

Article

CORONA High-Resolution Satellite and Aerial Imagery for Change Detection Assessment of Natural Hazard Risk and Urban Growth in El Alto/La Paz in Bolivia, Santiago de Chile, Yungay in Peru, Qazvin in Iran, and Mount St. Helens in the USA

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Abstract: Urban growth and natural hazard events are continuous trends and reliable monitoring is demanded by organisations such as the Intergovernmental Panel on Climate Change, the United Nations Office for Disaster Risk Reduction, or the United Nations Human Settlements Programme. CORONA is the program name of photoreconnaissance satellite imagery available from 1960 to 1984 provides an extension of monitoring ranges in comparison to later satellite data such as Landsat that are more widely used. Providing visual comparisons with aerial or high-resolution OrbView satellite imagery, this article demonstrates applications of CORONA images for change detection of urban growth and sprawl and natural hazard exposure. Cases from El Alto/ La Paz in Bolivia, Santiago de Chile, Yungay in Peru, Qazvin in Iran, and Mount St. Helens in the USA are analysed. After a preassessment of over 20 disaster events, the 1970 Yungay earthquake-triggered debris avalanche and the natural hazard processes of the 1980 Mt St. Helens volcanic eruption are further analysed. Usability and limitations of CORONA data are analysed, including the availability of data depending on flight missions, cloud cover, spatial and temporal resolution, but also rather scarce documentation of natural hazards in the 1960s and 70s. Results include the identification of urban borders expanding into hazard-prone areas such as mountains, riverbeds or erosion channels. These are important areas for future research, making more usage of this valuable but little-used data source. The article addresses geographers, spatial planners, political decision makers and other scientific areas dealing with remote sensing.

Keywords: urban sprawl; city expansion; disaster risk; land cover change; land use change; image interpretation; manual visual image interpretation; data usability; Geographic Information System; remote sensing

1. Introduction

Despite knowing more and more about disaster risk, losses keep mounting, researchers have observed since at least the year 1945 [1,2]. While there are several reasons for an increase of disaster losses such as increased awareness and reporting on registered disaster losses, insurance cover etc., many researchers and institutions attribute this increase to urban and settlement growth as well [3,4]. Population density and exposure of settlement areas to natural hazards such as earthquakes, floods or landslides are one of the most commonly used explanatory variables for disaster risk and resulting losses, often using remote sensing data for measuring this [5–7]. This is also reflected in the range of actions and activities fostering research and disaster risk reduction for urban areas, especially large cities



within campaigns of the United Nations or private institutions, recently for example, within 'resilient cities' campaigns [8–11]. Additionally, urban growth and sprawl are highly important areas for disaster risk research [12].

Within international agendas such as the Sendai Framework for Disaster Risk Reduction [13], one key priority is creating more knowledge about disaster risk and one of the methods often suggested is risk assessment. Monitoring on urban sprawl or land cover change considering natural hazards is also demanded in the context of Climate Change by the IPCC, especially for extreme events [14], and in the context of urbanisation by UN HABITAT [15].

Within risk assessment, spatial assessments are one among many other approaches [16] and are characterised by using data such as census data or Geographical Information Systems. Urban growth can be measured by comparing old land surveying maps, but one of the most useful data is remote sensing imagery from satellites since they capture large areas with a snapshot of their sensors. There is ample of research on utilising remote sensing data for urban growth [17–19] and mapping of many risk aspects, ranging from climate change affecting land cover change and contributing to flooding or rock falls risk [20], over earthquake risk in urban areas [21], or specific risks to slums [22]. Remote sensing imagery is also increasingly used for monitoring and documenting disaster losses, for example within international 'space charter' calls which provide high-resolution imagery often free of charge of disaster-affected areas immediately after the events [23].

1.1. Usage of Satellite Imagery in Context of Disaster and Natural Hazard Research

Since the 'international charter space and major disaster' has come into effect in the 2000s, an increasing number of (public) disaster loss imagery and related usage in literature can be observed [24]. Remote sensing imagery such as Landsat is widely used for mapping urban growth or related topics of urban settlements or populations [25], also concerning natural hazard or risk [26], using mainly Landsat at the beginning with visible geometric resolutions starting at 79 m per pixel in the year 1972, then 30 m per pixel since the year 1982, per pixel, later 15 m per pixel since the year 1999. A first literature survey also revealed a relatively low number of publications by comparison on utilising older satellite imagery, before the 1980s [26,27]. There might be several reasons for this; much of the now available satellite imagery before the 1980s is limited to the provision by the United States of America, who started in 1995 to disclose their previously classified former espionage imagery of several missions [28,29]. Additionally, since this imagery is not largely known beyond academic institutions teaching photogrammetry, it had not been publicised as much as other products. Another reason may be due to the type of imagery. CORONA and other film-based photo satellite data such as Zenit (see specifications in Sections 2.1 and 4.4) are greyscale photographic film images, in the visible range of the spectrum, with rather rare exceptions of colour or infrared film [30]. Most other remote sensing products typically used within Earth Observation and related data applications that often started in disciplines such as geodesy, geography, ecology or similar, were using multispectral information, not just greyscale visible information. For example, multispectral information such as infrared, or many other wavelengths is preferred in several band combinations to display and help separate land use categories such as vegetation from buildings etc. much better than just black and white images [31]. Therefore, it might be the case that CORONA and similar data are rather underestimated, which might explain the surprisingly low range of publications to be found under search terms such as "CORONA" and "natural hazard" for example (see Appendix A). However, publicly available CORONA imagery can, just like aerial imagery, provide a relatively high resolution, of up to 2–4 feet (0.6–1.2 m) per pixel. However, more important even, CORONA data is ranging back until the year 1960, often resembling the only known existing snapshots of a time and human footprint of those periods. Additionally, since urban growth has overgrown many formerly natural areas, this data offers unique insights of areas of potential exposure to natural hazards, when settlements have now grown into slopes of mountains or former riverbeds.

1.2. Description of CORONA and Other Old, Public Reconnaissance Satellite Imagery in General

CORONA had been a program providing satellite or aerial imagery, originally deployed by the United States of America for espionage purposes, especially of the Soviet Union and Chinese nuclear and strategic missile programs [29,32]. This includes high altitude planes such as the U2 mission since around the year 1956 [29,33] and then specifically, reconnaissance satellites launched by rockets and also equipped with panoramic photo cameras with a black and white film, taking imagery from 19 August of 1960 to May 1972 [28] with a return-capsule to earth instead of electronic transmission to save costs [29]. The program was called CORONA, a codename spelt out in capitals in military-style and comprises six satellite models and different photo camera models (see Table 1). The CORONA data has been declassified and made available in three stages; in the years 1996, 2002 and 2011 [34], with exceptions [32]. There is much older aerial imagery, often related to land surveying or war impact documentation, even with partly higher spatial resolution. However, this suite of imagery from reconnaissance and espionage imagery is unique, since it covers large parts of the planet surface, including areas never been mapped by aerial imagery before. It also uses images that cover areas much larger by one image than many aerial images. Additionally, one CORONA mission covered a larger area than all previous U2-missions together [28]. All missions together collected over 800,000 photographs and covered around 557 million square miles (896.4 km²) [29]. This comes at the cost of spatial resolution but enables analyses of larger areas based on a single timestamp and with similar sensor information. It also provides an archive of the landscape surface of the year 1960 to the 1970s at least, which enables methodological comparisons using the same material. The main usage, as this article tries to show, is documentation of changes of land use over much longer time when Landsat imagery became of wide usage since the year 1972, and especially with better resolution since 1982. It also enables documentation of geomorphological surfaces before urbanisation. Additionally, as a last characteristic feature, the data is available at low cost or even for free by the United States Geological Survey (USGS) for many countries and areas in the world. Limitations of this imagery include cloud coverage [35], which shrinks the number of areas that can be used for land use documentation, especially in humid areas. The spatial resolution also depends very much on the mission, hence also on the year and camera system used, but also on flight paths and swaths covered [36]. Coverage is also much more frequent for areas that were of strategic interest to the USA [35,36].

1.3. Short Overview of CORONA Satellite Imagery Concerning Urban and Hazard Aspects

CORONA imagery in general academic literature is mainly used in the fields of archaeology [37,38], geomorphology [39,40], land-use change [41], coast-line [42] or forest cover change [43]. After declassification in 1995, applications were expected for natural hazard monitoring such as volcanoes and land-use change monitoring such as for the Aral Sea [44].

Urban growth or sprawl is covered by studies in archaeology that are analysing impacts of urban sprawl on archaeological remains or cultural heritage [45,46]. Urban expansion and growth analyses are using such satellite imagery to compare different stages of development of cities [47,48], population growth [49] and interrelations with the environment and hinterland of cities [50]. For later lines of the CORONA series, the GAMBIT and HEXAGON images, usage in archaeology also exists on the same case studies [51] and are also applied for urban land cover analysis [52].

Urban growth in combination with natural hazards analyses has used CORONA images for detecting vegetation changes concerning gully erosion and pluvial flood damages [53]. Another topic is glacier outburst danger [54], glacial debris flows and glacier collapses [55] or glacier coverage changes in general [56].

Not explicitly concerning urban development or growth, CORONA and other satellite imagery are used for other natural hazard types, including landslide susceptibility mapping [57]. Due to CORONA data also consisting of stereo-pair images often, the extraction of digital elevation models (DEM) [58,59] is also common for usage in archaeology [60], land use and especially, glacier change or glacier lake outbursts [61]. Interestingly, usage of CORONA imagery seems rather rare for several

natural hazards, for example, regular floods and not only glacier outburst-related floods. However, even review papers on a large range of remote sensing imagery applications do not mention CORONA or related mission data [26,27]. This cannot be fully covered here but may warrant more extensive literature review analyses.

Based on this background, this article investigates the main guiding research question: How can satellite imagery ranging back to the 1960s help to map urban sprawl and reveal information about natural hazard risk?

To break this encompassing question down, the following aspects are broken down to be analysed in a qualified manner in this article:

- 1. How useful is old declassified satellite imagery to map urban sprawl and natural hazard risk?
- 2. Where are the limitations and what additional range of years going back from the 1980s can be added to map urban sprawl and natural hazards using openly available data?
- 3. With respect to urban change detection, what additional information about urban and physical morphology can be derived from these images?
- 4. Which are recommendable aspects and areas for further research?

Since these questions may be of general interest for many regions worldwide, the article will use example data from several regions in the world, to demonstrate the potential, but will also highlight limitations. Arid and semiarid regions in Latin America and central Asia were selected for similar natural conditions, the prevalence of natural hazard occurrence and high ranges of experienced disaster losses in the past. Additionally, of course, this partly avoids one major constraint of visible satellite imagery, cloud cover.

The article is further organised with a method and materials section, including a description of key features of such satellite imagery, a short overview on usages of similar satellite imagery concerning urban aspects, followed by an overview on the imagery used for the descriptive analysis in this article. The main part of this article follows in the assessment section, where examples from case studies are used to demonstrate usability as well as limitations. The following discussion section takes up the structure of the research questions to detail usefulness and limitations for other similar research. The conclusion section summarises the findings and highlights some future research options.

2. Materials and Methods

This article analyses the potential of using pre-1980s satellite imagery for disaster risk reduction and urban sprawl in combination. This is conducted descriptively by showcasing examples of imagery depicting either typical hazard or exposure features of natural hazards, or changes in urban and built infrastructure fabric. Therefore, the characteristics of such satellite imagery are described first, followed by a short overview of typical applications with respective literature, then a description of the satellite material and cases selected.

2.1. Methodological Background of the Manual Visual Image Interpretation

This article conducts a multitemporal image comparison by manual visual image interpretation. Manual visual image interpretation has a long history but has taken a major step in methodological development connected to the CORONA program. Image interpretation relies on sensor optics, accurate orientation, image calibration and many other aspects related to image generation and processing [21]. This first step already influences the products, satellite images, and hence, manual interpretation very much. However, image interpretation also relies very much on further processing and the skills of the interpreter. Next to providing a great amount of funding for the reconnaissance missions and hence, data retrieved, new centres for image interpretation were founded in the USA, including the National Photographic Interpretation Center (ibid., p. 200) adding to the US Geological Survey (ibid., p. 210). Education at universities was extended and methodological innovations included a new global mapping model of the globe, which helped establish the World

5 of 26

Geodetic System—WGS-1966, then 1972 and finally, 1984 WGS ellipsoid (ibid., p. 206), and next to an accurate model of the globe, several other factors constrain the manual interpretation. This includes lighting conditions (ibid., p. 222), broken film, image scene borders, dirt and training (ibid.).

In later literature on remote sensing and image interpretation, several factors influencing manual interpretation have been added [62]. Data obstacles are one factor, such as shown by the elements of image interpretation (texture, colour). Another area is the social environment, that includes sharing of experience, working environment, shared work by different persons, interruption of working days, etc. Perception and cognitive factors of the interpreter are influenced by experience and training, connected also to study backgrounds, for example on geology for detecting land features and natural hazards [63]. More specific abilities and constraints cover correct topography and sun angle interpretation, amodal completion of objects partly covered, contour identification, transparency and other options of shape discrimination, image representation and interpretation [64,65]. There is literature in the field of Geographic Information Systems and remote sensing dealing with information uncertainty, perception, data recognition obstacles and other uncertainties of the interpreter [66]. For instance, spatial and thematic conditions which imply the existence of an object ('existential uncertainty'), the uncertainty of spatial extend on an object ('extension uncertainty') or the precision of measuring the boundaries of an object ('geometric uncertainty') [67]. Many other aspects play a role such as completeness, positional accuracy, attribute accuracy, logical consistency, mapping technique, aggregation and overlay, interpolation, subjectivity and many more [68,69]. Uncertainties concerning geographic information include several aspects related to cognitive entities such as memory, thinking, that interrelate with imprecisions or inconsistencies generated by the human-machine relations such as ambiguity or approximation [70]. At the example of building identification factors such as overlapping roof structures or rising morphologic complexity, in general, are challenges for manual visual image interpretation, especially for very high-resolution optical satellite images [71]. Results are different according to individual interpreters regarding the number of objects, building size, orientation or density identified (ibid.). Concluding, the limitations of image interpretation are known in the field of GIS and remote sensing already and are not specific for greyscale photoreconnaissance imagery only.

2.2. Data Description and Screening Process

The selection of material followed the research questions. These questions include (a) identifying usefulness and (b) limitations when trying to track (c) change detection of urban development and other aspects related to natural hazards and disaster risk assessment and (d) showing up new areas for application. To cover this, examples from several countries and continents were targeted. Structuring this, several steps were conducted; the time phases were identified where the highest spatial resolution imagery of CORONA and similar missions are available. Table 1 lists variants of data available for the CORONA program, with its different missions and satellite models. The CORONA satellite models were called KEYHOLE, abbreviated KH, and numbered consecutively. Camera models and satellite modules were continuously enhanced and given specific code names, such as the ARGON on KH-5, the LANYARD on KH-6, and the code-named KH-7 GAMBIT and KH-9 HEXAGON missions [72]. The CORONA photo cameras used an acetate-based, later polyester-based 70-mm Eastman Kodak Film with 280 line pairs per millimetre over the entire image, while World War II aerial images often had a resolution of only 10-50 lines per millimetre [29]. Spatial resolution varied and also improved over the years, from around 40 to 2 feet (12 to 0.6 m), fitting the purpose to first provide broad overviews and later on, more detailed photo interpretation [32]. The low earth orbit altitudes could be as low as 92 to 75 miles (148 to 120.7 km) [32]. The Aerial Imagery is provided by USGS as digital scans, with the Medium Resolution Scan Product having approx. 400 dpi (dots per inch), the High-Resolution Scan Product—25 micron or 1000 dpi and the Declassified Imagery Standard Scan Product—7 micron or 3600 dpi (email retrieved from USGS EROS User Services on 8 September 2020). The scanned images are separated into tiles, which have to be stitched. File sizes for a full image are up to over 6 GB for the KH-9 products, for example. This has implications on available storage space

on mobile devices when gathering multiple images. While previews of the images are available by low resolution, not all images are already scanned and therefore ready for download free of charge by the USGS. The cost for one image not already available for download is USD 30 and it takes around 1–2 weeks until the images are provided.

The further screening process methodology is numbered from (i) to (vii) to better guide through the process steps. Based on images downloaded or ordered from the USGS Earth Explorer website (i), a first assessment was carried out (ii) on general usability for visual urban sprawl, urban fabric or natural features to be analysed, the result is briefly summarised in the last column of Table 1. While low-resolution images still permit to roughly track city borders, spatial ground resolutions between 25 and 40 feet (7.6–12.2 m) were found not precise enough to delineate buildings from other features and were excluded from further analysis.

CORONA Satellite Types	Time Coverage	Spatial Resolution (up to)	Usability/Limitations for Urban Features	
KH-1	8/1960	40 feet (12.2 m)	General locations of large urban settlements	
KH-2	12/1960-7/1961	30 feet (9.1 m)	General locations of large urban settlements	
KH-3	8/1961-12/1961	25 feet (7.6 m)	General locations of large urban settlements	
KH-4	2/1962-12/1963	10–25 feet ¹ (3–7.6 m)	Mapping urban borders, streets	
KH-4A	8/1963-9/1969	9–25 feet ¹ (2.7–7.6 m)	Mapping urban borders, streets	
KH-4B	9/1967-5/1972	6 feet (1.8 m)	Mapping urban borders, streets	
KH-5 ARGON	5/1962-8/1964	460 feet (140.2 m)	Not useful	
KH-6 LANYARD	7/1963-8/1963	6 feet (1.8 m)	Mapping urban borders, streets	
KH-7 GAMBIT	7/1964–6/1967	4, later 2 feet ¹ (1.2–0.6 m)	Very good; building types	
KH-8 KH-8A GAMBIT	1966–1984 ²	6 inches 1 , 2.5 inches or better 2 (15.24–6.35 cm)	Could not be accessed (not declassified yet)	
KH-9 ³ KH-9 HEXAGON	3/1973–10/1980 6/1971–4/1986	20–30 feet (6.1–9.1 m) 2–4 feet (0.6–1.2 m)	General locations of large urban settlements Very good; building types	

Table 1. Reconnaissance photographic film satellite imagery specifics and usability for visual analysis of urban sprawl (data from USGS Earth Explorer platform, accessed between July and Sept 2020, when not indicated otherwise).

Data details in sources [32]¹, [30]², and KH-9 data published in the 2002 batch³.

Based on the first data screening results (Table 1), the time range of 1962–1984 was identified for further analysis (iii). While the overall range of missions of KH-1 to KH-9 ranges from 1960 to 1986, available images on the USGS platform are limited to the years from 1962 to 1984 when launching missions started to become successful. To be able to detect urban structures for analysing potential natural hazard damages, the range of data was further narrowed down to resolutions of around 10 feet (3 m, KH-4 products, see Table 1) or better. To identify suitable areas and cases (iv), major disaster events worldwide between the years 1962–1984 were researched using the DESINVENTAR, EM-DAT databases and web-search. Results are displayed in Table 2, and cases were selected based on the highest numbers of casualties, area size, variety of disaster types and countries, and availability of CORONA images. Respective locations were checked (v) on the usability of reconnaissance imagery available from the USGS Earth Explorer website for that time frame by checking available images on their fit to the area of interest, resolution and cloud cover via the preview images, too. Very few cases could be identified where images before and after a disaster event are available in sufficient spatial resolution to permit the identification of both hazard and urban features. One major reason is lack of CORONA data of sufficient temporal and spatial resolution, cloud coverage or time fitting close enough to the events. In some cases that were checked, already one year after a flood or earthquake, no traces could be found of the natural hazard features or damaged houses anymore. It was especially difficult, however, to find images before and after an event in sufficient time intervals below one year

or better, three months. This is not conclusive, since certain events might have been missed out in the visual screening of many images by the author. Additionally, other disaster events were not selected since they resulted in lower numbers of casualties. The screening results in Table 2 in the last column indicate the problems in finding both an image within at least 3–6 months before and after the event of sufficient resolution and without cloud coverage. Those images finally selected for this article and the assessment results, are marked with an X.

Location	Hazard	Occurrence	Fatalities ¹	Available High-Resolution Satellite Data	
Qazvin, Iran	Earthquake	1962, Sept 1	12,000	1973	
Hamburg, Germany	Coastal flood	1962, Feb 16–17	300	Not useful	
Skopje, Macedonia	Earthquake	1963, July 26	1000	Not useful	
Longarone, (Vaiont), Italy	Landslide	1963, Oct 9	2000	Not useful	
Hope, BC, Canada	Landslide	1965, Jan 9	4	Not useful	
New Orleans, USA	Hurricane	1965, 27.8.–13.9.	80	29-MAY-65	
Florence, Italy	Flood	1966, Nov 4	100	Not useful	
Xingtai, China	Earthquake	1966, March 22	8000	KH-4A	
Dasht Bayaz and Ferdow, Iran	Earthquake	1968, Aug 31	12,000	KH-4B	
Tonghai (Kunming, Gejiu), China	Earthquake	1970, Jan 4	15,000	KH-4B	
Yungay, Peru	Earthquake	1970, May 31	70,000	1966 KH-4B	
Yungay, Peru	Landslide	1970, May 31	22,000	1966 KH-4B	
Qir, Iran	Earthquake	1972, April 10	5300	KH-4B	
Rapid City, South Dakota, USA	Flood	1972, June 9	230	KH-4B (until May 1972)	
HongKong	Landslide	1972, June 18	150	Not useful	
Darwin, Australia	Cyclone Tracy	1974, Dec 25	70	Not useful	
Tanghshan, China	Earthquake	1976, July 28	240,000	Only before event: KH-4B 1966, 11-JAN-1976	
New Jersey, USA	Wildfire	1963, April 7 Low resoluti		Low resolution 1963-08-29	
Big Sur, Monterey, California, USA	Wildfire	1977, August	4	Low resolution 1978	
Laguna Mountains, CA, USA	Wildfire	1970, Sept-Oct	16	KH4B, 19-NOV-1970	
Volcán de Fuego, Guatemala	Volcanic eruption	1974, Oct 15–21	0	Until 1969	
Mount St. Helens, USA	Volcanic eruption	1980, May 18	50	KH9-16, 30-JUNE-1980, D3C1216-100112A003	

Table 2. List of major disaster events between 1962 and 1984 and results of screening for available high-resolution CORONA images (based on information by USGS, DESINVENTAR and web search).

¹ Since fatality numbers often vary, numbers were rounded down.

Based on the preliminary data screening results so far, additional cases were selected (vi) that can demonstrate urban sprawl or natural hazard features. Visual and descriptive interpretation of the images was conducted to demonstrate usability and limitations. Several sources of imagery from CORONA missions were selected (vii) to demonstrate the capability of extracting urban sprawl and natural hazards. Additionally, openly available aerial images from the USGS portal were selected where suitable CORONA images were not available in high resolution (Table 3). For comparison of changes of urban features over time, openly available satellite data with high resolution were selected from OrbView3, since this was the most recent (2004–2007) data in the USGS Earth Explorer archive, with a much better spatial resolution (up to 0.9 m per pixel) than Sentinel data (10 m). IKONOS images were not available. Other platforms were tried, too, without success. Table 3 provides an overview of locations and images used in the results section. Images were analysed regarding histograms, then min–max and contrast adjusted for better display.

Location	CORONA Images	Images for Comparison	Hazards/Disaster Events on Images	Lat	Lon
El Alto/La Paz, Bolivia	KH-7, 5-JUNE-1967, DZB00403800013H008001_b ¹	OrbView3, 23-JUNE-2004, 001649892	Erosion and pluvial flood hazards	-16.5	-68.2
Santiago de Chile, Chile	KH9-3, 11_JUL-1972, D3C1203-100061F023_a ¹	OrbView3, 30-MAR-2006, 00161416	Earthquake and flood hazards	-33.4	-70.5
Yungay, Peru	KH-4A, 11-MAR-1966, DS1030-1030DA028_a	Aerial photo, 14-JUL-1970, AR6148000205138	Earthquake and landslide 1970, May 31	-9.12	-77.6
Qazvin, Iran	KH9-6, 22-AUG-1973, D3C1206-300399A001, KH9-14, 19-AUG-1978, D3C1214-401249F010_a ¹	Aerial image, 15-SEP-1955, ARA0158M0915124 OrbView3, 6-MAR-2005, 001640111	Earthquake 1962, Sept 1, flood hazard	36.3	50.0
Mount St. Helens, USA	KH9-16, 30-JUNE-1980, D3C1216-100112A003		Volcanic eruption and forest fire 1980, May 18	46.2	-122.2

Table 3. High-resolution CORONA images, aerial photography and OrbView3 satellite data used for visual interpretation (based on information by USGS).

¹ Ordered from USGS Earth Explorer for this article.

3. Results

Results are presented based on the selection process indicated above concerning urban sprawl, natural hazards and in some cases, disaster sites. A multitemporal image comparison was conducted by manual visual image interpretation.

3.1. Urban Change and Sprawl into Hazardous Areas

Urban growth or sprawl can easily be detected using CORONA images by visual interpretation of the greyscale photographic images if spatial resolution and cloud cover permit it.

3.1.1. El Alto and La Paz in Bolivia

The two cities of El Alto and La Paz in Bolivia, close to the Peruvian border and Lake Titicaca have experienced massive urban growth since at least the 1970s [73]. This can be monitored by several temporal snapshots from CORONA and other satellite images. Figure 1 shows a CORONA image from the year 1967, KH-7, with many areas around the airport still undeveloped. For comparison, an OrbView3 image from 2004 shows the extend of urban growth. Both images are not corrected to the same northern orientation since adjoining other tiles or images were not available to the West for KH-7 and further to the East for OrbView3 only with cloud cover. Erosion at the escarpment [74] of the 'altiplano' of El Alto bordering the valleys of La Paz (Figures 1 and 2), and related possible landslides and known problems with flood gushing down these steep valleys are one of the natural hazards affecting El Alto and La Paz [75,76]. Dependence on glacier melt for water supply and its interrelation with glacier lake outburst flood risk is another topic [77]. What has been former urban borders, where urban sprawl has taken place, now are two cities grown into a joint metropolitan area. The high resolution allows to visually compare gullies formed by erosion (Figure 2a, indicated by the arrows) that have been modified by construction works of the expanding city (Figure 2b) and buildings and roads exposed on both the plateau rim as well as on the steep flanks.



Figure 1. El Alto/La Paz, Bolivia. Area east of the airport in (**a**) 1967 and (**b**) 2004, showing urban growth on the plateau of El Alto, districts 1 and 2, towards the city of La Paz. White box A showing position of Figure 2. (Data, incl. coordinates: Table 3).



Figure 2. El Alto/La Paz, Bolivia. Area east of the airport in (**a**) 1967 and (**b**) 2004, showing urban growth into steep flanks of a valley (Data: Table 3).

3.1.2. Santiago de Chile

Santiago de Chile in Chile has experienced similar urban growth and sprawl along its western borders in a similar period, visible on CORONA images of the year 1972 and in the year 2006 on OrbView3 images for comparison (Figure 3). Additionally, as it is the case with La Paz, this urban growth expands into areas potentially exposed to multiple natural hazards. In the case of Santiago de Chile, the growth to the east expands into mountainous terrain with landslide and erosion risk, exacerbated by the nearby San Ramos Fault [78]. River valleys (Figure 3a) expose settlement and infrastructure to river floods, with steeper valleys and snowmelt from the Andes contributing to the hazard development. By comparison, in the year 2006 the city has grown over the pediment to the east and even onto the mountains, but also the river has been trained and enclosed by built-up area (Figure 3b). Several hills within the 2006 city area have now been fully overgrown by the built environment (Figure 4, and white box B in Figure 3). Additionally, a former ravine/riverbed with a form of a gully (in Figure 4a) has been filled, then overgrown with roads and settlement area (Figure 4b). This hill and the former riverbed close to it are areas where exposure towards floods and erosion should be analysed further. However, transformation also includes more vegetation cover on that hill as compared to the year 2006, which is a good measure to reduce erosion.



Figure 3. Santiago de Chile, Chile. Area east of city centre in (**a**) 1972 and (**b**) 2006, showing urban growth into bordering mountainous area. Inlet in (**b**) shows trained river area, and the white box B indicates the location of Figure 4. (Data: Table 3).



Figure 4. Santiago de Chile. Area east of city centre in (**a**) 1972 and (**b**) 2006, showing hill and rivers transformed by urbanisation. (Data: Table 3).

3.2. Natural hazard and Disaster Examples

It was quite difficult finding examples of natural hazard events on CORONA images, due to

several factors. First of all, the availability of images in high resolution and without cloud cover before and after an event. However, the search on suitable events also revealed a gap in the documentation of natural hazard events in general, and in South America more specifically (see discussion). It also seems, that even despite known underreporting in the time before the 1970s [79,80], also natural hazard events were less common for hazards such as hurricanes or earthquakes, as in comparison to the later 1980s or earlier than the year 1960 [81]. Besides, for events such as earthquakes or wildfires, identifying traces of damages with the available spatial resolution was also found challenging. Therefore, in the following not only examples from Latin America and Asia, as was originally planned, are shown, but also from other countries hit by natural hazard events between the years 1960 and 1984.

3.2.1. Landslides and Mass Movements

Certain types of gravitational mass movement can be detected quite well on photo imagery since the surface reflection does drastically change over often large swathes of land. While large rock or mountain slides will be quite difficult to detect if the surface with vegetation can stay more or less intact, certain types of landslides such as mudflows result in different surface material as compared to the surrounding landscape, with characteristic homogenous reflectances. The example of the landslides that took place in rural Peru in 31 May 1970 is one such case of a material mass movement. Triggered by the Ancash earthquake, the northern part of the Nevado Huascarán mountain collapsed, causing a major glacier icefall that together triggered a massive debris flow or avalanche [82]. The (old) city of Yungay (Figure 5a) that had around 17,000 inhabitants was almost totally covered by that debris avalanche (Figure 5b) and only 400 people survived [83]. The old city of Yungay is left as a memorial and the new city of Yungay now is situated immediately north of it. The debris flow came down at speeds between 280 and 400 km per hour over more than 11 km, and people on the slightly elevated hill of the cemetery (Figure 5d) were among those who survived. The CORONA image of 1966 shows the settlement before the disaster, and while the resolution is not optimal at around 9 feet (2.7 m) or more, the settlement area can be detected (Figure 5a). The near-infrared aerial images were selected for comparison since no high-resolution CORONA image was available after the disaster (Figure 5b-d). They reveal the extent of the damage quite in detail.



Figure 5. Yungay, Peru. The urban area before and after destruction by a landslide (a) 1966 (CORONA image) and (b) 1970 (Aerial image, near-infrared), with (c) (white box A in (b)) details of debris covering road layout and city area and (d) (white box B in (b)) round shape of elevated cemetery area saving people due to elevation (Data: Table 3).

3.2.2. Earthquake and Flood Hazard

Qazvin and the nearby plain close to the Ipak Fault, Iran experienced a major earthquake in 1 September 1962, (Table 1) with 12,225 victims [84]. This area is notable since it is along with the Alborz mountain range with major fault lines close by. Cities in close distance of around 150 km such as Tehran and Karaj, have experienced massive urban growth since the 1970s [85], and the city of Qazvin also experienced great urban growth rates (Figure 6). However, urban growth started a bit later and is not as massive in scale as Karaj, for example. While the images reveal that Qazvin has doubled its built-up area between the years 1973 and 2005 (Figure 6), the city of Karaj has expanded more than 10 times in a similar period [85]. No images close to the earthquake fault line could be acquired, and in Qazvin itself, no traces of earthquake in the year 1962. However, it is of interest, too, how a city develops in the vicinity to natural hazards. Additionally, for Qazvin it seems that built-up area has expanded into hazard-prone areas such as riverbeds. Close up views of the images reveal a transformation in the urban fabric between the years 1955–2005 (Figure 7). Built-up area expands into the former riverbed, including new building types with larger blocks since the year 1973, south of the northern roundabout, followed by smaller houses even closer to the river in the year 1978.



Figure 6. Qazvin, Iran. Urban area in (a) 1955, (b) 1973 and (c) 2005. (Data: Table 3).



Figure 7. Qazvin, Iran. Urban area around a riverbed in (a) 1955, (b) 1974, (c) 1978 and (d) 2005. (Data: Table 3).

3.2.3. Volcanic Eruptions

Volcanic eruptions in South America happened in the time between the years 1962–1984, but either documentation is scarce or major urban areas were not affected. The example of Mount St. Helens was selected, although it also did not affect an urban, because it is one well-researched and known event, and reveals many different effects of a volcanic eruption. The event included a collapse of a mountain flank, lava flows (Figure 8a) and burnt forest area (Figure 8b). The near-infrared CORONA image reveals areas of forest still intact as well as burned (Figure 8c, arrow). That differentiation is more difficult to discern in the same image converted into greyscale (Figure 8d).



Figure 8. Mount St. Helens, Washington, USA. Lava lobes in (**a**), (near-infrared) lava streams cutting through the forest in (**b**), burnt forest in infrared in (**c**) and in (**d**) converted to greyscale for comparison. (Data: Table 3).

4. Discussion

The main research question guiding this article, "How can satellite imagery ranging back to the 1960s help to map urban sprawl and reveal information about natural hazard risk?" was addressed by both investigation of availability and usefulness of materials and methods in Section 2 and expressed by selected examples from cases in five different countries in Section 3. To detail and interpret this further, this discussion section follows the sequence of the four more detailed research questions.

4.1. Addressing the Usefulness for Urban Sprawl and Natural Hazard Identification

Regarding the detailed research question, "How useful is old declassified satellite imagery to map urban sprawl and natural hazard risk?", the usefulness in general has been verified, with some limitations outlined in the following. 'Usefulness' was analysed in the sense of opportunities provided by such declassified satellite data for visual interpretation. While usage for visual interpretation or DEM extraction of CORONA data varies over disciplines, it also appears as if CORONA data is not as widely applied as other satellite data (see Section 1.3). Especially for the topic of natural hazards, few cases could be identified by the literature search, while applications for urban growth or sprawl are more common. Limitations may lie within the literature search, see the next research question below, or since such data is less known or since it might be less useful. However, the question is not why it is not used more widely since this would demand a more qualitative investigation by a survey on authors using other satellite data. However, this might be less informative than analysing the options for natural hazards detection by investigating the data. Hence, the usefulness of CORONA data was then analysed by specific examples of urban areas and natural hazard processes in the results section. The results of the CORONA images show that urban features, especially buildings (mainly, roofs) and roads, can be identified when high-resolution images are selected, without cloud cover. This excludes a large number of images provided by the USGS Earth Explorer platform, which often are available with cloud cover or with medium or low resolution. 'High-resolution' follows the nomenclature provided by USGS for the declassified class 1 suite of CORONA images, where spatial resolutions of 6 feet (1.8 m) or better (Table 1) were found especially useful to investigate houses whether they are intact after an earthquake or other natural hazard impact, or trees were felled by a storm. KH-4A was also used in the Yungay case for lack of alternatives and the resolution of around 9 feet (2.7 m) was just useful to identify the city area of old Yungay (the year 1966 was a later stage of the missions and therefore likely to result in the better range from 9 to 25 feet (2.7–7.6 m) (see Table 1). The manual visual image interpretation highly depends on the geometric resolution resp. image quality and some sources on remote sensing in general suggest a minimum of 1 m (around 3 feet) for identifying buildings, for example [86]. Sources related to CORONA image interpretation of missile launching sites or airports report that even in medium resolution interpreters with a certain training could identify individual aircraft or missile models [29]. Training and experience is also reported for other fields such as archaeology or similar data such as aerial images [63,72]. In this article, identification of individual features such as buildings may have been constrained by the authors' lack of training and experience. Individual houses or structures could only be identified when they exposed a peculiar pattern, such as public spaces with crossing roads (Figure 9a, example box C). Other features are vaguely recognisable in the CORONA image, such as roads (Figure 9a, example box A) or the circular walls of a cemetery mound (Figure 9a, example box B). The aerial image from the year 1970 in near-infrared shows much higher spatial resolution (Figure 9b,c), but only covers around 1.5 km per image, while the CORONA images typically cover an area approximately 14.6 km long and 227.8 km wide [29]. The higher resolution of the aerial image permits the comparison of intact and partly collapsed rooftops (Figure 9, top right image, house indicated by the white line).



Figure 9. Detail of Yungay city, Peru in (**a**) KH-4A image from 1966 with an aerial image from 1970 in comparison (**b**,**c**), showing limits of spatial resolution (Data: Table 3).

For comparing the resolution, aerial images were shown in Section 3, as for the case of Yungay, or relatively modern OrbView3 images for other cases. They show how more details can be detected when using spatial resolutions of 2 feet (0.6 m) or better. Some cases of data analysis are not shown in the article, where for example the city of Kunming in China was analysed on images from the year 1965 (KH-7 image with high resolution), and after the earthquake in the year 1970, with a KH-4B image from 1970, but house structures could not be reliably compared for damages, due to the spatial resolution of the KH-4B image not being sufficient. Certain types of natural hazard were found easily identifiable, such as landslide debris cover, as in the results section it is demonstrated for the case of Yungay. This is due to the mudflow characteristic of a rather homogeneous surface that also is distinct from the surrounding land use features, therefore permitting easy identification. The volcanic lava or ash/debris flows from Mount St. Helens cutting through forests also exhibit a stark contrast easy to identify. Urban growth into former riverbeds (Figures 3 and 8) as well as into erosion-prone areas around gullies (Figures 2 and 4) or flanks of hills and mountains (Figures 1 and 3) are areas that warrant further investigation since CORONA images here really help with change detection and also, identification of previous surfaces before urban development has overgrown them. Earthquake damage, but especially forest fire traces or forest storm damages were found difficult to identify. Several cases of larger forest fires in California or South America (Table 2) were analysed but spatial resolution often was not high enough. Additionally, other spectral information than greyscale provides better opportunities to distinguish burned versus intact forests, as the Mount St Helens infrared images (Figure 8) reveal. However, colour images or infrared images were rather rare on CORONA missions which limits their availability. Image interpretation however also depends on the skills of the interpreter on image analysis [63] and trained experts are capable of identifying features even under lower resolutions than shown in this article [29]. Coming back to the large range of image interpretation uncertainties identified in the state of the art (Section 1.1), the following seemed to play a major role in this article; existential uncertainty did not play a major role, since the analysis was informed by a preselection of images from locations where historically, natural hazards had taken place. Extension uncertainty played a role especially for the Yungay case since it was hard to find the

buried city of old Yungay under the very large extent of the debris avalanche. Geometric uncertainty of measuring the boundaries of objects has not been a major constraint, except for the details discussed for each image, such as building size, etc. It was found that image interpretation also depends on many factors such as a definition of what is a city boundary, too. In this article, only buildings and directly related spaces such as parking lots were mapped as a boundary, while adjacent parks or larger empty space areas were not mapped as urbanised areas. Comparison with recent satellite imagery helped in image orientation, but often only few features could be identified such as river courses to help identify locations within a city that had overgrown previous land cover. Concluding, individual image interpretation skills and personal perception certainly played a major role in this article and the examples presented.

4.2. Limitations of Data Availability

Availability of images is also illustrated by the findings of data according to known disaster cases (Table 2) and the examples of results in Section 3. However, these findings also point to several limitations which are addressed by the following research question; "Where are the limitations and what additional range of years going back from the 1980s can be added to map urban sprawl and natural hazards using openly available data?" Therefore, limitations have been verified, but also an additional range of 20 years of data usability since 1960. In the results section, example CORONA images from the years 1966–1980 were used, and the temporal change detection range extended by aerial images back to the year 1955, and by high-resolution satellite images from OrbView3 to the year 2006 (Table 2). From significant disasters (Table 1), examples from the earthquake in 1962 in Qazvin, Iran up to the Mount St. Helens, USA eruption in the year 1980 are provided. However, it became evident that the declassified data batch number two, released in the year 2002 was hardly useful since most images are provided only in resolutions of 20 feet (6.1 m) or more. The declassified data batch number three from KH-7 and KH-9 images was found especially useful due to its high resolution. Since this batch was released in the year 2011, it might be a valuable resource for other researchers, that may have been overlooked a bit. The declassified data batch number one (USGS Earth Explorer platform) dates back to the year 1960 and is a very useful source to expand urban growth change detection assessments. Finding data close to disaster events, however, is quite a challenge due to limited image availability or coarse resolution or cloud cover. Indirectly, this promotes case study selection from arid or semiarid regions, too, due to more chances of low cloud cover, as compared to humid regions with frequent clouds and related weather patterns. An exception might be areas of interest to the original mission purpose such as Vietnam, where intelligence information about war resources was of key interest to the USA [29], and hence, a great number of images are available for this region when checking the USGS portal. Comparing the same periods of urban growth between cities such as La Paz/El Alto and Santiago de Chile generally are possible, but exact periods often difficult, since image availability and quality (cloud cover) diminish options to find the same years. For certain applications such as vegetation and land-use change, this is even more difficult when trying to find images from the same month or season. To provide an example for the search on natural hazards, CORONA images capturing earthquake damage were not found for Latin America for that period, and some areas such as Kunming or Xingtai, China or Qir, Iran were tried, but either image resolution was not sufficient, or CORONA or aerial imagery images either before or after were not available.

For consistency, only the USGS Earth Explorer platform was accessed and used in this article. Original archives were not visited which provide on-site film negative inspection, also due to travel restrictions during the on-going SARS-CoV2/corona pandemic. Other satellite image archives were investigated, but no comparable data accessibility of CORONA images was found. Additionally, for more recent images with similarly high resolution as the OrbView3 data, no comparable site or satellite product was found with a similar coverage fitting to the case study sites selected, or with similarly high resolution, without charge. The idea was to demonstrate how openly available data can be used, however, some of the scenes were only accessible by preview images. Hence, the CORONA

image scenes for El Alto, Santiago de Chile, Qazvin and Kunming, China (not shown) were ordered from the USGS site and delivered within 10 days for USD 30 each plus a USD 5 service charge. The image used in Figure 11b,c had already been ordered in 2003 for then USD 18 for landslide assessment [87]. Other images were available for free download already and did not require payment. Interestingly, although the service charge was paid, those images were not made immediately available for free download until submission of the article, around two months later. The information about costs can be helpful to fellow researchers without funding or partners in developing countries especially [88]. Delivery times also are important in planning research and have an impact on number of additional scenes to be checked.

However, in addition to data availability reasons related to CORONA data and the data platform, other reasons play a role, too. Identification of suitable images is also influenced by the search method of the author, related to finding suitable disaster cases as well as literature using CORONA images. Finding information about natural hazard events or related disasters in the 1960s and 1970s, but also in the early 1980s was found difficult in comparison to events after 1985, or the 1990s. Especially for South America, even data entries in the United Nations database of DESINVENTAR often are rather vague, scarce or start only in the 1990s, for example, entries for forest fires in Chile. Other studies confirm that documentation for forest and wildfires appears to be coarse, with reliable data for Chile starting in the years 1984–85 [81]. The EM-DAT database is even less useful in this case, since the detailed data tables provide few further information on the events, additional sources or damage types, as compared to DESINVENTAR. For specific natural hazards, certain data platforms were also tried, such as the Darthmouth Flood Observatory which is great for events until it stopped recording in the year 2008, but it also only started recording events since 1985. There were no findings on earthquakes in South America, hurricanes, or wildfires that were significant enough to inflict damages over areas large enough or, where CORONA images were available in either sufficient temporal or spatial resolution. Hence, the original ambition of this article was given up, to cover South America for some context consistency, only. However, from the perspective of visual interpretation, other factors such as cultural or political context were found less significant for this demonstration of usability of CORONA data research and, therefore, examples of significant natural hazard events worldwide were added. While more than the 21 cases in Table 2 were searched, certainly many other good examples are likely to be missed by the author. Especially examples of coastal or river flooding are missing. However, since the main purpose of this article is to illustrate the general wider applicability of using CORONA data in combination with other aerial and satellite data for change detection of urban and natural hazard features, the selection may help to indicate this at least.

Further limitations may lie in the identification of studies and literature already dealing with CORONA image analysis of urban growth, sprawl or natural hazards and other hazard types. Search terms are documented in a list in Appendix A and this list indicates also areas for further literature search. To enable researchers worldwide free access to the same search platform, the free Google Scholar search site was selected. A literature search for the main body of the introduction and Section 2.2 was conducted on 23 August to 5 September 2020. It cannot be excluded, that there might be biases by the search algorithm trained by previous searches by the author. However, since the main purpose of this article was not to provide an exhaustive literature review article, the selected examples are from either highly cited papers or those influential in starting research in their discipline. The search was also hampered a little bit by the collision of search terms similar to the same terms or abbreviations used in other contexts. For example, the term "GAMBIT" is overlapping with the normal usage of the word 'gambit' in other contexts, not the satellite name. The term "CORONA" was mainly colliding with authors with such a name, interestingly, not with the SARS-CoV2 'corona' virus or COVID-19 infection at the time of the search.

4.3. Extracting Additional Information Next to Location and Exposure

Referring to the third research question, "With respect to urban change detection, what additional information about urban and physical morphology can be derived from these images?" the usefulness for change detection has been verified, as well as some further examples of information to be derived such as change of building density, capturing previous land surfaces, identification of water irrigation infrastructure and digital elevation models. One example is building and road densification processes related to urban growth. This includes less space between individual buildings or groups of buildings (Figures 3 and 4) or construction of more roads and connection on the same building area (Figure 7). In addition, also visible are modifications in house construction, especially by changes in rooftop diversity and material types (Figure 7a). Riverbeds closed in or overgrown by buildings and roads and river training by artificial embankments or walls can also be identified (Figures 3 and 10a). CORONA but also even older aerial imagery can help to identify presettlement land surfaces too (Figure 10b). This is especially helpful in hazard-prone areas such as former riverbeds or sediment fans, river valleys (Figure 10a) or gullies overgrown (Figures 2 and 4) or only overgrown but transformed in their shape by roads and property lots incised into the hill slopes (Figure 4).



Figure 10. Details of (**a**) Santiago de Chile, north of the city centre, Plaza Baquedano on (**a**) KH9-3 image from 1972 and (**b**) riverbed in El Alto, directly west of the airport on KH-7 image from 1967 (Data: Table 3).

There are, however, even more opportunities provided by CORONA data. One important area is the application of the stereo-optical photographs taken by the CORONA missions. They permit not only visual interpretation with specific hardware viewers known from orthophotography and photogrammetry [31] that adds height information to the observer. This can help to better identify features such as building heights, topography and more. The availability of stereo-pairs of many of the images also permits extraction of height information to create three-dimensional digital elevation, surface or terrain models (DEM, DSM, DTM) [29,54,58–60,89–92]. These are used in literature for identification of and change detection of artificial human construction of many kinds, including city dwellings, walls, channels etc. [60]. However, old human channels or irrigation systems as the 'qanats' in Iran (Figure 11a) are also important to maintain into modern times for irrigation [93]. However, they also pose hidden hazards underneath areas overgrown by urban growth in cities such as Tehran when becoming unstable [94].



Figure 11. Feature identification eased by (**a**) snow cover helping to find water irrigation tunnel entry pits for maintenance in Tabriz, Iran (Data: KH-7 image from 5 Feb 1967, DZB00403600041H010001_a). Identification of narrow mudflows in Alborz mountains, Iran, eased by DEM overlay (**b**) on the top right image and of the (**c**) landslide scarp (A) and slump mass (B) on the lower right image (KH-4B from 31 May 1970, DS1110-2170DF039).

Of course, DEMs are also very useful for identifying any type of gravitational mass movements such as landslides, mudflows (Figure 10), rock falls, avalanches or glacier outbursts, based on any type of high resolution aerial or satellite data [95]. There is a strong interrelation between urban sprawl and topography-related natural hazards, due to hill and mountain slopes being attractive settlement options in growing large metropolitan areas to escape smog, heat and traffic. Therefore, it can be observed in several countries around the world, in Tehran, Iran as well as in Santiago de Chile, that urban growth reaches bordering mountainous areas, despite known earthquake fault lines nearby and the additional risk of landslides, as well as pluvial floods and erosion. Additionally, it is also interesting to combine such satellite data with additional information such as demographic statistics, which in some cases reveals that the more affluent occupy those areas. In other areas, it can be the urban poor, seeking cheap land in the favelas in Brazil, for example. In the case of the example from Santiago de Chile (Figure 4), the overgrown hill reveals, by close inspection in map portals such as Google Maps, that it is characterised by houses with swimming pools on the hill, making it likely that this points to wealthier neighbourhoods. Due to data property issues, however, such recent satellite imagery is not on display here.

4.4. Recommendable Aspects and Areas for Further Research

While the above sections already have indicated areas of interest for further research, the final research question, "Which are recommendable aspects and areas for further research?" highlights two areas specifically. Urban borders are of general interest for natural hazard research, too, since cities are expanding into areas with novel hazard exposure. Since more and more knowledge about natural

hazards and related risks is produced [2] and also made public by many cities themselves [8], and more and more risk and planning maps publicly available [96], it could be expected that building into hazard-prone areas is avoided or at least, accompanied by respective building or management measures. This appears to remain a challenge even in areas with high national importance, such as megacities or national capitals, though [85]. This often is related to different responsibilities of administrations, or competing interests and the attraction of those properties still available in city centres close to the river of on the mountain ranges. It would be interesting to conduct more research on urban areas that have recently expanded and what percentage grows into more or less hazard-prone areas, adding to the total ratio of exposed area per city. In the case of Santiago de Chile, it appears that especially growth into the Eastern parts of the beginning mountain ranges could be of special interest, since it is growing towards a major earthquake fault line and hence, at least building codes and construction types should be adapted. However, urban sprawl is also of special interest, within urban areas but also at the borders, when it leads to different types of settlements with different infrastructure supply quality. For example, areas in the North of Santiago de Chile differentiating into more wealthy areas with regular tap water infrastructure next to poorer settlements reliant on water trucks [97]. Or comparing areas in the West of Santiago de Chile, which experiences a lot of growth and sprawl and includes more fractions of non-wealthy groups, but where health infrastructure is not keeping pace [98]. Santiago de Chile is just one example, and the same would be of interest for the vast expanding case of La Paz, growing into even more remote flanks of valleys and mountains, and El Alto growing rapidly into the altiplano plain with broad river flood-prone areas.

A second area recommendable for further investigation is the usage of similar but much less regarded reconnaissance satellite imagery. Especially from Russia and China, it is known that they also conducted satellite missions similar to CORONA mission of the USA for photoreconnaissance. However, while the Russian Zenit satellites, based on Vostok modules also retrieved photoreconnaissance data since the year 1960 (DAY p. 164), they are not as easily accessible. This is due partly to the Russian language used and hence, problems for English speaking people, but also, a public access central data platform similar to the one by USGS seems to be missing, still. Stereo pair photo data were gathered from Komet missions, under the SPIN-2 project, since the year 1981 with the sensors KVR-350 and KVR-1000 [99], with a spatial resolution of up to 10 or 2 m or even better and areas covered measuring from 300×200 km to 40×160 km, respectively [100]. Several sensors exist, similar to KVR-350 and 1000 [101] and follow up missions have names such as Zenit-4 or Resurs-F1. Applications seem similar to CORONA at first sight, such as including applications for archaeology [72] or measuring ice masses [102]. Due to language problems, also Chinese reconnaissance satellite data before the year 1985 could not be found immediately (see Appendix A). However, it would be worthwhile to complement the picture of available pre-1980 satellite imagery beyond data from the United States only.

5. Conclusions

While CORONA photoreconnaissance satellite imagery has found some application in fields ranging from land use to urban growth change and for certain natural hazards as well, it seems the full potential of images has not been exploited yet. Using those images for change detection alone, in urban growth and urban sprawl studies, could extend the range often used back to the beginning of Landsat image availability in the 1970s to the earliest available CORONA images in the year 1960. Besides, more and more aerial images become publicly available through platforms such as the USGS platform Earth Explorer and can help to further extend the range of years to the 1950s or even earlier. As for natural hazards, it is found that not for all types of natural hazards and not all countries CORONA imagery has been applied yet. However, the real value lies in combining both change detection of urban growth and natural hazards since urbanisation is ongoing and therefore, many cities are expanding their area into new hazard-prone areas such as riverbeds or mountains. CORONA imagery not only reveals growth into such areas but also provides a glance onto the landscape before urbanisation. This may help to identify former riverbeds, hills, erosion channels or

even former underground irrigation structures as shown by the examples in this article. Additionally, since there is an ongoing trend on urban research concerning disaster risk, it may also be worthwhile analysing sprawl into different types of topographic environments in compliance with studies on different patterns of vulnerability [103] of people, their buildings and infrastructure.

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Conflicts of Interest: The author declares no conflict of interest.

Appendix A

List of search terms used to identify literature: CORONA imagery CORONA image AND urban sprawl OR urban growth GAMBIT urban growth CORONA image urban growth hazard CORONA image urban sprawl hazard CORONA image urban sprawl natural CORONA image urban growth landslide CORONA image landslide, CORONA image flood, CORONA image wildfire, Incendios forestales bolivia historicos China satellite reconnaissance image CORONA satellite AND Santiago de Chile OR La Paz OR Yungay OR Qazvin OR Mount St. Helens digital elevation CORONA satellite digital surface CORONA satellite digital terrain CORONA satellite photogrammetry CORONA satellite

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