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Master thesis

An enhanced understanding of rare, surprising and extreme events

by

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University of Stavanger

2020

Summary

This thesis is written on the topic of rare, surprising and extreme events. The thesis concerns the following main issue:

What is the meaning of and relationship between different metaphors used to describe rare, surprising and extreme events?

This issue is treated in Part II of the thesis in the form of a scientific paper. Part I of the thesis represents an introductory part constituting a theoretical foundation of important terms, concepts and principles that are particularly relevant in the understanding of rare, surprising and extreme events, and how they can be managed.

A short summary and main conclusions from the paper in Part II is provided as follows:

Paper: "On the meaning of and relationship between dragon-kings, black swans and related concepts"

Dragon-kings, black swans, grey swans and perfect storms are metaphors used to describe rare, surprising and extreme events. These metaphors are commonly referred to in both scientific and non-scientific literature, at times interchangeably. Although much effort has been made to enhance the understanding of these concepts, their meaning and relationship has not been sufficiently clarified from a risk science perspective.

In the paper, we look further into each of these metaphors, reviewing a selection of existing interpretations and definitions and creating a structure to highlight similarities and differences between the metaphors. The structure is centred around the features of knowledge and predictability, both of which are considered essential features for the understanding of the metaphors. Furthermore, we discuss some of the implications the use of these metaphors have for risk management, with particular emphasis on responsibility and accountability. Our claim is that the responsibility and accountability features are related to the ability to take the knowledge dimension into account when assessing and managing the risk of rare, surprising and extreme events, and can therefore be considered relevant for all metaphors.

Based on the analysis, we provide some recommendations on how the metaphors should be defined and used. Due to lack of metaphorical context, we suggest that the use of the grey swan metaphor is avoided. We argue that the dragon-king and perfect storm metaphors can be covered by the definition of black swans as "surprising extreme events relative to the present knowledge/beliefs". They are, however, still considered justified as independent metaphors. Furthermore, we present our recommended definitions for the dragon-king and perfect storm metaphors.

Preface

This master thesis is submitted in partial fulfilment of the requirements for the Master of Science degree in Risk Management at the University of Stavanger. The process of writing the thesis has been a joy, a nuisance, and everything in between. But first and foremost, it has been inspiring to be given the opportunity to immerse myself in the field of risk.

I would like to express my utmost gratitude to my supervisor, Professor Terje Aven. The end result of this thesis would not have been the same without his tireless efforts to guide me through this process, providing support when needed and sharing his knowledge generously. Working with, and learning from, Professor Aven has been an inspiration and a privilege.

I would also like to thank my parents and parents-in-law for facilitating this process by ensuring that my three children have been cared for and loved at times when I have been physically (or mentally) absent.

Lastly, I would like to thank my best friend, the love of my life, and father of my three children. Thank you for your patience, for providing your family with endless love and support, for pushing me out the door for a run when you saw that I needed one, and for continuously being the person that inspires me the most.

Contents

Part I

1. Introduction

1.1 Background

The use of metaphors to describe and communicate scientific phenomena and concepts is pervasive. Although metaphors can be considered "indispensable tools for both practicing and communicating science" (Taylor & Dewsbury, 2018, p. 4), several authors have emphasised the powerful impact metaphors have on the way we perceive phenomena (see e.g. Lakoff & Johnson, 1980; Ortony, 1975; Pigliucci, 2005; Thibodeau & Boroditsky, 2011). The use of metaphors need to be followed by "careful consideration (…) not only to the ways in which metaphors may contribute to public misunderstanding, but also to how their use may unintentionally reinforce particular social and political messages that undermine the goals of inclusive science" (Taylor & Dewsbury, 2018, p. 4).

Metaphors for rare, surprising and extreme events are applied across a variety of scientific fields and disciplines, such as finance, medicine, engineering, physics and social science. In the present thesis, we have concentrated on four such metaphors: the black swan, the grey swan, the perfect storm and the dragon-king. These metaphors are frequently referred to in both scientific and non-scientific literature. A list of results from various scientific search engines illustrates the extensive use of these terms, as seen from Table 1 below.

Table 1: Results from various scientific search engines for each of the metaphors

Inserted search phrase	*Number of search results*		
	Scopus	Web of Science	Google Scholar
"Black swan"	811	407	40 900
"Grey swan" or "Gray swan"	22	7	453
"Dragon-king"	70	32	5220
"Perfect storm"	1236	786	67 600

By taking a closer look at how the metaphors are applied, we find that the metaphors are subject to different interpretations. Furthermore, we can observe overlapping use of the metaphors, i.e. that different metaphors are used to describe the same events. This may be caused by the many different interpretations of the metaphors, but it could also be due to common characteristics between the metaphors. However, as the use of these concepts appears to be somewhat inconsistent, and several of the metaphors have not been sufficiently defined from a risk perspective, it may be difficult to determine the cause of the overlapping use of the metaphors. The current situation is characterized by the lack of a proper structure providing perspectives on what these concepts mean in a risk context, how they are related and which aspects of rare, surprising and extreme events they describe. Furthermore, the lack of stringency in the use of the metaphors has implications for risk communication and risk management. The choice of strategies to confront events should be contingent on the characteristics of the risk problems, and without a clear understanding of what these characteristics are, it hampers the process of selecting suitable tools and approaches.

In order to approach the issues highlighted above, there is a need to clarify what these metaphors mean in a risk context, how they are related and ensure that the concepts are interpreted and applied according to established frameworks and principles within risk science.

1.2 Aim of thesis

The aim of the present thesis is to enhance the understanding of rare, surprising and extreme events by clarifying the meaning of and relationship between some of the most commonly applied metaphors for such events: black swans, grey swans, perfect storms and dragon-kings. Furthermore, the aim is to use this enhanced understanding to provide new insights into how events reflected by these metaphors can be managed.

1.3 Structure

The thesis is structured as follows:

Part I constitutes the theoretical foundation and context for the article presented in part II. Chapter 2 consists of a brief introduction to rare, surprising and extreme events and the related concepts of knowledge and uncertainty. In Chapter 3, we look further into how the process of classifying risk problems, and how this classification can be used to identify suitable risk management strategies. Furthermore, we give a short overview of some relevant strategies. Lastly, we briefly touch upon how we may learn from previous events and near-misses.

Part II consists of an article on the meaning of, and relationship between, black swans, grey swans, perfect storms and dragon-kings. The article consists of a review and discussion of common interpretations and definitions of each metaphor, followed by a structure presenting the differences and similarities between the metaphors. The structure focuses in particular on the knowledge and predictability features. Some implications the use of these metaphors have for risk management and decision making are discussed, with special emphasis on accountability and responsibility.

2. Rare, surprising and extreme events

2.1 Introduction

Rare, surprising and extreme events receive much attention in scientific literature in general, and risk science literature in particular. Events of this type are found across numerous fields, and are frequently discussed in relation to for example engineering, finance, natural science and climate research (see e.g. Ancey, 2012; Murphy & Conner, 2012; Sornette & Woodard, 2010; Stott et al., 2016). Common examples of such events are the September 11th terrorist attacks (2001), hurricane Katrina (2005), the financial crisis (2008) and the Fukushima nuclear power plant accident (2011).

The disastrous implications of some of these events have revealed a "vulnerability of communities to natural hazards and the crippling effect they have on the social and economic well-being" (Masys et al., 2016, p. 131). These vulnerabilities become particularly apparent "within (…) social/technological/economic/political/ecological interdependent systems" (Masys et al., 2016, p. 132). However, even though we may be aware that systems and structures are subject to interdependencies, we face the challenge that, in many cases "the dependencies of the various components of a network on each other only become clear when failures (catastrophes) occur in the network such as the rapid spreading of a computer virus over the Internet, the collapse of a global financial system, or the large-scale breakdown of an electrical power grid" (Masys et al., 2016, p. 134). Take, for example, the Fukushima nuclear power plant accident in 2011. In this scenario, the combination of the earthquake and tsunami occurring adjacently, together with vulnerabilities in the emergency response structures, contributed to creating a "complex network structure and behaviour that unravelled with the trigger of the tsunami resulting in a cascade-like event revealing the lack of preparation, insufficient vulnerability analysis and response" (Masys et al., 2014, p. 776). However, it was difficult to envision such an interplay upfront, and hence, this particular scenario had not been taken into consideration in the risk assessments conducted.

The concepts of knowledge and uncertainty are highly relevant to include when discussing rare, surprising and extreme events. This type of events often involve uncertainty, both related to outcomes as well as consequences. These uncertainties are linked to the knowledge dimension, where "describing uncertainties is about describing not only the knowledge itself but also the quality of this knowledge" (Zio & Aven, 2018, p. 7f). Furthermore, uncertainties may be reduced (or increased) through strengthened (or impaired) knowledge.

2.2 The meaning of the term 'surprise' in relation to rare, surprising and extreme events

The term 'surprise' has been discussed by several authors, including Kay (1984) and Gross et al. (2010). Kay defines a surprise as an event "whose occurrence was not anticipated, or which has been allocated such a low probability that the possibility of its occurrence was effectively discounted" (Kay, 1984, p. 69). According to Gross et al. (2010), and event can be considered a surprise "when it occurs unexpectedly and counter to accepted knowledge" (Gross et al., 2010, p. 1). Furthermore, we may distinguish between several categories of surprises, for example 'known' surprises and 'unknown' surprises, or 'anticipated' surprises and 'unanticipated' surprises (Gross et al., 2010). For example, we may refer to a surprise as anticipated "if we know that something is going to happen, but not when and in what form" (Aven, 2014b, p. 116). When referring to 'surprises' in relation to rare, surprising and extreme events, it is based on the perspective that surprises may be of different types and categories.

2.3 The meaning of the term 'extreme' in relation to rare, surprising and extreme events

The multidisciplinary relevance of extreme events has led to a wide range of interpretations for each of the term 'extreme'. Efforts have been made to find generic definitions of this term in order to enhance the understanding and communication of this type of events across the various disciplines (see e.g. Broska et al., 2020; McPhillips et al., 2018). In order to clarify what is meant by 'extreme events', we need to understand what the term means in a risk context.

The term 'extreme' is often seen in relation to the consequences or impact of an event. Slovic and Weber (2002) define extreme events as events that "cause much harm to people, property and the natural world" (Slovic & Weber, 2002, p. 2). In some cases, extreme events are referred to as events that exceed some predefined threshold value (Farazmand & Sapsis, 2019; Kantz, 2015).

McPhillips et al. (2018) distinguish between two categories in the understanding of 'extreme events': the first category consists of definitions that evaluates these events based on their magnitude of occurrence. The second category constitutes the definitions that include impact in addition to magnitude. Of these, the authors recommend the former type of definitions, as "conflating the events with impacts could jeopardize our ability to assess resilience to extreme events" (McPhillips et al., 2018, p. 451). However, as argued by Broska et al. (2020), this approach "could cause the underestimation of the importance of resilience efforts for minor events with major impacts. Furthermore, a narrow definition focussing on the occurrence alone – though maybe in some areas advisable – would exclude vital aspects in other scientific fields and spheres of application" (Broska et al., 2020, p. 2). One of the main challenges in finding a generic definition of the term 'extreme event', is "the wide variety of events falling under the category extreme events, [making] it impossible to define clear-cut thresholds for when an event is to be called extreme" (Broska et al., 2020, p. 8).

When referring to the term 'extreme' in relation to rare, surprising and extreme events, it is with regards to the consequences/impact of events. Hence, 'extreme events' are understood as events with extreme impact, or events with extreme consequences (in line with the interpretations by e.g. Aven (2014b), Baldassarre et al. (2016) and Flage and Aven (2015)).

2.4 Knowledge/background knowledge

Knowledge can be defined as "justified beliefs" (SRA, 2015, p. 6).

The concept of knowledge needs to be seen in relation to whose knowledge we are talking about, and at what time. Knowledge may be considered subjective, in the sense that what is known by person *x* may not be known by person *y*. Furthermore, the concept is dynamic; it develops as a function of time, and what is unknown at time *s* may have become known at time *t* (Aven, 2014b).

Background knowledge in a risk context refers to data, model assumptions and other factors that form a basis for the assessments made. The background knowledge can be related to assessments made on both the consequences and the uncertainties for a given event (Aven, 2015a). There exist several methods to assess the strength of knowledge. Two of them are further elaborated in Section 2.5.

2.5 Strength of knowledge

"The value of the risk assessment and management (…) stands on the quality of the methodologies and approaches adopted, and on the strength of the knowledge K on which these are built" (Zio & Aven, 2018, preface). Assessing the strength of the background knowledge, and making this information available to stakeholders and decisionmakers, increases the possibility of revealing important aspects of risk that could be concealed in the assumptions and data supporting the risk assessments. Incorporating evaluations on the background knowledge into the risk descriptions presented, contributes to creating an awareness that "surprises relative to the assigned probabilities could occur if the background knowledge on which the probabilities are conditioned turns out to be wrong" (Flage & Aven, 2009, p. 17).

2.5.1 Method 1 to assess the strength of knowledge: The use of criteria

In order to evaluate the strength of the background knowledge supporting these assessments, Flage & Aven (2009, p. 14) suggest a list of criteria to be met in order for the background knowledge to be considered strong:

- The assumptions made are seen as very reasonable
- Large amounts of reliable and relevant data/information are available
- There is a broad agreement among experts
- The phenomena involved are well understood; the models used are known to give predictions with the required accuracy

On the other hand, if few or none of the conditions are met, the background knowledge is weak. For cases in between, the background knowledge is considered to have medium strength.

2.5.2 Method 2 to assess the strength of knowledge: Assumption deviation risk

Another way of assessing the strength of background knowledge, is using "assumption deviation risk". This method consists of converting all assumptions that form the basis for the probabilistic analysis, into a set of uncertainty factors. A crude risk analysis is performed, assessing the deviations from the conditions defined by the assumptions. Based on the analysis, each deviation is assigned a risk score. This score reflects the magnitude of the deviations, and what the impact is on the occurrence and consequences of an unwanted event. The assumption deviation risk is meant to serve as an indication of the criticality of the assumption (Aven, 2013).

There are several approaches to determine the assumption deviation risk score. Aven (2013b) suggests that a crude analysis could be conducted by using the criteria mentioned in approach a). If all the criteria for strong knowledge are considered true, the strength of knowledge would be assessed strong, and hence the assumption deviation risk could be judged as low. The same assessment could be made in the case where the validation of the criteria in a) indicates a weak strength of knowledge, in which case the assumption deviation risk would be considered high.

Aven (2013b) also describes a more detailed approach, where one or more deviations are selected and analysed based on the

- magnitude of the deviation
- probability of this magnitude to occur
- effect of the change on the consequences

A crude analysis of these three elements results in a risk score category of either low, medium or high. This is followed by an overall assessment of the strength of knowledge supporting the judgements for each deviation. This assessment could trigger an adjustment of the risk score (e.g. weak background knowledge would result in the risk score going from medium to high, or from low to medium)

Applying this approach on a selection of assumptions will result in a number of assumption deviation risk scores. These scores can be used to make an overall assessment of the strength of knowledge supporting the probabilistic risk analysis. A low number of risk scores categorized as high would indicate a strong background knowledge, while a large number of risk scores graded as high would suggest a weak background knowledge. Scenarios in between would be considered cases of background knowledge with medium strength (Aven, 2013b).

2.6 Uncertainty

The ISO guide to risk management terminology describes uncertainty as "(…) the state, even partial, of deficiency of information related to, understanding or knowledge of, an event, its consequences or likelihood" (ISO, 2009). Aven (2011b) describes uncertainty as follows: "uncertainty means that we do not know what the consequences of the activity will be or the value of unknown quantities" (Aven, 2011b, p. 725).

We distinguish between two different types of uncertainty, aleatory (sometimes referred to as stochastic) and epistemic (sometimes referred to as knowledge-based). Aleatory uncertainty is related to the "variation in defined populations represented by probability models" (Aven, 2014a, p. 84), and described using frequentist probabilities. Epistemic uncertainty is described using subjective probabilities, and refers to a fundamental lack of knowledge on the phenomena, often interpreted as lack of knowledge on the parameters of the probability model. (Flage et al., 2014a). While epistemic uncertainty is reducible, for example by acquiring new knowledge and data on the system or phenomena, aleatory uncertainty is irreducible, and therefore in some cases referred to as "irreducible uncertainty" (Helton & Burmaster, 1996).

A special case of uncertainty is the concept of 'scientific uncertainty', often referred to in relation to the precautionary principle. There are many interpretations of the meaning of scientific uncertainties (see Aven 2011a), but the concept is most commonly related to "a lack of understanding of how the consequences (outcomes) are influenced by underlying factors: it is difficult to establish an accurate prediction model that would lead to a precise description of a 'cause-effect relationship'" (Aven, 2014b, p. 162).

Uncertainty needs to be seen in relation to the knowledge dimension, as "the uncertainty is relative to the background knowledge, i.e. altered background knowledge could cause decreased or increased uncertainty" (Flage & Aven, 2009, p. 12).

3. Managing the risk of rare, surprising and extreme events

3.1 Introduction

Risk management can be understood as "all measures and activities carried out to manage risk, including the identification of threats/hazards, the assessment of risk and risk-informed decision making" (Aven, 2014b, p. 161). An important aspect of risk management is the balance between development and protection. This balancing act involves considerations on how to attain an equilibrium between pursuing new opportunities on one hand, and avoiding losses on the other. The tools and strategies applied to manage risk influence this balance: while some approaches give more weight to development (such as cost-benefit analyses), others support protection (such as cautionary-precautionary strategies) (Aven, 2014b).

When it comes to managing the risk of rare, surprising and extreme events, there is a need to highlight the protection part of the balance, as our focus is on reducing uncertainties. On the other hand, we need to ensure that the focus on protection does not limit development. As stated by Renn: “dealing with uncertainty involves two objectives: providing resilient strategies to be prepared for surprises and finding an adequate and fair balance between assumed overprotection and underprotection” (Renn, 2017, p. 188). In order to choose the appropriate tools and strategies to manage the risk of this type of events, it is essential to understand the characteristics of the events, with special emphasis on the knowledge and uncertainty dimensions.

3.2 Risk problem classification

By classifying risks based on e.g. their characteristics or the magnitudes of certain values, suitable risk management strategies can be identified for each class. This process contributes to simplifying the risk management process; instead of having to choose appropriate strategies for each specific risk, we are able to assign suitable strategies for a set of risks with, for example, similar characteristics (Kristensen et al., 2006). Although establishing generic strategies for each class of risk problems is a useful approach, it should be emphasized that “[using] a risk classification scheme for the identification of, for example, appropriate risk management strategies, does (…) not exclude that other considerations or aspects of the risk may overrule or put to side the recommendations given by the classification scheme.” (Kristensen et al., 2006, p. 421). Hence, such classifications should be supplemented by assessments and considerations that go beyond the characteristics or aspects highlighted in the classification scheme.

Aven (2014b) distinguishes between three categories of risk problems, based Aven and Renn (2010):

1. Risk problems with small uncertainties

Risk problems belonging to this class are characterized by a strong knowledge base. The risks are not necessarily low, but we are aware of the potential consequences and can make accurate prediction of the occurrence of events.

2. Risk problems with moderate uncertainties

This class represents risks problems with uncertainties in the range between small and large. For these problems, the knowledge base is weaker than in the case of small uncertainties, but we may still rely on some dominating explanations and beliefs.

3. Risk problems with large (deep) uncertainties

For risk problems of this class, the knowledge base is weak. The theory/data supporting our hypotheses is poor, and we cannot make accurate or reliable predictions on the occurrence of events and/or their consequences. In some cases, the large uncertainties may be related to complexity, i.e. difficulty in understanding the interactive effects between different components (Aven, 2014b).

3.3 Risk management strategies

The three main strategies commonly used to manage risk are risk-informed strategies, cautionary/precautionary strategies and discursive strategies. The latter uses “measures to build confidence and trustworthiness through the reduction of uncertainties, clarification of facts, involvement of affected people, deliberation and accountability” (Aven, 2014b, p. 160). The discursive strategy is mostly relevant for risks characterized by high ambiguity, i.e. risk problems where “there are different viewpoints about the relevance, meaning and implications of factual explanations and predictions for deciding about the tolerability of the risk, as well as management actions (…), or if the values and priorities of what should be protected or reduced are subject to intense controversy" (Aven & Renn, 2010, p. 129). As the discursive strategies are not highly relevant for the risk problems we are concerned with in the present thesis (rare, surprising and extreme events), we will not elaborate further on this topic here, but refer to Renn (2017) and Aven and Renn (2010) for a more detailed presentation of this topic.

Choosing appropriate risk management strategies implies using approaches and tools that are adapted to the context and characteristics of the risks we are considering. For example, if we are managing risk problems with large uncertainties, the choice of strategy should reflect this, and we need to rely on tools that take the uncertainty dimension into consideration. Similarly, for risk problems with very small uncertainties we may (to a larger extent) rely on risk-based approach, where decisions are made based on the comparison of quantitative descriptions of risk to some given benchmark or criteria. However, for most situations, the optimal choice would entail a combination of the different strategies, the key being to "[obtain] a satisfactory balance between these approaches and strategies" (Aven, 2014b, p. 203).

When it comes to rare, surprising and extreme events, the knowledge/uncertainty and surprise dimensions are of utmost importance (Aven, 2014b). Hence, incorporating these dimensions into the tools and approaches used to manage this type of risk problems, is essential. In order to sufficiently highlight these aspects in the risk management process, there is a need to adapt several of the approaches and procedures that have mainly been applied with a probability-based perspective. Several authors have called for a need to better reflect uncertainty and knowledge in risk assessments (see e.g. (Aven, 2013c, 2015b; Aven & Zio, 2011; Flage & Aven, 2009). This issue has been particularly highlighted for rare, surprising and extreme events (for example by Flage et al., (2014b). Building on this acknowledgment, there have been several suggestions on how approaches can be adapted to better reflect uncertainties and knowledge (see for example the modified use of the risk acceptance criteria and ALARP processes suggested by Aven (2014b), the extended risk matrix approach by Aven (2017b) and the proposed adaption of the safe job analysis (SJA) by Veland and Aven (2015)).

Based on the classification of risk problems from Section 3.2, an overview of appropriate risk management strategies and tools is presented by Aven (2014b), as seen in Table 2 below.

Table 2: Risk problem categorizations and their implications for risk management (from Aven, 2014b, p. 164)

Risk problem category	*Management strategy*	*Appropriate instruments*
Small uncertainties	Risk informed Routine-based risk treatment (risk reduction)	Statistical analysis Risk assessments Cost-benefit analyses Trial and error Technical standards Economic standards Education, labelling, information Voluntary agreements

Risk problem category	*Management strategy*	*Appropriate instruments*
Moderate uncertainties	Risk informed (risk agent)	Risk assessments, broad risk characterisations Cost-benefit analyses Tools include: • Containment • ALARP (as low as reasonably practicable) • BACT (best available control technology), etc.
	Risk informed	Risk assessments Cost-benefit analyses
	Robustness focused (risk absorbing system)	Improving buffer capacity and performance of hazard/threat risk target through for example: • High performance standards of barrier systems • Additional safety factors • Redundancy and diversity in designing safety devices • Improving coping capacity To come extent also measures mentioned for large (deep) uncertainties
Large (deep) uncertainties	Risk informed and caution/precaution-based (risk agent)	Risk assessments. Broad risk characterisations, highlighting uncertainties and features such as persistence, ubiquity, etc. Tools include: • Containment • ALARP (as low as reasonably practicable) • BACT (best available control technology), etc.
	Risk informed Robustness and Resilience focused (risk absorbing system)	Risk assessments. Broad risk characterisations. Improving capability to cope with surprises: • Diversity of means to accomplish desired benefits • Avoiding high vulnerabilities • Allowing for flexible responses • Preparedness for adaption

3.3.1 Risk-informed strategies

By applying a risk-informed strategy, the risk assessments and their results are used as input to the broad process of managerial review and judgement, in which decision-makers (or other stakeholders) consider the assessment in light of its limitations, the assumptions made and other reflections that may not have been captured in the assessment, but that are relevant to the decision-making process (such as political aspects and strategic objectives) (Aven, 2014b).

Risk-informed strategies are particularly relevant for rare, surprising and extreme type of risk events, as they highlight uncertainties in the risk assessments, and focus on the strength of the background knowledge supporting the assumptions. Hence, potential vulnerabilities in the assessments caused by poor knowledge can be identified and addressed.

3.3.2 Cautionary/precautionary strategies

The cautionary/precautionary strategies are built on the following principles:

1. The cautionary principle, stating that "in the face of uncertainty, caution should be a ruling principle" (Aven, 2014b, p. 170)
2. The precautionary principle, expressing that "if the consequences of an activity could be serious and subject to scientific uncertainties, then precautionary measures should be taken, or the activity should not be carried out" (SRA, 2015, p. 8)

The precautionary principle can be considered a special case of the cautionary principle, related specifically to scientific uncertainties. A large share of risk-informed decisions is subject to this type of uncertainty to some degree. Hence, an essential element in the application of the precautionary principle is making conscious judgements as to if, when and how the application of the principle can be justified. By applying this principle, we are expressing that "we find the lack of scientific uncertainty to be so significant that precautionary measures are required" (Aven, 2014b, p. 170). However, there are no clearly defined, predetermined limits or criteria to base these judgments on. They are influenced by factors like uncertainty characterisations and predictions from the risk assessments, as well as how the risk is perceived by stakeholders and other people involved (Aven, 2014b).

The precautionary principle is linked to the concept of resilience, as explained by Renn (2017):

> "According to the precautionary approach, risk management is driven by making the social system more adaptive to surprises and, at the same time, allows only those human activities or interventions that can be managed even in extreme situations (regardless of the probability of such extremes occurring" (Renn, 2017, p. 193).

According to cautionary/precautionary thinking, we may "pursue a cautious strategy that enables learning by restricted errors. The main management philosophy for this risk class is to allow small steps in implementation (containment approach) that enable risk managers to stop or even reverse the process as new knowledge is produced or the negative side effects become visible (Aven & Renn, 2010, p. 128). Furthermore, focusing on "precaution means a strict policy of containment, constant monitoring, continuous research and the development of substitutes" (Klinke & Renn, 2001, p. 167).

3.3.3 Robustness and resilience focused strategies

Strategies belonging to this category are built on the concepts of robustness and resilience.

Robustness is referred to as “the antonym of vulnerability” (SRA, 2015, p. 7), with the interpretation of vulnerability as “the degree to which a system is affected by a risk source or agent” (SRA, 2015, p. 7). Hence, according to these interpretations, if a system is considered to have high vulnerability, it is not robust. Equally, if the system is judged to have low vulnerability, it can be considered robust. An important aspect in the understanding of the vulnerability concept, is that we are concerned with events that the system is known to be exposed to (Aven, 2014b). Hence, the application of robustness focused approaches needs to be supplemented by assessments on uncertainty and the possibility of surprising events occurring relative to the judgements made; we cannot “exclude the fact that extreme consequences may occur (…) even when the system is considered robust” (Aven, 2014b, p. 187).

Resilience refers to “the ability of the system to sustain or restore its basic functionality following a risk source or an event (even unknown)” (SRA, 2015, p. 6). Furthermore, a system can be considered resilient if it “sustains functionality despite large info-gaps (info-gap: the disparity between what is known, and what needs to be known to ensure specified goals)” (SRA, 2015, p. 6).

When it comes to resilience, a main objective is to create systems that are able to withstand surprising events. Renn (2017) describes the difference between the concepts of robustness and resilience in the following: “In contrast to robustness, where potential threats are known in advance and the absorbing system needs to be prepared to face these threats, resilience is a protective strategy against unknown or highly uncertain hazards” (Renn, 2017, p. 179). For resilience focused strategies, “we are concerned about the performance of the system not only in the case of a specific [risk source] or [event], but for other risk sources and events as well”, making these strategies “especially suited for confronting unknown and uncertain categories of events” (Aven, 2017a, p. 536).

3.4 Decision making

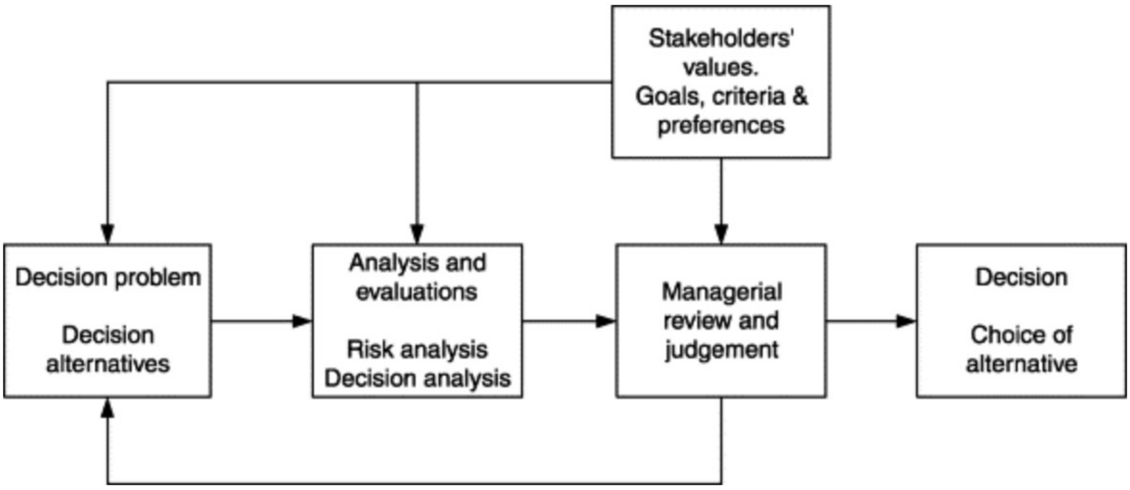
Aven and Kørte (2003) distinguish between two different approaches to decision making:

1. Decision-making as an exercise of modelling alternatives, outcomes, uncertainty and values, and choice of the alternative which maximises/minimises some specified criteria.

2. See decision-making as a process with formal risk and decision analyses to provide decision support, followed by an informal managerial judgement and review process resulting in a decision (Aven & Kørte, 2003, p. 290).

In the present thesis, including the paper in part II, the second approach is adopted. According to this perspective, decision making is based on the results of the risk assessments, but include considerations that go beyond this information, such as “benefits related to the activity studied, as well as strategic and political concerns that could be important for the decision to be made” (Aven, 2013a, p. 2086). A structure of the decision-making process in line with the adopted approach is shown below.

Figure 1: Basic structure of the decision making process (Aven & Kørte, 2003)



An important element in the decision making process is the managerial review and judgment, in which decisionmakers evaluate the risk assessments in view of the assumptions made and the limitations they may represent (Aven, 2013a). With regards to managing the risk of rare, surprising and extreme events, such considerations are of particular importance, as they highlight inter alia the background knowledge supporting the assumptions and may contribute to disclosing the potential for surprising events in relation to this knowledge. However, “The process of managerial review and judgement relies on meaningful information from the risk and decision analyses” (Aven & Kørte, 2003, p. 298). In order to ensure that these considerations are made based on relevant information, it is essential that the preceding stages of the risk management process are performed using approaches that give sufficient weight to the aspects of uncertainty and knowledge.

3.5 Learning from previous events and near-misses

A near-miss, in the context of rare, surprising and extreme events, can be defined as an event that “did not result in extreme consequences; the barriers worked and avoided the extreme outcomes” (Aven, 2014b, p. 123). Another term is ‘near accident’, defined as an event that “does not emerge as an accident just owning to functioning of one or more safety barriers whose failures would be sufficient to escalate the near accident to the accident” (Khakzad et al., 2015, p. 1337), which is seen as an interpretation analogue with the definition by Aven (2014b).

According to Paté-Cornell, “the first way to reduce risks—and especially poorly known ones—is the systematic observation and recording of near-misses and precursors” (Paté-Cornell, 2012,

p. 1828). Hence, near-misses can provide valuable information on the system, and how it may fail; the "occurrence of a near accident would convey some information about the occurrence of the extreme event, which can be quantified using the concept of mutual information." (Khakzad et al., 2015, p. 1340). The advantage in learning from near-misses, is that it allows us to attain important knowledge on the possible paths to failure for a system, without paying the price of the large consequences associated with full-scale accidents. While "near misses are often described as free lessons" (Hopkins, 2008), learning from previous events (by this we mean events that developed into extreme events), comes at a higher cost. In any case, learning is essential in order to prevent similar events from occurring in the future.

Learning from previous events and near-misses can also be linked to the concepts of resilience and vulnerability; In order to build resilient systems (and be able to sustain them), learning is an essential factor (Weick & Sutcliffe, 2011). Furthermore,

> "awareness of vulnerability increases opportunities for learning. People need to be reminded that even though they think they understand their system and the ways in which it can fail, surprises are still possible. They have neither seen every possible failure mode nor imagined every one that is possible." (Weick & Sutcliffe, 2011, p. 152)

However, one of the challenges faced, is that you need to "keep learning without knowing in advance just what you will be learning or how it will be applied" (Weick & Sutcliffe, 2011, p. 73).

Important prerequisites for learning from previous events and near-misses, are clear definitions of what constitutes a near-miss, ensuring that there are effective systems where the lessons learned can be shared with all parts of the organization where they might be applicable, and furthermore, ensuring that this information is not only contained in people's memory, but also incorporated in (written) guidelines, procedures and standards (Murphy & Conner, 2014).

When it comes to the use of precursor signals and warnings, the challenge is to "avoid missing or ignoring early signals and precursors of serious events, or, on the other hand, exaggerating them" (Aven, 2014b, p. 147). We may refer to 'false negatives' in the cases where a risk situation was present, though there was no indication of this, and 'false positives' in situations where there were erroneous signals indicating that a risk situation was present, when this was de facto not the case. It may be difficult identifying these 'false negatives' and 'false positives' in advance, as we cannot rely on knowledge of the true underlying state of the system (Aven, 2014b). This leaves us with the issue of "[managing] a tradeoff between the credibility of the signal (and the severity of the potential event that it reveals) and the risk of a false alert."(Paté-Cornell, 2012, p. 1831). Furthermore, how well these signals are communicated and responded to, is determined by the organizational structure and culture (Paté-Cornell, 2012).

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Part II

Paper – On the meaning of and relationship between dragon-kings, black swans and related concepts

On the meaning of and relationship between dragon-kings, black swans and related concepts

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Abstract

Different metaphors have been introduced to reflect the occurrence of rare and surprising types of events with extreme impacts, including black swans, grey swans and dragon kings. Despite considerable research on clarifying the meaning of these concepts, their relationship still remains unclear. The present paper aims at meeting this challenge, by reviewing current definitions and interpretations found in the literature and referred to in practice, analysing these definitions and interpretations, and providing a structure for improved understanding of the differences and similarities between the various metaphors. The paper also discusses some of the implications the use of these concepts have for risk management and decision making.

1. Introduction

Rare and surprising events with extreme impacts have been given a substantial amount of attention in scientific environments for decades. Examples of such events are the terrorist attacks on September 11th 2001, the financial crisis in 2008 and the Fukushima nuclear accident in 2011. Common for these events is that we failed to predict them, their chain of events came as a surprise and our existing mechanisms for prevention were insufficient.

Events of this type are found across numerous fields, from engineering and technology, to finance and social science. This wide-ranging relevance has led to efforts from multiple disciplines to examine and understand the nature of these events, and how they can be confronted.

There exist several metaphors aimed at describing this type of events. The most well-known is the 'black swan', popularised by Taleb in his book "The Black Swan – The impact of the highly improbable" (Taleb, 2007). Its origin is usually linked to a Dutch expedition to Western Australia in 1697 discovering black swans on the Swan River. Up to that point in time all observed swans in the Old World had been white. As discussed by Taleb (2007) and Hammond (2009), the metaphor was also used earlier – it is for example stated that in the 16th century London, the black swan was a common metaphor used to describe the impossible.

Taleb (2007) refers to black swans as events with three attributes: firstly, it is an outlier, lying outside the realm of regular expectations, as nothing in the past can convincingly point to its possibility. Secondly, it brings an extreme impact. Lastly, despite its outlier status, it is rendered explainable and predictable in retrospect. Inspired by Taleb's work, many risk researchers have further discussed the meaning of a black swan. For example, Aven (2013, 2014, 2015) looks closer into three possible interpretations:

1. An unknown unknown with extreme consequences
2. A surprising extreme event relative to one's beliefs/knowledge
3. A surprising extreme event with a very low probability (Aven, 2014, p. 12) (1.1)

Following the black swan metaphor, Taleb (2007) introduced the related concept of 'grey swans'. Several authors have referred to this metaphor when discussing rare and surprising events with extreme impact (e.g. Akkermans & Wassenhove, 2013; Murphy & Conner, 2014; Stein & Stein, 2014). Taleb describes them as "modelable extreme events" (2007, p. 272), events whose occurrence is rare, but not unexpected. Other authors refer to grey swans as 'known unknowns', e.g. Hole and Netland, stating that "a gray swan is a metaphor for a large-impact and rare event that's somewhat predictable, yet many overlook it. It's the "known unknown," a rare event that some know is possible, but no one knows when or whether it will occur." (Hole & Netland, 2010, p. 21).

Other interpretations of grey swans seem to link them more to a subset of 'known knowns', resembling the last (1.1) of the black swan interpretations discussed by Aven (2014). Examples of this are the practical understanding and use of the metaphor in financial markets, see for example the definition given by Investec (2019) and Investopedia (2019). Another example is Lin and Emanuel, who interpret grey swans as high-impact, low-probability events with a degree of predictability:

> "Some high-consequence events that are unobserved and unanticipated may nevertheless be predictable (though perhaps with large uncertainty). Such to-some-extent-predictable, low-probability, high-impact events may be referred to as "grey swans" (or, sometimes, "perfect storms")" (Lin & Emanuel, 2016, p. 106)

In their interpretation of grey swans, Lin and Emanuel link the grey swan concept to another metaphor: 'perfect storms'. This metaphor originated from the occurrence of a category 1 hurricane in 1991, later named "The Perfect Storm" and made famous by Sebastian Junger (1997) in his book with the same name. This storm arose from meteorological phenomena that were known to occur, but the conjuncture of the different weather systems resulted in a storm with extreme dimensions. In medical science, the metaphor of perfect storms is often used to describe scenarios where we face synergetic effects between multiple well-known medical phenomena (see e.g. de Ferranti & Mozaffarian, 2008; Wells et al., 2007).

Catanach Jr. and Ragatz describe a perfect storm as "an unexpected dramatic event resulting from a confluence of unpredictable circumstances. No individual contributing factor is powerful enough to create the resulting "storm"; collectively their confluence creates an effect that is exponentially more devastating and unimaginable" (2010, p. 20).

The metaphor of perfect storms has been discussed in relation to black swans by Paté-Cornell (2012) and Aven (2014). Aven states that "in relation to perfect storms, the variation in the phenomena is known and we face risk problems where the uncertainties are small; the knowledge base is strong and accurate predictions can be made" (2014, p. 122).

We see that the metaphor of perfect storms has been related to events that can be accurately predicted, events that can be predicted to some extent, and even events with circumstances that are unpredictable. Some of the interpretations link perfect storms to a rare combination of known events, whereas other definitions emphasize the effects of a synergetic relationship between the events.

Another metaphor used to describe these rare, surprising and extreme events, is the "dragon-king" (Sornette, 2009). This metaphor is composed of two terms: 'dragon' and 'king'. The term 'king' was introduced by Laherrère and Sornette (1998) to describe extreme outliers that strongly deviate from an overall pattern of events , much like the fortune of kings greatly exceeds the wealth of the population in general. Sornette later coupled this term with 'dragon' to incorporate the extraordinary characteristics of these events "whose presence, if confirmed, has profound significance" (Sornette, 2009, p. 5).

The use of metaphors in general contribute to creating discussion and attention around important issues, so also within the risk field. When the black swan concept was introduced, there followed an "increased interest and enthusiasm for discussing risk issues" (Aven, 2013, p. 49). Metaphors do not only make complex and abstract concepts comprehensible, they also influence the way we perceive the phenomena. A study conducted by Thibodeau and Boroditsky (2011) concluded that the metaphors we are presented with "can have a powerful influence over how people attempt to solve complex problems", and notably they found that "people do not recognize metaphors as an influential aspect in their decisions" (Thibodeau & Boroditsky, 2011, p. 10). The metaphors also need to be used carefully because of features like "highlighting and hiding", sometimes referred to as "partiality of insight" (Morgan, 2006), which means that "in allowing us to focus on one aspect of a concept (…), a metaphorical concept can keep us from focusing on other aspects of the concept that are inconsistent with that metaphor" (Lakoff & Johnson, 1980, p. 10). Reasoning from the logic of Lakoff and Johnson, applying multiple metaphors (black swan, grey swan, dragon king, perfect storm) to describe a single phenomenon (rare, surprising and extreme events), allows us to highlight different aspects of the phenomenon, contributing to a more complete understanding. However, in order to understand the contribution from each metaphor, we need to understand how the metaphors are related, their similarities and differences. The above discussion has shown that this is difficult, given the many existing definitions and interpretations used. It is observed that different metaphors are applied to the same event. For example, the Macondo accident in 2010 has been referred to as a black swan by Aven (2014) and Murphy (2011), and a grey swan by Yang et al. (2015) and Murphy and Conner (2014). The nuclear disaster at Fukushima in 2011 is also referred to by multiple metaphors: a black swan (Song & Kim, 2014), a grey swan (Akkermans & Wassenhove, 2013) and even a dragon-king (Wheatley et al., 2017). Many of these overlaps can be explained by different definitions and interpretations, but there is also a need for questioning the underlying rationale for these metaphors. For example, how should a grey swan be defined and relate to a black swan? To what extent is it meaningful to associate grey swans to for instance known unknowns? The scientific risk literature has only to some extent clarified the meaning of and relationship between these metaphors. The current situation is somewhat chaotic and hampers the effective communication of risk related to rare, surprising and extreme events. From a risk science point of view, it can be argued that the field is suffering from a rather high degree of inconsistency and lack of stringency in relation to important risk concepts.

In the present work, we will look closer at these challenges. The main aim of the paper is to present a logic and structure for clarifying and enhancing our understanding of these metaphors. First, in Section 2, we provide an overview of some of the most common definitions and interpretations of the different metaphors, following up and systematizing the discussion in this introduction section. In Section 3, we present the above announced structure and in Section 4 we discuss the implications the use of these metaphors have for risk management and decision making. Lastly, some conclusions are made in Section 5.

2. Overview of current definitions and interpretations

In this section, we provide an overview of definitions and interpretations of the four metaphors: black swan, grey swan, perfect storm and dragon-king. The overview is not all-inclusive but considered sufficient to show how these metaphors are commonly understood and used.

2.1 Black swans

Table 1 presents a set of definitions and interpretations of black swans found in the literature.

Table 1: Definitions and interpretations of the black swan metaphor

Source	Definition/interpretation
Taleb (2007, p. xvii)	“First, it is an outlier, as it lies outside the realm of regular expectations, because nothing in the past can convincingly point to its possibility. Second, it carries an extreme impact. Third, in spite of its outlier status, human nature makes us concoct explanations for its occurrence *after* the fact, making it explainable and predictable”
Makridakis et al. (2009, p. 795)	“(…) rare and unique events that are completely unexpected, and even outside the realm of our imaginations“
Hole and Netland (2010, p. 21)	“A black swan is a metaphor for a large-impact and rare event that comes as a total surprise to everybody. This type of event is the “unknown unknown,” a rare bombshell event that no one has considered.”
Catanach Jr. and Ragatz (2010, p. 20)	“A low-probability, high-impact occurrence that can be either positive or negative in its effect, that is prospectively unpredictable but that everybody could see coming after it occurs”
Marsh and Pfleiderer (2012, p. 2)	“(…) what has come to be known as the problem of “unknown unknowns” or “black swan events”, i.e., extreme events that are not well enough understood for their probabilities to be accurately modelled”
Yukalov and Sornette (2012, p. 54)	“The concept of black swan is essentially the same as Knightian uncertainty, i.e., a risk that is a priori unknown, unknowable, immeasurable, not possible to calculate.”
Aven (2013, p. 49) Aven (2015, p. 83)	“a surprising extreme event relative to the present knowledge/beliefs” “a surprising extreme event relative to one’s knowledge/beliefs”
Yang et al. (2015, p. 102)	“[Black swans] are unforeseeable and catastrophic events”
Murphy (2016, p. 13)	“(…) black swans are rare, catastrophic and unpredictable events”
Baldassarre et al. (2016, p. 1754)	“Some of these unknown unknowns may occasionally result in the so-called “black swans”: unexpected events with an extremely high impact on the system, which are essentially impossible to forecast.”
Faggini et al. (2019, p. 106)	“(…) outlier’s events, the risks of which cannot be anticipated, are referred to as Black Swans”
Ale et al. (2020, p. 3)	“The unknown unknowns are the most problematic and the most discussed. These are the real black swans.”
CFI (2020)	“A black swan event, a phrase commonly used in the world of finance, is an extremely negative event or occurrence that is impossibly difficult to predict. In other words, black swan events are events that are unexpected and unknowable.”

As seen from the list of interpretations and definitions above, the black swan is often linked to the so-called 'unknown unknown'. However, authors interpret the 'unknown unknown' concept in different ways. Hole and Netland (2010) uses the expression to describe something "no one has considered". According to Aven and Krohn (2014), 'unknown unknown' events are "unthinkable and/or unknown to the scientific community" (Aven & Krohn, 2014, p. 9). Haugen and Vinnem (2015) have a similar interpretation, stating that 'unknown unknowns' are events that "no one really can foresee is possible at all, regardless of probability (…)" (Haugen & Vinnem, 2015, p. 2).

Others refer to the unknown unknown as "unexpected events" (Baldassarre et al., 2016, p. 1754) or "not well enough understood for their probabilities to be accurately modelled" (Marsh & Pfleiderer, 2012, p. 2).

The latter two interpretations represent scenarios where there exists some sort of expectation for the event; the event has been identified in the risk assessment, but the variation in the phenomena is subject to large uncertainties and inaccurate modelling. However, if the 'unknown' is in fact unknown, no expectations will exist, as we do not have anything to found our expectations on.

Another interpretation of 'unknown unknowns' is proposed by Feduzi and Runde (2014), who describe them as events "that the decision-maker does not imagine and therefore does not even consider" (Feduzi & Runde, 2014, p. 270). By relating 'unknown unknowns' to the knowledge of the decision maker alone, we discount the possibility of the knowledge existing elsewhere. It could be an unknown known; Unknown to the decision maker but known to others. Unlike the 'unknown unknowns' described by Aven and Krohn (2014), 'unknown knowns' are potentially identifiable through a more thorough risk analysis.

As defined by Taleb (2007), a black swan is retrospectively predictable. After its occurrence, the sequence of events leading to the black swan is exposed, rendering it explainable and foreseeable in hindsight. From several of the interpretations above, this attribute has developed into the assumption that black swans are prospectively *unpredictable* ((Catanach Jr. & Ragatz, 2010; Murphy, 2016). However, this assumption can be questioned (e.g. Aven, 2014; Lindaas & Pettersen, 2016). It may be unpredictable using probabilistic risk assessments, as we cannot rely on large amounts of reliable data from past events or detailed modelling of relevant phenomena. However, other types of risk assessments based on signals and warnings could give predictions of such events, though they may be inaccurate and subject to deep uncertainties.

The terrorist attacks on September 11th have been referred to as a black swan by several authors (e.g. Nafday, 2009; Nuñez & Logares, 2012; Taleb, 2007; Yang et al., 2015). This event undoubtably came as a surprise for many, both laymen and security professionals (Aven, 2014). It was, however, well-known for the terrorist group responsible for planning and executing the attack. In the aftermath of the event, it became clear that the government had been made aware of Islamic terrorist groups planning an attack on U.S territory by hijacking aircrafts (Sanger, 2002). The possibility of the aircrafts being used as missiles was certainly apparent, as several similar attempts had been made during the 90's (Bazerman & Watkins, 2005). Although the details of such a potential attack was difficult to predict, such as the exact location, targets and scope, it can be argued that "government agencies and officials had all of the data they needed to know of dangerous deficiencies in airline security that could be exploited" (Bazerman & Watkins, 2005, p. 366). The knowledge of such a scenario was available, but did not trigger any preventive measures. Hence, the event was a 'known known' to the terrorist organizations as well as government officials, but a 'unknown known' to the airport security officers. This example illustrates that the interpretation of the black swan is contingent on whose knowledge we are referring to, and at what time. The definition of a black swan by Aven (2014) as "a surprising extreme event relative to the present beliefs/knowledge" (Aven, 2014, p. 116) captures this aspect. Based on this definition, Aven (2014) distinguishes between three categories of black swans:

a) Events that were completely unknown to the scientific environment (unknown unknowns)
b) Events that were not on the list of known events from the perspective of those who carried out the risk analysis (or another stakeholder), but known to others (unknown knowns)
c) Events on the list of known events in the risk analysis but not believed to occur because of negligible judged probability

2.2 Grey swans

Table 2 presents a set of definitions and interpretations of grey swans found in the literature.

Table 1: Definitions and interpretations of the grey swan metaphor

Source	Definition/interpretation
Taleb (2007, p. 37)	"They are near-Black Swans. They are somewhat tractable scientifically – knowing about their incidence should lower your surprise; these events are rare but expected"
Nafday (2009, p. 193)	"(…) the random uncertainty of probabilistic models (what Donald Rumsfeld called "known unknowns" or Taleb refers to as "Gray Swans")"
Hole and Netland (2010, p. 21)	"A gray swan is a metaphor for a large-impact and rare event that's somewhat predictable, yet many overlook it.1 It's the "known unknown," a rare event that some know is possible, but no one knows when or whether it will occur"
Nuñez and Logares (2012, p. 17)	"Grey Swans may be associated with events that are rarer than White Swans, with consequences ranging from large to irrelevant"
Murphy and Conner (2014, p. 110)	"The Black Swan pathway plus the recognition of similar pathways constitute some of the most valuable lessons-learned from a Black Swan event. Unfortunately, these valuable lessons-learned are often forgotten over time and the white swan becomes greyer and greyer unless efforts are made to keep the lessons-learned fresh."
Stein and Stein (2014, p. 1281)	"(…) they are better viewed as ''gray swans'' that—although novel and beyond recent experience—could have been foreseen and mitigated"
Khakzad et al. (2015, p. 1336)	"(…) gray swan (GS) is used to address accident events that are predictable but with larger uncertainties"
Lin and Emanuel (2016, p. 106)	"Some high-consequence events that are unobserved and unanticipated may nevertheless be predictable (though perhaps with large uncertainty). Such to-some-extent-predictable, low-probability, high-impact events may be

	referred to as "grey swans" (or, sometimes, "perfect storms")"
Gholami et al. (2018, p. 32037)	"a gray swan is a metaphor for a partially-predictable, high-impact, and rare (PHR) event, which is disregarded by many people"
Akkermans and Wassenhove (2018, p. 10)	"Grey swan events are still very unlikely, but have occurred before, (…), and can in principle be foreseen by management"
Investec (2019)	"Unlike their cousins, grey swan events are possible and knowable, even though they may be regarded as unlikely. Like black swans though, their impact can be huge. In short, probabilities can be assigned to such events and so, presumably, their potential impact can be measured"

In his book, Taleb (2007) relates the black swan to its more scientifically tractable cousin – the grey swan. The grey swan does not represent an analogy per se; the meaning of the metaphor builds on the black swan. Taleb (2007) describes them as "near-Black Swans", events that are "rare and consequential, but somewhat predictable, particularly to those who are prepared for them and have the tools to understand them" (Taleb, 2007, p. 37).

The definition by Taleb (2007), as well as several of the other interpretations above, relate grey swans to the 'known known'. They are described as foreseeable and predictable, but unlikely to occur. Some authors relate grey swans to incidents that are known to have occurred before (e.g. Akkermans & Wassenhove, 2018; Murphy & Conner, 2014), while others describe them as "beyond recent experience" (Stein & Stein, 2014), or even "unobserved" (Lin & Emanuel, 2016). Hence, the background knowledge supporting the predictions may differ, but the predictions are in any case uncertain.

According to some of the definitions above, the grey swan metaphor reflects the 'known unknown'. With such an interpretation, the black swan/grey swan metaphors are combined by the known/unknown taxonomy. However, in order to justify this classification, we need to be clear on what the 'known' and 'unknown' in this expression are referring to. Judging from the interpretations above, there is large consensus that grey swans represent events that we know could occur, i.e. events that have been identified in the risk analysis. This justifies the 'known' in the partitioning. Based on the definition by Hole and Netland, an event being 'unknown' is taken to mean that "no one knows when or whether it will occur" (Hole & Netland, 2010, p. 21), whereas Gholami et al. (2018) relate grey swans to the following interpretation of 'unknown' events: "When probabilities cannot be assigned to at least part of the space (i.e., outcomes are specified but probabilities are not), the situation is unknown." (Gholami et al., 2018, p. 32037). Nafday (2011) takes a similar approach, describing grey swans as known events with unknown likelihood.

The interpretation from Gholami et al. (2018) requires some further consideration. It is stated that grey swans can be categorized as events where we can specify outcomes but not probabilities. This statement cannot be justified, as subjective (also known as knowledge-based) probabilities can always be assigned. Hence, there exists no such scenario where probabilities cannot be assigned to known outcomes. However, the subjective probabilities could produce poor predictions, as the knowledge supporting the probabilities could be weak. We are in a state of what Stirling (2007) calls "incomplete knowledge", in which attempts to assign probabilities in "are neither rational nor "science-based"" (Stirling, 2007, p. 310). Using probabilities alone to describe uncertainties for this type of situations is not sufficient (Flage et al., 2014).

2.3 Perfect storms

Table 3 presents a set of definitions and interpretations of perfect storms found in the literature.

Table 2: Definitions and interpretations of the perfect storm metaphor

Source	Definition/interpretation
Merriam-Webster's dictionary	"A critical or disastrous situation created by a powerful concurrence of factors"
Reinstein and McMillan (2004, p. 955)	"(…) a "perfect storm"- a concurrence of unpredictable, rare and unusual conditions that combined to create a unique, devastating event"
Gardiner (2006, p. 398)	"(…) an event constituted by an unusual convergence of independently harmful factors where this convergence is likely to result in substantial, and possibly catastrophic, negative outcomes"
Emanuel and Fuchs (2008, p. 2789)	"A "perfect storm" occurs when a confluence of many factors or events—no one of which alone is particularly devastating—creates a catastrophic force. Such confluence is rare and devastating"
Catanach Jr. and Ragatz (2010, p. 20)	"An unexpected dramatic event resulting from a confluence of unpredictable circumstances. No individual contributing factor is powerful enough to create the resulting "storm"; collectively, their confluence creates an effect that is exponentially more devastating and unimaginable"
Frederick and Monsen (2011, p. 187)	"A perfect storm is when several remotely possible and individually innocuous events occur at the same time, which then feed off each other and lead to a dramatic and possibly disastrous event"
Paté-Cornell (2012, p. 1824)	""Perfect storms" involve mostly aleatory uncertainties (randomness) in conjunctions of rare but known events."
Aven (2014, p. 120-122)	Rare event that may occur, where we understand the underlying phenomena: known variation of these phenomena described by frequentist probabilities

As mentioned in Section 1, the origin of the 'perfect storm' expression was the category 1 hurricane that hit the east coast of the United States in 1991. It developed into a case of several rare, but well known phenomena, each with large, but not devastating magnitude, appearing in an unusual conjunction where the interactions between the phenomena gave a synergistic effect that resulted in a devastating event. Hence, building on the original meaning of the metaphor, perfect storms can be interpreted as events where, although each event as well as the conjunction of events can be considered rare, we can make accurate predictions about the phenomena and their combinations. However, we may experience surprises relative to our knowledge due to the synergistic effects of the conjunction.

The metaphor has become a popular expression in both scientific and non-scientific literature. In Google Scholar, a search for "perfect storm" yields over 68 000 results. Looking more closely at the different contexts where the perfect storm metaphor is applied, reveals some discordance as to how the term is understood.

In all of the above interpretations, perfect storms are related to the concurrence of events. However, when we dive further into each separate event constituting the combination, the interpretations diverge. In some cases they are described as unusual, or even unpredictable. Others refer to them as rare, but known. If we consider how the perfect storm metaphor is applied in medical science literature, the events involved are in many cases well known to occur. For example, the metaphor is used to describe the relationship between phenomena like cancer and diabetes (Suh & Kim, 2011) and puberty and obesity (Jasik & Lustig, 2008), none of which can be considered rare or unexpected.

Furthermore, the combination of these events is subject to different interpretations. While some refer to the combination as rare and unusual, many applications of the perfect storm metaphor concern events that are closely related and known to occur at the same time. For example, the metaphor is used to describe the combination of different risk factors in adolescent driving (Allen & Brown, 2008), including the propensity towards risky behaviour, and peer influence. A combination of these factors is not rare, several references to the connection between these factors are found in the scientific literature (see e.g. Reynolds et al., 2014). In this case, the perfect storm is used to describe a scenario where the conjuncture of known, related events creates a negative outcome that is amplified by the interactions between the different factors.

The synergy in the concurrence of events is emphasized in several of the interpretations above, as well as in many of the examples from medical science literature. The extent to which these synergistic effects are understood may vary, depending on our knowledge of the phenomena.

The perfect storm is thus related to the 'known known', events that have been identified in the risk analysis, where some sort of judgement has been made about the possibility of occurrence. Hence, there is a link to both black swans and grey swans. The perfect storm metaphor has been discussed in relation to the black swan metaphor by Paté-Cornell (2012), who distinguishes between the two by relating them to different types of uncertainties: "“Perfect storms” involve mostly aleatory uncertainties (randomness) in conjunctions of rare but known events. “Black swans” represent the ultimate epistemic uncertainty or lack of fundamental knowledge" (Paté-Cornell, 2012, p. 1827). In line with this reasoning, Aven (2014) discusses perfect storms in relation to the type c) black swan mentioned in Section 2.1 (surprising, extreme events not believed to occur because of very low judged probability), stating that perfect storms are events that can be predicted (using frequentist probabilities) with large accuracy and small uncertainty, whereas black swans of type 3 are described using subjective probabilities, and cannot be predicted with this level of accuracy.

Lin and Emanuel (2016) link the perfect storm metaphor to grey swans, as seen from their definition of a grey swan in Section 2.2. Both metaphors describe known events that can be modelled, but modelling grey swans often involve large uncertainties, whereas perfect storms can be modelled with accuracy and small uncertainties. However, as perfect storms are related to the conjuncture of events, there may be uncertainties related to this conjunction that could influence the accuracy of the predictions.

2.4 Dragon-kings

Table 4 presents a set of definitions and interpretations of dragon-kings found in the literature.

Table 3: Definitions and interpretations of the dragon-king metaphor

Source	Definition/interpretation
Sornette (2009, p. 1)	“dragon-kings (…) refer to the existence of transient organization into extreme events that are statistically and mechanistically different from the rest of their smaller siblings”
Sornette and Ouillon (2012, p. 2)	“extreme events that do not belong to the same population as the other events”
Ale et al. (2020, p. 5)	“the existence of transient organization of phenomena that can emerge into extreme events. These extreme events lead to so-called meaningful outliers. These are events or data points that coexist with series of similar events that are distributed according to a regular distribution such as a power law.”
Faggini et al. (2019, p. 112)	“[dragon kings] are the result of the same system properties that give rise to the power law, but they violate the power law because those properties have been arranged in such a way as to create severe instability, producing a systemic risk. Moreover, the presence of a positive feedback mechanism “creates faster-than-exponential growth, making them larger than expected””
Janczura & Weron (2012, p. 79)	“[dragon kings] are the result of positive feedback mechanisms that make them much larger than their peers. Being outliers to heavy-tailed behavior, these dragon-kings are unaccounted for by power law”
Wheatley et al. (2017, p. 108)	“[Dragon King] is a double metaphor for an event that is both extremely large in size or impact (a “king”) and born of unique origins (a “dragon”) relative to other events from the same system”
Süveges & Davison (2012, p. 131)	“The catastrophe could justly be called a “Dragon-King”: apparently impossible from scientific extrapolation or common sense based on the past”

As mentioned in Section 1, the dragon-king metaphor is twofold: the ‘king’ part of the metaphor is related to the extreme size and impact of the event, while the ‘dragon’ describes its unique origin, i.e. the extraordinary generating mechanisms of the event (Wheatley et al., 2017).

According to Sornette (2009), “the key idea is that catastrophic events involve interactions between structures at many different scales that lead to the emergence of transitions between collective regimes of organization” (Sornette, 2009, p. 11). Hence, we are talking about complex system structures, in which the interactions causes the system to move towards a state of instability. Dragon-kings emerge as a result of a phase transition, tipping point or bifurcation generated by this gradual maturation of the system. Sornette uses boiling water to illustrate this characteristic: when water is heated, it follows a gradual, predictable increase of temperature, until it reaches the boiling point (what Sornette refers to as the tipping point), after which the behaviour of the water becomes unstable, i.e. transforms into vapour. Sornette (2009) argues that these bifurcations and tipping points create some early warning signals that give these events a potential for predictability.

The definition presented when the metaphor was introduced has created less room for diverging interpretations of the metaphor. However, although the references from scientific literature indicate a large level of consensus on the meaning of the metaphor, its relationship to the black swan and grey swan metaphors remains unclear.

According to Yukalov and Sornette (2012), black swan events are inherently unpredictable due to their shared properties with the rest of the population. From this view, “a great earthquake is just an earthquake that started small ... and did not stop“ (Sornette, 2009, p. 5). The only property distinguishing these extreme events from similar ones with lower impact, is their size.

We struggle with the understanding of this reasoning. If black swan events are seen as part of the same population as the rest of the observations, can they be termed outliers? Recall the interpretation of a black swan by Yukalov and Sornette (2012), as “a priori unknown, unknowable, immeasurable, not possible to calculate” (Yukalov & Sornette, 2012, p. 54). This statement essentially defines black swans as ‘unknown unknowns’, and the comparison of black swans and dragon-kings is made based on this perspective. However, if black swans are unknowable, how can we state that they have shared properties with the rest of the population?

The dragon-king, the black swan and the grey swan are all described as outliers. But what is an outlier? According to Hawkins (1980), an outlier is “an observation that deviates so much from other observations as to arouse suspicion that it was generated by a different mechanism” (Hawkins, 1980, p. 1). Rousseeuw and Hubert (2011) have the following interpretation of outliers:

> “In real data sets, it often happens that some observations are different from the majority. Such observations are called *outliers*. Outlying observations may be errors, or they could have been recorded under exceptional circumstances, or belong to another population.” (Rousseeuw & Hubert, 2011, p. 73)

These definitions are rather vague. However they both indicate that an outlier is an observation stemming from a different population than the one studied. This leads us to considerations of probability models supporting the observations. If the data we observe come from a distribution F, the outlier comes from a distribution G which could strongly deviate from F. The interpretation of probability models in case of rare and surprising events is however not straightforward. Can such models at all be justified? These models are based on frequentist types of probability which require a population of a huge number of similar units.

When it comes to the dragon-king metaphor, outliers are interpreted as events found “beyond the extrapolation of the fat tail distribution of the rest of the population” (Sornette, 2009, p. 5). Based on such a perspective, outliers are not only extreme values in the distribution, they deviate from the distribution as a whole. Again, we need to interpret the definition in terms of probability models. However, to identify the observations that deviate from the model, the generating mechanisms of the phenomena must be well understood. If we consider some of the examples provided by Sornette (2009), dragon-king outliers are identified in distributions of French cities, earthquakes and financial draw-downs. For each of these systems, we can rely on a thorough understanding of the phenomena involved, as well as large amounts of accurate and reliable data. In a rank-size distribution of French cities, Paris is seen as an outlier found beyond the tail of the distribution. Referring to the outlier definition by Rousseeuw and Hubert (2011) , this observation is neither due to an error, nor recorded under exceptional circumstances, and hence, according to the argumentation above, this indicates that Paris belongs to a different population.

The dragon-king metaphor is largely focused on the dynamical process that causes the event to become an outlier. According to Yukalov and Sornette (2012), there are amplifying mechanisms that are specific to dragon-kings, and as a consequence of these, the events may be knowable and predictable using precursors. These precursors are found by observing dynamic variations in the phenomena. In order to analyse the behaviour of a phenomena over time, it is implied that the phenomena involved is known, understood, and that there exist some sort of data to build the analysis on. Hence, dragon-kings concern the 'known knowns', events that we know could occur, where there is available historical data to support the assumptions made.

3. A structure for improved understanding of the differences and similarities between the various metaphors

Similarities and differences between the metaphors are discussed in relation to two of the most central aspects of rare, surprising and extreme events: knowledge and predictability. A general overview of the main differences and similarities are highlighted in Table 5 below.

Table 5: Overview of metaphor characteristics for black swans (BS), grey swans (GS), perfect storms (PS) and dragon-kings (DK)

	BS	**GS**	**PS**	**DK**
Knowledge				
Known/unknown (Categories within the taxonomy that are related to the metaphors)	**Unknown unknown** **Unknown known** **Known known**	**Known unknown** **Known known**	**Known known**	**Known known**
Available data/theory (The existence of historical data, observations and scientific theories)	**No/yes** Data/theory may be available, but reliability is limited	**No/yes** Data/theory may be available, but reliability is limited	**No/yes** Reliable data/theory on each individual event is available, data/theory on the concurrence could be limited	**No/yes** Reliable data/theory on the system is available, data/theory on each individual event could be limited

Understanding of phenomena (Inter alia knowledge on the underlying mechanisms causing the extreme events, triggering factors and the interplay between system components)	**Weak/medium** Underlying mechanisms of events are undisclosed, but may be attainable by applying available data/theory	**Weak/medium** Underlying mechanisms of events are undisclosed, but may be attainable by applying available data/theory	**Medium/strong** We have strong knowledge of the mechanisms and behaviour for each contributing event. Knowledge on the concurrence may be weaker	**Medium/strong** Knowledge on the mechanisms and behaviour of the system as a whole may be strong, but could be influenced by a weaker knowledge on the mechanisms of each part
Knowledge base (The collection of knowledge on which risk assessments are based)	**Weak/medium**	**Weak/medium**	**Medium/strong**	**Medium/strong**
Predictability				
Prediction methods (Methods used to disclose the development of extreme events)	**Signals and warnings**	**Signals and warnings**	**Signals and warnings, or probabilistic risk assessments**	**Signals and warnings, or probabilistic risk assessments**
Prediction accuracy (The degree to which the prediction models reflect the actual state of the world)	**Low/medium** Predictions are based on subjective judgements and limited amounts of data/theory	**Low/medium** Predictions are based on subjective judgements and limited amounts of data/theory	**Medium/high** Predictions on each individual factor is based on reliable data and theories, and can be modelled with large accuracy. For the confluence, the prediction models may rely on a weaker knowledge base, depending on the existence of relevant data/theory for the interplay	**Medium/high** Predictions are based on large amounts of relevant and reliable data/theory for the concurrence, but the accuracy of the prediction models may be influenced by a weaker knowledge base on the contributing factors

3.1 Knowledge

Knowledge can be interpreted as "justified beliefs" (SRA, 2015), and constitutes an essential element in the understanding of, and distinguishing between, metaphors for rare, surprising and extreme events. All risk assessments are contingent on some background knowledge, covering "inter alia assumptions and presuppositions, historical system performance data and knowledge about the phenomena involved" (Flage & Aven, 2009, p. 11). Knowledge captures some important aspects of rare, surprising and extreme events: whose knowledge we are talking about (what is known by person X may not be known by person Y) and at what time (what is unknown today, may be known tomorrow) (Aven, 2014, p. 16). Another dimension of knowledge is the strength (or weakness), which is determined by factors such as availability of relevant data, degree of understanding of the phenomena involved and the existence of accurate models (Aven, 2014, p. 103).

When referring to black swans as 'unknown unknowns', they represent a "lack of fundamental knowledge (…), where not only the distribution of a parameter is unknown, but in the extreme, the very existence of the phenomenon itself" (Paté-Cornell, 2012, p. 1824). However, as argued in Section 2, other interpretations can be justified (represented as black swans of type b) 'unknown knowns' and c) 'known knowns'), where the knowledge exists, but we either fail to attain it (as in the case of the former), or our "justified beliefs" turn out to be false (as in case of the latter). While the 'unknown knowns' are first and foremost related to black swans, the category of 'known knowns' can be used for all of the four metaphors. Initially, this may seem like a uniting feature, but at closer eye, large variations in knowledge can be found within this single category.

The grey swan is, by several definitions, referred to as a 'known unknown'. Consider the development of vaccines as an example. Based on similar situations concerning the development of new drugs/vaccines, there is strong knowledge that a novel vaccine could have some type of side effect. However, in the early phase of development, we cannot know what these side effects are, or when they will occur. In this sense, we can talk about a 'known unknown': we have justified beliefs that the vaccine will carry some side effects (known), but we cannot say in advance what these side effects will be and when they will occur (unknown).

The generating mechanisms for black and grey swans are not clearly specified in any of the definitions from Section 2. The interpretations of these metaphors are first and foremost centred around characteristics that relate to our knowledge of their occurrence. Ricci and Sheng state that "Black Swans are observed and obtain from an undisclosed underlying physical mechanism" (Ricci & Sheng, 2017, p. 7). The unknown mechanism of these events is part of the "lack of fundamental knowledge" (Paté-Cornell, 2012, p. 1824) associated with black swans. In fact, it is this very lack of knowledge that gives rise to them; "Surprising extreme events may occur as we do not fully understand what is going on" (Aven, 2013, p. 46).

Recall the definition of a black swan by Aven (2013) as "a surprising event relative to our present knowledge/beliefs" (Aven, 2013, p. 49). Regardless of whether an event is driven by complex or simple mechanisms, we may experience black swans because our knowledge is poor, we do not have a thorough understanding of the system and its behaviour and consequently, surprises may occur relative to our beliefs. Nevertheless, there exists a link between the swan metaphors and complex mechanisms; for risk problems characterised by large (deep) uncertainties, as in the case of black and grey swans, complexity could be a contributing factor as "uncertainty may results from an incomplete or inadequate reduction of complexity" (Aven & Renn, 2010, p. 12).

When it comes to the second group, constituting the perfect storm and dragon-king metaphors, the focus shifts towards system complexity and interactions. The distinction between a 'known known' perfect storm and a 'known known' dragon-king lies within the understanding of the system as a whole.

The perfect storm is used to describe situations where we have several (well-known) phenomena occurring together, creating a (less known) interplay. Hence, we have strong knowledge about how the separate parts of the system behave - the knowledge about how this interplay affects the total may vary. For dragon-kings, however, we can rely on large amounts of data on the performance/behaviour of the system as a whole. The distinction touches upon an important idea in the theory of complex systems: a system is more than the sum of its parts. In order to illustrate the difference: consider a stock market. In a perfect storm situation, we have knowledge of the different factors that influence the behaviour of the stock market, such as politics, unemployment and inflation. We can use this knowledge to make some judgements about how the stock market will behave, but these judgements are only based on what we know about each factor separately. Hence, behaviour that emerges from the interaction of these factors may be subject to weak knowledge. When referring to the dragon-king metaphor, on the other hand, we approach the problem from a different angle; the starting point is our knowledge about the behaviour of the stock market, and we may use this information in an attempt to attain knowledge on how the contributing factors influence the system. Hence, we may have data on the behaviour of the system as a whole, but we do not necessarily understand how the different factors contribute to the behaviour of the system, or their interrelations.

For perfect storms and dragon-kings, the focus is mainly on the mechanisms that cause events to cascade into extreme events. As seen from the definitions in Section 2, perfect storms are often referred to as a confluence of events, whose interplay amplifies the effects and causes a disastrous outcome. Dragon-kings are related to a similar interaction, where the behaviour of the system is shaped by "positive feedback mechanisms that lead to faster-than-exponential unsustainable growth regime" (Sornette, 2009, p. 8). Both metaphors are associated with scenarios where we face a number of different elements whose synergistic effects shape the behaviour of the system as a whole.

The perfect storm is focused on the mechanisms leading up to the conjunction, at which point the system causes mechanisms that we may have weaker knowledge about. Consider, for example, the Fukushima nuclear accident. In March 2011, an earthquake struck the north-eastern coast of Japan, creating a massive tsunami. The Fukushima Nuclear Power Plant was flooded, resulting in the meltdown of three reactors, and causing major release of radiation. The event was not unforeseen, but the probability was judged as negligible, and so the government and the operator of the nuclear power plant "were reluctant to invest time, effort and money in protecting against a natural disaster which was considered unlikely" (Aven, 2014, p. 8). Both the initial earthquake and the following tsunami were phenomena known to occur, and the plant had been designed to withstand the impact of such events. However, assessors had not considered how the concurrence of these events could amplify the consequences, and the designed solutions and emergency response strategies were not adapted to the catastrophic interplay that arose from the concurrence (WNA, 2018). Hence, the plant was to some extent prepared to handle the mechanisms of each event separately, but failed to handle the mechanisms that emerged when the earthquake and the tsunami occurred adjacently.

The mechanisms of dragon-kings are extended to include the system behaviour beyond the confluence; the growth caused by positive feedback mechanisms will lead to a maturation of the system, in which a tipping point is reached and the system will change regime (e.g. the bursting of financial bubbles, transition from liquid to vapor or the birth of a child) (Sornette &

Ouillon, 2012). By monitoring the mechanisms of the phenomena over time, important knowledge can be attained on the system behaviour. This knowledge may be used to identify useful precursors that could provide information on when and how the instability in the system will occur and, furthermore, how to prevent it. The financial drawdown of 2007 cascaded into a global economic recession due to the "transient bursts of dependence between successive large losses" (Sornette, 2009, p. 7). These dependencies caused the financial system to follow complex mechanisms of positive feedback and amplifications, all of which could be observed in real time by modelling the large amounts of data available. However, at that time, the observed financial growth was thought to be sustainable, and these mechanisms were not recognized as paths to financial instability. The generating mechanisms of the event were not sufficiently understood, and crucial information contained in the behaviour of the system was left undisclosed (Sornette & Woodard, 2010). This example illustrates how our lack of knowledge on the contributing factors influences our understanding of the system as a whole.

Dragon-kings often represent the situations where we can rely on large amounts of data, which can be used to decipher the phenomena. One of the main characteristics of these events is the slow maturation towards instability, where dependencies have an amplifying effect and cause the system or event to take off into an unsustainable growth. Hence, in order to identify these events, we need to understand the existing dependencies and how they influence the system, as well as when the unsustainable growth causes the system to reach its maturation point, and the crisis occurs. Such an understanding may be unattainable for some cases of rare, surprising and extreme events where the phenomena are not understood to this extent. Let us again consider the September 11th terrorist attacks. Surely, there existed knowledge on the development of Islamic extremism, the formation of terrorist groups and the increasing enmity between Western society and parts of the Muslim world. However, the development of radical Islamism is a synthesis of factors, ranging from social and behavioural phenomena, to foreign policies and the expanding role of the internet (Ranstorp, 2010). Furthermore, Ranstorp states that

> "Understanding the processes of radicalization and recruitment is a complex task as there are no single causes or mechanisms that are transferable from case-to-case. Rather it is the complex interplay between these factors being played out simultaneously across the global and local levels and across different geographic contexts down to the individual level." (Ranstorp, 2010, p. 3)

For such scenarios, we neither possess the sufficient knowledge and understanding of the system/phenomena, nor can we rely on large amounts of relevant data to use in our modelling.

Disclosing the mechanisms that give rise to rare, surprising and extreme events may contribute to enhancing our understanding of what triggers the formation of these events, enabling us "to learn about the mechanism that causes the extremes by examining the states that precede the extreme events" (Farazmand & Sapsis, 2019, p. 8). However, as the knowledge base for the metaphors ranges from weak to strong, the path to obtaining this knowledge differs. For systems that are subject to large amounts of reliable data, disclosing the underlying mechanisms is considerably more tractable than for systems associated with scarce and unreliable data.

3.2 Predictability

In discussions of rare, surprising and extreme events, the predictability feature is given much attention. So also when it comes to the metaphors used to describe these events. The focus is partly directed towards the importance of prediction as a tool for managing the risk of such scenarios, but the feature is also frequently used to distinguish the different metaphors (e.g.

black swans from dragon-kings (Sornette, 2009) or grey swans from black swans (Masys, 2012)).

Although several of the metaphors discussed in this article have been characterised as unpredictable (from the definitions in Section 2), the theoretical potential for predictability exists in all metaphors. However, the methods of prediction will vary, as they are conditioned on the model accuracy, uncertainty representation and knowledge of the phenomena in question. Similarly, the strength and accuracy of these predictions will depend on the same factors.

The issue of prediction is linked to the knowledge dimension, as "accurate predictions require detailed knowledge of the present state of the system, which is usually unavailable. The partial knowledge of the current state together with the chaotic nature of the system leads to uncertainty in the future predictions." (Farazmand & Sapsis, 2019, p. 1).

Black swans are often associated with risk problems categorized by large/deep uncertainties. For such scenarios, "an essential feature is the lack of justifiable prediction models." (Aven, 2014, p. 149). However, black swans can also occur in situations characterised by moderate uncertainties, in which "some dominating explanations and beliefs exist, but the knowledge base is considerably weaker than the category of small uncertainties" (Aven, 2014, p. 162). In either case, we cannot ensure accurate predictions , as the judgements need to be based on a number of assumptions and hypotheses. The inherent uncertainty of black swan events has led to the presumption that black swans are prospectively unpredictable. This view has been challenged by several authors, including Paté-Cornell (2012), Aven (2013, 2014) and Lindaas and Pettersen (2016), arguing that these events can be predicted using signals and warnings: "Obviously, the truly unimaginable cannot be envisioned upfront, but signals (for instance, medical alerts that a new virus has appeared, or new intelligence information) can be observed, suddenly or gradually" (Paté-Cornell, 2012, p. 1825). Precursor signals and warnings can be used as a form of dynamical risk assessment, where information, observations and knowledge of the system is attained, processed and reimplemented. In this way, the prediction model is subject to a continuous improvement process, ensuring that the assumptions and theory that the model is built on corresponds to the system behaviour (Aven, 2014). Furthermore, the process of scientific research may contribute to disclosing important information related to the occurrence of these events. For example, we may discover a new virus through medical research, despite there being no precursor signals or warnings of such a virus.

Lindaas and Pettersen (2016) refer to the process of predicting black swans as "de-blackening" them, and present two strategies for this purpose: the epistemological approach, where black swans are de-blackened by transferring knowledge from those who know to those who do not know. The second strategy, called "imaginative de-blackening", involves "transforming tacit knowledge – in a loose sense of the word – into explicit knowledge" (Lindaas & Pettersen, 2016, p. 1238). For both strategies, communication plays an important part: "In an epistemic perspective, communication ensures the transference of knowledge; from an imaginative perspective, communication ensures the elicitation of ideas" (Lindaas & Pettersen, 2016, p. 1239).

The predictability of grey swans is, unlike that of its black cousin, a less disputed topic. As seen from the definitions in Section 2.2, this feature is a recurring characteristic in the interpretations of grey swans, and often used to distinguish between grey swans and black swans (implicitly or explicitly interpreting black swans as unpredictable). However, as we have argued above, black swans are theoretically predictable, although the methods and accuracy of the predictions will depend on which type of black swan we are dealing with. For black swans of type c), as well for grey swans, the event has been identified in the risk assessment and hence, we have a stronger foundation of knowledge supporting our predictions; we have a justified belief that this event could occur. Black swans can, however, also be categorized as 'unknown unknowns' and 'unknown knowns' (referred to as type a) and b) in Section 2.1), in which cases the events have not been identified in the risk assessment, and thus, the methods and accuracy of predictions are reflected by this.

From the definition by Taleb (2007), grey swans are referred to as "somewhat predictable, particularly to those who (…) have the tools to understand them" (Taleb, 2007, p. 37). This captures an essential aspect of prediction, not only for grey swans, but for all of the metaphors in this article: the predictability of events needs to be seen in relation to the tools we apply to predict them.

For the perfect storm metaphor, the predictability becomes distinctively twofold. When assessing each contributing event separately, we find ourselves in a situation where "the variation in the phenomena is known and we face risk problems where the uncertainties as small, the knowledge base is strong and accurate predictions can be made" (Aven, 2014, p. 122). When predicting aspects of the phenomena that concern the effects of the confluence, however, we may have weaker knowledge to found our assumptions on, and the methods of prediction need to be adapted accordingly. Consider, for example, the origin of the metaphor: The category 1 hurricane that hit the coast of North-America in 1991. The event consisted of three separate weather systems, each of which were known to occur regularly. Meteorologists were able to use precise probabilities to predict the behaviour of these phenomena accurately. However, when the separate weather systems merged to form what was later known as 'the perfect storm', meteorologists could not necessarily rely on similar situations, as the combination of these events was rare. Depending on the scientific strength of knowledge on this concurrence, accurate predictions of the storm could be made.

A recurring issue when discussing the predictability of rare, surprising and extreme events, is the limitations of using historical data to predict the future; or what Sornette refers to as "the ubiquitous tendency to extrapolate new behaviour from past ones" (Sornette, 2009, p. 12). In fact, this argument forms the basis for his assertion of the inherent unpredictability of Taleb's swans: we cannot predict these events, because our predictions will be founded on the assumption that the events will behave in the same way as previous observations. However, what Sornette refers to as prediction by "the extrapolation of the power law distributions in their tail" (Sornette, 2009, p. 5), essentially means attempting to predict black swans based on probabilistic risk assessments. We share his scepticism towards this approach, which is why we argue that the prediction of black and grey swans needs to be founded on approaches that better highlight the dimension of knowledge, such as using signals and warnings, and adaptive risk analysis (Aven, 2014).

One of the challenges faced by risk assessors today, is the increasing complexity of modern society and what Masys et al. (2016) call the "engines of civilization", meaning

> "an intricate framework of diverse networks (…), which are all built up of many (relatively) simple components (agents such as humans, power stations, businesses, airports etc.) that interact with each other leading to patterns of interaction exhibiting extreme (unlimited) complexity and potentially resulting in emergent forms of behavior that are difficult (if not impossible) to predict." (Masys et al., 2016, p. 134)

When discussing the predictability of dragon-kings, it is with regards to the idea that "there may be a set of basic universal rules (generic organising principles) that would allow one to predict the emergent behavior in a complex network" (Masys et al., 2016, p. 135). The predictability of dragon-kings is associated with the identification of precursor signals and warnings, which can be obtained by understanding and monitoring these distinctive generating mechanisms. Hence, though Sornette states that dragon-kings "may be forecasted probabilistically" in terms of simulation and modelling of the events, the use of signals and warnings represent an extended approach, much like the that of black swans, grey swans and perfect storms.

It needs to be addressed that the simulation and modelling used to predict dragon-kings is also associated with uncertainty. It has been argued that "simulations may be questioned in terms of their representation, the rules encoded in the representation, and the data used for calibration and initial conditions" (Johnson, 2006, p. 37). This is also known as the "can you trust it?"-problem (Casti, 1997), which highlights some of the challenges faced when using simulation and modelling to predict the behaviour of complex systems, such as poor data, poor use of data and misinterpretation of results (Johnson, 2006).

4. Discussion

Metaphors have a powerful impact on the way we communicate and perceive a concept, as mentioned in the introduction. Black swans, grey swans, perfect storms and dragon-kings have become well-known terms in the risk literature, and represent important contributions to the understanding and communication of rare, surprising and extreme events.

An important element in the understanding of these concepts, is acknowledging that the characteristics of the metaphors need to be seen in relation to the current approaches we are applying to manage them. An event is not unpredictable per se, though it may be unpredictable using the risk assessment tools at hand. This acknowledgement triggers some central features within risk management: responsibility and accountability. These are terms that often arise when discussing the metaphors in the present article, but what do they actually mean in this context? Sornette and Ouillon (2012) state that "in a world where catastrophes (…) are pure surprises, no one can be responsible" (Sornette & Ouillon, 2012, p. 2). Catanach Jr. and Ragatz (2010) pose the rhetorical question: "if the event could not be predicted, or its causes were so unique, then how could anyone be held accountable for contributing to its occurrence?" (Catanach Jr. & Ragatz, 2010, p. 20). However, we cannot (and should not) dismiss responsibility and accountability on these grounds, as the surprise dimension, as well as the predictability feature, need to be seen in relation to knowledge: a surprise occurs relative to some expectation of what is to come, and these expectations are built on our knowledge at the time. Accuracy of predictions depend on the knowledge base. Whether we are dealing with an 'unknown unknown' black swan, or a 'known known' dragon-king, we have a specific foundation of knowledge on the phenomena, and the tools and strategies that we apply to manage the events should reflect this. We argue that responsibility and accountability are related to the ability to take the knowledge dimension into account when assessing and managing the risk of rare, surprising and extreme events: risk assessors are responsible for ensuring that the risk assessment techniques are performed in such a way that the knowledge and surprise dimensions have been sufficiently highlighted. We need to acknowledge that the predictability and knowability of events are properties that first and foremost depend on the limitations (or strengths) of the risk assessors. Furthermore, in what is referred to as managerial review and judgement, decision-makers are accountable for taking these limitations into account, along with considerations on other aspects that may not have been captured in the assessment (such as political, strategic and ethical concerns) (Aven, 2014). Based on this reasoning, the claim that events reflected by the black swan metaphor are merely an "act of God", for which no one can be held responsible or accountable, does not hold; lack of knowledge does not imply a lack of responsibility and accountability. Rather, it emphasizes the need for suitable approaches to address this lack of knowledge in risk assessment and decision-making.

Let us consider the September 11th terrorist attacks as an example. As argued in Section 3.1, the complex causality of this event makes it a challenging task to disclose its underlying mechanisms. The scenario is characterised by a weak knowledge, as data is scarce and unreliable, and a large part of the system's mechanisms are not well understood. Taleb (2007) states the following regarding the terrorist attacks: "had the risk been reasonably *conceivable* on September 10, it would not have happened" (Taleb, 2007, p. x). In our view, the risk was *conceivable* but failed to be *conceived*, and here lies the essence of responsibility and accountability: there exists a gap between the conceivable and the conceived, and this gap may be closed by applying tools and strategies that support the continuous enhancement of knowledge. By strengthening our knowledge, focusing on transferring and spreading information, questioning key assumptions and presuppositions, rigorously searching for new knowledge and counteracting our "optimistic illusions about the future that prevent us from envisioning looming catastrophes" (Bazerman & Watkins, 2005, p. 374), we may prevent these events from occurring. In the case of September 11th, the knowledge of a possible attack using airplanes as missiles existed, but a number of crucial assumptions were left unchallenged (e.g. that the largest threat towards aircraft security was the use of explosives, that terrorists were mainly concerned with negotiating the release of captive extremists, and suicide attacks would serve limited potential for this purpose, that it was most likely that future terrorist attacks would have similar methods and magnitudes as previous attacks) (National Commission on Terrorist Attacks upon the United States, 2004). These were assumptions that, had they been confronted, could have been modified and corrected by obtaining available intelligence information. Furthermore, there was a failure to transfer knowledge to central decision-makers:

> "At an organizational level, the 9/11 Commission Report documents that while the FAA [Federal Airline Administration] had a 40-person intelligence staff, [the] Administrator (…) and her deputy did not regularly review intelligence briefings, nor were they aware of the great amount of information on hijacking threats that existed within their own agency." (Bazerman & Watkins, 2005, p. 370)

The terrorist attack on September 11th came as a surprise relative to what was believed or known at the time; it was a black swan. However, no one seemed able to "connect the dots", and so the terrorists were able to carry out the most lethal terrorist attack ever experienced on US territory. The event was *conceivable*, in the sense that signals and warnings existed; they had even been clearly communicated to government officials (Bazerman & Watkins, 2005). Nevertheless, the event was not *conceived*, as decision-makers did not respond adequately to these signals and warnings, nor was necessary action taken to attain new knowledge that could have provided essential information for preventing the event from occurring.

The distinction between "conceivable" and "conceived" captures the essence of our statement in the beginning of this section; We need to understand the characteristics of the events in relation to how they are managed. The September 11th events were not conceivable using the approaches that were actually taken, but that does not make the event inconceivable per se; had the adequate tools and strategies been applied prior to the event, it could have been conceived. The same distinction needs to be emphasized for other words frequently used to describe the metaphors in this article (unpredictable vs. unpredicted, unknowable vs. unknown, unforeseeable vs. unforeseen). Interpreting the metaphors as unpredictable, unknowable or unforeseeable not only removes much of the relevance these metaphors have for risk management (if an event is not only unknown, but unknowable, is it even relevant to discuss this event from a risk perspective?), it also indicates that responsibility and accountability for these events does not exist: the events are essentially impossible to manage. Furthermore, it represents an inconsistency: by interpreting an event as inherently unknowable or unpredictable, predictability and knowability are seen to be objective properties of the event. However, as we have shown, the metaphors and their predictability are related to knowledge, and knowledge is not objective.

5. Conclusions

The metaphors presented in this article are commonly referred to when discussing rare, surprising and extreme events. Comparisons of the different metaphors are frequently made in scientific literature (Ale et al., 2020; Catanach Jr. & Ragatz, 2010; Faggini et al., 2019; Janczura & Weron, 2012; Masys et al., 2016; Sornette, 2009). However, the present use of the metaphors appears somewhat unsystematic, as the metaphors are subject to different interpretations and definitions, and their meaning and relationship has not been sufficiently clarified. To enhance our understanding of the main characteristics of the metaphors, we have reviewed and discussed a selection of interpretations and definitions. Based on this, we have created a structure in which we present some of the similarities and differences between the metaphors, centred around the knowledge and predictability features. We have shown that all events reflected by these metaphors are theoretically predictable and knowable.

Several authors have explored the meaning of the black swan metaphor in a risk context (Aven, 2013, 2014, 2015; Aven & Krohn, 2014; Lindaas & Pettersen, 2016; Paté-Cornell, 2012). These efforts have contributed to relating the concept to general frameworks of risk assessment and risk management. We argue that the black swan should be seen as a surprising, extreme event relative to the present beliefs/knowledge (Aven, 2013), emphasizing that 'the present beliefs/knowledge' is that of the person(s) being surprised. Hence the question of whether the event is a black swan or not is in the eyes of the beholder. This interpretation is in line with the views of Taleb (2007) as well as the historical context of the concept. In line with the definition by Aven (2013), we may distinguish between three types of black swan, as presented in Section 2.1; 'unknown unknowns', 'unknown knowns' and a subset of 'known knowns'. When it comes to the term 'surprise', it clearly applies to 'unknown knowns' and 'known knowns', but is less obvious for 'unknown unknowns', as there may not exist a prior expectation for such events. However, when referring to a black swans as 'a surprising, extreme event relative to the present beliefs/knowledge', we include per definition also 'unknown unknowns'. See discussion on black swans in relation to surprises in Aven (2014).

The history of the black swan metaphor not only provides a fascinating anecdote, it places the meaning of the concept in a broader perspective. The grey swan cannot be placed in a similar context; the grey swan per se does not represent something rare or extreme. The interpretation of grey swan events as rare, surprising and extreme is not meaningful unless they are seen in relation to the black swan concept. Furthermore, the grey swan metaphor is based on the notion that black swans are 'unknown unknowns', i.e. unpredictable, unknowable events. However, we have shown that limiting black swans to this category alone is not consistent with the meaning of the black swan metaphor in a risk context; black swan events can be considered predictable and knowable in theory. A closer look at the September 11th events leads us to conclude that the black swan metaphor also reflects events belonging to the categories 'unknown knowns' and 'known knowns', in line with Aven (2014).

As there exists no metaphorical interpretation of the grey swan, we should avoid using this term as a metaphor. Grey swan events are covered by our recommended definition of black swans.

Connecting grey swans to 'known unknowns' does not justify the use of the metaphor as a distinct genus of swans. For example, we may discuss to what extent a 'known unknown' can be considered a surprise. Referring to the example of vaccines in Section 3.1; if we know that there will be a side effect, but we cannot say in what form, can it be termed a surprise when a side effect occurs? On the other hand, if we know that an event could occur, but not when and in what form, it could be termed an "anticipated surprise", in line with Gross (2010). Furthermore, events can be interpreted differently (e.g. the side effects of a vaccine can also be interpreted as an 'unknown unknown'; it was completely unknown that such a side effect would occur at that particular time or in that specific form), and the 'known' and 'unknown' in the expression may be subject to different interpretations, as mentioned in Section 2.2. We do not put forward these issues in an attempt to solve them, but rather to highlight the complexity related to the known/unknown taxonomy and its application for rare, surprising and extreme events.

Like the black swan, the origin of the perfect storm metaphor can be placed in a historical context. The metaphor was coined by Junger (1997) to describe the category 1 hurricane that struck the east-coast of North America in 1991. We argue that the definition of the metaphor should reflect the characteristics of the original event, which was a rare conjunction of well-known phenomena whose interplay had an amplifying effect, resulting in an extreme event.

Can a perfect storm be classified as a black swan? As discussed in Aven (2015), the answer depends on the perspective taken and how we more specifically interpret the perfect storm metaphor. If we have a situation with perfect knowledge about the variation of all the phenomena considered, the event should not come as a surprise. It is rare, but we know that the event will occur sooner or later. However, it is also possible to argue differently. With strong knowledge about the variation in all the phenomena considered, the event is judged so unlikely to occur the next 100 years, say, that it is not believed to occur. Consequently it can be viewed as a black swan of type c) if it should in fact occur. The fact that there could be uncertainties related to the interplay of phenomena, supports this latter interpretation – there is an additional element of potential surprise. As commented above, we also need to be precise on who is potentially surprised. Take the original 'perfect storm' event. For the scientists, who had strong knowledge on the different weather systems that formed the concurrence, the event was, as the name implies, a perfect storm. The fishermen who were caught in the storm, however, did not have this strength of knowledge on the phenomena, and the event came as a surprise for them – a black swan.

The perfect storm metaphor is related to the dragon-king by their common, specified mechanisms of amplifying interactions between multiple factors, leading to an extreme event. We argue that perfect storms and dragon-kings represent different perspectives on these mechanisms, illustrated by the stock-market example from Section 3.1. The original definition of dragon-kings as "the existence of transient organization into extreme events that are statistically and mechanistically different from the rest of their smaller siblings" (Sornette, 2009, p. 1) is mainly a description of the specific mechanisms of these events. The dragon-king theory represents valuable insights to risk, but in order to clarify how this metaphor contributes to enhancing our understanding of extreme events, we need to provide a clear definition of what the dragon-king metaphor means in a risk context. We argue that a dragon-king should be seen as an extreme event resulting from emergent behaviour caused by the amplifying interplay of a confluence of uncertain factors. By this interpretation, dragon-kings are linked to perfect storms, as they describe similar phenomena. However, for perfect storms the contributing events are well-known, while for the dragon-kings, this may not be the case. Consider, for example, human birth, referred to as a dragon-king by Sornette (2009). We may observe the mechanisms of increasing contractions in the uterus, resulting in a phase transition where the birth of the baby represents a dragon-king. However, what exactly triggers the onset of labour is not known, though there exist several theories (Bovbjerg et al., 2014). Hence, it can be considered a dragon-king, as we have some knowledge on the system (the behaviour of the uterus), but we do not have strong knowledge on the contributing factors to this behaviour, as would be the case for the perfect storm.

A dragon-king can be considered a black swan (of type c)), as the event is known but there is a potential for surprises because of the uncertainties related to the emergent behaviour of the system.

Events can be characterised in different ways and may therefore also be described by different metaphors. The financial crisis of 2008 is an example. Which metaphor is used, depends on the perspective: The event can be seen as a result of emergent behaviour of the system (dragon-king) or as the result of the amplifying interactions between a confluence of events (perfect storm).

Based on the reflections above, we present our recommended definitions of the metaphors in table 6.

Although the perfect storm and dragon-king metaphors can be viewed as black swans, they are justified as independent metaphors. They draw attention to some specific types of situations, for which some aspects of the phenomena considered are well-understood whereas others are subject to rather weak knowledge. The metaphors can help us identify and highlight areas where the risks related to potential surprises are highest and thus, where focus on enhancing knowledge should be directed.

Table 6: Recommended definitions/interpretations of the metaphors, including examples

Metaphor	Recommended definition/interpretation	Example
Black swan	A surprising, extreme event relative to the present beliefs/knowledge (Aven, 2013, p. 49)	The September 11th terrorist attacks
Grey swan	Should not be used as a metaphor due to lack of metaphorical context	
Perfect storm	A rare confluence of well-known phenomena creating an amplifying interplay leading to an extreme event Can be viewed also as a black swan	The financial crisis of 2008
Dragon-king	An extreme event resulting from emergent behaviour caused by the amplifying interplay of a confluence of uncertain factors Can be viewed also as a black swan	The financial crisis of 2008

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