

White Flight

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Abstract

This research explores the phenomenon of “white flight”, a dynamic in which Whites in a particular neighborhood begin to leave when Blacks begin to move in. We present a brief overview of literature providing a variety of perspectives on this issue, and then present an in-depth analysis of one mathematical model of the phenomenon. We then present our own mathematical model, based on spatial cellular automata techniques, including the variables of race, socio-economic status (SES) and number of dependents. General findings suggest that the complexity of the problem far surpasses our ability to effectively model “white flight” behavior.

Introduction

The dynamics of race and race relations have played a central role in the history of the United States since the earliest days. Over the centuries, the complex and highly interdependent relationship between the races, in particular between black and white, has transformed from slavery to Jim Crow to our present day debates over diversity and affirmative action. For our project, we have focused our attention on one aspect of this complicated issue.

While the Civil Rights movement of the 1960's brought about the end of legal segregation in America, it was hardly the end of racial segregation. As more and more Blacks began to move up in terms of socio-economic status and into wealthier, predominantly White communities, increasing numbers of Whites began to move out. For decades, researchers have struggled to understand the factors generating this “White Flight” phenomenon.

Our report begins with a brief literature review presenting a variety of perspectives on this complicated dynamic, followed by an analysis of one particularly compelling exploration of the issue. We then present a mathematical model of “White Flight” based upon a spatial cellular automata conception of the problem. The report concludes with an analysis of the implications and limitations of our model.

Literature Review

A complete review of the literature related to segregation and the White Flight phenomenon is beyond the scope of this project. However, in our limited time, we read through a variety of analyses of the issue. The few articles described below were deemed most relevant to our efforts, and highlight the complexity inherent in this systemic dynamic.

Detroit Divided (Farley, Danziger, & Holzer, 2002) explores the current racial dynamics in this notoriously segregated city. This study argues that: “the racial divide is as central to this metropolis as it enters the twenty-first century as it was to Philadelphia a hundred years ago when W.E.B. Dubois proclaimed the color line to be “the problem of the century”. The degree of segregation in the city is striking: by 1990, Whites lived in neighborhoods that averaged 92% White. Most suburbs were less than 4% Black, while urban core of Detroit was more than 80% Black. The study documents numerous examples of blatant systemic discrimination that served to maintain these high levels of segregation for decades. It also highlights a change in Black residential preferences. In 1976, 38% of Blacks were willing to consider moving into predominantly white neighborhoods; in 1992, this number has gone down to 31%. The reduction is attributed to “a defensive reaction to the reality of white hostility”. The study also recognizes ongoing discrimination in hiring practices in the region.

According to Poe (2002), the situation in Atlanta could hardly be more different. The article claims that in the Atlanta community, “White flight—at least the classic, knee-jerk strain of the post-Jim Crow era—is history.” The last decade brought a 39% decrease in the number of Atlantans living in segregated neighborhoods. Some suburban communities that were once primarily Black are now attracting middle class whites. While noting that racial fear still lingers to some degree and some highly segregated neighborhoods still exist, the article suggests that the situation in Detroit is hardly universal. The story of present day Atlanta is a tale of increased racial tolerance and integration.

In an article in the *New Yorker*, Gladwell (1996) introduced the notion of a “tipping point” to the general public. The term describes a dynamic in which a relatively small change at some point in a trend suddenly yields a dramatic change in outcome. Although Gladwell explains how the term relates to phenomena as diverse as the dynamics of crime reduction to the spread of epidemics, the term seems to have originated in an early study of racial segregation. In a paper written in 1971, sociologist Thomas Schelling developed a mathematical model designed to simulate the dynamics of white flight. He discovered that the arrival of small numbers of Blacks in a white neighborhood had minimal impact. However, when the percentage of Blacks reached 20%, a dramatic increase in the number of Whites leaving the neighborhood occurred. In a subsequent book, Gladwell presented additional examples of situations governed by similar tipping points.

Hong's (2002) presentation of a study by the Public Policy Institute of Californians attests to the ostensible decline in racial segregation of neighborhoods. In 1990, 56% of the segregated neighborhoods in Los Angeles County were primarily white whereas by 2000, 70% of the segregated neighborhoods were Latino; this was despite a decline in the total number of segregated neighborhoods in the County – from 35% of neighborhoods in 1990 to 26% by 2000. The study, which looked at segregation in terms of the effects of immigration and economic patterns, attributed the change to increased population growth among the Latino community; this in turn differs from traditional definitions of segregation based on notions of laws, racism and

prejudice.

Hwang and Murdoch (1998) present the concept of “homophily” - people being attracted to those similar to themselves and repelled by others that are racially different informs extensive studies on racial segregation. Linked to the concept are so-called race-related factors e.g. quality of housing and education provision, health and sanitary conditions, crime and violence rates etc. In exploring the relationship between such characteristics and attitudes, the paper questions if segregation is the result of in-group attraction or out-group avoidance. Population studies conducted in the 1980s appear to disprove the presumed effects of homophily e.g. in the case of upwardly mobile Hispanic populations settling and growing faster in white neighborhoods than in predominantly Hispanic neighborhoods. Notwithstanding the results, the authors assert that homophily remains important in terms of its relevance to minority members at different stages of assimilation i.e. when relatively new to a society and hence more vulnerable, as opposed to presumed status attainment among more established minority members.

In *'Ethnic segregation in cities'*, Van Kempen and Ozuekren (1998) present an overview of perspectives and approaches in explaining ethnic spatial segregation in cities i.e. the residential separation of groups within a broader population. The survey provided the basis for the authors' assertion that a full account of segregation should consider both micro and macro developments e.g. individual characteristics as well as economic, institutional, social and other related factors beyond. Observations were drawn from a comparison of studies based on various perspectives e.g. 'traditional' human ecology, behaviorist and ethnic-cultural approaches, as well as Marxist, neo-Marxist and neo-Weberian approaches. Despite their relative ability to elucidate aspects of segregation, studying the problem in terms of selective individual characteristics i.e. race, education level or socioeconomic status fail to paint a complete picture in terms of exceptions that may be derived from composite factors. The study also acknowledges that segregation varies at different levels without implying corresponding segregation at other spatial levels i.e. neighborhood versus city. This perspective allows the incorporation of macro influences and contexts e.g. immigration, state policies and implications on the labor market and socioeconomic status that impinge on individual actions/choices in terms of segregation.

Ratcliffe (1998) explores the concept of social exclusion in the UK where he considers perceptions encountered in general studies of disadvantaged social segments e.g. minorities, women, the disabled and other so-called urban under-classes. As a term however, the author questions its utility in elaborating or providing fresh perspectives to contextual issues or policy recommendations. Its introduction of concepts of exclusionary states and processes within institutionalized contexts, encompassing gender and differential ethnic status, instead appear to add further complex dimensions that inform more sociological and intuitively psychological explanations.

White flight Simulation

Our simulation was carried out using Netlogo, which has a pre-programmed model based on the

findings of Schelling (refer to Netlogo Segregation model). His demonstration of the effect small individuals can have on the social pattern of racial segregation is represented in Netlogo by a grid with 2000 individuals, comprising 1000 whites and 1000 blacks, that have been given enough space on the grid to allow movement. The individuals are assigned a threshold for the number of neighbors that have the same color as themselves i.e. an individual may desire 10% of its neighbors to be the same color. If it finds the actual number of neighbors to be equal to or more than this threshold, it may then choose to stay; otherwise, it will keep moving until the assigned condition is satisfied. The whole algorithm is carried out until all the individuals are satisfied.

The initial individual threshold of similarity was varied between 0% and 70%, while the average similarity for the whole grid was recorded at each time step and represented in Figure 1. As more and more individuals become satisfied, the average similarity begins to become constant and as the initial similarity is increased, the final average similarity increases too, which shows an increase of segregation. This is also shown in Figure 2, where the initial similarity is plotted against the final similarity. From the graph, it is clear that for an initial similarity of 30%, individuals end up with a far higher similarity of 72%, thus the effect of small individual preferences on global patterns.

The patterns of migration today suggest that people tend to consider more than just ethnic characteristics when moving from place to place. The Netlogo program was modified in order to take this into account, by adding two further assigned factors that individuals would have to consider: the economic status of the neighborhood they live in and the ability of individuals to move from place to place. These factors are easily modeled in Netlogo and were some of the most influential factors involved in migration patterns. Each individual sought to be 60% happy with the position it occupied and gave scores out of five for each factor depending on its level of satisfaction. For example, if the condition for race similarity was satisfied, 5 marks would be given for that factor.

Firstly, an income level (random number between 0 and a maximum) was assigned to each individual with each level representing a salary range i.e. 100 representing the highest salary range found in a population and 0 representing the lowest. The individual finds the economic status of its neighborhood by taking the average of the income levels of the surrounding neighbors and comparing to its own income level. The closer average income is to its own income level, the higher the score. The maximum for the income range of white individuals were set at 100 while the maximum for black individuals was varied between 15 and 100 to show the effect on the final similarity and hence the effect on segregation. This can be seen in Figure 3, where the initial desired similarity is fixed at 30%. The graph suggests that the more equal both races are in terms of wealth, the less the segregation. This could be because the similarity becomes less important if the income level requirements are satisfied and vice versa.

Secondly, each individual was assigned a random number between 0 and 10 to represent their mobility rating. Individuals with low ratings are less able to move for a number of reasons, such as a high number of dependants or old age. Conversely, individuals give high scores where they

are able to move if the need arises. The graph in Figure 4 shows the effect of all three factors on the final average percentage of similarity and compares that to the previous results of Figure 2 and 3. It seems that the level of segregation fell by nearly 20% when each individual has to consider three factors as opposed to one factor.

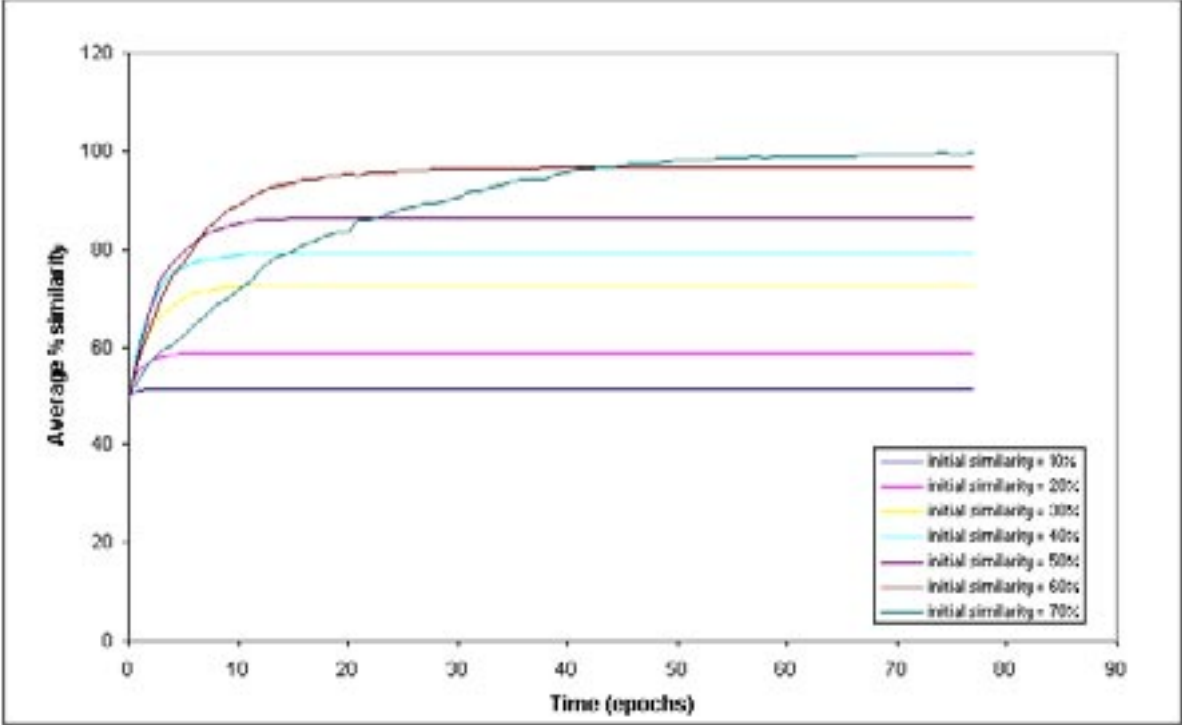


Figure 1: The variation of the average % similarity over time

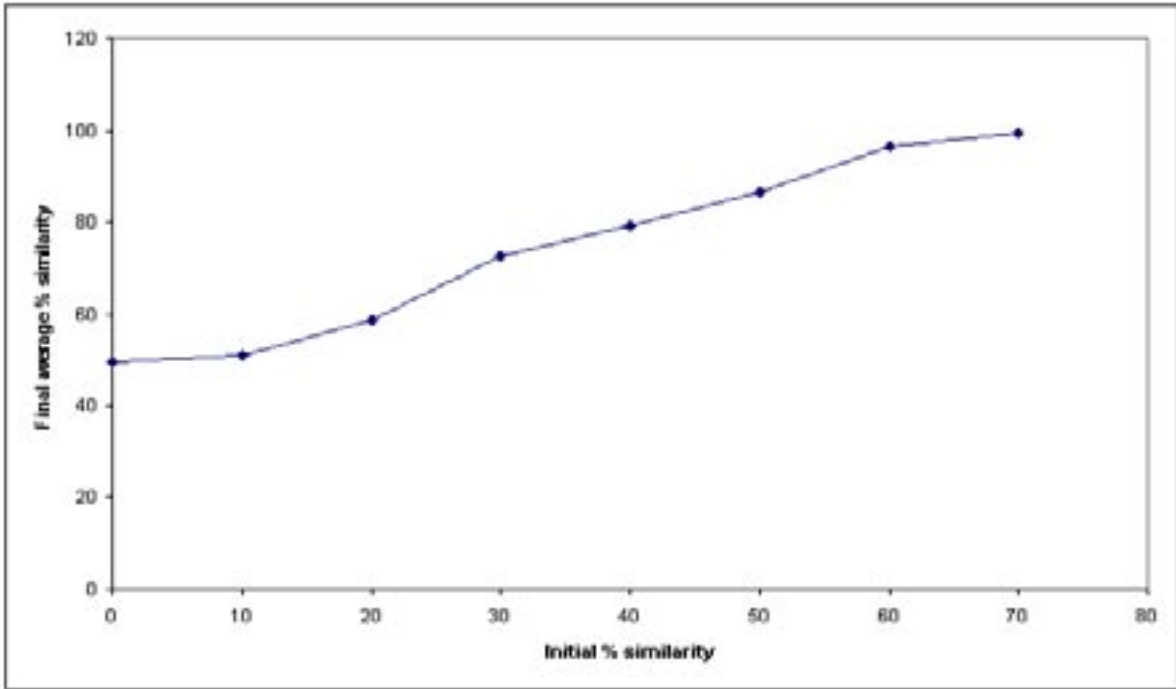


Figure 2: The effect of the initial % similarity on the final average % similarity

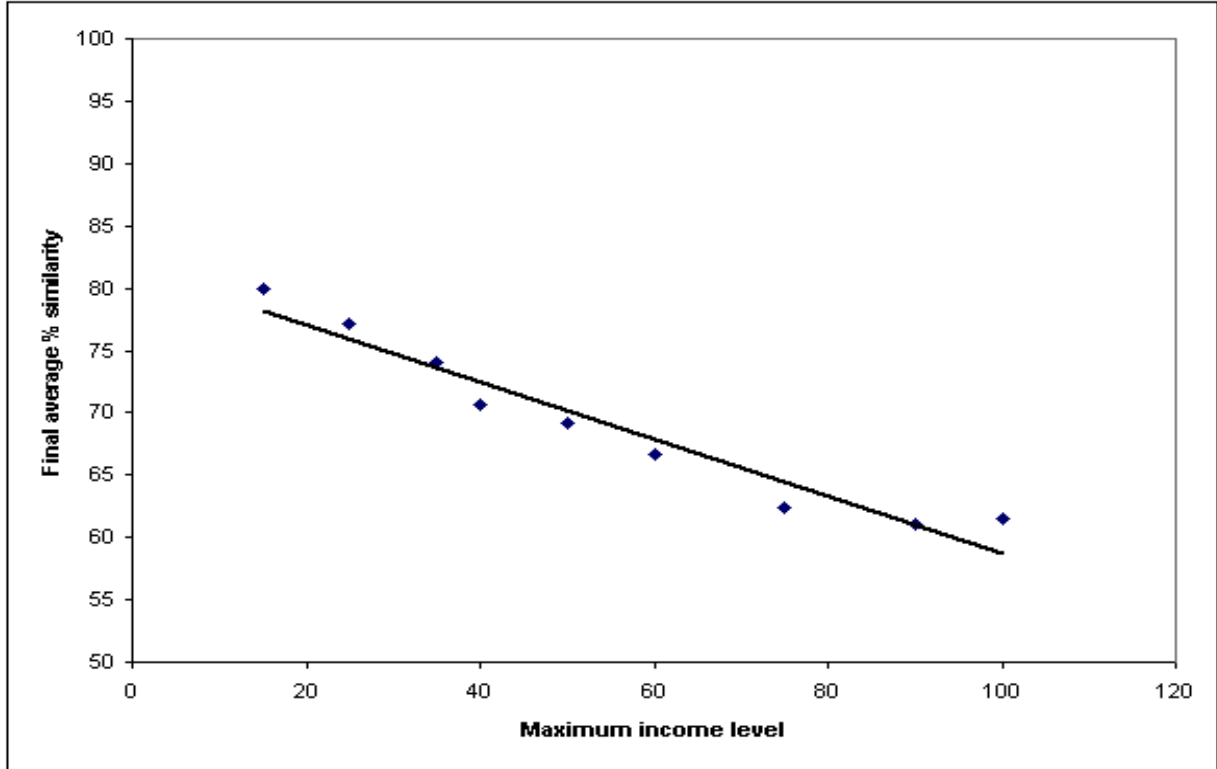


Figure 3: The effect of the income level on the final average % similarity

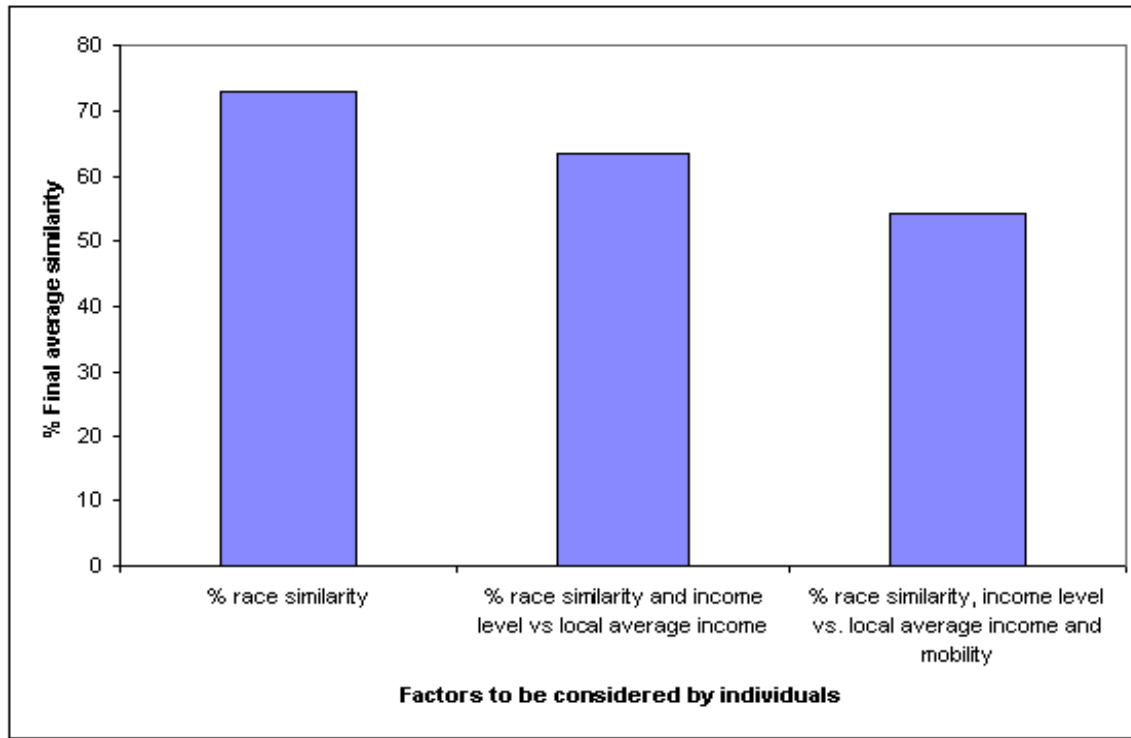


Figure 4: The effect of the number of factors each individual has to consider on the final average % similarity

Analysis of a nonlinear model of racial segregation dynamics

As a counterpoint to our empirical approach, we attempt in the following section to explore the conceptual strengths and limitations of a complex, nonlinear model of socio-spatial urban segregation by Yishaq and Meron (2002), the merits of non-linear versus linear models for describing such phenomena, and the limitations of non-linear models.

The model demonstrates non-linear mathematical correlations of socio-spatial phenomena, studying in particular the example of urban segregation. The authors demonstrate that mathematical models can describe types of patterns of socio-spatial phenomena in urban neighborhoods, and thus can be used to describe such phenomena as racial segregation dynamics.

This includes a general principle of reflexivity of the nature of macro-scale social change, as well as complexity unaccounted for by such descriptions as economic bifurcations. The model looks at both in- and out-migrations around city neighborhoods, using coarse parameters e.g. “could be either socio-economic or ethnicity”. It also focuses on the assumption that individuals move to or from neighborhoods based “solely on socio-economic considerations.”

The major claim Yishaq and Meron (2002) make is that the model establishes relationships between (1) segregation and neighborhood process and change, and (2) mathematical entities such as bifurcations. An example of a bifurcation is economic boundaries between rich and poor

neighborhood patches; at the boundaries, economic influx from rich to poor can tend to increase economic status of the poorer patch. By enabling the representation of spatial patterns with more complex regularities than could be captured by linear models, the model provides mathematical regularities of patterns of racial in- and out-migration, both locally and non-locally in Tel Aviv.

In considering the limitations of such models however, it is observed that they may be inadequate in accounting for differentials such as cultural factors. Yishaq and Meron's relevant parameters in Israel would differ from similar studies in the USA. Socio-economic variables are culturally dependent and social cohesion will vary greatly between New York City and Tel Aviv, and the model may not be able to incorporate the historical racial, economic, and social forces that have created such greater instability.

We can diagram different variables that this model may address and analyze the choice of parameters according to their incorporation of less complex to more highly complex components. In general, the intuition is that simpler aspects would be more robust and easier to model, whereas more complex aspects would be less robust and harder to model. This would suggest a negative correlation between robustness of the modeling.

The Yishaq and Meron (2002) model may be fine-tuned to include more elaborate, culture-specific and local factors. This may include social cohesion factors such as strength of forces that give meaning and unification within neighborhoods i.e. forces controlling or spurring white flight, such as religious beliefs, cultural and familial traditions and practices, and historical influences that have lent force to cohesive or disruptive correlations between economic and social stability.

For instance, some Jewish neighborhoods in New York have stronger cultural traditions and also stronger correlations of jobs and passing jobs through families. Significantly, such factors often create extreme micro-climates in a city like New York. Within Brooklyn, districts such as Crown Heights, Bensonhurst, and Williamsburg have highly rigidified racial and socio-economic boundaries, with Williamsburg demonstrating more internal stability than the other two districts. Ironically, the model developed for Tel Aviv assumes a greater social cohesion, which would have to be greatly adapted to model differences between Williamsburg and Crown Heights.

While such a model could become more refined in describing socio-spatial phenomena, it could not be so highly refined in understanding that phenomena. Non-linear models like Yishaq and Meron's can more fully portray the dynamics of complex systems according to quantitative data, such as work, housing, and other economic data. We may also be able to quantitatively describe qualitative data e.g. how many people are Jews or Muslim in a neighborhood. However shifting social paradigms cannot be adequately described as these involve qualitative descriptions of qualitative or quantitative data. For ethical purposes, complexity theory may describe complex systems more rationally and accurately than purely classical science but it does not necessarily aid understanding of complex cognitive and conscious processes. This suggests that ultimately, complex cognitive and conscious processes and the ideas and ideologies they create cannot be adequately described by such models.

There are increasing degrees of chaos and complexity manifested along a continuum i.e. from physical to bio-physical, biological and more complex biological organisms, up to the highly complex cultural ideas created by humans. At the latter level, there is not only unpredictability but also imagination, myth and metaphor. These conceptual tools are the bases for revolutionary changes, which can alter the paradigm in which the model is used. In other words, even if this model were to be adapted for use within certain social, economic and political climates and micro climates such as Israel and the USA, this does not account for micro or macro social paradigm shifts. Similar to the Kuhnian model for scientific development, there are paradigm shifts in social development that remap the very concepts one wishes to model.

Within certain physical systems, it does not matter if not all the data can be mapped as long as there remains statistical predictability. In biological systems you can see periodicity between prey and predator relationships e.g. foxes outstripping rabbits; but there are some emergent phenomena that cannot be completely understood. Biological systems manifest emergent properties that include evolutionary novelty, which in turn increases complexity.

Changes are even more complex and influential at the level of conscious phenomena. Micro-scale cognitive and conscious events in social systems may evoke much more serious and radical changes, both in ideas e.g. social patterns like racial interaction on the landscape, as well as actual fundamental changes in biophysical systems, as in the case of genetically modified organisms.

It is important to map hubris on its true coordinates. Complex analyses describe more dynamism of systems more rationally than linear analyses. However, non-linear analyses do not necessarily advance understanding of intelligence and how intelligence can transform environments. Formerly, after Plato, Man strove to understand himself but how far has Man really come? Now, we are attempting to take Plato's words a radical step further by striving to know as we are simultaneously reinventing ourselves and our environments, genetically and otherwise. Non-linear models as we know them, as linear models, seemingly remain inadequate in incorporating understanding of the conscious functioning affecting the systems we are trying to describe.

Conclusion

Various approaches used in studying the white flight phenomenon since Schelling's study have yielded useful perspectives. In the main however, many approached the problem in terms of a linear treatment of selected variables, which inherently impose limits of scale on findings. This can be shown from the simulation discussed in this report - relationships between the factors analyzed i.e. percentage similarity, income and mobility have not been considered on account of an assumption that there is a linear effect of each on the final degree of segregation. The discovery that additional variables to our Netlogo model resulted in seemingly less segregation appears counter-intuitive. However this could also be due to inadequate understanding of how the different variables inter-relate and their relative importance to different individuals.

The difficulty in modeling variables such as perception of different races and the variety of needs of individuals also points to the possible inadequacy of the modeling tool and techniques, as well as the need for more robust conceptualizations. In this regard, the use of non-linear approaches in the Yishaq and Meron (2002) model enabled more direct correlations and additional dimensions for analyzing complex phenomena in socio-spatial urban segregation. Despite its limits as identified by our team, the model is useful in illustrating the salience of variables that may not be intuitively relevant in previous research approaches.

Notwithstanding the model's potential to extend the study of white flight, it is clear that all models are inherently constrained in explaining this highly complex phenomena; the subject remains fertile ground for future research.

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Appendix A

The code used to generate the results; the code and comments added to the original program found in the Netlogo Segregation model is written in red:

```
;; -- the reds were changed to whites and greens to blacks to keep the model similar to the white flight
scenario
globals [
  percent-similar ;; on the average, what percent of a turtle's neighbors
                    ;; are the same color as that turtle?
  percent-unhappy ;; what percent of the turtles are unhappy?
]
turtles-own [
  happy?           ;; for each turtle, indicates whether at least %-similar-wanted percent of
                    ;; that turtles' neighbors are the same color as the turtle

  income-level ;; --variable that ranges between 5 and 100 to represent a salary range
  mark1
  mark2
  mark3
]
patches-own [
  reds-nearby    ;; how many neighboring patches have a red turtle?
  greens-nearby ;; ditto for green turtles
  local-income  ;;-- changes with the individual that stands on it
  total-local-income ;;-- used to find the average income in the area
  total-nearby  ;; sum of previous two variables
  av-income
  mobility
]
to setup
  ca
  set-default-shape turtles "box"
  cct number
  [
    setxy (random screen-size-x) ;; randomize the turtle locations
          (random screen-size-y)
    ifelse who < (number / 2)    ;; turn half the turtles red, the others green
    [ set color white set income-level random wincome set mobility random 10] ;;--set by the sliders
    [ set color brown set income-level random bincome set mobility random 10] ;;--set by the sliders
  ]
  if any other-turtles-here    ;; make sure each turtle is in its own patch
  [ find-new-spot ]
end
```

```

]
update-variables
do-plots
end
to go
move-unhappy-turtles
update-variables
do-plots
if not any turtles with [not happy?] [ stop ]
end

to move-unhappy-turtles
ask turtles [
  if not happy?
    [ find-new-spot ]
]
end
to find-new-spot
rt random 360
fd random 10
if any other-turtles-here
  [ find-new-spot ]      ;; keep going until we find an unoccupied patch
end
to update-variables
update-patches
update-turtles
update-globals
end
to update-patches
ask patches [ set local-income 0 ]
ask turtles [ ask patch-here [ set local-income income-level-of myself ]]
ask patches [
  ;; in next two lines, we use "neighbors" to test the eight patches surrounding
  ;; the current patch
  set reds-nearby count neighbors with [any turtles-here with [color = white]]
  set greens-nearby count neighbors with [any turtles-here with [color = brown]]
  set total-local-income sum values-from neighbors [local-income]
  set total-nearby reds-nearby + greens-nearby
  if(total-nearby != 0) [ set av-income (total-local-income / total-nearby) ]
]
end
to update-turtles

```

```

ask turtles [
  if color = white
  [
    if(%-similar-wanted * total-nearby / 100 = 0) [ set mark1 0 ]
    if(%-similar-wanted * total-nearby / 100 > 0)
    [
      ifelse(reds-nearby / (%-similar-wanted * total-nearby / 100 )) >= 1.000
      [ set mark1 5 ]
      [ set mark1 (reds-nearby / (%-similar-wanted * total-nearby / 100 )) * 5.000 ]
    ]
    if(av-income = 0) [ set av-income 1 ]
    if((income-level / av-income) <= 1) [ set mark2 5.000 * (income-level / av-income)]
    if((income-level / av-income) > 1 and (income-level / av-income) <= 2) [ set mark2 5.000 * (2 -
(income-level / av-income))]
    if((income-level / av-income) > 0.5 and (income-level / av-income) < 1.3) [ set mark2 5.000 ]
    if((income-level / av-income) > 2) [ set mark2 0 ]

    set mark3 (10 - mobility) / 10 * 5
    if(mobility < 5) [set mark3 5]
  ]
  if color = brown
  [
    if(%-similar-wanted * total-nearby / 100 = 0) [ set mark1 0 ]
    if(%-similar-wanted * total-nearby / 100 > 0)
    [
      ifelse(greens-nearby / (%-similar-wanted * total-nearby / 100 )) >= 1.000
      [ set mark1 5 ]
      [ set mark1 (greens-nearby / (%-similar-wanted * total-nearby / 100 )) * 5.000 ]
    ]

    if(av-income = 0) [ set av-income 1 ]
    if((income-level / av-income) <= 1) [ set mark2 5.000 * (income-level / av-income)]
    if((income-level / av-income) > 1 and (income-level / av-income) <= 2) [ set mark2 5.000 * (2 -
(income-level / av-income))]
    if((income-level / av-income) > 0.5 and (income-level / av-income) < 1.3) [ set mark2 5.000 ]
    if((income-level / av-income) > 2) [ set mark2 0 ]

    set mark3 (10 - mobility) / 10 * 5
    if(mobility < 5) [set mark3 5]
  ]
  set happy? (mark1 + mark2 + mark3) > 9.000
]

```

```
end
to update-globals
  locals [ similar-neighbors total-neighbors ]
  set similar-neighbors
    sum values-from turtles with [color = white] [reds-nearby] +
    sum values-from turtles with [color = brown] [greens-nearby]
  set total-neighbors
    sum values-from turtles [total-nearby]
  set percent-similar (similar-neighbors / total-neighbors) * 100
  set percent-unhappy (count turtles with [not happy?]) / (count turtles) * 100
end

to do-plots
  set-current-plot "Percent Similar"
  plot percent-similar
  set-current-plot "Percent Unhappy"
  plot percent-unhappy
end
```

Appendix B

Results for Figure 1:

Time	10	20	30	40	50	60	70
0	49.88717	50.80344	49.7979	49.16761	48.9776	49.87838	49.78173
1	51.03548	55.53754	58.13121	60.99887	59.64855	58.16475	53.78763
2	51.24298	57.1336	63.64526	67.77274	67.70428	63.98511	56.99758
3	51.24298	58.08538	66.4659	72.72286	74.3149	69.81678	59.12385
4	51.24298	58.69425	68.76628	75.61292	77.48259	74.93582	60.64412
5	51.24298	58.79787	70.11887	76.44013	79.72559	77.59415	62.59811
6	51.24298	58.9404	71.09121	77.62306	81.5764	80.66202	64.66731
7	51.24298	59.02778	71.71964	78.08263	83.37616	83.90493	66.44391
8	51.24298	59.02778	72.15252	78.14815	83.91193	85.73703	68.60391
9	51.24298	59.02778	72.49919	78.66924	84.62528	87.92638	69.81402
10	51.24298	59.02778	72.50652	78.92023	85.41097	89.22639	71.91597
11	51.24298	59.02778	72.70063	79.25806	85.70511	90.62252	73.50292
12	51.24298	59.02778	72.70063	79.20696	86.07941	91.73776	75.88958
13	51.24298	59.02778	72.77316	79.28088	86.15706	92.64822	77.90422
14	51.24298	59.02778	72.85156	79.28756	86.26506	92.93803	78.8728
15	51.24298	59.02778	72.85156	79.38094	86.41182	93.53163	79.51449
16	51.24298	59.02778	72.85156	79.38094	86.414	94.11394	80.91567
17	51.24298	59.02778	72.85156	79.38094	86.46218	94.34673	81.64341
18	51.24298	59.02778	72.85156	79.38094	86.52642	94.97875	83.05111
19	51.24298	59.02778	72.85156	79.38094	86.51252	95	83.60402
20	51.24298	59.02778	72.85156	79.38094	86.51469	95.37663	83.48723
21	51.24298	59.02778	72.85156	79.38094	86.52858	95.06424	86.1323
22	51.24298	59.02778	72.85156	79.38094	86.52858	95.49875	86.29946
23	51.24298	59.02778	72.85156	79.38094	86.54248	95.56952	86.7613
24	51.24298	59.02778	72.85156	79.38094	86.54248	95.74501	87.52708
25	51.24298	59.02778	72.85156	79.38094	86.54248	95.96926	88.34697
26	51.24298	59.02778	72.85156	79.38094	86.54248	95.89342	88.70351
27	51.24298	59.02778	72.85156	79.38094	86.54248	96.06398	89.57695
28	51.24298	59.02778	72.85156	79.38094	86.54248	96.23352	89.6088
29	51.24298	59.02778	72.85156	79.38094	86.54248	96.3428	90.13248
30	51.24298	59.02778	72.85156	79.38094	86.54248	96.30152	90.57239
31	51.24298	59.02778	72.85156	79.38094	86.54248	96.26667	91.86756
32	51.24298	59.02778	72.85156	79.38094	86.54248	96.34165	91.96947
33	51.24298	59.02778	72.85156	79.38094	86.54248	96.32826	92.84954
34	51.24298	59.02778	72.85156	79.38094	86.54248	96.30967	92.95689
35	51.24298	59.02778	72.85156	79.38094	86.54248	96.3451	93.68549
36	51.24298	59.02778	72.85156	79.38094	86.54248	96.45379	94.25182
37	51.24298	59.02778	72.85156	79.38094	86.54248	96.39159	94.28485
38	51.24298	59.02778	72.85156	79.38094	86.54248	96.56417	94.36323
39	51.24298	59.02778	72.85156	79.38094	86.54248	96.54902	95.13815

Results for Figure 2:

Initial % similarity	Final % similarity
0	49.8
10	51.24298316
20	59.02777778
30	72.8515625
40	79.3809447
50	86.54247631
60	96.72105428
70	99.55049446

Results for Figure 3:

Maximum income for black individuals	Final % similarity
15	80
25	77.08363743
35	74
40	70.64836449
50	69.1103307
60	66.65221162
75	62.38185255
90	61.06616585

Results for Figure 4:

% race similarity	72.85156
% race similarity and income level vs local average income	63.28676
% race similarity, income level vs. local average income and mobility	54.36457