Uncertainties in estimating global potential yields and their impacts for long-term modeling

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Abstract
Estimating realistic potential yields by crop type and region is challenging; such yields depend on both biophysical characteristics (e.g., soil characteristics, climate, etc.), and the crop management practices available in any site or region (e.g., mechanization, irrigation, crop cultivars). A broad body of literature has assessed potential yields for selected crops and regions, using several strategies. In this study we first analyze future potential yields of major crop types globally by two different estimation methods, one of which is based on historical observed yields (“Empirical”), while the other is based on biophysical conditions (“Simulated”). Potential yields by major crop and region are quite different between the two methods; in particular, Simulated potential yields are typically 200% higher than Empirical potential yields in tropical regions for major crops. Applying both of these potential yields in yield gap closure scenarios in a global agro-economic model, GCAM, the two estimates of future potential yields lead to very different outcomes for the agricultural sector globally. In the Simulated potential yield closure scenario, Africa, Asia, and South America see comparatively favorable outcomes for agricultural sustainability over time: low land use change emissions, low crop prices, and high levels of self-sufficiency. In contrast, the Empirical potential yield scenario is characterized by a heavy reliance on production and exports in temperate regions that currently practice industrial agriculture. At the global level, this scenario has comparatively high crop commodity prices, and more land allocated to crop production (and associated land use change emissions) than either the baseline or Simulated potential yield scenarios. This study highlights the importance of the choice of methods of estimating potential yields for agro-economic modeling.

Keywords Agricultural intensification · Yield gap · Global agricultural models · Scenario uncertainty

1 Introduction
Global food demand from an increasing—and increasingly wealthy—future world population will necessitate an increase in global agricultural production. How and where this increased production takes place will have profound socioeconomic and environmental impacts. The effects of agriculture on food security, land use change, and global nutrient cycles, among others, will in turn have implications for the achievement of aspirational targets such as the Sustainable Development Goals (United Nations General Assembly, 2015). To improve human food security while reducing environmental impacts, identifying areas with the potential for high future agricultural productivity has long been a focal area in the research community (Valin et al., 2013). Global agro-economic models have been used in a number of assessments of future food security (e.g., Hasegawa et al., 2018; Janssens et al., 2020); however, scenario outcomes in such models are known to be sensitive to future yield levels (Nelson et al., 2014). Therefore, accurate assessments of potential future agricultural productivity provide both researchers and policymakers with critical information for strategic planning for sustainable food supply (Cohn et al., 2014; Gerten et al., 2020; Pugh et al., 2016; van Ittersum et al., 2016).

However, determining potential yields around the world is both conceptually and practically difficult (Silva & Ramisch, 2018), and existing estimates have large ranges of
uncertainties, even without considering the effects of future climate change. For a given crop at a given location, the maximum possible productivity is determined by characteristics of the crop, the local climate, soil constraints, and the availability of irrigation water (Lobell et al., 2009). This potential yield represents the highest yield possible for a given crop in a given location. Similarly, the water-limited yield is the maximum possible yield of rainfed crops. A yield gap can then be calculated by comparing current yields to the estimated potential yield. The size of the yield gap is an indication of the degree of improvement that is possible from actual yield levels (Fig. 1).

A number of research teams have estimated potential yields globally; the strategies used can broadly be grouped into observation-based and model-based assessments. The first strategy, used in Mueller et al. (2012), relies on historical records of crop yields and environmental data to estimate potential yields. In Mueller et al. (2012), the potential yield of each crop, grid cell, and irrigation level (i.e., with and without irrigation) is estimated as the 95th percentile of observed yields globally in the grid cell’s corresponding climate bin. This strategy, hereafter referred to as “Empirical,” benefits from being grounded in observational crop yield data, but may omit management practices that are not present in the historical data of any given climate bin. The second strategy, hereafter referred to as ”Simulation,” relies on simulation models of crop growth, which estimate the yield at any location based on local environmental factors and explicit assumptions about management practices. Examples of this approach include Global Yield Gap Atlas (van Ittersum et al., 2013), GAEZ v3.0 (Fischer et al., 2012), and Schils et al. (2018). While calibrated crop model derived estimates are widely accepted in agronomic research as the best way to estimate potential yields (van Ittersum et al., 2013), scaling such site-based estimates to produce global datasets carries large uncertainties (Ruane et al., 2017). And, while potential yield estimates developed from each of these strategies have been used for future scenario generation and assessment as well as for policy recommendations, there have not been any global assessments of the differences between potential yields estimated by the

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**Fig. 1** Definitions of potential yields and yield gaps (adapted from van Ittersum et al., 2013). Potential yield is attainable in irrigated or otherwise non-water-limited production, while the water-limited yield is that expected under rainfed conditions.
two approaches described above, or the long-term consequences thereof for future agriculture and food security.

Our objectives in this study are to examine the differences in potential yields globally using different methods of estimation that are available in the literature, and to analyze how these may shape the future of the agricultural sector globally in scenarios where yield gaps are closed in upcoming decades. We first compare two estimates of global gridded potential yields, one based on Mueller et al. (2012; “Empirical”), and the other based on recent global gridded crop model simulation results, using 11 models (Müller et al., 2019; “Simulated”). We then use these data to construct two future yield gap closure scenarios in the Global Change Assessment Model (GCAM), and assess the differences in projected land use change, crop prices, and regional food self-sufficiency around the world between these two scenarios and compared to a reference scenario. Finally, we discuss the reasons for the discrepancies between the scenarios, and implications for future research on the spatial targeting of future agricultural intensification.

2 Methods

2.1 Empirical potential yields

Data on potential yields in the “Empirical” scenario were extracted from the database of Mueller et al. (2012), which uses climate analogue techniques. Specifically, gridded (0.05° × 0.05°) estimates of current yields and of average climate are used to map yields from geographic coordinates to a climate space with growing degree days and annual precipitation as coordinates. This climate space is subdivided into 100 growing degree day – precipitation bins where harvested area is distributed equally among all bins. Within each climate bin, the 95th percentile yield is taken as the attainable yield level for those climate conditions, and that yield value can then be applied for all geographical areas falling within the same bin (See Mueller et al., 2012, supplementary information on “Calculating climate bins and yield gaps” for more detail). Crops mapped were barley, cassava, cotton, maize, millet, groundnuts, potatoes, rapeseed, rice, rye, sorghum, soybeans, sugar beet, sunflower seed, wheat, sugar cane, and oil palm. Where data were available—in crop and climate bins with an adequate number of observations of both rainfed and irrigated crop production—a separate water-limited yield was also provided; as such, the dataset includes separate estimates of potential yield for rainfed and irrigated cropping systems.

2.2 Simulated potential yields

For estimating model-based potential yields, we use data from the Global Gridded Crop Model Intercomparison Project, Phase 1 (GGCMI; Müller et al., 2019). While other datasets are available that estimate potential yields (e.g., Global Yield Gap Atlas, GAEZ), the GGCMI data are especially suitable for this study for several reasons: (1) it includes a large number of individual models participating (11 models), using (2) standardized reporting practices, with (3) bulk download availability; and (4) full global coverage. In the GGCMI Phase 1 exercise, models used a common set of input assumptions and weather data to create global gridded yield estimates (0.5° × 0.5°) for each crop represented. The selection of crops was model-specific; across all models, up to 15 were available, and the individual models represented between 2 and 13, shown in Table 1. For this analysis, we use crop model output data driven by historical weather data as emulated by AgMERRA (Ruane et al., 2015). Rainfed and irrigated production were modeled separately. For each crop/irrigation combination and in each grid cell, we combine all model and scenario results and consider the maximum value among those model outputs to be the potential yield. The methods used to expand the potential yield estimates from the crops available in these datasets to the full set of FAO crop commodities is detailed in the Supplementary Materials.

2.3 GCAM

The Global Change Analysis Model (GCAM; (Calvin et al., 2019)) is a publicly available human-Earth systems model of future agriculture and land use, energy, water, and climate. The agriculture and land use module contains 384 land use regions, derived from the intersection of 32 geopolitical market regions and 235 hydrologic basins (di Vittorio et al., 2020). Within each of these land use regions, 368 of which have agricultural production, land is allocated to a range of competing uses, including commercial uses such as crop production, grazing, or forestry, as well as non-commercial uses (i.e., natural vegetation). In this study there are 15 crop commodities represented, 6 animal commodities, as well as (in future years) dedicated grass and tree bioenergy crops that can be used for a variety of purposes in the energy and industrial sectors. Changes in land allocation from the base year, 2010, are driven by changes in the relative profitability of each potential land use, using a nested logit choice formulation. The future production of each crop within each land use region reflects dynamics within the land use region, the parent geopolitical region, and the globe as a whole. One driver of changes in production and land use is future assumed yield improvement, which is exogenous, specific to each land use region, crop, and irrigation level. Default yield
improvement rates are based on the country-level projections of Bruinsma (2011).

Demands for agricultural crop commodities in GCAM are driven by four explicitly modeled uses in each of 32 market regions: food, animal feed, biofuel feedstocks, and other demands. The price elasticities of demand for food and other uses are exogenous, whereas demands of feed and biofuel feedstocks are driven by explicitly represented animal commodity and liquid fuel production sectors, respectively. As such, the price elasticity of the demands for these uses of crop commodities are largely determined by the levels of demand of the final products (e.g., beef, motor gasoline), and the prices and availabilities of non-crop-based options (e.g., pasture forage, crude oil, respectively). The market equilibrium supply, demand, and price of each crop commodity are all endogenous in each future model time period.

GCAM 5.2, used in this study, contains an updated representation of trade from GCAM 5.1 and prior versions, which used Heckscher-Ohlin equilibrium (Zhao et al., 2021) a method which freely allows inter-regional shifting in agricultural product trade over time in response to regionally differentiated changes in production and/or consumption. The revised approach used in this study explicitly represents the competition between domestic and imported sources of crops with a logit choice function in each region that is calibrated to the historical choices. As compared with prior studies using GCAM, this update tends to dampen changes in trade patterns that occur in response to differential changes in producer prices; modeled responses are more similar to models that use Armington elasticities to regulate future trade changes (e.g., GTAP; (Corong et al., 2017)).

### 2.4 Scenario design

This study assesses three scenarios: a reference scenario, and two yield gap closure scenarios. The GCAM reference scenario is built from a range of future assumptions pertaining to future population, economic development, technological improvement, and service demand levels (see Calvin et al., 2019 for a full description). The scenario is generally based on the “SSP2 Middle of the Road” Shared Socioeconomic Pathway (SSP2) (Riahi et al., 2017), with future yield improvement levels based on Bruinsma (2011). It is included in this study to provide a benchmark yield scenario, where yields increase to levels that are generally considered reasonable in the agro-economic modeling community. From this baseline, two additional yield gap closure scenarios are constructed, in which all crops and land use regions are assumed to reach their potential yields by 2090, using the two different methods of estimating potential yields (“Empirical” and “Simulated”).

These potential yield estimates are determined from present-day crops and management practices, and do not take into account the potential yield gaps that could result from technological improvements or other factors.
into account future technological changes such as improved crop cultivars (Reynolds et al., 2021), robotics, or genetic engineering for optimal photosynthesis (Long et al., 2015). The scenarios do not include impacts of climate change or other global change-related drivers (e.g., CO₂ fertilization, ozone pollution) on yields, given the high degree of uncertainty of what the impacts will be (Elliott et al., 2015), as well as the lack of understanding of climate change impacts on different management system types. Similarly, the costs of production in all regions and scenarios are assumed constant per unit of output over time; within any crop and region, there is no increase or decrease assumed in non-land production costs, even as yields increase.

These scenarios are constructed as all-else-equal; for example, they do not assume any additional socioeconomic developments, or infrastructural improvements that might be consistent with realization of higher-than-baseline yield improvement rates and yield gap closure. Instead, the scenarios allow analysis of how this one uncertain variable—future yield improvement—drives changes in future outcomes for agriculture and land use. The yield gap closure scenarios are implemented by imposing linear yield improvements from the model base year of 2010, to the estimated potential yield in 2090, for each land use region, crop, and irrigation level. Because we are focused on the impacts of realized yield gap closure, rather than the transition itself, our analysis similarly focuses on the year 2100.

3 Results

3.1 Differences in yield potential estimates

This section compares “Empirical” estimates of global gridded potential yields by Mueller et al., 2012) and “Simulation” results of an ensemble of crop growth models from the Global Gridded Crop Model Intercomparison project (GGCMI) (Elliott et al., 2015; Müller et al., 2019). A comparison between both of these estimates of potential yield and the Global Yield Gap Atlas for comparable agricultural crops, regions, and irrigation levels is provided in the Supplementary Materials (Figs. S1, S2).

These two estimates of potential yields show strikingly different patterns of future potential yields around the world (Fig. 2). Simulated potential yields tend to be higher overall than Empirical potential yields, and the distribution of yields shows marked geographic differences, particularly with respect to latitude. Empirical potential yields are highest at temperate latitudes, and tend to be lower in the tropics for maize, rice and wheat, while soy yields do not show any broad latitudinal patterns. By contrast, the Simulated potential yields are highest near the equator for rainfed maize, rice, and soy, leaving only wheat, a typically temperate zone crop, with temperate zone peaks and low equatorial yields. A further demonstration of the uncertainty in potential yields highlighted by these two methods can be found in Figure S3, which shows the potential yield differences by continent and major crop type.

The distinct spatial patterns of potential yields are further demonstrated in Figs. 3, S4. In the case of rainfed maize (Fig. 3, left panels), global mean Simulated potential maize yields are 56% higher than Empirical mean potential yields. In addition, Central America and parts of Eastern and Southern Africa have some of the highest Simulated yields—over 15 t/ha in some places—while the Empirical potential yields in these areas are well below 10 t/ha, and sometimes even below 5 t/ha. The low Empirical potential yield values represent the upper end of observed yields in these and other climatically similar regions, where smallholder maize yields are often 1–2 t/ha. However, trials on experimental stations in climatically similar regions have attained yields commensurate with the simulated results (Neumann et al., 2010; van Ittersum et al., 2013); this is documented in detail in Assefa et al. (2020) and Silva et al. (2021).

For irrigated rice (Fig. 3, right panel), the potential yield is higher in the “Empirical” than the “Simulated” scenario in northern latitudes, especially in Europe, while the pattern of comparatively low Empirical-based potential yields in the tropical regions is again observed. Global coverage of the modeled potential yields also identifies places which, while they are not currently major rice producers, have high potential yields for the crop, particularly in Central Asia and parts of the Middle East. This result indicates that if water were in fact available for irrigation, the potential for increased rice production would be significant. However, this result also highlights that global gridded potential yields alone, by either method, do not necessarily translate into realizable outcomes.

3.2 Differences in projected global agriculture and land use

This section assesses the differences in land use, crop production, agricultural commodity prices, and regional food self-sufficiency among three scenarios of future yield improvement in GCAM. The Reference scenario uses GCAM’s default future yield growth assumptions, which have been used in a number of studies (Calvin et al., 2019; Popp et al., 2017). The yield assumptions are not built around realizing maximum potential yields, and a recent analysis (Zeist et al., 2020) indicates that they tend to remain well below such levels in all regions, across a wide range of scenarios. Both Simulated and Empirical scenarios, by contrast, do close yield gaps, reaching the potential yield estimates in 2090. Thus the only difference between Simulated and Empirical scenarios is which method is used to...
Fig. 2  Mean potential yield varies across latitudes, highlighting the differences between “Empirical” and “Simulated” potential yield estimates
estimate final potential yield levels for all crops and regions. More broadly, the exogenous rates of yield improvement for each crop, geographic region, and irrigation level are the only differences between the three scenarios, so any differences in the model outputs can be understood to arise from different future yields.

While all three scenarios result in production increases on a global scale (Fig. 4), differences in the degree and geographic distribution of the increase lead to widely varying implications for food security, global trade, and the environment. For most crops, total global production in the future is similar between all three scenarios because of low assumed price elasticities of demand in GCAM. However, the differences in yields among the scenarios lead to very different outcomes for the regional distribution of future agricultural intensification and crop production. In the Simulated scenario, production increases dramatically in Africa, and to a lesser extent in Asia (Fig. 4). Increased local production results in higher final self-sufficiency ratios in the Simulated scenario than in the Empirical scenario (Fig. 5).

In the Reference and Empirical scenarios, the balance between agricultural commodity demand growth and agricultural productivity growth leads to increased future allocation of land to crop production globally. In contrast, the Simulated scenario sees a reduction in total global cropland (Fig. 6), with significant shifts in maize production towards Africa and in wheat production away from Europe. As a result of the shifts in geographic production towards Africa, total forested land in Africa decreases by 13% from 2010 to 2100 in the Empirical scenario; this reduction is only 8% in the Simulated scenario, where significantly higher yields allow the increased production to take place with lower levels of land conversion.

Fig. 3 Maps of potential yield in maize (left) and rice (right) using modeled yield levels from the Global Gridded Crop Model Intercomparison Project (top), and empirically estimated potential yields from Mueller et al. (2012) (middle). The bottom row shows the difference between the two estimates. Note that empirical yield information is available only on current crop land, while modeled yields are calculated over total land area. Yields are in tons/ha.
Because of the significant growth in productivity in the Simulated scenario, global crop prices are reduced as well (Fig. 7). Despite increases in agricultural commodity demands due to assumed population and economic growth, commodity prices in the “Simulated” scenario are reduced considerably—decreases range from 19% for maize to over 40% for wheat. By contrast, both the “Reference” and the “Simulated” scenarios show small increases in prices for most crops from 2010 to 2100.

Fig. 4 Change in production for major crops by continent from 2010 to 2100, based on GCAM model results with Simulated and Empirical potential yield achievement, as well as the GCAM reference scenario whose yield growth is derived from FAO projected yield increases
Fig. 5 Self-sufficiency in staple grains by continent, based on GCAM model results using modeled and empirical estimates of potential yield and compared to the GCAM reference scenario which uses FAO projections for yield increases. Includes maize, wheat, rice, and the composite commodity “OtherGrain”.

Fig. 6 Change in land use for food crops and forest by continent, based on GCAM model results using modeled and empirical estimates of potential yield and compared to the GCAM reference scenario which uses FAO projections for yield increases.
Discussion and conclusions

The yield gap closure scenarios in this study are differentiated only by their methods of estimating potential yields. Using the Empirical method, historical observations in similar climates determine the potentials; for example, the high yields attained in the USA’s Corn Belt are reflected in the potential yield estimates of all areas around the world with similar climates. But if a given climate zone only includes low-input, low-yielding production systems in the historical observed yield data, then the resulting potential yield estimates by this Empirical method do not reflect high-yielding management practices. In contrast, the crop models used to generate the Simulated potential yields generally assume optimized management practices. This can be seen in the maps of potential yield data (Fig. 3), where Empirical potential yields of maize in particular are low throughout the tropical latitudes. Note that these discrepancies don’t invalidate either method; for research questions with high uncertainty such as future potential yields, there are benefits to assessing a plurality of heterogeneous outcomes.

In GCAM, achieving potential yields by these two different estimation methods returns very different pictures of future agriculture and land use; differences are especially prominent in Eastern Africa and Western Europe, two regions that are important agriculturally and follow diverging pathways in the two yield gap closure scenarios. Using the Empirical potential yields to close yield gaps in GCAM, Eastern Africa’s terminal yields of major staple crops remain low; maize yields are less than 4 ton ha$^{-1}$. In the Empirical yield gap closure scenario in GCAM, food crop prices increase 60% between 2010 and 2100, and imports more than double from 14% of food calories in 2010 to 30% in 2100. In contrast, using Simulated yield estimates, maize yields in Eastern Africa reach 13 ton ha$^{-1}$ by 2100, leading to a dramatic increase in production. Prices decrease by over 30% from the base year. Imported food makes up only 19% of total consumption, and agricultural exports increase by over 80% from the base year. Thus while the Empirical scenario presents a picture of worsening food security in this region, the Simulated scenario shows the opposite. In addition, land use change emissions are 20% lower in the Simulated scenario than in the Empirical scenario.

Fig. 7 Change in global average crop prices for four major crops from 2010 to 2100, based on GCAM model results using modeled and empirical estimates of potential yield and compared to the GCAM reference scenario which uses FAO projections for yield increases.
Yield levels in Western Europe are generally similar between the Simulated and Empirical scenarios; this is consistent with the findings of Schils et al. (2018), that present-day observed yields of wheat and barley in this region are near their water-limited potential. Still, modeled outcomes for the region do differ between the scenarios, due to the equilibrium impacts of yield differences elsewhere. Most notably, between 2010 and 2100 wheat production in the region declines in the Empirical scenario, while increasing in the Simulated scenario. Price differences between scenarios are less pronounced in Europe than in Eastern Africa. Maize prices increase by 27% in the Empirical and 15% in Simulated scenarios. Larger differences are seen in wheat and other grain prices, where prices decrease 15–30% in the Simulated scenario, while rising slightly in the Empirical scenario.

The scenarios offer several insights with implications for future agriculture and land use. For one, the divergence in future potential yields between the two potential yield estimation methods imply significant uncertainty in yield gaps for many agriculturally important regions and crops, independent of other factors that have been studied such as climate change. Crop model estimates of the impact of climate change on maize yields have seen variations among models corresponding to 50% of current yields (Knox et al., 2012). By comparison, differences between Empirical and Simulated potential yields are over 200% of current yields in nine of the 32 GCAM regions, and over 400% in three regions.

Second, this study has highlighted the wide range of outcomes that result from realizing different estimates of potential yield. Estimates of potential maize yields in much of Africa and South America differ by 5–10 ton ha\(^{-1}\), while estimates for wheat in the same areas differ by 4–7 ton ha\(^{-1}\). Although it is a yield gap closure scenario, the Empirical scenario results in increased dependence on imports over time in these key regions, as the impacts of increases in commodity demand due to population and economic growth outpace those of the assumed productivity improvements. This leads to higher commodity prices, cropland expansion into lands with natural vegetation land cover at present, and increasing reliance on agricultural commodity imports. Food prices have implications beyond the agricultural sector, as food price increases have been linked to social and political unrest (Bellemare, 2015) as well as worsening nutrition outcomes (Iannotti & Robles, 2011). Thus understanding the potential for future agricultural productivity is a key component of future scenarios not only for agriculture, food security and land use, but impacts a range of linked human-earth systems.

Third, the comparison between the two yield gap closure scenarios demonstrates divergent strategies for the agricultural sector to use yield gap closure to meet future global agricultural commodity demand. Focusing on intensification in sub-Saharan Africa may be a good strategy if the Simulated potential yields are understood to be achievable; i.e., if present-day barriers to yield improvement can be addressed over time. However, if such barriers to intensification in these regions are believed to hold over time, then the Empirical scenario shows that development and deployment of technologies to maximize yields in regions that practice industrial agriculture (e.g., Europe, North America) will be important for meeting global food demand, due to relatively minor future yield (and production) increases that can be expected in much of Africa. Yield increases of the magnitude allowed by the Simulated potential scenario are biophysically possible, as demonstrated in experimental settings (van Bussel et al., 2015). However, the discrepancy between Empirical and Simulated potential yields highlights the need to move beyond current ‘best practices’ in those areas to increase production. Investment both in improving technology and in removing barriers to its use will be needed to ensure food security, limit cropland expansion, and lower food prices for consumers. However, achieving high yields on farmers’ fields requires additional investments in technology development and dissemination, as well as coordinated improvements in rural infrastructure (Tittonell & Giller, 2013). In the future, any such strategy will be complicated by climate change impacts and other global change-related stressors (e.g., novel pests, weeds and diseases), but also by technological advancements in crop breeding, genetic engineering, and agricultural technologies in general.

In conclusion, efforts to model the global agricultural sector in upcoming decades rely on estimates of future yield improvement. Estimating such yields is challenging, as future yield improvements reflect local soil and climate conditions, agricultural technology and management practices, and also infrastructural conditions determining access to equipment and to markets, as well as other political and economic factors. This work has identified and explored the large difference in potential yield estimates between those derived using current yield statistics and those derived from crop growth models, in a number of key regions for future agriculture and land use. Because differing potential yield estimates may constrain intensification, with significant feedbacks to the agricultural sector at global scales, it is important that scenario-based assessments similarly incorporate such constraints, at the smallest scales possible (whether grid cells or larger land use regions), and define how potential yields are estimated in places with significant present-day yield gaps and institutional barriers. As shown here, realizing potential yields can impact the long-term sustainability of the agricultural sector, with implications for regional and global economies, human well-being, and the environment.
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Data availability underlying data are publicly available.

Code availability GCAM model code is publicly available; supplemental code available upon request.

Declarations

Conflicts of interest The authors declared that they have no conflict of interest.

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