

1 **Title:**

2 Benefits of a Fire Mitigation Ecosystem Service in The Great Dismal Swamp National Wildlife Refuge

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11

12 **Abstract**

13 The Great Dismal Swamp (GDS) National Wildlife Refuge delivers multiple ecosystem services,
14 including fire mitigation. Our analysis estimates benefits of this service through its potential to reduce
15 catastrophic wildfire related impacts on the health of nearby human populations. We use a combination of
16 high-frequency satellite data, ground sensors, and air quality indices to determine periods of public
17 exposure to dense emissions from a wildfire within the GDS. We examine emergency department (ED)
18 visitation in seven Virginia counties during these periods, apply measures of cumulative Relative Risk
19 (cRR) to derive the effects of wildfire smoke exposure on ED visitation rates, and estimate economic
20 losses using regional Cost of Illness (COI) values established within the US Environmental Protection
21 Agency BenMAP framework. Our results estimate the value of one avoided wildfire within the refuge to
22 be \$3.96 million (2015 USD), or \$306 per hectare of burn. Reducing the frequency or severity of
23 unexpected and uncontrolled peatland wildfire events has additional benefits not included in this estimate,
24 including costs related to fire suppression during a burn, carbon dioxide emissions, impacts to wildlife,
25 and negative outcomes associated with recreation and regional tourism. We suggest the societal value of
26 the public health benefits alone provides a significant incentive for refuge managers to implement strategies
27 that will reduce the severity of catastrophic wildfires.

28

29 **Keywords**

30 Ecosystem services, fire mitigation , wildfire, human health, geospatial information, Great Dismal Swamp
31 National Wildlife Refuge, remote sensing

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1 **1. Introduction**

2 Ecosystem Services (ES) are the benefits provided by the natural environment that are of value to
3 human populations. ES are threatened by development, pollution, fragmentation, overexploitation of
4 resources, and climate change. As part of a multi-year study on the ES of the Great Dismal Swamp (GDS)
5 National Wildlife Refuge, the U.S. Geological Survey (USGS), in coordination with the Fish and Wildlife
6 Service (FWS), examined the economic implications of health effects related to catastrophic peat fire. The
7 GDS is a highly-altered system that has been ditched, drained, and logged, all of which may be increasing
8 the frequency and severity of wildfires (Reddy et al., 2015). The GDS is currently undergoing active
9 hydrologic management designed to rewet the peat soils and provide refuge managers with the ability to
10 actively manage soil moisture using a series of water control structures. These structures are expected to
11 result in multiple benefits including additional carbon sequestration, restoring desired vegetation
12 communities, and reduce the duration and severity of wildfires (Reddy et al., 2015). Sleeter et al. (2017)
13 provides an in depth discussion of the current and desired states within the GDS across multiple
14 dimensions including carbon stock/flow, vegetation, and soil moistures.

15 Benefits of a fire mitigation ecosystem service are closely linked to the health and hydrology of the
16 soils within a peatland ecosystem. Catastrophic wildfire in a peatland is often associated with low water
17 levels, and characterized by long-burning ground fires deep within the peat (>0.5m) that release large
18 quantities of carbon into the atmosphere (Reddy et al., 2015). Within the GDS, low water levels due to
19 centuries of drainage and human disturbance can be worsened in drought years, emphasizing the
20 importance of control and versatility in hydrological management regimes. Conversely, periodic surface
21 wildfires play a critical role in healthy peatland vegetation communities to help perpetuate native trees
22 including Atlantic White Cedar and pond pine (Sleeter et al., 2017; Reddy et al., 2015; Laderman et al.,
23 1989). In this paper, we investigate the public health benefits of avoided catastrophic peat wildfires through
24 improved hydrological management, and the implication for adjacent human populations. These benefits
25 are identified as a cost of illness (COI) measure, and are assumed to be a lower bound in the true economic
26 value of reducing wildfire severity and frequency. This assumption is explained in sections 3.2 and 3.3.

27 In recent years, two catastrophic wildfires burned large areas of vegetation within the refuge,
28 producing dense smoke plumes that moved into neighboring communities. The South One Fire of 2008
29 (SOF) was ignited by heavy machinery, burning from June 9th through October 13th, and spanning an
30 estimated 1,976 hectares. During the 121-day burn, the cost of fire suppression exceeded twelve million
31 dollars and distributing smoke into the popular Hampton Roads area of southeastern Virginia, home to an
32 estimated two million people (US Census, 2010). In 2011, the Lateral West Fire, ignited by a lightning
33 strike, swept through the footprint of the SOF burning an estimated 2,630 hectares over the course of 111
34 days from August 4th to December 1st. Both fires quickly destroyed the aboveground vegetation,

1 concurrently burning deep into the organic peat soils with an average fire depth of 0.8 meters to 1.1 meters
2 (Reddy et al., 2015). Fire events of this magnitude are considered catastrophic and extremely damaging to
3 the ecosystem, and under current conditions are expected to recur twice every 100 years, or an annual 2%
4 probability (MTBS 2014). Emergency department data was made available for high exposure days
5 (explained in section 3.1) during the 2008 SOF, and will be the fire examined within this analysis.

6 Peat soils, such as those within the refuge, have been shown to produce a unique composition of
7 emissions when ignited (Blake, 2009). This combustion results in the intermittent release of dense plumes
8 containing volatile organic compounds, PM_{2.5} (particulate matter with a diameter of <2.5 μm), and PM₁₀
9 (particulate matter with a diameter of <10 μm), which are considered particularly threatening to the
10 cardiorespiratory health of exposed communities (Geron, 2013; Blake, 2009; Hinwood, 2005; Joseph,
11 2003).

12 The health effects of wildfire emissions have been assessed using a number of different approaches
13 and vary based on geographic location, ignition source, fuel, atmospheric conditions, topography, duration,
14 season, and other physical variations of wildfires (Tse, 2015; Youssouf, 2014; Kochi, 2010 & 2016;
15 Rappold et al., 2011; Vora, 2010). Johnston et al. (2012) emphasize the substantial contribution of
16 landscape fires to harmful global emissions and provide annual mortality estimates resulting from such
17 fires. While in aggregate these estimates are substantial (200k-600k deaths per year globally), Kochi
18 (2016) recommends that mortality should not be considered for individual fire events in the lower quartiles
19 of susceptible acreage, short lived, or infrequent. Wildfires within the GDS are estimated to be both
20 infrequent and on the lower quartiles of susceptible acreage (< 4k hectares) (MTBS, 2014). Following this
21 recommendation we examine effects related to morbidity and assume mortality is not a primary outcome
22 of GDS wildfires. This assumption is supported by the fact that there was no recorded loss of life directly
23 or indirectly attributable to either the 2008 or 2011 GDS wildfires (communication with GDS and FWS
24 staff). Our focus therefore is on symptoms related to morbidity in nearby populations resulting from brief
25 exposure to dense wildfire smoke plumes (EPA, 1999 and 2004).

26 Rappold et al (2011) examined the causal effect of peat fires on emergency department (ED) visitation
27 rates in 42 North Carolina counties during a 2008 catastrophic fire in the Pocosin Lakes National Wildlife
28 Refuge, a peatland with similar vegetation and hydrologic characteristics as those of the GDS. Rappold et
29 al (2011) provide the estimates of cumulative Relative Risk (cRR) used in our analysis. cRR measures the
30 ratio of the probability of a given occurrence over a discreet timeframe; for our purposes, the occurrence
31 ratio is defined as those at risk of an emergency department visit in the absence of harmful smoke exposure,
32 to observed visits during exposure. These calculations are explained in detail in section 3.3. Johnston et
33 al. (2014) employ a similar approach over an eleven-year time period in Sydney, Australia. Using ground-
34 based PM sensors they examine the relationship between harmful PM levels due to confirmed fire events

1 and ED visitation. Although the fuel source of the fires in their study is largely dissimilar to the organic
2 peat soils in our region, they also find a significant relationship (measured in cRR) between ED visitation
3 and smoke exposure days. The likeness of fuel source in Rappold et al (2011) to that of the SOF, and the
4 GDS in general, provides the opportunity for a robust application and extension of their methods.

5 The valuation literature on the economic costs of wildfire is largely focused on geographic areas
6 dissimilar to the GDS (Moeltner, 2013; Richardson, 2012). Richardson et al (2012) employs a defensive
7 behavior method during a 2010 California wildfire to derive willingness to pay (WTP) to avoid smoke
8 exposure. When compared to values derived using COI methods, WTP is considered a more appropriate
9 measure of the true value of fire mitigation services (EPA, 2007; Hanemann, 2001; Loomis, 1991). The
10 authors estimate a WTP/COI ratio of 9:1, suggesting the true value of fire mitigation could potentially be
11 as much as, or more than, nine times higher than COI estimates. Moeltner et al (2013) conducted an
12 intertemporal analysis of wildfires in the western United States and found the marginal effects of wildfires
13 on public health to have a lower-bound of \$150-\$200 per 40 hectares of wildfire, aggregated to
14 approximately \$2.2 million over the course of a fire season in their study area.

15 Our analysis adds to the literature by exploring the economic cost of wildfire through localized
16 outcomes on public health, attributable to wildfire smoke emissions from a nearby forested peat wetland.
17 We extend the wildfire literature by providing unique estimates of the ES benefits resulting from a change
18 in refuge management regimes. Using spatially targeted COI estimates we provide a local measure of the
19 potential benefits to public health as result of improved hydrology and wetland restoration. This study also
20 contributes to a growing body of literature exploring the versatility and applicability of remote sensing
21 methods by using high-frequency satellite data as a foundation for our analysis. Lastly, we propose that
22 the methods described in the following sections may provide a concise and systematic process for
23 researchers and land managers to employ when examining the many benefits of a fire mitigation ecosystem
24 service when larger more in-depth studies are not feasible. Our final estimates rely heavily on the
25 managers' ability to provide accurate fire probabilities and estimate the reduction in these probabilities as
26 result of their management actions. We recommend the methods in this paper, not the estimates, offer
27 external validity for additional research. The ES benefit estimates are unique to this refuge, and researchers
28 should consider the similarity of their study area to ours before performing any direct transfer of these
29 estimates.

30 31 **2. Study Area**

32 The GDS encompasses approximately 54,000 hectares of protected habitat located in southeastern Virginia
33 and northeastern North Carolina. Similar to other southern swamps in the eastern United States, the
34 wetland provides a unique habitat for a variety of flora and fauna, and numerous opportunities for

1 recreational activities. However, the GDS is highly disturbed due to centuries of drainage, logging, and
2 human encroachment, which together have led to drier and less-desirable conditions within the refuge
3 (Reddy et al., 2015). This has shifted fire dynamics within the GDS by exposing organic peat soils to a
4 higher probability of catastrophic wildfire and increasing the frequency and intensity of large fire events
5 (Frost, 1987). In addition to actively managed vegetation through mechanical removal of debris and
6 controlled burns, GDS refuge managers have been developing a grid of culverts and water control
7 structures to aid in the distribution of wetland hydrology with the intent to restore peat moisture to more
8 optimal levels. Our intent is not to provide a full cost/benefit analysis for these management actions, but
9 instead to estimate the benefits of their proposed design. Refuge managers are expected to weigh these
10 benefits with the costs when making their decisions. The refuge sits 40 kilometers inland from the Atlantic
11 coastline, and experiences a west to east atmospheric current. This current typically carries smoke plumes
12 originating from within the GDS out to sea; however, seven Virginia counties (Chesapeake, Isle of Wight,
13 Norfolk City, Portsmouth City, Southampton, Suffolk, and Virginia Beach) surrounding the refuge are
14 prone to smoke exposure from these plumes before they are eventually carried off the coast. Franklin
15 county was omitted due to limitations in acquiring emergency department data. These counties lie within
16 the Tidewater region of Virginia (Appendix I, Figure 1). Five counties in northern North Carolina are
17 suspected to have been exposed to plumes from the SOF as well - Gates, Camden, Currituck, Pasquotank,
18 and Perquimans. However, due to a wildfire in the Pocosin Lakes National Wildlife Refuge during our
19 study period, it is difficult to determine the origin of the smoke over these counties. As such, we limit our
20 study to the seven Tidewater counties to avoid over-estimation of the fire mitigation service.

21

22 **3. Materials and Methods**

23 Our methodology to estimate the benefits of a fire mitigation ES in GDS was performed in four distinct
24 stages: 1) determine geographic area and populations vulnerable to dense smoke plumes originating within
25 the refuge; 2) apply measures of cRR to health outcomes attributable to wildfire smoke exposure; 3)
26 estimate the economic cost of a wetland wildfire using localized values for COI and lost wages; 4) apply
27 site specific fire probability and forecasted reductions through proposed management actions. The
28 resulting cost estimate is what we consider to be the public health benefit of a fire mitigation ES.

29

30 **3.1. Area of impact**

31 We determine geographic area and temporal exposure to SOF smoke plumes using a combination of
32 remote sensing techniques, ground-level sensors, and air-quality indices. We examine daily geostationary
33 aerosol smoke product (GASP) satellite readings acquired from the National Environmental Satellite Data
34 and Information Service (NESDIS) for the Tidewater region. These data provide high-resolution measures

1 of aerosol optical depth (AOD) – at four kilometer square grids - and are collected in 30-minute intervals
 2 during daytime hours. AOD is a unitless measure ranging from 0 to 2; higher values indicate dense
 3 atmospheric conditions and are considered a good predictor of harmful PM2.5 concentrations (Al-Saadi,
 4 2005; EPA, 2009). We generate daily 24-hour averages of AOD measurements for the seven Tidewater
 5 counties.

6 In addition to smoke plumes, AOD can also be influenced by ambient air pollution. To help distinguish
 7 between pollution and wildfire contributions to AOD measurements, we examine historical levels within
 8 the region during both fire and non-fire years. In 2008 during non-fire months (January to June; November
 9 and December), the daily AOD average for the Tidewater region was 0.33 with a standard deviation of
 10 0.22. Similarly, during non-fire years (2005-‘07; 2009-‘10) AOD averages in the study area were 0.34
 11 with a standard deviation of 0.26 (Table 1). The dense nature of the plumes during the SOF can bring these
 12 levels up to 2.0. As such, we determine a threshold for harmful smoke exposure to be in excess of 1.25
 13 (consistent with assumptions in Rappold et al., 2011), and require at least 10% of the county be exposed
 14 above this level. Our estimates rely on these thresholds, we have chosen conservative exposure levels,
 15 consistent with the literature, to avoid overestimation in the resulting benefits. Using these parameters,
 16 over the 121-day period each of the seven Tidewater counties examined was exposed between one and six
 17 days, with a total of 14 days when at least one county received harmful smoke exposure.

18 Satellite-sourced AOD may not always be an appropriate measure of ground level conditions.
 19 However, peat wildfires typically result in low-lying smoke plumes, supporting the use of GASP readings
 20 when determining human exposure to wildfire smoke plumes (Rappold et al., 2011). An alternative to
 21 GASP AOD is to utilize ground level particulate matter measurements from devices within the region. A
 22 benefit to ground level monitors is that their

23 elevation is closely representative of human
 24 exposure to PM2.5 (Boyouk, 2010);
 25 however, there are several limitations
 26 associated with these monitors. They have
 27 less ability to accurately determine readings
 28 across a given region due to their fixed
 29 location and the frequency of readings
 30 (Youssouf, 2014). For example, some
 31 monitors produce values once per day while
 32 others are as infrequent as once every four
 33 days. Twenty-four hour averages of these
 34 readings are a good estimate of high

Table 1: Exposure Metrics

		Exposure Metrics			
		Timeframe	AOD	AQI	LRC-PM2.5
Non-fire years	Annual		0.34 (0.26)	41.79 (18.58)	10.90 (6.11)
	S.O.F. months		0.37 (0.24)	46.98 (20.43)	12.67 (7.16)
2008	Non-fire months		0.33 (0.22)	38.09 (17.40)	9.75 (5.53)
	S.O.F. months		0.39 (0.24)	56.76 (34.81)	17.51 (15.93)
	Exposed days		1.45 (0.19)	112.42 (59.92)	46.83 (32.75)

Note: Mean values displayed with standard errors in parentheses. Non-fire months refers to the months outside of the 121-day S.O.F. burn. Non-fire years include ‘05-‘07 and ‘09-‘10. SOF months of non-fire years are provided for seasonal reference. Exposed Days are those that have 24-hour averages \geq the AOD threshold of 1.25. AQI = Air Quality Index; LRC=Langly Research Center Monitor; PM2.5 = particulate matter \leq 2.5 μg . AOD = aerosol optical depth.

1 exposure levels at a given location, but weather patterns may prevent the monitors from detecting high
 2 levels of PM2.5 due to wildfire smoke plumes (Youssef 2014). The NASA Langley Research Center
 3 (LRC) is the only ground monitor in the seven-county study area providing daily PM2.5 levels. 7 of the
 4 14 exposed days determined using GASP AOD were also days that the ground monitor provided readings.
 5 We use these data and the resulting Air Quality Index (AQI) measures of the region to compare estimates
 6 of heavy exposure determined by the GASP data (see Table 1).

7 While the 14 GASP AOD high-exposure days also received high PM2.5 estimates from the ground
 8 monitor when available, the standard errors are much larger for the LRC ground monitor and AQI. When
 9 smoke plumes reach the monitor, this provides a good measure of local air quality; however, much of the
 10 Tidewater region isn't captured by these readings and results in a much larger estimation error for the
 11 region. GASP high exposure days have an average AOD of 1.45 and a notably tighter deviation from the
 12 mean as they provide a much more spatially and temporally targeted reading derived through the satellite
 13 measurements. Over the same months as the SOF in the five non-fire years, the 24-hour AQI average for
 14 this region was 46.98. Daily levels of AQI above 63 are considered moderate to unhealthy, and correspond
 15 with measured PM2.5 conditions in excess of 35 µg/cm.ⁱ The AQI and PM2.5 levels included in Table 1
 16 are produced using the U.S. EPA AirData archives.ⁱⁱ

17

18 **3.2. Health outcomes**

19 We examined the incidence of five cardiorespiratory related
 20 illnesses during the SOF. Periods of brief yet heavy exposure to
 21 wildfire smoke have been widely recognized to have negative
 22 impacts on five specific diagnoses: asthma, chronic obstructive
 23 pulmonary disease (COPD), pneumonia/acute bronchitis,
 24 congestive heart failure (CHF), and miscellaneous
 25 cardiopulmonary symptoms (EPA, 2004 and 1999). These
 26 outcomes can be identified by using the International Classification
 27 of Diseases, Ninth Division, Clinical Modification (ICD-9-CM)
 28 system, which are used by emergency departments to classify patient diagnoses for symptoms of
 29 morbidity. Eleven ICD-9-CM codes fall under the five symptoms identified above, and are used in our
 30 analysis. In cooperation with Virginia Health Informationⁱⁱⁱ (VHI) we explore daily ED visits in each of
 31 the seven Tidewater counties. Table 2 provides a summary of the symptoms and corresponding ICD-9-
 32 CM codes.

33 Smoke exposure might not result in an immediate visit to the ED (Pope, 2008; Braga, 2001); as such
 34 we consider a window for ED visitation due to a single initial day of heavy smoke exposure. Rappold et

Table 2: Disease Classifications

Symptoms	ICD-9-CM
Asthma	493
C.O.P.D.	491-492
Pneumonia	481-487
C.H.F.	428
Cardiopulmonary	786

ICD-9-CM = International Classification of Diseases, Ninth Division, Clinical Modification system; COPD = chronic obstructive pulmonary disease; CHF = congestive heart failure.

1 al. (2011) employ a distributed lag model (Peng, 2009) to determine a 5-day lag period in which those
 2 who have been exposed to heavy smoke plumes may experience symptoms related to exposure. Following
 3 Rappold et al. (2011), we define the visitation window to be the initial day of exposure plus a 5-day lag
 4 period. During the SOF there were 548 total ED visits for the eleven ICD-9-CM codes throughout the
 5 seven Tidewater counties.

6 Not all the ED visits during the visitation window are a result of the wildfire. A background rate of
 7 ED visits for the same symptom classifications would occur regardless of smoke exposure. Rappold et al.
 8 (2011) produce estimates of cRR for ED visits associated with brief but heavy exposure to wildfire smoke
 9 using a quasi-poisson generalized linear model. Daily estimates of relative risk are then used to determine
 10 a measure of cRR over the visitation window. In addition to a point estimate, they establish statistically
 11 significant bounds for each symptom. The point estimate and corresponding bounds provide the upper and
 12 lower bounds for our valuation estimates. Rappold et al. (2011) explicitly states measures of relative risk
 13 to be:

$$14 \quad \text{Daily RR: } \exp(\beta_{ijt}) = \frac{\mu_{ijt}^{Exposed}}{\mu_{ijt}^{Not Exposed}} \quad (1)$$

15 Equation (1): β is determined through the quasi-poisson regression described above; μ denotes the
 16 observed/expected number of visits conditional on exposure; i, j, t denote the symptom i in county j on
 17 day t .

$$18 \quad \text{Cumulative RR: } \exp\left(\sum_{t=0}^5 \beta_{ijt}\right) \quad (2)$$

19 Equation (2): β_{ijt} is determined through the distributed lag model (Peng, 2009); t denotes the days of
 20 visitation from $t = 0$ (day of exposure) to $t = 5$ (lagged exposure days); symptom i in county j . This is
 21 the coefficient we use in the following equation to determine excess visits due to the SOF. By applying
 22 estimates of cRR for each ICD-9-CM code to the observed visitation during the SOF, we statistically
 23 identify the counterfactual - visits not due to the wildfire. Explicitly stated:

$$24 \quad \text{Excess Visits} = \mu_{ijt}^{Exposed} - \frac{\mu_{ijt}^{Exposed}}{\exp\left(\sum_{t=0}^5 \beta_{ijt}\right)} \quad (3)$$

25 **3.3. Economic Valuation**

26 The final step in our analysis is to associate an economic cost with each excess visit from equation 3.
 27 We use regional COI values highlighted within the BenMAP model framework (EPA, 2007). BenMAP
 28 provides COI by zip code; however, while the estimates vary by diagnosis they remain consistent
 29 throughout the Tidewater region. These data and the program are available through www.epa.gov/benmap.
 30 While the BenMAP COI estimates incorporate all direct costs of hospitalization associated with each ED

1 visit by ICD-9-CM diagnoses, they fail to account for the disutility associated with symptoms or lost
 2 leisure, and expenses incurred relating to defensive or avoidance behavior. We account for a portion of
 3 these costs by using local estimates of symptom days for each hospitalization diagnoses (EPA, 2007) in
 4 conjunction with median daily income for each county. We assume individuals to be out of work for the
 5 extent of the symptom days. These symptom days do not include time lost during the recovery after the
 6 hospital visit, lost productivity, or lost recreation, which have all been shown to significantly increase
 7 traditional COI estimates (Chestnut, 2006). To keep our estimates conservative, we only consider lost time
 8 during the hospital visit.

9 The likelihood of ED visits and their associated COI are known to vary by age (EPA, 2007), so we
 10 consider COI and symptom-day estimates of two age categories. For asthma, COPD, and pneumonia
 11 diagnoses, the first age category falls between 18 and 64, and the second is above 64 years of age. For
 12 CHF only groups above 65 years of age are considered, and for miscellaneous cardiopulmonary all patients
 13 over 18 are a single COI group. These age categories are determined within the BenMAP framework to
 14 have different costs and symptom days associated with each diagnoses. We use wages as a proxy to
 15 determine the value of time lost during the ED visit. As recommended by the EPA (2007), daily per-capita
 16 median income is applied to the number of symptom days associated with each diagnosis. This data is
 17 derived from the Bureau of Labor Statistics^{iv} for each of the seven Tidewater counties. While any group
 18 categorized above 64 years of age is assumed to be out of the work force, wages are still used to estimate
 19 a portion of the disutility during an ED visit for groups above this age threshold. We aggregate the direct
 20 costs of hospitalization (COI) with the opportunity costs (lost wages: LW). Total valuation for the benefits
 21 of avoided wildfires in the GDS is calculated using equation (4), an aggregate of values across all seven
 22 counties:

23
$$Cost\ of\ One\ Fire = \sum_{j=1}^7 [EV_{ij} * (COI_{ij} + LW_{ij})] \quad (4)$$

24 **4. Results**

25 Our analysis indicates that a single catastrophic wildfire event in the GDS results in an estimated 161
 26 excess ED visits throughout the seven Tidewater counties. For each symptom, Table 3 provides a summary
 27 of measures of cRR, total ED visitation, and ED visitation attributable to the wildfire. The majority of
 28 symptoms that resulted in excess ED visits were for morbidity diagnoses surrounding pneumonia, totaling
 29 41. An estimated 34 visits were related to COPD, in addition to considerable ED visits for asthma, C.H.F.,
 30 and other cardiopulmonary symptoms.

31 The economic cost associated with these health effects is an estimated \$3.69 million. The upper and
 32 lower bounds surrounding our estimate range from \$696,475 to \$5.73 million, and are a direct result of
 33 the 95% confidence interval of the cRR estimates.^v Table 4 summarizes the direct COI, opportunity costs,

1 and total costs associated with the
 2 health outcomes attributable to the
 3 SOF. These are conservative
 4 estimates and only include the cost of
 5 hospitalization and lost wages during
 6 the visit. It is important to note that
 7 our analysis does not attempt to
 8 quantify the total economic or public
 9 health costs associated with a
 10 wildfire in the GDS. It is likely that
 11 additional, or less-severe, symptoms
 12 were experienced by people within
 13 the exposure area who did not seek
 14 medical attention from the
 15 emergency departments examined

Table 3: Tidewater ED visits during the SOF

Diagnoses	cRR (95% C.I.)	Total Visits (Age)	Excess Visits (95% C.I.)
Asthma	1.65 (1.25-2.17)	53 (18 ≤)	20 (11-38)
C.O.P.D.	1.73 (1.06-2.83)	83 (18 ≤)	35 (5-53)
Pneumonia	1.59 (1.07-2.17)	112 (18 ≤)	41 (7-60)
C.H.F.	1.37 (1.01-1.85)	119 (65 ≤)	32 (1-54)
Cardiopulmonary	1.23 (1.06-1.43)	181 (18 ≤)	33 (10-54)

Note: Total Visits are observed over the duration of the SOF for the 7 counties exposed to heavy plumes from the burn. Excess Visits are determined using equation 3. The age of patients whose visits were considered is consistent with Rappold et al. (2011). Final valuation uses these EV and COI varies by age group within BenMAP framework: www.epa.gov/benmap.

16 within our study. The expenses and/or disutility that these people incurred are not accounted for in our
 17 estimates. Additionally, this analysis does not include the real costs associated with active fire suppression,
 18 the social losses of carbon dioxide emissions from wildfire, the impacts to wildlife, or the lost opportunities
 19 associated with recreation and tourism during a fire event. Our values should therefore be considered a
 20 conservative estimate of total losses to social welfare from one wildfire.

21 When considering fire mitigation as an ecosystem service, it is necessary to assess the annual cost
 22 associated with a wildfire. Under current (disturbed) conditions, the Monitoring Trends in Burn Severity
 23 (MTBS) estimates that the GDS is expected to experience a catastrophic wildfire like the SOF twice every
 24 100 years - a 2% annual probability.^{vi} In terms of the health effects that we considered, this translates to
 25 an annual risk of \$73,843 in total costs (Table 4). A peat wetland that was functionally restored would
 26 likely experience fewer and/or less severe catastrophic fires. GDS land managers estimate that
 27 implementation of proposed management actions such as completing the system of water control structures
 28 and restored soils could reduce expected annual fire incidence from 2% to 1%, and potentially reduce the
 29 duration of catastrophic wildfires by 50%. A reduction of this magnitude would be associated with a
 30 \$36,922 savings in expected annual costs to public health.^{vii} This ecosystem service value, along with other
 31 costs associated with wildfires, should be considered in cost-benefit analyses of hydrologic restoration
 32 within the GDS.

33 Evaluation of the costs of wildfires on a per hectare basis is another way we consider how the
 34 magnitude of such a fire alters economic losses. To estimate values by total acreage burned, we examine

1 the size and scope of the SOF. The SOF burned 1,976 surface hectares within the refuge. On a per hectare
 2 basis, we estimate the health costs associated with the SOF to be \$306.

3

4 **Table 4: Endpoint Valuations for one Wildfire Within the GDS**

	South One Fire	Annualized Costs (Current Hydrology)	Annualized Benefits (Improved Hydrology)
5 Cost of Illness	\$ 3,575,000	\$ 71,511	\$35,756
6 Opportunity 7 Cost	\$ 116,605	\$ 2,332	\$ 1,166
8 Total	\$ 3,692,000	\$ 73,843	\$36,922
Per Hectare	\$ 306	\$ 8	\$ 3.75

Note: MTBS estimates the current annual probability of a catastrophic fire within the GDS is 2%. With improved hydrology this estimate is believed to fall by 1%. Per hectare estimates are specific for peat wetland environments containing dense organic soils and medium-dense above ground biomass with nearby populations. All values are reported in 2015 U.S. Dollars.

9 **5. Discussion**

10 The dangers of public exposure to wildfire smoke, such as the plumes generated during the SOF, can
 11 be costly. This analysis indicates that a single catastrophic fire within GDS has potential costs to public
 12 health ranging from \$696,475 to \$5.723 million. In terms of ES, the functionality of the ecosystem is of
 13 interest when studying a fire mitigation service. For every catastrophic fire event that is avoided or for
 14 every fire that has a shortened duration, the value is gained by society. Under current conditions, fire events
 15 of this magnitude recur twice every 100 years, or an annual 2% probability (MTBS 2014). On an annual
 16 basis, we estimate the public health costs attributable to wildfire in the GDS to be between \$13,930 to
 17 \$114,446. If management actions could reduce the recurrence of catastrophic fire to one event every 100
 18 years, or if the severity/duration of each fire were decreased by 50%, the annualized savings would be
 19 between \$6,965 to \$57,233.

20 The values estimated by this analysis are a conservative, partial estimate. The true costs remain
 21 unknown, and the intent of this study is to further refine estimates of just one of the many costs the public
 22 experiences during a wildfire event. Valuation of this ES does not account for avoidance behavior for
 23 those at risk of smoke exposure, changes to economic activity resulting from wildfires, the costs to
 24 suppress or extinguish the fire, the value of carbon emissions (lost carbon stock), or impacts to wildlife
 25 and biodiversity on the refuge as a result of the event. We provide a conservative value estimate for the
 26 public health parameter intended to provide support to management decisions within the GDS. A
 27 shortcoming of this study, and similar studies, is the limited size and scope of historical wildfires within
 28 the GDS, in addition to the limited access to emergency department visitation data. We propose the true
 29 underlying relationship between wildfire size and emergency department visitation to be non-linear and
 30 highly dependent on proximity and density of communities to the fuel source. Factors other than wetland

1 hydrology which are likely contribute to this relationship might include public air quality notices and the
2 greater atmospheric patterns which distribute smoke plumes upon various populations. This is an area for
3 future research and we propose this analysis will partner well with studies which examine other factors
4 contributing to the relationship between public health and wildfire or wetland management.

5 Public land managers outside the GDS might find these estimates useful, especially for peat wetland
6 areas susceptible to wildfire, and for management actions aimed at reducing the probability of wildfire for
7 these areas. When doing so, it is important to consider the true underlying costs of wildfires by exploring
8 the use of ratios such as those developed in Richardson (2012), EPA (2007), and Dickie (2004). These
9 ratios are indicative of how high the true value of avoided wildfires could potentially be. Assuming a
10 WTP/COI ratio of 9:1 (Richardson, 2012), our results translate to a WTP in the order of \$6.27 million to
11 \$51.51 million to avoid a single catastrophic wildfire event.

12 13 **6. Conclusions**

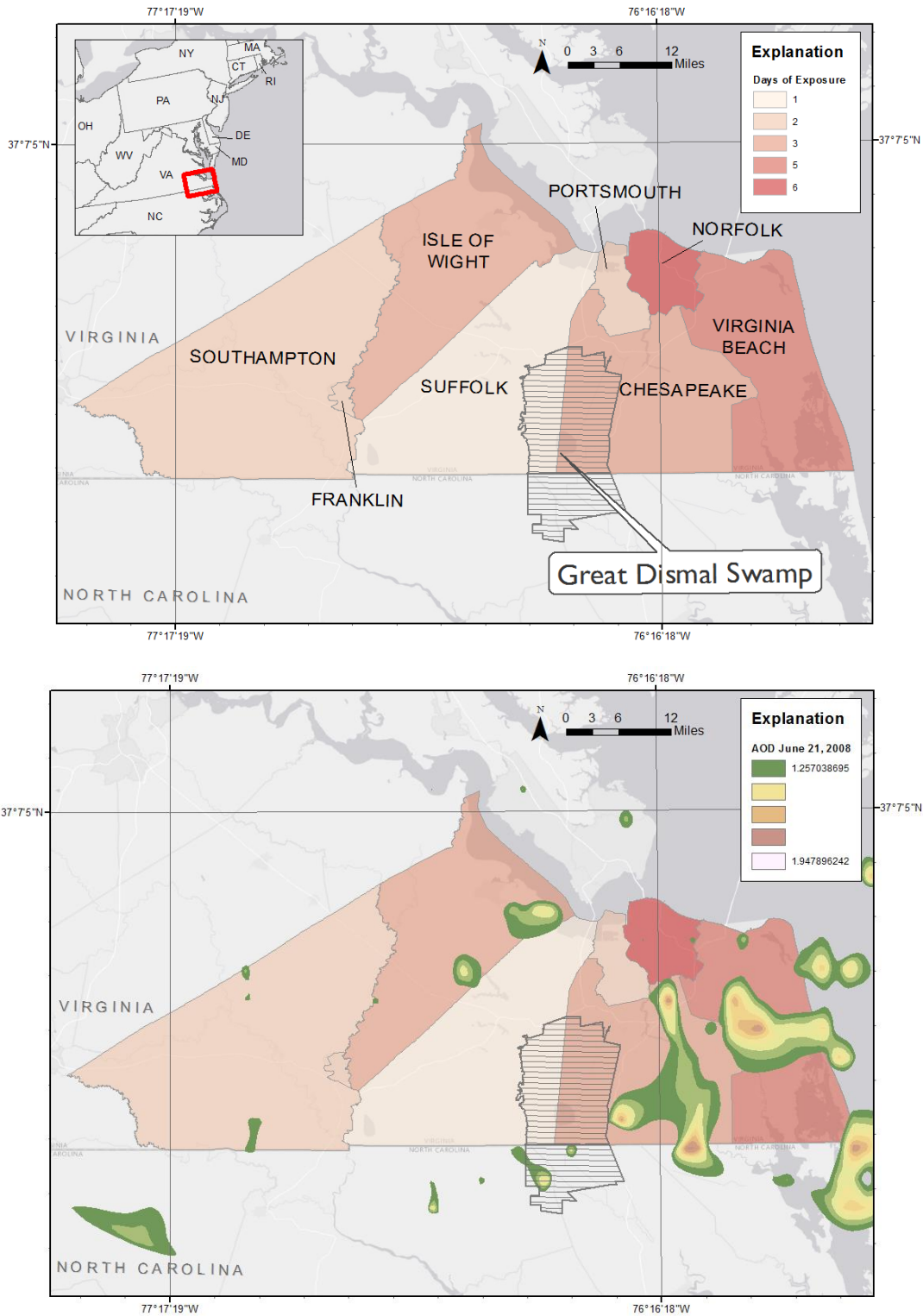
14 Our analysis adds to the existing literature exploring the economic cost of wildfire through outcomes
15 on public health, attributable to localized wildfire smoke emissions from a nearby forested peat wetland.
16 We extend these costs into management space by providing estimates of the benefits of land management
17 aimed at reducing the duration or severity of wildfire. The methods described above provide a concise and
18 systematic process for researchers and land managers to employ to examine the benefits of a fire mitigation
19 ecosystem service. For this study we were limited to select days of emergency department data during a
20 single historical fire within the GDS. Clearly this is a shortcoming of this study; however, our estimates
21 and methods provide an important contribution to this literature, and we encourage other researchers to
22 replicate these methods in similar wetland areas to help uncover the true underlying relationship between
23 wetland management and public health risks of peat wildfires. Emergency department data such as these
24 are often difficult or costly to acquire. For this reason we propose that a statistically sound functional
25 transfer of the measures of cumulative relative risk from Rappold et al (2011) provides a feasible approach
26 when larger, more in-depth studies are not practical. We also contribute to a growing body of literature
27 exploring the versatility and applicability of remote sensing methods by using high-frequency satellite data
28 as a foundation for our analysis. By using localized COI we propose that the end point estimates derived
29 within our analysis are an accurate value for this region, and any similar research should explore the COI
30 estimates corresponding to the same region as the study.

31 The GDS provides many ecosystem services and the current efforts to restore the wetland's hydrology
32 could potentially increase the flow of these services. A reduction in the occurrence or severity of
33 catastrophic wildfires in GDS would have multiple benefits including the potential avoidance of negative
34 public health effects. Valuation of the fire mitigation ecosystem service as a part of a portfolio of services

1 provides important information to refuge management about the total potential benefits associated with
2 wetland restoration. Climate change and continued drying conditions could potentially increase the
3 probability of catastrophic fire, and considering the full range of these valuations will be an important step
4 in protecting the overall welfare of the public.

1 Appendix I

Figure 1: Study Area. Top panel provides total number of days VA counties were exposed to heavy smoke plumes during the Great Dismal Swamp South One Fire (at least 10% of county above daily Aerosol Optical Depth (AOD) average of ≥ 1.25). Bottom panel provides a snapshot of AOD readings for June 21, 2008 when Chesapeake and Virginia Beach were both above the exposure threshold due to heavy smoke plumes from the SOF.



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ⁱ Additional information regarding the AQI can be accessed through the U.S. EPA and/or AirNow.gov

ⁱⁱ EPA AirData archives: <https://www.epa.gov/outdoor-air-quality-data/download-daily-data>

ⁱⁱⁱ ED visits during the duration of the SOF burn were made available to the researchers through Virginia Health Information for the current analysis and under privacy agreements cannot be released.

^{iv} Bureau of Labor Statistics provides wage data by county: <https://www.bls.gov/data/#wages>

^v These confidence intervals are listed in Table 3 under the point estimate for each estimate of cRR. To create the upper and lower bounds in our valuation, these values were used in equation 3.

^{vi} Monitoring Trends in Burn Severity (MTBS) provides 30 years of historical data to determine fire probabilities for the GDS. Recent scenarios suggest annual probabilities could in fact be larger, especially when coupled with climate change projections.

^{vii} Peat wetland hydrologic restoration and water control structures are expected to contribute to the reduced magnitude of impacts (especially duration) of wildfires and potentially reduced incidence; however, the precise effects are not fully understood. Therefore, we use 50% reductions in duration and/or incidence as a hypothetical to illustrate the potential value of avoided health effects.