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Forecasting Models: An Economic and Environmental Applications

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ABSTRACT

Forecasting plays a critical role in the development of organizational business strategies. Despite a considerable body of research in the area of forecasting, the focus has largely been on the financial and economic outcomes of the forecasting process as opposed to societal benefits. Our motivation in this study is to promote the latter, with a view to using the forecasting process to advance social and environmental objectives such as equality, social justice and sustainability. We refer to such forecasting practices as Forecasting for Social Good (FSG) where the benefits to society and the environment take precedence over economic and financial outcomes. We conceptualize FSG and discuss its scope and boundaries in the context of the "Doughnut theory". We present some key attributes that qualify a forecasting process as FSG: it is concerned with a real problem, it is focused on advancing social and environmental goals and prioritizes these over conventional measures of economic success, and it has a broad societal impact. We also position FSG in the wider literature on forecasting and social good practices. We propose an FSG maturity framework as the means to engage academics and practitioners with research in this area.

Keywords: Forecasting Models, Forecasting for Social Good, FSG, Economic and Environmental Applications

INTRODUCTION

A forecast is a calculation or prediction of some future event or circumstance, typically as a consequence of logical investigation or analysis of relevant data. Today, forecasting is widely employed across many industries, particularly in business, marketing, economics, and finance. A perfect forecast of future demand, as in the manufacture of consumable goods, is crucial for delivering exact inventory, lowering transportation costs, and ultimately raising profit (Markridakis, 1996). The two main types of forecasting methodologies are qualitative and quantitative. Qualitative approaches are essentially informed, intuitive assumptions that may or may not be based on historical evidence. Quantitative approaches provide a plausible prediction from historical data using mathematical or statistical models. Quantitative methods have the benefit over qualitative ones in that they can be completely replicated by any forecaster and are backed by mathematical and statistical theory.

Every day, businesses make operational, tactical, and strategic decisions. Regardless of the sector or industry, these decisions reflect what the future may hold in store. Forecasting can play a crucial role as an integral part of the decision-making process in such situations (Hyndman and Athanasopoulos, 2018). In areas of commercial or economic concern, this concept is well understood. Decades of research have been conducted on the relationship between forecasting and business decision-making (González-Rivera, 2016; Sanders, 2016; Gilliland et al., 2016; Ord et al., 2017). Numerous significant contributions have been made in these fields (e.g., macroeconomics and the financial sector, retail industry and supply chains, energy industry and tourism (Fildes and Stekler, 2002; Fildes et al., 2008; Syntetos et al., 2009; Athanasopoulos et al., 2011; Hong et al., 2014)) regarding how forecasting can enhance organisational decision-making. However, the majority of these studies have focused on enhancing forecasting processes (and their integration into decision-making) in the presence of financial or economic motivations. On the other hand, forecasting has received little consideration when the focus is on obtaining societal benefits regardless of their financial or economic implications. In this article, forecasting practices are referred to as Forecasting for Social Good (FSG).

While there is a growing recognition among agencies, organisations, and governments that data-driven decision-making tools, such as forecasting models, may offer significant improvements to society (Iyer and Power, 2014), there is no unified body of research that provides guidance on the conceptualization, implementation, and evaluation of forecasting models for social good in practise. Although some research has been conducted in this field (Gorr and Harries, 2003; Nsoesie et al., 2014; van der Laan et al., 2016; Wicke et al., 2019; Litsiou et al., 2019), academic contributions and practical applications have been sluggish and sporadic. This is exemplified by the fact that the development and utilisation of forecasting models in organisations with social missions (particularly in health, humanitarian operations, and the third sector) is significantly underdeveloped. Evidence (Getzen, 2016; Cacciolatti et al., 2017; Lu et al., 2018) suggests that this may be due to a lack of awareness, skills, and understanding of the value of forecasting, but the reality remains that such organisations do not exploit (relevant) forecasting capabilities to a large extent. Major review papers in the fields of forecasting, as well as operations research and operations management when forecasting is explicitly considered (Fildes et al., 2008; Syntetos et al., 2009; Boylan and Syntetos, 2010; Syntetos et al., 2016; Makridakis et al., 2020), do not consider FSG-related work. The dearth of academic contributions may be attributable to the paucity of existing work upon which to build, or to the publication of relevant work in periodicals that are not widely read by the forecasting community (Soyiri and Reidpath, 2013; Nsoesie et al., 2014; Dietze, 2017; Goltsos et al., 2019). Given the preceding context, we believe it is time to address explicitly the definition of FSG and its position within the larger body of knowledge. This exercise will facilitate the discussion of forecast implementation and evaluation issues, leading to the proposal of a research agenda; it will also enable organisations to advance their social missions and profit from the value forecasting may offer. The objectives of this paper are threefold:

- increase academics' and practitioners' awareness and interest in the prospective impact of FSG;
- encourage academicians and practitioners interested in the FSG agenda to participate;
- stimulate the development of novel forecasting methodologies tailored to applications for social good.

The remaining sections of the article are structured as follows. Section 2 defines the FSG domain, its scope, and its relationship to (other) data-driven social welfare initiatives and forecasting domains. The third section proposes a framework for positioning based on (i) the maturity of the forecasting process (theory) and (ii) the use of forecasting for social benefit (practise). In addition, it supplies an indicative research agenda. Section 4 concludes with a summary of our conclusions.

Doughtnut theorem:

Raworth (2017) proposed doughnut theory, which provides a framework for considering how to create a world in which humanity flourishes. Instead of economies that need to grow regardless of whether they help us flourish, we need economies that help us thrive regardless of whether they grow. The objective is to meet everyone's requirements within the means of the planet. As shown in Figure 1, the theory combines the concepts of social foundation and ecological ceiling into a singular framework.

The social foundation derives from the social priorities outlined in the Sustainable Development Goals of the United Nations (UN General Assembly, 2015). The objective is to ensure that no one is left in the doughnut hole below the social foundation and lacks access to sustenance, clean water, and gender equality, and that everyone has a political voice and access to housing.

The ecological ceiling consists of nine planetary boundaries devised by environmental scientists (Rockstro m et al., 2009) that represent the capacity of life-supporting systems on the planet. To preserve them, humanity must exist within these ecological boundaries while meeting the social foundation's requirements for all.

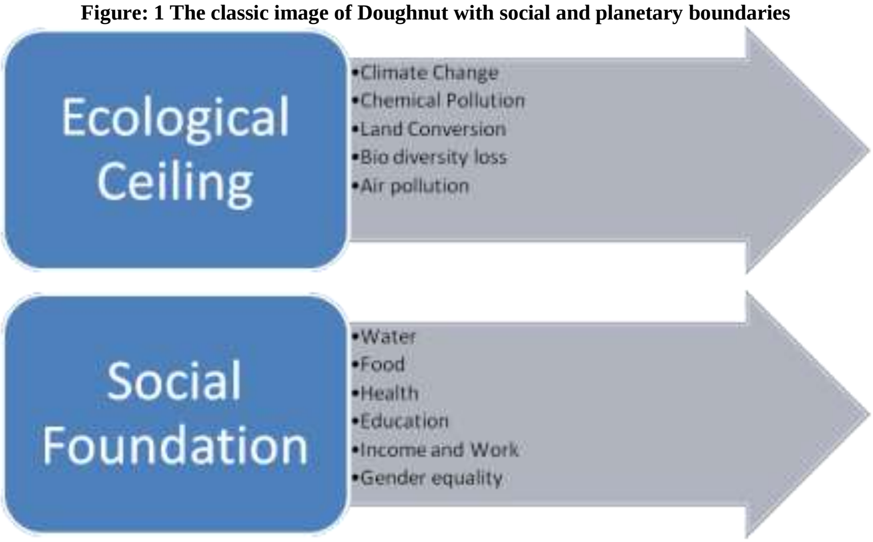
Between the social foundation and the ecological ceiling lies a space where it is possible to satisfy the needs of all people within the means of the living planet - an ecologically secure and socially just space where humanity can flourish.

This is the space into which we must simultaneously proceed from both sides, in ways that promote the well-being of all people and the health of the entire planet. To accomplish this on a global scale requires action on multiple levels, including research and its applications. Multiple academic disciplines, countries, sub-regions, and cities around the world have adopted the framework (Cole et al., 2014; Dearing et al., 2014; Hoornweg et al., 2016; Amenta and Qu, 2020; Bennett, 2020).

Definition and scope of Social Good Forecasting:

The Doughnut framework enables the development of multi-metric 'compasses' to inform the decision-making process (Dearing et al., 2014). To promote the well-being of all people and the health of the entire planet, the decision-making process must support all activities that bring us into the Doughnut space - an environmentally safe and socially just space where humanity can flourish. We note that forecasting is one of the primary components of any decision-making process.

Figure: 1 The classic image of Doughnut with social and planetary boundaries



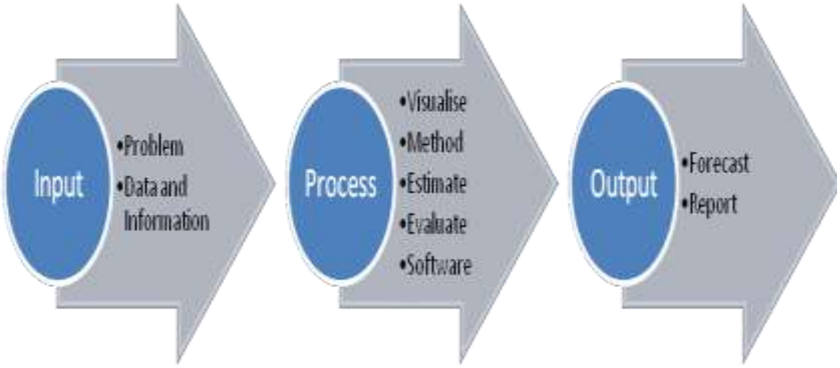
Source: Doughnut (economic model) (2020)

We define forecasting as a genuine prediction of the future based on all the information available at the time the forecast is generated, including historical data and knowledge of any future events that may have an impact on the outcome(s) (Goodwin, 2018; Hyndman and Snelgrove, 2002).

Athanasopoulos, 2018). The forecasting process begins by receiving inputs in the form of a problem description, data, and information. Next, an appropriate forecasting method is identified, and the inputs are processed and formulated to implement the method using software and make the forecast, when necessary, incorporating human judgment and uncertainty assessments.

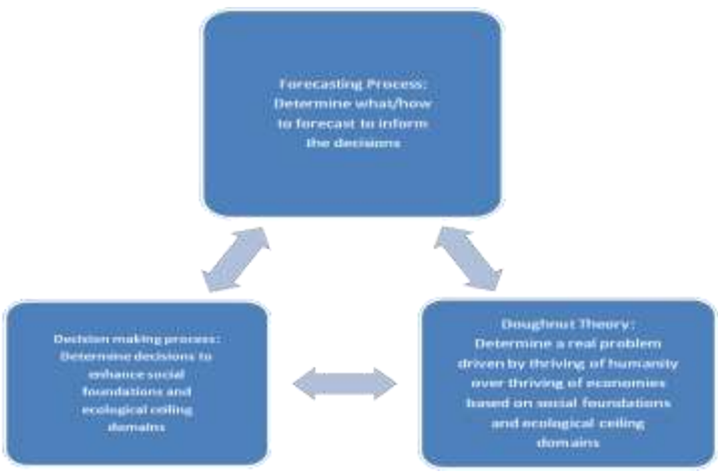
Authentic forecasting is also possible in the absence of available data and without the use of statistical methods or software. We may instead rely on structured management judgement, such as the Delphi method, forecasting by analogy, surveys, scenario forecasting, and other methods of judgmental forecasting.

Figure: 2 Forecasting Process



Forecasting is utilized to assist decision-makers in making more informed and potentially better choices. Consequently, forecasts must be tailored to provide answers to the queries a decision maker requires in a given set of circumstances. In the case of FSG, we argue that the forecasting process should be determined by a decision-making process that guides a community into an ecologically secure and socially just environment in which it can flourish. The relationship between the Doughnut theory, the decision-making process, and the forecasting process in FSG is depicted in Figure 3.

Figure: 3 Forecasting for Social Good Process



FSG is a forecasting method that seeks to inform decisions that prioritise the flourishing of humanity over the flourishing of economies by bolstering social foundations and ecological systems. Local and international ceilings affecting the general public.

Consequently, FSG contributes to the solutions to real problems that are primarily motivated by the desire for the flourishing of humanity by strengthening the social foundation within the planetary capacity. Profitability and other growth-oriented metrics may be considered, but they are not prioritized.

Now we'll address our second question, which is what characteristics constitute a forecasting process an FSG. We argue that a forecasting process must possess four characteristics in order to qualify for FSG: (i) it must be concerned with a real problem; (ii) the problem must be primarily driven by thriving humanity rather than thriving economies; (iii) the proposed solution must improve the social foundation and ecological ceiling; and (iv) it must have an impact on the general public. These are discussed further below.

Real Problem:

FSG emphasises the problems that directly affect people/humanity and are experienced in daily.

life, as opposed to the theoretical problems that predominate. While the scope of other similar initiatives, such as Data Science for Social Good (Paolotti and Tizzoni, 2018), may be limited to real problems in sectors such as government and/or the voluntary sector, our definition of FSG is all-encompassing and encompasses all organizations, regardless of industry and whether they are government, commercial, or voluntary. Consequently, the scope and character of the problems that the forecasting process is attempting to solve could range from a task in a profit-driven organization, such as waste reduction forecasting, to an entire sector, such as forecasting for humanitarian and disaster relief operations. This is significant because commercial organizations are swiftly altering their thinking and positioning in relation to social good, and they should not be excluded from the definition (Rostami-Tabar, 2019). This dimension emphasizes an essential aspect of FSG, namely the collaborative effort and continuous interaction between the problem owner and forecaster to define the problem, design the model, evaluate and implement the solution, and relate it to the decision-making process. The collaborative efforts will generate questions that are not only essential for the survival of humanity, but also offer opportunities for innovative research.

Prioritise the flourishing of humanity over the flourishing of economies:

The second characteristic focuses on the objectives of resolving the actual issues at hand. The outputs of the FSG prioritise the flourishing of humanity over the flourishing of economies. Consequently, one of the defining characteristics of FSG is whether the purpose of informing decisions - via the forecasting process- to solve the actual problem is primarily driven by social/environmental considerations or economic growth. FSG is not primarily motivated by economic growth, as the objective is to assist humanity flourish within environmental constraints regardless of economic growth. There has been a significant shift in how we view the forecasting process. The objective is to ensure that decisions and actions based on forecasts assist humanity in entering the doughnut-shaped space, an ecologically secure and socially just environment in which humanity can flourish. The process of forecasting may also result in economic expansion. However, it falls within the purview of FSG if the primary objective is to better the human and global condition.

The third aspect of FSG relates to how the benefits of the forecasting outputs are measured. In a conventional scenario for business forecasting, the outputs or empirical utility will be associated with the financial or economic implications. In the case of FSG, however, the principal output of the forecasting process is the social foundation. Forecasting should inform decisions aimed at strengthening the social foundation while simultaneously maintaining or enhancing the ecological ceiling. Consequently, we require indicators and metrics that permit us to measure both components. The twelve dimensions of Doughnut's social foundation are derived from internationally agreed minimum social standards outlined in the United Nations' Sustainable Development Goals (SDG) (United Nations, 2019). At the international level, the SDG indicators have been developed /refined by hundreds of multidisciplinary specialists. In addition, they are already incorporated into national and transnational policies and cited in academic literature (Cancedda et al., 2018; Biermann et al., 2017). Water, food, health, education, income & employment, peace and justice, political voice, social equality, gender equality, housing, networks, and energy comprise the social foundation of Doughnut. Various studies have quantified social foundation using metrics such as nutrition, sanitation, income, access to energy, education, social support, equality, democratic quality, employment, self-reported life satisfaction, and healthy life (Steinberger and Roberts, 2010; Cole et al., 2014; Dearing et al., 2014; Raworth, 2017; O'Neill et al., 2018).

According to Rockstro m et al. (2009), the ecological ceiling consists of nine dimensions that are crucial to our planet's ability to support human existence. Beyond these limits are intolerable environmental degradation and potential Earth system tipping points. This includes the depletion of the ozone layer, ocean acidification, nitrogen and phosphorus loading, chemical pollution, freshwater depletion, land conversion, air pollution, climate change, and biodiversity loss. Phosphorus, nitrogen, ecological footprint, material footprint, CO2 emissions, and greenhouse gas emissions are indicators used in various studies (Knight and Rosa, 2011; Dearing et al., 2014; Lamb and Rao, 2015; O'Neill et al., 2018).

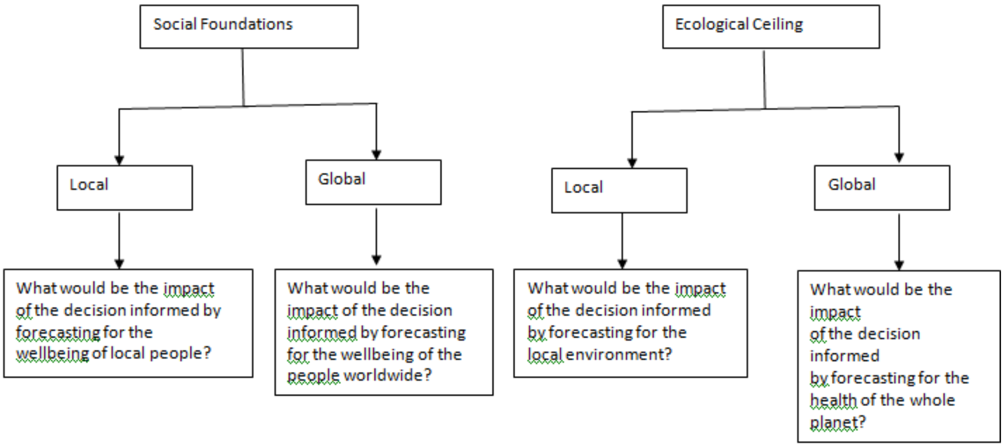
When a prognosis is used to inform a decision, a penalty is incurred if the forecast turns out to be inaccurate. In place of current functions based on statistical, economic, and financial KPIs (Berk, 2011; Lee, 2008), the FSG proposes to use revised penalty functions that incorporate social foundation and ecological ceiling indicators. FSG guides decisions that improve social foundation indicators and do not contravene any fundamental ecological ceiling measures. Defining new metrics for social foundation and ecological ceiling at the local and global levels requires additional work, and this is one of humanity's most significant challenges.

Forecasting publications, conferences, and practices have traditionally emphasized methodological advances and profit-driven objectives. Allowing researchers and practitioners to participate in FSG research would necessitate a radical transformation.

Impact on the general public: The final criterion emphasises on who benefits from the use of forecasting. FSG prioritizes both the local and global levels, as opposed to focusing solely on its local beneficiaries. FSG can be used at multiple dimensions, from the individual to the national level, as a transformative action tool that incorporates local and global social and ecological metrics. Organizations should guarantee that these metrics are measured using internal rather than external activities, such as charitable donations.

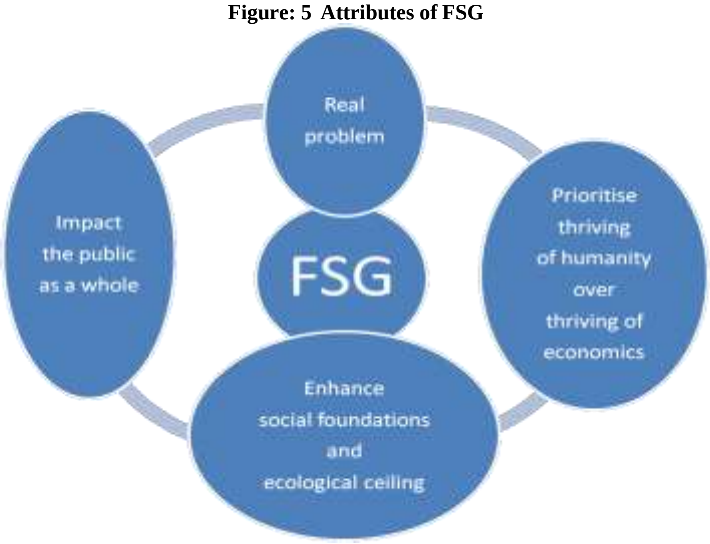
FSG begins by posing the following question: How can the forecasting process inform decisions that contribute to the flourishing of humanity while preserving the health of all people and the planet? As depicted in Figure 4, the benefits of FSG can be evaluated through four lenses resulting from the combination of two types of benefits (social foundation and ecological ceiling) and two dimensions (local and global) figure 4.

Figure: 4 FSG beneficiary



In this section, we first clarified the meaning of Forecasting for Social Good (FSG) before delineating its four characteristics. Any forecasting process qualifies as FSG if it focuses on a real problem, is primarily driven by thriving of humanity over thriving of economies, enhances social foundation and ecological ceiling, and impacts the public at both local and/or global levels.

Figure: 5 Attributes of FSG



These four characteristics of FSG can be understood as pertaining to both the problems driven by thriving humanity and decisions made in light of forecasts generated by the forecasting process to enhance social foundation and ecological ceiling, as illustrated in figure 3.

This article focuses on research that relies substantially on forecasting. However, there are other FSG-related data-driven initiatives that may overlap with FSG. In addition, the FSG forecasting process may differ from other areas of forecasting in terms of its input, process, and output. In the following section, we discuss the FSG process and its overlap with other data-driven social good initiatives.

Domains relevant to FSG:

Forecasting process in FSG compared to other forecasting domains:

The unique characteristics of FSG discussed in Section 2 can result in various alterations throughout the forecasting process, including the input, process, and output from Figure. 2 that are discussed in this subparagraph.

Input:

- Problem: As discussed in section 2.1, the forecast problem must be real and predominantly driven by a flourishing humanity over economic growth by enhancing the social foundation within ecological limits.
- Data and Information: The data and information utilised in FSG initiatives are frequently more accessible to the public than when commercial interests are considered (OCHA, 2020). However, privacy concerns may necessitate confidentiality, especially when the endeavour involves individual-level data. To protect individuals, data at the level of the individual, such as health, social services, or real estate prices, must be anonymized or made confidential. However, data at higher levels of aggregation can often be shared. For instance, the Centre for Disease Prevention and Control (CDC, 2020) in the United States and the National Health Services (NHS, 2020) in the United Kingdom has shared aggregated healthcare data. In addition, we anticipate observing a large amount of missing data, poorly recorded data, the need to integrate information from diverse data sources and data types, and the requirement for the contextual understanding of domain applications.

Process:

- Software: The development of free, open-source forecasting software has provided a platform for socially beneficial applications worldwide. This is due to the fact that it is free for the user to install and use, and has a large community of users, maintainers, and developers. The forecast package for R (Hyndman, Athanasopoulos, Bergmeir, Caceres, Chhay, O'Hara-Wild, Petropoulos, Razbash, Wang and Yasmeen, 2020), first released in 2006 and downloaded over 2 million times in 2019, is the most popular open-source forecasting software. For tidy forecasting and modelling, tidyverts (Hyndman, Wang, and O'Hara-Wild, 2020) and tidy models (Kuhn and Wickham, 2020) were introduced more recently (Hyndman, Wang, and O'Hara-Wild, 2020). The CRAN Task View for Time Series lists several additional R packages for forecasting (Hyndman, 2020). Python is open-source software that has been used to develop forecasting tools. Python's Stats models library (Seabold and Perktold, 2010) enables statistical forecasting, whereas scikit learn library (Garreta and Moncecchi, 2013) is primarily utilized for machine learning. Commercial software such as Oracle, SAP, Simul8, Optima, Tableau, SAS, Forecast Pro, and others, which include forecasting modules, may also be utilized in FSG.
- Method: It is essential to observe that FSG may or may not employ a novel statistical forecasting technique. FSG encompasses both the innovative development of research in response to societal challenges and the application of existing methodologies in novel ways. Moreover, difficulties in FSG often have small datasets, or in some instances, no data is available or the data is incomplete and of questionable quality. Therefore, it may be more appropriate to employ well-structured qualitative approaches in such situations. This could also result in the development of novel forecasting methods that focus on incomplete and small data sets. We should also observe

that the significance of aligning projects with a real problem in social foundations and ecological ceiling emphasizes the distinction between applying exciting forecasting methodologies to a dataset in domain applications and FSG and aligning projects with a real problem. To provide solutions that can effectively contribute to attaining the objective, the latter must have a broader understanding of the context in which the forecasting method will be applied. FSG is concerned not only with the forecast accuracy of a method, but also with its reproducibility, interpretability, and transparency. Inadequate documentation of the methods and computer code underlying the study may detract from their value and impede their application and implementation. (Hyndman, 2010; Boylan et al., 2015; Boylan, 2016; Haibe-Kains et al., 2020). Developing techniques to estimate model parameters with novel loss functions driven by FSG is also a component of new methods.

- Estimation: Ideally, the loss function used to estimate parameters in the forecast model of FSG should be expressed in terms of the decision maker's utility function based on social good metrics, as opposed to statistical measures such as Mean Squared Error and Information Criteria or financial KPIs. In the Emergency Department forecasting, a loss function that factors for patient waiting time, staff well-being, staff retention, pressure on other health services, and extra resource costs is an example of a social good loss function.
- Evaluation: Instead of forecast error or financial KPIs, the performance of forecasting methods should be evaluated based on metrics of social foundation and ecological ceiling at both the local and global levels, as described in Section 2.2.

Output:

- Report: When forecasting is intended to benefit society and the public as a whole, the results should be extensively disseminated to maximize the forecast's utility. FSG will frequently be of interest to and scrutinized by a large audience. Thus, it is possible that transparency and trust will become more important than sheer predictive ability. Consider the recent and ongoing conversation about earthquake predictions in Italy (Benessia and De Marchi, 2017), pension disputes in higher education in the United Kingdom (Wong, 2018), and the recent COVID19 pandemic (Shinde et al., 2020). In certain circumstances, forecasters may be held liable. For instance, weather forecasts are broadly accessible via websites, apps, and other media. Modern reporting tools such as Rshiny and Dashboard make it simple to develop user-friendly web interfaces for forecast reporting. Examples of applications of Rshiny for FSG include the FluSight Network, which provides weekly real-time influenza forecasts for the United States, the COVID-19 Forecast Hub, and the modelling of COVID-19 (Reich et al., 2019; Hill et al., 2020). While forecasts designed specifically for the desired application in social good should provide the best information, in some cases forecasts generated for other purposes can be used to provide good information for social good decision making, e.g., climate models can be used for early warning in predicting droughts, which can inform humanitarian disaster relief planning (Travis, 2013; Coughlan de Perez et al., 2015).

CONCLUSION

Forecasting is an integral component of organisational decision-making, but its relationship with non-economic/financial utility has been limited. Better integration of forecasting with environmental and social KPIs is both possible and desirable, and relevant practises are gaining increasing attention as a means of protecting and generating social good. With the support of the International Institute of Forecasters (IIF), forecasting for social good (FSG) was recently introduced as a self-contained field of study, enabling focused academic research and facilitating a constructive exchange of ideas between academia and the private and public sectors (Rostami-Tabar, 2018, 2020b).

In this paper, we have attempted to formalise FSG further in order to increase academics' and practitioners' awareness and interest in its potential impact, to encourage academics and practitioners to engage in this important agenda, and to inspire the development of new forecasting methodologies tailored for social good applications.

We find the Doughnut theory accommodating in terms of arriving at a useful definition of FSG: it is concerned with actual social problems in terms of both application and performance measurement, and it emphasises the importance of society as a whole. In contrast to other data science, statistics, and operations research initiatives that emphasise social good, FSG is not limited to specific organisational contexts or sectors and capitalises on the fundamental advancements in the field of judgmental forecasting to decouple substantive contributions from the availability of (quantitative/hard) data. Comparing the maturity of research in various areas of forecasting to FSG practise enables us to identify opportunities for bridging the divide between FSG theory and practise. When theory lags behind practise, there is an opportunity to incorporate existing theory in order to advance practical applications. When theory remains behind practise, it is necessary to advance forecasting research by incorporating the insights and lessons learned from practical applications. In areas where neither sufficient knowledge nor, empirical evidence has been accumulated, the forecasting community is obligated to invent new methods.

The FSG guidelines presented in this paper are not intended to be exhaustive, and we acknowledge that relevant work may lie outside of our working framework. The purpose of FSG is to encourage engagement with significant global and societal issues and to facilitate the emergence of best (forecasting) practises. In other words, we hope that a definition of FSG and its introduction as a distinct field of study will result in a greater appreciation of forecasting as a facilitator of greater social welfare. By defining what constitutes FSG, academics and practitioners will be able to calculate the opportunity cost of ignoring its scalable agenda. In addition to establishing a connection between forecasting and its social utility, it emphasises direct capacity development and the enhancement of forecasting expertise in underdeveloped economies. We hope that our paper will encourage and inspire forecasting professionals to knowledge to a worthy cause, and we anticipate pertinent developments in the coming years.

Declaration by Authors

Conflict of Interest: The author declare no conflict of interest.

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