The Disaster of Unequal Aid Distribution: How The Unequal Consequences of Natural Disasters Affect Conflict

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Abstract

While natural disasters may be indiscriminate in their targets the subsequent damage is not divided equally across the different segments of society. Through studying trends of aid distribution we find that the ability to mitigate and recover from the harms of a natural disaster is distributed according to existing socio-economic structures favouring the privileged. By applying relative deprivation theory this study explores how horizontal inequalities of aid increase economic inequalities. Subsequently, economic inequalities can be employed to mobilise organised violence, given there is a financial opportunity presented by international development aid. A sub-national empirical analysis is conducted that includes 171 first order administrative divisions across five South East Asian countries. Using data covering the World Bank's aid distribution from 1995-2009 an indicator is calculated that measures the level of inequality. The binary logistic regression finds that the more unequal the aid distribution, the less likely organised violence is to occur.

Keywords: aid distribution, natural disaster, relative deprivation, organised violence, subnational

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Introduction

A hurricane will destroy luxury resorts and fishing villages alike, while wildfires burn everywhere from golf courses to council housing. The indiscriminate nature of disasters has earned it a reputation as 'the great equaliser', and yet the suffering communities endure after a disaster is not equally distributed. Society is fragmented in a diverse number of ways and the factions prepare and recover from disasters according to the resources they have at hand. While recovering from a disaster the unequal structures organising society are recreated once again. Consequently, the inequality of resources, like emergency relief aid, are highlighted amongst the damage. This moment of stark comparison offers the marginalised group motive and opportunity to take up arms and call for the equal redistribution of resources. In spite of this, the causes and consequences of inequality are rarely addressed in the environmental security literature.

As extreme weather events such as floods, droughts and wildfires are expected to continue their upwards trend in the following decades, the importance of researching the social consequences of natural disasters grows alongside it (Vinod, 2014). In investigating the following question "*How does the interregional unequal distribution of disaster aid affect the occurrence of violent conflict?*" this research contributes to the environmental-security literature. Moreover, this exploration highlights the significant impact, whether positive or negative, aid agencies' policy can have on all segments of the population.

A sub-national empirical analysis is conducted that includes 171 first order administrative divisions across five South East Asian countries. Using data on the World Bank's aid distribution from 1995-2009, an indicator is calculated that measures the inequality of aid distribution by

indicating if that case received more or less aid in relation to other administrative divisions that year. This study finds that the aid inequality indicator has a significant and negative relationship with the occurrence of organised violence and this relationship is not affected by the incidence of natural disasters.

After a brief review of relevant literature this paper provides an overview of relevant concepts and theories that help conceptualise the hypothesis. The following section explains the case selection, variables, and regression analysis. Finally, the results of the binary regression are explained and considered alongside the theorised hypothesis.

Literature Review

In the decade of 2004-2015 extreme weather events, such as flooding and droughts, have grown in number and intensity, while meteorological disasters have more than doubled in frequency (Vinod, 2014, p. 3). Scholars expect this upwards trend to continue until anthropogenic carbon emissions are reduced to meet the 1.5 °C maximum threshold set out by the Paris Climate Agreement (Rogelj, Elzen, Höhne, Fransen, Fekete, Winkler, 2016). Only then will greenhouse gasses that disrupt the carbon cycle and alter global temperatures cease to affect extreme weather events. As environmental scientists have predicted more frequent and intense natural disasters, the impetus to research the social consequences of natural disasters has escalated (Hsiang, 2018).

Civil and social conflict are among the theorised consequences of climate change and despite being researched extensively the field still finds contradicting results. Some authors argue that the scarcity of resources following a natural disaster leads to an increased risk of conflict due to

growing deprivation of and increased competition for resources (Wood & Wright, 2015; Nel & Righarts, 2008). While others argue in favour of natural disaster's power to unify people under one 'survivor' identity, halting regular levels of conflict (Slettebak, 2012). The literature's contradicting findings motivate an exploration of potential intervening variables that mediate the natural disaster-conflict relationship.

Natural disasters have far reaching effects on the economy, national trust and natural resources of those affected, which in turn can all play a role in determining the risk of conflict (Collier & Hoeffler, 2004). The detrimental economic effects of a natural disaster vary according to the level of the severity and the development of the affected. In cases of moderate natural disaster some sectors can even grow. For example, a moderate flood can benefit the growth of a nation's agricultural sector as it points towards more rainfall in the rest of the country. Less developed states and sectors, however, suffer the largest losses and are more sensitive to the consequences of disaster (Rigolini & Christiaensen, 2012). The grievances of a natural disaster also pose a turning point for the identity of a nation as it is a moment for residents to evaluate their trust in their government and neighbours (Wood & Wright, 2015; Kang & Skidmore, 2018). Finally, natural disasters have been found to destroy food production, contaminate water sources, and burn homes (Hsiang, 2018). This harm will disproportionately affect already impoverished people that are reliant on these essential resources to survive (De Silva & Kawasaki, 2018).

Particularly this destruction of essential resources has been considered as a source of conflict as it has direct implications on the economy and citizen's wellbeing. First, a disaster can create an immediate scarcity in resource supply. This could lead to the victims becoming more competitive

for resources in response to the increased stakes to collect them (Wood & Wright, 2015; Brancati, 2007). Second, natural disasters can suddenly increase the demand for essential resources in certain places, like medical equipment for health centers in the most affected areas of a disaster. This supply-induced scarcity and demand-induced scarcity are frequently studied as the mechanisms that explain how natural disasters lead to conflict (Böhmelt et al., 2013; Koubi et al., 2012).

The literature, however, lacks perspective on cases where scarcity is induced via resource distribution. Homer-Dixon (1999) introduces this phenomenon as *structurally-induced scarcity*, a situation where resources are unequally divided and concentrated within a certain group while the rest suffer from a scarcity. In this case there can be sufficient supply and a manageable amount of demand, but distribution is what creates scarcity and grievances.

This role of distribution becomes even more essential in the context of a natural disaster. The destructive effects of the disaster place pressure on the supply and demand of resources, thus putting government and international agencies in a uniquely powerful position. These bodies are able to distribute any available resources, like materials, funds or equipment, that can restore the loss of a citizen's essential necessities. The main origin of these resources are multilateral and bilateral aid organisations that distribute international development aid (IDA). We define aid as the distribution of food, water, shelter, and medical care by local, governmental or international agencies (Wood & Sullivan, 2015). Under the right circumstances this aid offers an opportunity to increase the wellbeing of the citizens, alleviate poverty, and invest in creating new jobs (World Bank, 2021).

Rather than distributing according to needs, the aid is found to be distributed according to existing socio-economic structures. Fink & Radaelli (2010) illustrate this trend occurring at a national level; They find that donor governments working via the World Bank allocate emergency relief payments according to political ties and the recipient's level of development. This trend is also prevalent at the subnational level; Song, Brazys, & Vadlamannati (2021) and Aldrich (2010) studied cases in India where education and poverty aid allocation, respectively, were strongly influenced by the caste system. Additionally, Briggs (2017) finds that poverty relief aid in Africa flowed towards the wealthiest segments of society.

Although this phenomenon of unequally distributed aid has been observed by a number of authors, the research has focused on the causes of inequality rather than the consequences (Aldrich, 2010; Song, Brazys & Vadlamannati, 2021; Briggs, 2017; Domingue et al., 2019; Fink & Redaelli, 2010; Rosvold, 2018).

The consequences of a more general type of inequality, economic inequality, has been researched, however. In a study by Ezcurra (2019), the level of interregional inequality, measured by regional income inequality, was found to be positively and significantly correlated with the incidence of civil conflict in that state. The article concludes that states with higher regional income disparities are more prone to conflict as any calls for redistribution from the disadvantaged group will cause tensions amongst the elite, the government, and the disadvantaged.

In another empirical set up exploring the consequences of economic inequality, water conflict could be predicted according to inequality, measured through the GINI coefficient (Gunasekara,

2014). Contrary to the latter, Cederman et al. (2015) distinguish their article through measuring group-level inequalities rather than individual-level inequalities. The authors found that economic inequality between different factions of society does drive conflict in cases where groups are relatively poor compared to the country average (p. 818). In this case the group bonds allow the individuals to aggregate their grievances and action to achieve organised violence. The article explains that the group ties existing across the society enables both the deprived groups, who feel disadvantaged, and the well-off groups, who feel they pay too much taxes, to take up arms (Cederman et al., 2015). In sum, the literature has established the impact that economic inequality has for inciting civil conflict.

Due to increasing levels of economic inequality and the decreasing government mechanisms to manage these levels of inequality, it has become increasingly relevant to study the consequences and potential dangers of economic inequality. On both a national and global scale the levels of economic inequality have reached a historical peak and have only increased in the past five decades (Dzuverovic, 2013). This trend is expected to continue according to the UN's World Social Report (2020) as economic inequalities are growing in over 70 percent of the global population. Furthermore, due to the global spread of neoliberalist mechanisms like Import-Substitution-Investment or welfare policies, states are unable to regulate the chasm between the rich and the poor as they have done in the past (Dzuverovic, 2013).

Considering the contested findings in the disaster-conflict relationship and the gap in the research concerning structurally-induced scarcity I aim to look at the distribution of aid as an intervening variable upon the disaster-conflict relationship.

Theoretical Framework

Disaster and Economic Inequality

To understand the inequality-conflict relationship completely we must not only look at the consequences of inequality, but also its causes. I argue that natural disasters aggravate economic inequalities in the following ways: (1) unequal distribution of vulnerability and (2) unequal distribution of aid.

Slettebak (2012) defines a climate-related natural disaster as "when a natural hazard affects a vulnerable population so forcefully that it causes substantial death and/or damage" (p. 164). This definition, adopted throughout this essay, introduces us to the concept of *vulnerability* which points to how the characteristics of an individual affects their ability to anticipate, mitigate, and recover from harm during a natural disaster (De Silva & Kawasaki, 2018). This preparation can be in the sector of infrastructure, insurance, or a state's social safety net. The wide spectrum of vulnerability is demonstrated in the case of Dutch and Bangladeshi flooding where despite the states being exposed to similar flooding levels, the Dutch are more effective at limiting harm due to their better funded climate adaptation strategies (Warner et al., 2018).

Levels of vulnerability can vary between and within states, but the overarching trend shows that the distribution of vulnerability reproduces existing economic disparities. In other words the wealthy are more protected from damages, while the already impoverished groups are more vulnerable (Verchick, 2012). In the case of the 2011 Bangkok floods these levels of vulnerability were concentrated outside urban areas. Inner-cities hosting wealthier individuals and corporations

suffered less harm due to their infrastructure compared to suburban or rural areas. These unequal levels of vulnerability also manifested economically as the flood would more harshly affect the livelihood and working conditions of the poor (Marks et al., 2020). Without action to rectify the levels of vulnerability this gap of economic inequality grows with every disaster.

Economic inequality can also be aggravated after a natural disaster through the distribution of aid. While the unequal distribution of all kinds of aid is an unfortunate, yet common, finding in the development literature the consequences of this trend have rarely been considered (Aldrich, 2010; Brazys & Vadlamannati, 2021; Briggs, 2017; Domingue et al., 2019; Fink & Redaelli, 2010; Rosvold, 2018). Distributing aid is frequently seen as a technocratic job where the resources are distributed to the most needy through an organised bureaucratic system. However, unequal aid distribution is found to be rather biased towards those already enjoying a high socio-economic standing (Aldrich, 2010; Rosvold, 2018).

The articles exploring the distribution of aid identified several elements that played a role in the inequality. First, social standing within a community helps determine whether an individual or group is offered economic opportunities, consequently it helps determine whether they receive a piece of the community's allocated aid (Takasaki, 2014; Domingue et al., 2019). For example, upon researching the post-tsunami aid distribution in Southern India Aldrich (2010) found that one's caste, economic status, and family standing were successful in predicting aid allocation. The author argues that marginalised groups lack the social connections within a community to organise the appropriate resources for themselves. A cycle then develops where social marginalisation is translated into economic marginalisation and so on.

Second, political objectives at a national scale help determine how the aid is distributed. International aid organisations often only go so far as to allocate aid to a certain government, but how that aid is distributed within the state is undefined. The aid organisations distribute nationally with the intention of utilising the local government's knowledge and its ability to assess which segment of their population is the most in need (Takasaki, 2014). In the case of development aid in the Philippines the author concludes that even when the international donors are focused on prioritising need over politics, the national organisations that distribute the allocated aid are found to favour projects for the benefit of the politically dominant group (Rosvold, 2018). Similar trends are found in Africa where aid flows to the political centers where the wealthiest people were concentrated (Briggs, 2017). In sum, we find that those in powerful and prosperous positions enjoy the help of aid while the political minority groups stay deprived of this resource.

Third, aid is distributed according to the political objectives of the international donors. States take into consideration the size, political alignment, and foreign reserves of a country to decide whether they will contribute to emergency aid. Consequently this selection determines that a specific type of country that adheres to an acceptable political ideation and has reached a sufficient level of development will be consistently favoured. Thereupon less developed states with low foreign reserves are not allocated aid they might desperately need (Becerra, Cavalla & Noy, 2012). It is for this last reason that multilateral aid organisations are seen as more effective at distributing aid according to need in comparison to bilateral organisations as the donors need to compromise their goals with their co-donors (Briggs, 2017).

Using previous literature we can posit that post-disaster aid can replicate and exacerbate economic inequalities by being distributed according to existing social and political structures.

An unequal distribution of aid or vulnerability is not inherently unfair as the need for these resources can be unevenly distributed. However, upon reviewing the previous cases outlining the distribution of aid and vulnerability we find that there is a bias towards those who have already secured a higher socio-economic status. It is for this reason that we will interpret the inequality of distribution to increase these economic inequalities rather than reduce them. In sum, we find that natural disasters offer ample opportunity to widen the gap between the rich and the poor. Moving forward this research will consider how the unequal distribution of aid, specifically, plays into the consequences of growing economic inequalities.

Mobilising Inequality

Several mechanisms enable the inequalities exacerbated by natural disaster to be mobilised for conflict. The aggregation of group-level inequalities, existing social networks, relative deprivation, and a loss of absolute wellbeing have all been found to affect the inequality-conflict relationship. We require these mechanisms to translate economic inequality into an organised movement that is willing and able to apply violence to reach their goals of redistribution. Kofi Annan, former UN Secretary General, put it simply when addressing the World Bank : “Simple inequality between rich and poor is not enough to cause violent conflict.” (World Bank, 1999)

The scale at which we recognise economic inequality is rather critical when we consider its effect on the probability for violence to occur. Several individuals experiencing economic inequality

have limited political power to make a change for themselves, while a group that has endured the unfair distribution of resources has a larger platform to incite change through politics or force. In other words, we must distinguish between horizontal and vertical inequalities. Horizontal inequalities measure the unequal distribution of resources between groups that are differentiated in other ways be this religious, race or regional, rather than measuring the inequalities amongst individuals like vertical inequalities do (Ostby, 2008).

In the context of this analysis we find horizontal inequalities more relevant to consider as the literature on the inequalities of aid and vulnerability have frequently found that the distribution is decided according to existing socio-economic divisions (Aldrich, 2010; Brazys & Vadlamannati, 2021; Briggs, 2017; Domingue et al., 2019; Fink & Redaelli, 2010; Rosvold, 2018). Moreover, inequality-conflict empirical research supports the notion that economic inequality measured at a group level rather than at an individual level research is better able to identify a significant and positive relationship between the two variables. The inequality-conflict literature reached a turning point when vertical inequality indicators, like the GINI coefficient, were replaced by group-level indices. The change of this indicator helped establish a positive relationship between economic inequality and conflict that previously had been unclear (Mach, 2019; Cederman et al., 2014; Stewart, 2000).

When measuring inequalities at the group level we can identify potential patterns of inequality that overlap with identity-based cleavages. In cases of economic inequality a group identity exists whether it is the reason for the discrimination or it is created by the common grievances of the discrimination. Studying if there is an existing social network that unifies those that are

experiencing economic inequality provides insight into the extent this group can be mobilised efficiently. This social network offers an established forum to aggregate experiences and grievances that then can be translated into action (Ostby, 2008). In cases where the economic inequality overlaps with social cleavages existing leaders within the regional, ethnic or religious communities will be able to utilise their existing ties and the trust within the community to organise a political or violent movement rather than needing to build this from the ground up (Østby, 2008). I argue that a collective action problem can be aptly overcome due to the social networks of the marginalised group.

Conflict may emerge once a group joins to aggregate their grievances. Once this happens they are capable of recognising their horizontal inequality and see that they are relatively deprived in comparison to another group. In applying Gurr's Relative Deprivation Theory to a group-level we understand it as the discrepancy between the group's expectations of their life conditions and the actual capabilities to fulfill these expectations (Dzuverovic, 2013, p. 4). When the group perceives others' wellbeing to be up to their expected standards they see that a different lifestyle is possible. For example, when a sufficient amount of aid is distributed in one region of a country a region lacking aid recognises that in theory there is enough aid to meet their needs. Consequently, appeals towards the government or more affluent groups to redistribute can escalate towards more violent conflict (Cederman et al., 2015).

When we apply the Relative Deprivation theory to the setting of a natural disaster we find that not only can communities feel deprived relative to other social or regional groups, they could be suffering from absolute deprivation and comparing current circumstances to their pre-disaster

comforts and resources (Jaggers & Moore, 2005). The instantaneous nature of natural disasters can arguably heighten the effects of the Relative Deprivation theory due to the sudden absolute deprivation. The swift loss in capabilities and resources caused by a natural disaster's destruction does not give those affected the time to readjust their expectations of their wellbeing. In this period where those affected are adjusting to their post-disaster capabilities they can be more sensitive to the inequalities they experience relative to other groups (Dzuverovic, 2013).

Organised Violence

Once the shared grievances caused by economic inequalities are compiled within a community, the existing social ties provide a forum for the group to organise a type of political violence. This analysis will be examining economic inequality's relationship with violent conflict, rather than non-violent conflict. In studying violent conflict as the outcome variable the analysis stays aligned with the Relative Deprivation Theory. The theory outlines economic inequality in particular as a mechanism to instigate a sufficient amount of frustration to motivate conflict (Džuverovic, 2013). This frustration stems from a lack of wellbeing and a stifled ability to self-actualise economically and Gurr (1970) concludes that this lack can quickly generate a call to action towards collective violence.

Aid induced economic inequality offers unique circumstances that arguably offer both opportunity and grievances necessary to mobilise violent conflict (Collier & Hoeffler, 2004). Economic inequality has been considered as an atypically severe grievance that could potentially act as a potent motive for violent conflict, yet an opportunity to act on this motive still needs to be presented (Džuverovic, 2013; Collier & Hoeffler, 2004; Ostby, 2008).

Collier & Hoeffler (2004) mainly recognise the required financial support to create an opportunity to mobilise. While they suggest opportunity by extortion of natural resources, donations from diasporas and subventions from hostile governments, I argue that the presence of aid in a state can offer financial opportunity to start or continue violent conflict. Wood & Sullivan (2015) found a significant and positive relationship between the allocation of humanitarian aid and increased rebel violence. Furthermore, the distribution of aid offers an additional opportunity to act: the unequal distribution is a turning point where the economic inequality becomes explicitly visible in the community (Džuverovic, 2013). This window of opportunity is a designated period of time communal outrage can mobilise. In sum, the aid allocation that feeds the economic inequality is the same that offers opportunity for rebellion.

When examining an array of examples that explore the economic inequality-conflict relationship we discern two targets of violence that are included in the analysis: (1) the marginalised group violently opposing the government and/or (2) the marginalised group opposing a group in possession of more wealth (Ezcurra, 2019; Gunasekara, 2014; Cederman et al., 2015). The first instance considers the government to be the main responsible body that can redistribute wealth or change systemic inequality. The second option aims to do the redistribution themselves and fund further political violence (Wood & Sullivan, 2015). For this reason we will be defining our violent conflict as intra-state organised violence between the government and a civilian group or between two civilian groups where there are at least 15 lethal casualties (Pettersson & Öberg, 2020; Sundberg & Melander, 2013).

When we consider the possibility of organised violence after a natural disaster we find conflicting evidence within the disaster-conflict literature. The findings offer strong empirical and theoretical arguments that support people's tendency to cooperate after a disaster. These articles highlight natural disasters' power in unifying people despite the lack of resources and increased grievances. When experiencing a common tragedy a 'survivor identity' can be created that trumps existing societal divisions and makes people more willing to cooperate (Slettebak, 2012). For example in the case of drought in East Africa we find that after disasters where a population shares equal harms and trials intra-and inter-ethnic trust can even expand (De Juan & Hänze, 2021).

The great weakness of this unifying effect of disaster is that it relies on the shared identity of survivors to overpower existing social cleavage. However this perception can be shattered quickly when the population recognises that the damages of the disaster have not been distributed equally. Upon reflecting on the unequal vulnerability to disaster and the unequal distribution of aid after a disaster we find that the social cleavages can be strengthened rather than diminished. Where natural disasters increase economic inequalities the opposite of cooperation can occur, mainly conflict (Gunasekara, 2014; Ezcurra, 2019; Cederman et al., 2015).

Previous literature has established theoretical insights presenting how aid distributed after a natural disaster frequently feeds into existing socio-economic divisions and thus increases economic inequality. Growth of economic inequality amongst ethnic, religious or regional cleavages brings a communal grievance as well as the group identity to the forefront. The unequal distribution of aid after a natural disaster not only alerts the presence of inequality, but also shows that achieving more capabilities is possible. The relationships created or existing within the marginalised group

could be utilised to mobilise the group to achieve particular goals of redistribution through politics or force. Lastly, the theory points towards how these economic grievances can be accompanied by an opportunity to incite violence against the government or other civilian groups after a natural disaster.

This leaves us with the following hypothesis:

H1: The more unequal aid distribution is after a natural disaster, the higher the probability of organised violence.

Methodology

Unit of Analysis and Case Selection

In order to evaluate the relationship between unequal aid distribution and the occurrence of organised violence a quantitative analysis will be conducted at a subnational level. Georeferenced data will be applied to explore this question statistically in SPSS and geospatially in qGIS.

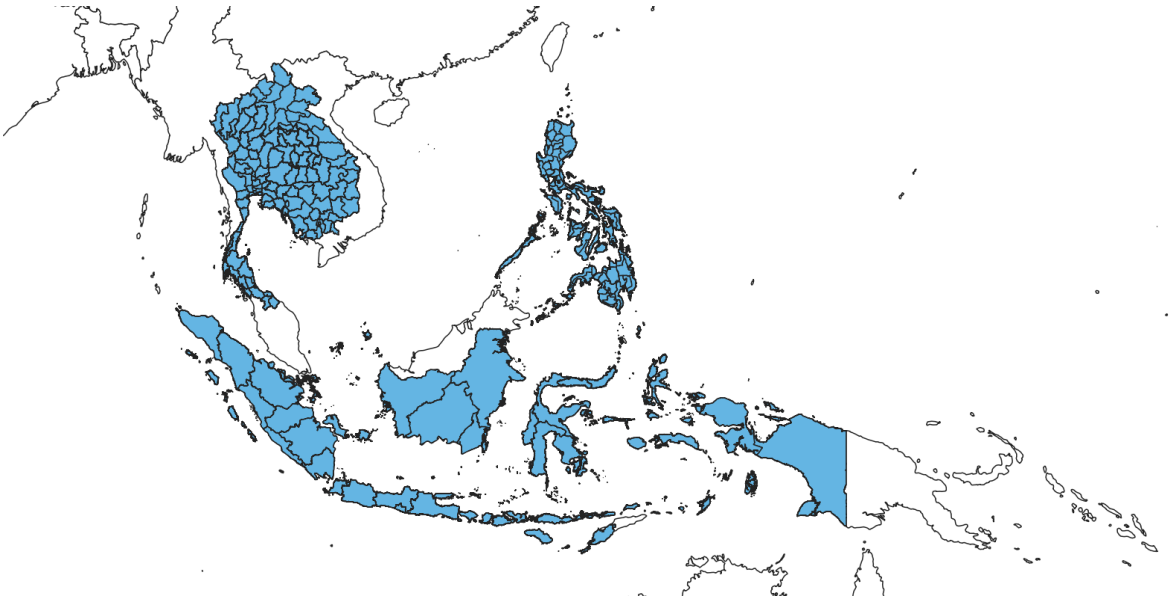
The assessed cases are measured in the unit of first-order administrative divisions, the largest geographical divisions made by the state. These borders frequently overlap with the limits of cities and towns in addition to overlapping with regional culture and customs (Ezcurra, 2019). The first-order administrative division of a state provides an appropriate scale to balance geographic precision and data availability when measuring both horizontal aid inequalities and violent conflicts. The regional divisions capture the aggregation of certain socio-economic groups that potentially influence the aid distribution process and the mobilisation for conflict, while they avoid having to label the boundaries of certain social groups. This is relevant because the borders

between ethnic or religious groups are dynamic and can shift over time. Furthermore these identities are frequently more complex than one identifying characteristic (Ezcurra, 2019). In this way the regional divisions allow us to view the state through the administrative lense of the government.

Using this method this paper will be comparing aid distribution within a country where groups share a government and similar characteristics. This mirrors reality as personal relative deprivation theory argues that because of these similarities citizens are likely to compare their wellbeing within a national framework (Callan et al., 2017).

The chosen cases are first administrative orders based in the region of South East Asia. The environmental security literature has primarily featured the African continent in its research due to the availability of data, however this has resulted in limited investigation on the conflict risk natural disasters pose to other regions (Hendrix, 2017). South East Asia offers a compelling area of research as the region's coastal environment, warm climate, and proximity to the ring of fire makes it susceptible to natural disasters (Vinod, 2014). It is therefore increasingly relevant to study if processes following these natural disasters, like aid distribution, contribute to violent consequences. The available data allows the research to include 171 administrative districts across five states: Cambodia, Indonesia, Laos, Philippines, and Thailand, in the years of 1995-2009. These cases and their territorial boundaries are presented in Figure 1.

Figure 1. Presentation of the selected first order administrative divisions



Independent Variable

The World Bank offers a comprehensive database outlining all its approved aid projects under the International Bank for Reconstruction and Development (IBRD) and International Development Aid (IDA) from 1995-2014. The data set presents the allocated and disbursed amounts of aid in USD in addition to coding the geographical location of the project with coordinates. Using the variable Total Disbursed Aid from the georeferenced dataset we can grasp how the aid is disbursed across the state's first administrative orders. Consequently, we'll find if this distribution is unequal across regions and potentially feeds horizontal inequalities.

International development aid streams from a wide variety of donors and is allocated with a wide range of objectives: rebuilding after a conflict, emergency relief, and poverty alleviation (Collier & Dollar, 1999). The World Bank is a multilateral donor created in 1944 that supplies aid for the fore-mentioned objectives, but focuses most efforts towards supporting economic development. It has become a key player in the field of development aid in their attempt to reduce extreme poverty

by 2030 and increase the wellbeing of low- and middle-income countries (Briggs, 2017). Embedded in this goal is providing aid for mitigating disaster risk and supporting disaster relief (World Bank, 2021)

The World Bank's aid distribution qualifies as an adequate proxy for the global patterns of development aid due to its multilateral nature and common protocol for deciding aid. The aid distribution by the World Bank accounts for a significant portion of international development aid due to the participation of multiple prominent donors (World Bank, 2021). Moreover, the multilateral nature of the organisation requires it to balance the diverse interests of the donors allowing the patterns of distribution to reflect the dominant interests of several donors (Briggs, 2017). Finally, the World Bank applies common protocol to plan aid allocations like evaluating the severity of need, the political system or the development level (Becerra, Cavallo & Noy, 2012; Collier & Dollar, 1999).

All aid projects will be considered in the analysis without regard to their original purpose. While the data set codes the original purpose of each sum of aid I argue that any new aid distributed after a natural disaster will feed into the feeling of relative deprivation. Despite aid being intended for other purposes, it will be applied to bettering the wellbeing of that community in some way. Consequently, any improvement in the community's welfare can be compared with those that haven't received that benefit. Moreover, funds for aid projects that had previously been planned are frequently merged with aid allocated to a state after a disaster. This means that aid categorised for non-emergency relief intentions can be re-allocated in the wake of a disaster (Becerra, Cavallo & Noy, 2012)

The horizontal aid inequality will be calculated from the World Bank data into the variable *Aid Inequality* by normalising the standard deviation from the mean. The indicator measures the inequality of aid distribution by indicating if that case received more or less aid in relation to other administrative divisions that year. The variable is calculated by subtracting the population's mean from the district's allocated aid annually and then dividing this result by the population's standard deviation. The aid distributed amongst a state's first order divisions in a given year is considered the population in this equation. Then, only negative values are included, while the positive values are coded as 0 (see Figure 2). This transformation ensures that the variable measures cases where the level of aid inequality discriminates against the case. Finally, for the sake of interpretation, the coefficient is divided by -1 so that a one-unit increase in the variable indicates an increase in inequality. The *Aid Inequality* variable measures the level of aid inequality within a state each year where a one unit increase indicates more discriminatory inequality.

Figure 2. Equation for Aid Inequality indicator

$$\frac{x_i - \overline{\mu}_t}{\sigma_t}$$

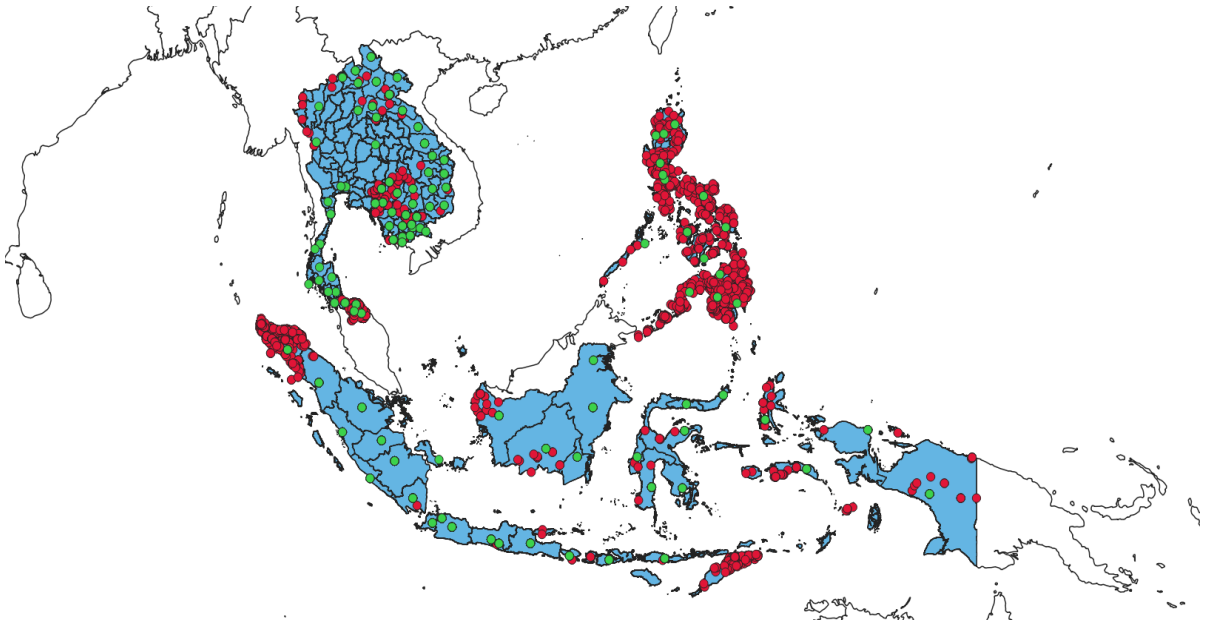
Dependent Variable

The occurrence of conflict is measured by the UCDP Georeferenced Event Dataset (GED) Global version 20.1 (Pettersson & Öberg, 2020; Sundberg & Melander, 2013). This georeferenced dataset is UCDP's most disaggregated data set covering individual events of organized violence measured in longitude and latitude. The UCDP defines organised violence as lethal events that are state-based, non-state based, or one-sided that have resulted in more than 25 fatalities in a calendar year (Högbladh, 2020).

Using the UCDP data set a count variable can be made aggregating the annual occurrence of conflict at the subnational level. The count variable has been coded into a binary variable, *Organised Violence*, where 1 codes for the occurrence of organised violence and 0 codes for no occurrence of organised violence. The occurrence of violent conflict is determined by an accumulation of unrelated factors and so due to its multicausal nature we cannot claim aid-induced economic inequality to be the sole reason for violent conflict to emerge. We can, however, determine if this economic inequality plays a role (Džuverovic, 2013).

In Figure 3 the georeferenced data on aid and conflict has been presented. Each distribution of aid is represented by a green dot and each case of conflict is represented by a red dot. This presentation offers how these data points relate to each other geospatially. The map shows that certain cases of aid distribution and conflict occurrence overlap, however, no clear trends can be determined.

Figure 3. Presentation of Aid Projects and Conflicts among selected cases 1995-2009



Interaction Effect: Occurrence of a Natural Disaster & Aid Inequality

The analysis includes a binary variable, *Natural Disaster*, coding the occurrence of natural disasters in a given year according to the EM-DAT Public database. The included natural disasters: droughts, floods, wildfires, storms and insect infestations are all reportedly heightened in frequency and intensity by anthropogenic climate change (Hsiang, 2018. Classen et al., 2005).

The *Natural Disaster* variable is used to conduct an interaction effect with the independent variable *Aid Inequality*. The interaction effect will indicate whether the effect of *Aid Inequality* depends on the interaction with *Natural Disaster* or vice versa. We expect that in cases of natural disaster *Aid Inequality* has a higher effect on the conflict variable due to the sudden loss of resources after a natural disaster. This will increase the absolute deprivation of those affected and it will require time to recalibrate and lower the citizen's acceptable standard of living. In this period of time the sensitivity for resources and by extension resource inequality will increase the probability for conflict to occur (Dzuverovic, 2013). This interaction effect helps us explore the role of natural disasters in strengthening or diminishing this relationship between aid inequality and the occurrence of organised violence.

Control Variables

Vulnerability to natural disasters has been considered in this analysis alongside aid inequality as a variable that affects the level of economic inequality after a natural disaster. To differentiate between the two effects we apply a proxy for vulnerability, the percentage of households able to access electricity. A variable that indicates the level of infrastructure has frequently been used to measure vulnerability (Marks et al., 2020; Vechick, 2012, Cederman et al., 2015). Access to

electricity is considered a basic service that has a high effect in determining a settlements' sensitivity towards climate change (Ahumada-Cervantes et al., 2014). This sensitivity causes harm immediately after a natural disaster, but also has longer lasting effects when attempting to rebuild.

Using the Global Data Lab's dataset the variable *Vulnerability* is configured to represent the percentage of households in the first-order administrative division that has access to electricity in that year (Global Data Lab, 2020). It is expected that the higher the accessibility to electricity the less likely conflict will occur as better infrastructure mitigates harms and economic losses.

Using data from the Global Data Lab's Subnational HDI the variable *Subnational HDI* is applied to measure the quality of life within a first-order administrative division. This variable is relevant as it measures the absolute level of deprivation in a certain administrative district. The less citizens have to start with the more deprived they become after the effects of a natural disaster. A high subnational HDI can point towards more governmental safety nets like income maintenance payments, unemployment insurance and public healthcare that can in turn affect the citizens feelings of deprivation after a natural disaster (Deryugina, 2016). For this reason it is expected that the lower the subnational HDI, the lower the quality of life, the more likely conflict will occur.

Like the UNDP's national HDI the Global Data Lab's subnational indicator reflects the citizen's wellbeing by incorporating three dimensions (1) education, measured in average years of schooling, (2) health, measured in life expectancy at birth, and (3) standard of living, measured in gross national income per capita. The indicator ranges from 0 to 1 where the closer the score is to

1 the better the quality of life (Global Data Lab, 2018). Due to this one unit range the HDI indicator has been multiplied by 100 to allow for better interpretation of the effect size.

Lastly, *Population* is a well-established control variable as it offers insight into the relative demand for aid. Aid allocation is found to grow according to the number of fatalities, not according to the level of need (Evangelidis & van den Bergh, 2013). This creates many instances where aid allocation does not align with the present population and potentially creates more inequalities. For this reason it is expected that the bigger the population the more likely organised violence is to occur. The data has been collected from the Global Data Lab's database and measures the annual population of a division in millions (Global Data Lab, 2020).

Results

A binary logistic regression using the *AidDistribution* variable as the independent variable and *Organised Violence* variable as the binary dependent variable will be applied as the estimation model. This regression allows us to predict the probability that an observation falls into the category of (1) organised violence occurred or (0) organised violence did not occur according to the independent and control variables.

The assumptions for the binary logistic regression have been met and are presented in the Appendix. The adherence to the assumption strengthens our confidence in the accuracy of the presented results. Upon measuring collinearity we find that each of the predictor and control variables has a VIF coefficient ≤ 10 and thus are below the threshold of establishing collinearity (Dormann et al., 2013). We do discern potential concern for collinearity with regards to

Vulnerability and *Regional HDI* as the VIF coefficient is >5, however as they are control variables, this will have a limited influence on the analysis. Furthermore, using the Box-TidWell test we find that the independent and control variables are linearly related to the outcome variable's log odds, except for the *Population* variable. Finally, the sample includes 2565 cases which offers us a sufficiently large sample size to complete this analysis.

Table 1. Presentation of Models 1 and 2

	Model 1.1	Model 1.2	Model 2
I**ntercept**	-1,789*** (0,001)	-3.746*** (0,001)	-3,923*** (0,001)
Aid Inequality	-0.235 (0.182)	-0,755*** (0,004)	-0,165 (0.751)
Natural Disaster		0.194*** (0,001)	0,202*** (0,001)
Vulnerability		-0,016** (0,030)	-0,016** (0,033)
Regional HDI		0,044* (0,068)	0,046* (0,059)
Population		-0,062*** (0,001)	-0,062*** (0,001)
Aid Inequality x Natural Disaster			-3,923 (0,205)
Nagelkerke's R	0,001	0,281	0,282
N	2565	1349	1349

Table 1 presents a summary of the results of Model 1 and 2. The first model presents the relationship between the independent variable *Aid Inequality* and *Organised Violence* while controlling for *Vulnerability, Regional HDI,* and *Population*. Model 2 includes an interaction effect between *Aid Inequality* and *Natural Disaster* which helps explore whether this relationship

between *Aid Inequality* and *Organised Violence* changes according to the occurrence of a natural disaster that year or not.

Model 1.1 presents the effect of the independent variable on the occurrence of organised violence and includes all 2565 cases. This baseline model offers limited findings on the aid inequality-violence relationship. We find that the inequality of aid distribution has an insignificant and negative effect on the occurrence of organised violence (b = -0.235, Wald $\chi(1) = 1{,}778$, p = 0,182). The probability of getting a value of Wald as or more extreme than Wald χ (1) = 1,778 under the null hypothesis (The equality of aid distribution has no effect on the occurrence of organised violence) is larger than 5 per cent, hence we cannot reject the null hypothesis at the 5% level.

In the following model, the control variables *Natural Disaster, Vulnerability, Regional HDI,* and *Population* are introduced into the analysis. In excluding cases that have missing data on these controls the analysis is left with 1349 complete cases. The varying sample sizes have limited effects on our results since we aim to only make conclusions with regards to South East Asia. Due to the analysis including 171 of the region's 275 first order administrative divisions both of the models have a sufficiently large sample size to infer effect sizes at a 95% confidence level.

The inclusion of the controls increase the significance of the independent variable's effect resulting in *Aid Inequality* having a very significant negative effect on the probability of organised violence (b = -0,755, Wald $\chi(5) = 8{,}398$, $p < 0{,}01$). To understand the effect size more precisely we consider the odds ratio Exp(B) = 0,470. We find that a one unit increase of the independent variable will multiply the likelihood of organised violence to occur by 0,470. This means that an increase in the

variable *Aid Inequality*, indicating that there is an increase in discriminatory inequality, lowers the chances of organised violence occurring.

This result, the more that aid inequality discriminates against a certain case the less likely violence will occur, contradicts the theorised positive relationship between *Aid Inequality* and *Organised Violence*. An alternative explanation to understand this outcome relates to the requirement of opportunity to mobilise. Using conclusions from Collier & Hoeffler (2004) and Wood & Sullivan (2015) our theoretical framework argued that if there is aid present in the state violent actors can procure this wealth and use this as a financial opportunity to mobilise conflict. When considering these results the presence of aid in the country may not have been enough of a financial opportunity to mobilise. The lack of aid in the first order administrative division itself may stunt the mobilisation towards conflict due to lack of funds.

When considering the rest of the model we find that each of the control variables present a significant result. The variable *Natural Disaster* presents a significantly positive effect (b = 0,194, Wald χ (5) = 13,134**, p<0,01). For every additional natural disaster that occurs in a given year, the likelihood of organised violence is multiplied by 1.214 (Exp(B) = 1.214). This highly significant result offers insight into a core debate held in the environmental security literature: 'Does a natural disaster increase the probability of conflict occurring?'. The result presents support for theories that expect the consequences of natural disasters, like the destruction of natural resources, to increase the occurrence of conflict (Brancati, 2007; Böhmelt et al., 2013; Koubi et al., 2012; Wood & Wright, 2015; Nel & Righarts, 2008)

The *Vulnerability* variable exhibits a significantly negative effect (b = -0,016, Wald χ (5) = 4,738**, p<0,05). Despite having limited effect size the effect is as predicted, the higher the percentage of administrative division's households that has access to electricity the less probable it is that organised violence will occur. An area's level of infrastructure helps explain resilience against conflict.

While it was expected that an increase in a region's HDI would lower the probability of organised violence occurring, the results of the *Regional HDI* variable vary from the predicted effect (b = 0,044, Wald χ(5) = 3,342** p<0,10). An increase in Regional HDI increases the chance for conflict by 1.045 times (Exp(B) = 1.045) meaning that the better the quality of life is in a first order administrative division the more likely conflict is to occur.

This conclusion arguably aligns with the results of the independent variable, *Aid Inequality*, as it points towards the requirement of financial opportunity to mobilise conflict. The cases that received less or no aid compared to the other divisions made conflict less likely to occur. Cases with a higher HDI, which incorporates the regional GDP level, are more likely to encounter organised violence. In both these results those that are equipped with more resources, aid or GDP, are more likely to experience organised conflict.

The *Population* variable presented a significantly negative effect (b = -0,062, Wald χ(5) = 14,138** p<0,01). This result implies that an additional one million residents to a first order administrative division will decrease the chances of organised violence occurring.

When comparing Model 1.1 and 1.2 we find that the control variables noticeably improve the model's explanatory power. Because logistic regression is not based on the method of least squares we apply the pseudo R-squared measure, Nagelkerke's R^2, to measure the explanatory value of the models. Although this measure cannot be interpreted as R^2 the range from 0 to 1 can be used as a measure of the model's overall performance, where the closer to zero the worse the predictive value and vice versa (Steyerberg et al., 2010). In Model 1.1 the Nagelkerke's R^2= 0,001, this low result shows that the independent variable had a very low improvement to the baseline model. When we include the control variables in Model 1.2 the measure increases to Nagelkerke's R^2= 0,281 which represents the model's moderate explanatory power.

In Model 2 the interaction effect between *Aid Inequality* and *Natural Disaster* is explored. While the explanatory power of Model 2 is marginally better than Model 1 (Nagelkerke's R^2 = 0,282) the results, however, do not reflect our hypothesis. The results of the interaction variable are not significant (b = -3,923, Wald $\chi(5)$ = 0,205** p = 0,205). According to these results we cannot reject the null hypothesis: the occurrence of one or more natural disasters does not affect the aid inequality-organised violence relationship.

In sum, the binary logistic regression has not supported our hypothesis: The more unequal aid is distributed after a natural disaster, the more likely organised violence will occur. On the contrary, the results from Model 1.2 and Model 2 demonstrate that *Aid Inequality* presents a significant negative effect on the occurrence of organised violence that is not influenced by the presence of one or more natural disasters.

Conclusion

Throughout this study we have explored how the distribution of aid after a natural disaster can exacerbate economic inequalities to the point that conflict occurs. Our subnational analysis investigates the relationship between the inequality of aid distribution between 171 first order administrative divisions across South East Asia and the occurrence of organised violence. The empirical results offer significant insight into the aid inequality-organised violence relationship, but does not support the theorised hypothesis: The more unequal aid distribution is after a natural disaster, the higher the probability of organised violence occurring.

The findings reveal that aid inequality is negatively related to the occurrence of organised violence. This means that despite the presented theory, the less aid a case is distributed in comparison to other administrative divisions that year, the less likely it is for organised violence to occur. Additionally, the number of natural disasters does not alter the effect size of the independent variable. Altogether the findings show that the more unequal aid distribution is, at any point in time, the lower the probability of organised violence occurring.

In an attempt to explain these results we consider whether the lack of aid distributed to an administrative district specifically leads to insufficient financial opportunity to mobilise towards violence (Collier & Hoeffler, 2004). Aid distributed in a state has proven to sustain organised violence (Wood & Sullivan, 2015). However, bearing in mind the analysis' results, this trend may not develop in an administrative division when aid is not distributed to that division specifically. The availability of funds and resources presents itself as a relevant variable in determining the occurrence of violence. This notion is strengthened by the significant and positive effect of

regional HDI. The higher the HDI of an administrative division, which includes the local GDP, the higher the likelihood for organised violence.

To contextualise the findings, the following limitations of the analysis are addressed. First, due to the nature of a sub-national analysis the research suffered from certain data constraints. While in recent years data on South East Asia has expanded in scope and precision, reliable data points covering subnational levels of electricity accessibility, HDI, and population size pre-2000s were limited. Any cases missing a variable were excluded thus causing the models including the control variables to not represent the pre-2000s years as accurately. Second, the independent variable, *Aid Inequality*, only measures the development aid allocated and disbursed by the World Bank. Aid agencies frequently complement each other's work by dividing and conquering the areas that are in need of aid. By only considering aid allocated from one source the analysis cannot measure the aid inequality as precisely (Takasaki, 2014). For example the analysis locates inequalities between cases while in reality another organisation is providing aid that would resolve the inequalities. Third, the cases are measured at the first order administrative division. This unit allows for an analysis to be conducted sub nationally while still having a relatively broad range of data available. Despite being subnational these divisions still cover large areas and are not uniformly divided across the studied countries. I argue that the analysis could be improved by using a smaller and more uniform unit like dividing a region in a grid.

The findings presented in this analysis offer promising implications for future research. By identifying that the number of natural disasters has a positive effect on the probability of violence occurring, this analysis highlights the importance of studying the changes in the climate that

increase the frequency and intensity of natural disasters. Furthermore, this analysis provides an impetus to qualitatively study aid inequality in relation to conflict. A case study approach allows the research to discern what mechanisms lower the probability of violence occurring.

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Appendix

Assumptions

Multicollinearity Statistics

	Tolerance	VIF
I**ntercept**	0.868	1.151
Aid Inequality	0.919	1.088
Natural Disaster	0.868	1.151
Vulnerability	0.129	7.777
Regional HDI	0.578	1.729
Population	0.578	1.729

Box Tidwell

	Exp(B)
Log Aid Inequality	-0,001
	(0.984)
Log Natural Disaster	0,264
	(0,826)
Log Vulnerability	0,315
	(0,101)
Log Regional HDI	0,005
	(0,166)
Log Population	-0,041***
	(0,001)

Descriptive Statistics

	N	Minimum	Maximum	Mean	Standard Deviation
Conflict	2565	0	1	0.14	0.345
Aid Inequality	2565	0	4.90	0.1783	0.36028
Natural Disaster	2565	0	23	4.81	4.265
Vulnerability	1470	0	100	69.88	31.937
Regional HDI	2310	28.00	77.10	58.648	9.95504
Population	1349	0.01	43.60	8.4143	8.54450