Title:

On the complexity of model complexity: viewpoints across the geosciences

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Abstract

It is the core task of geoscientists to gain insight into the complex systems of nature. Yet, complexity may be perceived very differently and a plethora of models with different degrees of complexity is available. How do we, geoscientists, decide what model complexity is warranted? Does this differ among disciplines? And, how do we even define model complexity? We developed a short questionnaire to investigate the geoscientific community's views on complexity in models. The response was overwhelming, with 618 completed responses. The results show that the number of processes explicitly included and the number of interactions / feedbacks incorporated were seen as important determinants of complexity. Confidence was not per se higher in the simulations of a complex model compared to a simple one. Interestingly, neither gender, the discipline within the geosciences, nor career stage or work sector, explained the characterization of model complexity. The results of the questionnaire demonstrate that there is no general consensus on how model complexity is perceived or should be defined, and that formal definitions are not broadly or generally accepted. In an environment seeking greater collaboration and interdisciplinarity, these results indicate the need for conscious dialogue about this topic among different model users.

Keywords: model complexity, geosciences, perception, questionnaire

1. Introduction

Nature is complex and if geoscientists are ever to understand its intricate feedbacks there is a need for increased collaboration across fields/disciplines of geosciences (Paola et al. 2006, Liu et al. 2007, Van der Ploeg et al. 2017). Unfortunately, that seems to be easier said than done for various reasons, including: 1) Interdisciplinary work is more difficult to fund (Bromham et al. 2016), 2) Different approaches exist to address complexity, reductionist and synthesist/hierarchical (Paola 2011, Kleinhans et al. 2005), the choice often driven by data availability (Grayson and Blöschl, 2000), 3) Scaling of environmental processes is possible only if they can be described by the same set of equations, which is often not the case (Roth, 2008, Van der Ploeg 2017), 4) Model selection may be driven by familiarity (Addor and Melsen, 2018). While these and multiple other factors make collaboration within and across disciplines challenging, it is our view that different approaches to addressing complexity, in addition to being a topic on its own, exacerbates the other challenges, and therefore is an important starting point in the quest for increased collaboration in geosciences.

Choices about the level of complexity are an inevitable part of the scientific realm, controlled by, among other things, funding and available time. While it is the core task of geoscientists to gain insight into this complex system, such differences may lead to problems when applying for funding, or working together on a research project, and may in essence hamper scientific progress to better understand nature.

Understanding nature often involves use of numerical models, ranging from simple linear equations to complicated frameworks of multiple models including feedbacks and emergent behaviour, crossing scales and disciplines. Frameworks for best practice in environmental model use exist (Jakeman et al., 2006), including a sceptical review of the model at every step of development and application. Given that all geoscientists study a complex system, the Earth, and different aspects of that complex system, it is not surprising that a plethora of models with different degrees of complexity exists. It is conceivable and understandable that different disciplines apply models for different applications or purposes (Desjardins et al., 2018), such as forecasting (e.g. Weerts et al., 2011), what-if scenario analysis (e.g. Panagos et al., 2015; Grum et al., 2017) or for improved process understanding (e.g. Paola and Leeder, 2011; Veldkamp et al., 2017), this can result in different perceptions of model complexity. However, in light of the need for increased collaboration, these differing perceptions of complexity raise a number of questions. How do we, geoscientists, make our decisions on what degree of model complexity is warranted or justified? Does this differ among disciplines? And, how do we even define model complexity? These questions, and more, need answers in order to understand current perspectives and develop approaches that allow for more interdisciplinary collaboration. Moreover, increased clarification and understanding of how current approaches differ, and the reasoning behind them, may further the ability of the geoscience community to address the complexity of nature.

Therefore we set out to learn how geoscientists, whose disciplines essentially describe the same part of the Earth system but who often choose different approaches to both measuring and modelling, view complexity in models. To do so we developed a short questionnaire which was distributed through social media and geoscientific mailing lists. Our starting hypothesis was that perceptions regarding model complexity would differ by discipline. The response was overwhelming, with 200 responses on the first day and more than 600 fully completed within one month. In addition, we received multiple responses from authors in various geoscience disciplines, who had published their viewpoint on complexity, further reflecting the relevance of this discussion. This paper presents our findings, starting with an overview of the various definitions of model complexity that we received and could find in the literature, and then reporting on the findings of the questionnaire. Discussion of the results is organized around two related questions: 1) Addressing complexity across the geoscience realm – what can we learn from each other? and 2) Which gaps - if any - need to be bridged to better address complexity and increase interdisciplinary collaboration?

2. Definitions of and dealing with model complexity

What became quickly evident when reviewing what we received in response to the questionnaire and found in the literature was that a multitude of definitions for and approaches to model complexity exist, within and between disciplines. As noted by Lloyd (2001) and Guthke (2017) a strict definition of model complexity does not exist. Therefore, this section does not aim to offer a complete overview of definitions across all disciplines of the geosciences. Rather, we present a variety of examples of how model complexity is viewed in this discipline of research, to set the stage for our study. Interestingly, in addition to the many existing definitions of model complexity, we noted many publications in which authors refer to model complexity without actually providing their definition for it. Perhaps authors assume their definition is the generally shared one. As the rest of this section will show, this assumption generally does not hold.

For ecological modelling purposes, García-Callejas and Araújo (2016) mention the, in their opinion, “loose definition” of model complexity, as: having to perform a larger number of operations to obtain the desired outcome for data that are more difficult to comprehend. Within the context of Earth observational networks Baatz et al. (2018) define it differently: inclusion of multiple disciplines (or processes) and ecosystem compartments may increase model complexity.

Within hydrology, model complexity is defined more than once in terms of process and spatial complexity (Seibert et al. 2019). Process complexity addresses the number of hydrological processes that the model explicitly represents. Spatial complexity addresses the degree of spatial discretization and connectivity (Clark et al., 2016), such as “spatially explicit models with different degrees of spatial discretization and connectivity, and spatially implicit lumped hydrologic models”. Shoups and Hopmans (2006) use slightly different wording and include temporal complexity; model complexity is defined by them in terms of: amount of relevant hydrological processes and the spatial and temporal discretization of a numerical simulation model.

In the context of pyrolysis Bal and Rein (2013) posit that an increase in complexity depends on inclusion of a higher number of mechanisms, resulting in a higher number of parameters on physical properties (effective properties), mathematical constants, experimental constants and calibration factors. In their view increasing complexity leads to increasing uncertainty. The appropriate level of complexity is a trade-off between reducing the error of prediction and the increase of uncertainty of the prediction. Nevertheless, choices in model complexity are often subjective.

Wainwright and Mulligan's book on Environmental Modelling (2013) define five types of model complexity, 1. Process complexity, 2. Spatial complexity, 3. Temporal complexity, 4. Process inclusivity, 5. Integration of feedback loops. In their view, an optimal model is one that contains enough complexity to explain observed phenomena or emergent behaviour.

Instead of defining model complexity directly, Larsen et al. (2016) focus on a clear definition of the detail that is needed to appropriately address complexity. They distinguish between representational detail - such as the number of state variables, processes, interactions, and spatiotemporal extent, and computational detail - such as spatiotemporal resolution, and mechanistic versus phenomenological description. Model complexity in this definition then refers to high computational detail. Along the same line of thought, Getz et al. (2018) present a complexity typology for ecological models, and categorize them according to three types of complexity: 1. Process complexity, which refers to the amount of detail for the (in)dependent variables, and includes transformations, deterministic vs stochastic processes and scale; 2. Structural complexity, referring to the amount of detail for the functions that describe the dependence of the independent variables on the dependent variables, and includes spatiotemporal patterns, feedback mechanisms, traits and hierarchy; and 3. Utility complexity, which refers to the purpose for which the model is going to be used, such as exploratory, management and/or fidelity. These three complexities then make up a 3D matrix in which models can be placed.

In addition to the definitions of complexity, ways to quantify the level of complexity have been proposed as well. Sivakumar and Singh (2012) demonstrate the correlation dimension method to identify the catchment system complexity for streamflow data. Snowling and Kramer (2001) present an index of complexity, in which the number of state variables, number of processes flowing to or from a state variable, the number of parameters, and the number of mathematical operations are used to rank the models relative to each other. Shoups et al. (2008) discuss model complexity control within the discipline of hydrology. Complexity control in general consists of 1. Specification of model structures with varying degree of complexity, and 2. A check on the ability of the specified models to echo observations. In their paper they describe a few complexity definitions, which can be tied to statistical theory. One of these is Aikaike's information criterion (Aikaike 1970), in which model complexity is defined as the number of parameters related to data availability. A disadvantage of this method is the underlying assumption of infinite observations. Another method that addresses this and works for finite observations is structural risk minimization proposed by Cherkassky and Mulier (2007). It includes the Vapnik-Chervonenkis dimension, which is related to a model's data fitting flexibility, as an expression of model complexity. So, even though definitions to quantify model complexity can be helpful in ranking models, the multitude of available ways to do this quantification still makes a comparison of complexities challenging.

If models are to be used for management or policy, a different way of addressing the needed level of complexity can be to involve stakeholders right from the start in a 'shared vision model.' This was done for regulation of flows and water levels in the Lake Ontario and the St.Lawrence River, USA/Canada (Pete Loucks, personal communication).

Interestingly, we did not find or receive any other references that dealt with defining complexity where stakeholders were involved.

It goes without saying that the multitude of definitions for and approaches to model complexity creates problems or at least challenges for scientists to collaborate or advance across or within geoscience disciplines. We also think that the efforts to clarify or propose new definitions and approaches to this topic, and the rapid and enthusiastic response to our questionnaire, indicate that this is a recognized challenge. The question is, how to move forward and accomplish the vision contained in the words of Grand (2000) in "Creation: Life and how to make it": Complexity is that which contains high information content with high utility, if it only contains high information content (or high amounts of involved processes) it is merely complicated.

3. Methods

3.1 Questionnaire

To assess the opinion of as many people as possible, both in and outside academia, we developed a short questionnaire using SurveyMonkey software. Based on expert recommendations, the questionnaire was kept short, i.e. possible to fill out within 5-10 minutes, in order to get many replies. The questionnaire was pilot-tested using a panel of 10 people from both within and outside our institute and ranging in age / career development stage. The main changes after testing included rephrasing of some of the questions to make them clearer / less ambiguous, changing the number of options to select from in answering the question from one to multiple options (e.g. for field of work), addition of answer options that were suggested by the test panel and adding the opportunity to give additional comments at the end of the questionnaire. It was then launched in mid-October 2018 to personal contacts and science networks using email lists of the community that were known to us, such as 'geomorph-list', Gilbert Club mailing list, About Hydrology list (see reference section for links to these lists), and through social media (twitter, LinkedIn). The questionnaire was closed after almost one month on 12 November 2018.

The complete questionnaire can be seen in the supplementary material. It was split into two parts, one with background questions and one with questions related to people's opinion on model complexity. Questions in part one were related to work sector (i.e. academia, public sector, private sector), career stage (from (under)graduate student/intern to company owner/emeritus professor), primary field of work/discipline (e.g. hydrology, soil science, geomorphology etc.), age class and gender. Questions in the second part related to (i) the use of models, (ii) opinions on what models are or can / should do, (iii) how people characterise complexity in models, (iv) the relation between model complexity and uncertainty, (v) factors that impact the decision to use a simpler/more complex model and (vi) opinions on how to use model complexity and factors that warrant using (more) complex models. Questions were designed as 5-point Likert scale questions (5 scales from strongly disagree to strongly agree), questions for which only one answer could be chosen and questions where multiple answers could be selected. For details, see the complete questionnaire in the supplementary material.

3.2 Data analysis

A total of 682 responses to the questionnaire was collected. Out of these 682, 618 respondents filled out the complete questionnaire. Since all questions were compulsory to fill out in order to continue to the next question, incomplete responses indicated respondents that had quit the questionnaire at some point. For consistency, we only used the 618 complete questionnaire results for the analysis; the 64 incomplete responses were omitted.

The SurveyMonkey webtool provided the questionnaire results both in Excel format and in CSV format. The data from the complete sample of respondents was analyzed using Excel (discussed in Results Section 4.1). Analysis of the responses of different sub-groups of the sample was conducted using R version 3.4.3 (R Core Team, 2013; discussed in Results Section 4.2). Responses to questions were split into groups based on responses to other questions. For example, the responses to the question 'How would you characterize complexity?' were split based on the discipline of the respondent. If respondents had filled out more than one option - for example, two disciplines such as hydrology and soil science - their response is accounted for in the sub-groups of both disciplines.

A total of 47 different combinations of groups and answers were assessed, representing all sensible combinations of general questions and model complexity questions. For each combination, bar plots were created, which were visually inspected to identify patterns in the response. If any patterns were identified, the relationship was statistically tested with the Chi-squared Test of Independence. This test was chosen because it is non-parametric and can be applied to categorical (nominal) data. The obtained p-values have been interpreted in line with the most recent guidelines in statistics as discussed in Wasserstein et al. (2019) and are reported with the results. We therefore refrain from any further reporting on whether relations are 'significant'.

4. Results

4.1 Questionnaire results

4.1.1 Background questions

The majority of the respondents work in research, either in academia (67%) or in the public sector at a research institute (19%), while almost 6% work in consultancy. Over 60% of the respondents were rather young (25-34 and 35-44 years old) and two-thirds (69%) were male versus 29% female. The career stage of the respondents corresponded with their relatively young age, with over half being graduate (MSc and PhD) students and post-docs in academia. None the less, senior researchers and assistant and associate professors together made up 25% of the respondents. Outside academia, respondents were mainly mid-career (31%) and senior (32%) researchers/consultants, with a fair representation of juniors (19%).

Regarding field of work, respondents were allowed to select multiple answers. More than half of the respondents (54%) did so, indicating that they do not relate their work strictly to one discipline. Where only one answer was given, most people worked in hydrology, followed by geomorphology, soil science and environmental sciences (Fig. 1, dark coloured part of the bars). The light coloured part of the bar in Fig. 1 indicates the total number of respondents who selected that field of work in combination with any other.

>> Fig. 1 approximately here

In terms of model use, the majority of respondents work with models daily or weekly (27 and 35% respectively), while 20% use a model regularly (e.g. once a month on average). Respondents use models in various ways. Application of existing models was the most common use, with the purpose of investigating processes and their outcomes being the most frequently selected reason. Application of models for scenario analysis was the next most selected purpose. Model application to support policy and management was the least selected although still 32% of the respondents use models for this purpose.

Modellers' degree of (dis)agreement with a number of statements about model (use) in general (i.e. not yet about model complexity) are displayed in Fig. 2. Overall there was a tendency towards agreement with the statements. In line with the answers to the previous question on model use, respondents tended to (strongly) agree with the view that models are tools to investigate processes and their outcomes (95%; agree and strongly agree combined). There was also agreement on the view that models are exploratory tools (87.3%), with slightly less agreement (83.9%, agree and strongly agree combined) on the view that models are a set of theories / used for hypothesis-testing. The statement that models represent / predict reality was either not clear, or respondents did not have a strong opinion. Just over one third of the replies were neutral (34.9%), with slightly more in agreement (36%) and slightly less in disagreement (29.1%). A similar spread can be seen for the statement that models objectively represent our current state of knowledge. Strong agreement was expressed with the view that models support decision-making (85.6%, agree and strongly agree combined). More variation exists regarding the statement that models are useful when data is absent, with a small majority in agreement (49%, versus 27.1% disagreement). Most respondents (69.5%) agreed with the somewhat bold statement that 'all models are wrong, but some are useful' (a statement generally attributed to statistician George Box).

>> Fig. 2 approximately here

4.1.2 Model complexity questions

Modellers were asked how they would characterize complexity in a model, with multiple selection of options allowed (14 options were given, plus the option 'other, please specify'). Results are shown in Fig. 3. Clearly, the number of processes explicitly included and the number of interactions / feedbacks incorporated were seen as most relevant in terms of model complexity. A second group of answers selected relatively often was the representation of processes that act over multiple temporal or spatial scales, the number of input variables and the non-linearity of processes included. The length of the code, the ease of use of the model (e.g. GUI) and computer calculation time were not considered very important as characterising model complexity. Also, respondents did not think the data at one's disposal compared to the required data was important for model complexity. The most commonly mentioned factor by respondents (n=49, about 8%) that chose the "Other" option related to number of parameters.

>> Fig. 3 approximately here

Answers to the question of whether increasing model complexity results in increased or decreased uncertainty revealed a clear message: only 3% of the respondents thought uncertainty would decrease with increasing model complexity, and 15% thought it would increase. Also striking is the number of respondents who consider complexity and uncertainty to be unrelated (19%). The largest percentage of respondents, replied that ‘it depends’, either on the duration, frequency and quality of available observations / measurements (25%) or on the number of different variables and states that are observed / measured (19%). (Data presented in following section, Fig. 7)

The most important factor indicated for deciding whether to use a simple or more complex model was the research question at hand (Fig. 4). Secondly, the availability of input data was considered important, while the level of understanding of the system and the spatial and/or temporal scale at which the model would be applied were considered of less importance. In line with replies to the previous question, model runtime was not deemed very important at all, nor was the reputation of the model or the experience with the model in the respondent’s organisation.

>> Fig. 4 approximately here

Finally, the community’s opinions about how to deal with model complexity as represented by degree of (dis)agreement with seven statements, showed a high degree of agreement with two statements, agreement with two others and clear disagreement with the remaining three (Fig. 5). The greatest agreement (84% ‘strongly agree’ and ‘agree’ combined, and less than 5% disagreeing) was with the statement that explanation of rationale for model selection in reports would increase understanding of relevance and usability of results. This was closely followed by the degree of agreement that reduced complexity models can be as useful as complex models to increase our understanding of environmental processes (79% agreement, with a slightly larger number of respondents disagreeing). A majority agreed that discussion of model complexity should be a priority, with less than 10% disagreeing but a larger percentage of neutral replies. New observation techniques are seen as a justification to allow us to increase model complexity by more than 50% of respondents, while increased computer power was not seen as a good reason to do so by 50% of the respondents. The greatest amount of disagreement was with the statements that you can have more confidence in the simulations of a complex model as compared to a simple one (>60% disagree and <10% agree), and that models would be improved by making them more complex (95% disagree or neutral).

>> Fig. 5 approximately here

4.2 Data analysis results

In this section, we present the results from relating answers to the different questions to each other in order to explore which factors influence one’s characterization of model complexity.

4.2.1 Discipline

Our starting hypothesis was that the way model complexity is characterized can be related to the discipline of the modeller. Fig. 6 shows the response to complexity characterization, by research discipline. No clear pattern is revealed: The number of processes explicitly included in the model, and the number of feedbacks / interactions included are still the main characterization of complexity for the majority of the research disciplines. One exception is spatial planning, which places more value on “representation of processes over several scales” than “number of processes explicitly included”. Some other minor differences can be found, such as “calculation time” being slightly more important in meteorology compared to other disciplines, but here we have to note that not all disciplines were equally represented and meteorology was the most underrepresented discipline. Also the Chi-square test confirms that no clear relationship exists between discipline and the definition of complexity ($p=0.99$), although the test is slightly less robust due to the high number of dimensions involved (10 fields, 14 complexity-answers).

>> Fig. 6 approximately here

The results of the questionnaire therefore do not support our hypothesis. Also the response to the question of whether increased model complexity leads to increased or decreased model uncertainty, did not reveal clear patterns related to the discipline of the modeller, as can be seen in Fig. 7. There is a general agreement that model uncertainty does not decrease with increasing complexity. A relatively higher percentage of spatial planners believes that model uncertainty increases with increased complexity, whereas a relatively higher fraction of water quality modellers state that this depends on the variables and states of which observations are available. The Chi-square test confirms that no clear relationship exists between discipline and the perceived relation between model complexity and model uncertainty ($p=0.65$).

>> Fig. 7 approximately here

4.2.2 Other factors

Fig. 6 shows that the way one would characterize model complexity is not necessarily influenced by the discipline of the modeller, despite different disciplines having different model uses (spatial planners work on average more for policy support, and meteorologists do, on average, less with scenario-analysis). None of the other factors investigated (age, gender, career stage, work sector, model experience) showed distinct differences in how one would characterize model complexity, except for a few small points. For example, "Number of input variables" as characterization of model complexity decreases with increasing model experience, perhaps indicating that an experienced modeller knows how and where to collect the required input data and does not relate that to complexity of the model itself.

A general lack of clear patterns also holds true for the question: "Which of the following do you think most impact your decision to select/use a simpler or more complex model?", but we did observe one trend. Even though the Chi-square test indicates that no clear relationship exists between age and how to decide on warranted model complexity ($p=0.63$), some patterns are visible in individual answers. Whereas "The research question at hand" is by far the most selected answer among all groups, there was an interesting decline in selection of the options "Reputation of the model" and "Runtime" with increasing age. "Runtime" was selected by 9.3% of the respondents <25 years of age, 5.6% of the respondents between 25-34, between 2.0 and 2.7% for respondents in the age groups between 35 and 64, and 0% for respondents >64. Consistent with this finding, we also observe a decline in "calculation time" as characterization of complexity with increasing age (from 26.6% of the respondents below 25 years old selecting this option, to 5.3% of the respondents >64 selecting it). This suggests that, apparently, older modellers are less impatient for models to produce fast output and/or have a different reference as to what is fast or slow (e.g. compared to how long a model would run more than a decade ago).
"Reputation of the model" was selected by 7.0% of the respondents <25, between 2.9 and 4.0% for all respondents between 25 and 64, and 0% by respondents >64. Model reputation might be more important for younger researchers since they cannot rely on their own track record and publishing using a model with a good reputation is perhaps easier than publishing with an obscure or new model.

As shown in Fig. 7, the majority of the respondents do not believe that model uncertainty decreases with increased model complexity, irrespective of the discipline of the respondent. There is, however, a relation visible between frequency of model use, and the belief that model uncertainty will decrease with increasing complexity, which also seems to be confirmed by the statistical test (Chi-square p-value is 0.076, although some caution should be taken in interpreting this value given the low number of respondents with limited modelling experience). Whereas 40% of the respondents that have used a model once (n=5) selected 'decrease', this number declines with increasing model use frequency; 7% for people who use models rarely (n=17) to 2.7% for people using models daily (n=174). This response can thus be related to experience with modelling. Furthermore, and in line with the 'decrease'-answer, the 'decrease'-group agrees, compared to the other groups, more with the statement "I have more confidence in the simulations of a complex model compared to a simple model". Compared to the other groups, a larger portion of the 'decrease'-group agrees with the statement that "Increased computer power is a good reason to increase model complexity ". These results seem to imply that more experience with a model leads to more caution, or perhaps even suspicion, towards model complexity and increasing model complexity.

Given that this is a special issue on women in geoscience, we also investigated differences between men and women on the perception of model complexity. Only a few minor differences were found. On the question 'How would you characterize model complexity?', the number of processes and the number of feedbacks/interactions are the two most chosen characteristics for both genders. However, from the female respondents a slightly higher fraction selected 'feedbacks/interactions', while from the male respondents, a higher fraction selected 'processes'. Furthermore, scenario analysis and process investigation are the most frequent model uses for both genders. It should be noted however, that female respondents are underrepresented and that neither gender is equally distributed over career stage, discipline, and work sector, making it difficult to directly relate the described (minor) differences to gender alone. Generally, it can be concluded that gender does not influence characterization and perception of model complexity. Indeed, neuro-imaging of 1400 human brains revealed that male/female brain patterns cannot be distinguished from one another (Joel et al. 2015).

Summarizing, we find that the characterization of model complexity and the relation between model complexity and model uncertainty can to some extent be related more to model experience and age than to gender.

4.2.3 Additional comments from respondents

At the end of the questionnaire, respondents were given the opportunity to provide additional comments. Multiple people commented that, in many cases, their answer to many of the questions would be 'it depends', and feedback given on the questionnaire included that people expected a (clearer) definition of both 'a model' in general and 'model complexity' in particular to be given. Several comments included a phrased definition of complexity: Quite a number of people commented in several ways that data availability is a key point. For example, 'It doesn't matter that we can simulate all these complex, interacting processes if we don't have the data to parameterize the model'. Several comments related to model complexity mentioned that model parsimony is important and that a model should be as simple as possible, but not simpler. There were also multiple comments stating that increasing model complexity should only be done if it leads to improved results. A particular comment illustrating the 'it depends' position was 'the main point about model complexity is in the balance between the goal of the model (i.e., what answer at what scale is desired (specific case/generic) and what will be done with it (policy/decision support vs. testing proof of principle) and the uncertainty in data/knowledge available (can we provide input, assess sensitivity and uncertainty, do we have data to validate model(components)?)'.

Additional points of attention that were raised included: Open access to model code, that is needed to generalise models and to improve their code; that we did not include assessment of regional origin or cultural background / formation of modellers, which could well be a factor distinguishing differences in opinions on model complexity; the 'trilemma' of model choice: complexity versus precision versus communicability, which can be related to both the need for open access of code and the use of the model (outcomes), e.g. for policy making. A remark on simple versus complex models was that he/she thought that complex models are needed to build good simple models and that simple models often follow complex models, because simplification is only possible if you can say something about the effect of simplification.

5. Discussion

As already noted**,** contrary to our hypothesis - perceptions regarding model complexity differ between disciplines within geoscience - we found no differences between geoscience disciplines. It is important to note that our survey results indicate the questionnaire mainly reached academia, and thus we cannot tell how model complexity is perceived by other groups of stakeholders working with models. The responses show very heterogeneous perceptions of model complexity, and seem to be more individual than related to science discipline or modeller type. In our opinion, this is even more worrisome than a difference in perception between disciplines because individual scientists often work within the same discipline and may implicitly assume their definition of model complexity is everyone's definition. As an author team this is something we can attest to; despite having more or less similar backgrounds, during discussions we often had different ideas of some of the definitions discussed.

What we can learn from each other is that although many of us may tend to think there are huge differences in perception of model complexity across science disciplines, in reality a colleague in the same office may view model complexity differently compared to our own perception. This also relates to one of the critiques mentioned in the comments given at the end of the questionnaire - the lack of a given definition of model (use) and model complexity in the questionnaire. As noted, we deliberately did not include a definition of model complexity, because it was not our aim to focus or restrict ourselves to discussing a particular definition; rather, we wanted to investigate modellers' opinions about complexity and investigate if and how they differed, e.g. between scientific disciplines. It is possible, however, that the questionnaire design was in line with our own definition of complexity and, therefore, not flexible enough to capture all definitions. The heterogeneity in responses demonstrates that the definition of complexity does not necessarily differ between disciplines, but does differ among individuals. The comments on the questionnaire seem to show that the definition of complexity includes many 'it-depends'-booleans, which can explain why so many definitions are present in the literature.

What needs to be changed? From the high number of responses to our questionnaire and the various definitions of model complexity present in the literature, model complexity is clearly a topic that resonates within the geoscience community. Many of the authors notifying us of their publication on the topic were very opinionated about which definition we should be using in general. Such passionate opinions were also noticed by Guthke (2017) regarding the use of model complexity in groundwater hydrology. Although we did not find a difference between male and female perception of model complexity, from our literature search and responses received, male authors seem to be more concerned than female authors about the need for a strong definition. Seeing the makeup of the model user community within geoscience, a unified definition still seems a long way off.

At the same time, other scientists call for reduced model complexity and exploratory modelling approaches. Exploratory modelling arises from the realization that simple processes can lead to complex phenomena (Larsen et al. 2014). Identifying the underlying processes by using simple models and connecting different components of the system is employed frequently to learn more about the processes and feedbacks, for example, for ecology (e.g., Tilman, 1994), hydrology (e.g., Porporato, D'Odorico, Laio, & Rodriguez- Iturbe, 2003), and geomorphology (e.g., Saco, Willgoose, & Hancock, 2007). However an opposite view, the notion that we first need to know the entire system before we can simplify our models (i.e. that simple models follow more complex ones), also exists as expressed in one of the comments to the questionnaire.

Guthke (2017) argues there is a need to define a defensible range of complexity, in terms of specific model goals and available observations, thereby bridging a goal oriented model complexity choice and a statistically motivated choice of model complexity. In addition to this suggestion, Larsen et al. (2016) present several potential strategies to decide on the level of detail (recall their definition of complexity), considering state variables, spatiotemporal dimension, spatial extent, boundary conditions, resolution, and representation of coupling. Such strategies, in combination with their presented decision tree may be instrumental in guiding discussions between involved actors about what level of detail representing model complexity is useful. Such discussion on model complexity has been noted as important by the respondents to the questionnaire. In light of the increasing call and need for interdisciplinary collaboration, these discussions must happen.

6. Conclusions

The evidence strongly suggests that the ultimate choice of how complex a model needs to be is determined by the actors involved. Therefore, we think it is better to not attempt to develop yet another, "better", definition of model complexity. Combining the insights from the questionnaire with the multitude of definitions in the literature, we think and conclude that aiming for a single definition of model complexity is neither feasible nor desirable.

Instead we deem it of much greater importance that geoscientists, in order to collaborate and communicate more effectively, clearly state and discuss how they address model complexity, in research proposals, projects, and publications. Just as data management has received increased attention, and data management plans are increasingly recognized as being for the common good, a model complexity management plan could aide consortia of researchers and others in their progress towards understanding the complexity of nature. Therefore, following Grand’s advice, rather than making things more complicated by just adding another definition of complexity to the list, we aim for high information content with high utility, and suggest a practical approach to dealing with model complexity: never assume that a definition is generally accepted, always be explicit about your assumptions, ask about others’ perspectives and be clear about the approach you are taking and why. In this way, we can avoid, or at least greatly reduce, complications with complexity.

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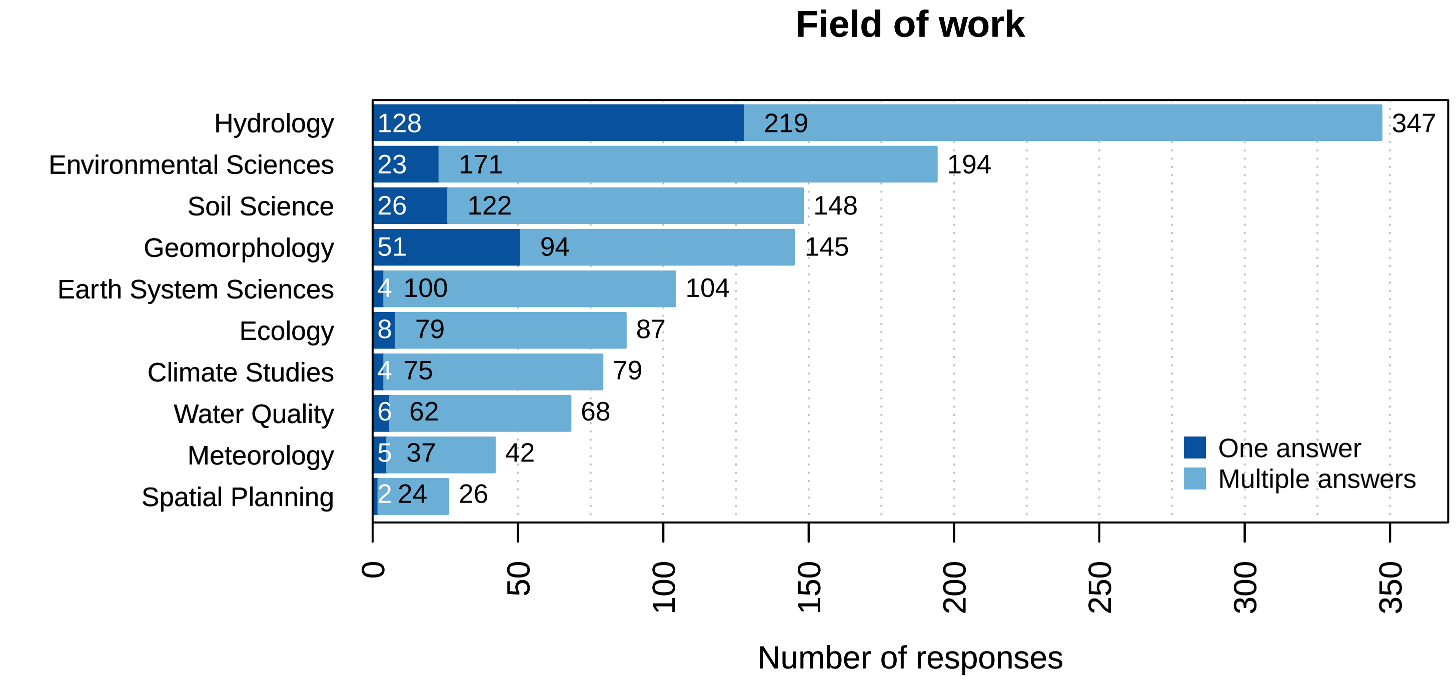
Highlights:

- Response to our questionnaire was overwhelming with >600 complete responses
- No difference in perception of model complexity was found between disciplines
- Definitions and perceptions of model complexity were very heterogeneous
- Model complexity is clearly a topic that resonates within the geoscience community
- So: be explicit about your assumptions and clear about the approach you take and why

Figure_1



Field of work
Hydrology
Environmental Sciences
Soil Science
Geomorphology
Earth System Sciences
Ecology
Climate Studies
Water Quality
Meteorology
Spatial Planning
128
219
347
23
171
194
26
122
148
51
94
145
4
100
104
8
79
87
4
75
79
6
62
68
5
37
42
2
24
26
One answer
Multiple answers
0
50
100
150
200
250
300
350
Number of responses

Figure_2

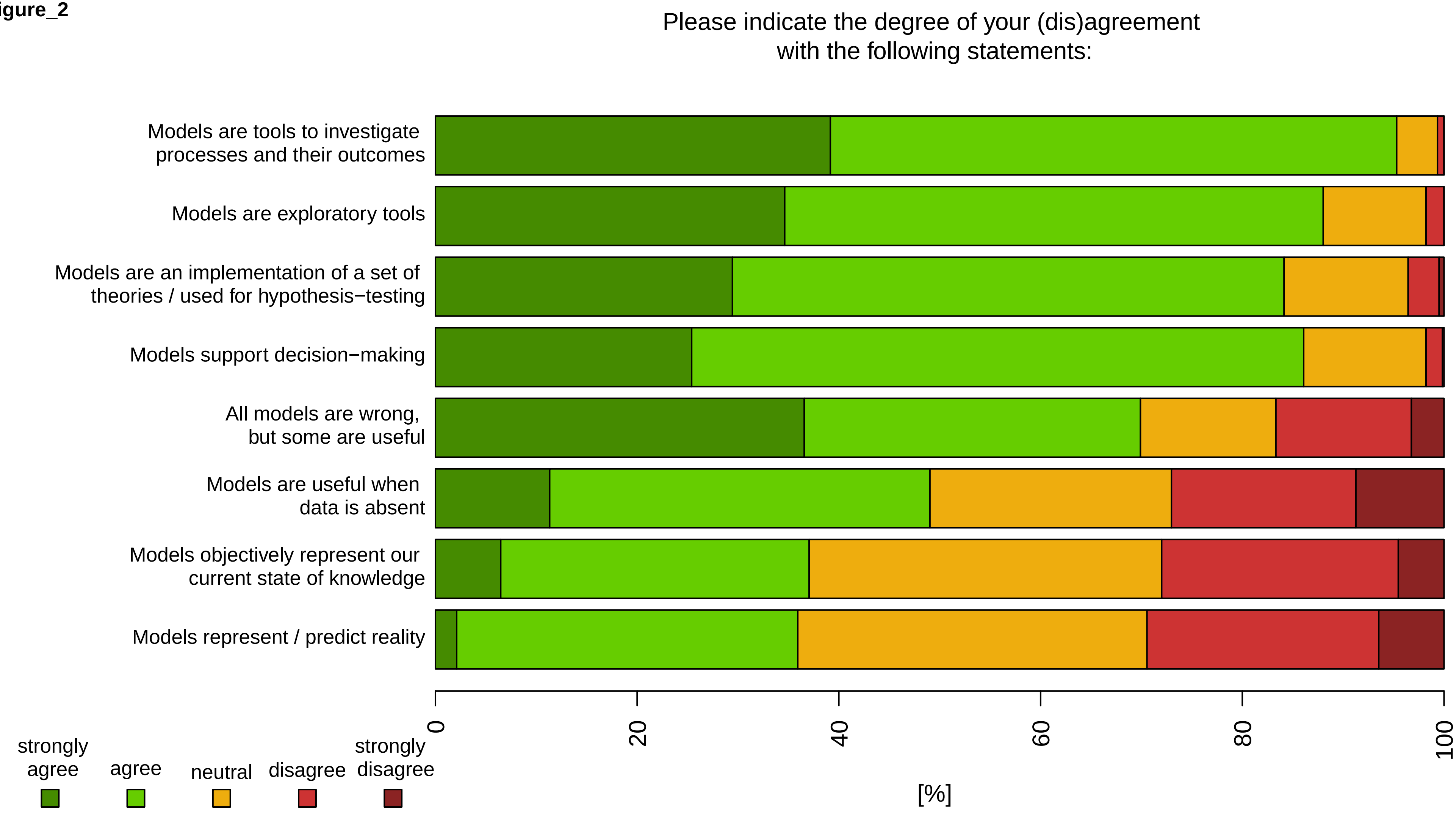
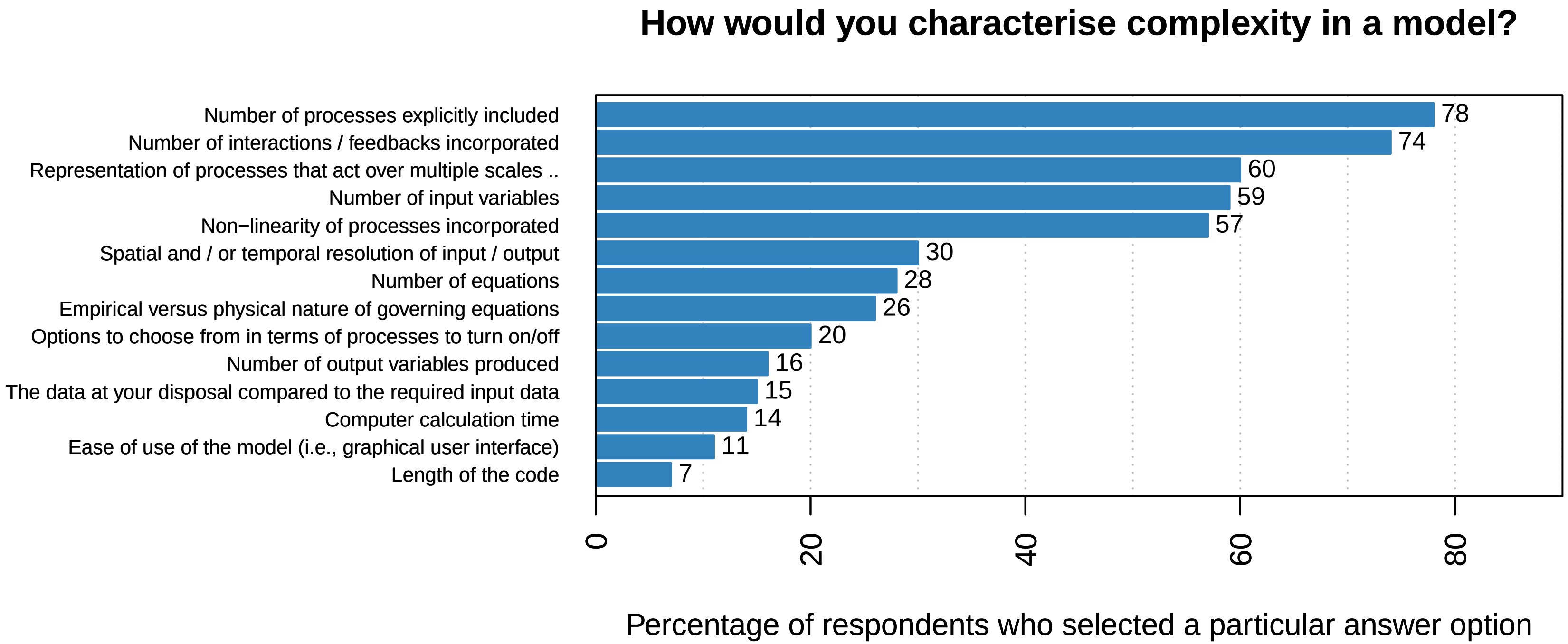

Please indicate the degree of your (dis)agreement
with the following statements:
Models are tools to investigate
processes and their outcomes
Models are exploratory tools
Models are an implementation of a set of
theories / used for hypothesis−testing
Models support decision−making
All models are wrong,
but some are useful
Models are useful when
data is absent
Models objectively represent our
current state of knowledge
Models represent / predict reality
0
20
40
60
80
100
[%]
strongly
agree
agree
neutral
disagree
strongly
disagree

Figure_3



How would you characterise complexity in a model?
Number of processes explicitly included
Number of interactions / feedbacks incorporated
Representation of processes that act over multiple scales ..
Number of input variables
Non−linearity of processes incorporated
Spatial and / or temporal resolution of input / output
Number of equations
Empirical versus physical nature of governing equations
Options to choose from in terms of processes to turn on/off
Number of output variables produced
The data at your disposal compared to the required input data
Computer calculation time
Ease of use of the model (i.e., graphical user interface)
Length of the code
78
74
60
59
57
30
28
26
20
16
15
14
11
7
0
20
40
60
80
Percentage of respondents who selected a particular answer option

Figure_4

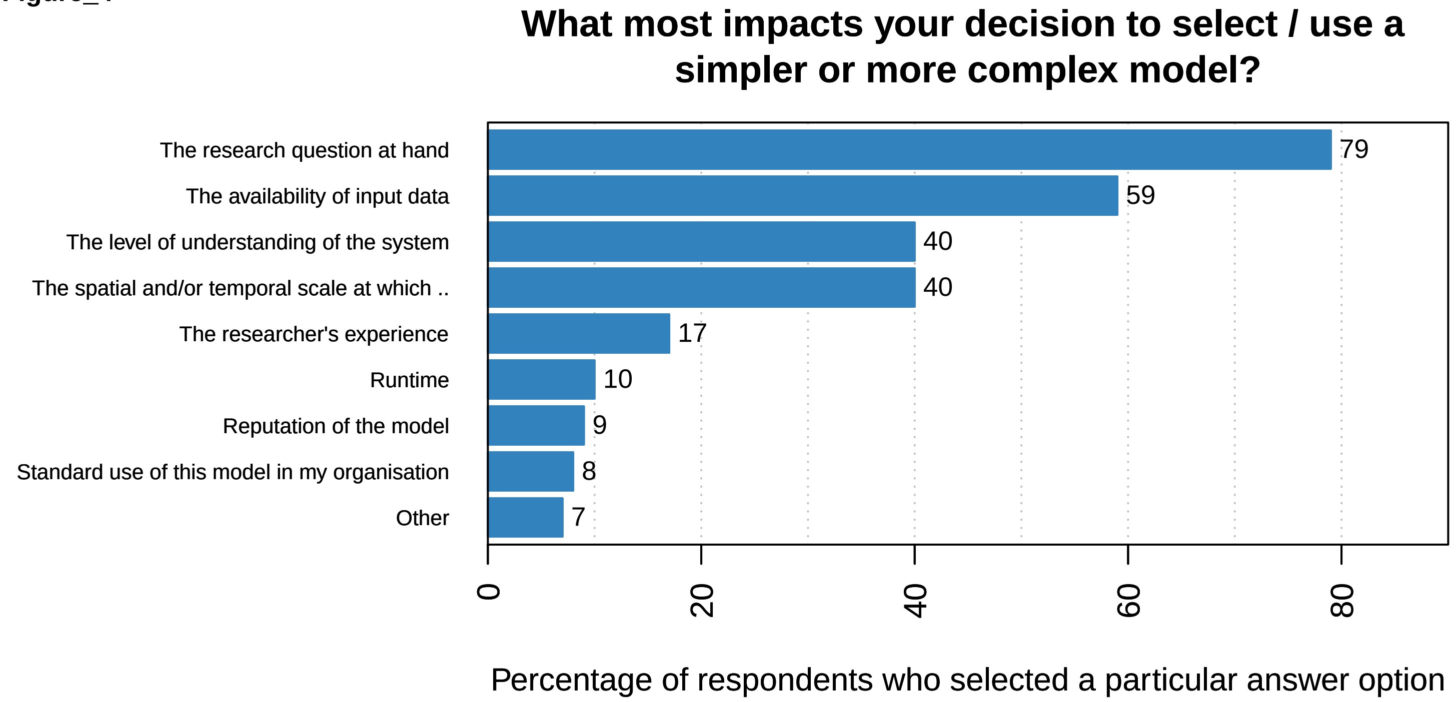

What most impacts your decision to select / use a simpler or more complex model?
The research question at hand
The availability of input data
The level of understanding of the system
The spatial and/or temporal scale at which ..
The researcher's experience
Runtime
Reputation of the model
Standard use of this model in my organisation
Other
79
59
40
40
17
10
9
8
7
0
20
40
60
80
Percentage of respondents who selected a particular answer option

Figure_5

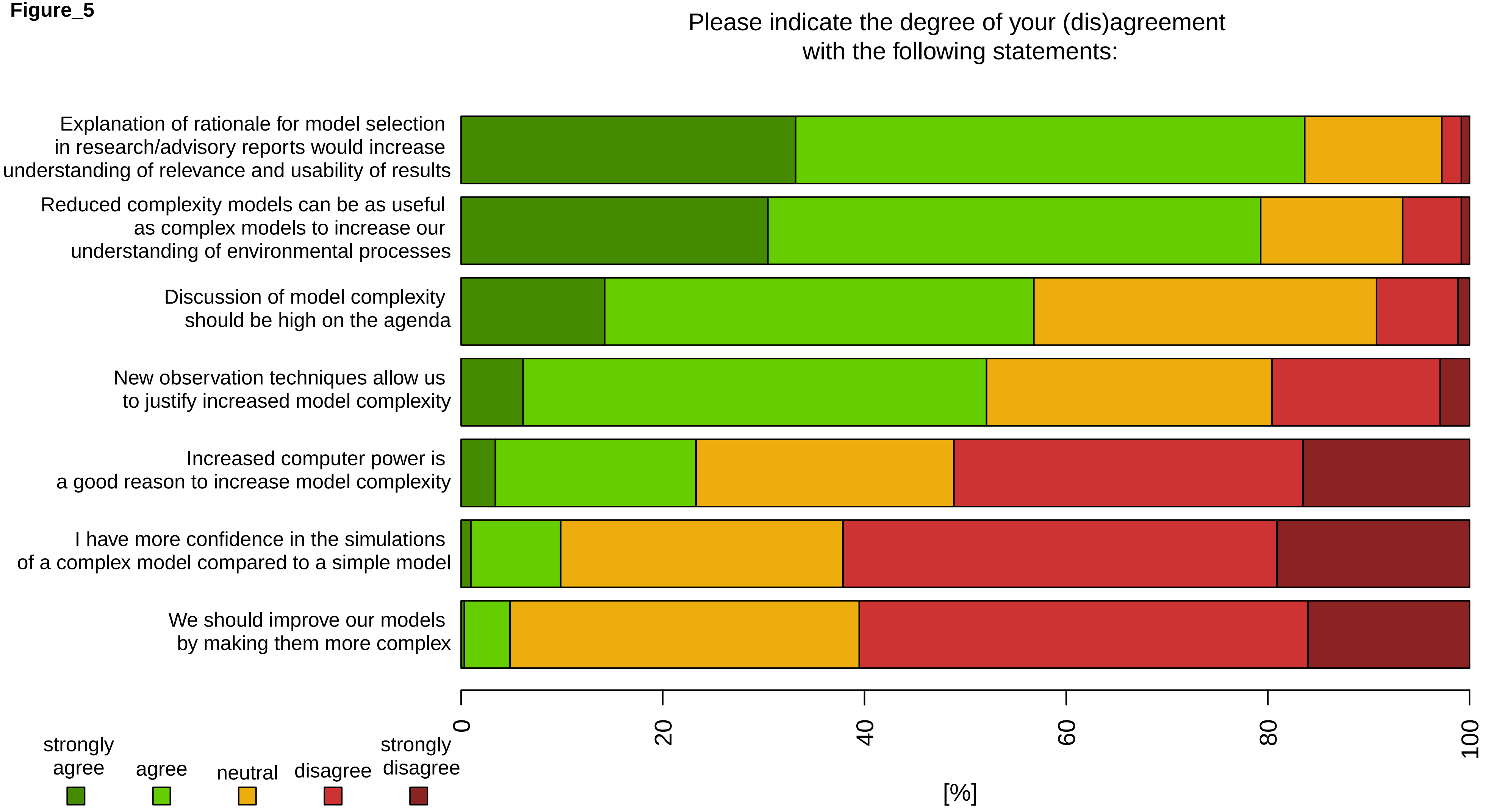

Please indicate the degree of your (dis)agreement with the following statements:
Explanation of rationale for model selection in research/advisory reports would increase understanding of relevance and usability of results
Reduced complexity models can be as useful as complex models to increase our understanding of environmental processes
Discussion of model complexity should be high on the agenda
New observation techniques allow us to justify increased model complexity
Increased computer power is a good reason to increase model complexity
I have more confidence in the simulations of a complex model compared to a simple model
We should improve our models by making them more complex
0
20
40
60
80
100
[%]
strongly agree
agree
neutral
disagree
strongly disagree

Figure_6

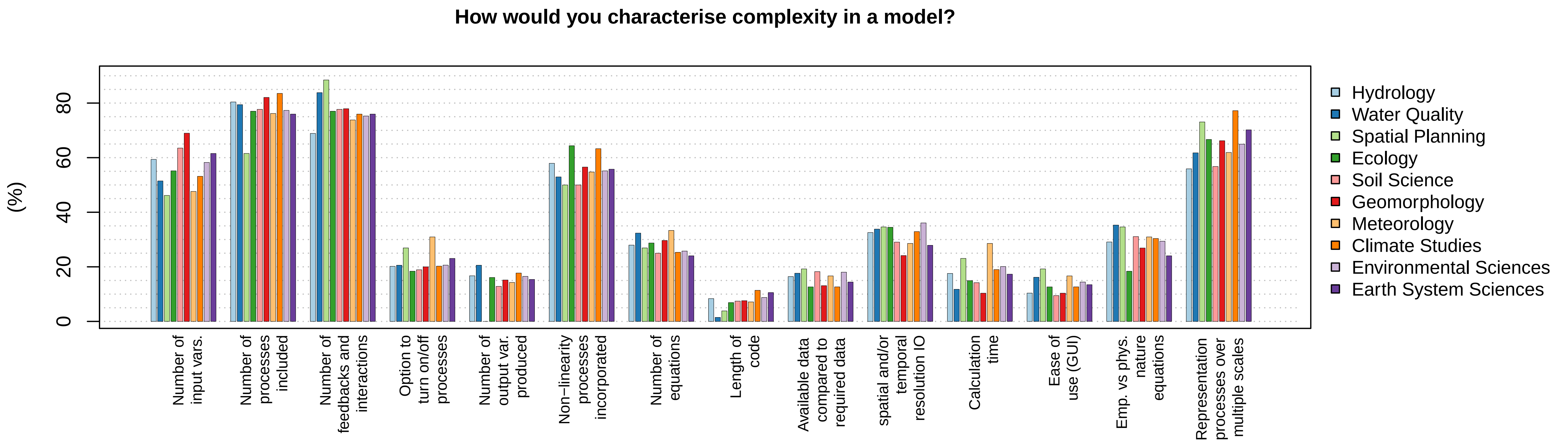

How would you characterise complexity in a model?
(%)
0
20
40
60
80
Number of input vars.
Number of processes included
Number of feedbacks and interactions
Option to turn on/off processes
Number of output var. produced
Non−linearity processes incorporated
Number of equations
Length of code
Available data compared to required data
spatial and/or temporal resolution IO
Calculation time
Ease of use (GUI)
Emp. vs phys. nature equations
Representation processes over multiple scales
Hydrology
Water Quality
Spatial Planning
Ecology
Soil Science
Geomorphology
Meteorology
Climate Studies
Environmental Sciences
Earth System Sciences

Figure_7

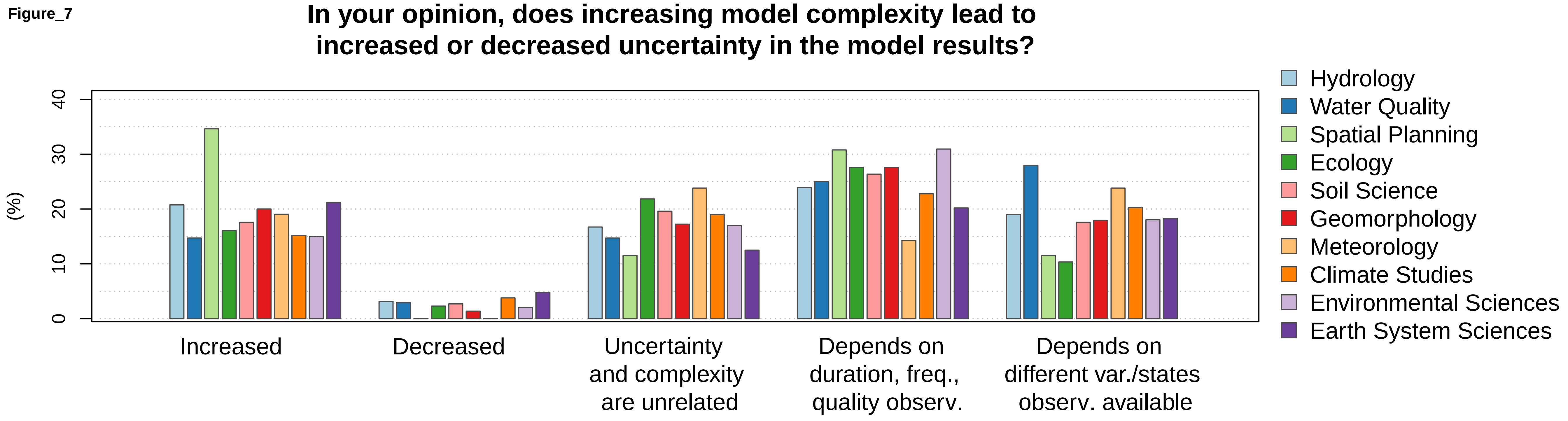

In your opinion, does increasing model complexity lead to increased or decreased uncertainty in the model results?
(%)
0
10
20
30
40
Increased
Decreased
Uncertainty and complexity are unrelated
Depends on duration, freq., quality observ.
Depends on different var./states observ. available
Hydrology
Water Quality
Spatial Planning
Ecology
Soil Science
Geomorphology
Meteorology
Climate Studies
Environmental Sciences
Earth System Sciences

Figure captions

Fig 1: Distribution of field of work of respondents. Dark coloured part of bar indicates number of respondents selecting only one field of work. Light coloured bar indicates the total number of times that field of work was selected in combination with another field of work.

Fig. 2: Respondents replies to statements about models.

Fig. 3: Respondents' opinion regarding characterization of complexity in a model. Note that the total percentage exceeds 100% because respondents were allowed to select multiple options.

Fig. 4: Respondents' replies to what most impacts their decision to select / use a simpler or more complex model. Note that the total percentage exceeds 100% because respondents were allowed to select multiple options.

Fig. 5: Respondents replies to statements about model complexity.

Fig. 6: Response to the question "How would you characterize model complexity?" divided over the different disciplines. Note that the total of the percentages exceeds 100 since respondents were allowed to select multiple answers. Each bar indicates the percentage of that particular discipline that chose a specific option.

Fig. 7. Response to the question "Does increasing model complexity lead to increased or decreased uncertainty in the model results?" divided over the different disciplines. The bars per discipline add up to 100, since each respondent could only select one answer.