Space Policy 57 (2021) 101429

Contents lists available at ScienceDirect

Space Policy

journal homepage: www.elsevier.com/locate/spacepol

Earth Observation and Economic Studies: A Cross-fertilization Perspective☆

Massimo Florio, Valentina Morretta*

University of Milan, Department of Economics, Management and Quantitative Methods, Italy

A R T I C L E I N F O

Article history:
Received 8 May 2020
Received in revised form
20 January 2021
Accepted 12 April 2021
Available online 25 May 2021

Keywords:
Earth observation
Socio-economic impact of satellite images
Scientometrics
Cost-benefit analysis
Econometrics

JEL classification:
O30
Q55
R14
C80
E01

A B S T R A C T

Over the past decade, an increasing number of satellite images and other earth observation (EO) data have become available to a wide range of final users, including economists and other social scientists, boosting the amount of information they can obtain to study, analyze, and manage different research topics in their fields. In turn, economists are promoting advancement in the quantification of the benefits related to the increasing use of EO services and applications by governments, firms, and citizens. Drawing from recent literature, and our own research, we explore, on one side, how social scientists, and particularly economists, can significantly benefit from EO data, and conversely, how socio-economic impact studies of EO can take advantage from a specific set of economic methods. This article suggests that cross-fertilization and interplay between economics, social sciences, and remote sensing science are needed to advance understanding of our societies and to more rigorously evaluate the socio-economic impact of EO services and applications. The article suggests possible new research avenues.

1. Introduction

There is increasingly widespread awareness of the importance of space technologies and how vast can be their impact on our contemporary lifestyles, daily habits, socio-economic activities, and well-being. Among different domains of the space sector, earth observation (EO) involves the collection of a wide variety of chemical, biological, and physical information about our planet, via remote sensing technologies [32]. During the last few years, this space sector has rapidly grown [56] and become a highly strategic tool which enables a wide array of data, services, and applications for governments, firms, scientists, and citizens, with a rising impact on our societies [23,66].

While the United States, Russia, and the European Union are at the forefront of this sector, EO data are gaining growing importance worldwide in several fields [40]. Indeed, they provide crucial support in the analysis and management of several important aspects concerning our societies, such as scarcity of food, water, climate change, human health, disasters, habitat endangerment, and safety of citizens [40]. Hence, they play an increasing role in building societies that are capable of addressing critical challenges for the benefit of future generations [23,26].

Social sciences, in a broad sense, try to explain how society works, including, for instance, what drives economic growth, employment, and what makes people happy [57]. Social sciences, at large, include several disciplines such as anthropology, economics, political science, sociology, social psychology, among others. In this article, we focus exclusively on socio-economic issues, mainly studied by economists; yet, there is a tradition of studies in economic sociology, economic history, and other fields that also

☆ The present article is part of a three-year project "Cost-benefit analysis of public policy in the space industry" carried out by the University of Milan (Department of Economics, Management and Quantitative Methods) and funded by the Italian Space Agency (ASI). We are grateful to other colleagues at the Department of Economics, Management, Quantitative Methods, to the editor, and the two anonymous reviewers for their helpful suggestions on a previous version of the article. The usual disclaimer applies.

* Corresponding author.
E-mail addresses: massimo.florio@unimi.it (M. Florio), valentina.morretta@unimi.it (V. Morretta).

https://doi.org/10.1016/j.spacepol.2021.101429
0265-9646/

contributes to the understanding of such issues. Thus, we shall use the words economics and economists at the broader meaning of respectively economic studies and social scientists focusing on economic issues.

In this vein, this article aims at exploring the mutual relations between EO, economics, and other social sciences in two directions: first, how economists can take advantage of EO data; second, how economists may contribute to the study of the socio-economic impact of EO data.

We make two claims: first, we claim that from one side, EO is becoming increasingly important in the study of different socio-economic issues and is contributing to a growing scientific literature which takes advantage of newly available data. We also suggest that there is unexploited potential, and we point to the possible further impact of EO data on socio-economic studies. From the other side, we claim that economists, and mainly applied welfare economists,[1] may increasingly contribute to strengthening methodologies for the quantification of socio-economic benefits deriving from the exploitation of EO data with an impact into the real life.

Our findings on the first issue draw from a scientometric analysis and systematic review of the literature and the identification of five main areas where EO data availability is positively contributing to empirical socio-economic studies. However, we also critically discuss the fact that the impact of EO data on such studies may still be mostly unexpressed, and we discuss possible improvements to facilitate the use of such data.

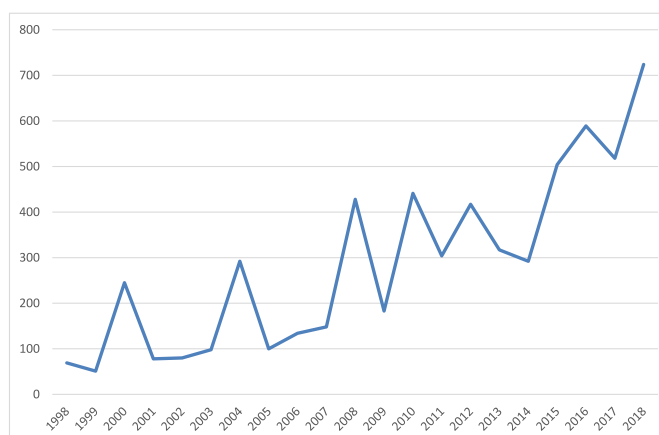
On the second issue, based on selected examples of the literature on the socio-economic impact of EO data, and our own research, we identify some helpful economic methods, and we critically discuss them. We suggest that there is much room for improvement in this area of studies, as certain empirical methods available to economists, such as econometric methods based on quasi-experimental settings, social cost-benefit analysis techniques, and other quantitative approaches, did not find yet frequent applications in the estimation of the socio-economic benefits of EO data. Again, our findings point to the need for cross-fertilization between remote sensing science and applied economics, particularly applied welfare economics.

This article is structured as follows: Section 2 provides an overview of the use of EO data in the field of economics and related social sciences, i.e., how data are currently supporting the study of different socio-economic phenomena and possible future extensions. Section 3 provides an overview of economic methods that have been deployed to estimate the socio-economic benefits of EO data and discusses the unexploited potential arising from more extensive use of new quantitative methods. Finally, section 4 concludes the article pointing to the need for dialog and collaboration between remote sensing scientists and economists and sets a future research agenda.

2. The contribution of EO data to the study of socio-economic issues

In this section, we explore different ways in which EO data can contribute to support research in the field of social sciences with a particular focus on socio-economic subjects.

By doing a simple search on *Scopus*, which is the largest database of peer-reviewed literature, including scientific journals, books, and conference proceedings,[2] we have identified 6012 peer-reviewed publications during the period 1998–2018, related to earth observation and belonging to the category of "social sciences," as for the classification of the database.[3] More specifically, we searched for publications containing the combination of words "satellite remote sensing" into the title, or keywords or abstract.[4] These knowledge outputs represent less than 10% of the total scientific publications related to EO, which are still much more prevalent in other fields such as material sciences, earth science, engineering, and so on. However, the number has been rapidly increasing during the last few years, as Fig. 1 shows. For instance, the number of publications in 2018 is seven times higher than that twenty years before. Most of these publications come from China (16%), followed by India (11%), United States (11%), Germany (6%), Italy (4%), Japan (4%), and several other European and non-European countries. Twenty-two percent of these publications are funded by the National Natural Science Foundation of China, 6% by the National Aeronautics and Space Administration (NASA), 4% by the National Science Foundation, 3% by the National Basic Research Program of China, 2% by the European Space Agency (ESA), and 1% by the European Commission. Fifty-one percent of such publications are journal articles, 44% conference papers, while the remaining percentage includes books, book chapters, reviews, editorials, and so on. While being classified as documents in "social sciences," 19% of these publications also belong to the category of "computer science," "earth and planetary science" (14%), "environmental science" (9%), "agricultural and biological sciences" (3%), and "engineering" (3%) while the remaining is fragmented across several other fields of studies. Only 120 documents, during the whole period, have been published within the category "economics, econometrics, and finance" as defined by *Scopus*. However,



Source: Own elaboration from Scopus

Fig. 1. Number of publications related to earth observation in "social sciences" (1998–2018). **Source:** Own elaboration from Scopus.

[1] Welfare economics is a branch of economics that studies how the allocation of resources and goods affects social welfare. It seeks to evaluate costs and benefits of changes to the economy and drive public policy toward achieving beneficial socio-economic outcomes for the society. https://www.investopedia.com/terms/w/welfare_economics.asp#:~:text=Welfare%20economics%20is%20the%20study,of%20people%20in%20the%20economy.

[2] https://www.scopus.com/home.uri.

[3] We have performed a manual check by titles for about 15% of these publications to see these were properly categorized.

[4] We found 1800 documents when computing a research on Scopus by using the combination of words "earth observation", 9586 with "satellite data", and 4448 with "satellite imagery". The increasing trend of publications during the period and related statistics are consistent to all queries. Date of the query: January 2021.

again, this sub-branch of literature in social sciences has been rapidly growing over the last years where the number of publications in 2018 is more than six times higher than that in the initial period (Fig. 2). Eighty-one percent of publications in economics are journal articles, and we find "Space Policy", the "Journal of Cultural Heritage", "Environment Development and Sustainability", "Resources, Conservation & Recycling", "Ecological Economics", "Marine Policy", "Forest Policy and Economics", "Journal of Environmental Economics and Management", and "World Development" among the top 10 most popular journals of publications.[5] We have also spotted other articles in top journals, such as "The Journal of Economic Perspectives" edited by the American Economic Association and the "Quarterly Journal of Economics" which is a "blue ribbon" journal in the field, edited at the Harvard Department of Economics.[6]

To better understand why economists and other social scientists are increasingly interested in EO data, we have selected some topics in the academic literature that provide several examples where satellites are boosting the amount of information social scientists can obtain to study different socio-economic phenomena [18] (Table 1). By providing high-spatial-resolution images of the Earth, with wide frequency and geographical coverage, EO gives the possibility to build new useful data sets at a lower marginal cost than terrestrial surveys. Hence, EO data can be used by social scientists to answer numerous research questions requiring a geographical setting. We can classify these topics into five main research strands.

2.1. Night lights as an indicator of economic growth

First of all, the increasing availability of EO data is particularly useful in the study of developing economies (but also in some developed countries at subnational levels), where usually the lack of ground-based data limits the possibility to study economic growth adequately. Traditionally economists rely on data obtained by extensive surveys of firms and households. The process is usually rather labor-intensive, as each statistical unit needs to be contacted by an officer and asked questions about output, prices, stocks at the firm level or on consumption, and income at the household level. While these surveys can be currently based on online systems (In the past, they were mostly based on surface mail or in-person interviews.), the coverage of internet is uneven, particularly in less developed economies. Even surveys by telephone may be difficult in some rural areas. This creates two problems: considerable costs of data collection and heterogeneity of coverage, hence issues of reliability. The problem is not entirely solved by such proxies as the data on the consumption of electricity for the same reasons (In developing countries, millions of people are not connected to the networks or illegally connected.).

In this respect, Henderson et al. [35] have demonstrated that satellite night lights data are a useful proxy for gross domestic product (GDP) growth at temporal and geographic scales for which traditional data are of poor quality or simply unavailable. Whatever be the kind of access to the electricity network by a household or a small business in the black economy, it has been observed that night lights are statistically correlated with electricity consumption, which in turn is a well-known proxy for overall standard of living. Moreover, the change over time of night lights is a proxy of economic growth.

In this vein, Lee [46] uses data on night lights to investigate how regional inequality in terms of the spatial distribution of economic activities evolves when a country such as North Korea, for which official statistics are almost not existent, become isolated because of sanctions decided by the international community. Storeygard [65] studies whether Sub-Saharan cities, which are better connected to the main port of their country, grow faster than cities with poorer road connections when the oil price rises. As data on income in the region are poorly available, the author uses information on satellite night lights over a period of 30 years as a proxy of GDP growth and find that an oil price increase of the magnitude experienced between 2002 and 2008 induces the income of cities near the main port to increase by 7% of GDP relative to otherwise identical cities 500 km farther away. Clark et al. [13] also use satellite night lights as an independent benchmark for comparing various Chinese economic indicators, showing that the rate of Chinese growth is higher than what is reported in the official statistics.

The spatial dimension of economic growth is, traditionally, of major interest for economists and demographers because it is well known that growth reshuffles the urban-rural patterns, and major migrations may only add to this interest. Hence, it should be explored in future if there are other types of EO data beyond night lights that can be exploited to study economic development through their correlations with GDP broken down at appropriate geographical units (see for example Vogel et al. [67]).

2.2. Housing and built environment

Second, satellite data are also handy to construct new detailed data sets on specific items that are not available from official statistics nor other sources, such as detailed indicators of housing quantity, quality, or built-up land cover [67]. Again, traditionally, statistics in this area needed long, costly, and cumbersome procedures, such as census officers asking questions to households and firms every ten years or visually inspecting dwellings, a tradition that goes back over more than twenty centuries [2], particularly in ancient Egypt and in the Roman Republic.

The collection of these data is not easier in contemporary economies not only because of the large number of slums and other shantytowns after the disruption of traditional villages in developing countries but also because of the fast change of the built

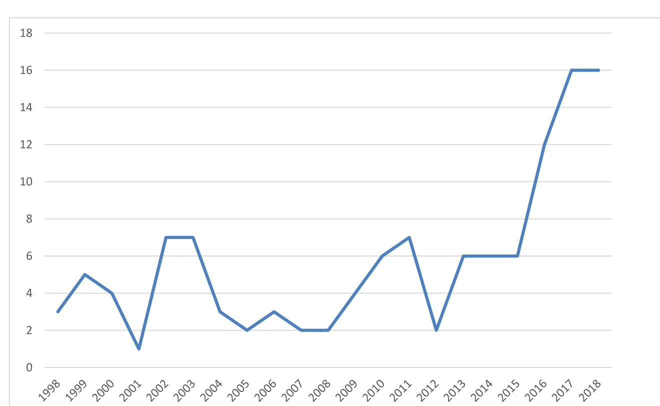


Fig. 2. Number of publications related to earth observation in "economics, econometrics and finance" (1998–2018). **Source:** Own elaboration from Scopus.

[5] Please note that not all documents included in these journals, although all related to economic subjects, necessarily relate to the contribution of EO data to socio-economic issues.

[6] We spotted these journals by using the Scopus query "satellite data". With this query, we run a risk to include documents related to other types of satellite data beside EO (e.g., navigation). However, by performing a manual check, we noticed that many documents are related to EO and are not included in our main query "satellite remote sensing".

Table 1
The contribution of EO data in the study of socio-economic issues: selected examples.

Contribution of EO data	Main references
Night lights as an indicator of economic growth	[13]
	[35]
	[46]
	[65]
Provision of housing and built environment information	[49]
	[67]
Satellite data as indicators of environmental policy effectiveness	[10]
	[12]
	[38]
	[53]
Economic data comparability at fine-grain geographical level	[14]
	[17]
	[36]
EO data in econometric models as exogeneous variables	[30]
	[43]
	[58]

Source: Own elaboration

environment in developed economies. Moreover, the type of housing and built environment is correlated to a number of socio-economic dimensions.

In this respect, social scientists are increasingly supported by experts of remote sensing and machine learning. For example, Marx et al. [49], by combining a resolution of 0.5-m satellite images of the Kibera slum in Nairobi between 2009 and 2012 and data collected from a big survey with dwellers, show how ethnic patronage affects both the determination of rental rates and housing quality. The authors find that slum residents pay lower rents and live in higher quality dwellings (measured through the luminosity reflected by corrugated iron roofs) when they have the same ethnicity as the locality chief, showing that ethnic patronage has both distributional effects and consequences on welfare in the residential market of the slum. Vogel et al. [67] use satellite data to analyze local economies by defining urban markets with built-up land cover classified from daytime satellite imagery in India. By constructing this innovative data set with an artificial intelligence algorithm, the authors can capture more markets, more urban population, and more variation in the spatial distribution of economic activity than with night-time light intensity.

2.3. Satellite data as indicators of environmental policy effectiveness

Third, satellite data are also beneficial as a benchmark when available official statistics are not credible or disguised, for example, due to political reasons. For instance, Chen et al. [12] compare aerosol optical depth data from MODIS[7] with the air pollution index of Beijing, which is not always considered reliable as based on official statistics. They show that air quality effectively improved during the preparation of the Olympic games because of the government commitment in taking measures such as traffic controls and introduction of emission standards, among others, for a total cost of USD 10 billion. Just one year after the end of the Olympics, however, such effect weakened by 60%. These results suggested that actual environmental improvement depends on the sustained political motivation behind the interventions. Burgess et al. [10] cannot rely on official statistics to study deforestation in Indonesia. Hence, by combining MODIS data on deforestation with geographic information system (GIS) data on administrative districts over the period 2001–2008, they found that, as national logging rules are enforced at the local level, potentially corrupt local bureaucrats and politicians respond to incentives of deforestation consistently with their rent maximization. Jayachandran [38], by combining daily satellite measures of airborne smoke and dust with info from the 2000 census on “missing children”, estimates the impact of air pollution due to illegal forest fires in Indonesia on infant and fetal mortality. The author finds that the spread of pollution of a big illegal fire in 1997 caused 16,400 infant and fetal deaths with a striking difference in the mortality rates between richer and poorer places. In addition, a recent study conducted by the OECD estimates that a 1-μg/m3 increase in PM2.5 concentration causes a 0.8% reduction in real GDP that same year in Europe, due to reductions in output per worker caused by absenteeism at work or reduced labor productivity [53].

Given the paramount importance of environmental policies by governments, and the lack of good data on their actual implementation and success (usually relying on scattered and uneven ground sampling), it seems that EO data may be very helpful to environmental economists to ensure credibility of their analyses.

2.4. Economic data comparability at fine-grain geographical level

Fourth, satellite data are also helpful to perform geographical comparisons among statistics that otherwise would not be comparable. For example, Costinot et al. [14] attempted to quantify the consequences of climate change on agricultural productivity in three different scenarios, by using a rich data set (FAO and GAEZ[8]) which contains data on soil, topography climatic condition to predict the yield, crop by crop, for each of 1.7 million fields covering the surface of the Earth. They find that in the best scenario, climate change amounts to a 0.26% decrease in world GDP with a heterogeneous effect across countries.

In a political economy perspective (the branch of economics interested in the interplay between economic performance and politics), Hodler and Raschky [36] looked at regional favoritism using a panel of 38,427 subnational regions from 126 countries with observations from 1992 to 2009. By combining satellite data on the intensity of night lights from NOAA with resources cited in the codebook of the Archigos database and various Internet sites, the authors mapped 1990–2010 political leaders' birthplaces and found that subnational regions have more intense night-time light

[7] MODIS (or Moderate Resolution Imaging Spectroradiometer) is a key instrument aboard the NASA Terra and Aqua satellites (https://modis.gsfc.nasa.gov/about/).

[8] Global Agro-Ecological Zones data set based on GIS/Satellite-solutions.

when being the birth region of the current political leader. They also show that regional favoritism is most prevalent in countries with weak political institutions and poorly educated citizens.

More recently, the importance of earth observation data has also been highlighted to understand changes caused by the COVID-19 pandemic. One study has focused on the effect of the pandemic on global issues such as energy consumption, emissions, climate change, poverty, globalization, and biodiversity [17]. The authors believe that while short-term impacts derive from the reduced human activity, longer term impacts are likely to result from indirect effects of the economic recession on global poverty, green investment, and human behavior [17].

2.5. EO data in econometric models as exogeneous variables

Lastly, another way in which satellite data are increasingly used in social sciences is when geography, weather, or other aspects of the Earth are used as a source of exogenous variation for estimating the impact of various "treatments" [43]. For example, Sawyer et al. [58] use satellite data on the use of land provided by the United States Geological Survey (USGS) to show how geography determines housing supply. They construct a measure of exogenously undevelopable land in cities due to geographical constraints by calculating the area lost to internal water bodies and wetlands and land which exhibits slopes above 15%. They find that residential development is constrained by the presence of sloped terrain and that land constrained area show inelasticity in housing prices and are more highly regulated. Flückiger and Ludwig [30] show that negative economic shocks in the fisheries sector are associated with an increase in maritime piracy. They use the variation in the phytoplankton abundance for 109 countries measured by satellite data in the period 2004–2009, as a source of such shocks to avoid endogeneity problems between piracy and fish catches. They find that phytoplankton abundance is positively related to fish catches but negatively associated with the incidence of piracy. Lower abundance of phytoplankton deteriorates economic opportunities in the fishery sector increasing the relative attractiveness of engaging in piracy activity.

The aforementioned examples suggest that there is a huge potential for the use EO data in the context of socio-economic research. Economists are increasingly interested in testing their hypotheses and models with rigorous econometric methods that require large and frequent microdata, possibly available in such a way that statistical variation over space and time can be fully exploited for the estimation of regression coefficients.[9]

This potential is, however, not yet fully exploited. Beyond the long-lasting discussion within the space community on the users' uptake initiative [24], there are some additional issues that are specific to social sciences. These are possibly arising by the fact that the dialog between economists and scientists in remote sensing and related disciplines has been so far rather limited. The first constraint relates to the format of the data. Even when satellite data (not often) are available freely and openly, they are usually in formats not readily useable by economists[10]. To give an example, when data are available in a common shapefile format, they need to be converted by a geographic information system (GIS) software which groups observations in the unit of analysis considered (e.g., countries, regions, provinces). However, this skill is not common among social scientists, for example, it is not typically part of a postgraduate curriculum in applied economics. Hence, economists must often ask support to GIS experts. Clearly, the availability, in the first place, of data already in a format ready-to-use for socio-economic studies would boost their use.[11] This would require that remote sensing experts consult economists and other social scientists at an early stage of the design of EO user-systems so that users can, at the same time, download the data and the software needed to process them in a way that is meaningful for economics analysis. One may look elsewhere to see how this can be done, for example, online genomics data are provided to biologists by the European Bioinformatics Institute (EMBL-EBI) along with relatively simple software and online tutorials.[12] Currently, EMBL data are in the range of 3 million unique IP access per month and around 30 million requests to the website per day [20]. This dissemination achievement would not have been possible without investment in software, online tutorials, and a close dialog with the scientific community of users, beyond computation biology.

Second, satellite data often display spatial dependence which consists in correlation among nearby units. It is commonly observed that data collected for points in the geographical space are not independent, meaning that observations from one location tend to exhibit values similar to those from nearby locations, as in the case of night lights. This problem typically arises when dealing with any geographical data but become particularly severe when higher data resolution is considered [33]. Consequently, when EO data are used as an independent variable of the econometric analysis, the estimation of regression coefficients is potentially biased. Spatial econometrics is a technique designed to incorporate dependence among observations (regions, cities, or points in space) that are in close geographical proximity. Hence, the ability to deal with spatial econometric analysis is a technical skill needed to estimate relationship among variables in a correct way in a geographic setting [18,47]. This is something economists are more frequently accustomed to consider in econometric analysis, but it would be an advantage if the design of EO systems would consider the implications of spatial correlation for the provision of data at the proper level of aggregation. An example is a software giving the possibility to easily increase or decrease the level of data aggregation according to social scientists' specific needs, particularly when they need to set the analysis in the form of panel data (observations repeated over time in a matrix form).

In addition, possible measurement errors deriving from the application of algorithms in remote sensing science can also affect the interpretation of socio-economic phenomena by social scientists leading to misleading conclusions [18]. For example, Kimani et al. [41] studied the performance of seven satellite products to collect rainfall data in West Africa. Accurate rainfall observations are crucial to support better agricultural and water management

[9] Regression coefficients are estimates, based on the available sample of data, of the unknown population parameters and describe the relationship between dependent and independent variables.

[10] For data formats, see https://earthdata.nasa.gov/esdis/eso/standards-and-references#data-formats for NASA and http://earth.esa.int/SAFE/ for ESA. Some data providers make available tools that support the exploitation of the data (see https://earth.esa.int/eogateway/search?skipDetection=true&text=&category=Tools%20and%20toolboxes), although these are rarely known by economists and other social scientists.

[11] Economists usually deal with cross-sectional data (They observe many subjects, i.e., individuals or firms or countries at the one point of time.); time series (They observe a single subject, i.e., a country over a period of time.); panel data (They observe several subjects over a period of time.). For example, to easily perform econometric analysis with EO data on night lights, economists would ideally need a spreadsheet or CVS panel data format file where each row represents an administrative geographical unit (e.g., region A, region B, region C) in a certain year and each column disclose the related night light intensity value for that region in that particular year; or in the case of EO data on cultivated crops, they would require an a spreadsheet or CVS format file where each row represents a geographical area (e.g., squared meter field A, squared meter field B) and each column disclose the squared meter amount of crop A, crop B, and so on.

[12] https://www.ebi.ac.uk.

decision-making, particularly in less developed economies. The authors show that satellite observations lead to systematic overestimation of rainfall in mountainous areas and underestimation when elevation is <2500 and need to be combined with wind direction and elevation data. However, most economists are unaware of the delicate treatment of the original satellite data that is needed before these are disseminated, and again, this issue calls for some form of interdisciplinary dialog.

3. The contribution of economics to the estimation of the socio-economic benefits of EO data

In the previous section, we have provided some examples on how EO data can contribute to advancing research in economics and related social science fields and producing new knowledge "*per se*". Here, in turn, we discuss how economists can contribute to empirically estimating the socio-economic benefits deriving from services and applications based on EO data. Here, we focus exclusively on the last segment of the EO value chain. The so-called *downstream* sector broadly includes all the products and services which can exist only thanks to the availability of EO data and concerns the conversion of data into value-added applications, products, and services which are ultimately used by final users for different purposes [25,52]. Hence, we do not consider here the benefits for firms which are able to extrapolate the information from EO data (intermediate users), rather we focus exclusively on the benefits for final users of EO applications.

We provide selected examples of socio-economic benefits related to the last generation of satellites designed, built, and managed by government-sponsored space agencies, such as the European Space Agency (ESA) and the National Aeronautics and Space Administration (NASA) where public investments and related policies in EO space programs rely on the prediction and estimation of current and future benefits in the long term [66].

In the last 20 years, various methodologies have been applied to evaluate the socio-economic benefits derived from the use of EO data [37,55,68], drawing on varying techniques, including applied welfare economics, gross revenue estimates, value-added analysis, and general equilibrium modeling [63]. Each of this method has advantages and disadvantages [37,63]. Here, we review some of the most popular approaches, and we provide a critical discussion of pros and cons of each of them from the perspective of applied welfare economics, pointing to possible further contributions and development of the current evaluation methods.

3.1. The value of information

The value of information (VOI) approach consists in quantifying the welfare change between a state in which a certain action is taken, based on currently available information, and a different state in which the same action is taken using improved information [31,48].

Most commonly, studies on VOI of earth observation refer, among others, to the value of weather information on issues such as agricultural productivity and natural resource management [48]. However, exploitation of EO data is increasingly contributing to generating knowledge in several other fields which can be concretely used by a broader range of final users (e.g., governments, firms, and citizens) to make decisions or inform policies about different issues. Understanding the value of such information is extremely important to justify investment in EO infrastructure and related applications [63]. For example, a report by NASA [51] evaluated the benefits of the Volcanic Ash Advisory Center's use of AURA data looking at flight cancelations and revenue losses due to Eyjafjallajökull Vulcan eruption in 2010. The analysis based on VOI found that, during this event, the use of NASA satellite data reduced the probability of an aircraft experiencing a volcanic ash incident by approximately 12%, saving USD 25–72 million in avoided revenue losses due to unnecessary delays and avoided aircraft damage costs. If the data had been used from the beginning of the incident, an estimated additional USD 132 million in losses and costs might have been avoided.

Bernknopf et al. [6] supported by VALUABLES[13] estimated the value of information deriving from the Gravity Recovery and Climate Experiment (GRACE) satellite mission for drought monitoring. Even though quantification of the actual VOI was not possible because of the unavailability of county-level data to estimate the effects of drought assistance on local agricultural outcomes, the authors show how using satellite data may have changed county eligibility for drought assistance.

The VOI approach gathers a very diverse set of methodologies, and it is often combined with cost-benefit and cost-effectiveness analysis. For example, another report of VALUABLES uses this approach to show that exploiting the information provided by LANDSAT satellite is the most cost-effective way to manage and mitigate threats caused by wildfires. EO data allow saving USD 35 million in five years compared to the information provided by aerial inspection [7]. However, this study demonstrates the cost savings of satellite imagines, without quantifying the potential benefits of improved information in increasing the protection of natural and anthropic resources. Indeed EO-derived information is valuable when it informs decisions and actions; hence, it is strictly linked to its use [15,48].

Other interesting case studies on VOI are reported in the article by Kruse et al. [42]. VOI methods are instrumental to the estimation of the socio-economic benefits of EO as they allow transforming the usage of EO information into an economic value. However, one of the main drawbacks of this approach is that, in some cases, it is based on the estimation of the willingness to pay based on stated preferences, which relies on surveys of individuals and private/public institutions to estimate the maximum amount they would be willing to pay for the information; hence, it is based on subjective opinions linked to socio-economic and cultural conditions. This is why a crucial point consists of carefully designing the contingent valuation experiment. Besides the challenge of interviewing a representative sample of the reference population, another important issue is getting people to tell the truth. The hypothetical bias is the difference between monetary values people say they would be willing to pay in a hypothetical scenario with what an individual might actually pay in the real setting [29]. Policy consequentiality techniques are strictly connected to the truth-telling issue and commonly used for improving the realism of the survey by conveying to respondents the idea that their choice will actually impact the decision to invest in EO [29]. Hence, ex-ante hypothetical bias and ex-post mitigation measures are essential to estimate the WTP in a more robust way [4,44].

3.2. The value chain approach

The value chain approach consists in tracing the impact (usually on added value or income) of the use of the EO applications through subsequent steps within the EO value chain, from first-tier direct users to other indirect users (e.g., citizens groups which can indirectly benefit from EO applications) to the whole society at large. At each step of the value chain, the benefits are assessed, summed up, and the value calculated. This methodology has become popular for

[13] A collaboration between Resource for the Future (RFF) and NASA to measure how satellite information can benefit people and environment.

the calculation of the benefits of Copernicus, where interesting cases of analysis are provided by the European Association of Remote Sensing Companies (EARSC). For example, in Belgium, a group of potato farmers have started using an application based on EO data to get information on their fields for better management practices [60]. This information can help to improve yields by up to 20% and the overall quality of potatoes, hence increasing revenues and income for the farmers and the whole potato industry value chain (agronomists, consultants, processors, distributors, supermarkets, and so on) up to the final consumers. Overall benefits along the value chain are estimated around €1 million to €2 million without considering a range of not quantified benefits such as environmental gains [60].

In road infrastructure and management, a new mapping service, showing ground motion based on EO, is supporting public administration in Norway. EARSC estimates an economic benefit of between €3.8 million and €8.7 million per year mainly deriving from saving costs in constructionand management of the road infrastructure [59]. Benefits again are summed up along the value chain from the *Norwegian Public Road Administration* to the road constructors up to the road users, citizens, and society.

Sawyer et al. [62] also estimated the economic value generated by the use of satellite imagery in supporting navigation in the Baltic Sea. Satellite imageries replace helicopters in helping icebreakers finding the best routes through the ice. These benefits are estimated between €24 million and €116 million per year and include reduced fuel costs of icebreakers, helicopters, and ships; reduced operational costs of ships due to arrival delays; and savings from reducing collision (insurance and damage). Other benefits arise within port infrastructures (which can operate more efficiently), factories, and citizens that can be sure supermarkets are properly stocked [5,62].

While this approach is very informative, final figures should be interpreted with some caution. First of all, in the language of applied welfare economics, the analysis should always consider the incremental net benefit, rather than the gross benefit. Let us consider, for example, the study by Sawyer et al. [61]. They examined the impact of satellite imagery on forest management in Sweden [61]. This case study shows how satellites have contributed to the decrease in illegal cutting and lack of immediate replanting and precommercial thinning. The cost of collecting such imageries was €64,000 against a benefit of €16.1 and 21.6 million per annum. Benefits derived from a decreased cost of physical inspections and using aircraft among others (the counterfactual), plus the long-term value, increase as a result of higher timber production and enhanced quality. Other noneconomic benefits include the creation of an archive of images, improved interagency cooperation, and wildlife protection.

In this example, the economic benefit possibly arises in two ways: either because satellite data make less costly the detection of fraud, normalized with some parameters, such as the forest area (This would be a cost-effectiveness indicator.) or because compliance increases because of the higher probability that the infringement is detected and fines apply—in this case, the economic benefit is the long-term monetary value of forest preservation. However, in both cases, these gross benefits should be compared with those of the alternative techniques available for inspection, such as ground observation or use of helicopters or airplanes as discussed in the study by Sawyer et al. [61]. Drones are also, in some case, an alternative option to be considered.

Thus, the whole value chain method should be robust in terms of a careful selection of the counterfactuals ("What if"). The counterfactual analysis is more and more difficult the more downstream the chain effect is expected. This happens because causation becomes more fuzzy, a well-known issue in applied welfare economics.

Moreover, the value chain approach crucially relies on values which, in simple terms, are quantity (output or consumption) times prices (of goods or services). Economists know very well that in distorted markets, because of monopolies, duties, externalities, and asymmetric information, prices are poor indicators of marginal social values. These distortions are often considerable in sectors such as agricultural, environment, or health, among others. Thus, critical scrutiny is needed of the actual meaning of the "value" in the value chain method practical applications because when prices are distorted, the social value may differ from the market value, with the latter may be above or below the former, according to the specific market considered.

3.3. Cost-benefit analysis

Among quantitative methods, Social Cost-Benefit Analysis (CBA) is one of the most helpful microeconomic tools for the evaluation of economic advantages or disadvantages of an investment decision from the point of view of the EO final users and the society at large. It consists of evaluating the social costs and benefits of this decision in "money terms" to assess the welfare change attributable to it [22]. In CBA, time series of benefits and costs are discounted to bring the value flows back to a common date. All discounted costs and benefits are then summed up to calculate the net present value of the social benefits allowing comparability and ranking for competing alternatives of collecting the information. In this evaluation, welfare economists can offer significant support to the space community, for example, significantly adapting lessons learned from other subjects [3,28,54,64].

The CBA technique has been used to estimate the expected benefits of entire EO programs such as GMES/Copernicus and weather forecast satellites [8,9,21,45] but less often for single applications and services based on EO data [1,34]. An example of CBA for specific EO service is provided by USGS on the *National Map*, a service that offers complete, user-friendly, and accessible data to decrease the cost or improve the outcome of spatial-data applications. The National Map was found to bring a net present value of 2.05 billion USD allowing to recover the costs of the initial investments in 14 years [34].

In CBA, as in other rigorous impact assessments, the decision to invest in EO services and applications must always be based on the incremental approach which compares the net benefits of a scenario "with EO data" with a counterfactual scenario "without EO data". A looser version of economic analysis is cost-effectiveness analysis, where costs but not benefits are given a monetary value. In this vein, Dawes et al. [16] carried out a case study in the United States, illustrating the benefits of EO data in monitoring air quality. In monetary terms, their analysis shows that satellites could provide, in short time and for free, $PM_{2.5}$ information to 82% of the 18.1 million people currently living in unmonitored areas of Georgia, Colorado, and Missouri. In contrast, the purchase, installation, and operation of ground infrastructures would have cost USD 25.9 million and covered only 44% of those unmonitored people in 5 years.[14]

CBA, different from VOI and the value chain approach, also introduces significant value corrections which consist in evaluating cash flows at their shadow prices. Shadow prices capture the social opportunity costs of goods and services as market prices are often

[14] A wide range of nonmonetary values and benefits also emerged from a set of interviews with different stakeholders including better support to public health programs or more effective health alerts.

distorted, as mentioned previously, because of inefficiencies (e.g., a situation of monopoly, subsidies, and so on) and are ultimately estimated using different methods, including their marginal cost or willingness to pay [22]. The analysis also includes the monetary value of positive and negative externalities and nonmarket effects derived from the use of EO applications such as reduced pollution, reduced travel time, or traffic accidents among others [22]. This quantification is not very common within the space sector, where such effects are often discussed in qualitative terms. For instance, getting information on issues such as air quality and other atmospheric conditions at a lower marginal cost has benefits in terms of lives saved, which in cost-benefit analysis can be quantified in terms of quality-adjusted life-years (QALY)[15] and the value of the statistical life (VSL)[16] [27], reduced health expenses, and higher economic returns.

CBA is a rigorous method for estimating the net benefits of a service and application based on EO data. We are inclined to suggest more widespread use of this approach in the impact analysis of EO data, but with some caution. End users often use EO data in combination with other sources; hence, it is occasionally difficult to determine the paternity of EO data benefits (*quantification dilemma)* [55]. Another limitation to its application may derive from the difficulty in capturing the benefits along the value chain (from direct to indirect users). In addition, the quantification of social benefits into monetary terms is often based on the willingness to pay which, as previously explained, requires due caution as stated preferences methods, that are the most common way to estimate the WTP, needs careful experimental design.

3.4. Treatment econometric methods

Treatment econometrics focuses on how to causally interpret the effect of some intervention (or treatment) on an outcome. This set of methods have been increasingly used in economics to evaluate public policies, for instance, programs to fight poverty, and environmental and health policies, such as the exposure to pollution and so on [19].

Treatments econometric could be, in principle, used to estimate the impact of EO services and applications on an outcome variable of interest. One possible way to carry out the analysis would be the comparison of a treatment group, which has access to the EO service, with a control group, which does not have access to the service. While, to the best of our knowledge, there are yet no examples of such applications, EO data are already increasingly used to support the evaluation of different policies, hence it would just be a matter of a further step for the space sector to take advantage of frontier methods of empirical analysis. For example, Jayachandran et al. [39] evaluated a Payments for Ecosystem Services (PES) program in western Uganda that offers cash payments to forest owners if they conserve their forest. They measure the causal impacts of PES through a randomized controlled trial. They find that deforestation, measured with satellite data, declined in treatment villages compared with control villages during the study period.

Another way is looking at the trend over time for a particular outcome based on the collection of historical data from periods before the use of EO application compared with the periods after the use of the application. A tentative of a similar approach has been undertaken by researchers from NASA [51] who tried to investigate how a prototype of Malaria Early Warning System (MEWS), based on satellite weather forecasting, could help to assess the higher risk of malaria outbreaks and target interventions of prevention in Botswana. By using EO data, they tried to understand how this early warning system could have impacted the malaria rates over time (before and after MEWS). However, results were weak because of the short period of analysis and too many confounding factors the analysts were not able to account for. Chang et al. [11] investigated the impact of COVID-19 on air pollution in two cities of Taiwan, which were not subject to economic or mobility restrictions. Using a difference-in-differences approach and satellite data on air quality and transportation, they estimated that pollution increased relative to 2017–2019 because of a shift in preferences for mode of transport away from public transportation and toward personal automobiles. Miller [50] used state-, year-, and month-level fixed effects, among other control variables, to show that areas with weather warning systems in the United States have fewer fatalities and injuries from tornadoes and hurricanes than would have occurred without the weather warning system.

While this set of methods is becoming increasingly popular among economists (as also highlighted by the 2019 Nobel prize in economics to Ester Duflo, Michael Kremer, and Abhijit Banerjee), applications within the space sector are still very limited. Although this method has some complications (e.g., it is essential to accurately take into account confounding factors) to attribute welfare changes to the availability of the EO service, we suggest that it has important potential. The impact of satellite data, when used in some areas, compared with a control group of other areas using other sources of information lends itself to quasi-experiment econometric analysis. The application of such methods may convincingly reveal the potential, if any, to increase policy effectiveness with satellite data.

4. Concluding remarks

In this article, we have reviewed the current and potential cross-fertilization between Earth observation and socio-economic studies.

From one side, we have examined how social scientists and economists can increasingly use satellite data in the analysis of different socio-economic issues. Indeed, EO is contributing to a growing scientific literature which takes advantage of the newly available data to answer a varied set of research questions. By providing high-spatial-resolution images and other data on the Earth, with wide frequency and geographical coverage, EO gives the possibility to build new useful data sets advancing the process of understanding our societies. Drawing on scientometric techniques and the analysis of the literature, we have identified five research strands where EO data availability is significantly contributing to empirical socio-economic studies. Future research on this issue could be based on a more systematic classification of the content of scientific publications in social sciences stemming from EO, for example, by supporting manual categorization with text mining techniques as the Latent Dirichlet Allocation (LDA) method.[17]

[15] This is a unit of measurement for valuing health outcomes. It is designed to capture in one single measure an individual's gain in utility from improvement in both quality of life and length of life. https://www.sciencedirect.com/topics/medicine-and-dentistry/quality-adjusted-life-year.

[16] This is the marginal rate of substitution between income (or wealth) and mortality risk. https://strata.org/pdf/2017/vsl-full-report.pdf.

[17] https://radimrehurek.com/gensim/about.html With this methodology, the title and abstract of each document is considered as a set of words that, combined together, form one or more subsets of latent topics characterized by a particular distribution of words. The idea behind is that when an article is related to a certain topic, particular words are expected to appear more frequently. The model allows the classification of the main topic of a given document by providing the probability of being in a specific topic class in case the document discusses multiple topics.

However, despite this important contribution, we have highlighted the unexploited potential because of limitations to the use of EO data in social sciences, possibly arising by the lack of sufficient dialog between economists and scientists in remote sensing and related disciplines. Such constraint relates, among others, to the format of the available data, that does not make them user-friendly; to issues of the spatial dependence of EO data which can bias econometric analysis; and to issues of treatment of the original data, which is often unknown to economists in terms of possible statistical bias. Hence, we stressed for more collaboration and interchange between remote sensing scientists and economists when designing EO systems. This could be achieved, for example, by strengthening the data support services of publicly available EO data, which may become available to efficiently provide the appropriate format of data, and level of aggregation, according to specific users' requests. Despite an increasing diffusion of important initiatives (for example, the creation of the NASA Socioeconomic Data and Applications Center [SEDAC][18] and the USGS Landsat Analysis Ready Data which have started disclosing data sets that are of interest to, and useable by, social scientists[19] or several GEO initiatives[20] to improve the availability, access, and use of open EO data to impact policy and decision-making in a wide range of sectors), we believe the potential use of EO data in the study of socio-economic phenomena is still unexpressed (as mentioned for example by Tassa [66]) and would require further publicity and technical efforts, for more widespread use. This could also be realized through a more effective and systematic dialog between researchers, academics, and EO experts, for example, through the organization of recurring thematic meetings, ad hoc training on the use of data, the design of customized products to better match the demand and supply of data within the scientific community. We also suggest that some good worked examples and tutorials in the EO data platforms should be given having in mind a social scientist who wants to use the data with his/her typical research questions and methods.

On the other hand, we have discussed how economists, and in particular, welfare economists can contribute to empirically estimating the socio-economic benefits deriving from services and applications based on EO data. This is a relevant issue, as government, private, and public institutions should rely on the prediction and estimation of current and future benefits in the long term before deciding the optimum level of investment in EO systems. By focusing on the last segment of the EO value chain, we have reviewed some of the most popular estimation approaches, providing a critical discussion of the pros and cons of each of them. We have also highlighted that whilst some of these methods are becoming popular in the space sector, a higher involvement of welfare economists is needed. Experts of the EO sector and consulting companies may need to design more robust methods for the quantification of socio-economic benefits deriving from the exploitation of EO data with an impact into real life. As a matter of fact, while there is a nonnegligible grey literature in this area, it is perhaps revealing that only a small fraction of this research is eventually published in peer-reviewed economic journals, that require that the empirical evidence is tested with econometric or other quantitative methods.

We suggest that there is room for improvement in this area of studies, as certain empirical methods available to economists, such as econometric methods based on quasi-experimental settings, contingent valuation experiments, social cost-benefit analysis techniques, and other quantitative approaches familiar to economists, did not find yet frequent applications in the understanding of the socio-economic benefits of EO data. Several international efforts are being made in this direction, such as the creation of the VALUABLES consortium or the GEOVALUE community[21] (with a focus on the value and socio-economic impacts of geospatial information for decision-making). Further interactions could also be further pursued through the organization of ad hoc interdisciplinary workshops, recurring meetings, dedicated training, the creation of a common glossary, and funding opportunity by space agencies for interdisciplinary working groups to achieve common goals.

Hence, we conclude by recommending a more systematic dialog, collaboration, and cross-fertilization between experts of EO data applications and economists interested in socio-economic subjects as this interplay may highly benefit both. Indeed, this interaction would lead to easier access to data (e.g., for econometric modeling) and would boost, from one side, research in the socio-economic field and, from the other side, would support a more precise estimation of the current and potential socio-economic benefits of EO leading to more calibrated investment decisions.

Nowadays this interaction is also essential to better analyze interactions between human activities and the Earth system; to study the causes, consequences, and solutions to problems that arise from global change;[22] as well to advance a system dynamics model of social, economic, and environmental earth systems and their interdependencies.[23] This interaction would also be instrumental in pushing forward important projects to monitor the health of the planet, to support policy-making and its implementation, perform simulations, improve modeling and predictive capacities, and reinforce industrial and technological capabilities and artificial intelligence, as well as high-performance computing (e.g., Destination Earth initiative).[24]

Authorship statement

All persons who meet authorship criteria are listed as authors, and all authors certify that they have participated sufficiently in the work to take public responsibility for the content, including participation in the concept, design, analysis, writing, or revision of the manuscript. Furthermore, each author certifies that this material or similar material has not been and will not be submitted to or published in any other publication before its appearance in the *Hong Kong Journal of Occupational Therapy*.

Authors' contributions:

Category 1.

Conception and design of study: V. Morretta and M. Florio

Acquisition of data: V. Morretta

Analysis and/or interpretation of data: V. Morretta and M. Florio

Category 2.

Drafting the manuscript: V. Morretta

Revising the manuscript critically for important intellectual content: V. Morretta and M. Florio

Category 3.

Approval of the version of the manuscript to be published: V. Morretta and M. Florio

[18] https://sedac.ciesin.columbia.edu/.

[19] https://www.usgs.gov/core-science-systems/nli/landsat/us-landsat-analysis-ready-data?qt-science_support_page_related_con=0#qt-science_support_page_related_con.

[20] http://www.earthobservations.org/index.php.

[21] http://geovalue.org.

[22] https://globalchange.mit.edu/research/research-tools/global-framework.

[23] https://iiasa.ac.at/web/home/research/researchPrograms/EcosystemsServicesandManagement/Felix_Model.html.

[24] https://ec.europa.eu/digital-single-market/en/destination-earth-destine.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this article.

References

[1] P.G. Almirall, P.Q. Ros, M. Craglia, M. Moix, The Socio-Economic Impact of Spatial Data Infrastructure of Catalonia, Office for Official Publications of the European Communities, 2008. https://inspire.ec.europa.eu/reports/Study_reports/catalonia_impact_study_report.pdf.
[2] H. Alterman, Counting People: the Census in History, Harcourt, Brace & World, 1969.
[3] S. Anand, A. Sen, Human development and economic sustainability, World Dev. 28 (12) (2000) 2029–2049.
[4] K. Arrow, R. Solow, P.R. Portney, E.E. Leamer, R. Radner, H. Schuman, Report of the NOAA panel on contingent valuation, Fed. Regist. 58 (1993) 4601–4614.
[5] J. Aschbacher, ESA's Earth Observation Strategy and Copernicus, in: Satellite Earth Observations and Their Impact on Society and Policy, Springer, Singapore, 2017, pp. 81–87.
[6] R. Bernknopf, D. Brookshire, Y. Kuwayama, M. Macauley, M. Rodell, A. Thompson, P. Vail, B. Zaitchik, The Value of remotely sensed information: the Case of GRACE enhanced drought severity index, Wea. Cilm. Soc. 10 (2018) 187–203, https://doi.org/10.1175/WCAS-D-16-0044.1.
[7] R. Bernknopf, Y. Kuwayama, R. Gibson, J. Blakely, B. Mabee, T.J. Clifford, D. Goodrich, The cost-effectiveness of satellite Earth observations to inform a post-wildfire response, Res. Future (2019). https://media.rff.org/documents/Valuables_Wildfires.pdf. Working Paper 19–16 July 2019.
[8] Booz & Co, Cost-benefit analysis for GMES, European Commission: Directorate-General for Enterprise & Industry, 2011. https://www.copernicus.eu/sites/default/files/2018-10/ec_gmes_cba_final_en.pdf.
[9] M.T. Borzacchiello, M. Craglia, Socio-economic benefits from the use of earth observation, Joint Res. Centre (2011). https://core.ac.uk/download/pdf/38621966.pdf.
[10] R. Burgess, M. Hansen, B.A. Olken, P. Potapov, S. Sieber, The political economy of deforestation in the tropics, Q. J. Econ. 127 (4) (2012) 1707–1754.
[11] H.H. Chang, C. Meyerhoefer, F.A. Yang, 'COVID-19 Prevention and Air Pollution in the Absence of a Lockdown' (No. W27604), National Bureau of Economic Research, 2020.
[12] Y. Chen, G.Z. Jin, N. Kumar, G. Shi, The promise of Beijing: evaluating the impact of the 2008 Olympic Games on air quality, J. Environ. Econ. Manag. 66 (3) (2013) 424–443.
[13] H. Clark, M. Pinkovskiy, X. Sala-i-Martin, 'China's GDP Growth May Be Understated' (No. W23323), National Bureau of Economic Research, 2017.
[14] A. Costinot, D. Donaldson, C. Smith, Evolving comparative advantage and the impact of climate change in agricultural markets: evidence from 1.7 million fields around the world, J. Polit. Econ. 124 (1) (2016) 205–248.
[15] M. Craglia, K. Pogorzelska, The economic value of digital earth, in: Manual of Digital Earth, Springer, Singapore, 2020, pp. 623–643.
[16] S. Dawes, G. Burke, A. Pash, T. Dye, Socioeconomic Benefits of Adding NASA Satellite Data to AirNow, NASA, 2013. https://www.ctg.albany.edu/media/pubs/pdfs/sti_finalreport.pdf.
[17] N.S. Diffenbaugh, C.B. Field, E.A. Appel, I.L. Azevedo, D.D. Baldocchi, M. Burke, S.M. Fletcher, The COVID-19 lockdowns: a window into the Earth System, Nat. Rev. Earth Environ. (2020) 1–12.
[18] D. Donaldson, A. Storeygard, The view from above: applications of satellite data in economics, J. Econ. Perspect. 30 (4) (2016) 171–198.
[19] E. Duflo, R. Glennerster, M. Kremer, Using randomization in development economics research: a toolkit, Handb. Dev. Econ. 4 (2007) 3895–3962.
[20] EMBL-EBI, The European Bioinformatics Institute- Innovation & Traslation, 2019. https://www.embl.org/files/wp-content/uploads/Innovation_and_translation-2019.pdf.
[21] Eumetstat, The Case for the Eps-Second Generation Programme, World Meteorological Organization, 2014. https://www.wmo.int/pages/prog/sat/meetings/documents/CM-12_Doc_03-02-01_EUMETSAT-EPS-CostBenefitStudy.pdf.
[22] European Commission, Guide to Cost-Benefit Analysis of Investment Projects, Economic appraisal tool for Cohesion Policy, 2014–2020. https://ec.europa.eu/regional_policy/sources/docgener/studies/pdf/cba_guide.pdf.
[23] European Commission, Space Strategy for Europe, Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions, 2016, COM, 2016, p. 705 (final).
[24] European Commission, Copernicus User Uptake Engaging with Public Authorities, the Private Sector and Civil Society Final Version, 2016. https://www.copernicus.eu/sites/default/files/2018-10/Copernicus_User_Uptake_Engaging_with_Users_0.pdf.
[25] European Commission, Big Data in Earth Observation, 2017. July 2017, https://ec.europa.eu/growth/tools-databases/dem/.
[26] European Council, Space Policy for a Sustainable Economy, Council adopts conclusions -European Council of the European Union, 2020. https://www.consilium.europa.eu/en/press/press-releases/2020/06/04/space-policy-for-a-sustainable-economy-council-adopts-conclusions/?utm_source=dsms-auto&utm_medium=email&utm_campaign=Raumfahrtpolitik+f%C3%BCr+eine+nachhaltige+Wirtschaft:+Rat+nimmt+Schlussfolgerungen+an%20.
[27] M. Florio, Applied Welfare Economics, Routledge, 2014.
[28] M. Florio, Investing in Science: Social Cost-Benefit Analysis of Research Infrastructures, MIT Press, 2019.
[29] M. Florio, F. Giffoni, A contingent valuation experiment about future particle accelerators at CERN, PloS One 15 (3) (2020), e0229885.
[30] Matthias Flückiger, Markus Ludwig, Economic shocks in the fisheries sector and maritime piracy, Elsevier, J. Develop. Econ. 114 (C) (2015) 107–125.
[31] J. Gallo, R. Bernknopf, S. Lev, Measuring the socio-economic value of data and information product derived from earth observations and other geospatial products, in: J.B. Kruse, J. Crompvoets, F. Pearlman (Eds.), GEOValue: the Socio-Economic Value of Geospatial Information, Taylor & Francis Group, London, 2018, pp. 33–48.
[32] GEO (Group on Earth Observations), What is Earth Observation?, 2020. https://www.earthobservations.org/g_faq.html.
[33] D.A. Griffith, Y. Chun, Spatial autocorrelation and uncertainty associated with remotely-sensed data, Rem. Sens. 8 (7) (2016) 535.
[34] D. Halsing, K. Theissen, R.L. Bernknopf, A Cost-Benefit Analysis of the National Map, vol. 1271, US Department of the Interior, US Geological Survey, 2004.
[35] J.V. Henderson, A. Storeygard, D.N. Weil, Measuring economic growth from outer space, Am. Econ. Rev. 102 (2) (2012) 994–1028.
[36] R. Hodler, P.A. Raschky, Regional favouritism, Q. J. Econ. 129 (2) (2014) 995–1033.
[37] B. Hof, C. Koopmans, R. Lieshout, F. Wokke, Design of a methodology to evaluate the direct and indirect economic and social benefits of public investments in space, SEO Rap. (2012) 42.
[38] S. Jayachandran, 'Air quality and early-life mortality evidence from Indonesia's wildfires', J. Hum. Resour. 44 (4) (2009) 916–954.
[39] S. Jayachandran, J. De Laat, E.F. Lambin, C.Y. Stanton, Cash for Carbon: a Randomized Controlled Trial of Payments for Ecosystem Services to Reduce Deforestation (No. W22378), National Bureau of Economic Research, 2016.
[40] P. Kansakar, F. Hossain, A review of applications of satellite earth observation data for global societal benefit and stewardship of planet earth, Space Pol. 36 (2016) 46–54.
[41] M.W. Kimani, J.C. Hoedjes, Z. Su, An assessment of satellite-derived rainfall products relative to ground observations over East Africa, Rem. Sens. 9 (5) (2017) 430.
[42] J.B. Kruse, J. Crompvoets, F. Pearlman (Eds.), GEOValue: the Socio-Economic Value of Geospatial Information, CRC Press, 2018.
[43] M. Kudamatsu, GIS for credible identification strategies in economics research, CESifo Econ. Stud. 64 (2) (2018) 327–338.
[44] R.J. Johnston, K.J. Boyle, W. Adamowicz, J. Bennett, R. Brouwer, T.A. Cameron, et al., Contemporary guidance for stated preference studies, J. Assos. Environ. Res. Econ. 4 (2017) 319–405, https://doi.org/10.1086/691697.
[45] M. Lafaye, Benefit assessment of the application of satellite Earth observation for society and policy: assessing the socio-economic impacts of the development of downstream space-based Earth observation applications, in: Satellite Earth Observations and Their Impact on Society and Policy, Springer, Singapore, 2017, pp. 93–103, 2017.
[46] Y.S. Lee, International isolation and regional inequality: evidence from sanctions on North Korea, J. Urban Econ. 103 (2018) 34–51.
[47] J.P. LeSage, R.K. Pace, Spatial econometric models, in: Handbook of Applied Spatial Analysis, Springer, Berlin, Heidelberg, 2010, pp. 355–376.
[48] M.K. Macauley, The value of information: measuring the contribution of space-derived earth science data to resource management, Space Pol. 22 (4) (2006) 274–282.
[49] B. Marx, T.M. Stoker, T. Suri, There is no free house: ethnic patronage in a Kenyan slum, Am. Econ. J. Appl. Econ. 11 (4) (2019) 36–70, https://doi.org/10.1257/app.20160484.
[50] B.M. Miller, The not-so-marginal value of weather warning systems, Weather Clim. Soc. 10 (1) (2018) 89–101.
[51] NASA, *Measuring Socioeconomic Impacts of Earth Observations*, a Primer, Applied Sciences Program NASA Earth Science, 2013. https://www.nasa.gov/sites/default/files/files/SocioeconomicImpactsPrimer.pdf.
[52] OECD, Space and Innovation, OECD Publishing, Paris, 2016.

[53] OECD, The economic cost of air pollution: evidence from Europe, in: Antoine Dechezleprêtre, Nicholas Rivers, Balazs Stadler (Eds.), Economic Department Working Papers No. 1584, 2019.
[54] J.C.V. Pezzey, M.A. Toman, The Economics of Sustainability, Routledge, London, 2017.
[55] PwC, Study to Examine the Socio-Economic Impact of Copernicus in the EU Report on the Copernicus Downstream Sector and User Benefits, 2016. October 2016.
[56] PwC, Copernicus Market Report, vol. 164, 2019, ISBN 978-92-79-98973-5, https://doi.org/10.2873/011961.
[57] H.W. Riecken, Social science and contemporary social problems, Items 23 (1969) 1–6.
[58] A. Saiz, The geographic determinants of housing supply, Q. J. Econ. 125 (3) (2010) 1253–1296.
[59] G. Sawyer, D. Boyle, N. Khabarov, G*round Motion Monitoring in Norway* European Association of Remote Sensing Companies, Sentinels Benefits Study (SeBS), 2020. https://earsc.org/sebs/wp-content/uploads/2020/07/Ground-Movement-Monitoring-in-Norway-final.pdf.
[60] G. Sawyer, C. Oligschläger, N. Oligschläger, A Case Study: Growing Potatoes in Belgium, European Association of Remote Sensing Companies, 2019. Sentinels Benefits Study (SeBS), https://earsc.org/sebs/wp-content/uploads/2019/08/1_full-report-Growing-Potatoes-in-Belgium.pdf.
[61] G. Sawyer, A. Dubost, M. De Vries, Copernicus Sentinels' Products Economic Value: a Case Study of Forest Management in Sweden, European Association of Remote Sensing Companies, 2016.
[62] G. Sawyer, A. Dubost, M. de Vries, I. van de Kerk, Copernicus Sentinels' Product Economic Value: A Case Study of Winter Navigation in the Baltic, EARSC, 2015.
[63] A. Smart, A. Coote, B. Miller, R. Bernknopf, A review of socio-economic valuation methods and techniques, chapter 10, in: J.B. Kruse, J. Crompvoets, F. Pearlman (Eds.), GEOValue: the Socio-Economic Value of Geospatial Information, CRC Press, 2018 (2018).
[64] N. Stern, The Economics of Climate Change: the Stern Review, Cambridge University Press, Cambridge, 2007.
[65] A. Storeygard, Farther on down the road: transport costs, trade and urban growth in sub-Saharan Africa, Rev. Econ. Stud. 83 (3) (2016) 1263–1295 (2016).
[66] A. Tassa, The socio-economic value of satellite earth observations: huge, yet to be measured, J. Econ. Poil. 23 (1) (2019) 34–48 (2020).
[67] K.B. Vogel, R. Goldblatt, G.H. Hanson, A.K. Khandelwal, Detecting Urban Markets with Satellite Imagery: an Application to India, NBER working paper 24796, 2018.
[68] WMO (World Meteorological Organisation), Valuing Weather and Climate: Economic Assessment of Meteorological and Hydrological Services, vol. 1153, WMO N, 2015.