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Detecting historic informal settlement fires with sentinel 1 and 2 satellite data - Two case studies in Cape Town

Lesley Gibson[a,*], Jeanine Engelbrecht[b,c], David Rush[a]

[a] School of Engineering, University of Edinburgh, UK
[b] CSIR Meraka Institute, South Africa
[c] Department of Geography and Environmental Studies, Stellenbosch University, Stellenbosch, 7600, South Africa

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ABSTRACT

Increasing global urbanisation is leading to a rise in the number of people living in informal settlements, challenging our ability to achieve sustainable development goals. As a consequence of high building density, inadequate building methods and flammable building materials, informal settlements are highly vulnerable to the devastating impacts of fire. Databases on historic fire occurrence, location and extent are scarce, especially in the Global South. This paper explores the potential for remote sensing technologies to fill this gap. Two case studies in Cape Town representing fire of different extent and build back characteristics, are used to demonstrate that Sentinel-1 and Sentinel-2 data can be used to detect known historic informal settlement fire. A pixel based approach applied to Sentinel-2 band 2 reflectance and Sentinel 1 backscatter and interferometry are highlighted. The concept of spatial autocorrelation is explored with both Sentinel-2 and 1 data showing that a 3 x 3 pixel standard deviation kernel and hotspot analysis can complement the pixel approach. Further research is required to test these methods within a time series change detection algorithm to identify unknown historic informal settlement fires. .

1. Introduction

Informal settlements are residential areas where inhabitants have no security of tenure and are often located in geographically and environmentally hazardous or undesirable areas. Variously referred to as slums, shanty towns or favelas, they are indicative of poverty and inadequate living conditions [1], usually lack basic services and the housing may not comply with current planning and building regulations [1]. Due to the global urbanization process increasing the total number, as well as the share (relative to rural dwellers), of urban dwellers worldwide [2], the number of informal settlement dwellers is rising as a consequence. While informal settlements are a global urban phenomenon, they are seen to be a consequence of rising urbanisation in developing countries [3] in particular. Urban infrastructural development can no longer keep pace with rising population growth [3] and rapidly increasing poverty and informal settlements characterise urban conditions in the Global South [4]. The most deprived and excluded form of informal settlement characterised by poverty, are known as slums where, in addition to insecure tenure, slum dwellers lack access to public space and green areas and are constantly exposed to eviction, disease and violence [5].

Informal settlements vary widely between and within cities. They are generally characterised by dwelling units of a make-shift nature with construction methods of dubious quality [6]. Commonly recycled materials [7] such as metal sheeting, cardboard, plastic, timber, concrete and other material (Fig. 1a) are used in construction. Spatially, informal settlements are characterised by high roof density, a lack of public or green open space in close proximity to residential areas, small substandard building sizes, an organic layout [8], irregular and narrow streets and non-uniform building orientation [9]. [7,10] provide photographic evidence of the many forms of informal settlements.

Due to their construction and landscape characteristics, informal settlements are vulnerable to a range of natural and anthropogenic hazards. In particular, poor infrastructure and the use of domestic fuels for heating and cooking makes informal settlement communities vulnerable to fire hazards [11]. Fires are devastating to inhabitants as often all personal belongings, clothing and important documents are lost and fatalities sometimes occur [12]. Fires are reported to be often started by cooking on open fires, using unstable stoves and combustible fuels, and unsafe electrical connections [13]. Fires then spread quickly due to high density of dwellings which also impedes fire fighters access to the scene [12]. Further, specific social factors play a role in fire

* Corresponding author.
E-mail addresses: Lesley.Gibson@ed.ac.uk (L. Gibson), JEngelbrecht@csir.co.za (J. Engelbrecht).

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Fig. 1. a) Imizamo Yethu informal settlement in Cape Town illustrating the makeshift nature of building methods and materials, narrow pathways and combustible materials between dwellings, b) collapse of a dwelling due to a fire and c) new dwellings constructed from starter building kits provided by City of Cape Town post-fire.

ignition and spread including ignorance of fire safety practice alongside the broader challenges of poverty and other forms of deprivation and marginalisation [13]. Since informal settlements are characterized as generally unplanned and lacking in formal infrastructure, when a fire breaks out, lack of fire hydrants and water supplies together with inadequate road access prevent fire fighters efficiently tackling the fire [13].

Fires which typically burn in the formal planned housing built environment are usually limited to the room/building of fire origin due to a design philosophy of compartmentation [14] i.e. sub-dividing structures into compartments with fire-resisting walls and floors. Informal settlement dwellings, however, are not created with such a philosophy, therefore, each dwelling unit can potentially be conceptualised as a discrete fuel package, with a range of properties relating to ignition and fire intensity. These "fuel packages" are non-uniform both in size and distribution over large areas. Flame radiation, direct flame impingement, and fire brands (small particle of ignited material being carried in buoyant air flows) are the main spread mechanism, all of which are affected by topography and wind.

In the event of a fire in an informal settlement, poor construction methods and flammable construction material contribute towards rapid fire development resulting in collapse of small dwellings (Fig. 1 b) in as little as 2–5 min [15]. Combustible insulating materials, such as cardboard, which is often used to clad the insides of the steel sheet walls of dwellings, once ignited, can increase the speed of fire development and may cause the walls to buckle and collapse [15]. The high density and close proximity of individual dwellings as well as the presence of combustible material within and between dwellings, cause fires to spread rapidly between dwellings.

Cities were for many years considered as polluters and threats to the environment however, urban areas are now being seen as places where economic, social and environmental development can take place through Sustainable Development Goals (SDG) [2]. However, with informal settlements growing at a faster rate than any other urban development [7], this will be challenging. SDG no 11 aims to "make cities and human settlements inclusive, safe, resilient and sustainable" and identifies as a specific target, "access for all to adequate, safe and affordable housing and basic services and upgrade slums" by 2030.

SDG Goal no 11 further aims to substantially increase the number of cities and human settlements adopting and implementing integrated policies and plans towards *inter alia* resilience to disasters by 2020 [5] with the Sendai Framework aiming to substantially reduce global disaster mortality by 2030 [16]. The Sendai Framework sets out priorities for action in order to achieve this goal through (1) understanding disaster risk, (2) strengthening disaster risk governance to manage disaster risk, (3) investing in disaster risk reduction for resilience, and (4) enhancing disaster preparedness for effective response and to "Build Back Better" in recovery, rehabilitation and reconstruction [16]. Thus the frameworks and policies are in place globally to support the improvement of living conditions and reduce disaster risk for those who currently find themselves in inadequate housing in informal settlements.

To meet this goal, understanding of factors influencing fire spread is necessary. It has already been stated that informal settlements have a propensity to fire ignition and their vulnerability is thought to increase with high building density, use of inadequate building methods and flammable building materials, as this is understood to enable rapid fire spread from the dwelling of origin. To test the impact of spatial layout, density and type of building materials etc. on the rate of spread from dwelling of origin, reliable data on fire incidence and impact is required but is rarely available in low- and middle-income countries (LMIC) [13]. Where data does exist, the lack of standard operating procedures, inconsistencies in record taking and the lack of formal data repositories imply that few historical records are readily accessible. For example, the City of Cape Town has a fire incidence database available online, with the location of fires identified on a map grid with resolution approximately 800 m × 800 m. Often multiple blocks are entered for one fire making the identification of the exact fire location very difficult. Since databases on fire occurrence, location and extent are scarce, the potential role of remote sensing technologies to populate an inventory of informal settlement fires should be considered. With a spatial database of historic informal settlement fire which have spread beyond the dwelling of origin, it becomes possible to start analysing the particular risk factors contributing towards the propensity for spread.

Remote sensing is a key tool in monitoring long term environmental and anthropogenic change and satellite remote sensing is particularly useful for detecting change over time due to the availability of long term records and regular, repetitive image capture. The literature has revealed that satellite remote sensing technology is not yet being used for informal settlement historic fire detection and given the synoptic, objective and repeatable nature of remote sensing, an investigation into the possibilities of using this technology to build a spatial database of informal settlement fires is timeous.

Mapping a fire extent with remote sensing is essentially a classification process whereby spectrally homogeneous pixels (in this case, a burn scar) are identified and placed into a feature information class. In this way, the extent and shape of the feature are determined or mapped and can be vectorised and analysed post-classification in relation to neighbouring features or changes detected over time. Methods which only consider bi-temporal images, assuming a known fire with one image captured pre-fire and the other post-fire, can be investigated to understand the spectral response of the surface to fire. These methods however assume that a remote sensing image is available pre and post-fire.

Change detection on the other hand, identifies a significant change from one date to the next but that change is detected at the unit of analysis level (usually the pixel). This is a distinct and unique challenge for identifying unknown historic informal settlement fires using remote sensing as, in order to capture the changes which occur on the land surface, high temporal resolution imagery is required. Ideally (1) a pre-fire image, (2) an immediate post-fire but pre-rebuild image, and (3) a post rebuild image should be present in a time series in order to detect the fire event. However, data with temporal resolution high enough to capture these events (such as MODIS) typically has inadequate spatial resolution for informal settlements.

This paper aims to demonstrate that, using two case studies in the City of Cape Town, informal settlement fires which spread beyond dwelling of origin can be detected using Sentinel-1 and Sentinel-2 data. The case studies demonstrate observed change for two separate known fires (the first in Imizamo Yethu and the second in Kosovo) using (1) optical data (Sentinel-2) and (2) synthetic aperture radar (SAR) data (Sentinel-1) firstly in a pixel based approach. The concept of spatial autocorrelation in the fire detection concept is then explored through applying a 3 x 3 standard deviation kernel and hot spot analysis to both Sentinel-2 and Sentinel-1 products. General conclusion from the case studies are presented in Section 3 as is the potential of applying these techniques within change detection algorithms to detect unknown informal settlement fires.

2. Case studies

Informal settlement fires result in abrupt and rapid change as dwellings are completely destroyed and collapse or are partially destroyed and torn down post-fire for rebuild. Communities affected by informal settlement fires tend to re-establish themselves very quickly as inhabitants have no alternative accommodation and re-erect their structures rapidly so as not to lose the land they have occupied [12]. In other cases, the fire event is used to initiate reblocking, a process of upgrading informal settlements through spatial reconfiguration in order for services and infrastructure to be installed [17] and in these cases, rebuild happens over a longer time period. From a remote sensing fire detection perspective, there are thus two differing scenarios: the first is where rebuild takes place almost immediately post-fire and the second is where a process of reblocking and service provision results in a slower build back over the course of weeks or even months. For the purposes of demonstration, two fires, one in Imizamo Yethu and the other in Kosovo, representing different environments, extents and rebuild scenarios are selected in the City of Cape Town (Fig. 2).

The first settlement of Imizamo Yethu, established in 1991 has a long history of fire [18]. It was originally designed to accommodate 3000 people with a plan to build brick houses on individual serviced sites [11]. However once established, a major influx of new residents occurred [11] and by 2011, according to Ref. [19], no substantial improvements had been implemented. A ratio of one toilet to eleven households (http://ismaps.org.za/desktop.html#) was observed and the exact number of occupants was unknown but estimated in the region of 16 000 to 36 000 [19] with a settlement density given as 228 households per hectare (http://ismaps.org.za/desktop.html#). The settlement is located on steep mountain land with a height difference of 130 m from the bottom to the top of the settlement, with the main access roads at the bottom of the settlement, thus limiting the ability of emergency services to access the upper parts of the settlement as the roads deteriorate with steepness of slope [20]. Further, should a fire start in the lower part of the settlement, the settlement is at greater risk of fire spread as fire spreads faster upslope as flames tilt over potential fuel, increasing radiation, causing direct flame contact and convective heat transfer to potential fuel [21].

The Imizamo Yethu case study is a fire (Fig. 3) which burned on 11 March 2017. It covered a large spatial extent (4.2 ha) through part of the settlement on the slope of the mountain, it included a large portion of vegetation, and because of the reblocking process which was put in place after the fire, rebuild was not immediate and is not complete to date (https://ewn.co.za/2018/09/28/court-cases-stall-city-of-ct-s-imizamo-yethu-reblocking-project). This fire killed 4 people, destroyed 2194 homes and left 9700 people homeless and is described in detail by Ref. [22]. This fire was widely covered by the media (e.g. http://ewn.co.za/2017/03/13/imizamo-yethu-residents-pick-up-pieces-after-fire).

The second settlement of Kosovo, located approximately 4 km southwest of Cape Town International Airport on City of Cape Town land, was established 10–15 years ago. Kosovo is characterized by overcrowding with a density of 212 households per hectares (http://ismaps.org.za/desktop.html#) and a high water table making it prone to seasonal flooding and health risks associated with inadequate drainage and sanitation services [23] as there is only one toilet per three households (http://ismaps.org.za/desktop.html#). High summer temperature, wind-blown sand and seasonal fire exacerbate living conditions for residents of this settlement [23]. The Kosovo case study is a smaller fire (730 m2) which was unreported in the media but was recorded in the City of Cape Town fire incidence database (https://web1.capetown.gov.za/web1/opendataportal/DatasetDetail?DatasetName=Fire%20incidence). This fire took place on 21 December 2017 in the Kosovo informal settlement (Fig. 3), on level topography and affected fewer than twenty dwellings which were rebuilt almost immediately post-fire (Google Earth imagery confirmed dwellings were rebuilt by 30 December 2017).

The two case studies thus represent different spatial and temporal scales and will demonstrate that Sentinel 1 and 2 data (SAR and optical, respectively) can detect fires in both these scenarios.

2.1. Mapping informal fire occurrences - pixel based approaches using optical and SAR data

2.1.1. Sentinel-2

The potential for the use of remote sensing to identify informal settlements historically affected by fires and to map fire extent have been recognised by observing satellite data captured before and after a fire event [24]. When observing satellite imagery of an informal settlement pre- and post-fire (Fig. 4), the large scale collapse of dwellings is apparent as both a change in image texture as well as spectral characteristics which is likely to be a remote sensing indicator of a fire event. The City of Cape Town provide victims of fires with starter building kits (Fig. 1c) to enable them to rebuild their homes [25] and the new roofing material is more reflective (Fig. 4c) than the old material which may have been discoloured and degraded (Fig. 4a). This morphological and spectral response change due to a fire event is thus distinguishable in the visible wavelengths in aerial photography or satellite imagery. New roofs erected for reasons other than fire will also exhibit the same response. In a preliminary assessment of the spectral response of an informal settlement fire with a quick post fire rebuild [24], proposed a hypothesised roof albedo response curve (Fig. 4d). The premise is that by charting variation in surface albedo over time, detection of the distinctive shape of the theoretical informal settlement fire curve will indicate an informal settlement fire. Thus, when viewing time series of albedo, the albedo will gradually decrease with age of the roofs, drop off vertically post-fire and increase sharply shortly thereafter to a higher level than pre-fire albedo with the introduction of new roofing material.

[26] demonstrated the detection of a fire on 28 November 2015 in Masiphumelele, Cape Town using albedo [27] calculated from Landsat ETM + surface reflectance in Google Earth Engine however it was found that differences in scene brightness resulted in some false change being detected. Using the local variance method on SPOT 6 data, Wheeler also found the optimal spatial resolution for informal settlement mapping in Cape Town to be 9 m [26], indicating that a sensor such as Sentinel-2 with a resolution of 10 m in some bands may be an optimal choice for Cape Town informal settlements. Analyzing Sentinel-2 data [28], revealed that out of the high resolution bands (blue, green, red and near-infrared at 10 m), the difference between pre and post fire reflectance was most pronounced in the blue band. Further, ASTER Spectral library [29] reveal lower reflectance by oxidized galvanized steel sheets (described as completely oxidized, weathered, galvanized bare steel from roof and vent covers. Sample No.: 0525UUUSTLa) than reflectance by galvanized steel sheets (Sample No.: 0526UUUSTLa) in all the high-resolution Sentinel-2 bands (Fig. 5) thus excluding the

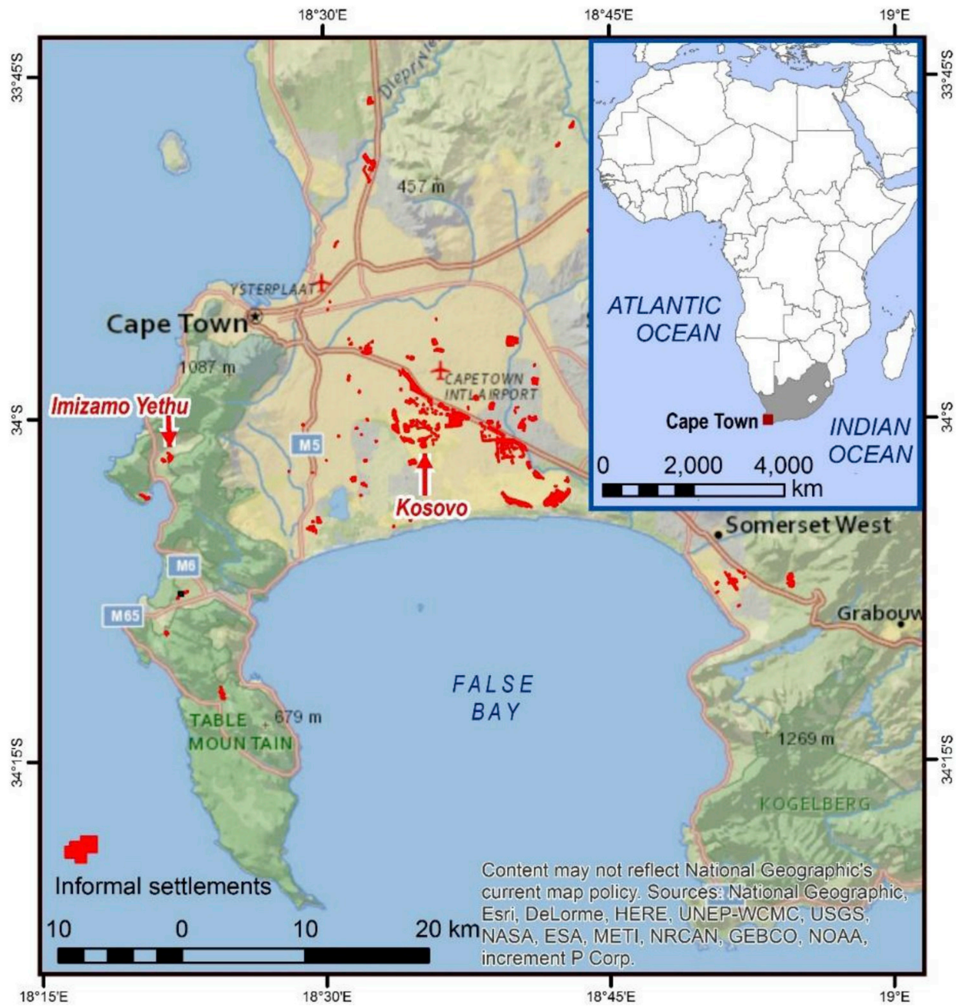

Fig. 2. City of Cape Town informal settlements with the locations of Imizamo Yethu and Kosovo indicated.

benefit of using a ratio approach with these bands. It should also be noted that a larger discrepancy is present in the shortwave infrared bands however the reduced spatial resolution of these bands excluded them from this study. To avoid a potential confounding influence of vegetation, the green and more importantly the near infrared band should be avoided due to chlorophyll being highly reflective of light in these portions of the electromagnetic spectrum (EMS). Thus, either the blue or red band should be suitable to detect the change in surface reflectance in event of an informal settlement fire. The temporal frequency of Sentinel-2 is 10 days since June 2015 and 5 days since March

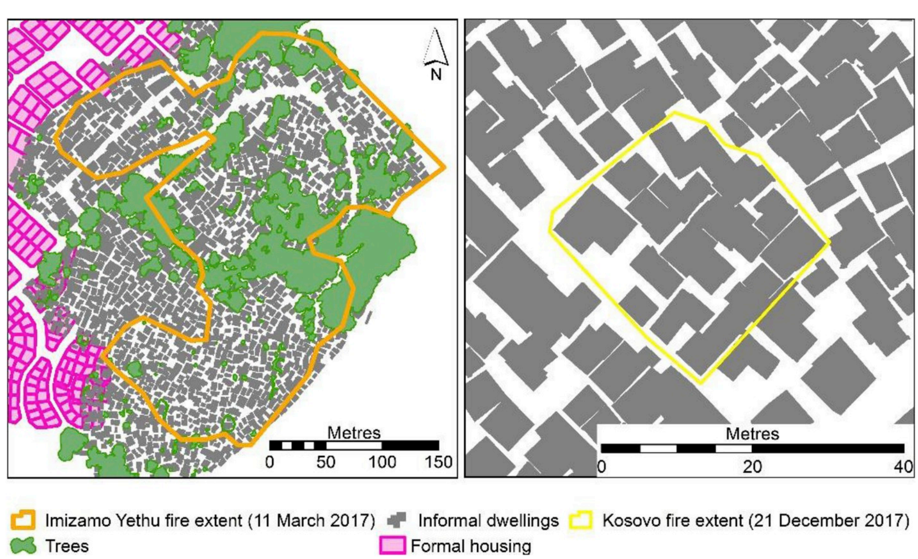

Fig. 3. The extent of the fires in the two case studies - Imizamo Yethu (left) and Kosovo (right).

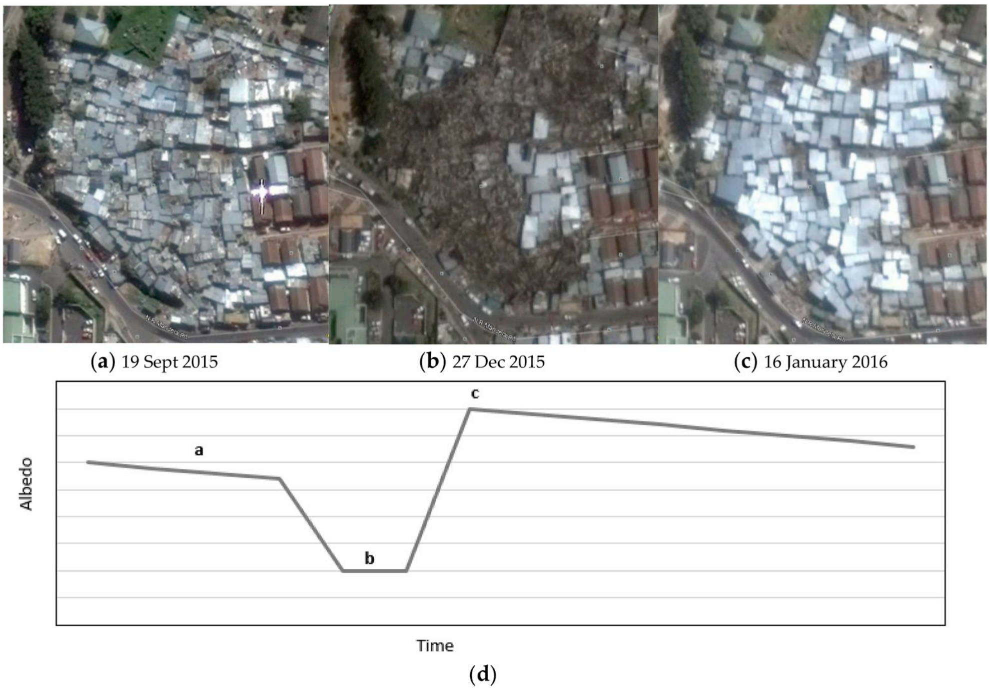

Fig. 4. Morphology change as consequence of fire which occurred on 26 Dec 2015 in Imizamo Yethu, Cape Town; a) pre-fire image showing degraded and discoloured roof material; b) collapse and charring of dwellings immediately post-fire; c) post-fire rebuild with new roofing material. Source of imagery: GoogleEarth; d) hypothesised roof albedo response curve with lettering referring to event shown in the figure.

2017 when Sentinel-2A and Sentinel-2B were launched, respectively. Therefore, the high temporal and spatial resolution of Sentinel-2 blue band is used to demonstrate that informal settlement fires, at two different spatial and temporal scales in Cape Town, can be detected using a freely available Sentinel-2 data.

The Sentinel-2 MSI: MultiSpectral Instrument, Level-1C blue band (B2) was selected, downloaded and preprocessed (atmospheric correction using Dark Object Subtraction (DOS-1) within the Semi-Automatic Classification Plugin version 6.2.8 [30] in QGIS 3.4. In the first instance, B2 alone is used to illustrate that the fire event and its effect can be observed visually at Sentinel-2 spatial and temporal resolution. In the case of the Imizamo Yethu fire, an image captured 9 days before the fire on 2 March 2017 (Image id: 20170302T081841_20170302T084108_T34HBH), the day after the fire (Image id: 20170312T082001_20170312T084235_T34HBH) and five months after the fire (Image id: 20170804T081559_20170804T084931_T34HBH) were selected to test if B2 reflectance would follow the hypothesised roof albedo response curve, even though rebuild was only partial five months post-fire.

With reflectance measured as a ratio from zero to one, where zero equals complete absorption and one equals 100% reflectance, a simple threshold classification of B2 reflectance (Fig. 6) shows pre-fire (2 March 2017) reflectance to be largely in the region of 0.15–0.25, with the vegetated areas showing lower reflectance values (expected due to chlorophyll absorption) [31]. reported reflectance from metal roofing to range from approximately 0.15 for old roofing to just over 0.2 for new roofing in the blue portion of the EMS. This indicates a mix of both old and new roofing in the area pre-fire. The day after the fire (12 March 2017), the reflectance drops to below 0.15 for most of the burn area and five months after the fire (4 August 2017), B2 reflectance values exceed 0.25 in those regions of the settlement (northwest) where dense rebuilding has occurred. The pre and post fire zonal statistics of the fire extent (Table 1) confirm the proposed roof albedo response curve (Fig. 4), at least in the blue band, for all statistics except the minimum reflectance value. Despite rebuild not being complete by 4

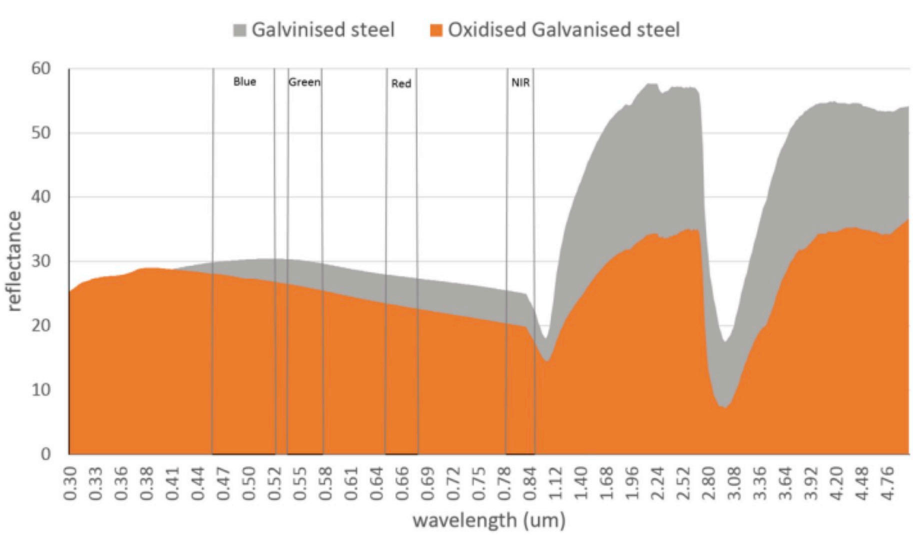

Fig. 5. Spectral response from the ASTER spectral library [29] of galvanised steel and oxidised galvanised steel indicating lower reflectance of oxidised galvinised steel in all four of the high resolution Sentinel-2 bands.

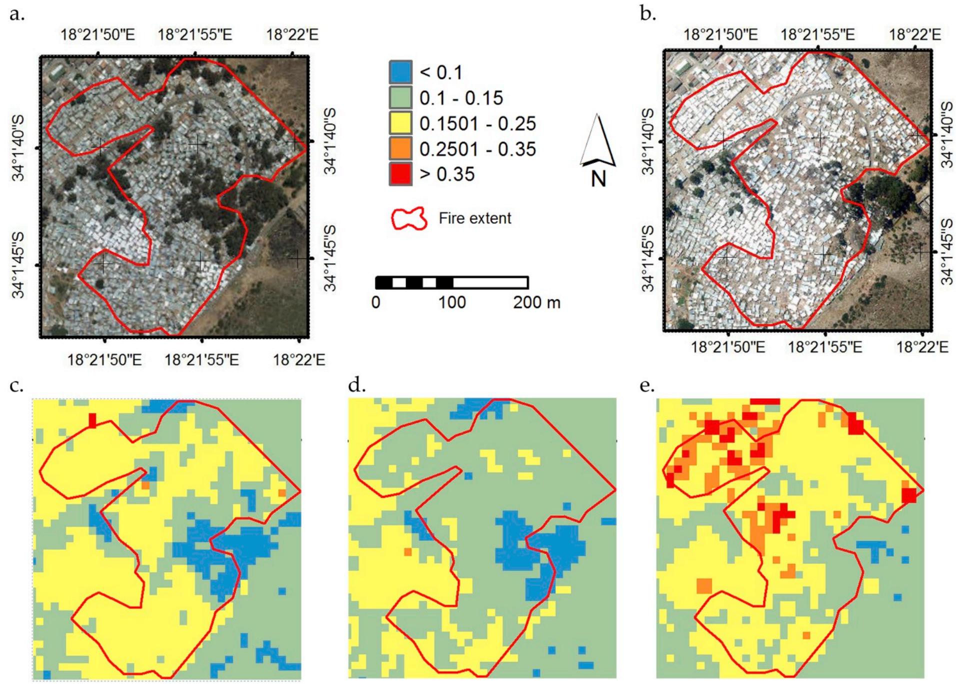

Fig. 6. Imizamo Yethu fire on 11 March 2017. City of Cape Town aerial photography captured a. pre-fire (January 2017), b. post-fire (February 2018). Sentinel-2 B2 reflectance (scale 0 to 1) captured c. pre-fire (2 March 2017), d. immediately post-fire (12 March 2017) and e. Five months post-fire (4 August 2017).

Table 1
Zonal statistics of Sentinel-2 B2 reflectance for the area in Imizamo Yethu affected by the fire on 11 March 2017.

	Min	Max	Mean	Median	StDev
2 March 2017	0.084	0.522	0.155	0.162	0.035
12 March 2017	0.085	0.200	0.134	0.137	0.020
4 August 2017	0.104	0.780	0.198	0.175	0.077

August 2017, the mean and median reflectance of the burnt area increased by 27.7% and 8.0% respectively from their pre-fire values. The difference between the mean and median values and the very high maximum value recorded post fire indicate sun glint from new roofs is a factor influencing mean values. The use of the median in analyses may therefore represent more realistic values than using the mean.

In Kosovo, the rebuild took place extremely quickly and although an image was available the day after the fire (22 December 2017), the high cloud cover on that day (30%) prevented its use. Thus, a pre-fire image captured on 28 September 2017 (Image id: 20170928T082001_20170928T084418_T34HBH) and a post-rebuild image captured on 11 January 2018 (Image id: 20180111T082309_20180111T084759_T34HBH) were selected and this illustrates cases where images immediately post-fire and pre-rebuild are not available.

The pre-fire (28 September 2017) reflectance in B2 was almost exclusively in the 0.15–0.25 range, indicating a mix of new and old roofs. The post-fire image (11 January 2018) revealed an increase in B2 reflectance to over 0.25 for the majority of the burned area. The high-resolution aerial photograph captured in February 2018 (Fig. 7 b) confirms the presence of new roofs in the fire extent. As with the case of Imizamo Yethu, the zonal statistics (Table 2) corroborate this with an increase in all statistics post fire, even though an image captured immediately post fire and pre-rebuild is not available and thus the dip in reflectance is not captured. The Kosovo fire revealed an increase in post-fire reflectance of 65.5% and 65.4% when considering the mean and median respectively. This increase in reflectance exceeds the reflectance post-fire recorded in the Imizamo Yethu case study, likely since in Kosovo, the rebuild was complete and in Imizamo Yethu, the aerial photograph taken in February 2018 (Fig. 6 b) reveals open ground where dwellings have not yet been replaced.

The spectral changes after a fire event are likely to vary on a case-by case basis. For example, in areas that don't benefit from the distribution of starter building kits as part of disaster relief efforts, the rebuilt homes may not present such high reflectance differences if recycled or reclaimed materials are used. In these cases, an alternative to the optical approach may be required. An approach using synthetic aperture radar data can be considered as a complimentary tool for identifying burned areas in informal settlement. In general, when using optical data, the difference in the spectral response of areas affected by fires and areas unaffected by fire are used for burned area extraction. Similar principles can be applied when using Synthetic Aperture Radar (SAR) data, where different SAR backscatter responses would be observed when comparing burnt and unburnt areas.

2.1.2. Sentinel-1

The use of SAR data for burned area extraction in vegetated regions have been considered in various investigations [32–41]. These approaches generally rely on the sensitivity of SAR backscatter to vegetation structure and biomass and attempts to identify areas where vegetation is removed after a fire. Although these investigations identified burned areas with various levels of success, informal settlement fires are generally not associated with the removal of significant amounts of vegetation, limiting the applicability of these algorithms.

Nevertheless, the sensitivity of SAR backscatter to the physical characteristics (orientation, shape and size distribution) [42] of the surface observed may still yield a significant response when pre-burn and post-burn scenes are compared for areas affected by informal settlement fires. Specifically, a very strong backscatter response is generally associated with urban areas where vertical structures prove to be strong reflectors of the SAR signals [43]. It is anticipated that the collapse of houses associated with fires in informal settlements may result in a decrease in SAR backscatter response depending on the wavelength of the data and the characteristics of the debris-field immediately after the fire event. After clearing of the debris, this contrast between pre-

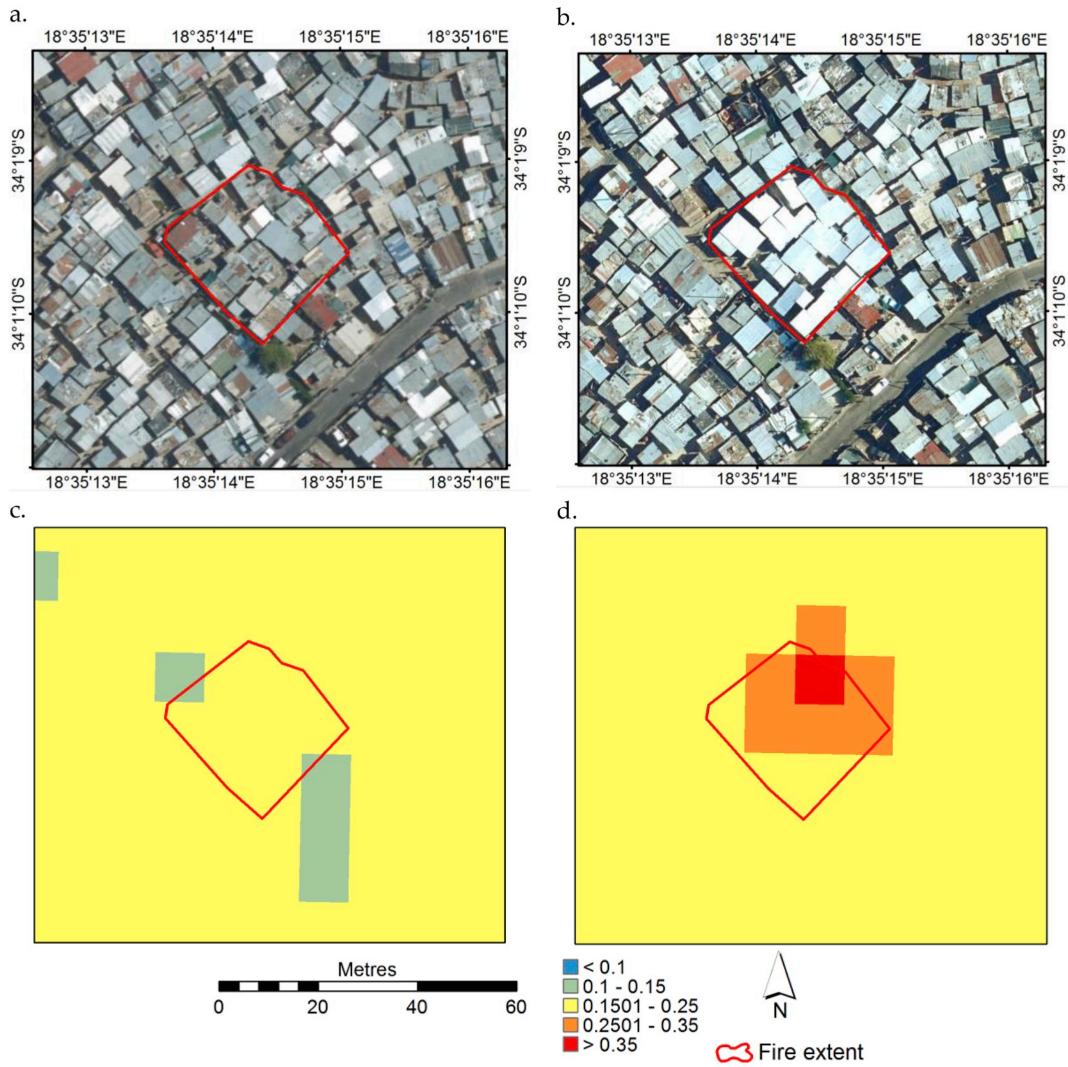

Fig. 7. Kosovo fire on 21 December 2017. City of Cape Town aerial photography captured a. pre-fire (January 2017), b. post-fire (February 2018). Sentinel-2 B2 reflectance captured c. pre-fire (28 September 2017), and d. post-fire (11 January 2018).

Table 2
Zonal statistics of Sentinel-2 B2 reflectance for Kosovo fire of 21 December 2017.

	Min	Max	Mean	Median	StDev
28 September 2017	0.150	0.187	0.165	0.153	0.014
11 January 2018	0.191	0.3741	0.273	0.253	0.067

Table 3
Sentinel-1A image acquisition dates for the Imizamo Yethu and Kosovo fires.

Area and condition	Image date
Pre-fire Imizamo Yethu	2017/02/24
Pre-fire Imizamo Yethu	2017/03/08
Post-fire Imizamo Yethu	2017/03/20
Pre-fire Kosovo	2017/12/02
Pre-fire Kosovo	2017/12/14
Post-fire Kosovo	2017/12/26

burn and post-burn SAR backscatter is expected to be maximised, assuming data is available for the period after clearing but before rebuild.

To investigate the effect of informal settlement fires on SAR backscatter, pre-burn and post-burn calibrated backscatter was derived from Sentinel-1A data for the 11 March 2017 Imizamo Yethu and 21 December 2017 Kosovo fires. The Sentinel-1 sensor currently provides a 12-day revisit interval for the areas of interest, representing the highest revisit interval for SAR data that are routinely acquired. Although higher revisit frequencies can be provided by SAR constellations (like TerraSAR-X and Cosmo-Skymed), these sensors do not routinely capture data for all areas around the globe, unless specifically tasked. Therefore, data is generally unavailable for the mapping of historical fire events.

The dates of image acquisition is summarised in Table 3. The SAR backscatter data, processed to ~14 m pixel spacing in ground range, is presented in Fig. 8 and Fig. 9 for the Imizamo Yethu and Kosovo fires respectively. It is observed that, for backscatter in both the Vertical-Vertical (VV) and Verical-Horizontal (VH) polarisations, the change in backscatter observed for the burnt area, as derived from zonal statistics (Table 4 and Table 5 for the Imizamo Yethu and Kosovo fires respectively) is marginal with less than 2 dB change observed between pre-burn and post-burn conditions. In the case of the Imizamo Yethu fire where rapid rebuild was not observed, the high backscatter response even after the fire may be attributed to the debris field, leading to high surface roughness conditions and, consequently, a high backscatter response. In the case of the Kosovo fire, the rapid rebuild resulted in high backscatter values that are normally associated with structures in

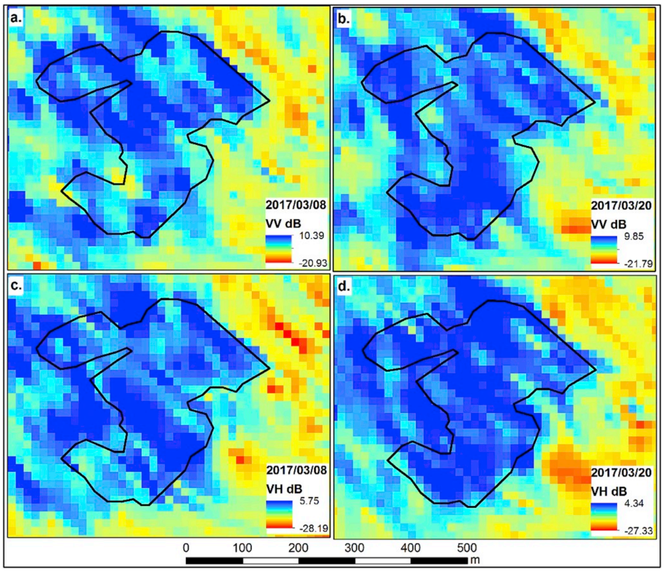

Fig. 8. SAR backscatter for the 11 March Imizamo Yethu fire indicating a. pre-fire backscatter in VV polarization, b. post-fire backscatter in VV polarization, c. pre-fire backscatter in VH polarization and d. post-fire backscatter in VH polarization.

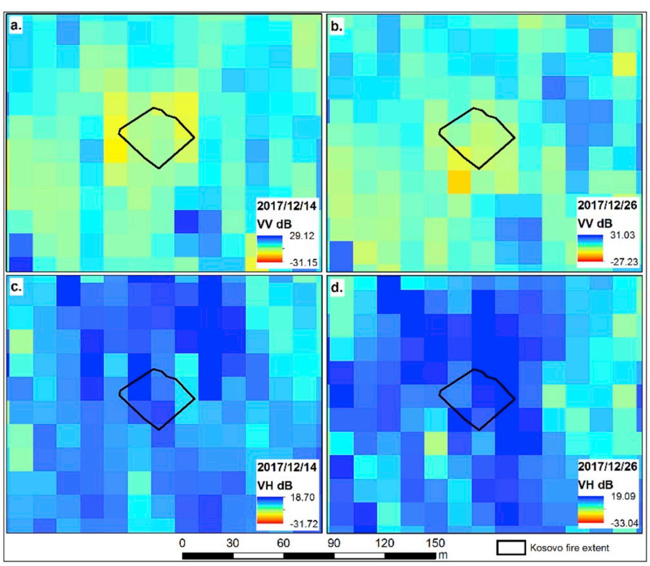

Fig. 9. SAR backscatter for the 21 December Kosovo fire indicating a. pre-fire Backscatter in VV polarization, b. post-fire backscatter in VV polarization, c. pre-fire backscatter in VH polarization and d. post-fire backscatter in VH polarization.

Table 4
Zonal statistics for the calibrated Sentinel-1A backscatter for the Imizamo Yethu fire.

Image date	Min	Max	Mean	StDev
2017/03/08 VV	−14.258	5.788	−5.278	3.023
2017/03/20 VV	−10.845	5.214	−4.837	2.219
2017/03/08 VH	−16.560	−2.885	−11.519	2.232
2017/03/20 VH	−17.040	−1.882	−10.593	2.052

urban environments. The results suggest that a change in SAR backscatter in response to a fire event in informal settlements cannot be used as a diagnostic feature and these results will thus not be considered in the spatial autocorrelation approaches shown in Section 2.2.

Table 5
Zonal statistics for the calibrated Sentinel-1A backscatter for the Kosovo fire.

Image date	Min	Max	Mean	StDev
2017/12/14 VV	−10.815	−7.304	−8.749	1.361
2017/12/26 VV	−9.114	−6.975	−8.187	0.729
2017/12/14 VH	−14.301	−8.859	−11.586	1.811
2017/12/26 VH	−12.189	−7.046	−9.710	1.865

In cases of rapid rebuild and due to the lack of consistent SAR backscatter changes in pre- and post-fire conditions, a SAR derivative known as interferometric coherence may provide an alternative solution. In the context of informal settlement fires, interferometric coherence can be viewed as an indicator of the level of change experienced in a resolution cell between two image acquisitions [44]. Where stable land cover conditions is experienced between two image acquisitions, as is associated with most urban areas, the coherence between the two image acquisitions will be high. In contrast, changing land cover conditions as observed in natural landscapes, rural areas or areas experiencing significant changes will exhibit low coherence values [44–47]. Low coherence is also prevalent in vegetated areas where signals decorrelate rapidly, even over short time periods. In the case of informal settlements, in pre-burn conditions the lack of vegetation associated with informal settlements as well as the stable building structures is expected to be associated with high interferometric coherence. In contrast, in the case of an informal settlement fire, the destruction of dwellings present a significant change between data acquisitions that will result in low coherence when one pre-burn and post-burn scene is used to generate the coherence product. Furthermore, even if rebuild after the fire takes place rapidly between the two image acquisitions, the change in the structure and orientation of the dwellings between pre-burn and post-burn scenes is expected to still result in a decrease in coherence depending on the size of the fire and the resolution of the sensor.

To test this hypothesis, the pre-burn and post-burn datasets were used to derive interferometric coherence for the Imizamo Yethu and Kosovo fires. For each case, two pre-fire scenes were used to create a pre-fire interferometric coherence product. Additionally, one pre-burn and one post-burn scene was used to derive an across-burn interferometric product. After rebuild, if two post-rebuild scenes are used to create the coherence product, coherence would once again be expected to be high. Therefore, the contrast between pre-fire coherence and post-rebuild coherence products would be minimal and is not considered to be suitable for identifying areas affected by fire.

The results indicate that, for the Imizamo Yethu fire, presented in Fig. 10, there is a significant decrease in interferometric coherence when pre-fire coherence and across-fire coherence values are compared. The zonal statistics (Table 6) for the burnt area suggests that a ~64% decrease in coherence is observed in VV polarisation coherence product and ~56% decrease for the VH coherence results. This suggests that the expected decrease in coherence may be more prominent in the VV polarisation coherence products. It is also observed that low coherence values are associated with stands of vegetation (as can be observed on the optical image in Fig. 10e) particularly in the VV polarization products. This low coherence conditions prevails for both pre-burn VV coherence (Fig. 10a) as well as the across burn coherence (Fig. 10 b). Therefore the decrease in coherence values that marks the fire extent would not be present for these areas, minimizing the potential for errors of commission.

For the Kosovo fire, relatively low interferometric coherence values are observed even for the pre-burn VV coherence product (Fig. 11 a) with the post-burn product exhibiting similarly low coherence values (Fig. 11 b). Therefore, the anticipated decrease in coherence is not observed. On the other hand, a 66% decrease in coherence values between pre-fire to post-fire conditions are observed for the VH

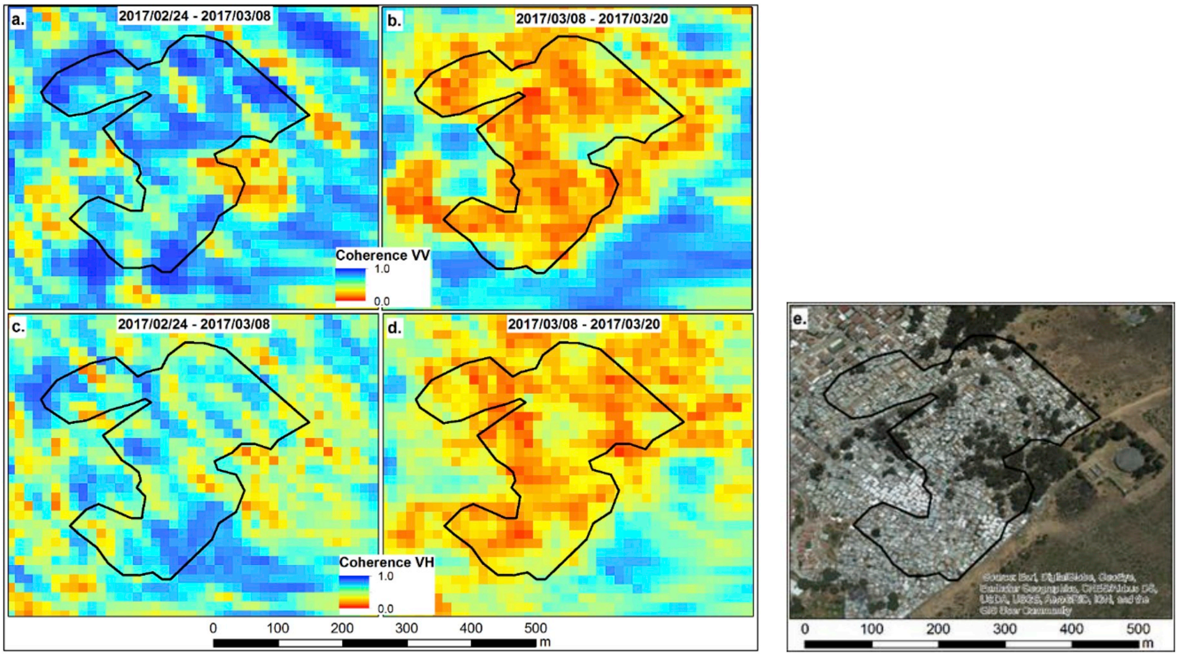

Fig. 10. SAR coherence for the 11 March Imizamo Yethu fire indicating a. pre-fire coherence in VV polarization, b. across-fire coherence in VV polarization, c. pre-fire coherence in VH polarization and d. across-fire coherence in VH polarization and e. an optical image for context.

Table 6
Zonal statistics for the Sentinel-1A coherence for the Imizamo Yethu fire.

Coherence date	Conditions	Min	Max	Mean	StDev
2017/02/24 - 2017/03/08 VV	Pre-burn	0.086	0.938	0.695	0.166
2017/03/08 - 2017/03/20 VV	Across-burn	0.041	0.739	0.251	0.117
2017/02/24 - 2017/03/08 VH	Pre-burn	0.140	0.874	0.596	0.154
2017/03/08 - 2017/03/20 VH	Across-burn	0.046	0.523	0.265	0.102

polarisation coherence products (Fig. 11 c and d, Table 7). This suggests that, in the case of the Kosovo fire, the VH coherence products may be more suitable for identifying changes between pre-fire and post-fire conditions. However, low coherence values are also observed outside of the burnt area for the VH across-burn coherence (Fig. 11 e), suggesting that other sources of change may be affecting the results. This points to the limitation of using coherence for mapping burnt extent since changes induced by factors other than fire can be identified in the process and will act as sources of errors of commission.

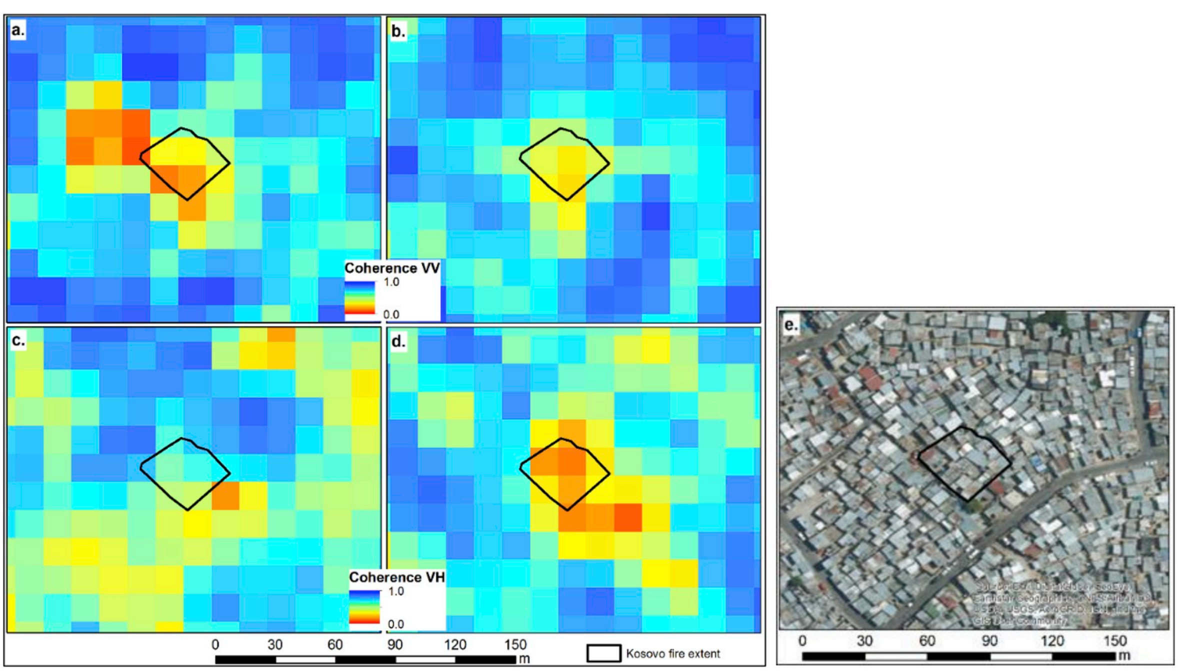

Fig. 11. SAR coherence for the 21 December Kosovo fire indicating a. pre-fire coherence in VV polarization, b. across-fire coherence in VV polarization, c. pre-fire coherence in VH polarization and d. across-fire coherence in VH polarisation.

Table 7
Zonal statistics for the Sentinel-1A coherence for the Kosovo fire.

Image date	Min	Max	Mean	StDev
2017/12/02 - 2017/12/14 VV	0.188	0.575	0.378	0.129
2017/12/14 - 2017/12/26 VV	0.289	0.490	0.379	0.074
2017/12/02 - 2017/12/14 VH	0.482	0.744	0.615	0.086
2017/12/14 - 2017/12/26 VH	0.140	0.299	0.207	0.053

2.2. Spatial autocorrelation

An alternative approach to the rather simplistic method of considering single band reflectance and interferometric coherence values, is to consider the reflectance response of a pixel relative to its neighbours. According to Tobler's first law of geography [48], "Everything is related to everything else, but nearest things are more related than distant things". In the event of a fire, this law is disrupted in that a fire results in a burn scar representing an abrupt discontinuity between the burned area and unburned area although within the burned area spatial autocorrelation will remain intact or may even increase. Spatial autocorrelation thus helps detect the perimeter of fire as a pixel which was previously strongly spatially correlated with its neighbours, will undergo a rapid change in spatial autocorrelation indicators if a fire occurs in this location but does not affect the neighbouring pixels. Indeed, this principal has been applied to mapping wildfire severity [49] and with this philosophy in mind, two approaches using ArcGIS software are tested: a kernel approach and hot spot analysis.

2.2.1. Kernel approach

The first spatial autocorrelation approach is to consider a 3 x 3 pixel moving window kernel as unit of analysis. A kernel or moving window filter, through generalising neighbourhood values, filters out noise and identifies true change and, when using VHR imagery, the contextual information provided by using a kernel approach balances out the spectral deficiency of these images [50]. However to exploit the principal of a disruption in spatial autocorrelation being indicative of an abrupt change event, rather than using the kernel to generalise neighbourhoods, an approach to enhance change in homogeneity is used by calculating the standard deviation of pixel values within a kernel. A high kernel standard deviation value represents heterogeneity within the kernel whereas lower standard deviation value represents a more homogenous scenario. Using this method, kernels comprising pixels at the edge of the fire extent should experience an increase in standard deviation from pre-fire to post fire and rebuild since, in the case of Sentinel-2 B2 reflectance, the boundary between new roofs and old roofs should be reflected as an increase in heterogeneity. In the case of Sentinel-1 interferometric coherence, the decrease in coherence for the fire-affected area observed in the across-burn coherence products compared to the unburnt areas would similarly lead to an increase in the heterogeneity near the boundaries of the fire extent.

In the case of the Imizamo Yethu fire, when applying the standard deviation kernel to the B2 reflectance values, the pixels within the fire extent become more homogenous immediately post fire (Fig. 12 b). Five months later, the heterogeneity (described by kernel standard deviation) has increased by 130% from pre-fire levels with highest values observed in those areas where rebuild has occurred (Fig. 12 c).

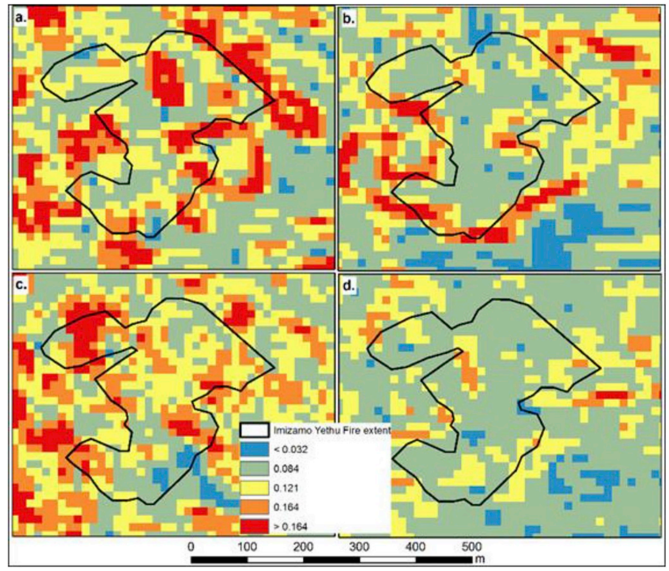

Fig. 13. The 3 x 3 pixel kernel standard deviation for SAR coherence for the 11 March 2017 fire indicating a. pre-fire coherence in VV polarization, b. across-fire coherence in VV polarization, c. pre-fire coherence in VH polarization and d. across-fire coherence in VH polarization.

When considering the 3 x 3 pixel standard deviation applied to the SAR coherence products (Fig. 13), an increase in homogeneity is observed for the SAR across-fire coherence product when compared to the pre-fire coherence with an average of 24% and 35% decrease in standard deviation observed for VV and VH polarisations respectively. For the VV polarization across-fire coherence product (Fig. 13 b), an increase in heterogeneity around the edges of the fire is also apparent. These effects are less noticeable on the VH cross coherence product (Fig. 13 d).

The standard deviation of the 3 x 3 pixel kernel of B2 reflectance for Kosovo (Fig. 14) shows relative homogeneity prior to the fire with the fire extent clearly flagged with higher heterogeneity (250% up from pre-fire levels) post fire and rebuild.

In the case of the 3 x 3 pixel coherence products, the increase in the homogeneity of coherence values, as observed for the Imizamo Yethu fire, was less evident in the case of the VV coherence product (Fig. 15 b) with a decrease in standard deviation of 16% observed. In contrast, the VH coherence product exhibited a mean increase in standard deviation of 8%. This is due to the across-fire VH coherence resulting in a more heterogeneous ring around the burn extent, exceeding the size of the fire with a more homogenous enclosed area representing the post-fire

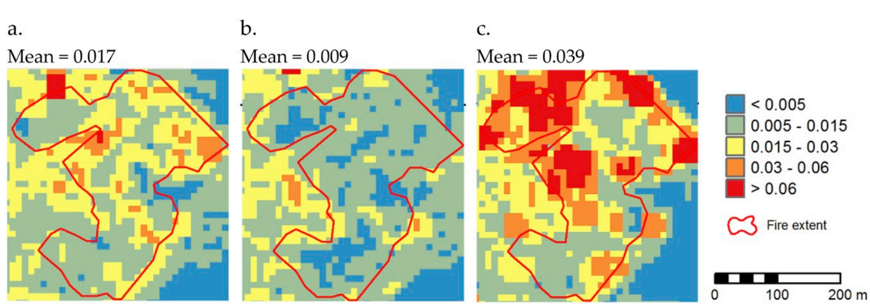

Fig. 12. Sentinel-2 B2 3 x 3 pixel kernel standard deviation for Imizamo Yethu a. pre-fire (2 March 2017), b. immediately post-fire (12 March 2017) and c. five months post-fire (4 August 2017).

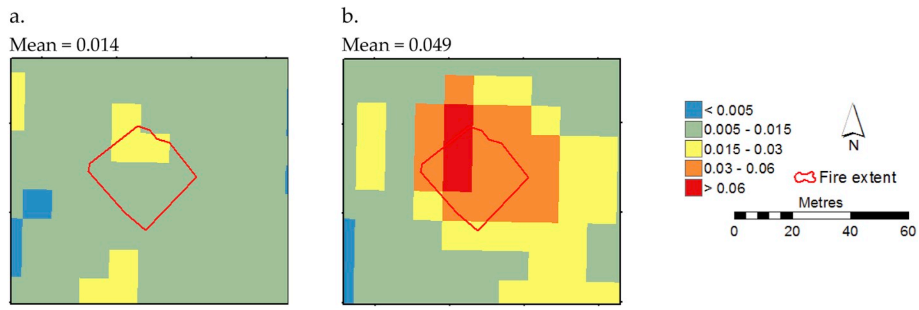

Fig. 14. Sentinel-2 B2 3 x 3 pixel kernel standard deviation for Kosovo a. pre-fire (28 September 2017), and b. post-fire and rebuild (11 January 2018).

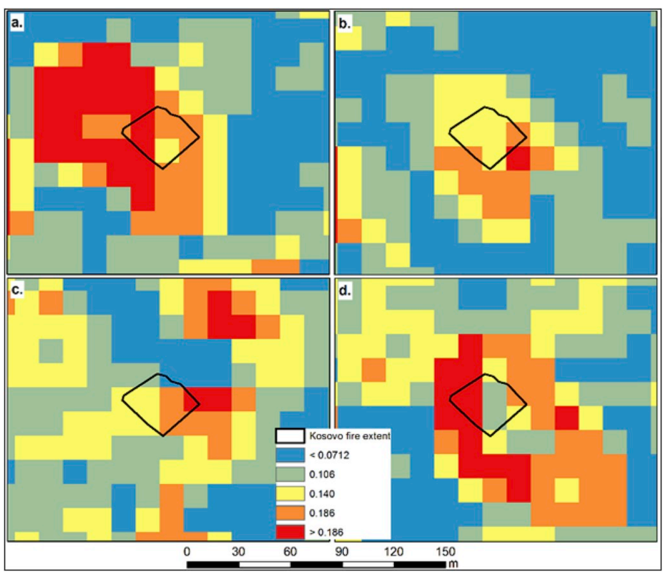

Fig. 15. The 3 x 3 pixel kernel standard deviation for SAR coherence for the 21 December Kosovo fire indicating a. pre-fire coherence in VV polarization, b. across-fire coherence in VV polarization, c. pre-fire coherence in VH polarization and d. across-fire coherence in VH polarization.

rebuild. This is likely due to the small size of the fire in relation to the course resolution of the data and with respect to the 3 x 3 kernel.

2.2.2. Hot spot analysis

The second approach based on spatial autocorrelation principles is hot spot analysis. This approach uses the Getis-Ord Gi* statistic [51] optimized to only consider a pixel's immediate neighbours (including diagonals) by setting the distant band to 15m. The Getis statistic provides a measure of local clustering or concentration by evaluating values within a radius distance of the point of interest as a proportion of the sum of all values under investigation [52]. Thus, the entire Imizamo Yethu and Kosovo settlements were used in each case respectively.

Hot spots represent clustering of high values and cold spots represent clustering of low values. The distance band can be adjusted to increase the size of the neighbourhood to be considered in the analysis however if the value is set too high, the presence of smaller hot spots may be missed. In ArcGIS, the z-score (standard deviation) and p-value (the probability that the observed spatial pattern was created by some random process), are used to create a confidence level bin (Gi_Bin) by categorizing extreme z-values with low p values as being either hot spots or cold spots, with a high degree of confidence [53]. So, whilst the standard deviation approach only considers the immediate neighbours of a pixel, the Getis-Ord-Gi* considers the local neighbours against values from a larger area.

The results of Getis-Ord-Gi* (Fig. 16) of B2 reflectance indicate many hot spots within Imizamo Yethu prior to the fire (Fig. 16 a), and the vegetation is identified as statistically significant cold spots. Immediately post-fire (Fig. 16 b), the burning/collapse/removal of dwellings results in the removal of most hot spots within the fire extent and five months post fire (Fig. 16 c), those areas which have been rebuilt, are once again identified as hotspots.

The potential contribution of the interferometric coherence products for the identification of changes related to fire events in informal settlements were confirmed through the evaluation of the Getis-Ord Gi* statistics for pre- and across-fire coherence products. For the Imizamo Yethu area, both hot spots and cold spots are observed in the pre-burn coherence products (Fig. 17 a and c). However, in the across-burn coherence products, most hotspots have disappeared and the burnt area is characterised by cold spots (Fig. 17 b and d).

The Getis-Ord-Gi* result for B2 reflectance for the Kosovo fire indicate no significant hot spots before the fire (Fig. 18 a) but hot spots with a high degree of confidence are identified post rebuild (Fig. 18 b).

With respect to the coherence products, no high-confidence hot spots are present on the pre-burn coherence products (Fig. 19 a and c) and an increase in higher confidence-level cold spots are observed for the across-burn coherence products for both VV and VH coherence products (Fig. 19 b and d respectively).

2.3. Discussion and considerations for future research

These case studies have demonstrated that two known informal settlement fires at two different scales can be detected using Sentinel-1 and -2 data. However when moving towards detecting unknown fires, a change detection approach is needed. When the spectral characteristics of fire affected settlements are considered, although the spectral response directly after a fire and following rebuild may differ on a case-by-case basis, a fire essentially represents an abrupt change in the land surface. This may not necessarily be measured as absolute reflectance values in post-fire scenes, as was shown in this paper, but it may rather be more useful to consider a percentage increase in reflectance from one scene to the next, relative to general scene brightness. The founding principle in remote sensing change detection is that (1) a change in land cover must result in a change in electromagnetic radiation reflected by the surface and (2) this change must be large when compared with change in reflectance caused by other factors [54]. The case studies have shown that the use of new roofs post-fire result in a large change in Sentinel-2 B2 reflectance and thus even if an image immediately post-fire is not available, the detection of increased reflectance post-fire is achievable. Similarly, should an image post-fire and pre-rebuild be available, a significant decrease in VV and VH coherence can indicate a fire but if an image is only available post-rebuild, a significant decrease in VH coherence may be observed. These results suggest the potential to apply change detection methods to unknown informal settlement fires detection using both Sentinel 1 and Sentinel 2 data.

Regardless of whether optical or microwave remote sensing technology is used, the time series change detection techniques should be looked to for detection of abrupt change. A time series approach recognises that change is not simply the contrast between conditions at

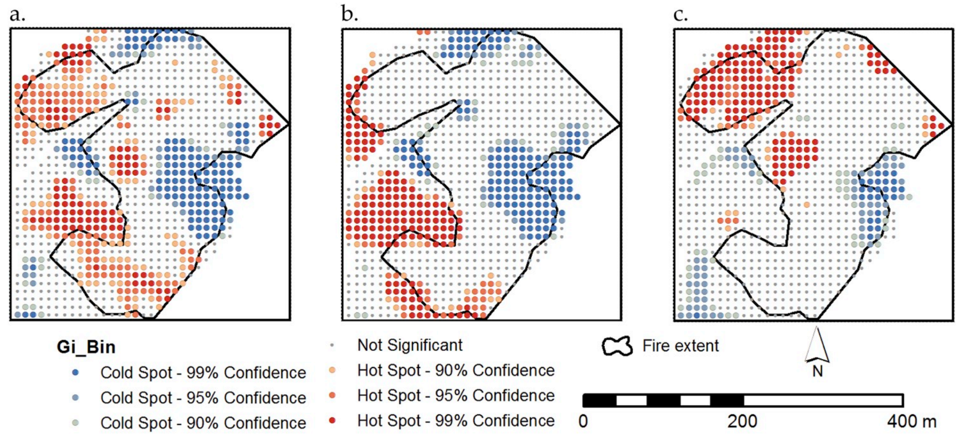

Fig. 16. Getis-Ord-Gi* results for Imizamo Yethu on a) 2 March 2017, b) 12 March 2017 and c) 4 August 2017.

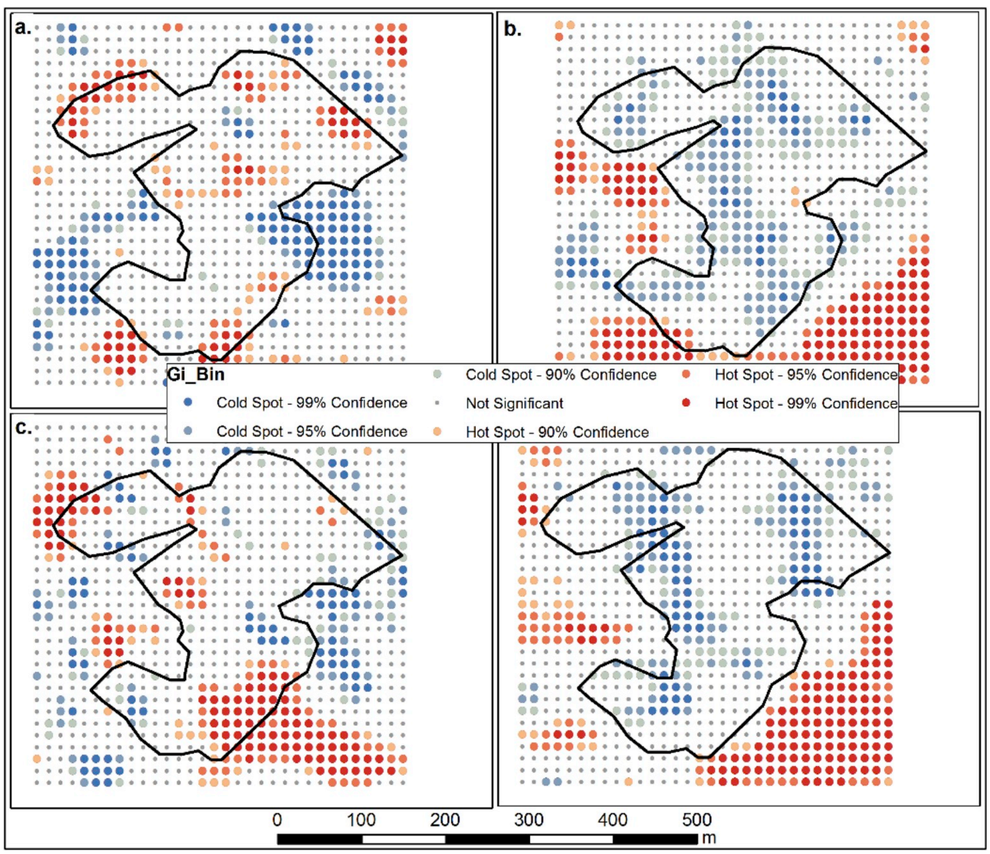

Fig. 17. The Getis-Ord-Gi* results derived from the SAR coherence for the 11 March Imizamo Yethu fire indicating a. pre-fire coherence in VV polarization, b. across-fire coherence in VV polarization, c. pre-fire coherence in VH polarization and d. across-fire coherence in VH polarization.

two points in time but rather a continual process operating at different temporal scales [55]. The opening of the Landsat archives in 2008 led to a dramatic rise in the use of Landsat data and has allowed for increased change detection and time series analyses on this higher resolution data to be conducted [56]. With the opening of the Landsat archive, techniques previously applied only to coarse resolution data, due to the temporal constraints and associated data costs of higher resolution data, were able to be utilised at Landsat scale and across the temporal Landsat archive [57] and these techniques may also be applied to Sentinel data which operates at an even higher temporal and spatial resolution [55]. group multitemporal change detection approaches using Landsat data from the literature on the basis of whether they aim to detect deviations (including disturbances such as fire) or trends. Those focussing on deviation use a presumed stable condition gleaned from multitemporal images to detect a change in spectral response away from the stable condition and this allows better separation of true change from background noise [55]. On the other hand those that seek to detect trends use time-series fitting algorithms to separate longer duration signals from noise caused by, for example phenology, sun angle and geometric misregistration [55].

[58,59] developed models to predict the spectral response of a pixel and deviations from the model predictions are flagged. Since it is the detection of catastrophic change which is of interest, the statistical boundary methods [59]; Goodwin and Collett, 2014), are attractive in that they flag a predefined deviation from the mean or median value of a predetermined number of previous images in a time series. For

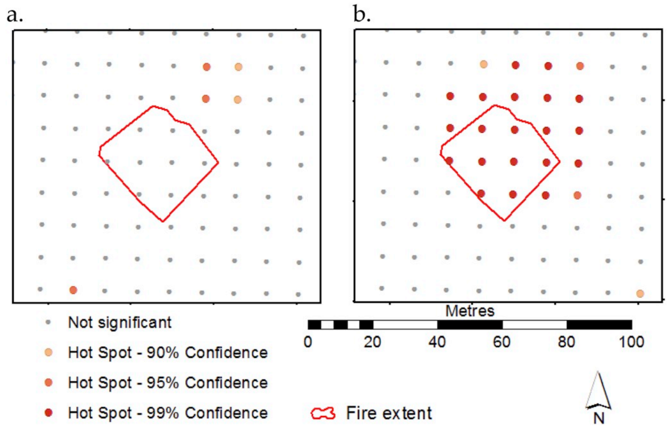

Fig. 18. Getis-Ord-Gi* results for Kosovo on a) 28 September 2017, and b) 11 January 2018.

example, statistical quality control charts to detect statistically significant change, proposed by Ref. [59] use quality control chart concepts, in particular Shewhart charts, to detect disturbed pixels which signal a deviation from data-driven control limits. Assuming that a pixel's value is normally distributed across the time series, pixel values which fall outwith predetermined control limits, are flagged and can be investigated further.

The pixel as unit of analysis is a convenient means of comparing change between two images and is favoured by some [60], however it has been criticised [61] for being susceptible to producing false and noisy change pixels due to within class spectral variability [50,62], and image registration errors [63], especially when using very high resolution imagery. It is therefore generally better suited to coarser resolutions or more homogenous regions. Thus should the pixel be used as the unit of analysis in historic informal settlement fire detection, the heterogeneity of the environment is likely to lead to false positives but the data will be analysed at the highest possible resolution for a particular dataset i.e. no generalisation occurs prior to analysis.

A likely challenge to any approach will be errors of omission and commission. Therefore, it is not only pixel values which should be used but spatial autocorrelation indicators [49], such as demonstrated in the case studies, can be used either in the detection of a historic fire or to help in the reduction of errors of commission (false positive) by having two approaches confirming a result. Thus, the hypothesis to be tested in future research is that an abrupt change in pixel values over time combined with a disruption in spatial autocorrelation is indicative of real abrupt change whereas abrupt temporal change at pixel level without a corresponding spatial autocorrelation disruption is indicative of noise.

Since informal settlements vary significantly between cities, it may be that a method developed in Cape Town may not be successfully applied to another city or region. Although the ultimate aim is to have a method to detect informal settlement fires globally, in the development of the method, a variety of methodologies may need to be explored. For example, the differing reflectance of sheet metal used as roofing material pre and post fire may be applicable to sub-Saharan Africa where tin and iron sheeting is commonly used as roofing material [64], however only when new material is used for roofing post-fire. In a region where timber or plastic roofing dominates, this approach will not be suitable and since a change in shape, orientation and size of dwellings are expected after a fire, interferometric coherence may be a more suitable approach, particularly for tropical regions where cloud cover may reduce the number of optical images available for analysis. Finally, a change in roofing material detected with a multitemporal change detection method is not necessarily a result of fire and may be

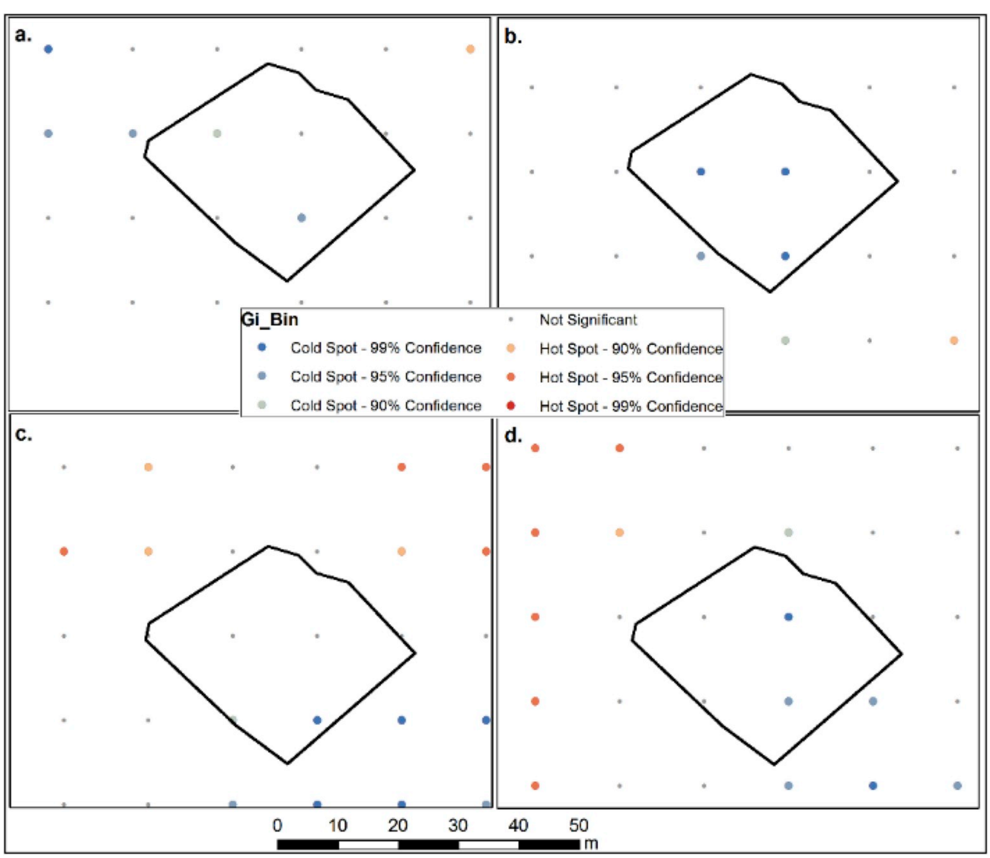

Fig. 19. The Getis-Ord-Gi* results derived from the SAR coherence for the 21 December Kosovo fire indicating a. pre-fire coherence in VV polarization, b. across-fire coherence in VV polarization, c. pre-fire coherence in VH polarization and d. across-fire coherence in VH polarization.

caused by other events such as floods, storms and large-scale evictions. Local knowledge and ground truthing will always be required to determine the precise cause of the change in the particular informal settlement.

3. Conclusions

The case studies have shown that both optical and SAR remote sensing technology have potential to detect an informal settlement fire when the date of the fire is known. In the case of optical imagery, Sentinel-2 B2 demonstrated an increase in pixel reflectance of 65% post rebuild in Kosovo with a lower increase in Imizamo Yethu where rebuild was not complete. Similarly the kernel standard deviation of B2 reflectance revealed an increase in post-fire heterogeneity which was more pronounced in the case of Kosovo (250%) than in Imizamo Yethu (130%). However the hypothesis that the 3 x 3 pixel standard deviation kernel would highlight the boundary of the fire was not observed in either case. For Imizamo Yethu this is likely due to the reblocking and slow rebuild resulting in more gaps between dwellings than existed prior to the fire and in the case of Kosovo, the size of the fire with respect to a 3 x 3 kernel mean that delineation of a boundary using this method was not achieved. The hotspot analysis on the Sentinel 2 B2 reflectance data identified new hotspots with 99% confidence in the case of the Kosovo fire and for those areas where rebuild had occurred in the Imizamo Yethu fire. As a general conclusion, the change in pixel reflectance of Sentinel 2 B2 data follows the hypothesised roof albedo response curve (Fig. 4 d) and this response is significant as confirmed by the clustering of rebuild hotspots in both case studies.

Pertaining to SAR, the evaluation of backscatter characteristics suggest that there is no consistent increase or decrease in SAR backscatter from pre-burn to post-burn conditions for the two case studies. Although high backscatter is generally associated with urban areas and vertical structures, low backscatter in urban areas can also be induced by unfavourable viewing geometry, non-reflective building materials and vegetation related signal attenuation [43]. Since backscatter is affected by factors such as moisture conditions and surface roughness, the derivation of a universally applicable algorithm may remain problematic in these areas. Further, the success of an algorithm that exploits SAR backscatter for the identification of burnt areas will be dependent on the image acquisition interval compared to the rebuild timeframe. If, for example, an area is destroyed by a fire, and rapid rebuild takes place before the next image acquisition, a change in backscatter may not be perceivable depending on the resolution of the sensor. Therefore, in cases of rapid rebuild, coherence appears a more reliable approach when using SAR data. The decrease in VV coherence was 63% in the case of the Imizamo Yethu fire but was not observed in the Kosovo fire whereas VH coherence decreased by 56% and 66% in the Imizamo Yethu and Kosovo fires respectively suggesting the use of VH coherence may be the more reliable method for detecting rebuild of dwellings and VV coherence may be useful in detecting the removal of dwellings. However, inferences from just two case studies should be treated with caution and tests on other known fires would be required to confirm this result.

The 3 x 3 pixel standard deviation applied to the VV coherence data detected the edge of the burn extent in some locations for Imizamo Yethu however when applied to VH coherence, the edge was not observed. The hot spot analysis revealed cold spots present post fire when applied to VV coherence data and to a lesser spatial extent, cold spots were observed when applied to VH coherence. For Kosovo, the 3 x 3 pixel standard deviation revealed a decrease in VV coherence heterogeneity and the presence of a ring structure formed in the 3 x 3 pixel standard deviation of VH coherence was not captured in the statistics as its boundary exceeded that of the burn extent. Cold spots were observed for both coherence products in Kosovo. It should be noted that signal decorrelation between two scenes, leading to low coherence values, can be caused by any change in the surface, and low coherence can also be observed in areas unaffected by fire. Thus, as with the optical approach, the detection of change through the interferometric coherence approach is not indicative of the cause of the change. The large scale removal of houses may also be induced by causes other than fire, including, for example, floods. Therefore, careful interpretation of the results in conjunction with ancillary data, such as local knowledge, weather data and others, would be needed to verify the results and draw accurate conclusions.

Urbanisation is a global phenomenon with projections estimating a further 2.5 billion people will be added to the global urban population by 2050 with nearly 90% of this increase concentrated in Africa and Asia [65]. Since informal settlements grow at a faster rate than any other urban development [7], it is inevitable that this increase in global urbanisation will result in increased numbers of people living in informal settlements. Fires in informal settlements pose a challenge to sustainable development goals and have devastating consequences for those inhabitants who experience them. It is apparent that intervention strategies should be put in place to help in fire prevention but for this to be effective, reliable data on fire incidence and impact is needed but is rarely available in low- and middle-income countries [13]. The synoptic nature of satellite remote sensing make it an attractive proposition for fire detection in informal settlements and the development of an accurate fire identification method is needed for this particular urban environment in order to build a database of the frequency, extent and impact of historic and ongoing fire.

This paper has formulated the problem of informal settlement fires and has demonstrated that Sentinel-1 and Sentinel-2 data can detect known informal settlement fires in two different settlements in Cape Town representing different settlement and fire scenarios. Both a pixel based approach and approaches which consider a pixel's neighbour were shown to record differences in the post-fire and post-rebuild images when compared with pre-fire images. Future research should focus on incorporating these techniques into the analysis of dense time series data in order to detect unknown historic informal settlement fires in Cape Town.

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Conflicts of interest

The authors declare no conflict of interest.

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