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Evaluation of the relationship between fire, land cover and armed conflict in West Iran

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Abstract

The presence of political instability might facilitate the risk of armed conflict events to emerge. Not only would these disputes threaten human livelihoods, but they are further capable of negatively affecting the environment. Since armed conflict and its influences on ecosystems are compound and challenging to examine due to limiting accessibility to the areas caused by the danger of ongoing fighting, remote sensing can be used to evaluate both direct and indirect impacts of conflict on the ecosystem.

One environmental aspect induced by armed conflicts are changes in fire activity. Not only are ecosystems more vulnerable to fires under periods of armed conflicts but intentional ignited forest fires can also play a crucial part in military strategy. Nonetheless, the relationship between armed conflict, fire and land cover in West Iran has not been extensively studied, where previous research in the Middle East have investigated Israel, Syria, Lebanon, Turkey, and Iraq. The aim of this study is to narrow the knowledge gap in this region by assessing how land cover and fires in West Iran relate to armed conflict through answering the hypothesis: Armed conflict leads to elevated fire occurrence that cannot be explained by climate alone.

Data surrounding conflict events is acquired from a combination of two geocoded event databases, where one gives insight into armed conflict events that were characterized by at least one fatality and the other includes diverse political acts. Information regarding vegetation fire occurrence was obtained from an active fire dataset. The land cover dataset used was specifically created for Iran and climatic data included temperature and precipitation data on a monthly resolution.

Using tools such as spatial GIS analysis, bivariate global- and local Moran's I and Spearman rank correlations, a statistically significant spatial relationship was found between conflict and fire incidents, represented as localized clusters of high conflict and high fire occurrence. These clusters did have lower correlations to the climatic variables compared to the provincial level, implying that these fires might have indeed originated from the surrounding conflict. In addition, the analysis of the relationship between conflict and land cover showed, that while most conflicts did take place in cities, a higher proportion of these events can be classified as non-violent in comparison to the types that materialised on croplands.

The results highlight that in localized clusters, climatic variables often failed to explain fire occurrence, suggesting that the impact of conflict on fire events is spatially confined and does not affect areas further away. Hence, research conducted on conflict impact on the ecosystem should not only place an emphasis on the local scale, but also focus on the type of conflict that land systems are exposed to. Given that agricultural systems, especially, had a higher proportion of potentially damaging conflict instances, evaluating the effect of conflict on this environment will be crucial.

Table of Contents

1 Introduction

Political instability enhances the risk of armed conflicts, which not only pose a great threat to human livelihoods, but are further capable of impacting the environment, hence making it essential to examine their ecological effects (Mitri et al., 2011). These induced changes on the ecosystem are complex; in some areas exposed to continuous fighting land degradation might arise, while biodiversity might be restored when anthropogenetic pressures are reduced in other conflict-affected regions (Elard, 2007; Kim, 1997).

One environmental aspect caused by armed conflict is increased fire activity, where accidental ignitions might occur due to collateral damage or intentional fires originating from conflict events (Linke & Ruether, 2021; Mohamed et al., 2020). Indirect actions brought about by conflict, such as population movements away from the violence-affected areas, enhance the susceptibility of nearby vegetated areas to fire (Elard, 2007; Mitri et al., 2011). Especially vulnerable are agricultural fields, where conflict induced land abandonment results in a low workforce and lack of access which in turn heightens fire risk (Mitri et al., 2011). Additional effects of indirect nature primarily include the actions of people towards the ecosystem under times of armed conflict, such as shifts in their decision making and changes in their exploitation/usage of natural resources (Mubareka & Ehrlich, 2010).

Previous research has shown that emergence of armed conflict might lead to land abandonment and hence negligence of the usual land management (Viedma et al., 2015). This lack of management would then allow biomass to accumulate, especially for land covers characterized by forest and other wooden vegetation forms, increasing the fire risk as a consequence. Not only are these ecosystems more susceptible to fires under armed conflicts but intended forest and agricultural fires can also play a crucial part in military strategy (Dinc, 2021; Linke & Ruether, 2021; Mitri et al., 2011). Furthermore, this issue is amplified by the fact that once a fire has been ignited, it is often difficult for local authorities to control its extent and successfully extinguish it during periods of armed conflict (Mitri & Gitas, 2008).

This illustrates the challenges of examining both armed conflict and its influences on ecosystems, further complicated due to limiting accessibility to the concerned regions given the danger of active fighting (Gorsevski et al., 2012). Thus, remote sensing offers an appropriate measure to assess both direct and indirect impacts of conflict on the ecosystem.

1.1 Aims and Objectives

Armed conflict and its association to fire and land cover in West Iran have not been extensively assessed, although previous studies in the Middle East have covered Israel, Syria, Lebanon, Turkey, and Iraq (Dinc, 2021; Eklund et al., 2021; Levin et al., 2016; Mitri et al., 2011; Zubkova et al., 2021). The purpose of this thesis is to help fill the research gap in this region by evaluating how land cover and fire dynamics in West Iran interact with armed conflict through the following hypothesis and subsequent research questions.

Armed conflict leads to elevated fire occurrence that cannot be explained by climate alone.

1. Which land cover is primarily affected by fire events or armed conflicts?
2. What is the temporal and spatial relationship between fire and conflicts? Is there a detectable difference between the pre- and the armed conflict period?
3. To which degree are climate or climatic anomalies responsible for fire occurrence in conflict-affected areas?

Furthermore, this pattern will be analysed, discussed, and placed into context by comparing it to studies conducted on fire behaviour in other conflict zones. With these research questions in mind, a quantitative analysis is conducted that will provide insight into the existence of enhanced fire occurrence due to conflict events. Throughout this analysis knowledge about the spatial relationship between fire and conflict will be obtained. To delimitate the time window, the focus is set on the armed conflict that began in 2016 in West Iran, while the years from 2012-2015 will serve as a baseline to be compared to the period (2016-2020) most affected by armed conflict.

2 Background

Factors that drive fire dynamics and influence propagation are elaborated in this section. Firstly, an explanation of the climatic conditions needed for vegetation fires to occur, will provide insight into fire dynamics under normal circumstances as well highlight how the local community utilises fire in the agricultural sector. Subsequently, the impact of armed conflict on fire risk and land cover is described and how this impact has been measured in previous studies. Finally, the history of the Kurdish population in Iran is presented as well as the geopolitical situation of interest for this study.

2.1 Vegetation fires

The occurrence of fires is primarily steered by factors including climate, fuel availability and something causing the ignition (Viedma et al., 2015). To some degrees a lack of firefighting resources might aid fire development further. Moreover, humans themselves, as well as climate might alter the quantity of ignition instances or fuel supply, by increasing the amount of biomass present (Zubkova et al., 2019). Thus, there is an influence on the ability of fires to advance and potentially escalate. Anthropogenic influences on fire regimes such as land management, population growth and other components of socioeconomic origin might, in turn, impact fires through modifications on fire size, severity, and changes in seasonality (Bowman et al., 2011; Pausas, 2004). Growing industrialization might possess the ability to cause elevated fire occurrence, due to biomass accumulation after lands have been abandoned, which is particularity pronounced in environments characterized by limited biomass presence (Martínez-Fernández et al., 2013; Viedma et al., 2015). Under normal conditions the local population would remove shrubs in these agricultural fields thus preventing afforestation and causing these ecosystems to be fuel-limited (Pausas, 2004). Incentives to control fire regimes differ substantially, encompassing everything from warfare strategies, arson, and resource management practices to safeguarding infrastructure and cities (Bowman et al., 2011). Regardless of the multitude of fire applications and refined usage people are not always able to manage the fires they ignite, nor contain the advancing of fires that were naturally ignited (Bowman et al., 2011).

In arid, low productive and often seasonally water restricted ecosystems fuel supply is the main constraint of fire development (Daniau et al., 2012). Thus, fires tend to take place after higher-than-normal precipitation events (Bradstock, 2010). To be able to predict the amount of burned area, moisture availability is a suitable proxy, as it aids the needed biomass build-up (Daniau et al., 2012). This elevated fire activity arises due to the rainfall enhancing biomass production, which then leads to adequate amounts of fuel present to sustain fires (Bradstock, 2010). Despite rainfall normally promoting fire occurrence; people might modify the landscape through management practices such as intensified grazing pressures or through their decision making by planting easily ignitable vegetation types; consequently, there are shifts in fuels on either temporal or spatial time scales (Bowman et al., 2011). In general, precipitation advocates fuel aggregation and resulting fires in these arid regions whereas in systems that are energy restricted, rainfall increases biomass moisture content and dampens fire advancement (Daniau et al., 2012).

A study conducted by Abatzoglou et al. (2018) found that rainfall events 14 to 25 months before the fire season starts, are strongly positively related to burned area in unforested land covers in semi-arid ecosystems, due to these precipitation events generating the essential biomass accumulation. They also discovered the greatest correlations in environments that can be described with high average climatic water deficit (CWD), which is conforming with fire regimes that are fuel-limited. On the other hand, their analysis showed lower correlations between aridity and fire occurrence in low productive, biomass-scare ecosystems and unforested land cover classes, given thar fuel supply is the main limitation on fire dynamics in these regions.

2.2 Agriculture and fire dynamics

A fire ignition model created by Eskandari and Chuvieco (2015) found that wildfires in Iran are primarily linked to environments that are not arid, in proximity to croplands, with large distances to roads and towns. Ignition likelihood depends on factors such as a region's water abundance and is associated with a higher fire potential compared to more arid areas due to the latter having lower fuel availability in the form of biomass (Eskandari & Chuvieco, 2015).

In Iran's Northern provinces it is suggested that fires ignited at the junction of farmlands and forests might arise due to local farmers carelessness, such as them being inconsiderate when setting agricultural waste products on fire or might be due to deliberate clearing of croplands (MNRA, 2011 as cited in Eskandari & Chuvieco, 2015; GNRA, 2011 as cited in Eskandari & Chuvieco, 2015).

Jaafari et al. (2017) evaluated wildfire probability in the Iranian Zagros Mountains and they argued that altitudes of 1500-2000 m, where the presence of sporadic forests and suitable soils facilitating agriculture are found, were subjected to more ignitions than anticipated given their smaller area coverage in the region. They elaborate further how fires are often intentionally ignited; serving as a tool for weed and shrub eradication from croplands or to attain ecosystem services which aids the generation of income for locals, including reestablishment of pasture biomass or forms of hunting. Unofficial accounts allude that some of these ignitions arose due to conflict and tensions amid the population.

A study conducted in north-western Iran by Jahdi et al. (2020) found that in this region wildfires are primarily induced by agricultural practices. These include, for example, the traditional usage of fire as a tool by locals engaging in farming and animal herding to discard remaining waste material after harvest or create free areas for grazing. Moreover, these findings agree with other research conducted on fire likelihood, which concluded that the highest fire risk exists on land use categories linked to farming, hence attributing human endeavour a substantial role in fire instances (Adab et al., 2018). To add on, the ignition of agricultural remains is an essential form of human-induced biomass burning, particularly in developing nations (Adab, 2017). Through these activities larger agricultural fires can be promoted if multiple smaller ignitions take place at the same time and over widespread regions, usually observed during harvest periods (Zha et al., 2013). Furthermore, the linked existence of farmlands and other natural vegetation has been identified as an important parameter in fire risk modelling implying a relationship between agricultural practices and its possible impact on fire occurrence (Adab et al., 2018). These fires then are able to advance to other surrounding natural vegetated places, which is a behaviour observed not only in Iran but also in the Mediterranean (Ganteaume et al., 2013). A study conducted by Adab (2017) in the Iranian province Golestan discussed that a landscape comprising of mixed farmland and natural vegetation cover has plenty of fuel available to foster fires. In many regions fire is utilized as main mechanisms behind transforming forests into farmlands or within agricultural systems such as shifting cultivation (Ketterings & Bigham, 2000).

2.3 Impact of armed conflict

The relationship between armed conflict and how it might impact fire dynamics is not well researched and studied (Zubkova et al., 2021). In environments with a large abundance of vegetation, where anthropogenic sources dominate fire ignition, conflict would lead to a reduction of fire occurrence once inhabitants are forced to relocate (Gorsevski et al., 2012). As it was observed during conflict driven periods in South Sudan where fire activity decreased, which was partially attributed to changes in the practices of the local population. Under normal conditions, they engaged in transforming forests into agricultural fields, however due to political instability they had to unwillingly desert their villages, stopping the occurrence of said transformational fires. On the contrary, in other regions the displacement of people away from the conflict impacted areas, might promote and enhance the vulnerability of vegetation to fires (Elard, 2007; Mitri et al., 2011). This is particularly true for agricultural land covers, where land abandonment caused by conflict, leads to missing workforce and insufficient access, inducing an increased fire risk (Mitri et al., 2011).

In addition to these ecosystems already being more susceptible to fires under armed conflicts, accidental ignitions might occur due to collateral damage or intentional fires originating from conflict events, heightening fire activity (Linke & Ruether, 2021; Mohamed et al., 2020). Furthermore, intentional ignitions of forests and agricultural lands can be utilized as a crucial part of the military strategy (Dinc, 2021; Linke & Ruether, 2021; Mitri et al., 2011). Moreover, the timing of armed conflicts might have the potential of causing economical drawbacks and jeopardizing food security, especially when targeting agricultural field before harvest season (Zubkova et al., 2021). This was observed in Syria, where the burned area observed increased twofold in May. Since most of these fires occurred on agricultural lands, which do not get harvested until June, food security might have been threatened.

Additional factors to consider regarding the increased fire activity is the usage of lower quality fuels combined with a shortage of an educated workers in the agricultural sector resulting from extended periods of conflict and population deracination (Schon et al., 2019). Unintentional fire ignition during harvest season especially in arid ecosystems can have immense consequences. Flares originating from bad fuel, or a discarded burning cigarette could initiate a fire that not only propagates fast but also impacts a large extent. This would be exacerbated when firefighting services are not provided or insufficient, such as in times of armed conflict.

Another study conducted on fire dynamics in Lebanon under armed conflict found that the prevalence of fires has a spatial pattern (Mitri et al., 2011). The highest fire risk was detected in vegetation-rich lands adjacent in close proximity to agriculture, large metropolitan areas and neighbouring suburbs. However, lower fire risk could be found close to low population-density villages and in remote areas further away from infrastructure and settlements.

Furthermore, the role of armed conflict in inducing land use changes was studied by Baumann et al. (2015) associated with the Nagorno-Karabakh conflict between Armenia and Azerbaijan in the years 1991–1994. Their main findings were that armed conflict impacts land use considerably, however these repercussions are localized either within the conflict-affected area or in the regions were refugees settled. This localized effect could be observed given that land abandonment progressively weakened with enhanced distance to the conflict zone, where at distances over 35 km, farmland expansion and deforestation effects were more frequent. To add on, new agricultural land development rates were noted to peak 75 km away from the conflict-affected regions. Moreover, the movement of displaced people can further initiate land use altercations, which happen at greater distances from the actual combat zone leading to changes that would not occur under normal circumstances. Hence, they concluded that armed conflicts and other socioeconomic disturbances stand for processes that might generate remote connections to land use. They noted that the local impacts are indeed associated with the conflict and could proceed in both enhanced or weakened strains on the environment, including activities of unregulated logging, hunting and mining, since the government is not able to implement the laws (Stevens et al., 2011). On the other hand, it has been observed that the effects of armed conflicts can impact land use at great distances from the active battle zone. For instance, land abandonment tends to be less severe at distances further away from the conflict-affected zone and changes to the land system might increase once displaced people initiate activities. Post-conflict environments and stabilization can lead to the refugees to returning and continuing their previous land management activities by re-establishing agricultural lands and utilizing forest resources. Antipersonnel mines or other undetonated bombs that were used during conflict times might still pose a threat even after the conflict itself is resolved (Pearn, 2003).

2.4 How to measure the impact of armed conflict?

Before starting to assess the effect of armed conflict it is necessary to obtain conflict data. Commonly used datasets in conflict studies are the Uppsala Conflict Data Program (UCDP) (Dinc, 2021; Schon et al., 2021; Eklund et al., 2021), the Integrated Crisis Early Warning System (ICEWS) (Linke & Ruether, 2021; Zubkova et al., 2021) and the Armed Conflict Location and Event Data Project (ACLED) (Linke & Ruether, 2021; Zubkova et al., 2021). Which dataset is adopted mainly depends on the scope of the study and time frame. For example, ACLED only covers events from 2017 on, while UCDP is limited to having at least one fatality taking place before being recorded. Similarly, the type of fire data varies between studies as well: Some utilized active fire products, which range from 1 km spatial resolution (Dinc, 2021; Schon et al., 2021) to 375 m (Eklund et al., 2021), while others focus on burned area instead (Zubkova et al., 2021).

In order to assess the impact of armed conflict, both remote sensing and model applications are suitable tools. A remote sensing approach is for example utilised in a study by Dinc (2021), where their study area in Turkey was divided into 5 km x 5 km fishnets and then the spatial autocorrelation between fire and conflict occurrence was evaluated using the bivariate local Moran's I. Moreover, a study conducted on Iraq by Eklund et al. (2021) used a partial correlation analysis, where a 10 km x 10 km fishnet was applied. Variables included within the fishnets were the distance to conflicts, land use variability and spatial clustering of fire points acquired from the Getis-Ord Gi* analysis. Another option to quantify the relationship between conflict and environmental aspects is to use models, such as the ordinary least squares (OLS) regression model. For example, Linke and Ruether (2021) applied the OLS regression model to Syria in order to check whether most conflicts are occurring during the growing seasons, compared to other times in the year and if lack of rainfall during the growing season was linked to more violence started by the government or rebel groups. A similar approach was used by a study conducted on Sierra Leone by Burgess et al. (2015), where they investigated the relationship between conflict events and forest cover change. The impact of conflict on land cover changes can be conducted by either comparing satellite imagery before or during an active conflict event to the post-conflict situation (Gorsevski et al., 2012) or by calculating the rate of land cover change with advancing distance to the battle zone (Bauman et al., 2015). Furthermore, statistical testing can be used to examine the significance of a relationship, such as through the application of a Spearman rank test. This method was utilized for example in studies to see whether significance exists in the relationship between conflict and fire counts or between burned area and climatic variables (Dinc, 2021; Zubkova et al., 2021).

2.5 Kurdish separatism in Iran

Kurds are one of the largest ethnic groups that do not own their own state and they are a substantial minority concentrated in Iran, Iraq, Turkey, and Syria (Tezcür & Asadzade, 2019). In Iran most Kurds live within the north-western provinces in Ilam, Kurdistan, Western Azerbaijan and Kermanshah, which are located in close proximity to the borders of Turkey and Iraq. Most Kurds in these regions identify as Sunni, Shiite and Yarsani Kurds, and are also present in considerable numbers. Although exact numbers regarding their population size are lacking, due to the Iranian government not compiling ethnicity data in their censuses; researchers assessed that Kurds account for 10 % of the total Iranian inhabitants (McDowall, 2021).

The way in which the Kurds are represented on the political stage and how their rights can be supported within national systems regulated by other ethnic majorities, is an essential part of the Kurdish Question (Tezcür & Asadzade, 2019), which arose after the collapse of the Ottoman Empire in 1922 (McDowall, 2021). Since the beginning of the 20th century conflicts between the Kurds and their countries of residence have been occurring where the lack of Kurdish independence, statelessness, as well as political oppression and exclusion are partly responsible for said rebellions (Tezcür & Asadzade, 2019). Throughout history they experience diverse forms of oppression and discrimination within politics. Examples include constraints on using their language as well as genocide practised against civilians and committed using chemical gas during the Anfal Campaign 1987/8 in Iraq (Hiltermann, 2007). During this campaign, villages and agricultural fields were demolished, destroying their livelihoods (HRW, 1993). Survivors were either imprisoned or displaced against their will.

The Kurdistan Free Live Party (PJAK) has risen within recent years and has, comparable to other settled Kurdish parties a rather restricted function in regards to religion nationally (Tezcür & Asadzade, 2019). After the capture of the head of the Kurdistan Worker's Party (PKK) organization in 1999, deadly protests occurred in Kurdish cities in Iran directed against the Turkish government. These clashes between the Kurdish demonstrators and Iranian security troops, marked the expanding of Kurdish activism across borders (Tezcür & Asadzade, 2019). In 2004 the PKK disassociated from their aim to create a sovereign Kurdish state in favour of installing individual organizations in Syria and Iran. After the PJAK establishment, they managed to recruit substantial numbers of Iranian Kurds and started aggressions near bordering areas of Iran, Turkey, and Iraq before suspending hostilities in 2011 (Tezcür, 2016).

In Iran Kurdish nationalism has its roots in a time of the Pahlavi dynasty aiming to create a modern state in the midst of World War I (Vali, 2014). In 1945 the Kurdistan Democratic Party of Iran (KDPI) was established, and just one year later they were the main drivers leading to the declaration of the Mahabad Republic, which marks the first occasion of Kurdish sovereignty in modern times. Although this state had a short duration and only encompassed a small geographical extent, it aided the resurgence of Kurdish culture (Tezcür & Asadzade, 2019). Ultimately, this short self-rule evolved into a symbol of national identity, through the initial support of schools, plays, and publications in the Kurdish language (Koohi-Kamali, 2003; Vali, 2014). Uproar and mass demonstrations occurred in 1978 leading to the revitalization of Kurdish nationalist activism, with distinctions between different Kurdish political actors (Tezcür & Asadzade, 2019). While the KDPI advocated for Kurdish sovereignty and a democratic Iran, the Komala party desired to emancipate Iranian Kurds by means of extensive armed uprising. The fight of autonomy came to a halt in 1981, as the Iranian regime successfully reclaimed authority over crucial cities (Ahmadzadeh & Stansfield, 2010). At the same time, Kurdish military organizations engaged in criminal warfare activities in the Iran-Iraq War from their remote locations in the mountains adjacent to the borders. Following the execution of the head of the KDPI's and his replacement shortly after, by Iranian officers, Kurdish activists re-entered inactivity in the 90s.

The government of Iran approved restricted amounts of Kurdish culture and freedom, after a reformist was elected as president in 1997 (Ahmadzadeh & Stansfield, 2010; Tezcür & Asadzade, 2019). This included bilingual TV programs as well as the establishment of Kurdish literature institutions within universities in Kurdish dominated provinces. To add on, the government has been aiming to bring them closer together with the Kurds by repairing ethnic concerns and linking political differences (Romano & Gurses, 2014). Although recent developments appear more favourable towards Kurdish minorities, Iran has persisted to be rigid when it comes to taking up political requests from the Kurds (Tezcür & Asadzade, 2019).

2.6 Geopolitical situation

Since April 2016 the region has been experiencing continuous violent disputes primarily between the Democratic Party of Iranian Kurdistan (PDKI) and the Iranian Revolutionary Guards (IRGC), where conflicts arose due to the Kurds experiencing enhanced discomfort with their current situation (Mallya, 2018). The IRGC, a distinct force from the regular military, was established as section of the state's armed forces after the country's Islamic revolution in 1979, and as branch of Iran's military they are entrusted to protect Iran's revolutionary rule (Katzman, 2019). This clash has been further elevated due to economic injustice, as Kurdistan has been historically been one of the poorest provinces in Iran (Aghajanian, 1983). Other political parties in favour of the Kurdish separation associated with and supported the PDKI, resulting in additional outbreak of violence with Iran's revolutionary guards (Dorsey, 2017). Simultaneously, the left leaning Kurdish rebel organization PJAK took up their attacks against the Iranian state again after having agreed to a ceasefire with the IRGC in 2011.

3 Data and Methodology

This section starts with an introduction of the study area, climate conditions as well as the time frame of interest. Afterwards, all datasets used in this study are presented. Lastly, the methods are explained which aimed to answer the hypothesis and research questions.

3.1 Study area

The study area (Fig. 1) focused on the provinces Kurdistan, West Azerbaijan and Kermanshah which are the regions primarily impacted by the Western Iran Clashes and are the residences of most Iranians Kurds (Koohi-Kamali, 2003). Furthermore, the province Ilam will also be included in the analysis, which has a substantial Kurdish population, but did not experience intense armed conflicts (Davies et al., 2022; Sundberg & Melander, 2013).

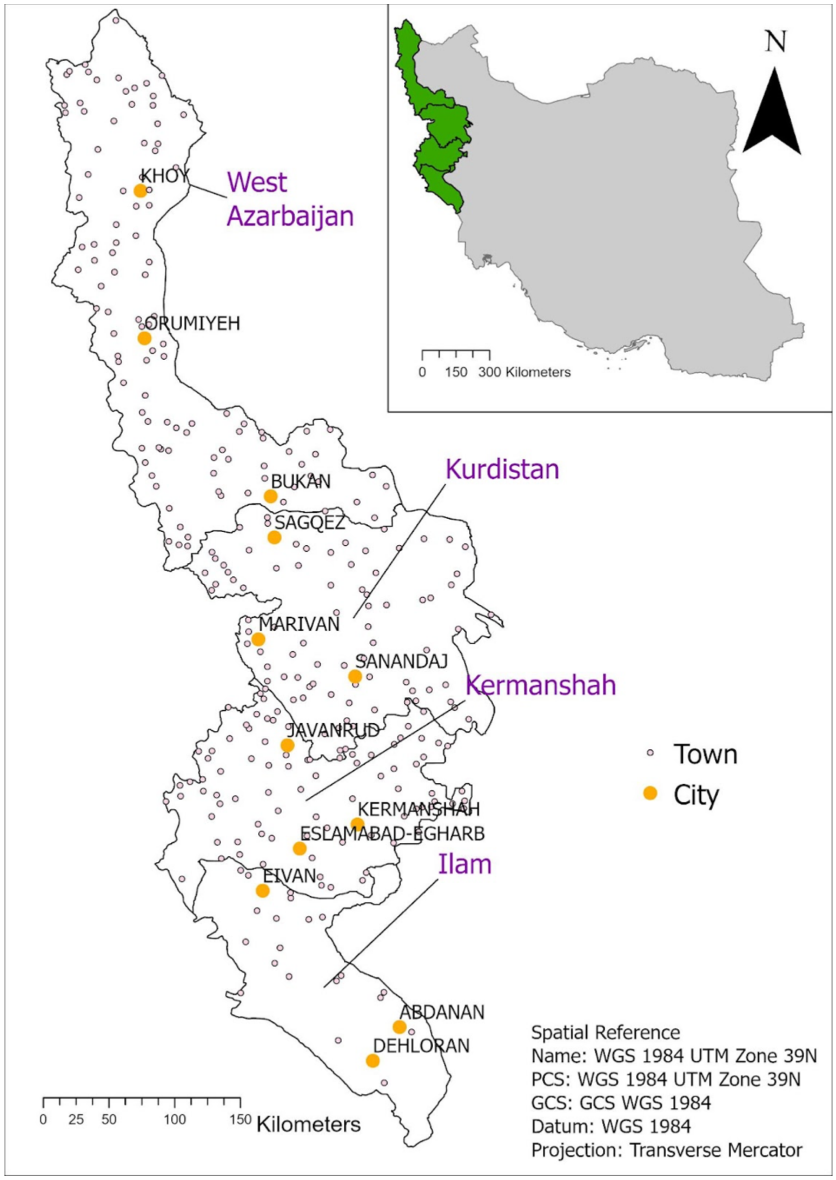

Figure 1. Map over the study region showing major cities for each province and the location of the study area within Iran.

West-Azerbaijan is the largest of the four provinces covering an area of 43,660 km² when accounting for Lake Urmia and has a population of 3.26 million. The climate can be described as semi-arid climate with cold wet winters and dry hot summers (Eisavi et al., 2015). Large parts are mountainous and have a rather mild climate due to the effect of air currents from Mediterranean Sea and Atlantic Ocean. (Omarzadeh et al., 2022). Agriculture dominates the province's economy; especially important are the grain, fruit, and timber industries (Eisavi et al., 2015). In West-Azerbaijan the most common land uses present are infrastructure and other build-up areas, bare soils, grasslands, agricultural fields, and bodies of water.

Slightly smaller in size is **Kurdistan** with 28,817 km^2 with a residing population of 1.6 million (Karimyan et al., 2020). The Zagros Mountains are located in this province, which receive 500 mm or precipitation yearly, primarily in the form of snow (Sharifi et al., 2009). As the western part is subject to higher rainfall amounts, oak forests can flourish.

Kermanshah has an area of 24,998 km^2, is dominated by mountains and has 1.94 million inhabitants (Doabi et al., 2018). There the climate is considered to be arid and semi-arid, with an average of 450 mm of rainfall annually and temperatures of 16 °C (Doabi et al., 2018). Similarly to the aforementioned provinces, agriculture also plays an important role, where wheat, chickpea, barley, and corn are the agricultural output (Doabi et al., 2018).

The smallest province in this study is **Ilam** with an area extent of 19,086 km^2 and 0.55 million inhabitants (Ghasemi et al., 2013). It is dominated by mountains and plains that follow the West Zagros range; thus elevation varies between 50 m to 3060 m above sea level. Given the large elevation differences, it further poses an influence on the climatic conditions, where annually 200 mm of precipitation falls in the southern and 500 mm in the northern part. While oak forests and rangeland characterize the natural vegetation, the main activities of the local community include farming and other forms of livestock management.

Through this study two **main periods** will be investigated, the first one including the years 2012 to 2015 and the second one covering the years 2016-2020. The first period (period A) is characterized by low instances of armed conflict, however compared to the latter period more political activity takes place in the forms of demonstrations, political accusations, and disapproval. The armed conflict period (2016-2020), from here on referred to as period B, had the highest number of armed conflict events recorded, especially in the beginning of the clashes. Although less events are registered in the ICEWS database, most events taking place are of a more violent nature.

3.2 Data

In this section, all utilized datasets are described as well as how they were obtained and modified for the specific usage.

Spatial information regarding the **administrative boundaries** was obtained from the Database of Global Administrative Areas (GADM) version 4.1. This information helped to define the study area spatially and clip all further dataset to the provinces of interest (GADM, 2022). Other spatial data used was a layer containing all cities, towns and settlements in Iran (Kishvar, 2013).

The **Uppsala Conflict Data Program (UCDP)** dataset provides the data about conflicts and violence in the region where at least one fatality occurred, with corresponding coordinates (Davies et al., 2022; Sundberg & Melander, 2013). Conflict events are extracted from news sources, where in the initial stage a database search is conducted, utilizing specific search terms to locate relevant news articles that describe instances where violence is applied (Sundberg & Melander, 2013). Furthermore, reports from various NGOs and governments are assessed as well. In some situations, case-oriented studies and research findings are examined to further strengthen and add additional information on reliability of the event (Sundberg & Melander, 2013). Before the conflict event is included into the dataset, a so-called triple checking process is applied to ensure quality and reliability (Eck, 2012). This dataset is offered in the geodetic datum WGS84 (World Geodetic System 1984). Each armed conflict event provides information regarding participating actors, news source origin, geographic location (coordinates), number of fatality instances and conflict type (state-based, one-sided or non-state-based violence) (Sundberg & Melander, 2013). The global dataset was modified, such that only instances in Iran and the years of interest were selected. Furthermore, the geocoded events were uploaded into ArcGIS where they were clipped with the province layer to only portray conflict occasions that took place within the boundaries of interest.

The **Integrated Crisis Early Warning System (ICEWS)** provides conflict data where agitations occurred between individual people, organizations or countries (Boschee et al., 2015). These events are geocoded and include information regarding the actor, the type of conflict and towards whom the actions are directed. Unlike the UCDP, events do not need to include a minimum of one fatality case to be accounted for in the database, instead events are characterized and added from news articles with the help of an event coder. ICEWS acquires and collects events by applying an automated system, which looks through news articles published online and extracts the articles' details. This is generated through implementation of the BBN ACCENT coder, a natural language processing tool, which is able to derive how different actors are connected in the article from the given text (Linke & Ruether, 2021). Afterwards, instances of conflict are coded into the dataset by utilizing the Conflict and Mediation Event Observations (CAMEO) taxonomy of event type, which can differentiate between source (i.e., the 'Source Name' variable) and target actor. Moreover, metadata regarding geographic and temporal aspects are derived and related to the appropriate events acquired within a news publication (Boschee et al., 2015). The total downloaded ICEWS data for West Iran from 2012-2020 include 1662 incidents.

The **Global Precipitation Climatology Centre (GPCC) Full Data Monthly Product Version 2022** dataset consists of gridded **precipitation** based on rain gauges for the global land surface area (Schneider et al., 2020). This dataset encompasses the years 1891 to 2020 and offers monthly precipitation at a resolution of 0.25°. On a monthly basis data is acquired from all stations, near real time and non-real-time, if a climatological normal (at least 10 years of data, without fragments) for the station is provided. Moreover, data coverage per month varies from only 6000 stations in 1891 to the best coverage of around 54 000 in 1970 and 1986-7. After 2019, the number of stations decreased to 10 000 due to a lag in data transfer to and post data treatment at GPCC. However, the database is constantly extended by the arrival of data updates from recent years. Over 190 nations report their rain gauge data to the GPCC and additional climate data from other global and local institutes (e.g. Global Historical Climatology Network, FAO, and CRU) have been incorporated in the database as well. Thus, GPCC has the most extensive global compilation of in situ measurements on both monthly and daily resolution.

Land surface temperature data were obtained from the ERA5 dataset, and it provides temperature at 0.1° spatial resolution (Hersbach et al., 2020). The land surface temperature dataset is available from 1950 onwards and supplies temperature data on monthly resolution acquired two meters above the Earth's surface. In this dataset temperature is computed through interpolation between the minimum model level and the land surface, whilst accounting for the state of the atmosphere.

The Visible Infrared Imaging Radiometer Suite (VIIRS) Active Fire product (VIIRS 375m (S-NPP)) data product is available from 2012 onwards, which makes it suitable to be used for the time frame of this study as a source for the essential fire data, which records daily fire occurrence at spatial resolution of 375 m. To only assess the influence of vegetation fires, the dataset was filtered to only include “presumed vegetation fires” and other types of static fires were omitted, thus reducing the fire count from over 115 000 to around 35 000 during the investigated period.

The **land cover data** used in this study was specifically created for Iran and was generated through application of object-based classification with google earth engine (GEE) big data processing. As satellite input data, Sentinel-1 and Sentinel-2 imagery with 10 m spatial resolution were used (Ghorbanian et al., 2020). This method yielded an overall accuracy of 95.6 % and a Kappa Coefficient of 0.95 for the assessed year 2017. Before this study, a land cover classification was generated in 2016 by the Iranian government, which failed to successfully distinguish between rangeland and forests, thus overestimating the amounts of forests present in Western Iran. Iran was divided into 13 different land cover classes, including sand, clay, kalut, outcrop, salty lands, marshlands, uncovered plains, cities, forest, wetland, water bodies, rangelands, and croplands.

3.3 Methodology

In the following sections the methodology is elaborated on to answer the research questions mentioned under aim and address the broader hypothesis. Through this analysis various software were utilized, including ArcGIS Pro, GeoDa and SPSS. Working and analysing spatial data, as well as generating and visualizing maps was conducted with ArcGIS Pro. Statistical tests were obtained through the application of GeoDa and SPSS. GeoDa is primarily used to calculate both global and local bivariate Moran’s I (which is currently not possible to do in ArcGIS Pro) and SPSS is utilized to compute the Spearman rank correlation coefficients.

3.3.1 Armed conflict, fires, and land cover

To determine which land use is primarily affected by conflict and fire, the land cover classes on which each of these events occurred were evaluated for each year, and it was determined whether changes in affected land cover occurred between the years.

As the given **land cover layer** contained 13 different classes (Fig. 2), including various soil types, the classes were merged to continue working with 5 classes of interest (Fig. 3). I decided to work with these classes since croplands and rangelands not only encompassed large portions of the study region, but also since these are essential when investigating fire dynamics. The remaining classes within the original land cover layer, embodied various types of soil. Hence, given the lower amounts of biomass, differentiating between the classes is not as important when analysing fire instances. On the other hand, the original land cover class ‘cities’ was kept, for the importance of conflict events. In the end I created a land cover layer that included cities, water bodies, bare soil or sparse vegetation, croplands, and rangelands. While forest play an essential role in fire dynamics, they were insufficiently present in the study area and only 4 out of over 100 000 fires (all fire types included) during the investigated period occurred on forested ground. Thus, forests were merged into the rangeland category, given that this was the only suitable land cover class for categorization. The original land cover covering sand, clay, kalut, outcrop, salty lands, marshlands, wetlands, and uncovered plains are all found in the bare soil/sparse vegetation category. The dominating land usage in the region are croplands and rangelands followed by bare soils (Fig. 3).

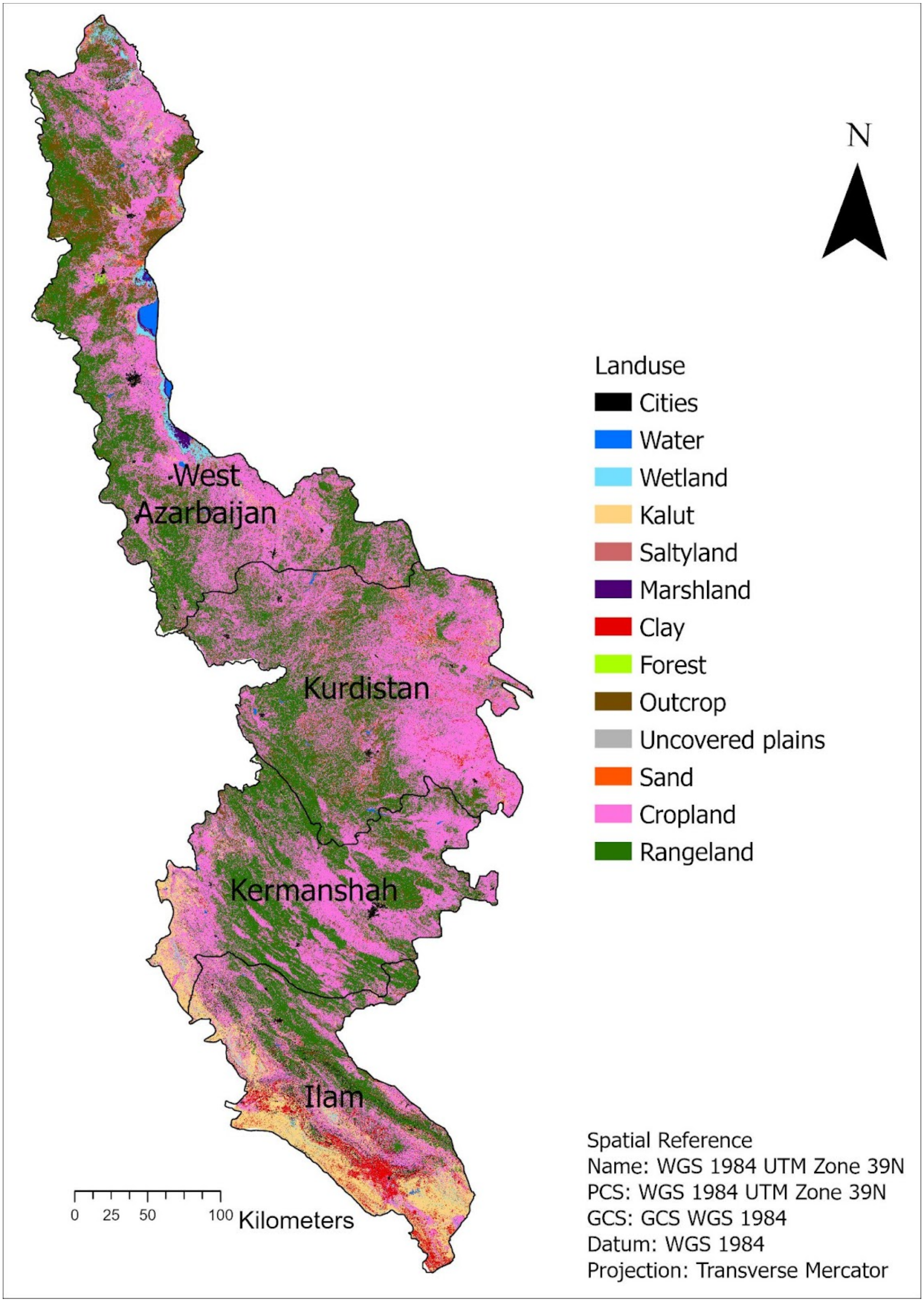

Figure 2. The original land cover layer with 13 classes in total.

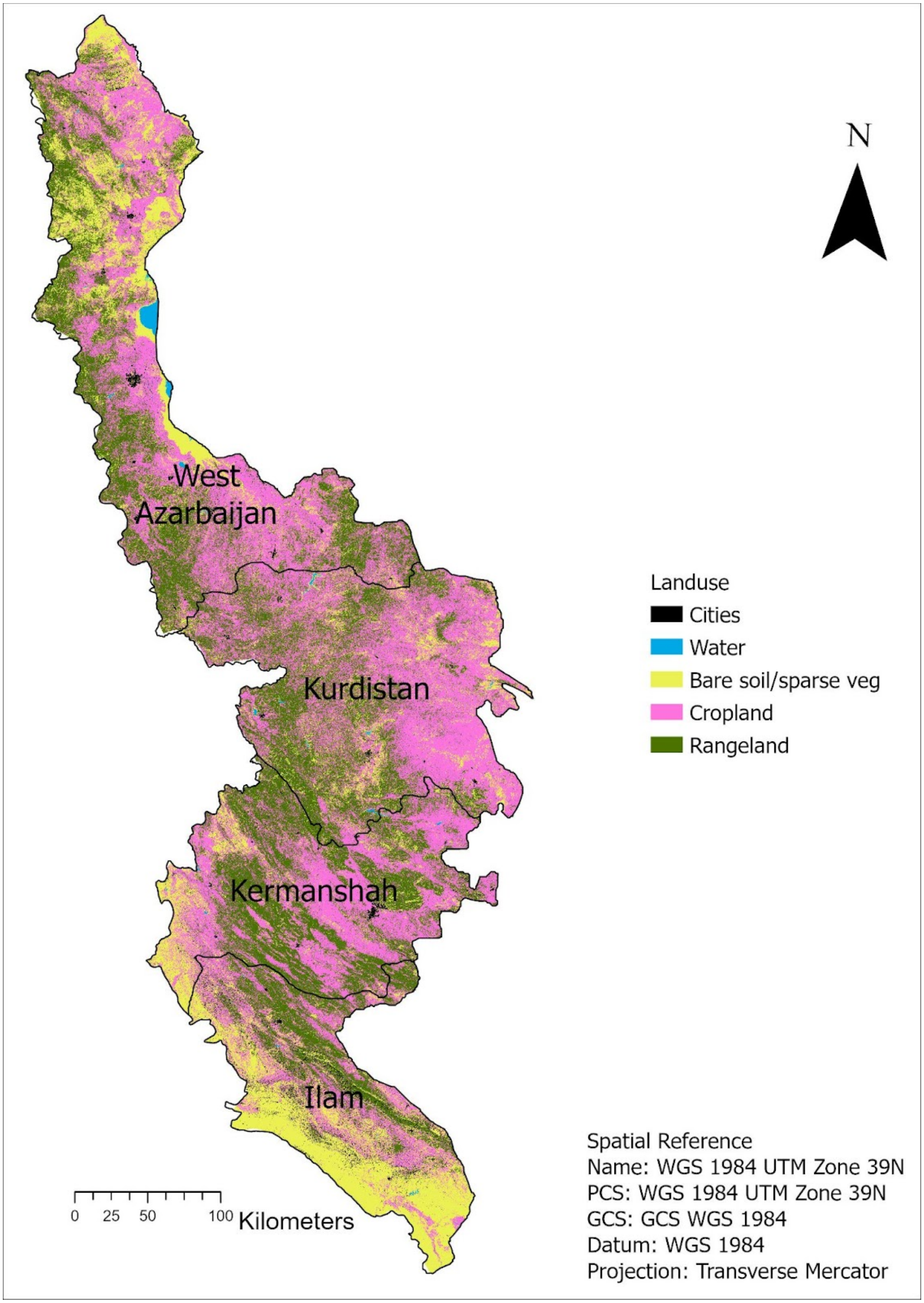

Figure 3. The simplified merged land cover layer used for the remaining analysis. The land cover categories are cities, water, bare soil/sparse vegetation, cropland, and rangeland.

Event data from the ICEWS was downloaded on a yearly basis. As all types of events are included, I applied a filter to the data to be able to extract events that might not aid this analysis (Fig. 4). The graph below illustrates the 3 filters I applied to the ICEWS dataset: violent events (yellow line), conflict events (grey line) and neural/positive events (blue line). The conflict events (grey line) were obtained by selecting only the events that had a negative intensity value within the dataset. Included are acts such as violent protest and riots, demonstrations, accusations, conventional and unconventional military strategies, arrests, and abductions, fighting with various weapons, enhanced military, or police presence. Violent events are similar to the conflict events; however, these were filtered further to exclude demonstrations, coercions and accusations. On the other hand, when the event texts expressed acts of visits, approval, aid provision, consulting, or other forms of non-violent encounters they were categorized as neutral or positive political actions. This distinction was made to be able to see whether changes in the political behaviour itself took place once armed conflict started to increase due, for example, to lower rates of content and approval of the government. Armed conflict events belong to the UCDP dataset (red line). Finally, I conduced the remaining part of the analysis with a combination of the filtered conflict events (grey line) and armed conflict events from the UCDP database that were not present in the ICEWS dataset. In order to decide which UCDP event to merge or include as separate occasion, I manually checked whether the event is already present in the ICEWS dataset. Spatially overlapping events were check based on the event description and dating. Hence, if the description matched, I deducted that this describes the same conflict. For UCDP events that were not located in proximity to any ICEWS events, I concluded that these armed conflict events are missing in the other database and extended these instances to the conflict dataset used for analysis. In the case that a UCDP and an ICEWS event were in close proximity, but the description nor dating matched, I deemed them as separate instances. However, if the event text and date described the same event, I concluded that there might have been an issue in geocoding and the dataset was not extended. The total number of UCDP events included or merge can be found in the Appendix A, Table A1.

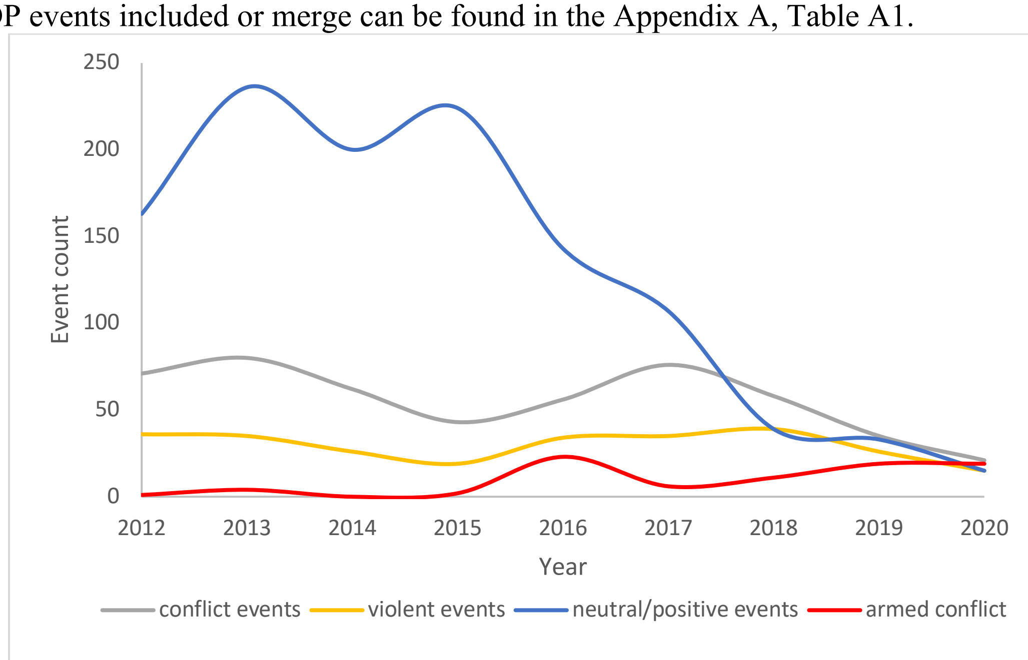

Figure 4. Difference in event counts based on intensity filter of Integrated Crisis Early Warning System (ICEWS) dataset or Uppsala Conflict Data Program (UCDP) dataset usage. Conflict and violent events were obtained by filtering the data based on negative intensities. Neutral or positive events had non-negative intensities. Armed conflict events are acquired from the UCDP dataset.

3.3.2 Spatial correlation between conflicts and fires

To acquire understanding regarding the spatial relationship between fire and conflict events, the bivariate Moran's I statistics were used as an index of spatial autocorrelation. Two types of Moran's I statistics exist: one global and one local, where the spatial relationship across the entire study region can be obtained through the global Moran's I (Moran, 1948). The local Moran’s I can be acquired through the application of the local indicators of spatial association (LISA), which is a statistical tool created to represent hotspots within the regions (Anselin, 1995). These tool’s will be elaborated on in detail once the temporal and spatial scales have been defined.

Addressing the **temporal componen**t of the relationship, each analysis was conducted on a yearly basis to avoid the mistake of correlating fires to conflict events that occurred years apart. Given that the dominant land cover present in West Iran is characterized by crop and rangeland and as this study aims to investigate fires directly or indirectly caused by armed conflict or political instability, it is necessary to omit fires belonging to the regular management practices, such as the agricultural burning of waste material during harvest season. Wheat is the most common crop type by land occupied and produced yield (USDA, 2023). Whereas October to June define the whole growing season in the region, this can be further divided into an early (October, November, December), mid (January, February, March) and late (April, May, June) growing period (Nouri et al., 2017). Sowing tends to occur between October and November and harvest is conducted in June or July (JICA, 2004). Thus, fires occurring on croplands between June and July were removed in this analysis, as these are defined as presumed agricultural fires originating from the local management activities.

On the other hand, rangelands do not experience this mechanism, hence fires occurring during the months June and July are preserved. While most fires occur in the study region between June to October (Fig. 5), I included the months prior in the spatial correlation analysis, since fires stemming from conflict events during the wheat growing season might be crucial for local economics yield losses. Therefore, fire and conflict events taking place from January to October were assessed, including the mid and late growing season for wheat and the main fire season for rangeland burnings.

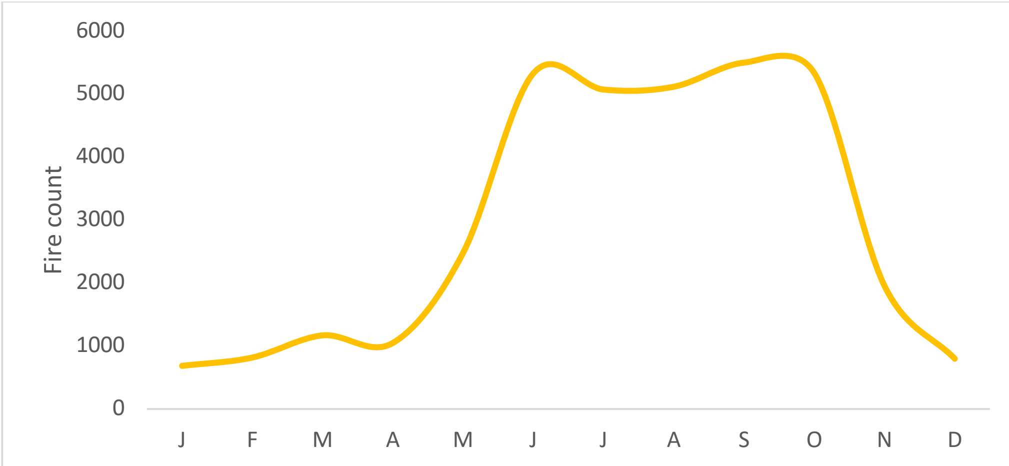

Figure 5. All recorded vegetation fires between 2012 to 2020 divided by month. Fire season takes place from June to October.

To assess the co-occurrence of conflict and fire on a **spatial scale**, a 10 by 10 km fishnet was applied to the whole study region. Then conflict and fire events, filtered according to the aforementioned season of interest, were extracted for each fishnet cell and their counts were noted. Finally, the fishnet layer was obtained which then posed as input for the following autocorrelation analysis. While the fishnet polygon remained the same for all years, each year had different amounts of conflict and fire present within the polygons, hence in total 9 different inputs were generated.

In the first part of the spatial analysis the spatial autocorrelation between conflict and fire events were evaluated using the **global bivariate Moran's I**, which calculates how the variables are related across all units within the whole study region (Moran, 1948). The global bivariate Moran's I is calculated according to the following equation (Moran, 1948):

$$I_{ap} = \frac{\mathrm{N}\Sigma_{i=1}^{N}\ \mathrm{N}\Sigma_{j\neq i}^{N}\ \mathrm{W}_{ij}\mathrm{z}_i^a\ \mathrm{z}_j^p}{(N-1)\Sigma_{i=1}^{N}\ \Sigma_{j\neq i}^{N}\mathrm{W}_{ij}}$$

Equation 1. Computation of the global bivariate Moran's I

Where I_{ap} represents the resulting bivariate global Moran index, N describes number of units, which in this study is defined as total number of fishnet polygons, W_{ij} is the computed weight matrix, z_i^a defines the number of conflict points for polygon i and z_j^p describes the number of fire events in polygon j.

The values acquired from the global Moran's I are within the range from −1 to 1, where Moran's I > 0 indicates a positive spatial correlation between conflict events and fire occurrence. On the other hand Moran's I < 0, would indicate a negative spatial correlation. To be able to assess whether the relationship is statistically significant, permutation tests can be utilized (Anselin, 1995). Here testing was done by applying 99999 randomisations, to assure that the yielded outputs have validity.

Furthermore, the **local indicators of spatial association (LISA)** were applied, which are statistical tool created to represent hotspots within the regions (Anselin, 1995), thus resembling the Gi and G*i statistics of Getis and Ord (1992). Moreover, LISA can be utilized to evaluate the impact of distinctive areas on the overall global Moran's I statistic and might aid to recognise deviations from the general pattern (Anselin, 1995). Testing for statistical significance was conducted by executing 99999 perturbations. To visualize the results, an agglomeration map can be generated, with four different quadrants relating to the amount of local spatial autocorrelation. These quadrants include: HH, expressing the existence of a high number of conflict events and high number of fire occurrence, LH, showing low conflict numbers and high fire occurrence; LL, illustrating low number for both conflict and fire events, and finally HL, indicating high number of conflict events while fire occurrence is minimal (Cheng, 2016).

Through the application of local spatial autocorrelation, a statistical measurement was obtained that calculates for each geographical unit in the entire study area the affinity of said unit to have a characteristic value, which is correlated with values in surrounding regions (Anselin, 1995). In situ correlations are not accounted for. LISA provides spatial association for each unique polygon unit according to following equation:

$$I_B = \frac{\Sigma_i(\Sigma_j \mathrm{W}_{ij}(\mathrm{d})x_i \times y_i)}{\Sigma_i x_i^2}$$

Equation 2. Computation of the local bivariate Moran's I

Here $x_i \times y_i$ is cross product of the attribute values for the first variable at location i and the attribute value of the second variable at location j, where j must be one of the neighbours of i as defined in the weight's matrix $w_{ij}(d)$.

For visualization simplicity and to aid comparability between the periods, the yearly attained results are summarized according to period A (2012-2015) and period B (2016-2020). The summary is based on an application of a majority filter, where in order to be shown in the final map, the cluster needs to be present in at least three of the years. This is not the case where there are instances of high conflict - high fire clusters (HH) and high conflict - low fire cluster (HL), which only had to be registered in at least one year to be visualized, given that these are the regions of substantial interest. Moreover, the distance from each HH cluster to the nearest city or town was calculated. This was done to assess whether conflict and fire events tend to occur in cluster that have towns located within, or whether these events have a more remote character.

To measure the spatial autocorrelation between conflict and fire events it was necessary to provide a **weights matrix** as input in GeoDa, which delimits for each geographical unit the corresponding neighbourhood of influence. Then a comparison was made between the value of each individual unit to the weighted average of the surrounding values (i.e., its neighbours). For the purpose of this study the weights were assembled based on contiguity of the created fishnet polygon, where contiguity defines which polygons are chosen as neighbours for an individual target polygon. Here for the generated weights matrix, queen contiguity (Fig. 6) was utilized, which means that for a given fishnet polygon all 8 neighbours are considered. For simplicity reasons only the first order of contiguity was considered. Thus, the values of units further away from the immediate surrounding neighbours were not influencing the results of the target polygon. Given that each fishnet was a 10 by 10 km matrix it made sense not to account or correlate conflict events to fires occurring further away than 10 km, as these might not be directly impacted by said conflict event.

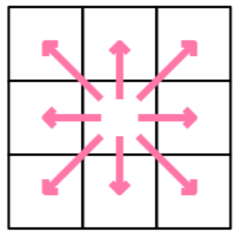

Figure 6. Continuity case that was utilized in the weight matrix: Queens Case. For a target polygon all 8 neighbours are considered.

3.3.3 Climate impact on fire dynamics

To acquire knowledge regarding the effect of climate on fire dynamics, fire counts, land surface temperatures and precipitation data were analysed by computing the yearly average conditions during the fire season over West Iran. Fire season in this context constitutes of the months in which most fires occur (June to October) (Fig. 3) as well as the month prior, given that climatic condition before the start of the fire season also influence fire activity. Then these yearly values were compared to the fire season mean of a 30-year period (1991-2020) to calculate the yearly anomaly (for both temperature and precipitation) . Since the active fire dataset did not provide data prior to 2012, the annual values were compared to the fire count mean computed for the study period. With the help of this **Z-score index (ZSI) analysis** (Kreyszig et al., 2008) it was possible to conclude which years during the fire season were especially warm and dry, amplifying the risk of fires. Moreover, the same analysis was executed for the province with the lowest recordings of armed conflict events (Ilam) and the province with the highest numbers of conflict events (Kermanshah). The Z-score index is calculated according to following equation:

$$Z = (x - \mu)/\sigma$$

Equation 3. Computation of the z-score

Where x indicates each individual year, μ describes population mean, and σ defines the standard deviations. Here the population mean consisted of the average climatic situation (temperature and precipitation) present during the fire season (May to October) between 1991 to 2020. For fire occurrence, the population mean contained the average fire counts during the fire season between 2012-2020. The final z-scores acquired do not have units and describe how many standard deviations below or above the population mean the annual value lies. If a z-scores surpasses -1.645 or +1.645, it reached the threshold needed for statistical significance at 90 % confidence level.

To characterize the interplay between fire and climate in more detail a correlation analysis was conducted. This was done by computing the **Spearman rank** correlation coefficients between both fire counts and temperature/precipitation annually for the whole study region and separately for each province. A second correlation analysis was conducted where locations were divided according to findings from the spatial correlation study. Thus, locations that showed a high clustering of conflict and fire events were further investigated on the relationship between fire and climate variables. The aim for the latter calculation was to show whether difference exists regarding fire dynamics in proximity to conflict events, or if climate alone is highly significant for these areas.

In this section the statistical analysis conducted is elaborated on, which was used to evaluate the relationship between climatic variables and fires for the total study area and the individual provinces from 2012 to 2020. Three steps were taken to determine, which statistical tool is appropriate to utilize:

1. Assess datasets for normality.
2. Check for monotonic relationship presence between temperature and precipitation to fire occurrence.
3. Statistical Hypothesis Test definition

To determine whether the datasets follow a **normal distribution** their kurtosis and skewness values need to be computed. Skewness is a measure that characterizes the symmetry of the variable distribution, where a normal distribution has a skew value of zero indicating symmetric distribution (Pallant, 2020). Positive skewness values imply a longer tail towards the right of the distribution compared to the left hand side, meaning that most values are aggregated left of the mean (West et al., 1996). The opposite holds true of negative skewness, where most values are found right of the mean and the left hand side trail is longer than the right (West et al., 1996). Kurtosis on the other hand describes the peaks in the distribution, where distributions with positive kurtosis are characterized by having a high peak (leptokurtic) and negative kurtosis have a flat curve (platykurtic) (West et al., 1996). Here, values for skewness and kurtosis have to lie within the range of -2 to +2 in order to be considered normally distributed (George & Mallery, 2010).

After calculating the skewness and kurtosis values for each of the 12 datasets, two had kurtosis values above the aforementioned range (sees Appendix, Table 2), which implies the lack of normal distribution. Thus, the dataset had to be analysed more in detail in regard to normality which was conducted with the help of the Shapiro-Wilk test (Shapiro & Wilk, 1965). Here the computed statistical probability (p-value) was evaluated to a 95% level of confidence, where the level of significance is $\alpha = 0.05$ (Fisher, 1934). While p-value $< \alpha$ indicates non-normal distribution, p-values $> \alpha$ define the existence of normality. After calculating the p-value for all dataset, non-normal distributions were found of every variable (see Appendix A, Table 2), meaning the null-hypothesis that the data is normally distributed has to be rejected as in all cases p-values $< \alpha$ hold true. Thus, a Spearman rank correlation test is suitable to utilize.

To be able to apply the Spearman rank test, the datasets need to be evaluated to determine whether a **monotonic relationship** exists. A monotonic relationship is present if an increase in one variable leads to an increase or decrease in the other variable. Unlike in linear relationships this increase/decrease does not have to occur at the same rate. The Spearman's correlation coefficients

(r_s) were computed to evaluate whether a monotonic relationship between fire instances and climatic variables exists, and the appropriate hypothesis tested. These coefficients range between -1 and 1, where the direction is defined by the sign (negative or positive) and the value describes how strong the relationship is. The null-hypothesis H0 = $r_s = 0$ expresses that no monotonic relationship is present between the fire and temperature/precipitation datasets. While H1 = $r_s \neq 0$, the alternative hypothesis describes the existence of a monotonic relationship. Every fire dataset compared to its climatic variables had $r_s \neq 0$ (see Appendix A, Table 3A), which means that null hypothesis had to be rejected and their relationship is monotonic and the prerequisites for the Spearman rank test are fulfilled.

Given that the datasets are of monotonic nature, the statistical test suitable is the **Spearman rank** correlation test (Spearman, 1961). This test, through the application of ranks, calculates the correlation between the variables about the average ranks. Similarly, to the previous test, null and alternative hypotheses need to be formulated. Here the null hypothesis states that no statistically significant relationship exists between the climatic variables and fire occurrence, while the alternative hypothesis states that statistical significance is present between the datasets. The testing starts with ranking each dataset individually in an order of increasing values. In the case when ranks are matching, their average gets taken. These ranks are then utilized to compute the Spearman's correlation coefficients (r_s), for each dataset pair (e.g., Ilam fires to Ilam temperature), where the calculations follow the equation below:

$$r_s = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n^3 - n}$$

Equation 4. Computation of the Spearman's correlation coefficients

In this case the sample size *n* is equal to 108, d_i^2 defines the square of the difference among ranks and *i* describes the individual noted value in the data. In the next step the obtained correlation coefficient will be utilized to attain the t-value from the student's t distribution, where the degrees of freedom given by the sample size -2. A level of confidence is set to 95% corresponding to $\alpha = 0.05$ (Fisher, 1934).

$$t = r_s \sqrt{\frac{(n-2)}{(1 - {r_s}^2)}}$$

Equation 5. Computation of the student's t distribution

After the p-value is obtained by calculating the absolute t-value and the degrees of freedom, it can be used to conclude whether the null hypothesis needs to be kept by conducting a comparison to $\alpha = 0.05$, which would be the case if $p > \alpha$. The opposite is given once $p \leq \alpha$, which means that the null hypothesis has to be dismissed and the alternative holds true.

4 Results

The results obtained from the different analyses conducted mentioned under Data and Methodology are presented in this section, starting with finding about the relationship between conflict and fires, as well as between conflict and land cover. Subsequently, outputs of the spatial autocorrelation analysis using the global and local bivariate Moran's I are elaborated on. Finally, the relationship between fires and climatic variables is explored, also in relationship to the results acquired during the spatial autocorrelation analysis.

4.1 Armed conflict, fire and affected land cover

During the study period over 35000 fires were recorded by the VIIRS instrument, belonging to the presumed vegetation fire classification (Fig. 7). The highest number of fires took place in 2017 followed by 2016 and 2019, while 2012 experienced the least number of fires. Moreover, when dividing fire occurrence by province, the highest fire counts could be found in the two southern provinces Ilam and Kermanshah. On the other hand, Kurdistan and West Azerbaijan occasionally passed the 500-fire count annually.

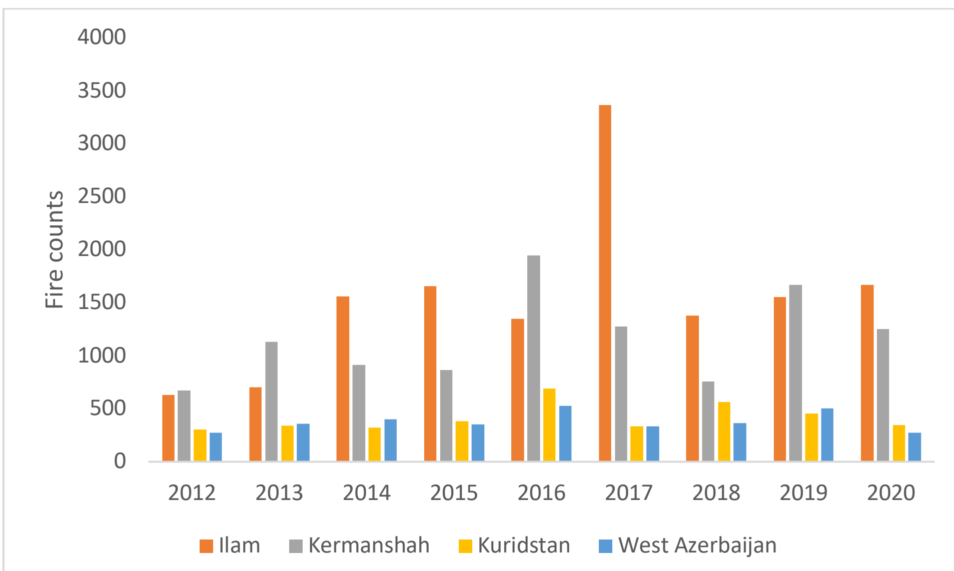

Figure 7. Vegetation fires counts recorded during 2012-2020 per individual province. Presumed agricultural harvest fires are filtered out (i.e., fires that take place in June and July on cropland).

Investigating the land cover categories affected by fires, it can be deduced that most fires occurred on croplands and bare soil/sparsely vegetated areas (Fig. 8). Croplands were the primarily impacted land cover class in 2016, 2019 and 2013, where the first two years showed a strong increase in the number of fires on agricultural fields. This can be observed even though presumed agricultural fires in June and July were excluded. On the other hand, 2017 emerged distinctively having over 3000 fires recorded on the bare soil/sparce vegetation category, whereas half the amount was common with around 1500 fire events on that land cover during the other years investigated. The lowest fire counts were recorded in cities, where in general 220 to 300 fires took place annually.

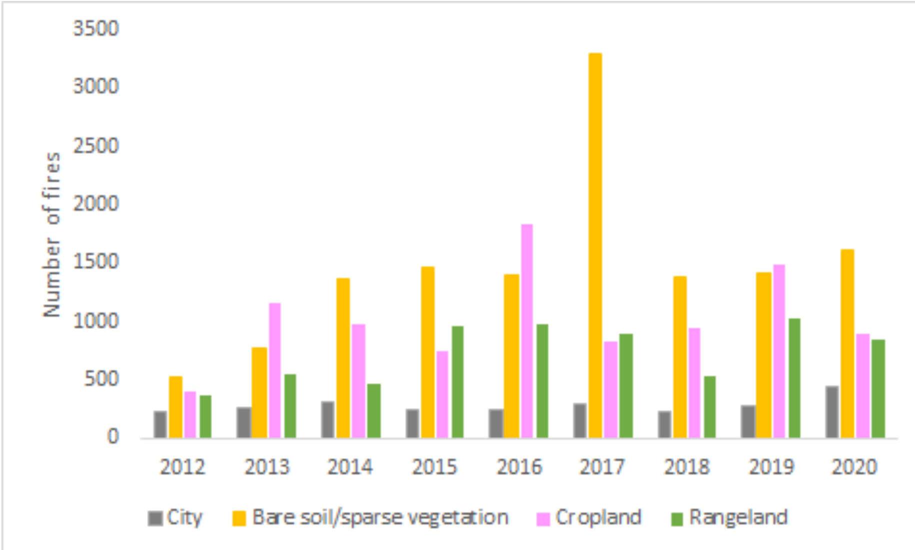

Figure 8. Vegetation fire occurrence based on land cover for the years 2012-2020. Presumed agricultural harvest fires are filtered out (i.e., fires that take place in June and July on cropland).

When analysing which land cover was dominantly affected by conflict, it became apparent that most conflict events occurred within cities (see Appendix A, Fig. 1A). However, after filtering out the cities, a substantial number of conflict events seemed to take place on croplands, peaking in 2016 with over 25 entities (Fig. 9). Another substantial peak could be further observed in 2018. Rangelands did not appear to be considerably impacted by conflict events as this land cover category, except for the year 2016, rarely recorded more than 5 events annually. Similar trends apply to the bare soil/sparsely vegetated land cover type, where the maximum number of 12 conflict events took place in 2012, while less than 6 were detected from 2013 onwards.

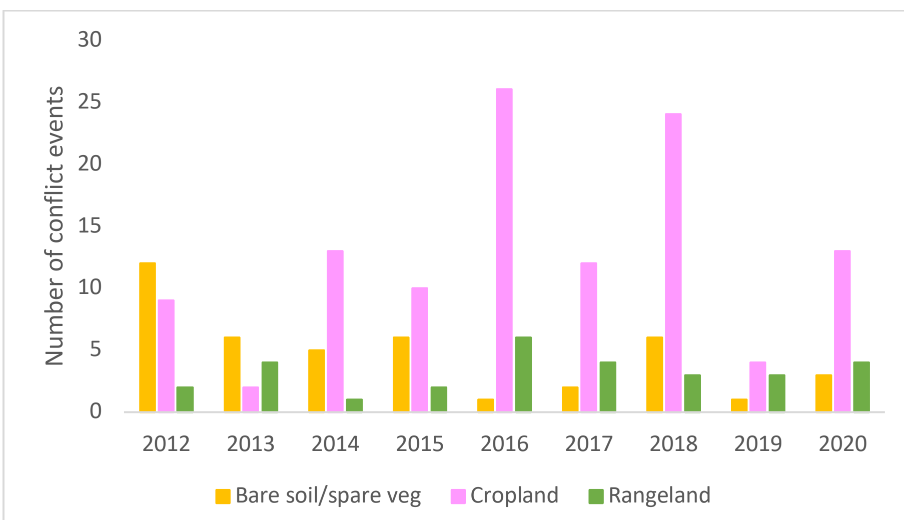

Figure 9. Conflict occurrence (ICEWS and UCDP datasets) based on land cover for the years 2012-2020. Cities are filtered out to visualise the impact of conflict on natural land covers.

However, the type of conflict is just as important to discuss as the land cover when linking it to potential fire occurrence. Given that the ICEWS dataset provides information regarding conflict event type, it was then possible to display event type per land cover category (Fig. 10). Unlike the graph above cities were kept in order to differentiate, which type of conflict primarily takes place within the confinement of towns and the conflict type impacting croplands. Arrest and other forms of detainments dominated in cities with an event count close to 50. No other land cover class experienced as many demonstrations or rallies as the city one. Similarly, political acts that could be described as criticism or denouncements towards the government primary took place in cities as well. When looking into conflict events that occurred on croplands, it is noticeable that the use of conventional military force had the highest event count with 25 records. Moreover, croplands were the land cover where fighting involving tanks, small arms and weaponry took place. Other types of conflict events that happen on agricultural lands were arrest, denouncements, and the usage of unconventional violence. What can be deduced from this assessment is that while most conflicts did materialise within cities, around two thirds of these events were of less violent nature compared to the event types that effect croplands.

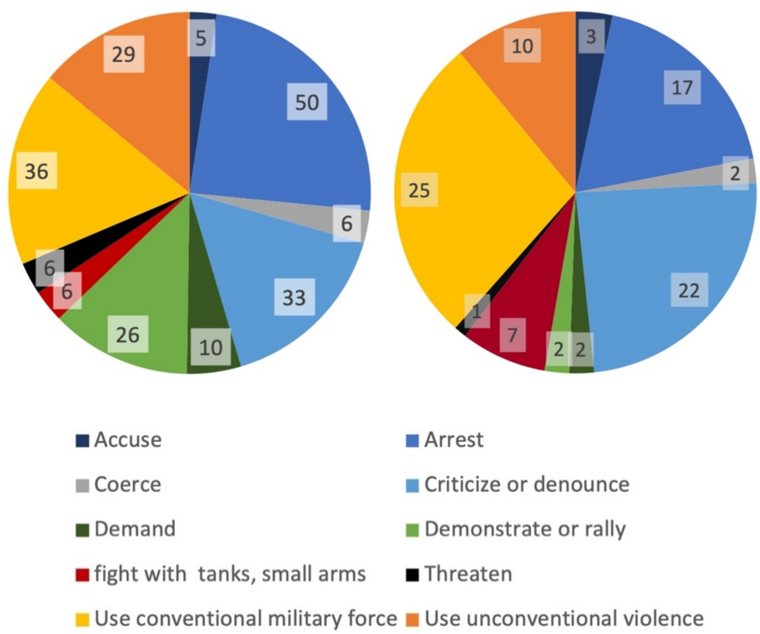

Figure 10. Type of ICEWS conflict event that impacts cities (left) and croplands (right).

4.2 Spatial relationship fire and conflict

Once the intensity filter to the ICEWS event dataset was applied, it became apparent that neutral events (blue line) started to decline once armed conflict started to increase (Fig. 3). On the other hand, less yearly variation can be seen in the political actions that are of a more violent nature (yellow line). However, event activity was observed to be the lowest in the latter three years of the study period, where 35 conflict events (grey line) and 33 neutral/positive events (blue line) took place in 2019 and 2020 had the smallest occurrence of events with 21 conflict and 15 non-conflict events. The highest number of conflict events was recorded in 2013 with 80 conflict instances and 236 neutral events, while the highest number of armed conflict events can be observed in 2016 with 23 recordings. During the spatial relationship analysis only the relationship between fire occurrence and conflict events (grey line) as well as missing UCDP data (Appendix A, Table A1) were assessed, while the politically neutral instances (blue line) were disregarded (Fig. 3).

The statistical results for the g**lobal bivariate Moran's I** analysis applied to the whole study region are summarized in the table below (Table 1). While the years 2012, 2013, 2014 and 2016 were statistically significant at a level of 0.01, the Moran's I values obtained imply the presence of a very weak, positive spatial autocorrelation between conflict and fire events. The Moran's I was the highest for both years 2014 and 2016. Since that the z-values were always positive, this indicates that the linkage between conflict and fire is not spatially dispersed, but instead a tendency towards clustering exists. On the other hand, no significant global bivariate spatial dependency can be found between conflict and fire occurrence in the years 2017 (Moran's I =0.002; $p > 0.05$) and 2020 (Moran's I = 0.006; $p > 0.05$). Although the remaining years showed a statistically significant spatial dependence between the variables at a confidence level of 95%, (i.e. $p < 0.05$), the global Moran's I yielded does not deviate substantially from 0, hence they were spatially correlated to an even lower degree than the years 2014 and 2016.

Table 1. Results from the global bivariate Moran's I applied for the whole study region on yearly basis. A p-value of 0.01 indicates statistical significance at 99% confidence level, while a p-vale > 0.05 implies a lack of statistical significance.

Year	Moran's I	z-value	p-value
2012	0.020	3.58	0.01
2013	0.021	3.98	0.01
2014	0.024	4.32	0.01
2015	0.011	1.90	0.02
2016	0.024	4.37	0.01
2017	0.002	0.31	0.12
2018	0.006	1.07	0.04
2019	0.015	2.68	0.03
2020	0.006	1.00	0.09

Given the results acquired from the global bivariate Moran's it became apparent that the spatial correlation between the variables over the entire study area, was either not statistically significant (2017, 2020) or positively correlated but to a rather weak degree (2014, 2016). As outliers were not included in this analysis, the **local bivariate Moran's I** was computed to find clustering in the studied landscape and to understand the patterns of conflict and fire on a local scale.

The results from the **local bivariate Moran's I** indicated a shift in clustering of high conflict-high fire occurrence between the two periods (Fig. 11 & 12). While in the years 2012-2015 (period A), these clusters were primarily located in the provinces of Kermanshah. During period B periods clusters can be found more north in the Kurdistan province. In Kermanshah, more than twice as many high conflict-high fire clusters could be observed during period A in comparison to period B. While the clusters present were more spread-out throughout the entire province in period B, the latter period showed a more condensed concentration in the centre of the region. Furthermore, only a few locations in both periods could be characterized as HL meaning high conflict and low fire occurrence. Lower numbers of this type of clustering, hence, suggests that most areas where a higher numbers of conflict events are found, tend to surround places with higher fire occurrences as well. Both time periods had high fire counts and low conflict events in the southern part of Ilam. Moreover, it was interesting to note that the HH clustering in the Kermanshah, was surrounded in general by high fire occurrence clusters, which was not given in the clustering of other provinces.

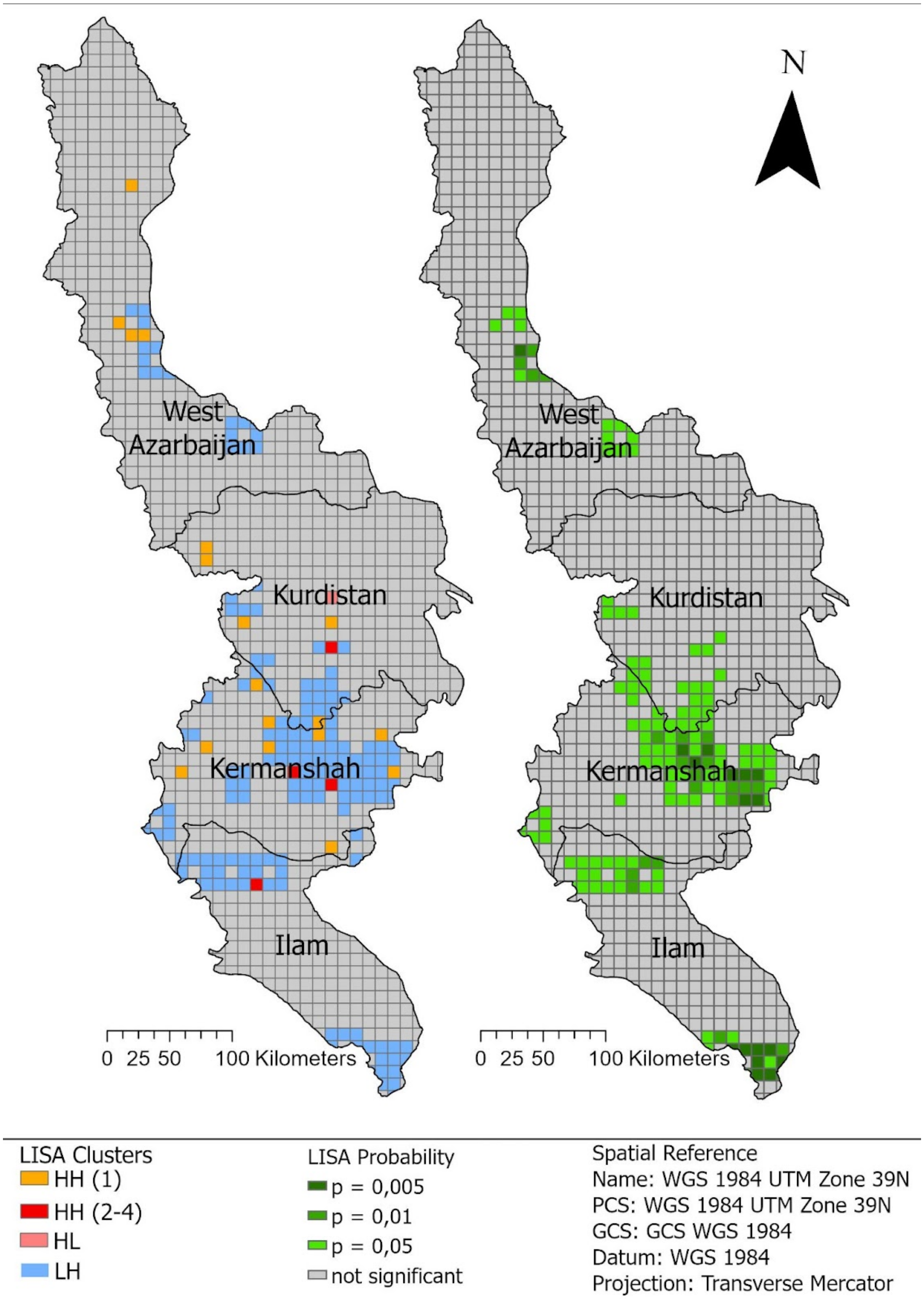

Figure 11. Results LISA averaged between period A (2012-2015). HH means high conflict and high fire occurrence, which is further divided according to frequency; where HH (1) indicates one instances and HH (2-4) describes multiple years yielding this cluster. HL describes high conflict occurrence and low fire amounts, and LH low conflict occurrence and high fire occurrence. Included are the averaged probabilities for said relationships on the left of each cluster map.

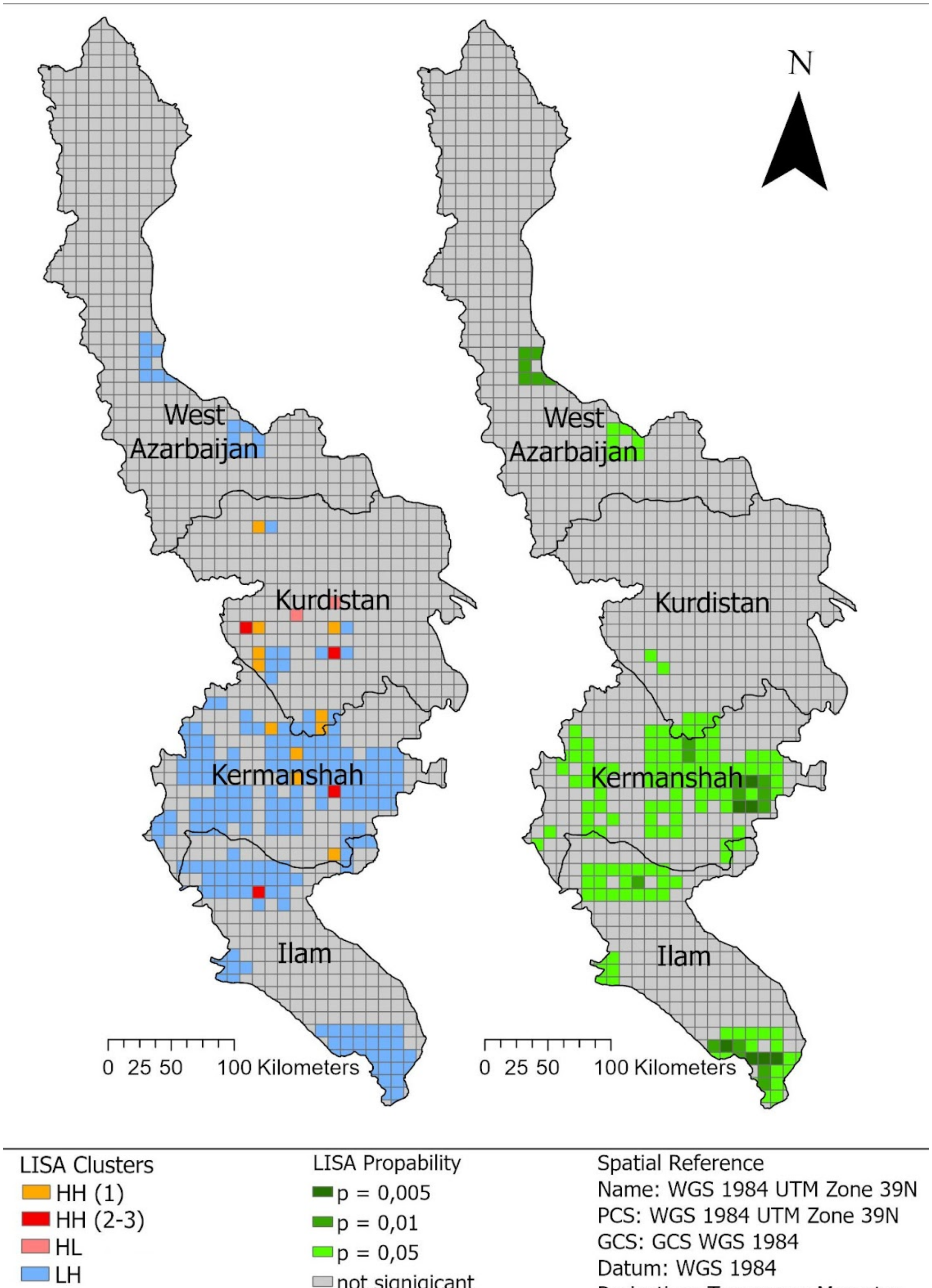

Figure 12. Results LISA averaged between period B (2016-2020). HH means high conflict and high fire occurrence, which is further divided according to frequency; where HH (1) indicates one instances and HH (2-4) describes multiple years yielding this cluster. HL describes high conflict occurrence and low fire amounts, and LH low conflict occurrence and high fire occurrence. Included are averaged probabilities for said relationships on the left of each cluster map.

4.3 Fire and climate

In the first part of this section, the results from the **Z-scores analysis** for the entire study are presented, as well as the ones for the provinces Kermanshah and Ilam. These two locations where chosen based on the outcome of the LISA analysis, with Kermanshah being the province with the highest number of high conflict-high fire clusters and Ilam having the least amount of said clusters. Afterwards the results from the Spearman rank correlation between fire occurrence and climatic variables are shown, moving from the whole study region, towards a provincial level and finishing with the individual clusters high conflict-high fire obtained in the LISA assessment.

When investigating the Z-scores of fire occurrence, precipitation, and temperature over the entire study area, it became clear that no statistically significant temperatures anomalies were observed. However, three years were shown to be outside 1 standard deviance of the mean temperature value for the period 1991-2020 (Fig. 13). Both 2015 and 2017 had positive anomalies being warmer than mean conditions during the period 1991-2020, while 2013 was the only year which was colder than usual. On the other hand, for precipitation three negative anomaly could be identified in 2016, 2017 and 2020 which was more than 1 standard deviation below the mean. The positive anomalies could be observed in 2015 and 2018, where both years managed to cross the 90 % significance threshold. Moreover, the 2015 precipitation anomaly had highest recorded deviation from the mean, making this period usually wet. Lastly, the anomalies for fire counts were investigated, where three years did not stay within 1 standard deviation of the mean value. In the year 2012 fire counts were below normal, which was also statistically significant ($p = 0.10$). While in 2017 and 2019 more than average fire occurrence was noted.

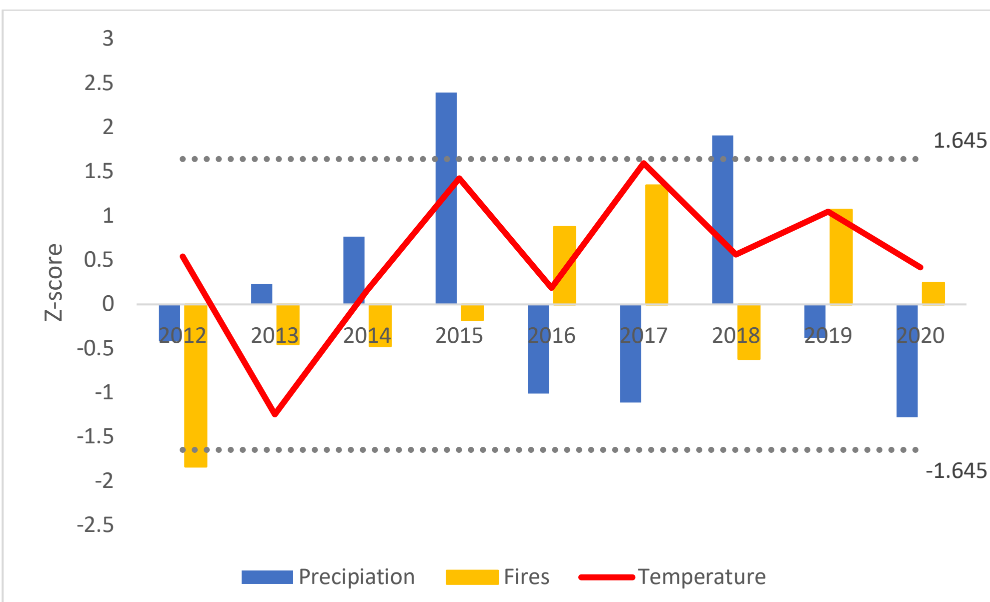

Figure 13. Z-scores analysed for the whole study area. The grey dotted line describes the threshold needed for the Z-scores to acquire statistical significance at 90% confidence level ($p = 0.10$).

A different pattern emerged in **Ilam**, where the year 2017 stood out as having both the lowest highest temperatures recorded and above normal fires occurrence compared to the other years (Fig. 14). Temperatures in Ilam were outside 1 standard deviance of the temperature mean for the period

1991-2020 in 2013, 2015 and 2017. Notably, 2013 is the only years that was especially cold with a statistically significant (p = 0.10) negative anomaly falling over 2 standard deviations below the mean value. When assessing precipitation, three years showed anomalies that are not within 1 standard deviation of the precipitation mean value. These years were 2017, 2018 and 2019, all having positive anomalies, where the z-scores managed to cross the critical value to obtain statistical significance at 90% confidence level. For fire occurrence, three years were observed to have anomalies that diverge more than 1 standard deviation from the average. Where 2012 and 2013 had fire counts below normal, while 2017 had above average fire counts that were further statically significant (p = 0.10).

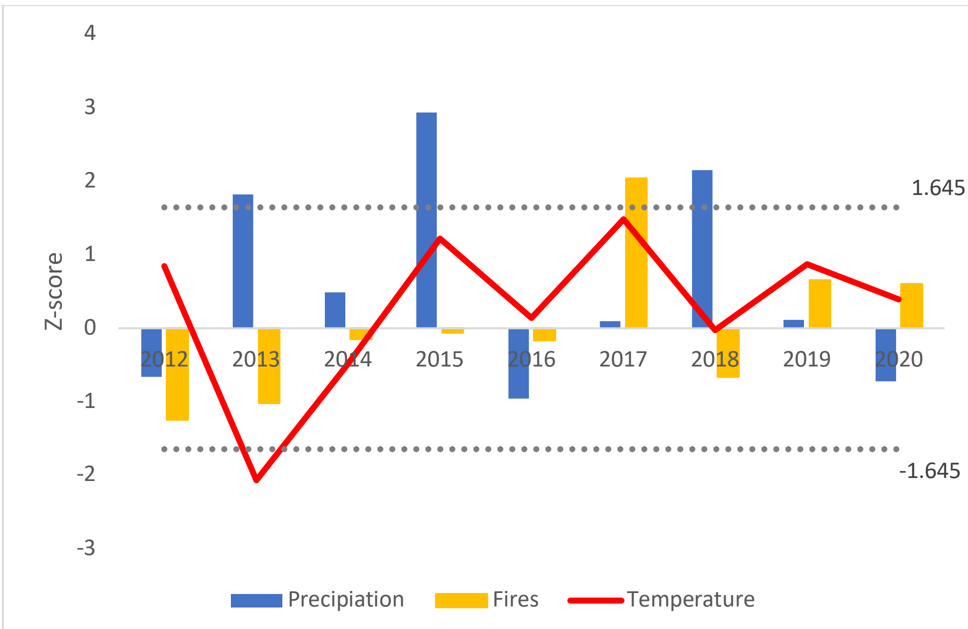

Figure 14. Z-scores analysed for Ilam. The grey dotted line describes the threshold needed for the Z-scores to acquire statistical significance at 90% confidence level (p = 0.10).

In **Kermanshah,** three years had temperatures above 1 standard deviation of the mean, while the remaining years of the study period stayed within (Fig. 15). The year 2013 particularly appeared to be the only years with colder than average conditions. Precipitation showed similar variance, where three years were outside 1 standard deviation of the precipitation average. Both 2015 and 2018 had positive anomalies, with each year having statistical significance. The year 2020 was wetter than usual, however threshold for statical significance at 90 % level was not crossed. Fire counts above 1 standard deviance of the mean were observed in three years. While fire counts were lower than normal in 2012; 2016 and 2019 showed to have positive anomalies. In the year 2016, coinciding with the start of armed conflict in the region, the fire counts were the highest recorded and this anomaly was statistically significant (p = 0.10).

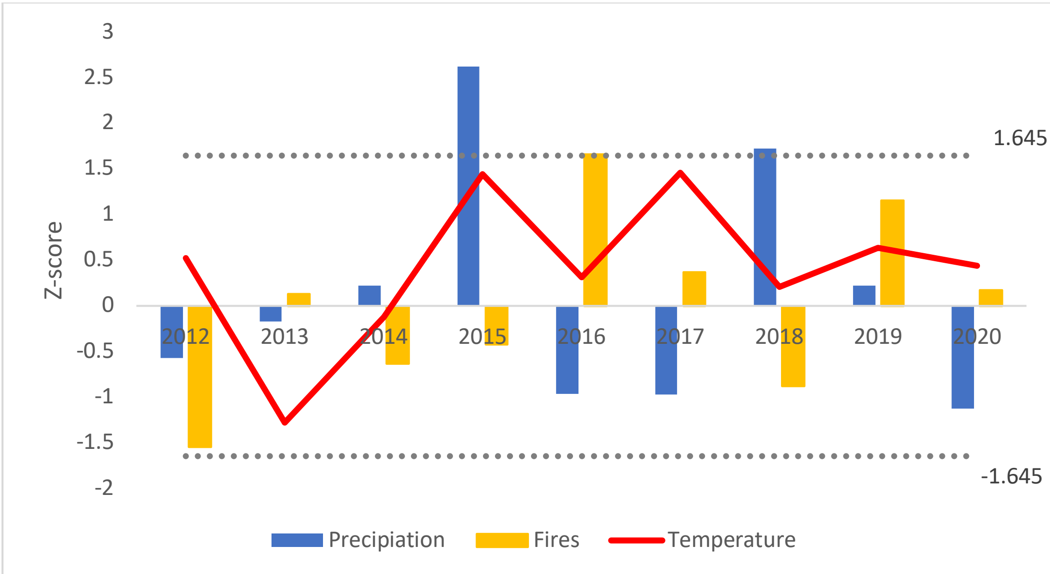

Figure 15. Z-scores analysed for Kermanshah. The grey dotted line describes the threshold needed for the Z-scores to acquire statistical significance at 90% confidence level ($p = 0.10$).

The results from the **Spearman rank** correlation are depicted below (Table 2). Here the relationship between fire and climatic variables was assessed monthly in order to have a higher sample pool and acquire higher temporal precision, instead of relying on yearly averages. When accounting for the variables over the entire study region, the relationship between fire and temperature yielded a correlation coefficient value of 0.72, indicating the presence of a strong positive relationship that is highly significant. The same statistical significance could be seen for precipitation, but the direction of the correlation is strongly negative.

Table 2. Spearman rank correlation results for the entire study region between fire counts and temperature and fire counts and precipitation on monthly resolution (N=108) during the period 2012-2020. Excluded are the presumed agricultural fires during harvest season. Statistical significance at $p < 0.001$ is indicated by ***.

Statistical variables	Temperature	Precipitation
Correlation	0.72	-0.74
T statistic	10.67	11.16
p value	***	***

Once the studied area has been dissected according to the provinces, it can be observed that all provinces portray statistically significant correlations between fire occurrence and temperature as well as precipitation ($p < 0.001$) (Table 3). Moreover, the relationship between fire counts and precipitation was negative, which implies that less precipitation promotes higher numbers of fire to take place. Conversely, higher temperature would indicate higher fire occurrence as can be deduced from the positive correlation values. While Kurdistan had the strongest positive correlation values of 0.76 for the interplay of temperature and fire events, the province Kermanshah had the strongest negative correlation towards precipitation with -0.71. Although a significant relationship ($p < 0.001$) exists between the fire counts and climatic variables in the province Ilam, it stood out as having the weakest correlation values assessed at 0.53 and -0.49 for temperature and precipitation respectively.

Table 3. Results of Spearman rank correlation for each province between fire counts and temperature; fire counts and precipitation on monthly resolution (N = 108) during the period 2012-2020. Excluded are presumed agricultural fires during harvest season. Statistical significance at p < 0.001 confidence level is indicated by ***

Province	Statistical variables	Temperature	Precipitation
Ilam	Correlation	0.53	-0.49
	T statistic:	6,32	5,75
	p value	***	***
Kermanshah	Correlation	0.73	-0.71
	T statistic:	11.01	10.22
	p value	***	***
Kurdistan	Correlation	0.76	-0.70
	T statistic	11.92	9.98
	p value	***	***
West Azerbaijan	Correlation	0.73	-0.66
	T statistic	10.88	8.92
	p value	***	***

In the last step of the correlation analysis, the relationship between fire and climatic variables was assessed for the individual high conflict-high fire clusters obtained from the local bivariate Moran's I application. In total 28 clusters were deemed interesting, and the outputs of the Spearman rank correlation are presented below.

The first aspect worth mentioning for high conflict-high fire cluster obtained for period A is, that the correlations for all locations were substantially weaker compared to the correlations for the provinces, in which the clusters are located (Table 4). The strongest correlations were found for location 6 during the period 2012-2016; this cluster had a significant mild positive relationship between fire and temperature, with a coefficient of 0.45 and a significant mild negative relationship between fire and precipitation, with a coefficient of 0.5. However, even though these coefficients were significant, they were indeed weaker that the coefficients found for the province Kurdistan, where the cluster is located (Table 3). Moreover, most clusters did not have any significant relationship to the climatic variables, indicated by the yellow shade in the table, or the relationship was significant but at a lower level of 0.05 (light green shading). Another pattern that arose is that locations at greater distance from towns tend to have no significant correlations between fire occurrence and the climatic variables. In general, most locations that did not have a town or city within its cluster follow this pattern. For locations where towns were present in the cluster (distance town = 0), correlations tend to be higher between fire and temperature occurrence, while being either significant at 99% or 95% confidence level when analysing the whole period. Apart from location 14, all other clusters detected in Kurdistan had slightly higher correlations between fire and climatic variables during period A compared to the whole study period (2012-2020) and most of these correlations were also statistically significant at 99% confidence level. On the other hand, the opposite trend could be observed for clusters within Kermanshah. Locations 1 and 19 had to be omitted as it was not possible to compute correlations for period B due to fire counts within the clusters being too low, correlations for the whole period can be found in the Appendix, Table 4A.

Table 4. Results Spearman rank correlation, for each high conflict-high fire location obtained for period A (2012-2015), between fire counts and temperature and fire counts and precipitation on monthly resolution during the period 2012-2020 and during period A (2012-2015). Excluded are presumed agricultural fires during harvest period. Significance at 99% confidence level is indicated by ** and statistical significance at 95% confidence level by *. No symbol implies lack of statistical significance.

		2012-2020		2012-2015			
Location	Province	Temperature Correlation	Precipitation Correlation	Temperature Correlation	Precipitation Correlation	Distance town (m)	Total nbr Conflict
4	Kurdistan	0.21*	-0.24*	0.32*	-0.33*	3755	4
6	Kurdistan	0.30**	-0.30**	0.45**	-0.50**	0	16
7	Kermanshah	0.12	-0.17	0.09	0.00	5934	14
9	Kermanshah	0.25**	-0.35**	0.24	-0.38**	0	6
10	Kermanshah	0.39**	-0.32**	0.38*	-0.27	0	64
11	Ilam	0.23*	-0.22*	0.37*	-0.36*	0	14
12	Kermanshah	0.45**	-0.42**	0.28	-0.23	0	15
14	Kurdistan	0.44**	-0.37**	0.34*	-0.20	0	3
16	West Az.	0.35**	-0.21*	0.48**	-0.41**	0	10
17	West Az.	0.13	0.00	0.19	-0.03	0	4
20	Kermanshah	0.47**	-0.39**	0.31*	-0.25	6686	1
21	Kermanshah	0.14	-0.20	0.23	-0.28	8424	1

22	Kermanshah	0.15	-0.12	0.25	-0.16	5030	3
23	Kermanshah	0.40**	-0.38**	0.32*	-0.26**	0	6
24	West Az.	-0.13	0.00	-0.14	0.02	443	1
26	Kurdistan	0.36**	-0.36**	0.45**	-0.47**	0	15
29	West Az.	0.14	-0.12	0.17	-0.23	5210	2
30	Kurdistan	0.18	-0.28**	0.16	-0.35*	354	2
31	Kermanshah	0.37**	-0.32**	0.35*	-0.25	0	3
37	Kermanshah	0.29**	-0.42**	0.11	-0.23	5549	1

A similar pattern arose for the clusters identified for period B, where all locations had weaker correlations compared to the provinces they are based in (Table 5). The output generated by the local bivariate Moran's I for the period 2016-2020 classified less high conflict-high fire clusters in comparison to period A. Moreover, 9 of the clusters previous described appear to be important hotspots in this time interval once again. While locations 4 and 6, had significant but weaker correlations for period A, during period B these cluster are observed to lack a relationship between fire and climatic variables. Shared locations between the periods that were based in Kermanshah, show the opposite linkage, such as for location 7, 9, 10 and 12. Clusters at greater distances to cities or town had in general weaker (95 % confidence level) or no significant correlations. All correlations that were significant at 99% confidence level, have towns present within the clusters. However, one location (6) in Kurdistan and one location (11) in Ilam that had towns present, were the only clusters that had correlations which were not significant during the period 2016-2020. When assessing the total number of conflicts in each cluster, no conclusive arrangement can be identified.

Table 5. Results Spearman rank correlation, for each high conflict-high fire location obtained for period B (2016-2020), between fire counts and temperature and fire counts and precipitation on monthly resolution during the period 2012-2020 and during period B (2016-2020). Excluded are presumed agricultural fires during harvest period. Significance at 99% confidence level is indicated by ** and statistical significance at 95% confidence level by *. No symbol implies lack of statistical significance.

		2012-2020		2016-2020			
Location	Province	Temperature Correlation	Precipitation Correlation	Temperature Correlation	Precipitation Correlation	Distance town (m)	Total nbr Conflict
1	Kermanshah	0.16	-0.21*	0.21	-0.27*	18583	19
2	Kurdistan	0.08	-0.15	0.03	-0.05	4648	1
3	Kurdistan	0.21*	-0.15	0.30*	-0.33*	1929	5
4	Kurdistan	0.21*	-0.24*	0.11	-0.15	3755	4
5	Kermanshah	0.39**	-0.37**	0.25	-0.33*	0	2
6	Kurdistan	0.30**	-0.3**	0.2	-0.16	0	16
7	Kermanshah	0.12	-0.17	0.14	-0.27*	5934	14
8	Kermanshah	0.35**	-0.41**	0.43**	-0.49**	0	1
9	Kermanshah	0.25**	-0.35**	0.26*	-0.34**	0	6
10	Kermanshah	0.39**	-0.32**	0.19	-0.35**	0	64
11	Ilam	0.23*	-0.22*	0.08	-0.09	0	14
12	Kermanshah	0.45**	-0.42**	0.55**	-0.54**	0	15
13	Kurdistan	0.34**	-0.31**	0.34*	-0.28*	0	47
14	Kurdistan	0.44**	-0.37**	0.5**	-0.5**	0	3
15	Kermanshah	0.18*	-0.15	0.14	-0.11	5730	1

5 Discussion

In this section the obtained results are assessed by discussing the research questions they aim to answer. The acquired findings are placed into a larger scientific context by comparing them to studies conducted on the impact of armed conflict. Furthermore, based on the obtained knowledge ideas for the direction of future research are provided.

5.1 The role of land cover

Which land cover is primarily affected by fire events or armed conflicts?

When assessing the location of fires in West Iran, it becomes apparent that most fires occur on bare soil/sparse vegetated grounds and on croplands. Croplands are the most impact land cover in 2013, 2016 and 2019 even after presumed agricultural fires (intentional burnings of agricultural waste during harvest season) were omitted (Fig. 8). On the other hand, the land cover least impacted by the prevalence of fires are cities. This could be due high amount of build-up areas and infrastructure, not providing the needed biomass for fuel. Nonetheless, in cities greenery and vegetation exist in urban parks, which could explain the occurrence of fires. However, when investigating the land cover on which most conflicts emerge, croplands are the second most impacted class after cities (Fig. 9). This, in turn, yields high conflict-high fire clusters from the spatial analysis, which are dominated by croplands and rangelands. Hence, given that these have more biomass present compared to the other land covers and the danger of active fighting, their vulnerability to conflict induced fires increased. Similar findings are obtained by Zubkova et al. (2021), who analysed the relationship between conflict, climate, and fire between 2002-2020 in Syria. In Syria, violent conflicts during the civil war aided fire occurrence through both increased numbers of ignitions and weakened firefighting mechanisms. As many of the battle zones were localized within or surrounding farming lands, accidental ignitions due to collateral damage and deliberate fires set stemming from conflict were frequent during the growing season (Linke & Ruether, 2021).

When assessing the high conflict-high fire clusters, 13 out of 28 locations (46%) are situated outside of towns (Table 4 & 5). Due to the distance to infrastructure and towns, these places should have a lower fire risk according to Mitri et al. (2011). However, given that almost half of the identified hot spots occur on these remote locations, the normally lower fire risk might have been altered by the presence of conflict. On the other hand more susceptible regions to fires should be in proximity to larger cities, and their suburbs (Mitri et al., 2011). This type of land cover would characterise the other half of the cluster in West Iran which have towns present within. Additionally, climate in these cluster has stronger correlations to fire counts compared to their remote counterpart. Thus, it might be the case that some of these fires are occurring due to natural heightened fire risk. This would further illustrate that, while the fire risk tends to be lower for low population density settlements, conflict and active fighting might have the potential to change this risk factor.

Another aspect worth mentioning is post-conflict induced stability enhancing fire occurrence due to agricultural recultivation. A study done by Schon et al. (2021) in Syria ascribes the increase of fire activity in 2019 to agricultural revival. However, the peak in cropland fires observed in West Iran coincides with the timing of increased armed conflict in the region. Simultaneously, in the year 2016 agricultural lands also are the land cover class most impacted by a high number of conflict instances. Thus, this makes post-conflict induced stability an unlikely explanation.

5.2 Spatial relationship between conflict and fire

What is the temporal and spatial relationship between vegetation fires and conflicts? Is there a detectable difference between the pre- and the armed conflict period?

The results for the global bivariate Moran's I show a lack of global spatial autocorrelation between fire incidents and conflict events, however the application of the local bivariate Moran's I confirms the presence of confined high conflict-high fire clusters (Fig. 11 & 12). Similarly, the study by Baumann et al. (2015) found that the most instantaneous changes to land cover usually arose within the confinement of the conflict zone. Although this thesis' focuses on the impacts of conflict on fire dynamics rather than land use; the findings under section 4.2 confirm the existence of local effects. This implies that the effect of conflict on fire dynamics has a confined spatial pattern and thus might not impact fire occurrence further away from the active conflict zone.

Ilam, the only province not exposed to actual armed conflict during the study period, has indistinguishable between periods multiple low conflict-high fire clusters present (Fig. 11 & 12). Given that these low conflict-high fire clusters in the south of the province are detected during both periods, it is likely that these fires are primarily driven by climate. In addition to that, Ilam has the most fire counts compared to the other regions especially after 2014 high fire counts are recorded ranging at around 1500, peaking in 2017 with over 3000 entries (Fig. 7). This explains why the spatial extent for low conflict-high fire occurrence is larger during period B. Similarly, in Kermanshah multiple low conflict-high fire cluster are present, especially dominating during period B. This might also be explained by the fact that fire occurrence tends to be higher in the latter period, reaching a maximum of 1945 fires in 2016 (Fig. 7). Additionally, high conflict-high fire locations are primarily surrounded by low conflict-high fire cluster during period B, which might indicate a possible connection between fire occurrence in neighbouring clusters induced by conflict. These connections are also described by Bauman et al. (2015), where the effects of armed conflict can negatively impact land use up to 35 km from the active battle zone. Thus, in this study neighbouring areas of these HH locations would fall in periphery of conflict influence. On the other hand, in Kurdistan low conflict-high fire clusters do not take up the same spatial extent such as in the case in Kermanshah and Ilam (Fig. 11 & 12). Moreover, this province is also the only region where low conflict-high fire clusters are observed, which might have been caused by environmental constraints such as lack of biomass availability. Lack of fuel supply thus would result in the region experiencing less fire counts even in the presence of conflict. Nonetheless, with the start of increasing armed conflict, fire activity peaks in 2016 with around 680 entries, while during period A fire counts range between 300 to 380 per year (Fig. 7). Thus, given that the region is normally less fire active, the increase in high fire-high conflict clusters observed between period A to B is especially noteworthy. Another pattern analysed is that during both periods, West Azerbaijan has a low number of low conflict-high fire cluster, which have a similar spatial extent. High conflict-high fire cluster decrease from four in period A to none in period B. Given the lack of high conflict-low fire clusters, it might be that during period B lower concentrations of conflict events took place in this region, therefore lower numbers of high conflict-high fire clusters were present.

Coming back to the research question, the spatial relationship between conflict and vegetation fires is, given the lack of strong correlations acquired from the global bivariate Moran's, localised to confined clusters. While there is a detectable difference between the two periods, they also share a lot of high conflict-high fire hotspots. Indistinguishable of period assessed, most cluster are recorded in Kermanshah and Kurdistan. However, a shift northward can be observed from period A to B, where in the latter period clusters can be found in Kurdistan rather than in Kermanshah, as was the case for period A. Moreover, the cluster during period B have a more centred concentration, especially pronounced in the province Kermanshah.

5.3 The role of climate

To which degree are climate or climatic anomalies responsible for fire occurrence in conflict-affected areas?

When investigating the statistical significance between fire occurrence and climatic variables, it is noted that over the whole study region strong significant correlation exists (Table 2). The relationship between fire instances and temperatures is positive, while it is negative for precipitation. Similarly, on a provincial level, these relationships are also found to be statistically significant (Table 3). Given the strong relationships between fire counts and climatic variables, it alludes to the fact that when temperature increases so do fire events, while the opposite holds true when rainfall increases. However, it is observed that the correlations in Ilam are weaker compared to the other provinces, which is especially pronounced for the interplay between fire occurrence and precipitation where the correlation coefficient lies at -0.49. This mild correlation recorded in Ilam might have occurred due to a time lag, since this province comprises of higher concentration of bare soil/sparse vegetated lands (Fig. 3) compared to other parts of the study region. In these arid areas the precipitation events leading to biomass accumulation, do not occur instantaneously. Moreover, this vegetative accumulation, according to Ardakani et al. (2010) is indeed associated with fire activity in Iran. A similar time lag has been observed in Syria, where rainfall events force vegetation build-up 1 to 2 months later (Schon et al., 2021).

The temporal pattern acquired from the Z-scores over the whole study area (Fig. 13) reveals that in four years temperature deviates above 1 standard deviation of the temperature average for the period 1991-2020. Nonetheless, none of the anomalies are statistically significant. In general negative anomalies, meaning colder than usual temperatures are not common and are only detected during the fire season 2013. This lack of cold anomalies and the higher frequency of positive anomalies might be caused by increasing temperatures induced by climate change (Mansouri Daneshvar et al., 2019), with the latter 6 years showing larger positive temperature deviations compared to the period 1991-2011. This is especially true for 2017 where in combination with below usual rainfall, more fires are recorded. Precipitation on the other hand, shows more variability ranging from unusually dry conditions in 2016, 2017 and 2020 to wetter than usual in 2015 and 2018. Additionally, the wetter years are observed to have statistically significant anomalies ($p=0.10$). A previous study conducted on north-western Iran during the period 1980-2010 found similar trends of significant extreme precipitation events (Tabari et al., 2014). Fire activity in the whole study region seems to be peaking in 2017, while fire counts are significantly below average in 2012. In general, years past 2016 tend to have higher than average fire counts, whereas prior to 2016 fire occurrences tend to be lower than average (Fig. 13).

In Ilam a similar fire anomaly pattern can be observed as for the whole aggregated results. Noteworthy, is the enhanced fire activity in 2017 present in the whole study region and Ilam, where in Ilam the anomaly is statistically significant at 90 % confidence level. The same cannot be observed in Kermanshah as fire occurrence is within 1 standard deviation of the mean fire value (Fig. 15). Hence, it could be possible that the peak of higher-than-average fire occurrence in 2017 for the whole region, is primarily driven by the heightened fire occurrence in Ilam alone.

Kermanshah has three years with fire count anomalies above 1 standard deviation of the mean fire value. While 2012 has lower than normal fire activity, 2016 and 2019 have positive anomalies. Given that the years before armed conflict started to increase have the lowest fire counts observed in the province and the year in which armed conflicts started to increase show a positive anomaly that is significant at 90% confidence level, it might indicate that a force outside of climate is at play. Especially, since this fire anomaly in 2016 cannot be detected in Ilam, which is a region not impacted by actual armed conflict. Similarly, in 2019 even though precipitation within 1 standard deviation of the mean value, fire counts in Kermanshah show to be higher than usual, while climatic conditions are comparable in the neighbouring province Ilam no fire anomaly can be observed (Fig. 14 & 15). Furthermore, from the correlation coefficients acquired during the statistical analysis conducted on Kermanshah, it can be deduced that when rainfall increases, fire occurrence decreases (Table 3). Since 2019 shows slightly higher than average precipitation amounts, fire counts should decrease, as is the case in 2014. However, the opposite can be noted, hence further illustrating that a force outside of climate might be affecting fire dynamics during these two years. Therefore, these findings would imply that while climate plays a crucial role in a region's fire activity, it is not the only element to consider, other aspects on fire dynamics such as the increased armed conflict might explain the enhanced fire activity after the 2016. Similar conclusions are drawn by Dinc (2021) in their study examining conflict and fire activity in Dersim, a Turkish province. They elaborate that while dry weather is predicted to enhance fire risk, their climate and fire data does not provide a lot of evidence for a strong connection. Furthermore, they note that years in which many fires occur do not always coincide with dry years, similarly in dry years not all fire counts are high.

5.4 Fire, climate, land cover and the role of conflict

Armed conflict leads to elevated fire occurrence that cannot be explained by climate alone.

When assessing the correlation coeffects for the individual high conflict-high fire clusters, certain aspects are observed. Firstly, that period A (2012-2015) has more HH clusters than period B (2016-2020) (Fig. 11 & 12). This could have occurred since the ICEWS dataset has more events recorded for period A, compared to the latter years of the investigated period, especially for conflict events (Fig. 4 grey line). Only a few locations in both periods could be characterized as HL meaning high conflict and low fire occurrence. Lower numbers of this type of clustering, hence, suggests that most areas where a higher numbers of conflict events are found, tend to surround places with higher fire occurrences as well (Fig. 11 & 12). Both time periods have high fire counts and low conflict events in the southern part of Ilam, implying that these fires occur regardless of political situations and are most likely driven by climatic factors. Ilam, while not subject to armed conflict nor especially violent events, yields one HH cluster, present in both periods, where 14 different conflict events are detected in total. Given that for this cluster (Location 11), during period B no significant correlation between fire and climatic variables could be found, these fires might also originate from the political instability recorded in ICEWS dataset (Table 5). Thus, this instance illustrates that it is essential to not only study the prevalence of armed conflict, which is limited since at least one fatality must occur before the instance is documented, but also to utilise additional data describing the political situation.

Furthermore, regardless of period, clusters located at distances to town or cities, generally fail to have significant correlations between fire instances and climatic parameters (Table 4 & 5). Hence, it is possible that the fires there indeed originate from the conflict occurring within the cluster or in neighbouring areas. An explanation for this might be that the type of conflict taking place on land cover characterised as cities is different compared to that occurring on croplands i.e., further away for towns and infrastructure (Fig. 9). While most demonstrations, arrests, and acts of disapproval towards the government are concentrated in towns, more violent clashes and fights occur outside of cities (Fig. 9). Thus, the type of conflict taking place at greater distances from towns has a higher potential to lead to collateral damage in form of vegetation fire or intentional ignitions. Moreover, accidental vegetation fires in proximity to towns or infrastructure, have higher changes of being extinguished, preventing their spread which cannot be guaranteed for more remote locations. Another aspect mentioned by Schon et al. (2019), is lack of proper land management education and fuel usage of lower quality. Operating machinery with lower quality fuels might create sparks during combustion, leading to ignitions, which is more likely to cause accidental fires in remote regions. The combination of bad fire management practices and lower fighter-fighting abilities therefore might be able to influence fire spread. Moreover, currently policies exist in Iran that aim to stop using fire as measures to remove waste material, through economically fining the practice. However, it is unclear how well these laws are enforced especially on these remote agricultural croplands.

5. 5 Limitations

Even though the UCDP dataset is commonly used in conflict assessment, it did not provide enough events to be able to conduct the spatial autocorrelation analysis. Since 23 events are the maximum recorded number in the year 2016 and most years have records below 11, the ICEWS dataset is utilized additionally (Fig. 3). While it is impossible to assess the accuracy of the geocoded events of both dataset in Iran due to the danger associated with visiting active conflict zones, events that are present in both databases generally overlapped perfectly. Furthermore, a study by Eck (2012) investigated data quality of conflict events reported by UCDP. For this purpose, they analysed the geocoding for two events that took place in Algeria in 1997 and Burundi in 2000, finding that 5% and 2% were miscoded, for Algeria and Burundi respectively. Thus, given the extensive checking process mentioned in the data description under 3.3, the error margin of armed conflict instances can be assumed to fall within the same range in Iran. On the other hand, ICEWS has been described to underrepresent actual events (Ward et al., 2013). This is also observed in this study, especially in the later years where out of the recorded 55 armed conflict events in the UCDP database only 6 are reported in ICEWS (Appendix, Table 1). Hence, the final dataset analysed had to be extended by larger numbers compared to the years prior. Moreover, as the fishnet cells generated were 10 km by 10 km polygons, the actual location within the polygon is not as important. However, miscoded events that would fall outside of the polygon border, would be accounted for in the analysis output given that the 8 neighbouring cells around the target polygon were included. On the other hand, it is possible that the conflict event is coded to fall outside the 8 neighbour influence, hence not being counted. In general, the combination of both datasets should provide a good overview of the political situation in West Iran.

The VIIRS active fire data covers the period from 2012 onwards, which was sufficient to investigate fire activity during this study. However, the lack of fire data before 2012 made it impossible to assess fire anomalies on a larger time interval. Due to the smaller sample size influencing the mean value, it is difficult to assess whether fire counts that are higher than usual in period B would acquire the same deviation when compared to a longer period. Since fire data is recorded at 375m spatial resolution, smaller fires might be omitted. Although this study focuses on vegetation fires and the dataset was filtered to remove static fires, high numbers of fires are detected on bare soil/sparsely vegetated ground primarily located within Ilam. This alludes that either some of the fires recorded might not have vegetational origin or that land cover changes have occurred prior or past the creation of the land cover layer in 2017, which are not accounted for. Nonetheless, the VIIRS dataset is useful tool to understand fire activity in Iran as well as locating essential fire hotspots.

Regardless of total number of conflicts, distance to towns or which period is analysed, all clusters have weaker correlations between fire counts and climatic variables compared to the provinces they are based in (Table 4 & 5). These lower correlations could imply that another force is at play causing these fires or that it is an issue of spatial aggregation generate by the Modifiable Areal Unit Problem (MAUP). MAUP is a concept that elaborates on the fact that when spatial data is either divided into different zones or aggregated to coarser units, the correlation strength changes (Wong, 2004). During aggregation less variation within the data is present compared to the individual unit level. Thus, by changing the scale from provincial level to singular clusters, this might yield different correlations strengths. Nonetheless, cluster identified as high conflict-low fire (HL), are not common and only are detected on 3 instances. Hence, once a concentration of conflict events can be observed, high fire instances are in general present as well. Therefore, it can be deduced that while MAUP might have caused some altercations to the statistical correlation's strength, the low frequency of these HL clusters implies that climate alone cannot explain the fire occurrence in conflict-affected regions and some of these fires could have been induced by conflict.

While it is possible to obtain wheat harvest dates from various sources such as the FAO and ministries for the provinces of Kermanshah, delimiting the harvest period to June and July, exact timing for agricultural waste burning was difficult to determine. Hence, the presumed waste burning is set to coincide with the harvest period, choosing a different time interval might have yielded different results.

6 Conclusion & Future research

This study elaborates how spatial analysis and statistics can be applied to evaluate the relationship between fire, land cover and armed conflict in West Iran. Key findings regarding land cover are that fires occur primarily on bare/sparse vegetated grounds and croplands, while conflict events dominate cities and croplands. However, the type of conflict these two land cover classes are exposed to differs, with croplands being subject to a higher percentage of violent events.

The lack of strong spatial correlations acquired of the global bivariate Moran's I imply that the impact of conflict on fire occurrence is not overall present in the study area. Instead, conflict has been shown to have a more localised effect on fire activity in the form of confined clusters. While more clusters are detected during period A (2012-2015) compared to period B (2016-2020), overlap exists between the two periods. Therefore, these clusters might be conflict–fire hotspots irrespectively of investigated period. Since high instances of conflict and high fires occurred before the clashes started in 2016, this implies that political instability prior to the start of war already has the ability to lead to enhanced fire activity.

General correlation trends on the whole region and provincial level describe that fire counts increase with increasing temperature and the opposite linkage can be noted when precipitation increases. Compared to provincial level, the high conflict-high fire clusters either have significant but weaker correlations between fire counts and climatic variables or were missing significance at all. Lack of correlations might have arisen due to MAUP, which would require further investigation. Nonetheless, the few instances of high conflict-low fire clusters imply that once a larger concentration of conflict events are present, higher fires counts tend to be in the surrounding areas as well. Thus, while not all fires can be with certainty attributed to be originating from conflict given that correlation does not equal causation, the evidence presented suggests that a force outside of climate is at play.

Further research is necessary to assess the interplay of violent conflict events, the effect of fire activity on agriculture, food security and human livelihoods not only on a global level but also in the local clusters most impacted. Moreover, the findings of this study allude that croplands are especially vulnerable to conflict induced fires, given higher percentages of violent events as well as available biomass. Hence, emphasis should be placed on the agricultural sector, not only regarding fire management but also the type of conflict taking place on these land systems. Utilising additional census data regarding ethic background or population displacement, might aid to further strengthen the understanding of societal dynamics on distal and local impacts of fire dynamics and land cover, especially during times of armed conflict. Since the clashes took place between Kurdish parties and the government, data regarding the ethnic background could reveal whether areas with high density Kurdish population get particularly targeted during the ongoing conflict and if fire activity there can be observed to differ from the non-Kurdish dominated parts of the region. Population displacement data could be used to investigate if fire dynamics change at locations where these refugees settle. This can be extended by including land cover change to assess whether displaced people actively modify the landscape trough for instance, establishment of new cultivation lands. Thus, this would provide backbone for studies of indirect, remote connections between armed conflicts and the environment. Lastly, the application of an additional conflict event dataset in future studies, such as the Armed Conflict Location and Event Data Project (ACLED) might aid the spatial autocorrelation analysis, especially in a country such as Iran where armed conflicts due to its strict definition only constitute a small portion of occurring conflict events.

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Appendix A

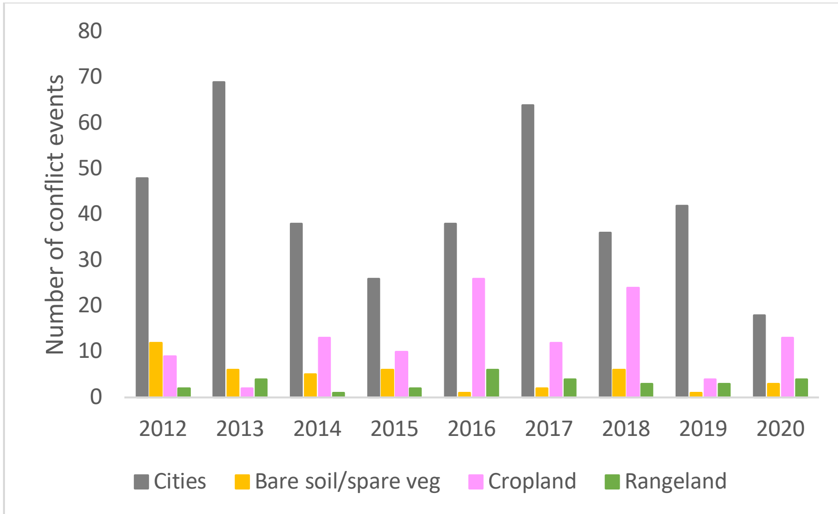

Figure A1. Land cover classes impacted by conflict events during the period 2012-2020. Unlike the figure in the main text body, cities are not filtered out here, illustrating that most conflict emerge in cities.

Table A1. Number of Uppsala Conflict Data Program (UCDP) events that were either already present in the Integrated Crisis Early Warning System (ICEWS) dataset i.e., 'existing instance' or that were missing i.e., 'separate instance'. The final conflict dataset, used for all analysis during this study, contained ICEWS events and included the missing UCDP instances.

Year	Existing instance	Separate instance
2012	1	0
2013	3	1
2015	2	0
2016	8	15
2017	0	6
2018	1	10
2019	4	15
2020	1	18

Table A2. Test to determine Skewness and Kurtosis of the datasets. Tests are conducted for datasets on fire counts, precipitation and temperature for each province. The accepted threshold for kurtosis and skewness to be considered normally distributed ranges between -2 to +2. The fire dataset for Ilam and Kermanshah has Kurtosis values above the threshold.

		Skewness		Kurtosis	
Dataset	N statistic	Statistic	Std. Error	Statistic	Std. Error
Fire Ilam	108	1.51	0.23	3.99	0.46
Fire Kermanshah	108	1.33	0.23	0.99	0.46
Fire West Az.	108	0.91	0.23	-0.10	0.46
Fire Kurdistan	108	1.93	0.23	3.90	0.46
Precipitation Ilam	108	1.30	0.23	1.19	0.46
Precipitation Kermanshah	108	0.90	0.23	-0.17	0.46
Precipitation West Az.	108	0.67	0.23	-0.49	0.46
Precipitation Kurdistan	108	0.82	0.23	-0.11	0.46
Temperature Ilam	108	0.02	0.23	-1.53	0.46
Temperature Kermanshah	108	0.08	0.23	-1.46	0.46
Temperature West Az.	108	0.01	0.23	-1.37	0.46
Temperature Kurdistan	108	0.05	0.23	-1.41	0.46

Table A3. Testing for Normality through applying the Shapiro Wilk test. The p-value was assessed at 95% confidence level ($\alpha = 0.05$). Non-normality is indicated when p-value < α and if p-value > α conditions for normality are given. Statistical significance at $p < 0.001$ is indicated by ***. All p-values are smaller than α, thus the data are not normally distributed.

Dataset	Statistic	df	Significance
Fire Ilam	0.88	107	***
Fire Kermanshah	0.80	107	***
Fire West Az.	0.73	107	***
Fire Kurdistan	0.89	107	***
Precipitation Ilam	0.80	107	***
Precipitation Kermanshah	0.85	107	***
Precipitation West Az.	0.92	107	***
Precipitation Kurdistan	0.88	107	***
Temperature Ilam	0.90	107	***
Temperature Kermanshah	0.91	107	***
Temperature West Az.	0.93	107	***
Temperature Kurdistan	0.92	107	***

Table A4. Excluded locations 1 and 19 for period A (2012-2015). Results Spearman rank order correlation between fire counts and temperature and fire counts and precipitation on monthly resolution. Correlations were computed for the whole study period 2012-2020. Calculations for period A were not possible due to lack of fire occurrence within the high conflict-high fire clusters. Excluded are presumed agricultural fires during harvest period. Significance at 99% confidence level is indicated by ** and statistical significance at 95% confidence level by *. No symbol implies lack of statistical significance.

		2012-2020		2012-2015			
Location	Province	Temperature Correlation	Precipitation Correlation	Temperature Correlation	Precipitation Correlation	Distance town (m)	Total nbr Conflict
1	Kermanshah	0.16	-0.21*	-	-	18583	19
19	Kermanshah	0.17	-0.09	-	-	5674	1