Supplementary table 2: Detailed content of studies using direct extraction from the publications (abbreviations are described at the end of the table)

ID	References	Year	Study setting (period)	Malaria data	Covariate data	Objective(s)	Analytical method	Key finding	Further studies/recommendations
1	Abellana et al.	2008	Manhica district, Maputo, Southern Mozambique (1996 – 1999)	Weekly clinical incidence (2 cohorts) for 115 neighbourhoods in children under 10 years old.	Sex, age groups, period, climate season.	To study the seasonal effect on the spatial distribution of the incidence of malaria	Spatial association - exploratory data analysis. spatial seasonal model.	Malaria incidence presents a spatial pattern with a higher incidence in the north and northeast of the study area.	Planning interventions which continue overtime in high incidence areas to control transmission.
2	Alegana et al	2016	Northern Namibia (Jan 2012 - May 2014)	Monthly case data (29 months) for 22 districts	Space-time covariates (EVI and precipitation)	To produce continuous spatial and temporal predictions of P. falciparum malaria	Bayesian spatio-temporal model	Priority districts identified for intervention.	Future approaches should incorporate a higher temporally varying denominator
3	Alegana et al	2013	Northern Namibia (Jan 2009 – Dec 2009).	Monthly malaria cases (12 months) for 273 facilities.	Rainfall, temperature, EVI, temperature suitability index	To predict malaria incidence at second administrative unit level.	Bayesian spatio -temporal zero-inflated Poisson CAR model.	Incorporating the environmental covariate explained spatial variation where data were absent.	The results could be improved by inclusion of more data and at different time points to draw more stable long-term spatio-temporal patterns.
4	Alemu et al	2013	Northwest Ethiopia (2003 – 2012)	Monthly reported cases (120 months) in 18 districts.	None	To identify patterns of malaria distribution by space and time.	ARIMA model - To evaluate the seasonal and annual patterns of malaria transmission 2. Poisson model - With the purely temporal, spatial and space-time scan statistics.	Three malaria epidemic years were observed in 2003, 2009, and 2010.	Further studies to identify the main causes of bigger malaria transmission risk in the detected districts.
5	Amek et al.	2012	Nyanza province, rural Western Kenya (2002 – 2004)	Monthly mosquito density and EIR	Climatic and environmental covariates (Land surface temperature, normalized difference vegetation index,	To describe the spatio-temporal dynamics of malaria	Bayesian geostatistical zero inflated binomial and	Spatio-temporal maps are useful in understanding variability in malaria epidemiology over small areas and	None

					rainfall, and elevation were extracted from remote sensing data. Distance to the nearest water source)	transmission intensity.	negative binomial models	providing high resolution exposure surface.	
6	Amratia et al.	2019	Bunkpurugu-Yunyoo district, Northern Region, Ghana (October 2010 – March 2013)	Microscopy-based malaria status of individuals sampled by parasitaemia household surveys	Elevation, NDVI, LST, Rainfall, Night-time lights, Population density, distance (urban centre, health facility, road-network, water bodies)	To characterize the micro-scale spatial heterogeneity of malaria risk.	Bayesian-geostatical probit models	Fine-scale parasitaemia data might be critical to guide district-level programmatic efforts to prevent and control malaria.	Fine-scale parasitaemia data can be useful for spatial predictions in neighbouring unsampled districts and does not have to be collected every year to aid district-level operations, helping to alleviate concerns regarding the cost of fine-scale data collection.
7	Appiah et al.	2011	Ghana, West Africa (1998 – 2010)	Monthly morbidity cases (156 months) reported to health facilities for 138 districts.	None	To produce evidence-based malaria risk maps, describing the risk pattern over space and time.	Lognormal ordinary kriging	Varied spatial and temporal distributions of the disease across the country with elevated cases mostly in the northern most and central parts of the country.	
8	Awine et al.	2018	Ghana, West Africa (2008 – 2016)	Malaria morbidity from routine health facility data (DHIMS repository)	Clinical data, Meteorological data	To explore and assess spatial and temporal heterogeneity of malaria cases	Autoregressive time series model, Univariate Time Series model	Distinguishable patterns which correlate with weather phenomenon in various zones of Ghana.	Elaborate modelling approach that allows for more dependencies of malaria morbidity dynamics to be incorporated may provide a platform to investigate the impact of intervention strategies using this data.
9	Bejon et al.	2010	Kilifi District, Kenya. (1998 – 2009)	Longitudinal data on febrile malaria episodes, asymptomatic parasitaemia (12 years) for 256 homesteads.	Remotely sensed data (LST, NLST, EVI) Environmental variables	To identify hotspots of malaria transmission.	Cluster analysis	Two statistically significant hotspots were identified; stable hotspots of asymptomatic parasitaemia and unstable hotspot of febrile malaria.	Hotspots of febrile Disease may be targeted by monitoring presentation at the local facility.
10	Bejon et al.	2014	Kilifi District, Kenya (2003 – 2011)	Malaria Positive fraction aggregated by 1500 homesteads	None	To determine the temporal and spatial scales of case clustering.	Spatial cluster analysis – Bernoulli model	Marked spatial variation between geographic regions suggesting differentiation in transmission characteristics.	Ecological models of malaria transmission needs to include data at a range of spatial scales in order to accurately predict malaria risk.
11	Belay et al.	2017	Southwest Ethiopia (2008 – 2010)	Mosquito abundance & time to malaria (23	Regional precipitations,	To explore jointly the association between longitudinal	Bayesian joint model	The Bayesian joint model identified the interaction between mosquito	More studies on the usefulness of joint models for malaria infection risk prediction.

				months) in 16 villages	temperature, relative humidity	measurement of mosquito abundance and time to malaria		abundance and incidence as being critical.	
12	Bennett et al.	2013	Malawi (2000 – 2011)	Cross-sectional community PfPR data from household surveys done between 2000 – 2011.	Ecologic and climatic predictors	To produce comparative geo-statistical risk maps.	Space-time Bayesian geo-statistical model.	Entire population of Malawi is under meso-endemic transmission risk, with elevated transmission along the shores of Lake Malawi and Shire river.	Focusing risk-map products to sub-national administrative units will improve/enable appropriate intervention targeting and goal setting at this level.
13	Bennett et al.	2016	Zambia (2006 – 2012)	Malaria parasite prevalence from MIS survey in 2006, 2008, 2010 & 2012.	Environmental covariates, Intervention coverage.	To assess the association between IRS and ITN coverage and climate variability and malaria parasite prevalence.	Bayesian geo-statistical models.	Climatic factors influencing Malaria transmission, including rainfall, Temperature suitability, and Vegetation cover (EVI), were positively associated with Malaria parasite prevalence in children across Space and time.	This analysis highlights the importance of accounting for climate variability when using cross-sectional data for evaluation of malaria control efforts.
14	Bennett et al.	2014	Zambia (2009 – 2011)	Monthly reported and clinically unconfirmed malaria cases from HMIS.	Climate, treatment seeking, healthcare access, reporting and testing	To assess the dose response relationship between ITN program intensity and confirmed malaria case incidence.	Bayesian geostatistical framework – INLA	Increased district-level ITN coverage is associated with lower confirmed case incidence	HMIS data can become a valuable tool for evaluating malaria program scale-up.
15	Bhatt et al	2015	Africa (2000 – 2015)	PfPR survey points across SSA	Optimized suite of temporally dynamic environmental and socio-demographic covariates.	To evaluate trends from 2000 - 2015	Bayesian space-time model	Widespread reductions in infection prevalence and case incidence	The development of robust surveillance systems is important for malaria control
16	Bisanzio et al	2015	Kwale County, Kenya (Oct 2012 – March 2015)	Hospital reported malaria cases (30 months).	Remotely sensed data, Rainfall data	To define spatio-temporal heterogeneity of malaria risk.	Bayesian space-time models. Structured additive regression (STAR) models	The seasonal trend of malaria prevalence among febrile cases was significantly associated with mosquito infestation levels recorded in sampled households	Passive surveillance based on geo-referenced malaria testing is an important tool that control agencies could use to improve the effectiveness of interventions targeting malaria (and other causes of fever) in high-risk locations.

17	BM & OE	2007	Ogun State, Nigeria (Not mentioned)	Malaria prevalence data from 20 surveys, from the Ministry of Health.	NDVI, population density, temperature, distance to the nearest water body.	To quantify uncertainties about impacts of malaria on mortality.	Bayesian hierarchical model, regression analysis.	The model produced in this Study is a reasonable representation of Malaria risk in Ogun State.	Full Mixed model with universal kriging to take account of spatial pattern.
18	Bousema et al.	2010	Korogwe, Tanga region, Tanzania (2004 - 2008)	Incidence data from a cohort study	None	To determine the spatial patterns in malaria transmission.	Cluster analysis	Five clusters of higher malaria incidence were detected and interpreted as hot spots of transmission.	Serological markers of exposure could potentially guide malaria control efforts
19	Ceccato et al	2007	Eritrea (1996 - 2003)	Monthly data on clinical malaria cases from 242 health facilities in 58 subzobas (districts) from HMIS database	Climatic/environmental data, remotely sensed data	To indicate the intensity and seasonality of malaria transmission.	Cluster analysis	For epidemic control, shorter-range warning based on remotely sensed rainfall estimates and an enhanced epidemic early-detection system based on data are needed.	Malaria risk stratification can be extended to smaller administrative units (subzobas).
20	Chipeta et al.	2019	Malawi (2000 – 2017)	PfPR prevalence surveys undertaken between 2000 and 2017	None	To explore the possible changes in malaria prevalence.	Spatial temporal geostatistical model	The leveraging of multiple national survey data from diverse research and health constituents improves the precision of predictions over sparse data collected during single cross-sectional national malaria or health surveys.	The analysis of sub-national variations in risk and epidemiological transitions should be triangulated with additional routine data from health information systems and malaria hospitalization.
21	Chirombo et al.	2020	Malawi (2004 – 2017)	Routine monthly paediatric outpatient clinical malaria case data from 27 districts.	Temperature, Rainfall, NDVI, Population, Literacy, Altitude, Urbanization	To quantify the strength of association of the various risk factors with district level variation in clinical malaria rates	Spatio-temporal generalized linear mixed model	The model outputs provide a resource that offers insight to programme managers on seasonality and disease burden that can help inform more targeted interventions.	Spatial statistical methods applied to readily available routine data provides an alternative information source that can supplement survey data in policy development and implementation to direct surveillance and intervention efforts.
22	Cissoko et al.	2020	Dire District, Northern Mali (2015 - 2018)	Weekly malaria case reports from 18 health areas.	Rainfall, Temperature, River height, Humidity, Wind speed, NDVI, Proximity to river, Propensity for flooding	To evaluate the impact of meteorological and environmental factors on the geo-epidemiology of malaria.	Cluster analysis and time series analysis	Health areas at greater risk of transmission, are characterized by proximity to the river, propensity for flooding, and high agricultural yield.	The identification of areas and periods of high transmission can help improve malaria control strategies.
23	Colborn et al.	2018	Mozambique (2010 - 2017)	Weekly case reports (7 years) of malaria in children under 5 years of age from 142 districts.	Climatic variables rainfall, temperature, humidity, barometric pressure, saturation vapor pressure deficit.	To estimate the probability of incidence occurence in the future.	Spatio-temporal model (Poisson regression)	The MEWS can thus be used to predict areas that may experience increases in malaria transmission beyond expected levels, early enough so that prevention and response	Period re-validation of the model due to variation in malaria transmission patterns. Framework developed could be used to monitor other

								measures can be implemented prior to the onset of outbreaks.	diseases with same transmission dynamics.
24	Coulibaly et al.	2013	Bandiagara, Mali (June 2009 – May 2010)	Malaria cases recorded during the first year of follow-up	Rainfall	To assess time and space distribution of malaria disease	Cluster analysis	Two hot spots of malaria transmission also found, notably along the Yana River.	Inclusion of environmental factors in defining the distribution of malaria patterns
25	DePina et al.	2019	Cabo Verde (2017)	Longitudinal data	Temperature, Relative humidity, Rainfall, Wind speed	To examine the spatial and temporal epidemiological profile of malaria across the country during the 2017 outbreak and to analyse the risk factors, which may have influenced the trend in malaria cases.	Cluster and Outlier Analysis	Mosquito breeding sites have been the main risk factor, while temperature and precipitation were positively associated with malaria infection	Further studies considering multiple areas and biological models of mosquito development are needed to improve detection of temperature effects on malaria transmission and the relative contribution of these risk factors.
26	Diboulo et al.	2016	Burkina Faso (2010/2011)	Malaria parasite risk in children aged 6 – 59 months from malaria indicator survey data (MIS).	Climatic/Environmental factors Socio-economic factors	To assess the effects of malaria interventions on the geographical distribution of parasitaemia risk	Bayesian geostatistical logistic regression models	This study provides estimates of the effects of malaria interventions at country as well as at local scale.	Model outputs can serve as benchmarks in evaluating the effectiveness of future control interventions.
27	Ferrão et al.	2017a	Chimoio Municipality, Mozambique (2006 – 2014)	Weekly malaria cases (counts) from district Epidemiological Bulletin.	Visibility, wind speed, Relative humidity, temperature.	To model the association between climatic variables and malaria cases.	Time series analysis	Seasonal pattern in malaria occurrence with peaks during January to March	The model can be applied in analysing the spread of other infectious diseases and optimizing control efforts
28	Ferrão et al.	2017b	Chimoio Municipality, Mozambique (2010 – 2014)	Malaria mortality data from Civil Registration records	Climate data, temperature (min/max), relative humidity, precipitation, evaporation	To characterize malaria mortality trends and its spatial distribution.	Time series analysis	Malaria mortality shows seasonal and spatial characteristics.	More data from additional sources in the country needed to generalize results nationally.
29	Ferrari et al.	2016	Kinshasa, DRC (2009 and 2011)	Malaria prevalence from two cross-sectional surveys	None	To map and interpolate malaria risk.	Inverse distance weighting	Prevalence of malaria, anaemia and reported fever was lower in urban areas.	Risk map provides a baseline assessment against which to assess the effect of future control efforts.
30	Gaudart et al.	2006	Bancoumana, Upper Niger Valley, Mali. (June 1996 – June 2001)	Malaria infection in children from a dynamic cohort from 22 surveys	Age, access to treatment, thatched roofs, seasonality, presence of breeding sites.	To identify, spatially and temporally, high-risk zones of malaria.	Time series analysis	Malaria parasitemia (primarily P. falciparum) was persistently present throughout the population with the expected seasonal variability pattern and a downward temporal trend.	Micro-epidemiological analysis orients control programs by prioritizing high risk zones.
31	Gemperli et al	2006	West and Central Africa (1950 -2002)	Malaria prevalence data from 1846 malaria surveys	Climatic, environmental and population data. NDVI, temperature, rainfall,	To estimate malaria transmission intensity for each location.	Bayesian linear geostatistical model	Malaria transmission increases as the maximum monthly temperature increases.	Using transmission model-based estimates for mapping

				extracted from MARA database.	land use, water bodies, population density, transmission seasonality, soil water storage index, agro-ecological zone				malaria risk across large areas of the African continent.
32	Gething et al.	2016	Sub-Saharan Africa (1990 – 2015)	Malaria incidence data and community-level parasite rates from 30 sites.	Environmental covariates. Clinical incidence, coverage of antimalarial drug treatment, case fatality rate, population distribution	To produce estimates of age-specific and sex-specific malaria mortality	Bayesian spatiotemporal	There was an overall decrease of 57% (95% uncertainty interval, 46 to 65) in the rate of malaria deaths.	Increased precision of future estimates may be realized by integrating hospital-based data on Malaria case fatality rates.
33	Giardina et al	2015	Mozambique (2011)	Malaria parasitaemia data from demographic and Health survey carried out in 2011, on children from 0 to 5 years old	Environmental factors Remotely sensed climatic factors	To model the risk of malaria.	Bayesian geostatistical logistic regression model	The use of MR variables tended to result in an overestimation of the number of infections.	Malaria parasitaemia risk estimation has important implications on the planning of control measures
34	Giardina et al	2012	Senegal (2008)	Parasitaemia risk (RDT) from MIS 2008 data	Environmental factors, socio-economic factors, malaria intervention measures	To estimate the burden of malaria.	Geostatistical zero-inflated binomial models (ZIB)	Malaria risk in children increases with age.	Zero-inflated formulations are more appropriate in modelling sparse geostatistical survey data, expected to arise as malaria research focusses on elimination.
35	Giardina et al	2014	Sub – Saharan Africa (2006 – 2012)	Parasitaemia risk from two MIS and DHS with malaria measurements	Rainfall, NDVI, altitude, LST night, LST day	To estimate the effect of malaria interventions.	Bayesian geostatistical logistic regression model.	Country-specific Spatial patterns of changes in parasitaemia risk between the two surveys, and the variation of intervention effects from one country to another and geographically within countries.	Maps can be used to predict malaria risk at different levels of intervention coverage.
36	Giorgi et al.	2018	Somalia (2005 – 2014)	PfPR prevalence data from cross-sectional surveys	None	To identify areas where prevalence lies below pre-specified thresholds	Spatio-temporal geostatistical binomial model	An overall decrease in PfPR from 2005 to 2014, with all regions, except Bakool, showing more than 90% probability of PfPR being < 5% by 2014.	NEP can be used to plan Future sampling efforts through the Identification of regions where The mapped NEP does not reach acceptable levels.
37	Gómez-Barroso et al.	2017	Bata district, Equatorial Guinea (June 2013 – Aug 2013)	Malaria prevalence from a representative cross-sectional survey of 444 households.	Environmental factors	To describe the current distribution of malaria prevalence among children.	Cluster analysis	A high prevalence of RDT based malaria among children in Bata District.	Spatial tools can help policy makers to promote new recommendations for malaria control.
38	Gosoniu et al.	2012	Tanzania (Oct 2007 – Feb 2008)	Parasitaemia risk in children aged 6 – 59 months from MIS data	Environmental and climatic data. Land surface, temperature, rainfall, normalized	To identify factors associated with child malaria risk and produce a risk map.	Bayesian geo-statistical modelling	Overall lower prevalence over the country attributed to the increase in intervention coverage.	Risk map could be used for monitoring and evaluation the ongoing interventions

					difference vegetation index, altitude, distance to nearest permanent water body.				
39	Gosoniu et al.	2010	Angola (2006 – 2007)	Parasitaemia risk in children aged 6 – 59 months from MIS data	Environmental and climatic data, socio-economic factors.	To assess coverage of the key malaria control interventions and measuring malaria-related burden.	Bayesian geo-statistical models	The geostatistical model predicted low disease risk in the south and south-east part of the country which is classified as mesoendemic unstable.	Estimates are important for planning/implementing control interventions and monitoring the impact of prevention and control activities.
40	Gosoniu et al.	2006	Mali (1977 – 1995)	Malaria prevalence data from MARA database for children between 1 -10 years at 89 sites.	Climatic and environmental data.	To quantify the environment-disease relations, identify significant environmental predictors of malaria transmission and provide model-based predictions of malaria risk together with their precision.	Bayesian stationary and non-stationary model - Logistic regression	The pooled data have shown an overall malaria prevalence of 44.0% (19, 156 children). The median malaria prevalence estimated at village level was 51.3%, ranging from 5.3% to 95.5%.	Stationarity assumptions are important as they influence the significance of environmental covariates. Further analysis with recent data
41	Houngbedji et al.	2016	Cote d'Ivoire (Nov 2011 - Feb 2012)	*P. falciparum* infection status from a cross-sectional survey of more than 5000 children from 93 schools.	Environmental data, demographic data	To identify spatially explicit indicators of P. falciparum infection and undertake a model-based spatial prediction of P. falciparum infection risk.	Bayesian geostatistical logistic regression	The produced smooth P. falciparum prediction map, in conjunction with uncertainty estimates, represent useful tools for scaling up current and future malaria control interventions.	In order to better understand the impact of ongoing malaria interventions, future predictive risk profiling should include other factors such as population density and more detailed information on intervention coverage.
42	Ihantamalala et al.	2018	Madagascar (2010 -2014)	Monthly reported cases of uncomplicated malaria from 112 health districts in the HMIS.	None	To derive a spatially refined characterization of malaria.	Cluster analysis	The incidence of malaria increased from 2010 to 2014 within each stratum. A high spatial heterogeneity in incidence between districts within the same stratification zone.	This work highlights the utility of routinely collected data and insight to be gained using simple clustering analyses.
43	Ikeda et al.	2017	Limpopo, South Africa (Jan 1998 – Dec 2014)	Malaria case data	Climatic factors. Temperature, precipitation, sea surface temprature	To analyse spatio-seasonal malaria incidence anomaly patterns	Artificial neural networks - SOM	This lagged association between regional climate and malaria incidence suggests that in areas at high risk for malaria, such as Limpopo, management plans should consider not only local climate	There's a need to strengthen cross-border control of malaria to minimize its spread.

								patterns but those of neighbouring countries as well	
44	Ishengoma et al.	2018	Muheza District, North-eastern Tanzania (1992 - 2017 and 1998 – 2017)	Malaria parasite prevalence for individuals aged 0 – 19 years in a cross-sectional survey.	Rainfall, intervention factors.	To describe the most recent trends of P. falciparum prevalence	Poisson model	A significant decline in the prevalence of P. falciparum infections observed up to 2012 was followed by a sustained resurgence of malaria.	A sustained multi-factorial surveillance needs to be undertaken to monitor changes in malaria transmission and determine other factors which could be associated with continued transmission and resurgence of malaria.
45	Kabaghe et al.	2017	Chikwawa district, Southern Malawi (April 2015 – April 2016)	Malaria prevalence in children aged 6 – 59 months from repeated cross-sectional surveys.	Elevation, NDVI, ITN, Age, SES	To describe the first field application of AGD sampling in continuous malaria prevalence surveys	Bayesian geo-statistical binary probit model	Malaria prevalence prediction maps showed spatial heterogeneity and presence of hotspots. Continuous malaria prevalence surveys using adaptive sampling increased malaria prevalence prediction accuracy	This approach can potentially empower both local and national programme managers to invest limited resources and efforts on high priority areas for elimination.
46	Kabaria et al.	2016	Dar es Salaam, Tanzania (2006 – 2014)	Malaria risk from parasite prevalence surveys – INFORM database	Vegetation, distance to water body, rainfall, temperature, wetness index, altitude	-To estimate their impact of intra-urban variations of malaria infection risk	Machine Learning Technique - Random forest classifier	The risk of Malaria infection varied across the city and the peri-urban suburbs.	Replication in other urban areas to identify environmental factors influencing heterogeneity in malaria risk patterns and vulnerability zones.
47	Kamuliwo et al.	2015	Zambia (Jan 2009 – Dec 2014)	Monthly reported district-level malaria cases among pregnant women (count data) from the DHIS.	Water body, population density, number of health facility reporting MiP cases, access to roads, IRS, LLINs.	To determine the burden and risk factors of malaria in pregnancy.	Negative binomial regression analysis	MiP decreased in Zambia between 2010 and 2013,, and was observed through the year with showed a strong seasonal pattern.	Mapping the distribution of MiP to track the future requirements for scaling up essential disease prevention efforts in stable hotspots
48	Kang et al.	2018	Madagascar (2011 – 2016)	Parasitaemia prevalence data in children aged 6 – 59 months from MIS data	Satellite derived environmental data and socio-demographic data	To assess changes in the prevalence of P. falciparum malaria infection among those under 5 years old.	Bayesian negative binomial spatio-temporal model	A comparison of the model-based estimates with the raw MIS results indicates there was an underestimation of the situation in 2016.	Methods contributes to monitoring sub-national trends of malaria prevalence for geographically progressive elimination.
49	Kangoye et al	2016	Ganze, Kilifi County, Kenya (Jan 2012 – Dec 2013)	Longitudinal data collected from 831 children aged 5–17 months, cross-sectional survey data from 800 older children and adults, and entomological survey data	None	To reports on the relationships between clinical, parasitological, serological and entomological markers of malaria transmission	Cluster analysis – Hotspot analysis	These findings may support the choice of either serology or PCR as markers in the detection of transmission hotspots for targeted interventions.	Findings may support the choice of either serology or PCR as markers in the detection of transmission hotspots for targeted interventions.

50	Kanyangarara et al.	2016	Mutasa District, Zimbabwe (Oct 2012 – Sept 2015)	Parasite prevalence for community-based surveys of 483 households.	Parasitological data, environmental covariates.	To develop a model-based prediction on environmental risk factors and obtain seasonal malaria risk maps.	Multivariate logistic regression	The predicted risk map for the rainy season showed that malaria risk increases from west to east of the study area	These findings underscore the need for strong cross-border Malaria Control initiatives to complement country-specific interventions.
51	Kazembe et al.	2006	Malawi (1977 - 2002)	Point-referenced prevalence of infection data for children aged 1–10 years collected from published and grey literature and geo-referenced.	Environmental covariates.	To predict and map malaria risk	Bayesian geostatistical logistic regression model	Relatively higher risk areas were predicted in the central and northern region districts as well as along the lakeshore districts on the east central side of the country.	Updating malaria maps should be carried out on a regular basis as new data become accessible
52	Kifle et al.	2019	Eritrea (2012 – 2016)	Monthly malaria incidence data from the National Health Management and Information System	Rainfall	To construct a national malaria stratification map, develop prediction models and forecast monthly malaria incidences based on rainfall data.	Cluster analysis	Change in rainfall patterns affect malaria incidence in Eritrea.	Using routine malaria case reports and rainfall data, malaria incidences can be forecasted with acceptable accuracy.
53	Kigozi et al.	2016	Uganda (Jan 2010 – May 2013)	weekly malaria case count data and test positivity rate series) in three sites located in varying malaria transmission settings in Uganda was explored	Environmental factor. Rainfall, Average daytime temperature, Enhanced vegetation index.	To assess temporal relationships between rainfall, temperature and Vegetation with malaria morbidity	Time series analysis - Cross-correlation analysis with pre-whitening	Weekly TPR and number of Malaria cases were highest at Kasambya followed by Nagongera and Kamwezi	There's need to incorporate local transmission differences when developing malaria early warning systems that have environmental predictors in Uganda
54	Kleinschmidt et al.	2000	Mali (1960 – 2000)	Malaria prevalence data in children under 10 from previous surveys	Environmental covariates, population density	To produce maps of malaria predicted risks.	Bayesian geostatistical approach	Model results indicates improvement of risk prediction brought about by geostatistical kriging at a local level.	A full mixed model with universal kriging to take account of spatial pattern
55	Kleinschmidt et al.	2001a	KwaZulu Natal, South Africa (1994 – 1995)	Malaria cases (ascertained by passive and active detection) in the mid-1994 to mid-1995 season, were extracted from the malaria control program database	Environmental factors, distance to the nearest water body, distance to the Mozambique border.	To undertake a spatial statistical analysis of malaria incidence	Spatial statistical analysis -Generalized linear mixed models (GLMM).	The predictor variables showed that even small differences in climate can have very marked effects on the intensity of malaria transmission, even in areas subject to malaria control for many years.	Model underlines the Importance of adjusting for confounding effects when investigating the association between malaria incidence and climatic factors.

				and allocated to 220 sections.					
56	Kleinschmidt et al.	2001b	West Africa (1998)	Parasite prevalence data in children less than 10 years of age from the MARA database.	Bio-physical environmental factors. Rainfall (monthly), temperature (minimum and maximum), NDVI, drainage density, estimated population density	To produce a malaria distribution map	Spatial statistical analysis -Generalized linear mixed models (GLMM).	Malaria risk predicted in children under 10 years in four categories.	Maps can be refined once sufficient additional data become available.
57	Kleinschmidt et al.	2002	KwaZulu Natal, South Africa (1986 – 1999)	Parasitologically confirmed malaria cases (13 years) from malaria incidence reporting system.	**None**	To investigate whether there has been geographic expansion of Malaria transmission in South Africa	Hierarchical full Bayesian spatial modelling – Poisson model	Spatial distribution of the recent rise in malaria incidence in South Africa is uneven, and strongly suggests an expansion of areas of high malaria risk.	Smoothing of small-area maps of incidence and growth in incidence (trend) is important for interpretation of the spatial distribution of disease incidence and the spatial distribution of rapid changes in disease incidence.
58	Mabaso et al.	2005	Zimbabwe (1988 – 1999)	Monthly malaria case data collated at a district level by the National Malaria Control Programme (NMCP).	Environmental covariates. Rainfall (monthly), vapour pressure, temperature (maximum and minimum), Normalized difference vegetation index.	To quantitatively describe and map malaria seasonality	Bayesian analytical framework (Spatio-temporal model with a Poisson distribution)	Highest risk coincides with areas of relatively high rainfall and elevated temperatures.	The use of a covariate adjusted empirical model may prove useful for predicting seasonal risk pattern across southern Africa
59	Mabaso et al.	2006	Zimbabwe (1988 – 1999)	Annual clinical malaria case data for children under the age of five reported in 58 districts covering the whole country	Climatic covariates, malaria data.	To describe year to year variation of malaria incidence.	Bayesian negative binomial models	A spatially varying risk pattern that is not attributable only to climate.	Need for the development of Climate-based Malaria early warning systems (MEWS) capable of predicting seasonal to inter-Annual variations.
60	Macharia et al.	2018	Kenya (1980 – 2015)	PfPR surveys data undertaken in Kenya over the study period	None	To predict annual malaria risk	A spatio-temporal geostatistical model	Elevated risk in counties along the lake region and coastal region.	The coverage of good quality laboratory and clinical services, reporting and, surveillance should be reinforced based exceedance probability.
61	Mfueni et al.	2018	DRC, Uganda, Kenya (2013 -2015)	Malaria data from the Demographic and Health Surveys (DHS) and Malaria Indicator Surveys (MIS)	None	To estimate the true prevalence of malaria	Bayesian multinomial modelling framework	The apparent prevalence found by light microscopy was systematically lower than the ones based on rapid diagnostic tests.	In the absence of a gold standard test, Bayesian models can assist in the optimal estimation of the malaria burden, using individual results from several tests and

									expert opinion about the performance of those tests
62	Midekisa et al.	2012	Amhara Region, Ethiopia (2001 – 2009)	Monthly malaria case data for 12 districts	Environmental data, meteorological data	To quantify the relationship between malaria cases and remotely sensed environmental variables	Time series - SARIMA models	Malaria risk indicators such as satellite-based rainfall estimates, LST, EVI, and ET exhibited significant lagged associations with malaria cases in the Amhara region and improved model fit and prediction accuracy.	This study highlighted the potential for integrating modelling approaches based on historical case data (early detection) and environmental data (early warning) to enhance the effectiveness of malaria risk forecasting efforts.
63	Millar et al.	2018	Bunkpurugu-Yunyoo District, Northeast Ghana (2010 – 2013)	Malaria status data from six biannual surveys, with a total of 10,022 children between the ages 6 to 59 months.	Demographic and socioeconomic, malaria intervention, remote sensed data.	To identify the factors that shape the spatiotemporal patterns of malaria prevalence	Bayesian probit regression model	Study risk factors did not exhibit prominent difference between the rainy and dry seasons.	These findings lend strong support for the usefulness of Bayesian model averaging (BMA) as a statistical tool for detecting complex patterns in malaria risk factors.
64	Mirghani et al.	2010	Gezira State, The Sudan (1999 – 2009)	Malaria data from cross-sectional surveys undertaken 88 villages.	None	To investigate the space-time clustering of P. falciparum infections	Cluster analysis – Bernoulli model	Low malaria transmission in the state of Gezira and the presence of spatial and space-time clusters in the south of the state.	Improved surveillance data that allows for the analysis of seasonality, age and other risk factors need to be collected to design effective small area interventions as Gezira state targets Malaria elimination.
65	Mlacha et al.	2017	Dares Salaam, Tanzania (2012 -2013)	Facility data of individual patients extracted from the laboratory registry books	None	To investigate whether routine data could be used for mapping spatial heterogeneities.	Cluster analysis	Recording simple points of reference during routine health facility visits can be used for mapping malaria infection burden on very fine geographic scales.	Techniques used here can be scaled up to other comparable low-income settings.
66	Mukonka et al.	2014	Nchelenge District, Luapula Province, Zambia (2006 – 2012)	Yearly aggregated information on cases of malaria, malaria deaths, use of malaria diagnostics, obtained from the Nchelenge District Health Office.	None	To report on the persistent high burden of malaria following the scale-up of control interventions and the presence of insecticide resistance.	Descriptive statistics	Malaria prevalence remained high, increasing from 38% in 2006 to 53% in 2012.	Quality information at fine spatial scales will be critical for targeting effective interventions and measurement of progress.
67	Mukonka et al.	2015	Zambia (Jan 2009 – Dec 2014)	Monthly reported, district-level, diagnostic data of	Year, population density, access to railroad in each	To investigate the progress of malaria diagnosis, spatial	Cluster analysis	Significant, spatio-temporal clusters of malaria spotted in 2014.	Incorporating other readily available geospatial or other analytical methods that will

				malaria incidence were collected from the National Malaria Control Center (NMCC).	district, proximity to water body, access to formal road.	distribution of the absolute number of cases diagnosed clinically as well as the determinants and underlying risk factors.			allow spatial decision support systems to thrive
68	Mwakalinga et al.	2016	Dares Salaam, Tanzania (2010 – 2013)	Malaria infections parasitological and entomological survey data	None	To describe how hotspots of spatially clustered locations with elevated infection prevalence and vector densities were mapped.	Cluster analysis	Seven hotspots of spatially clustered elevated vector density and eight of malaria infection prevalence detected in both phases	Routine, spatially comprehensive, longitudinal entomological, parasitological surveillance systems will be required to eliminate transmission
69	Ndiath et al.	2015	Keur Soce, Senegal (June – December)	408 confirmed malaria cases from demographic survey site.	Socio-economic, human predictors and environmental factors, bed net use, household size, temperature, rainfall.	To explore and analyse the spatial relationships between malaria occurrence and socio-economic and environmental factors.	Geographically weighted regression	Strong spatial relationship of malaria occurrence with modelling based on GWR and OLS showing important risk factors of malaria hotspots.	An understanding of the geographical variation and determination of the core areas of the disease provides explanation on possible proximal and distal contributors to malaria elimination.
70	Ndiath et al.	2014	Keur Soce, Senegal (Nov 2013)	Confirmed malaria cases from a cross sectional survey in 74 villages	Socio-economic factors	To identify malaria clusters	Cluster analysis	Considerable variation of malaria prevalence between villages which cannot be detected in aggregated data.	With malaria decline, intervention and treatment strategies may need to be adapted to the context of malaria hotspots.
71	Nguyen et al.	2020	Madagascar (2013 – 2016)	Monthly case reports submitted by health facilities.	EVI, Temperature, TCB, TCW, TSI	To construct a statistical modelling framework for characterising malaria seasonal patterns.	Spatio-temporal monthly proportion model	Monthly health facility data can be used to establish seasonal patterns in malaria burden and augment the information provided by household prevalence surveys.	Malaria seasonality maps are useful for targeting interventions such as seasonal malaria chemoprevention and indoor residual spraying.
72	Noor et al.	2013a	Namibia (1969 -1992)	Plasmodium falciparum prevalence data from 3,260 geo-coded time-space locations from	Ecological and climatic determinants, urbanization, temperature suitability index, EVI, annual average precipitation, proximity to main water features.	To provide an epidemiological and control context and the likely impact of interventions.	Bayesian model-based geo-statistical (MBG) framework	Low intensity transmission during a ten-year period of wide-scale control activities between 1969 – 1979.	The combination of climatic anomalies, insecurity, cross-border movement and a declining efficacy and coverage demonstrate how fragile control effects.

				archives covering an examination of 230,174 individuals.					
73	Noor et al.	2008	Somalia (2005, 2007)	Data from a national malaria cluster sample survey in 2005 and routine cluster surveys in 2007	Climatic and survey covariates, EVI, Precipitation and temperature, distance to permanent water bodies, temperature, month of survey.	To predict continuous maps of malaria prevalence and define the uncertainty associated with the predictions.	Bayesian geostatistical (kriging) techniques	The maps showed that malaria transmission in Somalia varied from hypo- to meso-endemic.	The use of geostatistical methods can help focus surveillance efforts and define those areas where uncertainty exists, guiding future sampling
74	Noor et al.	2012b	Sudan (Jan 2000 – Dec 2010)	Community PfPR data from cross-sectional surveys	Urbanization, precipitation, EVI, temperature, distance from water body	To generate a map of malaria risk	Space-time Bayesian geostatistical methods	Meso and hyperendemic risk were in the south.	Mapping should be a dynamic exercise to be updated with new empirical and environmental data every few years.
75	Noor et al.	2009	Kenya (1975 – 2009)	Plasmodium falciparum parasite rate data were assembled from cross-sectional community-based surveys undertaken	Urbanization, altitude, temperature (max), precipitation, enhanced vegetation index, distance to main water bodies.	To predict malaria risk.	Bayesian geo-statistical spatial-temporal framework	Majority of Kenyans live in areas of very low P. falciparum risk.	Tracking epidemiological changes of risk demands a rigorous effort to document infection prevalence in time and space to remodel risks and redefine intervention priorities.
76	Noor et al.	2014	Africa (2000 – 2010)	PfPR data from the combinations of medical intelligence reported case incidence.	Precipitation, TSI, EVI, urbanization.	To examine the change in malaria transmission intensity	Bayesian space-time model	Substantial reductions in malaria transmission have been achieved in endemic countries in Africa over the period 2000–10.	Future changes in malaria burden needs an extensive assembly of data to understand the complex array of factors.
77	Noor et al.	2013b	Northern Namibia (1967 – 1992)	Age-corrected geocoded community PfPR survey data	Temperature suitability index, enhanced vegetation index, annual average precipitation, proximity to main water features.	To estimate receptive and current levels of malaria risk	Bayesian space-time MBG model	Highest receptive risks were observed in the northern regions along the border with Angola and Zambia.	Receptive risk is an important component and demands the use of pre-intervention data and careful selection of a most parsimonious period likely to represent a point of rebound should malaria transmission re-establish.
78	Noor et al.	2012a	Somalia (2007 – 2010)	*PfPR* prevalence survey data	Climate and environmental predictors.	To measure the receptive risks of malaria.	Space time geostatistical model	The two maps show significantly divergent transmission scenarios in which the contemporary map describes the majority of Somalia as hypoendemic and while the receptivity map shows a largely mesoendemic transmission profile.	Compared with maps of receptive risks, contemporary maps of transmission mask disparities of malaria risk necessary to prioritise and sustain future control.
79	Nyadanu et al.	2019	Ghana (2010 – 2014)	Clinically diagnosed malaria cases for outpatient	Socio-demographic determinants.	To visualise the influence of sociodemographic	Cluster analysis	The incidence of malaria increased over time with cluster locations detected and the socio-demographics	To complement sophisticated spatial regression models, the easily interpretable ERMs and

				visits at all health facilities		risk factors on the geographical distribution of malaria at local level of public health administration in Ghana.	(Global and local Moran I indices)	had positive spatial autocorrelations with malaria incidence.	CCMs could be used to specify where disease-risk factor associations.
80	Okunola et al.	2019	Nigeria (2000 – 2015)	Malaria incidence from the Demographic and Health Survey database.	Rainfall, Temperature	To evaluate the spatial and temporal association between the incidence of malaria and some environmental risk factors in Nigeria.	Cluster analysis (Local Moran I indices)	The spatial statistical models adopted are important to design a prompt and early malaria transmission mitigation support system in suspected regions.	The models can help to generate malaria risk map and spatially channel available resources to the disease hot spots.
81	Onyiri	2015	Nigeria (1999 - 2007)	Malaria prevalence data from surveys, in published and unpublished sources.	Environmental variables (NDVI, EVI, Leaf area index, LST, Land use/Land cover, Distance to water bodies, rainfall)	To map malaria prevalence in Nigeria.	Statistical modelling - Logistic model	Malaria prevalence varies from 20% in certain areas to 70% in others.	National risk map will allow planners to identify malaria high-endemicity areas for appropriate intervention.
82	Ouedraogo et al.	2018	Ouagadougou, Burkina Faso (Jan 2011 – Dec 2015)	Weekly malaria cases extracted from the national epidemiological surveillance system and an independent malaria database	Meteorological factors; Rainfall (Amount and number of events), humidity (max and min weekly averages), temperature, wind speed.	To determine the spatio-temporal dynamic of malaria considering meteorological factors.	General Additive model (GAM), Cluster analysis	Study highlighted the spatial variability and relative temporal stability of malaria incidence in study area.	A real time monitoring system should be implemented based on the national monitoring system.
83	Ouédraogo et al.	2020	Burkina Faso (2013 – 2018)	Monthly count data on severe malaria cases and malaria deaths in children under 5, aggregated at district level.	Malnutrition, ACT, mRDT, Distance to health facility.	To quantify the strength of the association of malaria control programs with monthly mCFR trends.	Bayesian spatiotemporal zero-inflated Poisson model	Our findings highlighted locations that are most in need of targeted interventions and the necessity to sustain and strengthen the launched health programs to further reduce the malaria deaths.	Study findings could guide the NMCP in hierarchizing the health districts for the implementation of appropriate control interventions.
84	Peterson et al.	2009	Adama, Ethiopia (2003)	Clinical malaria infections incidence in residential compounds were obtained from a patient database at the Adama Malaria Laboratory.	Weather factors. Distance to breeding site, residential factors.	To describe the temporal and spatial clustering of malaria cases and identify factors associated with malaria clustering	Cluster analysis	Residential proximity to vector breeding sites, type and status of residential compound, temperature, and rain patterns were all important factors shaping malaria risk.	Small-scale malaria mapping can be used in conjunction with targeted vector control interventions to enhance the effectiveness of urban malaria control in Africa.
85	Pinchoff et al.	2015	Nchelenge District, Zambia (April 2012 – December 2014)	Prevalent malaria infections (RDT) using data from the cross-sectional surveys of 461 households	Landscape characterization. Normalized Difference Vegetation cover, distance to water body, Rainfall, distance to nearest road,	To generate and validate a high-resolution empirical risk map	Spatial prediction risk maps - Logistic regression models	Malaria increased with proximity to streams and during the rainy season. Household malaria risk was 50% higher during the rainy season compared with the dry season	Generating high resolution, predictive risk maps that highlight heterogeneity of malaria can help target limited resources more efficiently.

					slope, elevation, distance to health facility				
86	Raso et al.	2012	Côte d'Ivoire (1988 – 2007)	Plasmodium spp. infection prevalence using different data sources.	Environmental covariates. Rainfall (mean), NDVI, elevation, temperature, elevation, distance to water body.	To predict the geographical distribution of malaria infection risk in children at high spatial resolution.	Bayesian geo-statistical logistic regression	Diverse risk profile, with high risk pattern in the north-central and western area.	Future studies need to try to consistently and correctly report species-specific information on Plasmodium prevalence in order to improve control
87	Rouamba et al.	2020	Burkina Faso (2015 – 2017)	Community aggregated monthly MiP cases were downloaded from Health Management Information System and combined with covariates from other sources	Temperature, Rainfall, IPTp-SP, socio-economic factors.	To describe the spatio-temporal dynamics of MiP at the community-level and assessed health program effects.	Bayesian hierarchical spatio-temporal Poisson models, Cluster analysis	Endemic countries, in their effort to optimize malaria burden surveillance and assess the progress of health programs should integrate a disease modeling approach and a geographic information system in a routine surveillance platform to promote the production and regular update of information on the malaria risk and the MiP burden.	The provided risk maps are useful tools for highlighting areas where interventions should be optimized, particularly in high-risk communities.
88	Rumisha et al.	2014	Tanzania (Oct 2001 – Sept 2004)	Malaria entomological data were collected for the period of 3 years	Environmental factors, climatic factors.	To analyse large and highly variable entomological data for malaria transmission heterogeneity.	Bayesian geo-statistical binomial and negative binomial models with zero inflation	Malaria transmission was mostly influenced by rain and temperature, and the effect of environmental variables differs significantly between species.	The methodology described in this study allows estimation of EIR while adjusting for both, temporal and small area spatial variations in a systematic and thorough manner.
89	Selemani et al.	2015	Tanzania (Jan 1999 – Dec 2011; Jan 2002 – Dec 2012)	Individual and yearly malaria deaths were extracted from the Rufiji and Ifakara HDSS database.	Socio-demographic variables.	To examine spatial and spatio-temporal trends and clustering of mortality due to malaria.	Spatial and space-time clustering using a Poisson model	The clustering of malaria mortality indicates heterogeneity in risk of study areas	Priority control in hotspot villages and high-risk areas reported, including consistent significant clustering villages.
90	Selemani et al.	2016	Tanzania (1999 - 2011; 2002 – 2012)	Yearly malaria deaths were extracted from the Rufiji and Ifakara HDSS database covering the study period and aggregated yearly.	Environmental and climatic data.	To assess the effect of mosquito net ownership on malaria mortality in Tanzania.	Space time hierarchical model	Models with spatial and temporal random effect terms performed better for goodness of fit and the effect of mosquito net ownership was higher compared to other models.	Inclusion of Spatial and temporal terms in the Bayesian model framework is important.
91	Sewe et al.	2016	Western Kenya (2003 – 2012)	Malaria mortality data from a surveillance system database	Climatic factors	To explore the lagged association of climatic factors on malaria mortality in three areas in Western Kenya.	Distributed Lag Non-Linear Models	Lag patterns and association of remotely-sensed environmental factors and malaria mortality.	Development of locally based early warning forecasts for timely control actions.

92	Seyoum et al.	2017	Southwest Ethiopia (July 2008 – June 2010)	Annual malaria incidence for 2 years, from a longitudinal cohort study of 2040 children.	None	To explore the spatial and spatio-temporal distribution of P. falciparum and P. vivax malaria episodes	Cluster analysis	Hotspots of P. falciparum incidence in children were more stable at the geographical level and over time compared to those of P. vivax incidence during the study period.	Further research is needed to better understand the impact of asymptomatic and sub-microscopic infections in endemic areas of Ethiopia, and to assess whether their spatial distribution differs from that of symptomatic infections
93	Shaffer et al.	2020	Mali, Senegal and Gambia (2013 – 2016)	Plasmodium falciparum infection at four field sites in three different countries.	ITN, IRS	To test for spatial, temporal and spatio-temporal clustering of P. falciparum infection.	Cluster analysis (spatio, spatio-temporal)	Clustering of P. falciparum infection also affects the effectiveness of control interventions	Testing for spatial, temporal and spatio-temporal clustering permits the generation of hypotheses for the clustering observed and the testing of candidate interventions to confirm or refute those hypotheses
94	Simon et al.	2013	Botswana (2008 – 2012)	Annually aggregated, district-level malaria case data from the national passive malaria surveillance data for five years	Population data, IRS, LLIN coverage	To describe trends in malaria morbidity and mortality.	Poisson regression and hotspot analysis	Hotspot analysis revealed the variation of malaria transmission levels in the country.	Operational research regarding malaria related treatment seeking behaviour and malaria risk mapping
95	Siraj et al.	2015	Debre Zeit, Ethiopia (1995 – 2005)	Monthly P. falciparum confirmed cases confirmed from individuals self-presenting at the health facilities	Population density, temperature, rainfall, NDVI, altitude.	To explore other environmental and demographic factors that may contribute to malaria's highland reservoir	Generalized linear Mixed model	Inclusion of the random effects (both structured and unstructured) resulted in the best model	Importance of considering risk hot spots at different spatial scales.
96	Snow et al.	2017	Sub-Saharan Africa (SSA) (1900 – 2015)	PfPR data sourced from published and unpublished sources assembled for 21 years for children between 2 and 10 years.	None	To provide an empirical basis to define the long-term nature of malaria transmission cycles.	Bayesian hierarchical binomial model	An overall recession in malaria transmission intensity over the last 115 years. Independent abiotic factors related to economic growth may have contributed to this overall recession.	The unique endemicity that prevails in Africa cannot be ignored in any global effort to eliminate P. falciparum
97	Snow et al.	1998	Kenya (1960 – 1998)	Malaria data from community-based cross-sectional parasite surveys for children between 0 and 10 years.	Meteorological data, Remotely sensed data.	To define areas of Kenya unsuitable for stable transmission.	Fuzzy logic climate suitability model	Combined transmission, population and disease-risk model suggested that every day in Kenya approximately 72 and 400 children below the age of 5 years either die or develop clinical malaria warranting in-patient care, respectively.	Increasing need to provide spatial distribution maps of the clinical burden of *P.falciparum*

98	Solomon et al.	2019	Southern - Central Ethiopia (2014 – 2016)	Weekly malaria cases	LLINs, IRS	To assess asses the spatiotemporal patterns of malaria transmission in the presence of different malaria controls and to determine the risk factors for the observed malaria clustering.	Cluster analysis (purely spatial, purely temporal, and space-time)	Spatial, temporal, and spatiotemporal clustering of malaria was detected in all types of malaria infection. Malaria infection was not randomly distributed at the kebele, village, or household levels in areas with different malaria control interventions	The results of this study can be used in planning and implementation of malaria control strategies at micro-geographic scale.
99	Ssempiira et al	2018a	Uganda (Jan 2013 – Dec 2016)	District-aggregated monthly malaria cases, reported by two age groups, defined by a cut-off age of 5 years from the DHIS2.	Malaria interventions (ITN coverage), socio-economic and Climate data, remotely sensed data (LST, NDVI, rainfall, Altitude), distance to water bodies.	To estimate the effects of malaria interventions on its spatio-temporal patterns of the disease incidence	Bayesian spatio-temporal negative binomial model	The space - time patterns of smoothed malaria incidence revealed heterogeneously distributed burden of high intensity in children under 5 years, but rather homogeneous spatial patterns of low intensity in older individuals.	Close similarity of disease patterns obtained in this study to The population-based survey estimates highlight The relevance of routinely collected data in disease burden estimation.
100	Ssempiira et al	2018b	Uganda (Jan 2013 – Dec 2017)	Monthly data on confirmed malaria cases by RDT was extracted from the DHIS2 covering the period of five years	Environmental data, socio-economic data and malaria treatment seeking behaviour	To investigate the effects of climate on the spatio-temporal trends of malaria incidence .	Bayesian spatio-temporal Negative binomial model	Results have attested to a significant interplay between climatic and intervention effects and indicated that climatic factors have had a detrimental effect on malaria reduction gains achieved through accelerated interventions scale-up	NMCP should create synergies with The National Meteorological Authority (NMA) and harmonize interventions deployments
101	Ssempiira et al	2017b	Uganda (2014 – 2015)	Parasitological and interventions data obtained from the MIS data 2014–2015 for children aged 0 – 59 months	Environmental factors/ Demographic and socio-economic factors	To assess intervention effects on malaria prevalence.	Bayesian geostatistical logistic regression	Environmental factors, namely, land cover, rainfall, day and night land surface Temperature, and area type were significantly associated with Malaria prevalence.	This calls for epidemiological and entomological research in the different settings of the regions to determine the best tools suitable for each region.
102	Ssempiira et al	2017a	Uganda (2009 – 2014)	Parasitological and interventions data obtained from the MIS data of 2009 and 2014–2015.	ITN, LST, Rainfall, Area type, wealth index, IRS, ACTs, Altitude, Land cover	To quantify the effects of control interventions on parasitaemia risk changes between the two MIS in a spatio-temporal analysis.	Bayesian geostatistical and temporal models.	Results demonstrate an important protective effect of interventions on the decrease of parasitaemia odds from 2009 to 2014. ITNs, IRS and ACTs were associated with a parasitaemia odds reduction	The varying effects of interventions calls for selective implementation of control tools suitable to regional ecological settings.
103	Sturrock et al.	2014	Swaziland (Jan – April; 2011 – 2013)	Routinely collected health facility level malaria case data from 165 public facilities.	Environmental and ecological variables, temperature (Min, Max and Mean LST), NDVI, NDWI, EVI, TWI.	To predict Malaria risk, and associated uncertainty at fine resolution.	Hierarchical Bayesian geostatistical logistic model	Fine-scale predictions are able to discriminate between cases and pseudo-controls.	Mapping malaria risk using appropriate methods is an integral component of efficient resource allocation.
104	Yankson et al.	2019	Ghana (2016)	Malaria RDT outcomes collected from the 2016 MIS	Age, gender, SE, wealth status, IRS, residence, region	To analyse and map malaria risk in children under 5 years old.	Geo-statistical model - Binomial	-Prevalence was shown to increase with child's age, younger children have the lowest prevalence at 16% among children below 12 months,	Model-based geostatistical analysis in conjunction with active surveillance is an effective, practical strategy for

								and older children showing the highest prevalence at 28% among children between 48 and 59 months.	producing accurate local-scale maps that can pick up hotspot areas in disease burden that can benefit immensely from targeted interventions.
105	Yeshiwondim et al.	2009	East Shoa, central Ethiopia (Sept 2002 – Aug 2006)	Individual-level daily malaria morbidity data from six specialized Malaria diagnosis and treatment centers in 543 villages	None	To identify malaria "hotspot" villages and produce "hotspot" maps in different periods of observation.	GLM – Poisson model and cluster analysis	Statistical analysis of malaria incidence by sex, age, and village through time reveal the presence of significant spatio-temporal variations.	Determining the underlying differences in exposure or behavioral risk factors to prevent incidence spikes in certain age groups and in men.
106	Zacarias & Andersson	2011	Maputo province-Mozambique (1999 – 2008)	Monthly counts of malaria cases in each district	Environmental factors	To provide a spatio-temporal analysis of malaria incidence risk.	Bayesian geostatistical Poisson model	Malaria incidence was associated to humidity and maximum temperature.	Climatic predictors can be used to explain malaria incidence risk.
107	Zacarias & Majlender	2011	Maputo province-Mozambique (1999 – 2008)	Infant malaria cases at the district level provided by provincial health directorate	Environmental factors - rainfall, temperature (min/max/mean), humidity	To analyse the space-time variation of malaria incidence.	Space-time Poisson model	Malaria cases are mostly concentrated in months October to March which coincides with wet season in Mozambique	Findings may be useful for malaria control, planning and management.