Article

Using Satellite Data to Analyse Raw Material Consumption in Hanoi, Vietnam

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Abstract: In this work, we provide an innovative route for analysing urban expansion and population growth and their link to the consumption of construction materials by combining satellite data with material consumption analysis within the Hanoi Province (Vietnam). Urban expansion is investigated with the use of landcover maps for the period 1975–2020 derived from satellite. During this period, artificial surfaces and agricultural areas have increased by 11.6% and 15.5%, respectively, while forests have decreased by 26.7%. We have used publicly available datasets to calculate and forecast the construction materials consumption and measure its statistical correlation with urban expansion between 2007 and 2018. Our results show that official figures for sand consumption are currently underestimated, and that by 2030, steel and sand and gravel consumption will increase even further by three and two times, respectively. Our analysis uses a new method to assess urban development and associated impacts by combining socio-economic and Earth Observation datasets. The analysis can provide evidence, underpin decision-making by authorities, policymakers, urban planners and sustainability experts, as well as support the development of informed strategies for resource consumption. It can also provide important information for identifying areas of land conservation and ecological greenways during urban planning.

Keywords: land cover; material consumption analysis; construction materials; cloud computing; machine learning

1. Introduction

Rapidly urbanising populations around the world are placing increased pressure on the environment, the process of land use planning and the management of resources [1–3]. An improved understanding of the speed and scale of development and the structure evolution of cities is therefore essential to assess the impacts of urbanisation and for the development of policies directed towards resource efficiency and sustainability. Reducing the impact of the human footprint on the planet is becoming a priority in the agendas of national and international institutions because it is recognized as critical to underpinning economic development, as proven by objective 11 (Sustainable Cities and Communities) of the United Nations' Sustainable Development Goals (SGDs; https://sdgs.un.org/goals).

These issues are particularly important for lower-middle income countries like Vietnam [4], which are growing rapidly in terms of their economies, population numbers and standards of living [5]. Vietnam's population increased at an average growth rate of 1.1% between 2007 and 2018 and this trend is almost double in urban areas like the Hanoi Province (1.9%) due to both migration and political interventions, as highlighted by the General Statistics Office for Vietnam (GSOV) [6], and explained in more detail in

Section 2. This growth increases the demand for natural resources, whether this is land, raw materials for the construction of buildings and infrastructure, water or energy. Of particular interest is the consumption of construction materials in urban development, because increasing supplies within a short timeline often puts a strain on the environment and stock, production and reserves available from the local mineral sector [7].

There are various methods available for monitoring resource consumption [8], such as life cycle assessment (LCA), material input per unit of service (MIPS), materials flow analysis (MFA), substance flow analysis (SFA), ecological footprint (EF) and even environmental impact assessment. The focus and purpose of different methodologies is quite diverse. For example LCA and MIPS are product-oriented, ecological footprint and environmental impact assessment are used to determine the ecological and environmental impacts associated with regions or processes and SFA is used to model material flows related to specific substances. None of the above methods find common use in urban planning to monitor and forecast material flows for assessing supply disruption, undertaking assessments of resource efficiency, or quantifying potential environmental impacts associated with resource extraction, processing, use and disposal.

Methods such as Material Flow Analysis (MFA) that focus on spatial and social units are used to develop a systemic understanding of the material distribution in the urban environment [9]. MFA is a data intensive process and is highly dependent on a combination of different datasets (e.g., building and road stocks, mineral production, population census, construction statistics, etc.), which are not always available, complete or regularly updated, especially at the regional or local scale.

Land Use/Land Cover (LULC) from Earth Observation (EO) satellite data can provide critical information for constrainting such required datasets and for a better understanding of the evolution and distribution of the built environment and of open-pit extraction sites where the required raw material is extracted [10]. Being high-volume, low-value products, many construction materials (e.g., aggregates) are relatively expensive to transport and thus they tend to be sourced locally and can result in visible impact on the landscape [11]. This makes supply issues in rapidly urbanising areas a risk but linking EO data and resource consumption provides an opportunity for sustainable urban growth strategies to be developed.

The use of satellite derived information has increased rapidly in recent years for studying urban growth phenomena [12]. This is due to the surge of freely available spaceborne imagery, such as Landsat-8 from 2008 and Sentinel-2 from 2015, followed by the advent of cloud-based computing platforms that provide rapid access to datasets on a planetary scale [13] and the adoption of Machine Learning (ML) classification techniques [14].

However, the integration of LULC satellite data with the quantification of stocks and flows of raw construction materials has not yet been widely explored.

This is particularly needed in the Hanoi Province where, despite the fact that mining plays an important role for the economy of the area in terms of the supply of construction materials, little is known about its attributes such as spatial extent, type, scale, status and socio/environmental impacts. A recent study [15] has already highlighted concerns related to the lack of a resource management strategy for the responsible extraction of construction materials. Given that they represent a non-renewable resource, unsustainable mining practices can cause negative environmental impact, excessive energy usage, and extreme landscape alterations.

LULC offers a new perspective to analyse the building stock with high spatial and temporal resolution and support sustainable urban development at the regional scale. However, many users of the wealth of spatial datasets on LULC changes largely miss the connection with the underlying economic, production, trade and consumption phenomena that drives the observed changes [16].

The aim of this study is to analyse the relationship between LULC and population- and economic-datasets during the 2007–2018 interval. Such a holistic approach provides

opportunities to quantify the consumption of resources associated with the past and current infrastructure development like transport units and buildings. This information enables national and local authorities to understand the volumes associated with the current use of construction materials and to plan and design effective policies and strategies for future extraction and use of mineral resources, reducing negative environmental impacts and ensuring the security of supply.

The paper is structured as follows: an overview of the study area is given in Section 2, along with an overview of previous studies in the area. The datasets and the methodologies used are described in Section 3 and the results are presented in Section 4. The discussion (Section 5) focuses on the benefits and limitations of the methodology, while the conclusions (Section 6) provide observations on the use of the approach for future planning policies.

2. Hanoi Province

Hanoi Province is located in the northern part of Vietnam, within the Red River delta plain and nearly 90 km from the South China Sea. It encompasses Hanoi, the capital and second largest city of Vietnam with 7.4 million inhabitants [6], and represents the commercial, cultural and educational centre of Northern Vietnam. It is ranked as the third province of the country in terms of GDP per capita [17], behind Bà Rịa-Vũng Tàu and Ho Chi Minh City.

In 1986, the Government of Vietnam implemented economic reforms known as *Doi Moi* (renovation) that supported private ownership, encouraged deregulation and foreign investment [18]. Since then, the economy of Vietnam has achieved rapid growth in agricultural and industrial production, construction and housing, exports and foreign investments. Each of these have resulted in momentous landscape transformations as consequence of rapid urbanization [19].

In 2008, the administrative boundary was enlarged to more than three times its previous size and the Hanoi Province now encompasses an area of 3342.92 km^2 and 30 subdivisions (29 districts and 1 town; Figure 1). Three years later, Hanoi's lead planners (Hanoi People's Committee and the Vietnamese Ministry of Construction), together with international consultancies, developed the Hanoi Capital Construction Master Plan (HCCMP). The latter is a framework to guide the city's sustainable development to 2030 in sectors like transportation, access to clean water, sanitation and housing and to establish a socio-economic vision until 2050 [20]. Under the HCCMP, about 28% of the natural land in 2011 will be converted to built-up land to accommodate the rising urban population of Hanoi, projected to increase to ~9.2 million by 2030 [21]. As a result of the higher demands for housing and infrastructure, the amount of land that is built upon in the Province is projected to rise sharply, by almost three times, from 463.4 km^2 in 2011 to more than 1,295 km^2 by 2030 [22]. Consequently, there is an urgent need for urban planners and local authorities to monitor and regulate the upcoming urbanization and its environmental impact. The increase in urban development will indeed require additional quantities of raw materials, such as construction aggregates, cement, bricks and steel, whose extraction and manufacture can have negative effects on the surrounding environment. In addition, if an adequate supply of materials is not maintained, the ability to implement planed urban growth can be negatively impacted.

This increased demand for raw materials in Vietnam is already evident as the production of aggregates within Vietnam increased >60% between 2007 and 2018 (GSOV, 2018) [23].

The increasing demand for raw materials is already having negative consequences to the environment (e.g., pollution, riverbank erosion). For example, the extraction of sand, one of the primary materials used in numerous construction products, has led to informal mining activities [24] due to the slow response from national and local institutions to regulate the rights and obligations of the mining companies, the insufficient and

inconsistent implementation of the legal framework and lack of good mining practices [25].
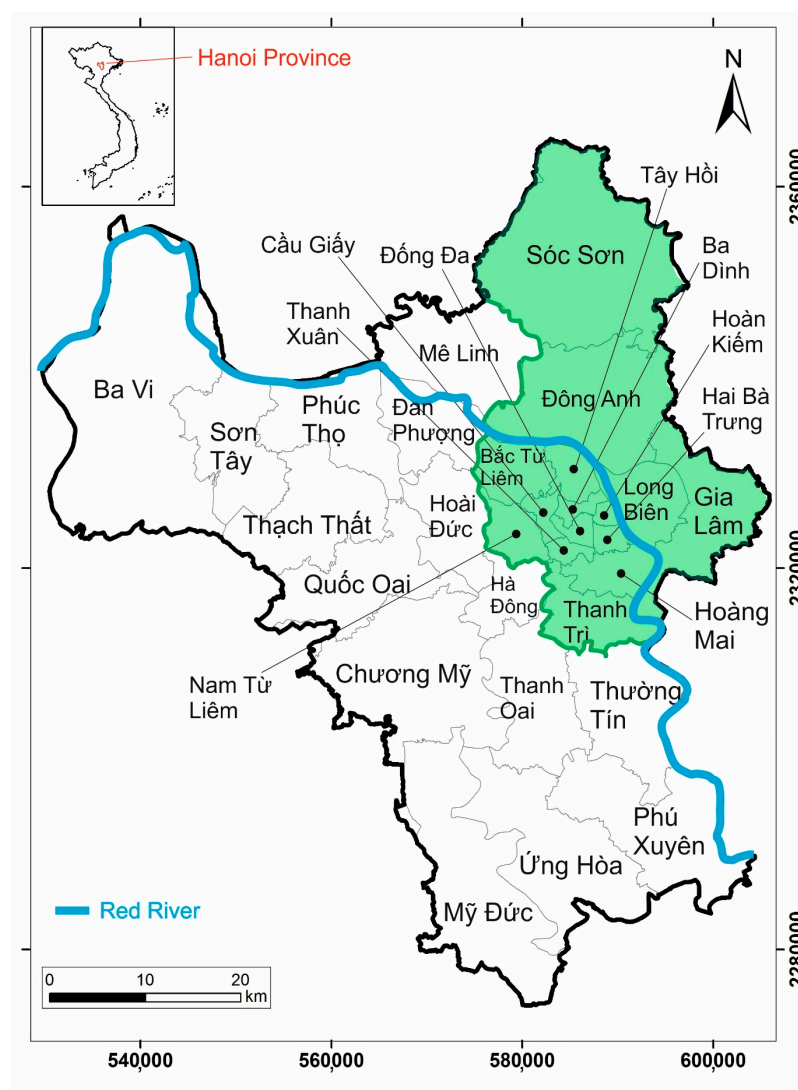

Figure 1. Location map of the main administrative boundaries of the 30 districts within the Hanoi Province with an indication of the pre-2008 Hanoi Province in green and the newly added area in white, previously known as Ha Tay Province. Coordinate system: WGS1984, UTM Zone 48N.

Despite the availability of datasets on production, trade and demand for construction-related mineral commodities (on a national level) and population, no study has correlated this information with Earth Observation datasets in Hanoi so far.

In Reference [26], information has been used to assess the current and future (up to 2030) material supply and demand, based on measured and predicted population growth, without including local data on the building stock, which was not available at the time. Recently, Reference [27] defined an MFA by not considering data on land cover but assumptions based on generic information about the total domestic net floor area derived from planning documents and expert knowledge without accounting for the different types of roads and buildings within each of these categories and the impact of informal mining activities. Neither of these studies considered the spatial aspects related to raw material consumption for Hanoi.

Similarly, environmental information, mainly represented by LULC maps [28–31], has not been analysed in connection with socio-economic driving factors, but to quantify changes in built-up areas.

We therefore aim to integrate, for the first time, LULC maps with existing datatsets available on population and housing, and with new calculations for material consumption, for a better understanding of the environmental and economic changes characterizing the expansion of the built environment in the Hanoi Province.

3. Materials and Methods

The analysis of the urban growth described in this paper has considered the extraction of LULC maps from satellite data (Section 3.1) and consumption data from population, housing, trade, supply and demand data (Section 3.2). Section 3.3 details how we have finally combined the two datasets.

3.1. Satellite Data

In this study, we used the Google Earth Engine (GEE) platform to access a total of 286 medium resolution (MR) satelite imagery for ninteen different years across the period 1975–2020. Cloud free images acquired on a single date were considered to derive the LULC maps and when the whole province could not be covered, a mosaic of different MR images across different dates within the same year was created (for more details on the input images used, see Supplementary Materials S1). This method allows for the production of spatially contiguous, cloud and haze-free, temporal series of surface reflectance composites of satellite data. If the mosaic did not allow the whole Province to be covered for a particular year, that year has been exluded in this work.

The MR dataset includes (for a detailed list of the satellite imagery used, see Appendix A):

- 18 Sentinel-2 (S2) acquisitions, from 2020 to 2015 with 10 m, 30 m and 60 m pixel spacing according to the thirteen spectral bands (from visible, RGB, to short-wave infrared). The S-2 imagery used corresponds to the Bottom-Of-Atmosphere (BOA) corrected reflectance. Cloud-free images were obtained by using the S2 QA (Quality Assurance) band to identify the presence of dense and cirrus clouds (ESA, 2020) [32].
- 2 Landsat-8 (L-8) images for the years 2014 and 2013 with 30 m pixel spacing along the RGB spectrum. The L-8 imagery used have been atmospherically corrected using LaSRC (USGS, 2019a) [33] and includes a cloud, shadow, water and snow mask, as well as a per-pixel saturation mask.
- 264 Landsat-5 (L-5) images for the period 2012 to 1986 with 30 m pixel spacing along the RGB spectrum. The L-5 imagery used have been atmospherically corrected using LEDAPS [34], and include a cloud, shadow, water and snow mask, as well as a per-pixel saturation mask.
- 2 Landsat-2 (L-2) for 1975 with 60 m pixel spacing along the Green, Red and Near-Infared spectrum. The L-2 imagery used belongs to the Tier 1 collection whose Digital Numbers (DNs) represent scaled, calibrated at-sensor radiance.

LULC maps have been processed in GEE computing platform using the Classification and Regression Trees (CART) classifier [35], a supervised and non-parametric ML classification algorithm often used for LULC analysis for its high accuracy and flexibility [36]. CART, unlike logistic and linear regression, does not develop a prediction equation, instead data are partitioned along the predictor axes into subsets with homogeneous values of the dependent variable, a process represented by a decision tree that can be used to make predictions from new observations [37]. At each node of the tree, one attribute of the data that most effectively splits its set of samples into subsets enriched in one class or the other is selected. BOA surface reflectance values have been used to train the classifier over user-made training sample sites. The data were randomly divided into training and validation samples with a proportion of 80% and 20%, respectively.

As the imagery was acquired at different times of the season across the years, each year was given its own independent training samples in order to overcome issues such as seasonal changes of land surface (e.g., phenology) that can alter the CART classifier in each image collection.

Given the different resolutions across the sensors, the training sites were assigned to a single layer encompassing the five main (level-one) land cover categories identified in the Corine nomenclature guidelines [38]: artificial surfaces, agricultural areas, forest and semi-natural areas, wetlands and water bodies (Table 1). In addition, the changes in land use types over time were detected and analysed from the resulting maps.

Table 1. The five categories of Land Use/Land Cover (LULC) classes used in this study.

Classes	Include
Artificial Surfaces	Urban fabric; industrial, commercial and transport units; mine, dump and construction sites
Agricultural areas	Arable land; permanent crops; pastures
Forest and seminatural areas	Forest areas and open space with little or no vegetation
Wetlands	Inland wetlands; paddy fields
Water bodies	Rivers; artificial canals; lakes

Dense and evenly distributed validation samples covering urban areas and non-urban areas were needed to assure the fairness and rationality of the validation. The validation points have been used to build a confusion matrix through which the overall accuracy of our classification has been assessed [39].

The different time intervals across the satellite data did not allow a maximum a posteriori Markov Random Field analysis (MAP-MRF) [40] to be performed to improve the overall accuracy. However, a post-classification reanalysis of the LULC data has been done by considering the pixel trajectories. The latter provides the complete sequence of land cover classes over the analysed period of time for every pixel [41]. It consequently uncovered additional information on the time and type of land cover transition, which can include single-steps (only one land cover change) or multiple-steps (more than one land cover change). It has been used as a tool to remove the occurrence of illogical or transient land-cover transitions in resulting land-cover change (for more details on post-classification, see Supplementary Materials S2). For example, a transition from urban to wetlands or to forests is considered illogical as it is unrealistic in most situations and would definitely not occur in a short time period.

3.2. Construction Materials Consumption Data

Five construction materials have been considered in this study: crushed rock aggregates, sand and gravel, cement, steel and bricks.

The publically available data at a province level resolution has been used to analyse past construction material demand and supply in Hanoi, following the so-called 'top-down' approach [42]. Additional information has been extracted from downscaling data from the national level statistics to province level, albeit based on some assumptions. These calculations can then be projected forward using forecasted information for population growth. The datasets utilised in the analysis of current and future construction materials for the Hanoi Province in this study were:

- Population in numbers of persons for Vietnam as a whole and the Hanoi province by from 1995 to 2018. To ensure consistent comparison across all years, the population of what was Ha Tay Province prior to 2008 (see Figure 1) was combined with the data for the Hanoi Province in all years [6].

- Projections of future population from 2019 to 2030 [43]. These projections are based on component analysis of the 2014 Intercensal Population and Housing Survey and take into account parameters such as age, mortality fertility and migration.
- Area of housing floors constructed per year in Hanoi in 2010 and from 2013 to 2017 (all the years available [6]).
- Mineral production statistics for Vietnam [23]. Data for aggregates are given in thousand cubic metres; therefore, some assumptions have been made to convert these figures into kg and the following densities were applied: crushed rock 2,500 kg/m^3 and sand and pebbles 1,640 kg/m^3. The densities applied were based on those the authors have used for previous work and were derived via consultation with the UK aggregates industry [26]. From 2007, information on the construction material production is consistent, so this year has been selected as the start year for our analysis.
- Mineral trade statistics for Vietnam taken from the UN Commodity Trade Database, a database of international trade statistics collated by the UN. Vietnam only report monetary value for trade so the imports and exports, reported by other countries in kg, to and from Vietnam were used instead [44]. We considered the 2007–2018 time interval only.

Calculations of apparent consumption were made for each of the five commodities using Equation (1):

$$AC = P + I - E \pm SC \tag{1}$$

where *AC* = apparent consumption, *P* = production, *I* = import, *E* = export and *SC* = stock change. Units are expressed as tonnes. Data for stock changes are not normally available, but over long time trends, it can be assumed that positive and negative stock changes balance each other out and effectively become zero.

The calculation for apparent consumption for sand and gravel was made more complex by the fact that reported sand data are expected to be underestimated due to issues with informal mining that is taking place along the Red River Delta where it is dredged from the river bed and banks [24].

We estimate that sand production and consumption was much higher than reported figures. As a result, cement has been used as a proxy for sand to predict future consumption using the methodology of sand production outlined by the UN Environment Programme (UNEP) [45], because there is a clear relationship between cement and sand in the production of concrete, the main use for both commodites in construction. This is not ideal, however, as sand is also used (in lesser quantities) in non-concrete applications such as mortar, road construction, construction fill etc.

The per capita consumption of construction materials will vary across a country like Vietnam because the type and quality of housing is likely to vary and the amount of industrial activity will be different. However, the assumption that the per capita consumption is similar across Vietnam amd allows the national level minerals production and trade statistics to be applied to a single province. It also provides a method by which predictions of future consumption of construction materials can be made because of the availability of data for expected population growth.

The production accounts for how the rate of urbanization highly influences the per capita consumption, as the more people move into urban centres, the more demand for housing, transport and other infrastructure accelerates.

For the projected figures, the average annual growth rate of consumption per capita in kg/person was calculated by applying the average percentage change for a time range with recorded data (9 years, 2008 – 2016) to the previous year's consumption per capita. This per capita figure was then factored up using the GSOV and UNFPA [43] figures to calculate consumption for Hanoi for each year from 2019 until 2030, the last year for which population forecast is available [21]. This process is shown in Equation (2):

$$PCH_i = CPC_{i-1} + \left(\frac{\sum_i^n PCCPC}{n \times 100} \times CPC_{i-1}\right) \times HP \tag{2}$$

where PCH = projected consumption for Hanoi for the ith year, n = total number of years, CPC = consumption per capita for Vietnam, $PCCPC$ = yearly percentage change in per capita consumption and HP = projected population for the Hanoi Province.

This top-down approach (Figure 2) is based solely on material consumption and population statistics and does not account for the complexity of our urban systems. For example, it does not account for changes in the building stock, in social trend and preferences, in transport infrastructure and other components of the urban environment, which may differentiate per capita consumption to the projection made. However, despite these limitations, the method provides a useful broad-brush approach for analysing Hanoi's expansion in the recent past and for forecasting the quantities of materials that may be needed to support future growth in line with the city expansion and the population growth.
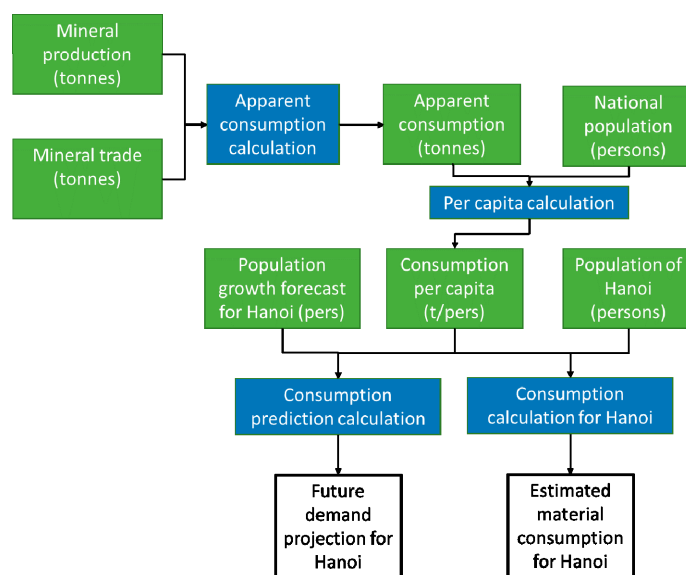

Figure 2. Schematic diagram explaining the steps involved in the top-down future supply and demand balance calculation.

Despite information in the area of housing, floors constructed are only available for a few years at the city level, and these data were included in the analysis because they provide an additional type of information to population growth by illustrating changes that may affect the styles of building and population density. Both of these have a direct impact on material consumption.

3.3. Method for Combining Datasets

Combining the satellite data (spatial) with material AC, population and construction of housing floors data firstly requires that datasets be converted to the same spatial or temporal reference system. The material apparent consumption and the other data mentioned in Section 3.2 are not available as a geospatial dataset and consequently only a temporal comparison has been possible.

To enable a correlation over the overlapping time interval, the following datasets have been analysed for every year available:

- Areas of artificial areas (km²) vs population (in thousand persons) between 2010 and 2017 (excluding 2011 and 2012).

- Areas of artificial areas (km²) vs area of housing floors constructed (m²) between 1996 and 2018 (excluding 1997, 2002, 2010, 2012 and 2016).
- Areas of artificial areas (km²) vs the AC of the five construction materials (t) between 2007 and 2018 (excluding 2010, 2012 and 2016).
- Population (in thousand persons) vs the AC of the five construction materials (t) between 2007 and 2018.
- Housing floors constructed (m²) vs the AC of the five construction materials (t) between 2010 and 2017 (excluding 2011 and 2012).

The statistical strength of these correlations has been expressed by the R-squared (R^2) value. R^2 is a statistical measure of fit that indicates how much variation of a dependent variable is explained by the independent variable in a regression model.

4. Results

4.1. Land Use/Land Cover (LULC)

The LULC maps associated with the urban expansion are summarised in Figure 3. The whole collection of LULC maps for every class is provided in Supplementary Materials S3.
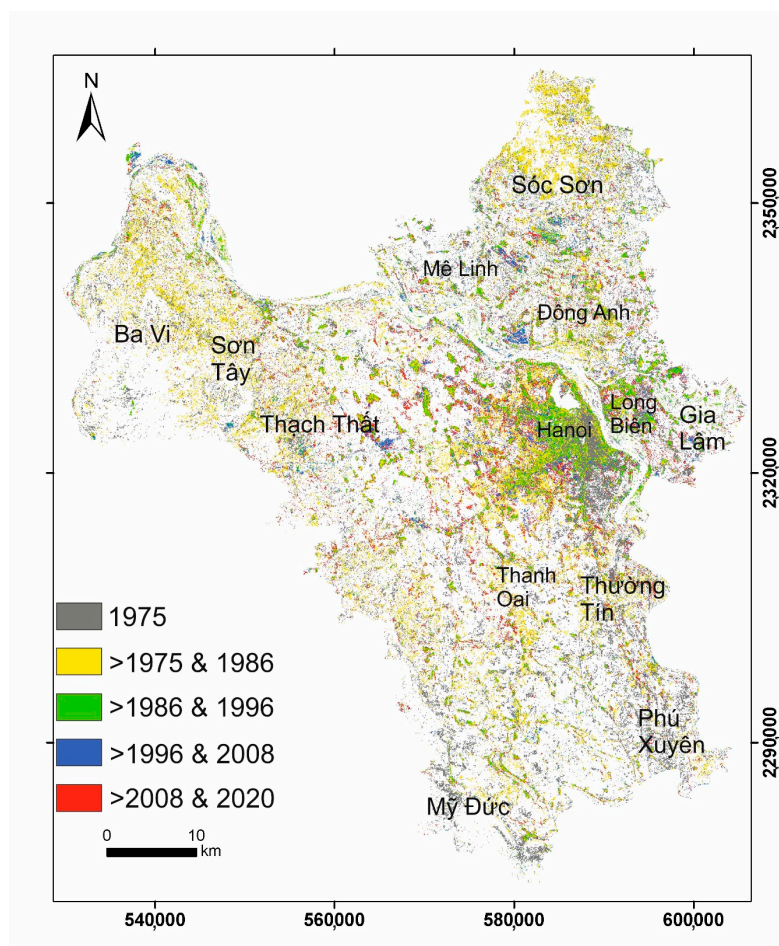

Figure 3. Expansion of the artificial surfaces area within the Hanoi Province across five decades. Starting from 1975, each colour corresponds to the extension of artificial surfaces at the end of each decade, approximatively. Coordinate system: WGS1984, UTM Zone 48N.

The CART supervised classification was an iterative process that involved visually identifying misclassified areas, increasing the number of samples, and subsequently re-running the classifier and accuracy assessment. This step was necessary because of the

heterogeneity of the land cover classes in the study area and their quick changes over time. On average the accuracy of the LULC maps, after the correction detailed in Supplementary Materials S2, is 82% with higher values (up to 98%) in S-2 and VHR imagery and lower values (down to ~70%) with Landsat data (see Appendix A). An average increase of ~2% in the overall accuracy is due to the post-classification reanalysis. Regardless of the sensors, the water bodies' class has the highest accuracies over the years (Table 2).

Table 2. Accuracy assessment of the LULC classification for the Hanoi Province for each class over the different years.

Class	Average Accuracy
artificial surfaces	0.86
agricultural areas	0.81
forest and seminatural areas	0.86
wetlands	0.74
water bodies	0.99

In general, the LULC maps reveal that Hanoi Province is a largely agricultural dominated landscape and this is uniformly distributed throughout the whole Province. The area of artificial surface has expanded from that seen in 1975, especially towards the west and south, along with the rise of small new conurbations in Thach That and Chuon My and the expansion of the airport area in Soc Son. Hanoi's urban spatial development is based on a model that is shaping many emerging cities in Asia, and includes a central core and small and medium satellite urban areas connected by a network of ring roads and radial axes.

Despite the reduction in forest cover, there are four main forest areas that still characterize the edge of the Province (Supplementary Materials S3): the Ba Vi national park, the Khu Sinh Thái Thiên Phú Lâm ecological park and two forests in Mỹ Đức. Most of the forest clearance is due to conversion to agricultural areas in the central part of the Province and to new extraction sites or urban developments in Ba Vi and Sóc Sơn districts.

During the Sentinel-2 period (2015–2020), mining areas represent ~3% of the artificial surfaces areas, most of them are located along the river courses. A significant difference in the spatial density of mines is observed between Mỹ Đức District (lower) and the adjacent Hòa Bình Province (higher).

Temporally, the largest change in LULC is related to the increase in artificial surfaces from 9.8% of the Province in 1975 to 21.4% in 2020 at the expense of forest and seminatural areas whose size has fallen from 32.5% in 1975 to 5.8% in 2020. The increase in artificial surfaces between the beginning of the 1990s and 2010s is >200km^2 in agreement with values reported in [28] for the same interval. Agricultural areas have always represented the majority of the LULC with a sharp increase from 51% in 1975 to >70% during the 1980s and 1990s and then a gradual decline to 66.5% in 2020 (Figure 4).
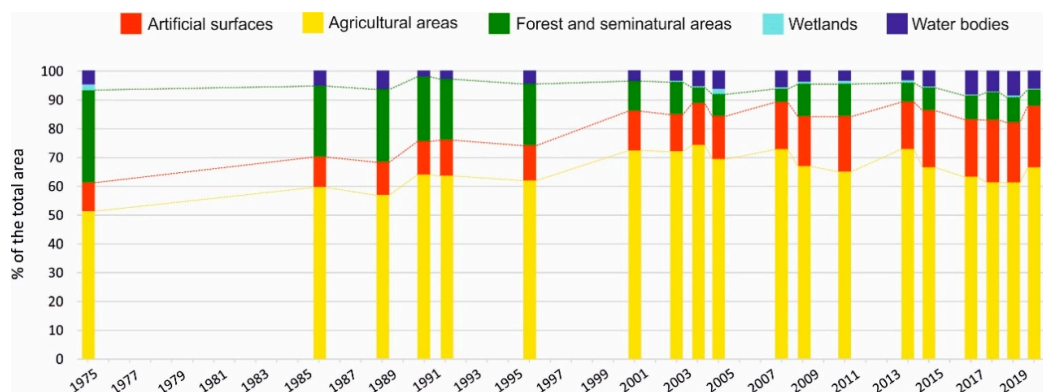

Figure 4. Percentage of the LULC size for each class within the Hanoi Province between 1975 and 2020.

Based on the trajectories analysis, between 1975 and 2020, only 18% of the Hanoi Province has not changed land cover and this is mostly represented by agricultural areas. Wetlands are not surprisingly ephemeral features so no pixel has been continuousoly classified in this category during the last 45 years. The low number of illogical transitions in the trajectories (<0.004%) confirms the high quality of our LULC changes (Supplementary Materials S2).

Around 37% of the Hanoi Province trajectories can be considered to be a stable one-step change, meaning that, during the time periods analyzed, only one transition between different land covers has occurred. Additionally, 45% of LULC involved two or more changes, meaning land cover had changed from one class to a second class which has successively changed again. This highlights a very dynamic environment within the Hanoi urban catchment.

The two most common one-step changes are from forest to agricultural areas (for a total of ~120 km²), especially between 1996 and 2001, and from agricultural areas to artificial surfaces (for a total of ~25 km²).

The combined analysis of the LULC trends and trajectories shows that the growth of the artificial surfaces (or simply urban growth) occurred at a yearly average rate of 0.26% across the 1975–2020 period. This expansion has mainly occurred at the expense of forests and seminatural areas until the 2000s and of agricultural areas afterwards.

4.2. Past and Future Consumption of the Construction Materials

The projections of material consumption for the selected construction materials are shown in Figure 5. This shows forecast consumption (vertical axis) for Hanoi to 2030. Confidence intervals, with a significance level of 0.05, are provided for the forecasted values to assess our prediction accuracy. Due to uncertainties around sand and gravel production figures, both the reported data for consumption and the projections made for estimated consumption using cement as a proxy to 2030 are plotted.

The AC calculated in this work is 1.8 times higher than the consumption reported in the official figures for 2018 and is projected to increase to 2.4 times by 2030.

The graphs indicate that, for all the commodities considered within this study, considerable increases in demand are to be expected.

Based on the historical data, the highest increase (relative to 2007) is observed for steel (+286%) followed by crushed rock (+106%), while the forecasted increase in AC for bricks is much smaller (+13%).
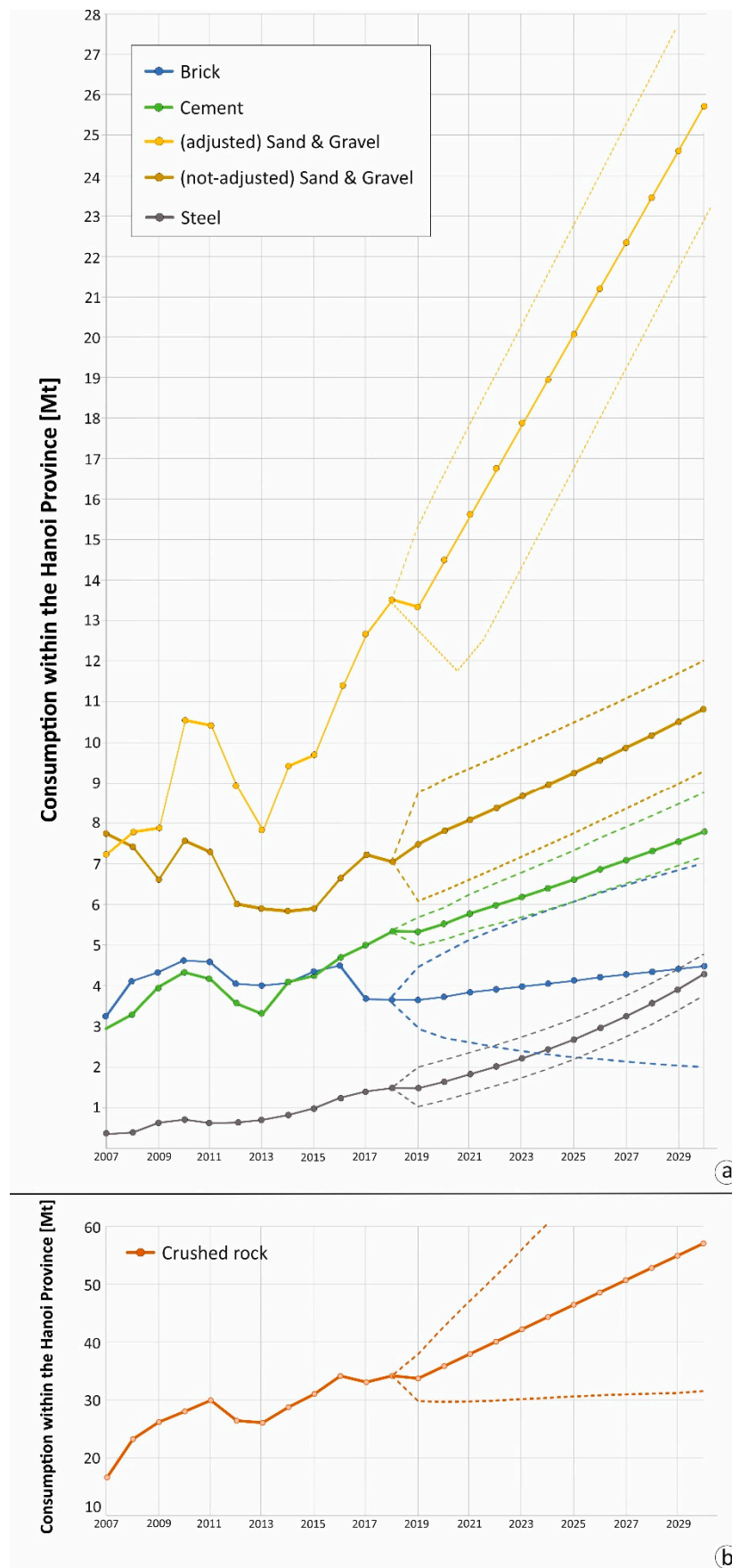
Figure 5. Projections and confidence intervals (dotted lines) for consumption of construction materials within the Hanoi Province for bricks, cement, (adjusted) sand and gravel, (not-adjusted)

sand and gravel and steel (**a**) and crushed rock aggregates (**b**). Note: a different scale for the consumption projection of crushd rock is used.

For each material, the predicted rise in forecasted demand to 2030 is summarised in Table 3. This analysis shows that for some of the commodities demand is likely to more than double over the next 12 years. For materials where supply shortfalls are already an issue, this increased demand will form a serious challenge in sourcing raw materials. There is a clear need for pro-active strategies and planning to maintain supply and to avoid negative effects, such as unlicensed extraction.

Table 3. Forecast material demand for the Hanoi Province.

Construction Material	Forecasted Demand in 2030 Compared to 2018 Data
Cement	Increase 1.4-fold
Steel	Increase 3-fold
Bricks	Increase 1.2-fold
Crushed rock	Increase 1.6-fold
Sand & gravel (adjusted)	Increase 2-fold
Sand & gravel (not-adjusted)	Increased 1.5-fold

4.3. Combination of the LULC Maps and Construction Material Analysis

The correlation scatterplots (Figure 6) revealed a strong positive correlation between the areas of artificial surfaces and population change ($R^2 = 0.73$). All artificial surfaces are the result of human actions and therefore it is logical that an increase in population will inevitably result in a larger area that is artificial rather than natural. Conversely, the R-squared between artificial surfaces and the construction of housing floors was weaker ($R^2 = 0.015$).

This suggests that the increase in artificial surfaces is connected to the rising population, but the increase in artificial surfaces is not entirely due to the construction of housing. The latter is not unexpected because the artificial surfaces category includes a wider range of land uses than just housing, such as roads, industrial or commercial premises and also mineral extraction sites.

The data for housing floors construction also relate to new housing and do not include the existing housing stock.
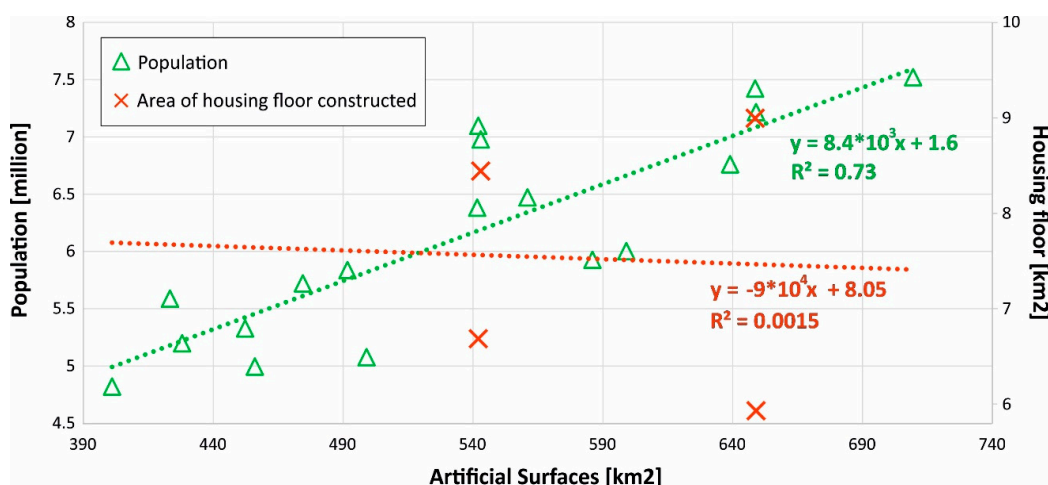

Figure 6. Correlation between artificial surfaces vs population (green) and housing floor construction (red). Linear fitting and R^2 values for each variable are provided.

Artificial surfaces have the highest R-squared correlation with the apparent consumption of cement, steel, crushed rock and the adjusted sand (Figure 7) with R^2 between 0.51 and 0.78.

Almost no correlation was observed with bricks ($R^2 = 0.03$) and non-adjusted sand ($R^2 = 0.08$). The former indicates that the amount of artificial surface in Hanoi has little effect on the quantities of bricks produced. This suggests that much of the construction taking place in Hanoi is being carried out with concrete instead of bricks and this is further supported by the strong correlation between artificial surfaces and crushed rock, cement and (adjusted) sand. The weaker correlation with non-adjusted sand data suggests a possible under-reporting of sand production in these figures.
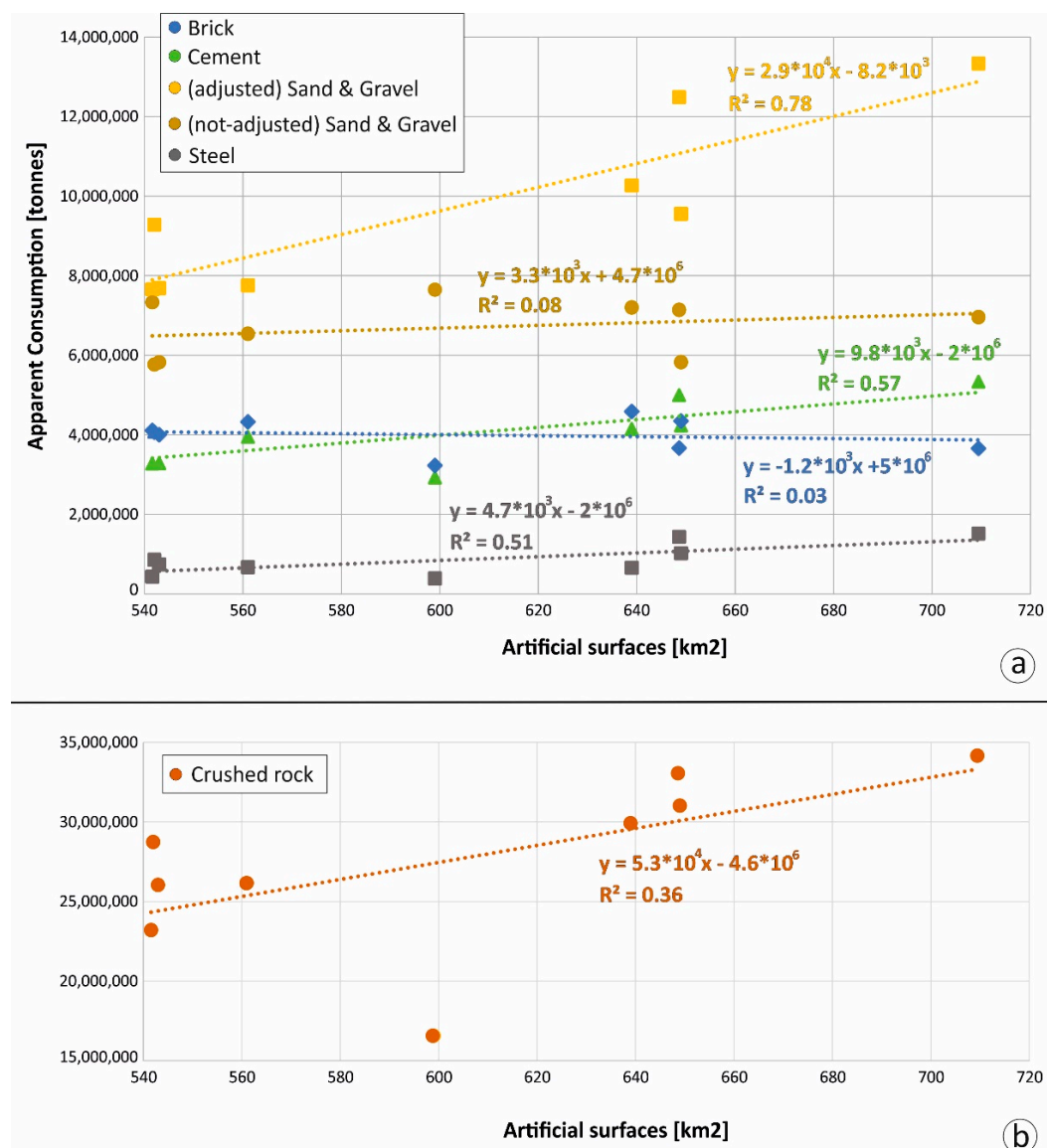

Figure 7. Correlation between artificial surfaces and AC of bricks, cement, (adjusted) sand & gravel, (not-adjusted) sand and gravel and steel (**a**) and crushed rock aggregates (**b**). Note: a different scale for the consumption projection of crushd rock is used. Linear fitting equations and R^2 values for each variable are provided.

The slope of these R-squared correlations reveal that, for every additional km^2 of artificial surfaces created, ~9.8×10^3 t of cement, ~4.7×10^3 of steel and ~2.9×10^4 of (adjusted) sand and gravel are needed.

The regression analysis using population as dependent variables (Figure 8) revealed that population growth has the strongest relationship with apparent consumption of cement, steel, crushed rock and sand and gravel (using the adjusted figures).
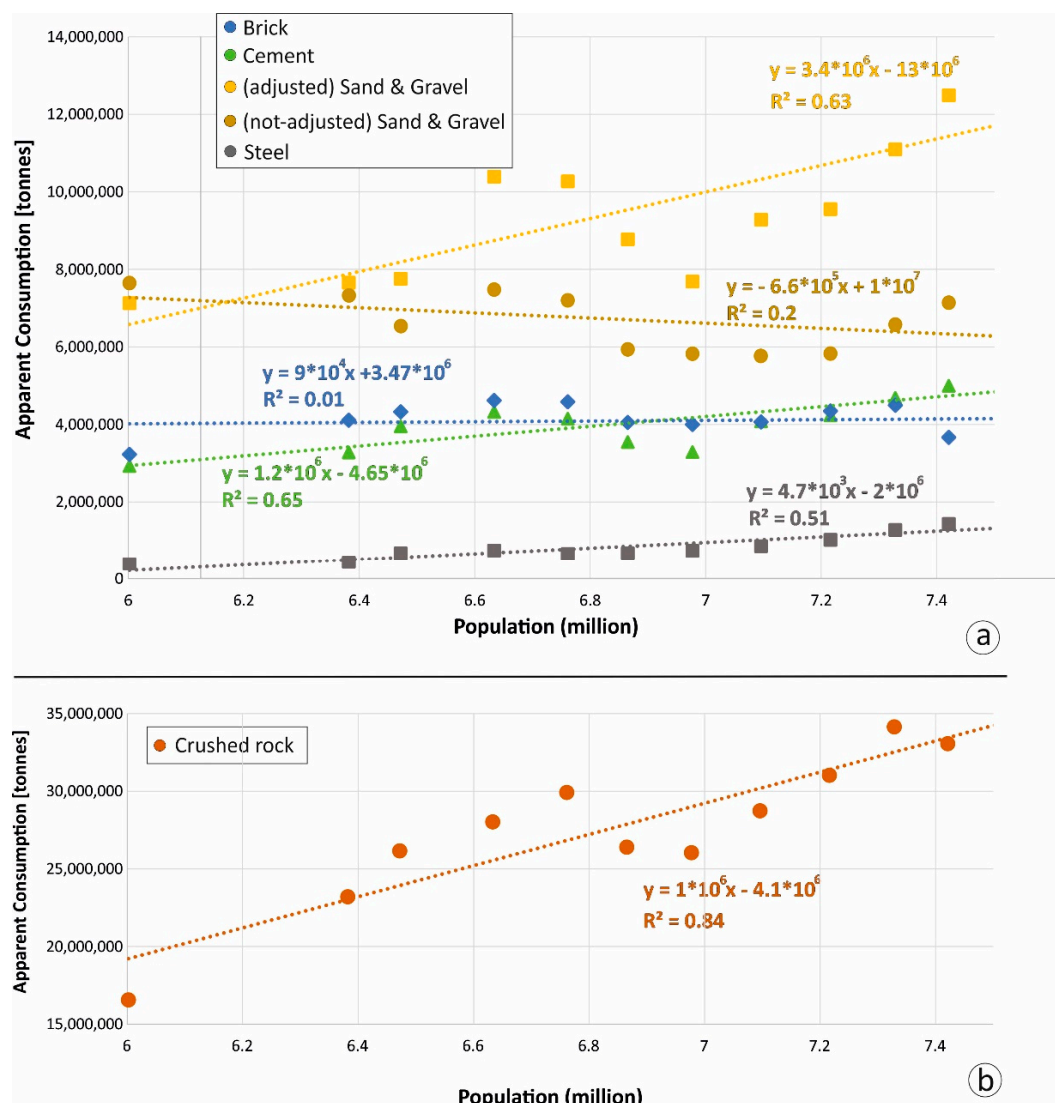

Figure 8. Correlation between population and AC of bricks, cement, (adjusted) sand & gravel, (not-adjusted) sand & gravel and steel (**a**) and crushed rock aggregates (**b**). Note: a different scale for the consumption projection of crushd rock is used. Linear fitting equations and R^2 values for each variable are provided.

These relationships have R^2 between 0.63 and 0.84. A low correlation is observed between population and AC of bricks and between population and *AC* of (not-adjusted) sand and gravel.

Positive relationships between apparent material consumption and population are to be expected because as the population in a city grows more construction of housing and infrastructure is required, which is inveitably reflected in the increasing area of artificial surfaces (see Figure 6).

Conversely, the areas of housing floors constructed [6] has a poor correlation with the AC of all the construction materials (Figure 9). The housing floor constructed per person has doubled from 44m^2 per person in 2010 to 93m^2 per person in 2018, a value much higher than the population increase during the same time interval (+13%). This suggests that housing is not the primary driver for material consumption over the time period for which data are available. This is not wholly unexpected because the

expanation of the city region will also include other types of construction, including new roads, railways and other infrastructure to support the population growth, as well as commercial and industrial buildings.
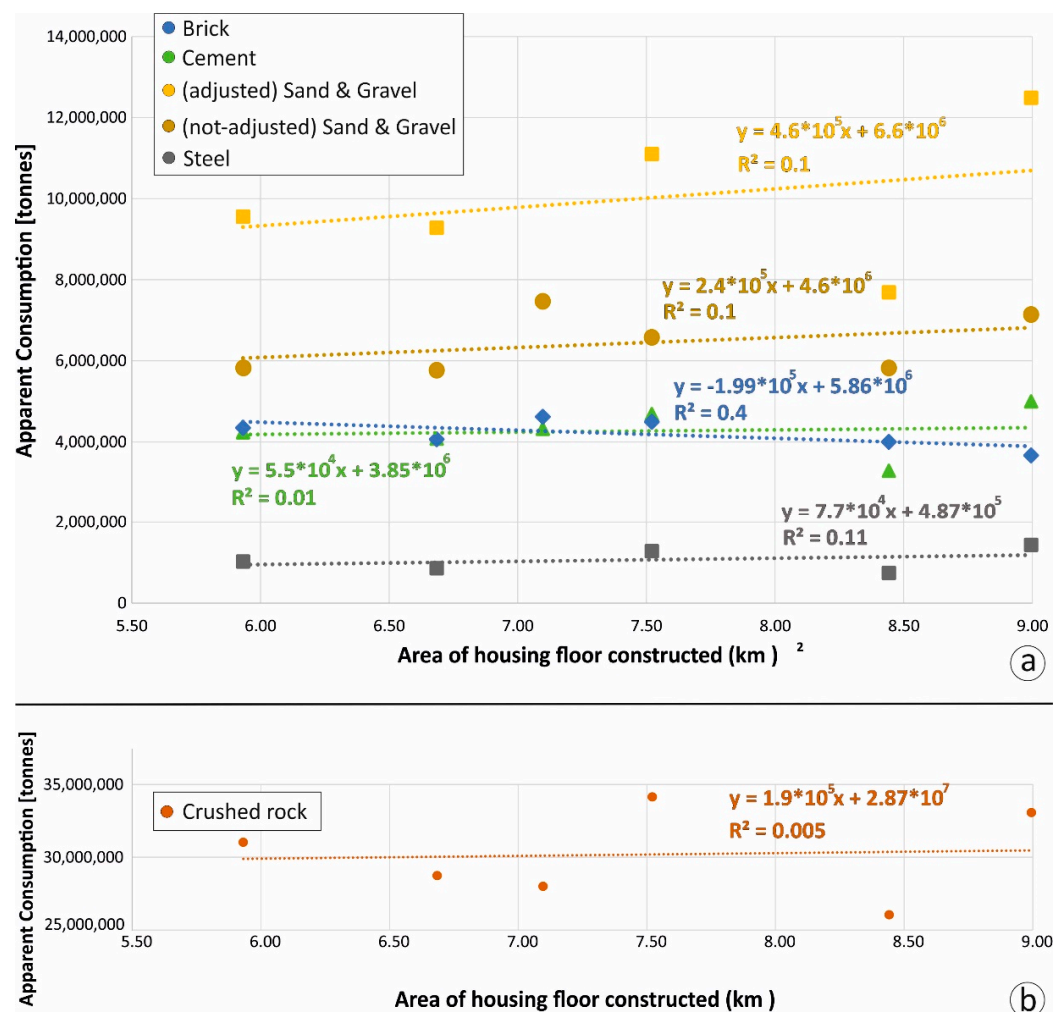

Figure 9. Correlation between the area of housing floor constructed and AC of bricks, cement, (adjusted) sand & gravel, (not-adjusted) sand and gravel and steel (**a**) and crushed rock aggregates (**b**). Note: a different scale for the consumption projection of crushd rock is used. Linear fitting equations and R^2 values for each variable are provided.

In this case the relationships have low R^2 (never exceeding 0.14) or a negative slope (bricks), which means that housing floor construction is not an indicative parameter for deriving AC of construction materials.

5. Discussion

We presented a method for combining mineral consumption and population statistics with satellite data in the Hanoi Province. The methods rely on quick access to EO databases, supervised classification of LULC maps followed by comparison with AC data derived from socio-economic datasets.

Due to economic development and administrative extension, Hanoi has experienced considerable changes in land cover, which are mainly driven by urban expansion, leading to an increase in residential, industrial and agricultural areas. Population growth, economic development and policy reform have played important roles in driving all of these changes.

Traditionally, data on urbanisation has come from census counts and population surveys, which are published infrequently, vary in terms of resolution and precision, and are subject to the availability of resources and the capacity to acquire reliable data [46]. Significant progress in the availability of remotely sensed data, ML techniques and cloud-based computing platforms have now added the capability to analyse the rate and pace of urbanisation in relationship with census datasets.

While the decadal satellite-derived maps present gaps, especially in the 1970s and 1980s due to lack of cloud-free acquisitions, the land cover change analysis encompasses sufficient information to map the Hanoi city expansion over the last 45 years.

Our findings show that most of the land cover changes involve deforestation to agricultural areas and, to a lesser extent, from forest to artificial surfaces (including mining) until the 2000s.

Thereafter, further temporal analysis of land cover changes and the LULC trajectories show a gradual shift to mainly the conversion of agricultural areas into artificial surfaces.

A reduction in agricultural areas at the same time as population is increasing in the city suggests that agricultural produce must be coming from further afield to feed people in Hanoi.

Compared to land cover changes observed worldwide, the average urban growth rate for Hanoi (0.26%) extracted between 1975 and 2020 is in line with urban growth rates observed between 1986 and 2010 in western world cities like Portland (USA), Prague (Czech Republic) and Frankfurt (Germany) but still below the rates (≥1.4%) of major Asian cities like Tianjin (China), Seoul (South Korea) and Bangkok (Thailand) [10,47]. The Hanoi urban growth rate is also below the rate of the largest city of Vietnam, Ho Chi Minh (0.94%), observed between 1990 and 2010 [48].

At this pace, Hanoi's artificial areas will be at ~850km^2 by 2030, below the target of 1295 km^2 of constructed land expected by the HCCMP, which includes five new satellite towns (Hoa Lac, Son Tay, Xuan Mai, Phu Xuyen and Soc Son) that are only partially developed in 2020.

The resolution of the satellite imagery is still not sufficient to characterize and quantify the building stock (e.g., residential, commercial) for a full MFA, but it is sufficient to characterise the past and current consumption of construction materials and to analyse their future demand. Higher resolution data will be needed to disentangle the different types of construction within the building stock and transport infrastructures, which at the moment are all included in the artificial surfaces class.

Similarly, we do not have enough information on the local geology or mine databases to separate the different types of materials extracted from the mines mapped in the Hanoi Province. Bringing this type of information into the analysis would allow for an understanding of how the mineral extraction industry can meet the demand on construction going forward.

Mining plays an important role for the economy of the Hanoi Province. However, little is known about its attributes, such as area, type, scale, and current status as well as socio-environmental impacts. The large extension of small-scale mining raises a concern regarding its socio-environment impacts for the Hanoi ecosystems and for local people, since it does not always follow environmental protocols [15].

The forecasted material consumption shows that, in 2030, crushed rock aggregates and sand and gravel will be the most required commodities by far (~57 Mt and ~26Mt respectively) and steel will be the material with the highest increase in usage (three times more than its use in 2018). This is perhaps unsurprising given the reliance on both concrete (the main component of which is aggregates in the form of sand with crushed rock or gravel) and steel in modern urban development.

Whilst steel, due to its high value, is an internationally traded commodity, sand and gravel represent a high-bulk and low-value commodity. Sand and gravel are therefore normally sourced within tens of kilometers from the point of consumption, which means

that the future increase in its AC will likely result into additional land cover changes within the Hanoi Province.

Additionally, the forecast identifies a huge volume of sand and gravel needed over the next 10 years in an already stressed market [26]. If sand and gravel cannot be supplied locally, this increasing demand can potentially outstrip the supply and result in a shortage. This might cause delays in construction, economic difficulties as a result of volatile prices and development targets to be missed.

The comparison of LULC and *AC* of construction materials presented in this work enables the characterisation of the spatio-temporal patterns of material metabolism for the infrastructure development. More importantly, it facilitates the investigation of the correlation between material utilisation, socio-economic development and environmental impact on a more refined level so that effective policies could be derived for sustainable infrastructure planning and environmental management of the HCCMP.

We considered a top-down approach made of a total of 20 correlations between artificial surfaces, population, housing floor constructed and *AC* of construction materials, which revealed the following main points:

- A clear correlation between the growth of population, artificial surfaces and *AC* of (adjusted) sand and gravel, cement, steel and crushed rock. The strength of the relationship between apparent consumption and population is a clear illustration of the need to plan for materials supply wherever population growth is expected.
- The poor correlation between the construction of housing floors and the *AC* of construction materials results from the former growing more than the latter and an overall increase of the surface of housing floors constructed per person. So far, little data is available to draw a specific conclusion from this comparison. It is likely that this trend can be explained by either different construction practices used for housing through the years, the decreasing proportion of construction materials used for housing compared to the quantity used for transport units and commercial infrastructure or the import of additional construction materials from other provinces of Vietnam.
- The AC of bricks is unrelated to population or artificial surfaces and is strongly and negatively related to housing floor construction. Such relationship means that the tonnes of bricks consumed per cubic metre of housing floor constructed are falling. Because housing is usually one of the largest processes by which the new bricks are being used (or consumed) this can be indicative of changing standards or building styles used for house contruction or that this material is mainly exported to elsewhere within the country.
- The official figures for the production of sand and gravel (non-adjusted) are poorly related to population, housing floor construction and artificial surfaces, which suggests a level of under-reporting of sand and gravel production occurring. We have therefore used cement as a proxy to estimate *AC* and forecast consumpion of sand and gravel. According to the revised calculation (see Section 3.2), the reported (official) values are currently almost two times lower than the likely true level of *AC*. Our adjusted values are much more strongly related to the changes in artificial surfaces and population. The weak correlation with the reported levels of sand production strongly supports the suggestion that these figures are under-representing the amount of sand that is being produced. It is very likely, therefore, that additional sand is being produced to meet the demand of construction in Hanoi and that this is originating from 'unofficial' sources within the province. As noted earlier, there is evidence for sand extraction taking place from river beds and banks in the Hanoi region [24], and, if this is not regulated, could have severe negative and irreversible effects on the environmental conditions of the rivers.

Some of the studied correlations are not as strong as expected, which may suggest some other factors (e.g., political or cultural) play important roles in affecting the change of construction materials. Further investigation of the driving factors is needed along with the support of data at a refined spatial/temporal scale. While current levels of publicly available data are sufficient for the analysis of material supply and demand at the national level, the analysis of material flows at the city level require considerable assumptions and estimation to be made by scaling national level data to the city level. New data and over a longer period at city level would allow for the development of a more comprehensive approach than the top-down method we adopted. Our top-down approach is based solely on material flows and population statistics and does not take into account urban growth plans, building stock information and the metabolism of urban development over time. In that sense, it is 'simplistic' and could be improved by incorporating some of the aforementioned factors into the model to drive a bottom-up material flows quantification [26]. Material flow analysis is suitable as a method for quantifying material input and use flows, but if we would like to quantify the impacts of materials to the environment, then additional data and methods would have to be considered (e.g., environmental impact assessment, LCA) [8].

The contrast between the smooth linear trend shown in projected consumption and more complex trends from measured statistical data illustrates the limitations of such simplistic modelling and how economic and political factors, which can alter such trends considerably, can only be constrained by confidence intervals.

The comparison between LULC maps with *AC* provides it is still an added value for a better understanding of possible future demand for construction materials in the area which can be used to develop informed regulatory framework, as requested in Reference [15], and can guarantee the balance between promoting sustainable economic growth prosperity and guaranteeing environmental protection. Such efforts go in the direction of two United Nations SDGs: no.11 (Sustainable Cities and Communities) and 12 (Responsible Consumption and Production).

From our analysis, we can state that, over the last 20 years, the reduction in forest and seminatural areas has been very limited. However, if the targeted urban growth is to be achieved in Hanoi, then the main threat to forest preservation is related to the increasing request for building plots and mining concessions, in particular for steel and sand and gravel.

6. Conclusions

The Hanoi Master Plan 2030 has been designed by the Vietnamese government to accommodate the growing population from 6.7 million in 2010 to 9.2 million by 2030 and promote economic development in the capital region. Indeed, urban areas in Vietnam contribute to most of the country's annual GDP and will create expanding markets for construction materials.

The rapid urbanisation has already determined drastic environmental changes in terms of land use [28,29] and despite this, an analysis of the impacts in terms of land use changes and future demand and supply of construction materials does not yet exist in the literature and has not been included in the city's main planning document, the HCCMP.

In this regard, satellite data have provided information on how we can assess the impact of the increasing population and demand for construction materials on landscape change. The latter is information that is easy to retrieve, especially at the national scale in Europe and North America, while LULC maps can be produced, based entirely on open-source data and software. Therefore, our methodology has the potential to be replicated elsewhere.

For the Hanoi Province, our work has identified the construction materials whose supply and exploration needs to be prioritised and where new legislative framework can be put in place to regulate and support businesses to realise more sustainable supply chains that can preserve or mitigate the impact of urbanisation on the natural landscape.

We have therefore analysed and demonstrated the close correlation among land cover changes, population growth and the apparent consumption of construction materials. These correlations provide reliable and consistent information to top-level institutions such as Provincial People's committee, MONRE and MOC (Ministry of Construction) to support more effective policies for the responsible use of non-renewable mineral resources or future strategies for an adequate supply of construction materials, proportionally to the urban expansion.

We aim to develop a full MFA for the Hanoi Province through higher resolution satellite data. The latter will provide information on the building stock and the infrastructure that will further shorten the distance between EO data to conventional economic tools.

Supplementary Materials: The following are available online at www.mdpi.com/2072-4292/13/3/334/s1, Supplementary Material S1: Images used to derive Land Use/Land Cover (LULC) maps; Supplementary Material S2: LULC trajectories correction; Supplementary Material S3: LULC maps.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

The satellite data used have a cloud coverage of ≤ 2% of the Hanoi Province and spans nineteen different years, years with cloud cover have a '*':

- 3 S-2 images acquired on 9/3/2020. Overall accuracy: 98%.
- 2 S-2 images acquired on 10/12/2019. Overall accuracy: 88%.
- 2 S-2 images acquired on 31/10/2018. Overall accuracy: 93%.
- 4 S-2 images acquired on 20/12/2017. Overall accuracy: 91%.
- 7 S-2 images acquired in 2015 *. Overall accuracy: 93%.
- 2 L-8 images acquired on 19/1/2014 *. Overall accuracy: 85%.
- 17 L-5 images acquired between July and November 2011 *. Overall accuracy: 78%.
- 2 L-5 images acquired on 5/11/2009 *. Overall accuracy: 89%.
- 35 L-5 images acquired in 2008. Overall accuracy: 87%.
- 36 L-5 images acquired in 2005. Overall accuracy: 83%.
- 2 L-5 images acquired on 9/12/2004. Overall accuracy: 86%.
- 43 L-5 images acquired on 2003. Overall accuracy: 86%.
- 35 L-5 images acquired on 2001. Overall accuracy: 75%.
- 2 L-5 images acquired on 30/9/1996. Overall accuracy: 85%.
- 39 L-5 images acquired in 1992. Overall accuracy: 74%.
- 2 L-5 images acquired on 20/11/1991. Overall accuracy: 80%.

- 49 L-5 images acquired in 1989. Overall accuracy: 83%.
- 2 L-5 images acquired on 1/7/1986. Overall accuracy: 80%.
- 2 L-2 images acquired on 29/12/1975. Overall accuracy: 86%.

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