While there is a clear scientific consensus linking global climate change to the increase in anthropogenic greenhouse gas emissions[[1]](#footnote-1), assessing the economic impacts of these climate changes faces both practical and methodological challenges. The effort to quantify and qualify the impacts of climate change on economic activity has led to a relatively recent but substantial contribution from economic literature, with the development of various tools and models. Integrated Assessment Models (IAMs) are among the first to combine climatic and economic components to estimate the damages caused by climate change on economic activity. They thus form the foundation of the economic analysis of climate change, with the objective of calculating the social cost of carbon (1). From the difficulty of gathering historical data to the non-linearity of the damage-temperature relationship, alternative approaches have been developed to address these challenges. Among them are econometric estimations, which strengthen the empirical foundations established earlier (2).

1. **The first IAM models: foundations of the economic analysis of climate change**

Driven by the work of W. Nordhaus, IAM models—introduced as early as the 1970s to combine multidisciplinary knowledge for analyzing interactions between multiple systems—were applied to assess the impacts of climate change. These models are generally divided into two main categories: optimization models, which aim to optimize key variables of climate policies (such as carbon emission reduction rates or carbon taxes), and policy evaluation models, which analyze the consequences of specific policies. These can be deterministic models, where each input and output is fixed and predictable, or stochastic models, which incorporate uncertainty by treating certain variables as probabilistic distributions. The DICE model (Nordhaus, 1992) thus introduced the quadratic damage function, which expresses economic damages—often measured as a percentage of GDP—as a function of climate change, specifically temperature increase (), through a relationship of the following type:

,

where and are parameters calibrated using empirical data.

In addition to greenhouse gas (GHG) emissions from economic production, the model also incorporates a carbon cycle, distributing emissions among various carbon sinks such as the atmosphere, surface oceans, and deep oceans. In response to the impacts of rising temperatures, the DICE model aims to estimate the optimal trajectory for GHG reduction—that is, the most efficient pathway to slow climate change given the inputs and available technologies. These decisions involve short-term costs, particularly in terms of investments or slowed economic growth. However, they help mitigate future climate damages, thereby creating a trade-off between current interests and those of future generations.

Une image contenant texte, capture d’écran, diagramme, ligne

Description générée automatiquementThe adjacent figure schematically illustrates the logic behind the DICE model. Other models, such as PAGE (Policy Analysis of the Greenhouse Effect, Hope, 1993) and FUND (Framework for Uncertainty, Negotiation, and Distribution, Tol, 1995), have been developed in parallel and incorporate region-specific damages. The PAGE model focuses on assessing uncertainties related to climate impacts and mitigation costs. It uses a probabilistic approach to estimate climate damages based on various warming scenarios, integrating uncertainties in key variables such as climate sensitivity and adaptation costs. The FUND model emphasizes the regional and sectoral effects of climate change, detailing impacts in areas like agriculture, health, or energy costs. Unlike PAGE, FUND explores the interactions between potential short-term benefits (such as reduced heating needs in some regions) and the overall costs of warming, providing a more granular view of regional disparities.

According to the Intergovernmental Panel on Climate Change (IPCC), IAMs “are convenient frameworks for combining knowledge from a wide range of disciplines in order to conduct coordinated exploration of possible future trajectories of human and natural systems, development of insights into key questions of policy formation, and prioritisation of research needs in order to enhance our ability to identify robust policy options.” Furthermore, IAMs play a central role in shaping climate policies. For instance, the work of Dietz and Stern (2015) shows that incorporating dynamics affecting total factor productivity (TFP) in these models significantly increases estimates of climate costs and justifies more ambitious mitigation actions.

1. **Towards more targeted empirical studies: statistical and econometric estimations**

Despite their usefulness, IAMs face significant criticism. First, the damage functions are often arbitrary and not based on robust empirical data. Weitzman (2011) particularly criticizes the assumption of quadratic damages, arguing that it underestimates catastrophic risks. Furthermore, IAMs fail to capture dynamic mechanisms such as economic agents' adaptation or technological innovations, which are essential for understanding responses to climate change. The assumption of constant parameters also presents issues. For instance, in DICE, the discount rate used to evaluate future costs varies according to the normative preferences of researchers, leading to divergent policy recommendations. Additionally, Tol (2018) highlights that IAMs tend to overlook the complex interactions between economic and climate systems, often assuming a unidirectional causality.

* *Regression models*

Considering the limitations of IAMs, empirical studies aim to establish causal links between climate variables and economic indicators. Authors such as Dell, Jones, and Olken (2012) use historical variations in temperature to quantify their impacts on economic growth. Their approach is based on regressions of the form:

where and represent temperature and precipitation for country i in year t, and includes additional controls.

Their results show that poor countries experience a significant decline in growth in response to rising temperatures, with an estimated effect of −1.3% per degree Celsius. In contrast, wealthy countries appear relatively resilient, highlighting disparities in adaptive capacity.

Hsiang's work (2016) builds on these analyses by modeling climatic effects as exogenous random variations, allowing for a robust identification of climate impacts. Hsiang also highlights nonlinearities in these relationships, suggesting that climate damages increase disproportionately beyond certain temperature thresholds.

* *Panel data models*

Panel data models represent another significant methodological advancement, leveraging spatial and temporal variations to better identify the effects of climate shocks. Kolstad and Moore (2019) examine both linear and nonlinear approaches applied to climate and economic data. They emphasize that fixed effects help control for omitted variables, thereby reducing bias. A typical specification includes terms such as:

where and capture country-specific and year-specific effects, respectively.

However, these models are not without limitations. Economic responses to short-term climatic variations (e.g., heatwaves) can differ significantly from the impacts of permanent climate changes due to economic agents' adaptation. For instance, Deschênes and Greenstone (2007) show that while annual weather variations are useful for identification, they do not necessarily reflect the structural effects of long-term climate trends.

1. Citer un rapport du GIEC par ex [↑](#footnote-ref-1)