

Abstract

Research is a fundamentally Constructionist learning enterprise. In this study, I illustrate how merging statistical methods and agent-based modeling helped me, as a Constructionist learner, gain a deeper understanding of school effects. The base computational school effects model incorporates results obtained from the analysis of the National Educational Longitudinal Study (NELS) data using Hierarchical Linear Modeling (HLM). This study reveals the relationship between different components of school-level variables and student achievement status and gains, and illustrates the benefits of constructing and using agent-based models to uncover mechanisms by which policy change can impact achievement.

Research Questions

1. What are the relationships between school-level factors and student achievement status versus gains, and how do the relationships differ?
2. What is the analytic purchase for constructing and using agent-based modeling as opposed to statistics in understanding school effects?

Methods

- NELS data from 1988 to 1992 (8th, 10th and 12th grades) in mathematics, reading, and science
- 2-level HLM model:

Level 1 model:

$$Y_{ij} = \beta_{0j} + \beta_{1j}(SES) + \beta_{2j}(OTHER) + \beta_{3j}(HISP) + \beta_{4j}(BLACK) + \beta_{5j}(MALE) + r_{ij}$$

Level 2 model:

$$\beta_{0j} = \gamma_{00} + \gamma_{01}(SchoolSES)_j + \gamma_{02}(URBAN)_j + \gamma_{03}(SUBURBAN)_j + \gamma_{04}(PRIV)_j$$

$$+ \gamma_{05}(NE)_j + \gamma_{06}(NW)_j + \gamma_{07}(W)_j + \gamma_{08}(ColPrep)_j + \gamma_{09}(AP)_j + \gamma_{010}(PTRatio)_j + u_{0j}$$

and

$$\beta_{ij} = \gamma_{i0}, i = 2..5.$$

• Agent-based modeling (NetLogo) is used to replicate statistical findings, and to understand the impact of changes in policy levers on student achievement outcomes.

• Rules governing agents (in this case, students) assume perfect rationality that aligns with assigned preference functions.

Analysis and Results

An Example of a Two-level HLM: 12th Grade Achievement Status and Gains by Domain

| 12th grade achievement status | | | | | | |
|---|-------------|--------|---------|--------|---------|--------|
| | Mathematics | | Reading | | Science | |
| Fixed Effects | | | | | | |
| level-1 | | | | | | |
| Intercept | 52.02* | 49.52* | 51.65* | 49.91* | 51.54* | 49.92* |
| SES | 4.83* | 4.01* | 4.27* | 3.48* | 4.26* | 3.54* |
| Hispanic | -2.25* | -1.83* | -1.88* | -3.34* | 0.31* | -2.54* |
| African Am | -5.19* | -4.72* | -4.35* | -1.60* | 0.31* | -5.72* |
| Other | -3.75* | -3.59* | -3.30* | -3.93* | 0.93* | -3.80* |
| Male | 0.82* | 0.81* | -2.33* | -2.33* | 0.19* | 2.80* |
| level-2 attributes | | | | | | |
| School SES | 2.29* | | 1.97* | | 2.37* | |
| Urban | 0.51 | | 0.56 | | -0.28 | |
| Suburban | -0.06 | | -0.20 | | -0.48 | |
| Private | 1.15* | | 1.00* | | -0.07 | |
| Northeast | 1.20* | | 1.29* | | 1.65* | |
| Northwest | 0.90* | | 0.66* | | 0.97* | |
| West | 0.56 | | 0.77* | | 0.78* | |
| level-2 treatment | | | | | | |
| College Prep | 0.91 | | 0.79 | | 1.06 | |
| AP Classes | 1.62* | | 0.78 | | 1.13* | |
| Pupil Teacher Ratio | -0.05 | | -0.03 | | -0.05 | |
| Random Effects | | | | | | |
| School-level variance (u _{0j}) | 5.24 | 4.41 | 3.65 | 3.16 | 4.64 | 4.98 |
| Student-level variance (r _{ij}) | 65.19 | 64.96 | 70.74 | 70.43 | 67.35 | 67.24 |

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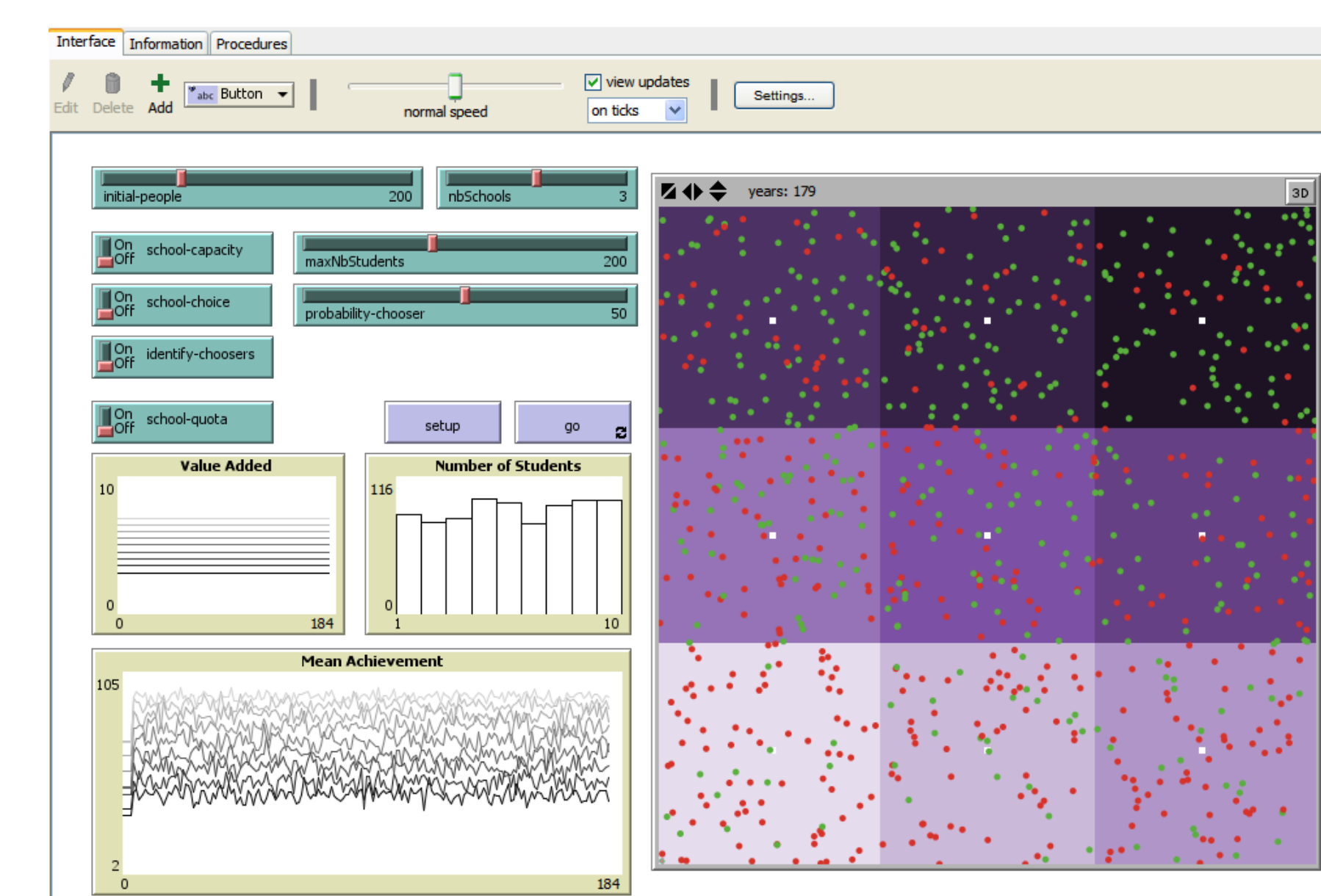
| Gains 10th to 12th grade | | | | | | |
|---|-------------|--------|---------|--------|---------|--------|
| | Mathematics | | Reading | | Science | |
| Fixed Effects | | | | | | |
| level-1 | | | | | | |
| Intercept | -0.21* | -0.67 | -0.14* | -0.33 | -0.29* | -1.18* |
| SES | 0.65* | 0.56* | 0.82* | 0.67* | 1.07* | 0.86* |
| 10th grade achievement | -0.11* | -0.11* | -0.23* | -0.23* | -0.26* | -0.27* |
| Hispanic | 0.19 | 0.22 | -0.21 | -0.31 | -0.39 | -0.34 |
| African Am | -0.46* | -0.47 | -1.41* | -1.32* | -1.80* | -1.64* |
| Other | -0.06 | -0.02 | -0.76 | -0.92 | -0.88 | -0.95 |
| Male | 0.54* | 0.55* | -0.93* | -0.94* | 0.96* | 0.98* |
| level-2 attributes | | | | | | |
| School SES | | 0.09 | | 0.20 | | 0.58* |
| Urban | | 0.06 | | 0.31 | | 0.07 |
| Suburban | | 0.11 | | 0.00 | | 0.04 |
| Private | | 0.45* | | 0.41 | | 0.01 |
| Northeast | | 0.42* | | 0.55* | | 0.90* |
| Northwest | | -0.12 | | 0.11 | | 0.15 |
| West | | -0.18 | | 0.74* | | 0.52* |
| level-2 treatment | | | | | | |
| College Prep | | -0.06 | | 0.38 | | 0.35 |
| AP Classes | | 0.26 | | -0.11 | | 0.15 |
| Pupil Teacher Ratio | | 0.01 | | -0.03 | | 0.00 |
| Random Effects | | | | | | |
| School-level variance (u _{0j}) | 0.53 | 0.48 | 1.29 | 1.20 | 1.45 | 1.38 |
| Student-level variance (r _{ij}) | 13.40 | 13.40 | 28.54 | 28.53 | 31.13 | 31.07 |

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Statistical results:

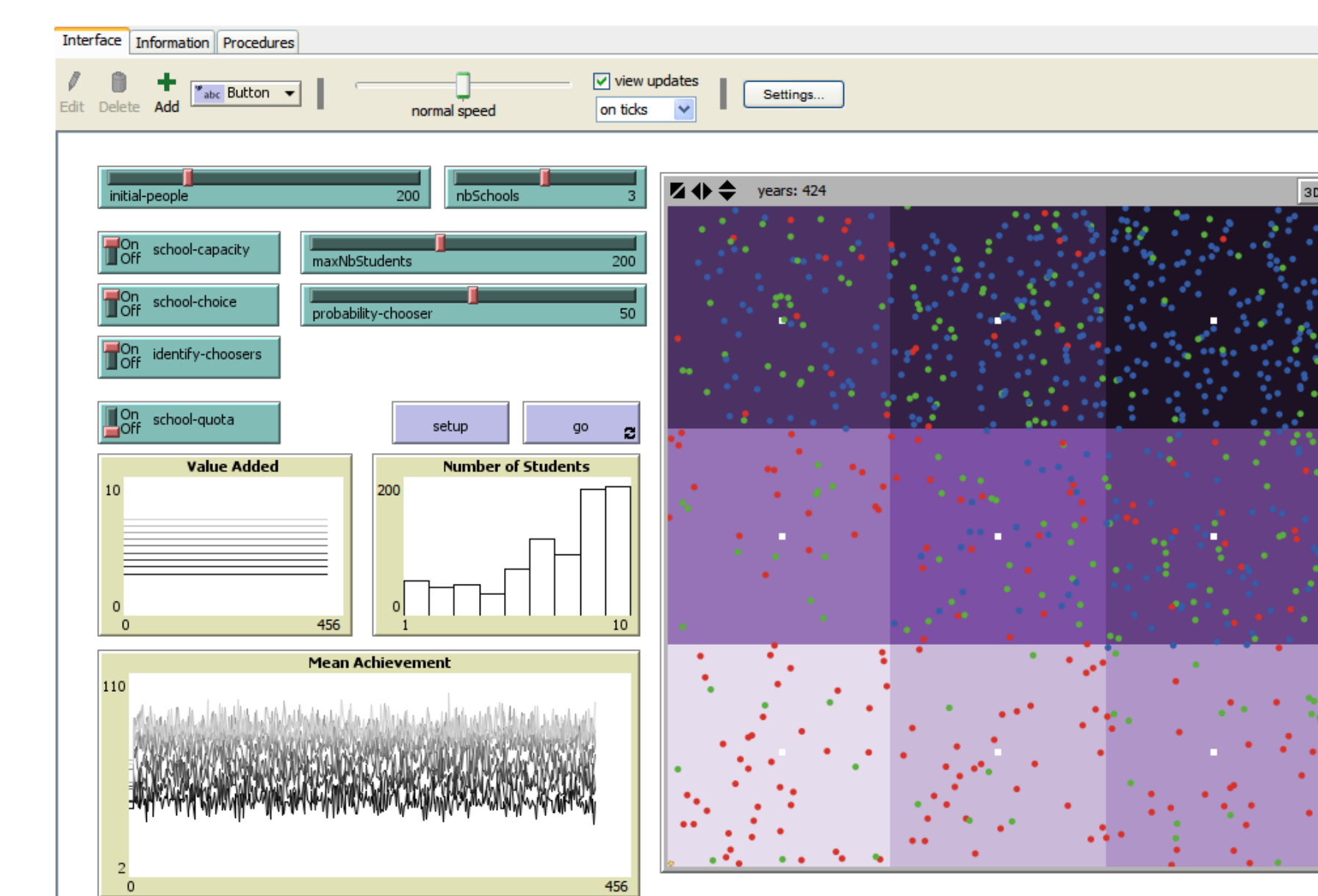
- ① School SES, region, and sector are significantly associated with achievement status
- ② Region and sector significantly associated with gain scores
- ③ Treatment variables are rarely significantly associated with student achievement
- ④ *Smaller* variation explained by between-school level factors in achievement gains, rather than status: implications for cluster randomized trials

Base Model: Replicating HLM Results on School Effects



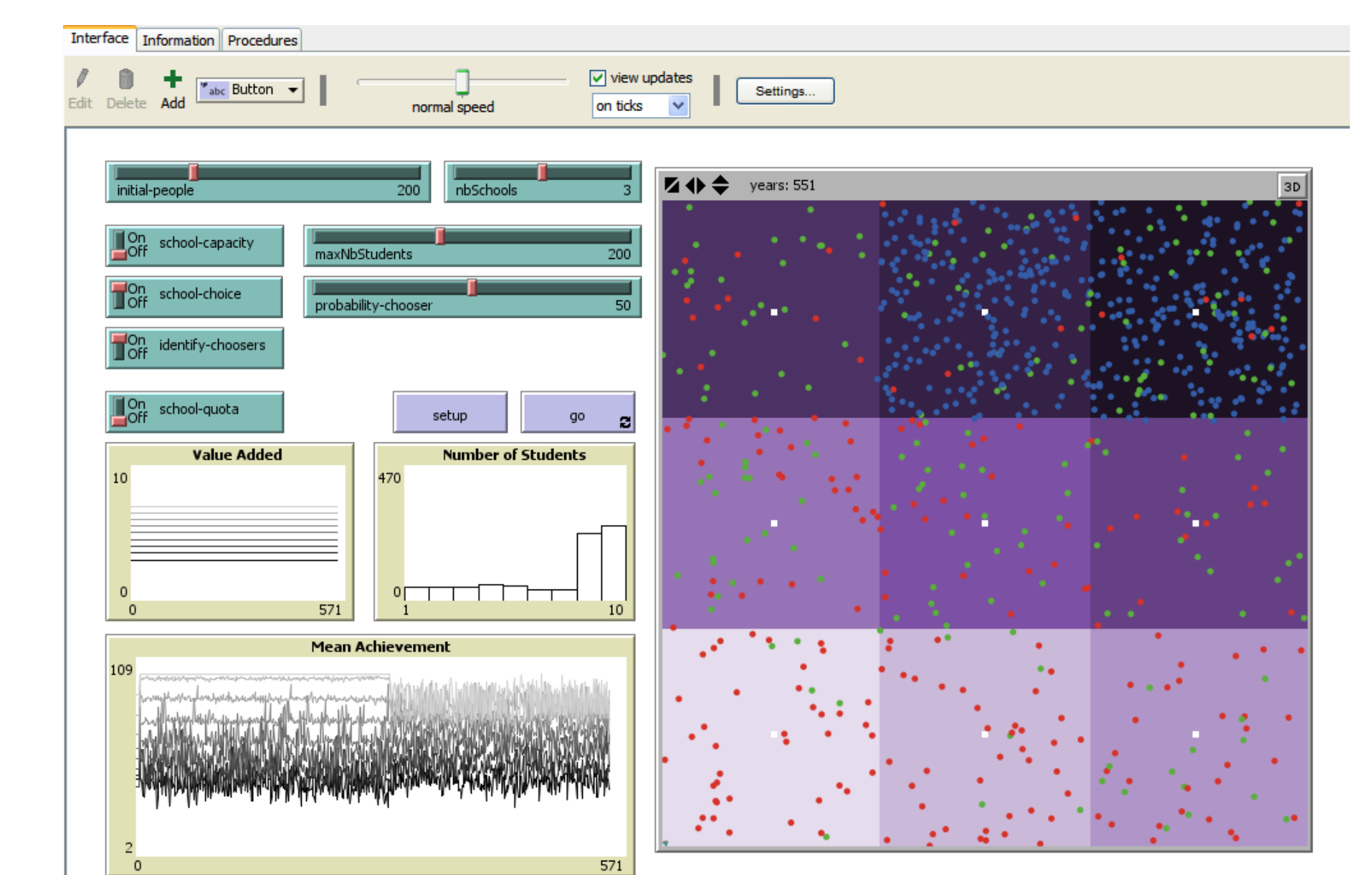
Schools with high SES generate more high performing students than other schools do

Example 1: Model with School Choice as a Policy Lever



With unlimited school capacity, schools with high SES attract more students with choice; with school capacity, students with choice spread across higher value-added districts

Example 2: Model with School Quota as a Policy Lever



With school quota, where schools select students, similar results hold with school capacity in terms of average achievement distributions; without school quota, there is more variation between schools

Conclusion

- **HLM and ABM as complementary methods:**
 - HLM is retrospective and descriptive: results suggest that school attributes are more highly associated with student achievement outcomes than treatment variables
 - ABM is prospective and generative: models can replicate statistical findings, and allow for computational experiments that illuminate mechanisms and distributions of the impact of educational reform
- **By building and using agent-based models, the researcher engages in school effects research as a Constructionist learner, where rules and mechanisms that give rise to systemic changes are foregrounded in the process.**

Future Work

- Reconceptualize school treatment and attribute variables: may be a false dichotomy
- Examine the correspondence between statistics and agent-based modeling
- Qualitative data collection from schools to inform agent rules

Select References

- Raudenbush, S. W. & Bryk, A. S. (2002). *Hierarchical linear models: Applications and data analysis methods (2nd ed)*. Thousand Oaks, CA: Sage Publications Inc.
- Maroulis, S., Bakshy, E., Gomez, L., & Wilensky, U. Why don't we know if school choice works? An investigation of the dynamic processes underlying market-based reforms in education.
- Wilensky, U. (1999). NetLogo. <http://ccl.northwestern.edu/netlogo/>. Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL.