ORBITAS
Navigating climate transition risks

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Technical Guidance

Material Climate Transitions

AN INITIATIVE OF
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This technical guidance describes the methods, data sources, and caveats related to the following reports, published as part of the ORBITAS "Climate Transitions in Tropical Agriculture" series, accessible at: *Agriculture in the Age of Climate Transitions*.

I. Research Report: Global Climate Transitions Analysis
II. Research Report: Measuring Materiality: Climate Transitions in Tropical Agriculture
III. Analyst Report: Indonesian Palm Oil
IV. Analyst Report: Peruvian Palm Oil
V. Analyst Brief: Colombian Beef Cattle

Partners	*This report was produced by Orbitas--a project of the Climate Advisers Trust--with support from the Norwegian Agency for Development Cooperation ("NORAD")***.** *Orbitas examines climate transition risks for capital providers financing tropical commodities.*
About this Report:	*This report serves as a technical guidance for practitioners and acts as an additional annex to ORBITAS' series of reports on climate transitions in tropical agriculture.*
Authors	***Concordian:*** *Shally Venugopal, Markus Walther, Kandice Harper, and Emily McGlynn* ***Vivid Economics:*** *Bryan Vadheim, Mateo Salazar, Jason Eis, Madison Cole, Alessa Widmaier, Devon Azevedo, and Oliver Walker.* ***IIASA/Oxford****:* *Nikolay Khabarov, Sylvain Leduc, Kim Moonil, Michael Obersteiner,* ***With contributions from:*** *Agronomy Capital Advisors*
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Summary of Approach

The Orbitas ***Agriculture in the Age of Climate Transitions*** series of reports evaluates to what extent global and local actions taken by the public sector, private sector, and consumers to transition to low carbon pathways (“climate transitions”) can impact both global agricultural sectors and specific industries. The series’ overarching aim is to help investor and corporate capital allocation and growth strategies better reflect climate transition risks and opportunities.

The series of reports and their associated methods collectively represent a first-of-its-kind undertaking to evaluate and quantify global and local climate transition risks. In contrast to other reports in the series that focus on the importance of this analysis and its results, this report provides specific guidance to practitioners attempting to replicate or delve further into the assumptions behind our land use, economic, and financial climate transition scenario analyses.

Climate transition scenario analysis is undoubtedly a complex undertaking with significant uncertainty. Nevertheless, this technical guidance provides an invaluable proof of concept to financial analysts, asset managers, companies (and their service providers) on how they may identify, evaluate, and disclose their exposure to climate transition risks in line with recent guidelines from the Task Force on Climate-related Financial Disclosures (TCFD).

We focused on upstream agricultural production and processing sectors and industries given their high exposure to land use restrictions relative to other supply chain actors, though certainly, downstream activities are also exposed to climate transitions.

We used--and suggest practitioners keep in mind--the following goalposts when evaluating climate transition risks through scenario analysis:

- **Step 1: Climate Transition Scenario Planning:** Creating plausible and realistic scenarios that reflect both global and national climate ambition.
- **Step 2: Sectoral Projections:** Understanding how climate transitions can affect sector-wide price, production, yields, and land use across a basket of tropical soft commodities and regions.
- **Step 3: Industry Impact Evaluation:** Cautiously downscale these projections to specific industries to model how producers will face risks, opportunities, and financial implications that impact asset and industry value. These include impacts on production costs, capital expenditures, land use and rents, sources of revenue, and overall production and demand for soft commodity products. The three industries examined are:
    - (1) Colombian beef cattle;
    - (2) Peruvian palm oil; and
    - (3) Indonesian palm oil.

- **Step 4: Company-Level Vulnerability Analysis:** Evaluate to what extent companies and business models are vulnerable to climate transition impacts previously identified.

Broadly, our methodological framework begins by defining realistic climate transition scenarios at both the global and national levels in Step 1. These scenarios ultimately used in this report represent increasing levels of ambition to address the climate crisis and draw from existing literature. Then, using these scenarios, in Step 2 we use the Potsdam Institute’s (PIK) open source land use model, MAgPIE (The Model of Agricultural Production and its Impact on the Environment), in conjunction with the energy system model REMIND (REgional Model of Investment and Development), to evaluate how global climate and food security-compatible pathways impact a basket of tropical soft commodities, including palm oil, beef cattle, soy, maize and cereals. These pathways vary by factors like climate and land conservation policies; technological progress; bioenergy pathways; and consumer diet shifts, and an implied price on greenhouse gases (GHG) emissions.

Using Step 2’s sectoral projections as an overarching narrative, Step 3 analyzes how national and industry-specific transition responses like land use moratoria or corporate zero deforestation commitments engender new norms in land use, influence industry expansion and contraction, and ultimately, flow through to materially impact agricultural companies’ assets, financial metrics, and growth potential. Finally, in Step 4, we use parallel methods to assess individual company and business model vulnerability to climate transition risks.

An important overarching caveat to all of our analysis is that existing global/regional land use integrated assessment models are not designed to provide the spatial specificity necessary to accurately inform local/regional industry dynamics. We acknowledge and intend to tackle (in our future work) these gaps between global modeling/results and industry-level applications. Meanwhile, in this series of reports we extract broader trends from our global and regional projections and then use these trends alongside national, industry-specific, and company-specific data to assess risk exposure and vulnerability.

a. Key Methods Outline

Each step of our analysis within the four aforementioned parts is outlined below.

STEP 1: Climate Transition Scenario Planning: Build global transition scenarios representing a range of policy, consumer, land use and technology trends. These transitions vary from climate change mitigation policies, to global area protections, to bioenergy pathways, to consumer demand shifts.

STEP 2: Sectoral Projections: Model how these global transition scenarios create fundamental economic shifts in commodity prices, production, and trade for palm, soy, and beef[1] using an open source land use allocation model developed by the Potsdam Institute for Climate Impact Research (PIK) called "MAgPIE": The Model of Agricultural Production and its Impact on the Environment.

STEP 3: Industry Impact Evaluation For each industry we used different methods in order to account for the type, size, maturity, and domestic economic importance, its contribution to global production, data availability and dependability, and industry actors:

- **Indonesian Palm:** Our evaluation of the Indonesian palm oil industry was the most robust given the size and maturity of the industry alongside spatial data availability. This evaluation includes asset-level, company-level, and industry-level analyses.
- **Peruvian Palm:** Since the industry is dominated by two related palm oil companies, company-level comparisons are not particularly relevant; instead, we focused primarily on asset-level projections using regional projections of palm oil prices, fresh fruit bunch (FFB) yields, production, and GHG costs to test asset-level cash flow impacts alongside industry-wide trends.
- **Colombian Beef Cattle:** For this insular industry with currently limited exposure to global supply chains, we examine regional projections of beef prices, production, and GHG costs, alongside local land use data and production costs to evaluate industry-level risks and opportunities.

While these methods vary by industry, generally, Step 3 includes the following three areas of analysis:

→ STEP 3A: Land Use Modeling

I. **Spatial Forest Cover Projections (OSIRIS):** Downscale global results and assumptions to specific geographies to predict changes in grid-cell level forest cover by considering competition for agricultural land against potential payments for afforestation.

II. **Spatial Land Use and Suitability Constraints:** Overlay projected forest area changes from Step 3 along local transition scenarios, current industry assets, and soil suitability to understand, spatially, where industry assets are at greatest risk, are protected, or may expand footprint.[2]

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[1] These and wood/timber are key sources of deforestation. We may also consider other tropical soft commodities-- coffee, cocoa, and sugar. Alternatively, we may look at maize/corn and grain/wheat prices as feedstock for beef cattle so we can better trace its value chain.

[2] Based on local policy scenarios as described later in this document.

→ *Step 3B: Financial Modeling*

I. **Pro Forma Asset Cash Flow Analysis (ACF):** Identify how global projections can create emissions costs, increases in the cost of inputs, production, and increases in land prices; understand and evaluate what options asset owners face under each set of global/local scenarios.

II. Pro Forma Company DCF Analysis: In Peru and Indonesia we developed company level discounted cash flow models to evaluate impacts on illustrative companies with varying asset mixes, balance sheets, sustainability characteristics, and management practices. This modeling not only uncovers how climate transitions impact key financial metrics but also tests company growth sensitivities to sustainability practices and financial standing.

→ *Step 3C: Industry Modeling*

Steps 3C-I and II below are currently only employed in the Indonesia analysis, but can be replicated in other sectors of similar size and maturity where data is available.

I. Industry Expansion/Contraction Analysis
Using the land use restrictions from Step 3A as bounds for industry expansion, and Step 3B's Asset Cash Flows, the "BeWhere" techno-economic model, projects economically-efficient expansion and contraction in the production and location of palm oil mills and associated assets.

II. Industry Value Analysis:
Using the results of Step 3, calculate changes in the net present value of land considering the future profitability of mills and plantations by each 25kmx25km grid cell.

STEP 4: Company-Level Vulnerability Analysis

Finally, we use the following methods to stress test the vulnerability of companies to the impacts identified by Step 3. These methods consider key aspects of company vulnerability to climate transitions including operational footprint, productivity, emissions intensity, market power, cost of capital, and balance sheet strength.

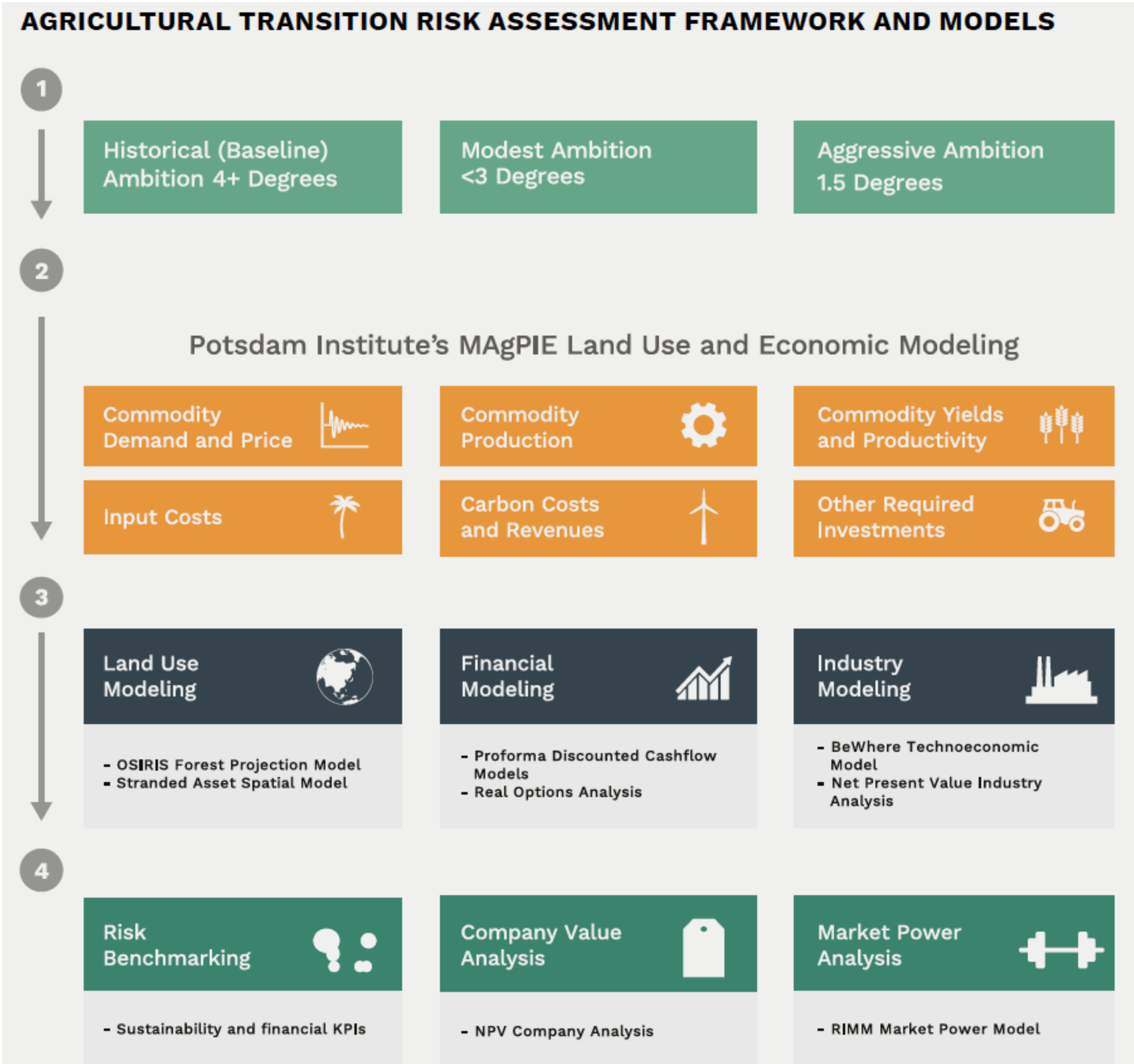
→ *Step 4A: Risk Benchmarking*

This simple, risk-focused approach provides a qualitative evaluation of company vulnerability by using sustainability and financial metrics that are easily procured from public databases and annual reports. As this step is relatively simple, it is not addressed in this Technical Guidance.

→ *Step 4B: Company Value Analysis*
This sophisticated Concordian analysis quantifies, in dollar terms, the discounted value of a company's optimized profits/losses under climate transitions based on its current operational footprint. To undertake this analysis we combine our industry value analysis with asset ownership data.

→ *Step 4C: Market Power Analysis*
This detailed economic modeling approach, which uses Vivid Economics' Reduced Industrial Market Model (RIMM) model, gives investors and companies insights into future industry dynamics and examines which types of business models are well-positioned under climate transitions.

Figure 1: Summary of Methods



Source: Authors

Box 1: Stranded Asset Definitions

For purposes of this report, we consider two types of stranding: “regulatory stranding” and “economic stranding”. An example of regulatory stranding is an unplanted concession on forestland that becomes worthless if the government bans all deforestation. In contrast, the same concession would suffer economic stranding if deforestation was allowed, but crude palm oil prices dropped, reducing the potential revenue of the potential future plantation on that concession, and hence reducing its asset value.

We define stranded assets as assets that become impaired, i.e., their fair market (FMV) value drops below their book value. FMV is defined as the Net Present Value (NPV) of the asset, i.e., the future cash flows of the asset, discounted by the cost of capital. For pure-play companies, the discount rate will be the firm-wide cost of capital, for other companies it should be the asset-level or subsidiary-level cost of capital. The book value is the asset price at purchase minus accumulated depreciation.

Note that asset stranding depends on what options are pursued; for example, land could become unusable for palm oil production, but if REDD+ payments are considered, the land could potentially be converted from palm to forests to generate REDD+ revenue. In this case, the land only becomes fully stranded if it cannot be converted to forest. Otherwise, an asset may be partially-written off based on its remaining salvage value.

Source: Report Authors

Step 1: Climate Transition Scenario Planning

To form the basis of all of our analysis, we constructed five global climate transition scenarios as shown in Figure 2 as outlined below. We drew on scenarios that were already available, and customized these to be fit-for-purpose in order to:

- Represent a range of outcomes relevant to investors;
- Align with parallel modeling exercises like those of the Task Force on Climate-related Financial Disclosures (TCFD) process and the Food and Land Use Coalition's 2019 Growing Better Report; and
- Demonstrate a reasonable range of temperature targets.

We then combined these global scenarios with national-level scenarios in our three regions of interest--Indonesia, Peru, and Colombia--as described below.

a. Global Climate Transition Scenarios

(1) **4C Business As Usual:** Representative of recent trajectories and existing policy measures, this represents a world in which little is done to address rising emissions. It includes only currently implemented land use policies globally, and serves as a point of reference to which other scenarios can be compared to isolate the implications of action. Warming in this scenario is likely to near or even exceed 4°C.

(2) **3C Already Committed Action:** A future in which some action is taken to stabilize, but not reduce emissions. A very low carbon price is introduced gradually in the coming decade, but pricing is not ever fully integrated into the land sector. This results in limited compensation for negative emissions, and, by extension, international markets for offsets and nature-based solutions are small. There is some uptake of bioenergy and biofuels but is limited by low carbon prices. Warming is kept to below 3°C.

(3) **2C Moderate Ambition:** A world that aims to limit warming to 2°C, but fails to reach that target due to lack of international coordination and less ambitious policy. Carbon prices are introduced, but lack of international support for, and coordination of, offset markets and limited emissions trading schemes keeps global average prices relatively low. Society recognizes the role that consumption habits play in climate change, and starts to reduce the share of the most emissions intensive meats in their diets.

(4) **1.5C Strong Ambition LI (LI = Land Intensification pathway):** This scenario represents a world in which well below 2°C targets are met through robust international offset markets and investment in technological change. Agricultural yields improve even faster than they have historically, with technologies like CRISPR and precision agriculture pushing the frontier of productivity in developed countries while technology transfer and agricultural extension programs fuel rapid catch-up productivity growth in developing countries. Technology investments also enable currently speculative negative emissions technologies like bioenergy with carbon capture and storage (BECCS) to take off at scale.

(5) **1.5C Strong Ambition LP (LP = Land Protection pathway):** Here, warming targets are met through coordinated international action. Like the 1.5C LI scenario, robust international offset markets develop to support a relatively high carbon price and strong land sector participation in which negative emissions are fully compensated to the same degree that positive emissions are punished. Bioenergy is limited by society due to concerns about its negative development impacts, but a market remains for sustainable bio-based feedstocks. New protection policies and better enforcement expand the natural area that is effectively protected, allowing forest cover to regenerate and expand substantially. Society also recognizes its role in sustainable consumption, collectively shifting diets away from the most emissions intensive products.

Figure 2: Indicative Global Policy Scenarios Used for Global Economic Modeling

Scenario	Mitigation policy*	Annual bioenergy demand	Productivity increase by 2050 relative to 2020	Area protection	Ruminant meat fadeout***
4C Business as usual	Currently implemented policies only. Consistent with a 3-4° global temperature increase.	27 EJ by 2100	37%	352 Mha (IUCN Category I,II)	No fadeout
3C Already Committed Action	\$13 per tonne CO_2e by 2050. Consistent with a 2-3° global temperature increase.	70 EJ by 2100	46%	352 Mha (IUCN Category I,II)	No fadeout
2C Moderate Ambition	\$30 per tonne CO_2e by 2050. Consistent with a 2-3° global temperature increase.	70 EJ by 2100	48%	352 Mha (IUCN Category I,II)	25% fadeout by 2050
1.5C Strong Ambition LI	\$115 per tonne CO_2e by 2050. Consistent with a below 2° global temperature increase.	157 EJ by 2100	108%	352 Mha (IUCN Category I,II)	25% fadeout by 2050
1.5C Strong Ambition LP	\$115 per tonne CO_2e by 2050. Consistent with a below 2° global temperature increase.	70 EJ by 2100	60%	2707 Mha (IUCN Category I to VI, both designated and proposed)	50% fadeout by 2050

Note: *Carbon prices presented are global averages in 2050 and are in 2019 USD.
**Ruminant meat fadeout – this is a gradual decrease in the role of ruminant meats (beef, lamb, mutton and goat) as a protein source. Fadeout scenarios replace ruminant meat with less carbon intensive protein sources, including poultry, fish, eggs, and alternative meats.
Source: Vivid Economics 2020.

b. Global-National Climate Transition Scenarios

Next, we combine the regional results from three of the global climate transition scenarios: 1) 4C Business As Usual, 2) 3C Already Committed Action, and 3) 1.5 C Strong Ambition LP **with *national* land use restrictions** to create *three global-national transition scenarios* for each industry:

1. "Historical Ambition:" In line with 4C Business as Usual, deforestation is permitted locally due to limited laws and regulations and/or enforcement.
2. "Modest Ambition:" In line with the 3C Already Committed Action, we assess local land use pathways with and without deforestation restrictions, whether for industrial or smallholder actors.
3. "Aggressive Ambition:" In line with 1.5 C Strong Ambition LP, we assume zero deforestation restrictions in line with enforced public laws and regulations or voluntary corporate "No deforestation, no peat, no exploitation" (NDP) pledges.

These three *global-national* climate transitions scenarios, detailed below by industry, are used in subsequent steps to assess impacts on land prices as well as the value chains of palm oil and beef cattle, including commodity prices, production, and agricultural productivity.

Figure 3: Indonesia: Global-National Transition Scenarios

	Scenario	Global Climate Transition (MAgPIE)	Local Climate Transition (National Land Use Rules)
1	Historical Ambition	4C Business As Usual	No new palm permits allowed on primary natural forest, peat forest, or peat (according to the Presidential Instruction No. 10/2011 and delineated by the indicative moratorium map). Otherwise permits can be issued anywhere. Smallholders are allowed to deforest for palm development inside the moratorium map, but the total amount of deforestation is capped by subsequent parts of our analysis.
2A	Modest Ambition - With Smallholder Deforestation	3C Already Committed Action	No conversion of primary or secondary forests or peatlands, even where already permitted and unplanted for large holders. In this sensitivity, smallholders are allowed to deforest for palm development, even in areas where they would be otherwise restricted by the local policy.
2B	Modest Ambition - No Deforestation	3C Already Committed Action	No conversion of primary or secondary forests or peatlands, even where already permitted but unplanted for large holders. In this sensitivity, smallholders are *not* allowed to deforest; instead, they face the

			same restrictions as large companies.
3	Aggressive Ambition - No deforestation	1.5C Strong Ambition LP	In addition to the restrictions from the Modest scenario, the government requires existing plantations to move away from peat soils with no compensation for relocation.

Figure 4: Peru: Global-National Transition Scenarios

	Scenario	Global Climate Transition (MAgPIE)	Local Climate Transition (National Land Use Rules)
1	Historical Ambition	4C Business As Usual	Deforestation allowed
2A	Modest Ambition - With Deforestation	3C Already Committed Action	Deforestation allowed
2B	Modest Ambition - No deforestation	3C Already Committed Action	No deforestation and no peat development allowed
3A	Aggressive Ambition - With Deforestation	1.5C Strong Ambition LP	Deforestation allowed
3B	Aggressive Ambition - No deforestation	1.5C Strong Ambition LP	No deforestation and no peat development allowed

Figure 5: Colombia: Global-National Climate Transitions

	Scenario	Global Climate Transition (MAgPIE)	Local Climate Transition (National Land Use Rules)
1	Historical Ambition	4C Business As Usual	Deforestation allowed
2A	Modest Ambition - With Deforestation	3C Already Committed Action	Deforestation allowed
2B	Modest Ambition - No deforestation	3C Already Committed Action	No deforestation and no peat development allowed
3	Aggressive Ambition - No deforestation	3C Already Committed Action	No deforestation and no peat development allowed

Step 2: Sectoral Projections-- Global and Regional

To evaluate economic and land use change impacts of Step 1's *global* transition scenarios, we use the Potsdam Institute's global land use allocation model: Model of Agricultural Production and its Impact on the Environment (MAgPIE). MAgPIE is a spatially-explicit partial equilibrium model, in which food demand is estimated using population, GDP, dietary assumptions, and demand elasticities from the Global Trade Analysis Project (GTAP) database, available at http://www.gtap.agecon.purdue.edu.

a. How MAgPIE Works

MAgPIE determines the "least cost way" to meet this food demand, while accounting for biophysical constraints including those on land and water, as well as potential crop yields. Biophysical limits are estimated in LPJmL (Lund-Potsdam-Jena managed Land), a separate PIK model that translates climate projections from global climate models into physical constraints relevant for agriculture. These limits are an input to MAgPIE, which takes them as given.

MAgPIE endogenously models investment in agricultural technological change and irrigation, and in so doing captures the effect of potential future increases in agricultural productivity. Consequently, the framework captures land use competition between varying uses, such as forestry, bioenergy, and agriculture and models how this competition evolves over time. A short general description of the model can be found on the MAgPIE home page on PIK's website as well as in Dietrich et al. (2019).[3]

Large scale outputs of MAgPIE include global cropping patterns, water scarcity and deforestation maps in 10-year projection increments (Figure 6). Using MAgPIE, we project global and regional changes and geographic shifts in commodity production, trade, prices, and land use change for a basket of soft commodities relevant to deforestation (see Figure 7) for the next 30 years in 5-year time steps.

As a global partial-equilibrium model, there are substantial limitations to its crop and country specific outputs, as there are technical constraints on MAgPIE's ability to incorporate the local information important to accurate representation of disaggregated outputs. This limitation and its implications are discussed in Step 5. For purposes of this project, we use projected *changes* (rather than absolute levels) in commodity price and production, commodity demand, agricultural productivity, factor costs per production unit, land prices, and the food price index. One exception is greenhouse gas (GHG) prices, which we convert to 2019 USD and use in absolute terms. GHG prices are generated through PIK's REMIND model[4], a general equilibrium model that uses intertemporal optimization to generate inputs for other more specialized models like MAGICC or MAgPIE.

Projections of energy-related agricultural inputs like electricity, pesticides, and diesel fuel are less reliable at the regional scale, and therefore we exclude these projections from our regional analyses. Instead, for our palm oil analyses, we 1) estimate on the ground emissions from fertilizer and on-plantation and transportation diesel use, and apply the carbon price to these emissions accordingly under each scenario as a proxy for higher costs, and 2) we assume that fertilizer application volume increases in an amount proportional to productivity increases. (Although it is important to note that higher yields may be achieved through sustainable practices rather than simply increasing fertilizer application). Fortunately, these less reliable costs comprise a smaller share of overall production costs for beef cattle and are thus disregarded.

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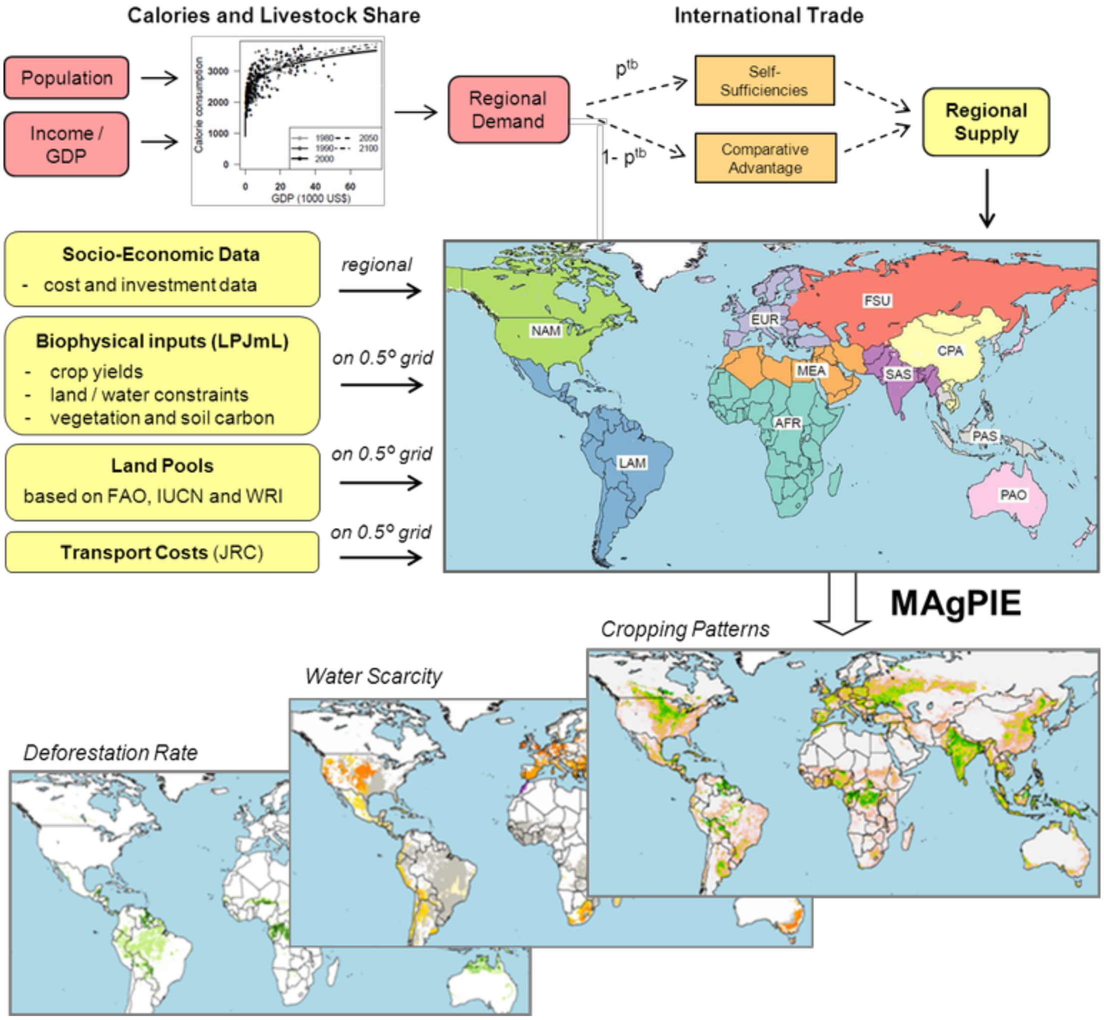
[3] Dietrich, J. P., Bodirsky, B. L., Humpenöder, F., Weindl, I., Stevanović, M., Karstens, K., Kreidenweis, U., Wang, X., Mishra, A., Klein, D., Ambrósio, G., Araujo, E., Yalew, A. W., Baumstark, L., Wirth, S., Giannousakis, A., Beier, F., Chen, D. M.-C., Lotze-Campen, H., and Popp, A.: MAgPIE 4 – a modular open-source framework for modeling global land systems, Geosci. Model Dev., 12, 1299–1317, https://doi.org/10.5194/gmd-12-1299-2019, 2019.

[4] According to PIK, "REMIND is is a global multi-regional model incorporating the economy, the climate system and a detailed representation of the energy sector. It solves for an inter-temporal Pareto optimum in economic and energy investments in the model regions, fully accounting for interregional trade in goods, energy carriers and emissions allowances. REMIND allows for the analysis of technology options and policy proposals for climate mitigation".

Figure 6: Flowchart of MAgPIE's Key Processes



Source: Potsdam Institute for Climate Impact Research

Figure 7: Indicative Outputs from MAgPIE

Category	Output description
Bioenergy Crops	• Production (Mt DM/yr), Productivity - rainfed or irrigated (tDM/ha) and Prices (US$/tDM) • Short rotation grasses and trees
Food Crops	• Production (Mt DM/yr), Productivity - rainfed or irrigated (tDM/ha) and Prices (US$/tDM) • Maize, Rice, Temperate cereals, Tropical cereals, Cotton seed, Groundnuts, Oilpalm, Other oil crops (incl rapeseed), Soybean, Sunflower, Sugar beet, Sugar cane, Tropical roots, Fruits, Vegetables, Nuts, Potatoes, Pulses
Livestock	• Production (Mt DM/yr) and Prices (US$/tDM) • Poultry, Eggs, Dairy, Monogastric meat and Ruminant Meat
Other agricultural products	• Production(Mt DM/yr), Productivity - rainfed or irrigated (tDM/ha) and Prices (US$/tDM) • Agricultural products such as forage, crop residues
GHG prices	US$/tGHG, specifically CO2, N20, CH4

Bioenergy Prices	US$/GJ
Cropland Prices	US$/ha
Food Price Index	Value in base year = 100
Food demand	• Yearly demand in Mt DM • Crops (Maize, Rice, Temperate cereals, Tropical cereals, Cotton seed, Groundnuts, Oilpalm, Other oil crops (incl rapeseed), Soybean, Sunflower, Sugar beet, Sugar cane, Tropical roots, Fruits, Vegetables, Nuts, Potatoes, Pulses, Livestock (Poultry, Eggs, Dairy, Monogastric meat and Ruminant Meat)
Feed demand	Yearly demand for feed (Mt DM)
Land Cover	• Million hectares (Mha) • Cropland (by crop type), Pastures and Rangelands, Primary, Secondary and Managed Forest
Nitrogen	Budgets - Inputs and Withdrawals (Mt Nr/yr)
Trade	• Volume (Mt DM/yr) and value (US$/yr) • Food Crops (Cereals, Sugar Crops and Other Crops), Bioenergy Crops, Livestock products and Secondary Products
Water	Agricultural withdrawal (Km^3/yr)

Source: Vivid Economics and Potsdam Institute for Climate Impact Research

b. Why MAgPIE?

MAgPIE was selected as the tool with the best overall fit for the purpose of this project, and as one that is accessible, transparent and auditable by the investment community since it is an open source tool. Figure 8 details how MAgPIE's capabilities supported delivery of our analytical goals as well as its key limitations.

Figure 8: MAgPIE's Ability to Meet Modeling Objectives

Modelling objectives	MAgPIE capabilities	MAgPIE limitations
Examine the implications of land-based carbon mitigation policies and other societal shifts on the AFOLU sector.	Mitigation policies can be implemented and tested straightforwardly in MAgPIE.	Global cost minimisation does not account for local policies and considerations. Threshold effects can cause abruptness in model outputs.
Assess price, production, and land use impacts on tropical soft commodities.	MAgPIE covers most of the key deforestation-linked commodities, including ruminant meat, oil palm, and soybeans.	The model is set up to satisfy caloric demand, meaning it models staple crops. It does not include commodities that are not calorically important, such as coffee or cocoa. MAgPIE groups beef, lamb, mutton, and goat together, implying we cannot separate these activities from one

		another within the modelling framework.
Disaggregate outputs spatially to obtain results at the regional or country level.	MAgPIE is connected to the dynamic vegetation model LPJmL, which uses a grid with a spatial resolution of 0.5°x0.5°. Outputs are aggregated at the regional and global levels.	Cells are assigned to one of 15 economic regions, and grid cells are clustered to make global computation tractable. This makes raw results unsuitable for localised estimation.
Provide estimates of the change in costs of agricultural inputs for regional analyses conducted by other workstreams.	MAgPIE produces estimates of the change in cost of water, fertiliser and energy to agricultural production.	Factor costs are based on area harvested, land use intensity, and a crop- and water-specific regional factor requirement meaning cellular factor costs are identical across cells within a region.

Source: Vivid Economics

c. MAgPIE Assumptions

Population & GDP

Across scenarios, we assume moderate income and population growth in line with historic trends. Modelled trends follow the "Middle of the Road" shared socioeconomic pathway (SSP2), which describes a world with intermediate challenges for adaptation and mitigation. Under SSP2, global population peaks at about 9.4 billion and levels off in the second part of the century. Income growth and economic development proceed unequally, with some countries and regions experiencing strong growth and others falling short of targets. The Shared Socioeconomic Pathways include well-developed narratives that trends in other socioeconomic indicators, like education and urbanisation, as well as implications for energy and land use systems. However, in this modelling exercise we simply use the population and GDP growth trajectories as a basis for all scenarios.

Global Trade Patterns

A continuation of current global trade patterns is adopted for the full set of scenarios. The trade module balances self-sufficiency and comparative advantages in production to manage crop balances and satisfy regional demand. Trade margins and tariffs are included in the optimisation processes that determine trade balances. Patterns of trade liberalisation are extrapolated from recent historical trends.

Mitigation policies

I. Carbon price level and pass-through

Carbon price level and pass-through to the land use sector are varied across scenarios to explore the impacts of pollutant pricing on land use allocation. The model incorporates a carbon price by multiplying the pollutant price by emissions at grid cell level. This policy lever increases the competitiveness of mitigation activities, which are only undertaken if they become the highest and best use value of land in a particular grid cell. One-off emissions (e.g., from deforestation) are discounted using an infinite time horizon to level them with yearly continuous management emissions (e.g., from fertiliser application)[5]. Carbon price levels are set to align with temperature targets set out in the development of the scenarios. The scenarios also consider the extent to which the AFOLU sector is included in a carbon pricing policy. Political sensitivities surrounding increasing the cost of production for farmers has meant that most carbon pricing schemes to date have not included coverage of the agricultural sector. In this scenario analysis, hesitance to regulate agricultural firms is captured by limiting the rate of pass-through to the sector by applying a carbon price reduction factor to cellular emissions costs.

II. Forestry policy and area protection

Protection policies are modelled as land set asides by removing national parks, heritage sites, and other conservation areas from the optimisation procedure. MAgPIE uses spatially explicit files (see, for example, IUCN's World Protected Areas Database) to remove grid cells from optimisation, effectively locking protected land to remain unchanged during the modelling as it solves for the least-cost way to meet exogenous food demand.[6] Land protection policies also include nationally implemented policies and nationally determined contributions to the Paris Agreement, both of which are taken from individual country reports. These ramp up until 2030 and then are assumed to be constant thereafter.

Afforestation is incentivised through the greenhouse gas emissions price. The carbon pricing policy is used to calculate the benefit of afforestation, which enters the objective function as a negative cost. The reward is calculated as the annualised present value of expected carbon dioxide removal multiplied by the corresponding carbon price. Carbon dioxide removal is based on vegetation age classes to capture sequestration potential and saturation. Afforestation is then modelled endogenously given the calculated reward.

Energy system

I. Bioenergy demand

Bioenergy demand pathways are set by assumption. First-generation bioenergy demand is assumed to increase until 2020 and then remain constant thereafter. Because first-generation bioenergy crops compete with food crops, it is expected that population pressure will stabilise demand for first-generation crops and shift demand toward second generation bioenergy crops, including dedicated bioenergy grasses and trees and agricultural, forest, and municipal wastes and residues. These demand pathways are also set by assumption and to align with global technical potential, which is estimated at about 100-400 EJ. There is wide variation in estimates of economic potential, but Popp et al. (2011) estimated the economic potential to be 100 EJ by 2050[7].

Food system

I. Crop productivity

The acquisition of yield-enhancing technologies is modelled endogenously. While the unit cost of making yield improvements is set by model assumption, acquisition of new technologies is triggered endogenously either through better cost-effectiveness compared to other investments or as a response to resource constraints. Investments are made at a regional level, and yield enhancements accrue over a 30-year timespan with diminishing marginal returns. The model is agnostic to the technology itself – i.e., uptake of genetically modified seeds is modelled in the same way as increased use of yield-enhancing equipment. The exception is irrigation, which is modelled separately. Irrigation cost pathways are set exogenously by region, and irrigation efficiency increases with GDP, representing better efficiency associated with more advanced irrigation systems. Pasture yields are set exogenously according to a pasture management factor.

[5] See MAgPIE documentation at https://rse.pik-potsdam.de/doc/magpie/4.3/56_ghg_policy.htm for more details.

[6] Barring these set asides, all land in the model is eligible to be changed to another land use, subject to biophysical constraints like soil and water input into MAgPIE from LPJmL. Land use conversions incur both an initial conversion cost and an ongoing management cost that depends on the land use, its region, and in some cases the biophysical constraints.

[7] Lotze-Campen, H., Popp, A., Beringer, T., Müller, C., Bondeau, A., Rost, S., Lucht, W. (2010): Scenarios of global bioenergy production: The trade-offs between agricultural expansion, intensification and trade. Ecological Modelling 221: 2188-2196. https://sci-hub.tw/https://onlinelibrary.wiley.com/doi/full/10.1111/agec.12092#support-information-section (Accessed 05/06/20)

II. Ruminant fadeout

The ruminant fadeout imposes a dietary shift on the food bundles that satisfy caloric budgets. MAgPIE is a partial equilibrium model, in which food demand is estimated using population, GDP per capita trajectories, and caloric budgets. MAgPIE then finds the least-cost way to meet that food demand. Fadeout scenarios replace ruminant meat with less carbon intensive protein sources, including poultry, fish, eggs, and alternative meats. The modelling presented in this report is agnostic to the nature of this substitution (i.e., does not consider shifts to a particular non-ruminant protein source).

Step 3A: Industry Impact Evaluation--Land Use Modeling

As detailed below, Step 3A takes downscaled regional results related to food prices, carbon prices, and land use from Step 2, and then:

I. Uses the OSIRIS model to predict changes in forest cover at high spatial resolution in Indonesia, Colombia, and Peru. This allows us to identify the effects of global and national climate policies on areas available for economically feasible agricultural expansion and to evaluate regionally specific costs associated with deforestation.
II. Uses land use restrictions (drawing from Step 1's global-national scenarios) and biophysical and/or sustainable development suitability maps to define growth constraints for industry producers. These growth constraints are used as an input to subsequent Steps in our analysis, particularly our industry modeling.

Step 3A-I: Spatial Forest Cover Projections (OSIRIS):

Our global-local climate transition scenarios from Step 1 impact projected forest area due to two climate transition drivers: First, national governments and/or agricultural producers follow strict zero-deforestation policies, which explicitly restricts agricultural expansion potential. Second, landowners are assumed to receive payments for newly stored forest carbon, resulting in large areas of forest expansion. This effect reduces the land area that is economically feasible for agricultural expansion. Both policies increase land use competition and real estate prices, thereby reducing financial returns to new land acquisition.

The OSIRIS model is able to capture the effects of both policies on forest area in each 0.05° x 0.05° grid cell (approximately 5.5 km x 5.5 km at the Equator) in ways that are consistent with MAgPIE results. OSIRIS is able to generate such high spatial resolution predictions because it is an econometric model. It uses grid cell-level historical observations of agricultural prices, yields, and forest area in tropical countries to find the most likely relationship between grid cell-level agricultural value and forest area. Under climate policies, OSIRIS can accommodate the effect of GHG prices on forest area by subtracting potential forest carbon value from agricultural value in each grid cell and, using the estimated historical relationship between agricultural value and forest area, separately predict both reforestation and, where applicable, deforestation in each grid cell for all future time steps. For more information about OSIRIS structure and inputs, see Busch et al. (2019)[8].

Methods

We run OSIRIS for each global climate transition scenario using MAgPIE/REMIND GHG prices. We also multiply the agricultural commodity price observations used in OSIRIS (which are 2000–2010 production-weighted average national farmgate prices for the top five producer countries of each crop (Busch et al. 2019)) by changes in the MAgPIE Food Price Index (FPI) ("multipliers" or "deltas") to generate grid-cell level agricultural value projections to 2050 by scenario. For scenarios where deforestation is not allowed, FPI values are increased by 10% from MAgPIE estimates to account for increasing agricultural prices if commodity supply is further constrained. We chose a 10% increase in this setting after performing sensitivity on 5% and 10% FPI increases, finding a small difference in forest area outcomes between the two, we chose to proceed with the conservative option, i.e. the option that would result in a larger area potentially available for agricultural expansion (higher FPI values result in higher economically feasible agricultural area). Using these inputs, OSIRIS provides area reforested and deforested (if applicable) for each grid cell and for each 10-year time step between 2020 and 2050. The results are linearly interpolated to 5-year intervals for use in Step 4.

[8] Busch, J., Engelmann, J., Cook-Patton, S.C., Griscom, B.W., Kroeger, T., Possingham, H., and Shyamsundar, P. (2019). Potential for low-cost carbon dioxide removal through tropical reforestation. *Nature Climate Change, 9*,463–466. doi:10.1038/s41558-019-0485-x

Important Caveats

There are two major sources of inconsistency between OSIRIS and MAgPIE. First, the definition of forest and data sources for historical forest area observations for OSIRIS are based on remote sensing analysis (Hansen et al. 2013), while MAgPIE uses forest observations as reported by the UN Food and Agriculture Organization (FAO). This results in a larger baseline forest area in OSIRIS. For example, the Indonesian Ministry of Environment and Forestry map is generally consistent with FAO reporting; the OSIRIS base forest map generally covers the areas defined as forest as well as those defined as shrubs and timber plantations in the Indonesian Ministry of Forestry map. To better align the OSIRIS and MAgPIE forest cover base maps, we limit the Hansen et al. (2013) tree cover algorithm to define forest as areas with ≥50% tree canopy cover, and remove all known palm plantation areas. This is distinct from assumptions used in Busch et al. 2019, wherein forest area is defined as ≥ 30% tree canopy cover. Adjusting the canopy cover threshold also provides better alignment with existing estimates of Indonesian forest cover loss over 2010–2020. Removing the palm plantation area from the forest cover map reduces the bias from mis-identifying palm plantation as forest. This bias would cause underestimation of the amount of deforestation (reforestation) for a given increase (decrease) in agricultural commodity prices.

Second, these two models have very different structures. MAgPIE predicts the future using economic optimization methods, while OSIRIS uses historical observed relationships between key variables. Because the optimization algorithm is not constrained by any historical inefficiencies, MAgPIE generally predicts larger forest area gain than OSIRIS under climate policy scenarios. Conversely, OSIRIS predicts larger forest loss than MAgPIE under the Historical scenario, due to large scale historical deforestation rates that exceed what MAgPIE estimates as economically optimal.

For our oil palm analysis in Peru, we estimate the amount of land available for palm development in each grid cell based on the amount of non-forest land in the grid cell that is predicted by OSIRIS. This estimation method implicitly assumes that any non-forest area within a grid cell is contiguous, which results in an upward bias of our estimate of area available for palm development; in reality, some of these non-forest areas could be highly fragmented and therefore expensive for palm development. For estimating the area available for industrial plantation development, we assume a minimum plantation size of 1,000 ha. Our method does not capture contiguous 1,000 ha non-forested regions that occur across multiple grid cells, which results in a downward bias of our potential industrial palm development estimate. It is not possible to gauge whether the resulting net bias is upward or downward. For smallholder palm development potential, we do not apply any size restriction for the plantations, but we only include non-forest areas within 100 kilometers of an existing mill.

The canopy cover threshold also means that non-forest areas can have up to 50% tree canopy cover, which results in overestimating the carbon sequestration losses (gains) from agricultural (forest) expansion.

Step 3A-II: Spatial Land Use and Suitability Constraints:

We use MAgPIE and OSIRIS results alongside our local land use restrictions (from the climate transition scenarios defined in Step 1 to bound future geographic expansion in each industry.

Generally, to estimate the expansion potential for each industry, we combine the OSIRIS-based forest area projections with additional geospatial data to determine the probable location of projected forest area changes within the bounds of the constraints defined by the local policies. Based on the resulting location, extent, and timing of forest cover changes, we estimate the amount of land available for industry expansion under the various climate transitions.

Depending on the industry, the additional geospatial data can include maps of:

- Peatlands
- Current land use
- Suitability: Biophysical suitability for growing oil palm or the Colombian planning department’s identification of cattle ranching suitability
- Industry assets: Plantations, concessions, and mills for oil palm; pastures for cattle
- Transportation infrastructure: Roads and ports

Based on different modeling objectives and data availability for the different industries, we use slightly different methods for each of our industry analyses. Each method is described below in more detail. For Peru and Colombia, geospatial analysis is used to estimate how much land is available or restricted for industry expansion and/or would be subject to other climate transitions. In Indonesia, the land use potential derived here is used in the economic optimization modeling for industry expansion in Step 6.

Indonesia

The main objective of the spatial analysis for the Indonesian oil palm sector is to estimate the maximum expansion potential of oil palm plantations for each 5-year time step for 2020–2050 for each of the four scenarios described in Step 1. While the OSIRIS model (Busch et al. 2019, described in Step 3) can directly apply a zero-deforestation restriction in its determination of land use (forest vs. agriculture), it cannot directly account for all of the local land-use restrictions associated with the policy scenarios (e.g., restrictions associated with development on peat or within moratorium area). We use a suite of spatial datasets (biophysical suitability map, moratorium map, peat map, and industry assets) and a derived set of land-use rules to determine the spatial placement of the OSIRIS-predicted forest cover changes that will maximize the land area available for palm plantations while adhering to the local policy restrictions (for example, predicted forest loss is first distributed on lands that are suitable for palm production in that vicinity). Subsequently, in Step 6, the BeWhere economic optimization model is applied to these results to predict the economically efficient amount of plantation area at each time step for each scenario.

OSIRIS projects changes in forest extent – separately deforestation and reforestation – at roughly 5.5 kilometer x 5.5 kilometer spatial resolution in 10-year time steps, which are linearly interpolated to 5-year time steps (Step 3). The forest projections from OSIRIS are representative of the global scenarios through the applied trajectories of carbon price (if relevant) and food price index. We aggregate the forest cover changes to the spatial resolution of the BeWhere model: 0.25° longitude x 0.25° latitude, which is roughly 25.5 kilometer x 25.5 kilometer in Indonesia. Thus, for each BeWhere grid cell for each time step and scenario, we know the area of the grid cell that is reforested and the area that is deforested (if applicable for the scenario).

We constructed an Indonesian base map roughly representative of 2015 by combining the following datasets:

- Oil palm concession map roughly representative of 2015 from a Greenpeace 2015 compilation of multiple data sources.[9] We use all concessions, regardless of level of permit issued.
- Moratorium map associated with Presidential instruction No. 10/2011, Version 8, based on a digitization from Greenpeace.[10]
- Peat map based on the Indonesian Ministry of Agriculture 2012, available through Global Forest Watch.[11]
- Map of biophysical suitability for growing oil palm from Pirker and Mosnier 2018.[12] This dataset (roughly 1 kilometer resolution) refers to suitability for industrial plantations, but we also apply it to smallholders under the assumption that smallholders can in fact modify soil properties like large companies. This assumption allows us to maximize the potential area available for palm production for both companies and smallholder farmers. Pirker and Mosnier 2018 assign each grid cell as either unsuitable for palm or as one of five grades of suitability. We assume land of any of the five levels of suitability is available for palm expansion.
- Forest cover representative of 2015 derived from Hansen et al. 2013.[13] Starting with a dataset indicating the percentage tree canopy cover in each 30 meter pixel in 2015, we re-grid to 100 meter resolution and then, to be

[9] Greenpeace (2015) based on agriculture plantations maps, provided by the Planning Department of the Ministry of Forestry, Indonesia, downloaded on July 29 2010 (appgis.dephut.go.id/appgis/kml.aspx), supplemented and updated by Greenpeace in several provinces with data gathered from provincial agencies (BPN/BAPPEDA) and corporate submissions to e.g. the RSPO.
[10] Digitized by Greenpeace from: MoEF (2015) Moratorium map on new concessions, 8th revision (PETA INDIKATIF PENUNDAAN PEMBERIAN IZIN BARU REVISI VIII) Ministry of Environment and Forestry, May 2015 http://webgis.dephut.go.id:8080/kemenhut/index.php/id/peta/pippib
[11] World Resources Institute."Peat lands." Accessed through Global Forest Watch on 18 February 2020. www.globalforestwatch.org
[12] Pirker J and Mosnier A (2018). Suitability map for industrial-scale oil palm cultivation for Indonesia. Accessed through IIASA on 3 May 2020: http://pure.iiasa.ac.at/id/eprint/15148/
[13] Hansen M., Potapov, P.V., Moore, R., Hancher, M. Turubanova, S.A., Tyukavina, A., Thau, D., Stehman, S.V., Goetz, S.J., Loveland, T.R., Kommareddy, A., Egorov, A., Chini, L., Justice, C.O., Townshend, J.R.G. High-Resolution Global Maps of 21st-Century Forest Cover Change. Science 15, 850–853, 2013.

consistent with the OSIRIS forest cover projections, we implement a threshold of 50% tree cover to delineate 2015 forest and non-forest pixels at 100 meter resolution.

- Industrial palm plantation map roughly representative of 2015 for Kalimantan and Sumatra from Austin et al. 2017.[14] For this project, Kemen Austin (1) updated the dataset to include Sulawesi, using remote sensing imagery from the period 2018–2019, and (2) updated the original Papua map using imagery from the period 2016–2019.
- Independent smallholder plantation map based largely on Danylo et al. 2020.[15] The dataset from Danylo et al. 2020, representative of roughly 2017, maps plantations of all sizes (smallholder and industrial), so we derive an approximation of smallholder palm distribution by finding the difference between the map of Danylo et al. 2020 and the industrial plantation map of Austin et al. 2017 including the modifications to the latter as described above. These two datasets differ in methods, timestamps, and inputs, so the resulting map of smallholder plantation areas is considered to be a rough -- but evidence-based -- approximation. The Danylo et al. 2020 dataset covers only part of Sulawesi and none of Papua, so for these islands we assume that smallholder area matches that reported by BPS, Indonesian's statistics bureau. We distribute the smallholder palm area on these islands by placing it largely in the vicinity of industrial plantations. As described below, we assume that smallholder palm area falling within concession boundaries is plasma plantation area, and we attribute all other smallholder plantation area to independent smallholders.

The above datasets were re-gridded to roughly 1 kilometer resolution, following conversion to a gridded format where necessary. In each 1 kilometer x 1 kilometer grid cell, the combined "land type" roughly representative of 2015 was determined based on the input datasets. There are 64 possibilities of land type, based on combinations of: 4 land covers (forest, industrial palm, smallholder palm, other) x 2 concession status (concession, non-concession) x 2 moratorium status (moratorium, non-moratorium) x 2 peat status (peat, non-peat) x 2 suitability status (suitable, unsuitable). Palm area on unsuitable land was reassigned as palm area on suitable land based on the assumption that if palm exists there in 2015, then the land is and always will be suitable for palm. For our analysis region, this accounts for < 0.2 million hectares of palm in 2015 (1% of total palm area). Smallholder palm occurring on concessions was re-assigned as industrial palm based on the assumption that this is more likely to be plasma palm area than independent smallholder area, and we treat plasma plantations like industrial estates given similarity in costs and yields. This accounts for 0.5 million hectares of palm (0.3 million hectares in Sumatra and 0.2 million hectares in Kalimantan). Following these re-assignments, there are 44 possible land types remaining. The resulting base map was overlaid on the BeWhere model grid, and the area of each of the 44 land types was calculated for each BeWhere grid cell. The result is the 2015 distribution of land categories at 25.5 kilometer x 25.5 kilometer resolution. The resulting oil palm plantation area in 2015 is 11.5 million hectares of industrial plantations and 2.7 million hectares of independent smallholder plantations.

We apply scenario-specific land-use transition rules to define how land area is transferred among these 44 categories in each BeWhere grid cell at 5-year time steps, taking into account the forest change projections from OSIRIS. The transition rules were designed to maximize the area available for palm development subject to the local policy constraints.

For example, consider the Historic Ambition scenario. In grid cells where forest loss is projected by OSIRIS, forest is first removed from areas where the resulting land category is considered available for development as palm under the scenario's land-use constraints, such as palm-suitable land inside concessions (available for industrial development) and palm-suitable land outside concessions that is also outside of the moratorium area (available for both industrial and independent smallholder development at a ratio of 70:30). In this scenario, independent smallholders are not constrained by the moratorium map, so a palm-suitable forest area that is outside of a concession but inside the moratorium area can be removed and counted as potential palm area for independent smallholders. Once all such forest area is exhausted in the grid cell, the remaining forest loss occurs on lands that are not considered to be available for palm development due to biophysical unsuitability, such as unsuitable land inside concessions and then unsuitable land outside concessions in non-moratorium areas. In grid cells where forest expansion is projected by OSIRIS, new forest is placed on non-palm plantation land before displacing any existing palm area. All non-forest,

[14] Austin, K.G., Mosnier, A., Pirker, J., McCallum, I., Fritz, S., and Kasibhatla, P.S. Shifting patterns of oil palm driven deforestation in Indonesia and implications for zero-deforestation commitments. Land Use Policy 69, 41–48, 2017. Dataset accessed through IIASA on 10 February 2020: http://pure.iiasa.ac.at/id/eprint/14829/

[15] Danylo O, Pirker J, Lemoine G, Ceccherini G, See L, McCallum I, Hadi, Kraxner F, et al. Data for: A map of the extent and year of detection of oil palm plantations in Indonesia, Malaysia and Thailand. 2020. Accessed at: https://dare.iiasa.ac.at/85/

non-palm lands that are biophysically unsuitable for palm are forested before any suitable land is forested. When suitable lands are forested, those that are potential independent smallholder palm area are forested before those that are potential industrial palm area, which is equivalent to saying that industrial palm development takes precedence over smallholder palm development. Forest expansion on suitable lands occurs outside of concessions before it occurs inside of concessions because it is assumed that existing concessions will be developed as palm before non-permitted areas are developed as palm. Similar logic was used to derive the transition rules for the other scenarios given the scenario-specific land-use constraints.

To create the 2020 land distribution, we begin with the 2015 land distribution map that includes forest area estimates derived from the satellite-based Hansen et al. 2013 dataset. In each grid cell, we calculate the difference between the 2015 forest cover based on Hansen et al. 2013 and the 2020 forest cover predicted by OSIRIS. We use the land-use rules to distribute the forest cover changes among land categories for this time step, resulting in a land distribution for 2020. Because the policy scenarios are not implemented until 2020 in our modeling framework, forest cover can decrease between 2015 and 2020 even for the policy scenarios that disallow deforestation. We derived separate land-use rules for this special case for this time step. For all subsequent time steps beyond 2020, all grid-cell-level forest changes correspond to those predicted by OSIRIS. The Historical Ambition scenario is the only Indonesian scenario for which deforestation is allowed. OSIRIS separately projects deforestation and reforestation in each grid cell, so for the Historical Ambition scenario, for each time step, we distribute any forest loss first before distributing any forest expansion. For the Aggressive Ambition scenario, which mandates removal of palm plantations from peat, we remove 50% of the palm area in 2025 and remove the remaining palm area in 2030.

Using this method, we estimate for each BeWhere grid cell for each of the four scenarios for each time step:

- Area of present-day (~2015) industrial palm that still exists
- Area of present-day (~2015) independent smallholder palm that still exists
- Area available for development of new industrial palm plantations
- Area available for development of new independent smallholder palm plantations

We use expert-vetted Indonesian oil palm yields (tons FFB per hectare), specific to existing industrial plantations (16.67 tons FFB per hectare), new industrial plantations (18.67 tons FFB per hectare), existing smallholder plantations (13.01 tons FFB per hectare), and new smallholder plantations (14.59 tons FFB per hectare). The land area corresponding to each of the four plantation types is multiplied by the respective yields to estimate the available biomass of fresh fruit bunches (tons FFB) in each grid cell at each time step for each of the four plantation types. Note that we assume new plantations will have an increased yield of 2 tons FFB per hectare for industrial plantations and 1.5 tons FFB per hectare for smallholder plantations, which we apply in 2020. These yield values are multiplied by proportional MAgPIE agricultural productivity changes to estimate yield improvements over time.

The available FFB from each of the four plantation types under maximum expansion potential is fed into the BeWhere model to determine the economically efficient distribution of palm plantations in Indonesia (Step 6). BeWhere seeks to deterministically estimate efficient locations and operational levels of Indonesian palm mills, given palm feedstock availability, areas for potential palm plantation expansion, palm oil prices, and other economic variables. The constraint map produced in this step provides our industry modeling (Step 3C) with the information needed to estimate how land use constraints impact a palm mill's financial viability in a specific location or suggests new capital expenditures in a new location.

Peru

The main objective of the spatial analysis for the Peruvian oil palm sector is to estimate the amount of biophysically suitable land available for oil palm cultivation for (1) companies and (2) smallholders in 2020, 2030, and 2040 under five scenarios:

1. Historic ambition without NDP restrictions
2. Modest ambition without NDP restrictions
3. Modest ambition with NDP restrictions
4. Aggressive ambition without NDP restrictions

5. Aggressive ambition with NDP restrictions

NDP restrictions refer to prohibitions on deforestation and on palm development on peatlands. The level of ambition of the scenario defines the stringency of the carbon price and the trajectory of the food price index that is applied to the OSIRIS model (Busch et al. 2019; described in Step 3) to project forest cover at 5.5 kilometer x 5.5 kilometer spatial resolution. For scenarios with NDP restrictions, OSIRIS directly enforces the zero deforestation restriction; however, because OSIRIS does not directly account for peat presence in its determination of land use (forest vs. agriculture), the restriction for development on peatlands is applied on top of the OSIRIS forest cover projections by geospatially combining the OSIRIS output with a map of peatlands from Gumbricht et al. 2017,[16] which was derived using a combination of remote sensing and modeling.

For both companies and smallholders, we limit palm development to land that is biophysically suitable for growing oil palm, based on a biophysical suitability map from Pirker et al. 2016,[17] who delineate six tiers of suitability based on characteristics of climate, soil, and topography. There may be some inconsistency between the peat dataset and the suitability map since the two datasets use different inputs for defining soil characteristics. We group the suitable, highly suitable, and perfectly suitable tiers of Pirker et al. 2016 into an overarching "suitable" category and group their not suitable, marginally suitable, and moderately suitable tiers into an overarching "unsuitable" category for palm development.

Using a nearest neighbor algorithm, the peat and suitability datasets were re-sampled from their original resolutions (roughly 125 meters for the peat dataset and roughly 900 meters for the suitability dataset) to the resolution of the OSIRIS forest cover data. Following re-sampling, each of the 5.5 kilometer x 5.5 kilometer grid cells is classified as either peat or non-peat and as either suitable for palm or non-suitable for palm. Re-sampling has only a negligible impact on the cumulative area of the parameter of interest (e.g., the re-sampled peat dataset suggests 74,476 square kilometers of peat in Peru, which differs by only 0.2% from that reported by Gumbricht et al. 2017), but it introduces additional uncertainty regarding the location of the parameter of interest.

For the scenarios without NDP restrictions, grid cells that are biophysically suitable for oil palm were assumed to consist of land available for palm development if at least 1,000 ha (33% of total area) of the grid cell is non-forest as determined by the OSIRIS model, which is consistent with our assumption about the minimum size required for a viable palm plantation. For such grid cells, all non-forest land located in areas that are biophysically suitable for palm is considered land available for industrial palm development. See Section 3 for a discussion on potential biases related to this estimation. For the scenarios with NDP restrictions, we additionally exclude palm development potential on any grid cells classified as peatland. For estimation of land availability for smallholder plantations, we follow the same general steps as for industrial plantations, except (1) we do not apply a minimum plantation size and (2) we restrict smallholder development to be within 100 kilometers of existing mills. We do not account for the location or extent of current palm plantations in any of our estimates.

Additional geospatial datasets used for plotting and analysis include:

- Oil palm plantation data representative of 2018 from Finer et al. (2018).[18]
- Mill data, including locations and installed capacity representative of 2020, compiled by Sociedad Peruana de Ecodesarrollo (SPDE) and Junta Nacional de Palma Aceitera del Perú (Junpalma Perú).
- Road and port data representative of 2018 from the Peruvian Ministry of Transport and Communications.[19]
- Administrative boundaries from GADM.[20]

[16] Gumbricht, T., Román-Cuesta, R.M., Verchot, L.V., Herold, M., Wittmann, F, Householder, E., Herold, N., Murdiyarso, D. (2017). Tropical and Subtropical Wetlands Distribution version 2. Center for International Forestry Research (CIFOR). doi: 10.17528/CIFOR/DATA.00058. V3, UNF:6:Bc9aFtBpam27aFOCMgW71Q==[fileUNF].
[17] Pirker, J., Mosnier, A., Kraxner, F., Havlík, P., and Obersteiner, M. (2016). What are the limits to oil palm expansion? Global Environmental Change, 40, 73–81. doi: 10.1016/j.gloenvcha.2016.06.007.
[18] Finer, M., Vijay, V., and Mamani, N. (2018). Oil Palm Baseline for the Peruvian Amazon. Monitoring of the Andean Amazon project (MAAP): 95.
[19] https://portal.mtc.gob.pe/estadisticas/descarga.html
[20] Version 3.6. https://gadm.org. Redistribution, or commercial use, is not allowed without prior permission.

Colombia

The main objective of spatial analysis of the Colombian beef cattle sector is to estimate the amount of cattle-suitable land available in the future under various scenarios.

To calculate land available for future beef cattle production, we use, in addition to the OSIRIS forest projections from Step 3, a dataset defining areas of suitability for grazing beef cattle in Colombia (SIPRA 2020).[21] We converted this file to a gridded dataset and re-sampled it to the resolution of the OSIRIS data outputs. We grouped the medium and high suitability classes from the input dataset into an overarching class defining land as suitable for beef cattle production. Since areas with low suitability would require material investments to modify the land (SIPRA 2020), we combine these low suitability areas with lands designated as unsuitable. Additionally, the input dataset includes land under a legal exclusion, which we also consider to be unsuitable for beef cattle production.

Separately, in each scenario for every time step (2020, 2030, and 2040), and for grid cells that are suitable for cattle ranching, the grid cell consists of land available for commercial development if more than 200 hectares of the grid cell is non-forest according to the OSIRIS forest projections. This is consistent with our assumption about the minimum ranch size for commercial operations.[22] For such beef-cattle-suitable grid cells, all non-forest land is considered available for legal expansion. To estimate suitable land available for legal expansion for small producers, we repeat the analysis without applying a minimum size restriction. Estimates of expansion potential indicate total land available for cattle production which includes land currently used for cattle ranching because of the limited availability of current spatial land use data, including the locations of existing cattle ranches.

The estimation method for suitable areas available for commercial beef cattle production implicitly assumes that any non-forest area in each grid cell is contiguous, which results in an upward bias of our estimate of area available for beef cattle production. Our methods do not capture contiguous > 200 hectare non-forested regions that occur across multiple grid cells, which results in a downward bias of our estimate of area available for cattle production. It is not possible to gauge whether the resulting net bias is upward or down. Furthermore, the OSIRIS simulations define forest as ≥ 50% tree canopy cover, which means non-forest areas can have up to 50% tree canopy cover.

To estimate the suitability of current pasture land for beef cattle, we combine the SIPRA 2020 beef-cattle suitability data with current (circa 2012) land use data from IDEAM 2012.[23] The IDEAM land use map, while somewhat outdated, is the most recently updated, publicly available pasture map. These pastures may not line up completely with the actual cattle ranching footprint, but they serve as a reasonable proxy in the absence of more robust data. Pasture land designations likely to represent cattle ranching – whether beef, dairy, or dual-purpose ranches – include clean pastures, wooded pastures, and weedy pastures. We additionally include as pasture land the pasture-containing mosaic classes, which are classes that include pastures in combination with crops and/or natural spaces. The 2012 land use map indicates 15.5 million hectares of pasture land and 11.6 million hectares of pasture-containing mosaic land. The combined area of pasture and pasture-containing mosaic land (27.1 million hectares) is lower than the 34 million hectares estimated by Departamento Nacional de Estadística (2014),[24] which may be due to differences in both land classifications and the timestamps of the datasets. The input datasets were gridded at 5.5 kilometer x 5.5 kilometer resolution for analysis and plotting. Using these two datasets, we find that 48% of the 2012 pasture area (13 million hectares) is suitable for beef cattle.

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[21] Dataset "Aptitud_Carne_Bovina_Dic2019" accessed June 2020 at: https://sipra.upra.gov.co/. Dataset description available at: https://catalogometadatos.upra.gov.co:8443/uprageonet/srv/spa/catalog.search#/metadata/7fcd9c54-f5c6-4602-8dc9-f09dac2f854c.

[22] González-Quintero, R., Sánchez-Pinzón, M.S., Bolívar-Vergara, D.M., Chirinda, N., Arango, J., Pantévez, H.A., Correa-Londoño, G., Barahona-Rosales, R., 2019. *Technical and environmental characterization of Colombian beef cattle-fattening farms, with a focus on farm size and ways of improving production*. Outlook Agric. 1–10. https://doi.org/10.1177/0030727019884336

[23] Dataset accessed July 2020 at: http://bart.ideam.gov.co/cneideam/Capasgeo/Cobertura_tierra_2010_2012.zip.

[24] DANE [Departamento Nacional de Estadística], "Encuesta de Sacrificio de Ganado" 2015-2019, https://www.dane.gov.co/index.php/estadisticas-por-tema/agropecuario/encuesta-de-sacrificio-de-ganado/encuesta-de-sacrificio-de-ganado-esag-historicos.

To estimate the suitability of current pasture land for oil palm cultivation, we again use the pasture and pasture-containing mosaic land use designations from IDEAM 2012 along with a map of biophysical suitability for oil palm from Pirker et al. 2016,[25] who delineate tiers of biophysical suitability based on characteristics of climate, soil, and topography. We consider all levels of suitable land from Pirker et al. 2016 – marginally suitable, moderately suitable, suitable, highly suitable, and perfectly suitable – as palm-suitable land. All input datasets were gridded at 5.5 kilometer x 5.5 kilometer resolution for analysis and plotting.

Additional datasets used for plotting and analysis include:

- Bovine population statistics by department (non-spatially explicit) for 2019 from ICA 2020.[26]
- Administrative boundaries from GADM.[27]

[25] Pirker, J., Mosnier, A., Kraxner, F., Havlík, P., and Obersteiner, M. (2016). What are the limits to oil palm expansion? Global Environmental Change, 40, 73–81. doi: 10.1016/j.gloenvcha.2016.06.007.

[26] Dataset accessed August 2020 at: https://www.ica.gov.co/areas/pecuaria/servicios/epidemiologia-veterinaria/censos-2016/censo-2020/bovinos-censo-2020.aspx

[27] Version 3.6. https://gadm.org.

Step 3B: Industry Impact Evaluation--Financial Modeling

In this step we use Step 2's regional projections alongside national and industry-level data to evaluate how assets and company cash flows--including capital costs, operational costs, and revenues-- will be impacted by Step 1's global-national climate transitions. Our financial modeling first starts with asset-level modeling (Step 3B-I). We then aggregate asset level cash flows into illustrative companies, and then use discounted cash flow models (Step 3B-II) to determine how a company's value and financial metrics would vary under climate transition scenarios.

Step 3B-I: Pro Forma Asset Cash Flow Analysis (ACF)

As mentioned, since MAgPIE's global and regional outputs are less reliable at the national level, generally, we take **current industry,** local capital expenditures, operational costs, productivity (crop yields or live weight gain, in the case of beef cattle), and prices, and then modify these according to *changes* predicted by MagPIE rather than using actual values from MAgPIE.

For each of the global climate transitions considered we extract the following 2020-2050 results for the Central and South America (CSA for Colombia and Peru) region or Other Developing Asia (ODA for Indonesia):

- Oil palm commodity prices (CPO and Palm Kernel Cake Prices) (2005 US$ per ton of dry matter)
- Ruminant Meat prices (2005 US$ per ton), production (tons of dry matter), and factor costs (2005 US$)
- Oil palm productivity (tons dry matter per hectare)
- Bioenergy price (2005 US$ per GJ of energy produced)
- Carbon dioxide, nitrous oxide, and methane prices (converted to 2019 USD)
- Land shadow price (2005 US$ per hectare)

Each of these MAgPIE time series are then normalized such that 2020 values equal 1 and all subsequent time steps reflect a percentage increase (or decrease) from 2020 values. Thus, subsequent analytical steps utilize MAgPIE results only as multipliers of 2020 values for that specific scenario. We refer to these results as "MAgPIE deltas" for this reason.

The one exception to this rule is GHG prices, which we take as absolute numbers. The GHG prices used in this report are generated by REMIND, a general equilibrium economic optimization model often paired with MAgPIE to estimate efficient global GHG prices given climate policy objectives. The REMIND GHG prices used here are an exogenous input to MAgPIE, but are generally consistent with the MAgPIE scenarios described below. Since the GHG prices are reflected in MAgPIE as 2005 US dollars, we multiply all GHG prices used in subsequent financial analysis by 1.6 to adjust to 2019 US dollars.[28]

We also assume for our Indonesia and Peru analyses that future increases in yield correlate with future increases in production cost for certain yield-related items such as labor and fertilizer costs. We based this assumption on research by Dietrich et al, finding that "production costs per area increase linearly with an increasing yield level." [29] Simply put, if MAgPIE predicted yields in 2025 to be105% of what they were in 2020, then we estimated the 2025 cost of certain operational costs to be 105% of what they were in 2020. In other words, we assumed a "cost-to-yield multiplier" of 1 for simplicity. Setting the "cost-to-yield multiplier" at 1 was reasonably close to the results we obtained when calculating it off the relative differences in cost and yields between very efficient producers and smallholder producers. Put mathematically:

> The estimate of the "cost-to-yield multiplier" x is based on the max and min yield numbers (y_{max} and y_{min}) and respective cost of production numbers (c_{max} and c_{min}):

$$x = [\,(c_{max} - c_{min}) / c_{min}\,] / [\,(y_{max} - y_{min}) / y_{min}\,],$$

[28] World Bank: Inflation, consumer prices (annual %). https://data.worldbank.org/indicator/FP.CPI.TOTL.ZG

[29] Dietrich, J. P., Schmitz, C., Lotze-Campen, H., Popp, A., & Müller, C. (2014). Forecasting technological change in agriculture—an endogenous implementation in a global land use model. *Technological Forecasting and Social Change*, *81*, 236-249.

This multiplier is applied to the yield's "delta multiplier" $ym_{mag}(t)$ estimated from the MAgPIE outputs (t is time, the year) to calculate the respective production cost increase *ci* in percent in the year *t* as compared to the year 2020:

$$ci(t) = (ym_{mag}(t) - 1) \cdot 100 \cdot x.$$

The initial 2020 cost of production c_{2020} is then multiplied by the "cost multiplier" $cm(t)$ to project the cost $c(t)$ in year t:

$$cm(t) = [\ 1 + ci(t) / 100\ ], \qquad c(t) = c_{2020} \cdot cm(t).$$

Figure 9 lists some of the variables considered as they relate to plantations and mills. Agronomy Capital Advisors (ACAL) provided input on the yields, costs, efficiency levels, size and processing capacity of these different assets. ACAL provided data for smaller companies whenever this information was not available online, and verified data related to smallholder farmers and medium-to-large companies.

The asset cash flow analysis generates a breakdown of revenues and major cost line items like labor, fertilizer, diesel fuel/transportation costs, and emissions costs, by scenario and for each asset. This asset cash flow model is used for our palm oil analysis in Indonesia, and feeds directly into steps 6, 8 and 9 forming the basis of our industry, market power and financial analyses.

Figure 9: Key Inputs Into Asset Cash Flow Analysis

Plantations:	**Mills:**
Plantation acreage (ha)	Mill processing capacity, tFFB/h
Yield, tFFB/ha/y	Mill OH, h/y
Labor, $/ha/y	ER, tCPO/tFFB
Fertilizer, $/ha/y	ER, tPK/tFFB
Diesel, $/ha/y	ER, tPKS/tFFB
Transportation, $/tFFB	Labor, $/tFFB
Replanting, $/ha/y	Other oper. cost, $/tFFB
Permit renewal, $/ha/y	Transportation, $/tCPO
Agent fee, % of FFB price	Maintenance, $/tFFB
Fertilizer, kgN/ha/y	Mill capex, $
Diesel, liters/ha/y	
Land use permit, $/ha	**Optional: KCU**
Land compensation, $/ha	Capacity per day, tPK/day
Land clearing, $/ha	Capacity, tPK/h
Seedling, $/ha	KCU OH, h/y
Planting, $/ha	ER, tPKO/tPK
Fertiliser to maturity (0-3 years), $/ha	ER, tPKM/tPK
PP&E (Building, Vehicles, Tractor, Housing, Community Building, Road infrastructure - Plantation), $/ha	Labor, $/tPK
	Other oper. cost, $/tPK
	Transportation, $/tPKO&PKM
	Maintenance, $/tPK
	KCU capex, $
	Optional: Methane (biogas) capture facility (MCF)
	Mills capacity (specific), tFFB/h
	Capex (specific), $
	Potential (specific), MW/(10tFFB/hour mill capacity)

	Optional: Gas Turbine with Generator
	Turbine capex, $/MW
	Connection to grid, $
	Average Annual Utilization rate, %

Source: Report Authors

Separate from this technical annex and report, IIASA is developing real options analysis methods to improve our understanding of what options plantation and mill owners have to increase yields and the resulting implications for capital needs. For this future model, IIASA will use the Asset Cash Flow model developed for this project and additional price scenarios at a finer temporal resolution for assets stress testing.

Step 3B-II: Company Discounted Cash Flow (DCF) Analysis

For the Indonesia and Peru reports, the Company DCF Analysis consists of detailed financial models, while for Colombia, we estimate the impact on key financial metrics based on publicly available data.

Indonesia

In Indonesia, the Company Analysis builds on the results of the Asset Cash Flow analysis. We convert asset cash flows to company-level cash flows by defining an asset mix and making assumptions about the company's stranding risk and financial profile. Specifically, we define the number and characteristics of plantations and mills. These characteristics include yield per hectare, mill capacity and capacity factor, and the presence of features like kernel crusher units, methane capture, and electricity cogeneration. We relied on expert input and simplified possible assets into the following types:

1. Five different sized-plantations, with production efficiency ranging from "best-in-class" to a "low-efficiency" and "smallholder" plantations
2. Three different mills with varying efficiency and capacity

The Indonesia model also quantifies asset stranding risk. The "Modest" and "Aggressive" scenarios include the assumption that governments take strident action to protect forests and peatlands. Unplanted concessions on forest territory become stranded, as does planted land located on peatland. Unplanted concessions on forest are stranding immediately in 2020, whereas planted land on peatland strands linearly from 2020 through 2030 at 10% annually. We quantify the stranding as an impairment expense on the company's income statement. Impairment from concessions is calculated as land price times stranding area; impairment from planted land is calculated as net present value per hectare of planted land times stranding area.

Financial assumptions include the minimum debt service coverage ratio required by the company's lenders, the cost of debt and equity, and the initial capital structure. The capital structure changes over time; existing debt is paid off in equal annual installments, while annual capital expenditures are financed entirely through new debt issuance. As a result, for companies operating just their initial assets, capital expenses are limited to annual replanting of trees and therefore the debt-to-equity ratio decreases over time, resulting in a gradually increasing weighted average cost of capital. In contrast, companies that invest in new assets issue significant amounts of debt,

While our Company Analysis in Peru and Colombia focused on "steady-state" companies that do not see changes in their assets year over year, our Indonesia analysis also assessed the impact of potential expansion. Specifically, we set up a model that checked for every year if a company could add 20,000 hectares of plantations and a mill to its assets. If doing so increased a company's enterprise value, and if the company's debt service coverage ratio would not go below the specified minimum if it financed the required capital expenditure through issuing new debt, then the model allowed the company to go through with the expansion. The yields of new plantations are modeled with a yield curve as a function of tree age, meaning no yield in the first three years, and then a gradual ramp-up until yields reach their peak in year 9, before gradually declining from year 14 onward. As seeds improve over time, the maximum yield of new plantations is also assumed to be higher by two tons FFB per hectare.

Peru

In Peru, we adapt a project finance model previously used in valuing an existing Peruvian palm oil plantation. The model considers a 10,000 hectare project with an on-site mill that relies on third-party suppliers for 6% of its FFB. To use assumptions consistent with the Indonesian model, we use a CPO price of $656 per ton for 2020, which reflects the 2003-2018 average price for Free On Board CPO of $711 net of a $55 export levy. We then modify this base price with MAgPIE projections on FFB and CPO price changes over time. Similarly, for yield assumptions, we start with a base yield curve (where yields increase with the age of the palm trees until they peak and then gradually decline) and then modify the yields in accordance with MAgPIE projections on yield increases depending on the transition scenario.

Finally, we calculate GHG emission costs by combining the MAgPIE GHG prices for the land sector with our estimates of the GHG emissions from on-site diesel use, transportation of FFB and CPO, fertilizer application, and methane release at the mill. For instance, the biggest GHG cost driver is methane release from mills. We arrive at 9.4 kg of methane for every ton of processed FFB, based on an estimated 0.6 cubic meters of methane effluent per ton of FFB, 0.39 tons of CO2-equivalent per cubic meter of methane, and assuming the global warming potential of methane is twenty-five times larger than CO2.

After modifying the model with the factors above, we get free cash flows aligned to our three transition scenarios. We convert these into enterprise values using a 12% discount rate and a terminal value based on a 2% growth rate.

Colombia

For the Colombian beef cattle industry our financial analysis is limited to estimating annual revenue and costs based on academic papers and cost averages published by Colombia's ranching association, FEDEGAN. Below is a list of the main assumptions and sources on which our projections are based.

Meat prices and production costs for ranchers: these are sourced from FEDEGAN. We assume ranchers receive an average price of $1.47 per kilogram of live cattle, and their production cost is $0.90 per kilogram of live cattle. These are the base prices and costs, which are modified by the MAgPIE results to account for differences in scenarios. For instance, under the Aggressive scenario, by 2040 meat prices are increased to 242% of the 2020 base value, and production costs to 109%. Furthermore, for production costs we differentiate between large and small producers, between conventional and intensive silvopastoral practices, and between different life stages of cattle. For instance, based on expert input, we assume large ranching operations incur only 69% of the production costs faced by the small producers; cow/calf ranchers are assumed to see production costs of $0.98 per kilogram of live cattle sold compared to $1.25 per kilogram for dual-purpose (i.e. milk and meat) ranchers; and intense silvopastoral systems face only 70% of the production costs of conventional ranching operations based on FEDEGAN data.

GHG prices and emission intensity: we use MAgPIE/REMIND GHG prices per ton of CO2-equivalent for land-use sector emissions, which are $0.40 (Modest Ambition) and $3.50 (Aggressive Ambition) in 2020, and reach $7 and $64 in 2040. For emissions intensity, we assume that a kilogram of live weight gain results in CO2-equivalent emissions ranging from 37.3 kg (large producers) to 52.2 kg (small producers), based on published research by Gonzalez-Quintero and others.[30] These numbers are for conventional ranching; for intense silvopastoral ranching, we adjusted them based on the research by Broom, Galindo and Murgueitio, [31] which collected data on differences in live weight gain per hectare per year, methane emissions per kilogram, and hectares needed per kilogram of meat per year.

[30] Gonzalez-Quintero, Ricardo, et al. "Technical and environmental characterization of very small, small, medium and large cow-calf operations in Colombia." REVISTA MEXICANA DE CIENCIAS PECUARIAS 11.1 (2020): 183-204

[31] Broom, D. M., F. A. Galindo, and E. Murgueitio. "Sustainable, efficient livestock production with high biodiversity and good welfare for animals." Proceedings of the Royal Society B: Biological Sciences 280.1771 (2013): 20132025.

The remaining revenue and cost items in our Colombia analysis are revenues from timber and carbon sequestration, and interest expense. Our estimates for them are based on research by Cuartas Cardona and others. [32] Timber revenues for intense silvopastoral ranching are assumed to be $16,526 per hectare; carbon sequestration revenue is based on a reported 7.55 tons of CO2-equivalent per hectare and year. Interest expense (and principal repayment) is estimated based on a 12% interest rate on assumed capital expenditure of $4,000 per hectare to convert to intense silvopastoral ranching, and equal annual principal payments over 15 years.

Data Sources

We use expert estimates from Agronomy Capital Advisors and financial data from Bloomberg to get the following indicators for a list of representative companies: Companies working capital, retained earnings, Total assets, EBIT, Market value of equity, Book value of total liabilities and Sales. For types of companies use expert estimates provided by Agronomy Capital Advisors.

[32] Cuartas Cardona, César A., et al. "Contribution of intensive silvopastoral systems to animal performance and to adaptation and mitigation of climate change." Revista Colombiana de Ciencias Pecuarias 27.2 (2014): 76-94

Step 3C: Industry Impact Evaluation-- Industry Modeling

Step 3's Industry Modeling and subsequent steps in our analysis were limited to Indonesia, though certainly, this type of analysis could be replicated for other industries of similar size and maturity. In this step we evaluate how climate transitions would impact the industry's optimal expansion and contraction (Step 3B-I), and as a result, impact the industry's value (Step 3B-II).

Step 3C-I: Industry Expansion/Contraction Analysis

Using the land use restrictions from Step 3A-II as bounds for industry expansion and Step 3B-I's proforma asset cash flow analysis, this step uses IIASA's "BeWhere" model to project economically optimized expansion and contraction in the production and location of palm oil mills and plantations in Indonesia.

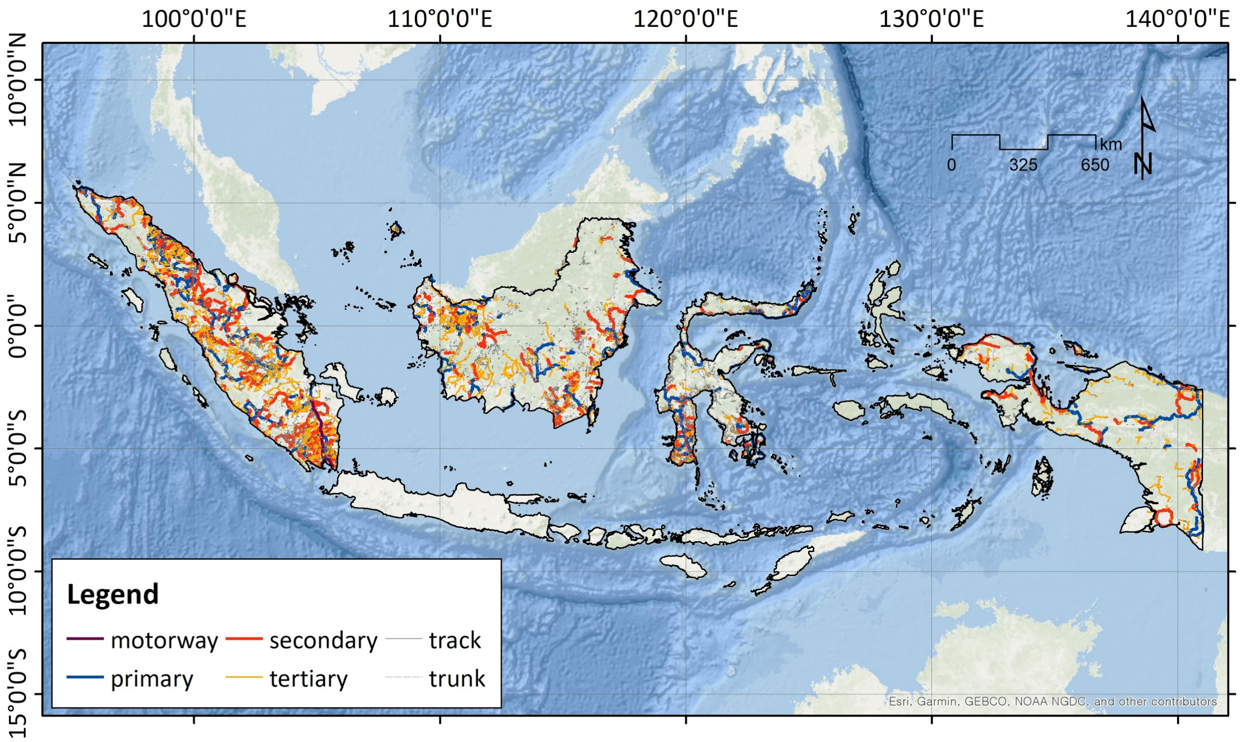
This model was originally designed for the second-generation biofuel production and used to optimize the location of potential second generation production plants but has been, and can be, adapted for different commodities and applications. In our case, it has been adapted to optimally solve for oil palm supply and processing at palm oil mills.

The BeWhere model is a spatially explicit techno-economic model. It minimizes the cost of the supply chain (from collection of the feedstock to delivery of the final product), and as such optimizes the locations of the production plants. The model is described in detail in Leduc et al. (2008) and Leduc et al. (2009).

Spatial Resolution

The islands of Kalimantan, Papua, Sulawesi and Sumatra have been gridded on a quarter of a degree resolution, which represents 2,353 grid points equally spread out over the four islands. For each grid point, the feedstock availability, collection cost as well as the area of production have been aggregated (based on step 4). From a detailed road network (Figure 10), every grid point is connected to each other. For each connection, the shortest distance has preliminarily been pre-processed and both distance and time have been recorded using the ARC-GIS software. The location and capacities of existing palm oil mills have been considered, and the distances and traveling time between all grid points and palm oil mills have been pre-processed.

Figure 10: BeWhere Indonesia Road Network



Source: OpenStreetMap [www.openstreetmap.org]

Methods

The model calculates the cost and emissions of the supply chain which includes and is limited to (1) feedstock production and collection, (2) feedstock transport to the mill, (3) process of the feedstock at the mill. Based on the minimization of the cost of the supply chain defined as

[supply chain cost + (supply chain emission) · (carbon cost)],

the model optimizes the number of mills that will operate for each time step. Based on the objective function defined above, the model optimizes the for following key outputs:

(1) Optimal locations of mills

(2) Optimal technology of the mills

(3) Optimal capacity of the mills

(4) Optimal number of mills

From these key outputs, the flows of feedstock are optimized, and thus pinpoint the origin and quantity of the feedstock. Moreover, all costs and emissions of each segment of the supply chain can be identified.

To prepare BeWhere for this project, we improved dynamic resolution, handling of the mill capacity at the grid level, and, of course, used modeling inputs specific to this project:

Dynamic Resolution

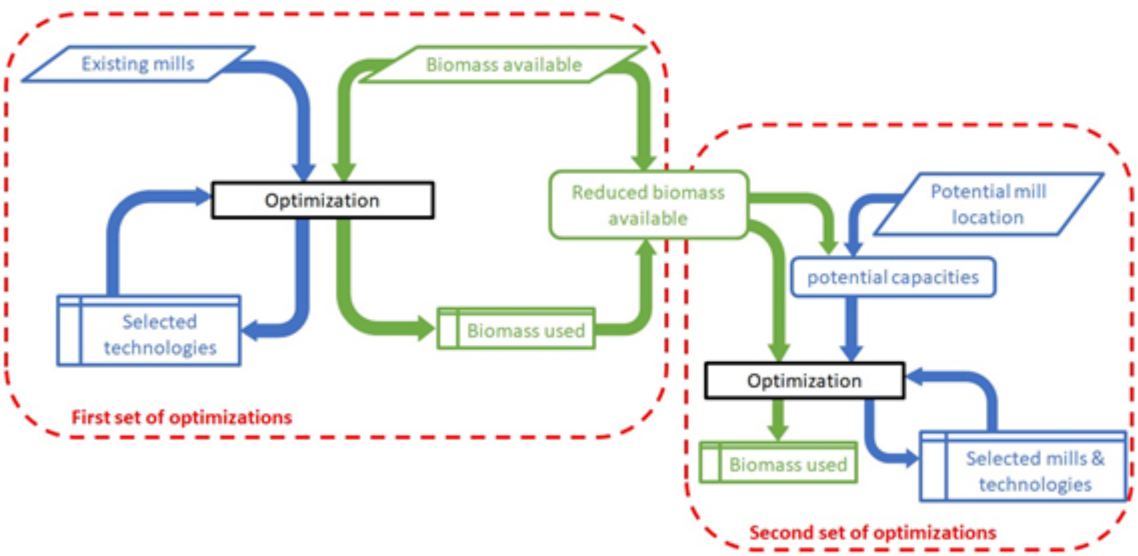
The model is run from 2020 to 2050 with 5-year time steps. It is run recursively dynamic, which implies that it optimizes the palm oil mills at every time step. The output from one simulation will be the input for the following period. Priority is given to the existing mills, which means that the model is first run for these mills over the full period. Then at each time step the feedstock used from these mills is reduced from the full available feedstock of the corresponding time step. From this reduced feedstock availability, the model is run one more time to identify if new mills would be set up. Each selected mill will be assumed as existing for the subsequent time step.

Mill Capacities

The capacity of the new mills varies from small, medium, and large with an hourly input of 20, 45 and 80 tons of FFB respectively. This capacity is usually met by a single grid point or/with the adjacent grid points. This means that in one grid point, provided enough biomass is available, there might be room for at least one new mill. In the model, the number of mills in one grid cell is linearly allocated by the amount of biomass available in that and neighboring grid cells.

The sequences of the optimizations and allocations of the mill capacities are presented in Figure 11.

Figure 11: Sequences of simulations Adapted in the BeWhere model.



If economically-feasible and if the infrastructure allows it, the mills have the possibility to be upgraded. The four technology improvements considered are (1) no improvement, (2) kernel crusher, (3) turbine integration and electricity generation, (4) combined kernel crusher and electricity generation or (5) shutdown of the mill when the feedstock is not available and/or production cost exceed potential revenue. Besides the technology improvements of the existing mills, the model can also include the setup of new palm oil mills with the different technologies defined previously. The parameters used for each technology are presented in Figure 12A and 12B.

Figure 12A: Key parameters of the mills per capacity and possible options for a technology upgrade.

Mill type	Maximum capacity (t/hour)	Setup cost (M$)	Operation cost ($/$t_{FFB}$)	Efficiency (t_{CPO}/t_{FFB})	CH4 emissions (t/t_{FFB})	Possible technology upgrade
Small	20	7	12	0.2	0.00936	Turbine
Medium	45	15.7	14	0.21	0.00936	Turbine
Large	80	20	16	0.23	0.00936	Turbine and/or kernel crusher

Figure 12B: Key parameters of the possible technologies for the upgrade of the mills.

Technologies	Setup cost (M$)	Efficiency	Emissions (t/t_{FFB})
Kernel crusher	1.1	PKO: 0.023 t/t_{FFB} PKM: 0.037 t/t_{FFB} PKS: 0.06 t/t_{FFB}	0.00936
Turbine (/MW)	1	0.0528 MWh/t_{FFB}	-0.39 t_{CO2}/m^3_{POME} (1)

(1) Average production of POME: 0.6 m^3_{POME}/t_{FFB}

Limitations

Due to the large amount of grid cells and time steps, the model has to be run recursively (optimization at each time step) rather than dynamically (optimization over the complete time span). This assumes that the decision on whether it is economic to set up new mills or upgrade mills to new technologies is taken at a specific year. A dynamic model would on the other hand consider the biomass availability and cost forecast until 2050 and eventually give a better investment forecast. Dynamic modeling cannot be applied using the current version of the model.

Key Sources

Leduc S., Schmid E., Obersteiner M., Riahi K. (2009). Methanol Production by Gasification Using a Geographically Explicit Model. Biomass and Bioenergy, 33(5):745–751.

Leduc S., Schwab D., Dotzauer E., Schmid E., Obersteiner M. (2008). Optimal Location of Wood Gasification Plants for Methanol Production with Heat Recovery. International Journal of Energy Research, 32(12):1080–1091.

Step 3C-II: Industry Value Analysis

In this step, we use the previous step's BeWhere results and inputs to estimate the net present value (NPV) of oil palm plantations in Indonesia as a measure of land asset value at the grid cell level. We compare spatially explicit NPV estimates across climate transition scenarios to help identify particular operating areas--and their associated companies-- that are most likely to be materially impacted by climate policy.

We calculate "mill+associated plantation" NPV by grid cell using the following equation:

$$NPV_k = \sum_{t=2020}^{t=2050} \rho^{t-1}\left[R_{kt} - \mathbf{1}(\mathbf{newmill})\frac{C_{kt}}{T_a} - OC_{kt} - GHG_{kt} + \mathbf{1}(\mathbf{t=2050}) \times TV_k)\right] -$$
$$\sum_{i=1}^{N_k}\sum_{j=1}^{4}\sum_{t=2020}^{t=2050} \rho_j^{t-1}\left[A_{ijt}(OC_{ijt} + \frac{C_{jt}}{T_a} - \mathbf{1}(\mathbf{t=2050}) \times TV_j) + GHG_{ijt} + Trans_{ijt}\right]$$

Where:

NPV_k	is net present value of mill–plantation system *k*
ρ	is the discount rate (13.7%)
R_{kt}	is the total revenue at mill k at time t
C_{kt}	is the capital cost of establishing or technology upgrade at mill k at time t
T_a	is the length of time over which capital costs are amortized (30 years)
OC_{kt}	is operational cost at mill k at time t
GHG_{kt}	is GHG costs at mill k at time t
TV_k	is the terminal value of mill k, only incurred at t= 2050
i	is the index of grid cells associated with mill–plantation system k, for i = 1,...,Nk
j	is plantation index, for large existing, large new, small existing, or small new
ρ_j	is the discount rate for plantation type j (18% for small, 13.7% for large)
A_{ijt}	is the area (hectares) of palm plantation type j in grid cell i at time t
P_{FFBjt}	is price per ton FFB for plantation type j for time t
Y_{FFBijt}	is per hectare FFB yield of palm plantation type j in grid cell i at time t
OC_{ijt}	is the per hectare operational cost of plantation type j in grid cell i at time t
	C_{jt} is the per hectare capital cost of new plantation type j at time t (for existing plantations, $C_j = 0$ for all *t*)
TC_j	is per hectare terminal cost of plantation type j, only incurred at t= 2050
GHG_{ijt}	is the GHG costs in grid cell i for plantation type j at time t
$Trans_{ijt}$	is the transportation cost in grid cell i for plantation type j at time t

Step 4: Company-Level Vulnerability Analysis

In Step 4 we take three different approaches to evaluating individual company and business models' vulnerabilities to climate transition risks. We do not discuss the first method, Step 4A-- Risk Benchmarking, as it is a simple approach that involves comparing publicly available sustainability indicators (e.g., SPOTT scores http://www.spott.org) and financial indicators (e.g., weighted average cost of capital). Data sources for Step 4C include Bloomberg, FactSet, and company annual reports.

Step 4B: Company Value Analysis

In this step we take Step 3C-II's Industry Value Analysis and apply it to the company level. Specifically, we take 30-year NPV results by scenario and allocate these to individual companies according to the fraction of total installed capacity in the grid cell belonging to that company, based on ownership information from the 2019 Universal Mill List.[33] Installed capacity for existing mill assets is from Harahap et al. 2020.[34] We performed additional subsidiary–parent matching to better assign parent companies to the original ownership data. For each company for each scenario, the grid-cell level NPV attributed to the company was summed over all grid cells where the company owns mills; these scenario-level results were used to derive company-level NPV differences relative to the Historical scenario.

This approach assumes that companies will maintain equal proportional mill and plantation capacity over time within each grid cell, and that companies do not relocate across grid cells over time. However, it does allow individual companies to expand and contract in accordance with trends predicted for each grid cell. The sum of NPV by company across all companies for Indonesia does not capture all profits across the industry. It excludes (1) profits for grid cells where mills did not exist in 2019 but exist in future projections (because no ownership can be assigned) and (2) NPV associated with mills with unknown ownership or belonging to a company that we did not consider in our analysis. The NPV calculation - at both grid cell level and company level - additionally excludes losses for grid cells where all mills go out of business in the first model time step (2020) and remain without mills in all future years (because grid-cell level NPV is zero since it captures profits only beginning in 2020).

Step 4C: Market Power Analysis

This step evaluates how climate transitions will impact the structure and composition of the Indonesian palm oil industry using inputs from our pro forma asset cash flow analysis and from our industry expansion and contraction analysis. This step aggregates industry assets into archetypical companies that represent different levels of vertical integration in the industry.

As further detailed below, we used the following three sub-steps to execute this step:

1. **Assess Current Industry Structure:** This step focuses on assessing the industry's current structure using a mix of top-down and bottom-up data. This assessment includes evaluating supply and demand within the palm oil supply chain, with an emphasis on the ownership structure of the assets, and the competitive dynamics that currently drive profitability throughout the market.

2. **Construct Representative Synthetic Companies:** Each of these companies represent different tiers of the market: fresh fruit bunch (FFB) producers, crude palm oil (CPO) producers and refined palm oil (RPO) producers, with varying levels of vertical integration, size, marginal costs, asset ownership and total liabilities.

3. **Assess Profitability Impacts:** We use our (Vivid Economics') Reduced Industrial Market Model (RIMM) that illustrates competitive dynamics of the market and estimates which companies are better positioned to capture excess rents and pass-through additional costs that arise from climate transitions. This model outputs a set of profitability pathways for each synthetic company and projects new industry structures under each climate transition scenario.

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[33] World Resources Institute, Rainforest Alliance, Proforest, Daemeter, Trase, Earthworm, Auriga, CIFOR, Transitions, Jason Benedict, Robert Heilmayr, Kim Carlson. "Universal Mill List." October 2019. Accessed through Global Forest Watch February 2020. www.globalforestwatch.org

[34] Harahap, F., Leduc, S., Mesfun, S., Khatiwada, D., Kraxner, F., and Silveira, S. Meeting the bioenergy targets from palm oil based biorefineries: An optimal configuration in Indonesia. Applied Energy 278, 115749, 2020.

1. Assess Current Industry Structure

Accurately assessing the current palm oil industry structure-- including supply and demand dynamics-- provides a baseline to understand how industry structure will change under each climate transition scenario. We use three main data inputs: Indonesian government national palm oil statistics (BPS Indonesia), the Universal Mill List (UML), Step 6's BeWhere outputs, and estimates from Agronomy Capital Advisors and other palm oil experts. We then reconcile top-down national-level data with bottom-up asset data, to ultimately evaluate the current market structure.

Top-down data is used as an input to determine total demand of palm oil, market prices and general production statistics. The total area dedicated to oil palm plantations was taken from USDA and GAIN's Oilseeds and Products Annual Report (2020) at 16.38 million hectares, as this is the most recent figure and incorporates a significant upward correction based on updated data. Market price of CPO was estimated using 15-year averages to Indonesia FOB prices ($118 per ton) with appropriate adjustments using the prevailing CPO-FFB price relationship and the Indonesian government's formula (ISCC System, 2018), resulting in $656 per ton. Lastly, RPO prices were calculated as $777 per ton based on estimated biodiesel prices of $740 per ton (Agronomy Capital Advisors based on various sources) plus an approximation of the premium that refined palm oil products command over biodiesel (5%). The aggregate production of FFB is calculated by combining information on oil palm hectarage with productivity figures. Multiplying total planted area with average yields (FFB per hectare) results in an aggregate number for FFB production in Indonesia, namely 263 million tons. It is assumed that raw and intermediate goods are neither exported nor imported before being turned into RPO in order to estimate aggregate CPO and RPO figures. This 'no international trade' assumption is important to pin down production quantities at each step in the value chain. From total FFB, the oil extraction rates, and this assumption, we can calculate total CPO and RPO production quantities.

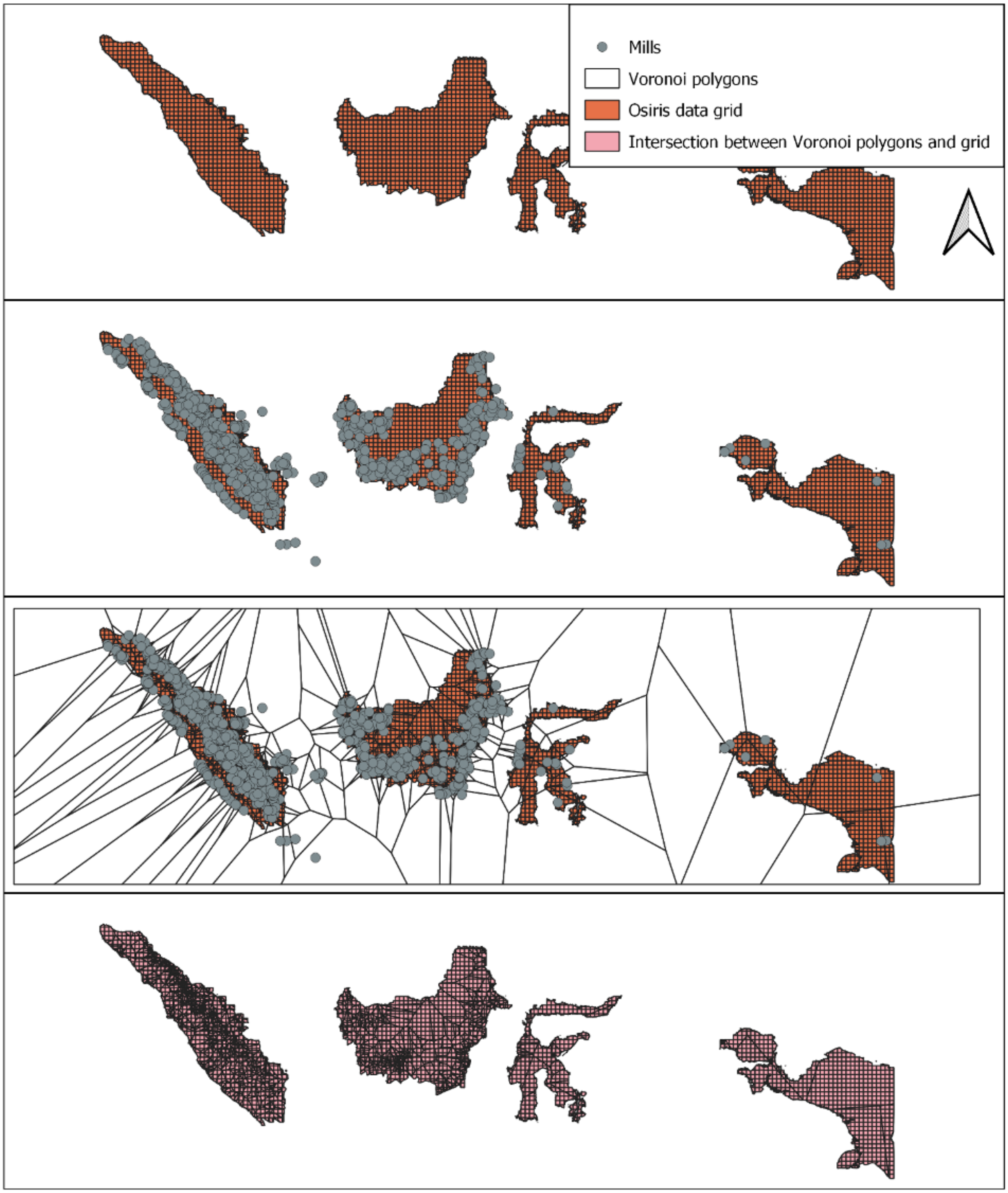
Two datasets are used to assign FFB production to companies: Step 3's OSIRIS' output data on the spatial distribution of FFB production over time and the Universal Mill List (UML). The Osiris data provided projections of the spatial distribution of FFB production circa 2020 in Indonesia at a 25 km by 25 km (Figure 13, panel A) resolution at five-year time intervals. FFB production is disaggregated by production from existing and new industrial plantations as well as existing and new independent smallholder farmers and given the transition scenarios explained in Step 1 (Historical, Modest A, Aggressive). The UML contains data on all mills in operation in Indonesia, giving their location, company name and a unique mill identification number (Figure 13, panel B).

Osiris outputs contain spatial data on FFB production, but do not assign this production to individual mills. To achieve this matching, we combine Osiris data with data from UML through the following procedure:

- **Task 1: Determine which plantations are closest to which mills.** Voronoi polygons are created around each mill from the UML using a 12% buffer[35] (Figure 13, panel C). The polygons simply delineate which areas of the analysis space are closest to each mill. As mills are not uniformly located across space, the polygons have different shapes and sizes.
- **Task 2: Use the intersection of the Osiris grid and Voronoi polygons to assign FFB production to each mill.** If the grid cells used in the Osiris data were very small, FFB production per cell could be easily attributed to each mill by summing up the FFB production per grid cell contained within each Voronoi polygon. However, since the grid cells used in the Osiris data are 25 km by 25 km, most Voronoi polygons cover certain grid cells only partially, making attribution less straightforward. To resolve this, the Voronoi polygons are intersected with the 25 km by 25 km Osiris data grid cell layer (Figure 13, panel D). Then, we determine the share of each grid cell area that is contained within the Voronoi polygon of Mill A, Mill B, etc. The FFB produced within this grid cell is then assigned to those mills in the same proportion. Note that the grid cell area is equal to or less than 625 km^2 (25km x 25km), as coastal cells may partially contain sea coverage.

[35] This buffer ensures that the Voronoi polygons cover all land area of Indonesia covered in the Osiris data instead of just extending to the outmost mill

Figure 13: Spatial Data and Methods (Panels A-D)



Source: Vivid Economics

Agronomy Capital Advisers provide expert inputs for missing data and verify the top-down and bottom-up figures. Local Indonesian experts estimate the oil extraction rates to be 21% for mills and 90% for refineries. Moreover, they approximate the average FFB yield per hectare of oil palm planted land to be 16 tons/ha (14.6 tons/ha for smallholder farmers, and 16.7 tons/ha for companies). The experts further provided verification of those figures outlined above by stating that these are representative of the industry to the best of their knowledge.

2. Construct Representative Synthetic Companies

This section uses outputs from Step 5 and 6, as well as industry financial data, and the Universal Mill List (UML) to construct five representative types of actors. The palm oil market value chain has three production steps, each with an associated asset: planting, milling, and refining. Four different company types with varying degrees of production integration, as well as independent smallholder farmers, are important players in the market:

1. Upstream separate (plantations only)
2. Upstream integrated (plantations + mills)
3. Fully integrated (plantations + mills + refineries)
4. Downstream separate (refineries only)
5. Smallholder farmers

Theoretically, there are six possible company types, however, research and expert verification indicate that only four archetypes of companies exist in practice. Hence, we do not consider midstream separate (mills only) and downstream integrated (mills + refineries) companies in this analysis.

Actor-level data is used to gain an accurate picture of the productive and financial characteristics of smallholder farmers and companies. For example, Agronomy Capital Advisers estimate that 30% of planted land is worked by independent smallholder farmers, each with an average land ownership of 3.5ha. Data for medium-to-large companies - such as asset ownership, degree of vertical integration and financials - is collated from firms' websites, annual reports, RSPO website, and S&P Capital IQ.

The remainder of this phase is dedicated to bringing together asset-level data and company-level data. Both asset-level data (UML, refinery list) and actor-level data (SHF data, company data) provide important insights for this analysis. Bringing them together proves a necessary exercise for constructing meaningful synthetic companies.

Independent smallholder farmers can be fully defined by their share of oil palm hectarage as well as their average land assets and yields. Given that independent smallholder farmers own 30% of planted area and the average land ownership is 3.5ha, the total number of SHF can be derived. From this and their average yields, their total FFB production is calculated. Together with the experts' cost estimate, this information suffices to draw conclusions about SHFs' cash-flows. This analysis only includes independent smallholder farmers in the SHF category, while Plasma smallholdings are assumed to be integrated into the company they supply.

Assets are allocated to company types based on asset-level data, company-level data, and expert verification. UML and the refinery list contain data on asset ownership, which can be matched by name to company-level information regarding their degree of vertical integration and by location to FFB production (Voronoi polygons). This enables the analysis to deduce which company type owns how many mills and refineries, and how much FFB it processes. Moreover, landholdings are assigned to companies based on companies' annual reports and expert verification.

Plantations and mills have different efficiencies and running costs; these are matched to companies based on their landholdings and processing capacities. The different profiles of plantations developed by experts are assigned to companies based on their total land ownership. Companies that have land holdings between two plantation profiles (i.e. more than one but less than another) are assumed to have a proportional mix of their costs and efficiency structure. For example, if the marginal cost of plantations with 100,000ha land holdings is $90 and that of plantations with 50,000ha is $100, a company with 60,000ha is assumed to face a marginal cost of $98. Similarly, mill profiles are matched with companies based on their annual processing capacity. We further assume that all refineries face the same marginal costs and productivity constraints.

Next, the number of firms represented by each synthetic company and their input sourcing patterns can be deduced. Knowing the asset holdings of synthetic companies and total assets in the market assists in determining the number of firms within each company type. Moreover, the production capacities at each production level determine the dual sourcing pattern, i.e. the share of input that is bought from external stakeholders rather than produced by the company itself.

This work further assumes that 'average is representative is synthetic', i.e. the analysis will be conducted with the average rather than a real-life firm for each company type. The rationale behind this assumption is that summing average companies produce aggregate figures comparable to those in the first phase, i.e. when current industry structures were analysed. This allows us to cross-check the data internally. Moreover, choosing one real-life company to be 'representative' would be somewhat a judgement call and may not give much information about other companies within the same type. The derived, representative figures result in synthetic actors, i.e. actors that represent the average company within the sector without skewing the characterization to one that necessarily exists in practice. .

The production figures are summed across all company types and compared to the aggregate data – the difference is negligible, and we adopt the summed numbers to ensure internal consistency. Summing FFB produced by all upstream-operative actors leads to a total of 276 million tons, compared to the estimate of 263 million tons from the first phase. The difference is 4.7% and therefore negligible. From this point onwards, this work adopts the summed numbers to ensure that the analysis is internally consistent.

The outputs of the outlined methodology are well-defined representative stakeholders in terms of their degree of vertical integration, asset ownership, production capacity, and financials. The above steps produce representative data for each of the five archetype companies/smallholders.

3. Assess Profitability Impacts

The last phase uses the RIMM model to project the industry structure to 2050 (in 5-year intervals) under different climate scenarios and to assess profitability impacts. The aggregate market structure and representative companies form the basis for this analysis as it most closely characterise today's Indonesian palm oil market.

Different climate scenarios are forecasted using the formulated structure as the base year structure, and drawing from Step 5's asset cash-flow analysis. Inputs include:

- **Demand shifts and share of third party sourcing:** MAgPIE forecasts the changes in price and quantity demanded of palm oil in 5-year intervals and under different climate scenarios, which allows us to estimate changes in demand. More specifically, we assume the current market equilibrium has unit elasticity and that this elasticity remains constant over time and across scenarios. MAgPIE forecasts the new market equilibrium (price and quantity) which, together with the aforementioned elasticity assumption, fully defines demand. The share of FFB that mills source from third party suppliers/smallholders (midstream dual sourcing) is calculated using the spatial analysis described above.
- **The number of actors represented by each synthetic company is another important input for the RIMM model:** This phase of the methodology takes our industry expansion/contraction analysis as a given. This means that the total number of market players is an exogenous variable to RIMM.
- **Changes in marginal costs of upstream and midstream production**: Predictions of shifts in marginal cost are taken from the asset-level data forecasts in Step 5 and aggregated for each synthetic company based on the number and efficiency of their assets (plantations and mills). Downstream marginal costs are kept constant as no information on their development is available.

Given data limitations, a few variables are assumed to remain constant over time and across scenarios. Demand is assumed to be linear and its slope constant over time and across scenarios. The MAgPIE inputs are used to determine one point on the curve which, together with the fixed slope, fully defines demand. Downstream dual sourcing and marginal costs are held fixed.

To ensure internal consistency while using data from different sources, all inputs and RIMM model results are applied as changes to the current industry structure rather than using their absolute values. This implies that the company structure as developed in sections 1.1 and 1.2 serves as the 'base year'. Inputs from the cash-flow model and MAgPIE are calculated as percentage changes and applied to the base year rather than using their absolute values. The same holds for RIMM model results., thereby ensuring internal consistency within this analysis is preserved.

The RIMM model is an oligopolistic competition model that predicts changes in profitability based on three core assumptions. Firstly, the model assumes stakeholders act based on profit-maximising behaviour at all times, i.e. each actor produces exactly the quantity that brings them the highest profit. Secondly, given the large number of smallholder farmers in Indonesia, RIMM assumes that the upstream production step operates under perfect competition. This implies an infinite number of upstream actors who sell their products at cost and hence make zero profits. Thirdly, it is assumed that markets clear.

The RIMM model sets up a profit function for each company type and maximises it with respect to quantity for each time step and each scenario. The profit functions are of the form

$$Profit = (marginal\ revenue - marginal\ cost) * quantity$$

where, the marginal revenue is the market price that in turn depends on quantity via the linear demand curve, and marginal cost is the input sourcing cost (either cost of producing internally or cost of purchasing at market price) plus the production cost. Each company type then maximises their respective profit function with respect to quantity simultaneously, i.e. the First-Order derivatives are set equal to zero and solved for quantity. The result of this exercise is the optimal quantity produced and the profits earned for each company type, as well as the market prices of FFB, CPO, and RPO.

In a last step, the analysis gives insights into the volatility of companies' profits should demand or costs change. While profitability is an important factor for companies, it is also crucial to know how profits are affected when certain exogenous factors change. For example, some companies may be more effective than others in passing increased costs to consumers and/or other companies. Similarly, some companies may be better equipped to leverage higher profits from an increase in demand. The impact on profitability can be calculated for each company type by maximising their respective profit function before and after a shock and comparing the results.

RIMM's output includes profitability scenarios for representative companies over time and across scenarios, while simultaneously providing information about future market equilibria and company sensitivity. The main output of this analysis is the future profitability of different company types, as well as their sensitivity to changes in exogenous factors over time and across scenarios.

ADDRESS	:	1320 – 19th St NW Suite 300, Washington DC 20036, USA
PHONE	:	+1 (202) 000-0000
EMAIL	:	info@orbitas.finance
WEBSITE	:	www.orbitas.finance