Article

HETEROGENEITY OF ON-ROAD TRAFFIC EMISSIONS IN NORWAY: A MODEL FOR TRANSITION

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Abstract: The way Norway is spearheading electrification in the transport sector is of global interest, and details of its policies and emission impacts represent a reference. We used the NERVE model, a bottom-up high-resolution traffic emission model, to calculate all exhaust emissions in Norway (2009-2020). This allows us to evaluate the co-benefit of policies to target climate change mitigation and air quality. We have analyzed local municipal data with regards to traffic growth, road network influences, vehicle composition, emissions and energy consumption. Light vehicle CO_2 emissions per kilometre have been reduced by 22% since 2009, mainly driven by an increaseing bio-fuel mixing and BEV share. BEVs are mostly located in and around the main cities, areas with young vehicle fleets, and strong local incentives. Beneficiaries of all BEVs incentives have been a subset of the population with strong economic indicators. The incentivized growth in the share of diesel-fuelled passenger vehicle has been turned, and together with Euro6 emission standards, light vehicle NO_x emissions have been halved since peaking in 2014. BEV represent an investment in emission reductions in years to come and current sales set up for an accelerated decline in emissions despite growth in traffic.

Keywords: bottom-up emission modelling; CO_2; NO_x; on-road traffic; electrification

1. Introduction

After a slow reemergence from nearly 100 dormant years, sales of battery electric vehicles (BEV) are now rapidly taking a larger share of the global new car sales market. Indications are that 2022 can be the peak year of world internal combustion engine (ICE) road passenger transport [1]. This was recently accelerated by the new mandate by the European Union on a ban on sales of ICE cars and vans from 2035, which has been signed on June 2022. BEVs have emerged first as small short range vehicles, and thereafter have diversified into a wide range of vehicles available in the market. For the past decade, Norway has spearheaded this transition with the worlds highest BEV car park fraction. This has been achieved behind strong financial incentives [2,3] to promote both buying and use of BEVs. Norway appear on pace to complete its stated aim of a full transition to 100% of sales by 2025. Similar aims are currently pursued globally by other countries and carmakers alike [e.g. 4,5].

The transport of passengers and goods on roads is one of the largest contributors to both air pollutants and *GHGs* emissions. In Europe, road transport contributes to 26% of total emissions. While total CO_2 emissions have decreased by 23% since 1990, CO_2 emissions from road transport have increased by 24% over the same period [6]. Technological improvements have been implemented to reduce emissions of regulated pollutants (NO_x, *CO*, PM, Particle number concentration, non-methane hydrocarbons) through stringent emission standards until the latest Euro 6/VI, and the new proposal for Euro 7/VII being discussed. However, technical improvements in vehicle technology have been somewhat offset by the still increasing transport demand and the growing number of motorized vehicles with high fuel consumption, such as sport utility vehicles (SUVs) [7].

The current fuel transition has not come by itself, but rather through enabling technologies and policy intervention [5]. The cost from loss of revenues by mitigation strategies to abate emissions remains a concern, and the still growing need for road transport, especially in developing countries, entails increase in emissions there in the years to come [8]. The

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numerous objections to BEV, mainly related to production of the vehicle, battery and electricity [9], also add uncertainty to how beneficial such a fuel transition is for reducing total CO_2 emissions. However, effective measures to reduce road transport emissions remain an essential task in reducing air pollution and achieving GHG reduction targets [10,11]. The focus on emission mitigation from vehicles has lead to producers to aim for low emission vehicles. While this has certainly reduced emissions, it has also lead to a high degree of test optimisation (and software cheating [12]) resulting in large discrepancies between manufacturers given emission and real-world observed emissions [13]. This growing difference is up to 70% for petrol-electric hybrid cars and on average $\sim$ 20% for a 2016 model car [14]. This leads to uncertainties in what emissions reductions are actually achieved for fossil-fuelled vehicles and poses a challenge for emission calculations and evaluation of policy effectiveness.

There exist a wide range of methods to estimate emissions largely dependent on their purpose. National reported emissions are used for regulatory purposes as part of international agreements (e.g., Paris Agreement on climate change) or directives (e.g., National Emission reduction Commitments, NEC-Directive). Sector specific national emissions of both $GHGs$ and air pollutants are reported separately to the UNFCCC and CLRTAP, respectively. Member states select input data and methods for each sector following existing guidelines and recommendations [e.g. 15,16]. There are, however, substantial benefits of having an integrated approach to tackle both climate change and air pollution, and in order to do this co-emitted emissions should be viewed holistically [17,18].

Beyond national scale resolution, emission maps are produced by several independent groups such as CAMS [19] and EDGAR [20]. Typically reliant on down-scaling by proxy national emissions, these give little insight in processes and thus are not able to answer questions on local policy interventions that include local scenarios. The estimation of emissions based on bottom-up approaches, as applied in this study, relies on combining activity data at high spatial resolution with emission factors in a way that represent the emission processes, and have the advantage of keeping the resolution of the activity data [21]. Air quality has always been a local concern and so high resolution emissions have always been a requirement. There has been so far limited demand for high resolution CO_2 emission inventories, but recently local authorities have started to set targets for their CO_2 emissions and they need more details in their emissions [22]. The use of bottom-up emission inventories offer great opportunities. This allows to identify which measures have a stronger impact and establish links between emissions and specific policies implemented at local level, or even to socio-economic factors.

In this study, we first present the NERVE bottom-up traffic emission model and the analysis of the input data use for Norway (Section 2). Thereafter, the results are included and discussed (Section 3) in relation to the most relevant factors affecting air pollutant and CO_2 emissions from on-road transport and their trends and spatial heterogeneity in relation to policy interventions and transport electrification. Section 4 summarises the main conclusions from the study.

2. Model and input data

The NERVE model was originally designed to calculate climate gas emissions from road transport in Norwegian municipalities [23]. It is an open source model distributed under an GNU public licence. More recent additions to the model include a diversification to calculate air quality components, hourly output on road link and updated The Handbook Emission Factors for Road Transport (HBEFA) version 4.1 emission factors, which are presented here. NERVE is based on highly detailed input data on roads, vehicles and emission factors for Norway. The type of input data is for the most part readily available in other countries. Thus, NERVE model has also been adapted to estimate traffic emissions for Abu Dhabi Emirate [24], urban areas abroad such as Dublin, Ireland [25] and currently also in Warsaw, Poland. It has also been used as to investigate effects of environmental speed limits on emissions [26], to relate tyre wear particles and CO_2 emissions [27] for global applications and in numerous local air quality assessments [28–30]. This study is based on the Norwegian input data, which are described in Fig. 1 and in the following sections.

2.1. Emission Factors

The emission factors (EF) used in the NERVE model are from HBEFA, which is a comprehensive EF database for different types of vehicles under different driving conditions. NERVE uses HBEFA version 4.1 [31]. EFs in HBEFA are produced for all relevant engine related emissions based on collaboration with mainly north European states. Warm engine emissions are based on emission measurements under real world driving cycles from the PHEM model [32]. Cold emissions are in HBEFA available per start and added to warm engine emissions (see Section 3.1).

The emission factors in HBEFA version 4.1 covers all vehicle categories; passenger cars (PC), Light Commercial Vehicles (LCV), buses and Heavy Duty Vehicles (HDV). Each vehicle category consists of several vehicle segments, which classify vehicles based on their most relevant properties affecting emissions; i.e., weight, emission standard (Euro Class) and engine fuel(s) [31]. In our study, about 780 vehicles segments are considered. Emissions from each vehicles segment vary with driving conditions, thus our HBEFA extraction consist of around 1 440 EFs for each vehicle segment that represent different driving conditions defined by signed speeds, inclination, congestion levels and road types (including separation between urban and rural roads).

Fig. 2 shows the CO_2 emission per kilometer of an Euro6 diesel PC for each of the driving condition (free flow, heavy, saturated, stop and go, and stop and go2) under varying speed and slope. CO_2 EFs of the vehicle in Fig. 2 vary from about 80 to 450 $g\ km^{-1}$. The highest emission factors are obtained for heavy congestion (St+Go2), where the driving cycle involves extensive acceleration and breaking, which increase emissions from a baseline of about 80 $g\ km^{-1}$ to above 300 $g\ km^{-1}$ for all other variables. Road gradient, here given as a two way slope (i.e., a kilometre with a slope of 2% first driven up, then down), is the second most influencing factor, along with signed speed and road type, which also have an significant influence on emissions. At the level of detail to which NERVE is built, it is therefore crucial to have a well defined road network, so that the actual traffic conditions of the vehicles are well matched and accounted for. This level of detail is also necessary to capture geographical differences in emissions.

2.2. Road properties and traffic conditions

Fig. 3 shows the road network in Norway split on European class road, regional and urban roads. The 4 biggest urban areas are also shown at higher level of detail, where we have highlighted different road features that influence emissions. The road network data rely for the most part on the Norwegian road authorities database (NVDB) that contain virtually all significant roads in Norway. In NVDB, each road link is defined as a geolocated object with certain attributes and an ID tag. The relevant attributes for modelling traffic emissions are the curvature, inclination, speed limit, the type of road and number of lanes.

The traffic on the NVDB roads is built up of 5 regional traffic modelling results obtained with the Norwegian Regional Transport Model (RTM). The RTM model is a four step transport model as described in [33]. It is widely used by authorities, industry and research [e.g. 34,35]. While the model for each region is unique, they are built on the same code and give similar results where they overlap. An extensive validation against traffic counting was done and some local corrections were applied [23]. The resulting annual average daily traffic (ADT) is in Fig. 3 represented by the width of each road. Transportation of goods and route buses are done independently [36].

A disadvantage of RTM is that it does not produce ADT for all the smallest roads. A portion of the traffic in each of the 14 000 small area districts across Norway are in RTM described on artificial connector roads. These connectors are straight roads from the geometric center to the nearest intersection. Thus, the driving distance on these roads are not properly represented and there are no alternative good source of data for traffic on these roads. In this set of traffic data, we have placed the traffic of the artificial roads back on the road network, giving each of the empty roads in the network the connector links ADT. The traffic on the smallest roads represents about 5% of the total ADT and 18% of the total driving distance for light vehicles (PC and LDV) when laid out on the road network by this method.

In each of the subplots of Fig. 3, the thickness of the line of each road is proportional to the ADT. Each trafficked road segment from RTM is matched to a HBEFA corresponding road type based on speed, urban (all Norway map) and type [details also in 23]. Road properties are important input as, for most vehicles, emissions can vary by a factor 4 or more between different driving conditions. In Oslo, the roads are colored by main type (Fig. 3), where the European and regional roads have about 20% of the total traffic whilst making up less than 1% of the total road network. The main roads in Bergen are relatively flat (Fig. 3), and so while mostly the road network and terrain have steep slopes, a significant portion of the traffic is on flat roads. Inside Trondheim, the signed speed is highlighted by color, where as in most cases the largest roads have a high speed limit. The congestion in Stavanger is the perhaps most relevant feature for determining the HBEFA emission factor for these roads. Congestion varies and even densely congested roads will also have a portion of uncongested traffic. For congestion, the travel time in the morning (7:00-9:00) and evening rush (15:00-17:00) is in NERVE compared to that on an uncongested travel time, and presented as % delay. Based on a sample of roads with congestion, counting indicates that about 40% of the traffic is during rush hour. Based on the % congestion, NERVE places fraction up to 40% in 'stop+go' situations. Only a limited amount of roads have rush hour congestion from RTM, mainly in and around the 4 largest cities. As a result slightly less than 1% of vehicle kilometers driven in Norway is in a state of congestion.

2.3. Fleet composition and mileage

NERVE relies on the Norwegian vehicle registry to determine which vehicle technologies are present at each road. The vehicle registry is annually produced by Statistics Norway and contains the registered address of each vehicle along with the bi-annual periodic control readings of odometer driving distance. The driving distances in the interim years are filled in the model by a simplistic assumption and for new vehicles the model bases itself on driving distances of newly bought vehicles in previous years. A fleet composition dataset at municipality level and per year is defined following as close as possible HBEFA in terms of type, vehicle weight, Euro emission standard and engine fuel(s). This provides an annual driving distance weighted fleet composition on a vehicle detail level for each municipality in Norway, which in addition closely resembles that of HBEFA. For all hybrid electric vehicles a constant 20% of the driving is assumed as electric.

Fig. 4 shows the Norwegian vehicle Euro emission standard mix from 2009 to 2020 in terms of fraction of kilometers driven for each of the Euro categories. The Euro 6/VI standard (white in Fig. 4) introduced in 2014 is quickly taking over. This process is fastest for the heavy vehicles. Buses and HDV have the shortest average age of 4.5 and 4.6 years, respectively. Over the 13 year period, this represents nearly a halving of the average age of buses, and in just 6 years after being introduced, approximately 70% of vehicles are Euro VI in 2020.

On the other hand, Norway has a slightly aged PC and LCV vehicle fleet, with an average age of 8.3 and 7.2 years in 2021 and 2022, respectively (Fig. 4). However, this number is, as for the buses and HDV, weighted by the driving distance. The average age is about 2.5 years older based on the number of registered vehicles (dotted lines in Fig. 4). This shows that newer vehicles of this type are driven significantly more than older vehicles.

NERVE assumes that vehicles operate out of their registered municipality. Thus, to account for the mobility across municipalities and obtain a vehicle mix on each road, a RTM simulation was performed to separate out the trips by their origin and the driving distance in each municipality. Accordingly, it was possible to use a mix of vehicles from the

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municipalities where the trip originated. Then, for each municipality, the traffic volume on the roads are comprised of a weighted part of several municipalities. In the case of leased or company vehicles, this may not be the case, but in both instances there is limited data to correct this assumption for, and as a general rule these data will be sufficient to describe the municipality vehicle fleet. As road traffic volume is determined by RTM, an error in this assumption will only influence the vehicle composition and thus, combining the two sets of data gives a more accurate results.

2.4. Traffic scaling factors

The 5 RTM models were run to produce an ADT on all roads for the year of 2016 (details in Section 2.2). For scaling annual traffic to hourly traffic, NERVE uses preset scales for week of the year, weekday and hour of the day, based on traffic counting and the Norwegian holiday calendar. For changes in traffic over the years, NERVE relies on changes in traffic counting. An increasing amount of traffic counters are placed along Norwegian, predominantly larger, roads.

Each traffic count requires a coverage of 80% in 2 consecutive years. A filtering is done if there is an increase of more than 50% or reduction below 80%. The latter was set low due to large reductions in airport and border areas during the pandemic. Short vehicles counts were used to scale light traffic, and long vehicles (>5.6m) to scale Heavy. Annual changes in ADT are done individually for each municipality if the criteria of at least 7 traffic counts are met, otherwise it is done at regional scale. This is calculated by all the counting stations that are not used in an other individual municipality within the county. The number of municipalities that have individual calculations vary with available counts. For 2020, 47 of 356 municipalities had an individual index. As these are generally the largest municipalities, they cover about 55% of the total traffic volume.

The year to year change in traffic as a whole is shown in Fig. 5 as measured by different metrics. After the recovery from the global financial crisis in 2009, traffic volume have increased every year until 2020 by all available metrics. The traffic index is published by Norwegian Road Authorities and is, since 2003, separated in short and long vehicles. The index is based on traffic counts, and the short index should therefore in theory be similar to the national index of NERVE (green line), which is based on roughly the same traffic counts. The National index of NERVE resembles the total driving distance of the vehicle registry. The exact reason for this is unknown, as the method for the traffic index is poorly documented.

2.5. The NERVE model

The core of the NERVE model is, as with any bottom-up emission model, to connect the activity data with the emission factors. Once the input data is on the corresponding formats, calculations are relatively straight forward. The basic calculation unit is the road-link, but vehicle distribution is on the scale of the 356 municipalities in Norway. To obtain emissions, NERVE first collects all road-links and the total traffic within the boundaries of each municipality (k) calculated as:

$$DD_k = \sum_r D(r) \times ADT(r) \times N_{days} \tag{1}$$

where D is the length of each road-link (r) and the annual daily traffic (ADT) is the average traffic over a year. N_{days} is the averaging period. DD_k is then the total distance driven within the domain of municipality k. DD_k is calculated separately for each of the traffic classes "Light = L", "Heavy = H" and "Buses = B". Each traffic class is then down into segments by the road vehicle driving distance data:

$$F_{k,Veh} = \frac{F_{Veh} \times N_{Veh}}{\overline{F_k} \times Ntot_k} \tag{2}$$

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Where N_{Veh} and $Ntot_k$ is the number and F_{Veh} and $\overline{F_k}$ the driving distance of the individual and total vehicles, respectively, in a given municipality. $F_{k,Veh}$ is the fraction of vehicle km of a given segment on the road expressed as the fraction of its total traffic class for each municipality.

To obtain the traffic on the roads of a municipality $F_k(Veh)$, the traffic exchange with other municipalities is used. This matrix describes the internal (I_k) and external (E_k) traffic based on the origin of the traffic:

$$F_k(\overline{Veh}) = I_k \times F_{k,Veh} + \sum_{j \neq k} E_j \times F_{j,Veh} \tag{3}$$

With this traffic exchange, $F_k(\overline{Veh})$ is the weighted mix of vehicles on the roads of each municipality. If there is no exchange of traffic with the outside ($I_k = 1$) and $F_k(Veh) = F_{k,Veh}$.

NERVE uses an HBEFA dataset extraction that contains 1 440 combinations of speed (V), road type (T), slope (S), urbanization (U) and finally congestion level (C). For each combination of these properties, the emission factor for a specific mix of vehicles can be found on any scale from individual road link, municipality, county or national. For a municipality with a given set of roads it is calculated as:

$$EF_k(V,T,S,U,C) = \sum_{Veh} EF(Veh,V,T,S,U,C) \times F_k(\overline{Veh}) \tag{4}$$

With the exception of congestion, the parameters determining the emission factor are static properties of the road. Congestion is from the RTM models and represented as the morning (07:00-09:00) and afternoon (15:00-17:00) rush hour delay (see section 2.2 and Fig. 4). The roads with a rush hour delay are assumed to have congestion. The volume of traffic that occur during these times are assumed to be affected by congestion.

3. Emission Results and Discussion

As most of the input data used in this study have limited or restricted access to the public, their statistical presentation and interpretation are of interest. In this section we describe mainly the results of the emission model, and discuss implications from Norwegian policies and emission distributions. While NERVE produces emissions for all available compounds of HBEFA we have chosen to focus the results on NO_x, CO_2 and FC_{MJ}. The latter is the only one for which there exists EFs for BEVs. However, it is just an average over all driving situations with no resolution on speed or slope. According to the documentation from HBEFA, it is primarily used to calculate well-to-wheel emission factors.

3.1. Cold-Start Emissions

Cold start emissions are available in HBEFA as emissions per start to be added to hot emissions. Cold start emissions are a function of engine temperature at start, ambient temperature and length of trip, and represent a gradual emission declining over time as engine reaches optimal working temperatures. To quantify cold start emissions, NERVE uses HBEFA combination of trip lengths and parking times for Norway. This was coupled to the vehicle fleets of each municipality and daily temperatures from observations. Cold start emissions were calculated for each municipality for equal assumptions of trip length and parking time following the HBEFA data for Norway. Total emissions in a municipality were calculated and added to road link annual emissions as an % increase in each municipality. HBEFA only has cold start emission factors and assumptions for light vehicles, and so only this is considered.

A sensitivity study was carried out varying one of the input parameters at the time Fig. 6, which results can be summarized as:

- At all temperatures, the inter-municipal difference in cold start emissions are about 10% (Fig. 6a) as a result of vehicle differences.
- There is about 15% decline in emissions from cold start between 2009 and 2020 due to renewed vehicles (Fig. 6b).

- The difference in emissions between the coldest and the warmest year in Oslo is about 20% (Fig. 6c).
- The same year difference in emissions for the same vehicle mix in different regions of Norway is less than 10% (Fig. 6d).

There are thus some geographic variances in the cold start emissions. The differences are from the region of Norway, temperature, fleet composition and potentially also between average trip length and parking time. Overall, the spatial variations are only important if emissions from cold start constitutes a large part of emissions. The share of total emissions that stems from cold start varies significantly between compounds (Tab. 1). From more than 90% for hydrocarbons to about 5% for NO_X and CO_2. However, there is increasing evidence that NO_X emissions increase with lower temperature than it is accounted for in HBEFA [37]. The evidence is especially for Euro 6/VI emission standard vehicles (see Fig 7 in [31]). This increase in emissions is the result of sub optimal functioning of cleaning systems for these vehicles during cold temperatures.

3.2. Benchmarking NERVE emissions

Emissions estimated at the road link are hard to validate at the individual level. However, several NO_2 and PM pollution level simulations have been done for Norwegian cities where NERVE model was used to produced traffic emissions as input data. The comparison between model results for NO_2, which main source in Norwegian cities is traffic, and observations have showed an hourly correlation of 0.5 to 0.8 without a clear bias [28,29].

At the national level, it is possible to compare NERVE CO_2 emissions to fuel sales derived emissions, which are used for the official reporting of $GHGs$ emissions to United Nations Framework Convention on Climate Change (UNFCCC). The almost direct relation between CO_2 and fuel sales makes it a robust estimate on a national level. Whilst there should be relatively low uncertainty in the amount of fuel sold at the national level, there are some uncertainties regarding the engine where the fuel is combusted. Both diesel and petrol are multipurpose fuels used in a wide range of engines, which also are not on-road vehicles. Among these can be listed; motorcycles, boats and yachts, snowmobiles, lawnmowers chainsaws and other small and industrial machines. Moreover, part of the fuel sold in Norway can be combusted in neighboring countries and vice versa. In sum, these factors make the CO_2 emissions from road traffic derived from fuel sales an indirect estimate, which with above uncertainties offer a very robust estimate of emissions at national level.

Emissions and derived EFs obtained with the NERVE model are compared to fuel sales based estimates. In Fig. 7 solid lines (1-3) represent EFs derived from fuel sales emissions produced by dividing total emissions from light vehicles by the driving distance of such vehicles (see Fig. 4), whereas the dashed lines (4-6) represent the estimated EFs from NERVE model. Both EFs decrease from around 170 $g\ km^{-1}$ in 2009 to about 130 $g\ km^{-1}$ in 2020. In the period between 2009 and 2012, the difference between the two set of EF is minimal before increasing to about 10% in 2016 (Fig. 7 bottom). Fig. 7 includes also two series of EFs, which are obtained by adjusting for the effect of bio-fuels (2&5) and the combined effect of bio-fuels and electric vehicles (3&6). The difference between the adjusted EFs and the total vehicle fleet EFs indicate the main cause of emission factors reduction.

Both the NERVE and fuel sales derived EFs have the same share of electric vehicle in their fleet, but somewhat different bio-fuel mix for light vehicles (Fig.7 bottom). The reason is that there is a difference between the % of bio-fuel mixed in petrol and diesel. NERVE has a somewhat higher share of emissions coming from petrol where the bio-mix is significantly lower. In the time period investigated here, the decrease in emissions per kilometre can be due to; 1) more fuel efficient vehicles; 2) bio-fuels mix; 3) increase in electric vehicles shares. Relative to 2009, 2020 is the first year where electric vehicles is the main cause of lowering

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EFs in Norway with a decrease slightly above 12%, whereas bio-fuels represent an 8-10 % decrease, and more fuel efficient vehicles contributed to 5% lower EFs.

Emissions from traffic have steadily grown since 1990 (Fig. 8), and the main driver is the annual increase in traffic volume up to 2020. As a result, a near doubling of vehicle kilometers has occurred on Norwegian roads over the last 30 year period (Fig. 5). Since 2009, CO_2 emissions have stabilized or been slightly reduced mainly due to the increase of bio-fuels and electric vehicle shares. Emissions in NERVE respond differently to all variables, such as driving conditions and the changes in the fleet composition. Emissions from the combustion of bio-fuels, such as bio-diesel, bio-ethanol or the different blends in diesel and gasoline, largely varies with the percentage of added bio-fuel, fuel type, and the type of vehicle [38]. HBEFA does not include EFs for bio-fuel neither for their blends and, to our knowledge, no other comprehensive EF database exists that covers all the variables included in the NERVE model. Therefore, whilst the bio-fuel mix is applied at national scale, only CO_2 emissions are considered to be influenced by the blend of bio-fuels in gasoline and diesel, and all other emissions compounds are considered to be unaffected. This may add some uncertainties specially regarding the production of aldehydes from the combustion of alcohol fuels blended in gasoline [39], or in relation to lower CO and higher NO_x emissions from bio-diesel than from conventional diesel [38].

In 2020, the COVID19 pandemic broke out and severe travel restrictions were put on the population in the spring of 2020. The impact on local traffic was initially similar across Norway, and at the end of the year there was a 6% drop in light traffic (Fig. 5). Locally the changes in traffic played out very differently for municipalities. With a summer dominated by domestic tourism, July saw an increase in overall traffic, whereas most of the rest of the year was below 2019 levels [40]. However, in several municipalities on the border with Sweden and in that one where Norway's main airport is located, the drop in traffic was above 40% in 2020. The small increase in EF in the model for 2020 is a result of the driving distance for PC was reduced more than that of LCV and given that the latter has a higher emission factor, the resulting EF is higher.

3.3. Influencing factors of emissions

While it is not directly possible to disentangle each component that determine road emissions based on NERVE, Fig. 9 shows scenarios where we changed a single component of road or vehicles at the time. This serves to illustrate the relative influence of each factor on CO_2 and NO_x emissions, along with fuel consumption. This enables an evaluation of the sensitivity to change and relative importance of each factor. The vehicle changes are aslo a good indicator of how emissions may change in going forward.

In the scenarios marked with red and blue background in Fig. 9, we made changes to the driving conditions while retaining the distribution of the vehicle fleet composition. Numbers for national average emission change are listed in Tab. 2. Emissions directly increase with road curvature, increase in slopes and notably with congestion levels (red background scenarios). The "optimized" scenario produces the lowest emissions, and if all traffic in Norway were driven under these driving conditions, CO_2 and NO_X emissions would be 18% and 29% lower than those calculated for 2020, respectively. Of the scenarios, the potentially strongest influence in emission factor from HBEFA comes from driving on congested roads ("max congested"). However, in reality the slope of the roads have more influence in most Norwegian municipalities than congestion. In HBEFA, the lowest emission factors are generally for rural roads, and there is a trade off between larger road types (lowers emissions) and speed that has a u-shaped emission factor curve bottoming around 60 $km\ hr^{-1}$ (see Fig. 2 for details). Thus, to lower emissions, there is potential in making better roads, but as most of the emission increases from road conditions comes from speed and road size properties not related to congestion and slope, how feasible any major changes are is doubtful.

At the bottom in Fig. 9, the emission changes are induced by introducing changes in the vehicle fleet composition while retaining the actual driving conditions. For NOx, most vehicle scenarios would reduce emissions to below 75%. The exceptions are changing all vehicles to LCV (94% diesel) and all PC running on diesel. Upgrading to Euro6 filtering systems would efficiently reduce all NOx emissions to less than a quarter of 2020 levels. Plug-in Hybrid Electric vehicles (PHEV) are also almost exclusively petrol electric in Norway and therefore have limited NOx emissions (-90%). In all these indicate that any renewal of the vehicle fleet, independent of fuel, would make emissions in the years to come significantly lower.

PC Petrol vehicles have on average 12% higher emissions of CO_2 than the average light vehicle, whereas PC diesel have slightly lower emissions (-10%). The average vehicle registered as LCV has significantly higher emissions (33%). In NERVE, PHEV are driven 20% of the time on electric engine, but outperforms that in CO_2 emissions, emitting 26% less than the average light vehicle. The EURO 6 scenario can be seen as renewing all vehicles in Norway, retaining the fuel compostion, the emissions reduction for CO_2 would be 17%.

Energy consumption and CO_2 emissions are very similar across all scenarios (Fig. 9) with one important exception, i.e., all BEV scenario. As in this study, only direct emissions are taken into account, CO_2 goes to 0, but total energy consumption drops by 68%. The reason for this is mainly ICE heat loss in combustion engines [e.g. 41,42]. This is one largely overlooked aspect of BEVs, that are marketed predominantly as climate friendly, they are very energy efficient, and also for most of Europe at least cost efficient.

3.4. Changes in NO_X emissions per municipality

The EF_{NOx} for light vehicles in all Norwegian municipalities for a given year is shown in Fig. 10 for 2009, 2014 and 2020. As each municipality has local vehicle fleet consisting of exchange of traffic with surrounding municipalities, it is representative of the traffic inside the municipality rather than the traffic of the vehicles registered there. The properties of the road network and congestion levels have important influences.

In 2007 a fiscal policy was introduced to benefit diesel cars. The new policy had a registration tax differentiated Certificate of Conformity CO_2 emissions [43]. Authorities also made announcements appealing to the public to use diesel versus petrol vehicles. Thus, the following years saw a fast shift in new car sales, and thereafter on the road share of diesel vehicles. Similar policies were introduced around the same time across Europe [44]. As a consequence diesel vehicle share growth escalated to a peak in 2015, with no apparent effect on the emission factors and CO_2 emissions from PC kept increasing (line 1&4 in Fig. 7 & Fig. 8).

The largest and most densely populated urban center is Oslo. Several of the larger surrounding municipalities follows in population density along with the other main cities in Norway. In 2009, there was a positive relation between population density and NO_x emission factor (fitted green line in Fig 10). The main reason for this is that these areas have congestion, for which NO_x emissions are more sensitive than other compounds (see Fig. 9). Following sales, an increased diesel share increases NO_x emissions in the most densely populated areas. In 2014, NO_x emission factors were lower than those in 2009 in low population density areas, presumably as a result of new vehicles being introduced predominantly near the urban centres and used PCs (predominantly petrol vehicles) being sold as second hand vehicles outside metropolitan areas. The effect of the policy thus lead to increased NO_x emission in urban areas, resulting in continued exceedances of NO_2 limit value in areas where many people live. Conversely, in 2020, high populated areas exhibit the lowest NO_x EF in Norway, whereas the highest are observed in low populated areas (fitted yellow line in Fig. 10). This is due to all new vehicles sold today have lower NO_x emissions than any old vehicles.

3.5. Implications of the electrification

The transition from an electric PC share below 1% in 2014 to above 20% in 2020 has not come by itself. In a similar way as the diesel financial incentives implemented in 2007, a fiscal policy to promote the purchase and use of BEVs has been developed over the last years. It started in 1990 with trial periods for temporary exemption from registration tax, and currently, the incentives include exemption from 25% VAT on new vehicles, permanent use of transit lanes, reduction in company car taxes, exemption from paying car ferries fees, and exemption or discount of parking and toll systems [3]. Several years of incentives have entailed to reach a 84% share of BEVs sales in Norway in January 2022.

In addition to reducing local direct CO_2 and air pollutant emissions, the electrical engine is highly efficient and able to utilize virtually all available energy for propulsion. This is unlike combustion engines, where around 65-72% of the energy is lost due to heat losses, friction and pumping losses [41]. The energy consumption per kilometer derived by the NERVE model reflects this aspect. BEVs use about a third of the energy on the road as combustion vehicles. By a full transition to BEV, the 32TWh that was used in road traffic in Norway could be reduced to about 12 TWh. For comparison, the total residential energy consumption in Norway was in 2020 50.6 TWh [45]. Without being directly transferable an energy saving of 20TWh is thus significant.

Even though the use of BEVs entails several advantages, there have been controversies regarding their overall sustainability. Environmental equity concerns have been pointed out in light of BEV's accessibility by higher socioeconomic consumers [46]. Based on the data in NERVE it is not possible to directly link economic data to car ownership on an individual vehicle basis. However, on municipality level there are several economic indicators that can be coupled with the data from NERVE. One such is the household income decile others include household income, Gini coefficient and other private wealth parameters [45]. Fig. 11 shows share of the population with income in the top 2 income deciles and the BEV share of the same municipality. Fig. 11 and the data for 2020 in Fig. 10 share several features.

Municipalities are distributed along the x-axis in a similar way for all three parameters, higher income, newer vehicles and higher population density. Financial benefits from use of BEV vehicles are most prominent in cities, where parking, congestion and toll station fee reductions have the highest impact and also more available charging infrastructure relative to local travel patterns. The most plausible argument is that these local incentives is the reason for the high share of BEV and that without these the transition would be significantly slower. However, the beneficiaries of local BEV policy can entail the shift of older vehicle technology from the urban to the rural areas, contributing to energy injustices and exacerbate rural vulnerabilities. Alternative policies have been suggested to avoid or minimize energy inequalities from electric mobility policies [46].

The life cycle environmental impact of BEVs have been extensively addressed in the literature, and concerns have been raised with regards to the high environmental cost from production [47]. The environmental impact of BEVs has been reported to be higher than that of conventional vehicles due to the battery manufacturing. However, their use phase represents an improvement compared with conventional vehicles, although it largely depends of the share of clean energy generation [48]. Different aspects during the use phase of BEV are still under debate, as for instance non-exhaust emissions from BEV in comparison with conventional vehicles [49]. There are two characteristics of BEVs that contributes to their relevance to non-exhaust emissions; i) BEVs combine regenerative braking and friction braking systems, whereas internal combustion vehicles rely on friction braking; ii) BEVs are currently heavier compared to their ICE equivalent. The regenerative braking systems contributes to reduce brake wear emissions, although their higher weight will potentially increase stronger break wear and higher resuspension [50–52]. Therefore, the contribution of the ware processes to PM emissions makes that the transition from internal combustion vehicles to BEVs will slightly reduce the threat to human health [53].

4. Conclusions

The need for high resolution emission inventories has long been part of the demand for air quality assessments and management. With emerging abatement strategies to mitigate climate change, bottom-up high detailed climate gas emission inventories are also needed to evaluate the most cost-effective strategies and monitor the status regarding set targets.

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The NERVE model incorporates both climate gases and air quality traffic emissions. A benefit of having a combined source of both is that they can be cross-validated. Previous studies have shown NERVE derived NO_2/NO_x concentration to be relatively unbiased at several places. Moreover, NERVE CO_2 emissions compare well with national estimates for fuel sales derived emissions. The high resolution emissions can be used to detail influencing factors and causes of regional changes.

We find that while improving road properties can potentially increase emissions, congestion, slopes and road curvature actuality increases NERVE traffic emissions relatively little. With current roads, there is only a marginal gain looking at road properties, with the possible exception on speed. To achieve significant emission reductions, the vehicle composition needs to be improved. For NO_x, the model results indicate that emissions have plummeted in the last few years, and is set to continue that decline with any renewal of the vehicle fleet. Cold start emissions are important for some components, but only make up about 5% of emissions for CO_2 and NO_x.

With traffic outgrowing fuel efficiency improvements, CO_2 emissions has been increasing for the past decades and emissions have continued to grow until 2015. Since then there has been a steady decline, first as an effect of increased bio-fuel share in ICEs. 2020 marked the first year that the BEV share was the most important cause of emissions reductions. With an accelerated growth in vehicles sales, followed by an increase road vehicle share of BEVs, emissions will continue to rapidly decrease. This will be most prominent for light vehicles, which will see their share of all tailpipe emissions drop.

The restructured tax policy that initially incentivized diesel ICE light vehicles failed to significantly reduce CO_2 emissions and entailed an overall increase in NO_x emissions, especially in densely populated areas. Today's BEV policy has co-benefits at targeting NO_x, CO_2 and fuel energy efficiency, all declining rapidly. While there are production concerns about BEVs, their introduction on roads is already impacting transport emissions, an the impact is set to grow. Also the heterogeneous distribution of BEVs across Norway shows that the financial incentives to buy electric vehicles foremost benefited a limited segment of the population. The economic benefit of incentives predominantly fall to people in areas with strong socioeconomic indicators.

There remain several open questions concerning the overall sustainability of BEVs, but the peak of ICE vehicles has clearly been reached in Norway. The geographical heterogeneity of electrification in the transport sector in Norway mirrors the international situation, and the disparities between countries. While emission reductions will be achieved fast in markets with young vehicle fleet, changes in emissions will be slower for other regions, and here especially NO_x can also increase in the short term.

4.1. Tables and Figures

Table 1. Norwegian total light vehicle emissions from cold and warm engine from the NERVE model.

Compound	Cold (kTon)	Hot (kTon)	Cold %
CH_4	0.39	0.18	68
CO	33.06	7.25	82
CO_2	270.1	4966	5.2
FC^*	85.75	1698	4.8
FC_{MJ}^{*+}	3.71	76.0	4.7
HC	6.30	0.72	90
$NMHC$	5.91	0.54	92
NOx	0.72	15.3	4.5
PM	0.06	0.31	17

*HBEFA FC is fossile fuels only, while FC_{MJ} includes electric consumption.$^+$ Unit is in TJ

Table 2. Total emission change for Norway. From Fig. 9.

Comp	PC	LCV	EURO 6	PC Electric	PC PHEV	PC Diesel	PC Petrol
Energy	-5.5	28.0	-12.4	-68.1	-22.3	5.0	10.0
CO2	-6.6	33.6	-17.4	-100	-26.6	10.2	12.5
NOx	-14.3	77.6	-92.8	-100	-90.3	59.2	-77.7
Comp	Optimized	No Slope	No Congestion	Max Congestion	Max Slope	Max Sinewy	
Energy	-18.0	-3.2	-1.3	177.2	16.8	1.2	
CO2	-18.2	-3.2	-1.4	178.0	16.9	1.3	
NOx	-29.9	-8.7	-1.8	159.2	49.8	3.1	

*

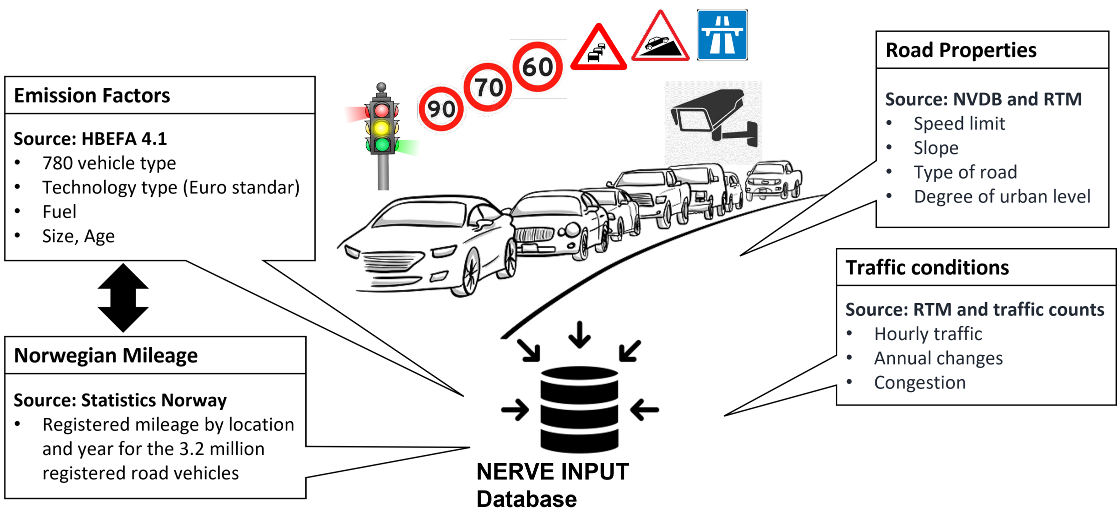

Figure 1. Schematic description of the input data that goes into the NERVE model, their sources and level of detail.

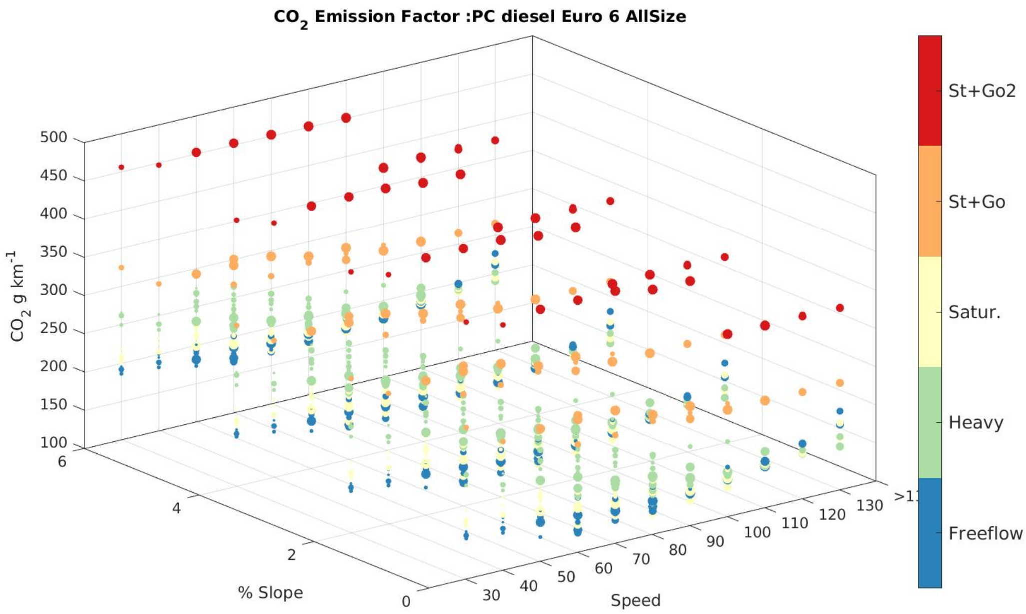

Figure 2. Example of CO_2 EFs for a diesel fuelled passenger vehicle wotj Euro 6 emissions standards. The colors of the dots refer to different congestion levels. We identified 12 HBEFA road type, access-> motorway which are separated by the size of each dot.

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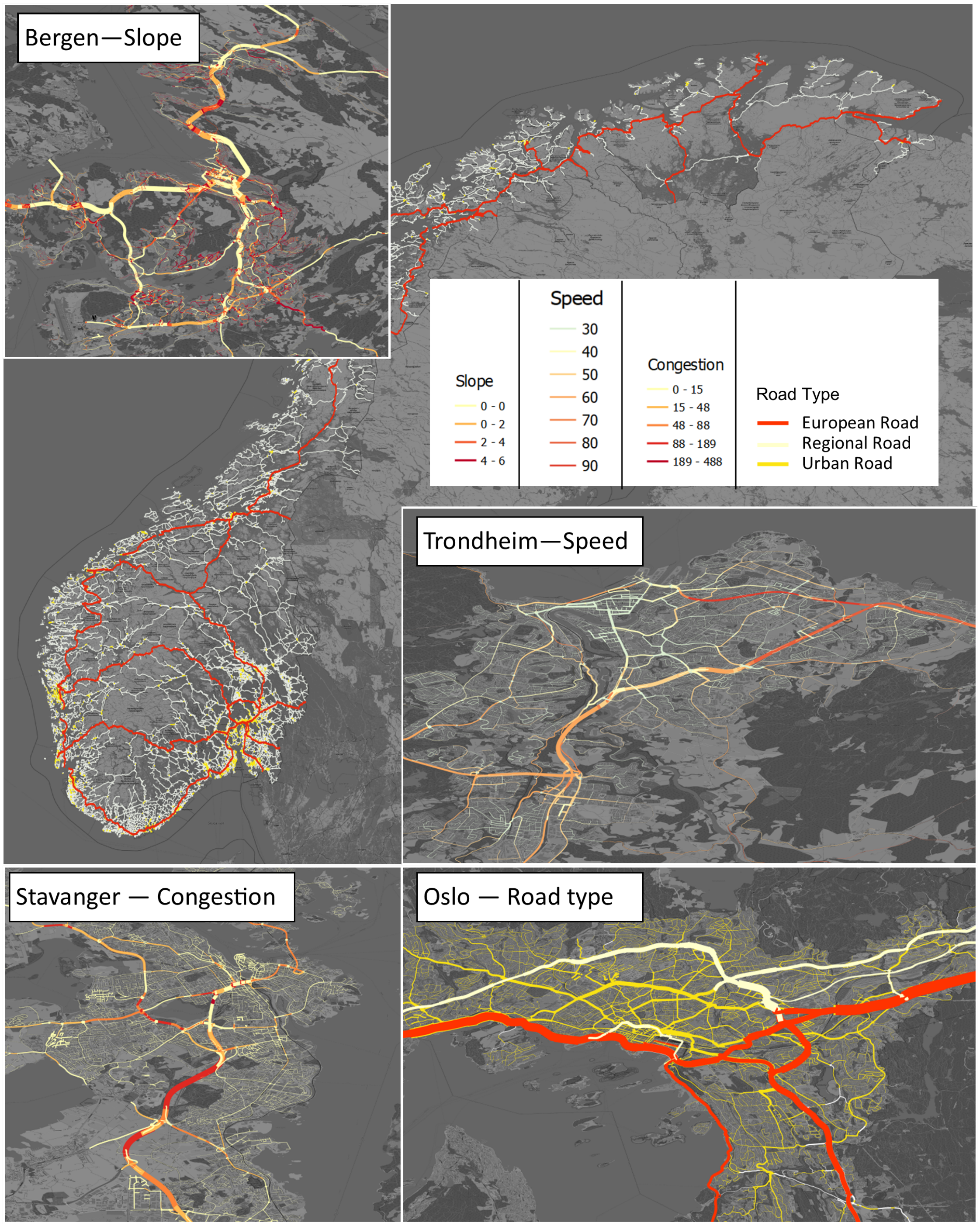

Figure 3. Road network in Norway split in types of roads as European, regional and urban roads. The zoom in the cities indicates the road network where the witch of each road link reflects the ADT, whereas the colour indicates different variables that affect traffic emissions, in that way Bergen network is coloured based on the slope, Trondheim on the speed limit, Stavanger according to the congestion level and Oslo based on the road type.

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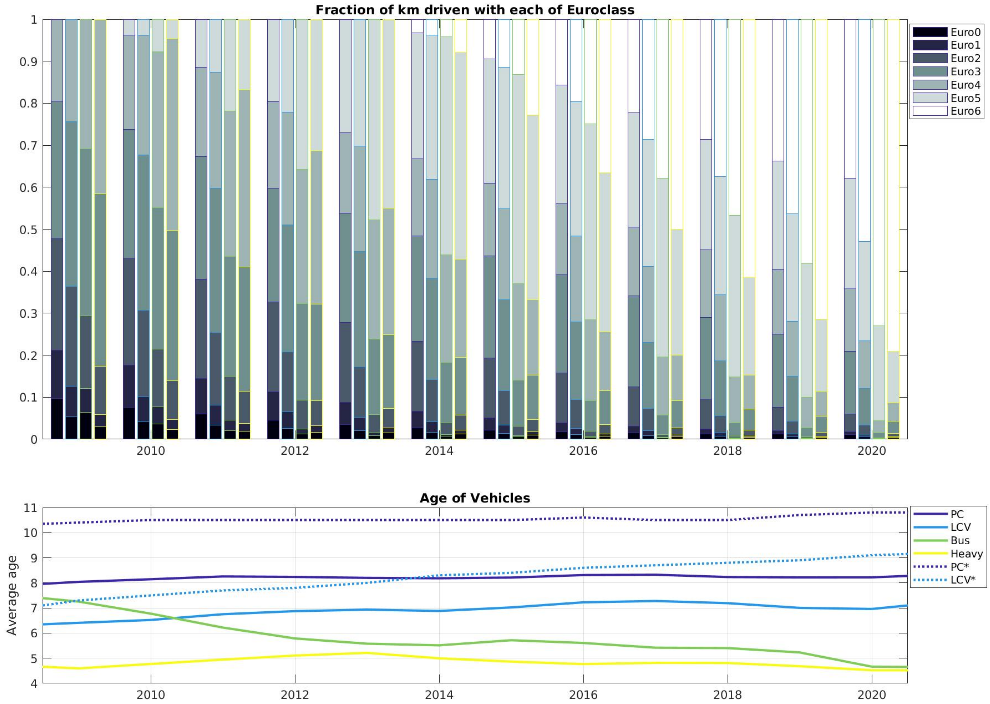

Figure 4. Top: The fraction of the total distance driven by each vehicle class with different emission standards (Euro class 0-6) in separate years. The edge of each bar is colored by the vehicle class. Colors correspond to bottom plot. Bottom: Each line is the average of each vehicle class over time, border color of bars in upper panel corresponds to the vehicle class.

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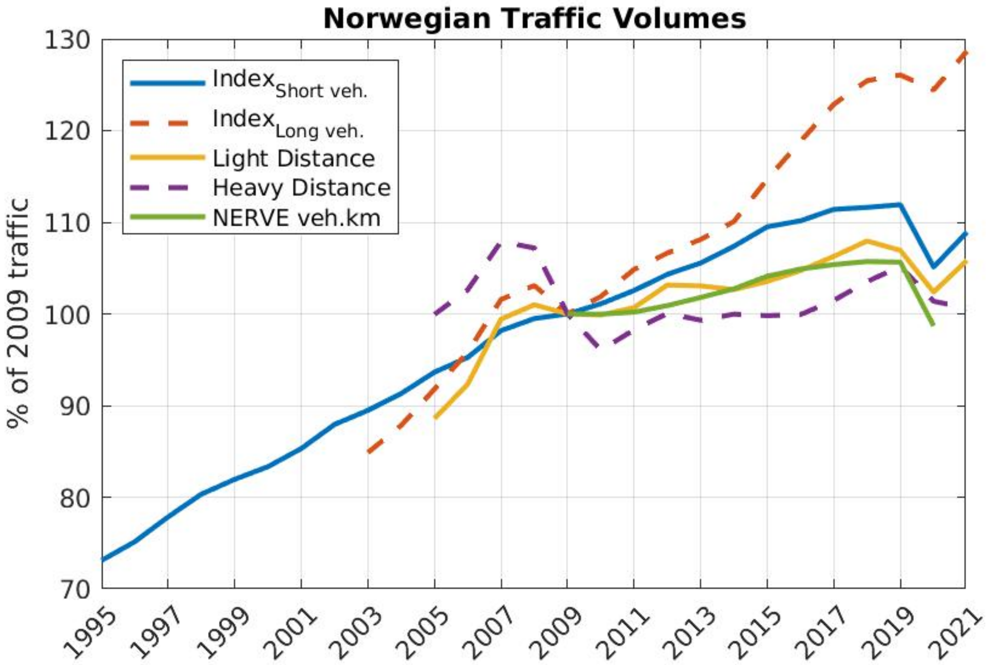

Figure 5. Annual volume of traffic by different metrics normalized to 2009. The Norwegian road traffic index (Index) is based on traffic counts and is shown separated for vehicles longer than 5.6 m (dashed red line) and shorter vehicles (blue line). Light (yellow line) and Heavy (dashed purple line). Distance are primarily based on odometer readings and is the total of all Norwegian registered vehicles. The green line shows the annual change in driving distance in the NERVE model (used for both light and heavy vehicles).

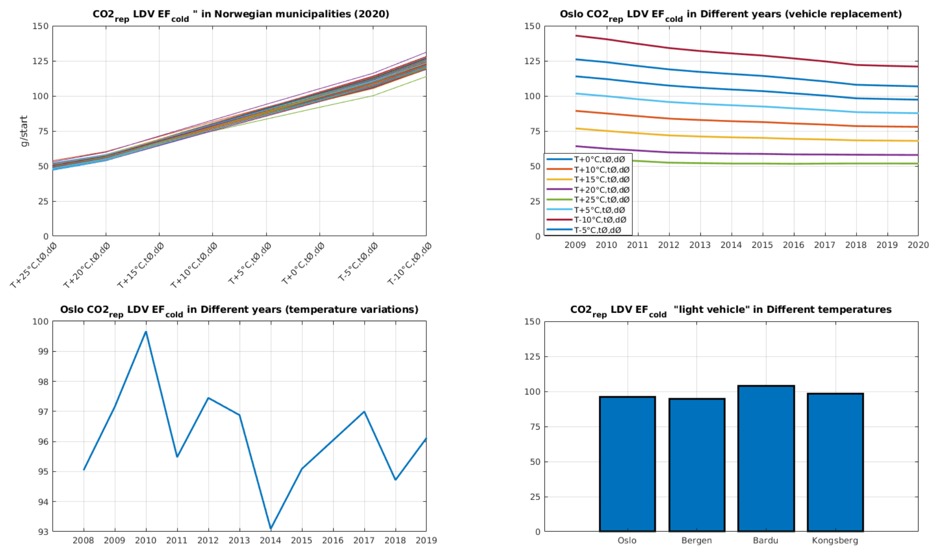

Figure 6. a) Cold start emissions in different municipalities at different temperatures. b) 2009-2020 cold start emissions in different years. c) cold start emissions for different years temperatures. d) cold start emissions in different regions of Norway.

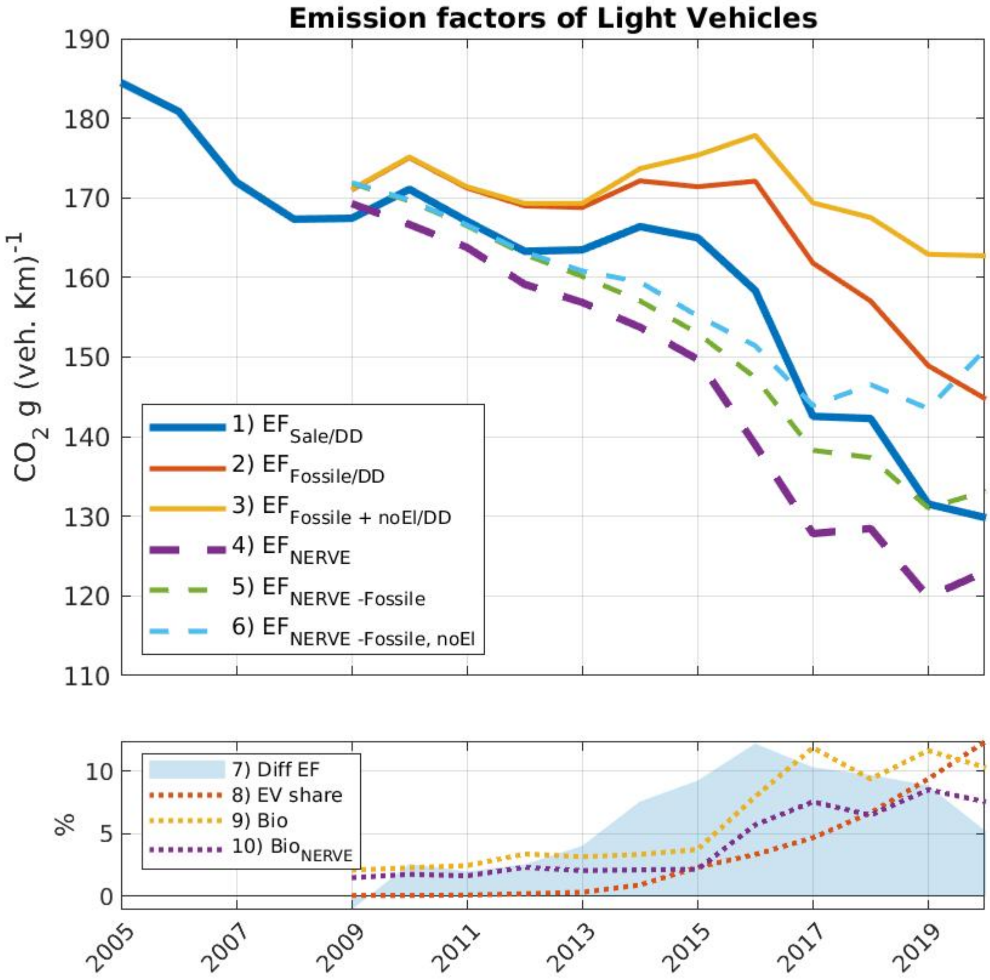

Figure 7. Top: Evolution of emission factors of light vehicles based on different metrics. 1) Official reported emissions based on fuel sales and actual driving distances. 2) same as 1) but added non fossil CO_2 emissions from bio-fuels. 3) same as 2) but used only non-electric driving distance (DD). 4-6) same as 1-3 but based on NERVE data. Bottom: 7) % difference between official reported emissions (1) and NERVE (4). 8) the % of energy originated from BEVs. 9-10) The % of energy in combustion originating from bio-fuels.

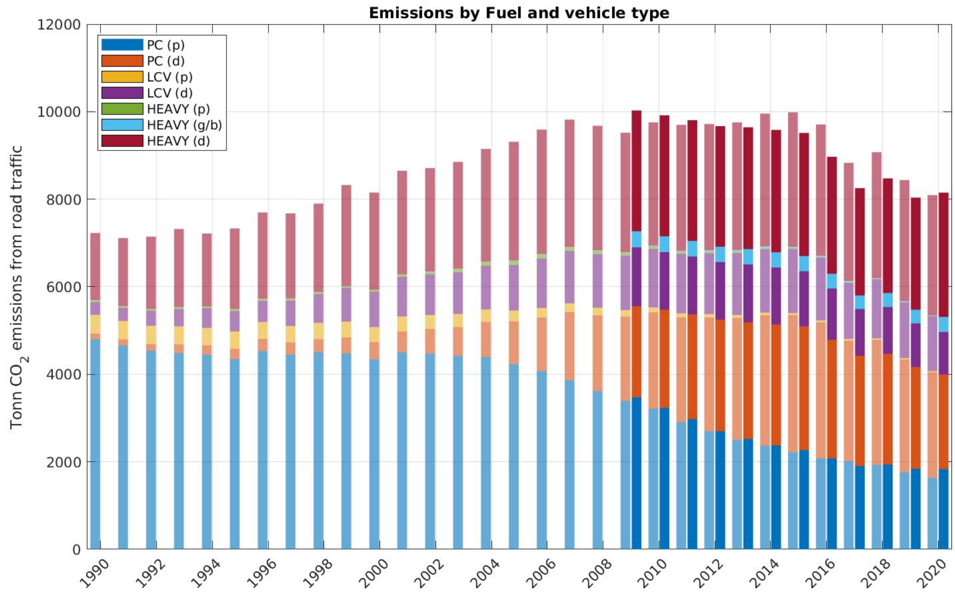

Figure 8. Bars: Emission by type of vehicle. Light shaded bars are based on reported fuel sales derived estimates. Solid bars (right shifted) are from NERVE model. p: petrol, d: diesel, g: gas, b: buses. In this representation, NERVE does not separate LCV fuel but separates buses where gas is separated for heavy vehicles in official statistics.

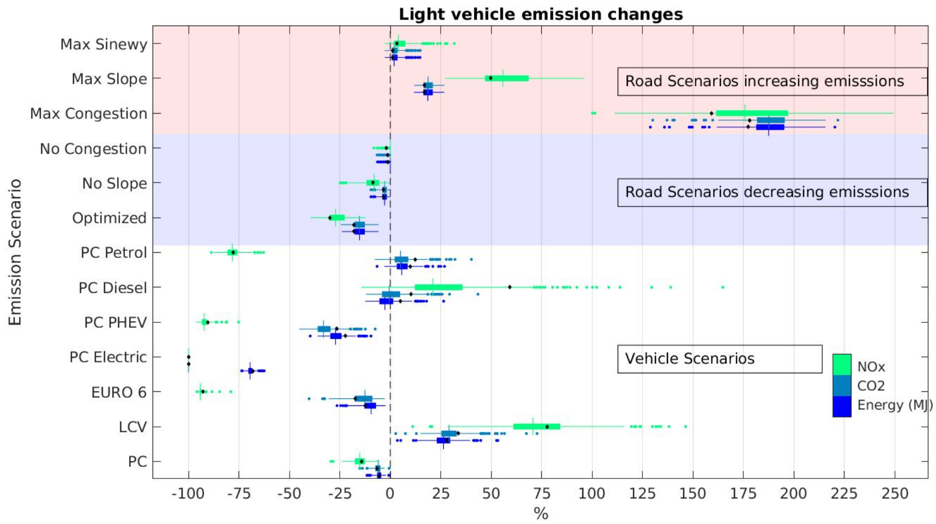

Figure 9. Changes from 2020 emissions, under different scenarios, for CO_2, NO_x and energy consumption (MJ). Each data point represents a municipality and the black dot the mean weighted by municipal driving distance. Scenarios: "Max Sinewy", we changed all roads in Norway to the smallest type of road the sign speed would allow, and chose sinewy roads where HBEFA had an own category for those. "Max Slope" we changed all roads into ±6% declination roads. "Max Congestion" we place all traffic in category "Stop+Go2". "No Congestion" we removed all congestion. "No Slope" we made all roads flat. "Optimized" assumes to be a rural motorway with a speed limit of 60 km/h, for which most vehicles have their lowest emission factors in HBEFA. "PC Petrol": all light traffic is petrol PCs, retaining the age / size distribution. "PC Diesel": all light traffic is diesel PCs, retaining the age / size distribution. "PC Electric": all light traffic is BEVs. "Euro6": all light traffic is Euro6, retaining fuel. "LCV": all light traffic is LCVs, retaining fuel and age. "PC": all light traffic is PCs, retaining fuel and age.

Figure 10. Each municipality is represented by a circle, the size of which corresponds to the number of vehicles registered and the color is by the 11 regions of Norway. Some selected municipality names are also rendered. Top: NO_x Emission factors in each municipality vs the corresponding population density in 2020. The bubble size is proportional to the number of vehicles registered in each municipality and colored by region. Data shown for 3 years with increasing opacity 2009, 2014 and 2020 along with fitted second order polynomial lines. Bottom: NO_x Emission factors in each municipality vs the average vehicle age in 2020.

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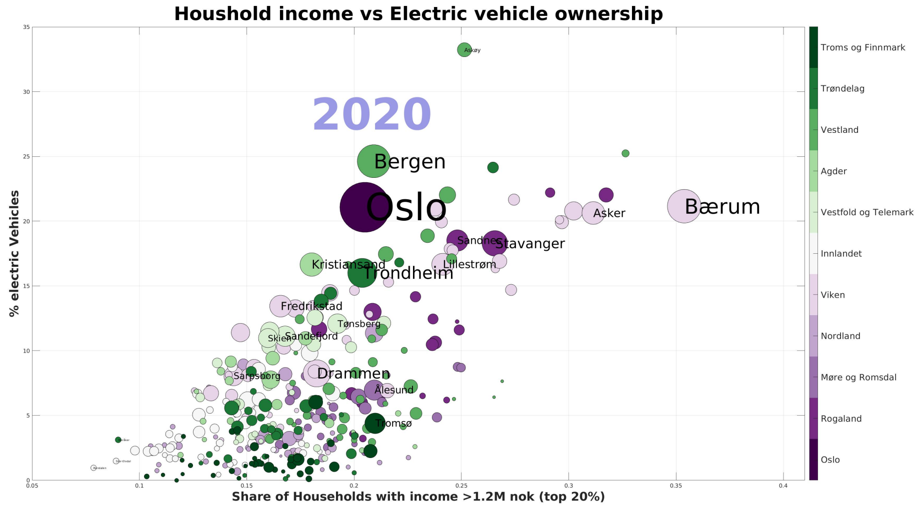

Figure 11. Share of *km* driven by electric light duty vehicles in Norwegian municipalities vs the share of population with income above the 20% national percentile in 2020. Colours and size as in Fig. 10

Author Contributions: This paper was conceptualized by H. Grythe and S. Lopez-Aparicio. H. Grythe developed the NERVE model, performed the simulations and carried out the data analysis. H. Høyem run the RTM traffic simulations and analysed the traffic data, developed annual scaling factors and revised the manuscript. T. Weydahl analysed the traffic data and developed annual scaling factors. S. Lopez-Aparicio and H. Grythe prepared the visualizations and original draft. All authors have read and reviewed the manuscript, and agreed to the published version of this manuscript

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Data Availability Statement: The code for the NERVE model is available at https://git.nilu.no/emissionmodels/NERVE. NERVE model output are available from several sources; through https://utslippskartlegging.nilu.no. Municipal emission data is published on https://www.miljodirektoratet.no/tjenester/klimagassutslipp-kommuner (climate gases) and it can be retrieved in gridded format at https://www.miljodirektoratet.no/tjenester/luftforurensning-utslippssystem-og-database/. For simulation scenarios specific for this study, can be shared by contacting heg@nilu.no.

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