Spatial finance

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Spatial finance: practical and theoretical contributions to financial analysis

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ABSTRACT

We introduce and define a new concept, 'Spatial Finance', as the integration of geospatial data and analysis into financial theory and practice, and describe how developments in earth observation, particularly as the result of new satellite constellations, combined with new artificial intelligence methods and cloud computing, create a plethora of potential applications for Spatial Finance. We argue that Spatial Finance will become a core future competency for financial analysis, and this will have significant implications for information markets, risk modelling and management, valuation modelling, and the identification of investment opportunities. The paper reviews the characteristics of geospatial data and related technology developments, some current and future applications of Spatial Finance, and its potential impact on financial theory and practice.

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spatial finance; green finance; financial analysis; geospatial; remote sensing

1. Introduction

'Spatial Finance' is the integration of geospatial data and analysis into financial theory and practice (Caldecott 2019). Existing geospatial datasets are being augmented and new ones made available as a result of rapid recent developments in earth observation and remote sensing. Advances in machine learning mean that these datasets can be processed in near-real time and at scale, making them relevant for many financial institution use cases. The combination of these technologies has the potential to transform the availability of information in our financial system. This could have a transformative effect on how risks, opportunities and impacts are measured and managed by financial institutions. We argue that this creates a significant opportunity for the financial services industry and particularly for financial analysis.

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Analyses based on geospatial data, such as drone or satellite imagery, have begun to become more prominent in a range of disciplines, such as economics, geology and climate science (Van der Meer et al. 2012; Donaldson and Storeygard 2016; Zhu et al. 2017). However, the potential for geospatial data and analyses to augment and enhance available financial data, analyses and decision-making has yet to be realised. This paper serves to introduce the concept of Spatial Finance and provide insight into the potentially transformative impact it could have on traditional financial theories and practices.

2. Characteristics of geospatial data

We think there are at least five key characteristics of geospatial data and analysis that serve to enhance traditional forms of financial data and analysis. These characteristics are comparability, assurability, timeliness, scalability and constant improvability:

1) Comparability. All remote sensing imagery can relatively easily be compared as each image provides an image of the surface of the Earth. As such, geospatial data provides opportunities to undertake standardised analyses ensuring that rigorous comparisons and insights can be drawn.
2) Assurability. All geospatial data is traceable and verifiable in nature. The data uses standardised georeferencing techniques (i.e. tagged with latitude-longitude coordinates), is timestamped, and will referenced back to a specific sensor or satellite. Detailed referencing of geospatial data is essential given the wealth of satellites and the increasing historical data that are available. This ability to accurately identify imagery also facilitates reproducibility in geospatial analyses. Geospatial data are basically images of the surface of the Earth. As such, geospatial data provide an unbiased view of the world at a certain point of time, which provides further quality assurances to its use in financial analyses.
3) Timeliness. The majority of current earth observation satellite constellations produce high temporal frequency imagery. This means images of a location are produced at least once every day. The frequency of this data allows near real time analyses to be undertaken, which significantly enhances the ability to make timely and accurate financial decisions.
4) Scalability. Advances in computer vision techniques, for example, improvements in image processing and classification models, as well as the accessibility of modern cloud-based processing, for example, Amazon Web Services (AWS), allow analyses at global scale to be undertaken with a higher degree of accuracy than has been attainable in the past. It is possible to train an algorithm to detect changes across the entire global corpora of images, including all the most recent, as well as across a back catalogue of images going back in time. For example, it is possible to track how many solar PV panels were installed globally in the last week and understand how solar PV growth has changed by country or city each week over the last 10 years (Kruitwagen and Story 2020). Global scale financial analyses have often been impeded by differences in jurisdictional disclosure requirements and a lack of alternative sources of information. Geospatial data and analysis can overcome some of these barriers, for example, by allowing the collecting of consistent production data at the asset-level for facilities in the same sector across multiple jurisdictions, irrespective of different disclosure requirements and practices.

5) Constant improvability. Geospatial data and analysis benefit from a virtuous cycle. There has been a significant increase in the number of satellites that have been launched over the last ten years and these look set to grow further as launch costs fall and technologies improve. All of these satellites are providing an increasing amount of geospatial data based on the different sensors that are being used. As a result of this constantly improving source of data, new spatial analytical methods and better algorithms to process this imagery have and will continue to be developed. These improvements allow us to obtain new insights and to analyse imagery at faster rates and at larger scales. These drivers act to increase the quality and scale of analysis, while reducing costs.

This paper serves to highlight these important advantages of geospatial data and analyses and emphasise how these attributes can be used to enhance financial analysis and decision-making.

3. Developments in geospatial data capture, processing and storage

Significant enhancements in numerous fields including computer science, engineering and finance serve as the backbone for the potential emergence of Spatial Finance. Not all geospatial data is the same. As a result, the type of analyses to be conducted will inform the type of geospatial data that is required. Remote sensing data, a form of geospatial data, can differ along a number of dimensions, including the spatial resolution, revisit rate and the sensors that are deployed.

Spatial resolution refers to the size of a pixel. For example, Landsat has a 30 m resolution, which means that each pixel represents an area of 30 m x 30 m. Very High Resolution (VHR) satellites can provide spatial resolutions down to 0.3 m. Typically, spatial resolution varies between 1 km to 0.3 m. Increasing the spatial resolution also exponentially increases the size of the images and the processing time required to analyse the data. The spatial resolution requirement will vary based on the type of analysis that is required. For examining and categorising large areas, such as land classification-based modelling, relatively coarse spatial resolution can suffice. Whereas, VHR will be required for the identification of smaller objects, such as vehicles.

Geospatial data also differs based on the revisit rate or temporal resolution. The majority of remote sensors will provide geospatial data for a location between one month to a day. The revisit rates of newer satellites typically provide imagery every day allowing almost real time analysis to be undertaken. Not all optical geospatial data is usable as a result of cloud cover or other impeding atmospheric conditions. However active, microwave-based instruments are available that collect geospatial data day and night and irrespective of cloud cover. Geospatial data, in some form, exists for almost every location on the surface of the Earth for the last few decades. With the increasing number of satellites being launched over the last decade, the coverage and quality of geospatial data will continue to improve.

Earth observation satellites will house one or more sensors, which can detect energy in one or more bands of the electromagnetic spectrum. Across this spectrum, remote sensing sensors are typically classed as either active or passive instruments. Active instruments, such as synthetic aperture radar, generate their own energy which is then recorded after it has reflected back from earth. The key benefits of these instruments are that they allow data capture night and day, irrespective of cloud cover and they are good at capturing surface characteristics such as structure and moisture (Woodhouse 2006). Passive instruments, such as optical sensors, detect energy that is emitted or reflected from any object on the surface of the planet. While optical imagery is the most widely known, these sensors can also detect signals outside of the visible spectrum, in particular providing infrared imagery. The use of these different satellite bands or a combination of them can provide a variety of different insights. For example, certain sensors can be used for the detection and monitoring of GHG emissions in the atmosphere (Chen et al. 2013; Caldecott et al. 2018).

Satellite data can be open source, which anyone can access and analyse, or be provided by private commercial satellite providers. The most frequently used open source satellite data is sourced from NASA's Landsat programme or the European Space Agency (ESA) Sentinel programme. Typically, open source geospatial data has relatively courser spatial (>10 m) and temporal resolution. Whereas the commercial geospatial data providers will often have VHR (>0.3 m), high frequency data or will undertake specialised missions deploying uniquely developed sensors.

Satellite imagery by itself is not meaningful from a finance perspective. Some form of analysis needs to be undertaken to quantify and provide worthwhile insights from these raw images. Typically, these forms of analysis involve some form of image classification or identification, whereby machine learning or artificial intelligence driven approaches are implemented to identify specific object or objects of interest. These objects can include anything that is visible from space on the surface of the Earth, such as natural features (e.g. forests, sand, rocks) or urban areas (e.g. residential, commercial, or industrial buildings). Non-visible characteristics, such as the atmospheric composition, can also be derived using these types of approaches.

With petabytes of data being beamed back to Earth on a daily basis and the increasing number of satellite launches, evaluating geospatial data at scale using traditional methods dependent on direct human analysis would be unfeasible. Significant advancements in machine learning algorithms and techniques allow global scale assessments to be undertaken. For example, recent studies have developed global change models that are capable of detecting changes around key issues, such as vegetation drought monitoring (Zou, Li, and Yu 2018). These advancements also allow global models to be run in order to identify and categorise specific objects all around the world, such as solar photovoltaic (PV) panels (Kruitwagen and Story 2020). Convolutional Neural Networks (CNN) are the leading method for image processing and classification. CNNs can be used to learn sophisticated features and identify objects and object features in an image. CNNs have been used for similar image identification problems, such as facial recognition. In conjunction with these improvements in computer science is the greater availability of modern cloud-based processing. Greater access to processing power makes deploying the CNN models significantly more scalable, allowing analyses at a global scale to be attainable. The substantial enhancements in satellite technology, computer science and processing power have made it easier to undertake spatial analyses and have provided the opportunity to run analyses that in the past were unfeasible.

Spatial analyses can also be further enhanced via other alternative techniques. Natural Language Processing (NLP) can be used in conjunction with web scraping techniques to pull through meaningful information that can be integrated and can serve to validate the spatial analyses. From a finance perspective, NLP can be particularly useful for identifying who owns an asset, which obviously cannot be determined solely by analysing satellite imagery. Furthermore, with the revolution in social media and the democratisation of the internet alternative approaches such as crowd sourcing can be utilised. Existing platforms such as OpenStreetMap (OSM) provide openly available information that can prove useful for validation purposes. Crowd sourcing can also be deployed to verify any spatial analyses that have been undertaken. These crowd sourcing approaches are invaluable to further enhance algorithm development as well as ensure the quality of the final analyses that are being produced.

4. Practical applications

In this section, we explore the current examples and potential practical applications of Spatial Finance.

4.1. Current uses

Spatial Finance applications are not new, however, many applications to date are still nascent or quite niche (Christiaen, 2021). Some of the most mature use cases for Spatial Finance today include commodities trading, insurance assessments and economic data analyses.

Commodities traders can potentially use Spatial Finance to gain a trading advantage. Geospatial data can be used to better understand the flow and availability of various commodity classes to make more informed trading decisions. For example, traders have been advantageously using geospatial data to understand oil storage levels (Clark and Murtaugh 2017). Furthermore, extensive research has been undertaken to understanding and predicting future agricultural yields, which can inform agricultural commodity trading (see Launay and Guerif 2005; Salazar, Kogan, and Roytman 2007; Zilmann 2018). These types of geospatial analyses are relatively simple to undertake, however, they can significantly improve a trader's understanding of a commodity market.

The insurance industry has utilised geospatial data for a number of years. The primary use of remote sensing by insurers is to understand ex-post damages caused by extreme events, such as floods and fires (De Leeuw et al. 2014). The use of geospatial data in instances of extreme events greatly facilitates the assessment of damages extending over a wide area. Spatially driven damage assessments can also prove invaluable when it becomes difficult to adequately access areas on the ground, which can often arise after extreme events. Remote sensing data is increasingly used to develop weather index insurance products for the agriculture sector, particularly in emerging markets where coverage of sensor-based weather data is low. For instance, to model drought conditions based on rainfall and soil moisture observations, where a breach of the index triggers an automated insurance pay-out (Black et al. 2016).

Finally, numerous efforts have also been made to understand broader macroeconomic output and trends using remote sensing. Visible lights in the night have been used extensively to predict economic activity and trends (Doll, Muller, and Morley 2006; Elvidge et al. 2009; Henderson, Storeygard, and Weil 2012; Jean et al. 2016).

The detection of visible lights can also be achieved relatively cheaply using satellite data with a coarse spatial resolution of up to 1 km. The use of night lights as a proxy for economic activity is most valuable for regions with limited economic information, such as regions in Africa. Using VHR imagery it is possible to detect other factors that can be used in estimating economic activity at a city or country level. For example, VHR imagery can be used to identify cars, which can then be used to monitor the amount of traffic at shopping malls (Kearns 2015). Furthermore, economic activity indicators can also be derived by tracking ships coming in and out of ports (Sweeting 2018). Although these techniques are relatively well established in the economics literature very few empirical studies have attempted to link earth observation data to financial analysis.

4.2. Spatial analysis in finance literature

Within the finance literature, there have been very few attempts to assess geospatial impacts in empirical and theoretical settings. Based on an examination of the top financial journals[1], there have been very few attempts to assess geospatial impacts in empirical and theoretical settings. Prior work has used data that has been derived from satellites as independent variables in empirical papers. For example, papers have looked at the link between weather and stock returns or the valuation of weather derivatives using temperatures derived from satellites (Cao and Wei 2005; Jacobsen and Marquering 2008; Dorfleitner and Wimmer 2010). Empirical financial work will often employ proxies within their modelling framework. For example, economic wealth or activity will sometimes be proxied by nightlight intensity derived from satellites (Brei, Mohan, and Strobl 2019). These types of satellite derived proxies will often be developed by one study and then used in numerous subsequent papers. For example, Saiz (2010) developed a measure of developable land based on elevation modelling and the presence of water evident from satellite imagery, which has then been used in other papers to assess housing prices (Han 2013; Adelino, Schoar, and Severino 2015). The existing literature will, therefore, sometimes use variables in their models that have been derived from geospatial data, however, it is very uncommon for geospatial data to be the basis of a finance paper.

In one of the few papers that has made a concerted effort to link geospatial data to finance, Zhu (2019) examines whether the availability of alternative data, in particular car counts in parking lots derived from satellite imagery, improves price informativeness and serves to discipline managers. The empirical findings indicate that the use of alternative data increases price informativeness as a result of reduced information costs. The introduction of alternative data also results in reduced opportunistic trading from managers and improved managerial investment efficiency. In related work, Katona et al. (2020) find evidence that unequal access to satellite derived parking lot counts can increase information asymmetry between sophisticated and individual investors. These findings highlight that although geospatial data can be useful in improving the availability of information without equal access to this information asymmetries will continue to persist. Overall, these papers demonstrate the growing potential for the incorporation of geospatial data in the finance literature. With the relative lack of Spatial Finance based papers, there are significant opportunities for future research.

Data collected from geographically disperse locations are typically not independent, they will frequently exhibit spatial dependency. Spatial dependence arises when observations from one location have similar values to other observations in close proximity. Spatial dependence is frequently evident in a variety of empirical finance studies. For example, the capital structure of firms is highly dependent on country specific factors (de Jong, Kabir, and Nguyen 2008), international stock markets exhibit varying degrees of linkages (Asgharian, Hess, and Liu 2013) and loans are priced differently depending on the distance between the bank and the borrower (Bellucci, Borisov, and Zazzaro 2013).

Spatial econometrics is a subfield of econometrics that employs analytical techniques to address spatial dependence in regression models (Paelinck and Klaassen 1979; Anselin 2013). Despite this toolset being available to address spatial dependence, very few empirical finance analyses employ these spatial econometric models. Most cross-country assessments will typically include a dummy variable to control for country specific factors, however, they will not typically do much more to address spatial dependency. The importance of spatial econometrics has been increasingly applied across a variety of empirical economic investigations, however, it has yet to be fully embraced in the finance literature.

The lack of the use spatial econometric models within the finance literature can in part be attributed to the absence of comprehensive and relevant geospatial data. Typically finance studies when assessing geographic factors will rely on available spatial characteristics, such as the address of a company's headquarters (for example Eckel et al. 2011; Cotugno, Monferrà, and Sampagnaro 2013). Given the spatially diverse nature of multi-national corporations, the use of the headquarters location is unlikely to capture spatial factors effectively. Spatial finance can play an important role in improving the quality of the geospatial data that can be employed in these models. As such, Spatial Finance could greatly improve the robustness and could enhance the ability to undertake new forms of spatially based empirical finance investigations.

4.3. Asset-level data

One of the key data inputs required to produce meaningful Spatial Finance driven insights is asset-level data. Being able to identify the exact location of physical assets and understand who owns them is crucial for deriving insights into risks, opportunities and impacts. Properly mapping assets and understanding their key features is fundamental for Spatial Finance.

Sectoral asset-level databases with locations of assets on a global scale containing details of relevant asset characteristics are rare and challenging to create.[2] The datasets that do exist are typically incomplete in terms of the number of assets that they cover globally as well as the information that is provided for each asset. However, asset-level databases can readily be developed through the use of some of the spatial techniques previously described. For example, it is possible to develop algorithms that identify major industrial facilities in a particular sector of the global economy. After this initial asset identification has been undertaken further details (such as the capacity, utilisation rates, primary production processes being utilised) about these facilities can also be extracted using similar spatial methods. Finally, alternative techniques, such as NLP and crowd sourcing, can be used to validate the facility level information as well as identify other relevant pieces of information, such as the owner of the asset. Despite the lack of asset-level datasets, existing collaborative efforts, such as the GeoAsset Project, have been established in order to make accurate, comparable and comprehensive asset-level data publicly available, using these types of techniques. This has led to the publication of its first version of a global asset database for the cement and steel sectors (McCarten et al. 2021a, 2021b).

The degree of success of these approaches for developing asset-level datasets will vary depending on the asset in question. Spatial methods have been successfully deployed for the detection of: buildings (Cote and Saeedi 2013), solar PV (Bradbury et al. 2016, Kruitwagen and Story 2020), wind turbines (Vanhellemont and Ruddick 2014), offshore oil platforms (Liu et al. 2016), aircrafts (Zhang et al. 2016), ships (Zou and Shi 2016) and cars (Chen et al. 2016). However, for assets with no distinguishing visible characteristics it may be better to rely on alternative techniques for localisation purposes. Spatial methods can also be applied more broadly to identify numerous other visible and non-visible features. These features could include linear assets (roads, railroads, pipelines), natural resources (forests, wetlands, grasslands), or the atmospheric composition of emissions from assets. If an object of interest is visible from the sky, then it can most likely be categorised and identified through an automated approach.

The use of asset-level data is fundamental for Spatial Finance and provides the basis for a significant number of applications, some of which are outlined in the next few sections. Asset-level data is a form of geospatial data and has the same desirable comparable and unbiased quality. As a result, it is easier to undertake fundamental analyses on individual assets and compare with other assets than to do a comparison at a company-level. Asset-level data also allows bottom-up analyses to be undertaken, where assessments can be undertaken at the asset-level and can then be aggregated to the company, country or even global scale. Understanding the characteristics of assets in detail facilitates the assessment of valuation, risks, impacts and opportunities (Caldecott and Kruitwagen 2016). As a result, the development of these fundamental asset-level datasets is crucial for the viability of undertaking more detailed financial assessments.

4.4. Environmental and climate assessments

Many environmental and climate change risks are inherently spatial. Geospatial datasets of current and future climate and environmental outcomes can be overlayed on to a map of a company's assets to determine the exposure that individual assets have to various environmental and climate risk factors. These asset-level risk exposures can then be aggregated up to the company-level to understand overall company vulnerability. As a result, Spatial Finance can not only help to measure and then manage such risks but can also be invaluable for understanding positive and negative impacts or externalities on the global and local environment thus helping to better align portfolios and loanbooks with environmental outcomes. Spatial finance can also be used to assess risks, impacts and opportunities associated with other sustainability related issues.

Observable details about assets can be used to obtain a more informed insight into facility level emissions. For example, it would be possible to use identifiable facility characteristics (such as capacity, fuel type, production type and production output) to model asset-level emissions. Although these calculation methods will only provide estimates this approach will crucially provide a more fundamental understanding of emissions, which can then easily be aggregated up to understand the emission exposures of companies or portfolios.

Alternatively, emissions can be measured directly by using some of the unique satellite sensors. Techniques have been developed in recent years that would allow for emissions to be traced back to a particular point source (Bovensmann et al. 2010). Unfortunately, the majority of current satellites with sensors capable of discerning GHG emissions in the atmosphere do not have adequate spatial resolution to be capable of tracing emissions back to individual facilities. However, upcoming satellite launches, most notably GHGSat (Ligori et al. 2019) and SCARBO (Witze 2018), will provide the spatial resolution required to undertake these point source emissions assessments. This type of emissions analysis will also provide crucial insight for policy and regulatory makers about how to tackle climate change. For example, Chen et al. (2013) examine remotely sensed aerosol optimal depth to derive insights on Chinese air pollution policy interventions around the 2008 Beijing Olympic Games. They find significant air quality improvements in areas where policies restricted plant operations and enforced strict traffic controls. This work highlights the important role that remote sensing will have on measuring emissions and will also provide an understanding of operational or stranding risks that could arise from future policy or regulatory interventions. Existing projects, such as Climate TRACE[3], have already been established in order to monitor greenhouse gas emissions using geospatial data in order to make more informed policy and sustainability related decisions. Furthermore, being able to identify the highest emitting facilities and companies will also have significant implications for any potential legal liability associated with climate change. This is of particular importance considering the growing movement of climate change related litigation (Setzer and Vanhala 2019; Peel and Osofsky 2020; Setzer and Byrnes 2020).

Geospatial data is also inherently important for understanding the exposure of physical assets to extreme physical climate risks. These climate risks include flooding, sea-level rise catastrophe (such as hurricanes or cyclones), drought, heat stress and water stress. Significant work has been undertaken to understand the impact of flooding, sea-level rise and catastrophe events on economic outcomes and asset valuations (Hallegatte et al. 2011; Hsiang and Jina 2014). However, there is still a substantial amount of work that needs to be undertaken to understand the valuation impact that will likely be caused by future extreme weather-related events. Climate models require historical climate patterns in order to predict the future likelihood of these extreme events. As such, geospatial data is an important input into these forward-looking climate models (Yang et al. 2013). These climate models can then be used to understand the hazard risk for individual assets. These models can also be used to produce other downside risk assessments, such as Value at Risk (VaR) based analyses. Spatial methods can also be used to identify the potential resilience of assets to being damaged by extreme weather events. For example, it is possible to identify the elevation of an asset using a remote sensing based digital elevation model, which can be used to understand flooding susceptibility. Furthermore, it would also be possible to identify other asset characteristics (e.g. barriers) or features of the surrounding environment (e.g. mountains) that may reduce risk exposure to physical climate change. This type of analysis is important for not only understanding the risk exposure of existing assets, but it can also be used by corporates to identify the optimal location to build new infrastructure.

Spatial analyses are also integral for understanding environmental risks and impacts. These environmental issues can include actual or potential threats that can be caused by air and water pollution, deforestation and the destruction of species. The significant increase in the temporal availability of geospatial data also provides opportunities to undertake time series assessments to understand changes in these environmental features. For example, recent work has been undertaken to monitor in real time deforestation in vulnerable regions (Finer et al. 2018). Using these types of assessments, it is also possible to identify causality and as such assign culpability for environmental impacts. This kind of causality attribution method will also have significant implications on potential legal liabilities, where environmental law cases are becoming more prominent and frequent (Stern 2013; Alder and Wilkinson 2016).

4.5. General applications

This section examines how Spatial Finance can be used more generally for the purposes of: examining key operational risks, valuation modelling and identifying investment opportunities. Operational risks that can be better understood through Spatial Finance and as a result be more effectively managed include: supply chains, competition risk and stakeholders or counterparty risk exposures.

Spatial finance is ideally suited for analysing supply chains due to their spatially disperse nature. Once an understanding of where suitable suppliers are located has been undertaken it is then possible to overlay potential transportation routes. Using this coupled with other spatial analyses, in particular assessing weaknesses to climate change, it is possible to identify vulnerabilities. Once any vulnerabilities have been identified appropriate actions can then be taken to appropriately manage any risks. This type of analysis can also be useful for developing and optimising new or existing supply chains. Once potentially suppliers and transportation routes have been identified the risk return profile of potential supply chains can then be optimised. This type of optimisation and risk assessment approach can be applied to even the most sophisticated multi-national corporations.

Using asset-level data it becomes easier to understand the competitive risk firms face or will face in the future. Geospatial data is ideal for tracking and understanding where competitors are located and the relative size and operationality of their facilities. Assessing the construction and progress of new facilities also provides valuable insights into potential future changes in supply and demand in regions. Drawing upon this analysis can facilitate improved management of competition risk. Similarly, this type of exposure analysis can be applied to other key stakeholders or counterparties to better understand the risks associated with those parties and the possibility of future defaults on payments that may arise. Using this approach particularly financially vulnerable party can more readily be identified and appropriate risk mitigation strategies can be implemented.

The development of asset-level datasets can also enhance valuation modelling. In particular, the use of asset-level data and the characteristics that can be derived from the modelling of assets can be used to augment traditional valuation approaches driven by financial information enhancing overall valuation modelling. The key advantage of this type of spatially driven valuation approach primarily stems from the timely nature of geospatial data, which can provide a near real time understanding of the utilisation of assets and any other relevant characteristic changes, such as wear on key components or inventory stockpiling. There is also the potential to uncover another factor, such as a spatial interaction term based on spatial proximity to other companies, that is significantly correlated with returns that could further enhance Fama and French's (2015) five factor model, thus improving existing asset pricing models.

Investment opportunities can also begin to be identified by tracking local developments, particularly in terms of land use changes. Land use classifiers can be used to distinguish between urban and non-urban land use over time (Burchfield et al. 2006). Employing temporal analyses, it would be possible to use these future predictors of development coupled with demographic information to obtain a greater understanding of changes in potential demand. This info will be useful from the corporate perspective to understand the potential for new investment opportunities but could also be used to improve valuation models. Similarly, agricultural land use decisions can be informed from remote sensing. Prediction of future crop yields can inform the choice of crops to grow in order to maximise agricultural output and profitability. Remote sensing can also be used to identify various mineral deposits and can therefore inform decisions where to establish new mines (Van der Meer et al. 2012). There are numerous ways in which Spatial Finance could potentially be deployed to identify investment opportunities, the exact nature of the opportunity will naturally drive the spatial analyses that need to be undertaken.

As previously mentioned, macroeconomic data can also be collected using earth observation sensors. The recent advancements in sensor technology, particularly the higher spatial resolution, also provide opportunities to undertake more detailed spatial analyses to determine key economic indicators in a timelier manner. For example, it would be possible to track production across key sectors as well as track trade routes to determine the level of demand and supply for various goods within an economy. This enhancement in providing timelier economic data can also particularly be useful from a policy perspective as it will be easier to identify economic inflection points earlier and employ appropriate economic interventions. All of these details could also be fed into other important financial analyses, such as credit risk models, to further enhance our understanding of the financial health of the markets.

5. Impact on financial theory

Spatial finance not only has numerous practical applications, but it could also have potentially significant impacts on financial theory. The key theoretical implications of Spatial Finance could be driven by improved informational efficiency. Spatial finance provides the opportunity to collect data that may not have been obtainable before. It also provides opportunities to undertake different forms of analyses adding rigour to existing approaches. Spatial finance will enhance valuation and risk models providing more accurate, unbiased and timely information about corporations. Spatial finance could also play an important role in the validation and verification of corporate disclosures. These insights can be used to reduce information asymmetries and enhance investors' ability to monitor corporate activities.

Zingales (2015) argues that society at large has a distrust of finance. This antifinance sentiment can in part be attributed to recent financial crises as well as the numerous cases of widescale fraudulent corporate activities that have been uncovered over the past two decades. One theoretical implication of improved information asymmetries is that there could be fewer opportunities for fraudulent activity. Opportunities to commit fraud are one of the key factors in driving the occurrence of fraud, along with pressures and rationalisations (Cressey 1953). When there is a lack of corporate transparency as a result of being unable to effectively verify and validate financial statements, there are significant opportunities for fraudulent activity. The improved validation that Spatial Finance can provide could also facilitate the detection of accounting fraud or identify any materially false or misleading statements made by a firm's management. This theoretical improvement in fraud detection could also serve to disincentive managers from committing fraud in the first place. As such, Spatial Finance could play an important role in enhancing society's confidence in the financial markets.

Remote sensing can also be used to directly monitor other forms of illegal activities. Prior work has established methods for directly monitoring illegal environmental practices (Lega et al. 2014). These approaches can be adapted and deployed for the purposes of discerning other readily identifiable illegal or unethical activities from space, such as the use of sweatshops. These illegal activities can bear significant financial and reputational costs directly and in the long term on companies and the top management (Karpoff, Scott Lee, and Martin 2008a, 2008b). The reputational risks run by undertaking these activities coupled with the increased likelihood of being caught should theoretically disincentive managers from undertaking these illegal practices.

Most financial theories have assumptions based on the availability of information. Improved transparency from the mainstreamed use of geospatial data could have implications for a number of financial theories. Information asymmetries can result in suboptimal investment policies as caused by misvaluations. As a result, signalling theory states that financial decisions can be viewed as signals to the market to correct for these misvaluations. As such, investors will often view the actions of insiders closely to gauge whether there is a misvaluation. For example, insider's trading activity are often viewed as signals of a company's financial position. Investors typically view managers selling their shares as a signal that the company is overvalued and vice versa. By improving the information efficiency through geospatial data and analyses the relative importance of these signals could be lessened as significant misvaluations should be less frequent, potentially invalidating the signalling theory.

The pecking order theory relates to the raising of capital, with equity being the least preferred means to raise capital as investors believe that managers will typically only issue new equity if they believe the firm is overvalued (Myers and Majluf 1984). As a result, internal funds are the preferred method of funding new projects and the cost of external financing increases with information asymmetries. By removing information asymmetries firms should become relatively indifferent between the various ways to raise capital. The improved transparency provided by Spatial Finance could therefore have theoretical implications for the preference of raising capital.

6. Conclusion

Spatial finance can significantly enhance our understanding and improve financial modelling of valuations, risks, impacts and opportunities. The advantages of geospatial data over traditional forms of financial data include comparability, fundamentality, timeliness and scalability. These facets allow spatial analyses to obtain information that was heretofore unavailable at a global scale in near real time. These significant enhancements in data and analytical availability improve the efficiency of information in financial markets and can serve to optimise financial decision-making.

The key practical hurdle for mainstreaming the use of Spatial Finance is education. There will be a need for significant capacity building and training to ensure that the geospatial data and analytics are understandable and are being appropriately applied in the financial decision-making process. The adoption of Spatial Finance will also require a new approach to teaching finance at academic institutions. This adjustment in teaching will need to emphasise this multidisciplinary approach to understanding financial issues. The geospatial data and analytics community as well as financial practitioners will also need to work together to establish an understanding of the culpabilities and needs each industry faces. The geospatial data industry is still developing, which provides an opportunity for financial decision-makers to work with this community to fulfil their data and analytic requirements.

There are of course other barriers to the uptake of Spatial Finance. As outlined asset-level data is a crucial element for undertaking the majority of spatially driven risk, impact and opportunity assessments. The current lack of comprehensive of asset-level data tied to ownership, therefore, represents a key hurdle that must be overcome in order to mainstream Spatial Finance. Initiatives, such as the GeoAsset Project, are facilitating the open source development of asset-level datasets, however, there still remains a lot of work before we have global datasets covering all sectors.

Even though Spatial Finance has the potential to improve information asymmetries there remains an inequality in the current ability to undertake geospatial analyses. One potential avenue for improving access to geospatially derived information could be through Spatial Finance's role in the future of reporting. It would not only complement the implementation of new disclosure requirements, such as the Task Force on Climate-related Financial Disclosures (TCFD), but the development 'spatial reporting' to complement traditional financial reporting would significantly enhance spatial transparency improving market efficiency.

Spatial finance will have a potentially transformative impact on the financial industry. The development of Spatial Finance use cases in coming years will not only serve to enhance traditional financial risk, valuation and management practices but also facilitate improved financial market transparency. New opportunities for data and analytics will continue to become feasible as the technology and methods continue to develop. Although a relatively new concept Spatial Finance could have potentially significant implications for traditional financial practice and theory.

Notes

1. This examination was based on searches in the top finance journals using the following keywords: 'spatial', 'geospatial', 'satellite', 'remote sensing', 'drone' and 'earth observation'.
2. One notable exception is in the power sector, where there has been a growing acceptance of the use of asset-level data and an understanding of the importance of using this data,

particularly for addressing key financing issues associated with climate change and other key environmental vulnerabilities.
3. https://www.climatetrace.org/.

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References

Adelino, Manuel, Antoinette Schoar, and Felipe Severino. 2015. "House Prices, Collateral, and Self-Employment." *Journal of Financial Economics* 117 (2): 288–306.

Alder, John, and David Wilkinson. 2016. "Environmental Law and Ethics." *Macmillan International Higher Education*.

Anselin, Luc. 2013. *Spatial Econometrics: Methods and Models*. Dordrecht: Springer Science & Business Media.

Asgharian, Hossein, Wolfgang Hess, and Lu Liu. 2013. "A Spatial Analysis of International Stock Market Linkages." *Journal of Banking & Finance* 37 (12): 4738–4754.

Bellucci, Andrea, Alexander Borisov, and Alberto Zazzaro. 2013. "Do Banks Price Discriminate Spatially? Evidence from Small Business Lending in Local Credit Markets." *Journal of Banking & Finance* 37 (11): 4183–4197.

Black, Emily, Elena Tarnavsky, Ross Maidment, Helen Greatrex, Agrotosh Mookerjee, Tristan Quaife, and Matthew Brown. 2016. "The Use of Remotely Sensed Rainfall for Managing Drought Risk: A Case Study of Weather Index Insurance in Zambia." *Remote Sensing* 8 (4): 342.

Bovensmann, H., M. Buchwitz, J. P. Burrows, M. Reuter, T. Krings, K. Gerilowski, O. Schneising, J. Heymann, A. Tretner, and Joerg Erzinger. 2010. "A Remote Sensing Technique for Global Monitoring of Power Plant CO2 Emissions from Space and Related Applications." *Atmospheric Measurement Techniques* 3: 781–811.

Bradbury, Kyle, Raghav Saboo, Timothy L. Johnson, Jordan M Malof, Arjun Devarajan, Wuming Zhang, Leslie M. Collins, and Richard G. Newell. 2016. "Distributed Solar Photovoltaic Array Location and Extent Dataset for Remote Sensing Object Identification." *Scientific Data* 3 (1): 1–9.

Brei, Michael, Preeya Mohan, and Eric Strobl. 2019. "The Impact of Natural Disasters on the Banking Sector: Evidence from Hurricane Strikes in the Caribbean." *The Quarterly Review of Economics and Finance* 72: 232–239.

Burchfield, Marcy, Henry G. Overman, Diego Puga, and Matthew A. Turner. 2006. "Causes of Sprawl: A Portrait from Space." *The Quarterly Journal of Economics* 121 (2): 587–634.

Caldecott, Ben. 2019. "Viewpoint: Spatial finance has a key role." *Investment Pensions Europe*, November 2019.

Caldecott, Ben, and Lucas Kruitwagen. 2016. "How Asset Level Data Can Improve the Assessment of Environmental Risk in Credit Analysis." *S&P Global Ratings*.

Caldecott, Ben, Lucas Kruitwagen, Matthew McCarten, Xiaoyan Zhou, David Lunsford, Oliver Marchand, Phanos Hadjikyriakou, Valentin Bickel, Torsten Sachs, and Niklas Bohn. 2018. "Climate Risk Analysis from Space: Remote Sensing, Machine Learning, and the Future of Measuring Climate-Related Risk." Working Paper.

Cao, Melanie, and Jason Wei. 2005. "Stock Market Returns: A Note on Temperature Anomaly." *Journal of Banking & Finance* 29 (6): 1559–1573.

Chen, Yuyu, Ginger Zhe Jin, Naresh Kumar, and Guang Shi. 2013. "The Promise of Beijing: Evaluating the Impact of the 2008 Olympic Games on Air Quality." *Journal of Environmental Economics and Management* 66 (3): 424–443.

Chen, Ziyi, Cheng Wang, Chenglu Wen, Xiuhua Teng, Yiping Chen, Haiyan Guan, Huan Luo, Liujuan Cao, and Jonathan Li. 2016. "Vehicle Detection in High-Resolution Aerial Images Via Sparse Representation and Superpixels." *IEEE Transactions on Geoscience and Remote Sensing* 54 (1): 103–116.

Christiaen, Christophe. 2021. "State and Trends of Spatial Finance 2021: Next Generation Climate and Environmental Analytics for Resilient Finance." *Smith School of Enterprise and the Environment - Spatial Finance Initiative*.

Clark, Aaron, and Dan Murtaugh. 2017. "Satellites Are Reshaping How Traders Track Earthly Commodities." *Bloomberg*, December 16.

Cote, Melissa, and Parvaneh Saeedi. 2013. "Automatic Rooftop Extraction in Nadir Aerial Imagery of Suburban Regions Using Corners and Variational Level Set Evolution." *IEEE Transactions on Geoscience and Remote Sensing* 51 (1): 313–328.

Cotugno, Matteo, Stefano Monferrà, and Gabriele Sampagnaro. 2013. "Relationship Lending, Hierarchical Distance and Credit Tightening: Evidence from the Financial Crisis." *Journal of Banking & Finance* 37 (5): 1372–1385.

Cressey, Donald R. 1953. *Other People's Money; a Study of the Social Psychology of Embezzlement*. New York, US: Free Press.

de Jong, Abe, Rezaul Kabir, and Thuy Thu Nguyen. 2008. "Capital Structure Around the World: The Roles of Firm- and Country-Specific Determinants." *Journal of Banking & Finance* 32 (9): 1954–1969.

De Leeuw, Jan, Anton Vrieling, Apurba Shee, Clement Atzberger, Kiros Hadgu, Chandrashekhar Biradar, Humphrey Keah, and Calum Turvey. 2014. "The Potential and Uptake of Remote Sensing in Insurance: A Review." *Remote Sensing* 6 (11): 10888–10912.

Doll, Christopher N. H., Jan-Peter Muller, and Jeremy G. Morley. 2006. "Mapping Regional Economic Activity from Night-Time Light Satellite Imagery." *Ecological Economics* 57 (1): 75–92.

Donaldson, Dave, and Adam Storeygard. 2016. "The View from Above: Applications of Satellite Data in Economics." *Journal of Economic Perspectives* 30 (4): 171–198.

Dorfleitner, Gregor, and Maximilian Wimmer. 2010. "The Pricing of Temperature Futures at the Chicago Mercantile Exchange." *Journal of Banking & Finance* 34 (6): 1360–1370.

Eckel, Stefanie, Gunter Löffler, Alina Maurer, and Volker Schmidt. 2011. "Measuring the Effects of Geographical Distance on Stock Market Correlation." *Journal of Empirical Finance* 18 (2): 237–247.

Elvidge, Christopher D., Paul C. Sutton, Tilottama Ghosh, Benjamin T. Tuttle, Kimberly E. Baugh, Budhendra Bhaduri, and Edward Bright. 2009. "A Global Poverty Map Derived from Satellite Data." *Computers & Geosciences* 35 (8): 1652–1660.

Fama, Eugene F, and Kenneth R French. 2015. "A Five-Factor Asset Pricing Model." *Journal of Financial Economics* 116 (1): 1–22.

Finer, Matt, Sidney Novoa, Mikaela J. Weisse, Rachael Petersen, Joseph Mascaro, Tamia Souto, Forest Stearns, and Raúl García Martinez. 2018. "Combating Deforestation: From Satellite to Intervention." *Science* 360 (6395): 1303.

Hallegatte, Stéphane, Nicola Ranger, Olivier Mestre, Patrice Dumas, Jan Corfee-Morlot, Celine Herweijer, and Robert Muir Wood. 2011. "Assessing Climate Change Impacts, Sea Level Rise

and Storm Surge Risk in Port Cities: A Case Study on Copenhagen." *Climatic Change* 104 (1): 113–137.
Han, Lu. 2013. "Understanding the Puzzling Risk-Return Relationship for Housing." *The Review of Financial Studies* 26 (4): 877–928.
Henderson, J. Vernon, Adam Storeygard, and David N. Weil. 2012. "Measuring Economic Growth from Outer Space." *American Economic Review* 102 (2): 994–1028.
Hsiang, Solomon M, and Amir S Jina. 2014. "The Causal Effect of Environmental Catastrophe on Long-Run Economic Growth: Evidence from 6,700 Cyclones." NBER Working Paper, 0898-2937.
Jacobsen, Ben, and Wessel Marquering. 2008. "Is It the Weather?" *Journal of Banking & Finance* 32 (4): 526–540.
Jean, Neal, Marshall Burke, Michael Xie, W. Matthew Davis, David B. Lobell, and Stefano Ermon. 2016. "Combining Satellite Imagery and Machine Learning to Predict Poverty." *Science* 353 (6301): 790.
Karpoff, Jonathan M., D. Scott Lee, and Gerald S. Martin. 2008a. "The Consequences to Managers for Financial Misrepresentation." *Journal of Financial Economics* 88 (2): 193–215.
Karpoff, Jonathan M., D. Scott Lee, and Gerald S. Martin. 2008b. "The Cost to Firms of Cooking the Books." *Journal of Financial and Quantitative Analysis* 43 (3): 581–611.
Katona, Zsolt, Marcus Painter, Panos N. Patatoukas, and Jean Zeng. 2020. "On the Capital Market Consequences of Alternative Data: Evidence from Outer Space." Working Paper.
Kearns, Jeff. 2015. "Satellite Images Show Economies Growing and Shrinking in Real Time." *Bloomberg Businessweek*, July 9.
Kruitwagen, Lucas, and Kyle Story. 2020. "A Global Inventory of Utility-Scale Solar Photovoltaic Generating Units ", Working Paper.
Launay, Marie, and Martine Guerif. 2005. "Assimilating Remote Sensing Data Into a Crop Model to Improve Predictive Performance for Spatial Applications." *Agriculture, Ecosystems & Environment* 111 (1): 321–339.
Lega, M., C. Ferrara, G. Persechino, and P. Bishop. 2014. "Remote Sensing in Environmental Police Investigations: Aerial Platforms and an Innovative Application of Thermography to Detect Several Illegal Activities." *Environmental Monitoring and Assessment* 186 (12): 8291–8301.
Ligori, Michael, Laura Bradbury, Robert Spina, Robert Zee, and Stephane Germain. 2019. "Ghgsat Constellation: The Future of Monitoring Greenhouse Gas Emissions." Working Paper.
Liu, Yongxue, Chao Sun, Yuhao Yang, Minxi Zhou, Wenfeng Zhan, and Wangyu Cheng. 2016. "Automatic Extraction of Offshore Platforms Using Time-Series Landsat-8 Operational Land Imager Data." *Remote Sensing of Environment* 175: 73–91.
McCarten, M., M. Bayaraa, B. Caldecott, C. Christiaen, P. Foster, C. Hickey, D. Kampmann, et al. 2021a. "Global Database of Cement Production Assets." *Spatial Finance Initiative*.
McCarten, M., M. Bayaraa, B. Caldecott, C. Christiaen, P. Foster, C. Hickey, D. Kampmann, et al. 2021b. "Global Database of Iron and Steel Production Assets." *Spatial Finance Initiative*.
Myers, Stewart C., and Nicholas S. Majluf. 1984. "Corporate Financing and Investment Decisions When Firms Have Information That Investors Do Not Have." *Journal of Financial Economics* 13 (2): 187–221.
Paelinck, J. H. P., and L. H. Klaassen. 1979. "Spatial Econometrics." *Gower*.
Peel, Jacqueline, and Hari M. Osofsky. 2020. "Climate Change Litigation." *Annual Review of Law and Social Science* 16: 1. null.
Saiz, Albert. 2010. "The Geographic Determinants of Housing Supply." *The Quarterly Journal of Economics* 125 (3): 1253–1296.
Salazar, L., F. Kogan, and L. Roytman. 2007. "Use of Remote Sensing Data for Estimation of Winter Wheat Yield in the United States." *International Journal of Remote Sensing* 28 (17): 3795–3811.
Setzer, Joana, and Rebecca Byrnes. 2020. "Global Trends in Climate Change Litigation: 2020 Snapshot." Working Paper.
Setzer, Joana, and Lisa C. Vanhala. 2019. "Climate Change Litigation: A Review of Research on Courts and Litigants in Climate Governance." *WIRES Climate Change* 10: 3.

Stern, Rachel E. 2013. *Environmental Litigation in China: A Study in Political Ambivalence*. Cambridge and New York: Cambridge University Press.

Sweeting, Martin. 2018. “Modern Small Satellites-Changing the Economics of Space.” *Proceedings of the IEEE* 106 (3): 343–361.

Van der Meer, Freek D, Harald MA Van der Werff, Frank JA Van Ruitenbeek, Chris A Hecker, Wim H Bakker, Marleen F Noomen, Mark Van Der Meijde, E John M Carranza, J Boudewijn De Smeth, and Tsehaie Woldai. 2012. "Multi-and Hyperspectral Geologic Remote Sensing: A Review.” *International Journal of Applied Earth Observation and Geoinformation* 14 (1): 112–128.

Vanhellemont, Quinten, and Kevin Ruddick. 2014. “Turbid Wakes Associated with Offshore Wind Turbines Observed with Landsat 8.” *Remote Sensing of Environment* 145: 105–115.

Witze, Alexandra. 2018. “Europe Eyes Fleet of Tiny Co2-Monitoring Satellites to Track Global Emissions.” *Nature* 562: 176–177.

Woodhouse, Iain H. 2006. *Introduction to Microwave Remote Sensing*. London: CRC Press.

Yang, Jun, Peng Gong, Rong Fu, Minghua Zhang, Jingming Chen, Shunlin Liang, Bing Xu, Jiancheng Shi, and Robert Dickinson. 2013. “The Role of Satellite Remote Sensing in Climate Change Studies.” *Nature Climate Change* 3: 875.

Zhang, Fan, Bo Du, Liangpei Zhang, and Miaozhong Xu. 2016. “Weakly Supervised Learning Based on Coupled Convolutional Neural Networks for Aircraft Detection.” *IEEE Transactions on Geoscience and Remote Sensing* 54 (9): 5553–5563.

Zhu, Christina. 2019. “Big Data as a Governance Mechanism.” *The Review of Financial Studies* 32 (5): 2021–2061.

Zhu, Xiao Xiang, Devis Tuia, Lichao Mou, Gui-Song Xia, Liangpei Zhang, Feng Xu, and Friedrich Fraundorfer. 2017. “Deep Learning in Remote Sensing: A Comprehensive Review and List of Resources.” *IEEE Geoscience and Remote Sensing Magazine* 5 (4): 8–36.

Zilmann, Erik. 2018. "Spoiler Alert! Satellite Data Offers Commodities Traders Early View of Crop Acreage & Yield.” *Planet*, August 27.

Zingales, Luigi. 2015. “Presidential Address: Does Finance Benefit Society?” *The Journal of Finance (New York)* 70 (4): 1327–1363.

Zou, Quan, Guoqing Li, and Wenyang Yu. 2018. “Mapreduce Functions to Remote Sensing Distributed Data Processing—Global Vegetation Drought Monitoring as Example.” *Software: Practice and Experience* 48 (7): 1352–1367.

Zou, Zhengxia, and Zhenwei Shi. 2016. “Ship Detection in Spaceborne Optical Image with Svd Networks.” *IEEE Transactions on Geoscience and Remote Sensing* 54 (10): 5832–5845.