Doctoral Thesis in Energy Technology

Geospatial Open-Source Modelling for Integrated Energy Access Planning
New Tools and Methods to Bridge the Energy Access Gap

BABAK KHAVARI

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Geospatial Open-Source Modelling for Integrated Energy Access Planning

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Abstract

In 2015 the United Nations (UN) General Assembly agreed on the Sustainable Development Goals (SDGs), a set of 17 goals defined by 169 targets to be reached by 2030. Amongst them is SDG 7. SDG 7 states “Ensure access to affordable, reliable, sustainable and modern energy for all”. The first target of SDG 7 mentions access to electricity and clean cooking specifically. Access to electricity brings with it myriad benefits across several sectors, including residential, health and education. Access to clean cooking can help reduce adverse health and environmental effects, as well as high opportunity costs related to current cooking practices, amongst other benefits.

While SDG 7 has been recognized as a key pillar to achieve sustainable development, its achievement has remained elusive. As of 2021, 675 million people worldwide were estimated to lack access to electricity. The largest access gap is found in Sub-Saharan Africa (SSA) where only 50% of the population had electricity access. For clean cooking the situation is worse, with around 2.3 billion people globally lacking access. Again, the access gap is most pronounced in SSA with only 18% of the population in the region using clean cooking. The situation in SSA is further exacerbated by the fact that the population increases faster than the clean cooking access rate.

For electricity access modelling Geographic Information Systems (GIS) and the use of geospatial data is being increasingly leveraged. As every case in a study area is unique and requires context-specific information, the spatial dimension of GIS can help to more effectively model towards universal electricity access. Resource availability, fuel
costs and access to infrastructure change spatially and a geospatial approach helps to capture this. Such reasoning can also be applied to clean cooking. Yet, at the time of writing this thesis, there was no geospatial tool comparing the relative costs and benefits of different cooking solutions. This work aims to advance the state-of-the-art in geospatial modelling approaches to support integrated energy planning towards universal electricity and clean cooking access.

Geospatial electrification modeling, while proven useful, is still a new field with many on-going developments. One such significant development was the move from raster population datasets to aggregated vector settlements. Raster datasets divide an area into uniform units with each unit including some piece of information about the area. It can be beneficial to have uniform units in modelling, but for this reason rasters fail to capture the size and shape that population settlements naturally have. On the other hand, aggregating raster datasets to vector settlements may impact modelling results. With this in mind, the first research question explores how the aggregation of data changes modelling results in geospatial electrification models. Paper I presents an open-source algorithm for the creation of aggregated vector settlements from raster data. In Paper I this algorithm is applied to 44 countries in SSA. As part of the algorithm, night-time lights are used to assess electrification rates within settlements and population density is used to assess the urban-rural divide of each country. The electrification rates and urban-rural divide is subsequently validated against survey data and compared to previous results. Following this, Paper II compares results produced by the Open Source Spatial Electrification Tool (OnSSET) as the level of population aggregation changes. This is
done for three case studies (Benin, Malawi and Namibia), by producing 26 population bases for each country. Two of the population bases are rasters with different resolutions, three use the method developed in Paper I and 21 are clustered using the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm. Paper II also presents the first Global Sensitivity Analysis (GSA) conducted for geospatial least-cost electrification models. The GSA enables comparisons between the importance of parameters that previous research has identified as important and the importance of population aggregation.

The second research question explores if, and how, GIS can be used to develop clean cooking tools comparing different cooking solutions. To this end, Paper III presents OnStove. OnStove is the first geospatial tool comparing the relative costs and benefits of different cooking solutions. In Paper III the tool is described and applied for the first time to 44 countries in SSA. The tool is open-source and all data used to run the analysis (as well as the results) are published and made available for a broader public. Two main scenarios are developed for SSA assessing differences between current cooking practices and potential pathways for maximizing net-benefits (defined as total benefits minus total costs). In addition to the main scenarios, 680 additional scenarios are developed as part of a GSA to assess the impact of uncertainty of 33 parameters on key outputs.

Finally, the last research question assesses how integrated energy access planning impacts the results of existing geospatial electrification (OnSSET) and clean cooking (OnStove) tools. This is done by combining the two aforementioned tools in Paper IV in a case
study of Kenya. The results describe how the least-cost technology mix and Levelized Cost of Electricity (LCoE) changes across Kenya as the increased electricity load following the inclusion of electric cooking is accounted for in OnSSET. On the cooking side the paper outlines how the competitiveness of electric stoves change as the electrification rate increase and the LCoE change. Paper IV also deepens the insights on research questions one and two as a new resolution is used to generate the population clusters using the algorithm developed in Paper I and new developments are done to OnStove.
Sammanfattning


Även om mål 7 har visat sig vara viktigt, har dess uppnående förblivit flyktigt. År 2021 uppskattades 675 miljoner människor världen över sakna tillgång till el. Det största tillgångsgapet återfinns i Afrika söder om Sahara (SSA), där endast 50 % av befolkningen hade tillgång till el. När det gäller ren teknik för matlagning är situationen desto värre, med cirka 2,3 miljarder människor globalt som förlitar sig på icke-rena matlagningsbränslen. Återigen är tillgångsgapet mest påtagligt i SSA, där endast 18 % av befolkningen använder ren matlagning. Situationen i SSA förvärras ytterligare av att befolkningen ökar i snabbare takt än tillgången till ren teknik för matlagning.

För modellering av tillgång till elektricitet används alltmer geografiska informationssystem (GIS) och geospatial data. Eftersom varje fall i ett område är unikt och kräver kontextspecifik information, kan geospatial data effektivisera modelleringen mot universell tillgång till
elektricitet. Tillgänglighet av resurser, bränslekostnader och tillgång till diverse infrastruktur förändras över ett undersökningsområde och geospatiala metoder hjälper till att inkludera dessa förändringar. Det finns ingen anledning att tro att detta inte gäller även för frågan om ren teknik för matlagning. Ändå finns det hittills inga geospatiala verktyg som jämför de relativa kostnaderna och fördelarna med olika matlagningsslösningar.

Spatial Electrification Tool (OnSSET) med olika nivåer av populationsaggregering. Detta görs för tre fallstudier (Benin, Malawi och Namibia), genom att producera 26 populationsbaser för varje land. Två av baserna är raster med olika upplösningar, tre använder metoden utvecklad i Publikation I och 21 är aggregerade med hjälp av Density-Based Spatial Clustering of Applications with Noise (DBSCAN)-algoritmen. Utöver detta presenterar Publikation II den första globala känslighetsanalysen för geospatiala elektrifieringsmodeller. Den globala känslighetsanalysen möjliggör jämförelser av betydelsen av parametrar som tidigare forskning har identifierat som viktiga och betydelsen av populationsaggregering.

Den andra forskningsfrågan utforskar om, och hur, GIS kan användas för att utveckla verktyg för modellering av olika matlagningslösningar. För att svara på denna fråga presenteras OnStove i Publikation III. OnStove är det första geospatiala verktyget som jämför de relativa kostnaderna och fördelarna med olika matlagningslösningar. Publikation III beskriver verktyget och tillämpar det för första gången på 44 länder i SSA. Källkoden är öppen och all data som används för att köra analysen (samt resultaten) är publicerade och tillgängliga för en bredare allmänhet. Två huvudscenarion utvecklas för SSA för att bedöma potentiella skillnader mellan den nuvarande situationen och en situation där nettovärdet (definierat som totalt värde minus total kostnad) i regionen maximeras. Utöver de två huvudscenarierna utvecklas 680 scenarion som en del av en global känslighetsanalys för att bedöma 33 parametrars påverkan av viktiga resultat.

Den sista forskningsfrågan utvärderar hur resultaten från ett geospatialt elektrifieringsverktyg (OnSSET) och ett geospatialt
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During my PhD journey I have had the privilege to work with and amongst many bright and supportive people, without whom this journey would have been much harder. I would like to extend my gratitude to all of them. First, I would like to thank Professor Mark Howells. Thank you Mark for inspiring me to pursue a career in this field and for putting trust in me and my work back when I was completely unproven and new to the field. This journey would not have started at all had it not been for your support. The PhD journey was by no stretch of the imagination an easy one, but I imagine it would be much harder had it not been for my supervisors. Therefore, I would like to also thank Associate professors Francesco Fuso Nerini and Will Usher. Your assistance and quick answers to my queries have been invaluable. I would also like to thank Professor Viktoria Martin whose guidance and counseling greatly improved the quality of my work.

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List of appended papers

This thesis is based on the following scientific publications:

**Paper I**


**Paper II**


**Paper III**


**Paper IV**

Glossary

**Grid** – the centralized national power grid.

**Stand-alone systems** – electricity is generated in a decentralized manner, generally up to a few hundred watts. These systems are typically single-household systems.

**Mini-grids** – electricity is generated in a decentralized manner, usually from systems with generating capacity up to a few megawatts. They can be either isolated from the centralized grid or grid-connected.

**Clean cooking** – defined as fuels and stove combinations that fall below the maximum emission limits introduced in the World Health Organization’s Air Quality Guidelines.

**Traditional cooking** – defined as fuels and stove combinations that do not fulfill the requirements introduced in the World Health Organization’s Air Quality Guidelines.

**Improved cook stove** – stoves which burn traditional fuels more efficiently and cleaner than their traditional counterparts.

**Integrated planning** – defined in this thesis as planning towards both main indicators of Sustainable Development Goals target 7.1 simultaneously, i.e., universal electricity and clean cooking access.
## List of abbreviations

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ALRI – Acute Lower Respiratory Infection</td>
<td>LCoE – Levelized Cost of Electricity</td>
</tr>
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<td>AQG – Air Quality Guidelines</td>
<td>LPG – Liquefied Petroleum Gas</td>
</tr>
<tr>
<td>CBA – Cost-benefit analysis</td>
<td>MAUP– Modifiable Areal Unit Problem</td>
</tr>
<tr>
<td>COI – Cost of Illness</td>
<td>MCA – Multi-Criteria Analysis</td>
</tr>
<tr>
<td>COPD – Chronic Obstructive Pulmonary Disease</td>
<td>MoM – Method of Morris</td>
</tr>
<tr>
<td>CO$_2$-eq. – Carbon dioxide equivalent</td>
<td>MTF – Multi-Tier Framework</td>
</tr>
<tr>
<td>DBSCAN – Density-Based Spatial Clustering of Applications with Noise</td>
<td>O&amp;M – Operation and Maintenance costs</td>
</tr>
<tr>
<td>DMIM – Delta Moment-Independent Measure</td>
<td>OnSSET – Open Source Spatial Electrification Tool</td>
</tr>
<tr>
<td>EPC – Electric Pressure Cooker</td>
<td>RQ – Research Question</td>
</tr>
<tr>
<td>ESMAP – Energy Sector Management Assistance Program</td>
<td>SALib – Sensitivity Analysis Library</td>
</tr>
<tr>
<td>GHG – Greenhouse Gas</td>
<td>SDG – Sustainable Development Goal</td>
</tr>
<tr>
<td>GIS – Geographic Information System</td>
<td>SSA – Sub-Saharan Africa</td>
</tr>
<tr>
<td>GSA – Global Sensitivity Analysis</td>
<td>UN – United Nations</td>
</tr>
<tr>
<td>HAP – Household Air Pollution</td>
<td>USD – United States Dollar</td>
</tr>
<tr>
<td>ICS – Improved Cook Stove</td>
<td>VSL – Value of Statistical Life</td>
</tr>
<tr>
<td>IHD – Ischemic Heart Disease</td>
<td>WHO – World Health Organization</td>
</tr>
</tbody>
</table>
Contents

1. Introduction ............................................................................................. 1
   1.1. Literature gaps and research questions ......................................... 6
   1.2. Aim................................................................................................. 19
   1.3. Thesis organization ...................................................................... 20
       1.3.1. Appended publications .................................................... 20
       1.3.2. Additional publications and contributions ...................... 25

2. Methods .................................................................................................. 30
   2.1. Geospatial electrification modelling ............................................. 31
       2.1.1. Pre-processing steps ......................................................... 32
       2.1.2. Calibration......................................................................... 35
       2.1.3. Scenario set-up ............................................................... 36
   2.2. Geospatial clean cooking modelling ........................................... 37
       2.2.1. GIS processing ................................................................. 38
       2.2.2. Calibration......................................................................... 38
       2.2.3. Determining net-benefits .................................................. 40
   2.3. Integrated planning for electricity and clean cooking ............. 49
   2.4. Uncertainty and Global Sensitivity Analysis in geospatial energy models .................................................. 52
   2.5. Geographic coverage ................................................................... 58
       2.5.1. Geographies covered outside of main publications... 60
3. Results.......................................................................................... 61

3.1. Response to Research Question 1.......................... 61

3.1.1. Impact on data extraction.......................... 61

3.1.2. Impact on calibration.......................... 63

3.1.3. Impact on scenario results.......................... 64

3.1.4. The effect of cell-size in clustering............... 73

3.2. Response to Research Question 2.................. 76

3.2.1. Scenarios............................................... 77

3.2.2. A geospatial cost-benefit analysis for SSA........ 78

3.2.3. Affordability as a barrier......................... 83

3.2.4. Uncertainty and sensitivity in clean cooking access
modelling ................................................................................. 90

3.3. Response to Research Question 3................ 92

3.3.1. Scenarios............................................... 92

3.3.2. Impact on stove selection and benefits......... 93

3.3.3. Impact on electrification planning............... 99

3.3.4. Financial implications.......................... 101

4. Conclusions............................................................................ 104

4.1. Addressing the research questions................ 106

4.2. Limitations and future work........................ 113

4.3. Scientific contributions and impact of the thesis .... 116
List of Figures

**Fig. 1.** Simplified schematic of the work conducted as part of this thesis. ................................................................. 31

**Fig. 2.** ERCs for the diseases included. X-axis shows the PM$_{2.5}$-concentrations and y-axis shows the Relative Risk. Created based on data from [87]. ................................................................. 41

**Fig. 3.** Simplified schematic of the soft-link. ........................... 52

**Fig. 4.** Examples of electrified settlements in the start year in northern Namibia, with eps 200 metres (left) and eps 500 metres (right). ... 63

**Fig. 5.** Grid-connected population for the three countries across scenarios. An eps of 0 are raster scenarios, where the first group of observations have a spatial resolution of 100 metres and the second group 1 km. An eps of 150 metres is the clustering approach from Paper I and the other eps-values are different DBSCAN-scenarios. 66

**Fig. 6.** National plots showing how population connected to mini-grids changes across scenarios. ................................................................. 67
Fig. 7. National plots showing how population connected to stand-alone PV changes across scenarios. ................................................................. 69

Fig. 8. National plots showing how average LCoE changes across scenarios. ................................................................................................. 71

Fig. 9. National plots showing how total investments changes across scenarios. ................................................................................................. 73

Fig. 10. Technology-mix of new connections in Kenya using either clusters based on 100 metre (left) or 1 kilometre (right) resolution rasters. ............................................................................................. 76

Fig. 11. Geospatial distribution of optimal stove selection, summary statistics and population shares of each stove; a) social scenario and b) private scenario. .......................................................................... 80

Fig. 12. Total costs and monetized benefits throughout SSA following a full stove switch; a) social scenario and b) private scenario. ........ 82

Fig. 13. Total costs per household in the private scenario (ND = natural draft, FD = forced draft). ................................................................. 85

Fig. 14. Total costs per household in the social scenario (ND = natural draft, FD = forced draft). ................................................................. 86

Fig. 15. Affordability ratio for the optimal stoves (private scenario); a) household shares for each stove, b) geospatial distribution of the total annual cost per household as percentage of the minimum wage, c) Household share for each technology categorized by household average quantiles (ND = natural draft and FD = forced draft). .... 88

Fig. 16. Affordability ratio for the optimal stoves (social scenario); a) household shares for each stove, b) geospatial distribution of the
total annual cost per household as percentage of the minimum wage, 

c) Household share for each technology categorized by household 
average quantiles (ND = natural draft and FD = forced draft). ....... 89

Fig. 17. The importance of different parameters with regards to the 
total net-benefit, only parameters with effects higher than 1% of the 
maximum are shown; a) \( \mu^* \) (bars) and confidence interval of the 
effects (lines), b) \( \sigma \)-values representing the effects due to interactions 
with other parameters or due to non-linearity................................. 91

Fig. 18. Summary without integrated planning (urban prio); a) the 
stove shares with highest net-benefit, b) geospatial distribution of 
stoves with highest net-benefit, c) number of households selecting 
each category of stove in relation to their relative wealth. The dashed 
lines show the borders between quintiles and d) costs and benefits 
for each stove selected. .......................................................................... 96

Fig. 19. Summary integrated scenario (urban prio); a) stove shares 
with highest net-benefit, b) geospatial distribution of stoves with 
highest net-benefit, c) number of households selecting each stove in 
relation to the relative wealth. The dashed lines show the borders 
between quintiles and d) total costs and benefits for each stove 
selected. ...................................................................................................... 98

Fig. 20. Geospatial distribution of least-cost electrification 
technologies and the share of different technologies amongst new 
connections; a) non-integrated results, b) integrated urban prio 
results........................................................................................................ 100

Fig. 21. Impact on LCoE from including electric cooking; a) geospatial 
distribution of LCoE without electric cooking, b) geospatial
distribution of LCoE with electric cooking (urban prio) and c) CDFs of LCoE with (blue lines) and without (red lines) electric cooking for each wealth quintile. ................................................................. 103

List of Tables

Table 1. PM$_{2.5}$-concentration target as set by WHO's AQG [17] .......... 3

Table 2. The relation between each research question and appended paper. ......................................................................................................................... 24

Table 3. The methods used in Paper II for population aggregation. 34

Table 4. The average constants as estimated by Burnett et al. and used in OnStove [87] ........................................................................................................ 42

Table 5. Cessation lags for each disease. Describes the percentage of health benefits that come each year after a switch, e.g., for the case of COPD 30% of the health benefits come after one year, another 20% is added after two years etc. Full benefits are assumed to come after the fifth year [92]. ............................................................................................... 45

Table 6. Parameters which were included in the GSA conducted in Paper II. ...................................................................................................................... 55

Table 7. The input parameters used in the GSA of Paper III and their ranges ........................................................................................................................................ 56

Table 8. Factor ranking between the assessed parameters based on $\delta$-values from DMIM. .................................................................................................. 70

Table 9. Stove shares and benefits across non-integrated scenarios. ...................................................................................................................................... 94
Table 10. Shares of new connections for each category of least-cost technology across scenarios. ........................................................... 99

Table 11. Geospatial datasets used in OnStove............................ 140

Table 12. Socio-economic data used in OnStove.......................... 142

Table 13. Techno-economic data used in OnStove........................ 144

Table 14. Traditional stoves assessed as part of this work............ 148

Table 15. Clean stoves assessed as part of this work. ................. 149
1. Introduction

Access to energy is crucial for the prosperity of individuals and the societies in which they live [1], [2]. So much so that energy was included in the Sustainable Development Goals (SDGs) agreed upon by the United Nations (UN) General Assembly in 2015 [2]. In total there are 17 goals defined by 169 targets. SDG 7 states “Ensure access to affordable, reliable, sustainable and modern energy for all”. The first target of SDG 7 (target 7.1) deals with energy access in particular ("Ensure universal access to affordable, reliable and modern energy services") [1], [2]. To track the progress towards this target two indicators are used, indicator 7.1.1 – Proportion of population with access to electricity and indicator 7.1.2 – Proportion of population with primary reliance on clean fuels and technologies (for cooking, heating and lighting) [3].

Access to electricity and clean cooking have been highlighted as particularly important for other development goals, yet progress towards universal access is slow. As of 2021, 675 million people lacked access to electricity and 2.3 billion people lacked access to clean cooking, relying instead on traditional fuels (e.g., wood, coal and charcoal) [3]. This is an improvement from the levels before the implementation of the SDGs (958 million and 2.7 billion people without access to electricity and clean cooking respectively), but not enough to meet the targets by their intended target year (2030). If current trends continue, 660 million and 1.9 billion people are projected to remain without access to electricity and clean cooking respectively by 2030 [3]. The situation is direst in Sub-Saharan Africa (SSA) and industrializing Asia, where a majority of the population
without access live [3], [4]. Furthermore, national heterogeneity is present, as urban populations tend to have higher access rates (both to electricity and clean cooking) than their rural counterparts [1], [3], [4].

Previous research has criticized the binary nature of the two SDG 7.1 indicators. The people with access to electricity do not necessarily have access to reliable and affordable electricity, and many of those who have access to clean cooking still fuel stack with traditional fuels [5], [6], [7], [8]. Fuel (or stove) stacking is when users combine several stoves, often with at least one traditional, emitting more emissions than using exclusively clean options [9]. This is mentioned in the latest Tracking SDG 7 report, which highlights that the 2.3 billion people previously mentioned have a primary reliance on traditional fuels. That is, the total population with some reliance on traditional fuels is likely higher [3].

The Multi-Tier Framework (MTF) initiative launched by the Energy Sector Management Assistance Program (ESMAP) aims at moving away from the previously binary classification of access by categorizing levels of access into separate tiers [10]. The MTF includes levels for both electricity and clean cooking access. For electricity, three closely related matrices are used: one on supply, one on services and one on consumption. For the supply framework, peak capacity and availability are included across tiers, while tier 4 and 5 (the highest tier) also include requirements with regards to reliability, quality, affordability (also available in Tier 3), legality, as well as health and safety. The services matrix indicates the services that each tier gives access to (e.g., task lighting, television and phone charging).
Lastly, the consumption matrix gives information on annual and daily consumptions in kilowatt-hours (kWh). For cooking, the MTF accounts for indoor air quality, stove efficiency, convenience (in terms of fuel collection and preparation time), affordability, safety, as well as quality and availability of primary fuel [10].

Clean cooking is typically defined as fuels and stoves that fulfill the emission requirements introduced in the World Health Organization’s (WHO) Air Quality Guidelines (AQG) [11], [12], [13], [14], [15]. When referring to cooking, the concentrations of PM$_{2.5}$ (particulate matter of diameters up to 2.5 µm) and carbon monoxide are of special interest [16]. There is strong evidence of causality between the concentration of PM$_{2.5}$ and diseases such as Acute Lower Respiratory Infections (ALRI), Chronic Obstructive Pulmonary Disease (COPD), Ischemic Heart Disease (IHD), lung cancer and stroke [3], [17]. The AQG sets interim and final targets for the concentrations of PM$_{2.5}$ and carbon monoxide. The interim targets are aimed at regions where meeting the final targets in the short-term is considered unlikely. Note however that interim targets, even in these cases, are merely to be treated as steps towards the final goal. See Table 1 for the targets given for PM$_{2.5}$-concentration in the AQG [17].

<table>
<thead>
<tr>
<th>Target</th>
<th>Annual mean PM$_{2.5}$-concentration (µg/m$^3$)</th>
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<tbody>
<tr>
<td>Interim Target 1</td>
<td>35</td>
</tr>
<tr>
<td>Interim Target 2</td>
<td>25</td>
</tr>
<tr>
<td>Interim Target 3</td>
<td>15</td>
</tr>
<tr>
<td>Interim Target 4</td>
<td>10</td>
</tr>
<tr>
<td>Final Target</td>
<td>5</td>
</tr>
</tbody>
</table>
The slow progress towards SDG 7 has far-reaching effects and its consequences for the other 16 SDGs are well-documented. The use of traditional fuels for cooking produces a considerable amount of Household Air Pollution (HAP), and air pollution is recognized as one of the biggest threats to human health [17]. Globally, more than 3 million annual deaths are attributed to HAP stemming from the use of traditional fuels for cooking, with most deaths occurring in SSA and Asia [3]. Beyond causing damage to those directly using traditional fuels, HAP also seep out to the surroundings, contributing to ambient air pollution. Smith et al. write how in 2010, 37% of the total outdoor combustion-derived PM$_{2.5}$-concentration in southern SSA could be attributed to traditional cooking [18]. It is estimated that the yearly health damages of traditional cooking costs 1.4 trillion USD [3]. These health effects are highly gendered as most of the cooking in households are done by women, exposing them to a majority of the emissions [1], [3], [16], [19], [20]. Furthermore, much of the fuel collection and preparation in households using traditional fuels are done by women, and an estimated 0.8 trillion USD are lost yearly due to loss of productivity following the lack of clean cooking [3]. In cases where traditional fuels are not collected directly by the households themselves, households are often forced to spend a considerable share of their disposable income on purchasing fuels [19], [21]. Beyond the direct effects on people, the reliance on traditional cooking also impacts the environment negatively. The use of traditional cooking leads to deforestation and is responsible for approximately 2% of the global emissions [3], [22], [23], [24]. It is estimated that the damages on climate costs society around 0.2 trillion USD yearly. These costs include the cost of carbon footprints
from direct fuel use, emissions connected to non-renewable harvest of biomass, CO₂-emissions from fuel production and black carbon (particles of carbon) emissions [3]. Fusco Nerini et al., through expert elicitation, find interactions (synergies and trade-offs) between SDG 7 and 143 out of the 169 targets spanning across all SDGs. They explicitly mention synergies to e.g., SDG 3 (“Ensure healthy lives and promote well-being for all at all ages”), SDG 4 (“Ensure inclusive and equitable quality education and promote lifelong learning opportunities for all”) and SDG 5 (“Achieve gender equality and empower all women and girls”) [2]. Mazorra et al. also make connections between access to clean cooking and SDGs 3 and 5. Furthermore, Mazorra et al. connect SDGs 7 and 13 (“Take urgent action to combat climate change and its impacts”), as the use of firewood and charcoal for cooking emits several pollutants [1]. Guta et al. and Rosenthal et al. argue separately for connections between SDG 7 and, SDGs 3, 5, 13 and 15 (“Protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and halt biodiversity loss”) [4], [15]. Literature has also highlighted the connection between increased electricity access and poverty reduction [2], [25]. Closely related to this is the potential of electricity to enable productive uses in sectors such as agriculture, commercial and industrial activities [26]. Access to electricity also prolongs the window in which people can be productive, which has been shown to have a connection to children’s ability to get quality education [26]. From a health perspective access to electricity is critical. The WHO emphasises that SDG 3 cannot be reached without access to electricity in health facilities [27]. Electricity has also been shown to
have a preventive effect on the spread of different diseases as people with adequate access to electricity can use televisions and radios to gain information more effectively [26], [27], [28]. Jeuland et al. conduct a literature review to assess the positive and negative impacts of energy on different parts of society [25]. Their review shows that while energy has a positive impact on most other SDGs, the effects of increased energy consumption are not always positive, and sometimes difficult to quantify. Cooking is an example of this. They state that while traditional cooking has been shown to have adverse effects on health, gender and climate, there is less evidence that the adoption of improved cook stoves results in improvements with regards to these aspects. In addition, Jeuland et al. find that the evidence in the literature is sometimes contradictory amongst studies [25].

1.1. Literature gaps and research questions

In the electricity sector there is a variety of technology-configurations that can be used to increase access, each best suited for different situations. Extending the central power grid is suitable when demand is large enough to motivate the investment. This often makes it an appropriate option in areas where the population density is high or where there are large amounts of productive and/or public uses of electricity [29]. However, extending the grid to last mile populations would oftentimes not be economically feasible, as people in remote areas tend to use less electricity (if at all) and live further away from the existing network [30], [31], [32]. Therefore, they risk being left un-electrified in cases where alternatives are not available. Off-grid options, such as mini-grids or stand-alone technologies, may be more
suitable for electrifying areas further away from existing grid infrastructure or with more disperse demand [31], [33]. This is echoed by the MTF which highlights that off-grid systems are more economically viable at lower tiers of consumption [10].

Many of the barriers and enablers to increased electricity access in accordance with SDG target 7.1 are inherently geospatial. For example, when selecting an off-grid option attention has to be given to fuel transportation costs (in case of e.g., diesel) and energy resource availability (e.g., in the case of renewables), both of which can be expected to vary spatially [34]. In these instances, the use of Geographic Information Systems (GIS) can assist in creating more heterogeneous policies and plans accounting for local contexts [35], [36], [37]. A GIS is a set of tools enabling storage, modification and analysis of large quantities of information. What separates a GIS from other types of information systems is that the data stored in these systems have a spatial component [38]. With the use of GIS, the suitability of different technologies can be modelled in a more spatially explicit manner. This is important if we are to reach SDG 7.1, as a mix of solutions are likely needed to do so [3], [39].

Beyond the context-specific challenges that exist with regards to different technologies, much of the energy planning efforts in areas without current access is hampered by data gaps [40]. The data gaps are not limited to non-existent data, but also to data not being open. This risks leading to policy-making not being data driven, as it creates gaps in data collection, maintenance and curation. GIS can be used as a tool to curate, digitize and share data, consequently increasing the efficiency of planning efforts [41]. When data gaps exist, or when
data collection is time-consuming, geospatial data and remote sensing can be used to create proxies or predictive approximations [33], [42], [43], [44], [45]. For these proxies, it is important to note that their accuracy can be challenged, but they are potentially important in cases where more recent data is not available. In addition to guiding the selection process of different technologies and bridging data gaps, GIS is a powerful communication tool that can help visualize results and facilitate coordination between stakeholders [29].

GIS has been increasingly leveraged in the electricity access sector through different tools, such as the Open Source Spatial Electrification Tool (OnSSET), the Reference Electrification Model (REM), GeoSim and Network Planner, in both peer-reviewed journals and policy documents [30], [33], [46], [47], [48]. However, while the use of GIS carries with it clear advantages it also introduces numerous challenges. One such challenge is the level of spatial aggregation used to represent models and their data. Many of the early geospatial electrification models were based on raster layers of different spatial resolutions, treating each cell as more or less a separate entity during the modelling process. The size of the cell impacts the size of each one of these entities. The larger the size, the more people (and demand for electricity) fit in it. This in turn can influence how modellers and tools perceive the relative competitiveness of different technology-configurations.

In later years, a larger number of geospatial electrification studies have moved from rasters towards vector population clusters. Vectors in the context of GIS are either points, lines or polygons. They are
usually used to represent real life objects with discrete boundaries. Polygons are most often used for population settlements in geospatial electrification modelling. These polygons are created by aggregating raster pixels or building structures based on distance and sometimes additional criteria [31]. The move towards more aggregated data is motivated by the fact that planners and policy makers rarely, if ever, plan their electricity sectors by dividing their area of interest into uniform areas the way a raster does. Instead, the planning efforts tend to be carried out on project level, which could include only specific towns or villages.

Blechinger et al. conducted a least-cost electrification analysis in 2019 for five federal states in Nigeria using population clusters [40]. Korkovelos et al. conducted the first OnSSET analysis using aggregated raster cells as population settlements rather than the previously used raster approach [31]. Blechinger et al. create their clusters using population data together with data on the locations of schools and polling units, while Korkovelos et al. aggregate population cells without the involvement of additional data. As population count tends to be used as a proxy for residential demand in many of these models, aggregating populations can be expected to lead to larger shares of grid connections. The effect of population aggregation on the least-cost technology mix is not assessed in either one of these studies, and is generally missing from the discussions on geospatial electrification models. The only exception to this, is a study conducted by Ellman [49]. Ellman, compares the effect of two different clustering approaches on the least-cost electrification mix using the REM tool. Each cluster in Ellman’s study is a grouping of customers. The clusters are formed by first creating off-grid clusters.
Each one of these off-grid clusters represent REM’s estimate of how clusters should be formed to minimize the cost of off-grid electrification. In the next step, the off-grid clusters are grouped together using two different approaches to determine where grid-extension is less costly than off-grid technologies. In the first approach each off-grid cluster is allowed to be evaluated individually to identify areas for grid-extension, but in the second approach all off-grid clusters are grouped into larger clusters evaluating grid extension. This allows for the costs of grid-extension and off-grid options to be compared. The two approaches used give rise to different levels of grid connections. This is attributed to one of the methods leading to many smaller clusters which do not justify connections to the grid, while the other approach leads to larger clusters. The two different clustering approaches are applied on a case study of the Vaishali District, India [49].

In a review of geospatial least-cost electrification models, Morrissey highlights one area for future research as understanding how the clustering of households impact the choice of least-cost technology. He states that future research should focus on understanding the differences that rasters and population settlements produce in least-cost electrification models and that there is a need to assess how different clustering algorithms influence the results [33]. The various approaches to population aggregation in the literature, in combination with its effects not being thoroughly assessed in the field, leads to the first research question (RQ):

**RQ1: How do different levels of spatial aggregation affect the results of geospatial electrification models?**
In policy documents describing the cooking sector and the transition from traditional to clean cooking, authors sometimes report “costs of inaction”. As an example, ESMAP estimates that current cooking practices costs 2.4 trillion USD yearly [50]. The costs directly impacting private households constitute a majority of these costs. Furthermore, the estimated losses far outweigh the costs of transitioning to clean cooking, which the IEA estimates to be around 8 billion USD per year [51]. This indicates that the cooking sector may be suffering from a market failure. Market failure can be defined as inefficient distribution of goods and services in the free market, making it difficult for the market to clear at a social optimum (maximizing net-benefits when accounting for all incremental costs and benefits affecting society as a whole) [52]. When markets work well, private interest can be assumed to ensure that a social optimum is reached [53].

Cost-Benefit Analysis (CBA) is a powerful decision-making tool for understanding if externalities are one cause of the divergence between real world outcomes based on private behavior and the social optimum [53]. A CBA quantifies all the costs and benefits of a policy action in monetary terms. The monetary terms are expressed in a specific currency (e.g., USD), and can be viewed as weights for each positive or negative consequence of the assessed policy action. Once the weights are assigned, the net-benefit can be calculated (as benefits minus costs). The net-benefit indicates whether the policy action leads to larger benefits than costs or vice versa, which in turn indicates whether the policy should be pursued or not [53].
The Benefits of Action to Reduce Household Air Pollution (BAR-HAP) was the first tool developed to compare policy interventions for a transition to cleaner cook stoves [54]. BAR-HAP allows for 16 pre-defined transitions, 15 from traditional fuels to either Improved Cook Stoves (ICS) or clean options and one from Liquefied Petroleum Gas (LPG) to electric stoves. Beyond specifying pure transitions, the user can include policy interventions aimed at specific transitions. These policy interventions include subsidies (stove or fuel), financing, behavioral change communication campaigns, or technology and fuel bans. Each policy intervention in BAR-HAP, except for technology and fuel bans, is coupled with an assumption of its effectiveness. The analysis can be run on either national, urban or rural level [54].

Progress towards universal clean cooking access is slow, and in some countries even outpaced by population growth. To try to understand why, a number of policy reviews [3], [17], [55] and peer-reviewed articles [9], [14], [56], [57], [58] assess the barriers and enablers of clean cooking adoption. Some of the factors that influence adoption and/or sustained use of clean cooking are affordability [1], [11], [13], [14], [15], [57], [58], [59], [60], accessibility [1], [14], [15], [58], [59], [60], [61], reliability [1], [12], [13], [15], [58], cultural preferences [13], [15], [57], household dynamics (typically gender-driven, the decision makers are not the same people as the ones carrying the majority of the burden, who tend to be women) [1], [15], [62], lack of consumer awareness [1], [13], [15], [59] and perception [1], [15], [57], [58] as well as lower valuation of non-economic benefits (e.g., health and time benefits of switching to clean cooking) [11].
Puzzolo et al. conduct a systematic literature review assessing enabling and inhibiting factors for adoption and sustained use of clean cooking fuels (specifically biogas, LPG, solar cookers and alcohol fuels) [63]. They categorize the drivers into seven separate domains:

- Fuel and technology characteristics (e.g., fuel savings, safety issues and time savings)
- Household and settings characteristics (e.g., education and socio-economic status)
- Knowledge and perception (e.g., total perceived benefits),
- Financial, tax and subsidies (e.g., program subsidies)
- Market development (e.g., demand creation and supply chains)
- Regulation, legislation and standards
- Program and policy mechanisms (e.g., user training and post-acquisition support)

For LPG, Puzzolo et al. find relative and fluctuating fuel costs to be an inhibitor. Furthermore, as the fuel cost increases, people are more likely to fuel-stack. Additionally, households that have to travel longer distances to refill their LPG cylinders are less likely to adopt LPG stoves. Other inhibitors included the initial cost of the LPG stove, lower levels of education and safety concerns. For biogas, lacking manure supply and knowledge of positive externalities, lower temperatures, freely available biomass, poor road quality and high upfront costs are all found to be inhibitors. On the other hand, time savings (due to higher efficiency of the stove), higher levels of wealth and education, higher prices of alternative fuels and land holdings all seem to increase the potential uptake of biogas stoves. For solar
cookers, reduced fuel expenditures, time savings (when fuels had to otherwise be collected), higher income and health benefits were seen as enablers, while the investment cost and the fact that all food could not be cooked on these stoves were seen as inhibitors. For alcohol-based fuels, the reduced cooking times, availability of markets, cleanliness and beliefs about safety were enablers, while the main barrier was the upfront cost [63].

In a separate article, Puzzolo et al. assess the need for developing adequate supply networks for adopting clean cooking and sustaining its use [64]. Unreliable supply, whether it is due to a shortfall in fuel or fluctuating price, is often a cause for fuel stacking or abandonment of clean fuels. They identify how different cooking fuels require different supply considerations. While some fuels such as pellets and biogas can be produced locally, others, such as LPG, depend on supply networks at a larger scale. Subsidies and taxes are also identified as powerful tools to either increase or decrease the attractiveness of specific fuels [64].

Many of the factors used to explain people’s willingness, reluctance and ability to switch to cleaner fuels laid out above are inherently geospatial and context-specific, which is also recognized in the literature. Rahut et al. assess determinants of cooking fuel choices in Ethiopia, Malawi and Tanzania, and point out how the location of the household plays an important role in choice of cooking fuel [65]. Kelebe et al. mention how many of the socio-economic and environmental factors assessed vary spatially in their study of what impacts small-scale biogas adoption in households located in Tigray [36]. Rehfuess et al. in their review of enablers and barriers of ICS
write that geography and climate are important factors for adoption [66]. Das et al. discuss how the value of subsidies for clean cooking or taxation of traditional options vary based on the specific setting in which a beneficiary is located [67]. Bharadwaj et al. argue that previous research has been emphasizing the endogenous factors explaining the choice of cooking fuels while forgetting the equally important external factors [68]. The external, or exogenous, factors lay outside of the control of the households and include aspects such as geography and supply chain options. Their analysis concludes that external factors (such as accessibility, road access, elevation and forest cover) all impact the suitability of different cooking fuels [68].

In July of 2020, Sustainable Energy for All (SEforALL) hosted a workshop on the use of GIS in clean cooking where participants discussed the data needs and concerns [41]. It was mentioned that while GIS has been widely used in electrification planning, it had yet to become popular for clean cooking. A concern raised was that most of the efforts focused on individual fuels without comparing them to alternatives. Participants of the workshop agreed that the use of GIS in clean cooking could serve as a tool for fuel-specific decision making and to create a framework on costs and benefits of different strategies and policies.

A geospatial framework to effectively compare the relative benefits and costs of different cooking transitions was, at the time of writing, not available. Against this background, the second research question is:
RQ2: How can GIS be effectively utilized to compare different cooking alternatives for achieving universal clean cooking access?

Electricity is considered a clean cooking fuel. Yet, there is a stark contrast between electricity and clean cooking access rates, indicating that in many countries few households use their electricity for cooking [3]. The discrepancy between electricity and clean cooking access rates indicates that electricity access does not translate directly to the use of less polluting cooking fuels. Newell & Daley argue that the reason could be because the two goals are rarely interlinked in the political sphere [69]. Therefore, many electricity-related projects fail to consider electric cooking as a load in their expansion plans for electricity access. Furthermore, Newell & Daley highlight that there are considerable differences in the amount of funding that the two goals receive, with the clean cooking sector suffering from low investments. They argue that a major reason for this could be that clean cooking and its benefits are fragmented, spanning across different national ministries (e.g., the ministry of environment and the ministry of health) [69]. Batchelor et al. argue along the same lines, stating that the separation of clean cooking and electricity at the political level is the cause for the highly divergent access statistics [70]. They argue that a large portion of the investment is already in place (in terms of infrastructure), and if integrated planning efforts were to be employed, scaling clean cooking with electricity becomes possible. They conclude that electrification and clean cooking planning need to be integrated [70].
There are trends in the energy sector that could make electricity a more competitive cooking fuel. Previous research indicates that some of the most salient barriers to using electricity for cooking are high perceived costs, weak grid infrastructure, load shedding and network failures [5], [13], [71], [72]. However, while prices of certain traditional fuels, such as charcoal, are increasing, the price of renewable off-grid systems are decreasing [5], [73]. This, in combination with more advanced and cheaper power storage systems for mini-grids and efficient cooking appliances makes electricity more accessible and viable as a cooking fuel [5], [13], [72], [73], [74], [75], [76]. Dagnachew et al. assess the synergies and trade-offs between SDG target 7.1 and the other two targets of SDG 7 ("increase substantially the share of renewable energy in the global energy mix" and "double the global rate of improvement in energy efficiency") [77]. Their results suggests synergies between the three SDG 7 targets, and they argue that planning energy systems with all SDG 7 targets in mind could be beneficial for off-grid electricity systems, as it increases the type of activities that can be sustained by these (e.g., cooking) [77].

Sánchez-Jacob et al. develop integrated scenarios to assess how inclusion of electric cooking affects the REM tool [78]. In a case study of Rwanda, they develop three scenarios, one without and one with electric cooking, as well as one where half the meals are cooked with electricity. They compare four cooking fuels based on costs; electricity, fuelwood, charcoal and LPG. They conclude that electric cooking is cost-competitive with LPG in grid-connected households, but not in off-grid areas [78]. Lee et al. use the REM tool in a similar manner, this time comparing the costs of cooking with LPG or
electricity in a region of Uganda [29]. Their analysis is aimed at finding the economic viability of electric cooking. Assuming LPG costs 2.5 USD/kg across the study area, they find electric cooking to be economically favorable for 42% of the population. They further mention that increased adoption of electric cooking causes a positive feedback loop. Thanks to economies of scale the cost of electricity decreases as people switch to electric cooking. This makes electric cooking viable for a larger share of the population, reaching an equilibrium when 82% of the population use electric cooking. These two studies focus on the techno-economic aspects of electric cooking, and do not account for different cooking solutions having different benefits [29], [78]. Others have argued similarly about electric cooking being competitive with LPG from a cost perspective [72], [74].

The need for integrated energy access planning is also acknowledged beyond academia. The World Resources Institute (WRI) in collaboration with the Clean Cooking Alliance (CCA) has started to model clean cooking in addition to electricity in the Energy Access Explorer (EAE). At the time of writing, this has been done for Nepal and Kenya [79]. SEforALL is building integrated planning platforms considering both electrification and clean cooking, currently available for Malawi and Nigeria [80]. SEforALL also hosted a workshop on integrated planning in July of 2020. In this workshop participants agreed that electric cooking should be included in electrification planning efforts, but warned that this might complicate existing electricity models [41]. Lastly, the UN lists eight recommendations to increase the pace towards SDG 7.1 in their theme report on energy access from 2021. The second recommendation calls for integrated
energy plans in which clean cooking is incorporated into electrification planning [81].

Academic literature also highlights cautionary tales of cases where an integrated planning approach has been missing. An example of this is seen in Nepal, which has a high rate of electricity access but low clean cooking access. The government of Nepal has vocalized an ambition to increase the share of electric cooking to overcome the lack of clean cooking access and dependency on LPG imports [82]. However, large parts of the existing electricity supply network is not suitable for electric cooking due to inadequate electricity transmission and distribution infrastructure, and would require a second round of investments to upgrade [76], [83].

The increasing focus on, and need for, integrated energy plans, as well as increasing efficiencies of electric cooking appliances leads to the third research question:

**RQ3: How are the results of geospatial energy models (both electricity and clean cooking) impacted as an integrated planning approach is incorporated?**

1.2. Aim

The selected research questions inform the overall aim of this thesis:

*To advance the state-of-the-art in geospatial modelling approaches to support integrated energy planning towards universal electricity and clean cooking access.*
1.3. Thesis organization

1.3.1. Appended publications

The RQs are answered through four publications appended in this thesis. Their content and connections to each RQ is expanded on below. Following the papers, Table 2 summarizes the relations between each paper and RQ.

Paper I


**Content:** An open-source workflow is developed aimed at generating population clusters using openly available population density raster datasets. The cluster generation is carried out by aggregating the raster cells in the input data based on their proximity to each other. Beyond population counts, the resulting population settlements include urban-rural classification based on population density, and estimates of electricity access rates based on night-time light intensity. The urban-rural classification and electricity access rates are validated against data from the World Bank and available Demographic and Health Surveys. The code used to produce the datasets is open-sourced and published, as is the population clusters for 44 countries in SSA. Paper I provides methodologies used in subsequent papers to compare different population aggregations to answer RQ 1.
**Author contribution:** Conceptualization, methodology, data collection & processing, software development, analysis, validation and write up of original draft were conducted by the thesis author under the supervision of F. Fusco Nerini and M. Howells. Co-authors A. Korkovelos and A. Sahlberg supported the validation. All authors were involved in reviewing the manuscript.

**Paper II**


**Content:** The effect of different levels of population aggregation in OnSSET is assessed. This is done by using, for the first time in geospatial electrification modelling, a Global Sensitivity Analysis (GSA). By running 2,080 scenarios each for three countries in SSA, the paper describes OnSSET’s sensitivity to different important parameters subject to uncertainty. Conducting a GSA with parameters connected to population aggregation allows for 1) contrasting the importance of population aggregation to the importance of other parameters which previous research has identified as important and 2) assess whether the importance of the population layer changes as other parameters do. This paper provides insights for RQ 1.
Author contribution: The author of this thesis led the conceptualization, methodology and software developments, the formal analysis, investigation, visualization, data curation and wrote the original draft. Co-authors A. Sahlberg, W. Usher and A. Korkovelos supported the development of the Methodology. Co-author A. Sahlberg also supported the software development. Co-author F. Fusó Nerini supported the conceptualization and together with W. Usher provided supervision during the writing process. All authors where involved in reviewing the manuscript.

Paper III


Content: The first geospatial tool assessing and comparing the relative costs and benefits of different stoves over any given study area is introduced (OnStove). The tool is applied for the first time to 44 countries in SSA. The costs and benefits of nine different stoves are determined and compared for every square kilometre of the region across two main scenarios. The paper also presents a GSA for 33 parameters using 680 additional scenarios aimed at understanding the main drivers in the net-benefit equation. In addition, the paper presents affordability estimates for the stoves assessed across SSA. As part of the paper, the code and data used are open-sourced to facilitate and encourage replication and modification of the results. This paper lays the foundation for answering RQs 2 and 3.
Author contribution: The author of this thesis conceptualized the paper, together with co-authors C. Ramirez and M. Jeuland. The data collection and curation, model development and formal analysis was done by the author of the thesis together with co-author C. Ramirez. The writing of the original draft was led by the author of this thesis. M. Jeuland provided validation, and provided supervision together with F. Fuso Nerini. All authors were involved in reviewing the manuscript.

Paper IV


Content: Presents the first geospatial integrated planning effort for both universal electricity and clean cooking access, taking into account more than techno-economic parameters. This is done by soft-linking OnStove with OnSSET. The soft-link takes the least-cost technology mix, the Levelized Cost of Electricity (LCoE) and current electrification status from OnSSET and incorporates them into OnStove. After running OnStove the stoves with the highest net-benefits are identified and as the share of electric cooking either increases or decreases the demand in OnSSET is modified. The change in demand in OnSSET in turn impacts the least-cost technology mix and LCoE, which are then fed back into OnStove. This iterative process is repeated until equilibrium is reached. Equilibrium in this context is defined as when no additional electric cooking occurs and no-one
who is not cooking with electricity is paying for an additional demand. The paper is applied to a case-study of Kenya and contributes to answering RQs 1, 2 and 3.

**Author contribution:** The author of this thesis did the literature review, data curation, OnStove developments, formal analysis, wrote the original manuscript draft and led the conceptualization. Co-author A. Sahlberg contributed to the conceptualization. Co-author C. Ramirez contributed to the OnStove developments. Co-author S. Odera drafted the Kenya case study. Co-authors E. Onsongo, K. Nayema, D. Ronoh and V. Otieno collected data on the ground. Co-author A. Gurung supported data collection, stakeholder consultation and supervision Co-author F. Fusó Nerini provided supervision throughout the manuscript writing. All authors were involved in reviewing the manuscript.

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<tr>
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<tr>
<td><strong>RQ1:</strong> How do different levels of spatial aggregation affect the results of geospatial electrification models?</td>
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<td><strong>RQ2:</strong> How can GIS be effectively utilized to compare different cooking alternatives for achieving universal clean cooking access?</td>
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<td><strong>RQ3:</strong> How are the results of geospatial energy models (both electricity and clean cooking) impacted as an integrated planning approach is incorporated?</td>
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Table 2. The relation between each research question and appended paper.
1.3.2. Additional publications and contributions

While the research presented in this thesis draws mainly on the four appended publications, insights are also drawn from the other projects, publications and capacity building efforts that the author of this thesis has been a part of. These efforts are listed below.

Co-authored peer-reviewed journal articles


IV. A. Sahlberg, B. Khavari, I. Mohamed, and F. Fuso Nerini, “Comparison of Least-Cost Pathways towards Universal


Reports


II. “A GIS approach to electrification planning in Benin”, consultation report prepared for SNV under the contract PO6978, 2019.


VI. “A Vision for Clean Cooking Access for All”, special report by IEA. Contributed with OnStove analysis for Sub-Saharan Africa, 2023

Platforms


IV. Energy Access Explorer Nepal. A platform enabling on-the-fly geospatial multi-criteria analysis related to clean cooking solutions. It also includes a number of pre-cooked OnStove scenarios visualizing the highest net-benefit stoves and other relevant outputs from OnStove across Nepal (2022).

V. Energy Access Explorer Kenya. WRI’s existing Energy Access Explorer of Kenya was expanded with clean cooking analysis using OnStove. The electricity side of the platform was also expanded with OnSSET to facilitate integrated planning efforts for both increased electricity and clean cooking access (2023).

Capacity building efforts

The workshops listed below are capacity-building efforts focusing on geospatial least-cost electrification and clean cooking modelling. Each workshop included participants from the policy and power sectors, as well as academia. Many of the participants were new to geospatial data and tools. For these trainings, the author of this thesis
was one of the trainers and developed lectures, exercises, tools and acquired data used by the participants.

I. OnSSET trainer at the ICTP Summer School on Modelling Tools for Sustainable Development, 2018, 2019 and 2022

II. OnSSET trainer at the Energy Modelling Platform for Africa, 2019

III. OnSSET trainer in Benin as part of an SNV funded project in 2018 and again as part of a World Bank funded project in 2020.

IV. OnSSET trainer in Somalia as part of a Ministry of Energy and Water Resources funded project, 2021

2. Methods

This section outlines the methods and tools used to inform this thesis. In the initial phase, a literature review was undertaken to increase understanding regarding the use of geospatial tools for energy modelling and more specifically, how they can be used for modelling universal energy access in accordance with SDG target 7.1. The literature review informs the quantitative analysis which is centred around two geospatial energy modelling tools, OnSSET and OnStove. OnSSET is a least-cost electrification tool calculating the cost of electrifying different settlements with different technology-configurations (grid, mini-grid or stand-alone), and OnStove is a clean cooking tool comparing the net-benefits of different stoves. Beyond the two main tools, important pre- and post-processing steps such as aggregation of population settlements and GSA in the field of geospatial energy modelling have been developed and explored to gain further understanding of the robustness of these models. The following paragraphs describe in more detail the different methods employed throughout this thesis (see Fig. 1 for an overview).
Fig. 1. Simplified schematic of the work conducted as part of this thesis.

2.1. Geospatial electrification modelling

OnSSET was originally developed at KTH, and has since grown to become one of the most frequently used geospatial electrification tools in the literature. The OnSSET workflow can be divided into three separate steps, the first step is pre-processing of the input data to form the input file. Next, the study area is calibrated and the last step is the scenario runs. Further explanation of each step is provided in the sections below.
2.1.1. Pre-processing steps

Generally there are two pre-processing steps included in an OnSSET analysis:

1. **Generation of population settlements** – The population settlements is the base layer in OnSSET. Most openly accessible geospatial population layers come in the form of rasters or census data. OnSSET was originally developed to function with raster population layers. Rasters divide a study area into a uniform grid, where every unit of the analysis has the same shape and size. From a computational standpoint it is beneficial to have uniform units of analysis as this simplifies comparisons and interpretability of results. However, rasters fail to capture the true size and shape of settlements. Therefore, OnSSET was later modified to run with aggregated vector settlements (note however that the tool can still do studies using raster populations).

In Paper I, an open-source code was developed to generate aggregated vector settlements using raster datasets as input. The code described in Paper I can also estimate electrified population in settlements using night-time lights and the urban-rural split using the total population and population density in each settlement. The cluster methodology developed as part of Paper I outputs clusters with the following attributes:

- A unique identifier
- Country (or region) name
• Number of people in each cluster  
• Maximum night-time light intensity in each cluster  
• The number of people in the cluster who live in areas with visible night-time light  
• Area of each cluster in square kilometres  
• Urban or rural classification

Beyond this, OnSSET is agnostic to the method used to generate the population clusters. For example, Paper II assess the impact of different levels of spatial aggregation in OnSSET across 26 different population bases each for three countries. The population bases all stem from the same original raster dataset (the High Resolution Settlement Layer, HRSL [84]). HRSL’s native spatial resolution is 30 metre. In Paper II, two population rasters were created by resampling HRSL to 100 metre and 1 kilometre resolutions. These two datasets help to contrast the previously more frequent raster approach to the now more common cluster approach, but also the difference between different raster resolutions. Three population layers were created using the clustering approach described in Paper I. The algorithm presented in Paper I allows the user to divide clusters based on administrative boundaries to account for potential local interests of different stakeholders and policy makers. Three different divisions of administrative boundaries were used (admin level 0, 1 and 2). Lastly, Density-Based Spatial Clustering of Applications with Noise (DBSCAN) was used to generate 21 population bases. The implementation of
DBSCAN takes inputs for eps and minPts. eps determines the search radius from any point to other points, determining the point's neighbourhood. minPts defines the minimum number of points within the neighbourhood in order for the first point to be considered a core point. Core points can extend the cluster to additional points. Non-core points inside of a core point's neighbourhood will be considered part of the cluster, but can not extend the cluster further. The DBSCAN-clusters were created with eps ranging from 200 to 500 metres with steps of 50 metres and minPts of 1, 3 and 5 (see Table 3).

Table 3. The methods used in Paper II for population aggregation.

<table>
<thead>
<tr>
<th>Resampling to</th>
<th>100 metre</th>
<th>1 kilometre</th>
</tr>
</thead>
<tbody>
<tr>
<td>Clustering from Paper I</td>
<td>Admin 0</td>
<td>Admin 1</td>
</tr>
<tr>
<td>DBSCAN</td>
<td>eps: 200 metre, minPts: 1, 3 and 5</td>
<td>eps: 250 metre, minPts: 1, 3 and 5</td>
</tr>
</tbody>
</table>
2. Creating an OnSSET input file – Following the generation of population clusters the other geospatial datasets relevant for the analysis are extracted to the population layer. A wide range of geospatial datasets are used in OnSSET related to the location of available and planned infrastructure (e.g., substations and medium-voltage lines), energy resource availability (e.g., global horizontal irradiation and wind speed) and difficulty of expanding existing infrastructure (e.g., digital elevation and land cover maps). For a full list of geospatial datasets used in OnSSET refer to ref. [31].

2.1.2. Calibration

The calibration determines the total population, the urban-rural split and the current electrification status for every settlements in the start year. For the population calibration, a factor is multiplied with the population of each cluster to ensure that the total population matches values as entered by the user [30]. To determine urban-rural split, OnSSET labels the largest settlements as urban until the total urban population matches (or is as close as possible to) what is entered by the user. To calibrate electrification rates, three geospatial datasets and corresponding thresholds are used. The first threshold is for night-time light intensity and sets a minimum intensity limit for settlements that can be assumed to be electrified. The second threshold concerns population size in the settlement and indicates the smallest population count that a settlement can have and still be considered electrified. Lastly the distance to electricity related infrastructure is taken into account (distribution transformers, medium- or high-voltage lines, in this order and
depending on availability). This threshold indicates how far away a settlement can be from electricity related infrastructure and still be considered electrified. Initially all settlements who fulfill all thresholds are considered electrified. Next, the calibrated electrification rate is compared to the one entered by the user. If the calibrated value is higher than what was intended, the thresholds are made more stringent and vice versa. This process is repeated until the calibrated electricity access rate and the actual electrification rate match [31].

2.1.3. Scenario set-up

After calibration the least-cost technology in different settlements is determined. This is done in two steps. First, the demand is determined in all settlements. OnSSET allows two different approaches for this. The first approach lets the user select one tier for urban settlements and one tier for rural settlements. These tiers tend to draw from ESMAP’s MTF, but can also be customized by the user [10]. The second approach was first described by Korkovelos et al. and enables more spatially heterogeneous demand levels by reading the demand directly from another geospatial dataset [31]. Korkovelos et al. use geospatial representations of poverty rates and nominal GDP to generate estimates of electricity demand. Areas with low poverty and high GDP are assumed to have the highest demand, while areas with high poverty rates and low GDP have the lowest demand [31].

After determining the demand in every settlement of the study area, the costs of electrifying each settlement is calculated for each technology. The costs of off-grid technologies are determined first. All off-grid options include the cost of generation, distribution
networks (for mini-grids), and renewable off-grid technologies (mini-grids and stand-alone) include cost of storage. Options that are non-renewable or have a part that is non-renewable (e.g., hybrid mini-grids) include fuel costs. Once the costs of all off-grid technologies are determined, they are compared to the cost of extending the grid. Grid electricity is often produced in large-scale centralized power plants and then transmitted and distributed through electricity networks to end-users. These type of systems, benefit from economies of scale, lowering per unit costs as production increases. The cost of extending the grid depends on the distance to be covered and the difficulty of doing so. Beyond the grid extension costs there are costs associated with grid-strengthening, distribution within settlements and adding necessary generation capacity. For all the options, the LCoE is calculated in every settlement. Whichever technology-configuration provides the lowest LCoE is selected as the least-cost technology [30].

2.2. Geospatial clean cooking modelling
As part of this thesis the first geospatial tool comparing the relative costs and benefits of different stoves, OnStove, is developed. OnStove is an open-source python-based tool drawing on geospatial, techno- and socio-economic data to model the cooking transition (refer to Annex A: OnStove input data for lists of input data). Whichever stove provides the highest net-benefit in different parts of the study area is selected. The tool is run in three steps and the sections below describes each step in more detail.
2.2.1. GIS processing
OnStove is a raster-based tool. A population raster with information regarding number of people in each pixel creates the base layer of the model. Each dataset (vector or raster) is cropped to the borders of the study area. Once this is done, all datasets are aligned ensuring they have a common projection system and, in the case of rasters, the same cell-size and completely overlapping grid cells. This is important as there are often mismatches between different data sources. OnStove also allows for calculation of least-cost paths and proximity maps when required. Least-cost paths can be used to determine the collection times or fuel costs of different fuels when relevant and proximity maps can be used to estimate likelihood of electricity access in different parts of the study area.

2.2.2. Calibration
The second step in OnStove calibrates the geospatial information based on socio-economic statistics specified by the user. In this step 1) the urban and rural areas are identified 2) the total population is calibrated, 3) the current electricity access is calibrated and 4) the current stoves used across the study area are identified.

The urban and rural areas can be determined either directly using an external raster (e.g., [85]) or be calibrated manually. In case of manual calibration, start values of population density used as cut-offs between rural and urban areas are given. These values are iteratively changed until the total urban rate matches the rate entered by the user [86].
Next, the population calibration ensures the correct number of people are living in the study area and that the urban-rural division remains the same as originally defined by the urban-rural calibration. This is done by multiplying population in each cell by a specific factor depending on their urban-rural classification.

Electricity access is determined using a multi-criteria analysis (MCA). The MCA utilizes three geospatial datasets to estimate the number of electrified people in each raster cell of the study area, while ensuring that the study area’s electricity access rate matches statistics entered by the user. The three geospatial datasets used to estimate the likelihood of electricity access are night-time light intensity, population density and distance to electricity related infrastructure (distribution transformers, medium- or high-voltage lines, in this order and depending on availability). The user can also enter weights for each of the three criteria in the MCA to impact the results.

The last step of the calibration is to determine current cooking shares in the study area. The current cooking situation is used to estimate a baseline for the number of deaths, cases of disease, time spent cooking and collecting fuels, greenhouse gas emissions and costs, assuming current practices continue. The calibration can be done in two ways. In the first approach, the user can define one cooking solution as the base fuel (e.g., traditional biomass), assuming everyone in the study area use this fuel. The other option is to specify urban and rural shares of different stoves, assuming that all urban cells have the same shares of stoves, as will all rural. Electric and biogas stoves are exceptions to this and would only be available for cells that permits their use. Electric cooking is available in the baseline
only where at least a portion of the population is considered to be electrified. For biogas stoves, OnStove uses geospatial data to ensure that manure supply, temperature and water availability is sufficient. The baseline calibration ensures that requirements for electric and biogas cooking are met at the same time as the total shares across the entire study area matches those entered by the user.

2.2.3. Determining net-benefits
Here, net-benefits are defined as total benefits minus total costs. The benefits accounted for in OnStove are reduced number of cases of COPD, ALRI, IHD, stroke, and lung cancer, as well as avoided deaths caused by these diseases, reduced cooking and collection times and reduced Greenhouse Gas (GHG) emissions (all compared to the baseline). For costs, OnStove considers capital (investment costs with a netted-out salvage to account for differing stove lives), operation and maintenance (O&M) and fuel costs. Each separate category of benefits (health, environment and time) has a weight assigned to them, as do the costs. The default value for each weight is one. By changing the weights of one or several benefits (hence changing their relative sizes), users can put a larger emphasis on specific benefits. This gives users the ability to run scenarios aimed towards specific aspects of the clean cooking transition. Each benefit and cost in OnStove is described in more detail below.

Changes in morbidity and mortality
As the concentration of PM$_{2.5}$ is one of the main drivers of health effects caused by traditional cooking [3], [17], the starting point of the morbidity and mortality calculations are PM$_{2.5}$-specific Exposure-
Response Curves (ERC) for different diseases (Fig. 2). The ERC of each disease describes how the Relative Risk (RR) of said disease (y-axis) changes as the concentration of PM$_{2.5}$ (x-axis) changes.

Fig. 2. ERCs for the diseases included. X-axis shows the PM$_{2.5}$-concentrations and y-axis shows the Relative Risk. Created based on data from [87].

Fig. 2 indicates that the RR increases sharply in the beginning as PM$_{2.5}$-concentrations increase and then level off at higher concentrations. The relationship between ERC and RR in Fig. 2 is described by Equation 1, adopted from the work of Burnett et al. [87].

The equation indicates that when the PM$_{2.5}$ – concentrations are below a certain threshold the RR of disease is equals to 1 (no increased risk). As the PM$_{2.5}$ – concentration increases, so does RR.
\[
\begin{align*}
&\text{if } \varepsilon \ast 24h \text{ PM}_{2.5} < z_{rf}, \text{RR} = 1 \\
&\text{if } \varepsilon \ast 24h \text{ PM}_{2.5} \geq z_{rf}, \text{RR} = 1 + \alpha \ast (1 - e^{(-\beta \ast (\varepsilon \ast 24h \text{ PM}_{2.5} - z_{rf})\delta)})
\end{align*}
\]  

(1)

Where \( \varepsilon \) is an exposure-adjustment factor used to model potential behavioural change as a new stove is adopted [54], \( 24h \text{ PM}_{2.5} \) is the 24h-average PM\(_{2.5}\)-concentration, RR is the relative risk and \( z_{rf}, \alpha, \beta \) and \( \delta \) are disease specific constants determined experimentally [87]. Burnett et al. estimate values for the disease-specific constants by running a large number of simulations of RR for COPD, ALRI, IHD, stroke, and lung cancer. In OnStove the average values of these runs are used for the calculation of RR (see Table 4) [87].

**Table 4.** The average constants as estimated by Burnett et al. and used in OnStove [87].

<table>
<thead>
<tr>
<th></th>
<th>COPD</th>
<th>Lung cancer</th>
<th>IHD</th>
<th>Stroke</th>
<th>ALRI</th>
</tr>
</thead>
<tbody>
<tr>
<td>( z_{rf} )</td>
<td>7.337</td>
<td>7.345</td>
<td>7.449</td>
<td>7.358</td>
<td>7.298</td>
</tr>
<tr>
<td>( \alpha )</td>
<td>22.485</td>
<td>152.496</td>
<td>1.647</td>
<td>1.314</td>
<td>2.383</td>
</tr>
<tr>
<td>( \beta )</td>
<td>0.001</td>
<td>0.000167</td>
<td>0.048</td>
<td>0.012</td>
<td>0.004</td>
</tr>
<tr>
<td>( \delta )</td>
<td>0.694</td>
<td>0.76</td>
<td>0.467</td>
<td>1.275</td>
<td>1.193</td>
</tr>
</tbody>
</table>

The disease specific RR is used to determine the Population Attributable Fraction (PAF) in every square kilometre of the study area (Equation 2). The PAF for each disease is used to estimate the proportional reduction in mortality and incidence rates of a disease if a specific behaviour is suspended (in this case the behaviour refers to population cooking with traditional fuels) [88].

\[
\text{PAF}_i = \frac{sfu \ast (RR_k - 1)}{sfu \ast (RR_k - 1) + 1}
\]  

(2)
Where \( sfu \) refers to the current share of the population using traditional stoves and \( RR \) is the disease-specific relative risk calculated with Equation 1, \( i \) refer to each stove and \( k \) refers to each disease. \( sfu \) is taken from the calibration and as the fuel shares are specific to each raster cell in the analysis, \( PAF_i \) is as well.

PAF is used to estimate the share of mortality and incidence rates connected to a specific action. PAF, as calculated in Equation 2, can therefore be used to estimate the mortality and incidence rates caused by the use of traditional fuels [88]. Specifically OnStove calculates the reduced number of deaths and sickness following a switch to cleaner cook stoves. This is done on a cell-basis using equations 3 and 4.

\[
\text{Mort}_k = \text{Population} \times (PAF_0 - PAF_i) \times MR_k \quad (3)
\]

\[
\text{Morb}_k = \text{Population} \times (PAF_0 - PAF_i) \times IR_k \quad (4)
\]

Where \( \text{Population} \) is the total population in each cell of the study area, \( MR_k \) and \( IR_k \) are the mortality and incidence rates respectively for each disease (provided as inputs to the model from an external source e.g., [89]), \( PAF_0 \) is the PAF of the baseline and \( PAF_i \) is the PAF-value of the new stove that is switched to.

The reduced number of cases and deaths are translated to monetary values using Costs of Illness (COI) and Value of Statistical Life (VSL) respectively. COI is disease specific, including the direct medical expenses and the cost of lost productivity [90]. VSL captures people’s willingness to pay for a small reduction in their own risk of death [91].
Incorporating these parameters into equations 3 and 4 gives equations 5 and 6:

\[
P_{M,m_b} = \sum_{k} \left( \sum_{t=1}^{5} C_L_{k,t} \cdot COI_k \cdot \frac{Morb_k}{(1 + \delta)^{t-1}} \right) \tag{5}
\]

\[
P_{M,m_r} = \sum_{k} \left( \sum_{t=1}^{5} C_L_{k,t} \cdot VSL \cdot \frac{Mort_k}{(1 + \delta)^{t-1}} \right) \tag{6}
\]

Where \( Morb_k \) and \( Mort_k \) are the reduced number of cases and deaths from disease \( k \) respectively, \( CL_k \) is the cessation lag of each disease (accounting for the fact that benefits of stove-switch are not instantaneous, see Table 5), \( \delta \) is the discount rate and \( t \) is the number of years from the switch. Finally \( Morb \) and \( Mort \) describe the monetary value of reduced cases and reduced deaths in the study area [92].
Table 5. Cessation lags for each disease. Describes the percentage of health benefits that come each year after a switch, e.g., for the case of COPD 30% of the health benefits come after one year, another 20% is added after two years etc. Full benefits are assumed to come after the fifth year [92].

<table>
<thead>
<tr>
<th></th>
<th>COPD</th>
<th>Lung cancer</th>
<th>IHD</th>
<th>Stroke</th>
<th>ALRI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Year 1</td>
<td>0.3</td>
<td>0.2</td>
<td>0.2</td>
<td>0.2</td>
<td>0.7</td>
</tr>
<tr>
<td>Year 2</td>
<td>0.2</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td>Year 3</td>
<td>0.17</td>
<td>0.24</td>
<td>0.24</td>
<td>0.24</td>
<td>0.07</td>
</tr>
<tr>
<td>Year 4</td>
<td>0.17</td>
<td>0.23</td>
<td>0.23</td>
<td>0.23</td>
<td>0.07</td>
</tr>
<tr>
<td>Year 5</td>
<td>0.16</td>
<td>0.23</td>
<td>0.23</td>
<td>0.23</td>
<td>0.06</td>
</tr>
</tbody>
</table>

Changes in emissions

OnStove assesses the change in emissions caused directly by stove-switch, as well as transportation and production emissions related to relevant fuels. As starting point the amount of fuel used for cooking per year is determined using Equation 7.

\[
f = \frac{E \times \frac{\text{meals}}{\text{day}} \times 365}{\text{eff}} \quad (7)
\]

Where \( E \) is the energy required for cooking a meal and \( \text{eff} \) is the efficiency of the stove. Once fuel use is determined, the reduction in emissions is calculated using Equation 8.

\[
\text{Reduced emissions} = f_0 \times \gamma_0 - f_i \times \gamma_i \quad (8)
\]

Where \( \gamma \) denotes the carbon intensity of the fuel, \( 0 \) denotes the current situation and \( i \) the stove that the population switch to [92]. \( \gamma \) is fuel-specific and takes into account emissions of \( \text{CH}_4, \text{N}_2\text{O}, \text{CO}_2, \text{CO} \), organic carbon and black carbon and their respective 100-year Global Warming Potentials according to Equation 9 [92].
\[ y_i = \sum_j \varepsilon_{i,j} \cdot GW P_j \quad (9) \]

Where, \( \varepsilon_{i,j} \) is the emission factor of stove \( i \) with regards to pollutant \( j \) and \( GW P \) is the 100-year global warming potential of each pollutant.

Certain stoves have fuel specific emissions. For electricity and charcoal, production emissions are added to the emissions caused by direct stove use. For LPG transportation emissions are included. For all biomass and charcoal options, the emissions connected to national fractions of non-renewable harvest of biomass is included [23], [37]. Non-renewable biomass refers to the fraction of biomass harvested at a faster pace than the incremental growth rate [37]. As fraction of non-renewable biomass increases, so does the level of net carbon emissions. Therefore, in the case of biomass and charcoal, Equation 9 is modified in accordance to Equation 10:

\[ y_i = \sum_j \varepsilon_{i,j} \cdot GW P_j \cdot \psi \quad (10) \]

Where \( \psi \) is the fraction of non-renewable biomass. This modification is done in the case of \( CO_2 \) only and the emissions of other pollutants are assumed to remain the same [37].

The reduced emissions are monetized and discounted before being inserted in the net-benefit equation using the social cost of carbon (Equation 11). The social cost of carbon (\( c^{CO_2}, \) USD/tonne) is used to estimate the net-present value of future climate change derived damages [93].
\[ \text{Carb} = c^{CO_2} \times \text{Reduced emissions} \times \frac{1}{(1 + \delta)^{t-1}} \quad (11) \]

**Changes in cooking times**

Different stoves are assumed to have different efficiencies and preparation requirements, which contributes to changes in cooking times [92]. Some fuels also require time for collection - as an example firewood is in rural areas of SSA often collected by the end-users themselves. The changes in time following a stove-switch are monetized (opportunity cost) using the minimum wage in the study area and a geospatial relative wealth distribution [94]. The relative wealth distribution is reclassified to range between 0.2 and 0.5 (the poorest areas get the lowest value while the richest areas get the highest value). These values are incorporated as a shadow value of time, estimating the value of lost time, and are consistent with other literature in the field assessing the value of time [56], [95].

For fuels that require collection (biomass and biogas options), OnStove determines the least-cost path with regards to time. In the case of biomass, the collection time is multiplied by two to account for travel to the closest biomass supply and back. Some additional time is also added at the collection site. For biogas, the end-user is assumed to collect manure. The availability of manure is determined using a geospatial dataset of headcounts of different livestock [96]. The users of biogas stoves are assumed to collect manure within the cell in which they live. If manure is not available or only available to sustain cooking for a part of the population, biogas is not (or only partly) available.
Investment costs

High upfront cost is a barrier to wider uptake of clean stoves. OnStove accounts for these costs in the net-benefit equation. The investment cost in OnStove has a salvage cost assuming straight-line depreciation netted-out to account for investments being done across equipment with varying technical lifetimes (Equation 12).

\[
Capital = inv - salvage \quad (12)
\]

Where

\[
Salvage = inv \times \left(1 - \frac{used \ life}{technology \ life}\right) \times \frac{1}{(1 + \delta)^{used \ life}} \quad (13)
\]

Some of the stove options in OnStove assume additional investments beyond the stoves themselves. Biogas stoves requires investments in digesters, first-time adopters of LPG have to invest in an LPG cylinder. For the case of electricity, the tool determines the cost of adding generation capacity necessary for every additional household cooking with electricity.

Fuel costs

Fuel costs are entered directly by the user. For the case of LPG the fuel cost is diversified spatially taking into account either the travel time to the closest settlement of at least 50,000 people or (if available) the closest LPG supply point using motorized transport (similar to the approach used by ref. [34]). If a fuel is assumed to be collected (e.g., as may be the case for biogas or biomass), the fuel cost is zero.
**O&M costs**

The O&M costs include yearly general operation and maintenance costs of each stove. These costs are entered directly into the techno-economic specification file.

**Net-benefits**

Once all the costs and benefits are determined for each stove in the analysis, the net-benefit is calculated. The net-benefit is defined as total benefits (reduced morbidity, reduced mortality, reduced emissions and time saved) minus the total costs (capital, fuel and O&M costs) as outlined in Equation 14.

\[
\text{Net-benefit} = (Morb + Mort + Time + Carb) - (Capital + O&M + Fuel) \quad (14)
\]

Whichever stove has the highest net-benefit is selected in each cell as long as fuel supply is available (relevant for electric and biogas stoves as outlined above). OnStove allows for restrictions that force positive benefits for as long as possible. This would restrict a stove option from being selected solely due to its low costs if there is another stove that provides positive benefits.

### 2.3. Integrated planning for electricity and clean cooking

Access to electricity and clean cooking are related. Electricity is a clean cooking fuel and it has been argued in the literature that an investments towards increased electricity access is by extension also an investment towards increased clean cooking access. Furthermore, as electric cooking shares increase, so does electricity demand, which in turn may impact the least-cost technology mix. This highlights the
need for integrated planning efforts accounting for both increased clean cooking and electricity access. Paper IV presents an integrated energy access study for Kenya using OnStove and OnSSET (see an overview in Fig. 3). This approach overcomes limitations in both tools. OnStove does not account for improvements in electricity access rates which creates a risk of missing out on the full potential of electric cooking. Furthermore, OnStove does not account for the cost of transmission and distribution, while OnSSET does. The integrated approach also enables OnSSET to account for how demand from electric cooking impacts the least-cost technology mix. The steps of the integrated approach are as follows:

1. **Running OnSSET** – The method described by Korkovelos et al. is used to estimate demand across Kenya [31]. The electricity consumption for cooking is added to all clusters falling below MTF tier 4. In the initial step it is consequently assumed that everyone will eventually cook with electricity. The OnSSET analysis is run year-by-year and returns the electrification status across modelling years, least-cost technology mix and LCoE in each cluster.

2. **Running OnStove** – The least-cost technology mix and the electrification status from OnSSET are used to identify settlements that could potentially cook with electricity (settlements using either mini-grids or grid) in every year. The LCoE from OnSSET is used in OnStove’s net-benefit equation as the fuel cost for electric stoves. OnStove as presented in Paper III answers the question “What should be adopted today to maximize net-benefits across a given study
area?”. In Paper IV, OnStove is expanded with a timeline, running the analysis year-by-year. The prioritization of who gets clean cooking access first can be done based on either population density, highest current costs or highest current drawbacks. When a stove is selected, it is assumed that the stove is kept until its technical life reaches the end, after which reinvestments are allowed into a new (or the same) type of stove. OnStove returns net-benefits for every square kilometre for each stove, as well as the stove with the highest net-benefit.

3. **Demand update in OnSSET** – Once the stove with the highest net-benefit in each settlement has been identified in OnStove, the demand in OnSSET is altered to account for electric cooking demand only in the settlements that would have the highest net-benefit with an electric stove. OnSSET is subsequently rerun.

4. **Reach equilibrium** – Steps two and three are repeated until the demand in OnSSET no longer needs updating after which the analysis is concluded and results presented.
2.4. Uncertainty and Global Sensitivity Analysis in geospatial energy models

Uncertainty in models can present itself at different stages of analysis and be connected to different parts of the modelling effort. Walker et al. identify three dimensions of uncertainty, out of which one is labelled location [97]. The location-dimension discusses these different stages and how they relate to uncertainty. The locations used by Walker et al. are: context, model uncertainty, inputs, parameter uncertainty and model outcome uncertainty [97]. Understanding the location of uncertainty is important as it may dictate what efforts should be taken to mitigate said uncertainty.
The location context relates to model boundaries used in the analysis. In the field of energy planning this could relate to different divisions of study areas – a national government focusing on the entire country or local decision makers focusing on their constituencies. Model uncertainty relates to uncertainty connected to either the computational implementation of the model, or to the relationships between different parameters in the model. Location input refers to data crossing the system boundaries driving changes seen in the model and parameters used to describe the reference case. The parameter-location refers to constants in the model and includes exact, fixed, chosen or calibrated constants. The last location, model outcome uncertainty, is connected to all previously mentioned locations and their propagation through the model [97].

Results from models relying on large quantities of input data, such as OnStove and OnSSET, are inherently subject to uncertainty. These types of uncertainties can be assessed using different methods, such as scenarios or sensitivity analysis depending on the level of uncertainty [97]. Scenarios provide descriptions of plausible futures and enables analysts to explore their models under different assumptions [97]. A sensitivity analysis on the other hand enables an analyst to explore how uncertainty in the output is related to uncertainty in different inputs [98].

In sensitivity analysis a distinction can be made between local and global methods [98]. In a local sensitivity analysis, the sensitivity of a model as it pertains to an input is assessed by moving said input a defined range from its starting point, while keeping all other inputs constant. The change in output over the change in input is then
defined as the sensitivity of the output with regards to that input. However, problems arise with local methods when the output has a non-linear response to said input or when said input interacts with other inputs in the model [99]. To overcome these challenges a GSA can be used instead. In a GSA, all inputs are moved simultaneously through their entire range of possible values while ensuring that each portion of the range is equally sampled [99].

To the knowledge of the author of this thesis, the GSA conducted in Paper II appended to this thesis is the first of its kind in the field of geospatial electrification modelling. In the field, sensitivity analyses are common; however they tend to be local [30], [31], [34]. In Paper II a GSA is used to assess the impact of different input parameters and population aggregations on investment costs, technology mix and LCoE in the OnSSET results. The method used is the SALib-implementation of the Delta Moment-Independent Measure (DMIM) as described by Borgonovo and Plischke et al. [100], [101], [102]. The DMIM method as described in refs. [101] and [102] outputs $S_1$ and $\delta$-values for each input assessed. The $S_1$-value of an input explains the decrease in variance seen in the output if uncertainty in said input was to be completely eliminated. The $\delta$-value explains an input’s influence on the entire distribution of the output [101]. Beyond different levels of population aggregation, eight parameters that previous research has highlighted as important are assessed (see Table 6) [31], [32]. 80 variations of each parameter in Table 6 are assessed with each population layer to produce a total of 2,080 scenarios per country (see 2.1.1 Pre-processing steps for a description of the population layers). This approach allows for increased understanding of the relative importance of population aggregation,
as well as insights into how the importance of population aggregation may change as other parameters change.

**Table 6.** Parameters which were included in the GSA conducted in Paper II.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Demand (kWh/person/year)</td>
<td></td>
</tr>
<tr>
<td>Grid generation cost (USD/kWh)</td>
<td></td>
</tr>
<tr>
<td>PV cost (USD/kW)</td>
<td></td>
</tr>
<tr>
<td>Grid capacity investment cost (USD/kW)</td>
<td></td>
</tr>
<tr>
<td>Discount rate (%)</td>
<td></td>
</tr>
<tr>
<td>LV line cost (USD/km)</td>
<td></td>
</tr>
<tr>
<td>MV line cost (USD/km)</td>
<td></td>
</tr>
<tr>
<td>Transmission and distribution losses (%)</td>
<td></td>
</tr>
<tr>
<td>eps</td>
<td></td>
</tr>
<tr>
<td>minPts</td>
<td></td>
</tr>
<tr>
<td>Method of aggregation (resampling, clustering from Paper I or DBSCAN)</td>
<td></td>
</tr>
<tr>
<td>Administrative division used</td>
<td></td>
</tr>
</tbody>
</table>

OnStove relies on a large number of geospatial, socio- and techno-economic input data. Uncertainty in these input data can potentially propagate through the tool. To assess the effect of uncertainty in these parameters, a GSA was conducted as part of Paper III. The Method of Morris (MoM) was used for the GSA [103], [104]. MoM is computationally effective, allows for a large number of parameters to be assessed and can be used for factor fixing (the process of identifying unimportant parameters). Results of a screening-analysis such as the one done in Paper III can help inform more detailed sensitivity analyses in the future. In Paper III, 33 parameters (listed in Table 7) are assessed through 680 scenarios. The parameters cover different types of costs and each of the benefit-categories included in OnStove.
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Minimum value</th>
<th>Maximum value</th>
</tr>
</thead>
<tbody>
<tr>
<td>VSL*</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>COI – Stroke</td>
<td>3,970 USD [105]</td>
<td>40,800 USD [105]</td>
</tr>
<tr>
<td>COI – ALRI</td>
<td>6 USD [92]</td>
<td>60 USD [92]</td>
</tr>
<tr>
<td>COI – COPD</td>
<td>30 USD [92]</td>
<td>1,057 USD [92]</td>
</tr>
<tr>
<td>COI – IHD</td>
<td>18.5 USD [92]</td>
<td>72.5 USD [92]</td>
</tr>
<tr>
<td>COI – LC</td>
<td>110 USD [92]</td>
<td>4,750 USD [92]</td>
</tr>
<tr>
<td>Social discount rate</td>
<td>2% [106]</td>
<td>5% [106]</td>
</tr>
<tr>
<td>Minimum wage**</td>
<td>2 USD/month</td>
<td>269 USD/month</td>
</tr>
<tr>
<td>Social cost of carbon</td>
<td>0 USD/MT [106]</td>
<td>220 USD/MT [106]</td>
</tr>
<tr>
<td>fraction of non-renewable biomass **</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Diesel cost**</td>
<td>0.09 USD/l</td>
<td>1.6 USD/l</td>
</tr>
<tr>
<td>LPG cost</td>
<td>0.3 USD/kg [92]</td>
<td>1.2 USD/kg [92]</td>
</tr>
<tr>
<td>Pellet cost</td>
<td>0.13 USD/kg [107]</td>
<td>0.25 USD/kg [54]</td>
</tr>
<tr>
<td>Grid generation cost**</td>
<td>0.013 USD/kWh</td>
<td>0.157 USD/kWh</td>
</tr>
<tr>
<td>Charcoal cost</td>
<td>0.06 USD/kg [92]</td>
<td>0.45 USD/kg [92]</td>
</tr>
<tr>
<td>Traditional biomass investment cost</td>
<td>0 USD [54]</td>
<td>0.5 USD [107]</td>
</tr>
<tr>
<td>Biomass ICS (natural draft) investment cost</td>
<td>25 USD [107]</td>
<td>43 USD [54]</td>
</tr>
<tr>
<td>Traditional charcoal investment cost</td>
<td>0.5 USD [107]</td>
<td>4 USD [54]</td>
</tr>
<tr>
<td>Charcoal ICS investment cost***</td>
<td>25 USD [54]</td>
<td>67 USD [54]</td>
</tr>
<tr>
<td>Electric stove investment cost</td>
<td>36.3 USD [54]</td>
<td>70 USD [107]</td>
</tr>
<tr>
<td>LPG stove investment cost</td>
<td>27.5 USD [54]</td>
<td>55 USD [107]</td>
</tr>
<tr>
<td>Biogas stove investment cost****</td>
<td>406 USD [107]</td>
<td>550 USD [54]</td>
</tr>
<tr>
<td>Pellet stove investment cost</td>
<td>34 USD [54]</td>
<td>75 USD [54]</td>
</tr>
<tr>
<td>Stove Type</td>
<td>PM$_{2.5}$</td>
<td>24-hr µg/m$^3$</td>
</tr>
<tr>
<td>------------</td>
<td>------------</td>
<td>----------------</td>
</tr>
<tr>
<td>Biomass ICS (forced draft) investment cost</td>
<td></td>
<td>37 USD [54]</td>
</tr>
<tr>
<td>Traditional biomass PM$_{2.5}$</td>
<td>500</td>
<td>24-hr µg/m$^3$</td>
</tr>
<tr>
<td>Biomass ICS (natural draft) PM$_{2.5}$</td>
<td>100</td>
<td>24-hr µg/m$^3$</td>
</tr>
<tr>
<td>Traditional charcoal PM$_{2.5}$</td>
<td>256</td>
<td>24-hr µg/m$^3$</td>
</tr>
<tr>
<td>Charcoal ICS PM$_{2.5}$</td>
<td>35</td>
<td>24-hr µg/m$^3$</td>
</tr>
<tr>
<td>Electric stove PM$_{2.5}$</td>
<td>5</td>
<td>24-hr µg/m$^3$</td>
</tr>
<tr>
<td>LPG stove PM$_{2.5}$</td>
<td>10</td>
<td>24-hr µg/m$^3$</td>
</tr>
<tr>
<td>Biogas stove PM$_{2.5}$</td>
<td>5</td>
<td>24-hr µg/m$^3$</td>
</tr>
<tr>
<td>Pellet stove PM$_{2.5}$</td>
<td>73</td>
<td>24-hr µg/m$^3$</td>
</tr>
<tr>
<td>Biomass ICS (forced draft) PM$_{2.5}$</td>
<td>110</td>
<td>24-hr µg/m$^3$</td>
</tr>
</tbody>
</table>

* Elasticity between Gross National Income (GNI) per capita and VSL. The base GNI value is powered by a value within the range given in this table (see the Supplementary File of Paper III for the relation between GNI and VSL).

** The range found amongst the countries of the analysis.

*** Range given in BAR-HAP [54]

**** Biogas stove price is given as 550 in both sources, but there is a projection of expected price in 2030. This is used as the lower value of the range.

The output parameters for which the sensitivity of the model is assessed are the shares of the different stoves in the analysis, total net-benefit in the region, total health costs avoided, total time saved, total
emissions avoided, total investment costs and total fuel costs. MoM returns a μ* - and σ-value for each one of the 33 inputs assessed. μ* is the absolute value of the output’s average variation given the variation in each input and describes the importance of each input in relation to the assessed output. σ is the standard deviation of the variation and gives insight into how much each parameter interacts with other parameters (or if its effects are non-linear) [103].

2.5. Geographic coverage

The four publications appended to this thesis all focus on countries in SSA. The region is chosen due to its large access gap with regards to both clean cooking and electricity [3]. In the year 2000, SSA was home to 19% of the population cooking with traditional fuels. In 2021, this share had increased to 41% and it is projected to grow to almost 60% by 2030 [3]. In the region around 82% of the population cook with traditional fuels as their primary option and there is a stark contrast in clean cooking access rates between urban (36%) and rural areas (5%) [3]. For electricity access, SSA is lagging behind as well, and more than 80% of the global population without access lives in the region [3]. As of 2021, only half of SSA was estimated to have electricity access. Like clean cooking, there is a considerable difference between urban and rural access rates (81 and 29% respectively). The latest tracking SDG 7 report highlights SSA as the region where efforts should be concentrated if we are to reach SDG 7 [3]. Papers I and Paper III are applied to 44 countries across SSA.

In Paper II, Benin, Malawi and Namibia were selected as case studies to assess the effect of spatial aggregation on the results of least-cost
electrification modelling. These countries were selected as they have vastly different national population densities and starting electrification rates. Malawi has one of the highest national population densities in SSA, Namibia one of the lowest, and Benin is towards the middle. Furthermore, at the time of writing the paper, Malawi had a comparatively low electricity access rate (18%), while Namibia had a comparatively high one (54%) and Benin was situated in between (42%).

In Paper IV, Kenya is used to assess the effects of integrated planning accounting for both increased electricity and clean cooking access rates. Kenya has shown an impressive increase in electricity access since the year 2000 (from 15 to 77%). Much of this increase is attributed to the large number of off-grid systems being deployed in the country [3]. The clean cooking access rate is however lagging behind and currently stands at 24%. The country aims at reaching universal clean cooking access by 2028 through efforts such as (but not limited to) information campaigns, targeted subsidies and financing mechanisms. Additionally Kenya is one of the first countries in Africa, developing a designated National eCooking Strategy (KNeCS) promoting electric cooking in the country [110]. The difference between electricity and clean cooking access rates, together with the development of KNeCS, calls for leveraging the electricity access rate to improve the clean cooking rate in the country.
2.5.1. Geographies covered outside of main publications

In addition to the four academic publication directly appended to this thesis, the work draws on insights from other geographies covered by papers and reports presented in section 1.3.2 Additional publication and contributions. This work includes Burkina Faso, the Democratic Republic of Congo, Madagascar, Nepal, Somalia and Tanzania. Insights and developments with regards to the RQs have also been drawn from the development of the Global Electrification Platform (GEP). The GEP includes the aforementioned countries (with the exception of Nepal) as well as Angola, Bangladesh, Botswana, Burundi, Cambodia, Cameroon, Central African Republic, Chad, Comoros, Congo, Cote d’Ivoire, Djibouti, Equatorial Guinea, Eritrea, Eswatini, Ethiopia, Gabon, Gambia, Ghana, Guinea, Guinea-Bissau, Haiti, Honduras, Lesotho, Liberia, Mali, Mauritania, Federal States of Micronesia, Mozambique, Myanmar, Nicaragua, Niger, Nigeria, Pakistan, Papua New Guinea, Rwanda, Sao Tome and Principe, Senegal, Sierra Leone, Solomon Islands, South Africa, South Sudan, Sudan, Timor-Leste, Togo, Uganda, Vanuatu, Zambia and Zimbabwe.
3. Results

The following sections discuss the results of the appended publications and their relation to each RQ.

3.1. Response to Research Question 1

**RQ1: How do different levels of spatial aggregation affect the results of geospatial electrification models?**

The Modifiable Areal Unit Problem (MAUP) is a well-known concept in GIS, explaining how different levels of aggregation affects results of models – even when everything else is kept constant. The impact of spatial aggregation on geospatial models and analysis has been shown in various fields, spanning from urban planning to environmental sciences [111], [112]. RQ 1 aims at assessing this concept in the field of geospatial electrification.

3.1.1. Impact on data extraction

In OnSSET, geospatial datasets describing the suitability of different technology-configurations are extracted to the settlement file. This forms the input file needed for the subsequent steps. Here, the impact of using different population layers on the data extraction is studied.

For layers assessing the suitability of renewables (global horizontal irradiation and wind velocity), the largest discrepancy is seen in Benin where the population weighted average wind speed changes at most by 1.6% between population layers. Travel time to urban centers of at least 50,000 people is used in OnSSET to estimate diesel costs, which is relevant for the LCoE of diesel generators and hybrid
technologies. The population-weighted average travel time across different population layers ranges 12, 16 and 50% depending on country assessed. 50% difference is seen in Malawi, where – across the 26 different input files – the smallest weighted average is 0.65 hours and the largest is 0.98 hours.

To determine the suitability of extending the central power grid, OnSSET accounts for distance to closest substation, distance to closest road, the land cover, terrain slope and elevation. The population-weighted average distance to closest substation ranges 27, 47 and 39% for Benin, Malawi and Namibia respectively across the assessed input files. For road distance the same is 92, 169 and 87%. Note that the population-weighted average of distance to closest road is always below 2.5 km and like travel time, large percentage differences do not translate to large absolute differences. Elevation changes at most by 1.2% in Benin and less than 1% across the other two countries. Land cover also changes slightly between different levels of aggregation, as does terrain slope.

These results indicate that spatial aggregation impacts the data extraction of OnSSET, but not significantly. These impacts span the entire range of datasets, subsequently affecting the calibration of electrified population, the extension of the grid and the suitability of off-grid systems. Any potential distortion caused by aggregation can be assumed to propagate through the model and impact the final results of the analysis.
3.1.2. Impact on calibration

As the size of settlements change following different aggregation methods, so does the settlements’ populations, maximum night-time light intensities and distances to medium-voltage lines. OnSSET aims to match the national electrification rate entered by the user, but which settlements that are assumed electrified to achieve this may differ. OnSSET assumes all currently electrified settlements are connected to the grid. With larger eps and cell-sizes, or smaller minPts values, the currently electrified clusters generally increase in size with the consequence of increasing population. Therefore, as the currently electrified settlements cover more people more grid-connections will be forced across the study area in the scenario results. Furthermore, the existing grid connections are used as starting points for extension. Different settlements being selected as electrified in the calibration translates to different starting points (and consequently costs) for grid extension (see Fig. 4).

**Fig. 4.** Examples of electrified settlements in the start year in northern Namibia, with eps 200 metres (left) and eps 500 metres (right).
3.1.3. Impact on scenario results

Least cost technology mix

Fig. 5 shows the number of people connected to the grid across scenarios in Paper II. The scenarios are coloured based on their eps. An eps of 0 represents raster-based scenarios, an eps of 150 represents the clustering approach from Paper I and the other values relate to the eps used in DBSCAN. The results built on the clusters from Paper I are repeated three times, as they use three different version of administrative divisions. DBSCAN-results are presented three times per eps, as each eps has three different values for minPts. The raster scenarios are divided into two groups based on their resolution (left-most group has a spatial resolution of 100 m and the right-most group a resolution of 1 km). Each dot represents a scenario.

As settlements in OnSSET are treated separately when determining the LCoE, larger demands per settlement can be assumed to drive the overall technology mix towards higher grid shares. This is the general behaviour seen in the results as well. For all countries, the results of rasters-scenarios included in the analysis are distinctively different, with the lower resolution scenarios having larger number of people connected to the grid. For both Benin and Malawi, this dynamic is also seen in the vector-based scenarios, larger eps increases the modelled competitiveness of the grid. While the general results of Namibia shows the same behaviour, larger vector settlements do not necessarily lead to more grid connections. Depending on which settlements are considered electrified in the start year in Namibia in the DBSCAN-scenarios, the other parameters may not be favourable.
enough to justify grid extension further. This is a result of large settlements (in terms of area), low population densities and low per capita electricity consumptions. This explains the gap in the DBSCAN-results of Namibia with eps larger than 200 metres seen in Fig. 5. Grid connections change on average 6.5, 14.8 and 2.9 percent for Benin, Malawi and Namibia respectively for different values of minPts in the DBSCAN-scenarios. In Namibia the minimum number of grid connections in the custom clustering is higher than in the DBSCAN-scenarios, unlike in the cases of Benin and Malawi. This is due to the custom clustering approach calibrating lower shares of more clusters as electrified in the start year than their DBSCAN counterparts in Namibia. This leads to more grid connections being forced in the scenarios as no currently electrified settlement is allowed to switch to either mini-grids or stand-alone.
Fig. 5. Grid-connected population for the three countries across scenarios. An eps of 0 are raster scenarios, where the first group of observations have a spatial resolution of 100 metres and the second group 1 km. An eps of 150 metres is the clustering approach from Paper I and the other eps-values are different DBSCAN-scenarios.

In contrast, the population connected to mini-grids generally decrease with larger settlement size (Fig. 6). In Benin and Malawi there are scenarios completely without mini-grids. However, in Namibia mini-grids are always present in the results. In the DBSCAN-scenarios, mini-grids always decreases with increasing size of settlements. Furthermore, larger eps in DBSCAN seem to reduce the
sensitivity of the results to other parameters as the spread of scenarios decrease. The higher resolution rasters break the pattern as they have higher shares of mini-grid than their lower resolution counterparts. This is due to the modelled competitiveness of the grid decreasing considerably for these scenarios, as the population in each unit of analysis (and consequently demand) decreases.

Fig. 6. National plots showing how population connected to mini-grids changes across scenarios.
Fig. 7 shows the number of people having stand-alone PV as their least-cost technology across scenarios. In general their perceived competitiveness decrease with larger settlement size. This is to be expected as stand-alone technologies do not benefit from economies of scale. Therefore, as the size of settlements (and consequently the electricity demand in each unit of analysis) increase the share of stand-alone PV decrease. Exceptions to this are the clusters generated using the method described in Paper I for Namibia. The different methods of generating clusters (Paper I or DBCSAN) results in clusters with slightly different spatial alignments. This difference translates to differences in electricity demand (which is read from another spatial layer). In the case of Namibia this difference is large enough for the smaller settlements produced with the method from Paper I to still have lower shares of stand-alone PV.
Fig. 7. National plots showing how population connected to stand-alone PV changes across scenarios.

**Levelized Cost of Electricity**

LCoE is the breakeven cost of each technology-configuration and is used to define least-cost in OnSSET. Across the scenarios assessed the population-weighted average LCoE ranges between 0.21 – 0.68, 0.18 – 0.55 and 0.11 – 0.3 USD/kWh for Benin, Malawi and Namibia respectively. Table 8 shows the factor ranking (ranking of factors based on their influence on the output) for the five most impactful...
parameters across each country with regards to LCoE. The cost of PV-panels is the most important parameter across all countries. The choice of eps also ranks as important in all three countries. For Benin, all four factors following the cost of PV-panels are related to the population aggregation. Method of aggregation relates to the method used to generate the population layer (raster, DBSCAN or the clustering approach from Paper I).

**Table 8.** Factor ranking between the assessed parameters based on $\delta$-values from DMIM.

<table>
<thead>
<tr>
<th>Rank</th>
<th>Benin</th>
<th>Malawi</th>
<th>Namibia</th>
</tr>
</thead>
<tbody>
<tr>
<td>1$^{st}$</td>
<td>PV-panel cost</td>
<td>PV-panel cost</td>
<td>PV-panel cost</td>
</tr>
<tr>
<td>2$^{nd}$</td>
<td>Method of aggregation</td>
<td>Demand</td>
<td>Discount rate</td>
</tr>
<tr>
<td>3$^{rd}$</td>
<td>eps</td>
<td>eps</td>
<td>eps</td>
</tr>
<tr>
<td>4$^{th}$</td>
<td>minPts</td>
<td>Discount rate</td>
<td>Method of aggregation</td>
</tr>
<tr>
<td>5$^{th}$</td>
<td>Administrative division</td>
<td>LV line cost</td>
<td>Grid losses</td>
</tr>
</tbody>
</table>

Fig. 8 displays how LCoE changes across scenarios. In the case of Benin, the 100 m resolution rasters and the clusters developed as part of Paper I lead to the highest LCoE, while the rasters of 1 km resolution and the DBSCAN-scenarios lead to the highest LCoEs in Malawi and Namibia respectively. While Table 8 indicates that eps, minPts and administrative division are amongst the most important parameters for LCoE in Benin, Fig. 8 indicates very small differences...
in LCoE for DBSCAN-scenarios in Benin, hence showing that the results are not very sensitivity to eps and minPts. Furthermore, the results created with the custom clustering approach introduced in Paper I are also robust to the choice of admin boundaries. This indicates that the $\delta$-values of eps, minPts and administrative division in Table 8 are most likely a result of strong correlations to the method of aggregation as it forces these parameters into specific values.

Fig. 8. National plots showing how average LCoE changes across scenarios.
Total investments

The investments required to implement the scenarios is an important policy insight from modelling efforts such as these. The investments range between 1.6 – 4.5, 3.8 – 10.5 and 0.9 – 2.5 billion USD for Benin, Malawi and Namibia respectively. For all countries raster-based scenarios are found to be the most expensive ones. Across the countries, electricity demand, method of aggregation and eps are of significance for the total investment costs. Fig. 9 displays scatterplots of total investments across scenarios. In general, the DBSCAN-scenarios of Benin and Malawi show an increase in total investments alongside a larger share of grid connections, while the Namibia costs are more robust to larger eps-values.
3.1.4. The effect of cell-size in clustering

In Paper IV, OnStove and OnSSET are soft-linked for the development of integrated energy access scenarios. This requires results from each tool to be read by the other tool. Therefore, the results have to be spatially aligned with regards to coverage and resolution. OnStove is raster-based and, at the time of writing, hardcoded to a spatial resolution of 1 kilometre. On the other hand, OnSSET clusters are
often produced from rasters with spatial resolutions of 100 metre (as
done in e.g., Paper II and the Global Electrification Platform), as
higher resolution rasters would increase the computational costs
considerably. To allow for transferring results from one tool to the
other, the resolutions have to match (otherwise the change in cell size
would create a mismatch between results). Therefore, to match the
spatial resolution of OnStove, the OnSSET-clusters in Paper IV are
generated using rasters with a spatial resolution of 1 kilometre
instead of the 100 metre resolution rasters typically used. To evaluate
the impact of this, one set of OnSSET results are produced using
clusters from 100 metre resolution rasters and another set of results
are generated using clusters from 1 kilometre rasters.

Paper IV presents a case study of Kenya. As of 2021, the national
electrification rate was estimated at 77%, with a smaller share of
mini-grid connections [3]. As indicated previously, this impacts the
resulting technology shares in OnSSET, as OnSSET by default assumes
grid-connections in all currently electrified settlements and prohibits
already grid-connected settlements from switching to mini-grids or
stand-alone. In Paper IV the choice of technology-configurations in
the start year is overridden to include mini-grids alongside the grid
using a manual calibration.

For the manual calibration of Kenya’s currently electrified
settlements four geospatial datasets are used: population
distribution, locations of distribution transformers, existing medium-
voltage lines and locations of mini-grids. The medium-voltage lines
data includes the distribution lines connected to mini-grids, as well as
the distribution lines of the main grid. Therefore, the dataset is
divided in two parts, one for the mini-grids and one for the grid. Settlements with at least a distribution transformer overlapping medium-voltage lines from the main grid are assumed to be grid connected. Settlements overlapping mini-grids and distribution transformers are assumed to be connected to a mini-grid. In both cases (grid and mini-grid) it is ensured that the electrification rates match the rates reported for Kenya. This approach to calibration is used both for the case where 100 metre and 1 kilometre rasters are used to produce the clusters.

Fig. 10 compares new connections of each technology-category in Kenya by 2030 using clusters produced with the two resolutions. The comparison indicates that the least-cost technology mix is impacted by the resolution of rasters when creating the clusters. The version using lower resolution rasters (1 kilometre) gets a higher grid share, in line with the results of Paper II (larger settlements leading to larger shares of grid). Perhaps, contrary to what would be expected, the share of stand-alone increases when the clusters are created using a 1 kilometre raster. The reason for this is that the population density decreases considerably in certain clusters as their area increase, making stand-alone systems more feasible than mini-grids. This shows that as clusters increase in size, the population density eventually decreases past the point of which larger settlements start benefiting stand-alone options.
3.2. Response to Research Question 2

*RQ2: How can GIS be effectively utilized to compare different cooking alternatives for achieving universal clean cooking access?*

Several of the barriers and enablers to the adoption and sustained use of different cooking fuels identified in the literature are geospatial in nature. Yet, a geospatial CBA tool comparing the relative costs and benefits of cooking fuels is absent. In response to this, OnStove is developed, presented and applied to 44 countries in SSA as part of Paper III. This is the first analysis of its kind, presenting a geospatial tool accounting for the benefits and costs of transitioning to different stoves. OnStove is open-source and scalable. Together with Paper III, the tool and its manual was made publicly available to enable reproducibility and applications on other geographies and with updated input data.

*Fig. 10.* Technology-mix of new connections in Kenya using either clusters based on 100 metre (left) or 1 kilometre (right) resolution rasters.
3.2.1. Scenarios

The study in Paper III includes two main scenarios, one using a social valuation of costs and benefits, and one private. The main difference between these scenarios is the scope of the analysis. While the social scenario looks to maximize net-benefits, taking into account all incremental costs and benefits impacting society as a whole, the private scenario looks at costs and benefits from the view of the decision maker (in this case the households who switch stoves). The social scenario includes all the benefits (reduced morbidity, reduced mortality, time saved and GHG emissions avoided) and costs (capital, O&M and fuel) included in the net-benefit equation. This means that the social scenario includes externalities that are not directly linked to the households themselves (GHG emissions avoided and societal costs of morbidity and mortality). The private scenario on the other hand, only accounts for the benefits and costs directly experienced by the households (excluding externalities). Furthermore, the private scenario uses a higher discount rate than the social scenario, which is consistent with private individuals’ preferences [92].

In both scenarios nine stoves are compared. Three clean ones (LPG, electric and biogas), four ICS (charcoal ICS, biomass natural and forced draft ICS and pellets forced draft ICS) and two traditional (charcoal and biomass). ICS are often viewed as ‘transitional’ options as they are dirtier than clean stoves, but cheaper and more similar in their operation to traditional options, thereby, removing some of the barriers for their adoption [11], [66], [74], [113]. These stoves tend to use traditional fuels in more efficient ways than their traditional counterparts, reducing both the time needed for fuel collection and
cooking [113]. The success of ICS in reducing adverse health effects stemming from HAP has been questioned by some [1], [4], [12], [63], [74]. However, due to them being an important alternative in cases where infrastructure and clean fuels are not easily accessible, they are included in the analysis. Inclusion of traditional stoves is important as it enables for assessments of whether these are worse or better than clean stoves from a net-benefit perspective. Without giving the possibility of selecting traditional stoves it would be difficult to argue for them having lower net-benefits than improved or clean stoves. Coal and kerosene stoves are not included in the analysis as they are explicitly discouraged by the WHO [114]. Kerosene however is currently prevalent in SSA and is therefore still used for calibration of the baseline. See Annex B: Stoves assessed for descriptions of the stoves used in the thesis.

3.2.2. A geospatial cost-benefit analysis for SSA

Both main scenarios from Paper III show a stark contrast between current cooking practices in SSA and what is socially or privately optimal (here “optimal” refers to the stove mix with the highest net-benefit). In the social scenario – where the full suite of benefits are taken into account – most of SSA would benefit from switching to clean cooking. No traditional stoves are selected and only around 160,000 people would cook with forced draft biomass ICS. The most prevalent solution is LPG at 67% of the total population, while around 31% of the population would benefit most from electric cooking. The share of electric cooking is significant, as electric cooking was only an option in areas where electricity access is currently available. This means that the current electricity access rate used in the analysis
(48%) is the maximum potential for electric cooking. In the private scenario, traditional stoves are still never chosen, but ICS grows to a total market share of 20% (17% charcoal, 2% forced draft biomass and 1% natural draft). LPG grows to a market share of 75% and the share of electric cooking shrinks to around 4% of the total population. See Fig. 11 for the geospatial distributions of stoves across SSA in the social and private scenarios.
Fig. 11. Geospatial distribution of optimal stove selection, summary statistics and population shares of each stove; a) social scenario and b) private scenario.
Fig. 11 also includes summary statistics for each scenario. The social scenario leads to higher benefits than the private one, but both of them bring considerable improvements compared to current practices. In the social scenario 463,000 deaths are avoided annually, while 338,000 deaths are avoided annually in the private scenario. The deaths avoided account for number of deaths caused by COPD, IHD, lung cancer, stroke and ALRI. This can be contrasted to the total number of estimated deaths in SSA caused by these diseases and attributed to HAP exposure, estimated at 655,000 in 2019 [115]. The health costs avoided in the region due to reduced morbidity and mortality is estimated at 66 and 45 billion USD yearly for the social and private scenario respectively. This can be contrasted to the health costs of inaction for SSA, which amounts to 96 billion USD yearly [50]. Yearly avoided emissions amount to 586 and 482 million tonnes of CO₂-eq across the two scenarios. This is considerably lower than what the World Bank indicates as the cost of environmental and climate degradation due to current cooking practices in SSA. The World Banks’ estimate includes GHG emissions, warming effects of black carbon emissions, forest degradation and losses in agricultural productivity. In both scenarios each household also saves almost one hour per day on average due to faster cooking and reduced collection times (compared to an estimated five hours spent per day [50]).

The OnStove analysis for SSA indicates that the benefits of adopting cleaner cook stoves far outweigh the costs (Fig. 12). These findings are in line with previous research on clean cooking access, which also find the benefits to be greater than the costs (e.g., [54], [92]). In the social scenario the total monetized benefits amount to 102 billion
USD per year, compared to total costs of 22 billion USD per year. The largest benefit category in the social scenario is health (reduced morbidity and mortality), followed by reduced GHG emissions. On the cost side, fuel costs is an important cost for LPG adoption, as is investment costs for electricity. For biogas and biomass forced draft ICS, the fuel costs are on the benefit side, indicating fuel savings. The private scenario’s benefits, while lower, also outweigh its costs (76 billion USD compared to 15 billion USD per year). The magnitude of the difference between benefits and costs across SSA indicates that the investment towards universal clean cooking access is worthwhile.

Fig. 12. Total costs and monetized benefits throughout SSA following a full stove switch; a) social scenario and b) private scenario.

While the benefits outweigh the costs considerably in both scenarios, it is important to note that certain costs (and benefits) of the
transition are not included. E.g., Jeuland et al. include learning and program costs in their CBA for clean cooking, as do Das et al. [54], [92]. The learning cost is the time it takes to learn how to use the new technology expressed in monetary values. Program cost is the cost of promoting a stove. Neither learning nor program costs are included in OnStove. Jeuland et al. discuss that the number of estimates for these costs are too low to differentiate them across interventions or contexts [92]. Including them in OnStove would therefore require more data and not necessarily affect the geographic variation, but instead only modify the overall net-benefits.

3.2.3. Affordability as a barrier

Affordability is one of the more salient barriers to adoption and sustained use of clean cooking. Affordability is not to be equated to low costs, but rather it is a ratio between total expenditures and expenditure in fuels and stoves [7]. A universal definition of what is considered affordable is not available, but there are some different widely used measures. In Paper III the costs of adopting clean cooking was compared to two of these measures: ESMAP’s MTF and India’s Council of Energy, Environment and Water (CEEW) framework. MTF defines any technology with the levelized cost of cooking amounting to less than 5% of a household’s income as affordable [7]. However, it does not specify what type of income is being referred to (gross, disposable or net) [7]. The CEEW-framework defines affordable as expenditures on fuels amounting to less than 6% of a household’s total monthly expenditures [7].
To assess the affordability ratios for the two main scenarios, first cost maps are created for each stove from both social and private perspectives. The cost maps are relative to the current stove situation and therefore can have negative values in cases where a certain stove is cheaper than what is currently used. The results show large differences between the different stoves and the two scenarios. As expected the cheapest technologies are traditional stoves and ICS options, while the cleaner options are more expensive in both scenarios. One exception to this is the forced draft pellet ICS, which in many regions is comparable to the cost of clean options. In the private scenario (Fig. 13) the cost ranges between -8 USD/year to more than 377 USD/year, while the range in the social scenario (Fig. 14) is -9 USD/year to more than 178 USD/year. The discrepancy between the scenarios is due to the private scenario having a higher discount rate.
Fig. 13. Total costs per household in the private scenario (ND = natural draft, FD = forced draft).
Fig. 14. Total costs per household in the social scenario (ND = natural draft, FD = forced draft).
Affordability estimates were created by using the cost maps together with estimates of national values for minimum wage. Fig. 15 and Fig. 16 show the affordability ratio (the ratio between cost of cooking using the stove with the highest net-benefit and the minimum wage in each country) spatially and by stove option for the private and social scenarios respectively. While the benefits of adopting clean cooking is indeed larger than the costs, assessing the affordability ratio reveal that the transition is unaffordable for a majority of the population in SSA.
Fig. 15. Affordability ratio for the optimal stoves (private scenario); a) household shares for each stove, b) geospatial distribution of the total annual cost per household as percentage of the minimum wage, c) Household share for each technology categorized by household average quantiles (ND = natural draft and FD = forced draft).
Fig. 16. Affordability ratio for the optimal stoves (social scenario); a) household shares for each stove, b) geospatial distribution of the total annual cost per household as percentage of the minimum wage, c) Household share for each technology categorized by household average quantiles (ND = natural draft and FD = forced draft).
3.2.4. Uncertainty and sensitivity in clean cooking access modelling

OnStove draws on a large number of inputs across three categories; geospatial data, techno- and socio-economic parameters. Therefore, as with any model, the results produced in OnStove are inherently uncertain. This is especially the case in a study like the one produced as part of Paper III, where an entire region with differing costs and benefits are included. To assess the sensitivity of the model to uncertainties, a Global Sensitivity Analysis using the Method of Morris is conducted for 33 parameters as part of Paper III. Fig. 17 shows how the assessed parameters affect the total net-benefits across SSA. The graph only shows parameters with an effect of at least 1% of the most impactful parameter. All four benefits included in the net-benefit equation are represented amongst the seven most important parameters. This indicates that parameters across the entire net-benefit equation are influential, highlighting that knowledge of non-monetary aspects of the clean cooking transition and their proper quantification could help in the transition to cleaner cook stoves. For the full results of the sensitivity analysis, refer to the supplementary material of Paper III.
Fig. 17. The importance of different parameters with regards to the total net-benefit, only parameters with effects higher than 1% of the maximum are shown; a) $\mu^*$ (bars) and confidence interval of the effects (lines), b) $\sigma$-values representing the effects due to interactions with other parameters or due to non-linearity.
3.3. Response to Research Question 3

**RQ3:** How are the results of geospatial energy models (both electricity and clean cooking) impacted as an integrated planning approach is incorporated?

Electricity and clean cooking access are interlinked. On the one hand, electricity is a clean cooking fuel, available only if the required electricity infrastructure is in place. On the other hand, electric cooking increases electricity demand, in turn impacting the least-cost electrification technology mix. Yet, increased electricity and clean cooking access are often planned for in silos. This risks leading to lost opportunity. Using a case study of Kenya, Paper IV explores how the results of OnSSET and OnStove change as an integrated approach is used and both indicators are planned for together.

3.3.1. Scenarios

In Paper IV, four scenarios are run to examine the effect of an integrated approach compared to planning in silos. In each scenario, OnStove and OnSSET are first run separately, and then soft-linked for an integrated approach as described in 2.3 Integrated planning for electricity and clean cooking. The first three scenarios differ based on the order in which clean cooking access is achieved, while the last one differs with regards to available stoves to select from. The first scenario assumes that clean cooking reaches areas with the highest population density first (called urban prio from hereon), while the other two scenarios assume that access first reaches areas with the highest current costs (cost prio) and areas with the largest current drawbacks (benefit prio) respectively. For these three scenarios the stoves included are traditional biomass, traditional charcoal, charcoal
ICS, biomass ICS, LPG, biogas, ethanol, electric pressure cookers (EPCs), electric hobs and induction hobs (see Annex B: Stoves assessed for descriptions of the stoves used in the thesis). In the scenario that differs based on available stove options, EPCs are removed and clean cooking access is assumed to be prioritized based on highest population density. The removal of EPCs is done to mimic a situation in which people forego EPCs due to e.g., concerns about their compatibility with different cuisines.

3.3.2. Impact on stove selection and benefits

The current shares of cooking fuels in Kenya are taken from a previous survey conducted by partners on the ground. This data indicates the national clean cooking rate to be 28%. This is close to what is stated in the Tracking SDG7 report of 2023 (24% in 2021 [3]). Kenya aims at universal clean cooking access by 2028 and it is assumed that the country reaches universal electricity access by 2026.

In the non-integrated scenarios, five stoves provide the highest net-benefit across Kenya: biogas, electric hobs, EPCs, LPG and, in the case where EPCs are not available, electric induction hobs. Electric stoves are highly competitive from a net-benefit perspective and virtually everyone with electricity access would benefit the most from adopting one of these stoves. Their high level of competitiveness is due to comparatively high LPG costs and their cleanliness at the point of use. Furthermore, the electricity generation mix of Kenya is comparatively clean with around three quarters of the installed capacity coming from renewables [116]. This benefits the electric
options environmentally. Out of the available electric options, induction hobs are never used when EPCs are available, due to them being outcompeted by the lower capital costs of electric hobs and the higher efficiencies of EPCs.

EPCs are the most used stoves for all scenarios when allowed, maximizing net-benefits for 44-57% of the population. The share of electric hobs range between 20 and 56% across scenarios with a large increase in the scenario without EPCs. Health benefits due to reductions of PM$_{2.5}$-concentrations is the most significant category of benefits. Deaths avoided for the four scenarios range from 44,600 to 47,700 during the modelling period (2021-2028). Time saved is similar between scenarios, and the average household saves around 1.5 hours per day from reduced cooking and fuel collection times. Reduced emissions range between 50 and 53 million tonnes of CO$_2$-eq. See Table 9 for summary statistics of the four non-integrated OnStove scenarios.

Table 9. Stove shares and benefits across non-integrated scenarios.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Stove shares</th>
<th>Deaths avoided</th>
<th>CO$_2$-eq avoided</th>
<th>Time saved</th>
</tr>
</thead>
<tbody>
<tr>
<td>Urban</td>
<td>Biogas: 0.2%</td>
<td>45,600</td>
<td></td>
<td>~1.5</td>
</tr>
<tr>
<td></td>
<td>LPG: 22.4%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>EPC: 44.1%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Electric hob: 33.3%</td>
<td></td>
<td></td>
<td>~1.5</td>
</tr>
<tr>
<td>Cost</td>
<td>Biogas: 6.8%</td>
<td>44,600</td>
<td>53 Million tonnes</td>
<td>~1.5</td>
</tr>
<tr>
<td></td>
<td>LPG: 15.8%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>EPC: 45.9%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Electric hob: 31.5%</td>
<td></td>
<td></td>
<td>~1.5</td>
</tr>
<tr>
<td>Benefit</td>
<td>LPG: 19.7%</td>
<td>47,700</td>
<td>50</td>
<td>~1.5</td>
</tr>
<tr>
<td>-----------</td>
<td>------------</td>
<td>--------</td>
<td>----</td>
<td>------</td>
</tr>
<tr>
<td>Urban</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Biogas: 3.0%</td>
<td>45,600</td>
<td>53</td>
<td>~1.5</td>
</tr>
<tr>
<td></td>
<td>LPG: 22.4%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>EPC: 57.1%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Electric hob: 20.2%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>EPCs</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Biogas: 0.2%</td>
<td>45,600</td>
<td>53</td>
<td>~1.5</td>
</tr>
<tr>
<td></td>
<td>LPG: 22.4%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Induction hob: 21.7%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Electric hob: 55.7%</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Fig. 18 shows the summary of results for the non-integrated urban prioro, no scenario with EPCs included. Assessing the distribution of wealth and comparing it with the adoption of different stoves show how electric hobs are particularly important at higher levels of wealth, while EPCs are more prevalent in the lower part of the wealth spectrum.
Fig. 18. Summary without integrated planning (urban prio); a) the stove shares with highest net-benefit, b) geospatial distribution of stoves with highest net-benefit, c) number of households selecting each category of stove in relation to their relative wealth. The dashed lines show the borders between quintiles and d) costs and benefits for each stove selected.
With an integrated approach the competitiveness of electric cooking increases, which now maximizes net-benefits for between 85 and 91% of the population. The main reason for this is the increasing electricity access rate. Without integration, the current electricity access rate acts as an upper limit for adoption of electric cooking. However, in the integrated scenarios 100% electricity access is reached by 2026 using the technology mix indicated by OnSSET. Anyone who is electrified through either a grid or mini-grid connection is assumed to be able to cook with electricity.

Without integration, OnStove uses the grid generation cost as the fuel cost for electric stoves, but with an integrated approach the LCoE from OnSSET is used instead. The LCoE includes the cost of adding capacity, as well as transmission and distribution costs. Therefore, the fuel costs in the integrated scenarios for electric stoves are higher than the fuel cost used in the scenarios without integration. This increase in fuel cost is however not enough to offset the competitiveness of electric stoves. However, it makes the efficiency of EPCs more important and in the integrated scenarios the EPC-shares increase to range between 59 and 79% when included as a possible option.

Deaths avoided remain between 45,000 and 48,000 during the modelling period. Time saved remain similar to the scenarios without integrated planning, while avoided emissions decrease. See Fig. 19 for the summary of results when an integrated version of the urban prio scenario is used.
**Fig. 19.** Summary integrated scenario (urban prio); a) stove shares with highest net-benefit, b) geospatial distribution of stoves with highest net-benefit, c) number of households selecting each stove in relation to the relative wealth. The dashed lines show the borders between quintiles and d) total costs and benefits for each stove selected.
3.3.3. Impact on electrification planning

The technology-configurations included in the electrification analysis of Paper IV are grid, stand-alone PV, mini-grid hybrids (PV-diesel) and mini-grid hydro. Table 10 display the share of technology categories (grid, mini-grid or stand-alone) amongst the newly electrified population throughout the modelling period. Similar to the case of population aggregation, the overall technology mix moves towards more grid and mini-grids as demand in settlements increase (in Paper IV due to inclusion of electric cooking). As the order in which different parts of Kenya receive clean cooking impacts the share of electric stoves, it also affects the least-cost electrification mix.

Table 10. Shares of new connections for each category of least-cost technology across scenarios.

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>Share of new connections</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Grid</td>
</tr>
<tr>
<td>Non-integrated results</td>
<td>61.9%</td>
</tr>
<tr>
<td>Urban prio in OnStove</td>
<td>71.8%</td>
</tr>
<tr>
<td>Cost prio in OnStove</td>
<td>66.3%</td>
</tr>
<tr>
<td>Benefits prio in OnStove</td>
<td>76.2%</td>
</tr>
<tr>
<td>Urban prio without EPCs in OnStove</td>
<td>71.7%</td>
</tr>
</tbody>
</table>

Both with and without integrated planning, but more frequently with, currently existing mini-grids are incorporated into the grid as this becomes economically viable. See Fig. 20 for the spatial differences in least-cost technology mix between the non-integrated results and the urban prio scenario with integrated planning. Both panels display results for 2026.
Fig. 20. Geospatial distribution of least-cost electrification technologies and the share of different technologies amongst new connections; a) non-integrated results, b) integrated urban prio results.
3.3.4. Financial implications

To reach universal electricity access in the non-integrated case an estimated 3.3 billion USD is needed between 2021 and 2026. With an integrated approach this cost increases to range between 4.1 and 4.8 billion USD depending on the OnStove prioritization used. The increase in investment cost is driven mainly by more generation capacity required to meet the larger demand, but also additional transmission and distribution lines.

Similar to the case in Paper III, all stoves’ total benefits outweigh their total costs. Investment cost in the cooking sector ranges between 400 and 500 million USD regardless of integrated or non-integrated planning. Note that the OnStove costs do not include the cost of adding generation capacity which is instead incorporated into OnSSET’s LCoE (or OnStove’s grid generation cost in the non-integrated case). The total investment cost modelled as part of Paper IV relates to providing clean cooking and electricity in the residential sector and does not model the costs and benefits of transitioning in e.g., educational or health facilities. These costs can be contrasted to the total costs that the Kenyan government has set aside for the transition to universal clean cooking access by 2028 (606 million USD). This cost includes not only residential customers, but also public institutions and small enterprises. The actions covered by these costs are initiatives such as communication strategies, targeted subsidies, and consumer financing [3].

Without integration, the fuel cost of electric stoves is lower than current practices. This is because electric stoves often replace LPG,
which is expensive and less efficient than EPCs (and consequently requires more fuel purchases). With an integrated approach, cost of electricity in OnStove increase as OnSSET adds costs. Still, the electric stoves have lower fuel costs than current practices even with this increase accounted for. This explains the increase in importance of EPCs seen when comparing Fig. 18 to Fig. 19. With an increase in fuel costs, more efficient stoves that reduce fuel consumption increase in importance.

Fig. 21 displays how LCoE changes with the inclusion of electric cooking demand in OnSSET. Larger demands typically decrease the LCoE, especially in areas where the technology-configuration switches from off-grid to grid. Most of these cases are seen in northern Kenya where population densities (and consequently demand) is otherwise too low to economically justify grid extension. This is evident by comparing the maps in Fig. 21 with the maps in Fig. 20. Beyond low population densities, many of the settlements that switch following the inclusion of electric cooking also have the lowest relative wealth in the country. Panel c) in Fig. 21 displays how the LCoE changes across wealth quintiles, highlighting that the regions with the lowest relative wealth have the largest decrease in LCoE following integrated planning.
Fig. 21. Impact on LCoE from including electric cooking; a) geospatial distribution of LCoE without electric cooking, b) geospatial distribution of LCoE with electric cooking (urban prio) and c) CDFs of LCoE with (blue lines) and without (red lines) electric cooking for each wealth quintile.
4. Conclusions

This section concludes the thesis. First a short general conclusion is presented, after which each research question is addressed in more depth. Following this, some important limitations of the work are discussed and lastly, there is a section on the impact of this thesis.

This thesis aimed to advance the state-of-the-art in geospatial modelling approaches to support integrated energy planning towards universal electricity and clean cooking access. As part of this thesis, the first geospatial cost-benefit tool for comparing the relative costs and benefits of different stoves was presented. Furthermore, this work included the first GSA for geospatial electrification and clean cooking models. Additionally, the first open-source geospatial integrated energy access study was conducted as part of this thesis. Beyond the academic publications appended, the thesis has been informed by additional projects and capacity building efforts which the author has conducted (listed in section 4.3. Scientific contributions and impact of the thesis).

The studies included here shows energy access challenges to be context-specific. In Paper II, different parameters impact the choice of least-cost technology in OnSSET to different extents across countries. In papers III and IV, while clean cooking is the preferable option across most geographies, there is heterogeneity both across and within individual countries with regards to which clean stove has the highest net-benefit. This indicates that planners and policymakers should select their data and models with care to best reflect
their specific cases. It is also important to remember that these models do not forecast the best set of options for universal energy access, but rather provide different scenarios to explore. The context-specific nature of energy access highlights the importance of geospatial tools in the field.

This research indicates that technology-selections are time sensitive. In Paper III, one scenario showed 20% of the population in SSA to have the highest net-benefit by adopting some type of ICS. ICS has however been criticized for not meeting emission reduction goals set by the WHO. These stoves are therefore often viewed as transitional stoves rather than final. This was seen in Paper IV as well. Across all scenarios (but more frequently in the integrated ones), some of the existing mini-grids were integrated into the main grid with higher demands, following the inclusion of electric cooking. Furthermore, Paper IV shows how electricity becomes cheaper as more people adopt electric cooking, in turn making electric cooking more competitive. This highlights that as demand changes with time, it should be reflected in planning efforts.

Both OnSSET and OnStove can be used to inform energy access plans and, due to them being computationally cheap, compare a large number of different scenarios. Both tools can be regarded as high-level tools aimed at providing starting points for policy-makers and planners. By allowing for large number of scenario runs, the costs (and in the case of OnStove, benefits) of different policies can be compared.
4.1. Addressing the research questions

RQ1: How do different levels of spatial aggregation affect the results of geospatial electrification models?

Previous research assessing MAUP and its impacts on geospatial studies suggest two approaches to combat the issue. The first, is to define an “ideal” scale or zoning regiment. Paper II shows that different levels of aggregation change the modelled competitiveness of different technologies in different directions and with diverse magnitudes. Introducing an “ideal” scale would therefore risk creating biases. In Paper II, the second approach suggested in the literature (a multiscale sensitivity analysis) is applied. In general, the results indicate that vector-based scenarios lead to more grid connections than those based on rasters and larger vector-settlements lead to larger shares of grid in the least-cost technology mix. As the least-cost technology mix changed, so did required investments and LCoEs. As rasters tend to misrepresent the size and shape that settlements naturally have, moving to vectors is advisable to properly quantify settlements’ distances to infrastructure and within-settlement costs. Furthermore, vector settlements better represent the scale at which electrification planning is typically done (which tends to be on project or settlement level). The difference in results between the three assessed countries indicates that it is not reasonable to expect all study areas to behave the same. Doing case-specific assessments can help mitigate some of the uncertainty surrounding the parameters associated with population aggregation.

Paper II presented the first GSA conducted in geospatial electrification studies. This provided the ability to assess the
importance of population aggregation methods in relation to other potentially important parameters. A GSA enables analysts to explore uncertainty more robustly when there is non-linearity in the output with regards to one or several inputs, or when there are interactions between different inputs. Therefore, a GSA can provide deeper insights into the effects of uncertainty in different parameters. The GSA highlights population aggregation as an important parameter for geospatial electrification studies. This indicates that researchers in the field need to assess how spatial aggregation impacts their tools and studies. Failure to do so may cause errors in the models that propagate through to the results. However, the implementation of a GSA can become computationally expensive if model complexity is high and model runs take long. The use of a GSA is therefore subject to trade-offs and should be planned accordingly. Researchers working with highly detailed tools could conduct GSAs on artificial datasets covering smaller (and computationally cheaper) regions to gain more understanding of how their tools react to uncertainty. Lastly, modelers must gain an understanding of the unique contextual factors shaping how population settlements are formed in their specific case studies.

Beyond population aggregation, Paper II indicated that a number of other parameters are particularly important for how the least-cost technology mix changes. Electricity demand was highlighted as one such parameter in accordance with previous literature. Therefore, understanding how to quantify demand (both residential and non-residential) is important. Furthermore, understanding how demand changes with time, perhaps as a direct result of increased electricity access and consumption, is also important. As the GSA also show
technology costs to be important, understanding what the current costs in the study area are, as well as how they may develop in the future due to different types of drivers, is also important. Certainty in these parameters is difficult to achieve and therefore the use of sensitivity analyses or scenarios are important to build more robust models.

**RQ2: How can GIS be effectively utilized to compare different cooking alternatives for achieving universal clean cooking access?**

Paper III presents the first geospatial clean cooking tool comparing the relative costs and benefits of different stoves, OnStove. Beyond presenting the tool, Paper III includes its first application for 44 countries across SSA. The tool is open-source, and the code as well as the data produced in the paper are publicly available allowing for replications and modifications of the results.

The results of Paper III highlights the need for a mix of fuel-stove combinations to achieve a clean cooking transition which maximizes net-benefits for as many people as possible. The results being spatially heterogeneous highlights the importance of GIS. Costs, benefits, people’s ability to pay and fuel availability varies spatially. Understanding how these aspects change across a study area is important for policy makers and planners as it increases the understanding of where financial policies such as subsidies or investments towards infrastructure and behavioral change campaigns can have the largest impact. The use of GIS can help highlight potential areas for intervention with regards to clean cooking and estimate the level of investment that should be made in
different technologies in different parts of a study area. A tool like OnStove can help increase the understanding of benefits and costs following a transition to clean cooking, as well as its context-specific differences.

Paper III presents two main scenarios as well as 680 scenarios as part of a GSA. None of the scenarios show traditional cooking (biomass or charcoal) to have the highest net-benefit anywhere in the region, and most people would maximize their net-benefit by adopting some form of clean cooking. This is in stark contrast with the current situation in SSA, where 82% of the population were estimated to cook with traditional stoves in 2021. Therefore, interventions are urgently needed to overcome the barriers hindering a transition to cleaner cook stoves. The net-benefit in OnStove is calculated in the absence of the costs of these interventions. This means that the net-benefit in OnStove can be interpreted as the upper-bound of these intervention costs if a positive net-benefit is still to be reached (i.e., how much can be spent on interventions, if we are still to at least break even from a net-benefit perspective?). Furthermore, excluding intervention costs avoids making assumptions about the effectiveness of these interventions. This is important as the effectiveness would most likely vary both spatially, by transition and by intervention.

The GSA in Paper III indicates that parameters across all categories of benefits are significant for the total net-benefit of different stoves. Therefore, a successful transition to clean cooking needs to account for all of these benefits simultaneously, and focusing on one benefit at a time may lead to sub-optimal transitions. It is important that the benefits are well-quantified and understood, and the methods of
their valuations transparent and open. Increasing the general understanding of these parameters, their valuation and their connection to traditional cooking can help in increasing the pace of the transition to cleaner stoves.

Previous research has highlighted different financial interventions such as subsidies, taxes and command-and-control regulations as methods to sway people away from current cooking practices [8], [62], [63], [68]. Out of these options, subsidies (or more generally, policies that encourage desired behavior, rather than discouraging undesired behavior) would probably be the easiest one to implement as certain traditional fuels (e.g., biomass) are often collected rather than purchased. These types of interventions may be especially important in SSA as results of Paper III highlights how the stoves with the highest net-benefits are unaffordable for most. However, subsidies need to be implemented with care as there are plenty of examples where they have either failed to reach those who need them the most, or have ended up becoming unsustainably expensive for governments and potentially tax-payers [8]. Geospatial tools can highlight where these subsidies are needed the most.

The general literature on clean cooking highlights many barriers in addition to financial constraints needing to be overcome for a widespread adoption of clean cooking. Furthermore, the stove selections indicated in Paper III diverge considerably from current practices and indicates benefits across multiple categories (health, time and environment) as important for a successful transition. This indicates that financial instruments such as subsidies are most likely not sufficient for bringing clean cooking to scale on their own. Instead
there is a need for multiple different types of interventions. Education and decent employment options could raise opportunity costs of time, which could encourage a transition away from inefficient cooking and fuel collection. Decent employment could also help increase health valuation, as this is often correlated to economic status. Health benefits can also be better appreciated against the background of information campaigns highlighting the health-drawbacks of traditional cooking. Lastly, both main scenarios in Paper III suggest major transitions to cooking fuels that are currently not widely used across SSA. This highlights the need for investments in new (and strengthening of existing) supply chains and markets.

**RQ3: How are the results of geospatial energy models (both electricity and clean cooking) impacted as an integrated planning approach is incorporated?**

As seen in grey and peer-reviewed literature, there are differences between levels of clean cooking and electricity access, even though electricity itself is considered a clean cooking fuel. This indicates a potential disconnect between the targets of universal electricity and clean cooking access. Previous research has highlighted how the investments towards the targets are uneven, with the electricity sector receiving considerably more money. One reason for this could be that the benefits of clean cooking span across several different realms of society and consequently, different branches of governments. Goldemberg et al. imply this as they say that clean cooking “lies at the intersection between climate, health and energy access” [117]. This is highlighted in Paper III as it showed how inputs
across all parameters of the net-benefit equation rank amongst most important for total net-benefits.

Integrated energy access planning can help bridge some of the gap between electricity and clean cooking access. These planning efforts favor a higher level of grid and mini-grid connections in the electricity sector as the electric load of cooking is included in the total demand. This is in line with the results of RQ 1, where larger shares of grid and mini-grids generally followed an increase in electricity demand (in that case, following larger units of analysis). This technology shift is followed by a decrease in LCoE, especially in areas where people have lower abilities to pay. This indicates that an integrated approach could significantly impact the results of least-cost electrification studies. On the cooking side, the integrated approach results in larger shares of electric cooking, especially favoring stoves with higher efficiencies. Paper IV highlights that while the adoption of electric stoves can have high up-front cost, the continuous fuel costs are in many cases not only competitive with LPG, but in fact lower.

Beyond putting more financial emphasis on the clean cooking transition, integrated planning can help avoid problems highlighted in the literature. This is especially the case where electric cooking shares cannot be increased or sustained due to limitations on current infrastructure. This is important as both papers III and IV show electric stoves to have the highest net-benefits in an absolute majority of cases when available. Not having the possibility to select an electric stove due to infrastructure constraints may therefore force people to forego higher net-benefits (across all benefit categories, as well as potential fuel cost reductions).
While electric cooking achieves the highest net-benefit for a majority of the population that have access to it, it is important to highlight that there are still salient barriers that need to be overcome for successful adoption (and sustained use) of electric cooking. Different financing mechanisms could help relax the affordability constraints mentioned in the literature, ensuring that electricity is available when needed helps with reliability constraints and reduces the need for fuel-stacking with traditional fuels, after-sale maintenance ensures proper functioning of the new stove long-term and can help sustain stove use and information campaigns can be used to inform people of the benefits of adopting cleaner stoves. While integrated planning is important, it is most likely not enough to take electric cooking to scale and need to be combined with these types of efforts.

4.2. Limitations and future work

The work presented in this thesis advances the state of art in geospatial integrated energy access modelling. However, there are a number of limitations which future research should aim at overcoming.

Specific methods, tools and case studies have been used to answer the RQs. As an example, in light of the results of Paper II it is worth noting that the behavior seen, may be OnSSET specific. Many tools in the field can be assumed to function similarly, but tools not utilizing pre-defined clusters may behave differently. Therefore, researchers should spend time understanding how other tools behave when spatially aggregating data.
Furthermore, the GSA in Paper II uses a specific method for sampling (Latin-hypercube for eight parameters and manual sampling for five). Had a different sampling method been used, a different method of GSA could have been used instead of DMIM, which could have provided additional insights. The same applies for different geospatial datasets. The use of GIS in energy modelling is still a new field, but it is growing and today there is a plethora of data sources to choose from. In all papers appended to this thesis different sources of datasets have been chosen based on what was considered the best option at the time. Different data sources could have potentially impacted the results. The same can be said about the case studies selected as part of the thesis. As part of papers II and IV, specific case studies were selected. The case studies were selected either because they had characteristics that were deemed interesting for the purpose of the RQs or because they were countries in which parallel work with partners on the ground was being conducted by the author of this thesis. Some aspects of the results may look different in other case studies and it may be worth increasing the number of countries and regions assessed.

Paper II highlights demand as one of the more important parameters for the choice of least-cost technology. Similarly, Paper IV indicates that demand for electric cooking significantly impacts the least-cost technology choice. This emphasizes the need for further research on the demand-side. Increased understanding of how residential demand varies not only between, but also within, settlements is important for improving the results of geospatial energy access studies (both electrification and clean cooking). The quantification of
non-residential demand is also important, as is the evolution of demand. These topics should be investigated further.

This thesis introduces the first geospatial clean cooking tool which compares the relative costs and benefits of different stoves. While this is an important development in the field, there are still several improvements that could make the tool more useful. Firstly, fuel-stacking is not included. This is important as fuel-stacking is often considered a way of mitigating affordability or reliability constraints and is often the norm in industrializing countries. Previous research has shown how fuel-stacking changes both the potential benefits and costs connected to cooking (in comparison to using exclusively clean stoves), but also that fuel-stacking is so ingrained into cooking practices that perhaps modelling efforts should not be aimed at eliminating fuel-stacking but rather encourage cleaner fuel-stacks. Fuel-stacking should be assessed in OnStove moving forward, ideally by allowing users to enter stacking-shares of different stoves. Furthermore, detailed modelling of the baseline is an important step forward. The baseline currently assumes the same ratio of stoves in each urban and rural cell for as long as electricity access and biogas availability permits it. Future research should aim at enhancing the calibration of the baseline perhaps by leveraging geospatial data, country-specific surveys, and different algorithms to assess the geographic spread of existing fuel-stove combinations within a given country or region. This would in turn impact the net-benefit calculations as all the costs and benefits are relative to the baseline.

Finally, affordability is an important barrier for both electricity and clean cooking access. While OnSSET models least-cost technologies
and OnStove maximizes net-benefits, these scenarios cannot automatically be assumed to be affordable. While some simple assessments of affordability were included as part of papers III and IV, it is important to develop this aspect of the thesis further.

4.3. Scientific contributions and impact of the thesis

Beyond the four publications that are appended to this thesis, this work has resulted in a number of additional contributions. This section lists contributions made by the author of this thesis with regards to methodological advancements, applications, outreach and capacity buildings.

<table>
<thead>
<tr>
<th>Methodological additions</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Developed a GIS-based methodology to create settlement clusters from open-source raster layers agnostic to source of input data and study area.</td>
</tr>
<tr>
<td>• Open-sourced the GIS data extraction of OnSSET, first through the development of QGIS plugins and later with different python scripts.</td>
</tr>
<tr>
<td>• Modified a version of OnSSET to facilitate global sensitivity analysis.</td>
</tr>
<tr>
<td>• Co-led the development of the first geospatial clean cooking tool comparing the relative costs and benefits of different stoves, OnStove.</td>
</tr>
<tr>
<td>• Developed a workflow for soft-linking OnSSET and OnStove allowing for integrated energy access planning.</td>
</tr>
</tbody>
</table>
Applications

- Applied, as part of Paper I, an open-source clustering algorithm on 44 countries in SSA and validated the electrification rates and urban rural classifications against published data. As part of Paper II, I compared the produced clusters with previously common raster based analysis to highlight potential impacts of the spatial aggregation in geospatial electrification modelling.

- Applied the first GSA for geospatial electrification and clean cooking modeling as part of papers II and III respectively.

- Applied OnStove for the first time as part of Paper III. As part of this publication the code base, all input data and a manual explaining OnStove were also produced and released. The application of OnStove was carried out for 44 countries in SSA.

- Applied the first soft-link between OnSSET and OnStove as part of Paper IV to generate integrated energy access scenarios in Kenya.

- Led the integration of OnSSET, OnStove and integrated energy access scenarios into the World Resources Institute’s Energy Access Explorer of Kenya.
• Co-led the development of the first geospatial clean cooking platform in Nepal together with the Clean Cooking Alliance, World Resources Institute, Nepal Open University and Kartoza.

• Supported the modelling efforts for the first geospatial electrification study in Somalia, examining pathways towards universal electricity access in the country by 2030. This work was carried out for the Ministry of Energy and Water Resources of the Federal Government of Somalia.

• In 2018 I supported an application of OnSSET in Benin. In 2020 I led the application of OnSSET in Benin. As part of both projects I co-led capacity building efforts connected to OnSSET. As part of the latter project, I also led the development of an open-source platform for the sharing of input data and results.

• Contributed with modelling of least-cost electrification scenarios for SSA for the IEA’s World Energy Outlook in 2019.

• Contributed with clean cooking analysis using OnStove for SSA as part of IEA’s A Vision for Clean Cooking Access for All in 2023.
• Supported the development of the Global Electrification Platform (GEP) with data collection, model development and scenario runs for 58 countries.

### Outreach, capacity building and impact

• Co-authored 6 academic publication


• Contributed to the development of a free and open online course on OnSSET and the GEP ([https://www.open.edu/openlearncreate/course/view.php?id=11533](https://www.open.edu/openlearncreate/course/view.php?id=11533)), and another course on OnStove ([https://www.open.edu/openlearncreate/course/view.php?id=11562](https://www.open.edu/openlearncreate/course/view.php?id=11562)). These courses takes participants from start to finish in both tools and makes geospatial energy access modelling available to a broader public.
• Made geospatial energy access modelling openly available through the development of (and contributions to) open-access platforms:

- The Global Electrification Platform
- Benin Electrification Platform
- Somalia Electrification Platform
- Energy Access Explorer Nepal
- Energy Access Explorer Kenya

References


[11] D. Stanistreet *et al.*, “Barriers and Facilitators to the Adoption and Sustained Use of Cleaner Fuels in Southwest Cameroon: Situating ‘Lay’ Knowledge within Evidence-Based Policy and


[17] World Health Organization, “WHO global air quality guidelines. Particulate matter (PM2.5 and PM10), ozone, nitrogen dioxide,


[74] F. Lombardi, F. Riva, M. Sacchi, and E. Colombo, “Enabling combined access to electricity and clean cooking with PV-


[86] L. Dijkstra et al., “Applying the Degree of Urbanisation to the globe: A new harmonised definition reveals a different picture


[112] A. Clark and D. Scott, “Understanding the Impact of the Modifiable Areal Unit Problem on the Relationship between Active Travel and the Built Environment,” Urban Stud., vol. 51,


Annex A: OnStove input data

OnStove relies on three categories of input data. The first category is geospatial data. These datasets include rasters and vectors capturing spatially explicit information about the study area. Table 11 below lists the geospatial datasets used in OnStove and their purpose.

Table 11. Geospatial datasets used in OnStove.

<table>
<thead>
<tr>
<th>#</th>
<th>Dataset</th>
<th>Type</th>
<th>Purpose</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Population</td>
<td>Raster</td>
<td>Used as basis for the analysis and serves as a proxy for residential cooking demand.</td>
</tr>
<tr>
<td>2</td>
<td>Administrative boundaries</td>
<td>Vector polygon</td>
<td>Polygon determining the boundaries of the analysis.</td>
</tr>
<tr>
<td>3</td>
<td>Urban-Rural status</td>
<td>Raster</td>
<td>Determines the urban-rural split.</td>
</tr>
<tr>
<td>4</td>
<td>Transformers</td>
<td>Vector points</td>
<td>Used to calibrate electrified people if available.</td>
</tr>
<tr>
<td>5</td>
<td>Medium-voltage lines</td>
<td>Vector lines</td>
<td>Used to calibrate electrified people if available and transformers are not.</td>
</tr>
<tr>
<td>6</td>
<td>High-voltage lines</td>
<td>Vector lines</td>
<td>Used to calibrate electrified people if available and transformers or medium-voltage lines are not.</td>
</tr>
<tr>
<td>7</td>
<td>Night-time lights</td>
<td>Raster</td>
<td>Used to calibrate electrified people.</td>
</tr>
<tr>
<td>8</td>
<td>LPG supply points</td>
<td>Vector points</td>
<td>Used to determine the cost of LPG if available. The base cost of LPG added in the techno-economic file is assumed to have a transportation cost added to it. The closer a settlement is to the closest</td>
</tr>
<tr>
<td></td>
<td><strong>Travel time</strong></td>
<td><strong>Raster</strong></td>
<td><strong>Description</strong></td>
</tr>
<tr>
<td>---</td>
<td>----------------</td>
<td>------------</td>
<td>----------------</td>
</tr>
<tr>
<td>9</td>
<td>If LPG supply points are not available, the travel time to closest urban settlements of at least 50,000 people is used to estimate LPG cost.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>Walking friction</td>
<td>Raster</td>
<td>Measures the time needed to travel through a grid cell of the study area by foot. Used to estimate the time needed for fuel collection in cases where this is assumed to be done by foot.</td>
</tr>
<tr>
<td>11</td>
<td>Motorized friction</td>
<td>Raster</td>
<td>Measures the time needed to travel through a grid cell of the study area by motorized transport. Used to estimate the time needed to transport LPG from the closest supply point in cases where LPG supply points are available.</td>
</tr>
<tr>
<td>12</td>
<td>Livestock</td>
<td>Raster</td>
<td>Biogas is assumed to be produced using manure from livestock. The head count of different livestock determines the biogas potential across the region.</td>
</tr>
<tr>
<td>13</td>
<td>Forest cover</td>
<td>Raster</td>
<td>Used to determine closest biomass supply point to estimate the time of collection for biomass stoves.</td>
</tr>
<tr>
<td>14</td>
<td>Relative wealth index or poverty</td>
<td>Raster</td>
<td>Used to estimate the opportunity cost in the net-benefit equation.</td>
</tr>
<tr>
<td></td>
<td>Parameter name</td>
<td>Description</td>
<td></td>
</tr>
<tr>
<td>---</td>
<td>----------------------</td>
<td>-----------------------------------------------------------------------------</td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>Water scarcity</td>
<td>Raster Used to identify areas that are not suitable for biogas production.</td>
<td></td>
</tr>
<tr>
<td>16</td>
<td>Temperature</td>
<td>Raster Used to identify areas that are not suitable for biogas production.</td>
<td></td>
</tr>
</tbody>
</table>

Table 12 below lists the socio-economic data for the Area Of Interest (AOI) entered by the user in the socio-economic file.

**Table 12.** Socio-economic data used in OnStove.

<table>
<thead>
<tr>
<th>#</th>
<th>Parameter name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Country_name</td>
<td>Name of the AOI</td>
</tr>
<tr>
<td>2</td>
<td>Country_code</td>
<td>ISO-2 code of the AOI</td>
</tr>
<tr>
<td>3</td>
<td>Start_year</td>
<td>Start year of the analysis</td>
</tr>
<tr>
<td>4</td>
<td>End_year</td>
<td>End year of the analysis</td>
</tr>
<tr>
<td>5</td>
<td>Population_start_year</td>
<td>Total population in the AOI in the start year</td>
</tr>
<tr>
<td>6</td>
<td>Population_end_year</td>
<td>Total population in the AOI in the end year</td>
</tr>
<tr>
<td>7</td>
<td>Urban_start</td>
<td>Urban ratio in the AOI in the start year (ratio)</td>
</tr>
<tr>
<td>8</td>
<td>Urban_end</td>
<td>Urban ratio in the AOI in the end year (ratio)</td>
</tr>
<tr>
<td>9</td>
<td>Elec_rate</td>
<td>Electrification rate in the AOI in the start year (ratio)</td>
</tr>
<tr>
<td>10</td>
<td>rural_elec_rate</td>
<td>Rural electrification rate in the AOI in the start year (ratio)</td>
</tr>
<tr>
<td>11</td>
<td>urban_elec_rate</td>
<td>Urban electrification rate in the AOI in the start year (ratio)</td>
</tr>
<tr>
<td>12</td>
<td>Mort_COPD</td>
<td>Mortality rate in COPD in the AOI (deaths per 100,000).</td>
</tr>
<tr>
<td>13</td>
<td>Mort_IHD</td>
<td>Mortality rate in IHD in the AOI (deaths per 100,000)</td>
</tr>
<tr>
<td>14</td>
<td>Mort_LC</td>
<td>Mortality rate in lung cancer in the AOI (deaths per 100,000)</td>
</tr>
<tr>
<td></td>
<td>Description</td>
<td>Definition</td>
</tr>
<tr>
<td>---</td>
<td>------------------------------------------------------------------------------</td>
<td>-----------------------------------------------------------------------------</td>
</tr>
<tr>
<td>15</td>
<td>Mort_ALRI</td>
<td>Mortality rate in ALRI in the AOI (deaths per 100,000)</td>
</tr>
<tr>
<td>16</td>
<td>Mort_STROKE</td>
<td>Mortality rate in stroke in the AOI (deaths per 100,000)</td>
</tr>
<tr>
<td>17</td>
<td>Morb_COPD</td>
<td>Prevalence in COPD in the AOI (cases per 100,000)</td>
</tr>
<tr>
<td>18</td>
<td>Morb_IHD</td>
<td>Prevalence of IHD in the AOI (cases per 100,000)</td>
</tr>
<tr>
<td>19</td>
<td>Morb_LC</td>
<td>Prevalence of lung cancer in the AOI (cases per 100,000)</td>
</tr>
<tr>
<td>20</td>
<td>Morb_ALRI</td>
<td>Incidence of ALRI in the AOI (cases per 100,000)</td>
</tr>
<tr>
<td>21</td>
<td>Morb_STROKE</td>
<td>Prevalence of stroke in the AOI (cases per 100,000)</td>
</tr>
<tr>
<td>22</td>
<td>Rural_HH_size</td>
<td>Rural household size</td>
</tr>
<tr>
<td>23</td>
<td>Urban_HH_size</td>
<td>Urban household size</td>
</tr>
<tr>
<td>24</td>
<td>Meals_per_day</td>
<td>Meals per day</td>
</tr>
<tr>
<td>25</td>
<td>infra_weight</td>
<td>Weight of distance to infrastructures when determining the likelihood of electricity access (transformers, medium- or high-voltage lines)</td>
</tr>
<tr>
<td>26</td>
<td>NTL_weight</td>
<td>Weight of night-time light intensity when determining the likelihood of electricity access</td>
</tr>
<tr>
<td>27</td>
<td>pop_weight</td>
<td>Weight of population density when determining the likelihood of electricity access</td>
</tr>
<tr>
<td>28</td>
<td>fnrb</td>
<td>Fraction of non-renewable biomass in AOI</td>
</tr>
<tr>
<td>29</td>
<td>COI_ALRI</td>
<td>Cost of illness for one case of ALRI in the AOI</td>
</tr>
<tr>
<td>30</td>
<td>COI_COPD</td>
<td>Cost of illness for one case of COPD in the AOI</td>
</tr>
<tr>
<td>31</td>
<td>COI_IHD</td>
<td>Cost of illness for one case of IHD in the AOI</td>
</tr>
</tbody>
</table>
The techno-economic data includes data regarding the stoves used in the analysis. Table 13 below lists the techno-economic data entered by the user as well as brief descriptions of each parameter. The last column in the table below indicates which stove each entry is relevant for. The techno-economic specification also defines which stoves to include in the analysis.

<table>
<thead>
<tr>
<th>#</th>
<th>Parameter name</th>
<th>Description</th>
<th>Relevant for</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>name</td>
<td>The name of the stove.</td>
<td>All</td>
</tr>
<tr>
<td></td>
<td>Field</td>
<td>Description</td>
<td>Scope</td>
</tr>
<tr>
<td>---</td>
<td>----------------</td>
<td>------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
<td>-------------</td>
</tr>
<tr>
<td>2</td>
<td>inv_cost</td>
<td>The initial investment cost of the stove</td>
<td>All</td>
</tr>
<tr>
<td>3</td>
<td>inv_change</td>
<td>The ratio with which the initial investment cost change from year to year (default is 1)</td>
<td>All</td>
</tr>
<tr>
<td>4</td>
<td>tech_life</td>
<td>Technical life of the stove</td>
<td>All</td>
</tr>
<tr>
<td>5</td>
<td>fuel_cost</td>
<td>Fuel cost</td>
<td>All</td>
</tr>
<tr>
<td>6</td>
<td>energy_content</td>
<td>Energy content of fuel</td>
<td>All</td>
</tr>
<tr>
<td>7</td>
<td>pm25</td>
<td>Daily average (24-hour) concentration of particulate matter of a diameter less than 2.5 micrometers</td>
<td>All</td>
</tr>
<tr>
<td>8</td>
<td>efficiency</td>
<td>Efficiency of the stove</td>
<td>All</td>
</tr>
<tr>
<td>9</td>
<td>time_of_collection</td>
<td>Time needed for fuel collection per day</td>
<td>All</td>
</tr>
<tr>
<td>10</td>
<td>time_of_cooking</td>
<td>Time needed for cooking per day</td>
<td>All</td>
</tr>
<tr>
<td>11</td>
<td>om_cost</td>
<td>Yearly operation and maintenance cost</td>
<td>All</td>
</tr>
<tr>
<td>12</td>
<td>current_share_urban</td>
<td>Current use of stove in urban settlements</td>
<td>Relevant for all the stoves in baseline</td>
</tr>
<tr>
<td>13</td>
<td>current_share_rural</td>
<td>Current use of stove in rural settlements</td>
<td>Relevant for all the stoves in baseline</td>
</tr>
<tr>
<td>14</td>
<td>n2o_intesity</td>
<td>Nitrous oxide intensity of the fuel in use. In the case of electricity this is determined using the power plant mix of the study area.</td>
<td>All but electricity</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>---</td>
<td>---</td>
<td>---</td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>ch4_intensity</td>
<td>Methane intensity of the fuel in use. In the case of electricity this is determined using the power plant mix of the study area.</td>
<td>All but electricity</td>
</tr>
<tr>
<td>16</td>
<td>bc_intensity</td>
<td>Black carbon intensity of the fuel. In the case of electricity this is determined using the power plant mix of the study area.</td>
<td>All but electricity</td>
</tr>
<tr>
<td>17</td>
<td>oc_intensity</td>
<td>Organic carbon intensity of the fuel. In the case of electricity this is determined using the power plant mix of the study area.</td>
<td>All but electricity</td>
</tr>
<tr>
<td>18</td>
<td>co_intensity</td>
<td>Carbon monoxide intensity of the fuel. In the case of electricity this is determined using the power plant mix of the study area.</td>
<td>All but electricity</td>
</tr>
<tr>
<td>19</td>
<td>co2_intensity</td>
<td>Carbon dioxide intensity of the fuel. In the case of electricity this is determined using the power plant mix of the study area.</td>
<td>All but electricity</td>
</tr>
<tr>
<td>20</td>
<td>draft_type</td>
<td>The type of draft used for the stove (natural or forced). Relevant for the biomass and pellet stoves. Default is natural.</td>
<td>Biomass ICS and pellets</td>
</tr>
<tr>
<td></td>
<td>Variable</td>
<td>Description</td>
<td>Scope</td>
</tr>
<tr>
<td>---</td>
<td>--------------</td>
<td>-----------------------------------------------------------------------------</td>
<td>------------------------</td>
</tr>
<tr>
<td>21</td>
<td><code>collected_fuel</code></td>
<td>Boolean (true or false). Describing whether the fuel is collected or bought.</td>
<td>Biomass stoves</td>
</tr>
<tr>
<td>22</td>
<td><code>capacity_[FUEL]</code></td>
<td>Installed capacity of different grid-connected power plants</td>
<td>Only for electricity</td>
</tr>
<tr>
<td>23</td>
<td><code>generation_[FUEL]</code></td>
<td>Electricity generated by different grid-connected power plants</td>
<td>Only for electricity</td>
</tr>
<tr>
<td>24</td>
<td><code>is_base</code></td>
<td>Determines if a single stove is the base stove or not. This is a boolean with a default value of False for all technologies, if it is turned true the fuel will be assumed as base-fuel for everyone</td>
<td>All</td>
</tr>
<tr>
<td>25</td>
<td><code>epsilon</code></td>
<td>Exposure adjustment factor.</td>
<td>All</td>
</tr>
</tbody>
</table>
Annex B: Stoves assessed

The following sections outline the stoves assessed with OnStove as part of the projects and publications in this thesis.

Traditional cooking

Traditional cooking fuels include solid fuels (wood, charcoal, crop residue, coal, animal dung) and kerosene. These types of stoves often have simple designs and are incapable of controlling the heat transfer or controlling combustion, leading to low efficiencies [16]. These stove-fuel combinations do not fulfill the requirements set by the Air Quality Guidelines (AQG). Table 14 describes the traditional stoves included.

Table 14. Traditional stoves assessed as part of this work.

<table>
<thead>
<tr>
<th>Stove</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Traditional biomass</td>
<td>The most common type amongst the traditional stoves. These stoves are often simple and many times not bought, but instead built by the users themselves. Fuel is also often collected by the end-users. Research indicates that factors such as availability of supply networks for competing fuels and access to information on negative impacts from traditional cooking have positive impacts on suspension of traditional biomass. On the other hand proximity to wood fuel have a negative impact on the suspension of wood fuel, as do higher costs of competitive fuels and alterative fuels’ potentially large purchase size [15], [63].</td>
</tr>
<tr>
<td>Traditional charcoal</td>
<td>Popular option to traditional biomass stoves, especially in urban areas of SSA [118]. These stoves tend to be cleaner than traditional biomass stoves in</td>
</tr>
</tbody>
</table>
Charcoal is often produced using aboveground biomass in either pit or surface earth-mound kilns. The conversion rate from wood to charcoal in these kilns is around 20%. The production of charcoal is emission intensive and can lead to forest degradation [118], [119]. Traditional charcoal stoves are often crafted locally from recycled metal. Due to lacking insulations they have very low efficiencies [120].

| Kerosene      | Kerosene is explicitly discouraged in the AQG due to emissions and safety concerns. The fuel is therefore not available as a choice in the OnStove studies. However, as it is prevalent in SSA currently, it is used as a base fuel. Kerosene is a liquid fuel produced from petroleum. The availability of Kerosene has been shown to act as a barrier to LPG-uptake [15]. |

Clean cooking

Clean cooking fulfills the emission requirements set by the WHO’s AQG and a transition to these type of fuel-stove combinations is expected to have benefits for health, gender and environmental issues. Table 15 describe the clean stoves included in the analysis.

Table 15. Clean stoves assessed as part of this work.

<table>
<thead>
<tr>
<th>Stove</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electricity</td>
<td>Electricity can be used as fuel to power different types of cooking appliances either through the national grid or (when using certain appliances) through different types of off-grid systems. The different options are many and range from induction hobs to electric pressure cookers (EPCs) [5]. The stoves are virtually free of emissions during use and therefore fall within the category of clean options</td>
</tr>
</tbody>
</table>
Salient barriers to these type of stoves are recurring fuel costs, up-front costs connected to stove purchase, lack of awareness of the benefits of switching and, at times, incompatibility with current cooking practices and cuisine [5].

**Electric hob** – Portable electric hob.

**Induction hob** – Portable induction hob. These stoves are more costly than the electric hobs, but also have higher efficiency which reduces their fuel requirements.

**EPC** – EPCs are the most energy efficient stoves modelled in OnStove as part of the work presented in this thesis. The food cooked in an EPC is contained in a sealed chamber where the pressure increases with increased heating. Once the pressure has increased, it is kept close to this level during the cooking process. This increases the efficiency and reduces the cooking times considerably.

**LPG**

LPG consists of a mix of different gases, mainly propane and butane. LPG is typically distributed and sold in cylinders of various sizes. Using these pressurized cylinders one or several burners can be fed by gas and used to cook. LPG is a viable option to traditional cooking in areas that are un-electrified and lack ability to produce sufficient biogas quantities [63].

**Biogas**

Biogas is a gas consisting mainly of methane produced by anaerobic digestion of organic material [121]. Biogas is not as widely used as LPG as it requires large water consumptions [122], favorable temperatures [123] and an adequate amount of material (e.g., livestock for manure or agricultural residues). A digester is used to produce biogas from
decomposing organic material. Biogas stoves are burner-type stoves similar to the case of LPG.

**ICS**

Burns traditional fuels such as biomass and charcoal in more efficient ways and with greater ventilation, reducing fuel needs and health impacts. Four stoves are included:

- Biomass with natural draft ventilation (wood fuel)
- Biomass with forced draft ventilation (through the use of a fan and with wood fuel)
- Biomass with forced draft ventilation (through the use of a fan and with pellets as fuel)
- Improved charcoal stove