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Spatial distribution of individuals with symptoms of depression in a periurban area in Lima: an example from Peru

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Abstract

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AUTHORSHIP CONTRIBUTIONS

JJM, RGH and WCH were responsible for the design and conduct of CRONICAS cohort study. PRG proposed the research idea and wrote the depression study protocol, with supervision from JJM and ABO. RHG advised and provided critical input about the area where the study was implemented, informing the conception of the idea and the implementation of the fieldwork study. BBW and GCE provided critical input on spatial analysis. ABO, MVG, FDC, JJM and GCE performed data analysis and interpretation of results. ABO drafted the first version of the manuscript. All authors have critically reviewed this manuscript and have given final approval of the version submitted for publication.

CONFLICT OF INTEREST

None declared.

Purpose—To map the geographical distribution and spatial clustering of depressive symptoms cases in an area of Lima, Peru.

Methods—Presence of major depressive episode was assessed using a short version of the Center for Epidemiologic Studies Depression Scale (CES-D). Data were obtained from a census conducted in 2010. One participant per selected household (aged 18 years and above, living more than 6 months in the area) was included. Residence latitude, longitude and elevation were captured using a GPS device. The prevalence of depressive symptoms was estimated, and relative risks (RR) were calculated to identify areas of significantly higher and lower geographical concentrations of depressive symptoms.

Results—Data from 7946 participants, 28.3% male, mean age 39.4 (SD: 13.9) years, was analyzed. The prevalence of depressive symptoms was 17.0% (95% CI: 16.2%–17.8%). Three clusters with high prevalence of depressive symptoms (primary cluster: RR=1.82; p=0.003 and secondary: RR=2.83; p=0.004 and RR=5.92; p=0.01), and two clusters with significantly low prevalence (primary: RR=0.23; p=0.016 and secondary: RR=0; p=0.035), were identified. Further adjustment by potential confounders confirmed the high prevalence clusters but also identified newer ones.

Conclusions—Screening strategies for depression, in combination with mapping techniques, may be useful tools to target interventions in resource-limited areas.

Keywords

depression; hotspot; spatial clustering; Peru; mental health

INTRODUCTION

Psychiatric disorders, particularly depressive disorders, contribute close to 14% of the global burden of disease (1). Depressive disorders are among the most disabling diseases, and are among the ten leading causes of the global burden of disease (2–4). In Peru, mental health is considered to be one of the national investigation priorities (5). Accordingly, this research focuses on establishing a geographical profile of depression symptoms with the context of mental health.

While person, place and time comprise the three fundamental elements of epidemiologic research (6), many previous studies have underutilized an understanding of place to interrogate the underlying mechanisms of disease. Geographic information systems (GIS), including mapping and geo-spatial analysis, are powerful tools used often for the investigation of infectious disease (7–9) and less frequently for the study of non-transmissible conditions (10, 11). To date, these methodologies and types of analysis are relatively new in mental health research, with a few exceptions (12–16). Many existing reports are based on passive epidemiologic surveillance, especially in studies of schizophrenia (17–19), and these approaches have barely been used in resource-constrained settings.

Several factors have been associated with a major depressive episode such as gender, age, education level, and even migration (20, 21). Knowing how diseases and risk factors are

spatially distributed can contribute to an understanding of their dynamics. Some diseases tend to cluster in areas of high or low prevalence (hot or cold spot, respectively); once identified, the next step is to assess whether clusters can be explained by known or new risk factors (11). Therefore, the aim of this study was to describe by mapping and characterizing the spatial distribution of cases with high probability of major depressive episode in a resource-constrained area.

MATERIALS AND METHODS

Study design and setting

This is a cross-sectional study using data from a census conducted in Las Pampas de San Juan de Miraflores, in Lima, Peru. The census formed the sampling framework for sex- and age-stratified random selection of participants for a prospective cardio-pulmonary cohort (22).

Las Pampas de San Juan de Miraflores is a high-density periurban area located in the south of Lima, with close to 60 000 inhabitants living in 4 km², a great number of whom are migrants from the Andean regions. According to the 2007 National Institute of Statistics and Informatics (INEI) census, 60% of the study area population has at least one unmet basic need, 65% has no health insurance and 25% of households are overcrowded or otherwise inappropriate for habitation (23).

Participants and Selection Criteria

Only one participant per household (the household's respondent for the census) was included (male or female, aged 18 years and above and living in the area of study for a minimum of the last 6 months, consecutively). The participant provided a voluntary self-report of depressive symptoms, alongside socio-demographic information for all household members. This ensured that the collected data about depressive symptoms were recent.

Procedures

Data were collected as part of a census conducted between January and June 2010. Following consent, fieldworkers completed a standardized one-page form for household data, including contact information and socio-demographic variables for all household members. The household respondent was the only person who gave personal data about depressive symptoms.

The geographic position of the household was obtained (latitude, longitude and elevation) using a consumer GPS device (Garmin® eTrex H model) with a high-sensitivity receptor and 10-meter precision. Household locations were collected under the main entrance to each household, following the instructions in the device User Guide (24). These data were then recorded on the respondent data form and periodically uploaded to a personal computer.

Outcome variable

The variable of interest, defined as the presence of depressive symptoms consistent with the diagnosis of major depressive episode, was assessed using a short version of the Center for

Epidemiologic Studies Depression Scale (CES-D) (25). This version comprised only two questions and has been used for population screening. It has been reported that the ability for detecting depression cases using this scale is greater when the number of questions is reduced (26). Our short version was previously piloted, demonstrating high reliability scores (Cronbach's $\alpha = 0.85$) when compared to the full-length version of the scale. The two questions of this study were assessed regarding the previous seven days of the participant evaluation: (1) *"I felt that I could not shake off the blues even with help from my family or friends"* and (2) *"I felt depressed"*. Responses to both questions had four options: rarely or never (less), some or a little of the time (1 or 2 days), occasionally or a moderate amount of time (3 or 4 days), and most or all of the time (5 to 7 days). These categories, scored from 0 to 3 for each question, were summed to produce an overall score. Participants with 3 points or more were defined as having depressive symptoms. This cutoff value was derived from the pilot result, where the sensitivity and specificity were over 90% for detecting depressive symptoms using clinical diagnosis of major depressive episode according to DSM-IV criteria as the gold standard.

Other variables

Socio-demographic data, used as potential confounders and recorded during the census, included participants' sex, age (<40 or ≥ 40 years), education level (primary or less, secondary, and superior/technical), and migrant status (defined according of having been born in Lima or not).

Statistical and Spatial analysis

STATA 13 for Windows (Stata Corp, College Station, Texas, US) was used for description of the study population. To analyze the spatial distribution we used: (1) SaTScan, a statistical package for cluster detection and modeling using the spatial scan statistic, developed by Kulldorff (11) and freely available online; and (2) QGIS v.2.8 (QGIS developer team, Open Source Geospatial Foundation) to map georeferenced household points.

Descriptive statistics and the prevalence of depressive symptoms were calculated with 95% confidence intervals (95%CI) in STATA. Then, spatial clustering was assessed using SaTScan. The purely spatial (no temporal variable included) binomial model for the spatial scan statistic was selected to detect clustering of high and low prevalence (27). This iteratively tests for statistically significant clustering using a circular 'scanning window'. The window is repeatedly reconstructed, centered on each household coordinate, and the window radius expands at each iteration from zero until the time at which 50% of study households (default) are within the circle. As such, this method is able to detect clusters of varying locations, sizes and densities. Further, it does not require the specification of cluster size and location, therefore decreasing the probability of selection bias (28).

The resulting spatial scan statistic is based on the likelihood ratio test, calculating a relative risk (RR) to test whether positive and negative cases were randomly distributed throughout the study area. If this hypothesis is rejected, then the presence of a circular cluster of high or low prevalence is inferred. The cluster's relative risk, p-value, radius and centroid

coordinates (geometric center) are reported as model outputs. In other words, the statistic assesses whether the relative risk of cases (those with depressive symptoms) versus controls (those without symptoms) are significantly different inside and outside of the scanning window (28). Within this context, relative risk is defined as the number of observed cases divided by the number of expected cases, both within the scanning window and outside it. This iterative calculation process is repeated using Monte Carlo simulation to compute p-values; this study used 999 iterations, as suggested by Kulldorff (11). This simulation enables the estimation of most likely clusters, that is, the top cluster (least likely to be due to chance), and any secondary significant clusters, provided that they do not overlap.

This procedure was performed twice, first including the entire study population without adjusting for covariates, and a secondary analysis with selected socio-demographic variables (sex, age, education level, and migration status) as covariates. The adjustment for categorical covariates was made using multiple data set approach (28). Due to the number of variables restriction using SaTScan software (28), sex and age, as major covariates, were included in all the models. In addition, two specific models were created: the first one combined both sex and age with education level, and the second model combining sex and age with migration status. The boundary bias, explained by Griffith (29), was also considered when clusters were near the border of the data analyzed.

Finally, using the reported geographic information, QGIS™ was used to create map layers to illustrate the spatial distribution of potential cases of depressive symptoms. For visualization, data was jittered to avoid subject's identification.

Ethical approval

Oral informed consent was obtained by all adult participants in the study prior the procedures. This study was originally approved on April 20, 2010 by the Institutional Review Board of Universidad Peruana Cayetano Heredia in Lima, Peru.

RESULTS

Description of the population

Of the 9561 participants contacted, 1050 (10.9%) refused to participate, 455 were too young (<18 years), 105 did not have GPS data, and 5 had incomplete responses, resulting in a study population of 7946 participants, 2218 (28.3%) males, and a mean age of 39.4 (SD: 13.9).

The prevalence of depressive symptoms was 17.0% (95%CI 16.2%–17.8%). Results stratified by selected socio-demographic variables are shown in Table 1. A higher prevalence of depressive symptoms was observed amongst women, those aged 40 years, those with the lowest education level, and among migrants (Table 1).

High- and low-prevalence geographic clusters of depressive symptoms

The spatial analysis identified three statistically significant clusters of high depressive symptoms prevalence. The most likely cluster (RR=1.82; p=0.003) had a 200 meter radius and contained 276 participants, whereas the two secondary clusters (RR=2.83; p=0.004 and RR=5.9; p=0.04) featured smaller radii (96 and 18 meters, respectively) and smaller

numbers of participants (59 and 7, respectively). However, note that the one secondary cluster featured a 100% prevalence of depression symptoms.

Conversely, only two clusters of low prevalence were observed. The most likely cluster ($RR=0.23$; $p=0.016$) had a 170-meter radius, with less than 4% prevalence of depression symptoms. The secondary low-prevalence cluster ($RR=0$; $p=0.034$) featured zero cases of depressive symptoms among a study population of 64 within a 74-meter radius.

Characteristics of cluster are shown in Table 2. Spatial distributions of the cases with depressive symptoms and location of high- and low-prevalence clusters are shown in Figure 1. Additional information regarding the distribution of sex, age, education level, and migration status according to high- and low-rates clusters are shown in Supplementary Figure 1.

Adjusted cluster analyses

A total of 7798 out of 7946 (98.1%) participants with complete information regarding sex, age, educational level and migration status were used in the adjusted models. When adjusting by sex, age and educational level, two significant clusters of high prevalence of depressive symptoms were identified (Figure 2, cyan). The most likely cluster ($p=0.02$) had 160 meters radius and contained 236 participants, 70 of those have depressive symptoms. Relative risks for each stratum are shown in Table 3. On the other hand, two significant clusters were identified using a model adjusted by sex, age and migration status (Figure 2, orange). The most likely cluster ($p=0.01$) had 390 meters radius and 28 out of 641 participants in the cluster had depressive symptoms. The strata-specific relative risks are in Table 4.

The analysis did not identify clusters with low prevalence of depressive symptoms when the model was adjusted by sex, age and educational level. In contrast, sex, age and migration status model identified only one cluster with 170 meters radius ($p=0.0041$) and 25 out of 301 participants inside the cluster have depressive symptoms (Supplementary Table 1 and Supplementary Figure 2).

DISCUSSION

Main findings

Using a population-level screening tool we found the overall prevalence of depressive symptoms to be nearly 20%. The use of geographic information systems enabled the identification of spatial patterns of cases with depressive symptoms: three clusters of significantly high prevalence and two clusters of significantly low prevalence were found. Further adjustment by age, sex, and education level or migration status provided additional insights by confirming clusters previously identified or suggesting newer ones. In addition, socio-demographic variables were not homogeneously distributed in the study area (Supplementary Figure 1).

Interpretation of results

It is well known that older individuals and women have a higher probability of depression (30, 31); low education level has also been associated with elevated depression rates (21, 32). In this sense, our findings do not differ from previous reports in literature. Our spatial models report different patterns of depressive symptoms among males and females. These findings might be relevant for diagnostic and treatment interventions in these populations' strata.

According to INEI census data from 2007, the mean age in the adult population (18 years) in the study area was 29.5 years (23), 10 years lower than the observed mean in this study. This difference is likely due to a selection bias, where a person who stays at home during the day is more likely to have been the household census respondent, particularly women or older residents.

When our clusters are superimposed on socio-economic data available from INEI census information, they correspond with the lowest socio-economic areas (33), and therefore explain the high number of participants with depressive symptoms observed (34). Alternatively, the clustering of depressive symptoms among women and older participants may be explained by the aforementioned selection bias. However, other factors may play a role in the clustering of cases; as such, further study is needed.

The results obtained in demographic-adjusted models deserve more discussion. The model adjusted by sex, age, and educational level show that independently of the age category, the greatest risk of depressive symptoms occur in people with superior or technical education among males. In contrast, the greatest risk occurs in the lowest educational level among females. In both sexes the lowest risk showed in the secondary education level in most of cases (Table 3). The sex, age and migration status model show that in both age categories migrant males have the highest relative risk of depressive symptoms. The opposite pattern was present among females, where non-migrant women had the highest risk for depressive symptoms (Table 4).

The prevalence of depressive symptoms found in this study (17.0%) was triple the prevalence reported in Lima city in a previous report (6.7%) (5). A total of 70% of enrolled participants were women, a group with a relatively elevated risk of depression (3, 32). This, taken together with an older mean age among participants (39.4 years) than the census-derived average age (29.5 years) may explain the high prevalence of depressive symptoms observed in this study. Despite this, our findings may provide evidence that the true population prevalence of depressive disorders in periurban and low-income areas is disproportionately high (35, 36). About two thirds of the study population were migrants, and a great proportion of them left Andean areas (23). Migration process were due to economic advantages in the capital of Peru, Lima, but also because of the period of political violence, which could have impacted the mental health of participants (37).

Relevance

Geographic mapping is a useful method for producing a quick visual summary of patterns of disease prevalence, contributing to an understanding of underlying mechanisms, and helping

to identify high- and low-risk populations (38). In this study area, some neighborhoods characteristics (i.e. built environment and social structures) might explain the elevated risk of depression. For example, there are few specialized health centers for mental health and there is a lack of human resources (39). Clusters with a high prevalence of depressive symptoms were in deprived areas (33), for example, households were built with mud and thatch, and there was no electricity, water or sanitation services. In addition, safety and crime rates are not uncommon. On the other hand, areas with low prevalence are located in the commercial sector of the setting. Of note, and paradoxically, one of the low prevalence areas, located at the highest elevation area, shares many of the environmental characteristics of the high prevalence areas, particularly higher deprivation in terms of infrastructure. This finding cannot be explained by the present analysis and signals an area for future research to identify factors behind this paradox towards better depressive symptom profiles, including resilience.

Strengths and limitations

This study is strengthened by the active mapping of nearly 90% of households in the area. Most previous reports are based on passive surveillance of reported cases of depression among those who seek help in the healthcare systems; however, by using census-derived sampling, we were able to produce a more comprehensive population-based profiling of depression risk. Additionally, our use of cluster detection comprises a novel application in the field of mental health research. Recent advances in geographic information systems and spatial modeling, in addition to the growing availability of high-resolution satellite imagery for mapping health data and the built environment, have facilitated rapid growth and increasing sophistication in spatial epidemiology (40). Further expansion of these technologies will enrich our understanding of mental health burden, thus holding promise for the design of place-specific screening strategies and interventions in resources-constrained settings.

This study was, however, limited by the use of a screening tool rather than a diagnostic tool; as such, we could not collect detailed information on other known factors associated with depression. Because the census is designed to collect information regarding the general population, resources were not available to perform a comprehensive clinical case identification. A selection bias may occur because only one person per household responded to the questions regarding depressive symptoms, which accounts for the disproportionately high number of female and older respondents in our sample. In addition, this study reports only self-reported symptoms of depression and not the diagnosis of a depressive disorder; as such, the use of the quick screening instrument provides only a cursory approach to the magnitude and concentration of the problem. Despite of relatively high sensitivity and specificity of our screening tool, this could result in the misclassification of cases with depressive symptoms. Finally, in this phase of the fieldwork, other features of the built environment were not mapped, such as parks and recreational areas. Although several high- and low-prevalence clusters were found in this study, additional small-scale clusters could not be identified due to a lack of statistical power.

Conclusion

In conclusion, we found strong evidence of the existence of geographical clusters of depressive symptoms in a periurban area of Lima, Peru's capital. We found high-and low-prevalence clusters among the sampled population, and variable patterns of clusters of depression symptoms and selected socio-demographic variables. The utility of screening strategies in combination with mapping techniques and spatial analysis are underscored for their power to identify high-risk areas and focus interventions, particularly in resource-limited areas.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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LIST OF ABBREVIATIONS

95%CI	95% confidence intervals
CES-D	Center for Epidemiologic Studies Depression Scale
GIS	Geographic information system
GPS	Global positioning system
INEI	National Institute of Statistics and Informatics
QGIS	Quantum geographic information system
RR	Relative risk
SD	standard deviation

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REFERENCES

1. Prince M, Patel V, Saxena S, Maj M, Maselko J, Phillips MR, et al. No health without mental health. *Lancet*. 2007; 370(9590):859–877. [PubMed: 17804063]
2. Ferrari AJ, Charlson FJ, Norman RE, Patten SB, Freedman G, Murray CJ, et al. Burden of depressive disorders by country, sex, age, and year: findings from the global burden of disease study 2010. *PLoS Med*. 2013; 10(11):e1001547. [PubMed: 24223526]
3. Jacob KS, Sharan P, Mirza I, Garrido-Cumbrera M, Seedat S, Mari JJ, et al. Mental health systems in countries: where are we now? *Lancet*. 2007; 370(9592):1061–1077. [PubMed: 17804052]
4. Murray CJ, Vos T, Lozano R, Naghavi M, Flaxman AD, Michaud C, et al. Disability-adjusted life years (DALYs) for 291 diseases and injuries in 21 regions, 1990–2010: a systematic analysis for the Global Burden of Disease Study 2010. *Lancet*. 2012; 380(9859):2197–2223. [PubMed: 23245608]
5. Estudio Epidemiológico Metropolitano en Salud Mental 2002. Informe General. *Anales de Salud Mental*. 2002; XVIII(1 y 2):1–199.
6. Moore DA, Carpenter TE. Spatial analytical methods and geographic information systems: use in health research and epidemiology. *Epidemiologic reviews*. 1999; 21(2):143–161. [PubMed: 10682254]
7. Hanafi-Bojd AA, Vatandoost H, Oshaghi MA, Charrahy Z, Haghdooost AA, Zamani G, et al. Spatial analysis and mapping of malaria risk in an endemic area, south of Iran: A GIS based decision making for planning of control. *Acta Trop*. 2012
8. Levy MZ, Bowman NM, Kawai V, Plotkin JB, Waller LA, Cabrera L, et al. Spatial patterns in discordant diagnostic test results for Chagas disease: links to transmission hotspots. *Clin Infect Dis*. 2009; 48(8):1104–1106. [PubMed: 19278335]
9. Lin H, Shin S, Blaya JA, Zhang Z, Cegielski P, Contreras C, et al. Assessing spatiotemporal patterns of multidrug-resistant and drug-sensitive tuberculosis in a South American setting. *Epidemiol Infect*. 2010;1–10.
10. Elebead FM, Hamid A, Hilmi HS, Galal H. Mapping Cancer Disease Using Geographical Information System (GIS) in Gezira State-Sudan. *J Community Health*. 2012
11. Kulldorff M, Feuer EJ, Miller BA, Freedman LS. Breast cancer clusters in the northeast United States: a geographic analysis. *Am J Epidemiol*. 1997; 146(2):161–170. [PubMed: 9230778]
12. Berke EM, Gottlieb LM, Moudon AV, Larson EB. Protective association between neighborhood walkability and depression in older men. *Journal of the American Geriatrics Society*. 2007; 55(4): 526–533. [PubMed: 17397430]
13. Bhana A, Pillay YG. The Use of the Geographical Information System (GIS) to Determine Potential Access and Allocation of Public Mental Health Resources in KwaZulu-Natal. *African Journal of Psychology*. 1998; 28:222–233.
14. Fortney J, Rost K, Zhang M, Warren J. The impact of geographic accessibility on the intensity and quality of depression treatment. *Medical care*. 1999; 37(9):884–893. [PubMed: 10493467]
15. Kim D. Blues from the neighborhood? Neighborhood characteristics and depression. *Epidemiologic reviews*. 2008; 30:101–117. [PubMed: 18753674]
16. Salinas-Perez JA, Garcia-Alonso CR, Molina-Parrilla C, Jorda-Sampietro E, Salvador-Carulla L. Identification and location of hot and cold spots of treated prevalence of depression in Catalonia (Spain). *International journal of health geographics*. 2012; 11:36. [PubMed: 22917223]
17. Garcia-Alonso CR, Salvador-Carulla L, Negrin-Hernandez MA, Moreno-Kustner B. Development of a new spatial analysis tool in mental health: identification of highly autocorrelated areas (hot-spots) of schizophrenia using a Multiobjective Evolutionary Algorithm model (MOEA/HS). *Epidemiol Psychiatr Soc*. 2010; 19(4):302–313. [PubMed: 21322504]
18. Ghosh D, Sterns AA, Drew BL, Hamera E. Geospatial Study of Psychiatric Mental Health-Advanced Practice Registered Nurses (PMH-APRNs) in the United States. *Psychiatr Serv*. 2011; 62(12):1506–1509. [PubMed: 22193800]

19. Moreno B, Garcia-Alonso CR, Negrin Hernandez MA, Torres-Gonzalez F, Salvador-Carulla L. Spatial analysis to identify hotspots of prevalence of schizophrenia. *Soc Psychiatry Psychiatr Epidemiol.* 2008; 43(10):782–791. [PubMed: 18500483]
20. Elovainio M, Pulkki-Raback L, Jokela M, Kivimaki M, Hintsanen M, Hintsala T, et al. Socioeconomic status and the development of depressive symptoms from childhood to adulthood: A longitudinal analysis across 27 years of follow-up in the Young Finns study. *Soc Sci Med.* 2012
21. Park JH, Kim KW, Kim MH, Kim MD, Kim BJ, Kim SK, et al. A nationwide survey on the prevalence and risk factors of late life depression in South Korea. *J Affect Disord.* 2012
22. Miranda JJ, Bernabe-Ortiz A, Smeeth L, Gilman RH, Checkley W. Addressing geographical variation in the progression of non-communicable diseases in Peru: the CRONICAS cohort study protocol. *BMJ Open.* 2012; 2(1):e000610.
23. Instituto Nacional de Estadística e Informática. Censos Nacionales 2007: XI de Población y VI de Vivienda: Sistema de Consulta de Resultados Censales. Available from: <http://desa.inei.gob.pe/censos2007/tabulados/>.
24. Garmin Ltd. , editor. Garmin. E-Trex H Personal Navigator: Owner's Manual. Kansas, US: 2007.
25. Radloff LS. The CES-D Scale: A self-report depression scale for research in the general population. *Appl Psychol Meas.* 1977; 1(3):385–401.
26. Santor DA, Coyne JC. Shortening the CES-D to improve its ability to detect cases of depression. *Psychol Assess.* 1997; 9(3):233–243.
27. Fritz CE, Schuurman N, Robertson C, Lear S. A scoping review of spatial cluster analysis techniques for point-event data. *Geospatial health.* 2013; 7(2):183–198. [PubMed: 23733283]
28. Kulldorff M. SaTScan User Guide for version 9.4: Information Management Services, Inc. 2015
29. Griffith DA. The boundary value problem in spatial statistical analysis. *Journal of regional science.* 1983; 23(3):377–387. [PubMed: 12279616]
30. Screening for depression in adults: U.S. preventive services task force recommendation statement. *Ann Intern Med.* 2009; 151(11):784–792. [PubMed: 19949144]
31. Hertaigh BO, Loerbroks A, Thomas GN, Engeland CG, Hollands MA, Fischer JE, et al. Age-dependent and -independent associations between depression, anxiety, DHEAS, and cortisol: From the MIPH Industrial Cohort Studies (MICS). *Psychoneuroendocrinology.* 2011
32. Cwikel J, Zilber N, Feinson M, Lerner Y. Prevalence and risk factors of threshold and sub-threshold psychiatric disorders in primary care. *Soc Psychiatry Psychiatr Epidemiol.* 2008; 43(3): 184–191. [PubMed: 18026679]
33. Instituto Nacional de Estadística e Informática. Sistema de Información Geográfica para Emprendedores Lima. Perú: INEI; 2011. Available from: <http://sige.inei.gob.pe/sige/>. [cited 2012 Enero 23]
34. Schmidt MI, Duncan BB, Azevedo e Silva G, Menezes AM, Monteiro CA, Barreto SM, et al. Chronic non-communicable diseases in Brazil: burden and current challenges. *Lancet.* 2011; 377(9781):1949–1961. [PubMed: 21561658]
35. Gonzalez HM, Haan MN, Hinton L. Acculturation and the prevalence of depression in older Mexican Americans: baseline results of the Sacramento Area Latino Study on Aging. *Journal of the American Geriatrics Society.* 2001; 49(7):948–953. [PubMed: 11527487]
36. Lu Y. Mental health and risk behaviours of rural-urban migrants: Longitudinal evidence from Indonesia. *Popul Stud (Camb).* 2010; 64(2):147–163. [PubMed: 20408057]
37. Pedersen D, Tremblay J, Errazuriz C, Gamarra J. The sequelae of political violence: assessing trauma, suffering and dislocation in the Peruvian highlands. *Soc Sci Med.* 2008; 67(2):205–217. [PubMed: 18423959]
38. Elliott P, Wartenberg D. Spatial epidemiology: current approaches and future challenges. *Environ Health Perspect.* 2004; 112(9):998–1006. [PubMed: 15198920]
39. Instituto Nacional de Salud Mental. Estudio epidemiológico metropolitano en salud mental 2002. Informe General. *Anales de Salud Mental.* 2004; 18(1–2):1–199.
40. Kleinschmidt I, Pettifor A, Morris N, MacPhail C, Rees H. Geographic distribution of human immunodeficiency virus in South Africa. *Am J Trop Med Hyg.* 2007; 77(6):1163–1169. [PubMed: 18165541]

HIGHLIGHTS

- Previous reports regarding mental health and geographic distribution are based on passive surveillance among those who seek help in the healthcare systems.
- Spatial patterns of cases with depressive symptoms were found suggesting that neighborhood characteristics may play a role in the development of depressive symptoms.
- Using a population-level screening tool, almost one in five individuals presented symptoms of depression in the study area.

Figure 1.
Distribution of cases with depressive symptoms and significant high- and low-prevalence clusters in Pampas de San Juan de Miraflores

Figure 2.

Location of adjusted clusters for high rates of depressive symptoms in Pampas de San Juan de Miraflores. *Orange* = sex, age and educational level covariates adjustment and *cyan* = sex, age and migration status adjustment

Table 1

Description of the study population

Characteristics	Depressive symptoms		p-value
	No [N (%)]	Yes [N (%)]	
Sex			
Female	4518 (80.3)	1110 (19.7)	< 0.001
Male	1986 (89.5)	232 (10.5)	
Age			
Under 40 years	3512 (86.2)	563 (13.8)	< 0.001
40 years and more	2959 (79.2)	775 (20.8)	
Education level			
Primary or less	1354 (75.7)	434 (24.3)	< 0.001
Secondary	3468 (83.7)	674 (16.3)	
Superior/Technical	1676 (87.9)	231 (12.1)	
Migrant status			
No	2733 (85.8%)	454 (14.3%)	< 0.001
Yes	3769 (80.9%)	888 (19.1%)	

* Results may not add due to missing values.

Table 2

Characteristics of clusters with high and low prevalence of depressive symptoms

	High prevalence (Hot spot)		Low prevalence (Cold spot)	
	Most likely cluster	Secondary clusters	Most likely cluster	Secondary cluster
Coordinates	12.177 S; 76.956 W	12.184 S; 76.957 W	12.189 S; 76.954 W	12.185 S; 76.952 W
Altitude (meters)	211	175	130	219
Radius (meters)	200	96	170	74
Population size in cluster	276	59	151	64
Observed cases	83	28	6	0
Expected cases	46.96	10.04	25.69	10.89
Relative risk (RR)	1.82	2.83	0.23	0
p-value	0.003	0.004	0.016	0.034

Characteristics of most likely clusters to high prevalence of depressive symptoms adjusted by sex, age and educational level (Coordinates = 12.187 S, 76.955 W; 160 meters radius; $p=0.015$)

Table 3

Variable combination			Population size in cluster	Observed cases	Expected cases	Relative risk (RR)
Sex	Age	Educational level				
Male	<40 years	Primary or less	3	1	0.62	1.71
		Secondary	24	3	2.18	1.4
		Superior/Technical	8	2	0.67	3.13
	>40 years	Primary or less	8	1	1.1	0.91
		Secondary	12	1	1.41	0.71
		Superior/Technical	5	3	0.54	6.13
Female	<40 years	Primary or less	13	7	3.11	2.38
		Secondary	59	21	9.71	2.26
		Superior/Technical	27	2	2.96	0.67
	>40 years	Primary or less	43	23	11.65	2.05
		Secondary	29	5	6.57	0.76
		Superior/Technical	5	1	1.02	0.98

Table 4

Characteristics of most likely clusters to high prevalence of depressive symptoms adjusted by sex, age and migration status (Coordinates = 12.178 S, 76.954 W; 390 meters radius; $p=0.014$).

Variable combination		Population size in cluster	Observed cases	Expected cases	Relative risk (RR)
Sex	Age	Migration status			
Male	<40 years	Migrant	3	0.51	6.33
		No migrant	2	0.78	2.6
	>40 years	Migrant	3	0.57	5.44
		No migrant	0	0.29	0
Female	<40 years	Migrant	4	1.48	2.73
		No migrant	4	1.19	3.41
	>40 years	Migrant	11	4.85	2.3
		No migrant	1	0.24	4.12