

Determinants and spatial variations of Korea's National Cancer Screening Program in 2018 and 2022: Focus on Weighted Ordinary Least Squares Regression and Local Indicators of Spatial Association

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Abstract

Background

The Korean National Cancer Screening Program (KNCSP) addresses prevalent cancers; however, there is a lack of comprehensive understanding regarding municipal-level disparities in screening engagement and spatial patterns. This study aimed to analyze the correlation between municipal health metrics and cancer screening rates, and to determine if spatial clustering persisted even after adjusting for these metrics.

Methods

We calculated screening rates for stomach, colorectal, liver, breast, and cervical cancers using a customized National Health Insurance Service (NHIS) KNCSP database and linked 10 municipal indicators from the Korean Community Health Status Indicators (K-CHSI) related to cancer screening rates in 2018 and 2022. We evaluated the unadjusted correlation between the screening rate and municipal indicators and estimated the adjusted associations using a weighted regression model. Residual local indicators of spatial association were employed to identify clusters of municipalities with higher or lower participation and to detect emerging spots.

Results

In 2018, the screening rate was highest for breast cancer (77.6%) and stomach cancer (76.1%). By 2022, breast and stomach cancer screening rates remained the highest, with breast cancer at 62.3% and stomach cancer at 62.1%. General health examination rate in 2022 was the most significant positive factor for breast cancer screening ($\beta = 0.582$, $SE = 0.067$, $p < 0.001$) and stomach cancer screening ($\beta = 0.502$, $SE = 0.086$, $p < 0.001$). Conversely, the elderly population ratio was the most substantial negative factor for cervix cancer screening ($\beta = -0.481$, $SE = 0.067$, $p < 0.001$). Spatial analysis revealed Local Indicators of Spatial Association (LISA) maps displaying localized high- and low-participation clusters in screening rates, while residual LISA identified clusters that deviated from the expected rates after regression adjustment.

Conclusion

Factors influencing the municipal KNCSP screening rate between 2018 and 2022 were primarily linked to general health examinations and population aging. However, the persistent presence of cold spots/hotspots in the residual spatial analysis indicates the potential presence of other contributing factors beyond those considered in the analysis. Integrating population-weighted regression with

residual spatial diagnostics can aid in identifying and prioritizing municipalities for focused local evaluations and customized implementation strategies.

Introduction

Cancer remains a significant contributor to the disease burden in South Korea. In 2021, the age-standardized cancer incidence rate was approximately 289.3 per 100,000 individuals, with stomach, colorectal, lung, liver, and breast cancers representing a considerable proportion of the new cases [1]. To address this challenge, South Korea has established the National Cancer Screening Program (KNCSP). Initially focusing on screening for stomach, breast, and cervical cancers [2], the program has expanded to include lung cancer screening, now encompassing six cancer types (stomach, colorectal, liver, lung, breast, and cervix) [3].

Evidence from observational and case-control studies indicates that organized screening in Korea has led to decreases in cancer-specific mortality, especially for stomach and colorectal cancers, and has demonstrated favorable cost-effectiveness in national evaluations [4–6]. Although there have been general enhancements in screening uptake since 2004, national screening surveys have indicated variations in participation rates and the rate of progress among different cancer types, age brackets, and socioeconomic classes [7]. These disparities suggest that the advantages of screening are not uniformly accessible to all demographic groups.

Importantly, differences in screening participation cannot be explained solely by individual characteristics [8]. Previous studies have shown that multi-level analyses indicate that municipal contexts, such as local deprivation and urbanicity, may influence screening rates, even when considering individual-level factors [9]. These results imply that screening participation might be influenced by factors that differ among municipalities, potentially masking significant local variations and inadequately addressing municipal-level discrepancies.

However, the current research has not fully characterized how municipal-level contextual factors relate to screening participation across multiple KNCSP cancers and over time at the national scale. Additionally, municipal screening performance is likely to be geographically structured: neighboring municipalities often share healthcare markets, transportation networks, administrative practices, and sociocultural environments [10]. Consequently, disparities in participation may arise not only as isolated high- or low-performing municipalities but also as spatially contiguous patterns that can concentrate advantages or disadvantages across broader regions [11]. Spatial epidemiology offers a complementary set of tools for this purpose [12]. Spatial analyses are commonly utilized to characterize geographic disease patterns [13] and to identify statistically significant clusters (“hotspots” and “coldspots”) [14], aiding policy decisions by assisting in prioritizing areas and allocating resources for prevention and control [12].

Therefore, we conducted this study to examine municipal-level disparities in KNCSP screening participation, identify associations between participation and municipal health indicators, and assess

whether the spatial structure remains after accounting for these indicators by evaluating the residual spatial autocorrelation and localized residual clusters.

Methods

Data sources

A repeated cross-sectional study was carried out at the municipal level (si-gun-gu) [15]. The analytic cohort was established using the National Health Insurance Service (NHIS)-customized database, comprising individuals eligible in 2018 who had undergone national cancer screening at least once. The study focused on the five cancers covered at that time: stomach, colorectal, liver, breast, and cervical cancer. Lung cancer screening, introduced in 2019, was excluded due to the unavailability of a precise 2018-based eligible target population for consistent comparison [2]. The NHIS-customized KNCSP data (2018–2023) was linked to the K-CHSI database [16]. Municipal covariates from the K-CHSI (2018 and 2022) were used to characterize community health status and its determinants [16]. All analyses were based on harmonized 2022 Statistical Geographic Information Service municipal boundaries, consistent with 2018 ($n = 250$) [17–19].

Variables

We selected 10 municipal-level indicators potentially related to cancer screening participation: (1) elderly population ratio, (2) population density, (3) national basic livelihood security recipient rate, (4) general health examination rate, (5) obesity rate (self-reported, age-standardized), (6) hypertension diagnosis experience rate, (7) diabetes diagnosis experience rate, (8) number of clinics per 100,000 population, (9) financial independence, and (10) health expenditure cost. These indicators were chosen to represent key contextual domains associated with cancer screening participation, including socio-demographic composition, preventive care engagement, population health profiles, healthcare resource availability, and municipal fiscal capacity [7, 20]. In cases where municipal-level values were unavailable, missing values were imputed using the corresponding higher-level administrative values to maintain nationwide spatial coverage.

Statistical analysis

We calculated the cancer screening rates (%) of the NHIS-customized database populations for 2018 and 2022. Subsequently, we analyzed the simple correlation between the community indicators and the cancer screening test rate using the Pearson correlation coefficient (r). To delve deeper into the correlation, we employed the Ordinary Least Squares (OLS) regression model, with the number of screening-eligible populations at the municipality level serving as a weight [21, 22]. Given that the KNCSP liver screening occurs semiannually [23], the primary analysis considered annual completion as the screening completion in both halves of the year. Additionally, sensitivity analyses utilized municipality-

level liver screening rates from the NHIS health screening statistical yearbooks (2018 and 2022), following the same linkage and modeling procedures [24, 25].

We evaluated global residual spatial autocorrelation by employing Moran's I [26] and examined local clustering through Local Indicators of Spatial Association (LISA) [27]. LISA analysis was conducted using (i) observed municipal screening rates and (ii) OLS model residuals (residual LISA) to determine if spatial clustering persisted after adjusting for the chosen municipal indicators [28, 29]. The residuals of the OLS regression were used for the residual LISA to confirm whether there was a regional imbalance other than in the selected municipal indicators [30]. The statistical analyses were carried out using SAS 9.4 and R software (version 4.5.1).

Results

Across all municipalities, the screening rate in 2018 was highest for breast cancer (77.59%) and stomach cancer (76.08%), followed by cervical cancer (62.73%), colorectal cancer (46.21%), and liver cancer (29.29%). In 2022, the screening rate decreased for stomach cancer (62.14%), colorectal cancer (37.25%), breast cancer (62.27%), and cervical cancer (54.76%), while it increased for liver cancer (41.29%), indicating cancer-site-specific temporal patterns (Table 1). The municipal covariates also exhibited minor heterogeneity each year.

Table 1

Descriptive statistics of cancer screening rate and municipality variables in 2018 and 2022.

Characteristics	2018		2022	
	Mean	SD	Mean	SD
Screening rate (%)				
stomach cancer	76.08	3.41	62.14	3.24
colorectal cancer	46.21	4.85	37.25	4.41
liver cancer	29.29	5.97	41.29	7.69
breast cancer	77.59	3.54	62.27	4.57
cervix cancer	62.73	6.88	54.76	7
Variables				
Elderly population ratio (%)	19.42	8.01	23.32	8.87
Population density, people/km ²	3856.76	5892.5	3827.39	5747.87
National basic livelihood security recipient rate (%)	4.01	1.53	5.44	1.93
General health examination rate (%)	76.22	3.29	74.17	3.34
Obesity rate self report standardization rate (%)	31.52	3.81	32.83	3.68
Hypertension diagnosis experience rate (%)	19.45	2.29	20.31	2.54
Diabetes diagnosis experience rate (%)	7.96	1.29	9.03	1.54
Number of clinics per 100,000 population	57.01	31.23	60.62	35.33
Financial independence (%)	28.93	14.44	25.29	13.42
Health expenditure cost (%)	2.32	0.8	2.57	0.78
SD=standard deviation.				

Pearson correlations (Figure S1) were analyzed to depict raw municipality-level associations between screening participation and candidate covariates and to guide subsequent multivariate modeling. The correlations varied depending on the cancer site and year, showing stronger associations in 2022 for breast and cervical cancer screening, particularly with general health examination rates and indicators of urbanicity and fiscal capacity. To account for potential confounding and intercorrelated covariates, population-weighted OLS models were employed to estimate the adjusted associations. The results of the Pearson correlation analysis can be found in Supplementary Table 1.

All population-weighted OLS models were statistically significant (F-test, $p < 0.001$) for both years (Supplementary Table 2). The standardized regression coefficients are listed in Table 2 (β , standard error;

SE), and full estimates (SEs, p-values) are also provided in Table 2. All VIF were estimated to be less than 5, and multicollinearity was not confirmed.

In 2018, the two largest absolute standardized coefficients for breast cancer screening were observed in the general health examination rate ($\beta = 0.390$, SE = 0.089, $p < 0.001$) and population density ($\beta = 0.269$, SE = 0.075, $p < 0.001$). Regarding cervix cancer screening, the most significant inverse coefficient was associated with the elderly population ratio ($\beta = -0.466$, SE = 0.093, $p < 0.001$), followed by the general health examination rate ($\beta = 0.199$, SE = 0.085, $p = 0.020$). In the context of stomach cancer screening, financial independence exhibited the largest inverse coefficient ($\beta = -0.326$, SE = 0.135, $p = 0.017$), while the elderly population ratio displayed the second-largest coefficient in absolute magnitude ($\beta = 0.226$, SE = 0.101, $p = 0.025$). For colorectal cancer screening, the hypertension diagnosis experience rate demonstrated the most substantial positive coefficient ($\beta = 0.294$, SE = 0.078, $p < 0.001$), with the subsequent largest coefficient in absolute magnitude associated with the number of clinics per 100,000 population ($\beta = -0.207$, SE = 0.136, $p = 0.130$), although it was not statistically significant. Concerning liver cancer screening, the elderly population ratio exhibited the most significant inverse coefficient ($\beta = -0.420$, SE = 0.118, $p < 0.001$), while the national basic livelihood security recipient rate displayed the most substantial positive coefficient ($\beta = 0.280$, SE = 0.111, $p = 0.012$).

By 2022, the rate of general health examinations is expected to play a more significant role in the screening for several cancers. In breast cancer screening, the general health examination rate showed the highest positive coefficient and strengthened ($\beta = 0.582$, SE = 0.067, $p < 0.001$), while the second-largest coefficient in absolute magnitude indicated an inverse association with the elderly population ratio ($\beta = -0.212$, SE = 0.081, $p = 0.009$). In cervix cancer screening, the most substantial inverse coefficient with the elderly population ratio persisted ($\beta = -0.481$, SE = 0.067, $p < 0.001$), with the second-largest coefficient once again attributed to the general health examination rate ($\beta = 0.304$, SE = 0.059, $p < 0.001$). Regarding stomach cancer screening, the general health examination rate emerged as the dominant factor ($\beta = 0.502$, SE = 0.086, $p < 0.001$), while the second-largest coefficient, inversely associated with financial independence ($\beta = -0.203$, SE = 0.143, $p = 0.156$), was not statistically significant. In colorectal cancer screening, the rate of hypertension diagnosis experience remained the most significant coefficient ($\beta = 0.256$, SE = 0.074, $p = 0.001$), with the general health examination rate emerging as the second-largest factor ($\beta = 0.245$, SE = 0.108, $p = 0.024$). For liver cancer screening, the elderly population ratio continued to show the most substantial inverse coefficient ($\beta = -0.416$, SE = 0.110, $p < 0.001$), while financial independence represented the second-largest inverse coefficient ($\beta = -0.347$, SE = 0.106, $p = 0.001$); the rate of national basic livelihood security recipients also remained positive and similar in magnitude ($\beta = 0.333$, SE = 0.082, $p < 0.001$).

Because liver cancer screening is recommended semiannually for high-risk individuals [23], we compared the strict annual completion definition (liver1) with a yearbook-based definition (liver2). As demonstrated in Supplementary Table 3, liver2 resulted in a significantly higher screening rate and a more limited range than liver1 in both 2018 and 2022, while the general trend of adjusted associations

was largely consistent across definitions. The residual spatial autocorrelation also stayed positive under both definitions, although Moran's I was slightly greater for liver1 than for liver2.

The global Moran's I calculated for residuals from the weighted OLS models was significantly positive for all cancer sites in both years (all $p < 0.001$; Moran's I = 0.201–0.416; Supplementary Table 4), indicating that the remaining spatial autocorrelation was not explained by the included municipal covariates. We further assessed the local clustering using LISA for both raw screening rates and model residuals (residual LISA) (Fig. 1). The cluster type of LISA is classified into "high-high," "low-low," "high-low," and "low-high" based on the values of each municipality and the average value of adjacent regions. After adjusting for municipal indicators, the number and extent of significant local clusters generally decreased; however, residual clusters remained at several cancer sites and years. These findings suggest that the selected municipal indicators explained some, but not all, of the spatial patterns in screening participation.

Discussion

Across municipalities, screening participation levels and temporal changes varied by cancer site. In 2018, the screening rate was highest for stomach and breast cancer, moderate for cervical cancer, lower for colorectal cancer, and lowest for liver cancer (requiring completion in both halves of the year). By 2022, the screening rate had decreased for stomach, breast, cervical, and colorectal cancers, while liver cancer screening had increased, showing diverse time trends across sites within the same national program framework.

Across the Pearson correlation and weighted OLS analyses, two municipal characteristics consistently emerged as significant correlates of the screening rate: the general health examination rate and the ratio of elderly population. Specifically, for breast and cervical cancer screening, the associations with the general health examination rate and urbanicity-related indicators were more pronounced in 2022 compared to 2018. Conversely, municipalities with a higher proportion of elderly residents tended to exhibit lower screening rates. In contrast, colorectal screening exhibited weaker associations with municipal covariates and consistently low model explanatory power, indicating that a considerable portion of the variation between municipalities may be influenced by factors not included in the analyzed contextual indicators. Despite achieving a moderate-to-high global model fit for several types of cancer, the residual Moran's I remained significantly positive across all locations and years [26]. Additionally, the residual LISA analysis identified municipalities that consistently deviated from the model-predicted screening rates, suggesting that the remaining spatial clustering was not explained by the covariates [28].

In sensitivity analyses for liver cancer screening, residual Moran's I differed slightly between definitions, indicating that the strict semiannual-completion definition might capture slightly larger between-municipality disparities [23]. Conversely, the weighted OLS results, including correlations and

standardized coefficients, exhibited consistent trends and a similar pattern of significant associations across definitions [24, 25].

These patterns align with the general premise from previous studies that screening rate reflects both individual-level propensity and enabling local environments, including access, health information exposure, and the broader preventive-care “culture” reflected in general health examination rate [9]. Colorectal cancer screening showed weaker municipal-level associations and a consistently lower model explanatory power than screening at other cancer sites. One possible interpretation is that this pattern reflects the distinctive screening modality used in the NCSP for colorectal cancer, which relies on fecal occult blood testing rather than facility-based imaging or examination procedures [31, 32]. Prior qualitative and mixed-method evidence suggests that colorectal screening uptake may be strongly influenced by embarrassment, disgust, avoidance, and perceived inconvenience of the test process, in addition to structural access barriers [32–34]. Accordingly, the comparatively weak municipal associations observed in our study may indicate that participation in colorectal screening is shaped more strongly by individual-level psychological or behavioral barriers than by area-level indicators alone [31, 34]. However, this interpretation should be considered with caution because low explanatory power may also reflect unmeasured confounding at the provider, programmatic, or community levels.

The public health and policy implications of this study are as follows: First, integrating municipal screening rate indicators into routine subnational equity monitoring may help identify areas where the screening rate remains persistently lower than expected, given the observed context [35]. Such “residual” patterns are particularly informative because they point to municipalities that may require additional local investigation beyond standard structural determinants.

Secondly, the robust and increasingly consistent association between cancer screening and general health checkup participation, particularly breast and cervical cancer screening, indicates that screening rates may cluster within wider preventive care engagement at the community level. This suggests that interventions aimed at enhancing cancer screening uptake might be more effective when integrated with broader preventive care initiatives rather than being implemented in isolation. These findings advocate for a place-based equity approach to improving the KNCSP: Municipalities with persistently low screening rates should receive priority for targeted local assessment and customized implementation strategies, while enhancing community-wide preventive care involvement could have positive impacts across various screening programs. Future studies should consider a multi-level analysis that systematically examines individual and regional factors influencing cancer screening to more precisely investigate the determinants of screening behavior.

This study had several limitations. First, the analysis is based on municipal averages; therefore, individual-level causal inference is not possible, and ecological fallacy remains a concern [15, 36]. Second, we compared the two time points (2018 and 2022). The 2022 estimates may reflect, in part, changes in healthcare utilization and program operations during and after the COVID-19 pandemic. Thus, temporal comparisons should be interpreted rather than as causal effects of specific events or policies.

Third, some K-CHSI indicators require harmonization and imputation at the municipal level when more granular values are unavailable, which may introduce measurement errors and attenuate associations. Fourthly, while we included a set of 10 municipal indicators spanning demographics, deprivation, chronic disease burden, healthcare supply, and fiscal context, other potentially important determinants were not measured (e.g., transportation accessibility, local outreach intensity, private screening utilization, provider practice patterns, and sociocultural factors). In particular, the relatively weak associations for colorectal cancer screening may reflect the fact that important determinants of fecal test uptake, such as embarrassment, aversion, and perceived inconvenience, were not captured by the municipal indicators used in this study. Such omitted factors may partly explain the residual spatial clustering observed in Moran's I and the residual LISA.

Fifth, regression diagnostics indicated influential observations were present [21, 22]. We kept these influential municipalities to maintain the real-world spatial structure essential for interpretation. However, some models still exhibited residual non-normality, and there are lingering concerns about multiple testing [29]. Despite these limitations, this study offered a systematic municipal-level evaluation of screening participation across five cancers and illustrated the enhanced benefits of integrating regression with residual spatial diagnostics.

Finally, as the population of the NHIS customized database study included individuals who had undergone the KNCSP at least once, the screening rate consistently exceeded that of the entire population. Consequently, there may be limitations in generalizing the study results, but it also presents significant strengths. The study utilized a nationwide dataset at the municipality level encompassing all 250 Sigungu and five cancer screening programs at two time points. Furthermore, through a combination of regression-based assessment and residual spatial diagnostics, the study successfully differentiated between geographic patterns explained by measured municipal indicators and those that persisted independently. The sensitivity analysis for liver screening further enhanced the robustness of the primary interpretation, demonstrating that the overall pattern of key associations and residual spatial structure remained largely consistent across alternative definitions.

Conclusion

In this nationwide municipal assessment, screening participation exhibited significant geographic variation and divergent time trends within Korea's organized KNCSP between 2018 and 2022. The screening rates have decreased for stomach, colorectal, breast, and cervical cancers, while there has been an increase in liver cancer screening. Notably, the cancer screening rate correlated systematically with certain community health indicators, with higher screening rates observed in municipalities showing greater involvement in preventive care and a more favorable demographic context. This suggests that screening disparities are reflective of broader community-level conditions rather than isolated individual behavioral differences. These results advocate for a place-based equity approach to improving KNCSP, emphasizing the prioritization of municipalities with consistently low or below-expected participation

rates for targeted local assessments, context-specific outreach, and customized implementation strategies.

Declarations

Author Contributions

All authors contributed to and approved the final draft of the manuscript.

Conception and design: Dae Hun Ryu, Mina Suh, Eun Kyo Kang, Chang Kyun Choi Hyeon Ji Lee, Sokbom Kang

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Data availability

The data that support the findings of this study were derived from the National Health Insurance Service (NHIS) customized database, the Korean Community Health Status Indicators (K-CHSI) database, and Statistical Geographic Information Service (SGIS) municipal boundary data.

The NHIS customized data are not publicly available because they contain individual-level health insurance and cancer screening records provided under approval for the current study and are subject to data protection and institutional access restrictions. These data may be made available from the NHIS

upon reasonable request and after approval through the NHIS data access procedures (research management number: NHIS-2025-01-1-006).

The K-CHSI data are publicly available from the Korea Community Health Survey website and can be downloaded by selecting the file download option:

<https://chs.kdca.go.kr/chs/rdr/rdrInfoProcessMain.do>

The SGIS municipal boundary data are available from the Statistical Geographic Information Service website, subject to the provider's terms and conditions of use:

<https://sgis.kostat.go.kr>

The linked analytic dataset generated and analyzed in the current study cannot be shared publicly because it incorporates restricted NHIS customized data. Aggregate results supporting the findings of this study are included in this article and its supplementary information files.

Conflict of Interest Statement

All authors declare no potential conflict of interest relevant to this article.

Ethics approval and consent to participate

This study was approved by the Institutional Review Board of the National Cancer Center, Korea (IRB No. NCC2024-0220). The requirement for informed consent was waived by the Institutional Review Board because this study used de-identified secondary data.

Consent for publication

Not applicable.

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Table 2

Table 2 is available in the Supplementary Files section.

Figures

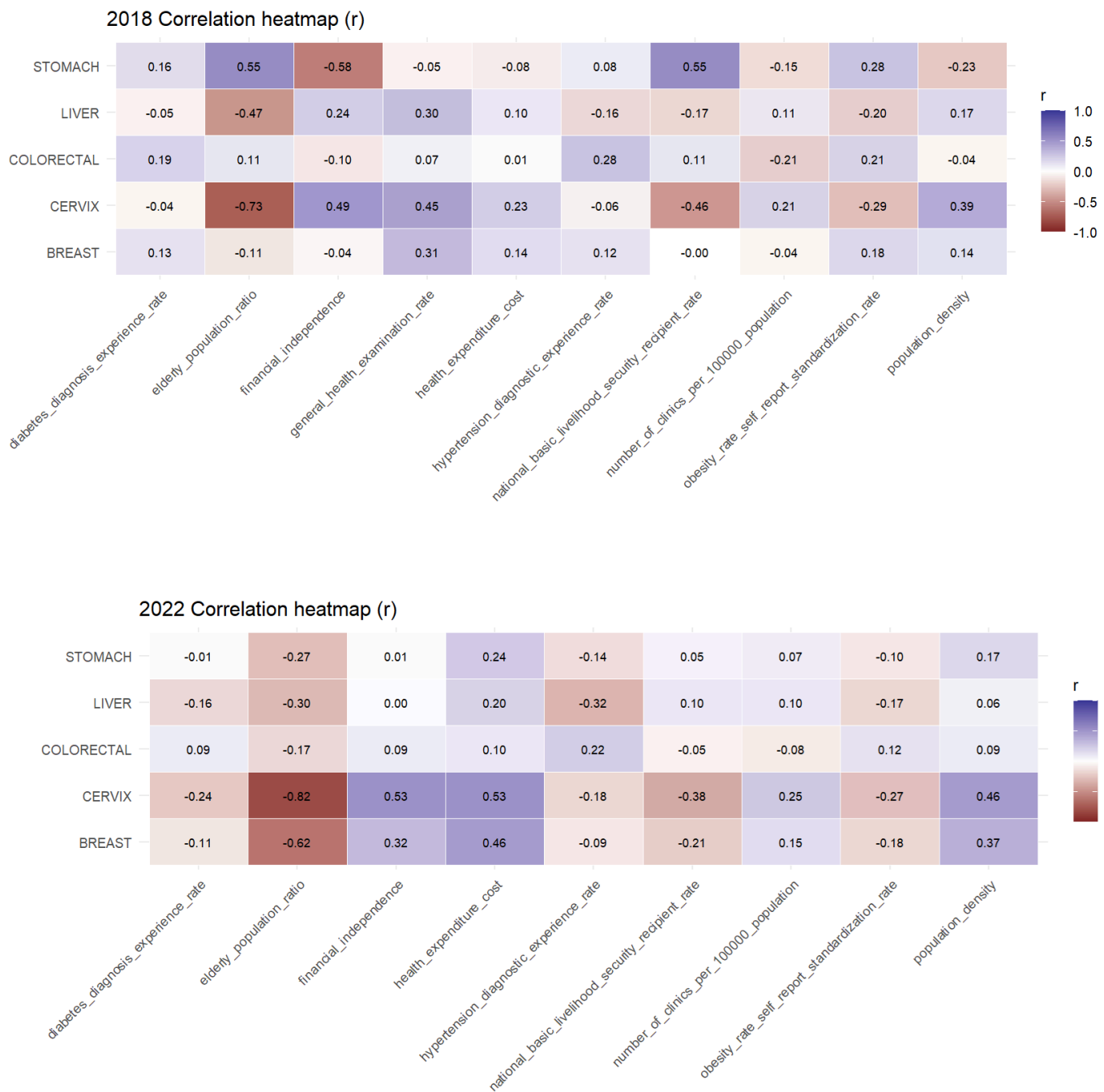


Figure 1

Local indicators of spatial association (LISA) cluster maps of observed screening rates and OLS residuals by cancer site in 2018 and 2022.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

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