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Reducing racial segregation of public school districts

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ABSTRACT

Racial segregation in public education has been declared as unconstitutional for over 60 years in the United States. Yet many public school districts remain largely separate and unequal. A commonly used approach to reduce school segregation is redelineating school attendance zones to create more racially diverse classrooms. However, there is a need for a school districting approach that can minimize racial or socioeconomic segregation at the district level. In this paper, we develop a spatial optimization model that delineates school attendance zones with the aim of minimizing racial segregation of school district to enable the assessment of the impacts of school attendance zones on the racial segregation of school district. Applications of this model to Riverside Unified School District (RUSD) and San Diego Unified School District (SDUSD) in California, USA show that it is possible to reduce racial segregation by 64% at RUSD and 56% at SDUSD, demonstrating the potential of the proposed model.

1. Introduction

The racial and ethnic diversity of public K-12 schools in the U.S. have increased considerably in recent years. This is partly due to various desegregation measures implemented by school districts across the nation and partly because of the continuous decrease in the proportion of non-Hispanic white students [1–3]. However, hundreds of school districts in the U.S. are still under desegregation orders, and many others are actively developing integration plans to remedy de facto residential segregation in their districts [4,5].

A variety of desegregation techniques have been used, including public school choice, magnet schools, and busing of students within school districts and/or across multiple school districts [6]. While the public school choice and magnet schools are increasingly popular across the nation, more than 70% of children still attend the assigned public school based on school attendance zone (SAZ) boundaries delineated by school districts [7]. Adjusting SAZ boundaries or busing hav been considered to be essential strategies for reducing school segregation since the U.S. Supreme Court strongly encouraged segregated school districts to redraw SAZ to improve racial diversity in the 1970's [3, 8–10].

Many school districts and scholars have developed student assignment approaches that take into account racial and ethnical diversity. For example, many school districts under desegregation orders in the 1980s and 1990s adopted race-based student assignment policy requiring that each school has a certain percentage of minority students [11]. The race-based assignment policy was gradually replaced with socioeconomic-based assignment policy requiring that each school has a certain percentage of socioeconomically disadvantaged students since the early 2000s [9,11]. A variety of optimization models that are used to determine assignment of students to schools were also developed to support the integration of these requirements [12]; Diamond and Wright 1987; [13–17]. For example, the Generic School Districting Problem (GdiP) by Ref. [14] include constraints to limit the percentage of minority students that can be assigned to each school. While these racial or socioeconomic quotas can increase racial or socioeconomic diversity of some individual schools, previous research shows that racial or socioeconomic segregation at the district level may not be reduced on aggregate, as diversity decreases in one school could be offset by diversity increases in another school of the district [9,11,18]. Currently, methods designed to minimize racial or socioeconomic segregation at the district level remain underdeveloped. Such an assignment approach will allow district planners and researchers to assess the impacts of school attendance zones on the racial or socioeconomic segregation of the school district.

In this paper we propose a new method that designs SAZs with the

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aim of minimizing racial segregation of a school district. Specifically, we develop a spatial optimization model that determines student assignment to schools in a way that minimizes racial segregation measured for the school district while maintaining geographic proximity of assigned students to schools. A comparison between the actual SAZs and the counterfactual SAZs generated using this model can highlight the potential of school districts to reduce racial segregation by adjusting SAZ boundaries. In the next section, we provide a review of existing school districting methods. This is followed by details of our proposed model. Finally, the proposed method is applied to the analysis of racial segregation of Riverside Unified School District and San Diego Unified School District in California, USA.

1.1. School districting

The problems that focus on the assignment of students to schools by determining SAZ boundaries are widely referred to as school districting [14–16]. School district planners originally relied upon student pin maps where each pin represents a student home location to manually delineate SAZ boundaries. As computing resources have become increasingly cheaper and powerful, a variety of optimization models and solution techniques have been developed to assist with school districting.

Much early work focuses on formulating the school districting problem as network flow problems where students are treated as commodity flow from neighborhoods to schools because of the existence of fast algorithms for network flow problems [14,19–23]. However, the network flow problem cannot capture many unique characteristics of school districting problems, such as flexible capacity range, racial balance of schools, SAZ zone stability, and multiple competing district planning goals [15]. Since the 1990s, scholars have adopted a more general mathematical programming formulation of the school districting problem. Here we present the classic formulation of the Generic School Districting Problem (GdiP) by Ref. [14]. Consider the following notation:

Parameters:

i = index of census units (I entire set)
j = index of schools (J entire set)
S_i = number of students in census unit i
N_i = number of minority students in census unit i
C_j = capacity of school j
D_{ij} = transport cost from census unit i to school j
FN^{high} = fractional upper bound on minority enrollment
FN^{low} = fractional lower bound on minority enrollment

Decision variables:

$$x_{ij} = \begin{cases} 1, & \textit{if students of unit i are assigned to school j} \\ 0, & \textit{otherwise} \end{cases}$$

The number of students at census unit i is denoted as S_i whereas the minority students is represented by N_i. Each school has a prespecified capacity C_j. The transportation cost between census unit *i* and school *j*, which is usually travel distance or travel time, is precomputed and noted as D_{ij}. The minority enrollment percentage at each school is specified by a fractional lower and upper bound (FN_{high} and FN_{low}). Binary decision variables X_{ij} are used to ensure that all students at one census unit are assigned to the same school because splitting neighborhoods is usually undesirable due to negative social and political impacts [15,16]. With this notation the GdiP is formulated as follows:

$$\min \sum_i \sum_j D_{ij} S_i x_{ij} \tag{1}$$

Subject to:

$$\sum_j x_{ij} = 1, \ \forall i \in I \tag{2}$$

$$\sum_i S_i x_{ij} \le C_j, \ \forall j \in J \tag{3}$$

$$\sum_i \left(FN^{low} S_i - N_i\right) x_{ij} \le 0, \ \forall j \in J \tag{4}$$

$$\sum_i \left(N_i - FN^{high} S_i\right) x_{ij} \le 0, \ \forall j \in J \tag{5}$$

$$x_{ij} \in \{0, 1\}, \ \forall i \in I, \ j \in J \tag{6}$$

The objective (1) is to minimize the total travel costs of the students of each census unit to their assigned schools. Constraint (2) ensures that each census unit is assigned to exactly one school. Constraint (3) stipulates that no school violates capacity usage. Constraints (4) and (5) specify the minimum and the maximum minority enrollment at each school. Constraint (6) imposes binary integer restrictions on decision variables. This formulation contains $|I|*|J|$ decision variables and $3|J| + |I|$ constraints, where $||$ indicates the number of members in the associated set.

Many research efforts have extended the GdiP to incorporate other districting requirements and objectives. For example, geographical compactness of SAZ is integrated in Refs. [24,25]; multiple grades are taken into account in Refs. [15–17]; school opening and closure are considered in Refs. [17,26,27]; test score distributions are incorporated in Ref. [28]; geographical contiguity of SAZ is imposed in Refs. [25,29]. As the GdiP and its extensions are NP-hard in nature (Cohen 1979), various solution algorithms have also been used or developed for the school districting models. While some work uses existing integer-programming (IP) solution algorithms in commercial or open-source solvers to get optimal or near-optimal solutions of the models [17], a majority of literature relies upon customized heuristic algorithms to solve the models efficiently. Examples of these approaches include an implicit enumeration algorithm by Ref. [30]; a hybrid heuristic by Ref. [14]; a local search algorithm by Ref. [28]; a multi-stage regionalization algorithm by Ref. [25]; a spatially-constrained clustering algorithm by Ref. [29] and others. In addition, open-source spatial decision support systems (SDSS) integrating school districting optimization models have also been developed to allow district planners to interactively determine school attendance zones based on both modeling results and other policy considerations [16,31].

As the literature makes plain, school districting is an important and well-studied problem. However, none of the previously developed methods assigns students to schools in a way that minimizes racial or socioeconomic segregation of the school district, despite the fact that it remains among the major goals that school districts wish to achieve. This paper aims to fill this research gap by developing a new school districting model that can minimize racial segregation at the district level.

1.2. School districting to minimize segregation

While there is a lack of school districting methods that explicitly minimize racial/ethnic segregation of school districts, a large literature has measured racial/ethnic segregation patterns of public schools using various segregation indices. For instance, Farley et al. (1980), [32,33]; and [34] used the dissimilarity index to examine the racial/ethnical segregation of schools. [35] used the Gini index to measure school segregation and compare it with residential segregation patterns. [18, 36] used the entropy index to assess school district racial/ethnic segregation.

Here we calculate the racial segregation of school district using the dissimilarity index given that it is the mostly widely used segregation measure and it is easy to interpret [37,38]. Specifically, the dissimilarity index of a school district, D, represents the percentage of the minority students that would have to change their schools for the two social groups to be evenly distributed across the entire school district. Following the previous notation the D can be defined as:

$$D = \frac{1}{2}\sum_j\left|\frac{\sum_i x_{ij}N_i}{N} - \frac{\sum_i x_{ij}W_i}{W}\right| \tag{7}$$

where the W_i represents the number of white students at census unit i, and N and W is the total number of non-white and white students in the school district, respectively. As x_{ij} is a binary variable indicating whether students at i is assigned to j, $\sum_i x_{ij}W_i$ and $\sum_i x_{ij}N_i$ represents the number of white and non-white students assigned to school j, respectively. The D varies from 0.0 to 1.0, with larger values indicating higher levels of segregation.

With the definition of D our school districting model to minimize racial segregation is formulated as follows:

$$\min D \tag{8}$$

Subject to:

$$\sum_j x_{ij} = 1,\ \forall i \in I \tag{9}$$

$$\sum_i S_i x_{ij} \le \left(1 + FC_j^{high}\right)C_j,\ \forall j \in J \tag{10}$$

$$\sum_i S_i x_{ij} \ge \left(1 - FC_j^{low}\right)C_j,\ \forall j \in J \tag{11}$$

$$D_{ij}x_{ij} \le T_j,\ \forall i \in I, j \in J \tag{12}$$

$$x_{ij} \in \{0,1\},\ \forall i \in I,\ j \in J \tag{13}$$

where T_j = maximum transport cost allowed for students assigned to school j, FC_j^{high} = fractional upper bound on capacity usage at school j, and FC_j^{low} = fractional lower bound on capacity usage at school j.

Objective (8) is to minimize racial segregation among schools in the school district. Constraints (9) ensure that each census unit is assigned to exactly one school. Constraints (10) and (11) stipulate that no school violates capacity usage lower bound and upper bound. Constraints (12) specifies the maximum travel cost allowed for a school assignment. Constraints (13) impose binary integer restrictions on decision variables.

There are several important differences between this new model and the GdiP. First, this model has the objective of minimize the racial segregation among schools but GdiP focuses on minimizing the transportation cost. Second, this model sets a capacity range requirement for each school by using FC_{high} and FC_{low} rather than a simple capacity constraint in GdiP. This allows for the consideration of the potential of expanding existing schools and the utilization balance among all schools. For example, if $FC_{high} = FC_{low} = 20\%$, each school could accommodate as many students as 120% of current capacity and as few students as 80% of current capacity. Third, the geographic proximity between students and assigned schools are maintained by ensuring that no student will travel further than T_j to get to the assigned school. Such constraints, equation (12) could also encourage geographic compactness of the identified SAZs.

While the dissimilarity index, D, has an absolute value operator, it can be linearized by introducing additional variables and constraints [39]. Specifically, we introduce auxiliary variable, z_j, to linearize the objective function, and the model can be reformulated as follows:

$$\min\frac{1}{2}\sum_j\left|\frac{\sum_i x_{ij}N_i}{N} - \frac{\sum_i x_{ij}W_i}{W}\right| = \min\frac{1}{2NW}\sum_j\left|\sum_i (N_iW - W_iN)x_{ij}\right| = \min\frac{1}{2NW}\sum_j z_j \tag{14}$$

Subject to:

constraints (9) – (13)

$$\sum_i (N_iW - W_iN)x_{ij} \le z_j,\ \forall j \in J \tag{15}$$

$$\sum_i (W_iN - N_iW)x_{ij} \le z_j,\ \forall j \in J \tag{16}$$

This linearized model has $(|I|+1)^*|J|$ decision variables and $(|I|+4)^*|J| + |I|$ constraints, which is larger in size compared with the original GdiP. As a result, this new model can be solved using existing IP solvers, although solving this model optimally might be computationally demanding as are the GdiP and other school districting models in this class.

1.3. Case studies

We apply the proposed model to evaluate the racial segregation of San Diego Unified School District (SDUSD) and Riverside Unified School District (RUSD) in California, USA. We obtain the 2015–2016 public school data from the National Center for Education Statistics Common Core of Data (NCES CCD). The NCES CCD reports the school location and number of enrolled students for each grade offered and classify them into seven racial/ethnic categories: Hispanic, non-Hispanic American Indian/Alaska Native, non-Hispanic Asian, non-Hispanic Black, non-Hispanic White, non-Hispanic Hawaiian Native/Pacific Islander, and non-Hispanic Two or More races. Here non-Hispanic White is considered as the majority and all other racial/ethnic categories are considered as the minority. All elementary schools that offer 1st grade are included in the study. Since most racial diversity requirements are imposed for the base year, we calculate racial segregation for school district using only 1st grade students [15]. In addition to the NCES CCD school data, the number of non-Hispanic White and minority students for 1st grade at each census block group is obtained from the 2014–2018 American Community Survey (ACS) school enrollment data to determine student assignment using the proposed model. The block group is the smallest unit for which the Census reports school enrollment by race.

The 2015–2016 NCES CCD shows that there are 30 elementary schools at RUSD that offer 1st grade. The total number of enrolled students for 1st grade is 2,890, with 625 non-Hispanic White students and 2265 students of minorities. Table 1 shows the number of the current enrollment from the NCES CCD. The column “NCESSCH” is the unique school ID from the NCES CCD. While the district student enrollment is 19% non-Hispanic White students in RUSD, five out of 30 schools have more than 40% non-Hispanic White students. Fig. 1 depicts the existing student assignments to each school based on the SAZs delineated by the RUSD. As it shows, these five schools, including Tomas Rivera Elementary, Benjamin Franklin Elementary, Woodcrest Elementary,

Table 1
The current 1st grade student enrollment at RUSD.

School	Total current enrollment	Non-Hispanic White student current enrollment	Minority student current enrollment
Tomas Rivera Elementary	95	42 (44%)	53 (56%)
Adams Elementary	73	13 (18%)	60 (82%)
Alcott Elementary	99	27 (27%)	72 (73%)
Bryant Elementary	59	13 (22%)	46 (78%)
Castle View Elementary	87	19 (22%)	68 (78%)
Emerson Elementary	100	10 (10%)	90 (90%)
Fremont Elementary	73	4 (5%)	69 (95%)
Harrison Elementary	71	18 (25%)	53 (75%)
Hawthorne Elementary	109	17 (16%)	92 (84%)
Highgrove Elementary	82	3 (4%)	79 (96%)
Highland Elementary	86	14 (16%)	72 (84%)
Jackson Elementary	87	8 (9%)	79 (91%)
Jefferson Elementary	138	17 (12%)	121 (88%)
Liberty Elementary	91	8 (9%)	83 (91%)
Longfellow Elementary	111	3 (3%)	108 (97%)
Madison Elementary	92	9 (10%)	83 (90%)
Magnolia Elementary	74	15 (20%)	59 (80%)
Monroe Elementary	100	11 (11%)	89 (89%)
Mountain View Elementary	101	11 (11%)	90 (89%)
Pachappa Elementary	109	27 (25%)	82 (75%)
Victoria Elementary	83	12 (14%)	71 (86%)
Washington Elementary	124	28 (23%)	96 (77%)
Woodcrest Elementary	81	37 (46%)	44 (54%)
William Howard Taft Elementary	102	23 (23%)	79 (77%)
Benjamin Franklin Elementary	97	40 (41%)	57 (59%)
John F. Kennedy Elementary	134	60 (45%)	74 (55%)
Lake Mathews Elementary	109	55 (50%)	54 (50%)
Mark Twain Elementary	154	56 (36%)	98 (64%)
Patricia Beatty Elementary	83	7 (8%)	76 (92%)
REACH Leadership Academy	86	18 (21%)	68 (79%)
Total	2890	625 (22%)	2265 (78%)

John F. Kennedy Elementary, and Lake Mathews Elementary, are all sited in south Riverside where most residents are non-Hispanic White. While many SAZs are contiguous, ten out of 30 schools are fragmented, such as Victoria Elementary and Jefferson Elementary. It is also important to note that the actual SAZ might split block groups because the school district may not define the SAZs according to block group boundaries. As the NCES CCD enrollment data do not specify where the students at each school are coming from, we assign a block group to a school if its centroids fall inside of the SAZ to assess the students' travel time. We calculated the travel time between block group centroids and schools using ESRI StreetMap Premium. The average travel time for the students is 3.88 min.

We first use the index of dissimilarity to measure the actual racial segregation of RUSD based on the NCES CCD enrollment. The results show that the Dissimilarity index in RUSD, according to the currently-drawn school attendance zones is 0.33, indicating that 33% of either group must move to a different school for the two groups to be equally distributed. [34]. indicated that a score of 60 or above is considered very high, a score of 40–50 represents moderate levels of segregation, and a score of 30 or less is considered low. The question, then, is whether it is possible to further reduce the racial segregation of RUSD by reallocating students within RUSD. If so, how much racial segregation could be potentially reduced?

We then apply the proposed school districting model to address these questions. The 2014–2018 ACS shows that there are 153 block groups within RUSD. These block groups have 3299 1st grade students, with 623 non-Hispanic White students and 2676 students of minorities. Compared with the NCES CCD enrollment, these block groups have 14.15% more students, 0.32% less non-Hispanic white students, and 18.15% more students of minorities. These differences could be attributed to private school enrollment and survey collection period differences. As the NCES CCD does not report school capacity, we use the total number of enrolled students as a proxy for the school capacity (Cj). The fractional lower and upper bound on capacity usage, FC_j^{low} andFC_j^{high}, are both set as 0.3 across all the schools for simplicity to ensure that the maximum number of students assigned to each school is 1.3 times of current enrollment and the minimum number of students assigned is 0.7 times of current enrollment. The travel time between block group centroids and schools are pre-calculated using ESRI StreetMap Premium and the maximum transport cost Tj is set as 30 min.

The school districting model is structured using Python, and subsequently solved using a commercial IP solver, Gurobi. Computational processing was carried out on a MS Windows-based, Intel Core i-9 CPU (2.30 GHz) computer with 32 GB of RAM. It takes 101 s to solve the model optimally. The results show that the minimum level of racial segregation we could achieve at RUSD by reallocating students is 0.12, which is a 64% reduction compared with the current Dissimilarity value of 0.33. Table 2 shows the number of non-Hispanic White and minority students allocated to each school by the model. The student assignment identified from the model clearly reaches a much more evenly distributed racial diversity across these schools. The maximum share of non-Hispanic White students is 31% at Washington Elementary. The share of non-Hispanic White students in these five schools that have more than 40% of non-Hispanic White enrolled students are now significantly reduced under the model-determined assignment. For example, the student body at Tomas Rivera Elementary will be only 9% non-Hispanic White compared with current enrollment at 44%; The student body at Woodcrest Elementary will be only 11% non-Hispanic White compared with the current share of 46%. The model-determined student assignments are shown in Fig. 2. Compared with the existing assignments (Fig. 1), the model-determined assignments clearly result in greater travel time for students and more fragmented and irregular attendance zone boundaries, albeit with greatly reduced racial/ethnic segregation. The average travel time for the students becomes 12.57 min. In addition, as many as 3224 students (97%) will need to change school based on this segregation minimization assignment. The average compactness, measured as the ratio of the delineated zone's area and the area of its bounding circle, decreases from 0.31 for Figs. 1 to 0.10 for Fig. 2.

We also use the proposed model to evaluate the racial segregation of SDUSD. The 2015–2016 NCES CCD shows that there are 149 elementary schools at SDUSD that offer 1st grade. The total number of enrolled students for 1st grade is 9,856, with 2341 non-Hispanic White students and 7515 students of minorities. The results show that the current Dissimilarity index in SDUSD is 0.54. According to the 2014–2018 ACS,

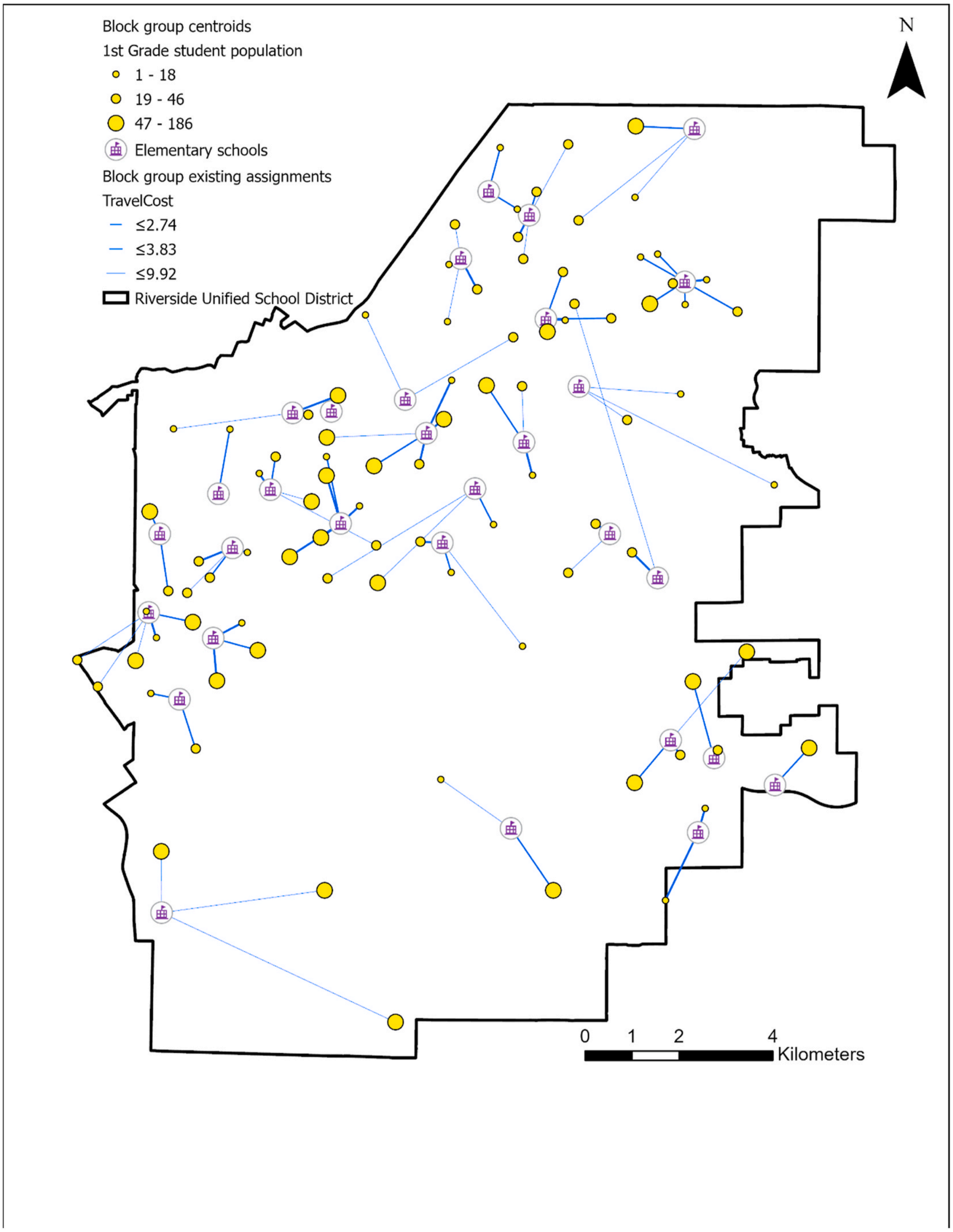

Fig. 1. Existing student assignments at RUSD (Only block groups with nonzero student population are shown here).

there are 688 block groups within SDUSD. These block groups have 9731 1st grade students, with 2480 non-Hispanic White students and 7251 students of minorities. Compared with the NCES CCD enrollment, these block groups have 1.27% less students, 5.94% more non-Hispanic white students, and 3.51% less students of minorities. We use the same parameters in the model as the RUSD and it takes Gurobi 17 s to identify the optimal solution. The results show that the minimum Dissimilarity value we could achieve at SDUSD by reallocating students is 0.24. This is a 56% reduction compared with the current segregation score of 0.54. The existing student assignments to each school based on the SAZs delineated by the SDUSD are depicted in Fig. 3, whereas the model-determined student assignments are shown in Fig. 4. Similar to the RUSD, the model-determined assignments also result in longer travel time and more fragmented and uneven attendance zone boundaries. The average travel time for the students based on existing assignments is 2.77 min but that based on model assignments is 16.86 min. In addition, as many as 9680 students (99%) will need to change school based on this segregation minimization assignment. The average compactness of the delineated zones varies more at SDUSD, 0.42 for existing and 0.05 for model-determined student assignments.

2. Discussion

The results from our two case studies make clear that school segregation by race can be reduced substantially in both San Diego and Riverside (while maintaining low commute costs) by redrawing school

Table 2
Model determined 1st grade student assignment.

School	Total number of students allocated	Non-Hispanic White students allocated	Minority students allocated
Tomas Rivera Elementary	123	11 (9%)	112 (91%)
Adams Elementary	87	14 (16%)	73 (84%)
Alcott Elementary	123	23 (19%)	100 (81%)
Bryant Elementary	55	10 (18%)	45 (82%)
Castle View Elementary	70	7 (10%)	63 (90%)
Emerson Elementary	110	20 (18%)	90 (82%)
Fremont Elementary	88	10 (11%)	78 (89%)
Harrison Elementary	88	12 (14%)	76 (86%)
Hawthorne Elementary	134	25 (19%)	109 (81%)
Highgrove Elementary	92	17 (18%)	75 (82%)
Highland Elementary	104	17 (16%)	87 (84%)
Jackson Elementary	96	18 (19%)	78 (81%)
Jefferson Elementary	179	47 (26%)	132 (74%)
Liberty Elementary	96	18 (19%)	78 (81%)
Longfellow Elementary	144	27 (19%)	117 (81%)
Madison Elementary	114	20 (18%)	94 (82%)
Magnolia Elementary	83	14 (17%)	69 (83%)
Monroe Elementary	128	24 (19%)	104 (81%)
Mountain View Elementary	103	19 (18%)	84 (82%)
Pachappa Elementary	85	15 (18%)	70 (82%)
Victoria Elementary	59	7 (12%)	52 (88%)
Washington Elementary	161	50 (31%)	111 (69%)
Woodcrest Elementary	70	8 (11%)	62 (89%)
William Howard Taft Elementary	115	19 (17%)	96 (83%)
Benjamin Franklin Elementary	121	22 (18%)	99 (82%)
John F. Kennedy Elementary	174	50 (29%)	124 (71%)
Lake Mathews Elementary	141	37 (26%)	104 (74%)
Mark Twain Elementary	199	33 (17%)	166 (83%)
Patricia Beatty Elementary	69	13 (19%)	56 (81%)
REACH Leadership Academy	88	16 (18%)	72 (82%)
Total	3299	623 (19%)	2676 (81%)

attendance zones. Despite these encouraging results, there are several issues in both the modeling framework and its application to urban policy objectives that warrant further discussion. Focusing first on the optimization model, our results point to potential extensions or additional considerations that could be useful in further work. As we demonstrate in the case studies, while the student assignment plans identified by the proposed model minimize racial segregation, they also lead to more fragmented and uneven attendance zone boundaries compared with existing SAZs. To avoid generating fragmented districts, it may be necessary to incorporate compactness and/or contiguity constraints into the optimization procedure, if fragmentation leads to increases in costs elsewhere in the education system (e.g., the designation of efficient bus routes that optimize driving time, student safety, and fleet availability).

In addition, the case studies also show that the minimization of district segregation could lead to substantial increase of student travel time even with geographic proximity constraints. The proposed model could account for geographic proximity by integrating an additional objective of minimizing total travel cost as in equation (1) instead of strict travel cost threshold constraints as in equation (12). A variety of travel cost thresholds, including 10 min, 15 min, 20 min, 25 min, and 30 min, are tested. For RUSD the same optimal solutions are obtained for 20 min, 25 min and 30min whereas no feasible solution can be obtained for 10 min and 15 min. However, for SDUSD only 30 min yields feasible solutions whereas the model becomes infeasible for all other travel cost thresholds. Given the high percentage of students who need to change schools, it might be necessary to incorporate another school stability objective that minimizes student school changes as shown in Ref. [15]. It is also possible to allow partial assignment of census units to schools, although some literature indicates that it is usually not desirable to split neighborhoods [16]; Also notable is the model solution time. While the model is solved optimally for RUSD and SDUSD, the problem is NP-hard, and could require a customized heuristic solution algorithm to enable its application to large-scale school districts.

Toward the goal of policy development and analysis, we argue the results from our case studies provide a unique way of conceptualizing a policy agenda focused on social justice. Redrawing school districts is a costly, time-consuming, and (potentially) politically contentious process. Historically, when school districts have sought to use their own resources to facilitate school integration, bussing students across district boundaries has been the policy vehicle of choice. This is no surprise, given the large costs associated with redistricting and the relative flexibility with which bus routes can be altered. The results in this paper, however, demonstrate that in addition to achieving better integration in practice, rezoning procedures can be ethically transparent and value neutral. While we postulate that a low level of racial segregation is a socially-desirable goal, the modeling framework is flexible to examine other goals such as reducing class segregation or minimizing commute distances to reduce energy. As [40] has extensively documented, there has been much heterogeneity in the particular demographic and political conditions that impinge on district formation, policy, and functioning across the US.

We argue that our modeling framework offers a reproducible approach to addressing school segregation issues that can foster a much needed standardization across the educational landscape.

One potential criticism of our proposed redistricting solution is that in many cases students are not assigned to their "closest" school but sometimes a few miles away. Thus, at first blush, this assignment may seem politically infeasible, first because local pushback from parents might prohibit a district's willingness to adopt the proposed solution, and second because certain logistics may make the solution too costly to implement in practice. For example, Riverside County often relies on shifting resources from local transit agencies rather than a dedicated bussing system for students, in which case the increased travel times incurred in our solution may be too costly. Toward the first issue we believe it is counterproductive to argue about the potential of *political* feasibility regarding a redistricting procedure that respects a set of resource constraints. Even if some localities find the proposed solution unpalatable, there may well be districts somewhere in the country that are willing to partake in a conversation about redistricting and what values a solution should embody; optimization models such as the one presented in this paper open the door for such an exploration. Toward the second issue, we argue that the tradeoff between transportation costs and social equity is precisely the kind of conversation these kinds of models are designed to produce. While it may be too costly *right now* to implement the redistricting procedure we outline above, that simple fact can trigger discussions regarding the optimal use of public budgets and the best ways to prioritize local development. If it is true that school segregation has consequences for student achievement in the long-run

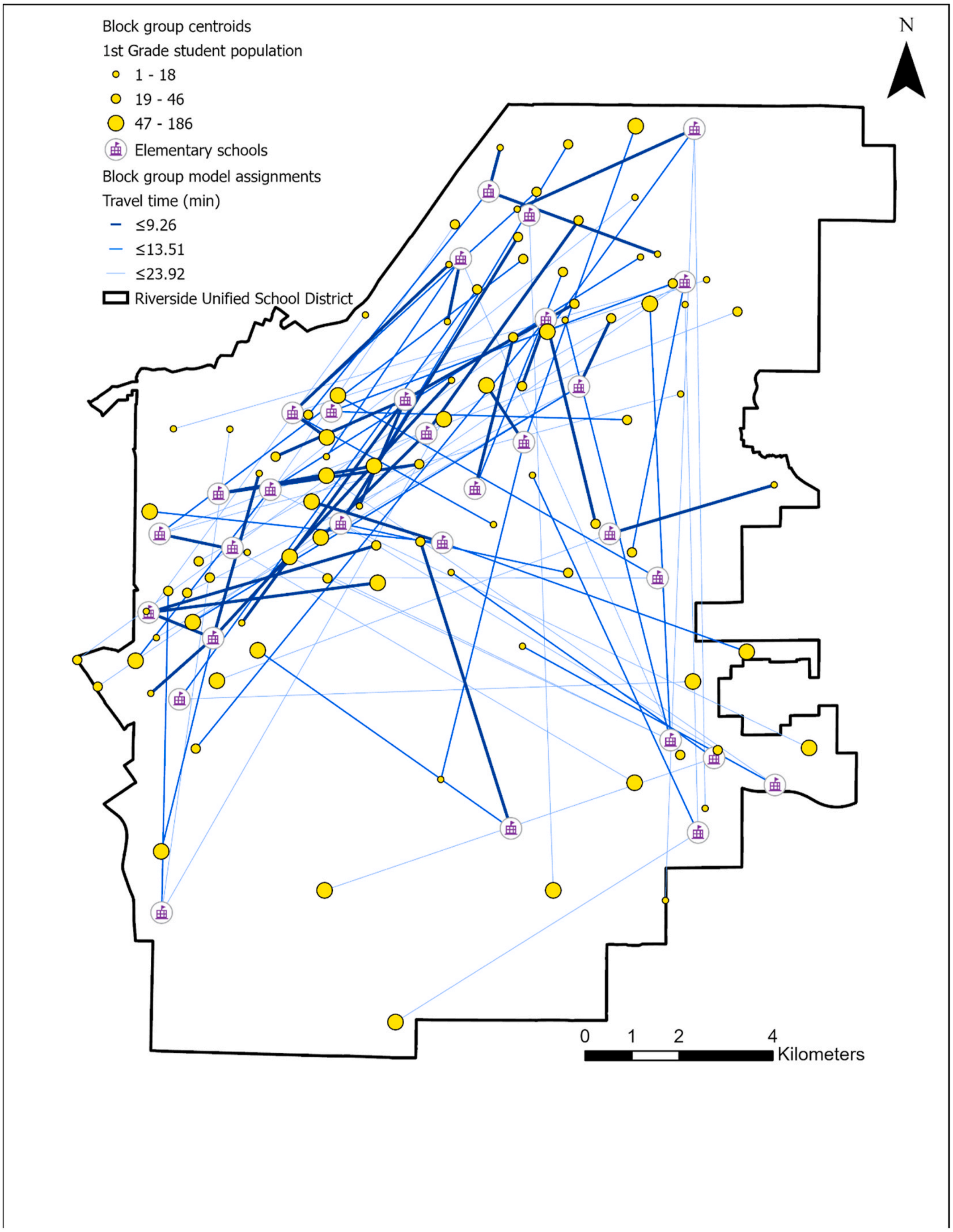

Fig. 2. Model determined student assignments at RUSD (Only block groups with nonzero student population are shown here).

[41], then it is conceivable that some communities may be willing to pay for that public good [42,43].

What is unique about optimization modeling as a method for defining school attendance zones is that it lays bare the assumptions, values, and tradeoffs associated with different zoning schemes. Rather than relying on consulting firms or purely political processes, optimization models require that objectives be stated up-front, and that potential costs and benefits be stipulated as formal model constraints. If nothing else, the formalization of objectives and constraints forces both analysts and local residents to consider what values they bring to the table during school zoning procedures, and can help facilitate a discussion. Although school segregation by race appears relatively low in both San Diego and Riverside, our model shows that it can be lowered dramatically by adjusting the zoning procedure. While such zoning adjustment may not be realistic to implement because of the increased student travel time and fragmented zone boundaries given budget and policy constraints, it can serve as a benchmark for school district planners and decision makers to work towards the goal of reducing segregation at the school district level.

3. Conclusion

In this article we propose a new approach to estimate the effect of SAZs on racial segregation of school district. Specifically, we develop a school districting optimization model that assigns students to schools in a way that minimizes racial segregation of school district while

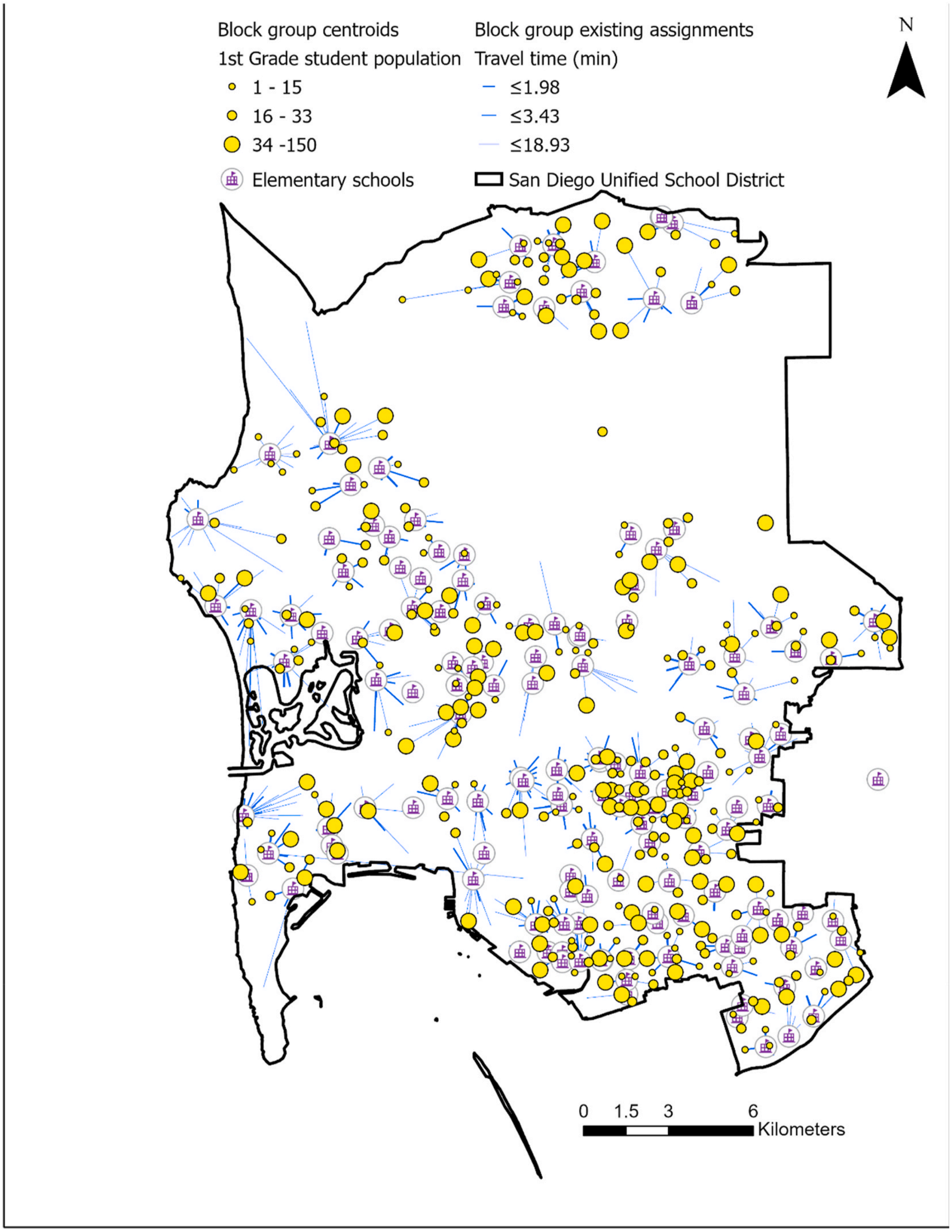

Fig. 3. Existing student assignments at SDUSD (Only block groups with nonzero student population are shown here).

maintaining geographic proximity of assigned students to schools. Then we compare the actual SAZs with the counterfactual SAZs generated using this model to enable the assessment of racial segregation at the level of school district. The applications of this method to RUSD and SDUSD highlight the potential of both school districts to reduce racial segregation by adjusting SAZ boundaries. These two case studies demonstrate that our proposed model can identify a student assignment plan that can minimize racial segregation of school district while maintaining geographic proximity of assigned students to schools and conforming with capacity limits. By comparing these counterfactual student assignment plans with the existing SAZs, we show that both RUSD and SDUSD can significantly reduce racial segregation by adjusting SAZ boundaries.

In addition, we show that using spatial optimization modeling as a method for developing urban policy is a modern solution to a historically challenging problem. Our model runs on consumer hardware, achieves optimality in only a few minutes, and can be extended to incorporate other social or topographical considerations. Thus, in addition to the pro-social outcomes suggested by our case studies, adopting spatial optimization modeling as a common framework can be a major boon for urban planning and infrastructure provision. In many jurisdictions across the United States, planning for adequate school capacity is mandatory and regulated through adequate public facilities ordinances (APFOs) or through the assessment of impact fees (as is the case in both case study cities of San Diego and Riverside) [44,45]. The model we present in this paper shows that San Diego and Riverside could

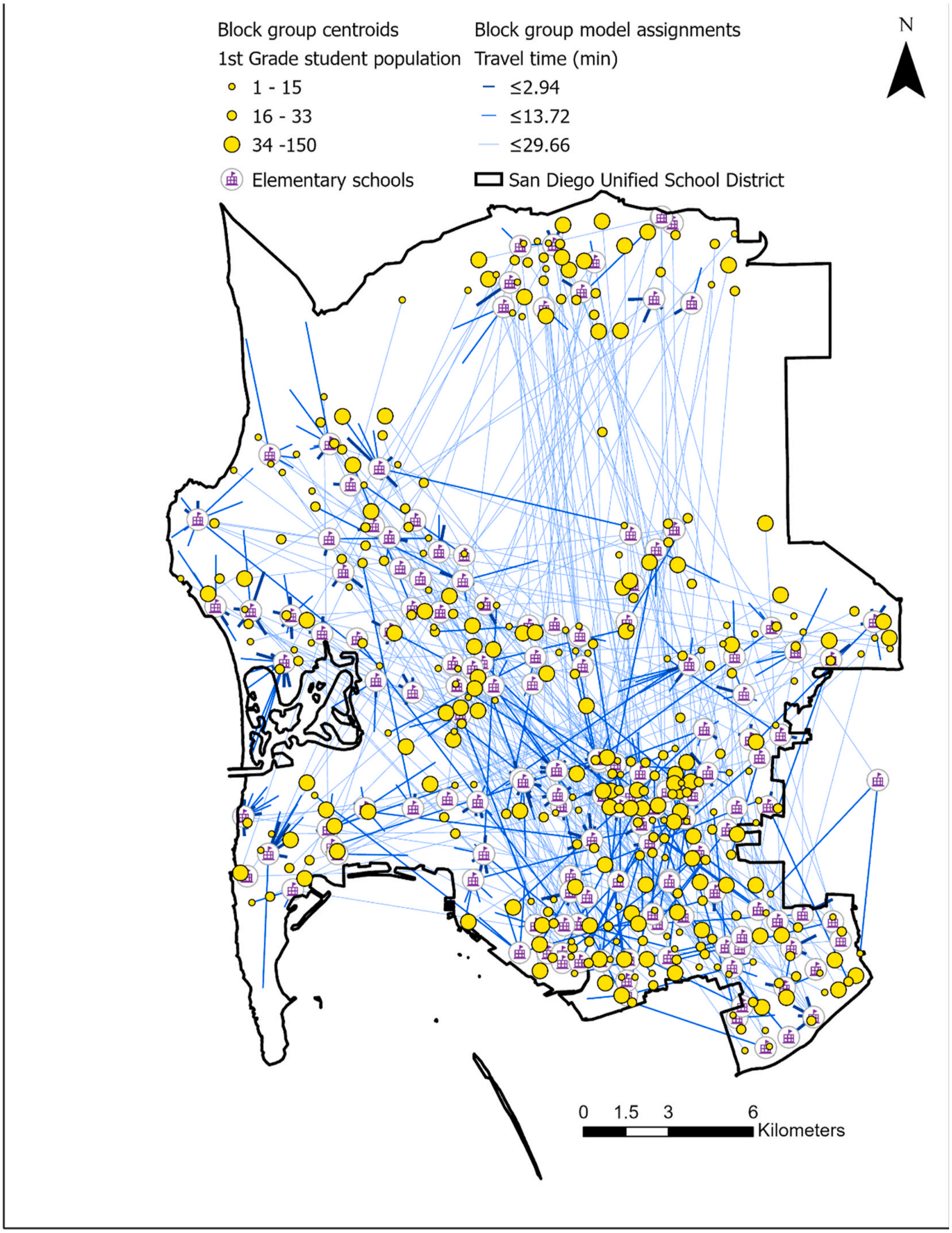

Fig. 4. Model determined student assignments at SDUSD (Only block groups with nonzero student population are shown here).

reduce their racial segregation by redrawing school attendance zones, but the same model could also be used to reallocate students according to travel costs or existing capacity constraints. Thus, while our example is focused on the specific goal of school integration, the framework provides general utility for a wide variety of urban planning and policy applications.

Further, and perhaps more importantly, our work here demonstrates the value of open-source analysis for public policy decision making. School districting is a politically contentious process, with cascading implications for property values, educational opportunity, and racial and socioeconomic inequality. For that reason, the use of racially-explicit goals in determining primary school attendance is a complex issue, as demonstrated by PARENTS INVOLVED IN COMMUNITY SCHOOLS v. SEATTLE SCHOOL DIST (2007), in which the U.S. Supreme Court held that the use of racial quotas was unconstitutional but that race could still be a factor in helping guide attendance decisions. More recently, one of the country's leading school districts is making headlines for its consideration of racial integration as a redistricting goal [46]. In these latter cases, the work we present in this paper can be particularly useful, because the open-source code lays bare the assumptions, objectives, and approaches built into the model at its outset. If nothing else, exposing these parameters helps elucidate the underlying intentions of the redistricting exercise (in this case, to maximize school-level segregation—without compromising reasonable commuting times for each individual student).

Thus, apart from the substantive results presented above, we believe that the codification of a school redistricting exercise into a spatial optimization problem helps chart a defensible course through contentious territory. From a legal perspective, the formal application of objectives and constraints in the model can be mapped onto the legal doctrines from prior case law (e.g. the stipulation that racially-oriented objectives be limited in scope) to ensure that goals designed for ethical outcomes conform to legal precedent. From a practical perspective, adopting a spatial optimization model can help a school district provide transparency into its decision-making process, rather than obscuring analytical details behind a consultant's shield. Further, by codifying these methods in open-source software, the technical burden is reduced for lower-resource school districts seeking to adopt similar goals in their redistricting approaches. Since these are the very issues being addressed in school districts throughout the country [46], the time is ripe to expand and refine the methods presented in this paper so that they might be used for maximum effect in local education systems.

Author statement

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