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Investigating the relationships between climate hazards and spatial accessibility to microfinance using geographically-weighted regression

Brian A. Johnson[a,*], Henry Scheyvens[a], M.A. Baqui Khalily[b], Akio Onishi[c]

[a] Natural Resources and Ecosystem Services Area, Institute for Global Environmental Strategies, 2108-11 Kamiyamaguchi, Hayama 240-0115, Japan
[b] Institute for Inclusive Finance and Development, PKSF Bhaban, Plot: E-4/B, Agargaon A/A, Sher-e-Bangla Nagar, Dhaka 1207, Bangladesh
[c] School of Data Science, Yokohama City University, 22-2 Seto, Kanazawa-ku, Yokohama, Japan

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ABSTRACT

Microfinance institutions (MFIs) in Bangladesh provide a variety of financial services to poor households that can help them cope with natural disasters (e.g. floods) and adapt to environmental changes (e.g. increasing soil salinity). However, due to the limited geographic range in which MFI branches can provide their services, households located far from a branch typically do not have access to microfinance. In this study, we measured how spatial accessibility (SA) to microfinance varied across 18 sub-districts (upazilas) of southwest Bangladesh, a region heavily affected by climate-related hazards including flooding and high soil salinity. Our objective was to identify if accessibility to microfinance was negatively affected by climate hazards due to, e.g., higher lending risks in hazard-prone areas. For this, we incorporated geospatial data sets related to flood hazard, soil salinity, population density, and transportation infrastructure as explanatory variables for regression modeling of SA. We tested both ordinary least squares (OLS) regression and geographically-weighted regression (GWR) approaches, and found that GWR was better able to predict SA. The GWR model for the SA measure "distance to nearest branch" had the strongest relationship with the explanatory variables (adjusted $R^2 = 0.717$), and in this model (and four of five other models tested), high flood hazard and high soil salinity were negatively correlated with accessibility to microfinance. To increase microfinance accessibility in these climate hazard-prone areas, additional funding for MFI outreach activities (e.g. utilizing national/international climate change funds), reduction of transaction costs, and further experimentation with adapting/packaging MFI services, may be required.

1. Introduction

1.1. Overview of this study

Accessibility to goods and services often varies across space due to differences in population, demographics, transportation infrastructure, etc., at different geographic locations. Geographic variations in the spatial accessibility (SA) to a particular service – i.e. the number of service providers available at a location and the spatial connectivity (distance or travel time) between the location and the potential service providers [1] – have been studied in relation to various services including: health care [1–4], daycare [5], urban parks [6,7], public transportation [8,9], supermarkets [10,11], and financial services [12,13]. Several studies have analyzed the relationships between service accessibility and demographics to identify whether certain segments of the population (e.g. low-income households or minority groups) were particularly lacking in services [6,10]. In contrast, little research has focused on the relationships between climate hazards and accessibility to services. As one example, Khan and Rabbani [12] examined the relationship between households' distance to the nearest major river (i.e. a flood hazard indicator) and their accessibility to microfinance services in two districts of northern Bangladesh (a flood-prone region). Based on results of ordinary least squares (OLS) regression, they found that households located nearer to rivers (i.e. higher flood hazard) had lower accessibility to microfinance.

Microfinance services can be defined as financial services (e.g. small loans, savings accounts, insurance, and remittance services) made available to and tailored for low-income people [14]. Among their various benefits, microfinance services have been found to help low-income households cope with/recover from floods and other extreme weather events [15,16]. The results of the study by Khan and Rabbani [12] were mainly significant because microfinance institutions (MFIs) have poverty alleviation as their main objective [17], and the households in the flood-prone areas were among the poorest and most

* Corresponding author.
E-mail address: johnson@iges.or.jp (B.A. Johnson).

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vulnerable.

Building on the work of Khan and Rabbani [12], this study further investigates the relationships between climate hazards and accessibility to microfinance, with a focus on the southwestern region of Bangladesh. In addition to flood hazards (due to storm surge, tidal flooding, and/or river flooding, depending on the location), we also analyze the relationship between high soil salinity and accessibility to microfinance, as high soil salinity is another major environmental problem in southwest Bangladesh. Salinity levels in this region have been rising over the past few decades, particularly in the dry season, due to a combination of lower dry-season fresh water levels, land subsidence, and sea level rise [18–20]. In areas with high soil salinity, agricultural productivity is typically significantly reduced, and in severe cases all crops may be lost [21,22]. In these high soil salinity areas, microfinance has been shown to, among other things, help agriculture-dependent households adopt alternative livelihoods like crab fattening, vegetable cultivation in "clean" soils held in polythene bags, and poultry raising [23].

Despite the importance of microfinance in areas with high flood risk and/or high soil salinity, it is possible that access to microfinance is lower in these areas because it is more difficult for MFIs to generate sufficient income to cover their working costs (e.g. due to risks of loan non-repayment after severe floods or crop losses). To test this hypothesis, we performed regression modeling to analyze the relationship between accessibility to microfinance and flood hazard/high soil salinity. Our goal was to identify if microfinance accessibility needs to be increased in the climate hazard-prone areas. Some other novel aspects of this study are: (1) we employed multiple SA measures (distance to nearest branch, a gravity model-based measure, and a kernel density estimation-based measure) to reduce uncertainties caused by adopting an overly narrow definition of SA, and (2) we compared global (OLS) and local (geographically-weighted regression (GWR)) regression approaches to determine which provided a better fit (i.e. higher R^2) for modeling the relationships between SA and the potential spatial determinants (i.e. independent variables).

1.2. Importance of microfinance to poor households in climate hazard-prone areas

In Bangladesh, the microfinance sector is characterized by: MFIs rather than formal banks as the main providers; savings, loans and informal insurance as the main financial products; rural women (mobilized into small groups) as the main clients; weekly meetings between local MFI field officers and client groups as the main delivery mechanism; and the packaging of financial services with non-financial services (e.g. training on livelihood activities and extensions services) by many of the MFIs [24]. The significance of the microfinance sector in Bangladesh can be seen in its operations and outreach, with over 14,000 branches being operated by Microcredit Regulatory Authority (MRA)-licensed MFIs [25] and over 41 million active members in MFI schemes [24].

Several past studies have theorized that microfinance could assist households to cope with and recover from extreme weather events as well as adapt to long-term climate changes. Hammill et al. [26] argued that microfinance can build adaptive capacity by enabling households to accumulate assets and strengthen their coping mechanisms. Fenton and Paavola [27] viewed microfinance as having strong links with autonomous adaptation, i.e. a continual process of adjustment by households to climate change. Scheyvens [24] concluded that microfinance can contribute to adaptation by filling the "adaptation deficit," i.e. the shortage of adaptive capacity that a household has because of its lack of capital in its various forms.

These assertions are also supported by a number of empirical studies. Rahman [15] found that his sample of clients of one MFI (Grameen Bank) had greater capacity to cope with and recover from the 1987 and 1988 floods in Bangladesh than a control group as, inter alia, they had been able to diversify their occupational pattern to include greater self-employment. Khandker and Pitt [28] found that participants in three microfinance programmes were adding microfinance to their existing set of consumption smoothing strategies to lessen the impacts of seasonal hunger and other household stresses. Khandker and Pitt [28] observed that households were using microfinance in ways that diversified their income sources, and that most were using loans to finance nonfarm activities, thus reducing their vulnerability to seasonal fluctuation in agricultural income. More recently, Khan et al. [29] investigated how ex-ante access to microfinance impacts the strategies of poor households in north-western Bangladesh to cope with *monga*, a seasonal event coinciding with the low time in the agricultural seasons when employment/income opportunities are very limited. They found that households with ex-ante access to microfinance relied less on coping strategies that potentially erode the long-term asset base of the household (e.g. asset sales). Another study by the same researchers investigated the coping strategies of households in south-western Bangladesh exposed to super cyclones Sidr and Aila (in 2007 and 2009, respectively) and tropical storm Mahasen (in 2013) [16]. They found that households without ex-ante access to microfinance relied more on erosive coping strategies – sale of assets and use of informal loans (which usually carry very high interest rates) – than households with ex-ante access to microfinance.

In summary, there is growing evidence that access to microfinance can help households cope with climate hazards. However, we are aware of only one previous study that has investigated how climate hazards affects households' accessibility to microfinance [12].

1.3. Spatial accessibility (SA) measures

Several measures of SA have been developed and applied in past studies. One commonly used measure is the number of service providers within a specific geographic zone (e.g. a census block, neighborhood, or city) divided by the population of the zone. While this ratio measure has the benefit of being easy to interpret, it does not take into account peoples' ability to cross borders to access services in other nearby zones [4]. Another relatively simple measure of SA is the distance from a consumer's location to the nearest service provider, but this measure has been criticized for the opposite reason of the ratio method; it fails to account for the number of service providers available to the consumers [30,31]. One SA measure that takes into account both the number of service providers available and the distance to the service providers is based on the gravity model (GM) [32]. GMs estimate the potential interactions between a population at a specific point (e.g. a census block or city/town centroid) and the service providers located within a reasonable distance of the point, with service providers located farther from the point having less weight in the calculation [4] The simplest version of the GM, which only accounts for the potential supply of a service (not demand), is calculated as:

$$SA_i = \sum_j \frac{P_j}{d_{ij}^{\beta}} \tag{1}$$

where SA_i is the spatial accessibility at point i, P_j is the number of providers at point j, and d_{ij} is the distance (or travel time) from point i to j, and β is a distance weighting function. Although more sophisticated versions of the gravity model also take into account demand for a service [2,5], we limit our focus to the simpler version because factors determining demand for microfinance are still not very well understood [12]. In addition to the GM, another SA measure that takes into account both the number of and distance to service providers is based on kernel density estimation (KDE) [33]. KDE for measuring SA is generally done by passing a kernel (i.e. a fixed-size moving window) over a map of service provider points and counting the number of service providers within the kernel. Similarly to the GMs, for KDE a distance weighting function is typically applied to reduce the weight of providers located farther from the center of the kernel; e.g. a Gaussian kernel function

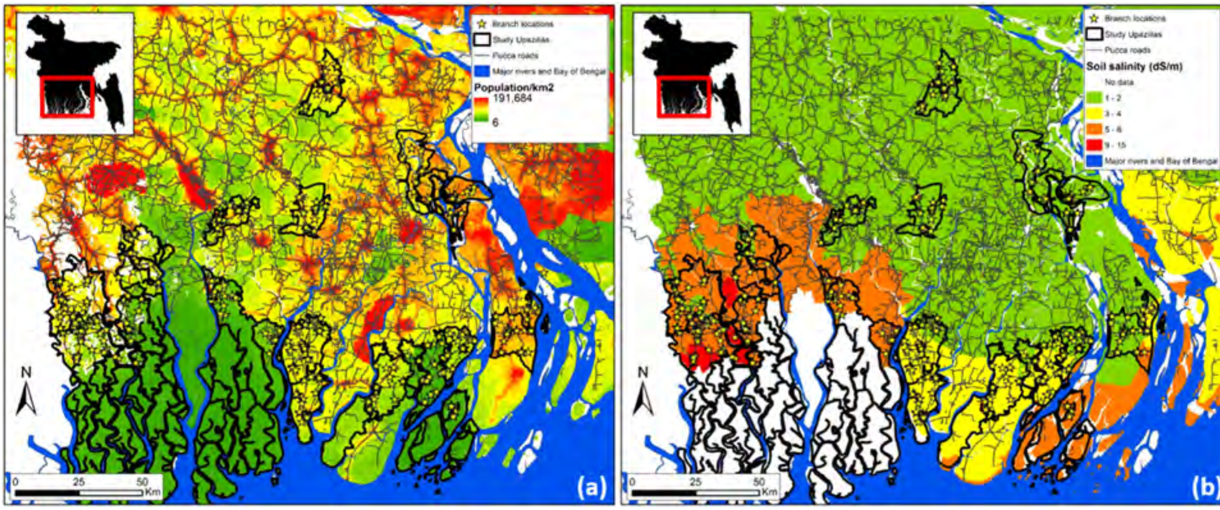

Fig. 1. Geospatial data sets used in this study.

[31]. Although we have only briefly explained the basics of KDE here, detailed descriptions of its mechanics are provided in Silverman [33] and more recently in Scott [34]

2. Methods

2.1. Study area and data

The study area consisted of 18 sub-districts (upazilas), randomly selected from nine districts in southwest Bangladesh (Fig. 1). Several geospatial data sets covering these upazillas were collected for the purpose of calculating SA and performing the regression analysis in this study. First, a field survey was conducted to obtain the GPS locations of the major MFI branches in the 18 selected upazilas, and these branch locations were georeferenced and mapped using Geographic Information Systems (GIS) software. Next, data sets related to the potential spatial determinants of SA were gathered from various online sources. Gridded population data for the year 2015 ("population per 100 m x 100 m grid cell") was obtained from the WorldPop website [35]. The population counts in this data set are downscaled from upazila-level census population counts using several ancillary geospatial data sets and a random forest regression modeling approach, as detailed in Stevens et al. [36]. A data set with the locations of paved ("pucca") roads, created by the Bangladesh Local Government Engineering Department (LGED) and current to 28 September 2014, was downloaded from the Humanitarian Data Exchange website [37]. A polygon data set with the boundaries of major rivers and the Bay of Bengal, created by the U.S. National Renewable Energy Laboratory (NREL), was downloaded from WFPGeoNode [38]. Finally, a polygon data set with soil salinity information, created by the Bangladesh Agricultural Research Council (BARC), was obtained from the BARC website [39]. All of these maps were projected into a common coordinate system (Universal Transverse Mercator) and overlaid onto one another, as shown in Fig. 1.

2.2. Generating maps of SA and its potential spatial determinants

After collecting the geospatial data sets, we used them to generate maps of the dependent and independent variables for the OLS and GWR regression analysis. A map of potential microfinance consumer locations (points) was generated using the WorldPop gridded population data set. The gridded population data was first resampled from 100 m to 1 km spatial resolution to reduce errors from the population downscaling methodology, and then the centroid of each 1 km × 1 km grid cell was used as a potential consumer point. Due to the downscaling methodology used by Stevens et al. [36], no grid cells in the WorldPop data set have populations of zero. However, because areas that contain no population (no potential consumers) should be excluded from the regression modeling of SA, we discarded all point centroids located in areas designated as forests (likely to have no, or very little, population) in a crowdsourced forest map of Bangladesh [40].

Next, information related to each spatial determinant of SA was assigned to the consumer points. The population per km^2 at each consumer point was calculated from the resampled WorldPop data set (Fig. 2(a)). The Euclidean distance from each consumer point to the nearest road, in m, was calculated from the LGED roads data set (Fig. 2(b)). The Euclidean distance from each consumer point to the nearest major river, in m, was calculated from the NREL major rivers data set (Fig. 2(c)). The percent of the land area (per km^2) with high soil salinity levels (> 4 dS per meter (dS/m)) was calculated from the BARC soil salinity data set (Fig. 2(d)). Soils with salinity levels > 4 dS/m were defined as having high soil salinity because yields of most crops are reduced when salinity levels exceed this level [22].

Finally, maps of SA were generated using the MFI branch points as the service provider locations. The first SA measure calculated was the Euclidean distance to the nearest branch, in Km, measured from each consumer point. Euclidean distance was chosen for this SA measure instead of actual travel distance or travel time (other common ways of measuring distance which utilize roads GIS data) because the roads GIS data available was not complete/up-to-date. The second SA measure calculated was a GM-based measure. For this GM-based SA measure, Eq. (1) was applied with a β value of 1 (i.e. inverse distance weighting) and a search range of 10 km. We chose a β value of 1 (instead of a higher exponent) because MFIs, not being motivated primarily by profit, are typically willing to have their staff travel a reasonable distance to provide microfinance services to households that need it, and the 10 km search range was selected because past research found that MFI branches typically restrict their operations to within 8–10 km [12]. The third SA measure calculated was a KDE-based measure, and for this we applied the same kernel function (Epanechnikov function) and kernel radius (10 km) as the previous study on microfinance by Khan and Rabbani [12].

2.3. Regression modeling

Next, OLS and GWR regression modeling approaches were used to analyze the relationships between the SA measures and the independent variables. Both OLS and GWR are linear regression models, with the main difference being that OLS is a global regression model and GWR is a local model [41]. GWR has been found to be particularly useful for dealing with data exhibiting spatial non-stationarity due to its ability to

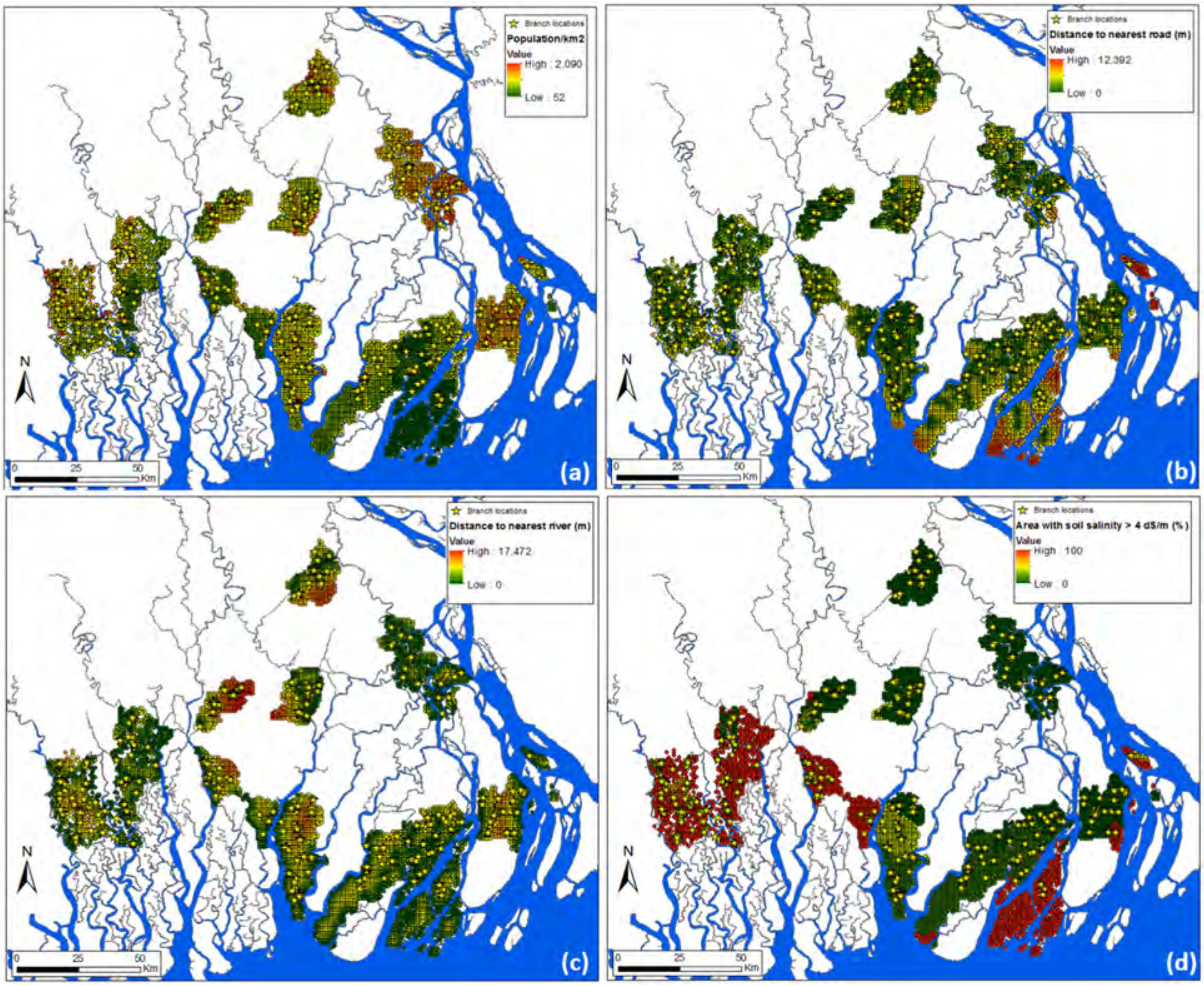

Fig. 2. Values of the potential spatial determinants of spatial accessibility (SA) to microfinance at the consumer point locations.

model locally-varying relationships between independent and dependent variables [42]. In past studies involving spatial data, GWR has been shown to lead to more accurate modeling of various phenomena including land values [9], urban park accessibility [7], and surface water salinity [43], compared with global regression models. A GWR model is calculated for each location of interest (i.e. each potential consumer point location) using either: (a) a fixed distance approach (i.e. including all data points within a specific distance), or (b) an adaptive distance approach (i.e. including a specific number of nearest data points). GWR typically employs a kernel weighting function, e.g. a Gaussian or bi-square kernel function [44], to allow data points located nearer to the location of interest to have more influence in the regression calculations. For GWR calculations in this study, we used the adaptive distance approach. GWR models with several different numbers of nearest neighbors were tested, and the model with the lowest Akaike's Information Criterion (AIC) value [45] was selected as the most appropriate one. Variable coefficients for GWR vary locally (as do the t- and p-values of the coefficients), so to calculate global variable coefficient values we used the mean of the local coefficient values. In addition, we mapped the local variable coefficients to show the spatially varying relationships between SA and each independent variable. All GWR modeling was done using the GWR4 software package version 4.09, which is freely available online [46].

3. Results and discussion

3.1. Maps of SA

Maps of each of the three SA measures are shown in Fig. 3. In all three maps, it is clear that areas located nearer to rivers (i.e. more flood-prone areas) typically had lower accessibility to microfinance. The southeastern part of the study area in particular had quite low SA values. This area, in addition to being located near rivers and the Bay of Bengal, also has quite high soil salinity, as shown in Fig. 2(d). Comparing the three SA maps, there are some slight differences. In the KDE map (Fig. 3(c)), SA values are very high in areas with a dense concentration of MFI branches, but decrease rapidly outside of these densely concentrated areas, leading to a larger number of consumer points with SA values of 0 (no accessibility to microfinance). The GM map has a similar pattern, but the decrease in SA values with distance from branches is more gradual, leading to fewer consumer points with SA = 0. As KDE and GM are quite similar in terms of how they are calculated, the differences in our study are likely due to the parameters we selected (selecting a higher β value for the GM measure would lead to a map similar to the KDE map). The distance to nearest branch map (Fig. 3(a)) had the most gradual changes in SA values across space, and because it is a simple distance-based measure, no consumer points have SA values of 0. It should be noted that higher values indicate higher SA in the GM and KDE maps, while lower values indicate higher SA in the distance to nearest branch map.

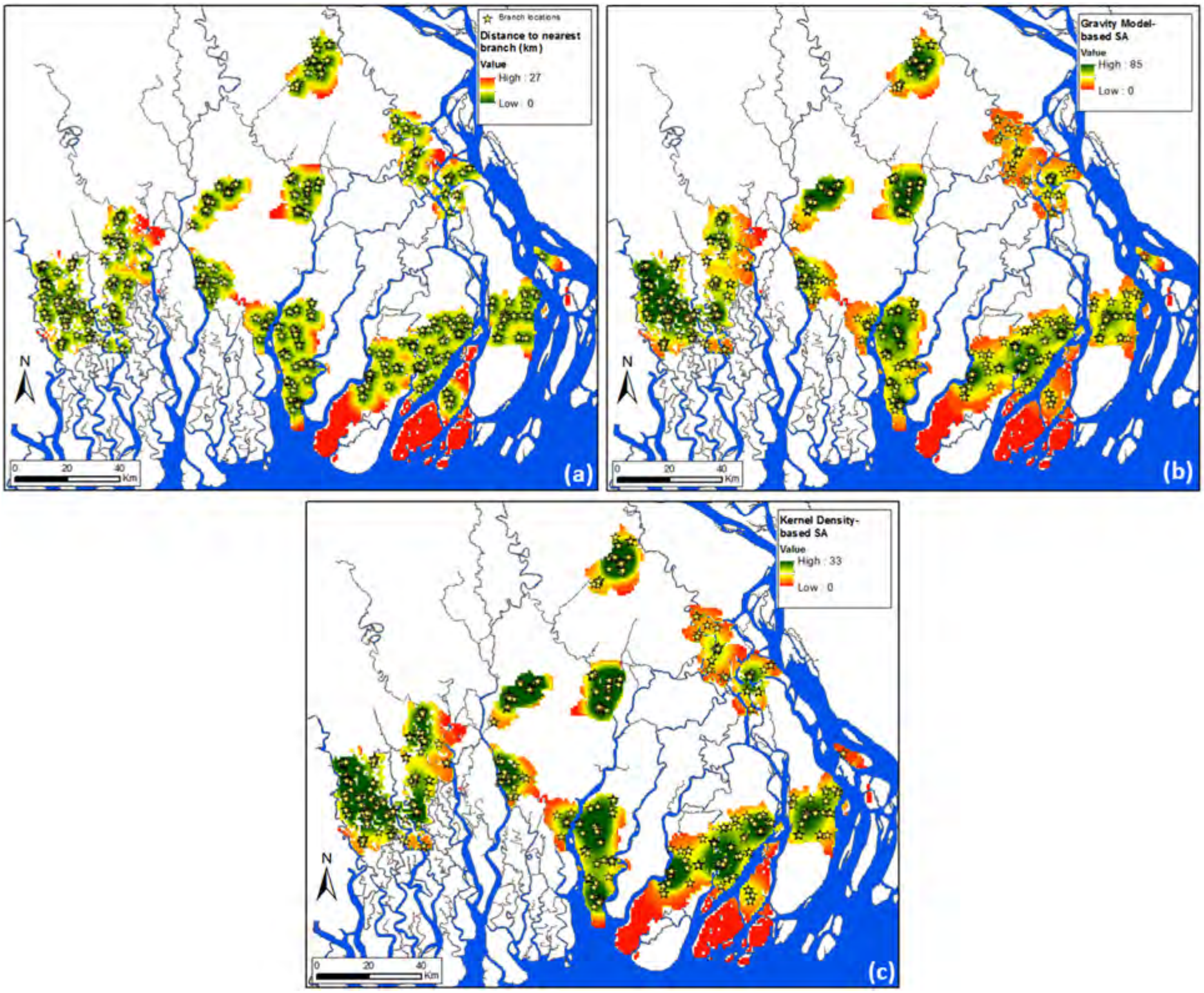

Fig. 3. Maps of spatial accessibility (SA) to microfinance, as measured by: Euclidean distance to nearest branch **(a)**, gravity model (GM) **(b)**, and kernel density estimation (KDE) **(c)**.

3.2. Regression modeling results

3.2.1. OLS results

The adjusted R^2 values of the OLS regression models ranged from 0.221 to 0.259 (see Table 1 for all OLS model results), indicating a somewhat weak global relationship between SA and the spatial determinants we considered. In general, the directions of the relationships (i.e. positive or negative) between SA and the variable coefficients of the independent variables were as expected. Population density and distance to rivers had a positive relationship with SA in all three OLS models, and distance to roads had a negative relationship with SA in all three models. These relationships were in line with the results of the previous study on accessibility to microfinance [12].

The global relationship between high soil salinity and the SA measures were less clear, as there was a negative relationship for two regression models (distance to nearest branch and KDE), as we had expected, but a positive relationship for the GM model. For the KDE model, the relationship was negative as expected, but the t-value was not significant at $p > 0.05$. Based on these mixed OLS model results, we could not reject the null hypothesis of there being no global relationship between high soil salinity and accessibility to microfinance. Assuming that demand for conventional microfinance services may be affected (either positively or negatively) by agricultural productivity, the absence of a global relationship between high soil salinity and SA could potentially be due to spatial variations in the productivity (e.g.

Table 1
OLS regression modeling results for each SA measure.

Variable	Coefficient	t-value
(a) "Distance to nearest branch"		
Adjusted $R^2 = 0.259$		
Intercept	−1263.523	−4.042**
Population per km^2	−342.734	−18.533**
Distance to River (m)	−0.033	−1.806*
Distance to Road (m), natural log. transformed	1025.212	27.313**
% area with soil salinity > 4 dS/m	7.519	6.686**
(b) "Gravity model" measure		
Adjusted $R^2 = 0.221$		
Intercept	1233.162	28.756**
Population per km^2	36.352	14.329**
Distance to River (m)	0.023	9.447**
Distance to Road (m), natural log. transformed	−138.808	−26.956**
% area with soil salinity > 4 dS/m	0.346	2.244**
(c) "Kernel density estimation" measure		
Adjusted $R^2 = 0.244$		
Intercept	0.169	29.882**
Population per km^2	0.00438	13.09**
Distance to River (m)	0.000006	17.755**
Distance to Road (m), natural log. transformed	−0.0168	−24.807**
% area with soil salinity > 4 dS/m	−0.000015	−0.735*

* t-value significant at $p < 0.10$;
** t-value significant at $p < 0.05$,

Table 2
GWR modeling results for each SA measure.

Variable	Coefficient
(a) "Distance to nearest branch"	
Adjusted R^2 = 0.717	
Intercept	−21.781
Population per km^2	−109.731
Distance to River (m)	−0.085
Distance to Road (m), natural log. transformed	533.608
% area with soil salinity > 4 dS/m	29.519
(b) "Gravity model" measure	
Adjusted R^2 = 0.437	
Intercept	1006.83
Population per km^2	42.672
Distance to River (m)	0.022
Distance to Road (m), natural log. transformed	−96.421
% area with soil salinity > 4 dS/m	−2.201
(c) "Kernel density estimation" measure	
Adjusted R^2 = 0.571	
Intercept	0.1372
Population per km^2	0.00366
Distance to River (m)	0.000006
Distance to Road (m), natural log. transformed	−0.00918
% area with soil salinity > 4 dS/m	−0.00046

crop yields or frequency of crop failure) of saline lands in the study area, as agricultural productivity is also affected by various other soil properties as well as local climate conditions.

3.2.2. GWR results

The adjusted R^2 values of the GWR models ranged from 0.437 to 0.717, indicating stronger relationships between SA and the spatial determinants than the OLS models. This result was consistent with the results of other studies that compared GWR and OLS for analysis of phenomenon with locally-varying relationships between the dependent and independent variables [7,9,43]. However, to our knowledge, ours was the first study on accessibility to finance/microfinance that utilized GWR. Based on our comparison results, we suggest future studies on the topic also consider using a GWR approach.

Comparing the R^2 values achieved for the three different SA measures (Table 2), it is clear that the value for the "distance to branch" measure was much higher than for the other two measures. The lower R^2 values for the GM and KDE SA measures may have been due to fact that their values were truncated at 0 (SA = 0 for any location 10 km or more from a MFI branch), while the "distance to branch" SA measure was a true continuous variable and thus probably better suited for linear regression analysis. However, because there is no real change in access to microfinance services for households 10 km or further from the nearest branch (all are likely to lack access to microfinance), it is not advisable to consider only a "distance to branch" SA measure for regression analysis.

The relationships between SA and the pseudo-global GWR variable coefficients (i.e. the mean of the local variable coefficients) (Table 2) were all in line with our hypothesis: In all three GWR models, population density and distance to rivers were generally positively correlated with SA, while distance to roads and high soil salinity were negatively correlated with SA. Maps of the locally varying relationships between SA and the climate hazard variables, shown in Fig. 4 (for all points with t-values significant at < 0.05), indicate that there were some differences in the local relationships between the dependent and independent variables for each SA measure. In most cases, the direction (positive or negative) of the relationships between SA and the independent variables were consistent, particularly for the GM and KDE measures (likely due to their relatively similar calculation methods), but in some areas the directions of these relationships were opposite. Fig. 4 thus illustrates the benefit of using multiple SA measures to analyze relationships between SA and its spatial determinants, as results in areas where GWR models disagree can be understood to have higher uncertainty than results in areas where all models agree. From the Fig. 4 maps, it is clear that the in the western and southeastern parts of the study area (upazillas Kaliganj, Shyamnagar, Mongla, and Patharghata), all models agreed that SA was negatively related to flood hazard level (i.e. distance to nearest river), while results were more mixed in the northern parts of the study area (e.g. upazillas Muladi and Mehendiganj). In some of the northern parts of the study area (green areas in Fig. 4(a)-(c), e.g. upazilla Nazirpur), SA was actually higher in areas located nearer to rivers. This result was unexpected, but may potentially be due to lower flood hazard levels near rivers in the northern region due to higher land elevations. In these areas, the convenience of having branches located near rivers (e.g. for water transportation) may have outweighed the climate risks. In regards to the relationship between high soil salinity and SA, all models agreed that SA was negatively related to high soil salinity throughout most of the study area, with exceptions being some of the northeastern areas (where results were not statistically significant) and a section of the southern coastal upazilla Patharghata.

3.2.3. Policy implications

Our results indicated that accessibility to microfinance services was generally lower in areas that were more vulnerable to flooding and high soil salinity (i.e. climate hazards). This may be explained by the interplay of supply and demand side factors. On the supply side, MFIs may be less willing to provide financial services to these areas, fearing that savings deposits and loan repayments may be interrupted by climate hazards. The MFIs' physical assets (branch offices) would also be greater exposed to damage in these areas. On the demand side, households in the hazard-prone areas may be less interested to join microfinance schemes when only conventional microfinance products are offered. Especially in areas where land productivity has frequently been affected by climate hazards in the past, households may find it difficult to identify opportunities for low-risk, productive investments and thus be reluctant to take out loans. This may lead some to conclude that lower accessibility to microfinance in climate hazard-prone areas is not a policy issue. However, here a mistake is being made in confusing demand for conventional microfinance services with need for appropriate financial services.

While much variation can be observed in microfinance products, many MFIs continue to base their products on the original or "classic" Grameen model, which assumes that borrowers can attend weekly group meetings and invest loans in activities that generate a weekly stream of income sufficient to repay the loan in regular instalments [47]. This was a low-cost approach that enabled rapid expansion of microfinance services to many areas of Bangladesh, but not to those areas most exposed to climate and other environmental hazards. Recognizing that this conventional model was ill-suited to climate hazard-prone areas, an alternative model called PRIME ("Programme Initiatives for Monga Eradication") was developed [24]. PRIME aimed to eradicate seasonal hunger (*monga*), focusing first on the northwest region of Bangladesh, and later on the southwest region. In areas where land productivity had declined because of high soil salinity levels, PRIME coupled financial services with training on a variety of alternative livelihoods such as crab fattening and homestead livestock raising that were not dependent on cropping. The Chars Livelihoods Programme (CLP), funded by the UK and Australian governments, also sought to bring financial services to highly vulnerable areas that fell outside the reach of existing MFI programmes, specifically chars (river islands) [24]. PRIME and the CLP enabled participating households to build assets, diversify livelihoods and cope better with shocks [16]. However, as externally funded programmes, their lifetime was limited. Unlike conventional microfinance schemes that can operate at or above cost recovery, subsidization is required for appropriate financial services in climate hazard-prone areas to enable product flexibility and to couple these with essential non-financial services.

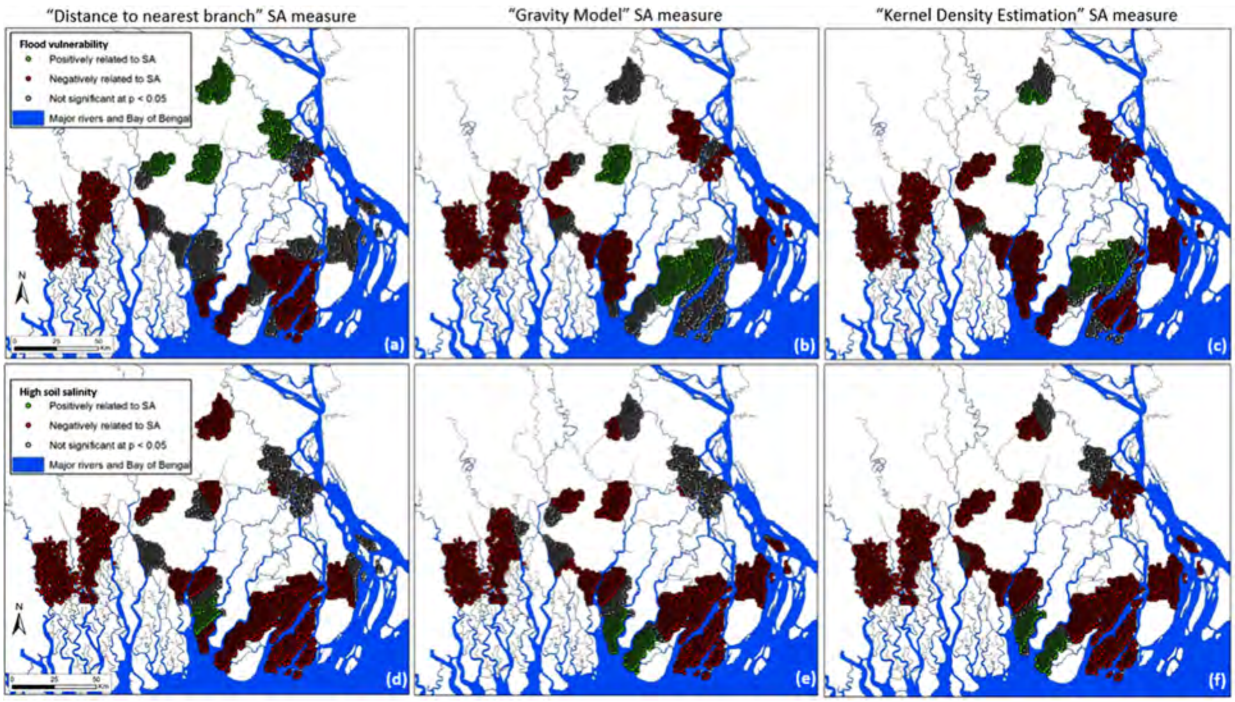

Fig. 4. Maps of GWR local relationships between flood hazard (inverse of "distance to nearest river" variable) and accessibility to microfinance for the: "Distance to nearest branch" **(a)**, Gravity Model **(b)**, and Kernel Density Estimation **(c)** SA measures. Maps of GWR local relationships between high soil salinity (based on the "% land area with soil salinity > 4 dS/m" variable) and accessibility to microfinance for the: "Distance to nearest branch" **(d)**, Gravity Model **(e)**, and Kernel Density Estimation **(f)** SA measures.

This points to some important policy issues for increasing microfinance accessibility and usage in climate hazard-prone areas. First, a funding mechanism for microfinance outreach in these areas is required, and means for reducing the costs of targeted programmes (without reducing their effectiveness) need to be identified. Appropriate sources of funding for the outreach activities could include the Bangladesh Climate Change Resilience Fund and the Bangladesh Climate Change Trust Fund, both of which pre-allocated 10% of their total funding to support grassroots and community level adaptation. Regarding cost reduction, cellular networks can be used to reduce the costs and risks of fund transfers. For this, regulatory restrictions that limit the use of mobile phones for the delivery of microfinance services would need to be relaxed.

Second, there is need for further experimentation with the packaging of financial and non-financial services in these climate hazard-prone areas. Reviews of PRIME and the CLP suggest a basic set of good practices for MFI outreach in remote, marginal and other localities highly vulnerable to climate hazards [16,48]. These include providing flexible savings and loan products that reflect highly irregular income flow; providing alternative forms of financial support such as cash-for-work; building community institutions; providing basic educational and health services; and packaging loans with training/extension on climate-resilient livelihoods, risk reduction activities and microinsurance. Further experimentation is now needed to realise the full potential of MFIs in climate change adaptation. In particular, various ways to couple microfinance services with climate-resilient livelihood activities such as the cultivation of salt-tolerant rice varieties can be tested. The development of microinsurance products for health and assets is another priority. As poor households are highly exposed to risks, have low ability to pay premiums, and are typically unfamiliar with formal insurance, innovations will be required [49]. It may be necessary to tie insurance into the delivery of other services and to combine insurance with risk reduction.

3.2.4. Discussion of uncertainty

It is necessary to mention several sources of uncertainty in our study. The first source relates to the geospatial datasets used. The WorldPop gridded population data contains population counts that are downscaled from their original census units, so the population grid counts are affected by the size of the census units as well as the accuracy of the downscaling methodology [36]. Although our resampling (i.e. aggregation) of the population grid data from 100 m to 1 km resolution may have reduced the effects of these downscaling errors, the population counts still contain some errors. Secondly, the roads GIS dataset used was current to September 2014, and because Bangladesh's infrastructure is developing at a rapid pace, several recently built roads are not included. Thirdly, although we attempted to collect the locations of all major microfinance branches in the study area (e.g. branches registered with the Microcredit Regulatory Agency, branches belonging to the major MFIs, and branches operated by the Bangladesh government) for calculating the SA measures, it is likely that we missed some small branches in our field survey.

The second source of uncertainty relates to the definition of microfinance accessibility used (i.e. the SA measure selected) as well as the method for calculating the selected SA measure. To reduce uncertainty in regards to the definition of microfinance accessibility, we employed three different SA measures, and assessed the relative agreement/disagreement between the regression models generated using each SA measure when interpreting the results. In terms of the uncertainty related to our calculations of SA, it should be noted that the SA measures we employed were all based on Euclidean distance measurements. As can be seen in the map in Fig. 1, Southwest Bangladesh contains many rivers that, while posing a flood risk, also provide an important transportation network [50]. Thus one limitation of our SA measures is that they do not consider the potential of MFI's to service larger areas via river transportation. Unfortunately, we are unaware of any existing SA metrics that can account for the differences between land and water transportation. Euclidean distance-based SA measures, however, are not without merit in our study. Indeed, in previous research conducted in Bangladesh, results of a survey of 1959 ultra-poor households indicated that household microfinance borrowing rates were positively correlated with a Euclidean distance-based measure of SA (KDE) (Khan and Rabbani, [12]). That said, in future work it would be useful to investigate to what degree MFI branches rely upon river transportation for their operations and outreach. Indeed, spatial variations in the use of river transportation could offer one potential explanation for why "distance to river" was positively correlated with SA in the northern part of our study area (Fig. 4).

4. Conclusions

In this study, we investigated the relationships between climate hazards (flood hazard and high soil salinity) and spatial accessibility (SA) to microfinance in southwest Bangladesh. Coastal areas in this region suffer from extreme flooding (storm surge, tidal flooding, and/or river flooding, depending on the specific location) in the monsoon season and high soil salinity in the dry season. While microfinance services can help households cope with these extreme conditions, the services are not accessible in areas located far from any microfinance branches. To first understand variations in accessibility to microfinance in the region, we calculated and mapped three different commonly-used SA measures: "distance to nearest branch", "gravity model-based SA", and "kernel density estimation-based SA". Next, values of four potential spatial determinants of SA were calculated: "population density", "distance to nearest paved road", "distance to nearest river", and "percent of land with soil salinity > 4 dS/m". The relationships between SA and these explanatory variables were investigated using ordinary least squares (OLS) regression and geographically-weighted regression (GWR) modeling approaches. The GWR models were better able to predict SA based using these explanatory variables, and the GWR model predicting "distance to nearest branch" had the highest prediction accuracy (adjusted $R^2 = 0.717$). In all of the GWR models (and two of the three OLS models), high flood risk (measured by "distance to nearest river") and high soil salinity (measured by "percent of land with soil salinity > 4 dS/m") were generally negatively related to accessibility to microfinance, indicating a need for greater efforts to make microfinance accessible in these climate hazard-prone areas.

Finally, it should be noted that our study was limited to the supply side of microfinance, so in future work it would be beneficial to further investigate the relationship between climate hazards and microfinance demand (to better understand the demand side) as well as the relationship between climate hazards and MFI branch performance (to better understand the service providers' perspectives).

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