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ECLIPSE

Evaluating the **Cl**imate and Air Quality **I**m**p**acts of **S**hort-Liv**e**d Pollutants

Collaborative Project

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PU	Public	
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RE	Restricted to a group specified by the consortium (including the Commission Services)	
CO	Confidential, only for members of the consortium (including the Commission Services)	

The attached draft paper (with additional material) addresses how impacts of small perturbations can be modelled by various approaches. These perturbations represent contributions by individual components or regions, or mitigation measure. Such perturbations can be difficult to isolate and quantify by GCMs due to signal-to-noise issues. In ECLIPSE we have developed metrics – based on idealized perturbations of various components using complex and detailed chemistry and climate models. These metrics are then used to quantify the impacts of mitigation measures. The calculated responses are compared to those obtained with GCM and uncertainties are accounted for. The studies indicate the metrics can be used when signal-to-noise problems makes GCMs inapplicable for smaller perturbations. This approach allows for quantifications of responses to specific mitigation measures, leading to reduced uncertainties in the regional impacts. As an example we include a case showing how the Regional Temperature change Potential (RTP) concept can be used to calculate contributions by regions and components to climate change in the Arctic for the domestic sector.

We have also tested how uncertainties in metrics and correlations between models may affect the net impact of an idealized mitigation effort (attached).

A comparison of RTPs to GCMs in a possible SLCFs mitigation scenario

Authors: Borgar Aamaas[1], Terje Berntsen[1,2], Jan Fuglestvedt[1]

Abstract

Science question: How well do the RTPs simulate the response to a possible SLCF mitigation scenario simulated by GCMs?

The purpose of this study is to compare the regional temperature development as calculated by the metrics to the regional temperature development as calculated by the GCMs.

1. Introduction

About GCMs, complexity in climate captured by GCMs

About emission metrics, RTPs (simple)

About the loop (emission metrics produced based on RF calculations, those metrics used to find an optimal mitigation scenario, the climate impact of this scenario is calculated in this paper), what other ECLIPSE papers this builds on

Anthropogenic impacts on climate are mainly caused by emissions of carbon dioxide (CO_2). However, also a number of components with shorter atmospheric lifetimes contribute to climate change. This include components such as methane with an adjustment time shorter than the typical time horizon of climate mitigation targets, but longer than atmospheric mixing times, and very short-lived components with lifetimes shorter than the atmospheric mixing times (here denoted VSLCFs). The VSLCFs include black carbon aerosols (BC) and ozone precursors (NOx, CO and VOCs). For VSLCFs the location and timing of the emissions will affect magnitude and pattern of the radiative forcing and thus also potentially the regional climate impacts (Shindell and Faluvegi, 2009).

Recently several multi-model studies have calculated globally distributed radiative forcings due to emissions of VSLCFs (or their precursors) in specific regions (Fry et al., 2012, Yu et al., 2013, Bellouin et al., 2015). Building on these simulations and including regional component specific climate sensitivities (Shindell and Faluvegi, 2009) as well a global climate impulse response function (Boucher and Reddy, 2008), absolute regional temperature potentials (ARTP) have been calculated (Shindell and Faluvegi, 2010; Collins et al., 2013; Aamaas et al., 2015b; Sand et al., 2015). The ARTP is similar to the absolute global temperature change potential (AGTP) metric developed by Shine et al. (2005), but uses the regional temperature change in broad latitude bands as the impact parameter. The ARTP is a metric that relates a unit mass pulse emission of climate forcer (or a pre-cursor) at time in a certain region to the annual mean surface temperature change in broad latitude bands at a given time after the emissions took place (Shindell and Faluvegi, 2010).

When the ARTPs are known they provide a simple and powerful tool to evaluate the response (in the broad latitude bands) to any given combination of mitigation of climate forcers (including VSLCFs) across regions, activities and time. Using the GAINS model and GTPs from Aamaas et al. (2015a), Klimont et al. (2015) have developed transient mitigation scenarios for SLCFc (including methane). In this scenario so-called maximum feasible technological reduction (MFTR) are done as long at the net GTP (across all components, including co-emitted species with negative GTPs) are positive (i.e. that mitigation is assumed to cause a cooling). Note that the costs of mitigation have not been considered.

The ARTP method is a strong linearization of the non-linear climate system and is based on regional climate sensitivities only from the GISS global climate model (Shindell and Faluvegi, 2009), except for the Arctic sensitivity to BC in the Arctic (Flanner, 2013; Lund et al., 2014; Aamaas et al., 2015). Global climate models now include the VSLCFs and can thus be used to simulate the net of mitigation also of the VSLCF, however, for practical reasons they require that the net forcing signal is large enough to give a statistically significant response. In principle a GCM can always give a significant signal, it is only a matter of doing long enough simulations (or enough ensembles), but in practice computer resources are strong limitations. Thus, using the ARTPs to calculate how different regions, activities and components contribute to the impacts is important to be able to identify the cost-effective mitigation options.

Here we use the ARTPs from Aamaas et al. (2015b) to simulate the transient responses to the MFTR mitigation scenarios. The impact of the total mitigation has also been simulated with several GCMs (Baker et al., 2015). This provides a unique opportunity to evaluate the ARTP based results with GCMs that are independent of the GISS model used to derive the regional climate sensitivities. We also apply the ARTP method to analyze how different regions and activities contribute to reduced Arctic warming in the MFTR scenario.

2. Material and methods

The evaluation of the RTP-based method for estimating transient climate response to future changes in emissions of SLCFs presented here is based on two sets of detailed radiative forcing calculations of regional emissions of individual SLCFs as reported in Bellouin et al. (2015) and Sand et al. (2015). The choice of regional/seasonal resolution and processes/species included in the analysis differed between the two studies. In the study reported in Sand et al., the focus was on the contribution to Arctic warming from emissions in the Arctic Council nations, while in the EU-project ECLIPSE (Bellouin et al.,) the focus was on impacts of emissions in EU and China. Both studies included a rather large and inhomogeneous Rest Of the World (ROW) region. In the Sand et al. study emissions from individual activities (e.g. transport and domestic heating and cooking) were treated separately, while the short-lived ozone precursors (NOx, CO and nmVOCs) were lumped together. In the Bellouin et al study emissions from all sectors were lumped, while emissions during Northern hemisphere summer and winter (April-Oct and Nov-March) were treated separately. Also separate calculations for the the short-lived ozone precursors were done. The models used for the two studies were not the same, except for NorESM which participated in both studies (Table 1).

Figure 1 shows the regions used by Bellouin et al. (2015) and Sand et al. (2015).

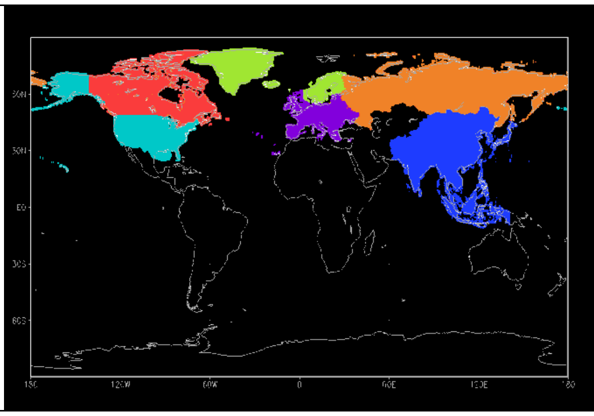
MapECLIPSE	

Figure 1

The MFTR scenario for SLCF is presented in detail in Klimont et al., (in prep for ACP, 2015). The construction of the mitigation scenario was done based on a metric using the global temperature change potential, assuming that all mitigation options would lead to a gradual ramp-up over 15 years starting in 2015, i.e. that 100% of the mitigation is achieved by 2030, and then kept at 100%. The metric evaluates the global temperature change in 2035 (i.e. 20 years after the start of the mitigation), using a gradually time horizon shorter time-horizon for mitigation taking place closer to 2035.

Figure 2 shows the regional emission changes for the regions used by Sand et al. Mitigation by sector and regions is given in Table S1 in the supplementary.

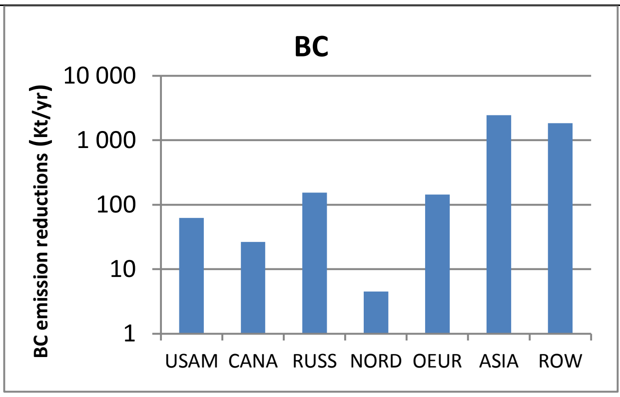
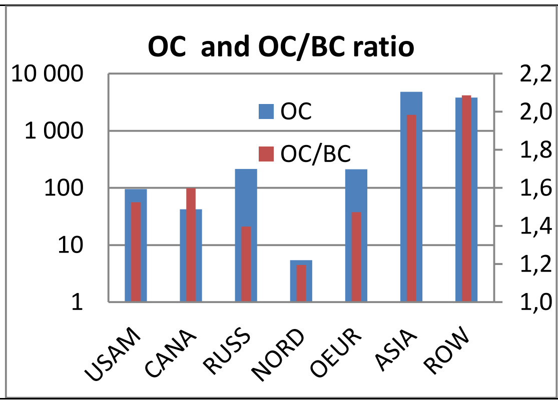
	
SO2	NOx
CO	CH4

Figure 2 shows the regional emission changes for the regions used by Sand et al.

When the global distribution of the radiative forcing per unit emission has been simulated the absolute regional temperature change potentials (ARTP), following Shindell and Faluvegi (2010) and Collins et al. (2013), were calculated. The ARTP an emission metric that quantifies climate response in terms of annual mean surface temperature change in broad latitude bands following a given emission. The generalized expression for calculating the ARTP is:

$$ARTP_{i,m}(t) = \sum_l \int_0^t \frac{F_l(t\prime)}{E_i} \cdot RCS(i,l,m) \cdot R(t-t')dt' \qquad (1)$$

Where $F_l(t)$ is the radiative forcing in latitde band l as a function of time (t) after the pulse emission E_i of component i. The *RCS(i,l,m))* is a matrix of regional response coefficients based on the RTP concept (unitless, cf. Collins et al., 2013), where m denotes the latitude band of the respons. The climate impulse response function (R) is a temporal temperature response to an instantaneous unit pulse of RF (in $K/(Wm^{-2})$, thus including the global climate sensitivity.

$$R(t) = \sum_{j=1}^{2} \frac{c_j}{d_j} \exp(-\frac{c_j}{d_j})$$

From Boucher and Reddy (2008) we use $c_1 = 0.631K(Wm^{-2})^{-1})$, $c_2 = 0.429K(Wm^{-2})^{-1})$, $d_1 = 8.4$ yr, d2 = 409.5 yr, giving an equilibrium climate sensitivity of $1.060K(Wm^{-2})^{-1})$ (3.9K for CO_2 doubling).

For both sets of forcing estimates (i.e. from Bellouin et al. and Sand et al.) the regional response coefficients and the climate impulse response function are equal, however, since the models and separation of emissions (in sectors, regions, and seasons) are different, the ARTPs are also different. Thus the ECLIPSE based ARTP are given as functions of respons band, emission region, emission season, component, and time-horizon (m,r,s,i,t), while the AMAP based set of ARTPs are functions of response band, emission region, activity, component, and time-horizon (m,r,a,i,t).

Aamaas et al. (2015) present the ARTPs based on Bellouin et al. (2015), while the ARTPs using the radiative forcing simulations from Sand et al. is given in the SI. The ARTPs can be can be calculated for the individual models providing forcing estimates. However, here we have used the best estimates provided be Bellouin et al and Sand et al. to calculate two sets of ARTPs. Results from individual models are used to provide model ranges as an estimate for the forcing contribution to the uncertainty in the ARTPs.

These sets of ARTs can now be used to calculate the annual mean surface temperature respons in the latitude bands (m) of any given scenario of emissions of SLCPs. To do so, first the emission must be aggregated geographically, over sectors and/or seasonally according to how the ARTPs are defined. Then individual contributions to the temperature change in latitude band *m* at time *t* is calculated by (here AMAP case) for emissions of component *i*, by activity *a* in region *r* at time *t'* is given by:

$$\Delta T(m,r,a,i,t) = \int_{o}^{t} E(r,a,i,t') \cdot ARTP(m,r,a,i,t-t') \cdot dt' \qquad (2)$$

To calculate the total temperature change in latitude band *m* at time *t* from all emissions in all regions, activities, components, and taking place during the years *t'* between *t*=0 and *t* the individual contributions given by (2) are simply summed up over all components, regions and activities:

$$\Delta T(m,t) = \sum_i \sum_r \sum_a \Delta T(m,r,a,i,t) \qquad (3)$$

GCM simulations.

To validate the RTP-based method described above we compare the results (given by eq. 3) with the results from fully coupled GCMs. The GCMs have simulated two emission "scenarios", first a 100% global step-change reduction of anthropogenic emissions of the individual SLCFs (BC, OC, SO2, …) (Baker et al., 2015a), and secondly transient simulations of MFTR scenario (Baker et al. 2015b) have been performed using four GCMs. Not all GCM include all the relevant components and processes (i.e. oxidant gas-phase chemistry or the impact BC deposited on snow). Table 2 gives an overview of the GCM models used and the processes represented in each of them. For details see Baker et al. (2015a and 2015b).

The surface temperature responses due to the MFTR mitigation scenario have been estimated by four global climate models (Baker et al., 2015b).

Model	Climate sensitivity (K/Wm^{-2})	BC-atm	BC-snow	OC	SO4	Ozone	Methane	Ozone-PM
ECHAM-HAM	0.72	x		x	x		x	
NorESM		x	x	x	x	x	x	x
CAM4	0.7	x		x	x	x	x	x
HadGEM	1.1	x		x	x	x	x	x
GCM-mean								
RTP	1.06	x	x	x	x	x	x	x

Table 2.

3. Results

To close the loop we first compare the global average temperature response (mean for the decade between 2040 and 2050) as estimated by the global GTP metric (for regional emissions, as decribed in Aamaas et al., 2015a) with the corresponding estimate from the transient GCM simulations (Baker et al., 2015b). The transient global annual response in surface temperature for the GTP-based estimate is shown in figure 3

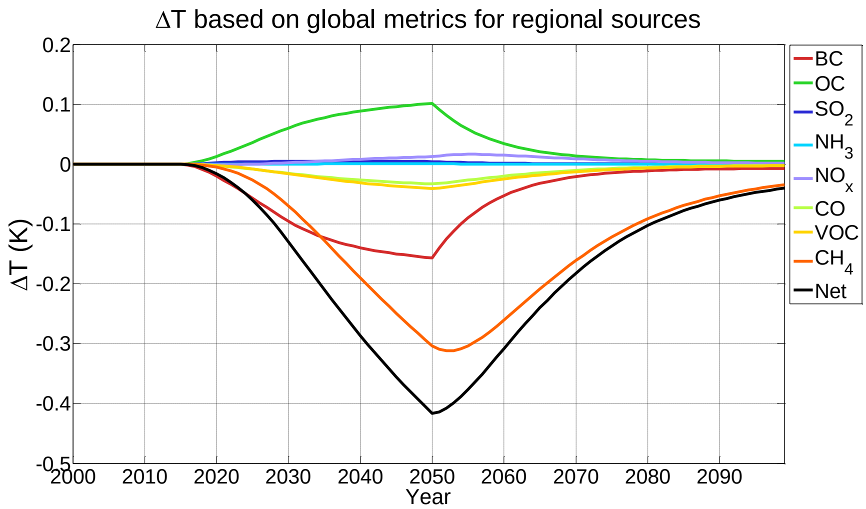


Figure 3: GTP-based transient global annual response in surface temperature for the MTFR scenario for reductions of SLCFs.

Figure 4 shows the decadal mean (2040-2050) global means surface temperature response from the simulations with the fully coupled GCMs (Baker et al., 2015b). The GCMs all have different climate sensitivites than what is used for calculating the GTPs (1.06 K/Wm^{-2}, from Boucher and Reddy (2008)), thus the mean response in the GCMs will be different from the GTP-based response shown in figure 3 above. To make a fair comparison we have scaled the climate sensitivity by the GCM average in the estimate presented in Figure 4 below.

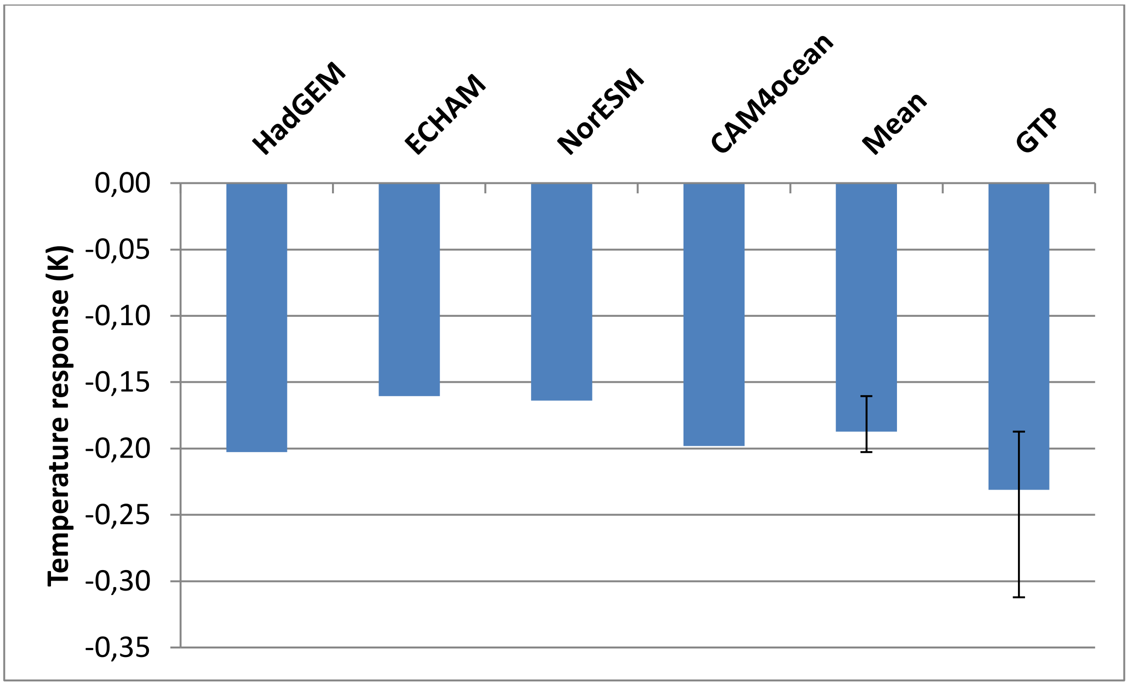


Figure 4: Decadal mean (2040-2050) global surface temperature response for the MTFR scenario for reductions of SLCFs from the GCMs compared to the corresponding estimate using the GTPs.

The GCMs provide a lot more details about the impact of the mitigation, such as geographical and temporal distribution of the temperature response and impacts on other climate variables. However, this comes at a cost of long and costly computer simulations, often prohibiting estimates of the impact of individual mitigation efforts. In the following we investigate if the ARTP approached outlined above is robust enough to provide robust regional resolution with a simple metric based approach.

Figure 5 shows the

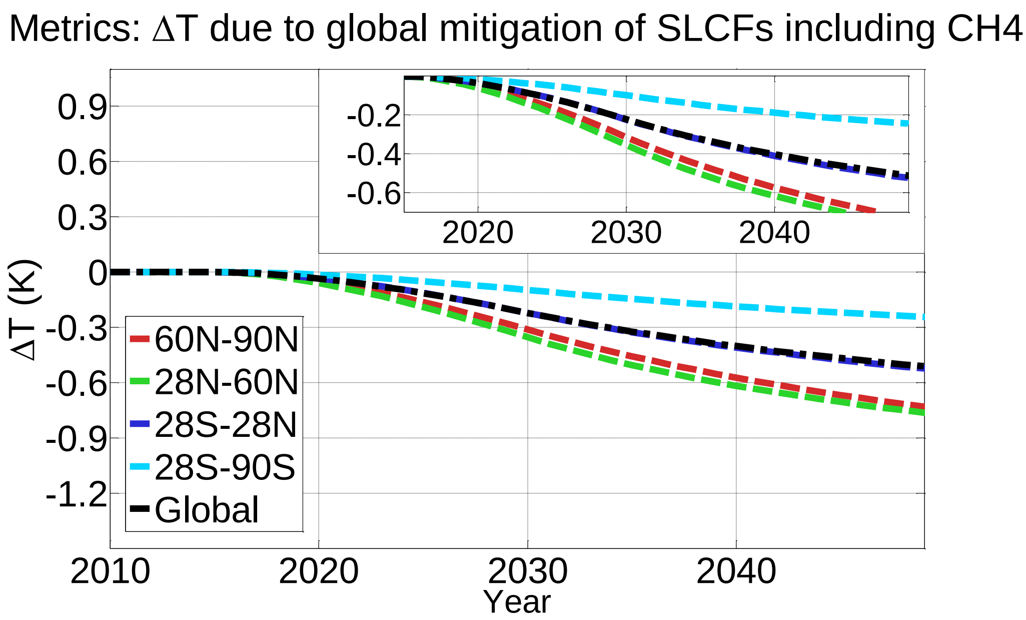


Figure 5: ARTP-based (ECLIPSE) transient annual response in surface temperature for the MTFR scenario for reductions of SLCFs.

The responses shown in figure 5 can now be compared to the results from the GCM simulations (for the same latitude bands) to evaluate the robustness of the ARTP approach. Figure 6 shows a scatter plot of the responses in each latitude band compared to the individual GCM results. The GCMs indicate a clear Arctic amplification, while the RTP based estimates show the largest response for the key source regions in NH mid latitudes. This is probably due to the relatively weak Arctic amplification in the GISS model that has been used to estimate the regional climate sensitivities (Shindell and Faluvegi, 2009). So far only this model (the GISS model) has performed all the necessary simulations to establish these regional climate sensitivities for a suite of forcing components. For future use of the ARTP method to evaluate the regional responses of various emission mitigations, it is therefore important that more GCM models perform these simulations in order to better understand and limit the uncertainty in these regional climate sensitivities.

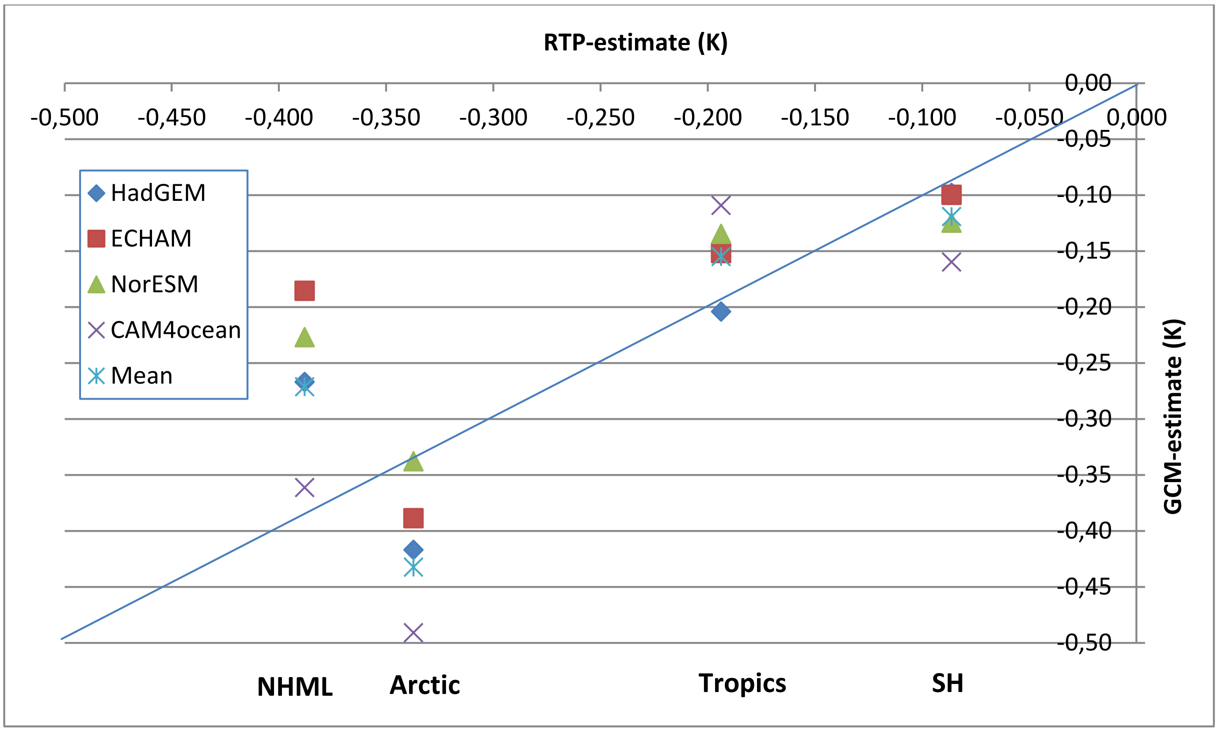


Figure 6: Regional temperature responses (2040-2050 average) in different regions by different models due to the MTFR scenario of SLCFs (including methane) compared to the ARTP-based estimates.

Acknowledgements

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Section 3.1.3 from the paper "Multimodel emission metrics for regional emissions of short lived climate forcers" by Aamaas et al. also contributes to this Deliverable:

3.1.3 Robustness for individual species

The differences in the emission metric values between the emission regions and seasons of emissions, seen for the best estimate holds generally in each model, which strengthens our confidence in the modeled variations between regions and seasons. For emissions of aerosols and their precursors, the magnitude of GTP20 values is higher in summer than winter in 88 % of the model cases and another 8% are marginally the other way. The consistency between the individual models and our best estimate based on the models is 100% for SO_2. The metric values for European emissions are larger in magnitude for most cases than China. In summer, this is true for 92% of the cases and 58% in winter in addition to 17% that are marginally the opposite. Yu et al. (2013) also observed that the regional dependency in RF was robust for a number of models with the same regional pattern as in our study.

For the ozone precursors, the variation in GTP20 values observed for the best estimate also holds for most of the models. For both regional and seasonal variability, 83% of the model cases agree with the best estimate. For CO, all cases agree that the GTP20 values are larger for Chinese emissions than European emissions and for winter than summer, even though the relative differences in GTP20 values between Europe and China in summer and winter are relatively small. The findings for NO_x and VOC are also relatively robust, where the model cases agree 83% for NO_x and 67% for VOC. As for the aerosols, the trends we model are in support of the literature (Collins et al., 2013).

3.1.4 Robustness in total climate impact

Emission metrics are used to quantify the climate impacts of different sets of emission changes following either mitigation policies or changes caused by some other mechanisms (e.g. technological development). However, the uncertainties given by the model ranges for individual regions, seasons and species shown in Figure 2 and Figure 3 do not provide a good indication for the robustness of the *net* impacts estimated by the emission metrics, because there might be significant correlations between species. By robustness here, we mean how uncertain is the total climate impact of a given set of emission changes (changes of multiple species, seasons and regions) and related to this how robust would a ranking (in terms of net climate impact) of possible mitigation measures be, given the individual uncertainties shown in Figure 2 and Figure 3.

Models with more efficient vertical transport and/or slow removal of aerosols by wet scavenging will tend to give longer lifetimes for the aerosols and thus stronger RF per unit emission for all aerosol species, and thus emission metric values for the individual species and seasons would be correlated. This means that the ranking of measures and the net impact of measures that lead to reduction in emissions of co-emitted species that cause a cooling effect could be more robust. Similar effects can be expected across ozone precursors due to non-linear chemistry effects and removal efficiencies, for instance, such correlations across models were observed for NO_x from aviation by Holmes et al. (2011). To investigate this we first focus on the correlation. To put all species on a common scale we calculate the normalized variability (across species, regions and seasons) for the best estimate (NV_{BE}) and for the individual model estimates (NV_m)

$$NV_{BE}(r,s,i) = \frac{M_{BE}(r,s,i) - M_{BE,min}(i)}{M_{BE,max}(i) - M_{BE,min}(i)} \qquad (2.9)$$

and

$$NV_{m}(r,s,i) = \frac{M_{m}(r,s,i) - M_{BE,min}(i)}{M_{BE,max}(i) - M_{BE,min}(i)} \qquad (2.10)$$

$M_{BE}(r,s,i)$ denotes the best estimate for the emission metric value for species *i*, region *r* and season *s*, while $M_m(r,s,i)$ denotes the emission metric value from a single model *m* for species *i*, region *r* and season *s*.

The values of NV_{BE} are numbers between 0 and 1. Figure 4 is a scatter plot between NV_{BE} and all the individual NV_m values, where the colors indicate model and shapes of the symbol indicate component. Since the processes that could lead to correlations are somewhat different for aerosols and ozone precursors (e.g. non-linear chemistry effects for the latter) the species are split into two separate panels.

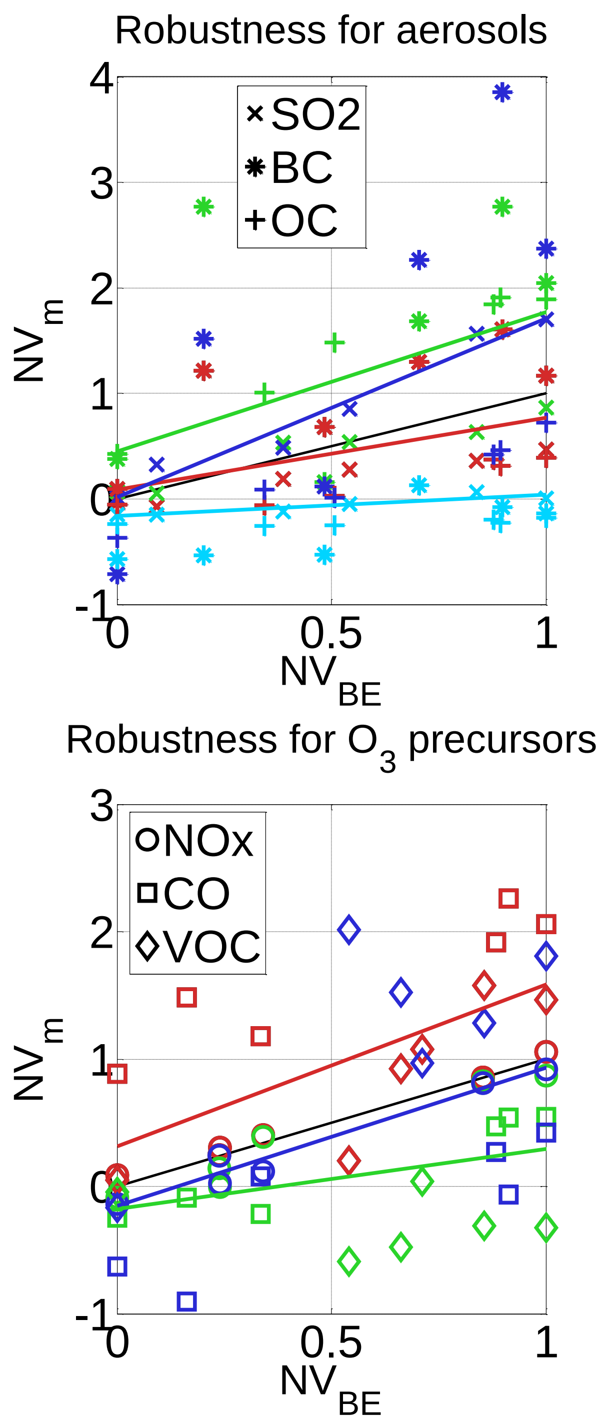

Figure 1: Scatter plot of the normalized variability of the model estimates (NVm) versus NVBE for the best estimate. Colors of the symbols indicate individual models (red: OsloCTM2, green: NorESM, blue: HadGEM3, and light blue: ECHAM6) and the shape of the symbol indicate individual species. Left panel: Aerosols and aerosol precursors (BC, OC, and SO_2). Right panel: Ozone precursors (NOx, CO, and VOC). The black line is the one-to-one line. The estimates use the GTP20 emission metric.

Figure 4 clearly shows the correlation between the species for the individual model emission metrics. For the aerosols, HadGEM and particularly NorESM tend to give higher (in absolute terms, i.e. more negative for cooling agents) emission metric values compared to the best estimate, while ECHAM gives much lower values. For the ozone precursors, the picture is the opposite, with NorESM being lower than the BE while the OsloCTM is higher. This indicates that for both aerosols and ozone precursors there are generic features in the models related to representation of key processes (e.g.

vertical mixing, wet scavenging, ozone production efficiency etc.) that systematically affects the emission metric values.

These correlations between the estimates for the individual species have to be taken into account when the uncertainty in the net effect of a multi-component mitigation policy is estimated. Since different SLCFs are often co-emitted, most mitigation options will affect emissions of several species at the same time. The uncertainty in the estimate of the net effect depends on the composition of the mitigation, i.e. mix of species, regions, and sectors. To be useful for policymaking, the emission metrics should be robust enough so that there is trust in the sign of the net effect of a mitigation measure and that the uncertainty in the emission metrics does not hinder a ranking of different measures when cost-efficiency is considered. Figure 5 shows the estimates of the net effect (here in terms of reduced warming after 20 years, i.e. using AGTP20 for pulse emissions) when using the sets of emission metrics from the individual models. First, we consider a global mitigation of a 10% reduction in emissions of all SLCFs for which the best estimate is positive for the AGTP20 (BC, OC, and VOC), and then a 10% global reduction of all SLCFs (an extreme case of also reducing the co-emitted cooling species OC, SO_2, and NO_x). The shipping sector is not included in this sensitivity test as the best estimate is only based on two models. ECHAM6 did not calculate RFs for the ozone precursors, therefore, values for the best estimate is given for those species. NH_3 is not included, as only OsloCTM2 provided RF estimates of that. These scenario estimates are based on emission inventories for 2008 (Klimont et al., 201X, in prep to ACP). For a 10% reduction in emissions of the warming SLCFs (BC, CO, and VOC), the best estimate gives a global reduction in temperature of -0.55 mK 20 years after a pulse, with a spread of -0.39 to -0.83 mK. When the cooling components are included, the best estimate gives a global warming of 0.48 mK, with models ranging from 0.05 to 0.46 mK. Hence, all models agree that a reduction of those six SLCFs will cause warming, but for two of the models only a marginal warming.

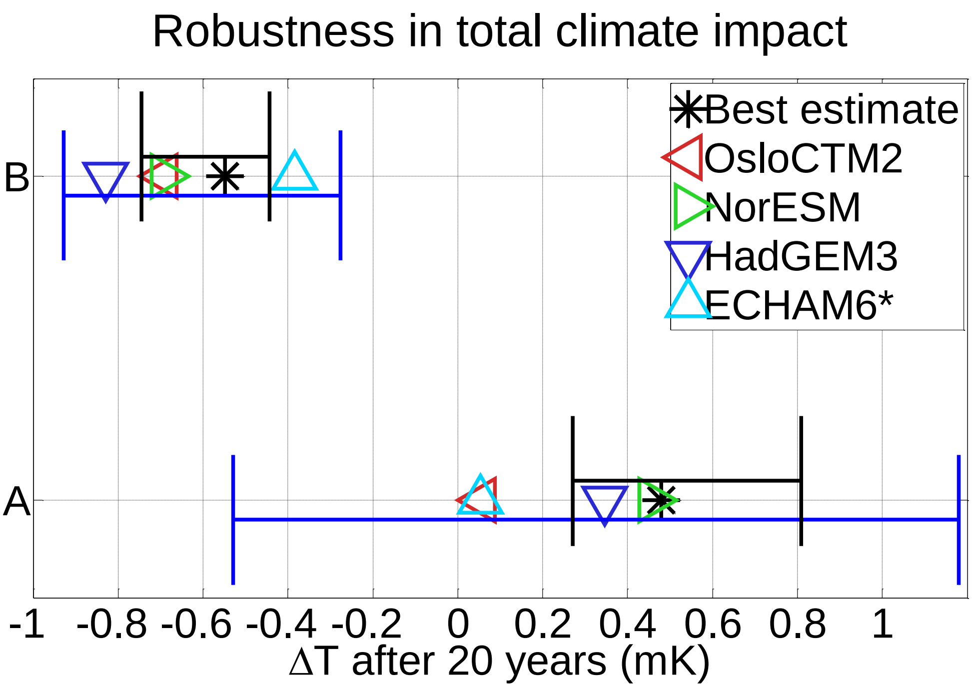

Figure 2: Emission metric-based estimate of change in global mean temperature by 10% reduction in emissions of all SLCFs based on 2008 global emissions with positive best estimate AGTP20 values (BC, OC, and VOC, labelled B), and 10%

global reduction of all SLCFs (also including OC, SO_2, and NO_x, labelled A). Colored symbols use sets of emission metrics from individual models. Blue bar is given based on summing contributions using all MAXs and MINs in Figure 2 and Figure 3. The black bar is the uncertainty assuming the metric estimates are all independent.

The black bars in Figure 5 give the uncertainty in the net global temperature effect assuming all the metric values are independent. This gives a similar or narrower uncertainty interval than the spread of the estimates using the individual model metrics, again showing that there is considerable correlation between in the model estimates. However, if the difference between the models were 100% systematic (i.e. one model always giving the lowest estimates by magnitude and another model giving the highest), then the model based interval would be given by the blue bar in Figure 5. From this analysis, we conclude that the uncertainty for an estimate of the net temperature effect of multi-component emission change is enhanced due to the correlations, however, for mitigation measures that mainly change emissions of species with positive GTPs, the sign of the global temperature signal is robust.

Since not all processes are included in all the models, the average of all models in Figure 2 will differ from the best estimate. This deviation is observed in both scenarios, but clearest for a mitigation scenario including both warming and cooling SLCFs, as the net climate impact is a sum of large positive and negative numbers. The processes not included are dominated by cooling. Three out of four models do not include the cooling from the semi-direct effect of BC, as well as the mainly cooling from nitrate for the ozone precursors and SO_2. As a consequence, the individual models tend towards more cooling or less warming than the best estimate for a mitigation scenario of SLCFs.

Our findings show that the robustness is largest for individual species, i.e., what region and season of emissions to mitigate for an individual species. Next follows a subgroup of species that correlates, such as aerosols. Lowest robustness is given for mitigation for all SLCFs. However, we observe that all models agree whether two hypothetical mitigation scenarios give warming or cooling.

The following figures give examples of application of RTPs for calculations of contributions to Arctic climate change by component and region for the domestic sector based on the ECLIPSE mitigation scenario.

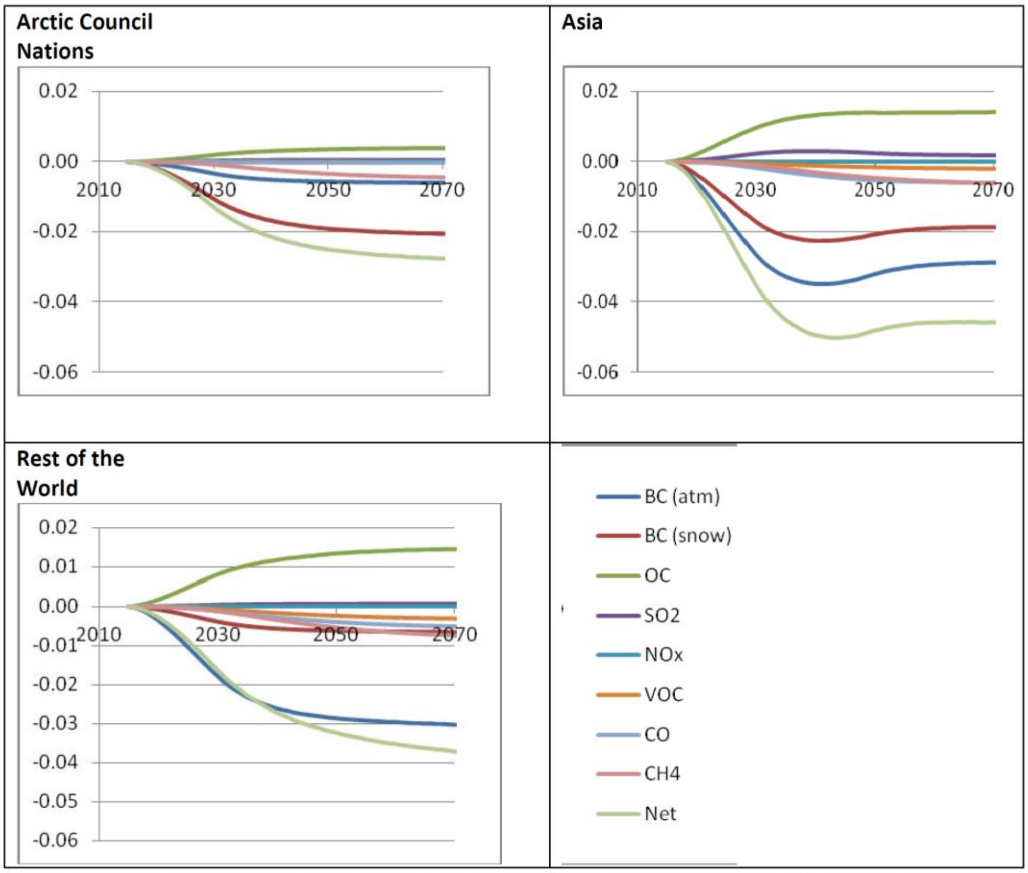

Fig. 1 Potential Arctic surface temperature change (°C) by regional mitigation of domestic burning in the ECLIPSE SLCF emission scenario

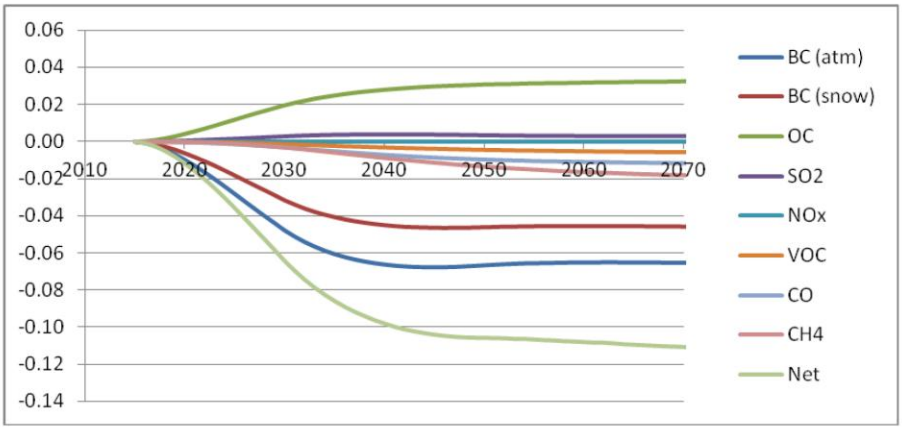

Fig. 2 Total potential Arctic surface temperature change (°C) by global mitigation of domestic burning in the ECLIPSE SLCF emission scenario