Multiscalar Network of Natural Resource Development and Community Consent

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I. Introduction

Extractivism simply defined is a productive process where natural resources are removed from the land or mined for sale in global markets. However, there is a lot more to it; extractivism finds it roots in geopolitical, economic and social relations produced through history and dating back to early European colonial expansion. Today, these relations often go unquestioned in decisions around natural resource development, while global corporations continue to exploit, plunder and degrade people and environments in which their projects exist. This is evident in the increasing number of environmental and natural resource development related conflicts reported globally (www.ejatlas.org). With this being said, there is also often a lot of community support for major extractive projects. While come fight for resource companies to require their consent before they are permitted to develop, extractive corporations promise in return employment and economic benefits to the affected communities. Alongside environmental and sociocultural repercussions of cumulative resource development, this also leads to political asymmetry within communities, often resulting in highly heated public debate and at times even violence [1].

Research shows that extractive industries can address growing opposition to their projects by obtaining consent from affected communities and groups [2]. This has manifested in several regulator tools, social and economic impact assessments, community consultations, and guidelines around free, prior, and informed consent, that attempt to give communities a voice in how their neighbouring resources are being managed. However, in theoretical cases where consent could be obtained, the tools still fraught in their failure to recognize the economically coercive nature of extractive projects when community livelihoods have been previously tied to employment income from projects with finite production lives.

Antonio Gramsci, the 20th century political philosopher linked macro-theories to the social and economic understandings of individuals and communities by describing ideological expansion as a function of both coercion and consent [3]. the dominant political or social contexts were said to be upheld through violence or economic force, and at the same time, reinforced through the habits we form, the stories we internalize, and how these impact the enactment of our social reality. In line with Gramsci's thought, we categorize any agreement to develop a resource under economic force (where development also impacts communities ability to meet needs outside of markets) as coercion, not consent.

Through a mutliscalar network model we explore the relational dimensions of cumulative resources development and illustrate how community consent can be impacted by potentially coercive economic relationships. The model connects information flows at the community level with greater trends in the development of economic relationships at the regional level. Resource development can come in many forms, with varying ownership models, regulatory structures, and motives. In this paper we consider ’resource development’ as large extractive projects, that are export oriented, profit-motivated and corporate owned. In section II we describe out methods and the set up of the model. Section III reviews some novel results. And, Section IV connects the model behaviours with hypotheses form political ecology literature. In all, we demonstrate how a social network model can account for the impacts of higher scale dynamics and historical trends.

II. Methods

The multi-scalar network model contains both micro and macro scales. The macro-scale model is regional in scope, while the micro-scale model describes mechanisms at the community decision-making scale. Weighted edges between nodes in the macro graph can influence the micro-scale networks at each node in the macro graph. This can be thought of as additional weighted connections between only the community nodes in the macro network.

i. Macro Network Details

The macro-scale represents a bipartite graph of community and resources nodes. There are two types of edges in this graph, the first are the main bi-partite edges between resources and community nodes. These edges signify that connected communities have authority over a resources. The second type of edges are weighted connections between community nodes. These edges are meant to represent how connected two communities are in terms of how much different communities should influence each other. We will introduce the remaining macro network details and relevant parameters next.

The outer bi-partite network of communities and edges can be generated either randomly, according to three parameters: the number of communities, the number of resources, and the probability that any given resource and community will be linked, or this outer network can be initialized as a bi-partite chain. The bi-partite chain is generated such that an equal number of resource and community nodes are connected with edges to make a minimal chain. In the case that more resource nodes or more community nodes is specified, the additional nodes will connect to an existing part of this chain randomly in one place. Similar to the randomly generated outer structure, we also introduce a parameter which we call p extra which allows for a percentage of possible additional edges to be added randomly (where all edges satisfy the bi-partite constraints). By tuning this p extra parameters, we can make the outer network close to the random network if desired or fully bi-partite.

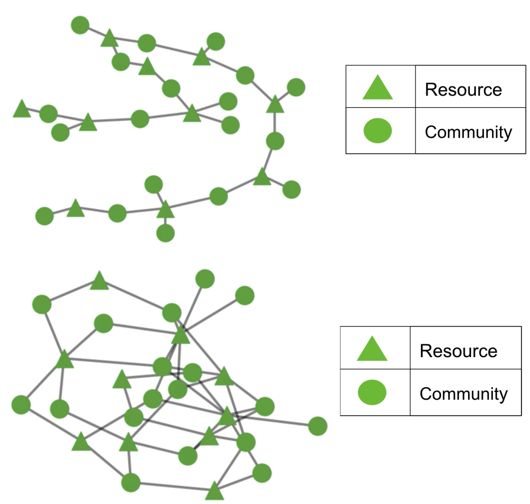


Figure 1: *Network with low p extra value (top) compared with network with high p extra value (bottom).*

The weighted connections between community nodes represent a fully connected graph with the exception of the case where no path exists between two community nodes in the macro graph; in this case, that edge will not exist in this graph. The weights of the edges are calculated based on the distance between community nodes in the bipartite projection of the macro graph. Each weighted edge between community a and b, E_{ab} is calculated as: $E_{ab} = \rho d^s_{ab}$. Where ρ is drawn from a random uniform distribution between 0 and 1, d_{ab} the distance between two nodes in the bipartite projection of the macro network (as projected onto the community nodes), and parameter s is a user-defined parameter which represents the "Distance Scale." The distance scale being a measure of how highly physical distance between two community nodes should weight the connection between them, where $s = 0$ would ignore it fully, and higher values would place more emphasis on assigning higher weights to nodes which are closer in the projected graph.

Every round non-developed resources are set to 'developed' if the majority of neighboring communities are in favor of developing. There are two optional parameters that can make this process more flexible. The first controls the threshold of neighboring communities that need to be in favor of developing for the resource to be developed (this is fixed at .5 in the base version). The other is an optional offset of the micro-graph voter model round and the macro graph resource voting rounds. The base has resources voted on after each completed round of the micro-scale voter model. This can be changed to vote on the resources in the macro scale every n rounds (1 is the default) of the micro-scale.

The state of each community node, either yes or no, is determined after each time-step from that community node's associated micro-scale network. That said, there also exists an overriding condition where communities neighboring at least one developed resource are in favor of developing. Therefore, if a resource is developed, all neighboring communities (i.e., the rest of the communities which voted no) automatically switch to pro-development. These two processes control nodes in the macro-scale network switching state.

At the start of each time step, the weighted edges between community nodes are used to calculate for each community an adjusted spread rate at each time-step. This adjusted spread is calculated by first determining the weighted percentage of neighbors a community node has that are already leaning towards developing (e.g., if a node has two weighted edges, one with weight 1 to a node in state "yes" and one with weight 2 to a node in state "no", the weighted fraction would be 1/3). The adjusted rate is then computed as the base spreading rate plus an "additional spread" term, which is computed as (1 - the base spreading rate) multiplied by the weighted fraction of "yes" neighbors and then scaled further by an "outside influence" parameter (between 0-1).

ii. Micro Network Details

The micro-scale represents a network at each community node. Each network is representative of that community. Within each network there are binary edges generated by a small world network designed to represent connections between individuals in the community. Communities interact with the macro network based on the "adjusted spread rate" of each community as well as in interactions where a neighboring resource is developed, thus forcing a community to be pro development. The details for this network are discussed next.

This network is generated as a random small-world network with parameters controlling the number of nodes, the number of neighbors each node is originally connected to (in the small world ring topology), and then lastly, the probability that each edge is randomly rewired. These parameters are fixed across each community's micro-scale network (i.e., if the number of nodes is 100, all micro-scale networks will have 100 nodes), but each network is randomly generated according to a different random seed. We chose a small world network as it might roughly mimic a real communities network of social interactions.

Each node is an individual, and the connections represent social interactions. Individuals have two states: in favor of development -or- not. Nodes within this network can only be switched to pro-development, and once switched, cannot return to being opposed to development. This assumption where individuals once pro-development they cannot change back is certainly a simplification from reality. We decided to introduce this mechanic as a way of simplifying the spreading process.

We introduce a parameter to control the number of pro-development nodes originally in the network. We typically set this parameter to .1, representing that to start a random 10 percent of nodes across different micro-scale networks start "pro-development."

At every time-step, each node currently in the no state has a chance of changing to the yes state with a probability determined by two factors, 1. the percentage of nodes that node has which are already in the "yes" state, 2. the communities current spread rate, which is determined by a combination of an initially assigned base spread rate, and the weighted influence of that communities connection to other pro-development communities in the "third network". This influence can be further determined by another parameter, which we call the "Outside Influence", where a value of 0, would fix the spread rate at the originally assigned base spread rate, and a value of 1, on the other extreme, would apply the highest weighting possible to a community's weighted edges to positive nodes in calculating that community's adjusted spread rate.

Every round, one step of the voter model is run. If the majority of nodes are in favor of development, the community as a whole is set to 'in favor' within the macro-scale. In this way each micro network can influence the macro network.

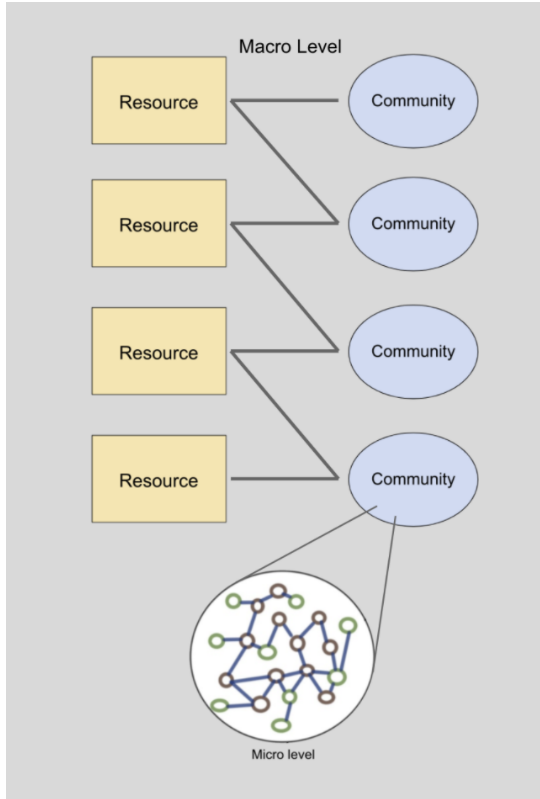


Figure 2: *Overview of the macro and micro scales of the model.*

III. Results

The default parameters in which results were generated, unless otherwise noted, are as follows:

- The outer macro-network is generated as a bi-partite chain with 100 resource nodes and 100 community nodes. Additionally, a "p extra" value of .001 is set, which corresponds to adding an additional 10 random connections to this network.
- The micro-networks for each community nodes were generated as Watts-Strogatz random small-world network 100 nodes, each node originally connected to 3 neighbors and a chance of .2 for any edge to re-wire.
- There is a random 10 percent of nodes in each micro-scale network set to be originally pro-development.
- Fixed thresholds of .5 for both the percent of nodes needed to be pro-development in a micro-scale for that node in the macro-scale network to switch to pro-development and also for the threshold of communities bordering a resource node, for that resource node to be developed.
- A "distance scale" of 2, and an "outside

influence" scale value of .15

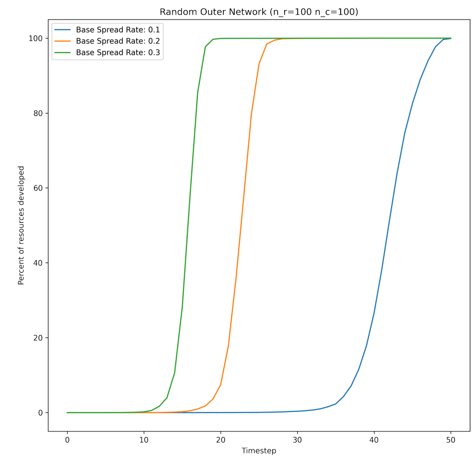
- A base spreading rate/chance of .1.
- Voting every 1 round for if a resource is developed.
- All resources begin as not developed.

All simulations show results as averaged over 128 random repetitions.

We first examine in Figures 3 and 4, how the choice of the outer network as fully randomly generated versus as initially a bi-partite chain with some additional edges, influences the rate in which our simulation becomes fully developed. By comparing the two initializations under a range of different spread rates, we see that the bi-partite structure serves generally to slow down development. Investigating the role of network density further in Figure 4, we find that by adjusting the extra density of the bi-partite structure, we can bridge the gap between the fully bi-partite outer structure and random network. Essentially at higher values of extra edges, the slowing factor that the bi-partite structure allows at lower densities is dampened and behaves more similarly to the randomly generated network.

Across both networks, Figure 3 shows that the the rate of idea spread through a community is positively correlated with the rate of resource development. The communities where people adopt new ideas slowly exploited their resources slowly since the default opinion for the majority of citizens was set as anti-development. This rate is roughly analogous to the base contagiousness of a disease in an SI model. The degree to which changing this parameter can influence the rate of development is of interest. Note for example, how the a base spread rate of .2 and .3 are far closer to each other in terms of the time it takes to reach peak development across both the top and bottom figures relative to a base spread rate of .1. This seems to indicate that once a base spread rate is sufficiently high, it will converge towards full development, constrained only by the topology of the different networks.

Next, we investigate how the number of community nodes relative to the number of resources nodes in the macro network can influence development. Figure 5 shows simulations where the number of community nodes ranges from 50 to 200, relative to 100 resource nodes. There is very little difference between 50 and 100 community nodes, however, when the number of communities increases to 125, and then to 200, full development is reached



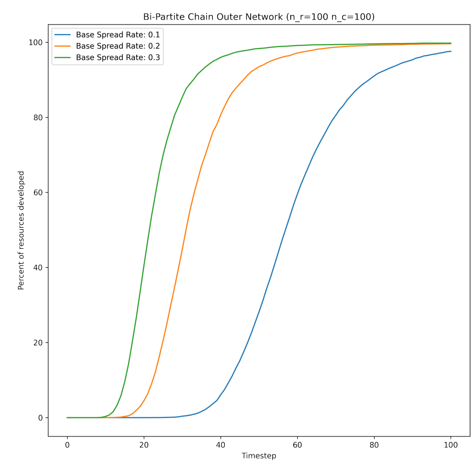


Figure 3: *This figure shows a comparison between changing the base spreading rate on a random outer network (top) versus changing the base spreading rate on a bi-partite network (bottom). Note that the timescale for the bottom plot is twice as long (up to 100) than then the top figure (up to 50).*

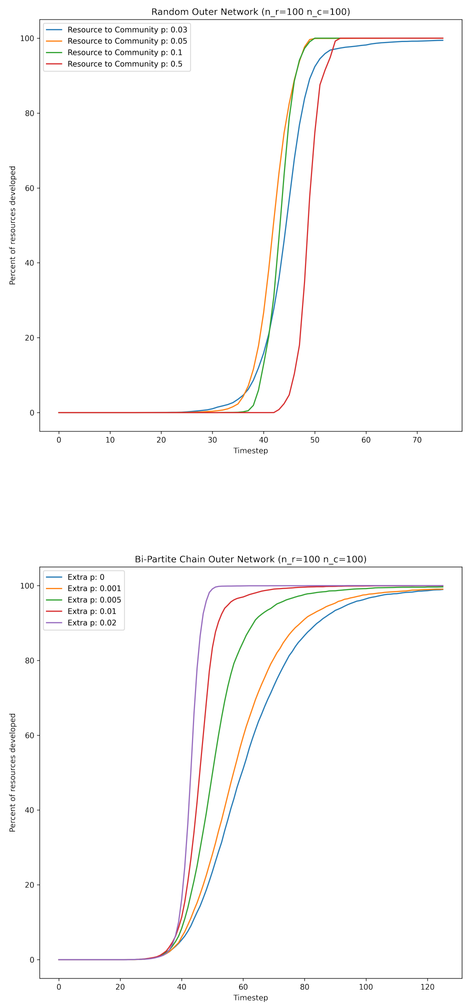


Figure 4: *This figure shows another comparison between a random outer/macro network (top figure) and a bi-partite macro network (bottom figure). It investigates how changing the density of each network can influence the rate of development. In both cases, the respective density, or probability that a random edge is added is plotted at different values. Note that the degree to which these densities are manipulated are not necessarily equivalent with each other.*

within a shorter time-span. This is likely due to the random wiring of additional community nodes to the original bipartite chain (length= 50), meaning that some resource nodes were

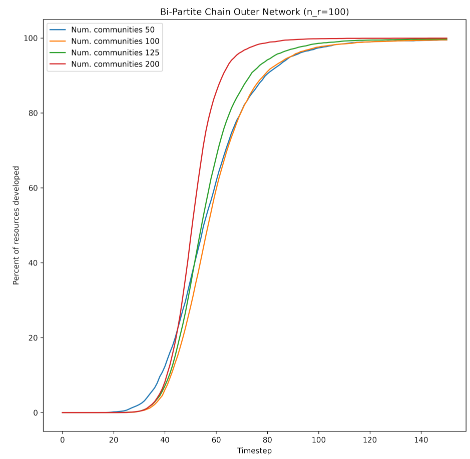


Figure 5: *This figure shows how adding extra communities, relative to the fixed number of 100 resource nodes, can effect rate of development.*

connected to multiple communities. This behavior is perhaps less expected. Intuitively, we might imagine that the more neighbors a resource has should make it be harder for that resource to flip to being developed, as it must gain consent from more neighbors. However, because the voting threshold is set at 50 percent, a resource having exactly 2 connected community nodes, needs both communities to vote 'yes' to development. This is not the case when there are three neighbors, in this case only 2/3's of the resources neighbors need to flip, versus one hundred percent in the previous case. As we increase the density of the bi-partite network, the model behaves more closely to a random network.

In Figure 6 we attempt to determine the influence of two parameters in the system, on the top, the "Outside Influence" parameter, and on the bottom, the "Distance Scale" parameter. In theory, we designed these parameters in order to control how much a communities internal micro network spread should be influenced by that communities connections in the macro network, and how much distance in the macro network should influence these macro graph connections. What this series of simulations

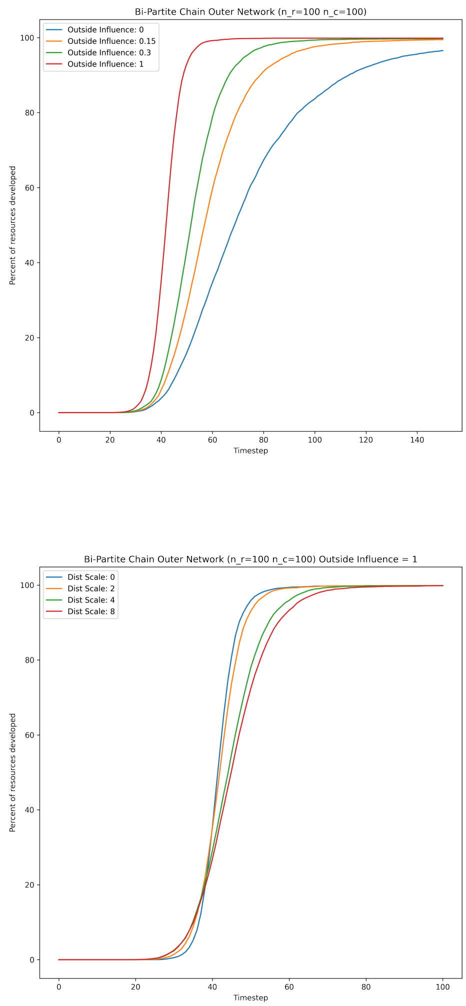


Figure 6: *This figure examines the influence of two parameters, first the upper graph looks at how changing the scalar term "outside influence" can either increase or decrease the rate in which development of the full system occurs. The bottom graph examines the parameter "distance scale" with a fixed maximum "outside influence" of 1.*

shows us is that the outside influence parameter can influence the system a relatively large amount when compared to the distance scaling. In particular, when we remove all outside influence, we observe the slowest rate of development, versus when we have the outside

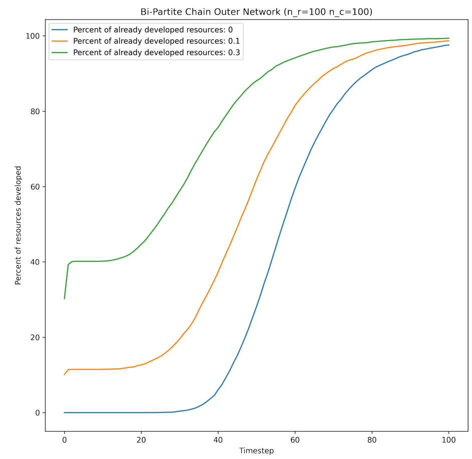


Figure 7: *This figure shows how adjusting the percent of communities which start at developed, from the previous default of none, can speed the rate in which initial development occurs.*

influence set to 1, we see the fastest rate of development. This figure directly relays utility about some of our modeling choices, indicating that the rate of development, and the internal decision structure of communities, are sensitive to the outside influence parameter, but less so to the distance scale parameter.

In Figures 7, 8 and 9, we delve into the question of how future development can be influenced by existing development. Figure 7 and the top rows of Figure 8 and 9 show the same simulation, where we model starting at no resources developed, 10 percent of resources developed and 30 percent of resources developed as initial conditions. The base behavior of starting with more resources developed is that the speed of development increases. What is interesting about Figure 7, modeling a bi-partite outer network, is that we observe the time in which all resources are developed stays about the same across all three levels of starting development. So while the rate in which around 90 percent of resources become developed is quite dependant on the starting percent of resources developed, the last few resources, which are maybe well isolated, still take on average just

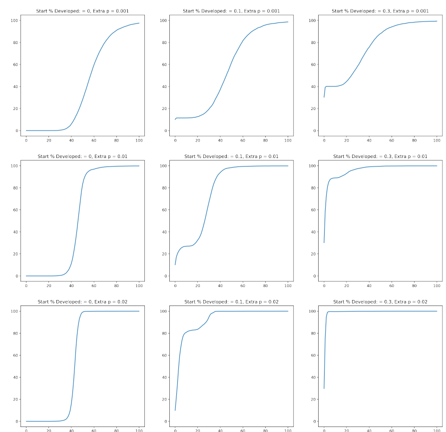


Figure 8: *Similar to figure 7, this figure investigates how the choice of the percent of communities which start as developed are influenced further by the extra density of the outer macro bipartite network. Note the top row of this figure has the exact same curves as Figure 5, where moving left to right, the starting percent of developed communities moves higher. Moving down though represents introducing a higher density to the macro network.*

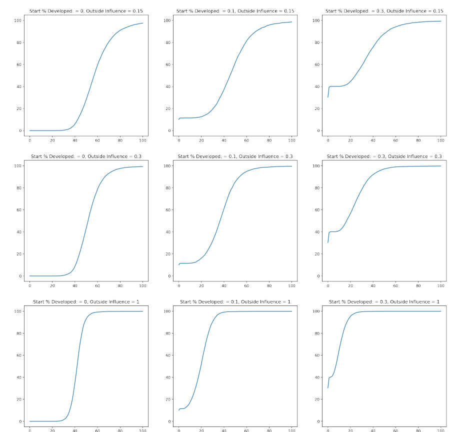


Figure 9: *Similar to figure 8, this figure investigates how the choice of the percent of communities in which start as developed are influenced when interacting with adjusting the outside influence scaling factor. Moving down represents increasing the weight of the outside influence.*

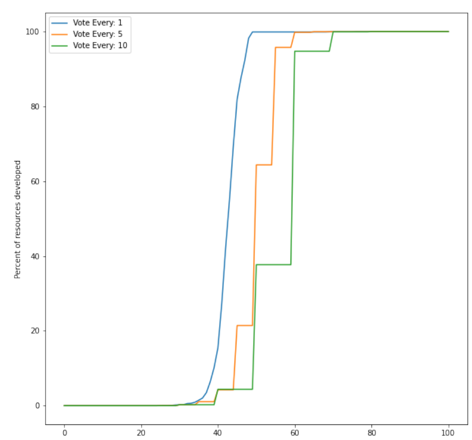


Figure 10: *This figure examines how adjusting how often voting over a resource can occur can slow development, but also lead to more drastic spikes of development.*

as long to become developed. However, this behavior doesn't necessarily hold when we change the outer network or rate of outside influence.

When initial conditions are set to 10 percent developed, we see a slight jump right at the start, and a more dramatic similar spike at the start when starting with 30 percent of resources developed (jumping up to 40 percent developed after a few timesteps). When a resource is developed, all surrounding communities become pro-development (demonstrateing an economic relationship). Due to this, an early fraction of developed resources will trigger a chain reaction. As we show in Figure 8, the size of this reaction, is directly related to the density of the macro network. In Figure 8, if we follow the middle column, where the starting developed resources are fixed at 10 percent, we can see that by increasing the density the slope and peak of the early jump dramatically increases (Middle figure jumping to 20 percent developed after 20 timesteps, and bottom middle jumping to 80 percent developed). This behavior is even more dramatic when initial conditions are set at 30 percent developed resources (shown on the far right column of Figure 8). In this case, we see that the early jump is initially from 30 to 40 percent, then increasing the density it jumps from 30 to around 85 percent and increasing the density once more, jumps after only a few timesteps to fully developed. The model displays a positive feedback loop behaviour in response to early resource development.

In Figure 9 we examine how changing the Outside Influence parameter, instead of the density of the network, can interact with the starting percent of developed resources. In this case, we see that the behavior of the system is almost identical to what we observed in Figure 7, with the exception of changes to steepness or slope of how quickly development occurs. Essentially, we see that development will start to kick off at roughly the same time-step, but will more quickly reach a state of being fully developed. The hold out behavior we saw in Figure 7 too, is washed away by turning up the outside influence parameter.

Lastly, we examine how changing the rate of how often voting for a resource can occur influences development. Figure 10 shows how adopting more realistic time-scales for how often voting over a resource occurs can delay the spread of developed resources. This makes intuitive sense given the mechanisms we have built into the model where once a resource is developed, its neighboring communities that were in the minority (voted "no", but the resource was still developed) are instantly changed to developed. Therefore, by slowing the "spreading" of how often votes over resources can occur, the rate at which resources are developed will noticeably slow. One can imagine that the structure of the network will also affect how much changing this rate will serve to slow this development, where in networks with resources connected to larger numbers of communities, the benefit from extending the time between votes will diminish.

IV. Discussion

The model suggests that regions with greater initial resource development, assumed here to mean a greater livelihood dependence on income and economic benefits from industry, are more likely to come to consensus in favor of development and exhaust all resource development opportunities within a shorter time frame. The model demonstrates a positive feedback towards development once an early base saturation is reached. This supports the hypothesis that economic relationships with industry, whether a community consents to them or not, leads to a more favourable outcome for those wishing to develop additional resources. This points toward an important consideration for regions and communities intending to manage cumulative resource developments with intentions towards ethical and sustainable development.

The behaviour of the outside influence parameter indicated a potential positive relationship between remote communities favor towards development and their degree of connectedness with other pro-development communities. One might imagine that a remote community without previous influence from industry might be less inclined to invite major resource development projects, and inversely, the potential for a highly connected community to sway in favour of resource development in the face of economic benefits and access to modern material comforts. Conjecture is beyond the scope of this paper, however, there is potential for the model to further the development of hypotheses in regard to remote communities and their relationships with extractivism.

The model results support case study findings in the nexus of extractivism and community development. Major resource developments are capable of altering land-human relationships and severing people from alternative economies. This has been seen in the US Appalachia with communities transitioning from subsistence agriculture to coal mining [4]. And similarly in the Canadian Arctic, where the impacts of industrial development: including relocation to work camps, restrictive work schedules, and a reorientation of socially important roles within communities, have led to the reduced consumption of traditional foods, the break-up of food sharing networks, the loss of control over traditional lands and the weakening of supporting cultural institutions [5]. These are only two examples of many, where environmental and socioeconomic effects of major resource developments reduced the ability for communities to practice the various other ways of meeting needs that exist outside of markets, developing a greater dependence on monetary incomes. Since extractive resources are often linked to boom and bust markets and have limited productive lifespans, there is a perceived need to continuously develop more and more in order to maintain household incomes [6].

Our model is unable to broadly confirm these findings, however, there is a lot of potential for models like this to support social science research in explaining different possible mechanisms and illustrating theoretical concepts. The model presented here contributes an important piece to the study of social phenomenon using network models by demonstrating an approach that is able to take into account the cumulative effects of resource development at a regional scale and asses their potential impact on decision making at the community level.

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