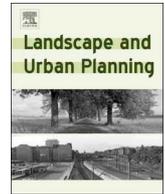




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journal homepage: www.elsevier.com/locate/landurbplan

Beyond proximity: Extending the “greening hypothesis” in the context of vacant lot stewardship

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ABSTRACT

Research increasingly shows that greening activity can spur contagious or imitative behavior among nearby neighbors within residential landscapes. Krusky et al. (2015) examined this phenomenon in the context of vacant lots and found support for a “greening hypothesis” that residential yards near vacant lots that were converted to community gardens exhibited higher levels of care than yards near untended vacant lots. Although such activity implies a temporal, causal relationship, research to date has only tested the spatial dimension of greening through correlational measures of proximity assessed at one point in time. We extend this work by analyzing vacant lot greening as a function of time, space, scale of analysis, and other factors. We studied residential property owners ($N = 321$) who purchased nearby city-owned vacant lots through the Chicago Large Lot Program. Improvements made in the condition and care of large lots in the year after purchase were positively related to the proximity, condition and care of the individual’s previously owned property, and signs of use and care of the lot before purchase (blotting). We also examined whether block-level indicators of care and disorder were associated with improvements made to lots purchased on the block. We found few associations but discovered these same block-level indicators of care and disorder more strongly predicted the percent of large lots sold on that block, suggesting that greening activity may be bidirectional. These findings expand understanding of the dynamics of vacant lot stewardship and have implications for building more robust theories of urban greening.

1. Introduction

A landscape’s appearance plays an important role in people’s environmental preferences and can affect other ways in which they perceive, engage with, and value landscapes (Gobster, Ribe, & Palmer, 2019). Residential landscapes with well-maintained homes and attractive yards, on tree-lined streets, near public green space can contribute to improved neighborhood quality of life (Douglas, Russell, & Scott, 2019), increased property values (Crompton, 2004), and other positive individual and social outcomes (Krekel, Kolbe, & Wüstemann, 2016; Root, Silbernagel, & Litt, 2017). Although the cultural norms that underlie these preferred landscape characteristics are most often studied in suburban settings (Nassauer, Wang, & Dayrell, 2009; Uren, Dzidic, & Bishop, 2015), recent research shows they also apply to the improvement of urban neighborhoods diminished by high levels of vacancy. In a study of vacant lot greening in Flint, Michigan (USA), Krusky et al. (2015) found that residential yards located near vacant lots that had been transformed into community produce (vegetable) gardens were better maintained than yards near untended vacant lots, providing support for their “greening hypothesis.” Noting the prevalence of such

patterns across their study area, the authors concluded that greening initiatives can play a catalytic role in community revitalization efforts.

The proximal relationship that underlies the greening hypothesis has been identified in other residential landscape contexts, including similarity in front yard planting designs (e.g., Minor, Belaire, Davis, Franco, & Lin, 2016; Zmyslony & Gagnon, 2000) and clustering of easement gardens (Hunter & Brown, 2012) within neighborhoods. These studies underscore the potential of urban greening in neighborhood improvement and more broadly demonstrate how nearby nature can promote positive behavioral change (Norwood et al., 2019; Roberts, McEachan, Margary, Conner, & Kellar, 2018). But though the process of greening described by the investigators implies a temporal aspect, studies to date have focused primarily on the spatial (proximal) relationships between properties. Moreover, the studies also imply a causal agent and direction of change, yet again they provide little insight into how changes originate and spread across the landscape.

A vacant lot repurposing program in the City of Chicago provided the opportunity to address these knowledge gaps. The Chicago Large Lot Program sells city-owned vacant lots in high-vacancy neighborhoods to nearby property owners for a nominal fee, with the

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<https://doi.org/10.1016/j.landurbplan.2020.103773>

Received 2 October 2019; Received in revised form 6 February 2020; Accepted 7 February 2020

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goals of reducing municipal maintenance burdens, creating local wealth through ownership, and stabilizing population loss (City of Chicago, 2014a). To help evaluate the program, we studied the greening activity undertaken by new owners of “large lots” (i.e., lots purchased under the Chicago Large Lot Program), and in a previous paper detailed the types and magnitude of changes made in the condition (level of maintenance) and care (signs of stewardship and occupancy) of lots purchased (Gobster, Hadavi, Rigolon, & Stewart, 2020). Additional information collected on owner- and block-level characteristics now allows us to extend work on the greening hypothesis to examine how owner proximity and other factors affect vacant lot stewardship.

2. Background and hypotheses for research

Our research examines changes in lot-level condition and care relative to two other scales of analysis: the purchaser’s originally owned property and the block in which the large lot was purchased. At these two scales, our hypotheses fall into five conceptual categories described in the subsections below. Fig. 1 provides a layout of concepts and hypotheses described in this section and Table 1 summarizes each of the eleven hypotheses tested. Four of the five conceptual categories cover hypotheses relating to large lot-owned property level relationships: proximity, occupant type, behavioral antecedents of care, and blotting; while the fifth covers hypotheses relating to large lot-block level relationships.

2.1. Proximity and care

The benefits of nearby nature in urban settings are well documented, with investigations spanning more than four decades (e.g., Kaplan, 1973; Lewis, 1979). Kaplan and Kaplan (1989) found that visual and physical access to natural environments can play an important role in environmental preference, residential satisfaction, and human health and well-being; that even small green areas such as yards and gardens can provide important benefits; and that it is often proximity and not size that matters in determining frequency of use and beneficial outcomes.

Kaplan and Kaplan (1989) also noted that some types of green spaces and activities bring people in closer contact with nature, and that of these, gardens and gardening can deepen connections with nature for individuals and engage the nearby community. This ability to generate broader engagement has since been described spatially by urban ecologists, who have documented the “mimicry” in planting designs and species selections across nearby front yards (Minor et al., 2016; Zmyslony & Gagnon, 1998, 2000; for a counterexample see Kirkpatrick, Daniels, & Davison, 2009) and “spatial contagion” of easement gardens within neighborhoods (Hunter & Brown, 2012). In these studies, the proximal nature of activity is of central interest and shows a decrease with distance—Minor et al. (2016) found patterns of mimicry decline for front yards more than nine lots away (~67 m), whereas Hunter and Brown (2012) found that the peak clustering of

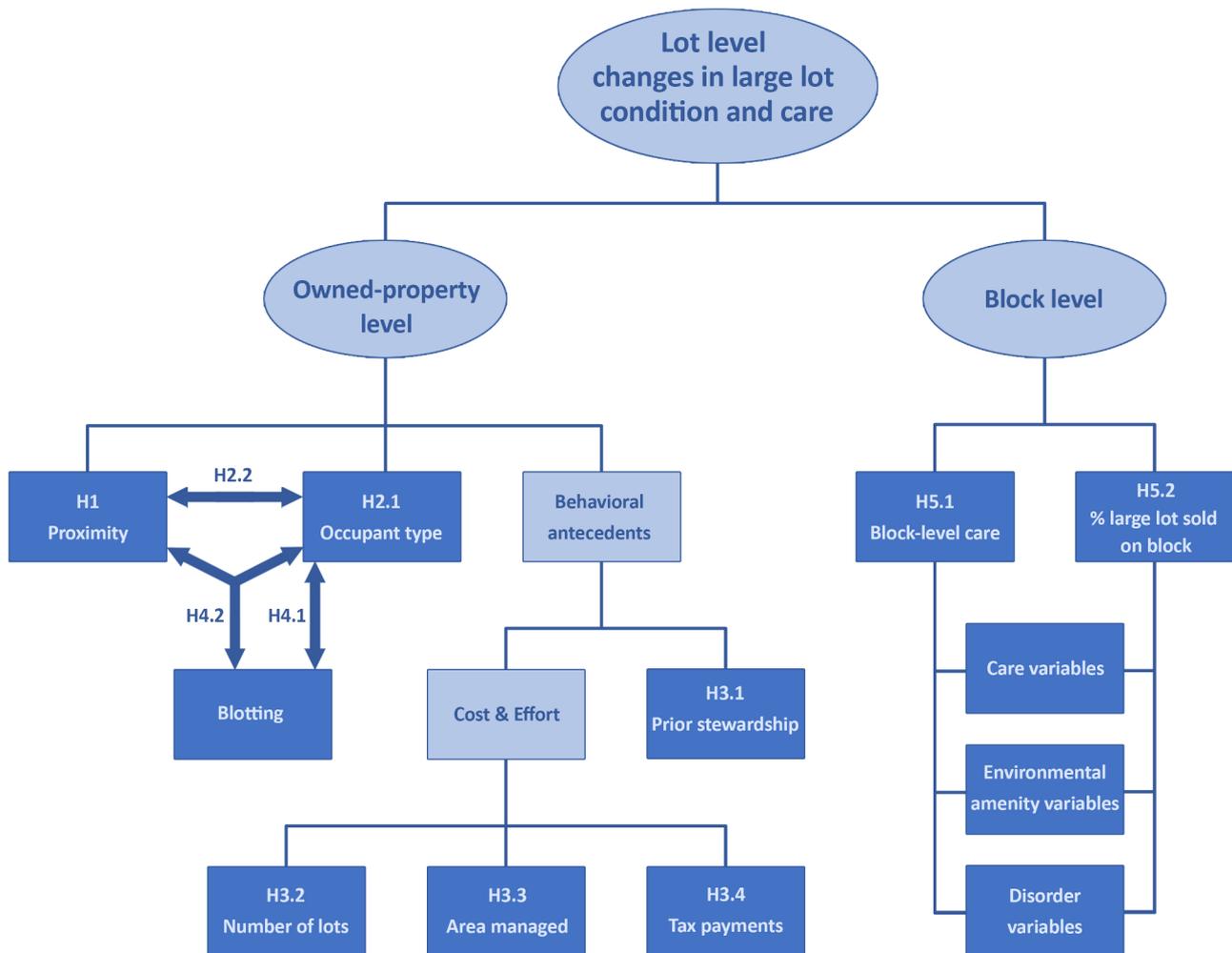


Fig. 1. Conceptual diagram of the research. The ovals at the top of the diagram portray the scale relationships examined, while the boxes portray the concepts studied. The numbered, darker boxes correspond to concepts tested by hypotheses and the numbered arrows are hypothesized interaction effects between concepts. See text and Table 1 for further details.

Table 1
Summary of hypotheses tested in the paper.

Number	Concept	Hypothesis
H1	Proximity	The condition and care of large lots would increase with greater proximity between the large lots and the purchaser's original property.
H2.1	Occupant type	Large lots purchased by owner-occupants would show bigger improvements in condition and care than if the purchaser's original property was in absentee ownership or vacant.
H2.2	Owner-occupant \times proximity	The interaction term between owner-occupant and proximity would have a positive sign, indicating that large lots purchased by owner-occupants who live in greatest proximity would show the biggest improvements in condition and care.
H3.1	Prior stewardship	Owners whose original property showed a high level of condition and care would extend higher levels of care to their purchased large lots than owners whose original property showed a low level of care.
H3.2	Number of lots	Owners who purchased a single large lot would extend higher levels of care to it than owners who purchased two lots.
H3.3	Area managed	Owners whose combined property area was smaller would extend higher levels of care to their large lots than owners whose combined property area was larger.
H3.4	Tax payments	Owners whose large lot property taxes were fully paid would extend higher levels of care to their large lots than owners who carried a large deficit in their tax payments.
H4.1	Blotting \times owner-occupant	The interaction term between blotting and owner-occupant would have a positive sign, indicating that large lots that were both blotted and purchased by owner-occupants would show the biggest improvements in condition and care.
H4.2	Proximity \times owner-occupant \times blotting	The interaction term between proximity, owner-occupant, and blotting together would have a positive sign, indicating a synergistic effect of these three variables on improvement in large lot condition and care.
H5.1	Block-level care	Large lots purchased on blocks showing high levels of care and environmental amenities and low levels of disorder would show higher levels of condition and care than lots purchased on blocks with low levels of care and amenities and high levels of disorder.
H5.2	Percent of large lots sold on block	A higher proportion of available large lots would be sold on blocks showing high levels of care and amenities and low levels of disorder than on blocks with low levels of care and amenities and high levels of disorder.

easement gardens occurred within a 91 m radius of a given garden.

Proximity is also the central concept behind the greening hypothesis examined by [Krusky et al. \(2015\)](#), who extended the work described above into the important issue of urban vacancy. Flint, Michigan, like many post-industrial cities in the US and globally, has suffered major population loss resulting in a large number of vacant properties in need of repurposing. Drawing on other research that greening can positively impact revitalization efforts, [Krusky et al. \(2015\)](#) posited that well-maintained community produce gardens in high-vacancy neighborhoods would lead nearby homeowners to maintain their own yards at a higher level than residents who lived by similar open parcels that remained vacant and untended. Referencing the 91 m proximity threshold identified by [Hunter and Brown \(2012\)](#), [Krusky et al. \(2015\)](#) studied two residential areas and measured the maintenance levels of yards within 100 m and 50 m of 19 different produce gardens, comparing them with yards of similar proximities to a sample of vacant lots. While the investigators found significant differences in yard maintenance between garden- and vacant lot-proximate lots in support of their greening hypothesis, their data and research design prevented them from determining causality as to whether “the greening effect radiated from the produce gardens or if engaged residents created the produce garden” ([Krusky et al., 2015, p. 74](#)). The authors suggested that future research could consider ownership to determine the origin and direction of the greening relationship.

Data from our large lot study provide such an opportunity because the ownership and timing of greening activity are known. Our earlier work assessed the maintenance condition and care of large lots before and after purchase and found that significant changes were made, including an increased percentage of lots with gardens and other “cues to care” ([Nassauer, 1995](#)), reductions in parked vehicles, and improvements in the condition of mature trees ([Gobster et al., 2020](#)). While that analysis provided the temporal and directional evidence to support a causal relationship between ownership and improvements in condition and care, the particular requirements of the Large Lot Program also provide a natural experiment of sorts to test the effects of proximity on lot improvements. Unlike most vacant lot “side yard” programs in the US ([Ganning & Tighe, 2015](#)), the Large Lot Program does not stipulate that residents share a common property boundary with a vacant lot in order to purchase it; they only need to own property on the block or adjacent block. In practice, this distance spans the range identified by the studies mentioned above, and thus we anticipated that improvements in the condition and care of large lots would increase with

greater proximity between the large lots and the purchaser's original property (H1: “Proximity”).

2.2. Ownership and care

2.2.1. Occupant type

For many vacant residential lot resale programs, in order to qualify for purchase of a city-owned lot at a low price, the applicant must be an owner-occupant of the adjacent lot (e.g., [Cuyahoga Land Bank \(Cleveland\), n.d.](#); [Land Bank of Kansas City, MO, n.d.](#); [Philadelphia Land Bank, n.d.](#)). This requirement assumes that owner-occupancy carries a heightened level of responsibility, tenure and fiscal stability, and commitment to neighborhood improvement over absentee owners or renters. Each of these reasons may be generally true (e.g., [McCabe, 2013](#)); however, they can limit the scope of programs, particularly in areas where there is a high percentage of rental units ([Ganning & Tighe, 2015](#)). Other programs stipulate that the owned property need only be an occupied residence (e.g., [City of St. Louis, MO, n.d.](#); [Detroit Land Bank Authority, n.d.](#); [New Orleans Redevelopment Authority, n.d.](#)), and although there is some evidence that absentee owners and renters may be less likely to maintain their residences than owner-occupants ([Garvin, Branas, Keddem, Sellman, & Cannuscio, 2013](#); [Goldstein, Jensen, & Reiskin, 2001](#)), it is unknown whether this also applies to vacant lot greening. The Large Lot Program also requires an applicant to own property on the block, but there are no restrictions on whether they are an owner-occupant or even if their owned property is just another vacant lot. This flexibility provides another range of conditions to test, and because homeownership generally has positive effects for neighborhoods ([Aarland & Reid, 2019](#); [Heidelberg & Eckerd, 2011](#)), we expected that large lots purchased by owner-occupants would show bigger improvements in condition and care than if the purchaser's original property was in absentee ownership or vacant (H2.1: “Occupant type”). Furthermore, we expected a positive sign to the interaction term between owner-occupant and proximity to the large lot, indicating that large lots purchased by owner-occupants who live in greatest proximity would show the biggest improvements in condition and care (H2.2: “Owner-occupant \times proximity”).

2.2.2. Behavioral antecedents of owner care

Another ownership-related factor concerns the behavioral antecedents of vacant lot care. A growing body of research has examined how homeowners perceive and manage their yards and gardens (e.g.,

Cook, Hall, & Larson, 2012; Giner, Polsky, Pontius, & Runfola, 2013). These studies suggest that behavioral changes by individual property owners can enhance the delivery of ecosystem services (Goddard, Dougill, & Benton, 2010; Larson et al., 2016). Among the factors that predict environmental behavior (Harland, Staats, & Wilke, 1999; Kurz & Baudains, 2012), prior stewardship behavior has particular relevance to vacant lot management. Specifically, prior behavior can be a good predictor of future behavior if it is closely aligned with future behavior, frequently practiced, and similar with respect to cost and effort (Moore & Boldero, 2017; Oulette & Wood, 1998). We expected that owners whose original property showed a high level of condition and care would extend higher levels of care to their purchased large lots than owners whose original property showed a low level of care (H3.1: "Prior stewardship"). With respect to cost and effort, we anticipated that owners who purchased a single large lot, whose combined property area was smaller, or whose large lot property taxes were fully paid would extend higher levels of care to their large lots than owners who purchased two lots, whose combined property area was larger, or who carried a large deficit in their tax payments (respectively, H3.2: "Number of lots"; H3.3: "Area managed"; H3.4: "Tax payments").

2.2.3. "Blotting" interactions

In our initial coding of large lot condition and care, we observed that nearly a third of the city-owned vacant large lots in our sample showed signs of use and/or stewardship prior to purchase (Gobster et al., 2020). This un sanctioned activity has been termed "blotting" (Armborst, D'Oca, & Theodore, 2008) and includes such things as fencing and mowing lots, parking cars, and planting flowers in vacant lots owned by the city. We expected that blotting would affect observed changes in large lot condition and care and the results of our previous study confirmed our hypotheses. We found that although unblotted large lots exhibited bigger changes in condition and care after purchase than blotted ones, additional care was invested in blotted lots after they were purchased and their overall level of care was higher than unblotted lots (Gobster et al., 2020). Our added data on ownership cannot identify who used or stewarded the parcels prior to purchase, but it does allow us to test whether occupant type and blotting have an interactive effect on changes in large lot condition and care. We expected that the interaction term between blotting and owner-occupant would have a positive sign, indicating that large lots that were both blotted before purchase and purchased by owner-occupants would show the biggest improvements in condition and care (H4.1: "Blotting \times owner-occupant"). This interaction would support the assumption that blotting takes place by those who own and occupy property on the block (Armborst et al., 2008). Furthermore, we expected that the interaction between proximity, owner-occupant, and blotting together would have a positive sign, indicating a synergistic effect of these three variables on improvement in large lot condition and care (H4.2: "Proximity \times owner-occupant \times blotting").

2.3. Block-level effects

Krusky et al. (2015) investigated the greening hypothesis at two scales of analysis, parcel-level measures of yard maintenance and neighborhood-level measures of disorder, social capital, and participation. Such social-ecological frameworks contend that human behavior is influenced at multiple levels, from intrapersonal to public policy (McLeroy, Bibeau, Steckler, & Glanz, 1988). Along related lines, Nassauer et al. (2009) found that neighborhood norms of residential landscape design had dramatic effects on individual homeowner landscaping preferences. Following this work, we hypothesized that changes made to large lots purchased on blocks exhibiting high levels of care and environmental amenities and low levels of disorder would show higher levels of condition and care than those purchased on blocks with low levels of care and amenities and high levels of disorder (H5.1: "Block-level care").

Finally, while Krusky et al. (2015) assumed a causal, directional path of greening extending from produce gardens to nearby yards, they also discussed how relationships between landscape aesthetics and resident behavior can be bidirectional. In the context of our work, this suggests that blocks exhibiting higher levels of care may be seen as more attractive locations in which to purchase a large lot than blocks exhibiting lower levels of care. Other research has shown that neighborhoods with attractive environmental features such as trees and nearby public green space are associated with increased property values (e.g., Staats & Swain, 2020; Donovan, Landry, & Winter, 2019) and greater housing demand (e.g., Koprowska, Łaskiewicz, & Kronenberg, 2020). To test this bidirectionality, we examined the degree to which block-level characteristics would have a motivating influence on whether individuals chose to buy lots on that block. We expected that a higher proportion of available large lots would be sold on blocks exhibiting high levels of care and amenities and low levels of disorder than on blocks with low levels of care and amenities and high levels of disorder (H5.2: "Percent of lots sold").

3. Methods

3.1. The research setting

The Chicago Large Lot Program began in 2014 as part of the implementation of the Green, Healthy Neighborhoods Plan (City of Chicago, 2014b). Under the program, qualified property owners in targeted high-vacancy areas are able to purchase one or two city-owned vacant lots on their block or the adjacent block for \$1 each, with the provision that they maintain the lots, pay the property taxes, and fence the property if it is not immediately side-adjacent to their existing owned property. The city's Department of Planning and Development expected that at least initially, most purchasers would use their large lot as private or shared green space (City of Chicago, 2014a).

The first wave of large lot sales was offered in 2014 in Greater Englewood and East Garfield Park, two community areas located on the south and west sides with high land vacancy, a large proportion of African American residents, and high poverty profiles (City of Chicago, 2014b). In Greater Englewood, 209 qualified applicants purchased 275 out of 4,062 available lots (7%) on 185 different blocks. In East Garfield Park, 112 qualified applicants purchased 149 out of 418 available lots (36%) on 67 different blocks. In total, our study examined 424 large lots distributed across 321 owners and 252 blocks.

3.2. Variables and their measurement

Our variables derive from multiple data sources including large lot and owner address information from the City of Chicago and Large Lot Program website (LargeLot.org, n.d.), property boundary and lot size information from the Cook County property tax portal (Cook County, n.d.), and aerial and street-level imagery from Google, Bing, and our own field photography. As illustrated in Fig. 2 and described in the subsections below, these data sources were used to develop and measure variables at three different scales of analysis corresponding to the purchased large lots ($N = 424$), previously owned property ($N = 321$), and block where large lots were purchased ($N = 252$). Census block group data would provide yet another scale of analysis to test for socio-demographic effects such as undertaken by Krusky et al. (2015) but, given the relatively high homogeneity of resident demographics in our two study areas (Stewart et al., 2019), we did not include it in the present study.

3.2.1. Large lot condition-care index and its temporal sequence

Our main dependent variable was lot-level condition and care, an index of seven, binary-coded features developed in our earlier study based upon a visual assessment of street-level images of the 424 large lots. The seven items were selected for the index from a larger set of

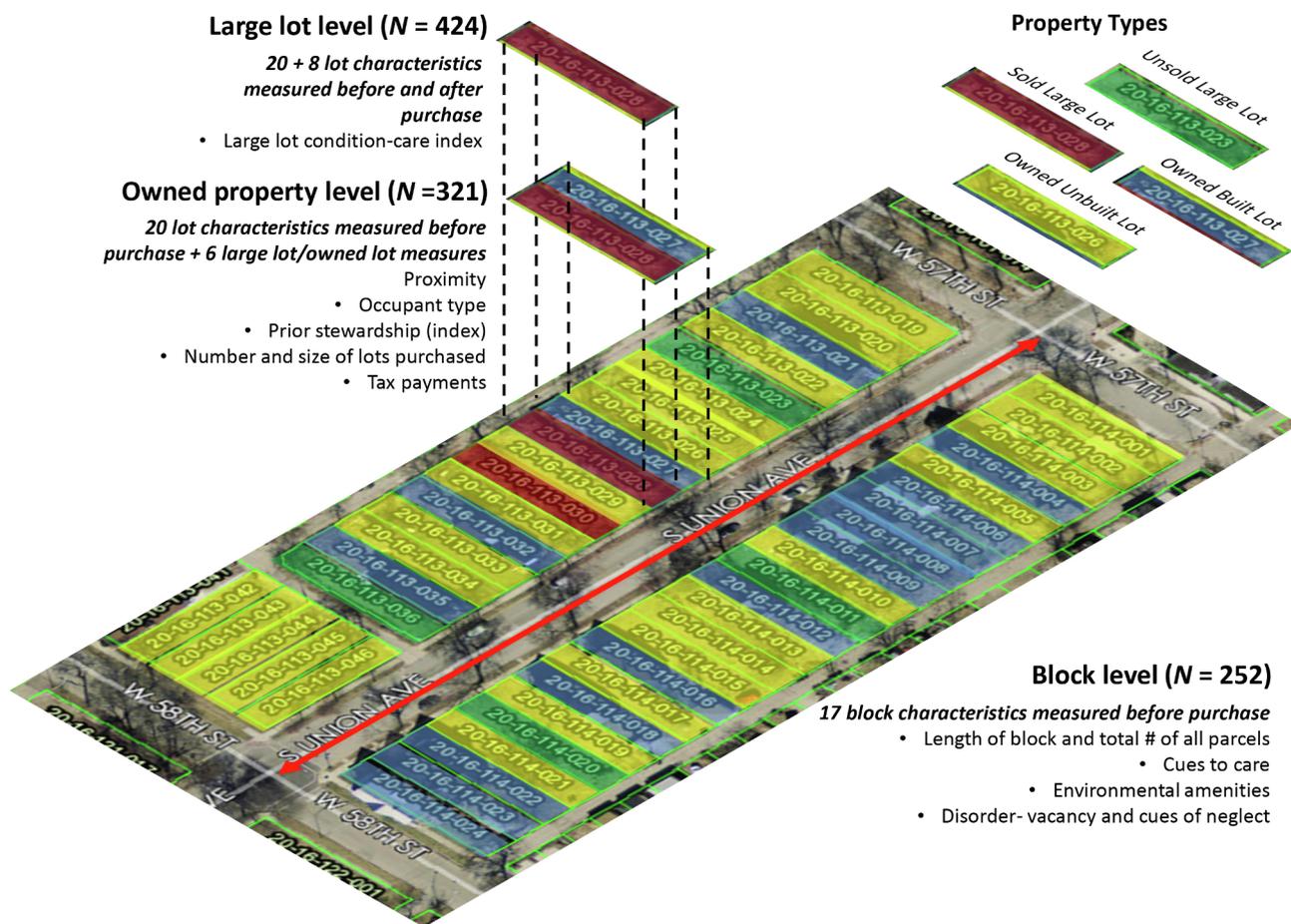


Fig. 2. Illustration of large lot-, owner-, and block-level units of analysis and corresponding variable sets used in the study. See Supplementary Appendix 1 for full description of variables. (For interpretation of the colours in this figure legend, the reader is referred to the web version of this article.)

variables (see Supplementary Appendix 1) as they dealt specifically with lot condition and care and showed acceptable internal consistency when added together to form the index. The items included: the visual condition of lot features including pavement, shrubs and small trees, mature trees, and fencing (0 = absent or not in good condition, 1 = good condition); and the presence of cues to care including gardens, yard ornamentation, and social/recreational uses (0 = absent, 1 = present). To capture the temporal nature of changes made, the variable was treated as a repeated measure and assessed by rating images of the purchased lots taken just before (fall 2014) and one growing season after (fall 2015) purchase (Cronbach’s alpha = 0.753 before purchase and 0.698 after purchase).

Because our tests of the proximity and ownership hypotheses and their interactions with blotting (Hypotheses 1–4) used the owner ($N = 321$) as the unit of analysis, we averaged the values of the condition-care index for those owners ($n = 103$, 32%) who had purchased two large lots.

3.2.2. Proximity

Proximity was measured as a four-level ordinal variable (1 = low or farthest, 4 = high or closest) reflecting the degree of adjacency between the purchased large lot and the owner’s previously owned property (Fig. 3). Large lots and owner lots were identified by their property identification numbers (PINs) and located spatially using the Cook County property tax portal. The highest level of proximity (i.e., 4) was assigned to owner/large lot pairs that were immediately side adjacent, with the next highest level to lots that were front, rear, or diagonally adjacent (i.e., 3). This distinction reflects more than just

physical distance, and in the latter cases entails having to cross a street or alley to access the purchased property, which could present an added burden if running a hose or carrying heavy materials to the large lot. Lots two-to-four lots away from each other were assigned the next level of proximity (i.e., 2) and lots five or more lots away the most distant level (i.e., 1).

For analysis purposes, proximity values were averaged for owners who had purchased two large lots. However, if their second large lot was immediately side adjacent to their first large lot, we considered both lots to be at the closest proximity level to the owner’s original property, again reflecting burden level versus simple distance.

3.2.3. Occupant type

We used a two-stage process to code the occupancy status of the large lot purchaser’s originally owned property on the block. First, we checked the tax bill mailing address on the Cook County property tax portal for correspondence with the owned property. Second, we examined the street-level image of the owned property to code whether the lot was vacant or had a habitable structure. Given these values, we coded occupant type as a categorical variable with three levels: owner-occupant, owner-absentee, or owner-vacant.

3.2.4. Owner lot condition-care index

We used street-level imagery to assess the visible characteristics of the large lot purchaser’s previously owned lot relating to condition and care prior to purchase. In addition to the seven indicators mentioned above for large lots, we also included indicators reflecting the condition of turf and buildings. All measures were converted to binary variables



Fig. 3. Demonstration of proximity coding showing a hypothetical owner’s property (center, blue with dashed border), proximity values (ordinal scale with 1 = low or farthest, 4 = high or closest) for available large lots (green), and other vacant lots on the block (yellow). Solid border around the two large lots at the top of the photo shows coding if two lots are purchased directly side adjacent to one another (see text). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

(0 = absent or not in good condition, 1 = good condition) and added together to form a nine-item index of owner lot condition and care (Cronbach’s alpha = 0.711).

3.2.5. Cost and effort measures

Using lot data from the Cook County property tax portal we calculated the total lot area owned by each large lot owner, including their previously owned lot on the block plus newly purchased large lot(s). Total lot area ranged from 250 – 3000 m², with a median value of 800 m². The typical Chicago lot is 290 m².

Property tax data were also retrieved. We noted how much the last tax assessment (2018, first half) was per lot, whether the owner had paid, and from that calculated the amount of taxes unpaid (delinquent). We multiplied this value for the number of lots purchased to arrive at a total amount per owner (\$0 - \$3143 USD, median \$0, SD \$416). As a measure of cost and effort, this variable reflects both the magnitude of the investment and the commitment to paying it.

3.2.6. Blotting

Adapting definitions by Armbrorst et al. (2008) and Dewar, Nassauer, and Dueweke (2013), we coded lots as blotted if, prior to purchase, they were fenced and showed signs of regular mowing, or if they were unfenced but were mown and showed at least one other sign of care or occupancy such as parked cars or gardens. We used Google Street View imagery taken prior to lot purchase to code this binary variable.

3.2.7. Block-level measures

The block-level analysis used blocks as the unit of analysis, considering all blocks where at least one large lot was sold (N = 252). Blocks were defined as the area between two street intersections and included lots facing both sides of the street (see Fig. 2). Our definition differs from the one used under which blocks were purchased (see Fig. 3) because our primary concern in this analysis was the view of the streetscape in front of where the owner’s lot is located and not in the alley behind it. This definition conforms to similar types of analyses (e.g., Maroko, Weiss Riley, Reed, & Malcolm, 2014; Mooney et al., 2014) and also avoids overlap between blocks. Because blocks varied in length (70–410 m, median 200 m) and number of lots (6–107, median 35), most of the block-level predictor variables were standardized for comparison by dividing values by total block length or lot number.

Block-level variables were measured using Google Earth (aerial) and Google Street View (street-level) imagery and linked to aerial imagery from the Cook County property tax portal showing individual parcels. In the assessment, a researcher examined the aerial images and made “virtual walks” down the block in Street View and inventoried features selected as predictors of our two dependent variables (see below). Most of the images were taken in the summer-fall of 2014, representing conditions when lots were selected for purchase.

Block-level predictors were adapted from previous studies that examined lot and block-level attributes as part of neighborhood quality of life assessments. These assessments typically use aerial and street-level images or field observation to inventory conditions relating to care

(Dewar et al., 2013), disorder (Mooney et al., 2014; Sampson & Raudenbush, 2004), or amenities influencing concepts such as walkability (Hajna, Dasgupta, Halparin, & Ross, 2013). Using this literature for general guidance, we coded multiple indicators to test in our models, anticipating some would perform better than others. Indicators of care and environmental amenities included the number of street trees (on the public easement between street and sidewalk) and big trees (canopy trees in yards and on the public easement), the presence of street calming features (e.g., speed humps, traffic circles), the presence of public or semi-public open space (green or hardscape) on or immediately adjacent to the block, and the number of lots exhibiting cues to care (e.g., gardens, play equipment). Indicators of disorder included the number of vacant lots (open and with vacant buildings), number of lots exhibiting cues to neglect or mistreatment (e.g., eroded ground, abandoned vehicles) and percent of the block with unwalkable (e.g., broken concrete) sidewalks (see Supplementary Appendix 1 for details).

These initial measures were used as-is or standardized using lot number and block length information and a subset was selected for modeling purposes (see next section). Two dependent variables were used in the prediction models, the large lot condition-care index (for Hypothesis 5.1) and the percent of large lots sold on the block (for Hypothesis 5.2). For the former, values of the index were averaged for the number of large lots sold on the block (1–8, mean 1.69, median 1). For the latter, the number of large lots sold was divided by the number of all large lots available for sale on that block (1–27, mean 4.2, median 3). Sales data came from the LargeLots.org website.

3.3. Analysis and modeling

We tested our hypotheses with different multivariate linear models to address the owner and block levels of analysis. For the models where large lot condition and care was the dependent variable, we used hierarchical linear modeling (HLM) because we have repeated measures of our dependent variable before and after the purchase of large lots and because of its flexible assumptions of normality (Raudenbush & Bryk, 2002). To account for this temporal sequence, we repeated the data matrix to create a binary variable, time, with the top half of the matrix representing conditions before purchase (time = 0) and the bottom half after purchase (time = 1). In the HLM models, we treated time along with the other independent variables as fixed effects and used owner ID (for owner-level models) and block ID (for block-level models) as grouping factors (random-effect intercepts). Because all owners purchased at least one lot, time represents the “treatment” in our mixed-effects models. The models were estimated using maximum likelihood ratio, and *t*-tests of independent variable significance used Satterthwaite’s formula. Model fit was examined using the Akaike Information Criterion (AIC) and the marginal R^2 (estimating the variance explained by the fixed-effects variables).

Besides time, the other independent variables included in the owner-level models were input as either continuous or binary variables. Proximity, the owner condition-care index (prior stewardship), size of combined lot areas (area managed) and tax payments unpaid were included as continuous variables. Occupant type was recoded as two binary variables, owner-occupant and owner-absentee, and number of lots owned and blotting were also included as binary variables.

While we had specific hypotheses driving selection for each of the independent variables in our owner-level models, the hypotheses for our block-level models were more general and we had developed a number of different measures of block-level care, amenities, and disorder (Supplementary Appendix 1). To help guide the selection of particular independent variables, we examined bivariate correlations and selected predictors that correlated highest across both dependent variables and were not highly correlated with each other (see Thompson, 1978).

For the block-level model where the percent of large lots sold was the dependent variable, we used an OLS regression model, entering all

independents in a single step. Independent variables were checked for multicollinearity with variance inflation factors (VIF) and model fit was assessed using R^2_{adj} . Both HLM and OLS models were estimated with RStudio, using the packages lme4, lmerTest, and sjstats to fit the mixed-effects models and estimate the marginal R^2 (R Core Team, 2013). All model assumptions, including the normal distribution of residuals (see Pinheiro & Bates, 2000), were tested and met.

3.3.1. Sensitivity analysis and post-hoc tests

For the owner-level models, we also conducted a sensitivity analysis to evaluate whether results of the proximity and occupant type variables were sensitive to the ordinal and categorical nature of these two variables, respectively, or whether simplified versions of these variables would yield similar results (see Greenland, 1996). The analysis also permitted us to simplify the post-hoc tests of the interaction effects between these variables as described below.

For the sensitivity analysis, we recoded the proximity and occupant type variables as binary and re-ran HLMs with those binary variables. Specifically, the proximity variable was coded as 1 = close if the large lot was immediately adjacent to the owner’s original lot (coded as 4 in the main analysis, see Fig. 3), and 0 = far if otherwise. We coded occupant type as 1 = owner-occupant if the owner of the property was living on the premises, and 0 = not owner-occupant if otherwise (i.e., absentee or vacant lot). Accordingly, we also built the interaction variables described earlier (for Hypotheses 2.2, 4.1, and 4.2) using the recoded binary proximity and occupant type variables.

For the post-hoc tests, we used Tukey-adjusted *p* values to test for significance between paired estimated marginal means of the three simplified interaction variables. We ran post-hoc pairwise comparisons for the interaction terms in the sensitivity analysis because the binary nature of the proximity, blotting, and occupant type variables made the post-hoc tests easier to interpret (2x2 cells for Hypotheses 2.2 and 4.1, and 2x2x2 cells for Hypothesis 4.2) than for the related ordinal proximity (7 possible values) and categorical occupant type variables (3 possible values) used in the main analysis. The emmeans package in R calculates Tukey adjusted estimated marginal means for pairwise comparisons between cells of cases resulting from interaction terms (for example, owner-occupant and blotted vs. owner-occupant and non-blotted for Hypothesis 4.1).

4. Results

4.1. Owner-level models

Table 2 reports the unstandardized coefficients of the owner-level HLM main and interaction effects models. As discussed in our earlier paper (Gobster et al., 2020), large lot condition and care was significantly associated with time and prior blotting, and these variables remained important predictors in all models (see Tables A1–A4 in Supplementary Appendix 2 for complete specifications of all models, including *p* and *t* values and 95% confidence intervals). Model 1 in Table 2 shows the main effects of the additional owner-related variables examined in this paper, and here proximity and the level of care given to the purchaser’s own lot were significantly associated with large lot condition and care ($p = 0.017$ and $p = 0.008$) in support of the proximity (H1) and prior stewardship (H3.1) hypotheses, respectively. The occupant type binary variables owner-occupant and owner-absentee and the cost and effort related variables of lot number, size, and tax payments showed no significant associations with large lot condition and care and thus the occupant type (H2.1), number of lots (H3.2), area managed (H3.3), and tax payments (H3.4) hypotheses are not supported.

We then introduced interaction terms in three separate models (Models 2–4 in Table 2). The two-way interactions between proximity and owner-occupant and blotting and owner-occupant were each significant and had positive signs ($p = 0.044$ and $p = 0.002$), in support of

Table 2
Owner-level models predicting condition and care.

Variable/(concept)	Hypothesis tested	Model 1 (main)	Model 2	Model 3	Model 4
<i>Fixed effects</i>					
(Intercept)		-0.410	-0.036	-0.306	-0.179
Time		0.623***	0.624***	0.624***	0.624***
Proximity	H1	0.123*	-0.033	0.128*	0.071
Owner-occupant (occupant type)	H2.1	0.043	-0.557	-0.121	-0.091
Owner-absentee (occupant type)	H2.1	-0.043	0.020	0.052	0.066
Owner condition-care Index (prior stewardship)	H3.1	0.078**	0.086**	0.086**	0.088**
Number of lots owned	H3.2	0.039	0.059	0.028	0.039
Size of combined lot areas (area managed)	H3.3	0.006	0.003	0.001	-0.001
Tax payments unpaid	H3.4	-0.001	-0.001	-0.001	-0.001
Blotting		1.156***	1.160***	0.461	0.560**
Proximity × owner-occupant	H2.2		0.220*		
Blotting × owner-occupant	H4.1			0.902**	
Proximity × owner-occupant × blotting	H4.2				0.257***
<i>Random effects</i>					
Intercept variance (owner ID)		0.557	0.541	0.525	0.517
AIC		1709.8	1707.7	1702.6	1699.7
Marginal R ²		0.272	0.279	0.288	0.293

N = 321. [^]p < .10, * p < .05, ** p < .01, *** p < .001.

Hypotheses 2.2 and 4.1, respectively. Similarly, the three-way interaction between proximity, owner-occupant, and blotting was significant and had a positive sign (p = 0.0005), in support of Hypothesis 4.2. Each of these interaction terms improves model fit, with model 4 incorporating the three-way interaction providing the best fit (lowest AIC value).

The sensitivity analysis shown in Table 3, in which the proximity and occupant type variables were recoded as binary, confirmed the results of the main models reported in Table 2. All the significant regression coefficients in the four models presented in Table 2 (main analysis) are also significant and have the same sign in Table 3 (sensitivity analysis). This shows that results for proximity and occupant type (and related interaction terms) are not sensitive to the ordinal and categorical nature of these two variables. In other words, proximity is significantly associated with large lot condition and care regardless of whether the variable is coded as ordinal or binary (H1), while occupant type shows no significant associations with large lot condition and care for neither its categorical nor binary version (H2.1).

The results of the post-hoc tests for the three interaction terms in the sensitivity analysis are summarized in Table 3 and described in more detail in Table A5 of Supplementary Appendix 2 (the three interactions were all significant). At least one pairwise comparison of the estimated

marginal means is significant for each interaction term (see Table A5). Overall, the post-hoc tests suggest that blotting and to lesser extent proximity are stronger determinants of the statistical significance and of the positive sign of the three interaction terms than occupant type. In addition, the post-hoc tests showed that occupant type serves as an effect modifier of these variables in relation to large lot condition and care. For the interaction between occupant type and proximity, large lots located in greatest proximity to the original property where an owner-occupant resided had higher estimated marginal means in condition and care than large lots located farther from an original property with an owner-occupant (p < 0.01), in further support of Hypothesis 2.2. For the interaction between occupant type and blotting, large lots purchased by owner-occupants that were also blotted had significantly higher condition and care than 1) large lots purchased by owner-occupants but were not blotted (p < 0.001), 2) without an owner-occupant that were also blotted (p < 0.05), and 3) without an owner-occupant and were not blotted (p < 0.001), in further support of Hypothesis 4.1. Finally, 14 out of the 28 pairwise comparisons were significant in the post-hoc test for the three-way interaction between proximity, occupant type, and blotting (H4.2; see Table A5). The largest effect sizes were for pairwise comparisons including blotted and non-blotted large lots (see the t ratios in Table A5).

Table 3
Sensitivity analysis for owner-level models predicting condition and care using binary-coded proximity and occupant type variables.

Variable/(concept)	Hypothesis tested	Model 1 (main)	Model 2	Model 3	Model 4
<i>Fixed effects</i>					
(Intercept)		-0.323	-0.107	-0.134	-0.144
Time		0.623***	0.624***	0.623***	0.623***
Proximity <i>binary</i>	H1	0.343**	-0.068	0.351**	0.183
Occupant type <i>binary</i>	H2.1	0.097	-0.214	-0.147	-0.024
Owner condition-care Index (prior stewardship)	H3.1	0.078***	0.087**	0.086**	0.083**
Number of lots owned	H3.2	0.055	0.069	0.045	0.056
Size of combined lot areas (area managed)	H3.3	0.009	0.004	0.004	0.004
Tax payments unpaid	H3.4	-0.001	-0.001	-0.001	-0.001
Blotting		1.152***	1.153***	0.476	0.889***
Proximity × occupant type	H2.2		0.570 ^a		
Blotting × occupant type	H4.1			0.881 ^b	
Proximity × occupant type × blotting	H4.2				0.647 ^c
<i>Random effects</i>					
Intercept variance (owner ID)		0.550	0.534	0.519	0.526
AIC		1705.6	1702.8	1698.6	1700.3
Marginal R ²		0.276	0.284	0.291	0.288

N = 321. [^]p < .10, * p < .05, ** p < .01, *** p < .001. ^a Tukey adjusted post-hoc test was significant for the pairwise comparison between owner-occupant, far and owner-occupant, close (p < 0.01). ^b Tukey adjusted post-hoc test was significant for three pairwise comparisons out of six (p < 0.05 – see Table A6). ^c Tukey adjusted post-hoc test was significant for 14 pairwise comparisons out of 28 (p < 0.05 – see Table A6).

Table 4
Block-level HLM model of large lot condition-care (H5.1).

	Estimate	Conf. Int.	Std. Error	df	t	p
<i>Fixed effect</i>						
(Intercept)	-0.423	-1.033 - 0.188	0.310	312	-1.361	0.174
Time	0.656	0.518 - 0.793	0.070	249	9.363	0.000
Presence public/semi-public greenspace	0.324	0.069 - 0.578	0.129	249	2.502	0.013
Average number of cues to care per lot	1.209	-0.207 - 2.625	0.720	249	1.679	0.095
% block with vacant lots	0.201	-0.676 - 1.079	0.446	249	0.451	0.652
% block unwalkable	-0.148	-0.364 - 0.067	0.110	249	-1.351	0.178
<i>Random effects</i>						
Intercept variance (block ID)	0.716					

AIC = 1484.5, marginal $R^2 = 0.107$.

4.2. Block-level models

Table 4 reports the HLM model results for large lot care as a function of time and block-level indicators of care and disorder. The presence/absence of public/semi-public green space was significant ($p = .013$) and the average number of cues to care per lot approached significance ($p = .095$). With much of the variance in the marginal R^2 (0.107) provided by the time variable (as emerged in step-by-step models, data not shown), the other variables in the model do not provide statistically significant support the block-level care hypothesis (H5.1) that high levels of block care and low levels of disorder lead owners to improve the condition of their large lots.

Finally, the percent of large lots sold on a block (Table 5) was strongly associated with the average number of cues to care per lot and the percent of block with vacant lots (both $p = .001$), and less strongly associated with the number of big trees per lot ($p = .013$) and the presence of green space on the block ($p = .084$). Together, the indicators of block-level care and disorder explain a much larger proportion of variance of the percentage of large lots sold (Table 5) than the block-level model of large lot care (Table 4), lending stronger support for the percent of lots sold hypothesis (H5.2) that high levels of block care and low levels of disorder lead to a higher proportion of large lot sales.

5. Discussion

5.1. Beyond proximity

That simple acts of cleaning and greening by individuals can inspire others around them to do the same, for themselves and for their community, is a powerful idea and one that underlies the greening hypothesis and its variants. Although investigators have described this process in relation to private yards (Minor et al., 2016; Zmyslony & Gagnon, 1998, 2000), easement gardens (Hunter & Brown, 2012), and community gardening on vacant lots (Krusky et al., 2015), work to date has provided only correlational evidence of these proximal relationships. The conditions for purchasing vacant property under the Chicago

Large Lot Program provided us with the opportunity to look beyond proximity, and knowledge of ownership, activity over time, and other factors that we were able to link to improvements in the condition and care of large lot purchases serve to extend the greening hypothesis along several important dimensions.

Causal inference is an essential part of the greening hypothesis, and support for causality is enhanced when research designs incorporate a temporal sequence that aligns with the hypothesized cause/effect relationship. As Krusky and colleagues (2015) recommended for future research, knowledge of ownership is a key determinant of the agency and directionality of greening activity, and because we knew who the large lot purchasers were, we were able to attribute changes made after the time of purchase directly to them. While a significant portion of large lots in our sample showed signs of blotting prior to purchase, our pre-post research design showed that levels of large lot condition and care increased after purchase for both blotted and unblotted lots, further strengthening the idea that ownership matters.

But our findings also revealed that ownership matters in complex ways. Although proximity to the newly purchased large lot from the owner's original property was significantly associated with the level of care extended (H1: proximity), our data showed no difference whether owner-occupancy led to higher care than absentee ownership (H2.1: occupant type). Furthermore, while the HLM models incorporating interaction terms that included ownership were significant, had positive coefficient signs, and showed improvements in model fit (H2.2, 4.1, 4.2), the post-hoc tests indicated that most of their significance could be attributed to proximity and blotting rather than occupant type. In addition, the post-hoc tests showed that occupant type served to modify the effect of these variables and clarify the conditions under which proximity and blotting influenced large lot condition and care. In the case of proximity, being immediately adjacent to a purchased large lot resulted in a significantly higher level of care if the owner lived there versus if it was in absentee ownership or vacant (see post-hoc tests for H2.2). Likewise, large lots that were blotted before purchase showed bigger improvements in condition and care if they were purchased by owner-occupants than if they were in absentee ownership or vacant (see post-hoc tests for H4.1). Further knowledge of these synergistic

Table 5
Block-level OLS model of percent of large lots sold on block (H5.2).

	Estimate	Conf. Int.	Std. Error	t	p
(Intercept)	0.531	0.331 - 0.732	0.102	5.222	0.000
Presence street calming features	0.034	-0.044 - 0.112	0.040	0.845	0.399
Presence public/semi-public greenspace	0.070	-0.009 - 0.148	0.040	1.738	0.084
Average number of big trees per lot	0.126	0.011 - 0.240	0.058	2.166	0.031
Average number of cues to care per lot	0.731	0.290 - 1.172	0.224	3.267	0.001
% block with vacant lots	-0.442	-0.712 - -0.172	0.137	-3.228	0.001
Average number of cues to neglect per lot	0.045	-0.415 - 0.505	0.233	0.192	0.848
% block unwalkable	-0.013	-0.080 - 0.054	0.034	-0.393	0.695

$F = 8.626$ (7, 241), $p < .0000$, $R^2_{adj} = 0.177$.

relationships could have important implications for vacant lot resale programs, helping to ensure broad participation that maximizes the equitable transfer of properties to residents and minimizes the risk that the lots will become poorly managed (Armborst et al., 2008; Ganning & Tighe, 2015).

The condition and care of the owner's previously owned lot turned out to be an important predictor of large lot condition and care (H3.1: prior care), surpassing proximity in significance in our main effects model and maintaining a high level of significance across all interaction models. This finding supports research showing that prior pro-environmental behavior can be a good predictor of future such behavior if it is similar and specific (Harland et al., 1999; Oulette & Wood, 1998). Because most applicants of vacant lot reuse programs intend to undertake some sort of greening activity, at least in the early years of ownership (Gobster et al., 2020), application forms could ask the extent to which they have had prior experience in different greening activities. This screening could be used by planners to estimate management capacity so that an appropriate level of assistance might be provided. This would both help ensure that new lot owners will be able to achieve their plans and help realize the overall success of the program in revitalizing communities.

Finally, our measures of cost and effort added little to the prediction of large lot condition and care, with no differences found on the number of lots purchased, total area of lots owned, or tax payments (Hs 3.2–3.4). It could be that these variables insufficiently captured the types of costs and effort described by behavioral theory (Moore & Boldero, 2017), or it may be that the burden created by the number and size of lots and by the level of tax payments did not exceed the threshold where it would show significant reductions in condition and care. With respect to the Large Lot Program, this latter point could be further explored for those owners who have purchased additional lots since the initial offering. For example, an owner who bought two lots in the initial offering is theoretically eligible to purchase two more lots for each lot owned in a second offering, and in fact some residents have now accumulated several lots in their neighborhood this way. If large accumulations of property by individuals leads to reduced upkeep or land holding for future resale, these behaviors could suppress the revitalization potential of the program.

5.2. From lots to landscapes

In order to understand relationships at the owned property and block levels, large lot values were averaged for the number of owners ($N = 321$) and blocks ($N = 252$). Because the change in large lot condition and care was our primary dependent variable of interest, this averaging was necessary but may have introduced error into our models, particularly at the block level when several large lots were purchased on a block. When we examined percent of lots sold on a block as a second block-level dependent variable, the number of significant indicators of care and disorder increased substantially, as did the percentage of variance explained, and in comparing the performance of the two models (Tables 4 and 5), the issue of error is a plausible explanation.

High-resolution ground and aerial imagery and parcel-level data are ideal for the type of fine-scale analysis of landscape change needed for evaluation of the Large Lot Program and has been used in numerous other studies of neighborhood quality of life (e.g., Rundle et al., 2011; Ye et al., 2019). Like the work of Krusky et al. (2015), these fine-scale assessments are often integrated with data from larger geographic areas such as census tracts to draw more general conclusions consistent with social-ecological health models (McLeroy et al., 1988) and to make comparisons between neighborhoods and cities (e.g., Bader & Ailshire, 2014). Given the rapid distance decay of contagious and imitative behavior found in previous studies, we suggest that the block is the appropriate scale of analysis to detect the adoption and diffusion of greening practices. Although our model only weakly supported the

hypothesis that blocks with high levels of care and environmental amenities like public green spaces spurs owners to improve their newly purchased large lots (H5.1: block-level care), we believe further work is warranted, including better ways to account for changes across a longer time span.

The performance of our second block-level model using the percent of large lots sold on the block is encouraging. Although there is still a great deal of variance left unexplained, the predictor terms attained respectable levels of significance and support our contention that high levels of block care and the presence of environmental amenities would lead to a higher proportion of available large lots being purchased (H5.2: percent of lots sold). The finding is also encouraging in that block-level care may affect owner actions both before and after purchase, supporting the idea raised by Krusky et al. (2015) that greening behavior may be bidirectional in nature. Together, both of our block-level models deepen understanding of how actions undertaken by property owners on individual lots contribute to the greater good of the neighborhood, and how the neighborhood landscape can affect the norms and behavior of individual lot owners. In each of these ways, the neighborhood landscape, as seen by visitors from the street and experienced by residents within homes and yards, is a critical scale of concern for research and planning (Sullivan, 2001).

6. Conclusions

In the context of the greening hypothesis initiated by Krusky et al. (2015), our work supports a causal, directional, and temporal relationship between several physical and behavioral factors and increased vacant lot care. As a primary characteristic of nearby nature, proximity expresses itself in numerous ways across the urban landscape, and figures prominently not only in patterns of residential greening but also with respect to public access to greenspace (Crompton, 2004), the provision of ecosystem services (Stessens, Khan, Huysmans, & Canters, 2017), environmental justice concerns (Rigolon, 2017), and other issues. But by itself, proximity usually provides only correlational evidence of attraction or repulsion between people and green space, and without further knowledge about why proximity matters, it is difficult to develop standards or guidelines to ensure that people's greenspace needs are met. Because our study design captured urban landscape change across time and at different scales of measure, we were able to document the impact of a vacant lot re-purposing program and its potential for a catalytic effect on neighborhood revitalization. It shows that prior stewardship as an individual variable and occupant type as an effect modifier of proximity strengthen our ability to predict changes in vacant lot condition and care. Continued research efforts, using temporal and ownership data, examining patterns across scales of analysis, and incorporating other social and environmental information, will strengthen our understanding of proximal relationships in the landscape and help build more robust theories of urban greening.

Acknowledgements

This work was supported in part through USDA Forest Service Northern Research Station Cooperative Research Agreement 15-JV-11242309-075 with the University of Illinois-Urbana-Champaign. The authors thank Rose Grenen for research assistance, and Sonya Sachdeva and Michelle Kondo and two anonymous reviewers for their helpful comments in improving this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.landurbplan.2020.103773>.

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