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# Forest Cover and Weather Shocks: Land Use on the Quest For Adaptation and Conservation

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# Forest Cover and Weather Shocks: Land Use on the Quest For Adaptation and Conservation

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*A mio fratello Vittorio.  
Con l'augurio che tu sappia sempre cogliere serenamente  
e con integrità le opportunità della vita,  
goderti il viaggio e perseverare.*



**Forest Cover and Weather Shocks:  
Land Use on the Quest For Adaptation and Conservation**



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## Long abstract

Tropical and subtropical forests cover approximately 2.28 billion hectares, accounting for 56% of the total global forest area. They play a crucial role in climate regulation and carbon storage. Unfortunately, between 1990 and 2020, over 90% of observed deforestation affected these ecosystems, equating to around 12.69 million hectares per year. This loss is interlinked to climate change and weather shocks: although forests are a vital tool on the fight against climate change, they also endure its effects. Consequently, countering deforestation poses a strategic challenge, particularly in developing countries where the livelihoods of rural populations depend on agriculture and forest products. Yet, the influence of extreme weather events on adaptation strategies involving land use changes has often been overlooked, despite the fact that these adaptation practices could themselves depend on and affect forest conservation efforts. This thesis aims to explore these links and evaluate the synergies as well as potential trade-offs between climate risks, adaptation, and land use dynamics, with a focus on forests. In the first chapter we analyse the impact of droughts and forest degradation on overall deforestation in the major tropical forest basins between 1990 and 2020. The results highlight a positive correlation between deforestation and droughts, although spatial, climatic, and temporal variations exist. Nevertheless, a gradual decrease in this impact is observed over time, especially with a reduction in degradation, emphasizing the importance of understanding these dynamics to guide conservation policies. Then we examine the relevance of agricultural seasonality of major staples, maize and cassava. Findings reveal that, in the Democratic Republic of Congo, deforestation decreases if the growing season is affected by a drought but increases if the drought affects the harvesting one. This analysis underscores the need for conservation policies that consider the adaptation needs of local populations to climate shocks. In the third and last chapter we focus on the long-term impacts of dam construction and subsequent changes in water flow on land use in sub-Saharan Africa. Results indicate a significant reduction in agriculture but an increase in forest cover, with variable consequences depending on the distance from the dam, both upstream and downstream. This analysis also highlights a decrease in agricultural productivity but a diversification of economic activities, emphasizing the challenges and opportunities associated with such infrastructure and their potential role in climate shock adaptation and support to conservation.

Overall, this thesis contributes to a better understanding of the interactions between weather shocks, adaptation, and deforestation. Moreover it provides crucial insights to guide sustainable development policies and natural resource management in tropical countries: by recognizing the varying impacts of weather shocks on land use and livelihoods, policymakers can better tailor targeted interventions to address specific needs and vulnerabilities of local communities. This approach - which encompasses the global, regional and local scale - wants to support development pathways that benefit both people and the planet. By leveraging the lessons from this research, policymakers can forge a more resilient and sustainable future for forested regions, thereby advancing the global agenda for climate action and biodiversity conservation.

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# Résumé en Français

## Introduction

Réunis en 2021 lors de la 26<sup>e</sup> Conférence des Parties (COP26) des Nations Unies, les dirigeants mondiaux ont approuvé la *Glasgow Leaders' Declaration on Forests* et se sont ainsi engagés à mettre fin à la déforestation en moins d'une décennie. La Déclaration reconnaît que "[...] pour atteindre nos objectifs d'utilisation des terres, de climat, de biodiversité et de développement durable, tant au niveau mondial que national, il faudra entreprendre des actions transformatrices supplémentaires dans les domaines interconnectés de la production et de la consommation durables; [...] des finances et de l'investissement; et du soutien aux petits exploitants, aux peuples autochtones et aux communautés locales, qui dépendent des forêts pour leur subsistance et jouent un rôle clé dans leur gestion".

Deux ans plus tard, lors de la COP28, cet engagement a été de nouveau renouvelé avec les dirigeants annonçant un financement supplémentaire de 186,6 millions de dollars pour des projets liés à la nature et au climat, dirigé en particulier vers la préservation des forêts, des mangroves et de l'océan. Ces fonds financeront en partie ou compléteront de nombreuses autres actions en cours, émanant de pays individuels ou de partenariats, qui soutiennent également les efforts mondiaux de conservation. Parmi les exemples, citons la *Three Basin Alliance*, qui vise à coordonner les efforts de protection des forêts tropicales dans les bassins amazonien, congolais et du Bornéo-Mékong-Asie du Sud-Est ; le règlement de l'Union Européenne 2023/1115, qui donne la priorité à la réduction de l'empreinte de consommation de l'UE en encourageant la commercialisation de produits issus de chaînes d'approvisionnement sans déforestation ; le plan de la Chine pour les zones protégées, s'engageant à désigner 25% de son territoire comme parcs nationaux et réserves naturelles d'ici 2035. Des initiatives moins récentes, telles que le Fonds Amazonie du Brésil et la *International Climate and Forest Initiative* de la Norvège, toutes deux lancées en 2008, continuent de mobiliser des financements pour sauver les forêts tropicales du monde tout en améliorant les conditions de vie de ceux qui y habitent.

Les déclarations faites lors des COP et ces actions politiques parallèles illustrent l'importance de protéger et de gérer les écosystèmes forestiers en reconnaissant leur rôle dans le soutien à la biodiversité et à la vie humaine. Conformément au 15<sup>e</sup> objectif de développement durable, elles soulignent le rôle des forêts dans l'atténuation des vulnérabilités environnementales et sociales, ainsi que le risque pour les économies qui dépendent de leurs services écologiques, afin que les pays puissent répondre aux besoins des générations présentes et futures tout en luttant contre le changement climatique.

En effet, les forêts sont le moyen disponible de séquestration du carbone le plus efficace, capable de compenser les émissions anthropiques. Elles offrent également de nombreux avantages économiques, environnementaux et socio-culturels aux communautés locales (Canadell and Raupach, 2008; UNPD, 2023) : selon les estimations de l'ONU, les forêts soutiennent plus de 1,6 milliard de personnes, dont 12,5% dépendent directement d'elles pour leur survie (UNPD, 2023; Brack, 2018).

La qualité et la superficie des forêts sont impactées par le changement climatique, affectant leur croissance, leur productivité et leur composition en espèces, réduisant ainsi leur capacité d'atténuation (Ometto et al., 2022). Ces changements sont provoqués par des modifications de températures, de précipitations et de niveaux de CO<sub>2</sub>, ainsi que par des facteurs secondaires tels que l'augmentation des incendies et la propagation des ravageurs et maladies (Kirilenko and Sedjo, 2007; Ometto et al., 2022).

De plus, les stratégies d'adaptation peuvent aggraver ces impacts, qui sont souvent exacerbés par des facteurs non climatiques tels que la conversion des terres à d'autres fins comme l'agriculture, l'infrastructure ou l'exploitation minière (Ometto et al., 2022). La proximité des forêts est un

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déterminant important des stratégies d'adaptation ou de gestion des chocs. Un exemple frappant de ce rôle est la possibilité pour les populations vivant près des forêts de collecter des produits forestiers non ligneux (PFNL), afin d'atténuer les chocs de revenu, ou d'étendre les zones agricoles. Malheureusement, ces stratégies peuvent entraîner une forme de changement d'utilisation des terres, principalement au détriment de la couverture forestière, menaçant ainsi davantage les moyens de subsistance et la sécurité alimentaire des populations rurales. Cependant, la littérature économique a principalement abordé théoriquement les synergies entre les variables climatiques - en particulier les chocs climatiques -, les stratégies d'adaptation des utilisateurs des terres et les changements d'utilisation des terres. Les articles abordant cette question n'ont que marginalement quantifié dans quelle mesure un événement extrême peut affecter la variation de la couverture forestière (Girard et al., 2019).

L'objectif de cette étude est donc d'analyser les effets des événements météorologiques extrêmes - en particulier des sécheresses - sur la déforestation, en tenant compte de tous les facteurs et forces sous-jacents qui peuvent influencer le choix et l'intensité du défrichement des terres ou de la préservation des forêts. La zone d'intérêt regroupe les pays moins développés, en développement et certains pays émergents, qui se caractérisent par une grande dotation en forêts tropicales et qui sont donc les plus menacés par la dégradation de l'environnement et les impacts du changement climatique.

Les conclusions de cette étude peuvent fournir aux décideurs des idées pour orienter les stratégies de gestion forestière qui tiennent compte du bien-être des ménages ruraux et répondent à leurs besoins d'adaptation, en se conformant aux principes énoncés dans la Déclaration de Glasgow.

## Changement climatique, chocs météo et agriculture

Dans son dernier rapport, le GIEC déclare que les émissions anthropiques de gaz à effet de serre ont entraîné une augmentation à la fois de la fréquence et de l'intensité de certains extrêmes météorologiques et climatiques (Seneviratne et al., 2021). Jusqu'à présent, ces impacts ont été hétérogènes selon les régions du monde, certaines étant moins touchées que d'autres. Cependant, à l'avenir, des augmentations supplémentaires de la température mondiale et des variations dans la distribution des précipitations peuvent entraîner des changements significatifs dans les extrêmes météorologiques pour toutes les régions. Il est établi que que les sécheresses agricoles et écologiques, c'est-à-dire *"une période exceptionnelle de pénurie d'eau pour les écosystèmes existants et la population humaine, due à une faible pluviométrie, à des températures élevées et/ou à un vent fort."* (van Diemen et al., 2019)<sup>1</sup>, deviennent de plus en plus fréquentes sur tous les continents (Seneviratne et al., 2021). Il convient de noter que les variations des précipitations, et en particulier les déficits en eau, peuvent également impliquer une variabilité et une saisonnalité de l'offre et, par conséquent, de la demande en ressource (Rodríguez-Iturbe, 1992). Cette variabilité est susceptible d'accentuer les risques pour de nombreux ménages ruraux, en fonction de leur exposition au changement climatique, de leur sensibilité à ces changements, ainsi que de leur capacité à répondre et à s'adapter (Baez et al., 2013). Les chocs, et en particulier les sécheresses, sont susceptibles d'avoir un impact sur la santé et le niveau d'éducation des communautés rurales en raison des répercussions sur les revenus agricoles (Arceo-Gómez et al., 2020; Baez et al., 2013; Carpena, 2019; Udmale et al., 2015; Di Falco et al., 2011). En effet, les sécheresses réduisent la productivité agricole et l'élevage tout en augmentant les ravageurs et la mortalité (Begna, 2020; Bogale and Erena, 2022). Par exemple, Udmale et al. (2015)

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<sup>1</sup>van Diemen et al. (2019) décrivent en outre les sécheresses agricoles et écologiques comme *"une période présentant un déficit anormal en humidité du sol, résultant d'une combinaison de pénurie de précipitations et d'une évapotranspiration excessive, et pendant la saison de croissance, ayant un impact sur la production de cultures ou la fonction des écosystèmes en général."*

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montrent que les sécheresses ont entraîné une perte de plus de 80% des rendements des cultures vivrières dans les zones vulnérables de l'Inde, entraînant ainsi une réduction des surfaces cultivées et des pertes d'emplois. Ces circonstances se traduisent par une perte de revenus totale de plus de 85% par rapport aux années normales. De manière similaire à Udmale et al. (2015), Noack et al. (2019) ont constaté que, dans les zones tropicales, les ménages touchés par une sécheresse ont subi une perte de revenus de 45%. Dans ce contexte, la biodiversité plus élevée offerte par les forêts s'est révélée essentielle pour atténuer les impacts négatifs causés par les sécheresses. Néanmoins, les impacts des sécheresses sur les revenus des ménages dépendent du contexte, tout comme les stratégies d'adaptation qui pourraient être mises en place par les ménages.

## Stratégies d'adaptation dans les contextes ruraux

Les stratégies d'adaptation peuvent être définies comme l'ensemble des actions que les ménages pourraient mettre en place pour éviter une perte de revenu, de biens ou de bien-être suite à un choc. Comme le décrivent Girard et al. (2021) dans leur méta-analyse, l'adaptation est un phénomène complexe et multidimensionnel. Dans un contexte rural, les stratégies peuvent être différenciées en fonction du moment, de la durée et de l'emplacement de l'action compensatoire. La variable temporelle correspond au moment où la stratégie est adoptée par rapport au moment où le choc s'est produit, distinguant ainsi entre la gestion et l'adaptation : les stratégies de gestion sont toutes les actions mises en place après le choc (ex-post), pour essayer de compenser la perte ; en revanche, les stratégies d'adaptation sont un ensemble d'actions anticipatives (ex-ante) mises en place pour prévenir une perte. La durée, quant à elle, permet de faire la distinction entre les stratégies à court terme et à long terme : les stratégies à court terme sont considérées comme temporaires tandis que les stratégies à long terme sont permanentes. Enfin, l'emplacement définit si ces stratégies sont mises en œuvre sur l'exploitation agricole ou en dehors de celle-ci. Les stratégies sur l'exploitation agricole sont toutes les solutions qui impliquent des activités agricoles et d'élevage et peuvent être organisées en cinq macro-catégories principales (Akinyi et al., 2021) : gestion des cultures, des risques, des sols/terres, de l'eau et du bétail. À l'opposé, les solutions en dehors de l'exploitation agricole sont celles qui impliquent une relocalisation partielle ou totale des activités économiques loin de l'agriculture. Cela inclut des solutions telles que la migration temporaire ou permanente, à longue ou courte distance, vers des zones urbanisées à la recherche d'opportunités d'emploi. De telles solutions peuvent être adoptées par l'ensemble du ménage ou seulement par certains de ses membres. Les caractéristiques de chaque stratégie sont largement décrites par Girard et al. (2021); Di Falco et al. (2020); Akinyi et al. (2021); Ayanlade et al. (2022).

Les stratégies à court terme sur l'exploitation agricole comprennent des changements dans la variété des cultures, la gestion des champs et la gestion des risques, tandis que les stratégies à court terme hors exploitation agricole impliquent la recherche d'emplois hors exploitation agricole ou la migration saisonnière. Les stratégies à long terme sur l'exploitation agricole englobent la production agricole et la relocalisation du bétail, l'acquisition d'actifs et la plantation d'arbres, tandis que les stratégies à long terme hors exploitation agricole incluent la recherche d'emploi dans les zones urbaines ou la migration à longue distance.

La littérature propose une subdivision entre le court et le long terme, ainsi qu'entre les stratégies anticipatoires et d'adaptation, cependant ces catégories sont principalement adoptées pour des raisons de simplicité. Ces différences ne sont qu'indicatives car la durée, ainsi que le choix des stratégies, dépendent à la fois du ménage et du contexte. Tout d'abord, l'adoption ou la non-adoption des stratégies d'adaptation dépend de la sensibilisation au changement climatique du ménage, de la perception qu'il en a et de son aversion au risque (Di Falco et al., 2011). Les caractéristiques des ménages sont la principale source d'hétérogénéité : l'âge, le sexe, la taille de la famille affectent la



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gamme des adaptations que le ménage pourrait adopter. De plus, plus le niveau d’alphabétisation, l’accès aux informations climatiques et la richesse sont élevés, plus la probabilité d’adaptation est grande Di Falco et al. (2011). La possession de terres, ainsi que la richesse, l’accès au marché et aux crédits, influencent le choix entre les solutions sur et hors exploitation agricole, tandis que les caractéristiques environnementales des exploitations définissent mieux le type de stratégie à mettre en place Alam (2018); Di Falco and Veronesi (2014); Di Falco et al. (2011).

Les réseaux et les effets de pairs sont également essentiels pour déterminer la résilience aux chocs ainsi que la probabilité d’adopter une stratégie spécifique. Di Falco and Veronesi (2014) ont constaté que plus le nombre de parents dans le village est élevé, mieux l’exposition au risque est gérée. De même, Di Falco et al. (2020) ont constaté que l’apprentissage par les pairs est le principal mécanisme par lequel le choix d’adapter ainsi que l’adoption d’une certaine stratégie se propagent.

Di Falco and Veronesi (2013) a prouvé que seule la combinaison de plusieurs stratégies a un impact positif sur les revenus. Néanmoins, bon nombre de ces réponses peuvent, directement ou indirectement, impliquer l’utilisation de terres boisées ou de PFNL, suggérant donc qu’elles pourraient avoir un impact sur l’environnement, entraînant potentiellement un changement d’utilisation des terres (Girard et al., 2021). Indépendamment du déclencheur, il y a un accord général sur le fait que le changement d’utilisation des terres, en particulier dans le cas de la déforestation, peut être une conséquence de la gestion des risques et de l’adaptation aux risques où les forêts pourraient être soit un outil de diversification du portefeuille, soit une assurance (Delacote, 2007). Conformément à Angelsen and Wunder (2003), les ménages peuvent exploiter les forêts selon différentes stratégies : spécialisées, diversifiées ou de gestion. Chaque stratégie est généralement définie par le niveau d’intégration des ménages sur le marché et par la part de leurs revenus provenant des PFNL, qui fonctionnent comme une assurance en cas de choc négatif sur les revenus. Delacote (2007) a montré que, en cas de stress économique, la dépendance aux produits forestiers ou aux terres agricoles peut également varier en fonction de l’aversion au risque des ménages. Il est donc clair que, pour les communautés rurales, les sécheresses peuvent constituer un risque potentiel qui pourrait donc affecter l’équilibre des ménages entre l’agriculture et la dépendance à la forêt. Par exemple, lorsqu’un choc météo se produit ou est prévu, un ménage peut choisir d’augmenter sa dépendance aux PFNL, utilisant ainsi les forêts comme un "filet de sécurité" (Delacote, 2007, 2009). Ce choix peut potentiellement favoriser l’augmentation de la couverture forestière mais, en même temps, une récolte excessive peut entraîner une dégradation de la forêt et donc entraver la capacité d’adaptation de l’écosystème. D’autre part, un ménage peut choisir de défricher la forêt dans le but de maintenir ou d’augmenter la production agricole. Il en découle donc que les changements de couverture forestière et de qualité (dans les deux sens) dus à un meilleur entretien, à une surexploitation ou à un défrichement peuvent être un résultat non intentionnel de l’adaptation (Rodriguez-Solorzano, 2014).

Les changements dans l’occupation des terres peuvent également être induits par des stratégies d’adaptation qui ne dépendent pas directement des forêts, telles que la diversification à travers des emplois hors exploitation agricole, la migration, le développement des infrastructures, l’élevage de bétail, etc.. Ces aspects sont abordés par Rodriguez-Solorzano (2014) qui a approfondi la recherche sur les effets de l’adaptation des agriculteurs sur la couverture forestière en fonction de leur perception de la variabilité climatique. De plus, indépendamment de la stratégie adoptée, l’expérience des ménages face aux chocs précédents peut également influencer leur réaction ultérieure (Di Falco et al., 2011; Di Falco and Veronesi, 2014, 2013). Les effets d’un choc peuvent varier en fonction, par exemple, de son timing, de sa fréquence ou de son intensité. Par exemple, Desbureaux and Damania (2018) ont prouvé que la réponse des ménages ruraux varie en fonction de la période du calendrier agricole touchée par une sécheresse.

De même, l’adaptation aux chocs peut être constituée par des changements lents dont l’effet cumulatif ne peut être perçu que sur le long terme. Pour cette raison, des auteurs tels que Rodriguez-

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Solorzano (2014) ont choisi d'étudier le nombre de sécheresses vécues sur une période plus longue plutôt que celles vécues au cours d'une seule saison de croissance. En revanche, une fréquence ou une intensité élevée du choc peut entraîner une érosion de la capacité d'adaptation des ménages (Desbureaux and Damania, 2018), également en raison de l'existence d'une boucle de rétroaction entre la déforestation et les sécheresses (Staal et al., 2020) et donc d'une relation non linéaire entre la nature et la société.

Dans l'ensemble, il est possible de conclure que lorsqu'ils sont touchés par une sécheresse qui affecte le revenu agricole, les ménages ruraux tendent à compenser la perte avec les revenus collectés dans leur environnement immédiat, notamment à partir de la forêt (Wunder et al., 2018; Noack et al., 2019; Castro et al., 2022). En conséquence, la vulnérabilité des communautés forestières peut être exacerbée dans un contexte de changement climatique (Ofoegbu et al., 2017) où la qualité et l'étendue de la forêt sont menacées, car cette dégradation diminuerait leur capacité à faire face aux chocs. En même temps, en cas de choc, une telle dépendance des communautés rurales à l'égard des forêts est susceptible d'orienter, intentionnellement ou non, le maintien, voire l'augmentation de la couverture forestière Girard et al. (2021). Par conséquent, malgré le faible risque généralement associé à l'exploitation forestière, il est clair que celle-ci peut constituer à la fois un filet de sécurité et un piège de pauvreté en cas de stress économique (Delacote, 2007). Cela montre la nécessité d'une meilleure compréhension des phénomènes afin de mieux développer des stratégies à long terme de lutte contre la pauvreté tout en préservant le capital naturel. En effet, l'intensité et la direction de ces impacts restent encore floues mais, grâce au rôle de plus en plus reconnu des forêts tant du point de vue environnemental qu'économique, les études empiriques se multiplient. La disponibilité accrue de données géographiquement et temporellement désagrégées permet désormais aux chercheurs d'étudier ces questions à une échelle plus large car, jusqu'à présent, la plupart des études se sont concentrées sur l'Amérique du Sud ou concernaient des zones très limitées. Les prochains paragraphes discuteront des principaux facteurs qui peuvent conditionner le choix entre les stratégies d'adaptation et la déforestation, et qui doivent donc être pris en compte dans notre analyse.

## Impacts sur l'utilisation des sols

Les études sur les moteurs de la déforestation remontent à la première moitié du 19<sup>ème</sup> siècle, lorsque Thünen (1826) a abordé les modèles d'allocation des terres (Ferretti-Gallon and Busch, 2017). Depuis lors, ces moteurs ont été analysés sous plusieurs perspectives. Cela est en partie dû à la nature particulière du phénomène, qui nécessite une approche multidisciplinaire, en prenant des éléments d'un éventail de disciplines allant des sciences du climat à l'économie (Duval and Wolff, 2009). Les causes de déforestation, largement décrites par Ferretti-Gallon and Busch (2017) dans leur méta-analyse, sont généralement divisées en moteurs proches, c'est-à-dire les actions anthropiques directes qui différencient l'utilisation des terres, et les forces sous-jacentes, c'est-à-dire les conditions socio-économiques et environnementales favorisantes (Girard et al., 2019). Malgré le faible consensus sur la manière de traduire ces déclencheurs en variables réelles à inclure dans un modèle empirique (Ferretti-Gallon and Busch, 2017), ceux-ci sont généralement classés sous trois principaux groupes de variables : sociodémographiques (1), politiques et institutionnelles (2), ainsi qu'économiques (3) (Duval and Wolff, 2009). En réalité, la relation entre la déforestation et la dépendance des populations à la forêt est complexe, multidimensionnelle et influencée par une myriade de facteurs, y compris les chocs, l'adaptation et la couverture forestière. Cela rend difficile de discerner des tendances claires (Duval and Wolff, 2009). Étant donné le faible consensus dans la littérature sur les variables à inclure dans les modèles empiriques (Duval and Wolff, 2009), les paragraphes suivants discutent des plus importantes, en mettant en évidence les preuves et les lacunes pour chacune. En revisitant le cadre classique décrit dans la section précédente, ces variables seront regroupées en

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trois principaux groupes: variables physiques et environnementales, variables sociodémographiques et variables politiques, institutionnelles et économiques. Bien que, pour simplifier, dans notre discussion, ces variables soient attribuées à une seule catégorie, elles peuvent en réalité englober plus d'une catégorie.

En commençant par les variables physiques et environnementales, des éléments tels que l'altitude, les zones climatiques et les occurrences d'autres chocs abiotiques jouent un rôle crucial dans la formation de la couverture forestière. Un exemple en est l'accessibilité, qui est déterminée par l'effet de l'altitude ou de la pente des terres. Ces paramètres déterminent la faisabilité de l'exploitation des zones forestières, tandis que la proximité des terres défrichées et la disponibilité des infrastructures réduisent le coût d'opportunité de leur exploitation. Un autre exemple est celui des zones climatiques, qui définissent la typologie forestière et donc la portée de l'utilisation des terres. De plus, les incendies, qu'ils soient naturels ou anthropiques, et les ravageurs contribuent de manière significative à la déforestation en impactant la fonctionnalité du biome ainsi qu'en exacerbant la perte de couverture forestière et de services écosystémiques. Par conséquent, l'état de l'environnement peut également influencer les dynamiques de déforestation, reflétant la relation complexe entre l'activité humaine et les écosystèmes naturels.

Les variables sociodémographiques telles que la densité de population, l'ethnicité et les schémas de migration ont des implications variables pour la déforestation. Alors que les zones densément peuplées exercent souvent une pression sur les ressources naturelles, entraînant des taux de déforestation accrus, les schémas de migration peuvent soit exacerber soit atténuer la déforestation en fonction de divers facteurs tels que les envois de fonds et les pratiques locales d'utilisation des terres. L'ethnicité joue également un rôle, influençant les stratégies d'adaptation et les décisions de gestion des terres, les communautés autochtones adoptant souvent des pratiques plus durables que les groupes non autochtones.

Enfin, le domaine des variables politiques, institutionnelles et économiques introduit des complexités supplémentaires. Ces variables sont étroitement interconnectées avec celles discutées précédemment et démêler leurs effets n'est pas simple. Les variables économiques, telles que la présence de marchés mieux intégrés, offrent des opportunités d'emploi hors exploitation agricole mais impliquent également un développement plus important des infrastructures par rapport aux zones rurales (ce qui conduit souvent à une augmentation de la déforestation). La force des institutions et l'efficacité des politiques, y compris les mesures de conservation et les régimes fonciers, façonnent directement les résultats de la déforestation. Ces facteurs sont à leur tour liés et affectés par des investissements externes et des conflits qui compliquent davantage la compréhension de leurs effets. Par exemple, les acquisitions de terres à grande échelle, motivées par divers intérêts économiques, peuvent à la fois entraîner la déforestation et conduire à des conflits sociaux, soulignant l'interconnexion entre le développement économique, l'utilisation des terres et les dynamiques sociales. Les conflits, qu'ils soient déclenchés par la rareté des ressources environnementales ou d'autres facteurs externes, peuvent avoir des impacts divers sur la conservation des forêts, influençant l'accès aux terres et les pratiques de gestion, exacerbant ou atténuant ainsi la déforestation en fonction du contexte et des acteurs impliqués.

En résumé, comprendre la déforestation comme une stratégie d'adaptation nécessite une approche holistique qui prend en compte l'interaction et les synergies de nombreux facteurs. Ce n'est qu'en analysant de manière exhaustive ces variables interconnectées qu'il sera possible de proposer des solutions efficaces pour répondre aux défis complexes de la conservation de l'environnement et du bien-être humain.

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## Contributions

Dans les paragraphes précédents, nous avons souligné que, bien que les forêts soient un outil important dans la lutte contre le changement climatique, elles sont également affectées par celui-ci. Par conséquent, la lutte contre la déforestation constitue un défi stratégique, en particulier pour les pays les moins avancés et en développement où les moyens de subsistance des populations rurales dépendent à la fois de l'agriculture et des forêts. Pourtant, l'influence des événements météorologiques extrêmes sur les stratégies d'adaptation impliquant des changements d'utilisation des terres a souvent été négligée, bien que ces pratiques d'adaptation puissent elles-mêmes dépendre de, et affecter, la conservation des forêts.

Cette thèse vise à explorer ces liens et à évaluer les synergies ainsi que les éventuels compromis entre les risques climatiques, l'adaptation et les dynamiques d'utilisation des terres, en mettant l'accent sur la superficie et la qualité de la couverture forestière. Plus spécifiquement, cette thèse vise à comprendre la direction, l'intensité et le timing des changements d'utilisation des terres et de la déforestation en réponse aux sécheresses - en évaluant également l'influence des variables environnementales, sociales et économiques sur les choix d'utilisation des terres.

Tout d'abord, le premier chapitre analyse l'impact des sécheresses sur la dégradation et le défrichement des forêts dans les principaux bassins forestiers tropicaux entre 1990 et 2020. Les résultats mettent en évidence une corrélation positive entre la déforestation et les sécheresses, bien que des variations spatiales, climatiques et temporelles existent. Fait intéressant, une diminution progressive de cet impact est constatée au fil du temps, en particulier lorsque la dégradation diminue. Il a été démontré que la dégradation agit comme un précurseur de la déforestation. Cependant, dans les régions où les forêts sont déjà dégradées, les stratégies d'adaptation mises en place après les sécheresses se révèlent moins intensives en termes d'utilisation des terres. Ce chapitre complète l'analyse des tendances récentes de la déforestation, discutées par Pendrill et al. (2022); Hansen et al. (2013); Winkler et al. (2021); Vancutsem et al. (2021), et apporte des perspectives sur le rôle joué par les extrêmes météorologiques.

Pour mieux comprendre les sources d'hétérogénéité observées dans l'analyse à l'échelle mondiale du chapitre 1, nous approfondissons le sujet à l'échelle nationale - en République démocratique du Congo. Plus précisément, nous nous penchons sur l'importance de la saisonnalité agricole pour les principales cultures telles que le maïs et le manioc. En effet, comme indiqué dans la revue de littérature, les chocs impactent principalement les ménages ruraux en diminuant leurs revenus agricoles. Par conséquent, les ménages peuvent être contraints de compenser cette perte en recourant aux forêts. Nous soutenons que le choix et la manière d'utiliser les ressources forestières, en les préservant ou en les défrichant, dépend du calendrier agricole des cultures. Nos résultats révèlent que la déforestation diminue si la saison de croissance est affectée par une sécheresse, suggérant une relocalisation vers des emplois hors exploitation agricole. En revanche, la déforestation augmente si la sécheresse affecte la période de récolte, suggérant qu'une action d'anticipation est mise en place sur l'exploitation pour la prochaine saison agricole. Grâce à cette précision, et en ne considérant que la République démocratique du Congo - une zone où l'agriculture est la principale source de revenus -, nous sommes en mesure d'isoler plus efficacement les réponses d'adaptation des agriculteurs. Dans cette analyse, nous prenons également en compte certaines des variables politiques, institutionnelles et économiques discutées précédemment, à savoir la proximité des villes, les politiques de conservation et les conflits.

Enfin, nous nous concentrons sur les impacts à long terme des infrastructures, en étudiant la construction de barrages et les changements ultérieurs dans les flux d'eau sur l'utilisation des terres en Afrique subsaharienne. Les barrages sont un élément clé des infrastructures dans la quête de durabilité et de développement, mais comprendre comment ils peuvent déterminer les modèles de changement d'utilisation des terres est une première étape pour évaluer les variations de la vulnérabilité des

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populations rurales dans leur environnement.

Les résultats indiquent une réduction significative des terres agricoles ainsi qu'une augmentation de la couverture forestière, avec des conséquences variables selon la distance au barrage, tant en amont qu'en aval. Cette analyse met également en évidence une diminution de la productivité agricole mais une diversification des activités économiques, soulignant les défis et les opportunités associés à de telles infrastructures et au développement, ainsi que leur rôle potentiel dans l'adaptation aux chocs climatiques et le soutien à la conservation.

En plus de l'analyse empirique, cette thèse entreprend également une revue complète de la littérature existante, englobant les domaines de l'économie, de la science des données et des études environnementales. En synthétisant les résultats des recherches antérieures, elle cherche à identifier et à combler certaines lacunes dans la compréhension de la déforestation ainsi qu'à apporter de nouvelles perspectives sur les relations complexes entre les sécheresses, la déforestation, l'adaptation et le développement. Nous soulignons que les récents progrès dans la littérature existante ont été marqués par deux avancées significatives : l'utilisation de données géoréférencées, facilitée par une accessibilité et une précision améliorées, et l'adoption de plans quasi expérimentaux. Par conséquent, dans cette étude, les deux approches ont été largement utilisées. Les trois principales enquêtes présentées ici - concernant les moteurs de la déforestation à l'échelle mondiale, régionale et nationale - dépendent toutes de données géoréférencées, garantissant une approche uniforme. D'autre part, s'appuyer uniquement sur des données géoréférencées entrave l'observation directe des stratégies d'adaptation qui ne peuvent donc être que déduites. Pour dépasser cette limite importante de notre étude, les recherches futures devraient intégrer des données au niveau des ménages dans l'analyse. Cependant, la faible couverture et la portée limitée des enquêtes disponibles à ce jour peuvent limiter la portée et la validité externe des résultats.

Nos résultats mondiaux soulignent l'importance de comprendre ces dynamiques pour informer les politiques de conservation. Ces politiques doivent tenir compte à la fois des besoins d'adaptation des populations locales aux chocs climatiques, mais aussi de la boucle de rétroaction positive existant entre les chocs, la déforestation et l'adaptation. De plus, les politiques devraient considérer que l'adaptation peut avoir des impacts contrastés sur l'environnement, par exemple en favorisant ou en réduisant la déforestation en fonction du moment et de l'intensité du choc et de la stratégie adoptée. Bien que l'adaptation soit primordiale pour le bien-être des ménages ruraux, parmi les plus vulnérables et les plus durement touchés par le changement climatique, les politiques d'atténuation ne doivent pas être négligées, surtout à la lumière de cette boucle de rétroaction et de la non-linéarité des impacts. Au contraire, elles devraient être intégrées aux efforts d'adaptation pour éviter l'aggravation des risques existants. De même, tout en planifiant des infrastructures - destinées soit au développement, à l'adaptation ou à l'atténuation, comme les barrages pourraient l'être - nos résultats soutiennent l'analyse future des impacts des projets pour estimer les effets environnementaux et socio-économiques spatiaux et temporels. Encore une fois, il convient de souligner que les coûts et les avantages ne sont pas également répartis. Ces résultats pourraient également soutenir des mesures de compensation plus équitables, particulièrement essentielles pour les plus pauvres qui sont généralement exclus des consultations et de la prise de décision.

En conclusion, en reconnaissant les complexités liant chocs-adaptation-environnement, sur lesquelles cette thèse s'efforce de jeter partiellement la lumière, les futurs processus de planification et de prise de décision pourraient aborder de manière plus efficace les vulnérabilités inhérentes aux systèmes humains et environnementaux, assurant ainsi un avenir durable pour tous, tant les générations présentes que futures, en accord avec la *Glasgow Leaders' Declaration on Forests* .

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## List of Acronyms

CC - Climate Change  
COP - Conference of Parties (United Nations)  
DC(s) - Developing Country(es)  
DRC - Democratic Republic of Congo  
EWE - Extreme Weather Event  
IPCC - Intergovernmental Panel on Climate Change  
LSLA - Large-Scale Land Acquisitions  
LDC(s) - Least Developed Country(es)  
NTFP - Non Timber Forest Products  
PA(s) - Protected Area(s)  
UN - United Nations

# 1 Introduction

Reunited in 2021 at the 26<sup>th</sup> United Nations Conference Of Parties (COP26), the world’s leaders endorsed the Glasgow Leaders’ Declaration on Forests and thus committed to halt deforestation in less than a decade. The declaration recognises that “*[.] to meet our land use, climate, biodiversity and sustainable development goals, both globally and nationally, will require transformative further action in the interconnected areas of sustainable production and consumption; [.] finance and investment; and support for smallholders, Indigenous Peoples, and local communities, who depend on forests for their livelihoods and have a key role in their stewardship*”.

Two years later, at the COP28, this commitment was further renewed with leaders announcing an additional 186.6 million dollars of new financing for nature and climate projects, directed in particular towards the preservation of forests, mangroves, and the ocean. These funds will partly finance or complement numerous other ongoing actions, arising from single countries or partnerships, which are further supporting global efforts for conservation. Some examples include the Three Basin Alliance, which aims at coordinating efforts to protect tropical rainforests in the Amazonian, Congo and Borneo-Mekong-Southeast Asia Basins; the European Union regulation 2023/1115, which prioritises the reduction of the EU’s consumption footprint by encouraging the commercialisation of products from deforestation-free supply chains; China’s plan for protected areas, committed to designate 25% of its landmass as national parks and nature reserves by 2035. Less recent initiatives, such as Brazil’s Amazon Fund and Norway’s International Climate and Forest Initiative, both launched in 2008, still work to leverage financing to save the world’s tropical forests while improving the livelihoods of those who live there.

The declarations made at the COPs and these parallel policy actions highlight the importance of protecting and managing forests ecosystems by recognising their role in supporting biodiversity and human life. In line with the 15<sup>th</sup> sustainable development goal, they underscore the role of forest in mitigating environmental and social vulnerabilities, as well as the risk for the economies that rely on their ecological services, so that countries can meet the needs of present and future generations while fighting climate change.

Indeed, forest are the most efficient available means of carbon sequestration capable of compensating anthropogenic emissions. They also offer numerous economic, environmental, and socio-cultural benefits to local communities (Canadell and Raupach, 2008; UNPD, 2023): in accordance with UN estimates, forests support more than 1.6 billion people, of which the 12.5% depends directly on them for their survival (UNPD, 2023; Brack, 2018).

Forest quality and cover are being impacted by climate change, affecting their growth, productivity, and species composition, and therefore reducing their mitigating ability (Ometto et al., 2022). These changes are driven by alterations in temperatures, precipitation, and CO<sub>2</sub> levels, as well as through secondary channels such as increased fires and the spread of pests and diseases (Kirilenko and Sedjo, 2007; Ometto et al., 2022).

Moreover, adaptation strategies may further exacerbate these impacts which are often compounded by non-climatic factors such as conversion of land for other uses like agriculture, infrastructure, or mining (Ometto et al., 2022). Proximity to forests is an important determinant of adaptation or coping strategies. A clear example of this is the possibility for populations living near forests to collect non-timber forest products (NTFP), in order to smooth income shocks, or to expand agricultural area. Unfortunately, these strategies may induce some form of land use change mostly at the detriment of forest cover, therefore potentially further threatening the livelihood and food security of rural populations. However, knowledge on the synergies between climate variables - in particular weather shocks -, land users’ adaptation strategies and land use change have been addressed mainly theoretically by the economic literature. Papers addressing this issue have only



marginally quantified the extent to which an extreme event may affect variation in forest cover (Girard et al., 2019).

The scope of this study is thus to address the effects of extreme weather event (EWE) - in particular of droughts - on deforestation, taking into account all the drivers and underlying forces that may influence the choice and intensity of land clearing or forest preservation. The area of interest is least-developed, developing (LDCs - DCs) and some emerging countries, which are characterised by a high rainforest endowment and are therefore the most endangered by environmental degradation and climate change impacts.

The findings of this study may provide policymakers with insights to guide forest management strategies that consider the well-being of rural households and address their adaptation needs, aligning with the principles outlined in the Glasgow Declaration.

## 1.1 Climate change, weather shocks and agriculture

In its latest report, the IPCC states that anthropogenic greenhouse gas emissions have led to an increase in both the frequency and intensity of some weather and climate extremes (Seneviratne et al., 2021). So far, these impacts have been heterogeneous across global regions, with some being less impacted than others. Looking forward however, further increases in global temperature and swings in precipitation distributions may cause significant changes in weather extremes for all regions. Evidence shows that agricultural and ecological droughts, i.e., *"an exceptional period of water shortage for existing ecosystems and the human population, due to low rainfall, high temperature and/or wind."* (van Diemen et al., 2019)<sup>2</sup>, are already the more and more frequent on all continents (Seneviratne et al., 2021). It should be noted that variations in precipitation, and in particular water deficits may also imply variability and seasonality of supply and therefore, demand, of the resource (Rodríguez-Iturbe, 1992). Such variability is likely to place more risk on many rural households, depending on their exposure to climate change, sensitivity to those changes, as well as their capacity to respond and adapt (Baez et al., 2013). Shocks, and in particularly droughts, are likely to impact rural communities health and education levels through shocks on agricultural income (Arceo-Gómez et al., 2020; Baez et al., 2013; Carpena, 2019; Udmale et al., 2015; Di Falco et al., 2011). Droughts indeed reduce agricultural and farming productivity while increasing pests and mortality (Begna, 2020; Bogale and Erena, 2022). For example, Udmale et al. (2015) show that droughts have caused a loss of more than 80% of staple's yields in vulnerable areas of India, therefore inducing a reduction of cultivated areas and causing employment losses. These circumstances are reflected in a total income loss of more than 85% compared to normal years. Similarly to Udmale et al. (2015), Noack et al. (2019) found that, in the global tropics, households affected by a drought experienced an income loss of 45%. In this context, higher biodiversity offered by forest proved to be essential in mitigating negative impacts caused by droughts. Nevertheless, droughts' impacts on the household incomes are context dependent and so are the adaptation strategies that could be put in place by households.

## 1.2 Adaptation strategies in rural contexts

Adaptation strategies can be defined as the the set of actions that households could put in place to avoid an loss of income, or a assets, or well-being following a shock. As described by Girard et al. (2021) in their meta-analysis, adaptation is a complex and multi-faced phenomenon. In a rural context, the strategies can be differentiated in function of the time, duration and location of the

---

<sup>2</sup>van Diemen et al. (2019) further describe agricultural and ecological droughts as *"a period with abnormal soil moisture deficit, which results from combined shortage of precipitation and excess evapotranspiration, and during the growing season impinges on crop production or ecosystem function in general."*

compensatory action. The time variable is moment at which the strategy is adopted with respect to the time the shock has happened, therefore distinguishing between coping and adaptation: coping strategies are all those ex-post actions put in place after the shock has already happened, to try to compensate for the loss; conversely, adaptation strategies are a ex-ante set of anticipatory actions put in place to prevent a loss. Duration, instead, distinguishes between short versus long term strategies: short-term strategies are considered to be temporary while long-term to be permanent. Lastly, location defines whether these strategies are implemented on-farm or off-farm. On-farm strategies are all those solution that involves agricultural and farming activities and could be organised in five main macro-categories (Akinyi et al., 2021): crop, risk, soil/land, water, and livestock management. At the opposite, off-farm solutions are the one that imply a partial or total relocation of economic activities away from agriculture. These include solutions such as temporary or permanent, long or short distance, migration to urbanised areas seeking for job opportunities. Such solution could be taken on by the entire household or just some member of it. The characteristics of each strategy are widely described by Girard et al. (2021); Di Falco et al. (2020); Akinyi et al. (2021); Ayanlade et al. (2022), the main ones are reported in Table 1.

Table 1: Schematizing main adaptation strategies. Based on Di Falco et al. (2020); Girard et al. (2021); Akinyi et al. (2021)

	<b>On-farm</b>	<b>Off-farm</b>
<b>Short-term</b>	Change crop variety, type & calendar (A) Reduce or extend farm size & livestock (A, C) Change field management, fertilisers & soil preparation (A) Agroforestry, NTFP (A, C) Risk management, insurance	Seek off farm employment (A, C) Seasonal migration (A)
<b>Long-term</b>	Agricultural production & livestock relocation (A) Livestock diversification Assets and infrastructures acquisition (A) Planting trees (A)	Seek off farm employment in urban areas (A, C) Long distance migration (A)

In Table 1 there is a subdivision between long and short term, as well as between anticipatory (A) versus coping (C) strategies, adopted for simplicity. Nevertheless, these differences are only indicative as the duration, as well as the choice of the strategies are both household and context dependent. Firstly, the adoption or non-adoption of adaptation strategies depends from the household's climate change awareness, the perception he has of it and his aversion to risk (Di Falco et al., 2011). Household's characteristic are the primary source of heterogeneity: age, gender, family size affect the range of adaptations that the household could embrace. Additionally, the higher the literacy, access to climate information, wealthiness the higher the probability to adapt Di Falco et al. (2011). The ownership of land, as well as wealthiness, access to market and credits, do influence the choice between on-farm versus off-farm solutions while the environmental characteristic of the farms then define better the type of strategy to be put in place Alam (2018); Di Falco and Veronesi (2014); Di Falco et al. (2011)

Network and peer effect are also essential in determine resilience to shocks as well as the likelihood to adopt a specific strategy. Di Falco and Veronesi (2014) found that the higher the number of relatives in the village the better risk exposure is managed. Similarly, Di Falco et al. (2020) found that learning via peers is the main mechanism through which the choice of adapting as well the adoption of a certain strategy spreads.

Di Falco and Veronesi (2013) proved that only the combination of multiple strategies has a positive impact on revenues. Nevertheless, many of these responses may, directly or indirectly, involve use of

forested lands, or NTFP, therefore suggesting that they could have a feedback on the environment, potentially leading land use change (Girard et al., 2021). Independently of the trigger, there is a general agreement on the fact that land use change, in particular in the case of deforestation, can be a consequence of risk management and risk adaptation where forests could be either a tool for portfolio diversification or insurance (Delacote, 2007). In accordance with Angelsen and Wunder (2003), households may exploit forests following different strategies: specialized, diversifying, or coping strategy. Each strategy is generally defined by the level of integration in the market of households and by the share of their income derived from NTFP which function as insurance in case of negative income shock. Delacote (2007) proved how, in cases of economic stress, the reliance on forest products or agricultural land may also vary with respect to the risk aversion of households. It is then clear that, for rural communities, droughts may constitute a potential risk which could therefore affect households' equilibrium between agriculture and forest reliance. For example, when an EWE occurs or is expected to occur, a household may choose to increase its reliance on NTFP, thus using forests as a "safety-net" (Delacote, 2007, 2009). This choice may potentially favour the increase of forest cover but, at the same time, an excessive harvesting may lead to degradation in the forest and therefore hinder the coping capacity of the ecosystem. On the other hand, a household may choose to clear forest with the objective of maintaining or increasing agricultural output. It then follows that changes in forest cover and quality (in both directions) due to better maintenance, over-exploitation or land clearing may be an unintended outcome of adaptation (Rodriguez-Solorzano, 2014).

Changes in land cover may also be led by adaptation strategies that do not rely directly on forests, such as diversification through off-farm jobs, migration, infrastructure development, cattle ranching, etc.. (further discussed in section 1.3 and 3.2). These are addressed by Rodriguez-Solorzano (2014) who deepened research on farmers' adaptation effects on forest cover based on their perception of climate variability. Additionally, independently of the strategy adopted, also the experience that households had from previous shocks may influence the way they react later on (Di Falco et al., 2011; Di Falco and Veronesi, 2014, 2013). The effects of a shock may vary for instance depending on its timing, frequency or intensity. For example, Desbureaux and Damania (2018) proved that rural households' response varies depending on the period of the agricultural calendar that has been hit by a drought. Similarly, adaptation to shocks may be constituted by slow changes of which the cumulative effect can be perceived only in the long-term. For this reason, authors such as Rodriguez-Solorzano (2014) chose to investigate the number of droughts experienced during a longer time span rather than the one experienced in a single growing season. On the other hand a high frequency or intensity of the shock may lead to an erosion of households' coping capacity (Desbureaux and Damania, 2018), also due to the existence of a feedback loop between deforestation and droughts (Staal et al., 2020) and therefore of a nonlinear relationship between nature and society.

Overall, it is possible to conclude that when hit by a drought that affects agricultural income, rural households may tend to compensate the loss with income collected from the environment around them, particularly from forest (Wunder et al., 2018; Noack et al., 2019; Castro et al., 2022). As a result, forest communities' vulnerability may be exacerbated in a climate change context (Ofoegbu et al., 2017) where forest quality and extension are threatened, as the loss would deplete their capability to cope with shocks. At the same time, in the eventuality of a shock, such reliance on forests by rural communities is likely to orient, intentionally or not, forest cover maintenance or deployment (Girard et al., 2021). Therefore, despite the low risk generally associated with forest harvesting, it is clear that forest exploitation may constitute both a safety-net and a poverty trap in the occurrence of economic stress (Delacote, 2007). This proves the need for a deeper understanding of the phenomena in order to better develop long term poverty alleviation strategies while preserving natural capital. Indeed, the intensity and direction of these impacts is still unclear but, thanks to the always more recognised role played by forest both from an environmental and an economic

perspective, empirical studies are on the rise. The higher availability of precise geographically and temporally disaggregated data now allows researchers to investigate these issues at wider scale as, so far, most studies focused on South America or concerned very limited areas. In the following paragraphs will be discussed the main factors which can condition the choice between adaptation strategies and deforestation which should therefore be taken in account in our analysis.

### 1.3 Impacts on Land uses

Studies on the drivers of deforestation may be traced back to the first half of the 19<sup>th</sup> century, when Thünen (1826) addressed land allocation patterns (Ferretti-Gallon and Busch, 2017). Since then, these drivers have been analysed under several perspective. This is in part due to the particular nature of the phenomenon, which requires a multidisciplinary approach, taking elements from a range of disciplines going from climate science to economics (Duval and Wolff, 2009). Triggers of deforestation, widely described by Ferretti-Gallon and Busch (2017) in their meta-analysis, are generally divided into proximate drivers, i.e., direct anthropogenic actions that differentiate land use, and underlying forces, i.e., enabling socioeconomic and environmental conditions (Girard et al., 2019). Despite the fact that there is a low consensus on how to translate these triggers into real variables to be included in an empirical model (Ferretti-Gallon and Busch, 2017), these are generally classified under three main groups of variables: sociodemographic (1), political and institutional (2), as well as economical one (3) (Duval and Wolff, 2009).

Truly, the relationship between deforestation and populations' reliance on forest is complex, multifaceted, and influenced by a myriad of factors including shocks, adaptation and forest cover. This makes it challenging to discern clear patterns (Duval and Wolff, 2009). Given the low consensus in the literature on which variables to include in empirical models (Duval and Wolff, 2009), the next paragraphs discuss the most important ones, highlighting evidence and shortcomings for each. Revisiting the classic setting described in the previous section, these variables will be clustered into three main groups: physical & environmental variables, sociodemographic variables and political, institutional & economic variables. Although, for simplicity, in our discussion these variables are allocated to a single category they may actually encompass more than one. Those are schematized in Figure 1.

Starting with physical and environmental variables, elements such as elevation, climatic zones, and occurrences of other abiotic shocks play a crucial role in shaping forest cover. An example of this is that accessibility is determined by elevation or land slope effects. These parameters determine the feasibility of exploiting forested areas, while the proximity to cleared land, and infrastructure availability reduce the opportunity cost of its exploitation. Another example is climatic zones, which define forest typology and therefore the scope of land use. Additionally, fires, either natural or anthropogenic, and pests significantly contribute to deforestation by impacting the functionality of the biome as well as exacerbating the loss of forest cover and ecosystem services. As a result, the health of the environment may further influence deforestation dynamics, reflecting the intricate relationship between human activity and natural ecosystems. The literature which addresses physical and environmental variables is further detailed in Box 1.

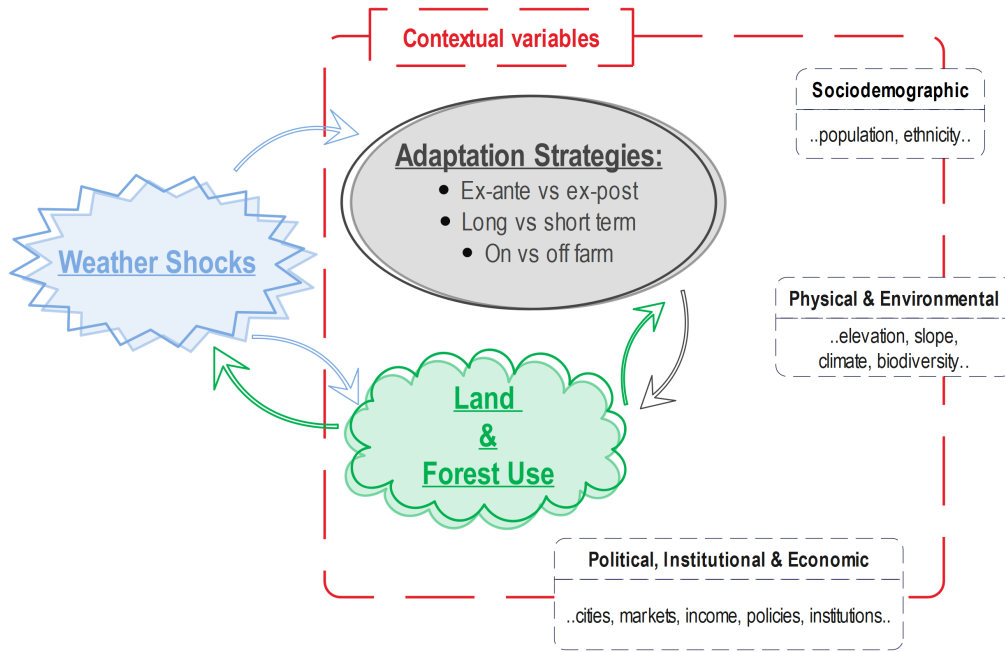


Figure 1: Links between adaptation strategies, land use and shocks, sources of heterogeneity.

### Box .1

### Physical and environmental variables

**Elevation and land slope:** Accessibility determines how convenient it is to exploit a certain plot and therefore to clear the forest. It is generally expressed also as a function of ruggedness (Butsic et al., 2015). In their meta-analysis Ferretti-Gallon and Busch (2017) found elevation and land slope to be associated with low forest cover and low clearing.

**Climatic zone:** Climatic zones define forest characteristics (e.g.: its flora composition) and as a result its pattern of land use. Householders relying on environments with similar characteristic tend to share similar livelihood patterns and potentially apply similar adaptation strategies. Delacote and Leblois (2020) have included climatic zones in their analysis, while peers' effects on adaptation choices are discussed by Di Falco et al. (2020)

**Fire occurrence:** Despite the well-known role played by forests as carbon sinks, deforestation is one of the activities that contributes the most to greenhouse gas emissions (Aragão et al., 2008), in part because of aggressive land management techniques, such as slash and burn procedures. However, fires may be not just a means to clear land, but also a consequence of this clearing. As investigated by Aragão et al. (2008), variation in forest cover may exacerbate the intensity of drought triggering positive feedback loops between clearing and wildfire occurrences.

**Health of the environment:** The quality of ecosystem services and the provision of sufficient NTFP depends on the health of the environment. In the literature on this topic, health is generally proxied by the biodiversity level. The quality of ecosystem services was taken in account in the theoretical model proposed by Delacote and Leblois (2020), who showed that biodiversity reduces the negative impacts of droughts on agricultural productivity. Similarly,

**Physical and environmental variables**

Noack et al. (2019) proved that higher biodiversity levels smooth the impacts of droughts on agricultural income. It is important to highlight that forest loss directly contributes to the degradation of these services at large scale (Grima and Singh, 2019) and that a biodiversity loss may therefore lower the opportunity cost of forest clearing.

**Proximity to cleared land:** The proximity of a forest lot to cleared land increases its probability of being deforested as well (Zaveri et al., 2020; Ferretti-Gallon and Busch, 2017). This relationship may be explained by an increase in accessibility but also by the tendency of householders to imitate their neighbours' deforestation decisions Poufoun (2016).

**Infrastructures & accessibility:** In general, infrastructures reduce transportation costs and make frontier land more accessible (Ferretti-Gallon and Busch, 2017). When poorly planned, infrastructures may eventually increase the depauperating of natural resources (Nelson, 2008; Nelson et al., 2019). Ruf et al. (2015) further researched the role played by road density in the occurrence of droughts and demonstrated that proximity to roads may lead to an increase in deforestation. Additionally, the choice of patterns of minor roads may be endogenous to local clearing decisions (Ferretti-Gallon and Busch, 2017). Further elements relating to accessibility are discussed in the paragraph on "Cities, roads and travel time".

**Waterway, irrigation & dams:** Although the distance of the cleared land from waterways was not found to be a significant deforestation driver by Ferretti-Gallon and Busch (2017), the presence of irrigation infrastructure may assume a different value when considering EWE: Zaveri et al. (2020) proved that, in case of drought, the availability of irrigation infrastructure could buffer the impact of the shock on agricultural productivity, thus preventing the expansion of new cropland into forest.

Sociodemographic variables such as population density, ethnicity, and migration patterns have varying implications for deforestation. While densely populated areas often exert pressure on natural resources leading to increased deforestation rates, migration patterns can either exacerbate or alleviate deforestation depending on various factors such as remittances and local land use practices. Ethnicity also plays a role, influencing adaptation strategies and land management decisions, with indigenous communities often exhibiting more sustainable practices compared to non-indigenous groups. The literature which addresses sociodemographic variables is further detailed in Box 2.

**Box .2****Sociodemographic variables**

**Population:** The effect of population on deforestation is extremely dependent on the socioeconomic and geographical context. The high nutritional demand implicit in a growing or densely populated areas is generally coupled with increased pressure on agriculture and other natural resources (Nguyen Van and Azomahou, 2007). Therefore, it is reasonable to assume that in these areas forest cover may be at higher risk, as illustrated by Ferretti-Gallon and Busch (2017). On the other hand, Nguyen Van and Azomahou (2007) and Ogundari et al. (2017) did not find the existence of an environmental Kuznet curve for deforestation. In cities, higher incomes may lead indirectly to a relief of the pressure on forest due to a lower demand for fuelwood, replaced by other forms of energy (Nguyen Van and Azomahou, 2007). Moreover, agglomeration implies demand for other services, potentially diverting the labour force of householders living in the cities' periphery from

## Sociodemographic variables

agriculture to other off-farm activities. Conversely, higher employment may increase the local demand for agricultural products, creating a positive feedback loop between cleared land and population growth which has not yet been disentangled (Ferretti-Gallon and Busch, 2017). In general, connections and services play a bigger role than population itself (see Box 1), as the relationship between population and deforestation is not significant when taking into account other development variables such as roads and infrastructure (Araujo et al., 2014).

**Ethnicity:** Adaptation strategies, namely including the choice to clear land, may also be influenced by network effects between neighbouring areas (Girard et al., 2019). This implies the existence of an underlying mechanism similar to the one of price transmission which was proven to be stronger between areas sharing the same ethnicity (Aker et al., 2014). Similarly, cultural background and ancestral reliance on the land have a strong influence on how rural populations choose to exploit the land: Ferretti-Gallon and Busch (2017) has shown that the presence of indigenous people reduces deforestation, though this may only have local validity. Lastly, areas where inhabitants share the same ethnicity as the one of political leaders may benefit from more investments: the interrelation between ethnic favouritism and deforestation were studied by Abman and Carney (2020). The authors found that in Malawi, regions where inhabitants shared the same ethnicity as the president received more subsidies for fertilisers: the boost in productivity of cultivated land plots eased the pressure on forest therefore reducing deforestation. Nevertheless, it should be underlined that favouritism may include many different typologies of investments (such as roads), which in turn may have ambiguous effects on forest cover.

**Migration:** Migration is a multi-faceted adaptation strategy: it can involve single individuals or families, be temporary or long term and may imply out-migration or simply the relocation of on-field production activities. As a result, it influences land use through multiple channels, leading to ambiguous outcomes which raise some disagreement in the literature. Out-migration influences land cover through remittances: while the relocation of migrants may ease the pressure on local resources, Solórzano (2016) hypothesized that remittances may be reinvested in land acquisition or land-intensive activities (such as cattle ranching) therefore inducing an indirect land use change. On the other hand, Duval and Wolff (2009) study the effect of remittances on GDP per capita and find that these were incentivising investments on instruments and technologies, hence diverting the pressure away from forests. Similarly, the higher economic availability supports households' legal access to land, reducing their reliance on abusive areas (Duval and Wolff, 2009). Farmers' migration, instead, may imply the relocation of on-field production activities to new areas where risk perception is lower (Zaveri et al., 2020). Less risk-prone areas may in turn attract more migrants, thus creating a feedback loop driven by an agglomeration effect (see paragraphs on population or cities in Box 2). The coexistence of these opposite potential outcomes explains why Rodriguez-Solorzano (2014) suggested migration to be a potentially neutral strategy.

Lastly, the realm of political, institutional, and economic variables introduces additional complexities. As shown in the following Box (3), these variables are closely interconnected with the ones previously discussed (Box 2 and 3) and disentangling their effects is not straightforward. Economic variables, such as the presence of better integrated markets (in cities) offers opportunities for off-farm employment but also implies a higher development of infrastructure compared to rural areas



(therefore often leading to increased deforestation). Institutions' strength and policies' effectiveness, including conservation measures and land tenure systems, directly shape deforestation outcomes. These factors are in turn interlinked with and affected by external investments and conflicts which further complicate understanding of their effects. For example, large-scale land acquisitions, driven by various economic interests, can both drive deforestation and lead to social conflicts, highlighting the interconnectedness between economic development, land use, and social dynamics. Conflicts, whether triggered by environmental scarcity or other external factors, can have diverse impacts on forest conservation, influencing land access and management practices thus exacerbating or mitigating loss depending on the context and actors involved.

**Box .3****Political, institutional and economic variables**

**Cities, markets & travel time:** In cities, efficient connections and short travel time reduce the transportation cost of agricultural products to consumption centres, thus boosting deforestation in surrounding areas (Ferretti-Gallon and Busch, 2017). The proximity to efficient markets may push households to increase their farming and agricultural activities to support the nutritional demand of growing populations, which are typical for cities<sup>a</sup>. On the other hand, good market integration and the availability of off-farm job opportunities could allow for more efficient shock absorption in the occurrence of EWE, therefore reducing the pressure on forests (Zaveri et al., 2020). Nevertheless, Zaveri et al. (2020) noticed that in the aftermath of a drought, the likelihood of crop expansion actually increased, even when controlling for access to markets (proxied by travel time to cities). Similarly, Desbureaux and Damania (2018) found that in the aftermath of a drought, land clearing was three times higher in areas close to where communities were installed. Those outcomes may be explained by the higher availability of credit and insurance when closer to decision centres (Araujo et al., 2014), which in part may reduce the perceived risk represented by EWE.

**Prices & income:** Prices of agricultural and forestry products are considered to be some of the most direct influences on agents' land management choices (Araujo et al., 2014). High profitability of certain agricultural products may foster the expansions of cultivated frontiers (Araujo et al., 2014; Ferretti-Gallon and Busch, 2017). For this reason, Ferretti-Gallon and Busch (2017) suggest the implementation of deforestation models applying agricultural prices rather than closeness to cleared land. It is evident that land management and labour allocation choices should be compared to the profitability of agricultural products as well as to the income derived from off-farms jobs. As expected, Araujo et al. (2014) finds that higher off-farm wages are related to slower deforestation rates. This relationship is however influenced by farm size, with smallholders being less responsive, highlighting information asymmetries that different income groups may be subject to. Interestingly, poverty was found to be negatively related to deforestation (Ferretti-Gallon and Busch, 2017).

**Policies & institutions:** In DCs, Nguyen Van and Azomahou (2007) found that improvements in institutions reduced deforestation. On the other hand, Ogundari et al. (2017) found that political liberty significantly increased land clearing in Sub-Saharan Africa. These two opposite results may indicate the need to assess more targeted political actions such as the role played by conservation or development policies as well as the level of public engagement. For example, Ferretti-Gallon and Busch (2017) and Desbureaux and Damania (2018) show that protected areas (PAs) are an effective tool to prevent land-use changes. Contrary to this, the exclusion of farmers from decision-making processes reduces their cooperation in protecting



natural resources (Rodriguez-Solorzano, 2014), eventually limiting the benefit on forest cover induced by PA. The involvement of farmers in forest maintenance, e.g. through the payment for ecosystem services, was instead proven to be negatively related to deforestation and positively related to forest regrowth (Ferretti-Gallon and Busch, 2017). Lastly, the role played by institutions and policies should not be underestimated when considering that it may influence the attraction of external investments or the development of other social phenomena which, in turn, may have unintended outcomes on forest cover (see paragraphs on external investments and conflicts).

**External investments:** Areas targeted for large-scale land acquisitions (LSLA) were identified by Davis et al. (2020b) to be predominantly located in forested regions. This makes them more susceptible to deforestation compared to analogous areas unaffected by such investments. Nevertheless, the authors highlighted that the outcomes on land-use were significantly dependent on the typology of investment and its final purpose. In general, productive and export-oriented LSLA, such as oil and tree plantations, were connected to higher deforestation compared to logging activities. Only mining activities lead to ambiguous results, depending on the location and the type of minerals extracted. However, even in the cases of LSLA which do not imply changes in land use, the exclusion of householders from the areas of informal use may force them to relocate to new land, fostering deforestation elsewhere. The effect of forced displacement may have different outcomes on deforestation (see Duval and Wolff (2009) and the paragraph on migration for further information). Lastly, it is also important to consider that unwelcome LSLA may lead to social instability and conflicts (Balestri and Maggioni, 2019) which, in turn, could have an effect on deforestation (see paragraph on conflicts).

**Conflicts:** A meta-analysis by Vesco et al. (2020) showed that extreme weather events can create a scarcity effect on renewable resources, which triggers conflicts. It follows that conflicts may be a secondary consequence of reduced coping capacities of the environment. At the same time, forest cover may also be affected by conflicts, independently of their triggers. The literature on this topic underscores several pathways through which forests may be affected by conflicts, both positively and negatively. These effects vary depending on underlying socioeconomic factors and the array of actors involved. For example, as armed conflicts generally arise in rural areas and militias tend to use forests as shelter, local populations tend to limit their incursion in these forests, thus reducing their reliance on NTFP (Clerici et al., 2020; Grima and Singh, 2019). For the same reasons, locals are forced to relocate their activities to other areas less subject to guerrilla, clearing new land (refuge effect and migration effect discussed by Clerici et al. (2020)). On the other hand, the presence of organised armed groups can imply road building, defoliation and unsustainable forest harvesting at the detriment of cover quality and extension (Butsic et al., 2015). Following conflicts, authorities typically face resource constraints in managing PAs and forests, as international aid is often redirected towards peacekeeping efforts. Consequently, this scenario tends to facilitate illegal land use and deforestation, thereby diminishing ecosystems' capacity for service provision (Clerici et al., 2020; Grima and Singh, 2019). Additionally, conflicts have different outcomes when associated with other land-use variables, such as external investments (Busch and Ferretti-Gallon, 2017; Balestri and Maggioni, 2019). An interesting case is highlighted by Butsic et al. (2015), who studied the relationship between deforestation, warfare, and land use in the Democratic Republic of Congo. The authors found that the presence of armed

**Political, institutional and economic variables**

militia was interfering with mining activities, therefore reducing deforestation connected to the mines and offsetting the impacts of conflicts alone. When considering the relationship between warfare and PA instead, Butsic et al. (2015) found that those were effective in preserving forests even in the presence of conflicts. Indeed, the prevention of illegal forest use does not guarantee the protection of forest biodiversity and the maintenance of efficient ecosystem service provision (Butsic et al., 2015). Therefore, since conflicts can be both a potential cause and consequence of deforestation, it is be useful to control for endogeneity bias and to distinguish between their typology, the actors involved as well as the duration of events (Butsic et al., 2015).

**Borders:** Despite the fact that households tend to imitate the deforestation strategies of their neighbours (Poufoun, 2016), the presence of borders may imply a discontinuity in these patterns Delacote and Leblois (2020). This may result from different policies in effect (see paragraph on policies & institutions) or different cultural habits such as language (see paragraph on ethnicity).

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<sup>a</sup>On the relationship between population growth and deforestation see also the brief review from Nguyen Van and Azomahou (2007).

As said, empirical studies linking weather shocks, adaptation strategies and land use change which try to disentangle the role played by the aforementioned variables are now on the rise. These studies, with a specific focus on dry shocks, are further discussed in Section 2.2, an introduction on pantropical deforestation, and in Section 3.2, a brief literature review on how droughts impact deforestation.

In summary, understanding deforestation as an adaptation strategy requires a holistic approach that considers the interplay and synergies of numerous factors. Only by comprehensively analyzing these interconnected variables can it be possible to draft effective solutions to address the complex challenges of environmental conservation and human well-being.

## 1.4 Contributions

In the previous paragraphs we highlighted how, although forests are a important tool in the fight against climate change, they also endure its effects. Consequently, countering deforestation poses a strategic challenge, particularly for LDCs and DCs where the livelihoods of rural populations depend both on agriculture as well as on forests. Yet, the influence of EWE on adaptation strategies involving land use changes has often been overlooked, despite the fact that these adaptation practices could themselves depend on, and affect, forest conservation.

This thesis aims to explore these links and evaluate the synergies as well as potential trade-offs between climate risks, adaptation, and land use dynamics, with a focus on forest cover extension and quality. More specifically, we want to understand the direction, intensity and timing of land-use change and deforestation as a response to droughts - also by assessing the influence of environmental, social and economic variables on use choices.

One key aspect of this research lies in its approach which encompasses multiple disciplines from economics to data science. Indeed, the entire analysis relies on georeferenced data. The use of this type of data allows for the consistent investigation of the topic of interest at different geographical scales - global, regional and local. As detailed further in each chapter, an intensive data management is part of the added value of the work presented in this manuscript.

First, in Chapter 2, we explore global responses to drought, in term of changes in cover and quality of tropical forests. This initial steps allowed me to assess general trends in terms of direction and intensity of the responses while also testing for climate and policy heterogeneity. The chapter complements analysis of recent deforestation trends, discussed by Pendrill et al. (2022); Hansen et al. (2013); Winkler et al. (2021); Vancutsem et al. (2021), and adds insights on the role played by weather extremes. In the following chapters we further dig into the potential channels leading to a response involving land use change.

In Chapter 3, we examine the relevance at national scale of shocks happening at any point of the agricultural calendar in function of major staples' seasonality. Through this refinement, and by considering only the Democratic Republic of Congo - an area where agriculture is the main source of income -, we am able to better isolate farmers' adaptation responses. In this analysis we also take into account some of the political, institutional and economic variables discussed previously (See Box 3), namely proximity to cities, conservation policies and conflicts. This piece of work has been published in Vaglietti et al. (2022b).

In the last chapter (4) we study the role played by dams (See Box 1 - Physical and environmental variables) in determining land-use change. Dams are a key piece of infrastructure in the quest for sustainability and development, but understanding how they may determine land use change patterns is a first step to assess swings in rural populations' vulnerability in their surroundings.

At global level, the results highlight a positive correlation between deforestation and droughts characterised by a gradual decrease over time (Chapter 2). Spatial and temporal heterogeneity exist: for example, in the Democratic Republic of Congo, deforestation decreases if a staples' growing season is affected by a drought; contrarily, deforestation increases if the drought affects the harvesting season. These second results highlight the need to disentangle the channels which drive adaptation choices, such as agriculture (Chapter 3). Agricultural and forested land extension were found to also be driven by infrastructure availability. In sub-Saharan Africa, dams reduced agricultural land extension and productivity but increased forest cover, highlighting their potential for conservation. Some heterogeneity exists depending on the distance from the dam and its purpose, both upstream and downstream (Chapter 4).

Overall, this thesis provides crucial insights to guide sustainable policies and natural resource management in tropical countries: by recognizing the varying impacts of weather shocks and development policies on land use and livelihoods, decision-makers can better tailor targeted interventions to address specific needs of local communities. Moreover, by leveraging the lessons from this research, policymakers can forge a more resilient and sustainable future for forested regions, thereby advancing the global agenda for climate action and biodiversity conservation.

## 2 Pantropical Deforestation and Degradation

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### Abstract

Understanding the links between extreme weather events and deforestation is key in order to assess potential synergies and trade-offs between climate-related risks, adaptation and mitigation through forest conservation. Thanks to the availability of a new gridded database on tropical forests, we investigate how droughts and forest degradation influenced global deforestation in the main tropical forest basins - Africa, Asia, South America and Oceania - between 1990 and 2020. Further we search for potential sources of heterogeneity: spatial heterogeneity through continents and climate zones, time heterogeneity through the temporal evolution of this link; intensity heterogeneity by considering diverse thresholds of droughts. In line with the literature assessing tropical forests and weather shocks, global deforestation is found to increase when droughts occurs. Yet some spatial, climate and temporal heterogeneity exists across continents. When looking at the evolution over time (1990 to 2020), a gradual reduction of the impact is observed both global and continental level: the initially positive relation between deforestation and droughts becomes negative by the end of the period. A reduction is also observed in degradation at global level, and more specifically in the African tropical forests sub-basin and in the American one. Droughts intensity also affect the deforestation-response, but does not seem to have a strong impact on the degradation-response. Finally, in areas characterized by strong forest conversion to agricultural or other anthropic uses, both deforestation and degradation are reduced in the eventuality of a droughts, suggesting a reallocation of inputs to land-saving activities. Those results are important when considering agricultural populations' vulnerability to extreme weather events, and the potential environmental feedback of this vulnerability.

## 2.1 Introduction

Halting deforestation is a compelling step to maintain global warming below 1.5°C, to conserve biodiversity, to prevent the emerging of infectious diseases, as well as to support both environmental and economic recovery (FAO, 2022a,b). Its importance is stressed also by the 15<sup>th</sup> sustainable development goal (Life on Land) which promotes the implementation of sustainable management strategies for all types of forests in order to restore terrestrial ecosystem functionality.

Nevertheless, in a changing climate, halting this process and restoring forest health may be demanding challenges. In fact, changes in  $CO_2$  concentrations, in temperatures and in precipitations patterns are likely to alter the standing biome or affect forest extension, thus vanishing conservation efforts. Among others, damage factors include extended fires seasons and higher fires intensity due to reduced forest moisture (IUFRO, 2018), proliferation of parasitic species or pathogens, and extreme weather events (Kirilenko and Sedjo, 2007). Only in 2015 about 0.3% of the forested global surface monitored by FAO (2020), 3,828 thousand ha circa, was affected by severe weather events: of the monitored areas in Africa 1.1% of the monitored areas in Africa was affected by a severe weather event while 0.6% in South America and 0.3% in Asia.

Those extreme weather events also affect populations well-being, in particular in rural areas of developing countries. Coping strategies undertaken after severe weather events, especially droughts, are numerous. Further, they are likely to have environmental feedback, especially in terms of land-use change and deforestation: some strategies can be considered land-intensive and increase deforestation (e.g: agricultural expansion, pasture displacement); other ones are land-saving and decrease deforestation (e.g: migration, forest-related or non-agricultural activities) (Girard et al., 2021). Yet only few papers have empirically assessed the links between droughts and deforestation at various spatial levels. Focusing on Madagascar, Desbureaux and Damania (2018) show that a mild or moderate drought triggers deforestation, while severe droughts reduces it. Focusing on Ivory coast, Ruf et al. (2015) did not find a significant relationship between droughts, relocation of cocoa plantations and deforestation. In the Democratic Republic of Congo, Vaglietti et al. (2022b) show that the links between droughts and deforestation strongly depends on the time of the agricultural season. Focusing on multiple developing countries, Zaveri et al. (2020), found that dry anomalies caused around 15% of deforestation from 2000 to 2013. Staal et al. (2020) show that, in the Amazon, deforestation tends to increase by 0.13% for every millimeter of water deficit. In the case of African rainforests, Gou et al. (2022) find a negative correlation between monthly rainfall amounts and forest disturbances in 2019 and 2020. Focusing on Western and Central Africa, Leblois (2021) shows that drier rainy seasons are related to larger deforestation.

To the best of our knowledge, no global analysis of how extreme weather events affect forest cover and forest degradation has been performed so far. We aim to cover this gap in the main tropical forests basins: South America, Africa, Asia and Oceania. Thanks to the availability of a database on tropical forest degradation and cover loss (developed by Vancutsem et al. (2021)), we assess how both deforestation and degradation responds to droughts occurrence. Additionally, potential sources of heterogeneity in the deforestation and degradation-responses to droughts are investigated: spatial heterogeneity, by assessing the drought-deforestation link at continental level and for various climate regimes (through rainfall endowment); temporal heterogeneity, by assessing how this link evolves in time (over pentads); drought intensity heterogeneity; heterogeneity related to land-uses and management, public policies and biodiversity conservation by investigating drought-responses in areas characterized by high agricultural expansion, protected areas and Indigenous People's lands.

This paper is built as follows: Section 2.2 presents the status of pan-tropical forest, discussing the observed patterns of degradation and deforestation as well as the challenges imposed by climate shocks; Section 2.3 and 2.4 introduce respectively the methodology and the data in use; Lastly Section 2.5 illustrates the main results.

## 2.2 Pan-tropical deforestation, degradation and droughts occurrence

Tropical and subtropical forests, i.e., a completely closed canopy of trees in a moist environment around the equator characterized by high regular rainfall and constant frost-free temperatures (OECD, 2003), cover around 2.28 billion hectares representing the 56% of the total global forested area. Their characteristics determine a strong capability to regulate the climate and store carbon, as well as conserve biodiversity. Despite their importance, tropical and subtropical forests were affected by more than the 90% of the clearing observed in the years between 1990 and 2020, corresponding to about 12.69 million ha per year (FAO, 2020). Vancutsem et al. (2021) estimated, for the same period, that around the 17.2% of tropical moist forests has disappeared. Considering actual deforestation trends, Vieilledent et al. (2022) estimated that 48% of the world's tropical moist forests will have disappeared by the end of the 21st century.

Forest vulnerabilities to stressors differ between tropical forests sub-basins (Saatchi et al., 2021), with the fastest loss being observed in Asia followed by Africa and America (Vieilledent et al., 2022). Estimates may slightly differ in function of the definitions of forest cover and forest loss adopted, the different measurement techniques applied (Romijn et al., 2015) and thus may also vary in function of the driver and the intensity of deforestation. Agriculture, whether large or small scale, and commodity-driven land-use change are recognised as the main drivers of forest loss at global level, especially in tropical areas (Curtis et al., 2018). Considering agriculture driven deforestation, Africa was identified as the largest hot-spot in the last decade (FAO, 2020) due to shifting agriculture. Row crops and cattle were instead dominant in Central and South America, while oil plantation in Southeast Asian countries (Curtis et al., 2018). The general expansion and intensification of agriculture is also a threat for tropical biodiversity (Zabel et al., 2019), and therefore for forest quality. Those trends are potentially further exacerbated by large-scale land acquisitions dynamics which tend to be granted in areas characterized by higher forest density, albeit their impact on forests depends on the intended final use of land (Davis et al., 2020a). De Sy et al. (2019) estimated that investments and installment of infrastructures has instead a minor impact, between 1.3% to 3.3% in the decade between 1990 and 2000, although these are likely to increase ecosystem fragmentation (Nayak et al., 2020). Urbanization, according to Curtis et al. (2018), also played a peripheral role, accounting for around 1% of total observed clearing.

In this context, climate feedback and particularly extreme weather events are of crucial importance, as they are likely to influence the resilience of rural communities and their dependence on tropical forest resources (FAO, 2022a). In fact, weather shocks may impact the forest cover by influencing rural households' adaptation strategies: these strategies may be land-intensive, and therefore fostering deforestation, while others may be land-saving, and reduce deforestation (Girard et al., 2021). Further, the socio-economic context, as well as forest endowments influence the choice of adaptation strategies and the reliance of rural household on forests (Noack et al., 2019; Senganimanjje et al., 2021; Delacote, 2007). These dynamics are still overlooked, and tend to be investigated only at local level. Example of these studies in tropical forest contexts are: Vaglietti et al. (2022b) in the Democratic Republic of the Congo, Ruf et al. (2015) and Leblois (2021) in West Africa or Desbureaux and Damania (2018) in Madagascar. In fact, forest quality is an essential prerogative for the provision of effective and long lasting environmental services as well as to support a sustainable land use (FAO, 2022a), while, on the other hand, forest degradation is often considered a precursor of deforestation (Achard et al., 2007). Here again, the factors leading to forest degradation are strongly context-specific, and the links between droughts occurrence and degradation are likely to be too.

Given the relevance of healthy forests for climate regulation and households stability, it is paramount to better understand the nexus between shocks, deforestation and forest quality both at global and local level. Therefore we address this topic in two manners, by investigating: (1) both the deforestation and degradation-responses to droughts; (2) the sources of heterogeneity of those response at

various scales.

### 2.3 Methodology

To investigate the relation linking droughts to deforestation and degradation, we apply a linear model, with time and pixel fixed effect, as follows (Equation 1):

$$\text{Log}(D_{it} + 1) = \beta_0 + \beta_1 S_{it} + \gamma_i + \delta_t + u_{it} \quad (1)$$

Where  $D$  corresponds to our dependent variable, either deforestation or degradation, while  $S_{it}$  to our independent variable: a dummy indicating whether a drought occurred in a unit of observation  $i$  at year  $t$ . The terms  $\gamma_i$ ,  $\delta_t$  and  $u_{it}$  are instead the individual fixed effect, the time fixed effect and the error term.

We base our analysis on gridded georeferenced data, therefore our unit of observation is at pixel level. For each unit yearly, from 1990 to 2020, are observed: total deforestation, total degradation, and cumulative rainfalls. From cumulative rainfalls is derived the Standardized Precipitation Index, the SPI, developed by McKee et al. (1993). The index allows to compare precipitation patters between periods and times: ranging from -3 to +3, takes positive values whenever there is a positive deviation in precipitations while negative in case of precipitation shortages. Whenever the index falls below -1 the event is commonly considered as a drought. Therefore, our explanatory variable is built as a dummy that takes values 1 whenever the yearly average SPI is lower than -1 and 0 otherwise. The model is further expanded to take in account:

- Different shock thresholds by including additional dummies to assess the response of deforestation and degradation to the intensity of droughts, as in Equation 2:

$$\text{Log}(D_{it} + 1) = \beta_0 + \beta_1 \text{Slow}_{it} + \beta_2 \text{Smild}_{it} + \beta_3 \text{Saverage}_{it} + \beta_4 \text{Shigh}_{it} + \gamma_i + \delta_t + u_{it} \quad (2)$$

Where each independent variable is a dummy representing a different SPI threshold: *Slow* corresponds to a  $-0.5 \leq \text{SPI} < -1$ , *Smild* corresponds to a  $-1 \leq \text{SPI} < -1.5$ , *Saverage* corresponds to a  $-1.5 \leq \text{SPI} < -2$  and *Shigh* corresponds to a  $\text{SPI} \leq -2$ .

- Different land policies such as protected areas (PA) or indigenous peoples' territories (IPL). The relationship was estimated by interacting the explanatory variable (the drought) with a second dummy indicating the presence of a PA or IPL. The resulting model could be resumed as follows (Equation 3):

$$\text{Log}(D_{it} + 1) = \beta_0 + \beta_1 S_{it} + \beta_2 Tm_{it} + \beta_3 S_{it} * Tm_{it} + \gamma_i + \delta_t + u_{it} \quad (3)$$

Where  $Tp$  is equal to 1 if the pixel falls in a PA or in a IPL.

It is also applied to different subset of the data to take into account: temporal heterogeneity, i.e., time trends (subdivision by pentads); spatial heterogeneity, i.e., climate (subdivision by long term rainfall endowments); land use (analysis only of areas where deforestation was leading a land use change characterized by high agriculture or other anthropic uses).

## 2.4 Data

The database that has been produced has a panel-like structure, with deforestation, degradation and rainfalls yearly observations from 1990 to 2020. Those are coupled with PAs and IPL which are instead cross-sectional data.

Deforestation and degradation data are derived from the database on Tropical Moist Forests (TMF) (Vancutsem et al., 2021). The authors provide, with a resolution of 30m at the Equator, a most probable year of first disturbance occurrence (degradation and/or deforestation) between 1990 and 2020. TMF data also provides sequential pixel-level dynamics of changes in the states of tropical forest by identifying losses due to tree plantation, agriculture and other anthropic uses or interventions as well as the initial types of forest cover (bamboo, mangroves, etc.). Similarly, they also provide pixels affected by degradation, with degraded forest intended as "a closed evergreen or semi-evergreen forest that has been temporary disturbed during a period of maximum 2.5 years" due to major disturbances such as selective logging, fires, and unusual weather events (Vancutsem et al., 2021).

Annual cumulative precipitations, as well as the SPI index and the regional rainfall endowment (which is based on the precipitation quantiles), are derived by the monthly global gridded precipitation by CHIRPS (Funk et al., 2015). The gridded pixels have a dimension of 0.05deg, i.e., around 5.55km at the equator. This resolution, the lowest one, was therefore used as a unit of measure of our analysis: the data on forest cover and forest degradation were therefore aggregated to respect the same standard. SPIs were calculated empirically for each pixel, standardizing monthly precipitation series values with the long run (1981-2020) mean and standard deviation following Leblois (2021).

Location of PA and Indigenous People Lands (IPL) are withdrawn respectively from the World Database on Protected Areas (UNEP-WCMC, 2014) and the IPL (Garnett et al., 2018) which provides a shapefile of land under the control of local communities or under specific indigenous people rights. Codes are provided upon requests to the corresponding authors, while the descriptive statistics regarding the final panel database is provided as supplementary material in Appendix A.1.

## 2.5 Results

Our results are discussed over two sections. First we focus on the impacts of droughts on deforestation and what leads those impacts heterogeneity. In a second part, we will apply the same type of analysis to forest degradation.

### 2.5.1 Deforestation

To assess the impacts on deforestation we initially explore global result, before searching for continental heterogeneity, thereafter we assess heterogeneity related to local climate and time. Third we investigate whether the intensity of droughts influences the impacts. Finally, the impact of initial land use and of public policies is investigated. As shown later, a similar workflow is also applied when investigating degradation.

#### Global and continental

Considering our whole dataset, from 1990 to 2020, global tropical deforestation is shown to increase with the occurrence of droughts (Table 2 column 1). When performing the same analysis at the continental level, our results show that this positive link is homogeneous for the four sub-basin of tropical deforestation, Africa, Americas, Asia, Oceania (column 2 to 5 of Table 2); the only source of heterogeneity being the amplitude of this effects: twice as much for Oceania than for Americas. These results confirm and generalize what was found by Vaglietti et al. (2022b) and Leblois (2021)



for Sub-Saharan Africa. This positive relationship between droughts occurrence and deforestation suggest that coping strategies implemented in the following of a drought imply a switch in land use: such as relocation of livestock or agricultural land expansion (Girard et al., 2021).

Table 2: Global and regional deforestation in droughts eventuality, full sample 1990-2020

Sub-basin	<i>Dependent variable:</i>				
	(1)	(2)	(3)	(4)	(5)
	Global	Africa	Americas	Asia	Oceania
Year SPI $\leq$ -1	0.051*** (0.007)	0.032* (0.019)	0.027** (0.011)	0.040*** (0.010)	0.059** (0.027)
Time and pixel FE	Yes	Yes	Yes	Yes	Yes
Observations	27,441,293	7,585,731	12,595,238	5,854,474	769,234
R <sup>2</sup>	0.865	0.822	0.890	0.887	0.870
Adjusted R <sup>2</sup>	0.860	0.816	0.886	0.884	0.866
Residual Std. Error	1.025 (df = 26556059)	1.167 (df = 7340999)	0.893 (df = 12188909)	0.946 (df = 5665589)	0.921 (df = 744389)

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

## Local climate heterogeneity

As suggest by Leblois (2021), these results may be exacerbated by the ease in forest access whenever the environment dries up, specially in particularly humid forests. In order to take into account this potential source of spatial heterogeneity related to local climate, we divide each sub-basin of deforestation in three additional regions, according to each pixel and continental long term average annual cumulative precipitation quantiles (1990-2020): *high* rain endowment, *mid* rain endowment, and *low* rain endowment.

At the continental level, it is interesting to notice that the positive link between droughts and deforestation is almost exclusively driven by dry local climate areas for both Americas, Africa and Oceania (Table 3, third column of (a), (b) and (d)). It is the opposite in the case of Asia, where this link is exclusively driven by more humid areas (Table 3 - first column of (c)). The way droughts influence deforestation may have evolved over time. In order to investigate this potential temporal heterogeneity, we divide our sample and run the analysis by the 6 pentads between 1990 and 2021. At global level, the deforestation response to droughts tends to decrease (Figure 2): it is particularly high in the pentad between 1990 to 1994 (+7.5%, A14 column 1), but it decreases over time and even becomes negative after 2015. Indeed, in the last pentad (2015-2020), global tropical deforestation significantly decreases in the eventuality of a drought: (-0.5%, Table A14 column 6).

This tendency is also confirmed when focusing on the continental scale (Figure 2): during the first pentad tropical forest loss increases with droughts in Africa (+6.4%, Table A15 column 1), America (+6.5%, Table A16 column 1), Asia (+3.1%, Table A17 column 1) and Oceania (+15%, Table A18 column 1). Thereafter, in each of the four region is observed a decreasing intensity in the relation: in America decreases of 52 percentage points (going from +6.5% in the first pentad to +1.3% between 2010 and 2014, Table A16 column 1 and 5) and in Oceania of 100 percentage points (going from +15% in the first pentad to +1.3% in the last one, Table A18 column 1 and 6).

Table 3: Deforestation and droughts in areas divided by precipitation quantiles (high, mid, low)

(a) Africa				(b) Americas			
	<i>Dependent variable:</i>			<i>Dependent variable:</i>			
	Deforestation			Deforestation			
	(1) high	(2) mid	(3) low	(1) high	(2) mid	(3) low	
Rain							
Year SPI $\leq -1$	0.008 (0.025)	-0.029 (0.026)	0.067*** (0.020)	0.026 (0.019)	0.012 (0.011)	0.076*** (0.017)	
Time and pixel FE	Yes	Yes	Yes	Yes	Yes	Yes	
Observations	2,527,120	2,527,647	2,530,964	4,199,880	4,199,291	4,196,067	
R <sup>2</sup>	0.842	0.820	0.825	0.883	0.882	0.901	
Adjusted R <sup>2</sup>	0.837	0.814	0.819	0.879	0.878	0.897	
Residual Std. Error	1.174 (df = 2445569)	1.156 (df = 2446079)	1.047 (df = 2449289)	1.026 (df = 4064369)	0.834 (df = 4063799)	0.761 (df = 4060679)	
(c) Asia				(d) Oceania			
Year SPI $\leq -1$	0.077*** (0.015)	0.006 (0.016)	0.014 (0.010)	-0.046 (0.052)	0.130** (0.053)	0.180*** (0.027)	
Time and pixel FE	Yes	Yes	Yes	Yes	Yes	Yes	
Observations	1,951,109	1,951,543	1,951,822	256,618	256,122	256,494	
R <sup>2</sup>	0.875	0.837	0.911	0.841	0.860	0.897	
Adjusted R <sup>2</sup>	0.871	0.832	0.908	0.836	0.855	0.893	
Residual Std. Error	0.983 (df = 1888139)	1.005 (df = 1888559)	0.790 (df = 1888829)	1.021 (df = 248309)	0.948 (df = 247829)	0.738 (df = 248189)	
<i>Note:</i>				*p<0.1; **p<0.05; ***p<0.01			

More precisely the relation becomes negative in Africa after 2015 (-2%, Table A15 column 6) and Asia (-0.9% between 2005-2009 and -1.4% after 2015, Table A15 column 4 and 6). The observed decrease is consistent with the global deforestation trends reported by FAO and UNEP (2020), although not connected to weather shocks, who reported in the same time span (1990-2020) a gradual reduction in hectares cleared per year.

Those results suggest that the coping strategies implemented in the aftermaths of a drought have changed over time, from deforestation-enhancing strategies to forest-saving strategies. In his theoretical framework, while analyzing the extraction of Non-Timber Forest Products (NTFP) as safety nets against agricultural risks, Delacote (2007) shows that coping strategies may positively or negatively influence deforestation, depending on a trade-off between a *portfolio* effect and an *insurance* effect: when droughts occur, agricultural households may want to increase the share of their agricultural activities or reduce it, depending on the capacity of forests to provide livelihoods, the level of agricultural productivity and the intensity of risk. Our empirical results are consistent with a dominance of a *deforestation-driving strategies* in the early periods, progressively replaced over time by a dominance of a *forest-conservation* effect. This may be due to an increased intensity of droughts, a decrease in average agricultural productivity or an increase in forest products value.

When crossing the time trends and regional rainfall endowment (low, middle and high), the overall decreasing tendency of the deforestation response to droughts is confirmed (results are synthesized in table 4 while further details are provided in the Appendix A.2.2). Yet some heterogeneity related to rainfall endowment can be distinguished. A inversion of the response from positive to negative is observed in low rainfall areas of Africa, as well as mid rainfall areas of Asia and high rainfall areas of Americas.

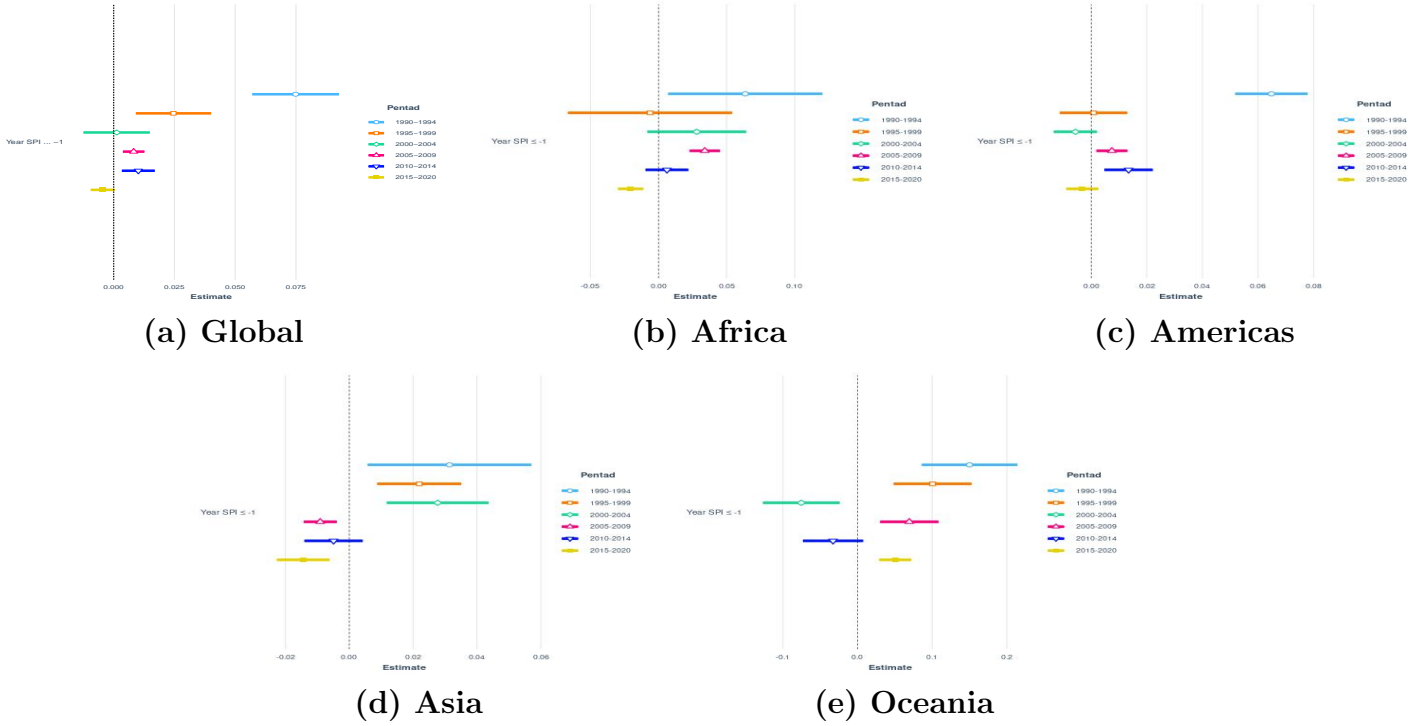


Figure 2: Deforestation trends over pentads whenever a drought occurs, i.e. the annual SPI falls below -1

Besides the decreasing trend (yet with positive response) is observed in low rainfall areas of Americas and Oceania, mid rainfall areas of Oceania and high rainfall areas of Asia. Nevertheless, we also observe increasing trends in low rainfall areas of Asia and high rainfall areas of Oceania; as well as bell curves in mid and rainfall areas of Africa (negative to positive to negative), and mid rainfall areas of Americas (positive to negative to positive).

Table 4: Time trends of the deforestation-response to droughts, across continents and rainfall endowments

<i>Continent:</i>	<i>Rainfall endowment:</i>		
	Low	Mid	High
Africa	+ to -	- to + to -	- to + to -
Americas	+ to + (decreasing)	+ to - to +	+ to -
Asia	- to +	+ to -	+ to 0
Oceania	+ to + (decreasing)	+ to + (decreasing)	0 to +

## Drought intensity

The deforestation response to drought is likely to be influenced by the droughts intensity. Indeed, a severe drought may restrain the set of coping strategies available to agricultural agents, in comparison to a more moderate droughts, with potential implications in terms of land use and deforestation. Overall, an increased drought intensity increase the positive deforestation response (Figure 3 , Table A31). This result is confirmed at the continental scale, except for Africa, where

the deforestation response to drought is quite stable (and even become slightly negative) when the intensity of drought increases. Overall this result suggest that the coping strategies that could be implemented when droughts get more severe are more forest-resource intensive, leading therefore to more deforestation.

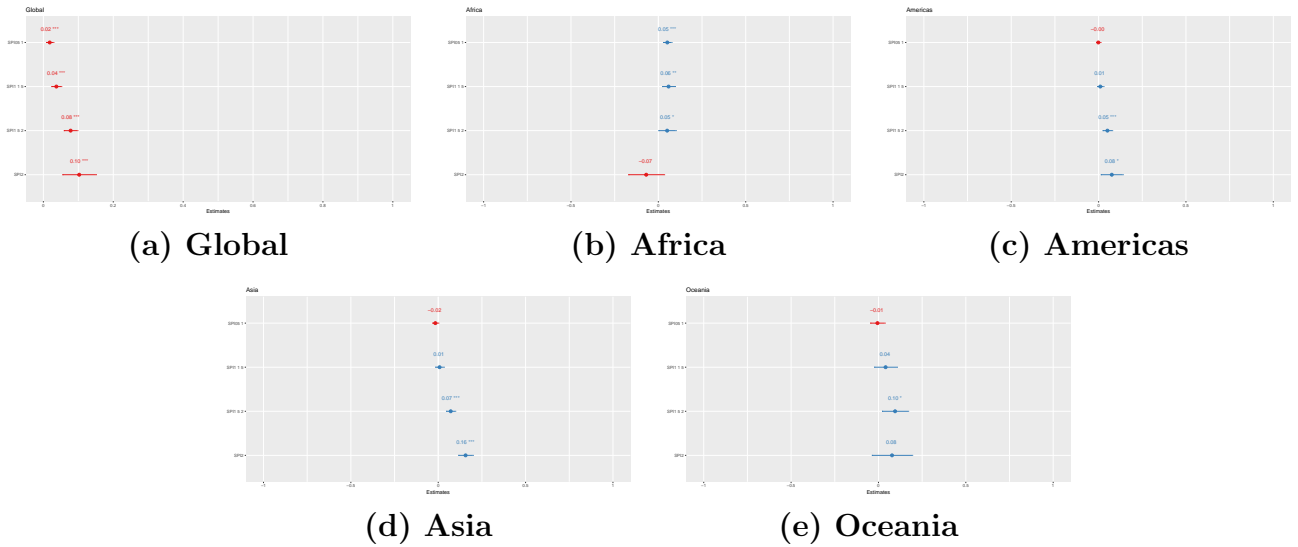


Figure 3: Deforestation with respect to drought intensity, i.e.,  $-1 < SPI \leq -0.5$ ,  $-1.5 < SPI \leq -1$ ,  $-2 < SPI \leq -1.5$  &  $SPI \leq -2$

### Agricultural land expansion and anthropic uses

The land use following deforestation, and more particularly the level of agricultural expansion and anthropic uses, can also explain heterogeneity in the deforestation-response to droughts (Table 5)). At the global level, the increase of deforestation in case of a drought is lower in areas with a high conversion to agricultural or anthropic uses<sup>3</sup>. This result is robust at the continental scale - except for the Americas - and consistent with the fact that the economic benefit of deforesting may be lower when land has already been massively converted to agriculture. One could consider that, the marginal benefit from agricultural expansion whenever agricultural lands are already dominant decreases while the marginal benefit from forest conservation increase. In this case, following Delacote (2007), the *portfolio* effect is larger and the *insurance* effect is smaller, which can explain why the interaction between land-use and droughts negatively influence deforestation. Angelsen and Wunder (2003) shown that the share of NTFP income over total household income varies in function of the coping strategies adopted, with different outcomes in terms of environmental pressure (Angelsen et al., 2014).

<sup>3</sup>In this analysis, these areas are characterized by a forest conversion to agricultural or anthropic uses higher than in the remaining 75% of the other observations in the continent (  $3^{rd}$  quartile).

Table 5: Deforestation following arid years interaction with share of agricultural conversion and anthropic uses

Sub-basin	Dependent variable:				
	(1) Global	(2) Africa	(3) Americas	(4) Asia	(5) Oceania
Year SPI $\leq$ -1	0.062*** (0.007)	0.088*** (0.028)	0.020** (0.008)	0.097*** (0.017)	0.100*** (0.031)
SPI $\leq$ -1 * Athropic uses	-0.193** (0.096)	-0.771*** (0.247)	0.126 (0.127)	-1.188*** (0.276)	-0.597*** (0.194)
Time and pixcel FE	Yes	Yes	Yes	Yes	Yes
Observations	27,441,293	7,585,731	12,595,238	5,854,474	769,234
R <sup>2</sup>	0.865	0.822	0.890	0.887	0.871
Adjusted R <sup>2</sup>	0.860	0.816	0.886	0.884	0.866
Residual Std. Error	1.025 (df = 26556058)	1.167 (df = 7340998)	0.893 (df = 12188908)	0.946 (df = 5665588)	0.921 (df = 744388)

Note:

\*p&lt;0.1; \*\*p&lt;0.05; \*\*\*p&lt;0.01

### Protected areas and indigenous people's land

As shown in Vaglietti et al. (2022b) for Democratic Republic of Congo, protected areas tend to mitigate the impacts of droughts on deforestation. At the global scale, this result is confirmed: when a drought occurs, deforestation tends to increase in protected areas (PA) but less than in non-protected areas (-1.5 percentage points, Table A34 column 1 and Figure 5 (a)), particularly for the earliest and latest pentads. At the continental scale, this mitigating effect appears particularly true for Asia (Figure 5 (b)).

When focusing on Indigenous People's Lands, the responses to droughts tend to increase forest clearing in first three pentads, while the clearing is mitigated in the latest three ones (Figure 4 (b), Table A32).

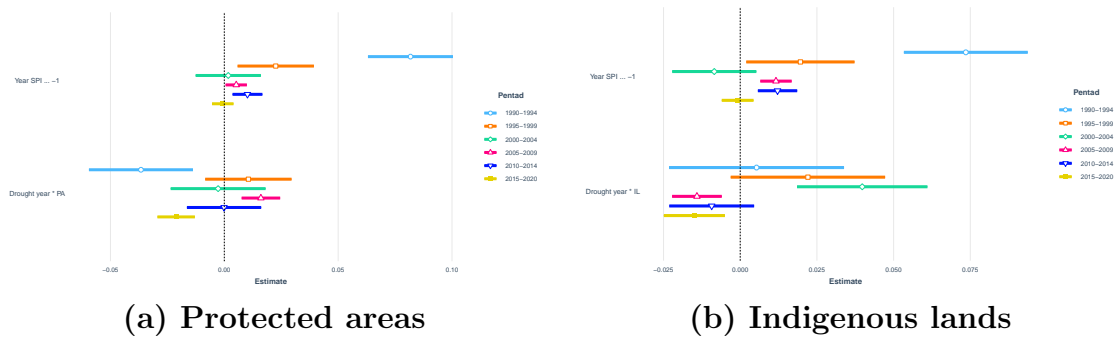


Figure 4: Deforestation trend in protected areas (a) and indigenous people's lands (b) whenever a drought occurs, i.e. the annual SPI falls below -1

This results may suggests a shift in coping strategies in those areas, from land-intensive ones to more land-saving ones, as well as a increment in the most recent period in the degree of recognition and protection of those areas. When investigating the role of IPL at sub-basin level, deforestation tend to increase in indigenous people's lands in Africa and Oceania (Table A35 and Figure 5 (c), (d)). Such result may indicate a higher dependency of local population on forests, and therefore a increase in forest clearing whenever a potential income shock is perceived). Overall a strictly negative relation between deforestation and drought is observed in the last pentad (2015-2020) in the Americas (respectively -2.2% in PA and -2.5% in IPL, Table A38 and A39), in Asia (-2.8% in

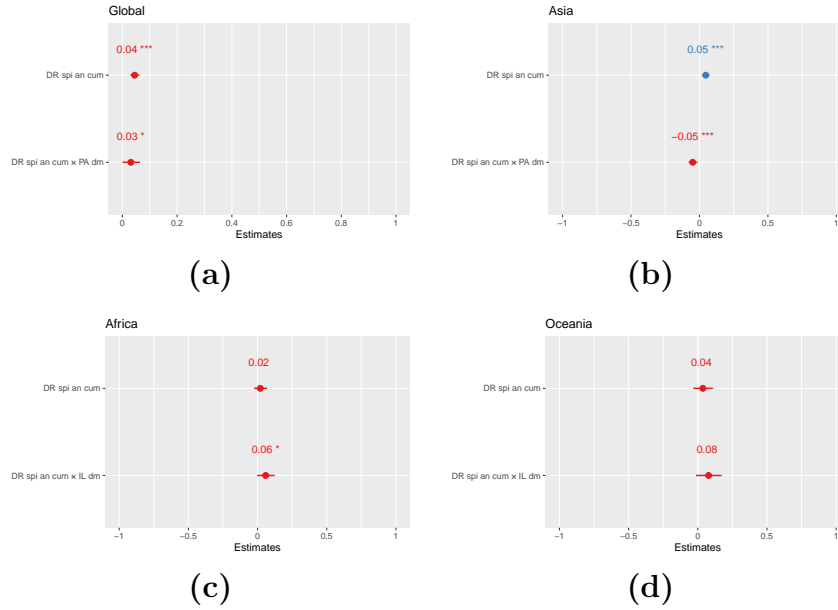


Figure 5: Deforestation trend in protected areas and indigenous people’s lands whenever a drought occurs, i.e. the annual SPI falls below -1: **(a)** Global **(b)** Asia **(c)** Africa **(d)** Oceania

PA, Table A40 ) and Oceania (-5.9% in PA and -6.5% in IPL, Table A42 and A43). These results suggest an evolution in the protection policies effectiveness and a potential change in adaptation strategies towards more environmentally sustainable ones. Nevertheless it must be highlighted that IPL definition is socio-political, and that land use and traditional value is likely to differ by location, and that many of the boundaries are contested: other areas may be relevant for Indigenous People’s but not being signaled as such in the database in use. Therefore, our results should be cautiously interpreted.

### 2.5.2 Degradation

Similarly to what seen in Section 2.5.1, coping strategies following droughts can also have an impact on forest degradation. For example, the safety-net role of Non-Timber Forest Products collection is frequently mentioned in the literature (Delacote, 2007). This activity can lead to forest degradation (and possible poverty traps) whenever excessive labor is allocated to it (Delacote, 2009). Therefore, forest degradation can have negative impacts on local populations, but can also represent a first step toward deforestation: degraded forests can be perceived as less valuable, and therefore their conversation to other land uses may look as a easier and more profitable alternative.

At global level, no impact is observed of the impact of droughts on forest degradation (Table 6 column 1). Yet, there is a significant heterogeneity between continents: forest degradation tend to increase with droughts in Africa (+3.1%, Table 6 column 2), while it tends to decrease in the Americas (-3.4%, Table 6 column 3). For what it concerns the Americas, this result is driven by areas with mid precipitation endowment (Table A44 (b), column 2).

The global insignificant result potentially hides some temporal heterogeneity, with a decreasing trend over pentads (Figure 6): indeed, a positive impacts of droughts on degradation is found in the earliest pentads, which become negative in the third latest. Here again, this result suggests a shift of adaptation strategies from forest-degrading ones to forest-conserving ones.

Table 6: Global and regional degradation in droughts eventuality, full sample 1990-2020

Sub-basin	Dependent variable:				
	Degradation				
	(1)	(2)	(3)	(4)	(5)
	Global	Africa	Americas	Asia	Oceania
Year SPI $\leq -1$	-0.005 (0.006)	0.031*** (0.012)	-0.034*** (0.008)	0.004 (0.011)	-0.004 (0.025)
Time and pixel FE	Yes	Yes	Yes	Yes	Yes
Observations	27,441,293	7,585,731	12,595,238	5,854,474	769,234
R <sup>2</sup>	0.924	0.905	0.925	0.949	0.908
Adjusted R <sup>2</sup>	0.922	0.902	0.922	0.947	0.905
Residual Std. Error	0.761	0.885	0.678	0.700	0.855
Residual Std. Error	(df = 26556059)	(df = 7340999)	(df = 12188909)	(df = 5665589)	(df = 744389)

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

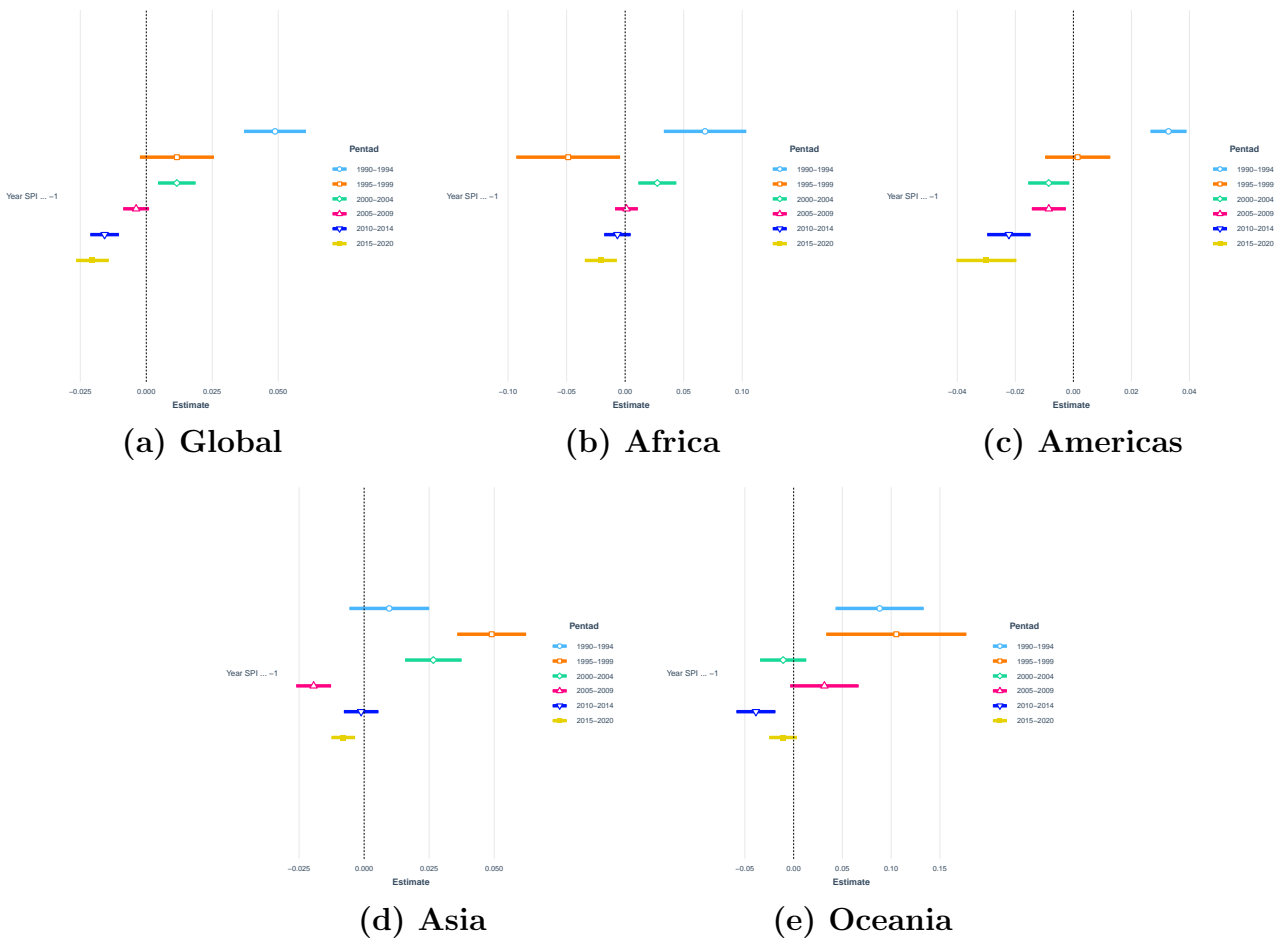


Figure 6: Degradation trend over pentades whenever a drought occurs, i.e. the annual SPI falls below -1

### Drought intensity

Droughts intensity does not seem to strongly affect the degradation-response (Figure 7). At the global level, the degradation-response seems to be slightly increasing with intensity (passing from negative to positive). This result appears to be driven by Asia, while intensity only slightly and negatively impact the degradation-response for Africa and Oceania.

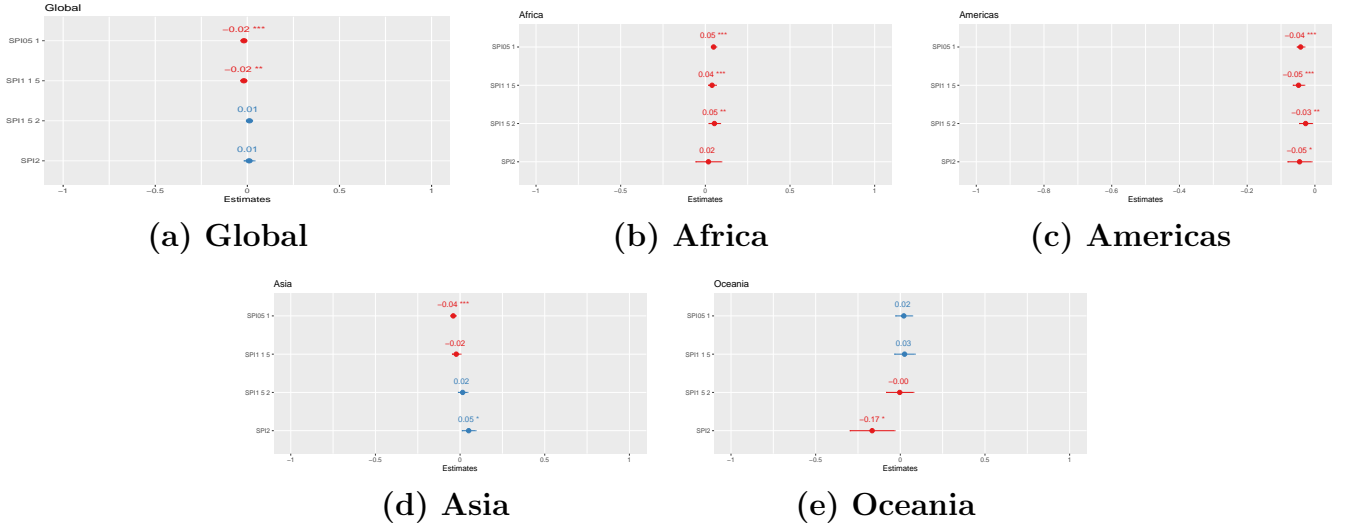


Figure 7: Degradation with respect to drought intensity, i.e.,  $-1 < SPI \leq -0.5$ ,  $-1.5 < SPI \leq -1$ ,  $-2 < SPI \leq -1.5$  &  $SPI \leq -2$

### Agricultural land expansion and anthropic uses

When looking at the interaction between droughts and land uses, one can see that the degradation-response to droughts is lower in areas where anthropic uses are predominant (-1.3% at global level, Table 7). It is particularly the case for Asia and Oceania. This result suggest that, in these areas, coping strategies may rely less on forest products harvesting, which leads to lower labor allocation to forests and smaller forest degradation.

Table 7: Degradation following arid years, interaction with land use: i.e., share of agricultural conversion and anthropic uses

	<i>Dependent variable:</i>				
	Degradation				
Sub-basin	(1) Global	(2) Africa	(3) Americas	(4) Asia	(5) Oceania
$SPI \leq -1$	0.003 (0.006)	0.017 (0.016)	-0.026*** (0.006)	0.060*** (0.014)	0.043 (0.029)
Year $SPI \leq -1$ * Anthropic use	-0.130* (0.073)	0.190 (0.146)	-0.134 (0.096)	-1.161*** (0.178)	-0.678*** (0.160)
Time and pixel FE	Yes	Yes	Yes	Yes	Yes
Observations	27,441,293	7,585,731	12,595,238	5,854,474	769,234
R <sup>2</sup>	0.924	0.905	0.925	0.949	0.908
Adjusted R <sup>2</sup>	0.922	0.902	0.922	0.947	0.905
Residual Std. Error	0.761 (df = 26556058)	0.885 (df = 7340998)	0.678 (df = 12188908)	0.700 (df = 5665588)	0.855 (df = 744388)

Note:

\* p<0.1; \*\* p<0.05; \*\*\* p<0.01



## Degradation as a precursor of deforestation

As mentioned earlier, degradation can be seen as a first step toward deforestation. Therefore it is of interest to investigate whether degradation and droughts interact to foster deforestation. Indeed, we first find that degradation does imply larger levels of deforestation, which support our initial intuition (Figure 8, Table A45). Further, the robustness of the deforestation-response to droughts is largely confirmed.

The interaction between degradation and droughts is negative, especially for the Americas (-4.7%), Asia (-4.3%) and Oceania(-3.3%); yet not for Africa, where deforestation increases in areas highly degraded and subjected to dry shocks. For Africa, the positive impact of droughts on deforestation described in Section 2.5.1 is shown to be driven by areas where forests are degraded. This result suggest that coping strategies following droughts are less land-intensive in areas where forests are already degraded in the Americas, Asia and Oceania. In contrast, they are more land-intensive in Africa.

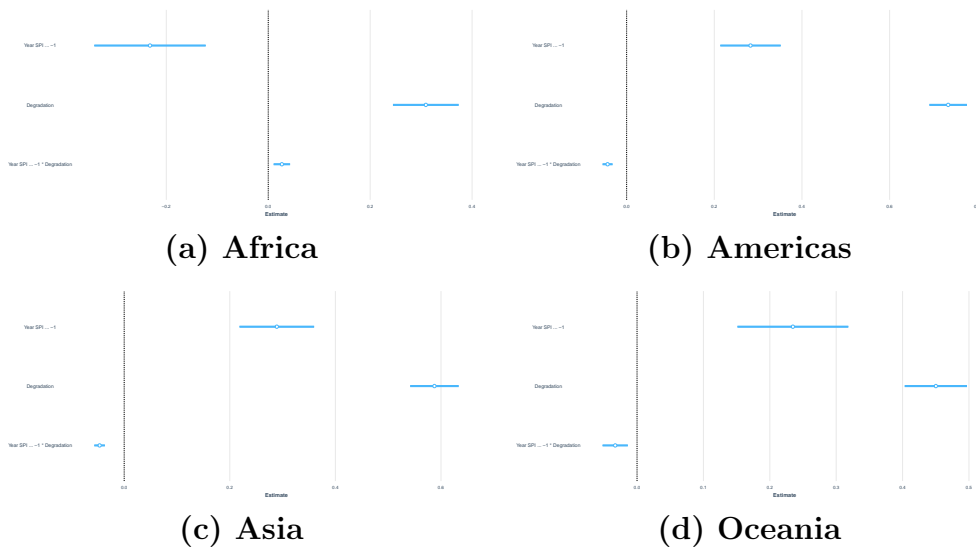


Figure 8: Deforestation and degradation with respect to drought intensity

## 2.6 Conclusions

In line with the literature assessing regional deforestation-response to weather shocks, our results confirm that deforestation increases when droughts occur therefore highlighting the global dimension of the phenomenon. Yet, we find sources of spatial, climate and temporal heterogeneity across continents. Further, investigating the forest degradation-response to droughts also brings interesting new results. Furthermore, also delving into the degradation-response to droughts has yielded intriguing new insights, especially in better delineating degradation response as a precursor to deforestation.

Our main insights are the following: First, both at global and continental level, the deforestation and degradation-response to droughts decreases over time (period 1990-2020), eventually even becoming negative in some forest basin. Second, the deforestation-response is also influenced by the droughts' intensity, while it does not appear to be the case for the degradation-response. Third, both deforestation and degradation are reduced in the eventuality of a droughts in areas with strong agricultural and other anthropic uses. Fourth, protected areas and Indigenous peoples' lands influence the deforestation and degradation responses to droughts.

In context of climate change, where extreme weather events are expected to intensify, those results shed light on the importance to have a good knowledge on the adaptation strategies undertaken in the tropics. In particular, it is essential to avoid mis-adaptation practices that enhance a vicious circle of forest losses and climate change and vulnerabilities. Indeed, the findings in this paper suggest that in many places and contexts, coping strategies implemented in the aftermaths of a drought are land-intensive and increase deforestation. This is particularly the case in the following areas and contexts: low rainfall areas of Africa, Americas and Oceania, and the high rainfall zones of Asia; when droughts are more intense in Americas, Asia and Oceania; and in places where agricultural use is smaller. Those results suggest that the factors explaining coping strategies to droughts should be carefully investigated, as well as their environmental feedback.

On a positive note, in the most recent years we observe an inversion in the droughts-deforestation response, i.e., land clearing decreases when a weather shock hits. These results may imply both a switch in strategies - underlying a change in perception on the relevance of forest -, as well as that ongoing conservation policies, such as the installment of protected areas widely discussed in this article, are able to offset the shock. Being a large scale analysis, this study misses to disentangle local responses and infra-annual variability. Additionally, with the exception of land use and land use policies, it misses to analyse contextual economic factors (such as cities and infrastructures), which are instead discussed in the following chapters.

### 3 Droughts and deforestation: Does seasonality matter?

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#### Abstract

Extreme weather events, particularly droughts, have strong impacts on the livelihoods of populations in rural areas. In a context of low access to insurance and credit markets, households respond to such shocks by implementing different risk-management strategies, which in turn are likely to have an impact on the environment, in particular through land-use changes and deforestation. This paper contributes to the emerging literature on the links between droughts and deforestation: (1) distinguishing responses to previously experienced droughts versus current droughts, and (2) disentangling the time of the agricultural season at which droughts occur. We show that deforestation declines whenever a drought occurs during the growing season, while it increases whenever a drought occurs during the harvesting season. These impacts are mitigated within protected areas and are exacerbated in more accessible locations, i.e., areas within 4 hours of travel time of main/major cities. By contrast, deforestation outcomes following droughts that occur during the planting season depend on whether the crop considered is maize or cassava.

#### Acknowledgement

This piece of work has been published in Vaglietti et al. (2022b).

### 3.1 Introduction

In a context of climate change, shocks linked to meteorological hazards threaten a large number of actors, particularly in countries relying on subsistence rainfed agriculture. In these areas, which are characterized by poor access to credit and insurance markets, a large number of risk-management strategies may be implemented by rural households. Some of these strategies are likely to be related to forest cover change, as they may engender agricultural expansion, forest loss and degradation or, conversely, abandonment of agricultural lands. Such outcomes emphasize the potentially decisive role of meteorological hazards on land use changes.

The literature has recently begun to address the link between droughts and forest loss. Our contribution is two-fold. First, risk-management strategies to face extreme weather events may be implemented either *ex-ante* or *ex-post*. Agricultural households adopt *ex-ante* adaptation strategies based upon their experience of past droughts in an attempt to anticipate future ones. On the other hand, these same households may implement coping strategies when a drought actually occurs (*ex-post*), as a short-term response to the shock. Our first contribution is to deepen the analysis of household risk-management strategies by comparing how the experience of past and current droughts affect forest loss. Despite only the shock-response strategies having an impact on land-use change are addressed here, the more general terms adaptation and coping are used instead of risk-management. It allows to highlight the differences in the time-response of the strategies: adaptation is used for response induced by past shocks while coping is used for responses induced by current shocks.

Second, the literature addressing deforestation usually deals with annual droughts without looking at the timing of shocks across the agricultural season. However, the timing of rainfall is particularly important. In this article, the effects of experienced and current droughts are broken down according to seasonality, i.e., the time of the agricultural cycle at which a drought occurs.

Our second contribution is to distinguish the impact of droughts on deforestation by analyzing whether they occur during the planting, growing or harvesting season, in a very similar fashion than in Noack et al. (2019) who address the impact of drought on income. Therefore, our results can be considered complementary to the ones obtained by Noack et al. (2019) and can be interpreted as the environmental impact of changes in sources of income following a drought. We focus on the Democratic Republic of Congo (DRC), which hosts the world's second largest tropical forest and where subsistence agriculture is the main cause of forest loss. We consider the country's two main cultivated crops, i.e., maize and cassava.

In line with other authors, we found that the occurrence of at least one drought in the previous three years induces deforestation reduction. In contrast, current droughts have different effects on same year deforestation, depending on the particular season in which they occur. For instance, the occurrence of drought during the maize planting and growing seasons induces a reduction in deforestation rates while droughts that occur during the harvesting season an increase. Additionally, we investigate how the occurrence of droughts influences the effectiveness of protected areas (PA), which tend to mitigate the impact of droughts on forest loss.

The paper proceeds as follow: Section 3.2 presents the literature on droughts and deforestation. Section 3.3 describes our case study, data and identification strategy. Section 3.5 presents our results. The last section discusses how observed adaptation practices may be related to our results and concludes.

### 3.2 Literature review: How do droughts impact deforestation?

The impact of degradation and deforestation on climate conditions is well known (Duku and Hein, 2021; Maeda et al., 2021; Leite-Filho et al., 2019; Lawrence and Vandecar, 2015), while the opposite mechanism, i.e., the influence of extreme weather events on adaptation strategies involving land-use

changes, has been overlooked. The literature explicitly linking extreme weather events, adaptation and land-use change is rather scarce and still emerging. Yet as discussed in Girard et al. (2021), adaptation practices related to weather shocks are likely to have an impact on land use.

Some theoretical work has been done to analyze how weather events (and other types of shocks) may impact deforestation. Focusing on non-timber forest products (NTFP) as a safety net against agricultural risk, two mechanisms can be identified. In the long run, Delacote (2007) shows that increased risk can lead to lower deforestation. Indeed, if agriculture becomes riskier, land holders may decrease the share of agriculture in their activity portfolio, which leads to lower agricultural expansion and deforestation. In the shorter run, Delacote (2009) shows that greater agricultural risk may lead to increased labor allocation to NTFP, which can lead to further forest degradation. In turn, forests biome quality and richness have an essential role in income stabilization, as proven by Noack et al. (2019). These papers are part of a larger literature identifying the safety-net role of common property resources first investigated by Baland and Francois (2005) and empirically assessed through an experiment in Brunette et al. (2020).

Two empirical strategies to approach such issues co-exist and involve data challenges. On the one hand, a branch of the literature (blue box in Figure 9) uses data from households surveys and connects weather shocks with adaptation strategies. Some strategies may be related to land-use changes, but the impact on deforestation may not be assessed, mainly because of a lack of proper spatialization of the data. In this literature, it is shown that the occurrence of drought may lead to: mixed-farming systems (Biazin and Sterk, 2013; Campbell et al., 2005); migration with implications both in land use of departure and destination (Reid et al., 2000; Tsegaye et al., 2010); field relocation and spatial diversification (Reenberg, 1994; Reenberg and Paarup-Laursen, 1997; Reenberg et al., 1998); and land expansion (Roncoli et al., 2001).

Rodriguez-Solorzano (2014) evaluates the effects on forest cover of the adaptation strategies of farmers based on their perception of climate variability. The author found that diversification through off-farm jobs led to forest conservation. In contrast, cattle ranching was identified as a deforestation-driving activity. Eventually migration and pooling were found not to be statistically significantly related to deforestation. The choice of the pursued strategy was eventually found to be connected to the perceived cash benefit derived from forests, as well as to the households' proximity to commercial and administrative centers: the higher the perceived benefit from NTFP, the higher the willingness of households to preserve the forest cover. Overall, the literature tends to show that adaptation practices implemented under weather shocks are diverse and quite context-dependent.

The second literature branch, which consists of only a few papers, directly deals with the deforestation feedback of weather shocks, relying on remote sensing data (red box of Figure 9). While these data allow for a fine assessment of the relationship between shocks and deforestation, they lack household data on the precise adaptation strategies implemented. Desbureaux and Damania (2018) study the relationship between droughts and deforestation in Madagascar. They found that the intensity of a drought may lead to divergent adaptation choices and, consequently, may have opposite effects on deforestation. The authors highlight that a mild or moderate drought tends to push farmers to expand agricultural land, which triggers deforestation. More severe droughts push farmers to rely less on agricultural production, which reduces deforestation.

Following a shock, the relationship between rainfall variations and deforestation may be driven by the expansion of plantations. Ruf et al. (2015) did not find a significant relationship between droughts, relocation of cocoa plantations and deforestation in Ivory Coast. Alternatively, Zaveri et al. (2020), who addressed a similar issue in multiple developing countries, found that dry anomalies caused around 9% of the rate of cropland expansion from 2000 to 2013 and 15% of the deforestation. In the same vein, Staal et al. (2020) found that for every mm of water deficit in the Amazon, deforestation tends to increase by 0.13%.

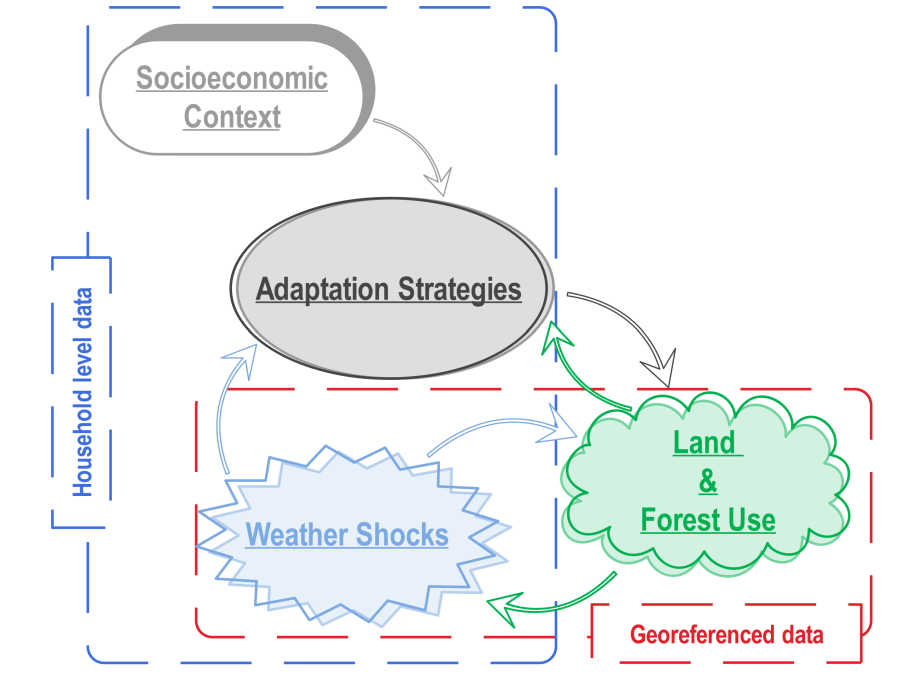


Figure 9: The two sets of empirical literature on droughts, adaptation and land-use change

In the case of African rainforest, Gou et al. (2022) showed the negative correlation between monthly rainfall amounts and forest disturbances in 2019 and 2020. Most forest disturbance activities indeed occur during the driest months of the year. Focusing on Western and Central Africa, Leblois (2021) shows that poor rainy seasons are related to greater deforestation. Moreover, agricultural land endowment and remoteness influences the magnitude of droughts impacts. When the forest cover is large, a short rainfall season leads to a 15% increase in deforestation. In remote areas, the increase in deforestation reaches 20% when the proportion of crop area is small. He and Chen (2021) found that extreme heat leads to increases in land holdings and cropland and reduces the forest area. In Ethiopia, only households without enough assets expand cropland, expansion which may substitute for migration and off-farm employment.

Our paper contributes to this second branch of the literature by investigating: 1/ how experienced and current droughts may have diverse effects on deforestation; 2/ how seasonality, that is, the time of the agricultural cycle at which droughts occur, influences the impact on deforestation; 3/ how conservation policies (here protected areas) and distance to cities influence these relationships.

### 3.3 Droughts and deforestation in the Democratic Republic of Congo

In this section, we first present some contextual issues related to the choice of this case study. Next, we briefly describe the data before presenting the identification strategy.

#### 3.3.1 Case study

Among the countries of the Congo River Basin, which include Cameroon, the Central African Republic, the Republic of Congo, Equatorial Guinea and Gabon, the Democratic Republic of Congo retains the highest share of dense forest, for a total of approximately 155.500.000 ha (World Bank, 2013; Kengoum et al., 2020). Forest accounts for about 55% to 67% of the national territory, depending on the definition of forest adopted. The typologies of forest vary throughout the country, depending on

the different agro-climatic zones that the country encompasses. The most common forest typologies are: dense rainforest, swampy forest, dry forest and forest–savannah mosaic (Kengoum et al., 2020). The presence of these various biomes is conditioned by the high diversity of climates in the country. Mean annual precipitations fluctuate around 1,500 mm per year but vary consistently by zone. For example, along the west coast annual cumulative rainfall is only 800 mm, while near the Equator it reaches 2,000 mm. The spatial variability is coupled with a strong inter-annual variability: the nethermost areas are characterized by two rainy seasons (March to May and September to December), while the southeastern area has a single rainy season (July to August) (The World Bank Group, 2021). As shown in the data section, these seasons are reflected in the agricultural seasonality cycle (Sacks et al., 2010).

### 3.3.2 Deforestation in DRC

Most studies addressing the deforestation dynamics in the DRC are generally part of a wider analysis which focuses on the entire perimeter of the Congo River basin. Among others, the report on deforestation trends by the World Bank (2013) suggests the importance of an exclusive focus on the case of the DRC: the report highlights that while deforestation trends in the tropical forests of the DRC are still lower than those observed in neighboring countries, forest degradation is increasing. This may be due to the peculiarities of the country, where sociopolitical instability has prevented the installation of a widespread agriculture and logging industry. In fact, despite being the country with the largest share of biomass and forested area, the DRC has the lowest level of logging activity in the region (World Bank, 2013). Indeed Fuller et al. (2019) assessed the impacts of China’s wood commodity imports from the Congo basin finding the trade from DRC to be negligible with respect to trade with its neighboring countries. This result highlights the fact that forest loss is driven primarily by slash-and-burn agriculture rather than by the commercial timber harvest. Similarly, Tyukavina et al. (2018) found small-scale clearing the most dominant form of deforestation: small households were accountable for more than 90% of the total DRC forest cover loss.

Unfortunately, despite the DRC’s peculiarities in terms of deforestation drivers and rates, which make the country an interesting case study, the literature addressing the DRC’s deforestation factors is rather limited. Achille et al. (2021) investigated the DRC’s dense forest clearing and degradation dynamics between 1990 and 2018. The authors showed that the total net deforestation rate was around 2.12%, while degradation was 0.12%, with a substantial acceleration after 2005. The authors identified four main deforestation drivers in particular: 1) the population’s heavy dependence on wood for fuel; 2) the practice of itinerant agriculture 3) the presence of mining quarries (also addressed by Davis et al. (2020b) and Butsic et al. (2015)); 4) poor regulatory capabilities in the enforcement of land use rights and land protection. Results are in line with Molinario et al. (2020), who investigated the period between 2000 and 2015. The drivers identified by Achille et al. (2021) are also potentially connected to the sociopolitical instability, which is recognized as having significant effects on deforestation in developing countries (Van and Azomahou, 2007). For example, Butsic et al. (2015) found that conflicts in the DRC are a significant driver of deforestation. The authors also found protected areas effective in preventing land clearing, even in the presence of conflicts.

In the DRC, deforestation and degradation are mainly driven by small-scale, subsistence and mostly rainfed agriculture. Given the significant weather variability in the country, addressing how weather shocks, adaptation strategies and forests are connected is of crucial importance, especially considering the fundamental insurance role played by forest biomes in the Congo basin (Somorin et al., 2012). As mentioned before, the studies addressing the links between deforestation and weather shocks are even more limited, and none have focused on the DRC. For example, while studying the effect of the poor rainy season in Western and Central Africa, Leblois (2021) also considers a small portion of the north-western DRC’s tropical forests. Similarly, other global studies, such as Zaveri

et al. (2020), address the issue of rainfall anomalies in developing countries but do not examine local dynamics and socio-economic factors.

### 3.3.3 Data description

To investigate the effects of droughts on deforestation, we use three main georeferenced data sets. Final data, information on how these were retrieved and processed, as well as codes for the econometric analysis are available in the data repository supporting this publication (Vaglietti et al., 2022a).

First, the Global Forest Change 2000–2020 database by Hansen et al. (2013) offers the fundamental information used to define our dependent variable:

- a. the percentage (0–100%) of tree canopy cover for the year 2000 per output grid cell, which represents the canopy closure for all vegetation greater than 5m in height. This variable was provided as a georeferenced database composed by 1 arc second gridded pixel cells (i.e., measuring approximately 30 by 30 meters at the Equator). It was then reshaped to meet the definition of the precipitation database (0.05 decimal degree, around 30km<sup>2</sup> at the Equator, set as a standard for our unit of the present analysis).
- b. a mask layer indicating the state of a cell between mapped pixels, waters or unmapped areas. The mask layer was also reshaped to obtain the total mapped ha for each cell.
- c. the year of gross forest cover loss during the period 2000–2020, built as a dummy for each cell indicating whether it was deforested and in which year. A cell is considered as deforested by Hansen et al. (2013) only when a clear forest cover cut is observed, i.e. the cell is characterized by a  $\sim 0\%$  crown cover replacement. This selection isolates forest loss attributable to human activities while excluding canopy disturbances.

Through the aggregation procedure to meet the standard resolution set for the present analysis, this variable was reshaped and transformed to obtain the percentage of each cell deforested every year. We then calculated the total forested area lost for each year in each pixel, through the combination of the data on forest cover loss and the mask layer on mapped areas (point b). The lost area, expressed in hectares, correspond to the final dependent variable applied in the analysis.

Forest cover in the year 2000 and the average yearly loss, by pixel, are represented in Figure 10.

A second essential data set is the Crop Calendar proposed by Sacks et al. (2010), which provides the georeferenced agricultural calendar for multiple crops. It allows us to divide the country into homogeneous areas of production based on the crop’s agricultural cycle and compute the duration of the planting, growing and harvesting season for each cell and crop.

Due to the importance of maize and cassava in the local diet (respectively 50% and 33% of the total daily intake) (Marivoet et al., 2018), these two crops were selected to define the cropping-homogeneous regions of the DRC. Eventually we distinguish four regions (north, center, south and extreme south), each of which is characterized by a different cropping calendar (see data paper).

The cassava planting season extends from April to August in the north, and from October to February in the center, south and extreme south regions and has a single cropping cycle per year. Maize, on the other hand, is characterized by a double cropping cycle per year, so that in the north the planting seasons are from February to March and from June to July. A notable exception is



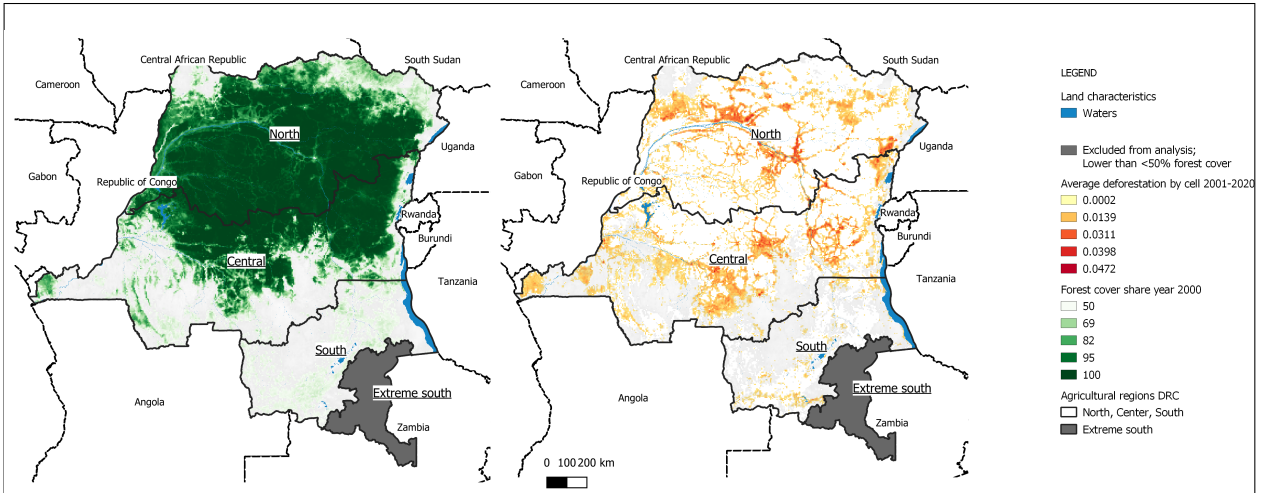


Figure 10: Forest cover in the year 2000, average deforestation 2001-2020, by cell and by agricultural region. Source: GADM (2021), Hansen et al. (2013) and Sacks et al. (2010)

the extreme south region (corresponding to the Haut-Katanga province), which is characterized by a single cropping season even for maize. For this reason, this region was excluded from the analysis.

The duration of seasons in each region was used to estimate a seasonal drought index, based on the average Standardized Precipitation Index (SPI) (McKee et al., 1993). The SPI is a standardized index of precipitation quality which informs how much a rainfall observation at a specific time deviates from its long term mean. The index assumes the value of zero whenever the observed rainfalls are around the mean, a positive value (up to +3) for positive deviations, (i.e., a surplus in rainfall) and a negative value (up to -3) when there is a deficit in rainfall. Commonly, the SPI threshold to consider a deficit as a drought is -1. The SPI was calculated on the basis of the monthly precipitation (retrieved from CHIRPS - Funk et al. (2015)). The drought intensity associated with each grid cell was thus obtained by averaging the monthly SPI for each crop season. Finally, a synthetic drought index was developed, taking value equal to 1 whenever the seasonal average SPI was falling below minus one, and 0 otherwise (dummy variable). A similar approach to seasonality was undertaken by Noack et al. (2019). In particular, the authors used the agricultural calendar to quantify the shares of households' income generated in each season and thereafter the effect of seasonal droughts on income. Nevertheless, the drought index the authors applied is computed as a continuous variable expressing water endowments anomalies associated to the income periods.

Two supplementary variables were added to investigate potential heterogeneity sources. To assess the effectiveness of public policies that addressed forest protection, we used the World Database on Protected Areas (UNEP-WCMC, 2014). The database provides georeferenced polygons delimiting any protected areas, as well as information about their status, including the year in which the protection was put in place. We then associated a fixed dummy variable to each cell to indicate whether or not the observation was included in a protected area in the year 2000. Lastly, the proximity to cities was retrieved from the Travel Time to Major Cities database (Nelson, 2008), which provides for each cell the estimated time required in the year 2000 to reach the nearest city of at least 50,000 inhabitants. Lastly, a dummy variable was created to control for proximity indicating whether a cell was closer than four hours of travelling from a city. From the processing and merging of the above-mentioned data, we obtained a disaggregated panel database that was constituted of grid cells of approximately 30km<sup>2</sup> at the Equator. Due to the peculiarity of the original Global Forest Change database, the present analysis covers the years from 2001 through 2020. We use as a benchmark the original state of the forest and the enforced protected areas in the year 2000 (pre-

analysis levels) in order to prevent our assessment from potential reverse causality. The final panel database was filtered to maintain only cells that had on average a 50% forest cover in the year 2000: the choice, which allows to retain medium to high forest cover areas, is based on similar thresholds applied by Achard et al. (2007, 2014) and Verhegghen et al. (2012). For computation matters, the panel was then further randomly sampled to maintain only 35% of the observations, corresponding to 25,958 pixels observed over 20 years (2001-2020).

### 3.3.4 Descriptive statistics

In the year 2000, the average forest cover of each observation was 86%. Our analysis focuses on forested areas: as highlighted in the data section (3.3.3), we consider a cell as forested if it had at least 50% of cover in the year 2000. Between 2001 and 2020, in each of these cells, an average of 13 hectares was lost every year (about 0.43% of their area). This result is consistent with results obtained by multiple authors. Achille et al. (2021) found a yearly deforestation rate of 0.42% between 1990 and 2018. Our indicator is slightly higher than the average deforestation rate observed by other authors which instead spans from 0.15% to 0.4% in function of the years considered (results resumed by Kengoum et al. (2020)). This gap should not surprise, as it can be explained by the increasing trend already observed by Achille et al. (2021) and suggested by the World Bank (2013) or simply by the particular definition of forests used by each author.

The average cumulative annual rainfall in the DRC reaches 1,692 mm. However, the very large variability in the descriptive statistics (Appendix B.1, Table B1) can be explained by the country's wide extension, which defines both the spatial heterogeneity in climate and the observed seasonal intra-annual variations over crop-specific agricultural calendars. For instance, the cumulative rainfall over the cassava agricultural cycle (one per year) ranges from 849 mm during the planting season to 844 mm during the harvesting season. For what concerns the maize's two annual agricultural cycles, the average cumulative rainfall during the planting seasons is 319 mm (with the first season receiving an average of 100 mm of rain more than the second). During the growing and harvesting seasons, precipitation is approximately 740 mm and 400 mm, respectively.

The observed cells, which covers the entire country with the exclusion of the Haut-Katanga province, are located at an average travel distance of nine hours and 43 minutes from the nearest main city.

## 3.4 Identification strategy

As mentioned earlier, we distinguish 1/ current and experienced droughts; and 2/ the timing of the drought, to assess how they relate to deforestation.

On the one hand, responses to current droughts are expected to have short-term effects related to coping strategies that may be implemented once the shock occurs. On the other hand, the experience of one or multiple droughts in past years is expected to induce long-term effects related to the outcomes of adaptation strategies.

Our dependent variable  $L_{it}$  is the number of hectares of forest lost in cell  $i$  at year  $t$ . The explanatory variables are dummies indicating whether or not there has been a drought during any of the cassava or maize agricultural seasons. A season is considered to be affected by a drought whenever the average monthly SPI falls below -1: in that eventuality, the explanatory variable assumes value equal to 1 and zero otherwise. An important factor is that while the cassava agricultural calendar is composed of a single cycle and only two seasons (planting and harvesting), maize is characterized by two cycles per year (planting/growing/harvesting). Thus, two planting, two growing and two harvesting seasons are observed each year.

In our analysis, both maize cycles are considered jointly. The dummies take the value 1 independently from the cycle that has been hit by drought; that is, if in year  $t$  a drought hits the cell  $i$  only in the maize planting season of the first agricultural cycle, then variable  $Droughts\_Maize\_PL1, 2_{it}$  takes the value of 1. Similarly, if both the first and second planting seasons are hit by drought, then variable  $Droughts\_Maize\_PL1, 2_{it}$  also takes the value of 1.

In order to estimate these impacts, a fixed-effect panel linear regression model is applied. Short-term effects and seasonality are investigated through the following Equation (4):

$$\begin{aligned} \text{Log}(L_{it} + 1) = & \beta_0 + \beta_1 Droughts\_Cassava\_PL_{it} + \beta_2 Droughts\_Cassava\_HA_{it} \\ & + \beta_3 Droughts\_Maize\_PL1, 2_{it} + \beta_4 Droughts\_Maize\_GR1, 2_{it} \\ & + \beta_5 Droughts\_Maize\_HA1, 2_{it} + \gamma_i + \delta_t + u_{it} \end{aligned} \quad (4)$$

The same methodology applies when studying the effects of experienced droughts on current deforestation (Equation (5)). The effect of experienced droughts, as in the aim of model (5), is considered as the effect of any drought that occurred in the 3 years prior to the observed deforestation. Again, the dummy is equal to 1 whenever at least one drought has occurred during any of the two agricultural cycles in the three previous years.

$$\begin{aligned} \text{Log}(L_{it} + 1) = & \beta_0 + \beta_1 Exp\_Droughts\_Cassava\_PL_{it} + \beta_2 Exp\_Droughts\_Cassava\_HA_{it} \\ & + \beta_3 Exp\_Droughts\_Maize\_PL1, 2_{it} + \beta_4 Exp\_Droughts\_Maize\_GR1, 2_{it} \\ & + \beta_5 Exp\_Droughts\_Maize\_HA1, 2_{it} + \gamma_i + \delta_t + u_{it} \end{aligned} \quad (5)$$

In both the models (4) and (5),  $\gamma_i$ ,  $\delta_t$ , and  $u_{it}$  represent the cell fixed effect, the time fixed effect and the error term, respectively. Standard errors are clustered at the sector level WRI (2009), corresponding circa to level 3 of the Global Administrative Area Database (which includes provinces, districts, territories and sectors) GADM (2021).

In Appendix B.3, the same models are further developed to better investigate the effect of droughts in each of the two agricultural cycle of maize. Thus, we developed an explanatory variables, again constructed as a dummy, for each of the six maize agricultural seasons observed over a year (first cycle plant, growing, harvesting and second cycle plant, growing, harvesting).

The model of Equation (4) is further developed to investigate the sources of heterogeneity. In particular, we investigate:

- a. the role of protected areas. The relationship was estimated by interacting the explanatory variable with a dummy indicating the presence of a PA. More precisely, whenever deforestation was taking place in an area that was protected in the year 2000 (corresponding to the year prior to the beginning of our analysis);
- b. the role played by the proximity to cities. The relationship was estimated by interacting the explanatory variable with a dummy indicating whether the deforested cell is at a travel distance of less than four hours from a main city (i.e., a city is considered to be of interest when registering more than 50,000 inhabitants in the year 2000);
- c. the role played by the baseline forest cover. Two approaches are undertaken: First by repeating the models presented in Equation (4) and Equation (5) but maintaining respectively only observations characterized by low forest cover (i.e., minor or equal than 75% in year 2000) or by high forest cover (i.e., higher than 75% in year 2000);

Second by interacting both the models with a dummy indicating observations with high forest cover (i.e., assuming value equal to 1 whenever the baseline forest cover is higher than 75%).

Lastly three main robustness checks are undertaken by:

- a. converting the dependent variable using an inverse hyperbolic sine transformation of the forest loss, that allows us to retain the multiple zeros present in our database (Summary statistics available in the Appendix B.1). Therefore, the dependent variable of both (4) and (5) is substituted by  $\operatorname{arcsinh}(L_{it})$  while the explanatory variables remain unchanged;
- b. reducing models presented in Equation (4) and (5) to individually study cassava and maize cycles;
- c. excluding from the panel years affected by the Second Congo War.

## 3.5 Results and discussion

### 3.5.1 Seasonality matters

The main purpose of this paper is to investigate the effects of droughts on deforestation; first, discerning between experienced and current droughts, and second, investigating the role of seasonality. Again, by seasonality, we mean a period of the agricultural cycle – either planting, growing or harvesting. Recalling that the cassava agricultural cycle is composed of only two seasons, planting and harvesting, is of utmost importance. This peculiarity is due to the reproduction methodology: as cassava is diffused by stems obtained by the plants cropped in the prior agricultural season, and not by seeds, the growing period is less observable with respect to other crops where germination time is required.

#### Experienced droughts

Experienced droughts over the entire agricultural period do not appear to influence deforestation (Appendix B.2, Table B2, column 1). Yet distinguishing the seasons allows us to sharpen the analysis. Table 8, column (1) illustrates the effects of experienced droughts, i.e., those that occurred during the three years before the observed deforestation. While previous shocks during the cassava agricultural cycle do not seem to induce any deforestation, experienced droughts hitting the maize growing or harvesting season tend to decrease deforestation in the following years. More precisely, droughts that occurred during the maize growing season reduce current deforestation by 2.6%, i.e., of 0.33 hectares less than the average 12.96 hectares lost on average in each cell; while they reduce it during the harvesting season by 1.9%. The overall consequence of experienced droughts is reduced deforestation. This result suggests that household adaptation strategies may imply a reallocation of the activity portfolio from agriculture to off-farm activities, including a higher reliance on NTFP harvesting.

These results are in line with the results from Desbureaux and Damania (2018), who found that repeated droughts in the past tend to decrease deforestation. This outcome was also predicted in a theoretical model by Delacote (2007), who suggest that a higher perceived risk in agriculture may lead households to diversify their livelihood strategy, reducing their share of agriculture but relying more on forests, which would lead to a lower deforestation rate. Nevertheless, a household's higher reliance on NTFP may imply a higher level of forest degradation (Delacote, 2009), which has not been investigated in this paper.

Interestingly, when we exclude the war years prior to 2004 to check the robustness of the previously discussed results, results concern experienced droughts that occurred anytime over the agricultural year proved to be significant, confirming that experienced droughts tend to reduce deforestation. These outcomes suggest that there is room for further research investigating the interactions between conflicts, droughts and deforestation.

### Current droughts

When we look at the occurrences of current droughts over the entire agricultural period, they have no significant influence on deforestation (Appendix B.2, Table B2, column 1), but if we distinguish these occurrences by season, they do. Column (2) of Table 8 reports the effects of current droughts affecting the deforestation rate in the same year the shocks are observed. Interestingly, deforestation rates take different directions in function of the agricultural season affected. A shock in the cassava planting or maize harvesting season increases deforestation by 5.7% and 5.9%, respectively, while droughts in the maize planting or growing season decrease forest clearing by 3.0% and 6.9%, respectively.

Focusing on cassava, experienced and current droughts do not have the same link with deforestation. This may be explained by the peculiarity of the crop itself. Cassava has a long agricultural cycle which spans the entire year. Thus, the cycle can be adjusted with respect to the households' experience of the previous years and to better match previously observed rainfall patterns. Instead, for what it concerns current droughts, a shock during the planting season may induce households in the short term to expand the agricultural area to maintain the same level of production: indeed the first three to four months are the most delicate time of the cycle, when the cassava stem needs a substantial amount of moisture to properly develop the roots (Oshunsanya and Nwosu, 2018). Otherwise cassava can be considered quite resistant to weather shocks (Okogbenin et al., 2013), which can explain our non-significant results about droughts occurring during the harvesting period.

Focusing on maize, it is more difficult to adjust the timing of the planting and harvesting seasons due to the double cropping system adopted in the DRC. Thus households, when observing a drought at the beginning of the cycle or in the most delicate period of it, the growing season, may immediately reallocate their portfolio, in order to reduce the risk of loss. These results may be compared to those obtained by Leblois (2021) in the Guineo-Congolian regions, where the author found that a drought during the rain season reduces deforestation.

The interpretation of increased deforestation during the maize harvesting period is different. Two main contemporaneous mechanisms may be suggested: first, experiencing a drought during a harvesting season may increase households' expectations of observing a drought in the following planting season. Thus, households may anticipate the shock and clear land during the harvesting period to have a wider area dedicated to agriculture in the following cycle and to thus maintain the level of output. Second, considering that the harvesting period is generally the driest of the cycle, a drought occurring in that season may significantly ease accessibility to forests, reducing the efforts required by clearing. A similar eventuality was also suggested by Leblois (2021), in analyzing the effects of a short rainy season on deforestation. The two highlighted mechanisms, working together, may explain greater forest loss when droughts occur during the maize harvesting season.

These results are complementary to the ones proposed by Noack et al. (2019). In the eventuality of droughts during the growing season, the authors observed that the share of rural income coming from forest products was increasing. This result therefore justifies our findings that deforestation decreases in the eventuality of a shock during the growing season, potentially due to a higher opportunity cost of maintaining the forest asset rather than expanding the agricultural area amid the agricultural cycle. In turn, in the eventuality of a shock during the harvesting season, Noack et al. (2019) observed

an increase in the share of income generated through agriculture while we observe an increase in deforestation. As in rural areas an increase in agricultural income may be reached mainly through the expansion of the cultivated surfaces, Noack et al. (2019) support our hypothesis that forest is lost due to agricultural land expansion.

A general takeaway from these results is that inter and intra-annual dynamics are characterized by extremely different responses which also vary depending on the crop grown in the area. In fact, drought responses clearly depend on the crops affected, notably on the type of seasonal growing periods, e.g., double cropping or single cropping. It follows that, in order to effectively protect forests, policy makers should carefully consider the relationship between the vulnerability of local farmers, weather events and deforestation.

Table 8: Deforestation in response to experienced and current droughts. Analysis of cells characterized by at least 50% forest cover in the year 2000. The observations are then sampled to maintain the 35% of their total; Graphical representation of deforestation in response to experienced and current droughts.

<i>Dependent variable:</i>		
	Log of deforested hectares + 1	
	(1) Experienced Droughts	(2) Current Droughts
<b>Cassava</b>		
Planting	-0.0186 (0.0248)	0.0569** (0.0249)
Harvesting	-0.0597 (0.0441)	-0.0636 (0.0535)
<b>Maize</b>		
Planting 1,2	0.0150 (0.0172)	-0.0304** (0.0136)
Growing 1,2	-0.0256* (0.0150)	-0.0689*** (0.0199)
Harvesting 1,2	-0.0194* (0.0115)	0.0592*** (0.0129)
Observations	519,160	519,160
F Statistic (df = 5; 493178)	37.6635***	73.8697***
<i>Note:</i> *p<0.1; **p<0.05; ***p<0.01		
Time and cell fixed effects, clustered at the sector administrative level		

### 3.5.2 Looking for sources of heterogeneity in the land-use response to weather shocks

In this section, we investigate the sources of heterogeneity influencing deforestation, as a response to current droughts. The interactions with the first model are not presented, due to the already low significance of the effect of experienced droughts (Table 8, column 1). In particular, we analyze the influence of conservation policies, economic pressure and forest cover. Conservation policies

are represented by protected areas, while economic pressure is measured by proximity to cities, which entails lower transport costs and better outside options for households. The current drought indicators were interacted with these two variables (Table 9). The influence of the forest endowment is instead investigated in function of the observed forest cover share in year 2000 (Table 10 and Table 11).

The general seasonality effects that are found in the previous section are robust to the addition of these interactions. Overall, protected areas tend to mitigate some (positive or negative) effects of droughts on deforestation, while proximity to cities tends to exacerbate them.

### **Impact of protected areas**

The interactions between protected areas and seasonal droughts is significant in two seasons: the maize growing and harvesting seasons (Table 9, column 2). In both cases, the presence of protected areas mitigates the overall impact of droughts, whether it is positive or negative.

During the maize harvesting season, the presence of protected areas offsets the increased deforestation (-4.5%) that is generally observed during a drought in the same season but in a non-protected location (+6.4%). This result is in line with Desbureaux and Damania (2018) who found that, in Madagascar, protected areas mitigate the impact of droughts.

Conversely, the decrease in deforestation when a drought occurs during the maize growing season (-8%) is over compensated for when it takes place in protected areas (11.6%). Even if counter intuitive, this result may be explained by the peculiarities of the location of protected areas as well as by the growing season. In fact, the growing season can be considered more sensitive to droughts, in the sense that, in low input agriculture, it allows for almost no margin of adjustment. Moreover, protected forests are a warranty of high ecosystem services provision (for example NTFP collection) in areas that are generally remote and where reallocation to off-farm/forest jobs is mostly unlikely. A similar result was observed by Noack et al. (2019), who highlighted the role of biodiversity in reducing drought shocks on income. Therefore, thanks to this smoothing effect, the opportunity cost to clear forest for cultivation increases. The combination of these two factors may induce greater pressure on forest resources in drought periods, leading to a higher deforestation rate.

### **Proximity to cities**

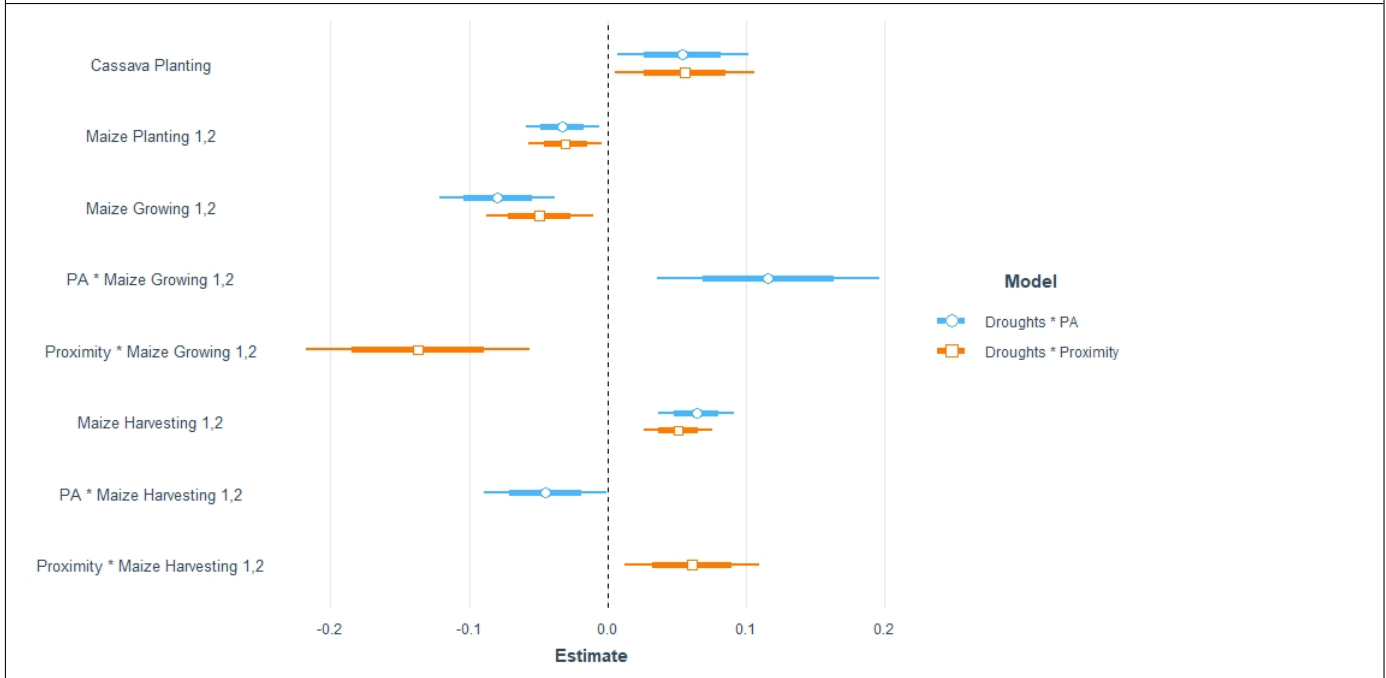
The variable proximity can be considered as a proxy of accessibility to markets, as well as to off-farm jobs. As for the presence of protected areas, we found a significant impact of the interaction between droughts and proximity to cities, in the case of the maize growing and harvesting seasons (Table 9, model 2). In both cases, proximity to cities exacerbates the (positive or negative) impact of droughts on deforestation.

During the growing season, proximity to cities tends to preserve more forests by reducing land clearing (-13.7%), while the overall effect is positive (+4, 9 %). Conversely, in the harvesting season, proximity amplifies deforestation in case of droughts (6.1%), while the general effect is negative.

This magnification of the drought effect further confirms the likelihood of the previously suggested coping strategies: during the growing season, where adjustments to maintain the same level of output are no longer possible and labor is free, better access to off-farm jobs reduces deforestation. Instead, during the harvesting season, the increment in deforestation suggests that proximity to cities may induce households to increase land exploitation in an attempt to maintain the same output level in the subsequent seasons. In this specific context, any eventual production surplus can be placed in a more efficient market with respect to the ones in remote areas. These effects are likely to add up with the deforestation trends of higher income areas, where households demand is generally oriented

Table 9: Deforestation and current droughts; Interaction with protected areas (installed before the year 2000) and proximity to main cities. The analysis considers cells characterized by least 50% forest cover in the year 2000. Total observations are then sampled to maintain only the 35% of the total; Graphical representation of interaction with protected areas and proximity to main cities.

<i>Dependent variable:</i>		
	Log of deforested hectares + 1	
	(1) Current droughts * Protected Areas	(2) Current droughts * Proximity
<b>Cassava</b>		
Planting	0.0541** (0.0241)	0.0556** (0.0259)
Harvesting	-0.0598(0.0570)	-0.0487(0.0532)
<b>Maize</b>		
Planting 1,2	-0.0325** (0.0136)	-0.0306** (0.0137)
Growing 1,2	-0.0796*** (0.0214)	-0.0492** (0.0197)
Harvesting 1,2	0.0640*** (0.0139)	0.0511*** (0.0125)
<b>Interactions:</b>	<b>Protected Areas *</b>	<b>Proximity *</b>
Protected Areas (PA)		
* Cassava Planting	0.0115(0.0762)	0.0269(0.0531)
* Cassava Harvesting	-0.0635(0.1149)	-0.1262(0.1233)
* Maize Planting 1,2	0.0230 (0.0485)	-0.0060(0.0282)
* Maize Growing 1,2	0.1161*** (0.0409)	-0.1371*** (0.0413)
* Maize Harvesting 1,2	-0.0453** (0.0226)	0.0610** (0.0247)
Observations	519,160	519,160
F Statistic (df = 10; 493173)	41.6811***	45.8807***
<i>Note:</i> *p<0.1; **p<0.05; ***p<0.01		
Time and cell fixed effect, clustered at the sector administrative level		



towards more land-intensive goods and where the demand for agricultural products increases faster than for forest ones (Alix-Garcia et al., 2013).



### 3.5.3 Forest cover

As introduced in Section 3.4, we applied two complementary approaches to estimate the influence of forest cover on droughts impacts. In line with our main analysis, both methods confirm the existence of heterogeneity depending on the time of crop and the timing of shock across the agricultural season, as well as the pixel share of forest cover.

In the first approach, the model assessing current and experienced droughts (Section 3.4 Equation 4 and 5) are applied to two subsets of our total sample, distinguished in function of the observed baseline forest cover: low ( $\leq 75\%$ ) and high ( $> 75\%$ ).

Regarding current droughts in the maize growing and harvesting season, where respectively deforestation decreases and increases, the impacts are smoothed in dense forest (Table 10, column 3 and 4). A difference of -1.02 percentage points is observed when comparing deforestation in the maize growing season in low cover areas (-7.8%) versus high cover ones (-6.7%). Similarly, a difference of -3.19 percentage points between low and high forest cover cells is observed when comparing the deforestation increases following a drought in the harvesting season (respectively +7.4% and +4.3%).

This is potentially due to the limited capacity to adjust in the short term in areas characterised by dense forests where relocation of inputs is only foreseeable in the long term. This hypothesis is confirmed by the strong reduction in deforestation observed in the experienced drought model (Table 10, column 1 and column 2). In particular, experienced droughts occurring during the cassava agricultural cycle influences more significantly deforestation in low forest cover areas while maize is more influential in high cover ones (Table 10, column 1 and 2).

Table 10: Deforestation and droughts over the main agricultural periods and cycles, differentiating between low ( $\leq 75\%$ ) and high ( $> 75\%$ ) forest cover in year 2000.

<i>Dependent variable:</i>				
Log of deforested hectares +1				
	Experienced droughts		Current droughts	
	(1) Low forest cover	(2) High forest cover	(3) Low forest cover	(4) High forest cover
<b>Cassava</b>				
Planting	-0.1245*** (0.0407)	0.0211 (0.0295)	0.0967** (0.0379)	0.0458 (0.0314)
Harvesting	-0.2240** (0.1060)	-0.0020 (0.0346)	-0.1069 (0.1673)	-0.0886** (0.0435)
<b>Maize</b>				
Planting 1,2	0.0634 (0.0391)	-0.0075 (0.0159)	-0.0403 (0.0270)	-0.0196 (0.0133)
Growing 1,2	-0.0083 (0.0234)	-0.0376** (0.0175)	-0.0780** (0.0310)	-0.0678*** (0.0232)
Harvesting 1,2	0.0158 (0.0236)	-0.0306** (0.0119)	0.0749*** (0.0222)	0.0430*** (0.0134)
Observations	141,920	377,240	141,920	377,240
F Statistic	54.2955***	41.4728***	26.6673***	41.3791***
	(df = 5; 134800)	(df = 5; 358354)	(df = 5; 134800)	(df = 5; 358354)

*Note:*

\* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$   
Time and cell fixed effects, clustered at the sector administrative level

In second instance, both the models are further interacted with a dummy variable indicating high forest cover (Table 11), in a similar fashion as done in investigating the role of protected areas or proximity to cities (discussed in the previous paragraphs).

In line with our main results, experienced droughts tend to decrease deforestation. Nevertheless, for what it concerns the entire agricultural cycle of cassava, is observed an increase in deforestation in areas characterized by high forest cover. These results may reflect the potential different importance of the two crops in function of the forest cover, potentially related to their biological characteristics, and suggesting that in dense forest cassava expansion may be a long term adaptation strategy at the detriment of maize cropping. For what concerns the interaction of forest cover with current droughts,

high forest cover tends to mitigate drought impacts in the maize harvesting season, in a manner that is similar to the one observed in protected areas. No significant impact in deforestation is observed in the maize growing season, contrarily o what is observed in protected areas which therefore would require a targeted attention of protection policies (such as PA).

Table 11: Deforestation and droughts over the main agricultural periods and cycles, interaction with high baseline forest cover. Total observations are then sampled to maintain only the 35% of the total observations.

	<i>Dependent variable:</i>	
	Log of deforested hectares +1	
	(1) Experienced droughts * High forest cover	(2) Current droughts * High forest cover
Cassava		
Planting	-0.1082** (0.0428)	0.0558(0.0362)
Harvesting	-0.2078* (0.1079)	-0.0551 (0.1710)
Maize		
Planting 1,2	0.0600 (0.0371)	-0.0572** (0.0263)
Growing 1,2	0.0040 (0.0243)	-0.0761** (0.0332)
Harvesting 1,2	-0.00001 (0.0219)	0.1023*** (0.0212)
Interactions:	High forest cover ×	High forest cover ×
× Cassava Planting	0.1300** (0.0508)	-0.0023 (0.0435)
× Cassava Harvesting	0.2078* (0.1090)	-0.0121 (0.1695)
× Maize Planting 1, 2	-0.0643* (0.0365)	0.0406 (0.0269)
× Maize Growing 1, 2	-0.0434 (0.0289)	0.0077 (0.0383)
× Maize Harvesting 1, 2	-0.0273 (0.0222)	-0.0599*** (0.0226)
Observations	519,160	519,160
F Statistic (df = 10; 493173)	45.2956***	43.4697***

*Note:* \* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$   
Time and cell fixed effects, clustered at the sector administrative level

### 3.5.4 Robustness checks

We provide three main robustness checks of the previous models (displayed in Appendix B.3). In the first check, the dependent variable is transformed using an inverse hyperbolic sine transformation. Results, displayed in Table B3 (Appendix B.3) are not significantly different than those obtained applying the model of Equation (4). Secondly, the cassava and maize cycles are individually studied. Again, intensity, direction and significance did not remarkably vary from the main models discussed in the results section (Appendix B.3, Table B4 and Table B5 ). Lastly, the DRC has been shaken by a long period of instability. The Second Congo War took place between 1998 and 2003. It affected the role of the State, compromising its functioning (Butsic et al., 2015; Sanchez de la Sierra, 2020), as well as households' behaviors concerning land use and forest access. For this reason, the Equation (4) is estimated excluding the years of war. Again the significant variables maintain the same intensity and direction as in the previously discussed models (Appendix B.3, Table B6).

## 3.6 Conclusion

In a context of climate change, extreme weather events and droughts put many rural populations at risk in the developing world, especially in areas where agriculture is rainfed. Many adaptation strategies can be implemented and depend on socio-economic contexts. Such practices are likely to have environmental impact, especially on land-use change and deforestation.

This paper, which focuses on the Democratic Republic of Congo, contributes to the scarce literature linking land-use changes to droughts. First, we underline the differences between experienced (past) and current droughts with respect to their impact on deforestation: while experienced droughts impact deforestation in several seasons, current droughts influence it in different directions depending on when they occur. The main intuition behind these results is that an experienced drought can be understood as an indicator of future drought expectations by land holders, influencing long-term adaptation. In contrast, current droughts are the variable that land holders consider for implementing their short-term coping strategies.

Second, in the literature addressing deforestation dynamics, droughts impacts are aggregated over the whole agricultural cycle, if not over the entire year. Our results show that seasonality, i.e., the time of the cycle at which the drought takes place, matters. We distinguish between the planting, growing and harvesting seasons of the DRC's two main cultivated crops: casava and maize. The effect of droughts varies with respect to the crop affected and the structure of its agricultural cycle (single or double cropping). Multiple deforestation outcomes are possible: in the case of maize, a drought in the planting or growing season decreases deforestation, while it tends to increase it in the harvesting season.

Third, some sources of heterogeneity of these impacts are investigated: namely the impact of proximity to cities, of protected areas and of forest cover observed in year 2000, before the beginning of the analysis. Protected areas have been proven to offset the (positive or negative) impact of droughts on deforestation, in two distinct seasons of the maize cycle: in the growing season, the impact of droughts on deforestation is less negative within PAs than outside; in the harvesting season, it is less positive. In contrast, proximity to cities amplifies the effect of a drought on deforestation: in the growing season, droughts reduce deforestation more near cities than further away from them; in the harvesting season, droughts increase deforestation more. Nevertheless, impacts may vary in function of the local forest cover and relative importance of cassava and maize.

In light of these results, it appears that policymakers should take into account the interactions between droughts and coping strategies to be able to prevent undesired deforestation outcomes and simultaneously ensure better livelihood resilience to local populations. These considerations imply a need for even more importance given the increasing interest of the international community in preserving tropical forests, and in particular the Congo Basin. Part of the COP26 incentives were devoted to supporting sound governance and the development of an economic model that aims to support agriculture or energy investments with a reduced impact on forests.

The remote sensing data used in this analysis is highly informative, both on the state of forests and on the intensity of weather events. Yet the local population's perception of and reactions to shocks are not explicitly considered. In particular, adaptation and coping strategies, including input reallocation, are not directly observed. Our results open questions and challenges for further research in order to link droughts, farmers' responses to shocks and forest use.

## 4 Dams construction: forest cover, land use change and productivity

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### Abstract

The literature concerning land use change resulting from dam construction is notably limited, often concentrating on isolated or regional case studies at specific junctures in time.

Similarly, impact analysis aimed at assessing the feasibility of new projects rarely estimate their long-term impacts on land use change when it is driven by indirect factors. Given these limitations, it is therefore difficult to generalise results for land use dynamics during planning, construction and operation phases. This paper investigates the effects of water flow changes due to dam construction on land use in Sub-Saharan Africa, focusing on agricultural and forested areas. We also test for changes in agricultural productivity and economic activities to assess how dams may affect rural households' resilience to climate shocks. To run the analysis, we updated the existent databases on dams for the entire Sub-Saharan Africa, which were partly incomplete, and developed an ad-hoc hydrological model. It was therefore possible to run a sub-continental analysis and generalise the magnitude of the impacts.

Agricultural land is most adversely affected, being replaced by water and forest in the upstream watershed, and by urbanisation and forest in the downstream one. These effects tend to be stronger and more persistent as the distance from the dam increases: the loss in productive area in the immediate surrounding of a dam suggests that dams may not benefit local areas directly but rather those located further away, raising questions about the effectiveness of compensation measures. We also observe a stronger impact on land-use change in the first 5 years following the dams' construction, suggesting that the effectiveness of dams in the area under analysis may decrease over time, potentially due to the embedded characteristics of these infrastructures. Contrary to what is commonly found in the literature, we do not observe an increase in agricultural productivity (NPP). However, our results suggest a relocation of activities away from agriculture, as evidenced by an increase in nightlights.

These findings will serve as a valuable support for policymakers in evaluating the impact of future projects, as well as in providing more efficient compensations to local communities and planning environmental restoration.

## 4.1 Introduction

There is a generalised consensus on electrification being a necessary condition to support sustainable development while also tackling the deforestation challenge in sub-Saharan Africa (SSA). In fact, access to electricity allows to reduce the pressure that local populations put on forest resources (Bakehe and Hassan, 2022; Tanner and Johnston, 2017; Ly et al., 2023; Ly, 2023). However, this economic growth might entail some fragility, contingent on the energy sources it relies on: among the others, hydropower infrastructures, while crucial for securing future national energy needs, may interfere with local natural ecosystem dynamics as well as with activities on which populations rely. (Égré et al., 2007).

Hydropower supports 16% of Africa’s actual energy needs (IEA, 2022). To meet future expected demand and improve energy access, the total installed capacity should reach, by 2030, between 55 to 84 GW (IRENA, 2021). Existent and planned infrastructures will be mainly located in sub-Saharan Africa (IEA, 2022), a region highly affected by forest loss and degradation (Vancutsem et al., 2021). Despite the existence of Environmental Impact Assessment plans and Hydropower Sustainability Standards, on the basis of which operators and developers evaluate their projects (AfDB, 2023), numerous authors are denouncing a lack of long term monitoring of socio-ecological transformation following dams commissioning (Rufin et al., 2019; Kirchherr et al., 2016; Égré et al., 2007). Given the unbalanced distribution of the costs and benefits of these infrastructures (Athayde et al., 2019; Égré et al., 2007) - where economic benefits are mainly provided at the national level (Égré et al., 2007), but costs (either direct or indirect) are mostly borne at the local level - these authors also underline the need for a better definition of direct and indirect effects (Athayde et al., 2019) to further improve existing standards.

As highlighted by Rufin et al. (2019), studies on the influence of dams on Land Use and Land Cover Changes (LULCC) dynamics are currently limited to case studies (single dams or complexes). Therefore, they miss to provide a clear regional or global understanding of the temporal and geographical extension of impacts. Given the expected boom in hydropower infrastructures all over SSA (IEA, 2022; IRENA, 2021), it is now of paramount importance to fill this gap as a first step to improve future impact analysis, support sustainable development and mitigate the social costs for populations relying on affected areas<sup>4</sup>. The urgency is underscored by the presence of a feedback loop connecting land use alterations, climate risks, and dams efficiency (IEA, 2020; Woldemichael et al., 2012; Cole et al., 2014).

The purpose of this paper is threefold: first, to review the existing literature on the impacts of dams, particularly focusing on their effects on land use and forest loss. The review encompasses both the direct and indirect consequences of dams, as well as the mechanisms through which these impacts occur. To achieve this, the paper draws upon frameworks established by previous studies, such as the environmental impact schemes developed by Rufin et al. (2019) and the social impact frameworks proposed by Kirchherr et al. (2016). Second, the paper tests how water flow changes due to dam commissioning influence land use, in particular the dynamics between forest cover and other productive uses (either urban or agriculture). These are assessed over time and space both in the upstream and downstream areas of the infrastructure thanks to the development of ad-hoc hydrological models. The analysis includes 37 dams built between 1993 and 2023 in SSA, thanks to the updating of previously existing databases on dam construction. The need of running a continental investigation including both time and distance is highlighted by the meta-analysis of the literature on dams from Rufin et al. (2019); Kirchherr et al. (2016).

Lastly, building on the literature stream opened by Duflo and Pande (2007); Strobl and Strobl (2011), we also test for changes in agricultural productivity and economic activities to understand

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<sup>4</sup>Compensation schemes discussed by Égré et al. (2007)

the drivers of LUC and assess how dams may increase or decrease resilience to climate shocks for rural households.

## 4.2 Dams construction: implications for LUC

Dams' impact on the environment and LULCC could be based on the "matrix framework" developed by Kirchherr et al. (2016) for the social impact of dams, which distinguishes between direct and indirect impact, as well as on the list of impacts identified by Rufin et al. (2019) in their meta-analysis. Direct and indirect effects are also likely to differ according to the timing of the dams' development: pre-construction, construction, commissioning and operation.

Direct impacts mainly encompass the unavoidable effects that occur following impoundment and infrastructure construction: the main effect being land loss due to flooding. Those preliminary operations are likely to primarily affect forest and cultivated surfaces upstream (Rufin et al., 2019). Conversely, downstream, construction is anticipated to redirect the natural flow of the river.

Indirect impacts on land use are instead secondary unintended effects of direct social or environmental direct impacts. Infrastructures tend to influence local climate (Degu et al., 2011; Wol-demichael et al., 2012) and habitat connectivity, not only of the rivers (Anderson et al., 2018), but also of the surrounding forests and landscape (Alamgir et al., 2020), enhancing long term changes during operation times. Downstream communities are likely to be affected by resources distribution (e.g., from changes in river discharge patterns, fish availability, land habitat degradation) leading to new complexities where environmental impacts trigger social ones (Wang, 2012). These socio-environmental impacts are further aggravated by the need to displace and relocate communities directly affected by land requisition for the infrastructure installment. The number of displaced people frequently being underestimated, environmental assessments provided at the dam planning phase are also likely to underestimate the land and compensation needs for individuals. This can result in a failure to provide adequate compensation, affecting the ability to restore the living conditions to their previous state in the new area (Chen, 2009; Fearnside, 2016; World Commission on Dams, 2000). In affected areas, the increased cost of production and living after relocation leads to adverse environmental disequilibrium both upstream and downstream, inducing significant land use change (Chen, 2009). These dynamics are further exacerbated by shifts in economic and cultural values. As the economic value of the remaining agricultural lands potentially rises (Dufflo and Pande, 2007), those displaced, with restricted access and control of productive resources, may find it challenging to maintain their previous livelihoods level without adequate support systems (World Commission on Dams, 2000) in an environment that is different from the one previously known. Authors such as Winemiller et al. (2016) are however skeptical that rural communities affected by big infrastructures will ever obtain benefits from energy supply and job creation exceeding the costs bared due to lost fisheries, agriculture, and property. Furthermore, the detachment from their cultural roots and unfamiliarity with the new environment (World Commission on Dams, 2000) may contribute to the adoption of land use practices that are less suitable to the local conditions.

Studies trying to assess the magnitude of these impacts are scarce and mainly focused on the Amazons. These investigate mainly hydrology, nutrients and biodiversity changes (Timpe and Kaplan, 2017) and are a first base to understand how local populations will continue to rely on certain environmental services and respond to them. Fewer are the studies that assess the magnitude of these indirect impacts on land use or forest loss and degradation.

Chen et al. (2015); Velastegui-Montoya et al. (2020) found that dams construction induced a significant forest loss in the buffer around the dam from 5 to 80 Km. Forest loss and disturbances evolved, mainly upstream up to 25 years after construction.

Table 12: Schematizing direct impacts on LUCC, socio-environmental impacts and the following indirect impacts on LUCC. Watershed - Up: upstream; Dw: downstream. Timeline - T1: planning; T2: construction; T3: operation.

Social and Environmental Impacts	Direct Impacts on LULCC	Indirect Impacts on LULCC
Land appropriation (Up; T1, 2)	Flooding (Up; T2)	Relocation of agricultural activities,) forest loss (Up, Dw; T1,2)
Alteration of river flow (Up, Dw; T1, 2)	-	Changes in agriculture practices due to altered water availability (Dw; T2, 3)
Displacement of local communities (Up towards Dw; T1, 2 )	Change in land values (Up, Dw; T1, 2,3)	Changes in agricultural and farming practices, urbanization. Following soil erosion and sedimentation affecting adjacent areas
	Restoration and compensation practices, e.g., PA institution or afforestation programs (Up, Dw; T2, T3)	

Relocation of grazing areas was instead found to have a more contained detrimental effect in terms of loss and degradation (30km) but with impacts extending over a longer period of time (30 years) (Guerrero et al., 2020).

On the other hand, forest cover quantity and quality could affect dams' efficiency. In fact, high deforestation rates or degradation may lead to high sedimentation of debris (Hedin et al., 1988) while forest cover may have a protective role in the surrounding of dams (Makino and Rudolf-Miklau, 2021). Despite this, and despite the paramount role of PA in the fight against climate change, especially in SSA (Duncanson et al., 2023), 20% of dams worldwide are located in Protected Areas (PA), which are already largely subject to downgrading, downsizing and degazettement (PADD) (Thieme et al., 2020). Similarly, environmental and social complexities add up whenever indigenous lands are affected (Fearnside, 2006) considering their role in granting forest conservation Sze et al. (2022); Garnett et al. (2018).

In contrast, we may expect to observe a reduction of the pressure on land in the command areas, thanks to the increase in productivity observed by the pioneering works of Dufflo and Pande (2007) and Strobl and Strobl (2011). The increase in productivity is nevertheless dependent on multiple factors, such as the degree of failures of irrigation adoption (Jones et al., 2022) due to: poor accessibility of other complementary inputs that are required in a more intensive agriculture (Jones et al., 2022), the existence of informal uses (De Fraiture et al., 2014), unauthorised cuts in favour of privileged sections of the population (Ashraf et al., 2007) or poor water policies (Simango et al., 2021).

Thanks to this extensive analysis at pixel level, we want to assess the magnitude and trend of land use change induced by dams construction, also with respect to the dams' purposes. This leads us to investigate whether or not changes in land use are actually driven by an intensification or extensivisation of the agricultural system and a relocation of activities following services delivered by the dams.

### 4.3 Data

We investigate the impact of 37 dams built between 1994 and 2023, which are compared to other 55 still at planning status. The dams and the related information (such as the coordinates, commissioning year, typology, dimensions, scope, reservoir, ..) are based on the FAO AQUASTAT African Dams database (FAO, 2015) which was last updated in 2015. More recent data have been retrieved manually with the support of grey literature, news, and technical materials. Dams characteristics are

presented in Appendix C.1.1. The watersheds of each of the 92 dams under analysis were identified through two complementary strategies to precisely define and distinguish the upstream versus the downstream area of influence: this step is a further improvement with respect to what has been done so far in the literature (for example by Duffo and Pande (2007) or Strobl and Strobl (2011)) because it allows to disentangle the effects in the immediate surrounding of the dams. The upstream area is identified through the development of a hydro-geological model (Whitebox R, Wu and Brown (2022)) based on a high-definition digital elevation model of the African continent (0.3s grid from Hydrosheds (Lehner et al., 2008)). The downstream area is instead based on the hydrological sub-basins provided by Hydroshed (Lehner and Grill, 2013), and where selected following the same strategy as applied by Strobl and Strobl (2011). Their extension was updated to avoid overlapping with the area of the upstream basins identified through the hydrological model: When the sub-basins provided by Hydroshed were overlapping with the upstream ones, the area of Hydroshed basin was by default assigned to the upstream basins.

Land use in each watershed is derived by ESA Copernicus available for the years 1992-2020 (Copernicus Climate Change Service, 2019): which provides gridded global coverage of land use type at 300\*300 m at the equator. The LU ESA Copernicus pixels falling inside our watersheds are therefore our units of analysis. On the basis of the centroids of these pixels, we retrieved the local Nightlights intensity (Li et al., 2020) as a proxy of economic activity and the Net Primary Productivity (Running et al., 2015; Busetto and Ranghetti, 2016) as a proxy of land productivity.

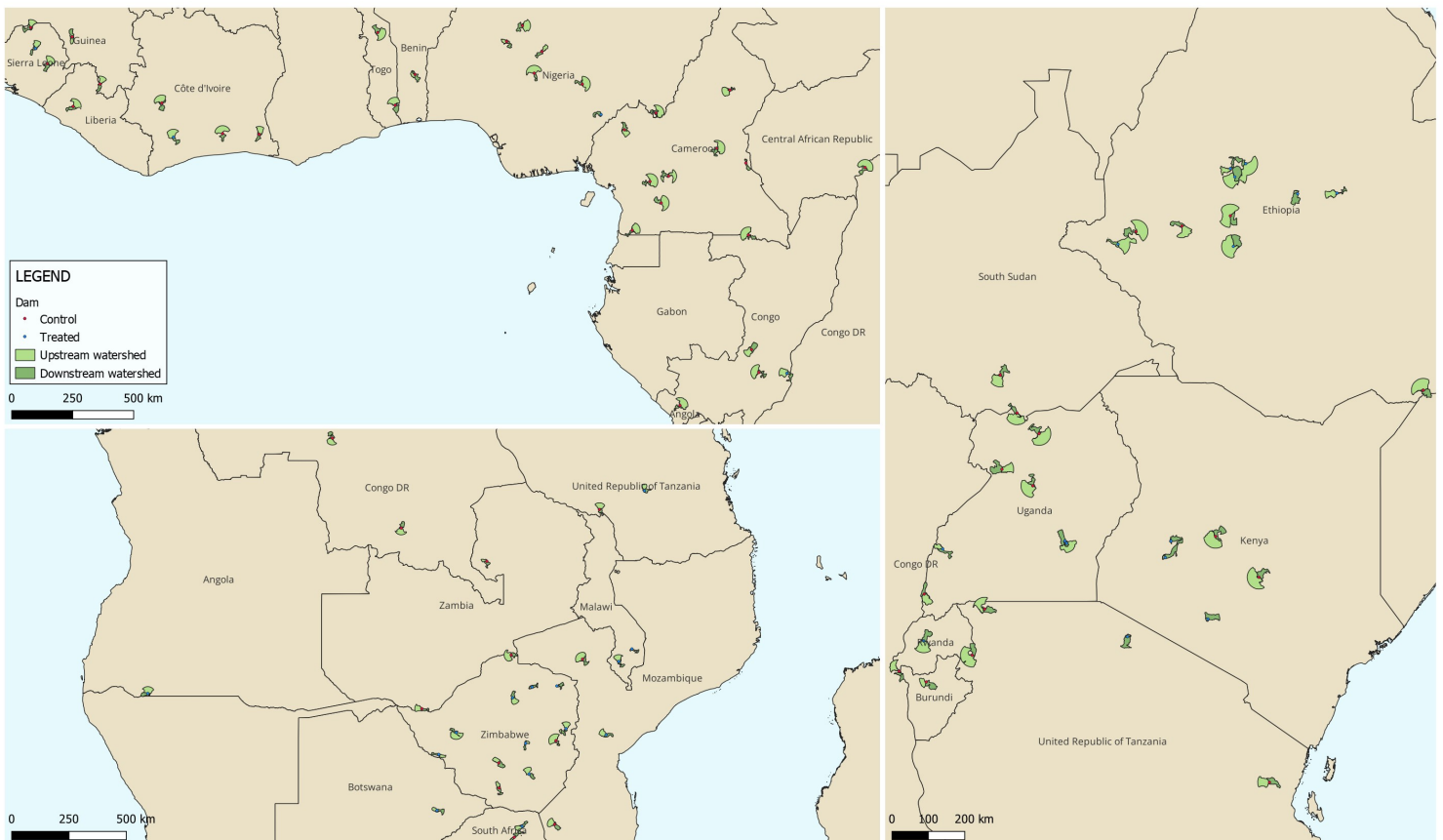


Figure 11: Dams and watershed locations - built and planned

The final database characteristics are presented in Appendix C.1.2. The time-span covered by each of the databases included in the analysis in Figure 12.



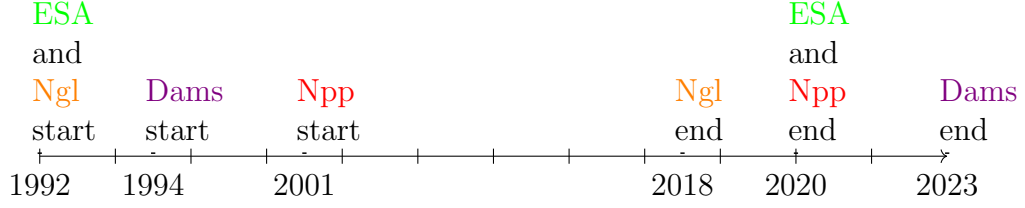


Figure 12: Databases timeline

## 4.4 Identification strategy

### 4.4.1 Event study

To estimate the causal effect of dam construction over time we apply a Staggered difference-in-difference (did) methodology, which compares over time outcomes between a treatment group and a control group, both before and after an intervention takes place "by differencing the differences" as expressed in Equation 6.

$$Y_{igt} = \mu_g + \eta_t + \sum_{k=-L}^{-1} \tau^k D_{gt}^k + \sum_{k=0}^K \tau^k D_{gt}^k + \epsilon_{igt} \quad (6)$$

Where  $Y_{igt}$  is a dummy indicating whether a pixel (unit of observation) falls in a certain land category between Agriculture, Irrigated land, Forest, Urban, Waters;  $D_{gt}$  is an indicator for whether initial-treatment group  $g$  is receiving treatment (i.e., is affected by the construction of the dam) in period  $t$  and therefore  $D_{gt}^k$  are lags/leads of treatment

where the superscript  $k$  indexes the time periods relative to the introduction of the treatment. In this equation,  $D_{gt}^k$  are dummy variables for both pre-treatment periods ( $k = -L$ , the beginning of the period under analysis, to  $-1$ ) and post-treatment periods ( $k = 0$ , the treatment time, to  $K$  the end of the period under analysis). While  $\tau$  represents the average effect of the treatment on the treated for  $k$  period: it measures the differential change in the outcome for the treated group compared to the control group in period  $k$  relative to the baseline period. Clustering is at dam level and includes pixel and time fixed effects. The methodology applied follows the ones proposed by Sun and Abraham (2021), matching results and the relative time period are discussed respectively in Appendix C.2 and C.3.

The analysis is repeated separately for the upstream and downstream area as well as for buffers of proximity to the dam: 5km, 10km, 15km, 20km, 25km and 30km.

### 4.4.2 Impact analysis

Estimate the causal effect of dam construction with respect to their purpose. Impact analysis typically involves comparing the outcomes of a treatment group that received the intervention to a counterfactual group that did not receive the intervention: in this case are compared the 342409 pixels that are not affected by dams construction to 375790 that are.

$$Y_{it} = \alpha + \beta_1 D_{it} + \lambda_i + \gamma_t + \beta_n X D_{it} + \epsilon_{it} \quad (7)$$

$$Y_{it} = \alpha + \beta_1 D_{it} + \lambda_i + \gamma_t + \beta_2 H D_{it} + \beta_3 I D_{it} + \beta_4 W D_{it} + \epsilon_{it} \quad (8)$$

where again  $Y_{it}$  is a dummy indicating whether a pixel (unit of observation) falls in a certain land category between the ones investigated;  $\beta D_{it}$  is the treatment dummy, i.e., an indicator equal

to one in pixel-years after the commissioning of the dam;  $\lambda_i$  and  $\gamma_t$  are respectively the pixel and year fixed effects;  $\beta_n X D_{it}$  is a vector of characteristics of the dams in terms of purpose (each dam can be single or multipurpose). The main purposes investigated are: hydro-power, irrigation; water supply. Lastly,  $\epsilon_{it}$  is the error term.

Again, clustering is at dam level and the analysis is repeated separately both for the upstream and for the downstream area at each buffers of proximity to the dam: 5km, 10km, 15km, 20km, 25km and 30km.

#### 4.4.3 Additional analysis

The same analysis are repeating having as a dependent variable 1) nightlights, 2) Net Primary Productivity.

The upstream and downstream sample in those cases are also split in function of their land use. I.e.: the effect in the entire sample, in areas where the land category is agriculture, forest or urban.

#### 4.4.4 Robustness checks

The impact analysis is first assessed in its simplest form, i.e., without the dams characteristics, to estimate only the effect of treatment so that it is comparable to the Average Treatment Effect on the Treated (ATT).

### 4.5 Results

#### 4.5.1 Upstream watershed

In the event study analysis, we observe that dams induce a general loss in agricultural area (Table C3, C4; Figure 13, 14). In the upstream catchment, agricultural land is reduced particularly in the buffer area within 10 km from the dam (-1.5%). The effect is the strongest in the first years from commissioning (Figure 13) to slowly stabilize later on in the years after the construction. This result is matched by an increase of water surfaces in the same distance buffer as above, respectively +1.9% and +1.6%, confirming that the reduction is due to the impoundment related to construction and the following flooding adjustments ( Table C19; Figure 27). Agricultural shrinks in that area may be justified also by further water seepage and logging as well as an increase in soil salinity which in turn tends to reduce agricultural productivity in the area (Strobl and Strobl, 2011; Dufflo and Pande, 2007; Blanc and Strobl, 2014)

Agricultural areas tend to shrink also at further distances from the infrastructure, between 20 to 30 km upstream (respectively -0.9% and -2.5%). The loss is compensated by forest extension (respectively +1.5% in the buffer between 20 to 25km upstream and +3% above up to 30km; Table C5, Figure 15). Such dynamic may suggest that the abandonment of agricultural land following the dams' construction (at least 5 years) could be imposed by more stringent water use policies necessary to guarantee the replenishment of the reservoir (Blanc and Strobl, 2014). This hypothesis is supported also by the significant drop in NPP observed in the upstream watershed from above the 5km buffer (-11% at the 10km buffer up to - 30% in the 30km buffer; Table C13, Figure 25).

The comparisons of the ATT of the event study for each land use are reported in Table 13.

Restrictions upstream are also discussed by Dufflo and Pande (2007) which highlights how those can reduce resilience to shocks upstream: the authors, in line with our results, also found a reduction of agriculture in the upstream watershed of Indian dams. The impact of the restrictions combined with the loss in resilience, may erode the profitability of agriculture and encourage land abandonment or switch to other economic activities in favour of unmanaged forest regrowth.

<b>Upstream</b>	5	10	15	20	25	30
Agriculture	<b>-0.0150***</b>	<b>-0.0158**</b>	-0.0017	0.0008	<b>-0.0097***</b>	<b>-0.0249***</b>
Forest	0.0135	0.0016	-0.0064	0.0007	<b>0.0152***</b>	<b>0.0309***</b>
Waters	<b>0.0188***</b>	<b>0.0164***</b>	<b>0.0040***</b>	0.0004	$1.51 \times 10^{-5}$	0.0002
Irrigation	$8.71 \times 10^{-5}$	-0.0002	$-7.02 \times 10^{-5}$	$2.52 \times 10^{-5}$	$1.37 \times 10^{-5}$	<b>-0.0002*</b>
Urban	-0.0003	0.0003	<b>0.0014*</b>	<b>0.0007***</b>	$7.96 \times 10^{-5}$	-0.0005
Nightlights	<b>-1.319***</b>	0.0967	0.0346	0.0083	-0.0437	-0.0323
NPP	-0.1211	<b>-0.1119**</b>	<b>-0.2736***</b>	-0.0783	<b>-0.1871**</b>	<b>-0.3034***</b>
<b>Downstream</b>	5	10	15	20	25	30
Agriculture	<b>-0.0114*</b>	<b>-0.0165**</b>	0.0040	0.0068	<b>0.0092*</b>	0.0026
Forest	<b>0.0470***</b>	<b>0.0402***</b>	<b>0.0129*</b>	<b>0.0117**</b>	0.0009	-0.0066
Waters	<b>0.0009**</b>	<b>-0.0015*</b>	-0.0008	0.0008	-0.0024	0.0005
Irrigation	-0.0027	-0.0040	-0.0013	0.0007	-0.0002	0.0001
Urban	-0.0026	<b>0.0027***</b>	<b>0.0037**</b>	<b>0.0097***</b>	$-4.72 \times 10^{-5}$	0.0018
Nightlights	<b>-0.9228***</b>	<b>0.5483***</b>	<b>0.7431***</b>	<b>0.5645**</b>	0.1748	0.0949
NPP	-0.1351	-0.0336	-0.0877	0.0048	0.1220	-0.0207

Table 13: ATT by land use an distance, upstream and downstream watershed

#### 4.5.2 Downstream watershed

Similarly, a loss of agricultural area is also observed in the downstream watershed (Figure 14). Such a reduction is compensated, above the 10 km buffer both in the upstream and downstream watershed, by an increase of urbanised area (Tables C9, C10; Figure 21,22). Thus suggesting that the relocation of local populations is likely to happen at the detriment of productive land, the most easily accessible in the short term. In fact, up to 20 km buffer from the dams, forest cover also tends to increase and stabilize in the long term (Table C6, Figure 16), potentially thanks to the benefits for the riparian vegetation provided by the stabilization of water discharge following the implementation of the new infrastructure (Azami et al., 2004) in combination to environmental compensations and reparation interventions. This effect may exacerbate inequalities and economic shocks: in fact, populations living upstream are relocated elsewhere or downstream, where the value of productive land may increase if it becomes a target for large scale land acquisitions (Tatlhego and D’Odorico, 2022), thereby reducing households’ purchasing power.

A reallocation of activities away from agriculture may be due, especially during construction, to service provision: such a relocation is inferred in the downstream area through an increase in nightlights within the same buffer zones, where urbanization is also found to be on the rise (Table C12, Figure 24).

No significant change is observed in irrigated surfaces (Tables C7, C8; Figure 19,20) except if irrigation is a specific purpose of dams and only in the command area the closest to the dam (+ 2.6% at 5km buffer): therefore suggesting that there is little adoption of informal sources of irrigation as also found by Jones et al. (2022); Simango et al. (2021) and contrasting with Tatlhego and D’Odorico (2022). On the other hand, whenever hydropower is one of the purposes of the dam, agricultural land reduces both upstream and downstream (Table C15, C16). This reduction is not matched by an increase in urban surfaces (Table C17, C18), implying that the benefits of energy provisions are relocated outside the closest hydrological basin (as also underlined by Égré et al. (2007)). These results are in contrast with what observed instead by Duffo and Pande (2007), who instead found an increase in agriculture and irrigation. Considering that hydropower dams tend to be significantly larger than the ones for other purposes, these results are instead in line with what found by Blanc and Strobl (2014) on large dams, who proved that the effect on productivity is small and mainly concentrated in the immediate proximity of the dam.

**Agriculture Upstream**

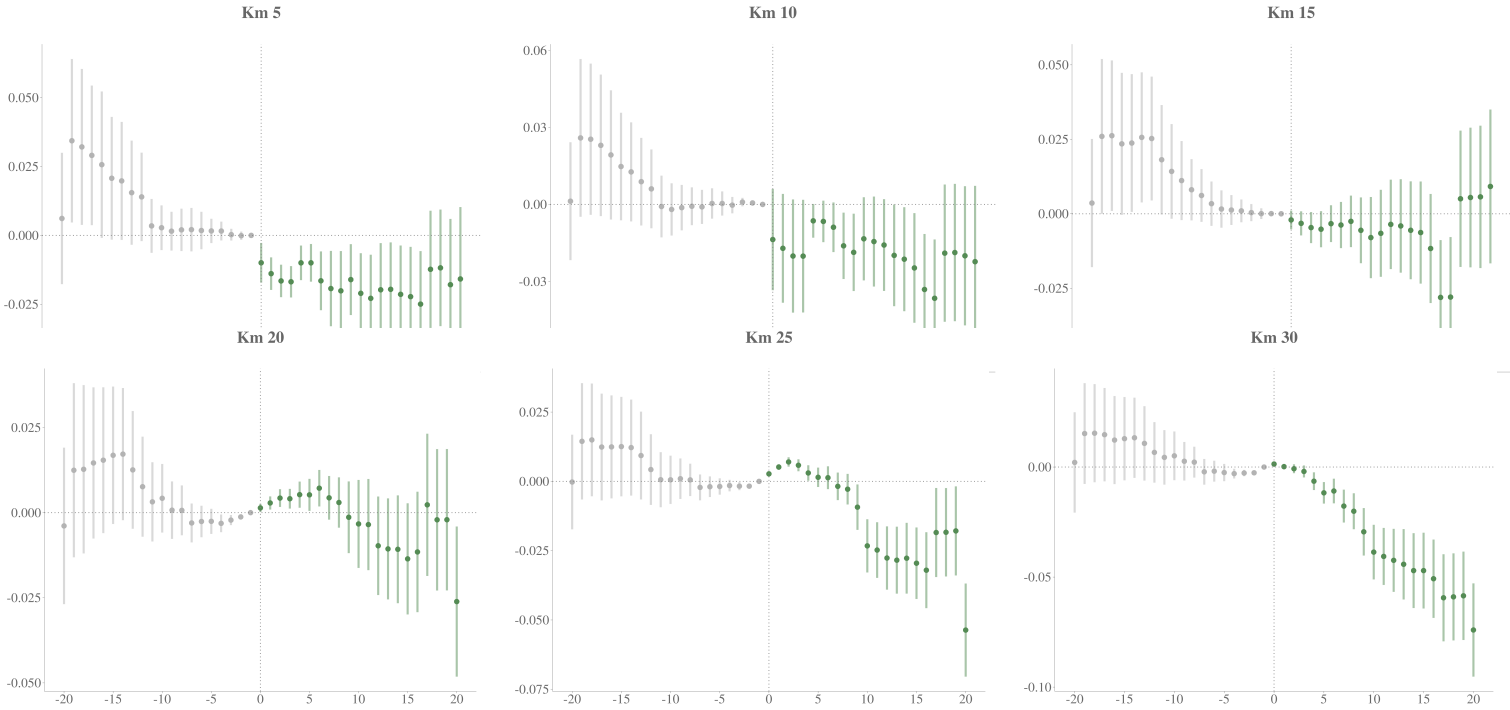


Figure 13: Event study, change in agricultural land in the upstream watershed by distance from the dam

**Agriculture Downstream**

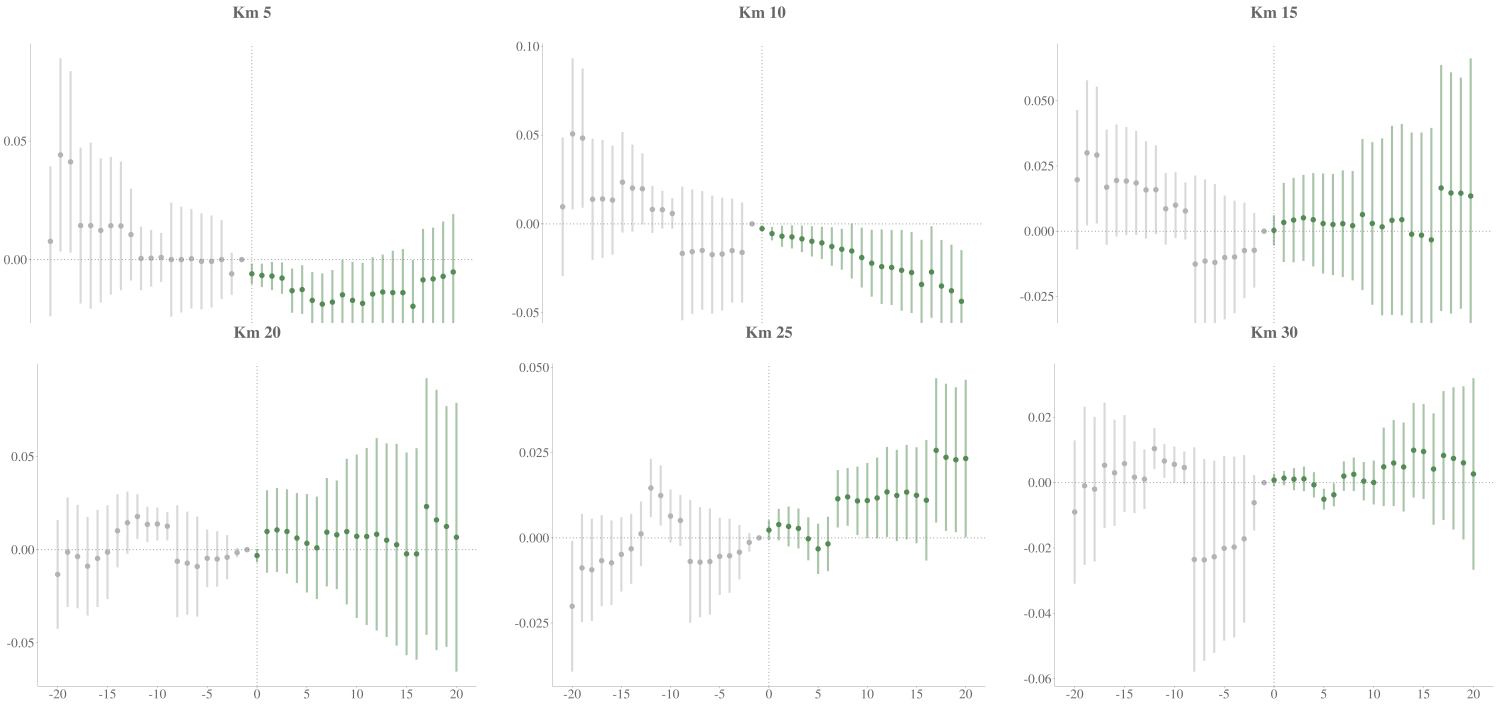


Figure 14: Event study, change in agricultural land in the downstream watershed by distance from the dam

Similarly, no significant change in productivity was perceived in the downstream area. This result

is in line with the preliminary assumptions of Strobl and Strobl (2011) who highlighted that, in the case of African floodplains, dams may negatively affect productivity in downstream areas that do not benefit directly from infrastructures nor receive, any longer, the ecosystem services provided by the upstream areas. However, our results are in contrast to the ones of Strobl and Strobl (2011); Dufflo and Pande (2007); Blanc and Strobl (2014) who instead had found an increase in productivity at least in the immediate watershed where the dam is also located. Overall, our results are affected by numerous limitations: first of all the ESA land-use database is likely to not be sensitive enough to appreciate LUC in specific areas (such as the tropical ones). Additionally, according to the user guidelines, it does not assure to detect intra-category changes and therefore our analysis may fail to capture changes between rainfed and irrigated agriculture. Therefore, these results should be interpreted carefully. For what it concerns forest we will therefore test the clearing and regrowth using other available datasets, such as Hansen et al. (2013) or Vancutsem et al. (2021) although it covers only tropical areas. Second, we do not directly investigate socioeconomic dynamics and impacts: the study would provide further insights if rural households surveys were covering the regions considered but, unfortunately, no such database is available to date.

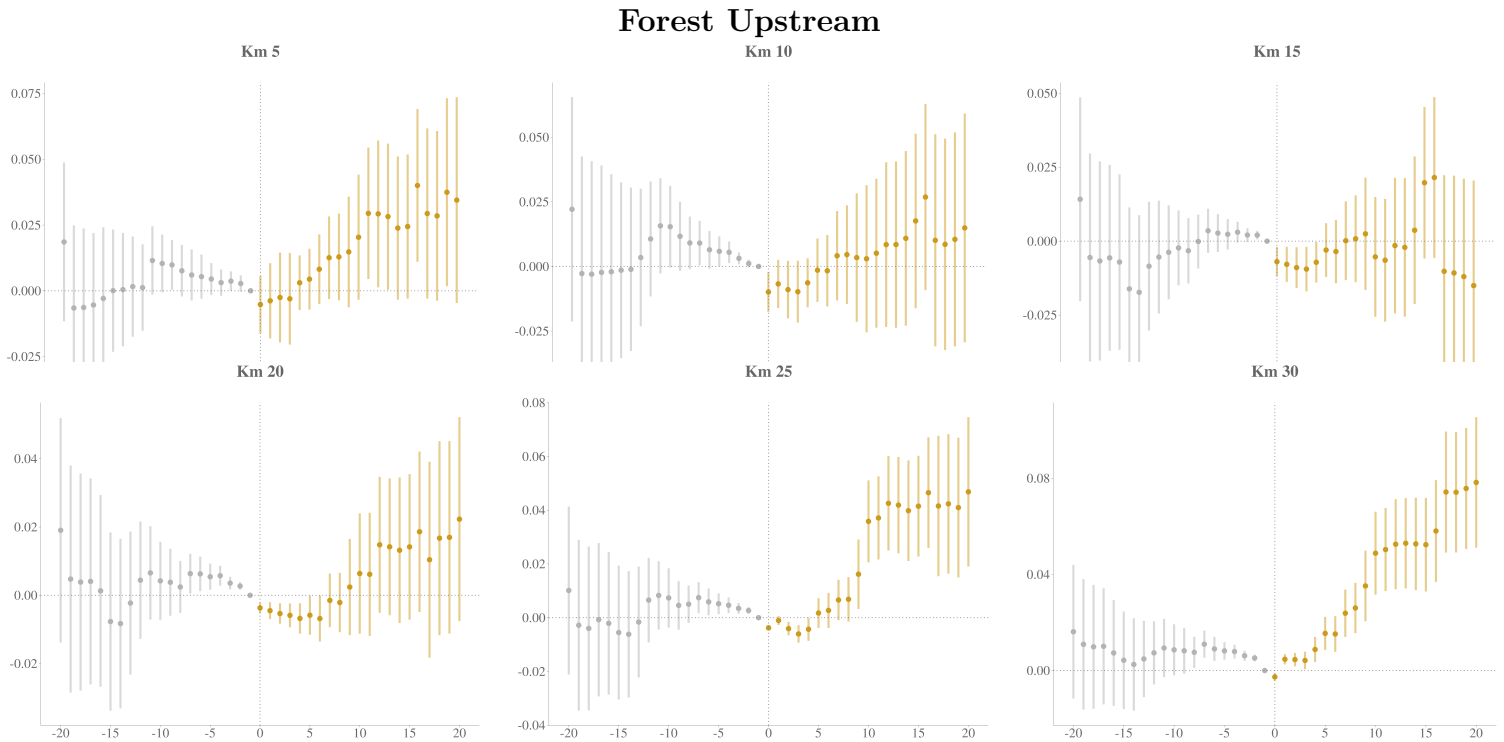


Figure 15: Event study, change in forested land in the upstream watershed by distance from the dam

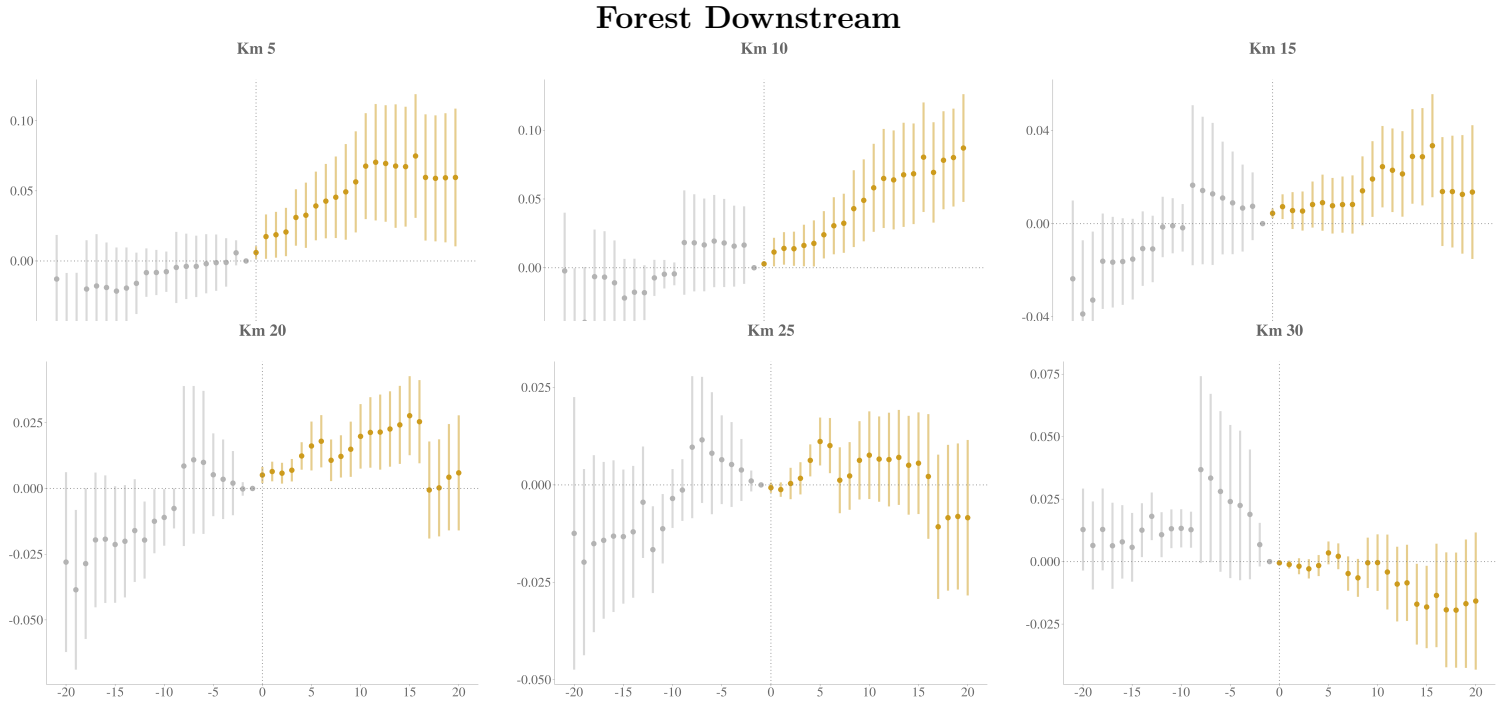


Figure 16: Event study, change in forested land in the downstream watershed by distance from the dam

## 4.6 Conclusions

This study reviews the potential feedback effect between dams construction, land cover, land use and social changes (interrelation between Rufin et al. (2019) and Kirchherr et al. (2016)).

We focus in particular on the spatial and long-term land-use and cover changes induced by dams in Sub-Saharan Africa: such a large scale analysis follows the literature stream started by Duflo and Pande (2007); Strobl and Strobl (2011) but further explores the relevance of proximity or distance from the dams both in terms of time and space. Additionally, we brought two methodological advancements. First, on the data standpoint: we built a detailed database of catchment and command of dams under analysis, which did not exist for the African context (Strobl and Strobl, 2011). This allowed us to properly distinguish upstream and downstream watersheds for each infrastructure, therefore disentangling the uncertainty of impacts in the immediate surrounding of the dams. Secondly on the econometric approach: we applied a Staggered Difference-in-Difference (Sun and Abraham, 2021), which - according to the authors' knowledge - hasn't yet been used in the literature on dams and land use change. Such a methodology allows to disclose the timings of the changes, and potential non linear dynamics. Further space for improvement concerns both the data used for both land cover and the socioeconomic impacts: additional research will be needed in the future with higher availability of georeferenced data that may fit our purposes.

Overall, contrary to what expected, we found that dams are not detrimental to forest extension if not for the forested surfaces affected by the flooding, despite the numerous records of dam installments in protected areas and Indigenous Lands. This could be a positive unintended outcome of water flow stabilization. Nevertheless, the status and healthiness of the standing forest biomes should be further analysed to verify that these are not undermined by degradation. In fact, on the other hand, agriculture did not benefit from the infrastructures and therefore local populations may have turned to non-timber forest products for livelihoods. This hypothesis is justified by the fact that we observed

a generalised shrinking in total cultivated surfaces but no signs of their intensification. Unfortunately, the data in use does not allow us to test for ecosystems' integrity and human well-being, on which dams' impacts should not be neglected (World Commission on Dams, 2000; Jones and Bull, 2020).

Nevertheless, our results can help inform the upcoming projects foreseen by the Africa Hydropower Modernisation Programme AfDB (2023), which highlights the strategic role hydropower is called to play for the future of the continent: Sub-Saharan countries will progressively need to increase their domestic power supply to support local development as well as the improvement of living standards (as of now in rural areas 74% of population has still no access to electricity). Additionally, numerous infrastructures need urgent renovation AfDB (2023). Even if maintenance, improvement in efficiency, as well as increase of already existing installed capacity should be a priority with respect to the construction of new dams, in order to avoid other irreversible shortcomings connected to the infrastructures (Garrett et al., 2021), our results and final considerations are essential for future project impact analysis: such as for drafting ad hoc compensation strategies, long term land use policies to support local populations by guaranteeing a fair and sustainable development for all.

## 5 General Conclusion

This work investigates the economics of land use as an adaptation response to weather shocks by analysing global to local deforestation outcomes.

At first, we analyse the impact of droughts on forest degradation and clearing in the major tropical forest basins between 1990 and 2020. The results highlight a positive correlation between deforestation and droughts, although spatial, climatic, and temporal variations exist. Interestingly, a gradual decline in this impact is evident over time, particularly as degradation diminishes. It has been demonstrated that degradation acts as a precursor to deforestation. However, in regions where forests are already degraded, coping strategies implemented after droughts have shown to be less land-intensive. To better understand the sources of heterogeneity observed in the global analysis, we deepen the topic at national scale - in the Democratic Republic of Congo. Specifically, we delve into the significance of agricultural seasonality for key staples such as maize and cassava. Indeed, as outlined in the literature review, shocks predominantly impact rural households by diminishing their agricultural income. Therefore households may need to compensate this loss by relying on forests. We argue that the choice of how to use forest resources, by preserving or clearing them, depends on the timing of the agricultural cycle of crops. Our findings reveal that deforestation decreases if the growing season is affected by a drought, suggesting relocation to off-farm jobs. On the other hand, deforestation increases if the drought affects the harvesting period, suggesting that some sort of on-farm anticipatory action is put in place for the following growing season. In the last chapter we focus on the long-term impacts of infrastructures, investigating dam construction and subsequent changes in water flow on land use in sub-Saharan Africa. Results indicate a significant reduction in agricultural lands but an increase in forest cover, with variable consequences depending on the distance from the dam, both upstream and downstream. This analysis also highlights a decrease in agricultural productivity but a diversification of economic activities, emphasizing the challenges and opportunities associated with such infrastructures and development as well as their potential role in climate shock adaptation and support to conservation.

In addition to empirical analysis, this thesis also undertakes a comprehensive review of existing literature, bridging the realms of economics, data science, and environmental studies. By synthesizing previous research findings, it seeks to identify and cover some of the gaps in understanding as well as contribute novel insights into the complex relationships between droughts, deforestation, adaptation and development. We highlight that recent advancements in the existing literature have been marked by two significant implementations: the utilization of georeferenced data, facilitated by enhanced accessibility and precision, and the adoption of quasi-experimental designs. Consequently, in this study, both approaches have been extensively employed. The three primary investigations presented herein - concerning the drivers of deforestation at the global, regional, and national scales - all depend on georeferenced data, ensuring a uniform approach. On the other hand, relying solely on georeferenced data hampers the direct observation of adaptation strategies which hence can be only inferred. To overcome this significant limitation of our study, future research should integrate household-level data into the analysis. However, the low coverage and limited reach of such surveys available today may constrain the breadth and external validity of our findings.

Our global findings underscore the significance of comprehending these dynamics to inform conservation policies. These policies must account for both the adaptation needs of local populations to climate shocks but also for the positive feedback loop existent between shocks, deforestation and adaptation. On top of this, policies should consider that adaptation may have contrasting impacts on the environment, for example by either fostering or reducing deforestation with respect to the time and intensity of the shock and the strategy adopted. While adaptation is paramount for the well-being of rural households, which are among the most vulnerable and the most severely impacted



by climate change, mitigation policies should not be overlooked, especially in light of this feedback loop and non linearity of impacts. Instead, they should be integrated alongside adaptation efforts to prevent the exacerbation of existing risks. Similarly, while planning for infrastructure - meant either for development, adaptation or mitigation, as dams could be - our results support future project impact analysis in estimating spatial and temporal environmental as well as socioeconomic effects. Again, it should be highlighted that costs and benefits are not equally distributed. These outcomes could also support more equitable compensation measures, particularly essential for the poorest who are generally excluded from consultations and decision-making.

In conclusion, by acknowledging the complexities linking shock-adaptation-environment, on which this study endeavors to shed partial light on, future planning and decision-making processes could more effectively address the inherent vulnerabilities within human and environmental systems, thus ensuring a sustainable future for all, both present and future generations, in alignment with the Glasgow Leaders' Declaration on Forests.

## Bibliography

- Abman, R. and Carney, C. (2020). Agricultural productivity and deforestation: Evidence from input subsidies and ethnic favoritism in Malawi. *Journal of Environmental Economics and Management*, 103:102342.
- Achard, F., Beuchle, R., Mayaux, P., Stibig, H.-J., Bodart, C., Brink, A., Carboni, S., Desclée, B., Donnay, F., Eva, H. D., et al. (2014). Determination of tropical deforestation rates and related carbon losses from 1990 to 2010. *Global change biology*, 20(8):2540–2554.
- Achard, F., DeFries, R., Eva, H., Hansen, M., Mayaux, P., and Stibig, H. (2007). Pan-tropical monitoring of deforestation. *Environmental Research Letters*, 2(4):045022.
- Achille, L. S., Zhang, K., and Anoma, C. J. K. (2021). Dynamics of deforestation and degradation of forests in the democratic republic of congo from 1990 to 2018. *Open Journal of Ecology*, 11(5):451–461.
- AfDB (2023). Africa hydropower modernisation programme: Continent-wide mapping of hydropower rehabilitation candidates.
- Aker, J. C., Klein, M. W., O’Connell, S. A., and Yang, M. (2014). Borders, ethnicity and trade. *Journal of Development Economics*, 107:1–16.
- Akinyi, D. P., Karanja Ng’ang’a, S., and Girvetz, E. H. (2021). Trade-offs and synergies of climate change adaptation strategies among smallholder farmers in sub-saharan africa: A systematic review. *Regional Sustainability*, 2(2):130–143.
- Alam, G. (2018). Determinants of and barriers to adaptation: evidence from hazard-prone rural households in bangladesh. *Bangladesh J Pol Econ*, 34(2):307–330.
- Alamgir, M., Campbell, M. J., Sloan, S., Engert, J., Word, J., and Laurance, W. F. (2020). Emerging challenges for sustainable development and forest conservation in sarawak, borneo. *PloS one*, 15(3):e0229614.
- Alix-Garcia, J., McIntosh, C., Sims, K. R., and Welch, J. R. (2013). The ecological footprint of poverty alleviation: evidence from mexico’s oportunidades program. *Review of Economics and Statistics*, 95(2):417–435.
- Anderson, E. P., Jenkins, C. N., Heilpern, S., Maldonado-Ocampo, J. A., Carvajal-Vallejos, F. M., Encalada, A. C., Rivadeneira, J. F., Hidalgo, M., Cañas, C. M., Ortega, H., et al. (2018). Fragmentation of andes-to-amazon connectivity by hydropower dams. *Science advances*, 4(1):eaao1642.
- Angelsen, A., Jagger, P., Babigumira, R., Belcher, B., Hogarth, N. J., Bauch, S., Börner, J., Smith-Hall, C., and Wunder, S. (2014). Environmental income and rural livelihoods: a global-comparative analysis. *World development*, 64:S12–S28.
- Angelsen, A. and Wunder, S. (2003). Exploring the Forest—Poverty Link: Key Concepts, Issues and Research Implications. *CIFOR Occasional Paper*, 40:1–20.
- Aragão, L. E. O., Malhi, Y., Barbier, N., Lima, A., Shimabukuro, Y., Anderson, L., and Saatchi, S. (2008). Interactions between rainfall, deforestation and fires during recent years in the Brazilian Amazonia. In *Philosophical Transactions of the Royal Society B: Biological Sciences*, volume 363, pages 1779–1785.

- Araujo, C., Combes, J. L., and Féres, J. G. (2014). Determinants of Amazon deforestation: The role of off-farm income. *Environment and Development Economics (CHECK THE VERSION)*, 24(2):138–156.
- Arceo-Gómez, E. O., Hernández-Cortés, D., and López-Feldman, A. (2020). Droughts and rural households' wellbeing: evidence from Mexico. *Climatic Change*, 162(3):1197–1212.
- Ashraf, M., Kahlown, M. A., and Ashfaq, A. (2007). Impact of small dams on agriculture and groundwater development: A case study from Pakistan. *Agricultural Water Management*, 92(1-2):90–98.
- Athayde, S., Mathews, M., Bohlman, S., Brasil, W., Doria, C. R., Dutka-Gianelli, J., Fearnside, P. M., Loiselle, B., Marques, E. E., Melis, T. S., et al. (2019). Mapping research on hydropower and sustainability in the Brazilian Amazon: advances, gaps in knowledge and future directions. *Current Opinion in Environmental Sustainability*, 37:50–69.
- Ayanlade, A., Oluwaranti, A., Ayanlade, O. S., Borderon, M., Sterly, H., Sakdapolrak, P., Jegede, M. O., Weldemariam, L. F., and Ayinde, A. F. (2022). Extreme climate events in sub-Saharan Africa: A call for improving agricultural technology transfer to enhance adaptive capacity. *Climate Services*, 27:100311.
- Azami, K., Suzuki, H., and Toki, S. (2004). Changes in riparian vegetation communities below a large dam in a monsoonal region: Futase dam, Japan. *River Research and Applications*, 20(5):549–563.
- Baez, J. E., Kronick, D., and Mason, A. D. (2013). Rural households in a changing climate. *The World Bank Research Observer*, 28(2):267–289.
- Bakehe, N. P. and Hassan, R. (2022). The effects of access to clean fuels and technologies for cooking on deforestation in developing countries. *Journal of the Knowledge Economy*, pages 1–17.
- Baland, J.-M. and Francois, P. (2005). Commons as insurance and the welfare impact of privatization. *Journal of Public Economics*, 89(2):211–231.
- Balestri, S. and Maggioni, M. A. (2019). This Land Is My Land! Large-Scale Land Acquisitions and Conflict Events in Sub-Saharan Africa. *Defence and Peace Economics*, 6:1–7.
- Begna, T. (2020). Effects of drought stress on crop production and productivity. *International Journal of Research Studies in Agricultural Sciences*, 6:34–43.
- Biazin, B. and Sterk, G. (2013). Drought vulnerability drives land-use and land cover changes in the rift valley dry lands of Ethiopia. *Agriculture, Ecosystems & Environment*, 164:100–113.
- Blanc, E. and Strobl, E. (2014). Is small better? a comparison of the effect of large and small dams on cropland productivity in South Africa. *The World Bank Economic Review*, 28(3):545–576.
- Bogale, G. A. and Erena, Z. B. (2022). Drought vulnerability and impacts of climate change on livestock production and productivity in different agro-ecological zones of Ethiopia. *Journal of Applied Animal Research*, 50(1):471–489.
- Brack, D. (2018). Sustainable consumption and production of forest products. In *United Nations Forum on Forests*.

- Brunette, M., Delacote, P., Garcia, S., and Rousselle, J.-M. (2020). Commons as a Risk-Management Tool: Theoretical Predictions and an Experimental Test. *Revue d'économie politique*, 130(3):405–439.
- Busch, J. and Ferretti-Gallon, K. (2017). What drives deforestation and what stops it? A meta-analysis. *Review of Environmental Economics and Policy*, 11(1):3–23.
- Busetto, L. and Ranghetti, L. (2016). Modistsp: An r package for automatic preprocessing of modis land products time series. *Computers & geosciences*, 97:40–48.
- Butsic, V., Baumann, M., Shortland, A., Walker, S., and Kuemmerle, T. (2015). Conservation and conflict in the democratic republic of congo: The impacts of warfare, mining, and protected areas on deforestation. *Biological conservation*, 191:266–273.
- Campbell, D., Lusch, D., Smucker, T., and Wangui, E. (2005). Multiple methods in the study of driving forces of land use and land cover change: A case study of se kajiado district, kenya. *Human Ecology*, 33:763–794.
- Canadell, J. G. and Raupach, M. R. (2008). Managing forests for climate change mitigation. *science*, 320(5882):1456–1457.
- Carpena, F. (2019). How do droughts impact household food consumption and nutritional intake? a study of rural india. *World Development*, 122:349–369.
- Castro, L. M., Encalada, D., and Saa, L. R. (2022). Non-timber forest products as an alternative to reduce income uncertainty in rural households. In *Sustainable Rural Development*. IntechOpen.
- Chen, G., Powers, R. P., de Carvalho, L. M., and Mora, B. (2015). Spatiotemporal patterns of tropical deforestation and forest degradation in response to the operation of the tucuruí hydroelectric dam in the amazon basin. *Applied Geography*, 63:1–8.
- Chen, S. (2009). Discussion of resettlement cost externalization of water resources and hydropower projects. In *Advances in Water Resources and Hydraulic Engineering*, pages 1427–1432, Berlin, Heidelberg. Springer Berlin Heidelberg.
- Clerici, N., Armenteras, D., Kareiva, P., Botero, R., Ramírez-Delgado, J. P., Forero-Medina, G., Ochoa, J., Pedraza, C., Schneider, L., Lora, C., Gómez, C., Linares, M., Hirashiki, C., and Biggs, D. (2020). Deforestation in Colombian protected areas increased during post-conflict periods. *Scientific Reports*, 10(1):4971.
- Cole, M. A., Elliott, R. J., and Strobl, E. (2014). Climate change, hydro-dependency, and the african dam boom. *World Development*, 60:84–98.
- Copernicus Climate Change Service (2019). Climate data store: Land cover classification gridded maps from 1992 to present derived from satellite observation. copernicus climate change service (c3s) climate data store (c3s). Date accessed: January 2023.
- Curtis, P. G., Slay, C. M., Harris, N. L., Tyukavina, A., and Hansen, M. C. (2018). Classifying drivers of global forest loss. *Science*, 361(6407):1108–1111.
- Davis, K. F., Koo, H. I., Dell'Angelo, J., D'Odorico, P., Estes, L., Kehoe, L. J., Kharratzadeh, M., Kuemmerle, T., Machava, D., Pais, A. d. J. R., Ribeiro, N., Rulli, M. C., and Tatlhego, M. (2020a). Tropical forest loss enhanced by large-scale land acquisitions. *Nature Geoscience*, 13(7):482–488.

- Davis, K. F., Koo, H. I., Dell'Angelo, J., D'Odorico, P., Estes, L., Kehoe, L. J., Kharratzadeh, M., Kuemmerle, T., Machava, D., Pais, A. d. J. R., et al. (2020b). Tropical forest loss enhanced by large-scale land acquisitions. *Nature Geoscience*, 13(7):482–488.
- De Fraiture, C., Kouali, G. N., Sally, H., and Kabre, P. (2014). Pirates or pioneers? unplanned irrigation around small reservoirs in burkina faso. *Agricultural Water Management*, 131:212–220.
- De Sy, V., Herold, M., Achard, F., Avitabile, V., Baccini, A., Carter, S., Clevers, J. G., Lindquist, E., Pereira, M., and Verchot, L. (2019). Tropical deforestation drivers and associated carbon emission factors derived from remote sensing data. *Environmental Research Letters*, 14(9):094022.
- Degu, A. M., Hossain, F., Niyogi, D., Pielke Sr, R., Shepherd, J. M., Voisin, N., and Chronis, T. (2011). The influence of large dams on surrounding climate and precipitation patterns. *Geophysical Research Letters*, 38(4).
- Delacote, P. (2007). Agricultural expansion, forest products as safety nets, and deforestation. *Environment and Development Economics*, 12(2):235–249.
- Delacote, P. (2009). Commons as insurance: safety nets or poverty traps? *Environment and Development Economics*, 14(3):305–322.
- Delacote, P. and Leblois, A. (2020). Coping mechanisms after a shock and land use : impacts of droughts on tree loss. *WORKING PAPER*.
- Desbureaux, S. and Damania, R. (2018). Rain, forests and farmers: Evidence of drought induced deforestation in Madagascar and its consequences for biodiversity conservation. *Biological Conservation*, 221:357–364.
- Di Falco, S., Doku, A., and Mahajan, A. (2020). Peer effects and the choice of adaptation strategies. *Agricultural Economics*, 51(1):17–30.
- Di Falco, S. and Veronesi, M. (2013). How can african agriculture adapt to climate change? a counterfactual analysis from ethiopia. *Land Economics*, 89(4):743–766.
- Di Falco, S. and Veronesi, M. (2014). Managing environmental risk in presence of climate change: the role of adaptation in the Nile basin of ethiopia. *Environmental and Resource Economics*, 57:553–577.
- Di Falco, S., Veronesi, M., and Yesuf, M. (2011). Does adaptation to climate change provide food security? a micro-perspective from ethiopia. *American journal of agricultural economics*, 93(3):829–846.
- Duflo, E. and Pande, R. (2007). Dams. *The Quarterly Journal of Economics*, 122(2):601–646.
- Duku, C. and Hein, L. (2021). The impact of deforestation on rainfall in africa: a data-driven assessment. *Environmental Research Letters*, 16(6):064044.
- Duncanson, L., Liang, M., Leitold, V., Armston, J., Krishna Moorthy, S., Dubayah, R., Costedoat, S., Enquist, B., Fatoyinbo, L., Goetz, S., et al. (2023). The effectiveness of global protected areas for climate change mitigation. *Nature Communications*, 14(1):2908.
- Duval, L. and Wolff, F. C. (2009). L'effet des transferts des migrants sur la déforestation dans les pays en développement. *Revue d'Economie du Développement*, 23(3):109–135.

- Égré, D., Roquet, V., and Durocher, C. (2007). Monetary benefit sharing from dams: A few examples of financial partnerships with indigenous communities in québec (canada). *International Journal of River Basin Management*, 5(3):235–244.
- FAO (2015). Aquastat database. Date accessed: 10 June 2022.
- FAO (2020). Global forest resources assessment 2020: main report.
- FAO (2022a). In Brief to The State of the World’s Forests 2022.
- FAO (2022b). World’s Forests State.
- FAO and UNEP (2020). The state of the world’s forests.
- Fearnside, P. M. (2006). Dams in the amazon: Belo monte and brazil’s hydroelectric development of the xingu river basin. *Environmental management*, 38:16–27.
- Fearnside, P. M. (2016). Environmental and social impacts of hydroelectric dams in brazilian amazonia: Implications for the aluminum industry. *World development*, 77:48–65.
- Ferretti-Gallon, K. and Busch, J. (2017). What Drives Deforestation and What Stops it? A Meta-Analysis of Spatially Explicit Econometric Studies. *Review of Environmental Economics and Policy*, 11(1):3–23.
- Fuller, T. L., Narins, T. P., Nackoney, J., Bonebrake, T. C., Sesink Clee, P., Morgan, K., Tróchez, A., Bocuma Meñe, D., Bongwele, E., Njabo, K. Y., et al. (2019). Assessing the impact of china’s timber industry on congo basin land use change. *Area*, 51(2):340–349.
- Funk, C., Verdin, A., Michaelsen, J., Peterson, P., Pedreros, D., and Husak, G. (2015). A global satellite-assisted precipitation climatology. *Earth System Science Data*, 7(2):275.
- GADM (2021). Global administrative areas (version 4.0.4). Digital geospatial data, University of California, Berkely.
- Garnett, S. T., Burgess, N. D., Fa, J. E., Fernández-Llamazares, Á., Molnár, Z., Robinson, C. J., Watson, J. E., Zander, K. K., Austin, B., Brondizio, E. S., et al. (2018). A spatial overview of the global importance of indigenous lands for conservation. *Nature Sustainability*, 1(7):369–374.
- Garrett, K., McManamay, R. A., and Wang, J. (2021). Global hydropower expansion without building new dams. *Environmental Research Letters*, 16(11):114029.
- Girard, J., Delacote, P., and Leblois, A. (2019). AGRICULTURAL HOUSEHOLDS’ ADAPTATION TO WEATHER SHOCKS IN SUB-SAHARAN AFRICA: WHAT IMPLICATIONS FOR LAND-USE CHANGE AND DEFORESTATION? Technical report, Climate Economics Chair, Paris.
- Girard, J., Delacote, P., and Leblois, A. (2021). Agricultural households’ adaptation to weather shocks in Sub-Saharan Africa: implications for land-use change and deforestation. *Environment and Development Economics*, 26(5-6):538–560.
- Gou, Y., Balling, J., De Sy, V., Herold, M., De Keersmaecker, W., Slagter, B., Mullissa, A., Shang, X., and Reiche, J. (2022). Intra-annual relationship between precipitation and forest disturbance in the african rainforest. *Environmental Research Letters*.

- Grima, N. and Singh, S. J. (2019). How the end of armed conflicts influence forest cover and subsequently ecosystem services provision? An analysis of four case studies in biodiversity hotspots. *Land Use Policy*, 81(October):267–275.
- Guerrero, J. V., Escobar-Silva, E. V., Chaves, M. E., Mataveli, G. A., Bourscheidt, V., De Oliveira, G., Picoli, M. C., Shimabukuro, Y. E., and Moschini, L. E. (2020). Assessing land use and land cover changes in the direct influence zone of the braço norte hydropower complex, brazilian amazonia. *Forests*, 11(9):988.
- Hansen, M. C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S. A., Tyukavina, A., Thau, D., Stehman, S. V., Goetz, S. J., Loveland, T. R., et al. (2013). High-resolution global maps of 21st-century forest cover change. *science*, 342(6160):850–853.
- He, X. and Chen, Z. (2021). Weather, cropland expansion, and deforestation in ethiopia. *Journal of Environmental Economics and Management*, page 102586.
- Hedin, L. O., Mayer, M. S., and Likens, G. E. (1988). The effect of deforestation on organic debris dams. *Internationale Vereinigung für theoretische und angewandte Limnologie: Verhandlungen*, 23(2):1135–1141.
- IEA (2020). Climate impacts on african hydropower. License: CC BY 4.0.
- IEA (2022). Africa energy outlook 2022.
- IRENA (2021). The renewable energy transition in africa: Powering access, resilience and prosperity.
- IUFRO (2018). Global fire challenges in a warming world.
- Jones, I. L. and Bull, J. W. (2020). Major dams and the challenge of achieving “no net loss” of biodiversity in the tropics. *Sustainable Development*, 28(2):435–443.
- Jones, M., Kondylis, F., Loeser, J., and Magruder, J. (2022). Factor market failures and the adoption of irrigation in rwanda. *American Economic Review*, 112(7):2316–2352.
- Kengoum, F., Pham, T., Moeliono, M., Dwisatrio, B., and Sonwa, D. (2020). *The context of REDD+ in the Democratic Republic of Congo: Drivers, agents and institutions*, volume 207. CIFOR.
- Kirchherr, J., Pohlner, H., and Charles, K. J. (2016). Cleaning up the big muddy: A meta-synthesis of the research on the social impact of dams. *Environmental Impact Assessment Review*, 60:115–125.
- Kirilenko, A. P. and Sedjo, R. A. (2007). Climate change impacts on forestry. *Proceedings of the National Academy of Sciences*, 104(50):19697–19702.
- Lawrence, D. and Vandecar, K. (2015). Effects of tropical deforestation on climate and agriculture. *Nature Climate Change*, 5(1):27.
- Leblois, A. (2021). Mitigating the impact of bad rainy seasons in poor agricultural regions to tackle deforestation. *Environmental Research Letters*, 16(5):054003.
- Lehner, B. and Grill, G. (2013). Global river hydrography and network routing: baseline data and new approaches to study the world’s large river systems. *Hydrological Processes*, 27(15):2171–2186.
- Lehner, B., Verdin, K., and Jarvis, A. (2008). New global hydrography derived from spaceborne elevation data. *Eos, Transactions American Geophysical Union*, 89(10):93–94.

- Leite-Filho, A. T., de Sousa Pontes, V. Y., and Costa, M. H. (2019). Effects of deforestation on the onset of the rainy season and the duration of dry spells in southern amazonia. *Journal of Geophysical Research: Atmospheres*.
- Li, X., Zhou, Y., Zhao, M., and Zhao, X. (2020). A harmonized global nighttime light dataset 1992–2018. *Scientific data*, 7(1):168.
- Ly, A. (2023). *Electrification, Environment, and Economic Development in Developing Countries*. PhD thesis, Université Paris sciences et lettres.
- Ly, A., Chakir, R. R., Creti, A., et al. (2023). Electrification and deforestation in cote d’ivoire: a spatial econometric analysis [electrification et déforestation en côte d’ivoire: une analyse spatio-économétrique]. *Working Paper*.
- Maeda, E. E., Abera, T. A., Siljander, M., Aragão, L. E., de Moura, Y. M., and Heiskanen, J. (2021). Large-scale commodity agriculture exacerbates the climatic impacts of amazonian deforestation. *Proceedings of the National Academy of Sciences*, 118(7).
- Makino, Y. and Rudolf-Miklau, F. (2021). *The protective functions of forests in a changing climate-European experience*. FAO: Food and Agriculture Organization of the United Nations.
- Marivoet, W., Ulimwengu, J. M., Vilaly, E., and Abd Salam, M. (2018). *Understanding The democratic republic of the Congo’s agricultural paradox: Based on the eAtlas data platform*. International Food Policy Research Institute.
- McKee, T. B., Doesken, N. J., Kleist, J., et al. (1993). The relationship of drought frequency and duration to time scales. In *Proceedings of the 8th Conference on Applied Climatology*, volume 17, pages 179–183. Boston.
- Molinario, G., Hansen, M., Potapov, P., Tyukavina, A., and Stehman, S. (2020). Contextualizing landscape-scale forest cover loss in the democratic republic of congo (drc) between 2000 and 2015. *Land*, 9(1):23.
- Nayak, R., Karanth, K. K., Dutta, T., Defries, R., Karanth, K. U., and Vaidyanathan, S. (2020). Bits and pieces: Forest fragmentation by linear intrusions in india. *Land Use Policy*, 99:104619.
- Nelson, A. (2008). Travel time to major cities: A global map of accessibility. *Office for Official Publications of the European Communities, Luxembourg*.
- Nelson, A., Weiss, D. J., van Etten, J., Cattaneo, A., McMenomy, T. S., and Koo, J. (2019). A suite of global accessibility indicators. *Scientific data*, 6(1):266.
- Nguyen Van, P. and Azomahou, T. (2007). Nonlinearities and heterogeneity in environmental quality: An empirical analysis of deforestation. *Journal of Development Economics*, 84(1):291–309.
- Noack, F., Riekhof, M.-C., and Di Falco, S. (2019). Droughts, biodiversity, and rural incomes in the tropics. *Journal of the Association of Environmental and Resource Economists*, 6(4):823–852.
- OECD (2003). The oecd glossary of statistical terms.
- Ofoegbu, C., Chirwa, P., Francis, J., and Babalola, F. (2017). Assessing vulnerability of rural communities to climate change: A review of implications for forest-based livelihoods in south africa. *International Journal of Climate Change Strategies and Management*, 9(03):374–386.



- Ogundari, K., Ademuwagun, A. A., and Ajao, O. A. (2017). Revisiting environmental kuznets curve in Sub-Sahara Africa: Evidence from deforestation and all GHG emissions from agriculture. *International Journal of Social Economics*, 44(2):222–231.
- Okogbenin, E., Setter, T. L., Ferguson, M., Mutegi, R., Ceballos, H., Olasanmi, B., and Fregene, M. (2013). Phenotypic approaches to drought in cassava. *Frontiers in physiology*, 4:93.
- Ometto, J. P., Kalaba, K., Anshari, G. Z., Chacón, N., Farrell, A., Halim, S. A., Neufeldt, H., Sukumar, R., Pörtner, H.-O., Roberts, D. C., Tignor, M., Poloczanska, E. S., Mintenbeck, K., Alegría, A., Craig, M., Langsdorf, S., Löschke, S., Möller, V., Okem, A., and Rama, B. (2022). *Climate Change 2022: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, volume Cross-Chapter Paper 7: Tropical Forests. Cambridge University Press, Cambridge, UK and New York, NY, USA.
- Oshunsanya, S. and Nwosu, N. (2018). *Soil-water-crop relationship: a case study of cassava in the tropics*. Intech Open.
- Pendrill, F., Gardner, T. A., Meyfroidt, P., Persson, U. M., Adams, J., Azevedo, T., Bastos Lima, M. G., Baumann, M., Curtis, P. G., De Sy, V., et al. (2022). Disentangling the numbers behind agriculture-driven tropical deforestation. *Science*, 377(6611):eabm9267.
- Poufoun, J. N. (2016). *Livelihoods strategies , deforestation and biodiversity conservation: a micro econometric analysis using rural households survey in the Tridom transboundary conservation landscape*. PhD thesis, Université de Lorraine.
- Reenberg, A. (1994). Land-use dynamics in the sahelian zone in eastern niger - monitoring change in cultivation strategies in drought prone areas. *Journal of Arid Environments - J ARID ENVIRON*, 27:179–192.
- Reenberg, A., Nielsen, T., and Rasmussen, K. (1998). Field expansion and reallocation in the sahel - land use pattern dynamics in a fluctuating biophysical and socio-economic environment. *Global Environmental Change-human and Policy Dimensions - GLOBAL ENVIRON CHANGE*, 8:309–327.
- Reenberg, A. and Paarup-Laursen, B. (1997). Determinants for land use strategies in a sahelian agro-ecosystem—anthropological and ecological geographical aspects of natural resource management. *Agricultural Systems*, 53:209–229.
- Reid, R., Kruska, R., Muthui, N., Taye, A., Wotton, S., Wilson, C., and Mulatu, W. (2000). Land-use and land-cover dynamics in response to changes in climatic, biological and socio-political forces: The case of southwestern ethiopia. *Landscape Ecology*, 15:339–355.
- Rodríguez-Iturbe, I. (1992). Droughts and climate change. In *AIP Conference Proceedings*, volume 277, pages 96–111. American Institute of Physics.
- Rodríguez-Solorzano, C. (2014). Unintended outcomes of farmers’ adaptation to climate variability: Deforestation and conservation in Calakmul and Maya biosphere reserves. *Ecology and Society*, 19(2).
- Romijn, E., Lantican, C. B., Herold, M., Lindquist, E., Ochieng, R., Wijaya, A., Murdiyarso, D., and Verchot, L. (2015). Assessing change in national forest monitoring capacities of 99 tropical countries. *Forest Ecology and Management*, 352:109–123.

- Roncoli, C., Ingram, K., and Kirshen, P. (2001). The costs and risks of coping with drought: Livelihood impacts and farmers' responses in burkina faso. *Climate Research - CLIMATE RES*, 19:119–132.
- Ruf, F., Schroth, G., and Doffangui, K. (2015). Climate change, cocoa migrations and deforestation in West Africa: What does the past tell us about the future? *Sustainability Science*, 10(1):101–111.
- Rufin, P., Gollnow, F., Müller, D., and Hostert, P. (2019). Synthesizing dam-induced land system change. *Ambio*, 48:1183–1194.
- Running, S. W., Mu, Q., Zhao, M., Myneni, R. B., Riveiro, B., Hunt, E. R., and Saatchi, S. S. (2015). Mod17a2h modis/terra gross primary productivity 8-day 14 global 500m sin grid v006 [data set]. *NASA EOSDIS Land Processes DAAC*.
- Saatchi, S., Longo, M., Xu, L., Yang, Y., Abe, H., Andre, M., Aukema, J. E., Carvalhais, N., Cadillo-Quiroz, H., Cerbu, G. A., et al. (2021). Detecting vulnerability of humid tropical forests to multiple stressors. *One Earth*, 4(7):988–1003.
- Sacks, W. J., Deryng, D., Foley, J. A., and Ramankutty, N. (2010). Crop planting dates: an analysis of global patterns. *Global ecology and biogeography*, 19(5):607–620.
- Sanchez de la Sierra, R. (2020). On the origins of the state: Stationary bandits and taxation in eastern congo. *Journal of Political Economy*, 128(1):000–000.
- Seneviratne, S. I., Zhang, X., Adnan, M., Badi, W., Dereczynski, C., Di Luca, A., Ghosh, S., Iskander, I., Kossin, J., Lewis, S., et al. (2021). Weather and climate extreme events in a changing climate (chapter 11). *Cambridge University Press*.
- Senganimalunje, T., Chirwa, P., and Babalola, F. (2021). Exploring the role of forests as natural assets in rural livelihoods and coping strategies against risks and shocks in dedza east, malawi. *Journal of Sustainable Forestry*, pages 1–23.
- Simango, B., Mabiza, C., Gumindoga, W., and Mhizha, A. (2021). The impacts of land reforms on water infrastructure use and investment: A case study of the biri dam, zimbabwe. *Physics and Chemistry of the Earth, Parts A/B/C*, 123:103050.
- Solórzano, C. (2016). Connecting climate social adaptation and land use change in internationally adjoining protected areas. *Conservation and Society*, 14(2):125–133.
- Somorin, O. A., Brown, H. C. P., Visseren-Hamakers, I. J., Sonwa, D. J., Arts, B., and Nkem, J. (2012). The congo basin forests in a changing climate: policy discourses on adaptation and mitigation (redd+). *Global Environmental Change*, 22(1):288–298.
- Staal, A., Flores, B. M., Aguiar, A. P. D., Bosmans, J. H., Fetzer, I., and Tuinenburg, O. A. (2020). Feedback between drought and deforestation in the amazon. *Environmental Research Letters*, 15(4):044024.
- Strobl, E. and Strobl, R. (2011). The distributional impact of large dams: Evidence from cropland productivity in africa. *Journal of development Economics*, 96(2):432–450.
- Sun, L. and Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, 225(2):175–199.

- Sze, J. S., Carrasco, L. R., Childs, D., and Edwards, D. P. (2022). Reduced deforestation and degradation in indigenous lands pan-tropically. *Nature Sustainability*, 5(2):123–130.
- Tanner, A. M. and Johnston, A. L. (2017). The impact of rural electric access on deforestation rates. *World development*, 94:174–185.
- Tatlhego, M. and D’Odorico, P. (2022). Are african irrigation dam projects for large-scale agribusiness or small-scale farmers? *Environmental Research Communications*, 4(1):015005.
- The World Bank Group (2021). Climate risk profile: Congo, democratic republic.
- Thieme, M. L., Khrystenko, D., Qin, S., Golden Kroner, R. E., Lehner, B., Pack, S., Tockner, K., Zarfl, C., Shahbol, N., and Mascia, M. B. (2020). Dams and protected areas: Quantifying the spatial and temporal extent of global dam construction within protected areas. *Conservation Letters*, 13(4):e12719.
- Thünen, J. H. (1826). *Der isolierte Staat in Beziehung auf Landwirtschaft und Nationalökonomie*. Perthes, Hamburg.
- Timpe, K. and Kaplan, D. (2017). The changing hydrology of a dammed amazon. *Science Advances*, 3(11):e1700611.
- Tsegaye, D., Moe, S., Vedeld, P., and Betemariam, E. (2010). Land-use/cover dynamics in northern afar rangelands, ethiopia. *Agriculture Ecosystems and Environment*, 139:174–180.
- Tyukavina, A., Hansen, M. C., Potapov, P., Parker, D., Okpa, C., Stehman, S. V., Kommareddy, I., and Turubanova, S. (2018). Congo basin forest loss dominated by increasing smallholder clearing. *Science advances*, 4(11).
- Udmale, P. D., Ichikawa, Y., Manandhar, S., Ishidaira, H., Kiem, A. S., Shaowei, N., and Panda, S. N. (2015). How did the 2012 drought affect rural livelihoods in vulnerable areas? empirical evidence from india. *International Journal of Disaster Risk Reduction*, 13:454–469.
- UNEP-WCMC (2014). World database on protected areas, accessed in june 2020. *Protected Planet website*.
- UNPD (2023). Issue brief: Forests, energy and livelihoods.
- Vaglietti, G., Delacote, P., and Leblois, A. (2022a). Data repository - supplementary materials to droughts and deforestation: Does seasonality matter? vaglietti et al. 2022. *Ann Arbor, MI: Inter-university Consortium for Political and Social Research [distributor]*.
- Vaglietti, G., Delacote, P., and Leblois, A. (2022b). Droughts and deforestation: Does seasonality matter? *Plos one*, 17(10):e0276667.
- Van, P. N. and Azomahou, T. (2007). Nonlinearities and heterogeneity in environmental quality: An empirical analysis of deforestation. *Journal of Development Economics*, 84(1):291–309.
- van Diemen, R. et al. (2019). Annex i: glossary. *Climate Change and Land: An IPCC Special Report on Climate Change, Desertification, Land Degradation, Sustainable Land Management, Food Security, and Greenhouse Gas Fluxes in Terrestrial Ecosystems*. IPCC. Retrieved from [https://www.ipcc.ch/site/assets/uploads/2019/11/11\\_Annex-I-Glossary.pdf](https://www.ipcc.ch/site/assets/uploads/2019/11/11_Annex-I-Glossary.pdf).

- Vancutsem, C., Achard, F., Pekel, J.-F., Vieilledent, G., Carboni, S., Simonetti, D., Gallego, J., Aragao, L. E., and Nasi, R. (2021). Long-term (1990–2019) monitoring of forest cover changes in the humid tropics. *Science Advances*, 7(10):eabe1603.
- Velastegui-Montoya, A., Lima, A. d., and Adami, M. (2020). Multitemporal analysis of deforestation in response to the construction of the tucuruí dam. *ISPRS International Journal of Geo-Information*, 9(10):583.
- Verhegghen, A., Mayaux, P., De Wasseige, C., and Defourny, P. (2012). Mapping congo basin vegetation types from 300 m and 1 km multi-sensor time series for carbon stocks and forest areas estimation. *Biogeosciences*, 9(12):5061–5079.
- Vesco, P., Dasgupta, S., De Cian, E., and Carraro, C. (2020). Natural resources and conflict: A meta-analysis of the empirical literature. *Ecological Economics*, 172(March):106633.
- Vieilledent, G., Vancutsem, C., Bourgoin, C., Ploton, P., Verley, P., and Achard, F. (2022). Spatial scenario of tropical deforestation and carbon emissions for the 21st century. *bioRxiv*.
- Wang, C. (2012). *A guide for local benefit sharing in hydropower projects*. World Bank, Washington, DC.
- Winemiller, K. O., McIntyre, P. B., Castello, L., Fluet-Chouinard, E., Giarrizzo, T., Nam, S., Baird, I. G., Darwall, W., Lujan, N. K., Harrison, I., et al. (2016). Balancing hydropower and biodiversity in the amazon, congo, and mekong. *Science*, 351(6269):128–129.
- Winkler, K., Fuchs, R., Rounsevell, M., and Herold, M. (2021). Global land use changes are four times greater than previously estimated. *Nature communications*, 12(1):2501.
- Woldemichael, A. T., Hossain, F., Pielke Sr, R., and Beltrán-Przekurat, A. (2012). Understanding the impact of dam-triggered land use/land cover change on the modification of extreme precipitation. *Water Resources Research*, 48(9).
- World Bank (2013). *Deforestation trends in the Congo Basin: reconciling economic growth and forest protection*. World Bank Publications.
- World Commission on Dams (2000). *Dams and development: A new framework for decision-making: The report of the world commission on dams*. Earthscan.
- WRI (2009). Administrative boundaries, democratic republic of congo. Shapefile, World Resources Institute.
- Wu, Q. and Brown, A. (2022). *'whitebox': 'WhiteboxTools' R Frontend*. R package version 2.2.0.
- Wunder, S., Noack, F., and Angelsen, A. (2018). Climate, crops, and forests: a pan-tropical analysis of household income generation. *Environment and Development Economics*, 23(3):279–297.
- Zabel, F., Delzeit, R., Schneider, J. M., Seppelt, R., Mauser, W., and Václavík, T. (2019). Global impacts of future cropland expansion and intensification on agricultural markets and biodiversity. *Nature Communications*, 10(1):2844.
- Zaveri, E., Russ, J., and Damania, R. (2020). Rainfall anomalies are a significant driver of cropland expansion. *Proceedings of the National Academy of Sciences of the United States of America*, 117(19):10225–10233.

## Appendix

### A Supplementary material to Chapter 2

#### A.1 Summary statistic by region, annual cumulative precipitation by quantiles, and time (pentades)

##### A.1.1 Climate zones

For each region, cumulative precipitation thresholds have been divided as follows (Table A1):

Region	Quantile 33	Quantile 66
Africa	1276.711	1590.804
Americas	1435.328	2023.236
Asia	1677.852	2644.690
Oceania	1628.707	2674.411

Low cumulative precipitation levels are considered  $q \leq 33.3$ , Average precipitations erage with  $33.3 < q \leq 66.66$  and high with  $q > 66.66$ .

### A.1.2 Africa

Table A2: Summary statistics for areas characterized by low precipitation endowment Africa

Pentad			P1					P2					P3									
Variable	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max	NotNA	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max
Deforestation	08220	20.687	114.359	0	0	6	9241	408220	118.649	395.356	0	1	67	17514	408220	326.572	842.414	0	5	244	24617	
Degradation	408220	98.813	350.504	0	0	40	14255	408220	208.512	585.733	0	1	128	14521	408220	350.389	1010.651	0	0	186	23981	
Yearly cumulative rain	408220	1045.924	219.312	0.031	913.831	1197.428	2063.513	408220	1087.799	217.468	0.027	960.803	1233.503	2402.601	408220	1052.882	217.938	0.023	931.83	1200.532	1866.313	
SPI $\leq -1$	408220	0.209	0.407	0	0	0	1	408220	0.123	0.329	0	0	0	1	408220	0.162	0.368	0	0	0	0	1

Pentad			P4					P5					P6									
Variable	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max	NotNA	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max
Deforestation	408220	500.158	1262.072	0	8	369	26399	408220	634.535	1612.63	0	8	461	27076	489864	719.55	1837.01	0	8	510	30054	
Degradation	408220	361.609	1085.347	0	0	155	23878	408220	354.2	1161.322	0	0	119	24329	489864	384.592	1375.22	0	0	95	24476	
Yearly cumulative rain	408220	1071.02	224.608	0.021	939.909	1224.594	1989.832	408220	1078.909	211.076	0.02	959.535	1219.659	1830.527	489864	1091.871	237.076	0.02	954.35	1243.747	2325.749	
SPI $\leq -1$	408220	0.155	0.362	0	0	0	1	408220	0.108	0.31	0	0	0	1	489864	0.163	0.369	0	0	0	0	1

Table A3: Summary statistics for areas characterized by average precipitation endowment Africa

Pentad			P1					P2					P3									
Variable	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max	NotNA	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max
Deforestation	407685	31.515	111.956	0	0	19	6256	407685	173.519	461.779	0	0	139	15592	407685	536.762	1077.702	0	15	549	20153	
Degradation	407685	273.514	494.157	0	8	322	9597	407685	534.069	830.797	0	22	696	10805	407685	968.308	1392.952	0	41	1303	21727	
Yearly cumulative rain	407685	1414.545	163.602	624.253	1304.323	1524.347	2421.685	407685	1467.681	175.088	640.015	1349.342	1586.562	2832.746	407685	1407.675	163.732	547.871	1304.432	1512.821	2233.421	
SPI $\leq -1$	407685	0.188	0.391	0	0	0	1	407685	0.122	0.327	0	0	0	1	407685	0.207	0.405	0	0	0	0	1

Pentad			P4					P5					P6									
Variable	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max	NotNA	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max
Deforestation	407685	947.457	1745.857	0	44	1006	27664	407685	1375.265	2456.294	0	64	1482	31414	489222	1798.502	3126.638	0	82	1947	32867	
Degradation	407685	1130.92	1640.454	0	42	1510	23757	407685	1162.446	1764.949	0	34	1515	20720	489222	1374.588	2206.474	0	29	1749	29295	
Yearly cumulative rain	407685	1418.443	161.754	671.705	1318.306	1521.592	2335.027	407685	1448.635	162.299	719.857	1338.855	1554.904	2338.276	489222	1450.024	180.153	713.515	1332.338	1554.915	2985.997	
SPI $\leq -1$	407685	0.134	0.341	0	0	0	1	407685	0.106	0.308	0	0	0	1	489222	0.156	0.363	0	0	0	0	1

Table A4: Summary statistics for areas characterized by high precipitation endowment Africa

Pentad			P1					P2					P3									
Variable	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max	NotNA	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max
Deforestation	407600	25.805	141.501	0	0	12	13011	407600	142.932	555.44	0	0	35	14360	407600	530.36	1343.046	0	3	315	21196	
Degradation	407600	387.985	685.972	0	10	452	14298	407600	570.256	960.736	0	17	688	14298	407600	1132.519	1645.869	0	66	1485	20659	
Yearly cumulative rain	407600	1909.451	404.067	827.117	1649.24	2044.079	4804.206	407600	1960.748	423.365	870.496	1684.848	2118.576	5093.62	407600	1886.681	377.877	831.346	1638.246	2019.791	4516.353	
SPI $\leq -1$	407600	0.154	0.361	0	0	0	1	407600	0.112	0.315	0	0	0	1	407600	0.183	0.386	0	0	0	0	1

Pentad			P4					P5					P6									
Variable	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max	NotNA	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max
Deforestation	407600	997.602	2093.482	0	12	842	28661	407600	1604.456	2992.092	0	32	1594	31246	489120	2220.333	3807.56	0	60	2474	33258	
Degradation	407600	1492.397	2078.065	0	104	1981	20511	407600	1714.301	2398.161	0	127	2253	20053	489120	2225.951	3009.515	0	212	2961	25957	
Yearly cumulative rain	07600	1909.119	414.759	957.48	1639.274	2029.445	4983.646	407600	1915.9	405.98	1033.123	1653.44	2049.168	5257.146	489120	1909.574	406.359	1031.009	1646.376	2046.822	6205.735	
SPI $\leq -1$	407600	0.141	0.348	0	0	0	1	407600	0.133	0.34	0	0	0	1	489120	0.191	0.393	0	0	0	0	1

### A.1.3 America

Table A5: Summary statistics for areas characterized by low precipitation endowment Americas

Pentad			P1						P2						P3							
Variable	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max	NotNA	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max
Deforestation	676785	239.466	796.725	0	3	142	24191	676785	515.335	1320.257	0	13	403	27767	676785	882.962	1960.562	0	28	818	30933	
Degradation	676785	270.888	684.162	0	2	225	20246	676785	403.103	879.524	0	4	376	20313	676785	574.279	1207.193	0	2	543	26517	
Yearly cumulative rain	676785	1043.81	337.42	4.652	797.268	1286.062	2381.862	676785	1068.489	337.308	5.739	833.08	1311.645	4131.891	676785	1057.133	300.296	5.067	849.224	1275.291	2302.983	
SPI $\leq -1$	676785	0.208	0.406	0	0	0	1	676785	0.141	0.348	0	0	0	1	676785	0.118	0.323	0	0	0	0	

Pentad			P4						P5						P6							
Variable	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max	NotNA	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max
Deforestation	676785	1104.022	2351.356	0	34	1063	31584	676785	1255.758	2616.793	0	39	1234	33126	812142	1303.922	2727.657	0	37	1279	33152	
Degradation	676785	635.015	1434.656	0	1	541	28479	676785	665.87	1585.06	0	0	511	28268	812142	762.397	1894.643	0	0	521	32839	
Yearly cumulative rain	676785	1106.72	325.886	4.984	874.94	1332.787	2686.777	676785	1066.843	341.816	4.686	820.286	1314.511	2857.158	812142	1036.09	332.198	5.051	794.455	1265.26	3589.988	
SPI $\leq -1$	676785	0.099	0.298	0	0	0	1	676785	0.156	0.363	0	0	0	1	812142	0.209	0.407	0	0	0	0	

Table A6: Summary statistics for areas characterized by average precipitation endowment Americas

Pentad			P1						P2						P3							
Variable	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max	NotNA	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max
Deforestation	677305	443.007	1126.19	0	15	366	34350	677305	1130.184	2562.457	0	41	932	34374	677305	2037.674	3970.288	0	100	1877	34376	
Degradation	677305	535.901	796.161	0	72	663	15078	677305	748.757	1057.695	0	110	953	22769	677305	1075.711	1425.423	0	181	1390	27523	
Yearly cumulative rain	677305	1665.344	288.929	542.32	1460.176	1866.118	3103.015	677305	1711.334	295.645	701.292	1497.39	1903.215	4694.541	677305	1682.424	260.356	471.424	1494.969	1853.548	3345.06	
SPI $\leq -1$	677305	0.21	0.407	0	0	0	1	677305	0.175	0.38	0	0	0	1	677305	0.13	0.336	0	0	0	1	

Pentad			P4						P5						P6							
Variable	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max	NotNA	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max
Deforestation	677305	2758.799	5040.565	0	142	2679	34350	677305	3136.689	5460.074	0	185	3216	34341	812766	3324.231	5730.42	0	198	3409	34333	
Degradation	677305	1212.767	1594.85	0	195	1592	27520	677305	1333.064	1790.191	0	196	1751	29291	812766	1598.361	2177.02	0	226	2108	31867	
Yearly cumulative rain	677305	1745.531	286.081	670.038	1540.691	1940.759	3777.745	677305	1781.781	336.46	650.823	1532.589	1997.221	3709.636	812766	1720.218	328.098	415.219	1487.483	1930.016	3935.99	
SPI $\leq -1$	677305	0.114	0.317	0	0	0	1	677305	0.114	0.318	0	0	0	1	812766	0.17	0.376	0	0	0	1	

Table A7: Summary statistics for areas characterized by high precipitation endowment Americas

Pentad			P1						P2						P3							
Variable	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max	NotNA	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max
Deforestation	677400	227.874	774.011	0	0	100	27855	677400	650.475	1901.421	0	2	301	34116	677400	1354.247	3193.252	0	7	944	34137	
Degradation	677400	493.524	859.137	0	33	561	20346	677400	702.726	1150.792	0	49	830	20327	677400	1075.263	1586.014	0	86	1352	20226	
Yearly cumulative rain	677400	2523.233	672.984	959.365	2093.696	2823.386	9003.78	677400	2566.57	698.996	1003.381	2110.27	2842.401	9611.56	677400	2613.23	693.754	1152.32	2155.344	2911.312	10215.37	
SPI $\leq -1$	677400	0.226	0.418	0	0	0	1	677400	0.21	0.407	0	0	0	1	677400	0.1	0.3	0	0	0	1	

Pentad			P4						P5						P6							
Variable	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max	NotNA	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max
Deforestation	677400	1988.947	4222.292	0	11	1627	34094	677400	2391.608	4742.451	0	19	2185	34120	812880	2702.231	5144.804	0	28	2644	34174	
Degradation	677400	1250.758	1722	0	121	1651.25	20069	677400	1372.364	1822.775	0	155	1850	21606	812880	1798.325	2325.348	0	266	2424	32124	
Yearly cumulative rain	677400	2672.867	682.855	1208.397	2232.202	2950.79	11172.19	677400	2703.985	693.156	853.86	2264.262	2983.882	10978.61	812880	2544.524	625.235	614.958	2143.163	2832.975	8708.01	
SPI $\leq -1$	677400	0.08	0.271	0	0	0	1	677400	0.099	0.299	0	0	0	1	812880	0.21	0.407	0	0	0	1	

A.1.4 Asia

Table A8: Summary statistics for areas characterized by low precipitation endowment Asia

Pentad				P1				P2				P3										
Variable	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max	NotNA	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max
Deforestation	314810	128.237	395.931	0	0	52	14651	314810	372.958	934.165	0	4	230	28947	314810	709.869	1679.36	0	8	503	34048	
Degradation	314810	287.454	718.798	0	0	138	12708	314810	549.485	1208.993	0	0	380	25668	314810	759.729	1570.095	0	0	571	25639	
Yearly cumulative rain	314810	1171.862	355.69	134.944	919.946	1425.166	2580.239	314810	1238.673	350.761	128.554	983.058	1501.319	2505.66	314810	1228.23	366.542	166.579	963.12	1494.256	2927.476	
SPI ≤ -1	314810	0.297	0.457	0	0	1	1	314810	0.187	0.39	0	0	0	1	314810	0.154	0.361	0	0	0	0	1

Pentad				P4				P5				P6										
Variable	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max	NotNA	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max
Deforestation	314810	971.684	2229.684	0	8	743	34229	314810	1099.907	2475.249	0	9	877	34344	377772	1086.33	2456.635	0	8	897	34344	
Degradation	314810	823.719	1694.795	0	0	611	25103	314810	843.62	1765.276	0	0	578	24896	377772	980.027	2095.014	0	0	617	24205	
Yearly cumulative rain	314810	1334.609	356.349	161.756	1092.022	1593.396	3081.24	314810	1329.502	375.386	133.37	1079.863	1585.788	3161.133	377772	1273.572	361.079	141.834	1027.399	1535.938	2850.187	
SPI ≤ -1	314810	0.072	0.258	0	0	0	1	314810	0.097	0.296	0	0	0	1	377772	0.16	0.367	0	0	0	0	1

Table A9: Summary statistics for areas characterized by average precipitation endowment Asia

Pentad				P1				P2				P3										
Variable	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max	NotNA	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max
Deforestation	314765	282.607	773.084	0	6	249	25174	314765	1023.676	2021.194	0	55	1144	33328	314765	2018.685	3179.057	0	169	2575	33957	
Degradation	314765	611.36	917.968	0	33	811	15852	314765	1321.282	1922.42	0	113	1828	32448	314765	2004.72	2668.951	0	197	2870	32473	
Yearly cumulative rain	314765	1976.862	380.937	826.622	1693.569	2237.381	3796.8	314765	2102.685	432.459	825.005	1792.705	2396.945	4662.453	314765	2125.805	422.22	893.524	1810.363	2407.953	4493.429	
SPI ≤ -1	314765	0.279	0.449	0	0	1	1	314765	0.186	0.389	0	0	0	0	1	314765	0.131	0.337	0	0	0	1

Pentad				P4				P5				P6										
Variable	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max	NotNA	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max
Deforestation	314765	2913.021	4177.956	0	263	3885	34409	314765	3518.999	4935.472	0	316	4685	34409	377718	3810.676	5392.252	0	325	4976	34402	
Degradation	314765	2275.089	2864.966	0	209	3351	32477	314765	2354.307	2964.513	0	192	3499	32478	377718	2781.12	3395.042	0	198	4246	32599	
Yearly cumulative rain	314765	2217.657	425.794	1082.061	1890.095	2511.534	5004.95	314765	2280.306	482.596	1069.588	1919.708	2582.62	4735.93	377718	2115.317	458.089	728.417	1788.524	2394.099	6057.77	
SPI ≤ -1	314765	0.074	0.262	0	0	0	1	314765	0.077	0.267	0	0	0	1	377718	0.203	0.402	0	0	0	0	1

Pentad				P1				P2				P3										
Variable	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max	NotNA	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max
Deforestation	314695	336.989	1101.37	0	4	236	28485	314695	1390.541	3002.43	0	36	1343	33562	314695	2586.733	4389.84	0	105	3076	34214	
Degradation	314695	759.521	1133.752	0	47	1006	17307	314695	1679.391	2232.776	0	182	2349	30979	314695	2566.293	2991.725	0	401	3659	31024	
Yearly cumulative rain	314695	2994.072	591.558	1262.331	2569.173	3350.828	8319.02	314695	3177.422	712.731	1035.023	2732.356	3599.851	8588.94	314695	3207.99	618.145	1182.363	2789.307	3580.006	8282.38	
SPI ≤ -1	314695	0.26	0.439	0	0	1	1	314695	0.208	0.406	0	0	0	1	314695	0.156	0.363	0	0	0	0	1

Pentad				P4				P5				P6										
Variable	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max	NotNA	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max
Deforestation	314695	3616.307	5536.839	0	146	4674	34400	314695	4450.392	6450.858	0	182	6027	34404	377634	4786.871	6833.125	0	183	6650.75	34410	
Degradation	314695	3070.225	3396.759	0	524	4429	30940	314695	3414.126	3735.705	0	593	4926	30940	377634	4065.422	4233.287	0	760	5986	32564	
Yearly cumulative rain	314695	3403.87	668.288	1685.146	2938.46	3767.755	9732.52	314695	3527.729	773.658	1651.964	2973.022	3927.55	10218.23	377634	3246.917	747.797	1381.146	2733.048	3669.247	10442.64	
SPI ≤ -1	314695	0.057	0.231	0	0	0	1	314695	0.048	0.215	0	0	0	1	377634	0.199	0.399	0	0	0	0	1

Table A10: Summary statistics for areas characterized by high precipitation endowment Asia



### A.1.5 Oceania

Table A11: Summary statistics for areas characterized by low precipitation endowment Oceania

Pentad		P1							P2							P3						
Variable	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max	NotNA	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max
Deforestation	41370	75.821	265.757	0	0	30	6530	41370	162.171	480.176	0	2	89	10271	41370	269.692	730.49	0	5	178	12869	
Degradation	41370	117.85	428	0	0	41	11567	41370	211.307	686.98	0	1	87	11581	41370	318.637	921.416	0	1	156	12294	
Yearly cumulative rain	41370	1042.665	365.302	83.678	777.784	1277.836	2670.815	41370	1257.737	420.767	63.846	947.058	1570.954	2932.851	41370	1155.343	455.714	71.086	783.45	1505.825	2862.754	
SPI $\leq -1$	41370	0.28	0.449	0	0	1	1	41370	0.025	0.157	0	0	0	1	41370	0.207	0.405	0	0	0	0	

Pentad		P4							P5							P6						
Variable	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max	NotNA	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max
Deforestation	41370	355.416	907.374	0	7	269	19574	41370	393.762	999.333	0	8	304	20051	49644	406.257	1059.325	0	8	316.25	20260	
Degradation	41370	438.018	1143.486	0	0	254.75	12448	41370	454.152	1210.079	0	0	253	16874	49644	558.787	1602.918	0	0	288	24640	
Yearly cumulative rain	41370	1219.63	415.068	69.913	933.193	1495.899	2684.665	41370	1316.336	460.644	79.626	983.252	1607.862	3324.104	49644	1046.256	330.464	97.024	805.368	1292.908	2342.47	
SPI $\leq -1$	41370	0.092	0.289	0	0	0	1	41370	0.051	0.22	0	0	0	1	49644	0.211	0.408	0	0	0	0	

Table A12: Summary statistics for areas characterized by average precipitation endowment Oceania

Pentad		P1							P2							P3						
Variable	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max	NotNA	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max
Deforestation	41310	161.559	420.291	0	1	133	12705	41310	487.435	962.842	0	5	537	14528	41310	813.475	1433.662	0	22	976	20567	
Degradation	41310	432.396	766.978	0	32	524	14537	41310	1148.258	1827.189	0	81	1466	23827	41310	1900.157	2418.67	0	250	2652	24135	
Yearly cumulative rain	41310	1999.661	449.117	930.31	1656.728	2310.204	4397.1	41310	2189.059	471.102	908.795	1856.182	2495.007	4175.87	41310	2080.544	464.432	703.851	1754.568	2380.07	4378.913	
SPI $\leq -1$	41310	0.257	0.437	0	0	1	1	41310	0.205	0.404	0	0	0	1	41310	0.187	0.39	0	0	0	0	

Pentad		P4							P5							P6						
Variable	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max	NotNA	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max
Deforestation	41310	950.849	1564.1	0	42	1197	20274	41310	1088.253	1741.903	0	65	1359	19963	49572	1010.077	1586.143	0	76	1259	20075	
Degradation	41310	2296.822	2641.095	0	411.25	3267	24216	41310	2575.963	2883.968	0	522	3588	26796	49572	3435.456	3649.459	0	789	4772	30405	
Yearly cumulative rain	41310	2212.933	424.244	889.124	1905.578	2511.419	4025.574	41310	2307.221	480.221	1146.135	1945.066	2610.152	4155.973	49572	2036.409	418.628	827.874	1729.248	2343.352	3712.66	
SPI $\leq -1$	41310	0.031	0.172	0	0	0	1	41310	0.042	0.2	0	0	0	1	49572	0.193	0.395	0	0	0	0	

Table A13: Summary statistics for areas characterized by high precipitation endowment Oceania

Pentad		P1							P2							P3						
Variable	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max	NotNA	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max
Deforestation	41390	58.424	228.753	0	0	21	11443	41390	200.76	589.365	0	0	97	12602	41390	379.808	1022.021	0	2	199	13388	
Degradation	41390	277.526	589.563	0	15	264	14383	41390	706.88	1572.078	0	30	595	23955	41390	1332.207	2209.618	0	108	1498.75	23942	
Yearly cumulative rain	41390	3530.272	883.89	1425.475	2819.893	4124.558	7072.23	41390	3416.827	902.715	1282.287	2808.492	3922.104	7513.51	41390	3454.004	746.116	1405.03	2896.511	3914.402	7170.06	
SPI $\leq -1$	41390	0.165	0.371	0	0	0	1	41390	0.299	0.458	0	0	1	41390	0.153	0.36	0	0	0	0	0	

Pentad		P4							P5							P6						
Variable	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max	NotNA	NotNA	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max
Deforestation	41390	434.308	1170.039	0	4	233	16344	41390	520.842	1319.988	0	8	349	19792	49668	514.682	1326.814	0	13	368	22932	
Degradation	41390	1661.051	2458.432	0	182	2042	23765	41390	1967.142	2687.815	0	273	2532	23954	49668	2766.777	3359.379	0	506	3713	26015	
Yearly cumulative rain	41390	3705.371	824.147	1773.22	3094.065	4187.66	7248.54	41390	3781.314	888.924	1708.83	3157.065	4242.716	8159.54	49668	3460.577	784.685	1580.603	2893.688	3942.202	6844.47	
SPI $\leq -1$	41390	0.046	0.21	0	0	0	1	41390	0.058	0.235	0	0	0	1	49668	0.185	0.388	0	0	0	0	

## A.2 Deforestation

### A.2.1 Global and regional 1990-2020

#### Global by pentades

Table A14: Deforestation response to droughts at global level by pentads

	<i>Dependent variable:</i>					
	Deforestation					
Sub-basin Pentad	(1) Global 1990-1994	(2) Global 1995-1999	(3) Global 2000-2004	(4) Global 2005-2009	(5) Global 2010-2014	(6) Global 2015-2020
Year SPI $\leq$ -1	0.075*** (0.009)	0.025*** (0.008)	0.001 (0.007)	0.008*** (0.002)	0.010*** (0.003)	-0.005* (0.003)
Time and pixel FE	Yes	Yes	Yes	Yes	Yes	
Observations	4,426,015	4,426,015	4,426,015	4,426,015	4,426,015	5,311,218
R <sup>2</sup>	0.949	0.969	0.973	0.995	0.995	0.992
Adjusted R <sup>2</sup>	0.936	0.962	0.967	0.994	0.994	0.991
Residual Std. Error	0.602	0.510	0.469	0.203	0.206	0.247
	(df = 3540807)	(df = 3540807)	(df = 3540807)	(df = 3540807)	(df = 3540807)	(df = 4426009)

*Note:* \* p<0.1; \*\* p<0.05; \*\*\* p<0.01

Regional by pentades

Table A15: Deforestation response to droughts in Africa by pentads

		<i>Dependent variable:</i>					
		Deforestation					
Sub-basin Period	(1) Africa 1990-1994	(2) Africa 1995-1999	(3) Africa 2000-2004	(4) Africa 2005-2009	(5) Africa 2010-2014	(6) Africa 2015-2020	
Year SPI $\leq$ -1	0.064** (0.029)	-0.006 (0.031)	0.028 (0.018)	0.034*** (0.006)	0.006 (0.008)	-0.020*** (0.005)	
Time and pixel FE	Yes	Yes	Yes	Yes	Yes		
Observations	1,223,505	1,223,505	1,223,505	1,223,505	1,223,505	1,468,206	
R <sup>2</sup>	0.886	0.948	0.950	0.993	0.993	0.994	
Adjusted R <sup>2</sup>	0.858	0.935	0.937	0.991	0.991	0.993	
Residual Std. Error	0.631 (df = 978799)	0.583 (df = 978799)	0.605 (df = 978799)	0.228 (df = 978799)	0.236 (df = 978799)	0.212 (df = 1223499)	

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table A16: Deforestation response to droughts in Americas by pentads

		<i>Dependent variable:</i>					
		Deforestation					
Sub-basin Period	(1) Americas 1990-1994	(2) Americas 1995-1999	(3) Americas 2000-2004	(4) Americas 2005-2009	(5) Americas 2010-2014	(6) Americas 2015-2020	
Year SPI $\leq$ -1m	0.065*** (0.007)	0.001 (0.006)	-0.006 (0.004)	0.007*** (0.003)	0.013*** (0.004)	-0.003 (0.003)	
Time and pixel FE	Yes	Yes	Yes	Yes	Yes		
Observations	2,031,490	2,031,490	2,031,490	2,031,490	2,031,490	2,437,788	
R <sup>2</sup>	0.966	0.972	0.983	0.995	0.996	0.991	
Adjusted R <sup>2</sup>	0.958	0.965	0.979	0.994	0.994	0.989	
Residual Std. Error	0.492 (df = 1625187)	0.473 (df = 1625187)	0.373 (df = 1625187)	0.193 (df = 1625187)	0.189 (df = 1625187)	0.255 (df = 2031484)	

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table A17: Deforestation response to droughts in Asia by pentads

		<i>Dependent variable:</i>					
		Deforestation					
Sub-basin Period	(1) Asia 1990-1994	(2) Asia 1995-1999	(3) Asia 2000-2004	(4) Asia 2005-2009	(5) Asia 2010-2014	(6) Asia 2015-2020	
Year SPI $\leq$ -1	0.031** (0.013)	0.022*** (0.007)	0.028*** (0.008)	-0.009*** (0.003)	-0.005 (0.005)	-0.014*** (0.004)	
Time and pixel FE	Yes	Yes	Yes	Yes	Yes		
Observations	944,270	944,270	944,270	944,270	944,270	1,133,124	
R <sup>2</sup>	0.930	0.969	0.981	0.997	0.996	0.993	
Adjusted R <sup>2</sup>	0.913	0.961	0.976	0.996	0.995	0.992	
Residual Std. Error	0.716 (df = 755411)	0.499 (df = 755411)	0.394 (df = 755411)	0.172 (df = 755411)	0.183 (df = 755411)	0.241 (df = 944264)	

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table A18: Deforestation response to droughts in Oceania by pentads

		<i>Dependent variable:</i>					
		Deforestation					
Sub-basin Period	(1) Oceania 1990-1994	(2) Oceania 1995-1999	(3) Oceania 2000-2004	(4) Oceania 2005-2009	(5) Oceania 2010-2014	(6) Oceania 2015-2020	
Year SPI $\leq$ -1	0.150*** (0.033)	0.100*** (0.027)	-0.075*** (0.026)	0.069*** (0.020)	-0.033 (0.021)	0.050*** (0.011)	
Time and pixel FE	Yes	Yes	Yes	Yes	Yes		
Observations	124,070	124,070	124,070	124,070	124,070	148,884	
R <sup>2</sup>	0.928	0.979	0.965	0.992	0.990	0.979	
Adjusted R <sup>2</sup>	0.910	0.973	0.956	0.990	0.988	0.975	
Residual Std. Error	0.661 (df = 99251)	0.412 (df = 99251)	0.520 (df = 99251)	0.239 (df = 99251)	0.259 (df = 99251)	0.357 (df = 124064)	

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

**A.2.2 Regional by pentads and rainfall endowment**  
**Africa**

Table A19: Deforestation response to droughts in Africa in areas with low cumulative rainfalls

<i>Dependent variable:</i>						
Deforestation						
	(1)	(2)	(3)	(4)	(5)	(6)
Sub-basin	Africa	Africa	Africa	Africa	Africa	Africa
Period	1990-1994	1995-1999	2000-2004	2005-2009	2010-2014	2015-2020
Rain	Low	Low	Low	Low	Low	Low
Year SPI $\leq$ -1	0.157*** (0.030)	0.023 (0.028)	0.013 (0.012)	0.036*** (0.006)	0.008*** (0.003)	-0.005** (0.002)
Observations	408,220	408,220	408,220	408,220	408,220	489,864
R <sup>2</sup>	0.834	0.939	0.969	0.997	0.998	0.998
Adjusted R <sup>2</sup>	0.793	0.924	0.961	0.996	0.998	0.998
Residual Std. Error	0.709 (df = 326571)	0.591 (df = 326571)	0.435 (df = 326571)	0.148 (df = 326571)	0.115 (df = 326571)	0.103 (df = 408214)

*Note:* \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table A20: Deforestation response to droughts in Africa in areas with middle cumulative rainfalls

<i>Dependent variable:</i>						
Deforestation						
	(1)	(2)	(3)	(4)	(5)	(6)
Sub-basin	Africa	Africa	Africa	Africa	Africa	Africa
Period	1990-1994	1995-1999	2000-2004	2005-2009	2010-2014	2015-2020
Rain	Mid	Mid	Mid	Mid	Mid	Mid
Year SPI $\leq$ -1	0.035 (0.046)	-0.111** (0.050)	-0.002 (0.027)	0.020*** (0.007)	0.020** (0.008)	-0.022*** (0.005)
Observations	407,685	407,685	407,685	407,685	407,685	489,222
R <sup>2</sup>	0.901	0.953	0.942	0.994	0.994	0.996
Adjusted R <sup>2</sup>	0.877	0.941	0.928	0.992	0.992	0.995
Residual Std. Error	0.620 (df = 326143)	0.581 (df = 326143)	0.617 (df = 326143)	0.195 (df = 326143)	0.197 (df = 326143)	0.156 (df = 407679)

*Note:* \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table A21: Deforestation response to droughts in Africa in areas with high cumulative rainfalls

<i>Dependent variable:</i>						
Deforestation						
	(1)	(2)	(3)	(4)	(5)	(6)
Sub-basin	Africa	Africa	Africa	Africa	Africa	Africa
Period	1990-1994	1995-1999	2000-2004	2005-2009	2010-2014	2015-2020
Rain	High	High	High	High	High	High
Year SPI $\leq$ -1	-0.088*** (0.025)	0.104** (0.045)	0.010 (0.035)	0.018 (0.011)	-0.018 (0.011)	-0.024*** (0.009)
Observations	407,600	407,600	407,600	407,600	407,600	489,120
R <sup>2</sup>	0.927	0.948	0.944	0.991	0.989	0.987
Adjusted R <sup>2</sup>	0.908	0.935	0.930	0.988	0.986	0.985
Residual Std. Error	0.499 (df = 326075)	0.568 (df = 326075)	0.697 (df = 326075)	0.290 (df = 326075)	0.312 (df = 326075)	0.308 (df = 407594)

*Note:* \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Americas

Table A22: Deforestation response to droughts in America in areas with low cumulative rainfalls

Sub-basin Period Rain	Dependent variable:					
	Deforestation					
	(1) Americas 1990-1994 Low	(2) Americas 1995-1999 Low	(3) Americas 2000-2004 Low	(4) Americas 2005-2009 Low	(5) Americas 2010-2014 Low	(6) Americas 2015-2020 Low
Year SPI $\leq$ -1	0.072*** (0.011)	-0.033*** (0.013)	0.027*** (0.004)	0.007** (0.003)	0.016*** (0.002)	0.023*** (0.003)
Observations	676,785	676,785	676,785	676,785	676,785	812,142
R <sup>2</sup>	0.961	0.968	0.991	0.998	0.999	0.997
Adjusted R <sup>2</sup>	0.952	0.960	0.988	0.998	0.999	0.997
Residual Std. Error	0.492 (df = 541423)	0.447 (df = 541423)	0.238 (df = 541423)	0.101 (df = 541423)	0.086 (df = 541423)	0.136 (df = 676779)

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table A23: Deforestation response to droughts in America in areas with middle cumulative rainfalls

Sub-basin Period Rain	Dependent variable:					
	Deforestation					
	(1) Americas 1990-1994 Mid	(2) Americas 1995-1999 Mid	(3) Americas 2000-2004 Mid	(4) Americas 2005-2009 Mid	(5) Americas 2010-2014 Mid	(6) Americas 2015-2020 Mid
Year SPI $\leq$ -1	0.070*** (0.009)	0.005 (0.008)	-0.017*** (0.007)	0.013*** (0.003)	0.019*** (0.004)	-0.0002 (0.004)
Observations	677,305	677,305	677,305	677,305	677,305	812,766
R <sup>2</sup>	0.964	0.971	0.984	0.995	0.995	0.992
Adjusted R <sup>2</sup>	0.954	0.963	0.980	0.994	0.994	0.990
Residual Std. Error	0.480 (df = 541839)	0.449 (df = 541839)	0.322 (df = 541839)	0.180 (df = 541839)	0.168 (df = 541839)	0.209 (df = 677299)

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table A24: Deforestation response to droughts in America in areas with high cumulative rainfalls

Sub-basin Period Rain	Dependent variable:					
	Deforestation					
	(1) Americas 1990-1994 High	(2) Americas 1995-1999 High	(3) Americas 2000-2004 High	(4) Americas 2005-2009 High	(5) Americas 2010-2014 High	(6) Americas 2015-2020 High
Year SPI $\leq$ -1	0.040*** (0.014)	0.026** (0.013)	-0.023** (0.010)	0.008 (0.006)	0.008 (0.010)	-0.010** (0.005)
Observations	677,400	677,400	677,400	677,400	677,400	812,880
R <sup>2</sup>	0.967	0.972	0.976	0.994	0.993	0.986
Adjusted R <sup>2</sup>	0.958	0.964	0.970	0.992	0.992	0.983
Residual Std. Error	0.496 (df = 541915)	0.517 (df = 541915)	0.504 (df = 541915)	0.259 (df = 541915)	0.261 (df = 541915)	0.360 (df = 677394)

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Asia

Table A25: Deforestation response to droughts in Asia in areas with low cumulative rainfalls

Sub-basin Period Rain	Dependent variable:					
	Deforestation					
	(1) Asia 1990-1994 Low	(2) Asia 1995-1999 Low	(3) Asia 2000-2004 Low	(4) Asia 2005-2009 Low	(5) Asia 2010-2014 Low	(6) Asia 2015-2020 Low
Year SPI $\leq$ -1	0.001 (0.010)	-0.020** (0.009)	-0.003 (0.009)	-0.003 (0.003)	0.005** (0.002)	0.002 (0.003)
Observations	314,810	314,810	314,810	314,810	314,810	377,772
R <sup>2</sup>	0.945	0.981	0.984	0.999	0.999	0.996
Adjusted R <sup>2</sup>	0.932	0.976	0.980	0.999	0.999	0.995
Residual Std. Error	0.602 (df = 251843)	0.364 (df = 251843)	0.344 (df = 251843)	0.084 (df = 251843)	0.080 (df = 251843)	0.190 (df = 314804)

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table A26: Deforestation response to droughts in Asia in areas with middle cumulative rainfalls

Sub-basin Period Rain	Dependent variable:					
	Deforestation					
	(1) Asia 1990-1994 Mid	(2) Asia 1995-1999 Mid	(3) Asia 2000-2004 Mid	(4) Asia 2005-2009 Mid	(5) Asia 2010-2014 Mid	(6) Asia 2015-2020 Mid
Year SPI $\leq$ -1	0.007 (0.022)	0.030*** (0.011)	0.073*** (0.013)	0.005** (0.003)	-0.023*** (0.007)	-0.037*** (0.006)
Observations	314,765	314,765	314,765	314,765	314,765	377,718
R <sup>2</sup>	0.912	0.952	0.970	0.996	0.995	0.991
Adjusted R <sup>2</sup>	0.889	0.940	0.963	0.995	0.994	0.989
Residual Std. Error	0.757 (df = 251807)	0.551 (df = 251807)	0.409 (df = 251807)	0.150 (df = 251807)	0.170 (df = 251807)	0.227 (df = 314759)

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table A27: Deforestation response to droughts in Asia in areas with high cumulative rainfalls

Sub-basin Period Rain	Dependent variable:					
	Deforestation					
	(1) Asia 1990-1994 High	(2) Asia 1995-1999 High	(3) Asia 2000-2004 High	(4) Asia 2005-2009 High	(5) Asia 2010-2014 High	(6) Asia 2015-2020 High
Year SPI $\leq$ -1	0.071*** (0.021)	0.037*** (0.011)	0.004 (0.015)	0.006 (0.007)	-0.015 (0.014)	-0.011 (0.008)
Observations	314,695	314,695	314,695	314,695	314,695	377,634
R <sup>2</sup>	0.920	0.963	0.978	0.993	0.992	0.989
Adjusted R <sup>2</sup>	0.900	0.953	0.973	0.991	0.990	0.986
Residual Std. Error	0.752 (df = 251751)	0.551 (df = 251751)	0.416 (df = 251751)	0.241 (df = 251751)	0.251 (df = 251751)	0.293 (df = 314689)

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Oceania

Table A28: Deforestation response to droughts in Oceania in areas with low cumulative rainfalls

Sub-basin Period Rain	Dependent variable:					
	Deforestation					
	(1) Oceania 1990-1994 Low	(2) Oceania 1995-1999 Low	(3) Oceania 2000-2004 Low	(4) Oceania 2005-2009 Low	(5) Oceania 2010-2014 Low	(6) Oceania 2015-2020 Low
Year SPI $\leq$ -1	0.267*** (0.056)	0.085** (0.037)	0.005 (0.035)	0.049*** (0.007)	-0.002 (0.004)	0.024*** (0.009)
Observations	41,370	41,370	41,370	41,370	41,370	49,644
R <sup>2</sup>	0.913	0.987	0.969	0.997	0.998	0.995
Adjusted R <sup>2</sup>	0.892	0.984	0.961	0.996	0.998	0.994
Residual Std. Error	0.677 (df = 33091)	0.271 (df = 33091)	0.427 (df = 33091)	0.135 (df = 33091)	0.098 (df = 33091)	0.173 (df = 41364)

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table A29: Deforestation response to droughts in Oceania in areas with middle cumulative rainfalls

Sub-basin Period Rain	Dependent variable:					
	Deforestation					
	(1) Oceania 1990-1994 Mid	(2) Oceania 1995-1999 Mid	(3) Oceania 2000-2004 Mid	(4) Oceania 2005-2009 Mid	(5) Oceania 2010-2014 Mid	(6) Oceania 2015-2020 Mid
Year SPI $\leq$ -1	0.115** (0.045)	0.135*** (0.032)	-0.048 (0.036)	0.042 (0.026)	-0.057 (0.053)	0.040** (0.017)
Observations	41,310	41,310	41,310	41,310	41,310	49,572
R <sup>2</sup>	0.924	0.976	0.965	0.992	0.990	0.978
Adjusted R <sup>2</sup>	0.905	0.970	0.956	0.990	0.987	0.974
Residual Std. Error	0.711 (df = 33043)	0.444 (df = 33043)	0.515 (df = 33043)	0.232 (df = 33043)	0.251 (df = 33043)	0.327 (df = 41304)

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table A30: Deforestation response to droughts in Oceania in areas with high cumulative rainfalls

Sub-basin Period Rain	Dependent variable:					
	Deforestation					
	(1) Oceania 1990-1994 High	(2) Oceania 1995-1999 High	(3) Oceania 2000-2004 High	(4) Oceania 2005-2009 High	(5) Oceania 2010-2014 High	(6) Oceania 2015-2020 High
Year SPI $\leq$ -1	-0.020 (0.044)	0.046 (0.046)	-0.098* (0.051)	0.076 (0.049)	0.024 (0.040)	0.113*** (0.026)
Observations	41,390	41,390	41,390	41,390	41,390	49,668
R <sup>2</sup>	0.945	0.971	0.956	0.987	0.983	0.959
Adjusted R <sup>2</sup>	0.931	0.964	0.945	0.984	0.979	0.951
Residual Std. Error	0.526 (df = 33107)	0.480 (df = 33107)	0.588 (df = 33107)	0.312 (df = 33107)	0.348 (df = 33107)	0.486 (df = 41384)

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

A.2.3 Drought intensity

Table A31: Global and continental deforestation response with respect to drought intensity

Sub-basin	Dependent variable:				
	Deforestation				
	(1)	(2)	(3)	(4)	(5)
	Global	Africa	Americas	Asia	Oceania
-1 < SPI ≤ -0.5	0.018*** (0.005)	0.051*** (0.012)	-0.002 (0.006)	-0.016* (0.009)	-0.006 (0.021)
-1.5 < SPI ≤ -1	0.037*** (0.007)	0.059*** (0.019)	0.010 (0.009)	0.008 (0.012)	0.041 (0.033)
-2 < SPI ≤ -1.5	0.078*** (0.010)	0.050** (0.025)	0.051*** (0.014)	0.071*** (0.013)	0.095** (0.038)
SPI ≤ -2	0.102*** (0.024)	-0.069 (0.052)	0.076** (0.032)	0.157*** (0.021)	0.078 (0.059)
Time and pixel FE	Yes	Yes	Yes	Yes	Yes
Observations	27,441,293	7,585,731	12,595,238	5,854,474	769,234
R <sup>2</sup>	0.865	0.822	0.890	0.887	0.870
Adjusted R <sup>2</sup>	0.860	0.816	0.886	0.884	0.866
Residual Std. Error	1.025 (df = 26556056)	1.166 (df = 7340996)	0.892 (df = 12188906)	0.946 (df = 5665586)	0.921 (df = 744386)

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

A.2.4 Protected areas and indigenous lands

Table A32: Effect of Indigenous Peoples' Lands in dry periods by pentad at global scale

Sub-basin	Dependent variable:					
	Deforestation					
Period	(1)	(2)	(3)	(4)	(5)	(6)
	Global	Global	Global	Global	Global	Global
	1990-1994	1995-1999	2000-2004	2005-2009	2010-2014	2015-2020
Year SPI ≤ -1	0.074*** (0.010)	0.020** (0.009)	-0.008 (0.007)	0.012*** (0.003)	0.012*** (0.003)	-0.001 (0.003)
Drought * IL	0.005 (0.015)	0.022* (0.013)	0.040*** (0.011)	-0.014*** (0.004)	-0.009 (0.007)	-0.015*** (0.005)
Time and pixel FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,426,015	4,426,015	4,426,015	4,426,015	4,426,015	5,311,218
R <sup>2</sup>	0.949	0.969	0.973	0.995	0.995	0.992
Adjusted R <sup>2</sup>	0.936	0.962	0.967	0.994	0.994	0.991
Residual Std. Error	0.602 (df = 3540806)	0.510 (df = 3540806)	0.469 (df = 3540806)	0.203 (df = 3540806)	0.206 (df = 3540806)	0.247 (df = 4426008)

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table A33: Effect of protected areas in dry periods by pentad at global scale

Sub-basin	Dependent variable:					
	Deforestation					
Period	(1)	(2)	(3)	(4)	(5)	(6)
	Global	Global	Global	Global	Global	Global
	1990-1994	1995-1999	2000-2004	2005-2009	2010-2014	2015-2020
Year SPI ≤ -1	0.082*** (0.010)	0.023*** (0.009)	0.002 (0.007)	0.005** (0.002)	0.010*** (0.003)	-0.001 (0.002)
Drought * PA	-0.037*** (0.012)	0.011 (0.010)	-0.003 (0.011)	0.016*** (0.004)	-0.0001 (0.008)	-0.021*** (0.004)
Time and pixel FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,426,015	4,426,015	4,426,015	4,426,015	4,426,015	5,311,218
R <sup>2</sup>	0.949	0.969	0.973	0.995	0.995	0.992
Adjusted R <sup>2</sup>	0.936	0.962	0.967	0.994	0.994	0.991
Residual Std. Error	0.602 (df = 3540806)	0.510 (df = 3540806)	0.469 (df = 3540806)	0.203 (df = 3540806)	0.206 (df = 3540806)	0.247 (df = 4426008)

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01



Table A34: Effect of PA on deforestation drought-response at global and continental scale (1990-2020)

<i>Dependent variable:</i>					
Deforestation					
Sub-basin	(1) Global	(2) Africa	(3) Americas	(4) Asia	(5) Oceania
Year SPI $\leq$ -1	0.045*** (0.007)	0.026 (0.020)	0.020** (0.009)	0.046*** (0.010)	0.061** (0.029)
Drought * PA	0.031** (0.015)	0.038 (0.024)	0.032 (0.024)	-0.049*** (0.015)	-0.015 (0.031)
Time and pixel FE	Yes	Yes	Yes	Yes	Yes
Observations	27,441,293	7,585,731	12,595,238	5,854,474	769,234
R <sup>2</sup>	0.865	0.822	0.890	0.887	0.870
Adjusted R <sup>2</sup>	0.860	0.816	0.886	0.884	0.866
Residual Std. Error	1.025 (df = 26556058)	1.167 (df = 7340998)	0.893 (df = 12188908)	0.946 (df = 5665588)	0.921 (df = 744388)

Note: \* p<0.1; \*\* p<0.05; \*\*\* p<0.01

Table A35: Effect of IPL on deforestation drought-response at global and continental scale

<i>Dependent variable:</i>					
Deforestation					
Sub-basin	(1) Global	(2) Africa	(3) Americas	(4) Asia	(5) Oceania
Year SPI $\leq$ -1	0.046*** (0.008)	0.020 (0.022)	0.025*** (0.010)	0.040*** (0.013)	0.037 (0.035)
Drought * IPL	0.019 (0.012)	0.059** (0.030)	0.013 (0.021)	0.0002 (0.015)	0.078* (0.045)
Time and pixel FE	Yes	Yes	Yes	Yes	Yes
Observations	27,441,293	7,585,731	12,595,238	5,854,474	769,234
R <sup>2</sup>	0.865	0.822	0.890	0.887	0.870
Adjusted R <sup>2</sup>	0.860	0.816	0.886	0.884	0.866
Residual Std. Error	1.025 (df = 26556058)	1.167 (df = 7340998)	0.893 (df = 12188908)	0.946 (df = 5665588)	0.921 (df = 744388)

Note: \* p<0.1; \*\* p<0.05; \*\*\* p<0.01

Table A36: Africa, effect of PA on deforestation drought-response by pentad

		<i>Dependent variable:</i>					
		Deforestation					
Sub-basin	(1)	(2)	(3)	(4)	(5)	(6)	
Period	Africa	Africa	Africa	Africa	Africa	Africa	
	1990-1994	1995-1999	2000-2004	2005-2009	2010-2014	2015-2020	
Year SPI $\leq$ -1	0.082*** (0.030)	-0.026 (0.031)	0.030 (0.019)	0.028*** (0.006)	0.002 (0.009)	-0.020*** (0.005)	
Drought * PA	-0.114*** (0.036)	0.136*** (0.038)	-0.013 (0.028)	0.035*** (0.009)	0.029** (0.012)	-0.004 (0.008)	
Time and pixel FE	Yes	Yes	Yes	Yes	Yes		
Observations	1,223,505	1,223,505	1,223,505	1,223,505	1,223,505	1,468,206	
R <sup>2</sup>	0.886	0.948	0.950	0.993	0.993	0.994	
Adjusted R <sup>2</sup>	0.858	0.935	0.937	0.991	0.991	0.993	
Residual Std. Error	0.631 (df = 978798)	0.583 (df = 978798)	0.605 (df = 978798)	0.228 (df = 978798)	0.236 (df = 978798)	0.212 (df = 1223498)	

*Note:* \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table A37: Africa, effect of IPL on deforestation drought-response by pentad

		<i>Dependent variable:</i>					
		Deforestation					
Sub-basin	(1)	(2)	(3)	(4)	(5)	(6)	
Period	Africa	Africa	Africa	Africa	Africa	Africa	
	1990-1994	1995-1999	2000-2004	2005-2009	2010-2014	2015-2020	
Year SPI $\leq$ -1	0.065* (0.034)	-0.004 (0.035)	0.026 (0.020)	0.040*** (0.007)	0.010 (0.008)	-0.021*** (0.005)	
Drought * IPL	-0.006 (0.045)	-0.012 (0.062)	0.008 (0.026)	-0.029** (0.013)	-0.016 (0.015)	0.005 (0.007)	
Time and pixel FE	Yes	Yes	Yes	Yes	Yes		
Observations	1,223,505	1,223,505	1,223,505	1,223,505	1,223,505	1,468,206	
R <sup>2</sup>	0.886	0.948	0.950	0.993	0.993	0.994	
Adjusted R <sup>2</sup>	0.858	0.935	0.937	0.991	0.991	0.993	
Residual Std. Error	0.631 (df = 978798)	0.583 (df = 978798)	0.605 (df = 978798)	0.228 (df = 978798)	0.236 (df = 978798)	0.212 (df = 1223498)	

*Note:* \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table A38: Americas, effect of PA on deforestation drought-response by pentad

		<i>Dependent variable:</i>					
		Deforestation					
Sub-basin	(1)	(2)	(3)	(4)	(5)	(6)	
Period	Americas	Americas	Americas	Americas	Americas	Americas	
	1990-1994	1995-1999	2000-2004	2005-2009	2010-2014	2015-2020	
Year SPI $\leq$ -1	0.069*** (0.007)	-0.006 (0.007)	-0.008* (0.004)	0.005 (0.003)	0.017*** (0.004)	0.002 (0.003)	
Drought * PA	-0.016 (0.012)	0.025** (0.010)	0.009 (0.007)	0.014** (0.006)	-0.017 (0.013)	-0.022*** (0.006)	
Time and pixel FE	Yes	Yes	Yes	Yes	Yes		
Observations	2,031,490	2,031,490	2,031,490	2,031,490	2,031,490	2,437,788	
R <sup>2</sup>	0.966	0.972	0.983	0.995	0.996	0.991	
Adjusted R <sup>2</sup>	0.958	0.965	0.979	0.994	0.994	0.990	
Residual Std. Error	0.492 (df = 1625186)	0.473 (df = 1625186)	0.373 (df = 1625186)	0.193 (df = 1625186)	0.189 (df = 1625186)	0.255 (df = 2031483)	

*Note:* \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table A39: Americas, effect of IPL on deforestation drought-response by pentad

<i>Dependent variable:</i>						
Deforestation						
Sub-basin Period	(1) Americas 1990-1994	(2) Americas 1995-1999	(3) Americas 2000-2004	(4) Americas 2005-2009	(5) Americas 2010-2014	(6) Americas 2015-2020
Year SPI $\leq$ -1	0.063*** (0.007)	-0.001 (0.006)	-0.011*** (0.004)	0.007** (0.003)	0.014*** (0.003)	0.002 (0.003)
Drought * IPL	0.008 (0.013)	0.012 (0.010)	0.033*** (0.008)	0.002 (0.006)	-0.007 (0.016)	-0.025*** (0.007)
Time and pixel FE	Yes	Yes	Yes	Yes	Yes	
Observations	2,031,490	2,031,490	2,031,490	2,031,490	2,031,490	2,437,788
R <sup>2</sup>	0.966	0.972	0.983	0.995	0.996	0.991
Adjusted R <sup>2</sup>	0.958	0.965	0.979	0.994	0.994	0.990
Residual Std. Error	0.492 (df = 1625186)	0.473 (df = 1625186)	0.373 (df = 1625186)	0.193 (df = 1625186)	0.189 (df = 1625186)	0.255 (df = 2031483)

*Note:* \* p<0.1; \*\* p<0.05; \*\*\* p<0.01

Table A40: Asia, effect of PA on deforestation drought-response by pentad

<i>Dependent variable:</i>						
Deforestation						
Sub-basin Period	(1) Asia 1990-1994	(2) Asia 1995-1999	(3) Asia 2000-2004	(4) Asia 2005-2009	(5) Asia 2010-2014	(6) Asia 2015-2020
Year SPI $\leq$ -1	0.036*** (0.013)	0.029*** (0.007)	0.028*** (0.008)	-0.009*** (0.003)	-0.006 (0.005)	-0.011*** (0.004)
Drought * PA	-0.041** (0.018)	-0.058*** (0.012)	0.001 (0.012)	-0.002 (0.007)	0.008 (0.008)	-0.028*** (0.007)
Time and pixel FE	Yes	Yes	Yes	Yes	Yes	
Observations	944,270	944,270	944,270	944,270	944,270	1,133,124
R <sup>2</sup>	0.930	0.969	0.981	0.997	0.996	0.993
Adjusted R <sup>2</sup>	0.913	0.961	0.976	0.996	0.995	0.992
Residual Std. Error	0.716 (df = 755410)	0.499 (df = 755410)	0.394 (df = 755410)	0.172 (df = 755410)	0.183 (df = 755410)	0.241 (df = 944263)

*Note:* \* p<0.1; \*\* p<0.05; \*\*\* p<0.01

Table A41: Asia, effect of IPL on deforestation drought-response by pentad

<i>Dependent variable:</i>						
Deforestation						
Sub-basin Period	(1) Asia 1990-1994	(2) Asia 1995-1999	(3) Asia 2000-2004	(4) Asia 2005-2009	(5) Asia 2010-2014	(6) Asia 2015-2020
Year SPI $\leq$ -1	0.022 (0.014)	0.016** (0.008)	0.011 (0.007)	-0.005 (0.003)	-0.006 (0.004)	-0.010*** (0.003)
Drought * IPL	0.022 (0.021)	0.013 (0.009)	0.043*** (0.013)	-0.008* (0.005)	0.003 (0.008)	-0.011 (0.007)
Time and pixel FE	Yes	Yes	Yes	Yes	Yes	
Observations	944,270	944,270	944,270	944,270	944,270	1,133,124
R <sup>2</sup>	0.930	0.969	0.981	0.997	0.996	0.993
Adjusted R <sup>2</sup>	0.913	0.961	0.976	0.996	0.995	0.992
Residual Std. Error	0.716 (df = 755410)	0.499 (df = 755410)	0.394 (df = 755410)	0.172 (df = 755410)	0.183 (df = 755410)	0.241 (df = 944263)

*Note:* \* p<0.1; \*\* p<0.05; \*\*\* p<0.01

Table A42: Oceania, effect of PA on deforestation drought-response by pentad

	<i>Dependent variable:</i>					
	Deforestation					
	(1)	(2)	(3)	(4)	(5)	(6)
Year SPI $\leq$ -1	0.128*** (0.035)	0.097*** (0.027)	-0.082*** (0.025)	0.080*** (0.022)	-0.037 (0.026)	0.062*** (0.012)
Drought * PA	0.102** (0.049)	0.107 (0.075)	0.042 (0.041)	-0.043** (0.020)	0.020 (0.030)	-0.059*** (0.015)
Sub-basin	Oceania	Oceania	Oceania	Oceania	Oceania	Oceania
Period	1990-1994	1995-1999	2000-2004	2005-2009	2010-2014	2015-2020
Time and pixel FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	124,070	124,070	124,070	124,070	124,070	148,884
R <sup>2</sup>	0.928	0.979	0.965	0.992	0.990	0.979
Adjusted R <sup>2</sup>	0.910	0.973	0.956	0.990	0.988	0.975
Residual Std. Error	0.661 (df = 99250)	0.412 (df = 99250)	0.520 (df = 99250)	0.239 (df = 99250)	0.259 (df = 99250)	0.357 (df = 124063)

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table A43: Oceania, effect of IPL on deforestation drought-response by pentad

	<i>Dependent variable:</i>					
	Deforestation					
	(1)	(2)	(3)	(4)	(5)	(6)
Year SPI $\leq$ -1	0.089** (0.037)	0.100*** (0.027)	-0.090*** (0.029)	0.078*** (0.029)	-0.039 (0.029)	0.071*** (0.014)
Drought * IPL	0.163*** (0.057)	0.049 (0.057)	0.057* (0.032)	-0.018 (0.026)	0.022 (0.034)	-0.065*** (0.018)
Sub-basin	Oceania	Oceania	Oceania	Oceania	Oceania	Oceania
Period	1990-1994	1995-1999	2000-2004	2005-2009	2010-2014	2015-2020
Time and pixel FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	124,070	124,070	124,070	124,070	124,070	148,884
R <sup>2</sup>	0.928	0.979	0.965	0.992	0.990	0.979
Adjusted R <sup>2</sup>	0.910	0.973	0.956	0.990	0.988	0.975
Residual Std. Error	0.660 (df = 99250)	0.412 (df = 99250)	0.520 (df = 99250)	0.239 (df = 99250)	0.259 (df = 99250)	0.357 (df = 124063)

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

### A.3 Degradation

#### A.3.1 Regional by pentads and rainfall endowment

Table A44: Degradation and droughts in areas divided by precipitation quantiles (high, average, low) in: (a) Africa, (b) Americas, (c) Asia, and (d) Oceania.

<b>(a) Africa</b>				<b>(b) Americas</b>			
<i>Dependent variable:</i>				<i>Dependent variable:</i>			
Degradation				Degradation			
	(1) hg	(2) av	(3) lw	(1) hg	(2) av	(3) lw	
Rain							
Year SPI $\leq$ -1	0.013 (0.015)	-0.020 (0.014)	0.020 (0.018)	-0.014* (0.008)	-0.038*** (0.006)	0.012 (0.017)	
Time and pixel FE	Yes	Yes	Yes	Yes	Yes	Yes	
Observations	2,527,120	2,527,647	2,530,964	4,199,880	4,199,291	4,196,067	
R <sup>2</sup>	0.880	0.911	0.906	0.922	0.907	0.927	
Adjusted R <sup>2</sup>	0.876	0.908	0.903	0.919	0.904	0.925	
Residual Std. Error	0.866 (df = 2445569)	0.784 (df = 2446079)	0.809 (df = 2449289)	0.542 (df = 4064369)	0.549 (df = 4063799)	0.768 (df = 4060679)	
<b>(c) Asia</b>				<b>(d) Oceania</b>			
<i>Dependent variable:</i>				<i>Dependent variable:</i>			
Degradation				Degradation			
	(1) hg	(2) av	(3) lw	(1) hg	(2) av	(3) lw	
Rain							
Year SPI $\leq$ -1	0.015 (0.013)	-0.029 (0.018)	-0.004 (0.008)	-0.002 (0.043)	0.047* (0.025)	0.091*** (0.022)	
Time and pixel FE	Yes	Yes	Yes	Yes	Yes	Yes	
Observations	1,951,109	1,951,543	1,951,822	256,618	256,122	256,494	
R <sup>2</sup>	0.882	0.915	0.972	0.885	0.879	0.898	
Adjusted R <sup>2</sup>	0.878	0.912	0.971	0.881	0.875	0.894	
Residual Std. Error	0.721 (df = 1888139)	0.709 (df = 1888559)	0.540 (df = 1888829)	0.726 (df = 248309)	0.752 (df = 247829)	0.860 (df = 248189)	
<i>Note:</i>				*p<0.1; **p<0.05; ***p<0.01			

#### A.3.2 Degradation as a precursor of deforestation

Table A45: Deforestation response to drought and degradation at continental level (1990-2020)

<i>Dependent variable:</i>				
Deforestation				
	(1) Africa	(2) Americas	(3) Asia	(4) Oceania
Sub-basin				
Year $\leq$ -1	-0.232*** (0.056)	0.283*** (0.035)	0.289*** (0.036)	0.235*** (0.042)
Degradation	0.309*** (0.033)	0.734*** (0.022)	0.588*** (0.023)	0.450*** (0.024)
Year SPI $\leq$ -1 * Degradation	0.027*** (0.008)	-0.043*** (0.006)	-0.047*** (0.005)	-0.033*** (0.010)
Time and pixel FE	Yes	Yes	Yes	Yes
Observations	1,896,456	3,148,856	1,463,603	192,293
R <sup>2</sup>	0.863	0.900	0.907	0.837
Adjusted R <sup>2</sup>	0.859	0.896	0.904	0.831
Residual Std. Error	1.077 (df = 1835247)	0.925 (df = 3047247)	0.874 (df = 1416357)	0.929 (df = 186057)
<i>Note:</i>			*p<0.1; **p<0.05; ***p<0.01	

## B Supplementary material to Chapter 3

### B.1 Chapter 3: Descriptive statistics

Table B1: Descriptive statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Forest Cover year 2000 (%)	519,160	86.0358	17.5015	50.0032	71.0436	99.6546	99.9996
Rainfall (mm/y)	519,160	1,691.9000	254.1412	629.4420	1,539.2810	1,842.6380	3,074.1600
Lost hectares	519,160	12.9631	29.1887	0	0	11.3	1,614
Travel time to 50k city (min)	519,160	583.9865	406.9662	13.3611	312.8889	729.1389	3,542.4440
Proximity, travel time j4h (dummy)	519,160	0.1423	0.3494	0	0	0	1
Rainfalls (mm)							
Maize Planting 1	519,160	373.4552	177.9664	29.9399	232.2017	533.5520	1,109.8310
Maize Planting 2	519,160	264.9211	100.1379	4.3111	194.2088	330.7671	902.5035
Maize Growing 1	519,160	710.6152	153.1911	271.5063	595.0576	820.3250	1,459.5060
Maize Growing 2	519,160	769.2537	139.6965	102.9565	682.9990	837.4545	1,588.2320
Maize Harvesting 1	519,160	338.5848	146.4111	2.1306	254.4054	437.2237	877.7123
Maize Harvesting 2	519,160	456.3089	124.5292	109.3898	365.7688	541.7220	1,109.8310
Cassava Planting	519,160	849.0816	139.1017	232.6096	766.8894	933.0655	1,635.3680
Cassava Harvesting	519,160	844.2288	250.0814	111.9972	669.1016	1,016.7890	1,761.0920
SPI							
Maize Planting 1	519,160	-0.0059	0.5942	-2.9203	-0.3855	0.3886	2.6239
Maize Planting 2	519,160	-0.0508	0.5940	-2.4539	-0.4410	0.3471	2.2145
Maize Growing 1	519,160	-0.0218	0.4530	-1.8037	-0.3290	0.2819	1.9149
Maize Growing 2	519,160	-0.0496	0.4631	-2.3159	-0.3497	0.2514	1.8733
Maize Harvesting 1	519,160	-0.0089	0.5841	-2.3795	-0.3895	0.3810	2.3714
Maize Harvesting 2	519,160	-0.0586	0.6319	-3.0377	-0.4641	0.3518	2.7167
Cassava Planting	519,160	-0.0499	0.4354	-2.2637	-0.3311	0.2303	1.8187
Cassava Harvesting	519,160	-0.0401	0.3596	-1.5003	-0.2808	0.1920	1.4081
Current droughts, dummy							
Maize Planting 1	519,160	0.0506	0.2193	0	0	0	1
Maize Planting 2	519,160	0.0568	0.2314	0	0	0	1
Maize Growing 1	519,160	0.0166	0.1278	0	0	0	1
Maize Growing 2	519,160	0.0211	0.1437	0	0	0	1
Maize Harvesting 1	519,160	0.0491	0.2160	0	0	0	1
Maize Harvesting 2	519,160	0.0647	0.2460	0	0	0	1
Cassava Planting	519,160	0.0175	0.1310	0	0	0	1
Cassava Harvesting	519,160	0.0037	0.0607	0	0	0	1
Maize Planting 1,2	519,160	0.1037	0.3048	0	0	0	1
Maize Growing 1,2	519,160	0.0363	0.1870	0	0	0	1
Maize Harvesting 1,2	519,160	0.1087	0.3112	0	0	0	1
All year	519,160	0.1891	0.3916	0	0	0	1
Experienced droughts, dummy							
Maize Planting 1	519,160	0.1422	0.3492	0	0	0	1
Maize Planting 2	519,160	0.1453	0.3524	0	0	0	1
Maize Growing 1	519,160	0.0453	0.2079	0	0	0	1
Maize Growing 2	519,160	0.0587	0.2351	0	0	0	1
Maize Harvesting 1	519,160	0.1313	0.3377	0	0	0	1
Maize Harvesting 2	519,160	0.1757	0.3806	0	0	0	1
Cassava Planting	519,160	0.0492	0.2162	0	0	0	1
Cassava Harvesting	519,160	0.0099	0.0992	0	0	0	1
Maize Planting 1,2	519,160	0.2672	0.4425	0	0	1	1
Maize Growing 1,2	519,160	0.0985	0.2980	0	0	0	1
Maize Harvesting 1,2	519,160	0.2830	0.4504	0	0	1	1
All year	519,160	0.4172	0.4931	0	0	1	1

## B.2 Chapter 3 Main Results

### B.2.1 Experienced droughts, current droughts, seasonality

Table B2: Deforestation and droughts over the main agricultural periods and cycles; experienced and current, yearly aggregation and by season

<i>Dependent variable:</i>					
Log of deforested hectares +1					
Droughts:	(1) Experienced & current yearly aggregation	(2) Experienced, detailed	(3) Current, detailed	(4) Current, aggregated	(5) Experienced, aggregated
Experienced, y	-0.0180 (0.0115)				
Current, y	-0.0005 (0.0110)				
<b>Cassava</b>					
Planting		-0.0182 (0.0255)	0.0605** (0.0250)	0.0569** (0.0249)	-0.0186 (0.0248)
Harvesting		-0.0576 (0.0420)	-0.0886* (0.0519)	-0.0636 (0.0535)	-0.0597 (0.0441)
<b>Maize</b>					
Planting 1		0.0094 (0.0172)	-0.0674*** (0.0187)		
Planting 2		0.0060 (0.0179)	-0.0243 (0.0227)		
Growing 1		-0.0531** (0.0227)	-0.0717*** (0.0275)		
Growing 2		0.0099 (0.0214)	-0.0589** (0.0253)		
Harvesting 1		-0.0352* (0.0192)	0.0915*** (0.0255)		
Harvesting 2		-0.0026 (0.0134)	0.0264* (0.0147)		
Planting 1,2				-0.0304** (0.0136)	0.0150 (0.0172)
Growing 1,2				-0.0689*** (0.0199)	-0.0256* (0.0150)
Harvesting 1,2				0.0592*** (0.0129)	-0.0194* (0.0115)
Observations	519,160	519,160	519,160	519,160	519,160
F Statistic	27.8757*** (df = 2; 493181)	33.7886*** (df = 8; 493175)	69.5683*** (df = 8; 493175)	73.8697*** (df = 5; 493178)	37.6635*** (df = 5; 493178)

Note:

\* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$   
Time and cell fixed effects, clustered at the sector administrative level

## B.3 Chapter 3 Robustness Checks

### B.3.1 Dependent variable: arcsinh

Table B3: Robustness check: the dependent variable is the arcsinh of the lost hectares; Deforestation and droughts over the main agricultural periods and cycles; experienced and current, yearly aggregation and by season

<i>Dependent variable:</i>					
Arcsinh of deforested hectares					
Droughts:	(1) Experienced & current yearly aggregation	(2) Experienced, detailed	(3) Current, detailed	(4) Current, aggregated	(5) Experienced, aggregated
<i>Yearly aggregation</i>					
Experienced, y	-0.0196 (0.0132)				
Current, y	0.0010 (0.0127)				
<i>Cassava</i>					
Planting		-0.0246 (0.0281)	0.0760*** (0.0289)	0.0720** (0.0287)	-0.0250 (0.0284)
Harvesting		-0.0718 (0.0487)	-0.0997* (0.0593)	-0.0701 (0.0611)	-0.0634 (0.0516)
<i>Maize, seasonality detailed</i>					
Planting 1		0.0081 (0.0195)	-0.0775*** (0.0220)		
Planting 2		0.0233 (0.0193)	-0.0297 (0.0270)		
Growing 1		-0.0555** (0.0248)	-0.0838*** (0.0320)		
Growing 2		0.0037 (0.0233)	-0.0632** (0.0292)		
Harvesting 1		-0.0270 (0.0219)	0.1083*** (0.0301)		
Harvesting 2		0.0025 (0.0147)	0.0326* (0.0170)		
<i>Maize, seasonality aggregated</i>					
Planting 1, 2				-0.0363** (0.0160)	0.0171 (0.0197)
Growing 1,2				-0.0769*** (0.0231)	-0.0302* (0.0171)
Harvesting 1,2				0.0705*** (0.0152)	-0.0204 (0.0133)
Observations	519,160	519,160	519,160	519,160	519,160
F Statistic	24.1449*** (df = 2; 493181)	24.0904*** (df = 8; 493175)	68.9845*** (df = 8; 493175)	74.2039*** (df = 5; 493178)	34.9552*** (df = 5; 493178)

Note:

\*  $p < 0.1$ ; \*\*  $p < 0.05$ ; \*\*\*  $p < 0.01$   
Time and cell fixed effects, clustered at the sector administrative level



B.3.2 Maize and cassava

Maize

Table B4: Deforestation and droughts over maize agricultural seasons. Yearly aggregation, current and experienced, aggregated and by season.

<i>Dependent variable:</i>					
Log of deforested hectares +1					
Droughts:	(1) Experienced & current yearly aggregation	(2) Experienced, detailed	(3) Current, detailed	(4) Current, aggregated	(5) Experienced, aggregated
<b>Yearly aggregation</b>					
Experienced, y	-0.0168 (0.0115)				
Current, y	0.0002 (0.0110)				
<b>Seasonality detailed</b>					
Planting 1		0.0082 (0.0170)	-0.0592*** (0.0179)		
Planting 2		0.0062 (0.0181)	-0.0215 (0.0229)		
Growing 1		-0.0561** (0.0224)	-0.0582** (0.0277)		
Growing 2		0.0054 (0.0220)	-0.0565** (0.0251)		
Harvesting 1		-0.0392** (0.0195)	0.0909*** (0.0258)		
Harvesting 2		-0.0039 (0.0134)	0.0244* (0.0148)		
<b>Seasonality aggregated</b>					
Planting 1, 2				-0.0243* (0.0130)	0.0145 (0.0172)
Growing 1,2				-0.0628*** (0.0200)	-0.0300** (0.0153)
Harvesting 1,2				0.0573*** (0.0133)	0.0218* (0.0117)
Observations	519,160	519,160	519,160	519,160	519,160
F Statistic	24.1580*** (df = 2; 493181)	39.4250*** (df = 6; 493177)	80.9361*** (df = 6; 493177)	104.8111*** (df = 3; 493180)	50.4334*** (df = 3; 493180)

Note:

\* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$   
Time and cell fixed effects, clustered at the sector administrative level

**Cassava**

Table B5: Deforestation and droughts over cassava agricultural seasons. Yearly aggregation, current and experienced, by season.

<i>Dependent variable:</i>			
Log of deforested hectares +1			
Droughts:	(1) Experienced & current yearly aggregation	(2) Experienced, detailed	(3) Current, detailed
Yearly aggregation			
Experienced, y	-0.0368 (0.0228)		
Current, y	0.0080 (0.0240)		
Seasonality detailed			
Planting		-0.0303 (0.0247)	0.0268 (0.0243)
Harvesting		-0.0763* (0.0451)	-0.0469 (0.0560)
Observations	519,160	519,160	519,160
F Statistic (df = 2; 493181)	28.0392***	38.3600***	8.6174***
<i>Note:</i>		* $p < 0.1$ ; ** $p < 0.05$ ; *** $p < 0.01$	
Time and cell fixed effects, clustered at the sector administrative level			

**B.3.3 Second Congo War**

Table B6: Robustness check: Excluding Second Congo War period (exclusion of years prior to 2003); panel including years 2004-2020; Deforestation and droughts over the main agricultural periods and cycles; experienced and current, yearly aggregation and by season

<i>Dependent variable:</i>					
Log of deforested hectares +1					
Droughts:	(1) Experienced & current yearly aggregation	(2) Experienced, detailed	(3) Current, detailed	(4) Current, aggregated	(5) Experienced, aggregated
<b>Yearly aggregation</b>					
Experienced, y	-0.0235* (0.0126)				
Current, y	-0.0013 (0.0117)				
<b>Cassava</b>					
Planting		0.0050 (0.0273)	0.0853*** (0.0256)	0.0786*** (0.0262)	0.0027 (0.0266)
Harvesting		-0.0635 (0.0445)	-0.0961* (0.0529)	-0.0691 (0.0547)	-0.0699 (0.0484)
<b>Maize, seasonality detailed</b>					
Planting 1		-0.0238 (0.0167)	-0.0856*** (0.0204)		
Planting 2		0.0440** (0.0195)	-0.0285 (0.0254)		
Growing 1		-0.0789*** (0.0301)	-0.0862*** (0.0272)		
Growing 2		0.0179 (0.0211)	-0.0482* (0.0258)		
Harvesting 1		-0.0804*** (0.0206)	0.0939*** (0.0260)		
Harvesting 2		-0.0019 (0.0159)	0.0401*** (0.0155)		
<b>Maize, seasonality aggregated</b>					
Planting 1,2				-0.0453*** (0.0150)	-0.0107 (0.0169)
Growing 1,2				-0.0645*** (0.0203)	-0.0223 (0.0182)
Harvesting 1,2				0.0721*** (0.0132)	-0.0291** (0.0132)
Observations	441,286	441,286	441,286	441,286	441,286
F Statistic	40.5554*** (df = 2; 415310)	69.3159*** (df = 8; 415304)	84.6469*** (df = 8; 415304)	92.5989*** (df = 5; 415307)	44.8462*** (df = 5; 415307)

Note:

\*  $p < 0.1$ ; \*\*  $p < 0.05$ ; \*\*\*  $p < 0.01$   
Time and cell fixed effects, clustered at the sector administrative level

# C Supplementary material to Chapter 4

## C.1 Summary Statistics

### C.1.1 Dams

Table C1: Summary Statistics, Dams

Group Variable	N	Mean	SD	Control				N	Mean	SD	Treated			
				Min	25pctile	75pctile	Max				Min	25pctile	75pctile	Max
Commissioning year	3	2024.667	0.577	2024	2024.5	2025	2025	37	2008.216	9.102	1993	2000	2015	2023
Country	55							37						
AGO	1	1.8%						0	0%					
BDI	1	1.8%						0	0%					
BEN	1	1.8%						0	0%					
BWA	0	0%						1	2.7%					
CAF	1	1.8%						0	0%					
CIV	3	5.5%						1	2.7%					
CMR	6	10.9%						2	5.4%					
COD	3	5.5%						0	0%					
COG	4	7.3%						1	2.7%					
ETH	4	7.3%						7	18.9%					
GIN	2	3.6%						0	0%					
KEN	2	3.6%						3	8.1%					
LBR	1	1.8%						0	0%					
MOZ	3	5.5%						0	0%					
MWI	0	0%						2	5.4%					
NGA	5	9.1%						2	5.4%					
RWA	0	0%						2	5.4%					
SLE	2	3.6%						1	2.7%					
SSD	2	3.6%						0	0%					
TGO	2	3.6%						0	0%					
TZA	3	5.5%						2	5.4%					
UGA	2	3.6%						4	10.8%					
ZAF	1	1.8%						1	2.7%					
ZMB	2	3.6%						0	0%					
ZWE	4	7.3%						8	21.6%					
Dam height [m]	11	60.045	40.555	13	29	85.5	141.5	28	41.143	29.326	0	17.5	47	110
Reservoir capacity [ <i>millionm</i> <sup>3</sup> ]	15	2191.189	4861.637	0	6.71	1030	16500	31	426.54	1149.727	0	3.2	179.25	5840
Reservoir area [ <i>km</i> <sup>2</sup> ]	4	5760.375	11453.171	0.2	3.275	5807.75	22940	16	63.791	138.663	0	0.308	32.558	540
Installed Capacity [MW]	47	358.921	662.488	9	69.5	300	3900	18	145.856	168.169	6.4	32.75	198.75	700
Upstream watershed [ <i>km</i> <sup>2</sup> ]	55	9841.007	4663.338	835.282	6613.005	13214.823	18890.651	37	6991.24	5192.025	237.225	2283.743	10907.631	17676.117
Downstream watershed [ <i>km</i> <sup>2</sup> ]	55	4248.591	1083.392	1917.801	3430.51	4758.766	7506.64	37	3926.526	1253.598	1312.758	3119.95	4556.083	7135.596
Existent dams upstream	55	0.091	0.348	0	0	0	2	37	0.081	0.277	0	0	0	1
Existent dams downstream	55	0.127	0.388	0	0	0	2	37	0.054	0.229	0	0	0	1
Multipurpose dam	55	1.073	0.325	1	1	1	3	37	1.541	0.96	1	1	2	5
Hydroelectricity	55							37						
No	8	14.5%						18	48.6%					
Yes	47	85.5%						19	51.4%					
Water Supply	55							37						
No	53	96.4%						24	64.9%					
Yes	2	3.6%						13	35.1%					
Flood Control	55							37						
No	55	100%						34	91.9%					
Yes	0	0%						3	8.1%					
Navigation	55							37						
No	55	100%						36	97.3%					
Yes	0	0%						1	2.7%					
Recreation	55							37						
No	55	100%						35	94.6%					
Yes	0	0%						2	5.4%					
Livestock Rearing	55							37						
No	55	100%						36	97.3%					
Yes	0	0%						1	2.7%					
Fishing.	55							37						
No	55	100%						34	91.9%					
Yes	0	0%						3	8.1%					

C.1.2 Database: pixel level

Table C2: Summary Statistics, Pixels.

Variable	N	Mean	SD	Min	25th Pctile	75th Pctile	Max
<b>Group: Downstream Control</b>							
Commissioning year [yr]	3808744	2949.603	215.874	2024	3000	3000	3000
Distance buffer from dam [km]	3808744	19.387	7.757	5	15	25	30
Multipurpose dam	3808744	1.023	0.156	1	1	1	3
Irrigation dam	3808744	0.122	0.327	0	0	0	1
Water supply dam	3808744	0.002	0.039	0	0	0	1
Hydropower dam	3808744	0.795	0.404	0	1	1	1
Installed capacity [MW]	3026295	367.804	622.108	9	96	304	3900
Upstream watershed [ $km^2$ ]	3808744	9603.56	4686.037	835.282	6194.962	13340.604	18890.651
Downstream watershed [ $km^2$ ]	3808744	4599.274	1146.722	1917.801	4005.731	5110.027	7506.64
Existent dams upstream	3808744	0.132	0.434	0	0	0	2
Existent dams downstream	3808744	0.128	0.363	0	0	0	2
Elevation [m]	3808744	829.246	467.29	8	491	1149	2977
Slope	3808744	0.071	0.083	0	0.022	0.085	0.711
Travel time from main cities [min]	3808744	292.805	216.156	0	137	392	1733
Population density in 1990 [people/pixel]	3808744	53.956	95.097	0	6.842	55.569	654.784
Net Primary Productivity	2626720	17207.165	10820.556	961	11174	19590	65535
Nightlight	3546072	0.74	2.28	0	0	0	58
Waters	3808744	0.048	0.213	0	0	0	1
Agriculture	3808744	0.35	0.477	0	0	1	1
Irrigated land	3808744	0.03	0.169	0	0	0	1
Urban area	3808744	0.002	0.045	0	0	0	1
Forested land	3808744	0.352	0.478	0	0	1	1
<b>Group: Downstream Treated</b>							
Commissioning year [yr]	4037931	2008.107	8.573	1993	2000	2014	2023
Distance buffer from dam [km]	4037931	19.225	7.833	5	10	25	30
Multipurpose dam	4037931	1.412	0.761	1	1	2	5
Irrigation dam	4037931	0.25	0.433	0	0	1	1
Water supply dam	4037931	0.348	0.476	0	0	1	1
Hydropower dam	4037931	0.52	0.5	0	0	1	1
Installed capacity [MW]	1992938	118.244	97.281	6.4	30	192	700
Upstream watershed [ $km^2$ ]	4037931	7157.427	5378.2	237.225	1064.724	10907.631	17676.117
Downstream watershed [ $km^2$ ]	4037931	4283.189	1271.031	1312.758	3438.963	5238.317	7135.596
Existent dams upstream	4037931	0.117	0.321	0	0	0	1
Existent dams downstream	4037931	0.053	0.223	0	0	0	1
Elevation [m]	4037931	1080.81	649.02	68	577	1491	3561
Slope	4037931	0.083	0.102	0	0.022	0.096	0.962
Travel time from main cities [min]	4037931	275.389	230.486	0	112	385	1444
Population density in 1990 [people/pixel]	4037931	105.875	292.407	0	12.28	92.612	13858.87
Net Primary Productivity	2784780	17190.362	9959.56	1265	12342	19148	65535
Nightlight	3759453	1.888	5.76	0	0	0	62
Waters	4037931	0.029	0.168	0	0	0	1
Agriculture	4037931	0.438	0.496	0	0	1	1
Irrigated land	4037931	0.013	0.113	0	0	0	1
Urban area	4037931	0.004	0.065	0	0	0	1
Forested land	4037931	0.338	0.473	0	0	1	1
<b>Group: Upstream Control</b>							
Commissioning year [yr]	6121117	2971.801	163.407	2024	3000	3000	3000
Distance buffer from dam [km]	6121117	19.927	7.399	5	15	25	30
Multipurpose dam	6121117	1.084	0.303	1	1	1	3
Irrigation dam	6121117	0.152	0.359	0	0	0	1
Water supply dam	6121117	0.009	0.093	0	0	0	1
Hydropower dam	6121117	0.87	0.337	0	1	1	1
Installed capacity [MW]	5323646	310.834	556.491	9	96	300	3900
Upstream watershed [ $km^2$ ]	6121117	12021.795	4523.71	835.282	8012.266	16084.976	18890.651
Downstream watershed [ $km^2$ ]	6121117	4197.153	1034.473	1917.801	3335.466	4729.867	7506.64
Existent dams upstream	6121117	0.094	0.321	0	0	0	2
Existent dams downstream	6121117	0.094	0.342	0	0	0	2
Elevation [m]	6121117	1069.839	629.537	22	564	1601	3009
Slope	6121117	0.086	0.086	0	0.028	0.112	0.776
Travel time from main cities [min]	6121117	354.649	300.207	0	159	445	2435
Population density in 1990 [people/pixel]	6121117	48.517	82.244	0	8.601	55.569	721.448
Net Primary Productivity	4221460	17313.956	8819.673	670	11865	20100	65535
Nightlight	5698971	0.526	1.963	0	0	0	54
Waters	6121117	0.011	0.102	0	0	0	1
Agriculture	6121117	0.38	0.485	0	0	1	1
Irrigated land	6121117	0.004	0.066	0	0	0	1
Urban area	6121117	0.001	0.031	0	0	0	1
Forested land	6121117	0.39	0.488	0	0	1	1
<b>Group: Upstream Treated</b>							
Commissioning year [yr]	6859979	2010.6	8.691	1993	2004	2017	2023
Distance buffer from dam [km]	6859979	19.666	7.729	5	15	25	30
Multipurpose dam	6859979	1.477	0.815	1	1	2	5
Irrigation dam	6859979	0.258	0.438	0	0	1	1
Water supply dam	6859979	0.269	0.443	0	0	1	1
Hydropower dam	6859979	0.706	0.455	0	0	1	1
Installed capacity [MW]	4696579	129.842	107.624	6.4	41	201	700
Upstream watershed [ $km^2$ ]	6859979	10527.629	4354.695	237.225	7462.366	14084.136	17676.117
Downstream watershed [ $km^2$ ]	6859979	4041.525	1251.626	1312.758	3119.95	4556.083	7135.596
Existent dams upstream	6859979	0.125	0.331	0	0	0	1
Existent dams downstream	6859979	0.038	0.192	0	0	0	1
Elevation [m]	6859979	1091.344	671.11	87	538	1545	4821
Slope	6859979	0.09	0.099	0	0.024	0.121	0.931
Travel time from main cities [min]	6859979	349.003	280.677	0	146	501	2112
Population density in 1990 [people/pixel]	6859979	69.753	139.683	0	9.035	70.701	2247.281
Net Primary Productivity	4731020	18174.309	11140.763	878	12945	20124	65535
Nightlight	6386877	1.008	3.545	0	0	0	59
Waters	6859979	0.036	0.188	0	0	0	1
Agriculture	6859979	0.418	0.493	0	0	1	1

Continued on next page

Table C2 – continued from previous page

Variable	N	Mean	SD	Min	25th Pctile	75th Pctile	Max
Irrigated land	6859979	0.006	0.077	0	0	0	1
Urban area	6859979	0.001	0.038	0	0	0	1
Forested land	6859979	0.4	0.49	0	0	1	1

## C.2 Matching

Matching is a preliminary procedure which allows to test for the comparability between treated and control groups as well as to address selection bias. As our controls are the watersheds of planned but yet not built dams, we wanted to check our assumptions by matching our unit of analysis on the basis of static (non-time varying) variables selected on their potential to determine both the suitability for dams construction as well as the land use. More precisely, both upstream and downstream pixels have been matched on the basis of the following: Latitude (y) and Longitude (x), which are included for a geographical and climate comparability; Elevation and Slope which determines land plot accessibility and suitability for dams infrastructures; Travel time to major city in year 2000 as a determinant of side services that a dams could provide and potential for jobs reallocation outside agriculture; Population density, in year 1990 from UN adjusted estimates, as a determinant of use and pressure of lands; Buffer distance from the dam for balanced group comparability between pixels in the watersheds.

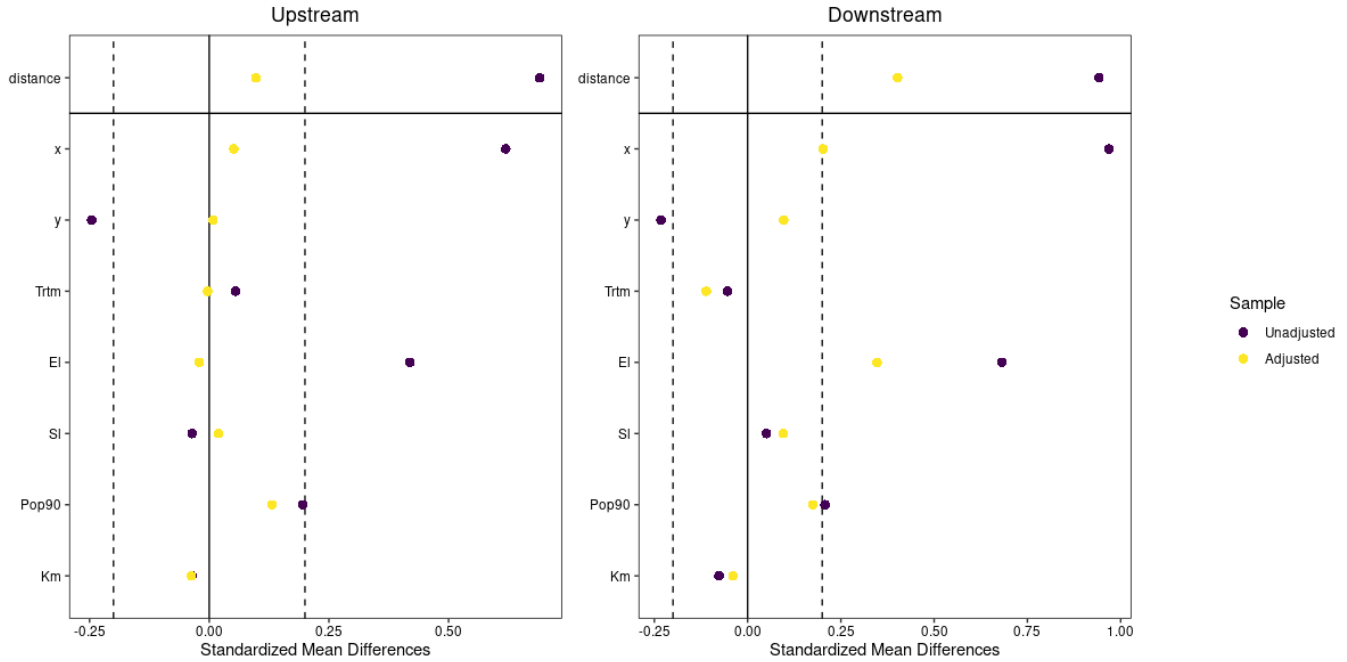


Figure 17: Matching score results

The after matching results (adjusted) significantly reduce the standardized mean difference improving the reliability of our model. The improvement is particularly significant for the upstream watersheds but works slightly less for the downstream groups. Nevertheless variables have not been changed to guarantee the comparability of the upstream and downstream models. Moreover, the standardized mean difference of the distance is anyhow significantly improved.

### C.3 Relevant time period

The relative time period covered by the data goes from -31 to +27. Figure 18 shows the percentage of treated pixel in each period. We chose to represent the DiD results where at least the 20% of pixels were included in the analysis both in the past and post - treatment period. Being this threshold reached at the 20th year after treatment, in the DiD plots is displayed only the relative time treatment from -20 to +20.

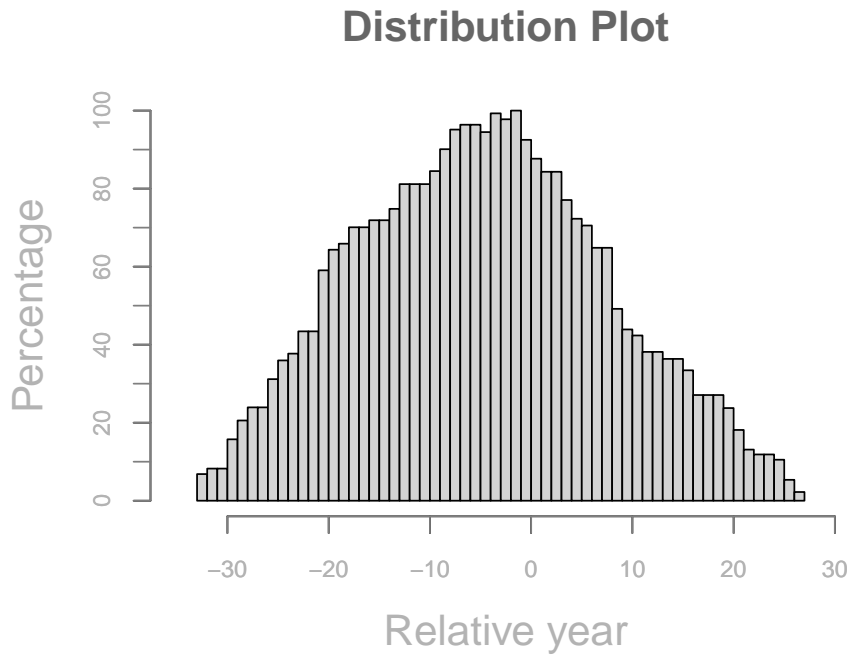


Figure 18: Matching score results



## C.4 Supplementary results

### C.4.1 DID Agriculture

Table C3: ATT on change in agriculture upstream watershed

Km	Agricultural Land Use					
	5	10	15	20	25	30
ATT	-0.0150*** (0.0056)	-0.0158** (0.0070)	-0.0017 (0.0054)	0.0008 (0.0042)	-0.0097*** (0.0032)	-0.0249*** (0.0045)
Observations	926,637	1,676,896	2,225,344	2,711,848	3,069,186	2,371,185
R <sup>2</sup>	0.96006	0.95907	0.95520	0.95010	0.95810	0.95854
Within R <sup>2</sup>	0.03257	0.03160	0.02800	0.02791	0.03490	0.03414
X fixed effects	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓	✓	✓

Table C4: ATT on change in agriculture downstream watershed

Km	Agricultural Land Use					
	5	10	15	20	25	30
ATT	-0.0114* (0.0063)	-0.0165** (0.0066)	0.0040 (0.0123)	0.0068 (0.0167)	0.0092* (0.0048)	0.0026 (0.0038)
Observations	416,324	1,504,723	1,503,911	1,398,641	1,377,007	1,646,098
R <sup>2</sup>	0.95094	0.94527	0.94754	0.94648	0.95675	0.96672
Within R <sup>2</sup>	0.05004	0.05061	0.03512	0.05781	0.02970	0.04625
X fixed effects	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓	✓	✓

## Forest

Table C5: ATT on change in forest upstream watershed

Km	Forested Land					
	5	10	15	20	25	30
ATT	0.0135 (0.0090)	0.0016 (0.0101)	-0.0064 (0.0073)	0.0007 (0.0055)	0.0152*** (0.0051)	0.0309*** (0.0058)
Observations	926,637	1,676,896	2,225,344	2,711,848	3,069,186	2,371,185
R <sup>2</sup>	0.94148	0.93759	0.93992	0.94147	0.94270	0.94378
Within R <sup>2</sup>	0.03235	0.02264	0.02592	0.02712	0.02435	0.03315
X fixed effects	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓	✓	✓

Table C6: ATT on change in forest downstream watershed

Km	Forested Land					
	5	10	15	20	25	30
ATT	0.0470*** (0.0156)	0.0402*** (0.0115)	0.0129* (0.0066)	0.0117** (0.0047)	0.0009 (0.0042)	-0.0066 (0.0047)
Observations	416,324	1,504,723	1,503,911	1,398,641	1,377,007	1,646,098
R <sup>2</sup>	0.93414	0.93124	0.94227	0.94417	0.95465	0.95525
Within R <sup>2</sup>	0.05124	0.05546	0.03071	0.03713	0.03252	0.04525
X fixed effects	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓	✓	✓

Irrigation

Table C7: ATT on change in irrigation upstream watershed

Km	Irrigated Land					
	5	10	15	20	25	30
ATT	$8.71 \times 10^{-5}$ (0.0001)	-0.0002 (0.0002)	$-7.02 \times 10^{-5}$ ( $8.25 \times 10^{-5}$ )	$2.52 \times 10^{-5}$ ( $7.66 \times 10^{-5}$ )	$1.37 \times 10^{-5}$ ( $6.69 \times 10^{-5}$ )	-0.0002* (0.0001)
Observations	926,637	1,676,896	2,225,344	2,711,848	3,069,186	2,371,185
R <sup>2</sup>	0.97991	0.98745	0.99086	0.97759	0.98306	0.98825
Within R <sup>2</sup>	0.00574	0.00097	0.00064	0.00319	0.00094	0.00150
X fixed effects	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓	✓	✓

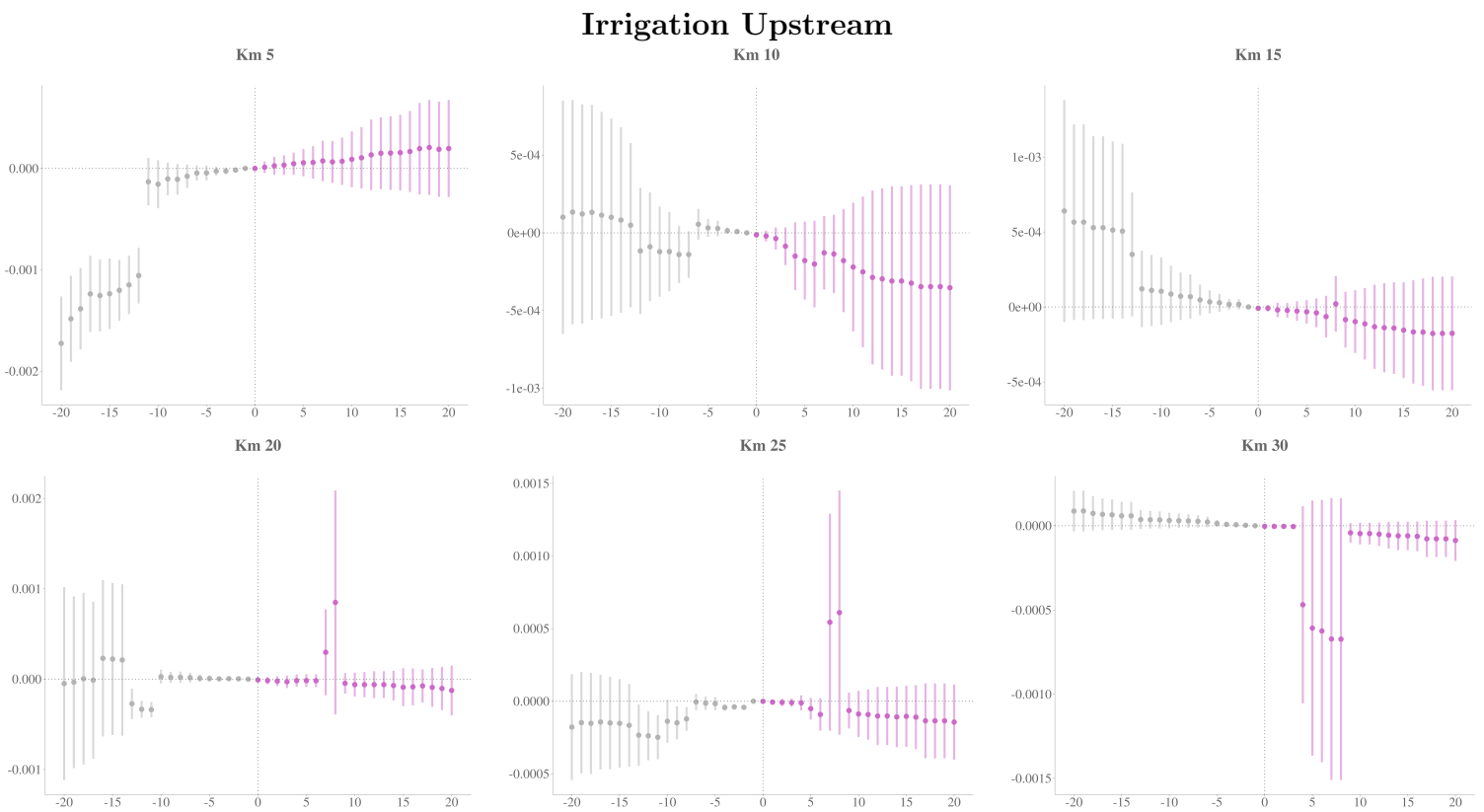


Figure 19: Event study, change in irrigated land in the upstream watershed by distance from the dam

Table C8: ATT on change in irrigation downstream watershed

Km	Irrigated Land					
	5	10	15	20	25	30
ATT	-0.0027 (0.0025)	-0.0040 (0.0044)	-0.0013 (0.0020)	0.0007 (0.0007)	-0.0002 (0.0002)	0.0001 ( $7.57 \times 10^{-5}$ )
Observations	416,324	1,504,723	1,503,911	1,398,641	1,377,007	1,646,098
R <sup>2</sup>	0.95845	0.93506	0.95938	0.97842	0.98533	0.99048
Within R <sup>2</sup>	0.00670	0.00382	0.00474	0.00623	0.01089	0.00826
X fixed effects	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓	✓	✓

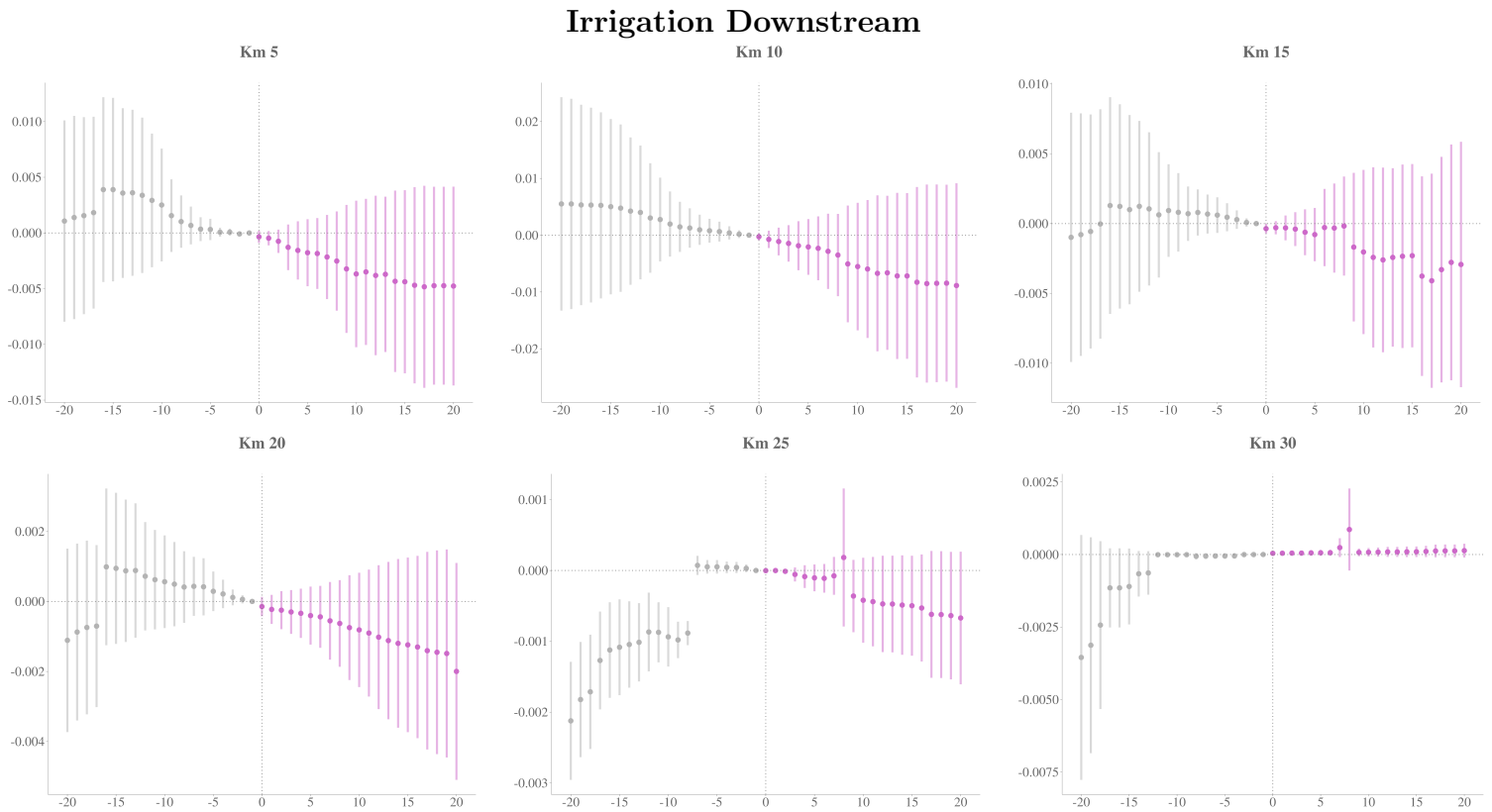


Figure 20: Event study, change in irrigated land in the downstream watershed by distance from the dam

Urban

Table C9: ATT on change in urban area upstream watershed

Km	Urban area					
	5	10	15	20	25	30
ATT	-0.0003 (0.0007)	0.0003 (0.0009)	0.0014* (0.0008)	0.0007*** (0.0002)	$7.96 \times 10^{-5}$ (0.0002)	-0.0005 (0.0004)
Observations	926,637	1,676,896	2,225,344	2,711,848	3,069,186	2,371,185
R <sup>2</sup>	0.74725	0.64738	0.71208	0.69337	0.68783	0.76304
Within R <sup>2</sup>	0.01580	0.00817	0.01328	0.01516	0.00240	0.00099
X fixed effects	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓	✓	✓



Figure 21: Event study, change in urban areas in the upstream watershed by distance from the dam

Table C10: ATT on change in urban area downstream watershed

Km	Urban area					
	5	10	15	20	25	30
ATT	-0.0026 (0.0020)	0.0027*** (0.0009)	0.0037** (0.0016)	0.0097*** (0.0030)	$-4.72 \times 10^{-5}$ (0.0025)	0.0018 (0.0013)
Observations	416,324	1,504,723	1,503,911	1,398,641	1,377,007	1,646,098
$R^2$	0.75063	0.58276	0.70721	0.65133	0.71991	0.77619
Within $R^2$	0.01702	0.01327	0.02886	0.10654	0.01161	0.01847
X fixed effects	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓	✓	✓

Urban Downstream

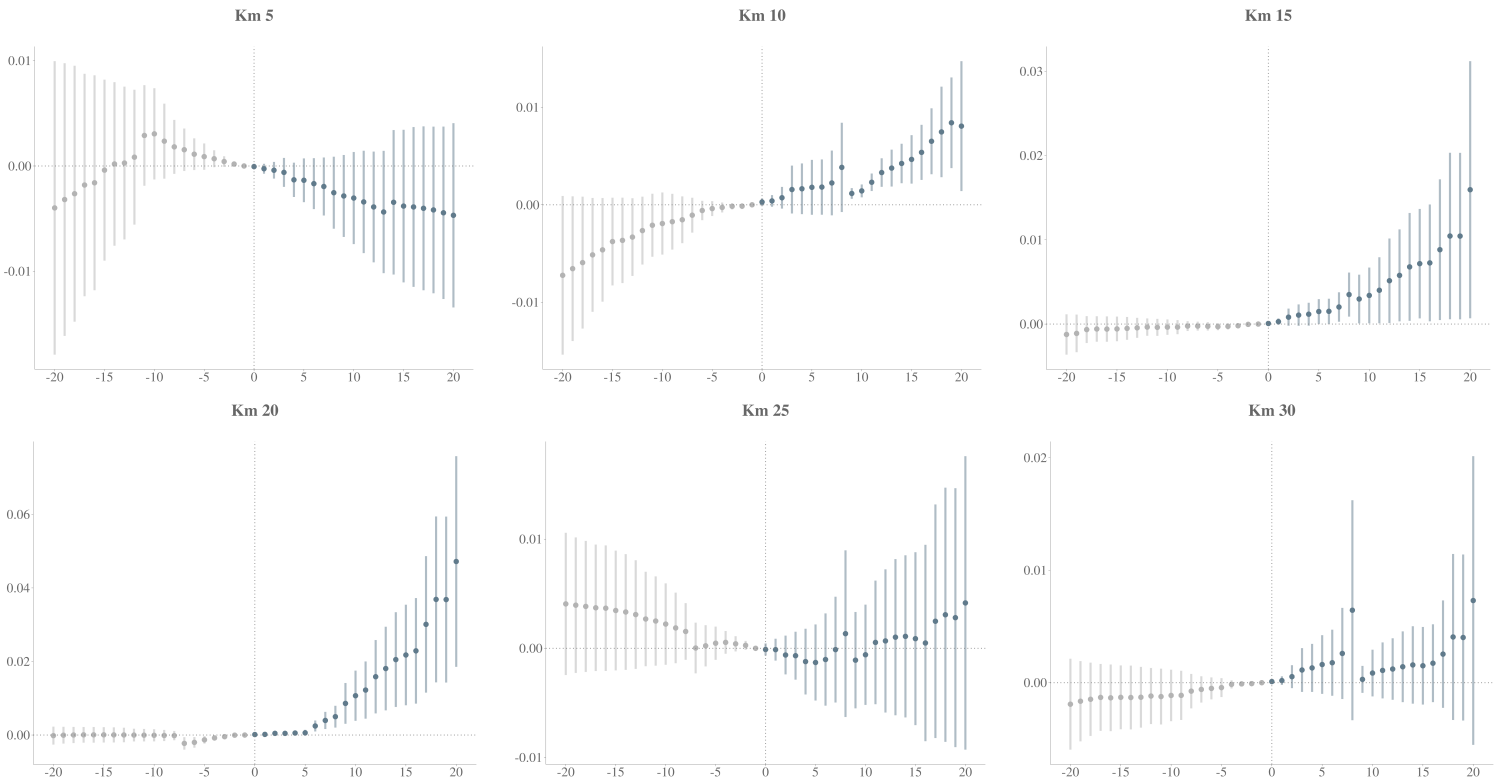


Figure 22: Event study, change in urban areas in the downstream watershed by distance from the dam

Nightlights

Table C11: ATT on change in nightlights in the upstream watershed

Km	Nightlights					
	5	10	15	20	25	30
ATT	-1.319*** (0.3333)	-0.0967 (0.1649)	0.0346 (0.1491)	0.0083 (0.1670)	-0.0437 (0.1718)	-0.0323 (0.1294)
Observations	862,731	1,561,248	2,071,872	2,524,824	2,857,518	2,207,655
R <sup>2</sup>	0.79459	0.71942	0.82318	0.83616	0.72776	0.66190
Within R <sup>2</sup>	0.29528	0.15213	0.21512	0.17795	0.17323	0.16130
X fixed effects	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓	✓	✓

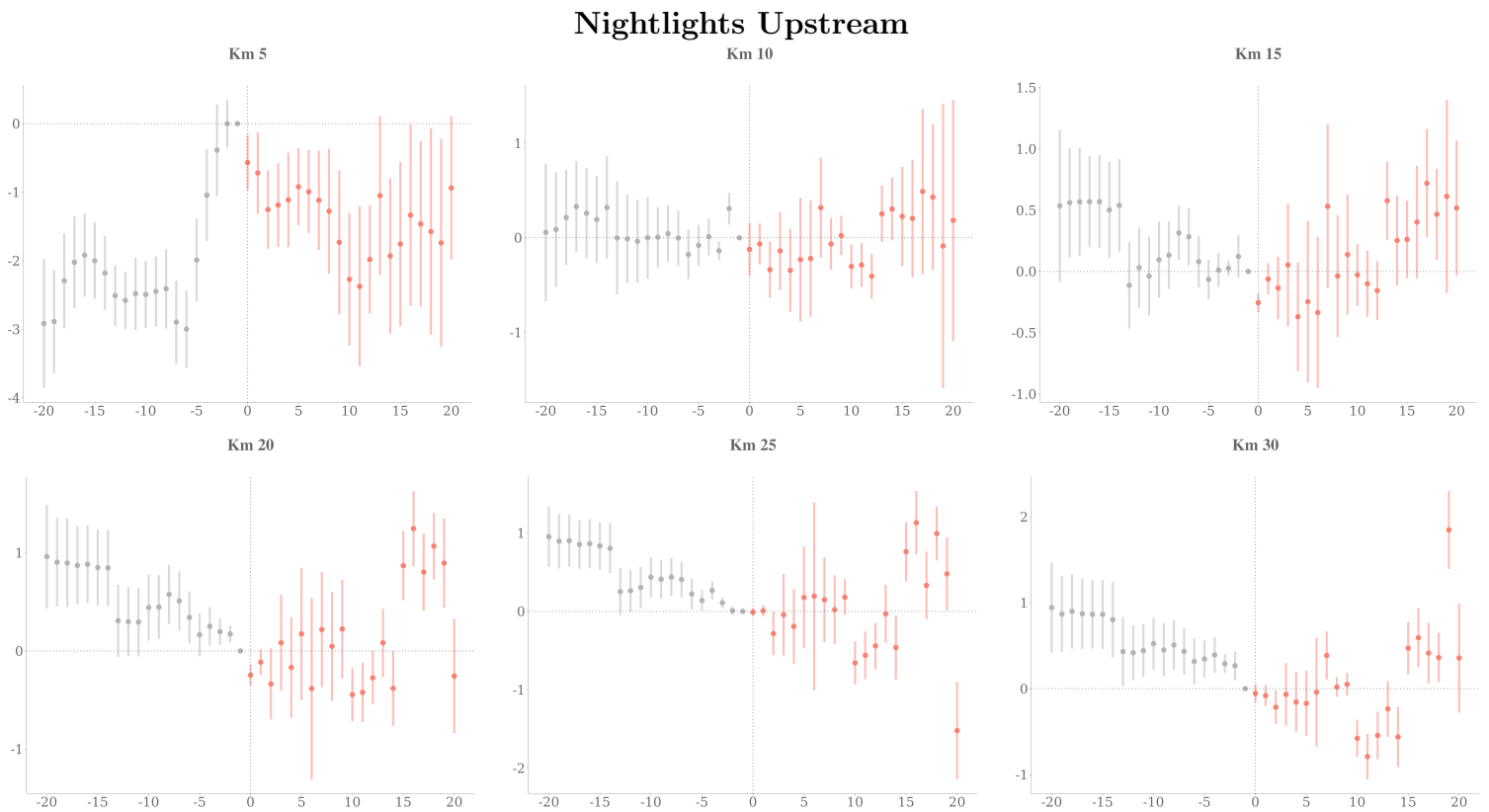


Figure 23: Event study, change in nightlights in the upstream watershed by distance from the dam

Table C12: ATT on change in nightlights in the downstream watershed

Km	Nightlights					
	5	10	15	20	25	30
ATT	-0.9228*** (0.2078)	0.5483*** (0.1571)	0.7431*** (0.2700)	0.5645** (0.2253)	0.1748 (0.2136)	0.0949 (0.2563)
Observations	387,612	1,400,949	1,400,193	1,302,183	1,282,041	1,532,574
R <sup>2</sup>	0.85964	0.82630	0.83545	0.85568	0.84720	0.81629
Within R <sup>2</sup>	0.27569	0.19969	0.19703	0.24511	0.21983	0.25254
X fixed effects	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓	✓	✓

Nightlights Downstream

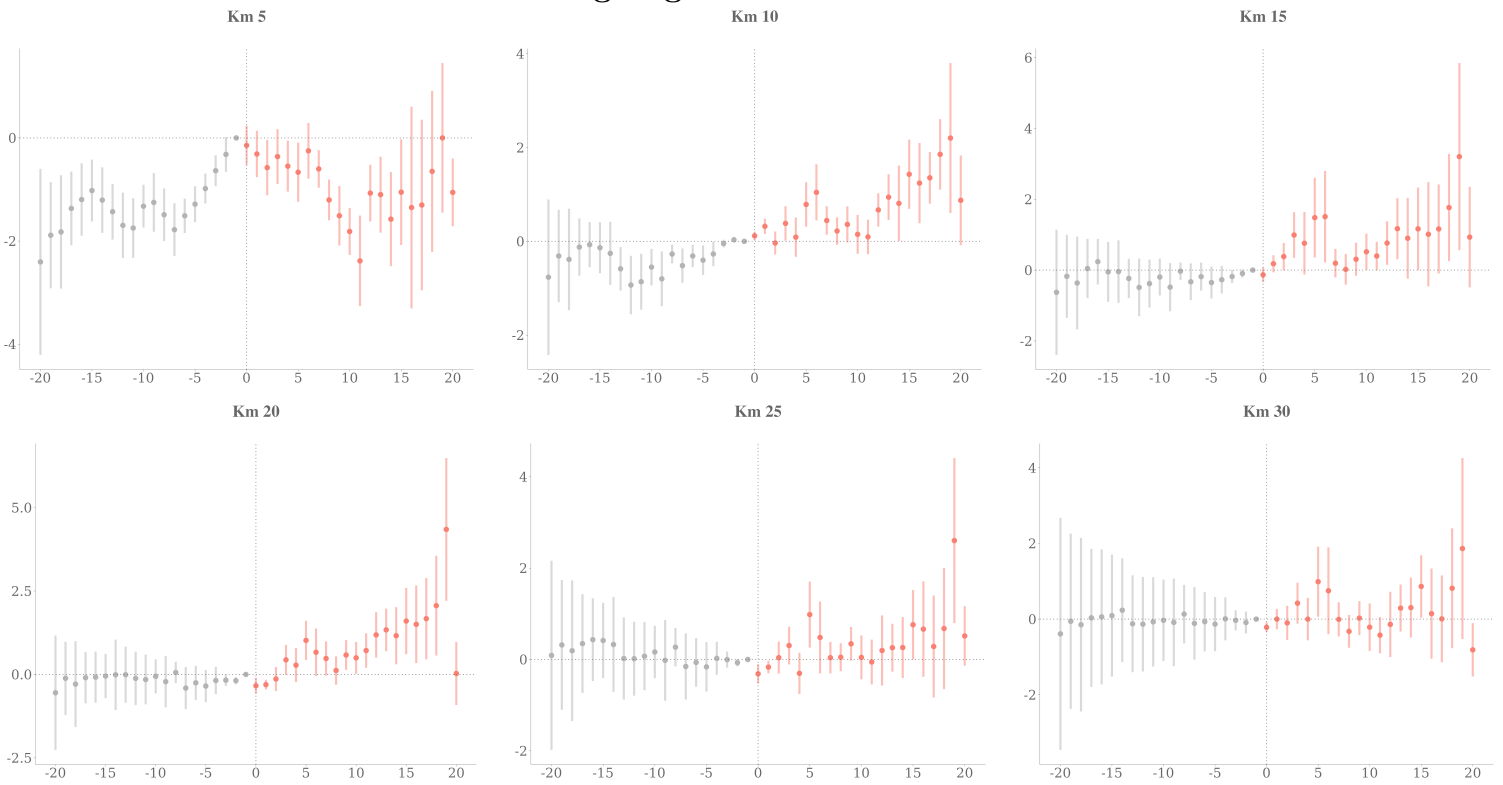


Figure 24: Event study, change in nightlights in the downstream watershed by distance from the dam



Net Primary Productivity

Table C13: ATT on change in Net Primary Productivity in the upstream watershed

Km	NPP					
	5	10	15	20	25	30
ATT	-0.1211 (0.1417)	-0.1119** (0.0464)	-0.2736*** (0.0684)	-0.0783 (0.0640)	-0.1871** (0.0938)	-0.3034*** (0.0830)
Observations	628,520	1,141,640	1,518,700	1,846,100	2,073,120	1,610,100
R <sup>2</sup>	0.25007	0.25345	0.26257	0.25047	0.24479	0.27667
Within R <sup>2</sup>	0.20229	0.20275	0.20980	0.19939	0.19621	0.23036
X fixed effects	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓	✓	✓

Net Primary Productivity Upstream

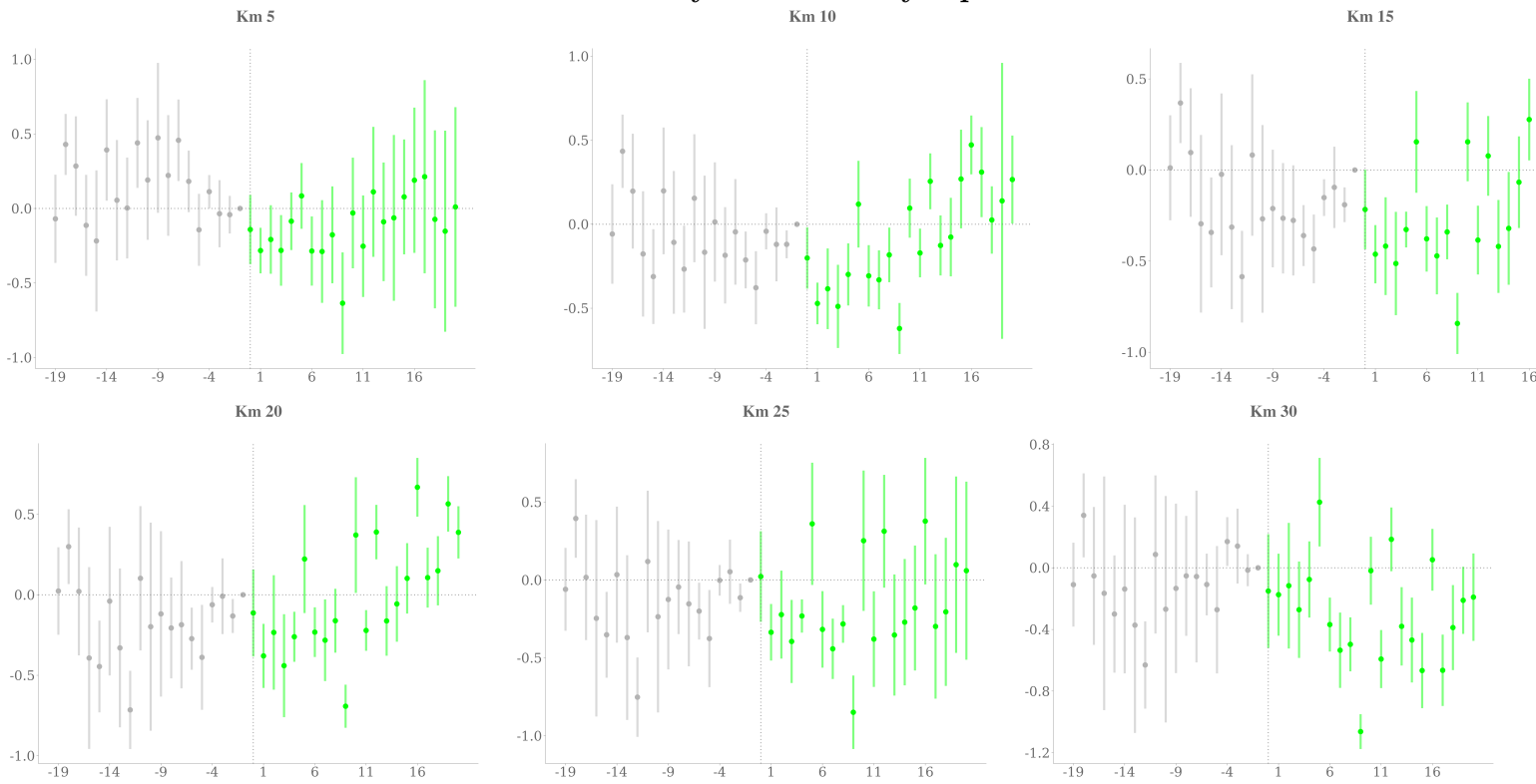


Figure 25: Event study, change in agricultural land in the downstream watershed by distance from the dam

Table C14: ATT on change in Net Primary Productivity in the downstream watershed

Km	NPP					
	5	10	15	20	25	30
ATT	-0.1351 (0.1196)	-0.0336 (0.0510)	-0.0877 (0.0603)	0.0048 (0.0483)	0.1220 (0.1073)	-0.0207 (0.0646)
Observations	284,700	1,031,260	1,028,920	949,100	932,260	1,111,020
R <sup>2</sup>	0.30976	0.25482	0.23640	0.26760	0.28876	0.26054
Within R <sup>2</sup>	0.24542	0.19264	0.17544	0.19698	0.22190	0.19608
X fixed effects	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓	✓	✓

Net Primary Productivity Downstream

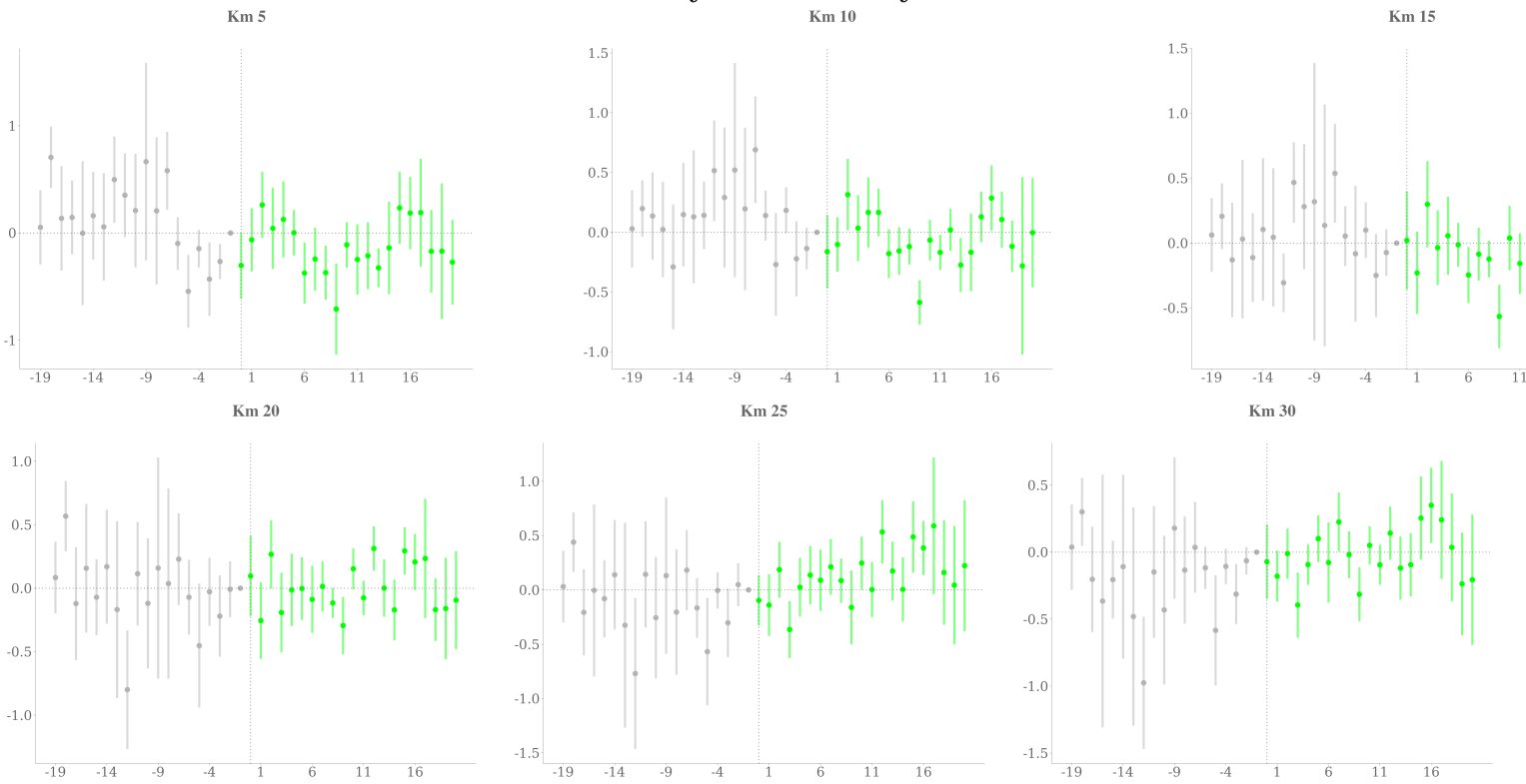


Figure 26: Event study, change in agricultural land in the downstream watershed by distance from the dam

**C.4.2 TWFE**  
**Agriculture**

Table C15: Change in Agricultural Land Use in the upstream watershed

Km	Agricultural Land Use					
	5	10	15	20	25	30
Treated	0.0023 (0.0098)	0.0226 (0.0297)	-0.0083 (0.0124)	-0.0435 (0.0266)	-0.0807* (0.0452)	-0.0775** (0.0350)
Hydropower	-0.0463*** (0.0142)	-0.0559 (0.0353)	-0.0221* (0.0129)	0.0261 (0.0255)	0.0733 (0.0445)	0.0744** (0.0353)
Irrigation	-0.0008 (0.0141)	-0.0506 (0.0466)	0.0035 (0.0095)	0.0452* (0.0269)	0.0303 (0.0335)	0.0124 (0.0219)
Water supply	-0.0081 (0.0083)	-0.0029 (0.0214)	0.0179 (0.0125)	0.0639** (0.0320)	0.1017** (0.0503)	0.0858** (0.0371)
Observations	926,637	1,676,896	2,225,344	2,711,848	3,069,186	2,371,185
R <sup>2</sup>	0.95904	0.95811	0.95408	0.94886	0.95678	0.95724
Within R <sup>2</sup>	0.00767	0.00892	0.00377	0.00382	0.00461	0.00403
Pixel and time FE	✓	✓	✓	✓	✓	✓
Cluster level	Dam	Dam	Dam	Dam	Dam	Dam

Table C16: Change in Agricultural Land Use in the downstream watershed

Km	Agricultural Land Use					
	5	10	15	20	25	30
Treated	-0.0034 (0.0159)	0.0327 (0.0514)	0.0557 (0.0418)	0.0367 (0.0288)	0.0241 (0.0167)	0.0427 (0.0328)
Hydropower	-0.0472* (0.0261)	-0.0679 (0.0553)	-0.0878** (0.0430)	-0.0759** (0.0341)	-0.0419* (0.0244)	-0.0587 (0.0374)
Irrigation	0.0263* (0.0145)	0.0576 (0.0391)	0.0475 (0.0416)	0.0403 (0.0386)	0.0310 (0.0248)	0.0458 (0.0453)
Water supply	-0.0074 (0.0166)	-0.0494 (0.0587)	-0.0553 (0.0538)	-0.0150 (0.0516)	-0.0243 (0.0216)	-0.0411 (0.0397)
Observations	416,324	1,504,723	1,503,911	1,398,641	1,377,007	1,646,098
R <sup>2</sup>	0.94877	0.94301	0.94623	0.94372	0.95560	0.96555
Within R <sup>2</sup>	0.00806	0.01140	0.01107	0.00922	0.00397	0.01280
Pixel and time FE	✓	✓	✓	✓	✓	✓
Cluster level	Dam	Dam	Dam	Dam	Dam	Dam

Urban

Table C17: Change in Urban area in the upstream watershed

Km	Urban Land					
	5	10	15	20	25	30
Treated	-0.0004 (0.0011)	0.0008 (0.0015)	0.0029 (0.0023)	0.0025 (0.0024)	0.0003 (0.0008)	-0.0004 (0.0005)
Hydropower	0.0027 (0.0024)	0.0028 (0.0028)	-0.0006 (0.0024)	-0.0019 (0.0025)	-0.0002 (0.0008)	0.0001 (0.0002)
Irrigation	-0.0024 (0.0015)	-0.0021 (0.0021)	-0.0041 (0.0027)	-0.0035 (0.0027)	-0.0007 (0.0009)	-0.0003 (0.0002)
Water supply	0.0005 (0.0015)	-0.0013 (0.0012)	0.0017 (0.0028)	0.0021 (0.0028)	0.0006 (0.0008)	-0.0002 (0.0002)
Observations	926,637	1,676,896	2,225,344	2,711,848	3,069,186	2,371,185
R <sup>2</sup>	0.74329	0.64489	0.70852	0.68889	0.68710	0.76282
Within R <sup>2</sup>	0.00040	0.00118	0.00106	0.00075	$5.92 \times 10^{-5}$	$6.71 \times 10^{-5}$
Pixel and time FE	✓	✓	✓	✓	✓	✓
Cluster level	Dam	Dam	Dam	Dam	Dam	Dam

Table C18: Change in Urban area in the downstream watershed

Km	Urban Land					
	5	10	15	20	25	30
Treated	-0.0025 (0.0022)	0.0027 (0.0035)	0.0015 (0.0018)	0.0016 (0.0034)	-0.0016 (0.0024)	0.0017 (0.0024)
Hydropower	0.0023 (0.0030)	-0.0029 (0.0038)	-0.0009 (0.0027)	-0.0034 (0.0051)	-0.0027 (0.0020)	-0.0027 (0.0024)
Irrigation	-0.0005 (0.0014)	-0.0018 (0.0039)	-0.0050 (0.0033)	-0.0096 (0.0083)	-0.0045 (0.0033)	-0.0046 (0.0038)
Water supply	-0.0019 (0.0014)	0.0052 (0.0052)	0.0067 (0.0047)	0.0190 (0.0165)	0.0088 (0.0058)	0.0102 (0.0072)
Observations	416,324	1,504,723	1,503,911	1,398,641	1,377,007	1,646,098
R <sup>2</sup>	0.74646	0.57788	0.69919	0.61233	0.71717	0.77313
Within R <sup>2</sup>	0.00057	0.00175	0.00227	0.00661	0.00193	0.00504
Pixel and time FE	✓	✓	✓	✓	✓	✓
Cluster level	Dam	Dam	Dam	Dam	Dam	Dam

## C.5 Robustness Waters

Table C19: ATT on change in waters upstream watershed

Km	Water area					
	5	10	15	20	25	30
ATT	0.0188*** (0.0038)	0.0164*** (0.0050)	0.0040*** (0.0015)	0.0004 (0.0004)	$1.51 \times 10^{-5}$ (0.0001)	0.0002 (0.0003)
Observations	926,637	1,676,896	2,225,344	2,711,848	3,069,186	2,371,185
R <sup>2</sup>	0.92361	0.91237	0.93290	0.96611	0.98651	0.96945
Within R <sup>2</sup>	0.09012	0.11779	0.03281	0.00572	0.00687	0.02484
X fixed effects	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓	✓	✓

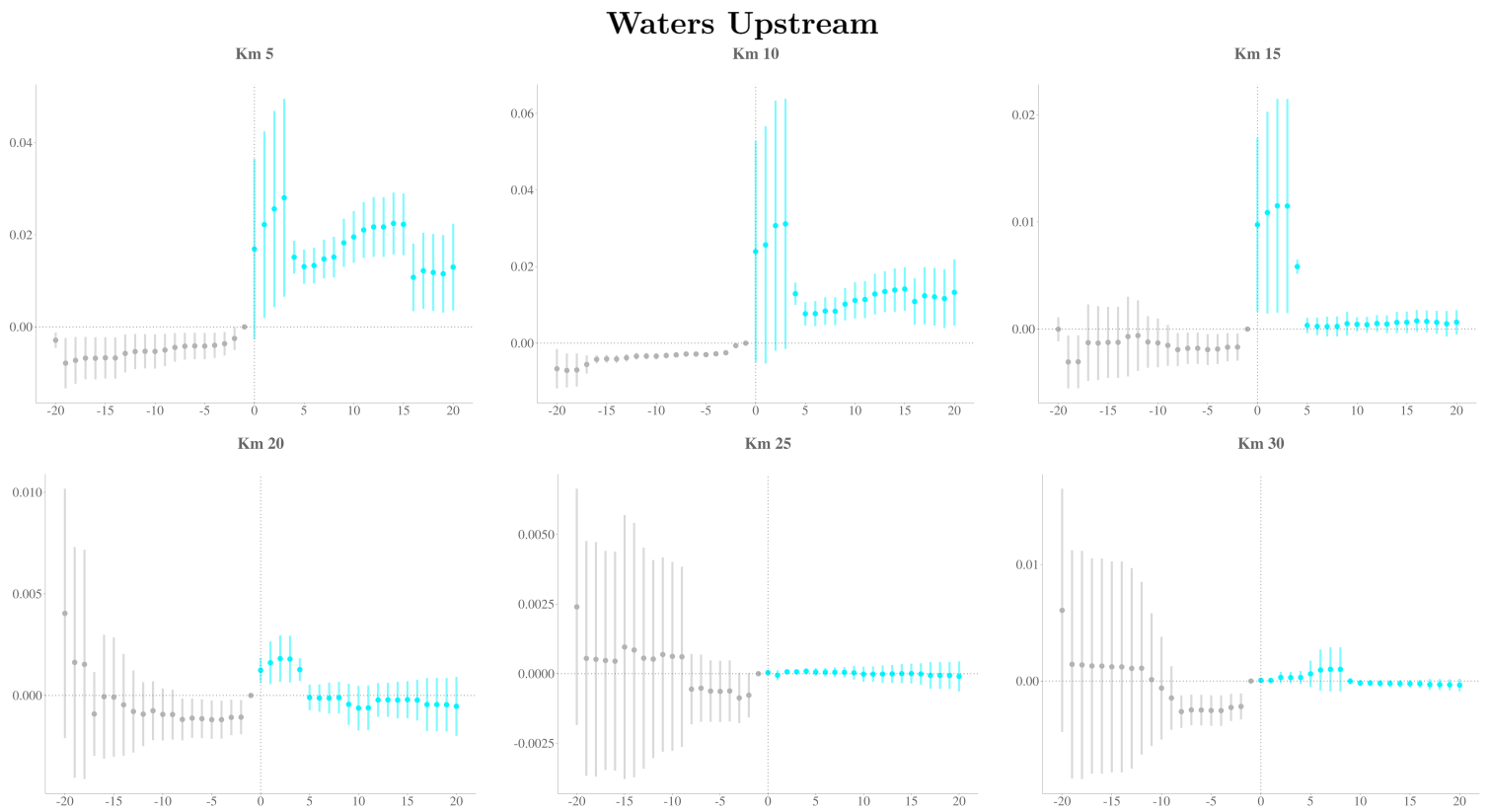


Figure 27: Event study, change in water surfaces in the upstream Watershed by distance from the dam

Table C20: ATT on change in waters downstream watershed

Km	Water area					
	5	10	15	20	25	30
ATT	0.0009** (0.0004)	-0.0015* (0.0009)	-0.0008 (0.0007)	0.0008 (0.0014)	-0.0024 (0.0024)	0.0005 (0.0016)
Observations	416,324	1,504,723	1,503,911	1,398,641	1,377,007	1,646,098
R <sup>2</sup>	0.98324	0.97354	0.98235	0.97982	0.97755	0.98816
Within R <sup>2</sup>	0.01221	0.00117	0.00045	0.00108	0.00177	0.00858
X fixed effects	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓	✓	✓

Waters Downstream

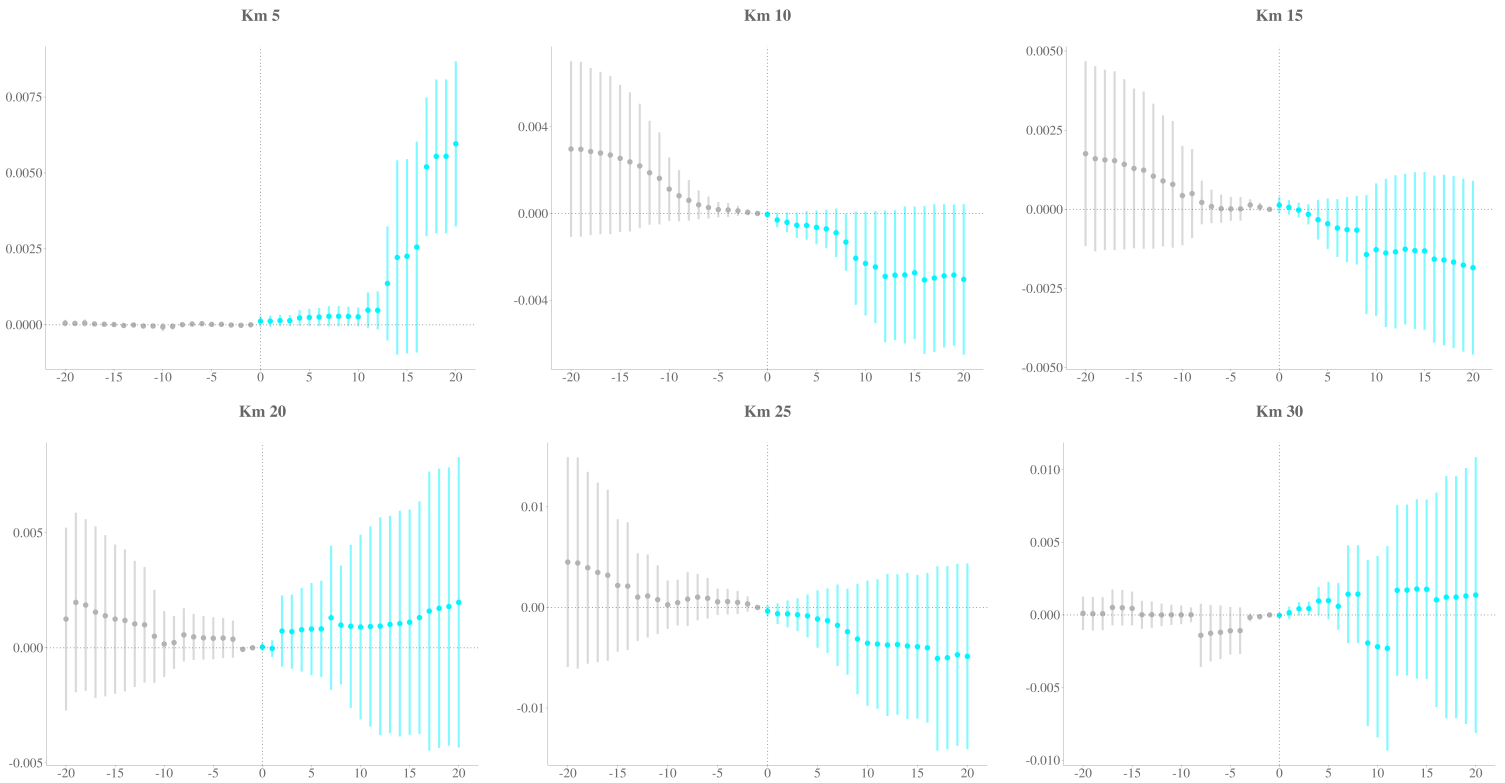


Figure 28: Event study, change in water surfaces in the downstream watershed by distance from the dam



# Remerciements

Dear Friends, Chères amies et chers amis, Care amiche e cari amici,

You know, it is typical of me doing things last second. It is indeed also the case of these acknowledgements. Nevertheless, when I think about this long adventure, my mind goes immediately to the people that have been part of it.

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À "La Coloc", merci d'avoir été ma maison, de m'avoir aidé à faire mes premiers pas à Paris, mais surtout merci pour chaque fois que le déjeuner à emporter était déjà prêt pour moi.

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Unfortunately, I'm not very good neither in expressing my feelings neither with words - if you don't trust me, ask my supervisors. Additionally, as always, I am running out of time. These few lines will never be enough to fully express how much each of you counted along this journey. I can only repeat myself thanking you again and saying how much your support meant to me.

See you at the next adventure.

