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Real Option Value for New Measurements of Cloud Radiative Forcing

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Abstract

One of the critical uncertainties in estimating future climate change is climate sensitivity. Climate sensitivity uncertainty is driven by uncertain low cloud feedback in the climate system. Low cloud feedback is very closely related to decadal changes in the effect of low clouds on reflected solar radiation or shortwave cloud radiative forcing. This study computes the real option value of higher accuracy cloud radiative forcing measurements using the Inter Agency Memo on the Social Cost of Carbon, thereby extending a previous study of real option value based on observing the decadal rate of temperature rise. The real option values for measuring cloud radiative forcing are roughly double that of measuring decadal temperature rise. This reflects the fact that triggering on temperature generally occurs earlier with less pronounced differences between the new and existing observing systems.

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Contents

1. Introduction.....	1
2. Brief Review of Previous Work on This Project	2
3. Triggering on Cloud Radiative Forcing.....	5
4. Observation Uncertainty and Decision Context.....	7
5. Results: Base Case.....	9
6. Sensitivity Analysis	15
7. Conclusions.....	18
References	20

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1. Introduction

The goal is to extend the work in Cooke et al. (2013, 2015) to measurements of percentage changes in Cloud Radiative Forcing (CRF). The motivation is both to show that the mathematical framework can be extended to additional climate variables and to use climate variables that are more physically related to climate sensitivity uncertainty than decadal temperature change. The real option value is computed for an enhanced Earth Observing System (EOS) that is able to observe changes in CRF more accurately than the existing systems. In the context of the Interagency Working Group on Social Cost of Carbon (IWGSCC 2009, 2013), the real option value becomes a monetization of the worldwide social value realized by the enhanced EOS. An example of such an enhanced EOS relative to CRF observations is to use future Climate Absolute Radiance and Refractivity Observatory (CLARREO) orbiting reference spectrometers to improve the calibration of the broadband Clouds and the Earth Radiant Energy System (CERES) radiation balance observations used to determine global CRF. CLARREO reference inter-calibration of CERES during orbit crossings would allow an increase of international standards traceability to an accuracy roughly 10 times higher than current CERES observations alone (Wielicki et al. 2013). CLARREO is currently planned for launch as a Pathfinder mission on the International Space Station (ISS) in 2020. While CLARREO is used as an example in this paper of advancing the accuracy of a key climate change observation relevant to societal decision making, it should be recognized that the economic value is *not* that of CLARREO alone but instead that of a complete advanced Earth Observing System that currently does not exist. This distinction is important because societal decisions will be made using multiple climate change observations and not a single observation. Nevertheless, climate sensitivity uncertainty remains one of the most critical scientific advances required to support future societal decisions.

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There has been much work on the value of learning about climate and the value of information (Kelly and Kolstad 1999; O'Neill et al. 2006; Webster et al. 2008; McInerney et al. 2011). This literature generally views learning as learning the value of some physical variables with certainty at some future time and computing the benefits. Hope (2015) considers a specific reduction of uncertainty at given times. Based on the PAGE09 integrated assessment model (which is also used in the IWGSCC) he reports: “*Approximately halving the uncertainty range for TCR [Transient Climate Response] has a net present value of about \$10.3 trillion (year 2005 US\$) if accomplished in time for emissions to be adjusted in 2020, falling to \$9.7 trillion if accomplished by 2030*” (1). Hope (2015) does not consider *how* the learning or uncertainty reduction will be achieved, though he does suggest that the learning will result from high resolution climate models run on super computers.

The present research’s point of departure is not an abstract hypothesis about future learning, but concrete Earth Observing Systems. A new proposed Enhanced EOS, and the Current EOS it is designed to replace, must acquire an uncertainty profile, whereby the variance in its measurement results is decomposed as a sum of variances resulting from natural variability, which cannot be removed by measurement, and instrumental uncertainty, which can be reduced by better instruments. When the measurement systems are profiled in this way, it becomes evident that (1) we never learn with certainty, we can only reduce uncertainty, and (2) regarding climate trends, *when* we learn depends on the length of the observation period, the measurement accuracy, and the unknown value of the underlying physical quantity. In this context, it is not appropriate to posit a given degree of certainty attained at a given time.

2. Brief Review of Previous Work on This Project

Cooke et al. (2013) computed the Value Of Information (VOI) of an Enhanced EOS, designed to measure the decadal rate of temperature rise with greater accuracy than current systems (denoted Current EOS or I/A/C to indicate the IASI/AIRS/CrIS weather satellite instruments). As for CRF, this earlier paper used the CLARREO advance in reference calibration of weather satellite instruments (I/A/C) to provide more accurate climate change observations (Wielicki et al. 2013). The primary distinction is between the accuracy of satellite systems designed for weather or research observations (I/A/C) and the accuracy of those designed for the more subtle decadal climate change signals.

The social cost of carbon (IWGSCC 2009) provided the framework for the valuation. For the new and current EOSs, the net present value of the expected averted climate damages was computed on the assumption that, upon observing a trigger value of the decadal temperature rise

with requisite confidence, one of three reduced emissions scenario would be chosen (the DICE optimal-, the Limit 2.5C stabilization-, and the Stern-Gore-emissions scenarios). Parameters for this calculation were taken from the IWGSCC memo. Per reduced emissions scenario the net present value of the expected averted damages was computed. Table 1 shows the results of switching to the DICE optimal emissions path under the discount rates stipulated by IWGSCC. This scenario is optimal for equilibrium climate sensitivity value of 3C and 5% discount rate.

Table 1. VOI for Enhanced EOS (CLARREO + I/A/C) and Current EOS (I/A/C) in Trill USD 2008, when the DICE Optimal Path is Chosen as the Reduced Emissions Path

VOI: BAU → DICE Optimum Emissions					
	<i>BAU and altered emissions path</i>	<i>Mean NPV damages [Trill USD 2008]</i>	<i>Stdev</i>	<i>Delta Mean Averted Damages: Increase in VOI with Enhanced EOS over Current EOS</i>	
	BAU 2.5%	345.39	158.66	Launch = 2020 Conf = 95% Trigger = 0.2C	
	BAU 3%	209.14	92.58		
	BAU 5%	43.02	16.13		
<i>Discovered by Enhanced EOS</i>	VOI-Enhanced EOS 2.5%	73.10	35.95		
	VOI-Enhanced EOS 3%	53.58	20.01		
	VOI-Enhanced EOS 5%	20.12	3.38		
<i>Discovered by Current EOS</i>	VOI-Current EOS 2.5%	90.65	41.05	2.5%	17.55
	VOI-Current EOS 3%	65.24	21.69	3%	11.67
	VOI-Current EOS 5%	23.26	2.87	5%	3.14

Note: Bold numbers are the differences in mean NPV of averted damages, per discount rate (from Cooke et al. 2013).

Sensitivity analysis is performed on the parameters of the “base case” decision context. Partial results are shown in Table 2.

Table 2. Sensitivity for VOI of Table 1

DELTA Mean Averted Damages Trillion USD (2008)						
Launch date	Switch to	Confidence	Trigger	2.5%	3%	5%
2020	DICE OPT	95%	0.2C/decade	17.55	11.67	3.14
2020	DICE OPT	97.5%	0.2C/decade	21.63	14.22	3.66
2030	DICE OPT	95%	0.2C/decade	14.79	9.16	1.88
2020	DICE OPT	95%	0.3C/decade	23.34	14.36	2.91
2020	STERN	95%	0.2C/decade	22.25	15.57	5.01
2020	STERN	97.5%	0.2C/decade	27.19	18.78	5.75
2020	STERN	97.5%	0.3C/decade	31.86	20.30	4.65
2030	STERN	97.5%	0.3C/decade	30.61	18.54	3.50

Note: Altered parameter values in red (from Cooke et al. 2013).

Cooke et al. (2015) departed from the IWGSCC (2013) guidelines in that abatement costs were taken into account, in addition to damages. Upon observing a trigger value with requisite confidence, society chooses an optimal reduced emissions path. The expected surfeit net benefits of the enhanced versus the present EOS are computed.

Table 3. Expected Net Benefits of Enhanced (CLARREO) and Current (I/A/C) EOS in the Base Case, Trill. USD (2008)

Net Benefits: E(BAU (Damage + Cost) – Red Em (Damage + Cost))				
Base Case: Trigger = 0.2C/decade; sigma = 1.65 (95% confidence); Launch 2020				
	Reduced emissions path	Discount rate		
Triggered on		2.50%	3%	5%
Enhanced EOS	DICE Opt	59.083	31.920	3.623
	Lim 2.5C	103.409	50.892	2.514
	Stern	107.075	48.868	–1.560
Current EOS	DICE Opt	49.188	25.987	2.635
	Lim 2.5C	88.002	42.559	1.965
	Stern	92.362	42.327	–0.352
Difference in net benefits Enhanced EOS – Current EOS				
	Reduced emissions path	Discount rate		
		2.50%	3%	5%
Surfeit net benefits	DICE Opt	9.894	5.933	0.988
	Lim 2.5C	15.408	8.333	0.549
	Stern	14.713	6.541	–1.208

Note: If the reduced emissions path is chosen before observing the trigger value, the expected surfeit net benefits are shown, with circles indicating optimal reduced emissions path per discount rate.

In computing the *Real Option Value* of the enhanced EOS, the choice of reduced emissions path is made after observing the trigger value. The results in Table 4 show that this choice option affords a modest advantage relative to choosing a reduced emissions path based on the discount rate (Table 3).

Table 4. Expected Surfeit Net Benefits in Base Case, by Year and by Discount Rate

Real Option Value of Enhanced EOS			
Discount rate	2.50%	3%	5%
Real option value	16.70	9.00	1.07

Note: Trigger = 0.2C/decade, sigma = 1.65 (95% Confidence), launch 2020 (from Cooke et al. 2015)

3. Triggering on Cloud Radiative Forcing

Decadal change in global mean shortwave cloud radiative forcing (CRF) is directly related to the magnitude of low cloud feedback, which is the dominant uncertainty for climate sensitivity (Soden et al. 2008; IPCC 2013). Shortwave or reflected solar CRF dominates low cloud feedback in the climate system because the cloud temperature for these cloud systems is very close to surface temperature, thereby greatly limiting their impact on longwave or thermal infrared cloud feedback. Total cloud feedback is the sum of longwave and shortwave feedback. As a result, we focus in this paper on uncertainty in decadal change observations of global mean shortwave CRF as a measure most directly linked to uncertainty in climate sensitivity.

We use the equations from Soden et al. (2008) to relate decadal change in CRF to equilibrium climate sensitivity (ECS) as defined in IPCC (2013). Let R_f denote the total anthropogenic radiative forcing of climate change by greenhouse gases, aerosols, and land change. T_s is global average surface temperature, and λ is climate sensitivity. Following Soden et al. (2008):

$$\Delta R_f / \Delta T_s = \lambda = \lambda_p + \lambda_L + \lambda_w + \lambda_\alpha + \lambda_{csw} + \lambda_{chw}. \quad (1)$$

Note $\Delta R_f / \Delta T_s$ is expressed in units of $\text{Wm}^{-2}\text{K}^{-1}$. The feedbacks are as follows:

λ_p = plank temperature feedback (pure σT^4 : i.e., no atmosphere) ~ -3.2

λ_L = temperature lapse rate feedback ~ -0.6

λ_w = water vapor feedback $\sim +1.6$

λ_α = snow and ice surface albedo feedback $\sim +0.3$

λ_{csw} = shortwave cloud feedback (this is what we vary to get cloud feedback relationship to sensitivity and SW CRF)

λ_{clw} = longwave cloud feedback (not given separately in the IPCC report; using Soden and Vecchi 2011, Figure 3 top, and averaging for all 12 of the climate models they used) $\sim +0.35$

Positive magnitude is a positive feedback, and negative magnitude is a negative feedback.

We use estimates from the IPCC AR5 report, chapter 9, Figure 9.43, and Table 9.5, CMIP5 mean (red dot in the figures) for everything except the LW cloud feedback, which is not given in the IPCC report. LW cloud feedback is taken from Soden and Vecchi (2011).

$$\lambda = \lambda_p + \lambda_L + \lambda_w + \lambda_a + \lambda_{csw} + \lambda_{clw}. \quad (2)$$

Solving for λ_{csw} with the values above,

$$\lambda_{csw} = \lambda - (-3.2) - (-0.6) - (+1.6) - (+0.3) - (+0.35) = \lambda + 1.55 \quad (3)$$

λ is simply related to the equilibrium climate sensitivity (*ECS*), as used in DICE, where ΔCO_2 denotes a doubling of atmospheric CO_2 concentration:

$$\lambda = \Delta R_f / \Delta T_s = (\Delta R_f \text{ for } \Delta CO_2) / (\Delta T_s \text{ for } \Delta CO_2) = -3.7 / ECS. \quad (4)$$

ECS in this definition is the amount of equilibrium global average surface temperature increase for an anthropogenic radiative forcing equivalent to a doubling of CO_2 . The factor 3.7 converts a doubling of atmospheric CO_2 to Wm^{-2} of radiative forcing. See IPCC (2013) for a discussion of the definition of radiative forcing. The idea here is that we set all of the feedbacks except SW cloud feedback equal to their average over the climate models. We then vary SW cloud feedback to obtain the range of climate sensitivity.

Combining (2), (3), and (4), the governing equation for the change in CRF is

$$\begin{aligned} 100\Delta CRF(em, t, ECS) / 50 &= 2 \lambda_{csw} \Delta T(em, t, ECS) = \\ &= 2[-3.7 / ECS - (\lambda_p + \lambda_L + \lambda_w + \lambda_a + \lambda_{clw})] \times \Delta T. \end{aligned} \quad (5)$$

In this equation, 50 is the global mean value of CRF_{sw} in units of Wm^{-2} and is used to convert the trend in Wm^{-2} into a trend in units of a fraction. A factor 100 converts fractions to percentages, resulting in the factor 2. We then have the decadal trend in shortwave cloud radiative forcing in units of %/decade. ΔT is determined by emissions scenario em , time t , and *ECS*. $\Delta T(em, t, ECS)$ is computed from DICE. Hence, the RHS is known and we can compute the theoretical value of $\Delta CRF(em, t, ECS)$ based on the IWGSCC certified DICE model, supplemented with Soden et al. (2008). ΔT represents the “true” global mean temperature change

under these assumptions. Parenthetically, we note that Roe Baker adopted by IWGSCC use $ECS = 1.2/(1-f)$, $f \sim Normal(0.62, 0.19^2)$, whereas Soden et al. (2008) used effectively $f \sim Normal(0.62, 0.1766^2)$. This difference is negligible.

If $\lambda_p \dots \lambda_{clw}$ are uncertain, there is a case to be made for including this uncertainty. Is it plausible that, say, $ECS = 10$ should be attributed solely to λ_{csw} ? Including these uncertainties would introduce complications, and in an initial study the gain in accuracy would not be compensated by the loss of perspicuity.

4. Observation Uncertainty and Decision Context

The physical variable of interest is percentage change in CRF per unit time, relative to the global mean value, which we denote ΔCRF . We assume that the theoretical value of ΔCRF is observed with some error. If $OBS(\Delta CRF)$ is the observed value when the true value is ΔCRF , then we assume $OBS(\Delta CRF) + \xi = \Delta CRF$ where ξ is normal with mean zero and variance σ^2 . To be 95% certain that $\Delta CRF > 0.2$, we must have

$$0.95 < P(\Delta CRF > 0.2) = P(OBS(\Delta CRF) + \xi > 0.2) = P(\xi/\sigma > (0.2 - OBS(\Delta CRF))/\sigma) \Leftrightarrow (0.2 - OBS(\Delta CRF))/\sigma < -1.65 \Leftrightarrow OBS(\Delta CRF) > 0.2 + 1.65\sigma. \quad (6)$$

Here, 1.65 is the 95th percentile of the standard normal variable ξ/σ . The parameter 0.2 is called the trigger value of ΔCRF and 1.65 is termed the confidence level, or simply the confidence. These parameter values are given by the decision context and are varied in order to examine the stability of the results. σ is derived from Leroy et al. (2008):

$$\sigma^2 = 12(\Delta t)^{-3}(\sigma_{var}^2 \tau_{var} + \sigma_{cal}^2 \tau_{cal} + \sigma_{orbit}^2 \tau_{orbit}). \quad (7)$$

The units of the variance components σ_{var}^2 , σ_{cal}^2 , and σ_{orbit}^2 are the squares of the physical units being measured, percentage change in CRF . The characteristic times τ_{var} , τ_{cal} , and τ_{orbit} are in years, hence the LHS is in units $(\text{percentage change} / \text{yr})^2$. The root of (7) is the uncertainty (standard deviation) in percentage change in CRF per year.

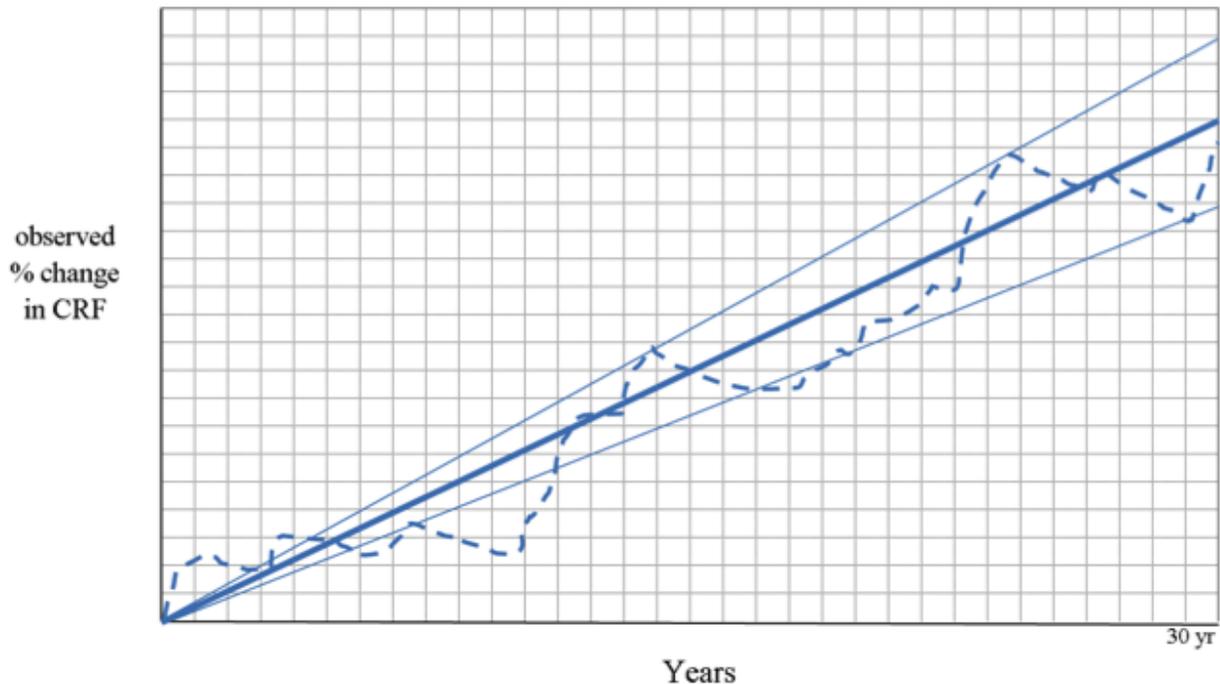
The values for variance and time scale used in (7) are given in Table 5 and are taken from Wielicki et al. (2013). Climate system internal natural variability variance σ_{var}^2 and time scale τ_{var} are based on 10 years of de-trended CERES observations of global average shortwave CRF, adjusted using the student-T distribution to account for the relatively short climate record. The values were also compared to a wide range of climate model unforced “nature” simulations that show similar variability to within $\pm 30\%$ (Wielicki et al. 2013). Calibration uncertainty variance σ_{cal}^2 and time scale τ_{cal} are taken from Wielicki et al. (2013) for CLARREO and from

Loeb et al. (2009) for CERES, based on instrument reliability estimates. Design reliability on orbit of the CERES instruments is $\sim 70\%$ at 10 years (85% at 5 years). Of the four CERES instruments on Terra and Aqua, three of the four instruments remain fully functional after more than 13 years. Orbital sampling uncertainty variance σ_{orbit}^2 and time scale τ_{orbit} are taken from uncertainty analyses using 10 years of simulated orbit sampling of an interpolated three hourly geostationary observation data set (Wielicki et al. 2013). In these cases, the Enhanced EOS is provided by CERES calibrated to a much higher standard of accuracy by CLARREO, while the Current EOS is the current standard CERES calibration uncertainty.

Table 5. Variance Decomposition for Percentage Change in CRF Relative to Global Mean

	CLARREO	CERES
σ_{var}	0.6	0.6
τ_{var}	0.8	0.8
σ_{cal}	0.15	1
τ_{cal}	10	10
σ_{orbit}	0.21	0.006
τ_{orbit}	1	1

Suppose after observing for $\Delta t = 30$ yrs, the observed percentage change CRF , with all the uncertainties in (7), shown as the dashed line in Figure 1. The bold line represents our estimate of the slope, and the thin lines represent our 90% central confidence band about the slope estimate. If the bold line is written as αt , then the upper and lower confidence bands are $(\alpha + 1.65\sigma)t$ and $(\alpha - 1.65\sigma)t$, respectively. If we change units to percentage change in CRF per decade, then our 90% central confidence on the percentage change per decade, after three decades, is $[((\alpha - 1.65\sigma) \times 30)/3, ((\alpha + 1.65\sigma) \times 30)/3]$. In other words, our uncertainty in the decadal rate of percentage change scales with 10σ . If we observe a decadal rate of percentage change in CRF, then we should replace σ in (6) with 10σ .

Figure 1. Observed Percentage Change in CRF over 30 Years

5. Results: Base Case

Information can have value only if it is used. Any calculation of value of information or real option value must therefore posit a decision context in which the information would be used. This is not a prediction of societal behavior, but a tool for quantifying the value of information. As in Cooke et al. (2013, 2015), we posit a trigger value and a confidence level. When the triggering variable is observed to exceed the trigger value with the given confidence level, society switches to one of three reduced CO₂ scenarios. For the Enhanced EOS (CLARREO calibration of CERES in orbit) and the Current EOS (CERES alone), the expected net benefits are calculated using the DICE integrated assessment model (Nordhaus 2008, Nordhaus and Sztorc 2013), for discount rates 2.5%, 3%, and 5% using the truncated Roe Baker distribution for ECS (IWGSCC 2013). Net benefits are the NPV of damages averted by switching emissions scenarios minus the NPV of abatement costs. The Real Option Value (ROV) of the Enhanced EOS is the surfeit expected net benefits of triggering the switch on the more accurate Enhanced EOS instead of the less accurate Current EOS.

Figure 2 plots the decadal change in CRF (i.e., %CRF per decade) from 2015 to 2115, for different values of ECS. For low values of ECS, the CRF decadal change is negative, indicating a negative cloud feedback in the climate system reducing climate sensitivity. Figure 2 shows a

monotonic increase in CRF decadal change with increasing climate sensitivity ECS. For ECS less than 4, the decadal change in CRF plateaus after roughly 2075, whereas it keeps increasing for higher ECS values. A decadal change in CRF of -0.1% is taken as the trigger value in the *Base Case*, observed with 95% confidence following a launch in 2020. Figure 2 shows that a trigger of -0.1% / decade is consistent with an ECS value above 2C. The IPCC (2013) report gave a most likely ECS value of roughly 3C. Those advocating little action on climate change anticipate a much lower ECS value in the neighborhood of 1.0C to 1.5C.

Figure 3, for comparison, shows the relationship between decadal change in global surface air temperature and ECS. As for CRF, ECS increases with increasing decadal temperature change. The 0.2C per decade warming used as the *Base Case* trigger in the earlier studies (Cooke et al. 2013, 2015) indicates an ECS of 2C or greater, similar to the *Base Case* in the CRF results. Comparison of Figures 2 and 3 allow determination of a rough equivalence of triggers for decadal change in CRF and temperature.

Figure 2. Percentage Change in CRF for Different ECS as Function of Year and ECS

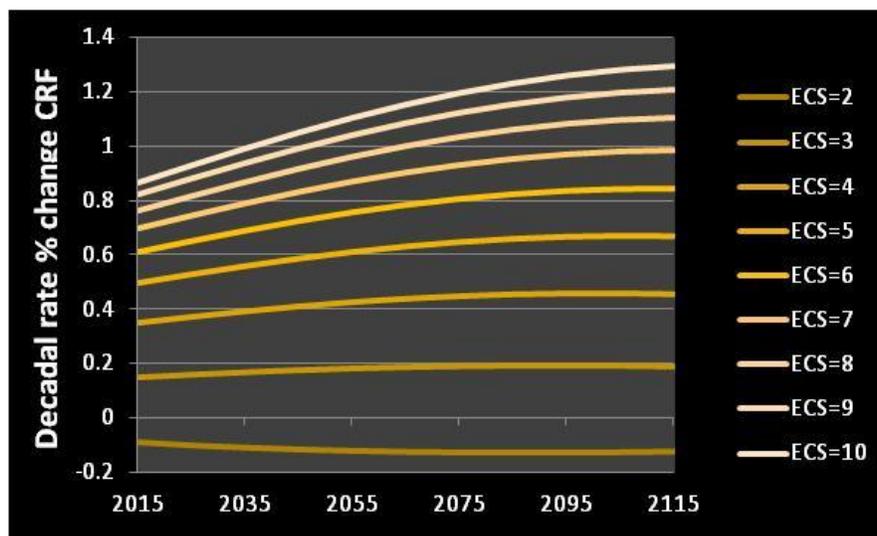
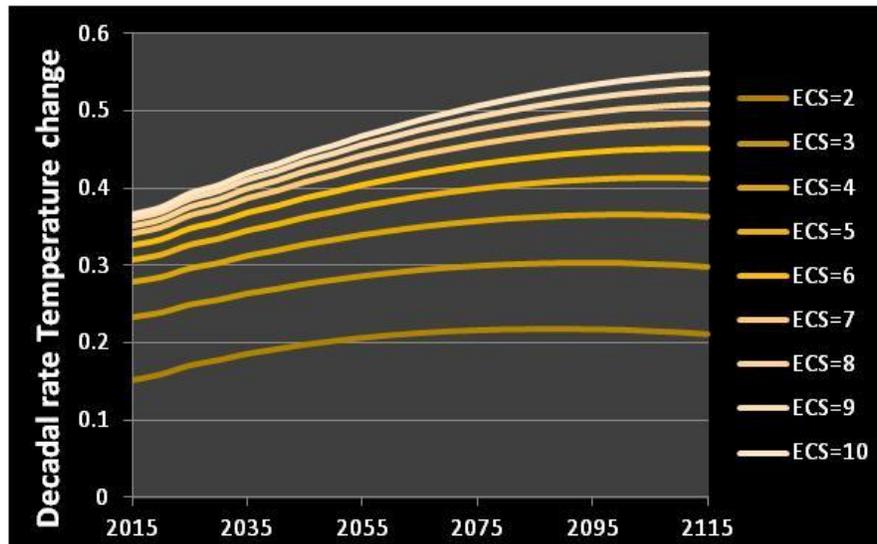


Figure 3. Decadal Temperature Change [C] for Different ECS as Function of Year



The *Base Case* in this study uses 2020 as the nominal start of the climate change observations used to constrain uncertainty in climate sensitivity. There are two reasons for this. First, a CLARREO Pathfinder satellite mission capable of improving the calibration of CERES in orbit has a planned launch date of 2020 on the International Space Station. Second, large uncertainty remains in anthropogenic aerosol indirect radiative forcing (IPCC 2013). Indirect aerosol forcing modifies cloud properties and therefore can be confused with cloud feedback changes in CRF. This remains a very active research area, and we assume here that the Enhanced EOS will have developed improved aerosol indirect effect observations by 2020. Finally, while aerosol radiative forcing is expected to reduce in magnitude in the future as China and India improve air pollution controls and coal use is reduced, CO₂ continues to build in the atmosphere with a very long lifetime, thereby becoming the dominant anthropogenic forcing in the next few decades. These considerations all suggest that 2020 is the earliest date to realistically consider starting the VOI comparison of an Enhanced EOS versus the Current EOS.

Figure 4 shows the difference for Enhanced EOS and Current EOS of expected net benefits of switching to each of the three reduced emissions paths, under each of the discount rates. Below ECS = 3.214C there is no triggering and hence no switch to a reduced emissions scenario.¹ Under the Roe Baker distribution the probability that ECS < 3.214 = 0.57. The DICE

¹ This applies in the Base Case; lowering the trigger value or the confidence level induces triggering at lower values of ECS.

path (which is optimal for ECS = 3 and 5% discounting) has marginally better net benefits than Lim 2.5 only with discount rate 5% and $ECS \leq 4.6$. With 2.5% discount rate the Stern path is optimal at all values of ECS, and for 3% it is optimal for ECS above 5.

Figure 4. Expected Surfeit Net Benefits from Three Reduced Emissions Scenarios for Different ECS Values and Different Discount Rates, Trigger Value -0.1, Confidence 1.65

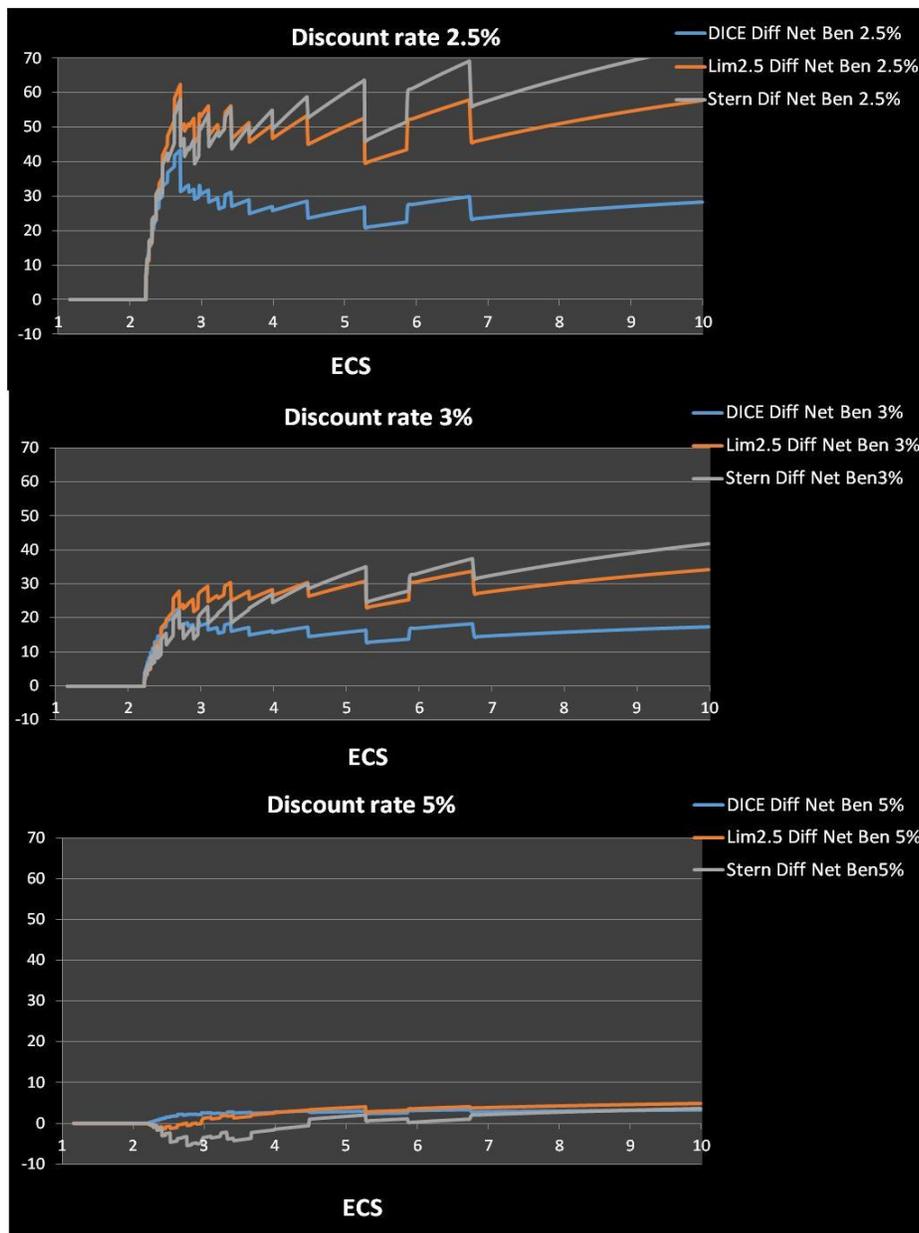


Figure 5 (from* Cooke et al. 2015) shows analogous information to Figure 4 for triggering on temperature. The surfeit expected net benefits of the Enhanced EOS versus Current EOS for a trigger on CRF observations (the real option value, see Table 6) are 38.8, 19.9, and 2.0

trillion USD (2008) and should be compared to the net benefits for temperature observations with 16.7, 9.0, and 1.1 in Table 4.

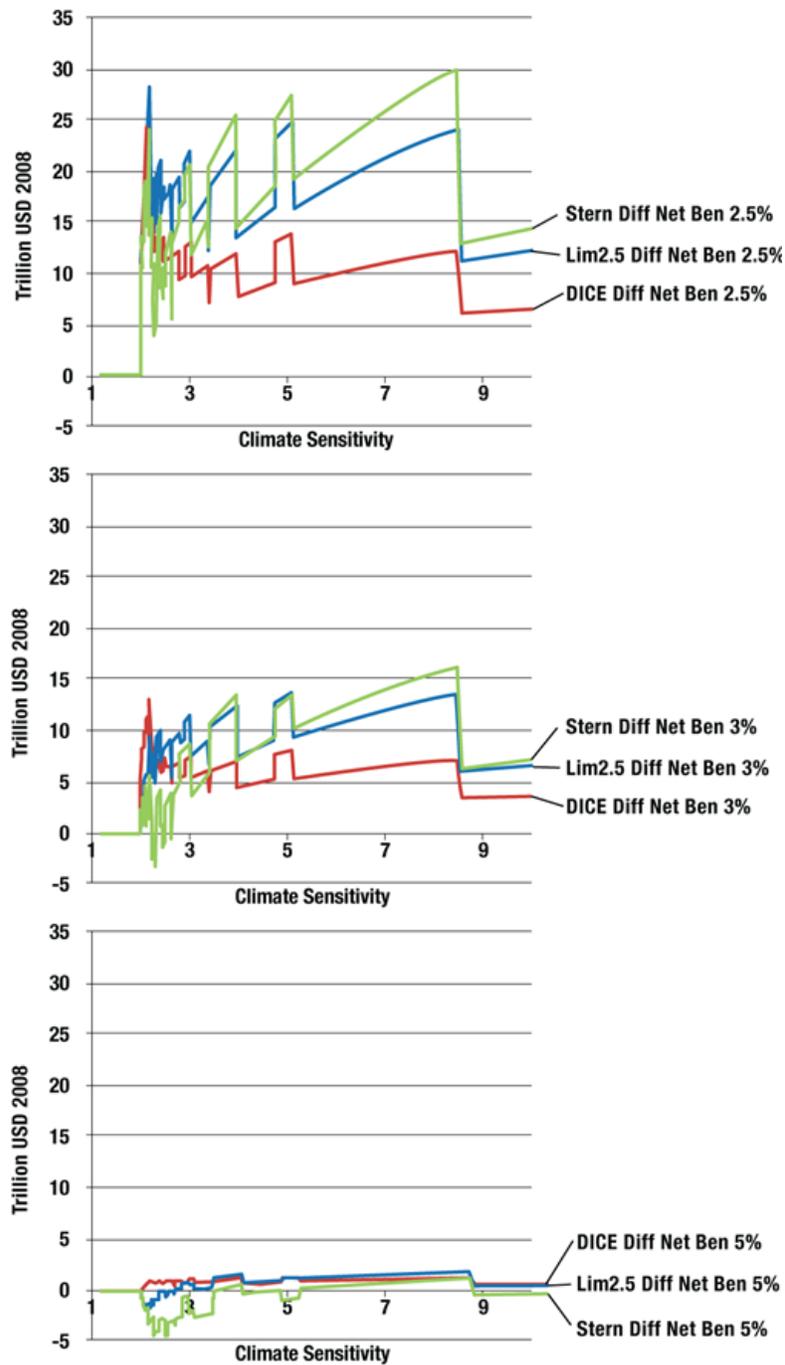
For the Base Case, Table 6 shows the breakdown of the surfeit expected net benefits according to the year in which the triggering occurs. Given the 5-year step size, triggering in a given year defines an interval of values of ECS, as depicted in Figure 6. “NoNoise” denotes the trigger time if we could observe CRF changes without natural variability; “Perf” denotes a perfect observing system subject only to natural variability. If the Enhanced EOS for CRF triggers in year 2040, then the admissible values of ECS lie between 3.98C and 5.86; greater values would have triggered before 2040, smaller values would trigger after 2040.

Upon triggering, for each admissible value of ECS, the difference in expected net benefits for each EOS is computed, accounting for the fact that the Enhanced EOS would trigger earlier than the Current EOS, with the time difference depending on the values of ECS. As a result, for two different admissible ECS values, the greatest surfeit net benefits might be realized by different reduced emissions paths. However, we have no way of discriminating between different admissible values of ECS, and therefore we must choose the emissions path with the greatest average surfeit net benefits over all admissible ECS values. Averaging these surfeit expected net benefits for all values of ECS sampled from the original truncated Roe Baker distribution yields the numbers reported as “**total**” in Table 6.

Instead of calculating as above, suppose we simply sampled a value of ECS from the truncated Roe Baker distribution, computed the trigger times for the Enhanced EOS versus the Current EOS, and chose the reduced emissions path with maximal surfeit expected net benefits. This is equivalent to saying that at the trigger time, we (somehow) know the exact value of ECS that caused the trigger, rather than merely knowing an admissible interval. Choosing an optimal emissions path in this case should realize a higher value than when we choose an optimal average over an admissible interval. These values are shown in “**choose policy per ECS.**” These are also the values that would be computed if we observed each year instead of using year time steps.² The advantages of this increased observation frequency are real, but relatively small.

² DICE uses 10-year time steps; we create 5-year time steps by interpolation.

Figure 5. Surfeit Net Benefits for Enhanced EOS (Triggering on Change in Temperature rise) versus Current EOS as Functions of CS



Notes: The horizontal axis is (unknown) climate sensitivity; the vertical axis is surfeit benefits as a function of climate sensitivity. Jumps are caused by the 10-year discretization (from Cooke et al. 2015)

The major conclusion is that the surfeit expected net benefits of the Enhanced versus the Current EOS are larger when triggering on decadal change in CRF (Table 6) than when triggering on decadal change in temperature (Table 4).

Table 6. CLARREO Surfeit Expected Net Benefits per Trigger Year

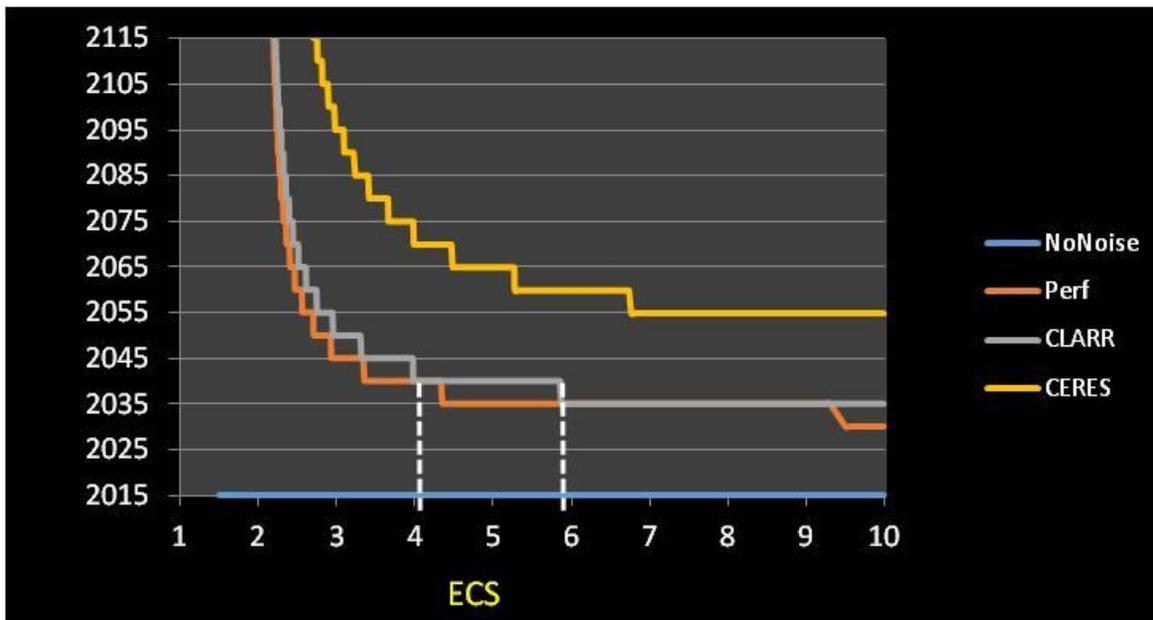
Real Option Value of enhanced EOS			
Expected Surfeit Net Benefits by trigger year Trill USD(2008)			
	trigger value	confidence	Launch date
Trigger on Delta CRF	-0.1	1.65	2020
	2.5%	3%	5%
2035	6.448	3.600	0.413
2040	10.153	5.379	0.604
2045	5.779	3.145	0.300
2050	4.898	2.568	0.235
2055	4.071	1.949	0.179
2060	2.725	1.230	0.101
2065	1.664	0.693	0.058
2070	0.942	0.391	0.032
2075	0.823	0.356	0.028
2080	0.611	0.258	0.020
2085	0.282	0.134	0.009
2090	0.205	0.086	0.006
2095	0.152	0.072	0.004
2100	0.131	0.055	0.003
total	38.8819	19.9167	1.9927
Best possible, choose policy per ECS	2.5%	3%	5%
	39.1541	20.0778	1.998

6. Sensitivity Analysis

The results for 28 variations on the CRF Base Case are shown in Table 7. As expected, the surfeit declines with increasing launch date and with increasing discount rate. Less obvious is the fact that it generally increases with increasing requisite confidence in the exceedence of the trigger value, though this was also observed in Table 2 for decision triggers based on temperature change. This is caused by the fact that high levels of confidence are attained proportionally later with the Current EOS than with the more accurate Enhanced EOS, making the difference in expected net benefits greater. Confidence levels 1.28, 1.65, and 2.3 correspond to the 90%, 95%, and 97.5% exceedence probabilities of a standard normal variable.

The most striking feature of Table 7 is the overwhelming importance of the discount rate. However, the percentage loss of ROV by delaying the launch by 5 years for trigger value -0.1 start at about 15% with successive 5-year delays getting suffering larger percentage losses.

Figure 6. Trigger Times as a Function of ECS, Trigger Value -0.1 , Confidence 1.65



Notes: If the Enhanced EOS triggers in 2040, then ECS is between 3.98C and 5.86C (dotted lines), and the Current EOS would trigger between 2070 and 2080

The complexity of the ROV calculations is revealed in the sensitivity analysis. Focus first on the 2020 launch date. For low trigger values, the ROV increases with increasing confidence. However, for trigger value 1, ROV decreases with increasing confidence. This can be understood from a close comparison of Figures 6 and 7. The higher confidence level in Figure 7 (2.3) as opposed to Figure 6 (1.65) pushes both the Enhanced EOS and Current EOS curves up, but pushes the Enhanced EOS curve farther. Higher trigger values would push both curves to the right, causing the triggering to occur later and only for very high values of ECS. The result is that for confidence 2.3, the Current EOS does not trigger at all on the value 1.0, whereas the Enhanced EOS triggers for $ECS > 7.7C$. Since this happens very late, the expected net benefits are actually less than the difference of expected net benefits when triggering at 1.65.

Finally, it should be noted that the parameters of the decision context, the discount rate, the requisite confidence level, the launch date, the trigger values, and so on will be taken by society for a host of reasons that are outside the framework of choosing an EOS. The decision context in an ROV calculation enables modeling a wide variety of realistic decisions by varying

the values of the decision parameters. As such, it provides an answer to the question of whether the value of a new EOS strongly depends on particular parameter values, or whether this value is sustained across a wide variety of possible parameter choices. As shown in Table 7, the dominant effect on ROV is the discount rate, followed by the CRF trigger value and the launch date of the Enhanced EOS, with confidence providing the smallest effects. While we provide a wide range of CRF trigger values for perspective, society is likely to respond to high confidence in ECS greater than 2.5C given the large climate change damages for business-as-usual emissions at climate sensitivities greater than about 2.5C (IPCC 2013). As a result, societal trigger values higher than 0.2 for CRF may be unlikely.

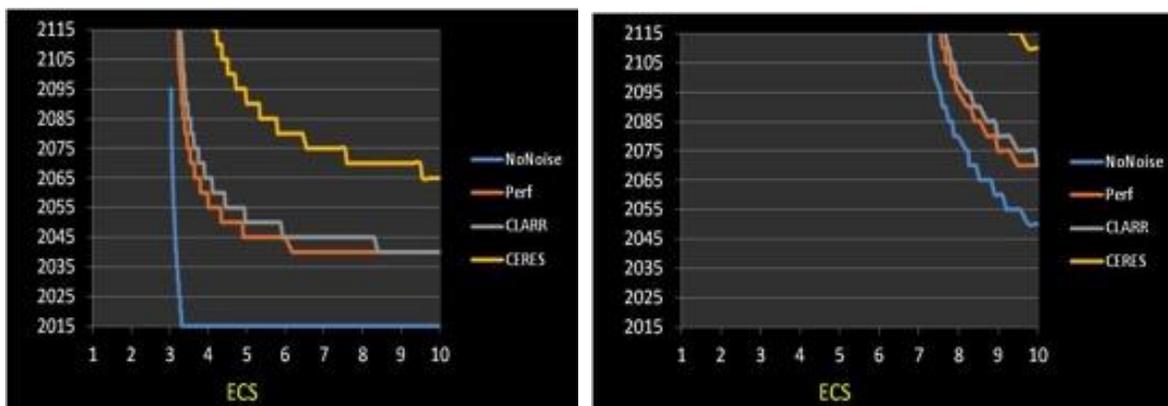
Table 7. Sensitivity Analysis

Real Option Value of Enhanced EOS					
2.5%	3%	5%	Trigger	Confidence	Launch
33.30	17.19	1.79	-0.10	1.28	2020
34.02	17.41	1.71	0.00		
32.65	16.67	1.54	0.10		
30.18	15.27	1.35	0.20		
28.01	14.08	1.18	0.30		
21.68	10.86	0.82	0.50		
14.03	7.00	0.49	0.70		
4.19	1.99	0.10	1.00		
38.81	19.89	1.99	-0.10	1.65	
38.81	19.62	1.81	0.00		
36.34	18.16	1.57	0.10		
33.36	16.68	1.39	0.20		
31.08	15.45	1.21	0.30		
23.21	11.52	0.81	0.50		
14.70	7.24	0.47	0.70		
4.23	1.98	0.09	1.00		
45.83	22.79	2.03	-0.10	2.30	
44.36	21.90	1.83	0.00		
41.22	20.32	1.61	0.10		
37.57	18.41	1.37	0.20		
34.04	16.68	1.16	0.30		
24.59	12.05	0.78	0.50		
14.90	7.25	0.43	0.70		
3.13	1.45	0.06	1.00		
33.78	17.00	1.61	-0.10	1.65	2025
28.60	14.15	1.29	-0.10		2030
23.35	11.33	0.96	-0.10		2035
17.66	8.25	0.65	-0.10		2040

7. Conclusions

A proposed new EOS designed to improve accuracy of Earth observations above existing systems presents society with a “real option.” Given the price of the new system, adoption will depend on questions like *Is it better than the existing system? How much better is it? What could we do with the new system that we couldn't do with the existing system? Could we do something better with our money?* Trying to structure such questions and provide quantitative answers involves computing the real option value of the new system—what is the option of basing future decisions on this new proposed system worth?

Figure 7. Trigger Times for Trigger Value 0.2 and Confidence 2.3 (left); Trigger 1.0 and Confidence 1.65 (right)



Information can have value only if it is used. Therefore, computing a real option value involves positing a decision context in which the new information would be used. This decision context may be compared to a thought experiment in physics. Thought experiments are “thought” because they cannot really be performed, but they illuminate fundamental physical relations and guide our experimental research programs. Similarly, a decision context must reflect essential elements of real decisions without presuming to predict how decisions will actually be performed.

The main conclusion from this study is that a higher accuracy Enhanced Earth Observing System has a real option value that is far above its projected costs, and this value is sustained across wide variations of the parameters of the decision context. Moreover, the option value is enhanced by triggering on the decadal rate of percentage change in cloud radiative forcing, as compared to the decadal rate of global temperature rise.

While the example used in this study is based on an enhanced accuracy in shortwave cloud radiative forcing (CRF) using a future CLARREO reflected solar spectrometer to more

accurately calibrate the CERES broadband instruments in orbit that observe global CRF, societal decisions will be made using multiple signals of climate change, so that an Enhanced EOS should be thought of as a wide range of observations designed at the higher accuracy required to more rapidly observe anthropogenic forcing of the climate system. The large real option value found for the examples in this study and in Cooke et al. (2015) suggest that an Enhanced EOS across a wide range of climate change observations would be a very effective societal investment.

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