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Land value dynamics and the spatial evolution of cities following COVID 19 using big data analytics

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Land value dynamics and the spatial evolution of cities following COVID 19 using big data analytics

Abstract

In this paper we present results of a land-use forecasting model that we calibrated with vast geo-referenced data of a major metropolitan area. Each land parcel includes information concerning regulations indicating permitted land-uses as well as the certain characteristics of existing buildings. Data concerning all real estate transactions include information about the assets and the price of the exchanges. Based on these data we estimated the spatial dynamics of land values in the metropolitan area over time and identified locations experiencing development pressures. This analysis allows us to forecast plausible futures of the urban spatial configuration. Taking the approach one step further, we propose simulations motivated by the natural experiment of COVID 19. We assumed that part of the behavioral changes observed during the pandemic will endure. The resulting simulations provide forecasts of the future spatial structure of the metropolitan area. Comparing the actual and the forecasted scenarios we interpret the spatial dynamics of the city as they would be if a business-as-usual-pre-Covid-19 scenario is realized, and possible trend changes if the impact of the pandemic is long lasting.

1. Introduction

Cities are three-dimensional objects with poorly defined, fuzzy boundaries. Their structure is in a constant state of flux. At times it changes quickly. At times, the change is imperceptibly slow. Following the industrial revolution (1760 -1840) cities spread out, and in the decades following the end of World War II Alonso style, compact cities leap-frogged out into the suburbs. In the USA, the construction of a massive interstate highway system led to the creation of secondary business districts, edge cities. Today, cities are porous with spatially continuous clusters of built areas of various sizes often, but not always, displaying fractality (Benguigui et al, 2000, 2001a, 2001b, 2004a, 2004b).

Ever since Adam Smith economists wondered why some places grow while other places stagnate. Modern economics sought answers by studying the economy as a self-organizing system. The evolving actions of interacting agents, responding to conditions created by their past actions, give rise to innovations and generate economies and diseconomies of scale creating conditions for endogenous growth (Broitman and Czamanski, 2020). It was not until the 20th century that tools created in the physical sciences became available to address the question how particular patterns of actions at a point in time will create new patterns in the next. Until then economists' inquiries were limited to the examination of consistencies between the actions of individuals and macro patterns (Chorafakis, G. 2020, Rosser, 2014). Assuming that all agents are the same and contrary to reality, economists focused on conditions for equilibrium. Modern contributions view equilibrium as possible, but not imperative, economic condition and study growth and spatial polarization as a far from equilibrium system (Broitman et al 2020, Broitman and Czamanski, 2020).

In the short run the spatial evolution of cities can be approximated by linear extrapolations. In the long-run it is the result of self-organizing processes subject to positive and negative feed-back effects. The net impacts on city structures are not easily discernable. The impact of disasters such as the Covid 19 pandemic complicate things further by causing the behavior of agents to change during the evolution, both in the short and in the long run.

The current paper is an attempt to sort out the forces responsible for the spatial evolution of cities. In particular, we focus on the COVID 19 natural experiment that changed significantly the demand for various land uses in cities and use it as a prism for studying urban dynamics. The rest of the paper consists of 4 sections. Section 2 presents an overview of our model. A preliminary application of the model is presented in section 3. In section 4 we present some results following the COVID 19 experience. Section 5 presents some conclusion and suggestions for future work.

2. A basic model of urban spatial dynamics

We assume that urban spatial dynamics are powered by a single predominant force: Land developers' choices subject to restrictions imposed by city planners determine the land parcels that are developed (Broitman & Czamanski 2012a, Czamanski & Broitman 2017). Particular urban spatial patterns are the result of developers' search process for parcels of land that can yield the highest returns (Broitman & Czamanski 2012b). Developers compare the value of land in its current use and the land value that can be obtained by converting it to the best and highest possible use. This comparison takes into account the land's location and quality, regulatory possibilities and the value of time required for obtaining construction permits (Broitman & Czamanski 2015). Therefore, the driving force of the model is the choices that land developers make concerning developable parcels of land. In this context, actual land values reflect both demand for various land uses and available parcels that satisfy the demand. In other words, the developers' behavior reflects both the demand and supply conditions. We applied this framework in the case of theoretical urban settings and under different scenarios (Broitman & Czamanski 2012, Czamanski & Broitman 2012, 2018). The model suggested in this paper, illustrated in Figure 1, is an effort to apply this framework to a real-world test case.
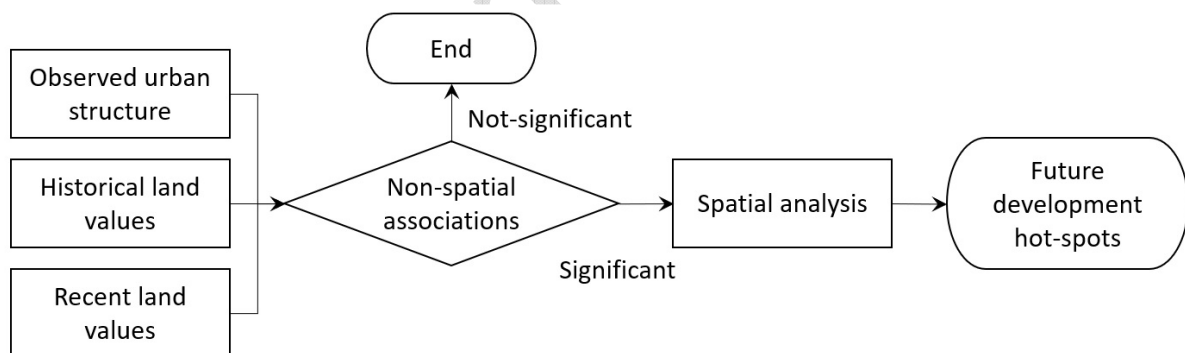

Figure 1: Model's logic

The observed urban structure includes features of the built area (spatial distribution, densities, etc.) and planning restrictions. These data represent the availability of potentially developable land parcels at various locations (the supply). Historical and recent land values represent the demand for developable land. We split the land value in two disjoint datasets because from a dynamic point of view they reflect two different realities: The traces of the historical land values are, to a large extent, already embedded in the observed built area. In comparison, the actual land values reflect current trends in preferences, at their initial phases of realization. We expect to find correlations among these (decision diamond in Figure 1), otherwise the observed urban dynamics are

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unintelligible. If this is the case, we perform a spatial analysis, aimed to answer the question of where future urban development is most likely. Finally, based on the spatial analysis and under plausible assumptions, we identify possible urban development hot-spots and the resultant urban spatial futures.

The study area

The study area is the central strip of Israel's coast, the most urbanized zone of the country. This area hosts 17 cities each with more than 50,000 inhabitants. Among these is the city of Tel Aviv. Tel Aviv and its area of influence is the most dynamic metropolis in Israel and is considered the economic heart of the country. Figure 2 shows the location of the study in Israel, and some of the most important cities located on it.

Figure 2: The location of the study area in Israel (left) and a zoom-in of the study area with some of its principal cities (right)

Data

The transactions dataset includes all real estate transactions performed in Israel during the period 1998 – 2020, as recorded by the Israeli Tax Authority. Each transaction includes the property price (in New Israeli Shekel), the dwelling size, number of rooms, the property age, the floor (if the property was not a detached house) and a few additional details. Each transaction can be localized by its cadastre system characteristics, which are its block number (generally smaller than a statistical area) and its parcel number. These features allowed us to geo-reference the transactions in the map. After clean-up of

outliers, records with missing data, and records that are located out of the study area, the resulting dataset includes 639,096 real-estate transactions.

An additional source is a detailed database of built structures created and maintained by the Survey of Israel, a governmental agency for mapping and geoinformatics. Each built structure is precisely located and information about its main characteristics is available. The most important details for our purposes are the footprint and the height of the built structure. After clean-up and exclusion of structures that are not proper buildings (for example, greenhouses or temporary structures), we selected the buildings located in the study area. This resulted in a dataset of 387,271 buildings, each one with its volume in cubic meters.

The final data source is a detailed spatial map of statutory plans pertaining to the entire study area. This source defines the locations of residential, commercial, industrial, agricultural and open areas with a great level of detail, classified in more than 30 land use categories.

Methods

Land valuation is performed daily by real estate appraisals (Davis et al 2019). The assessments pertain to specific properties, based on data about their physical characteristics, locations, and auxiliary data about the local real estate market (Glumac 2019). This traditional approach to assess the land value of a specific real estate property assumes that it can be calculated from the difference between the market price of the property and its construction costs (OECD 2015). Therefore, this method is useful for specific real estate properties, when both the market price of the entire structure (which can be a single house or an apartment building) and its construction cost are accurately known. However, this method can also be used for large scale regional assessment, provided that updated construction costs for each type of residence (such as private houses, detached houses or apartments located in different stories) are available. These data are available in Israel through Dekel corporation (www.Dekel.co.il) that reports detailed building costs of all dwelling types based on actual costs of all projects. In order to bring all the financial data to a common ground, we used the 2020 issue of the book, and calculated the actual value of all the transactions, taking into account changes in the consumer price index. For each transaction, the land value component was calculated as following:

$$LV = \frac{ApartmentP}{ApartmentS} - ConstructionC \qquad (1)$$

In Equation (1), the land value per square meter (LV) is the cost of a built square meter (the apartment/house price divided by its size) minus the construction cost of a square meter of the specific type of dwelling. One aspect of a traditional real estate appraisal that is not included in our land value calculation method is the built structure amortization. Although the construction year of the properties is recorded in the dataset, data about renovations is not available. This is the reason why there are few transactions with very low or even negative calculated LV.

The frequency distribution of the transactions with positive land values is right-skewed. Therefore, we selected a range from one standard deviation from the left of the distribution's mean, to two standard deviations to its right. After this selection, our final dataset containing the land values to be used in the analysis contains 373,457 transactions, 81.6% of the original dataset. In order to differentiate between past and ongoing spatial processes, we split the transaction dataset. Transactions from the period 1998-2014 were assumed to represent past urban trends, while transactions recorded in the last five years (2015-2020) reflect ongoing spatial and economic processes.

We used a kernel density (KD) smoothing procedure to create a continuous density surface of three of the variables of interest: The land value during both periods (1998-2014 and 2015-2020) and the building volume. The KD method is a non-parametric method of extrapolating data over an area of interest without relying on fixed boundaries for aggregation (Carlos et al, 2010). The most important parameter of the KD surface is the kernel bandwidth since it determines the degree of smoothness. Large bandwidths may result in over smoothed surfaces, while smaller ones may produce large differences between close locations (Gatrell et al, 1996). In this case we used a bandwidth of 500 meters, calculated for square cells of 50 meters side. The main advantage of the KD surfaces is the ability to combine the value observed in every single place with the values observed in its surroundings. Therefore, the KD surface express both the observed values and also their density over space. Since the KD has no units, once the KD surfaces were calculated, we normalized them to a range between 0 and 100 creating three different normalized KD surfaces: On one hand, the land value density in period 1998-2014 and in period 2015-2020, representing the spatial distribution of the demand for land in the study area. On the other, the built density that reflects the physical features of the built areas.

Following the flowchart in Figure 1, we first perform a non-spatial statistical analysis of the associations between the described datasets and, if the results turned out to be satisfactory, we proceeded to perform a detailed spatial analysis.

3. Preliminary results

There are several features of the study area clearly observed in Figure 3. Despite being a highly urbanized region, most of the area is covered by relatively low built density. The areas with high built density are in the urban cores, as shown by the upper right map. On the other hand, statutory plans have defined a complex network of open land patches, even near the city centers. But as the built density map clearly shows, even if the specifically legally determined open areas are preserved, these are threatened by built structures in their surroundings: This is indicated by the light gray patches in the upper-right map that cover part of the green patches defined in the upper-left map. The lower maps show how the preferences of the players in the urban arena change over time. Although the places with high willingness to pay land values are concentrated in both periods, their spatial distribution is different. But before discussing this changing spatial patterns, we will verify that the choice of the time periods make sense for the whole urban area. The study area is now covered by square cells of 50 meters, each with its own land value density during both periods and with its built density. Therefore, we calculate the association between both variables in Figure 4.
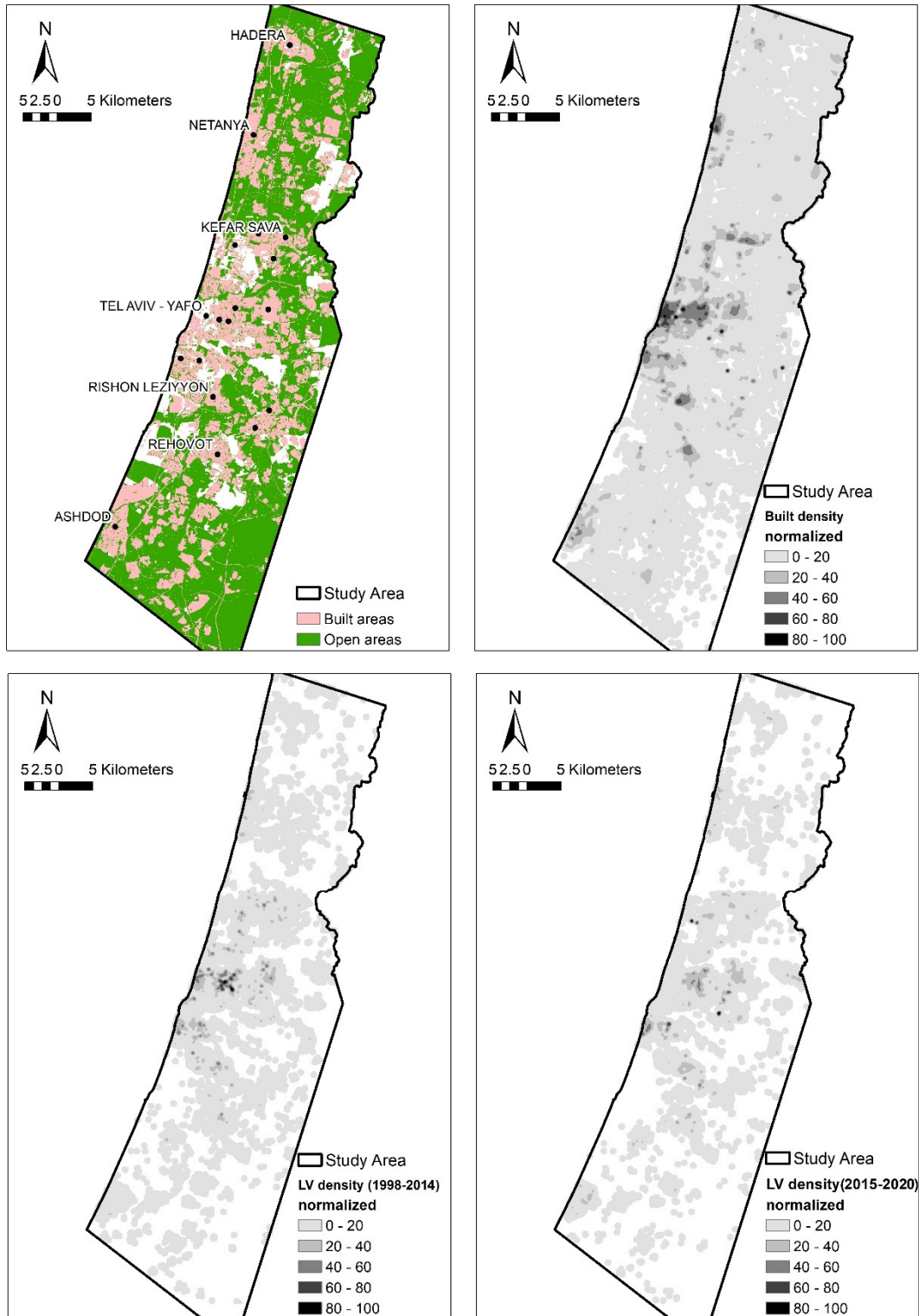
Figure 3: Spatial dataset created in the study area. Statutory plans (upper-left), built density (upper-right), land value density during 1998-2014 (lower-left) and land value density during 2015-2020 (lower-right)
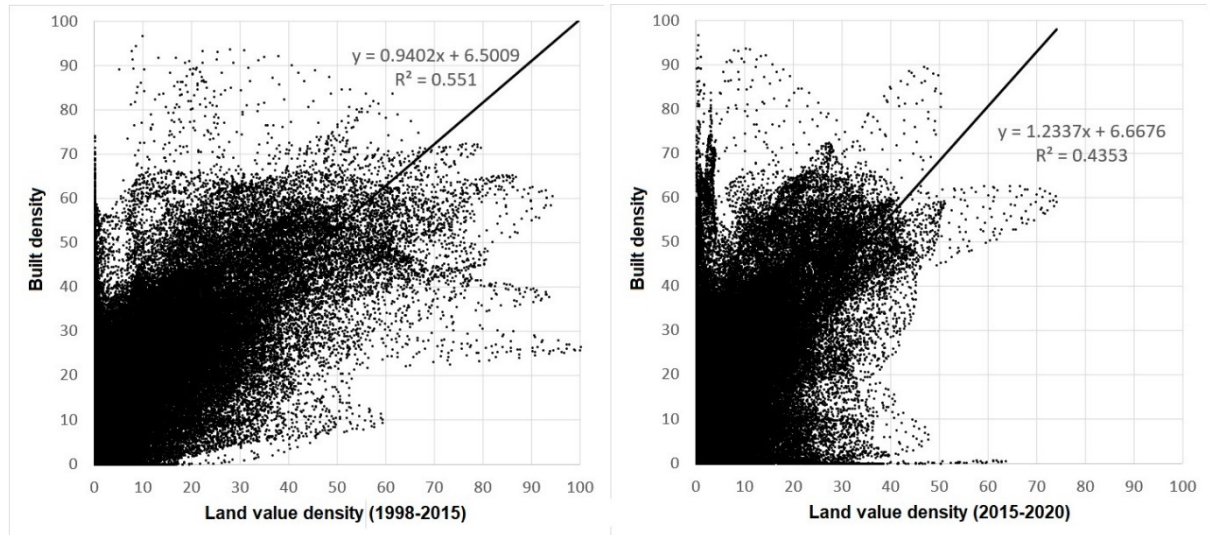
Figure 4: Land value densities and built density

The standard expectation supported both by empirical observations and theoretical models, is that the more densely built places are also those in which the land values are higher. The left chart in Figure 4 represents a mature urban structure: Despite the dispersion of both variables (caused by the presence of a wide range of urban cells, from all the area of interest, including central cities and rural areas), the land values calculated before 2015 explain 55% of the variation in building density. However, each additional percent of land value is associated with an increase of less than 1% in the density of buildings. This result reflects the inertia of urban areas that were developed long time ago according to lower density standards compared with those acceptable today. In comparison, the right chart in Figure 4 describes a more dynamic and modern urban structure, reflecting recent urban trends that characterize newly developing areas. The resulting power of association is lower (43%) since part of the demand was yet to result in concrete buildings. But on the other hand, the association is stronger and above 1, suggesting that in places where construction effectively takes place, the building density is high. The comparison between both charts supports the relevance of the differentiation between both periods.

Our next step is an effort to apply a formal model aimed to reveal and to test the associations between the observed land value density in period 2015-2020 (the dependent variable) and the following independent variables: The land use defined by the spatial plans, the observed built density and the land value density in the previous period (1998-2014). We implemented a logit regression using dummy variables as defined by Table 1.

Table 1: Variables of the logit regression

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Variable	Type	Values	
		0	1
D_1 - Plans	Dummy	Built areas	Open areas
D_2 – Built density	Dummy	Low (<20)	High (>20)
D_3 – LV density (1998-2014)	Dummy	Low (<3)	High (>3)

The original values of the variables used for the logit regression are continuous, but their distribution is not normal. Therefore, we converted them into dummies with threshold values defined according to their median value: 20 for the built density, and 3 for the land value density in the period 1998-2014.

Therefore, the logit regression is defined as following:

$$\text{logit}(p) = \log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 \cdot D_1 + \beta_2 \cdot D_2 + \beta_3 \cdot D_3 + \beta_4 \cdot (D_2 \times D_3) \qquad (2)$$

The probability for a certain event to occur (in this case, an increase in land value density during the period 2015-2020) is given by:

$$p = \frac{1}{1 + e^{-(\beta_0 + \beta_1 \cdot D_1 + \beta_2 \cdot D_2 + \beta_3 \cdot D_3 + \beta_4 \cdot (D_2 \times D_3))}} \qquad (3)$$

In other words, the probability for increasing land value density of a certain cell of 50 x 50 square meters in the study area is given by equation (3). The interaction between the built density and the LV density is meant to identify places in which a high demand together with a high density coexists. In these places, the probability should be lower than in places with more space available. The results of the logit regression are reported in Table 2. We can see there that the coefficients of the three variables are consistent with our expectations: Separately, existing built density and high land values during the first period increase the chance of high land values during the second one, but the combination of both in a single place hinders the probability further high land values.

Table 2: Logit regression results

Variable	Coefficients (β)	Significance (p)
Constant	-0.789	0.000***
D_1 - Plans	-0.226	0.000***
D_2 – Built density	1.699	0.000***
D_3 – LV density (1998-2014)	0.938	0.000***
D_2 X D_3	-1.094	0.000***

***p<0.001
Nagelkerke R^2 = 0.161

Finally, the land value increase probability for each type of cell were calculated using the regression results and equation (3) and included in Table 3.

Table 3 demonstrate the strength of the relations between the increase of land value density and the explanatory variables. The observed built densities appear to be the most influential factor, but also the observed land value densities in the previous period have a lower but still observable impact. This is consistent with the maps shown in Figure 3: Indeed, the spatial patterns of the land value density are different in the tested periods, but in both cases the areas coincide to a large extent with high built density areas. An additional conclusion is that there is an overlap between statutory plans and spatial preferences of players in real estate market: The probabilities to an increase land value density are quite similar both for planned built and open areas.

Table 3: Probabilities of land value increase in period 2015-2020

Plans (D_1)	Built density (D_2)	LV density 1998-2015 (D_3)	LV increase probability
Open areas	High	High	0.629
	High	Low	0.665
	Low	High	0.481
	Low	Low	0.266
Built areas	High	High	0.68
	High	Low	0.713
	Low	High	0.537
	Low	Low	0.312

Now that significant statistical associations between the different datasets were demonstrated, we proceed to the spatial analysis. A close look at the spatial distribution of the land values density during both periods confirm the impression that the preferences of the market players are different during both periods, as shown in figure 5.

The main observed change is shift of the higher land valued densities from the center of Tel Aviv to its eastern outskirts (the neighbor cities of Bene Brak and Givataim, and further on, Petah Tiqwa), and, to a lesser extent, to the south-eastern municipality of Rishon Leziyyon. In the south of Tel Aviv, the land value densities are high and stable in the cities of Bat Yam and Holon.
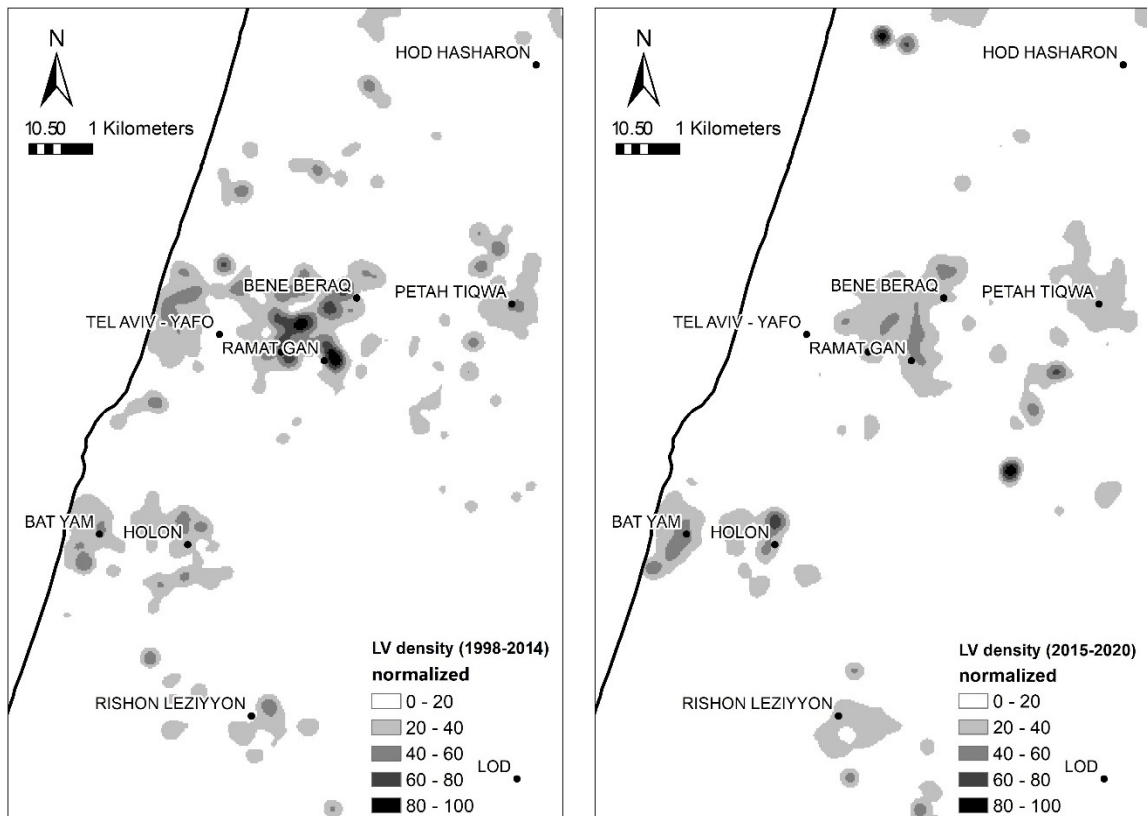
Figure 5: A zoom-in on the land value densities during 1998-2014 (left) and 2015-2020 (right)

Now we can proceed to the next and most important step of our suggested approach: The assessment of possible future urban structures. The rational of our approach is that urban areas are likely to develop towards places where the land value are high, and there are enough places to accommodate additional built structures. In other words, places in which the land value density is relatively high, and the built density is relatively low. In Figure 6, we show a spatial sensitivity analysis based on the assumption that in places where the built density is lower than 75 (recall that this is measured in a 0-100 scale), further urban development could be expected if the land value in its surrounding area is high enough. Choosing 75 as a threshold we exclude the highest built density quartile, following the common practice of using quartiles in urban measurement studies (Duque et al 2019, Mahtta et al 2019).
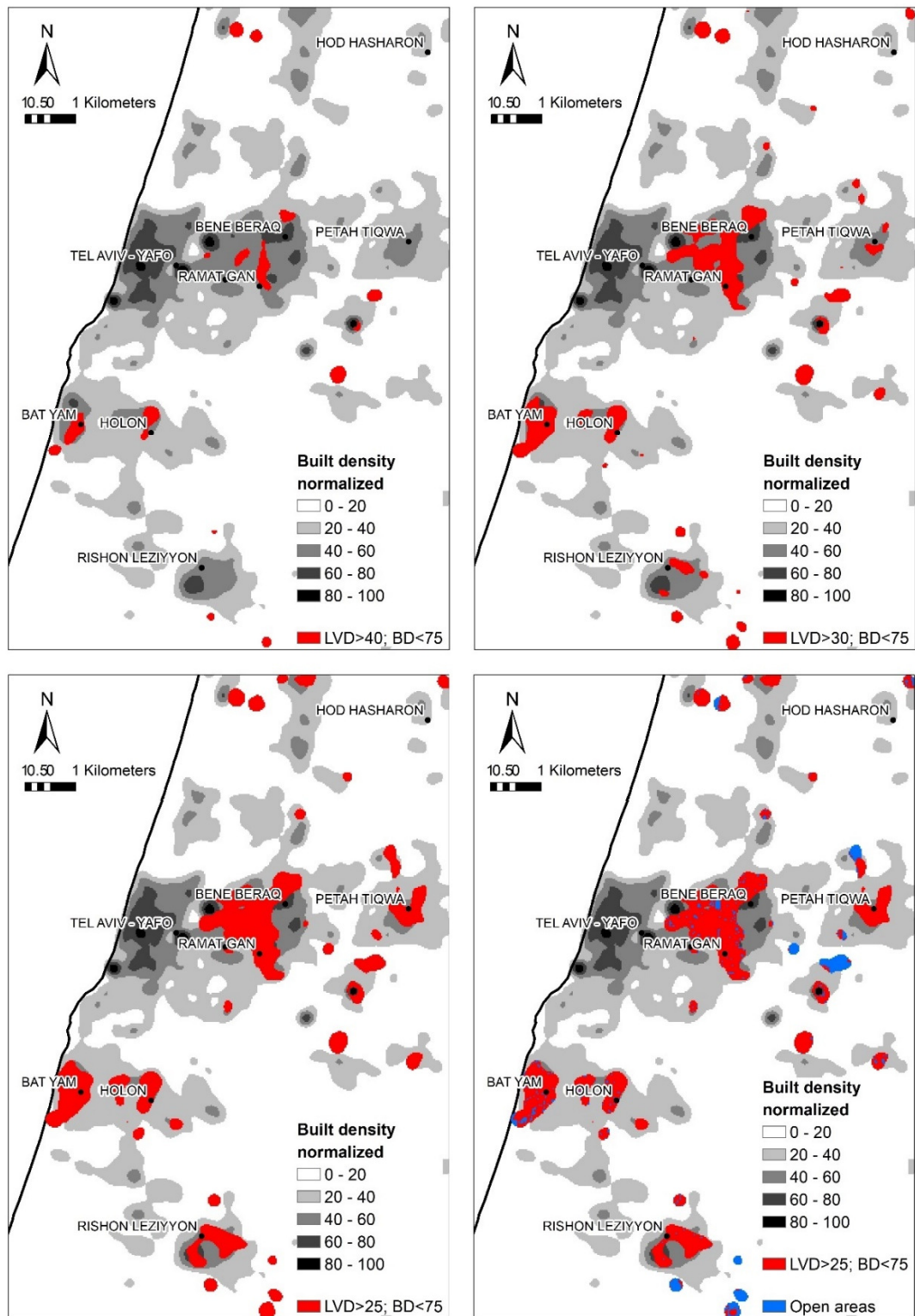
Figure 6: Future urban development areas locations assuming that suitable places have built densities lower than 75. Land value densities are higher than 40 (upper-left), 30 (upper-right) and 25 (lower-left). The lower-right chart shows the endangered open areas (in blue) by the last scenario.

Figure 6 contains spatial descriptions of the areas prone to urban development under specific assumptions. We kept constant the requirement of built density below 75 and tested the sensitivity of the scenarios to the observed land value density during period 2015-2020. The lower the required bottom threshold of the land value (in Figure 5, 40, 30 and 25), the larger the areas affected by future development pressures. Since we use a combination of land use density and built density, the areas marked in red cover relatively highly urbanized zones, buy also areas with very low built density, and even open areas. For example, in the lowest-right chart of Figure 6, the open areas threatened by future development are shown in blue.

Maps as those included in Figure 6 allow for a detailed descriptive identification of possible areas that may be under development pressures in the future. But these places are heterogeneous regarding their characteristics and spatially dispersed. In addition, their location sometimes are at times in contrast with spatial planning policies.

Summarizing, we have shown that in the study area, the urban built structure, and the dynamics of the land values are associated with possible future development pressures. The association was calculated using a regression model and it is significant. But the regression is spatially blind and cannot predict where it is likely to see these development pressures. In order to make a spatial prediction model, further assumptions are needed (as the acceptable built density and land value levels). But based on these assumptions, it is possible to locate specific future development hotspots, as shown by Figure 6.

4. Possible repercussions of COVID 19

The Covid-19 pandemic that spread worldwide during the last year, and the attempts to cope with it, are a great natural experiment that has implications also for the future spatial structure of cities. Even if the pandemic is controlled and ultimately eliminated during the coming months, there were several behavioral changes triggered during the quarantine and lockdown periods that are expected to persist. The pandemic forced large groups of people to experience home-based work and online shopping on a scale that was uncommon heretofore.[1] These behavioral changes imply possible changes in the demand for office space, housing, and retail space. Following the new work and shopping patterns, changes in rents and in the demand for building types and locations of income-generating real-estate are expected, including changes in access to

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[1] According to the OECD capacity for remote working can be above 50 per cent of the workforce and can affect lockdown cost differently across places. For example, this is the case in greater London and Washington D.C. Paris: OECD. https://bit.ly/3fgJRkF

recreational facilities, amenities and services. Also, the demand for housing, especially in the demand for high-rise apartments and for single family housing units is expected to experience modifications. However, reliable and sufficiently extended data about these issues are still unavailable. In our opinion, spatial changes will start to be evident only during the coming years.

However, using the framework suggested in this paper, it is still possible to simulate what-if scenarios connected with assumed impacts of the Covid-19 pandemics. One of the most plausible working hypothesis regarding the urban spatial structure after the pandemics, is the built density avoidance. The assumption is that, as a consequence of the experiences from the last year, people will prefer to avoid crowded spaces for any activity they do (work, leisure, shopping, sport, etc.). Combined with the expected decline of demand for large office or retail buildings, one possible consequence will be that future urban developments will be less dense and more spaced than they are actually. This working hypothesis can be implemented in our suggested framework by assuming that the places with actual high built density are no longer appealing. Instead of assuming that suitable places for future urban development need to have a built density less than 75 (in a 0-100 scale), we further reduce the preferences, testing a scenario with maximum suitable built density of 50. In other words, only places in which the actual built density is low, are considered. The results are shown in Figure 7: The upper left map was included already in figure 5 (LV density > 25 and built density < 75). The upper right map is obtained when the built density is forced to be lower than 50. Several areas that were previously considered suitable are not considered any more, and therefore the red spots appear more dispersed and pierced. But as consequence of this, the total suitable area (the red spots) is reduced. In order to compare accurately the scenarios, we need to define a similar area size prone to future development. The only way to do that is to reduce a bit the suitable land value density. This is done in the lower maps, using land value density larger than 22 (instead of 25). This creates a red spot that is similar in size to the upper-left map, but is distributed differently, according to the assumed post Covid-19 preferences.

Under the post Covid-19 scenario the areas prone to future development pressure are more dispersed and overlap more frequently with planned open spaces (Figure 7, lower maps). In other words, current statutory plans regarding land uses helps us to highlight future land use conflicts between urban development pressures and the provision of green and open spaces as envisioned by the planning authorities. This simulation results are consistent urban hypotheses and models published recently (Acuto 2020, Connolly et al 2020) and demonstrate the feasibility of the suggested methodology for the analysis of this type of emerging scenarios.
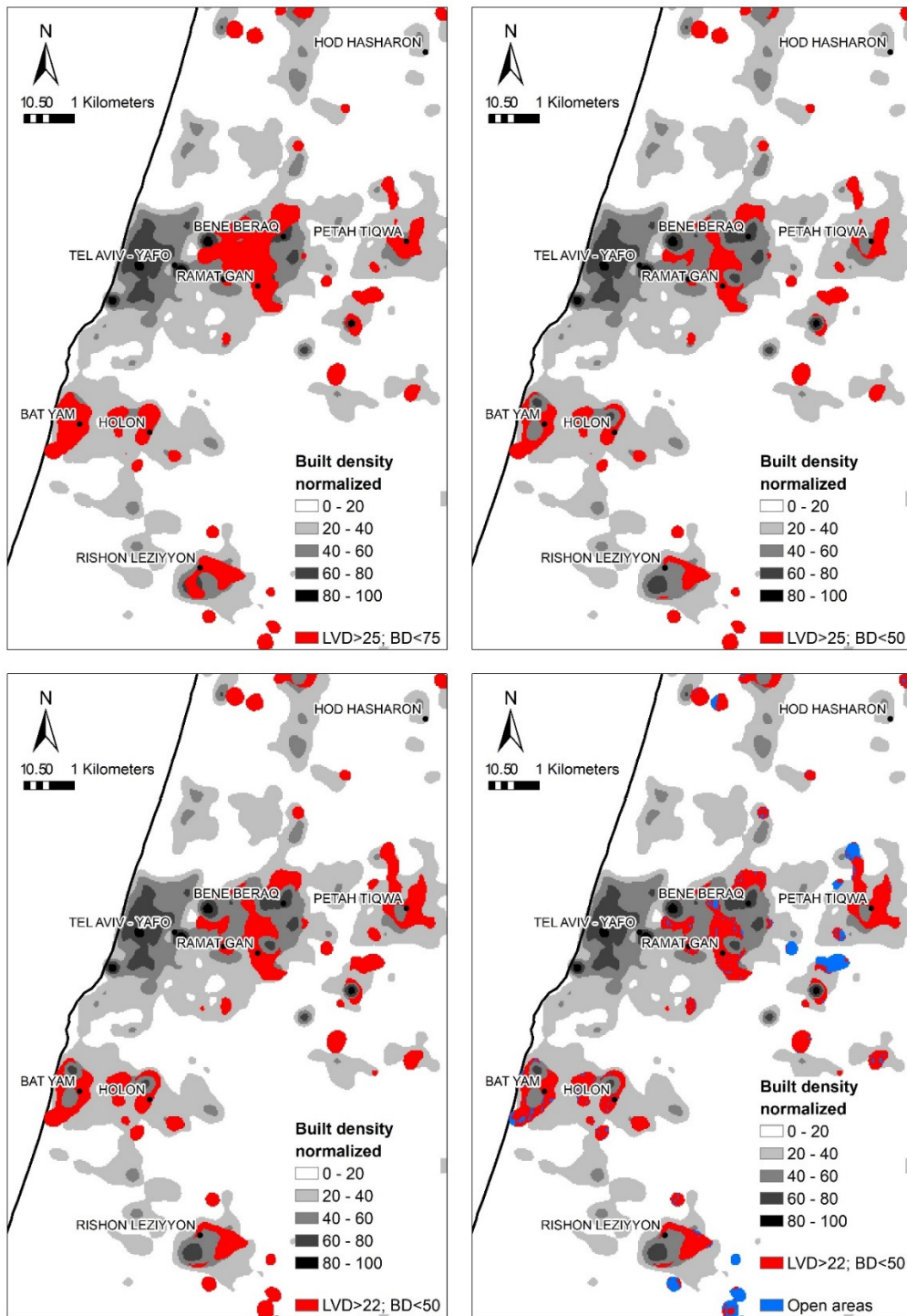
Figure 7: Effects of reducing the acceptable built density below 50 (upper right map) compared with the original 75 (upper left map). The maps below show how additional areas compensate the loss of suitable places (right) and the further potential harm to open spaces (right)

5. Preliminary conclusions

An urban system can be conceptualized as a huge spatial playground composed of different cities that contain a mosaic of residential, commercial, industrial, infrastructure, and open areas with dissimilar characteristics. There are lots of players in the playground (for example, households) pursuing different goals and continuously modifying the characteristics and composition of the playground itself. But behind the physical-morphological development of urban areas there are two main players that overshadow all the others: Real estate developers and planners. The adversarial interplay between them is the major force that shapes the dynamic spatial structure of metropolitan areas. In this paper we operationalize this concept by means of four variables: The actual physical shape of the built area (existing buildings) is the playground as it looks right now. Statutory plans represent the territorial ordering defined by urban planners. Historical land values reflect past preferences of real estate developers. Actual land values, in contrast, represent current trends that are likely to be influential in the near future. Using the suggested model, we are able to forecast the future shape of the playground, assuming a continuation of the actual trends. Moreover, modifying the assumptions, it is possible to speculate how different urban spatial trajectories will develop. We apply this to the case of a hypothetical change of land use preferences due to long last impacts of the Covid-19 pandemics.

The model suggested in this paper can be extended into a more extensive and detailed framework. Particularly, considering the observed behavioural changes since the outbreak of the Covid-19 pandemic, it is too early to summarize them. There are several plausible working hypotheses regarding the post-pandemic's spatial changes in urban areas. Working from home implies less commuting and less demand for office space, but also may result in increasing demand for dwelling size. On-line shopping implies less travel time and perhaps less retailing space, but the demand for warehouse space may increase as a result (Behrens et al 2021). In addition, attempts to solve the last mile problem may result in the spread of accessible but small warehouses. In turn, the connectivity among activity places (both intra-urban and inter-urban), together with the modal urban transport options that may exist in the future is an additional influence that was not contemplated in the suggested simple model. The simultaneous analysis of these plausible trends requires a multi-sector spatial-economic model based on detailed data about the cost and benefits of each type of players. We are confident that given the increasing availability of big data in general, and particularly the expected availability of data about observed effects of the pandemics, will allow to undertake this task in the near future.

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