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# Review Simulating cancer growth with multiscale agent-based modeling

Zhihui Wang<sup>a</sup>, Joseph D. Butner<sup>b</sup>, Romica Kerketta<sup>a</sup>, Vittorio Cristini<sup>a,b,c</sup>, 3 **01** 

Thomas S. Deisboeck<sup>d,\*,1</sup>

<sup>a</sup> Department of Pathology, University of New Mexico, Albuquerque, NM 87131, USA

<sup>b</sup> Department of Chemical Engineering and Center for Biomedical Engineering, University of New Mexico, Albuquerque, NM 87131, USA

<sup>c</sup> Department of Mathematics, Faculty of Science, King Abdulaziz University, Jeddah 21589, Saudi Arabia

<sup>d</sup> ThinkMotu LLC, Wellesley, MA 02481, USA<sup>2</sup>

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## ABSTRACT

There have been many techniques developed in recent years to in silico model a variety of cancer behaviors. Agent-based modeling is a specific discrete-based hybrid modeling approach that allows simulating the role of diversity in cell populations as well as within each individual cell; it has therefore become a powerful modeling method widely used by computational cancer researchers. Many aspects of tumor morphology including phenotype-changing mutations, the adaptation to microenvironment, the process of angiogenesis, the influence of extracellular matrix, reactions to chemotherapy or surgical intervention, the effects of oxygen and nutrient availability, and metastasis and invasion of healthy tissues have been incorporated and investigated in agent-based models. In this review, we introduce some of the most recent agent-based models that have provided insight into the understanding of cancer growth and invasion, spanning multiple biological scales in time and space, and we further describe several experimentally testable hypotheses generated by those models. We also discuss some of the current challenges of multiscale agent-based cancer models.

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#### 1. Introduction 20

Increasingly, cancer is understood as a large family of diseases 21 characterized by invasive, uncontrolled cell growth. Genetic muta-22 tions are considered to be the initial cause of the abnormal growth 23 24 of cells, hence the main area of focus has been in investigating the genes involved and the intrinsic cellular processes they affect and 25 regulate throughout tumorigenesis [1]. However, recent research 26 has shown that cancer cells not only influence the microenviron-27 ment around them for their benefit, but also engage the stroma and 28 29 other non-cancer cells to allow for tumor metastasis [2]. This is a complex, bidirectional interactive process, which cannot be eas-30 ily understood by using conventional wet-lab experiments alone, 31 whether in vitro or in vivo or both. Mathematical models and 32 computation simulations can help overcome these limitations by 33

Corresponding author. Tel.: +1 617 901 6992. 02 E-mail addresses: zwang@salud.unm.edu (Z, Wang),

ts.deisboeck@thinkmotu.com, deisboec@helix.mgh.harvard.edu (T.S. Deisboeck). <sup>1</sup> Thomas S. Deisboeck, MD MBA is currently on a leave of absence from Massachusetts General Hospital and Harvard Medical School, Charlestown, MA 02129, USA

http://dx.doi.org/10.1016/i.semcancer.2014.04.001 1044-579X/© 2014 Elsevier Ltd. All rights reserved. offering the ability to monitor in real-time, albeit in silico, tumor growth, cellular distribution and movement, and to observe the genetic mutations that lead to aggressive growth and metastasis [3].

Current computational cancer modeling approaches can be divided into three categories: discrete, continuum, and hybrid, i.e., the combination of both (interested readers should refer to [4–9] for in depth discussions on this topic). Briefly, discrete models employ experimentally derived, computationally coded rules to define the step-wise or discrete interactions between individual cells and provide insight on tumor microstructure, cell proliferation and death rates, and cell densities. Continuum models represent the tumor as a continuum and give information about the overall tumor morphology and nutrient distribution while neglecting the influences of individual cells in the environment. Hybrid modeling combines aspects of both discrete and continuum modeling to provide a more complete description of the tumor environment. Because discrete and continuum domains are often inescapably linked, directly influencing one another from the viewpoint of an in vivo system, the hybrid modeling approach has become the more desirable choice for many computational cancer researchers [4].

Agent-based modeling (ABM) is a discrete-based hybrid modeling approach, offering many advantages over other methods of studying cancer development [10]. For example, ABM enables

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the modeler to control the likelihood of genetic mutations and to know which mutations are occurring; this, in turn, allows 59 for simple determination of which cellular phenotypic changes 60 have the largest influence on tumor behavior. There are several types of ABM techniques that have been widely used in 62 cancer research, including lattice-based, lattice-free, Cellular 63 Potts, lattice-gas, and subcellular element modeling methods (detailed discussion of each ABM technique is beyond the scope of this review; see [11] for a thorough review). Each technique 66 has its advantages and disadvantages, and a particular tech-67 nique may be favored over another depending on the specific 68 cancer problem(s) being tackled. This implies that researchers 69 should choose an ABM technique solely dependent on their 70 research needs. It is also worth noting that, in the past ten years, 71 a number of ABM simulation packages have been developed 72 and applied to cancer research. Major open source package 73 examples include CompuCell3D (http://www.compucell3d.org/), 74 Chaste (http://www.cs.ox.ac.uk/chaste/), Repast (http://repast. 75 sourceforge.net/), and NetLogo (http://ccl.northwestern.edu/ 76 netlogo/), among others (see Refs. [12,13] for excellent reviews). 77 These packages have facilitated the overall process of developing an agent-based cancer model and also enabled computational oncologists to focus their time and energy more on the specific 80 cancer problems of interest.

In an agent-based model, each cell is often represented as an 82 agent. The agents have rules that they must follow in the course 83 of a simulation, both for their independent behavior and for inter-84 actions between other agents. A description of a simple ABM with 85 minimal rules is described as follows: Agents may receive signals 86 and input from the environment and their neighboring agents, 87 provide output to the environment and their neighbors, and make 88 'decisions' based on the input from around them and their internal, 89 sub-cellular decision making rules. An agent may grow, prolifer-90 ate, enter a quiescent state, or undergo apoptosis or necrosis in 91 response to surrounding environmental conditions. Cellular pro-97 liferation often requires enough room to grow or divide into (a 07 typical assumption for simplifying the development of an ABM), 94 and sufficient nutrients available to maintain cell viability. If nutri-95 ents are sufficient to sustain the cell but there is not enough room 96 to divide into, the cell enters into a quiescent state. In conditions 97 where nutrient or oxygen levels are not high enough to maintain cellular viability, cells enter into a hypoxic state. If sufficient oxygen supply is restored, the cell will return to a healthy state; if not, it will 100 undergo apoptosis after a defined length of time. Fig. 1 illustrates 101 a flowchart of this simple oxygen-dependent cellular phenotype 102 decision process. More accurate descriptions of the tumor envi-103 ronment and behaviors can be achieved through the additional 104 modeling of more phenotypic factors. 105

Recent ABM work has seen the introduction of more com-106 107 plex descriptions of cellular agents, pushing the technical frontier of modeling and mathematical descriptions of cancer behavior 108 towards a more complete understanding [14]. Most agent-based 109 models are computationally intensive because of the (tempo-110 ral-spatial) fine-resolution they operate on. Currently in the 111 quantitative cancer research field, agent-based models often 112 include components and/or simulate processes that occur at two 113 or more spatial or temporal scales, thus rendering them multiscale 114 models. A multiscale ABM is particularly suitable for exploring the 115 diversity of cellular and molecular dynamic features exhibited at 116 the single cell level, and for quantifying the relationship between 117 the molecular properties of individual cancer cells, microenviron-118 mental conditions, and the overall tumor morphology. In fact, in 119 many cases, cancer simulations should not be limited to a specific 120 biological scale, because cancer is an emergent collective phe-121 122 nomenon [15], dependent on the dynamic interactions of cancer 123 cells and the changing heterogeneous microenvironment [16,17].

More importantly, cancer development, invasion, and metastasis processes indeed occur across a large scale range, from the molecular and micro-scale with factors such as signaling molecules and cellular competition, to the macro-scale with environmental factors including tissue oxygen concentration and mechanical stresses on the growing tumor, i.e., spanning multiple spatial and temporal scales biologically [4]. In this review, we focus our discussion on multiscale ABM, especially on how this approach has been used to help advance different areas of cancer research towards new experimentally testable hypotheses. Some agent-based models are not specifically labeled with the 'multiscale' term; however, since they simulate or predict cancer behavior across different spatial and/or temporal scales, we still introduce them here, but our discussion is limited to the introduction of the most recent, representative multiscale ABM works in the literature. Interested readers can refer to other in depth reviews to have a more comprehensive understanding of ABM and its potential in cancer research [4,5,11,18].

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## 2. Overview of multiscale ABM methods

### 2.1. Scale ranges

A multiscale cancer ABM attempts to integrate across many spatiotemporal scales (from atomic to molecular, cellular, multicellular, organ, up to multi-organ systems) to provide a more complete and accurate representation of a variety of phenomena including cancer initiation, growth, invasion, and metastasis [4]. We only briefly describe the general methods for modeling cancer behavior on the molecular, microscopic (cellular/multicellular), and macroscopic (organ) scales.

Molecular scale modeling involves modeling the bulk average values of molecular interactions. This can include averaged receptor-ligand interactions, oxygen and nutrient concentration effects on cells, and cell-cell signaling molecule concentrations. Signaling molecules trigger cascades that cause changes in cell behavior, and oxygen and nutrient concentrations can allow cells to remain healthy or become hypoxic when they are reduced. These molecular interactions are commonly the smallest scale modeled in agent-based cancer models, and are usually represented using ordinary differential equations (ODEs) to describe the rate at which they are consumed or produced.

Microscopic scale interactions occur between cells. Cells must coexist in their environment, and both their movement and proliferative expansion is limited by their proximity to neighbors. It is at the micro-scale where cancer modeling allows for a mutation of healthy cells into cancerous phenotypes. Micro-scale modeling can be done using ABM (where each cell is modeled individually) or by describing local conditions using partial differential equations (PDEs) to calculate local environmental changes. Agents have rules that define interactions with their environment and other agents, depending on the availability of resources necessary for their survival, such as oxygen and glucose. Agents can interact with each other, influence their microenvironment, undergo taxis and mitosis, enter quiescence or die from hypoxia or apoptosis. Determination of agent behavior is based on the local environmental conditions and molecular signaling, and the biological rules posed on the agents by the modelers.

Macroscopic scale modeling involves factors that encompass the entire tumor tissue, hence spanning across the scale of many agents. Diffusion of nutrient, oxygen, and signaling molecules such as hormones, tumor tissue pH, and chemotherapy drug distribution over the entire tumor can be computed and provided as feedback to the microenvironment. Tumor morphology and vascularization are also sometimes modeled on the macro-scale, providing information on the extent of metastasis and nutrient

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