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ORIGINAL PAPER

Physical distancing as an integral component of pandemic response

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Abstract
It is well established that a variety of physical distancing measures are invaluable as part of the overall response to pandemics. COVID-19 is the most recent such pandemic, a respiratory disease transmitted through interaction, necessitating steps to minimize or eliminate the potential for exposure. Of course, this is driven by a desire to keep the economy moving, allow for social activity, continue education, support the livelihoods of individuals, etc. Regional science and supporting analytics have an important role in managing activity through the development and application of methods that enable spatial interaction that mitigates transmission. This paper details methods to plan for physical distancing at micro-scales, enabling the return of social, economic, entertainment, etc. activities. Geographic information systems combined with spatial optimization offers important spatial coronametrics for the mitigation of risk in disease transmission. Applications detailing office space occupancy and travel along with room seating are highlighted.

Keywords Spatial optimization · Location modeling · Pandemic

1 Introduction

A pandemic is generally accepted as being a disease outbreak occurring over a broad geographic area, involving or impacting a significant proportion of the population. Humans have experienced a number of pandemics through time, including HIV/AIDS (human immunodeficiency virus/acquired immunodeficiency syndrome), various forms of flu, cholera, bubonic plague and others. Most recently, the coronavirus disease 2019 (COVID-19) pandemic can be added to this list. COVID-19 is a respiratory illness spread through physical contact, originating in late 2019. Through July 2022 there have been more than 577 million cases of COVID-19 and

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more than 6.4 million deaths worldwide.[1] For many individuals (> 80%), the experience through incubation, acute and recovery stages is non-severe. Some people that are non-severe may be asymptomatic while others contend with some combination of fever, cough, shortness of breath, fatigue, achiness, headache, loss of taste/smell, sore throat, congestion, etc. Of great concern, however, are the severe cases, and may include serious respiratory complications like difficulty breathing, pneumonia, etc. Further, the elderly, the immunocompromised, those with underlying disease (e.g., cancer, kidney disease, lung disease, diabetes, heart conditions), individuals from certain racial and ethnic minority groups, and individuals with disabilities are particularly at risk of severe COVID-19. The fact that over 6.4 million deaths have been observed to date highlights the seriousness of severe COVID-19.

The social and economic implications of disease and sickness are profound. Healthcare expenses total over $4 trillion in the United States annually, representing some 19% of gross domestic product.[2] The International Monetary Fund estimates that the COVID-19 pandemic will cost the global economy $12.5 trillion through 2024 (Shalal 2022a). Not only has there been a major loss of life, but the COVID-19 pandemic has brought about a major economic downturn, sustained supply chain disruptions, increased unemployment and significant shifts in the demand for goods and services. Additionally, the loss of social contact, decrease in job productivity and other missed opportunities due to COVID-19 are substantial. There are also significant pandemic induced changes that have taken place as well, including a preference for and increase in remote work, housing shifts, automation and worsening of wealth disparities, among others. Related discussion can be found in Christopoulos et al. (2022), among others.

Fortunately, there exist a range of infectious disease co-existence strategies. These include but are not limited to vaccines, medications, treatments, quarantine/isolation, hand washing/disinfectants, face covering and physical distancing. Certainly for the COVID-19 pandemic, physical distancing has proven to be critically important in a number of ways. This is due to the respiratory spread of the virus, and the fact that it can be minimal beyond six feet or so (Murray 2020, CDC 2022). Given this, it is possible to practice physical distancing, but also arrange and coordinate social, work, shopping, education, etc. behavior accordingly. This paper focuses on geographic information systems (GIS) and spatial optimization modeling to design and allocate spaces that offer physical distancing opportunities to ensure a relatively safe separation between individuals and/or groups. Bringing people together for social, work, entertainment and other activities is important, so finding a balance between continued activities and responsible disease mitigation measures is critical, having both financial and intangible benefits. The aim of this paper is therefore to review and apply analytics as a component of spatial coronametrics in order to mitigate the

[1] According to the JHU Coronavirus Resource Center (https://coronavirus.jhu.edu/map.html), accessed 8/1/2022.

[2] 2020 estimate by the Centers for Medicare & Medicaid Services, Department of Health and Human Services—https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/NationalHealthExpendData/NationalHealthAccountsHistorical, accessed 8/4/22.

impacts of a pandemic like COVID-19 that spreads primarily through respiratory contact. The next section offers background for research focused on physical distancing. This is followed by spatial analytics to support planning, coordination and mitigation efforts. Analysis involving workspace and classroom arrangement to support physical distancing is then detailed. The paper ends with concluding comments and observations.

2 Background

After more than 2 years into the COVID-19 pandemic, approaches for interacting and existing in shared environments, especially workplaces, vary significantly. COVID-19 health precautions caused an immediate restructuring of many economic and business norms, and debates persist on the superiority of remote versus in-person work. At an international scale, the reallocation of labor sent a shockwave throughout the global economy and continues to shape the enduring COVID-19 economic landscape (Barrero et al. 2020). A survey from the U.S. based Pew Research Center found that only about 23% of workers held jobs that could be performed remotely before the pandemic, and that number peaked at 71% during the pandemic (Parker et al. 2022). Though many American workers have expressed positive sentiments about remote work, including having better work-life balance and the ability to meet deadlines, around 60% of respondents to the Pew survey reported feeling less connected to their co-workers, motivating the need to create hybrid arrangements that are amenable to and safe for in-person work.

For many parts of the United States, in-person work has been conducted in largely the same way since 2020, with some researchers noting the tethering effect of the workplace as a “social anchor” for individuals of different backgrounds, such as opposing political ideologies, to be exposed to one another (Goldberg 2022). Of course, there is evidence to suggest that most workers feel their workplace can do more to keep them safe from COVID-19 (Parker et al. 2022), and physical distancing is a prominent component of this conversation. The fields of public health, layout and design and location modeling, each address aspects of physical distancing in some form. Reviews of public health can be found in Cromley and McLafferty (2011), McLafferty and Murray (2017) and Lu and Delmelle (2019), among others. Cromley and McLafferty (2011) focus on the use and application of GIS and supporting spatial analytical methods, describing and identifying relevant geographic data that can relied upon in mapping and analysis of public health hazards, risks, disease spread, access to services, etc. McLafferty and Murray (2017)urray (2017 review a number of regional science issues in public health, touching on inequalities, determinants, development processes, surveillance as well as access and location modeling. Lu and Delmelle (2019) explore a range of public health contexts, detailing geospatial approaches to address heat exposure, cardiovascular illness, air quality variability and food and nutrition disparities, among others. Location and spatio-temporal relationships greatly influence public health risks and vulnerabilities.

The work on layout and design is expansive, focused on the physical placement of activities at both micro- and macro-scale. A review can be found in Francis et al.

(1992). Somewhat related is location modeling, also oriented toward the configuration of geographic activities. A review of general optimization approaches can be found in Church and Murray (2009) (see also Francis et al. 1992). Collectively, there has been considerable research done to date to support layout and location configuration and planning, with a range of modeling approaches available to achieve desired outcomes, objectives and aims.

The past 2 years has seen much research devoted to physical distancing associated with the COVID-19 pandemic. Murray (2020) considered classroom layout. Kudela (2020) addressed the configuration of individuals in an auditorium. Park et al. (2021) looked at stadium seating. Ugail et al. (2021) examined a number of contexts, including classroom, common area, workspace and atrium seating. Bortolete et al. (2022) investigated classroom seating. Burtner and Murray (2022) explored the combination of office layout and behavioral interaction. Contardo and Costa (2022) studied dining room table layout. Finally, Fischetti et al. (2023) focused on table placement in a restaurant and family group seating in an amphitheater, but also wind farm layout and beach umbrella placement. Collectively, spatial analytics to support pandemic physical distancing, particularly in the context of COVID-19, has advanced considerably. As a result, the potential to view this work in terms of more general spatial coronametrics is advantageous.

3 Methods

GIS and spatial analytics have proven to be fundamentally important in physical distancing analysis, planning, organization, management and mitigation efforts. Murray (2017) highlights that these methods are common in regional science. GIS represents the combination of hardware, software and procedures for capture, management, manipulation, analysis, modeling and display of geographic information (Cromley and McLafferty 2011; Church and Murray 2009). On the analysis side, GIS typically offers functionality to derive attribute summary, spatial summary, containment, polygon overlay, map algebra, distance, buffering, clustering and interpolation, among others, but it is the ability to simultaneously deal with attribute and spatial data that make it unique and important, particularly in the context of physical distancing.

Layout, design and spatial configuration planning are fundamental to pandemic mitigation efforts that involve physical distancing. GIS facilitates ad hoc and visual interactive location selection (Murray 2010). However, this generally lacks rigor, often bypassing problem specification and providing no basis to establish quality and/or meaning in derived plans. In contrast, spatial optimization and location modeling represent approaches that are based on mathematical formalization and theoretically driven solution approaches, with significance well established (Murray 2021). Discussion of spatial optimization and location modeling can be found in Church and Murray (2009) and Tong and Murray (2012, 2017), with the central elements being decisions to be made, a goal(s) to be optimized and constraining conditions. What makes them spatial or locational is that one or more of the elements and/or input are geographic in some manner.

Consider the vector of decision variables $\delta = \left[\, \delta_1 \;\cdots\; \delta_k \,\right]$ as a component of functions, giving $f(\delta)$ and $g(\delta)$. A generic spatial optimization / location model can be specified as follows:

$$Maximize\, f(\delta) \tag{1}$$

$$Subject\, to: \;\; g(\delta) \leq b \tag{2}$$

$$\delta \geq 0 \tag{3}$$

The objective, (1), involves the maximization of the functional values of the decision variables, and could be linear or non-linear, involving associated coefficients. The constraint, (2), stipulates a functional restriction on the combined values of the decision variables, linear or non-linear in form. While only a single constraint is indicated, in general a finite number of constraints are typically encountered. Finally, decision variable conditions are noted in constraints (3). This model is considered generic because of the ambiguous declaration of functions. However, in practice, very precise and unambiguous relationships and coefficients are required for operationalization. In fact, there are many different forms of spatial optimization/location models that have been proposed and applied in the context of COVID-19 physical distancing mitigation, as noted previously.

One modeling approach for physical distancing planning is the p-center problem, with discussion and solution found in Suzuki and Drezner (1996). The intent of the problem is to identify the locations of a fixed number of facilities (e.g., individuals, desks, workspaces, tables, etc.) in order to maximize the distance between the closest two facilities, where facilities may be sited anywhere in continuous space. This basic problem was noted in Murray (2020), Kudela (2020), Ugail et al. (2021), Bortolete et al. (2022) and Fischetti et al. (2023), with some calling it the free positioning or circle packing problem.

Consider the following notation:
j = index of facilities (e.g., individuals, desks, workspaces, tables, etc.)
Ω = region (or room, building, etc.) of analysis.
p = number of facilities to be sited.
Decision variables:
$\left(\lambda_j, \phi_j\right)$ = coordinates for where to site facility j
D = maximum distance between any pair of closest facilities.

With this notation and decision variables, the p-center problem(continuous space) can be formalized in specific terms.

$$Minimize\; D \tag{4}$$

$$Subject\, to: \;\; D \geq \min_{\substack{\hat{j} = 1, \dots, p \\ \hat{j} \neq j}} \sqrt{\left(\lambda_j - \lambda_{\hat{j}}\right)^2 + \left(\phi_j - \phi_{\hat{j}}\right)^2}\; \forall j = 1, \dots, p \tag{5}$$

$$D \geq 0 \tag{6}$$

$$\left(\lambda_j, \phi_j\right) \in \Omega \forall j = 1, \ldots, p \tag{7}$$

The objective, (4), seeks to minimize the maximum distance between sited facilities and the closest facility to each. Constraints (5) establish the maximum distance between each sited facility and the facility closest to it. Constraints (6) and (7) indicate conditions on decision variables. Note that this is now a problem specific instance of the more generic form offered in (1–3), involving spatial decision variables, $\left(\lambda_j, \phi_j\right)$, as well as explicitly tracking geographic distance between facilities.

Application of (4–7) requires a solution approach. As (4–7) is non-linear due to the min function in (5) along with decision variables under the radical, identifying an optimal solution via an exact approach is unlikely for practical problems. Because of this, Suzuki and Drezner (1996) devised a Voronoi diagram heuristic capable of identifying high quality results, in a computationally manner. Worth noting is that a Voronoi diagram is an approach discussed and found in GIS.

Another class of physical distancing spatial optimization/location models is the anti-covering location problem discussed in Moon and Chaudhry (1984) (see also Murray and Kim 2008). The intent is to select the most facilities (e.g., individuals, desks, workspaces, tables, etc.) possible from among a finite and discrete set of potential locations, with selected facilities required to maintain a prespecified separation distance between each other. This is also referred to as a node or vertex packing, stable/independent set and r-separation problems. Murray (2020), Park et al. (2021), Bortolete et al. (2022), Contardo and Costa (2022) and Fischetti et al. (2023) detail this problem in the context of COVID-19 physical distancing mitigation efforts.

Consider the following notation:
j = index of potential facility locations (discrete and finite in number).
R = required physical distancing standard.
$d_{j\hat{j}}$ = shortest distance or travel time between potential facilities j and $\hat{j}$

$$\Psi_j = \left\{\hat{j}, \hat{j} \neq j | d_{j\hat{j}} \leq R\right\}$$

$$n_j = \left|\Psi_j\right|$$

Decision variables:

$$X_j = \begin{cases} 1 \text{ if potential facility } j \text{ is selected} \\ 0 \text{ if not} \end{cases}$$

A mathematical formulation of the anti-covering location problem is the following:

$$Maximize \sum_j X_j \tag{8}$$

$$Subject\ to:\ n_j X_j + \sum_{\hat{j} \in \Psi_j} X_{\hat{j}} \leq n_j\ \forall j \tag{9}$$

$$X_j = \{0, 1\}\ \forall j \tag{10}$$

The objective, (8), is to maximize the number of facilities selected. This function could also include a coefficient representing a weight or benefit for facility selection, if some locations are deemed more preferable than others. Constraints (9) limit facility selection, requiring that selected sites not be within the restriction standard of other selected sites. Binary integer conditions are stipulated in constraints (10). GIS is critically important in structuring and applying (8–10) as spatial location, distance and location selection are at the core of this spatial optimization model.

Because (8–10) involves linear functions only with respect to decision variables, it may be solved optimally using commercial mixed-integer packages, enabling optimality to be established using exact methods if associated conditions are satisfied. The literature indicates success in solving small to large scale problem instances (see Murray 2020).

The anti-covering location problem seeks the most facilities that can be simultaneously sited while maintaining a minimum separation between facilities. This is an upper bound on what is possible, representing optimistic locational placement. It may be particularly informative to know what the worst possible siting configuration could be, effectively the opposite of objective (8). Niblett and Church (2015) proposed the disruptive anti-covering location problem, seeking the lower bound on what is possible without violating physical distancing standards. Murray (2020) demonstrated the utility of this information in the context of COVID-19 physical distancing mitigation. The formulation of the disruptive anti-covering location problem is as follows:

$$Minimize\ \sum_j X_j \tag{11}$$

$$Subject\ to:\ n_j X_j + \sum_{\hat{j} \in \Psi_j} X_{\hat{j}} \leq n_j\ \forall j \tag{12}$$

$$X_j + \sum_{\hat{j} \in \Psi_j} X_{\hat{j}} \geq 1\ \forall j \tag{13}$$

$$X_j = \{0, 1\}\ \forall j \tag{14}$$

The objective, (11), is to minimize the number of facilities selected, and can be contrasted with objective (8) above. Constraints (9) limit facility selection, requiring that selected sites not be within the restriction standard of other selected sites. Since the model is a minimization, a constraint is necessary to prevent the trivial non-selection of any facility, forcing the model to select facilities if there is no physical distancing violation. Thus, constraints (13) require selection of a facility site if no other selected facilities present a spatial conflict. Binary integer conditions are noted in constraints (14). As with the previous model, GIS is essential in structuring and applying (11–14) given inherently geographic component in this spatial optimization model.

The disruptive anti-covering location model, (11–14), is also linear in form, and can generally be solved for modest sized problem instances using general purpose mixed-integer programming packages (Murray 2020).

An important advancement in COVID-19 assessment and planning is the multi-objective approach of Burtner and Murray (2022) accounting for physical distancing and spatial interaction. The physical distancing criteria reflected in the anti-covering location problem, (8–10), as well as the disruptive anti-covering location problem, (11–14), remains the same, but included in facility selection is expected spatial interaction between sites selected. Spatial interaction is the byproduct of arrival, departure, restroom visits, coffee / water breaks, etc.

Consider the following additional notation:

$\alpha_{j\hat{j}}$ = overlapping length (or distance) of expected travel paths for occupancy of facilities j and $\hat{j}$.

Decision variables:

$$Y_{j\hat{j}} = \begin{cases} 1 \text{ if facilities } j \text{ and } \hat{j} \text{ both selected} \\ 0 \text{ if not} \end{cases}$$

The multi-objective model formulation is as follows:

$$Maximize \sum_{j} \beta_j X_j \tag{15}$$

$$Minimize \sum_{j} \sum_{\hat{j}>j} \alpha_{j\hat{j}} Y_{j\hat{j}} \tag{16}$$

$$Subject\ to: \ n_j X_j + \sum_{\hat{j}\in\Psi_j} X_{\hat{j}} \le n_j \ \forall j \tag{17}$$

$$X_j + X_{\hat{j}} - 1 \le Y_{j\hat{j}} \ \forall j, \hat{j} \in \Psi_j \tag{18}$$

$$X_j = \{0, 1\} \ \forall j \tag{19}$$

$$Y_{j\hat{j}} = \{0, 1\} \ \forall j, \hat{j} \tag{20}$$

There are two objectives. The first, (15), is to maximize the number of facilities selected, that same as objective (8) above. The second objective, (16), seeks to minimize expected spatial interaction between pairs of selected facility sites. Constraints (17) limit facility selection, requiring that selected sites not be within the restriction standard of other selected sites. Constraints (18) track the simultaneous selection of any pair of facilities. Binary integer conditions are noted in constraints (19) and (20). As with the previous model, (15–20) is dependent on GIS in range of ways, including derivation of path interaction, spatial proximity and visualization.

A challenging feature of the physical distancing and spatial interaction model, (15–20), is the two objectives. The model functions are linear, suggesting that solution using commercial mixed-integer software is possible. However, objectives (15) and (16) must be simultaneously optimized. Cohon (1978) notes that multiple objective problems generally have multiple optimal solutions that tradeoff preferences between objectives. They are known as non-dominated (or non-inferior) solutions (also Pareto), and are the byproduct of simultaneously optimizing both objectives. A non-dominated solution is the situation that one objective cannot be improved without degrading the other objective. Fortunately, approaches exist for dealing with multiple objectives, such as the weighting and constraint methods.

Collectively, these spatial optimization models rely on GIS to extract and represent spatial information, using this to structure and implement the mathematical formulations as well as in some cases carry out solution. Thus, GIS combined with spatial optimization forms the foundation of a class of spatial coronametrics that enable physical distancing to be address as part of pandemic response, sensitive to the needs for social, economic, educational, etc. activities to continue. The next section offers a demonstration of the utility of these spatial coronametrics.

4 Workspace Arrangement and Classroom Seating

In support of the University of California at Santa Barbara Instructional and Study Space Workgroup convened by the Executive Vice Chancellor, physical distancing plan development was undertaken for work and teaching spaces on campus. As noted in Murray (2020), a restriction distance of 8.58333 ft. (8′ 7″) was adopted based on the typical size of an individual (2.58333 ft., or 2′ 7″) along with the CDC recommended 6 ft. physical distancing standard.

The spatial optimization models were implemented using Python. The Voronoi diagram heuristic outlined in Suzuki and Drezner (1996) was structured to solve the p-center problem, (4–7), based on the use of a number of PySAL functions. The remaining models relied on Gurobi (version 9.5.0) for solution. Analysis was carried out on a laptop computer (Intel i9-10885H CPU, 2.40 GHz with 32 GB RAM) running Windows.

Three different spaces on campus were considered in the reported work that follows. The first is a workspace in Ellison Hall (room 3621) without fixed seating. The second is a lecture space (Buchanan Hall, room 1940) with 153 fixed seats. The third space involves the fourth floor of Ellison Hall, with 46 offices (fixed potential facility locations), three entries/exits, two bathrooms, and a lounge.

The workspace considered within Ellison Hall without fixed seating is shown in Fig. 1, an area of approximately 810 square feet. A portion of this area is not usable for workspace due to door access and other equipment, leaving a feasible area of approximately 495 square feet. Application of the p-center problem, (4–7), indicated

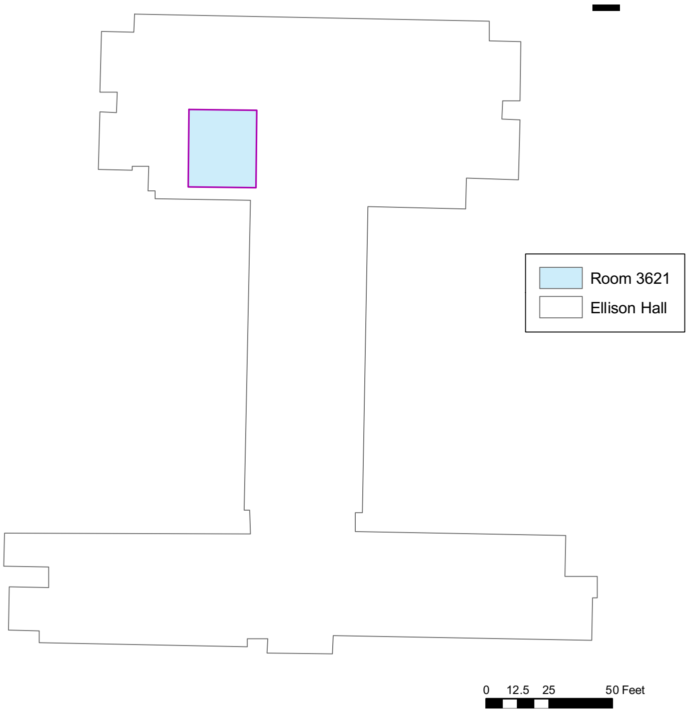

Fig. 1 Ellison Hall room 3621 workspace

that it was possible to configure 11 workspaces within the feasible area while maintaining the restriction distance of at least 8.58333 ft. In this case, it is possible to identify a configuration where workstations are no closer than 8.925 ft., as shown in Fig. 2. For illustrative purposes, a circular area around each workspace is given, with the radius representing half of the 8.58333 ft. physical distancing standard (e.g., 4.29167 ft.). Thus, no two workspace circles intersect, demonstrating that the physical distancing standard is met or exceeded within the feasible area. Note that it is not possible to maintain the distancing standard within the feasible area for more than 11 workspaces.

The lecture space involving Buchanan Hall (room 1940) with fixed seating is shown in Fig. 3. This is one of four lecture rooms within the building, each relatively close in size. Room 1940 has 153 fixed position seats, with four of these accommodating handicapped individuals. The initial effort involved the determination of how many seats could be occupied (and which ones) while maintaining the physical distancing standard of 8.58333 ft. To assess this, the anti-covering location problem, (8–10), was applied. The maximum possible is 17, and is shown in Fig. 4. There is no configuration of seating that would enable more than 17 individuals without violating the physical distancing standard. The minimum seating possible can be identified using the disruptive anti-covering location problem, (11–14). Analysis indicates that it is possible to seat as few as 10 individuals, and this configuration is shown in

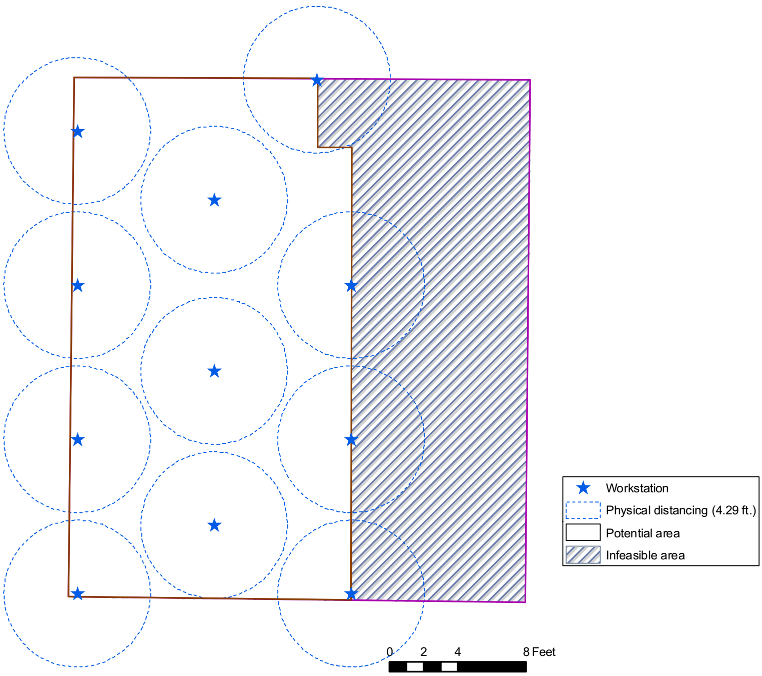

Fig. 2 Workspace configuration in 3621 Ellison Hall

Fig. 5. Depicted in Fig. 5 is that no seat is available within the standard given the selected seating configuration, made evident using a circle with radius 8.58333 ft. in this case. It is not possible to seat fewer than 10 without a feasible seat being available, in accordance to the physical distancing standard.

When considering the addition of potential interaction between individuals co-located within a floor or building, the bi-objective model, (15–20), can accommodate the opposing goals of maintaining physical distancing while allowing for movement of individuals between necessary facilities. The case study presented in Burtner and Murray (2022) involves assessing which offices are to be sited on a single floor with planned access to necessary facilities, and potential movements are represented by a network of paths. This floor contains 46 offices, two bathrooms, and a lounge room where food is stored and prepared. The network of paths was digitized based on derived hallway centerlines and shortest paths to offices and facilities. The bio-objective model was operationalized using both the weighting and constraint methods.

The results demonstrate that the physical configuration of facilities greatly influences dispersion potential as well as the ability to avoid incidences of interaction. Three restriction distances were found to align closely with the stringent management priorities of low building occupancy (met through a maximum physical distancing of 40.36 ft. between cited offices), low office adjacency (met at 20.12 ft.), and continued physical distancing (9 ft.). In general, maximizing space occupancy inherently contributes to higher potential incidences of interaction, but the extent

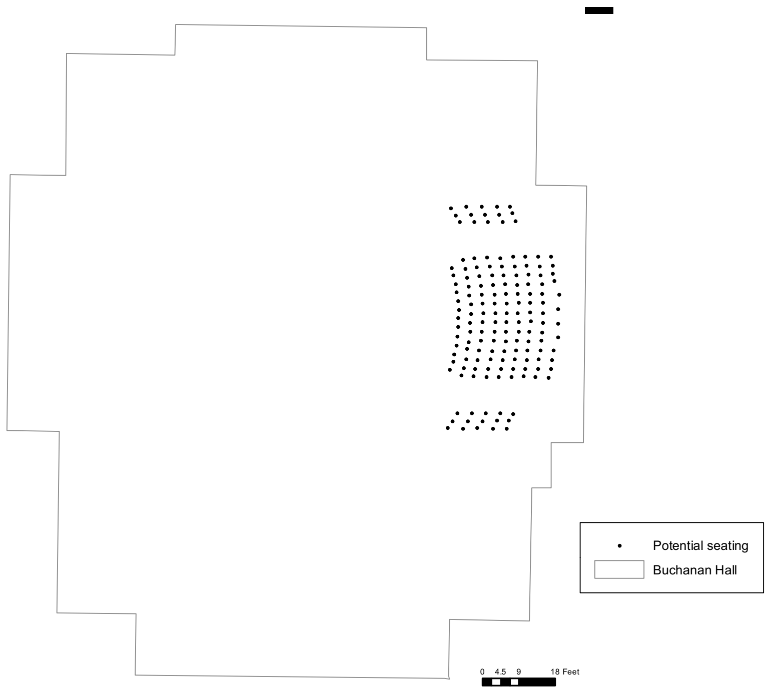

Fig. 3 Potential seating in Buchanan Hall (room 1940)

of that potential varies at different restriction distances. In some cases, while a given spatial configuration might maximize occupancy and meet a certain distancing standard, if the potential for interaction is too high, such configurations will be sub-optimal.

An example tradeoff configuration is given in Fig. 6, showing the location of three offices for a physical distancing standard of 112.58 ft. The expected paths that lead to certain necessary facilities (e.g., bathroom, lounge) are also shown, and an examination of the solution leads to interesting insights. More sited offices are only possible when the restriction standard decreases, but also spatial arrangement is critical in resulting path-overlap.

5 Discussion and Conclusions

Pandemic co-existence strategies are critical, and it is clear that continued work, entertainment, education, social interaction, etc. are critical in the presence of diseases like COVID-19. While respiratory spread of the virus may be prevalent, physical distancing and other mitigation efforts make activity possible. There is much that regional science has to offer physical distancing-based mitigation planning. In particular, GIS and spatial optimization / location models are fundamentally important. GIS offers functionality to extract geographic location, derive distance, evaluate

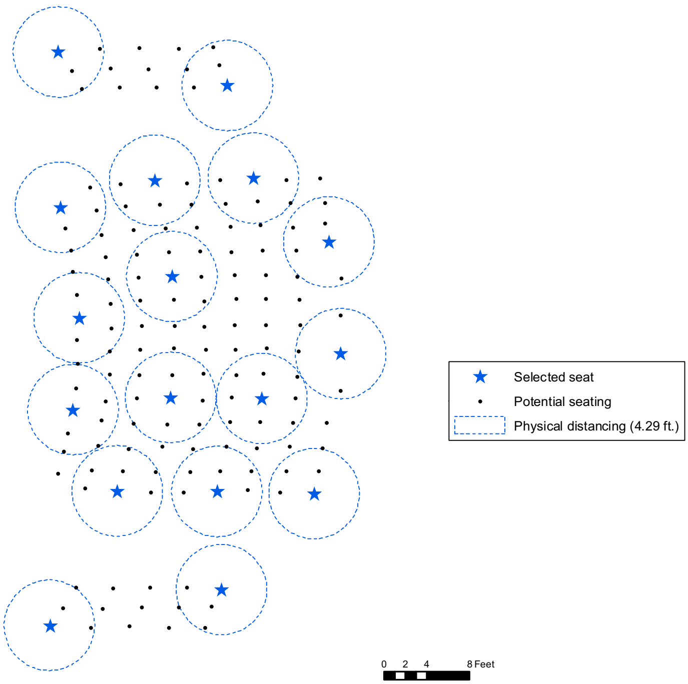

Fig. 4 Maximum possible seating configuration in Buchanan Hall (8.58333 ft. physical distancing standard)

buffering and visualize analytical findings. In some cases, GIS is even central in developed solution approaches, such as the Voronoi diagram heuristic used to solve the p-center problem. Combined with structured spatial optimization models, spatial coronametrics offer micro-scale planning and management insights that are indeed critical.

An interesting review of computational decision support for COVID-19 is offered in Yang et al. (2022). There is mention of Kudela (2020) and Ugail et al. (2021), along with the notion of physical distancing supported by optimization. Additionally, noted is the importance of simulation and artificial intelligence. It is not uncommon to see heuristics, ad hoc approaches, simulation and artificial intelligence used to address optimization models like those reviewed and applied in this paper. A critical point discussed in Murray (2020) was chance configurations in seating or workspace design. What if there is no detailed plan, but individuals are left to select, seat and/or position their workspaces as they wish? The anti-covering location problem and the disruptive anti-covering location problem, as an example, will give upper and lower bounds, respectively, on the seating capacities possible. Chance seating would therefore be within the range established by these bounds. However, finding extreme solutions in optimization problems is generally difficult because they are few among all possible seating / location configurations. The 153 seats in 1940 Buchanan Hall, as an example, would have 2^{153} seating configurations, or 11,417,981,541,647,679,048,466,287,755,595,961,091,061,972,992 (or 11.42×10^{45}). While many would be

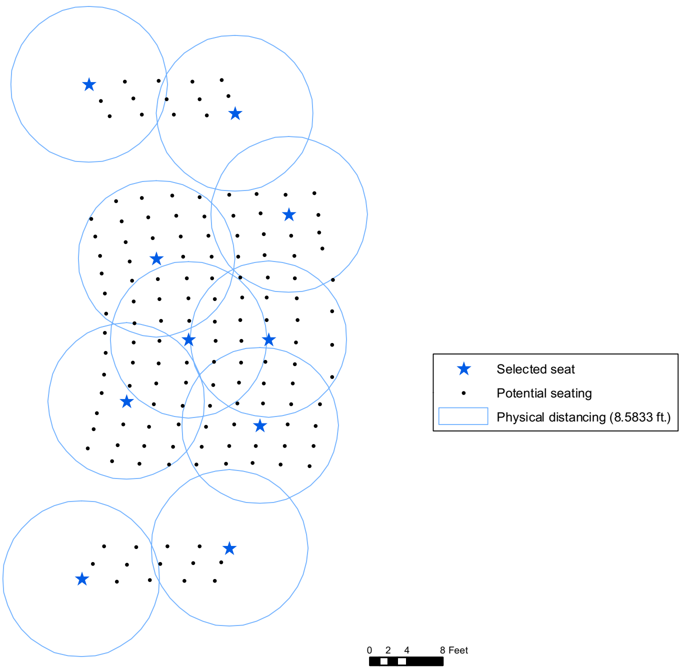

Fig. 5 Minimum possible seating configuration in Buchanan Hall (8.58333 ft. physical distancing standard)

infeasible with respect to the lower bound, (11)-(14), there remain an large number of seating configuration combinations. Finding extreme configurations by chance is highly unlikely. To illustrate this, 100,000 random feasible configurations, feasible with respect to (8)-(10) as well as (11)-(14), were identified. The distribution is shown in Fig. 7, where few if any of the extreme outcomes possible are found. This too was the conclusion illustrated in Murray (2020). The significance is that simulation along with heuristics, ad hoc approaches and artificial intelligence have limitations and may not provide good insights in physical distancing mitigation efforts.

Computational requirements for many problems using GIS combined with spatial optimization was generally minimal, requiring less than 1 s up to a few seconds to set up and solve in the cases of the p-center problem, (4)-(7), the anti-covering location problem, (8)-(10), and the disruptive anti-covering location problem, (11)-(14). However, processing and solution was more involved for the bi-objective model, (15)-(20). While less than 1 s was needed to solve for the tradeoff solution shown in Fig. 6 involving the selection of three offices, other problem instances were far more challenging, requiring hundreds of seconds or more. In fact, some instances had a remaining optimality gap that could not be resolved after 900 s. Add to this, complications associated with identifying tradeoff solutions using either the weighting

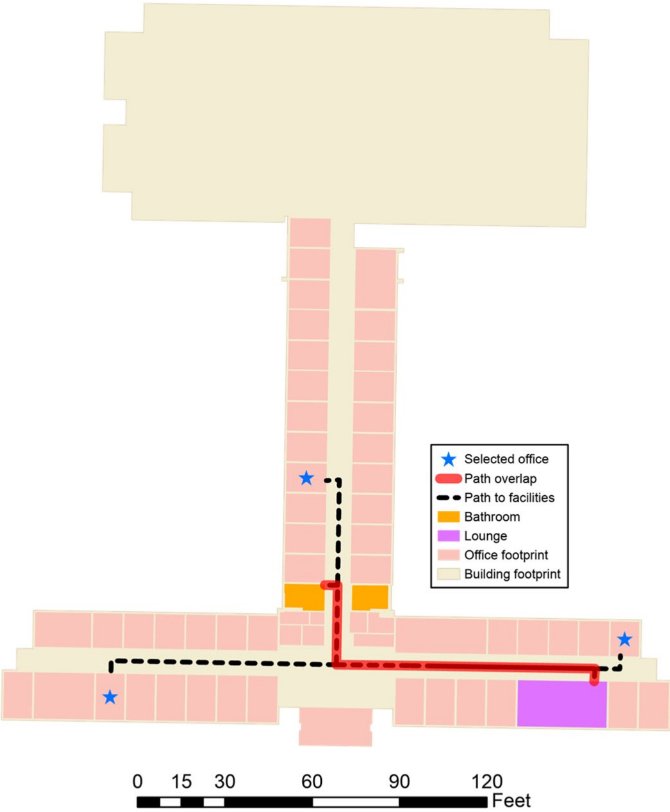

Fig. 6 Ellison Hall configuration of three offices, minimizing path-overlap (112.58 ft. physical distancing standard)

method or constraint method generally mean that hundreds or thousands of problem instances must be evaluated to obtain all non-dominated solutions from which evaluation for implementation can occur.

Regional science, and in particular spatial analytics like GIS and spatial optimization, has an important role in addressing a range of pandemic response mechanisms. With respect to COVID-19, a number of models have been developed and applied in the context of physical distancing and spatial interaction, representing some of the new tools that can be considered spatial coronametrics. Further, these are but a start, with many extensions and additional considerations possible.

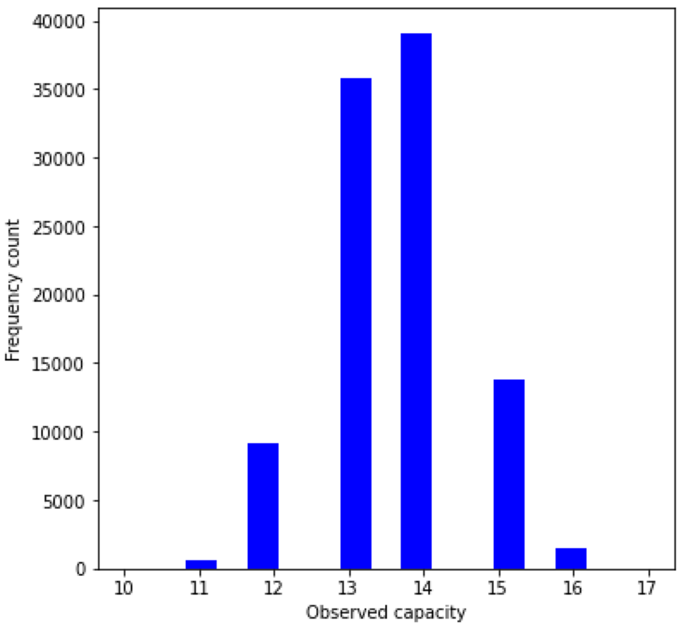

Fig. 7 Chance distribution in seating subject to physical distancing

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Declarations

Conflict of interest The authors indicate no conflict of interest.

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