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The potential of a mesopelagic fishing industry

An agent-based modelling approach

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Abstract

In the face of increasing anthropogenic pressures on our planet, it is becoming more and more essential to efficiently manage our resources in a sustainable fashion. The world's oceans could potentially help in this as they are home to a large number of underexplored resources. However, it is important to be mindful of the possible repercussions that interfering with ocean life could have on biodiversity and the carbon sequestration process that takes place there. One of these unexploited resources is mesopelagic fish. Although their population estimates are huge, in order for fishers to start fishing for these species, novel technologies would need to be adopted. This study uses Rogers' diffusion of innovation (DOI) model to establish what factors could be of influence in creating the necessary technology adoption in the context of mesopelagic fishing. The relative advantage, compatibility and complexity of the technology all relate to how fishers perceive the price of mesopelagic fish. Using this information, this study came up with two scenarios of how a market for mesopelagic fish could arise and implemented them in an agent-based model (ABM). Through analysis of these two scenarios an attempt was made to determine whether a learning effect could influence the rate at which a market could emerge. The results showed that price transparency could play a crucial role in the establishment of a mesopelagic fishing industry. But further research on the parameter values and the creation of a more competitive market could provide new insights on how such a mesopelagic fishing industry could emerge.

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1. Introduction

1.1 The potential of a mesopelagic fishing industry

Currently, according to the Food & Agriculture Organisation (FAO), the captured fish market represents a global value of USD 151 billion, which corresponds to nearly 100 million tons of wild caught fish a year. Approximately 3.3 billion people depend on seafood for their daily intake of animal protein, and nearly 40 million people are employed in fishery activities, making it one of the largest industries in the world (FAO, 2020). Fish population levels are constantly under pressure because of the rapidly increasing human population levels and climate change. Research carried out by the FAO in 2017 revealed that approximately 34% of exploited fish and shellfish stocks were fished above biologically sustainable limits and that these developments are affecting food insecurity throughout the world but especially in African and Asian populations (St. John et al., 2016).

To relieve the pressure on these overfished species, which are predominantly epipelagic species that live in the uppermost water column (0-200 meters), resource strategists have highlighted the potential of fishing within the mesopelagic regions of the world's oceans (200-1,000m depth) (Grimaldo et al., 2020, Gjsaeter, 1984). The biomass of species that live at these depths is estimated to be very large, making them an attractive source of nutrition. Mostly, the aim of harvesting these species would be to supply the fishmeal market, even though some species are considered suitable for human consumption. In addition to the high biomass potential, another benefit is the potential for use in nutraceutical products, which are products derived from food sources that are deemed to have a beneficial effect on health, such as fish oil (St John et al., 2016). Nutraceutical products are partly based on demand for "Omega 3" oils, which are fatty acids found in many mesopelagic species (Sutton et al., 2008). In short, the upward potential for harvesting mesopelagic species is enormous as there are options for establishing a bulk fish meal market as well as a market for nutraceuticals (St. John et al., 2016).

However there are also some caveats associated with mesopelagic fishing. Mesopelagic species play a critical role in the global carbon cycle and in maintaining ecological stability. They do this by providing essential ecosystem services. The first of these is the integral role they play in the marine food chain; as prey for tuna, sharks and other species (Potier et al., 2007). A second essential activity carried out by mesopelagic species is the transfer and sequestration of carbon to deeper oceanic layers (Hudson et al., 2014). Although not within the scope of this research, these key aspects will need to be carefully assessed when evaluating to what extent commercially harvesting mesopelagic species is sustainable.

Besides the ecosystem service implications, it is also crucial to understand how to sustainably manage and govern the exploitation of mesopelagic species from a governance perspective. Humans have the responsibility to manage fisheries by determining where to fish, how much to fish, when to fish and what gear to use. These decisions are made by formal institutions which impose regulations (e.g. gear restrictions) and incentives (e.g. individual transferable quotas (ITQs) or landing taxes), stakeholder decision-making processes (e.g. community-based management) and informal institutions such as social norms (Paoletti et al., 2021). To enable sustainable exploitation of the mesopelagic stocks, a robust governance system needs to be established, which maps the key interactions of the social, economic, ecological and governance systems.

The implementation of a successful governance system can only be achieved if the economic dimensions of a mesopelagic industry have been clearly analysed. Therefore a thorough assessment on whether it is economically viable to fish and process mesopelagic species is needed (Paoletti et al., 2021). According to earlier research, commercial exploitation of mesopelagic species has been attempted, but has not been very successful due to low commercial profits. In the 1980s, the Soviet Union sent out a fleet to fish for mesopelagic fish, but this expedition was swiftly abandoned due to low catch rates and high operating costs (Kock, 2000). A more recent example, was an Icelandic expedition in 2009/2010, which was also unsuccessful, because it proved not to be financially viable (Prellezo, 2019). Prellezo (2019) also explored the economic viability of a mesopelagic fishery in the Bay of Biscay and concluded that demand and fish prices would need to rise to make mesopelagic fishing commercially interesting. Prellezo (2019) also pointed out that the emergence of a mesopelagic fishing industry is currently hindered by the high associated operating costs and the lack of investment in novel technologies for fishing and processing mesopelagic species.

One of the main barriers to establishing a mesopelagic fishing market is that both fishers and processors are heavily dependent on one another. Fishers will only start fishing for mesopelagic species when they know that their catch can be processed. Similarly, processors will only start investing in new processing equipment when they know that fishers will catch mesopelagic fish. This leads to a situation where neither fishers nor processors take action. In terms of strategy problems, this can be referred to as a chicken-and-egg situation, where the value to two separate groups (fishers and processors) is dependent on the market penetration of the other (Ott et al., 2018). This means that mesopelagic fishing becomes valuable to fishers once processors are able to process these species and that mesopelagic processing becomes valuable to processors once fishers can catch mesopelagic fish.

So the successful emergence of a mesopelagic fishing industry is completely dependent on fishers and processors adopting new technologies that enable fishing and processing for mesopelagic species. In this case, technology adoption refers to the process that fishers or processors understand, consider, approve, and master a certain technology, and use it to fish for or process mesopelagic species (Tian et al., 2021). This means that mesopelagic fishing or mesopelagic processing in itself can be seen as a new technology. One way to research how such a market could emerge is to look at how the technology of mesopelagic fishing or processing could diffuse among fishers and processors.

Research on technology adoption is plentiful, and there are various theories that are used to analyse adoption paths of countless technologies (Taherdoost, 2018). Much of the current literature is in the field of information technology. Both Gangwar et al. (2013) and Salahshour Rad et al. (2018) provide a comprehensive review of the literature on information technology adoption. Many reviewed papers were case studies where a diffusion path of a certain information technology was analysed. A few examples are research by Caselli & Coleman (2001) into what drove the different rates at which computers were adopted in several countries, by Jaakkola et al. (1998) into mobile telephone diffusion in Finland, and by Leila (2021) who performed an exploratory study in which she provided an insight into how blockchain diffused in Tunisia.

Besides the large amount of literature in the field of IT, there are also numerous studies on aquacultural and agricultural technology adoption. For example, Kumar et al. (2018) pointed out factors that influenced technology adoption in various aquacultural practices while Kumar et al. (2020) researched adoption and diffusion mechanisms of improved agricultural practices in Nepal. However, literature on technology adoption in mesopelagic fishing is scarce as this is seen as a relatively new phenomenon and a technology that has not yet been widely adopted.

Nearly all of the aforementioned research papers use traditional mathematical models of innovation diffusion to model aggregate trends rather than individual decisions (Zhang & Vorobeychik, 2019). These well-known models follow the framework of the Bass model, which was originally designed for forecasting sales. This model assumes that the probability that an individual will adopt is linearly related to the number of past adopters (Bass, 1969). This means that all individuals are fully connected and homogeneous, which in reality is often not the case. Computational models that focus on fisheries, mainly evaluate what consequences different fishery policies could have, but do not look at interactions of individual agents and emergent behavioural patterns. This paper contributes to the understanding of the diffusion of innovations by modelling the individual behaviour of fishers in the context of an emerging mesopelagic fishing industry.

1.2 Research objective and research questions

The overarching research objective of this thesis is to explore in what way interactions of fishers and a processor can influence the emergence of a mesopelagic fishing industry. To break down this objective into some smaller manageable parts, the following research questions were formulated.

1. What factors drive technology adoption in fisheries and similar industries?
2. How could a market for mesopelagic fishing emerge with a pioneer in the industry?
3. How does the learning effect influence the emergence of a market for mesopelagic fishing?

1.3 Structure of the thesis

The second chapter describes the methods used for carrying out this research. It provides arguments for why these methods are deemed appropriate for this type of research. Chapter Three commences with a theoretical overview of different diffusion theories and argues why Rogers' diffusion of innovation (DOI) theory is most applicable in the context of this research. Furthermore, this section gives examples of innovations in agriculture and aquaculture as they could potentially resemble innovations in mesopelagic fishing. Lastly, the DOI theory is used as a basis for determining the variables that are to be used in the model. Chapter Four describes the general model structure and its dynamics, while Chapter Five provides an explanation and overview of the scenarios that are to be run in the model. Chapter Six is the result section, which compares the simulation runs and draws conclusions about how and when a mesopelagic fishing market could emerge. Chapter Seven is the discussion section in which the appropriateness of the model is analysed and improvements are suggested. Lastly, Chapter Eight offers a general conclusion to the specified research questions and discusses recommendations for future research.

2. Methods

Firstly, to find out what factors influence a fisher or processor's ability and willingness to adopt new technologies that enable mesopelagic fishing or processing, a literature review was conducted. This literature review consisted of three parts. Firstly, general technology adoption theories were compared and discussed, after which the most appropriate one was selected to be used in the other parts of the literature review. Secondly, the selected theory was put in the context of technology adoption in agriculture and aquaculture as these areas have been extensively researched. Thirdly, from the literature on agriculture and aquaculture, factors that could influence the emergence of a mesopelagic fishing industry were selected to be used in the modelling part of the research.

The second and third research question were answered by performing simulations in an agent-based model. The simulations were run using a scenario-based analysis as this simplified the countless potential futures to a manageable set of plausible and coherent narratives (Rounsevell & Metzger, 2010). Typically, these scenarios are formulated through the creation of qualitative storylines. In this model, an environment was created in which a pioneer fisher started fishing for mesopelagic species and the diffusion of this new technology was monitored. But in order to infer the impact of these developments, the storylines need to be translated into quantitative outcomes and this is where computational models come into play.

A computational method that lends itself well to this type of research is agent-based modelling (ABM), which is an approach that allows for the assessment of why and how interactions between different actors and their environment have particular outcomes (Bousquet & le Page, 2004). ABMs have been used to uncover interesting links in numerous fields. For example in urban planning to understand why more roads sometimes increase congestion or in business to understand how a lack of organisational structure can lead to excessive risk-taking and fraud. (Bonabeau, 2011; Pas & Principio, 1997). But also in the context of social-ecological systems (SES), which are systems shaped by interactions between people and ecosystems, ABMs have become increasingly common. This is mainly because they are well suited to studying interaction between agents and their environment (Gotts et al., 2019). Because ABMs have the capability to manipulate the agent-level decision-making processes, they are very flexible in terms of complexity and scale making it easier to provide a natural description of the system.

ABMs are a useful tool in the context of this study for several reasons. Firstly, ABMs have the ability to create heterogeneous agents which all have a distinct set of characteristics and behavioural rules. These agents can represent a person, but can also represent households, firms or even a nation. Fishers and processors possess different knowledge and have different perceptions and cost structures, resulting in different behaviour. ABMs can integrate these differences by translating these individual traits from the real world to 'agents' in the simulation system, with the aim of creating a simulation that is as close to reality as possible. Secondly, ABMs allow for interactions between individuals, meaning fishers may learn from other fishers. Individuals are able to influence each other's behaviour by 'learning' information. Lastly, ABMs allow for agents to follow rules that are not easily analysed through analytical aggregation or standard mathematical functions. (Bonabeau, 2002; Conte & Paolucci, 2014; Gotts et al., 2019). Despite these advantages there are also challenges associated with ABMs as they are often complex, not analytically tractable and difficult to validate empirically (Gotts et al., 2019). As ABMs grow larger and become more complex, it becomes harder to accurately represent reality (Collie et al., 2016).

For this research, NETLOGO was chosen as the modelling environment. According to Railsback & Grimm (2019) there is no single platform that is ideal for agent-based modelling. However, NETLOGO is seen as one of the most appropriate tools for working with agent-based models, because of its simple programming language and graphical interfaces. This graphical interface is very helpful when explaining your research to others and provides you with an extra check when programming. In addition to this, most published scientific ABM's are implemented in NETLOGO, hence the reason for choosing this software.

To analyse the results from the simulation runs in NETLOGO, Microsoft Excel and R were used to clean and process the output data. Further tests to obtain relevant results were also performed in R. The main reason for using R is that it is extremely useful for cleaning, analysing and creating plots and graphs for large datasets.

3. Factors driving technology adoption

This chapter aims to explore those factors that are most relevant in technology adoption. This is important because it can provide an indication of what elements could influence the emergence of a mesopelagic fishing industry. Firstly, a general overview of theories related to technology adoption is provided and an appropriate theory that can be applied to this study is chosen. Next, the chosen theory's relevance to aquaculture and agriculture are highlighted as these fields are quite closely related to mesopelagic fishing. Lastly, those factors that could drive technology adoption in mesopelagic fishing and processing are identified.

3.1 General adoption of technology theory

In economics, it is widely accepted that technological development is one of the key drivers of economic growth, because technological progress allows for a more efficient allocation of the product or service inputs, enabling the creation of more or better goods and services (Bayarçelik & Taşel, 2012). The rise of new technologies in various fields is changing the way businesses operate, communicate, and access services and information. Especially developments in Robotics, Artificial Intelligence, Internet of Things, Blockchain, Drones and 3-D printing are disrupting existing technologies. In the near future these new technologies will drastically change the way in which humanity designs, creates and experiences agriculture, health industries, engineering and education (Oyetade et al., 2020). To deal with this, people will have to learn to use and adopt these novel technologies. In the process of technological change, Schumpeter (1934) identified three key development steps; invention, innovation and diffusion. The first stage, the invention, is the creation of a novel good or process through the acquisition of new knowledge or from new combinations of existing knowledge. This is followed by the innovation stage where the invention is commercialised using a new production method or by marketing a new good in a different way. Diffusion is a consequence of a successful innovation. It is the part of the process where the innovative product or service becomes widely available for use through adoption by individuals or firms. Adoption and diffusion are closely related to each other. Adoption refers to the acceptance or rejection decision of a technology by an individual or an organization while diffusion refers to the stage in which the technology spreads to general use and application (Kee, 2017).

Rogers' (1995) defines diffusion as "the process by which an innovation is communicated through certain channels over time among the members of a society". Practically, on the demand side this means that consumers are starting to purchase and use the innovation. On the supply side, diffusion occurs when competitors start copying and incorporating the technological innovation in their own processes. Rogers' (1995) does not only define the concept of innovation as a technology but also as any "idea, object or practice that is perceived as new by an individual or other unit of adoption" (Rogers, 1995, p.11). In the context of this study, this definition would then refer to any idea, object or practice that enables fishers to fish on mesopelagic fish or enables processors to process mesopelagic fish. As one of the fundamental assumptions of this research is that the invention and innovation steps with regards to the new technology have already been completed, it will focus on the factors that influence the technology diffusion process.

Several studies on factors influencing diffusion of technology and innovations have been conducted in many different fields, and most have used one of four widely recognised models (Salahshour Rad et al., 2017). These are: the technology acceptance model (TAM), the theory of planned behaviour (TPB), the unified theory of acceptance and use of technology (UTAUT) and Rogers' (1995) diffusion of innovations (DOI) model. TAM delves into the nature of belief-attitude-intention-behaviour and its influence on technology adoption (Davis, 1989). TPB looks at which attitudes, subjective norms and perceived behavioural control variables are shown to influence the adoption of technologies (Ajzen, 1991). UTAUT, which is a combination of the TAM and the TPB models, highlights performance expectancy, effort expectancy, social influence and facilitating conditions as factors influencing technology adoption (Venkatesh et al., 2016). Lastly, Rogers' (1995) DOI model suggests that five perceived attributes affect the rate of technology adoption, namely: relative advantage, compatibility, complexity, trialability and observability.

None of the aforementioned models is perfect and all have both limitations and advantages. According to a comparative study by Khan & Woosley (1989), the TAM has been most widely used, but the main focus of these studies is related to the adoption of information technologies and fails to include social and human factors. Examples of social factors are education, income or risk preferences. As social factors play a crucial role in this research, TAM is deemed to be less applicable. TPB is also a well-known model that, similarly to TAM, draws on the intention-behaviour correlation. However, the critique on this theory is that in some cases intentions are poor predictors of behaviour (Ajzen, 2011). In our case, fishers may have the intention to go fishing each day, but due to a storm or issues with fishing gear they may be forced to stay in the harbour. This makes the predictive validity of intentions hard to accept in the context of our study. Similarly to TAM, UTAUT was also developed in the field of information technology and very few studies have been carried out in other fields (Khan & Woosley., 1989). Choosing UTAUT as the model for studying diffusion in an area that is not directly related to IT therefore seems unwise. The last option is DOI which takes a broader approach to technology adoption as its origins lie in anthropology, education, sociology and communication (Katz et al., 1963). DOI is seen as a good predictor of social and technical change and has been implemented in many different fields besides IT, such as education, mental health (Dingfelder & Mandell, 2011) and for environmental topics relating to waste management and dairy farms (Bishop et al., 2010). Despite its implementation in a broad range of areas, DOI also has some limitations. For example, the adoption of technology can be influenced by more than just the five listed factors provided by Rogers and is always dependent on the context of the research, which means it requires constant reconsiderations.

Even when taking these considerations into account, DOI is still deemed to be the most appropriate model for this research due to the fact that it has been used in studies related to environmental issues and has proved to be effective in including social factors. The other models are less generic and have less of a track record in including social factors, which are at the core of agent-based modelling research.

3.1.1 Rogers' diffusion of innovation model

Rogers (1995) bases his DOI model on his definition of diffusion, which is "the process by which an innovation is communicated through certain channels over time". From this definition, Rogers (1995) deduces four main elements, namely: the innovation, communication channels, time, and the social system.

Firstly, innovation refers to "an idea, practice or object that is perceived as new by an individual or other unit of adoption" (Rogers, 1995, p.11). The newness of this idea need not just involve new knowledge, because people may have known about an innovation, but not yet developed a favourable attitude toward it and therefore not adopted it. Thus, 'newness' can be expressed not just in terms of knowledge but also in terms of persuasion or a decision to adopt. Characteristics of innovations help to explain the different rates of adoption. Rogers' (1995) calls these the perceived attributes of an innovation. These are relative advantage, compatibility, complexity, trialability, and observability.

Secondly, a communication channel is defined as "the means by which messages get from one individual to another" (Rogers, 1995, p.17). Audiences can be informed through mass media channels (often the most rapid and effective way) but interpersonal channels are a more intimate way of exchanging information face-to-face. Often communication is more effective if individuals share common meanings and have similar social characteristics.

Thirdly, time is an important element of the diffusion process and plays a role in the innovation-decision process, the innovativeness and adopter categories, and the rate of adoption. The innovation-decision process is "the process through which an individual (or other decision-making unit) passes from first knowledge of an innovation to forming an attitude toward the innovation" (Rogers, 1995, p.22). Adopter categories are "classifications of members of a social system on the basis of innovativeness" (Rogers, 1995, p.22). These can be subdivided into: innovators, early adopters, early majority, late majority and laggards. Lastly, the rate of adoption refers to the speed of the adoption by individuals. Most innovations have an s-shaped rate of adoption which means that at first only a few individuals adopt the innovation (innovators), then diffusion increases and more and more individuals adopt (early and late majority), and in the end diffusion levels off and fewer individuals remain who have not adopted yet (laggards).

The fourth element is the social system. This is defined as "a set of interrelated units that are engaged in joint problem solving to accomplish a common goal" (Rogers, 1995, p.24). The members of a social system may be individuals, organisations or informal groups. The diffusion process is affected by the social structure of a system, through social norms, the roles of opinion leaders and change agents, the type of innovation decisions and the consequences of innovation.

In this study, the main focus will be on the first of these elements and more specifically on the characteristics or perceived attributes of an innovation as mentioned above. The reasoning for this is that these five perceived attributes (relative advantage, compatibility, complexity, trialability, and observability) focus on the technology itself and are a useful tool for describing the distinct characteristics of a technology. This enables us to gain insights about why fishers would be attracted to a certain technology and what the reasons could be for them to consider adoption. On the other hand communication channels, time and the social system focus on the speed at which a technology diffuses. These five different attributes taken from Rogers (1995) have been chosen because of their maximum generality and succinctness.

3.1.2 Perceived attributes

Each of the following paragraphs will provide a short explanation of what these five attributes are, giving some examples to clarify.

The first perceived attribute is relative advantage. It can be explained as the degree to which an innovation is perceived as better or more superior than the idea it replaces (E. M. Rogers, 1995). Relative advantage can be expressed in economic profitability or status giving, but usually the nature of the innovation determines the type of relative advantage that is important to the receivers (e.g. economic or social). A common feature among some of the products that have been improved from a technological perspective and gained a relative advantage was a decrease in the costs of production over time, ultimately leading to lower prices for consumers. A good example of such an innovation is the pocket calculator. When production of these calculators started in 1972 they sold for $250, but after a few years, due to technological improvements in the production of semiconductors (an essential part of the calculator), prices dropped to only $10. Such a significant drop in price during the diffusion process increases the rate of adoption significantly (E. M. Rogers, 1995). Another example where relative advantage plays a prominent role in driving adoption is the clothing industry. For example, generally, jeans are not of functional utility to the wearer, they are simply a practical and durable type of clothing. The main reason consumers buy designer jeans is the brand name on the rear pocket, which is a status-conferring attribute of the innovation. In conclusion, economic dimensions and social status play a key role in the rate of adoption, but there are also other factors that have an influence on technology adoption. For example an increase in comfort, savings in time and effort, and the immediacy of the reward are all subdimensions that have been found to influence the rate of adoption (Rogers, 1995).

Secondly, compatibility also affects an individual's adoption decision. It relates to "the degree to which an innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters" (Rogers, 1995, p.224). An idea that is perceived as more compatible tends to reduce uncertainty, making it more attractive for the receiver to adopt. An innovation can be compatible or incompatible with sociocultural values and beliefs, previously introduced ideas and with a receiver's needs for innovation. An example of a strong culturally held value is the Indian belief that you should not eat food with your left hand. This practice started centuries ago because traditionally the left hand was used after defecation and therefore unclean. However, nowadays most Indians have access to sanitary facilities, making it easy to wash their hands, but the unclean left hand still persists as a cultural belief. Promoting innovations that can influence deeply rooted values such as these is challenging and may lead to unsatisfactory results.

Although previously introduced ideas can be used to test an innovation and can help reduce uncertainty and encourage receivers to adopt, a negative experience can hinder the adoption rate of future innovations. Moreover, the degree to which an innovation meets the needs of a receiver is a crucial indicator of the compatibility of an innovation. Detecting these needs is a challenging job for change agents as they have to understand what people want. One way in which companies tackle this is by setting up client advisory committees or conducting surveys. In short, if an innovation is not compatible with cultural values, previously adopted ideas or a receiver's needs, its compatibility can decline rapidly.

Thirdly, complexity relates to how difficult the perceived innovation is to understand and use. Simply said; some innovations have a clear meaning to potential adopters whereas others do not. Graham (1956) looked into why canasta (a card game) and television diffused at different rates among upper and lower socioeconomic classes. One of his findings was that it related to the complexity of the two ideas. Canasta had to be learned through detailed personal experiences from other players, it was therefore seen as difficult and complex, while television on the other hand was seen as quite simple as it just required the ability to turn a knob.

Fourthly, trialability refers to the degree to which innovations can be experimented with. Novel ideas that are tried using instalment schemes, generally have higher rates of adoption than innovations where the entire investment sum has to be paid upfront. This is the case, because innovations that are perceived as divisible (e.g. through instalment payments) are also more trialable, which reduces uncertainty for adopters. Moreover, earlier adopters perceive trialability as more important than later adopters, because innovative individuals have no precedent to follow when they adopt, therefore they place more value on trials.

The last of the five attributes is observability, which relates to the extent to which results of an innovation are observable to others. Some innovations are easily observed and communicated to others, whereas others are not. An example is the difference between computer hardware (the equipment) and computer software (the computer programmes). Usually, software components are less visible to receivers and therefore less observable, this results in slower rates of adoption than observable innovations like the computer hardware.

The reasoning for naming these attributes 'perceived attributes' is because of the essential role that perception plays in explaining human behaviour (Rogers, 1995). Receivers' perceptions of the attributes of an innovation, which can differ from the attributes highlighted by experts or opinion leaders, affect the rate of adoption. It is not about reality itself, but about how individuals perceive reality and how their expectations and perceptions influence their behaviour. The advantage of these perceived attributes lies in the fact that they can help predict future rates of adoption for innovations. The five perceived attributes require more explanation and will be looked at individually in more detail in the context of aquaculture and agriculture.

These five perceived attributes may not, however, always be the five most important characteristics. It is, therefore, important to determine what the most relevant factors are by asking representatives from the industry in question, prior to assessing the quality of these attributes as predictors of adoption. As this is a very time-consuming process and because there is no existing market for mesopelagic fisheries and processors, this study will be based on assumptions rather than on respondents' answers. This makes the generalised perceived attributes particularly useful as a starting point for creating a list of more specific factors that could influence the rate of adoption within mesopelagic fishing and processing.

3.2 Adoption in aquaculture and agriculture

While literature on technology adoption in fisheries and fishing is quite scarce, literature on diffusion of technologies in aquaculture and agriculture is relatively extensive. Therefore, factors found in literature from these two industries will act as a reference point for determining the factors that could influence technology adoption in mesopelagic fishing and processing. In the literature on diffusion of technology in agriculture and aquaculture the perceived attributes mentioned in Chapter 4.1 play a prevalent role, as will be elaborated on further in this chapter.

3.2.1 Relative advantage

A study on the adoption of novel technologies in U.S. farms highlighted the economic aspects of relative advantage (Fliegel & Kivlin, 1966). It stated that innovations which are perceived as most rewarding and have low risk and uncertainty will be accepted most easily. Batz et al. (1999) believe the relative advantage to be particularly effective in aquaculture if it is perceived to create more utility in terms of productivity, cost effectiveness or riskiness. These three aforementioned factors will now be examined in more detail.

Productivity

Increased productivity is usually a key driver of technology adoption. In general, an increase in productivity can be seen as a change in the production function through either increased output from a given input level or from a reduced use of inputs for the same level of output (Mansfield, 1961). An example of a successful output-increasing technology in agriculture, was the use of hybrid corn seeds which enabled the breeding of superior corn (higher yields) for specific locations (Griliches, 1957). An example from aquaculture is taken from research carried out by Kumar & Engle (2017) which highlighted the importance of efficient aeration devices in increasing aquaculture yields. According to Kumar et al. (2018), the magnitude of difference in productivity between old and new technologies also influences the rate at which new technologies are adopted. There is a term for this known as leapfrogging where less productive firms have the tendency to switch to better technologies more quickly than productive firms (Brezis et al., 1993). An example is the Norwegian salmon industry, where new firms entering the market were able to leapfrog technologically by adopting new smolt production and hatchery techniques, ultimately leaving the so-called ‘productive’ firms behind (Sandvold, 2016).

Cost effectiveness

Another indicator of relative advantage is the cost effectiveness of a new technology (Katiha et al., 2005). New technologies require substantial investment. This can affect costs and cost effectiveness in several ways depending on the amount of money required for the initial investment and the effects on the fixed and/or variable costs (G. Kumar et al., 2018). According to Parente & Prescott (1994) technologies that require a high initial investment generally have slower adoption rates. One example is the catfish industry, where a high initial investment for alternative catfish production technologies resulted in non-adoption. Conversely, lower initial capital requirements cause faster adoption. A supporting example describes how low capital requirements in Vietnam stimulated the integration of aquaculture practices with livestock components. (Nhan et al., 2007).

Risk aversion

Thirdly, risk plays a role in the farmer’s decision to adopt a certain technology or not. Risks in farming can include variations in market prices, yields and input costs (G. Kumar et al., 2018). A very risky innovation may reduce the farmers’ relative advantage and slow down adoption (Ghadim et al., 2005). In general, different individuals have different perceptions of risk. A risk-averse individual tends to adopt technologies that are perceived to reduce risk, while a risk-taking individual may opt for risky technologies hoping that they yield higher returns (Ghadim et al., 2005). For example, in offshore threadfin farming, there is limited access to sufficient fingerlings and so this is seen as a risky endeavour, however the other side of the coin is that pursuing these activities can lead to greater profits (Kam et al., 2003).

3.2.2 Compatibility

For an agricultural or aquacultural innovation to be successful it needs to be compatible with the local, ecological and social conditions into which it is adopted. A relevant example is the growing public concern about genetically modified organisms (GMOs) within the EU. The EU has spoken out against technologies that enable genetic modification, for example, the production of transgenic fish as it believes that GMOs do not fit within the social norms and values of the EU. This example underlines how social conditions can play a role in the compatibility of innovations and how they may even inhibit adoption.

3.2.3 Complexity

Generally, farmers prefer the adoption of less-complex technologies as opposed to more complex ones. In aquaculture increased complexity can occur as a result of incremental changes to existing technologies, changes in management processes, design changes or radical innovations. (Joffre et al., 2017). Aquaponic technologies are an example. These are food production systems that couple aquaculture with hydroponics (i.e. cultivation of plants in water) whereby the nutrient rich aquaculture water is used to feed hydroponically-grown plants (Bosma et al., 2012). These technologies are generally deemed to be quite complex as they require complementary skills in bioengineering and plant and animal husbandry. Because of the added complexity many farmers are reluctant to adopt aquaponic technologies.

3.2.4 Trialability and Observability

In a study performed by Shang et al. (2021), 32 farm-level studies and 27 agent-based models were analysed to find out what factors from the TAM and DOI theories were significant. According to their empirical research on the adoption of digital farm technologies, observability and trialability were found to be of very limited significance. In research carried out by Dewees & Hawkes (1988) on technical innovation in the Pacific Coast trawl fishery, observability was omitted and the effect of trialability was also seen to be limited. Therefore, due to the lack of significance in earlier literature, observability and trialability will be not be covered from this point on.

3.3 Relevance for mesopelagic industry

This section will draw on the earlier sections in order to point out certain factors that could influence technology adoption in mesopelagic fishing and processing. As stated before, one of the assumptions of this research is that for a market to emerge, a new technology needs to be developed and consequently adopted by fishers and/or processors. New technologies often require a substantial investment, so it is understandable that fishers and processors might be reluctant to take the first step. In this specific case, both actors (i.e. fishers and processors) are dependent on one another and this relates to the network effect, whereby an increase in the number of users of a product improves the value of a good or service. Fishers will not invest in fishing equipment for mesopelagic species if they cannot sell the fish they have caught. Similarly, processors will not invest in processing equipment if there is no one to supply them with fish to process. This creates a chicken and egg situation where fishers are dependent on what processors do and processors are dependent on what fishers do.

A novel technology in the context of this research refers to an idea, object or practice that enables fishers to fish on mesopelagic fish or enables processors to process mesopelagic fish. For the purpose of this research the exact type of technological innovation (i.e. its functionalities) are not relevant but fishers considerations on why they would be willing to adopt and what drives this desire are. However, to provide a somewhat realistic scenario some suggestions of current developments and innovations in fishing and processing will be mentioned. As the type of innovation is deemed less relevant the focus shifts to the diffusion part of the process and what factors could influence this.

3.3.1 Potential innovations

Currently, fishing for mesopelagic species does not happen on a large scale, mainly because it is not considered to be commercially viable. Research on the viability of a mesopelagic fishing industry has been performed by Prellezo (2019) in the Bay of Biscay. Interestingly, this study concludes that technically, existing fleets could switch to mesopelagic fishing. It also explains that the operating characteristics of a bottom-trawl fleet make it technically feasible for it to be used to fish mesopelagic fish and suggests that a pelagic trawler would probably be the most effective vessel to do this. Minor adjustments, such as extending the length of the pelagic trawler lines would enable fishing at greater depth while smaller mesh sizes could increase catches as many mesopelagic species are relatively small. Clearly, these adjustments in the mesh size and line length are dependent on what type of mesopelagic species the fisher is targeting. However a technical issue that does arise is the ability of a trawler to store fish on-board. Mesopelagic fish tend to degrade far more rapidly after being caught than epipelagic species, which means trips would have to be shorter, unless investments are made in novel technologies that enable on-board processing (Paoletti et al., 2021). This is a crucial factor in this industry, because to process and extract the highly valuable sub-products such as omega-3, the fish must be fresh (Prellezo, 2019).

Processing facilities will also need to invest in novel technologies for processing in order to retrieve the most desirable compounds such as omega-3 and fatty acids from mesopelagic species. For example the *Benthosema glaciale* (glacier lantern fish) contains high levels of wax esters i.e. an ester that consists of a fatty acid and a fatty alcohol. If used in salmon feed, these esters may pose problems as salmon are restricted in their capacity to utilise them. So, for glacier lantern fish to be used in salmon feed, the oils need to be diluted (Grimaldo et al., 2020). Another issue is the quantity of undesirable substances found in samples of *M. muelleri* (type of mesopelagic fish). Grimaldo et al. (2020) found that the cadmium and arsenic levels were above the maximum limit for human consumption. Cadmium was mainly found in the protein part of the fish that is used to produce fish meal, while levels were significantly lower in the oil, so this could be used for human consumption. More efficient processing techniques that enable extraction of the right substances may be an innovative way to contribute to the viability of a mesopelagic fishing industry.

3.3.2 Linking the perceived attributes to relevant factors in mesopelagic fishing.

In this section, Rogers' (1995) five perceived attributes are used as a guideline for formulating factors that could influence the emergence of a mesopelagic fishing industry. As stated earlier on, observability and trialability have been omitted from this research due to their limited significance in agricultural and aquacultural research.

Relative advantage

As mentioned earlier relative advantage can be divided into three sub categories namely: productivity, cost effectiveness and risk aversion.

Productivity

As alluded to before, technologies that have a relative advantage are usually a key driver of technology adoption. For each fisher, productivity plays a key role in the determination of their price perception. Productivity can be defined as a change in the production function through either increased output from a given input level or from a reduced use of inputs for the same level of output (M. Rogers, 1998). Novel technologies, such as the ones mentioned earlier, have the potential to make fishing trips more productive. For example, because larger quantities of mesopelagic fish may be stored on board or smaller mesh sizes increase catch volumes. Similarly for processors, investments in novel technologies will need to be made to make processing more efficient and productive. The perception of the productivity of a technology may influence a fisher's price perception. It could for example increase, because fishers believe that more productive technologies will result in larger catches, and therefore have more market potential which would increase the value of mesopelagic fish. On the other hand fishers that perceive these technologies to be less productive will have a lower perception of the mesopelagic fish price as they see less of a potential for such a market to emerge.

Cost effectiveness

Both fishers and processors may have to spend a significant sum of money on investment. In fishing, small adjustments like extending the length of trawler lines and decreasing the mesh sizes of nets can be seen as small investments, but investing in on-board processing equipment is a large investment. For fishers it is therefore important to check whether investing in a novel technology is worthwhile. As mentioned earlier technologies that require high initial investment, such as on-board processing equipment generally have slower adoption rates, but could provide a competitive edge in a newly emerging market. While extending lines and decreasing mesh sizes can be seen as technologies with lower capital requirements and as such tend to have higher rates of adoption. A technology can be seen as cost effective when the benefits are worth at least more than the initial payment. Fishers, in this case, will evaluate whether making these initial investments is in fact cost-effective. Consequently, Fishers will use this evaluation to constantly monitor whether it is commercially viable to make the transition to mesopelagic fishing. Similarly, processors have the same choice to make regarding making the initial investment and adjusting their price perception.

Risk aversion

In the context of mesopelagic fishing it is logical to assume that some fishers will be more risk-averse than others. In research carried out by Dewees & Hawkes (1988) fishers' attitudes to technology adoption were measured by means of a questionnaire covering six type of innovations. A sample of 150 vessel owners was selected from Santa Barbara, California and Newport, Oregon. One of the results of this questionnaire was that risk aversion among fishers was, on average, evenly distributed across all innovations. Risk aversion was categorised into 'low', 'medium', and 'high' and the distribution was 38%, 27%, 35% respectively. A fisher's risk preferences affect many other factors. For example a risk-averse fisher is less likely to invest in expensive fishing equipment while a risk-loving fisher will do so more easily. Risk-averse fishers may also be very conservative in terms of their perception of the mesopelagic fish price as they consider fishing for a new type of fish to be very risky.

Compatibility

Compatibility or the extent to which technical innovations are compatible with social and local conditions are important for the uptake of these innovations. As the earlier example on the pulse trawl highlighted, a good technological innovation in itself is not enough for adoption. The technology needs to be in line with past experiences and existing values of fishers for adoption to be successful. The more a fisher feels this to be the case, the more likely they are to adopt this technology. So, this begs the question of whether these fishers will make the transition to mesopelagic fishing if it becomes viable? The answer to this question depends on where the fishing community is located, what they fish and the fishing values they uphold. In the case of mesopelagic fishing this relates to the social and governmental conditions that are in place. For example, will it be possible for fishers to get licences for smaller mesh sizes and how will the public perceive this new resource? In addition, has past experience made fishers cautious about mesopelagic fishing and are there any references to limits for sustainable fishmeal and oil processing? Moreover, it is crucial for governments to support research into sustainable harvesting. Norway is a good example. Its national government is co-investing in the exploration of mesopelagic fishing (Schadeberg et al., 2021). It could be argued that the extent to which fishers perceive mesopelagic fishing to be compatible with the local conditions directly influences their price perception of the fish. High compatibility could make local processors relatively enthusiastic about this new resource and the opportunities for a new market, meaning fishers may adjust their price perception upwards. While low compatibility could create resistance from local people as they believe mesopelagic fishing to be damaging to the ecosystem resulting in a lower price perception for fishers.

Complexity

As mentioned before, complexity relates to how difficult the perceived innovation is to understand and implement. And the perceived complexity of an innovation has a bearing on its rate of adoption. A rare example of an innovation in fishing underscores this. After World War II, in the USA, the only long range navigation (LORAN) systems available to fisherman were the ones the government had, as they were used in air force bombers at that time. These LORAN systems consisted of three parts; a sender, receiver and a generating device, all of which were large and cumbersome. While the advantages of the LORAN were recognised at the time, most fishermen were slow to adopt, because operating them required a significant amount of skill (Stephenson, 1980).

In relation to mesopelagic fishing, the industry workshop of the MEESO project, which aims to fill major knowledge gaps on mesopelagic organisms living in the oceans and assess whether they can be exploited in an ecological and economical way, highlighted the complexity associated with mesopelagic fishing (Schadeberg et al., 2021). One of its key takeaways was that there was considerable uncertainty for fishers regarding optimal towing speed, fuel use, most effective gear and on-board preservation. Processors ran into similar problems and had questions concerning what affordable on-board processing methods could be developed, the costs of developing new processing systems, and the amount of energy required to process mesopelagic species. These questions underline the complex nature of mesopelagic fishing, and it is therefore logical that fishers and processors perceive it to be complex. However, in the long run, if mesopelagic fishing becomes more popular the technology may become less complex as the aforementioned questions are answered. The extent to which mesopelagic fishing is viewed as complex could potentially influence a fishers' perception of the price of mesopelagic fish. High complexity, meaning considerable uncertainty would translate to a high price perception as fishers may be unsure about expected catches, the effectiveness of their gear and the duration of their trips, meaning that high fish prices will be needed to compensate for unforeseen costs. Low complexity on the other hand would mean a larger number of fishers could enter the mesopelagic fishing market relatively easily, translating into a lower price-perception as more fishers are capable of fishing for this resource. Consequently, fishers could expect the price of the fish to drop as mesopelagic fishing becomes less exclusive.

4. Model design

This model was constructed in order to provide an example of how a mesopelagic fishing industry could emerge. It does this by monitoring the behaviour of individual fishers in response to a pioneer in the industry and tracking how long it takes them to switch from epipelagic fishing to mesopelagic fishing. By creating an environment in which fishers constantly compare the viability of epipelagic fishing and mesopelagic fishing, the model aims to emulate the considerations that fishers would make when evaluating which option they prefer. For a market to come about there needs to be a buyer, a seller and a market price. In this model, the buyer is the processor, the seller is one of the fishers and the market price at which the fish is sold is determined by the price perceptions of fishers and the processor. These price perceptions differ from fisher to fisher, and they depend on the fishers' perception of the relative advantage, compatibility and complexity of the mesopelagic fishing technology.

Each ABM has two essential parts, namely (1) the environment and (2) the agents that populate the model. The following section will provide an in depth overview of both these parts and the variables that were used to create them.

4.1 Environment

The environment consists of 1024 patches, which are square cells that represent space. 32 of these patches are brown, to resemble land, while the other 992 are blue, to resemble the ocean. Figure 1 provides a graphical representation of the fishing environment. Each blue patch has its own variable which resembles the expected biomass of mesopelagic fish. This biomass value is taken from a random uniform distribution. (β_{it}). Where β_{it} is the biomass in patch i at time period t. When fishers land on one of these patches they fish the entire biomass and this then translates to the expected mesopelagic catch variable (ε_{ft}) which is an agent variable.

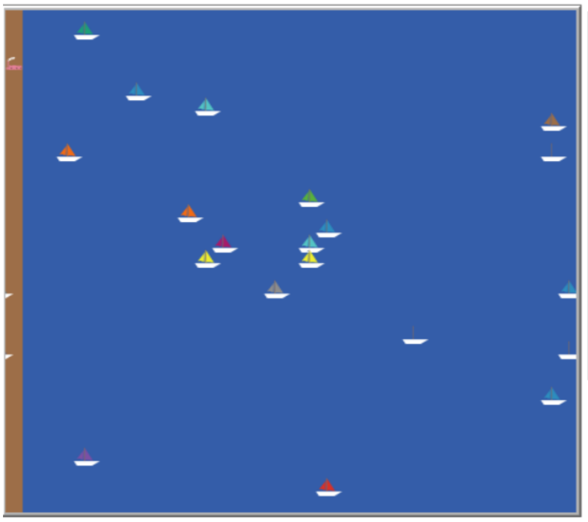


Figure 1: Fishing environment

4.2 Agents

This model recognises two types of agents: fishers and a processor

4.2.1 Fishers

Each fisher is characterised by the following variables: price perception of mesopelagic fish (π_{ft}); costs of mesopelagic fishing (γ_{ft}); costs of epipelagic fishing (ρ_f); and mesopelagic catch rate (ε_{ft}). Here f refers to the fisher and t refers to the time period.

Price-perception of mesopelagic fish (π_{ft})

Each fisher starts with an initial price perception for mesopelagic fish. The price perceptions for mesopelagic fish are assigned from a uniform random distribution. These values capture the fishers perception i.e. what they think mesopelagic fish will sell for. Appendix A1 provides an overview of the price perception of mesopelagic fish prices used within the model runs.

Fishing costs (γ_{ft} & ρ_t)

Technical innovation in fisheries plays a crucial role in their development especially with regards to the costs of fishing. These innovations can come about through innovative products or innovative processes, the former affect the physical properties of the products, whereas the latter do not. Both product and process innovations can effect technical change and reduce costs but there are a few different types of technical change. One of these is relevant for this research and is called 'disembodied technical change' (Squires & Vestergaard, 2013). This refers to a technical change that is not embodied in economic input, but can be viewed as a learning-by-doing-and-using type of change. Learning by doing is characterised by a fall in unit production costs and an increase in efficiency as producers gain experience. In this model the costs of fishing the mesopelagic fish decline with every time step:

$$\gamma_{ft} = \gamma_{ft-1} - x \;\forall f,t \tag{1}$$

Where γ_{ft} is the mesopelagic fishing costs of fisher f in time period t; γ_{ft-1} is the mesopelagic fishing costs of fisher f in time period $t-1$, and x is the amount by which mesopelagic fishing costs fall. This means that mesopelagic fishing becomes 'easier' or 'cheaper' for fishers over time. The assumption is that fishers become more experienced in and accustomed to using mesopelagic fishing gear, enabling them to work more efficiently.

The epipelagic fishing costs (ρ_f) are constant as it is assumed that fishers know their costs for fishing epipelagic species, because they have gained experience in the past. These epipelagic fishing costs are assigned from a uniform random distribution and are different for each fisher. As this is done uniformly each fisher has an equal chance of getting one of the values within the interval assigned to them. Appendix A2 provides an overview of the epipelagic fishing costs used within the model runs.

The mesopelagic fishing costs (γ_{ft}) are assigned to the fishers in a similar manner, but the mesopelagic fishing costs are considerably higher because it is assumed that initial investment is needed for new equipment or to adapt the gear they currently use. Besides this, the variable or operating costs for mesopelagic fishing are assumed to be higher than for epipelagic fishing, because the longer nets and smaller mesh size increase resistance and therefore increase fuel usage. But as mentioned earlier, it is assumed that these mesopelagic fishing costs will decrease over time, because of efficiency gains for fishers. Thus, after a fixed period of time the costs decrease by a fixed amount. Appendix A3 provides an overview of the mesopelagic fishing costs used within the model runs.

Mesopelagic catch rate (ε_{ft})

The expected mesopelagic catch (ε_{ft}) is directly related to the expected mesopelagic biomass per patch each timestep (β_{it}). This is the case because the biomass per patch i at time t is used as the expected mesopelagic catch of fisher f at time t. The following formula shows how the expected mesopelagic catch is calculated:

$$\varepsilon_{ft} = \varepsilon_{ft} + \varepsilon_{ft-1} \; \forall f, t \tag{2}$$

Where ε_{ft} is the expected mesopelagic catch of fisher f in time period t; and ε_{ft-1} is the expected mesopelagic biomass in time period $t-1$. As stated earlier, it is important to mention that in this formula $\varepsilon_{ft} = \beta_{it}$, meaning the expected mesopelagic catch of fisher f in time period t is equal to the biomass of mesopelagic fish of patch i for fisher f

In addition to this every fisher has a maximum capacity, which is reached once either the expected mesopelagic catch or the expected epipelagic catch reaches a certain value.

4.2.2 Processor

The processor in the model has only one variable, which is the processor's price perception of mesopelagic fish (θ). This variable is also an exogenous variable. It is an influential variable as fishers compare their own price perception to that of the processor, before engaging in a transaction.

4.3 Global variables

The epipelagic fish price is thought to be known by the fishers and is therefore included as a constant. Fishing for epipelagic fish is a market which already exists therefore it would be logical to assume that all fishers would know what this price is. The epipelagic fish price is referred to with δ.

In addition the expected epipelagic catch is an exogenous variable and it is referred to with ω. The reasoning for this is that it is based on the assumption that fishers have made an average biomass estimation and then calculated what their expected catch may be based on past experiences. It is calculated using the following formula:

$$\omega_t = \omega_t + \omega_{t-1} \; \forall t \tag{3}$$

Where ω_t is the expected epipelagic catch at time period t; and ω_{t-1} is the expected epipelagic catch at period $t-1$.

4.4 Utilities

Fishers choose to catch epipelagic or mesopelagic fish according to the expected utility from each layer (U_{mft} or U_{eft}), which is calculated as follows:

$$U_{mft} = \left(\pi_{ft} * \varepsilon_{ft}\right) - \gamma_{ft} \; \forall f, t; \tag{4}$$

$$U_{eft} = (\delta * \omega_t) - \rho_f \; \forall f \tag{5}$$

Where in (4), U_{mft} is the utility from mesopelagic fishing of fisher f at timestep t; π_f is the price perception of mesopelagic fish of fisher f at time t; ε_{ft} is the expected mesopelagic catch of fisher f at timestep t; and γ_{ft} is the mesopelagic fishing costs of fisher f at timestep t.

And where (5), U_{eft} is the utility from epipelagic fishing of fisher f at timestep t; δ is the epipelagic fish price; ω is the expected epipelagic catch; and ρ_f is the epipelagic fishing costs of fisher f.

The fisher evaluates both expected utilities each timestep and chooses to fish for either epipelagic or mesopelagic fish based on the higher utility value.

4.5 Ticks

Another important element in any ABM is time. In this case the model aims to monitor how long it takes for fishers to shift from epipelagic to mesopelagic fishing. Time in NETLOGO is monitored through 'ticks', which are essentially timesteps. One tick in this model resembles a fishing session of which there are two each day. Fishers are expected to fish 365 days a year, which means they have 730 fishing sessions each year. Fishing trips typically last ten fishing sessions, which equates to approximately five days before returning to the processor. It is assumed that fishers go out fishing again for another five days as soon as they have landed their haul. The entire model runs for 3650 ticks which translates to five years. Most social scientists agree on the fact that the response to an innovation by a group is typically differential as it depends on the type of innovation (Stephenson, 1980). This makes it difficult to choose an appropriate time scale.

4.6 Interaction between agents

4.6.1 Initialisation of the model

Fishers start at random spots in the ocean and the processor is created at a fixed spot on land. When the model is initialised fishers get assigned a price perception for mesopelagic fish (π_f), fishing costs for mesopelagic fishing (γ_{ft}) and fishing costs for epipelagic fishing (ρ_f). All of these values are drawn from a random uniform distribution. The single processor also gets assigned a price perception which in this case is also the maximum price the processor is willing to pay, this is a constant value throughout the model (∂). In addition to the agent variables also global variables like the epipelagic fish price (δ) and expected epipelagic catch (ω) are assigned a value which stays constant throughout the model runs.

4.6.2 Procedures each tick

The fishers carry out a few procedures in each timestep (tick). These procedures can be divided into two phases which occur in sequential order, namely: fishing and transacting.

Fishing

In the first phase, with each tick, fishers are asked to move to one of the eight neighbouring patches. The patch they move to is chosen randomly (uniform distribution), this means that there is an equal chance of moving to each one of the neighbouring patches. In addition, during each tick, fishers change their expected epipelagic catch variable (ω) and their expected mesopelagic catch variable (ε_{ft}). The expected epipelagic catch (ω) changes in accordance with the constant value set in the initialisation phase while the expected mesopelagic catch (ε_{ft}) changes with the value of the patch's expected biomass of mesopelagic fish (β_{it}), which is fished in its entirety from each patch.

In addition to this, during each tick the mesopelagic and the epipelagic utilities for each fisher are calculated. This means that at each point in time fishers are able to consider which type of fishing is more profitable. This determines whether fishers will fish for mesopelagic fish or for epipelagic fish.

Transacting

With each tick, both the expected mesopelagic catch (ε_{ft}) and expected epipelagic catch (ω) change in value up until one of catch variables reaches the maximum capacity. This is when fishers reach the second phase; transacting. Once fishers have reached their maximum capacity they stop fishing and move to the processor. When a fisher moves to the processor, the price perceptions of the fisher and processor are checked, this is called the transaction phase.

Both the fishers and the processor have a mesopelagic fish price perception ($\pi_{ft}\ and\ \theta$) and these are compared when the maximum capacity is reached. This is done using the following formula:

$$\pi_{ft+1} = \min\{\pi_{ft}, \theta\} \quad (6)$$

Where π_{ft+1} is mesopelagic fish price perception of fisher f at timestep $t+1$; π_{ft} is the mesopelagic fish price perception of fisher f at timestep t.

This check is carried out to determine whether the price perception of the fisher is higher or lower than the price perception of the processor. If the price perception of the fisher is higher they sell their fish for the price that the processor offers. In such cases, fishers learn the processor's price perception and can update their own price perceptions accordingly. If the price perception of the fisher is lower than that of the processor, the fisher sells the fish at their own mesopelagic price perception price. This is because the processor has no incentive to reveal their higher price perception, acknowledge that they believe the value of mesopelagic fish to be higher, and thus to pay more. This means that fishers do not learn the processor's price perception. It is important to note that the fisher sells the fish to the processor irrespective of the price offered, because otherwise it has to be disposed of and they earn nothing.

4.7 Parameterisation

This section will provide an overview of the parameters and the values selected for the model runs. For all of the model runs there were 50 fishers and a single processor. The reason for using these values is somewhat arbitrary, but running the model with more and less fishers did not influence the results. All variables used in the model will be mentioned in the same order as in section 4.6. Appendix B provides an overview of all the variables, values and symbols used in the model runs.

The price perception of mesopelagic fish (π_{ft}) is different for each fisher and is drawn from a uniform distribution randomly within the range of (10-15). These values were chosen somewhat arbitrarily. But an important assumption is that mesopelagic fish are more expensive than epipelagic fish because fishing for them is associated with higher costs.

Furthermore, the initial mesopelagic fishing costs (γ_{ft}) differ for each fisher and the values are randomly chosen from a uniform distribution within the value range of (1500-2000), which was also quite arbitrarily chosen. Over time the mesopelagic fishing costs fall, because it is assumed that fishers become more efficient over time, due to improvements in the fishing gear or more efficient use of current fishing gear. Equation (2) illustrates how these costs develop over time. In the model runs, the mesopelagic fishing costs (γ_{ft}) fall by x which is set to 100. This reduction in mesopelagic fishing costs happens every 180 ticks (or 3 months).

Moreover, the initial epipelagic fishing costs (ρ_f) differ for each fisher and the values are also randomly chosen from a uniform distribution. The value range is (700-1100). A lower range for epipelagic fishing was deemed more appropriate, because epipelagic fishing would not require adjustments to current fishing gear or investments into novel technologies. The epipelagic fishing costs (ρ_f) do not change over time.

In addition the expected mesopelagic catch (ε_{ft}) differs for each fisher and changes with each timestep, following equation (3). Each timestep a value is chosen randomly from a uniform distribution within the value range of (0-25). With 0 being the minimum of fish to be caught and 25 the maximum.

The mesopelagic fish price perception of the processor (θ) is set at 12.5 and remains a constant throughout the model runs. The reasoning for choosing this value is that this would create an environment in which fishers have higher price perceptions and lower price perceptions (10-15) than that of the processor, which would lead to different types of behaviour.

Similarly, the epipelagic fish price (δ) is set at 10 and remains constant throughout the model runs. This value was chosen somewhat arbitrarily, but is lower than fishers' mesopelagic fish perception, because of the assumption that fishers perceive mesopelagic fish to be more expensive due to higher costs associated with fishing for them.

Lastly, in the model runs, all fishers have an expected epipelagic catch (ω_t) of 12.5 each timestep. This value follows equation (4).

Once one of the expected catches $(\varepsilon_{ft}\ or\ \omega_t)$ reaches 125 the fishers stop fishing and return to the processor. This value was chosen as it resembles the typical duration of a fishing trip of 5 days (12.5 fish * 5 days = 125 fish). The value of 125 was chosen, because according to Paoletti et al., (2021) fishing trips for mesopelagic fishing cannot last longer than 5 days, because of the lack of on-board processing technologies. Therefore the maximum capacity of mesopelagic fish is set at 125 which resembles ten fishing sessions and five days of fishing.

5. Scenario design

As alluded to in earlier sections, the answers to how a market for mesopelagic fishing could emerge with a pioneer in the industry and how this is influenced by a learning effect will be addressed through a scenario-based approach. Two scenarios have been worked out for this purpose. (1) No learning between fishers; and (2) Sharing of price information between fishers.

5.1 Scenario 1: No learning between fishers

In this first scenario, a fisher decides to fish for mesopelagic species once the mesopelagic fishing costs have fallen far enough for the utility of mesopelagic fishing to become higher than the utility of epipelagic fishing. The fisher that start fishing for mesopelagic species first is called the pioneer and can differ within model runs due to the fact that mesopelagic catches are random. Usually this is a fisher with a high price perception and relatively low mesopelagic fishing costs. The fisher calculates the utility for epipelagic species as well as mesopelagic species and with each timestep evaluates their preference. The reason for the pioneer to embark on this journey is that the perception of the mesopelagic fish price differs from other fishers or because the fisher believes mesopelagic fishing costs to be significantly lower. In this scenario, fishers can learn the processor's price perception by visiting the processor. They can only find out this price perception if they fish for mesopelagic fish (colour is black). In this scenario every fisher keeps the information regarding the price to themselves.

5.2 Scenario 2: Sharing of price information between fishers

In the second scenario all variables are held equal, and the model has exactly the same procedures in place. The difference with Scenario 1 has to do with the price perceptions of mesopelagic fish. In this scenario, once the pioneer has visited the processor he does not just update his own price perception, but all other fishers also learn the processors' price perception. This means that all fishers are able to update their mesopelagic utility function. The biggest difference with Scenario 1 is that irrespective of whether the price perception of the fisher is higher or lower than that of the processor, the pioneer learns the price once the visit to the processor takes place. This means that there is complete transparency regarding the price of mesopelagic fish. The aim of this scenario is to see how a learning effect could influence the emergence of a mesopelagic fishing industry. A learning effect in this context relates to the extent to which fishers have the ability to learn from one another. The impact of this learning effect can be determined by comparing the results from Scenario 1, in which fishers do not share any information, to those of Scenario 2, where there is complete transparency of the processor's price perception.

6. Results

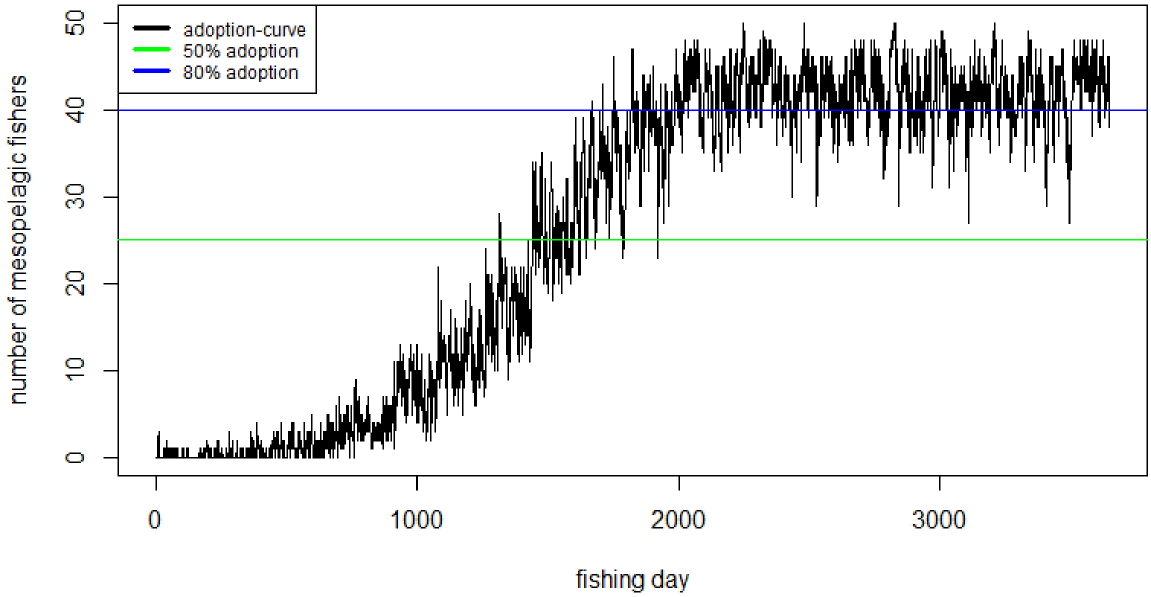
Both scenarios were implemented in NETLOGO with the variables mentioned earlier and the values mentioned in appendix B. To find out how a market could emerge for mesopelagic fishing with a pioneer in the industry it is useful to look at the rate of adoption. The rate of adoption is usually measured by determining the length of time it requires for a certain percentage of a population to adopt an innovation (Rogers, 1995). In this study, two categories were created, namely 50% adoption and 80% adoption. This was done in order to check within what timeframe 50% (25 fishers) and 80% (40 fishers) of the total number of fishers (50 fishers) had transferred to mesopelagic fishing. The simulation was run 2000 times for each scenario in order to establish how accurate the estimate was.

To establish at which point 50% and 80% of the fisher population had transferred to mesopelagic fishing, the number of fishers was counted for each timestep. The timestep at which the fisher transitions to mesopelagic fishing is defined as the 'transition point'. This transition point is calculated using a built-in NETLOGO function called 'count'. This function counts the number of mesopelagic fishers for each timestep. The transition point is calculated by finding the first timestep where 25 and 40 fishers are fishing for mesopelagic fish. Each simulation has different transition points due to the variable mesopelagic fish catches of fishers. The quartile ranges, median and standard deviation are calculated and used to find these transition points. The median and quartile ranges are chosen because they deal well with outliers and extreme values.

6.1 Scenario 1: Pioneer in the industry

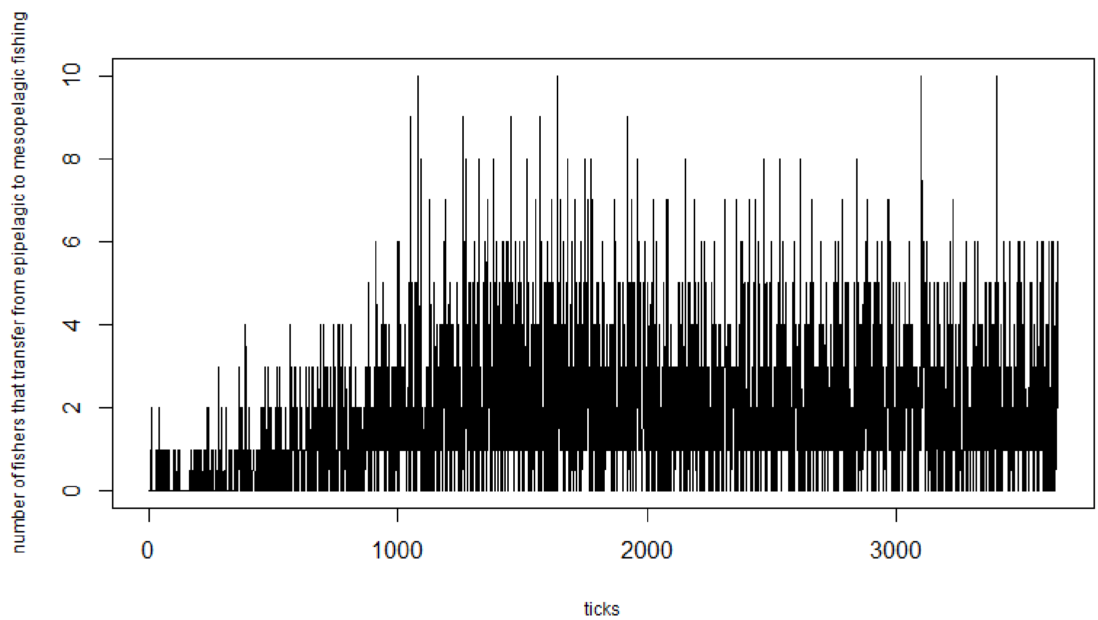
To check at which points 50% and 80% of the fisher population has transferred to mesopelagic fishing, an adoption path of all fishers was established. Figure 2 provides a cumulative rate of adoption curve in a sample run for this scenario. This sample run is representative, because it follows a similar pattern to that of the average number of mesopelagic fishers each timestep over all model runs, which is provided in appendix C1. In this curve, the number of mesopelagic fishers in the model are counted for each timestep. The pattern that emerges is somewhat similar to an s-shaped adoption path which is very common in the diffusion of innovations theory (Rogers, 1995). What this means is that adoption is usually slow at first. After this slow start, the adoption rate increases until approximately half of the potential adopters have adopted. After this, technology adoption continues but at a slower rate. Figure 2 shows a similar pattern. Under the green line adoption slowly increases, between the green and the blue lines, the rate of adoption decreases and above the blue line the number of fishers varies significantly, but stabilises. All of the simulation runs follow a similar pattern.

Figure 2: Scenario 1 – cumulative rate of adoption path (sample: run 1)



To check whether Scenario 1 actually follows Roger's idea of an s-curve, a graph is made in which the number of extra adopters per timestep are plotted, this can be seen in Figure 3. In traditional diffusion of innovations theory this should result in a bell curve in which an increase in the number of adopters per timestep up to approximately half of the potential adopters is reached, after this the number of adopters per timestep drops. The simulations show that up until fishing day 1000 there is a clear increase in the number of adopters per timestep, in line with a traditional bell curve. However, after that point, the number of extra fishers fluctuates significantly between 4 and 10 per fishing day right up until the model stops running.

Figure 3: Scenario 1 – number of fishers that transfer from epipelagic fishing to mesopelagic fishing per tick (sample run 1)



The reason for these fishers to behave like this is a combination of three things namely, relatively low initial epipelagic fishing costs, the < 12.5 initial mesopelagic price perception of fishers, and the expected mesopelagic catch. Firstly, fishers that have relatively low initial epipelagic fishing cost (near 750) end up with approximately equal costs for mesopelagic and epipelagic fishing, because the mesopelagic fishing costs fall until they reach 750. In addition to this, some fishers never learn the processors' price perception (actual price) which means they have a mesopelagic fish price perception of 10, 11 or 12. These two factors in combination with the random expected mesopelagic catch that can range from 0 to 25 have a large effect on the utilities and cause the fishers to switch between mesopelagic and epipelagic.

Because of this, a fisher who is fishing for epipelagic species, could switch halfway through the trip to mesopelagic fishing, because the utility function indicates that fishing for mesopelagic fish is more profitable. On arrival at the processor, the fisher sells his fish and is once again dependent on the expected random mesopelagic catch in order for mesopelagic fishing to become viable for him. This means the fisher could opt to switch back to epipelagic fishing. As mesopelagic fishing costs decline, more and more fishers stick to mesopelagic fishing all year round, because it becomes more viable for them.

To analyse on which fishing days 50% and 80% of the fishers adopted mesopelagic fishing, the quartile ranges, median and standard deviation were calculated (Table 1). As mentioned earlier, the model runs for 3650 ticks which is five years. For 50% of the fishers to transfer to mesopelagic fishing the median value is 1279 fishing days. At least 50% of the transition points lie between fishing day 1266 and fishing day 1301. To understand how much variance is found in the simulation runs, the coefficient of variation is calculated. This is done with the following formula $\frac{\sigma}{\mu} * 100$. It results in 3.48% for the 50% adoption category. The coefficient of variation helps to measure the degree of consistency and uniformity in the distribution of the dataset.

For 80% of the fishers the median transition point is fishing day 1647. And 50% of the transition points over all simulation runs lie between fishing day 1629 and fishing day 1679. Again the coefficient of variation is calculated to find the level of dispersion around the mean. For the 80% adoption category this was 3.19%. Table 1 provides an overview of these values.

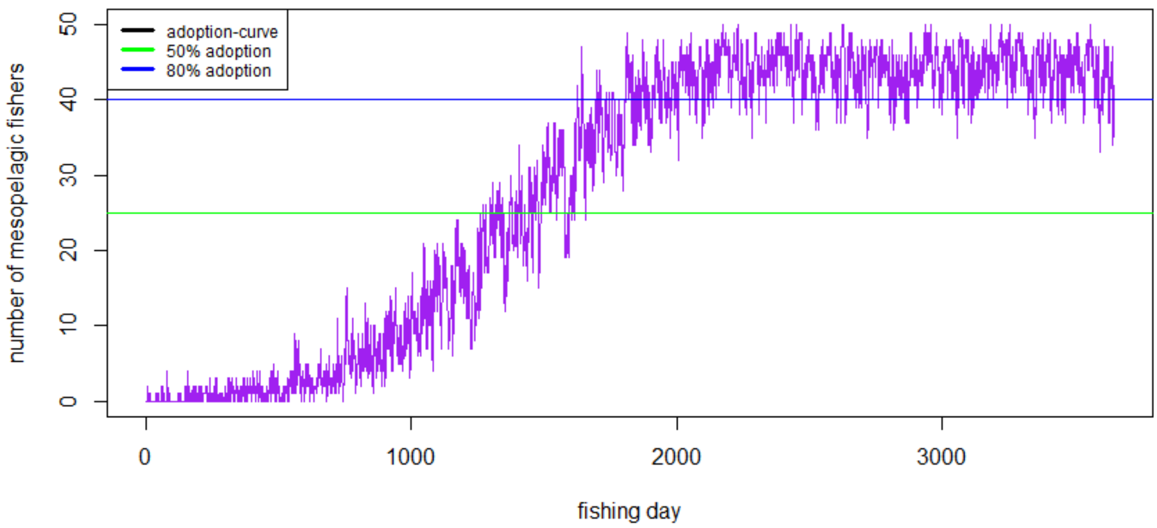
Table 1: Scenario 1 – quartile ranges, mean, median and std deviation of transition point over 2000 simulation runs

% of adopters	1st quartile	Median	Mean (μ)	3rd quartile	Std deviation(σ)	Coefficient of variation
50% or 25 fishers	1266	1279	1283	1301	44.6	3.48%
80% or 40 fishers	1629	1647	1654	1679	52.8	3.19%

6.2 Scenario 2: Pioneer fisher with learning

As was the case for Scenario 1, an adoption path for the fishers was established by tracking the number of mesopelagic fishers on each fishing day. This sample path in Figure 4 has a similar pattern to the path in Scenario 1. It also bears a resemblance to the s-curve described earlier. This sample run is also similar to the average number of mesopelagic fishers per timestep over all model runs. The graph can be found in Appendix C1.

Figure 4: Scenario 2 – cumulative rate of adoption path (sample run 1)



However, the aim of running Scenario 2 was to determine whether there is a learning effect within the model. An easy way of doing this is to compare the average mean transition point values of both scenarios with one another. Table 2 provides an overview of the quartiles, median, mean, standard deviation and coefficient of variation of Scenario 2. At first glance when comparing the medians of both scenarios there seems to be quite a significant difference. In Scenario 2 it takes 50% of the fishers 1176 fishing days to adopt while it takes the same percentage of fishers 1279 fishing days in Scenario 1. There is a similar trend at the 80% adoption level where in Scenario 2 the median is 1591 fishing days while in Scenario 1 the median is 1647.

Table 2: Scenario 1 – quartile ranges, mean, median and std deviation of transition point over 2000 simulation runs

% of adopters	1st quartile	Median	Mean (μ)	3rd quartile	Std deviation(σ)	Coefficient of variation
50% or 25 fishers	1121	1176	1181	1261	67.3	5.70%
80% or 40 fishers	1503	1591	1568	1626	69.0	4.34%

But to compare the means of transition points of these two sets of data statistically, an independent samples t-test was performed. A Welch's t-test was selected to do this. The reason for this choice is that this test does not assume variances to be the same as the standard Student's t-test does.

This test was performed for the 50% mean and the 80% mean of both scenarios. For both the same hypotheses were formulated. The null hypothesis is as follows and assumes that the mean of Scenario 1 is equal to the mean of Scenario 2. It is written as follows:

$$H0: m_1 = m_2$$

where m_1 is the 50% or 80% mean from Scenario 1 and m_2 is the 50% or 80% mean from Scenario 2. Logically the alternative hypothesis is as follows:

$$H1: m_1 \neq m_2$$

Table 3 provides an overview of the results of the t-test. Because the p-value 2.2e-16 is less than the alpha of 0.05 (95% confidence interval), we can reject the null hypothesis and conclude that there is sufficient evidence to say that the means of Scenarios 1 and 2 differ significantly at a 95% confidence level. Further confirmation is found in the high t-score which suggests that the means of both groups are quite different.

Table 3 : Welch's t-test comparing 50% and 80% mean of Scenarios 1 and 2

	Scenario 1	**Scenario 2**	**t-score**	**p-value**
% of adopters				
50%	1283 (44.6)	1181 (67.3)	56.3	2.2e-16
80%	1654 (52.8)	1568 (69.0)	44.5	2.2e-16

*() is the standard deviation

7. Discussion

The following discussion aims to highlight the limitations of the model and discuss its appropriateness.

7.1 Appropriateness and limitations of the agent-based model

The diffusion model described in this research aims to simulate how mesopelagic fishing could diffuse among fishers and how a market could emerge. The ABM represents a realistic geographic area, includes a range of heterogeneous agents with different perceptions and values, and uses rational decision-making. It was necessary to use this agent-based modelling technique in order to include these dynamics and to create a simulation that was as close to reality as possible. Other modelling techniques used in the diffusion of innovations like the Bass model fail to incorporate the heterogeneity of agents and are therefore less appropriate (Schwarz & Ernst, 2009).

One potential issue with this model is the extent to which it actually represents a realistic fishing environment. Many assumptions had to be made to build this model and therefore some may not be very realistic. The most important assumptions have to do with the fishers' drive for profit maximisation, the fishing costs, the biomass, the fact that only one processor was included, and the accurate representation of the maximum capacity of the fishers.

Firstly, the fishers drive for profit maximisation. Fishers make their decisions on what to fish for based on one decision-making algorithm. This algorithm makes fishers choose to fish for either epipelagic or mesopelagic fish based on their highest expected utility. Because utility in this research refers to profit fishers can be seen as being purely rational; so-called 'homo economicus'. In reality, fishers may make decisions that are not solely influenced by their desire for profit. There are other exogenous factors that are hard to model like weather conditions and the skills of the fisher. Weather conditions could influence the catch rates of fishers, adding a higher degree of unpredictability to the model. Furthermore, the skills of fishers in this model are assumed to be equal, while in reality different fishers use different techniques and have different skills. This would probably result in a faster initial adoption as skilled fishers would transfer to mesopelagic fishing relatively quickly, while lower skilled fishers would take longer to transfer. As in this simulation, fishers only focus on profit and these other variables are not taken into account, this model could be viewed as rather generic and its applicability to fisheries somewhat limited.

Secondly, in reality, the transition from epipelagic fishing to mesopelagic fishing requires an investment. Fishers in this model switch fishing gear instantly, once either mesopelagic or epipelagic fishing become more profitable, without requiring an initial investment. Including this in the model would probably result in slower adoption rates as this initial investment may hinder fishers from transferring. Besides this, opportunity costs would also rise, because new mesopelagic gear would need to be installed on the boat, meaning epipelagic fishing would not be possible, making the barrier to transfer even higher.

Thirdly, the way in which the biomass is calculated is somewhat unrealistic. The main reason for this is that the biomass in every timestep is independent of the biomass in the previous timestep. The current model uses a value from a random uniform distribution in each timestep. The reasoning for this is that the estimations of the mesopelagic biomass in literature vary a lot and therefore it is hard to quantify the amount in relation to the epipelagic fish species.

Fourthly, this model includes just one processor. In reality, there would be multiple processors in such an environment which compete with one another. However, this model could be viewed as a microenvironment in which there is a monopolistic market, where the processor enjoys considerable market power. Because there is only one processor, fishers are forced to take the price the processor is willing to offer. And fishers will always sell their fish no matter the price as otherwise they are stuck with their haul. In reality fishers may choose to enter negotiations with the processor about prices and the amounts of fish sold. The market is not competitive in this model as the one processor is the only point of transaction for fishers.

Lastly, it was hard to provide an accurate representation of the maximum capacity of the fishers. Epipelagic fishers generally have two ways of fishing. Scottish, Irish and Scandinavian countries fishers prefer to catch the fish quickly and in large numbers to then land their catch in ports enabling processing and freezing on land. This means fishing trips last only a few days. While, Dutch, French, English, German, Polish and Lithuanian fishers use so-called pelagic freezer trawlers which enable processing and freezing on-board. The fishing trips of these vessels usually take between 2 and 3 weeks (Pelagic Freezer-trawler Association, 2019). This means the maximum capacity of fishers that fish freshly are significantly lower than those of fishers using pelagic freezer trawlers. Moreover, in this study, the maximum capacity of the processor is not capped all, which means that the processor can take on all catches that fishers ship to him. This is also something that in reality is inaccurate as fish processing facilities also have limits to their capacity.

8. Conclusion

This thesis provides an overview of those factors that could drive technology in fishing. This was done by using Rogers' DOI model and applying it to mesopelagic fishing. Many of the perceived attributes highlighted by Rogers were related to the price perception of fishers. This price perception was therefore one of the key variables used in the agent-based model. This model was created in order to illustrate how a market for mesopelagic fishing could emerge using two scenarios. In the first scenario there was no learning between fishers, while in the second scenario fishers shared information on price. By comparing these two scenarios a potential effect of the learning could be established.

With regards to research question one, Rogers' DOI model proved to be helpful in identifying factors that could drive technology adoption. Especially, Rogers' perceived attributes were useful as they could be easily linked to how fishers determine their price perception. Relative advantage and the subcategories; productivity, cost effectiveness and risk aversion influence the price perception of fishers in one way or another. For example, fishers who believe that a mesopelagic fishing technology is productive will believe that this results in higher catches and potentially a higher market potential which could increase their perception of the mesopelagic fish price. On the other hand, fishers who perceive such technologies to be less productive, will most likely have a lower price perception. Moreover, the extent to which a technology is compatible with the social and local conditions are important for the uptake of mesopelagic fishing technologies. High compatibility suggests that local authorities encourage fishing for mesopelagic fish, while low compatibility could imply resistance from local communities as they believe that mesopelagic fishing damages the ecosystem. Lastly, the extent to which a mesopelagic technology is seen as complex could influence the price perception of fishers. Low complexity could enable fishers to enter the market relatively easily which could drive the price perception of fishers down, while high complexity, which is related to a lot of uncertainty (e.g. in catches), could result in higher price perceptions of fishers.

Regarding the model, the results from the simulation runs of this model provide an indication of what a diffusion path for mesopelagic fishing could look like. The results show a s-shaped adoption path which is a typical path of adoption for many technologies. However, one of the limitations is that this is just the case for these sets of variable values. It is therefore hard to argue that this is the exact way in which a mesopelagic fishing industry could emerge. Little data is available on mesopelagic fishing and so it is hard to choose appropriate parameter values. Furthermore, it is clear from this example that when such a market does emerge transparency on the price of mesopelagic fish will be helpful in stimulating adoption. In an extension of this model, further research could be done into the values of the variables used and how epipelagic prices and costs relate to mesopelagic prices and costs. This would help find, for example, realistic ratios in the price differences between mesopelagic and epipelagic fish.

It is difficult to infer what can be learned from such a hypothetical model and what policymakers can do with the information. One possible takeaway is that the rate of adoption may be quicker if a transparent market is established as the results show that price transparency increases the rate of adoption quite significantly. The results from the T-test show that there is a significant difference between the 50% and 80% mean number of fishers between the two scenarios. Where it takes considerably longer for fishers in Scenario one to reach 50% and 80% of the fishers. Policymakers could consider establishing innovation platforms to encourage research into new technologies, but they must always be wary of the potential detrimental impact these novel technologies may have.

In addition, these model results could provide processing companies and fishing companies with an indication of how a market for mesopelagic fishing could emerge. In order for this to occur, processing and fishing companies will have to make significant investments and these model results may give them an indication of the time it would take for mesopelagic fishing to diffuse. This information could then be used to calculate the payback period for their investments, for example.

For further research there are a number of things that could be considered. Firstly to include multiple processors and secondly to review the parameters used in this model.

The first recommendation is to include multiple processors, because this could help create a more realistic simulation environment. By doing this, the market may move from a monopolistic market to a more competitive one, where fishers are able to choose processors based on pricing, causing probable adjustments in the price perceptions of both fishers and processors. In addition, adding a bargaining element to the transaction would be an improvement as in this model fishers have to accept the price offered by the processor. In reality, fishers may bargain and move to another processor if they are not satisfied with the current offer.

Secondly, in order to review the parameter values it would be sensible to calibrate the model, which would check how sensitive the parameters used are. The fact that these parameter values result in these outcomes does not necessarily mean that other parameter values will provide similar results. By exploring different parameter values the predictions of the model may be far more reliable.

In short, although the model is somewhat generic it still could be of use for fishers and processors as it provides them with a scenario for the diffusion process of mesopelagic fishing. It seems that price transparency could play a key role in the rate at which a mesopelagic fishing industry emerges, although a calibration of the parameter values would substantiate this finding. Including multiple processors would create an entirely different environment in which competition occurs, this would probably be a more realistic depiction of reality and may therefore be a key element to incorporate in the model.

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10. Appendices

Appendix A:

A1: Uniformly random generated price perceptions

observer> show n-values 50 [(10 + (random (15 - 10)))]

observer: [14 10 13 10 10 12 12 11 13 14 14 13 13 14 12 12 11 14 10 10 13 13 14 11 14 12 14 10 13 14 11 13 12 10 10 11 11 13 14 14 10 12 11 14 13 13 13 14 11 12]

A2: Uniformly random generated epipelagic fishing costs

observer> show n-values 50 [(700 + (random (1100 - 700)))]

observer: [827 964 779 867 836 1007 1057 879 1060 1043 996 773 713 797 992 866 943 933 885 934 840 911 762 806 862 884 722 1015 746 966 1041 949 778 1050 1048 943 746 737 965 1070 1034 799 787 914 773 808 822 822 780 1043]

A3: Uniformly random generated mesopelagic fishing costs

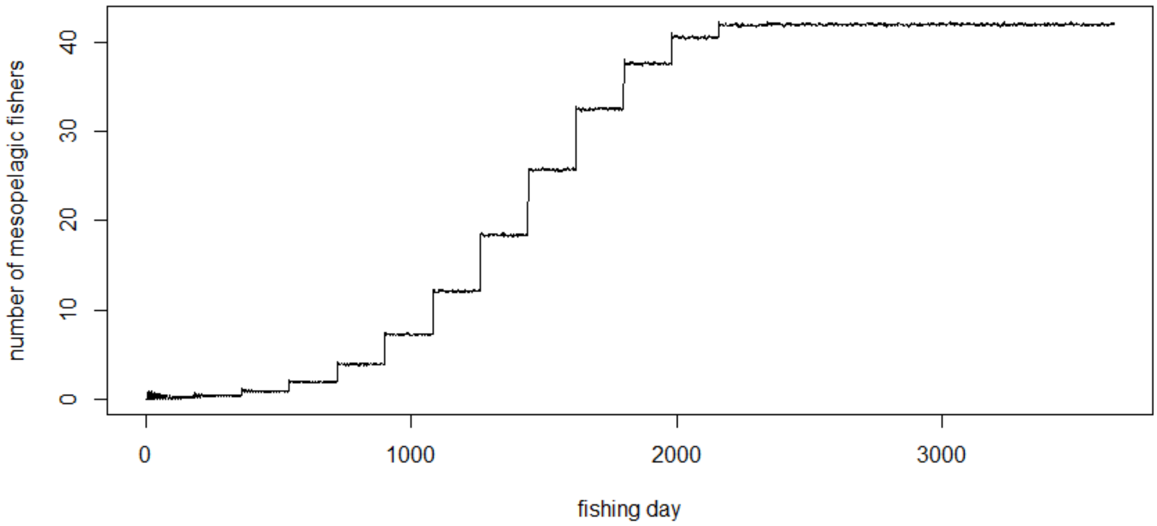
observer> show n-values 50 [(1500 + (random (2000 - 1500)))]

observer: [1857 1651 1863 1949 1632 1512 1665 1751 1570 1825 1819 1525 1701 1769 1558 1704 1592 1719 1895 1618 1703 1922 1601 1696 1756 1988 1935 1529 1632 1749 1551 1955 1675 1921 1832 1545 1968 1915 1921 1725 1778 1798 1827 1678 1743 1706 1774 1548 1804 1955]

Appendix B: Overview of model variables, values and symbols

Variables	Values	Symbols
Fisher variables		
Price perception of mesopelagic	10-15	π
Epipelagic fishing costs	700-1100	ρ
Mesopelagic fishing costs	1500-2000	γ
Expected epipelagic catch	12.5	ω
Expected mesopelagic catch	0-25	ε
Processor variable		
Price perception mesopelagic fish processor	12.5	θ
Global variables		
Price epipelagic fish	10	δ
Biomass mesopelagic fish per patch	0-25	β
Biomass epipelagic fish per patch	12.5	μ

Appendix C1: Average number of mesopelagic fishers each timestep over all model runs (No learning)



Appendix C2: Average number of mesopelagic fishers each timestep over all model runs (Learning)