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Preamble

African Journal of Science, Technology and Engineering (AJSTE) is an academic peer reviewed publication that hosts original, innovative research and scholarly articles that contribute to growth of knowledge in Science, Technology, Engineering and related disciplines. The journal provides an interactive platform for researchers to showcase the latest innovations and developments in the disciplines. The articles featured in this issue showcases groundbreaking research dedicated to advancing our understanding of the complex scientific phenomena describing assessment of land use and land cover changes in geographical section of Uasin Gishu County of Kenya, management of malaria in pregnancy, the role of public participation in health communication campaigns and use of rule based classification technique in identifying "sprawl" areas.

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MECHANISMS FOR PUBLIC PARTICIPATION IN HEALTH COMMUNICATION CAMPAIGNS: CASE OF THE UNIVERSAL HEALTH COVERAGE IN KENYA

Amukuzi, M. K.

Moi University

Email: mamukuzi@riarauniversity.ac.ke

Abstract

Public participation, partnerships, consultation and effective communication are paramount to sustainable public health management. Such interventions are presumed to have a positive impact on health outcomes. Kenya adopted Universal Health Coverage (UHC) as one of the big four priority agendas and piloted the program was implemented in 2018 in four Counties namely; Isiolo, Kisumu, Machakos, and Nyeri. The Pilot faced numerous problems including lack of adequate information that led to slow uptake and near failure of the program. There was slow response by the public, no guidelines as to what constitutes public participation and problems related to vastness of the country and ethnic diversity. The objective of this study was to analyze the mechanisms of public participation in health communication campaigns. A systematic review of secondary data was done. Results showed that public participation plan for implementation of UHC in Kenya was not clearly outlined.

Keywords: *Public Participation; Health Communication Campaigns; Universal Health Coverage.*

Introduction

Public participation is important for effective implementation of any key developmental programs. This has been clearly outlined in article 10 of the Constitution of Kenya 2010, where democracy and people's participation, human rights, among others, are identified as essential national values and principles of governance. In Africa, public participation is viewed as a key cornerstone to attainment and advancement of both democracy and good governance (Nthiga and Moi, 2021).

Public participation has been defined as the involvement of those who may be affected by or interested in a decision through formal or informal channels (Lee and Sun, 2018) and invariably involves engagement of individuals with the various structures and institutions.

According to Rural Health Information Hub (2023) health communication includes verbal and written strategies to influence and empower individuals, populations, and communities to make healthier choices. It was argued that this often integrates components of multiple theories and models to promote positive changes in attitudes and behaviours. Health communication campaigns thus need to include public participation for them to reach out to the desired population

The Universal Health Care concept started in the 1970s and 2000s when Southern and Western European countries introduced universal health coverage. They built on previous health insurance programmes to provide health coverage for their entire populations (Kahenda, 2021). Universal Health Coverage refers to a global health system that ensures all individuals have access to quality healthcare services without having to endure financial destitution. UHC has two fundamental goal namely: optimizing the impact of healthcare services, and eradicating financial crises, impoverishment or bankruptcy that may arise from high healthcare costs (Mwaniki and Ogoti, 2023).

In Kenya, the Universal Health Coverage pilot programme was launched in 2018 in Nyeri, Kisumu, Machakos and Isiolo Counties. These counties were selected as pilot sites based on the prevalence of unique health needs among their populations (Mwaniki and Ogoti, 2023). The goal was to eventually scale up the program to all the 43 Counties. However, according to Mwaniki and Ogoti (2023), of the four Counties, only Isiolo and Machakos carried the pilot to conclusion but with difficulties. Isiolo encountered difficulties with finances and budgeting (Thinkwell Global, 2020). Kisumu was a non-start from the beginning and Nyeri eventually terminated the pilot due to financial constraints.

According to the Ministry of Health report (2020), progress towards UHC is a means to realizing the right to health as enshrined in the Kenyan Constitution, and ambitions set out in Vision 2030, the Kenya Health Policy 2014 – 2030, Sessional paper No 2 of 2017, Health Act 2017 and the Big 4 Agenda. This is also in line with Kenya's commitment to Sustainable Development Goals (SDGs). The United Nations SDG Goal 3 aims to promote healthy lives and well-being. This goal addresses all major health priorities including: reproductive, maternal, newborn, child and adolescent health, communicable and non-communicable diseases as well as the universal health coverage.

Public participation globally

Public participation and communication campaigns have been researched widely and globally. In the declaration of Alma-Ata in 1978, Member States agreed that community participation was a fundamental component of primary health care and that the people have a right and duty to participate individually and collectively in the planning and implementation of their health care (WHO report 2020). Since then, health researchers, practitioners and policy-makers have worked to develop a meaningful set of practices that contribute to strengthening community participation. However, carefully designed, meaningful and sustained public engagement or participation requires considerable support (Abelson, 2010).

Countries such as Brazil, France, Japan, Thailand, and Turkey have shown how UHC can serve as a vital mechanism for improving the health and welfare of their citizens. Such mechanisms can also lay the foundation for economic growth grounded in the principles of equity and sustainability (The World Bank development report, 2021). Japan achieved Universal Health Coverage (UHC) in 1961. It has been leading in efforts to promote Universal Health Coverage (UHC) worldwide. The goal behind these efforts is to improve health outcomes by making access to high-quality health services more affordable and equitably distributed. Raman and Sheikh (2016) expound that community participation can be considered as the backbone of universal health coverage (UHC). This has been extensively demonstrated through the successful experiences of Thailand and Brazil, among others. They argue that optimized roles and effective performance of local or grassroots organizations are essential to the integration of community participation for delivering UHC.

Africa has made initiatives to overcome the barriers that have hindered accessibility to good health services. One such initiative is a conference by the WHO Regional Office for Africa, in collaboration with the Government of Cabo Verde. This forum was convened in Praia, Cabo Verde in March 2019, under the theme Achieving Universal Health Coverage and Health Security: The Africa We Want to See (WHO, 2021). Some of the recommendations at the conference were that the role of the community in attainment of Universal Health Coverage, health security and ultimately the Sustainable Development Goals are key. It was also observed that the public sector of Africa alone cannot achieve these interrelated goals and that other partners, such as the private sector, must be engaged.

In Rwanda, UHC means that all people have access to the health services at all times, without financial constraints. This includes a full range of essential health services, from health promotion to prevention, treatment to minimize out of pocket payment (Wilson, 2019; Mason, 2020). Thus, participatory planning is a hallmark of district development plans, which build from bottom-up consultations at the cell and sector levels (Brinkerhoff et al., 2009).

Challenges faced in the piloting the UHC programme in Kenya

Kisumu County was selected for piloting because of the prevalence of communicable diseases such as HIV and malaria, but there was no evidence from communication presented to highlight the voices of marginalized groups including women, sex workers, adolescent girls and young women, and the gay in society. This notable exclusion raised concerns that the needs of these groups were not prioritized and the objective of addressing health equity may have fallen short as a result (Hammonds et al., 2019).

Otambo et al., (2020), further carried out research in Kisumu County and revealed that there were misconceptions and misunderstanding of what UHC entailed both to the community and to health care workers. Planning and sensitization was inadequately done and barriers to effective implementation of UHC were noted. Thus, the communities were confused about the program and its importance. This failure to engage in the county-level consultations risked the legality of the entire UHC campaign. This approach is not in line with UHC 2030 commitments which can play a role in bringing diverse stakeholders together to try to direct the Kenyan UHC 2030 on a legitimate path that reflects the right to health commitments in the constitution.

Nyeri, another pilot County, also experienced problems. Thus, efforts to establish the program came to abrupt halt therefore inconveniencing citizens who had been registered for these services. Information was not given to the residents on how long the pilot program was on; neither were they advised not to discontinue their subscription to other service providers such as The National Health Insurance Fund (NHIF).

A research conducted by Infotrak People's Health Movement-Kenya, (2020) which is an independent civil society network of health professionals in Kenya, including researchers, human rights defenders, health activists, legal advisors, nurses, doctors, and public health professional observed that the pilot project faced several challenges, some of them being; exclusion of communities, human rights violations, inadequate information and resource allocation, corruption, and lack of strategic direction on its implementation Results of the survey pointed to key governance weaknesses including lack of effective citizen participation. This is not in line with the recommendations given by the Kenya Yearbook Editorial Board (2020) that prioritization of Health System Strengthening actions for UHC must be underpinned by a commitment to a human rights-based approach. This is premised on the principle that access to health services is universal, putting a particular emphasis on the poorest, vulnerable and marginalized groups and on the principle of non-discrimination. The Ministry of Health (2020) policy, draws from Article 35 of Constitution 2010 on 'Access to Information'; Thus, all citizens have a right to information held by the State. Additionally, the policy elucidates that, as per County Government Act 2012 part IX 93-95 on communication; county governments shall establish mechanisms to facilitate public communication and access to information in the form of media with the widest public outreach in the country. Therefore, information ought to have been disseminated to all citizens about the program before the pilot; its purpose, goal and duration so that there would be no misconceptions and apprehension of the program. In some places, citizens assumed that the registration process was a means of soliciting votes for the 2022 general election (Otambo et al., 2020).

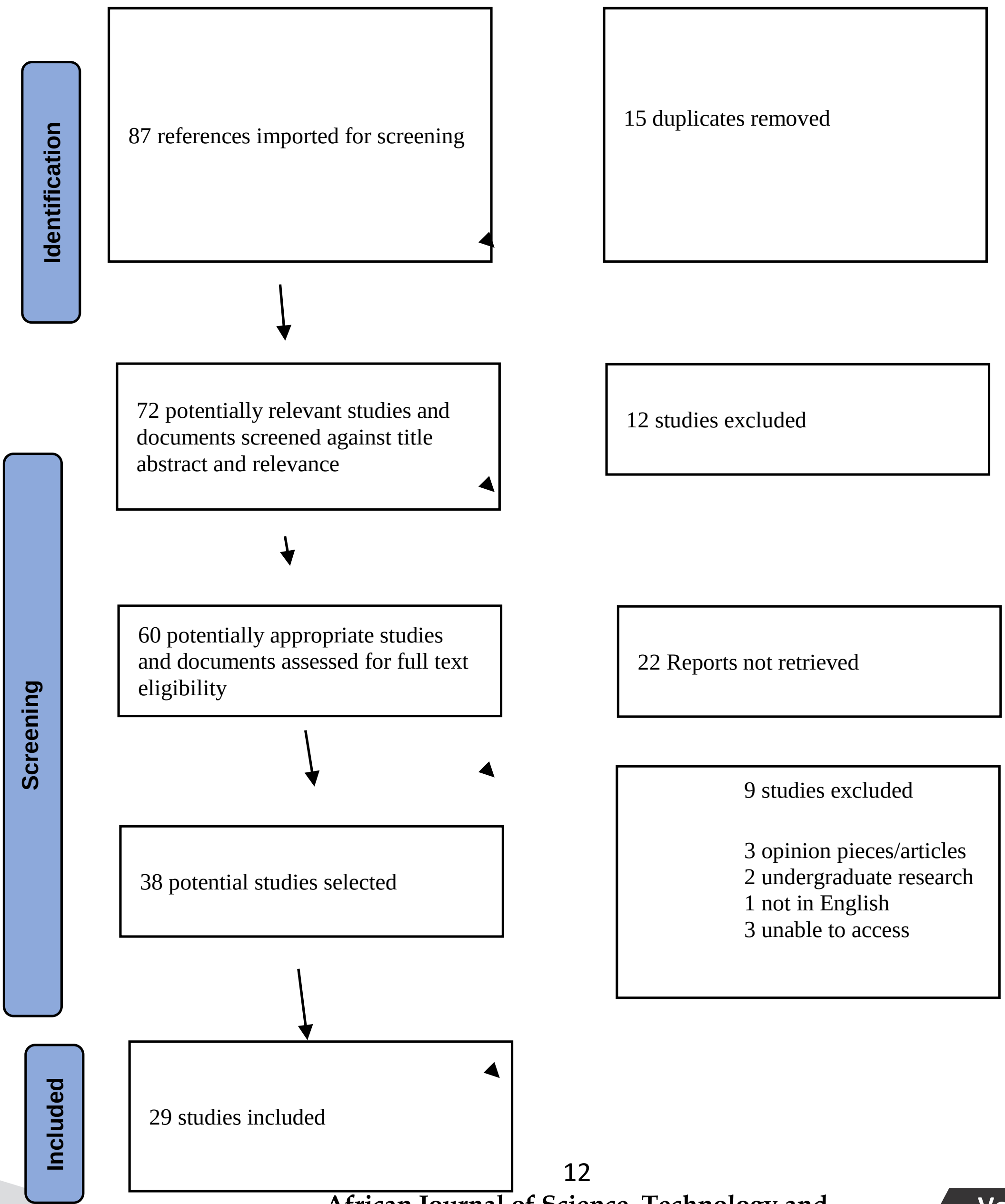
Methodology

The research used a systematic review of existing literature using the PRISMA statement for systematic reviews. This involved: Searching for relevant databases, identifying key words, reviewing abstracts and articles and documenting the results. Eligible studies included those that involve public participation and health communication campaigns and Universal Health Coverage both in Kenya and globally. The criteria also included reviews that examined documents and policies designed by professionals that mobilized communities to take up the benefits of healthcare. The review explored theory and practice on: Public participation including models, conceptual frameworks, lessons learnt, implementation, and sustainability.

Research Findings

This search identified 87 articles, of which 72 underwent full-text screening; 24 articles met the inclusion criteria for review. The PRISMA diagram is presented in Fig. 1.

Fig. 1. PRISMA Flow Diagram



The core set of (29) studies included: Those on public participation (6); Health communication (6); documents and policies (6); Universal health coverage (10).

Synthesis of findings

Key findings have been summarized from each of the sources of evidence, data synthesized and critically interpreted to answer the overarching review question as well as reflecting on public participation, health communication and the UHC program.

The Kenya Universal Health policy (2020-2030) has outlined various components that are envisaged to convey the health sector policy directions, strategies and implementation framework for the period between 2020 and 2030. The policy objectives include; to strengthen access to health services; to ensure quality of health services; to protect Kenyans from the financial risks of ill-health, and to strengthen the responsiveness of the health system in Kenya (Ministry of Health, 2020). These objectives have been clearly outlined but they have not adequately captured the mechanisms for public participation. However, it touches on principles such as; people-centeredness, that the programme should be responsive and appreciate transparency and accountability (Ministry of Health, 2020).

The UHC programme has succeeded in countries such as France, Brazil, Turkey among others. The elements of success include the emphasis on community mobilization which identifies community priorities, engages and empowers community members, and supports their ability to solve local problems. Ethiopia has been cited as one of the African countries that have made progress towards the achievement of the UHC programme. An institutionalized community approach is seen to be effective in making these strides (Wang et al., 2016). Ethiopia's government has used two strategies to enhance community participation and ownership namely: the creation of model families; and the health development army. These strategies aim to engage communities, identify locally prominent challenges that hinder uptake of services, and scale-up best practices (Assefa et al., 2020).

Strategies for public participation

According to Shams, (2018), health behavior is a behavior directed at promoting, protecting, and maintaining health. This also includes reducing disease risks and early death.

Shams suggests that in public health, three key approaches are important inorder to achieve behavior change. These include; education, marketing, and law enforcement for people who consider the behavior change but do not have the required knowledge or skills, education is effective. Equally enforcement of laws and regulation is appropriate for individuals who have no desire to change. This is where public participation brings people together for education and meaningful engagements.

The Ottawa Charter

In 1986, the first International Conference on Health Promotion meeting in Ottawa, Canada came up with a charter for action to achieve Health for All by the year 2000 and beyond. The conference was primarily a response to growing expectations for a new public health movement around the world (Government of Canada, 2017). According to WHO (2020), community engagement is the key to health promotion actions. The five health promotion actions described in the Ottawa Charter include developing personal skills; strengthening community action; creating supportive environments; building healthy public policy, and reorienting health systems. A platform for community engagement can be constructed in any setting. All or any of these health promotion actions can be used in a setting to create structures that tie communities to the UHC agenda and the SDGs.

Arbter et al., (2007) observed that in-depth preparation is essential for participation process to succeed. This way you achieve favourable conditions for the process to go well. Equally, while the process is being carried out, it is well worth checking repeatedly whether the necessary quality criteria are being observed, so that your project stays on course.

Recommendations

The principles outlined by The Kenya Universal Health policy (2020-2030) can be applied to public participation and health communication which as discussed earlier is about people being informed about key developments and here the focus is on healthcare. The programme can be made effective by letting the citizens have a say on the challenges they may have faced in the area of healthcare, what is working and the pain points. They should be allowed to give suggestions on how best the programme can work. Transparency and accountability require that citizens and all stakeholders are made aware of projects being undertaken that could possibly impact them in one way or another. Indeed, the need for ordinary citizens, entrepreneurs and lobbyists to be informed in detail before decisions that affect them are taken cannot be overstated.

Effective public participation through decentralized consultations, calls for needs assessment and planning at all levels, thus, regardless of the level of formality and rigor of the effort, all situation assessments should consider stakeholder voices for a credible process. Stakeholder concerns, issues, and interests must be listened to; the specific opportunities where public input can help to shape the decision identified and any issues or constraints that may affect public participation identified and addressed.

Conclusion

Public participation in health communication campaigns is key to success of the UHC program. This starts with needs assessment which will clearly outline the beliefs, expectations, values, perceptions and the kind of action to be taken.

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World Bank Development Report 2021: Data for better lives

MALARIA PREVENTION IN PREGNANCY: EFFECTIVENESS AND FUTURE STRATEGIES

Wangai, N. L.,[1] Kamau, K. K.,[2] Nderu, W.D.[3], Njoroge, W.[4], Munde E.[5], Marwa, N. I[6], Stanley, K. S[7], Kamau, N. L[8]

Kirinyaga University, Kenya[12345678]

Correspondence: kkamau@kyu.ac.ke

Abstract

Malaria remains a significant global health challenge, particularly for pregnant women in malaria-endemic regions. Malaria in pregnancy poses substantial risks to both the mother and the developing foetus, leading to adverse maternal and neonatal outcomes. Despite considerable progress in prevention and control efforts, there is a need for innovative and sustainable strategies to further reduce the burden of malaria in pregnancy. This review explores future preventive strategies for addressing this issue, focusing on advances in malaria prevention, antimalarial drugs, vaccines, vector control, and health system strengthening. By examining recent research and ongoing initiatives, on malaria prevention in pregnancy, we provide key findings on the effectiveness of the current interventions and challenges and provide insights into promising interventions that can be integrated into comprehensive malaria control programs to safeguard the health of pregnant women and their unborn children.

Keywords: *Malaria Prevention, Pregnancy, Effectiveness, Future Strategies*

Introduction

Malaria is a life-threatening human disease caused by *Plasmodium* parasites transmitted through a bite of infected female Anopheles mosquitoes (WHO 2014). Malaria burden disproportionately occurs among pregnant women alongside less than five-year-olds. Currently, malaria in pregnancy (MiP) is still of great public health concern, especially in areas where the disease is endemic (Uneke 2008). The burden of MiP is particularly significant in sub-Saharan Africa, where the majority of global malaria cases occur, and where the disease is a leading cause of maternal and infant mortality (Desai et al 2007).

The immune system undergoes changes during pregnancy that dampen immune responses so as to accommodate the developing foetus. These changes increase susceptibility of pregnant women to infections, including malaria. MiP poses risks to both the mother and the developing baby. One of the main complications of MiP is maternal anaemia which can lead to severe weakness, fatigue, and even death. Malaria may also lead to poor pregnancy outcomes that manifest as low birth weight and preterm delivery; a leading cause of infant mortality especially in sub-Saharan Africa (Desai et al. 2018). The presence of malaria parasites in the placenta can impair the exchange of nutrients and oxygen between the mother and the foetus, further compromising the health of the pregnant women and the foetus (Wu et al, 2012). Thus, babies born to mothers with malaria are at higher risk of long-term developmental challenges such as cognitive impairments (Fried et al. 2017). This may also increase risk of preterm birth or even stillbirth (Desai et al, 2018).

Owing to the apparent impact malaria exerts on pregnant women, the unborn child and less than five-year olds, multifaceted strategies are currently being implemented to prevent infection as well as avert and/or reduce mortality and morbidity. These interventions include the use of insecticide-treated bed nets, intermittent preventive treatment during pregnancy, and prompt diagnosis and treatment of malaria infections (Desai et al 2018 and Rogerson 2017). These interventions are further reinforced by conducting early malaria diagnosis and educating pregnant women on malaria preventive measures during antenatal care.

Efforts to combat MiP are made through national and international initiatives, such as the national malaria control programs, Roll Back Malaria Partnership and the World Health Organization's Global Malaria Program (Fried et al.2017). These initiatives aim to increase access to malaria preventive measures and effective treatment, as well as to improve overall quality of antenatal care. While tremendous progress has been made in reducing the burden of MiP over the years, there is still much work to be done to safeguard the well-being of pregnant women and their babies. Continued research, funding, and implementation of effective strategies are essential for the fight against MiP and safeguard good pregnancy outcomes for affected populations. This review aims to provide an update on the effective treatment and preventive strategies for MiP.

Methods

A systematic literature search was conducted to identify relevant studies on MiP treatment and preventive strategies. The search included electronic databases and academic journals, focusing on studies published between January 1, 2013 and January 1, 2023 in sub-Saharan Africa. Key terms used to retrieve published articles included "malaria", "malaria AND pregnancy", "malaria AND MiP prevention", "malaria AND MiP prevention" and "MiP AND treatment." Studies were included if they assessed the impact of at least one MiP preventive or treatment strategy such as intermittent preventive treatment (IPT), insecticide-treated bed nets (ITNs), and vector control strategies. The review excluded all studies that did not involve MiP.

Results

A total of 1,135 articles published between 2013 and 2023 were identified. Of these, 526 and 609 were publications on MiP preventive and treatment strategies, respectively (Figure 1). Fifty-six (56) studies on MiP prevention and 52 studies on MiP treatment were reviewed after removal of duplicated articles and after removal of articles that failed to meet the inclusion criteria.

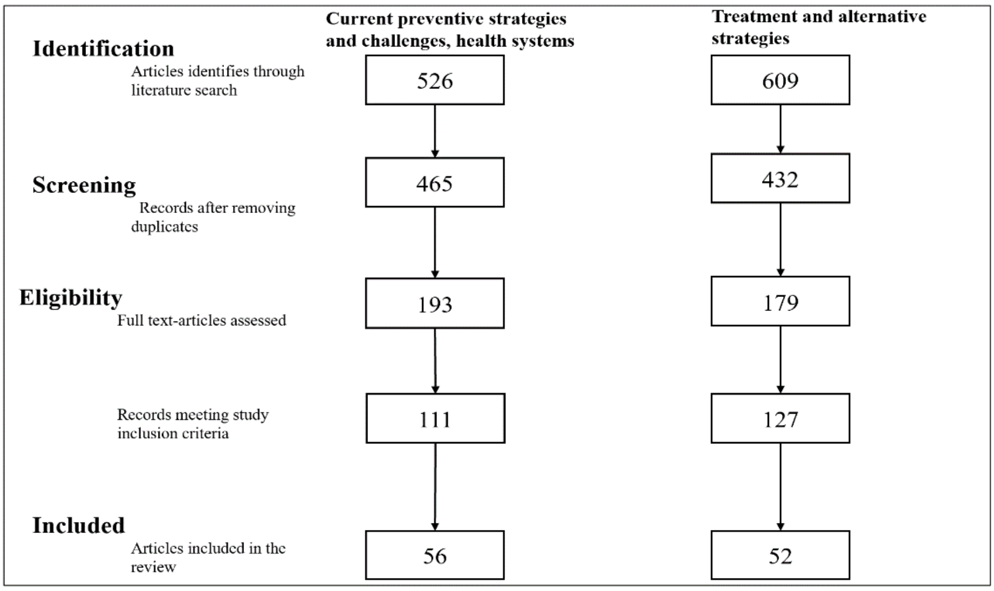

Fig 2: Selection Chart

Discussion

Over the past ten years, significant progress has been made towards bridging prevailing research gaps in MiP prevention and management. This study seeks to review MiP prevention and management strategies for a ten-year period based on studies published between 2013 and 2023.

Intermittent Preventive Treatment in Pregnancy (IPTp) is a key strategy recommended by the World Health Organization (WHO) for the prevention of MiP among pregnant women living in areas in moderate to high malaria transmission. IPTp involves administration of an antimalarial drug during pregnancy, typically sulfadoxine-pyrimethamine (SP) at specified intervals (Shulman et al, 2003). This approach helps to prevent malaria infection during pregnancy, reduce maternal anaemia, and improve pregnancy outcomes. Current WHO guidelines recommend that at least three IPTp doses should be administered from the second trimester of pregnancy with a minimum of one month between doses (Al Khaja et al 2021).

IPTp is mostly administered during routine antenatal care visits (Shulman 2003). Its popularity has grown over the years because it is cost-effective and substantially reduces the risk of malaria-related complications. These benefits are best realized where malaria parasites are sensitive to SP. However, when SP resistant malaria is prevalent, alternative antimalarial drugs may be used (Rogerson 2017) and (WHO 2004). Since IPTp is a valuable tool for MiP control, emergence of resistance to antimalarial drugs for IPTp would reverse gains attained so far (WHO 2014). This implies therefore that antimalarial drugs for IPTp ought to be used with caution to avert an increase and spread of antimalarial drug resistance. One strategy to delay increase of SP resistance is active surveillance of antimalarial drug resistance patterns and adopting IPTp accordingly. To date, efficacy of alternative antimalarial drug combinations of IPTp have been assessed. The efficacy of an IPTp comprising amodiaquine and SP was shown not to be superior to SP-based IPTp (Mlugu et al 2021). Nevertheless, mefloquine has been reported to be a promising alternative for SP IPTp because it has long elimination half-life that provides an extended period of post-treatment prophylaxis and prevents low birthweight (LBW) (D'Alessandro, 2007). In addition, mefloquine prevents placental malaria, clinical malaria, and maternal anaemia at delivery. Poor mefloquine tolerability, however, poses a major challenge for widespread use in IPTp (Figueroa-Romero et al 2022).

Besides mefloquine, other antimalarial drugs have been explored for IPTp or intermittent screening and treatment (IST). This includes co-trimoxazole and antimalarial drug artemisinin-based combination therapy. IPTp with a combination of co-trimoxazole and mefloquine in IPTp has been shown to be more efficacious than co-trimoxazole among HIV-positive women, than IPTp treatment with co-trimoxazole alone (Green et al 2016). However, use of this IPTp combination is limited by mefloquine's poor tolerability and propensity to increase maternal HIV viral load as well as mother-to-child HIV transmission (Suthar et al, 2015). Other studies have shown co-trimoxazole and SP efficacy to prevent LBW among HIV-positives is similar (Rogerson 2017 and Saito et al 2020). A three-day regimen of artemisinin-based combination therapy is currently being considered as alternative drugs to replace the single-dose regimen for SP-based IPTp or SP-based IST (Figueroa-Romero et al. 2022).

A clinical trial assessing acceptability of IPTp and IST treatment with dihydroartemisinin-piperaquine in Kenya highlighted concerns among pregnant women and health care providers on treatment compliance in field settings despite being acceptable in a clinical trial setting. Adherence to multi day regimens was perceived to be more common in the case of ISTp, as women could see positive results from the blood tests. Pregnant women generally found ISTp acceptable despite the discomfort of finger pricks. Conversely, health providers in Kenya, Ghana, and Malawi have been reported to favor IPTp over IST whereas some participants prefer hybrid strategy of IPTp and ISTp (Rogerson 2017). IST is amenable to field settings especially is the availability of cost effective and easy to use diagnostic methods. Thus, even though rapid diagnostics tests are suitable for low malaria transmission settings, more sensitive diagnostics are necessary in moderate to high malaria transmission settings due to high risk of reinfection.

Case management and treatment of MiP are crucial to ensure well-being of both the pregnant woman and the developing foetus. Equally prompt and effective management of malaria cases in pregnant women can reduce complications and improve pregnancy outcomes (Green et al, 2016). Diagnosis of malaria in pregnancy follows similar principles as that of the general population which rely on detection of malaria parasites using microscopy or rapid diagnostic tests (RDTs). It is important to note that pregnant women may have lower parasite densities, thus limiting detection of malaria parasites (Suthar 2015, Hill 2016). It is therefore recommended that healthcare providers should test for malaria, especially when mild malaria symptoms are observed and prompt malaria treatment should be given to malaria positive cases because of the likelihood of significant risks to both the mother and the foetus (Fried et al 2012). The choice of antimalarial treatment for MiP depends on several factors, namely severity of the infection, local drug resistance patterns, and safety profile of the drug in pregnancy (Saito et al, 2020). Artemisinin-based combination therapies (ACTs) are currently recommended as the first-line treatment for uncomplicated malaria in pregnant women (Brigss et al, 2019).

In severe malaria cases, hospitalization and parenteral therapy with intravenous artesunate are usually required. Supportive care should be provided to manage symptoms and complications in addition to antimalarial treatment. This may include interventions to address anaemia, such as iron supplementation or blood transfusions when necessary (D'Alessandro et al, 2018). Regular follow-up visits are essential to monitor treatment response, detect potential complications, and provide additional care as needed. This reinforces the importance of integrating malaria case management into antenatal care services. Healthcare providers involved in case management of MiP should thus, be trained regularly especially when treatment guidelines and protocols specific to pregnant women have been amended. Additionally, efforts to enhance availability and accessibility of quality-assured antimalarial drugs and diagnostic tools are essential to ensure effective case management (D'Alessandro et al. 2018).

Malaria transmission prevention and/or control are key pillars of the war on MiP. They complement the contribution of IPTp on MiP prevention as well as safeguard the positive outcome of ISTp and MiP case management. Use of insecticide-treated bed nets (ITNs) provide a physical barrier and prevent mosquitoes from biting during sleep, thereby reducing the risk of malaria transmission akin to ITNs, Vector control, such as indoor residual spraying, helps in reducing contact between pregnant women and malaria infective (Beir JC, 2018) ITNs namely bed nets that have been treated with insecticides are a critical intervention for protecting pregnant women from malaria infections. Pyrethroids are often used to treat bed nets and protect by either repelling and/or killing mosquitoes that come into contact with the nets. Pregnant women are particularly vulnerable to malaria infection because of a dampened immune system. By sleeping under ITNs, pregnant women have reduced exposure to malaria-infected mosquitoes and are at a lower risk of malaria infection.

Previous studies have demonstrated that consistent ITN use during pregnancy can be highly effective in preventing MiP and its potential consequences like maternal anaemia and negative pregnancy outcomes such as low birth weight and neonatal mortality (Mlugu et al, 2021, Figueroa-Romero, 2022). An additional benefit associated with use of ITNs is reduced placental parasitemia in pregnant women (McClure et al 2013). Noteworthy, high coverage and easy access to ITNs in malaria-endemic areas is necessary to effectively protect pregnant women from being infected with malaria parasites. ITNs coverage is currently being boosted by various strategies including the fact that pregnant women receive free INTs under mass INT distribution during campaigns, antenatal care programs, and community-based distribution programs (Bauserman et al, 2019). These efforts are further fortified by incorporating education of pregnant women about the importance of proper and consistent ITN use as well as regular treatment of the nets with effective insecticide.

The aforementioned have been instrumental in achieving key milestones attained so far in the prevention and/or control of MiP. In spite of the progress made over the last decades, studies have revealed that uptake of two doses of IPTp and ITNs among pregnant women in Africa remains unacceptably low (Walker et al 2017, Boene et al 2014). Some of the challenges faced by IPTp distribution programmes include unclear policies and guidance, lack of clarity on timing and regimen of IPTp, lack of data on gestational age, IPTp efficacy and poor knowledge on side effects (Desai et al 2007). These limitations have often led to incorrect administration in the first trimester. Compliance to treatment is uncommon. This is often compounded by frequent lack of IPTp and ITNs owing to heavy dependency of governments in malaria endemic regions on dwindling donor funding of malaria control programmes alongside increasing health care priorities (Desai et al 2018).

Outlook of MiP Control

The outlook for controlling malaria in pregnancy is generally positive, as there have been significant improvements in recent years. However, challenges remain, such as drug resistance and availability of healthcare services in resource-constrained settings. Global and national efforts are essential to sustain and further improve control of malaria in pregnancy.

It's important to note that the specific outlook can vary greatly by region, depending on factors like prevalence of malaria, healthcare infrastructure, and access to resources. The World Health Organization (WHO) and various international organizations continue to work together with the local governments towards reducing the burden of malaria in pregnancy through coordinated efforts and strategies.

Conclusion

Increased funding over the past decade has led to a significant increase in research studies aiming to find new drugs and strategies to replace sulfadoxine-pyrimethamine for IPTp. Valuable insights have been gained, suggesting potential benefits of more sustained protection with monthly regimens starting early in pregnancy. Effectiveness of sulfadoxine-pyrimethamine in improving birth outcomes has remained resilient, even in areas with a high prevalence of quintuple mutations. However, its effectiveness is compromised in women infected with the sextuple mutant parasite. Among the candidates studied, dihydroartemisinin-piperaquine shows promise as a replacement for IPTp, but further studies are needed to confirm its safety, efficacy, cost-effectiveness, and feasibility in HIV-negative women. Ongoing research is focused on exploring the feasibility and implementation of a 3-day dihydroartemisinin-piperaquine regimen.

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CAPABILITY OF RULE BASED CLASSIFICATION TECHNIQUE IN IDENTIFYING SPRAWL AREAS: A CASE STUDY OF AREAS AROUND ELDORET TOWN, KENYA

ODHIAMBO S[1]., MWASI B[2]., NGETICH J.[3]

University of Eldoret, Kenya.

Email: sodhiambo53@yahoo.com

Abstract

Use of satellite images to map urban land uses has been successful to varying degrees since the launch of medium resolution sensors producing images of 30 m spatial resolution. With this resolution, the extent of urban settlements can be detected. However, details of urban land use classes cannot be identified from 30m resolution images. With higher resolution images such as 10m Sentinel 2, most urban land use classes can be identified with fairly high classification accuracy using pixel-based classification techniques. Land use details, and hence classification accuracy can be improved using object-based image analysis (OBIA) techniques with the high resolution images. These techniques combine spectral, textural and spatial information to distinguish objects related to information classes. This study used rule based classification OBIA algorithms to accurately map urban land use classes and isolate the emerging sprawl settlements around Eldoret Town. Specifically, the study applied five variations of vegetation indices to extract land use/cover data from high resolution Sentinel-2 images of 2020 to identify urban sprawl areas. The analysis identified eleven urban sprawl areas with an overall classification accuracy of 91.67% and Kappa coefficient of 0.90. The findings confirm that use of rule based classification technique in LULC classifications gives high classification accuracy results.

Keywords: *Rule Based Image Analysis; Urban Sprawl Patterns*

Introduction

The world's rapid rate of urbanization is continuously increasing urbanization has been defined as the conversion of natural spaces to built-up areas for residential, commercial, and industrial land uses. It is important to note that the growth of urban areas is not uniform worldwide. In the UN Urbanization Prospects report 2021, 30% (225.3 million) of the World's population was living in urban areas in 1950, 56.61% (4.46 billion) in 2021, and it is expected to increase to 68% (6.68 billion) by 2050. It is projected that 90% of the projected growth of the World's urban population between 2021 and 2050 will occur in Asia and Africa (Zhang et al, 2014).

The rapid population growth calls for provision of more housing, schools, transportation network and utilities resulting in rapid but skewed urbanization driving change in land use/cover (LULC) patterns. One of the impacts of urbanization is increase of impervious surfaces resulting in more water runoff and hence water pollution and flooding (Wilson et al. 2003) as well as increase in urban temperature. Uncontrolled increase of impervious surfaces on lands that were formally agricultural lands, forests, grasslands, water bodies and wetlands coupled with population growth results in scarcity of food, environmental pollutions, destruction of ecological structure, and unemployment (Maktav and Erbek 2005). Therefore, a technique that can extract data from built-up areas more efficiently is urgently required to provide the data to urban planners to control auto-expansion of built-up areas.

Satellite remote sensing has continuously provided data with different spectral and spatial resolutions ranging from course (1km), low (80m), medium (30m), high (10-15m) and ultra-high (below 10m). High and ultra-high spatial resolution images have provided solutions for mapping and monitoring urban growth (Zhang et al 2014). Consequently, several image classification techniques have been used to extract built-up areas from satellite data. Results of these classifications vary depending on the satellite data used and the classification technique used. For example, the study by Bhatta et al. (2007) demonstrated that LISS-IV images of 5.8m pixel size, though able to show the sprawl patterns, also suffer 15 to 20 percent overall accuracy when used for the classification of cityscapes by pixels and mixed classes. However, rule based classification techniques have proven effective for extracting land uses in terms of their spectral values, shape, texture, morphology among others.

This study uses rule based image classification technique to isolate built-up areas in a mixed land use environment in order to identify the sprawl areas from high resolution Sentinel-2 satellite image of 2020 around Eldoret town.

Materials and methods

Study Area

The study area is areas around a gazetted Eldoret Municipality boundary in Uasin Gishu County, Kenya, and covers 58 sub-locations. It is bounded by Latitudes 00°52' 00''N and 00° 18' 00''N and Longitudes 34° 51 '00''E and 35° 31' 00''E covering approximately 1973km^2. Most location of the study area, that is, western part (Turbo area), eastern part

(Ainabkoi and Moiben areas), northern part (Ziwa area) and southern (Kapseret and Cheptiret areas) receive an average rainfall of between 625 mm to 1,560 mm, with two distinct peaks between March and June, August and September. Dry periods occur between November and February. Temperatures range between 7°C and 29° C with dominant soil types being Orthic Ferralsol (Fo) and Humic Nitosols (Hn). Generally, these conditions are favorable for livestock keeping, crop and fish farming. The interpolated population figures of the study area (58 sub-locations) for the years 2000, 2016 and 2020, shows a steady population increase from 437,049 to 774, 201 and 870, 271 respectively. Figure 3 shows the study area map.

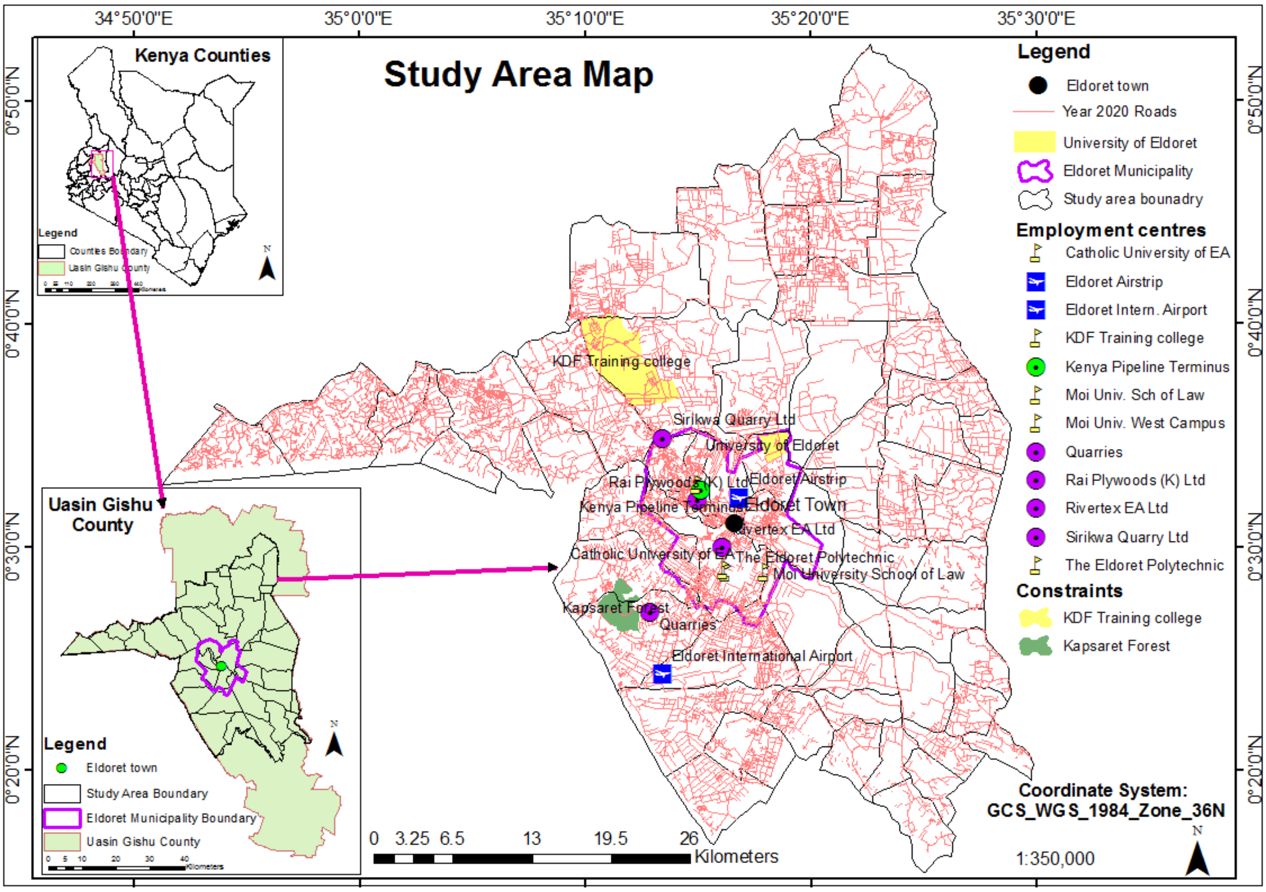

Fig. 3: Location of the study area

Data and Data Processing

Data for this study was obtained from both primary and secondary sources (Table 1).

Table 1: Characteristics of Data Used

S/No.	*Type of data used*	*Scale/Resolution*	*WRS_path/raw, Granules/Tiles*	*Years*
1.	Sentinel-2 image	10m	T36NYF-100×100km	12th Dec. 2020
2.	Sub-locations shapefile			2019

Primary Data

The data obtained from primary sources included; land use categories information obtained by classifying Sentinel-2 image for 12th December 2020 obtained from United States Geological Survey (USGS) website (USGS, https://earthexplorer.usgs.gov/).

Secondary Data

Secondary data used was sub-locations data covering the study area from Kenya National Bureau of Statistics (KNBS, 2019).

Methods

Figure 4 below describes the steps followed in obtaining urban sprawl areas for the year 2020.

Figure 4: Urban sprawl data extraction procedure

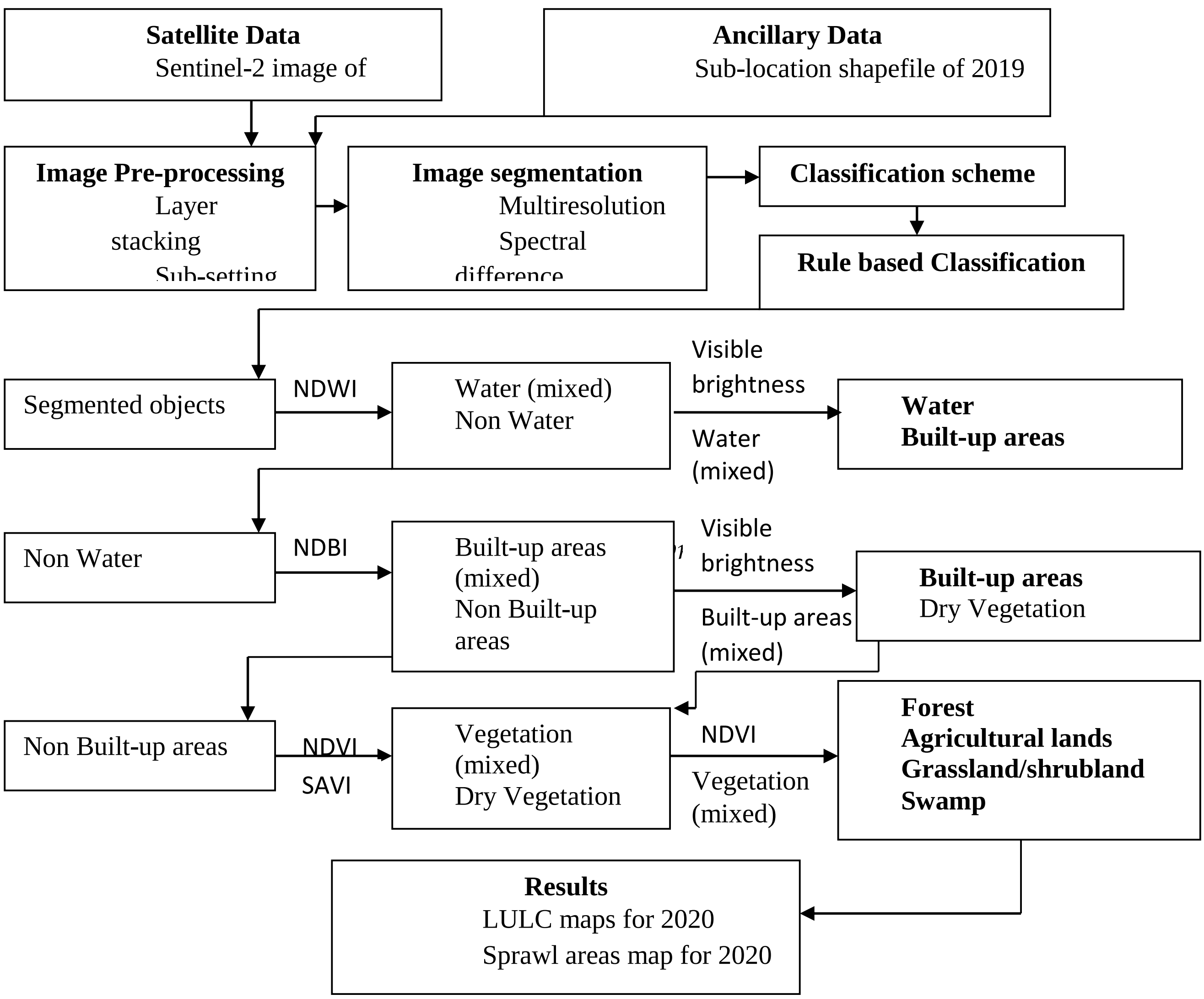

Image Pre-processing

Four bands were layer stacked for Sentinel-2 images of 2020 i.e. band 2 (blue), band 3 (green), band 4 (red) and band 8 (Near Infra-Red) all at 10 m spatial resolution. The composite image was then clipped using a sub-location shapefile to cover the study area.

Image Segmentation

Image segmentation was done in two steps namely; multiresolution and spectral difference segmentation algorithm.

In Multiresolution segmentation, the 'Scale parameter' was set to 35 since it's the restricting parameter that stops the object from getting too heterogeneous or is the average size of the object. Since there is no rule for 'Scale Parameter', trial and error was used and value 35 was found to be the best value for 'Scale Parameter'. 'Shape' (geometric form of the object) was set to weight of 0.3 since it defines the shape criterion to be used when segmenting the image. The higher its value, the lower the influence of colour on the segmented process hence care was taken not to put higher value to avoid distorting spectral information. Finally, 'Compactness 'was set to value 0.6. The higher its value, the more compact the image object may be and the NIR value was set to 2.

Spectral Difference segmentation was performed next in order to merge already segmented objects in multiresolution segmentation with the same spectral values together during the segmentation process. 'Maximum Spectral Difference' value was set to 15 and the NIR band to 3.

Land Cover Classification Scheme

Due to heterogeneous nature of the study area, a list of six land cover classes was identified during a reconnaissance survey of the study area considering their exhaustiveness to accommodate all land cover features (Table 2).

Table 2: Major Land Cover Classes in the Study Area

S/No.	Name	Description
1.	Built-up area	Human constructed structures, buildings, roads and other impervious surfaces
2.	Water	Rivers, ponds and other water bodies
3.	Forest	Both man-made and natural
4.	Agricultural lands	Both cultivated and non-cultivated
5.	Grassland/Shrubland	Both natural and planted
6.	Swamps	Both permanent and seasonal

The six land cover classes were inserted into the image processing software under class hierarchy.

Rule-Based Classification of 2020 image

Rule-based classification was done using eCognition developer. Five indices were used i.e. normalized difference vegetation index (NDVI), normalized difference water index (NDWI), normalized difference built-up index (NDBI), Visible brightness and soil adjusted vegetation index (SAVI).

First, NDWI (Green-NIR)/(Green+NIR) was applied on the segmented image and threshold NDWI values set between 0.5 to 1. The software assigns all objects in the image meeting the threshold into water class or else any object outside the threshold values is assigned to non-water objects. Since built-up areas also have high NDWI value (McFeeters, 1996), visible brightness (Red+Green+Blue)/3 was applied on water class to isolate built-up areas from it since built-up areas have higher values of visible brightness value than water features.

Secondly, NDBI (SWIR-NIR)/ (SWIR + NIR) was applied on non-water objects since they have higher reflectance value of SWIR than NIR and threshold NDBI values set between -1 to 1. The software assigns all non-water objects in the image meeting the threshold into built-up areas class or else it assigns them to non-built-up areas. Since drier vegetation also possesses higher NDBI value (Zha et al., 2003), visible brightness (Red+Green+Blue)/3 was applied because built-up areas have higher values of visible brightness value than drier vegetation features.

Third, NDVI (NIR-Red)/(NIR+Red) was applied on the non-built-up area objects and threshold NDVI values set between -1 to 1. All objects meeting the threshold were assigned into vegetation class and together with drier vegetation isolated by NDBI above. SAVI (NIR-Red) (1+k)/(NIR+Red+k) was applied to extract vegetation less than 15% cover mostly within Eldoret town since it has high reflectance in the NIR band. 'K' is the correction factor that ranges from 0-1 for very high vegetation density to very low density respectively. A correction factor of 0.6 was used. More threshold values were set to ungroup vegetation into forest, agricultural lands, grassland/shrubland and swamps.

After grouping the objects into the six LULC classes, classification was executed, and the raster classified image exported to ArcMap for post classification and generation of statistics.

2.3.5 Accuracy Assessment

Accuracy of classification results was done by creating a confusion matrix. The process produces four metrics namely, the user's accuracy, the producer's accuracy, the overall accuracy with and Kappa statistic (Congalton, 1991a). The producer's accuracy gives the percentage of correctly classified ground truth sites for each class. The user's accuracy gives the proportion of correctly classified sites in the classified image for each class while the overall accuracy is a combination of the two accuracy measures. The Kappa statistic expresses the probability that the values presented in the error matrix are significantly different from those from random samples of equal size (Benjamin, 2004). Sample points were randomly selected as reference data from original Sentinel-2 and google earth images of 2020. Thirty test pixels for each class were considered to be the best sample for assessing accuracy (Zhao, 2013). The test pixel was then overlaid on the classified image in order to generate a confusion matrix table. From the confusion matrix table, the four matrices were calculated using the formulae below;

1) **Overall accuracy**= $\frac{\text{Total No. of correctly classified pixels (diagonal)}}{\text{Total No. of Reference pixels}} * 100$

2) **User accuracy**= $\frac{\text{No. of correctly classified pixels in each category}}{\text{Total No. of classified pixels in that category (total row)}} *100$

3) **Producer accuracy**= $\frac{\text{No. of correctly classified pixels in each category}}{\text{Total No. of Reference pixels in that category (total column)}} *100$

4) **Kappa coefficient (T)** = $\frac{(TS*TCS)-\sum \text{(column total*row total)}}{TS^2-\sum \text{(column total*row total)}} *100$

Where; TS is Total samples; TCS is Total correctly classified samples

Finally, the LULC map for 2020 was then used to identify and map sprawl areas, and designed in ArcMap. Sprawl areas map 2020 was then finally generated.

Results and Discussions

LULC Maps for 2020

Fig 5 shows the LULC map for the year 2020.

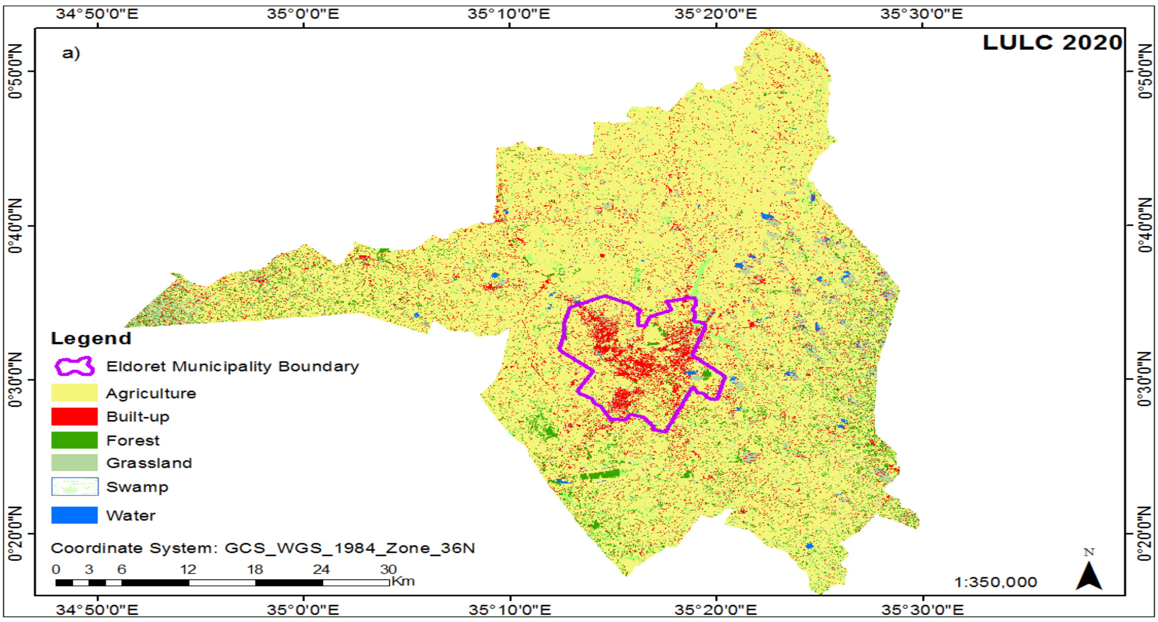

Figure 6: LULC Map of the study Area in Year 2020

Classification techniques by Rule-Based using the five indices (NDVI, NDWI, NDBI, SAVI and visible brightness) discriminated the six land cover classes i.e. built-up areas, agriculture/farmlands, water, grassland/shrubland, swamps and forest by use of their spectral values. Similar findings were reported by Mwakapuja et al (2013) in their study of usage of indexes for extraction of built-up areas and vegetation features from Landsat TM images, a case study of Dar Es Salaam and Kisarawe Peri-Urban areas in Tanzania.

Table 3: Summary of Land Use/Cover Classification Statistics for 2020 (area in km²)

LULC Type	2020	
	Area (km²)	**(%)**
Agriculture/Farmland	1524.82	77.29
Built up areas	138.912	7.04
Forest	106.757	5.41
Grassland/shrubland	123.475	6.26
Swamp	67.3586	3.41
Water	11.4492	0.58
Total	**1972.769**	**100**

3. 2 Classification accuracies for 2020

Table 4: User's and Producer's Accuracy Results by Rule Based Algorithm

LULC Type	2020	
	Producer's (%)	**User's (%)**
Agriculture/Farmland	87.10	90.00
Built-up Areas	96.55	93.33
Forest	100	90.00
Grassland	81.25	86.67
Swamp	90.32	93.33
Water	96.67	96.67

Table 5: Classification Accuracy Assessment for 2020 by Rule Based Classification Algorithm

Image	Overall Accuracy (%)	KappaCoefficient (%)
2020	91.67	90

Overall classification accuracy results obtained by use of indices (NDVI, NDBI, SAVI, NDWI and Visible Brightness) in rule based classification approach in extracting built-up areas were good. The overall accuracy for 2020 was 91.67% with Kappa Coefficient of 90.00%. The Producer's and User's accuracy also improved from 81.25% to 100% and 86.67% to 96.67% respectively. Examination of accuracies of land cover data however revealed that Sentinel-2 dataset met the minimum USGS total accuracy of ≥ 85% set out by Anderson et al. (1976).

Similar findings were reported by Mwakapuja et al., (2013) who pointed out that use of indices (NDBI, MNDWI and SAVI) in extraction of built-up areas has proved to be an effective method resulting in accuracy of 82.05% and can be used in other areas with similar characteristics.

3.3 Urban Sprawl Growth patterns for 2020

After extracting the built-up area class for the years 2020 in ArcMap, eleven urban sprawl growth patterns were identified and mapped. They were occurring in Moiben, Garage, Tugen Estate, Moiben Junction, Kiluka, Chirichir, Cheptiret, Kosachei, Magut, Maili Nne and Sololo trading centres as presented in Figures 7.

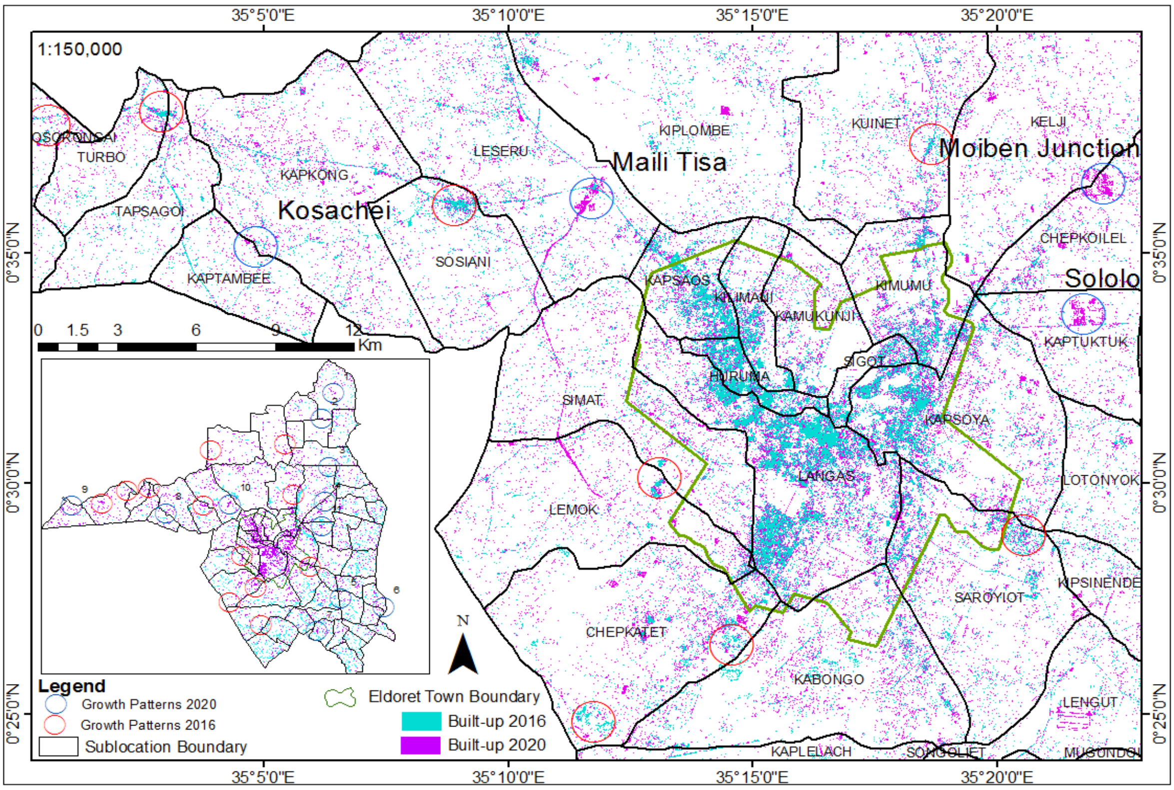

Figure 8: Urban Sprawl Growth Patterns 2020 Map of the Study Area

1. Conclusion

This study employed rule based techniques in extracting land cover classes. This technique gave good accuracy results (overall accuracy 91.67% and kappa coefficient of

90%) and hence can be used in extracting land covers in areas with similar characteristics since the LULC classes of particular interest for this study namely built-up area, forest, water, grassland/ or shrub land, swamp and agricultural or farmlands were isolated efficiently and accurately from Sentinel-2 images of 2020 by use of indices.

Disclosure statement: No potential conflict of interest was reported by author(s)

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ASSESSING LAND USE AND LAND COVER CHANGES IN THE CHEPKOILEL/SERGOIT RIVER CATCHMENT

ODHIAMBO, S.[1], ODENYO V. [1], KEMBOI G., JEPKIRUI M.

University of Eldoret, KENYA

Correspondence: sodhiambo53@yahoo.com

Abstract

Land cover refers to what is on the land, natural or man-made, while land use refers to human activities on land. Therefore, there is always a direct link between land cover and the actions of people in their environment. Land Cover and Land Use (LC/LU) changes involves intensification of an existing use, or a shift to a different use. Increasing demand for space for settlement and all types of development are the driving force. The study aimed to quantify the changes in LC/LU in the catchment during the period 1995 to 2020 and to examine their effects on the long term availability of potable water. Medium (Landsat 5) and high (Landsat 8 OLI and Sentinel-2) resolution satellite images of three dates were used and all the data processing and analysis was done in ArcGIS environment. Results showed that the catchment had lost 69% of its forest cover, while farmland increased by 44%; settlement in the catchment increased by 261% and wetland declined by 64% during the period. The upper zone, the main source of the water supply in the catchment, lost 46% of its forest cover during the period. We recommend that immediate steps be taken to increase forest/vegetation cover and implement land conservation in the catchment, especially the upper zone.

Key words: land cover/land use change, water availability, water catchment conservation

Introduction

Land cover refers to what is on the land, natural or man-made, while land use refers to anthropogenic activities on land. Thus, there is always a direct link between land cover and the actions of people in their environment. As stated by Ankana (2016) Land Cover and Land Use (LC/LU) changes involve either a shifting to a different land use or an intensification of an existing one. Increasing demand for space for settlement, agricultural investment and industrial activities across the world is currently being observed (Lambin and Meyfroidt, 2011); Cotula, 2015). This has led to unprecedented land-use and land-cover changes which have caused socioeconomic and environmental problems (Braimoh and Osaki, 2010). Many communities, particularly in developing countries, depend heavily on exploitation of the natural resources for their livelihood (Maithya *et al*., 2015***)***. As a result, human use of land has had and continues to have a profound effect upon the natural environment. The effects have, over time, resulted in observable patterns in land-cover/land-use (Tiwari and Saxena, 2011, Odenyo and Pettry, 1977). As noted, Gilani *et. al.* (2014), Land cover and Land Use changes are among the most important and easily detectable indicators of change in ecosystem and livelihood support systems.

This study examined the land use and land cover changes in the river Chepkoilel/Sergoit over the period 1995 to 2020 as a component of assessment of availability of potable water in the catchment. The river's catchment encompasses an agriculturally productive zone of Uasin Gishu County and includes the northern reaches of Eldoret municipality which has experienced tremendous expansion over the 25 years studied.

Materials and Methods

Materials

Study area

The study area traverses parts of three Kenya counties, that is, Elgeyo Marakwet County in the upper catchment, Uasin Gishu County in the mid and lower catchments and Kakamega County in the lower catchment. It is bounded by Latitudes 00°27' 30''N and 00°42'30''N and Longitudes 35°05'00''E and 35°32'30''E with elevation ranging from 2600m-2131m-1780m in the upper, mid and lower catchments respectively (Figure 9). The catchment receives an average rainfall of between 625 mm to 1,560 mm, with two distinct peaks between March and June, August and September.

The geology of the catchment is dominated by upper Uasin Gishu phonolite in the upper and mid catchment, lower Uasin Gishu phonolite with some spots of gneissose and banded microcline augen in the lower catchment (Figure 10).

The dominant soil type in the catchment is Orthic Ferralsols (Fo) covering mid and parts of upper and lower catchments; Humic Nitosols (Nh) covering parts of upper and lower catchments and Lithosols (l) conversing part of upper catchment (Figure 10).

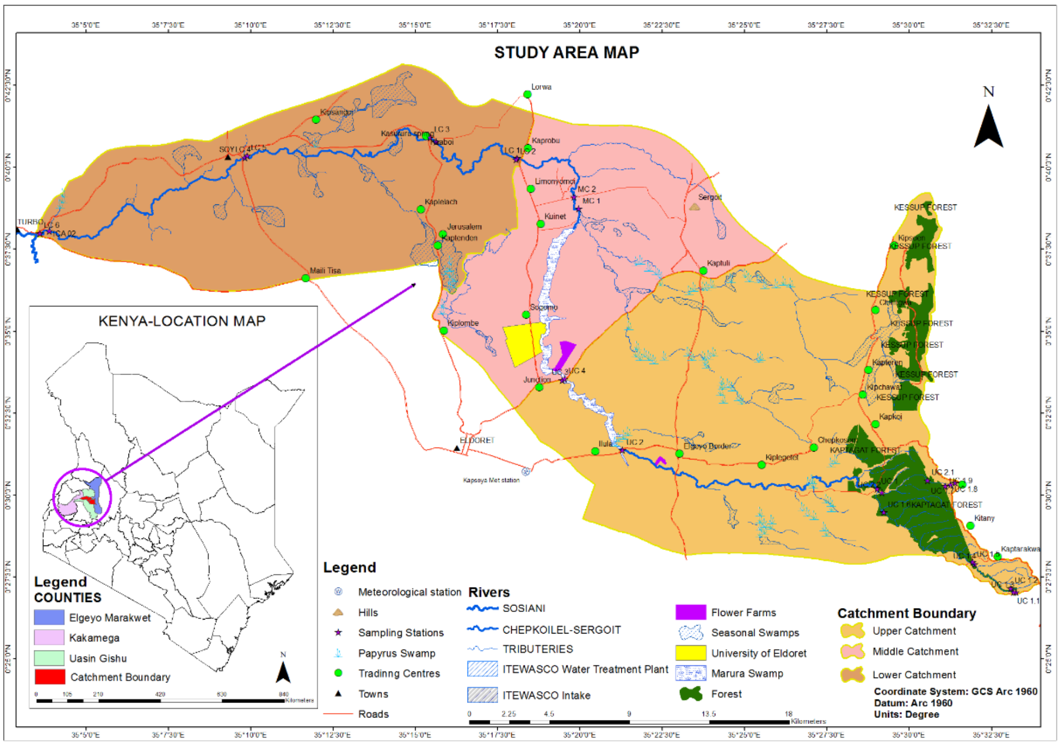


Fig 8: Location of the study area

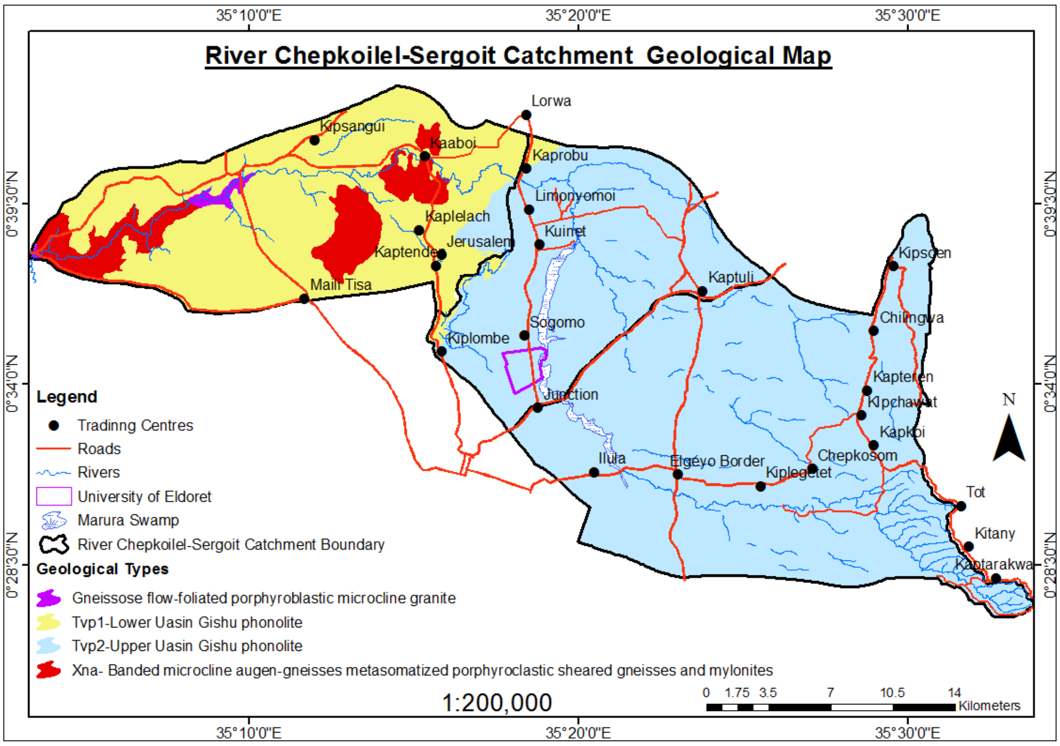


Figure 9: Geological map of the study area

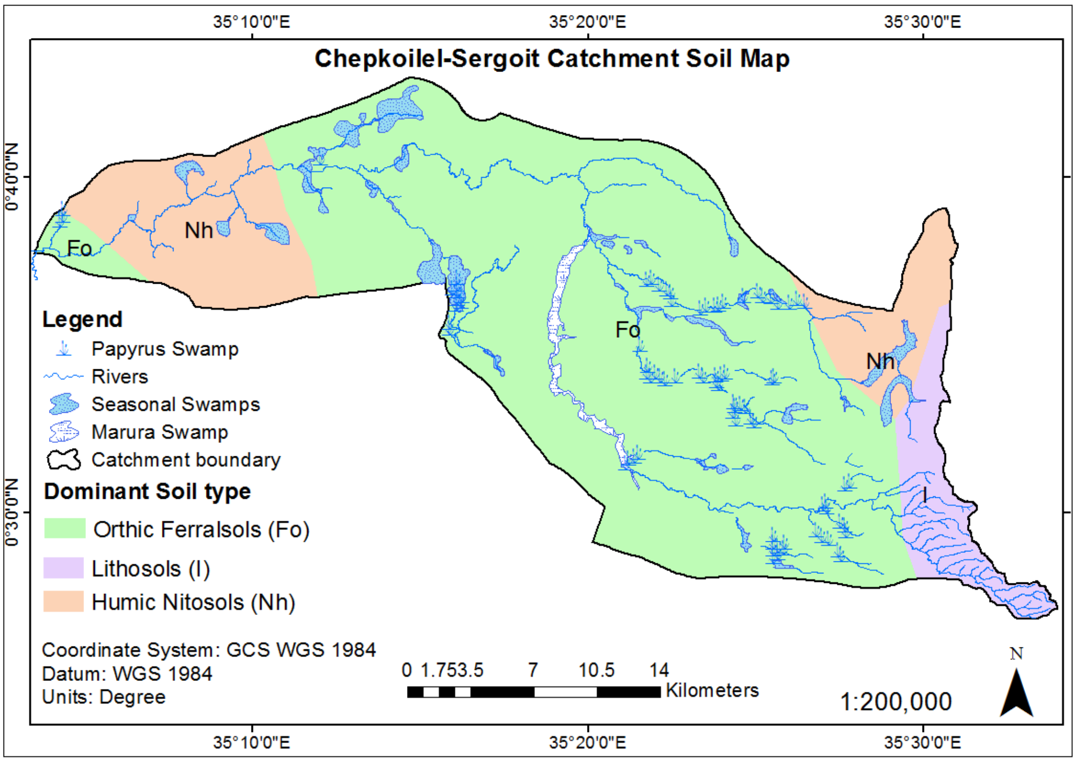


Fig. 10: Soil map of the study area

Datasets used

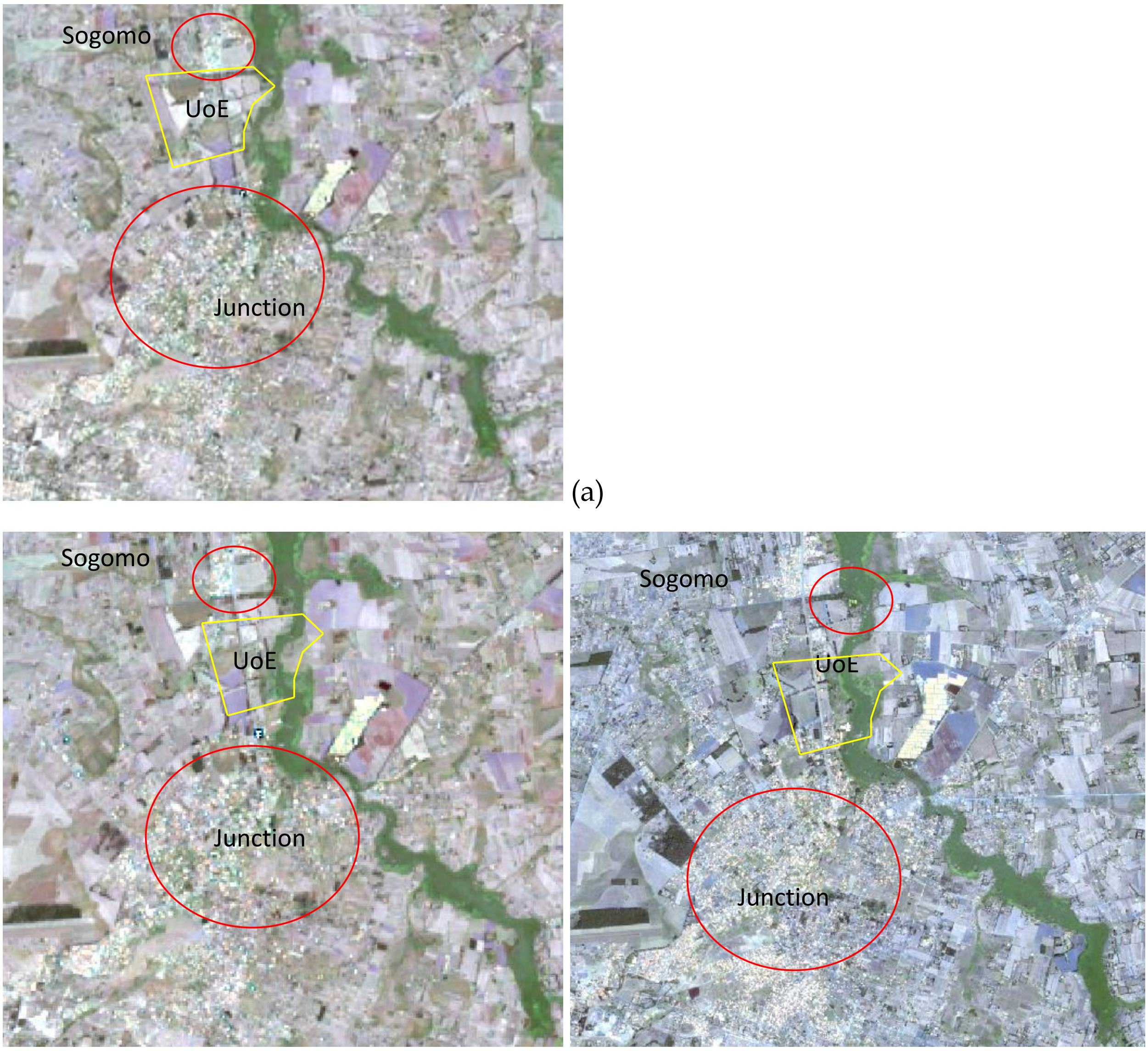
The data used in this study are as shown in Table 1.

Table 1: Datasets used in the study

S/No.	*Type of data used*	*Scale/ Resolution*	*WRS_path/row, Granules/Tiles*	*Date of acquisition*	*Source*
1.	Landsat 5 TM image	30m	169/060 and **170**/060	26th Jan. 1995 and 2nd Jan.1995	United States Geological Surveys website (USGS, https://earthexplorer.usgs.gov/).
2.	Landsat 8 OLI-image	30m and 15m	170/059 169/060	22nd Jan. 2014 and 2nd Jan. 2014	United States Geological Surveys website (USGS, https://earthexplorer.usgs.gov/).

3.	Sentinel-2 image	10m	T36NYF-100×100km	22nd Jan. 2020	United States Geological Surveys website (USGS, https://earthexplorer.usgs.gov/).
4.	Shapefile of study areas	1:50000			Digitized from topographical maps 89/3-Soy, 89/4-Eldoret, 90/3-Tambach, 103/2-Kaptagat and 104/1-Kipkabus all from Survey of Kenya.

All the images used in this study were taken during the dry season (January) in the study area since discrimination of land cover classes is more accurate than images taken during the rainy season (March-September).



(a)

(b) (c)

Figures 11(a), 11(b) and 11(c), showing physical growth of settlements in 1995, 2014 and 2020 images respectively of a section of mid catchment along Marura swamp partially fueled by the presence of University of Eldoret (UoE).

Methods

Image preprocessing

Pan sharpening was done on a composite image of Landsat 8 at 30m spatial resolution using its panchromatic band 8 at 15m spatial resolution in order to improve its cell size to 15m. Image processing was carried out in ArcGIS.

Layer stacking was done as follows: four individual monochrome bands i.e. band 1-blue, band 2-green, band 3-red and band 4- NIR all at 30m spatial resolution for Landsat 5 (1995); five bands i.e. band 2-blue, band 3-green, band 4-red, band 5-NIR at 30m spatial resolution and band 8-panchromatic for Landsat 8 at 15m spatial resolution (2014) and four bands i.e. 2- blue, band 3-green, band 4 - red, band 8-NIR for Sentinel-2 satellite image (2020) were layer stacked in order to produce three composite images.

Image sub setting was done using the shape file of the study area prepared as mentioned above to subset the three images (1995, 2014 and 2020) in order to limit and fit them to the study area.

Image mosaicking was done on Landsat 5 and 8 images of 1995 and 2014 respectively since none of their single path-row covered the whole study area, (i.e. WRS-path-row 169060 and 170060 for Landsat 5 and 170059 and 169060 for Landsat 8). The Sentinel-2 (T36NYF) satellite image was not mosaicked since it covered the whole of the study area.

Land cover classification scheme

From a reconnaissance survey, a total of five main Land cover/Land use classes i.e. farmland, forest, settlement, wetland/swamp and water, were identified, based on modified Anderson et. al. (1976) LU/LC classification system. These were used in the research in generating signature files for the final LU/LC classification. The used LU/LC content types identified are described in Table 2.

Signature file

Training samples were extracted for each land use type from high resolution google earth image of each of the three years and overlaid on the geometrically corrected image ready for classification to help guide in selecting the signatures for each of the five land-over classes. Ten signatures were created for each class, later merged into a single class. These provided the input samples for supervised classification.

Supervised classification

A supervised maximum likelihood classification (MLC) algorithm was subsequently applied to each image. The basic equation of MLC assumes that these probabilities are equal for all classes, and that the input bands have normal distribution.

Area calculation

After classification, the areas for each individual land cover class were calculated using field calculator geometry in ArcGIS. The algorithm multiplies the field of 'counts' with cell size for each image i.e. 30*30m (Landsat 5), 15*15m for Landsat 8 and 10*10m for Sentinel-2.

Accuracy assessment

Confusion matrix tables for 1995, 2014 and 2020 were created to assess accuracy of classification results. The process produces four metrics: the user's accuracy, producer's accuracy, the overall accuracy and the Kappa statistic (Congalton, 1991a). The Kappa statistic shows the probability that the values presented in the error matrix are significantly different from those from random samples of equal size (Benjamin, 2004).

Classification accuracy was done by comparing two datasets: one based on the analysis of remotely sensed data, and the other based on reference information (Congalton 1991); and a nonparametric kappa test was also used to measure the classification accuracy, as it accounts for all of the elements in the confusion matrix rather than the diagonal elements (Rosenfield and Fitzpatirck-Lins, 1986).

Change detection

Change detection was done by calculating the changes in land cover between two consecutive images. This was done for 1995-2014, 2014-2020 and 1995-2020. Figure 12 summarizes the various steps used in the study.

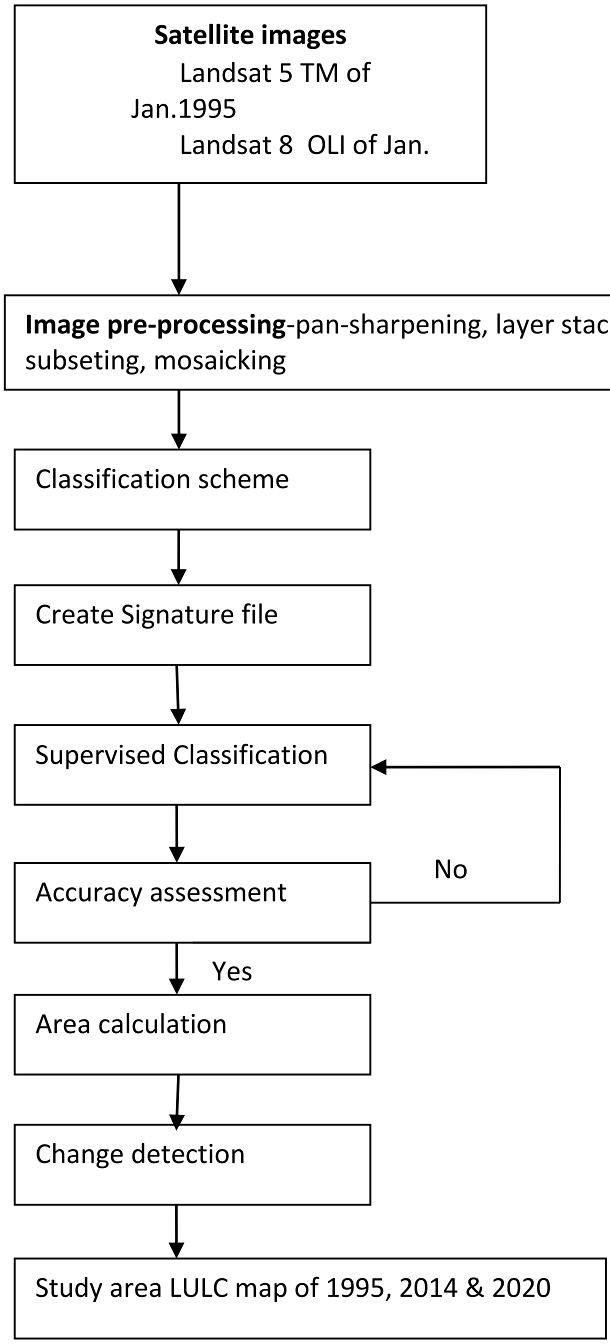
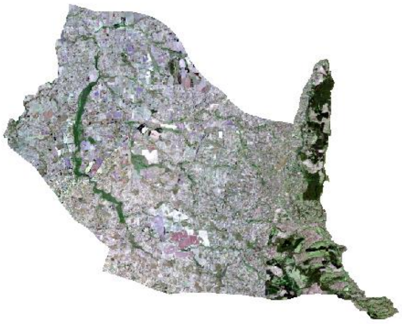


Figure 12: Flow Chart Summarizing Processes Used in the Study

Results and Discussion

Image subsetting and mosaicking

Image subsetting helps limit and fit the images to the study area while mosaicking combines two adjacent composite images to cover the whole study area. Figure 13 shows subset and mosaic image of 2014.



Figures 13: Shows subset and mosaic of mid and upper catchment of Landsat 8 of 2014 image.

Figure 14: Shows subset of 2014 Landsat 8 image with training samples of LULC classes (forest-blue, farmland-yellow, settlement-red, wetland/swamp-cyan).

Signature file

Signature file was created for the LULC classes with five fields (Table 2) of 2014 image i.e. ID, Class Name (indicate name of LULC class), Value (indicating number corresponding to class name), Colour (indicate the colour of training sample) and Count (indicating the number of samples of each class).

Table 2: Training sample manager

Training Sample Manager

ID	Class Name	Value	Color	Count
1	Forest	1		3143
2	Farmland	8		1074
3	Settlement	13		351
4	Swamp	18		324

Land cover classification scheme

The five Land Cover/Land Use classes identified from reconnaissance surveys i.e. farmland, forest, settlement, wetland/swamp and water, are described in Table 3.

Table 3: Land cover classification scheme

No.	Land cover	Description
1.	Farmland	Farms with crops, those under cultivation and those where crops had been harvested
2.	Forest	natural and planted
3.	Settlement	Human constructed structures and other impervious surfaces including rocky surfaces
4.	Wetland/ swamp	Natural
5.	Water	rivers, dams and any surface water

Supervised classification

The resulting Land Cover/Land Use maps for the three periods are presented in Figures 15-17. Notable in the 1995 map are the widespread extent of the forest and wetland/swamp complex cover types in the upper catchment-the headwaters of the river [Figure 17]. These were both forests planted for timber supply and natural forests dominated by indigenous vegetation. Notable also are the very widely scattered settlements in the lower catchment. Settlements in the middle catchment are likely influenced by the suitable topography (gentle slopes) of the Uasin Gishu plateau and proximity to Eldoret town.

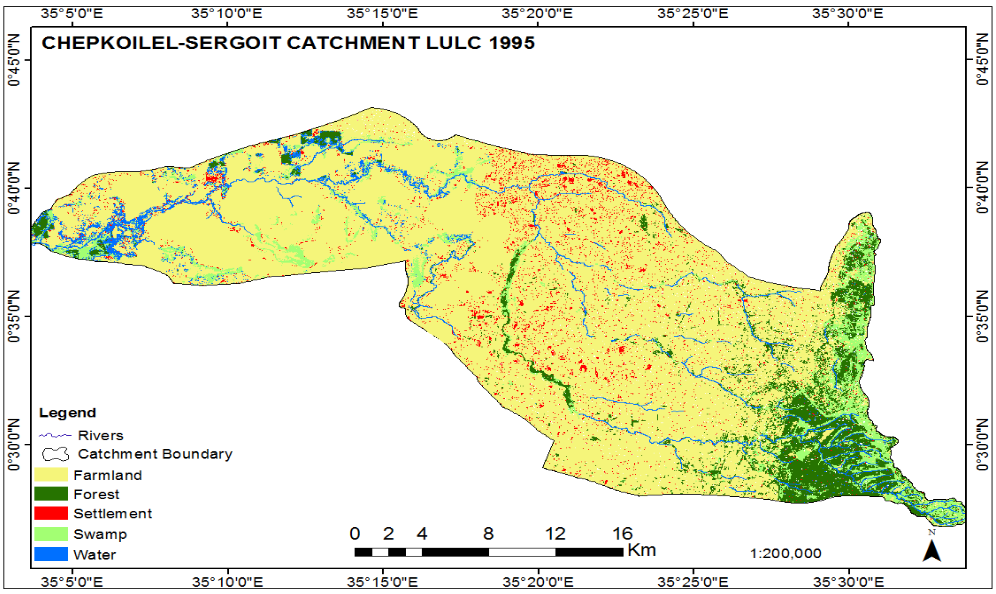


Figure 15: Land Cover/Land Use map of River Chepkoilel-Sergoit catchment in 1995

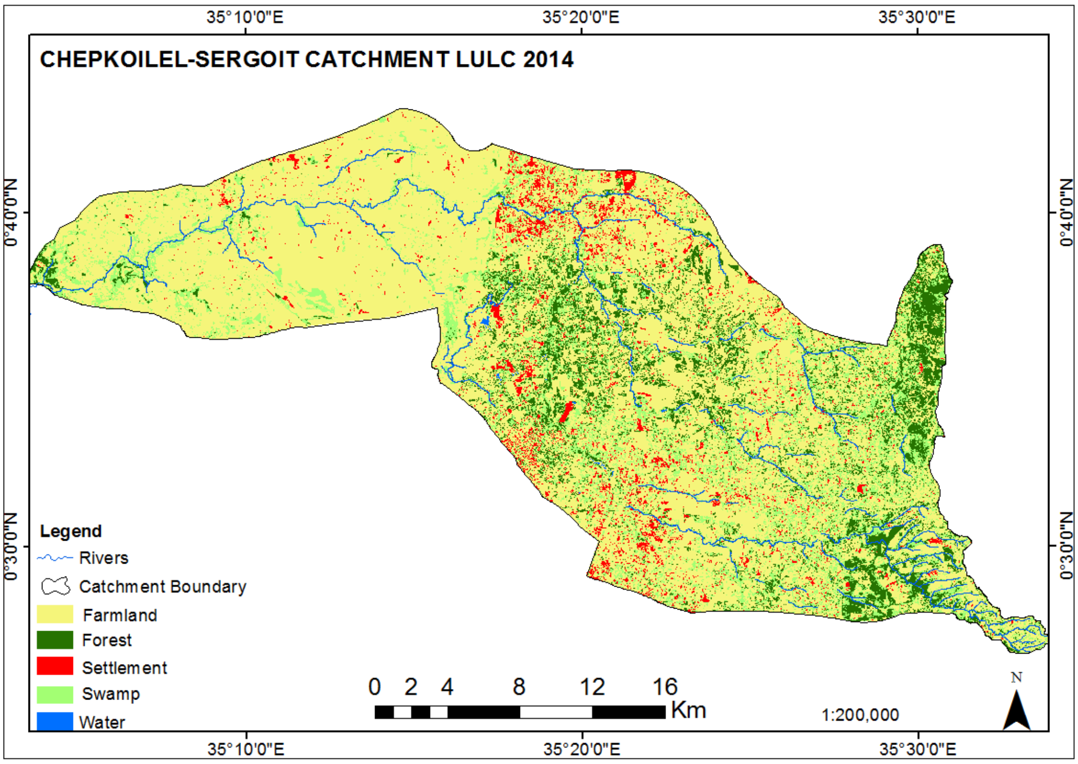


Figure 16: Land Cover/Land Use Map of River Chepkoilel-Sergoit catchment in 2014

By 2014 the forest-wetland/swamp complex had been substantially reduced, especially in the south-eastern corner of the catchment as shown in Figure 6(b). There is more farmland in the upper catchment. The middle catchment shows substantial increase in coverage of settlement areas and the lower catchment exhibits a modest increase also. Scattered patches of planted forest stands and wetlands/swamps (many of them seasonal) in the middle catchment are also well represented.

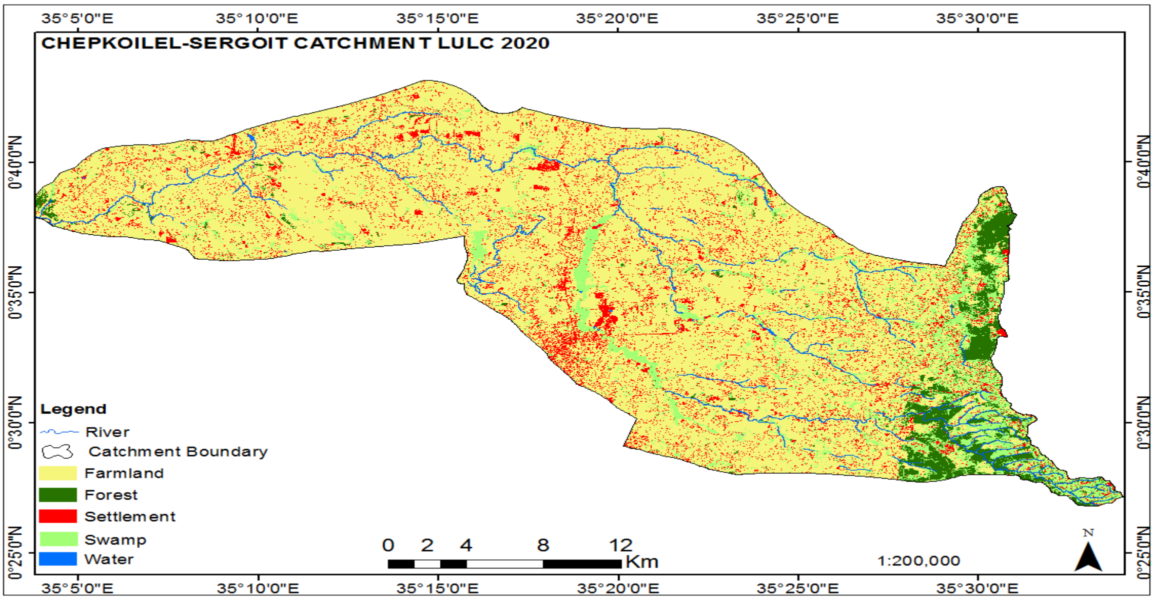


Figure 17: Land Cover/Land Use Map of River Chepkoilel-Sergoit catchment in 2020

In the 2020 map [Figure 17] the most remarkable feature is the extent to which settlement has spread throughout the catchment. High population growth and the impact of the growth of Eldoret town is clearly visible in the growth of settlements in the south-central part of the middle catchment which includes the northern suburbs and peripheries of the town, around the Marula wetland/swamp, and along the transport corridors leading northwards. This is also the location of the University of Eldoret, which has contributed substantially to the growth of settlements. Much of the forest areas in the upper catchment have been converted to farmland (commercial tea estates and other farms) and settlement is widespread throughout the area.

Accuracy assessment

Accuracy defines correctness and it measures the degree of agreement between a standard that is assumed to be correct and a map created from an image (Anand, 2017). A visually interpreted map or classified image is only said to be highly accurate when it corresponds closely with the assumed standard. In the context of image interpretation, accuracy assessment determines the quality of information derived from remotely sensed data.

Accuracy in LCLU classification is normally assessed through the use of three parameters: confusion matrix, kappa coefficient and overall accuracy. The matrix compares the actual target values with those predicted by the machine learning model, and the kappa coefficient is an index to express the accuracy of an image classification used to produce a thematic map (Rosenfield and Fitzpatrick-Lins, 1986), and is derived from the confusion matrix. The values of the kappa index vary from -1 to 1, and the closer it is to 1 the more accurate the results are. The overall accuracy, which is the number of correctly classified pixels across all classes, also derives from the confusion matrix.

Tables 4(a), 4(b) and 4(c) below show the confusion matrix and the values of the kappa matrix and overall accuracy for each of the Land Cover/Land Use maps in Figures 15-17. Overall accuracy for the 1995 map was 83.33% with a Kappa coefficient of 0.7916667, that of 2014 was 90.67% with a Kappa coefficient of 0.8833333, and that of 2020 was 92.67% with a Kappa coefficient of 0.9080268. The Kappa coefficients indicated near perfect agreement as per Cohen's (1960) statistics table. All the maps were within the acceptable range of accuracy in mapping with remotely sensed imagery (Anderson *et al,* 1976).

Table 4(a): Confusion Matrix Table for Landsat 5 TM of 1995

Land cover	Farmland	Forest	Settlement	Wetland	Water	Total User's
Farmland	22	4	4	0	0	30
Forest	0	26	2	2	0	30
Settlement	5	0	25	0	0	30
Wetland/swamp	0	6	0	24	0	30
Water	0	2	0	0	28	30
Total Producer's	27	38	31	26	28	150

Overall accuracy = 83.33%, Kappa coefficient = 0.7916667.

Table 4(b): Confusion Matrix Table for Landsat 8 OLI of 2014

Land cover	Farmland	Forest	Settlement	Wetland	Water	Total User's
Farmland	26	2	2	0	0	30
Forest	0	29	0	1	0	30
Settlement	2	1	27	0	0	30
Wetland/swamp	0	4	0	24	2	30
Water	0	0	0	0	30	30
Total Producer's	28	36	29	25	32	150

Overall accuracy = 90.67%, Kappa coefficient = 0.8833333.

Table 4(c): Confusion Matrix Table for Sentinel-2 of 2020

Land cover	Farmland	Forest	Settlement	Wetland	Water	Total User's
Farmland	27	1	2	0	0	30
Forest	0	30	0	0	0	30
Settlement	2	0	28	0	0	30
Wetland/swamp	0	3	0	26	1	30
Water	0	2	0	2	28	30
Total Producer's	29	36	30	28	29	150

Overall accuracy = 92.67%, Kappa coefficient = 0.9080268.

Area calculation

The areas for each individual land cover class were calculated using field calculator geometry in ArcMap. The 'field calculator' multiplies the field of 'counts' with cell size for each image. Since the pixel sizes in each image are known, the area covered by each LC/LU class was expressed in kilometers (Table 5).

Table 5 also shows how the LC/LU has changed in the 25 years covered in the study. It shows that between 1995 and 2020 farmland has increased by 44%, forest cover has reduced by 69%, settlement has increased by 261%, and wetland/swamp has declined by 64%.

Table 5: LC/LU class area coverage (km²)

Land cover	**Area km² 1995**	**Area km² 2014**	**Area km² 2020**
Farmland	368.87526	492.185971	531.975758
Forest	115.17321	78.770101	34.91184
Settlement	20.488982	31.285454	74.041202
Wetland/swamp	212.698	115.58859	77.486211
Water	0.902439	0. 564846	0.567436
Total area	**718.13789**	**718.394962**	**718.98244**

The study area was divided into three sections (upper catchment, middle catchment and lower catchment) to assist examination of factors contributing to environmental impacts of the catchment. Table 6 shows the Land Cover Land use of the three sections in 1995, 2014 and 2020, and the changes in cover over the period 1995 to 2020 and illustrates the tremendous changes that have taken place in the different sections of the catchment. Thus, all of the 26% (40km²) increase in Farmland cover in the Lower catchment happened between 1995 and 2014. Farmland also increased by 33% (163.6 to 207.4km²) in the Upper catchment in the period 1995 to 2020, and also increased by 157% (51.4 to 131.7km²) in the Middle catchment in the same period. Forest reduced from 57 1o 31km² (46%) in the Upper catchment between 1995 and 2020, most of the reduction happening between 2014 and 2020, and declined practically by 100% (22.8 to 0.8km²) in the Middle catchment between 2014 and 2020. Settlement more than doubled in the Middle section between 1995 and 2020 (9.3 to 19.03km²) and quadrupled (8.5 to 44.1 km²) in the Upper section of the catchment in the same period; The Middle catchment hosts the rapidly expanding Eldoret municipality and its suburbs, which contribute to the rapid rise in settlement. Also, the large planted commercial EATEC forest which covered much of the Middle catchment has been cleared. Wetland areas (seasonal and perennial) have also declined drastically from 55.5 to 8.9km² (89%) in the Middle section between 1995 and 2020.

Table 6: LC/LU class cover in the 3 sections of the catchment

Areas in km^2									
	1995			**2014**			**2020**		
Land cover	**Lower**	**Mid**	**Upper**	**Lower**	**Mid**	**Upper**	**Lower**	**Mid**	**Upper**
Farmland	153.67242	51.54218	163.66066	193.40886	103.415193	194.391884	193.041404	131.774289	207.416799
Forest	14.399596	43.743417	57.030193	4.878066	22.767225	50.981865	3.004438	0.756116	31.144979
Settlement	2.663141	9.3224x26	8.503415	4.341246	12.858011	14.029827	21.616125	19.03x1664	33.410585
Wetland /swamp	55.509104	57.457484	99.731413	24.579747	22.61943	69.134941	9.890651	10.354517	57.247536
Water	0.246639	0.042253	0.613547	0.000647	0.339621	0.224578	0.200222	0.101267	0.267553
Total area	**226.4909**	**162.107776**	**329.53923**	**227.20857**	**161.99948**	**328.763095**	**227.75284**	**162.01784**	**329.48744**

Conclusion

The study has shown substantial changes in Land Cover/Land Use of the catchment over the 25 years studied and that, since these processes are likely to continue and even accelerate in future, action to reduce these changes are urgently needed. Land cover and land use have significant effect on the efficacy of the hydrology of any catchment and the frequently observed dry wells and dry river channels during extended dry seasons in this catchment are at least partially due to these changes. This needs to be clearly incorporated in policies encompassing development in this catchment and especially the expansion of Eldoret Municipality. Soil/land conservation in the catchment, especially in the upper catchment, and wetland rehabilitation/ conservation throughout the catchment should be prioritized.

Recommendations

It is clear that doing nothing will lead to unsustainable water supply conditions in the catchment in a few decades. We therefore recommend that immediate steps be taken to increase forest/vegetation cover in the catchment, especially in the upper zone. Active land/water conservation effort on the catchment is urgent.

Funding

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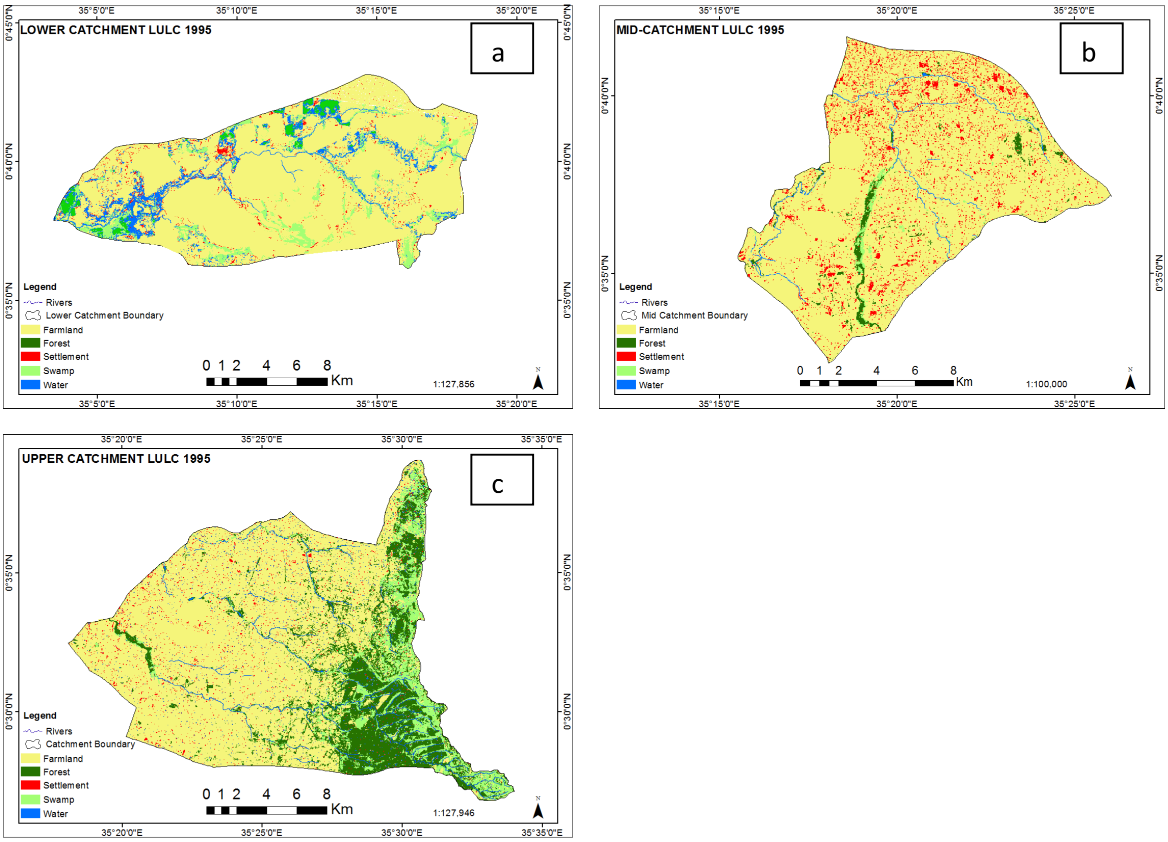
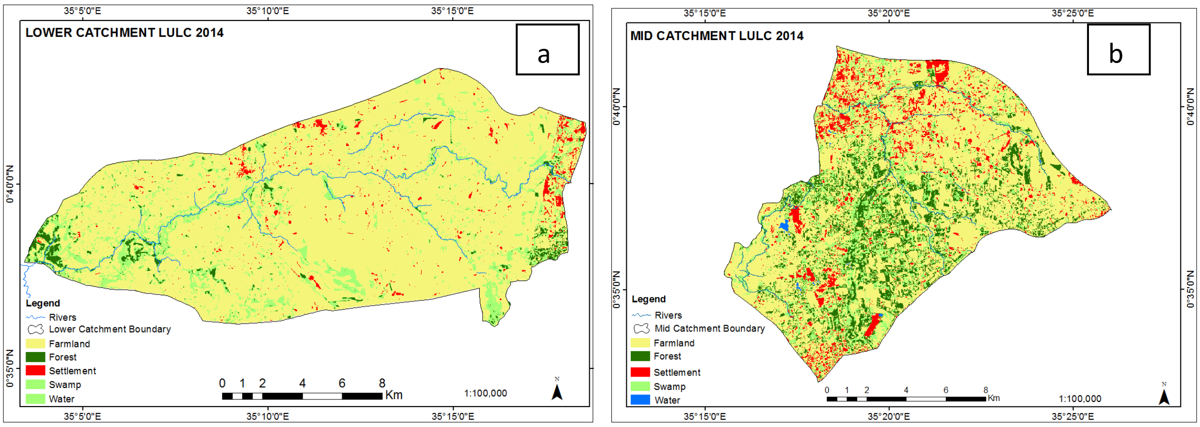
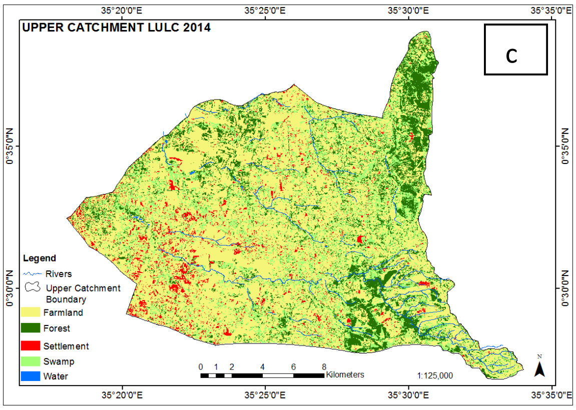
Annex 1

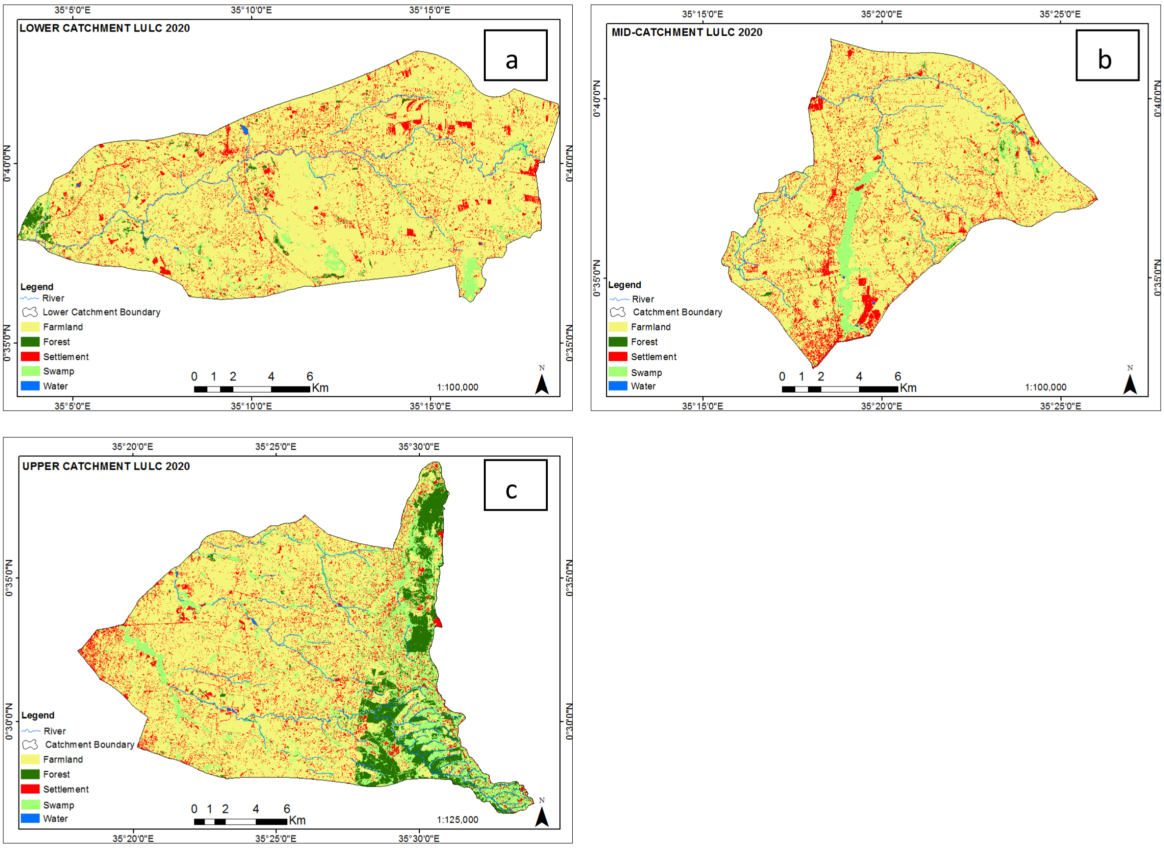


Annex 2: River Chepkoilel-Sergoit a) lower, b) mid and c) upper catchment 1995 LULC





Annex 3: River Chepkoilel-Sergoit a) lower, b) mid and c) upper catchment 2014 LULC



Annex 4: River Chepkoilel-Sergoit a) lower, b) mid and c) upper catchment 2020 LULC

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MOBILE +254709742000/+254729499650

Email: info@KyU.ac.ke

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