En-ROADS Technical Reference

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En-ROADS Technical Reference

Last updated June 2025

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Introduction

The En-ROADS Climate Solutions Simulator is a climate simulation tool for understanding how we can achieve our climate goals through changes in energy, land use, consumption, agriculture, and other policies. En-ROADS is a globally aggregated model of energy, economic, land use, and climate systems. The level of aggregation and several simplifying assumptions allow the model to return results in seconds and be accessible to policy makers and general audiences. En-ROADS is a simple climate model and complements the other, more disaggregated models addressing similar questions, such as integrated assessment models or general circulation climate models. Those larger disaggregated models are used for calibrating results in En-ROADS.



En-ROADS is being developed by Climate Interactive, Ventana Systems, UML Climate Change Initiative, and MIT Sloan.

This *En-ROADS Technical Reference* documents the En-ROADS model structure, equations, assumptions, and data sources. In addition, there is an En-ROADS User Guide more suited to general audiences. For a list of articles about the simulators see our Peer-reviewed Research page. Climate Interactive also provides extensive training materials for En-ROADS at learn.climateinteractive.org.

Please visit support.climateinteractive.org for additional inquiries and support.

Purpose and Intended Use

En-ROADS is designed to be used interactively with groups as a basis for scientifically rigorous conversations about addressing climate change. It is not intended as a tool for prediction or projections, nor does it cover every impact of the economics, energy use, or land use decisions. It is suitable for decision-makers in government, business, and civil society; or for anyone who is curious about the choices of our world.

En-ROADS is also useful for learning about the dynamic behavior of systems in general by highlighting those impacting the climate:

- The differences between high and lower leverage actions
- The response to policies based on incentives, supply-side and demand-side interventions, mandates and technology
- Delays in the system, including capital turnover, momentum in the carbon cycle, social and technological transitions, and more
- Effective and conflicting combination of actions
- The scale of required action, and the unintended consequences of some actions
- The feedback between climate change and economic growth

En-ROADS allows users to adjust many of the assumptions underlying these dynamics.

Model Structure

En-ROADS is a system dynamics model. It consists of a set of ordinary differential equations in time. Variables calculated by integration are called "stocks" (also called "levels"); components of the rate of change of a stock are called "flows"; variables used for intermediate steps or calculating other values include auxiliary, constant, data, and initial variables.

Equations represent both physical processes and human decisions. There is no assumption of equilibrium or optimal decision making. The model represents the climate, environment, economy, and energy systems at the global level of aggregation and at the system-wide level of analysis.

En-ROADS is constructed using Vensim modeling software from Ventana Systems, and transformed into an online simulation via the SD Everywhere converter built by Climate Interactive and Todd Fincannon.

En-ROADS is calibrated to an extensive set of historical data, and its endogenous behavior is grounded in and made consistent with other models, in particular the Integrated Assessment Models used by the Intergovernmental Panel on Climate Change (IPCC).

Simulation Method

The differential equations making up En-ROADS are non-linear and have no general closed form solution. Instead they are estimated numerically using the Euler method. At each time step (Δ t), auxiliary and flow variables are calculated from previous values of stocks, along with constants and data as needed. Each stock is then computed by adding its previous value to the product of Δ t times the sum of all its flows. A sufficiently small time step is required for good approximation - a value of one eighth (0.125) year is appropriate in En-ROADS given the characteristic times and delays in the system as modeled.

En-ROADS starts from initial values in the year 1990 and runs endogenously through 2100. The value of each variable is stored every year. Aside from a small number of exogenous values, the model runs free - calibrated to external data but not driven by data.

Causal Structure

At the highest level, En-ROADS calculates the concentration of each well-mixed greenhouse gas (CO₂, CH₄, N₂O, PFCs, SF₆, and HFCs), in the atmosphere, and the resulting climate change and other impacts. Greenhouse gas concentrations of each gas depend on its global cycle, driven by natural emissions and by anthropogenic emissions from energy, industry, and land use. Energy and industry emissions depend on total consumption (population times consumption per person), energy intensity of consumption, and emission intensity of energy and industry. Agriculture emissions and the land needed for farming depend on population and diets. The impacts of climate change create feedbacks that reduce consumption (by slowing economic growth), increase the land needed for agriculture (by lowering yield), and alter the biosphere.



Scope & Detail

The model represents key processes in the energy system for a single, global region. Distinctions among regions are obviously important in the real world, but would considerably complicate the accounting framework of the model, particularly by introducing trade issues, and dilute the impact of any intervention, rendering it less useful for rapid scenario experimentation.

En-ROADS is dynamic, showing behavior over time, and does not find "optimal" results. There are a small number of exogenous inputs selected by the user. All other values are calculated endogenously using assumptions that can also be adjusted by the user.

- Exogenous (user inputs):
 - Population
 - Base GDP growth
 - Technology breakthrough
 - Policy choices
- Endogenous:
 - Energy source choice
 - Energy carrier choice
 - Energy intensity
 - Energy variable and capital costs
 - Price, capacity, and utilization of fuels
 - Price of electricity and capacity and utilization of each source
 - Price of hydrogen and capacity and utilization of each source
 - Energy technology (learning by doing)
 - Nonrenewable resource depletion
 - Renewable resource saturation
 - Energy Storage
 - Carbon capture and storage
 - GHG & climate dynamics
 - Agriculture and land use
 - Sea level rise and other climate impacts
 - GDP adjusted for climate impacts
- Excluded:
 - Inventories
 - Labor

The energy system is modeled in great detail, including price, technology and other factors that affect the dynamics of energy and emissions across the full lifecycle for all sources, including potential new technologies.



Organization

En-ROADS is made up of several interconnected submodels which hold the equations. Model sectors are functional and may span one or many submodels. A particular variable is always calculated in only one submodel, but the results are passed to other submodels, and each variable may participate in many model sectors. The submodel listing below describes what sectors each contributes to. A more detailed description of equations and dynamics is organized by model sector in the chapters that follow.

- En-ROADS.mdl: Collects and organizes model output for testing, includes all sectors.
- Constants.mdl: Holds constants used across multiple sectors and submodels, such as unit conversions.
- **Calibration.mdl**: Provides interfaces and data connections for calibrating to historical data and comparing to other model projections under different scenarios.
- Population.mdl: User selected scenarios for population, part of the demand sector.
- **GDP.mdl**: User selected base economic growth, and slowed growth due to feedbacks, part of the demand sector.
- **EnergyDemand.mdl**: Desire for and choice between types of capital, and the use of capital. Part of the demand and market clearing and utilization sectors.
- EnergySupply.mdl: Investment, construction, use, and retirement of capacity in the energy sector, including fuel extraction and delivery and electricity generation. Part of the supply and market clearing and utilization sectors.
- **EnergyCostsRevenues.mdl**: Calculates cost dynamics of energy sources for learning, technology, and policies such as taxes and subsidies. Some cross-cutting energy technologies, such as efficiency and energy storage. Parts of demand, supply, and market clearing and utilization sectors.
- **EnergyPricing.mdl**: Adjusts prices to balance supply and demand, Part of the market clearing and utilization sector.
- Emissions.mdl: Calculates emissions from energy, end-use capital, and waste; and sums, accumulates and categorizes emissions. Emissions include CO₂, CH₄, N₂O, and F-gases.
- **CDR.mdl**: Calculates the amount of carbon dioxide removal (CDR), afforestation, and carbon capture and storage (CCS) indicated by policy and price signals.
- **BioenergyAgriculture.mdl**: Calculates food needs, land and CH₄ and N₂O emissions for agriculture, and the costs and land needed for bioenergy materials. Parts of Land Use, Land Use Change, and Forestry; Terrestrial Biosphere; Emissions; Demand and Supply sectors.
- **TerrestrialBiosphere.mdl**: Tracks the land area, carbon content in biomass and soil, and the transfers of carbon between air, biomass, and soil for each category of land use.
- **CarbonCycle.mdl**: Sums the carbon transfers from TerrestrialBiosphere.mdl, and tracks the stocks and flows of carbon and other greenhouse gases between emissions, removals, atmosphere, and oceans.
- **Climate.mdl**: Calculates radiative forcing, heat flows, and temperature changes in the atmosphere and oceans.
- **ClimateImpacts.mdl**: Calculates those impacts that depend directly on temperature, or use temperature change as a proxy for climate change impacts.
- PM25.mdl: Calculates pollution other than greenhouse gases produced from burning fuels.
- SeaLevelRise.mdl: Tracks thermal expansion in the oceans, water flows, and ice melt along with the acidification effects of dissolved CO₂.

In the model structure diagrams in the following chapters, there are four types of elements:

- 1. Variables with a box represent stocks, determined by integration.
- 2. Variables without a box are auxiliary variables.
- 3. Simple arrows indicate a causal relationship, one variable is a function of the other.

4. Pipes represent flows - the elements of the rate of change of stocks - shown flowing into, out of, and between stocks.

Demand

Population, GDP, and Capital

The demand sector defines the global energy demand for road and rail transport, air and water transport, residential and commercial (buildings), and industry end uses, all of which may be met by direct use fuel, electric, and hydrogen carriers. The model determines the energy demand according to the stock of energy consuming capital and its associated energy requirements.

Capital grows according to gross world product (GWP, but referred to in this document as GDP) as calculated by specified population scenarios and GDP per capita rates. GDP exogenously uses data reported by the World Development Indicators (2024) for each region. Projections assume GDP per capita growth rates converge from what they are in the period leading up to the last historical year and converge to 1.5% through 2100. Population uses the UN historical data through 2021, followed by their projections for different fertility scenarios. By default, En-ROADS assumes the medium fertility projections, but the model can vary continuously between the lower and upper 95% confidence intervals.

National Aggregation

En-ROADS calculates actions and outcomes for the entire globe as a single region, with the exception of population and GDP, which are calculated for seven smaller regions. These are the same regions used in C-ROADS.

Table 3.1 Regional Aggregation

Regions	Individual Nations
United States (US)	United States (US)
European Union (EU)	Austria, Belgium, Bulgaria, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxemburg, Malta, the Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden
Other Developed Countries	Albania, Andorra, Armenia, Australia, Azerbaijan, Belarus, Bosnia and Herzegovina, Canada, Faeroe Islands, Fiji, Georgia, Gibraltar, Greenland, Holy See, Iceland, Japan, Kazakhstan, Kyrgyzstan, Macedonia, Moldova, Montenegro, New Zealand, Norway, Russian Federation, Serbia, South Korea, Switzerland, Tajikistan, Turkmenistan, Ukraine, United Kingdom, Uzbekistan
China	China
India	India
Other Developing A Countries	Brazil, Indonesia, Hong Kong, Malaysia, Mexico, Myanmar, Pakistan, Philippines, Singapore, South Africa, Taiwan, Thailand
Other Developing B Countries	Afghanistan, Algeria, American Samoa, Angola, Anguilla, Antigua and Barbuda, Argentina, Aruba, Bahamas, Bahrain, Bangladesh, Barbados, Belize, Benin, Bermuda, Bhutan, Bolivia, Botswana, British Virgin Islands, Brunei Darussalam, Burkina Faso, Burundi, Cabo Verde, Cambodia, Cameroon, Central African Republic, Chad, Chile, Colombia, Comoros, Congo, Cook Islands, Costa Rica, Côte d'Ivoire, Croatia, Cuba, Democratic People's Republic of Korea, Democratic Republic of the Congo, Djibouti, Dominica, Dominican Republic, Ecuador, Egypt, El Salvador, Equatorial Guinea, Eritrea, Ethiopia, Falkland Islands (Malvinas), Federated States of Micronesia, French Guiana, French Polynesia, Gabon, Gambia, Germany, Ghana, Grenada, Guatemala, Guinea, Guinea Bissau, Guyana, Haiti, Honduras, Hungary, Iceland, India, Iran, Iraq, Israel, Jamaica, Jordan, Kenya, Kiribati, Kuwait, Lao People's Democratic Republic, Lebanon, Lesotho, Liberia, Libya, Macao, Madagascar, Malawi, Maldives, Mali, Marshall Islands, Mauritania, Mauritius, Mayotte, Mongolia, Montserrat, Morocco, Mozambique, Namibia, Nepal, New Caledonia, Nicaragua, Niger, Nigeria, Niue, Oman, Palau, Panama, Papua New Guinea, Paraguay, Peru, Qatar, Réunion, Rwanda, Saint Helena, Saint Lucia, Samoa, São Tomé and Príncipe, Saudi Arabia, Senegal, Seychelles, Sierra Leone, Slovakia, Slovenia, Solomon Islands, Somalia, Sri Lanka, Sudan, Suriname, Swaziland, Syrian Arab Republic, Timor-Leste, Togo, Tokelau, Tonga, Trinidad and Tobago, Tunisia, Turkey, Turks and Caicos Islands, Tuvalu, Uganda, United Arab Emirates, United Republic of Tanzania, Uruguay, Uzbekistan, Vanuatu, Venezuela, Vietnam, Wallis and Futuna Islands, West Bank and Gaza, Western Sahara, Yemen, Zambia, Zimbabwe

Notes:

- Other Developed Countries includes the Annex I countries within the UNFCCC process; the US and EU are also in the Annex I.
- Other Developing A Countries consists of the large developing countries with rising emissions.
- *Other Developing B Countries* consists of smaller developing countries, including the least developed countries and the small island states.

Capital

The capital-output ratio relates the capital demand to global GDP. This ratio is assumed to be fixed except for that it increases with the wealth gap closure, i.e., the closure of the gap between the average GDP per capita of developing countries and the initial average of developed GDP per capita.

Damage functions relating to GDP impacts from temperature change are described in detail in Damage to GDP. Energy requirements are embodied in the capital stock at the time of investment, which introduces a lag between the energy intensity of new capital and the average energy intensity of the capital stock.

The energy intensity of new capital is governed by a response to the total cost of ownership of each carrier for each end use and an exogenous user-specified technology trend. For each end use and carrier, two price effects, one based on energy costs and the other based on non-energy costs, also affect its energy intensity of new capital. Each price effect is formulated according to a distinct constant elasticity, such that as the cost relative to the reference increases, the energy intensity of that end use and carrier decreases. Likewise, as the cost relative to the reference decreases, the energy intensity of that end use and carrier increases.

The demand sector includes energy intensity of new and average energy consuming capital, which is disaggregated into three vintages, with energy requirements of each vintage, accounting for aging, early discarding and retiring, and retrofitting. Capital and energy requirements of that capital are disaggregated by end use (residential & commercial, industry, road and rail transport, and air and water), as well as by carrier. The model carefully tracks final and primary energy demand, where the former is the energy consumed by the end use capital, and the latter is the energy needed to be generated to meet that demand accounting for thermal efficiency that is less than 100% and other losses.

Carrier Choice

Energy is delivered to end use capital via six potential carriers; there are four direct use carriers, an electric carrier, and a hydrogen carrier. Each of the direct use fuel carriers matches 1:1 with each of the fuels, i.e., coal, oil, gas, and biomass.

Shares of each carrier are allocated on the basis of the relative attractiveness of options according to a logit-type choice function, e.g.:

$$Share[Carrier] = rac{Attractiveness[Carrier]}{\sum Attractiveness[Carrier]}$$

Attractiveness is an exponential function of cost, complementary assets (for all uses by the hydrogen carrier and transport uses by all other carriers), and other factors including phase-out policies, technical feasibility, and other effects. Cost attractiveness is determined according to the weighted average of attractiveness based on upfront capital costs and that based on the total cost of ownership (TCO), i.e., sticker price plus annual operation and maintenance costs plus energy costs. The weight reflects the value of how the buyers' attention is distributed between the sticker price and the TCO while making purchasing decisions and is specified for each end use.

Costs associated with the market price of energy are driven by the energy dynamics (e.g., extracted fuel commodity cycle, market clearing algorithms). Costs associated with the end use capital may be reduced by learning from end use experience, and for the electric carrier, adjusted with subsidies.

Complementary assets (CAs) reflect the availability of infrastructure to support the carrier. For nonhydrogen carriers, the effect applies only to the road and rail transport end use, reflecting fueling points/charging stations. For the hydrogen carrier, the effect applies to all potential end uses; the fueling infrastructure to meet future hydrogen demand is only available if policies support its building or, for air and water transport only, if direct use of fuels is banned. The installation of CAs is a function of the embodied carrier demand and, for the electric and hydrogen carriers, a policy to increase that. However, it is also constrained by a third order delay of the installation capacity. CAs have a normal lifetime but can also be retired early if the level exceeds the carrier demand. The level of CAs relative to that which is needed factors into the attractiveness of each carrier. Coal is assumed to have adequate availability for the relatively small amount of demand, notably for trains. The bio carrier uses the complementary assets of the oil carrier.

Fuel phase-out mandates also affect attractiveness, as described in Drivers of Cost of Supply.

The logit-determined shares are also subject to policies of phasing out fuel-powered capital, thereby deploying electric or hydrogen using new capital. These policies are phased in over time. For road and rail transport, which reflects approximately 85% of all transport capital, fuel phase-outs result in electrification because hydrogen cannot compete cost effectively for this sector. Conversely, fuel phase-outs for air and water result in the deployment of hydrogen because electricity cannot compete cost effectively for this sector.

Energy Intensity of New Capital

In the demand sector energy requirements are embodied separately for each end use and carrier. Energy intensity of each new unit of capital drives the embodied long-term requirements. Technological improvements and price of energy affect the energy intensity of new capital. The technological effect defaults to the historically observed improvements, assuming those persist into the future. However, the user may change those rates of improvement. Price effects for each end use and carrier are determined according to the long-term demand elasticities to the price of energy and to the non-energy costs of capital. The indicated price effect for each is delayed over time. There is also a fraction of the residential and commercial sector that is by definition electric, e.g., lighting and electronics.

Long Term Energy Requirements

The energy demanding capital that is installed is a function of the desired capital and that which is lost through discarding and retiring. The long term energy requirements are a function of the energy intensity of the capital that is installed and tracked through the capital lifetime through each vintage. Retrofitting for each end use also occurs, with the retrofits at the capital share and intensity of new energy.

Model Structure





Supply

Supply of Fuels, Electricity Generation, and Hydrogen Production

There are three main supply chains, each subscripted accordingly, to capture the stock and flow of supply capacity.

- 1. Fuels (coal, oil, gas, and biofuel);
- 2. Electricity generation from each of the electric paths (coal, oil, gas, biofuel, nuclear, hydro, wind, solar, geothermal, other renewables, and new zero-carbon); and
- 3. Hydrogen production from each of the hydrogen paths (electricity from the grid; dedicated renewables; dedicated nuclear; gas; coal; and biomass.
 - There are two distinct supply chains for hydrogen, one for energy and storage for variable renewable energy (VRE), and the other for feedstocks because the options for each differ as explained in Hydrogen Supply Choice
 - There is an additional supply chain to capture the stock and flow of electricity generation capacity by dedicated renewables and dedicated nuclear to meet the hydrogen capacity demands.

Carriers	Sources Used
Coal Carrier	Coal
Oil Carrier	Oil
Gas Carrier	Gas
Bio Carrier	Bio
Electric Carrier	Elec Paths
Hydrogen Carrier	Hydrogen Paths

The model assumes that each fuel is available only for its respective use if used as direct use fuel, i.e., nonelectric and nonhydrogen.

Each fuel is available for direct use and electricity generation; only coal, gas, and bio are available for hydrogen production. The electric only paths are mapped to the primary source, where the renewable types are aggregated to Primary Renewables. The hydrogen paths include electrolysis via the grid (Elec H), from dedicated renewables (Renew H), and dedicated nuclear paths (Nuclear H); steam methane reformation (SMR) via natural gas (Gas H); and gasification from coal (Coal H) and biomass (Bio H).

Primary Energy Sources	Primary Fuels	Elec Paths	Hydrogen Paths
Primary Coal	PCoal	ECoal	Coal H
Primary Oil	POil	EOil	
Primary Gas	PGas	EGas	Gas H
Primary Bio	PBio	EBio	Bio H
Primary Nuclear		Nuclear	Nuclear H
Primary Hydro		Hydro	
Primary Renewables		Wind Solar Geothermal Other Renewables	Renew H
Primary New		New	

 Table 4.2
 Primary Energy Sources, Electric Paths, and Hydrogen Paths

Hydrogen paths are classified by technology and color according to their source.

 Table 4.3
 Hydrogen Technologies and Colors

Source	Subscript	Technology	Color
Coal or biomass	Coal H, Bio H	Gasification	Brown
Gas	Gas H	Steam Methane Reforming (SMR)	Gray
CCS-enabled coal, gas, or biomass	Coal H, Gas H, Bio H	Gasification (coal and biomass), SMR (gas)	Blue
Electric grid	Elec H	Electrolysis	Yellow
Dedicated nuclear	Nuclear H	Electrolysis	Pink
Dedicated renewables	Renew H	Electrolysis	Green

For each fuel, the capacity, utilization, and costs affect its market price; markup values for each end use yield the market price to use the fuel directly. Markup values to use each fuel to generate electricity or produce hydrogen yield the fuel variable costs for each carrier. Market Clearing and Utilization details the market clearing and utilization of fuels, electricity sources, and hydrogen sources.

For each of these phases, the capacity represents the installed base of usable capital. It depreciates via a constant fractional rate, without age vintaging of the stock. The profitability, however, affects the rate of depreciation. Capacity must go through the development phase and then constructed before it can be used, introducing a delay between initiating and completing the acquisition of new capacity. The amount of capacity that is planned for construction accounts for the total capacity needed to meet the energy demand, including transmission and delivery losses, plus a reserve margin and expected growth of energy requirements.

For capacities of fuels, the desired capacity of each depends in part on the centralized effect of expected growth and normal utilization, as well as on the profitability and current capacity of each fuel. Any non-cost policies banning new capacity adjust the resulting desired capacity. For electric generation, the desired capacity of each source depends on the demand of electricity and the fraction invested in each source. For hydrogen production, the desired capacity of each source is a function of its use, the demand of each use, and the fraction invested for each use, where the feedbacks on construction costs and times from each use affect each other.

There is an additional supply chain for the dedicated renewables and dedicated nuclear hydrogen paths, driven by the demand of electricity from these paths to produce hydrogen. Capacities of renewables and nuclear paths for electricity generation for the grid and for these dedicated paths affect each other in terms of costs and supply constraints.

Desired capacities are adjusted by dividing by the capacity factor of each resource, requiring more of each energy path to be constructed to get the actual desired supply. The constructed supply is then multiplied by the capacity factor to yield the actual capacity. While the Actual Supply Capacity represents the amount of energy from each path that can be dispatched, the Energy Supply Capacity is the amount of capacity that is constructed.

The rate of capacity completion is constrained by the capacity to do so. This structure captures supply chain constraints, for example the fact that if wind turbine orders double overnight, completion of new turbines cannot also double immediately. It takes time to acquire labor and machinery and build up other aspects of the necessary supply chain. This has two consequences: with increasing pressure to construct capacity, the effective lead time increases, and the cost of new capacity rises.

Drivers of Cost of Supply

Several factors affect the cost of each supply source, including,

- A baseline or reference cost
- a learning-by-doing effect from the accumulation of experience in capacity installation
- an exogenous user-specified cost reduction from technological breakthroughs achieved through research and development (R&D)
- cost of fuels as determined by the fuel market price and efficiency of fuel use
- resource constraints
- source subsidies/taxes
- storage costs for variable renewables (solar and wind)
- soft costs for renewables
- emissions cost from carbon pricing

- qualifying electricity standards costs and penalties, Qualifying Electricity Standards (QES)
- a "pipeline overheating" premium from supply chain constraints on capacity installation

Resource Constraints

The Resource Constraints sector addresses the potential limits to available energy resources and the effects those limits may have on supply costs. The resource effect cost is a function of the depletion effect on cost and the supply curve effect on cost.

The depletion effect is dynamic, with cost increasing as cumulative production grows. This captures cost escalation with the depletion of fossil fuels. It is possible to discover unconventional resources, thereby reducing the depletion effect; however, it is assumed that the unconventional resources have a different carbon intensity, adjusted by the user. Biomass is not limited by depletion but rather by the supply constraints of each feedstock, i.e., wood, crops, and others, which reflects the limit of production of energy from a source from the saturation of production opportunities. These resource constraints affect the extraction costs of fuels, resulting in a greater market price. In turn, a greater market price of fuels drives up the variable costs to use those fuels for electricity or hydrogen production.

The supply curve constraint can also affect the cost to produce the electric only paths, i.e., nuclear, hydro, renewable types, and new zero-carbon; of these sources, the model defaults to only affect hydro and renewables. Supply limitations for these paths affect the capital costs, capturing, for example, the escalation in cost of wind power that occurs as the cheapest sites are exploited first.

Parameters are based on IPCC 2007 and IEA 2022 estimates.

Storage for Renewables

Storage capacity for variable renewable energy (VRE) must meet its demand when the source is not available. Variable renewables include wind and solar, whereas geothermal and other renewables are more constant in their generation. Models of hourly, daily, and seasonal variability of demand and renewable generation determined the storage coverage, i.e., energy per variable renewable capacity (EJ per EJ/year), and the average power needed from storage per variable renewable capacity (EJ/year per EJ/year). Sensitivity analyses of each category of coverage determined the relationships between these parameters and the share of VRE capacity to total electric generation capacity. These analyses also confirmed the effect that round trip efficiency (RTE) has on the required coverage; it scales 1/RTE such that the lower the RTE to use storage, the higher the maximum storage capacity for storage required. The resulting relationship between hours of coverage versus VRE share is consistent with that found by others, including Solomon et al. (2017), Shaner et al. (2018), and Albertus (2020).

Storage coverage to balance the different time scales of variability is defined in the model by duration.

- Hourly storage: up to 12 hours of coverage.
- Daily storage: 12-72 hours of coverage.
- Seasonal storage: greater than 72 hours of coverage.

Long duration energy storage (LDES)—generally daily and seasonal storage coverage—is increasingly required at higher shares of variable renewables in the electric grid, and requires a breakthrough cost reduction to enable its growth.

Besides storage, other demand response technology, long-distance transmission, and behavioral load management can minimize storage needs but only for short and medium coverage. Learning and investment increases the percent effect these options have on the storage requirements.

While the model assumes that storage requirements will not limit utilization, costs of renewables account for those for storage. Comparable to the experience and breakthrough effects for energy, storage costs also decrease with cumulative capacity installation and potential technological breakthroughs.

Storage could be in the form of batteries, compressed air, pumped hydropower, and other more novel options, including hydrogen. NREL's Store-FAST: Energy Storage Financial Analysis Scenario Tool, version: 1.2 (2019), provides the inputs for power and energy costs, including RTE, for several storage options. The levelized cost of each type adds the cost of electricity for it, which is the market price of electricity divided by the storage RTE.

Other than hydrogen, these technologies all become limited and/or more costly with longer durations of coverage. Cost effective long duration coverage is critical when the share of VRE exceeds approximately 70-80%. Hydrogen, despite having a much lower RTE, approximately 36%, has the potential to provide more cost effective long duration coverage than the other technologies. This is because, although the power costs associated with hydrogen far exceed those other storage options, the costs to store each hour of energy coverage is far less than the other options. Despite that cost effectiveness for long-term coverage, ancillary costs currently associated with hydrogen storage constrain its use. A subsidy for green hydrogen reduces these ancillary costs, thereby allowing it to take advantage of its cost attractiveness for long-term coverage.

Electricity for Storage

In addition to the power and energy costs, each storage option also requires electricity for charging and discharging. Electricity exceeding that which is generated from storage, determined from the sum of the average power needed from storage per variable renewable capacity from the hourly, daily, and seasonal models, is added to the industrial electric carrier demand. For example, an RTE of 100% requires no additional electricity; an RTE of 80% requires 0.25 times the power required; and an RTE of 36% requires 1.77 times the power required. By default, the electricity all comes from the grid for nonhydrogen storage. Hydrogen for storage comes preferentially from the grid and from dedicated renewables.

Hydrogen Leakage

Hydrogen leakage, defaulted at 2%/year, releases hydrogen to the atmosphere. While there is no direct radiative forcing from hydrogen, the climate structure accounts for its indirect effects on the radiative forcings of CH_4 , O_2 , H_2O , and aerosols (Sand et al., 2023).

Soft Costs and Subsidies for Renewables

The levelized cost of electricity (LCOE) of renewables, particularly wind and solar energy, have decreased dramatically since 1990, especially over the past decade. Two opposing forces have contributed to those declines with the energy generated by them. There have been historical subsidies for solar and wind, defined as a fraction of their direct costs, stimulating their growth. While the fraction of solar subsidies declined over time until 2020, that fraction and the fraction for wind is expected to remain constant through 2100 as Baseline subsidies, comparable to the fossil fuel subsidies embedded in their costs. However, the user can end them sooner. There have also been soft costs, i.e., indirect costs, that have made the investment in these sources less attractive than direct cost alone would suggest. It captures the soft costs as an initial level that declines with experience at a rate determined by a progress ratio. The values defining these subsidies and soft costs were estimated from literature and set through optimization to fit historical cost (IRENA, 2020; Lazard, 2021; IEA, 2020) and energy data (IEA, 2022; BP, 2022).

Sources of LCOE data for renewables are not consistently presented and only available for some years, therefore requiring conversions and bridging between datasets.

- IRENA: All LCOE results are reported in \$2019 USD. Reported values calculated excluding any financial support and using a fixed assumption of a real cost of capital of 7.5% in OECD countries and China, and 10% in the rest of the world, unless explicitly mentioned. All LCOE calculations exclude the impact of any financial support. Converted to \$2017.
- LAZARD 3.0-15.0: All LCOE results reported in nominal dollars. Each analysis assumes 60% debt at 8% interest rate and 40% equity at 12% cost; Unless otherwise indicated, the analysis herein does not reflect decommissioning costs, ongoing maintenance-related capital expenditures or the potential economic impacts of federal loan guarantees or other subsidies; Lazard's unsubsidized LCOE analysis indicates significant historical cost declines for utility-scale renewable energy generation technologies. Converted to \$2017.
- IEA Levelized Costs Data: Global average LCOEs and auction results for utility-scale PV by commissioning date. Last updated 26 Oct 2022. Data shown = LCOE in \$2017.
- IEA: Evolution of solar PV module cost by data source, 1970-2020. Last updated 26 Oct 2022. While the LCOE data for solar PV is not readily available before 2009, IEA's cost per watt of solar PV from IEA 1970-2020 provides data to estimate the LCOE from 1990. Using the ratio of annual costs per watt to that in 2010 and applying that ratio to the IRENA solar PV LCOE in 2010 provides an estimate of LCOE from 1990-2019.
- Berkeley. Median 30-Year LCOE without the ITC reported in \$2018. Converted to \$2017.

Utility vs distributed solar PV: There are differences between utility scale and distributed solar PV. According to IEA (2022), the fraction of PV that is utility scale grew from 24% to 50% of solar PV between 2010-2016, remaining at that level thereafter. Lazard provides utility scale and distributed cost data; accordingly, comparisons are made to the weighted average of these. The weights assume the trend of increasing utility scale relative to distributed increases at a comparable rate to history.

Onshore vs offshore wind: Likewise, there are differences between onshore and offshore wind. IRENA used the weighted average of the onshore fraction of wind, taken from IEA Wind Electricity Report, to get the weighted average of wind LCOE. From regional graphs of onshore vs offshore wind, they estimated wind to be 100% onshore until 2010, when offshore wind starts to present, decreasing down to 95% by 2019.

Instant and Embodied Supply Costs and Efficiencies

The embodied costs of supply are modeled in the Embodied Supply Costs sector. These costs factor into the utilization of energy capacity in the Market Clearing and Utilization sector. Embodied costs represent the actual physically-imposed costs, which are locked in at the time of capacity investment, i.e., new capacity development. Variable costs include operation and maintenance (O&M), and fuel costs. The fuel costs for direct use are the market price of each fuel marked up by constant specific to the end use and fuel. The fuel cost for each electric and hydrogen source requiring fuel is the market price of each fuel, accounting for a markup, divided by the embodied thermal efficiency of the source; fuel prices for the primary electric paths are 0. Unit profit, which is the revenue less the variable costs, may be adjusted by a tax/subsidy and/or carbon tax to the producers of delivered fuels.

As in the Demand sector, the construction pipeline is explicit but without vintaging of capital as there is in the demand side; costs are assumed to be well-mixed. All inputs to this sub-model are determined in other sub-models except for the Overheating cost sensitivity, which is set at 0.5. The embodied costs and efficiencies of supply are locked in at the time new capacity development.

The effects on costs apply to the levelized capital costs.

Electric Supply Choice

As in the Carrier Choice sectors, the fraction of new investment allocated to each of the electric energy sources is a function of its attractiveness relative to that of the other sources. Attractiveness synthesizes cost effect and the effect of a performance standard.

The cost, adjusted by any source subsidies/taxes, drives the cost attractiveness of each electric path relative to the other electric paths.

The performance standard effect is a function of a specified carbon intensity threshold and the carbon intensity of each energy source resource, defined in Emissions. The performance standard creates a soft threshold, beyond which sources with high emissions intensity (e.g., coal) are greatly diminished in attractiveness and are effectively eliminated from the investment mix. The effect of non-cost policies aims to capture any legislation or rule demanding no new investment in a specified source for a percentage of the global energy needs.

Hydrogen Supply Choice

Table 1 4 Hydrogen Investment Ontions

Comparable to that for the electric carrier, the fraction of new investment allocated to each of the hydrogen energy sources is a function of its attractiveness relative to that of the other sources. Attractiveness synthesizes cost effect and the uses of hydrogen.

The cost, adjusted by any source subsidies/taxes, drives the cost attractiveness of each hydrogen path relative to the other paths.

The options competing for attractiveness depend on the use. The fraction of each path for the supply chain for use as an energy carrier and for VRE storage uses the weighted fraction for each use.

Use	Options			
Energy Carrier	Yellow, Green, Pink, Blue			
VRE Storage	Yellow, Green			
Feedstock	Yellow, Green, Pink, Blue, Gray, Brown			

Model Structure







Market Clearing and Utilization

The Market and Utilization sector uses a market clearing theory to balance supply and demand given costs, prices, and assumed market attributes. Market prices depend on the demand/supply imbalance. They also depend on the cost of energy production by existing capacity, which depends on technological cost improvements, and resource constraints and overheating of capacity, all described in Supply.

Market Clearing of Fuels

The market clearing of fuels captures the supply/demand/price of each fuel at the extraction level, i.e., minemouth (coal), crude (oil), wellhead (natural gas), and feedstock (bioenergy). The production supply of fuels is a logistic function of the ratio of the market price to variable cost relative to the initial market price to variable cost; when that ratio equals 1, the utilization of production capacity is at the normal utilization of 0.8. The demand for fuels is the sum of the demand for each carrier. The indicated price of fuels is a function of the current price, the demand/supply imbalance, and the unit cost of production of existing capacity. The actual price is the indicated price lagged over the price adjustment time (0.5 years). The price of each fuel for each carrier that uses it is the market price of the extracted fuel increased by a carrier and end use specific markup value, plus the net of any taxes and subsidies. The price for the industry end use is also explicitly determined for the capacity with CCS.

The demand for each fuel for direct use (nonelectric and nonhydrogen) consumption is the product of the long term demand and its utilization, which is a linear function of price relative to the reference price; the response of utilization to price is given by the (negative) sensitivity. For industry, that demand is determined explicitly end use capacity using CCS and that not using CCS. The former is the product of utilization with CCS and the capacity using CCS equipment, determined by the CCS capacity and the utilization of that CCS capacity, all defined in Carbon Capture and Storage (CCS). The latter is the product of utilization without CCS and the capacity not using CCS equipment.

The demand for each fuel for electricity generation is determined in the market clearing for electricity. The actual production of fuels for direct use consumption for energy and feedstocks, power generation, and hydrogen production is constrained by the production of extracted fuels from their market clearing.

Market Clearing of Electricity

The market clearing for electricity is comparable to that for fuels. However, for electricity, the utilities aggregate the production from all sources and charge a single price to the consumer. Furthermore, the busbar price reflects the revenue of the utilities; the market price of electricity adds the transmission and distribution (T&D) costs to that. The consumer pays the T&D costs, defaulted to \$0.02/kWh, to the utility regardless of the electricity generator. T&D costs are not subject to the learning or breakthroughs; they are assumed to remain constant throughout the simulation (see EIA 2017 and Fares & King 2016). The generator's unit revenue may also be increased according to qualifying credits, explained below in Clean Electricity Standards, and by any applicable CCS subsidies. The busbar price relative to the variable cost of each production source determines the utilization of production capacity. As described for direct fuel use carriers for industry, for the primary fuels with potential CCS, utilization is determined explicitly for revenue and costs with and without CCS. The product of energy utilization with CCS and the capacity using CCS equipment, determined by the CCS capacity and the utilization of that CCS capacity, all defined in CCS. The latter is the product of utilization without CCS and the capacity not using CCS equipment.

The market price of electricity determines the utilization of the end use demand capital. The demand for electricity is the product of the long term demand and its utilization; electricity required for direct air capture, carbon capture and storage, and hydrogen production are added. The indicated busbar price is a function of the current busbar price, the demand/supply imbalance, and the average unit cost of production of existing capacity, weighted by the production of each electricity source. The actual price is the indicated price lagged over the price adjustment time (0.5 years).

Market Clearing of Hydrogen

The market clearing for hydrogen parallels that for electricity. However, there are two distinct market clearings for hydrogen, one for energy and the other for use as a feedstock. As explained in Hydrogen Supply Choice, the main difference is that, due to the inefficiencies in producing hydrogen with fuels, they would only be considered for use as an energy carrier if the associated emissions were abated by CCS. On the contrary, hydrogen as a feedstock needs hydrogen molecules as an input to certain chemical processes (e.g., producing ammonia NH3 for fertilizer production) and therefore the unabated fuels are often chosen as the most attractive sources. Another complexity with hydrogen production is that it can be used to store variable renewable energy for electricity. Hydrogen for this purpose is not included in the market clearing because it is not traded on the market; rather, the hydrogen produced for it is subtracted from the total produced for energy and VRE storage.

Moreover, hydrogen for VRE storage preferentially relies on the electric grid and dedicated renewable sources. Electricity from the grid that is used to produce hydrogen factors into the Market Clearing of Electricity. Convention differentiates the sources of hydrogen by color.

Tax and Subsidy Adjustments to Costs

A carbon tax on fuels and source taxes reduce the margin and profit of that source; conversely, source subsidies increase the margin and profit of that source. Source taxes/subsidies can be applied either to capital costs, as defaulted for electric and hydrogen sources, or to variable costs, as defaulted for fuels. Carbon taxes, which depend on the fuel's carbon density and fuel losses, increase the variable costs of that fuel. For fuel-generated electricity, the adjustment to the cost of fuel also depends on the thermal efficiency of that source. The increase in cost with a carbon tax can be partially offset with the net of CCS costs minus incentives.

Parameter values for source subsidy/tax inputs range from highly subsidized, defined to be 60% of the marginal cost in 2020, to very highly taxed, defined to be 200% of the marginal cost in 2020. For fuel-generated electricity, the percent thresholds apply to the marginal costs excluding those for fuel. Bounds are set to policy-relevant limits, which are source-dependent.

Clean Electricity Standards

Besides taxes and subsidies, market-driven credits or certificates are another mechanism to drive electricity to achieve target standards. En-ROADS allows the user to choose the sources to be counted as qualifying, the target percent of qualifying sources of electricity produced, the duration over which to achieve the target, and the base cost of the credits or certificates. The costs of buying certificates and potential fines for not reaching the standard are paid for by all sources, whereas only qualifying sources reap the revenue.



Model Structure





Figure 5.4 Market Clearing (Supply-Demand Balance) for Hydrogen for Energy





Land Use, Land Use Change, and Forestry

En-ROADS endogenously calculates the land use, land use change, and forestry (LULUCF) net C emissions by explicitly keeping track of each hectare of different land types; the fluxes of changing land types and the use of each land type due to land and energy demands and policies; and the coflow of carbon on the land. The terrestrial biosphere carbon (TBC) cycle accounts for these anthropogenic carbon emissions as well as natural emissions from biomass and soil respiration and releases as CH₄, accounted in the CH₄ cycle, and primary productivity of each land type.

The TBC cycle reflects that cutting down trees releases carbon and stops them from absorbing CO_2 from the atmosphere. While harvesting crops also releases carbon, the approximately annual or faster regrowth time allows the related carbon release to be considered net zero.

En-ROADS models different kinds of land that can be converted into the others, and the biomass and soil carbon on the land that can accumulate or be released. We have four different land uses: Forest, Agriculture, Other, Tundra; with Forest further divided into three cohorts (Young, 0-50 years; Medium, 50-100 years; and Mature, 100+ years) and whether or not it resulted from afforestation (9 total land uses).

Each type of land has carbon flows:

- From the atmosphere to biomass (primary production through photosynthesis)
- From biomass to soil (decomposition, etc.)
- From soil and biomass to the atmosphere (respiration, decay, burning)
- When land use changes, some of the carbon stays on the land and some is released to the atmosphere



We cut trees or remove biomass for two reasons: we want the material or we want the land (or both). The material is involved in concepts like bioenergy, wood products, and forest degradation. Needing the land means concepts like deforestation, afforestation, land use change, and agriculture. Those are the policies and scenarios where you can intervene in En-ROADS with each area described below.

Drivers of Deforestation and Degradation

Land that is converted from forest becomes either Farmland (driven by needs of the food system and bioenergy) or Other Land (non-farm deforestation). With six subcategories of forest (NonAF/AF, Young/Medium/Mature), the model assumes that the fraction of deforestation to farmland and to other is proportional to the land area of each to the total forest land.

The primary driver of deforestation has historically been to expand farmland, the need for which is driven by the food system drivers but also by the fraction of farmland expansion that comes from forest. Farmland needs that cannot come from forest comes from Other Land. Farm conversion from other land (mostly grasslands and scrub, but also deserts, barren, urban, etc.) has less effect on the carbon cycle than does deforestation. The fraction of farmland expansion that comes from forest is fixed (at 0.6) in the base case based on historical land use changes.

Non-farm deforestation is exogenous, a simple Baseline scenario based on the LUH data and projections. This reflects forest clearing for development and mining.

The fraction of farmland expansion coming from forests, and the rate of deforestation to other land may be modified by policy inputs. Those inputs come in two modes: from the main Deforestation slider, the input is a percent per year increase or decrease, which results in first order growth or decay relative to the Baseline scenario. In advanced settings, the user can set a year to halt which results in a linear transition to zero in the target year. The policies form reduction rates which are accumulated in a single stock called Relative deforestation which in turn multiplies each component of deforestation rate.

Forests are also harvested and allowed to regrow. The regrowing process can remove carbon from the atmosphere and is therefore often considered carbon-neutral. However, it can take decades to repay the carbon debt incurred with forest harvesting. All forests can be harvested for bioenergy or for wood products. The proportion of total harvest from each forest category is a function of available carbon on each category relative to the total carbon on all forests. A third element that is linked to the main deforestation slider is degradation of mature forest, i.e., forest of average age greater than 100 years. We include it because forest policies often link deforestation and degradation, as in REDD+. Although the terrestrial biosphere structure tracks removal and regrowth of biomass on all forest types, we limit the policies and graphs to degradation of mature forests. Harvest of mature forests is driven by the bioenergy structure, above, along with harvest for non-fuel wood. Nonfuel wood demand (lumber, paper, etc.) is a constant for each region times the population for each region. Structure exists for including a GDP per person effect but the sensitivity is zero.

The policy to directly control degradation is identical to the ones controlling the rate of non-farm deforestation (relative to Baseline) and farm expansion (fraction of expansion from forest), only it affects the fraction of mature forest available for harvest. The main deforestation slider increases or decreases degradation by a percent per year; the advanced view sets a year to halt degradation of mature forests, which also reduces the availability of wood for bioenergy and non-fuel harvest.

There are also command and control-type policies for land conservation; these limits do not address the drivers of deforestation or degradation, but rather prevent those drivers from affecting forest or mature forest. These policies represent the "year to halt" each component.

Food and Agriculture Drivers

Expanding farmland is a major driver of deforestation and other land use change. We start with the assumption that land will expand to meet food needs. We measure food in kilograms per year, and limit it to two types: crops and animal products. We model a single global food demand and a single global agriculture system. The variables involved in the causality from people to food to land are:



Food per person is modeled as a simple function of GDP per person, fitted to the FAO food balance data, and approaches an upper limit of 900 kg/person/year. There are no user controls for food per person, based on our assumption of meeting food needs.

Percent animal product is the fraction of global diet met by milk, meat, eggs, etc. Consumption of animal product in kg/person/year is a function of global average GDP per person, calibrated to FAO food balance data, from which the fraction is calculated. Under baseline GDP scenarios, it rises from its current value (24%) to a peak of 30% as GDP rises, set by the Food from livestock slider. The current consumption of milk, meat, etc. by region has range from 15% (China and Other Developing B) to over 40% (US), and not strictly arranged by GDP per person; traditional diets play a large part. It is still expected that global animal product consumption will grow over time as countries develop, but En-ROADS allows for users to vary that value between 10% to 40% to be reached in 2100.
Food waste is a single stock that is by default constant at 30%. 30% is the widely quoted but poorly studied value of the amount of food harvested but not consumed, anywhere along the value chain. Anecdotally, it is mostly between farm and market in developing countries, and retail or post-consumer in wealthy countries. If you change the Food waste setting, the new value is reached in 2100 with a linear path.

Food consumption for both crop and animal products is the product of population, food per person, and percent from livestock. Accounting for waste gives production needed to meet that consumption. An additional factor Livestock feed multiplier gives how much plant matter (feed, fodder, grazing vegetation, etc.) it takes to produce each kilogram of animal product. For now that is fixed at 10 kg plant / kg animal product. Farmland desired is then those needs for plant matter divided by yield.

Yield is the global aggregate production of crops, animal feed, pasture vegetation, etc., per year per hectare. The crop yield structure is designed to (1) have Baseline food demand result in land use changes matching LUH projections (2) allow for other yield growth scenarios (3) allow a feedback from temperature to yield (4) have lower yield growth if pressure on food demand is low.

In the data model and supporting files, we find the regression fit to FAO food balance data and use that along with the baseline assumptions to find baseline food demand. The rate of change in implied yield gives a baseline for the potential yield increase over time. The potential is modified up or down by the action of the Crop yield growth slider. The closure of the gap between the potential yield and maximum yield reduces the crop yield growth. The default of the maximum yield set to 2.5 times the 2020 yield implies a comparable growth rate observed since 1960.

The two endogenous reductions to crop yield are low food pressure and high temperature change. Food pressure requiring farming intensity to exceed normal intensity, defaulted to be 0.7, increases the rate of crop yield growth; the converse is true of farming intensity less than normal. It is measured by the ratio of crops needed relative to the crops produced under normal intensity of the farmland, defaulted to 0.7. The integral of crop yield growth is then reduced by the Effect of temperature on crop yield, defaulted to the mean of 4% decrease per degree C, consistent with the Zhao et al (2017) used for the impact table. However, the user may adjust this strength in Assumptions.

Farmland Expansion and Contraction

Farmland expansion occurs when the ratio of crops produced to the crops that could be produced at maximum intensity given the current farmland area exceeds the normal farmland intensity. Conversely, if that ratio is less than the normal farmland intensity, then what is not needed is converted to forest land via natural regrowth, whereas the rest degrades to other land.

Other Land Decreases and Increases

Afforestation policy, i.e. the action depending on the Afforestation slider of En-ROADS, is implemented as the conversion of other land to forest land, since the land identified to be available for afforestation, excludes existing forests and agricultural land and falls into the other land category. Afforestation, as a policy implementation, is formulated based on a user-defined fraction of the full potential of afforestable land, and its delayed conversion to afforested land, which results in the land flux of Land afforestation rate. This flux is then incorporated into the land use change module as a chain of conversions from the other land to young forests and then aging to medium and mature forests. Deforestation from afforested land to farmland and other land affects the efficacy of this policy. The model captures historical regrowth of other land to nonAF young forests. Other land also decreases with farmland expansion, as only a fraction of the expansion comes from forests.



Model Structure



Terrestrial Biosphere Carbon Cycle

The terrestrial biosphere carbon (TBC) cycle reflects the primary productivity of biomass, removing carbon from the atmosphere as it grows, the natural and anthropogenic carbon fluxes from biomass and soil stocks, the flux from biomass carbon to soil carbon, and the fluxes of biomass and soil carbon as methane to the methane cycle. These fluxes by land type are summed together to feed into the carbon cycle.

The Goudriaan and Ketner (1984) and IMAGE models have detailed biospheres, partitioned into leaves, branches, stems, roots, litter, soil, and charcoal. To simplify the model, these categories are aggregated into stocks of biomass (leaves, branches, stems, roots) and soil (litter, soil). First-order time constants were calculated in C-ROADS assuming equilibrium in 1850 for each category land type and C-ROADS region and aggregated across regions for use in En-ROADS. Charcoal is neglected due to its long lifetime. The results are reasonably consistent with other partitionings of the biosphere and with the one-box biosphere of the Oeschger model (Oeschger, Siegenthaler et al., 1975; Bolin, 1986).

Net Primary Productivity (NPP)

The natural ability of biomass to sequester carbon from the atmosphere provides a key sink in the carbon cycle. NPP is the gross primary productivity minus the autotrophic respiration. Forest, agricultural land, other land, and tundra all have primary production and respiration. Furthermore, all primary production is affected by the level of CO₂ in the atmosphere (the fertilization effect). Carbon stored in biomass and soil is also released through heterotrophic aerobic and anaerobic respiration, which increases with higher temperature (increased fire, pests, decay). With the major exception of forests, all land reaches equilibrium quickly. Accordingly, calibrating in C-ROADS, the initial unit NPP of each non-forest land type is set assuming equilibrium in 1850. The flux into the biomass is equal to the flux out from aerobic and anaerobic respiration and transfer to soil is divided by the land area.

Unlike the other land types, forests have the most complex growth and the most biomass, so are treated in the most detail. Trees take up carbon through photosynthesis / primary production, and lose it through respiration, fire, being eaten by animals, decay, etc. Some of the carbon lost from biomass ends up in the soil through decomposition. The net of these carbon flows is that forests grow in an S-shaped pattern, slowly at first, at a high rate in middle age, and then reach an equilibrium where very high primary production is balanced by very high respiration. The growth curves, primary production, respiration and soil transfer rates are initialized and calibrated with Land Use Harmonization (LUH) and OSCAR modeling output, and compared against Global Carbon Budget (2023), Houghton and Nassikas (2017), and SSP IAMs. The process involves determining the regional growth curves in C-ROADS and then aggregating to global inputs for En-ROADS.

- Initialize carbon in stocks of forest, farmland, tundra, and other biomass and soil from OSCAR 1850 output by 10 regions, disaggregated and re-aggregated to fit our 7 regions.
- Initialize fractional rate of biomass and soil C respiration and transfer biomass to soil from OSCAR 1850 output.
- Determine forest unit NPP Richard's growth curve parameters for each of 7 regions.
 - Set Test Pulse scenario in which all LULUCF is set to 0 EXCEPT for a pulse of 95 of mature forest in 1900; when Test Pulse = 1, all fertilization and temperature feedbacks are turned off.
 - Set unit NPP inputs within ranges determined from forest analyses and assure unit NPP curves are reasonable given the types of forests in each region, e.g., more tropical in India and Other Developing A and B and more temperate in Developed.
 - Iteratively adjust parameters to achieve near equilibrium prior to pulse and assure regrowth is reasonable given the types of forests in each region.
 - Determine forest unit NPP Richard's growth curve parameters for global aggregation.
- Create global TBC cycle in C-ROADS
 - Using land fluxes as sum of regional fluxes, set unit NPP inputs within ranges determined from forest analyses such that the global forest carbon aligns with sum of regional forest carbon.
 - vTest pulse
 - vTest Baseline
 - Unit NPP from all other land types remain constant
 - Use global rates calculated from 1850 output of OSCAR model of biomass to soil transfer, biomass to atm respiration and soil to atmosphere respiration.
 - Iteratively adjust parameters to achieve comparable global results as from C-ROADS.





Increasing forest biomass carbon from 1980s despite decreasing forest area due to fertilization effect. Supported by data, e.g., Table 1 in Xu et al. (2021) shows that tropical moist forests is the only biome that has had a decrease from 2000 to 2019, but that is outweighed by the forest C increase everywhere else. "Globally, woody carbon stocks are increasing slowly with an average annual gain of 0.23 ± 0.09 PgC year-1."





The logarithmic relationship of the uptake of C by the biosphere reflects the fact that the uptake is less than proportional to the increase in atmospheric C concentration (Wullschleger, Post et al., 1995). This formulation, though commonly used, is not robust to large deviations in the atmospheric concentration of C. As the atmospheric concentration of C approaches zero, net primary production approaches minus infinity, which is not possible given the finite positive stock of biomass. As the concentration of C becomes very high, net primary production can grow arbitrarily large, which is also not possible in reality. Accordingly, we instead use a CES production function, which exhibits the following: 1) the slope around the preindustrial operating point is controlled by the biostimulation coefficient, which can be loosely interpreted as CO₂'s share of plant growth (at the margin), with the balance due to other factors like water and nutrients; 2) there is a finite slope at zero CO₂, such that there are no singularities; and 3) it controls saturation at high CO₂.

$$NPP = NPP_0 \left(1 - \beta_b + \beta_b \frac{C_a}{C_{\mathrm{a},0}}^{CO_2 \cdot sat}\right)^{\frac{1}{CO_2 \cdot sat}}$$

NPP = net primary production

 NPP_0 = reference net primary production

 β_b = biostimulation coefficient

 C_a = C in atmosphere

 $C_{a,0}$ = reference C in atmosphere

 CO_2 ·sat = coefficient that determines the rate of CO_2 saturation

Natural Losses

Carbon stored in biomass and soil is lost due to fire and microbial/fungal respiration. Rates of the release from each carbon stock is increased with increasing temperature change.

Carbon in both biomass and soil is also released as natural methane, entering into the methane cycle as such. The fractional rates of these releases also increase with temperature change. We assume a linear relationship, likely a good approximation over the typical range for warming by 2100. The sensitivity parameter, set by the user, governs the strength of the effect. The default sensitivity of 1 yields the average value found in Friedlingstein et al., 2006. Additionally, the rate of methane from tundra increases as temperature exceeds a threshold, representing a tipping point in the model.

Anthropogenic Carbon Fluxes

Land Use, Land Use Change, and Forestry explains the land use changes and uses. Carbon emitted from LUC is a coflow of each land change, driven by the Fraction biomass C emitted and Fraction soil C emitted. The remaining carbon, i.e., 1 minus that fraction, drives the carbon transferred to the new land type.

Net removals from regrowth after harvesting and from afforestation account for the net primary productivity (NPP) and also for the carbon lost back to the atmosphere from aerobic and anaerobic respiration and to the carbon and methane cycles, respectively. In order to isolate the removals due to land changes, the model simultaneously calculates the removals for the counterfactual scenario of no land changes. Corresponding coflows, aerobic and anaerobic respiration, and transfers from biomass to soil drive the TBC cycle without harvesting and regrowth. Accordingly, the net removals due to land changes are taken as difference in net removals with and without the land changes.

The net carbon emissions from LULUCF are the gross emissions, i.e., the LULUCF released to the atmosphere from biomass and soil, minus the net removals due to the land changes.

A reduction in converting forests and in harvesting mature trees leads to a reduction in net emissions from LULUCF, eventually meaning negative emissions. Part of this is because demand for bioenergy from wood falls; the young and medium forests cannot make up for the reduced availability of biomass from mature forests, which makes wood more expensive. Increases from the other sources of biomass (crops and waste) only partially cover the reduction from wood.

Bioenergy

The amount of bioenergy used and the investment in bioenergy infrastructure is endogenously determined by cost and other attractiveness, along with all other energy sources. Within bioenergy, there are three feedstocks (wood, energy crops, and waste) likewise determined by cost. The basic structure is market clearing / market share / logit structures for both electricity and thermal use. The various components have independent learning curves.

Bioenergy markets interact with the land structure because flow constraints, and therefore costs, depend on the carbon and land available in the appropriate land use areas. In turn, harvesting for bioenergy removes the indicated carbon, converting any age of forest into new forest with low carbon content, or increasing the desired farmland.

The costs, learning curves, sensitivities and other parameters are set to be reasonable compared to IEA WEO scenarios.

LULUCF net emissions are reported in two ways, including those resulting from bioenergy and also excluding those when reporting bioenergy emissions are reported separately. Regardless of reporting, bioenergy emissions and resulting net removals are appropriately included in the TBC cycle and included as such in the main carbon cycle. Although reported as part of the energy emissions, bioenergy net emissions are not included with the Global C energy and industry emission flux of carbon into the atmosphere.

Emissions from bioenergy are a function of the fraction coming from each feedstock, i.e., wood, crops, and waste/other non-crop fast-growing feedstocks. The carbon intensity of each feedstock (GtonsC/EJ) and the fraction of bioenergy emissions that are captured through bioCCS before entering the atmosphere also affect emissions into the atmosphere. The available bioenergy feedstock can constrain the extracted bioenergy supply.

All forests supply bioenergy and wood for non-fuel products according to their carbon content. To isolate the removals due to harvesting for bioenergy, the model also calculates the counterfactual land areas and terrestrial biosphere carbon resulting from all fluxes excluding harvest and regrowth for bioenergy.

Forest Fires

Forest fires are emphasized due to the role of forests as carbon sinks and their slow regeneration post-burning. Shrub and grassland fires are considered carbon-neutral due to their rapid vegetation recovery.

Historical data from the Global Wildfire Information System (GWIS) database shows a steady decline in total annual wildfire burned area between 2002-2023 with forest fire burned area declining at a much slower rate compared to other vegetation types. Historical data from Global Forest Watch (GFW) shows a steady rise in severe 'stand-replacing' forest fires between 2001-2023 posing a threat to forest recovery. Furthermore, analysis by Jones et al. (2024) concludes that severe forest fires have been annually increasing, both in area and in intensity, over the past 2 decades particularly in areas where forest fires are linked to climate change.

Forest fires induced by climate change are explicitly modeled, estimated as a percentage of projected total forest area. Forest fires not induced by climate change are accounted for in the calculations of natural losses. Similar to natural losses, the rate of release from biomass and soil carbon stocks due to forest fires is increased with increasing temperature change.

Forest fires release CO₂ and methane into the atmosphere, contributing to temperature change, which feeds back to increase annual burned area. Mature and medium-aged forests experiencing fires degrade into young forests, and a portion of forest burned area is severely damaged to the extent that it cannot regrow. This deforestation effect is considered to be a subcategory of stand-replacing forest fires.

There is uncertainty on the impact of temperature change on wildfires in general, and on forest fires specifically. Literature such as Lange et al. (2020), and analysis of results from Knorr et al. (2016), suggests a strong linear effect of increasing temperature on annual wildfire burned area. This effect is estimated combining results from the literature with data from the GWIS database of historical wildfire area. Furthermore, there is uncertainty on the proportion of 'stand-replacing' burned area that is deforested. Data from GWIS and GFW were used to estimate the relationship between temperature and the proportion of forest fires that cause tree cover loss. Literature and expert judgement were leveraged to estimate the fraction of stand-replacing fires that cause permanent tree cover loss.

Model Structure



Emissions

En-ROADS models the emissions of well-mixed greenhouse gases (GHGs), including CO_2 , CH_4 , N_2O , PFCs, SF₆, HFCs, CFCs and HCFCs. For each gas, each potential source is modeled: energy production, energy-consuming capital, agriculture, and waste. CO_2 from energy is the largest source of total equivalent annual emissions, driven by total energy demand, energy choices, and energy supply infrastructure constructed to meet that demand. Other emission sources are ultimately driven by demand along with technology and practices which determine the emissions intensity of each activity for each gas.

Data for calibrating emissions are found under Initialization, Calibration, Model Testing. In particular, initial values for the non- CO_2 GHGs are taken from 1990 data from PRIMAP 2021, assuming Agriculture includes PRIMAP MAG and LU categories, and Waste includes PRIMAP Waste and Other categories. Values for CO_2 are calibrated to multiple sources.

Land use CO₂ emissions are a function of the land use changes and uses as defined in Land Use, Land Use Change, and Forestry and Terrestrial Biosphere Carbon Cycle.

Emissions from Energy Production

Energy production emissions include those from production capacity (infrastructure), construction of that production capacity, and from energy use. Emissions from each stage are calculated for electricity generation and non-electric use from each power source.

Energy use of fossil fuels and bioenergy produce the largest share of emissions. These depend on the GHG intensity of each source and use, and the primary energy used. Primary energy in turn depends on demand for each fuel, efficiency, and losses. Fossil fuels produce mostly CO_2 in every application; a small amount of CH_4 and N_2O are produced in some non-electric applications from incomplete combustion. Bioenergy produces CO_2 , CH_4 , and N_2O when burned.

Fossil fuel infrastructure produces CH₄ from off-gassing and leaks, the rate of which can be affected by policy controls.



Emissions from Energy Consuming Capital

End use capital represents all the constructed and manufactured materials that use energy or cause emissions. Capital is modeled in three economic sectors (residential & commercial, industry, transport) and three ages (vintage 1, 2, 3).

Besides the energy used by capital and the emissions calculated under energy use above, there are direct emissions specific to each sector.

Certain industrial processes release CO_2 without the combustion of fuels. Key examples include the calcination process for cement clinker production (CaCO₃ \rightarrow CaO + CO₂) and reduction of iron ore (Fe₂O₃+3CO \rightarrow 2Fe+3CO₂). Other processes use fossil fuels as feedstocks without combustion; examples include plastic and chemical production. These activities release CO_2 into the atmosphere as the products decay, rather than immediately. The amount of these non-energy processes depends on GDP, and, for cement and steel, on construction of infrastructure.

Industrial capital also emits F-gases (PFCs, SF_6 , and HFCs), N_2O , and a tiny amount of CH_4 as a byproduct of some processes.

Byproduct emissions are modeled as directly proportional to total industrial capital. The ratios are subject to changes in practices and technology. Included in these calculations are the emissions of F-gases used as propellants in foams, aerosols, fire extinguishers, etc - they might be emitted in any sector but are produced by industrial capital. Industry also uses F-gases as solvents, insulating gases, etc. This application is modeled as a stock of each F-gas in use which can leak, and will be discarded, recycled, or destroyed at end of life. The fractions for each flow are subject to changes in practices and technology, and the demand for F-gases for these applications can change if alternatives are adopted.

The largest emissions source from capital is refrigerants in cooling systems: refrigerators, heat pumps, air conditioners, etc. Demand for cooling (in GW capacity) is estimated from electric demand in the residential and commercial sector, and total energy demand in the transportation and industry sectors. The ratio of HFCs as refrigerants per GW of cooling demand is estimated from initial emissions rates and trends, and can change if alternatives are adopted. There are stocks of HFCs in current equipment and in discarded equipment, which emit depending on leak, recycling, and destruction rates, subject to changes in practices and technology.

Finally, ozone-depleting substances (ODSs, also called "Montreal gases", principally CFCs and HCFCs) are modeled as an aggregate group with averaged characteristics. There is an exogenous emission - calibrated to observed atmospheric concentrations - plus a user-adjustable assumed stock representing the uncertain remaining chemicals in stockpiles and obsolete equipment. ODS leak rates are fixed, but the stocks of ODS can be destroyed before they leak if action is taken.

Emissions from Agriculture

Agriculture is the largest sector source of both methane and nitrous oxide, as well as the largest driver of deforestation. Emissions from livestock and crops are modeled individually. The demand as described in the Land Section determines the amount of animal product, and crop production, including the crops grown for energy and livestock feed. The emission factors for CH_4 and N_2O for both crops and livestock have base improvement rates as observed from production and emission data. Policies to lower emissions from agriculture are modeled as an adoption process of best practices, such as better feed and manure management, fertilizer runoff reduction and so on. This brings the emission factors towards their minimum practical values.

Actions in the food and agriculture system also affect emissions from agriculture. Reducing the trend towards greater consumption of food from animals lowers emissions in two ways: by shifting some demand to crops, which have lower emission factors; and by reducing the need for crops for animal feed. Reducing food waste lowers the production needed to meet food demand, lowering the activity that produces emissions in both crops and livestock.



Emissions from Waste

The waste sector represents both landfill (garbage / trash / municipal solid waste) and wastewater (sewage). Both subsectors emit both CH_4 and N_2O . The production of waste is modeled as a ratio of waste per person, representing only the waste relevant for emissions. Waste per person follows a declining trend. The emission factors for waste are calculated from initial data. Both the production ratio and the emission factors are reduced by policy, as many actions (such as recycling and composting) overlap in their effects.

Model Structure



Carbon Dioxide Removal (CDR)

The carbon dioxide removal (CDR) submodel governs the storage of carbon by biological, chemical, and industrial means. It includes both CDR proper, and Carbon Capture and Storage (CCS). CDR refers to methods that take CO₂ from the atmosphere and sequester it as carbon somewhere else. The CDR methods we include are afforestation, soil carbon management, biochar, enhanced mineralization, direct air carbon capture and storage (DACCS), and bioenergy with carbon capture and storage (BECCS). CCS refers to methods that capture carbon from a fuel before or after combustion, so that less CO₂ is released to the atmosphere. CCS is modeled for fossil fuels (coal and gas) and bioenergy. There is overlap between CCS, BECCS, and DACCS including common technologies, storage sites, economic drivers, and infrastructure.

CCS and CDR methods are modeled at various degrees of detail. The amount and timing of removals are either set by, calibrated to, or grounded in a synthesis of literature, most frequently the Royal Society Report.

The carbon flows calculated by CCS and CDR structures are passed to the Carbon Cycle model and flow into biomass, soil, or sequestration stocks as appropriate. Each storage stock is subject to a leak or loss rate, adjustable in assumptions. In addition to carbon flows, this sector calculates the expenditures, energy needs, material flows, and land needs to show the impacts of relying on these techniques.

CDR Methods

Afforestation includes the land deliberately planted with trees as a means of carbon sequestration. Additional new forests might occur endogenously if farmland is abandoned, but that is not counted as "afforestation". Afforestation is specified by the user as a percent of the maximum area available for planting, adjustable as an assumption, and potentially limited by the area of Other Land available. Once the land is specified as afforested land, the growing forests sequester and store carbon according to the NPP and respiration drivers defined in Terrestrial Biosphere Carbon Cycle.

Agricultural soil carbon refers to techniques that increase the amount of carbon in farmland soil. It is specified as a percent of the peak rate of CO₂ removal, adjustable in the assumptions. The farmland carbon transfer parameters in the Terrestrial Biosphere Carbon Cycle submodel are then adjusted to achieve that rate, potentially limited by land availability. The assumption on soil carbon loss rate adjusts the parameters of the Terrestrial Biosphere Carbon Cycle submodel are then adjusted to achieve that rate, potentially limited by land availability. The assumption on soil carbon loss rate adjusts the parameters of the Terrestrial Biosphere Carbon Cycle as well.

Biochar refers to turning biomass into charcoal then burying the carbon in farmland as a soil amendment. It is specified as a percent of the peak rate of CO_2 removal, adjustable in the assumptions, subject to a loss rate.

Mineralization is a chemical process, also called enhanced weathering, where certain kinds of rock are spread onto farmland, where they absorb CO₂. This also has a beneficial effect on agriculture if the soil is too acidic. The user input sets the percent of suitable farmland (adjustable in the assumptions) and the rate of CO₂ absorption the amount of rock applied and the specific absorption potential. Gross absorption is adjusted by a loss rate (default zero) and the emissions from the energy used to mine, grind and transport the necessary rock.

Direct air carbon capture and storage (DACCS) (sometimes called DAC) is a set of technologies for chemically separating CO_2 from the atmosphere so it can be sequestered. The amount of CO_2 removed by DACCS is a function of the capture equipment and the capacity to transport the captured CO_2 , which is shared with CCS. The desired DACCS capacity is a function of the costs and potential incentives, which can come from carbon price or direct subsidies. DACCS capacity model has orders, completions and retirement, subject to delays and limits on construction capability. The cost of DACCS changes over time due to two competing dynamic forces. Learning, from accumulated experience, tends to lower costs. The sum of the pending and installed capacity, representing using up the sites with best access to CO_2 transport and storage, tends to raise costs. The energy required to operate DACCS equipment increases the energy demand for electricity, potentially increasing emissions. The gross capture by DACCS is stored in geological formations; an estimate of CO_2 emitted by its energy demand is subtracted to plot net removals.

Bioenergy with CCS (BECCS) is modeled under the CCS section below. It responds to price signals, including a carbon price and subsidies, rather than having a user input under the CDR section.

Carbon Capture and Storage (CCS)

Both fossil and bioenergy CCS are modeled as stocks of transport capacity (shared with DACCS), and individual capture capacities for each fuel and application, i.e., nonelectric industry and electricity generation for all end use sectors. Completion is subject to both development and construction delays, with a limit on overall growth rates as construction capability itself takes time to construct. The amount of CO₂ captured for each fuel and application, capture capacity, and available transport capacity. If transport capacity is limiting, it is shared in proportion to capture capacity. Figure 9.1 shows the capacity supply chain for electric CCS; that for direct use for industry and for hydrogen CCS parallels this structure.



For each fuel and application, CCS capacity adjusts over time to the desired amount, which is determined as the fraction of total energy capacity indicated by an s-shaped function of the ratio of marginal incentives to costs. As the incentives increase or costs decrease, more CCS projects are initiated up to a maximum where all energy capacity has CCS. Incentives for CCS can come from a carbon price, subsidies, or from a clean electricity standard. There is additional exogenous construction of CCS representing the historical and expected construction for R&D, demonstration projects and the like, calibrated to historical CCS data. The cost of CCS includes capture and transport equipment costs, the cost of storage, and the cost of energy, which is assumed to equal the market price of electricity from the Market Clearing sector. Equipment costs, and the energy needed to operate CCS, tend to decline following endogenous learning curves. The sum of the pending and installed capacity, representing using up the sites with best access to CO₂ transport and storage, tends to raise costs. Storage costs increase with cumulative use of storage. The balance of these dynamic changes can raise or lower total CCS costs over time, which will alter the amount of CCS for each application. Unit costs of existing CCS capacity are determined by sum of the embodied capital costs of CCS and the product of market price of electricity and the embodied energy intensity of using CCS, minus the variable incentives from the carbon tax avoided by what is captured and unit subsidies. The net of variable costs and incentives affect the market clearing utilization of each fuel that might be equipped with CCS compared to other energy sources. The ratio of incentives to variable costs determines the CCS utilization; if a plant has CCS equipment but the CCS incentives are no longer greater than its variable costs, the plant can still operate but without using its CCS. The net of costs and incentives also average into the unit costs of the total energy capacity for each fuel and application for decisions of investments in new energy (weighted by indicated CCS capacity), and in the effects of market prices and profitability effects (weighted by existing capacity).









Well-Mixed Greenhouse Gas Cycles

Carbon Cycle

Introduction

The carbon cycle sub-model is adapted from the FREE model (Fiddaman, 1997). While the original FREE structure is based on primary sources that are now somewhat dated, we find that they hold up well against recent data. Calibration experiments against recent data and other models do not provide compelling reasons to adjust the model structure or parameters, though in the future we will likely do so.

Other models in current use include simple carbon cycle representations. Nordhaus' DICE models, for example, use simple first- and third-order linear models (Nordhaus, 1994, 2000). The first-order model is usefully simple, but does not capture nonlinearities (e.g., sink saturation) or explicitly conserve carbon. The third-order model conserves carbon but is still linear and thus not robust to high emissions scenarios. More importantly for education and decision support, neither model provides a recognizable carbon flow structure, particularly for biomass.

Socolow and Lam (2007) explore a set of simple linear carbon cycle models to characterize possible emissions trajectories, including the effect of procrastination. The spirit of their analysis is similar to ours, except that the models are linear (sensibly, for tractability) and the calibration approach differs. Socolow and Lam calibrate to Green's function (convolution integral) approximations of the 2x CO₂ response of larger models; this yields a calibration for lower-order variants that emphasizes long-term dynamics. Our calibration is weighted towards recent data, which is truncated, and thus likely emphasizes faster dynamics. Nonlinearities in the C-ROADS carbon uptake mechanisms mean that the 4x CO₂ response will not be strictly double the 2xCO2 response.

Structure

The adapted FREE carbon cycle is an eddy diffusion model with stocks of carbon in the atmosphere, biosphere, mixed ocean layer, and three deep ocean layers. The model couples the atmosphere-mixed ocean layer interactions and net primary production of the Goudriaan and Kettner and IMAGE 1.0 models (Goudriaan and Ketner 1984; Rotmans 1990) with a 5-layer eddy diffusion ocean based on (Oeschger, Siegenthaler et al., 1975) and a 2-box biosphere based on (Goudriaan and Ketner 1984).

The global terrestrial biosphere carbon cycle fluxes and initial biomass and soil stocks are the sum of those by land type as defined in Terrestrial Biosphere Carbon Cycle.

The interaction between the atmosphere and mixed ocean layer involves a shift in chemical equilibria (Goudriaan and Ketner, 1984). CO_2 in the ocean reacts to produce HCO_3^- and CO_3^- . In equilibrium,

$$C_m = C_{\mathrm{m},0} \left(rac{C_a}{C_{\mathrm{a},0}}
ight)^{rac{1}{\zeta}}$$

 C_m = C in mixed ocean layer $C_{m,0}$ = reference C in mixed ocean layer C_a = C in atmosphere $C_{a,0}$ = reference C in atmosphere ζ = buffer factor

The atmosphere and mixed ocean adjust to this equilibrium with a time constant of 1 year. The buffer or Revelle factor, ζ , is typically about 10. As a result, the partial pressure of CO₂ in the ocean rises about 10 times faster than the total concentration of carbon (Fung, 1991). This means that the ocean, while it initially contains about 60 times as much carbon as the preindustrial atmosphere, behaves as if it were only 6 times as large.

The buffer factor itself rises with the atmospheric concentration of CO_2 (Goudriaan and Ketner, 1984; Rotmans, 1990) and temperature (Fung, 1991). This means that the ocean's capacity to absorb CO_2 diminishes as the atmospheric concentration rises. This temperature effect is another of several possible feedback mechanisms between the climate and carbon cycle. The fractional reduction in the solubility of CO_2 in ocean falls with rising temperatures. Likewise for the temperature feedback on C flux to biomass, we assume a linear relationship, likely a good approximation over the typical range for warming by 2100. The sensitivity parameter that governs the strength of the effect on the flux to the biomass also governs the strength of the effect on the flux to the ocean. For both effects, the default sensitivity of 1 yields the average values found in Friedlingstein et al., 2006.

$$\zeta = \zeta_0 + \delta_b \ln igg(rac{C_a}{C_{\mathrm{a},0}} igg)$$

 ζ = buffer factor ζ_0 = reference buffer factor δ_b = buffer CO₂ coefficient C_a = C in atmosphere $C_{a,0}$ = reference C in atmosphere

The deep ocean is represented by a simple eddy-diffusion structure similar to that in the Oeschger model, but with fewer layers (Oeschger, Siegenthaler et al., 1975). Effects of ocean circulation and carbon precipitation, present in more complex models (Goudriaan and Ketner, 1984; Björkstrom, 1986; Rotmans, 1990; Keller and Goldstein, 1995), are neglected. Within the ocean, transport of carbon among ocean layers operates linearly. The flux of carbon between two layers of identical thickness is expressed by:

$$F_{\mathrm{m,n}}=rac{(C_m-C_n)^e}{d^2}$$

 $F_{m,n}$ = carbon flux from layer *m* to layer *n*

 C_k = carbon in layer k

e = eddy diffusion coefficient

d = depth of layers

The effective time constant for this interaction varies with d, the thickness of the ocean layers. To account for layer thicknesses that are not identical, the time constant uses the mean thickness of two adjacent layers. The following table summarizes time constants for the interaction between the layers used in C-ROADS, which employs a 100 meter mixed layer, and four deep ocean layers that are 300, 300, 1300, and 1800 meters, sequentially deeper. Simulation experiments show there is no material difference in the atmosphere-ocean flux between the five-layer ocean and more disaggregate structures, including an 11-layer ocean, at least through the model time horizon of 2100.

Layer Thickness	Time Constant
100 meters	1 year
300 meters	14 years
300 meters	20 years
1300 meters	236 years
1800 meters	634 years

 Table 10.1
 Effective Time Constants for Ocean Carbon Transport

The sum of carbon removals by non-land based CDR, defined in Carbon Dioxide Removal, is another flux from the carbon in the atmosphere, which increases the stock of carbon sequestered. Carbon captured from CCS also increases that stock. The sum of carbon from that stock that is lost re-enters the atmosphere.

Other greenhouse gases

Other GHGs included in CO2 equivalent emissions

The basis for emissions is described in the Emissions section. En-ROADS explicitly models other well-mixed greenhouses gases, including methane (CH₄), nitrous oxide (N₂O), and the fluorinated gases (PFCs, SF₆, and HFCs). PFCs are represented as CF₄-equivalents due to the comparably long lifetimes of the various PFC types. HFCs, on the other hand, are represented as an array of the nine primary HFC types, each with its own parameters. Ozone-depleting substances (ODSs, also called "Montreal gases", principally CFCs and HCFCs) are represented as an aggregated stock with averaged parameters. The structure of each GHG's cycle reflects first order dynamics, such that the gas is emitted at a given rate and is taken up from the atmosphere according to its concentration and its time constant. Initialization is based on 1990 levels of data from GISS for CH₄ and N₂O and according to C-ROADS (2023) for F-gases. The remaining mass in the atmosphere is converted, according to its molecular weight, to the concentration of that gas. The multiplication of each gas concentration by the radiative coefficient of the gas yields its instantaneous radiative forcing (RF). This RF is included in the sum of all RFs to determine the total RF on the system.

For those explicitly modeled GHGs, the CO_2 equivalent emissions of each gas are calculated by multiplying its emissions by its 100-year Global Warming Potential. Time constants, radiative forcing coefficients, and the GWP are taken from the IPCCs Fifth Assessment Report (AR5) Working Group 1 Chapter 8. (Table 8.A.1. Lifetimes, Radiative Efficiencies and Metric Values GWPs relative to CO_2).

In addition to the anthropogenic emissions considered as part of the CO_2 equivalent emissions, CH_4 , N_2O , and PFCs also have a natural component. The global natural CH_4 emissions are from the anaerobic respiration of biomass, soil, and oceans. The global natural N_2O emissions are based on MAGICC output, using the remaining emissions in their "zero emissions" scenario. The global natural PFC emissions are calculated by dividing Preindustrial mass of CF_4 equivalents by the time constant for CF_4 . The units of each gas are: MtonsCH4, MtonsN2O-N, tonsCF4, tonsSF6, and tonsHFC for each of the primary HFC types. To calculate the CO_2 equivalent emissions of N_2O , the model first converts the emissions from MtonsN2O-N/year to Mtons N_2O /year.

The sensitivity of this release defaults to 0.1% per degree Celsius over a threshold, defaulted to 2 Degrees Celsius; the user may change these assumptions.

Cumulative Emissions

En-ROADS calculates the cumulative CO_2 with the initial value taken as the 1990 C-ROADS value starting in 1870. Cumulative emissions are determined through the simulation. The trillionth ton is a marker of cumulative emissions above which a two degree future is far less likely. Budgets are also presented from 2011 and from 2018, based on IPCC thresholds.

Model Structure





Climate

Introduction

Like the carbon cycle, the climate sector is adapted from the FREE model, which used the DICE climate sector without modification (Nordhaus 1994). The DICE structure in turn followed Schneider and Thompson (1981).

The model has been recast in terms of stocks and flows of heat, rather than temperature, to make the physical process of accumulation clearer to users. However, the current model is analytically equivalent to the FREE and DICE versions. While FREE and DICE used exogenous trajectories for all non-CO₂ radiative forcings, this version adds endogenous forcings from all well-mixed GHGs, i.e., CO_2 , CH_4 , N_2O , PFCs, SF₆, and each HFC type.

Structure

The climate is modeled as a fifth-order, linear system, with three negative feedback loops. Two loops govern the transport of heat from the atmosphere and surface ocean, while the third represents warming of the deep ocean. Deep ocean warming is a slow process, because the ocean has such a large heat capacity. If the deep ocean temperature is held constant, the response of the atmosphere and surface ocean to warming is first-order. Temperature change is a function of radiative forcing (RF) from greenhouse gases and other factors, feedback cooling from outbound longwave radiation, and heat transfer from the atmosphere and surface ocean to the deep ocean to the deep ocean layer.

$$egin{aligned} T_{ ext{surf}} &= rac{Q_{ ext{surf}}}{R_{ ext{surf}}} \ T_{ ext{deep}} &= rac{Q_{ ext{deep}}}{R_{ ext{deep}}} \ Q_{ ext{surf}} &= \int (RF(t) - F_{ ext{out}}(t) - F_{ ext{deep}}(t)) \, dt + Q_{ ext{surf}}(0) \ Q_{ ext{deep}} &= \int F_{ ext{deep}}(t) \, dt + Q_{ ext{deep}}(0) \end{aligned}$$

T = temperature of surface and deep ocean boxes

- Q = heat content of respective boxes
- R = heat capacity of respective boxes

RF = radiative forcing

 F_{out} = outgoing radiative flux

 F_{deep} = heat flux to deep ocean

$$egin{aligned} F_{ ext{out}}(t) &= \lambda \, T_{ ext{surf}} \ F_{ ext{deep}}(t) &= R_{ ext{deep}} \cdot rac{T_{ ext{surf}} - T_{ ext{deep}}}{ au \end{aligned}$$

 λ = climate feedback parameter

au = heat transfer time constant

Radiative forcing from CO₂ is logarithmic of the atmospheric CO₂ concentration, but also dependent on the N₂O concentration (IPCC AR6, 2023; NOAA, 2023). Forcing from CH₄ and N₂O is less than the sum of RF from each individually to account for interactions between both gases; CO₂ concentrations also affect forcings from N₂O. Forcing from each F-gas is the product of its concentration and its radiative forcing coefficient; the total forcings of F-gases is the sum of these products, as are the forcings from MP gases derived. The sum of other forcings, which include those from aerosols (black carbon, organic carbon, sulfates), tropospheric ozone, defaults to an exogenous time-varying parameter. The values use a composite of AR6 history 1750-2019 and their projections for SSP4 6.0 through 2100. The equilibrium temperature response to a change in radiative forcing is determined by the radiative forcing coefficient, κ , and the climate feedback parameter, λ . Equilibrium sensitivity to 2xCO2eq forcing is 3°C in the base case. The plot of that relationship is shown as Figure 11.1.

$$T_{ ext{equil}} = rac{\kappa \cdot lnig(rac{C_a}{C_{ ext{a},0}}ig)}{\lambda \cdot ln(2)}$$

 T_{equil} = equilibrium temperature

 C_a = atmospheric CO₂ concentration

- $C_{a,0}$ = preindustrial atmospheric CO₂ concentration
 - κ = radiative forcing coefficient
 - λ = climate feedback parameter



Model Structure



Sea Level Rise

Sea Level Rise (SLR) is modeled by extending the semi-empirical approach proposed by Vermeer and Rahmstorf (2009) in a way to accommodate the water impoundment by artificial reservoirs and to experiment with higher levels of contribution to SLR from ice sheet melting in Antarctica and Greenland than already assumed. The model is estimated from historical data 1900-2021, a period with low levels of warming that therefore may underestimate future sea level rise from the faster-than-historical rates of melt of the Greenland and Antarctic ice sheets. "Contribution to SLR from Ice Melt in Antarctica by 2100" and "Contribution to SLR from Ice Melt in Greenland by 2100" sliders allow users to capture these effects. Sliders are initialized with the mid-range estimates for the contribution of ice sheet melting in Antarctica/Greenland in the IPCC AR6 report.



Model Structure

Damage to GDP

In En-ROADS, economic growth can be reduced from what it would otherwise be, due to the effects of climate change on human activity. En-ROADS uses temperature change as a proxy for the multiple effects of shifting patterns of temperature, rainfall, disease, etc., that might affect the economy. Economists refer to these effects as the "damage function" and measure the net present value of potential damage as the social cost of carbon.

Literature on damage function

In the scientific literature, aggregate economic impact of climate change is expressed as a fraction of 'annual income', global GDP or GDP per capita. It is formulated as an increasing function of global mean temperature change from preindustrial times. Extensive research into the literature shows the vast disparity between estimates of damage at varying temperature changes. See Damage Function References.

We assessed the very low estimates (Nordhaus, 2007, 2013, and 2016; Weitzman, 2012), ranging from 1% at 2°C, 2-3% at 3°C, and 4-9% at 4°C, and 6-25% at 5°C, to be unrealistic.

The four sources we deemed most credible and covering a range of rates of increasing damage with increasing temperature change are:

- Burke et al. (2018)
- Burke et al. (2015)
- Dietz and Stern (2015)
- Howard and Sterner (2017)

Burke et al. (2015) estimate the macro impacts of climate change from micro impacts based on an extensive empirical study (e.g. daily temperature effect on labor productivity per person scaled up to annual and global). They conclude that, taking nonlinearities into account, the damage is much higher than the earlier estimates, which is 21% of GDP per capita by 2100 on average. Wealthy countries are not unaffected. Their estimates take different responses by countries into account. In the 'pooled response' formulation, rich and poor countries are assumed to respond identically to the temperature change. Short run estimates account for 1 year of temperature, whereas long run estimates account for 5 years of temperature change.

In their 2018 study where they focus on the impact of mitigation targets, they estimate 15%–25% loss in GDP per capita by 2100 for 2.5–3°C warming, and more than 30% for 4°C. Their damage function is widely used in recent studies that analyze the social cost of carbon (Ricke et al., 2018; Taconet et al., 2020; Glanemann et al., 2020). Dietz and Stern follow the formulation of Weitzman (2012), yet assume 50% damage at 4°C.

Through a meta-analysis, Howard and Sterner (2017) determined quadratic equations to define the damage function with varying assumptions:

- Preferred model for non-catastrophic damage
- Preferred model for total (non-catastrophic plus catastrophic) damages
- Preferred model for total damages plus productivity

Modelling the damage function in En-ROADS

The literature has a variety of damage function forms and values. In En-ROADS, we would like to capture all these, and to allow users explore a wider variety of damage values while keeping the model robust. Accordingly, there are five options in the model, four presets using the equations to reflect the chosen literature and one to customize the damage function with a logistic equation with user specified parameters. There is also an additional option to turn off the damage entirely.

For each source, the model uses the exact formula given, or determined if not provided, to capture the preset. Burke *et al* (2015 and 2018) do not define a damage function but instead show curves of damage vs. temperature change. Accordingly, we digitized the graphs and assessed regression analyses Ω with cubic, quadratic, and linear equations for Ω = Damage function = 1-1/(1+D). Cubic regression, i.e., Ω = 1-1/(1+ α *T+ β *T2+ γ *T δ)), best captures the fit for all relevant temperatures. Unlike Dietz and Stern (2015) and Burke *et al* (2015 and 2018), Howard and Sterner (2017) define Ω = D as noted below.

Burke et al, 2018 SR Pooled α = 0.3079; β = -0.0532; γ = 0.004; δ = 3

Burke et al, 2015 LR Pooled α = 0.3074; β = 0.0144; γ = 0.0168; δ = 3

Dietz and Stern, 2015 α = 0; β = 1/18.82; γ = 4 δ ; δ = 6.754

Howard and Sterner, 2017 Ω = D "Preferred model for total damages plus productivity" Ω = 1.145 * T2

For the customized damage function, we use a logistic function formulation with three parameters, L, k and x_0 , where L is the maximum damage, k refers to the steepness of the damage curve and x_0 is the inflection point.

$$D(t) = \frac{L}{1 + e^{-k(T(t) - x_0)}} \tag{1}$$

This allows for a function form that captures the damage function shapes and values presented in the literature and allows parameterization based on easily understandable user inputs (sliders) such as "the damage % at 1.5°C warming" and/or the "maximum damage" saturates at the maximum damage value entered by the users or at 100% so that the damage and GDP values are kept in realistic ranges for extreme temperatures.

Social Cost of Carbon

Social cost of carbon (SCC) is the marginal cost of emitting one extra tone of CO₂ in a given year. It is a commonly used metric in US administration and climate policy debate. En-ROADS shows the SCC in the present year (i.e. 2023) calculated according to the emission trajectory in the baseline scenario, and the subsequent economic damage of this emission trajectory which depends on the user inputs for the damage function, Social Discount Rate, and climate sensitivity assumptions.

To calculate SCC in En-ROADS, we adopt the approach followed by United States Interagency Working Group (IWG) (Greenstone et al., 2013), which calculated the SCC values used by the US government. This approach involved simulating the integrated assessment models until 2300, since atmospheric CO₂ has a very long lifetime and the economic damages from today's emissions are observed for centuries. Therefore, even though the normal time horizon of En-ROADS is until 2100, for SCC calculation it is extended until 2300. In other words, all scenarios displayed by En-ROADS cover the horizon through 2100, yet SCC is calculated based on two additional simulations run upon demand (when users click on the SCC table on UI) through 2300. For the post-2100 period in these simulations to 2300, we make the following assumptions following IWG:

- IWG assumes that population growth rate declines linearly after 2100, reaching zero in the year 2200, hence a stable population after 2100. In the En-ROADS population stabilizes by 2100 already in the baseline scenario.
- GDP per capita growth rate is assumed to decline linearly after 2100, from whatever value it takes in 2100 based on user inputs and damage, reaching zero in the year 2300.
- The rate of decline in the Carbon intensity of GDP (CO₂ emissions from energy / GDP) between 2090 and 2100 is maintained from 2100 through 2300. To formulate this assumption,
 - We calculate the average rate of change of the Carbon intensity of GDP in 2090-2100.
 - We compute the Post-2100 carbon intensity of GDP according to this new constant rate of change.
 - $\circ~$ We calculate the post-2100 CO_2 emissions from energy are as the multiplication of this Post-2100 carbon intensity of GDP * Global GDP.
- Net land use CO₂ emissions (LULUCF net emissions) are assumed to decline linearly after 2100, from any value they take in a scenario in 2100, reaching zero in the year 2200.
- Non-CO₂ GHG emissions (that of CH₄, N₂O, SF₆, PFC and HFC) are assumed to follow the same rate of change as CO₂ emissions. In other words, the post-2100 trajectory of all these GHG gases are set to follow the trajectory of CO₂.

With these assumptions for the 2100-2300 period, SCC is calculated with the following three main steps:

Step 1: Run a baseline damage scenario through 2300 and calculate the present value of damage

With any user-set assumptions for the economic impact of temperature rise (damage function) and other climate system assumptions, the damage, i.e. the percentage of global GDP loss (D) is calculated as in Equation 1 above. From there, annual Global GDP Loss (L) is calculated as the corresponding fraction of Global GDP (Gross World Product, GWP), Equation 2. These losses over time are discounted to the present year with the variable Present Value of Global GDP Loss (PVL) based on the user-set Social Discount Rate (r) as in Equation 3, where t_p is the present year. Present Value of Cumulative Damage until time is the accumulation of PVL as denoted in Equation 4 where t_0 and t_f are the initial and final time, respectively, i.e. 1990 and 2300.

$$L(t) = D(t) \cdot GWP(t) \tag{2}$$

$$PVL(t) = L(t) \cdot \frac{1}{(1+r)^{MAX\{0, t-t_p\}}}$$
(3)

$$CPVL(t) = \int_{t_0}^{t_f} PVL(t) \, dt \tag{4}$$

Step 2: Run an emission shock scenario through 2300 and calculate the present value of damage

The same scenario as in Step 1 is simulated with an additional 1 Gton of CO_2 emissions in the present year. In other words, the trajectory of CO_2 emissions is perturbed with the pulse of 1 GtonCO2 yr⁻¹ in the present year.

Step 3: Calculate SCC as the marginal damage between the two simulations

The difference between the Present Value of Cumulative Damage by 2300 in the two simulations yields the social cost of carbon. This formulation is denoted in Equation 5:

$$SCC(t_p) = \frac{CPVL^2(t_f) - CPVL^1(t_f)}{e}$$
(5)

 $CPVL^{1}(t_{f}) = Present Value of Cumulative Damage in the baseline damage scenario in the final time (2300)$ $<math>CPVL^{2}(t_{f}) = Present Value of Cumulative Damage in the emission shock scenario in the final time (2300)$ <math>e =amount of the emission shock (1 GtonCO2 yr⁻¹)

Damage Function References

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Other Impacts

Air Quality-PM2.5

The air quality sector simulates annual global emissions of PM2.5. En-ROADS estimates annual global emissions from three sources: energy generation (electricity), energy generation (non electricity), and other sources (including agriculture and open fires).



Ambient PM2.5 is considered the leading environmental health risk factor globally and is a top 10 risk factor in countries across the economic development spectrum. PM2.5 is fine particulate matter as defined by the mass per cubic meter of air of particles with a diameter of <=2.5 micrometers (μ m).

The components of PM2.5 are solid and liquid particles small enough to remain airborne and are defined as two forms:

- 1. Solids/liquid particles directly emitted to the atmosphere (primary PM).
- 2. Solids/liquid particles formed from gaseous precursors (secondary PM).

Components of PM2.5 may include (some of) the following:

- Carbons
- Sulfates
- Nitrates
- Chlorides
- Iron
- Calcium
- Other Organics (solid/liquid)
Sources of PM2.5 in En-ROADS – Overview

PM2.5 is generated from multiple sources. The chart was from research Global Sources of Fine Particulate Matter: Interpretation of PM2.5 Chemical Composition Observed by SPARTAN using a Global Chemical Transport Model (Weagle et al 2018).

En-ROADS aggregates these sources into the following sources:

- 1. Energy generation a. Electricity production b. Energy (non electricity) production
- 2. Non-energy generation a. agriculture, b. open fires, c. other sources.

PM2.5 from Energy Generation

En-ROADS calculates energy generated PM2.5 emissions by applying an emissions factor (EF) (in million metric tons (Mtons) emitted per exajoule (EJ)) for each fuel source to the annual rate of energy produced (in EJ/year).

 $EmissionRate[Fuel] = EF[Fuel] \times ElectricityProduction[Fuel]$

EFs for fuel sources are calculated in several input-output models. En-ROADS applies EFs estimated from analysis by the International Institute for Applied Systems Analysis (IIASA). The EFs for coal, oil, and gas were calculated using the GAINS model (IIASA) to estimate emissions/year from G20 countries/regions and then averaged. Countries included the United States, several EU countries, India (2 regions) and China (3 different regions). The EF for bio was calculated from the RAINS model (IIASA).

Estimates for EFs were not significantly different between electricity and non electricity (which includes industry). En-ROADS applies the same EFs to electricity and non electricity. Users can vary the EF assumption across a range (by source), with a range of 50% to 150% of the base EF (shown in the table below).

Table 14.1 Emission Factors by Fuel		
Source	EF (Mtons/EJ)	
Coal	0.1200	
Oil	0.0050	
Gas	0.0001	
Bio	0.0400	

PM2.5 from Non Energy Sources

Non-energy sources of PM2.5 are estimated by applying a per capita EF (Mtons/year/billion people) to global population (billion people). The per capita EF is set at the start of the scenario year.

In 2015, non-energy sources of PM2.5 accounted for 35% total PM2.5 emissions. En-ROADs uses that 35% as an estimate of the non-energy contribution to total prior to 2015.

The per capita PM2.5, is calculated in 2015 (Scenario Year) by dividing global non-energy PM2.5 (Mtons/year) by global population in billions (2015). For 2015 and remaining simulated years, non-energy PM2.5 (Mtons/year) is calculated by multiplying global population (billions) by the 2015 emissions factor.

рΗ

The pH sector of En-ROADS reflects the empirical function presented by Bernie et al. (2010). As the atmospheric concentration in the atmosphere increases, the pH of the ocean decreases by a third order response.

Other Impacts from Warming

The continuous increase in the global temperature is expected to cause a variety of impacts on ecology and human activities – in addition to sea level rise, increased ocean acidity and the loss in global GDP discussed in previous sections. More frequent and intense extreme weather events, major reduction in global crop yield and biodiversity loss are some examples of the other anticipated impacts of climate change. En-ROADS simulates four categories of such climate impact metrics (some categories containing more than one metric):

- Population Exposed to Sea Level Rise
- Probability of Ice-free Arctic Summer
- Crop Yield Decrease from Warming
- Species Losing More than 50% of Climatic Range

Building on the findings of four peer-reviewed climate studies, we formulated the relationship between global mean temperature (as well as sea level rise) and these metrics (primarily through interpolation and extrapolation).

Nature Impacts from Warming

Drawing on the IPCC's Sixth Assessment Report, we identified and formulated relationships between global mean temperature and impacts on ecosystems.

Ecosystem Shifts from Warming

A notable projected impact of climate change is the risk of ecosystem shift which was presented in Ostberg et al. (2013) and expanded in Warszawski et al. (2013). Climate change is expected to cause biogeochemical changes in land, which would affect flora and fauna and their interactions, thus impacting ecosystems. The assumption is the larger biogeochemical changes are, the higher the risk of ecosystems being disrupted.

Global land was classified into 16 categories as follows:

Table 14.2 Land Type Classification

Land types	
Tropical rainforest	Warm woody savanna, woodland & shrubland
Tropical seasonal & deciduous forest	Warm savanna & open shrubland
Temperate broadleaved evergreen forest	Warm grassland
Temperate broadleaved deciduous forest	Temperate woody savanna, woodland & shrubland
Mixed forest	Temperate savanna & open shrubland
Temperate coniferous forest	Temperate grassland
Boreal evergreen forest	Arctic tundra
Boreal deciduous forest	Desert

Warszawski et al. (2013) used an ensemble of global vegetation models to estimate the percentage of global land area at risk of experiencing ecosystem shifts, from one land type to another, under different temperature scenarios. We digitized the S-shaped relationship from Warszawski et al. (2013) Figure 3 into En-ROADS and linked it to our temperature projections to enable the user to track the impact of different policy scenarios on ecosystems. We converted the percentage to area in million hectares to make it more relevant to En-ROADS users.

Arid Land Expansion from Warming

One worrisome land type change is desertification as increased aridity can change an area's capacity to supply ecosystem services or host biodiversity. Increased aridity is often associated with desertification, although recent studies show the relationship is not one-to-one. We used a bias-corrected estimate from the CMIP5 model ensemble from Huang et al. (2016) Figure 2 to link temperature rise to the increased area of arid lands globally. Digitizing the relationship over time under two RCP scenarios, we estimated an exponential relationship between global arid land area and temperature over the 21st century.

Extinction Risk of Endemic Species

As the warming climate disrupts ecosystems, many species confined to a specific region (i.e., endemic species) are expected to be endangered with extinction due to small population sizes, loss of limited habitat, inability to move, and low capacity to adapt.

We digitized data from Manes et al. (2021) Figure 5(b) and fit a logistic curve to estimate the percentage of endemic species at extremely high risk of extinction, as a function of temperature relative to pre-industrial levels. A logistic curve was selected as it was robust for making projections under high warming scenarios, while satisfying a good fit with the data.

The temperature axis for Figure 5(b) was semi-qualitative. We thus made reasonable assumptions on the given temperature ranges, drawing on data from the CMIP6 (SSP) climate projections, to improve the analytical usability of the data from the figure.

Loss in Ocean Life from Warming

Climate change is expected to affect oceans in a variety of ways including changing the average water temperature, dissolved oxygen concentration, pH, and nutrient circulation. Such changes may disrupt marine ecosystems and ocean life, often represented in Earth system models as biomass.

We used data from Tittensor et al. (2021) Figure 1 and Figure 3(b) to estimate the relationship between temperature and the percent loss in ocean biomass, relative to pre-industrial levels, using a linear fit.

We presented three trophic levels to emphasize the phenomenon of trophic amplification, whereby species at a higher level in the food chain are more vulnerable to the effects of climate change due to reduced trophic efficiencies, lengthening of food chains, and higher metabolic costs (Lotze et al., 2019).

Health Impacts from Warming

Drawing on peer-reviewed literature we identified and formulated relationships between global mean temperature and impacts on human health.

Outdoor Labor Losses from Extreme Heat

As global temperatures rise, outdoor labor losses due to extreme heat are projected to increase. Parsons et al. (2021) illustrated this impact by linking changes in Global Mean Temperature to reductions in work capacity in outdoor heavy labor sectors such as agriculture, forestry, fisheries, and construction.

Using an exposure-response framework based on epidemiological data, the study estimated reduction in work capacity at different hourly Wet Bulb Globe Temperature (WBGT), with productivity losses of <1% at WBGT of 20°C, 10% at 27°C, 50% at ~32.5°C, and 90% losses at ~38°C. Using CMIP6 projections for the 21st century, the study generated estimates for daily WBGT for all countries included in the study (n=163) to aggregate global heavy labor workforce, reported in Figure 3(a) of the article.

We fit an exponential curve to the data from Figure 3(a) having adjusted temperature rise to be relative to preindustrial levels, and used the global workforce assumptions from the supplementary material of Parsons et al. (2021) to calculate the per worker annual hours/days of labor lost due to rising temperatures, which was converted into 12-hour workdays. By coding this exponential relationship into En-ROADS, we were able to estimate future outdoor heavy labor losses due to temperature rise.

Population Exposed to River Flooding

As global temperatures rise, more people are projected to be exposed to river flooding as the likelihood of extreme weather events rise.

The relationship between temperature rise and the population annually exposed to river floods was derived from Alfieri et al. (2017), Fig. 4(a) and Dottori et al. (2018), Fig. 1(b), defining flood exposure as residing in areas experiencing high-flow events with a return period larger than the value of local flood protections in a given year. These studies estimated vulnerable populations by overlaying population density maps with global flood hazard maps generated by a hydrological model, simulated with projections from 7 climate models.

We normalized the estimates from both studies to constant 2015 populations, allowing us to calculate percentage-based exposure. We fit exponential curves to both sets of results and averaged them to formulate the relationship between temperature rise and exposure to river flooding. Multiplying this estimated percentage by total population in En-ROADS gives the results shown in the graph for the population exposed to river flooding.

Population Exposed to Tropical Cyclones

As global temperatures rise, more people are projected to be exposed to hurricanes, typhoons, and tropical cyclones as the likelihood of extreme weather events rise.

Studies by Lange et al. (2020) and Geiger et al. (2021) estimated a relationship between temperature rise and the global population at annual risk of exposure to hurricanes, typhoons, or tropical cyclones, defining exposure as encountering hurricane-force winds (\geq 64 knots wind speed) for at least one minute in a given year.

We digitized and averaged data from these studies to estimate the percentage of the global population annually exposed, using an exponential fit to formulate the relationship between temperature rise and exposure to tropical cyclones in En-ROADS. Multiplying this estimated percentage by total population in En-ROADS gives the results shown in the graph for the population annually exposed to hurricanes, typhoons, or tropical cyclones.

Deaths from Extreme Heat

Vicedo-Cabrerra et al. (2018) used an exposure-response framework to estimate the relationship between historically observed daily temperature and excess mortality in each study location. The study used 3 Global Climate Models (GCM) to generate daily temperature estimates for all countries included in the study to project temperature-related excess mortality under the RCP8.5 scenario up to 2099, assuming no change in demographics or population vulnerability.

Using the results of Vicedo-Cabrerra et al. (2021) Fig. 4(a) we determined the retrospective global estimates for heat-related excess death, as well as those of West Asia and Southern Africa. Assuming the projected global trend of temperature effect on the excess heat-related mortality from Table S3 in Vicedo-Cabrerra (2018) applied to each of the two regions, future projections were estimated for West Asia and Southern Africa, overcoming one of the limitations of the 2018 study.

Subsequently, we converted the metric used in the above studies (% of total deaths) to a more commonly used 'annual deaths per 100,000 people' using World Bank Open Data for historical population and crude death rates. Finally, we fit exponential lines through the processed data points to get region-by-region as well as global relationships between temperature rise relative to pre-industrial levels and annual heat-related deaths per 100,000 population.

This methodology carries certain caveats. The assumption that the global trends in temperature-related excess mortality apply uniformly to West Asia and Southern Africa may be an underestimate of temperature-related excess mortality risks due to local vulnerabilities. The methodology also inherits sampling biases from the original study, as the data were limited to certain urban populations and geographical areas, as shown in the country list from Table S1 in Vicedo-Cabrerra (2018) below. Countries with an * are from Vicedo-Cabrerra (2021).

Regions	Countries/Territories
North America	Canada, United States
Central America	Mexico
South America	Brazil, Chile
North Europe	Finland, Ireland, Sweden, United Kingdom
Central Europe	Czech Republic, France, Moldova, Switzerland
Southern Europe	Italy, Spain
East Asia	China, Japan, South Korea
Southeast Asia	Philippines, Taiwan, Thailand, Vietnam
West Asia	Iran*, Kuwait*
Australia	Australia
Africa	South Africa*

Malaria and Dengue Exposure

As global temperatures rise, exposure to vector-borne diseases is projected to increase. Colón-González et al. (2021) illustrated an example of this impact by linking multiple RCP (Representative Concentration Pathways) scenarios to projections of global population at risk (PAR) of malaria and dengue diseases. Population at risk does not mean catching the disease, rather living in a location where the climatic conditions promote vector transmission for at least one month in a given year.

Using an ensemble of disease models to simulate the transmission of malaria and dengue in the 21st century, the study estimated the effect of warming on the length of disease transmission season (LTS), and the global PAR. The disease models were simulated on a global 0.5 × 0.5 degree latitude–longitude grid using projections of daily temperature, precipitation, and humidity from four global circulation models (GCM) under multiple RCP-SSP combinations.

We estimated the relationship between temperature and the percentage of the global population at risk of malaria, and at risk of dengue, by normalizing the population at risk projections from Figure (A8-Supplementary) and Figure (A9-Supplementary) by their respective SSP scenario population at temperatures corresponding to cutoff timepoints in each RCP scenario (e.g. 2030, 2050, 2100).

We fit a quadratic curve of best fit to that relationship as suggested in Colón-González et al. (2021). We then subtracted the estimated pre-industrial percentage of global population at risk to report the additional population at risk due to warming. We present the additional exposure per 100,000 people, a commonly used metric in Epidemiology reporting.

Crop Nutrient Decrease from CO₂ Concentration

As atmospheric CO₂ levels rise, crops grown under these conditions exhibit reduced concentrations of key nutrients such as zinc, iron, and protein, posing a threat to global nutrition (Myers et al., 2014). Zinc and iron deficiencies are significant public health concerns, with wheat, rice, and maize serving as critical dietary sources of these nutrients.

The relationship between rising atmospheric CO_2 levels and declining crop nutrients was derived from Myers et al. (2014). We digitized the mid-points of impact ranges reported in the paper and calculated the implied percentage change in nutrient content per each ppm increase in CO_2 concentration, given the ambient and elevated CO_2 levels reported in each experiment. This percentage change is built into En-ROADS and connected to CO_2 concentration. The linear relationship which we assume is further supported by Ziska et al. (2016).

While Myers et al. (2014) present nutrient reductions separately, we report average declines in zinc, iron, and protein (relative to 1995 as the baseline year) to ensure comparability with the "Crop Yield Decrease from Warming" graph.

Model Comparison – History

The purpose of this section of the En-ROADS Technical Reference is to supplement the historical comparison graphs in the En-ROADS application by sharing multiple comparisons of En-ROADS model behavior compared against measured historical data.

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- 1. Use of Historical Data in En-ROADS
- 2. Primary Energy Demand History
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- 4. Electricity Generated by Energy Source History
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- 7. Atmospheric Concentrations History
- 8. Radiative Forcing History
- 9. Temperature History

Use of Historical Data in En-ROADS

En-ROADS uses historical data for two purposes: initialization of the simulation and calibration. Certain variables in En-ROADS are initialized with their measured historical values from 1990, and then the model runs. We compare the model output from 1990 through present day to measured historical data to identify opportunities for model improvement.

The graphs below compare the En-ROADS Baseline Scenario to measured historical data for select variables. Not all variables and comparisons to history are included here. The historical data are derived from the following sources:

- Energy Institute. (2024). Statistical Review of World Energy.
- Global Carbon Budget: Friedlingstein, P., et al. (2025). Global carbon budget 2023. *Earth System Science Data, 17*(3), 965-1039. [CO₂ energy emissions only]
- IEA. (2020). Evolution of solar PV module cost by data source, 1970-2020.
- IEA. (2024). World Energy Statistics & Balances.
- IRENA. (2023). Renewable Power Generation Costs in 2022.
- Lazard. (2023). Lazard's Levelized Cost of Energy Analysis Version 16.0.
- Met Office: Morice, C. P., et al. (2022). An updated assessment of near-surface temperature change from 1850: the HadCRUT5 dataset. *Journal of Geophysical Research: Atmospheres, 126,* e2019JD032361. Data is from HadCRUT version 5.0.2.0 (2024), available at https://www.metoffice.gov.uk/hadobs/hadcrut5/data/HadCRUT.5.0.2.0/download.html.
- NASA GISS. (2025). *GISS Surface Temperature Analysis (GISTEMP), version 4.* NASA Goddard Institute for Space Studies.
- NOAA AGGI: NOAA. (2023). Annual Greenhouse Gas Index.
- NOAA ESRL: NOAA. (2025). Trends in Atmospheric Carbon Dioxide.
- PRIMAP: Gütschow, A., Busch, D., & Pflüger, M. (2024). *The PRIMAP-hist national historical emissions time series v2.6 (1750-2023)*. [Non-CO₂ greenhouse gas emissions only]

Five historical comparison graphs are also included in the En-ROADS app under *Graphs > Model Comparison— Historical* and are included and disaggregated here:

- Greenhouse Gas Net Emissions History
- Primary Energy Demand of Coal, Oil, and Gas History
- Primary Energy Demand of Wind and Solar History
- Marginal Cost of Solar Electricity History
- Temperature History

Primary Energy Demand History

Global primary energy demand of energy sources for the En-ROADS Baseline Scenario compared to historical data. This is measured in exajoules per year (joules x 10¹⁸/year) for electric and nonelectric sources combined.

Primary energy refers to the total energy from a raw energy source that is converted into consumable energy. For example, primary coal energy demand refers to the total energy in coal that is mined, processed, and consumed. Primary energy is greater than final energy consumption because it accounts for inefficiencies in fuel processing, thermal conversion, and transmission and distribution (T&D).

En-ROADS, as well as many other sources, assumes that nuclear energy has an efficiency of 100% conversion of primary energy into electricity generated. Some sources, like the IEA World Energy Statistics & Balances, assume that the primary energy equivalent from the electricity generation has an efficiency of 33%. To compare En-ROADS output to the IEA World Energy Statistics & Balances, we multiply the primary energy from nuclear in En-ROADS by 3.

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Final Energy Consumption History

Global total final consumption of energy sources in exajoules/year (joules x 10¹⁸/year) for electric and nonelectric sources combined in the En-ROADS Baseline Scenario compared to historical data.

Final consumption refers to the total energy consumed to meet the demand of all final energy uses plus the use of feedstocks for products like plastics. For example, how much electricity a lightbulb uses or how much fuel a truck burns are measures of final energy consumption. It does not include energy lost through transmission and distribution (T&D) or inefficiencies, which, in contrast, is accounted for in primary energy.

Final energy consumption is divided into two end uses: stationary (buildings and industry) and transport.

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Marginal Cost of Wind, Solar, and Geothermal Electricity History

The marginal cost of electricity production from wind, solar, and geothermal energy in dollars (\$US 2021) per kilowatt hour (kWh) in the En-ROADS Baseline compared to historical data. This is the marginal cost for energy producers to make electricity from a new solar, wind, or geothermal installation. The cost factors in how much it costs to build new energy generation facilities (the levelized capital costs), how much it costs to operate and maintain new facilities (0&M), and how much it costs to store the energy.

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Emissions History

Global greenhouse gas emissions (GHGs) in the En-ROADS Baseline Scenario and historical data, in gigatons of CO_2 or CO_2 equivalents per year. CO_2 equivalents are used to standardize the effect of all greenhouse gases in terms of CO_2 .

The Greenhouse Gas Net Emissions graph measures the total gross greenhouse gas emissions minus the total net anthropogenic carbon dioxide removal (CDR). Contributions to gross GHGs are from carbon dioxide (CO_2), nitrous oxide (N_2O), methane (CH_4), and the F-gases (PFCs, SF₆, and HFCs).

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Atmospheric Concentrations History

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Radiative Forcing History

The radiative forcing due to CO_2 , CH_4 , N_2O , and halocarbons in the atmosphere, in watts per meter squared (W/m²), in the En-ROADS Baseline Scenario compared to historical data. Halocarbons refer to F-gases (PFCs, SF₆, and HFCs) and Montreal Protocol gases.

Greenhouse gases absorb infrared radiation and re-radiate it back, causing an increase in surface temperature. Radiative forcing measures the difference between energy absorbed by the Earth and energy radiated back into space. When incoming energy is greater than outgoing energy, RF is positive and the planet will warm.

Temperature History

Temperature change from 1850 in the En-ROADS Baseline Scenario compared to historical data, in degrees Celsius. NASA GISS (GISTEMP v4) includes the average and the lower and upper 95% confidence intervals.

Temperature Change

Model Comparison – Future

This section describes how we test En-ROADS projections against future scenarios from other scientific models. These comparisons give us an opportunity to look for ways to improve En-ROADS and build our confidence that En-ROADS is appropriate to its purpose of improving decision-maker understanding of the dynamics of the climate-energy-land-economic system.

What Do We Mean by Comparisons? - One Example

To illustrate how En-ROADS compares with other models, consider the example of coal primary energy demand. The graph below compares coal demand in the En-ROADS Baseline Scenario with six scenarios produced by leading modeling organizations, including the Network for Greening the Financial System (NGFS), the International Energy Agency (IEA), and the Production Gap Report. The remaining graphs in the grid compare En-ROADS versions of NGFS scenarios to results from the models used by NGFS. Scroll down to see comparisons to additional key variables.

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1. Preliminary Findings

Our analysis shows that En-ROADS aligns well with future climate and energy scenarios modeled by major integrated assessment models (IAMs), including those used by the Network for Greening the Financial System (NGFS). When tested under similar conditions, En-ROADS' results are, on average, statistically as close to those of other IAMs as the IAMs are to one another. This suggests that En-ROADS reliably captures the dynamics of the energy, land, forest, and climate systems in alignment with widely accepted scientific models, while maintaining its strengths of speed, transparency, and ease of use.

Statistical measures, including high correlation (R²) and low error metrics like RMSE, demonstrate a strong alignment between En-ROADS and other IAMs. To explore these metrics, click the three dots in the upper-right corner of a comparison graph on this page and select *"Show Statistics."*

The following sections outline our methodology and scenario comparisons in greater detail.

2. Exceptions and Caveats

While we present a broad range of comparisons, not all variables and scenarios are included here. Additionally, it is important to note that these comparisons are not fully independent validation tests. When designing the model, we do not optimize our parameters to match the output of other IAMs, but we do conduct plausibility checks by comparing En-ROADS results to projections from other models. This approach ensures that En-ROADS remains aligned with broader scientific expectations while preserving its independent formulation.

One notable difference between En-ROADS and the other IAMs is in the modeling of bioenergy: IAMs used by NGFS typically assume lower net emissions from bioenergy than En-ROADS does. Our approach to bioenergy, which accounts for system-wide impacts, is described in Sterman, Siegel, & Rooney-Varga (2018).

3. Testing En-ROADS Against Other More Disaggregated Integrated Assessment Models

En-ROADS belongs to a category of more aggregated, decision-maker-oriented integrated assessment models (IAMs), complementing larger, more disaggregated models such as GCAM, MESSAGEix-GLOBIOM, and REMIND-MAgPIE. The larger models provide richer detail in many areas but take a significant amount of computational power to run and return results after a delay, sometimes in hours or days. En-ROADS, in contrast, returns results in less than a second, enabling real-time policy experimentation by decision-makers, and is designed for simplicity of use and transparency.

The diagram below illustrates these dimensions, with more scope and detail higher on the y-axis and more speed, simplicity of use, and transparency farther along the x-axis. More-aggregated IAMs such as En-ROADS enable users to gain insights that can be refined by more disaggregated models. In turn, the insights of more disaggregated models can inform the design and improve the performance of more-aggregated climate models. These feedbacks are depicted by the two arrows.



The sections below compare En-ROADS scenarios to scenarios generated by models used by four organizations: the Network for Greening the Financial System (NGFS), the International Energy Agency (IEA), the International Atomic Energy Agency (IAEA), and the Production Gap Report.

Click the arrows to reveal more information about these scenarios.

- ▶ NGFS: Network for Greening the Financial System. (2023). NGFS Phase 4 Scenario Explorer.
- ▶ IEA WEO: International Energy Agency. (2024). World Energy Outlook 2024.
- ▶ IAEA: International Atomic Energy Agency. (2024). *Energy, Electricity and Nuclear Power Estimates for the Period up to 2050.*

▶ Production Gap Report: SEI, Climate Analytics, E3G, IISD, and UNEP. (2023). *The Production Gap: Phasing down or phasing up? Top fossil fuel producers plan even more extraction despite climate promises.*

4. Understanding En-ROADS Scenario Comparisons

Baseline Scenario Comparisons

The first graph in each grid below compares the En-ROADS Baseline Scenario to low-climate-policy scenarios from the NGFS, IEA, IAEA, and Production Gap Report. Note that the En-ROADS Baseline Scenario represents the state of the world if societal and technological changes were to continue at their current rate of progress, without additional policies or action. Learn more in the En-ROADS Baseline Scenario chapter in the En-ROADS User Guide.

The En-ROADS Baseline Scenario uses different assumptions than the NGFS IAMs—for example, population in the En-ROADS Baseline Scenario is higher because it follows United Nations population projections, and the carbon prices in the NGFS Current Policies Scenario grow higher than the carbon price in the En-ROADS Baseline Scenario. The variation between the En-ROADS Baseline Scenario and the IAMs producing the NGFS Current Policies Scenario grow the IAMs themselves within the NGFS Current Policies Scenario.

Simulating NGFS Scenarios Using En-ROADS

Another test of En-ROADS is to determine if En-ROADS behaves similarly to the other IAMs when run under similar conditions, including population and economic growth assumptions. The remaining graphs in each grid below compare En-ROADS versions of NGFS scenarios to results from the IAMs used by NGFS. To perform this test, we adjust key settings—such as carbon price and deforestation—to align as closely as possible with each NGFS scenario. The exact inputs to the other IAMs are not published, so we used scenario descriptions and output comparisons to adjust En-ROADS settings to match the overall trends of the NGFS scenarios for these tests.

Note, atmospheric concentration data for NGFS Phase 5 (November 2024) has not been released, so the graphs here compare with NGFS Phase 4, which includes this data.

To view the En-ROADS versions of the NGFS scenarios in the En-ROADS app, click on the three dots on the top right of the graph and select *"Open Scenario in En-ROADS."*

Click the arrow to display the En-ROADS settings used to create the En-ROADS version of each NGFS scenario.

► En-ROADS Settings for Approximating NGFS Scenarios

Definitions of Statistical Measures

For each output variable under each scenario, we calculate statistical error measures to assess how close results from two models are to each other. Click on the three dots on the top right of the graph and select *"Show Statistics"* to open the statistics pane on a given graph.

Statistical measures of closeness included here:

- R² (coefficient of determination) shows how closely the results from one model match another. Higher R² values are better, as they mean the two models produce similar results.
- Symmetric Mean Absolute Percentage Error (SMAPE) measures the difference between two sets of results, adjusted for the size of the values. Lower SMAPE is better, as it means less error between the datasets. It's especially useful when values are very small, like near-zero emissions.
- Root Mean Square Error (RMSE) shows, on average, how much the two datasets differ. Lower RMSE is better, since it indicates smaller differences.
- Mean Squared Error (MSE) can be broken into three parts:
 - Bias (lower is better) shows a systematic gap between the datasets.
 - **Unequal variance (lower is better)** shows systematic differences in trends or direction of changes in response to policy.
 - **Unequal covariance (lower is better**, but usually **less concerning in long-term models)** reflects random, short-term differences.

5. Economic Input Assumptions Comparisons

The graphs below show global GDP (\$US 2021 purchasing power parity) and carbon price in the En-ROADS Baseline and En-ROADS versions of NGFS scenarios, alongside the NGFS IAMs. Unlike the other graphs on this page—which display model *outputs*—these two graphs represent two of the *inputs* that drive the simulations.

Economic Growth

Economic growth in the En-ROADS Baseline Scenario is affected by the economic impact of climate change. Learn more in the Explainer: Economic Impact of Climate Change in En-ROADS.

Carbon Price

The En-ROADS Baseline Scenario includes a carbon price rising up to \$5/ton CO₂ and continuing throughout the century. Learn more in this FAQ: How is the current global carbon price calculated?

6. Energy Comparisons

Total Primary Energy

En-ROADS, as well as many other sources, assumes that nuclear energy has an efficiency of 100% conversion of primary energy into electricity generated. Some sources, like the IEA WEO, assume that the primary energy equivalent from the electricity generation has an efficiency of 33%. To compare En-ROADS output to the IEA WEO, we multiply the primary energy from nuclear in En-ROADS by 3.

Primary Energy from Coal

Primary Energy from Coal with CCS

Primary Energy from Oil

Primary Energy from Natural Gas

Primary Energy from Natural Gas with CCS

Primary Energy from Bioenergy

Primary Energy from Bioenergy with CCS (BECCS)

Primary Equivalent Energy from Nuclear

En-ROADS, as well as many other sources, assumes that nuclear energy has an efficiency of 100% conversion of primary energy into electricity generated. Some sources, like the IEA WEO, assume that the primary energy equivalent from the electricity generation has an efficiency of 33%. To compare En-ROADS output to the IEA WEO, we multiply the primary energy from nuclear in En-ROADS by 3.

Primary Energy from Wind and Solar

Total Final Consumption of Energy Sources

Final Electric Energy Consumption

Total Final Energy Consumption - Electric Transport

Total Final Energy Consumption - Electric Buildings & Industry

Energy Intensity of GDP

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7. Emissions Comparisons

Greenhouse Gas Net Emissions

Greenhouse gas net emissions in En-ROADS include CO_2 emissions from bioenergy. In contrast, the IAMs modeling the NGFS scenarios appear to exclude bioenergy emissions from their accounting of greenhouse gas emissions. The graphs below compare En-ROADS to the NGFS IAMs for (1) greenhouse gas net emissions and (2) greenhouse gas net emissions excluding CO_2 from bioenergy.

CO₂ Net Emissions

 CO_2 net emissions in En-ROADS include CO_2 emissions from bioenergy. In contrast, the IAMs modeling the NGFS scenarios appear to exclude bioenergy emissions from their accounting of CO_2 emissions. The graphs below compare En-ROADS to the NGFS IAMs for (1) CO_2 net emissions and (2) CO_2 net emissions excluding CO_2 from bioenergy.

CO₂ Net Emissions from Land Use, Land Use Change, & Forestry (LULUCF)

 CO_2 net emissions from land use, land use change, and forestry (LULUCF) in En-ROADS include CO_2 emissions from bioenergy. In contrast, the IAMs modeling the NGFS scenarios appear to exclude bioenergy emissions from their accounting of CO_2 emissions. The graphs below compare En-ROADS to the NGFS IAMs for (1) CO_2 net emissions from LULUCF and (2) CO_2 net emissions from LULUCF excluding CO_2 from bioenergy.

N₂O Emissions

CH₄ Emissions

F-Gas Emissions

The Baseline Scenario in En-ROADS does not assume that the Kigali Amendment to the Montreal Protocol, which specifies 80% HFC phase out by 2047, is fully effective.

8. Carbon Sequestration Comparisons

CO₂ Sequestration from Afforestation and Reforestation

CO₂ Sequestration from Non-Afforestation Methods

Initialization, Calibration, Model Testing

En-ROADS initializes and calibrates to available historical data, primarily provided by the following sources:

Energy and Emissions

- Energy Information Administration (EIA) (2019)
- International Energy Agency (IEA) World Energy Balances and World Energy Statistics (2024)
- Energy Institute (EI) Statistical Review of World Energy (2024)
- International Atomic Energy Agency (IAEA) (2024)
- Global Carbon Budget (2024) (CO₂ Energy Emissions and Land Use Change Emissions)
- PRIMAP 2.6 (2024) (Non-CO₂ GHG Emissions only)
- Houghton and Nassikas (2017) (CO₂ Land Use only)

Land Areas

• Land Use Harmonization (LUH2) data (Hurtt et al., 2018)

GHG Concentrations, Radiative Forcings, Temperature Change, Sea Level Rise

- National Oceanic and Atmospheric Administration (NOAA) concentrations (2025) and radiative forcings (2023)
- Goddard Institute for Space Studies (GISS) GISTEMP4 Global Mean Estimates based on Land and Ocean
 Data 1880-2024 (2025)
- Met Office Hadley Centre HadCRUT5.0.2.0 temperature 1850-2024 (2025)
- National Aeronautics and Space Administration (NASA) satellite sea level rise (2023)

En-ROADS compares to projected values provided by the following sources:

- International Energy Agency (IEA) WEO (2024)
- Network for Greening the Financial System v4.2 (2024)
 - GCAM 6.0 (U.S.)
 - MESSAGEix-GLOBIOM 1.1-M-R12 (IIASA)
 - REMIND-MAgPIE 3.2-4.6 (Germany)
- SSP Version 2.0 scenarios (2018 Available at: https://tntcat.iiasa.ac.at/SspDb)
 - Netherlands Environmental Assessment Agency (PBL). Integrated Model to Assess the Global Environment (IMAGE): Detlef van Vuuren, David Gernaat, Elke Stehfest
 - International Institute for Applied Systems Analysis (IIASA). Model for Energy Supply Strategy Alternatives and their General Environmental Impact - GLobal BIOsphere Management (MESSAGE-GLOBIOM): Keywan Riahi, Oliver Fricko, Petr Havlik
 - National Institute for Environmental Studies (NIES). Asia-Pacific Integrated Model (AIM): Shinichiro Fujimori
 - Pacific Northwest National Laboratory (PNNL). Global Change Assessment Model (GCAM): Kate Calvin and Jae Edmonds
 - Potsdam Institute for Climate Impact Research (PIK). REMIND-MAGPIE: Elmar Kriegler, Alexander Popp, Nico Bauer
 - European Institute on Economics and the Environment (EIEE). World Induced Technical Change Hybrid-GLobal BIOsphere Management (WITCH-GLOBIOM): Massimo Tavoni, Johannes Emmerling

Our default settings are guided primarily by history, IEA WEO Stated Policies Scenario (STEPS), and NGFS Current Policies projections.

Land Calibration

The land use change module is calibrated in the regional C-ROADS based on the Land Use Harmonization (LUH2) data prepared for the Climate Research Program Coupled Model Intercomparison Project (CMIP6). Our output for each land type strongly aligns with historical data. However, our projections suggest more farmland and less forest than do the LUH projections and those of the NGFS models. The differences are due to our accounting for the temperature effect on reducing crop yield, which translates to more farmland expansion to meet food demands. The other models do not account for that feedback.

Response to Actions

En-ROADS also uses various scenario projections for model validation. We test the model against the NGFS projections for their 7 scenarios. We set population and GDP per capita controls to follow the given NGFS trajectories and exogenously use the average of the models' carbon price values for the given NGFS scenario, and assess the model output versus the IAMs' results. Learn more in the Model Comparisons—Future chapter.

An important caveat is that these other IAMs' assumptions other than carbon pricing are unknown. Accordingly, we force CDR and other GHG action to align with the NGFS projections for carbon removal and other GHG emissions. Reliably, for each scenario, the model captures the key dynamics of the NGFS models.

Although outdated now, we ran comparable assessments against all of the Shared Socioeconomic Pathway (SSP) of the IPCC's AR5 scenarios. Comparisons were against the output of 6 models for 5 SSP scenarios, each with up to 6 radiative forcing options, i.e., 1.9, 2.6, 3.4, 4.5, 6.0, and Baseline. Reliably, for each SSP storyline and RF level, the model captures the key dynamics of the SSP models.

Sensitivity Analyses

Extreme Testing

Sensitivity analyses provide insight into model robustness. Using a Latin grid, two tests for extreme conditions, one with standard controls and another with advanced controls, varied key actions. The extreme values for some variables are beyond the ranges available on the app but are tested for model robustness in Vensim. Output measures for each simulation were exported as a .csv file and assessed using an Excel workbook created to confirm reasonable model behavior.

Variable	Min	Max*
Basic Controls		
Source tax coal tce	0	1000
Source tax oil boe	0	1000
Source tax gas MCF	0	20
Source tax bio boe	0	1000
Source tax renewables kWh	-0.1	0
Carbon tax initial target	0	1000
Annual improvement to energy efficiency of new capital stationary	-1	5
Annual improvement to energy efficiency of new capital transport	-1	5
Electric equipment subsidy stationary	0	100
Electric equipment subsidy with required comp assets	0	100
Percent available land for afforestation	0	100
Non afforestation Percent of max CDR achieved		100
Advanced Controls		
Damage function on		1
No new coal	0	100
No new oil	0	100
No new gas	0	100
Utilization adjustment factor coal		100
Utilization adjustment factor oil	0	100
Utilization adjustment factor gas	0	100

 Table 15.1
 Sensitivity Analysis Definition (see Table 15.2 for normal slider ranges)

Variable		Мах
Basic Controls		
Source tax coal tce		110
Source tax oil boe	0	100
Source tax gas MCF	0	5
Source tax bio boe	0	30
Source tax renewables kWh	-0.03	0
Carbon tax initial target	0	250
Electric equipment subsidy stationary	0	50
Electric equipment subsidy with required comp assets	0	50

 Table 15.2
 Actual En-ROADS slider ranges (some values in Table 15.1 go beyond these limits)

Output variables for the sensitivity analyses include:

- Final energy by each carrier for each end use[EndUseSector, Carrier]
- Total Primary Energy Demand
- Primary energy demand of coal
- Primary energy demand of oil
- Primary energy demand of gas
- Primary energy demand of bio
- Primary energy demand of nuclear
- Primary energy demand of renewables
- Primary energy demand of hydro
- Market price of electricity
- Market price of fuels[Primary Fuels]
- Adjusted cost of energy per GJ
- CO2 emissions from energy
- Temperature change from 1850

Varying Key Assumptions

Additionally, using random triangular distribution, another set of sensitivity analyses tested the effects of varying key assumptions with actions. Results indicate that, regardless of these assumptions, the relative effect these actions have on the system are robust.

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