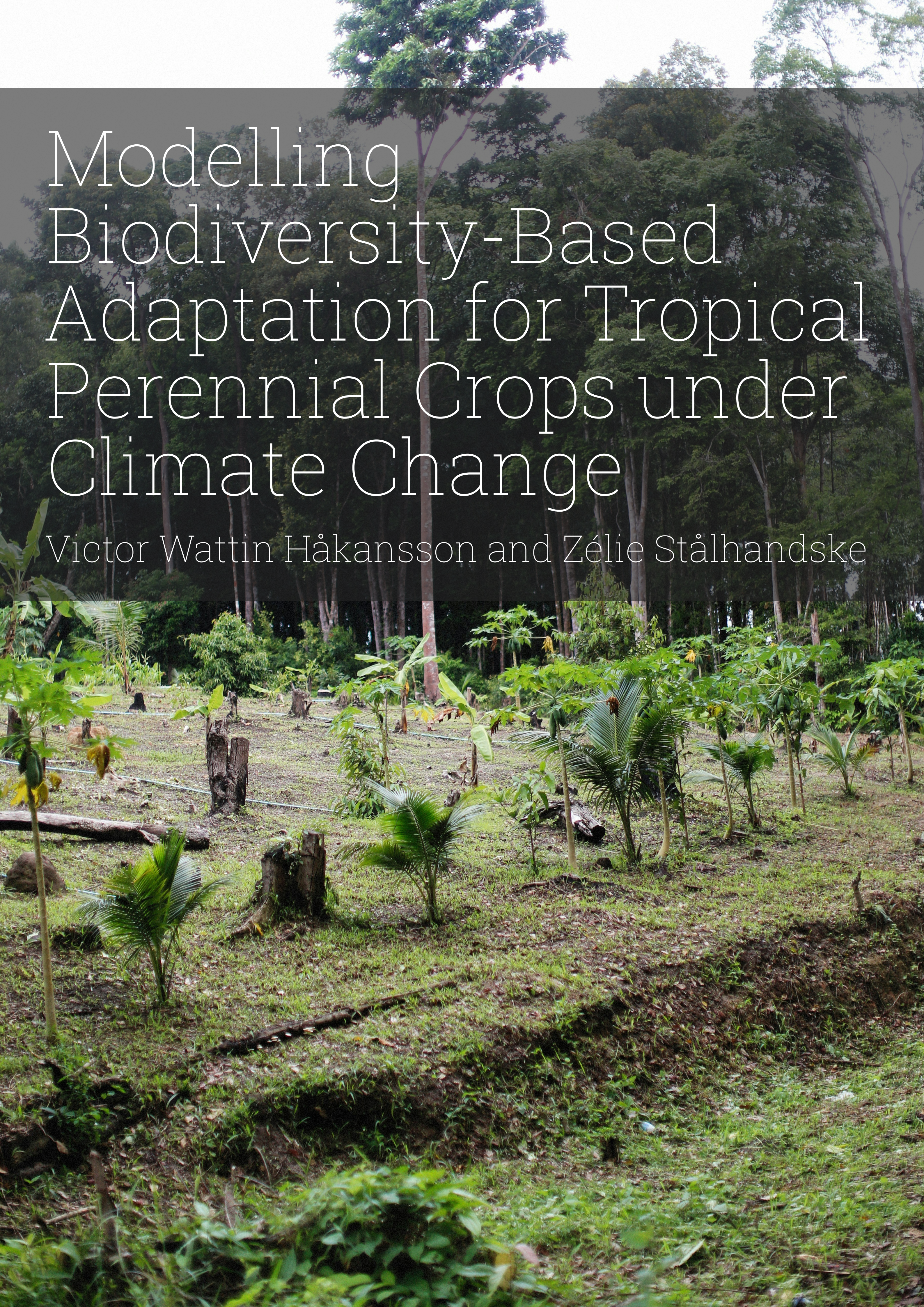

Modelling Biodiversity-Based Adaptation for Tropical Perennial Crops under Climate Change

Victor Wattin Håkansson and Zélie Stålhandske

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Cover: Banana agroforestry system by Alexey Demidov on Unsplash

Summary

This report has been developed as part of the BioFinCas project, which aims to support biodiversity-rich and climate-resilient agricultural systems for tropical crops. It combines a literature review with a prototype analysis designed to demonstrate how climate risk to perennial systems such as coffee and cacao can be assessed in a CLIMADA-compatible framework. The literature review synthesises current knowledge on climate hazards affecting tropical crops, the role of agroforestry and biodiversity in buffering these impacts, and existing modelling approaches, from suitability models to process-based and risk-based frameworks.

Building on this foundation, we constructed stylised agroforestry plot archetypes for the Dominican Republic, Guatemala, and Mexico. Each archetype includes main crops, associated shade species, and typical planting densities, and was translated into CLIMADA exposure files. These exposures were linked to both slow-onset suitability hazards (derived from species distribution modelling) and acute hazard representations (heat and drought extremes). Synthetic ensembles of extreme years were generated using GEV distributions, providing a first demonstration of how event-based risk analysis could be applied to agroforestry systems. Finally, a cost–benefit workflow was implemented to assess how alternative canopy interventions affect revenues, risks, and biodiversity outcomes.

Key initial insights include:

- **Suitability under warming:** Coffee shows sharp losses in climatic suitability, with more than half of current sites projected to fall below the threshold at $+4°$C, while cacao and many shade species remain comparatively resilient.
- **Extreme events:** The prototype demonstrates how risk analysis for drought and heat extremes could be integrated, but also highlights the lack of empirical vulnerability data for tropical crops and shade species. Developing robust impact functions should be a priority to make such analyses realistic.
- **Yield–shade trade-offs:** Present-day revenues generally lie close to observed canopy levels. Under warming, slightly higher shade can mitigate hazard losses, but excessive shade reduces yields, emphasising the need to balance productivity and resilience.
- **Cost–benefit analysis:** The framework allows revenues to be decomposed into structural (gain) and hazard-related (risk) components. While fruit trees diversify revenues, their contribution is overstated in the prototype since hazard risks are not yet modelled for secondary crops.

Key recommendations going forward:

- **Link local measurements with modelling:** collect microclimate and management data from agroforestry plots to fill data gab, and specifically measure the role of different species in providing ecosystem services.
- **Include species in the exposure:** represent agroforestry systems at the species level so that risks and benefits can be directly connected to ecosystem services such as nitrogen fixation, fruit provision, or shade.
- **Consider trade-offs:** evaluate adaptation measures in a multi-criteria way, recognising that choices which maximise shade or yield may reduce biodiversity or economic viability, and vice versa.

Overall, the combined review and prototype show that a biodiversity-informed, multi-criteria risk framework is both feasible and useful. They underline that adaptation measures—such as adjusting canopy cover or species composition—must be evaluated not only in terms of hazard buffering but also in terms of economic viability and biodiversity outcomes. Further work should focus on calibrating vulnerability curves with empirical data, improving the representation of ecosystem services, and co-developing decision-relevant outputs with local partners.

Acknowledgements

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Contents

1 Introduction

Perennial tropical crops such as coffee, cacao, and bananas form the backbone of global agricultural trade and rural livelihoods in many tropical regions. However, they are increasingly threatened by climate change through both the gradual shift in average climatic conditions, such as rising temperatures and altered rainfall patterns, and the increased frequency and intensity of extreme weather events, including droughts, heatwaves, storms, and extreme rainfall [22]. Unlike annual crops, perennials are harder to relocate or replant in response to these changes, making them particularly vulnerable to both slow-onset and sudden climate impacts.

Unlike many annual crops, coffee, cacao, and bananas are traditionally cultivated within agroforestry systems. In these systems, diverse tree species are integrated alongside crops, offering multiple ecological and livelihood benefits, including temperature regulation, improved soil moisture, and habitat connectivity.

However, the maintenance of these agroforestry systems is not uniform across regions. Trends vary depending on local policies, market forces, and farmer decisions. For instance, between 1996 and 2012, the share of coffee grown under shade increased in Mexico (from 10% to 30%), while it declined in Guatemala (from 45% to 40%) [24].

This decline in some areas is closely linked to the intensification of coffee production, often driven by efforts to boost yields and control disease outbreaks such as coffee leaf rust [20]. In many cases, farmers have shifted to high-yielding, disease-resistant varieties, frequently accompanied by reduced shade, denser planting, and greater agrochemical use. These shifts have simplified many coffee landscapes, with important implications for biodiversity, climate resilience, and the livelihoods that depend on them.

Agroforestry can however serve as a critical adaptation measure for perennial crops in a changing climate. The presence of larger trees can buffer crops against temperature extremes, improve soil moisture retention, and protect against droughts, storms, and heatwaves. With the planet facing a coupled biodiversity and climate crisis, agroforestry presents itself as a particularly powerful solution: it can simultaneously enhance the resilience of agricultural systems to climate stressors while conserving biodiversity, sequestering carbon, and sustaining key ecosystem services. Trees within these systems create habitat for a wide range of species, maintaining ecological connectivity and supporting local food webs even within managed landscapes.

However, the benefits of agroforestry are not guaranteed under future climatic conditions. The trees themselves are vulnerable to rising temperatures, shifting rainfall patterns, and increasing climatic variability [13]. Some species historically used for shade or soil improvement may no longer thrive under projected climate scenarios, potentially weakening the microclimatic buffering and ecosystem functions that agroforestry systems provide.

In response to these challenges, this work aims to assess the vulnerability of perennial tropical crops to both gradual climate change and extreme weather events, to explore the role of agroforestry and biodiversity in enhancing crop resilience, and to investigate how the biodiversity embedded within agroforestry systems may itself be at risk. This research is conducted within the BIOFINCAS project, which promotes biodiversity-rich and climate-resilient agricultural systems for tropical crops.

Our specific contribution has two components. First, we conducted a structured literature review synthesising current evidence on climate hazards affecting perennial crops, the buffering role of biodiversity and agroforestry, and the range of modelling approaches available—from suitability models to event-based risk frameworks and mechanistic process-based simulations. Second, we developed a prototype analysis, building on the CLIMADA modelling platform, to demonstrate how risks to perennial crops and associated shade trees could be quantified. This prototype combined (i) stylised agroforestry plot archetypes for the Dominican Republic, Guatemala, and Mexico, (ii) species-level suitability maps derived from species distribution models, (iii) synthetic event sets for heat and drought extremes generated with Generalised Extreme Value (GEV) distributions, and (iv) a cost–benefit workflow to test canopy interventions under different hazard scenarios. Together, these steps allowed us to explore the trade-offs between yield, risk reduction, and biodiversity, and to highlight the data and methodological gaps that need to be addressed for robust policy-relevant applications.

This first phase is therefore both a scoping and proof-of-concept exercise. By combining literature synthesis with a working prototype, it provides UNU and partners with (i) a clearer view of the main knowledge gaps, (ii) an operational starting point for biodiversity-informed risk analysis, and (iii) recommendations for the empirical data and model development needed in the next phase to deliver decision-relevant insights for farmers, practitioners, and policymakers.

Part I

Literature Review

2

Climate Hazard Impacts on Tropical Crops

Climate change affects tropical crops both through shifts in average climatic conditions and through extreme weather events. Long-term changes such as gradual increases in temperature, altered precipitation patterns, and changes in seasonality are described by the Intergovernmental Panel on Climate Change as slow-onset events. These can slowly erode crop suitability, reduce yields, and increase vulnerability to pests and diseases over time. Extreme events, by contrast, are short-lived but potentially devastating events, such as droughts, heatwaves, storms, or intense rainfall episodes. While slow-onset events can progressively reshape agricultural systems, extreme events often cause immediate and severe impacts on crop productivity and survival [22].

Coffee and cacao are perennial crops with distinct flowering and harvest seasons [11, 12], while bananas produce fruit continuously throughout the year [46]. Although the phenological cycles differ, all three crops are vulnerable to climate hazards year-round. Stressful conditions, even outside flowering or fruiting periods, can impair plant health, reduce future yields, or in severe cases, lead to tree death or farm abandonment.

In this chapter, we review existing research on the impacts of both slow-onset and extreme climate events on coffee, cacao and bananas, with a specific focus on Central America. For coffee, we focus specifically on Arabica coffee, as this represents over 94% of the coffee produced in the region [20]. We do not differentiate between specific cultivars, although we acknowledge that climate sensitivity and resilience may vary between varieties [38]. However, these traits often provide only partial protection and may not fully prevent yield losses or damage under severe or compound events.

2.1. Slow-Onset Climate Hazards

Most research linking climate change, and crop impacts focuses on modelling suitability, that is, identifying the average climatic conditions under which a crop can survive and remain productive. In this section, we reinterpret such findings through a hazard lens: instead of assessing where conditions are optimal, we examine when and where specific climate variables reach levels that may compromise crop viability. This allows us to identify slow-onset hazards, such as warming or prolonged water stress, that gradually erode growing conditions and increase the risk of long-term decline.

This chapter draws primarily on agro-climatic thresholds and tolerance ranges reported by the Food and Agriculture Organization (FAO) [16], which offer a consistent basis for evaluating suitability and hazard thresholds across different crops. While these thresholds are informative, many farms adapt to suboptimal conditions through measures such as irrigation, allowing cultivation to persist beyond the ideal climatic ranges [48].

2.1.1. Warming

All three crops are highly temperature sensitive and therefore vulnerable to slow-onset warming. Unlike acute hazards like droughts or storms, which cause short-term damage, gradual warming can steadily push temperatures beyond crop tolerance thresholds, reducing productivity and eventually making cultivation unviable.

For *Coffea arabica*, the ideal mean annual temperature lies between $17\,°\mathrm{C}$ and $22\,°\mathrm{C}$. The plant can tolerate up to $25\,°\mathrm{C}$ and down to $12\,°\mathrm{C}$, though with decreasing suitability. Once these limits are regularly exceeded, yields decline and production may no longer be sustainable.

Theobroma cacao (cacao) thrives between $22\,°\mathrm{C}$ and $25\,°\mathrm{C}$, tolerating a broader range from $20\,°\mathrm{C}$ to $27\,°\mathrm{C}$, with absolute limits between $10\,°\mathrm{C}$ and $38\,°\mathrm{C}$ depending on daily variation. Gradual warming may shift many regions toward marginal conditions, reducing yields even in the absence of extreme heat.

For bananas (*Musa spp.*), optimal temperatures range from $22.9\,°\mathrm{C}$ to $27.9\,°\mathrm{C}$, with tolerances up to about $30\,°\mathrm{C}$. Sustained exposure above this threshold can cause heat stress and reduced fruit quality. Because bananas grow continuously, even moderate warming in already warm areas can degrade productivity over time, potentially forcing shifts in cultivation zones or the adoption of adaptive measures.

2.1.2. Water Stress

Water availability is a key factor in the long-term viability of most crops. These crops depend on consistent rainfall and adequate soil moisture to support growth, flowering, and fruiting. When rainfall falls below critical thresholds or becomes erratic, it leads to water stress, a which gradually undermines productivity and, in severe cases, causes crop failure.

Coffea arabica grows best with $1200\,\mathrm{mm}$ to $1800\,\mathrm{mm}$ of annual rainfall. Below this range, flowering and bean development suffer, and irrigation may become necessary—an option often inaccessible to smallholder farmers.

Theobroma cacao similarly depends on high and well-distributed rainfall, thriving with $1200\,\mathrm{mm}$ to $3000\,\mathrm{mm}$ per year and tolerating a wider range from $900\,\mathrm{mm}$ to $7600\,\mathrm{mm}$. It is particularly sensitive to dry spells, with suitability decreasing when more than one to three dry months occur annually.

Banana (*Musa spp.*) is the most water-demanding of the three, ideally requiring $2000\,\mathrm{mm}$ to $2500\,\mathrm{mm}$ of annual rainfall. Its shallow root system and large leaves make it especially vulnerable to rapid water loss. Prolonged dry periods or shifts in rainfall patterns can reduce fruit size, delay flowering, or even lead to plant death.

Table 2.1: Climatic requirements and tolerances of coffee (arabica), cacao, and banana crops.

Parameter	Coffee (Arabica)	Cacao	Banana
Optimal Temp. (°C)	17–22	22–25	22.9–27.9
Tolerance Temp. (°C)	12–25	10–38 (abs.)	Up to 30
Optimal Rainfall (mm)	1200–1800	1200–3000	2000–2500
Rainfall Tolerance (mm)	>1000	900–7600	Somewhat lower possible
Dry Season Tolerance	Short dry season tolerable	Max. 1–3 dry months	Poor tolerance to dry spells

2.2. Extreme Events

The link between extreme events, or so called acute hazards, is less studied than the one to slow-onset hazards. We define extreme events as short-term events (from days to a month) that may destroy the production or lead to long-term impacts on the trees. The area may appear suitable on average, but these events can lead to short term or long term impacts. If these occur too frequently, the area may also become unsuitable on the long term. While climate suitability is often inferred from observations of where crops currently grow, evidence on the impacts of extreme events typically comes from controlled experiments, such as artificially induced droughts, or from post-event damage assessments in the field. However, it is important to note that experimental results may not fully translate to real-world conditions, where multiple stressors, management practices, and landscape variability interact in complex ways. Similarly, post-event assessments are often constrained by limited data availability or by the difficulty of isolating the effects of a single hazard from other contributing factors.

2.2.1. Heat stress

While gradual warming can reduce suitability over time, extreme heat events may have immediate and severe consequences for tropical crops. Rodrigues et al. (2016) demonstrated through an experiment that coffee trees can withstand sustained temperatures of 37/30$^\circ\mathrm{C}$ (day/night) with minimal impairment to photosynthetic performance, even under ambient atmospheric CO_2 concentrations of 380 $\mu\mathrm{L}\,\mathrm{L}^{-1}$. However, at 42/34$^\circ\mathrm{C}$, plants reached a physiological threshold beyond which irreversible, damage to the photosynthetic machinery occurred—particularly for *Coffea arabica*. Importantly, their experiments showed that elevated CO_2 concentrations (700 $\mu\mathrm{L}\,\mathrm{L}^{-1}$) substantially mitigated these impacts, preserving photosystem function and promoting greater thermotolerance. These findings provide cautious optimism that rising CO_2 levels may partially buffer the physiological impacts of warming on coffee, though field conditions introduce additional stressors that may offset these benefits [47].

Further experimental work by Marias et al. (2017) highlights the vulnerability of Coffea arabica to short-term extreme heat events. In growth chamber experiments, plants exposed to temperatures of 49$^\circ\mathrm{C}$ for 45 or 90 minutes exhibited severe physiological stress, including reduced photosynthesis, inhibited phloem transport, and impaired recovery of expanding leaves. Crucially, none of the heat-treated plants produced flowers or fruit in the following weeks, indicating a total loss of yield for that season. While mature leaves partially recovered over time, the experiment suggests that even brief, intense heatwaves—particularly under full sunlight—can lead to crop failure and longer-term damage [31].

A recent study by Kath et al. (2022) calibrated a function based on country yearly yields and found that yearly mean temperature was a good predictor of yields. However they found the vapor pressure deficit (VPD), which includes relative humidity alongside temperature, was a better predictor (see figure 2.1) [27]. These results for VPD are further described in the section on drought.

As for cacao, there is comparatively less research on the physiological response of the plant to extreme temperatures than coffee. In a controlled experiment using infrared heaters, leaf temperatures were increased by 7–8$^\circ\mathrm{C}$, exposing cacao plants to midday leaf temperatures between 37 and 40$^\circ\mathrm{C}$, well above the reported optimum of 34$^\circ\mathrm{C}$ and near the threshold of 38$^\circ\mathrm{C}$ for growth. Four weeks of heat exposure led to significant reductions in photosynthesis, chlorophyll content, and total biomass. While shading improved general plant performance, it only partially buffered the effects of heat, and physiological indicators like water-use efficiency remained primarily driven by temperature stress [35].

While little scientific evidence is available, extreme heat can also disrupt banana production, even where irrigation is available. In Brazil's semi-arid northeast, for example, banana farmers have observed that when temperatures reach around 40 °C and humidity is low, plants cease to function physiologically, halting growth despite adequate water supply. During a 2023 heatwave, some farms experienced a 15% reduction in the following year's harvest due to heat-induced stress [30].

2.2.2. Drought

Drought can take many forms, and definitions vary depending on the timescale and processes involved. Long-term drought, such as a persistent decline in average annual precipitation, is often used in crop suitability modelling to assess shifting growing zones. However, shorter-term droughts, spanning weeks to months, can also have severe impacts, particularly for perennial crops like coffee, cacao, and bananas. Even in the absence of changes in total annual rainfall, climate change may increase the frequency and intensity of dry spells, for instance by concentrating rainfall into fewer months. Moreover, rising temperatures can accelerate evapotranspiration and lead to drier soils, compounding water stress even where precipitation patterns remain stable.

Recent research has identified vapour pressure deficit (VPD) as a particularly effective indicator of drought-related stress for coffee plants [27]. VPD measures the difference between the amount of moisture in the air and the amount the air can hold when saturated; as temperatures rise, air can hold more moisture, increasing VPD. High VPD signals drier atmospheric conditions, which drive higher transpiration rates in plants and lead to accelerated water loss—even in well-watered soils. Using global Arabica coffee production data across 13 major producing countries, Kath et al. (2022) found that VPD during the fruit development season was the strongest predictor of interannual yield variability, with a clear non-linear threshold at $0.82\,\mathrm{kPa}$. Above this threshold, yields declined sharply (see figure 2.1).

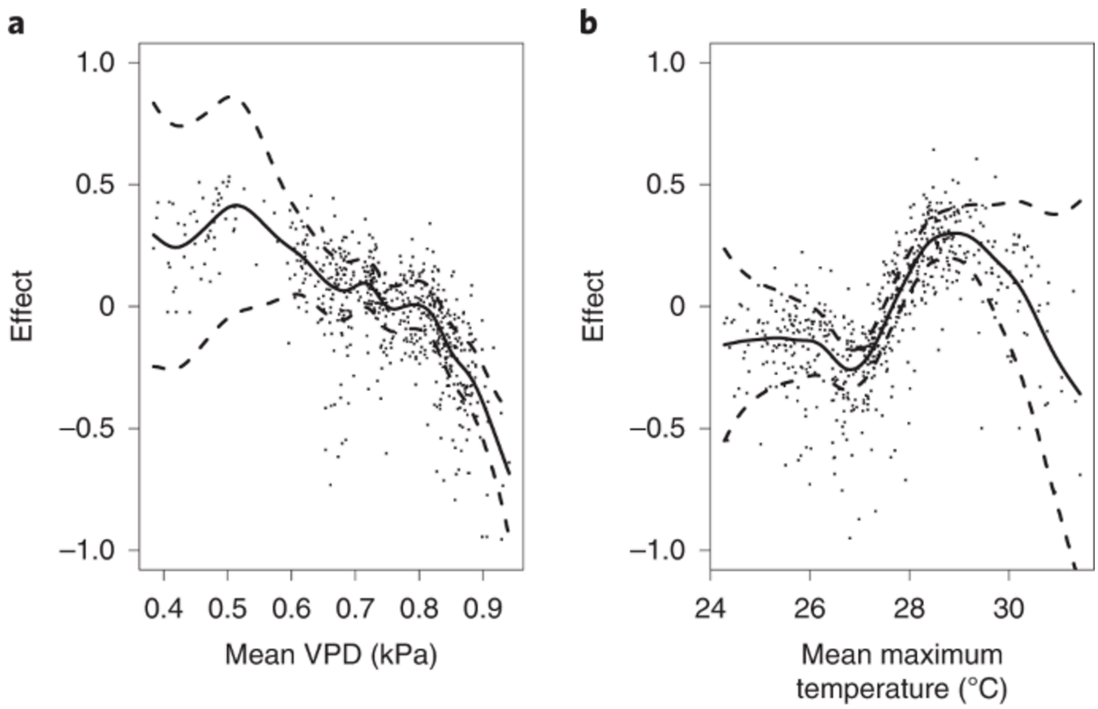


Figure 2.1: Figure from Kath et al. (2022) [27]. VPD in the growing season. b, Mean maximum temperatures in the growing season. The solid black line is the mean effect, and dashed lines are 95% confidence intervals. Points are partial residuals. Data are from country-level coffee yield data from between 1961 and 2017 for 13 of the most important coffee-producing countries globally (Brazil, Colombia, Costa Rica, El Salvador, Ethiopia, Guatemala, Honduras, Kenya, Mexico, Nicaragua, Peru, Tanzania and Venezuela).

In the case of bananas, while we did not find any quantitaitive relationship, a global expert survey identified delays in the onset of the rainy season and extended dry periods during the rainy season as the most critical weather-related threats to productivity across 15 agroclimatic regions [8].

In cacao systems, drought can sharply reduce yield even when other ecosystem processes appear only mildly affected. Schwendenmann et al. (2010) conducted a 13-month throughfall exclusion experiment in a cacao *Gliricidia* agroforestry system in Indonesia, where rainfall was reduced by approximately 50%. While changes in sap flux, litterfall, and CO_2 efflux were relatively small, cacao bean yield dropped by 45% during the harvest following the most intense period of soil moisture deficit. This finding suggests that reproductive processes in cacao may be particularly vulnerable to water stress, even when vegetative functions appear resilient [49].

2.2.3. Heavy Wind

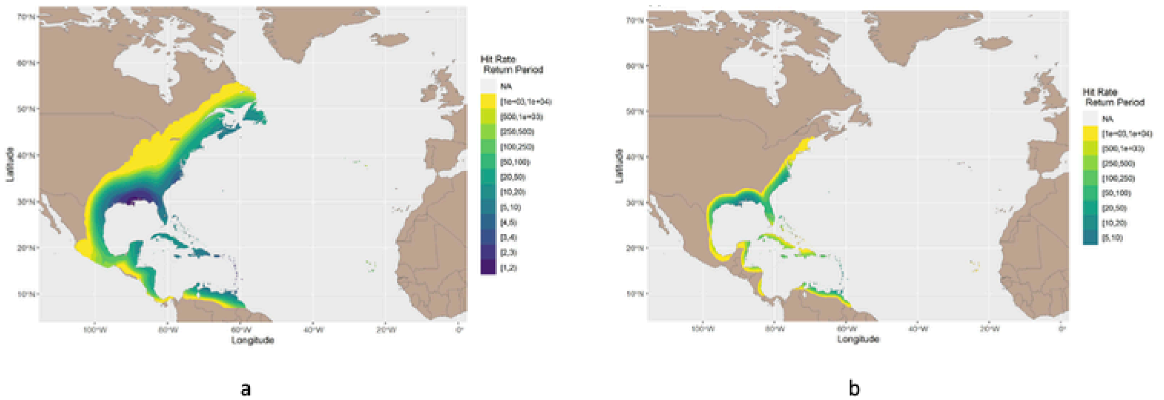


Figure 2.2: Tropical cyclone hazard maps for Category 1+ storms over the North Atlantic. Panel (a) shows the average annual number of direct and indirect hits, expressed in return periods. Panel (b) presents the same metric but for Category 4 and 5 storms only. Adapted from Carozza et al. (2024) [9].

Central America has repeatedly experienced damaging winds due to tropical cyclones, with severe consequences for agriculture. Among the three countries, the Dominican Republic is most consistently and densely exposed to strong tropical cyclone winds. Due to its relatively small size, a single storm can affect most or all of the country, including major agricultural regions. This is clearly shown in Figure 2.2, illustrates the high frequency of cyclone-strength winds across the island. Mexico is also exposed to tropical cyclone winds on both its Pacific and Atlantic coasts, though most coffee and banana production is concentrated inland or on the Pacific side. Guatemala, by contrast, experiences fewer direct wind impacts from tropical cyclones and is generally less exposed [9]. In Guatemala, hurricanes Iota and Eta in 2020 and 2021 have brought torrential rains and strong winds that devastated farming communities [25]. In the Dominican Republic, Hurricane Maria and Irma in 2017 caused widespread destruction, with about 11.35% of banana plantation areas affected [52]. Coffee plantation where also heavily affected, both intensive productions and agroforestry systems. In Mexico, events like hurricane Stans (2005) brought extreme winds, affecting agricultural zones and producers [10].

Such high winds can cause major damage to perennial crops like coffee, cacao, and bananas, breaking branches, uprooting trees, and stripping away fruit and foliage. For bananas in particular, plantations have been reported to suffer complete destruction at wind speeds above 44m/s, with damage observed even at speeds as low as 10m/s, as shown in figure 2.3 [26]. For coffee, one study assessed damages to coffee after hurricanes in the Dominican Republic. Initial reports suggested that up to 90% of coffee plants in Puerto Rico were destroyed by Hurricanes Irma and Maria in 2017. However, they performed a detailed field survey across 81 coffee plots revealing highly variable outcomes: nearly half the plots experienced less than 20% plant damage, while only 12 plots had severe damage affecting 80% or more of the plants. Damage varied even within individual plots and was significantly more likely on north- and south-facing slopes. No clear relationship was found between damage and factors such as distance from the hurricane's path, elevation, precipitation, or wind speed [32].

In the Dominican Republic, hurricanes Irma and Maria (2017) damaged an estimated 2,447 hectares, or 11.35%, of banana plantations across Monte Cristi, Valverde, and Santiago provinces. While this damage was attributed to the hurricanes, remote sensing and farmer surveys indicate that much of it may have been caused by flooding, as many affected areas were located near the Yaque del Norte river and experienced prolonged inundation following the storms [51].

As for cacao, experimental work shows that it is sensitive to mechanical stress from both intermittent and constant winds, even at moderate speeds around 4.5 m/s. Young leaves in particular show structural and physiological damage that can reduce productivity. While such controlled experiments highlight wind as a chronic stressor, field-based evidence on acute wind damage remains scarce. Observations following Hurricane Dean (2007), Jamaica's Ministry of Agriculture reported that 20% of the upper cocoa canopy layer was damaged [43]

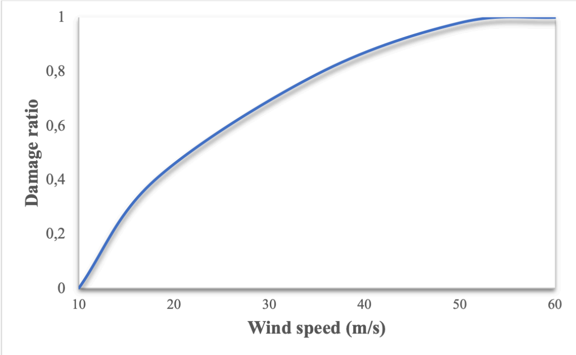


Figure 2.3: Damage ratio sustained by banana plantations during hurricanes as defined by Kaashoek et al. (2023) [26]

2.2.4. Heavy Precipitation and Flooding

For both cacao and coffee, heavy precipitation and flooding can damage new flowers or fruits and hinder the start of the next main crop [45]. Heavy precipitation can also lead to diseases, such as fungal diseases [44].

In the Dominican Republic, analysis of satellite imagery and farmer surveys after Hurricanes Irma and Maria revealed that storm damage to banana farms followed an 'all-or-nothing' pattern: when farms were flooded, damage was typically complete. About 11.4% of the regional banana area was affected, with 75% of impacted farmers reporting that 90% of their plantation area had been inundated. On average, 83% of in-progress banana production was lost. Remote sensing data showed canopy degradation continuing up to three months post-storm, highlighting the delayed and compounding nature of flood impacts. In addition to crop loss, farm infrastructure was also heavily damaged, including drainage systems, roads, and packing facilities.

In general, we found few quantitative assessments that relate flood depth or duration directly to crop damage, and overall, flooding appears to be a less consistent threat to production than drought.

2.2.5. Wildfires

All three countries are potentially exposed to wildfires, although comprehensive evidence on wildfire impacts on coffee, cacao, or banana systems remains scarce. Fire risk is particularly pronounced in regions where dry conditions and human activity coincide. For example, northern Guatemala, where cacao is grown under agroforestry systems, shows recurrent fire activity (see Figure 2.4), raising concerns for the resilience of these systems. Coffee production, typically concentrated in cooler, humid highlands, is less likely to coincide spatially with fire-prone areas, though some regions in Mexico may be exceptions. Banana plantations, often located in lowland tropical zones with seasonal dry periods, may also be vulnerable to fire, especially during drought years or in proximity to degraded or cleared land.

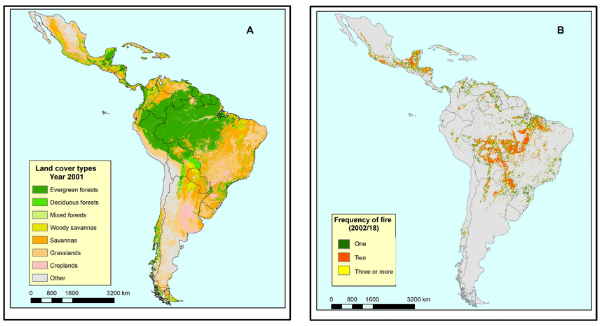


Figure 2.4: The magnitude of burning occurrences per land cover in Latin America. Distribution of (A) land cover types in Latin America and (B) selected forest pixels with fire frequency between 2002/2018 (one, two, and three or more occurrences) from Armenteras et al. (2021) [5]

3

The Role of Biodiversity in Climate Adaptation

3.1. Agroforestry Ecosystem Services for Climate Adaptation: Focus on Microclimate Regulation

Agroforestry systems, which integrate trees and crops, are increasingly recognised as nature-based solutions to help farmers adapt to climate risks. By modifying microclimatic conditions—such as temperature, humidity, wind speed, and soil moisture—agroforestry can buffer crops from environmental stressors while offering additional benefits like improved soil fertility, pest regulation, and pollination services.

3.1.1. Drought and Heat Protection

Agroforestry systems can reduce crop vulnerability to drought and heat by moderating temperature extremes and improving soil water retention. For example, a 13-month throughfall reduction experiment in Indonesia showed that complementary root structures between cacao and shade trees helped maintain ecosystem function and limit yield losses under artificial drought conditions [49]. In contrast, a field study in Ghana during the 2015/2016 El Niño drought found that cocoa experienced significant water competition under shade, resulting in higher mortality rates compared to full-sun systems [2]. These findings illustrate that the effectiveness of agroforestry as a drought adaptation strategy is highly context-dependent.

Similarly, a study in West Africa found that shade increased cacao yields by about 23% under normal rainfall, but yields dropped by up to 59% when water was severely limited, showing that shade alone cannot fully mitigate drought impacts [34].

Beyond water regulation, agroforestry can also reduce extreme temperatures. In coffee systems, high-shade regimes (60–80%) reduced daily maximum temperatures by 2–3°C, while moderate shade (30–60%) achieved reductions of 1–1.5°C [29]. In cacao systems, [21] demonstrated that high-shade cabruca plantations could be up to 6°C cooler than unshaded ones. However, excessive shading can reduce light availability and limit yields. Studies recommend an optimal shade range of 30–50% for coffee [50], while a meta-analysis for cacao found yield peaks at 25–45% shade, with declines beyond

40% [28]. These trade-offs highlight the need to balance microclimate benefits with crop productivity.

3.1.2. Wind Protection

Vegetation in agroforestry systems can also act as windbreaks, reducing mechanical damage to crops. Structural characteristics such as tree height, canopy density, and spatial arrangement influence wind buffering capacity. However, this protection has limits. After Tropical Cyclone Maria in Puerto Rico, even shaded coffee farms experienced severe damage, although farms with dense citrus intercropping showed reduced impacts, suggesting that low, dense canopies may offer better protection in extreme wind events [39].

Agroforestry systems themselves have shown resilience. In Fiji, for example, only 12.2% of tree stems in agroforests died three years after Category 5 Cyclone Winston, despite nearly half experiencing damage [33]. This underscores the importance of system structure not only for immediate crop protection but also for long-term recovery.

3.1.3. Flood and Heavy Rain Protection

Agroforestry may also reduce flood-related damage. A study in the Peruvian Amazon showed that young monocropped cacao plantations experienced up to 82% mortality following extreme flooding, while older or shaded agroforestry systems experienced lower mortality [14]. Low canopy cover in monocultures allowed sunlight to warm floodwaters, depleting oxygen and increasing root stress. Shaded systems reduced this effect by limiting light exposure at the water surface. The authors suggest integrating flood-tolerant species like *Mauritia flexuosa* (aguaje) and *Myrciaria dubia* (camu-camu) to improve system resilience in flood-prone areas.

In summary, agroforestry systems can offer substantial benefits for climate adaptation by moderating microclimatic extremes—reducing temperature, buffering drought, protecting against wind, and mitigating flood impacts. Beyond microclimate regulation, they also support ecosystem services such as improved soil fertility through nitrogen-fixing species, enhanced pollination, and natural pest and disease regulation through increased biodiversity. However, these benefits depend on system design, species selection, and local conditions. Poorly designed systems, such as those with excessive shade or high water competition, may undermine both productivity and resilience. Careful management is therefore essential to maximise the multiple benefits agroforestry can provide for climate adaptation.

4
Modelling Approaches

In this chapter, we review key approaches to model climate risk and adaptation for tropical perennial crops. We begin with climate suitability models—both statistical and envelope-based—built on long-term climatological averages and requiring relatively limited data. We then examine event-based risk models, following the IPCC framework, which simulate the impacts of discrete extreme events. Finally, we present process-based models that provide detailed simulations of crop–climate interactions, particularly useful for evaluating adaptation strategies, though they require extensive data and calibration.

4.1. Climate Suitability Models (Average Climatology)

One way to assess climate risk to tropical crops and agroforestry systems is through suitability modelling [17, 15, 40, 19]. These models estimate how conducive environmental conditions are to sustaining a crop or species under current or projected climates. Suitability can be defined statistically, using occurrence data; mechanistically, via biophysical simulations; or through threshold-based envelope models. Suitability scores, typically ranging from 0 to 1 or 0 to 100, are often converted to binary classifications (suitable/unsuitable) based on predefined thresholds.

4.1.1. Species Distribution Models and Maximum Entropy Models

Statistical models define suitability based on relationships between species occurrences and environmental predictors, such as bioclimatic variables. Species distribution models (SDMs), particularly the maximum entropy modelling approach (MaxEnt), are widely applied in tropical agriculture, especially for coffee and cacao [17, 15, 40].

4.1.2. Statistical Species Distribution Models (SDMs)

SDMs are commonly grouped into two categories:

- **Presence–Absence Models**, which use both presence and confirmed absence data, typically via regression methods such as Generalised Linear Models (GLMs) [17].
- **Presence–Only Models**, which rely only on observed presences, with MaxEnt being the most widely used approach [40, 15, 17].

MaxEnt

MaxEnt estimates relative suitability by comparing environmental conditions at presence sites to those across background points representing the broader landscape. Its output is a continuous score between 0 and 1 that reflects how similar locations are to known presences, but it does not represent a true probability of occurrence. Suitability thresholds—based either on domain knowledge or on statistical criteria such as the maximum sensitivity–specificity balance—are often applied to classify areas as suitable or unsuitable [19].

Applications of MaxEnt frequently rely on long-term bioclimatic averages, such as those provided by WorldClim[1], to assess future suitability. For example, Gomes et al. (2020) used MaxEnt to model future coffee suitability in Brazil, applying a 0.25 threshold based on observed plantation data [19]. Similarly, Heming et al. (2022) applied MaxEnt to assess cacao suitability in Bahia, Brazil, using empirically derived thresholds under RCP 2.6 and 4.5 scenarios [21].

4.1.3. Envelope-Based Models: EcoCrop and CLIMEX

Envelope-based models use expert-defined climate thresholds (e.g., temperature, precipitation) to classify suitability, rather than relying directly on occurrence data. Some, such as CLIMEX, allow calibration with presence records but remain fundamentally rule-based.

EcoCrop [42] applies monthly thresholds for temperature and rainfall, scoring suitability according to how well conditions fit within these limits. It is widely used in studies relying on datasets such as WorldClim. For instance, Mulinde et al. (2022) assessed coffee and banana suitability in Uganda using EcoCrop [37].

CLIMEX extends this approach by simulating weekly growth and stress responses, incorporating heat, cold, drought, and wet stress into an aggregated Ecoclimatic Index (EI). For example, Jaramillo et al. (2011) applied CLIMEX to project the potential spread of the coffee berry borer in East Africa under future climate scenarios [23].

4.2. Climate Risk Frameworks for Event-Based Impacts (Extreme Weather)

Event-based risk models assess the impacts of acute hazards such as droughts, cyclones, and heatwaves. These models typically follow the IPCC's risk formulation: Risk = Hazard × Exposure × Vulnerability. The CLIMADA platform implements this framework by combining hazard event sets, exposure data, and impact functions [6].

While these models are increasingly applied to various crops, their application to tropical perennials remains limited [26, 36]. An exception is a study by Kaashoek et al. (2023), who used cyclone simulations and banana production maps to estimate future risks. Their findings suggest that, under SSP5-8.5, up to 30% of global banana production could be affected by severe cyclones (1-in-100-year events) [26].

4.3. Mechanistic Process-Based Models

Mechanistic models simulate crop growth processes, including photosynthesis, water use, and biomass accumulation, in response to environmental drivers and management practices. They operate on daily or sub-daily scales and require detailed input data on climate, soil, crop traits, and management.

Examples include:

[1] `https://www.worldclim.org/`

AquaCrop [4]: Simulates yield based on water productivity. DSSAT and APSIM [7]: Model crop–climate–soil interactions. SpCAF [53]: Specializes in coffee agroforestry, simulating shade and CO_2 effects. These models require extensive calibration and data, making large-scale applications challenging. Nevertheless, they are increasingly used to derive vulnerability curves for drought and heat stress [36], supporting integration into risk models like CLIMADA.

4.4. Modelling of Agroforestry as an Adaptation Strategy

Agroforestry is often represented in models via ecological indicators such as canopy cover or shade percentage, which modify climate inputs or impact functions. For example:

Gomes et al. (2020) adjusted temperature projections based on empirical evidence of shade reducing Tmax by 3°C and increasing Tmin by 1°C, showing agroforestry could preserve up to 75% of coffee's current suitable area by 2050 [19]. Heming et al. (2022) used similar temperature adjustments based on canopy cover data to show cacao suitability retention under agroforestry [21] . De Sousa et al. (2019) and Abigaba et al. (2024) evaluated the suitability of tree species themselves, treating agroforestry system viability as a proxy for adaptation potential [13, 3]. However, these studies often apply temperature corrections post hoc, without accounting for existing agroforestry levels in training data. This, along with limited spatial precision of occurrence data, highlights gaps in modelling agroforestry's dynamic role in climate risk reduction.

Process-based models like that of Rahn et al. (2018) [41] offer more detailed simulations of how shade mitigates heat and drought stress, demonstrating that moderate shading can improve yields and reduce climate risks, particularly at lower elevations.

4.5. Reflections on Modelling Approaches

While suitability models are accessible and scalable, they rely on long-term averages and are limited in capturing extreme events. Event-based models address this by simulating acute shocks but often lack crop-specific vulnerability data. Mechanistic models offer detailed insights but require extensive, site-specific inputs, limiting scalability.

Agroforestry modelling remains fragmented, with few studies fully integrating both species suitability and functional microclimate modification. Bridging these gaps requires advancing models that link agroforestry structure to dynamic crop risk assessments under climate change.

5

Knowledge Gaps and Challenges

Based on our literature review, we identify the following key knowledge gaps that limit current climate risk and adaptation assessments for tropical perennial crops:

- **Capturing the Role of Extremes:** Most models focus on average climate suitability, yet extreme events may drive crop failure or even lead farmers to abandon crops in otherwise suitable areas. Better methods are needed to explicitly capture the impacts of extremes.
- **Modelling Agroforestry Benefits Against Both Chronic and Extreme Stress:** While agroforestry is known to buffer climate impacts, there is a lack of modelling approaches that quantify how it mitigates both slow-onset stresses (such as gradual warming) and extreme events (such as heatwaves or cyclones).
- **Identifying Effective Agroforestry Strategies Under Future Climate Conditions:** Uncertainty remains about which agroforestry systems and species will continue to provide climate regulation and other benefits in a changing climate.
- **Limited Empirical Data on Biodiversity and Ecosystem Functions Under Extreme Weather:** There is a lack of empirical evidence on how biodiversity and ecosystem services perform under extreme conditions, limiting model development and validation.
- **Linking Climate Risk Assessments to Farmers' Cost–Benefit Decisions:** Adaptation choices are ultimately shaped not only by biophysical suitability but also by farmers' economic considerations, such as establishment costs, expected yields, labour requirements, and long-term viability. Current modelling frameworks rarely integrate these cost–benefit trade-offs, yet they are central to decisions on whether to establish new crops, adopt agroforestry systems, or replace vulnerable tree species.

While this project cannot fully address all these gaps, its goal is to advance large-scale, model-based assessments and develop tools to improve understanding of the role of agroforestry in reducing the impacts of extreme events on tropical perennial crops.

6
Literature review summary

This review has laid the foundation for integrating biodiversity-informed adaptation strategies into climate risk modelling for tropical perennial crops—specifically coffee and cacao—within the BioFinCas project. By synthesizing ecological, climatic, and modelling literature, we highlight the role of agroforestry and related ecosystem services in enhancing resilience to both gradual climate change and acute weather extremes.

While much of the existing research has focused on long-term climate suitability under average conditions, there remains a critical gap in understanding how tropical crops are affected by extreme events such as heatwaves, droughts, or cyclones. This is especially true compared to the extensive risk modelling done for temperate or annual crops. Addressing this gap, the report proposes a novel event-based approach using the CLIMADA platform—allowing simulation of discrete hazards and year-by-year crop viability losses, with biodiversity and canopy structure as modifiers of hazard intensity and vulnerability.

Several modelling approaches were reviewed, from statistical suitability models to mechanistic simulations. We demonstrate how empirical relationships—such as between canopy cover and temperature reduction or vapour pressure deficit—can be used to parameterize adaptation measures. Suggested use cases include suitability threshold exceedance, VPD-driven yield loss, and cyclone-related wind damage, providing a flexible starting point for scenario development.

A key recommendation going forward is to co-develop and calibrate risk components with local stakeholders and data providers. This includes identifying biodiversity indicators that are both ecologically meaningful and feasible to integrate into spatial datasets. As the prototype evolves, attention should also be given to non-yield benefits, such as diversification, market access, and long-term system resilience.

Ultimately, this work supports the creation of a modular, data-driven framework for adaptation planning—one that links ecosystem services, climate risk, and agroecological transitions in a coherent, decision-relevant manner.

Part II

Analysis

This part of the document presents the analytical core of the study. We first describe the methods, including how representative agroforestry plots are defined for the main producing regions in the three focus countries, how future suitability and risks from extreme events are assessed, and how cost–benefit analyses of shade tree interventions are conducted. We then present the results of these analyses step by step, beginning with the typical agroforestry plots, the suitability projections, followed by risk assessments for extreme events, and finally the cost–benefit outcomes.

7

Methods

7.1. Agroforestry Systems Representation

All modelling components in this study assume a certain agroforestry composition. We constructed stylised, region-specific plot archetypes for the Dominican Republic, Guatemala, and Mexico. These archetypes are based on literature and expert knowledge and describe the main crop, associated shade species, per-hectare densities, shading contributions, and yields. (see click here accompanying Jupyter notebook).

Data sources

- **Dominican Republic:** Internal guidance from CEDAE/Centro Naturaleza (2023) specific to the Cibao Noroeste region, including typical agroforestry compositions for coffee, cacao, and banana systems across mountain, mid-elevation, and lowland zones.
- **Guatemala (coffee):** Rice (2008, 2011), based on surveys of 153 coffee farmers in the Western Highlands (900–1,400 m).
- **Guatemala (cacao):** Villanueva-González et al. (2023), based on 70 cacao agroforestry plots in Alta Verapaz (132–500 m).
- **Mexico (coffee):** López-Gómez et al. (2008), describing shade coffee systems in Veracruz across monoculture, simple polyculture, and diverse polyculture types.

Variables compiled

For each archetype, we compiled available information from published studies or expert consultations, and complemented it with reasonable ecological assumptions where direct measurements were unavailable. Where sources only reported species at the genus level (e.g. *spp.*), we assumed representative species, as the modelling chain required exact species identities. The variables sought for each system included:

- *Main crop species* and typical yield (t/ha/year),
- *Associated shade trees*,

- *Per-hectare densities* for each associated species (measured where available, otherwise estimated from typical plot-level totals),
- *Per-tree shading contribution* as a plausible range, inferred from literature or functional traits when not directly reported,
- *Typical plot size*, and
- *Geographic bounds* for typical locations and elevation ranges.

Based on this information, we generated a CLIMADA exposure file for each archetype, with each species represented as one row and the number of trees per hectare as the exposure value. To allow regional analysis, we also created ten representative plots per archetype at different latitude/longitude and altitude combinations within the typical bounds of each producing region. These locations are synthetic and should not be interpreted as real farms, but as stylised reference systems for modelling purposes.

These archetypes are therefore stylised representations, intended to reflect average conditions for the target region and system type. They should not be interpreted as exhaustive or precise inventories for individual farms, but as realistic reference systems for modelling purposes.

7.2. Species occurrence data

In addition to the stylised archetypes described above, this work makes use of georeferenced occurrence data for both main crops and their associated species. These records were compiled from multiple complementary sources:

- **GBIF (Global Biodiversity Information Facility)**, providing publicly available occurrence records for millions of species worldwide, including most target crops and companion species.
- **de Sousa et al. (2019)**, who compiled an extensive dataset of occurrence points for coffee and associated agroforestry species in Mesoamerica [13].
- **The Alliance of Bioversity International and CIAT (CGIAR)**, provided curated coffee occurrence data.

All records were cleaned to remove duplicates, incorrect coordinates, and observations outside the plausible range for the target crop. Only observations from the year 2000 onwards were retained from GBIF to reflect contemporary distributions. Records were spatially thinned to reduce sampling bias, ensuring a minimum separation distance between presences.

The selection of representative point locations used in the modelling is documented in a public Jupyter notebook: get_point_locations.ipynb.

7.3. Climate data

We used TerraClimate data [1] as the primary source of baseline and projected climate variables. TerraClimate provides monthly climate and climatic water balance data at $\sim$4 km $(1/24°)$ spatial resolution globally for the period 1958–present. For future projections, we used bias-corrected CMIP6 outputs provided within TerraClimate, selecting scenarios corresponding to global mean warming levels of approximately +2 °C and +4 °C relative to pre-industrial conditions. These scenarios represent mid- and high-warming pathways, allowing us to examine crop and shade system suitability under contrasting climate futures. Monthly variables were aggregated into biologically meaningful annual and seasonal metrics (e.g. extreme-month values, quarterly means, seasonal totals).

7.3.1. Climate Data for Suitability Modelling

A set of candidate bioclimatic predictors was derived from the monthly TerraClimate data, including variables related to temperature and precipitation means, extremes, and seasonality, as well as potential evapotranspiration (PET) and derived aridity metrics. Highly correlated predictors (Pearson's $|r| > 0.85$) were removed to minimise collinearity. The final predictor set included variables such as:

- Mean diurnal temperature range
- Isothermality
- Precipitation seasonality
- Temperature of the driest quarter
- Precipitation of the driest and wettest months
- Annual PET

In order to assemble the climate variables required for our analysis, we sourced data from TerraClimate. The full download and processing workflow is available in the accompanying Jupyter notebook: download_terra_climate.ipynb.

7.4. Agroforestry Species Suitability Modelling

We assessed current and future climatic suitability for coffee (*Coffea arabica*) and cacao (*Theobroma cacao*) production systems. Suitability modelling was chosen because many climate-related impacts on crops, particularly those driven by heat and drought, are highly co-dependent and non-linear. Simple single-hazard thresholds often fail to capture these interactions, whereas species distribution modelling can integrate multiple climatic variables simultaneously to reflect combined stressors.

7.4.1. Modelling approach

Our workflow comprised four main steps: (i) preparation of occurrence data, (ii) integration of expert knowledge, (iii) construction of predictor datasets, and (iv) training and evaluation of Random Forest classifiers.

Occurrence data cleaning Raw species occurrences were obtained from GBIF and other databases and cleaned to reduce spatial artefacts. First, isolated points without nearby neighbours were removed. Second, spatial thinning was applied (2.5 arc-min grid) so that only one presence per cell was retained. This procedure reduces sampling bias and over-representation of heavily surveyed locations.

Data augmentation We complemented cleaned occurrence records with points corresponding to the typical plots that we generated for each archetype. To increase robustness in under-sampled areas—particularly in the Dominican Republic, where occurrence records were especially sparse—we generated small random "jiggle" clouds of points around these synthetic plot locations. These additions help to capture plausible presences in known production zones that are poorly represented in the observations datasets.

Predictor variables Climatic predictors were derived from TerraClimate (1990–2014 baseline, plus bias-corrected future scenarios). We compiled a subset of bioclimatic and water-balance variables following de Sousa et al. (2022), including mean diurnal range, isothermality, precipitation seasonality, potential evapotranspiration, temperature and precipitation of driest/wettest quarters, annual deficit, and solar radiation. Background (pseudo-absence) points were generated within the study domain at a ratio of 3:1 relative to presences, with a minimum distance from known occurrences to reduce commission errors.

Model training For each crop, we trained Random Forest classifiers (300 trees, stratified train–test split, 70/30) on the combined presence–background dataset. Prior to fitting, we applied correlation filtering (Pearson $r > 0.85$) and variance inflation factor (VIF > 10) tests to exclude redundant predictors. Low-importance variables (mean permutation importance < 0.01) were also dropped in an iterative step. Model performance was evaluated using five-fold stratified cross-validation, reporting mean and standard deviation of the AUC.

Thresholding and mapping Continuous probability outputs from the models were converted into binary suitable/unsuitable classes using the maximum sensitivity + specificity criterion. This approach selects the threshold that jointly maximises sensitivity (the proportion of true presences correctly predicted as suitable) and specificity (the proportion of true absences correctly predicted as unsuitable), thereby balancing omission and commission errors. Trained models were then applied to present (baseline), future warming ($+2°$C), and high warming ($+4°$C) climate predictor stacks, yielding gridded suitability surfaces. In addition to mean suitability, we also tracked the standard deviation across trees to reflect model uncertainty.

7.5. Risk to agroforestry plots

All methods and code underlying this section are documented in a companion Jupyter notebook, available at: `https://github.com/zeliest/biofincas_climate_risk/blob/main/agroforest_risk/risk_agroforest_system.ipynb`.

7.5.1. Hazard data

We represented risks to agroforestry systems through a combination of slow-onset stressors and acute event hazards.

Slow-onset hazards Climatic suitability maps for coffee, cacao and other shade trees were converted into `Hazard` objects in CLIMADA. Each map represents a single ”event” corresponding to mean climatic suitability under a given climate scenario (baseline, $+2°$C, or $+4°$C). Unlike event-based hazards, these layers capture chronic stress, reflecting the long-term ability of climate conditions to support crop and shade trees growth. They do not contain multiple events over time, but a single static intensity field per species and scenario.

Acute hazards We also considered event-based climate extremes with direct short-term impacts on agroforestry systems:

- *Drought (SPEI):* Monthly precipitation and potential evapotranspiration from TerraClimate were aggregated into a 3-month Standardized Precipitation–Evapotranspiration Index (SPEI). Yearly minima were extracted and 100 synthetic years were sampled using a Generalized Extreme Value (GEV) distribution. The resulting CLIMADA hazard objects contain ensembles of extreme drought events, expressed in SPEI units.
- *Extreme yearly temperatures:* Annual maximum temperatures from TerraClimate were extracted to represent years with unusually hot conditions. Similar to the drought index, yearly maxima were fitted with a Generalized Extreme Value (GEV) distribution to generate 100 synthetic years. The underlying assumption is that exceptionally hot years could lead to tree mortality, even in the absence of other stressors. Hazard objects therefore contain ensembles of extreme heat years, expressed in degrees Celsius.

While more hazards could be considered, these serve as a demonstration. The distinction between slow-onset and accute events allows us to jointly assess the long-term decline in climatic suitability (slow-onset stress) and the impacts of discrete high-intensity events (acute hazards).

7.5.2. Exposures

Exposures were constructed from the agroforestry plot archetypes described in Section 7.1. For each region and crop system, we used archetype spreadsheets containing species composition, per-hectare planting densities, and shading contributions. The workflow to transform these data into CLIMADA-compatible `Exposures` objects comprised four steps:

1. *Species harmonisation* Scientific names were standardised across files (e.g. "*Inga spp.*" replaced for example by *Inga vera*), and main crops (*Coffea arabica*, *Theobroma cacao*) were always included in the target species list.
2. *Geolocation* Each archetype entry was assigned geographic coordinates (latitude, longitude) representing a centroid for the system. These were converted into a GeoDataFrame with WGS84 projection.
3. *Exposure attributes* For every species in the global target list, we created binary columns (`impf_<species>`) marking its presence at each site. The `value` column on which the impact are calculated was set to the number of trees per species, such that exposure values represent per-hectare planting densities.

The resulting exposures represent stylised one-hectare agroforestry plots, with explicit species composition.

7.5.3. Impact functions

To link hazards with species-specific damages, we defined impact functions (`ImpactFunc`) for both slow-onset and acute events.

Suitability (slow-onset) For each crop and associated shade species, we defined stylised impact functions that translate the modelled suitability into fractional loss. Suitability thresholds were determined during model training by maximising the sum of sensitivity and specificity, where sensitivity measures the fraction of true presences that are correctly predicted, and specificity measures the fraction of true absences that are correctly predicted. Below the threshold, impact is set to 100%, reflecting unsuitable climatic conditions, whereas above the threshold, impact is set to 0%. A fallback zero-impact function is used when no suitability estimate was available.

Drought (acute) For drought, intensity was expressed on the SPEI scale, and three vulnerability classes were represented using quadratic S-shaped functions. These curves were defined to capture different levels of drought sensitivity among species:

- *High vulnerability:* early onset of losses (already at moderate dryness), with damage rising steeply and reaching up to $\sim$40% under severe drought.
- *Medium vulnerability:* onset at somewhat drier conditions, with losses increasing more gradually and capped around $\sim$30%.
- *Low vulnerability:* tolerant species, with losses only occurring under the most extreme droughts and not exceeding $\sim$20%.

Heat (Accute) For heat, intensity was represented by mean annual temperature, and three quadratic S-shaped vulnerability curves were defined:

- *High vulnerability:* sensitive crops (e.g. coffee, cacao) where losses begin already at $\sim$26°C, with damage increasing rapidly under further warming.
- *Medium vulnerability:* fruit trees that tolerate moderately warmer conditions, with onset around $\sim$28°C and lower maximum losses.
- *Low vulnerability:* more heat-tolerant hardwoods and palms, where impacts only occur above $\sim$30°C and rise gradually to modest levels.

Adjustment for shade scenarios. In addition to species-based vulnerability classes, we introduced a heuristic adjustment to account for the effect of shade on hazard impacts. Agroforestry alternatives with reduced shade (`shade_-20`) were assumed to increase vulnerability to heat and drought, while increased shade (`shade_+20`) was assumed to decrease vulnerability. Operationally, this was implemented by shifting the assigned impact function class: for example, a medium-vulnerability species under the baseline scenario could be shifted to the high-vulnerability class under reduced shade, or to the low-vulnerability class under increased shade.

Assumptions and uncertainty The shapes, thresholds, and maximum losses of these impact functions, as well as the shade-based adjustments, are assumptions made in the absence of empirical data. To our knowledge, no quantitative studies exist that directly measure the hazard-specific vulnerability of tropical agroforestry species, or the effect of canopy shade on hazard impacts. The chosen functional forms and adjustments are therefore best viewed as plausible representations designed to capture the direction of expected effects (e.g. more shade reducing heat stress), while the exact magnitude remains uncertain.

Impact calculation All hazard–exposure combinations were evaluated with CLIMADA's `Impact` module, using the corresponding impact functions. For slow-onset suitability hazards, this yields a single impact value per species and scenario. For acute event hazards (drought, tropical cyclones), impacts are calculated for each synthetic event, resulting in impact distributions across ensembles of possible years or storms.

7.6. Cost--Benefit Analysis of Canopy Interventions

This section outlines the methodology implemented in the notebook `CostBenefit_Canopy.ipynb`[1].

The analysis is designed to (i) assess how future climate risks affect crop yield revenues, (ii) evaluate the potential of canopy composition adjustments as a mitigation strategy, and (iii) quantify the associated cost–benefit trade-offs. In addition, the framework can be applied to compare results across regions, providing a transferable tool for evaluating agroforestry adaptation strategies.

We apply the CLIMADA risk formulation,

$$\text{Risk} = \text{Hazard} \times \text{Exposure} \times \text{Vulnerability},$$

to evaluate the costs and benefits of alternative canopy and crop compositions. Benefits are quantified from two main sources: (i) reduced heat and drought losses due to canopy-induced cooling, and (ii) changes in crop revenue streams associated with adding or removing shade trees.

The revenue effects depend on two components. First, changes in canopy cover alter the relative yield of the main crop, as captured by the empirical yield–shade curve (see Figure 7.2). This curve reflects multiple interacting factors such as light availability, microclimate regulation, and soil processes. Since modelling all of these processes explicitly would require complex, multi-source data, we adopt a simplified approach by using empirical canopy–yield relationships from the literature. Second, adjustments in the number of main crops and secondary trees (fruit or shade species) directly influence revenues through their own yields and prices. Together, these mechanisms link canopy interventions to both productivity and resilience outcomes.

In this CLIMADA set-up, each canopy composition represents an *adaptation measure*, see Fig. 7.1. It modifies (i) *exposure*, through the number and type of shade trees and the resulting shade fraction, which in turn affects yields via the empirical canopy–productivity relationship and other ecosystem service contributions. At the same time, shade density influences (ii) the *impact function*, i.e. vulnerability, by buffering against heat and drought hazards. We represent this as a shift in the vulnerability curve: additional canopy reduces the effective hazard intensity through cooling, thereby lowering expected

[1] `https://github.com/zeliest/biofincas_climate_risk/blob/main/CostBenefit_Canopy.ipynb`

damages for a given event. Equivalently, this cooling effect can be modelled as a direct reduction in hazard intensity before it is passed through the impact function.

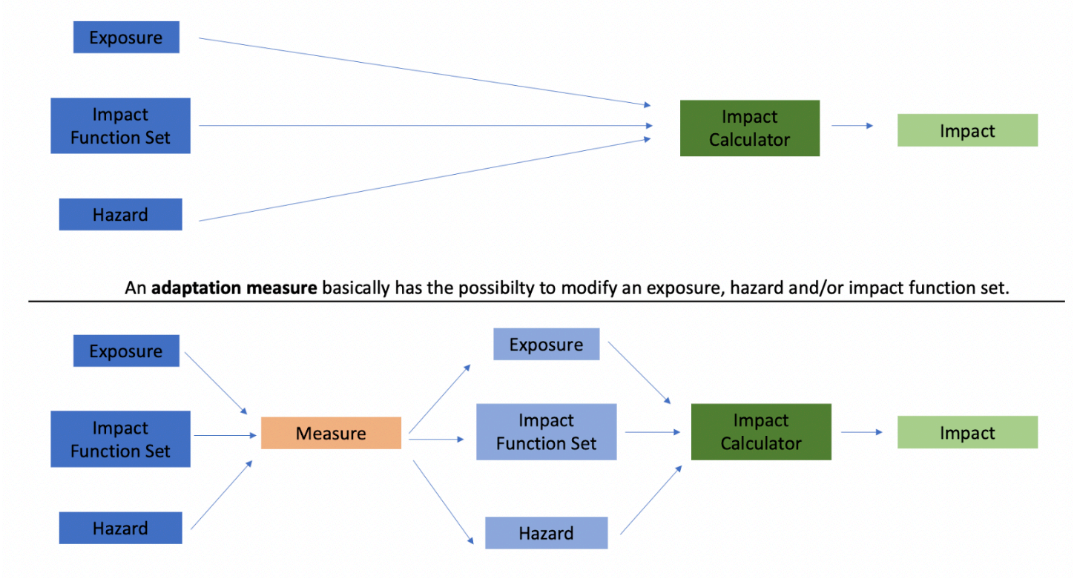


Figure 7.1: Representation of canopy composition as an adaptation measure in CLIMADA. Canopy changes can act on (i) *exposure*, through crop and shade-tree numbers, and (ii) *vulnerability*, by altering hazard impacts via microclimate buffering.

A new composition may involve planting or removing crops or shade trees relative to the current configuration, hereafter referred to as the *present* baseline. Costs and benefits are assessed relative to this baseline, which by default corresponds to the present composition and its associated yields.

It is important to note that canopy interventions are implemented using CLIMADA's new `AdaptationMeasure` class. This functionality allows more flexible modification of CLIMADA objects than previous class. To use it, the branch `feature/cb_refactoring` must be checked out.

7.6.1. Exposures

Agroforestry systems are represented as stylised plots with explicit area, crop, and shade-tree composition. Average compositions for different Central American countries are generated using the notebook introduced earlier in this chapter. Each record includes coordinates (lat/lon) and species-level attributes: `Plants/ha`, `Role` (main crop, e.g. coffee or cacao, or secondary crop, e.g. fruit or shade trees), baseline yield per plant or per area, unit prices, and unit costs (maintenance, establishment).

Because only a relative yield–canopy curve is available, the *present* (baseline composition) is taken as the expected yield under the observed canopy configuration. In the simplest case, this corresponds to historical yields under current practices. Alternative canopy scenarios are evaluated by adjusting this baseline yield according to the yield–canopy curve.

When switching crops, the same principle is applied: the baseline yield of the present composition is used as the reference. In such cases, the user must first define the expected yield per plant for the present canopy configuration and set the number of plants of the replaced crop to zero. For the alternative canopy compositions, yields are then adjusted to account for both plant numbers and canopy levels.

Finally, all yields are converted into annual revenues per species, ensuring that costs and benefits can be expressed in consistent monetary terms.

In our pilot data from Naturaleza, values are available only for the Dominican Republic. We therefore use average yields for both main and secondary crops as reference values, while noting that these can be replaced by site-specific data where available.

7.6.2. Hazard Data

As earlier mentioned, we use TerraClimate-based indicators to represent climatic stressors. The daily maximum temperature (`tmax`, unit = °C) is used as a proxy for heat stress, while the average vapour pressure deficit (`vpd`, unit = kPa) over the growing season is used to capture drought stress. These variables are first converted to mean monthly values and then aggregated to annual values. Hazard layers are formatted as CLIMADA hazard objects, where each year corresponds to one event in the hazard set. To extend the length of the hazard records and better represent extremes, we apply resampling methods, either through bootstrapping or by fitting a Generalised Extreme Value (GEV) distribution.

7.6.3. Impact Functions

Species-specific impact functions are used to link hazard intensity to expected damage. We define default functions based on empirical thresholds reported in the literature.

For **coffee (Coffea arabica)**, impact functions for heat and drought are derived from [27] Coffee is highly sensitive to elevated temperatures, with yield reductions above $\sim$25°C, and near-collapse at extreme conditions ($>$42°C sustained, $\sim$49°C in short bursts). It is also vulnerable to drought stress, represented here by vapour pressure deficit (VPD), with damage risk increasing steeply above $\sim$0.82 kPa.

For **cacao (Theobroma cacao)**, we construct impact functions based on evidence from the literature review. Cacao tolerates higher average temperatures than coffee, with stable growth up to $\sim$27°C, but begins to lose photosynthetic function near 37–38°C, with an absolute maximum around 38°C.

7.6.4. Canopy Intervention Scenarios

Alternative canopy scenarios are generated from the baseline by changing tree densities and/or species, tracked as `Added Plants/ha` in the corresponding exposure object. These differences trigger (a) updated exposure objects in CLIMADA and (b) cash-flow entries in the cost module.

7.6.5. Effects of Canopy

Yield–Shade relationship. We assume a hump-shaped relation between shade (s) and yield (Fig. 7.2): intermediate canopy maximises production, while too little or too much shade reduces yields. For coffee, we follow the synthesis in [18], with an optimum around 30–50% shade; for cacao, yields typically peak at 25–45% shade before declining at higher shade. Using these crop-specific curves, we (i) set the baseline yield at each plot's observed shade level and (ii) adjust yields for alternative scenarios according to their position on the curve, enabling consistent comparison across canopy configurations.

Cooling effect and risk reduction. Increasing canopy cover provides additional shading that cools the microclimate and reduces evaporative demand. As described in Section 7.5.3, we implement this by adjusting the hazard intensity fields according to shade (see Fig. 7.3):

$$T'_{\max}(s) = T_{\max} - \Delta T(s), \qquad \mathrm{VPD}'(s) = \mathrm{VPD} - \Delta\mathrm{VPD}(s),$$

with $\Delta T(s)$ and $\Delta\mathrm{VPD}(s)$ increasing in s. These adjustments effectively shift the vulnerability curves, so each plantation has a shade-dependent vulnerability profile. To relate daily cooling effects to reductions in monthly mean temperature or VPD, we apply a sensitivity factor that scales the hazard adjustment accordingly. This factor was derived from ERA5-Land daily reanalysis data (Copernicus Climate Data Store), using gridded fields of daily maximum temperature and vapour pressure deficit over Central America. Daily Tmax anomalies were compared with monthly mean VPD across the crop growing season, and a simple linear regression was fitted to estimate the relationship:

$$\Delta\mathrm{VPD}_{\text{monthly}} = \alpha \cdot \Delta T_{\text{daily}}.$$

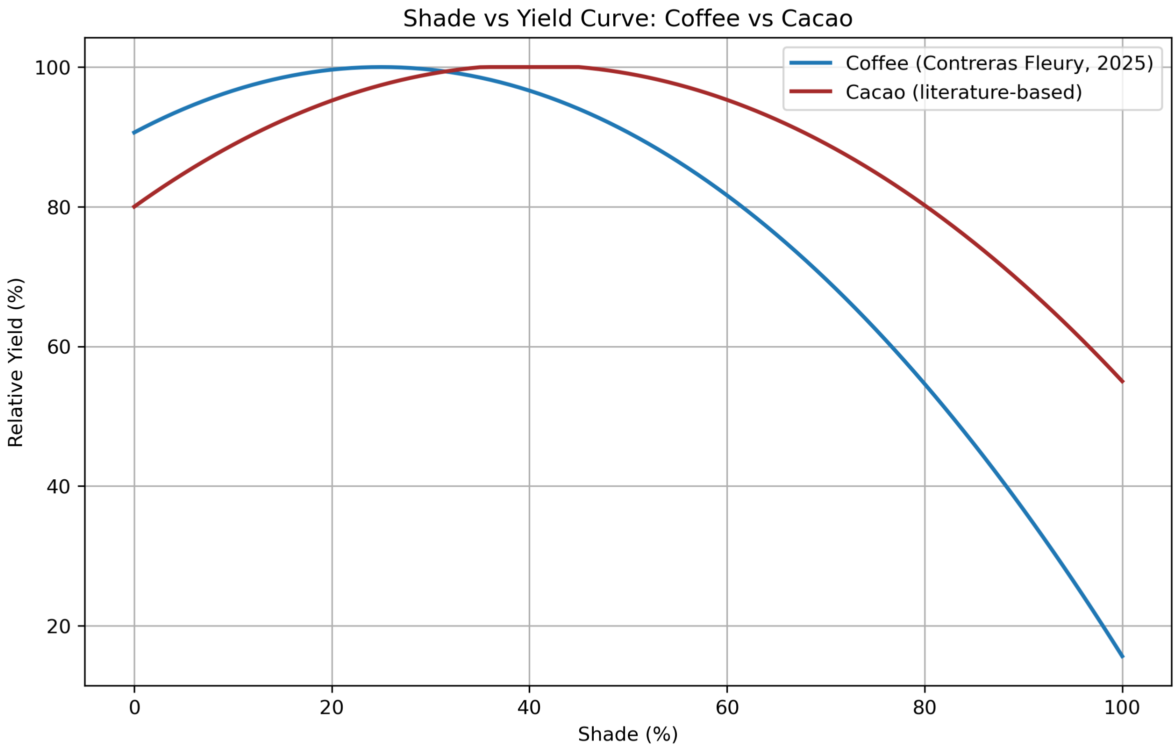


Figure 7.2: Relative yield (%) vs. shade (%) for coffee (blue; synthesis after [18] and cacao (red; literature-based). Both curves peak at intermediate shade and decline at low and high shade.

The fitted slope α provides a scaling coefficient that translates canopy-induced daily cooling (in °C) into expected reductions in monthly VPD (kPa). This sensitivity is then applied in the hazard adjustment function so that cooling effects are propagated consistently from daily to monthly scales.

7.6.6. Costs

Annual cash flows are calculated by comparing the baseline composition with alternative scenarios, accounting for increases, decreases, or maintenance of specific tree types. The following cost components are considered:

- **Establishment:** costs of nursery material, planting, and site preparation, applied to `Added Plants/ha` in the planting year.
- **Maintenance:** ongoing costs for pruning, replacement, and routine management. These costs decrease if trees are removed.

Many cost parameters are derived from values provided by *Naturaleza*. For species where no specific data are available, we apply a default price for plantation and maintenance.

7.6.7. Cost–Benefit Analysis Metrics

The cost–benefit analysis compares the net present value (NPV) of accumulated costs against the revenue streams of different canopy compositions. Revenues are determined by the number of plants and the yield–canopy relationship for the main crop, while for secondary crops revenues are adjusted by plant numbers only, as no canopy–yield curve is available. Benefits include changes in main-crop yields, $\Delta Y = Y(s_{\text{alt}}) - Y(s_{\text{base}})$, monetised via crop-specific prices; changes in fruit-tree revenues from the addition or removal of secondary species; and avoided losses, reflecting reduced damages from heat and drought due to canopy-induced cooling. All scenarios are evaluated relative to the baseline

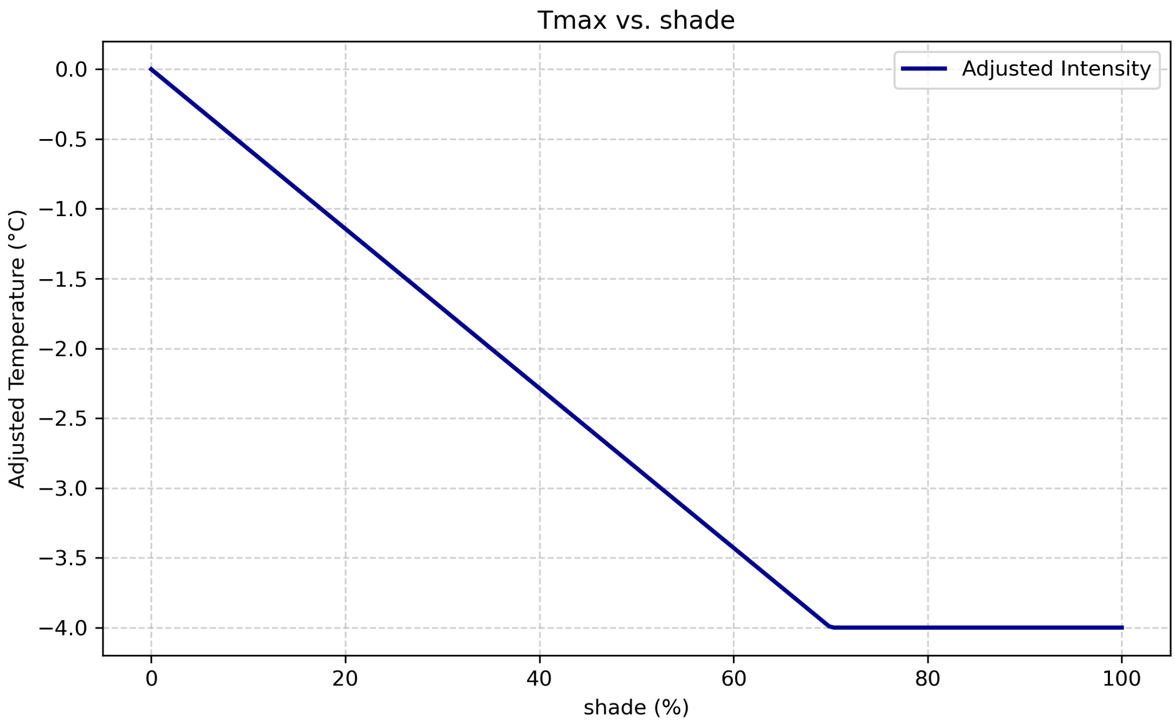


Figure 7.3: Stylised canopy–cooling response used to modify hazards: reduction in $T_{\max}$ and VPD as a function of shade (%).

composition by comparing the NPV of both costs and revenues. Cash flows are discounted at rate r to a common base year; future unit prices are indexed by an inflation assumption π so that NPVs are expressed in present currency units.

Expected annual revenue streams are obtained by estimating present and future yields. To do so, we separate two drivers: (i) the biophysical effect of canopy cover on yields and the canhage on number of crops planted, and (ii) the effect of climate hazards. Present yields already include the impact of current hazards, so we reconstruct a hazard-free potential yield and then adjust it with present and future loss fractions, being the expected annual loss (%). This allows revenue changes to be decomposed into a canopy-related gain and a risk-related component, which together determine whether an alternative canopy composition improves or reduces future revenues. The detailed equations for this decomposition are provided in the accompanying notebook.

7.6.8. Derivation of Risk and Gain Components

Because CLIMADA is a hazard–risk–vulnerability framework, we are interested in disentangling the drivers of revenue changes into those arising from hazard risk and those arising from structural changes in the agroforestry system. In practice, this means analysing when the benefits of increased canopy cover in mitigating hazard risk outweigh the yield penalties associated with shading or with limiting light propagation. To do this, we separate the cost–benefit results into two components: the *risk* effect, reflecting changes in vulnerability to climate hazards, and the *gain* effect, reflecting all other yield and revenue adjustments due to canopy composition.

From the cost–benefit metrics, we further derive two analytical components: the *gain* from canopy composition changes and the *risk* associated with climate hazards. Since the framework explicitly models vulnerability functions, the term *“risk”* here can be more precisely interpreted as the change in *vulnerability* to hazards, while *gain* summarizes all other contributions to revenue (e.g., yield shifts due to canopy cover and secondary-crop adjustments).

This decomposition clarifies how much of the revenue difference relative to the baseline is driven by structural changes in the agroforestry system versus hazard-related yield losses.

Formally, the decomposition builds on the calculated CB metrics (NPVs of costs and revenues) and separates the net change in revenues, ΔY, into:

$$\Delta Y = \Delta\text{Gain} + \Delta\text{Risk},$$

where ΔGain represents non-hazard factors, and ΔRisk captures the contribution of changing vulnerability to heat and drought.

The explicit equations and step-by-step derivation are documented in the accompanying notebook, where the estimation framework is applied to all canopy alternatives.

8

Key Results

8.1. Risk to Agroforest System

8.2. Results

8.2.1. Agroforestry plot composition and alternatives

We begin by characterising the typical agroforestry plots identified through expert consultation and literature review. These serve as the baseline for the design of alternative configurations that vary in shading intensity.

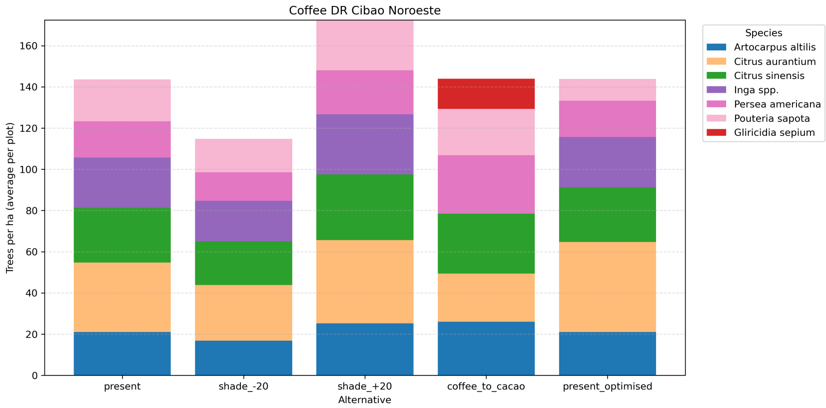


Figure 8.1: Composition of representative agroforestry plots for *Coffea arabica* in Cibao Noroeste. The stacked bars show the number of the associated shade tree species across different plot configurations. The "present" configuration reflects the baseline as observed, while alternative configurations explore systematic modifications: increasing or decreasing shade tree abundance by 20%, replacing cacao with coffee and its common shade associates, and an optimised configuration. The optimised configuration was constructed by reallocating half of the individuals of the worst-performing shade species (i.e. the one contributing the highest impact under a $+2°C$ scenario) to the best-performing species (i.e. the one contributing the lowest impact). Impacts were recalculated accordingly to reflect the new tree composition.

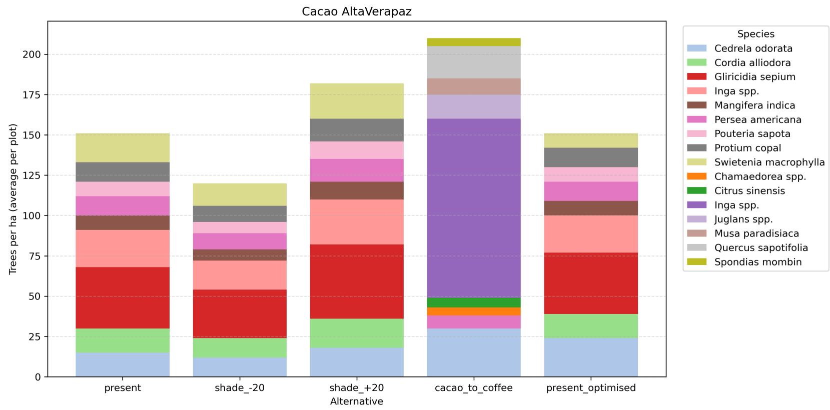


Figure 8.2: Same as Fig. 8.2, but for *Theobroma cacao* in Cibao Noroeste. The baseline composition of coffee plots is compared with the same set of alternative configurations, including the optimised redistribution of shade species to reduce projected impacts.

8.2.2. Suitability under climate change

We next assess the long-term climatic suitability of the main crops. Figure 8.3 shows examples of suitability maps under historical, +2 °C, and +4 °C scenarios. The maps illustrate three representative species: *Coffea arabica* (coffee), *Theobroma cacao* (cacao), and *Persea americana* (avocado) as a shade species. Areas are classified into categories that indicate whether they remain suitable, become newly suitable, lose suitability, or remain unsuitable under climate change.

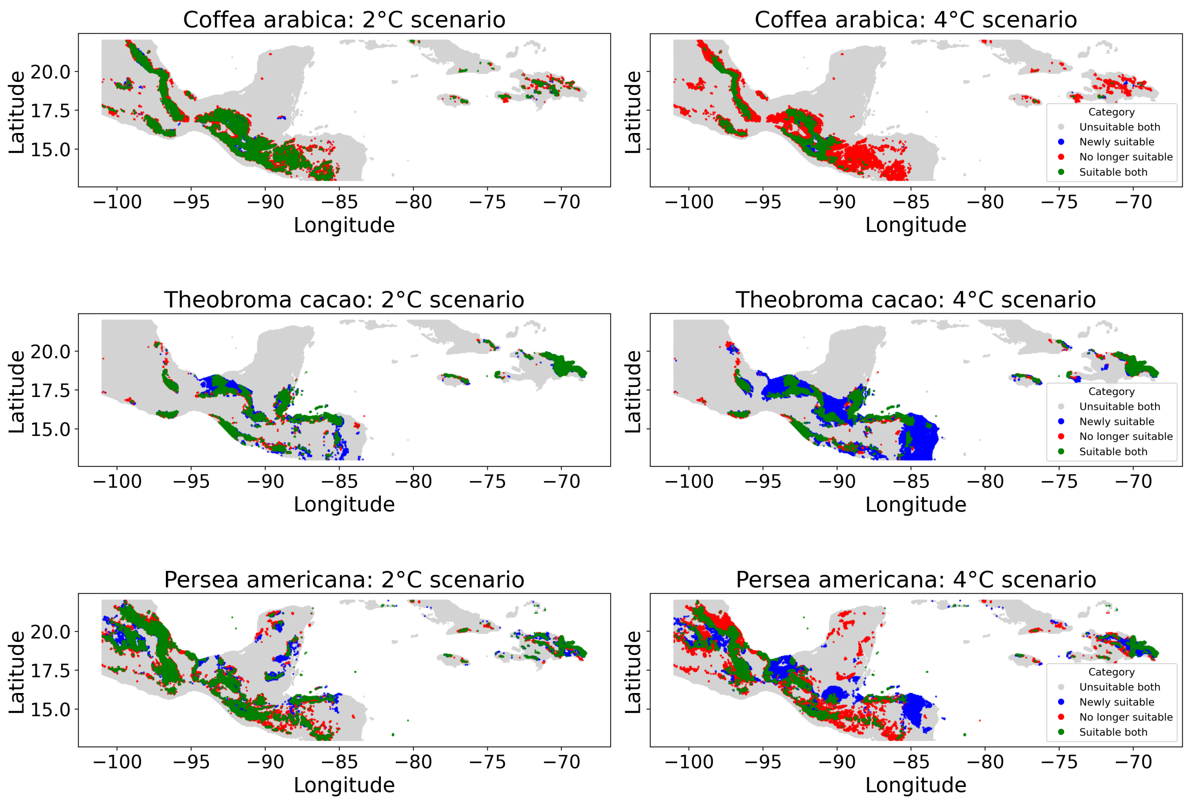


Figure 8.3: Examples of suitability maps under climate change. Categories indicate whether areas remain suitable, become newly suitable, or lose suitability under future warming (+2 °C and +4 °C) compared to the historical baseline. Results are shown for *Coffea arabica* (coffee), *Theobroma cacao* (cacao), and *Persea americana* (avocado) as a representative shade species.

At the locations where coffee and cacao are currently grown, we find strong differences in the response to warming. For coffee, climatic suitability decreases sharply, with an average reduction of about 0.19 under +2 °C and 0.52 under +4 °C. This translates into approximately 12% of current sites becoming unsuitable already at +2 °C and more than half (53%) at +4 °C. In contrast, cacao shows comparatively modest losses, with average reductions in suitability of 0.10 under +2 °C and 0.13 under +4 °C. The fraction of cacao sites falling below the suitability threshold remains small, around 4% under +2 °C and 8% under +4 °C. These results highlight that, within our dataset, coffee production areas are much more vulnerable to warming than cacao.

When averaging across all other shade tree species in the dataset, we find an average suitability loss of about 0.19 under +2 °C and 0.26 under +4 °C. This indicates that, while individual species differ in their responses, shade trees as a group are projected to experience moderate reductions in climatic suitability compared to coffee, and somewhat larger losses than cacao.

8.2.3. Case study: Cibao Noroeste

To illustrate the full framework, we present results for Cibao Noroeste in the Dominican Republic. By matching the climatic suitability projections to observed agroforestry plots, we can estimate how many trees are likely to become unsuitable under warming scenarios. Figures 8.4 and 8.5 show the change in average impacts per plot for representative coffee and cacao systems under warming scenarios.

At +2 °C, coffee plots (Figure 8.4) show additional losses across several shade tree species, whereas for cacao plots (Figure 8.5) some species show reduced risk (negative values), indicating potential gains in climatic suitability. At +4 °C, the patterns become more pronounced, with both stronger losses for sensitive species and larger gains for others. These negative bars therefore represent species that may find the climate more suitable under future warming.

It is important to note that these projections are based only on climatic suitability and do not account for the buffering effects of the agroforestry system itself, which can create local microclimates and reduce stress. Moreover, results are derived from a limited number of observations in the Dominican Republic, meaning that model uncertainty and threshold assumptions strongly influence the outcomes. The goal is therefore to highlight which species may be at greater risk and how system composition can amplify or mitigate these risks, rather than to predict exact mortality.

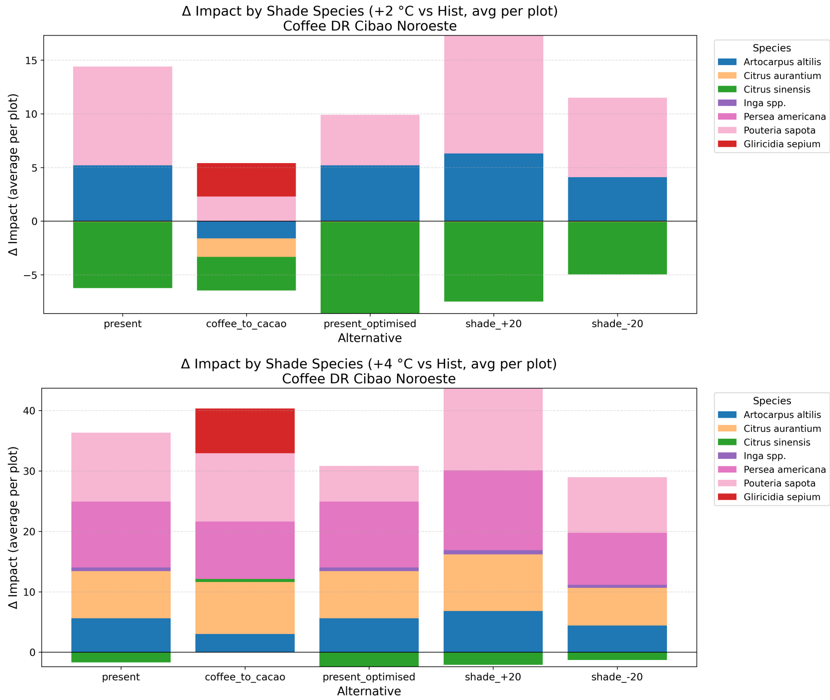


Figure 8.4: Change in number of shade tree impacts for a representative coffee plot in Cibao Noroeste under +2 °C (top) and +4 °C (bottom) compared to today. Positive bars indicate species with increased risk of unsuitability, while negative bars indicate species that gain in climatic suitability.

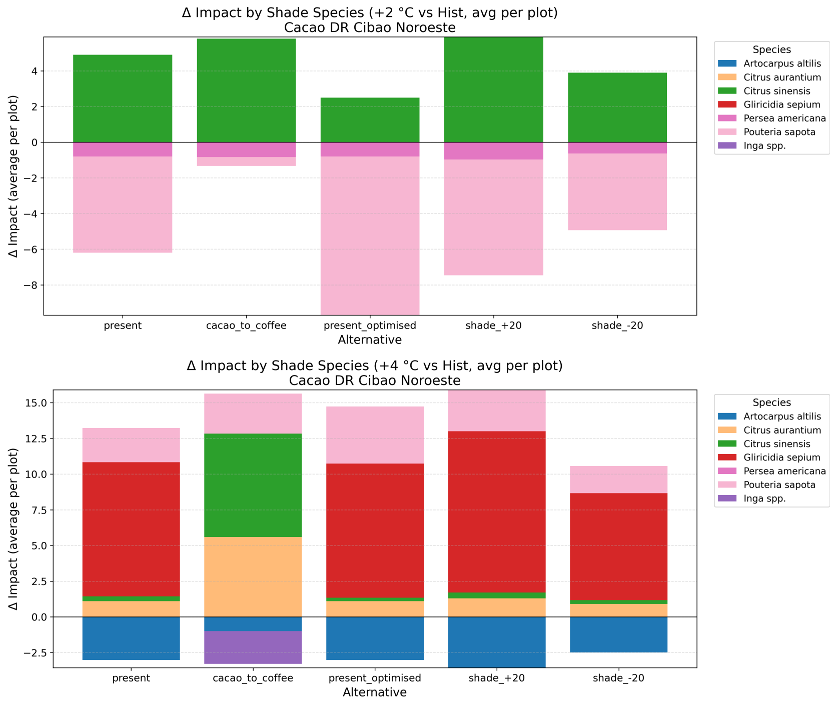


Figure 8.5: Change in number of shade tree impacts for a representative cacao plot in Cibao Noroeste under +2 °C (top) and +4 °C (bottom) compared to today. Negative values indicate species that benefit from warming through increased climatic suitability.

8.2.4. Regional comparison

We then compare Cibao Noroeste with other coffee- and cacao-producing regions included in our analysis. Figure 8.6 shows the relative change in climatic suitability for both shade trees (top panel) and the main crops (bottom panel), expressed as the percentage of trees per average plot that are at risk of becoming unsuitable under warming scenarios.

For shade species, the projected changes are generally more modest at +2 °C but increase further at +4 °C. In some systems, the change is negative, indicating that shade trees gain in suitability with warming. This reflects that certain tropical and subtropical species may benefit from higher temperatures or longer growing seasons in currently cooler regions. Conversely, in hotter and drier environments, shade species face increasing losses in suitability, with some plots projected to experience declines in more than 10–20% of shade trees per plot at +4 °C.

For the main crops, responses are more contrasted across regions. Coffee suitability shows relatively small changes in some regions, such as Veracruz in Mexico, consistent with its location in already climatically favourable zones where further warming does not immediately cross critical thresholds. By contrast, cacao in the Dominican Republic is projected to become less suitable under +2 °C, although in Cibao Noroeste some shade tree species display improved suitability, highlighting the importance of localised responses. At +4 °C, both crops and shade species show stronger declines across regions, emphasising that higher levels of warming will put entire agroforestry systems at risk. While some regions to not seem to experience impacts, this is because the suitability does not go below the threshold, not that there are no decreases in suitability.

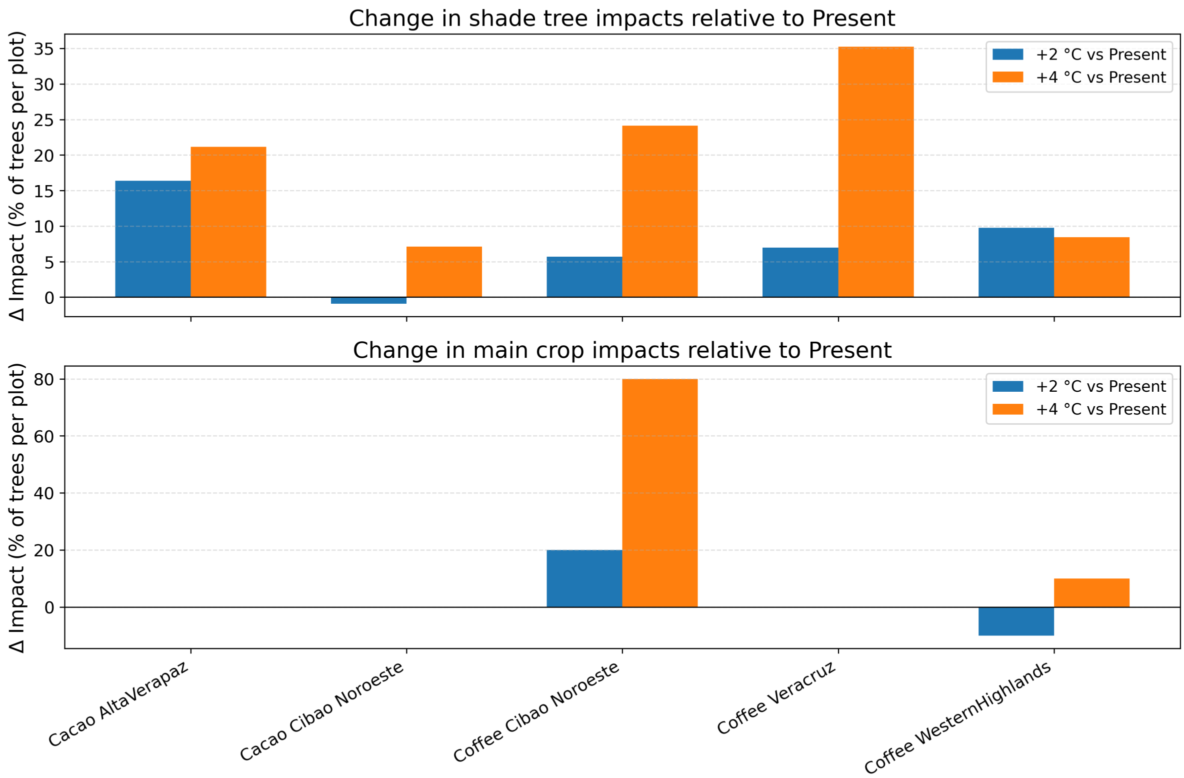
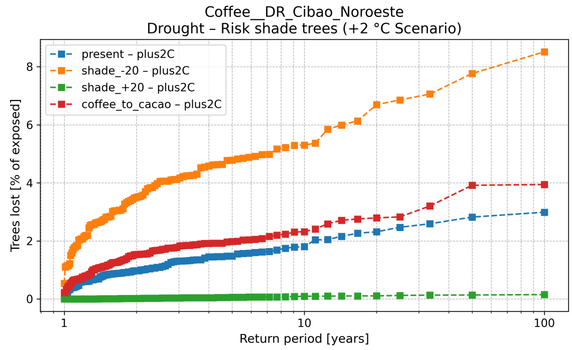


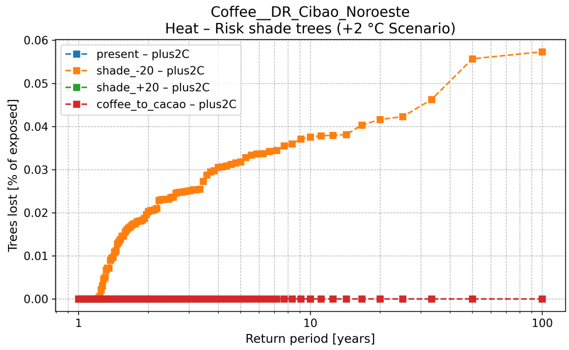
Figure 8.6: Regional comparison of projected changes in suitability under climate change, expressed as the percentage of trees per average plot that become more (negative values) or less (positive values) suitable. Top: shade tree species. Bottom: main crops (coffee and cacao). Bars show the change relative to present for +2 °C and +4 °C warming scenarios.

8.2.5. Accute Hazards Risk

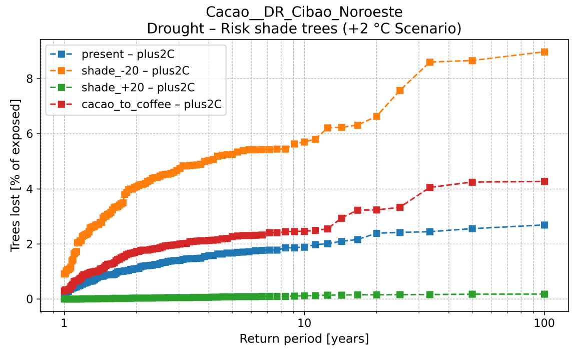
Finally, we examine the risk to agroforestry under two key acute hazards: drought and heat. For Cibao Noroeste, Figure 8.7 presents return period curves for coffee and cacao systems.



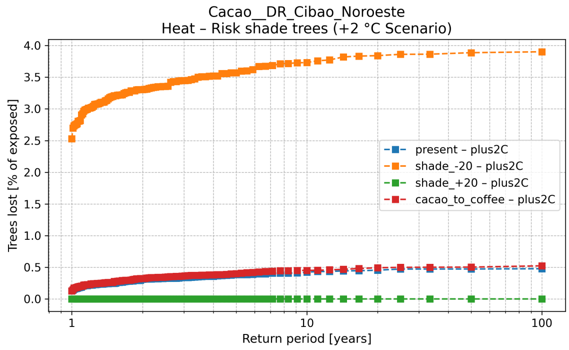
(a) Coffee – Drought



(b) Coffee – Heat



(c) Cacao – Drought



(d) Cacao – Heat

Figure 8.7: Return period curves for drought and heat in Cibao Noroeste. Panels compare coffee (top row) and cacao (bottom row) systems under a +2 °C climate scenario. Lines indicate different agroforestry alternatives.

The return period curves show that *drought* is a much more important driver of losses than drought, especially for coffee. Here, we only consider the risk to the shade trees, meaning that the fact that coffee is more sensitive to heat will not play a role. Coffee is generally at higher altitudes and therefore exposed to less heat. While the associated shade species are likely more vulnerable to heat, this is just a very simple model that demonstrate how extremes could be considered. Under the present and reduced-shade scenarios, heat-related losses increase steadily with return period, reaching several percent of exposed trees, while the increased-shade alternative (`shade_+20`) almost eliminates drought-related losses.

8.3. Cost–Benefit Analysis

The results presented here illustrate how the prototype notebook can be used to explore the costs and benefits of alternative canopy strategies in agroforestry systems. The framework allows users to define interventions such as planting or removing trees, or even switching the main crop, and then propagate these changes through exposure objects, yield–shade functions, and hazard modules. This makes it possible to estimate revenue streams and risk metrics for both present and future climate scenarios.

A key advantage of the approach is that it separates the drivers of change: the biophysical effects of canopy cover and crop composition, and the hazard-driven effects of heat and drought stress. By disentangling these components, it becomes clearer what portion of revenue changes are due to shifts in productivity along the yield–shade curve and what portion stem from hazard exposure. This focus on hazard $\times$ exposure $\times$ vulnerability reflects the core logic of CLIMADA, while adapting it to the specific context of agroforestry.

This set-up differs slightly from a conventional cost–benefit analysis of climate adaptation. In standard applications, the focus is often on the absolute reduction of hazard-related risk. Here, however, we also need to account for changes in exposure itself: increasing canopy can reduce vulnerability to hazards, but at the same time may reduce yields due to shading. By evaluating revenues rather than risk reduction alone, we capture both effects simultaneously and compare them against the baseline. This framing reflects the practical dilemma faced by farmers, who must balance the protective value of shade against potential yield penalties.

The workflow is designed to be transferable. Once yields, prices, and cost data are harmonised, the same analysis can be repeated across sites or countries, allowing comparisons of how canopy strategies perform in different contexts.

Although the shade optimum lies close to the current shade fraction, but under warming slightly higher canopy levels reduce losses, even if they cannot fully offset hazard intensification. This points to site-specific trade-offs: whether to favour fruit trees that provide direct income or non-fruit shade trees that prioritise resilience. In this way, the analysis addresses three central questions: (i) does the revenue-optimal shade fraction shift under warming, and by how much? (ii) if canopy is increased, are fruit trees or shade trees more cost-effective? and (iii) how sensitive are these results to the assumed yield–shade functions and hazard representations?

The results are analysed through the lens of canopy interventions, asking not only “what happens” but also “how canopy alters the outcome.” We demonstrate the cost–benefit (CB) workflow by scanning canopy cover around the present composition and passing these changes through the yield–shade functions and different hazard sets. “Today” uses the historical hazard set; “Future” refers to the chosen climate scenario (+2 °C or +4 °C). We evaluate two kinds of alternatives relative to the present plot: (i) vary average canopy cover by ± 50 percentage points around baseline, in 5 pp steps, holding the main crop mix fixed; and (ii) (optional) switch the main crop (e.g., coffee $\leftrightarrow$ cacao) while keeping the present shade distribution. For each canopy level we compute main-crop revenue via the yield–shade curve and then apply present/future hazard losses to obtain normalised changes vs. the baseline.

8.3.1. Case study: Cibao Noroeste

In the folder `cost_benefit/Results` we provide a comprehensive set of plots and metrics across locations, canopy compositions, and sites. Below, we summarise the main insights emerging from the cost–benefit workflow. Starting with the Dominican Republic as a case study and then comparing across countries, we extract the following take-aways:

- **Future risk:** At the present canopy, annual revenues decline by about -6% to -17% for coffee (best–worst across canopy: $\sim 0\%$ to -28%) and about -1% to -9% for cacao (range: $\sim 0\%$ to -16%) across the warming scenarios (Fig. 8.12).
- **Cacao vs. coffee:** Cacao is less sensitive to canopy adjustments and the present composition lies near its optimum, while coffee shows a much wider spread between best and worst shade levels (Figs. 8.9 and 8.12).
- **Hazards:** Drought (VPD) generally drives larger losses than heat (Tmax), especially for coffee under $+4°$C (Fig. 8.12).
- **Shade–risk trade-offs (crop-specific):** Added canopy buffers hazard losses and can shift the optimal shade slightly upward, but high shade carries yield penalties. The balance differs by crop due to the empirical yield–shade curves: Cacao benefits more from extra shade under future hazards, whereas coffe´s mitigation gains are smaller and high-shade penalties bind earlier (Figs. 8.9 and 8.10).
- **Cost–benefit:** Planting more trees does not fully offset main-crop losses under single-hazard assumptions. Secondary crops can partly compensate, but their climate vulnerability is not yet modelled (Figs. 8.14 and 8.15).

Shade Levels vs Main Crop

Here we quantify how main-crop revenue varies with average canopy cover across all sites for coffee and cacao. For the present climate ("today"), revenue changes reflect only the empirical yield–shade curve (see Fig. 8.9); For "today", changes are driven only by the yield–shade curve (Fig. 7.2); for "future", we combine the same curve with higher hazard intensity.

Fig. 8.9a. For heat stress (Tmax), under today's climate, revenue peaks near the observed baseline shade ($\sim$40%), close to the empirical optimum; modest deviations incur small penalties, while the extremes (around 20% or 60%) show larger losses (about -5%). Under +4 °C, revenues decline at all canopy levels, but the *smallest* declines occur at slightly higher shade (roughly 48–52%).

Attribution analysis of annual revenue change due to heat stress (Tmax) (Fig. 8.10a) shows that most of the decline is hazard-driven (red bars), but added canopy partly offsets losses by reducing vulnerability. Green bars indicate only modest direct yield gains from higher shade, meaning the main benefit comes from risk mitigation rather than yield potential. This suggests that in a warmer climate, the optimal shade level may shift slightly upward, though not enough to restore present-day revenues.

This is an important observation: because of canopy's cooling and hazard-mitigation effects, additional shade partly offsets future heat stress and shifts the revenue optimum upward. However, the effect is modest and not sufficient to restore today's revenue levels, see Fig. 8.9a. It is therefore important to extend the analysis over time, incorporating these changes into a net present value (NPV) framework, to capture the cumulative economic implications of different canopy strategies.

Illustratively, revenue at 40% shade falls by about -8% relative to today, whereas at 52% shade it falls by about -7%. Low shade performs worst (around -15% near 20% shade).

Figure 8.11a shows that the effect of a moderate warming of +2 °C (Tmax) on main-crop revenues is relatively small, with canopy shifts making little difference compared to the baseline. By contrast, Fig. 8.11b illustrates the impact of higher drought stress (+4 °C scenario with VPD), which reduces revenues by roughly 10% for the main crop, though still less severely than the +4 °C heat-stress case (cf. Fig. 8.9a). Together, these results suggest that under moderate warming the current optimal canopy remains adequate, while under more extreme scenarios additional shade becomes beneficial to buffer hazard impacts. However, the absolute values should be interpreted cautiously, as further refinement of hazard functions and yield–shade data is needed to improve realism.

Fig. 8.9b For coffee, the pattern is somewhat different from cacao. Under today's climate, revenues peak lower than the current average shade of about 40%, as the empirical yield–shade curve (cf. Fig. 7.2) suggests that slightly lower canopy would actually improve yields. This reflects cacao's broader tolerance of shade, with a more gradual peak and slower decline compared to coffee.

Under +4 °C, revenues decline across all canopy levels, but losses are again smallest at slightly higher shade. Low shade performs particularly poorly, while intermediate-to-high shade partly offsets hazard exposure. However, unlike coffee, the future benefit of adding shade is less pronounced because the yield penalty from excess canopy is stronger than the hazard mitigation gain. In fact, the results imply that reducing canopy somewhat below current levels may be optimal for cacao, even under warming.

Attribution analysis (Fig. 8.10a) shows that hazard-driven losses (red) dominate at low shade, while yield penalties (green) dominate at high shade. This double pressure means that cacao benefits less from hazard mitigation via shade compared to coffee. The results highlight how sensitive outcomes are to the empirical yield–shade curve, reinforcing the need for site-specific calibration.

This highlights two points: (i) the hazard-mitigation effect of shade narrows the gap between present and future revenues at higher canopy levels, but does not fully reverse yield penalties; and (ii) the analysis is sensitive to the empirical yield–shade curve used. Refining this curve with site-specific data will be critical, as it directly shapes whether future optima shift upward (as with coffee) or downward (as indicated here for cacao).

Overview of Yield Responses Across Hazards and Canopy Levels

To obtain an overview of how coffee and cacao respond across the different hazard scenarios and canopy settings, we summarise the results in Fig. 8.12. The figure brings together the historical baseline and the $+2°$C and $+4°$C futures, showing for each hazard type (VPD and Tmax) the present composition (dot or square) and the full span between best- and worst-performing canopy levels. From this synthesis three conclusions emerge: (i) future revenues decline in magnitude, with coffee showing a wider spread than cacao; (ii) cacao is less sensitive to canopy adjustments, while coffee performance depends strongly on shade level; and (iii) drought (VPD) generally induces stronger losses than heat (Tmax), especially for coffee under $+4°$C.

Important note on the impact of the yield–shade curve.

As illustrated in the plots, the assumed canopy–yield relationship has a strong influence on the results, as it can shift the location of the optimum and change the relative performance of different canopy levels. This underlines the importance of careful calibration with regional or site-specific data, or at a minimum, running sensitivity analyses to explore the effect of alternative curve shapes. Moreover, the shade–yield relationship itself may change under future climates, as ecosystem services (e.g., pollination, pest control, soil moisture, nutrient cycling) respond non-linearly to heat and drought. It is therefore best treated as scenario-dependent, with testing of alternative optima and curve widths, and recalibration wherever site-specific observations are available.

Additional revenue streams from fruit trees.

Before assessing the total benefits, it is important to note that monetary revenues include both the main crop (coffee or cacao) and any secondary crops (fruit trees). As more trees are planted, the revenue stream from the secondary crop increases alongside the main-crop revenues.

As shown in Fig. 8.15, increasing canopy by up to 50% proportionally increases the revenue stream from fruit trees. Unlike the main crop, there is no change here due to hazard impacts or a non-linear canopy–yield relationship, since no impact function is currently implemented for secondary crops. A key limitation, therefore, is that risk effects for fruit species are not captured; as discussed in the recommendations, this could be incorporated in future versions of the notebook.

Cost–benefit of total revenue

When combining main and secondary crops, we can assess the total revenue effect of alternative planting compositions.

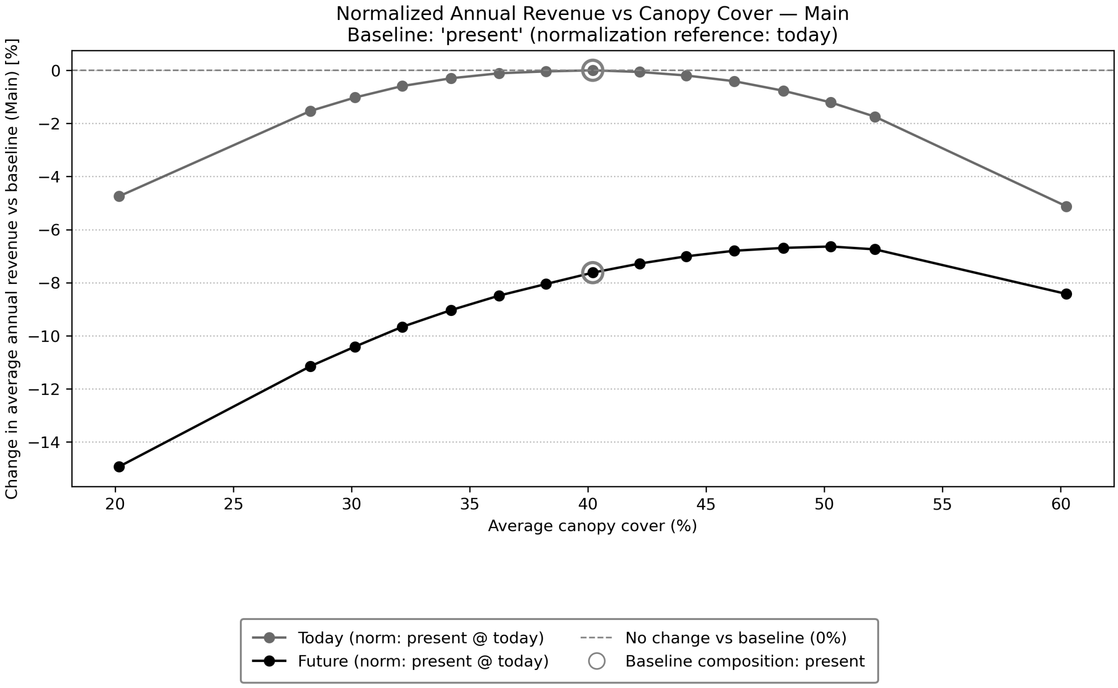
Figure 8.13 shows how total revenue changes with added shade trees. The increase from secondary crops is very large in this representation, to the point of dominating the total effect. This happens because revenues from fruit trees are treated as “risk-free” in the current implementation: they scale directly with the number of trees planted, without being exposed to hazard functions. In contrast, the main crop revenues are penalised by hazard-driven losses, making the relative contribution of fruit trees appear disproportionately strong.

The stacked species values (Fig. 8.14) illustrate this clearly: although the main crop (here cacao) still anchors the baseline, secondary crops quickly make up a very large share of the total once canopy is increased. In reality, this is likely overstated, since fruit species are also vulnerable to climate hazards. With proper impact functions, their contribution would be lower and more balanced relative to the main crop.

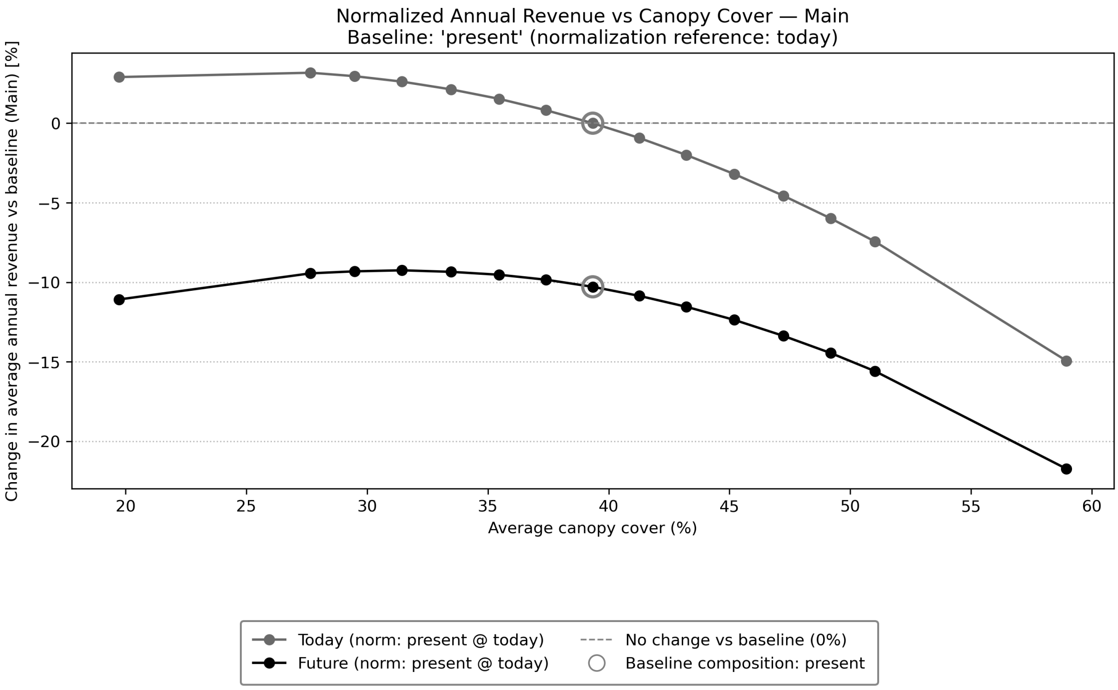
Finally, Fig. 8.15 shows the net benefits and benefit–cost ratio (BCR) when planting and maintenance costs are included. Here again, the dominance of secondary crops is visible, but it should be interpreted with caution: it reflects the assumption of risk-free revenues for fruit trees, rather than a realistic estimate of their vulnerability. In practice, the profitability of adding fruit trees would depend strongly on their actual sensitivity to heat, drought, and pests.

Overall, these results show that secondary crops appear dominant under the current assumptions, but this is misleading. While fruit trees certainly provide additional revenue and diversification, their role in the cost–benefit outcome is likely overstated until hazard impacts are properly included. The main crop remains the primary driver of risk-adjusted revenues, and future modelling should calibrate both main and secondary crops with realistic vulnerability curves to better reflect trade-offs.

Regional copariosn All the resutls are aviable on the github. We see simialr patterna in the the other regions where incresing shade for coffe couses more losses as this driver is domeintnat. Nad for cacao there are minor beift of increasing given the a anot the the other regions

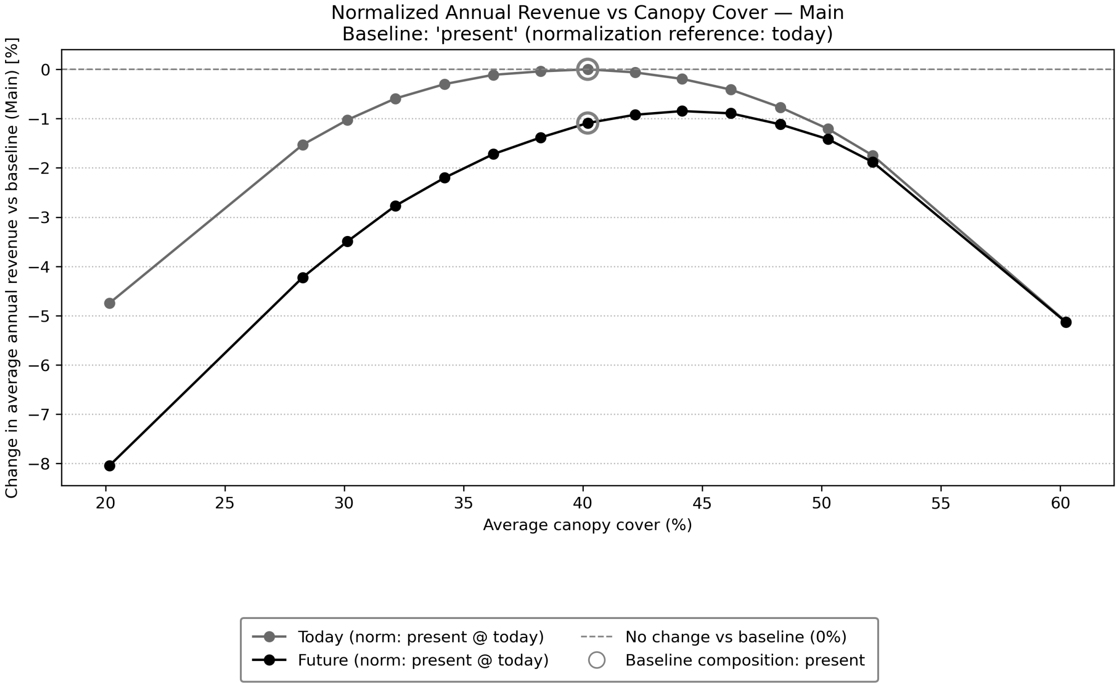


(a) Cacao: normalised change in average annual revenue vs. average canopy cover. Grey = present; black = +4 °C. Hollow marker: baseline shade (∼40%).

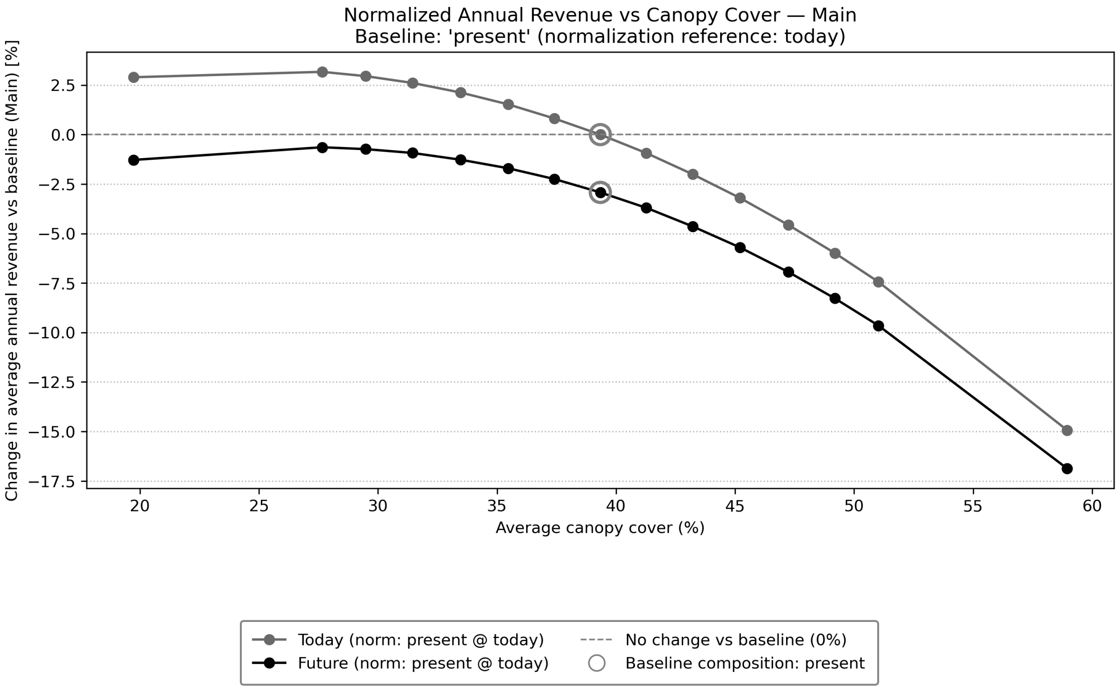


(b) Coffee: normalised change in average annual revenue vs. average canopy cover. Grey = present; black = +4 °C. Hollow marker: baseline shade (∼40%).

Figure 8.8: Main-crop revenue response to canopy cover under present and future hazards for heat stress(Tmax +4C).

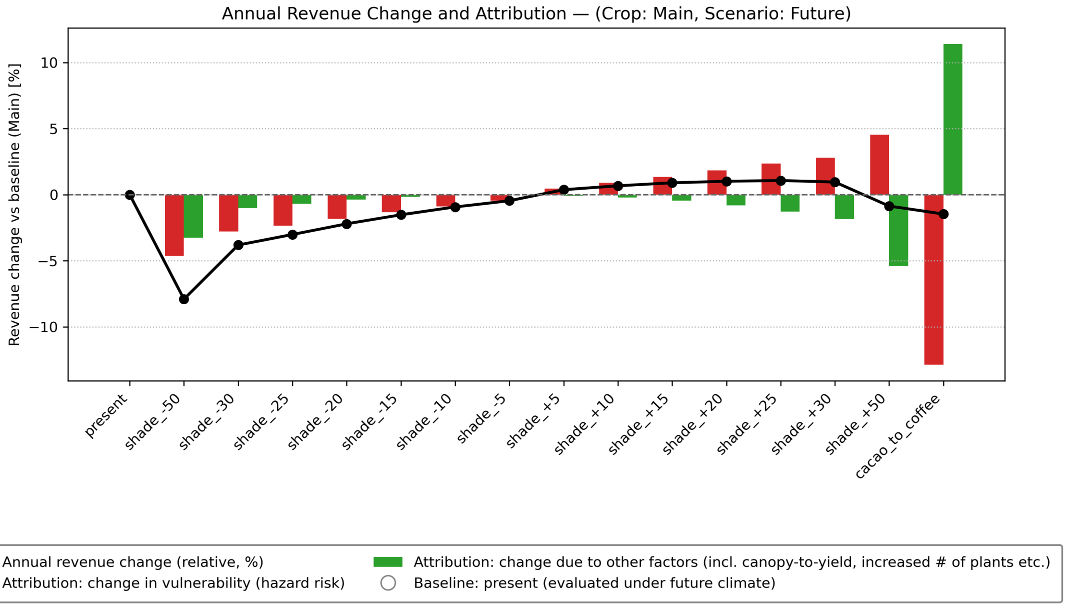


(a) Cacao: normalised change in average annual revenue vs. average canopy cover. Grey = present; black = +2 °C. Hollow marker: baseline shade (∼40%).

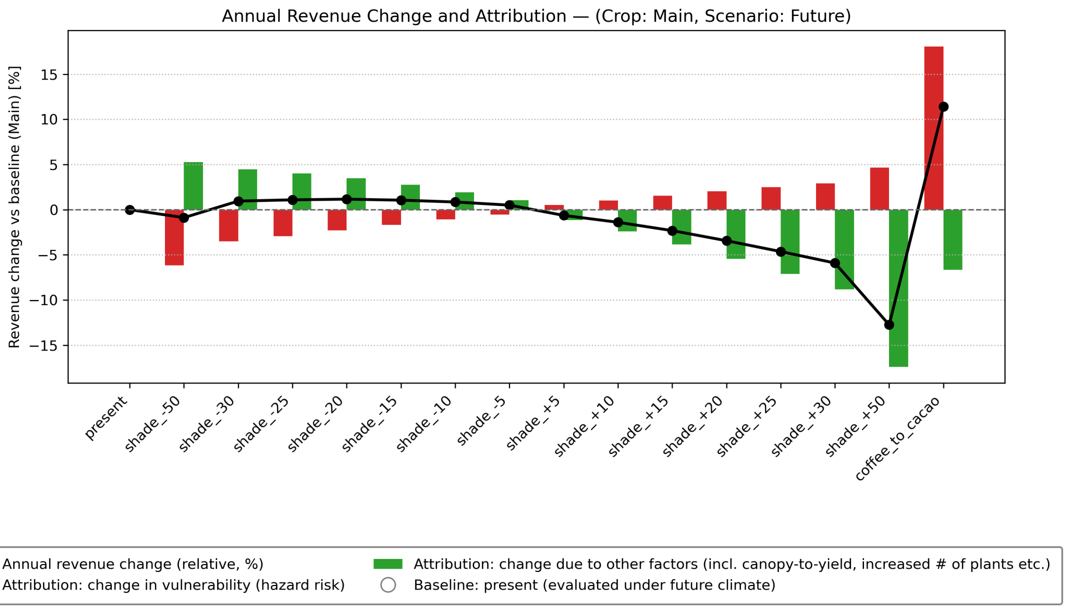


(b) Coffee: normalised change in average annual revenue vs. average canopy cover. Grey = present; black = +2 °C. Hollow marker: baseline shade (∼40%).

Figure 8.9: Main-crop revenue response to canopy cover under present and future hazard Tmax.

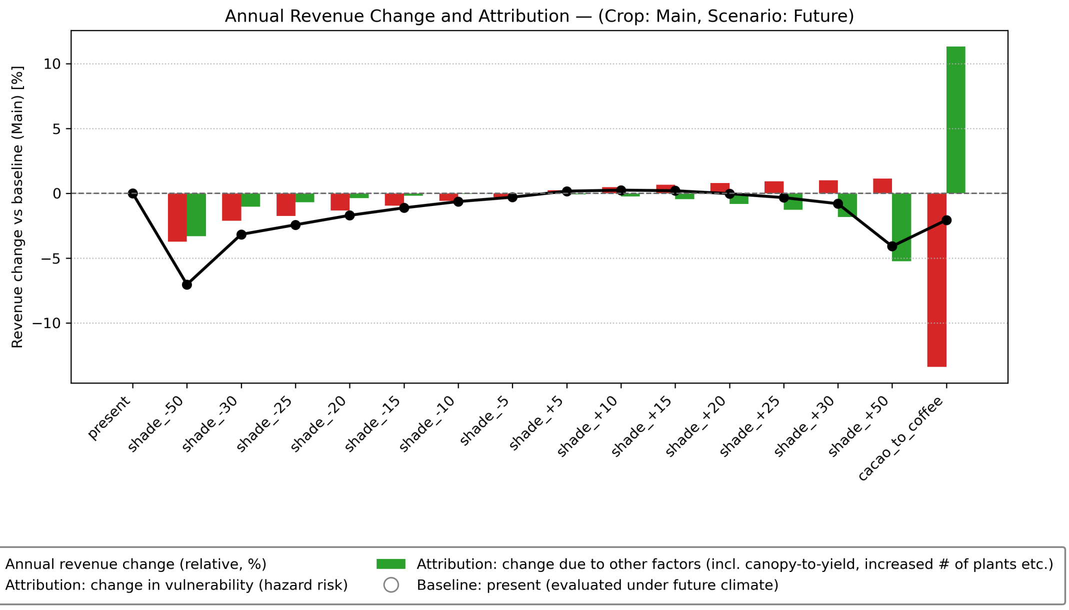


(a) Cacao: attribution of revenue change under +4 °C. Red = hazard (vulnerability) component; green = other factors (incl. yield–shade, plant numbers). Black line = total change vs. baseline.

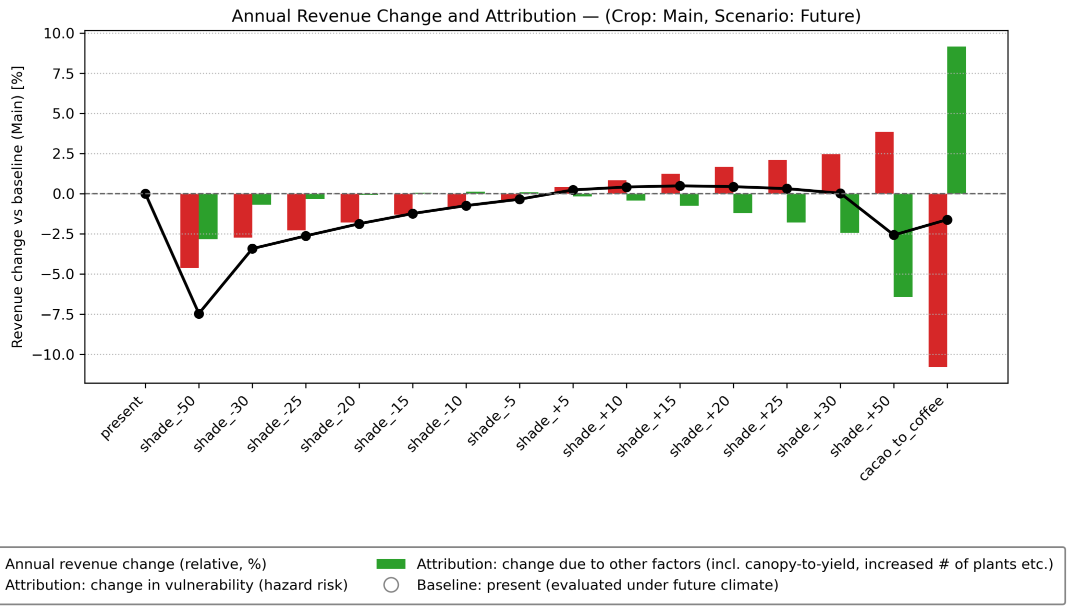


(b) Coffee: attribution of revenue change under +4 °C. Same colour scheme as above.

Figure 8.10: Decomposition of future revenue changes into hazard-driven (red) and canopy/yield-driven (green) components in Cibao Noroeste, Dominican Republic for hazard Tmax.



(a) Main revenue attribution under +2 °C (Tmax). Black line = main change vs. baseline; green = canopy/yield effects (incl. fruit trees); red = hazard-driven losses.



(b) Main revenue attribution under +4 °C (VPD). Same colour scheme as above.

Figure 8.11: Comparison of cacao revenue attribution under different hazard scenarios in Cibao Noroeste, Dominican Republic. Top: moderate warming (+2 °C Tmax) shows negligible effects. Bottom: drought stress (+4 °C VPD) reduces revenues by ∼10%, though less severely than the +4 °C Tmax case (cf. Fig. 8.9a).

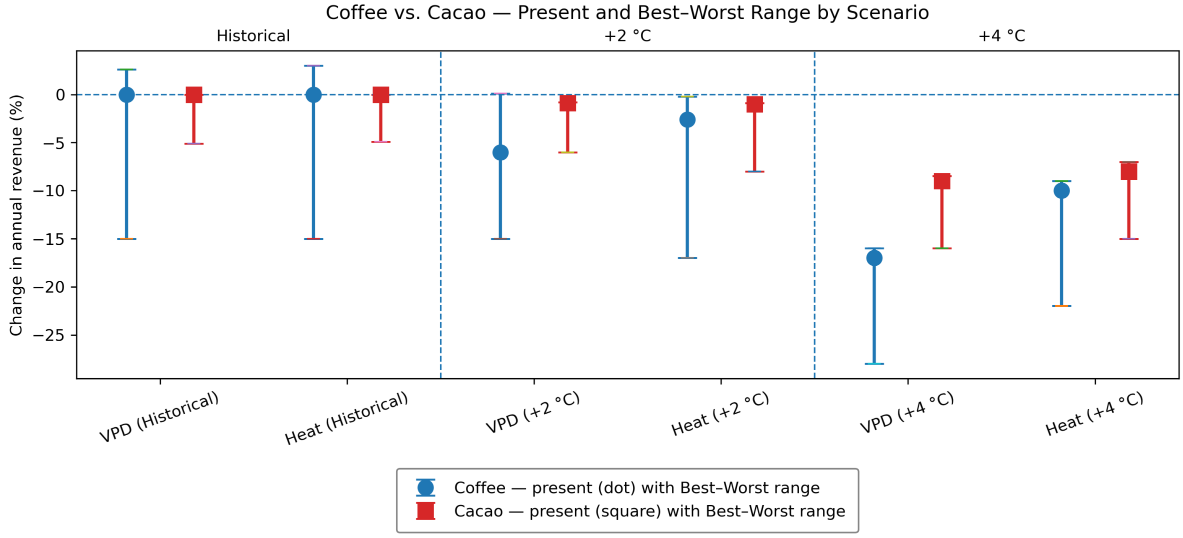


Figure 8.12: Synthesis of revenue changes for coffee (dots with range) and cacao (squares with range) in Cibao Noroeste, Dominican Republic, under historical, $+2°$C, and $+4°$C scenarios. Points mark the present composition; vertical bars span the best–worst outcomes across canopy levels. This overview highlights the wider sensitivity of coffee compared to cacao and the stronger losses under drought (VPD) than under heat (Tmax).

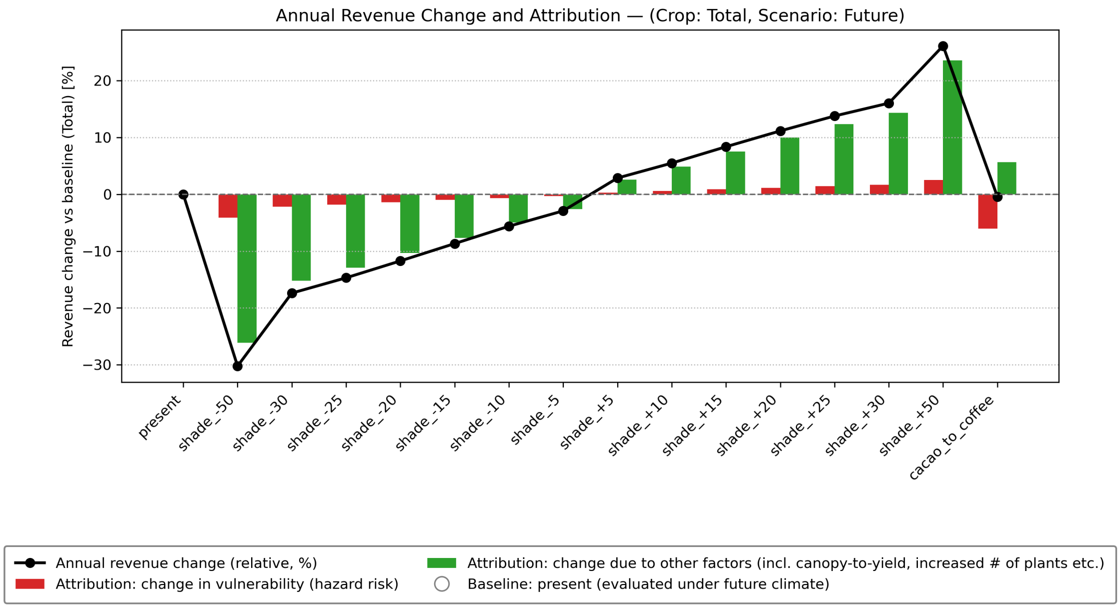


Figure 8.13: Total revenue attribution (main + secondary) for heat stress (Tmax) under the +4 °C scenario. Black line = total change vs. baseline; green = canopy/yield effects (incl. fruit trees); red = hazard-driven losses.

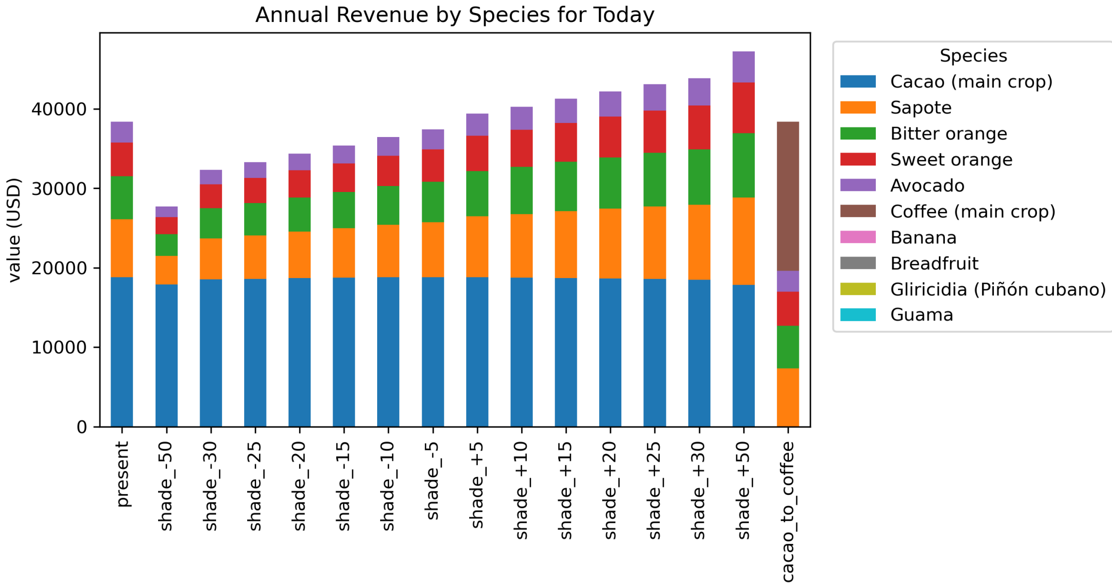


Figure 8.14: Annual revenue by species under the present climate in the Cibao Noroeste, Dominican Republic. Although cacao dominates the total baseline revenue, secondary crops such as sapote, citrus, and avocado rapidly expand their contribution when canopy is increased, as they are modelled without hazard penalties.

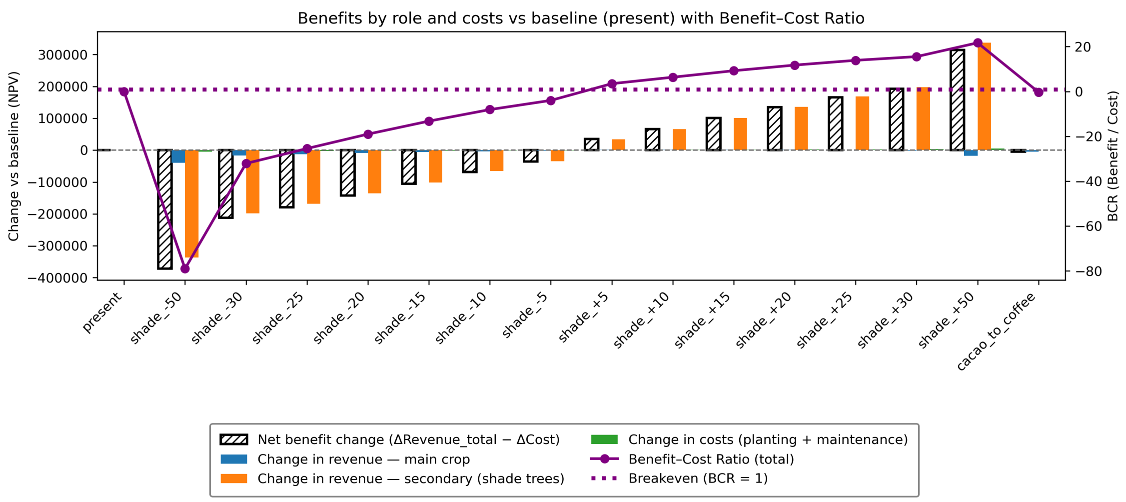


Figure 8.15: Cost–benefit by role (present climate), including planting and maintenance costs in Cibao Noroeste, Dominican Republic for Tmax +4C. The apparent dominance of secondary crops is an artefact of modelling them as risk-free. The purple line shows the resulting Benefit–Cost Ratio (BCR).

Part III

Conclusion and Recommendations

The preceding chapters have reviewed the climate risks facing tropical perennial crops, examined the potential of agroforestry as an adaptation strategy, and developed a prototype cost–benefit framework within CLIMADA to assess canopy interventions. This final chapter outlines practical recommendations for improving the modelling framework, for prioritising new data collection, and for ensuring that results are linked to real-world farmer decisions and policy processes. The goal is to make future analyses both more robust and more directly useful for adaptation planning.

9 Conclusions and Recommendations

Key learnings and results

This work has provided several key insights into the role of canopy composition and biodiversity in climate-risk assessments for perennial crops.

We initially focused on **shade as a central indicator**, since it is relatively easy to measure and directly affects crop microclimates. However, through the analysis it became clear that **canopy composition provides a stronger link to both risk and ecosystem services**. Shade can be achieved in many different ways—for example, by planting a single fast-growing tree species—but such an approach may contribute little to biodiversity, resilience, or income diversification. By contrast, canopy composition integrates not only the amount of shade but also the diversity of functions provided by different species, ranging from nitrogen fixation and soil improvement to timber, fruit, and habitat value.

Second, our analysis highlights **two main types of risk that must be distinguished**. On the one hand, there is the year-to-year variability that directly affects yields and farmers' short-term income. On the other hand, there are long-term risks to the agroforestry systems themselves: shade trees and associated species may become increasingly vulnerable under future climate conditions, threatening the stability of the system as a whole.

Third, the findings underline the **need for a multi-criteria decision framework**. Measures such as adjusting shade cannot be evaluated by a single outcome alone. For instance, maximising shade may reduce heat stress, but without considering biodiversity and income diversification, such a recommendation would be overly simplistic and could even be counter-productive.

Finally, the results show that **coffee appears generally more at risk of climate change than cacao across Central America**. While cacao and many shade trees retain suitability under warming, coffee suitability declines sharply, particularly under high warming scenarios. At the same time, increasing shade and canopy diversity consistently reduces climate risk, confirming the importance of agroforestry as an adaptation pathway.

This prototype demonstrates how canopy interventions can be analysed within a CLIMADA-compatible, cost–benefit workflow. Below we outline practical next steps to improve robustness, extend the scope to other ecosystem services, and support decision making.

9.1. How to reuse and extend the framework

- **Generalisation to other services.** Reuse the exposure–hazard–impact pipeline to represent additional ecosystem-service pathways (e.g., soil-moisture buffering, erosion control, pollination, pest regulation). Each pathway can be linked to (i) a modified hazard field (cooling, wind shielding), (ii) an adjusted vulnerability/impact function, or (iii) an auxiliary benefit stream in the cash-flow module.
- **Data harmonisation.** Prepare site/country templates with consistent units for yields, prices, and costs (establishment, maintenance). Calibrate present-day exposures so baseline revenues match partner data.
- **Transparent scenario handling.** Version yield–shade curves, cooling coefficients, and impact-function parameters by scenario (“today”, “+2 °C”, “+4 °C”) to avoid mixing assumptions.

9.2. Model fitting and calibration

- **Average yield fitting.** Fit the main-crop yield–shade curve to partner observations (by country/altitude band). Where data are sparse, use informative priors from the literature and report credible intervals.
- **Impact functions.** Calibrate heat/VPD damage functions against observed yield anomalies (coffee: cf. Kath et al.; cacao: thresholds from the agronomic literature), and extend to fruit species as data become available.
- **Cooling functions.** Validate $\Delta T(s)$ and $\Delta \mathrm{VPD}(s)$ with plot-level microclimate data where possible; otherwise run low/central/high sensitivity bands.
- **Secondary crops.** Add basic impact functions and price/yield checks for fruit trees to avoid over-weighting “risk-free” revenues.

9.3. Sensitivity analysis and uncertainty

The results are sensitive to several assumptions. Given limited time for detailed calibration, we recommend running a structured sensitivity analysis (both one-at-a-time and global, e.g., Morris/Sobol) on:

9.3.1. Uncertainties in the cost/benefit analysis

- **Yield–shade curve:** optimum location, curvature (width), and asymmetry.
- **Impact functions:** heat and VPD thresholds/slopes; event-set length (bootstrap/GEV).
- **Cooling coefficients:** magnitude and shape of $\Delta T(s)$ and $\Delta \mathrm{VPD}(s)$.
- **Economics:** prices, establishment and maintenance costs, and discount rate.

Some functions have been prepared for running these sensitivity analyses and similar approaches have been tested in experimental settings.

Suggested outputs: tornado charts for NPV/BCR, distributions of BCR under parameter uncertainty, and Pareto plots (revenue vs. risk vs. biodiversity).

9.3.2. Uncertainties in the risk to the agroforestry system

When assessing the risk to the agroforestry system itself, several layers of uncertainty need to be considered. On the hazard side, extreme events such as droughts and heatwaves can be generated through stochastic sampling (e.g. using GEV distributions) to reflect the range of possible intensities, rather than relying on single realisations. For slow-onset hazards such as climatic suitability, uncertainty can be represented by storing both the mean and standard deviation of suitability estimates, and by varying the suitability thresholds that define crop viability.

On the impact side, the functional form of species' vulnerability is itself uncertain. This can be reflected by defining ranges of impact functions (e.g. high, medium, and low vulnerability classes) rather than a single curve. On the exposure side, the number and composition of trees in a given system is not uniquely defined. Multiple plausible agroforestry configurations can be generated that still correspond to farmer descriptions, thereby sampling uncertainty in exposure.

Together, these sources of uncertainty propagate through the analysis and provide a range of potential risk estimates for the agroforestry system, rather than a single deterministic outcome.

9.4. Incorporating exposure change into CBA

Ensure that canopy scenarios update both (i) the exposure object (plants/ha by species/role) and (ii) the cost module (establishment for `Added Plants/ha` and updated maintenance). Secondary-crop revenues should be added as positive annual cash flows and—once impact functions are available—adjusted for hazard losses analogously to the main crop.

9.5. Biodiversity and multi-criteria adaptation

Biodiversity is a core outcome of the BioFinCas project alongside revenue and climate risk. Figure 9.1 is adapted from Contreras 2025 [18], who meta-analysed studies across Latin America to derive standardised biodiversity responses by shade class.[1] We use this stylised biodiversity–shade curve as a pedagogical indicator that can be calibrated with site data when available.

Link to multi-criteria decisions. Because shade simultaneously (i) raises biodiversity, (ii) shifts yield via the yield–shade curve, and (iii) reduces hazard exposure through cooling, BioFinCas decisions are naturally multi-criteria. We recommend three complementary formulations:

1. **Weighted-sum scoring:** maximise a composite score such as $w_1 \cdot \mathrm{NPV} - w_2 \cdot \mathrm{Risk} + w_3 \cdot \mathrm{Biodiversity}$ with stakeholder-defined weights w_i.
2. **Threshold (constraint):** maximise NPV subject to $\mathrm{Risk} \leq r^*$ and $\mathrm{Biodiversity} \geq b^*$.
3. **Pareto screening:** present the frontier of non-dominated canopy options (NPV, Risk, Biodiversity) to visualise trade-offs.

These approaches can be operationalised in CLIMADA once the forthcoming multi-criteria module becomes available. In the meantime, they would need to be implemented manually.

For now, biodiversity is included as a separate indicator in the CB matrix (not monetised); future work should test sensitivity to alternative biodiversity–shade curves and, where appropriate, explore shadow pricing or constraint-based targets agreed with partners.

[1] The thesis harmonises effect sizes and estimates mean responses by shade categories; medium shade (roughly 30–60%) tends to yield the largest and most consistent biodiversity gains, with diminishing returns at very high cover.

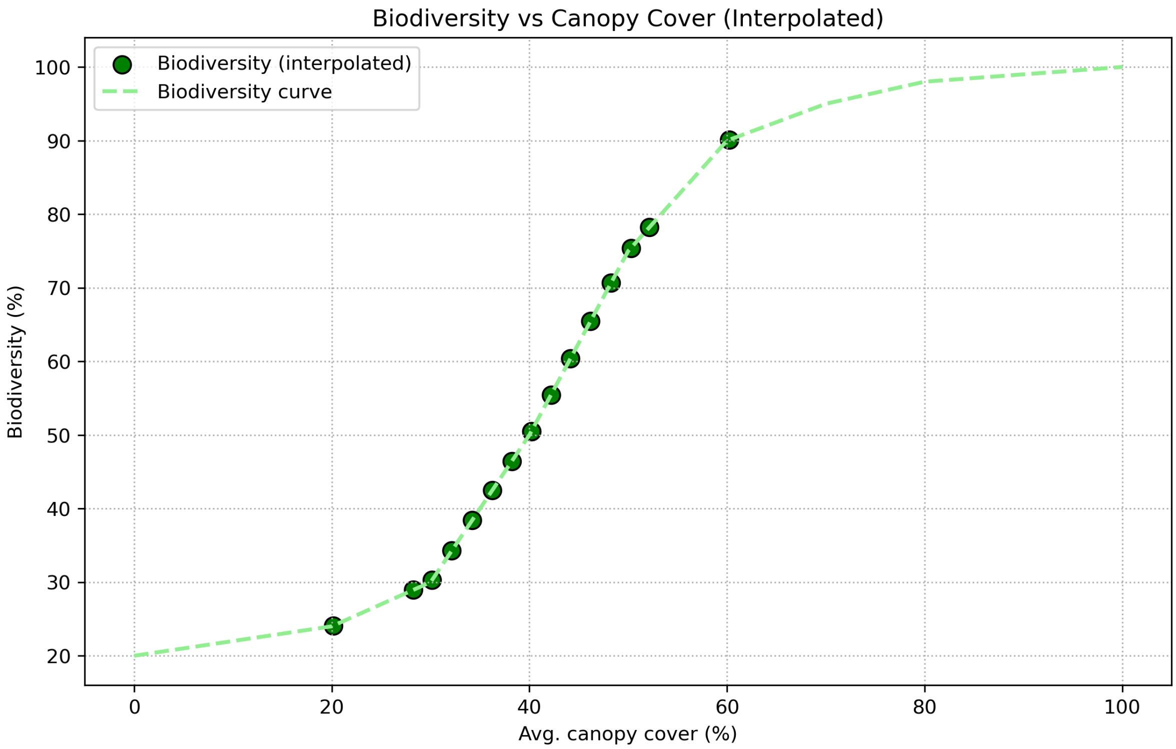


Figure 9.1: Illustrative relationship between canopy cover and a biodiversity index in coffee agroforestry. Curve adapted from the meta-analysis of Latin American coffee systems in Contreras 2005 [18], which synthesises biodiversity responses across shade bands.

9.6. Data and measurement priorities

To improve the robustness of future modelling, we recommend a targeted set of field measurements and inventories:

- **Microclimate observations:** Record temperature, humidity, and vapour pressure deficit inside agroforestry systems, ideally paired with nearby open-field stations to quantify cooling and buffering effects.
- **Species composition:** Systematically document the tree and crop species present in agroforestry plots, including their densities and spatial arrangements.
- **Canopy structure:** Quantify shading provided by the system (e.g. canopy cover, leaf area index, crown dimensions), as this directly influences cooling and hazard exposure.
- **Georeferencing:** Collect precise locations and elevation ranges of agroforestry plots to support integration with climate, hazard, and suitability data.

In addition, we recommend developing species-level models wherever possible. Species-specific modelling enables the linking of climate risks to ecosystem services. For instance, if a nitrogen-fixing tree is present, its vulnerability can be assessed directly, and the implications for nutrient cycling and soil fertility can be quantified. In contrast, aggregate system-level risk estimates are difficult to interpret in terms of specific ecosystem-service losses without species-level information.

9.7. Hazards that could be considered in CLIMADA

From discussions with Centro Naturaleza it became clear that river floods and wildfires are of particular interest. Both of these hazards are generally difficult to model at the fine spatial resolution of individual plots. For river floods, the ISIMIP data could be used to calculate regional trends under climate change, although it does not resolve localised flood dynamics. For wildfires, CLIMADA's wildfire module provides a way to estimate current risk, but modelling how this risk evolves under climate change remains challenging.

9.8. Next steps if more time were available

If additional time were available, several concrete steps could substantially strengthen the analysis:

- **Validation of plot archetypes.** Conduct surveys or discussions with local partners to validate the assumptions underlying typical plot configurations.
- **Focus the analysis.** Decide whether to prioritise suitability modelling, cost–benefit analysis, or extreme weather risk to shade trees, and simplify accordingly.
- **Suitability risk.** Explore sensitivities and uncertainties across scenarios; discuss methods with ecosystem modellers; and validate the suitability modelling algorithms.
- **Cost–benefit analysis.** Calibrate yield impact functions for fruit trees; seek input on socio-economic and biodiversity metrics for multi-criteria analysis; and run sensitivity tests for the yield–shade curve, impact functions, cooling effect, and economic assumptions.
- **Extreme event risk.** Develop empirical vulnerability curves for shade trees through expert elicitation (e.g., identifying years when trees died due to drought or cyclones); determine which hazards are most relevant; and carry out scenario analysis with uncertainty ranges.

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