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Forecasting for social good

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ABSTRACT

Forecasting plays a critical role in the development of organisational 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 conceptualise 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 prioritises 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. Finally, we highlight that FSG: (i) cannot be distilled to a prescriptive set of guidelines, (ii) is scalable, and (iii) has the potential to make significant contributions to advancing social objectives.

1. Background and motivation

Organisations make operational, tactical and strategic decisions every day. Regardless of the sector or industry, these decisions reflect the expectations of what the future may look like. This is where forecasting can play a crucial role as an integral part of a decision-making process (Hyndman & Athanasopoulos, 2018). This is well understood in areas with commercial or economic interests. Forecasting, and its link to business decision-making, has been a topic of research for decades (Gilliland, Tashman, & Sglavo, 2016; González-Rivera, 2016; Ord, Fildes, & Kourentzes, 2017; Sanders, 2016). Many important contributions have been offered in these areas (e.g., macroeconomics and the financial sector, the retail industry and supply chains, the energy industry and tourism (Athanasopoulos, Hyndman, Song, & Wu, 2011; Fildes, Nikolopoulos, Crone, & Syntetos, 2008; Fildes & Stekler, 2002; Hong, Pinson, & Fan, 2014; Syntetos, Boylan, & Disney, 2009)) on how forecasting may improve organisational decision-making. However, such studies have largely sought to improve forecasting processes (and their integration with decision-making) in the presence of financial or economic motivations. On the

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other hand, little attention has been paid to forecasting when the emphasis is on deriving some societal benefits regardless of the financial or economic implications. In this article, we refer to such forecasting practices as *Forecasting for Social Good* (FSG).

While there is a growing recognition from agencies, organisations and governments that data-driven decision-making tools such as forecasting models may offer significant improvements to society (Iyer & Power, 2014), there is not a cohesive body of research that offers guidance towards the conceptualisation, implementation and evaluation of forecasting models for social good in practice. Although some work has been done in this area (Gorr & Harries, 2003; Litsiou, Polychronakis, Karami, & Nikolopoulos, 2019; Nsoesie, Brownstein, Ramakrishnan, & Marathe, 2014; van der Laan, van Dalen, Rohrmoser, & Simpson, 2016; Wicke, Dhami, Önkal, & Belton, 2019), progress has been relatively slow and sporadic, both in terms of academic contributions and practical applications. This is exemplified by the fact that the development and use of forecasting models in organisations with social missions (especially in health, humanitarian operations and the third sector; i.e., voluntary and community organisations, social enterprises and co-operatives) are considerably under-developed. Evidence (Cacciolatti, Lee, & Molinero, 2017; Getzen, 2016; Lu, Goh, & De Souza, 2018) suggests that this may be due to a lack of awareness, skills and understanding of the value of forecasting, but the fact remains that such organisations are largely not exploiting (relevant) forecasting capabilities. Further, major review papers in the areas of forecasting, as well as operations research and operations management when forecasting is explicitly considered (Boylan & Syntetos, 2010; Fildes et al., 2008; Makridakis, Hyndman, & Petropoulos, 2020; Syntetos, Babai, Boylan, Kolassa, & Nikolopoulos, 2016; Syntetos et al., 2009), do not take into account work related to FSG. As one of the direct outcomes the first FSG workshop (Rostami-Tabar, 2018), Altay and Narayanan (2020) published an invited literature review paper on forecasting for humanitarian operations. The paucity of academic contributions may be due to the limited amount of existing work to build upon, or the fact that relevant work might appear in journals that are not frequently read by the forecasting community (Dietze, 2017; Goltsos, Syntetos, & van der Laan, 2019; Nsoesie et al., 2014; Soyiri & Reidpath, 2013). Given the background discussed above, we feel it is timely to explicitly address the definition of FSG and its positioning in the wider body of knowledge. This exercise will facilitate the discussion of both forecast implementation and evaluation issues, leading to the proposition of a research agenda; it should also allow organisations to advance their social missions and benefit from the value that forecasting may offer. The purpose of this paper is three-fold:

- to increase awareness and interest from academics and practitioners in the potential impact of FSG;
- to encourage interested academics and practitioners to engage in the FSG agenda;
- to inspire the development of new forecasting methodologies tailored to social good applications.

The remainder of the article is organised as follows. Section 2 defines the area of FSG, its scope and boundaries, as well as its relation to (other) data-driven social good initiatives and forecasting areas. Section 3 suggests a positioning framework on the basis of (i) the maturity of the forecasting process (theory) and (ii) the use of forecasting in social good (practice). It also provides an indicative agenda for further research. Finally, Section 4 presents a summary of our conclusions.

2. Forecasting for Social Good

In this section, we first explain the Doughnut theory used to frame our definition and scope of FSG. This theory is an alternative way of looking at growth economies. It prioritises people and the planet over economic growth, which can help us as a society to thrive within the limits of our planetary boundaries (Raworth, 2017). In this paper, the theory helps to create a common understanding of the term Forecasting for Social Good.

We attempt to answer the following two questions:

1. What is meant by FSG?
2. What attributes/features make a forecasting process aligned with FSG? Specifically, when does a forecasting process belong to FSG and when does it not?

2.1. Doughnut theory

Doughnut theory was proposed by Raworth (2017) and offers a framework for thinking about how a world is created in which humanity thrives. Raworth states that "instead of economies that need to grow, whether or not they make us thrive, we need economies that make us thrive, whether or not they grow". The aim is to meet the needs of all people within the means of the living planet. The theory combines the concept of social foundation with that of the ecological ceiling in a single framework, as illustrated in Fig. 1.

The social foundation is derived from the social priorities described in the United Nations Sustainable Development Goals (UN General Assembly, 2015). The idea is to ensure that no one is left in the hole of the doughnut below the social foundation, that no one falls short on essentials of life ranging from food and clean water to gender equality, and that everyone has a political voice and access to housing.

The ecological ceiling includes nine planetary boundaries developed by environmental scientists (Rockström et al., 2009) that represent the planet's capacity for critical life-supporting systems. In order to preserve them, humanity must live within these ecological boundaries while meeting the needs of all described in the social foundation.

Between the social foundation and the ecological ceiling lies a space in which it is possible to meet the needs of all people within the means of the living planet — an ecologically safe and socially just space in which humanity can thrive.

This is the space we must move into from both sides simultaneously, in ways that promote the well-being of all

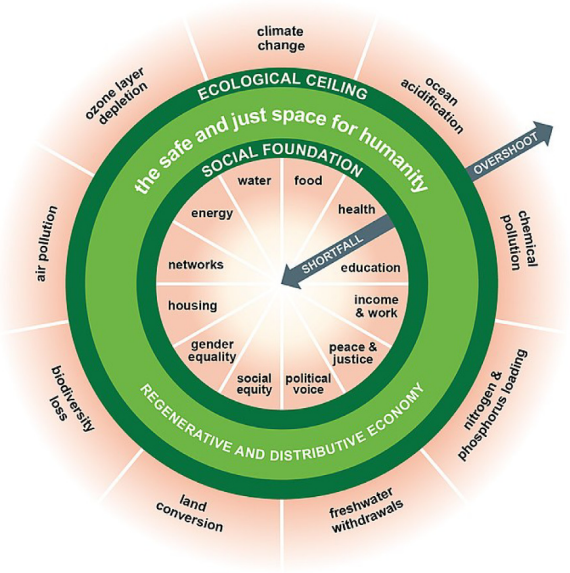

Fig. 1. The classic image of the Doughnut with social and planetary boundaries.
Source: Doughnut (economic model) (2020).

people and the health of the whole planet. Achieving this globally calls for action on many levels, including research and its applications. The framework has been adopted in multiple academic disciplines and in various countries, sub-regions and cities worldwide (Amenta & Qu, 2020; Bennett, 2020; Cole, Bailey, & New, 2014; Dearing et al., 2014; Hoornweg, Hosseini, Kennedy, & Behdadi, 2016).

2.2. Definition and scope of Forecasting for Social Good

The Doughnut framework allows multi-metric 'compasses' to be elaborated so as to inform the decision-making process (Dearing et al., 2014). In order to promote the well-being of all people and the health of the whole planet, the decision-making process needs to support all activities that bring us into the Doughnut space — an environmentally safe and socially just space — in which humanity thrives. We note that one of the main components of any decision-making process is forecasting.

We define forecasting as a genuine prediction of the future, given all the information available at the time the forecast is generated, including historical data and knowledge of any future events that might impact the outcome(s) (Goodwin, 2018; Hyndman & Athanasopoulos, 2018). The forecasting process starts by taking inputs in the form of a problem description, data and information; then, an appropriate forecasting method is identified and the inputs are processed and formulated to implement the method using software, before making the forecast and incorporating human judgement and uncertainty assessments when necessary.

Genuine forecasting can also take place in the absence of available data and not rely on statistical methods or use statistical software. Instead, we may rely on structured management judgement that includes the Delphi method, forecasting by analogy, surveys, scenario forecasting and other judgemental forecasting approaches.

Forecasting is used to help decision-makers make more informed and potentially better decisions. Therefore, forecasts need to be tailored to provide answers to the questions that a decision-maker needs in a particular set of circumstances. In the case of FSG, we argue that the forecasting process should be determined by a decision-making process that leads a community into an ecologically safe and socially just space where it can thrive. Fig. 3 shows the relationship between the Doughnut theory, the decision-making process and the forecasting process in FSG.

FSG is a forecasting process that aims to inform decisions that prioritise the thriving of humanity over the thriving of economies by enhancing the social foundation and ecological ceilings that impact the public as a whole on both local and global levels. Therefore, FSG contributes to the solutions to real problems that primarily aim to benefit humanity by enhancing the social foundation within planetary capacity. While profits and other growth-oriented metrics can be considered, they are not given priority.

Now we move on to our second question; i.e., what attributes make a forecasting process an FSG. We argue that to qualify as an FSG, a forecasting process needs to have four attributes: (i) it is concerned with a real problem; (ii) the problem is primarily driven by humanity thriving rather than economies thriving; (iii) the proposed solution enhances the social foundation and ecological ceiling; and (iv) it impacts the public as a whole. These are further discussed below.

Real Problem: FSG emphasises the problems that directly affect people/humanity and are experienced in daily life, as opposed to the problems mostly residing in the theoretical world. While the scope of other similar initiatives such as Data Science for Social Good (Paolotti & Tizzoni, 2018) might be limited to real problems in sectors such as the government and/or the voluntary sector, our definition of FSG is inclusive and encompasses all organisations irrespective of the industry and whether they are governmental, commercial or voluntary organisations. Hence, the scope and the nature of the problems for which the forecasting process is attempting to provide solutions could range from a task in a profit-driven organisation such as forecasting in order to reduce waste to a whole sector such as forecasting for humanitarian and disaster relief operations. This is important as commercial organisations are rapidly changing in terms of how they think and position themselves when it comes to social good, and they should not be excluded in the definition (Rostami-Tabar, 2019). This dimension highlights an important aspect of FSG - that is, the collaborative effort and continuous interaction between the problem owner and the forecaster to define the problem, design the model, evaluate and implement the solution and link it to the decision-making process. The collaborative efforts will lead to questions that are not only crucial for helping humanity to thrive but also providing opportunities for innovative research.

Prioritise humanity thriving over economies thriving: The second attribute focuses on the objectives of solving the real problems under consideration. FSG's outputs prioritise humanity thriving over economies thriving. Therefore, one of the key features that defines FSG is whether the purpose of informing decisions in the forecasting process in order to solve the real problem is driven primarily by social/environmental considerations or economic growth. FSG is not primarily driven by economic growth; i.e., the goal is to help humanity thrive within environmental boundaries whether the economy grows or not. This is a radical change in the way we look at the forecasting process. The idea is to ensure that decisions and actions informed by forecasts are helping humanity to move into the doughnut-shaped space, which is an ecologically safe and socially just space for humanity to thrive in. The forecasting process may also result in economic growth. However, it is within the scope of FSG if the primary focus is to improve human and planetary conditions.

Enhance social foundation within an ecological ceiling: The third dimension of FSG relates to how the benefits of the forecasting outputs are measured. In a traditional business forecasting scenario, the outputs or the empirical utility is associated with financial or economic implications. However, in the case of FSG, the forecasting process focuses on the social foundation as the primary output. Forecasting should inform decisions towards enhancing social foundation while maintaining or improving the ecological ceiling simultaneously. Therefore, we need indicators and metrics that allow us to measure both components. The Doughnut's social foundation includes twelve dimensions that are derived from internationally agreed upon minimum social standards described in the Sustainable Development Goals (SDG) defined by the United Nations (United Nations, 2019). SDG indicators are relatively well thought through at an international level and have been developed/refined by hundreds of multidisciplinary experts. Also, they are already being integrated into national and transnational policies, as well as being referenced in academia (Biermann, Kanie, & Kim, 2017; Cancedda, Binagwaho, & Kerry, 2018). The Doughnut's social foundation includes water, food, health, education, income & work, peace and justice, political voice, social equity, gender equality, housing, networks and energy. Various metrics such as nutrition, sanitation, income, access to energy, education, social support, equality, democratic quality, employment, self-reported life satisfaction and healthy life have been used in various studies to quantify social foundation (Cole et al., 2014; Dearing et al., 2014; O'Neill, Fanning, Lamb, & Steinberger, 2018; Raworth, 2017; Steinberger & Roberts, 2010).

The ecological ceiling consists of nine dimensions that are vital to our planet's ability to sustain human life as set out by Rockström et al. (2009). Beyond these boundaries lie unacceptable environmental degradation and potential tipping points in Earth systems. These boundaries include ozone layer depletion, ocean acidification, nitrogen and phosphorus loading, chemical pollution, freshwater depletion, land conversion, air pollution, climate change and biodiversity loss. Indicators used in various studies include phosphorus, nitrogen, ecological footprint, material footprint, CO2 emissions and greenhouse gas emissions (Dearing et al., 2014; Knight & Rosa, 2011; Lamb & Rao, 2015; O'Neill et al., 2018).

When a forecast is made to inform a decision, a penalty will arise if the forecast turns out to be different from the actual value. One of the ideas that needs to be investigated in FSG is the use of amended penalty functions based on social foundation and ecological ceiling indicators instead of current functions based on statistical, economical and financial KPIs (Berk, 2011; Lee, 2008). This does not necessarily mean that the amended penalty should be a single variable; i.e., a mixture of various metrics. Instead, individual amended functions could be used for each forecast variable. In FSG, an array of variables is forecast instead of a single variable to inform decisions. The array must include social foundations and ecological ceiling variables. As an example, the business forecasting process generally focuses on business KPIs such as operational and financial KPIs. However, for FSG, these must also include forecasting for ecological and social KPIs. In terms of presenting outputs to a decision maker, we believe that presenting both a forecast of a phenomenon and its accuracy alongside the FSG metrics is important. We also note that this is something that requires further discussion and debate.

FSG informs decisions that enhance social foundation indicators and do not violate any principle measures of the ecological ceiling. There is still more to be done when it comes to defining new metrics for social foundation and ecological ceiling at local and global levels, and this is one of the important challenges facing humanity.

Traditionally, forecasting publications, conferences and practices focus on methodological advances and profit-driven goals. This would require a radical shift to allow researchers and practitioners to become involved in FSG research.

Impact the public: The last dimension focuses on who may benefit from the application of forecasting. FSG gives priority to both local and global levels rather than focusing only on the local beneficiaries themselves. FSG can be used at multiple scales – from an individual to a nation — - as a tool for transformative action that embraces social and ecological metrics both locally and globally. Organisations should ensure that these metrics are measured through internal activities rather than external activities such as donations to a charity.

FSG starts by asking this question: How can the forecasting process inform decisions that help humanity to thrive whilst respecting the well-being of all people and the health of the whole planet? Following this question, the benefit of FSG can be assessed across four lenses that arise from combining two type of benefits (social foundation and the ecological ceiling) and two scales (local and global), as depicted in Fig. 4. This will help to avoid any harm that forecasting may cause by informing decisions that are beneficial on a local level while possibly having negative implications for wider communities and the planet.

In this section, we first clarified what is meant by Forecasting for Social Good (FSG) and then moved towards defining the four attributes of FSG. Any forecasting

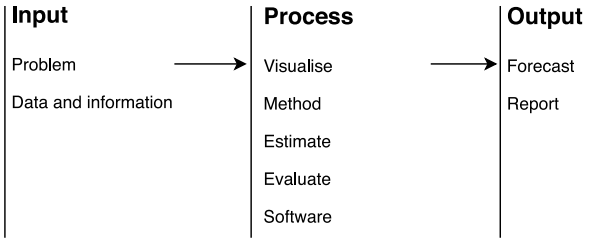

Fig. 2. Forecasting process.

process can qualify as FSG if it focuses on a real problem, is primarily driven by causing humanity to thrive over economies thriving, if it enhances social foundation and the ecological ceiling, and impacts the public as a whole at both local and/or global levels (see Fig. 5).

These four attributes of FSG can be understood to concern both the problems driven by a thriving humanity and the decisions being made in the light of forecasts generated by the forecasting process to enhance social foundations and the ecological ceiling, as illustrated in Fig. 3.

Throughout this article we focus on research that substantially relies on forecasting. However, there are other data-driven initiatives related to FSG which might overlap with FSG. Moreover, the forecasting process in FSG might be different in comparison to other areas of forecasting when it comes to its input, process and output In the next subsection we discuss the FSG process and how it overlaps with other data-driven social good initiatives.

2.3. Areas related to FSG

2.3.1. Forecasting process in FSG versus other areas of forecasting

The unique attributes of FSG discussed in Section 2 can lead to various changes throughout the forecasting process including the input, process, and output from Fig. 2, which shall be discussed in this subsection.

Input

- **Problem**: As discussed in Section 2.1, the forecast problem needs to be real and primarily driven by a thriving humanity over economic growth through improving social foundations within ecological boundaries.
- **Data and Information**: The data and information used in FSG projects can often be more publicly accessible than when there are commercial interests to consider (OCHA, 2020). However, confidentiality may be required for privacy reasons, especially when the project involves data on an individual level. For

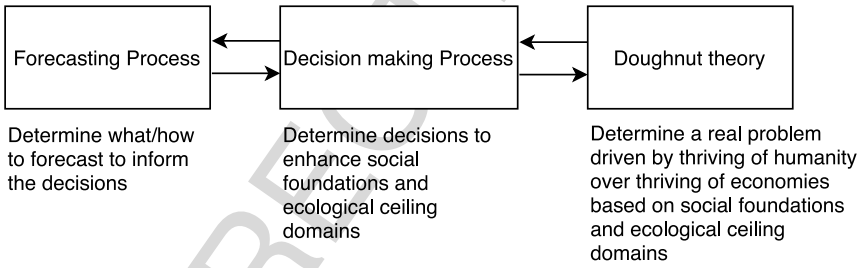

Fig. 3. Forecasting for social good process.

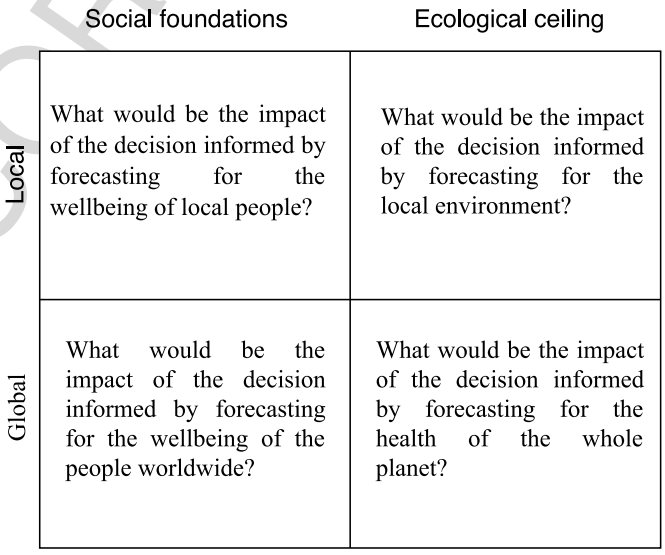

Fig. 4. FSG beneficiaries.

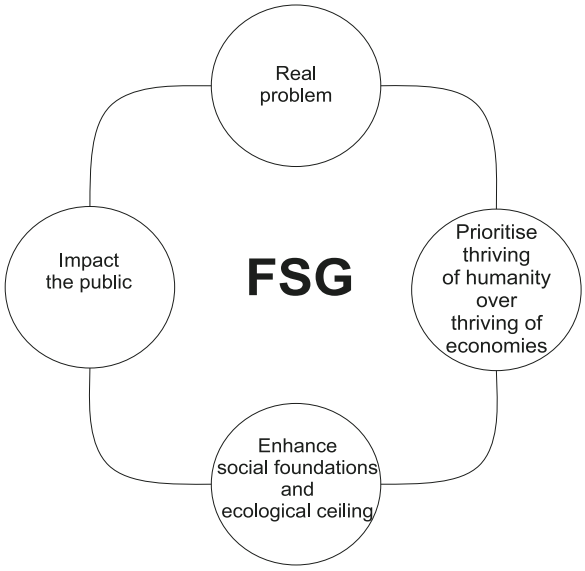

Fig. 5. Attributes of FSG.

instance, individual-level data on health, social services or even real-estate prices must be anonymised or made confidential in some way to protect individuals, but data at higher levels of aggregation can often be shared. Data for FSG tends to be aggregated and only available at the granular level (e.g., at a country level or yearly). For example, aggregated data in healthcare have been shared by Centers for Disease Control and Prevention (2020) in the United States and the (National Health Service, 2020) in the UK. Additionally, we expect to observe lots of missing data, poorly recorded data, the need to combine information from various data sources and data types, and the need for the contextual knowledge of domain applications. We have created a Github repository in order to collect and share public and private datasets to be used for FSG.[1]

Process

- **Software**: The development of free open-source forecasting software has provided a platform for social good uses everywhere. This is because it can be installed and used with no cost to the user while also having huge support from a community of users, maintainers and developers. The most widely used open-source forecasting software is the forecast 8package for R (Hyndman, Athanasopoulos et al., 2020), first released in 2006, and downloaded over 2 million times in 2019. More recently, tidyverts (Hyndman, Wang, & O'Hara-Wild, 2020) and tidymodels (Kuhn & Wickham, 2020) have been introduced for tidy forecasting and modelling. Several other R packages for forecasting are listed on the CRAN Task View for Time Series (Hyndman, 2020). Another open-source piece of software that has been used to create forecasting tools is Python. The Statsmodels library (Seabold & Perktold, 2010) in Python allows for statistical forecasting, and the scikit-learn library (Garreta & Moncecchi, 2013) is used more for machine learning. Commercial software such as Oracle, SAP, Simul8, Optima, Tableau, SAS, Forecast Pro and others might also be used in FSG given that they incorporate forecasting modules in their solutions.
- **Method**: It is important to note that FSG may or may not involve a novel statistical forecasting methodology. Indeed, the forecasting method used in FSG could be similar to any other forecast. While in some cases societal challenges may lead to innovative research development, the application of existing methods in novel ways is also included in FSG. Moreover, problems in FSG often have small datasets, or in some cases the data are not available at all, or the data are incomplete and their quality is unreliable. Therefore, the application of well-structured qualitative approaches in such circumstances might be more appropriate. This could also lead to new forecasting methods that concentrate on incomplete and small datasets. We should also note that the importance of aligning projects with a real problem in a social foundation and ecological ceiling highlights the difference between simply applying existing forecasting methodologies to a dataset in domain applications and FSG. The latter must have a broader appreciation for the context in which the forecasting method would be used in order to provide solutions that can effectively contribute toward achieving the goal. In FSG, we are not only interested in the forecast accuracy of a method but also its reproducibility, interpretability and transparency. Additionally, educating people on these matters and the strengths and limitations of forecast methods will help to promote the use of forecasts amongst all stakeholders. The absence of sufficiently documented methods and the computer code underlying the study may effectively undermine their value and become a barrier in their use and implementation (Boylan, 2016; Boylan, Goodwin, Mohammadipour, & Syntetos, 2015; Haibe-Kains et al., 2020; Hyndman, 2010). As in other forecasting areas, FSG could also be used in 'what if' assessments. Forecasts can inform policies on what would happen if certain actions were taken or in cases of inaction; e.g., what the average global temperature would be in the next 10 years if CO2 emissions were not reduced. In this respect, scenario planning could also be useful in predicting possible outcomes that result from actions(inactions) (Cairns, Goodwin, & Wright, 2016). Another part of new methods is developing techniques to estimate model parameters with novel loss functions driven by FSG.
- **Estimation**: The loss function that is used to estimate parameters in the forecast model of FSG could be stated in terms of the decision maker's utility

[1] https://github.com/bahmanrostamitabar/Forecasting-for-Social-Good-Data.

function based on metrics of social good rather than statistical measures such as the Mean Squared Error and Information Criteria or financial KPIs. This is an area that requires further investigation in order to understand whether it is better to use such loss functions or to separate forecasting from them. An example of a social good loss function in Emergency Department forecasting would be the use of a loss function that accounts for a patient's waiting time, the well-being of staff, staff retention, pressure on other health services and the costs associated with extra resources.

- **Evaluation**: The performance of forecasting methods should be evaluated based on metrics of social foundation and the ecological ceiling on both local and global levels as discussed in Section 2.2 rather than measures based on forecast errors or financial KPIs.

Output

- **Report**: When forecasting is intended to provide social good and to prioritise the public as a whole, the results should be widely reported in order to maximise the benefit of the forecast. FSG is often going to be of interest to, and hence scrutinised by, a wide audience. Thus, transparency and trust may emerge as being more important than raw predictive ability. Consider the recent and current discussion of earthquake predictions in Italy (Benessia & De Marchi, 2017), the pension dispute in higher education in the UK (Wong, 2018) and forecasting the spread of COVID-19 pandemic (e.g., positive cases, deaths and hospital admissions) at local, national and global levels (Shinde et al., 2020); in some domains, forecasters can be held liable. Weather forecasts are, for example, widely available on websites, apps and in other media. Modern reporting tools such as Rshiny and Dashboard make it easy to create user-friendly web-based interfaces for reporting forecasts. Examples of using Rshiny for FSG include the FluSight Network, which shares real-time forecasts of influenza in the US each week, the COVID-19 Forecast Hub and modelling COVID-19 (Hill et al., 2020; Reich et al., 2019). While forecasts specifically designed for a desired application for 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; for instance, climate models can be used for early warnings when predicting droughts, which can inform humanitarian disaster relief planning (Coughlan de Perez et al., 2015; Travis, 2013).

2.3.2. FSG versus other social good initiatives

Forecasting for Social Good is built on previous movements that aim to use technology in order to have a positive impact on society. One of the initial movements in that direction is Tech for Social Good, which broadly uses digital technology to tackle societal challenges (Chaudhary & Murata, 2015). Another related area is the "Green Supply Chain", which uses a range of technologies and measures to incorporate the ethical and environmental responsibilities into the core culture of contemporary business models (Min & Kim, 2012; Zhu & Sarkis, 2004). With the increase in the availability of data in the past decade and the interest in using the power of data to tackle societal challenges, these initiatives have slowly branched out, leading to data-driven initiatives for social good (Cuquet, Vega-Gorgojo, Lammerant, Finn, et al., 2017). Data Science for Social Good (DSSG), Artificial Intelligence for Social Good (AISG), Pro Bono Operations Research (Pro Bono OR) and Statistics for Social Good (SSG) are some of the more closely related movements to Forecasting for Social Good.

DSSG is defined as "applying data science to improve civic and social outcomes". The initiative was introduced to help non-profits and government organisations achieve more with their data (Moore, 2019). Several other forms of engagement have since been introduced to derive insights from data in order to help solve social issues. These engagements might be found in the form of fellowships, conferences, competitions, volunteer-based projects, innovation units within large development organisations, and data scientists employed directly by smaller social change organisations. Another similar initiative to DSSG is AISG, which focuses on the techniques usually utilised in the Artificial Intelligence field towards social good. DSSG and AISG terms have been used interchangeably in research. Pro Bono OR initiatives aim to connect OR/analytics professional volunteers with social good e3causes. Volunteers donate their time and skills to help nonprofit organisations make better decisions. SSG uses data analysis and statistical and computational techniques to tackle social problems. SSG focuses mainly on problems that stem from economic inequity such as poverty, hunger, human trafficking, and unequal access to education. Table 1 summarises the areas that relate to FSG.

DSSG, AISG, Pro Bono OR and SSG are broader terms that may include forecasting as a component. The need for forecasting is driven by the uncertainty surrounding future decisions that deal with societal challenges that need to be made in light of forecasts. FSG might differ from these movements in the following ways:

- While DSSG, AISG, Pro Bono and SSG initiatives are defined as domain applications, their scope might be limited to certain organisations or sectors. FSG is not defined by domain applications; it is inclusive and does not exclude anyone;
- FSG is still valid in the absence of data; the area of judgemental forecasting is a valuable tool in a lack of data. However, this is not the case with DSSG, AISG, Pro Bono OR and SSG;
- Our focus in FSG is narrowed down from general data science, artificial intelligence, statistics or operations research, to the use of forecasting for the improvement of the social good;
- FSG acts as a compass for the way we perform forecasting research and engage with society on various scales, from an individual to an organisation level;

Table 1
Related areas to FSG.

Related area	Main scope	Core techniques	Main application domains	Some initiatives	Reference
DSSG	Governments, nonprofits	Data Science, collect data (and questions), analyse (using visualisation and models), communicate	Education, health, criminal justice, sustainability, public safety, workforce development, human services, transportation, economic development, international development, humanitarian, disaster relief operations	Data Science for Social Good, AI4ALL, hack4impact, DrivenData, DataKind, United Nations Global Pulse	Catlett and Ghani (2015), Chou, Li, and Sridharan (2014), Ghani (2018), Niño et al. (2017)
AISG	Governments, nonprofits	Machine learning, Deep learning	Agriculture, education, environmental sustainability, healthcare, combating information manipulation, social care and urban planning, public safety, and transportation	USC center for artificial intelligence in society, NeurIPS, ICML, ICLR, Google, Facebook, IBM, Intel, Microsoft, U.S. government, Chinese government	Berendt (2019), Chui et al. (2018), Hager et al. (2019), Shi, Wang, and Fang (2020)
Pro Bono OR	Third sector, Nonprofits	Operations research/ operations management/ management science	Charities, trade associations, credit unions, social enterprises and voluntary organisations	INFORMS, OR Society	Johnson and Smilowitz (2007), McCardle (2005), Midgley, Johnson, and Chichirau (2018)
SSG	Economic inequities, developing nations	Data analysis, statistical and computational techniques	poverty, hunger, human trafficking, and unequal access to education	Statistics for Social Good, Statistics without borders	Ashley and Scheuren (2010), Hwang, Orenstein, Cohen, Pfeiffer, and Mackey (2019)

3. Research in FSG

In this section, we provide a framework that allows the forecasting community, researchers and practitioners to discuss the status of research in FSG and to discover new research opportunities in which they can come together to contribute to the area of forecasting for social good. Fig. 6 presents a 2 × 2 matrix of research maturity (Gregor & Hevner, 2013; Stokes, 2011) in FSG based on two dimensions: i) theory: the maturity of forecasting process research, and (ii) practice: the use of forecasting for social good.

In this framework, the forecasting process maturity is defined from initial to mature levels, where:

- **Initial**: It is characterised by a lower range of topics and methodologies, with a few researchers focusing on the area.
- **Mature**: It is characterised by well-developed forecasting processes that have been studied over time by many researchers, resulting in a body of knowledge that contains points of broad agreement.

We consider four areas of development, as illustrated in the FSG Research maturity framework in Fig. 6. We discuss each quadrant and explore some examples of research opportunities for each one.

Apply This quadrant is concerned with well-established forecasting process research that is regularly used for social good. This implies that users know at least conceptually the forecasting process and how to do it. Therefore, the forecasting process is applied widely for social good as routine work. Research opportunities and contributions to research might be less obvious but not impossible. For example, simple linear regression models are widely applied in social good practices such as in medicine, emergency departments and in emergency medicine services to inform policies (Boyle et al., 2012; Kuk & Varadhan, 2013).

Adopt This quadrant is related to well-defined forecasting processes that are not used widely for social good. We may face situations where the effective forecasting process is not available or used for social good, but it may exist in other areas. Therefore, forecasting processes can be adopted, refined or extended for a particular need of social good. It is also possible to adopt a well-defined forecasting process from one application of social good to another. Projects fitting this quadrant provide a great opportunity for research contributions towards applications and possibly knowledge. A large amount of research in social good might fall within this quadrant. For instance, the successful use of forecasting processes in load demand could be adopted to forecasting emergency department demand as both deal with sub-daily data (Rostami-Tabar & Ziel, 2020). van der Laan et al. (2016) employed the knowledge available in intermittent demand forecasting theory to forecast humanitarian needs for Medecins Sans Frontieres (MSF-OCA).

Advance This quadrant focuses on a situation where forecasts -in various forms of estimation- are used for social good, but the forecasting process is not mature. FSG practices can improve the effectiveness of the forecasting process and advance its level of maturity. There are research opportunities here to contribute to advancing forecasting process theory. For instance, practices in the area of energy forecasting have led to an advance in the theoretical framework of probabilistic load forecasting (Hong & Fan, 2016). In humanitarian and disaster relief operations, experts are using their own experience, expertise and opinions to estimate humanitarian relief needs and making decisions accordingly. Given the high level of uncertainty such as the impact of a disaster, its duration and demand and supply requirements in humanitarian and disaster relief forecasting, it is possible that there are developed methods for handling humanitarian and disaster relief operations where multiple perspectives need to be brought together quickly, and these methods may have wider applicability in forecasting problems (Altay & Narayanan, 2020). Therefore, it is likely that FSG practice may lead to improvements and advance research maturity in the judgemental forecasting process.

Invent This quadrant concerns innovative forecasting processes that are new to social good. This will contribute to both forecasting process research maturity and the use of forecasts for social good. For instance, the development of new forecasting methodologies, which are directly integrated in the decision-making process, and their accuracy are evaluated based on social good metrics, which is an important avenue. An accurate forecasting method evaluated based on statistical measures might not necessarily lead to an accurate social good metric. This is because the translation between forecast errors and social good metrics might not be linear. This is a well-known issue in forecasting for inventory control (Kourentzes, Trapero, & Barrow, 2020; Syntetos et al., 2009). Another example would be identifying appropriate loss functions for social good so as to estimate the parameters. It is crucial to produce forecasts that are tuned to social good loss functions rather than assuming that the most accurate forecasts based on statistical measures are always best. The social good context has asymmetric and unusual losses that should be taken into account. Forecasting for resource planning is a common task in health forecasting. A loss function that can balance the over versus under capacity could be used to optimise the forecasting model parameters. Finally, the limited capacity to record data in developing countries and the data quality issues related to that, especially when these are coupled with humanitarian crises, are very common. In this context, other similar humanitarian disasters may have data that could be applied to a new disaster/event. Therefore, developing new forecasting processes that specifically focus on small and messy datasets for social good is important.

We should note that the FSG research maturity framework is not prescriptive. It can serve as a tool to help researchers and practitioners map their research for social good practices. This will help them to prioritise their research agenda, identify areas where they can contribute to social good and create opportunities to advance FSG knowledge and close the gap between theory and practice in FSG.

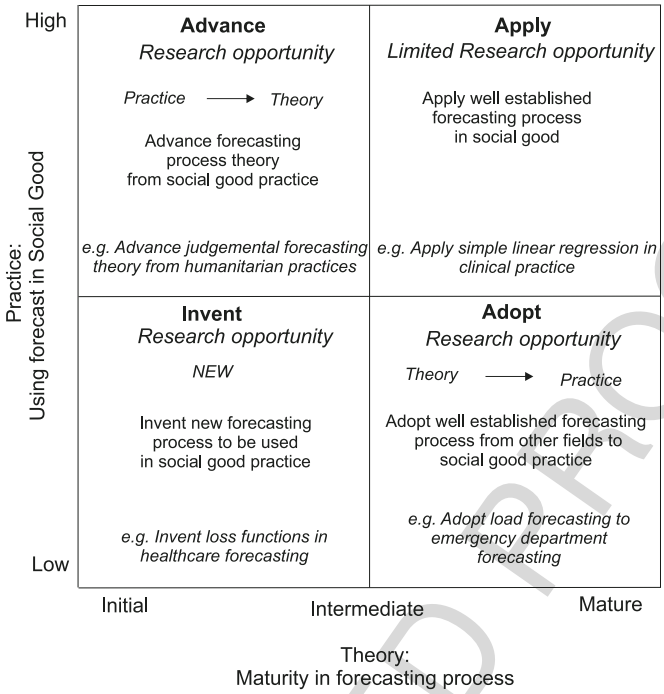

Fig. 6. FSG research maturity framework.

4. Conclusion

Forecasting is an integral part of organisational decision making, but its links to non-economic/financial utility have been limited. A better integration of forecasting with environmental and social KPIs is both feasible and desirable, and relevant practices have been receiving increasing attention as a means to safeguard and generate social good. With the support of the International Institute of Forecasters (IIF), Forecasting for Social Good (FSG) has recently been introduced as a self-contained area of scholarship, 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 further formalise FSG in order to increase awareness and the interest of academics and practitioners in its potential impact, encourage interested academics and practitioners to engage in this important agenda, and inspire the development of new forecasting methodologies that are tailored to social good applications.

We find the Doughnut theory useful in reaching a helpful definition of FSG; it is concerned with real social problems both in terms of application and performance measurement, and emphasises society as a whole. In contrast to other data science, statistics and operations research initiatives that emphasise social good, FSG is not restricted to particular organisational contexts or sectors, and capitalises on the fundamental advancements that have been made in the area of judgemental forecasting in order to dissociate substantive contributions from the availability of (quantitative/hard) data. Mapping the maturity of research in various areas of forecasting against FSG practice allows us to identify opportunities for bridging the gap between the theory and practice of FSG. When practice lags behind theory, there is an opportunity to adopt theory that already exists so as to advance practical applications. When theory lags behind practice, there is a need to advance forecasting research, building on the insights and lessons learned from practical applications. The forecasting community is called upon to invent new approaches in areas where neither sufficient knowledge nor empirical evidence have been accumulated.

The FSG guidelines we present in this paper are not intended to be definitive, and we recognise that relevant work may indeed fall outside of our working framework. The intention of FSG is to motivate engagement with important issues that our world and society face, and allow best (forecasting) practices to emerge. Specifically, we hope that a definition of FSG and its introduction as a self-contained area of inquiry will lead to an increased appreciation of forecasting as an enabler of greater social good. Qualifying what constitutes FSG should permit academics and practitioners to appreciate the opportunity cost of not engaging with its scalable agenda.

There are a number of ongoing initiatives in this area (DSSG, 2019; University of Southern California, 2016), including dedicated workshops (Rostami-Tabar, 2018, 2020b), International Journal of Forecasting special sections (Rostami-Tabar, Porter, & Hong, 2018; Rostami-Tabar, Porter, Zied, & Pinson, 2020), invited sessions in the International Symposium on Forecasting (Rostami-Tabar, 2019), and some longer-term work led by the first author of this paper on Democratising Forecasting (Rostami-Tabar, 2020a), a project the goal of which is to provide forecasting training to individuals in developing countries around the world. Just like FSG, this is

the product of a recognition of the benefits that forecasting tools can bring to advancing social justice goals. However, it goes one step further in not only making a connection between forecasting and its social utility but also emphasising direct capacity building and improving forecasting expertise in deprived economies. We hope our paper will motivate and inspire forecasting experts to put their knowledge to a good cause and we look forward to relevant developments in the years to come.

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 paper.

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