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MODELING THE ADAPTATION OF THE FOREST SECTOR TO CLIMATE CHANGE: A COUPLED APPROACH

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ABSTRACT

Large-scale environmental models have become a vital tool in studying the effects of climate change. Possibly due to the massive computational expense that many of these models require, the representation of social systems within these models is often limited. As part of an ongoing project on improving land-disturbance modeling in the Community Land Model (CLM), we have developed an economically motivated model of timber harvests that can be fully coupled to CLM. The model relies on simulating auctions between profit-maximizing agents in order to solve for a market solution level of timber harvest on the landscape. Using this model, we are able to improve the representation of this social system within CLM in a computationally manageable and unique way.

1 INTRODUCTION

The impact of climate change on forests and the wood products industry has been a subject of intense research (e.g. Sohngen, Mendelsohn, and Sedjo 2001). Land use change out of forestry has long been linked to large environmental impacts (Lebowski, Plantinga, and Stavins 2006). Furthermore, it is known that forest management can be influenced by a changing climate (Spittlehouse and Stewart 2004). This feedback loop is a difficult thing to endogenize within a model, as modeling both systems simultaneously represents a potentially huge computational effort. Despite the obstacles, there is a significant benefit to performing such an analysis. For instance, it becomes possible to investigate the impacts of future climate change on forestry at a regional scale, as well as adaptive economic behavior. It can also clarify ways in which human activity can manipulate environmental phenomena, such as wildfire frequency and pest outbreaks.

As part of a project investigating forest mortality in the western United States, we have developed an economically motivated, spatially explicit model of timber harvesting for the western United States within the Community Land Model (CLM) (Oleson et al. 2013). The community land model is a large-scale environmental model of land processes used as part of Community Earth System Model (CESM) (Hurrell et al. 2013). The harvest model presented here solves for the market equilibrium harvest pattern, and is based on economic theory. This project is novel in that it represents a major advance in coupling a theoretically consistent social science model to a large-scale environmental model, which allows for a more detailed study of the feedback between the two systems that was not possible before. Furthermore, it provides a door to run more detailed policy experiments using CLM.

This paper will provide the basic set up of the model, as well as its theoretical motivations and future goals. Since this is still a work-in-progress, the material provided below should be treated as preliminary with respect to the ultimate goal of the project, which is a fully coupled run with CLM. That being said, the algorithm we show does converge, and does solve for the market equilibrium, and does so in an interesting and novel way. Thus, it is useful at this point to provide the material below so that we can show what has worked for our group in the hope that it may further other efforts at integrating social systems models into large-scale environmental simulations.

1.1 Timber Harvest and Climate Adaptation

There is a large body of research on forestry and climate change adaptation. Much of the economics literature centers around changes in the productivity of the land, which in turn affects the returns on the land. This then affects management of that land. Papers such as Hanewinkel et al. (2013) and Lindner et al. (2010) study changes on the intensive margin, such as production intensity. The extensive margin, which covers decisions of land-use change, are also part of this literature (e.g. Dale 1997).

Land management, especially that of forests, can have a large effect on the environment as well. Large scale environmental changes or changes in land management, such as deforestation or development, play a significant role in diminishing the capacity of the environment to sequester carbon (Pielke et al. 2002). Sequestering carbon through forest management has been suggested as a viable option for policy makers (Latta et al. 2011; Galik and Jackson 2009). The recognition of forestry's potential as part of the solution to reigning in emissions highlights the importance of modeling the feedback between it and the environment.

1.2 Forest Sector Models

The model presented in this paper differs in a number of ways from the timber market models already in existence. For an in-depth review of forest sector models, see Latta, Sjølie, and Solberg (2013). A substantial difference between the model presented here and those presented in Latta, Sjølie, and Solberg (2013) is that most models focus on regional forest management, such as FASOM (Adams et al. 1996), whereas our model is spatially explicit. This is an important distinction, since the higher resolution allows the modeler to capture adaptive behavior, such as capacity changes across the landscape, or shifting harvest intensities. A regional model would be unable to observe this in detail, since the model is constrained to observing changes only at the regional level, and not the grid-cell level.

Our solution technique also differs dramatically from previous studies. Whereas many models use optimization techniques to maximize net surplus, our model employs a fixed point algorithm based on prices instead. By working in price space as opposed to quantity space, our solution technique is able to achieve two things. First, it dramatically reduces the number of variables the algorithm needs to adjust during the optimization process. Second, it allows the algorithm to find the solution to the problem outright, which is consistent with previous models since the fixed point it solves for (market equilibrium) maximizes consumer and producer surplus. Compared with previous models, our technique provides a faster way at solving for the solution.

Our solution considers different temporal scales as those presented in Latta, Sjølie, and Solberg (2013). Many models incorporate forward looking behavior, where the decision makers in the model consider potential future actions. Our model is constrained to a single time-period, though we do incorporate opportunity costs into the model through the discount rate and the decision whether or not to harvest.

A final difference presented here is that many models linearize the maximization problem, such as FASOM (Adams et al. 1996). A notable exception is the Timber Assessment Market Model (TAMM), which is a non-linear optimization model (Adams and Haynes 1980). Our model is similarly non-linear, since the mills compete with one another for timber. This non-linearity is necessitated by the resolution of our solution, which must be at the grid-cell level.

1.3 Timber Harvests in CLM

Currently, CLM doesn't incorporate timber harvests as an endogenous phenomenon within the model. Instead, harvests are prescribed by input datasets. There are multiple harvest scenarios crafted from different representative concentration pathways (RCPs). For our project, we use RCP 8.5 (Riahi et al. 2011; Moss et al. 2010; Van Vuuren et al. 2011). RCP8.5 is characterized by a steady increase of carbon emissions up to a level of 1370ppm by 2100 (Van Vuuren et al. 2011). Harvests in CLM are represented by annual percent removal of biomass from a grid-cell. Because the data tends to be downscaled from lower resolutions, the default harvests are spread out, where each individual grid-cell experiences a very low quantity of removal (Hurtt et al. 2006). These removals are sorted into one of five types: primary forest, primary non-forest, secondary mature forest, secondary young forest, and secondary non-forest (Oleson et al. 2013).

2 METHODOLOGY

In order to improve the representation of timber harvest within CLM, the model must be able to solve for a market equilibrium level of harvest in a short period of time, while also being able to communicate with CLM at regular time-steps. This involves designing an algorithm that can balance the amount of timber and wood products demanded by the market with those supplied by the landscape and mills respectively. Furthermore, the algorithm must provide an avenue to incorporate relevant economic datasets. In this section, we will describe the solution method and discuss the coupling procedure.

2.1 Solution Technique Overview

Properly selecting the scale of a model, along with other factors, is considered by Overton (1977) to be an important factor of a model's overall quality. Our model must therefore be at a scale that is able to accomplish all of our intended goals. These goals are: to produce fine-scale spatially explicit harvest patterns, to track the movement of biomass across the map, to incorporate new economically relevant datasets, and to link the model with macroeconomic GDP projections. We determined that the relevant scale for this model would therefore be at a regional level (or state level). A large reason for selecting this scale is that it coincides with the scale at which the relevant CLM simulations are run. One potential drawback is that timber moving in and out of the region, such as mill inputs, are not incorporated into the model.

Along with the spatial scale, this model can also be thought of as having an economic scale. We have identified three markets that drive harvest decisions. These markets include the timber market, intermediate goods market, and output market. The output market provides the main linkage between the model and the broader economic projections (such as GDP), while the timber market provides the main linkage between the model and CLM, as well as some of the other economic datasets (forest ownership, mill location, etc.). The intermediate goods market significantly influences both the timber and output market. In order for a solution (a particular set of harvest decisions and the corresponding price set) to be considered optimal, these three markets must be in equilibrium.

However, there are agent interactions on the landscape. Mills will compete with one another for timber inputs, and can sell intermediate goods to one another. Thus, the amount of timber a mill is supplied is a function not only of that mill's own price, but also a function of conceivably every mill's price. This agent interaction is difficult to solve for analytically, and so we simulate repeated auctions between the mills and timber plot owners to approximate the market solution.

2.2 Price Search Algorithm

The market solution in each of the three aforementioned markets (input, intermediate, and output) is solved using a price search algorithm. As opposed to quantity-based methods, our algorithm searches over price space. For our particular problem, this dramatically reduces the search-space. Furthermore, it allows the search to be guided by economic theory.

The price set for a given market is initialized with a guess. Each buyer is given their own offer price, and the sellers observe the entire price set. The sellers then calculate the marginal benefit of supplying to each buyer, and select the buyer that provides the largest benefit. The quantity supplied is then calculated from this value. Once the buyers observe how much product they have collected, they check to see if it matches what their demand would be given the price level. The supply ilicited by the offer price is then fed into the mill's demand curve to produce an implied price of timber. Then, a new price is calculated which is a linear combination of the initial offer price and the implied price. This new price is guaranteed to be closer to the equilibrium timber price. This process is illustrated by Figure 1 below.

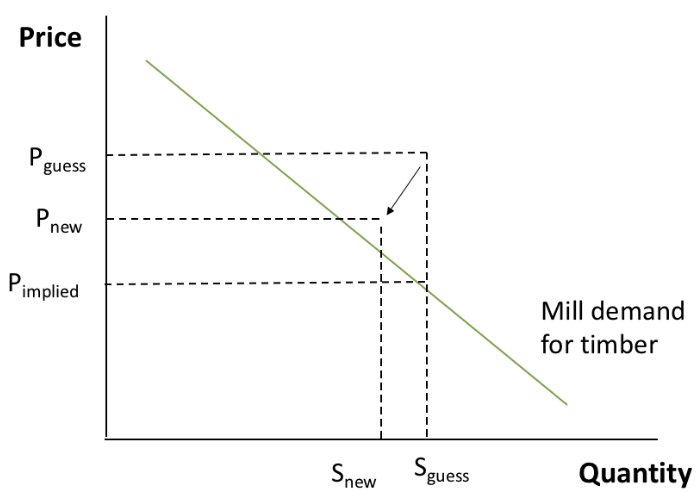

Figure 1: An iteration of the price search algorithm, demonstrating how it moves towards convergence.

Though Figure 1 depicts the price search algorithm for an individual mill, the same process describes the output market as well as the individual mill's demand for intermediate goods. The full algorithm (input, intermediate goods, outputs) can be characterized as a set of nested loops. That is, the input and intermediate goods loop is nested within the output loop. A series of auctions is simulated until the price search finds a solution for the input and intermediate goods markets. The amount of output produced is then checked against the amount demanded, output prices are adjusted in the same way described above, and then the input/intermediate loop is re-run with the new output prices. It is important to note that the mill's demand for timber will change depending on the output price of their product. The algorithm terminates when, for all three markets, the implied price is sufficiently close to the price guess, which implies that supply is equal to demand within a given tolerance.

2.3 Input and Intermediate Goods Market

The input and intermediate goods market is characterized by two different sets of agents: timber-plot owners and mills. Timber-plot owners are represented by CLM grid-cells. Timber plot owners are assumed to be profit maximizers who are faced with two decisions: where to send their timber (including sending it nowhere), and how much timber to send. This first decision is determined through the timber plot owner observing the growth rate of their particular cell, and comparing it with an exogenously specified interest rate. This interest rate is based on the findings of Provencher (1995). If the timber is growing faster than the interest rate, the plot owner will choose not to cut, otherwise, the plot is eligible for harvest.

2.3.1 Timber Plot Owner's Problem

Currently, the model is constrained such that a single plot can send their timber only to a single mill. The plot chooses the mill that has the highest gate-price, which is defined as the timber price minus transportation costs. Transportation costs are calculated from a road network dataset for the state of Oregon (ArcGIS Content Team 2012; Zamora-Cristales et al. 2015; Zomora-Cristales et al. 2013). Once the plot is deemed eligible for harvest, and a destination has been selected, the quantity harvested is determined through the timber plot owner choosing a quantity that maximizes their profit function, presented below.

$$\boldsymbol{\pi_{plot} = [Revenue - Cost] = P_1^{gate} t_1 - K\left(\frac{t_1^{\alpha}}{T_1^{\delta}}\right)} \tag{1}$$

Where the revenue consists of the gate-price (P_1^{gate}) multiplied by the timber sold *(t_1)*. Harvest costs are a function of timber sold and available timber *(T_1)*. There are three parameters: a scale parameter *($K > 0$)*, an exponential parameter on timber sold *($\alpha > 1$)* and an exponential parameter on available timber ($\delta \geq 0$). Note that the cost function as well as its first derivative are increasing in the quantity harvested. Previously, harvest costs have been modeled by Lyon and Sedjo (1983) as a function with a positive first derivative and negative second derivative. We deviate from this assumption in order to make the profit function concave, which is necessary for our algorithm. Choosing the amount of timber such that profit is maximized produces the supply function, presented below.

$$t_1^{supplied} = \left(\frac{T_1^{\delta} P_1^{gate}}{K\alpha}\right)^{\frac{1}{\alpha-1}} \tag{2}$$

As we can see from Equation 2, the supply function is increasing in the gate-price. This ensures that the supply function will, at some point, cross the mill's demand function, which will be described below. This is the equation used to calculate the amount of timber supplied to a given mill at a given offer price.

2.3.2 Mill's Problem

The mill's problem is a profit maximization problem where the mill sells outputs to the open market and intermediate goods to the other mills. The costs on the mills side include purchasing timber from plots and associated inputs, such as labor and electricity. A Leontief fixed-input production function is one of a few methods that have been used to model sawmill production (Latta and Adams 2000). While we model mill production as a substitutable input production function with decreasing returns to scale, we incorporate the fixed input approach as well. We assume that if we know how much timber or intermediate good is used, and we know what the associated input ratio is for the mill, then we can calculate the cost of the other inputs as a function of timber and intermediate goods alone. This results in the following mill profit function.

$$\pi_{mill} = P_O A(t_1 + \gamma t_2^{total})^{\beta} + P_2^{offer} t_2^{sold} - P_2^{Market} t_2^{purchased} - P_1^{Offer} t_1 - C_1 t_1 - C_2 t_2 \tag{3}$$

In Equation 3, we have two inputs: timber *(t_1)* and an intermediate good *(t_2)* such as chips. The intermediate good has a linear conversion factor ($\gamma \geq 0$) that converts it into units of input. For mills that don't use intermediate goods, we can set ($\gamma = 0$). Since there are three actions that the mill has with respect to the intermediate good (buy, sell, produce), we divide the intermediate good into three groups. The total intermediate good *($t_2^{total} = t_2^{produced} + t_2^{purchased} - t_2^{sold}$)* is what enters into the production function, where the market output price is given by *(P_O)*. The quantity of intermediate goods sold to the market (t_2^{sold}) is sold at the price the mill offers to other mills. The mill can also purchase intermediate goods from other mills ($t_2^{purchased}$) at the best price on the market (P_2^{Market}). Furthermore, the mill will purchase timber from plots (t_1) at the price the mill offers (P_1^{Offer}). Each unit of timber produced has a constant production cost, which for timber is ($C_1 > 0$) and for intermediate goods is ($C_2 > 0$). The production function has a scale parameter *($A > 0$),* and an exponential parameter ($0 < \beta < 1$).

The mill level demand curves for timber and intermediate goods are found by taking the derivative of profit with respect to timber and the intermediate good respectively. Because we have specified a production function with decreasing returns to scale, we get demand curves that are downward sloping. This ensures that, given our upward sloping timber supply curve, that we have a point at which the two curves cross. There are 16 varieties of mills in our model, each with the potential of having different inputs, production costs, and production parameters.

2.4 Output Market

One of the biggest distinctions between the previous two markets and the output market is that the output market is not inherently spatial, while the input and intermediate goods market are. Instead of selling to agents distributed spatially across a landscape, mills are assumed to sell their output directly to the market. Thus, the supply curve of the output market is an aggregation of all the individual mill level supply curves. The demand curves are constant-elasticity national-scale demand curves. The 16 mill types are grouped into 9 output groups. Elasticities for those output groups are given by past studies (Ince et al. 2011; Latta, Plantinga, and Sloggy 2016).

It is assumed that for each output group, Oregon produces a fixed proportion of that output. Changes in this proportion are not modeled, but could easily be incorporated into the model at a later date. These market demand curves provide a way to link the model with the greater socio-economic scenario in RCP8.5. Since RCP8.5 includes GDP and Population projections, these will be used to shift the market demand curves as the model progresses through time.

2.5 Parameterization

Because we utilize a set of generalizable functions to describe agent behavior, parameterizing these functions becomes an important consideration. We chose to use a particle swarm optimization (PSO) algorithm (Eberhart and Kennedy 1995) and a simulated annealing (SA) algorithm (Kirkpatrick 1984) in order to fit the model to historical harvest data. The historical harvest data was retrieved from multiple RPA assessments (Forest Service 2012) and consists of county level harvests recorded every five years since 1997. We also attempted to fit the model to output data, which was based on the regional capacity levels for each mill type (Spelter, McKeever, and Toth 2009). This resulted in a dual-objective optimization problem that both algorithms had a difficult time with. Generally, only one of the datasets (historic harvests or production targets) were fit well. For this paper, we use the set of parameters that were fit to historical harvests. In the future, an algorithm better suited to multi-objective optimization will be utilized, such as a specialized evolutionary algorithm (e.g. Coello, Coello, and Van Veldhuizen 2002).

2.6 Communication with CLM

A major difference between CLM and the harvest model is that CLM does not allow for horizontal flows between grid-cells, which is a necessary component of the harvest model. It would be computationally simpler to remove horizontal flows between grid-cells from the harvest model, but that also remove the model's ability to solve for an economic solution. In order to maintain the theoretical integrity, we needed to find a way to approximate grid-cell to grid-cell communication within CLM.

CLM simulates each grid-cell independently, and so is able to run the entire model in parallel. However, if we schedule a regular time step at which CLM communicates with the harvest model, we can initiate communication at every time step. We do this by running each grid-cell in CLM for the allotted time step, then stopping the simulation, collecting the results, feeding these results to the harvest model which simulates the annual harvest, then giving it back to CLM to begin a new time step. Instead of manipulating biomass directly, which would require a variety of extra manipulations as well, the harvest model alters the pre-existing annual harvest percentage dataset. This simplifies the interaction and lowers the potential for error.

3 RESULTS

As the model is still being updated and improved, the results presented here give only an example of what's possible with our approach. We are currently in the process of linking the model to CLM, and so the runs shown here are uncoupled, but based on CLM biomass data. We are also currently in the process of testing our model's compatibility with CLM through an uncoupled CLM run, where the harvest model generates harvest data without taking into account the feedback directly. This is done as a debugging exercise. The final goal of this project, as stated before, is to conduct a fully integrated run with CLM. Presented below are the preliminary results of the model for Oregon. We are also in the process of moving the model into other areas, such as Washington.

We present a set of model outputs from an uncoupled run for a single year. The biomass data is a CLM netcdf file from based on biomass levels in 2005, and the transportation costs are based on the network dataset described earlier. Our study area is the state of Oregon.

3.1 Spatial Distribution of Harvest

Perhaps the main deliverable from the harvest model to CLM is the spatial distribution and intensity of Harvest. Compared with the default harvest datasets from CLM (Hurtt et al. 2006) we would expect to see fewer grid-cells harvested at higher intensities.

Figure 2: The spatial distribution of harvests throughout the study region.

From Figure 2 we see that harvests are focused in the productive cascade regions as well as the southern part of Oregon. Furthermore, we observe significant harvesting in the east, which is something that the lower resolution default harvest data does not include (Hurtt et al. 2006). The harvesting occurring in the coastal range is relatively light compared with other regions. As expected, the harvests are more selective, with the total number of grid cells with harvests totaling 571 grid-cells.

Figure 2 only reveals where the harvests are occurring. Also relevant is the distribution of harvest magnitudes. As expected, the reduction in number of grid-cells exhibiting harvest results in those harvests being of a larger magnitude than the default dataset. This is a substantial departure from the default, and it will be of interest how CLM responds to a dataset with this large of a difference. For this current run, we have summarized the harvest magnitudes with the figure below. Harvest magnitudes are calculated as the percent of biomass removed from a grid-cell, which we call the harvest percentage. Figure 3 below shows what proportion of all harvested grid-cells have a harvest percentage within a given range.

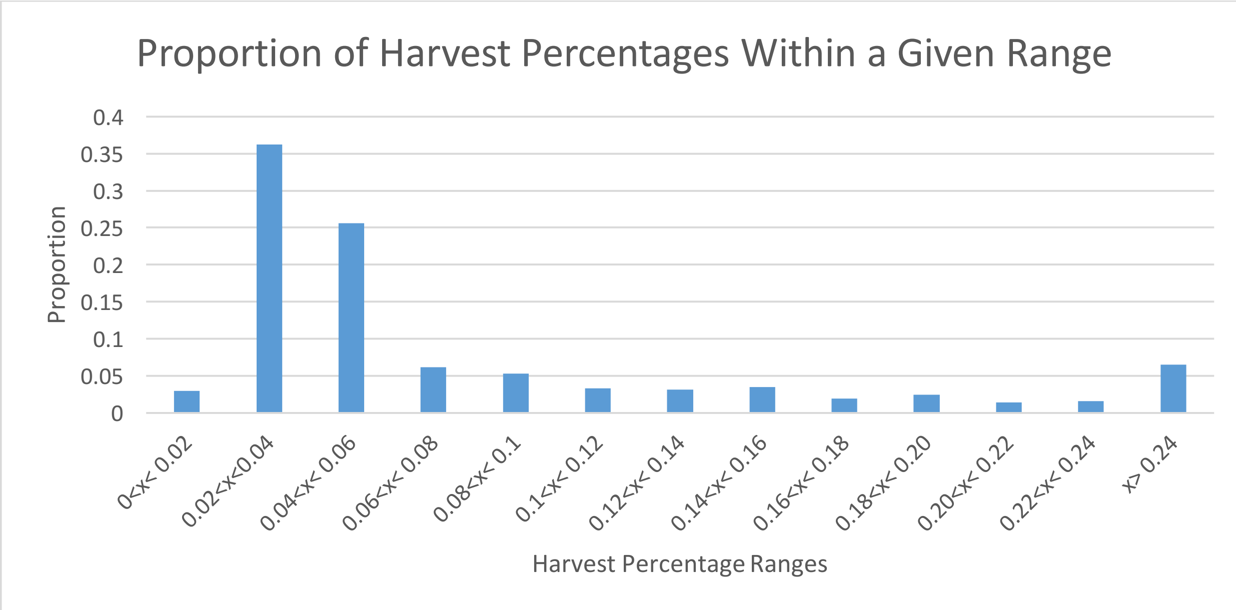

Figure 3: Distribution of harvest percentages.

The distribution of harvest percentages appears to be concentrated between 2% and 6%, and has a positive skew. There are also a few grid-cells that experience a relatively large amount of biomass removal (greater than 24%). The variety of harvest magnitudes that Figure 3 shows demonstrates that importance of modeling this system at a high resolution.

3.2 Mill Outputs

Along with harvest patterns and intensities, our model also produces output tables for each product included in our model. Table 1 below lists the output groups and the quantity produced for each output group for the model run presented in this paper

Table 1: Mill Outputs.

Mill Type	***Output Level***	***Unit (Thousand)***
Lumber	2,797	m3
Pulp	848	m3
Newsprint	261	Tons
Printing and Writing Paper	357	Tons
Paperboard	1,691	Tons
Pellets and Biofuel	1,497	m3
Plywood	3,244	m3
Oriented Strand Board	0	m3
Boards	1,533	m3

Aside from Oriented Strand Board (OSB), for which there are no mills in the study area, each output group is producing. The capability of the model to track mill outputs will later be extended to track carbon into these particular output pools. This will result in a more refined carbon accounting procedure for wood products than what's in the model already. Furthermore, this allows the model to track industrial shifts due environmental changes, which is itself a form of adaptation.

4 CONCLUSION

The harvest model presented in this paper presents a novel way to incorporate a social systems model into a large-scale environmental model. The level of integration required that we overcome two significant obstacles. The first was representing harvests in a spatially explicit way that was relevant and usable for a model such as CLM. The second was solving the problem using a method that, though more computationally expensive, was not restrictively so. Though in many ways this is still a work in progress, we have demonstrated a method that successfully overcomes both obstacles.

There are many extensions possible with this model. As stated before, the complete version of this model will provide a way to utilize CLM to run a specific class of policy experiments. A variety of economic scenarios can also be investigated with this model, especially those that involve ownership or harvest restrictions. Carbon policies, such as taxes or permit programs, are also a possibility. Another extension could be adapting the model for lower resolution runs.

Incorporating human behavior into climate models is a very difficult but necessary task. The benefits of modeling these feedbacks include a greater understanding of the effects of climate change as well as human behavior on the environment.

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