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Assessing the relative importance of psychological and demographic factors for predicting climate and environmental attitudes

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Abstract
In this paper, we seek to identify robust predictors of individuals' attitudes towards climate change and environmental degradation. While much of the extant literature has been devoted to the individual explanatory potential of individuals' characteristics, we focus on the extent to which these characteristics provide robust predictions of climate and environmental attitudes. Thereby, we adjudicate the relative predictive power of psychological and sociodemographic characteristics, as well as the predictive power of combinations of these attributes. To do so, we use a popular machine learning technique, Random Forests, on three surveys fielded in China, Switzerland, and the USA, using a variety of outcome variables. We find that a psychological construct, the consideration of future consequences (CFC) scale, performs well in predicting attitudes, across all contexts and better than traditional explanations of climate attitudes, such as income and education. Given recent advances suggesting potential psychological barriers of behavioural change Public (Weaver, Adm Rev 75:806–816, 2015) and the use of psychological constructs to target persuasive messages (Abrahamse et al., J Environ Psychol 265–276, 2007; Hirsh et al., Psychol Sci 23:578–581, 2012), identifying important predictors, such as the CFC may allow to better understand public's appetite for climate and environmental policies and increase demand for these policies, in an area where existing efforts have shown to be lacking (Bernauer and McGrath, Nat Clim Chang 6:680–683, 2016; Chapman et al., Nat Clim Chang 7:850–852, 2017).

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1 Introduction

Climate change and environmental degradation pose serious challenges to humankind in general and policymakers specifically. These threats demand far-reaching and substantial policy action in order to limit their negative effects. Citizens have substantial influence on which policies are and will be implemented, especially in democracies. While public opinion is not a sufficient condition for far-reaching responses to these climate and environmental challenges, it has substantial impact on policies in Western democracies (Anderson et al. 2017; Oehl et al. 2017; Wlezien 1995). However, public opinion also has the potential to bring political efforts to halt (see, for example, Dür and Mateo 2014). Generally, the connection between attitudes and real-world behaviour is well established in the social sciences (Fishbein and Ajzen 1975; Ajzen 1991). Thus, in order to understand the public's appetite for climate and environmental policy, the existing literature has largely focused on *explanations* of climate and environmental attitudes. However, it is unclear whether the factors that explain climate and environmental attitudes are also the best once to anticipate future public appetite for climate and environmental policies. Therefore, we propose that a logic of *prediction* is an important complementary tool that can assist policymakers.

The current literature highlights many factors as being relevant to *explain* individuals' climate and environmental attitudes. Sociodemographic factors, such as age and gender, individuals' resources, such as education, employment status, and income (Blocker and Eckberg 1989, 1997; Lee et al. 2015; Franzen and Vogl 2013; Inglehart 1995; Mohai 1992; Stern et al. 1993) and political variables, such as party proximity and political ideology (McCright and Dunlap 2003, 2011; Mildenberger et al. 2017) have been demonstrated to impact attitudes. Based on this research, the literature concludes that younger individuals, females, better educated, economically better situated individuals, and politically left individuals are more pro-environmental and pro-climate action. Furthermore, a meta-study by Hornsey et al. (2016) shows that political variables tend to outperform often used variables, such as education and gender as determinants of attitudes towards climate change.

Another branch of literature focusses on beliefs and values and their role in pro-environmental attitudes and behaviour (Poortinga et al. 2004; Steg et al. 2014). Egoistic and biospheric values explain support for pro-environmental behaviour. Biospheric values are shown to positively affect pro-environmental attitudes and behaviours, whereas egoistic values tend to be associated with less concern about environmental issues (De Groot and Steg 2007; de Groot and Steg 2008). Conspiracy beliefs are argued to be associated with climate scepticism (Lewandowsky et al. 2013), while others highlight general risk perceptions and awareness (Lee et al. 2015; Mindenberger and Tingley 2017; Whitmarsh 2011).

Finally, more general psychological concepts also receive substantial attention. Psychological factors often present hurdles for pro-environmental behavioural change (Steg and Vlek 2009; Weaver 2015). Thus, understanding the interaction between the environment and humans, and pro-environmental behaviour as a consequence, is crucial (Steg et al. 2013).

One particular psychological concept that has received attention is the consideration of future consequences (CFC) scale (Strathman et al. 1994; Bruderer-Enzler 2015). This measure is said to capture "*the extent to which people consider distant versus immediate consequences of potential behaviors*" (Strathman et al., 1994: 742). Bruderer-Enzler (2015) highlights that the consideration of future consequences correlates with measures of intended pro-environmental behaviour. Others establish the association between more general psychological concepts, such as the Big Five (Hirsh and Dolderman 2007; Milfont and Sibley 2012; Pettus and

Giles 1987) or the California Psychological Inventory (Borden and Francis 1978). Understanding the psychological underpinnings of pro-environmental and conservation behaviour is essential to challenge climate change and environmental degradation (Clayton and Myers 2015; Gifford 2008; Schmuck and Schultz 2002; Stern 1992). (Bamberg and Möser 2007) use observational techniques, such as correlations and meta-analytical structural equation models to confirm earlier findings by Hines et al. (1987). Psychosocial variables are substantially correlated with pro-environmental behaviour.

Understanding such psychological concepts, and their ability to predict individuals' attitudes and behaviour, becomes important for two reasons. First, Weaver (2015) discusses potential barriers of behavioural change. For policymakers to understand these barriers and design policies to avoid or leapfrog these hurdles, a profound understanding of psychological characteristics and their relation to climate-friendly and pro-environmental behaviour is essential (also see Steg and Vlek 2009). Second, research in other disciplines finds psychological targeting is effective to persuade individuals on digital platforms (Hirsh et al. 2012; Dubois et al. 2016; Matz et al. 2017; Abrahamse et al. 2007). Yet, by focussing on explaining climate and environmental attitudes, existing research has focussed less on our ability to *predict* these attitudes. Ultimately, explanatory and predictive power are two separate concepts (Shmueli 2010; Muchlinski et al. 2016), necessitating a different approach than the standard observational and experimental framework used to understand climate attitudes.[1]

Current meta-studies, such as Milfont et al. (2012), provide important starting points to better understand the relationship of attitudes and pro-environmental and climate-friendly behaviour. Milfont et al. (2012) explicitly assess the explanatory power of the time perspective; in their case also, amongst others, the here used CFC scale on different measures of environmental engagement. Analysing data from 19 independent samples in seven countries, they find an association of future orientation and pro-environmental attitudes and behaviour. In line with these findings, past or present orientation is not associated with pro-environmental attitudes and behaviour.

Their findings highlight the robustness of this explanation of pro-environmental behaviour beyond specific countries and contexts. Yet meta-analyses, in focussing on the *effect* of variables, do not explicitly test the predictive power of said variables, and thus whether they significantly improve predictive power in general as well as relative to other variables. Therefore, this paper complements such work by explicitly testing the predictive power of different variables and examining the overall predictability of climate attitudes in a variety of contexts, with the use of Random Forest models.

Our focus on the *predictive* capacities of variables is important as much emphasis is typically placed on *explanation* rather *prediction*, and at worse are conflated. While assessing predictive power is important scientifically, it also has relevance for policymakers. From the perspective of policymakers, the ability to predict the public's appetite for policies is likely more important than explaining potential changes in the variance of policy support. Moreover, the low predictive power of some variables, such as education and employment status, casts some doubt about their theoretical and practical worth. Substantially, the real-world consequences of the assessed attitudes are too important to simply focus on explanatory power and neglect their predictive power (Muchlinski et al. 2016; Shmueli 2010), obviating our ability to anticipate future developments in attitudes, and thus, policy.

[1] For a notable exception see Lee et al. (2015).

Table 1 Description of climate and environmental outcomes to predict in the surveys

China and USA	Switzerland
Reducing emissions (RE)...	Environmental concern scale (ECS) (Diekmann and Preisendörfer 2001)
1. ... is costly	1. Childrens' environmental conditions
2. ... fosters innovation	2. Heading towards catastrophe
3. ... motivates other countries	3. Angry about TV reports
4. ... shows country leadership	4. Limits of growth reached
5. ... without other countries not enough	5. People don't act consciously
6. ... based on Historical burden	6. Environmentalists exaggerate
	7. Politicians do not do enough
	8. Reduce living standard
	9. Environment prior jobs

In light of these trends and considerations, we use Random Forests (see e.g. Breiman 2001; Liaw and Wiener 2002), a popular machine learning technique, to assess the predictive power of common individual characteristics. We do so using data from three surveys fielded in China, Switzerland, and the USA. A Random Forest consists of constructing many decision trees, a non-parametric predictive modelling approach. Decisions trees consist of splitting the data into subgroups (e.g. male vs. female, high vs. low education), until an accurate prediction of the outcome can be formed based off of these splits. By aggregating the results of many trees, a Random Forest provides predictions that are more robust and less sensitive to overfitting than the result of a single decision tree, as well as not being dependent on parametric functional forms as in tradition statistical models such as linear regression.

Our results find that the CFC scale is a robust predictor of climate and environmental attitudes. Its predictive power is similar to that of knowing whether an individual does not believe in climate change and the political party an individual supports. Furthermore, by having strong predictive power and more variation than such discrete measures, the CFC leads to purer nodes. Surprisingly, other individual characteristics, such as income and education, are found to have low predictive power. Given their importance for other attitudes and behaviour (Fishbein and Ajzen 1975; Ajzen 1991), this paper highlights how variables that may be relevant for explaining individuals' attitudes are nevertheless not well suited to predict individuals' climate and environmental attitudes.

The paper is structured as follows. First, we introduce the survey data and methods. We then present the results from our Random Forest analysis, examining the relative predictive power of individuals' characteristics. The final section offers concluding thoughts.

2 Data and methods

We analyse three original surveys on climate attitudes from three different countries (China, Switzerland, USA). Our outcome measures, the environmental attitudes that we seek to predict, are briefly summarised in Table 1.[2] These items cover a wide array of attitudes

[2] Full item wording is located in the supplementary information (see Section SI.1).

individuals may hold concerning the environment and climate change, capturing many relevant issues regarding adaptation and mitigation. The first and second surveys targeted the population in both China and the USA ($n = 3007$ and $n = 3000$ respectively). In the USA ($n = 3000$), the survey was fielded from 28th November to 7th December 2016, and in China ($n = 3007$) from 7th December to 16th December 2016, by Ipsos. The US survey is representative of the general population in terms of age, employment status, gender, income and region. Participants from China were recruited from tier I and II cities and using a quota to ensure representativeness for age, employment status, gender, income and region (for more information on the study design, see Beiser-McGrath and Bernauer 2018).[3] Participants for the third survey in Switzerland were randomly selected car owners registered in the Canton of Zurich ($n = 1919$) and fielded from 28th September 2016 to 25th January 2017 and was self-commissioned. A random sample of 10,000 cars registered in the Canton of Zurich was drawn, and then invited to an online survey via a postal letter, resulting in 1919 full completions (for more information on the study design, see Huber et al. forthcoming).

To predict the outcomes, we include individual characteristics in line with the previous literature. Thus, we include standard demographics, such as age, gender, education and employment status. Additionally, political variables, such as political ideology, defined as self-placement on a left-right scale, and which political party individuals support are included. We measure climate scepticism by asking individuals, whether they believe climate change is caused by humans. Finally, the CFC scale consists of 12 items designed to capture the extent to which future outcomes play a role in individuals' current decision-making. Using principal component analysis, a dimension reduction technique, we estimate two dimensions from the twelve items. These two dimensions capture concern for immediate benefits and concern for future outcomes respectively (Bruderer-Enzler 2015).[4]

We use Random Forests, an ensemble supervised learning method, to predict climate and environmental attitudes. Random Forests are comprised of the construction of many classification trees, which consist of splitting predictor variables into subsets that best predict the outcome of interest. Random Forests constructs these trees with the use of bootstrapping, which involves resampling with replacement observations so as to construct many different samples from the original data, and then fitting a classification tree on each sample. The results of this are then averaged over to construct the final predictions (bootstrap aggregation or "bagging"). We estimate the Random Forests in the *R* (R Core Team 2015), using the 'randomForest' package (Liaw and Wiener 2002), which implements Brieman's Random Forest algorithm (Breiman 2001). For each forest, we grow 1000 trees and allow for the square root of the number of variables to be predictors for each tree.

We use two means to assess the importance of variables for predicting environmental attitudes. First, we use two common measures for Random Forests that consist of examining how inferences change when variables are permuted, i.e. their values randomly reshuffled. The first measure, mean decrease in accuracy, is concerned with prediction error. Specifically, the prediction error is calculated for every tree using the data that was not a part of that particular sample (out-of-bag data), and then again calculated after having permuted

[3]The properties of these sample are summarised in the supplementary information (see Section SI.2). For a comparison of sample and population, see Section SI.3 in the supplementary information.

[4]For full description of these variables see Section SI.1. Due to the political landscape in China, we could neither ask party identification nor political ideology.

the predictor variables. The difference between the two is then averaged. The second measure, mean GINI reduction, is concerned with how a given variable, when included, is able to reduce the level of complexity of the classification trees. A good predictor, will result in simpler classification trees, i.e. trees with a lower node impurity. Again, this measure is averaged across all classification trees.

Second, we re-estimate the analysis considering what would have happened if we had not had a given survey item or battery of items like the CFC in the first place. To do so, we re-estimate the Random Forests on our training dataset leaving out one or two variable(s) at a time and then save the proportion of outcomes in test dataset correctly predicted.[5]

Examining the effects of omitting pairs of variables upon the accuracy of our predictions is motivated by the possibility that the omission of certain combinations of variables may lead to a greater decline in predictive accuracy than the sum of their parts. Such conditionalities have been demonstrated in previous research attempting to explain policy attitudes. For example, Ansolabehere and Hersh (2013) find in the case of the USA that the impact of gender upon political participation is dependent upon race and vice versa. Therefore, we examine the potential differential impact of failing to measure certain pairs of variables, beyond their additive impacts.

3 Results

We start by displaying the pairwise relationships between our predictors and outcome variables in Fig. 1. We use R^2 to measure associations as this allows to compare factors and metric variables.[6] In general, the CFC Future scale substantially correlates with climate attitudes in China (left panel Fig. 1). In comparison, the CFC Immediate only strongly explains the first climate attitude [*RE 1*]. Neither of the standard demographics (age, gender, income, education and employment) show noteworthy correlations with climate attitudes. In the USA (middle panel Fig. 1), climate scepticism strongly correlates with climate attitudes, followed by political ideology and party identification. This strongly reassembles the literature (McCright and Dunlap 2003, 2011). The CFC scales only explain specific items [RE 3 and 4 for CFC Future and RE 1 for CFC Immediate]. Other variables do not strongly correlate with climate attitudes. In Switzerland, party identification, political ideology and climate scepticism tend to correlate strong with environmental attitudes. Other variables do not explain substantial shares of the dependent variable.

Having presented common measures of association, we turn to the results from the Random Forests. Figure 2 summarises the outcome from Random Forest regressions, displaying which variables are important for predicting environmental attitudes. We can see that some general patterns emerge. First, the consideration of future consequences scale, particularly the dimension capturing long-run concerns, is consistently classified as important using the GINI reduction measure and often for the accuracy measure. The key exception to this is the accuracy measure for the Swiss car drivers survey, with the measure only being in the top five predictors approximately half of the time. Second, education, employment and gender tend to be consistently poor predictors of environmental and climate attitudes. The GINI reduction measure highlights the potential importance of age as a predictor, while the accuracy measure partly confirms this observation. Third, individuals' political attitudes and

[5]Our test and train data are constructed by randomly splitting our data in half.

[6]In a bivariate regression, the R^2 is equal to Pearson's r, squared.

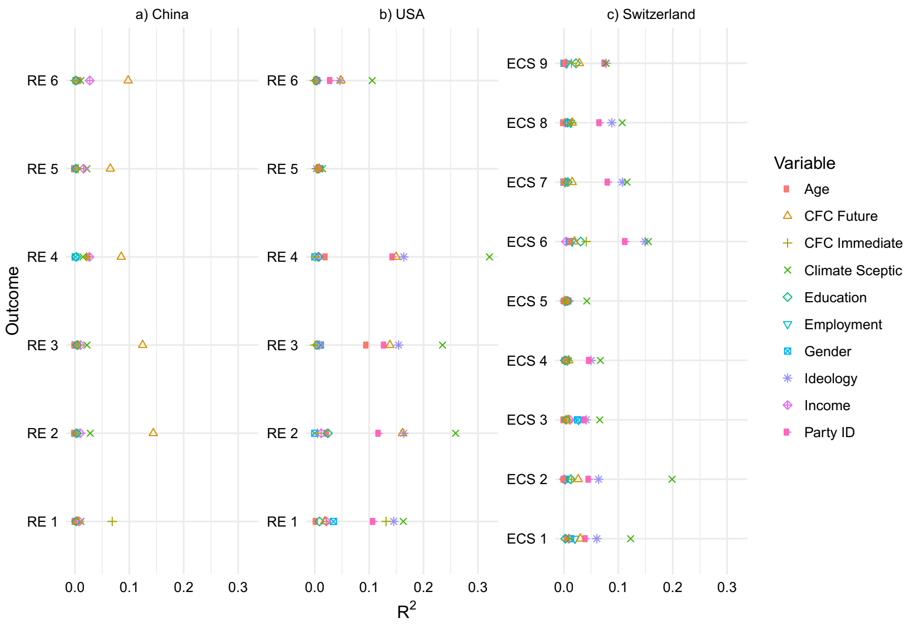

Fig. 1 The extent to which environmental attitudes are correlated with individual characteristics, measured by the R^2 obtained from bivariate regressions. Points indicate the respective R^2, with the shape and colour referring to the specific individual characteristic. Definitions of the outcomes can be found in Table 1

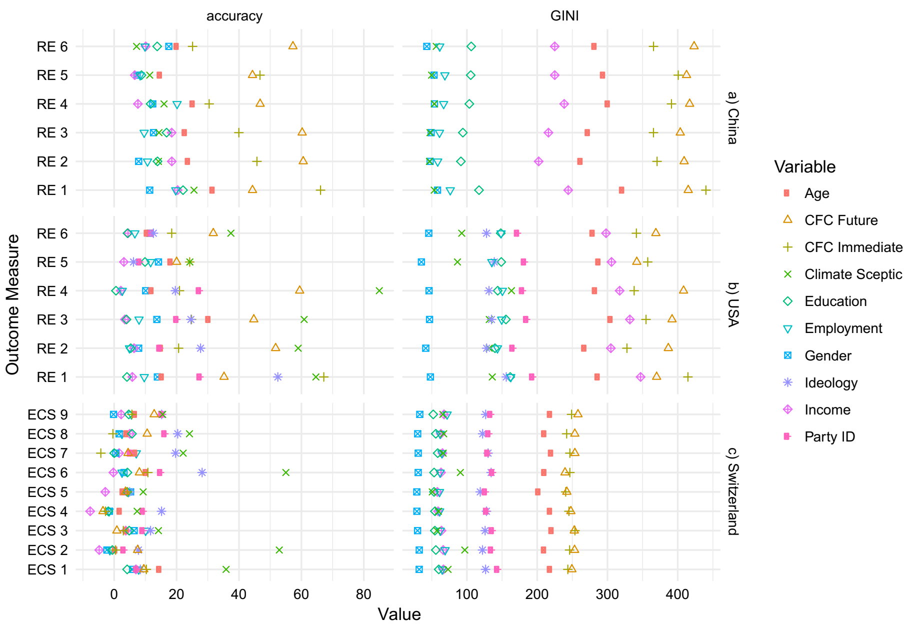

Fig. 2 Which variables are the most important Random Forests. Displayed are two measures of variable importance: (i) mean decrease in accuracy and (ii) mean GINI reduction. Mean decrease in accuracy measures how the accuracy of our predictions change if we permute the values of the named variable. Mean GINI reduction measures how node purity is affected by permuting the named variable

party support are important predictors in the USA and somewhat important in Switzerland, both regarding the accuracy and GINI reduction measure. While there are some similarities to Fig. 1, the CFC scales in particular perform better in *predicting*, than would be expected from *explaining*.

The results presented in Figs. 1 and 2 suggest striking similarities but also substantial differences between the contexts, especially political ideology and party identification have substantially different meanings in the USA and Switzerland. In the USA, especially recently, there is strong polarisation between the two major parties (Layman et al. 2006; Fiorina et al. 2008; Fiorina and Abrams 2008), with political issues sorted along party lines. Obviously, party affiliation is strongly associated with views on climate change (McCright and Dunlap 2011). On the other hand, Swiss politics are characterised by compromise rather than polarisation. Not surprising, positions on climate change are less contested.

Being a climate sceptic matters equally in all three countries and is by far the strongest explanation and predictor of climate and environmental attitudes in Switzerland and the USA. China, on the other hand, deviates as climate scepticism does not relate to climate attitudes.

Next, we turn to examining what would have happened if we had failed to include an item in the survey. To do so, we re-estimate the Random Forests leaving one factor out at a time and then calculate the proportion correctly predicted. Figure 3 shows the results from this analysis. We can clearly see that across countries, the omission of the CFC scale consistently leads to a decline the predictive accuracy of the Random Forests. This is strongest in the case of China and USA for certain outcomes, with omitting the CFC decreasing the proportion correctly predicted. Also noteworthy is that there is heterogeneity across countries in the ability to predict climate attitudes.

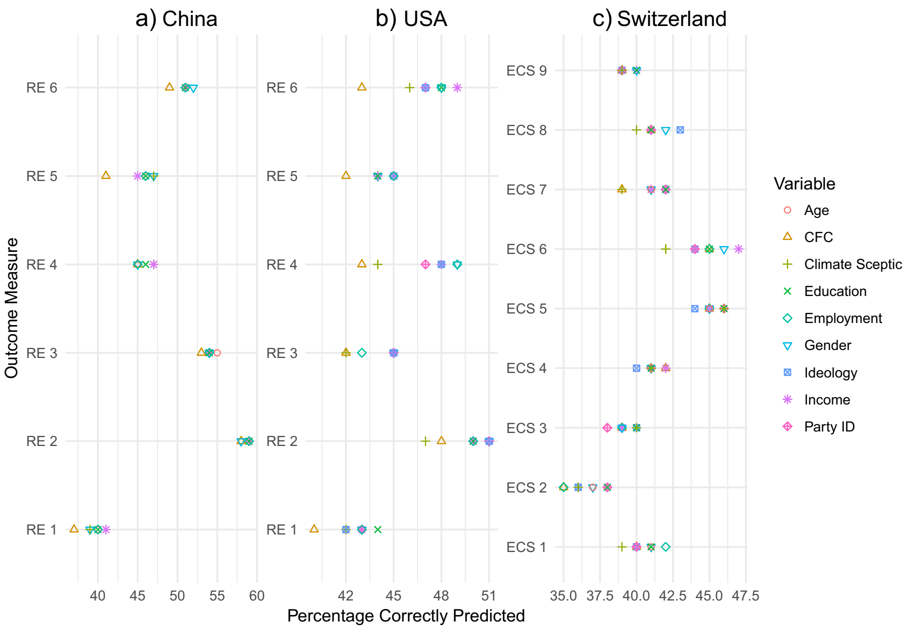

Fig. 3 How the accuracy of prediction changes when excluding a factor from the Random Forests

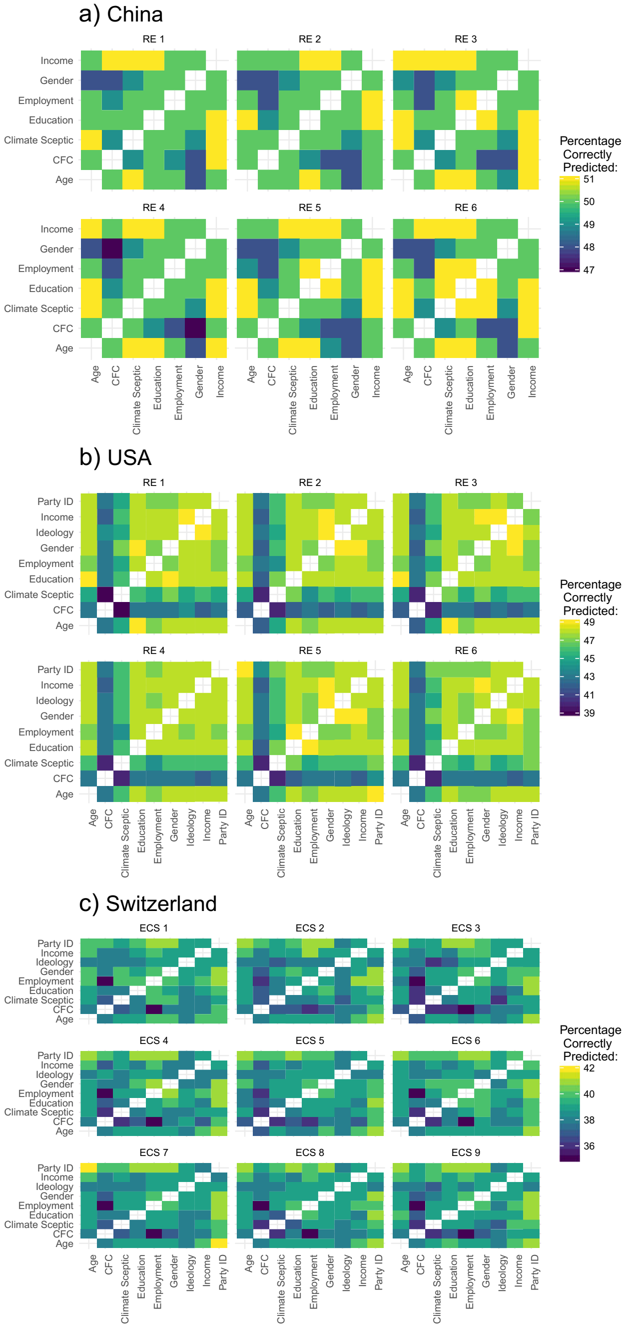

Fig. 4 How the accuracy of prediction changes when excluding two factors at a time from the Random Forests. Each cell corresponds to the proportion correctly predicted from the Random Forests when omitting both the row and column variable. The diagonal is omitted as refers to the decrease in prediction for the removal of one factor (as column and row are the same), which is also displayed in Fig. 3

Figure 4 displays how the predictive accuracy of the Random Forests change dependent upon the pairs of variables that are omitted. Tracing the horizontal and vertical path of the consideration of future consequences, we can see that failing to include it consistently reduces the predictive power of the model across all countries.

We can also see that there may be some interactions, in terms of larger decreases in predictive power when certain pairs of variables are omitted. We see across all three countries that the omission of the CFC in combination with age leads to a substantial decline in predictive power. Furthermore, there are some country specific patterns. In the case of China, we can see that omitting the CFC in combination employment and gender is particularly relevant. While in Switzerland, the CFC in combination with an individuals' climate skepticism or employment makes a difference.

4 Conclusions

Our findings highlight the importance of considering the CFC scales as an important explanation *and* predictor of climate and environmental attitudes throughout three different countries and different populations. These results have substantial consequence for which survey items to include. The CFC scales include 12 items, which is a marginal cost for the improved predictive power of the models at hand. Additionally, the results suggest that standard demographics might not suffice to acceptably predict climate and environmental attitudes.

These findings become particularly important in light of recent findings that emphasises the importance tailoring messages to elicit attitudinal and behavioural change (Abrahamse et al. 2007; Hirsh et al. 2012; Dubois et al. 2016; Matz et al. 2017; Lorenzoni et al. 2007). According to this research, tailored messages increase support for climate policy and foster pro-environmental behaviour. High predictive power of prior attitudes, as identified here, become of importance, if we think about how to optimise tailoring. As Bernauer and McGrath (2016) suggest, purely reframing is unlikely to shift people's opinions. Tailoring frames has the potential to overcome these hurdles and induce public support, where simple reframing is bound to fail. Thus, understanding and assessing predictive power is particularly important to understand how continuing demographic (Colby and Ortman 2014) and pyschological (Wei et al. 2017) changes will lead to changes in environmental attitudes. In return, this helps to better tailor frames in order to increase their impact.

At the moment, these psychological constructs are rarely included in more general surveys on environmental attitudes and politics, such as the ISSP Environment (ISSP Research Group 2012), which constitute one of the foundations of social science research on environmental and climate attitudes. While researchers are often ultimately left to use whatever items are included in such surveys, our findings nevertheless urge scholars to consider these questions for their own original surveys. In the case of the CFC scale, the number of items (twelve) is relatively small compared to the improvement of predictive power.

More generally, by focusing on overall prediction rather than specific inference about the effect of a certain variable, machine learning methods are less sensitive to problems such as low degrees of freedom (i.e. when the number of variables is close to the number of observations). Random Forests are able to do so by only using a randomly selected subset of variables for each tree. This means that while we may use many predictors as a whole, within each tree there is no degrees of freedom problem.

However, one limitation to machine learning approaches generally, and Random Forests specifically, is the choice of hyperparameters. Hyperparameters are parameters that are not estimated, but rather chosen a priori.[7] Examples of hyperparameters in the case of Random Forests are how many trees to include and the maximum number of variables allowed for a given tree. Naturally, the performance of the Random Forest to predict outcomes is dependent upon the hyperparameters chosen. This, however, is subject to researcher experimentation and can require considerable effort to find the "optimal" combination. As we wish to show in this paper the potential for Random Forests, we consider it sufficient to show this is the case for one set of hyperparameters. However, researchers who wish to use Random Forests more extensively to predict climate attitudes and behaviour, should devote attention to different specifications, which might affect the quality of their predictions.

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[7] One can think of these being the "settings" of the model.

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