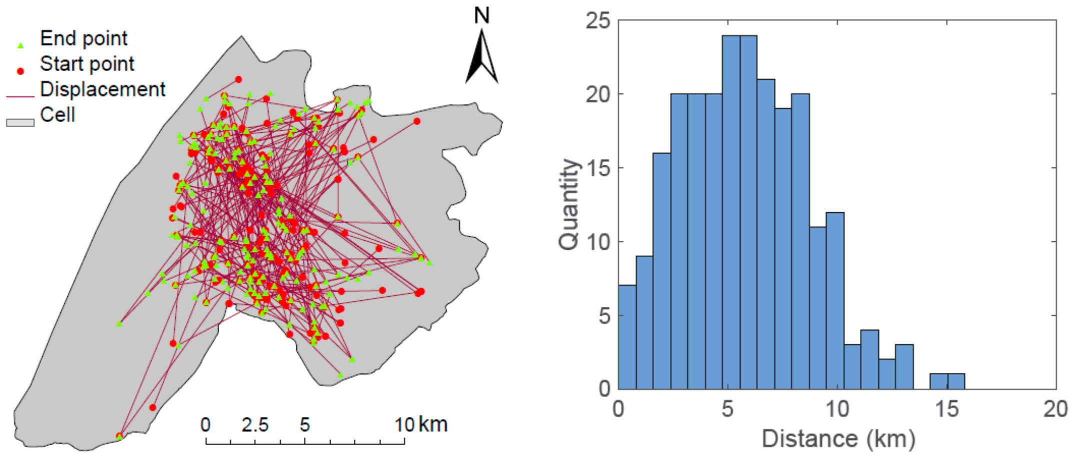

Figure 4. Displacements (significance < 0.001) and histogram of the distances.

4.3. Predictive Ability Analysis

In this section, we will assess the accuracy of crime prediction methods based on RNR and STCD phenomena. Based on an evaluation of both methods, the additional contribution of STCD on crime prediction will be estimated. Considering the high representation of the significant relations (significance < 0.001), the predictive ability is analyzed based on the high significance level patterns.

As introduced in the previous section, the dataset includes 8561 burglary records. Among these burglaries, nearly 34.75% and 10.64% of the burglaries could be captured using RNR and STCD, respectively (Table 2). Therefore, the crime prediction model using the near-repeat parameter identified in the quantitative analysis could capture 34.75% of future burglary events. Comparatively, the crime prediction model using the significant cell pairs identified in displacement detection could capture 10.64% of future burglary events. STCD has a lower crime prediction ability than RNR. The PAI of STCD also indicates that STCD has a lower predictive ability than RNR.

Table 2. Accuracy of crime prediction based on RNR and STCD.

Method	Capture Count	Capture Rate	PAI
RNR	2975	34.75%	14.85
STCD	911	10.64%	4.547
RNR + STCD	3596	42.00%	17.95
Increased by STCD	621	7.25%	3.1

When combined, the integrated method could capture 42% of burglaries, which is higher than the capture rates of either method but lower than the sum of the two capture rates. Similarly, the PAI index of the integrated method is higher than the PAIs of either single method but smaller than the sum of the two PAIs. The reason is that, among the successfully predicted burglaries, some burglaries were captured by only one method, while others were captured by both methods. Thus, although several emerging burglaries captured by STCD could be predicted by RNR, many burglaries could only be predicted by STCD rather than RNR. This part of the predicted burglaries increased the predictive ability of RNR, with a 7.25% capture rate and a PAI of 3.1. In summary, the STCD-based crime prediction method could contribute to the predictive ability of the current RNR-based crime prediction method.

5. Discussion

Spatial-temporal crime displacement has been identified in many countries. Utilizing a burglary dataset from one large city in China, our current research focuses on the topic of quantitative analysis of crime geographical displacement by providing a displacement detection framework. Following the experimental results, three hypotheses were confirmed in our current research.

In response to hypothesis 1, the existence of crime geographical displacement is confirmed. Many empirical studies have confirmed the feasibility of many Western criminology theories in China [30,31,33–35]. Our current research, which is probably the first investigation of crime geographical displacement in China, enriches the literature of the similarities shared by China and Western countries.

Many significant displacements were observed based on the method introduced in our current research. Such displacements can be interpreted as activities, such as offenders transferring to another node in their 'mental map' or seeking suitable opportunities on new targets, as the opportunities at the locations of previous crimes are blocked [13–15]. As such, many displacements may occur between places, which alternately provide opportunities for offenders. The research results statistically verified the existence of these place pairs. Furthermore, most of these displacements were supposed to not be too far away because many of the nodes or new targets are located within the offenders' routine area [5,6]. The experimental study indicated that many of the displacements were approximately 5 km away, and very few displacements were greater than 10 km. These results confirmed the inference of crime geographical displacements.

To answer hypothesis 2, the potential contribution of crime geographical displacement was assessed based on the predictive ability of RNR and crime geographical displacement. Many previous studies were based on the strong relation between close crime pairs [18,36–38]. Crime geographical displacement, as hypothesized, could contribute information to the existing crime prediction literature by identifying the frequent place pairs. This statistic-based method could improve the predictive ability of the RNR-based method by 7.25% and 3.1 in the capture rate and PAI, respectively. The results further indicated that crime geographical displacement contributes additional predictive power.

6. Conclusions

By proposing a new statistical method, this study contributes to the existing literature by detecting crime geographical displacement followed by examining the predictive ability of this phenomenon. Similar to Western countries, crime displacement to new places is a response to crime intervention initiatives in a large city in China. The crime geographical displacement detector detected the place pairs where statistically frequent displacements occur. Interestingly, the identified displacements were not too far away. These results showed the feasibility of inferring the displacement based on the Western criminology theories [5,6]. Most importantly, according to the theoretical analysis and comparative study, the crime predictive ability of geographical displacement, and of the RNR-based crime prediction method, was experimentally confirmed. This result could potentially improve crime prediction accuracy by bringing additional knowledge. The findings may help local police departments optimize police deployment by providing frequent crime displacement places and improving crime prediction accuracy.

There are some limitations to this study. First, the identification of geographical displacement in this paper could be more accurate with the data of crime prevention measures. Crime geographical displacement refers to activities as a response to crime prevention initiatives. In our current research, the geographical displacement was identified based on statistical methods. This may lead to some false identifications in the detection of geographical displacement.

Second, in the identification of geographical displacement, there are several assumptions that could lead false recognition. Before further application of this method, the assumptions should be acknowledged. For example, near-repeat and displacement were not distinguished but simply classified to displacement together.

Third, the space-time extent and volume of crimes in the identification of geographical displacement are all fixed. Actually, crime geographical displacement may exist on various space-time scales. Moreover, as a result of crime prevention benefits, the crime level may decrease in geographical displacement. Therefore, further multi-scale, crime-level-considered research is necessary to accommodate these limitations.

Finally, the geographical characteristics related to crime geographical displacement were not investigated in the crime spatial displacement detector. The involvement of geographical characteristic analysis could help explain the strategy of location selection in crime geographical displacement. In this method, significant geographical displacements could be examined and displayed. Future research may involve geographical characteristics to enhance the interpretability of frequently-displaced places and the applicability of the geographical displacement involved in the crime prediction method.

Author Contributions: Zengli Wang designed the experiments and wrote the paper; Lin Liu revised the paper; Hanlin Zhou prepared the figures and tables; Minxuan Lan processed the data.

Funding: This research was funded by the National Natural Science Foundation of China (No. 41501488).

Acknowledgments: The authors would like to acknowledge the editor and anonymous reviewers for their insightful and constructive comments. The authors would also like to acknowledge the Public Security Bureau of N city for providing the crime data.

Conflicts of Interest: The authors declare no conflict of interest.

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