https://doi.org/10.5194/egusphere-2026-6049
Preprint. Discussion started: 16 November 2026
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The energy module of FRIDA v2.1: endogenous investment and the timing of climate policy in the global energy system

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Abstract. Integrated assessment models that derive energy-transition pathways from cost optimization or prescribed scenarios often diverge from observed investment behaviour. Here we present the energy module of FRIDA v2.1, a feedback-based, fully coupled global integrated assessment model built using System Dynamics, in which energy investment is an endogenous process rather than a user or optimization choice variable. Total energy investment is set by a proportional–integral–derivative controller that responds to the relative mismatch between energy supply and demand, and is allocated across coal, oil, gas, solar, wind, hydropower, biofuel and nuclear technologies according to marginal costs that evolve with learning-by-doing, stepping-on-toes effects, resource scarcity, integration costs, climate damages and policy. Energy demand depends on population, GDP per person, energy prices, and climate-driven changes in heating and cooling degree days. Calibrated against 53 historical time series (1980–2023), the module reproduces observed trends in global energy supply, investment, and emissions. Using 100 000-member ensembles, we compare unforced endogenous model behaviour, in which warming exceeds 3 °C by 2100, with four stylised policy scenarios that differ in the timing of carbon taxes and renewable subsidies. All policy scenarios accelerate decarbonization, mainly through supply-side substitution rather than reduced demand, yet median warming remains above 2 °C. Implementing both instruments early lowers end-of-century warming by roughly a third of a degree compared with delayed implementation. Abrupt policy introduction carries a substantial risk of persistent macroeconomic disruption, showing that successful decarbonization depends not only on policy strength but also on its timing and sequencing.

1 Introduction

The green transition of the energy system and related costs are crucial in assessing the range of plausible futures over the next century (Aghahosseini et al., 2023; Way et al., 2022). An internally consistent and causally motivated, i.e. endogenous, representation of the processes that govern the development of the global energy system is, therefore, paramount, especially because feedback mechanisms within the system, together with the critical role that speed of the green-energy transition plays in shaping climate outcomes (Intergovernmental Panel on Climate Change (IPCC), 2023b). The pace of the energy

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transition is central to minimizing climate risks and safeguarding human systems: rapid and complete transitions can substantially reduce cumulative emissions, whereas delays increase the likelihood of surpassing dangerous warming thresholds (e.g., 1.5 °C), amplifying long-term risks (Intergovernmental Panel on Climate Change (IPCC), 2023a) and constraining future adaptive capacity (Di Febo, 2025; Slameršak et al., 2022). Although accelerated action requires significant upfront investment and sustained commitment, Integrated Assessment Models (IAMs) have demonstrated the benefits of such policy for avoiding the most severe consequences of climate change (Intergovernmental Panel on Climate Change (IPCC), 2023b). However, IAMs that optimize for least-cost or cost-benefit outcomes are built on strong assumptions about rational planning and market behavior (Pindyck, 2013), and their pathways often diverge from observed real-world investment patterns, including the continued investment in fossil fuels over recent decades (IEA, 2024).

We address this limitation in the FRIDA model a feedback-rich IAM designed to capture the dynamic interactions and co-evolution of human and natural systems capable of both future projections and reproducing observed historical behaviour (1980–2024). FRIDAv2.1 (Schoenberg et al., 2025a) closes two-way feedback loops between socio-economic activity and biophysical climate dynamics, linking Earth system processes with demographics, economic development, agriculture, energy use, and behavioral change. The model is built using the System Dynamics methodology (Forrester, 1961; Sterman, 2000), the model prioritizes feedback complexity over spatial or sectoral disaggregation to improve interpretability and reveal system-wide dynamics. A defining feature of FRIDA is its focus on endogenous model behavior (EMB): long-term trajectories that emerge from internal processes, calibrated to observed past behaviour, such as adaptive expectation formation, investment dynamics, behavioral responses, and climate interactions. Within FRIDA's economy module investments arise through the interplay of debt issuance, loan defaults, productivity improvements, and climate impacts, while consumption and government expenditure are driven by circular flow dynamics and government budgeting (Grimeland et al., 2026). Thereby, economic production and GDP are emergent properties of the model and are not bound to equilibrium assumptions.

Building on this foundation, we generate global energy investment as an emergent property of FRIDAv2.1's system structure, rather than as the outcome of a forward-looking optimization problem, or as prescribed by a scenario. FRIDA models individual feedback processes with choices depending on the information available up to each timestep including effects from climate impacts, adaptive behaviors, and their financial implications. Energy investments respond adaptively to current and historical supply–demand imbalances and investment costs. Energy demand is a function of GDP per person, average energy prices, and changing heating and cooling degree days. Investment costs are affected by learning dynamics, inter-technology competition, fossil resource scarcity, asset lifecycles, and transition-related financial risk drivers including taxes, subsidies, and emission regulations. FRIDA's energy module thereby produces system behavior representing real-world constraints and decision contexts.

We include technological change in the model both from learning-by-doing (experience-curve effects), whereby costs and performance improve with accumulated deployment, and learning-by-searching to reflect R&D-driven innovation (Arrow, 1962; Thomassen et al., 2020). Taken together, these learning effects ensure that cost and performance improvements

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emerge endogenously from past investment and research choices, thereby shaping future policy costs in a pathway-dependent manner. The impact of efficiency improvements on installed capacity is represented through a vintage structure distinguishing installation cohorts and degradation profiles. This enables realistic representation of operational lifecycles and replacement dynamics, ensuring that the model appropriately captures the full scope and effect of technological development that has occurred over the last 45+ years in renewable energy technologies, without future investments changing the efficiency of historically built capital.

To temper the effects of cost reductions from learning-by-doing and possible large subsidies on capital allocation we include stepping-on-toes dynamics. Following (Jones and Williams, 2000), this includes a limiting function on the marginal productivity of investment under simultaneous inflows to technologies, capturing both duplicative R&D and cost increases from material or manufacturing bottlenecks. Complementing this, the model allows a technology's marginal value to decline with increasing system share (e.g., due to grid integration limits, saturation, or spatial constraints), thereby affecting the relative competitiveness of other options and reflecting massive investment dependencies.

Fossil resource-base constraints cause an increase in marginal costs as extraction progresses, associated with accessing lower-quality or harder-to-reach reserves, which increasingly counteract the cost-reducing effects of learning-by-doing and discovery of untapped reserves. This interaction between geological limits and technological progress is essential for realistically representing how fossil fuel competitiveness evolves over time and how resource scarcity can accelerate or delay the transition toward low-carbon alternatives. Reductions in fossil fuel production, e.g. due to policy shocks, can induce stranding of assets in the secondary fossil energy sectors. Thereby, transition risks are reflected in investment choices, allowing us to assess the feasibility, lock-in, and the consequences of rapid decarbonization in a fully endogenous setting

The emissions produced from fossil fuels are tracked for four species (CO_2, CH_4, N_2O, SO_2) and form part of the overall emissions driving climatic change within FRIDA's climate module (Wells et al., 2026a). Under climate change energy production capital is damaged and the efficiency of thermal and hydro power plants reduced.

To investigate the full range of internally dynamically consistent plausible and possible futures, we systematically include uncertainty ranges wherever relationships are not fully known. These uncertainty ranges are constrained by the model likelihood function derived from comparing model results to past observations. Thereby, the model becomes capable not only of producing consistent trajectories but of revealing the range of plausible outcomes, divergence points, and nonlinearities that characterize century-scale transitions.

Operating at a global scope, the energy module of FRIDA allows technology, resource, and capital interactions to unfold across the entire energy system and interact with the wider human and natural systems while remaining sufficiently compact to enable transparent experimentation and robust uncertainty exploration. In short, we provide a global, behaviorally grounded energy system in which the logic of the energy transition emerges from interacting constraints and feedbacks, rather than being imposed through objective functions or requiring exogenous deployment assumptions, but one that is still able to represent the impact of global energy system policy.

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2 Module description

The primary purpose of the Energy Module is to simulate the global supply and demand for energy, the transition from fossil fuels to renewable sources, and the resulting greenhouse gas emissions. It operates on a continuous time basis, capturing the inertia of capital stocks, the delays in investment decisions, and the physical constraints of resource extraction and renewable capacity expansion. Unlike models that solve for a cost-optimal pathway, FRIDA's Energy Module simulates the evolution of the system based on calibrated decision rules, market signals (prices and costs), and policy interventions (taxes, subsidies, and regulations).

The Energy module is based on the representation of the energy sector of the MIND model (Edenhofer et al., 2005; Held et al., 2009). MIND was chosen as the basis as it satisfied a number of the requirements formulated in the introduction. The MIND model structure includes a representation, at the global scale, of dynamic costs based on both learning by doing, as well as resource scarcity, including vintaging of renewable energy production capacity and stepping on toes effects (requirements two, three, four, and five). For FRIDA we disaggregated fossil and renewable energy supply into their subcomponents, and endogenously modeled nuclear energy generation. Due to the difference in modelling philosophy of FRIDA compared to MIND (simulating rather than optimizing) an endogenous representation of energy investment was required based on energy supply and demand, which in turn required an endogenous representation of energy demand. The remaining requirements one and six are addressed through the systematic specification of uncertainty ranges for all parameters without known values during the calibration process enabling large ensemble runs (Schoenberg et al., 2025a; Schoenberg, 2025) and through a process connecting imbalances in fossil capital stocks and new investments also affecting defaults in FRIDA's economy sub module (Grimeland et al., 2026).

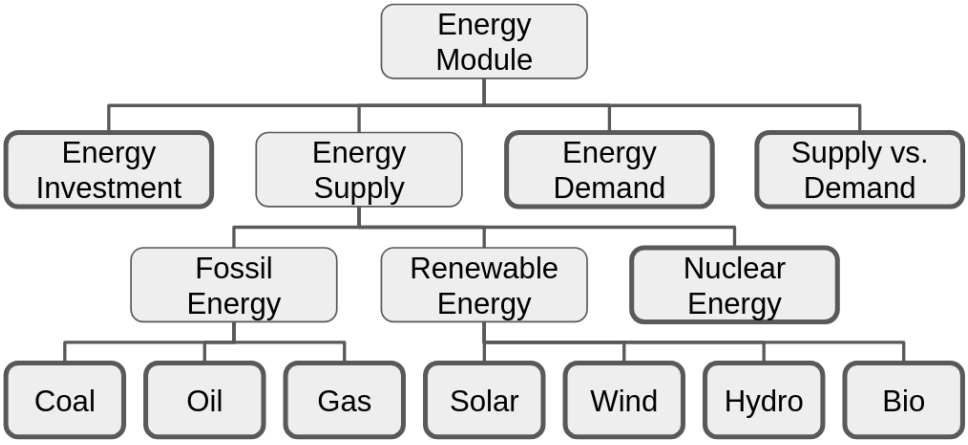


Figure 1: Sub-modules contained within the energy module. Modules with bold outlines are novel contributions compared to the MIND model.

Figure 1 shows all the sub-modules of the energy system in FRIDA, these are:

- **Energy Investment**: Allocates financial capital to different energy technologies based on marginal cost and policy.
- **Energy Supply**

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- **Fossil Energy** (Coal, Oil, Gas): Simulates the extraction of fuels and their conversion into secondary energy (electricity/heat).
- **Renewable Energy** (Solar, Wind, Hydro, Biofuel): Simulates the construction of capacity and generation of energy from non-fossil sources.
- **Nuclear Energy**: Tracks nuclear capacity and output.

- **Energy Demand**: Determines the total energy required by the global population and economy.
- **Energy Supply vs. Demand**: Reconciles production with consumption to generate investment signals.

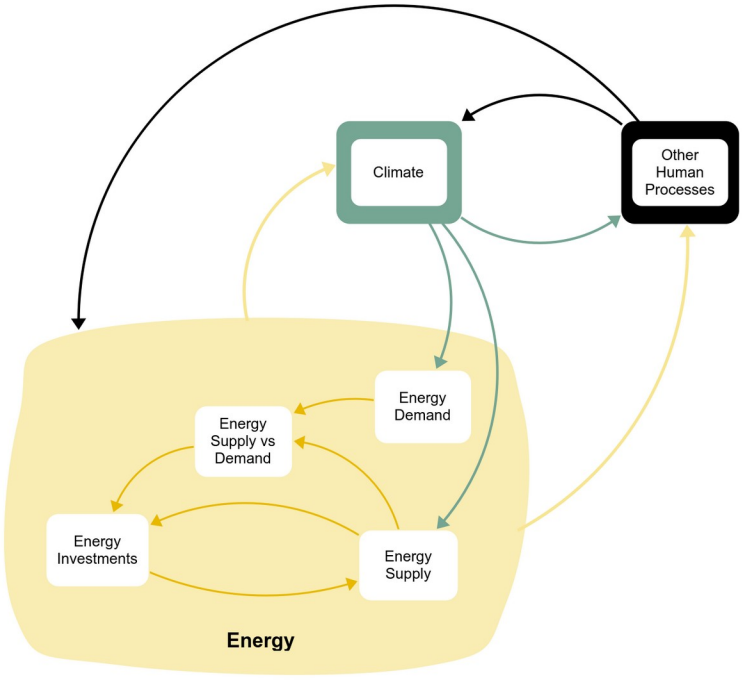


Figure 2: Representation of the high-level process aggregations in FRIDA's Energy module. This diagram depicts how the Energy module interacts with the rest of the model. The rest of the human processes are in black, the climate system in green, and the Energy module along with its first level-sub-modules are in yellow. The energy supply sub-module is further divided into sub-modules which represent each energy type individually (see Fig. 1). This figure is re-used with permission from (Schoenberg et al., 2025a).

The modules affect each other and the surrounding FRIDA model through multiple feedbacks, shown in Fig. 2. Emissions from the combustion of fossil fuels (coal, oil, gas) as well as bio-fuels flow into FRIDA's climate module (Wells et al., 2026a) affecting climate change. The imbalance between supply and demand for energy, together with the marginal net cost of energy production, affect inflation in FRIDA's inflation module. Taxes and subsidies, specified by the user of the model to regulate the technologies used in the production of energy, affect the government budget in expected ways. Finally, the investments flowing into the production of energy constitute a part of gross investments in FRIDA's economy module (Grimeland et al., 2026). Simultaneously, the module is itself also affected by feedbacks from the wider model, including

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from climate (Wells et al., 2026b). Economic developments, population dynamics, and climatic conditions affect the baseline demand for energy. Climatic conditions further affect the production efficiency of thermal power plants as well as hydropower plants.

To describe the full structure of the energy module we follow two strands. The first is to follow the money: Starting from how overall energy investments are determined, to the allocation of the overall investments to different energy technologies, to the production processes of energy by the different technologies, finally reaching total supply. The other strand is the demand for energy starting with general demand for energy based on GDP adjusted by climate impacts on heating and cooling energy demand. The two strands meet in the supply demand imbalance, which in turn drives the investments.

2.1 Energy investment

The Energy Investment sub-module is a key component of the Energy module, determining both the total volume of investment entering the energy system and its distribution across competing technologies. It represents the aggregated behavior of global energy investors as captured by time series of investments in the various energy technologies (IEA, 2024). Energy investments are determined in two steps: First, aggregate investments are determined based on the relative mismatch between energy supply and demand, normalized by total system supply. Second, the aggregate investments are allocated to the different energy technologies based on their marginal costs.

We model the aggregate energy investment behaviour (prior to allocation across energy sources) using a proportional–integral–derivative (PID) controller (e.g. (Lunze, 2020)). The controller adjusts total energy investment in response to the relative supply–demand mismatch, with the objective of minimizing this imbalance by investing only what is required to restore equilibrium. The controller output (energy investment) responds to the input signal (relative supply–demand mismatch) through three components: a proportional term that reacts to the instantaneous magnitude of the mismatch, an integral term that responds to the accumulated mismatch over time, and a derivative term that anticipates future imbalances by reacting to the rate of change of the mismatch. The weights of these three components are jointly calibrated with the other parameters of the Energy module to reproduce observed energy supply and investment dynamics over the historical period (1980–2023). As a result, investment decisions respond not only to current disequilibrium, but also to persistent small imbalances and to rapid shifts in system conditions. Conceptually, this formulation is consistent with the principles of Perceptual Control Theory, which posit that economic agents act not solely to maximize utility or output, but to regulate their perceived system states in the presence of external disturbances (Miller et al., 1960).

Aggregate energy investments are allocated across energy-producing technologies based primarily on their marginal cost of supplying an additional unit of output. For each technology, marginal costs of increasing the energy output are computed endogenously within the sub-module. Marginal production costs depend on existing capital stocks, learning effects, and other technology-specific characteristics described in the relevant sections below. Cost minimization alone, however, does not reproduce observed historical investment patterns. To account for persistent diversification in technology choice, a cost "spread" is introduced that allows a portion of total investment to flow to higher-cost technologies. This allocation

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mechanism is implemented using the ALLOCATE builtin function in Stella Architect (isee systems, 2025a). The ALLOCATE function sequences the investment opportunities by cost, with the lowest cost opportunities first. Then it apportions the overall opportunities based on a "width" that determines how much they overlap. If the width were 0 the lowest cost opportunities would be selected until the available investment was exhausted, in line with a fully cost minimizing decision maker. If the width were infinite, all opportunities would get the same fraction of their cost based on available investment. In between, lower cost investments are favored, but not exclusively. The value of width and spread was calibrated to reproduce observed technology-specific investment shares over the historical period. Exact definitions of the equations governing the ALLOCATE functions can be found in Appendix A.

To further reconcile cost-driven behavior with historical data, we apply time-dependent, technology-specific cost adjustment factors. These factors represent the monetary equivalent of non-cost preferences, policy incentives (e.g., subsidies and taxes), and other structural influences not explicitly captured in the cost formulation, which cause observed investments to deviate from the least-cost during the calibration period. These adjustment factors are calibrated to reproduce observed investment flows and the resulting technology mix that underpins current system performance. Forward-looking policy interventions can be imposed through additional, explicit, time-dependent taxes or subsidies. These may be applied to emissions from individual technologies, to the technologies themselves (e.g., nuclear, fossil, or renewable), or to the decommissioning rates of extraction capital. All such policy instruments modify the effective marginal costs that govern the investment allocation process. The framework also allows for structural constraints, such as a moratorium on fossil fuel energy beginning in a specified year. Under such a constraint, all new investment in fossil technologies is halted, and capital is reallocated to the remaining energy options.

2.2 Energy supply

FRIDA represents global energy supply through a modular system that links capital accumulation, endogenous technological change, and climate-driven infrastructure damage across fossil (coal, oil, gas), renewable (solar, wind, bio fuels, hydropower), and nuclear technologies. Building on the MIND model (Edenhofer et al., 2005; Held et al., 2009), these modules capture how resource scarcity, learning-by-doing, time-varying productivity improvements, and technology-specific constraints jointly shape the evolution of energy production. These sub-modules allow fossil extraction dynamics, renewable deployment processes, and climate feedbacks to be represented consistently, enabling the model to reproduce historical energy transitions and explore future pathways under shifting economic incentives, policy interventions, and climate impacts.

2.2.1 Fossil energy supply

FRIDA represents three fossil energy sources: coal, oil, and gas, each modeled using identical structures but parameterized per fuel source. The basis for these structures is the general structure of primary energy extraction and secondary energy conversion developed in the MIND model (Edenhofer et al., 2005; Held et al., 2009). Both in MIND and FRIDA, resource

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extraction is driven by investment in extraction capacity, while extraction efficiency depends on learning-by-doing effects (Arrow, 1962; Thomassen et al., 2020), and on scarcity effects arising from resource depletion (Nordhaus, 2002). Secondary energy conversion is represented by a constant elasticity of substitution (CES) production function, with primary fuel input and secondary energy capital as factors of production.

FRIDA departs from the original MIND formulation in three key ways:

- Fossil fuels are disaggregated into coal, oil, and gas, which share an identical structural representation but differ in parameterization.
- Biofuels are introduced as drop-in substitutes for fossil fuels in secondary energy production (currently implemented for oil).
- A time-varying total factor productivity (TFP) term is added to the secondary energy production function to capture the historically observed improvements in thermal power plant efficiency (Energy Institute, 2023).

In whole, each fossil fuel energy supply sub-module operates in the following manner. Extraction capital evolves through gross investment, depreciation, and an explicit decommissioning flow, which reflects regulatory constraints or structural damage from climate impacts. In contrast, secondary energy conversion capital does not include an explicit decommissioning term, as emissions from fossil energy supply are a function of extracted (and burned) fuel rather than incremental efficiency improvements in conversion, although this will affect the amount of investment into extraction, and hence fuel burning, needed to deliver the desired amount of energy. Energy emissions are directly calculated for CO_2 while emissions for CH_4, N_2O, and SO_2 are calculated using coupling factors based on initial ratios between these gases and CO_2 and exponential time trends capturing changes in the ratios over time.

The cost and performance of fossil fuel extraction are governed by two opposing mechanisms. First, resource depletion generates a scarcity effect: as cumulative extraction increases, remaining reserves become harder to access, raising marginal extraction costs (Nordhaus, 2002). Second, continued extraction induces learning-by-doing, which improves operational efficiency and reduces costs over time (Arrow, 1962; Thomassen et al., 2020). The extracted fuel is subsequently used by the secondary energy conversion sector to produce usable fossil energy.

Secondary fossil energy output is determined by a constant elasticity of substitution (CES) production function, which allows limited substitution between fuel and conversion capital. This function includes a time-varying total factor productivity term to reproduce historical gains in fuel-to-energy conversion efficiency, reflecting technological progress driven by research, development, and operational learning (Energy Institute, 2023).

2.2.2 Renewable energy technologies

The renewable energy module comprises four major technology classes: solar, wind, hydropower, and biofuels, each implemented through dedicated sub-modules built on a shared stock-flow and endogenous cost-learning architecture. All technologies expand through investment-driven installation flows, depreciate according to assumed lifetimes, and experience climate-induced capital damage, ensuring that climate impacts propagate directly into infrastructure integrity. Installation

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decisions are endogenously determined by the Energy Investment sub-module, allowing renewable capacity to compete with fossil technologies based on evolving costs, learning effects, and policy interventions.

While all sub-modules follow this unified framework, each technology incorporates additional structural elements. Solar and wind technologies share an intermittent-renewables formulation based on multi-vintage capital turnover. Hydropower adopts a site-scarcity-driven cost representation, and biofuels integrate explicit land-use constraints. Together, these modules describe the evolution of global renewable supply under dynamic feedbacks among investment, technological progress, infrastructure aging, and climate impacts.

Solar and wind

Although they are distinct technologies, with independent investment streams and buildout, solar and wind share the same structure. As in MIND (Edenhofer et al., 2005; Held et al., 2009), these sub-modules are characterized by a capital accumulation structure that utilizes a multi-vintage conveyor system to represent the aging of physical assets. The primary stock of installed capacity is arrayed by age group, allowing the model to track the productivity and eventual decommissioning of capacity over discrete intervals. This capacity is augmented by a construction flow, which is endogenously determined by the level of financial investment allocated to the sector, and is simultaneously diminished by capital damaged due to climate change, a flow representing the vulnerability of energy infrastructure to escalating surface temperature anomalies (Wells et al., 2026b) and references therein (Clarke et al., 2018; Rode et al., 2021; Van Vliet et al., 2016; Werning et al., 2024; Yalew et al., 2020).

Economic dynamics within these modules are governed by a non-linear cost-reduction framework centered on technological learning and deployment constraints. The reducible installation cost component is adjusted by the effect of learning on cost, which follows a power-law relationship relative to the cumulative capacity construction, representing learning by doing effects, following the equivalent structure in MIND. Also, as in MIND, this reinforcing feedback loop is moderated by a "stepping on toes" punishment mechanism, where unit costs increase as a function of the ratio between current and perceived cumulative construction (Jones and Williams, 2000). This formulation captures the diminishing returns and logistical complexities associated with rapid industry expansion and the exhaustion of prime geographic sites.

Integration costs and technical constraints are further addressed through the endogenous adjustment of the floor costs for capacity. Unlike MIND and static cost models, this structure incorporates a sensitivity to the solar and wind output share of total energy production. As the penetration of variable renewable energy increases, the model simulates the rising marginal costs of grid stabilization and energy storage requirements. This creates a balancing feedback on the sector's growth, ensuring that the economic evaluation of wind and solar capacity accounts for the systemic requirements of a high-penetration renewable grid.

The final generation of energy is a direct function of the accumulated capacity and technology-specific full load hours. The solar and wind energy output variables represent the realized secondary energy supply, which feeds back into the global energy balance. The investment flows into these modules are determined by the Energy Investment sub-module that

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accounts for the adjusted cost of these technologies, inclusive of learning effects, floor costs, and government interventions such as subsidies for newly installed solar and wind energy capacity, against fossil-based alternatives, thereby driving the long-term transition of the global energy mix.

Hydropower

The hydropower energy sub-module is centered on the hydropower energy capacity stock, which represents the global accumulation of hydroelectric infrastructure. This state variable is governed by a primary inflow, installation of hydropower capacity, and two distinct outflows: depreciation of capacity and the unique to FRIDA, capital Damaged due to climate change (Wells et al., 2026b). The depreciation rate is modeled as a first-order linear process based on an assumed infrastructure lifetime, while the climate-driven outflow represents the physical degradation of assets resulting from the surface temperature anomaly, introducing a direct link from the climate system to energy infrastructure integrity.

Energy generation is represented as the hydropower energy output, which is the product of the current capacity and the hydropower energy capacity efficiency. This efficiency is not static; it is defined by a baseline hydropower energy capacity efficiency modulated by the effect of climate change on hydropower energy capacity efficiency (Wells et al., 2026b). This formulation captures the hydrological sensitivities of power generation, where changes in global mean temperature alter river discharge patterns and evaporation rates, thereby impacting the operational performance of the installed capacity (Van Vliet et al., 2016). Consequently, the model accounts for both the quantity of infrastructure and its climate-dependent quality.

The economic structure of the module utilizes an endogenous cost function to simulate the scarcity of viable geographic sites. As the Hydropower Energy Capacity increases, the marginal cost per kilowatt rises, reflecting the transition from optimal to marginal locations. The rate of installation of hydropower capacity is then derived from the Investments in hydropower capacity divided by these capacity-dependent costs, creating a balancing mechanism that slows growth as the resource base is exploited.

Finally, the module integrates fiscal policy and external economic indicators to determine the cost net of taxes of extra energy output through capital. This variable incorporates the tax burden on installing capacity, which is a function of the tax for newly installed hydropower capacity and the start year. By calculating the cost of a marginal unit of energy, the module provides a standardized metric for investment priority algorithms located in the broader energy investment sector. This ensures that hydropower competes with other energy sources based on a comprehensive accounting of capital costs, technological efficiency, and regulatory interventions.

Biofuels

The biofuel energy module is architected around the biofuel production capacity stock, a state variable representing the global industrial capacity for biofuel production. This capacity evolves through a continuous-time stock-flow mechanism where the installation of bio capacity is the primary inflow, determined by the ratio of allocated investment to the prevailing installation cost. The stock is subject to two primary outflows: a standard depreciation of biofuel capacity, reflecting the physical aging of capital, and biofuel energy capital damaged due to climate change, which endogenizes the vulnerability of

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energy infrastructure to climate-induced thermal stress (Wells et al., 2026b). As in solar and wind, the economic dynamics within the module are characterized by an endogenous cost-reduction framework using both learning by doing, and a stepping on toes impact.

The module creates a feedback loop between the energy and land-use sectors. The biofuel production rate is constrained by the ratio of crop supply to demand, ensuring that energy related crop demand can not constrain food related crop demand and overall crop demands are consistent with global agricultural availability. Crops demanded for biofuel are calculated based on the available fuel production capital and the energy density of crops. The resulting energy output is quantified as bio fuel primary energy and subsequently converted to biofuel secondary energy output using oil production capacity, within the fossil energy submodule, which integrates it into the global liquid fuel supply chain.

2.2.3 Nuclear energy technology

The nuclear energy module is centered on the accumulation of nuclear energy capacity. This capacity is augmented by the installation of nuclear capacity and depleted through two primary mechanisms: physical depreciation of nuclear capacity and nuclear energy capital damaged due to climate change (Wells et al., 2026b). The latter represents a critical climate feedback where the damage rate of energy capital from surface temperature anomaly endogenously reduces the operational lifespan of the infrastructure. This is a catchall process with a large uncertainty range including the possibility of practically no damages. The primary output of the sector, nuclear energy output, is the product of the installed capacity and efficiency.

Nuclear capital efficiency is modulated by the effect of climate change on thermal power energy capacity efficiency, specifically accounting for the share of thermal power plants that are cooled by rivers (Van Vliet et al., 2016; Wells et al., 2026b). As surface temperatures rise, the efficiency of the thermal cycle is reduced due to cooling water temperature constraints, creating a non-linear degradation of energy output per unit of installed capacity. This structural link ensures that the energy supply sector is not merely a driver of climate change but is also fundamentally constrained by the resulting environmental shifts.

The economic dynamics within the module are governed by the same endogenous cost structure as in the solar and wind modules. Nuclear installation costs are composed of a non-reducible floor cost and a reducible installation cost component impacted by both learning by doing, and stepping on toes. Costs can furthermore be influenced through a tax or subsidy on installing capacity.

2.3 Energy demand

The energy demand sub-module endogenizes global energy requirements integrating socio-economic drivers, market price signals, and climate-induced changes to heating and cooling demand. The sub-module calculates the demand for energy as the product of the total population and per person energy demand. This per capita demand is determined as a baseline component driven by GDP per capita and a climate-sensitive delta, ensuring the model captures both economic trends and environmental feedback.

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The baseline component is driven by relative GDP per capita and aggregate per unit energy prices. The relationship between wealth and energy intensity is modeled using a log formulation, reflecting the empirical observation of diminishing marginal energy requirements as economies mature. Simultaneously, the module incorporates price elasticity through the effect of energy prices on demand. These prices are not instantaneous but are modeled as a first-order smoothing of the average marginal net cost of energy, representing price stickiness (Álvarez et al., 2006; Borenstein and Shepard, 2002).

To account for the physical impacts of anthropogenic warming, the module endogenizes the total change in energy used for heating and cooling due to climate change. This is achieved by mapping the surface temperature anomaly to cooling degree days (CDD) and heating degree days (HDD). CDD is formulated as a linear function of the temperature anomaly, while HDD follows an exponential decay, capturing the non-linear reduction in space-heating requirements as global mean temperatures rise. Both of these are calibrated to emulate behaviour predicted from spatially explicit models (Wells et al., 2026b; Werning et al., 2024). These climatic indices are then converted into energy units using specific intensity coefficients, allowing the model to simulate the shifting energy burden of climate adaptation.

3 Calibration and uncertainty

The energy module in FRIDA v2.1 was implemented in Stella Architect 3.8 (isee systems, 2025b) and simulated over the period 1980–2150 using fourth-order Runge-Kutta (RK4) integration. Consistent with the broader FRIDA model, the module was developed at a high level of aggregation to emphasize the dominant system-wide feedbacks governing energy demand, supply, technological change, and emissions. As a result, uncertainty in parameter values is unavoidable and is addressed through a structured calibration and uncertainty analysis procedure applied to the FRIDA model as a whole (Schoenberg et al., 2025a).

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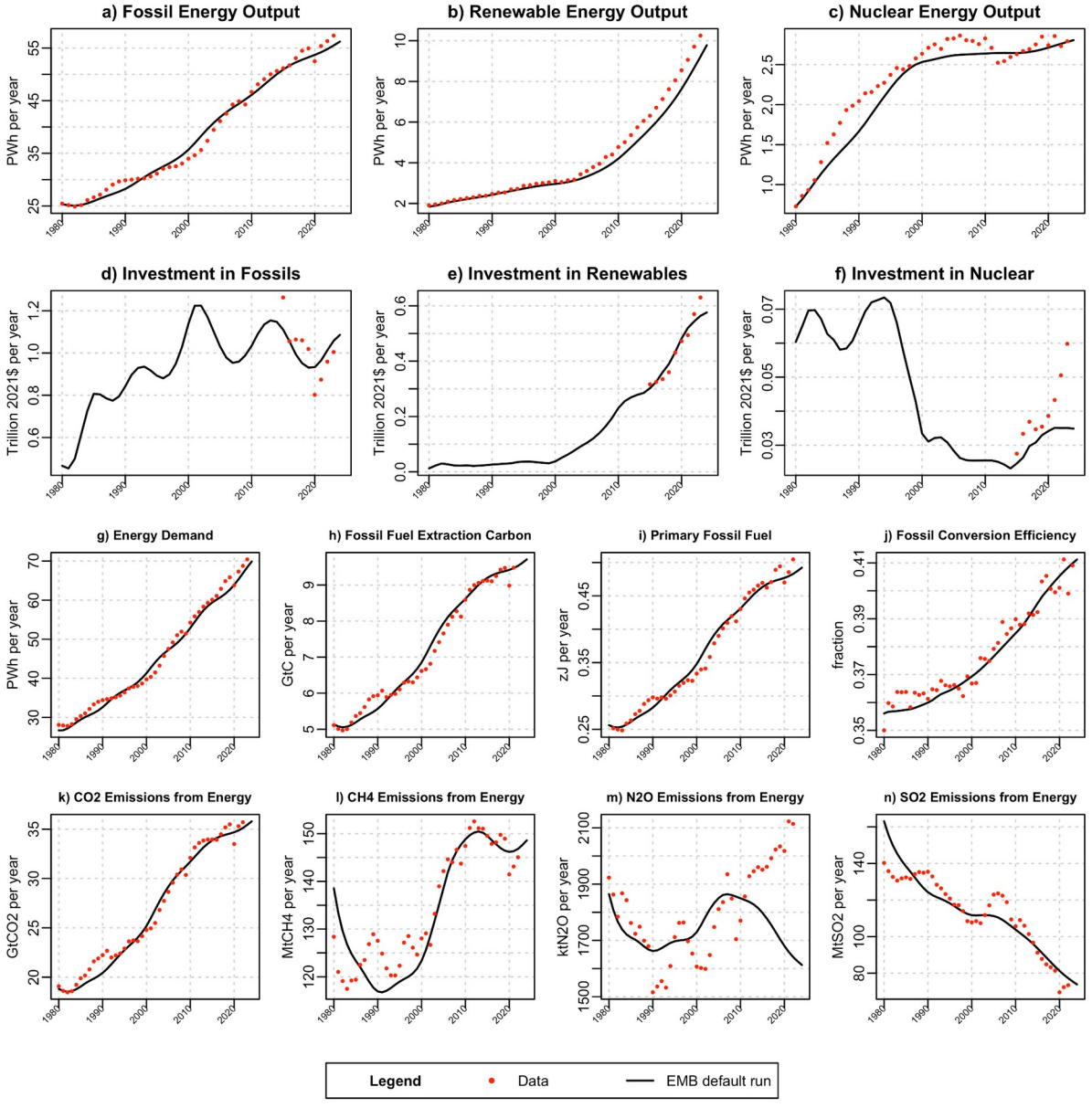


Figure 3: Historical calibration of the FRIDA v2.1 energy module (1980 to 2023). Comparison of observed data (red dots) and simulated values from the default model run (black lines) for key energy system indicators used in model calibration. Panels show aggregated fossil, renewable, and nuclear energy output (a–c); investment in fossil, renewable, and nuclear energy technologies (d–f); energy demand and fossil fuel extraction characteristics (g–j); and energy-related emissions of CO_2, CH_4, N_2O, and SO_2 (k–n). Overall, the close correspondence between observations and simulations across energy production, technology deployment, investment patterns, fuel-system characteristics, and emissions demonstrates the model's ability to reproduce major historical trends and dynamics of the global energy system over the 1980 to 2023 period.

Model calibration was performed using the BOBYQA optimization algorithm (Powell, 2009), implemented within Stella Architect. FRIDA adopts a partial-calibration approach in which individual modules are calibrated independently where

https://doi.org/10.5194/egusphere-2026-6049
Preprint. Discussion started: 16 November 2026
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possible to minimize the propagation of errors between model components. For the energy module, uncertain parameters lacking well-established empirical estimates were assigned broad prior ranges informed by the literature and expert judgement, while published parameter values were adopted directly where available. Calibration minimized the squared error between simulated and observed behaviour over the historical period 1980–2023.

Figure 3 presents the historical calibration performance of the FRIDA v2.1 energy module. The figure compares observed data (red markers) with the endogenous model behaviour generated by the calibrated Endogenous Model Behavior (EMB) default run (black lines) across the aggregation of the principal indicators used in the calibration process. Overall, the model reproduces the major historical trends in global energy demand, fossil, renewable and nuclear energy production, energy-sector investment, fossil-fuel extraction characteristics, conversion efficiency, and energy-related emissions. Agreement is particularly strong for aggregate indicators such as total energy demand, fossil energy output, renewable energy deployment, fossil-fuel extraction carbon intensity, primary fossil fuel share, fossil conversion efficiency, and energy-related CO_2 emissions. Larger deviations are evident for nitrous oxide (N_2O) reflecting the influence of processes not explicitly resolved within the energy module. Nevertheless, the calibrated EMB default run captures the dominant dynamics across the historical record, providing confidence that the model reproduces the principal structure and behaviour of the global energy system over the calibration period.

The calibration process was conducted against a comprehensive historical dataset comprising 53 time series spanning energy supply, demand, investment, technology deployment, and emissions. Structural and behavioural validation were undertaken throughout model development to ensure that historical patterns were reproduced through plausible causal mechanisms and feedback processes rather than through statistical fitting alone.

Given the deep uncertainty associated with future technological development, behavioural responses, socioeconomic change, and climate-energy interactions, calibration was followed by a formal uncertainty analysis. Following identification of a best-fitting parameter set, plausible parameter ranges were established around calibrated values while respecting literature-derived and expert-defined bounds. These ranges were subsequently used to characterize uncertainty in future model projections.

A global sensitivity analysis was then performed using Sobol-sequence sampling across all uncertain parameters within FRIDA, including those associated with the energy module. The analysis consisted of 100,000 ensemble simulations, enabling efficient exploration of the model's high-dimensional parameter space. Sampled parameters represented uncertainties associated with climate sensitivity, socioeconomic development, energy technologies, behavioural change, climate impacts, and other interacting feedbacks represented within the model.

The resulting ensemble provides probabilistic bounds around future energy-system trajectories and serves as the reference case for assessing policy interventions in the following sections. Model results are therefore presented as ensemble distributions, typically reporting the sample median together with associated uncertainty ranges, rather than as single deterministic projections. This approach ensures that uncertainties arising from parameter estimation, structural assumptions, and system complexity are explicitly represented in model outputs.

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4 Results

Table 1: Specification of the scenarios presented in this paper.

Scenario Name	**Taxation**	**Fossil energy Investment moratorium**	**Subsidies**
EMB	none	none	none
early subsidy and tax	Tax on CO_2 emissions ramping up to 300 $/t over 10 years starting in **2030**	2050	Subsidy on Solar, Wind, and Hydropower installation ramping up to 75% of installation costs over ten years starting in **2030** capped at .5% of GDP respectively.
early subsidy delayed tax	Tax on CO_2 emissions ramping up to 300 $/t over 10 years starting in **2040**	2050	Subsidy on Solar, Wind, and Hydropower installation ramping up to 75% of installation costs over ten years starting in **2030** capped at .5% of GDP respectively.
delayed subsidy early tax	Tax on CO_2 emissions ramping up to 300 $/t over 10 years starting in **2030**	2050	Subsidy on Solar, Wind, and Hydropower ramping up to 75% of installation costs over ten years starting in **2040** capped at .5% of GDP respectively.
delayed subsidy and tax	Tax on CO_2 emissions ramping up to 300 $/t over 10 years starting in **2040**	2050	Subsidy on Solar, Wind, and Hydropower ramping up to 75% of installation costs over ten years starting in **2040** capped at .5% of GDP respectively.

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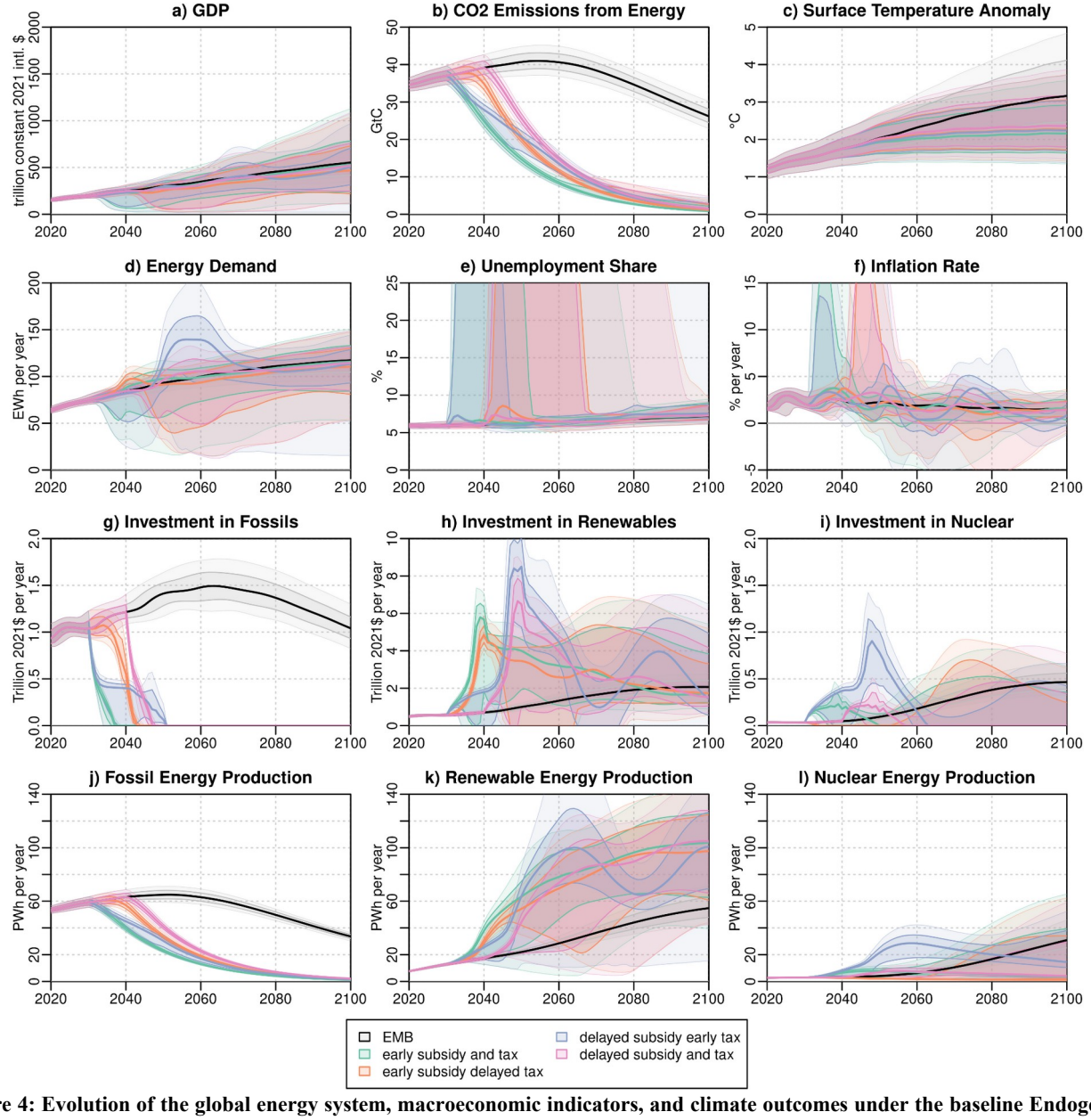


Figure 4: Evolution of the global energy system, macroeconomic indicators, and climate outcomes under the baseline Endogenous Model Behaviour (EMB) scenario and four policy scenarios that differ in the timing of renewable-energy subsidies and carbon taxation. Panels show (a) GDP, (b) CO_2 emissions from energy, (c) surface temperature anomaly, (d) energy demand, (e) unemployment rate, (f) inflation rate, (g) fossil-energy investment, (h) renewable-energy investment, (i) nuclear-energy investment, (j) fossil-energy production, (k) renewable-energy production, and (l) nuclear-energy production. Shaded regions indicate ranges containing 67% and 95% of outcomes of the respective 100k member ensembles.

Figure 4 compares the evolution of the global energy system under five scenarios: a baseline EMB scenario and four policy scenarios that differ in the timing of renewable-energy subsidies and carbon taxation (Table 1). Across all policy scenarios,

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decarbonization occurs substantially faster than in the baseline, although the timing and dynamics of the transition differ according to the sequencing of policy instruments.

In the EMB scenario, fossil energy investment continues to increase until approximately mid-century before gradually declining (Fig. 4g). Sustained investment supports relatively stable fossil energy production through much of the century (Fig. 4j), resulting in the highest emissions among all scenarios (Fig. 4b). Although renewable energy production grows driven by cost reductions through endogenous learning-by-doing effects (Fig. 4k), expansion remains insufficient to rapidly displace fossil fuels. Consequently, emissions decline only gradually and the surface temperature anomaly continues increasing throughout the century, exceeding 3 °C by 2100 (Fig. 4c).

All policy scenarios induce a rapid reallocation of investment away from fossil fuels and toward renewable energy systems. However, the timing and magnitude of these changes differ considerably. Scenarios that implement subsidies early exhibit an immediate increase in renewable investment (Fig. 4h), while scenarios introducing carbon taxes early show a particularly rapid decline in fossil investment (Fig. 4g). In all policy scenarios, fossil energy production declines substantially faster than in the EMB scenario (Fig. 4j), leading to markedly lower emissions and lower end-of-century temperature anomalies (Figs. 4b–c).

The effects of policy sequencing are especially visible in the delayed-intervention scenarios. When subsidies are introduced before carbon taxes, renewable investment begins increasing well before fossil investment fully declines. This creates a prolonged overlap period during which renewable investment expands while fossil production declines more gradually. By contrast, when carbon taxes are implemented before subsidies, fossil investment contracts rapidly and renewable investment subsequently exhibits large transitional spikes as capital is redirected into alternative energy technologies.

Across all policy scenarios, increases in renewable investment precede increases in renewable energy production. Renewable investment peaks between approximately 2035 and 2060 (Fig. 4h), whereas renewable production continues growing throughout much of the century (Fig. 4k). This lag reflects the time required for capital accumulation and infrastructure deployment. As renewable generation expands, fossil production steadily declines and renewable energy becomes the dominant source of energy in most policy scenarios by the end of the century.

Macroeconomic indicators show more stark differences between scenarios. In each policy ensemble, GDP in the median remains relatively unaffected in the long term, continuing to increase after a potential transient disruption at the point of policy intervention, but the probability bounds are extremely large, and skewed highly towards large disruptions at the point of introduction, and therefore low long-term GDP outcomes (Fig. 4a). Likewise, in the median of each policy ensemble unemployment and inflation experience relatively short, transient fluctuations during periods of transition, but the range of possible outcomes are extremely large, and for both unemployment and inflation are skewed highly up lasting for periods of upwards of 20 years (Figs. 4e–f).

Energy demand, like GDP, exhibits a similar long-term upward trajectory in the median across policy ensembles, while showing substantial declines in extreme cases where GDP declines. Importantly, however, energy demand displays more pronounced variations during the transition period (Fig. 4d). Across the policy scenarios, temporary accelerations and

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slowdowns in demand growth emerge before converging toward similar levels later in the century. The most pronounced example is the early-tax, delayed-subsidy scenario, which produces a substantial spike in energy demand. This effect arises from the interaction of high initial taxes, which increase energy costs paid, and subsequent deep subsidies, which create perceptions of energy as relatively inexpensive. Together, these dynamics generate a temporary surge in demand before longer-term convergence occurs as perceptions and costs converge. Nevertheless, the magnitude of these differences in energy demand remains smaller than the changes observed in the energy supply mix, suggesting that emissions reductions are driven primarily by transformations in energy production rather than by shifts in overall demand.

Nuclear energy plays a secondary role throughout the transition in these scenarios. Nuclear investment increases in several policy scenarios, particularly during periods of rapid fossil decline (Fig. 4i), and corresponding increases in nuclear generation are visible later in the century (Fig. 4l). However, although nuclear deployment contributes to the transition, both investment and generation remain substantially smaller than those associated with renewable energy technologies.

5 Discussion

The results demonstrate that policy timing and sequencing strongly influence the pathway of the global energy system transformation. While all policy scenarios achieve substantially lower emissions and warming than the EMB scenario, subsidies and carbon taxes affect different stages of the transition process and generate distinct patterns of investment reallocation.

The EMB scenario highlights the limitations of relying solely on endogenous technological progress to drive a complete transition. Although renewable technologies become more competitive through learning-by-doing effects, this process alone, without other non-market interventions, does not produce a rapid decline in fossil fuel dependence. As a result, emissions remain relatively high and warming exceeds levels achieved under all policy interventions.

The results suggest that renewable subsidies and carbon taxes operate through complementary mechanisms. Subsidies primarily stimulate investment in emerging low-carbon technologies, while carbon taxes accelerate the withdrawal of capital from fossil-based activities. This distinction is particularly visible in the investment trajectories. Early subsidies encourage the expansion of renewable capacity before fossil sectors fully contract, whereas early carbon taxes induce a more immediate reduction in fossil investment. These results match those of existing studies which urge a coordinated sequencing of subsidies and taxes to achieve more stable energy transitions (Acemoglu et al., 2016; Rezai and van der Ploeg, 2017).

Policy sequencing also has important implications for transition dynamics. When subsidies are introduced before taxes, renewable industries gain time to expand and accumulate productive capacity. This reduces the gap between declining fossil production and emerging renewable supply. By contrast, when taxes are implemented before subsidies, fossil-sector contraction occurs more abruptly and renewable investment responds through sharper adjustment cycles. The pronounced investment spikes visible in these scenarios indicate a more turbulent reallocation process than in scenarios where renewable industries are established earlier.

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The lag between investment and production observed across all policy scenarios highlights the importance of capital-stock dynamics. Large increases in renewable investment occur before renewable production reaches its highest levels. This temporal separation reflects both the continued learning-by-doing process where the same real dollar of investment produces more capital over time, but also the construction and deployment constraints and emphasizes that successful decarbonization requires sustained investment well before emissions reductions are fully realized.

The macroeconomic results suggest that an abrupt energy transition as those exercised in this paper have a large chance of causing severe economic harm. Persistent reductions of GDP were the result in more than half of the ensemble members and in 25% of cases a GDP was reduced below 1980 levels. This is caused by the combination of stranded fossil fuel assets, their knock-on effects through the global supply chain, energy subsidy induced inflation, and the resultant unemployment increases from each of those impacts that are likely to occur during periods of rapid structural change. The range of results also included outcomes with improved economic conditions. These occur for policy members with stronger climate damage parameters and where reductions in temperature provide a stronger benefit. This implies that policy-driven decarbonization in FRIDA does not require large long-term output losses when substantial reallocation of capital occurs, but that it is a reasonable potential outcome. It should be highlighted that the scenarios underlying these results include extreme changes to policies, and that much of the spikes in unemployment and inflation driving much of the economic hardships can be avoided through more gradual introduction of climate policy.

Even with these extreme policies it is not possible to drive median temperatures below two degrees of global warming relative to the preindustrial baseline. But, the timing of the policy matters, the early implementation of both taxes and subsidies achieves roughly a third of a degree reduction in temperature at the end of the century, compared to the delayed implementation.

In these four policy runs, the energy-demand results further indicate that emissions reductions are not primarily achieved through reductions in energy consumption. While short- and medium-term differences in demand emerge across scenarios, the dominant driver of climate outcomes is the changing composition of energy supply. Decarbonization therefore occurs mainly through technological substitution and investment-driven restructuring of the energy system rather than sustained demand reduction.

Finally, nuclear energy functions primarily as a complementary technology. Its role appears most significant in scenarios undergoing rapid fossil-fuel decline, where temporary increases in investment and production help compensate for falling fossil generation. However, renewable technologies remain the dominant source of new energy supply and account for the majority of emissions reductions.

Overall, the results emphasize that successful decarbonization depends not only on policy strength but also on policy sequencing. Early subsidies help establish alternative energy systems and reduce adjustment pressures, while carbon taxes accelerate the phase-out of fossil fuels. Among the policy scenarios explored here, those combining both instruments early produce the fastest emissions reductions and lowest temperature outcomes while avoiding some of the more pronounced investment and labor-market disruptions observed in delayed-policy scenarios.

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5.1 Limitations and future work

A key limitation of the present analysis is the highly aggregated representation of energy demand. Demand is modelled primarily as a function of global GDP, which constrains the range of behavioural and sector-specific responses that can occur under alternative policy regimes. A more disaggregated framework, separating buildings, transport, and industry, would permit demand to respond through a wider set of socio-economic and technological channels. In particular, transport demand could be represented using the framework already used within FRIDA from Rajah et al. (2025), which would have energy demand be influenced by social norms, personal norms, descriptive norms and habits, i.e., that energy prices, the composition of energy supply, and health-related effects associated with particulate emissions would all play a part in determining per capita energy demand. Such an approach would provide a more endogenous representation of demand and allow assessment of whether the central finding of this paper, namely that decarbonization occurs primarily through supply-side substitution, remains robust when demand can respond directly to the transition process.

A second limitation concerns the treatment of carbon capture and storage (CCS) and other negative emissions technologies. In the present model, CCS is represented exogenously and therefore does not influence investment decisions, technology competition, or emissions outcomes. As a result, the emissions reductions reported in this paper arise almost entirely through substitution between fossil, renewable, and nuclear energy sources. This places greater emphasis on capital reallocation, fossil-asset retirement, and the stranded-asset dynamics that contribute to the macroeconomic disruptions observed in the presented scenarios. An endogenous representation of CCS would introduce an additional abatement pathway, allowing emissions reductions to be achieved partly through emissions control within existing fossil-fuel systems rather than solely through changes in the composition of energy supply. Examining the sensitivity of emissions, temperature, investment, and macroeconomic outcomes to assumptions regarding CCS costs, deployment rates, and technological performance therefore represents an important direction for future research.

A third structural limitation of the present model is the lack of disaggregation of energy supply by energy carriers, i.e., liquid vs. electricity. Consequently, the analysis cannot identify which specific fossil technologies experience the greatest contraction, and potentially allows for more supply substitution than might otherwise be warranted. Disaggregating supply by carrier would allow technology-specific learning effects, retirement dynamics, and policy instruments to be represented explicitly, providing a more detailed assessment of transition risks and a closer approximation of how climate and energy policies are implemented in practice.

Finally, the policy experiments presented here are intentionally stylised. They are designed to explore the consequences of alternative timings and sequences of subsidies and carbon taxes rather than to replicate specific policy programmes. Policy interventions are introduced as discrete changes, and the resulting inflationary and labour-market disruptions should therefore be interpreted partly as consequences of the speed of adjustment rather than of decarbonization itself. Future work should examine more gradual and policy-realistic implementation scenarios, including phased policy introduction, technology-specific and sector-specific instruments, and interactions with demand-side measures. Combining such policy

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designs with more detailed representations of demand and supply would allow a more comprehensive assessment of transition dynamics and help distinguish the costs of decarbonization from the costs of decarbonizing rapidly.

6 Conclusions

With the FRIDA energy module demonstrated in this paper we constructed a dynamic global energy system module that is driven by energy investments based on past behaviour modes while incorporating cost motivated decision making. Costs react dynamically accounting for learning by doing and scarcity effects, affecting the response to the policy experiments shown. These policy experiments, designed to exercise the full range of the energy system as well as explore the implications of policy timing, demonstrated that the sequencing of policy interventions, first tax then subsidy, the reverse, or both delayed, can have a drastic impact on macroeconomic indicators. The impact on climate outcomes are mainly the result of delayed reductions in emissions, where the delayed phase out of fossil fuel causes more temperature increases to be locked in, resulting in higher end of century temperatures.

The central contribution of the work is the endogenous investment allocation framework. Rather than relying on optimization or exogenously prescribed deployment pathways, investments emerge from observed behavioural regularities, supply-demand imbalances, evolving technology costs, and policy incentives. The resulting investment allocator reproduces historical investment trends while remaining responsive to changes in economic, technological, and climatic conditions, suggesting that it provides a credible mechanism for representing long-term capital reallocation within the global energy system.

Beyond its standalone performance, the value of the Energy Module lies in its integration within the wider FRIDA model. Energy investments, production, prices, emissions, climate impacts, and macroeconomic outcomes are connected through explicit feedback loops, allowing developments in the energy sector to propagate throughout the broader Earth system. The module therefore serves as a key coupling mechanism between FRIDA's economy, climate, and societal components, enabling the investigation of transition dynamics that cannot be captured when these systems are considered independently.

Taken together, the results demonstrate that endogenous investment dynamics are both sufficient to reproduce historical energy-system behaviour and informative for exploring future transition pathways under uncertainty. By representing the energy transition as an emergent consequence of interacting feedbacks rather than as the outcome of a prescribed optimal pathway, the FRIDA Energy Module provides a useful platform for analysing the feasibility, risks, and consequences of alternative decarbonization strategies within a fully integrated assessment framework.

Appendix A: The ALLOCATE function

Assume there are n different requests for resources indexed by i that demand quantity q_i at priority p_i with a total requested quantity Q. We assume a width $w > 0$ (when w is 0 the solution to the allocation problem is to satisfy demand sequentially

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ordered by the priority, but we don't use this case in our model). For a given solution priority P the quantity chosen q_i' from provider i is given by the equation:

$$q_i' = \begin{cases} 0 & \text{if } P \geq p_i + w/2 \\ \dfrac{q_i(p_i + w/2 - P)}{w} & \text{if } p_i - w/2 < P < p_i + w/2 \\ q_i & \text{if } P \leq p_i - w/2 \end{cases} \quad \text{(A1)}$$

Thus we have a continuous monotone function for each provider that is 0 for P sufficiently high and q_i for P sufficiently low. Since the total amount chosen is the sum of these continuous monotone functions it is also continuous monotone and is 0 for P sufficiently high, and Σq_i for P sufficiently low. After dealing with the simple cases where Q is 0 ($q_i' = 0$), or Q is larger than the sum ($q_i' = q_i$) it follows that we can solve for P such that $\Sigma q_i = Q$. Thereby solving the allocation problem.

Code and data availability

FRIDA is released as a free and open-source model on GitHub https://github.com/metno/WorldTransFRIDA. The specific version used for this manuscript is available on Zenodo https://doi.org/10.5281/zenodo.15310860 (Schoenberg et al., 2025b). The full infrastructure to run scenario ensembles with FRIDA is hosted on GitHub https://github.com/BenjaminBlanz/WorldTransFrida-Uncertainty. A copy of the scripts used to generate the figures and the ensemble data they are based on is available on Zenodo https://doi.org/10.5281/zenodo.22940632 (Blanz, 2026).

Author contributions

Conceptualisation: BB, WS, AC, FM, MM. Data curation: BB. Formal analysis: BB, WS. Investigation: BB, WS. Methodology: BB, WS, FM, MM. Software: BB, WS. Visualization: BB. Writing – original draft: BB, WS. Writing – review & editing: BB, WS, AC, FM, MM

Competing interests

The authors declare that none of the authors has any competing interests.

Acknowledgements

The authors thank Sarah Mashadi for help with finding calibration data sources and for discussion of the model in early stages of development. The authors thank Beniamino Callegari, Martin Grimeland and Chris Wells for discussion of the model during the development and collaboration on the integration with FRIDA's economy and Climate systems respectively. This work used resources of the Deutsches Klimarechenzentrum (DKRZ) granted by its Scientific Steering

https://doi.org/10.5194/egusphere-2026-6049
Preprint. Discussion started: 16 November 2026
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Committee (WLA) under project IDs 33, 1275. The authors thank Jana Sillmann and Cecilie Mauritzen for advice and guidance and securing funding for the project.

Financial support

This research was supported by the European Union's Horizon Europe 2.5 – Climate, Energy and Mobility programme under grant agreement no. 101081661 (WorldTrans – Transparent Assessments for Real People). This work is further supported by FCT, I.P./MCTES through national funds (PIDDAC): LA/P/0068/2020 (https://doi.org/10.54499/LA/P/0068/2020), UID/50019/2025 (https://doi.org/10.54499/UID/50019/2025), UID/PRR/50019/2025 (https://doi.org/10.54499/UID/PRR/50019/2025), UID/PRR2/50019/2025 (https://doi.org/10.54499/UID/PRR2/50019/2025). The funder was not involved in any part of the development of this research.

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https://doi.org/10.5194/egusphere-2026-6049
Preprint. Discussion started: 16 November 2026
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