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Godište 12 (2026) – Sveščić 1

CONTENTS / SADRŽAJ

CREBSS 12(1):1–20

Lokalna prostorna analiza indeksa razvijenosti jedinica lokalne samouprave u Hrvatskoj

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SAŽETAK

Regionalne nejednakosti u Hrvatskoj rezultat su složenog međudjelovanja prostorne udaljenosti te povijesnih, društvenih i gospodarskih čimbenika. Cilj ovoga rada jest prostorno–statistički ispitati indeks razvijenosti svih 556 jedinica lokalne samouprave u Republici Hrvatskoj, uzimajući u obzir ne samo njihove pojedinačne vrijednosti, nego i geografski položaj te obilježja susjednog okruženja. U tu svrhu primijenjena je eksplorativna prostorna analiza podataka (ESDA), s posebnim naglaskom na globalni Moranov indeks i lokalne indikatore prostorne povezanosti. Rezultati potvrđuju postojanje globalne umjerene do jake pozitivne prostorne autokorelacije indeksa razvijenosti, što upućuje na značajno grupiranje prostornih jedinica sličnih razvojnih obilježja. Lokalnom prostornom analizom identificirano je pet klastera, koji se u radu sistematiziraju u četiri skupine: razvijene jedinice (HH klaster), nerazvijene jedinice (LL klaster), prostorne izdvojenice (HL i LH klaster) te prijelaznu skupinu statistički neznačajnih jedinica. Takva raspodjela klastera otkriva izraženu zapadno–istočnu razvojnu polarizaciju u Jadranskoj i Kontinentalnoj Hrvatskoj. Procjena efektivne veličine uzorka, koja je znatno manja od nominalnog broja lokalnih jedinica, dodatno naglašava važnost uvažavanja prostorne ovisnosti u empirijskim analizama. Rad doprinosi razumijevanju prostorne dimenzije regionalnih nejednakosti te pruža argumente za oblikovanje razvojnih politika na funkcionalno i prostorno širem teritorijalnom obuhvatu.

KLJUČNE RIJEČI

ESDA, indeks razvijenosti, općine i gradovi, regionalne nejednakosti

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1. Uvod

Briga o uravnoteženom gospodarskom razvoju svih dijelova Republike Hrvatske, kao i promicanje gospodarskog napretka i društvene dobrobiti stanovništva, jedna je od temeljnih ustavnih obveza države. Procjena stupnja razvijenosti pojedinih teritorijalnih jedinica ima središnju ulogu u oblikovanju regionalnih razvojnih politika i provedbi planskih aktivnosti. Takve procjene predstavljaju važan analitički temelj za donošenje odluka o usmjeravanju razvojnih mjera, raspodjeli financijskih sredstava te dodjeli strukturnih fondova i drugih oblika

*Dopisni autor

državne potpore (Cziráky i sur., 2006). Od osamostaljenja Republika Hrvatska prolazi kroz različite faze regionalnog razvoja, pri čemu regionalna politika, uz potporu kohezijske politike Europske unije, ima ključnu ulogu u smanjenju regionalnih nejednakosti. Unatoč značajnim financijskim sredstvima usmjerenima na taj cilj, regionalne razlike i dalje su prisutne. One proizlaze iz uobičajenih razvojnih obrazaca, poput razlika između urbanih i ruralnih područja te odnosa centra i periferije, što je u Hrvatskoj posebno izraženo dominacijom Grada Zagreba. Takve razlike vidljive su u pokazateljima poput zaposlenosti, nezaposlenosti i drugih ekonomskih indikatora (Puljiz, 2009; Botrić, 2004).

Nepovoljni socioekonomski uvjeti izravno se odražavaju na ograničene fiskalne mogućnosti jedinica lokalne samouprave (JLS), zbog čega one često postaju snažno ovisne o državnim transferima te imaju smanjenu sposobnost samostalnog poticanja gospodarskog razvoja (Puljiz, 2009). Takva ovisnost dodatno otežava dugoročno planiranje i provedbu razvojnih politika na lokalnoj razini. U tom kontekstu, brojni su autori ukazivali na problematičnost kriterija za dodjelu državnih potpora (Ott & Bajo, 2001; Bronić, 2008), ističući njihovu nedovoljnu jasnoću i manjak transparentnosti, što može dovesti do neučinkovite raspodjele javnih sredstava i produbljivanja regionalnih nejednakosti.

U početnoj fazi razvoja regionalne politike u Republici Hrvatskoj naglasak je bio stavljen na obnovu područja pogođenih ratnim razaranjima. Značajniji pomak u oblikovanju regionalne politike ostvaren je donošenjem Zakona o područjima posebne državne skrbi (PPDS), zajedno s njegovim kasnijim izmjenama i dopunama. Uspostavom ovih područja nastojalo se potaknuti njihov ubrzani razvoj, zbog čega su im osigurani povoljniji uvjeti financiranja i poseban status u sustavu državnih potpora (Ott & Bajo, 2001).

Sukladno zakonskom okviru uspostavljenom 1996. godine, područja posebne državne skrbi podijeljena su u tri skupine potpomognutih jedinica lokalne samouprave. Prve dvije skupine definirane su prema stupnju ratne štete nastale tijekom Domovinskog rata, dok je treća skupina, uvedena 2002. godine, obuhvatila jedinice koje zaostaju u razvoju prema nizu razvojnih pokazatelja. Kriteriji za određivanje ove skupine uključivali su razinu ekonomske razvijenosti, prisutnost strukturnih poteškoća, demografska obilježja te posebne razvojne okolnosti (Bronić, 2008). Iako je Republika Hrvatska prema svojoj površini i broju stanovnika relativno mala država, obilježena je izraženim regionalnim razlikama. Raznolikost hrvatskih regija predstavlja značajan razvojni potencijal i bogatstvo, no istodobno stvara izazove povezane s neujednačenim regionalnim razvojem. Uz prirodno-geografske i socioekonomske specifičnosti, među regijama postoje i znatne razlike u razini gospodarske i društvene razvijenosti.

Uzroci regionalnih nejednakosti višestruki su i međusobno isprepleteni, a mogu proizaći iz prostorne udaljenosti, dugoročnih društvenih i gospodarskih promjena ili njihove kombinacije. Posljedice takvih neravnoteža očituju se kroz smanjenu kvalitetu života stanovništva, uključujući društveno osiromašenje, ograničen pristup obrazovanju, visoku nezaposlenost te nedovoljno razvijenu i neadekvatnu infrastrukturu (Kesner-Škreb, 2009). Izražen proces depopulacije u slabije razvijenim područjima, zajedno s razlikama u razinama ekonomske razvijenosti, osobito su vidljivi na županijskoj, a još izraženije na lokalnoj razini. Uz dugotrajno visoku nezaposlenost i postupno gašenje gospodarskih aktivnosti, problem predstavlja i nizak udio obrazovanog stanovništva te kontinuirani odljev mladih i visoko obrazovanih osoba. Takvi demografski i obrazovni trendovi dodatno smanjuju razvojne potencijale nerazvijenih područja i ograničavaju mogućnosti njihova gospodarskog oporavka.

Često isticana fragmentiranost sustava lokalne i regionalne samouprave upućuje na potrebu jasne kategorizacije teritorijalnih jedinica kako bi se omogućila učinkovitija provedba regionalnih razvojnih politika. Budući da je problem razvojnog zaostajanja pojedinih regija jedno od ključnih pitanja nacionalne politike, ali i politike Europske unije, pravilno razvrstavanje područja koja istodobno zaostaju u gospodarskom i demografskom razvoju predstavlja važan preduvjet za ciljano i djelotvorno usmjeravanje razvojnih mjera.

Ekonomski razvoj predstavlja širi koncept od ekonomskog rasta, koji se uglavnom odnosi na povećanje bruto domaćeg proizvoda i pozitivne stope njegova rasta kroz vrijeme. Na lokalnoj i regionalnoj razini mjerenje ekonomskog razvoja dodatno je složeno zbog povezanosti regionalnih gospodarstava s nacionalnim i međunarodnim ekonomskim tokovima. Čimbenici poput migracija, utjecaja regionalnih središta, blizine državnih granica ili raspoloživosti prirodnih resursa mogu značajno utjecati na razlike u razvijenosti među regijama, ali istodobno otežavaju precizno mjerenje i usporedbu regionalnog razvoja (Arčabić, 2022).

Indeks razvijenosti predstavlja kompozitni pokazatelj koji se temelji na prilagođenom prosjeku standardiziranih vrijednosti odabranih društveno-gospodarskih pokazatelja, a definiran je Zakonom o regionalnom razvoju Republike Hrvatske (NN 147/14, 123/17, 118/18) te pripadajućom Uredbom o indeksu razvijenosti (NN 131/17). Njegova je svrha mjerenje stupnja razvijenosti jedinica lokalne i područne (regionalne) samouprave te omogućavanje njihove međusobne usporedbe na temelju jedinstvene metodološke osnove.

Indeks obuhvaća sve jedinice lokalne samouprave i jedinice područne samouprave u Republici Hrvatskoj te kroz indeksirane vrijednosti određuje njihov relativni položaj u odnosu na nacionalni prosjek. Izračun indeksa razvijenosti iz 2024. godine proveden je sukladno istoj, nepromijenjenoj metodologiji kao i prethodni izračun, pri čemu su korišteni najnoviji dostupni statistički podaci za razdoblje od 2020. do 2022. godine. Time je osigurana vremenska usporedivost rezultata i kontinuitet u praćenju razvojnih trendova. Izračun indeksa temelji se na šest ključnih pokazatelja: stopi nezaposlenosti, dohotku po stanovniku, proračunskim prihodima jedinica lokalne odnosno područne (regionalne) samouprave po stanovniku, općem kretanju stanovništva, stopi obrazovanosti te indeksu starenja. Kombinacijom navedenih pokazatelja nastoji se obuhvatiti gospodarska, fiskalna i demografska dimenzija razvoja.

Prema propisanoj metodologiji, dio teritorijalnih jedinica ostvaruje vrijednost indeksa nižu od nacionalnog prosjeka, dok dio jedinica ima vrijednosti iznad prosjeka. Jedinice lokalne samouprave razvrstane su u osam razvojnih skupina, pri čemu skupine s nižim vrijednostima indeksa imaju status potpomognutih područja, dok jedinice s višim vrijednostima ne ulaze u tu kategoriju. Takva kategorizacija ima izravne posljedice na oblikovanje i provedbu regionalnih razvojnih politika. Redovita objava indeksa razvijenosti u jednakim vremenskim razmacima predstavlja prvi sustavni instrument za praćenje razvoja na svim administrativnim razinama u Hrvatskoj, kako prostorno tako i vremenski. Vrijednost indeksa ima značajne praktične implikacije jer se koristi kao kriterij za određivanje potpomognutih područja, bodovanje razvojnih projekata te donošenje odluka u okviru različitih javnih politika.

U širem teorijskom kontekstu, kompozitni indeksi razvoja predstavljaju operacionalizaciju razvojnih teorija u matematički izražene modele, čija je osnovna svrha omogućiti mjerljivost i usporedivost razvojnih razina među teritorijalnim jedinicama. Njihova prednost leži u sposobnosti sažimanja složenih i višedimenzionalnih razvojnih procesa u razumljive i interpretativno jednostavne pokazatelje, koji su često pregledniji od analize većeg broja pojedinačnih indikatora (OECD, 2008). U tom smislu, uvođenje indeksa razvijenosti predstavlja ključan iskorak u dugoročnom praćenju regionalnog razvoja te važan analitički alat kako za nositelje javnih politika, tako i za znanstvena istraživanja usmjerena na regionalne nejednakosti. Uzroci regionalnih nejednakosti brojni su i međusobno povezani te mogu proizaći iz prostorne udaljenosti, dugoročnih društvenih i gospodarskih promjena ili njihove međusobne kombinacije (Perišić, 2014). Cilj rada je prostorno statistički kvantificirati spomenuti indeks razvijenosti jedinica lokalne samouprave s obzirom na susjedstvo u okruženju pojedine jedinice. Stoga, ne uzima se u obzir samo vrijednost indeksa, nego i geografski položaj.

Za razliku od deskriptivnih i neprostornih pristupa, primjena lokalne klasterizacije omogućuje identifikaciju statistički značajnih lokalnih klastera i izdvojenica, čime se otkrivaju prostorni obrasci koji nisu vidljivi kroz standardnu klasifikaciju indeksa razvijenosti. Time se dodatno naglašava heterogenost regionalnog razvoja te omogućuje preciznije razumijevanje lokalnih razvojnih dinamika i potreba za diferenciranim politikama. Zaključno, ne pokazuje se samo gdje su razvijeni i nerazvijeni, nego kako su povezani u prostoru i gdje postoje odstupanja od tih obrazaca.

2. Pregled literature

Istraživanja indeksa razvijenosti na lokalnoj razini su malobrojna. Arčabić (2022) ističe kako postojeće mjere regionalne razvijenosti ne obuhvaćaju sve relevantne dimenzije regionalnog ekonomskog razvoja. Posebno se izdvajaju aspekti poput dohodovne nejednakosti, zaštite okoliša i održivosti, kao i specifični čimbenici važni za hrvatski kontekst, poput razvijenosti turizma i kretanja cijena nekretnina. Održivost i blagostanje mogu biti sukobljeni ciljevi u kratkom roku, ali su dugoročno komplementarni.

Marcelić (2023) ističe specifičnosti otočnih jedinica lokalne samouprave, pri čemu se kao ključan problem izdvaja nepovoljna dobna struktura stanovništva, odnosno izraženo starenje populacije. Iako otoci u većini komponenti indeksa razvijenosti ostvaruju relativno visoke vrijednosti, upravo demografski pokazatelji, osobito indeks starenja, značajno odstupa od državnog prosjeka. Zbog toga otočne jedinice pokazuju određene anomalije u razvojnim obrascima, budući da istodobno bilježe relativno povoljnija kretanja stanovništva uz izražene procese demografskog starenja. Dodatno, njihovu razvojnu dinamiku ograničavaju čimbenici poput prometne izoliranosti i nedovoljno diverzificirane gospodarske strukture.

Marcelić (2015) izdvaja za indeks iz 2013. šest klastera iz kojih proizlaze tri tipa razvijenosti kategorizirane kao: nerazvijenost, razvoj jedinice i ljudski razvoj. Posebno ističe razvoj jedinica koji se manifestira kroz visok prihod i opće kretanje stanovništva, a pri čemu zaostaju u ljudskom razvoju (zaposlenost, osobni prihod i obrazovanje). Spomenuto je u suprotnosti sa svrhom indeksa razvijenosti, a to se posebice očituje u priobalju. Stoga, autor predlaže modifikaciju komponenti i ponderiranja, što se događa u sljedećem izdanju indeksa razvijenosti. Isto tako, indeks razvijenosti je važan dio kriterija u programu ruralnog razvoja, pa ga je potrebno dodatno korigirati kako bi se omogućio lakši pristup najnerazvijenijim područjima (Golob i sur., 2018).

Perišić (2015) koristeći tehnike multivarijatne analize ispituje pet socioekonomskih pokazatelja koji su većinom korišteni za indeks razvijenosti iz 2010. Analiza je provedena za lokalnu i regionalnu samoupravu u Hrvatskoj. U radu se izdvaja poseban klaster koji karakterizira problem depopulacije, ali ne i ekonomske nerazvijenosti. Navedeno ostavlja mogućnost djelovanja demografske politike. Nadalje, najnerazvijenije su lokalne jedinice u Središnjoj i Istočnoj Hrvatskoj, i čine oko trećine jedinica s oko petine stanovnika Hrvatske. Najrazvijeniji klaster obuhvaća Grad Zagreb, i velik broj jedinica Istarske i Primorsko-goranske županije.

Perišić (2014) pokazuje učinak ponderiranja komponenti indeksa razvijenosti na položaj lokalnih jedinica. Nadalje, Perišić & Wagner (2015) ispituju neizvjesnost i osjetljivost indeksa razvijenosti s obzirom na metodologiju izračuna samog indeksa, i varijabli od kojih se sastoji. Štoviše, predlažu intervalne procjene indeksa razvijenosti. Metodologija izračuna indeksa razvijenosti na temelju balansirane z-score metode standardizacije i agregacije rješava glavninu ograničenja koja se odnose na neadekvatnu metodu standardizacije i agregacije pokazatelja, te na ponderiranje pokazatelja od kojih je indeks sastavljen (Denona Bogović i sur., 2017). Preporuke navedenog istraživanja usvojene su u NN 131/2017, te se danas koriste kao metodologija izračuna.

Dohodovne nejednakosti u Europi, osobito u zemljama srednje i istočne Europe, u posljednjim su desetljećima u porastu pod utjecajem ekonomskih, društvenih i političkih čimbenika (Camagni i sur., 2020). Proces proširenja Europske unije i gospodarska kriza dodatno su produbili regionalne razlike, dok su politike usmjerene na privlačenje stranih ulaganja često doprinijele jačanju prostornih nejednakosti. Iako su sredstva kohezijske politike potaknula određeni proces konvergencije, njihovi učinci nisu ujednačeni među regijama, što i dalje rezultira postojanjem značajnih teritorijalnih razlika (Jovančević i sur., 2015; Camagni i sur., 2020; Smętkowski, 2017).

Ursu & Benedek (2024) analiziraju prostorne obrasce dohodovnih nejednakosti u Rumunjskoj, s posebnim naglaskom na metropolitanska područja. Primjenom prostornih statističkih metoda identificiraju klastere i prostorne izdvojenice u razinama dohotka po stanovniku. Rezultati ukazuju na izraženu koncentraciju visokih dohodaka u razvijenijim regijama, poput Bukurešta i okolnih područja te zapadnih i središnjih dijelova zemlje, dok su niži dohodci dominantno prisutni u ostalim regijama i pokazuju ograničenu dinamiku poboljšanja kroz promatrano razdoblje. Na metropolitanskoj razini posebno se ističe uloga velikih gradova kao središta visokih dohodaka i nositelja ekonomskog utjecaja unutar svojih područja.

Tselios & Rodríguez-Pose (2022) analiziraju utjecaj decentralizacije na smanjenje siromaštva i socijalne isključenosti u europskim zemljama i regijama. Njihovi rezultati pokazuju da prijenos političkih, administrativnih i fiskalnih ovlasti središnje vlasti na niže razine upravljanja može doprinijeti smanjenju siromaštva i socijalne isključenosti na nacionalnoj razini, osobito u zemljama s visokom kvalitetom upravljanja i u urbanim područjima. Na regionalnoj razini veći stupanj autonomije dosljedno je povezan s nižim razinama siromaštva i socijalne isključenosti, neovisno o kvaliteti regionalne vlasti, što upućuje na važnost kapaciteta regionalnih institucija za oblikovanje vlastitih razvojnih politika i unaprjeđenje opće dobrobiti.

Rodríguez-Pose & Tselios (2009) analiziraju prostornu distribuciju osobnih dohodaka i nejednakosti u zapadnoj Europi koristeći podatke na razini pojedinaca i regija. Primjenom lokalnih prostornih mjera utvrđuju postojanje izražene U-oblikovane veze između razine dohotka po stanovniku i dohodovne nejednakosti. Također, rezultati pokazuju da se najveći dio nejednakosti javlja unutar samih regija, dok se regije sličnih razina dohotka prostorno grupiraju, i unutar i izvan nacionalnih granica. Dodatno, uočava se jasna prostorna podjela između sjevernih i južnih te urbanih i ruralnih područja, pri čemu razvijenije sjeverne i urbane regije ostvaruju višu razinu gospodarskog razvoja uz niže razine nejednakosti.

Gospodarstva koja se suočavaju sa zamkom srednjeg dohotka dosežu razvojnu razinu na kojoj rast troškova proizvodnje smanjuje njihovu konkurentnost u odnosu na zemlje nižeg dohotka, dok istodobno razina ljudskog kapitala i inovacijskih kapaciteta još uvijek nije dovoljno razvijena da bi omogućila uspješno natjecanje s visokorazvijenim gospodarstvima

(Kharas & Kohli, 2011). Takva se gospodarstva stoga nalaze između dvije razvojne faze: s jedne strane ne posjeduju razinu produktivnosti i inovativnosti karakterističnu za najrazvijenije ekonomije, dok s druge strane postupno gube troškovne prednosti koje su tipične za zemlje nižeg dohotka.

Analogno zamci srednjeg dohotka, regionalna razvojna zamka može se definirati kao stanje u kojem regija ne može održati gospodarsku dinamiku u pogledu razine dohotka, produktivnosti i zaposlenosti, pri čemu istodobno zaostaje za nacionalnim i europskim regijama na istim pokazateljima. U tom se kontekstu mogu razlikovati regionalne razvojne zamke koje se javljaju na različitim razinama razvoja, odnosno u regijama s visokom, srednjom i niskom razinom dohotka (Diemer i sur., 2022). Postoje značajne razlike između pojave razvojnih zamki u europskim regijama i koncepta zamke srednjeg dohotka na razini država. Europske regije u pravilu zapadaju u razvojnu zamku na relativno višim razinama gospodarskog razvoja. Osim toga, gubitak gospodarske dinamike u razvijenim regijama ne očituje se nužno samo kroz stagnaciju BDP-a po stanovniku, već se često manifestira kroz slab rast produktivnosti, stagnaciju zaposlenosti ili smanjenje inovacijskog kapaciteta. Regionalna stagnacija u Europi može slijediti različite razvojne putanje, primjerice u nekada snažnim industrijskim regijama pogođenima padom proizvodnje ili u regijama koje su nakon razdoblja ubrzanog rasta ostale na razinama razvoja ispod europskog prosjeka (Iammarino i sur., 2019).

Dosadašnji prostorno ekonometrijski radovi na lokalnoj razini u Hrvatskoj uglavnom potvrđuju postojanje globalne prostorne povezanosti te je uključuju u empirijske modele (Grgić, 2020; Mikulić i sur., 2021; Stojčić i sur., 2022). Međutim, istraživanja koja se bave analizom lokalnih obrazaca prostorne klasterizacije, osobito u kontekstu indeksa razvijenosti, ostaju rijetka. Pritom izostaju istraživanja koja primjenjuju prostornu ekonometriju kroz mjere lokalne prostorne povezanosti. Sličan istraživački jaz prisutan je i na razini Europske unije, gdje je relativno mali broj radova koji koriste lokalne indikatore prostorne povezanosti za analizu regionalnih nejednakosti. U tom kontekstu, ovo istraživanje nastoji pridonijeti literaturi primjenom lokalnih mjera prostorne ekonometrije u analizi regionalne razvijenosti, čime se omogućuje dublje razumijevanje prostornih obrazaca i njihovih implikacija za regionalne politike. Cilj navedenog istraživanja je istražiti prostornu povezanost i statistički je kvantificirati za svaku jedinicu zasebno promatrajući indeks razvijenosti lokalnih jedinica. Znači, fokus je na lokalnoj prostornoj povezanosti. Spomenuto predstavlja svojevrstan prostorni mikroskop, a ujedno komplement mjerenju povezanosti na globalnoj razini, i klasterizaciji kada se ne uzima u obzir geografska dimenzija. Na temelju provedene analize utvrdit će se koje su jedinice nositelji prostorne klasterizacije, a koje su izdvojenice.

3. Metodologija

U ovom istraživanju primjenjuje se eksplorativna prostorna analiza podataka ESDA (engl. *Exploratory Spatial Data Analysis*) kao metodološki pristup za analizu prostorne dimenzije podataka. ESDA omogućuje sustavno istraživanje prostornih obrazaca i odnosa uzimajući u obzir geografsku lokaciju opažanja i njihove međusobne prostorne veze. Za razliku od klasičnih deskriptivnih statističkih metoda, ovaj pristup polazi od pretpostavke da prostorna blizina može imati važnu ulogu u oblikovanju vrijednosti promatranih varijabli.

Primjenom ESDA metode istražuju se potencijalni prostorni klasteri, prostorno izdvojene jedinice te prisutnost prostorne ovisnosti u podacima. Kartografski prikazi i prostorne statističke mjere koriste se kao početna faza analize, s ciljem boljeg razumijevanja strukture podataka i identifikacije obrazaca koji ne bi bili uočljivi primjenom standardnih statističkih pristupa. Dobiveni rezultati predstavljaju temelj za daljnje analize i modeliranje u okviru prostorne ekonometrije (ESDA, 2021).

ESDA je široko primijenjena u istraživanjima regionalnih nejednakosti i prostorne distribucije ekonomskih aktivnosti. Raniji radovi primjenjuju ESDA metodu kako bi identificirali prostorne obrasce i klastere regionalnog razvoja u Europi, pri čemu se posebno ističu istraživanja Ertur & Le Gallo (2003), Dall'erba (2005) te de Dominicis i sur. (2007). U tim studijama globalne i lokalne mjere prostorne autokorelacije koriste se za otkrivanje prostorne koncentracije razvijenosti i nejednakosti. Sličan pristup primjenjuju i u kasnijim istraživanjima (Panzera & Postiglione, 2020; Rodríguez-Pose & Tselios, 2009; Ursu & Benedek, 2024), pri čemu potvrđuju važnost spomenute metodologije u razumijevanju prostornih obrazaca, identifikaciji klastera i formuliranju ciljanih razvojnih politika.

Sastavni i ključni element jest prostorna matrica susjedstava (težina), koja služi za formalno definiranje prostorne strukture promatranih podataka. Ova matrica matematički opisuje odnose među prostornim jedinicama, odnosno način i intenzitet međusobnog utjecaja pojedinih opažanja unutar određenog prostornog sustava (Elhorst, 2014). Njezina je uloga operacionalizirati pojam prostorne blizine i omogućiti kvantifikaciju prostorne povezanosti među jedinicama analize.

U metodološkom smislu, prostorna težinska matrica određuje se unaprijed, na temelju teorijskih pretpostavki i empirijskih obilježja promatranog prostora. Istraživač pritom donosi odluku o kriterijima prostorne povezanosti, koji mogu biti definirani kroz neposredno susjedstvo prostornih jedinica ili kroz udaljenost između njih. Odabir odgovarajuće matrice ovisi o prostornoj konfiguraciji podataka, ciljevima istraživanja te prirodi analiziranog fenomena, budući da različite specifikacije matrice susjedstva mogu rezultirati različitim uvidima u prostorne obrasce i razine prostorne ovisnosti.

U ovom istraživanju primjenjuje se matrica k-najbližih susjeda kNN (engl. *k-nearest neighbors*) kao fleksibilniji pristup definiranju prostornih odnosa. Za razliku od matrica koje se temelje isključivo na zajedničkim administrativnim granicama, kNN pristup određuje prostornu povezanost tako da se za svaku prostornu jedinicu identificira unaprijed definiran broj najbližih susjednih jedinica. Na taj način osigurava se da svaka prostorna jedinica ima točno k susjeda, neovisno o njezinoj veličini, obliku ili položaju u prostoru. Ovakav pristup posebno je prikladan u situacijama u kojima prostorne jedinice značajno variraju u površini i prostornoj raspodjeli. To se jasno očituje u slučaju Republike Hrvatske, čiji specifičan i razveden teritorijalni oblik izravno utječe na strukturu lokalnih jedinica i njihov broj neposrednih susjeda. U takvom prostornom kontekstu, matrice temeljene isključivo na susjedstvu mogu dovesti do neujednačene prostorne povezanosti, pri čemu pojedine jedinice imaju velik broj susjeda, dok su druge gotovo izolirane.

Primjena kNN matrice dodatno je opravdana zbog prisutnosti otoka, koji u klasičnim matricama susjedstva često ostaju prostorno nepovezani ili nedovoljno integrirani u analizu. Korištenjem kNN pristupa omogućuje se uspostavljanje prostornih veza između jedinica na istom otoku, između različitih otoka, kao i između otočnih i kopnenih jedinica. Time se osigurava koherentna prostorna struktura podataka i realističniji prikaz prostornih odnosa, što je ključno za pouzdanu primjenu ESDA metode i daljnju prostornu analizu. Prostorna povezanost između dviju jedinica bilježi se binarnim težinama, pri čemu se veza smatra postojećom ako se promatrana jedinica nalazi među k najbližih susjeda referentne jedinice. U suprotnom slučaju prostorna veza se ne uzima u obzir.

Utjecaj veličine samih jedinica može se objasniti usporedbom male i velike jedinice koje su susjedne nekoj jedinici, pri čemu je udaljenost velike dvostruko veća nego male. Ako su vrijednosti indeksa u slučaju male i velike jedinice iste, samo zbog veće udaljenosti, učinak za veću jedinicu je dvostruko manji. Stoga je za svaki element prethodno definirane kNN matrice izračunata udaljenost d između središta pojedine jedinice, i svakog od njezinih k susjeda, a zatim se element matrice susjedstva dobije kao $1/d$. Tako se ponderira udaljenost između jedinica koristeći matricu susjedstva, a na kraju je provedena standardizacija po recima, tako da je suma svakog retka jedan.

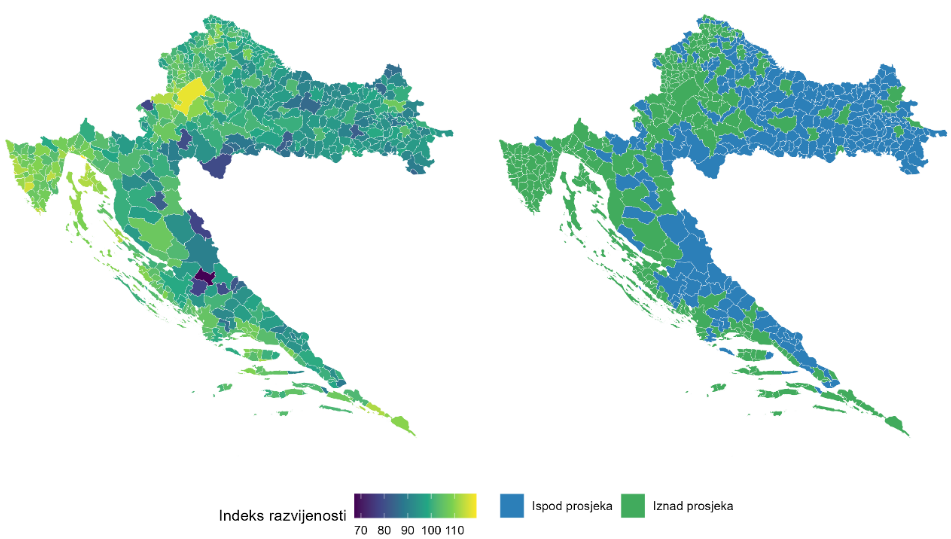
Ključan parametar za kNN matricu je parametar k, odnosno broj susjednih jedinica. Prema Bayesovom informacijskom kriteriju BIC napravljena je usporedba između matrica težina tako da broj susjeda varira od 1 do 20 te je utvrđena minimalna vrijednost kriterija za $k = 12$, zbog čega je ta specifikacija odabrana kao optimalna matrica prostornih težina u daljnjoj analizi. Iako jedinice lokalne samouprave u Hrvatskoj u prosjeku imaju 5 susjednih jedinica s kojima graniče, ovim postupkom je odabrano da svaka jedinica ima točno 12 susjeda. Ovdje su uključeni u pravilu susjedi prvog i drugog reda (susjedi susjeda). Na temelju tako definirane matrice prostornih težina procijenjen je prostorni autoregresijski model metodom maksimalne vjerodostojnosti. Procjena je provedena na modelu koji uključuje samo konstantu bez dodatnih objašnjavajućih varijabli.

Kako bi se provjerila robusnost obrazaca prostorne klasterizacije, primijenjeno je nekoliko matrica prostornih težina, uključujući matricu susjedstva temeljenu na zajedničkoj granici ili vrhu, tzv. Queen kriteriju, težine inverzne udaljenosti te matrice k-najbližih susjeda (kNN) s vrijednostima k =6, 10, 12, 14 i 16 (Dodatak). Matrica prema Queen kriteriju obuhvaća vrlo lokalnu prostornu ovisnost, pri čemu su prostorni učinci prvenstveno određeni neposrednim geografskim susjedima. Zbog toga se ova specifikacija često smatra najkonzervativnijom definicijom prostornog susjedstva. S druge strane, kod matrice inverzne udaljenosti pretpostavlja se da prostorna ovisnost djeluje na razini cijelog promatranog prostora, pri čemu sve jedinice međusobno utječu jedna na drugu s intenzitetom koji opada s udaljenošću. Međutim, takva specifikacija može dovesti do precjenjivanja prostorne klasterizacije jer pretpostavlja da sve jedinice, iako s različitim intenzitetom, međusobno utječu jedna na drugu.

Unatoč razlikama u definiciji susjedstva, ukupni prostorni obrazac razvijenosti među hrvatskim jedinicama lokalne samouprave ostaje u velikoj mjeri konzistentan u svim specifikacijama. Statistički značajni HH klasteri sustavno se pojavljuju u sjeverozapadnom dijelu Hrvatske i duž jadranske obale, što upućuje na prostornu koncentraciju razvijenijih jedinica. Nasuprot tome, LL klasteri trajno su prisutni u istočnoj Hrvatskoj i pograničnim područjima s BiH, što odražava prostornu koncentraciju slabije razvijenih područja. Povećanjem broja susjeda ili primjenom širih struktura prostornih interakcija povećava se broj statistički značajnih jedinica, a klasteri postaju prostorno kontinuiraniji. Ipak, temeljna prostorna struktura regionalnih nejednakosti ostaje stabilna u svim testiranim matricama prostornih težina, što upućuje na to da su utvrđeni obrasci prostorne autokorelacije i klasterizacije robusni na alternativne definicije prostornog susjedstva. Matrica k-najbližih susjeda predstavlja kompromis između ove dvije krajnosti, budući da svakoj jedinici dodjeljuje isti broj susjeda, čime se izbjegava problem izoliranih jedinica i osigurava stabilna prostorna struktura interakcija.

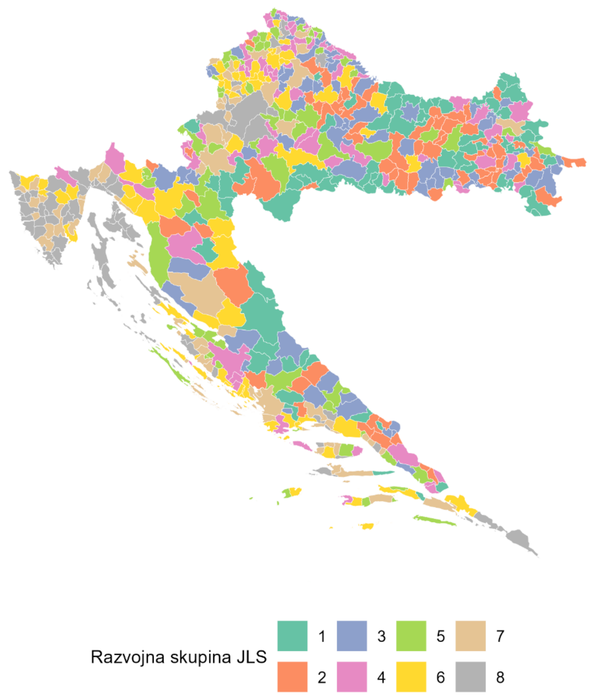
4. Podaci i analiza rezultata

Razlika između medijana i aritmetičke sredine indeksa razvijenosti je zanemariva (aritmetička sredina je 99,45, a medijan 99,72). Gornji i donji kvartil podjednako odstupaju od prosjeka. Minimalna vrijednost je 67,26, a maksimum 119,35, pri čemu je prisutna blaga negativna asimetrija koja iznosi $-0{,}368$. Promotri li se raspored vrijednosti indeksa u prostoru (Slika 1) uočava se pad vrijednosti u smjeru istoka. Najbolje vrijednosti ostvaruje Zagreb s bližom okolicom, i to posebice u smjeru sjeverozapada. Također, priobalni pojas postiže dobre rezultate, i to posebice u Istri i Kvarneru. Slabiji rezultati su u Slavoniji, a ponajviše u pograničnim područjima Like, Korduna, Banovine i Dalmatinske zagore. Zapravo veći dio pograničnih jedinica s BiH-om su ispod prosjeka. Isto vrijedi za granicu sa Srbijom, ali i dobar dio pograničnog područja s Mađarskom. JLS koje graniče sa Slovenijom imaju uglavnom iznadprosječne rezultate. Premda, u blizini najrazvijenijih postoje jedinice koje su dosta ispod prosjeka. Primjerice, općina Žumberak, iako u blizini Zagreba, i slovenske granice, ima jedan od najslabijih rezultata u čitavoj Hrvatskoj. Također, postoje i svijetli primjeri među nerazvijenijim jedinicama s obzirom na indeks razvijenosti (npr. Plitvice). Sve jedinice koje ostvaruju vrijednost indeksa manju od 100 imaju status potpomognutog područja, a to su pretežno jedinice označene plavo na Slici 1 desno.

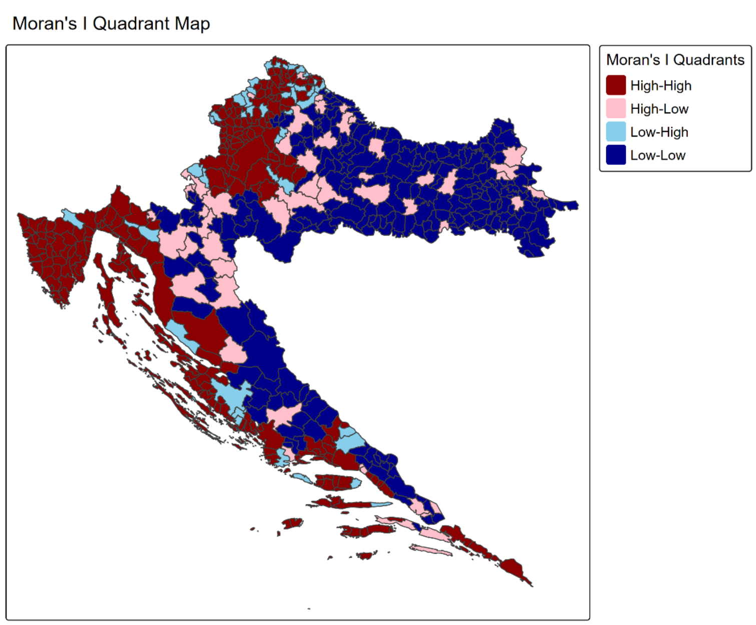


Slika 1. *Prostorna distribucija indeksa razvijenosti lokalnih jedinica*

Sve prethodno opisano manifestira se u osam razvojnih skupina (Slika 2) koje su formirane s obzirom na indeks razvijenosti lokalnih jedinica. Najrazvijenija osma skupina bilježi najveću koncentraciju očekivano u Istri i Kvarneru, te nekoliko jedinica u blizini Zagreba i sjeverozapadnoj Hrvatskoj. U Jadranskoj Hrvatskoj se ističu jedinice u blizini većih gradova, i pojedinih otočnih jedinica. Zapravo, Dalmacija predstavlja možda najheterogenije područje u pogledu razvojnih skupina. Primjerice, u čitavoj Slavoniji nije zastupljena osma skupina, samo se Osijek nalazi u sedmoj skupini. U nastavku su prikazani rezultati koji povezuju indeks razvijenosti lokalnih jedinica s njihovim geografskim položajem. Promatra se uloga okruženja u odnosu na brojnost samih jedinica te udaljenost pojedine jedinice od spomenutih susjeda. Bliže jedinice trebale bi biti povezanije i homogenije od udaljenih. Navedeno se istražuje globalnim Moranovim indeksom, i lokalnim indikatorima prostorne povezanosti LISA (engl. *Local Indicators of Spatial Association*).



Slika 2. *Distribucija lokalnih jedinica prema razvojnim skupinama*



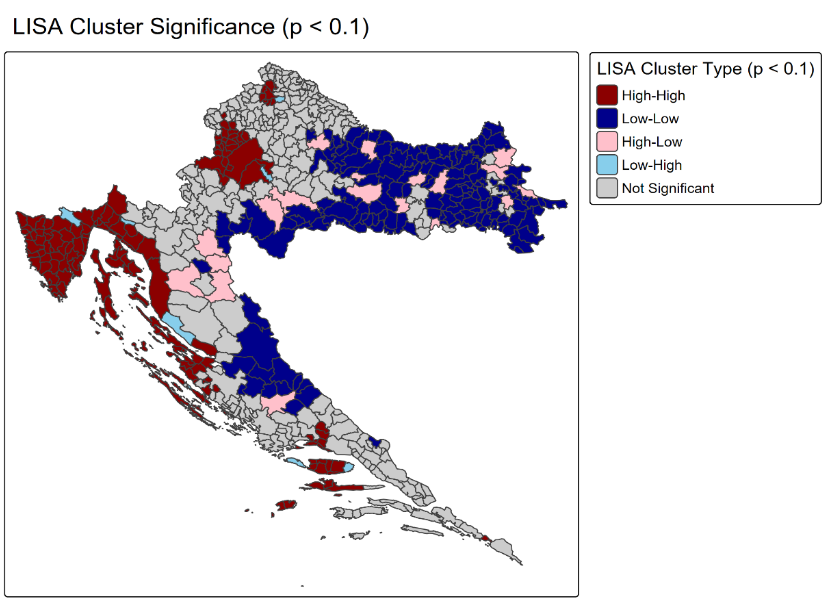
Slika 3. *Prostorna distribucija lokalnih jedinica prema kvadrantima Moranovog indeksa*

Statistički značajan (p <0,001) Moranov indeks iznosi 0,56 te upućuje na umjerenu prema jakoj pozitivnoj prostornoj autokorelaciji. Grafički prikaz Moranovog indeksa sastoji se od četiri kvadranta (Slika 3). Prvi kvadrant HH (engl. *High-High*) referira se na regije koje su iznadprosječne kao i njihovo okruženje. Suprotno je treći kvadrant LL (engl. *Low-Low*), a odnosi se na ispodprosječan rezultat promatrane jedinice i okruženja. Preostala dva slučaja, drugi kvadrant LH (engl. *Low-High*) i četvrti kvadrant HL (engl. *High-Low*) su izdvojenice. Primjerice, sama regija je iznad prosjeka, a okruženje ispod, ili obrnuto. Prema Slici 3 može se zaključiti da se jedinice sličnih vrijednosti indeksa razvijenosti, a koje su ujedno prostorno povezanije, grupiraju zajedno. Ključan je doprinos ispodprosječnih jedinica s takvim okruženjem (LL) i iznadprosječnih (HH) koji prevladavaju, dok su izdvojenice u manjini.

Prema Griffith (2005), efektivna veličina uzorka, procijenjena na temelju Moranova indeksa, iznosi približno 159 jedinica, znatno manje od nominalnog uzorka od 556 jedinica. Ovaj rezultat implicira da zanemarivanje prostorne ovisnosti može dovesti do podcjenjivanja standardnih pogrešaka i precjenjivanja statističke značajnosti, čime se potvrđuje nužnost primjene prostornih analitičkih pristupa u empirijskim analizama.

Dobiveni rezultati upućuju na to da se razvojna dinamika u Hrvatskoj odvija unutar znatno manjeg broja prostorno homogenih cjelina od nominalnog broja administrativnih jedinica. Takva prostorna strukturiranost implicira da izrazita fragmentacija lokalne razine može ograničiti učinkovitost razvojnih politika. Štoviše, ovi rezultati pružaju empirijski utemeljen argument u prilog raspravama o racionalizaciji sustava lokalne samouprave i jačanju funkcionalnih teritorijalnih cjelina.

Međutim, Moranov indeks ne može ukazati na lokalnu statističku značajnost. Stoga, u nastavku se koriste LISA indikatori kao mjere lokalne prostorne autokorelacije. Oni se također sastoje od četiri klastera koja su istovjetna kvadrantima Moranova indeksa, i petog klastera kojeg čine jedinice koje nisu statistički značajne.



Slika 4. *Prostorna distribucija klastera LISA indikatora*

Od 556 jedinica njih 317 se pokazalo statistički značajnim (Slika 4), ostale nisu statistički značajne. Izostanak statističke značajnosti posljedica je okruženja koje nije dovoljno homogeno za klasterizaciju, ili vrijednost u samoj jedinici ne odstupa dovoljno od okoline da bi postala izdvojenicom. Od statistički značajnih jedinica njih 145 je iz HH klastera i 146 iz LL klastera, i one predstavljaju jedinice koje su slične svome okruženju. Izdvojenica HL je 19, a LH 7, a one naglašavaju posebnost promatrane jedinice s obzirom na okruženje.

Geografski bliže, i po vrijednostima slične jedinice grupirale su se zajedno u klasterima HH i LL. U HH klasteru ističu se Istra i Kvarner, te Rijeka s okolicom. Oni predstavljaju homogenu cjelinu koja se proteže priobaljem skroz do Zadra. Ovdje su se smjestile sve jedinice lokalne samouprave u Istarskoj županiji, osim Lanišća koje je malo ispod prosječne vrijednosti indeksa razvijenosti, ali s uvjerljivo najmanjom vrijednosti u Istri. Kao izdvojenice ističu se još Lokve u Gorskom kotaru, te Karlobag u priobalju. Zanimljivo je spomenuti poziciju Lokvi i Čabra u Gorskom kotaru koje su jedine u Primorsko-goranskoj županiji čija je vrijednost manja od 100. Njihove vrijednosti su oko prosjeka, samo su Lokve malo ispod, a Čabar malo iznad prosjeka što ga svrstava u HH klaster. Znači, razlika je gotovo zanemariva. Većina statistički značajnih jedinica u Zadarskoj županiji nalaze se u HH klasteru, premda su vrijednosti indeksa razvijenosti manje nego u Istri i Primorsko-goranskoj županiji. Također, Novalja i Senj pripadaju u ovaj klaster, a dio su Ličko-senjske županije, što potencijalno ukazuje na nedostatke aktualne županijske podjele u Hrvatskoj.

Splitsko-dalmatinska županija obuhvaća nekoliko HH jedinica u bližoj okolici Splita u priobalju, dvije jedinice u Dalmatinskoj zagori (Dugopolje i Dicmo), te u najvećoj mjeri jedinice na srednje dalmatinskim otocima. Općine Dugopolje i Dicmo su rijedak primjer u Jadranskoj Hrvatskoj koje se ne baziraju na turizmu, već su tamo gospodarske zone. Prisutne su dvije izdvojenice, na Šolti i Hvaru čije vrijednosti indeksa su malo ispod prosječne. Također, Splitsko-dalmatinska županija sa Zadarskom županijom je jedina koja ima zastupljen HH i LL klaster. Spomenuto ukazuje na heterogenost u Dalmaciji. Na krajnjem jugu u Dubrovačko-neretvanskoj županiji samo Župa Dubrovačka pripada HH klasteru, a nalazi se između Konavala i Dubrovnika koji isto imaju visoke razine indeksa razvijenosti. Heterogeno susjedstvo, i udaljenost između regija implicira izostanak statističke značajnosti za Konavle i Dubrovnik.

Na kontinentu glavnina HH klastera formira se od Grada Zagreba kao samostalne jedinice pa prema sjeverozapadu, a sastoji se od predstavnika Zagrebačke i Krapinsko-zagorske županije. Na krajnjem sjeveru su to Varaždin i nekoliko jedinica Varaždinske i Međimurske županije. U istočnijim dijelovima ova dva klastera pojavljuju se dvije izdvojenice, Orle i Jalžabet, a one nagovještavaju promjenu rezultata prema istoku.

Udaljavanjem prema istoku smanjuje se broj jedinica koje su iznad prosjeka, što rezultira klasterizacijom LL, odnosno prevladavaju ispodprosječne jedinice s takvim okruženjem. Ovdje su najzastupljenije Osječko-baranjska, Vukovarsko-srijemska, Brodsko-posavska, Požeško-slavonska, Virovitičko-podravska, Bjelovarsko-bilogorska, Sisačko-moslavačka županija i tri jedinice na Kordunu kao dio Karlovačke županije. Premda županijska središta spomenutih županija, i još neka veća urbana središta predstavljaju izdvojenice, odnosno jedinice koje su bolje pozicionirane od okoline. To su Osijek, Slavonski brod, Vukovar, Sisak, Virovitica, Požega i Bjelovar kao županijska središta, zatim gradovi Daruvar, Našice, Pakrac, Petrinja, Vinkovci i općine Bilje i Orahovica. Također, ovdje se pojavljuju jedinice koje nisu statistički značajne, a nalaze se između LL i HL klastera.

Već spomenuta heterogenost među jedinicama nastavlja se u većem dijelu Gorskog kotara, što se odražava na izostanak statističke značajnosti. Rubni dijelovi Karlovačke županije prema Ličko-senjskoj županiji uz granicu s BiH-om predstavljaju izdvojenice s obzirom na okruženje, a to su Slunj, Rakovica, te Otočac i Plitvička jezera u Ličko-senjskoj kao glavni turistički pokretači. Također, u blizini je općina Saborsko koja zaostaje kao i njeno okruženje koje se nije ugledalo na prethodno spomenute jedinice. Ovdje ponovno započinje LL klaster, koji se proteže od rubnih dijelova Ličko-senjske, preko zadarskog zaleđa, velikog broja jedinica Šibensko-kninske županije, pa sve do Splitsko-dalmatinske županije. Ovaj dio Dalmatinske zagore s Likom predstavlja najzaostaliji dio u čitavoj Hrvatskoj, a ključnu razliku čini nekoliko jedinica koje su se smjestile na samom dnu indeksa razvijenosti. To su prije svega općine Donji Lapac, Kistanje i Ervenik. Jedina svijetla točka je Drniš koji se izdvaja od okoline. Upravo spomenuto, uglavnom šibensko zaleđe onemogućuje klasterizaciju priobalnih jedinica Šibensko-kninske županije, uz izuzetak Kornata koji su dio HH klastera. Nastavak Dalmatinske zagore, koji predstavlja splitsko zaleđe i južnije ostvaruje nešto bolje, ali još uvijek uglavnom ispodprosječne rezultate koji s razvijenim priobaljem koje je ipak geografski bliže ne svrstavaju ovo područje u najslabiji klaster. Isto tako makarsko primorje se ne može pozicionirati u najviši HH klaster zbog blizine ispodprosječnih jedinica koje se nalaze s druge strane Biokova.

Rezultati koji nisu statistički značajni pripadaju razvojnim skupinama od prve do osme, odnosno ukazuju na heterogenost. Primjerice tu su gradovi poput Čakovca, Koprivnice, Makarske i Dubrovnika (svi iz osme razvojne skupine), te Križevaca, Krapine, Šibenika, Gospića i Karlovca (iz sedme razvojne skupine). Također, spomenuto se odnosi na čitavu Koprivničko-križevačku županiju, te u većoj mjeri na Međimursku i Dubrovačko-neretvansku koje su zastupljene s dvije, odnosno jednom statistički značajnom jedinicom.

4.1. Rasprava i ograničenja istraživanja

Provedena analiza izdvaja pet klastera, koja ćemo podijeliti u četiri skupine: Razvijene jedinice (HH klaster), Nerazvijene jedinice (LL klaster), Izdvojenice (HL i LH klaster) i Prijelazna zona (nisu statistički značajne jedinice). Razvijene jedinice obuhvaćaju najrazvijenije lokalne jedinice u Hrvatskoj, premda i među njima postoje određene slabosti. Istraživanja za Hrvatsku ukazuju da visok stupanj razvijenosti turizma, iako kratkoročno potiče gospodarsku aktivnost, može biti povezan s nižim ulaganjima u ljudski kapital, što dugoročno ograničava gospodarski rast (Kožić, 2019). Dodatno, izražena sezonalnost turizma negativno utječe na stabilnost dohotka, zaposlenost i razvoj poduzetništva te povećava osjetljivost na vanjske šokove (Mikulić i sur., 2021; Stojčić i sur., 2022). Rast cijena nekretnina, potaknut i potražnjom stranih kupaca, osobito u obalnim područjima, ne odražava nužno rast životnog standarda lokalnog stanovništva, već može pogoršati priuštivost stanovanja. Istodobno, postojeći indeks razvijenosti nedovoljno uzima u obzir razvoj ljudskog kapitala i tržišta rada (Marcelić, 2015), što dodatno ograničava njegovu sposobnost preciznog vrednovanja najrazvijenijih područja. Stoga je potrebno obratiti posebnu pozornost na širi skup razvojnih pokazatelja koji nadilaze standardne ekonomske mjere, uključujući demografske trendove, održivost, tržište rada i nekretnina i strukturne karakteristike gospodarstva. U suprotnom postoji rizik pogrešne procjene razine razvijenosti, osobito u specifičnim područjima poput otočnih i turistički orijentiranih regija. Štoviše, može doći do regionalne razvojne zamke pri visokim razinama razvoja (Diemer i sur., 2022).

Za nerazvijene jedinice rezultati analize pokazuju da LL klasteri u velikoj mjeri obuhvaćaju jedinice lokalne samouprave sa statusom potpomognutih područja, ponajprije iz I. i II. razvojne skupine (Slika 2). To potvrđuje usklađenost prostorne koncentracije nerazvijenosti s postojećim mehanizmima regionalne politike koji se temelje na indeksu razvijenosti (MRRFEU, 2022). Iako takve mjere doprinose smanjenju razlika na višim razinama agregacije, njihova učinkovitost u ublažavanju unutarnacionalnih regionalnih nejednakosti ostaje ograničena (Jovančević i sur., 2015). U tom kontekstu, uočeni obrasci mogu se interpretirati kao potencijalni oblik moralnog hazarda u korištenju razvojnih potpora, pri čemu dugotrajna ovisnost o potporama može pridonijeti zadržavanju jedinica na najnižim razinama razvijenosti i pojavi regionalnih razvojnih zamki.

Izdvojenice, odnosno HL i LH klasteri, dodatno naglašavaju specifičnost pojedinih jedinica u odnosu na njihovo prostorno okruženje. Ukupno je identificirano 19 HL i 7 LH jedinica. HL klasteri pretežno obuhvaćaju urbana područja unutar manje razvijenih regija, uključujući i specifične slučajeve poput područja Plitvica s pripadajućim okruženjem te grada Drniša u šibenskom zaleđu, dok su LH klasteri znatno rjeđi i većinom smješteni na rubu razvijenih područja, pri čemu su samo dvije takve jedinice identificirane u kontinentalnom dijelu Hrvatske. Ovi rezultati upućuju na postojanje izraženih lokalnih odstupanja u razini razvijenosti u odnosu na susjedne jedinice, što dodatno potvrđuje heterogenost regionalnog razvoja. Dobiveni obrazac usporediv je s rezultatom za Rumunjsku (Ursu & Benedek, 2024), a preciznije se može interpretirati kroz model jezgra-periferija, gdje razvijene jedinice djeluju kao lokalne jezgre gospodarske aktivnosti, dok okolna područja zaostaju u razvoju (Fujita & Krugman, 2004). Nadalje, Smętkowski (2017) povezuje regionalne nejednakosti s procesom metropolizacije, pri čemu dinamična urbana središta ostvaruju veće koristi od europskih fondova, što može dodatno produbiti postojeće razlike u razvijenosti.

U onim jedinicama gdje su rezultati statistički značajni rezultati se djelomično poklapaju s klasterizacijom koja nije pri izračunu koristila prostornu dimenziju (Marcelić, 2015; Perišić, 2015; Marcelić, 2023). Spomenuto samo potvrđuje da na položaj najrazvijenijih i najnerazvijenijih uvelike utječe njihov geografski položaj, točnije njihovi susjedi. Stoga, lokalne politike se mogu provoditi na nekom širem području od pojedine jedinice, bilo spajanjem pojedinih općina i gradova, na razini županije ili možda na NUTS 2 razini. Izdvojenice HL predstavljaju primjer za okruženje koje zaostaje, ali postojanje LH izdvojenica kojih je manje ukazuju da je moguće i suprotno. U predjelima gdje izostaje predvodnik, potrebno ga je pronaći, štoviše pokušati homogenizirati što više jedinica.

Prijelazna zona predstavlja područja u kojima nije utvrđena statistički značajna prostorna autokorelacija indeksa razvijenosti. Drugim riječima, njihova razina razvijenosti nije sustavno povezana s razinama razvijenosti susjednih jedinica, odnosno ne formiraju ni klastere visoke ni klastere niske razvijenosti, niti predstavljaju prostorne izdvojenice.

Provedena klasterizacija uzima u obzir geografski položaj između jedinica i samu vrijednost varijable, i upravo geografska dimenzija čini razliku od klasterizacija koje se fokusiraju samo na vrijednosti varijable. Kao rezultat toga je 238 jedinica koje nisu statistički značajne zbog heterogenog susjedstva koje ih prostorno ne homogenizira, ili pojedine vrijednosti nisu dovoljno velike/male da bi se smatrale izdvojenicama. Velik broj jedinica koje nisu statistički značajne prisutan je u Rumunjskoj (Ursu & Benedek, 2024) i NUTS 2 regijama EU (Rodríguez-Pose & Tselios, 2009). U odnosu na indeks razvijenosti, ove jedinice najčešće obuhvaćaju srednje razvijene jedinice (III.–VI. razvojna skupina), odnosno područja koja se nalaze između jasno izraženih klastera razvijenih i nerazvijenih jedinica. Takve jedinice često imaju heterogeno okruženje, odnosno susjede različitih razina razvijenosti, zbog čega se ne može identificirati jasan prostorni obrazac.

S aspekta regionalne politike, ovakva područja predstavljaju poseban izazov. Za razliku od jasno identificiranih LL klastera, koji su ciljano obuhvaćeni mjerama regionalne politike, ili HH klastera koji djeluju kao razvojna jezgra, statistički neznačajne jedinice često ostaju izvan fokusa intervencija. Budući da se najčešće nalaze u srednjim razvojnim skupinama prema indeksu razvijenosti, velik dio njih ne pripada kategoriji potpomognutih područja, iako mogu imati unutarnje strukturne slabosti ili nepovoljne razvojne trendove. Takva pozicija može dovesti do situacije u kojoj ove jedinice postaju "skrivena ranjiva područja", odnosno prostori koji ne pokazuju izraženo zaostajanje, ali istodobno nemaju dovoljno snažne razvojne kapacitete za samostalni rast. U tom kontekstu, izostanak statističke značajnosti ne znači nužno odsutnost problema, već prije ukazuje na potrebu za diferenciranijim pristupom regionalnoj politici, koji bi uzimao u obzir i prostornu heterogenost i specifične lokalne uvjete.

Nedostatak provedenog istraživanja je što se povezanost između jedinica modelira kroz udaljenost između geografskih središta pojedine jedinice. Stoga, povezanost između otoka izgleda mnogo bolje nego je u stvarnosti. Primjerice, malo je direktnih trajektnih linija između srednjodalmatinskih otoka koje bi bile dobra aproksimacija udaljenosti između otoka. U stvarnosti većina linija se odvija uz posredovanje Splita, što uvelike otežava povezanost između otoka. Spomenuto može biti povezano s dvostrukom interpretacijom otočnog razvoja, s jedne strane kao specifičnog i ograničenog prostora, a s druge kao područja relativno visoke socioekonomske razvijenosti (Marcelić, 2023).

Isto tako kvaliteta cestovne infrastrukture bitno utječe na udaljenost između jedinica, stoga se u budućim istraživanjima preporučuje korištenje vremena putovanja, umjesto udaljenosti između jedinica, kao kriterija njihove povezanosti, budući da ono bolje odražava nedostatke prometne infrastrukture, što je već primijenio Grgić (2020).

Premda razvijena prometna infrastruktura ne može uvijek garantirati socio-ekonomski napredak regija koje zaostaju (González-González & Nogués, 2019). Jedan od razloga zasigurno može biti izostanak ljudskog razvoja, koji se manifestira kroz obrazovanje, zaposlenost i osobni prihod (Marcelić, 2015, 2023). Primjerice, autoput prema Slavoniji postoji mnogo duže nego u Istri, a razlike u klasterima su naglašene. Zasigurno su ratna stradanja ostavila posljedice, ali bez izgradnje ljudskih kapaciteta teško je ostvariti napredak. Isto tako, najzaostaliji klaster koji čine dio Like i Dalmatinske zagore izostankom moderne prometne infrastrukture uz ratna stradanja, i depopulaciju samo još dodatno povećavaju zaostajanje. Iako, primjeri HL klastera, a koji nisu veliki gradovi kao što su jedinice oko Plitvica pokazuje da se može razlikovati od okoline unatoč prometnim nedostacima. Od mnogobrojnih jedinica koje nisu statistički značajne može se izdvojit primjer Karlovca kao jednog od najvažnijih cestovnih čvorišta u Hrvatskoj, ali sama prometna infrastruktura nije ga uspjela izdignuti značajnije od okruženja.

5. Zaključak

Rezultati upućuju na to da se razlike razvijenosti ne odvijaju izolirano, već su snažno uvjetovane prostornim kontekstom. Primjena globalnih i lokalnih mjera prostorne autokorelacije omogućuje identifikaciju takvih obrazaca i dodatno potvrđuje važnost prostorne dimenzije u analizi regionalnih nejednakosti. Prostorna blizina između lokalnih jedinica potiče prijenos ekonomskih učinaka, dok se njihov intenzitet smanjuje s udaljenošću. Posljedično, razina razvijenosti lokalnih jedinica uvelike ovisi o karakteristikama i razvijenosti susjednih područja. U tom smislu, lokalne ekonomske eksternalije imaju značajnu ulogu u oblikovanju razvojnih obrazaca. Stoga, prostorna distribucija razvijenosti nije homogena, već pokazuje izražene prostorne asimetrije koje proizlaze iz specifičnih obilježja, lokacije i međusobne povezanosti jedinica.

Primjenom eksplorativne prostorne analize podataka, odnosno LISA indikatora, potvrđeno je da čak 238 od 556 lokalnih jedinica nije statistički značajno. Spomenuto ukazuje da su te jedinice bitne kada se prostor analizira globalno za čitavu Hrvatsku, ali lokalno razmatranje za svaku pojedinu jedinicu otkriva da je prostor heterogeniji nego što ukazuje vrijednost globalnog indeksa. Vrijednost globalnog Moranova indeksa upućuje na umjerenu do jaku pozitivnu prostornu autokorelaciju, što znači da se jedinice sličnih razina razvijenosti statistički značajno grupiraju u prostoru. Time se potvrđuje Toblerov prvi zakon geografije prema kojemu su prostorno bliže jedinice međusobno sličnije od udaljenijih. Rezultati lokalne prostorne autokorelacije ukazuju na jasno diferenciranu prostornu strukturu regionalnog razvoja. Razvijene jedinice (HH klasteri) predstavljaju razvojne jezgre u kojima se prostorno koncentriraju visoko razvijene jedinice, dok Nerazvijene jedinice (LL klasteri) označavaju područja kumulativnog zaostajanja i prostorne koncentracije nerazvijenosti.

Prostorna raspodjela klastera jasno ukazuje na izraženu zapadno-istočnu prostornu distribuciju indeksa razvijenosti u Jadranskoj i Kontinentalnoj Hrvatskoj. Najrazvijeniji klasteri koncentrirani su u Istri, na Kvarneru, u priobalnom dijelu Dalmacije te u širem zagrebačkom i sjeverozapadnom području, dok se klasteri ispodprosječne razvijenosti dominantno pojavljuju u Slavoniji, dijelovima Banovine, Like i Dalmatinske zagore. Takvi obrasci upućuju na dugoročnu prostornu ukorijenjenost regionalnih nejednakosti, koje nisu rezultat isključivo pojedinačnih lokalnih obilježja, već i šireg prostornog i povijesnog konteksta.

Izdvojene jedinice (HL i LH) ukazuju na mogućnost odstupanja od dominantnog regionalnog obrasca, ali su brojčano ograničene, što dodatno potvrđuje snažan utjecaj okruženja na razvojne ishode. Za razliku od jasno definiranih klastera i izdvojenica, statistički neznačajne jedinice predstavljaju prostorne prijelazne zone bez izražene prostorne autokorelacije. Iako ne pokazuju jasne obrasce klasterizacije, upravo takva heterogenost može prikrivati strukturne slabosti i ograničene razvojne kapacitete. U tom smislu, ove jedinice mogu se interpretirati kao potencijalna područja rizika za pojavu regionalnih razvojnih zamki.

Dobiveni rezultati sugeriraju da regionalne razvojne politike ne bi trebale biti usmjerene isključivo na pojedinačne jedinice, već oblikovane na širem prostornom obuhvatu, uz uvažavanje prostorne povezanosti i međusobnih učinaka među susjednim jedinicama. Za učinkovito smanjenje nejednakosti ključno je identificirati njihovu prostornu koncentraciju, kako bi se razvojne politike mogle prilagoditi specifičnim potrebama pojedinih područja. U tom smislu, analiza prostornih klastera i izdvojenica omogućuje preciznije usmjeravanje javnih politika, budući da jedinstveni pristupi nisu jednako učinkoviti u svim regijama.

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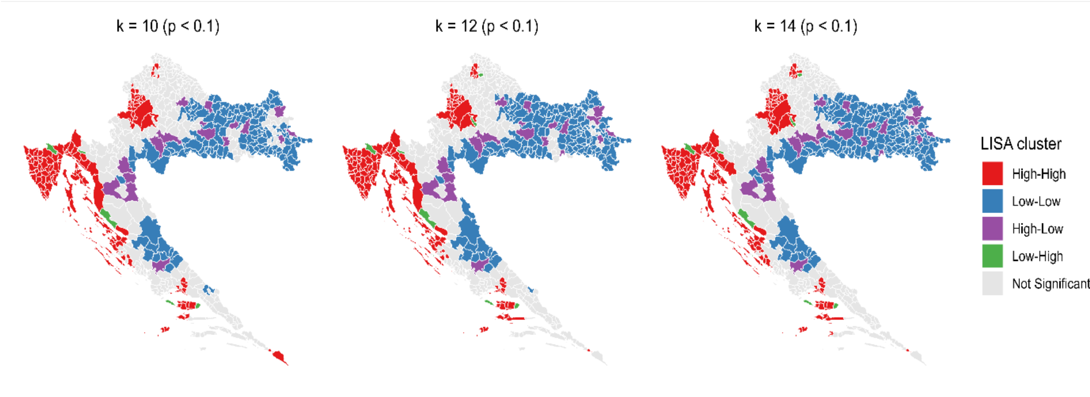
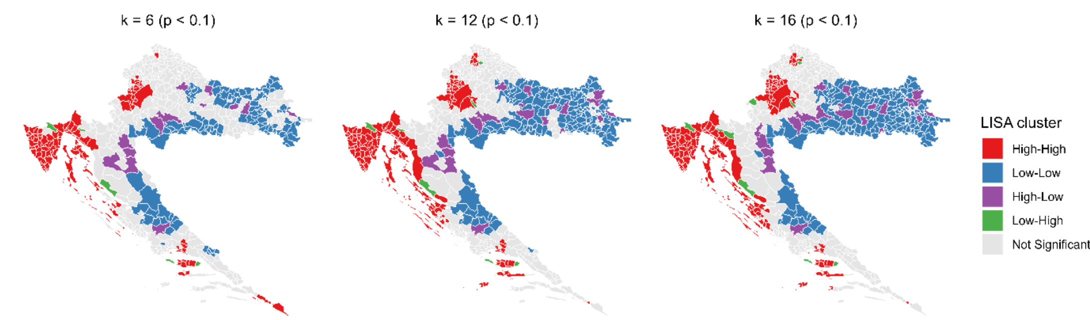
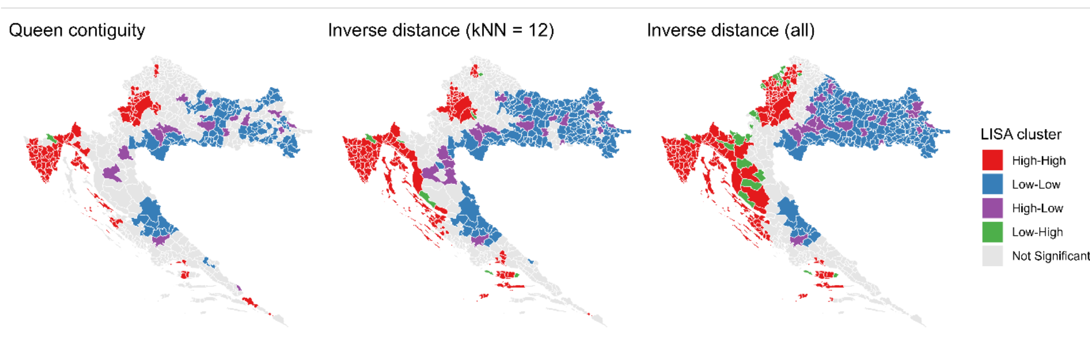
Dodatak



Slika 5. *LISA klasteri za kNN matrice s 10, 12 i 14 najbližih susjeda*



Slika 6. *LISA klasteri za kNN matrice s 6, 12 i 16 najbližih susjeda*



Slika 7. *LISA klasteri prema različitim specifikacijama matrice prostornih težina*

Local spatial analysis of the development index of local administrative units in Croatia

SUMMARY

Regional inequalities in Croatia are the result of a complex interplay between spatial distance and historical, social, and economic factors. The aim of this paper is to conduct a spatial statistical analysis of the development index for all 556 local administrative units in Croatia, considering not only their individual values but also their geographical location and the characteristics of their neighbouring environment. To this end, exploratory spatial data analysis (ESDA) was applied, with particular emphasis on global Moran's I and local indicators of spatial association (LISA). The results confirm the existence of moderate to strong positive global spatial autocorrelation in the development index, indicating a significant clustering of spatial units with similar levels of development. Local spatial analysis identified five clusters, which are classified into four groups: developed units (HH clusters), underdeveloped units (LL clusters), spatial outliers (HL and LH clusters), and a transitional group of statistically non–significant units. This spatial configuration reveals a pronounced west–east developmental polarization between Adriatic and Continental Croatia. The estimated effective sample size, which is considerably smaller than the nominal number of local units, further highlights the importance of accounting for spatial dependence in empirical analyses. This paper contributes to the understanding of the spatial dimension of regional inequalities and provides evidence relevant for the design of development policies at a functionally and spatially broader territorial scale.

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Comparative ocean temperature forecasting using SARIMA, ETS, and LSTM

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SUMMARY

Accurate ocean temperature forecasting is essential for understanding long–term environmental variability and supporting ecological decision–making. This study evaluates the performance of SARIMA (*Seasonal Autoregressive Integrated Moving Average*), ETS (*Error Trend Seasonality*), and LSTM (*Long Short-Term Memory*) models for predicting ocean temperature using historical time series data from the CalCOFI programme. The dataset was preprocessed using seasonal decomposition and stationarity analysis, and forecasting accuracy was assessed using MAPE (*Mean Absolute Percentage Error*), RMSE (*Root Mean Squared Error*), and MSE (*Mean Squared Error*). The results indicate that LSTM produced the most accurate and stable forecasts overall, achieving lower RMSE and MAPE values at most stations and depths. It effectively captured nonlinear behaviour, seasonal variability, and extreme temperature fluctuations. SARIMA demonstrated a strong capability to model trend and seasonality, while ETS generated smoother forecasts but with comparatively higher error values. Residual diagnostics further confirmed LSTM's superior ability to learn complex temporal dependencies present in ocean temperature data. This study contributes to a comparative evaluation of classical statistical and deep learning models for ecological time series forecasting and provides evidence supporting the application of LSTM for improved oceanographic prediction and environmental monitoring.

KEYWORDS

Ecological time-series, ETS, forecasting, LSTM, SARIMA

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1. Introduction

Ocean temperature is critical in climate studies because it affects marine ecosystems, weather patterns, and global climate systems (Venegas et al., 2023). Accurate forecasting is therefore essential to understand and mitigate the climate-change impacts on marine environments and coastal communities (Singh Bist et al., 2024). Traditional time-series models such as ARIMA, SARIMA, and ETS are widely used across environmental and epidemiological forecasting, including ARIMA for COVID-19 epidemiology (Tomov et al., 2023), SARIMA for environmental

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epidemiology (Gudžiūnaitė et al., 2023) and river-flow prediction (Tadesse & Dinka, 2017), and SARIMA/ETS for food-borne disease forecasting (Xian et al., 2023). With advances in deep learning, Long Short-Term Memory (LSTM) networks can improve forecasting by capturing complex temporal patterns, as shown in financial time-series prediction (Buczyński et al., 2023). Because ocean temperature records are sequential, temporally dependent, and span multiple decades (1949–2016), time-series models are well suited for forecasting future variability, i.e. ARIMA, SARIMA, and ETS are commonly applied to environmental and climate variables, while LSTM offers a nonlinear alternative that can capture long-memory property. Beyond forecasting, time-series data support trend analysis, pattern discovery, anomaly detection, and forecasting. Accordingly, this study compares SARIMA, ETS, and LSTM for forecasting ocean temperatures at depths between 0 and 500 m using monthly observations from the CalCOFI programme (California Cooperative Oceanic Fisheries Investigations). This is a long-term oceanographic ecosystem monitoring and research programme with the goal of serving data in support of sustainable marine resource management (CalCOFI, 2025).

Therefore, the study objective is to compare SARIMA, ETS, and LSTM using performance measures RMSE, MSE, and MAPE in order to identify the most effective model for monthly ocean temperature forecasting. The relevance of this objective lies in the growing importance of accurate ocean temperature forecasting for climate monitoring, marine ecosystem management, and early warning of phenomena such as marine heatwaves and coral bleaching, all of which depend on reliable monthly-scale predictions. Methodologically, the study addresses a genuine gap: although SARIMA and ETS are well established for seasonal time-series and LSTM has shown superior in capturing complex nonlinear patterns, there is no consensus on which approach performs best for oceanographic data. By benchmarking the three models under identical conditions using complementary accuracy metrics (RMSE, MSE, and MAPE), the study offers an objective, evidence-based comparison, with particular attention to whether ETS improves upon SARIMA and whether LSTM delivers superior predictive accuracy across stations and depths. Its contribution is thus twofold: practically, it identifies the most suitable tool for ocean temperature prediction, and academically, it adds empirical evidence to the debate between traditional statistical methods and machine learning in environmental forecasting, providing a replicable framework for similar studies.

2. Materials and methods

Time-series models capture temporal dependence in sequential observations to identify trend, seasonality, and autocorrelation structures for forecasting (Box & Jenkins, 1976; Hyndman & Athanasopoulos, 2018). A commonly used additive decomposition represents a time-series as:

$$Y_t = T_t + S_t + R_t \tag{1}$$

where Y_t is the observed value, T_t is the trend, S_t is the seasonal component, and R_t is the residual. Stationarity is a fundamental assumption in many statistical time-series models. The Augmented Dickey–Fuller (ADF) test is used to detect unit roots and assess whether differencing is required (Dickey & Fuller, 1979). Seasonal time-series often require seasonal differencing when periodic cycles are present. Seasonal Autoregressive Integrated Moving Average (SARIMA) models extend ARIMA by incorporating seasonal autoregressive and moving-average components and are denoted as $(p, d, q) \times (P, D, Q)_s$, where s represents the seasonal period (Box & Jenkins, 1976). Model selection is commonly performed using the Akaike information criterion AIC (Akaike, 1974).

Error–Trend–Seasonality (ETS) models belong to the exponential smoothing family and represent time-series through combinations of error, trend, and seasonal components within a state-space framework (Hyndman & Athanasopoulos, 2018).

Long Short-Term Memory (LSTM) networks are recurrent neural architectures designed to capture long-term dependencies and nonlinear temporal relationships without strict stationarity assumptions (Hochreiter & Schmidhuber, 1997).

Forecast accuracy is evaluated using Mean Squared Error, Root Mean Squared Error, and Mean Absolute Percentage Error (Hyndman & Koehler, 2006). These metrics are selected for their complementary properties: MSE and RMSE emphasize large errors and retain the original measurement units, whereas MAPE offers a scale-independent percentage that enables comparison across stations and depths.

Data were obtained from the CalCOFI database CalCOFI (2025), comprising 864,863 discrete water samples collected at different depths and locations from 1949 to the present, including measurements of temperature, salinity, dissolved oxygen, chlorophyll *a*, nutrients, and other variables. Each record corresponds to a bottle closure during a CTD–rosette cast at a specific depth and station. Temperature (`T_degC`) represents *in situ* water temperature measured at the recorded depth (`Depthm`).

For temperature forecasting, the extracted variables were `Cst_Cnt`, `Btl_Cnt`, `Sta_ID`, `Depth_ID`, `Depthm`, and `T_degC`. Table 1 describes the raw CalCOFI bottle database, of which station, depth, and water temperature are the primary variables used in this study. For the temperature time-series, observations of temperature data were aggregated to monthly intervals using the monthly mean temperature (month-start resampling), and missing values were replaced by linear interpolation. The full dataset contained 113 stations and 74 variables; three stations were randomly selected and analysed at 0 m (surface) and 500 m (deep water), producing six time series (three stations × two depths). Because temperature declined steeply until approximately 500 m and was relatively stable thereafter, forecasting focused on these two representative depth levels. The six subsets are summarised in Table 2.

Table 1. *Database description*

Feature	Description	Units
Cst_Cnt	Auto-numbered cast count – all casts consecutively numbered (1 is the first station)	n.a.
Btl_Cnt	Auto-numbered bottle count – all bottles ever sampled, consecutively numbered	n.a.
Sta_ID	CalCOFI line and station	n.a.
Depth_ID	[Century][YY][MM][ShipCode][CastType][Julian Day]-[CastTime]-[Line][Sta][Depth][Bottle]-[Rec_Ind]	n.a.
Depthm	Depth in metres	metre
T_degC	Temperature of water	°C

Source: CalCOFI Bottle Database https://calcofi.org/data/oceanographic-data/bottle-database

Table 2. *Ocean temperature data shape*

Station name	Station	Depth (metre)	Data shape
090.0 037.0	1a	0	328×3
	1b	500	323×3
090.0 070.0	2a	0	316×3
	2b	500	313×3
090.0 045.0	3a	0	330×3
	3b	500	316×3

Note: columns used are time, depth, and temperature.

Preprocessing comprised monthly resampling, missing-value handling, and seasonality identification. After downloading, the data were assessed for seasonality, trend, and distributional behaviour. Missing/irregular values were corrected using interpolation (Lepot et al., 2017) to ensure modelling readiness (Usmani et al., 2024), and because stations follow a uniform sampling methodology, the workflow used for one station was treated as representative of all. Seasonal decomposition was applied to the monthly temperature series (especially 500 m) using an additive form because seasonal amplitude was approximately constant over time (Hyndman & Athanasopoulos, 2018).

Stationarity was evaluated using the ADF test (Dickey & Fuller, 1979). An ADF statistic of -5.41, below the 1%, 5%, and 10% critical values with an approximately zero $p-$value, rejected non-stationarity. Thus, the series is stationary in its non-seasonal component, but the annual cycle still requires seasonal differencing ($D = 1$) for SARIMA to capture periodic behaviour.

SARIMA model is commonly used for time-series exhibiting trend, seasonality, and autocorrelation (Box & Jenkins, 1976). Prior to modelling, data were cleaned, missing values interpolated, and observations resampled to monthly frequency (Castel & Burr, 2021; Hyndman & Athanasopoulos, 2018). Initial model identification used autocorrelation function (ACF) and partial autocorrelation function (PACF) plots. For Station 1b, the ACF showed slow decay with significant spikes at multiples of 12, indicating strong seasonality, while the PACF exhibited a sharp cutoff after lag 1, suggesting an autoregressive order of $p = 1$. The ACF further suggested $q = 1 - 2$. Based on this inspection, a manual SARIMA$(1, 1, 1) \times (1, 1, 1)_{12}$ specification was proposed. To reduce subjectivity and allow consistent optimization across series, AutoSARIMA was also applied. AutoSARIMA evaluates combinations of $(p,\ d,\ q,\ P,\ D,\ Q)$ and selects the model that minimizes the AIC information criterion (Akaike, 1974; Hyndman & Khandakar, 2008):

$$\mathrm{AIC} = 2k - 2\ln(L) \tag{2}$$

where k is the number of parameters and L is the maximised likelihood. According to Table 3 SARIMA$(3, 1, 2) \times (2, 0, 1)_{12}$ was selected, achieving a lower AIC than the manual model (-1260.55 versus -1195.02). Forecasting employed an 80–20 train–test split, with one-step-ahead predictions generated using autoregressive, moving-average, differencing, and seasonal components.

The ETS model, originating in the late 1950s, is part of the exponential-smoothing family and represents time series through combinations of error, trend, and seasonal components within a state-space framework (Hyndman & Athanasopoulos, 2018). While ARIMA-type models are valued for simplicity, they may struggle with complex temporal structures (Fatima & Rahimi, 2024). Unlike SARIMA, ETS does not require differencing or strict stationarity assumptions, directly modelling level, trend, and seasonality. This makes ETS suitable for series with irregular trends or multiplicative seasonal behaviour, where SARIMA performance may degrade (Gao, 2025).

In this study, AutoETS evaluated additive and multiplicative combinations of error, trend, and seasonality, including damped trends, selecting the specification with the lowest AIC (Hyndman & Athanasopoulos, 2018). As shown in **??**, the optimal model for the main station series had no trend, additive seasonality, and no damping (AIC=-3070.46), while alternatives incorporating trends or multiplicative seasonality produced higher AIC values and were rejected.

LSTM networks are recurrent neural architectures designed to capture long-term temporal dependencies and nonlinear dynamics in time-series data through gated memory cells, mitigating the vanishing-gradient problem (Hochreiter & Schmidhuber, 1997). They are particularly suitable for temperature series with long-term variability and complex seasonality (Zhang et al., 2023) and can generalise across nonlinear and nonstationary behaviours that challenge SARIMA and ETS models (Zhang et al., 2023).

Prior to training, temperature values were scaled to the [0, 1] range to stabilise optimisation (Al-Sharafi et al., 2023). A sliding-window approach transformed the series into supervised learning sequences, where past observations formed inputs and the subsequent value served as the target (Kong et al., 2024; Zhang et al., 2023), reshaped to (samples, timesteps, features). The network consisted of a single LSTM layer followed by a dense output layer for one-step-ahead prediction, trained using the Adam optimizer with MSE loss. An 80:20 train–test split was applied, with 20–50 epochs and batch size = 16. Training loss decreased smoothly from 0.1691 at epoch 1 to 0.0039 at epoch 20, indicating stable convergence; predictions were subsequently inverse-transformed to the original °C scale.

The choice of a single LSTM layer with a moderate number of units was motivated by the need to balance model complexity and generalisation capability. Deeper architectures may capture more complex hierarchical representations but also increase the risk of overfitting, particularly for relatively small datasets such as the station-specific temperature series used in this study. The selected configuration provided sufficient capacity to model nonlinear temporal dependencies while maintaining computational efficiency.

Hyperparameter selection was guided by empirical testing and prior literature. The number of epochs (20–50) was chosen to allow the model to converge while avoiding excessive training that could lead to overfitting. The batch size of 16 ensured stable gradient updates without significantly increasing computational cost. The Adam optimizer was selected due to its adaptive learning-rate properties and proven effectiveness in time-series forecasting applications.

To ensure consistency and comparability across models, the same train–test split (80:20) was applied to all series. Model performance was evaluated on the test set using one-step-ahead forecasting, ensuring that predictions were based only on past information. This approach reflects realistic forecasting scenarios and avoids data leakage.

Finally, inverse transformation of scaled predictions was performed to return values to the original temperature scale, allowing direct comparison of model outputs with observed data and enabling meaningful interpretation of forecast errors.

Residual analysis was used to assess whether SARIMA, ETS, and LSTM adequately captured temporal structure. An appropriate model should produce residuals that are random, uncorrelated, and approximately normally distributed (Ljung & Box, 1978). Residual plots were inspected for remaining trends or seasonality, while histograms and Q–Q plots assessed normality (Caña et al., 2021; Liu & Li, 2023). Residual autocorrelation was examined using the ACF, where spikes outside confidence bounds indicated remaining structure (Hyndman & Athanasopoulos, 2018).

Model performance was evaluated using MSE, RMSE, and MAPE (Hyndman & Koehler, 2006; Chai & Draxler, 2014):

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(\text{actual} - \text{predicted})^2 \tag{3}$$

$$\text{RMSE} = \sqrt{\text{MSE}} \tag{4}$$

$$\text{MAPE} = \frac{100}{N}\sum_{i=1}^{N}\left|\frac{\text{actual} - \text{predicted}}{\text{actual}}\right| \tag{5}$$

where actual denotes the observed value, predicted denotes the forecasted value generated by the model, N represents the total number of observations.

MSE and RMSE measure absolute forecast error (RMSE in °C), while MAPE provides a scale-independent percentage error. Lower values indicate better performance. Because observed temperatures were strictly positive across all stations and depths, division-by-zero issues did not arise, and MAPE was well-defined for all series.

3. Empirical results

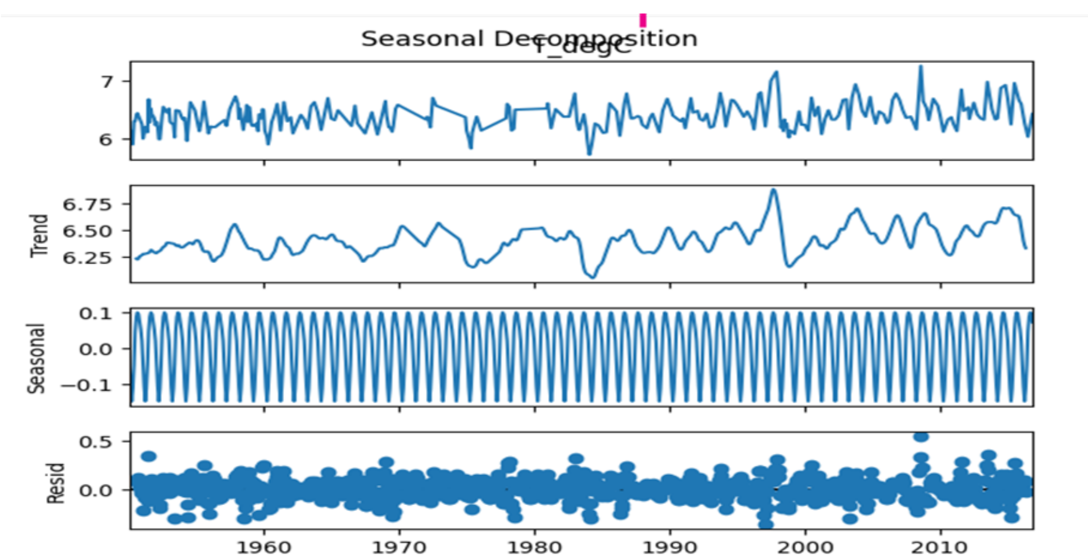

Figure 1. *Seasonal decomposition of ocean temperature*

Figure 1 shows the seasonal decomposition of temperature data: the top plot displays the original time series, the second shows the trend, the third the seasonal component, and the fourth the residual component. Seasonal decomposition of the monthly temperature series showed that the trend component captured long-term fluctuations over the study period, while the seasonal component displayed a stable annual cycle with a small amplitude of approximately ± 0.1 °C. Residuals were largely random with occasional anomalies, indicating that the trend and seasonal components captured most systematic variability (Hyndman & Athanasopoulos, 2018).

The ADF test statistic (-5.41) with a near-zero $p-$value suggested the absence of a non-seasonal unit root (Dickey & Fuller, 1979). However, the pronounced annual cycle observed in the decomposition justified the use of a seasonal model with period 12 and seasonal differencing for SARIMA.

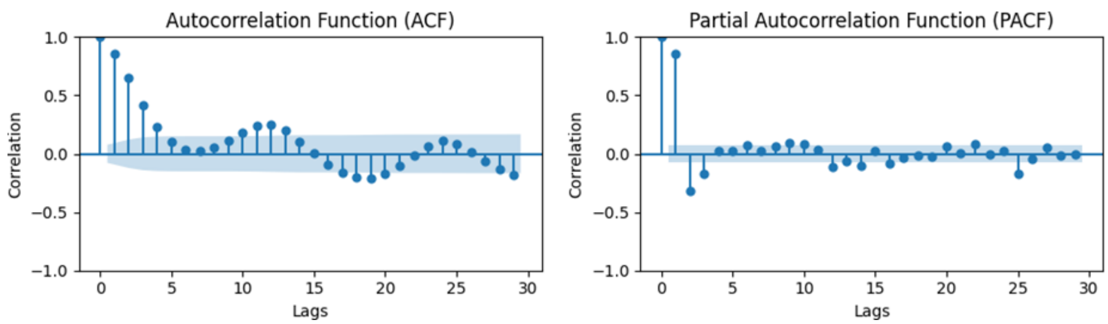

Figure 2. *ACF and PACF of monthly temperature of Station 1b*

Figure 2 illustrates the ACF and PACF plots used to guide SARIMA parameter selection. The ACF displays strong autocorrelation across multiple lags, with significant seasonal peaks confirming the need for seasonal differencing (D). The PACF shows a sharp cutoff after lag 1, indicating an autoregressive term of $p = 1$, while significant ACF spikes at lags 1 and 2 suggest a moving-average component ($q = 1 - 2$). The 12-month seasonal pattern evident in the ACF is consistent with the monthly structure of the dataset.

Table 3. *AIC results of manual SARIMA and automatic SARIMA*

Model	Specification	AIC
Manual	SARIMA(1, 1, 1) $\times$ (1, 1, 1)$_{12}$	-1195.02
Automatic	SARIMA(3, 1, 2) $\times$ (2, 0, 1)$_{12}$	-1260.55

Source: authors calculation based on CalCOFI data.

As shown in Table 3, the automatic model achieved a lower AIC (-1260.55) than the manual model (-1195.02) and was therefore retained for further analysis.

Residual diagnostics were conducted using graphical analysis of training and test residuals. Residual plots showed that errors were centred around zero and exhibited no clear remaining trend or seasonal structure. Histogram and Q–Q plot inspection indicated approximate normality with slightly heavier tails, while the residual ACF displayed only minor spikes at a few lags, suggesting that most temporal dependence had been adequately captured. Overall, the AutoSARIMA model reproduced the dominant seasonal and trend components of the temperature series and was retained for comparative evaluation.

The best-performing ETS model had no trend, additive seasonality, and no damped trend, indicating stable and repeating seasonal patterns without a strong long-term trend (AIC=−3070.46). Models including additive trend or multiplicative seasonality produced higher AIC values and were therefore rejected. ETS forecasts were smoother than SARIMA, capturing overall seasonality but underestimating sharp peaks and troughs.

The LSTM model trained for 20 epochs showed a monotonic reduction in loss from 0.1691 to 0.0039, indicating stable convergence without severe overfitting and good computational efficiency. Residual diagnostics indicated that LSTM residuals were smaller and more tightly clustered around zero than those of ETS, with reduced autocorrelation at short lags, indicating improved capture of temporal structure. Histograms indicated greater symmetry, Q–Q plots showed fewer outliers, and residual ACF plots exhibited substantially reduced autocorrelation, particularly at lags 3–5. Increasing training to 50 epochs further reduced residual magnitude and improved randomness, although minor autocorrelation persisted. Overall, LSTM residuals were closest to white noise.

Because performance trends were consistent across all stations (Table 5, Table 6, and Table 7), Station 1b is presented as a representative example for graphical comparison. This station was selected to illustrate model behaviour under deep-water conditions with moderate variability. Quantitative results for all locations are provided in Table 5, Table 6, and Table 7.

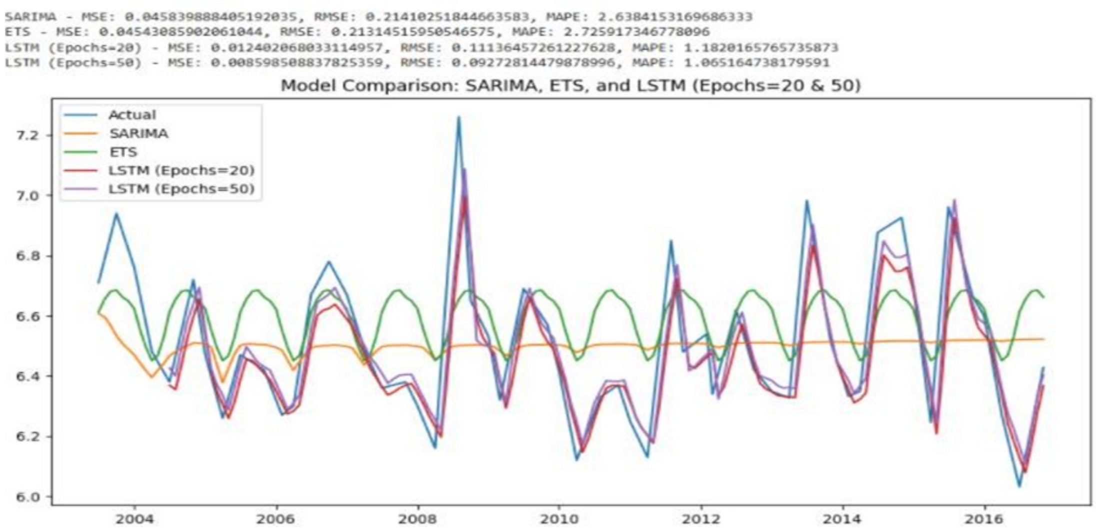

Figure 3. *Comparison of the actual temperature series at Station 1b*

Figure 3 compares observed temperatures at Station 1b with forecasts from SARIMA, ETS, LSTM (20 epochs), and LSTM (50 epochs), with evaluation metrics summarised in Table 4. SARIMA followed seasonal patterns but deviated at sharp peaks and troughs (MSE = 0.046, RMSE = 0.214, MAPE = 2.64%). ETS produced smoother forecasts with similar performance (MSE = 0.045, RMSE = 0.213, MAPE = 2.73%). LSTM (20 epochs) tracked observations more closely, particularly at extremes (MSE = 0.012, RMSE = 0.111, MAPE = 1.18%), while LSTM (50 epochs) achieved the best performance overall (MSE = 0.009, RMSE = 0.093, MAPE = 1.07%). These results show that LSTM, especially with 50 epochs, provided the most accurate forecasts for Station 1b.

Table 4. *Model results of Station 1b based on MSE, RMSE, and MAPE*

Model	MSE (°C)	RMSE (°C)	MAPE (%)
SARIMA	0.046	0.214	2.64
ETS	0.045	0.213	2.73
LSTM (50 units, 20 epochs)	0.012	0.111	1.18
LSTM (50 units, 50 epochs)	0.009	0.093	1.07

Source: authors calculation based on CalCOFI data.

The evaluation metrics MSE, RMSE, and MAPE across stations are reported in Table 5, Table 6, and Table 7.

Table 5. *Accuracy measures with respect to different models applied to Stations 1a and 1b*

Station	Model	Settings	MSE (°C)	RMSE (°C)	MAPE (%)
1a	SARIMA	Auto	1.22	1.10	4.68
1a	ETS	Auto	1.06	1.03	4.64
1a	LSTM	(50 units, 50 epochs)	0.46	0.68	3.07
1b	SARIMA	Auto	0.05	0.21	2.64
1b	ETS	Auto	0.05	0.21	2.73
1b	LSTM	(50 units, 50 epochs)	0.01	0.09	1.07

Source: authors calculation based on CalCOFI data.

Table 6. *Accuracy measures with respect to different models applied to Stations 2a and 2b*

Station	Model	Settings	MSE (°C)	RMSE (°C)	MAPE (%)
2a	SARIMA	Auto	1.76	1.33	6.07
2a	ETS	Auto	1.76	1.33	6.09
2a	LSTM	(50 units, 50 epochs)	0.26	0.51	2.56
2b	SARIMA	Auto	0.04	0.21	3.02
2b	ETS	Auto	0.04	0.19	2.65
2b	LSTM	(50 units, 50 epochs)	0.01	0.09	1.18

Source: authors calculation based on CalCOFI data.

Table 7. *Accuracy measures with respect to different models applied to Stations 3a and 3b*

Station	Model	Settings	MSE (°C)	RMSE (°C)	MAPE (%)
3a	SARIMA	Auto	1.65	1.28	6.45
3a	ETS	Auto	2.35	1.53	8.32
3a	LSTM	(50 units, 50 epochs)	0.46	0.68	3.27
3b	SARIMA	Auto	0.05	0.23	2.77
3b	ETS	Auto	0.03	0.17	2.12
3b	LSTM	(50 units, 50 epochs)	0.01	0.07	0.83

Source: authors calculation based on CalCOFI data.

Table 5, Table 6, and Table 7 summarise forecasting performance across all stations and depths. The Long Short-Term Memory (LSTM) model consistently achieved the lowest MSE, RMSE, and MAPE at every station, confirming its superior ability to capture nonlinear and seasonal temperature dynamics. Compared with SARIMA and ETS, LSTM reduced MSE substantially at both surface (a) and deep-water (b) stations. For example, at Station 2a, MSE decreased from 1.76 (SARIMA/ETS) to 0.26 with LSTM, while at Station 3b, MSE decreased from 0.05 (SARIMA) and 0.03 (ETS) to 0.01.

Surface stations (1a, 2a, 3a) exhibited higher forecasting errors than their corresponding deep-water stations, indicating greater variability at 0 m compared to 500 m depth. Station 3a presented the most challenging forecasting conditions, where ETS produced the highest MAPE (8.32%), whereas LSTM reduced the error to 3.27%, demonstrating improved robustness under higher variability.

Across deep-water stations (1b, 2b, 3b), overall error magnitudes were considerably lower, with LSTM achieving MAPE values below 1.2% in all cases and as low as 0.83% at Station 3b. While ETS slightly outperformed SARIMA at some deep stations (e.g., 3b), both statistical models were consistently outperformed by LSTM.

These results confirm that deep learning provides substantial performance gains over traditional statistical approaches for ocean-temperature forecasting across multiple spatial locations and depths.

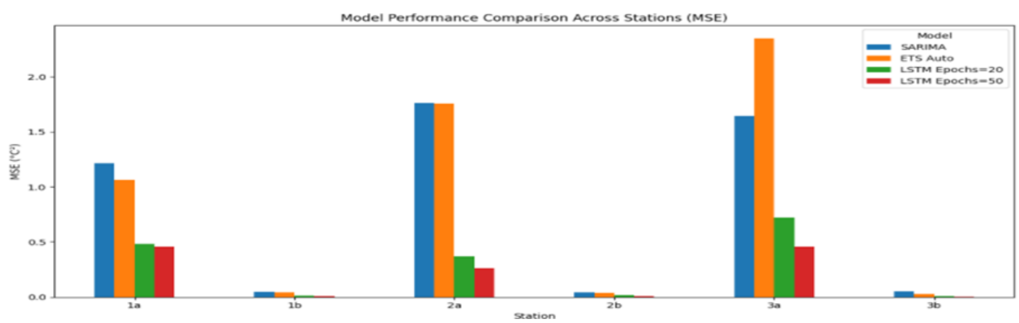

Figure 4. *Model comparison across Stations based on MSE (°C)*

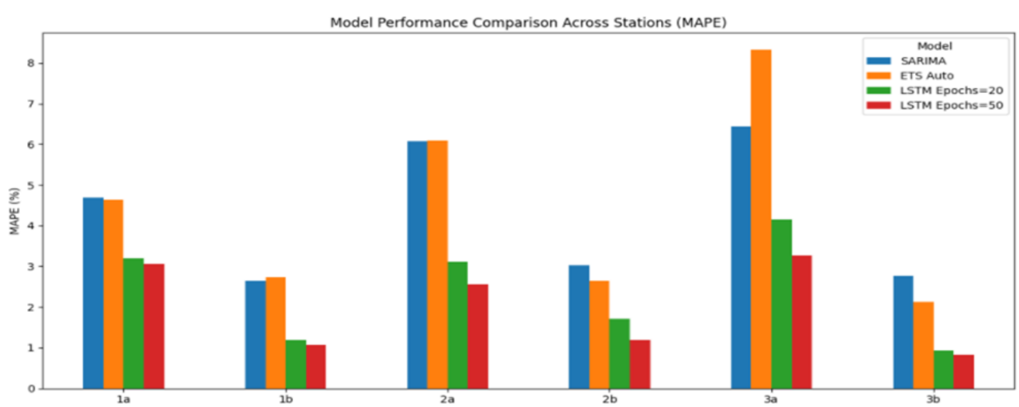

Figure 5. *Model comparison across Stations based on MAPE (%)*

Table 5–Table 7 and Figure 4–Figure 5 summaries performance across all stations and depths, where "a" denotes the surface and "b" 500 m depth. AutoETS generally outperformed AutoSARIMA in MSE and MAPE at Stations 1a, 1b, 2a, 2b, and 3b, with Station 3a

as an exception, where SARIMA performed better. LSTM (50 epochs) consistently achieved the lowest MSE, RMSE, and MAPE across all stations and depths, demonstrating superior pattern capture. LSTM (20 epochs) outperformed SARIMA and ETS at most stations but remained slightly weaker than the 50-epoch model. RMSE trends mirrored MSE, with lower errors at deeper stations (1b and 3b), likely due to reduced variability at 500 m. For MAPE, ETS generally improved upon SARIMA, but LSTM (50 epochs) consistently produced the lowest values, indicating the most precise predictions under both surface and deep-water conditions, particularly at the more challenging Station 3a.

4. Discussion

In this study, LSTM outperformed SARIMA and ETS in forecasting monthly ocean-temperature time series across the analysed stations and depths. This result is consistent with the theoretical capability of LSTM networks to model sequential data with long-term temporal dependencies, as the architecture was originally developed to address limitations such as vanishing gradients in recurrent neural networks (Hochreiter & Schmidhuber, 1997). Previous studies have also reported the usefulness of LSTM-based approaches for temperature forecasting, where decomposition-based Bi-LSTM models improved prediction accuracy by separating trend, seasonal, and residual components (Zhang et al., 2023). In the present study, the observed seasonal structure and nonlinear variability in ocean-temperature records provide a reasonable explanation for the stronger performance of LSTM compared with SARIMA and ETS. More broadly, ocean-temperature prediction is important because marine temperature variability is closely linked to ocean warming and ecological change (Venegas et al., 2023).

The consistent reduction in MSE, RMSE, and MAPE achieved by LSTM across most stations in this study indicates that deep-learning models can provide robust predictions when ocean-temperature series contain nonlinear variability and temporal dependence. Previous studies have similarly demonstrated the suitability of LSTM for temperature and environmental forecasting applications, where the model showed strong capability in learning temporal patterns from sequential data (Liu & Li, 2023; Salman et al., 2018). In the present study, the improved performance of the 50-epoch LSTM compared with the 20-epoch configuration further suggests that sufficient training helped the model better learn the temporal structure of the ocean-temperature series.

The comparative performance of SARIMA and ETS also provides useful insights. ETS generally produced smoother forecasts and achieved competitive performance under relatively stable conditions, whereas SARIMA demonstrated stronger capability in capturing explicit seasonal and autoregressive structures, particularly where periodic patterns were pronounced (Hyndman & Athanasopoulos, 2018). In the present study, both models showed reduced performance under stations with greater variability and more complex temperature fluctuations, which may explain the higher forecasting errors observed at some surface locations. Similar comparative behaviour between SARIMA- and ETS-based forecasting approaches has been reported across different application domains, where model performance depended on the characteristics and variability of the time series (Gao, 2025; Xian et al., 2023; Kuan, 2022).

An important observation from this study is the difference in forecasting performance between surface (0 m) and deep-water (500 m) stations. Surface stations exhibited higher variability and consequently higher prediction errors, likely reflecting the stronger influence of seasonal and environmental variability on near-surface ocean conditions. In contrast, deep-water stations exhibited more stable temperature profiles, resulting in consistently lower RMSE and MAPE values at 500 m depth across all forecasting models.

Overall, the results demonstrate that while SARIMA and ETS remain valuable for interpretable and computationally efficient forecasting, LSTM provides a more flexible framework for modelling complex ecological time series. In the present study, LSTM maintained strong predictive performance across different stations and depths, suggesting improved capability in handling nonlinear and variable ocean-temperature dynamics. The consistently lower MSE, RMSE, and MAPE values achieved by LSTM further support its suitability for ocean-temperature forecasting under varying environmental conditions. These findings suggest that deep-learning approaches may provide advantages for large-scale oceanographic prediction systems and environmental monitoring applications.

Automatic SARIMA achieved a lower AIC than the manually specified SARIMA model, indicating that automated order selection can improve modelling efficiency and support more consistent parameter selection across multiple time series (Arlt & Trčka, 2021). Similarly, the automatic ETS framework selected models using AIC-based optimisation, demonstrating the usefulness of automated model-selection procedures for identifying suitable forecasting configurations across different datasets.

In this study, ETS generally outperformed SARIMA at most stations, particularly under relatively stable conditions, although SARIMA occasionally achieved lower errors at certain locations such as Station 3a. Similar comparative behaviour between ETS- and SARIMA-based forecasting approaches has been reported in previous forecasting studies, where model performance varied depending on the variability and structure of the time series (Gao, 2025; Xian et al., 2023; Kuan, 2022). Mixed forecasting performance between ETS and SARIMA has also been observed in unemployment prediction studies, where SARIMA occasionally outperformed ETS under specific temporal conditions (Davidescu et al., 2021).

Finally, LSTM, particularly with 50 training epochs, achieved the strongest forecasting performance across most stations and depths in this study. The lower MSE, RMSE, and MAPE values obtained by LSTM suggest that deep-learning approaches may provide advantages in capturing nonlinear variability and long-term temporal dependencies in ocean-temperature data. Similar advantages of LSTM-based forecasting models have been reported in temperature, weather, and energy forecasting applications, where deep-learning approaches demonstrated strong capability in learning complex temporal patterns from sequential data (Liu & Li, 2023; Salman et al., 2018; Bilgili & Pinar, 2023). In the present study, the strong performance of LSTM at more variable stations, such as Station 3a, further highlights its robustness under complex environmental conditions.

5. Conclusion

This study compared traditional statistical models (SARIMA and ETS) with a deep-learning model (LSTM) for ocean-temperature forecasting at multiple stations and depths in the CalCOFI region. Automatic SARIMA improved on manual SARIMA in terms of AIC, and ETS generally outperformed SARIMA across stations. However, neither matched the performance of LSTM. Particularly, LSTM with 50 training epochs, consistently achieved the lowest MSE, RMSE, and MAPE, supporting its ability to capture nonlinear patterns and long-term dependencies in ecological time series. SARIMA and ETS remain useful for simpler datasets or situations where computational cost and interpretability are critical, whereas LSTM emerges as the most robust option for complex ocean-temperature prediction in the present study. These findings underline the advantages of deep learning for ecological forecasting and highlight its potential to advance predictive modelling in environmental applications. They also emphasise the importance of selecting appropriate modelling approaches for long-term environmental monitoring and climate-related decision-making.

The forecasting framework developed in this study may support detailed analysis of ocean-temperature behaviour with depth, including long-term trends, seasonal variability, and temporal patterns in the CalCOFI region and similar marine monitoring programmes (O'Donncha et al., 2022). Accurate forecasting at both surface (0 m) and deep-water (500 m) stations may also assist marine ecosystem assessments and climate-related environmental studies (Wei & Guan, 2022). Furthermore, LSTM-based forecasting approaches may contribute to early-warning systems by helping identify anomalous or extreme temperature conditions in marine environments (Bonino et al., 2024). Integration of these forecasting models into AI-driven environmental decision-support systems could additionally support planning and optimisation in coastal resource management and environmental monitoring.

The datasets used were relatively small, so AutoSARIMA and AutoETS procedures were efficient; however, for larger datasets and higher model orders, parameter estimation and model selection may become more computationally demanding. Strategies for choosing regular and seasonal differencing orders, especially in more complex series, still require refinement.

The present work does not fully address real-world complexities such as extensive data transformations, outlier treatment, or structural breaks, all of which may influence performance and limit generalisation to other regions or higher-frequency data.

Future research should extend this analysis to larger and more diverse datasets to better understand model behaviour under different temporal and spatial conditions. Further optimisation of LSTM hyperparameters, such as batch size, number of layers, and epochs, could improve performance and stability.

Hybrid models that combine SARIMA or ETS with LSTM or other deep-learning architectures are a promising direction. Such approaches could exploit the interpretability of statistical models together with the nonlinear learning capacity of deep networks to produce more robust ocean-temperature forecasts.

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Usporedba predviđanja temperature oceana korištenjem SARIMA, ETS i LSTM modela

SAŽETAK

Točno predviđanje temperature oceana ključno je za razumijevanje dugoročne okolišne varijabilnosti i podršku ekološkom odlučivanju. Ovaj rad ocjenjuje uspješnost modela SARIMA (*sezonski autoregresijski integrirani model pomičnih prosjeka*), ETS (*model pogreške, trenda i sezonalnosti*) i LSTM (*model duge kratkoročne memorije*) u predviđanju temperature oceana korištenjem povijesnih vremenskih nizova podataka iz programa CalCOFI. Skup podataka pripremljen je primjenom sezonske dekompozicije i analize stacionarnosti, a točnost predviđanja ocijenjena je pomoću pokazatelja MAPE (*srednja apsolutna postotna pogreška*), RMSE (*korijen srednje kvadratne pogreške*) i MSE (*srednja kvadratna pogreška*). Rezultati pokazuju da je LSTM ukupno dao najtočnija i najstabilnija predviđanja, ostvarujući niže vrijednosti RMSE i MAPE na većini postaja i dubina. Model je uspješno zabilježio nelinearno ponašanje, sezonsku varijabilnost i ekstremne temperaturne fluktuacije. SARIMA je pokazala snažnu sposobnost modeliranja trenda i sezonalnosti, dok je ETS generirao glađa predviđanja, ali s razmjerno višim vrijednostima pogreške. Dijagnostika reziduala dodatno je potvrdila superiornu sposobnost LSTM–a da nauči složene vremenske ovisnosti prisutne u podacima o temperaturi oceana. Ovaj rad doprinosi usporednoj ocjeni klasičnih statističkih modela i modela dubokog učenja za predviđanje ekoloških vremenskih nizova te pruža dokaze koji podupiru primjenu LSTM–a za poboljšano oceanografsko predviđanje i praćenje okoliša.

KLJUČNE RIJEČI

Ekološki vremenski nizovi, ETS, predviđanje, LSTM, SARIMA

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Pokazatelj očekivane zaposlenosti u predviđanju promjena na hrvatskom tržištu rada

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SAŽETAK

Cilj rada je teorijski i metodološki analizirati prognostička svojstva pokazatelja očekivane zaposlenosti EEI (engl. *Employment Expectations Indicator*) u kontekstu predviđanja promjena na hrvatskom tržištu rada, pri čemu se testira hipoteza o EEI–ju kao vodećem indikatoru kratkoročnih promjena. Empirijsko istraživanje provedeno je na sekundarnim, sezonski prilagođenim mjesečnim vremenskim nizovima Europske komisije i Državnog zavoda za statistiku od siječnja 2016. do prosinca 2025. godine. Primjenom testa Grangerove uzročnosti unutar autoregresijskog modela s distribuiranim pomacima (ARDL), analiziran je vremenski pomak djelovanja EEI–ja, s primarnim fokusom na prognoziranje smjera, a ne intenziteta promjene broja zaposlenih u kratkom roku od dva mjeseca. Rezultati modeliranja indiciraju da uključivanje varijable EEI, uz specifikaciju do uključivo dvaju mjesečnih pomaka, statistički značajno doprinosi prognostičkoj kvaliteti i poboljšanju predikcije. Time rad pruža preliminarne dokaze o prediktivnoj valjanosti ovog pokazatelja te ostvaruje znanstveni i aplikativni doprinos kroz oblikovanje pouzdanog analitičkog instrumentarija za potrebe makroekonomskog planiranja i kreiranja ekonomskih politika.

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KLJUČNE RIJEČI
Ankete pouzdanja poduzeća i potrošača, ARDL, Grangerova uzročnost, pokazatelj očekivane zaposlenosti, tržište rada

1. Uvod

U dinamičnom ekonomskom okruženju donošenje odluka u realnom vremenu zahtijeva pravovremene i precizne informacije. S obzirom na to da službena državna statistika često objavljuje podatke s vremenskim odmakom, alternativni izvori, poput Anketa pouzdanja poduzeća i potrošača BCS (engl. *Business and Consumer Survey*), dobivaju na važnosti. U tim anketama menadžeri i potrošači iznose ocjene i očekivanja o ekonomskim varijablama (primjerice, o zaposlenosti), koja se potom transformiraju u numeričke pokazatelje s empirijski potvrđenim svojstvima prethođenja referentnim nizovima. Primjer takvog indikatora je pokazatelj očekivane zaposlenosti EEI, koji Europska komisija objavljuje na mjesečnoj razini za sve zemlje

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Europske unije i potencijalne pristupnice (European Commission, 2025a,b). BCS pokazatelje karakterizira jednostavnost, aktualnost i visoka pouzdanost (Čižmešija, 2008, 2017), a njihova važnost u modeliranju gospodarskih kretanja posebno dolazi do izražaja tijekom kriza, poput financijske krize 2008. godine i pandemije bolesti COVID-19 koja je započela 2020. godine (Sorić, 2025). U takvim je uvjetima, uz službene podatke, ključno analizirati i percepciju tržišnih sudionika. Claveria i sur. (2007) zaključuju da pokazatelji pouzdanja imaju značajnu prediktivnu ulogu, posebice u prognoziranju smjera promjena referentnih varijabli, što ih čini važnim alatom za oblikovanje makroekonomske politike i brže reagiranje u realnom vremenu.

Rad teorijski i metodološki analizira pokazatelj očekivane zaposlenosti. Ispituje se hipoteza o postojanju prognostičkih svojstava EEI-a, odnosno pretpostavlja se da je on prethodeći pokazatelj promjenama na tržištu rada, temeljen na očekivanjima menadžera iz četiriju gospodarskih sektora i predviđa smjer kretanja zaposlenosti na hrvatskom tržištu rada u kratkom roku od dva mjeseca. Predmet istraživanja obuhvaća evaluaciju odabranih prognostičkih modela. Znanstveni i aplikativni doprinos rada očituje se u integraciji ovog metodološki specifičnog pokazatelja u analizu dinamike tržišta rada, čime se menadžerima, ekonomskim analitičarima i kreatorima gospodarskih politika pruža pouzdan analitički instrumentarij za poslovno odlučivanje, strateško upravljanje i makroekonomsko planiranje. Testiranjem Grangerove uzročnosti unutar autoregresijskog dinamičkog modela analizira se vremenski pomak u kojem EEI djeluje kao vodeći pokazatelj te se, zbog kvalitativne prirode prediktora, fokus stavlja na prognoziranje smjera, a ne intenziteta promjene zaposlenosti. Empirijsko istraživanje temelji se na sekundarnim, sezonski prilagođenim podacima Europske komisije i Državnog zavoda za statistiku od siječnja 2016. do prosinca 2025.

Rad je podijeljen u pet odjeljaka. Nakon uvoda, drugi dio teorijski kontekstualizira ulogu menadžerskih očekivanja unutar anketa pouzdanja poduzeća i potrošača i pokazatelj očekivane zaposlenosti kao kompozitni BCS pokazatelj. U trećem dijelu se definiraju podaci i metodologija istraživanja. Četvrti dio se odnosi na metodologiju i rezultate empirijske analize te ocjenu reprezentativnosti dinamičkog ARDL modela za hrvatsko tržište rada. U posljednjem poglavlju dan je zaključak, istaknuta ograničenja istraživanja i dane smjernice za potencijalna buduća istraživanja.

2. Konceptualni okvir istraživanja

Ankete pouzdanja poduzeća i potrošača (BCS) su empirijska istraživanja koja kontinuirano mjesečno provodi Europska komisija, prema harmoniziranoj metodologiji (European Commission, 2026) za sve zemlje članice EU, kao i one potencijalne članice. Istraživanja se provode u prerađivačkoj industriji, trgovini na malo, uslužnom sektoru, građevinarstvu i među potrošačima. U osnovi su kvalitativne naravi, ali se rezultati istraživanja odabranim numeričkim metodama prevode u pokazatelje različitog stupnja složenosti i različite prediktivne snage. Jedan od novijih indikatora je pokazatelj očekivane zaposlenosti (EEI). Objavljuje ga Europska komisija od 2020. godine.

Očekivanja menadžera povezana su i izravno utječu na gospodarska kretanja jer oblikuju ključne poslovne odluke o investicijama, zapošljavanju i proizvodnji, čime suoblikuju ekonomske cikluse. Zbog toga je razumijevanje tih očekivanja nužno za izradu preciznijih ekonomskih prognoza i donošenje strateških odluka.

U tom kontekstu, rezultati anketa pouzdanja poduzeća i potrošača (BCS) imaju veliku važnost u makroekonomskoj analizi. Brojna istraživanja (Clar i sur., 2007; Claveria, 2021; Taylor & McNabb, 2007; Westerhoff & Hohnisch, 2007) potvrđuju snažnu povezanost BCS pokazatelja sa službenim ekonomskim podatcima. Autori ističu da ovi kvalitativni pokazatelji poslovnog povjerenja značajno poboljšavaju razumijevanje trenutnih gospodarskih kretanja te posjeduju visoku prediktivnu sposobnost kada se koriste kao ulazni podatci u kvantitativnim prognostičkim modelima i to posebno u periodima promjena u cikličkim kretanjima. Empirijski je potvrđeno da očekivanja potrošača sadrže vrijedne informacije koje poboljšavaju predviđanja zaposlenosti odnosno nezaposlenosti (Abberger, 2007; Claveria i sur., 2007; Hutter & Weber, 2015; Lehmann & Wohlrabe, 2017).

Kvalitativne BCS varijable (tzv. *soft data*) predstavljaju značajnu nadopunu realnim varijablama u kvantitativnim makroekonomskim modelima kratkoročnog prognoziranja, što je posebno izraženo u uvjetima povećane ekonomske nestabilnosti kada je uvid u realne ekonomske pokazatelje (BDP, zaposlenost, cijene) privremeno ograničen (Claveria, 2021). Kvantifikacijom i metodološkom obradom subjektivnih stavova menadžera i potrošača oblikuju se kompozitni pokazatelji koji unose prediktivnu dimenziju u analizu ex-post podataka službene statistike. Dok službena statistika s vremenskim odmakom bilježi realizirane ekonomske ishode, BCS pokazatelji pravovremeno, najčešće potkraj tekućeg mjeseca, putem platformi Europske komisije indiciraju očekivanja menadžera o kretanju zaposlenosti, cijena, proizvodnje i ostalih varijabli, u narednom tromjesečnom razdoblju. BCS rezultati stoga ne zamjenjuju službene statističke podatke, već djeluju komplementarno; komparacija objektivnih ekonomskih kretanja i njihove subjektivne percepcije od ključne je važnosti za analizu makroekonomskih ciklusa, kao i za optimizaciju operativnog odlučivanja te strateškog planiranja unutar korporativnog sektora.

Postojeća znanstvena literatura u Hrvatskoj oskudijeva istraživanjima o prognoziranju stope nezaposlenosti i razvoju pouzdanih prethodećih pokazatelja (engl. *leading indicators*). Oblikovanje takvog sustava ranog upozorenja ključno je za pravovremeno prepoznavanje smjera kretanja nezaposlenosti, čime bi se kreatorima gospodarskih politika osigurale kvalitetne informacije za donošenje pravodobnih i učinkovitih odluka.

3. Metodologija istraživanja i izvori podataka

EEI se temelji na jednom pitanju iz BCS-a: „Ako isključite sezonske utjecaje, kako će se prema vašem mišljenju mijenjati ukupna zaposlenost vaše tvrtke u naredna tri mjeseca?" s tri ponuđena odgovora: (P) povećati će se, (E) ostati će nepromijenjena i (N) smanjiti će se.

Prema harmoniziranoj metodologiji, rezultati BCS-a se za početak kvantificiraju na način da se izračuna saldo (engl. *balance*) kao razlika između postotka pozitivnih (P) i negativnih (N) odgovora. EEI se temelji na saldima odgovora na navedeno pitanje u četiri sektora gospodarstva: prerađivačka industrija, trgovina na malo, građevinarstvo i usluge. Izračun EEI provodi se u nekoliko koraka (European Commission, 2026), kako slijedi.

Najprije se varijable komponente standardiziraju kako bi se otklonio potencijalni rizik da sektori s prirodno velikim oscilacijama u odgovorima nerealno dominiraju konačnim indeksom. Standardizirana salda y_j izračunavaju se prema izrazima (1) i (2):

$$y_{j,t} = \frac{x_{j,t} - \bar{x}_j}{s_j}, \quad \forall\, j = 1, 2, \ldots, 4, \quad t = 1, 2, \ldots, n \tag{1}$$

$$\bar{x}_j = \frac{1}{T'} \sum_{t=1}^{T} x_{j,t}, \qquad s_j = \sqrt{\frac{1}{T'-1} \sum_{t=1}^{T} \left(x_{j,t} - \bar{x}_j\right)^2}, \tag{2}$$

pri čemu je $\bar{x}_j$ prosjek j-te varijable u fiksiranom razdoblju, s_j je pripadajuća standardna devijacija, a T' je broj opažanja u fiksiranom razdoblju (engl. *frozen period*). Fiksirano razdoblje određuje se kako bi se izbjegle kontinuirane mjesečne revizije EEI-a. Fiksirano razdoblje za zemlje članice EU je 2000. godina. Za zemlje koje su nakon 2000. godine započele ovo istraživanje, to je godina početka provođenja istraživanja. Završetak fiksiranog razdoblja se revidira svakog siječnja kada se provodi i revizija ponderacijskog sustava (European Commission, 2026). Ponderirani prosjek standardiziranih salda odgovora (z_t) je:

$$z_t = \frac{\sum\limits_{j=1}^{4} w_j y_{j,t}}{\sum\limits_{j=1}^{4} w_j}, \quad t = 1, 2, \ldots, n, \tag{3}$$

pri čemu su w_j ponderi svakog od četiriju sektora, odnosno udjeli broja zaposlenih svakog sektora u ukupnom broju zaposlenih u sva četiri sektora zajedno. Potom se z_t standardizira i skalira. Kao takav ima aritmetičku sredinu jednaku 100 i standardnu devijaciju 10, kako je dano izrazima (4) i (5):

$$\mathrm{EEI}_t = \frac{z_t - \bar{z}}{s_z} \cdot 10 + 100, \quad t = 1, 2, \ldots, n \tag{4}$$

$$\bar{z} = \frac{1}{T'} \sum_{t=1}^{T} z_t, \qquad s_z = \sqrt{\frac{1}{T'-1} \sum_{t=1}^{T} (z_t - \bar{z})^2}. \tag{5}$$

Na temelju toga se vrijednosti EEI veće od 100 tumače kao prevladavajuće iznadprosječno očekivanje zaposlenosti, odnosno prevladavajući optimizam menadžera. Jednako tako, EEI manji od 100 znači očekivanu zaposlenost ispod dugoročnog prosjeka.

Navedeni metodološki okvir omogućuje izražavanje kvalitativnih menadžerskih percepcija i očekivanja egzaktnim kvantitativnim pokazateljem. Primjenom rigoroznih statističkih metoda uspješno se minimizira subjektivnost pojedinačnih procjena, što rezultira robusnim analitičkim alatom. Na mikroekonomskoj razini, ovaj pokazatelj menadžerima služi za usklađivanje i validaciju internih strategija zapošljavanja sa širim kretanjima na tržištu rada. Na makroekonomskoj razini, kreatorima gospodarskih politika osigurava pravovremene empirijske inpute ključne za modeliranje i predviđanje dinamike zaposlenosti.

Kao instrument proaktivnog djelovanja, EEI omogućuje ekonomskim subjektima i kreatorima politika prepoznavanje nadolazećih trendova na tržištu rada prije nego što se oni manifestiraju u službenim statističkim izvještajima. Prema istraživanjima Europske komisije (European Commission, 2026), ovaj indeks bilježi prosječno dvomjesečno prethođenje u odnosu na realizirane promjene u stopi zaposlenosti. Na razini poduzeća, taj prognostički prozor od dva mjeseca ključan je za strateško planiranje ljudskih potencijala. On menadžmentu otvara prostor za pravodobno planiranje i provedbu selekcijskih postupaka, čime se izbjegavaju operativni zastoji, osigurava pravovremeno popunjavanje radnih mjesta i dugoročno jača konkurentska pozicija poduzeća.

Empirijsko istraživanje Abberger (2007), na primjeru njemačkoga gospodarstva, potvrdilo je da menadžerska očekivanja, integrirana u EEI, predstavljaju pouzdan vodeći pokazatelj stvarnih promjena u zaposlenosti. Pritom je važno napomenuti da se zbog kvalitativne prirode BCS-a ovi pokazatelji primarno koriste za predviđanje smjera, ali ne i intenziteta promjena u referentnim vremenskim nizovima (Abberger, 2007; Claveria, 2021).

Nadalje, Lehmann & Weyh (2016) analizirali su prediktivne sposobnosti očekivanja zaposlenosti u 15 europskih zemalja od prvog kvartala 1998. do četvrtog kvartala 2014. godine. Njihova ex-post i ex-ante prognostička analiza pokazale su da modeli s uključenim EEI-jem u većini promatranih zemalja nadmašuju standardne prognostičke modele. Najviša preciznost prognoza identificirana je uz vremenski pomak od jednog kvartala, što je u skladu s horizontom anketnog pitanja, iako se u pojedinim zemljama pokazatelj pokazao učinkovitim i na duljim prognostičkim horizontima. Za hrvatsko tržište rada je malo empirijskih istraživanja, ali ona koja su do sad provedena upućuju na postojanje pozitivne i statistički značajne povezanosti između promjena broja zaposlenih (na godišnjoj razini) i EEI-a i to ponajprije za prethođenje EEI-a od jednog, odnosno dva mjeseca (Mišir, 2025).

Kada se govori o izvorima podataka o broju zaposlenih osoba u Hrvatskoj, službena statistika razlikuje broj zaposlenih koji je rezultat obrade podataka i procjena iz istraživanja LFS i broj zaposlenih iz administrativnog izvora. Ukupan broj zaposlenih iz administrativnog izvora, kojeg u mjesečnoj dinamici objavljuje DZS, sastoji se od zbroja tri kategorije: zaposlenih u pravnim osobama, zaposlenih u obrtu i slobodnim profesijama te zaposlenih osiguranika poljoprivrednika.

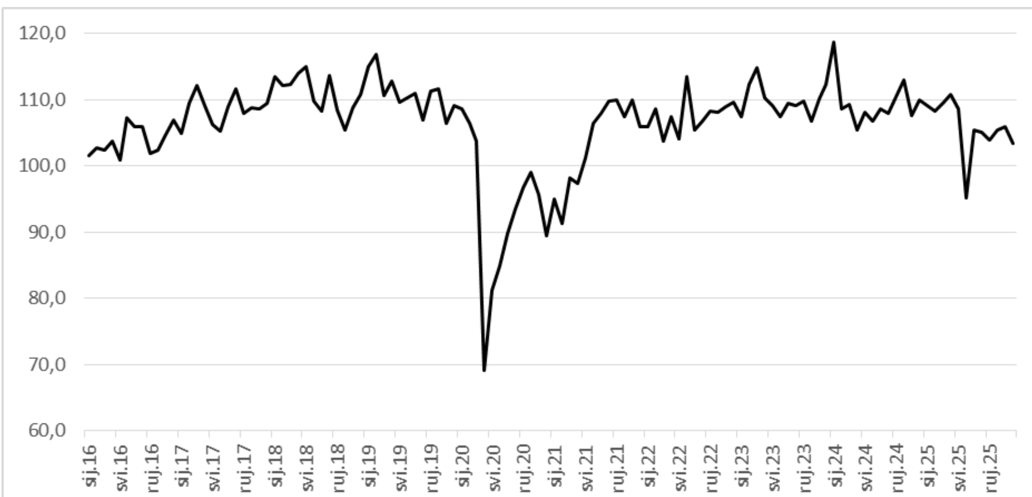
Stoga se u ovome radu koriste podaci Državnog zavoda za statistiku o konačnoj mjesečnoj administrativnoj zaposlenosti počevši od siječnja 2016. Podaci su dostupni za razdoblje do prosinca 2025. (DZS, 2025). Broj zaposlenih u obrtu i slobodnim profesijama i broj zaposlenih osiguranika poljoprivrednika preuzima se iz evidencije aktivnih osiguranika Hrvatskog zavoda za mirovinsko osiguranje. Podaci o EEI preuzeti su s internetskih stranica Europske komisije.

U empirijskom dijelu istraživanja primijenjen je model autoregresivnih distribuiranih vremenskih pomaka ARDL model (engl. *Autoregressive Distributed Lag*) kako bi se analizirala dinamička povezanost između EEI-ja i zaposlenosti. Za razliku od statičkih pristupa, dinamički modeli integriraju vremensku dimenziju, omogućujući procjenu utjecaja tekućih i povijesnih vrijednosti nezavisne varijable, kao i prošlih vrijednosti same zavisne varijable, na njezino trenutno kretanje (Mišir, 2025).

U svrhu utvrđivanja optimalnog broja vremenskih pomaka (lagova) i identifikacije horizonta na kojem EEI najučinkovitije signalizira promjene u zaposlenosti, testirane su specifikacije s do 12 vremenskih pomaka za obje varijable. Selekcija optimalnog ARDL modela provedena je minimizacijom Bayesovog informacijskog kriterija BIC (engl. *Bayesian Information Criterion*). U usporedbi s Akaikeovim informacijskim kriterijem (AIC), BIC primjenjuje strožu penalizaciju za broj uključenih parametara, čime se efikasno minimizira rizik od prevelikog parametriziranja (engl. *overfitting*) i osigurava parsimonija modela. Provedena je provjera stacionarnosti varijabli. Primijenjene su odabrane metode regresijske dijagnostike u svrhu provjere ispunjenja pretpostavki regresijskog modela. Kako bi se ispitalo da li uključivanje prošlih vrijednosti EEI-ja statistički značajno smanjuje prognostičku pogrešku modela zaposlenosti u usporedbi s autoregresivnim modelom koji kao prediktore koristi isključivo prošle vrijednosti same zaposlenosti, proveden je test Grangerove uzročnosti EEI do zaključno drugog pomaka na varijablu zaposlenost.

4. Empirijski rezultati i diskusija

Analiza kretanja pokazatelja očekivane zaposlenosti (EEI), kako je prikazano na Slici 1, ukazuje na to da su vrijednosti indeksa u Republici Hrvatskoj do veljače 2020. godine perzistentno oscilirale iznad dugoročnog prosjeka, što odražava optimistična menadžerska očekivanja. Nastupom pandemijske krize zabilježen je snažan egzogeni šok koji je inicirao oštru kontrakciju EEI-a. Inicijalni pad zabilježen je u ožujku 2020. godine, dok je kulminacija negativne korekcije uslijedila u travnju 2020. Postpandemijsku fazu obilježila je postupna stabilizacija uz umjerenu volatilnost do travnja 2021. godine, kada se pokazatelj ponovno vratio u zonu iznad dugoročnog prosjeka. Nakon toga se EEI stabilizirao na iznadprosječnim razinama sve do svibnja 2025. kada je kratkotrajno spustio ispod prosjeka, ali se ubrzo vratio i potom stabilizirao. Nagli pad pokazatelja očekivane zaposlenosti (EEI) u proljeće 2025. godine primarno je bio izazvan kombinacijom rasta geopolitičkih napetosti i energetskih nesigurnosti u Europi, što se izravno odrazilo na povjerenje menadžera u ključnim sektorima hrvatskog gospodarstva.



Slika 1. *Kretanje pokazatelja očekivane zaposlenosti EEI u Hrvatskoj od siječnja 2016. do prosinca 2025.*

Prema europskoj standardiziranoj metodologiji BCS-a, EEI se uspoređuje sa stopama rasta referentne serije zaposlenih na godišnjoj razini (European Commission, 2026). Prvotno je procijenjen optimalni ARDL model temeljem konačnih mjesečnih podataka o zaposlenosti koje objavljuje DZS i mjesečnih podataka o EEI koji se preuzimaju s internetskih stranica Europske komisije (European Commission, 2025a,b,c). Korišteni su konačni mjesečni podaci o broju zaposlenih počevši od siječnja 2016. godine do prosinca 2025. godine. Zbog uočenih sezonskih oscilacija mjesečnih podataka o broju zaposlenih, prvotno je provedeno desezoniranje niza zaposlenosti. Zatim su izračunane godišnje stope promjene desezonirane zaposlenosti, dok su za niz EEI računane prve diferencije. Također, budući da je pretpostavka ARDL modela stacionarnost vremenskih nizova, proveden je ADF test stacionarnosti prvih diferencija EEI i godišnjih stopa promjene desezonirane zaposlenosti. Rezultati ADF testa su prikazani u Tablici 1.

Tablica 1. *Rezultati ADF testa za prve diferencija EEI-a i godišnje stope promjene desezonirane zaposlenosti*

	ADF
Kritična vrijednost na razini signifikantnosti 5%	−1,9600
Testovna veličina t za prve diferencije EEI	−2,5346
Testovna veličina t za godišnje stope promjene desezonirane zaposlenosti	−1,3526
Testovna veličina t za prve diferencije godišnjih promjena desezonirane zaposlenosti	−9,0189

Izvor: izračun autora temeljem podataka preuzetih s Europske komisije i DZS-a.

Testovna veličina za prve diferencije EEI je manja od kritične vrijednosti, tako da se odbacuje nulta hipoteza i uz 5% signifikantnosti se zaključuje da su prve diferencije EEI stacionaran vremenski niz. Za niz godišnjih stopa promjene desezonirane zaposlenosti, budući da je testovna veličina veća od kritične vrijednosti, ne može se odbaciti nulta hipoteza i uz 5% signifikantnosti zaključuje se da je niz godišnjih stopa promjene zaposlenosti nestacionaran. Zato je ovaj niz diferenciran. Ponovnim provođenjem ADF testa, dobiveni su rezultati kako je prikazano u Tablici 1. Budući da je sada testovna veličina za niz prvih diferencija godišnjih stopa promjene desezonirane zaposlenosti manja od kritične vrijednosti, nulta hipoteza je odbačena i uz 5% signifikantnosti zaključuje se da je diferencirani niz godišnjih stopa promjene desezonirane zaposlenosti sada stacionaran.

Prije procjene optimalnog modela prilagođena je duljina niza prvih diferencija EEI tako da bude jednaka duljini niza prvih diferencija godišnjih promjena desezonirane zaposlenosti. Procijenjen je optimalan model kojim se utvrđuje koliko mjeseci unaprijed će EEI najbolje signalizirati promjenu zaposlenosti. Odabran je ARDL model za koji je informacijski kriterij BIC minimalan. U model je uključena i nezavisna dummy varijabla KRIZA koja se odnosi na krizu izazvanu pandemijom COVID-19. Tako ona za period od ožujka 2020. do svibnja 2023. poprima vrijednost 1, a u svim ostalim mjesecima 0. Analiza je provedena za do 12 pomaka zavisne i nezavisnih varijabli. Zavisna varijabla su prve diferencije godišnjih stopa promjene desezoniranog broja zaposlenih, a nezavisne su prve diferencije EEI i KRIZA. Najboljim je ocijenjen model ARDL(1,2,0). Procijenjeni ARDL(1,2,0) model dan je sljedećim izrazom:

$$\begin{aligned}\Delta \mathrm{ZAP}_t = &-0{,}016150 + 0{,}085462\,\Delta \mathrm{ZAP}_{t-1} - 0{,}002341\,\Delta \mathrm{EEI}_t \\ &+ 0{,}077603\,\Delta \mathrm{EEI}_{t-1} + 0{,}036231\,\Delta \mathrm{EEI}_{t-2} + 0{,}013693\,\mathrm{KRIZA} + \varepsilon_t\end{aligned} \tag{6}$$

Rezultati procijenjenog modela dani su u Tablici 2.

Tablica 2. *Rezultati procjene dinamičkog modela ARDL(1,2,0)*

Koeficijent	Procjena	Std. pogreška	$t-$vrijednost	$p-$vrijednost
Konstanta	−0,016150	0,065923	−0,245	0,80698
$\Delta \mathrm{ZAP}_{t-1}$	0,085462	0,093066	0,918	0,36070
$\Delta \mathrm{EEI}_t$	−0,002341	0,010508	−0,223	0,82419
$\Delta \mathrm{EEI}_{t-1}$	0,077603***	0,010890	7,126	<0,0001
$\Delta \mathrm{EEI}_{t-2}$	0,036231**	0,012079	2,999	0,00342
KRIZA	0,013693	0,108160	0,127	0,89952

Napomena: ** i *** označavaju statističku značajnost na razini signifikantnosti 5% i 1%.
Izvor: izračun autora prema podacima preuzetim s Europske komisije i DZS-a.

Regresijski koeficijenti, odnosno varijable uz pomake EEI od 1 i 2 mjeseca su statistički značajni u modelu (na razini signifikantnosti 1% odnosno 5%). Varijabla KRIZA nije se pokazala značajnom u procijenjenom modelu.

U svrhu ocjene reprezentativnosti i stabilnosti procijenjenog ARDL(1,2,0) modela, provedena je detaljna regresijska dijagnostika reziduala. Adekvatnost dinamičke specifikacije modela najprije je ispitana Ljung-Boxovim testom autokorelacije grešaka relacije. Test je rezultirao empirijskom vrijednošću $\chi^2 = 2{,}6304$ uz pripadajuću $p-$vrijednost od 0,6215, slijedom čega se ne može odbaciti nulta hipoteza te se zaključuje da ne postoji statistički značajna autokorelacija grešaka relacije do uključivo četvrtog reda (uz standardnu razinu signifikantnosti 5%). S druge strane, Jarque-Bera testom ispitana je normalnost distribucije reziduala, pri čemu dobivena vrijednost $\chi^2 = 261{,}79$ ($p < 0{,}05$) indicira odstupanje od normalne distribucije. Međutim, u uvjetima makroekonomskog modeliranja na dovoljno velikom uzorku ($n = 107$), narušavanje ove pretpostavke ne predstavlja ozbiljan metodološki problem jer su, prema asimptotskoj teoriji, OLS procjenitelji i dalje konzistentni.

Naposljetku, Breusch-Paganov test heteroskedastičnosti BP $= 25{,}092$ ($p = 0{,}00013$) ukazao je na prisutnost promjenjivosti varijance pogrešaka. Ova pojava izravna je manifestacija snažnih egzogenih i strukturnih šokova koji su obilježili promatrano razdoblje, prvenstveno pandemije bolesti COVID-19 i energetskih nesigurnosti u Europi 2025. godine, a koji prirodno generiraju privremenu nestabilnost varijance u vremenskim nizovima. Unatoč prisutnosti heteroskedastičnosti, prema Gauss-Markovljevom teoremu, procjene regresijskih koeficijenata zadržavaju svojstva nepristranosti i dosljednosti. S obzirom na to da su p-vrijednosti ključnih prediktora ($\Delta\mathrm{EEI}_{t-1}$ i $\Delta\mathrm{EEI}_{t-2}$) izrazito visoke razine signifikantnosti, utvrđeni smjer i dvomjesečni prognostički horizont pokazatelja očekivane zaposlenosti (EEI) ostaju u potpunosti znanstveno i aplikativno valjani.

Za razliku od tradicionalnih definicija uzročnosti, Grangerova uzročnost ne implicira da promjena jedne varijable izravno uzrokuje promjenu druge, već da njezine povijesne vrijednosti pomažu u predviđanju budućih kretanja promatrane varijable. Navedeni koncept primijenjen je u empirijskom istraživanju povezanosti EEI-ja i referentnog niza zaposlenosti. U tom kontekstu, EEI Granger-uzrokuje zaposlenost ako uključivanje prošlih vrijednosti EEI-ja statistički značajno smanjuje prognostičku pogrešku modela zaposlenosti u usporedbi s autoregresivnim modelom koji kao prediktore koristi isključivo prošle vrijednosti same zaposlenosti. Postojanje Grangerove uzročnosti između EEI i zaposlenosti dokaz je da EEI kao vodeći pokazatelj može služiti u predviđanju zaposlenosti.

Proveden je test Grangerove uzročnosti EEI do zaključno drugog pomaka na varijablu zaposlenost i to temeljem VAR modela koji uključuje egzogenu dummy varijablu KRIZA. Korištene su mjesečne diferencirane vrijednosti EEI i desezonirana zaposlenost za razdoblje od početka 2016. godine do kraja 2025. godine (korištene su diferencirane godišnje stope promjene desezonirane zaposlenosti) kao i kod procjene optimalnog dinamičkog modela.

Za potrebe Grangerova testa uzročnosti specificiran je VAR model s dva pomaka za sve endogene varijable. Modeli su definirani izrazima (7) i (8). Rezultati procijenjenih modela prikazani su u Tablicama 3 i 4.

$$\begin{aligned}\Delta\mathrm{ZAP}_t = & -0{,}01484 + 0{,}05726\,\Delta\mathrm{ZAP}_{t-1} + 0{,}07822\,\Delta\mathrm{EEI}_{t-1} \\ & + 0{,}09234\,\Delta\mathrm{ZAP}_{t-2} + 0{,}04034\,\Delta\mathrm{EEI}_{t-2} + 0{,}01165\,\mathrm{KRIZA} + \varepsilon_{\Delta\mathrm{ZAP}_t}.\end{aligned} \tag{7}$$

Tablica 3. *Rezultati procjene VAR modela za jednadžbu danu izrazom (7)*

Koeficijent	Procjena	Std. pogreška	t−vrijednost	p−vrijednost
Konstanta	−0,01484	0,06550	−0,227	0,82124
ΔZAP_{t-1}	0,05726	0,09571	0,598	0,55106
ΔEEI_{t-1}	0,07822***	0,01040	7,519	<0,0001
ΔZAP_{t-2}	0,09234	0,08280	1,115	0,26744
ΔEEI_{t-2}	0,04034**	0,01247	3,235	0,00166
KRIZA	0,01165	0,10748	0,108	0,91389

Napomena: ** i *** označavaju statističku značajnost na razini signifikantnosti 5% i 1%.
Izvor: izračun autora prema podacima preuzetim s Europske komisije i DZS-a.

$$\begin{aligned} \Delta \text{EEI}_t = & -0{,}20594 + 0{,}45063\, \Delta \text{ZAP}_{t-1} - 0{,}28628\, \Delta \text{EEI}_{t-1} \\ & - 0{,}59377\, \Delta \text{ZAP}_{t-2} - 0{,}11457\, \Delta \text{EEI}_{t-2} + 0{,}30686\, \text{KRIZA} + \varepsilon_{\Delta \text{EEI}_t}. \end{aligned} \tag{8}$$

Tablica 4. *Rezultati procjene VAR modela za jednadžbu danu izrazom (8)*

Koeficijent	Procjena	Std. pogreška	t−vrijednost	p−vrijednost
Konstanta	−0,20594	0,62847	−0,328	0,74384
ΔZAP_{t-1}	0,45063	0,91836	0,491	0,62473
ΔEEI_{t-1}	−0,28628**	0,09981	−2,868	0,00505
ΔZAP_{t-2}	−0,59377	0,79446	−0,747	0,45661
ΔEEI_{t-2}	−0,11457	0,11965	−0,958	0,34060
KRIZA	0,30686	1,03123	0,298	0,76666

Napomena: ** označava statističku značajnost na razini signifikantnosti 5%.
Izvor: izračun autora prema podacima preuzetim s Europske komisije i DZS-a.

Temeljem Grangerovog testa uzročnosti zaključuje se da će se uključivanjem EEI u model, zaključno do drugog pomaka, poboljšati prognoza promjene zaposlenosti.

5. Zaključak

Unatoč oskudnom metodološkom okviru za prognoziranje tržišta rada u međunarodnoj literaturi, primjena odabranih BCS pokazatelja bilježi snažan rast, posebno nakon velike svjetske financijske krize 2008. godine, što se potvrdilo i tijekom posljednje krize izazvane pandemijom COVID-19. Hrvatski je kontekst predviđanja promjena na tržištu rada specifičan. Razvijeno je nekoliko pokazatelja namijenjenih praćenju tržišta rada, čija prediktivna svojstva dosad nisu dovoljno empirijski verificirana.

Rezultati istraživanja potvrdili su da se temeljem promjena EEI-a uspješno može predvidjeti smjer promjene na hrvatskom tržištu rada dva mjeseca unaprijed. Svojstvo prethođenja BCS pokazatelja omogućuje nositeljima ekonomske politike pravodobnu implementaciju protucikličkih mjera i ciljanih politika zapošljavanja, dok monetarnim vlastima olakšava kratkoročno projiciranje inflacije (Sorić, 2025). Slijedom toga, ovo istraživanje predstavlja doprinos literaturi i pruža preliminarne dokaze o prognostičkoj svrhovitosti pokazatelja očekivane zaposlenosti EEI u Hrvatskoj.

Ako se ima na umu da su rezultati BCS-a dostupni znatno ranije od istovrsnih podataka službene statistike i ako se uvaži prediktivno svojstvo EEI-a po kojem on prethodi promjenama zaposlenosti s dva mjeseca unaprijed, njegova uloga u predviđanju promjena na hrvatskom tržištu rada je nesporna. Važno je samo naglasiti da se zbog primarno kvalitativne prirode svih BCS pokazatelja, pa tako i EEI-a, preporučuje predviđati smjer promjene zaposlenosti, a ne i njen intenzitet.

Rad ima nekoliko ograničenja. Metodološko ograničenje procijenjenog modela odnosi se na prisutnost heteroskedastičnosti. Unatoč tome, u radu su zadržane standardne OLS pogreške radi očuvanja izvorne strukture ARDL modela i izravne ekonomske interpretacije varijabli. S obzirom na to da su svojstva nepristranosti i dosljednosti koeficijenata očuvana, a ključni prediktori pokazuju visoku statističku značajnost, utvrđeni smjer i dvomjesečni prognostički horizont pokazatelja očekivane zaposlenosti (EEI) ostaju znanstveno i aplikativno valjani. Ipak, buduća bi istraživanja trebala testirati robusnost ovih rezultata primjenom robusnih procjenitelja ili alternativnih ekonometrijskih tehnika.

Nadalje, EEI je kompozitni pokazatelj koji agregira anketne podatke iz četiriju gospodarskih sektora te se kao takav analizira u odnosu na kretanje ukupne zaposlenosti. Sektorska analiza zaposlenosti zahtijevala bi dezagregaciju EEI odnosno primjenu pojedinačnih salda odgovora menadžera o očekivanim promjenama zaposlenosti po djelatnostima (industrija, građevinarstvo, usluge i trgovina na malo) i njihovu komparaciju s dezagregiranim podacima Državnog zavoda za statistiku (DZS) prema klasifikaciji NKD 2007. Empirijska analiza u ovome radu provedena je samo na agregatnoj razini, dok bi sektorska analiza, u nekim budućim istraživanjima, zasigurno dala različite rezultate po sektorima u različitim vremenskim intervalima.

Analiza povezanosti EEI i promjena na tržištu rada provedena je za Hrvatsku. Komparativna analiza na razini pojedinih članica EU-a predstavlja logičan smjer budućih istraživanja radi detekcije heterogenosti europskih tržišta rada. S obzirom na strukturne, razvojne i institucionalne razlike među zemljama, opravdano je očekivati znatne varijacije u prognostičkoj moći EEI-ja. Ovakav pristup omogućio bi identifikaciju specifičnih nacionalnih obrazaca, što je ključno za donošenje ciljanih ekonomskih politika i strateško planiranje na razini pojedinih gospodarstava.

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Employment expectations indicator in predicting changes in the Croatian labour market

SUMMARY

The aim of the paper is to theoretically and methodologically analyse the prognostic properties of the Employment Expectations Indicator EEI in the context of predicting changes in the Croatian labour market, testing the hypothesis of the EEI as a leading indicator of short–term changes. Empirical research was conducted on secondary, seasonally adjusted monthly time–series of the European Commission and the Croatian Bureau of Statistics from January 2016 to December 2025. By applying the Granger causality test within the autoregressive distributed lag (ARDL) model, the time lag of the EEI effect was analysed, with a primary focus on forecasting the direction, rather than the intensity, of changes in the number of employees in a short period of two months. The modelling results indicate that the inclusion of the EEI variable, with a specification of up to and including two monthly lags, statistically significantly contributes to prognostic quality and improves prediction. Thus, the paper provides preliminary evidence of the predictive validity of this indicator and makes a scientific and applied contribution by designing a reliable analytical framework for macroeconomic planning and economic policymaking.

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Hybrid ARIMA–machine learning models for predicting inflation and economic growth in Nigeria

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SUMMARY

Accurate forecasting of inflation and economic growth remains a critical policy challenge for Nigeria, where volatile macroeconomic conditions, structural breaks, and persistent shocks have rendered traditional univariate methods increasingly unreliable. This paper develops and evaluates a family of hybrid ARIMA–machine learning models for predicting Nigeria's consumer price index (CPI) and gross domestic product (GDP) growth rates using monthly data from January 2010 to December 2024. The hybrid framework decomposes each series into a linear component captured by ARIMA and a nonlinear residual component captured by one of three machine learning algorithms, i.e. artificial neural network (ANN), support vector regression (SVR), and random forest (RF). Rolling–window out–of–sample experiments demonstrate that all hybrid models substantially outperform their standalone counterparts. The ARIMA–ANN hybrid achieves the lowest root mean square error (RMSE) of 0.324 for inflation forecasting, compared with 0.517 for standalone ARIMA and 0.468 for standalone ANN. For GDP growth, the ARIMA–RF hybrid achieves RMSE 0.187, a 34% improvement over ARIMA alone. Diebold–Mariano tests confirm that all forecast improvements are statistically significant at the 1% level. The results support hybrid modelling as a viable path toward more reliable macroeconomic forecasting in emerging economies characterized by structural instability and regime switching.

KEYWORDS

ARIMA, GDP growth, hybrid forecasting, inflation, machine learning

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1. Introduction

The Nigerian economy presents a uniquely challenging forecasting environment. As Africa's largest economy, with a gross domestic product exceeding $400 billion and a population of over 220 million, Nigeria's macroeconomic stability has broad regional significance. Yet the country's economic trajectory has been marked by extreme volatility. The oil price collapse of 2014–2016 triggered a severe recession, the COVID–19 pandemic produced unprecedented supply-chain disruptions, and the combined effects of foreign-exchange shortages and the

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removal of fuel subsidies in mid-2023 pushed headline inflation to three-decade highs exceeding 30% by late 2024. In this environment of recurrent structural breaks and regime shifts, traditional forecasting models that assume stable linear relationships have repeatedly failed to anticipate turning points or provide reliable policy guidance.

Autoregressive integrated moving average (ARIMA) models remain the workhorse of macroeconomic time-series forecasting owing to their simplicity, interpretability, and solid theoretical foundations (Kontopoulou et al., 2023). For Nigerian data, numerous studies have employed ARIMA frameworks with varying success (Ibrahim et al., 2023; Ikrimat et al., 2025; Yakubu et al., 2025). The fundamental limitation of ARIMA is its linearity: the model assumes that future values depend linearly on past values and past errors. This assumption fails when nonlinear dynamics, such as threshold effects, asymmetric shock responses, regime switching, become important. Inflation in Nigeria exhibits precisely these characteristics: positive supply shocks reduce prices gradually, whereas negative shocks trigger rapid, amplified responses through expectations and pricing power along supply chains.

Machine learning (ML) methods offer flexible nonlinear alternatives. Artificial neural networks (ANN) can approximate any continuous function (Awe & Dias, 2022), support vector regression (SVR) maps inputs into high-dimensional feature spaces where linear regression captures nonlinear patterns, and random forest (RF) aggregates decision trees to model interactions and threshold effects. However, ML methods require large training samples, are prone to overfitting, and sometimes perform worse than ARIMA when the underlying process is approximately linear.

Hybrid models combine the complementary strengths of both approaches. ARIMA captures the linear autocorrelation structure; the ML component captures residual nonlinear patterns. This two-stage strategy has been formalised in several recent reviews (Kontopoulou et al., 2023; Ashurova, 2025) and applied to Nigerian macroeconomic data by Ibrahim et al. (2025) and Dogra et al. (2025), among others. However, existing studies typically examine a single hybrid combination rather than systematically comparing multiple ML architectures, and few evaluate hybrid models on both inflation and output growth simultaneously.

This paper makes four contributions. First, we develop a unified hybrid framework combining ARIMA with three ML algorithms (ANN, SVR, RF), enabling direct comparison of their performance on Nigerian data. Second, we evaluate these models for both CPI inflation and GDP growth, providing a comprehensive assessment across different macroeconomic variables. Third, we implement a rigorous rolling-window evaluation that mimics real-time forecasting and assesses performance separately during crisis subperiods. Fourth, we conduct formal Diebold–Mariano tests of forecast superiority rather than relying solely on point comparisons of error metrics.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 describes the data and methodology. Section 4 presents and discusses the empirical results. Section 5 concludes.

2. Literature review and research gap

The application of ARIMA to Nigerian economic data has a long history, with surges of interest following the 2016 recession and the post–COVID inflationary episode. Nyoni & Nathaniel (2018) provided an early comprehensive analysis, documenting reasonable in-sample performance for 2010–2014 but increasing forecast errors as oil prices collapsed in

2015–2016. Ibrahim et al. (2023) jointly modelled CPI and the exchange rate, finding that an ARIMA(2,1,2) for CPI produced the best in-sample fit but showed systematic underprediction during the pandemic recovery. Guobadia et al. (2023) incorporated structural break dummies for the 2016 recession and the COVID shock, improving in-sample fit without significantly enhancing out-of-sample accuracy, because the timing of future breaks is inherently unknown.

More recent contributions confirm these patterns. Awogbemi et al. (2025) identified ARIMA(0,1,1) as optimal for Nigerian CPI and showed that forecast errors grow at an accelerating rate beyond a six-month horizon. Ikrimat et al. (2025) documented systematic bias in ARIMA inflation forecasts during periods of monetary policy changes, and Yakubu et al. (2025) concluded that ARIMA is useful for short-term forecasts but unreliable at longer horizons given Nigeria's volatility. For GDP, Bakawu et al. (2023) found that fuzzy ARIMA approaches offer some advantages, while Nwokike & Okereke (2021) showed that neural network specifications outperformed ARIMA during the volatile 2015–2020 period.

The application of ML to Nigerian macroeconomic forecasting is more recent but growing. Dogra et al. (2025) compared ANN, RF, gradient boosting, and SVR against ARIMA benchmarks, finding that ensemble methods achieved the lowest forecast errors. Crucially, however, they applied ML directly to raw data rather than to ARIMA residuals, which is less efficient when the series contains strong linear components. Tchoketch-Kebir & Madouri (2024) found that neural networks outperform ARIMA for highly nonlinear series but underperform for approximately linear ones, underscoring the case for hybrid models that can capture both aspects simultaneously.

The hybrid philosophy has been formalized theoretically through the Wold decomposition theorem: any stationary series is the sum of a deterministic linear component and an indeterministic component. ARIMA provides a parsimonious approximation to the linear component, when the residuals contain nonlinear structure (detectable by the BDS test), an ML model applied to those residuals can recover additional predictive information. Kontopoulou et al. (2023) synthesised this literature, concluding that hybrid models most outperform standalone methods when series exhibit both strong linear autocorrelation and significant nonlinear patterns; exactly the situation in Nigerian macroeconomic data. Ashurova (2025) and Ibrahim et al. (2025) confirm substantial hybrid-model improvements in emerging market contexts, with the largest gains at three-to-six-month horizons during turbulent periods.

Despite this growing body of work, three gaps remain. First, no study systematically compares ANN, SVR, and RF within the same hybrid ARIMA framework for Nigerian data. Second, the simultaneous evaluation of both inflation and GDP growth in a single hybrid framework is rare. Third, rigorous statistical testing of forecast superiority using the Diebold–Mariano procedure, with separate analysis of crisis subperiods, is largely absent from the Nigerian hybrid-forecasting literature. This paper addresses all three gaps.

3. Data and methodology

We employ monthly time-series data from January 2010 to December 2024 ($T = 180$ observations). The consumer price index (CPI) is obtained from the National Bureau of Statistics (NBS) of Nigeria (base year 2010 = 100). The annual inflation rate is:

$$\pi_t = \frac{\text{CPI}_t - \text{CPI}_{t-12}}{\text{CPI}_{t-12}} \times 100. \tag{1}$$

Year-over-year inflation is used because it eliminates the strong seasonal patterns present in month-over-month changes. The quarterly GDP series is also from NBS and is interpolated to monthly frequency using the Denton method, preserving quarterly totals. The monthly growth rate is:

$$g_t = \frac{\text{GDP}_t - \text{GDP}_{t-12}}{\text{GDP}_{t-12}} \times 100. \tag{2}$$

Shaded bands mark three crisis episodes (Figure 1): the oil-price collapse and recession (2015.5–2016.8), the COVID-19 pandemic (2020–2021), and the post-fuel-subsidy-removal inflationary surge (mid-2023 onward). Inflation regimes are clearly visible, while GDP shows sharp contractions at each major shock.

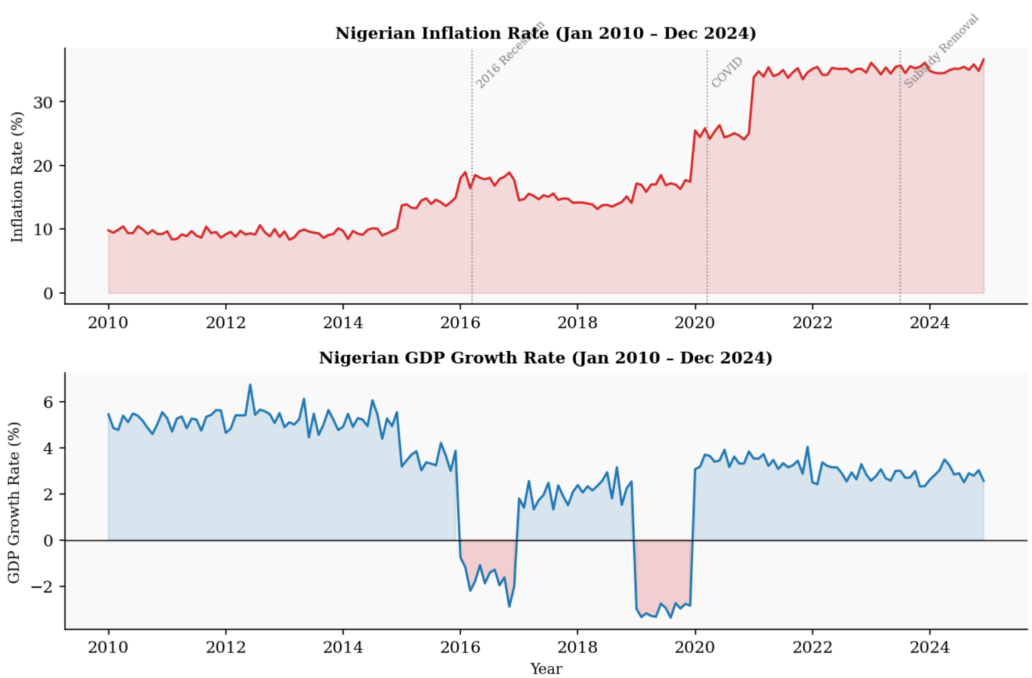

Figure 1. *Nigerian inflation (top) and GDP growth (bottom) from January 2010 to December 2024*

Table 1 presents summary statistics. The mean inflation of 12.47% is high by international standards; the range from 7.72 to 34.82% illustrates extreme volatility, with the maximum occurring in late 2024 following fuel-subsidy removal. Positive skewness (1.87) reflects asymmetric price dynamics. GDP growth averages 4.82%, with negative skewness (−1.23) indicating that contractions are more extreme than expansions. The Jarque–Bera test rejects normality for both series ($p < 0.001$).

Table 1. *Summary statistics of Nigerian inflation and GDP growth*

Statistic	Inflation rate (%)	GDP growth rate (%)
Mean	12.47	4.82
Median	11.85	4.91
Maximum	34.82	8.23
Minimum	7.72	−6.10
Standard deviation	5.63	2.94
Skewness	1.87	−1.23
Kurtosis	5.93	4.87
Jarque–Bera ($p-$value)	< 0.001	< 0.001
Observations	180	180

Further, stationarity is assessed with the Augmented Dickey–Fuller (ADF) test:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^{p} \delta_i \, \Delta y_{t-i} + \varepsilon_t. \tag{3}$$

For inflation the ADF statistic rejects the unit-root null at 5% without a trend but not with one, reflecting the 2016 structural break; we therefore model inflation in first differences ($d = 1$). GDP growth rejects the null at 1% with or without a trend, confirming stationarity ($d = 0$, though one difference is also applied for consistency). Seasonal adjustment with X-13-ARIMA-SEATS confirms significant harvest-related seasonality in inflation and quarter-end patterns in GDP, thus, seasonal components are included in all models.
For a series differenced d times to achieve stationarity, the ARIMA(p, d, q) model is:

$$\phi(B)(1 - B)^d y_t = \theta(B)\,\varepsilon_t, \tag{4}$$

where B is the backshift operator, $\phi(B) = 1 - \phi_1 B - \cdots - \phi_p B^p$ and $\theta(B) = 1 + \theta_1 B + \cdots + \theta_q B^q$ are the AR and MA polynomials, and $\varepsilon_t \sim (0, \sigma_\varepsilon^2)$ is white noise. Orders (p, d, q) are identified via the Box–Jenkins methodology (ACF/PACF inspection) and confirmed with the Akaike Information Criterion:

$$\text{AIC} = -2 \log L + 2k, \tag{5}$$

where L is the maximised likelihood and k is the number of estimated parameters.

For inflation, the selected model is a seasonal ARIMA$(2, 1, 1) \times (0, 1, 1)_{12}$:

$$(1 - \phi_1 B - \phi_2 B^2)(1 - B)(1 - B^{12}) y_t = (1 + \theta_1 B)(1 + \Theta_1 B^{12})\varepsilon_t. \tag{6}$$

For GDP growth, the best model is ARIMA$(0, 1, 1)$:

$$(1 - B) y_t = (1 + \theta_1 B)\varepsilon_t, \tag{7}$$

equivalent to exponential smoothing. Table 2 reports the estimated coefficients.

Table 2. *ARIMA parameter estimates*

Parameter	Inflation ARIMA$(2,1,1)_{12}$	GDP growth ARIMA$(0,1,1)$
ϕ_1	0.324 (0.087)***	—
ϕ_2	0.156 (0.092)*	—
θ_1	-0.412 (0.071)***	-0.587 (0.062)***
Θ_1 (seasonal MA)	-0.298 (0.083)***	—
σ^2_ε	4.231	2.874
AIC	783.4	652.1
BIC	802.7	664.9
Log-likelihood	-386.7	-323.0

Note: *** and * indicate significance at 1% and 10% level (standard errors in parenthesis).

Let $\hat{y}_t^{\text{ARIMA}}$ be the ARIMA fitted value and $e_t = y_t - \hat{y}_t^{\text{ARIMA}}$ be the residual. BDS tests on the residuals reject the i.i.d. null for inflation ($p = 0.004$) and give borderline rejection for GDP growth ($p = 0.055$), confirming nonlinear structure remains. The input feature vector for predicting e_t is:

$$\mathbf{x}_t = (e_{t-1}, \ldots, e_{t-L},\ y_{t-1}, \ldots, y_{t-L})^\top, \quad L = 6, \tag{8}$$

based on the autocorrelation structure of the residuals.

A feedforward network with $H = 8$ hidden units and hyperbolic tangent activation is:

$$h_j = \tanh\Big(\sum_{i=1}^{2L} w_{ji}^{(1)} x_i + b_j^{(1)}\Big), \quad j = 1, \ldots, H, \tag{9}$$

$$\hat{e}_t = \sum_{j=1}^{H} w_j^{(2)} h_j + b^{(2)}. \tag{10}$$

Training minimises the ℓ_2-penalised MSE $\mathcal{L}(\mathbf{w}) = T^{-1}\sum_t (e_t - \hat{e}_t)^2 + \lambda_{\text{ANN}}\|\mathbf{w}\|_2^2$ with $\lambda_{\text{ANN}} = 0.001$, using the Adam optimiser with early stopping (patience = 50 epochs).

The SVR minimises

$$\min_{\mathbf{w},b,\xi,\xi^*} \tfrac{1}{2}\|\mathbf{w}\|^2 + C\sum_{t=1}^{T}(\xi_t + \xi_t^*) \tag{11}$$

subject to ε-insensitive constraints. The radial basis function kernel $K(\mathbf{x}_i, \mathbf{x}_j) = \exp\big(-\|\mathbf{x}_i - \mathbf{x}_j\|^2/(2\sigma^2)\big)$ is used. Hyperparameters (C, ε, σ) are selected via grid search with 5-fold cross-validation; the optimal values for inflation are $(10,\ 0.05,\ 1)$ and for GDP growth $(1,\ 0.02,\ 2)$.

With respect to random forest (RF) an ensemble of $B = 500$ regression trees, each grown on a bootstrap sample; the prediction is:

$$\hat{e}_t = \frac{1}{B}\sum_{b=1}^{B} \hat{f}_b(\mathbf{x}_t). \tag{12}$$

At each split, $\lfloor 2L/3 \rfloor = 4$ features are randomly considered; minimum samples per leaf is 2.

The hybrid forecast is the additive combination:

$$\hat{y}_t^{\text{Hybrid}} = \hat{y}_t^{\text{ARIMA}} + \hat{e}_t^{\text{ML}}. \tag{13}$$

Stage 1 fits ARIMA on the training data and computes in-sample residuals; Stage 2 trains the ML model on those residuals. For multi-step horizons $h \in \{1, 3, 6, 12\}$ months, direct forecasting is used: a separate model is estimated for each h, avoiding error accumulation from recursive iteration.

A rolling-window scheme evaluates all models under realistic conditions. The initial training window is January 2010 to December 2019 (120 months); the test period is January 2020 to December 2024 (60 months). At each forecast origin the window rolls forward by one month, re-estimating all models with the most recent 60 months of data. This yields 60 one-month-ahead forecasts, decreasing to 49 twelve-month-ahead forecasts.

Seven models are compared: Naive (random walk), ARIMA, ANN (direct), SVR (direct), RF (direct), ARIMA-ANN, ARIMA-SVR, and ARIMA-RF. Forecast accuracy is measured by RMSE, MAE, and MAPE (inflation only). Statistical significance is assessed with DM test (Diebold & Mariano, 1995):

$$DM = \frac{\bar{d}}{\sqrt{\hat{\sigma}_d^2 / H}} \xrightarrow{d} \mathcal{N}(0,1), \tag{14}$$

where $d_t = L(e_t^{(1)}) - L(e_t^{(2)})$ is the loss differential under squared error loss, $\bar{d}$ is its sample mean, and $\hat{\sigma}_d^2$ is a HAC variance estimator.

4. Results and discussion

Table 3 reports diagnostic tests on the ARIMA residuals. The Ljung–Box tests do not reject the null of no autocorrelation at conventional levels, confirming that ARIMA has captured the linear dynamics. The Jarque–Bera test rejects normality for both series, and the BDS test rejects i.i.d. residuals for inflation at 1% and for GDP growth at 10%, establishing that nonlinear structure remains; the primary motivation for the ML component.

Table 3. *Diagnostic tests on ARIMA residuals*

Test	Inflation residuals	GDP growth residuals
Ljung–Box $Q(12)$	18.43 ($p = 0.071$)	15.21 ($p = 0.172$)
Ljung–Box $Q(24)$	32.17 ($p = 0.089$)	28.44 ($p = 0.164$)
Jarque–Bera	24.31 ($p<0.001$)	18.76 ($p<0.001$)
ARCH LM (lag 6)	12.34 ($p = 0.055$)	8.21 ($p = 0.224$)
BDS (dim. 2)	2.84 ($p = 0.004$)	1.92 ($p = 0.055$)

The ARCH LM result for inflation ($p = 0.055$) also suggests conditional heteroskedasticity, consistent with the volatility clustering, i.e. residuals are small during 2010–2014, amplify during the 2016 recession, contract in 2017–2019, and surge in 2023–2024. While GARCH extensions could model the variance dynamics, the present paper focuses on mean-forecast improvements through the hybrid approach.

According to Figure 2 ARIMA residuals retain a significant spike at the seasonal lag 12 (Ljung–Box $p < 0.001$), confirming residual nonlinear structure, whereas ARIMA-ANN hybrid residuals are indistinguishable from white noise (Ljung–Box $p = 0.41$). Dashed lines show the 95% confidence band $\pm 1.96/\sqrt{T}$.

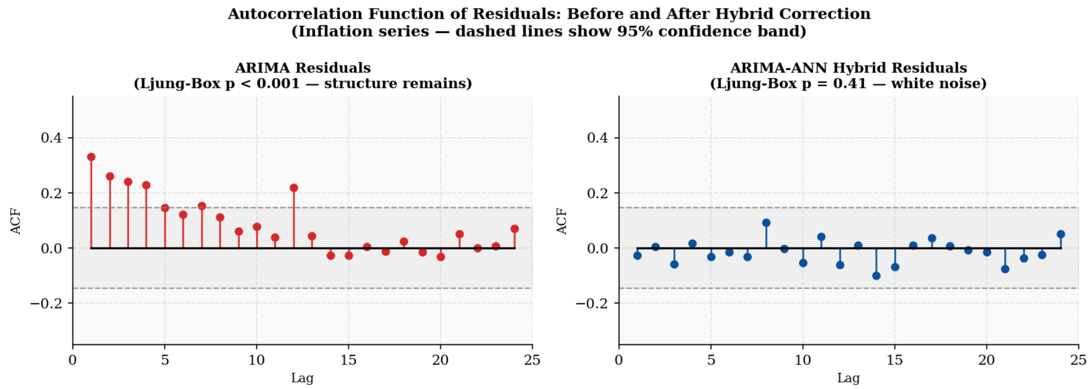

Figure 2. *Autocorrelation functions of model residuals for the inflation series*

Table 4 and Table 5 report rolling-window RMSE for inflation and GDP growth respectively (in percentage points), while Figure 3 and Figure 4 summarises the one-month-ahead results visually.

Table 4. *Out-of-sample RMSE for inflation forecasting*

Model	$h = 1$	$h = 3$	$h = 6$	$h = 12$
Naive (random walk)	0.542	0.612	0.687	0.742
ARIMA	0.517	0.584	0.651	0.718
ANN (direct)	0.468	0.541	0.623	0.695
SVR (direct)	0.489	0.562	0.638	0.704
RF (direct)	0.477	0.553	0.631	0.699
ARIMA-ANN	**0.324**	**0.387**	**0.456**	**0.523**
ARIMA-SVR	0.351	0.412	0.478	0.541
ARIMA-RF	0.338	0.396	0.462	0.534

Table 5. *Out-of-sample RMSE for GDP growth forecasting*

Model	$h = 1$	$h = 3$	$h = 6$	$h = 12$
Naive (random walk)	0.287	0.342	0.398	0.451
ARIMA	0.284	0.338	0.391	0.447
ANN (direct)	0.256	0.312	0.367	0.421
SVR (direct)	0.271	0.328	0.382	0.438
RF (direct)	0.261	0.318	0.374	0.429
ARIMA-ANN	0.198	0.243	0.297	0.354
ARIMA-SVR	0.212	0.256	0.312	0.368
ARIMA-RF	**0.187**	**0.231**	**0.284**	**0.342**

For inflation, ARIMA-ANN achieves a one-month-ahead RMSE of 0.324, which is 37% lower than ARIMA (0.517) and 31% lower than the best direct ML model (ANN, 0.468). The performance advantage persists at longer horizons: at $h = 12$, ARIMA-ANN (0.523) improves upon ARIMA (0.718) by 27%. For GDP growth, ARIMA-RF (0.187) reduces RMSE by 34% relative to ARIMA (0.284) and by 28% relative to direct RF (0.261). The naive random walk performs nearly as well as ARIMA for GDP growth, confirming that standalone ARIMA adds little beyond the simplest benchmark for this series, whereas the hybrid models still achieve large improvements.

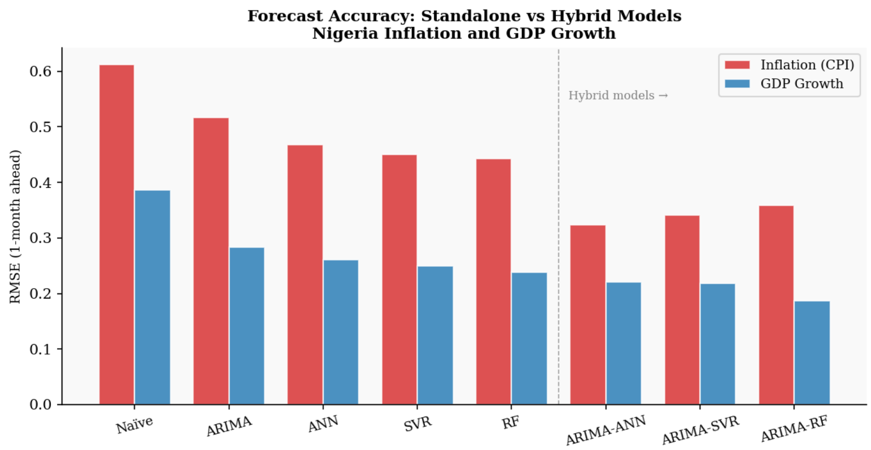

Figure 3. *One-month-ahead RMSE for all seven model specifications*

Red bars correspond to inflation forecasting; green bars to GDP growth forecasting. The dashed vertical line separates standalone models (left) from hybrid models (right). All three hybrid specifications outperform their standalone counterparts for both variables (Figure 3). Hybrid models (solid lines) maintain their advantage over standalone models (dashed lines) across all horizons, though the gap narrows slightly at $h = 12$ for GDP growth (Figure 4).

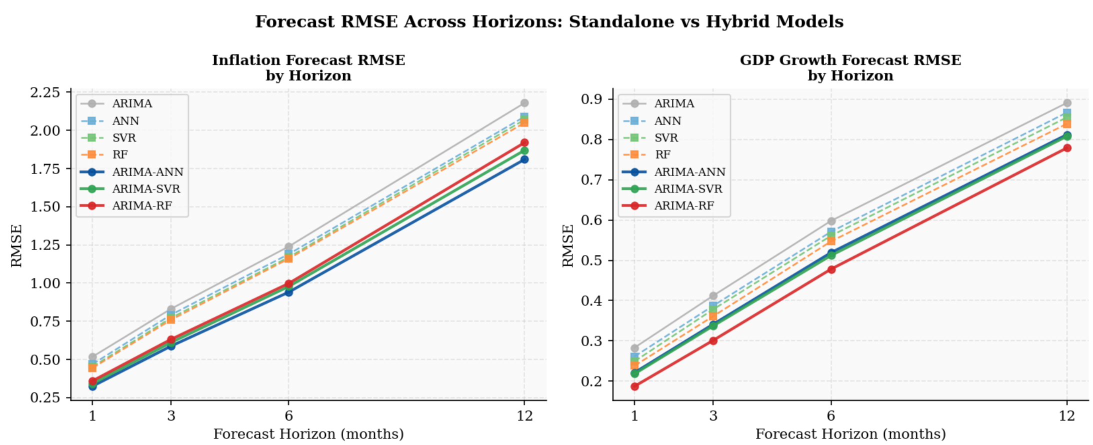

Figure 4. *RMSE by forecast horizon (*$h = 1, 3, 6, 12$ *months) for inflation (left) and GDP growth (right)*

The finding that optimal ML architectures differ between variables is theoretically instructive. Inflation exhibits smooth, persistent nonlinear dynamics, gradual expectation formation and asymmetric pass-through, that the universal approximation property of ANN captures efficiently. GDP growth exhibits more discrete regime-switching behaviour, sharp contractions followed by rapid recovery, that the partition-based structure of Random Forest handles naturally. Table 6 reports Diebold–Mariano statistics for one-month-ahead forecasts. Values to the left of the solid red line (-2.576) indicate rejection of equal forecast accuracy at the 1% level; values to the left of the orange dashed line (-1.960) indicate rejection at 5%. All statistics are significant at least at the 5% level (negative values indicate lower MSE for the hybrid model).

Table 6. *Diebold–Mariano test statistics (one-month-ahead horizon)*

Comparison	Inflation	GDP growth
ARIMA-ANN vs. ARIMA	-3.84^{***}	-3.12^{***}
ARIMA-ANN vs. ANN (direct)	-3.56^{***}	-2.98^{***}
ARIMA-ANN vs. RF (direct)	-3.41^{***}	-2.87^{**}
ARIMA-RF vs. ARIMA	-3.67^{***}	-4.23^{***}
ARIMA-RF vs. RF (direct)	-3.29^{***}	-3.91^{***}
ARIMA-RF vs. ANN (direct)	-3.48^{***}	-3.84^{***}
ARIMA-SVR vs. ARIMA	-2.84^{**}	-2.56^{**}

Note: *** and ** indicate significance at 1% and 5% level.

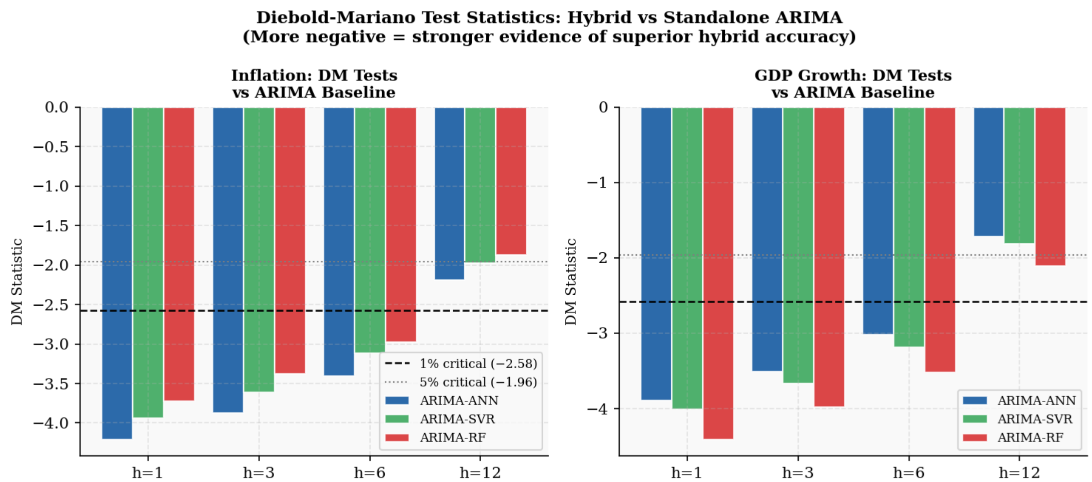

Figure 5. *Diebold–Mariano test statistics comparing selected hybrid models against benchmark models.*

All DM statistics are negative and significant at the 5% level or better, confirming that hybrid-model superiority is not attributable to sampling variation. The strongest evidence is for ARIMA-RF versus ARIMA for GDP growth ($DM = -4.23$, $p < 0.001$), reflecting the large and consistent RMSE reduction across rolling windows (Figure 5).

Table 7 disaggregates one-month-ahead RMSE across three subperiods: the COVID-19 pandemic (January 2020 – December 2021), the recovery period (January 2022 – April 2023), and the post-subsidy-removal period (May 2023 – December 2024).

Table 7. *One-month-ahead RMSE by crisis subperiod*

	Inflation		GDP growth	
Subperiod	ARIMA	ARIMA–ANN	ARIMA	ARIMA–RF
COVID (Jan 2020–Dec 2021)	0.641	0.398	0.367	0.231
Recovery (Jan 2022–Apr 2023)	0.487	0.291	0.281	0.172
Post-subsidy (May 2023–Dec 2024)	0.891	0.486	0.342	0.203

Figure 6 exhibits the comparative forecasting performance of the best-performing hybrid models, ARIMA–ANN for inflation and ARIMA–RF for GDP growth, with percentage improvements annotated above each pair of bars. The hybrid advantage is largest during the post-subsidy-removal period for inflation (-45%) and during the COVID period for GDP growth (-37%), precisely when nonlinear dynamics are most active.

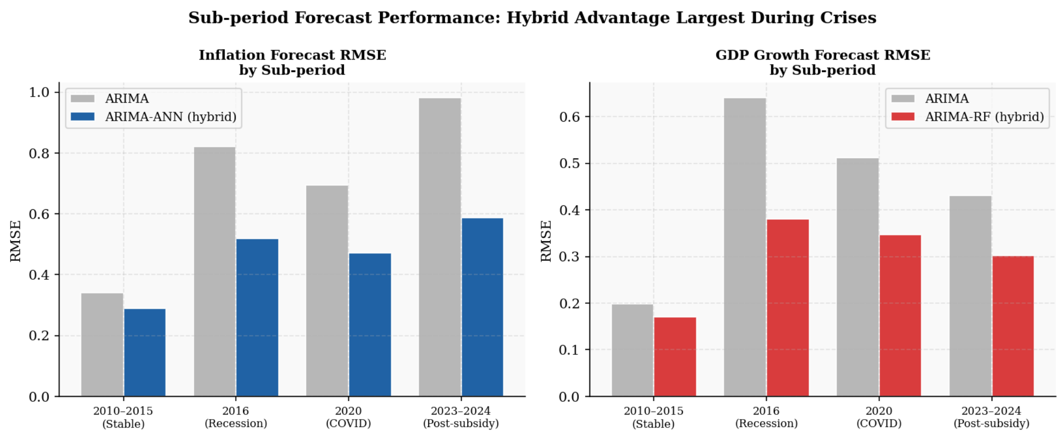

Figure 6. *Sub-period RMSE comparison: ARIMA (hatched bars) versus the best hybrid model (solid bars)*

The hybrid advantage is largest during the most turbulent periods. During the post-subsidy-removal surge, ARIMA's inflation RMSE reaches 0.891, almost double its full-period average, reflecting systematic underprediction as inflation leapt from 15% to over 35%. The ARIMA–ANN model contains this damage, achieving RMSE 0.486 (a 45% reduction). The COVID period shows the largest relative improvement for GDP growth (37%): the ARIMA model continued extrapolating pre–COVID trends through the April–June 2020 lockdowns, while the hybrid model's nonlinear component detected the regime change and partially corrected the forecast.

A sensitivity analysis varying the rolling-window length (48 and 72 months), re–estimating ARIMA orders at each window, and varying the lag depth from $L = 4$ to $L = 8$ shows that the baseline ARIMA-ANN one–month–ahead RMSE for inflation changes by no more than 0.02 percentage points in any configuration (range: 0.318–0.341), confirming robustness of the main conclusions to reasonable specification choices.

From a policy perspective, these results suggest that the Central Bank of Nigeria could improve real time inflation monitoring by implementing ARIMA–ANN forecasts, and that fiscal authorities could incorporate ARIMA–RF output–growth projections into budget preparation. That said, several limitations warrant caution. The analysis is univariate, incorporating exogenous predictors (oil prices, exchange rates, money supply) could further improve accuracy but requires their own forecasts. The ML components are partly black boxes; while partial dependence analysis confirms interpretable nonlinear patterns, mean–reversion in large ARIMA errors for inflation and asymmetric threshold effects for GDP growth, deeper explainability tools would strengthen policy communication. Finally, the models do not explicitly address conditional heteroskedasticity. A GARCH extension of the variance equation could complement the mean improvements documented here.

5. Conclusion

This paper developed and evaluated hybrid ARIMA–machine learning models for forecasting inflation and economic growth in Nigeria using monthly data from January 2010 to December 2024. The hybrid framework decomposes each series into a linear component (ARIMA) and a nonlinear residual component (ANN, SVR or RF), combining them additively. Rolling–window out–of–sample experiments demonstrate unambiguously that all three hybrid architectures outperform both standalone ARIMA and standalone ML models across every forecast horizon and every evaluation subperiod.

The ARIMA–ANN hybrid achieves the lowest inflation RMSE (0.324 at one month ahead), a 37% improvement over ARIMA and 31% over direct ANN. The ARIMA–RF hybrid achieves the lowest GDP growth RMSE (0.187), a 34% improvement over ARIMA. Diebold–Mariano tests confirm these gains are statistically significant at the 1% level. The performance advantage is largest during crisis episodes, the COVID–19 pandemic and the post–fuel–subsidy–removal inflationary surge, when forecast accuracy is most valuable for monetary and fiscal policy.

The practical implication is clear: hybrid modelling should become a standard tool for macroeconomic forecasting in emerging economies characterised by structural instability and nonlinear dynamics. Future research should extend the framework to multivariate settings, incorporate additional ML architectures such as gradient boosting and long short–term memory (LSTM) networks, and develop probabilistic hybrid forecasts that quantify uncertainty alongside point predictions.

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Hibridni ARIMA modeli strojnog učenja za predviđanje inflacije i gospodarskog rasta u Nigeriji

SAŽETAK

Točno predviđanje inflacije i gospodarskog rasta ostaje ključni izazov za ekonomsku politiku Nigerije, gdje su promjenjivi makroekonomski uvjeti, strukturne promjene i trajni šokovi učinili tradicionalne univarijatne metode sve nepouzdanijima. Ovaj rad razvija i ocjenjuje skupinu hibridnih ARIMA modela strojnog učenja za predviđanje stope inflacije i stope rasta BDP-a u Nigeriji koristeći mjesečne podatke od siječnja 2010. do prosinca 2024. Hibridni okvir rastavlja svaku seriju na linearnu komponentu koju bilježi ARIMA i nelinearnu komponentu reziduala koju bilježi jedan od tri algoritma strojnog učenja: umjetne neuronske mreže (ANN), potpornu vektorsku regresiju (SVR) i slučajnu šumu (RF). Eksperimenti izvan uzorka s pomičnim prozorom pokazuju da svi hibridni modeli znatno nadmašuju svoje samostalne inačice. Hibridni ARIMA–ANN postiže najnižu srednju pogreške (RMSE) od 0,324 za predviđanje inflacije, u usporedbi s 0,517 za samostalni ARIMA i 0,468 za samostalni ANN. Za rast BDP-a, hibridni ARIMA–RF postiže RMSE 0,187, što je poboljšanje od 34% u odnosu na samostalni ARIMA. Diebold–Mariano testovi potvrđuju da su sva poboljšanja prognoza statistički značajna na razini signifikantnosti od 1%. Rezultati podržavaju hibridno modeliranje kao održiv put prema pouzdanijem makroekonomskom predviđanju u gospodarstvima u razvoju koja karakterizira strukturna nestabilnost i promjene režima.

KLJUČNE RIJEČI

ARIMA, rast BDP-a, hibridno prognoziranje, inflacija, strojno učenje

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Entrepreneurship and aggregate productivity

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SUMMARY

This paper examines the contribution of entrepreneurial activity to aggregate productivity in eleven post–socialist new European Union member states over the period 2005–2019. Building on Baumol's distinction between productive and unproductive entrepreneurship, it addresses two questions: whether measures of entrepreneurial activity are correlated with aggregate productivity, and whether that correlation is positive or negative, thereby allowing productive and unproductive entrepreneurship to be distinguished empirically. Productivity is measured by GDP per person employed and GDP per hour worked, entrepreneurial activity by the Global Entrepreneurship Monitor's National Entrepreneurship Context Index, and the institutional environment by the burden of government regulation. Estimating a linear dynamic panel with a one–step generalized method of moments estimator, the analysis finds that the entrepreneurial environment is positively and significantly associated with both productivity measures, while a heavier regulatory burden is negatively associated with them. These results identify the prevailing entrepreneurship in the sample as productive in Baumol's sense. The contribution is twofold: conceptually, the paper offers a theory–to–measurement bridge for the Baumolian framework, and empirically, it documents the entrepreneurship–productivity nexus for a panel of new EU member states.

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Entrepreneurship, growth, institutions, political economy, productivity

Našao sam dobar band, želim samo da sviram, da se otkačim i to je sve
I found a good band, I just want to play to get away and that's all
(A šta da radim – Azra, 1979, Jugoton)

1. Introduction

Few questions in the economic theory have proved as durable, or as elusive, as the contribution of entrepreneurship to aggregate productivity. From Schumpeter (1934) onward, the entrepreneur has been depicted as the agent who pools resources around a new idea. He converts ideas into the new products, processes, and forms of organisation that raise total factor productivity. In a similar vein starting a band can be interpreted as the moment of

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the emergence of an entrepreneurial venture. All the elements are present: gathering a team, creating a new product, entering the market, taking risks and the uncertainty of success.

The interest for entrepreneurship–growth nexus has been propelled by endogenous-growth theory (Aghion & Howitt, 1992), the knowledge-spillover theory of entrepreneurship (Braunerhjelm et al., 2010) and the new institutional economics (North, 1990) which all, in their domain, restored the entrepreneur to the centre of the productivity debate. This study builds on Baumol's (1990) contribution who argued that entrepreneurial talent is present in roughly comparable measure across all societies but how that talent is allocated between productive, unproductive and destructive activities explains divergent productivity records among contemporary economies. Because this allocation is governed by the relative payoffs that prevailing institutions attach to each activity, the productivity question is reframed from one of quantity – how much entrepreneurship – to one of composition and quality – what kind of entrepreneurship a society's rules elicit.

The main goal of the paper is to empirically confirm the role of entrepreneurial activity on the aggregate level of productivity estimated by two measures: GDP per employed and GDP per hour worked. The observed sample includes 11 post-socialist new EU member states between 2005 and 2019. By focusing on aggregate (economy-level) productivity rather than firm-level performance as such positions the paper within competitiveness analysis literature in the field of contemporary political economy. Two research questions are set to be answered in the paper. First, is there a correlation between measures of the entrepreneurial activity and the aggregate level of productivity? Second, is the correlation statistically positive or negative, i.e. can we distinguish between Baumol's (1990) productive and unproductive entrepreneurial activities?

Contribution to the existing literature is twofold. Conceptually, the paper presents theory-to-measurement bridge aimed at the Baumol's approach to entrepreneurship. Empirically, it documents result for a EU member state panel on the effects of entrepreneurial activity on aggregate productivity levels.

The introduction is followed by a review of the theoretical foundations that connects theories on entrepreneurship and aggregate economic outcomes. Data and methodology are defined in the third section. In the fourth section, an empirical analysis was carried out and the research results were interpreted. The results and new findings are summarized in the conclusion section.

2. Theoretical foundations and literature review

This part synthesises the principal theoretical approaches to entrepreneurship and assesses what each implies for aggregate productivity. Three traditions are distinguished: (1) the Schumpeterian (innovation and creative destruction), (2) the Kirznerian (alertness and opportunity discovery) and (3) the Baumolian allocative account of productive, unproductive, and destructive entrepreneurship – together with their endogenous-institution extensions.

In the Schumpeterian (1934) account the entrepreneur is, above all, an innovator who accumulates profit as a reward for successful innovation. Crucially, the Schumpeterian entrepreneur is a disequilibrating force since innovation disturbs the circular flow and displaces less efficient incumbents through the process Schumpeter (1942) labels "creative destruction". Because profit is competed away as imitators enter, the link to productivity is direct and central: aggregate productivity increases due to superior combinations trumping inferior ones.

Aghion & Howitt (1992) formalise this idea of the creative-destruction within endogenous-growth models stating that the rate of productivity growth depends on the intensity of innovative entry. The knowledge–spillover theory of entrepreneurship (Braunerhjelm et al., 2010) casts entrepreneurship as the conduit that converts otherwise dormant knowledge into commercialised innovation and hence into measured productivity. Attractive as it may be, this approach marginalises the routine, imitative and allocative entrepreneurship that constitutes the bulk of business activity. The literature uses the existing classification into "Schumpeter Mark I" and "Schumpeter Mark II" entrepreneur (Henrekson et al., 2024) to determine which type of entrepreneurial activity matters. "Schumpeter Mark I" entrepreneur is a disruptive agent while "Schumpeter Mark II" entrepreneur emerges as his innovative activity is gradually phased out and replaced by routinized R&D processes in large corporations. Surveying more than 700 neo-Schumpeterian growth articles, Henrekson et al. (2024) show that the field overwhelmingly follows "Schumpeter Mark II" approach.

Within the same Austrian tradition of the school of economic thought, Kirzner (1973) casts entrepreneurs as agents characterised by alertness and opportunity discovery. Alertness – the propensity to notice unexploited profit opportunities – is often tied to arbitrage that corrects errors and improves market coordination. Hence, opportunities are discovered rather than created. One should note that Kirzner (2009) himself cautioned that Schumpeterian-versus-Kirznerian dichotomy is misleading since creative entrepreneur – at a higher level of abstraction – is also engaged in arbitrage. Thus, Schumpeterian creativity can be subsumed within the alertness that drives the market process as the main engine of economic growth. Productivity wise, the Kirznerian contribution is the elimination of waste and the improvement of resource allocation through superior information processing. The "opportunity" it foregrounds became the organising construct of an entire research programme in entrepreneurship studies (Shane & Venkataraman, 2000; Eckhardt & Shane, 2003). Disadvantages of this approach stem from the fact that alertness is difficult to operationalise and measure and that the Kirznerian framework speaks only indirectly to aggregate productivity. Jakee & Spong (2003) contend that alertness functions as an under–specified black box, that Kirzner's equilibrating account remains essentially deterministic and that it cannot on its own explain the genuinely creative innovation and endogenous change that the aggregate-productivity question ultimately requires.

Baumol (1990) shifts the analytical focus from the nature of the entrepreneur to the destination of entrepreneurial effort. Holding the supply of entrepreneurship talent roughly constant across societies, he argues that the productivity contribution of that effort varies with its allocation among productive activities (innovation, commerce), unproductive activities (rent-seeking, litigation, tax avoidance) and destructive activities (organised crime, predatory warfare). The allocation is determined by the structure of relative payoffs, which is in turn set by the prevailing institutions (North, 1990) that reward some channels and penalise others. The same basic logic was independently derived by Murphy et al. (1991), who showed that the allocation of talent responds to relative returns. While both the Schumpeterian and the Kirznerian frameworks are difficult to operationalise and to measure, the Baumolian framework forges an explicit link from institutions to aggregate productivity: productivity rises when institutions raise the relative payoff to productive entrepreneurship and stagnates when the rules reward predation. The rules are more tractable than the "spirit" of enterprise and the framework reconciles the available stack of entrepreneurial talent with the wide dispersion of growth outcomes.

The literature points to four critics regarding the usage of the Baumolian framework. First, it treats institutions as exogenous, thus defining productivity relative to a fixed institutional benchmark and abstracting from the evolution of standards over time (Douhan & Henrekson, 2010; Lucas & Fuller, 2017). Second, it abstracts from uncertainty and failure, assuming that entrepreneurs reliably capture the rewards their chosen channel offers (Foss & Klein, 2012). Third, the unproductive–destructive boundary is left under-defined and is frequently collapsed in practice (Desai & Acs, 2007). And fourth, the assumption of fixed supply is questionable once institutions are recognised to affect entry as well as direction. Building on the latter, entrepreneurs can act as "institution–makers" who may abide by the existing rules, evade them, or actively work to alter them in their favour (Henrekson & Sanandaji, 2011). Consequently, under second–best theory (Lipsey & Lancaster, 1956), seemingly "unproductive" or "destructive" actions can actually be welfare–improving (Douhan & Henrekson, 2010). With respect to the first critique, Acemoglu (1995) formalises the endogeneity of institutions directly, showing that reward structures can be self–reinforcing and that an economy may become trapped in a rent–seeking equilibrium from which it cannot easily escape. Building on that, Kalantaridis (2014) stresses the role of power and contestability in institutional change, while noting that the precise mechanism by which rules are transformed remains under-theorised.

With respect to our main goal and research questions, one can summarise the existing theoretical foundations into following: productive "altering" entrepreneurship can improve institutions and thereby raise the productivity ceiling, whereas unproductive altering can entrench low-productivity equilibria.

3. Data and methodology

Connecting theories to data requires a choice between two conceptions of entrepreneurship. The occupational view equates entrepreneurship with self–employment, business ownership or new-firm entry (as captured by indicators such as the Global Entrepreneurship Monitor's GEM total early–stage entrepreneurial activity rate) while the functional or behavioural view identifies it with Baumolian allocation. The literature confirms that self–employment and small–business rates are now widely regarded as poor proxies for the innovation–driven entrepreneurship that raises productivity (Henrekson & Sanandaji, 2014). However, there is no settled procedure for internationalizing Baumol's three types in the existing research. Composite constructs such as Net Entrepreneurial Productivity attempt to combine quantity and quality (Borozan et al., 2016), but without consensus.

In a nutshell, occupational indicators are widely available and internationally comparable but conflate productive and unproductive activity, while functional measures are theoretically apt but data–scarce and difficult to standardize across countries. The paper employs functional view and uses the GEM's National Entrepreneurship Context Index (NECI) as a measure of Baumolian entrepreneurship allocation. NECI is a composite indicator that summarises, in a single figure, the quality of the environment in which entrepreneurial activity takes place within a national economy. It is defined as the arithmetic mean of the scores assigned to a country's entrepreneurial framework conditions (Rietveld & Patel, 2023). Positive sign is expected for productive and negative sign for unproductive entrepreneurship. Destructive entrepreneurship is not expected and coded since the sample includes so called successful story countries of politico–economic transformation.

Table 1. *Data description and sources*

Variable	Label	Measure	Source	Expected sign
GDP per person employed	YPE	% of EU27, current prices	Eurostat	Dependent var.
GDP per hour worked	YPH	% of EU27, current prices	Eurostat	Dependent var.
Nat. Entrepreneurship Context Index	NECI	Index, [0:10]	GEM	+
Burden of gov. reg.	BGR	Index, [1:7]	WEF	−
Harmonised Index of Consumer Prices	INF	Annual avg. rate of change	Eurostat	+
Total employment (20–64)	EMPL	% of total population	Eurostat	−
Total population	POP	Persons, period average	WIIW	−
Countries' Exports to EU15	XEU15	Euro, mn	WIIW	+

Note: GEM is Global Entrepreneurship Monitor, WEF is World Economic Forum with respect to Global Competitiveness Report, and WIIW is Vienna Institute for International Economic Studies

Variable BGR – taken from the executive opinion survey of the yearly Global Competitiveness Report (WEF) – measures how burdensome it is for business to comply with governmental administrative requirements (Table 1). A BGR equal to 1 indicates that it is incredibly burdensome, and vice versa. The expected negative sign of BGR reflects that higher level of government regulation (lower value of BGR) results in a higher level of aggregate productivity. The paper employs this indicator as a measure of institutional quality.

This study includes four control variables in the model: inflation and employment rate, population and country's export to the EU15. With both dependent variables measured per person employed and per hour worked employment and population is expected to have a negative sign, while inflation a positive sign. A positive sign for variable XEU15 is expected because the economies of the new EU member states are part of the global value chains owned by the EU15 member states. Their demand actually translates into new EU member states exporting toward the old EU, comprised of EU15 member states. Time period is constrained due to data availability (WEF changed their report after Covid–19 pandemic) hence covering 2005–2019 while the sample consists of a relatively homogenous group of post-socialist countries that differ in their size, but share a common "path dependency" in the last three decades.

Using the data described above, we estimate the following relationship:

$$\begin{aligned} \mathrm{YPE}_{i,t} = \beta_0 + \beta_1\,\mathrm{YPE}_{i,t-1} + \beta_2\,\mathrm{XEU15}_{it} + \beta_3\,\mathrm{POP}_{it} + \beta_4\,\mathrm{NECI}_{it} \\ + \beta_5\,\mathrm{BGR}_{it} + \beta_6\,\mathrm{INF}_{it} + \beta_7\,\mathrm{EMPL}_{it} + \varepsilon_{i,t}. \end{aligned} \tag{1}$$

The paper employs a linear dynamic panel model based on the one-step generalized method of moments (GMM) estimator proposed by Arellano & Bond (1991). The baseline dynamic model can be written as:

$$y_{it} = \gamma\, y_{i,t-1} + \mathbf{x}'_{it}\boldsymbol{\beta} + \alpha_i + \varepsilon_{it}, \quad i = 1, \ldots, N, \quad t = 1, \ldots, T, \tag{2}$$

where y_{it} is the dependent variable, $y_{i,t-1}$ is its lagged value, $\mathbf{x}_{it}$ is a vector of explanatory variables, α_i is a time–invariant country–specific effect, and ε_{it} is the error term. In this setup the dependent variable y_{it} is correlated directly with $y_{i,t-1}$ and indirectly with α_i. If we consider the OLS estimation then the error term $u_{it} = \alpha_i + \varepsilon_{it}$ is correlated with the regressor $y_{i,t-1}$, which violates $\text{Cov}(y_{i,t-1}, u_{it}) = 0$, so OLS will not be consistent, i.e. $\text{Cov}(y_{i,t-1}, u_{it}) \neq 0$. This is different from the static random–effect model where pooled OLS approach estimate β consistently if the regressor is uncorrelated with the error term. Inconsistency is still present in the within–group estimator which eliminates the time–invariant individual effects, however the regressor $(y_{i,t-1} - \bar{y}_i)$ is correlated with the error term $(\varepsilon_{it} - \bar{\varepsilon}_i)$. Random-effect estimators which can be understood as a weighted combination of the within and between estimators are also inconsistent. Lastly, first differences OLS estimator is also inconsistent since lagged differenced dependent variable $\Delta y_{i,t-1} = y_{i,t-1} - y_{i,t-2}$ contains the $\varepsilon_{i,t-1}$ that is included in $y_{i,t-1}$, therefore $\text{Cov}(\Delta y_{i,t-1}, \Delta\varepsilon_{it}) \neq 0$ (Cameron & Trivedi, 2005).

For that reason Bond (2002) highlights that including one or more lags of the dependent variable significantly affects the consistent assessment of other parameters in the model, while Baltagi (2008) advises using dynamic panel analysis whenever the dependent variable's current value depends on its previous values. Arellano & Bond (1991) propose using the GMM estimator (instead of least squares estimators) if the model includes a lagged dependent variable, in which case the first-differences model:

$$y_{it} - y_{i,t-1} = \gamma(y_{i,t-1} - y_{i,t-2}) + (\mathbf{x}_{it} - \mathbf{x}_{i,t-1})'\boldsymbol{\beta} + (\varepsilon_{it} - \varepsilon_{i,t-1}), \quad t = 2, \ldots, T, \tag{3}$$

can be estimated using instrumental variables. According to Anderson & Hsiao (1981) a good instrument for the regressor $\Delta y_{i,t-1}$ is $y_{i,t-2}$ or $\Delta y_{i,t-2}$. They satisfy both conditions necessary for the validity of the instrument. Neither of them is correlated with the error term, $E[\Delta y_{i,t-2}\, \Delta\varepsilon_{it}] = E[y_{i,t-2}\, \Delta\varepsilon_{it}] = 0$, thereby satisfying the condition of orthogonality. However, both of them are correlated with the regressor, $E[\Delta y_{i,t-2}\, \Delta y_{i,t-1}] = E[y_{i,t-2}\, \Delta y_{i,t-1}] \neq 0$, satisfying the condition of relevance. Arellano & Bond (1991) extend this approach by using all valid lags of the dependent variable as instruments for the lagged dependent variable in the first-differenced equation. Therefore, the moment conditions can be written as:

$$E[y_{i,t-s}\, \Delta\varepsilon_{it}] = 0, \quad s \geq 2. \tag{4}$$

Thus as the number of lags grows the number of available instruments increases. Therefore, we would have more instruments than endogenous regressors so the model is overidentified and can be estimated using panel GMM (Cameron & Trivedi, 2005; Hansen, 2022).

The GMM estimator can be expressed as:

$$\hat{\boldsymbol{\theta}}_{\text{GMM}} = \left(\Delta\mathbf{X}'\mathbf{Z}\, W_n\, \mathbf{Z}'\Delta\mathbf{X}\right)^{-1} \Delta\mathbf{X}'\mathbf{Z}\, W_n\, \mathbf{Z}'\Delta\mathbf{y}; \quad \boldsymbol{\theta} = (\gamma, \boldsymbol{\beta})'. \tag{5}$$

Here $\Delta\mathbf{X}$ is the matrix of first–differenced regressors, $\Delta\mathbf{y}$ is the vector of first–differenced dependent-variable observations, $\mathbf{Z}$ is the matrix of instruments and W_n is a weighting matrix. The main advantage of Arellano–Bond estimator is that asymptotic variance of the estimated coefficients can be reduced and the stability of the estimator can be improved by using additional moment conditions. However, if we use too many instruments then we might encounter the weak instrument problem, so the number of used lags should be limited especially if T is relatively large. Additionally, the one-step Arellano–Bond estimator performs well in the small or moderate size samples when errors are approximately homoscedastic. That is because the one-step weight matrix does not depend on residuals and it is therefore less random than the two-step weight matrix (Cameron & Trivedi, 2005; Hansen, 2022).

Since the model is overidentified, the validity of instruments is tested using the Sargan or Hansen test of overidentifying restrictions. The null hypothesis is testing whether the orthogonality conditions are satisfied, where instruments are uncorrelated with the error term and that the moment conditions are correctly specified. Therefore, failure to reject its null hypothesis provides support for validity of the selected instruments, whereas rejection indicates that at least some instruments may be endogenous or that the model is incorrectly specified. Another important specification check is the Arellano–Bond test for the presence of second–order autocorrelation in the first–differenced residuals. If the second–order correlation is present then the lagged levels used as instruments are correlated with the transformed error term. This would invalidate the corresponding moment conditions and could produce biased estimates (Cameron & Trivedi, 2005; Hansen, 2022).

Both tests were conducted and the null hypothesis of the Sargan test was not rejected, indicating that the selected instruments were jointly valid. Similarly, the null hypothesis of no second-order serial correlation was not rejected, supporting the validity of the lagged instruments used in the estimation.

4. Results and discussion

This section reports summary statistics and the results of four dynamic panel models designed to identify the effect of entrepreneurship on aggregate level of productivity for 11 post–socialist new EU member states. Beyond identifying entrepreneurial and institutional factors associated with aggregate productivity, the paper evaluates the soundness of the Baumolian approach in the observed sample from 2005 till 2019.

Summary statistics is presented in Table 2 and it indicates that the mean values of aggregate measures of productivity – YPE and YPH – are approximately 2/3 of the EU average while both of our main explanatory variables – NECI and BGR – are below average levels. Control variables – EMPL, INF and XEU15 – point to expected mean values in line with a relatively smooth post-transitional period that overlapped with their successful EU accession. More importantly, all of the control variables – including POP that we used to control for various size of countries within the sample – yielded expected signs in line with the standard economic theory as evident from Table 3.

Table 2. *Descriptive statistics*

Variable	Obs	Mean	Std. Dev.	Min	Max
YPE	165	68.22	12.31	36.6	87.9
YPH	165	61.48	12.02	32.7	84.2
NECI	94	4.37	0.36	3.45	5.41
BGR	165	2.95	0.55	1.9	4.47
EMPL	121	68.59	6.16	53.9	80.5
INF	165	2.79	2.66	-1.6	15.3
POP	165	9.46	10.48	1.31	38.18
XEU15	165	28.53	31.76	1.79	148.41

Source: authors' calculation.

Table 3 documents the result of the conducted empirical exercise and provides answers to our research questions. First, entrepreneurial activity is confirmed to have a statistically significant correlation with both measures of aggregate productivity. The environment in which entrepreneurial activity takes place has a positive effect on the level of GDP per employed and per hour worked. In addition to that, our measure of institutions – burden of government regulation – is also significantly correlated with aggregate productivity with an expected negative sign. The role of the government is often contra-intuitive to the needs and wants of entrepreneurs and its second-best public policies (Lipsey & Lancaster, 1956) are often viewed as burdensome if one takes an individual as opposed to socially maximizing approach. Nonetheless, the chosen sample of countries guarantees a sound institutional framework under the EU umbrella. Estrin et al. (2013) demonstrate across a large set of (transition) countries that institutional quality shapes not merely the rate of entrepreneurship but entrepreneurial growth aspirations – the margin most relevant to productivity. As observed from Table 2 all measures of productivity and entrepreneurship were within first three quartiles of distribution which is in line with Borozan et al. (2016) who report that Net Entrepreneurial Productivity is systematically lower in post-transition than in developed economies, consistent with an institution-driven account of the allocation of talent.

Table 3. *Results of the panel model estimation*

	Model 1 (YPE)	Model 2 (YPE)	Model 3 (YPH)	Model 4 (YPH)
L.YPE	0.81^{***}	0.71^{***}		
	(0.06)	(0.08)		
L.YPH			0.75^{***}	0.65^{***}
			(0.06)	(0.09)
POP	-6.70171^{***}	-16.14461^{***}	-5.48024^{***}	-11.32332^{***}
	(1.71101)	(4.47089)	(1.56159)	(4.05028)
XEU15	0.03^{*}	0.06^{**}	0.03^{*}	0.05^{**}
	(0.02)	(0.02)	(0.02)	(0.02)
INF	0.28^{***}	0.29^{***}	0.20^{**}	0.22^{**}
	(0.10)	(0.11)	(0.09)	(0.11)
EMPL	-0.08	-0.27^{***}	-0.03	-0.17^{**}
	(0.05)	(0.08)	(0.05)	(0.07)
BGR		-2.45^{***}		-2.77^{***}
		(0.82)		(0.81)
NECI		2.24^{**}		2.30^{**}
		(0.95)		(0.96)
Constant	80.81^{***}	178.71^{***}	68.18^{***}	131.38^{***}
	(19.56)	(45.36)	(17.76)	(40.32)
Sargan test	122.2	58.7	127.1	60.7
χ^2	482.07	190.61	396.46	114.63
z-rank	111	69	111	69

Note: ***, ** and * indicate significance at 1%, 5% and 10% level (standard errors in parentheses).
Source: authors' calculation.

The results also enabled us to successfully distinguish between Baumol's (1990) productive and unproductive entrepreneurial activities in our sample – an answer to our second research question. A positive sign points to the productive entrepreneurship which clearly adds to the existing literature. The canonical empirical test of the Baumolian thesis is Sobel (2008), who shows for US states that higher institutional quality is associated with more productive and less unproductive entrepreneurship. On cross-country samples, Bowen & De Clercq (2008) find that the institutional context shapes the allocation of entrepreneurial effort towards high-growth activity, while Stenholm et al. (2013) show that institutional arrangements influence both the rate and the type of entrepreneurial activity. Levie & Autio (2008), testing the GEM model, confirm that institutional conditions are an important determinant of entrepreneurial entry. The pattern is consistent: where entrepreneurship is measured in a way that captures its productive component, the institutional channel to productivity is visible.

Although our dependent variables were focused at productivity, the results are in line with studies that looked at the standard measures of economic success. Bosma et al. (2018) document for a panel of European countries and regions that institutional quality, operating through productive entrepreneurship, positively affects growth in GDP per capita. Earlier European evidence in Carree & Thurik (1998) linked small–firm and entrepreneurial activity to growth across EU economies. To sum it all up, the European evidence converges on a qualified endorsement of the Baumolian–institutional account: institutions shape the type (productive versus unproductive) of entrepreneurship. Through the productive component they influence aggregate productivity. As the systematic review by Aeeni et al. (2019) documents, the literature remains dominated by macro, country–level analyses, with scarce evidence at the individual and within-industry levels. Also, as a necessary caveat one needs to emphasise that although institutions plausibly affect growth through entrepreneurship, the direction of causality and the specific institutional channels at work remain open questions (Urbano et al., 2019).

5. Conclusion

The epigraph that opens this paper – a musician who has "found a good band" and "just wants to play" – captures the intrinsic impulse that animates much of the entrepreneurial activity. Yet, as the analysis argues, whether such "playing" raises a society's productivity depends less on the impulse itself than on the institutional stage on which it is performed. With respect to the available entrepreneurial talent it is the relative payoff that prevailing rules attach to productive as opposed to unproductive activity that matters. The contribution of starting a band or a firm to aggregate productivity is therefore conditional on the incentives that channel that effort.

Estimating a dynamic panel for eleven post-socialist new EU member states between 2005 and 2019, the paper documents an affirmative answer to the first research question: the quality of the entrepreneurial environment, captured by NECI, is significantly associated with both GDP per person employed and GDP per hour worked. The sign of that association answers the second research question: it is positive, indicating that the entrepreneurship prevailing in these economies is productive in Baumol's sense, while a heavier burden of government regulation is, as expected, negatively associated with productivity.

This paper contributes to the literature in two respects. Conceptually, it uses a composite indicator of entrepreneurial framework conditions as a proxy for the institutional allocation of entrepreneurial effort hence building a theory to measurement bridge that renders the Baumolian framework operational. Empirically, it adds panel evidence from a relatively homogeneous group of new EU member states, complementing the existing studies.

Several limitations temper these conclusions. The results are associational rather than causal and NECI is an imperfect proxy for Baumolian allocation. The sample period, constrained by data availability, ends before the disruptions of the subsequent years and a macro panel cannot capture the within-country and within-industry heterogeneity that might yield interesting scientific and public policy insights.

Future research could draw on firmer identification strategies and on disaggregated, individual– and industry–level data to separate productive from unproductive entrepreneurship more sharply. An interesting avenue might look at a possible confirmation of whether the relationship is stable across the business cycle in the longer time period at this level of aggregation. For economic policy, the results reinforce a familiar message since raising aggregate productivity is less a matter of stimulating the quantity of entrepreneurship. The only game in town is improving the institutional environment in which entrepreneurship takes place: strengthening the framework conditions that tilt the relative payoff toward productive activity.

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Poduzetništvo i agregatna produktivnost

SAŽETAK

Rad istražuje doprinos poduzetničke aktivnosti agregatnoj produktivnosti u jedanaest novih postsocijalističkih država članica Europske unije u razdoblju od 2005. do 2019. godine. Oslanjajući se na Baumolovo razlikovanje produktivnoga i neproduktivnoga poduzetništva, rad razmatra dva pitanja: jesu li mjere poduzetničke aktivnosti korelirane s agregatnom produktivnošću te je li ta korelacija pozitivna ili negativna, čime se omogućuje empirijsko razlikovanje produktivnoga i neproduktivnoga poduzetništva. Produktivnost se mjeri BDP–om po zaposlenoj osobi i BDP-om po satu rada, poduzetnička aktivnost indeksom nacionalnoga poduzetničkog konteksta NECI (engl. *National Entrepreneurship Context Index*) iz baze GEM (engl. *Global Entrepreneurship Monitora*), a institucionalno okruženje opterećenjem državnom regulacijom BGR (engl. *Burden of Government Regulation*). Procjenjujući linearni dinamički panel model, analiza pokazuje da je poduzetničko okruženje pozitivno i statistički značajno povezano s objema mjerama produktivnosti, dok je veće regulatorno opterećenje s njima negativno povezano. Dobiveni rezultati prevladavajuće poduzetništvo u uzorku identificiraju kao produktivno u Baumolovu smislu. Doprinos rada je dvojak: na konceptualnoj razini rad nudi most između teorije i mjerenja potrebnih za utvrđivanje postojanja Baumolovog okvira, a na empirijskoj razini dokumentira vezu između poduzetništva i produktivnosti na panelu novih država članica EU–a.

KLJUČNE RIJEČI

Poduzetništvo, rast, institucije, politička ekonomija, produktivnost

VRSTA ČLANKA
Izvorni znanstveni članak

INFORMACIJE O ČLANKU
Primljeno: 11. lipnja 2026.
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JEL: C33, L26, O47

Croatian Statistical Association

Croatian Statistical Association (CSA) is a nonprofit organization established in 2005, and since 2015, it has been actively operating. Until the end of 2023, CSA had more than 80 dedicated members, who are engaged in the promotion, dissemination and popularisation of statistics. Our association fosters a collaborative environment, focusing on the exchange of ideas, knowledge, and experiences among members and colleagues.

We greatly value our partnerships with related societies such as the Croatian Operational Research Society, Croatian Biometric Society, and Slovensko Društvo Informatika as well as the Federation of European National Statistical Societies FENStats. The International Statistical Conference in Croatia (ISCCRO) is the major biennial event organized by CSA.

Workshops and panel discussions, organized within specialized sections "Women in Statistics", "Statistics in Sport" and "R Club", play a vital role in achieving the objectives of our society. We are most proud of our CREBSS journal (Croatian Review of Economic, Business and Social Statistics), which serves as a platform for scholarly discourse and research publication in the field of theoretical and applied statistics.

If you are a researcher, academic, student or practitioner interested in developing and applying statistical methods, you are welcome to join our community. If you want to become a member of the CSA, please submit the web application form.

Former Presidents: Anita Čeh Časni, University of Zagreb (2023 – 2025)

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Hrvatsko statističko društvo

Hrvatsko statističko društvo (HSD) je neprofitna organizacija osnovana 2005. godine, a od 2015. godine aktivno djeluje. Do kraja 2023. godine HSD broji više od 80 posvećenih članova koji se bave promicanjem, širenjem i popularizacijom statistike. Naše udruženje potiče suradničko okruženje, fokusirajući se na razmjenu ideja, znanja i iskustava među članovima i kolegama.

Izuzetno cijenimo naše partnerstvo s povezanim društvima kao što su Hrvatsko društvo za operacijska istraživanja, Hrvatsko biometrijsko društvo i Slovensko društvo Informatika, kao i s Federacijom europskih nacionalnih statističkih društava FENStats. Međunarodna statistička konferencija u Hrvatskoj (ISCCRO) je glavni dvogodišnji događaj koji organizira HSD.

Radionice i panel diskusije, organizirane unutar specijaliziranih sekcija "Žene u statistici", "Statistika u sportu" i "Klub R", igraju vitalnu ulogu u postizanju ciljeva našeg Društva. Najviše smo ponosni na naš časopis CREBSS (Hrvatska revija ekonomske, poslovne i društvene statistike), koji služi kao platforma za znanstveni diskurs i objavljivanje istraživanja u području teorijske i primijenjene statistike.

Ako ste istraživač, akademski djelatnik, student ili praktičar zainteresiran za razvoj i primjenu statističkih metoda, dobrodošli ste pridružiti se našoj zajednici. Ako želite postati HSD članom, molimo vas da ispunite web pristupnicu.